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CHAPTER – 1

INTRODUCTION

This chapter introduces the concept of Digital Twin (DT) technology in healthcare, focusing on its applications, challenges, and potential advancements. The objectives of the research work are highlighted. Chapter-wise thesis coverage is summarized at the end of the chapter.

Digital Twin (DT) technology has revolutionized various industries by creating virtual replicas of physical systems, enabling real-time monitoring, simulation, and optimization. Originally developed by NASA for spacecraft diagnostics, DT has evolved with advancements in AI, IoT, cloud computing, and big data analytics, significantly impacting healthcare. Traditional healthcare models rely on reactive, symptom-based interventions, often leading to delays and inefficiencies. DT technology shifts this paradigm by enabling predictive analytics, personalized treatment, and real-time decision-making. By continuously integrating patient data, DTs facilitate early disease detection, optimize medical workflows, and enhance hospital resource allocation. In complex medical fields like oncology, cardiology, and neurology, DTs help simulate treatment outcomes, improving precision and risk assessment. Additionally, DT-driven hospital management enhances operational efficiency by predicting equipment failures, managing patient flow, and optimizing staff deployment. The integration of AI, IoT, blockchain, and extended reality (XR) further strengthens DT applications. AI-powered models enable automated anomaly detection and predictive diagnostics, while IoT-connected devices provide continuous real-time health monitoring. Cloud computing enhances data storage and processing, whereas blockchain ensures secure medical records. XR technologies such as AR and VR improve medical training, surgical planning, and telemedicine. However, the increasing digitization of healthcare introduces cybersecurity challenges, including data breaches, ransomware attacks, and unauthorized access. Implementing encryption techniques, blockchain security, and regulatory compliance frameworks such as HIPAA and GDPR is essential for data protection. Beyond diagnostics and treatment, DT technology plays a crucial role in infectious disease detection and epidemic management by automating disease detection, improving diagnostic accuracy, and enabling remote monitoring. During the COVID-19 pandemic, AI-powered DT models helped predict disease progression, optimize hospital resources, and improve patient outcomes. The convergence of DT technology with the metaverse offers additional possibilities for digital healthcare, including immersive telemedicine applications, real-time disease modeling, and interactive medical training.

Hospitals can leverage DT-metaverse frameworks for resource optimization, predictive maintenance, and enhanced patient management. However, security concerns necessitate blockchain-based secure transactions, zero-trust security models, and AI-driven intrusion detection. Strengthening IoT security through advanced encryption, secure device authentication, and periodic security audits is crucial, as the increasing use of smart medical devices like pacemakers and infusion pumps exposes healthcare networks to cyber threats. AI-driven intrusion detection mechanisms further enhance DT-powered healthcare security by identifying and mitigating threats in real-time. Despite its transformative potential, DT technology faces challenges such as scalability, interoperability, computational complexity, and data security. Addressing these requires standardized data models, blockchain-based data integrity frameworks, and AI-driven security protocols. Establishing a unified and secure DT framework will enhance predictive diagnostics, automated healthcare interventions, and personalized treatment strategies, ultimately improving healthcare efficiency and accessibility. The rapid adoption of DT technology is bridging the gap between traditional healthcare models and next-generation intelligent systems, positioning DT as a transformative force in modern healthcare. By integrating AI, blockchain, and IoT, DT enables real-time disease monitoring, predictive diagnostics, and personalized treatment, driving the future of intelligent, data-driven healthcare systems. Continued interdisciplinary collaboration and technological advancements will be key to unlocking its full potential and shaping the future of digital healthcare with enhanced efficiency, security, and precision.

1.1 Scope of the Thesis: Digital Twin in Healthcare

This thesis investigates the role of Digital Twin (DT) technology in healthcare, focusing on its ability to enhance predictive analytics, personalized treatment, and real-time decision-making. While DT applications in industrial settings are well-established, their integration into complex, data-sensitive environments like healthcare remains an evolving field that requires further exploration. This study aims to bridge this gap by examining how DT frameworks can be designed, secured, and optimized to meet the demands of modern healthcare infrastructure. The primary scope of this research includes the development of a comprehensive DT framework incorporating key emerging technologies such as AI-driven predictive modeling, IoT-enabled data collection, blockchain-based security solutions, and edge computing for real-time healthcare applications. This study focuses on how AI and machine learning (ML) can improve diagnostic accuracy, predict disease progression, and enhance clinical decision-making. Furthermore, it investigates the role of blockchain technology in securing patient data, ensuring interoperability, and establishing decentralized, tamper-proof medical records for improved data integrity and privacy. The feasibility of integrating DTs into existing hospital management systems, clinical workflows, and telemedicine platforms will also be explored. A significant aspect of this research is the evaluation of interoperability challenges in DT-based healthcare systems. Current medical infrastructures rely on fragmented data ecosystems, where electronic health records (EHRs), IoT medical devices, and AI-driven analytics operate in silos. This study examines methods to standardize data integration across diverse healthcare platforms, enabling seamless communication and collaboration between digital twins and traditional healthcare systems. Additionally, regulatory and ethical considerations surrounding the adoption of DTs will be analyzed, particularly in compliance with global healthcare data protection laws such as HIPAA, GDPR, and country-specific medical data governance policies.

Beyond conventional medical applications, this thesis explores how DTs can be integrated with emerging digital environments such as the Metaverse. The potential of virtual healthcare ecosystems, immersive medical training, and AI-driven simulations for disease modeling and treatment planning will be assessed. This study will investigate how extended reality (XR) technologies—augmented reality (AR) and virtual reality (VR)—can improve surgical precision, physician training, and remote patient interactions. The feasibility of using digital twins as interactive healthcare avatars for real-time patient engagement will also be discussed. Another critical area within the scope of this thesis is cybersecurity and risk mitigation in DT-powered healthcare systems. With the increasing reliance on IoT-enabled medical devices, cloud storage, and AI-driven automation, the risk of data breaches, cyberattacks, and system vulnerabilities is heightened. This research will propose advanced security models, including AI-powered intrusion detection systems, multi-factor authentication mechanisms, and blockchain-based access control frameworks to safeguard patient data and healthcare operations. The study will also analyze how genetic algorithms and federated learning can optimize threat detection and enhance system resilience against cyber threats. The economic and technical feasibility of large-scale DT implementation will also be a focus, with an analysis of infrastructure requirements, cost-benefit considerations, and potential barriers to adoption in different healthcare settings. The research will incorporate case studies from various medical disciplines, including cardiology, oncology, and intensive care, demonstrating how DTs can be leveraged for remote patient monitoring, early disease detection, and optimized treatment strategies. This thesis does not aim to develop a fully functional DT prototype but will instead propose a conceptual and technical framework based on empirical research, computational modeling, and case study analysis. While the study explores DT applications in predictive diagnostics, personalized medicine, and hospital management, it does not delve into detailed hardware specifications or the financial modeling of DT adoption across different healthcare economies. Instead, the research prioritizes technical feasibility, system security, and integration challenges as key areas of exploration. By addressing these critical factors, this thesis contributes to the advancement of next-generation digital healthcare solutions, providing a structured, scalable, and secure DT framework. The findings aim to serve as a foundation for future research, policy development, and real-world DT implementations in healthcare, ultimately supporting data-driven decision-making, improved patient outcomes, and more efficient medical systems.

1.2 Research Gaps and Motivation for Research Work

Despite the transformative potential of Digital Twin (DT) technology in healthcare, several challenges hinder its widespread adoption and efficiency. The key research gaps include:

1. Healthcare DTs require vast computational resources, while traditional infrastructures struggle with high-dimensional models and bandwidth limitations. The early adoption of edge computing and cloud-based DT solutions further impacts scalability.
2. DT models rely on heterogeneous data sources, leading to inconsistencies in prediction accuracy. AI-driven DT models often exhibit biases due to limited training datasets, and the lack of standardization in data collection affects disease detection and treatment recommendations.
3. DT systems store sensitive patient data, making them vulnerable to cyber threats. Existing encryption and access control measures are inadequate, while unclear regulatory frameworks complicate secure deployment in healthcare settings.
4. Diverse healthcare providers use different EHR formats and imaging protocols, causing integration challenges. Standardized data models like FHIR and HL7 have been introduced but are inconsistently adopted, limiting seamless cross-platform communication.
5. Many healthcare institutions rely on outdated IT systems that are incompatible with real-time DT applications. High-frequency data exchange limitations and vendor-specific cloud-based DT solutions create inefficiencies in data transfer.

To address these challenges, a unified DT framework incorporating AI-driven predictive modeling, blockchain security, real-time IoT integration, and edge computing must be

developed to enhance healthcare efficiency, secure data transmission, and improve patient
137 outcomes. The increasing adoption of DT technology is driven by the urgent need for predictive and secure medical systems, enabling real-time data integration, outbreak detection, and decentralized healthcare. This study aims to advance DT as a cornerstone of modern, efficient, and data-driven healthcare systems.

1.3 Problem Statement

The integration of Digital Twin (DT) technology in healthcare can revolutionize patient monitoring, predictive diagnostics, and treatment planning. However, its widespread adoption is hindered by challenges related to scalability, data accuracy, security vulnerabilities, interoperability, and integration with existing healthcare infrastructure. Current healthcare DT models require high computational resources, face inconsistencies in data reliability, and lack standardized frameworks for secure and seamless data exchange. Furthermore, the absence of unified protocols limits cross-platform communication, reducing the effectiveness of real-time healthcare applications. To overcome these limitations, a comprehensive DT framework must be developed, incorporating AI-driven predictive modeling, blockchain-based security, real-time IoT integration, and edge computing. This study aims to address these gaps by designing a scalable, secure, and interoperable DT system that enhances healthcare efficiency, ensures data integrity, and improves patient outcomes.

1.3.1 Research Objectives

OBJECTIVE 1: To develop a Digital Twin Healthcare (DTH) model.

27 **OBJECTIVE 2:** To design a framework for data transmission between the physical system and the digital twin system.

OBJECTIVE 3: To evaluate the performance of the existing and proposed digital twin model.

1.4 Contributions in the Thesis

89 In this thesis, we focus on the development of a Digital Twin Healthcare (DTH) framework that integrates AI, IoT, and blockchain for real-time patient monitoring, predictive disease diagnosis, and secure medical data transmission. This research addresses key limitations of traditional healthcare systems, including inaccurate diagnostics, lack of real-time monitoring, and cybersecurity threats. The contributions of this thesis are structured according to the three research objectives as discussed below.

