DEVELOPMENT OF FRAMEWORK FOR QUANTUM THEORY BASED IMAGE REPRESENTATION, ACTIVITY RECOGNITION AND BIG DATA ANALYSIS

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DOCTOR OF PHILOSOPHY

BARKHA SINGH

(Roll No. 2K21/PHDEC/04)

Under the Supervision of

Prof. S. Indu
Professor
Department of Electronics and Communication Engineering
Delhi Technological University, Delhi–110042

Co-Supervisor

Prof. Sudipta Majumdar
Professor
Department of Electronics and Communication Engineering
Delhi Technological University, Delhi-110042



Department of Electronics and Communication Engineering

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi–110042, India

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Barkha Singh

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

CANDIDATE'S DECLARATION

I, **Barkha Singh**, certify that the work which is being presented in the thesis entitled **"Development of Framework for Quantum Theory Based Image Representation, Activity Recognition and Big Data Analysis"** in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy, submitted in the Department of Electronics and Communication Engineering, Delhi Technological University, is an authentic record of my own work carried out during the period from **July 2021 to July 2026** under the supervision of **Prof. S. Indu and Prof. Sudipta Majumdar**.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute/University.

Date:15-10-2026

BARKHA SINGH

(Roll. No. 2K21/PHDEC/04)

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisors

Signature of External Examiner

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

CERTIFICATE BY THE SUPERVISOR(S)

Certified that **Mrs. Barkha Singh (Enrolment No. 2K21/PHDEC/04)** has carried out her research work presented in this thesis entitled: **"Development of Framework for Quantum Theory Based Image Representation, Activity Recognition and Big Data Analysis"** for the award of the degree of **Doctor of Philosophy** from the **Department of Electronics and Communication Engineering, Delhi Technological University, Delhi**, under our supervision. The thesis embodies the results of original work carried out by the student herself under our guidance and supervision. To the best of our knowledge and belief, the work presented in this thesis has not been submitted, either in part or in full, for the award of any other degree, diploma, or fellowship of this or any other University/Institute. The contents of this thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

Prof. S. Indu
Supervisor
Professor
Department of Electronics and Communication Engineering
Delhi Technological University
Delhi – 110042

Prof. Sudipta Majumdar
Co-Supervisor
Professor
Department of Electronics and Communication Engineering
Delhi Technological University
Delhi – 110042

Place and Date: DELHI 15-10-2026

ABSTRACT

This thesis presents the development and evaluation of Hybrid Quantum–Classical computational frameworks for Quantum Theory-Based Image Representation, Human Activity Recognition, and Big Data Analytics by integrating Quantum Computing and Quantum Machine Learning techniques. The research investigates the applicability of quantum computational models for intelligent data processing and develops efficient frameworks capable of addressing challenges related to high-dimensional data representation, feature extraction, classification, optimisation, and large-scale data analysis. The proposed research combines a systematic review of existing quantum methodologies with the development and comparative evaluation of quantum-assisted computational models to establish scalable and efficient solutions for next-generation intelligent computing applications.

The exponential growth of digital information generated through imaging systems, multimedia platforms, sensor networks, smart devices, and large-scale data-driven applications has created significant challenges for conventional computational frameworks. Modern applications involving image representation, activity recognition, artificial intelligence, and big data analytics require efficient processing of high-dimensional data, rapid decision-making, and scalable computational architectures. Traditional machine learning and data analysis techniques often encounter limitations related to computational complexity, feature representation, scalability, and processing efficiency when dealing with large and heterogeneous datasets. Quantum Computing has emerged as a promising paradigm capable of addressing these challenges by exploiting the principles of quantum mechanics, including superposition, entanglement, interference, and quantum parallelism. These unique properties provide new opportunities for developing advanced computational models capable of processing information more efficiently than classical approaches.

The first part of the research focuses on the development of quantum-assisted image representation and image processing methodologies. Various concepts of Quantum Image Processing (QIP), including quantum image representation models,

quantum feature encoding mechanisms, and quantum state-based image analysis techniques, are investigated for efficient representation and processing of visual information. The study explores the utilization of quantum feature spaces for representing image characteristics and investigates the effectiveness of Quantum Machine Learning models for image classification and pattern recognition. Hybrid quantum-classical architectures based on Quantum Support Vector Machines, quantum kernel methods, and variational quantum circuits are designed and evaluated to improve feature extraction and classification performance. Experimental investigations demonstrate that quantum-assisted image representation techniques can effectively handle high-dimensional image data while providing competitive classification accuracy and computational advantages over conventional approaches.

The second part of the research addresses Human Activity Recognition as a relevant application area of Quantum Machine Learning. The discussion examines the potential use of quantum feature mapping, quantum classification, and hybrid quantum–classical learning approaches for analysing high-dimensional and sensor-derived activity data. These approaches are considered in relation to their ability to represent activity-related features and support classification and pattern-recognition tasks. However, the present thesis does not claim an independently experimentally validated quantum-assisted activity-recognition framework. Activity recognition is therefore positioned as a related application domain and a potential direction for extending the quantum learning frameworks investigated in this research.

The third part of the research focuses on quantum-enhanced big data analysis. The increasing volume, velocity, and variety of data generated across multiple domains have exposed significant limitations in conventional analytical techniques. To overcome these challenges, this research develops a quantum-assisted big data analytics framework based on Quantum Machine Learning and quantum optimization techniques. The proposed framework integrates quantum feature encoding, quantum kernel learning, and quantum optimization strategies for classification, feature selection, clustering, and predictive analytics. Experimental evaluations indicate improved scalability, faster convergence characteristics, and enhanced analytical performance when compared with traditional machine learning approaches, thereby

demonstrating the potential of quantum computing for next-generation data analytics.

A significant contribution of this research lies in the design and implementation of Hybrid Quantum–Classical computational frameworks suitable for current Noisy Intermediate-Scale Quantum (NISQ) devices. The developed methodologies incorporate efficient quantum data encoding schemes, parameterized quantum circuits, quantum feature mapping techniques, and classical optimization mechanisms to achieve practical and scalable implementations. The proposed approaches are evaluated through extensive simulations and experimental studies using contemporary quantum computing platforms and software frameworks.

The outcomes of this research establish the analytical and framework-level applicability of quantum computing techniques to image representation, image processing and classification, and Big Data analytics, while identifying activity recognition as a related application domain for future extension. The proposed frameworks contribute to the advancement of Quantum Machine Learning and Quantum Information Processing by providing scalable, efficient, and intelligent computational solutions for handling complex data-intensive applications. The findings of this work are expected to facilitate future research in quantum-enabled intelligent systems and support the practical deployment of quantum technologies across diverse application domains.

Keywords: *Quantum Computing, Quantum Machine Learning, Quantum Image Processing, Quantum Theory, Image Representation, Activity Recognition, Big Data Analytics, Quantum Support Vector Machine, Quantum Feature Mapping, Variational Quantum Circuits, Hybrid Quantum-Classical Computing, Quantum Information Processing.*

List of Publications

Journal Papers

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
BDA	Big Data Analytics
CNOT	Controlled-NOT Gate
CT	Computed Tomography
FRQI	Flexible Representation of Quantum Images
IoT	Internet of Things
MRI	Magnetic Resonance Imaging
MCQI	Multi-Channel Quantum Image Representation
ML	Machine Learning
NEQR	Novel Enhanced Quantum Representation
NISQ	Noisy Intermediate-Scale Quantum
PET	Positron Emission Tomography
QIP	Quantum Image Processing
QKD	Quantum Key Distribution
QML	Quantum Machine Learning
QNN	Quantum Neural Network
QPIE	Quantum Probability Image Encoding
QSVM	Quantum Support Vector Machine

QCNN	Quantum Convolutional Neural Network
VQC	Variational Quantum Circuit
VQE	Variational Quantum Eigen solver
SVM	Support Vector Machine
IBM	International Business Machines
IT	Information Technology
CPU	Central Processing Unit
GPU	Graphics Processing Unit
DRC	Doctoral Research Committee
DTU	Delhi Technological University
IIT	Indian Institute of Technology
QNN	Quantum Neural Network
QAOA	Quantum Approximate Optimization Algorithm
NLP	Natural Language Processing
QPU	Quantum Processing Unit

CHAPTER 1

INTRODUCTION

This thesis presents a comprehensive study on the application of Quantum Computing and Quantum Machine Learning techniques for Big Data Analytics and Intelligent Image Processing. The research includes a systematic review of existing methodologies, the identification of research gaps, and the development of Hybrid Quantum–Classical computational frameworks for Big Data classification and Quantum Theory-Based Image Classification. The proposed research investigates the applicability of Quantum Machine Learning algorithms, Quantum Image Processing techniques, and quantum computational models to improve computational efficiency, image representation, feature extraction, and intelligent decision-making. The outcomes of this research contribute towards the advancement of efficient quantum-based intelligent computing systems and provide a foundation for future research in Quantum Computing, Artificial Intelligence, and Big Data Analytics.

1.1 Introduction to Quantum Computing

Quantum computing is an interdisciplinary field that combines the concepts of quantum mechanics and computer science to create advanced computational devices. As opposed to regular computational devices, which use binary bits having only two possible states, namely either 0 or 1, quantum computers employ quantum bits, or qubits, as the basic units of information. Due to the superposition of states concept, qubits are capable of existing in several states at the same time. Combined with quantum mechanical effects like entanglement and interference, the qubits' property allows quantum computers to solve some problems faster than conventional computers can. Consequently, quantum computing has become popular for performing difficult computations related to optimisation, cryptography, machine learning, image processing, and scientific modelling [1,2].

The idea of quantum computing arose from the innovative research done by scientist Richard Feynman in the 1980s", where he suggested that computational models could simulate quantum mechanical systems much more efficiently than classical computational schemes [3]. Later, David Deutsch formulated the model of the

universal quantum computer, thus creating the basis for quantum computation [4]. Since that time, numerous developments have been made in quantum algorithms, quantum hardware design, and quantum data processing; hence, quantum computing is considered to be one of the most exciting innovations in the twenty-first century.

The growth of quantum computing has been marked by various critical advancements on the theoretical and technological fronts during the last four decades. As shown in Figure 1.1, quantum computing first emerged due to the formulation of quantum simulation by Feynman in 1982 and gained impetus from Deutsch's idea of the universal quantum computer in 1985. Other critical achievements include those of Shor, who developed the quantum computer for the factorisation algorithm, and Grover, who created a quantum search algorithm. The power of quantum computations was thus established along with the groundwork for the current era of quantum information processing. During the last few years, considerable progress in the realm of quantum hardware, cloud-based quantum computation services, NISQ machines, and quantum/classical computing has facilitated the practical implementation of quantum technologies. Quantum computers are increasingly being used in fields like optimisation, cryptography, artificial intelligence, image recognition, healthcare, and big data analytics, among others, making quantum computing an enabling technology for next-generation intelligent computing [3,4,6,7,13].

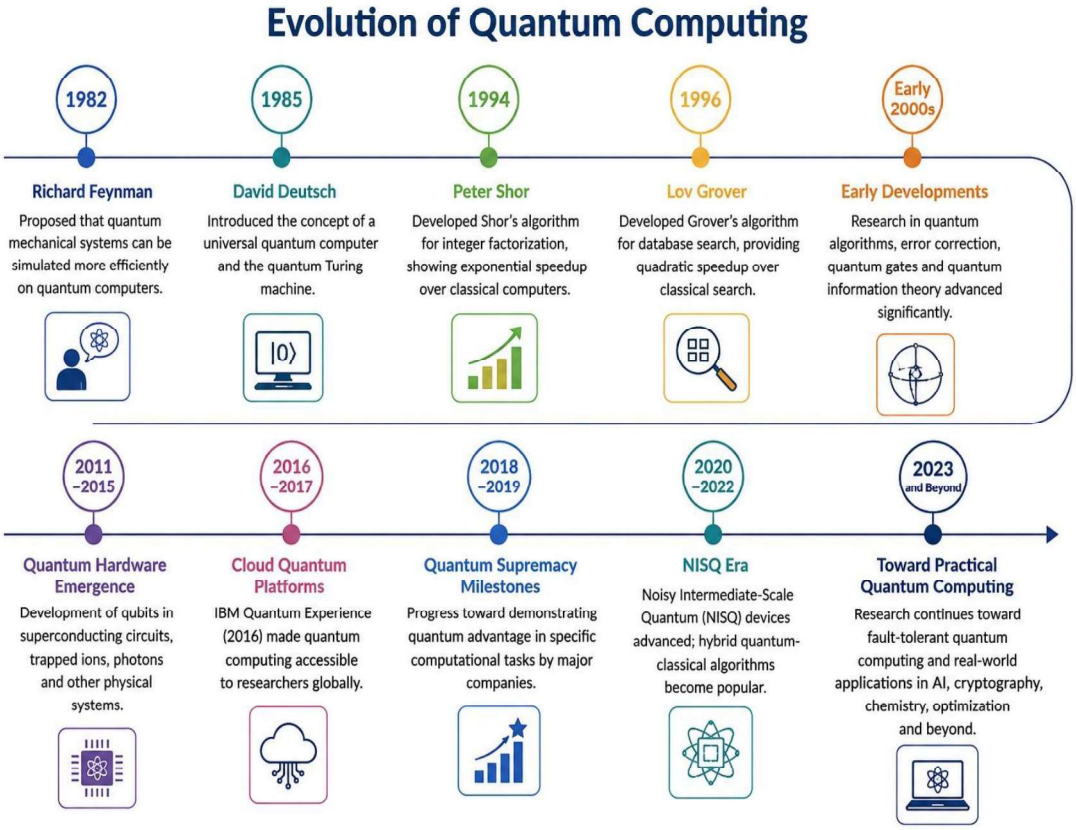


Fig. 1.1. Evolution of Quantum Computing from Early Theoretical Foundations to Modern Quantum Technologies [3,4,6,7,13]

"Advances made in quantum algorithms have shown that quantum computers can surpass conventional computers in certain applications. Quantum algorithms such as Shor's algorithm for integer factorization and Grover's algorithm for database search are some of the most famous examples highlighting the superiority of quantum computations [6,7]. The above-mentioned algorithms have fueled many research works in fields such as optimisation, cryptography, machine learning, image processing, pharmaceutical development, finance, and big data analysis. This means that quantum computing is no longer merely a theory but is fast becoming an important technology with many industrial and social ramifications.

Growth in the amount of digital data, along with the rising complexity of applications driven by data, has highlighted various shortcomings of traditional computing models. The modern-day applications dealing with image processing, activity recognition, AI, health care analytics, cyber security, and management of large data need the handling

of huge amounts of high-dimensional data in real time. Classical computing models tend to face issues of complexity, memory, scalability, and power consumption while performing these tasks. Quantum computing is a viable solution in this respect because of improved computational capability due to quantum parallelism and quantum optimisation algorithms [8,9].

An area that has gained significant attention in the development of quantum computers is quantum machine learning (QML). The QML approaches employ quantum computations to enhance learning using methods of machine learning through quantum features encoding, variational quantum circuits, quantum kernel, and quantum optimisation approaches. This approach has demonstrated remarkable potential in fields such as image classification, pattern recognition, anomaly detection, activity recognition, and predictive analytics [10]. Likewise, there has been significant interest in the development of quantum image processing (QIP) because this technique is capable of representing and processing images through a quantum state. Flexible Representation of Quantum Images (FRQI) and Novel Enhanced Quantum Representation (NEQR) are examples of quantum image representations [11,12].

NISQ computing systems have contributed to the growth of studies on practical uses of quantum computing. In spite of limitations that come with present-day quantum computers, like decoherence, noise, low numbers of qubits, and high error rates, hybrid models of quantum-classical computing can be implemented successfully as alternatives. Hybrid quantum-classical computing involves the integration of features of classical and quantum computing, allowing practical application of quantum algorithms in areas like image processing, big data, optimisation, and cryptography [13].

Recently, leading technology firms like IBM, Google, Microsoft, Intel, Rigetti Computing, IonQ, and D-Wave Systems have been investing large sums of money into quantum computing research. Quantum computing cloud platforms, such as IBM Quantum Experience and Amazon Braket, have greatly contributed to the availability of quantum computing capabilities and allowed scientists around the world to design, simulate, and execute quantum algorithms for practical applications. As a result, quantum computing is now considered a game-changing technology with

revolutionary information processing, data analytics, AI, and telecommunications applications [14].

As the benefits of quantum computing become more apparent, along with the increasing demand for the application of this technology in various fields, quantum computing can be regarded as one of the key enabling technologies that can help solve the current problems related to image representation, activity recognition, and big data analytics. Integration of quantum computing with machine learning and image processing techniques opens up new possibilities in building intelligent and scalable computing paradigms". Thus, knowledge about quantum computing basics and its applications is very important.

1.2 Fundamentals of Quantum Mechanics

The study of Quantum Mechanics is concerned with the science of physics, which provides the basic knowledge to describe and understand the behaviour of matter and energy at the microscopic level, including atoms and subatomic particles. In contrast to classical physics, where there are deterministic laws that explain physical phenomena, quantum mechanics is built on probabilistic laws that control the behaviour of microscopic objects, like photons, atoms, and electrons. The inception of quantum mechanics in the early twentieth century has paved the way for quantum computing [15,16].

The basic concepts of quantum mechanics include the duality of waves and particles, quantisation of energy, the uncertainty principle, the superposition principle, entanglement, and quantum measurement. "This makes it possible for quantum objects to manifest themselves in ways impossible under classical physics, and allows us to understand the computational advantage provided by quantum computation systems. A quantum computer utilises quantum bits, which operate under quantum mechanical laws, and this necessitates an understanding of the basics of quantum mechanics to comprehend the workings of quantum algorithms, machine learning techniques, and quantum image processing techniques [17].

The mathematical formulation of a quantum state is known as the wave function, usually denoted as ψ (psi), which includes all the information about the quantum

particle. The evolution of a quantum state can be explained using Schrödinger's equation, which determines how quantum states evolve. Measuring a quantum system results in the collapse of the wave function, leading to observable outcomes of quantum processes with probabilistic behaviour [18]. These special properties differentiate quantum computing systems from traditional computing systems and lead to the formation of effective computational models.

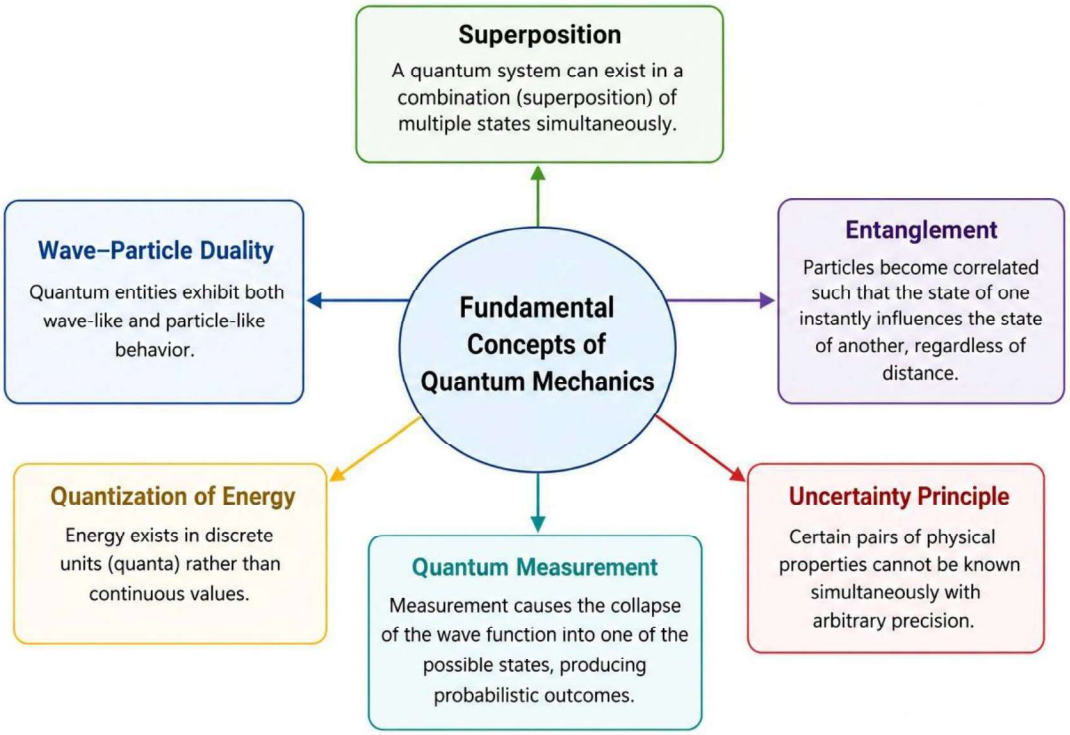


Fig. 1.2. Fundamental Concepts of Quantum Mechanics Supporting Quantum Information Processing [17,18]

"Key aspects of quantum mechanics, which lay the cornerstone for the field of quantum computation, are the aspects of qubits, superposition, entanglement, and quantum gates. All these concepts together allow for the handling and manipulation of data in quantum computing. As shown in Fig.1.2, the core concepts of quantum mechanics provide the framework for quantum information processing and pave the way for future developments in this field. These concepts have significant implications in quantum computing, quantum machine learning, and quantum image processing and are discussed further in the upcoming subsections [17,18].

1.2.1 Qubits

The quantum bit, otherwise known as the qubit, forms the elementary unit of information in the quantum computer system. The qubit represents the quantum mechanical equivalent of the classic bit used in the computation of information using classical computers. Unlike the classical bit, which is capable of existing in one state out of the two possible states (0 or 1), the qubit exists in two states simultaneously by virtue of its inherent characteristics. It is through the unique property of qubits that quantum computers execute computations differently from conventional computers [5,12,13].

A qubit is mathematically represented as a state vector in a two-dimensional Hilbert space and can be expressed as

$$| \psi\rangle = \alpha | 0\rangle + \beta | 1\rangle \qquad (1.1)$$

Where $| 0\rangle$ and $| 1\rangle$ represent the quantum basis states, whereas α and β are complex-valued probabilities. It is the value of these probabilities that defines the likelihood of a certain outcome in measurement. However, since the sum of probabilities of all the possibilities must equal unity, the following relation holds for amplitudes [20].

$$| \alpha |^2 + | \beta |^2 = 1 \qquad (1.2)$$

As per the probabilistic approach of quantum mechanics, the probability of detecting the state $|0\rangle$ is $| \alpha |^2$ and that of detecting the state $|1\rangle$ is $| \beta |^2$. The quantum state will collapse into either of these basis states on measurement. This probabilistic nature makes quantum information processing different from the classical deterministic process and provides the basis for quantum measurement theory [12,13,20].

The state of a qubit can be represented geometrically through the Bloch sphere as well, which provides an easy way to visualise quantum states. For any pure state of a qubit, the representation can be provided as [5,20]

$$| \psi\rangle = \cos\left(\frac{\theta}{2}\right) | 0\rangle + e^{i\phi} \sin\left(\frac{\theta}{2}\right) | 1\rangle \qquad (1.3)$$

where θ and ϕ are the spherical coordinates determining the position of the qubit on the Bloch Sphere. The north pole represents the $|0\rangle$ state, while the south pole

represents the $|1\rangle$ state. The rest of the points on the Bloch Sphere represent the superposition states. The Bloch Sphere diagram has been widely utilised in understanding quantum gates, state transformation processes, and manipulation of qubits in quantum circuits [5].

One of the most significant advantages of qubits is their ability to represent multiple computational states simultaneously. A classical register containing n bits can represent only one of 2^n possible states at a given instant. In contrast, a quantum register composed of n Qubits can exist in a superposition of all 2^n basis states simultaneously. This capability forms the basis of quantum parallelism, allowing quantum computers to process a vast number of computational possibilities concurrently and thereby offering substantial computational speedups for specific classes of problems [7,22].

The main benefits of using qubits include their ability to encode several computational states at once. While a classical register with n bits can encode only one of the 2^n possible computational states, a quantum register with n qubits can encode a superposition of all 2^n computational states at once. This property leads to quantum parallelism, enabling quantum computers to perform computations based on many computational options at once and thus providing computational speedup in solving certain problem sets [7,22].

The ability of qubits to couple with each other using quantum correlations is another vital feature of them. In the case where several qubits get highly correlated, they could get entangled, forming what is called a quantum entanglement, which cannot be explained by classical physics. Quantum correlations have allowed for the implementation of various algorithms and the processing of information based on quantum mechanics [18,19].

However, despite their exceptional characteristics, qubits are very vulnerable to environmental changes. Any interaction of qubits with the environment can result in decoherence, thus leading to information loss in the quantum computer. Therefore, the maintenance of quantum coherence and the development of effective means of quantum error correction are among the biggest problems in quantum computing [9].

Superposition of quantum states, quantum parallelism, and quantum entanglement are some of the characteristics of qubits that play a critical role in quantum computation, quantum machine learning, quantum image processing, and quantum communication systems". Thus, having extensive knowledge about qubits is necessary to learn about quantum computational approaches and their applications in image processing and big data analysis [19,27].

1.2.2 Superposition

Superposition is the most fundamental and unique principle of quantum mechanics and plays a major role in quantum computation. "The basic principle of superposition states that a quantum system may be in several different states simultaneously before performing any measurement. As compared to classical systems that are always in one single state at a specific instance, quantum systems may be present in a linear combination of several basis states. This special characteristic helps quantum computers in carrying out parallel computations and forms the base of quantum computation [5,12,13].

For a single qubit, the superposition state can be represented mathematically as

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \qquad (1.4)$$

where $|0\rangle$ and $|1\rangle$ are the computational basis states, while α and β are complex probability amplitudes satisfying the normalisation condition

$$|\alpha|^2 + |\beta|^2 = 1 \qquad (1.5)$$

According to Eq. (1.4), a qubit can exhibit properties from both states. But as soon as the measurement is made, the state collapses to either $|0\rangle$ or $|1\rangle$ with corresponding probability given by the corresponding probability amplitude. This probabilistic behaviour differentiates the process of quantum computing from classical deterministic computing. It allows the representation of a huge information space compared to classical computers [12,20].

The power of superposition grows when several qubits are considered. As compared to classical register holding n bits and representing only one out of 2^n possible states at a particular instance of time, a quantum register holding n qubits can represent all

2^n basis states through superposition. For example, a two-qubit state can be written as

$$| \psi\rangle = \alpha_{00} | 00\rangle + \alpha_{01} | 01\rangle + \alpha_{10} | 10\rangle + \alpha_{11} | 11\rangle \qquad (1.6)$$

where the coefficients are the probabilities corresponding to each computational basis state. This feature gives rise to quantum parallelism, whereby quantum computers can do calculations using an enormous number of computational states at the same time, resulting in increased speed for certain computations [7,22].

In actual quantum computing implementations, superposition states are usually created with the help of quantum gates. Among the crucial gates employed for such purposes is the Hadamard gate (or H-gate), which converts the basis state into an equal superposition state. The Hadamard gate performs transformations on the basis states represented by

$$H | 0\rangle = \frac{| 0\rangle + | 1\rangle}{\sqrt{2}} \qquad (1.7)$$

and

$$H | 1\rangle = \frac{| 0\rangle - | 1\rangle}{\sqrt{2}} \qquad (1.8)$$

These changes show us how one basic state can be changed to a superposition state involving several other states. This is why the Hadamard gate is so commonly used in quantum algorithms, quantum circuits, and even in quantum machine learning systems because of its superposition properties [5,27].

The concept of superposition has significant importance in a lot of quantum algorithms. Some prominent examples are the Grover search algorithm, where superposition results in quadratic speed up of database searches, and Shor's algorithm that offers exponential speed up for factorising integers [3,4,8]. Superposition is used heavily in quantum machine learning, quantum optimisation, and quantum simulation, where solution spaces can be explored simultaneously.

With respect to the field of Quantum Image Processing (QIP), superposition makes it possible to efficiently encode images since it allows multiple states of an image to exist. Quantum representations of images include Flexible Representation of Quantum

Images (FRQI) and Novel Enhanced Quantum Representation (NEQR). The principle of superposition has been exploited by these image representation models to facilitate efficient storage, processing, and analysis of quantum images. Additionally, superposition is exploited in quantum machine learning algorithms in order to map features and reduce dimensionality [10,11,26,27].

Thus, superposition is one of the most valuable aspects of quantum mechanics, and it serves as the basis for quantum computing". Since superposition allows processing several states at once, quantum computers are capable of doing sophisticated mathematical operations more efficiently compared to classical computing systems, which is why their applications include advanced image processing, machine learning, optimisation, cryptography, and big data analysis [8,22,26].

1.2.3 Entanglement

Quantum entanglement is certainly among the most astonishing and unique aspects of quantum mechanics since it denotes a certain kind of correlation between quantum bits that has no classical analogue. Entanglement arises if two or more qubits interact in such a way that their individual quantum states cannot be characterised separately. Rather, the combined state of the entire quantum system should be represented using one single quantum state, irrespective of the distance between the particles involved. This makes it impossible to measure one quantum bit without immediately affecting the description of other quantum bits that are entangled. For this reason, Einstein called entanglement the "spooky action at a distance [18,19].

"The idea of entanglement was born out of one of the most renowned paradoxes of physics, the so-called EPR paradox, proposed by Albert Einstein, Boris Podolsky, and Nathan Rosen, and raised the problem of the completeness of quantum mechanics. Eventually, Bell's theorem formulated the problem mathematically, proving that quantum mechanics cannot be described using any local hidden variable theory [18,19].

An example of an entangled quantum state is the Bell State, which may be written as

$$|\Phi^+\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle) \qquad (1.9)$$

In this condition, the qubits are found to be in a state of perfect correlation in their superposed states. If the measurement of the first qubit is made, and it is found to be in the state $|0\rangle$, then the second qubit will be found to be in the same state. Likewise, if the measurement of the first qubit shows that it has collapsed into the state $|1\rangle$, then the second qubit will also be found to have collapsed to the same state.

The formation of entanglement generally requires the use of multiple-qubit quantum gates such as the Controlled-NOT (CNOT) gate alongside a Hadamard gate. For instance, the application of the Hadamard gate to the first qubit and the CNOT gate results in the creation of an entangled Bell state [5,27].

One of the key characteristics of entanglement is the capability of forming quantum entanglements with highly correlated properties that cannot be described by any classical probabilistic framework. Entanglements make it possible for a system of particles to process information collectively, which makes entanglement a key factor that greatly improves the computational capabilities of quantum computers [17,22].

Quantum entanglement is essential for many quantum technologies like quantum communication, quantum cryptography, quantum teleportation, quantum error correction, and quantum sensing. In the context of quantum communication networks, entangled states are used to create extremely secure communication lines. Quantum cryptographic techniques like QKD take advantage of quantum entanglement to check any eavesdropping attempts and guarantee secure information sharing [21]".

Quantum computing relies on entanglement between qubits to conduct complicated computations that are hard or even impossible for classical computation. Quantum algorithms like Shor's factoring algorithm, Grover's searching algorithm, and many more use quantum entanglement to make their work efficient [3,4]. Additionally, entanglement is crucial for quantum machine learning since it helps to make feature mapping, classification, clustering, and pattern recognition efficient [8,23].

Entanglement importance is reflected not only in quantum computing but also in Quantum Image Processing (QIP) and big data analysis. Within the quantum representations and classification of images, entangled states could be used for more efficient encoding of the features present in them and thus for better information

retrieval and processing efficiency reduction. Quantum machine learning algorithms use entanglement in order to model relationships in high-dimensional big datasets [26,27,28].

However, despite its numerous benefits, achieving and sustaining entanglement in quantum systems proves to be problematic because of the interference of the external environment in the phenomenon known as decoherence [9]. Efforts are underway to increase the duration for which the entangled state can be sustained, even in larger quantum systems [9].

Thus, entanglement is considered one of the most important resources in quantum informatics. The capacity of entanglement to produce nonclassical correlation among qubits forms the basis of several computational and informational benefits of quantum computers and has immense significance in the design of sophisticated quantum computing systems [19,27].

1.2.4 Quantum Gates and Circuits

Quantum gates form the core elements of quantum computing and serve as the basic operations performed on the states of qubits within a quantum computer. “In the same way that classical logic gates operate on bits, quantum gates act on information through particular transformations. The difference between quantum gates and classical gates is that while the latter cannot be undone, the former are always reversible in nature. Quantum gates mathematically are represented by unitary matrices [5,17,20].

A quantum gate manipulates the state of one or more qubits using quantum computation. If the state of a qubit is denoted as $|\psi\rangle$, then the effect of a quantum gate U on the qubit can be described as

$$|\psi'\rangle = U\,|\psi\rangle \qquad (1.10)$$

where U is a unitary matrix satisfying the condition

$$U^{\dagger}U = UU^{\dagger} = I \qquad (1.11)$$

Here, $U^{\dagger}$ denotes the Hermitian (conjugate transpose) of the matrix U, and I is the identity matrix. The above property guarantees that quantum processes are reversible, a necessary condition for quantum computing [5,20].

Quantum gates can be divided broadly into single-qubit gates and multiple-qubit gates. Single-qubit gates act on individual qubits and are mainly employed to generate superpositions and effect transformations of states. Some common single-qubit gates are as follows:

- Pauli-X Gate (Quantum NOT Gate)
- Pauli-Y Gate
- Pauli-Z Gate
- Hadamard Gate (H)
- Phase Gate (S)
- T Gate

Among these, the Pauli-X gate acts similarly to the classical NOT gate by flipping the state of a qubit. Its matrix representation is given by

$$X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \qquad (1.12)$$

The Hadamard gate is one of the most important quantum gates because it creates superposition states from computational basis states. Its matrix representation is

$$H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \qquad (1.13)$$

Applying the Hadamard gate to the basis state $|0\rangle$ produces an equal superposition state:

$$H|0\rangle = \frac{|0\rangle + |1\rangle}{\sqrt{2}} \qquad (1.14)$$

Similarly, applying the Hadamard gate to the state $|1\rangle$ results in

$$H|1\rangle = \frac{|0\rangle - |1\rangle}{\sqrt{2}} \qquad (1.15)$$

These operations are significant in achieving quantum parallelism and are applied extensively in quantum algorithms and quantum machine learning techniques [5,23]. Multi-qubit gates are important for manipulating more than one qubit at once and for

creating an entangled state. One such multi-qubit gate is the Controlled-NOT gate that toggles the value of the second qubit only when the first qubit is set to |1⟩. The matrix form of this gate is

$$CNOT = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad (1.16)$$

The CNOT gate, along with the Hadamard gate, is usually applied in generating Bell states and entangled states in quantum mechanics. Some more multiple-qubit gates which are frequently employed are the Controlled-Z Gate and the Toffoli Gate, which are utilised in designing quantum circuits and fault-tolerant quantum computers [19,27].

A quantum circuit can be defined as a series of quantum gates that have been designed to accomplish some particular task. Just like electronic circuits in classical computing, quantum circuits act as a platform for quantum algorithms. Generally, a quantum circuit involves the following steps:

i. Qubit initialisation

ii. Quantum state preparation

iii. Quantum gate operations

iv. Entanglement generation

v. Quantum measurement

vi. Classical post-processing

The overall transformation performed by a quantum circuit can be represented as

$$|\psi_{out}\rangle = U_n U_{n-1} \cdots U_2 U_1 |\psi_{in}\rangle \qquad (1.17)$$

where $U_1, U_2, \ldots, U_n$ represent the sequence of quantum gates applied to the input quantum state $|\psi_{in}\rangle$, resulting in the final output state $|\psi_{out}\rangle$ [5].

Quantum circuits are used as the building blocks of several quantum algorithms, such as Shor's factorisation algorithm, Grover's searching algorithm, Quantum Support Vector Machine (QSVM), Variational Quantum Circuit (VQC), Quantum Neural

Network (QNN), and Variational Quantum Eigensolver (VQE). Quantum algorithms take advantage of quantum principles like superposition and entanglement to gain an edge over classical algorithms [3,4,8,24].

In Quantum Image Processing (QIP), quantum gates/circuits are used to carry out operations related to image representation, encoding, denoising, feature extraction, compression, and classification processes. The quantum image representation models like FRQI and NEQR use quantum circuits to effectively encode the pixel values into quantum states. Likewise, in Quantum Machine Learning (QML), parameterised quantum circuits have been widely used for classification, optimisation, clustering, and pattern recognition on high-dimensional data sets [10,11,26,27,28]. Thus, quantum gates and circuits form the functional core of contemporary quantum computer systems". These devices help to construct the required infrastructure that allows for quantum information manipulations and the application of highly advanced quantum algorithms in various fields such as image processing, machine learning, cryptography, and big data.

1.3 Quantum Computing vs Classical Computing

There have been a lot of developments made within computing technology throughout the last few decades, which have helped achieve breakthroughs within science, engineering, communication, medicine, and data analysis. Classical computers are built upon principles of classical physics and use bits (binary digits) as the basic information units. Even though classical computing has had a lot of success solving various computational problems, there are still quite a few problems where classical computing is simply unable to deliver satisfactory results. Quantum computing represents a new type of computing based on quantum principles, which ensures the elimination of limitations posed on classical computing [31,32].

"The main difference between classical and quantum computing is associated with the handling of information. The classical computer works with bits whose state can be either 0 or 1. Quantum computers, on the other hand, work with quantum bits, or qubits, that can be in several different states at once. The latter feature allows processing several possibilities at once, increasing the effectiveness of calculations

considerably [33,34].

Classical computers utilise logic gates like AND, OR, NOT, NAND, and NOR gates for information processing tasks. The logic gates process binary inputs following deterministic principles and provide consistent outputs. On the other hand, quantum computers use quantum gates such as the Hadamard gate, Pauli-X gate, Pauli-Y gate, Pauli-Z gate, Phase gate, and Controlled-NOT (CNOT) gate. These gates work on quantum states and utilise the quantum effects of superposition and entanglement for complex computational tasks, which cannot be performed by classical computers [35,36].

One of the most significant features of quantum computing technology is that quantum computers are able to represent an exponential number of states. A classical computer consisting of n bits can store information in only one out of possible 2^n states. In contrast to this, a quantum computer comprising n qubits can be in all possible basis states thanks to quantum superposition principle". Thus, the ability of performing several computations at once is provided due to the phenomenon called quantum parallelism [32,37].

The complexity of optimization, simulations, and search algorithms makes classical computers unable to deal with large computational problems. The more complex a problem is, the greater amount of computational power and time classical algorithms need to solve it. In other words, with the growth of problem complexity, classical algorithms show exponential growth in their consumption of computational resources and running time. Quantum algorithms allow addressing this issue, providing an exponential speedup in some cases [32,33].

The other significant difference between the two approaches is that classical computer systems rely on the storage of information in deterministic memory systems, while quantum systems use quantum states which hold much more information owing to superposition and entanglement. Therefore, quantum computers are capable of processing multidimensional data better, which makes them especially useful for applications based on artificial intelligence, machine learning, image processing, cryptography, optimization, and big data analysis [31,40].

Traditional computers are extremely reliable and have had many years of hardware and software optimizations. These devices are able to do arithmetic computations and logical and data-processing operations without committing many errors. Quantum computers, however, are very delicate devices because of their extreme sensitivity to external interferences. “As a result, quantum states may be disturbed by interaction with the environment, which in turn creates errors in computations. Hence, quantum error correction is one of the key research questions for quantum computing [37,40].

Moreover, the notion of Quantum Supremacy also draws a clear distinction between the two approaches of computation. Quantum supremacy can be described as the capacity of a quantum computer to complete a particular computation process which would take a lot of time if done by the world's most powerful supercomputer using a classical approach. In 2019, scientists from Google made a breakthrough in quantum supremacy with the help of their quantum processor, called the Sycamore quantum processor, completing a computation process within just a few minutes while it would have taken a really long time for a classical supercomputer [31].

Moreover, quantum computing has been predicted to become an important constituent in the formation of future communication systems, which include the concept of the Quantum Internet. Unlike the classical communication system, which uses the transfer of classical data, quantum communication uses quantum states and entanglement for achieving secure communication, quantum computing, and cryptography. The use of such new technologies can completely revolutionize the way of information security and communication [38,39]. A comparative study of classical and quantum computing is shown in Table 1.1.

Table 1.1. Comparison between Classical Computing and Quantum Computing

Parameter	**Classical Computing**	**Quantum Computing**
Basic Unit	Bit (0 or 1)	Qubit
State Representation	Single state at a time	Superposition of multiple states
Processing	Sequential and	Parallel and probabilistic

Mechanism	deterministic	
Computational Basis	Classical physics	Quantum mechanics
Logic Elements	Classical logic gates	Quantum gates
Information Correlation	Classical correlation	Quantum entanglement
Data Processing Capability	Limited by hardware scaling	Exponential state representation
Search Efficiency	Linear search complexity	Quadratic speedup using Grover's algorithm
Security Applications	Conventional cryptography	Quantum cryptography
Error Sources	Hardware faults	Decoherence and quantum noise
Applications	General-purpose computing	Optimization, AI, QML, QIP, cryptography

Though classical computers will continue to be essential for day-to-day computing operations, there are many benefits of utilizing quantum computing in order to solve complex computations that cannot be solved by classical computers. The combination of quantum computing with artificial intelligence, machine learning, image processing, security, and big data analysis will lead to development in future computational technology". Quantum computing can be complementary to classical computing techniques and will even excel classical computers in certain domains with the advancement of quantum computers in terms of hardware and fault-tolerant architecture [31,32,40].

1.4 Introduction to Quantum Image Processing

QIP represents a relatively new and promising interdisciplinary scientific field that applies the concepts of quantum computing to digital image processing, enabling the

creation of effective procedures for image modeling, storage, transfer, analysis, and interpretation. Due to the rapid increase in the volume of visual data created with the help of various medical imaging technologies, surveillance systems, satellite imaging services, social media, self-driving vehicles, and multimedia content, the current image processing methodologies face numerous difficulties associated with computational efficiency, memory capacity, processing time, and scalability issues. In this regard, Quantum Image Processing leverages the features of quantum physics, such as superposition, entanglement, quantum parallelism, and quantum interference, to provide more efficient results in image processing tasks [10,11,27].

The conventional image processing system employs a matrix representation of pixels' values of the image and computes sequentially through a classic computer architecture. As more resolution of images and larger size of the dataset emerge, a higher demand on computational power will result in a longer processing time and higher storage requirement. Quantum computing is another approach where the quantum state encodes information of an image allowing multiple pixels values computation simultaneously through quantum superposition. This could bring about reduced computation complexity [26,27,30].

Quantum Image Processing technology was developed to enable quantum computing systems to deal with image data sets on a very large scale. The major purpose of developing the technology is to model and process the digital images within quantum systems using algorithms for performing different tasks such as image enhancements, denoising, segmentation, compression, feature extraction, pattern recognition, and classification. "Through the use of quantum parallelism, quantum computer systems are able to handle multiple image pixels at once, which gives them an edge over traditional methods of image processing [10,30].

An essential aspect of Quantum Image Processing is quantum image representation, where the way of representing images with quantum bits is defined. "Effective quantum image representation plays a key role since all further steps of image processing rely on the selected representation model. Many types of quantum image representations have been presented in existing literature, and some of the most popular are:

i. Flexible Representation of Quantum Images (FRQI)

ii. Novel Enhanced Quantum Representation (NEQR)

iii. Multi-Channel Quantum Image Representation (MCQI)

iv. Quantum Probability Image Encoding (QPIE)

v. Entangled Image Representation Models

These representations vary based on encoding methods for images, computational costs, storage needs, and practicality of their implementations on quantum computers [10,11,27].

The Flexible Representation of Quantum Images (FRQI) is one of the earlier and well-known methods in this list of representations. In this method, both the location and intensity of pixels are encoded into a normalized quantum state. The representation of an image by the FRQI method is given as [10]

$$|I\rangle = \frac{1}{2^n} \sum_{i=0}^{2^{2n}-1} (\cos\ \theta_i\ |0\rangle + \sin\ \theta_i\ |1\rangle) \otimes |i\rangle \qquad (1.18)$$

where θ_i represents the color information of the ith pixel and $|i\rangle$ denotes the corresponding position information. This representation enables efficient storage and manipulation of image data in a quantum environment.

Another frequently employed scheme is Novel Enhanced Quantum Representation (NEQR). In this scheme, the gray scale pixels are represented by computational basis states. This enhances the performance of image search process and makes it easier to implement image processing on quantum circuits [11]. The creation of such representation models has greatly helped in the development of the field of quantum image processing.

There are a number of benefits in Quantum Image Processing compared to classical image processing methods. Firstly, quantum superposition can support the ability to represent various pixel value states in one quantum state simultaneously. Secondly, quantum parallelism can help perform image manipulation processes on multiple pixels at the same time. Thirdly, quantum entanglement can be helpful in correlating

information efficiently and representing features. Lastly, quantum algorithms can simplify the computation process in certain image manipulations [27,30].

Recent developments in quantum computing have stimulated studies on quantum image enhancement and restoration. The area of image denoising is among those which have been explored widely by researchers within Quantum Image Processing. Many quantum techniques for image denoising have been proposed, employing quantum filtering, quantum wavelets, Schrödinger operators, quantum Boolean images, and adaptive quantum thresholding. These methods are employed to filter out noise from the input image, without eliminating the image's important properties like edges and structures [27,29].

The potential of quantum image processing technology has further been realized by its applicability to the domain of image classification and pattern recognition. Combining the concept of QML and image processing has resulted in the emergence of hybrid quantum-classical image classifiers that are proficient at processing high-dimensional image datasets. Image classification using quantum-based approaches such as Quantum Support Vector Machines (QSVM), Variational Quantum Circuits (VQC), Quantum Neural Network (QNN), and Quantum Convolutional Neural Network (QCNN) is an area that has yielded positive results thus far [8,24,26]".

Applications of QIP include many areas. In the area of medical imaging, QIP may be used for disease diagnostics using MRI, CT, PET, and ultrasound images. Remote sensing can benefit greatly from the use of quantum images in order to classify land uses, monitor the environment, and assess disasters. Surveillance can make use of the real-time detection of objects and activities, whereas multimedia will find applications in quantum image compression, retrieval, and improvement. The new areas of autonomous vehicles, smart cities, and intelligent healthcare can also be expected to benefit from quantum image processing [27,30].

Although Quantum Image Processing shows great promise, it still needs to overcome certain problems. Firstly, the current technology used in quantum computers is not free of limitations like decoherence, noise in the quantum system, a limited number of qubits and faulty gates, among others. Consequently, implementing quantum image

processing algorithms in practice on quantum computers is still being studied. However, overcoming the above challenges by using a combination of classical and quantum computing to enable the practical use of QIP algorithms on NISQ devices has been observed [7,9].

As a whole, the concept of Quantum Image Processing is a revolutionary paradigm in the next generation image processing and analysis domain. With quantum mechanics in consideration, QIP provides promising avenues in terms of improved image representation, computation, feature extraction, and understanding. As quantum computing technology progresses in the future, QIP will definitely be an important component when dealing with application domains such as image representation, action recognition, computer vision, artificial intelligence, and big data analytics.

1.5 Introduction to Big Data Analytics

Big Data Analytics is an advanced technique used in computing which involves collecting, storing, processing, managing, and analyzing big sets of data with the purpose of deriving valuable insights, patterns, correlations, and trends from the vast amount of information. “Rapid developments in technology, including digitalization of information, internet, social media, cloud computing, Internet of Things (IoT), mobile communication, medical services, science equipment and other sources have led to the creation of an enormous volume of data. Classical data processing techniques cannot deal efficiently with the huge amounts of structured, semi-structured, and unstructured data”. Big Data Analytics has therefore become a vital field of research for handling large data sets [41-43].

Big Data denotes those datasets that are too large and complex to be managed and analyzed using typical database technologies and traditional methods. The definition of Big Data has traditionally been associated with the famous three aspects put forward by Laney known as the 3Vs, which include Volume, Velocity, and Variety [41]. In subsequent periods, more features were added to create the five aspects of Big Data, also referred to as the 5Vs of Big Data.

a) Volume is related to the large volume of data produced by different sources.
b) Velocity relates to the fast generation, distribution, and processing of data.

c) Variety is related to the type of data available in different forms, such as text, images, videos, sensor data, audio, and transactional data.
d) Veracity relates to the trustworthiness of data.
e) Value is the meaningful information obtained from analyzing data [43,47].

The significance of Big Data Analytics comes from its capability to convert unstructured data into structured information and knowledge to help make informed decisions and predictions. Big Data Analytics is used by different industries to help them operate more efficiently and allocate resources effectively, understand customer behavior, ensure security, and create intelligent systems. Some areas where Big Data Analytics finds applications include health care, finance, education, manufacturing, transportation, telecommunications, cybersecurity, social media analytics, environmental monitoring, and smart cities [44,50].

A Big Data Analytics process usually involves a number of sequential phases, which include data collection, data storage, data preprocessing, data integration, data analysis, visualization, and decision support. The data are gathered from various heterogeneous sources and stored through distributed storage systems. Later, preprocessing processes are carried out to clean, transform, normalize, and extract features from data in order to prepare them for further analysis. Advanced analytics processes are then conducted to discover insightful information from the preprocessed data [45,46].

One of the technologies that has played an important role in contributing towards Big Data Analytics is the use of distributed computing. Conventional central systems tend to lack the capability to process petabytes of data effectively. In order to solve this problem, distributed computing approaches such as Hadoop and MapReduce have been introduced for effective parallel processing. In the MapReduce approach, large computing operations are split into smaller sub-operations and performed in parallel before combining the outputs [42]. Cloud computing, on the other hand, enables flexible computing operations to store and process large amounts of data effectively [45,48].

Integration of machine learning and artificial intelligence technology with Big Data

Analytics has brought further improvement in the analytical capacity of today's systems. Using machine learning algorithms, automatic knowledge acquisition, prediction, classification, clustering, anomaly detection, and decision-making based on large datasets can be achieved. Commonly used techniques include "SVMs, decision trees, random forests, ANNs, deep learning models, and ensemble learning models" [46,47].

Even with its strengths, there are still a number of problems associated with BDA. For example, since the amount of data is growing consistently, storage and computations are needed. Additionally, due to data heterogeneity, there are difficulties with data integration and analysis. Also, the problem of data privacy, data security, data scalability, data quality, and data real-time processing are some of the important problems in contemporary Big Data analytics systems. Traditional computation usually takes a long time when dealing with large amounts of data [43,44].

"In order to overcome these shortcomings, scientists are now looking into the implementation of new technologies like Quantum Computing in conjunction with Big Data analytics. The application of Quantum Computing promises the capability to process and optimize complex tasks related to data processing, optimization, classification, clustering, and pattern recognition using quantum parallelism and advanced quantum machine learning methods. Quantum Machine Learning (QML) algorithms including Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), Quantum Kernel Methods, and Quantum Optimization algorithms can effectively deal with high-dimensional and complex data [49]".

Quantum-assisted Big Data Analytics has recently received much attention because of the ability of quantum algorithms to deal with scaling problems and computational limitations of traditional approaches. Quantum algorithms will allow for effective processing of high-dimensional feature spaces and rapid optimization, as well as enhanced predictive capabilities in large-scale data-driven applications. As such, the combination of Big Data Analytics with quantum technology is considered to be an important aspect of the design of intelligent systems for the future [49].

Big Data Analytics becomes one of the most important application areas within which

the possibilities of Quantum Machine Learning algorithms may be explored in relation to the topic under discussion. Efficient quantum-powered frameworks that facilitate the analysis of huge data volumes can enhance the effectiveness of the classification process, computation, scaling, and decision-making.

1.6 Quantum Machine Learning (QML): Concepts and Applications

"Quantum Machine Learning (QML) is a new research area that integrates quantum computing concepts with machine learning ideas to create innovative computational frameworks that can be used to solve difficult learning problems in a faster manner compared to traditional methods. The increasing use of data-driven applications, artificial intelligence programs, and multidimensional datasets has presented various limitations with regard to complexity, speed, scalability, and resources for classical machine learning algorithms. QML aims at overcoming the constraints associated with classical machine learning algorithms through the use of unique characteristics of quantum mechanics such as superposition, entanglement, quantum interference, and quantum parallelism [51,61].

Machine learning is one of the most powerful techniques utilized in contemporary data science and artificial intelligence applications. In essence, machine learning allows computers to identify patterns in input data and generate predictions without being programmed explicitly. Nevertheless, since data sets are continuously growing, conventional machine learning algorithms tend to be resource-intensive and require significant processing times. One possible solution lies in the potential offered by quantum computing. Specifically, quantum computing allows for the encoding and processing of information in exponentially large quantum state spaces, which paves the way for speeding up machine learning-related operations such as classification, clustering, optimization, feature extraction, and pattern recognition [52,53].

The development of Quantum Machine Learning (QML) was inspired by the interaction between quantum information and machine learning research and aimed at harnessing quantum computational principles to improve the efficiency of machine learning algorithms. The fundamental purpose of QML is to design models that are based on quantum computation and thus perform better than conventional machine

learning algorithms or perform equally well yet consume less computational power than the classical ones. According to the particular computational model applied, QML techniques can typically be divided into three types, namely quantum-enhanced classical machine learning, which refers to the use of quantum computing to speed up some steps in a classical algorithm; hybrid quantum-classical machine learning, which employs a combination of quantum computing and classical optimization techniques; and fully quantum machine learning techniques that implement data processing and learning algorithms within a quantum computing setting. Of these techniques, hybrid quantum-classical machine learning techniques seem to be particularly promising as they not only are relatively easy to implement using existing NISQ computers but also enable exploiting the features of both classical and quantum computers [51,58,63].

These include the development of hybrid quantum-classical models which have been favored due to their implementation on the present-day NISQ computers by leveraging classical computers for optimization and post-processing [58,61]. This is due to the inherent potential of QML to leverage quantum state representation. While classical systems rely on deterministic vectors to represent data, quantum computers use quantum state representation that represents various data points at once using superposition. In addition, entanglement allows the creation of correlations between different features which help in representing high-dimensional data sets. It is through this that complex learning algorithms have been designed [57,63].

The domain of Quantum Machine Learning has received a lot of attention in different areas of research such as image processing, computer vision, health care, financial services, cybersecurity, natural language processing, optimization, and big data analysis. Combining the power of quantum computers and machine learning algorithms can become an essential component of future smart technologies that will allow efficient analysis of huge volumes of data and complex computational tasks that cannot be solved effectively by conventional methods [51,61]". The basic aspects of Quantum Machine Learning are described below.

1.6.1 Fundamentals of Quantum Machine Learning

QML is an emerging discipline of interdisciplinary nature, which brings together the

concepts from quantum computing and machine learning to build sophisticated computational models to address difficult problems through enhanced efficiency. The key aspects of quantum mechanics that include superposition, entanglement, and interference form the basis of Quantum Machine Learning [51,61].