(I) <u>OBJECTIVE 1:</u> *To develop a Digital Twin Healthcare (DTH) model*

We proposed a novel AI-powered Digital Twin Healthcare (DTH) model that enables real-time patient monitoring and AI-driven diagnostics. The model integrates IoT sensors, deep learning-based medical imaging analysis, and cloud-based Digital Twin simulations to enhance disease detection accuracy and personalized healthcare recommendations. To demonstrate the effectiveness of the proposed model, two AI-driven Digital Twin applications were developed:

23

- CervixNet for Cervical Cancer Detection: A CNN-based deep learning model designed for early cervical cancer diagnosis using histopathological images. The model achieved 98.91% accuracy, outperforming traditional CNN architectures.
- MxSLDNet for Monkeypox Lesion Detection: A lightweight AI model optimized for monkeypox detection, reducing computational costs while maintaining high diagnostic accuracy compared to DenseNet-121 and ResNet-101.

The proposed DTH framework significantly improves healthcare decision-making by enabling continuous patient monitoring, AI-powered disease progression analysis, and real-time treatment adjustments.

110

(II) <u>OBJECTIVE 2:</u> *To design a framework for data transmission between the physical system and the digital twin system*

To ensure secure, real-time data exchange in Digital Twin Healthcare, we developed a Blockchain-ECC Hybrid Security Model, providing high-level data integrity and confidentiality. The key components of this framework include:

- Blockchain-Based Medical Data Storage: Patient health records are stored on a decentralized blockchain network, ensuring tamper-proof and immutable data storage.
- Elliptic Curve Cryptography (ECC) for IoT Security: ECC provides lightweight encryption for medical IoT devices, reducing the risk of data breaches while maintaining high-speed processing.
- Intrusion Detection System (IDS) using GAO-RF Algorithm: A Genetic Algorithm Optimized Random Forest (GAO-RF) model is proposed for detecting cyber threats in IoT healthcare networks.

By integrating blockchain security and AI-driven anomaly detection, the proposed secure Digital Twin framework prevents unauthorized access, data tampering, and cyberattacks, making real-time patient monitoring and healthcare data transmission more reliable.

(III) OBJECTIVE 3: *To evaluate the performance of the existing and proposed digital twin model*

The proposed AI-driven Digital Twin model was rigorously evaluated against state-of-the-art deep learning architectures to assess its diagnostic accuracy, computational efficiency, and security performance. The findings include:

- Higher Diagnostic Accuracy: The CervixNet model achieved 98.91% accuracy, outperforming traditional CNN-based models in cervical cancer detection.
- Computational Efficiency: The MxSLDNet model demonstrated higher accuracy with lower computational costs, reducing storage and processing requirements compared to DenseNet-121 and ResNet-101.
- Enhanced Security Performance: The Blockchain-ECC security framework significantly improved data privacy and cyber resilience, outperforming conventional cloud-based healthcare systems in security assessments.

These results confirm that the proposed Digital Twin Healthcare model is more scalable, accurate, and secure than existing AI-driven healthcare frameworks, making it suitable for real-time clinical applications.

41

1.5 Outline of the Thesis

This thesis is divided into seven chapters.

1 **Chapter 1: Introduction**

This chapter provides an overview of Digital Twin (DT) applications in healthcare, the significance of AI and IoT integration, and the motivation behind the study. It also outlines the research objectives, problem statement, and scope of the thesis.

2 **Chapter 2: Literature Survey**

A comprehensive review of existing research on Digital Twin technology, AI-driven healthcare systems, IoT-based monitoring, and security challenges. This chapter identifies the research gaps and justifies the need for the proposed study.

3 **Chapter 3: Digital Twin and Metaverse for Secure Healthcare Transformation**

This chapter explores the integration of Digital Twin and the Metaverse in healthcare, focusing on virtual healthcare ecosystems, patient engagement, and security frameworks to ensure secure and efficient digital transformation.

4 **Chapter 4: Digital Twin-Enabled Smart Healthcare Systems**

It discusses the implementation of AI-powered Digital Twins for real-time patient monitoring, predictive analytics, and personalized healthcare, highlighting the challenges and benefits of smart healthcare applications.

5 **Chapter 5: Securing Healthcare IoT with Digital Twin and AI-Driven Intrusion Detection**

This chapter focuses on cybersecurity threats in healthcare IoT systems, the role of blockchain and cryptographic techniques, and the implementation of AI-based intrusion detection models to secure patient data.

6 **Chapter 6: Digital Twin-Enabled AI for Monkeypox Detection**

131 This chapter details the development of MxSLDNet, a deep learning model for Monkeypox detection, including dataset preprocessing, model training, performance evaluation, and comparative analysis with pre-trained architectures.

7 **Chapter 7: Conclusion**

62 The final chapter summarizes the key findings of the research, highlighting its contributions to AI-driven healthcare systems. It also discusses limitations, potential improvements, and future research directions in Digital Twin-based medical applications.

CHAPTER - 2

LITERATURE SURVEY

29 *This chapter explores the evolution, core components, and applications of Digital Twin (DT) technology in healthcare. It provides a comparative analysis of existing DT frameworks, highlighting their integration with AI, IoT, and blockchain while addressing challenges in security, interoperability, and real-time processing. The chapter concludes by identifying key research gaps and future directions for optimizing DT adoption in healthcare.*

2.1 Introduction

49 Digital Twin (DT) is a virtual model of a physical object or system that enables the simulation of its behavior, performance, and characteristics. This technology has the potential to bring significant advancements across multiple industries, including manufacturing, logistics, healthcare, and urban development. Initially developed for the manufacturing sector, digital twins were primarily used to enhance the design and functionality of complex systems like aircraft engines and industrial equipment. However, their applications have expanded to include infrastructure, buildings, and even entire cities. A major advantage of digital twins is their ability to provide real-time data and insights into the operation and efficiency of a physical system. Continuously monitoring performance enables the early detection of issues and inefficiencies, allowing for proactive maintenance and optimization. In healthcare, digital twins play a crucial role in simulating and refining patient care pathways, reducing medical errors, and enhancing treatment outcomes. They also contribute to the design and management of healthcare facilities like hospitals and clinics. In urban planning, digital twins allow for the modeling and optimization of entire cities, including transportation networks, energy grids, and public services, leading to greater efficiency, sustainability, and improved quality of life. As a whole, digital twin technology has the potential to revolutionize various fields by offering real-time insights that enhance the functionality and performance of physical objects and systems. With continuous technological advancements, digital twins are expected to become even more widespread across different sectors.

2 2.1.1 Evolution of Digital Twin Technology

A chronological representation of the evolution of digital twin technology is illustrated in Figure 2.1. In 2002, Professor Michael Grieve introduced the idea of a "virtual digital expression equivalent to physical products" during the "product life cycle management" course

2 at the University of Michigan. He defined it as "one or a group of digital copies of a specific device that can abstract the real device and can be tested under real or simulated conditions [1].

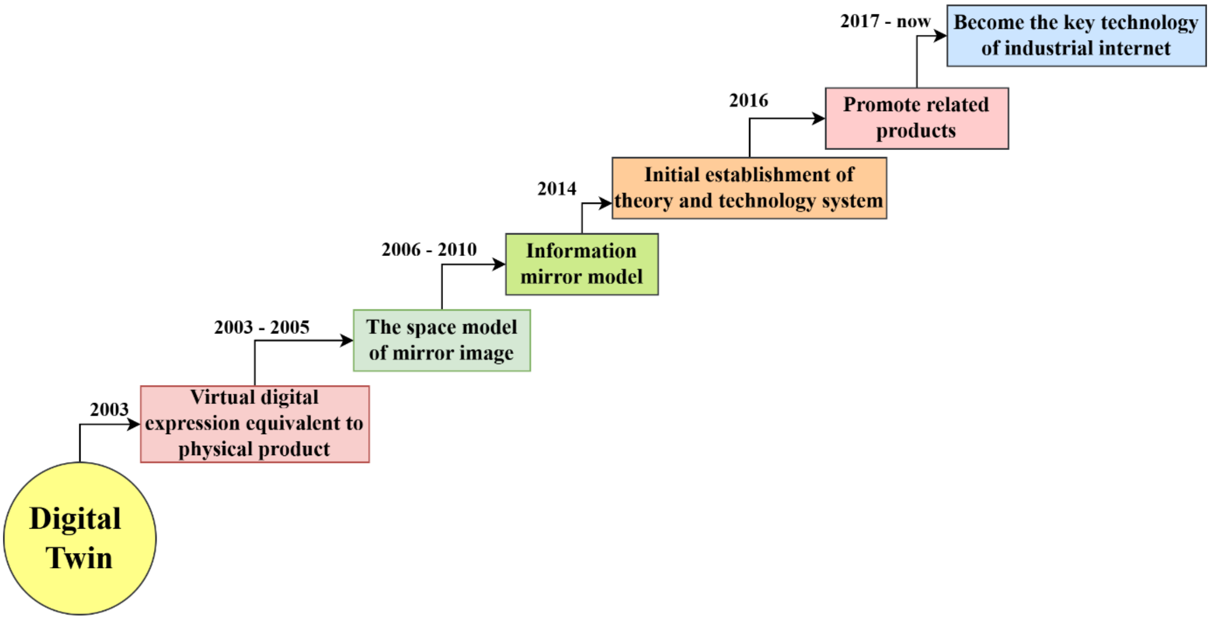

Figure 2-1: Evolution of Digital Twin Technology

From 2003 to 2005, this concept was termed the "mirrored spaced model," and between 2006 and 2010, it was referred to as the "information mirroring model." Although it is not a "digital 2 twin," it shares fundamental components such as virtual space, physical space, and the interface connecting them. In 2011, Professor Michael Grieve mentioned in his book "Virtual Perfect Model of Intelligent Manufacturing, Driving Innovation and Lean Products" that the digital twin consists of three key elements: physical products in the physical world, virtual models in the virtual space, and a data interface linking the physical world and virtual space [2]. In 2012, the National Aeronautics and Space Administration introduced the road map for "modeling, simulation, information technology and processing," bringing the concept of digital twin to public attention. In 2013, the U.S. Air Force's science and technology planning document, Global Horizon, recognized digital twins as a "game-changing" technology. By 2014, Boeing, GE, and other companies initiated a series of application research projects on digital twin, establishing a theoretical and technological framework for it. They later transitioned this 2 military technology to civilian applications, implementing a "digital twin supply system" in asset management and the development of the industrial Internet. At the 2016 Siemens Industry Forum, Siemens expanded the digital twin concept to include the digital twin of products, the digital twin of the production process, and the digital twin of equipment, enabling a comprehensive and precise reproduction of an entire enterprise. In [3], The authors described

2 the composition of digital twin from the perspective of the product, which primarily included product design data, product process data, product manufacturing data, product service data, and product retirement and scrap data. Meanwhile, some researchers proposed the composition of digital twin from the perspective of production, incorporating product design, process planning, production layout, process simulation, and output optimization [4], making it more comprehensive and better aligned with the needs of an intelligent factory. Additionally, the composition of digital twin was examined from the perspective of workshop structure,
2 encompassing the physical workshop, virtual workshop, workshop service system, and workshop twin data. The physical workshop represents the actual workshop, which receives
2 production tasks from the workshop service system and executes them based on the execution strategy optimized through virtual workshop simulation. The virtual workshop serves as the
2 equivalent mapping of a logistics workshop, primarily handling simulation analysis and optimization of production activities, real-time monitoring, as well as prediction and adjustment of production activities within the physical workshop. The workshop service system refers to the collective software systems within the workshop, playing a key role in operating the digital twin, driving the physical workshop, and receiving production feedback
25 from it [5], [6]. Since 2017, digital twin has developed from a new management paradigm for industrial production processes to a key technology of the industrial Internet.

2.1.2 Core Components of DTs

8 **Elementary components**

The elementary components are those without which a DT cannot exist:

- Physical Asset (could be either a product or a product lifecycle)
- Digital Asset (the virtual component)
- Information flow between the physical and digital asset (this could be 1-way or 2-way/bijective)

4 **Imperative components**

The imperative components add to the properties of DT, to make it an all-encompassing tool for simulation, real-time monitoring, and analytics. Without these, the uniqueness of DT ceases to exist. The existence of each of these components depends majorly on the domain and application of DT.

1 **IoT devices:** to collect sensors' information from different sub-components of the physical asset and edge devices. Requires: High-fidelity connection between IoT devices, for accurate and timely flow of information.

2 **Data:** gathered from different IoT components and software; it is required to monitor the system, guarantee correct behavior, and provide input to the machine learning system. Requires: Big data analysis and storage tools for extracting useful information from data.

3 **Machine learning:** for predictions and feedback, as well as to identify effective mitigation strategies, in exceptional circumstances. Requires: A joint optimization feature for the subcomponents of the DT.

4 **Security of data and information:** Security protocols for information sharing and authentication, and authorization mechanisms.

5 **DT Performance evaluation:** Evaluation metrics (e.g. accuracy, resilience, robustness, costs), and evaluation methods and tests.

2.1.3 How Digital Twin Differs from Other Technologies

The diverse applications of DT such as simulation, real-time monitoring, testing, analytics, prototyping, and end-to-end visibility, can be broadly classified as sub-systems of DT (for example, a DT can be used for testing during prototyping, for real-time monitoring and evaluation, or for both). It is the presence of all the components discussed that makes a DT different from these, as described in Table 2.1.

Table 2.1: How DT differs from existing technologies

Technology	**How the technology differ from DT**
Simulation	No real-time twinning
Machine Learning	No twinning
Digital Prototype	No IoT components necessarily
Optimization	No simulation and real-time tests
Autonomous Systems	No self-learning (learning from its past outcomes) necessarily
Agent-based modeling	No real-time twinning

The concept of digitizing and twinning is not new. Many similar concepts have preceded DT, however, for the reasons briefly described below, they differ.

- **Digital Shadow, Digital Model:** A Digital Model has only a manual exchange of data and it does not showcase the real-time state of the model. Digital Shadow is a saved data copy of the physical state, with one-way data flow from the physical object to the digital object [7]. DT, on the other hand, has fully integrated data flow, so that it properly and consistently reflects the actual state of the physical object.

- Semantic **Virtual Factory Data Models:** (VFDM) are virtual representations of factory entities [8]. These were used in manufacturing and industrial spaces [9]. DT differs from VFDMs due to the real-time synchronization property. VF is a data model only, whereas DT is real-time and synchronized.
- **Product Avatar:** is a distributed and decentralized approach for product information management with no feedback concept; it may capture information of only parts of the product [10].
- **Digital Product Memory:** DT is an extension of semantic/digital product memory, where a digital product memory [11] senses and captures information related only to a specific physical part, and thus it can be viewed as a DT instantiation.
- **Intelligent Product:** A DT can be seen as an extension of an Intelligent Product that uses new technologies such as IoT, big data, and machine learning [12].
- **Holons** As an initial computer-integrated manufacturing tool, holons formed the basis for all the technologies described above [13].
- **Product Lifecycle Management (PLM)**: [14] Discuss the difference between PLM and DT, where PLM is focused more on 'managing' the components, products, and systems of a company across its lifecycles, whereas a DT can be a set of models for real-time data monitoring and processing.

2.2 Digital Twin in Healthcare: An Overview

To gain a comprehensive understanding of the applications of Digital Twin technology in healthcare, existing research studies have been categorized based on their focus areas. Table 2.2 presents a classification of these studies, highlighting various domains such as virtual reality for training, cognitive assessment, health monitoring, mental health support, and remote healthcare delivery. This categorization helps in identifying key contributions and trends in the field.

Table 2.2: Classification of Research Studies on Digital Twin in Healthcare

Referenced Papers	Category	Description
[15], [16], [17], [18], [19]	VR for Training and Education	VR-based simulations for education and skills enhancement

[20], [21], [22], [23], [24]	Cognitive Assessment and Rehabilitation	Digital platforms for cognitive function assessment and improvement
[25], [26], [27], [28], [29], [30], [31]	Health and Well-being Monitoring	Continuous health monitoring using sensors and digital twins
[32]	Empathy and Understanding	Through Immersion Immersive experiences foster empathy and support
[33], [34], [35], [36]	Mental Health and Psychological	Support Digital interventions for mental health and stress relief
[37], [38], [39]	Remote Healthcare Delivery and Telemedicine	Digital twins and technologies for remote health assessments and care
[40]	Interactive and Assistive Technologies for Disabilities	Enhancing accessibility and support for individuals with disabilities
[41], [42], [43], [44]	Innovative Interfaces for Health Interaction	New interfaces for health applications, including rehabilitation and education

Virtual Reality (VR) for Training and Education: This category involves the use of VR to replicate real-world scenarios for educational purposes and skills training in healthcare. VR offers an immersive environment where users can engage with virtual patients or simulated situations, enhancing learning and skill development without real-world risks. A digital twin in this context would replicate user interactions within a virtual setting, providing personalized feedback and adjusting scenarios based on performance. Some digital twins in this category can track skill development, highlight areas for improvement, and customize training experiences. These technologies contribute to better intervention outcomes, improved patient care, and reduced medical errors by providing a realistic yet risk-free training platform, ultimately enhancing the expertise of healthcare professionals.

Cognitive Assessment and Rehabilitation: Digital twins in this category focus on evaluating and rehabilitating cognitive functions. Often incorporating immersive technologies such as VR and AR, these systems provide engaging experiences to assess and enhance cognitive abilities. A digital twin for cognitive assessment and rehabilitation would digitally represent an individual's cognitive performance, identify deficits, and track progress over time. It could tailor rehabilitation exercises based on the user's performance, offering a customized recovery plan. Personalized cognitive rehabilitation can improve cognitive function, aiding individuals in managing impairments more effectively. Enhanced cognitive capabilities contribute to better daily functioning and independence.

Health Monitoring and Management: This category involves continuous tracking and monitoring of health parameters and behaviors through sensor-based data collection, which is then analyzed by a digital twin to provide insights into an individual's health. These systems
112 integrate data from wearable sensors and environmental inputs to create a comprehensive health profile. By identifying patterns and predicting potential health outcomes, digital twins
143 can offer recommendations for maintaining or improving health. Continuous monitoring enables early detection of potential health issues, facilitating timely interventions and reducing the risk of complications. This proactive approach enhances overall healthcare management by preventing emergencies and optimizing long-term health outcomes.

Enhancing Empathy and Understanding through Immersion: This category focuses on using immersive technologies to create experiences that promote empathy and a deeper understanding of specific conditions or challenges faced by individuals. A digital twin in this context would replicate a person’s perspective, allowing others to experience their challenges through an interactive simulation. By adapting scenarios based on user interactions, these digital twins can enhance awareness and foster empathy. Such experiences can lead to increased societal support and improved interpersonal understanding. For individuals experiencing these simulations, greater awareness can lead to better social support and improved psychological resilience.

Psychological Support and Mental Health Interventions: Digital twins in this category focus on providing therapeutic interventions, stress relief, and coping strategies for mental health concerns. Some systems may integrate VR to create immersive therapeutic environments. A digital twin for mental health applications would offer personalized interventions based on an individual’s emotional state and mental health history. These digital twins can track progress and adjust therapies based on evolving needs. Personalized mental health support enhances accessibility and effectiveness, leading to better management of mental health conditions, symptom reduction, and an improved quality of life.

Remote Healthcare Delivery and Telemedicine: Digital twins in this category facilitate remote healthcare services, including assessments, consultations, and interventions, ensuring broader access to healthcare regardless of geographical barriers. These systems enable remote
22 monitoring and integrate health data from various sources to provide healthcare professionals with a comprehensive view of a patient’s condition. Additionally, they support decision-making by predicting health outcomes based on data trends. Remote healthcare delivery

improves accessibility, particularly for underserved populations, reduces travel-related costs and time, enhances chronic disease management, and allows for timely interventions, leading to better overall healthcare outcomes.

Assistive Technologies for Individuals with Disabilities: This category focuses on leveraging digital twins alongside assistive technologies to enhance accessibility and support for individuals with disabilities. These systems offer personalized support tailored to an individual's specific needs and capabilities by integrating assistive devices and adaptive technologies. By addressing unique challenges, digital twins significantly improve independence and daily functionality, empowering individuals to participate more actively in society. Improved accessibility and personalized support contribute to enhanced healthcare outcomes.

Innovative Interfaces for Healthcare Applications: This category explores novel interfaces
141 such as Brain-Computer Interfaces (BCI), Augmented Reality (AR), and Virtual Reality (VR) to facilitate healthcare applications, including rehabilitation, patient education, and interaction with healthcare systems. Digital twins using these advanced interfaces create intuitive and accessible ways for individuals to engage with healthcare information and services. These systems can adapt to user preferences and abilities, offering personalized experiences that improve engagement and effectiveness. The integration of innovative interfaces enhances the accessibility of healthcare services, increases adherence to treatment plans, and fosters better patient education, ultimately leading to improved health outcomes.