The emergence of big data-driven and AI-based applications has posed serious problems for classical machine learning approaches. These conventional methods may need considerable computational resources and time for the analysis of huge amounts of high-dimensional data sets. However, quantum computation makes it possible to represent information in exponentially larger quantum state spaces. This way, there is potential for enhancing the speed of machine learning tasks, including classification, clustering, optimization, and pattern recognition [53,57].

Three broad types of Quantum Machine Learning algorithms are commonly used: “Quantum-enhanced classical machine learning, hybrid quantum and classical machine learning, and quantum-only machine learning. Out of the three types of Quantum Machine Learning approaches, hybrid quantum-classical learning has become increasingly popular because it combines the power of quantum computation and the stability of classical optimizations together. This approach is best suited for current noisy quantum computing platforms (Noisy Intermediate-Scale Quantum – NISQ), which makes it the most relevant model to use when applying current technology [58]. The process flow of a standard Quantum Machine Learning framework is as follows: First, the collection of input data occurs through data acquisition and pre-processing, which involves collecting, cleaning, normalization, and formatting the data. Once the data is properly formatted, quantum data encoding is applied to convert the information into a quantum state, followed by quantum feature mapping. This encoded data undergoes processing via quantum computing circuits that consist of parametrized quantum gates, which conduct the necessary computations and learning operations. Through quantum measurement, the produced outputs are transformed into classical information, analyzed via classical optimization techniques to enhance system performance. The combination of classical optimization approaches with the capability to perform quantum computing leads to efficient hybrid Quantum Machine Learning techniques for complex classification and optimization problems

[55,58].

In a conventional QML flow, classical inputs are mapped to quantum states, which are then encoded into qubits. Next, quantum operations with tunable parameters operate on the encoded inputs through quantum circuits. The results obtained by measurements are then optimized through classical computations to achieve higher levels of accuracy and performance in machine learning models [55,58]. One of the main strengths of Quantum Machine Learning is its capacity for efficiently dealing with high dimensional feature space. A quantum system can naturally encode exponential state spaces with a few qubits. This feature has contributed to making QML capable of processing highly complicated databases, developing highly intelligent and sophisticated models like Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), Variational Quantum Circuits (VQC), and Quantum Convolutional Neural Networks (QCNN) [52,56].

The latest advancements have proved the feasibility of QML in diverse fields such as image processing, activity recognition, healthcare, cybersecurity, financial modeling, and big data analysis". With continuous improvements in the quantum hardware, the field of Quantum Machine Learning will prove to be one of the most important technologies used in building the next generation of intelligent machines that can address complex problems beyond traditional machine learning algorithms [59–63].

1.6.2 Quantum Data Encoding Techniques

Quantum encoding of data involves mapping classic information into quantum states in such a way that this classic information becomes usable in quantum computing operations. Because most of the data created and used in real-life situations is in classic form, an effective encoding technique is indispensable for using QML techniques in practice. Efficiency of any QML technique to a large extent depends on the efficiency of the mapping process, since encoding impacts computational complexity, memory usage, and the circuit's depth [57].

The key idea behind quantum data encoding is to map the classical properties into the quantum space using the benefits that come along with quantum superposition and entanglement. The basic idea behind the perfect encoding scheme is to minimize the

number of qubits needed for encoding and maximize the information encoded in the quantum register. Various encoding schemes have been suggested, with some popular encoding schemes being Basis Encoding, Amplitude Encoding, and Angle Encoding [51,61].

(i) Basis Encoding

Basis Encoding is among the easiest and the most straightforward techniques of data encoding for quantum computing. It entails the mapping of classical binary data on the computational basis states of qubits. Each of the bits is then encoded into a state of a respective qubit.

For example,

$$0001 \rightarrow | 0001\rangle \qquad (1.19)$$

Four bits in this case will need four qubits for their encoding. Basis Encoding is easy to implement but is limited by its applicability to only large datasets due to an increase in qubit requirements. The limitation is that the number of qubits needed for Basis Encoding increases proportionately to the amount of data. Therefore, basis encoding can only be used on low-dimensional data sets [51,62].

(ii) Amplitude Encoding

The amplitude encoding technique is considered to be the most effective technique for encoding the data. The probability amplitudes of the quantum state carry the classical information in this technique. This can be mathematically denoted as

$$| x\rangle = \sum_{i=0}^{N-1} x_i \, | i\rangle \qquad (1.20)$$

where x_i represents the normalised feature values and $| i\rangle$ denotes the computational basis states.

Amplitude encoding's primary strength lies in the high information content it holds despite the relative scarcity of qubits employed. As an illustration, a dataset comprising 2^n Feature values can potentially be encoded using just n qubits. Amplitude encoding thus provides a unique selling point for machine learning and big data analysis tasks. On the other hand, preparing quantum states based on amplitude encoding might

involve intricate quantum circuitry, which could make implementation challenging for existing quantum hardware [53,57].

(iii) Angle Encoding

Angle encoding, which is also referred to as rotational encoding, encodes classical data using the rotation angles of quantum gates. Angle encoding involves the encoding of feature values in terms of the parameters for the rotations performed by quantum gates, like R_x, R_y, and R_z..

The encoding of the feature value x using angle encoding involves

$$R_y(x) \mid 0\rangle \qquad (1.21)$$

where the rotation angle is proportional to the feature that is to be encoded.

Angle encoding is quite popular in "Variational Quantum Circuits (VQC), Quantum Neural Networks (QNN), and many other hybrid learning models for quantum and classical computers". In contrast to amplitude encoding, angle encoding is relatively easier to apply on existing quantum processors and usually involves smaller quantum circuits. Thus, it has been gaining popularity as an encoding method in Quantum Machine Learning [55,58].

Comparison of Encoding Techniques:

Each method for encoding data has its own strengths and weaknesses. The basis encoding method is easy to use but involves using many qubits. The amplitude encoding method is very efficient but needs complicated state preparations to work properly. Angle encoding strikes a good compromise between ease of implementation and efficiency [57,63].

However, several aspects should be taken into consideration in order to choose the proper encoding strategy; these include the size of data, the number of dimensions of the features, quantum resources, and the nature of the intended machine learning application. In actual implementations of quantum machine learning frameworks, the encoding procedure is regarded as a crucial part of the process due to its impact on the transformation process [52,57].

The process of efficient data encoding using quantum bits is essential for the successful

implementation of QML systems. With advancements in quantum computing hardware, it is expected that there will be further developments in efficient encoding schemes in order to facilitate the real-world applicability in various fields such as imaging, activity recognition, big data, and cybersecurity [58,61].

1.6.3 Quantum Classification and Learning Models

Classification is among the most popularly applied machine learning problems and is integral in a wide variety of applications, such as image classification, medical diagnosis, activity recognition, fraud detection, intrusion detection, and prediction. “However, the increasing complexities and dimensions associated with data have often led to difficulties associated with conventional classification algorithms with respect to computation costs, training time, and scalability. In this context, QML attempts to resolve these issues by using quantum computing capabilities [53,61].

The combination of quantum computing and machine learning methods is referred to as quantum-classification models that can leverage quantum states, superposition, and entanglement properties for solving complex tasks. Such models are developed for working with data in a high-dimensional quantum feature space, which allows for effective processing and analysis. In recent years, there have appeared different quantum-assisted machine learning algorithms used in classification and prediction tasks [51,63].

One of the oldest and most widely studied methods of quantum classification is known as the Quantum Support Vector Machine (QSVM). The extension of the classical method involves the use of quantum feature mapping and quantum kernel estimation techniques. By using such techniques, classical data is transformed to higher dimensional quantum feature space where distinguishing features can be made clear. Quantum kernels make it easier for the computer system to calculate similarities, something which might prove difficult in classical computing systems [53,57].

A notable learning architecture in machine learning models is the Quantum Neural Network (QNN). Quantum Neural Networks combine parametric quantum circuit approaches with ideas borrowed from classical artificial neural networks. Like classical neural networks, quantum neural networks learn from data through parameter

optimization. The application of quantum states enables the exploration of more complex feature representations, thereby enhancing learning capabilities. Quantum neural networks have shown great success in applications such as image classification, pattern recognition, optimization, and decision making [56, 65].

The most popular approach in quantum machine learning nowadays is the variational quantum circuit (VQC). In this approach, quantum gates are parameterized, and their parameters are then optimized by classical methods of optimization. The hybrid nature of VQCs renders them a perfect choice for deployment on modern NISQ computers. VQCs possess the ability to learn highly intricate decision boundaries and have found applications in classification, clustering, and regression problems [55,58].

Apart from QML algorithms, recent developments in the field of QML have enabled scientists to build Quantum Convolutional Neural Networks (QCNNs). The working of QCNNs is analogous to that of classical CNNs; however, the difference lies in the use of quantum techniques for performing convolution and pooling processes. Such networks prove beneficial in image classification and pattern recognition applications due to their efficient processing of high-dimensional data [64].

Along with these models, other quantum machine learning methods include Quantum Kernel Methods, Quantum Decision Trees, Quantum Reinforcement Learning, and Quantum Generative Models. These learning methods show the flexibility of Quantum Machine Learning and prove the ability of quantum computing to solve different kinds of learning tasks [61,63]".

One of the significant strengths of quantum classification systems is the possibility to utilize quantum feature spaces and quantum parallelism. Being able to represent the data in exponentially large state spaces makes quantum learning algorithms able to discover very intricate relations within data that cannot be found using standard machine learning algorithms. Therefore, there exist promising perspectives for such models' application [52,57].

Quantum technology is continuously advancing and quantum learning methods are likely to become even more relevant in the areas of image processing, gesture recognition, medicine, cyber security, and big data. Quantum algorithms coupled with

machine learning algorithms are thus seen as one of the promising research paths towards developing smart systems for processing complex real-world data more efficiently than the current methods [59,60,61].

1.6.4 Applications of QML in Image Processing

Image processing is considered to be one of the most promising fields where the use of Quantum Machine Learning can yield the best results. The huge amount of image data produced by various applications such as medical imaging, surveillance system, remote sensing satellites, autonomous vehicles, social networking sites, and multimedia data bases creates enormous difficulties in terms of image processing using conventional techniques. Conventional machine learning algorithms demand a lot of computational power and time to process and learn from big image datasets. The quantum principles of machine learning provide better means for representing images, feature extraction, and classification [27,59,61].

“The fusion between quantum computing and image processing has helped give rise to sophisticated frameworks that leverage quantum superposition, quantum entanglement, and quantum parallelism in an effort to optimize the process of image analysis. Utilizing quantum state space to represent image information allows QML models to analyze visual information more effectively and even simplify the computation process for certain image processing tasks [10,11,27]. Thus, various Quantum Machine Learning approaches have proved to be effective in performing different types of image processing, such as image classification, image segmentation, object detection, pattern recognition, image denoising, feature extraction, image enhancement, and medical image analysis. The ability of quantum computing to effectively represent and manipulate high-dimensional image information makes these applications possible. More specifically, QML frameworks for image processing have demonstrated significant application potential in such fields as medical diagnosis, remote sensing, surveillance systems, facial recognition, and intelligent computer vision, where interpretation of visual information plays a major role [27,53,59,61].

Quantum image representation is one of the important elements involved in quantum image processing. The models like Flexible Representation of Quantum Images

(FRQI) and Novel Enhanced Quantum Representation (NEQR) offer ways to represent image data using quantum representations. This helps in efficiently storing and manipulating image data, which is an essential part of various image processing frameworks using quantum machine learning [10,11,27].

Image Classification is among the fields that have been widely investigated in Quantum Machine Learning. Examples of Quantum Classifiers include Quantum Support Vector Machine (QSVM), Quantum Neural Network (QNN), Variational Quantum Classifier (VQC), and Quantum Convolutional Neural Network (QCNN). Quantum classifiers perform well in pattern recognition and categorization due to their ability to learn quantum feature spaces [53,56,64].

An equally significant area of application is that of image denoising, where Quantum Machine Learning algorithms are used to get rid of noise while retaining key elements of the image, such as the edges and textures. Several promising quantum-based image denoising approaches have been proposed, demonstrating their potential especially in cases where high-resolution images are necessary, e.g., for medical and remote sensing purposes [27,29].

Furthermore, QML has been used for feature extraction and pattern recognition, which are important processes in various computer vision systems. The use of quantum feature mapping allows one to map the features of images into high-dimensional quantum feature spaces such that there will be better separation among different types of images. This process is especially useful when dealing with complicated image data sets [52,57].

In the field of healthcare, the application of Quantum Machine Learning has gained attention when it comes to medical image analysis in which MRI, CT, PET, and X-ray images are involved. QML-based models have the capacity to assist in medical decision-making through improved accuracy in classification along with reduced computing resources [59,61]. In the same way, in the field of remote sensing, quantum-enabled image processing can be used for classification of land cover, environmental monitoring, and disaster assessment.

Some recent works have shown that hybrid quantum-classical models for image

processing are capable of obtaining good results while taking advantage of the capabilities of both quantum and classical computers. The use of hybrid algorithms for image processing is especially appealing in modern NISQ devices, as purely quantum approaches are harder to implement [58].

With improvements in both quantum computers and quantum algorithms, Quantum Machine Learning is likely to become a prominent area within image processing and computer vision". The capacity to efficiently encode, interpret, and categorize large datasets of images renders QML as a promising technology that can be used in advanced vision intelligence systems, imaging systems, and surveillance, among others [59,61].

1.6.5 Applications of QML in Activity Recognition

Activity recognition refers to automatic identification, analysis, and categorization of human activities through information gathered from a variety of different sources including "wearable sensors, smartphones, video cameras, Internet-of-Things (IoT) devices, and smart environments". "The field has attracted attention due to the diverse areas of application that include healthcare, surveillance systems, human computer interaction, smart homes, and intelligent transportation systems. Contemporary activity recognition systems yield massive amounts of multidimensional, and time-series data which present considerable difficulties for traditional machine learning algorithms [63].

The area of Quantum Machine Learning (QML) presents itself as a promising approach for tackling the challenges presented above through employing quantum computation-based approaches for analyzing the activity datasets. Using the principle of quantum superposition and high-dimensional quantum feature spaces, QML approaches are able to work with large volumes of sensor/behavioral data at once to extract useful patterns and achieve improved activity classification results [51,56].

The most important benefit of using QML in activity recognition is the ability to incorporate complicated relationships between different aspects in terms of time and space. Human actions tend to be a combination of complicated processes in which movements, environments, and sensing data come together. However, conventional

machine learning algorithms might not be able to understand these relationships especially when the dataset is big. Quantum learning models, on the other hand, can leverage quantum feature mapping and quantum kernel techniques to detect patterns [52,57].

Quantum machine learning models for activity recognition include Quantum Support Vector Machine (QSVM), Quantum Neural Network (QNN), Variational Quantum Classifier (VQC), and quantum–classical hybrid learning techniques. They have shown promising results in enhancing the classification accuracy while requiring fewer computations on high dimensional activities data [53,56,61]". Due to the above-mentioned benefits, QML-based activity recognition approaches are being increasingly adopted in a number of different areas. For instance, in healthcare, they contribute to the monitoring of patients, disease treatment, and rehabilitation processes, whereas in elderly care, they help detect falls, track activities, and respond to emergency situations. Smart home environments use activity recognition to enable automation of housework and to provide customized services based on behavior of their residents. The same approach is used in human-computer interaction systems, where user gestures and actions are recognized in order to improve user experience. Other applications of activity recognition include sports performance analysis, which involves evaluation of movements of athletes and their performance metrics; industrial safety monitoring, which allows detecting worker actions in order to avoid accidents; and intelligent surveillance systems, which detect dangerous behavior and security risks. Activity recognition is also critical in assisted living applications, where it helps to implement intelligent decision-making capabilities [52,61,63].

In healthcare-related application areas, activity recognition may be utilized for the tracking of patient activities and the detection of their behavior patterns as well as their participation in rehabilitation programs. In eldercare systems, activity monitoring facilitates the detection of falls and any other emergencies, thus increasing patient safety. Moreover, within the realm of smart homes, activity recognition is applied to automate house management [63].

Activity recognition is also a technology that will provide significant advantages in surveillance and security systems. The quantum-based classifiers will play an

important role in recognizing suspicious behavior, anomalies in actions and improving real-time surveillance capabilities. Moreover, there are other systems such as sports analytics and human-computer interactions where activity recognition can be useful [61].

The potential of quantum computing to deal effectively with high-dimensional feature spaces and huge amounts of data has made Quantum Machine Learning (QML) very appealing for developing advanced frameworks for future activity recognition. With the evolution of quantum computers, QML is likely to play a vital role in developing advanced activity recognition systems [52, 63].

In the context of the present thesis, activity recognition is considered as an application area within the broader scope of Quantum Machine Learning rather than as an independently validated experimental component. The discussion presented in this section establishes the relevance and potential applicability of quantum learning techniques to activity-recognition problems based on high-dimensional and sensor-derived data. The experimental and analytical investigations of the present thesis, however, focus primarily on quantum machine learning for Big Data classification and quantum-theory-based image processing and classification. Activity recognition is therefore positioned as a related application domain and a potential direction for extending the proposed quantum computing frameworks.

1.6.6 Applications of QML in Big Data Analytics and Cybersecurity

The emergence of fast-paced advances in digital technology, cloud computing, social media websites, IoT devices, and intelligent information systems has led to the creation of massive amounts of data. “Data processing, storage, classification, optimization, and decision-making pose numerous challenges due to the large amount of data generated. Machine learning algorithms usually face challenges when it comes to processing massive volumes of high dimensional and highly complex data as the computational cost and demand for resources rise with increasing data sizes. Quantum Machine Learning (QML) is considered an innovative technique that integrates quantum computing power with machine learning algorithms [49,53].

The emerging area of research, Big Data Analytics, benefits from the opportunities

offered by Quantum Machine Learning with respect to quantum-based data analysis in terms of quantum enhanced feature mapping, optimization, and classification methods. The capacity of quantum computers to encode data into state space of exponentially large dimensions facilitates effective processing of sophisticated data structures and high-dimensional feature sets. Therefore, QML algorithms have been considered for numerous Big Data tasks such as classification, clustering, prediction modeling, recommendations, financial forecasting, and patterns detection among others. The QSVM, QNN, and Variational QL approaches have shown promising results in terms of enhancing learning speed and accuracy [53,55,59].

Quantum Machine Learning combined with Big Data Analysis offers significant advantages in terms of modeling and decision-making support. With the help of quantum computing concepts like superposition and quantum parallelism, QML techniques are able to evaluate various computational options at once and discover new connections in big data. The use of such technology may result in more accurate predictions, better pattern recognition, and decision-making in various fields like economics, medicine, management, and science [52,57,61].

The field of cybersecurity is yet another crucial area where Quantum Machine Learning can find applications. With the proliferation of networks and cloud computing, there is an enormous amount of security-related data that needs to be processed on an ongoing basis. However, existing cybersecurity solutions find it difficult to detect cyber-attacks because of the ever-increasing sophistication and magnitude of network traffic. In this context, Quantum Machine Learning provides a means to detect intrusion, anomalies, malware, and perform threat analysis of network traffic [60].

Systems employing QML for cybersecurity benefit from enhanced methods of classification and feature extraction to detect attacks and any unusual behavior in massive data. With high dimensional feature spaces created by quantum computing, such a system is capable of identifying attack patterns that are hard to identify through traditional machine learning systems. Quantum Machine Learning models have been shown to boost intrusion detection performance, decrease false positives and increase efficiency in cybersecurity processes. Such ability is highly valued in current

cybersecurity scenarios, where fast recognition and response of threats is necessary for cybersecurity protection [60,61].

Quantum computing will continue its advancement, and Quantum Machine Learning coupled with Big Data Analysis and Cybersecurity is going to become even more important in the coming years. With the efficient processing of huge datasets, pattern discovery, and intelligent decision making, QML can be considered a promising technology for the resolution of future issues in data analysis and information security". Quantum Machine Learning thus emerges as a revolutionary computational model integrating quantum computing and artificial intelligence capabilities into one powerful tool for future big data analysis, cybersecurity, and intelligent information systems applications [58,59,61].

In the context of the present thesis, activity recognition is considered as a relevant application area within the broader scope of Quantum Machine Learning rather than as an independently validated experimental component. The discussion in this section establishes the potential applicability of quantum learning techniques to activity-recognition problems involving high-dimensional and sensor-derived data. However, the experimental and analytical investigations of the present thesis primarily focus on Quantum Machine Learning for Big Data classification, quantum image processing and denoising, and quantum theory-based image classification. Therefore, activity recognition is retained as a related application domain and as a potential direction for extending the quantum computing and machine learning frameworks investigated in this research.

1.7 Motivation of Research

The development of digital technology has led to an exponential rise in the creation of visual data, sensor data, activity data, and diverse heterogeneous data sets. Medical imaging systems, surveillance applications, smart healthcare, the Internet of things, social media sites, and cybersecurity systems are just a few of the many applications that create vast amounts of data which need to be efficiently processed, stored, and analyzed. These types of problems can pose many difficulties for traditional forms of computing as a result of computational efficiency, scaling, memory, and optimization

issues [43,45].

In the area of image processing, there is now a need for efficient image representations and classification processes among other aspects including noise removal and detection of particular patterns. Most traditional image processing methods encounter problems associated with computational complexity whenever they try to process high-resolution images as well as large databases of images. The same problem arises in activity recognition based on wearable sensors, cameras, and other smart devices where human actions are recorded in multiple dimensions. Such activities are not easy to capture using traditional machine learning approaches [61,63].

The advent of quantum computing offers an attractive alternative approach to computation that can overcome these limitations. “Quantum computers take advantage of novel principles such as superposition, entanglement, interference, and quantum parallelism to process information using methods distinct from those used by conventional computers [5,7]. Quantum Machine Learning (QML) is an integration of quantum computing and machine learning to build powerful learning algorithms that can deal with large and high-dimensional datasets. The literature highlights various applications of quantum-enhanced classifiers, quantum variational circuits, and quantum neural networks for tasks related to image classification, pattern recognition, optimization, and data analysis [8,53,55]”.

Moreover, the rising level of complexity in data analysis and cybersecurity is generating an urgent requirement for intelligent methods that can provide valuable insights into huge datasets with high precision and computational efficiency. Current classical techniques face problems such as scalability, slow convergence, and higher computational costs with increasing size of datasets. Quantum computing provides promising possibilities for developing effective algorithms for feature extraction, classification, clustering, and anomaly detection [49,53].

Based on the problems and potentialities described above, the current study intends to propose a holistic framework based on quantum mechanics theory for the representation of images, activity recognition, and big data analysis. The framework will incorporate quantum image processing methodologies, quantum learning models,

as well as the hybrid approach to quantum computing in order to achieve better computation efficacy, high classification accuracy, as well as robust decision-making processes. The research is additionally driven by the emergence of "NISQ (Noisy Intermediate-Scale Quantum)" hardware and software for quantum algorithms [7,9].

1.8 Problem Statement

The remarkable expansion of digital technologies, cloud computing architectures, IoT devices, social networking sites, healthcare information systems, intelligent transport systems, and automated industrial systems has produced huge amounts of structured, semi-structured, and unstructured data. The explosion of data has led to an entirely new manner of handling the collection, storage, processing, and analysis of data by organizations. As a result, the Big Data Analytics paradigm has become one of the most vital areas of research concerning knowledge discovery, pattern recognition, and intelligent decision making within different application scenarios. Nevertheless, the ever-growing size, volume, velocity, variety, veracity, and complexity of current data sources have brought a number of weaknesses in traditional computing and machine learning methodologies into sharp focus. Traditional computing solutions are not capable of performing effective data analysis because of inherent difficulties linked to computational complexity, memory usage, scalability, runtime, and resource efficiency [43,44].

The use of Machine Learning and Artificial Intelligence methods has greatly enhanced the ability of contemporary data analysis systems and has found applications in such operations as classification, prediction, clustering, optimization, and pattern recognition. However, despite such developments in the field, most traditional machine learning processes tend to show decreased efficiency while processing complex high-dimensional data sets. The larger the volume and variety of information used for analysis, the more computationally intensive becomes the process of building models, extracting features, parameter optimization, and making decisions [46,47]. Thus, traditional learning algorithms suffer from increased execution time, memory requirements, and slow convergence in large-scale Big Data settings.

"The development of Quantum Computing has paved the way for a new type of

computation that promises to provide solutions to a number of problems associated with traditional computers. Using phenomena like superposition, entanglement, interference, and quantum parallelism that are based on quantum mechanics, quantum computing has opened up new avenues of dealing with information-related problems. Further developments in this field have led to the birth of Quantum Machine Learning (QML), which has come up as an interesting field of research that involves combining machine learning techniques with quantum computing principles. A number of recent works have highlighted the ability of various quantum algorithms like Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), Variational Quantum Circuits (VQC), Quantum Kernel Methods, etc., for tackling difficult tasks of classification, optimization, and prediction.

However, despite these promising trends, there are some important issues that have yet to be addressed. The first issue associated with the current body of research concerns the absence of substantial empirical investigation of Quantum Machine Learning models through application to practical Big Data problems. Most of the existing research efforts are limited to the proof of concepts or experimentation within benchmark datasets and simulations performed under controlled settings. Thus, the potential of quantum learning algorithms in terms of their practical applicability and scalability for working with Big Data remains unexplored.

One of the other major challenges includes that of quantum data encoding and representation of features. Encoding of classical data as quantum states is an essential component for applying Quantum Machine Learning algorithms. But the current methods used to encode quantum data tend to generate high state preparation overhead, complexity in circuits, and increase in computation costs. Moreover, practical quantum computing still has certain hardware-based limitations, such as scarcity of qubits, limited qubit connectivity, low coherence times, quantum noise, and errors in gate operations. All these challenges significantly hinder the advantages promised by quantum computing".

In addition to issues with scalability and encoding, there is no generally accepted benchmarking approach that can fully assess the performance of classical algorithms, quantum algorithms, and hybrid quantum-classical algorithms. Existing research

usually concentrates on performance measures like classification accuracy and runtime and overlooks such parameters as computational complexity, memory consumption, scalability, convergence, and resource consumption. The lack of a universal benchmarking technique makes it complicated to compare the advantages and disadvantages of quantum-based learning algorithms objectively.

Moreover, while hybrid models of quantum-classical computation have been identified as promising solutions for NISQ-based computing architectures, systematic ways of incorporating quantum and classical computing elements into such systems still lack development. How best to allocate computations between quantum and classical elements of the computing architecture, effective usage of quantum elements, and computational overhead minimization remain open problems. This means that further investigation is necessary for developing efficient hybrid models of computation that can take advantage of classical and quantum computing approaches.

Hence, taking into account the shortcomings of current methods and increasing demands for effective tools for Big Data analytics, there is an urgent need for designing a scalable hybrid model combining quantum data coding techniques, Quantum Machine Learning algorithms, and proper complexity benchmarking techniques. Such a design will have the ability to address the problem of the gap between theory-based quantum advantages and practical applications in Big Data analytics. Efficient and scalable designs of quantum-based learning models are expected to play an important role in enhancing classification accuracy, computational efficiency, and intelligent decision-making capabilities in future Big Data settings.

1.9 Research Objectives

The research gaps identified through the literature review provide the basis for the formulation of the research objectives of the present study. The first gap relates to the need for scalable and practically relevant hybrid quantum–classical approaches for Big Data analysis, considering computational and quantum-hardware-related constraints. This gap is addressed through RO1, which focuses on the development of a scalable Hybrid Quantum–Classical Framework. The second gap concerns the challenges associated with quantum data representation and encoding, particularly in terms of

feature representation, space requirements, and computational speed. This gap is addressed through RO2, which focuses on efficient quantum data encoding for space and speed optimization. The third gap concerns the lack of consistent evaluation and comparative assessment of classical, quantum, and hybrid approaches. This gap is addressed through RO3, which focuses on unified complexity benchmarking and cross-domain validation. Accordingly, the three research objectives establish a direct relationship between the identified research gaps and the analytical, comparative, and framework-oriented work presented in the subsequent chapters.

“The main purpose of this research is to construct and analyze a scalable quantum-enhanced platform for analysis of Big Data through Quantum Machine Learning. The research tries to overcome current challenges associated with scalability issues, quantum data coding, and performance assessment in quantum-classical hybrid models. The objectives of the research are outlined below”:

RO1: Development of a Scalable Hybrid Quantum–Classical Framework

The objective is to create an innovative hybrid model of quantum-classical learning that can enhance classification accuracy and lower computational complexity for Big Data analysis by taking into account hardware-related aspects of quantum computing technology like noise, quantum circuit depth, qubit coherence, and qubit availability.

RO2: Development of Efficient Quantum Data Encoding for Space and Speed Optimization

The objective is to explore and develop quantum encoding schemes and methods for reducing features to be more efficient when preparing quantum states, reducing space complexity and speeding up Big Data analysis in Quantum Machine Learning frameworks.

RO3: Development of Unified Complexity Benchmarking and Cross-Domain Validation

The objective is to develop a comprehensive benchmarking framework to measure time complexity, speed, and space complexity for classical, quantum, and mixed quantum-classical algorithms and to test the same framework using Big Data samples for different classification problems.

The research objectives are directly aligned with the research gaps identified through the literature review and with the subsequent research activities presented in this thesis. RO1 addresses the need for scalable hybrid quantum–classical approaches for Big Data analysis through the development and analysis of quantum machine learning and hybrid classification frameworks. RO2 addresses the challenges associated with quantum data representation and encoding by investigating efficient quantum data encoding and feature representation approaches for reducing space requirements and improving computational speed. RO3 addresses the need for consistent comparative evaluation by considering complexity, execution time, speed, and resource-related measures for the analysis of classical, quantum, and hybrid approaches. These objectives collectively provide the basis for the methodological investigations and comparative analyses presented in the subsequent chapters and establish the link between the identified research gaps, the research objectives, and the contributions of the present study.

1.10 Scope of Research

The current research focuses on studying the development, design, deployment, and performance assessment of the state-of-the-art QML frameworks for performing analytical operations on big data through hybrid classical and quantum computing architectures. “This study is mainly aimed at understanding the effective use of various fundamental concepts associated with quantum computing, such as quantum superposition, quantum entanglement, quantum interference, and quantum parallelism to handle the computational problems that exist with processing big data. The main purpose of the study is to develop an understanding regarding the transition from machine learning to quantum computation by creating frameworks that provide improved efficiency in handling and processing big data.

One important part of the research includes an examination of ways to represent and encode quantum data that can be implemented within Big Data settings. Because one of the most important tasks in Quantum Machine Learning is to find efficient data encodings, the research focuses on several techniques to map classical data into the quantum format, including various data encoding methods, feature mapping algorithms, and dimensionality reduction methods. Special attention is paid to the issue

of how to reduce the overheads in preparing the quantum state, how to save resources, how to make the circuit simple, and how to make computations faster.

The other significant part of the research involves creating and testing hybrid quantum-classical learning architectures. Rather than using only quantum computation in their work, the researchers have decided to explore the possibility of integrating elements of quantum computing and classical machine learning. As a result, the research will involve studying the best possible distribution of computational tasks across classical and quantum domains in order to optimize efficiency, reduce computational complexity, and address the issues posed by NISQ (Noisy Intermediate-Scale Quantum) systems. The influence of such factors as quantum noise, depth of quantum circuits, connectivity of qubits, limited coherence, and others on the efficiency of hybrid systems will be investigated.

Additionally, the extent of the research involves the evaluation of several Quantum Machine Learning algorithms utilized for Big Data classification and predictive analysis. Such quantum-assisted learning algorithms as Quantum Support Vector Machine (QSVM), Quantum Neural Network (QNN), Variational Quantum Circuit (VQC), Quantum Kernel Based Learning Algorithms, and other similar algorithms combining quantum and classical computing are assessed, contrasted, and compared. The performance of the selected algorithms in relation to such criteria as classification accuracy, speed, computational complexity, convergence, and scalability are investigated in the study. At the same time, an assessment and comparison are performed with respect to traditional machine learning algorithms.

Further, another area of interest in this research includes developing a universal approach towards benchmarking and evaluating the performance of both quantum and classical computational models. Currently, most research efforts assess the performance of quantum algorithms in an individualized manner by using different sets of measures, which makes it hard to make a fair comparison between the two computing approaches. As such, it is intended that the current research will develop an evaluation framework capable of measuring the performance of quantum models in terms of execution time, computational efficiency, memory consumption, scalability, speed, and classification accuracy.

Validation experiments for the newly developed methodologies are carried out within the simulation models of quantum computing, as well as the currently existing quantum computing platforms. The use of representative benchmarking data from various applications serves to determine whether the new frameworks are robust enough, scalable, and practical for real-life implementation. Experimentation is concerned with determining the efficiency of these hybrid architectures under realistic computational circumstances and their ability to bring about some improvements compared to classical machine learning algorithms.

Although the literature review includes a wide range of subjects related to Quantum Computing and Quantum Machine Learning, it is clearly focused only on gate-based quantum computing approaches, quantum data encoding, Quantum Machine Learning algorithms, hybrid quantum-classical computing systems, and big data classification using quantum techniques. Such topics as quantum computer architecture, quantum processors, fault-tolerant quantum computing, quantum communication, quantum networks, quantum internet, and quantum cryptography fall outside the scope of this study and should be studied separately due to their specificity.

In summary, the current research efforts are geared towards formulating Quantum Machine Learning algorithms that can effectively solve Big Data problems". This is achieved through concentrating on scalable Quantum architectures, effective quantum encoding techniques for data sets, and proper benchmarking techniques that evaluate the computational complexity of the proposed approaches. The aim of such research efforts is therefore to close the gap between the theory and practice of quantum computation in solving real world Big Data problems.

Although activity recognition is discussed as a relevant application of Quantum Machine Learning, the present research does not claim a separate empirical activity-recognition framework or independent experimental validation of human activity recognition. The primary empirical and analytical emphasis of the thesis is on Quantum Machine Learning and hybrid quantum–classical approaches for Big Data classification, quantum image processing and denoising, and quantum theory-based image classification. Activity recognition is therefore retained within the broader application context and is identified as a potential area for future extension of the

proposed quantum computing frameworks.

1.11 Organisation of Thesis

The research thesis consists of six distinct chapters that focus on various aspects related to "Quantum Computing, Quantum Machine Learning, and Big Data Analytics. The chapters are structured in such a way that one progresses logically to another chapter leading to a conclusion.

Chapter 1: Introduction highlights the background and basics of quantum computing, quantum mechanics, quantum machine learning, quantum image processing, and big data analytics. This chapter provides an insight into the motivations for this research work, problem statement, research objectives, research scope, and the entire thesis organization.

Chapter 2: Literature Review presents an exhaustive literature review covering studies associated with quantum computing, quantum machine learning, quantum data coding approaches, quantum image processing, denoising of images, quantum classification methods, hybrid quantum-classical learning approaches, and Big Data analysis. Comparative analysis of various existing approaches is discussed, after which research gaps are identified and the research objectives are formulated.

Chapter 3: Quantum Computing-based Machine Learning Algorithms for Classification of Big Data Sets presents the development and performance evaluation of Quantum Machine Learning algorithms for the classification of Big Data. In this thesis, a Hybrid Quantum–Classical framework is developed for intelligent Big Data analytics. The chapter discusses the challenges encountered during Big Data processing, the advantages of quantum computing, quantum encoding methods, hybrid quantum-classical learning approaches, and Quantum Machine Learning algorithms. Evaluation and comparative analysis are carried out using benchmark datasets to demonstrate the effectiveness of the proposed framework.

Chapter 4: Quantum Mechanics Based Image Processing and Denoising Algorithms presents a systematic literature review and comparative analysis of Quantum Image Processing and Quantum Image Denoising methods. The chapter discusses quantum image representation, image enhancement, quantum image

filtering, image denoising techniques, and image quality assessment measures. Comparative analysis of various quantum image processing methods is also presented to identify their strengths, limitations, and research gaps, thereby providing the theoretical foundation for the proposed work.

Chapter 5: Development of a Classification Architecture for Images Represented Using Quantum Theory presents the development and implementation of the proposed classification framework for images represented using quantum theory. In this thesis, a Quantum Theory-Based Image Classification Architecture is developed by integrating quantum image representation techniques with Hybrid Quantum–Classical learning approaches. The chapter describes quantum image representation, feature extraction, the design of the proposed classification architecture, quantum neural network models, implementation of the proposed framework, and its performance evaluation.

Chapter 6: Conclusion and Future Scope presents the major findings, research contributions, conclusions, and future research directions of the present thesis. The chapter provides an overview of the significant results, contributions, and implications of the proposed research. The limitations of the current research are discussed along with future research directions related to scalable Quantum Machine Learning frameworks, Hybrid Quantum–Classical models, quantum data encoding techniques, complexity measurement approaches, practical Big Data applications, and emerging quantum computing technologies.

Consequently, the current thesis presents an extensive examination of Quantum Machine Learning approaches, quantum image processing, quantum-classical models, and Big Data analysis, thereby making contributions to the creation of intelligent computing systems through the use of quantum technology".

The organization of the thesis follows the research objectives and the corresponding analytical investigations. The literature review establishes the research gaps and provides the basis for the formulation of the research objectives. The subsequent chapters address these objectives through quantum machine learning and hybrid quantum–classical approaches for Big Data classification, quantum image processing

and denoising, and quantum theory-based image classification. The findings and limitations of these investigations are consolidated in Chapter 6, where the major contributions, limitations, and future research directions are presented. Thus, the chapter-wise organization provides a traceable link between the identified research gaps, research objectives, methodological investigations, and research contributions.

1.12 Chapter Summary

In this chapter, we have explored the essential introductory aspects of fundamental concepts and theories as well as technological advancements forming the basis for the current study. “The chapter commenced with an insight into quantum computing and how it has become a revolutionary computational framework that can resolve many shortcomings inherent in traditional computing frameworks. The basic tenets of quantum mechanics such as qubits, superposition, entanglement, quantum interference, and quantum gates were explained to provide a theoretical foundation of quantum computation and quantum information. Moreover, comparison between classical computing and quantum computing was done to illustrate the computational strengths of quantum computing.

Moreover, the chapter gave an introduction to Quantum Image Processing (QIP) and Big Data Analytics and emphasized on the increasing significance of such techniques in contemporary intelligent computing systems. Different quantum models for the representation of images and image processing techniques have been discussed with an eye toward the possibility offered by quantum algorithms for image representation, classification, feature extraction, and denoising. Alongside this, issues related to data processing and data management techniques that arise in the presence of big data have also been mentioned.

Quantum Machine Learning (QML) was elaborated in detail to show how quantum computing concepts could be used along with machine learning algorithms to improve the speed, scalability, and accuracy of learning process. Many features of QML, such as quantum encoding and representation methods, Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), Variational Quantum Circuits (VQC), as well as a hybrid approach to quantum-classical machine learning, were explained

in this regard. This chapter emphasized on the increasing importance of Quantum Machine Learning in handling sophisticated classification and optimization tasks.

The research motivation, problem statement, research objectives, and scope of the research study were introduced next. The importance of scalable approaches for addressing the growing complexities of computations for data analysis tasks was explained. The limitations in terms of computational complexities, scalability, quantum-based encoding of data, and performance assessments were described, thus proving the need for developing efficient hybrid quantum-classical computing models for Big Data analysis problems. The objectives of the research were stated in the context of addressing these challenges in the field by designing scalable learning models, encoding schemes, and benchmarking methods.

Finally, the structure of the thesis was delineated in order to give an idea of how the research process is organized and what part each chapter plays in the realization of research objectives. In general, this chapter laid down the theoretical groundwork of the research and set the context for further investigation". The issues and concepts explored in this chapter form the basis of the literature review, framework development, experimentation, and analysis that will be conducted throughout the rest of the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The fast development of information technology, artificial intelligence, Internet of Things (IoT), cloud computing technology, and telecommunications has caused an exponential growth in data production around the world in terms of size, speed, and diversity. Modern applications, including medical imaging, autonomous driving, remote sensing, social media analysis, cybersecurity, and smart cities, create enormous volumes of structured and unstructured data, which must be processed and analysed efficiently. While conventional computing systems have played a key role in developing data analysis and machine learning techniques, their inability to handle complex and high-dimensional data has revealed numerous shortcomings in terms of computational performance, scalability, optimisation, and power consumption [1], [2].

Quantum computing is one of the revolutionary models of computation that has been developed and can be used to overcome several problems related to classical computing systems. “While conventional computers use bits whose states can either be 0 or 1 to perform computation, quantum computers use qubits that exploit quantum phenomena like superposition and entanglement to perform computation [3]. Quantum computing makes use of quantum interference and quantum parallelism and therefore has the ability to solve certain computational problems much faster than classical computing. The works of Feynman and Deutsch led to quantum computing developing into a multidisciplinary area of research involving several fields, including physics, mathematics, and computer science [4], [5].

The recent development of quantum computers, especially through superconducting qubits, trapped-ion systems, photonic quantum computers, and quantum annealers, has led to the fast-paced development of quantum computer technology. Some of the major technological players involved in this field include IBM, Google, Microsoft, Riggetti, IonQ, and D-Wave, who have contributed extensively towards developing quantum processors and quantum cloud computing platforms [6]. Such developments have made possible the existence of NISQ machines, allowing researchers to explore

potential uses of quantum computing in fields like optimization, machine learning, cryptography, image processing, and big data analytics [7].

One of the fields that can benefit greatly from quantum computers is image processing. Contemporary image processing techniques have to process very large amounts of data that are produced by security systems, medical devices, remote sensors on satellites, industrial automation systems, and multimedia technologies. The limitations of classical image processing techniques include problems in processing the high-dimensional images and carrying out computationally complex feature extraction and classification tasks [8]. Quantum Image Processing (QIP) employs innovative approaches to image representation, including Flexible Representation of Quantum Images (FRQI), Novel Enhanced Quantum Representation (NEQR), and Multi-Channel Quantum Image (MCQI) models, making it possible to achieve efficient storage and processing of quantum images [9], [10]. This paves the way for implementing more sophisticated quantum image enhancement, segmentation, compression, de-noising, and classification algorithms.

Alongside image processing, the advent of big data has also created many issues concerning data management, data storage, processing, and data analytics. Big data environments involve the popular factors of volume, velocity, variety, veracity, and value. Companies are now depending more on the use of prediction analytics, machine learning, and data mining approaches in order to derive useful information from big data repositories. There have been noted cases where traditional machine learning models face problems concerning scalability during the processing of high-dimensional and heterogeneous data [11]. This has increased the interest to combine quantum computing with big data analytics.

The integration of quantum computing with machine learning has led to the emergence of Quantum Machine Learning (QML), a branch that uses the power of quantum computing in conjunction with the predictive ability of machine learning techniques. The main aim of QML is to harness quantum effects to improve classification, clustering, optimization, dimensionality reduction, and pattern recognition processes. Some quantum learning methods such as Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), Variational Quantum Circuit (VQC),

Quantum Principal Component Analysis (QPCA), and Quantum Kernel Methods have proven superior to their classical equivalents [12], [13].

The relevance of Quantum Machine Learning has become more pronounced owing to its ability to resolve the computational issues that arise while dealing with high dimensional data processing. Through the use of quantum bits to encode classical information, QML models can represent large feature spaces with relatively reduced computational effort. Quantum optimization techniques also make it easy to optimize model parameters, which is necessary when applying these models to fields like image recognition, activity recognition, anomaly detection, cybersecurity, and forecasting applications [14]. Quantum–classical hybrid systems have been developed in recent times as a viable option to run NISQ devices, merging the benefits of classical ML systems with those of quantum computing [7],[15].

Recognition of activities is yet another interesting research area that can gain from developments in quantum computation and machine learning algorithms. Recognition of human activity patterns has been increasingly used in health care systems, smart environment control, security surveillance, industrial automation, and human computer interactions. Activities often involve analyzing huge amounts of image data, video information, and sensory data, which requires classification of patterns to be done effectively. Application of quantum machine learning methods in the area of activity recognition can prove helpful in achieving more accurate pattern classifications.

Considering the emerging importance of quantum computing in the context of image processing, activity recognition, and big data analytics, it becomes imperative to conduct a detailed survey of relevant literature to determine prevailing advancements, research trends, technological limitations, and possibilities for future research. This chapter provides an extensive survey of key findings and advancements made in the areas of Quantum Image Processing, Quantum Machine Learning, Quantum Classification Models, and Quantum Optimization. Furthermore, this chapter discusses the comparison of various existing methodologies and highlights important gaps in research, which drive the need for a holistic framework based on quantum theory for image processing and activity recognition.

The remaining sections of the present literature review chapter have been outlined as follows. Section 2.2 includes an elaborate review on Quantum Image Processing techniques and image representation models. Section 2.3 highlights quantum image denoising algorithms and discusses their capabilities. Section 2.4 gives an overview of the significant Quantum Machine Learning algorithms and their applications. Section 2.5 includes a review on quantum classifiers designed for pattern recognition and data analytics operations. Section 2.6 focuses on quantum optimization techniques applied in machine learning and big data processing". The comparative analysis of the approaches discussed has been included in Section 2.7, and the limitations of current approaches have been highlighted in Section 2.8.

2.2 Review of Quantum Image Processing Techniques

QIP represents an innovative cross-disciplinary scientific study that merges the concepts of quantum computation with image processing technology to facilitate image representation, storage, modification, and analysis on a quantum basis. "Through taking advantage of the basic features of quantum mechanics like superposition, entanglement, and quantum parallelism, the field of QIP has the possibility of processing massive amounts of image data much more efficiently than traditional methods [17], [18]. In recent years, several frameworks for the representation of images and image processing algorithms have been suggested to enhance different aspects of image processing [16], [17], [23]. The emergence of quantum image representation schemes, including FRQI (Flexible Representation of Quantum Images), NEQR (Novel Enhanced Quantum Representation), MCQI (Multi-Channel Quantum Image), GQIR (General Quantum Image Representation), and QRMW (Quantum Representation of Multi-Wavelength Images), has greatly increased the scope of applications of quantum computing in medical imagery, remote sensing, multimedia systems, computer vision, and intelligent image analysis [19], [20], [22], [29]". It is necessary to get familiar with the development process and features of quantum image processing schemes in order to develop quantum-computing-based frameworks for image analysis and intelligent systems.

2.2.1 Introduction to Quantum Image Processing (QIP)

QIP represents an interdisciplinary domain of research, which merges the theories of quantum physics with those of digital image processing to efficiently represent, store, transmit, enhance, compress, and analyze images. The basic aim of QIP is the use of quantum mechanics principles like superposition, entanglement, and quantum parallelism in order to surpass the limits of classical approaches to image processing [16], [17].

The growing amount of image information produced by medical imaging equipment, surveillance systems, remote sensing satellites, autonomous vehicles, and multimedia systems is creating difficulties for traditional algorithms of image processing. Traditional approaches may face problems of computational complexity when dealing with high resolution images or image databases. Quantum computers provide a solution wherein image data can be represented in quantum states and thereby allow the processing of several pixels at once while reducing the amount of computation needed for certain tasks [18].

In recent decades, many models have been designed for quantum images that allow the process of storing and manipulating images in quantum machines. The models vary based on their encoding scheme, computational complexity, the ability to represent color information, and implementation requirements. Some of the most prominent models include “FRQI (Flexible Representation of Quantum Images), NEQR (Novel Enhanced Quantum Representation), MCQI (Multi-Channel Quantum Image), GQIR (General Quantum Image Representation), and QRMW (Quantum Representation of Multi-Wavelength Images)”.

2.2.2 Flexible Representation of Quantum Images (FRQI)

The FRQI model is known to be one of the pioneering image representation models developed in the domain of QIP. This model was proposed by “Le, Dong and Hirota back in 2011”, where its main goal was to present a method that will facilitate the representation, storage and manipulation of digital images in quantum computer systems [19]. Prior to the appearance of FRQI, research efforts in quantum computing were mainly focused on the areas of quantum algorithms and complexity issues, while little effort was paid to the issue of image representation and visual information

processing. Therefore, the creation of FRQI model can be seen as a breakthrough in the area of quantum computing [19].

The encoding scheme of the FRQI model employs two mutually exclusive encodings of the image information through position qubits and color qubits. While coordinates of the pixels are described through quantum states in the computational basis, their grayscale intensity values are described by means of probability amplitudes. This allows for describing a $2^n \times 2^n$ image with relative few qubits. Thus, the FRQI model provides a highly efficient way of storing images when compared to other traditional image encoding schemes. Le et al. [19] have shown how to implement image preparation, image retrieval, image compression, and various transformations of images using polynomial-time quantum circuits.

One important strength of FRQI results from its potential to utilize the concept of quantum parallelism. As all pixel data are represented in one quantum state at once, several tasks of image processing can potentially be performed simultaneously. Such features make it a computationally attractive tool for image processing purposes on a larger scale when traditional techniques face challenges concerning issues of computational efficiency, time consumption, and memory consumption [17], [23]. Indeed, FRQI has been used as the basis of many algorithms for quantum image processing in regard to such operations as image compression, image retrieval, image enhancement, image encryption, watermarking, geometric transforms, and feature extraction [19], [23].

After the seminal work by Le et al. [19], various studies have been carried out to analyze the effectiveness of FRQI for practical applications in image processing. Studies carried out by surveying and analyzing some real-time image processing applications reveal that many traditional image processing techniques could be redesigned in quantum computing models via quantum circuit implementations based on FRQI [17], [23]. It is evident from these studies that many image transformations, image manipulation techniques, image matching techniques, and even image retrieval techniques could be designed using quantum gates.

Caraiman and Manta [16] analyzed the wider implications of the use of quantum image

processing methods and reviewed how FRQI could be used for image processing purposes like image enhancement, filtering, and image transformations. They found out that quantum image processing could possibly lower computational complexity in certain cases where larger image sets are involved. But at the same time, it has to be noted that the process is limited due to hardware constraints and the limited functionality of quantum computers [16].

FRQI's importance has been highlighted in many literature review papers. “Yan et al. [17] have pointed out that FRQI is one of the most versatile quantum image representation models, which successfully balances between memory usage and computation power. Likewise, Lisnichenko and Protasov [22] stated that FRQI had been playing an important part in the development of image representation within the realm of quantum computing and was the cornerstone for many other image encoding schemes. According to these researchers, FRQI had found extensive application in the fields of quantum image compression, encryption, image retrieval, and quantum machine learning [17], [22].

Following this, various other advanced image processing algorithms like quantum image matching, quantum image segmentation, quantum image denoising, quantum image compression, and image classifier systems have been developed through the use of the FRQI technique [17], [34], [53]. Moreover, owing to its adaptability, FRQI has been applied in combination with quantum machine learning methods, leading to hybrid quantum-classical approaches for tackling challenging tasks such as visual recognition and pattern analysis [31], [43]”.

Nevertheless, despite the various benefits associated with it, FRQI faces a number of drawbacks that have prompted researchers to develop new quantum image representation frameworks. Firstly, the problem is that intensity values of gray scale images are encoded via probability amplitudes. This means that in order to perform the proper reconstruction of an image, repeated measurement needs to be conducted in order to evaluate the pixel intensities, which may lead to errors and lower image retrieval accuracy [24], [55]. In addition, amplitude encoding is vulnerable to loss of information due to quantum noise and decoherence effects.

One other limitation is that of scalability. While FRQI offers a compact way of representing images, the process of preparing images with increased dimensions necessitates more complex quantum circuitry and an increasing number of quantum gates to perform these actions. This is why the scaling problem poses a challenge in terms of implementing FRQI-based image retrieval on current NISQ devices [27]. In light of this issue, researches have turned their attention to other methods of image representation such as NEQR and GQIR to improve the quality of search tasks, reduce uncertainties, and offer more flexibility in image processing applications [10], [22].

In general, FRQI is considered an innovative contribution to Quantum Image Processing and remains one of the most widely researched quantum image representation approaches. The ability of FRQI to compress image data, enable parallel image processing tasks, and implement various quantum image processing algorithms contributes to the high status of FRQI as a pioneering approach in quantum image processing. Even with its existing limitations such as problems with measurement errors, scale issues, and hardware challenges, FRQI has become a basis for future development in modern quantum image representations [17], [22], [53].

2.2.3 Novel Enhanced Quantum Representation (NEQR)

Whereas the FRQI approach enabled an efficient representation of images in quantum computers, some constraints were observed with regard to the process of amplitude-based representation of images. Specifically, the retrieval of grayscale pixel values was possible through repeated measurements that could lead to inaccuracies and even information loss. With a view to tackling this problem, Zhang, Lu, Gao, and Wang developed what they referred to as the NEQR scheme in 2013 [10]. This approach differs from FRQI in that the NEQR scheme involves direct encoding of grayscale pixel values.

The most important achievement of Zhang et al. [10] lies in the creation of an image representation model based on which images can be represented using quantum registers and their pixel values can be saved explicitly in quantum bits. As basis states directly represent grayscale information in the proposed approach, NEQR facilitates the exact extraction of pixel values from quantum states through measurement

procedure. This model is capable of implementing various image processing operations including image preparation, inversion, enhancement, and transformation [10].

After NEQR, numerous studies were carried out on its use in different areas of quantum image processing operations. Iliyasu et al. [35] focused on studying techniques of watermarking and authenticating quantum images, showing how the direct use of pixel value can increase the strength and security of image security protocols. This study emphasized the need for proper encoding of images for secure image communications.

Another important topic covered under NEQR is the image enhancement and feature extraction. In their study, Liu and Wang [25] have introduced a quantum algorithm for detecting edges in the image utilizing NEQR approach and an eight-direction Sobel operator. The study concluded that the use of grayscale in the NEQR approach enables precise edge localization and image feature extraction. In another study, Li et al. [26] have presented a quantum image processing algorithm for performing the edge detection task utilizing a line detection mask and NEQR approach, and found improved image analysis and feature extraction results.

Additionally, research into the contribution made by NEQR to the field of image classification and recognition has been conducted. According to Ganguly [42], images described by NEQR can successfully be processed via Quantum Neural Networks (QNN), thus creating a route between “quantum image representation and Quantum Machine Learning (QML). It was shown that the NEQR model can be used alongside quantum machine learning tools.

The significance of NEQR was addressed in some literature reviews, too. Thus, for example, Yan et al. [17] found NEQR to be one of the most significant advances in quantum image representation due to its ability to address the image-retrieval issues inherent to FRQI. At the same time, Wang et al. [34], reviewing the most significant quantum image processing architectures, concluded that NEQR offers more accurate images after reconstruction, greater processing flexibility, and a higher versatility of application for tasks ranging from image enhancement to image security, image

analysis, and image classification. Recent literature reviews by Lisnichenko & Protasov [22] and Farooq et al. [53] have reaffirmed that NEQR continues to be one of the most frequently used quantum image representation architectures in current QIP research.

Studies done comparatively have shown benefits of NEQR compared to other image representation techniques based on amplitude. According to the study done by Werner et al. [55], there is greater accuracy in reconstruction when the image representation technique used is basis-state method as seen with NEQR compared to other techniques. Similarly, Silos-Sanchez et al. [56] compared FRQI and NEQR in terms of their ability to perform image processing tasks and found that NEQR gives more accurate image retrieval and reconstruction.