2.3 Comparative Analysis of Existing DT Frameworks in Healthcare

The development of Digital Twin (DT) frameworks in healthcare has gained momentum, with researchers exploring various approaches to enhance patient monitoring, diagnosis, surgery simulations, and personalized treatment. However, despite significant advancements, several limitations persist, particularly in security, data synchronization, and interoperability. To systematically analyze existing research, the table below compares different DT frameworks based on their applications, security measures, and limitations.

Table 2.3: Comparative Table of Existing DT Frameworks in Healthcare

Ref.	Application	Technology Used	Security Features	Limitations
Liu et al. [28]	Cloud-based DT framework for elderly healthcare	Cloud Computing, IoT, Big Data	Secure cloud storage, real-time patient monitoring	Data privacy concerns, potential latency in cloud-based services
Chakshu et al. [45]	Carotid stenosis detection	Digital Twin, AI	Secure data analysis	Data accuracy: potential false positives in AI-driven diagnostics, limited dataset availability for model training
Majdoubi et al. [46]	Smart healthcare framework	Blockchain	Privacy-preserving mechanisms	Scalability issues, processing overhead due to privacy-preserving cryptographic operations, risk of slow transaction speeds in peak demand scenarios
Dietz et al. [47]	Secure DT information management	Blockchain-based Decentralized Application (DApp)	Fine-grained access control	Implementation complexity: integration challenges with legacy healthcare systems, high transaction costs on blockchain networks
Raj et al. [48]	Enhancing DTs with blockchain	Blockchain, IoT, AI	Decentralized security	Integration challenges: interoperability issues between different blockchain protocols, potential vulnerabilities in smart contracts
Akash et al. [49]	Healthcare DT system design	Blockchain	Structured data management	Data collection challenges: requires standardized data formats across different healthcare institutions, high storage demands
Elyan et al. [50]	DT for intelligent, context-aware IoT healthcare	IoT, Machine Learning, AI	Secure patient monitoring using ECG-based heart rhythm analysis	Requires large-scale real-time data processing, potential biases in AI-based diagnostics

Meijer et al. [51]	Methodological challenges in healthcare DTs	Narrative review	Real-time Scenario	Data standardization and integration issues; computational complexity
Amofa et al. [52]	Remote patient monitoring	IoT-enabled DTs	Blockchain-based encryption	High computational cost: requires significant computational resources for encryption, scalability issues in large healthcare networks
Okegbile et al. [53]	Human Digital Twin (HDT) for personalized healthcare	AI, Blockchain, Cloud-Edge Computing	Secure and real-time data synchronization between physical and virtual entities	Complexity in modeling human physiological changes, lack of standardization for HDT implementation
Morrone et al. [54]	Women's health monitoring	AI, Digital Twin	Real-time data tracking	Uncertainty in AI effectiveness; challenges in inducing behavioral change among patients
Pellegrino et al. [55]	Conceptual framework for DT in healthcare	Systematic meta-review	Real-time Scenario	Integration challenges across diverse healthcare systems; need for standardization
Vijay et al. [56]	Secure blockchain transactions	Federated Learning, LSTM	Secure data transactions	Model complexity: requires substantial computational power for LSTM autoencoders, and training time increases with large datasets
Mishra et al. [57]	DT-based diabetes prediction using federated learning	IoT, Medical Fog Computing, AI, Federated Learning (FL)	Privacy-preserving AI model, secure decentralized data handling	High dependency on IoT infrastructure, requires large-scale dataset for training
Bera et al. [58]	Secure communication in DT-enabled IoT healthcare	Quantum-resistant cryptography (RLWE), Scyther tool for security verification	Protection against quantum attacks, secure transmission in DT-enabled IoT systems	High computational overhead due to lattice-based cryptographic techniques, scalability issues

Digital Twin (DT) frameworks in healthcare face several key challenges related to security, data synchronization, and interoperability. Security strategies often rely on blockchain for data integrity and secure transactions; however, scalability remains a significant issue. Emerging techniques like Federated Learning and Homomorphic Encryption enhance privacy-preserving AI models, but they introduce high computational overhead. Additionally, the Zero-Trust Architecture improves security by enforcing strict access controls, yet it adds operational complexity in large-scale healthcare systems. In terms of data synchronization and processing, many DT frameworks struggle with real-time data processing, particularly in ICU monitoring and emergency medical applications. While cloud-based DTs offer scalability, they also
27 introduce latency issues and dependency on external cloud providers. On the other hand, Edge Computing and IoT-based DTs provide low-latency solutions, but they face constraints related to power consumption and computational resources. Interoperability and regulatory challenges further hinder widespread adoption, as integration with Electronic Health Records (EHRs) remains difficult due to standardization issues across different healthcare systems. Furthermore, regulatory compliance with laws such as GDPR and HIPAA is not consistently addressed across all DT implementations. The Metaverse-DT framework shows promise for medical training and simulation, but its ethical and legal guidelines are still underdeveloped, raising concerns about its real-world application in healthcare.

2.4 Major Findings

1. **Enhanced Personalized Healthcare:** Digital Twin (DT) technology enables real-time patient monitoring, predictive diagnostics, and tailored treatment plans, leading to improved precision medicine and individualized healthcare solutions.
2. **Smart Hospital Management and Optimization:** DT-driven simulations assist in optimizing hospital workflows, resource allocation, and predictive maintenance, ultimately improving healthcare efficiency and patient outcomes.
3. **AI and IoT Integration for Data-Driven Healthcare:** The fusion of AI, IoT, and DT provides advanced analytics in medical imaging, wearable health monitoring, and patient-specific simulations, enhancing diagnostics and early disease detection.
4. **Remote Patient Monitoring and Telemedicine:** DT facilitates real-time remote healthcare services, reducing hospital visits while ensuring effective chronic disease management, elderly care, and emergency response.

5 **Epidemiological Modeling and Public Health:** DT supports disease forecasting, pandemic simulations, and vaccination strategy development, enabling better preparedness and response to public health crises.

6 **Revolutionizing Surgical Planning and Training:** Virtual anatomical DT models improve preoperative planning, medical training, and robotic-assisted surgeries, reducing procedural risks and enhancing precision.

7 **Biomedical Engineering and Regenerative Medicine:** DT plays a crucial role in bio-fabrication, 3D bioprinting, prosthetics, and organ simulation, accelerating innovation in regenerative medicine and personalized medical implants.

8 **Accelerated Drug and Medical Device Development:** DT enables virtual clinical trials, reducing the time, cost, and risk associated with drug development and medical device testing, thereby streamlining regulatory processes and safety evaluations.

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2.5 Challenges and Ethical Considerations

Despite the numerous benefits of Digital Twin technology in healthcare, several challenges remain:

1 **Data Privacy and Security Concerns:** The integration of real-time patient data in DT

142 raises significant concerns about data breaches, unauthorized access, and compliance with healthcare regulations such as HIPAA and GDPR.

2 **High Computational and Infrastructure Requirements:** DT models require substantial computational power, cloud storage, and advanced imaging technologies, making implementation costly and resource-intensive for many healthcare institutions.

3 **Interoperability and Standardization Challenges:** Lack of universally accepted standards for DT integration across various healthcare systems and devices limits seamless data exchange and cross-platform compatibility.

4 **Limited Availability of High-Quality Data:** The accuracy of DT models relies on large, high-quality datasets, which may be unavailable, incomplete, or inconsistent, affecting the reliability of medical simulations and predictions.

5 **Regulatory and Ethical Considerations:** The widespread adoption of DTs in healthcare is hindered by unclear regulatory frameworks and ethical concerns related to digital simulations of human bodies and disease progression modeling.

76

6. **Integration with Existing Healthcare Systems:** Many healthcare institutions use legacy systems that are not easily adaptable to DT technology, leading to operational disruptions and resistance to digital transformation.
7. **Validation and Clinical Acceptance:** DT applications in healthcare require extensive clinical validation to ensure accuracy and safety, yet the lack of standardized evaluation methods and limited real-world case studies hinder widespread clinical acceptance.

2.6 Conclusion

The historical development of Digital Twin technology, from its early applications in aerospace to its transformative role in healthcare, underscores its potential to shape the future of medicine. By integrating AI, big data, and IoT, DT is revolutionizing patient care, disease prediction, and
51 medical research. However, addressing challenges related to data privacy, interoperability, and ethical considerations will be essential for its widespread adoption in healthcare systems worldwide.

CHAPTER – 3

DIGITAL TWIN AND METAVERSE FOR SECURE HEALTHCARE TRANSFORMATION

This chapter explores the integration of Digital Twin (DT) and Metaverse technologies in healthcare, focusing on their role in secure healthcare transformation. Key advancements, applications, and challenges are discussed, along with a conceptual framework for DT implementation. The chapter concludes with an analysis of future trends and security considerations in DT-enabled healthcare.

3.1 Introduction

Digital healthcare technology has undergone a transformative shift, integrating advanced digital tools to enhance patient care, streamline medical operations, and improve healthcare outcomes. Key innovations such as electronic health records (EHRs), telemedicine, wearable devices, and AI-driven solutions aim to make healthcare more accessible, efficient, and patient-centered. These advancements address challenges like rising costs, limited medical access, and the increasing demand for personalized and preventive care. Among these innovations, Digital Twin (DT) technology stands out, creating virtual replicas of patients to simulate and analyze physiological conditions and treatment responses. By leveraging real-time data, AI, and machine learning, DT enables predictive analytics, remote monitoring, and precision medicine, leading to more accurate diagnoses, optimized treatment plans, and personalized healthcare recommendations. Integrating DT with IoT, AI, and cloud computing further enhances its capabilities, allowing real-time simulations, improved medical training, and comprehensive patient insights. Technologies like augmented reality (AR) and virtual reality (VR) amplify DT's potential in surgical planning and medical simulations, transforming healthcare into a more precise and patient-focused system. DT technology is increasingly recognized for addressing challenges such as inefficient data management, delayed interventions, and limited treatment personalization. The COVID-19 pandemic highlighted the need for real-time patient monitoring, predictive analytics, and data-driven decision-making, where DT played a crucial role in enabling early disease detection and proactive interventions. Additionally, DT facilitates the creation of digital models for hospital operations and medical devices, enhancing resource utilization and reducing medical errors. Despite its benefits, DT adoption in healthcare raises security and privacy concerns. Given the sensitivity of medical data, robust cybersecurity measures—such as encryption, blockchain, and advanced authentication—are essential to safeguarding patient information and maintaining healthcare system integrity. Addressing these concerns is crucial for fostering trust and ensuring seamless DT integration.

Real-world applications of DT technology illustrate its transformative impact. Institutions like the Cleveland Clinic use DT for surgical planning, while GE Healthcare employs it for predictive maintenance of medical imaging equipment. The Mayo Clinic leverages DT to optimize treatment plans for critical illnesses, and Philips integrates DT with smart devices for real-time patient monitoring. Siemens Healthineers applies DT to hospital design, improving workflows and operational efficiency. The emergence of the Metaverse, combining AR, VR, AI, and blockchain, further expands DT's potential in healthcare. It enables remote consultations, interactive medical training, and virtual simulations, fostering collaborative medical research and improving diagnostics and treatment methodologies.

This study explores DT's role in healthcare security and privacy within the Metaverse framework. It contributes by designing a secure DT integration framework, proposing a six-axis Metaverse-based model for healthcare challenges, and reviewing DT applications from 2000 to 2024. The study also examines distributed trust mechanisms, emphasizing the need for strong security measures to ensure data integrity and patient safety. As technology advances, DT is set to revolutionize healthcare by enhancing diagnostic accuracy, optimizing treatment planning, and improving medical training. The integration of DT with blockchain, 5G, and quantum computing could further enhance security, interoperability, and scalability. Embracing DT technology will drive unprecedented efficiency, accuracy, and patient-centered care, shaping the future of digital healthcare in the Metaverse era.

3.2 Data Selection for Digital Twin in Healthcare

To provide a comprehensive review of Digital Twin (DT) and Metaverse applications in
40 healthcare, we conducted a systematic literature review (SLR) following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [59], [60]. This approach ensures a structured, transparent, and reproducible methodology for identifying, selecting, and analyzing relevant studies.

3.2.1 Search Strategy & Data Sources

We searched five major academic databases to collect relevant research papers:

- IEEE Xplore (for technology-driven DT research)
- PubMed (for biomedical and healthcare applications)
- Scopus (for interdisciplinary studies)
- Web of Science (for high-impact research papers)
- Google Scholar (for additional gray literature and preprints)

To maximize coverage, we used a combination of Boolean operators (AND, OR) and keyword variations:

- ("Digital Twin" OR "Healthcare Digital Twin") AND ("Security" OR "Privacy")
- ("Metaverse" OR "Augmented Reality" OR "Virtual Reality") AND ("Healthcare Applications")
- ("Blockchain" OR "AI") AND ("Healthcare Data Security" OR "Digital Twin Cybersecurity")

Studies published between 2000 and 2024 were considered, with a focus on recent developments (2018-2024).

3.2.2 Inclusion & Exclusion Criteria

96 To ensure the relevance and quality of the selected papers, we applied the following inclusion and exclusion criteria:

Inclusion Criteria:

- Studies written in English.
- Research papers that explicitly discuss Digital Twin or Metaverse applications in healthcare.
- Studies that address security, privacy, or interoperability challenges in DT-based healthcare systems.
- Peer-reviewed journal articles, conference papers, and high-impact white papers.

Exclusion Criteria:

- Duplicate studies.
- Papers focusing on non-healthcare applications of DT and Metaverse (e.g., manufacturing, aerospace).

- Opinion articles, editorials, or commentaries without empirical data.
- Studies with incomplete methodologies or insufficient technical details.

3.2.3 Study Selection & Evaluation Process

To ensure reliability and validity, we implemented the following three-stage selection process:

a) **Title & Abstract Screening**
- Two independent reviewers scanned titles and abstracts to exclude irrelevant papers.
- Discrepancies were resolved through discussion and consensus.

b) Full-Text Review
- Studies that passed the initial screening were read in full and evaluated for relevance.
- Papers were excluded if they lacked concrete technical discussions.

c) Quality Assessment
- Selected studies were evaluated using the CASP (Critical Appraisal Skills Programme) checklist.
- Each paper was scored on:
  i. Methodological rigor (was the study well-designed?)
  ii. Relevance to DT-Metaverse healthcare
  iii. Depth of security/privacy discussion

3.2.4 Data Extraction & Analysis

From each selected study, we extracted the following key information as shown in Table 3.1:

Table 3.1: Data Extraction and Analysis

Category	Details Extracted
Study Type	Survey, Experimental, Conceptual Framework
Domain	Digital Twin, Metaverse, AI, Blockchain in Healthcare
Use Cases	Patient Monitoring, Surgery, Medical Training, Drug Development
Security Measures	Blockchain, AI-driven Privacy, Homomorphic Encryption
Key Findings	Contributions & Limitations of Each Study

3.2.5 Scalability Challenges and Solutions in Digital Twin Healthcare Systems

Although Digital Twin technology presents numerous advantages in healthcare, scalability remains a critical challenge. To address this, the following solutions and methodologies have been identified:

1. **AI and Machine Learning Integration**
    - AI-driven models can optimize resource allocation, improve predictive analytics, and enhance the real-time processing capabilities of Digital Twins.
    - Federated Learning can ensure distributed AI training across multiple healthcare facilities without compromising patient data privacy.
2. **Interoperability Standards**
    - Adoption of FHIR (Fast Healthcare Interoperability Resources) and HL7 (Health Level Seven) standards can enhance seamless data exchange between different DT healthcare systems.
    - Implementing standardized APIs for cross-platform DT integration will improve scalability and system-wide connectivity.
3. **Robust Security and Privacy Frameworks**
    - Blockchain-based decentralized identity management can provide secure access control without relying on centralized databases.
    - Homomorphic encryption allows secure computation on encrypted patient data, reducing risks associated with data breaches.
    - Zero-trust architecture (ZTA) ensures that only authenticated users and devices access Digital Twin systems, mitigating potential cyber threats.
4. **Cloud-Edge Hybrid Infrastructure**
    - A combination of cloud computing for large-scale data processing and edge computing for real-time analytics can enhance scalability.
    - Deploying edge AI models can reduce latency and enable localized decision-making without burdening centralized cloud servers.
5. **Dynamic Resource Allocation & Load Balancing**
    - AI-powered dynamic workload distribution algorithms can prevent system overloads in high-demand healthcare environments.
    - Software-defined networking (SDN) and network function virtualization (NFV) can improve scalability by dynamically managing healthcare data traffic.

By incorporating these methodologies, Digital Twin systems can achieve greater scalability, efficiency, and security, making them more viable for large-scale healthcare applications. The publications on DTs published annually from 2003 to 2024, as reported by the Web of Science Core Database, are displayed in Figure 3-1. According to the figure, the quantity of published literature on DT has gradually increased after 2016. Furthermore, using information from many research papers cited in this study and their respective references, Figure 3-3 illustrates a percentage analysis of healthcare diseases in the digital twin (DT) system.

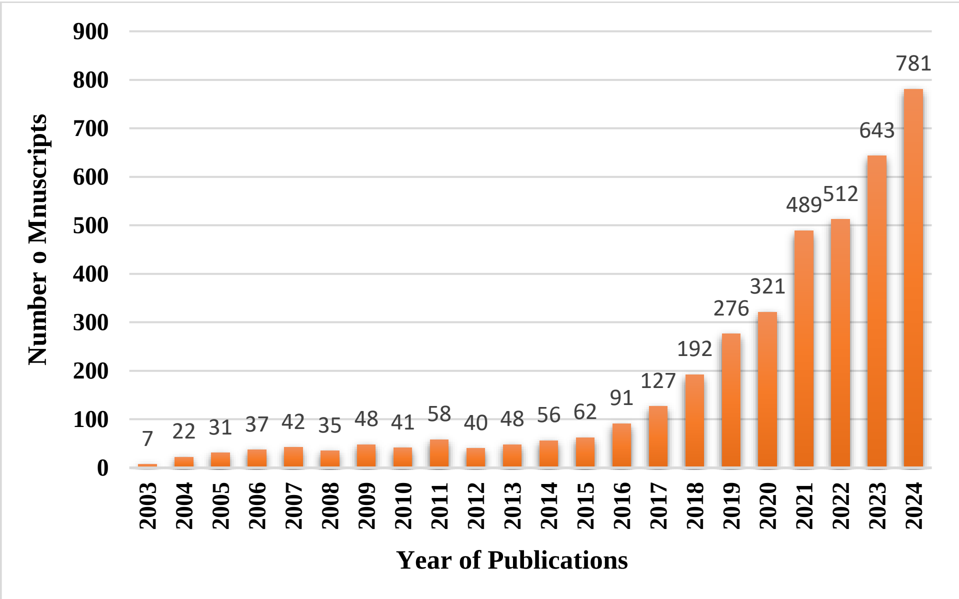


Figure 3-1: Number of publications per year on digital twins in healthcare

This review examines a diverse range of 25 articles across various medical domains, as shown in Figure 3-2. These encompassed 3 papers in surgery, 7 in cardiovascular, 3 in the context of COVID-19, 3 related to pharmacy, 4 in orthopedics, 2 in cancer research, and 3 exploring digital technologies in other disease areas. Our inclusive approach ensures articles are written in English and focused on integrating digital technologies (DT) to construct patient models, aid in diagnosis, or personalize therapy. The work excludes duplicated or irrelevant articles, those lacking DT integration, and those limited to conference abstracts, proposals, or viewpoints. This review provides insights into the evolving landscape of utilizing DT to advance medical practices and improve patient outcomes across multiple disciplines.