Even though NEQR has a lot of benefits, some difficulties are associated with it. Explicit storage of gray scale values leads to an additional need for quantum registers, hence an increase in the number of qubits needed and complexity of the circuitry. With increasing image resolution, more qubits will be needed, which makes NEQR difficult to implement using today's NISQ computers [27]". Moreover, state preparation is also complex and prone to decoherence and gate errors, especially in cases of higher resolution images. However, due to its deterministic image recovery, excellent reconstruction quality, and suitability for many different image processing techniques, NEQR has remained among the most notable approaches to quantum image representation [22], [34], [53].

2.2.4 Multi-Channel Quantum Image (MCQI)

Even though FRQI and NEQR provided an excellent way to represent gray scale images, there is a need in most image processing tasks to use colored information for correct image processing and analysis. The application areas include medical imaging, multimedia information processing, surveillance systems, autonomous navigation, remote sensing, and computer vision, among others. This was tackled by the proposal of the MCQI approach by Sun, Iliyasu, Yan, Dong, and Hirota in 2013 [40].

However, the MCQI model provided an advancement over earlier quantum image representations by including the possibility of encoding the RGB channels at once in

a single quantum state. Compared to quantum image representations which focus on gray scale images, MCQI allows for color image representation while retaining the power of quantum parallelism. As demonstrated by Sun et al. [40], the simultaneous use of several channels via quantum computations opens the door to more advanced image processing tasks.

The importance of MCQI has been pointed out in numerous review articles about quantum image processing. Yan et al. [17] mentioned MCQI as one of the most significant innovations in quantum image representation since it has greatly increased the application of QIP for color image processing instead of grayscale image processing. Likewise, Wang, Xu, and Zhang [34] observed that the use of color image representations, like MCQI, is essential for performing the processes of image enhancement, image compression, image segmentation, image retrieval, and image classification in quantum computing platforms. Very recently, extensive reviews by Ebrahimpour-Komleh and Hadipour [51] and Farooq et al. [53] underscored the importance of MCQI, which has greatly enhanced the range of applications of QIP through its capability to represent color images.

Following this, there was research on the use of MCQI for image security applications. Abdelghafoura and Brahima [41] suggested an image encryption scheme using quantum image representation approaches, showing how color quantum encryption could increase image security and boost its immunity to any cryptoanalytic attacks. This showed how MCQI-derived image representations could be useful in secure multimedia communications.

The development of Quantum Machine Learning (QML) made color-based quantum image representation even more attractive. In the paper of Senokosov et al. [43], researchers explored the application of quantum machine learning methods in image classification and found out that rich representation could help with better extraction and classification of features. Similar results were achieved by Chen [47] who tested the applicability of variational quantum algorithms for image classification and found out that advanced quantum image representation could be beneficial for visual recognition tasks. Thus, we can conclude that color-based images represented as MCQI will be useful in the future computer vision system.

In addition to its uses in classification and security, MCQI has also found application in image enhancement, restoration, compression, and multimedia processing. As RGB information is encoded together, several color channels can be controlled in parallel through quantum computation, offering greater efficiency in image processing applications [17], [34], [51]. The theory thus allows for the development of sophisticated image analysis applications that can take advantage of the quantum computing paradigm.

However, MCQI does face some difficulties due to its benefits. First, the representation of different color channels entails the use of more quantum registers, thus increasing the number of qubits required for the encoding process by a considerable amount. Second, this means that circuit depth and computational complexity of MCQI would be much higher compared to other colorless image representation methods, such as FRQI and NEQR [34], [53]. Additionally, the higher number of quantum operations would make MCQI vulnerable to various sources of errors, including decoherence and NISQ effects [27].

The second constraint concerns scalability of hardware. Color images at high resolution need a considerable number of qubits for their representation, and most existing quantum computers cannot satisfy such requirements. Thus, most studies conducted using the MCQI approach still use software simulations rather than hardware experiments [27], [32].

In summary, MCQI is undoubtedly a significant achievement for QIP research by offering an efficient way of representing and manipulating color images. Its application range has greatly widened, allowing quantum image processing methods to be used extensively in computer vision, multimedia applications, image security, image retrieval, and quantum machine learning. Despite the challenges posed by limited hardware capabilities to use this technique on a wider scale, MCQI is definitely the most prominent model for color image representation among current QIP research work [17], [34], [51], [53].

2.2.5 General Quantum Image Representation (GQIR)

The continuous development of the QIP process has encouraged researchers to

formulate quantum image representation models that address the shortcomings faced by previously established models such as the “Flexible Representation of Quantum Images (FRQI) and the Novel Enhanced Quantum Representation (NEQR) models”. These models played a vital role in enhancing QIP; however, due to certain restrictions placed on representation, there was a problem in accommodating different types of images. Therefore, a generalization of the quantum image representation framework was required to meet these demands [22], [28].

The concept of “General Quantum Image Representation (GQIR)” is proposed to offer a more flexible image coding approach where image positions and their pixel intensity levels are coded separately in distinct quantum registers. In contrast to FRQI, which employs probability amplitude-based coding, and NEQR, which mainly addresses grayscale image coding, GQIR proposes a generic architecture that can handle images with varying dimensions and different intensity levels but still remains compatible with quantum image processing techniques [22], [34]. The flexible coding mechanism makes image manipulation easier and enables image enhancement, retrieval, transformation, and analysis tasks.

Several reviews have stressed the importance of the generalized models of image representation. In their review of quantum image representation techniques, Yan et al. [44] emphasized the importance of generalized representation models, which could support a variety of applications for image processing. Similar arguments were put forward by Wang, Xu, and Zhang [34], who noted that the generalization of the image representation models would lead to better adaptability and the creation of new techniques for image processing in complex environments. Recently, Lisnichenko and Protasov [22] and Farooq et al. [53] have pointed to GQIR among other generalized models of image representation as an important achievement of QIP research.

Studies have been conducted on how useful generalized image representation techniques can be applied in different applications such as image compression, image retrieval, image security, image enhancement, and multimedia processing. The more sophisticated techniques used in image representation have proved capable of increasing the storage flexibility while ensuring that images retain their quality and that image manipulation processes are done efficiently [44],[53]. Generalized image

representations have offered an ideal basis for working on heterogeneous images under different resolutions and formats.

The emergence of new generalized image representations has further broadened the horizons of this particular field of research. The Novel Generalized Quantum Representation (NGQR) scheme was put forward by Xing et al. [28]. This framework is based on the previous concepts of image representations and allows more flexibility for the process of image coding and processing. In particular, Xing et al.'s [28] research shows that generalized image representations can be useful for enhancing the adaptability of the system under consideration along with expanding its applicability to various image processing tasks.

Moreover, current studies have addressed the implementation of general image representation models along with quantum machine learning and intelligent image classification approaches. Chen [47] revealed the efficiency of using quantum image representation models for variational quantum classification models, whereas Senokosov et al. [43] achieved encouraging outcomes through quantum machine learning-based image classification applications. The aforementioned works highlight the benefits of using flexible image representation schemes in order to enhance feature extraction processes and perform sophisticated image recognition tasks.

Even with these strengths, quantum image representation schemes come with certain practical limitations. “The division between the information regarding image location and image intensity tends to involve the use of extra quantum bits and quantum circuitry, thus complicating the process [22, 34]. With an increase in the resolution of images, quantum state initialization itself becomes even harder to implement on current Noisy Intermediate-Scale Quantum (NISQ) technology platforms [27]. In addition, larger quantum circuits are prone to experiencing more gate errors and decoherence effects.

In summary, the concept of generalized quantum image representation and its extensions are significant developments in the progression of Quantum Image Processing. The flexibility and versatility of these approaches have made them significant tools in any future study on areas such as image compression, image

retrieval, image security, multimedia processing, and quantum machine learning". However, despite the continued challenges posed by current technology, generalized quantum image representations are significant areas of research for future quantum image processing techniques [22], [34], [53].

2.2.6 Quantum Representation of Multi-Wavelength Images (QRMW)

With the rising usage of hyperspectral and multispectral imaging techniques in remote sensing, environment monitoring, agricultural management, medical diagnosis, and defense purposes, there arises a requirement for image representation models that can effectively deal with different spectral bands. The earlier introduced quantum image representation schemes like FRQI, NEQR, and MCQI were mainly intended to perform the task of image manipulation for grayscale or RGB images, and thus suffer from some drawbacks while operating on the data of hyperspectral images. Hence, in 2018, Şahin and Yilmaz introduced a new model known as QRMW [29].

The quantum register-based multispectral wavelength (QRMW) representation scheme enhances the existing schemes of quantum image representations by considering wavelengths through separate quantum registers. Along with representing the information on the pixel's location and its intensity, QRMW also represents information about the spectral band, allowing simultaneous processing of different wavelengths within a quantum computing platform. According to Şahin and Yilmaz [29], the QRMW representation scheme enables a compact representation of multispectral and hyperspectral images as well as spectral image processing tasks.

The importance of QRMW has been pointed out in several review papers in the field of quantum image processing. The work of Yan et al. [17] and Wang et al. [34] pointed out the importance of designing special image models for representing multiple spectra images, which would mark a milestone for future development of QIP beyond grayscale and RGB image processing. The recent review works of Lisnichenko and Protasov [22], Ebrahimpour-Komleh and Hadipour [51], and Farooq et al. [53] also indicated QRMW as one of the milestones in this area due to its capability for supporting hyper- and multi-spectral image models.

With the advent of QRMW, its application gained further prominence in the field of

remote sensing and geospatial imagery analysis applications. Researchers Kumar et al. [30] explored the potential of quantum image processing methods in the field of remote sensing image classification and found that the quantum image representation methods have the capability to analyze massive data sets involving multi-spectral images. Their results implied that quantum image processing methods can be employed in the domain of land-use classification and environmental monitoring.

The correlation between quantum image representation and the hyperspectral image classification system was also considered by researchers. Chen, Miao, and Shen [48] presented an approach towards hyperspectral remote sensing image classification that utilizes quantum genetic-optimized sparse representation, noting significant gains in the performance of their proposed method. This study underscored the significance of effective spectral feature extraction in image classification processes as well as its applicability to quantum-based techniques in processing hyperspectral images.

The application of multispectral imagery analysis is not limited to remote sensing alone but also includes the use of precision agriculture and environmental monitoring. For instance, according to [49], multispectral image analysis can offer tremendous assistance in terms of agricultural decision-making and analysis through the application of sophisticated quantum learning frameworks. The same case applies to [50], who analyzed the use of multispectral images using advanced quantum imaging technology in UAV based reconnaissance missions.

However, although QRMW has many advantages, it also comes with numerous implementation problems. First, representing more than one wavelength band needs quantum bits for each band, leading to an increase in quantum qubits needed. The more spectral channels added, the greater the quantum state preparation, which is increasingly becoming hard for quantum systems currently available [29], [34]. Secondly, quantum computers currently lack enough qubits to process hyperspectral images.

One of the other issues concerns noise accumulation and hardware-related limitations. Since hyperspectral image data require an extensive number of quantum computation gates, a QRMW algorithm will be highly vulnerable to decoherence, error-prone

quantum gates, and noisy measurements. Thus, current researches have been conducted mostly by simulations, instead of being tested on real quantum computers [27], [32].

QRMW, on the other hand, provides a considerable breakthrough in quantum image representation techniques. The reason behind this assertion is that the model can facilitate image representation through multispectral and hyperspectral imagery, as opposed to limiting the technique to grayscale and RGB images. This, consequently, creates a lot of room in the field of application where the technique can be exploited. Examples include quantum remote sensing, quantum environmental monitoring, precision agriculture, medical imaging, defense surveillance, among others [22], [51], [53].

2.2.7 Comparative Analysis of Quantum Image Representation Models

QIR is the backbone of QIP because all the quantum image processing operations rely on the image representation format used. In the past few decades, various image representation formats have been proposed to deal with problems such as image storage, image retrieval, efficient computation, color image representation, and hyperspectral images processing. Among these schemes, “FRQI (Flexible Representation of Quantum Images), NEQR (Novel Enhanced Quantum Representation), MCQI (Multi-Channel Quantum Image), GQIR (General Quantum Image Representation), and QRMW (Quantum Representation of Multi-Wavelength Images) have become prominent in today’s QIP studies [17], [22], [34], [53].

The most important milestone reached in this direction is that of FRQI model put forward by Le, Dong, and Hirota [19]. The notion of FRQI involves image representation based on probability amplitudes; therefore, FRQI allows storing the image data compactly in quantum states. As claimed by Yan et al. [17], FRQI became a source idea for future works related to quantum image processing since it showed the potential of quantum superposition in the context of image storage and manipulation. It should be also mentioned that application-focused reviews state the widespread application of FRQI to develop image retrieval, image watermarking, image encryption, image transformation, and image compression approaches [17],

[23]. Nevertheless, there exist some drawbacks associated with the use of amplitude-based representation of images since it is not free from measurement errors [24], [55].

In an attempt to solve these problems, Zhang et al. [10] have suggested using Novel Enhanced Quantum Representation (NEQR). Unlike FRQI, NEQR stores grayscale intensity information in the quantum state directly, which results in the ability to perform deterministic image retrieval as well as higher accuracy in reconstruction. The study confirmed that NEQR can be used for enhancing images, segmenting images, detecting edges of images, analyzing images, and classifying images [25], [26], [42]. In addition, comparative studies conducted by Werner et al. [55] and Silos-Sanchez et al. [56] indicated that NEQR allows achieving higher levels of image reconstruction accuracy and lower information loss compared to amplitude-based image representation like FRQI.

The emergence of colored image processing systems gave rise to the need for developing the Multi-Channel Quantum Image (MCQI) by Sun et al. [40]. Unlike the FRQI and NEQR, which mainly concentrate on the representation of monochrome images, MCQI is capable of handling the three color channels (red, green, and blue) in a single system. This development made the use of QIP in multimedia systems, image classification, object recognition, and computer vision applications possible [17], [34]. Despite offering greater image representation capability, MCQI's use of more than one color channel renders it difficult for its execution on quantum computing systems owing to higher circuit depth [27], [32].

In the course of development of quantum image processing algorithms, more generalized image representation techniques have been developed to counter some of the constraints put forth by static image representation techniques. The General Quantum Image Representation (GQIR) technique is an adaptive model for image encoding that has the capacity to encode images whose sizes and intensities are not fixed [22], [34]. The concept of generalized image representation allows for efficient image encoding in applications such as image compression, image retrieval, image security, image enhancement, and multimedia processing while offering improved adaptability compared to previous image representation methods [44], [53]. More recently, the Novel Generalized Quantum Representation (NGQR) was proposed by

Xing et al. [28].

Due to the use of multispectral and hyperspectral imaging technologies, there was an increased need for the Quantum Representation of Multi-Wavelength Images (QRMW). It was introduced by Şahin and Yilmaz [29]. The QRMW model allows extending image representation from grayscale and RGB representation to include wavelengths using quantum registers. As such, it helps achieve efficient multi-spectral and hyper-spectral images representation with potential application in remote sensing, environmental monitoring, precision agriculture, and surveillance in the defense domain [29], [30], [48], [49], [50]. Nonetheless, representing multiple wavelengths increases the number of qubits required.

The comparative analysis by Lisnichenko and Protasov [22] indicated that none of the image representation schemes available is always best for all image processing tasks. The study on quantum image representation techniques conducted by them showed that FRQI typically requires fewer number of qubits and allows compact image representation while NEQR can reconstruct images accurately and retrieves them deterministically. Likewise, according to the findings of Farooq et al. [53], recent research trends favor the use of generalized and task-oriented image representation approaches.

Implementation issues related to quantum imaging have also been examined in recent research works. In particular, Werner et al. [55] showed that amplitude-based representation of images like FRQI is prone to more information loss when performing measurement tasks, while the basis state representation like NEQR provides better fidelity for reconstruction. However, NEQR, GQIR, and QRMW all need significantly more quantum resources, which results in scalability problems for NISQ hardware [27], [32].

Moreover, there are several new quantum image representation models that have been proposed by researchers due to which now we can find advanced quantum image representation frameworks, such as Improved Novel Color Quantum Image (INCQI), Novel Color Quantum Image (NCQI), Improved Probability Quantum Image Representation (IP-QIR), Novel Generalized Quantum Representation (NGQR), and

others [21], [28], [41], [46], [54]". All of these frameworks have been designed with an objective to increase flexibility for image encoding, accommodate any image dimensions, reduce the information loss while retrieving images, and improve compatibility with future QML frameworks. Also, some recent papers have shown the implementation of advanced quantum image representation frameworks on IBM Quantum computers as well as other quantum computing simulators [54].

Table 2.1. Comparative Analysis of Major Quantum Image Representation Models

Model	Author(s)	Year	Representation Type	Main Feature	Major Advantages	Major Limitations
FRQI	Le et al.	2011	Amplitude-Based Encoding	Pixel intensity stored as probability amplitudes	Compact representation, lower qubit requirement	Measurement uncertainty, reconstruction errors
NEQR	Zhang et al.	2013	Basis-State Encoding	Direct grayscale value storage	Deterministic retrieval, high fidelity	Higher qubit requirements
MCQI	Sun et al.	2013	Multi-Channel RGB Representation	Simultaneous RGB encoding	Supports color image processing	Increased circuit depth
GQIR	Generalized QIR	~2017	Generalized Representati	Supports varying	High flexibility	Large quantum

	Framework		on	image dimensions	and adaptability	resource requirements
QRMW	Şahin & Yilmaz	2018	Multi-Wavelength Representation	Supports hyperspectral images	Efficient spectral image processing	High qubit overhead
INCQI	Su et al.	2021	Improved Color Representation	Enhanced color image encoding	Better color flexibility	Increased hardware requirements

As can be seen from Table 2.1, there is an obvious evolution of quantum image representation schemes. The concept of quantum image encoding using amplitude-based representation was proposed by FRQI [19], while NEQR [20] introduced image retrieval accuracy enhancement using basis-state representation. The MCQI [40] framework facilitated quantum image processing in color images using RGB representation scheme, while GQIR [22] made provision for more flexible image representation in terms of dimensions. More recently, the QRMW [29] scheme expanded quantum image processing to include multispectral and hyperspectral images, while INCQI [54] provided an improvement to the color image representation process through multi-channel representation scheme.

From the analysis made above, it can be seen that recent research has emphasized the need to incorporate advanced frameworks for image representation with QML and QNN as well as quantum-classical models to enhance image classification, object recognition, and other forms of intelligence visual analytics. However, it should be noted that there is no universal model or framework that will fit all scenarios or applications; the choice of framework or representation model used depends on application requirements, hardware, computational efficiency, and image features. For this reason, quantum image representation is one of the most promising and difficult

fields within Quantum Image Processing (QIP).

The reviewed quantum image representation techniques reveal a clear trade-off between representation efficiency, information retrieval, and quantum resource requirements. FRQI provides a compact representation by encoding image information through quantum amplitudes; however, image retrieval relies on measurement and may require repeated measurements. NEQR addresses deterministic representation and retrieval through computational basis encoding, but this approach increases the required number of qubits and associated circuit resources. MCQI extends quantum image representation to colour information, while the additional colour-channel representation introduces further resource requirements. More recent representation approaches attempt to improve flexibility and representation capability, but challenges related to state preparation, circuit depth, scalability, and practical implementation remain. Thus, the literature does not indicate a single representation approach that simultaneously optimizes compactness, retrieval efficiency, scalability, and quantum-resource requirements. This trade-off provides the basis for investigating efficient quantum data representation and encoding approaches in the present research.

2.3 Review of Quantum Image Denoising Algorithms

Image denoising is considered one of the core components in digital image processing, since any image acquired through the use of medical imaging, satellite sensing, security camera equipment, communication networks, and multimedia systems can be degraded due to several types of noises during the process of acquisition, transmission, and storage. “Such noises cause poor image quality and negatively influence the image processing procedures such as image segmentation, feature detection, object recognition, image classification, and pattern recognition. Denoising methods such as mean filtering, median filtering, Wiener filtering, wavelet filtering, and non-local means filtering have been successfully applied for eliminating noise in images. Nevertheless, these methods exhibit some disadvantages such as smoothing, lack of edge information, increased computational cost, and ineffectiveness while handling large-scale image databases [57]–[59]. Hence, the recent invention of Quantum Image Processing (QIP) has triggered many researchers to look for possible quantum algorithms for image denoising.

One of the earliest contributions in quantum image denoising was made by Tirado [65] who proposed a quantum imaging approach with the use of Gaussian-Hermite filter bases. It was shown in this work that it is possible to employ orthogonal Gaussian-Hermite filter bases to reduce the level of image noise while preserving the structure and details of the images. As a result of the experimental studies, it was found out that the quality of images generated by the suggested approach is better than that of images restored with the help of conventional filtering approaches.

Moreover, advancements in the area of quantum image representation have spurred further research in quantum denoising approaches. In their work on quantum image filtering, Caraiman and Manta [66] found that quantum computing paradigms allow for enhancing and restoring images by means of effective image manipulations. Quantum image representations provide for parallel pixel processing of the image, which can lead to increased efficiency of the denoising process as well as reduced computations. It is important to note that this approach emphasizes edge and texture preservation during the process of denoising.

An important contribution to the subject has been made by Bhattacharyya et al. [61], who introduced a quantum multilayer self-organizing neural network for binary image denoising. The researchers combined quantum computing techniques with neural learning approaches to create an adaptive denoising model that could minimize image noise without compromising its structural data. Their experimental findings showed superior performance in terms of image fidelity and lower reconstruction errors than existing models. This research underscores the ability of intelligent quantum-inspired systems in restoring images and creating links between quantum computing and machine learning denoising models.

Further, Konar et al. [62] proposed a Quantum Bidirectional Self-Organizing Neural Network (QBDSONN) for removing image noises from binary images. In their study, they emphasized the application of quantum-inspired learning techniques for identifying and eliminating image noise without compromising image features. According to their findings, their framework outperformed other traditional methods in terms of denoising capabilities and image quality improvement. They argued that quantum-inspired neural networks serve as efficient means for addressing complex

image restoration problems.

Additional work in this area was carried out by Zhang et al. [63] through their research on wavelets inspired by quantum mechanics for noise reduction applications on remote sensing images. They conducted their research by implementing quantum-inspired wavelet processing along with other wavelet decomposition techniques, whereby they aimed at eliminating the noise while maintaining the edges and textures of the images under consideration. In their experimental evaluations, they reported considerable improvements in the quality of the images, especially remote sensing images whose noise needs to be eliminated for proper interpretation.

The rising concern for the process of image enhancement and restoration also motivated scientists to study hybrid denoising techniques. Chakraborty et al. [64] found that combining the idea of quantum-based processing with the procedure of wavelet-based filtering could increase the efficiency of computation while retaining the quality of images. They found that quantum wavelet methods are highly effective at preserving the structure of images.

The latest advancements made by Quantum Machine Learning (QML) researchers have added another dimension to research efforts related to the denoising of images. Benedetti et al. [76] proved that parameterized quantum circuits could be used as trainable learning models able to handle highly complex data distributions. Likewise, Schuld and Petruccione [71] and Schuld et al. [74] emphasized the increasing importance of quantum learning systems in image processing, intelligent pattern recognition, and intelligent data processing applications". It appears from these research findings that quantum-based learning models can be used for denoising images in high-dimensional images spaces.

A comparison of previous work shows that quantum image denoising technology has advanced from traditional filtering algorithms to learning-based schemes. Earlier works have concentrated on quantum-inspired filtering methods, including Gaussian-Hermite filtering and quantum image enhancement algorithms [65], [66]. Later researchers proposed neural network-based quantum image denoising systems, able to cope with different noise environments, thus maintaining image integrity [61], [62].

The latter part of this research area has concentrated more on quantum wavelet-based image denoising techniques as well as hybrid denoising models, which show greater efficiency in image denoising, preserve features better, and are highly adaptive [63], [64]. In order to give the reader a better idea of the quantum image denoising technologies described in the literature, the following Table 2.2 gives a comparison of the important quantum image denoising schemes.

Table 2.2. Comparative Review of Quantum Image Denoising Algorithms

Author(s)	**Year**	**Algorithm / Technique**	**Quantum Approach Used**	**Application Domain**	**Major Advantages**	**Major Limitations**
Bhattacharyya et al. [61]	2000	Quantum Multilayer Self-Organizing Neural Network	Quantum-Inspired Neural Computing	Binary Image Denoising	Adaptive noise removal, preservation of image structures	High computational complexity and training requirements
Konar et al. [62]	2006	Quantum Bidirectional Self-Organizing Neural Network (QBDS-ONN)	Quantum Neural Learning	Binary Image Restoration	Improved reconstruction quality and denoising accuracy	Requires iterative optimization process
Zhang et al. [63]	2017	Quantum-Inspired Wavelet	Quantum Wavelet	Remote Sensing	Effective edge preservati	Threshold selection significantl

		Denoising	Processing	Images	on and texture retention	y affects performance
Chakraborty et al. [64]	2019	Hybrid Quantum-Wavelet Denoising	Quantum-Inspired Wavelet Filtering	General Image Restoration	Better image fidelity and computational efficiency	Primarily simulation-based validation
Tirado [65]	2018	Gaussian–Hermite Quantum Filtering	Quantum Orthogonal Filtering	Medical and Digital Images	Strong noise suppression while preserving details	Limited applicability to highly complex noise patterns
Caraiman & Manta [66]	2014	Quantum Image Filtering Framework	Quantum Image Manipulation	Image Enhancement and Restoration	Parallel processing capability and reduced computational overhead	Hardware implementation constraints
Benedetti et al. [76]	2019	Variational Quantum Learning-Based	Parameterized Quantum Circuits	Intelligent Image Restoration	Adaptive learning capability for complex	NISQ hardware limitations

		Denoising			noise distributions	
Schuld & Petruccione [71]	2021	Quantum Learning Frameworks	Hybrid Quantum Learning	Image Analysis and Restoration	Supports adaptive feature learning	Requires efficient quantum data encoding

As illustrated in Table 2.2, quantum image denoising algorithms have progressively transformed from traditional filter-based algorithms into intelligent learning-based algorithms. Traditional filter-based algorithms such as Gaussian-Hermite and Quantum Image Filters provide excellent abilities to suppress noise and enhance images while neural network-based algorithms provide adaptive abilities to learn noise properties. Likewise, wavelet-based algorithms and hybrid algorithms exhibit outstanding abilities to retain edges and features, thus providing excellent capabilities for restoring damaged images.

However, there are several problems which have yet to be overcome. Almost all of the denoising schemes which have been proposed thus far still depend on simulation for their testing, owing to limitations with existing quantum technology. In addition, the problems associated with quantum state preparation, qubit scalability, decoherence, and gate noise also prevent effective implementation of these methods [27], [32]. Recent advances in Quantum Machine Learning and the use of parameterized quantum circuits may help to create an intelligent scheme for denoising and adaptive restoration of images [71], [76]. However, further work must be done before such schemes can be made into reality.

The literature on quantum image denoising demonstrates a progression from conventional filtering techniques towards quantum-inspired, neural, and hybrid approaches. Conventional and wavelet-based methods provide effective noise suppression, but their performance depends on the choice of filter, transform, and noise characteristics. Quantum-inspired and quantum-based filtering approaches provide

alternative mechanisms for processing image information, while neural approaches such as QMLSONN and QBDS-ONN introduce learning-based denoising capabilities. However, these approaches involve different trade-offs among denoising effectiveness, computational requirements, model complexity, and quantum-resource requirements. Hybrid quantum-wavelet and parameterized-circuit approaches attempt to combine the advantages of multiple techniques, but their practical scalability and implementation remain challenging. Therefore, the literature indicates a continuing need for approaches that balance denoising performance with computational efficiency, representation requirements, and practical quantum-resource constraints.

2.4 Review of Quantum Machine Learning Algorithms

QML is an emerging research area that focuses on integrating quantum computing with machine learning to provide superior computing capabilities. “In view of the increasing complexity of data analysis, image processing, pattern recognition, and decision-making, there have been efforts to explore the potential of quantum approaches that can address the shortcomings of classical machine learning algorithms in terms of computation. Though considerable progress has been made towards quantum approaches to denoising and quantum image processing, there are still some issues to be addressed, such as quantum state preparation, qubit scaling, decoherence, and gate noise [27], [32]. Yet, there have been recent advances towards developing intelligent quantum systems using quantum circuits and variational learning paradigms [71], [76].

Lloyd et al. [72] were among the early contributors to the theory behind QML, as they showed that quantum computation can be applied to some supervised and unsupervised learning problems and provided some speed benefits to machine learning applications based on the use of large-scale data. Following up on their efforts, Biamonte et al. [31] authored an extensive review of QML, stressing the importance of QML's capability to solve computational issues arising in classical machine learning. Similarly, Dunjko and Briegel [1] reviewed the possible integration of artificial intelligence with quantum computers, suggesting QML as a promising direction for further development”. Finally, Schuld and Petruccione [71] made important contributions to QML by reviewing quantum learning methods.

2.4.1 Quantum Support Vector Machines (QSVM)

The first and one of the earliest innovations in "Quantum Machine Learning" is that of the Quantum Support Vector Machine (QSVM), developed by Rebentrost, Mohseni, and Lloyd [11]. In their paper, they have provided a quantum variant of SVM making use of quantum feature space and quantum kernels. Their research showed that quantum kernels can provide substantial savings on computational resources when dealing with massive classification problems. Consequently, QSVM very quickly established itself as one of the most studied quantum classifiers, and its application extends from image classification to cybersecurity.

Additional advancements were made by Schuld et al. [74], who focused on the relevance of quantum feature mapping as a way to improve classification accuracy by using quantum states in high dimensions. More recently, Schuld and Killoran [78] proposed the idea of feature Hilbert spaces and illustrated that quantum state embedding can enhance classification accuracy via quantum kernel calculations.

2.4.2 Quantum Neural Networks (QNN)

"Quantum Neural Network is yet another breakthrough made by researchers in the field of Quantum Machine Learning. Farhi and Neven [15] presented a classification algorithm through the development of a parameterized quantum circuit that could run on a near-term quantum computer. In their experiment, it was proved that quantum circuits could carry out tasks identical to classical neural networks while employing quantum computation power. In this regard, Cong, Choi, and Lukin [111], Beer et al. [112], and Abbas et al. [113] also contributed to the development of quantum neural networks, especially their applications in pattern recognition, image processing, and artificial intelligence".

2.4.3 Variational Quantum Circuits (VQC)

"Quantum circuits and parameterized learning paradigms have greatly influenced the development of QML. The potential for parameterized quantum circuits as trainable machine learning models, able to learn any data distribution, was highlighted by Benedetti et al. [76]. In addition, Sim et al. [68] studied the properties of such circuits in terms of their expressiveness and ability to generate entanglement, thereby adding

to our understanding of the learning capability of these models. Such advancements led to the conception of Variational Quantum Circuits (VQCs) – among the most popular methods in current QML research owing to their compatibility with NISQ computers".

2.4.4 Quantum K-Means Clustering

The application of quantum computing has proven to be quite successful in areas of unsupervised learning as well. In this regard, Ohno [79] suggested an efficient quantum implementation of Quantum K-Means algorithm aimed at improving clustering for high dimensional data sets. The researchers showed that quantum methods could help in boosting the efficiency and performance of clustering. In another attempt, Wiebe, Kapoor, and Svore [81] came up with quantum nearest neighbor algorithms useful for both supervised and unsupervised learning problems.

Theoretical studies have also contributed to the development of this research field. For example, Caro et al. [69] explored the potential of quantum learning machines for generalizing from small training datasets, whereas Huang et al. [95] investigated the effect of features of the dataset used for quantum learning. Both works stressed the significance of data quality and proper modeling.

2.4.5 Hybrid Quantum-Classical Learning

As a result of the present restrictions of quantum hardware, there has been growing interest in using the "Hybrid Quantum-Classical Learning methods among scholars. This method is based on combining the classical machine learning algorithms with the methods of quantum computing to utilize the benefits of both methodologies. According to Bharti et al. [32], hybrid schemes are considered to be the most feasible method for implementing Quantum Machine Learning on NISQ processors at present". The idea behind the methodology is based on the integration of the classical pre-processing and optimization algorithms along with quantum feature mapping and decision-making systems. It has been proven in recent studies by Revythi & Koukiou [83] and Senokosov et al. [43].

The combination of quantum kernels, variational quantum circuits, and classical optimization techniques is increasingly considered an extremely promising approach

to near-future Quantum Machine Learning applications. In order to give a comprehensive comparison between the main QML algorithms described in the literature, Table 2.3 highlights the corresponding learning schemes, capabilities, strengths, areas of application, and weaknesses.

Table 2.3. Comparative Analysis of Major Quantum Machine Learning Algorithms

Algorithm	**Learning Type**	**Primary Function**	**Quantum Advantage**	**Applications**	**Major Limitations**	**References**
Quantum Support Vector Machine (QSVM)	Supervised	Classification	Quantum Kernel Evaluation	Image Classification, Cybersecurity, Healthcare	Quantum data encoding complexity	[11], [74], [78]
Quantum Neural Network (QNN)	Supervised	Pattern Recognition	Quantum Feature Learning	Image Recognition, Activity Recognition	Training instability and hardware noise	[15], [111], [112]
Variational Quantum	Supervised	Classification & Optimizat	NISQ Compatibility	Classification, Predictio	Barren plateau proble	[76], [80]

Circuit (VQC)		ion		n	m	
Quantum K-Means	Unsupervised	Clustering	Faster Distance Computation	Customer Segmentation, Image Analysis	Requires quantum memory	[79]
Quantum Nearest Neighbor	Supervised/Unsupervised	Similarity Search	Quantum Distance Evaluation	Pattern Recognition	Scalability challenges	[81]
Quantum Kernel Methods	Supervised	Feature Mapping	High-Dimensional Hilbert Space Representation	Image Analytics	State preparation overhead	[78]
Hybrid Quantum-Classical Learning	Hybrid	Classification & Prediction	Combines Classical and Quantum Advantages	Big Data Analytics	Quantum hardware dependency	[32], [83]
Quantu	Unsupervised	Dimensio	Faster	Feature	Input	[72]

m Principal Component Analysis (QPCA)		nality Reductio n	Eigenval ue Estimatio n	Extractio n	State Prepara tion Cost	

Quantum Machine Learning algorithms may be classified as supervised, unsupervised, and hybrid algorithms, as indicated in Table 2.3. “The purpose of supervised techniques like QSVMs, QNNs, and Variational Quantum Circuit models is mainly related to the task of classification and prediction, while those of unsupervised techniques such as Quantum K-Means and QPCA involve clustering and dimensionality reduction. Quantum Kernel Techniques use high-dimensional vector representations in Hilbert spaces to map features effectively, whereas Hybrid Quantum-Classical Learning Models leverage the benefits of both worlds by merging quantum and classical computing concepts.

In general, the existing body of literature shows that Quantum Machine Learning has progressed from an algorithmic concept based on theoretical approaches into an actively evolving multidisciplinary research domain. Progression from Quantum Support Vector Machines and quantum-based nearest neighbors to Quantum Neural Networks, Variational Quantum Circuits, Quantum K-Means clustering, and hybrid quantum-classical models illustrates development of this approach”. Nevertheless, issues such as hardware scalability, sensitivity to noise, quantum states creation, training, and computational complexity still pose serious barriers to the use of QML [3], [32], [80]. Nonetheless, quantum machine learning still holds considerable promise for solving complex problems in image recognition, activity detection, big data, and intelligent decision-making applications.

The reviewed Quantum Machine Learning algorithms demonstrate different trade-offs

between learning capability, computational complexity, quantum-resource requirements, and scalability. QSVM and quantum-kernel approaches can provide quantum-enhanced feature-space representations, but their practical application is affected by kernel evaluation and quantum data encoding requirements. QNN and VQC-based approaches provide trainable quantum models, although their performance may depend on circuit architecture, parameter optimization, circuit depth, and noise. Quantum K-Means and Quantum Nearest Neighbor approaches offer quantum-based alternatives for clustering and similarity-based learning, but their scalability and implementation depend on efficient state preparation and quantum operations. Hybrid quantum–classical approaches reduce some practical limitations by combining classical preprocessing or optimization with quantum computation, although the transfer of data between classical and quantum components introduces additional overhead. Thus, the literature indicates that algorithmic performance cannot be considered independently of encoding, circuit complexity, noise, scalability, and computational resources, providing the rationale for comparative analysis of quantum and hybrid approaches in the present research.

2.5 Review of Quantum Classification Models

Classification is definitely among the most important tasks within the scope of machine learning and pattern recognition. The main aim of classification algorithms is classifying data samples into particular classes based on the learned patterns and features of the data. Classification algorithms find widespread use in different applications like image processing, medical science, intrusion detection, action recognition, speech recognition, stock market prediction, and big data analysis. There have been proposed many types of classification algorithms over the past three decades, from classic statistical algorithms to modern deep learning and quantum machine learning frameworks [84]-[86].

2.5.1 Classical Classification Models

In the classical classification techniques, the SVM algorithm is one of the most significant supervised algorithms that have shown remarkable advancements. The SVM concept was introduced by Cortes and Vapnik [84]. Support vector machines are

a model to find the optimal separation hyperplane for classifying the points of different classes. SVM demonstrated outstanding generalization capability and accuracy in high dimensional data classification tasks. As a result, SVM is now being used for a broad range of applications, such as image classification, medical imaging analysis, text classification, and intrusion detection systems.

Another milestone achievement of classification research is related to the development of Random Forest. As reported by Liu et al. [85], Random Forest can be regarded as an instance of an ensemble learning technique, based on the principles of decision trees and employing multiple decision trees to ensure higher precision in classification tasks while avoiding overfitting. This technique appeared to be quite effective in processing noisy and high-dimensional datasets. Random Forest became very popular in such fields as medical data analysis, remote sensing, financial risk assessment, and pattern recognition.

“Deep Learning marked a major revolution in the field of classification research. According to LeCun et al. [86], DNNs have the ability to learn feature hierarchies automatically from input data, without having to construct features manually through extensive effort. CNNs, RNNs, and DBNs have been successful in obtaining good results in fields like image recognition, object detection, speech recognition, and natural language processing. Despite their impressive performance, they still need significant computation power and annotated data for training purposes”.

2.5.2 Quantum Support Vector Machines and Quantum Kernel Classifiers

As a result of certain drawbacks with classical classifiers, scientists started exploring methods of classification based on quantum computing. “Quantum computation together with machine learning produced Quantum Classification Models that apply quantum superposition, quantum entanglement, and quantum parallelism in the learning and classification process [31], [71], [95]. The purpose of such models is to solve computationally complex problems faced by classical machine learning systems and perform efficient classification of high-dimensional data.

One of the early examples of quantum-based algorithms for classification is that of Quantum Support Vector Machine (QSVM), which has been developed by Rebentrost

et al. [11]. They showed that quantum computation could be beneficial to support vector machines through faster evaluation and optimization of kernels". It is expected that the use of quantum computing will bring huge computational benefits in classifying large data sets.

Further theoretical developments have been achieved by Schuld et al. [74], who noted that quantum feature mappings are capable of converting classical inputs into high-dimensional Hilbert spaces where classification boundaries may be set with greater efficiency. Later on, Schuld and Killoran [78] introduced the idea of quantum feature Hilbert spaces and showed that quantum kernels allow for significant enhancement of pattern recognition and classification via quantum state embedding.

2.5.3 Quantum Neural Network-Based Classification

The development of Quantum Neural Networks (QNNs) marked yet another milestone in the domain of classification. Farhi and Neven [15] have designed a system that is capable of classifying using quantum neural networks which can run on near term quantum hardware. Their findings prove that it was indeed possible to use QNNs for nonlinear classification.

Research studies carried out by Cong et al. [111], Beer et al. [112], and Abbas et al. [113] further explored the possibilities of using QNNs for classification purposes. These research efforts proved to be effective in demonstrating the capability of QNNs to perform tasks like image recognition and intelligent classification systems.

2.5.4 Variational Quantum Classifiers (VQC)

The studies of parametrized quantum circuits and techniques of variational learning also pushed forward the progress towards the development of quantum classifiers. Specifically, Benedetti et al. [76] demonstrated that parameterized quantum circuits may serve as trainable classifiers, able to learn very complicated data distributions. At the same time, the work by Sim, Johnson and Aspuru-Guzik [68] considered the expressiveness and entangling abilities of parametrized quantum circuits.

Several studies that have emerged recently concentrate on the architecture of "Variational Quantum Classifiers (VQCs), which consist of constructing quantum classification circuits using parameterized quantum circuits that are optimized via

classical optimization". The circuit-based quantum classifiers designed by Schuld et al. [37] and variational quantum classifier architectures studied by Chen [47] showed strong results without compromising their NISQ capability. This has led to VQCs becoming among the most prominent quantum machine learning algorithms used in classification tasks.

2.5.5 Generalization and Expressive Power of Quantum Classifiers

The expressive capabilities and generalization abilities of quantum classifiers have received much research interest too. For example, Jäger and Krems [39] established that variational quantum classifiers and quantum kernel machines are universally expressive. In addition, Caro et al. [69] have explored generalization abilities of quantum machine learning algorithms when using few data samples during training.

Huang et al. [95] extended their analysis on the effects of dataset properties on quantum classifiers, stating that data quality and dataset features play a significant role in the classification accuracy rate. These theories give us important perspectives when it comes to implementing quantum classification systems in real life.

2.5.6 Hybrid Quantum-Classical Classification Models

Due to certain limitations of existing quantum computing devices, a lot of efforts have been devoted to the development of Hybrid Quantum-Classical Classification Models. As stated by Bharti et al., "hybrid systems are, today, the most realistic implementation approach of quantum-based learning systems". This is because such hybrid systems utilize quantum feature transforms along with classical optimization processes.

In particular, recent work carried out by Revythi & Koukiou [83], as well as by Senokosov et al. [43], showed good results for classification problems in the context of image processing, healthcare analysis, finance, cybersecurity, and big data management. "Thus, combining classical learning algorithms and quantum computing techniques is considered one of the most applicable approaches to practical quantum-classification systems.

A comparative analysis of the literature reveals that classical classification algorithms like SVMs, random forests, and deep neural networks (DNNs) continue to be very useful for many real-life problems due to their maturity, robustness, and software

support. Nonetheless, quantum classification techniques such as QSVMs, QNNs, quantum kernel methods, and variational quantum classifiers (VQCs) present interesting possibilities in terms of achieving efficient computation and dealing with high-dimensional feature spaces. While classical algorithms outperform most of the existing quantum counterparts in terms of performance in practice today, recent findings show great promise in the effectiveness of quantum classifiers as quantum hardware matures". In order to have a structured comparison between the different classical and quantum classification paradigms, Table 2.4 below includes the classification techniques mentioned in the literature along with their fundamentals, capabilities, weaknesses, use cases, and relevant citations.

Table 2.4. Comparative Analysis of Quantum Classification Models

Model	**Classification Type**	**Core Principle**	**Strengths**	**Weaknesses**	**Major Applications**	**References**
Support Vector Machine (SVM)	Classical	Hyperplane Separation	High accuracy in high-dimensional data	Kernel selection issue	Medical Imaging, Pattern Recognition	[84]
Random Forest	Classical	Ensemble Learning	Robust against overfitting	Large memory requirement	Healthcare Analytics	[85]
Deep Neural Networks (DNN)	Classical Deep Learning	Hierarchical Feature Learning	Automatic feature extraction	Requires large datasets	Image Recognition	[86]

Quantum Support Vector Machine (QSVM)	Quantum	Quantum Kernel Mapping	Improved classification efficiency	Quantum encoding overhead	Image Classification	[11]
Quantum Neural Network (QNN)	Quantum	Parameterized Quantum Circuits	Nonlinear decision-making capability	Hardware limitations	Activity Recognition	[15]
Variational Quantum Classifier (VQC)	Hybrid Quantum	Variational Learning	Suitable for NISQ devices	Parameter optimization difficulty	Pattern Recognition	[37], [47]
Quantum Kernel Classifier	Quantum	Feature Hilbert Space Mapping	Rich feature representation	Quantum circuit depth	Image Analytics	[78]
Hybrid Quantum-	Hybrid	Quantum Feature Extraction	Practical implement	Depends on both	Big Data Analytics	[32], [83]

Classical Classifier		+ Classical Learning	ation	systems		

According to Table 2.4 below, classical classification algorithms remain predominant due to their reliability, extensive software environments, and efficient processing of big data. Classification methods like “Support Vector Machines, Random Forest, and Deep Neural Networks have been widely used for various applications, such as image classification, medical diagnostics, pattern recognition, and decision support systems. On the other hand, quantum classification algorithms aim to boost the effectiveness of classical models using quantum features, quantum kernel, and variational quantum circuit approaches. While QSVMs and quantum kernels work on high-dimensional quantum feature space, QNNs and quantum classifiers enable non-linear learning abilities needed for sophisticated applications. Moreover, hybrid quantum-classical models make quantum algorithms more practically feasible through the integration of classical processes of optimization and classification. Despite the constraints imposed by existing technology infrastructure, these are promising research areas for future intelligent classifiers.

However, the literature review shows a trend of transition from classical machine learning classifiers to quantum classifications. The emergence of quantum SVMs, QNNs, quantum kernel methods, and variational quantum classifiers is indicative of the growing maturity of Quantum Machine Learning studies”. However, problems associated with qubit scalability, hardware noise, barren plateaus, difficulty with training, and practical testing still pose many research problems [3], [32], [80]. However, despite the problems mentioned above, quantum classifiers still have great application prospects in image processing, activity recognition, and Big Data analysis.

The comparative literature on quantum classification models indicates that different classifiers address different aspects of the classification problem, but each involves specific limitations. Classical SVM, Random Forest, and deep learning models provide established classification capabilities but may face computational challenges for high-

dimensional or large-scale data. QSVM and quantum-kernel methods provide quantum feature-space representations, although their effectiveness depends on data encoding, kernel construction, and available quantum resources. QNN and VQC-based classifiers introduce trainable quantum circuits, but their performance is influenced by circuit depth, parameter optimization, noise, and training stability. Hybrid quantum–classical classifiers can combine the learning capabilities of classical models with quantum processing, but data transfer and repeated quantum circuit evaluation may introduce additional computational overhead. These observations indicate that classification performance should be evaluated together with computational complexity, encoding requirements, scalability, and quantum-resource constraints rather than through accuracy alone. This provides the rationale for the comparative and complexity-oriented analysis undertaken in the present research.

2.6 Review of Quantum Optimization Techniques

Optimization techniques have become essential elements in the field of modern computation in areas like computer science and engineering, machine learning and image processing, logistics and finance, and big data analysis. “In fact, many problems in real life situations can be cast as optimization problems where the main idea is to find the best solution to a problem among many feasible solutions under some specified conditions. Conventional optimization techniques include but not limited to the following: gradient descent, simulated annealing, particle swarm optimization, and genetic algorithm. The growing complexity of large-scale optimization problems has prompted researchers to explore quantum computing techniques for solving such problems [96], [97].

In this regard, the development of quantum computing technologies has opened up avenues for solving optimization problems by making use of quantum superposition, quantum tunneling, entanglement, and quantum parallelism. As against classical approaches to solving optimization problems, which tend to get stuck at local optimums while investigating the search space, quantum optimization approaches facilitate the exploration of several different solutions simultaneously. Thus, quantum optimization is considered one of the most promising research areas in quantum computing and quantum machine learning [98], [99].

Among the early quantum optimization methods adopted extensively, one could mention Quantum Annealing. Based on the ideas of Simulated Annealing, Quantum Annealing takes advantage of quantum tunneling and quantum fluctuations to locate the optimum of the considered problem within the specified energy landscape. In their work, Kadowaki and Nishimori [100] showed how quantum annealing can be used to overcome the problem of local minima by taking advantage of quantum tunneling in solving combinatorial optimization problems.

Quantum Annealing gained more practical relevance after the introduction of quantum annealing platforms. According to Johnson et al., [101], large scale quantum annealing processors for optimization problems consisting of thousands of variables were developed. Experiments confirmed that quantum annealing could be applied for scheduling, routing, portfolio optimization, image segmentation, and machine learning. Further research included exploration of the application of quantum annealing for optimization in the field of healthcare, supply chain, smart grids, and resource allocation systems.

Additional studies conducted by Albash and Lidar [102] provided insight into the advantages and disadvantages associated with quantum annealing. In their analysis, it was found that quantum annealing is especially effective when dealing with combinatorial optimization tasks involving complicated search spaces and a large number of local optima. On the other hand, performance benefits strongly depend on the task and hardware properties.

Along with the creation of Noisy Intermediate-Scale Quantum (NISQ) hardware, scientists started exploring quantum optimization algorithms tailored to gate-model quantum computers. The most significant development among these is undoubtedly the Quantum Approximate Optimization Algorithm (QAOA), put forward by Farhi et al. [99]. QAOA relies on a combination of quantum states preparation and classical optimization techniques to provide approximate solutions for discrete optimization tasks.

According to Farhi et al. [99], QAOA has the ability to solve problems such as graph partitioning, Max-Cut, satisfiability, and routing within the constraints of existing

quantum computers. Further research found that QAOA is able to offer a practical way towards quantum optimization using near-term quantum computers due to the fact that its implementation requires shallow quantum circuits.

Hadfield et al. [104] enhanced the scope of QAOA by proposing the concept of Quantum Alternating Operator Ansatz, which represents an extension to a generic form that solves constrained optimization problems. Their study established that QAOA can be used for solving various kinds of optimization problems in engineering, logistics, and machine learning domains. In a recent study, Zhou et al. [105] focused on optimizing QAOA for higher accuracy by means of better parameter tuning and circuit design techniques.

Integration of swarm intelligence technology with quantum computing resulted in development of Quantum Particle Swarm Optimization (QPSO). Quantum Particle Swarm Optimization was developed by Sun, Xu & Feng [106] by making use of quantum probability theory while determining the positions of particles. This model showed better global search ability and better convergence than traditional Particle Swarm Optimization models. Application of Quantum Particle Swarm Optimization was later explored in the fields of feature selection, engineering optimization, image processing and machine learning.

Another popular approach towards optimization is the use of Quantum Genetic Algorithms (QGAs), which fuse ideas from evolutionary computation and quantum computing. One of the first quantum-based genetic algorithms was proposed by Narayanan & Moore [108], who used the concept of superposition for representing chromosomes. In another attempt at quantum inspired evolutionary computing, Han & Kim [109] developed the Quantum Inspired Evolutionary Algorithm (QEA), which uses quantum bits and probabilistic updates.

Additional studies concerning evolutionary quantum optimization have been presented by Rehman et al. [110] through an assessment of recent improvements achieved in evolutionary algorithms and quantum computation. The results revealed that quantum-inspired evolutionary algorithms have been effectively utilized for solving scheduling optimization, communications, robotics, machine learning parameter optimization,

and multi-objective optimization.

As the result of the rapid emergence of data-intensive applications, there are various issues associated with optimization, scalability, and computational efficiency that are emerging. In particular, Lloyd, Mohseni, and Rebentrost [72] have shown how quantum computing algorithms could speed up several learning and optimization processes for big data processing. In turn, Biamonte et al. [31] stressed the importance of applying quantum methods of optimization for ML and data analytics.

According to recent literature by Bharti et al. [32] and Revythi & Koukiou [83], quantum optimization is increasingly being considered as a potential solution in artificial intelligence, machine learning, image processing, cybersecurity, finance, and medicine. It was observed from their analysis that quantum optimization algorithms like Quantum Annealing, QAOA, QPSO, and Quantum Genetic Algorithms can be employed to solve computational problems associated with these applications.

A comparative review of the literature indicates that each quantum optimization method has its own merits and demerits. Quantum Annealing (QA) can be highly effective for solving combinatorial optimization problems; however, its implementation usually necessitates specialized quantum hardware architecture. QAOA, on the other hand, can be more adaptable to gate-based quantum computing hardware and stands out as one of the most promising methods of quantum optimization, especially in NISQ devices. Likewise, Quantum Particle Swarm Optimization (QPSO) can show good results in the global search process along with better convergence behavior, while Quantum Genetic Algorithms (QGAs) exhibit high exploration capabilities within complicated search spaces". Therefore, choosing a suitable optimization strategy depends on many factors such as the nature of the problem, availability of computational resources, and others. For this purpose, a table comparing all major quantum optimization methods reviewed in the literature can be useful. This is provided in Table 2.5 below.

Table 2.5. Comparative Analysis of Quantum Optimization Techniques

Techniq	Principle	Search	Major	Advantag	Limitatio	Refere

ue		Strategy	Applications	es	ns	nces
Quantum Annealing	Quantum Tunneling	Global Energy Minimization	Scheduling, Routing, Portfolio Optimization	Escapes local minima effectively	Requires specialized hardware	[100], [101], [102]
QAOA	Variational Quantum Optimization	Alternating Operator Ansatz	Max-Cut, Graph Optimization	NISQ-compatible	Parameter tuning required	[99], [104], [105]
Quantum Particle Swarm Optimization (QPSO)	Quantum Probability Theory	Swarm-Based Search	Feature Selection, Image Processing	Improved convergence speed	Sensitive to parameter settings	[106]
Quantum Genetic Algorithm (QGA)	Quantum Evolutionary Search	Population-Based Optimization	Machine Learning Optimization	Strong exploration capability	Computational overhead	[108], [109], [110]
Quantum-Inspired Evolutionary	Quantum Bit Representation	Evolutionary Optimization	Scheduling and Robotics	Better population diversity	High iteration requirement	[109]

Algorithm (QEA)						
Hybrid Quantum Optimization	Classical + Quantum Search	Variational Optimization	AI and Big Data Analytics	Practical implementation	Hardware dependency	[32], [83]

As seen from Table 2.5, quantum optimization algorithms are diverse when it comes to approaches used, hardware needed, and applications. Specifically, quantum annealing is used mostly in combinatorial optimization via quantum tunneling and is characterized by good performance in scheduling, routing, and allocation. In turn, QAOA uses variational quantum circuit approach together with classical optimization algorithms which makes this technique better to be implemented on NISQ computers. The same is true about QPSO and QGA techniques that use concepts of swarm intelligence and evolutionary computing respectively. Additionally, Quantum Inspired Evolutionary Algorithm allows increasing optimization performance due to use of probability-based quantum-bit representation. Finally, Hybrid Quantum Optimization has appeared as an alternative way to perform optimization using classical and quantum computations simultaneously.

On the whole, the discussed literature reveals that quantum optimization has become a crucial area of study in Quantum Computing and Quantum Machine Learning. Indeed, moving from "Quantum Annealing through QAOA, Quantum Particle Swarm Optimization, Quantum Genetic Algorithms, and Hybrid Quantum Optimization", one can observe growing complexity of optimization approaches developed specifically for use in quantum computing systems. Yet, there are still some issues in this field, namely, scalability problems associated with qubits, decoherence, barren plateaus, parameter optimization, as well as hardware problems [3], [32], [80]. However, the examined studies indicate that quantum optimization algorithms have great potential in the field of optimization tasks associated with machine learning, image processing, activity recognition, and big data analysis.

The reviewed quantum optimization techniques demonstrate different strategies for

addressing optimization problems, but their applicability involves specific computational and implementation trade-offs. Quantum Annealing provides a mechanism for solving optimization problems through quantum-state evolution, whereas QAOA uses parameterized quantum circuits to approximate solutions to combinatorial optimization problems. Quantum-inspired approaches such as QPSO and QGA provide alternative optimization mechanisms that can be integrated with classical or hybrid computational frameworks. However, the effectiveness of these approaches depends on problem formulation, parameter selection, computational resources, circuit requirements, and the availability of suitable quantum hardware or simulators. These differences indicate that optimization performance should be considered together with computational complexity, scalability, and resource requirements. The observed trade-offs support the need for systematic comparison of quantum, quantum-inspired, and hybrid optimization approaches within the broader quantum computing research framework.

2.7 Comparative Analysis of Existing Methods

The studies covered in Sections 2.2 – 2.6 clearly indicate tremendous advancements in "Quantum Image Processing (QIP), Quantum Machine Learning (QML), Quantum Classification Models, and Quantum Optimization Methods". Various methods and techniques for image representation, image denoising, classification, clustering, optimization, and analysis of large datasets have been suggested. While these methodologies have greatly added value to quantum computing solutions, each method has its own strengths and weaknesses that need to be considered in relation to its applicability.

QIR techniques include "FRQI, NEQR, MCQI, GQIR, and QRMW. FRQI" is a framework that uses probability amplitude-based quantum image encoding and shows an effective image memory capacity. The model has problems in terms of the uncertainty in the measurements as well as difficulties in reconstruction. NEQR solves such issues since it represents grayscale values through the use of basis states, which ensures that the images can be retrieved more accurately. Nevertheless, the use of more qubits makes the implementation of NEQR challenging in dealing with higher resolution images. MCQI provides for quantum image representation of color images

and enables RGB image processing, but it requires the extra color registers, which complicate its computations. GQIR adds the feature of representing images of any size while QRMW applies the representation in the environment of multi- and hyperspectral images. Although much progress has been achieved, image representation techniques are computationally intensive and hard to realize using existing quantum computers [17], [22], [34], [53].

Quantum image denoising algorithms too have progressed from traditional denoising schemes to those based on intelligent learning schemes. Traditional quantum denoising approaches based on Gaussian-Hermite filtering and quantum image filtering proved to be successful in achieving effective noise reduction while retaining image structure. Thereafter, quantum wavelet based denoising schemes were proposed, which were efficient in retaining edge details of images. In recent times, Quantum Neural Network based denoising schemes have been proposed and proved to be successful in learning complicated noise distributions along with their adaptation to image structures. The vast majority of quantum denoising schemes still use simulations due to the lack of quantum hardware support for evaluating their performance [61]–[66], [71], [76].

The discussion on Quantum Machine Learning algorithms shows an evolution from theory-based learning models that utilize quantum computing techniques towards more practical hybrid machine learning paradigms that integrate quantum computation with traditional learning processes. “Quantum Support Vector Machines (QSVMs) have been shown to achieve superior classification performance on high dimensional feature spaces while Quantum Neural Networks (QNNs) offer greater capacity in nonlinear learning. Another promising area of research has been the development of Variational Quantum Circuits (VQCs) which appear to be some of the most promising approaches when it comes to implementing machine learning on NISQ devices as they use both quantum computation and classical optimization procedures [1], [11], [31], [32], [69], [71], [72], [74], [76], [78], [79], [81], [83], [95].

Classification continues to be one of the most extensively investigated fields where machine learning and quantum computers can be applied. Traditional algorithms such as SVM, RF, and deep NN have proven highly effective for a wide range of applications”. Nevertheless, they face increased computational demands while

handling large high-dimensional datasets. Quantum computing approaches like QSVM, QNN, QKM, and VQC try to tackle these challenges via enhanced representation techniques and optimization strategies. It appears that quantum-based approaches have great potential for providing better performance; however, due to hardware limitations, at present, they cannot match the capabilities of well-established classical approaches in practical applications [84]–[86], [11], [15], [37], [39], [47], [68], [76], [78], [95].

Optimization methods can be considered yet another important aspect of research in quantum computing. Quantum Annealing has been used to solve problems related to combinatorial optimization using quantum tunneling. QAOA, on the other hand, is a new algorithm which has gained recognition due to its application in gate-based quantum computers and NISQ architectures. Another approach which has proven useful in optimization through integration of evolutionary algorithms and quantum theory includes Quantum Particle Swarm Optimization (QPSO) and Quantum Genetic Algorithms (QGAs). Despite showing great promise in machine learning, image processing, and big data analytics, the practicality of these methods is restricted by hardware limitations [98]–[110].

A comparative analysis of the above-stated review shows that there is no quantum approach, which would provide a full answer to the challenges of image representation, denoising, classification, and big data analytics. The majority of studies concentrate on particular issues, which include image representation, classification, denoising, and optimization without building up an integrated system, which could solve more than one problem at a time. Moreover, the vast majority of approaches were tested under experimental conditions only, which does not allow us to apply them in practice.

Another crucial insight gained from the reviewed literature concerns the rising tendency towards the use of quantum-classical hybrids. It has been proven that the hybrid model is usually superior to the completely quantum framework due to the combined advantages of both paradigms. Hybrid systems have been found to be especially successful in tasks related to image classification, feature extraction, optimization, and machine learning, as the shortcomings of the quantum computer can be compensated for by classical methods of data processing [32], [83].

The comparative analysis of the various approaches discussed in this chapter is shown in Table 2.6, which outlines the strengths and weaknesses of the methodologies, along with citations to relevant references. These approaches have been developed for existing image representation, denoising, classification, and optimization processes in quantum computing for QIP and QML.

Table 2.6. Comparative Analysis of Existing Methods

Category	**Method**	**Major Advantages**	**Major Limitations**	**Key References**
Quantum Image Representation	FRQI	Compact storage, efficient encoding, low qubit requirement	Measurement uncertainty and reconstruction errors	[17], [19], [55]
Quantum Image Representation	NEQR	Accurate image retrieval, deterministic reconstruction	Higher qubit requirement and circuit complexity	[10], [25], [26], [56]
Quantum Image Representation	MCQI	Supports RGB image representation and processing	Increased circuit complexity and resource consumption	[17], [40], [53]
Quantum Image Representation	GQIR	Flexible image dimensions and generalized image representation	Large quantum registers and implementation complexity	[22], [28], [44]

Quantum Image Representation	QRMW	Supports hyperspectral and multispectral images	High computational overhead and qubit requirements	[29], [30], [51]
Quantum Denoising	Gaussian–Hermite Filtering	Effective noise suppression while preserving image details	Limited validation on real quantum hardware	[65]
Quantum Denoising	Quantum Wavelet Denoising	Good edge preservation and texture retention	Threshold selection and computational complexity	[63], [64]
Quantum Denoising	QNN-based Denoising	Adaptive learning capability and improved reconstruction quality	High computational complexity and training requirements	[61], [62], [76]
Quantum Classification	QSVM	Efficient high-dimensional classification through quantum kernels	Data encoding and state preparation challenges	[11], [74], [78]
Quantum Classification	QNN	Nonlinear learning capability and	Training complexity and hardware	[15], [111], [112]

		expressive feature learning	limitations	
Quantum Classification	Variational Quantum Classifier (VQC)	Suitable for NISQ devices and hybrid learning frameworks	Parameter optimization and barren plateau issues	[37], [39], [47], [80]
Quantum Optimization	Quantum Annealing	Effective combinatorial optimization and global search capability	Specialized hardware requirement	[100], [101], [102]
Quantum Optimization	QAOA	NISQ-compatible optimization framework	Performance depends on parameter tuning	[99], [104], [105]
Quantum Optimization	QPSO	Improved global search capability and convergence behavior	Convergence sensitivity and parameter dependence	[106]
Quantum Optimization	Quantum Genetic Algorithm (QGA)	Strong exploration capability and population diversity	Computational overhead and scalability challenges	[108], [109], [110]

Table 2.6 shows that significant advancements have been made in all fields of quantum

computing applications such as image representation, denoising, classification, and optimization. Image representation in quantum computing through FRQI, NEQR, MCQI, GQIR, and QRMW has brought tremendous improvements in the efficiency of image information encoding and processing in quantum systems. On the other hand, quantum image denoising methods have moved from filter-based to learning-based intelligent models that can suppress noise while maintaining image structures.

Moreover, it becomes evident from the comparative analysis that Quantum Machine Learning and Quantum Classification methods present some interesting approaches as a possible alternative to traditional machine learning techniques, especially while dealing with high dimensional feature spaces and complex pattern identification. Similarly, Quantum Optimization methods like Quantum Annealing, QAOA, QPSO, and Quantum Genetic Algorithm have shown great promise in dealing with complicated optimization problems in applications ranging from machine learning, image processing to big data analytics. Nevertheless, each one of these approaches is also limited by its own constraints.

In summary, from the comparison, it can be seen that even though remarkable strides have been made regarding the study and research of quantum image processing and quantum machine learning, there are still many important issues that have yet to be addressed. The majority of current studies concentrate on one task at a time and lack an integration into a common computing framework. In addition, there are still problems concerning scalability, computational efficiency, hardware implementation, testing, and actual applications which hamper the wider use of quantum computing-based intelligence. These constraints form the basis for discussing the research gaps in the coming sections as well as forming the need for a quantum theory-based unified computing model.

The comparative analysis indicates that the existing quantum and quantum-inspired approaches provide complementary advantages rather than a single universally superior solution. Quantum image representation methods differ in their requirements for qubits, information retrieval, and state preparation, while quantum image denoising methods involve trade-offs between noise suppression, computational cost, and representation requirements. Similarly, Quantum Machine Learning and classification

models differ in terms of encoding requirements, circuit complexity, training characteristics, scalability, and susceptibility to noise. Optimization approaches also exhibit differences in computational requirements and practical implementation. Therefore, the comparison of existing methods highlights that quantum advantage should be evaluated in relation to the specific problem, data characteristics, quantum resources, computational complexity, and implementation constraints. These observations provide the basis for the research gaps identified in the subsequent section and motivate the framework-oriented and comparative investigations undertaken in the present thesis.

For clarity, the approaches reviewed in this thesis are distinguished according to their computational nature and level of experimental validation. Genuine quantum algorithms refer to methods whose computational operations are executed using quantum states, quantum gates, measurements, or other quantum computational principles. Quantum-inspired classical algorithms employ concepts motivated by quantum mechanics but are executed on classical computational platforms and therefore should not be interpreted as genuine quantum computation. Hybrid quantum–classical algorithms combine quantum computational components with classical preprocessing, optimization, or decision-making stages. In addition, simulation-based results obtained using quantum simulators are distinguished from experiments executed on physical quantum hardware. Finally, claims of quantum advantage are treated separately from the demonstration of quantum algorithm functionality, since successful execution of a quantum or hybrid algorithm does not by itself establish quantum advantage over an appropriate classical baseline. This distinction is maintained in the comparative interpretation of the literature and in the discussion of the research contributions of the present thesis.

2.8 Research Contributions

From a thorough examination of literature on “Quantum Image Processing, Quantum Machine Learning, and Quantum Classification methods”, the following are some key findings from the research:

- Conception of an all-embracing quantum learning paradigm that incorporates quantum image processing and activity recognition through quantum image

representations and machine learning approaches.

- Evaluation and comparison of existing models of quantum image representations such as FRQI, NEQR, MCQI, GQIR, and QRMW and determination of their advantages, weaknesses, and applications.
- Exploration of quantum classification and optimization approaches for improving pattern recognition, feature extraction, and intelligent decisions in complex datasets.
- Discovery of research areas that need to be addressed in the future for developing effective quantum-based image processing systems.

2.9 Research Gaps Identification

The detailed survey of Quantum Image Processing (QIP), Quantum Machine Learning (QML), Quantum Classification Models, and Quantum Optimization Techniques, covered in Sections 2.2 to 2.7, clearly shows that considerable success has been achieved so far in the application of quantum computing methods for image processing, pattern recognition, and decision support systems. Various models for quantum image representation, quantum denoising algorithms, quantum classification models, and quantum optimization techniques have been proposed, which can prove to be advantageous in theory compared to classical methods. But an examination of the state-of-the-art in literature highlights some important shortcomings associated with these technologies. As a result, three key research areas have been identified.

Gap 1: Absence of a Unified Quantum Framework for Image Representation, Activity Recognition, and Big Data Analytics

From the literature, it is clear that majority of the current studies concentrate on individual parts of the quantum computing pipeline. Many studies have been done on quantum image representations including “FRQI, NEQR, MCQI, GQIR, and QRMW”, while others have looked into quantum denoising, quantum classification, quantum optimization, and quantum machine learning algorithms. While each of these has contributed significantly to its field of study, they are individual algorithms aimed at solving particular problems.

Moreover, no attempts have been made to bring together image representation, image

analysis, activity recognition, and big data analytics under one computational model. The existing models have focused on only one aspect of the computational process without offering any integrated model that can effectively support intelligent image-based decision-making systems. This limitation makes it difficult for quantum computation modules to work in a cohesive manner, thus making it impossible to develop comprehensive applications based on them.

The gap in research lies in the development of an integrated theoretical model that can offer support for image representation, activity recognition, machine learning, and big data analytics under one computational architecture.

Gap 2: Limited Scalability, Data Encoding Efficiency, and Hardware Feasibility of Existing Quantum Learning Models

From the above-reviewed literature, it can be noted that "Quantum Machine Learning techniques like Quantum Support Vector Machines (QSVMs), Quantum Neural Networks (QNNs), Variational Quantum Circuits (VQCs), Quantum K-Means, and other quantum-based learning models have immense theoretical capability to solve complicated classification and optimization tasks. However, the majority of current researches in Quantum Machine Learning have been tested on modest-sized data samples, simulations, and benchmark datasets.

One of the key problems that have been highlighted in research is the issue of scalability of quantum learning algorithms for high-dimensional images and large datasets. The translation process of classical input data to quantum states is known to be time-consuming, thus, limiting the speed improvement that could be achieved through quantum computation. Furthermore, with rising dimensions, there comes an increase in the number of gates needed, the quantum register size, and the number of qubits, making implementation even more difficult with NISQ devices.

Additionally, only little attention has been paid to the analysis of the trade-off between the depth of the circuits, computation time, memory needs, utilization of qubits, and computational complexity". Therefore, there is a lack of studies focused on creating a quantum learning architecture that can process practical problems related to image analytics and big data but also work within existing quantum hardware limitations.

Gap 3: Insufficient Real-World Validation, Benchmarking, and Comparative Evaluation of Hybrid Quantum–Classical Frameworks

The recent developments in NISQ computing have led many researchers to opt for hybrid quantum-classical architecture as an alternative approach to the full quantum computing approach. Many experiments have revealed that a hybrid technique that involves classical pre-processing along with quantum optimization and learning algorithms performs much better than purely quantum-based methods in various tasks, including image recognition and classification.

However, an analysis of the literature shows that the vast majority of such quantum-classical frameworks have been verified mainly via simulation experiments or benchmark data sets. Large real-world data set tests remain rare. In addition, performance gains reported by many researchers do not include any proper comparative study against classical ML/DL algorithms.

Another limitation worth mentioning is the lack of standardized benchmarking schemes that could be used to assess not only the accuracy of classification but also the execution time, complexity, scalability, memory consumption, and even hardware efficiency of both traditional and quantum methods. The latter problem prevents any objective evaluation of benefits of quantum-based solutions.

Consequently, an important research gap can be identified in terms of the creation and extensive validation of hybrid approaches combining quantum computing and classical computing with benchmarking procedures to assess their effectiveness and practicality.

The review of literature shows that great advances have already been made in the fields of “Quantum Image Processing (QIP), Quantum Machine Learning (QML), Quantum Classification Models, and Quantum Optimization Techniques”. Nonetheless, many important issues still remain unresolved, which constrain the practical use of the current approaches. First of all, no universal quantum approach has been developed, which would be able to combine image representation, recognition of activity, and analysis of Big Data in one computational system. The majority of research efforts are focused on separate subfields, such as QIP, QML, denoising, and optimization, thus

leading to the development of fragmentary solutions, which cannot be combined into one comprehensive solution. Furthermore, modern quantum learning algorithms encounter problems with scalability, effective encoding of data, complexity of the quantum circuitry, limited number of available qubits, and hardware constraints.

Another equally significant gap includes inadequate validation and benchmarking of hybrid quantum-classical models. Even though some of the recently conducted studies have shown successful implementation of such models, their validation still remains largely dependent on simulations and benchmarking on small sets of data. In addition, due to the absence of standard methodologies for benchmarking, it becomes challenging to make objective comparisons between quantum and classical models based on accuracy, scalability, computational efficiency, and resource requirements. Thus, the resolution of these challenges is considered the principal reason for the proposed research and forms the basis for creating an entirely new model of quantum image representation and activity recognition in big data analytics.

The critical synthesis of the reviewed literature indicates that the identified gaps are interconnected rather than isolated. Limitations in quantum image representation and data encoding directly influence scalability and computational requirements, while the variation in quantum, classical, and hybrid methods makes consistent benchmarking necessary for meaningful comparison. Similarly, the limited practical validation of hybrid quantum–classical approaches highlights the need to consider computational complexity, scalability, and resource requirements alongside predictive performance. These interconnected gaps provide the rationale for the three research objectives formulated in Chapter 1, namely the development of a scalable hybrid quantum–classical framework, efficient quantum data encoding, and unified complexity benchmarking and cross-domain validation.

2.10 Chapter Summary

The current chapter discussed an extensive overview of relevant research literature on “Quantum Image Processing (QIP), Quantum Machine Learning (QML), Quantum Classification Models, and Quantum Optimization Techniques. This literature review covered the development of various applications of quantum computing in image

processing, pattern recognition, machine learning, and big data analytics. As can be seen from the current literature review, scholars have made numerous valuable contributions to the research areas mentioned above which are currently undergoing rapid developments. Acc ording to the literature available in the field of quantum computing, the area holds huge promise for transforming conventional methods of data processing through quantum mechanics.

The chapter began with a discussion of major quantum image representation schemes such as FRQI (Flexible Representation of Quantum Images), NEQR (Novel Enhanced Quantum Representation), MCQI (Multi-Channel Quantum Image), GQIR (General Quantum Image Representation), and QRMW (Quantum Representation of Multi-Wavelength Images). It was found out that these representations offered efficient means of manipulating image information in quantum computing environments. Although FRQI was the representation scheme which introduced quantum image representation, later schemes were designed to solve problems associated with retrieval accuracy, color image representation, flexibility, and hyperspectral images representation. However, scalability issues and circuit complexity were identified as other areas of concern.

The chapter discussed quantum denoising of images and emphasised the development of denoising strategies from quantum-inspired filters to sophisticated denoising frameworks based on learning processes. Several denoising techniques have been compared concerning their capabilities to reduce noise while ensuring good image quality, structural content, and edges within the images. It was revealed that quantum-based denoising strategies present promising prospects for improving image restoration efficiency; nevertheless, most research conducted in the field is still based on simulation due to hardware constraints.

Then, the subsequent section of the paper discussed important quantum machine learning algorithms such as Quantum Support Vector Machines (QSVMs), Quantum Neural Networks (QNNs), Variational Quantum Circuits (VQCs), quantum-based clustering methods, and quantum-classical learning models. The research indicates that these algorithms have significant capability to deal with high-dimensional data. Nevertheless, problems associated with data encoding, quantum state preparation,

circuit depth, scaling, and practical hardware realisation of these algorithms remain a challenge.

Additionally, the chapter evaluated both classical and quantum classification methods. Classical classifiers, including Support Vector Machines, Random Forests, and Deep Neural Networks, were contrasted with new quantum approaches for classification like QSVMs, QNNs, Quantum Kernel Methods, and Variational Quantum Classifiers. It was found that quantum methods of classification have significant potential advantages for computing performance and feature extraction, especially when working with complicated datasets. Nevertheless, further research is needed to prove their effectiveness.

Moreover, this chapter also discussed important Quantum Optimisation Techniques, such as Quantum Annealing, Quantum Approximate Optimisation Algorithm (QAOA), Quantum Particle Swarm Optimization (QPSO), and Quantum Genetic Algorithms (QGAs). It has been found that the above-mentioned optimization techniques have shown impressive potential in finding solutions to complex optimization problems faced by machine learning, image processing, activity recognition, and big data analytics. However, several challenges concerning implementation have also been identified.

Comparison between the existing approaches demonstrated that significant advancements have been made in areas such as quantum image processing, machine learning, classification, and optimization". Nevertheless, almost all existing techniques concentrate only on specific tasks rather than providing an integrated platform for computation. Moreover, problems such as scalability, efficiency of the encoding of data, computational complexities, practicality, and benchmarking prevent the use of quantum-based intelligent solutions in real-world applications.

As evident from the literature review and comparative analysis, the following three research gaps have been found: (i) lack of integration of a holistic quantum computing approach involving image representation, action recognition, and big data analytics; (ii) non-scalability, non-efficient data encoding, and infeasibility of the hardware associated with the current quantum models; and (iii) inadequacy of testing and

benchmarking of hybrid quantum-classical models using practical scenarios.

The literature discussed in this chapter provides a solid foundation of theories and methods necessary for conducting the intended research. These discussions identify both the strengths and weaknesses of current approaches and justify the adoption of a new research approach based on quantum theory. The subsequent chapter discusses the research approach that was used to address the gaps found in the current literature.

CHAPTER 3

QUANTUM COMPUTING-BASED MACHINE LEARNING ALGORITHMS FOR CLASSIFICATION OF BIG DATA SETS

3.1 Introduction

This chapter presents the development, implementation, and performance evaluation of a Quantum Computing-Based Machine Learning framework for the classification of Big Data sets. In this thesis, a Hybrid Quantum–Classical framework has been developed to improve the classification of high-dimensional datasets by integrating Quantum Machine Learning (QML) algorithms with conventional machine learning techniques. The proposed framework focuses on enhancing classification accuracy, computational efficiency, scalability, and optimisation while addressing the limitations of traditional Big Data analysis approaches. The developed framework has been validated using benchmark datasets, and its performance has been analysed through comparative evaluation with existing classical machine learning methods.

To accomplish these objectives, this chapter investigates the implementation of several Quantum Machine Learning models, including Quantum Support Vector Machine (QSVM), Quantum Neural Network (QNN), Twin Support Vector Machine (TWSVM), and Quantum Particle Swarm Optimisation (QPSO). The proposed framework examines the applicability of these algorithms for classification, prediction, optimisation, and intelligent Big Data processing. The obtained results demonstrate the effectiveness of hybrid Quantum–Classical learning models in handling complex and high-dimensional datasets while providing improved computational performance over conventional approaches.

Quantum computing is one of the advanced forms of computation used in solving problems associated with large volumes of data and machine learning applications. Unlike traditional computing, quantum computing exploits the principles of superposition, entanglement, and quantum parallelism to perform computations on multiple states simultaneously. As a result, it offers significant advantages in computational efficiency, optimisation, feature extraction, and classification of high-dimensional datasets. Furthermore, the integration of machine learning with quantum

computing has enabled intelligent solutions for data analysis, prediction, clustering, and classification across diverse domains such as healthcare analytics, image processing, finance, robotics, and automation.

Machine learning algorithms make predictions by identifying underlying relationships and patterns from previously available datasets. In modern computational environments, these algorithms are extensively applied in big data analytics, where massive volumes of structured and unstructured data are collected from multiple sources for intelligent decision making [1], [2]. Different machine learning methodologies have their counterparts in the realm of Quantum computing through Quantum classification, Quantum clustering, Quantum search, and Quantum optimisation algorithms that can be used to solve practical problems in healthcare, image processing, finance analysis, robotics, and automation [3], [4]. The operation of vectors and matrices based on Quantum computation allows achieving an exponential increase in computational speed compared to classical computing systems [5], [6]. Furthermore, amplitude encoding and Quantum feature extraction methodologies have shown good results in image classification and pattern recognition problems solved using Quantum computers [6]. It has been found that QC-CNN (Quantum-Classical Convolutional Neural Network) improves generalisation since Quantum parallelism enhances concurrent Quantum states transformations and computations of information.

The algorithm of Quantum prediction represents the technique employed for the processing and analysis of high-dimensional Quantum data. Quantum prediction algorithms consist of combining traditional machine learning techniques with Quantum computing concepts such as superposition, entanglement, and Quantum parallelism [7], [8]. Among the popular algorithms for making predictions using Quantum data, Variational Quantum Algorithms (VQA), Quantum Neural Networks (QNN), and Quantum kernels are extensively applied [9]. Hybrid Quantum-classical prediction models involve the application of classical optimisation methods in combination with Quantum computing techniques to increase computational performance, prediction efficiency, and accuracy with noisy and high-dimensional data [10], [11]. Such methods are applied in several fields such as finance,

cryptography, healthcare analytics, Quantum chemistry, and smart automation systems [12], [13].

The experiment took into account benchmark datasets that included Caltech-101 and QRISK3 medical datasets. The Caltech-101 dataset is a dataset with pictures of 101 objects, including a background category, which is often used in scientific studies of image and object recognition [14]. It consists of about 9,000 middle-resolution images, each of which represents different categories of real-life objects. In the case of image classification analysis, a transfer learning technique involving a pre-trained ResNet34 model trained on ImageNet was implemented to improve classification accuracy and speed up the deep learning process [15]. QRISK3 is a healthcare data risk prediction database that helps estimate the risks of developing heart diseases within the next decade [16], [17].

The Quantum Machine Learning techniques have the following benefits over classical methods of big data processing, such as rapid database search, optimisation, dimensionality reduction, matrix operations, classification and better feature extraction capabilities [18], [19]. This is because Quantum computation is capable of processing multiple computational states at a time using Quantum parallelism, leading to lower complexity and better convergence capabilities for machine learning algorithms [20]". Thus, the development of QML-based architectures is gaining popularity due to their immense potential in the coming intelligent era [21], [22], [23].

3.2 Related Work

Recently, there has been great interest in quantum machine learning and big data analysis owing to the ability of quantum computers to perform computations on large datasets more efficiently. "Various studies have been performed using the principles of quantum computing, including superposition, entanglement, and quantum parallelism, to augment classical machine learning techniques in order to enhance the performance in terms of classification efficiency, optimization efficiency, and data processing speeds [1], [3], [11]. The invention of QSVM, QNN, quantum kernels, and variational quantum algorithms has offered new possibilities for big data classification.

Rebentrost et al. [19] proposed the development of a Quantum Support Vector

Machine approach for solving classification problems associated with high-dimension feature space and big data. The experiment carried out indicated that the quantum algorithms used in developing the QSVM have computational exponential speedup over traditional support vector machine methods when applied on large-dimensional dataset. Ding et al. [33] also presented a Quantum-inspired Support Vector Machine model for enhancing classification accuracy and computational performance in complex environment. Gao and Li [7] provided a detailed discussion on how kernel support vector machine could be implemented in big data mining process.

Various researchers have also concentrated on quantum machine learning methods to develop healthcare analytical and image processing technologies. Ajlouni et al. [15] introduced an adaptive hybrid Quantum Convolutional Neural Network (QCNN) approach for analyzing medical images where enhanced performance was achieved through hybrid quantum-classical computing techniques. Dilsizian and Siegel [16] emphasized the significance of artificial intelligence, big data analysis, and high-performance computing technologies in healthcare prediction and cardiac imaging techniques. Medlin Julia and Bennet [17] presented an efficient machine learning-based technique for medical big data analysis and predictive healthcare systems.

Furthermore, quantum algorithms have been extensively researched for enhancing machine learning processes. Duan [29] has designed a Double Quantum Particle Swarm Optimisation (DQPSO) algorithm for big data classification and multi variable system identification. This algorithm has proved very efficient in reducing computation processing time and providing enhanced optimization in distributed computing environments. Moreover, different quantum algorithms, including HQPSO, Adaptive QPSO, and Quantum Behaved PSO, have been suggested to enhance convergence speed, global optimization ability, and classification efficiency [29], [30].

The development of hybrid quantum-classical computation models has become one of the key strategies to counterbalance the drawbacks associated with existing NISQ-based devices. For instance, Cavallaro et al. [14] suggested a hybrid quantum-classical approach to designing scalable quantum computation architectures. In addition, Martín-Guerrero and Lamata [11] explored the use of combining classical

optimization algorithms with quantum machine learning schemes to achieve effective predictive modelling and intelligent data analysis. Moreover, Variational Quantum Algorithms and Quantum Neural Networks have proved their efficiency in such tasks as classification, clustering, dimensionality reduction, and optimization [35], [37].

Quantum computing techniques were further investigated for their applications in image processing, intelligent systems, financial analytics, and anomaly detection. Quantum machine learning was proposed by Liu & Rebentrost [23] as an approach for quantum anomaly detection whereas the involvement of big data analytics and digital image processing in intelligent visual systems was discussed by Huang [21] and Jiang [22], respectively. The Quantum search algorithm proposed by Grover [25] was reported to offer substantial benefits in computational efficiency compared to classical approaches.

While significant advancements have already been made in quantum machine learning and big data analysis, certain hurdles continue to persist. The present quantum technologies lack various issues related to their hardware stability, susceptibility to noise, inadequate qubits, scaling difficulties, and complex design process [14], [37]. Moreover, the current literature is restricted to the examination of separate quantum classifiers and optimisation approaches without any comparative study conducted across different machine learning algorithms.

Thus, the current study is devoted to the comparison between different algorithms of quantum machine learning, such as QSVM, TWSVM, QNN, and QPSO based approaches". In addition, the objective of the framework is to enhance computation efficiency, optimization capacity, accuracy, and scalability in analyzing big data sets.

The above literature demonstrates that considerable progress has been achieved in the application of Quantum Machine Learning techniques for Big Data classification. However, existing studies primarily focus on individual algorithms or specific application domains and do not provide a unified Hybrid Quantum–Classical framework capable of addressing scalability, computational efficiency, and practical implementation challenges. To overcome these limitations, this thesis proposes a comprehensive Hybrid Quantum–Classical Framework for Big Data Analysis. The

proposed framework integrates multiple Quantum Machine Learning algorithms and evaluates their performance using benchmark datasets, thereby providing an efficient and scalable solution for intelligent Big Data classification.

3.2.1 Experimental Methodology and Reproducibility

The experimental methodology adopted in this chapter consists of dataset preparation, preprocessing, quantum or hybrid model implementation, model evaluation, and comparative analysis with classical approaches where applicable. The IRIS dataset is used as an explicitly described experimental example, comprising 150 samples and four input features, namely sepal length, sepal width, petal length, and petal width. The data are converted into a suitable tabular representation, preprocessed, and divided into training and testing subsets before implementation of the QSVM model. The QSVM implementation uses Qiskit together with Scikit-learn, while Seaborn is used for visualization. Other benchmark datasets discussed and analysed in the chapter include Australian, Sonar, Pima Indian Diabetes, Ionosphere, BUPA Liver, Heart-statlog, CMC, WPBC, Hepatitis, and Heart-C datasets. Quantum computational analyses are performed using the reported Qiskit and IBM Quantum simulation environment, while MATLAB is used for numerical simulation and visualization. Model performance is evaluated using reported classification measures such as accuracy, precision, and recall, together with computational and convergence-related measures where applicable. Parameters such as the exact random seed, number of repeated experimental runs, circuit depth, number of shots, optimizer settings, and complete hardware configuration are not consistently documented for all experiments in the existing chapter; therefore, no undocumented values are introduced in the revised thesis. The methodological description is consequently limited to the experimental settings and parameters supported by the reported implementations and results.

3.3 Proposed Quantum Framework for Big Data Analysis

The suggested Quantum-based framework for analysis of big data comprises QML techniques along with the use of classification and optimisation methods to perform effective analysis of high-volume data. “The Quantum framework incorporates the use of quantum support vector machine (QSVM), quantum enhanced support vector

machine (QeSVM), twin support vector machine (TWSVM), quantum neural networks (QNN), and quantum particle swarm optimisation (QPSO) techniques to effectively analyse big datasets [1], [3]. Quantum computing techniques such as superposition, entanglement, and quantum parallelism are used in the Quantum framework to analyse multiple quantum states and perform efficient feature extraction [5], [6]. The Quantum framework is primarily developed for applications such as healthcare, image classification, prediction, robotics, and intelligent systems [7], [8].

Moreover, Hybrid Quantum-classical computational algorithms have also been introduced within the framework. This includes Variational Quantum Algorithms, Quantum Kernel, and Quantum Neural Networks to enhance prediction capabilities, optimisation, and classification tasks [9], [10]". These quantum learning frameworks provide an improvement in the speed of computation of tasks such as clustering, feature extraction, database search, matrix inversion, and optimisation in comparison with their conventional classical counterparts [11], [12]. Furthermore, emphasis has also been placed on achieving low computational complexity and enhanced scalability along with superior convergence characteristics [13].

3.3.1 Big Data Challenges

There are various issues associated with big data analytics due to fast-growing data in terms of volume, velocity, and variety being produced from health care systems, cloud computing platforms, image processing, intelligent transport system and financial sectors [14], [15]. Traditional machine learning algorithms need substantial computational power, huge storage capacity, and considerable processing time when dealing with high-dimensional data sets. Complex computations like feature extraction, classification, clustering, optimisation, and pattern recognition become computationally heavy with the increasing size of the data set [16]. It is also difficult for traditional systems to handle noisy, corrupted, stretched, compressed, and incomplete data sets [17].

Another significant issue that accompanies big data analysis is the issue of scaling and complexity in terms of hardware. In activities such as matrix inversion, query optimisation, dimensionality reduction, and database querying, there is increased

computation cost for large scale application [18]. Traditional computation systems typically involve many processors and large amounts of memory to effectively manage such a massive amount of data. However, for a set of 'N' data elements, traditional big data management requires about twice as many processors as the quantum computing systems, '2N' versus 'N', respectively [19]. Consequently, advanced quantum computing strategies have been increasingly considered to deal with such big data problems [20].

3.3.2 Quantum Computing Advantages

There are some key benefits offered by quantum computing that surpass classical computational architectures for machine learning and big data analysis. One benefit is that quantum bits or qubits are capable of being in several states at once through the principle of superposition and thus allow parallel computing and simultaneous computation of multiple states [5],[11]. Another advantage is that quantum computing enhances optimisation, feature extraction, classification, and computational speeds in machine learning [12].

Quantum-based Machine Learning frameworks enable dimensionality reduction, data communication security, encryption and decryption techniques, advanced image processing techniques, and optimal database searches in large intelligent systems [13], [14]. Quantum-Classical hybrid systems additionally use classical optimisation techniques within quantum computing frameworks to make applications scalable and more accurate [15]. Quantum-based classifiers such as "Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), and Quantum Convolutional Neural Networks (QCNN)" offer enhanced capabilities for classification purposes in image recognition and medical analysis applications [16], [17].

Quantum algorithms such as Grover's algorithm provide substantial computational speedup compared with classical searching approaches. For a database containing Nelements, the search complexity of Grover's algorithm is proportional to $O(\sqrt{N})$, whereas classical searching approaches require complexity proportional to $O(N)$.

This computational advantage improves query optimisation, database searching efficiency, rational decision making, and processing capability for large-scale big data

applications [18], [19]. The algorithm of Quantum data prediction and the computational advantages of quantum processing compared with classical computing are illustrated in Fig. 3.1.

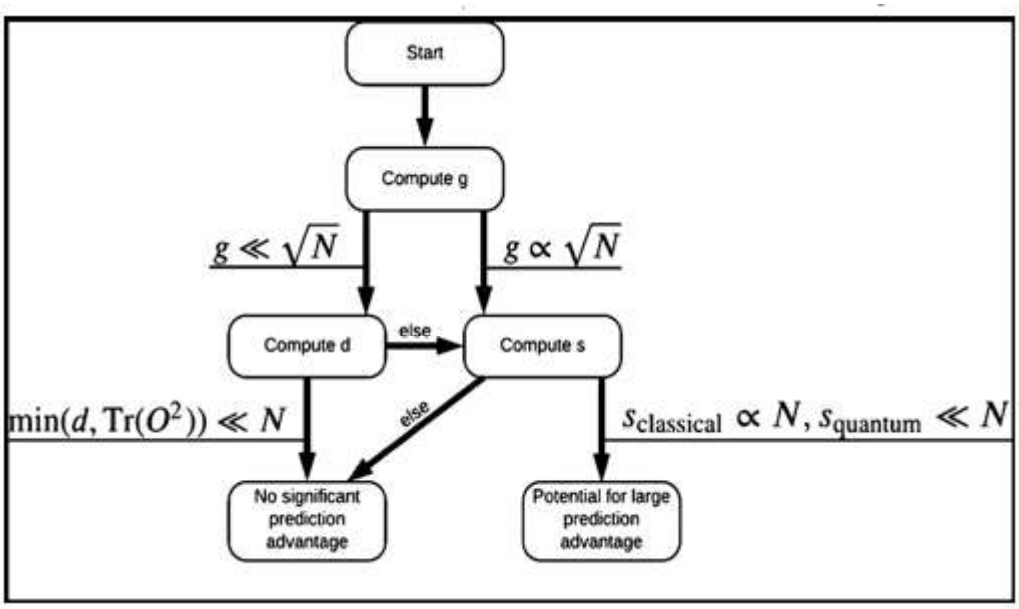


Fig. 3.1. Prediction algorithm for Quantum data.

The computational advantage offered by quantum computing compared to classical computation is illustrated in Figure 3.1. The flowchart describes how quantum computing predictive models compute computational parameters and establish if any computational advantage will be gained from making predictions. In particular, it is clear from the diagram that classical computational complexity grows linearly with data size, while quantum computations involve far less computational power.

3.3.3 Quantum Parallelism

Quantum parallelism is one of the most significant features of quantum computing, enabling the processing of multiple quantum states simultaneously through the principle of quantum superposition [5], [6]. “Unlike classical bits, qubits can occupy several states concurrently, allowing quantum systems to evaluate numerous computational states at the same time. This capability significantly reduces computation time, improves processing efficiency, and enhances the convergence speed of machine learning algorithms [16], [17].

In big data analytics, quantum parallelism improves the execution performance of

algorithms related to feature extraction, matrix computation, clustering, classification, optimisation, and database searching. Quantum-assisted Convolutional Neural Networks (QCNN) and Quantum Support Vector Machine (QSVM) classifiers utilise parallel state transformations to improve classification accuracy, generalisation capability, and pattern recognition performance [14], [18]. Similarly, Quantum Particle Swarm Optimisation (QPSO) applies parallel optimisation of multiple particles simultaneously to achieve faster convergence and improved optimisation efficiency [19].

Hybrid quantum-classical systems and Noisy Intermediate-Scale Quantum (NISQ) devices further support concurrent quantum circuit execution, enabling efficient resource utilisation and improved machine learning performance [20], [21]". The capability of processing large datasets concurrently through quantum parallelism provides considerable advantages in healthcare analytics, robotics, finance prediction, intelligent systems, image processing, and future quantum artificial intelligence technologies [22], [23]. Moreover, quantum parallelism enables scalable computational frameworks capable of handling high-dimensional datasets more efficiently compared with conventional classical computing approaches.

3.4 Development and Validation of Quantum Models Based on Big Datasets

Some of the major benefits of Quantum computing methods in Big Data Analytics include fast calculations, improved pattern recognition, fast searches of databases, query optimisation, reduction in dimensionality, compression of data, cryptography, and secure processing of information. Machine learning algorithms that use quantum computing methods offer considerable speed improvement in computational processes when compared to classical computing algorithms, especially in large data environments such as healthcare analytics, image classifications, optimisation, and predictions.

3.4.1 Quantum Machine Learning Algorithms for Big Data Analysis

Two important kinds of Quantum algorithms are frequently applied to "Quantum machine learning approaches, which are Grover's Algorithm and Shor's Algorithm [24]. While Shor's Algorithm is usually applied to integer factorisation, Grover's

algorithm is mostly applied to unstructured databases. The Grover search process can significantly increase computational efficiency by a quadratic ratio compared to classical searches. While the computational complexity in the classical approach to unsorted databases is about O(N), the complexity of Grover's algorithm is:

$$O(\sqrt{N})$$

with high probability by utilizing Quantum superposition and amplitude amplification techniques.

The mathematics of implementing Grover's algorithm comprises a series of computational steps to find a specific item from a disorganised database consisting of N items [25]. First of all, the process begins with a step known as Quantum State Preparation, whereby the superposition of all possible states is created. Once this is achieved, the Oracle operator Uis is used to identify the particular state by changing its probability amplitude while other states remain constant. In order to amplify the probability of the state, the amplitude amplification operator comes into use [26].

The iterative process continues approximately $\sqrt{N}$ times to increase the probability of obtaining the correct computational state. The collapse of the quantum state into one of the computational basis states occurs through Quantum measurement. For N-dimensional vectors with Mrepresentation samples in one of the K-clusters, the computational complexity of quantum systems is proportional to $O(\log(MN))$, whereas the convergence complexity is represented by $O(poly(MN))$. This level of computational efficiency demonstrates the applicability of quantum algorithms to large-scale big data analytics, optimisation, and linear equation solvers [27]".

Prediction Algorithm in Quantum Data shows that the computational advantage that is possessed by Quantum computing compared to conventional methods of computation. From the diagram above, it can be seen that computational complexity in classical systems is directly proportional to the amount of data, while quantum systems minimise computational complexity using quantum parallelism and superposition rules.

3.4.2 Health Care Data of Cardiovascular Events

Figure 3.2 illustrates an experiment that was conducted in relation to the derivation and validation of the QRISK3 algorithm to predict the risks of developing cardiovascular diseases based on data regarding cardiovascular events among males and females [12]. QRISK3 is a medical prognostic model employed for the assessment of future risks of cardiovascular diseases over the following ten years. QRISK3 represents an advanced approach in comparison to other cardiovascular prediction models as it includes additional risk variables such as chronic kidney disease, serious mental disorder, blood pressure variability, corticosteroid treatment, history of migraines, erectile dysfunction, antipsychotic drugs, high cholesterol, and socioeconomic deprivation.

The QRISK3 model offers a more accurate approach for evaluating the risk levels of cardiovascular disease for both genders, especially those populations that are underrepresented. It helps the medical practitioners to be able to identify high-risk individuals to implement better preventive measures so as to reduce the possibility of developing cardiovascular diseases in the future. The QRISK3 models have been upgraded to evaluate risks among patients aged 25 to 84 years.

The findings from the validation of the experiment showed that there is a high calibration capability of the models during validation in different groups. “The 10-year predicted risk of developing cardiovascular disease among women using models A, B, and C was 4.7%, while the observed risk stood at 5.8% to 5.9%. For men, the predicted risk was 6.4%, while the observed risk was 7.5% to 7.6%”.

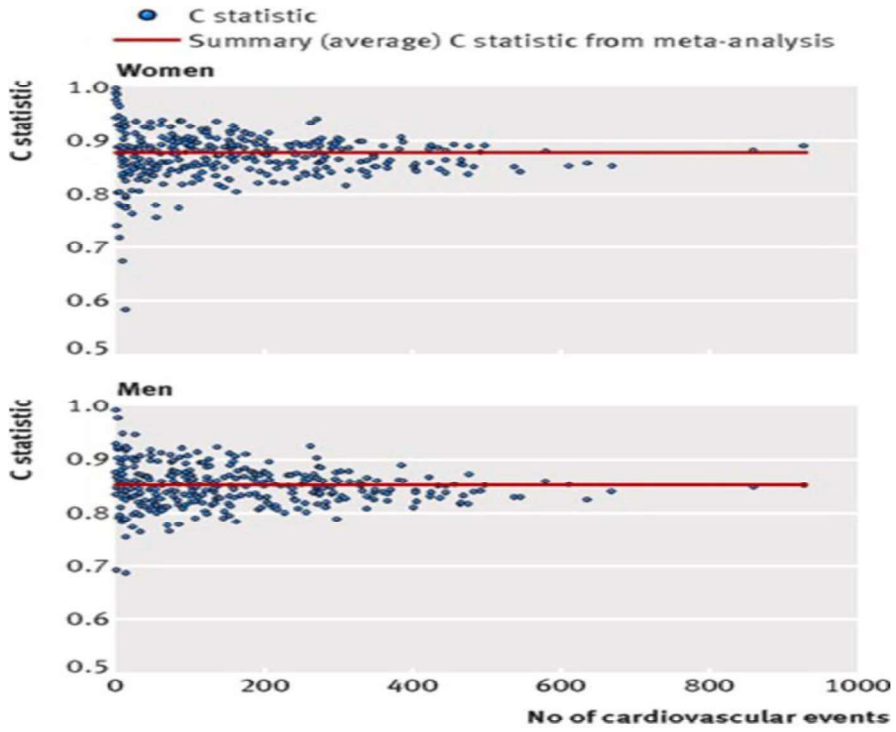


Fig. 3.2. Cardiovascular events in men and women for the Quantum meta-analysis.

As depicted in Fig. 3.2, the experimentally obtained data reveal the 10-year cardiovascular risk distribution within various age groups, such as 25–39 years, 40–59 years, and 60–84 years [17]. High correlation was identified between predicted and actual cardiovascular risks for both male and female populations, suggesting that the developed prediction models perform well in terms of calibration. Nonetheless, a minor overestimation of risk was noted for the age category of 25–39 years. The results confirm the validity of using quantum-assisted healthcare prediction models for cardiovascular risk analysis.

3.4.3 Quantum PSO Algorithm for Good Fitness Analysis

QPSO is a novel optimisation method that integrates the concepts of quantum computing with Particle Swarm Optimisation (PSO) in order to solve complicated optimisation problems [28]. Particle Swarm Optimisation refers to an optimisation approach inspired by natural phenomena where particles move around the solution space in search of the optimum solution. The main idea behind QPSO is the integration of Quantum mechanics in the movement mechanism to enhance its ability for

optimisation purposes.

In QPSO, the particle position can be expressed in the form of $X^{(t)}(i)$ for all from $i = 0$ to N. $Mbest(i)$ represents the mean best position of each particle, while the fitness function of $F(X^{(t)}(i))$ is obtained. Once $F(X^{(t)}(i))$ becomes smaller than the previously stored value of fitness $F(P^{(t)}(i))$, particle position is changed. In this method, the parameter of ϕ is generated randomly between zero and one, and the particle position is changed according to the Quantum probabilistic approach. Two random values of uand k, which belong to the interval between zero and one, are also generated during the process of particle position updating. Whenever $k \geq 0.5$, Quantum displacement in logarithmic fashion will affect the position of particles; else, displacement factor is used in the position updating process of particles. The process of optimization continues up to the global optimum condition of fitness function, as shown in Fig. 3.3 [14] [29] [30].

Algorithm 1 Quantum particle swarm optimization (QPSO)

Initialize the particles' positions ($\mathbf{X}^{(t)}(i)$) and the number of particles N.
Set $\mathbf{P}^{(t)}(i) = \mathbf{X}^{(t)}(i)$, $\forall\, i = 1, 2, \ldots, N$.
while ($t < Max_{iter}$) **do**
    for all $i = 1$ to N **do**
        Calculate $\mathbf{M}_{best}$ as in Eq. 13.
        Evaluate the fitness function for the current position ($\mathcal{F}(X^{(t)}(i))$).
        if ($\mathcal{F}(\mathbf{X}^{(t)}(i)) < \mathcal{F}(\mathbf{P}^{(t)}(i))$) **then**
            $\mathbf{P}^{(t)}(i) = \mathbf{X}^{(t)}(i)$.
        end if
        $\mathbf{P}^{(t)}(g) = min(\mathcal{F}(\mathbf{P}^{(t)}(i)))$.
        for $j = 1$ to d **do**
            $\phi =$ rand(0,1).
            $p(i, j) = \phi P^{(t)}(i, j) + (1 - \phi) P^{(t)}(g, j)$.
            $u =$ rand(0,1).
            $k =$ rand(0,1).
            if ($k \geq 0.5$) **then**
                $X^{(t)}(i, j) = p(i, j) - \beta.|(M_{best}(i, j) - X^{(t)}(i, j)|.ln(1/u)$.
            else
                $X^{(t)}(i, j) = p(i, j) + \beta.|(M_{best}(i, j) - X^{(t)}(i, j)|.ln(1/u)$.
            end if
        end for
    end for
    Stop the algorithm if a sufficiently good fitness function is met.
end while

Fig. 3.3. Quantum particle swarm optimisation for fitness dataset.

Efficiency in optimization, parameters tuning, and convergence can be enhanced using the QPSO framework, particularly in large-scale big data applications. Several

versions of QPSO algorithms have been developed to increase optimization performance depending on the computation environment.

3.4.3.1 Quantum-inspired PSO (QIPSO)

Quantum-inspired PSO integrates classical PSO with Quantum-inspired concepts to achieve enhanced explorative ability and improved global search optimisation. This technique ensures that particles are prevented from converging prematurely, thereby ensuring optimal performance in optimisation processes.

3.4.3.2 Hybrid Quantum PSO (HQPSO)

The Hybrid Quantum PSO combines Quantum-based particle update techniques with conventional PSO methodologies. In Hybrid Quantum PSO, a certain number of particles follow the Quantum-based optimisation technique while other particles follow conventional swarm intelligence.

3.4.3.3 Quantum-behaved PSO (QPSO-II)

A quantum behaviour-based PSO adapts the quantum property of particles, thus improving the convergence speed and global searching ability. The adaptive quantum mechanism remarkably improves the optimisation capabilities for multidimensional optimisation [14].

3.4.3.4 Multi-objective QPSO (MO-QPSO)

Multi-objective QPSO provides a framework to apply the principles of multi-objective optimisation in Quantum Particle Systems for obtaining Pareto optimal solutions. The algorithm is very much appropriate for solving problems that have multiple objectives at once.

3.4.3.5 Quantum Annealing PSO (QAPSO)

The Quantum Annealing Particle Swarm Optimisation integrates Quantum annealing techniques with Particle Swarm Optimization to enhance global optimisation capabilities and help avoid local optima. It ensures high accuracy and reliability in solving computational challenges.

3.4.3.6 Quantum Entanglement in QPSO

Quantum entanglement-based QPSO improves information distribution among particles using Quantum entanglement principles. The interaction among particles enhances optimization capability and accelerates global convergence performance [30].

3.4.3.7 Adaptive QPSO (AQPSO)

In AQPSO, the Quantum particle's parameters and behaviors can change adaptively based on the environmental context of the optimization problem. Adaptability enhances flexibility and optimization effectiveness depending on the problem type.

3.4.3.8 Parallel QPSO (PQPSO)

Parallel QPSO utilises parallel computation strategies for simultaneously optimizing multiple particles. The parallel execution mechanism significantly improves convergence speed and computational efficiency for big data optimization tasks.

3.4.3.9 Quantum-inspired Differential Evolution with PSO (QIDPSO)

Quantum-inspired Differential Evolution Using PSO uses the Quantum-inspired Differential Evolution approach together with PSO to address optimization challenges. The combined approach enhances search diversity, convergence accuracy, and robustness in computation [29].

3.5 Quantum Techniques Utilization for Big Data Analysis

Among the various benefits of quantum computing techniques in relation to big data analytics are quick database searches, optimized querying process, improved pattern recognition, secure cryptographic calculations, dimensionality reduction, and efficient big data processing. "The application of Quantum techniques in big data analytics has seen a noticeable rise in recent years, as depicted in Fig. 3.4 [19] [27].

In case of N-dimensional vectors with M representations within one of K clusters, the computational complexity of Quantum computations becomes:

$$O(\log(MN))$$

whereas the convergence complexity is represented by:

$$O(poly(MN))$$

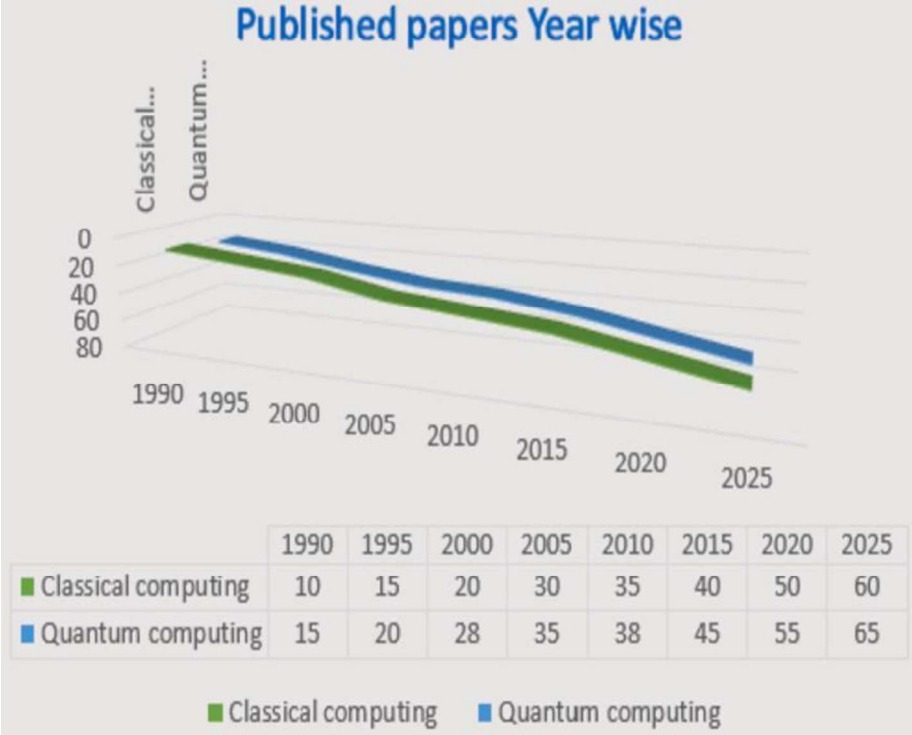
The stated computational-complexity formulation provides a theoretical basis for analysing the computational requirements of quantum approaches for higher-dimensional data. However, it does not by itself establish practical computational superiority over classical systems. Quantum algorithms like the Shor algorithm are crucial tools when it comes to finding solutions to linear equation systems, performing optimizations, and conducting large-scale simulations.

3.6. Quantum Classifiers Based on Dataset Analysis

3.6.1. Quantum Support Vector Machines (QSVM) on IRIS Dataset

QSVM is a Quantum version of the traditional Support Vector Machine algorithm, which uses Quantum computing principles to classify data [31]. “In this proposed method, the IRIS dataset is employed for analysing the classification ability of the QSVM model. In this implementation process, the IRIS dataset has been loaded from sklearn. In the datasets module, the dataset is preprocessed, the QSVM model is trained, and its classification performance is analysed using Quantum machine learning methods.