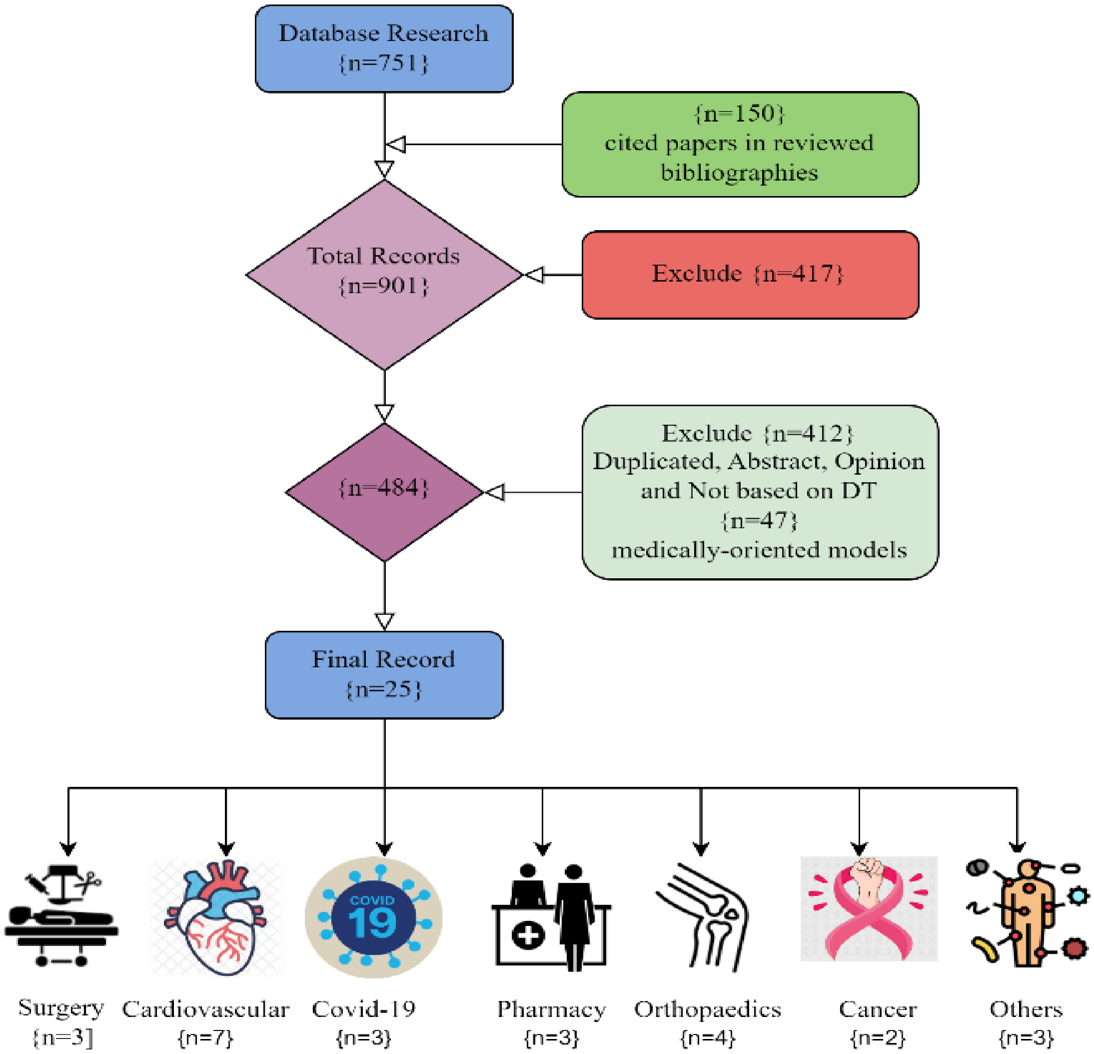
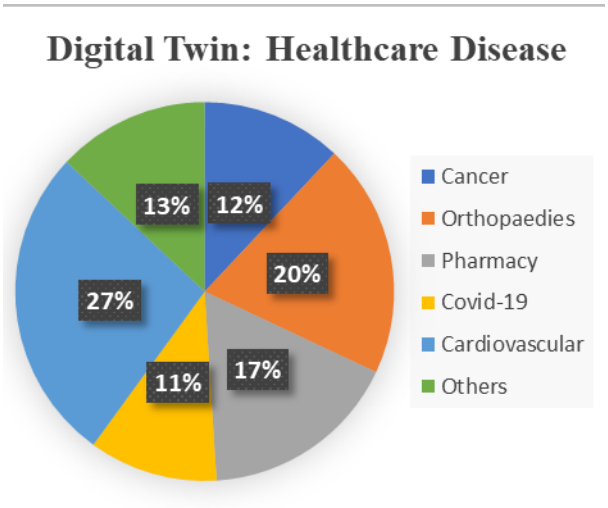


Figure 3-2: Flowchart for illustrating Digital Twin in Healthcare



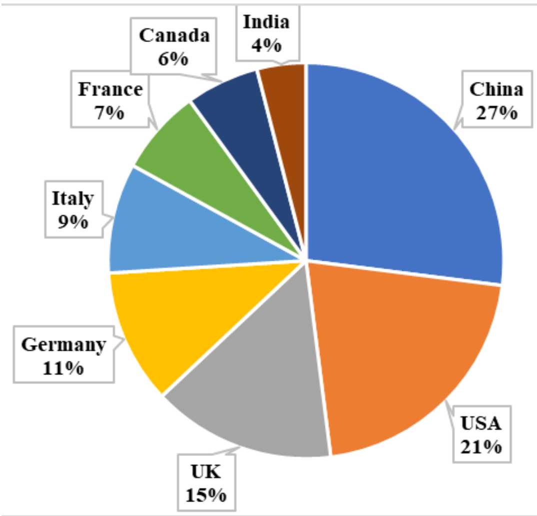


Figure 3-3: Distribution of articles on digital twins among different healthcare diseases & Countries

3.3 Digital Twin in Healthcare: State-of-the-Art

In the future, with artificial intelligence (AI), 6G, and intelligent sensors, the healthcare system will be able to seamlessly connect the real-world patient and digital replica via the healthcare digital twin (HDT) to accomplish secure healthcare [61], [62]. Future doctors, for example, can remotely study and monitor patients and detect and predict health concerns. This digital twin then gets this information ready for analysis by powerful computers. By constantly checking a patient's health and looking for anything unusual, this system can help doctors in many ways, from suggesting treatments to figuring out how medications will work and even planning healthy lifestyles for patients to follow as shown in Figure 3-4.

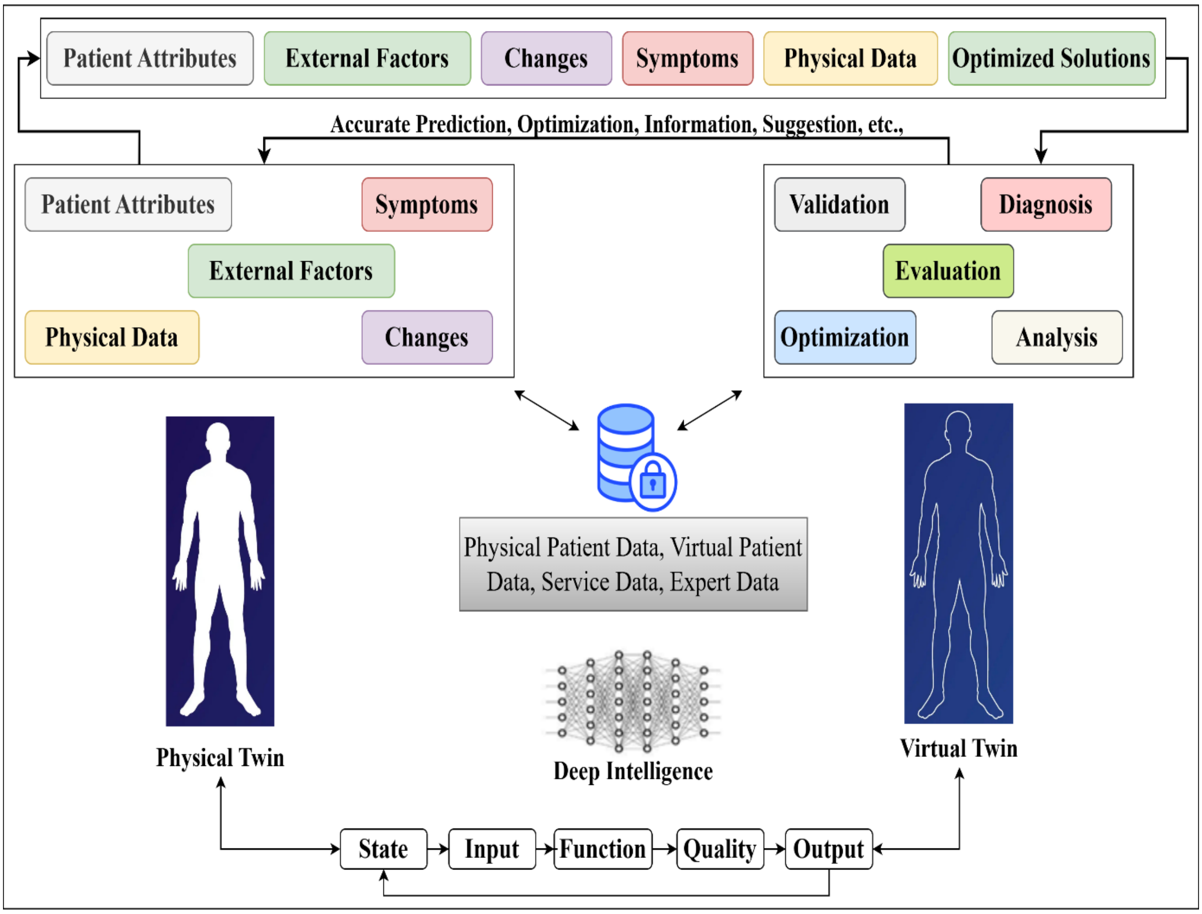


Figure 3-4: Conceptual Framework of Secure Digital Twin for Healthcare

3.3.1 Three-Axis of the Digital Twin

1. **Data Prediction:** In this part, the system uses wearable sensors to collect real-time information about a patient's health to see if anything is wrong. This information is then stored in a safe and big online storage space (cloud database) for a short time. Here, the information is cleaned up and made ready for super smart computers (machine learning)

to analyze it and predict future health problems. Both patients and other parts of the system can see this information in another safe online storage space (Result Database) so they can add comments, updates, or corrections if needed.

2. **Supervision:** Doctors use the information from the prediction models in the Result Database to recommend treatments for patients. This information, along with the doctor's knowledge and keeping track of the patient, helps doctors make better healthcare decisions. Because the information is updated constantly, doctors can find and track problems with a patient's health more easily and take the right steps to fix them. This way, doctors can give patients the right medicine and help them live healthier lives. Doctors can also check the findings from the system and suggest ways to make it work even better.

3. **Comparison:** The DT system also makes its predictions more realistic by comparing a patient's information with information from similar patients. This comparison helps the system make more accurate predictions, which in turn helps doctors make better decisions about patient care. These decisions can involve copying, changing, or stopping treatments altogether based on real-time information and the patient's past, present, and predicted future health.

The DT framework is demonstrated in this Figure 3-4, which also suggests possible application scenarios and an DT architecture enabled by blockchain and cloud edges. Digital twin (DT) technology offers a novel approach to medical simulation by combining it with multidisciplinary, multiphysics, and multiscale models. This improves the current healthcare system by providing proactive, accurate, and effective personalized health services (PHS). The physical twin (PT), virtual twin (VT), and healthcare data are the three main components of DT. Figure 3-4 illustrates these elements visually: VT in the virtual world, PT in the physical world, and an interlinkage that links PT and VT through reliable data links so that they can develop simultaneously in the virtual and physical worlds. Through real-time data analysis and ongoing health status monitoring, this synchronization facilitates efficient risk management, cost savings, and future forecasting by anticipating possible health issues before they arise. 37 HDT can provide accurate, timely, and efficient PHS by integrating the patient, the virtual object, and the healthcare data. HDT can, therefore, contribute to developing innovative drugs and vaccines without endangering human health. It will also improve disease prevention and surgical procedures, recommend lifestyle modifications, maximize the efficacy of treatment plans tailored to each patient, and reduce the time it takes for innovative, cutting-edge medications to be introduced to the market. All of these advantages will reduce the total cost of healthcare. Healthcare Digital Twins (HDT) can anticipate an individual's health status in the future, enabling proactive steps for preventive healthcare. By using DT, healthcare can be highly personalized, providing tailored diagnoses and treatment recommendations, making it a game-changer for the healthcare industry. Despite the enormous potential impact of DT on healthcare, there are important issues to resolve. These challenges include verifying that Personalised Health Services (PHS) are efficiently provided by DT, maximizing the application of AI and ML techniques to offer these services, and guaranteeing accurate medical data collection. The work emphasizes the transformative potential of creating individualized DT for achieving PHS. However, it's crucial to document the entire process of conceiving, representing, and implementing DT models before deployment. A comprehensive understanding of human molecular systems is necessary to ensure accurate medical data collection. We have made significant progress in understanding human molecular systems because of several ongoing projects like the Human Cell Atlas, the Whole-cell computational model project, and the Genome project. Leveraging extensive molecular insights allows for precise medical data collection using various advanced sensing devices.

3.3.2 Key Technologies for Digital Twin Implementation

DTs: information modeling that can abstract human specifications, communication that
105 facilitates bi-directional data transmissions between devices, and data processing that can extract meaningful information from heterogeneous multi-source data [63]. Similarly, there are two ways in which DTs differ from traditional DTs in other contexts: First, because intra-body and inter-body interactions differ, DTs rely on sophisticated communication techniques. Second, a flawless human-twin link may only sometimes be possible because people are not (and may not want to be) born with embedded sensors. Individual medical data are typically acquired through medical examinations [64]. Thus, Figure 3-5 summarises the essential
14 technologies, which are then explored as follows.

a) **Connectivity:** Two-way communication between PT-VT pairs, typical VTs, neighboring VTs, and VTs and domain experts is made possible by connectivity. To ensure VT and PT coexist, HDT modeling requires perfect data flow, high-speed connectivity, minimal latency, real-time synchronization, and edge intelligence. LoRaWAN, 6G, and tactile internet can be used to construct HDTs that ensure Ultra-Reliable and Low Latency

Communications (URLLC) connectivity and secure private data/information exchanges [65]. The requirements encompassing communication delay involve upload and download latency, data processing time, computing duration, and network reliability. Prioritized scheduling greatly aids PT-VT communications by factoring in the criticality-based classification of PT data. Adjusting dynamic priority levels becomes essential to minimize weighted latency, especially addressing concerns where low-priority class levels might experience communication capacity limitations.

b) **Data Collection:** Efficient safeguarding and translation of data formats are essential for gathering data from IoT devices, mobile devices, wearables, medical records, and embedded sensors. Intelligent sensing devices and equipment are necessary for accurately detecting attributes, metrics, and alterations in the physical environment of the patient twin (PT). Users and experts regularly update the Healthcare Digital Twin (HDT) with digital health data to monitor the PTs' health conditions. Biosignal sensing is a critical tool for data collection, allowing the recording of biological events in specific locations and times. This approach yields valuable insights into physiological factors that enhance Personalized Health Services (PHS) and supports lifetime health management by monitoring organ and physical environment changes in all PTs.

c) **Data Processing:** Most data preprocessing involves conversion, filtering, and cleaning. Data must be transformed into valuable formats. Missing data, inconsistent data, human input mistakes, improper data type, regional structures, numerical units, file change, and missing anonymization issues may be present. The KNN-imputation algorithm estimates missing values [66]. High-quality data is another danger to HDT. Data fusion, feature tuning, feature selection, and building require substantial computational infrastructure and take time to ensure accurate representation. Three processes are needed for data fusion: mining, optimization, and processing. Data processing methods include distributed processing and multiple programming.

d) **Modeling Framework:** In complicated systems, humans function in intricate settings. Because of this, HDT modeling is complex. Even though an augmented DT model and a reference model were used to represent the cyber-physical interaction, we still need to understand the modeling framework for HDT fully. While one study used a convolution neural network-based framework [67], another provided a computational cell-to-cell network [68]. Real-time, ultra-fast connectivity between PTs and VTs; rapid simulation framework validation execution and calibration; ongoing HDT model optimization; and

HDT virtualization through sophisticated modeling techniques like Modelica, 3DMax, and SolidWorks are all included in HDT modeling [69].

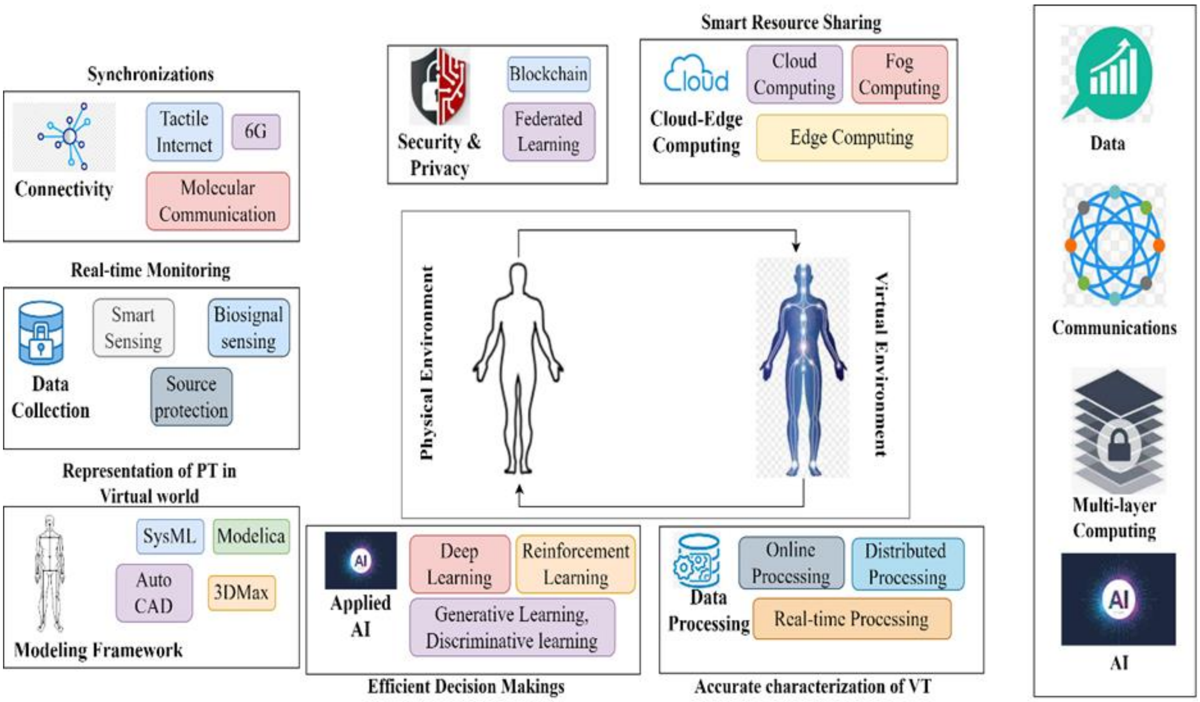


Figure 3-5: Key Technologies for Digital Twin Implementation in Healthcare

e) **Applied AI:** Applied AI [70] Will bridge real-world and virtual environments for rapid decision-making. Optimizing numerous machine learning algorithms will speed up HDT development and improve AI-based communication. Machine-learning methods can be modified and optimized to improve HDT development. HDT requires learning anything accurately and continuously, producing reliable facts, recommendations, and precise future projections that provide meaningful insights into the issue and potential remedies. Applied AI will accurately portray VTs, giving medical practitioners and specialists valuable information for preventive and maintenance care.

14

f) **Cloud Computing:** Cloud-edge computing helps shift complex computing and storage tasks to the cloud, enabling faster processing of time-sensitive functions at the network's edge. Edge intelligence is vital for deploying healthcare digital twins (HDT), ensuring innovative task processing at edge nodes by collecting and analyzing medical data to offer real-time insights and recommendations [71].

Digital Twins, which are virtual copies of real things or processes, open up new possibilities in healthcare by making personalized medicine, predictive analytics, and remote tracking possible. Even though Digital Twins could be helpful, they still need to be easier to use on a large scale in healthcare for several reasons.

1. **Technological Hurdles:**
    a. Data Integration and Quality: Healthcare data is often inconsistent and spread across many systems, making it hard to combine and guarantee their quality for Digital Twin models.
    b. Real-time Data Processing: To make quick decisions based on real-time patient data, you need a strong computer network and programs to quickly handle large amounts of data.
    c. Security and Privacy: Protecting private patient data from cyber threats and ensuring privacy laws are significant issues in implementing the Digital Twin.

2. **Interoperability Issues:**
    a. Standardization: Different healthcare systems and devices can only talk to each other slowly because they use different standard protocols and formats for data exchange. This makes it harder to add Digital Twins to current workflows.
    b. Integration with Electronic Health Records (EHR): Digital Twins need to seamlessly connect to EHR systems to use all of a patient's data successfully. However, this integration is still hard to achieve because of the different EHR platforms and data formats.

3. **Scalability Challenges:**
    a. Resource Allocation: To make Digital Twin systems bigger to handle more data and users, much money must be spent on computing power, which may be too much for many healthcare organizations.
    b. Model Complexity and Maintenance: As Digital Twin models get more complicated, keeping them accurate and valuable over time gets more brutal. This means that they need to be updated and checked all the time.

To make it easier for Digital Twins to fit into healthcare ecosystems, frameworks for sharing data and security procedures are being developed for all of them, and money is being put into scalable computer systems and advanced analytics tools to help process ample healthcare information in real-time and getting everyone involved to work together to come up with the best ways to create, test, and use Digital Twins in healthcare settings.