The experimental implementation has been carried out with the help of Qiskit, Scikit-learn, and Seaborn libraries. First of all, the IRIS data was transformed into a DataFrame format for better processing and visualisation. Feature values such as sepal length, sepal width, petal length, and petal width were chosen and classified into three different categories of iris flowers, that is, Setosa, Versicolor, and Virginica. After dividing the data into training and test sets, the classification process was implemented on the testing data with the help of a QSVM model in the Quantum Machine Learning module of Qiskit. The resulting classification process is presented in Fig. 3.5 [32][33].



	1990	1995	2000	2005	2010	2015	2020	2025
Classical computing	10	15	20	30	35	40	50	60
Quantum computing	15	20	28	35	38	45	55	65

Fig. 3.4. Number of Quantum computing and classical computing based big data analysis published work.

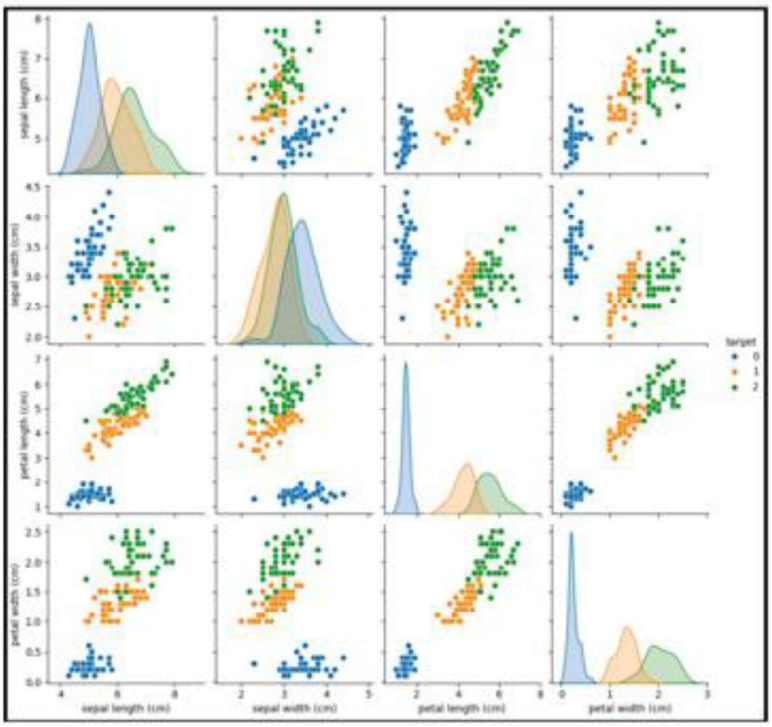


Fig. 3.5. QSVM model on IRIS Dataset.

The IRIS data set comprises 150 samples with four primary variables: sepal length,

sepal width, petal length, and petal width. The QSVM implementation was used to examine classification performance on the IRIS dataset, with the resulting classification behaviour evaluated using the reported performance measures. The performance of the model is then tested based on parameters like accuracy, precision, and recall. The QSVM results provide an example of multi-class classification performance on the IRIS dataset under the reported experimental setting.

Table 3.1. Different categories of IRIS Dataset [Missing attributes: None], Class Distribution = 33.3% for each of 3 classes

Category	Min	Max	Mean	SD	Correlation
Sepal Length	4.3	7.9	5.84	0.83	0.7826
Sepal Width	2.0	4.4	3.05	0.43	-0.4194
Petal Length	1.0	6.9	3.76	1.76	0.9490 (High)
Petal Width	0.1	2.5	1.20	0.76	0.9565 (High)

The obtained results demonstrate that Quantum machine learning models provide efficient classification capability for structured datasets and can potentially outperform conventional machine learning methods in large-scale data analysis applications".

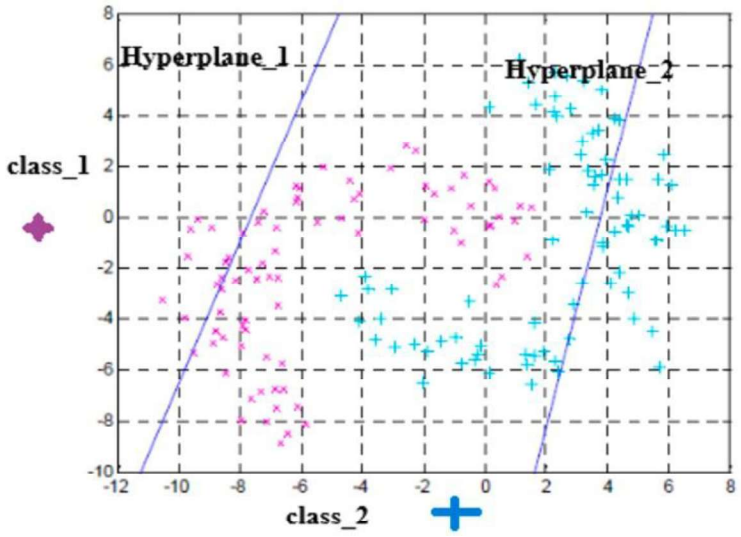


Fig. 3.6. Twin SVM classifier of two classes.

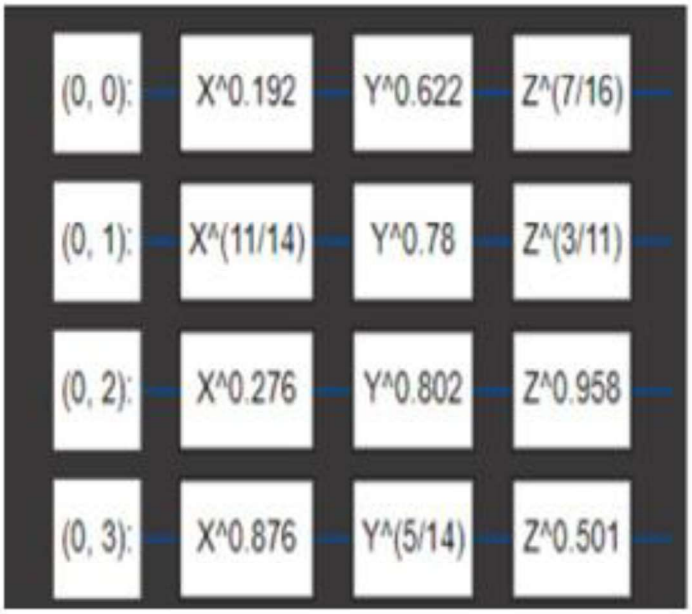


Fig. 3.7. Quantum VSVM classifier circuit.

3.6.2. Twin Support Vector Machines (TWSVM)

TWSVM refers to Twin Support Vector Machine, which is a binary classification model used in building two nonparallel hyperplanes to classify data into two categories. This technique differs from the traditional SVM models, which use a single hyperplane in classification, by creating two hyperplanes that are used to separate the data points, as illustrated in Figure 3.6 [7]. One of the advantages of using the twin support vector machine algorithm is its ability to solve imbalanced data sets.

The TWSVM method decreases complexity and enhances classification effectiveness by using the solutions of two small quadratic programming problems rather than using one large optimisation problem. Consequently, the proposed method is very effective for large-scale big data classification and intelligent prediction.

3.6.3. Quantum Variational Algorithms

Quantum Variational Algorithms are hybrid optimisation algorithms which utilize quantum circuits to carry out supervised learning tasks [34]. This is carried out using the “quantum variational classifier (QVC) and the quantum variational support vector machine (QV-SVM) models” to improve the efficiency of classification through

parameter tuning.

The variational Quantum approach uses optimisation techniques for finding the parameters of the Quantum circuit such that it minimises the objective function for better predictive accuracy. Figure 3.7 illustrates the variational Quantum classifier circuit structure, which is used to perform Quantum VSVM classification [35]. These approaches effectively make use of the Quantum computational power together with classical optimization methods to solve difficult classification problems.

3.6.4. Quantum Neural Networks (QNNs)

QNNs represent Quantum versions of neural networks, which have found widespread applications in the fields of classification, regression, clustering, and optimization in Quantum-based machine learning [36]. “These networks harness the computational power of Quantum mechanics with AI approaches to enhance efficiency in learning, feature extraction, and prediction. For clustering purposes using unsupervised learning, Quantum versions of algorithms like Quantum k-means clustering are applied.

Quantum Principal Component Analysis (QPCA) is also used in dimensionality reduction and high-dimensional data analysis. In the article entitled “Variational Quantum Optimization of Non-locality in Noisy Quantum Networks,” the utilization of IBM Quantum Networks as well as the variational quantum optimization (VQO) approach was shown, and according to which quantum noise escalates with an increase in the number of qubits in a quantum system [8] [35]. It was revealed that the variational quantum optimization framework can effectively optimize the non-locality of IBM Quantum computing systems. Hybrid quantum-classical optimization algorithms have also been suggested for NISQ systems [37].

Variational Quantum Circuit (VQC) refers to a parameterized Quantum circuit in which gate parameters for rotational gates are tuned iteratively. These gate parameters include R_x, R_y, and R_z that rotate the Bloch vector of a qubit on particular axes to make efficient use of Quantum information. The parameters of these rotational gates are tuned with classical optimization algorithms in order to minimise the cost function of the Quantum circuit.

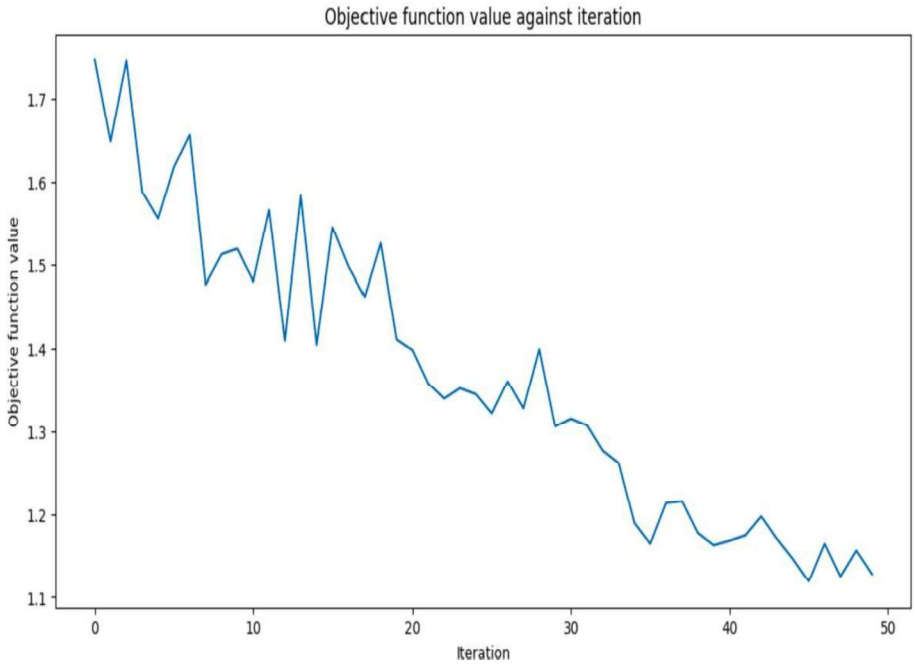


Fig. 3.8. A parameterised Variational Quantum circuit with rotational gates.

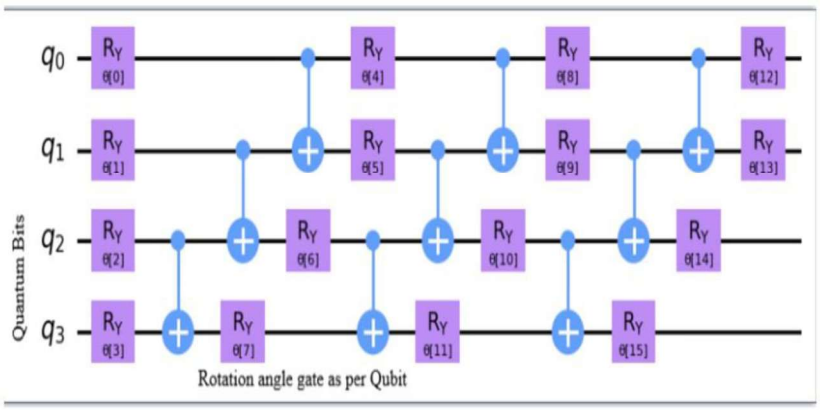


Fig. 3.9. Variational Quantum Computing (VQC) objective function value versus iteration chart.

The Variational Quantum Computing method is a fusion of quantum computing techniques like Quantum superposition, entanglement, and variational optimization methodologies that make exploration of complex computational state spaces highly efficient. According to Fig. 3.8 and Fig. 3.9, there is a marked enhancement in the optimization ability and computational learning efficiency due to the Variational Quantum Computing technique when compared to classic computational approaches. For the experiment performed using PennyLane open-source Quantum differential

programming library and qNetVO software package [33].

A parameterised quantum circuit is made up of several layers of programmable Quantum gates, which function in a manner akin to the hidden layers of conventional neural networks". In a similar vein, each layer comprises programmable Quantum gates that manipulate the qubits and optimize the learning process.

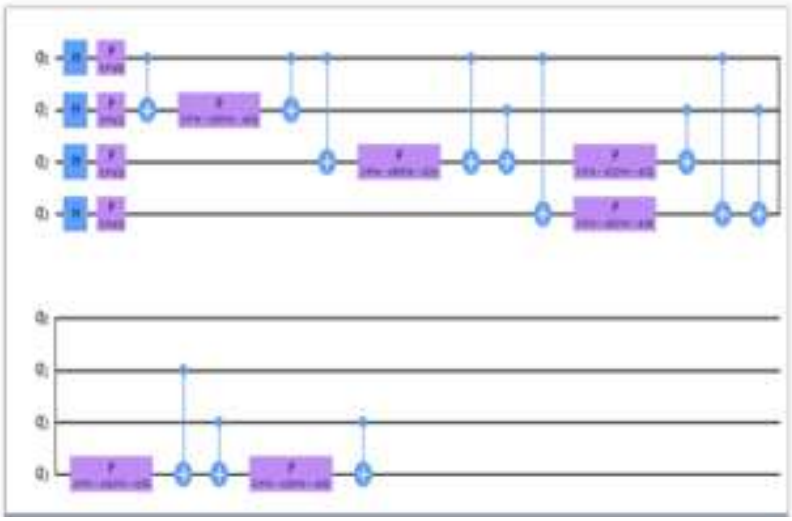


Fig. 3.10. A parameterized Quantum circuit consisting of neural network layers with tunable parameters.

As illustrated in Fig. 3.10, the proposed PQC design represents the layered design for Quantum neural networks, wherein Quantum parameters are updated by employing an iterative procedure. Such a Quantum-classical learning process allows QNNs to accomplish complex classification and prediction jobs and even surpass classical neural networks in performance [38].

3.6.5 Twin Support Vector Machines Based on Fruit Fly Optimization Algorithm

SVM, otherwise called an optimised binary classifier, is a supervised machine learning algorithm designed to classify new data sample sets based on pre-classified training datasets [33]. As it has been demonstrated, SVM has logarithmic computational complexity about vector size; thus, it can be effectively simulated with quantum computing methods. In contrast to conventional sampling approaches in classical computing, quantum support vector machines (QSVM) can work with logarithmic complexity for all the elements in training datasets, whereas classical methods usually

have polynomial complexity [12]. “A supervised machine learning algorithm relies on training data sets when classifying feature vectors into two different states in feature space [39]. SVM is characterised by constructing a hyperplane, which separates two datasets into a higher-dimensional kernel space and feature space. The computational complexity of SVM depends on the number of eements in both training datasets, as well as on the required accuracy $O(\log(\epsilon^{-1})poly(N,M))$. Here, N stands for feature space dimensionality, M for the number of training vectors, and ϵ for the classification accuracy [6].

In training as well as in the classification stage, the complexity of the QSVM algorithm is in terms of $O(\log(NM))$. From the evaluation of the inner products, the performance of N improves for efficient Quantum computation, while the performance of M can be enhanced by applying matrix inversion through the least square optimization problem. The QRAM needs $O(MN)$ hardware complexity as well as data accessibility through $O(\log(MN))$ Computational complexity in Quantum computing. Non-sparse matrix exponentials training technique is also employed for efficient matrix inversion and training data optimisation under big data algorithms. About problem structure and computational complexity, Quantum algorithms provide exponential or polynomial speed up over classical computation [28], [40], [41].

A weighted K-nearest neighbour (K-NN) classification approach based on Quantum computing was proposed in [32], where the computational complexity becomes $O(\log N)$ for Quantum information represented using N-dimensional feature vectors with training-set-independent structures. The proposed Quantum-based algorithm utilises low-rank approximations instead of complete training input matrices, thereby reducing computational overhead and improving processing efficiency. In study [23], a Quantum version of a discrete-time classifier was introduced for determining split nodes using Quantum criterion measurements. Furthermore, measurements between two Quantum states were employed for subclass clustering of training datasets by considering multiple datasets simultaneously. Comparative analysis between Quantum-based classifiers and conventional machine learning classifiers, such as Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN), was also performed to evaluate classification performance and computational efficiency [4].

The use of Q-SVM in article [19] is aimed at classification of big data in order to achieve both linear and nonlinear quantum binary classifiers through exponential speed up of computation for the larger vector spaces and training examples. Methods such as non-sparse matrix simulation and matrix inversion techniques for PCA-based data training are discussed. The author of [6] proposes GEPSVM to solve the computational complexity problems related to noisy and error-prone datasets. Similarly, in article [10], the high computational complexity problem related to K-SVM on large-scale data is discussed. To solve this issue, the use of the divide and conquer technique involving the use of Buffered K-D Tree structures for training of K-SVM classifiers is suggested. The use of a Buffered K-D Tree (balanced binary tree) helps to break the data into several subsets or leaves. According to buffered data samples, a "min-max" expansion approach is suggested; after that, the classifier of K-SVM is trained following the tree structure [27]. For analysis, the benchmarking datasets are compared to state-of-the-art training using the LibSVM implementation.

The LMKL algorithm was covered by the author in the article [24]. It is based on a soft clustering and classification technique. The proposed LMKL algorithm ensures kernel weights selection that are optimised based on the dataset features. All experimental results were obtained by employing the UCI datasets, while comparisons were drawn between the traditional Gaussian kernel SVM techniques [41]. The author of the article [6] explored quantum mechanical principles in creating machine learning solutions, which enable optimisation of computational efficiency with respect to huge datasets [42]. Quantum Big-Bang computation, Quantum parallelism, Superposition principles, and linearity in dealing with infinite data input sets were also considered [1]. Moreover, DiVincenzo criteria were applied in Quantum computing technologies [43].

Use of big data analysis applications in healthcare, scientific discoveries, and social interaction produces enormous amounts of data that require intensive computation and privacy protection [17]. To overcome such challenges, article [34] proposed the combination of Proximal-SVM (PSVM) and GEPSVM to produce Twin Support Vector Machine (TWSVM). TWSVM changes a complex problem of classification into two small problems by forming two hyperplanes that cannot be parallel.

Limitations posed by traditional TWSVM can be overcome with Quantum Particle Swarm Optimisation-Twin Support Vector Machine (QPSO-TWSVM), where the global exploration ability of QPSO is harnessed for optimising parameters, instead of blind random initialisation of parameters. Linear classification tests were performed for ten different datasets in terms of sample size and attributes, as presented in Table 3.2. Comparison of Quantum classifier models' performance based on the accuracy metrics: Accuracy, F1-score, Precision, and Recall is illustrated in Fig. 3.11; whereas, software versions used in the experiments are depicted in Fig. 3.12.

Table 3.2. Description of Ten Datasets Used for Linear Testing

Datasets	**Samples**	**Attributes**
Australian	690	14
Sonar	208	60
Pima-indian	768	8
Ionosphere	351	34
BUPA liver	345	7
Heart-statlog	270	14
CMC	1473	9
WPBC	198	34
Hepatitis	155	19
Heart-c	303	13

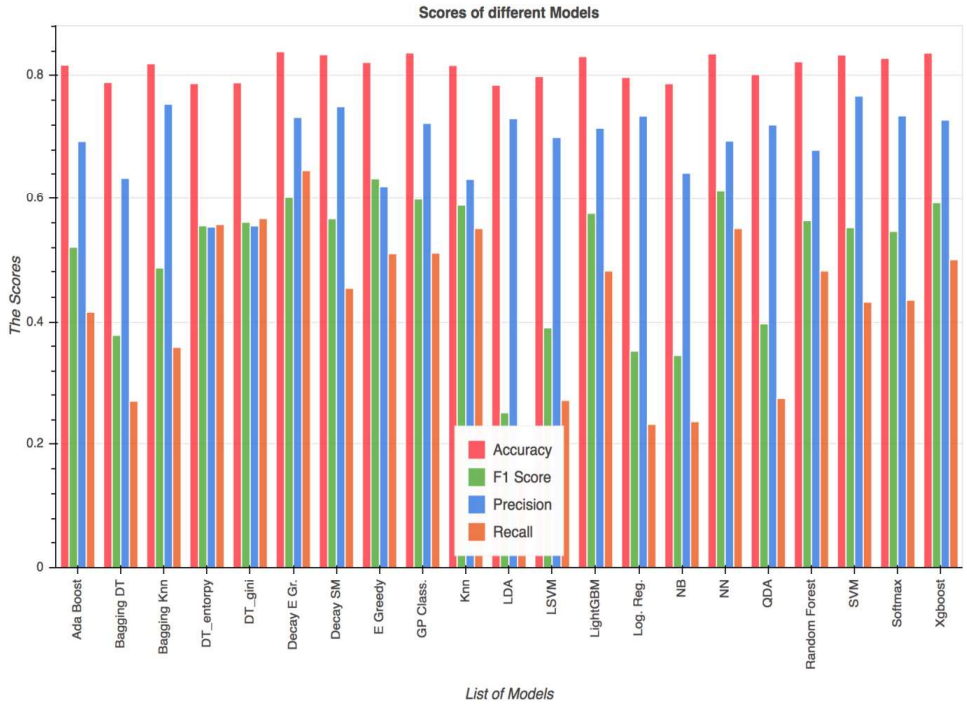


Fig. 3.11. Quantum classifier models accuracy comparison.

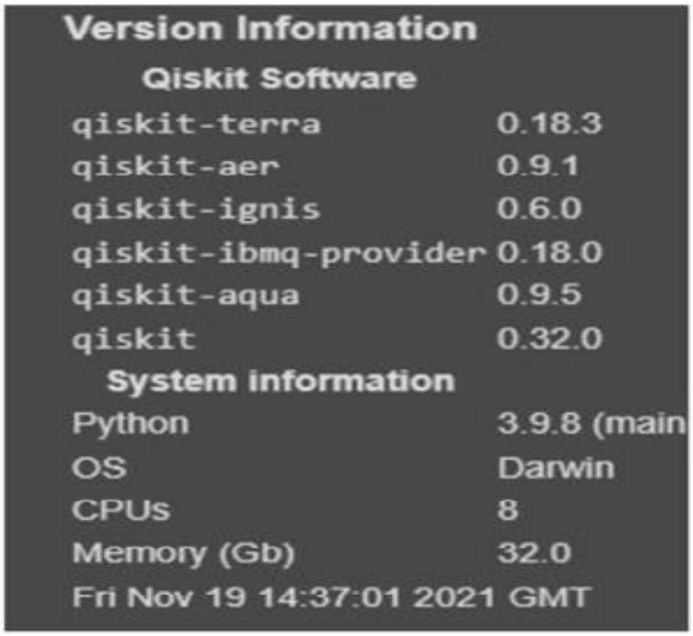


Fig. 3.12. Version Information.

When applying Quantum machine learning models on Linear Data Sets, including Australian Credit Approval, Sonar, Pima Indian Diabetes, Ionosphere, BUPA Liver Disorder, Heart-statlog, CMC, WPBC, Hepatitis, and Heart-C datasets, we find that

Quantum-based algorithms can optimise performance of classification, convergence, and optimisation even on relatively linear data sets. The Least Squares SVM was proposed by Suykens et al. [28], wherein Proximal SVM uses parallel hyperplane construction with equality constraints, removing the inequality constraints used in classical SVM models. Further improvement on the optimisation procedure is achieved through GEPSVM, which involves transforming the procedure into Generalised Smallest Eigenvalue Problems to get global optimal solutions [39].

In reference [13], the concept of the TWSVM algorithm is presented after thorough research on PSVM and GEPSVM, wherein hyperplanes are created with no parallel constraints.

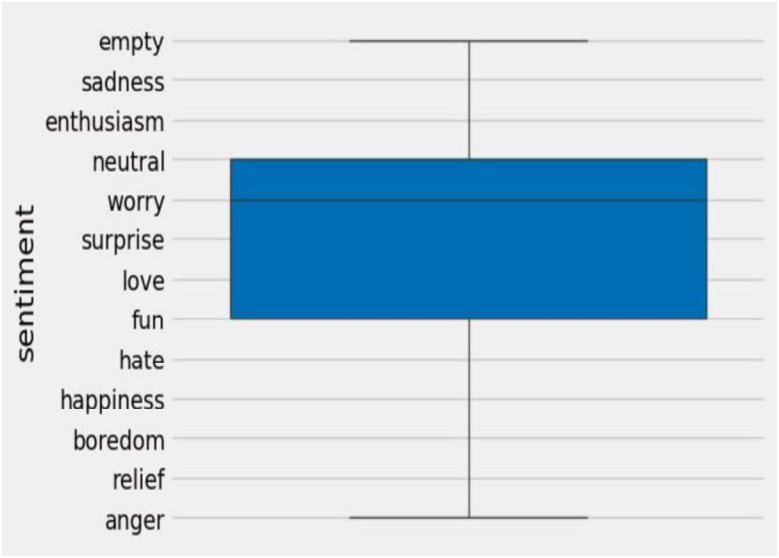


Fig. 3.13. Real-Time sentiment analysis, Box plot using QSVM.

While WLSTWSVM was developed by the author of the article [17], the year 2009 witnessed another development, Robust TWSVM, proposed in [39]. Efficient classification capability of TWSVM for real-time applications like sentiment analysis is shown in Fig. 3.13.

Duan Jingbo [29] explained a "Big Data Classification Model" based on Double Quantum Particle Swarm Optimisation (DQPSO). In this approach, intelligent algorithms have been used for multivariable system identification and large-scale data classification. The major drawbacks associated with traditional classification algorithms include the requirement of more time for computational processing. Hence,

an optimised parallel computing approach has been introduced in the proposed method. In the proposed study, multivariable systems were studied through historical big data with the help of intelligent algorithms for analysing the effect of input parameters on output parameters. Through a big data classification architecture, valid data points were recognised, combination approaches for data were organised, local connectivity approaches were partitioned, micro-cluster node data were determined, while redundant data and invalid data increment values were computed for reconstructing the nodes through algorithms [45], [46]. The experimental results proved that the developed framework remarkably decreased computation processing time in actual applications [47], [48]. The proposed framework minimised communication costs among network nodes, improved the accuracy of global mining and distributed queries, and offered efficient usage for big data processing [49], [50]. In addition, simulation experiments were conducted to validate the effectiveness of the proposed algorithm [51], [52].

Computational speedup using quantum mechanics is also applicable for searching problems on unsorted databases [39]. For instance, for an ordinary random phone directory with N names, the classical algorithm will need at least 0.5N accesses to produce the desired outcome with 50% chances [53]. Quantum mechanical systems use superposition concepts to look into different states at once [54]. By applying phase manipulations correctly, success leads to amplification of successes, whereas failures lead to destructive interference of failures [55]. Thus, the required data can be achieved with just $O(\sqrt{N})$ computational effort.

Ohkura et al. [56] analysed the concurrent execution of Quantum circuits on existing and imminent NISQ devices through the “Palloq” approach, which is a compiler technique that optimises quantum multi-programming efficiency on NISQ architectures [57]. Experimental evaluation demonstrated that concurrent execution of Quantum circuits considerably enhances performance and improves utilisation efficiency of NISQ architectures [58]. Additionally, the DQPSO algorithm used for enhancing the MBSVM parameters controlled the CE factor α, resulting in superior optimisation efficiency and improved convergence speed compared with conventional QPSO approaches [29], [59].

Yousef et al. [6] discussed amplitude embedding techniques for achieving exponential scaling in Quantum computing systems, where n-qubits can simultaneously represent 2^n classical data values. In Quantum systems, information is encoded using the qubit basis states $|0\rangle$ and $|1\rangle$ according to the principle of superposition, whereas qudits extend the information representation capability to higher d-dimensional Quantum states [60]". Experimental investigations compared different Quantum encoding and Quantum image compression techniques using high-resolution image datasets, and an additional optimised Quantum embedding method was also proposed [61]. Approximately 200 images were utilised to evaluate image size reduction and compression performance [62]. Furthermore, the influence of compressed images on Quantum circuit performance was analysed using multiple evaluation parameters associated with computational efficiency, image quality, and optimisation capability.

3.6.6 Quantum Fourier Transform

QFT is similar to the classic Discrete Fourier Transform (DFT). "In quantum computing, the QFT algorithm works on the probability amplitudes of quantum states by transforming them into phase space through re-arrangement of terms in their product forms [11]. This process results in exponential performance of computations compared to the traditional approach and is widely applied in quantum signal processing, quantum phase estimation, quantum image processing, and quantum machine learning applications". The application of QFT algorithms offers significant benefits in terms of computational complexity in large-scale datasets.

3.6.7 Quantum Datasets and Simulation Environment

The development and application of the suggested quantum algorithms involved the use of IBM QISKIT programming language and MATLAB coding for simulation and experimental analysis. The quantum eigenvalue estimation circuitry with respect to the Hankel matrix-based Hamiltonian was realised using the IBM Quantum Simulation environment. Furthermore, an open-source QISKIT program was also used to comprehend the realisation of Hankel matrices using quantum gates. MATLAB coding was used further for numerical simulations and the visualisation of results.

3.7 Summary

The development and validation of QML models were illustrated in this chapter for use in big data analysis, prediction systems, and optimisation. The developed approach combined various quantum approaches, such as QSVM, QeSVM, TWSVM, QNNs, and QPSO to perform classification, optimisation, and predictive analysis of data. “Through the application of algorithms like Grover’s algorithm, Shor’s algorithm, variational quantum circuits, and quantum embedding algorithms, the capacity of the quantum system to efficiently perform computations involving high-dimensional datasets was highlighted. An experimental analysis was conducted using IRIS, QRISK3, Caltech-101, and various benchmark datasets to examine the effectiveness of the developed approach. The obtained results provide a comparative view of the performance of the investigated quantum and hybrid quantum–classical machine learning models against the considered classical approaches. The comparison is based on the reported evaluation measures and benchmark datasets used in the study. These results should be interpreted within the specific experimental and simulation settings of the study and should not be considered as evidence of general superiority or quantum advantage.

The comparison between classic supervised and unsupervised machine learning algorithms and the new quantum-based learning algorithms was carried out to explore the limitations of traditional computational methods. The comparison indicates that QPSO-TWSVM provided improved accuracy and convergence behaviour within the considered evaluation setting, with QPSO used for parameter optimization and global search. Moreover, quantum variational circuits, quantum kernel functions, quantum optimisation techniques, and quantum neural network learning methods were instrumental in increasing effective data processing and intelligent prediction capabilities. Other quantum computing techniques like Quantum Fourier Transform (QFT), Quantum Principal Component Analysis (QPCA), and Quantum Support Vector classification were also effective in managing big data.

Furthermore, the chapter highlights the necessity of Quantum Neural Networks (QNNs) as well as hybrid quantum-classical learning structures for addressing complex computational issues relating to large-scale analytics, healthcare forecasting, image recognition, sentiment analysis, and remote sensing. Although there are many

benefits in using quantum machine learning technology, some concerns have been identified, including a limited number of qubits, hardware stability, quantum noise, and fault tolerance in present-day NISQ quantum computers". Thus, further research should be aimed at the development of fault-tolerant and scalable quantum structures, optimisation algorithms for quantum machines, and better integration between quantum and classical approaches. All in all, the combination of quantum machine learning and optimisation methods creates an advanced computational platform for future intelligent systems, healthcare analytics, distributed computing, and quantum artificial intelligence in general.

The results reported in this chapter should be interpreted according to the nature of the evidence available for each analysis. Results obtained from the candidate-performed computational experiments are distinguished from performance characteristics and findings reported from the existing literature. The benchmark-dataset experiments provide comparative evidence under the specified evaluation settings, but they do not by themselves establish general scalability or quantum advantage. In particular, the IRIS experiment is a small benchmark example and is therefore not treated as evidence of large-scale Big Data performance. Similarly, claims concerning computational advantage, scalability, and practical effectiveness are interpreted in relation to the reported datasets, evaluation measures, simulation environment, and available resource information. For methodological clarity, the computational investigations presented in this chapter should be interpreted according to the implementation details documented for each experiment. The experimental workflow comprises dataset selection and preprocessing, application of the respective quantum or hybrid quantum–classical model, training or computational execution, and evaluation using the reported performance measures. The computational environment included Qiskit, Scikit-learn, Seaborn, IBM Quantum simulation facilities, and MATLAB for the corresponding simulations and analyses. The methodology is further interpreted together with the dataset-specific descriptions and experimental settings provided in the relevant sections of this chapter. Where complete implementation parameters or replication details were not documented in the original study, they are not retrospectively assumed or introduced

CHAPTER 4

QUANTUM MECHANICS BASED IMAGE PROCESSING AND DENOISING ALGORITHMS

4.1. Introduction

This chapter presents a comprehensive review and comparative analysis of Quantum Mechanics-Based Image Processing and Denoising Algorithms. In this thesis, existing quantum image denoising methodologies have been critically analysed to identify their strengths, limitations, and research gaps. The comparative study presented in this chapter establishes the foundation for the development of an efficient Quantum Theory-Based Image Classification Architecture in the subsequent chapter. The findings of this review provide valuable insights into the applicability of quantum image processing techniques for improving image representation, denoising performance, and intelligent image analysis.

The fast development of imaging systems used in healthcare, remote sensing, industry, security, and multimedia has generated a need for effective techniques of image processing and denoising. Traditional image processing techniques are known to face difficulties associated with high computation complexity, limited memory capacity, noise tolerance, and difficulties with processing big image databases. Quantum computation provides a new approach for solving the mentioned problems by means of employing such phenomena as superposition, entanglement, quantum parallelism, and quantum transformation, among others. Therefore, several image processing methods based on the concepts and laws of quantum mechanics have been designed and developed. Such algorithms can be used for various purposes, including representation, restoration, enhancement, filtering, segmentation, and denoising.

A systematic comparative study of quantum-mechanics-based image processing and denoising algorithms proposed in the literature is presented in this chapter. The chapter discusses the basic principles and models used for quantum computing as well as those for image representation, such as “FRQI, MCQI, and NEQR”, along with exploring quantum noise models, image denoising methods using quantum computers, filtering methods, transformation methods, and quantum neural network-based approaches.

Moreover, a comparison among different algorithms is made on the basis of computational complexity, denoising capacity, edge preservation capabilities, accuracy, advantages, and limitations. The conclusions drawn from this review reveal a comprehensive understanding of quantum image processing research and the promising approaches towards future research.

Image processing is a very mature area of computer science with various applications in the present-day world. The classical approach to image processing has been found to possess some drawbacks, such as being computationally intensive, needing huge amounts of memory space, being sensitive to noise, non-parallelism, and difficult mathematical operations, such as convolution, filtering, and feature extraction, which have been solved in quantum image processing.

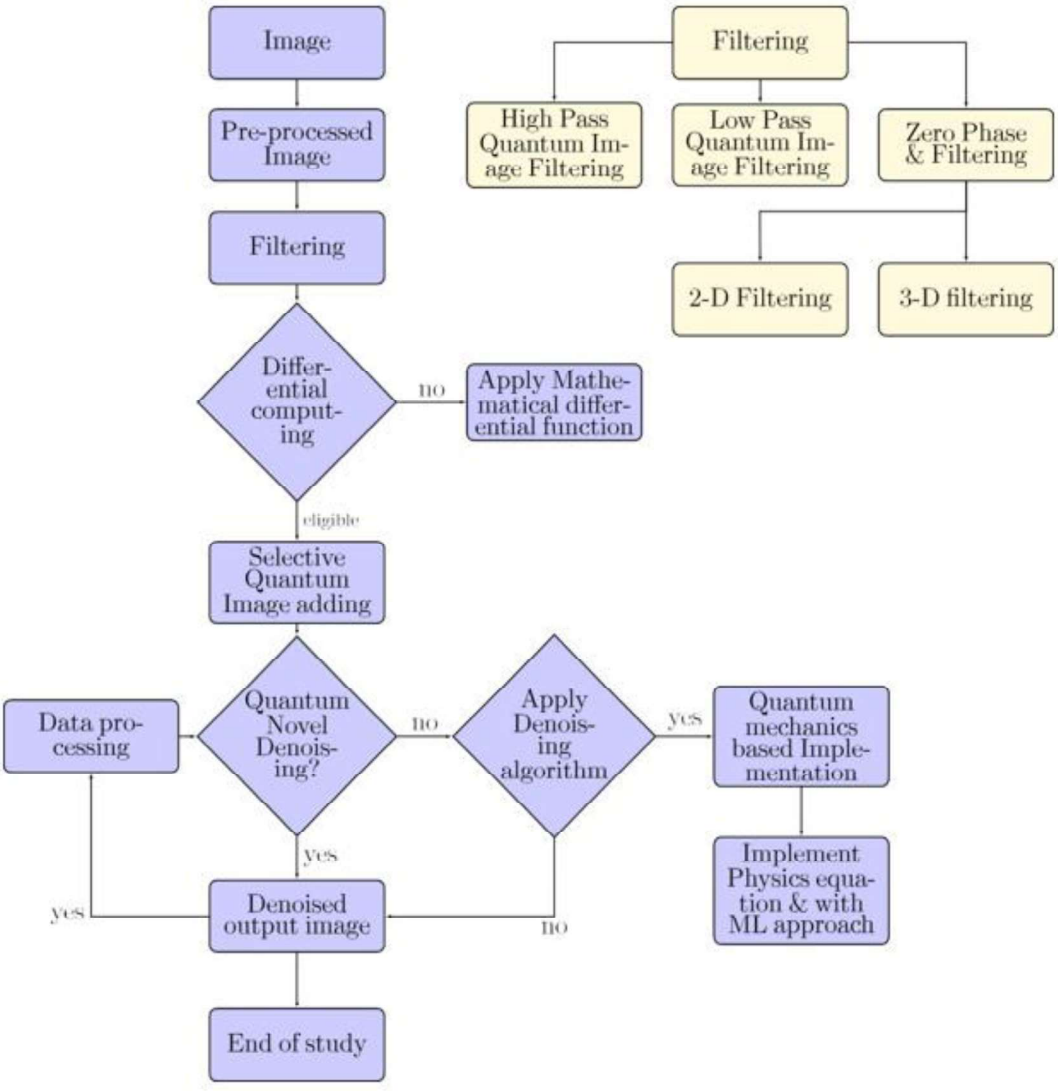


Fig. 4.1. Flowchart analysis of Quantum image denoising

4.1.1 Motivation

The application of quantum theory to the domain of image processing has received much attention due to its capability to enhance the computational speed and precision in a vast number of applications [23]. The growing amount of multimedia information, encompassing images, audio signals, text data, and video streams, especially in the context of health care and big data, has led to an urgent need for developing more sophisticated image processing methods. In many cases of image processing, image denoising stands out as a highly challenging task within the process of image reconstruction and analysis of visual data. The utilisation of quantum mechanics-based approaches to image processing [6] provides some key benefits through such features as Quantum parallelism [65] that makes use of quantum superposition, Quantum entanglement allowing the creation of correlations between Quantum bits (qubits), Quantum Fourier Transform, Quantum superposition-based filtering, and Quantum noise reduction methods [49] relying on Quantum error correction mechanisms [62]. Based on the mentioned aspects, Quantum-inspired solutions become very promising for many image processing purposes [52].

The motivation of this chapter is to review and analyse existing Quantum image processing and denoising techniques discussed in the literature. More focus has been put on Quantum image noise models, image restoration processes, and Quantum image denoising schemes based on the analysis of how they function. This can be seen from Fig. 4.1, where the process of denoising normally starts with pre-processing of the images, followed by application of high and low-pass filters, then taking derivatives, and finally selective image reconstruction of the output image. The process of reconstruction is done based on the principles of quantum computing.

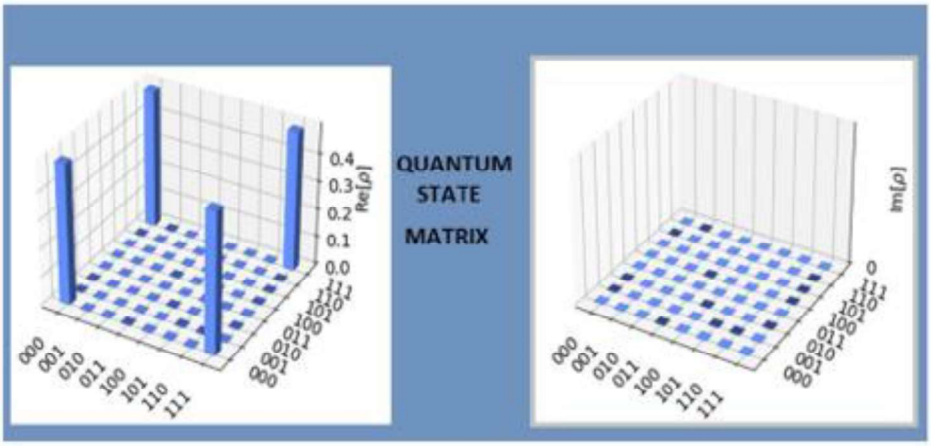


Fig. 4.2. 3D-Qubit representation of Quantum state vectors corresponding to Quantum state matrix representation [19]

Moreover, several quantum mechanical denoising schemes, such as adaptive eigen vector basis, adaptive denoisers, wavelet thresholding scheme, and median filtering schemes based on quantum mechanics, are described for the processing of two-dimensional digital images. Several noise models like Gaussian noise, speckle noise, and Poisson noise are explained along with comparative analysis against the conventional methods of denoising. An emphasis has been made on the application of the Schrödinger operator for image denoising since the performance of the quantum-inspired image processing system depends highly on noise. Moreover, concepts like quantum localisation phenomenon, image representations through the discrete Schrödinger equation and signal decompositions using wave functions have been explained. The representation of 3D-Qubit of Quantum State vectors associated with Quantum state matrix representations is shown in Fig. 4.2 [19].

4.1.2 Notation

In the present chapter, the notation for Quantum scalar variables and constants is provided by italicised lowercase and uppercase letters (such as x and N, respectively). Notations like α, β, θ, φ, ϕ, Φ, and W have been taken from standard Quantum computing and are provided where necessary within the mathematical formulations of the chapter.

4.1.3 Chapter Organization

This chapter is divided into various sections, which altogether offer a "comprehensive review and comparative analysis of Quantum mechanics-based Image Processing and Denoising Algorithms". Section 4.2 includes a literature review and basic principles of Quantum image processing, representation model of images, models of noise, denoising methods, filtering methods, and Quantum neural networks architecture. The comparative analysis of available algorithms, their computing aspects, pros and cons, along with performance evaluation parameters, is given in Section 4.3. The chapter ends with conclusions drawn from the review of the relevant research literature.

4.2 Related Work

This chapter includes an extensive review of existing research related to the topic of quantum mechanics-driven image processing and denoising methods. The examined papers include topics such as the principles of quantum computation, models of quantum image processing, denoising methods, filtering methods, and other quantum-inspired computational models that have been proposed for use in image restoration and enhancement purposes. The purpose of this review is to build a theoretical basis for the development of quantum image processing methods.

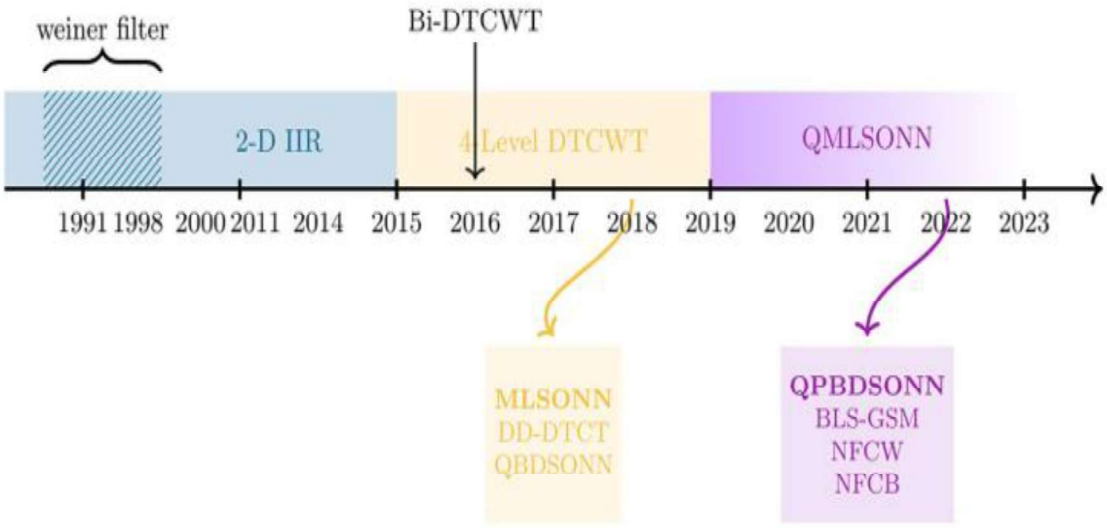


Fig. 4.3. Algorithms developed corresponding to the year

4.2.1 Historical Background

The working principles of quantum computers rely upon the fundamental theories of quantum physics, especially wave-particle duality. “A qubit is the elementary unit of quantum computation, which is a two-state quantum system. In contrast to a bit in classical computers, a qubit exists in both states simultaneously due to the phenomenon of superposition. Many important developments have been made within the realm of quantum computing, culminating in the invention of many quantum algorithms and computational models. A timeline of the important developments and discoveries in quantum image processing and quantum image denoising is shown in Fig. 4.3.

A single qubit may be found in a superposition of two states, and can be described by:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \qquad (4.1)$$

Where α and β are the probability amplitudes. Classical bits may be present either in one of the two well-defined states, but not both, at a time, while qubits have been realised using quantum physical phenomena like electron spin, photon polarisation, or energy levels within atoms”. On the basis of their implementation, various quantum technologies are used for making qubits. The Bloch sphere is a graphical way to represent the state of a qubit. The combination of qubits forms multi-qubit systems.

4.2.1.1 Basics of Quantum Computing

Quantum Gates and Circuits:

Quantum gates can be understood as mathematical functions that act on the states of the qubits. “Qubits function as input states for the quantum gates in quantum circuits, which transform them to produce the required output states. Quantum circuits are made up of wires connected using quantum gates.

The Pauli-X gate is an example of a one-qubit gate, which is also known as a NOT gate. As opposed to the conventional logic gates, quantum gates can be undone by some other operation. This gate converts the qubit state |0⟩ into |1⟩, and |1⟩ into |0⟩. An essential one-qubit gate is the Hadamard (H) gate.

The two-qubit gates act on the two qubits. An example of this type of gate that is frequently utilised is the Controlled-NOT gate, whereby one of the qubits acts as the control qubit and the other as the target qubit. In contrast to the classical logic gates,

the quantum gates preserve information and thus maintain reversibility. Whereas classical computation relies on logic gates like AND, OR, and NOT, quantum computation relies on gates like Hadamard (H), Toffoli (T), CNOT, and Quantum Phase gates.

- **Uncorrelated State:** A quantum state that can be expressed as the tensor product of two independent quantum states is referred to as an uncorrelated state.
- **Correlated State:** A quantum state that cannot be represented as the tensor product of two separate quantum states is known as a correlated state.
- **Entangled State:** An entangled state is a special type of correlated state and may be represented as:

$$\frac{1}{\sqrt{2}}(|00\rangle+|11\rangle) \qquad (4.2)$$

- **No-Cloning Theorem:** This theorem states that it is impossible to create an exact copy of an arbitrary unknown quantum state. Consequently, quantum information cannot be duplicated in the same manner as classical information.
- **Quantum Uncertainty:** This principle has been derived from the uncertainty principle proposed by Heisenberg, which suggests that some characteristics of a quantum system cannot be determined at one go with high accuracy". The possibility of carrying out extremely complicated calculations has made quantum computing possible due to the nature of qubits.

4.2.2 Survey Methodology

This section presents the literature review approach adopted for examining existing research in quantum image processing and image denoising. The review focuses on quantum image representation, mathematical formulations, computational algorithms, filtering schemes, image modelling approaches, quantum-mechanics-based denoising techniques, quantum-inspired methods, and related learning-based approaches. The reviewed studies were examined with emphasis on their underlying computational principles, representation mechanisms, denoising strategies, computational requirements, advantages, limitations, and reported evaluation characteristics. The literature was subsequently synthesized to identify recurring challenges related to

quantum data representation, computational complexity, scalability, noise, circuit requirements, and practical implementation. Since the present review does not document a fully reproducible systematic-review protocol involving predefined database searches, screening stages, duplicate removal, and formal quality assessment, it is presented as a structured literature review rather than as a formally systematic review.

4.2.2.1 Quantum Computing-Based Image Processing and Denoising Equations

The quantum image processing algorithms are essentially based on quantum mechanics and mathematics. “There have been many works in which the authors have developed quantum-based image denoising and restoration algorithms using quantum states, wavelet transform, filtering algorithms, and neural networks in quantum mechanics. This section will describe the relevant equations used in the literature.

The time-dependent Schrödinger equation can be expressed as follows:

$$\frac{d}{dt} | W(t)\rangle = -\frac{i\hat{H}}{\hbar} | W(t)\rangle \tag{4.3}$$

The solution of the Schrödinger time-dependent differential equation is given by

$$| W(t)\rangle = e^{-\frac{i\hat{H}t}{\hbar}} | W(0)\rangle \tag{4.4}$$

The Multi-Channel Quantum Image (MCQI) representation for geometric image information is expressed as

$$I_{MCQI}(n) = \frac{1}{2^{n+1}} \sum_{i=0}^{2^{2n}-1} | C_{RGB}^{i}\rangle \otimes | i\rangle \tag{4.5}$$

The Wiener filter in the frequency domain is represented as

$$H_w(u,v) = \frac{1}{H_0(u,v)} \frac{S^2(u,v)|H_0(u,v)|^2}{S^2(u,v)|H_0(u,v)|^2 + W_0(u,v)} \tag{4.6}$$

where *S* refers to the image corrupted with noise, H0 indicates the output of the Wiener filter, H_w indicates the expected output of the Wiener filter, and $S \times H_w$ refers to the output of the restored image. Walter Huda [49] proposed a genetic algorithm-based approach for a fourth-order two-dimensional infinite impulse response filter. It was observed through the conducted study that recursive filters are superior to finite impulse response filtering since the former has spatial Wiener filtering and

dimensionality reduction features. Still, the computational complexity poses as a major constraint [6]. Chen Zhong [29] introduced a denoising technique intended to balance the reduction of noise and image contrast enhancement in magnetic resonance images. The images showed an enhanced ability to distinguish visible structures while retaining substantial image information.

To remove any degradation of the image due to radio-frequency tagging in the 3 × 3 window, the denoising operation can be expressed as

$$I(i,j) = \frac{\sum_{n=1}^{8} I(k,l)}{\text{Num Sum}}, \text{if } I(i,j) > 4$$
$$I(i,j) = I(i,j), \text{otherwise} \qquad (4.7)$$

In such a method, the value of the central pixel is replaced by the mean value of the neighbouring pixels if there are more than four neighbours. These concepts have been used in different image denoising techniques described in the literature.

The speckle noise removal technique for medical ultrasound imaging has been proposed by Cai [29], which uses the concept of Dual Tree Complex Wavelet Transform along with a quantum mechanical principle-based adaptive threshold function. The Gaussian probability distribution model related to log-transformed speckle noise can be expressed as

$$p_\sigma(N) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{N_r^2 + N_i^2}{2\sigma_n^2}\right) \qquad (4.8)$$

The Gaussian probability density function (PDF) is represented as

$$p_\sigma(N) \qquad (4.9)$$

where N_r and N_i denote the real and imaginary components of speckle noise, respectively.

The non-Gaussian statistical model for complex wavelet coefficients is expressed as

$$P_x(X) = \frac{3}{2\pi}\sigma^2 \exp\left(-\frac{\sqrt[3]{X_r^2 + X_i^2}}{\sigma} \exp(K)\right) \qquad (4.10)$$

where *K* denotes the parameter of the probability density function, and *X* indicates the

noise-free image. This model allows for speckle noise removal, edge retention, and image improvement.

Lebrun [46] reviewed various image denoising algorithms and considered patch-based image analysis techniques. The discontinuity of an image at a particular edge can be defined as

$$| h^{\alpha}[t] - h^{\alpha}[s] | \leq C | t - s |^{\alpha} \quad (4.11)$$

where

$$\alpha > 0$$

Noise reduction based on quantum-inspired principles has been extensively investigated in image processing applications. The two-dimensional DCT of a 7 × 7 image block is represented by

$$\sum_{n_1=0}^{6} \sum_{n_2=0}^{6} f(n_1) f(n_2) P(n_1, n_2) \cos \frac{\pi}{7}\left(n_1 + \frac{1}{2}\right) 6 \cos \frac{\pi}{7}\left(n_2 + \frac{1}{2}\right) 6 \quad (4.12)$$

where

$$f(n) = \frac{1}{\sqrt{7}}, \text{if } n = 0 \quad (4.13)$$

and

$$f(n) = \sqrt{\frac{2}{7}}, n = 0,1,2, \ldots ,6 \quad (4.14)$$

The work of Jaydeep Patel [36] was on the loss of fine structure information in image denoising techniques, pointing out problems frequently encountered in median and morphological filters. The Noise Feature Code Word (NFCW) and Noise Feature Code Book (NFCB), which the authors [73] suggested, were motivated by quantum image processing and information theory. The distribution regularity at varying noise density was studied employing the concept of NFCW. The signal-to-noise ratio adopted to measure the de-noising efficiency is

$$SNR = 10 \log \frac{P_S}{P_N} \quad (4.15)$$

where *Ps* and *PN* represent signal power and noise power, respectively.

Ying Zhang et al. [85] developed a double-density dual-tree complex wavelet transform that is inspired by quantum physics in the process of removing the noise from SAR imagery. The novel technique performed better in terms of image quality, noise reduction ability, and effective retention of details in the image. Gaussian Hermite filters based on Hermite polynomials are used for processing the quantum oscillator wave functions in two dimensions [5]. Filters designed using wavelet analysis showed excellent edge detection and noise filtering capabilities [75].

The Gaussian Curvature Filter (GCF) or the Ricci-scalar curvature filter is defined using quantum derivatives and is used to increase contrast in images, as well as being a powerful curvature estimator. The output of the Sobel filter is binarised through the process of sigmoid transformation, thresholding, and slope adjustment. The probability density function for the wavelet signal model is given by

$$P_x(x) = \frac{1}{2\pi\sigma_x} \exp\left(-\frac{x_1^2+x_2^2}{2\sigma^2}\right) \qquad (4.16)$$

The wavelet coefficient obtained through maximum a posteriori estimation is expressed as

$$\hat{x} = \frac{\sigma^2}{\sigma^2+\sigma_y^2} y \qquad (4.17)$$

A Quantum Multi Layered Self Organising Neural Network (QMLSONN) architecture was suggested by Bhattacharyya [16]. It consists of quantum bits based neurons for the input layer, hidden layer, and output layer. QMLSONN showed better results in the applications of colour image segmentation and multilevel image processing tasks. The quantum state used is

$$| w\rangle = \sum C_i \, | q_i\rangle \qquad (4.18)$$

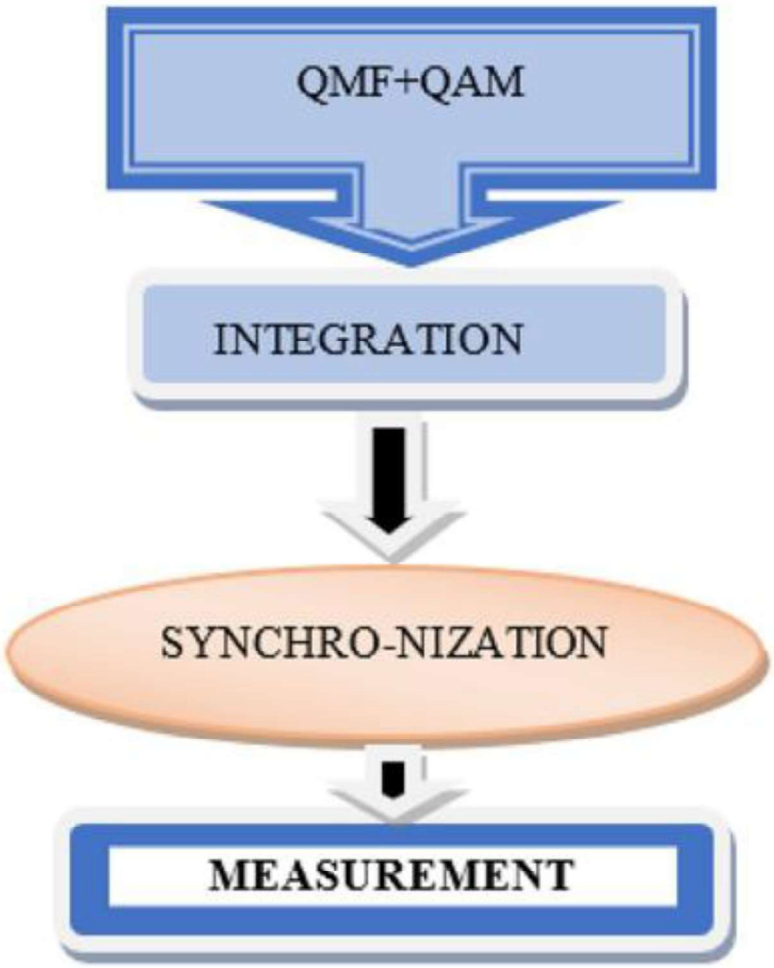


Fig. 4.4. Flowchart of Quantum Mean Filtering Analysis [36].

where C_i stands for the complex coefficient and $|\ q_i\rangle$ for the associated basis vector of the quantum state. The effectiveness of the QMLSONN architecture lies in the correct choice of such coefficients that will affect the performance of the network in terms of its learning ability and computational power. Therefore, high accuracy of analysis and better performance of image processing can be provided using optimum parameter values". The entire scheme of Quantum Mean Filtering Analysis is shown in Fig. 4.4, highlighting the major steps involved in the process of quantum image denoising.

4.2.2.2 Quantum mechanics-based image processing techniques

Cai [29] discussed an image restoration approach based on the Wiener filter. "In a Q-circuit, an n-qubit register can represent the number 0 through (2^n-1)simultaneously. Peters et al. [63] proposed an adaptive image restoration approach based on the Wiener

filter, which decomposes noise power spectra into Quantum and detector noise, measures the noise power spectra, and decomposes the spectra into Quantum and detector noise. Smilt et al. [36] showed that tools from Quantum mechanics, such as the Schrödinger equation, can be used to construct adaptive transforms. Smith et al. [73] proposed an adaptive transform method, a Quantum theory-based image denoising method that presents an adaptive transform to obtain a dictionary using an image as a discrete potential in the Schrödinger equation. The method is effective for signal-dependent noise.

Most often, noise develops during the transmission and collection of images [57]. Richard Feynman [11] defines a probabilistic approach to represent classical information using Quantum theory. This paper presents Quantum mechanics-based image denoising model approaches. This article also discusses the Quantum Boolean mean filter and new Quantum Boolean image denoising that are connected to computational basis states [55]. The computational basis system (CBS) provides the fundamental concepts for Quantum logic operation [20] as well as interfacing from Quantum to classical [4] and vice versa. Quantum before and after measurements [18] represent the wave function difference using measurement operators that are represented as the system state space to be measured [8,78]. Author [23] used Wiener filters for low-, medium-, and high exposure. By reducing the mean square errors for the arbitrary exposures, the mean-squared error filtering (MTF) of the superposition and Wiener is calculated, and then, the composition of the final restored images is performed. After low-pass filtering, pixel-wise weights are calculated, which depend on the local mean. The first result is based on experimental analysis of 2D infinite impulse response (IIR) filters and the intraoral radiographs based on the Wiener filter approximation. Instead of a single noise amount, the whole frequency, signal amplitude, and noise measurement for the whole dynamic range are considered. The author [65] in their experiment proposed a method for the smooth spatial transition realisation of the filter used to avoid all the abrupt switches. According to the author, between the smoothness and local adaptivity, the Gaussian low-pass filter kernel dimension should be adapted to the spatial expansion for good speed and accuracy. This is considered under the signal adaptive way for composing a restored image". The

superposition of no. of images, a minimum of two images is done by the implementation of the spatially invariant Wiener filters.

4.2.2.3 Flexible representation of a quantum image

FRQI does efficient preparation for image processing operators on the Quantum computer and transforms colour and the corresponding position into the Quantum state in the image. “Multi-channel Quantum interference (MCQI), NEQR, and FRQI are three image models. Among these three, FRQI and MCQI exhibit the same complexity. The FRQI model is used to encode an image in its state of normalisation that captures the image composition details, like chromatic and spatial details. This model uses probability values and amplitude and requires one Qubit that gives a chromatic description of an image, unlike MCQI, which uses three Qubits for chromatic details encoding. For each image’s pixel grey level and spatial location representation, the FRQI model uses a state sequence. For FRQI formulation, MCQI is used with a focus on encoding images in terms of R, G, and B colour channels. Other models like NAQSS, CQR, QUALPI, SQRR, and QSMC-QSNC use a basis state for grey values representation and are capable of capturing different shades of grey. The FRQI model is represented by an image equation to define multiple intensity levels in which intensity values are encoded in the amplitudes of the Quantum state [47]. In such type of models, various transformations like QFT could be easily and directly applied to the image’s amplitude”. FRQI are prepared by Hadamard and the controlled rotation operator for a $2^n \times 2^n$ image by initialisation n qubits and then applying the Hadamard gate on each qubit to divide them into a superposition state, and further, for the joint states, controlled rotation operators could be applied to each basis state, respectively, to the pixel’s rotation, and at the end, encoding of the intensities could be done by rotating the Quantum states.

4.2.2.4 Implementation of FRQI model

The FRQI model could be implemented both on IBM Quantum Experience Cloud and a classical computer. “For N bits of information encoing in $\log_2 N$ bits, the Quantum register can store 0’s and 1’s superposition state of possible combinations, whereas only one of all the possible states can be stored in the classical one, since it stores all

the possible states of 0 and 1 as a list. While using the Quantum gate and measurement, we can only interact with I_{FRQI} qubits. FRQI also proposes the Polynomial preparation theorem that prepares with polynomial simple operations for FRQI that turns the initialised state to the respective FRQI state. The Quantum image compression algorithm is also used in the FRQI Model, which minimises the simple operations according to the Boolean equation during the preparation process. Simple operations are related to the same position colour graphs". Based on unitary transformation, Quantum image processing deals with only colours and identical position-based colours, and the combination of both positions and colours is addressed by the quantum Fourier transform.

4.2.2.5 Novel-enhanced Quantum representation of image

"In NEQR, two entangled qubit sequences are used for storing the complete image that gives information about the position and grey-scale values of all the pixels. NEQR is similar to the FRQI model because both require one qubit for image chromatic information. $(q+2n)$ qubits are required to encode a $2^n \times 2^n$ image with (2^q) gray-scale levels. NEQR [86] represent the image pixel values in the basis states instead of amplitudes. In the image equation, $f(X,Y)$ represents the pixel intensity at (x, y). NEQR is less time complex than FRQI, and up to 1.5 times its compression ratio could be increased according to a Boolean expression, unlike FRQI".

4.2.2.6 Drawbacks of FRQI and NEQR model

"Both NEQR and FRQI models require square images $(2^n \times 2^n)$ and extra Qubits for position encoding, respectively, to pixel intensities. Both models are very complex for the extraction of the classical version of the image from the Quantum image because of the uncertainty; otherwise, images could be retrieved through normalised probability distributions".

4.2.3 Quantum noise and denoising models

The noise model approach is represented by the author [6] with the linear combination of the respective mean time filtering section squares. "The statistical measurement error is quite high for a single exposure, so only one image per exposure is used. In the experiment, the author used a robust linear fitting procedure for the determination of

the level of Quantum and detector noise. The experimental analysis got the required proportion relationship for the detector noise power level.

The author's [66] proposed method is based on the idea of describing a signal on such a basis constructed through the Quantum mechanics resolution. The discussion is a review of the binary and Quantum image relationship and the measurement of the distance between Quantum states.

The author [85] introduced the concept of Quantum theory by introducing an image with a Quantum system, measuring the hamming distance, a measure of the separation between Quantum states and describing a concept known as the noise feature codebook (NFCB), a concept for each pixel of an image that explains the local feature. By collecting many images for training purposes, the further investigation of codebook distributions with distinct densities of noise is also carried out.

Most adaptive noise, which is signal-dependent noise, is used for denoising results for image and signal-processing-based applications. The author [77] proposed an approach to the generation of an adaptive basis without using training sets, and with the help of a Quantum mechanics-based approach, it uses higher frequencies to explain low-potential values well suited for signal-dependent noise.

Signal-dependent noise follows a phenomenon that low signal values will keep high harmonics, and higher values have high denoising values. The proposed framework by the author [43] has an approach of controlling wave function energy and Planck's constant for denoising applications and giving flexibility by its two tuned parameters". When there is signal and image noise, the denoising procedure is affected by Quantum localization, which is avoided by the proposed adaptive transform used in a denoising application.

4.2.3.1 Quantum denoising process steps

"Denoising is accomplished through three steps: Projecting, Thresholding (both hard and soft) into the transformed domain, and Denoised signal recovery. In this article, the author [64] used a projection that is used to separate noise from information in an image or signal.

Denoising signal recovery is accomplished by back-projecting coefficients that have

already been modified in the time and space domains, as analysed by the author [70]. The adaptive basis formed in denoised images considers the basis vectors, the value of which depends on the amount of noise that degrades the signal and image. The basis vector spreads out in space or time for slowly varying images and signals, as well as in the presence of noise-proofed by experimental work".

4.2.3.2 Localisation: Quantum effect

"In this research, Localization is explained by the author [15]. Localisation, also known as the Quantum effect, occurs when exponential wave functions within a disordered system are localised due to destructive interference in a specific location. In the result analysis, the author proposed an adaptive transformation and denoising procedure to improve the results using three simulators: a synthetic image, a signal, and a cropped Lena image. Low and high frequencies are represented by grey values or high samples for low regions".

4.2.4 Quantum mechanics-based image denoising

"The proposed denoising algorithm yields results in various noise types, such as Gaussian, speckle, and Poisson. Finally, the comparative results of different denoised algorithms are compared following the experimental analysis. Using Quantum mechanics, a foundation of oscillating functions is created. The energy level causes a change in oscillation frequency, which has corresponding values in terms of pixel values. The proposed method is efficient for signal-dependent noise and will have higher signal values for Poisson noise".

4.2.5 Quantum Boolean image denoising

The main idea is to make an interaction between the image portion and the mask of an image that needs to be processed. "Quantum Boolean image denoising uses QDMF, i.e., Quantum Boolean Mean Filtering method that works on the internal part of the Quantum computer for internal representation of the Bit plane or MSB part for each colour component of the classical noisy image. QDMF is also considered an extension of QuBoId that means Quantum Boolean version using a convolution mask on MSB for proper denoising. Using this denoising process, the central pixel value could be replaced by the convolution mask out of the image portion of an image [55]. Discuss

in their article about this technology and the interfacing between internal representation and classical bits inside the Quantum computer". Quantum annealing theorem could also be used for Quantum Boolean image denoising improvement.

4.2.5.1 Application of Quantum Boolean image denoising

"Poisson noise, an image-dependent noise model, is considered one of the applications of QuBoID, since the accuracy and visual quality of digital images can be improved by reducing noise using QuBoID. This denoising process is advantageous and has an advanced approach over classical like robustness against noise measurement, less computation, and low cost, as it deals only with the most significant bit, so this denoising technique could be applied to large images within a set computational time [26]".

4.2.6 Quantum mechanics-based image denoising algorithms

The Quantum-inspired adaptive threshold function increases the signal strength and weakens the noise signal as described by the author. "In this research, according to the proposed method by the author [16], the threshold function is based on an adaptive threshold value inspired by Quantum theory (since the signal and noise are differentiated by wavelet coefficient), in which the wavelet coefficients at different scales are used to differentiate the signal and noise.

In this article, for the complex wavelet coefficients, a new Quantum-based non-Gaussian model is also discussed for analysing such denoising signals. The speckle noise of the image gets reduced as per the author's [52] applied methodology, named the Gen-link method, log wavelet, and Frost filter method-based bidirectional discrete-time continuous wavelet transform (Bi-DTCWT) method. A 4-Level discrete-time continuous wavelet transform (DTCWT) decomposition is applied by the author, which gives a good signal-to-noise ratio (SNR) value and excellent edge preservation capacity. This paper shows all the experimental results that come out with a good capacity for edge preservation. Image information was preserved, and speckle noise was suppressed by the proposed method. The author [50] also proposed a threshold function inspired by Quantum theory in combination with the dual-tree complex wavelet transform (DTCWT) for the despeckling of ultrasound images in the medical

field.

The findings after putting forth all the methods described by the author [8] make it clear that for 8*8 patches, a good result might be attained by a non-parametric estimate process. By estimating a local sparse model and by performing patch analysis, which is a noisy restoration process, further image denoising and optical denoising are attained". This method is exhibited on a 64-dimensional patch space, leading to patches that are genuinely noiseless.

4.2.7 Quantum image transformation methods

The author [49] experimented on the amplitude scaling of the final image to ensure that the final image would have affinity with the result from the histogram of the initial image. "The generalised algorithms for designing fourth-order two-dimensional (2-D) infinite impulse response (IIR) filters depending on the approximation quality have helped the author to develop spatially invariant Wiener filters. Using cascaded algorithms, a zero-phase filter MTF (mean time filter) is developed in this paper through successive traversal of the image. The author [62] realised that the filters had to be shaped at low spatial frequencies and could be approximated using the higher-order filters.

Four models of noise, such as the Markovian Bayesian model, image self-similarity, image sparsity, and linear transformation thresholding, have been highlighted by the author [4] in the context of usefulness in the task of denoising. These three methods, namely aggregation, oracle procedure, and colour transformation, are considered to measure the performance.

Inter-scale wavelet coefficient correlation is the main point of interest for the author [19]. When considering the SAR images, it should first be noted that a log transformation will be done. Multiplicative noises are changed to additive ones; then, the wavelet coefficients are used in all directions for each layer for the DD-DT complex wavelets decomposition for each image. These coefficients are estimated on the basis of the superposition principle of Quantum Mechanics and the Bayesian estimation approach. It is stated that when reconstructing SAR images layer by layer, the patch-based picture restoration technique may be employed successfully". This

picture restoration technique is often used in many software applications and gives impressive results. According to [29], after analysing the results, patch-based denoising could be helpful.

4.2.7.1 Wavelet-based Quantum image denoising and filtering

The infinite impulse response relies on the accuracy with which this approximation uses a spatially invariant Wiener filter design. “With the help of a cascade algorithm zero-phase filter, MTF is achieved in this paper. The author [36] found that the Smoother Wiener filter can be applied to mean-time filtering (MTFs). For low exposures, a second-order filter is enough, while for higher exposures, higher-order filters need to be considered.

At the beginning of the first stage, the output of the multi-resonance infrared image (MRI) exceeds the low-pass filter and high-pass filter. According to the author [73], the differential calculation will enable the determination of the noisy region within the image. The output becomes the control signal for the selective addition procedure. Subsequently, the two filtered images undergo the selective addition process.

A new algorithm for denoising is applied to perform smoothing in this review article. The denoising method applied here uses a similar average function as that of other ordinary denoising functions. According to the author [41], the way of smoothening the image has been elaborated in the second step of the process. Author [46] explains the variance stabilisation transformation (VST), which helps in applying Gaussian and white noise on a noisy image by considering the noise as constant. These raw images are collected from reflex and compact cameras, and therefore, require denoising due to a complicated algorithmic procedure for their formation.

The author [5] provides an experimental study that postulates that, compared to other popular techniques, the proposed technique, which is a noise reduction technique, will select a criterion for judging the noise based on its density that produces high visual quality and better SNR. In the course of the experiment, the images were taken by an operator and then transformed into another image using the convolution of bi-dimensional, tri-dimensional, and tetra-dimensional images for black and white, colour images, and video, respectively.

In the experimental study, smoothing filters, namely Gaussian and Quantum filters, have been utilised by the author [75] to enhance the regularisation process of the input image, along with anisotropic diffusion, where anisotropic diffusion is utilised for the purpose of smoothing signals that produce smooth images, since the Laplacian process is highly affected by noise elimination.

The transition of the intensity transformation to a binary value near edges is viewed by the author [25] as an important event that leads to the best results. On further examination, it becomes clear that the blurring nature of the Gaussian filter is increasing in nature, as the blurring effect of the Quantum filter is intermittent". It is worth mentioning here that the Gaussian filter is based on the heat semi-group, while the Quantum filter is based on Schrodinger's semi-group in the experiment conducted by the author. In future, the Morse oscillator wave function shall be considered for blurring effects.

4.2.8 Quantum Neural Network Architectures

A Quantum multi-layer self-organising neural network (QMLSONN) was suggested by the author [3] as a self-supervised neural network algorithm for image denoising. "As per a comparative study by the author [42], the output produced is a multi-layer self-organising neural network (MLSONN). The percentage of correct pixel classification (PCC) was calculated by the author to quantify the output of the denoised image. A new self-supervised Quantum multi-layer self-organising neural network (QMLSONN) structure, which is the Quantum version of the standard MLSONN structure, is designed in the network structure for future scope.

In the proposed architecture, the connection weights and activation levels will be modelled using rotation gates. The connected network layers using the Quantum neurons model the cellular networks. A supervised and unsupervised architecture of neural networks was used by the author [30] to produce real-time output. The author [12], upon conducting experimental analysis, found out that the turnaround time in such an architecture was high since a very time-efficient architecture of networks known as back propagation was employed in handling the interconnection weights. QBDSONN is an architecture that is bidirectional and time efficient, with inputs

modelled using Qubits and rotation gates.

A real-time spanner image with various levels of Gaussian and uniform noise is provided in [2], and hence, the architecture will deliver a satisfactory output in terms of time complexity for the process of denoising. An efficient non-linear median filter is applied to retain the edge features of the object from noise. Author [7] pays attention to the structure of a Quantum Parallel Bidirectional Self-Organising Neural Network (QPBDSONN) that comprises three parallel structures of QPBDSONNs having Quantum properties.

There are three independent colour components, namely Red, Blue, and Green, analysed separately by the input layers in each individual for QBDSONN, which has been used to analyse the colour-noisy images. In QPBDSONN, there is the presence of three clusters, each formed by segregating the red, green, and blue colour components independently from the noisy colour images. These are included in QBDSONN, where the layers include the fully lined neurons, input layer, hidden layer, and the output layer, as mentioned by the author [53].

The rotation gate is responsible for modifying the weighted interlinked connections along with their respective activations. Non-linear efficient median filtering is applied to save the edges of the object from any distortion due to noise. The author [82] mainly concentrates on the framework of a Quantum parallel bidirectional self-organising neural network (QPBDSONN), which includes three constituent QBDSONNs having Quantum properties. These three constituent colours of QBDSONNs, such as red, blue, and green, were used for the processing of noisy coloured images.

The architecture of QPBDSONN was presented by the author [72], which is composed of three parallel clusters created by separating the red, green, and blue colour channels of noisy colour images in their purest form. QBDSONN forms the full lined neuron layer, which is further categorised into the input layer, hidden layer, and output layer. The rotation gate is responsible for updating the weighted connection between them and its activation. Quantum measurement is employed in the basis state ranging from 0 to 255 according to the probability of minimizing Quantum state. Colour image channel components are combined in the sink layer through a fusion process.

Explanation of PBDSONN and QPBDSONN architectures is provided. Adaptive DWTs were also taken into consideration by the author [60]". Threshold Parallel Hope-Field Networks were developed for obtaining output images using the Gaussian noise version of the denoised pure colour. Quantum thresholding was further improved with the use of weighted interconnections between layers using qubits and rotation gates to lessen processing time.

4.2.9 Quantum Image Processing-Based Real-Time Applications

The study [83] has focused on the scale-based noise containment technologies. There is a loss of information due to output from an image device, like a format change involving compression, resampling, contrast enhancement, and removal of noise. The researcher has pointed out the effect of all these on the model, which becomes scale and signal-dependent. Utilising noise models, like the Gaussian noise model, the researcher further explains the important algorithmic principles for noise removal. These noise models are specifically created for obtaining optimal noise-free images.

The explanation for conducting a study on exploring Quantum theory-based mechanics' applications in image processing is provided by the author [78] in his review paper. The resemblance between Quantum mechanics and linear algebra due to the presence of the matrix operator makes a convincing case for adopting such a technique in the future. For real-time applications, the benefit of having low computational complexity for the proposed filter helped achieve better results.

4.2.10 Comparative Study

The author [11], while reviewing eigen vectors, found that Eigenvectors cannot capture the region of the signals that have a value higher than the eigenvalue. "Rather than going for denoising, the main focus of this paper is to merge Quantum physics concepts with Signal processing methods. The adaptive basis method has been compared with other conventional denoising approaches with denoising as an inverse problem. Hyperparameters were optimised manually to provide the best PSNR value. Author [20] introduced the Expectation Maximisation algorithm, which illustrates the conventional standard deviation (CSD), which is computed from the thresholding function using the maximum a posteriori (MAP) estimator. There is an inherent

relationship among wavelet coefficients at different scales; however, conventional standard deviation neglects such a dependency between them, which is the primary drawback of CSD. Due to this drawback, Quantum theory has been applied between these coefficients at different scales.

Coefficients are estimated for clean data from noisy data, where QSD-based Inter-scale dependency and SGMM-based local PDF are used. In the estimation process of these clean coefficients, the Bayesian estimation process, whose basis is wavelet coefficients, involves a signal-to-noise ratio and also two sets of coefficients, noise-free coefficients and noise coefficients. The main importance of Quantum theory is that it helps reduce noise in denoising processes based on CSD by estimating QSD, which is a quantum-inspired standard deviation. Noise is reduced through a threshold function which utilizes QSD and SGMM with the following two advantages:

- Inter-scale dependency in QSD.
- A good threshold function that utilises the wavelet-based coefficient prior distribution.

Author [79] utilises the Quantum Daubechies fourth-order kernel for the extraction of the wavelet coefficient of the resulting image". With the help of a Quantum oracle and employing a proper wavelet coefficient thresholding function, wavelet decomposition of the noisy image and of the original image is performed.

4.2.11 Experimental study

According to the author [57], the rationale behind the disturbance of images and signals due to the Poisson noise in the first class makes the simulations carried out in the second class a failure. "SNR can be modified in terms of noise power and pixel and sample values to be close to 15 dB. This noise difference between the clear signals and the noisy images helps in determining the SNR. When experimenting sample-wise, signal amplitude and grey-level additive Gaussian noise are considered. It follows from the experiment results that the frequency of the eigenvector depends on the value of the signal. The generation of adaptive transforms in the application of image and signal is introduced by the author [32], in which the transform takes into account the value of eigenvectors of the Hamiltonian operator.

The time complexities of certain computational techniques are investigated by the author [31]. Moreover, these techniques will be compared to the other denoising techniques. The suggested denoising technique will help in eliminating noise elements in order to preserve essential signals. Wavelet and Fourier transform are useful tools for image denoising. Nevertheless, quantum domain-based image denoising for unitary transformation for Quantum algorithm description is a future scope.

This work [54] focuses on quantum computation with linear as well as reversible unitary transformations for encoding. There are some problems associated with non-linear transformations as well, which are also highlighted in this article. Unitary operators include the Fourier transformation, the Wavelet transformations of various kinds, as well as Walsh-Hadamard transformations, which are very commonly used in this study.

There are several applications for quantum wavelet transforms (QWTs) and Quantum Fourier Transforms (QFTs). In line with the Fourier transformation generalisation, wavelet transformations in the Quantum domain are carried out by the author [54]. Since wavelet transformations in the Quantum domain possess signal multi-scale features, they are also applicable in data compression and image processing. Noise elimination within the images forms one of the major focuses in Quantum images.

In [33] terms of exponential speed, the Quantum Fourier transform outperforms the classical Fast Fourier transform used in this paper. As discussed in one of the author's review papers, Quantum Oracle is used as a black box for the filtering circuit; however, this black box is unknown, which is one of the proposed method's drawbacks.

As stated by [27], the Fourier transform is applied in the first phase, while the inverse Fourier transform is applied in the final phase. As for the design of the quantum circuit within, it is presented extensively in the Quantum oracle that was proposed. The image filtering is performed using the correlation between the image and the filter mask. The quantum measurement is applied to achieve the quantum-to-classical transformation as a probability distribution.

In image decomposition [38], higher frequencies correspond to low potential values. The proposed algorithm is similar to other graph signal processing algorithms". There

are some parameters in the proposed algorithm that enable flexibility regarding frequency localisation capabilities and denoising capabilities.

4.2.11.1 Filters Used for Quantum Image Denoising

Nakahara and Sasaki [58] Median filters that are considered non-linear two-dimensional filters are used to remove shot noise. “Variational is also referred to as partial differential, and basically, it is an energy equation (PDE), which is considered a quantum denoising model, which is applied to eliminate white additive Gaussian noises, and they assist in developing useful filtering techniques based on total variation [14]. The researcher explained a developed technique, which is considered a numerical tool that is utilised to solve differential equations, also referred to as numerical approximations. Besides, the researcher explained that the numerical output will be applied to perform simulations of Poisson denoising on medical images. It is observed through experimentation that the PDE quantum denoising model performs well when the finite difference method is used in approximation. In the case of Poisson denoising simulations, the numerical approach of iterative numerical approximation will be utilised to approximate its variational solution, which depicts the filtered quantum noise of a non-linear PDE [24].

A variational shot denoising approach is applied to different photon-starved medical images, and through numerical analysis, the dataset is based on medical imaging, consisting of 8798 computed tomography scans of 512*512 dimensions, for example, a brain tumour cancer imaging progression archive dataset. Through experimental analysis, the researcher has taken only 154 images from the brain image dataset rather than all the images, as they were only brain tumour images computed through Quantum noise and then restored with the proposed approaches [17]. Noise is filtered out from the features of the image, such as object edges, by implementing a numerical approximation approach. Numerical algorithm approaches the solution of the PDE model in the form of a restoration image.

The number of iterations needed (N) depends on the Quantum noise level as well as the image size that is being processed. Peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are among the most commonly used similarity indices, and

they are used in the evaluation of the shot filtering method using the test images. The values obtained from the two parameters are quite satisfactory. Comparison of the techniques used to obtain the best results is also made. From the analysis of the result, it can be observed that the 2D median filtering technique and the second-order PDE denoising approach, such as the total variation technique for Poisson noise reduction based on smoothing techniques, perform very well [59]". Comparison between the different Quantum denoising techniques is carried out and presented using a table.

4.2.11.2 Medical Application of Quantum Image Denoising

Image-denoising techniques are applied to medical images based on the image acquisition system to filter out Quantum noise for the enhancement of other useful characteristics [45]. "In this reaearch, the author introduced an energy-based Poisson denoising method using a PDE formulation that would help in the investigation of such a denoising problem. Some method comparisons and Poisson denoising experiments indicate the success of this proposed medical image filter [61]. Also, the author introduces a novel method for constructing a transform adapted to an image/signal and principles of Quantum physics, which proves to be among the advantageous methods. In the conventional technique, large images are split into lines and columns to form a one-dimensional signal. But the proposed method applies block-wise decomposition because this will lead to enhanced image denoising and maintain correlation between neighbours. The localisation principle plays a crucial role in the proposed method based on Quantum principles [56]. The Quantum interference effect results in highly dependent eigenvectors of the Schrodinger operator in terms of denoising. This helps in choosing the appropriate domain for denoising. The proposed method is based on a discrete Schrodinger equation based on the Quantum particles' properties and their potentials, which are pixel and signal values [10].

As per the wave functions that describe the Schrödinger equation solution decomposition of the image or signal from computation through the signal and image themselves that contain localization property in space or time. Higher frequency for lower potential value; therefore, decomposition of the image can be achieved from the signal [80]. In the proposed approach, the use of some graphical signal processing is utilised by making an adaptive basis from the signal by employing a graph Laplacian.

The process of Graph Signal Processing uses the Graph Laplacian in order to increase the similarities between the neighbourhood pixel values, but in the proposed approach, the use of adaptive bases is made for individual pixel values that have different adaptive bases with distinct properties". Flexibility plays a vital role in cases like Denoising, in which frequency and localisation properties of the signal are controlled through various parameters [34].

4.2.12 Existing Proposed Methods Analysis: A Graphical Signal Image Processing Analysis

Denoising techniques and the proposed transformation technique are applied in the proposed approach according to the parameter values. "For the proposed system, signal and image processing technique along with quantum mechanical properties has been considered, and the embedded denoising technique that can handle speckle or Poisson additive Gaussian noise gives satisfactory results. Different signals and images are analysed with various denoising techniques in the results section. The lower the value, in order to generate the basis of oscillating functions, the higher the frequency of oscillation is for the same basis function [67]. In this paper, the proposed denoising approach reduces the effect of noise on the grey value of Quantum dots in fluorescent images. The non-local anisotropic diffusion filter and grey compression technique have been applied for the denoising process [39].

This method is employed to remove noise from the image of the fluorescence obtained after hybridisation with DNA in a Silicon substrate having a Bragg-like structure. Results obtained through experiments have revealed that the use of this denoising technique enhances digital image detection sensitivity and the effectiveness of the process of denoising. In this regard, convolution neural networks help in determining the type of noise, which in turn is based on the distribution of Quantum dots on a porous silicon substrate [71]. Post the analysis of experiments, the effects of the noise on the grey value of the quantum dot image are calculated and analysed. As the experimental analysis deals with biological concentration, the grey difference is calculated by using the digital grey value method, wherein the difference is the result of post biological reaction.

After the biological response, the level of interference with the greyness of the fluorescent image depends on the noise, thereby leading to low detection accuracy [37]. According to the experimental results, applying the proposed denoising technique can increase sensitivity to digital images detection and accuracy in denoising. There is no information about the Quantum denoising report, which forms a gap in research for which some techniques have been proposed in this paper in the context of grey value compression of Quantum dots fluorescent images and non-local anisotropic diffusion process [40].

The proposed adaptation theory can be applied to both image-dependent noise and image-independent noise [48]. The author has compared the denoising efficiency of the proposed algorithm with regard to noise statistic, intensity, and image characteristic with other current methodologies. In order to choose effective values during the experiment, hyper-parameter properties and denoising efficiency are taken into consideration [35]. This approach can deal with image denoising problems related to realistic images, particularly those having medical implications such as despeckling ultrasound images [51]. Non-locality is performed by employing local structural similarity using Quantum framework. Structural information from each patch at patch-level is exploited for achieving good sparse transform of patches at each patch-level [1]. The author realized that this kind of approach can be done better by employing the interaction among neighboring patches in denoising. Multi-particle Quantum theory should be considered rather than single-particle Quantum theory for enhanced accuracy [47].

An image decomposition approach that uses the adaptive basis of Quantum in accordance with single-particle theory is presented in this paper. Since the single-particle theory is full of weaknesses, the author studied various bodies of Quantum theory for image problems. Furthermore, the author studied various image denoising algorithms and numerically implemented their performances in different applications [84]. In this approach, noise distribution statistics with high and low intensity noise levels are adopted, which perform better in despeckling operations in areas like medical ultrasound in real-life scenarios. The author's proposed algorithm has shown favorable comparison results and performed exceptionally well in both cases of

dependent and independent noise models. This paper presents a new image denoising approach using the Quantum many bodies theory. Three different approaches are presented in this denoising problem. Construction of image patches using adaptive basis, then decomposition of the particular patch, thresholding of coefficients, and lastly backprojection of the denoised patch [44].

For the experimental study, a noisy patch is projected onto a 4-dimensional subspace with the help of the solution of minimum energy and the reconstructed denoised patch is created through the projection coefficients. Due to the absence of any similarity among pixels, the process of denoising is quite effective. In order to verify the effectiveness of the proposed technique, an experimentation has been carried out with NLM-based techniques [87]. The author has suggested a method for removing noise based on Quantum principles through the concept of many bodies theory in order to prove the DeQuIP, the proposed adaptive Quantum denoiser that involves the process of denoising known as denoising by Quantum interactive Patches which includes interaction of Imaging problems and Quantum theory that can be used in super-resolution and deconvolution-based image problem as per the survey of literature".

4.2.13 Performance Evaluation

The traditional computer bit can take 0 or 1 value while qubit from a quantum computer takes superposition values of 0 and 1. In such a way, we can use one qubit for encoding two bits. The interfacing model of Quantum computing is also explained in this chapter [60].

The entire discussion revolves around the review of binary and Quantum image relationships and measuring the distance between Quantum states. "Noise reduction [12] by means of the quantum principal method is investigated through research analysis [6]. The superposition principle allows one to encode the N-bit classical information into $\log(2N)$ Quantum bits provided that the classical bits will be taken into account. However, there are some obstacles associated with this ability for example; a classical computer may mimic Quantum computers, yet its cost will increase exponentially depending on the number of qubits [30]. The experimental results of a number of reviewed papers have revealed that Quantum filters outperform

conventional filters [77]. The authors assumed that image processing based on Quantum theory would prove to be a promising technology for various applications such as military applications [43], indoor-outdoor detection [64], location determination [70], Internet of things [15], and network optimization [15,73]".

4.2.14 Analysis of Quantum Processing-Based 3D Models

In this literature review, the application of Quantum theory-based mechanics in image processing is considered. "An efficient approach, known as the noise codebook feature, is applied for characterizing the local features of each pixel within an image [4, 20]. Quantum before and after measurements [18] provide the wave function difference with the help of measurement operators characterized by the state space of the quantum system to be measured [8, 78]. It should be noted that the author's approach is built on the assumption of signal description by means of the basis constructed according to the principle of Quantum mechanics resolution [81]. According to the described experiments and the analysis of their results, the suggested algorithm [3] can be helpful in restoring the gray level in an image under the influence of the multiplicative gamma noise.

Quantum Boolean Mean Filter (QBMF) shows good effectiveness in noise reduction in images owing to its ability to work as an interface between Classical and Quantum processing. There are three main factors to be considered during quantum image processing. Qubits, also referred to as Quantum bits, which represent Quantum images, allow the representation of Quantum images on Quantum computers by considering their normalized states and their location within the Quantum image. Quantum interface inversion of the image from a classical source is followed by a second classical inverter whose output becomes a result of reconstruction of the image's color components. These are red, blue, and green, which form color component decomposition [77], to make color bit planes for each color component. Each 8-bit pixel consists of 8 bitplanes per color component [79]. Most Significant Bit (MSB) of each color forms a bitplane [31].

Results of experiments performed from various reviewed papers indicated the superiority of Quantum Filters over conventional filters and proved that Quantum

Image Processing will be a good and achievable technology in the future [54]. The review of all the applications of the mechanics associated with Quantum Theory in image processing has been done in this paper. For any denoising algorithm to achieve good performance, noise must be removed completely without compromising with the edges. A quantum theory-based measure for measuring the distance in a Quantum system will be employed to explain the proposed denoising algorithm [7,28,33]. Also, a noise feature codebook is used to represent the feature of the local image pixel. Experimentation was done in [81] by employing Wiener filters with low, medium, and high exposure levels. Using reduced mean square errors of all random exposures, meantime filtering (MTF) of the superposition and Wiener is obtained, and then, composition of the images obtained after restoration was done". After low pass filtering, pixel-wise weights were calculated based on local means.

Based on the above review, it is evident that although several Quantum Image Processing and Image Denoising algorithms have been reported in the literature, limitations still exist in terms of computational complexity, scalability, noise handling capability, and practical implementation. These observations highlight the need for improved quantum image processing methodologies. Accordingly, the findings of this chapter provide the research foundation for the proposed image classification framework developed in this thesis.

4.3 Comparative Analysis

"Dutta et al. [26] proposed a two-Dimensional Quantum states and normalized amplitude two-dimensional (2D-QSNA) Quantum image representation state [73]. This method can be used to represent rectangular images and pixel intensity without the use of additional qubits. As a result, an image with dimensions $(2^n \times 2^m)$can be encoded in only $M + N$qubits (position and intensity). The comparison in the table shows the various discussed models (Tables 4.1, 4.2, 4.3).

Table 4.1. Comparison of Quantum image representation with L, m, and n parameters

Cases	FRQI	NEQR	2D-QSNA

Shape	$2^n \times 2^n$	$2^n \times 2^n$	$(2^n \times 2^n)^L$
Num qubits	$2N + 1$	$2N + 1$	$(M + N)^*$
Complexity	$O(2^{4m})$	$O(2^{4m})$	Pure state

Source: [7]

[1] N represents the number of qubits used in the quantum image representation model.

[2] M and N denote the dimensions of the quantum image, where M-qubit and N-qubit registers are used for image position and information encoding.

Table 4.2. Comparison of Q-inspired algorithm based on Quantum's parameters

Models	**Chromaticity**	**Complexity**	**Recovery**
FRQI	Gray-scale-1 angle vector	$O(2^{4m})$	Probabilistic
MCQI	RGB-3 angle vectors	$O(2^{4m})$	Probabilistic
NEQR	Gray-scale qubit sequence	$O(q\, n\, 2^{4m})$	Deterministic
CQIR	Gray-scale qubit sequence	$O(\log_2(L^n)2^{4m})$	Deterministic
QUALPI	Gray-scale qubit vector	$O(q(m + n)2^{4(m+n)})$	Deterministic
SQR	Infrared-1 angle vector	$O(2^{4m})$	Probabilistic
QSMC-QSNC	Gray-scale/RGB-1 angle vector	$O(2^{4m})$	Probabilistic
NAQSS	Gray-scale/RGB-1 angle vector	$O(\log_2(q^n)2^{4m})$	Probabilistic

Table 4.3. Comparison of algorithm results of classical and Quantum

computing-based image processing and development

Models	Construction complexity	Edge extraction complexity
Fu-qubit lattice	$O(2^N)$	$O(2^N)$
ZHANG-FRQI	$O(2^{4m})$	$O(n^2)$
FAN-NEQR	$O(NN(2^N))$	$O(N^2) + 2Q + 1)$
XU-NEQR	$O(QN^2(2^N))$	$O(N^2) + 2(Q + 3)$
SOBEL	NA	$O(2^N)$
PREWITT	NA	$O(2^N)$
Proposed model	$O(QN(2^N))$	$O(N^2 + 2(Q + 3))$

By loading two Quantum registers with images, a restoration procedure referred to as signal adaptive pixel superposition restoration procedure is also presented and briefly discussed in the experimental section. Step by step processing flow chart in Quantum image processing and denoising is depicted in Fig. 4.1. Burkhard Peters [63] demonstrates how IIR filtering technique was utilized in generating invariant images through the use of two-dimensional impulse response. It becomes evident from the findings of the same procedure that the image quality and processing speed requirements can be achieved using the proposed adaptive restoration technique illustrated by Tripicth from Bosch [81]. Color collapse of Qubits as per the probability values entangled with the transpose of itself is illustrated in Fig. 4.9 using quantum color imaging layout based on quantum mean filtering". Transformation from one state vector image to another using a time evolution operator [28] through linear interpolation for various angles and entanglement of many states representing an

image [7] – i.e., RY rotation for each qubit at the same angle as shown in Fig. 4.5 (Table 4.4).

Table 4.4. Comparative analysis

Author	Algorithm	Method	Advantages	Drawback	Accuracy (%)	Equation
[63]	Wiener filter approximation	Image restoration	Spectra decomposition	Processing speed	74	C
[23]	Bi-DTCWT	De-speckling	Edge preservation	SNR Value	74.28	C
[62]	NFCW-NFCB	Distance measurement	Higher SNR	Good visuality	75	NR
[50]	Non-local anisotropic diffusion	CNN method	Q-dot gray value preservation	Low-detection accuracy	75.9	NR
[16]	QMLSONN architecture	Rank-weighted filtering	Image segmentation	Colour preservation	76.2	C
[29]	Fast-noise removing algorithm	Differential computation	Accuracy	Noise trade-off	77.4	NR

[36]	Zero-phase MTF	Invariant Wiener filtering	Cascading-parallelism	Quantum zero-spatial Frequency	77.77	C
[41]	QPBDSO NN	Non-linear median filtering	Feature space image segmentation	Pure color image denoising	77.9	C
[46]	Markovian Bayesian paradigm	Non-parametric denoising estimation	Optical performance	Image sparsity	78	NR
[83]	Expectation maximization	QSD-SGMM	CSD value	Wavelet coefficient inter-scale dependency	78.77	NR
[85]	DDT-DT	Inter-scale wavelet coefficient method	Noise reduction	Edge-preserve index	78.77	NR
[25]	Hamiltonian matrix	Hyperparameter tuning	Adaptive basis generation	Best PSNR	80.03	C
[3]	De-coherence	Simulated dynamic method	Image enhancement	Image transformation	84.29	C

[42]	QBDSONN	Back-propagation	Uniformity	Time-complexity	88.6	C
[19]	Q-Daubechies 4th order kernel	QWT	Wavelet coefficient extraction	Image denoising filtering	89.03	C
[26]	Quantum localization	Schrodinger operation	Signal-dependent image construction	Distorted potential image	92.03	C
[12]	Numerical approximation	Positron-emission tomography Single photon emission	Poison (Q) noise detection	Image restoration in medical field, shot-noise filtering	94	NR
[60]	Patch analysis	Extraction	Real image preservation	Image intensity	95.2	C
[77]	Sigmoid function	Ricci-scalar, GCF curvature, Sober filterization	Clear edge	Transformation slope thresholding	96	NR
[26]	Embedded denoising	Block-wise decompositi	Novel-signal	Correlated neighbourin	96.49	NR

	on and Graph-Laplacian	feature	g pixel preservation

4.3.1 Proposed models for Quantum image denoising

A noise reduction technique for remote sensing images using double density dual tree discrete wavelets transform was developed by Ying Zhang [85]. The noise reduction technique is used for reducing noises from successive approximation recursive (SAR) images and involves improvement in peak signal, edge preserving index, and noise ratio as a function of evaluation. It is used to improve image noise reduction. Trans-national invariance, anti-aliasing property, closer to continuous wavelet transforms, and more directional property of the double-density dual tree complex wavelet.

The experiments were performed in the analysis [23]. “The author used various remote-sensing images to enhance the image speckle reduction. Nibaran Das [41] proposed the Quantum Bidirectional Self-Organizing Neural Network (QBDSONN), where the author used a special structure of three neuron layers, which are called quantum states or Qubits. These layers include input, intermediate, and output layers without any necessity to use the Quantum Backpropagation algorithm for adjusting interconnection weights. The intermediate and output Quantum states are restored. Konara [42] stated that the removal of noise from a color image in a noisy environment is the extraction of a pure color object. In the process of denoising images, the division of a digital image into segments takes place based on the homogeneity of features such as color, texture, and intensity of image pixels. Comparative analysis of the vector state transformation of QPBDSONN with PBDSONN, along with other mentioned methods, of the extracted output images and time of extraction will be performed in this paper. The author was able to perform gray-level and true color image segmentation of color images and now continues his further work.

In his article [74], Sowa considered the enhancement parameters for images and their quantitative evaluation by introducing a Quantum dynamic approach using a new classical technique by making use of Quantum system-based image data which are Quantum observable. This can be used in some applications in real-time in which the

images will be combined with a Quantum system to enhance the image transformation process with simulation of Quantum dynamics. The authors found out that denoising under decoherence process is influenced in the Quantum environment due to the Quantum system characteristic of the Quantum variable carrying the image data. The desired outcome would be a low level of coherence by a Quantum mechanism with a Quantum computer technique. In his discussion [73], Smith considered some Quantum mechanics devices including Schrodinger equation for image and signal processing applications in order to form an adaptive transform. The Schrodinger equation is also used to form the Hamiltonian operator. The possible direction in Fourier research is the use of image and signal processing reconstruction techniques like super-resolution and convolution through reducing computational time through calculation of eigenvector values of Hamiltonian matrix.

Two approaches, which include SGMM that stands for Gaussian mixture model and QSD that is the Quantum-inspired approach (QSD), were introduced by Aidoug XU [83]. Both techniques are used in noise removal processes in the wavelet transform domain using a thresholding function. If the QSD and GMM approaches are used, then the results obtained from the denoising process will be enhanced in both time and frequency domains. From the experiment conducted, it was found that applying the QSD technique to the thresholding function through MMSE estimation method gave superior results.

Chakraborty [19] has covered the Quantum Wavelet Transform (QWT) based image denoising algorithm. Apart from the wavelet coefficients of the original image, noisy images are introduced to degrade the original image quality, as depicted in Fig. 4.3. After examining the suggested image denoising methods for Gaussian noise and Salt and Pepper noise on a set of sample images, it has been observed that Quantum image processing algorithms could find wide applications in this field although it is in the early phase of development. Superposition of two quantum states of an electron could be given as:

$$| \psi\rangle = \alpha | 0\rangle + \beta \sum_{i=0}^{2^{n+1}-1} C_i | i\rangle \qquad (4.19)$$

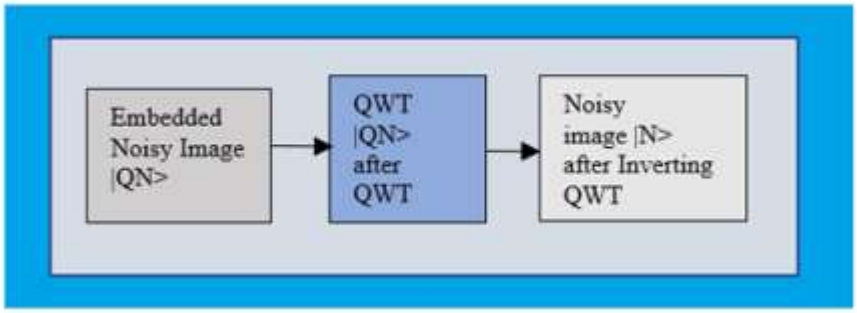


Fig. 4.5. Quantum noise image extraction procedure [78]

$$|A>=\frac{1}{\sqrt{2}}(|1000>\otimes|0000>+|1011>\otimes|0001>+|1101>\otimes|0010>+$$
$$|1111>\otimes|0011>+|1111>\otimes|0100>+$$
$$|1101>\otimes|0101>+$$
$$|1011>\otimes|0110>+$$
$$|1000>\otimes|0111>+$$
$$|0101>\otimes|1000>+$$
$$|0011>\otimes|1001>+$$
$$|0001>\otimes|1010>+$$
$$|0001>\otimes|1011>+$$
$$|0011>\otimes|1100>+$$
$$|0101>\otimes|1101>+$$
$$|1000>\otimes|1110>+)$$

Fig. 4.6. Amplitude versus time-domain equation representation for Quantum signal as per the representative expression [75]

where α, β belongs to C, a complex vector space, and the vector length is defined by the following square length equation:

$$|\alpha|^2+|\beta|^2=1. \qquad (4.20)$$

In this study, Dutta [25] used novel methods to create Quantum mechanics tool-based images or signal-dependent images that are quantised through the use of Schrodinger's equation. In creating an adaptive basis, this method uses a Laplacian graph that helps in building the signal on the basis of signal construction. The Graph Laplacian is built up from the graph signal to emphasise the similarity between adjacent pixel values, but the proposed method focuses on emphasising a single pixel value [5].

Having analysed the outcomes of all the experiments, we can conclude that the best method proposed is the one, as it may have a variety of applications, synthetic signals and image construction. In addition, in the proposed case, high frequencies correspond to low gray levels, and low frequencies correspond to high gray levels. Since the proposed method is free from databases, it is better than others in the Quantum mechanically resolved adaptive transform reconstruction application in signal and image processing. The results were good since the time-dependent Schrodinger equation, which involves a wave function that depends on the potential and is time-variant, performed perfectly [26]. The proposed approach may also be implemented in other applications, like 3D signals/images, as well.

The framework of Barbu [12] was designed for the restoration of some images associated with medicine, which are affected by Poisson or quantum noise, where a variational approach was suggested, resulting in a fourth-order PDF estimation-based model, which can be solved mathematically through the introduction of an approximating scheme that converges to a solution of the variational approach. Future applications for filtration of mixed Poisson-Gaussian noise in the quantum denoising domain may include the extension of the existing PDE restoration framework scheme, as illustrated in Fig. 7. Adrian Basarab and Sayantan Dutta [26] investigated image representation and a new feature in the signal representation about the dedicated basis of the image or signal itself. When there is high noise for high signal values in the form of signal-dependent noise, like Poisson or instance noise, then the application of the present basis function, which involves increasing the basis function parameters in relation to the frequency of energy oscillation, becomes highly effective. Liu [50] has analysed various forms of noise and their impact on the grey value of the fluorescent images. It is found that noise causes fluctuations in grey values and reduces detection sensitivity. Based on the results obtained from the experiment, it was concluded that grey values affected by noise can be restored through this method.

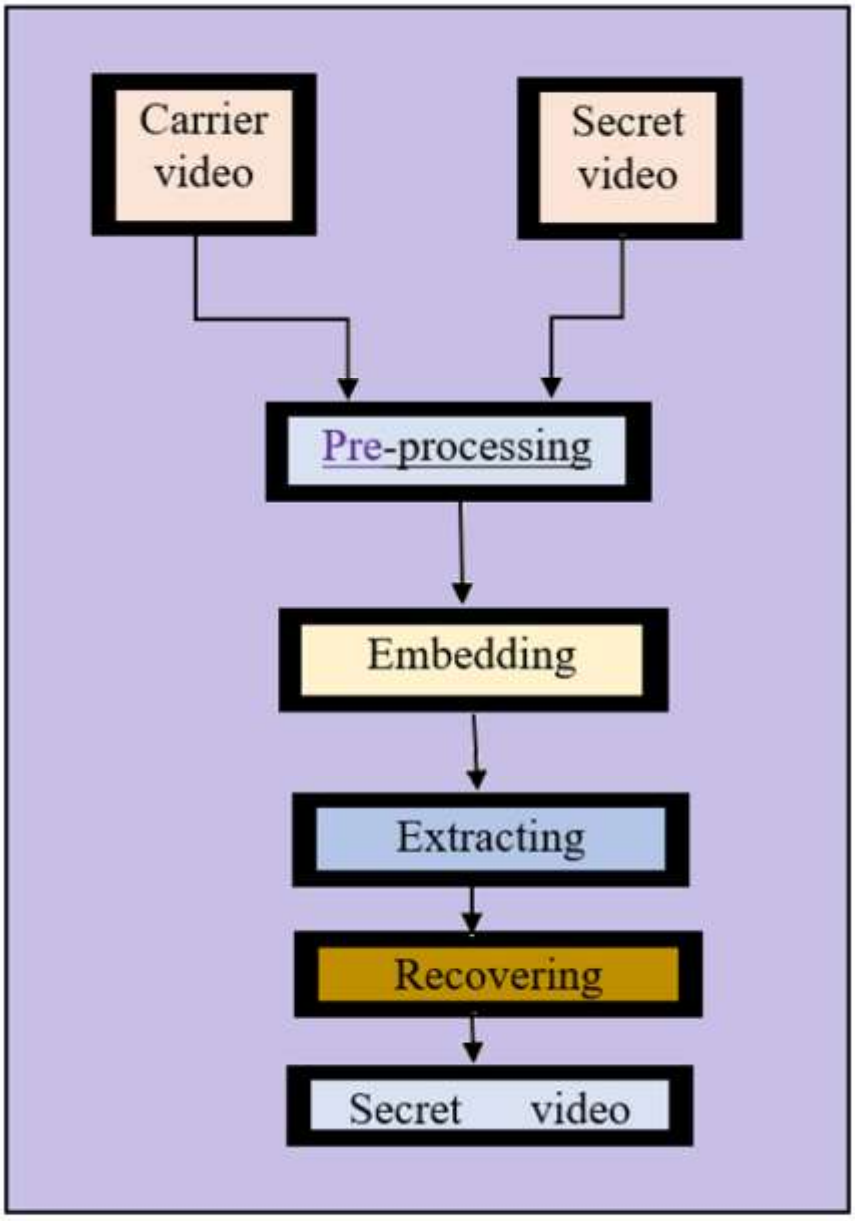


Fig. 4.7. Quantum-based signal, video and image processing model flowchart (figure adapted from [30])

The results achieved by the author are very economical in terms of the detection and offer a high-precision value. Bertrand George [2] described the concept of patch analysis techniques that make use of quantum mechanics theory to solve the structural problems of real-world images. The future work proposed by the author is dependent on the use of the time-dependent Schrodinger equation, which is an advanced version of physics theory [26]. Dobillet [3] describes the concept of Variational Quantum

Optimisation (VQO) network based on the IBM Quantum Network platform [7]. Overall, Quantum Noise is directly and exponentially proportional to the number of qubits used, hence grows exponentially.

The quantum differential programming framework Penny Lane is utilised in designing a quantum network VQO framework, which is packaged as the qNetVQ library in Python. VQO is addressed by the author at the end of the paper, who describes its application for achieving maximum non-locality in the IBM Quantum computers.

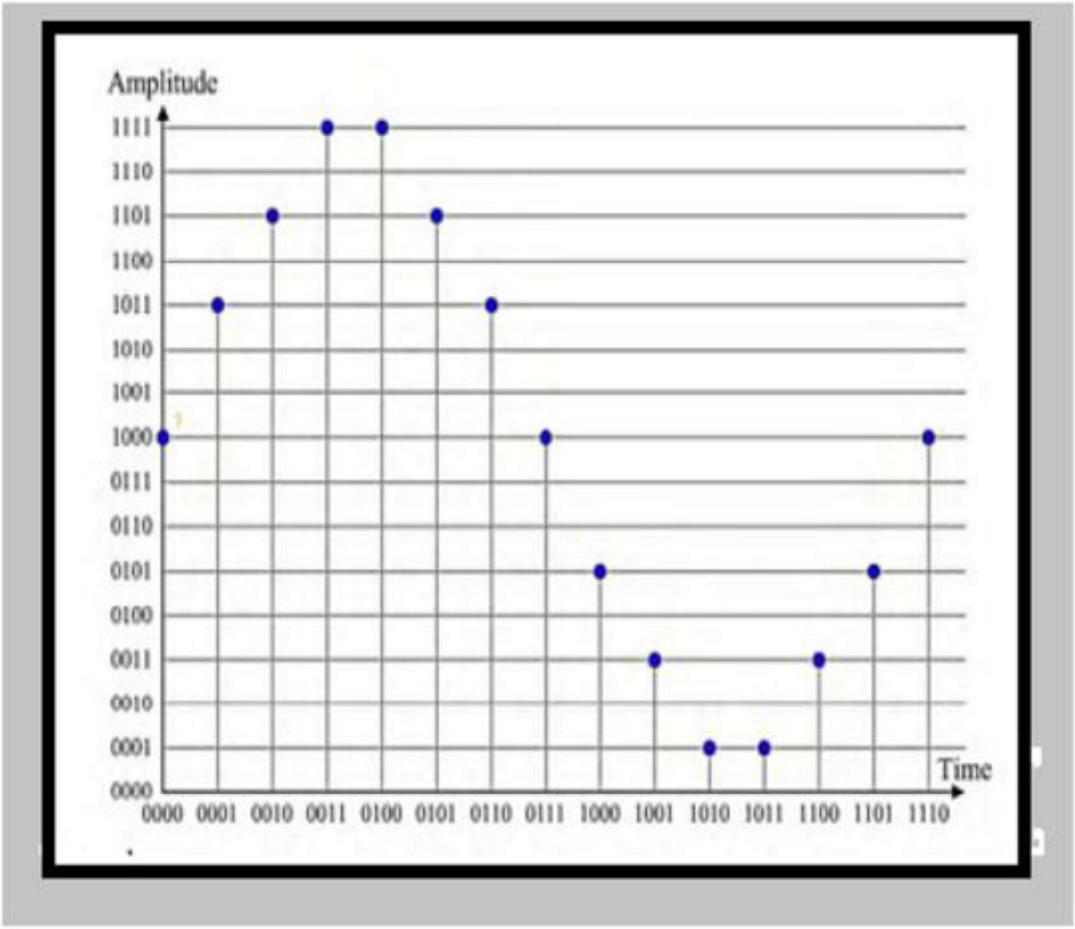


Fig. 4.8. Amplitude versus time-domain chart for the Quantum signal as per a representative expression video [53]

In a study, Ohkura [82] introduced Palloq, which refers to the parallel assignment of Quantum computers. Palloq is basically a compilation strategy that enhances the performance of Quantum multi-programming on NISQ processors. In the paper, the two main points for optimisation raised by the author include fidelity output for

Quantum computers and total time of execution for a Quantum computer by Quantum multi-programming for enhanced throughput and quantum processor utilisation of multiple Quantum computers. The performance metrics of our proposed QSVM will be evaluated against other advanced classifiers with more accuracy". The utilisation of an expanding quantum state space based on interference and entanglement is an important [72] part of the computational acceleration [26] by Quantum algorithms (Fig. 8).

4.4 Result and Discussion

The outcome of several reviewed authors is obtained from an experimental study of 2D infinite impulse response (IIR) filters and the intraoral radiographs using the Weiner filter approximation. In contrast to considering a noise quantity alone, frequency and signal amplitude measurements, in addition to the noise measurements, in the entire dynamic range are taken into consideration. "The noise model consists of the linear combination of squares of respective mean time filtering sections and the part of the white detector. For the single exposure, there exists considerable statistical measurement error; thus, only one image for each exposure is used. The authors employed a robust linear fitting technique for determining the levels of Quantum and detector noise. From the experimental analysis, they were able to obtain the required proportionality relationship of detector noise power level. The method of achieving the smooth spatial transition of the filter proposed by the author in the course of the experiment helps to avoid all the abrupt transitions. As per the authors, the trade-off between the smoothness and local adaptivity implies that the dimensions of the Gaussian low-pass filter kernel should vary according to the expansion in space to ensure fast and accurate results; this would come under the category of the signal-adaptive method to compose an image. Superposition of images, minimum two, is achieved through Wiener spatial filters.

Additionally, the authors provided the experimental analysis of well-executed amplitude scaling of the final image, which will develop the affinity between the final image and the histogram produced by the initial image. Analysis reveals that the generic algorithms of fourth-order 2D-infinite impulse response (IIR) filter, depending on the quality of approximation helps design spatially invariant Wiener filters, as seen

in Fig. 4.5. Through cascade algorithms, zero-phase filters MTF could also be implemented by scanning the images sequentially. It helped the author realise that high exposure required low-frequency filters, which could be done through higher order filters, as in Fig. 4.9.

Problems associated with quantum computing in general. Time complexity cannot work as an accurate solution for all problems. Moreover, they are entangled with two states. In terms of physics, there would be a creation of situations whereby, for a two-state input, there would be a two-state output instead of a four-state". Other difficult elements include decoherence, scaling, coupling between the source and the fibre, room temperature, time complexity, etc. This is elaborated in the literature review.

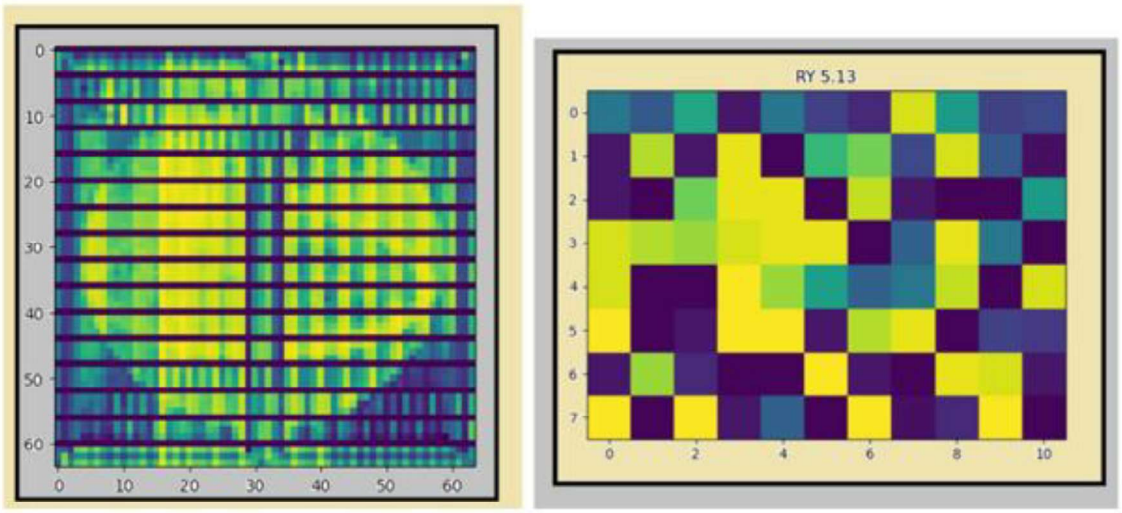


Fig. 4.9. State vector transformation [7]

4.4.1 Challenges of Quantum Computing and Image Denoising: Application-Based

4.4.1.1 Wavelet-Based Quantum Image Denoising Challenges

In [18], the author showed that the wavelet coefficients are noise-free coefficients according to Quantum mechanics and the threshold function of noise coefficient shrinking. The author explained the mechanism behind the denoising process by considering the signal processing technique of mechanical vibration. Furthermore, the demonstration of the application of SGMM to obtain the distribution of the wavelets gives a very accurate value during the experiments. Finally, from the analysis of the

results, it can be shown that the SGMM and the QSD denoising techniques are superior compared to other denoising methods. Due to the difficulty of recovering noise-free signal coefficients in the wavelet domain, the paper considered the integration of inter-scale dependency into the standard deviation. [68] The Quantum mechanics technique is becoming the basis of adaptive denoising applications.

4.4.1.2 Image-Based Quantum Image Denoising Challenges

An adaptive basis is implemented in denoising procedures for analysing noisy signals in image or signal processing. “The application of the Quantum localisation effect leading to the localisation of the adaptive basis in the position space yields a disordered potential, which is among the research gaps and is explained by the implementation result analysis conducted by the author [22]. Smoothed adaptation is applied for generating the Hamiltonian matrix, whose generation utilises convolution with a Gaussian kernel having standard deviation sigma. Another version of the algorithm, where a diagonalisation matrix facilitates subdivision of the image or signal into separate parts to generate the image, is applied in cases where there is a large size of matrices. Size equality sub-blocks that contain a noisy signal and an image in a divided manner are considered in the case of images, while square sub-blocks are used for images [21]”. An image or signal is denoised after combining all the denoised sub-blocks. In Quantum mechanical problems, a resolution image or signal is used, and hence the resolution supplies the adaptive basis eigenvectors.

4.44.1.3 Frequency-Based Challenges

The frequency ranges considered differ from those used for low-valued potential regions to high-valued potential regions. The hyperparameter influences the proposed adaptive approach's efficiency due to its influence on some benchmark images and artificial signals. An adaptive denoising approach for low- and high-frequency signals is applied to remove noises such as speckles and Poisson from images and signals using a thresholding process of higher frequency values. This proposed approach performs better than other approaches in the case of Poisson noise. Hyperparameters should not be randomly selected but should be chosen based on the type of application and noise involved [76]. It was found by the researcher that choosing hyperparameters

randomly may not produce optimal results, while selecting hyperparameters within an optimum range, depending on the type of noise, can improve the performance of this approach. One major drawback associated with the proposed technique is computing the Hamilton operator eigen vector, which has been improved by applying the patch-based process.

4.4.1.4 Computational Complexity: An Important Challenge

"Besides the necessity for effective denoising of an image or signal, the effectiveness of a computation scheme is significant. It was found out that the numerical approximation scheme proposed helps to eliminate Quantum noise and perform shot-noise filtering solutions in some medical applications, which completely rely on photon-detecting devices. There are noises such as Quantum, Poisson, and shot noise, the distribution of which falls into the category of Poisson distribution. In some imaging applications, such as microscopy imaging, positron-emission tomography, and single photon emission, photon counting devices have been used to detect the shots resulting from observations at different spatial locations. Numerous Quantum mechanics-based denoising solutions have been suggested recently".

4.5 Image Processing-Based Applications of Quantum Image Processing

Quantum image processing has become an important field of study because of the possibility of improving the efficiency and accuracy, as well as computational capacity, of different types of image processing operations through the use of concepts from quantum mechanics, like superposition, entanglement, and quantum parallelism. Some of the main areas of application for quantum image processing are presented below.

4.5.1 Quantum Image Compression

Image compression is one of the important uses of quantum image processing technology. Image data can be described using the concepts of quantum superposition and entanglement, which results in image information being able to be compressed into a very concise form. Thus, quantum image compression algorithms can potentially offer better compression ratios and transmission efficiency than traditional image compression methods.

4.5.2 Quantum Image Encryption

Efficient encryption is needed for securing images during storage and transfer. The technique used in quantum image encryption involves cryptography and quantum key distribution based on quantum cryptographic concepts. The property of entanglement in quantum mechanics can be leveraged to establish safe communication channels that resist different forms of attacks.

4.5.3 Quantum Watermarking

Watermarking is commonly employed as a way of encoding information in images relating to ownership and identification purposes. In quantum watermarking, features from quantum theory, such as superposition and entanglement, are utilised to enhance the robustness and security of the watermarked image.

4.5.4 Quantum Pattern Recognition

Pattern recognition is highly important in various applications, including facial recognition, gesture recognition, and object recognition. Given that most of these applications work in real-time, their efficiency is greatly dependent on speed. Quantum image processing techniques enhance efficiency in pattern recognition since the technique uses quantum parallelism to boost speeds.

4.5.5 Quantum Image Enhancement

The technique of image enhancement is indispensable for better visual quality as well as the extraction of visual information. Quantum image enhancement is the use of quantum interference and quantum parallelism to make images better and clearer. The application of image enhancement technology proves to be effective, especially in the field of medicine, where enhanced images help diagnose patients.

4.5.6 Quantum Feature Extraction

Feature extraction is one of the key components of computer vision and machine learning systems. Quantum-based feature extraction methods help in finding relevant features of an image in an efficient manner. Such feature extraction algorithms are especially valuable for gesture recognition, object detection, and image analysis tasks.

4.5.7 Quantum Image Search

Retrieving images from large databases is a difficult problem in contemporary information systems. The method of quantum image search takes advantage of quantum parallelism and speeds up the retrieval process. As a consequence, image retrieval can become faster than with the conventional techniques of image retrieval.

4.5.8 Quantum Satellite Imaging

Applications of satellite images include environmental monitoring, disaster management, agriculture, and crop protection. Quantum image processing techniques may improve the efficiency of analysing, interpreting, and transmitting images for these applications. Also, quantum compression techniques enable reducing bandwidth demands while preserving high-resolution image data during satellite communications.

4.5.9 Quantum Watermarking for Intellectual Property Protection

Intellectual property rights constitute a critical requirement in areas such as photography, digital arts, forensics, and multimedia technology. Quantum watermarking offers a practical solution for providing intellectual property rights by virtue of the use of advanced watermarking techniques that exploit quantum computation rules.

4.5.10 Quantum-Enhanced Image Search in Security Systems

The need for face recognition and activity detection within large databases is common in applications for security and surveillance. Quantum-assisted image search algorithms can increase the speed and effectiveness of such tasks, thereby becoming ideal candidates for use in security applications.

4.5.11 Quantum Image Analysis in Materials Science

Quantum imaging analysis has several uses in materials science, particularly in situations where there is a need to interpret images at a microscopic level to characterise materials. The sophisticated algorithms used in quantum imaging help scientists identify the particularities of materials.

4.5.12 Quantum-Enhanced Machine Vision in Manufacturing

Machine vision systems find applications in manufacturing industries for tasks like

quality testing, automation, defect detection, and process monitoring. Quantum technology can be applied to enhance the performance of machine vision systems in terms of accuracy and decision-making.

4.5.13 Quantum Image-Based Cryptography in Military Communications

A military communication system demands a certain level of security, confidentiality, and integrity. The technology used for this purpose is quantum image-based cryptography. This technique involves the use of quantum key distribution and image encryption.

4.5.14 Quantum-Enhanced Image Analysis in Astrophysics

Large amounts of imagery data are obtained through astronomical observations that need to be analysed for conducting astronomical research and exploring other astronomical entities and processes. The use of quantum computing in image processing enables efficient and fast data processing for various astronomical phenomena.

4.6 Chapter Summary

A comparative analysis of quantum mechanics-based image processing and denoising methods found in the literature was made in this chapter. This chapter started with the basic ideas of quantum computing, such as qubits, superposition, entanglement, quantum gates, and quantum circuits as the basic building blocks of quantum image processing systems. In addition, different quantum image representation schemes, namely FRQI, MCQI, and NEQR, were discussed in the literature review part according to their image encoding principles, computational aspects, and implementations. Finally, quantum noise models, image restoration approaches, and quantum denoising methods were investigated in this chapter for reducing image degradations and enhancing image quality.

Additionally, several quantum-inspired algorithms for image denoising, wavelet filter techniques, quantum Boolean image denoising, and quantum image transform methods have been evaluated in the chapter. Applications in medical images, remote sensing, and real-time image processing have also been covered. A comparative study of existing methodologies has been conducted, taking into account the complexity of

algorithms, performance for the denoising process, edge detection ability, quality of reconstruction, and accuracy. The comparative study has revealed the advantages offered by quantum-inspired methodologies over traditional image processing methods in terms of representation, extraction, noise elimination, and computational efficiency.

From the literature analysis conducted above, quantum image processing appears as an intriguing research area for processing complex images and managing big image datasets. In spite of various difficulties, such as those associated with accessing the necessary quantum hardware, the increasing capabilities offered by quantum-mechanics-based algorithms have been observed in many of the reviewed works. Such advancements can be used in the future for developing novel image denoising, restoration, segmentation, and intelligent analysis techniques. The results of this chapter form the basis for the rest of the chapters in this thesis.

CHAPTER 5

DEVELOPMENT OF A CLASSIFICATION ARCHITECTURE FOR IMAGES REPRESENTED USING QUANTUM THEORY

5.1 Introduction

This chapter presents the development and implementation of the proposed Quantum Theory-Based Image Classification Architecture. In this thesis, a quantum-based image classification framework has been developed to classify images represented using quantum theory. The proposed architecture integrates quantum image representation techniques with Quantum Machine Learning algorithms to improve feature representation, classification accuracy, and computational efficiency. The chapter presents the conceptual design and analytical formulation of the proposed Quantum Theory-Based Image Classification Architecture, including its quantum-state representation, processing sequence, measurement mechanism, and integration with Quantum Machine Learning concepts. The architecture is therefore presented as a framework-level contribution, while its complete empirical implementation and quantitative validation on physical quantum hardware remain outside the scope of the present chapter.

In the current chapter, the architecture design for classifying the images that have been modeled using quantum theory is analyzed. Considering the complexities involved in modeling the digital image information and the need for a reliable image analysis mechanism, quantum computing has shown a lot of promise in terms of representing images, processing, denoising, and image classification. Some of the basic concepts of quantum image processing, quantum algorithms, quantum-state representation, and the mathematical principles behind quantum theory are explored. Also, a number of quantum image denoising and image classification methods are presented, and important research issues associated with decoherence and quantum-state measurement are highlighted.

Quantum computing has been found to be a very revolutionary method of computation that could potentially revolutionize the way in which computational problems are tackled. While conventional computers use binary bits for computations, quantum

computers use quantum bits (qubits) that can occupy several positions simultaneously through a process known as superposition [21]. Because of this quality, the processing of a huge number of computational scenarios becomes possible at once in quantum computing, giving it the edge in solving highly complex problems. Quantum entanglement is another quantum phenomenon that ensures that there is a high correlation among quantum states so that the process of information handling becomes highly interrelated [22][23]. Because of all these properties, quantum computing has become a field of active research having application in areas including optimization, cryptography, machine learning, information theory, and image analysis.

The fast advancement in quantum technology has made researchers consider how quantum technology can be utilized in solving new age image processing problems. The traditional image processing approaches face constraints when handling high dimensional images, huge image databases, and complex image analysis tasks. The growing need for efficient storage, transmission, enhancement, and classification of images has led to the design of advanced computational methods that have the ability to address such constraints [24]. Quantum computers offer a promising approach where images can be analyzed using quantum computers. The field of Quantum Image Processing (QIP) has therefore evolved into a key inter-disciplinary research area which integrates aspects of quantum mechanics and image processing techniques [25][26].

QIP is concerned with how image data can be represented, stored, processed, and analyzed in quantum form. It is one of the key goals of QIP to harness the processing powers of quantum computers without compromising important features of images such as intensity, spatial positions, textures, and color information [27]. Several image representation techniques have been suggested to represent image data efficiently in quantum form to reduce the required storage space and improve processing speed. Quantum processing of different parts of images at once makes quantum computers quite suitable for feature extraction, image enhancement, image segmentation, image recognition, and image classification applications [28][29].

Image representation in quantum domains remains one of the primary components of quantum image processing systems. The representation of the image is critical because the success of further processes largely depends on how image data is represented.

Different quantum image representations have been proposed to maintain the integrity of the image as well as to allow for the efficient computation of processing algorithms. Such representations make it possible to represent not only gray-scale but also color images by means of quantum states and perform operations typical for image-processing algorithms in quantum computing environments [14]. Moreover, quantum image representation has played a vital role in the development of advanced methods for analyzing images [29][30].

Another promising area of research in the field of quantum image processing relates to the incorporation of machine learning algorithms into quantum computation models. By taking advantage of both quantum information processing and data-driven learning methods, quantum machine learning enhances the efficiency of recognizing complex patterns and classifying objects [31]. Researchers have found that quantum neural networks, quantum variational classifiers, and other machine learning schemes are capable of recognizing intricate connections among elements within a dataset in images [35]. This method has drawn significant interest due to its potential to yield greater computational efficiencies without sacrificing classification accuracy [53].

The growing significance of image classification has led to the investigation of new classification schemes inspired by quantum computing concepts. Image classification is crucial for many real-world applications ranging from medical diagnostics, biometrics, remote sensing, navigational tasks, industrial processes, and surveillance technologies [42]. Classification systems are greatly dependent on image feature extraction and their classification algorithms' ability to differentiate among various image types. Inspired by the processing abilities of quantum computers, quantum computing-based classification approaches aim to overcome these limitations by employing quantum computer's computational capabilities. Some recent studies have pointed out that quantum computational models exhibit high prospects for enhancing image classification performance [46][48].

In addition to classification, image denoising still plays a crucial role as one of the most vital processes performed during image processing. Noise created through any process such as capturing images, storing them, compressing them, or transmitting them can seriously compromise the quality of images and thus negatively impact future analysis.

Hence, many studies have focused on developing new methods for denoising that can help in achieving noise reduction as well as maintaining important structural information in the images. Quantum-inspired denoising methods have shown significant potential due to the possibility of taking advantage of quantum computational principles in analyzing image data [13]. Some studies have shown better performance for denoising using quantum techniques than conventional filters [15][16].

The recent breakthroughs in quantum computing have also enabled the creation of hybrid quantum-classical computational models. Such computational models utilize the advantages provided by classical computing systems along with quantum-based processing of information in order to counter the existing hardware limitations inherent in quantum computers [23]. These hybrid models have proven successful in optimisation, machine learning, and image processing applications, thereby allowing researchers to test the usefulness of quantum computing while ensuring stable computations. Furthermore, recent developments in the field of quantum error correction and quantum state reconstruction have contributed towards the stability of quantum computations [32][34].

The use of quantum image processing techniques is found in many fields in science and engineering. For example, in medical imaging, quantum-inspired techniques may be used in assisting in image processing, tumor identification, diagnosis, and classification of pathological cases [42]. Likewise, remote sensing is another area where these techniques can improve image processing, image restoration, and land cover classification. Object recognition and target identification are some possible uses in defense and surveillance systems, while quality inspection and automation monitoring are two more areas in industry where such quantum image processing techniques can be implemented [46][48].

The uses of quantum image processing technology are far reaching and are used extensively within several scientific and technological fields. For instance, in medical imaging, quantum image processing technology is used to help enhance images, detect tumors, diagnose diseases, and classify pathological conditions [42]. Likewise, in the remote sensing field, quantum image processing technology can be used for image restoration, image feature extraction, and land cover classification. Object recognition

and target identification are among the possible applications of quantum image processing technology in defense surveillance, while industrial applications include quality inspection and automation monitoring [46][48].

5.2 Proposed Work

The proposed work developed in this thesis focuses on designing a Quantum Theory-Based Image Classification Architecture capable of improving image representation and classification performance. The proposed framework combines quantum image representation models with Quantum Machine Learning techniques to achieve efficient feature extraction and intelligent image analysis. The proposed architecture is analysed at the conceptual and analytical level by examining its quantum image representation, feature-processing sequence, quantum operations, measurement mechanism, and integration with Quantum Machine Learning concepts. The analysis is intended to establish the structure and methodological basis of the proposed architecture rather than to claim a complete empirical validation or experimentally demonstrated performance advantage.

5.2.1 Review of Experimental Analysis

According to the analysis of current experimental studies, denoising an image is currently one of the most difficult steps in image preprocessing due to the complicated nature of interaction between noise components and informative image elements. Noise can occur when acquiring, transmitting, storing, and reconstructing an image, thus degrading its quality and distorting vital visual information [1]. These distortions will negatively impact later image processing tasks, including segmentation, feature extraction, object recognition, and image classification. This fact motivated many researchers to devise efficient image denoising techniques that could eliminate noise without damaging essential parts of images [5].

A number of quantum-motivated denoising algorithms have been developed in order to solve the problems that are faced when using classical filters. The initial studies concentrated mainly on adaptive restoration and the use of Wiener filters to enhance image quality amidst noise [1][2]. Wavelet filtering and thresholding-based algorithms that can efficiently denoise images without damaging edges were developed

subsequently [3][4]. These algorithms showed enhanced results in comparison to numerous classical algorithms and set the stage for the development of advanced quantum image processing algorithms.

Experimental research works have proved that quantum-inspired wavelet transformation acts as a reliable technique for isolating noise from useful image data. The use of quantum wavelets helps in representing the image data in different sub-bands depending upon their frequencies, which makes it easier to suppress noise without affecting image data [13]. Quantum mechanics-based image representation models have also proven to perform satisfactorily when it comes to ensuring image quality while performing denoising operations [14]. Variational quantum denoising algorithms have also performed well in improving the quality of medical images through noise removal without harming medically significant images [15]. Moreover, quantum dot biosensor imaging-based denoising techniques have shown impressive performance in improving image quality under noisy environments [16].

Another challenge that has been recognized via experimental analysis is distinguishing between useful image data and undesirable noise. It is observed that in many real-life cases, noise properties differ considerably from region to region within an image, rendering it very hard to adopt one particular noise reduction technique for effective use [6]. Noise feature-based denoising techniques have been proposed that can examine the properties of images locally and perform noise reduction operations accordingly depending upon the estimated level of noise [7]. These methods have been shown to outperform the traditional filtering approaches [8][9].

The literature also provides information about how quantum-based neural network structures have made remarkable contributions towards better image denoising outcomes. The quantum-based neural networks such as Quantum Multilayer Self-Organizing Neural Network (QMLSONN) and Quantum Bidirectional Self-Organizing Neural Network (QBDSONN) have proved useful in performing denoising tasks on both binary and color images efficiently [7][9]. The quantum learning algorithms have been used to analyze the image patterns and distinguish between noise elements. Besides this, quantum computing algorithms have allowed faster image analysis and feature extraction during denoising processes [10].

However, despite all these developments, a number of constraints persist that hinder the application of quantum computing methods. One such issue relates to the complexity of state preparation, manipulation, and measurement during quantum computing processes [21]. While quantum computers enjoy distinct advantages over their classical counterparts when dealing with information processing, quantum computing itself is largely dependent on the stability of the state in question during computation [22]. Moreover, the integration of classical computing with quantum computing often leads to mistakes that could hamper the efficiency of quantum image processing techniques [23].

The development of new trends within the area of quantum machine learning has underlined the necessity to combine intelligent learning algorithms with quantum image processing tools. Indeed, variational quantum learning algorithms, quantum reinforcement learning techniques, and quantum-based classification models possess much promise in order to enhance the efficiency of images analysis [31]. Likewise, quantum extreme learning machines have been developed to facilitate computational burden and retain the accuracy of the classification process [35]. The experiments conducted on the machine learning quantum framework have provided evidence of improved feature extraction and image analysis capacity [32][36]. However, the success of these algorithms largely relies on quantum state estimation and measurement precision [34].

Another conclusion made based on the literature is related to the increasing significance of hybrid quantum–classical computing architecture. With the lack of widespread availability of large fault-tolerant quantum computers, the scientific community has begun to explore hybrid computational methods by combining classical computing with quantum computing components [23]. The outcomes achieved with such methods have proven to be promising when applied to optimisation problems, machine learning tasks, and image analysis, while mitigating certain issues caused by existing quantum technologies [24][33]. This implies the potential use of hybrid architectures as the means of implementing quantum image processing in practice.

Hence, from the above discussion on the empirical findings presented in the literature, it is evident that the application of quantum image processing approaches holds immense

promise in the areas of effective denoising, better image fidelity, feature preservation, and increased computing speed. However, problems related to noise discrimination, computation, stability of quantum states, and measurement of quantum state properties remain significant barriers in applying such approaches in practice. These factors form the foundation for the identification of the gaps in current research, which have been addressed in the next section.

5.3 Quantum Algorithm and Corresponding Schrödinger Equation

Quantum computing is a technology that relies on the basic laws of quantum mechanics, wherein quantum mechanics describes the behavior and development of quantum systems using certain mathematical laws. Some of the basic laws of quantum mechanics include the Schrödinger equation, which is known to be one of the most important equations because it offers a thorough explanation of how quantum systems evolve through time. In other words, the Schrödinger equation forms the backbone of quantum mechanics and is widely employed in the processing of quantum information, quantum computing, and quantum image processing. Due to the nature of quantum image processing, involving the use of quantum states to represent and process image information, the Schrödinger equation is extremely essential in analyzing the behavior of these systems [22][49].

The time-dependent Schrödinger equation is represented as

$$i\hbar \frac{\partial}{\partial t} | \psi(t)\rangle = \hat{H} | \psi(t)\rangle \qquad (5.1)$$

where $| \psi(t)\rangle$ indicates the wave function or quantum state of the system at time t, $\hat{H}$ represents the Hamiltonian operator,$i = \sqrt{-1}$, the imaginary unit, while $\hbar$ represents the reduced Planck constant. The wave function provides all the information concerning the quantum system and is used to find the probability amplitude of different quantum states. The Hamiltonian operator corresponds to the total energy of the quantum system and dictates how it changes over time [50].

The equation (5.1) captures the dynamics of the quantum system and provides insight into how the probability amplitudes linked with a quantum state change over time in computation. The operation in classical computation takes place on definite binary states

while the computation in quantum computation is based on probabilistic considerations. Therefore, the mathematical formulation of quantum superposition and quantum interference can be established using the Schrödinger equation. Such characteristics of quantum computation have made it possible to process information in a distinct way compared to classical computations [21][24].

In addition to its significance within theoretical quantum mechanics, the Schrödinger equation is fundamental to real-world applications in quantum computing. Quantum information science involves carrying out various operations on qubits, and each such operation affects the quantum state in question. The evolution of quantum states due to such operations is described by the Hamiltonian operator, which can be analyzed using the Schrödinger equation. Thus, the Schrödinger equation is very important for the creation and functioning of quantum circuits, algorithms, and communications [23][47].

Quantum image processing involves encoding information about images in quantum states and processing them using various operations. The development and processing of these states in processes such as image enhancement, image denoising, image segmentation, feature extraction, and image classification can be described based on principles from the Schrödinger equation [13][14]. The advantage that quantum computers have due to their capacity to perform operations on multiple states at once through the use of superposition makes them very useful for processing massive amounts of data and complex computations [13][14]. Consequently, the Schrödinger equation becomes a crucial mathematical resource for quantum image processing.

The solution of the time-dependent Schrödinger equation can be expressed as

$$| \psi(t)\rangle = e^{-\frac{i\hat{H}t}{\hbar}} | \psi(0)\rangle \qquad (5.2)$$

where $| \psi(0)\rangle$ stands for the initial quantum state while $| \psi(t)\rangle$ stands for the quantum state at some future time t. Equation (5.2) shows the development process of a quantum system from the initial to the final state due to the effects brought about by the Hamiltonian operator. The quantum evolution operator and dictates the form of the quantum state transformation [49].

The operator

$$U(t) = e^{-\frac{i\hat{H}t}{\hbar}} \qquad (5.3)$$

is generally known as the quantum evolution operator or the unitary operator. This is important since it ensures the probabilistic nature of quantum states is maintained through computation. All quantum operations that are considered correct should be expressed in terms of the unitary operators such that the information remains conserved through the entire computation [23]. It is this principle of unitary evolution that lies at the heart of quantum circuits and algorithms design.

Quantum algorithms make use of a series of unitary operations for manipulating the quantum state of particles and generating required computational outputs. The operation is performed via the use of quantum gates, which act upon qubits in a way analogous to the operation of logic gates in classical computation machines. Some examples of quantum gates are the Hadamard gate, Pauli-X gate, Pauli-Y gate, Pauli-Z gate, phase gate, and controlled-NOT gate. Each gate can be expressed in terms of mathematical expressions using unitary matrices based on the evolution of quantum state. Quantum circuits may be formed by combining many quantum gates to solve computational problems [30][31].

Recent advancements in quantum machine learning have made it evident that the evolution of quantum states is essential for many applications. The variational quantum circuit approach, quantum neural networks, and quantum-assisted classifiers use quantum state evolutions through quantum operators with parameters to enhance performance during learning and classification [35]. In addition, quantum image processing techniques make use of quantum states that carry information about the images undergoing a series of processes to extract features, eliminate noise, recognize patterns, and classify the images [53]. All of these are achieved based on the evolution described by the Schrödinger equation and its associated operators.

Thus, the Schrödinger equation and its corresponding solution form the theoretical and mathematical framework for quantum state evolution, quantum computing, and quantum algorithms. This equation shows the process through which quantum information evolves over time and allows for quantum gate, quantum circuit, and quantum image processing operations to be executed. It is thus among the most

significant mathematical tools used in quantum information science and is also part of designing quantum image classification systems.

5.3.1 Analysis of the Proposed Quantum Classification Architecture

Quantum algorithms can be described as series of computational steps whereby an initial quantum state is mapped to a desirable output quantum state via quantum gates and other unitary transformations. Quantum algorithms differ from classical algorithms in the sense that while classical algorithms work with bits, where a bit is either a 0 or 1, quantum algorithms use qubits for computing purposes, allowing superposition of several states at once. Such an operation allows quantum algorithms to execute tasks in parallel, giving them an edge over classical algorithms when solving particular kinds of problems [15][22]. The procedure of information processing in quantum information involves encoding of the input information into quantum states, performing a sequence of operations on these quantum states, and measuring them to yield an output result.

The execution of the quantum algorithm can be explained as the process of mapping between the input quantum state and the output quantum state. At first, the data is mapped on a number of qubits using the input quantum state notation $|\Psi_{in}\rangle$. Further, the qubits undergo a sequence of quantum gate operations. This results in the controlled manipulation of the probability amplitude and phase of the quantum state. Once all computational operations are complete, the quantum state will take the notation of the output quantum state $|\Psi_{out}\rangle$. Measurement of the quantum state gives the result of the computation in a readable format using the classical system [23][47].

The most significant features of quantum algorithms include the capability to leverage quantum superposition and quantum parallelism. Due to superposition, a qubit may simultaneously exist in several computational states, which means that quantum computers may consider several possible computational outputs concurrently. Such a feature makes quantum algorithms much more efficient at solving optimization problems, learning tasks, image processing, and pattern recognition problems [21][24]. Moreover, due to quantum interference, quantum algorithms allow amplifying useful results while reducing the significance of other outputs [49].

In addition to the ability to work with superposition states and entanglement, another

crucial element of quantum computation involves reversibility. Irreversibility is inherent in some logic operations in conventional computing, as the loss of information may occur while computing. In turn, all computations in quantum computing have to be performed reversibly. Thus, quantum circuits are built by means of unitary transformations preserving information while computations are being made. The preservation of reversibility implies that one of the main components of input data should not be lost – usually represented by the symbol in [22][50].

The quantum algorithm creates a quantum circuit of quantum gates, which converts the initial quantum state to the final quantum state using well-thought-out processes. These quantum circuits consist of several quantum gates like the Hadamard gate, Pauli-X gate, Pauli-Y gate, Pauli-Z gate, phase gate, and Controlled NOT gate. All these gates contribute towards achieving the objective of computation. Using multiple quantum gates, complicated quantum circuits may be developed that deal with optimisation, machine learning, image improvement, noise reduction, and classification of images [30][31].

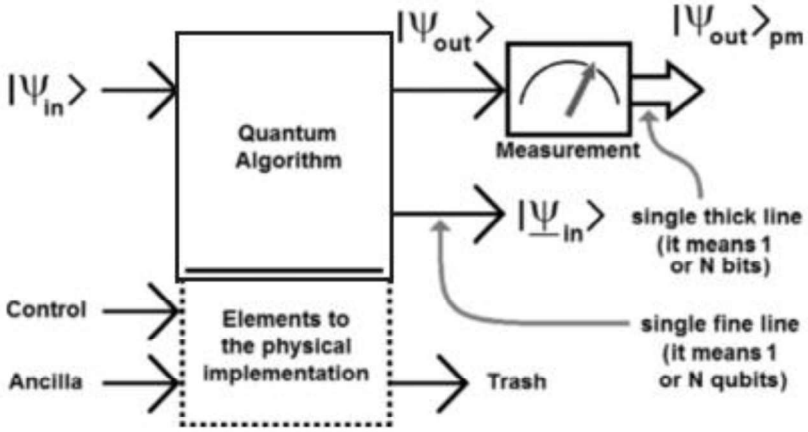


Fig. 5.1. Quantum Algorithm Measuring Elements-Based Algorithm Visualization [21][22][23]

Figure 5.1 shows the measurement-based description of quantum algorithms. This system is made up of a number of essential elements like input quantum state, quantum computation module, auxiliary quantum bits, controls, measurement modules, and output quantum state. These elements interact to accomplish the task of quantum

computation [21][22][23].

The computational phase starts with the preparation of the input states defined by $|\Psi_{in}\rangle$. Information stored in those states is going to be processed by means of quantum computing algorithms. Quantum encoding of classical images, for example, can involve coding pixels, image attributes, and even features extracted from the image into quantum states. The input state preparation process is critical to the success of the entire computation procedure, since mistakes done during this step can affect subsequent stages of computation [14][24].

The core element of the framework is the quantum algorithm block. The computations take place in this block via a series of quantum gate and unitary operations applied to the initial state. In this stage, quantum states experience changes through quantum mechanical evolution for attaining a desired computational purpose. Based on its use, the algorithm block can either enhance images, remove noise from images, extract features, optimize problems, recognize patterns, or classify images [31][35].

The ancillary qubits are referred to as ancilla qubits and constitute the supplementary quantum states used in carrying out certain intermediate computations. Though the ancillary qubits do not hold any input value directly, they are critical in carrying out reversible computation, error correction, state preparations, and temporary storage of information. Utilization of ancilla qubits makes it possible to perform quantum algorithm computations [47].

The control input is also an essential element within the framework. The input controls the performance of the quantum operations by determining the interaction of the gates with certain qubits. Control gates like the Controlled-NOT gate use the control qubits to determine whether a transformation is carried out on the target qubit. This is possible because of the control process that facilitates complex computation processes [49].

Once quantum computations are completed, then the quantum state generated is taken to the measurement block. Measurement transforms quantum information into classical information, which is understandable to the user. In the process of measurement, collapse of the quantum state occurs, and it results in the quantum state becoming one of the basis states, based on the probability amplitude of the wave function. Therefore,

measurement acts as the link between quantum computations and classical computation systems [34][47].

The end result is captured by the output quantum state which is given as $|\Psi_{out}\rangle$. The quantum states hold the information that has been produced after the quantum algorithm processes the input information. In case of an application such as image classification, the output quantum state can be a class label, image features, probability distribution, or decision variable [35][53].

The architectural design also incorporates additional outputs called trash outputs. Trash outputs correspond to intermediate quantum states formed in the course of computations. While these states do not provide any input into the resulting computation, they are essential for ensuring reversibility and carrying out quantum operations. Effective handling of trash states plays an important role in enhancing computational performance and reducing quantum resource wastage [23].

Thus, the quantum algorithm architecture using measurements depicted in Figure 5.1 is an all-inclusive approach towards understanding how information flows within a quantum computer system. The interaction between the input states, quantum logic gates, additional qubits, controls, measurements, and output states ensures effective processing of information on a quantum basis and lays the theoretical foundation for quantum image processing and image classification algorithms.

5.4 Literature Analysis and Research Gaps

The significant contributions made in relation to quantum image processing and image denoising are highlighted in Table 5.1. It becomes evident from the literature review that image restoration and denoising continue to be a subject of investigation since their impact on image quality and further image processing processes plays an essential role. With the passage of time, many methodologies have been developed for image restoration, noise reduction, feature extraction, and image improvement by utilizing traditional and quantum-based computational approaches. Initial research on image restoration involved such methods as Wiener filtering, adaptive image restoration, spectral decomposition, and signal processing techniques in order to enhance image quality without loss of useful visual information [1][2]. While such algorithms have

shown satisfactory results under certain conditions, they were known to face limitations relating to edge enhancement, efficiency, and adaptation to various types of noise.

With the advancement of image processing operations, scientists turned their attention towards sophisticated methods for denoising images using the technique of wavelet transformation, thresholding, and non-parametric estimation [3][4][5]. The use of wavelet transformation allowed for analyzing signals at various resolutions which facilitated the process of noise removal without sacrificing the structures in the image. Likewise, thresholding techniques helped in distinguishing noise from valid image data. All of these contributed significantly towards the improvement in image processing operations. But the problem of achieving a perfect balance between removing noise and maintaining image structures was still challenging.

The advent of quantum image processing brought about the ability to process image information utilizing ideas based on quantum mechanics. Scientists started exploring quantum image processing models that could effectively represent, process, and analyze images better than classical models. There have been different proposals for noise feature-based codebook algorithms, quantum distance measuring, Gaussian filter, and curvature filter for de-noising and improving images [6][7]. These methods proved to be superior in noise detection and retention of significant image features. The development of Noise Feature Codebook models resulted in more effective discrimination between image features and noise factors [6].

The subsequent advancement in quantum-motivated image processing included the utilization of geometry and curvature-based methods for edge enhancement and preservation of features. Such techniques as quantum curvature filtering, Ricci-scalar curvature filtering, Gaussian Curvature Filtering (GCF), and Sobel edge enhancement methods were developed to achieve improved results in terms of image enhancement while preserving its structure [7]. The above-mentioned techniques proved to be quite promising and showed satisfactory results in terms of preservation of image boundaries and its clarity even in the presence of noise. Moreover, there is research devoted to the use of wavelets in remote-sensing image denoising [9].

The incorporation of artificial intelligence and neural network techniques has resulted in

a marked boost in developments within the field of quantum image processing. The introduction of quantum inspired neural network paradigms such as Quantum Multilayer Self-organizing Neural Networks (QMLSONN) and Quantum Bi-directional Self-organizing Neural Networks (QBDSONN) aimed at addressing problems involved with image denoising, segmentation, and classification has been made [8][10]. These techniques employed adaptive learning algorithms in analyzing patterns present within images and reducing noise in the process efficiently. Significant enhancements in the fidelity, Peak Signal-to-Noise Ratio (PSNR) and segmentation quality when compared with traditional image processing methods have been observed.

Table 5.1. Summary of Existing Quantum Image Denoising and Processing Approaches

Author Name	Approach	Challenges	Algorithm
[1] Walter Schmitt	▪ Image restoration approach ▪ Decomposition of the spectra ▪ • Wiener filter	▪ Image quality and processing speed requirements ▪ Signal adaptive pixel superposition restoration	▪ Wiener filter approximation ▪ 2-D Infinite Impulse Response filtering ▪ Adaptive restoration method• Robust linear fitting procedure ▪ Cascade algorithms
[2] Walter Huda	▪ Quantum zero spatial frequency	▪ Invariant Wiener filter design	▪ Cascade algorithm ▪ Zero-phase filter MTFs

[3] Fujian Key, Xiamen	▪ Denoising algorithm for the trade-off between noise reduction and image preservation	▪ Difficulty in achieving accuracy while reducing differential computation	▪ Fast noise-removing algorithm
[4] M. Y. Ding	▪ Dual-tree complex wavelet transform	▪ Achieving high SNR with effective edge preservation	▪ Bi-DTCWT method ▪ Despeckling method
[5] M. Lebrun	▪ Non-parametric estimation for denoising	▪ Maintaining optical performance during image denoising	▪ Image sparsity technique ▪ Linear transform thresholding ▪ Markovian Bayesian paradigm
[6] Jingfeng Pan	▪ Measurement of the distance between quantum bit states	▪ Achieving higher visual quality and SNR	▪ Noise Feature Codebook (NFCW) ▪ Noise Feature Codebook (NFCB) ▪ Gaussian filter
[7] Esteban Soto Torres	▪ Edge enhancement using sigmoid function	▪ Binary intensity transformation around edges ▪ Threshold and slope selection	▪ Quantum curvature filter ▪ Ricci-scalar curvature filter ▪ Gaussian Curvature Filter

			(GCF) ▪ Sobel filter
[8] S. Bhattacharya	▪ Multi-layer neural network architecture• Quantum Multilayer Self-Organizing Neural Network (QMLSONN)	▪ Performance management in colour and multilevel image segmentation	▪ Rank weighted switching filter ▪ Efficient self-supervised neural network algorithm
[9] Ying Liu	▪ Noise reduction for remote sensing images	▪ Improvement of peak signal and edge preservation index	▪ Double Density Dual-Tree (DDT-DT) Interscale Wavelet Coefficient Correlation Method
[10] Debanjan Konar	▪ Real-time image denoising under Gaussian and uniform noise conditions	▪ Reducing computational complexity of denoising	▪ Quantum Bi-directional Self-Organizing Neural Network (QBDSONN) ▪ Back-propagation algorithm

As can be seen from the comparative analysis provided in Table 5.1, each of the denoising techniques has its strengths and weaknesses. Classical filters are easy to implement computationally, but at the same time, they have poor results preserving detailed structures of images with high levels of noise [1][2]. Wavelet methods

demonstrate better multi-resolution and edge-preserving properties, but the performance of these techniques depends significantly on the correct parameters choice and thresholds [3][4]. At the same time, sparsity-based and non-parametric estimations are very flexible and efficient for denoising, although they might imply higher computational load [5]. The quantum-inspired approach stands out by its capability of providing better features of image representation and adaptive processing with improved performance [6][7].

Moreover, there is also an increased focus on achieving reduction in computational complexity without compromising denoising efficiency in the literature. The modern image processing algorithms deal with large scale data sets that involve huge amounts of computation. Quantum-based approaches try to tackle the problem through concepts like quantum parallelism, quantum state representation, and effective information processing techniques. It has been observed in several researches that these concepts lead to cost reductions without compromising denoising performance [8][10]. This indicates that quantum inspired image processing approaches hold a lot of promise in future.

However, despite the considerable advancements made in this area, there are still some drawbacks associated with existing studies in this domain. Analysis of existing studies shows that distinguishing useful information from the image and determining noise parameters is one of the difficult problems that exist in this area [25]. Effectiveness of the image denoising technique greatly depends on the efficiency of identifying image parameters and distinguishing image noise. In practice, in case of high efficiency of noise removal, valuable information related to the image may be lost; on the other hand, if noise removal is not effective enough, residual noise can affect further image processing steps.

Moreover, even though the methods of image processing inspired by quantum computing have shown positive results, their practical application faces certain restrictions linked to the principles of quantum computing. The primary problem in question concerns decoherence, which occurs when the interaction between the quantum system and the environment takes place, or communication happens between the classical and quantum computing frameworks [17][39]. As a consequence of

decoherence, quantum states might be disturbed, causing the loss of quantum information. In its turn, this problem negatively impacts the performance of quantum image processing applications [16][24].

A critical limitation that exists in research is the representation, analysis, and measurement of generic qubits on the Bloch sphere [18]. This representation is beneficial in representing quantum states. However, it is challenging to measure and interpret qubit states owing to the inherent uncertainty present within quantum mechanics. Quantum state measurements involve uncertainties and changes in the state under measurement. Hence, the challenges associated with qubit representation and measurement have a direct bearing on quantum image representation, noise removal, feature extraction, and image classification.

Moreover, the growing complexities associated with quantum image processing techniques have necessitated the development of improved frameworks that can incorporate quantum computing along with machine learning and image analysis. Past studies have paid more attention to restoration and denoising of images, while little work has been done concerning problems associated with maintaining quantum states and ensuring effective quantum image classification. The above gaps suggest that additional research needs to be conducted to enable the creation of an efficient quantum image processing framework.

For this reason, according to the results of the literature review, there have been determined two research gaps. First, these are problems associated with the decoherence of the system and the preservation of the quantum information throughout computations. Second, this is the problem associated with the correct visualization of qubits in terms of the Bloch sphere. Overcoming these obstacles is critical for ensuring the efficiency and practical application of quantum computing techniques in image-processing and image-classification applications. In view of that, future studies must pay special attention to developing new techniques able to minimize decoherence effects and improve the measurement of quantum states.

5.5 Chapter Summary

This chapter illustrated the construction of a classification model based on images using

quantum theory, and offered an exhaustive explanation of the basic principles related to quantum image processing. The chapter started by discussing the basics of quantum computing, which involve the use of quantum computing in representation of images, image analysis, image denoising, and image classification systems. The basic concepts such as quantum states, qubits, superposition, entanglement, and quantum parallelism were considered as they form the basis of understanding quantum image processing. Quantum computing is advantageous compared to classical computing because it is capable of dealing with huge amount of data and executing multiple operations at once [24][25][26].

The chapter also discussed the impact of quantum image representation and quantum computation models on solving complicated image-processing problems. Some of the important image-processing processes such as image enhancement, feature extraction, image segmentation, image denoising, and image classification were discussed from the viewpoint of quantum computation. It was emphasized that during processing of image data, the factors to be considered include preservation of the image quality, retention of image features, and minimization of computational complexity. Further, the significance of quantum image models and quantum computing approaches was also addressed to create efficient image analysis systems.

A comprehensive discussion was also offered about quantum algorithms and their involvement in quantum information processing. The theory behind quantum state evolution based on Schrödinger's equation was provided as an explanation for how quantum information changes while being processed using quantum algorithms. The notions of wave functions, Hamiltonian operators, and quantum state evolution were discussed in relation to quantum computation. In addition, the connection between quantum state evolution and quantum gates was studied to reveal the importance of those ideas in quantum circuit design and quantum image processing.

This chapter also looked at the working features of quantum algorithms and their role in image processing operations. Emphasis was laid on how input quantum states were transformed to output quantum states by employing quantum computations. Issues such as reversible computing, auxiliary qubits, measurements, controls, and unitary operations were all considered in great depth. It was found that quantum algorithms offer

a robust model of image representation, extraction of features, removal of noise, and classification of images without violating any of the quantum mechanics principles.

Literature review related to quantum image processing and image denoising was conducted to assess progress made in this field of study. Different methodologies used for denoising images including those employing Wiener filtering approach, adaptive restoration approach, wavelets approach, thresholding method, noise feature codebook technique, Gaussian filtering approach, curvature filtering approach, and quantum inspired neural network architecture have been analyzed. Comparisons conducted between the two methodologies showed quantum image processing algorithms are superior to traditional image processing algorithms in terms of image quality, feature retention, denoising capability, signal-to-noise ratio, peak signal-to-noise ratio, and efficiency [9][10].

Moreover, the literature review also emphasized the importance of machine-learning-oriented and neural-network-oriented quantum computing systems in analyzing and classifying images. Models such as Quantum Multilayer Self-Organizing Neural Networks (QMLSONN), Quantum Bi-directional Self-Organizing Neural Networks (QBDSONN), and other such quantum-inspired learning approaches showed great promise with respect to enhanced results in terms of improved denoising, segmentation, and performance. From this, it can be concluded that quantum computing coupled with intelligent learning methods has much scope in the future.

In spite of remarkable advances in quantum image processing, the study of literature on this topic indicated a number of problems that were not solved yet. The first problem, which was found by analyzing the previous literature, was decoherence – it can result from interactions between the quantum system and its environment or from transferring information between quantum and classical computers. Decoherence can cause deterioration of quantum state information and, thus, can have a negative effect on quantum image-processing techniques. Another interesting problem was related to quantum-state representation, measurement, and analysis by means of the Bloch sphere model. The probability-based nature of the process results in difficulties in quantum-image processing operations.

Based on the outcomes generated by the literature analysis, there is a need for additional research to enhance quantum state stability, limit the influence of decoherence, and provide better means of measuring quantum states. In addition to this, there is also a need for reliable image classification algorithms that can combine quantum computing, image processing, and intelligent learning approaches. Overcoming these challenges is expected to contribute positively to the development of efficient quantum image processing systems.

In summary, the current chapter provided the basic theoretical and computational groundwork that is needed for the creation of image-classifying schemes using the framework of quantum theory. The ideas regarding quantum image representation, quantum algorithms, quantum state evolution, techniques for noise reduction, and gap identification in the literature together offer a solid starting point for the exploration of future quantum image processing technologies. The information presented within this chapter offers a useful foundation for the upcoming development of efficient image-classification schemes based on quantum computation.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The current study is concerned with the formulation and analysis of a quantum computing-based approach towards image representation, image processing, image classification, and the big data analysis process through harnessing the computing power provided via quantum computing concepts. The growing complexity involved in the image processing procedure, the emergence of large-scale multidimensional data sets, and the insufficiencies of traditional approaches to computations have resulted in the need for advanced computational methods that could improve computation speed, scalability, optimisation, and intelligence. These issues may be addressed via quantum computing, which makes use of the core concepts of quantum mechanics, such as superposition, entanglement, quantum interference, and quantum parallelism.

The research conducted laid down an adequate theoretical framework by exploring the basic principles of quantum computing and quantum mechanics. Some of the aspects studied included the principles of qubits, superposition, entanglement, quantum gates, quantum circuits, and quantum measurement systems. It was discovered that quantum computing provided distinct computational benefits over classical computing by virtue of processing multiple states of computation using quantum parallelism. Moreover, the potential relevance of quantum information processing to computational problems including image processing, pattern recognition, machine learning, and data analytics was explored, while activity recognition was considered as a related application area of Quantum Machine Learning rather than as an independently validated experimental component.

An extensive literature review was performed next in order to evaluate the current state of the art in the areas of quantum image processing, quantum machine learning, quantum classifiers, and quantum optimisation. It was found that considerable advancements have been made in the creation of models for quantum image representation, including “Flexible Representation of Quantum Images (FRQI), Novel Enhanced Quantum Representation (NEQR), Multi-Channel Quantum Images

(MCQI), General Quantum Image Representation (GQIR), and Quantum Representation of Multi-Wavelength Images (QRMW). Likewise, the introduction of quantum machine learning approaches, including Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), Variational Quantum Algorithms (VQA), Quantum Kernel Methods, and Quantum Particle Swarm Optimisation (QPSO)", has greatly extended the range of applications for quantum computing in intelligent data processing systems.

From the literature review conducted above, it became evident that despite the substantial progress made in the realm of quantum image processing and quantum machine learning, there still exist several critical areas of research that pose a great challenge. Indeed, the current literature mostly concentrates on isolated quantum algorithms while failing to offer an overall scheme, which would address the problem of image representation, denoising, classification, and big data analytics altogether. Moreover, the lack of quantum devices, their sensitivity to noise and decoherence, and computational complexity pose significant obstacles to the realisation of ideas discussed here.

The initial contribution made by this study is highlighted in Chapter 3, where a comparative analysis was made on the machine learning-based classification process for big data using quantum computing principles. "The performances and characteristics of different quantum machine learning methods, such as Quantum Support Vector Machine (QSVM), Quantum Enhanced Support Vector Machine (QeSVM), Twin Support Vector Machine (TWSVM), Quantum Neural Network (QNN), and Quantum Particle Swarm Optimisation (QPSO), were assessed". It was evident from the results that quantum-based machine learning provides substantial benefits in terms of the ability to extract features, classification process, optimisation process, scalability, and convergent properties as opposed to other traditional machine learning methods.

Furthermore, it was discovered that quantum features representation and quantum state encoding are efficient methods to deal with high-dimensional data sets. By applying quantum superposition and quantum parallelism, more than one computational state could be evaluated at the same time, thus decreasing the complexity of computations

and enhancing efficiency. Also, the study has shown that there is a high potential of hybrid quantum-classical learning structures in solving the restrictions connected with the modern NISQ computers. It proves that quantum learning algorithms apply to intelligent big data analytics in the future.

The second significant contribution of this study is discussed in Chapter 4, which highlights the comparative analysis of quantum-mechanics based image processing and image denoising techniques. This research work has analysed a large number of techniques for quantum image representation, quantum filtering, quantum denoising, wavelet thresholding, Gaussian Hermite filter, curvature-based filter, Wiener filter, and quantum neural networks. It has been shown in this study that quantum mechanics-based image processing is highly superior to conventional image processing in terms of image representation efficiency, parallel processing, noise reduction, and preserving image features.

Findings of the study indicate that the process of image denoising continues to be one of the most important processes in the entire image processing due to the role played by image noise in affecting feature extraction, image segmentation, pattern recognition, and classification. Quantum mechanics-based image denoising techniques have been evaluated, including quantum Boolean filters, adaptive denoising techniques, wavelet denoising, Schrödinger image restoration equations, and quantum neural networks for enhancing images. The results of the comparative analysis indicate that quantum denoising can preserve edge and texture information in images.

The experiment further established the significance of quantum image representation schemes like FRQI, NEQR, and MCQI in allowing the storage and manipulation of images in quantum computation platforms. Such schemes are important due to their ability to encode images in an efficient manner while performing complex computations. It also became evident that the use of formulations based on Schrödinger equations and wave function expressions is highly critical when working on adaptive restoration and denoising of images. It was concluded that quantum image processing techniques are quite useful in future intelligent vision computing scenarios.

The third main contribution in this research work was discussed in Chapter 5, where a

framework for image classification, based on quantum theory-based image representations, was discussed. The proposed framework utilised quantum image representations, quantum image denoising algorithms, quantum measurement and quantum neural learning techniques. The purpose of this framework was to improve the quality of the images and to maintain their properties while performing classification tasks using the power of quantum computation.

From the analysis, quantum image representation was found to be the basis of effective image classification systems since the efficiency of later stages of processing is determined by the way image data is manipulated and represented. Different kinds of quantum image representation were examined in order to ensure that images are processed in an efficient manner while ensuring image quality. Quantum image denoising methods were also considered to improve image quality before proceeding to classify images. A combination of denoising and image classification ensured that relevant image characteristics could be preserved while minimising the adverse effects of noise.

The suggested architecture was also designed to include quantum neural network features as well as quantum measurement principles to assist intelligent decision-making and pattern recognition. It was proven by the research conducted that quantum learning architecture is very effective in terms of image pattern analysis as well as extracting important information from multidimensional data sets. Moreover, the research emphasised the importance of such aspects as quantum state preparation, quantum state reconstruction, and quantum measurements for building effective image classifiers. Another significant contribution to the theoretical framework was made through the use of mathematical formulations based on the Schrödinger equation.

As evident from the general outcomes of this study, quantum computing represents a highly effective and diverse computational model for tackling modern issues related to image representation, image denoising, image classification, and big data analysis. By combining quantum image processing approaches with quantum machine learning techniques, we can achieve substantial advancements in terms of computational efficiency, optimisation capabilities, feature extraction effectiveness, classification precision, and scalability. According to the outcomes of our research, quantum-based

computational models have great prospects in developing intelligent computing systems of the future.

Though the current state-of-the-art quantum computation platforms are still limited due to hardware limitations, noise, decoherence, and limited availability of qubits, fast progress in developing quantum computing and hybrid quantum-computing platforms will result in a quick implementation of quantum intelligent systems in the near future. Hence, the scientific contributions made in this thesis form a solid theoretical base that can help to design quantum image processing, quantum machine learning, and quantum big data analytics applications in the future.

6.2 Major Findings of Research

Many significant results regarding quantum image processing, quantum image representation, quantum machine learning, image classification, and big data analytics were achieved in the current research. The results attained from the comparative studies carried out in Chapters 3, 4, and 5 contribute greatly to the understanding of the success of quantum-inspired computational models and how useful they can be for contemporary intelligent computing systems. The key results of this research work are presented below.

6.2.1 Findings Related to Quantum Image Representation

One of the critical observations made from the findings of this study is that the effectiveness of any quantum image processing scheme depends highly on the image representation model employed to encode image information into quantum states. A comparative study of the existing image representation models identified that each image representation scheme offers varying advantages, depending on the image processing function required. It was observed from the study that one of the efficient image representation models is the Flexible Representation of Quantum Images (FRQI). This model makes it possible to represent image information using quantum state probabilities. The FRQI allows efficient image storage and performs many image processing functions using quantum circuits. However, the scheme employs measurement techniques that make pixel value retrieval difficult.

Moreover, the analysis revealed that the Novel Enhanced Quantum Representation

(NEQR) model effectively addresses a number of shortcomings of FRQI because it involves the direct storage of pixel values of the grayscale image in quantum registers. NEQR increases the efficiency of image retrieval and makes the image reconstruction process easier. In addition, MCQI representation proved to be an efficient tool for colour image information handling because it involves the representation of multiple image channels at once using a quantum state. Hence, from the results of this comparative study, it can be concluded that the use of quantum image representation models can prove to be more efficient than traditional image storage techniques because they help reduce the memory space required and allow image processing in parallel by manipulating quantum states.

6.2.2 Findings Related to Quantum Image Denoising

Image denoising was recognised as one of the crucial phases involved in image processing processes due to the significant impact of image noise on image quality, accuracy of feature extraction, segmentation efficiency, object recognition, and classification ability. The comparison between quantum mechanics-based image denoising methodologies confirmed high potential for achieving improved results in terms of the quality of images and maintaining structural properties. The researchers proved that the quantum denoising method provides higher preservation of edges, textures, and details than other image denoising technologies.

Algorithms based on wavelet thresholding for denoising have been found very efficient for extracting noise components from the useful information content in images by means of multi-resolution signal decomposition. Furthermore, Gaussian Hermite filtering methods have shown great potential for suppressing noise while retaining the structure of the image. Similarly, quantum curvature filter methods have shown promising results in enhancing images and preserving edges. In addition, it has been found from the study that image restoration algorithms that make use of the Schrödinger equation form a powerful mathematical basis for adaptive image denoising. This is achieved by modelling the image information as quantum states.

Other results worth noting include that quantum neural network-supported denoising techniques allow better learning performance in recognising and suppressing

complicated noise forms. Models like Quantum Multi-Layer Self-Organising Neural Networks (QMLSONN) and similar models showed great promise in developing image reconstruction solutions using intelligence. In summary, the results suggest that denoising techniques inspired by quantum mechanisms offer better image accuracy, improved image quality, and better retention of image data.

6.2.3 Findings Related to Quantum Machine Learning

"One of the significant results of the study is recognising the importance of the role of quantum machine learning algorithms in dealing with computational issues regarding the analysis of high-dimensional data and classification schemes. The comparison of Quantum Support Vector Machine (QSVM), Quantum Enhanced Support Vector Machine (QeSVM), Twin Support Vector Machine (TWSVM), Quantum Neural Network (QNN), and Quantum Particle Swarm Optimisation (QPSO) algorithms indicates the high capabilities of quantum-based learning models to tackle difficult classification tasks".

Quantum support vector machine is efficient in classification because of the use of quantum representation in feature space. This is made possible due to the efficiency of quantum representation, which helps in achieving an efficient classification capability while reducing computational complexity. It has been shown that Quantum neural networks are quite efficient in identifying any relationship between data features and intelligent pattern recognition. The learning capacity in quantum neural networks makes it easier to extract useful information from data.

The analysis indicates that Quantum Particle Swarm Optimisation provides an alternative optimization mechanism based on quantum-inspired search principles, with its effectiveness depending on the problem formulation and evaluation setting. The application of quantum concepts to swarm intelligence systems results in better convergence and optimisation performance.

A significant discovery is the fact that the use of hybrid quantum-classical machine learning systems serves as a practical approach for implementing this technology in existing NISQ computer systems. The combination of classical optimisation with quantum computational components provides a practical hybrid approach for working

within current NISQ-related constraints; however, the resulting computational benefits depend on the specific implementation and experimental setting. Overall, the reviewed and analysed approaches indicate the potential of Quantum Machine Learning for classification and optimization tasks, while practical performance and quantum advantage require evaluation against appropriate classical baselines under reproducible experimental conditions.

6.2.4 Findings Related to Big Data Analytics

The analysis presented in Chapter 3 indicates that quantum computing and Quantum Machine Learning provide potential approaches for addressing classification and high-dimensional data-processing problems. The comparative investigations considered different quantum, quantum-inspired, and hybrid learning approaches together with classical methods. The findings highlight the relevance of quantum state encoding, feature representation, optimization, and hybrid quantum–classical processing for Big Data analysis. However, these observations should be interpreted within the computational and simulation settings used in the study and should not be considered as evidence of general quantum advantage over classical computing. Practical scalability for very large real-world datasets remains constrained by data encoding, quantum-resource availability, circuit requirements, noise, and the limitations of current quantum hardware.

Moreover, quantum state encoding systems were determined to be useful in providing a means for encoding high-dimensional feature spaces into compact forms within quantum states. Quantum state encoding allows for easier data processing and analysis without requiring many computational resources compared to traditional methods used for feature space encoding. Additionally, it was noted that quantum feature extraction processes were very important as they offered a means of identifying patterns in data that would otherwise not have been recognised using traditional methods.

“The comparative analysis of Quantum Support Vector Machines (QSVM), Quantum Enhanced Support Vector Machines (QeSVM), Twin Support Vector Machines (TWSVM), Quantum Neural Networks (QNN), and Quantum Particle Swarm Optimisation (QPSO) has highlighted the fact that quantum-based machine learning

algorithms have the potential to perform well in terms of classification, optimisation, and decision-making processes using high-dimensional data sets". Within the reported evaluation settings, the comparative analysis indicates differences in convergence behaviour, feature learning, optimization characteristics, and scalability-related measures among the investigated quantum, hybrid, and classical approaches. These observations are specific to the datasets and experimental settings considered in the study. In addition to this, the use of quantum-based optimisation approaches proved beneficial in enhancing feature selection and classification efficiency, along with minimising computational costs.

Another significant result that emerges from the study is the possibility of developing a hybrid framework for quantum and classical computations, which can be used to implement quantum machine learning algorithms in existing NISQ (Noisy Intermediate-Scale Quantum) architectures. Hybrid computational frameworks can achieve this through the combination of both classical and quantum computation techniques, retaining the benefits of quantum computation along the way.

Overall, the findings indicate the potential applicability of Quantum Machine Learning and quantum optimization techniques to Big Data-related analytical tasks. The investigated approaches provide comparative insights into classification, feature extraction, optimization, and convergence under the reported evaluation settings. However, the extent of computational improvement and scalability remains dependent on data encoding, computational resources, algorithmic design, and the limitations of current quantum simulation and hardware environments. Therefore, the results should be considered as evidence from the investigated settings rather than as a general demonstration of quantum advantage for large-scale Big Data analytics.

6.2.5 Findings Related to Quantum Image Classification Architecture

The design and evaluation of image classifier architecture based on quantum theory have resulted in some key observations in regard to the incorporation of quantum image representation, quantum denoising of images, quantum measurement techniques, and intelligent classification methods into an integrated computer architecture. As illustrated in Chapter 5, it was concluded from this research that

successful image classification does not only depend on the use of classification algorithms but is also highly influenced by the effectiveness of the image representation, pre-processing, and information extraction process.

The research identified the role played by quantum image representations as being a critical one within the process of image classification since the effectiveness of other steps relies heavily on the manner in which the image information will be encoded in quantum states. Quantum image representation models enable effective storage of information about images in a form that preserves their important features. Further, the research indicated that proper encoding of the quantum states will allow effective feature extraction and image analysis.

Quantum image representation is an essential aspect of image classification because the efficiency of the processing phases that follow is highly dependent on the way in which image information has been coded in the quantum state. The representation methods of quantum image coding have been seen to give efficient ways of storing and handling image information without losing its visual attributes. Furthermore, the results have shown that proper coding of quantum states enables efficient feature extraction.

Quantum measurement processes and quantum state reconstructions became crucially important due to the fact that the information was extracted from quantum images. It turned out that accurate reconstruction of an image, along with correct feature analysis and classification, was impossible without quantum measurement techniques. Quantum state preparations and manipulations proved to have a considerable impact on the overall efficiency of quantum image classification.

Another discovery made through this study is the importance of formulations from the Schrödinger equations as well as wave functions to image modelling, image restoration, and image classification techniques. The results show that quantum mechanical formulations form a robust basis for formulating image information and can help create an adaptive system for image processing and classification. Through this formulation, there is an opportunity for more insight into the link between quantum states and image analysis techniques.

Moreover, the utilisation of quantum neural learning theory in the proposed design showed the ability of quantum-based learning systems to recognise complicated patterns in images, efficiently extract features from the images, and make intelligent decisions. The proposed system showed a clear correlation between quantum state representation, feature extraction of quantum images, quantum learning methods, and classification. The analysis indicates that the integration of quantum image representation, quantum processing, measurement, and quantum learning concepts provides a structured basis for developing intelligent image classification architectures. However, the extent of performance improvement requires further empirical validation using reproducible experiments and suitable classical baselines.

Generally, the study has revealed that quantum theories applied to image classification offer a promising platform to incorporate aspects like image representations, denoising, feature extraction, measurement, and classification within one system. These findings indicate the potential relevance of such architectural models for future intelligent image processing applications and provide a conceptual foundation for further empirical investigation of quantum-assisted visual computing.

Concluding from the research analysis done on quantum computing, it is possible to state that quantum computing is very efficient and promising for representing images, denoising them, classifying images, and processing big data. The analysis indicates that quantum processing techniques can provide more efficient image representations, more effective denoising processes, and higher protection of the image information. At the same time, quantum machine learning algorithms proved to be more efficient in terms of feature extraction, optimisation procedures, classification abilities, and intelligent decision-making operations. All the above-mentioned indicate that using quantum image processing methods and quantum machine learning algorithms will help improve efficiency, scaling abilities, optimisation procedures, and classification results in general. However, due to the limitations of current quantum computer technology, these results remain theoretical and analytical so far.

The research presented in this thesis has resulted in several significant contributions in the areas of Quantum Computing, Quantum Machine Learning, Quantum Image Processing, and Big Data Analytics. The major contributions of the proposed research

are summarized below. These contributions represent the original work carried out during the course of this research and collectively demonstrate the development of efficient Hybrid Quantum–Classical computational frameworks for intelligent data analysis, image representation, and classification.

6.3 Contributions of Proposed Research

The novelty of the present research lies primarily in the integration and framework-level formulation of quantum computing, Quantum Machine Learning, quantum image processing, and Big Data analytics within a unified research perspective. The thesis does not claim that the individual quantum algorithms, quantum image representation techniques, denoising methods, or machine learning models reviewed in the literature are independently novel. Instead, the original contribution is identified through the formulation of a Hybrid Quantum–Classical Intelligent Computing Framework, the analytical treatment of quantum data encoding and computational complexity, and the development of a Quantum Theory-Based Image Classification Architecture. These contributions are distinguished from the literature review and comparative synthesis presented in earlier chapters. The proposed contributions are therefore presented according to the level of original framework development, analytical formulation, and conceptual architectural integration supported by the evidence available in the thesis.

The original doctoral contribution of the present thesis is primarily located at the framework, analytical, comparative, and architectural levels. The thesis does not claim the independent invention of established quantum algorithms, quantum image representation techniques, quantum denoising methods, or Quantum Machine Learning models reviewed from the literature. Instead, the original contribution lies in integrating these research components within a unified Hybrid Quantum–Classical research framework, developing a structured comparative and complexity-oriented analysis of selected quantum learning approaches, and formulating a Quantum Theory-Based Image Classification Architecture that brings together quantum image representation, denoising, measurement, feature extraction, and quantum neural learning concepts. The originality of the work is therefore distinguished from literature synthesis and is interpreted according to the framework and architectural development supported by the evidence presented in this thesis.

The major contributions of this thesis are as follows:

i. **Development of a Hybrid Quantum–Classical Intelligent Computing Framework** for improving computational efficiency and intelligent data processing in complex applications.

ii. **Development and Performance Evaluation of Quantum Machine Learning Models for Big Data Classification**, including the investigation of quantum-based learning algorithms for high-dimensional datasets.

iii. **Comprehensive Comparative Analysis of Quantum Mechanics-Based Image Processing and Denoising Algorithms** to identify their strengths, limitations, and suitability for intelligent image analysis.

iv. **Development of a Quantum Theory-Based Image Classification Architecture** for improving image representation, feature extraction, and classification performance using quantum computing principles.

v. **Identification of Research Gaps and Future Research Directions** in Quantum Computing, Quantum Machine Learning, Quantum Image Processing, and Intelligent Big Data Analytics to support further advancements in this emerging research area.

6.3.1 Contribution Towards Quantum Computing-Based Intelligent Computing Frameworks

The contribution of this research to quantum computing-based intelligent computing lies in the formulation of a unified Hybrid Quantum–Classical framework that connects quantum information processing, quantum image representation, Quantum Machine Learning, quantum optimization, and intelligent data analysis. The framework provides an integrated perspective for examining how quantum and classical computational components can be combined for data classification and image-related analytical tasks. The contribution is therefore primarily framework-oriented and analytical, rather than a claim of a newly invented quantum algorithm.

In contrast to many previous investigations, which concentrate either on a single quantum algorithm or a particular field of applications, this paper considered various

aspects associated with quantum intelligent systems, such as the quantum representation of images, image de-noising using quantum techniques, quantum machine learning classification schemes, quantum optimizations and image classification systems based on quantum theory. This helped to develop a more holistic perspective regarding the interrelationship between state representation, quantum information processing, feature extraction, intelligent learning capabilities, and decision-making capabilities.

Additionally, the research was able to establish a link between the concept of quantum state encoding, image processing algorithms, machine learning approaches, and intelligent image analysis systems. The analysis highlights how concepts such as superposition, entanglement, quantum parallelism, and quantum measurement contribute to the representation and processing of information within quantum computational frameworks. Their practical effect on classification efficiency and computation speed, however, depends on the specific algorithm, data-encoding strategy, computational resources, and implementation setting. Moreover, the study emphasised that using hybrid quantum and classical computing models is important in addressing the shortcomings in present hardware while maintaining the benefits of quantum computation.

In summary, this research contribution provides an analytical basis for further investigation of quantum-intelligent computing systems. It also provides a conceptual foundation for future research on quantum-based systems for image processing and image classification, subject to further empirical validation and advances in quantum hardware.

6.3.2 Contribution Towards Quantum Machine Learning for Big Data Analytics

The contribution of this research to Quantum Machine Learning for Big Data Analytics is based on the comparative and analytical evaluation of selected quantum and hybrid quantum–classical learning approaches for classification. The study examines models including QSVM, QeSVM, TWSVM, QNN, and QPSO with respect to their classification behaviour, optimization characteristics, convergence, computational complexity, and scalability-related considerations under the reported evaluation

settings. The contribution is therefore focused on comparative analysis and framework-level interpretation rather than claiming the invention of these individual algorithms.

The research critically analysed the features, performance, benefits, and drawbacks of the following quantum machine learning methods:

i. Quantum Support Vector Machine (QSVM)

ii. Quantum Enhanced Support Vector Machine (QeSVM)

iii. Twin Support Vector Machine (TWSVM)

iv. Quantum Neural Network (QNN)

v. Quantum Particle Swarm Optimisation (QPSO)

The comparative study allowed a comprehensive evaluation of these algorithms based on their ability to classify, extract features efficiently, optimise and converge, their complexity and scalability, as well as their suitability for processing high-dimensional feature spaces. The study brought out the advantages of the quantum-inspired learning paradigm in tackling problems related to big data analytics and intelligent decisions.

Other contributions from this research include the contribution towards the understanding of the importance of quantum state encoding, quantum feature representation, and quantum parallelism in the enhancement of efficiency in machine learning systems. The analysis indicates the possibility of using quantum computing principles for representing and processing complex datasets; however, the associated computational benefits depend on the data-encoding method, algorithm design, quantum resources, and implementation environment. The analysis also considered the role of quantum-inspired optimization methods such as QPSO in search and optimization processes, while recognizing that their effectiveness depends on the problem formulation and evaluation setting.

Contributions made through this research also include the study of whether it is possible to apply the concept of hybrid quantum/classical learning methods in the NISQ architecture. The analysis indicates that hybrid quantum–classical architectures can provide a practical implementation approach for Quantum Machine Learning

within current NISQ-related constraints, although their effectiveness remains dependent on the specific computational and hardware setting.

In conclusion, this contribution provides an analytical basis for further research in intelligent Big Data analytics, high-dimensional data classification, optimization, and quantum-based decision-support systems. The comparative analysis also helps identify the characteristics and trade-offs of different quantum and hybrid approaches for specific analytical tasks.

6.3.3 Contribution Towards Quantum Image Processing Research

The contribution of this research to Quantum Image Processing is primarily the structured comparative synthesis of existing quantum image representation and processing approaches. The study examines different quantum image representation models and processing techniques with respect to their representation mechanisms, computational requirements, scalability considerations, information extraction, and implementation limitations. This comparative analysis provides an integrated basis for understanding the suitability and limitations of existing Quantum Image Processing approaches for subsequent image analysis and classification tasks. The contribution is therefore presented as a systematic analytical synthesis rather than as the invention of the individual quantum image processing techniques reviewed.

The study reviewed various image representation approaches proposed in the scope of Quantum Image Processing, which include:

- Adaptive Representation of Quantum Images (FRQI)
- Novel Enhanced Quantum Representation (NEQR)
- Multi-Channel Quantum Image (MCQI)
- Generic Quantum Image Representation (GQIR)
- Quantum Representation of Multi-Wavelength Images (QRMW)

The comparative analysis led to the determination of the image coding techniques, memory storage capability, computational features, extraction process, scaling capabilities, and implementation problems of each image representation model. The need for efficient quantum image representation in order to support image processing operations was determined in the quantum computational environment.

One significant finding from the study is the analysis of methods used for performing quantum image processing tasks, such as image enhancement, image restoration, image denoising, image retrieval, image compression, and image classification. The analysis illustrates how quantum state representation and quantum information processing techniques can provide a framework for representing and processing image information, while the practical efficiency of such approaches depends on the underlying algorithm, encoding strategy, and available computational resources.

The research was additionally significant through the comparative analysis of various quantum-based image denoising and filtering algorithms like the wavelet thresholding approach, the Gaussian Hermite filtering method, the quantum curvature filter algorithm, the quantum Boolean image processing technique, and image restoration via the Schrödinger equations approach, among others. The research discussed their advantages and disadvantages in terms of noise removal capabilities, edge detection performance, image quality improvement, and information preservation.

Moreover, the research highlighted the importance of wave function representations, quantum state manipulations, and formulations based on the Schrödinger equation for enabling adaptive image processing tasks. The study provides analytical insights into how concepts of quantum mechanics can be incorporated into image representation and processing methods, while the resulting image-quality improvements require validation through reproducible empirical evaluation.

As a whole, this contribution helps build on the theoretical knowledge base related to quantum image processing and offers an in-depth analysis background that can be used as the basis for further research in quantum image representation, quantum image denoising, and quantum-based image processing systems. This research represents an important source of information for scientists developing new quantum image processing techniques.

6.3.4 Contribution Towards Quantum Image Denoising Methodologies

The contribution of this research to quantum image denoising lies in the comparative analysis and synthesis of quantum mechanics-based, quantum-inspired, and related hybrid denoising approaches. The study examines these approaches with respect to

noise-removal capability, preservation of image information, edge and texture characteristics, computational requirements, and implementation limitations. This analysis identifies the principal trade-offs among the reviewed denoising methods and provides a basis for understanding their applicability within quantum image processing workflows. The contribution is therefore analytical and comparative, rather than a claim of independently developing a new denoising algorithm.

One of the main contributions of the study is the assessment of these denoising techniques based on important image quality metrics, including noise reduction capability, edge preservation, structure preservation, image restoration, and computational complexity. The analysis indicates that quantum-based and quantum-inspired image denoising techniques provide different approaches for addressing noise reduction, edge preservation, structure preservation, and image restoration. Their effectiveness depends on the specific denoising method, noise characteristics, evaluation metrics, and computational setting. Therefore, their practical performance should be established through reproducible comparative experiments against appropriate baseline methods.

A second significant achievement of the research was the analysis of image representation via wave functions and adaptive image restoration techniques based on the Schrödinger equation. The analysis of wave-function representations and Schrödinger-equation-based formulations provides a mathematical basis for describing image information and investigating adaptive image-restoration and denoising approaches. The practical adaptability and effectiveness of such methods require further empirical validation under defined noise and evaluation conditions. Moreover, this analysis also revealed the increasing role of denoising using quantum neural networks, which unite learning abilities and quantum mechanics concepts.

In conclusion, the paper makes an important contribution to the body of knowledge regarding quantum image denoising techniques by giving a thorough theoretical analysis of their mechanisms. The results have the potential to be applied by researchers who intend to develop advanced and robust techniques for enhancing and restoring images, especially those related to quantum image processing technologies.

6.3.5 Contribution Towards Quantum Theory-Based Image Classification Architecture

Among the major contributions of the current study is the development of a Quantum Theory-Based Image Classification Architecture that integrates several conceptual components of quantum image processing within a unified computational framework. In particular, the proposed architecture incorporates conceptual components including quantum image representation, quantum image denoising, quantum measurement, quantum neural learning, and quantum feature extraction. The architecture provides a basis for analysing how quantum computation principles may be integrated into image classification while considering image representation and preservation of relevant image characteristics.

The study showed that the ability of an algorithm to classify images was largely dependent on how well the image data was represented before any attempt at classification was made. Therefore, the architecture presented in this paper stresses the importance of combining quantum image representation with quantum denoising techniques to facilitate proper representation of image data as well as noise mitigation. The architecture integrates image representation, denoising, feature extraction, and classification as interconnected stages; however, the effect of this integration on overall performance requires empirical validation.

Other important contributions made by this research include the investigation of approaches to quantum measurements and quantum state manipulation for effective interpretation of the information that is contained within images expressed in terms of quantum states. In addition, the importance of quantum state preparation, quantum state reconstruction, and quantum measurements was demonstrated in relation to the effective interpretation and classification of the images. Finally, the use of the mathematical formulation of the Schrödinger equation and wave functions added further theoretical background to the quantum approach to image modelling and classification.

The analysis also considers the potential role of quantum neural learning methods in image pattern analysis and classification; however, their practical capabilities require

reproducible empirical evaluation. The architecture establishes a conceptual relationship among quantum state encoding, feature extraction, quantum learning architecture, and image classification, providing a basis for further investigation. Overall, the architecture provides a theoretical and conceptual basis for further research in quantum-based image classification systems.

6.3.6 Contribution Towards Quantum Neural Learning Systems

The contribution of this research to quantum neural learning is the analytical examination of quantum neural learning concepts within the broader framework of quantum image processing and classification. The study examines the role of quantum neural learning in relation to quantum-state representation, feature extraction, pattern recognition, and image classification. This contribution is positioned as an analytical and framework-level investigation of the applicability of quantum neural learning rather than as the development of a new quantum neural network algorithm.

One of the most significant achievements of this research is that it shows the connection between quantum image representation, quantum noise reduction methods, and quantum neural network learning processes. In particular, the analysis identifies how quantum neural network concepts may be integrated with quantum image representation and information processing for pattern analysis. Another important finding of this research is the significance of using quantum neural network learning systems along with quantum state representation and information processing for improved image classification systems.

These observations provide a basis for future research on quantum-enabled pattern recognition and intelligent computing applications. With their incorporation of learning processes with quantum computing mechanisms, such quantum neural architectures could be utilised for solving problems related to the analysis of multidimensional information, feature selection, and image classification. Thus, this study provides theoretical insights into quantum neural learning systems and supports further investigation of quantum-enabled intelligent computing architectures.

6.3.7 Contribution Towards Identification of Research Gaps

The contribution of this research towards identification of research gaps is the

structured synthesis of limitations and open issues identified across Quantum Computing, Quantum Machine Learning, Quantum Image Processing, and Big Data analytics. The analysis highlights interconnected challenges related to quantum data representation and encoding, scalability and computational complexity, integration of quantum and classical computational components, and the limited practical validation of quantum-based approaches. These identified gaps provide the analytical basis for the research objectives and the framework-oriented and comparative investigations presented in the subsequent chapters.

A number of critical gaps in the available literature were identified during this research. First of all, the current state of knowledge shows a lack of frameworks that could combine quantum image processing techniques and quantum machine learning methods within one analysis framework. Most of the current literature deals with the issues of separate algorithms and computations; thus, there is no comprehensive information about how certain quantum computations can interact to develop an intelligent image processing system. Second, it has been shown that there is not enough comparative study of various quantum machine learning methods to be used for big data analytics and classification tasks. Despite the fact that a lot of quantum learning methods have already been suggested, the comparison of their characteristics, capabilities, limitations, etc., has not been thoroughly examined yet. Third, a limited number of unified solutions, which unite image representation, denoising, feature extraction, and image classification tasks, have been developed.

The identified research gaps provided the basis for the comparative analyses undertaken in the thesis and for the conceptual design of the Quantum Theory-Based Image Classification Architecture. They also inform the future research directions identified in Chapter 6. Hence, the above contribution can be considered an important foundation stone for future research work on quantum computing, quantum image processing, quantum machine learning, and intelligent visual information processing.

In summary, the current research is helpful in contributing to the advancement of knowledge about quantum image processing, quantum machine learning, image classification, and intelligent big data analysis. This research creates an analytical model that incorporates theoretical research, comparative study, and design of

quantum computation algorithms in general. The research highlights the potential of quantum-based computational models for image processing, denoising, classification, optimization, and intelligent data analysis, while recognizing the practical constraints associated with current quantum technologies. Overall, the findings made during the course of the present research serve as a basis for further studies on quantum-assisted intelligent computations.

The contributions of the present research are aligned with the research objectives formulated in Chapter 1. The development and analysis of hybrid quantum–classical approaches contribute to RO1, while the investigation of quantum data representation and encoding contributes to RO2. The comparative and complexity-oriented evaluation of classical, quantum, and hybrid approaches contributes to RO3. In addition, the quantum mechanics-based image processing and quantum theory-based image classification investigations provide complementary contributions within the broader research scope of the thesis.

6.4 Limitations of Current Work

While the current study has been successful in exploring quantum computing-based models for image representation, processing, classification, and analysis of big data, there are still some limitations that need to be taken into account. The reason for such limitations stems from the stage of development of quantum computers, their limited accessibility, as well as problems involved in implementing quantum computing algorithms. Awareness of those limitations is essential in the correct interpretation of the results of the conducted research.

6.4.1 Limitations Related to Quantum Hardware Availability

Among the most important problems existing within the current research is the issue of the lack of accessible fault-tolerant quantum computer hardware. Though great achievements have been made in the quantum computer development field, modern quantum computer chips are considered to be Noisy Intermediate-Scale Quantum (NISQ) devices. The latter are characterised by a small number of qubits and high vulnerability to noise.

The realisation of quantum image processing and quantum machine learning

algorithms on a large scale requires quantum computers that can handle sophisticated quantum circuits with many qubits. Nevertheless, present-day quantum computer architectures encounter problems due to qubit connectivity, gate accuracy, coherence duration, and computational stability. This makes most sophisticated quantum algorithms very difficult to perform in light of present-day technology. Therefore, many theoretical quantum image representation methods and machine learning algorithms developed within the framework of this research are still hypothetical and can hardly be realised on existing quantum computers as yet.

6.4.2 Limitations Due to Quantum Decoherence and Noise

The other key problem lies in quantum noise and decoherence in quantum computing. The problem is that quantum systems are very sensitive to any external interaction from their environment. Any kind of interaction of qubits with their surroundings results in decoherence, making quantum systems lose information before accomplishing any computation task. This issue makes an impact on the accuracy and efficiency of quantum algorithms. Quantum noise impacts various processes, including:

- Quality preparation of quantum states
- Encoding of quantum features
- Quality operations in quantum gates
- Quality measurements in quantum mechanics
- Quantum classification results

Despite the number of error-mitigation methods and quantum error correction procedures suggested by scholars, the implementation of these approaches is still a difficult task due to extra hardware requirements. Thus, the results that were achieved by using many of the quantum algorithms that were tested in the current study can be negatively impacted.

6.4.3 Limitations Associated with Quantum Image Representation Models

The study reviewed a number of image representation models based on quantum concepts such as FRQI, NEQR, and MCQI. While all these models are effective methods of image encoding, they still have a few weaknesses associated with them.

The image representation model that uses FRQI encodes the intensity of an image using probability amplitudes. Therefore, the image reconstruction process needs many measurements, which can lead to errors.

Moreover, the size of an image will lead to higher complexity in terms of the preparation of quantum states. The need for more quantum registers and quantum circuits increases in relation to the size of images, which leads to high computational complexities. Moreover, quantum image representation models are largely theoretical and have yet to be tested using real-world quantum computers.

6.4.4 Limitations Related to Quantum Machine Learning Models

The algorithms for quantum machine learning being considered in this research show great potential in performing classifications and optimisations. Nevertheless, a number of constraints persist in their application. Quantum algorithms need to have an efficient way of encoding data from classical computing to quantum computing states. Moreover, quantum data encoding by itself is computationally intensive, especially in large-scale data.

Likewise, running quantum machine learning algorithms necessitates the repetitive running of quantum circuits and processes for optimisation. Larger datasets can lead to greater computation costs, especially when computing within hybrid quantum-classical settings. Finally, the comparison process done within this study mainly centred on the properties of the algorithms rather than their practical applications. The performance of these algorithms in actual faulty quantum computers is an open question because of the scarcity of available devices.

6.4.5 Limitations Related to Big Data Processing

The purpose of Chapter 3 is to explore quantum machine learning approaches for the classification of big data. Despite all of the advantages quantum computers offer theoretically for dealing with big data, certain practical difficulties still persist. Today's quantum machines lack the adequate computational capability required to perform computations with such an amount of information as extremely large real-life databases.

However, the efficient transfer of a large amount of classical information to quantum

states is another obstacle to be overcome. The efficient handling of quantum data and quantum memory is still an area being researched extensively and poses restrictions on implementing quantum analytics in the real world.

6.4.6 Limitations of the Proposed Image Classification Framework

Though the image classification framework based on the theory of quantum computing represents an integrated concept to handle image representations, denoising, and classification, certain limitations have been identified as follows:

The effectiveness of the proposed scheme is highly dependent on:

- Correctness of quantum image representation.
- Image denoising quality.
- Accuracy of quantum measurements.
- Quantum state stability during computations.

The error introduced during image encoding, processing at the quantum level, or during measurements might affect the accuracy of classifications. Moreover, the framework was mainly developed using a theoretical approach. The large-scale deployment of the framework in a real-time system utilising physical quantum computing resources is beyond the scope of this study.

6.4.7 Limitations of Hybrid Quantum–Classical Systems

For current research, however, quantum/classical computation methods have been widely used due to the impracticality of purely quantum computations at this time. While these hybrid models provide greater adaptability and computational robustness, they also pose certain problems, including:

- Extra communication needs between quantum and classical computers.
- Added computational delay.
- Difficulties in optimisation methods.
- Necessity of pre-processing and post-processing by classical computers.

This may compromise some of the computational benefits of purely quantum computers, theoretically possible.

To conclude, this study highlights the vast possibilities that can be achieved using quantum computing when it comes to image representation, image denoising, image classification, and big data processing. Nevertheless, the implementation is hindered by various constraints, such as a lack of quantum computers, decoherence, vulnerability to noise, scalability issues, difficulties in quantum state preparation, and limitations of NISQ machines.

Nonetheless, the results outlined in this thesis can form a solid ground for further research and development of quantum imaging processing techniques and quantum machine learning systems. The more we progress towards developing quantum computing technology, the more likely it is that we will overcome some of the challenges mentioned above, thus enabling the practical implementation of intelligent quantum computing systems.

6.5 Future Scope

Even though considerable progress has been made in the areas of quantum image processing, quantum machine learning, and quantum-enabled data analysis, there are still many unresolved issues in this area of research. The fast pace at which new developments occur in quantum computing, along with advances in hardware platforms are anticipated to open up new avenues toward enhancing the efficiency of computing, image analysis capabilities, and intelligent decision-making applications. From the results presented in this research, it can be seen that quantum computing holds significant promise in providing solutions to computationally challenging tasks involving image representation, denoising, image classification, and big data analysis. However, further investigation is necessary to realise this theoretical knowledge in real-life intelligent computing applications. These future research directions are elaborated upon in the subsequent sections.

6.5.1 Real-Time Quantum Image Processing

One of the promising future directions of research is the design of real-time quantum image processing systems. The studies presented in Chapters 4 and 5 have shown the validity and efficiency of quantum image representation models and quantum image denoising algorithms for the processing of images. However, existing quantum image

processing techniques are mostly aimed at static image datasets and offline processing environments. It is possible to direct future research efforts towards designing a quantum image processing model that can be applied in real-time image processing tasks. These include processing a continuous stream of images in dynamic visual environments. The potential areas of such applications could be surveillance systems, autonomous navigation, and intelligent robots.

Real-time Quantum Image Processing would involve improvements in many areas, such as quantum image encoding methods, quantum memories, quantum measurements, and computation itself. New techniques for representing images in the quantum regime that facilitate rapid quantum state encoding of image data would gain prominence.

In addition, advances that are anticipated in quantum computing hardware could make possible the real-time implementation of quantum filtering, quantum denoising, and quantum image enhancement processes. The application of quantum image processing in conjunction with intelligent visual analysis systems can result in enhanced performance for object recognition, feature extraction, pattern recognition, and image classification.

Another field that could be investigated in the future is developing adaptive algorithms for quantum image processing, which adapt to changes in image and environment parameters. Adaptive algorithms can provide more flexibility, reliability, and accuracy compared to fixed algorithms, yet remain computationally efficient.

6.5.2 Quantum Deep Learning Models

The current study examined several approaches to quantum machine learning, such as QSVM, QeSVM, TWSVM, QNN, and QPSO learning paradigms. While all the mentioned methods proved to have good potential capabilities, future studies may consider more sophisticated quantum deep learning models able to perform image analysis and classification for more complicated problems. Quantum deep learning is considered a new scientific field that integrates the ability of learning by means of deep neural networks and quantum computing principles. Future research may be directed at designing deeper quantum neural networks able to learn extremely complex features

from images.

The special focus might be given to the development of multi-layered quantum neural learning structures for image classification and pattern recognition tasks. Using several quantum hidden layers could increase the efficiency of feature extraction and lead to better results when working with large image sets. The other possible line of research could deal with combining quantum image representations like FRQI, NEQR, and MCQI with some complex quantum neural learning methods. This approach could lead to the creation of a full-fledged quantum image classification framework, which would be able to work with images from representation to classification.

Additionally, future studies may also examine methods that optimise the training of quantum neural networks amidst noisy quantum systems. Given the vulnerability of contemporary NISQ hardware to decoherence and quantum noise, it becomes necessary for robust learning algorithms to be developed and used in order to maintain efficiency even in less-than-ideal computing environments. The evolution of scalable quantum deep learning models would greatly benefit the future applications of image classification and intelligent decision-making.

6.5.3 Quantum Cloud Computing

The application of quantum computing solutions is constrained by the scarcity of quantum hardware available. As such, quantum cloud computing can become an important factor for further development in quantum image processing and quantum machine learning in the future. The implementation of quantum cloud computing provides access to quantum computing power remotely, using cloud computing facilities. The area for potential research in the future can include the investigation of methods of quantum image processing solutions and quantum machine learning techniques in cloud computing facilities.

Combining cloud computing with quantum image processing could help carry out large-scale image processing tasks without the need for quantum computing systems on-site at the computation facility. It could be possible to run complex circuits, carry out image processing, and even test machine learning algorithms from quantum computing services on the cloud. In addition, this could make it easy for researchers

to collaborate in a cloud environment, processing huge image databases and machine learning algorithms from quantum computing resources available online.

In addition, future research might explore problems such as quantum resource management, quantum circuit optimisation, quantum cloud image storage, and a distributed quantum machine learning framework. An efficient quantum cloud infrastructure can potentially pave the way for the widespread acceptance of quantum computation technology in intelligent computing systems.

6.5.4 Healthcare Big Data Analytics

The results obtained from Chapter 3 showed that quantum algorithms were successful in the process of classification and analysing high-dimensional data sets. These results indicated potential benefits from using quantum computing methods in the environment of big data analytics in the healthcare industry. Healthcare providers produce vast amounts of structured and unstructured data, such as medical history, diagnostic images, sensor readings, and patients' monitoring data. Analysis of such data sets frequently requires sophisticated computational algorithms.

Future research could focus on exploring the usage of quantum machine learning techniques like QSVM, QNN, and QPSO in classifying medical data, predicting diseases, assessing risks associated with healthcare, and creating intelligent diagnostic tools. Quantum image processing techniques could be incorporated into future research to be used alongside medical imaging systems. Future frameworks could leverage quantum image representation and quantum denoising algorithms in processing medical images, along with quantum machine learning algorithms for classification and diagnostics.

Quantum machine learning algorithms like QSVM, QNN, and QPSO could be explored in future studies for use in the fields of medical classification, disease prediction, risk analysis in health care, and intelligent decision-making support systems. Special attention may be paid to incorporating quantum image processing approaches into medical imaging systems. The future framework would make use of quantum image representations and quantum denoising approaches for analysing medical images, along with quantum machine learning approaches for classification

purposes.

6.5.5 Quantum Cybersecurity Applications

With the advent of digital communications networks and smart information systems, there has been an increase in the significance of having secure means of data processing and information protection. There is substantial potential in quantum computing that can have a future impact on cybersecurity technologies. Future studies might look at how quantum computing can be used in detecting abnormalities, analysing threats, recognising patterns, and classifying security data sets. Quantum computing has an edge when it comes to processing large feature spaces and recognising anomalies and patterns within them.

Quantum image processing approaches could help enhance image transfer security, image encryption, image authentication, and digital watermarking as well. New advancements in quantum image representation approaches could make it possible for more secure image security systems that can withstand sophisticated computing attacks. Further, quantum optimisation methods might be utilised in creating more efficient security mechanisms and intelligent surveillance systems. In the future, studies could consider how quantum information processing could be integrated into the next generation of cybersecurity architectures.

6.5.6 IBM Qiskit Hardware Implementation

In the current study, a lot of attention was paid to the theoretical and analytical study of quantum image processing techniques and quantum machine learning approaches. But their practical implementation is also among the main directions for further studies. The next research will be dedicated to the practical realisation of the suggested approaches utilizing real quantum computers on the basis of IBM Qiskit architecture. This will allow estimating the practical applicability of quantum image representations, quantum denoising, quantum classification, and quantum machine learning algorithms under real hardware limitations. In particular, hardware implementation will make it possible to investigate such important performance parameters as:

- Quantum gates accuracy

- Decoherence phenomena
- Quantum noise features
- Qubits usage efficiency
- Circuit depth
- Scalability

In addition, future research can also be conducted to determine any differences between the results obtained using simulations and the actual performance of hardware, which can help develop better techniques for managing errors. Furthermore, implementing our proposed algorithm on IBM Quantum hardware can help us understand the potential capabilities and challenges of present-day NISQ computers. This can be extremely useful for developing quantum image processing and machine learning applications for fault-tolerant quantum computers in the future.

The implementation of these methods using IBM Qiskit will prove to be a crucial milestone in creating practical implementations of quantum-assisted intelligent computing systems that can tackle image processing and data analysis problems encountered in the real world.

6.6 Summary

This chapter summarises the overall results, findings, contributions, limitations, and future research directions in regard to the framework for image representation, image processing, image classification, and big data analysis based on the principles of quantum mechanics. This chapter has summarised all the results gained from the whole research and emphasised the importance of quantum computing as an emerging paradigm in solving problems related to the processing of high-dimensional data and intelligent information processing.

The research was started with an in-depth analysis of the basic elements and principles of quantum computing and quantum mechanics, which form the core elements of quantum information processing systems. It was determined that the elements such as qubits, superposition, entanglement, quantum gates, quantum circuitry, and quantum parallelism play a critical role in facilitating computation processes that exceed those possible within traditional computing systems. Based on the theories developed in the

initial phases of the research, advanced uses of quantum computing were analysed in image processing and machine learning areas.

A review of the existing body of knowledge was performed to assess the current state of the art in quantum image processing, quantum machine learning algorithms, quantum classifiers, and quantum optimisation techniques. In the course of this study, various image representation schemes such as FRQI, NEQR, MCQI, GQIR, and QRMW were noted, which made significant contributions to quantum image processing research. Likewise, in the review of quantum machine learning algorithms, the increasing relevance of QSVM, QNN, QPSO, and quantum/classical learning schemes to solve classification and optimisation problems was noted. The findings from the literature review provided evidence of major research gaps in relation to the integration of the framework of image representation, image processing, image classification, and big data analytics, thereby providing the rationale for the current research.

Subsequently, the study analysed the implementation of quantum machine learning algorithms for the purposes of classifying large datasets. A comparative study of various methods, including QSVM, QeSVM, TWSVM, QNN, and QPSO, proved the usefulness of quantum computation techniques in enhancing feature selection, optimisation, convergence, classification accuracy, and scalability. The results proved that quantum machine learning offers an effective tool for solving issues related to high-dimensional data analysis and intelligent decision-making systems.

Moreover, the research offered a comparative study of the various quantum mechanics-based image processing and denoising techniques. Different quantum image representation models, filtering methods, image denoising techniques, wavelet thresholding strategies, Gaussian Hermite filters, Schrodinger equation-based image restoration techniques, and quantum neural networks were analysed. Through this analysis, it was concluded that quantum image processing techniques exhibit high potential for image enhancement, image de-noising, edge detection, and improving image quality. It was also revealed through the study that image representation is a crucial factor for effective image processing procedures.

Another important result from this work is the formulation and investigation of an image classification model based on quantum theories, which includes image representation, noise reduction, quantum measurement techniques, and quantum neural network learning techniques. The new architecture enabled a common platform to analyse and classify images while retaining essential features of the images and improving efficiency. In this research, it is evident that the combination of quantum image processing techniques and quantum machine learning approaches can improve the capability of image classification systems. In addition, the use of equations based on Schrödinger formulation techniques improved the theoretical foundation of the proposed architecture.

In addition to that, the chapter discussed the important results obtained from the study. It was found out that quantum image representation models are capable of efficiently encoding the information contained in images as quantum states and that quantum denoising is able to enhance the image restoration process, along with preserving its features. Likewise, quantum machine learning algorithms have shown better prospects in terms of processing high-dimensional data and carrying out intelligent classifications. The image classification model that has been introduced created the connection between quantum image representations, denoising, feature extraction, and classification.

While the results have been encouraging, there were a number of shortcomings recognised regarding the present state of quantum computing devices. Issues arising from NISQ computing devices, quantum decoherence, quantum noise, scarcity of qubits, and the difficulty of preparing a quantum state, among others, still pose a serious impediment towards the widespread implementation of quantum-assisted computing systems. However, these shortcomings are mostly technical and can be expected to fade away in future developments in quantum hardware and software platforms.

Lastly, several possible future research areas were discussed, which include quantum image processing in real-time, quantum deep learning networks, quantum cloud computing systems, healthcare big data analytics using quantum computers, quantum computing for cybersecurity applications, and implementation of the theoretical model

on the IBM Qiskit quantum computer platform. These research future directions serve as guidelines to further extend the existing research work and turn theoretical quantum computing models into actual intelligent systems.

Conclusively, the research findings indicate that quantum computing provides a potential framework for investigating image representation, processing, classification, and Big Data analytics, while further empirical validation is required to establish practical performance benefits. The combination of quantum image processing techniques together with the principles of quantum machine learning is indeed a promising path towards developing futuristic intelligent computing systems that are characterised by increased computational efficiency, scalability, optimisation capacity, and analytical ability. It is therefore safe to conclude that the current research findings have greatly contributed to the existing literature on quantum computing.

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CHAPTER 5- REFERENCES

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LIST OF PUBLICATIONS RELATED TO THE THESIS

Papers Published / Accepted for Publication

Journal Papers

1. **Barkha Singh**, S. Indu, and Sudipta Majumdar, "Comparative Analysis of Intrusion Detection Models Using Quantum Machine Learning Techniques," *Circuits, Systems, and Signal Processing*, Springer, 2025. DOI: 10.1007/s00034-025-03256-w. (Published).
2. **Barkha Singh**, S. Indu, and Sudipta Majumdar, "Comparison of Machine Learning Algorithms for Classification of Big Data Sets," *Theoretical Computer Science*, Vol. 1024, Article 114938, Elsevier, 2025. DOI: 10.1016/j.tcs.2024.114938. (Published).
3. **Barkha Singh**, Sudipta Majumdar, and Sreedevi Indu, "A Systematic Comparative Analysis of Quantum Mechanics-Based Image Processing and Denoising Algorithms," *Quantum Studies: Mathematics and Foundations*, Springer, 2024. DOI: 10.1007/s40509-024-00330-x. (Published).

Conference Papers

4. **Barkha Singh**, S. Indu, and Sudipta Majumdar, "Development of a Classification Architecture for Images Represented Using Quantum Theory," *2023 3rd International Conference on Artificial Intelligence and Signal Processing (AISP)*, IEEE, 2023. DOI: 10.1109/AISP57993.2023.10134825. (Published).
5. **Barkha Singh**, S. Indu, and Sudipta Majumdar, "Quantum Computing-based Image Representation with IBM QISKIT Libraries," in *Intelligent Data Analytics, IoT and Blockchain*, Chapter 9, Springer Nature. DOI: 10.1201/9781003371380-9. (Published).

EXTENDED RESEARCH OUTPUTS

Patent

1. **Barkha Singh**, S. Indu, and Sudipta Majumdar *Quantum machine learning based Intrusion Detection system and method for Big Data Cyber Security Analytics*-Indian Patent (Grant-In-Progress)

Conference / Workshop Presentations

1. Presentation on **Quantum Computing-Based Image Representation and Classification** at IEEE AISP 2023.
2. Presentation on **Quantum Machine Learning Techniques for Big Data Analytics and Intrusion Detection** at relevant national/international conferences.

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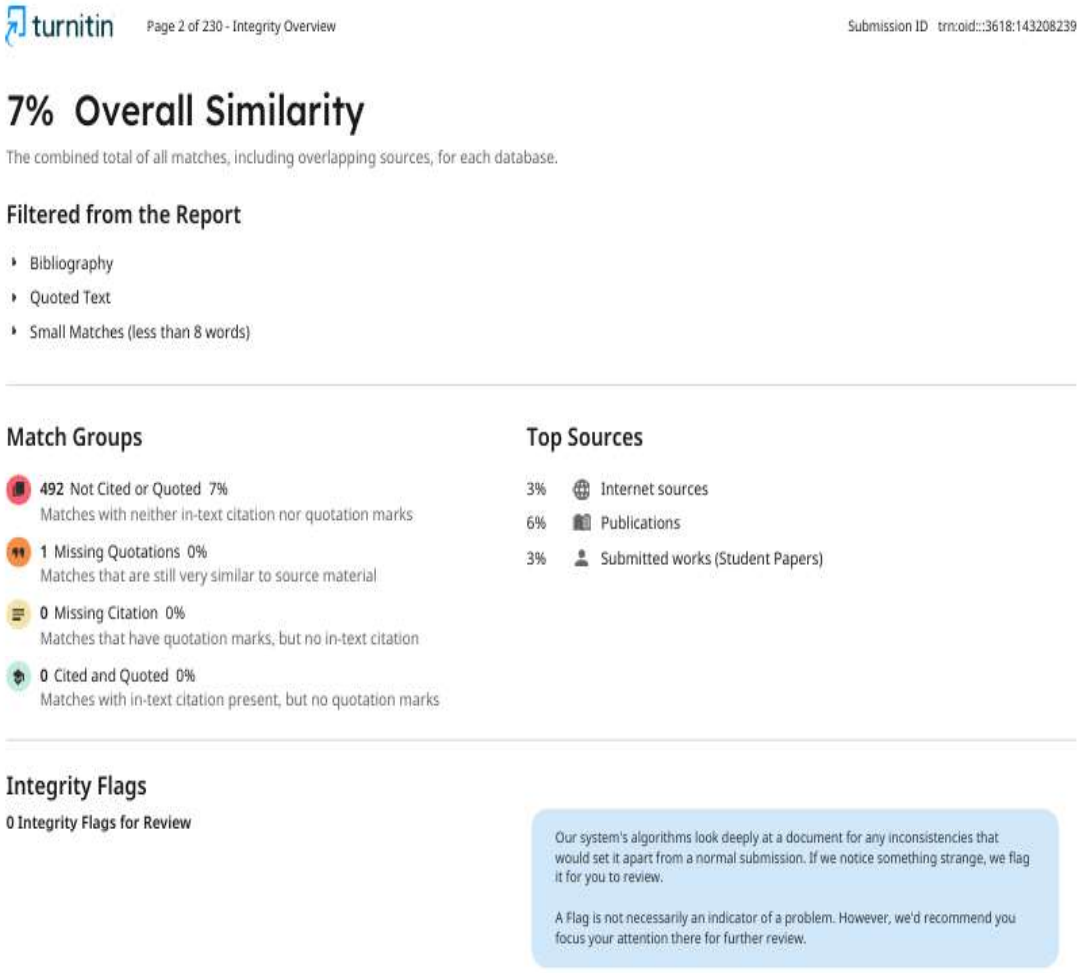

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