3.4 Metaverse in Healthcare: State-of-the-Art

3.4.1 Six-Axis of the Metaverse Implementation in Healthcare

83 The following Figure 3-6 demonstrates the Six-Axis of the Metaverse Implementation in Healthcare.

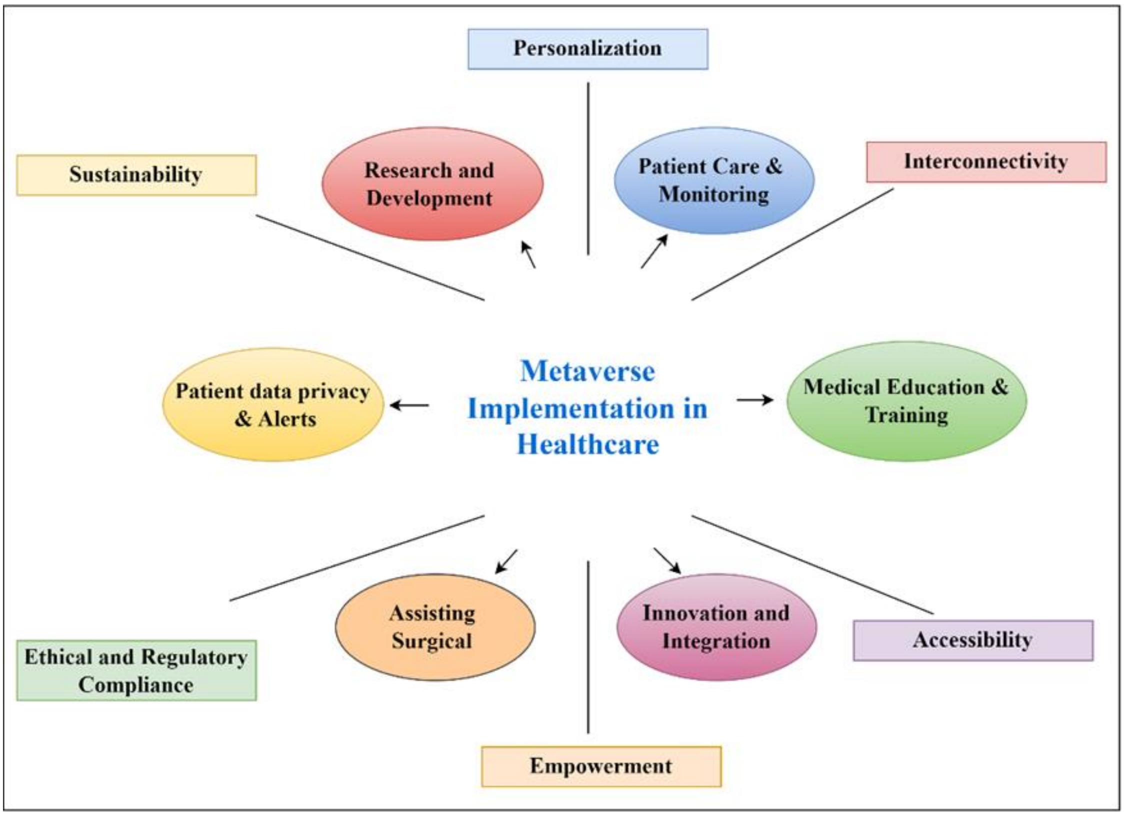


Figure 3-6: Six-Axis of the Metaverse Implementation in Healthcare

a) **Personalization:** This axis tailors healthcare experiences and interventions to individual needs, preferences, and characteristics. Personalization involves leveraging data, AI algorithms, and other technologies to deliver targeted treatments and recommendations for each patient.

b) **Interconnectivity:** This axis emphasizes the interconnectedness of various elements within the healthcare metaverse. Integrating different platforms, devices, and systems enables seamless communication, data sharing, and collaboration among healthcare providers, patients, caregivers, and other stakeholders.

c) **Accessibility:** This axis addresses the accessibility of healthcare services, information, and resources within the metaverse. It involves removing barriers to access by ensuring that healthcare solutions are available to all individuals, regardless of their location, socioeconomic status, or physical abilities.

21 d) **Empowerment:** This axis actively empowers individuals to participate in their healthcare journey. It involves providing patients with the knowledge, tools, and support they need to make informed decisions, manage their health effectively, and engage in shared decision-making with healthcare providers.

e) **Ethical and Regulatory Compliance:** This axis highlights the importance of upholding ethical principles and regulatory standards within the healthcare metaverse. It involves ensuring the responsible use of technology, protecting patient privacy and confidentiality, and adhering to relevant laws and guidelines governing healthcare practices.

f) **Sustainability:** This axis addresses the long-term sustainability and resilience of healthcare systems and interventions within the metaverse. It involves considering environmental, economic, and social factors to minimize waste, optimize resource utilization, and promote equity and inclusivity in healthcare delivery.

3.4.2 Security & Privacy challenges in DT-Metaverse Healthcare

It has attracted much interest since Neal Stephenson introduced the concept of a computer-generated universe with actual economic systems in his well-known science fiction book Snow Crash [72]. Stephenson was the first to introduce the metaverse concept, which provided the foundation for a computer-generated universe. It includes immersive public areas that combine
133 aspects from the actual and virtual worlds [73]. As a result of the recent development of a wide range of technologies, the metaverse is progressively transforming from an abstract ideal into
6 a practical reality. Wearable sensors [74], non-fungible tokens (NFTs) [75], Augmented reality (AR) [76], 5G connectivity [77], Blockchain [78], [79], [80], Virtual reality (VR) [81], [82], Brain-computer interfaces (BCI) [83] and Artificial intelligence (AI) [84] are some examples of these technologies. Global interest in this innovation has grown, leading major tech
6 companies like Microsoft, Tencent, NVIDIA, and "Meta" (formerly Facebook) to invest in its continued development [85]. The development of the metaverse [86] can be distinguished into three distinct phases, which are referred to respectively as DTs [87], digital natives [88], [89], and surreality. Figure 3-7 depicts the basic framework for analyzing security and privacy in DT-Metaverse. Collecting and analyzing vast amounts of data to produce DT of physical items is necessary to build a usable metaverse in the real world. Quality of user experience (QoE)

relies heavily on the availability and accuracy of such data. The DT-based metaverse benefits significantly from adding blockchain technology to this framework. To begin, security & privacy permits verification of the integrity of each DT with its physical counterpart. This procedure aids in guaranteeing the accuracy of the collected and processed data. As a result, information can be accessed more quickly and openly than ever before. Incorporating numerous DTs into the building of the 3D virtual environment is another way in which blockchain facilitates cross-location interaction among users of the same virtual space. Metaverse service transactions and related data are likewise recorded on the blockchain and made available to the DT layer, providing audibility and facilitating iterative improvements to the developed digital models. [87].

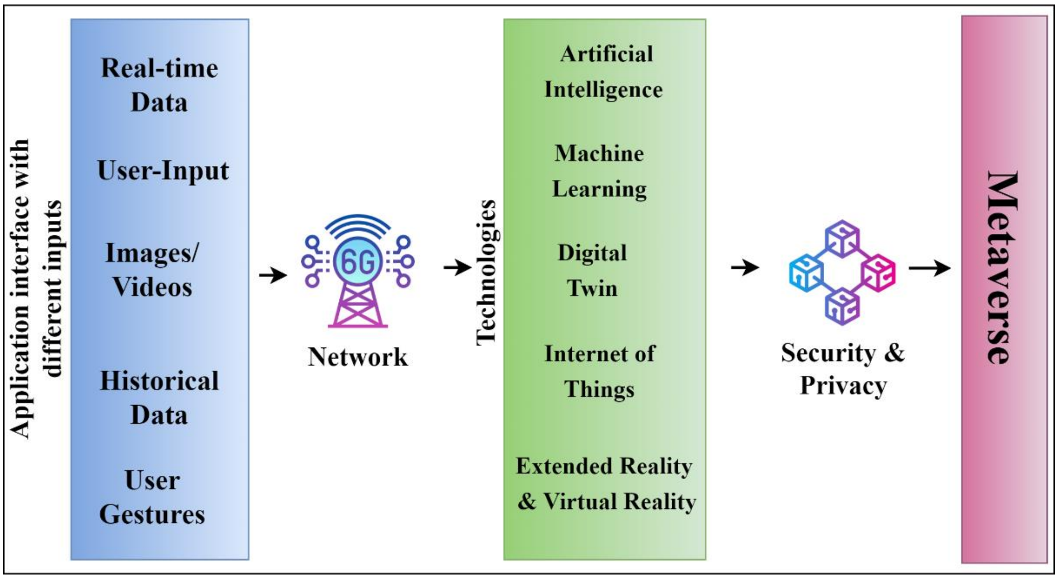


Figure 3-7: Security and Privacy in DT-Metaverse

The metaverse allows users to embody themselves through avatars by fusing in cyberspace the virtual and the physical aspects of their lives. In addition, the incorporation of methods and technologies such as artificial intelligence (AI) [90], [91], Machine learning (ML) [92], [93], Deep learning (DL) [94], internet of things (IoT), [95], [96], edge computing [97], [98] and cloud computing [99] further enhances this transformational technology [100], [101]. Even though the metaverse has seen significant progress in areas such as social media [102], diagnosis [103], [104], and treatment planning [105], its application in the medical field, particularly in cancer diagnosis, treatment, and examination, requires additional enterprise, deliberation and research [106]. The metaverse has witnessed significant developments in social media, diagnosis, and treatment planning. The proposed Digital Twin (DT)-Metaverse framework consists of several integrated components, aimed at enhancing healthcare operations, improving patient care, and ensuring data security. The framework includes the following layers:

1. **Digital Twin Layer**
    - Creates virtual replicas of patients, medical devices, and hospital workflows.
    - Integrates real-time physiological data from IoT sensors and medical imaging.
    - Supports predictive analytics for disease prevention and treatment planning.

2. **Security and Privacy Layer**
    - Implements blockchain-based access control to protect sensitive health data.
    - Uses homomorphic encryption, federated learning, and multi-party computation (MPC) for secure AI-driven medical analysis.
    - Prevents cyberattacks on healthcare DT models through intrusion detection systems.
    - Enforces IoT-driven data encryption and anomaly detection to prevent malicious tampering.

3. **AI-Driven Decision Support System**
    - Employs machine learning models to analyze patient data and predict disease progression.
    - Assists in diagnosing conditions, optimizing treatment plans, and recommending personalized therapies based on real-time DT insights.
    - Implements AI-based disease prediction models and precision medicine for patient-specific treatment.

4. **Dynamic Resource Allocation & Scheduling**
    - Uses a priority-based scheduling system for efficient healthcare resource allocation.
    - Reduces waiting times by dynamically prioritizing critical patients in the digital twin system.

5. **Interoperability & Data Exchange Layer**
    - Ensures seamless integration between hospital information systems (HIS), electronic health records (EHRs), and cloud-based healthcare DTs.

- Facilitates real-time data exchange for continuous patient care across different healthcare providers.

6. **Perception Layer (Data Acquisition)**
   - Real-time collection of patient vitals, medical records, and wearable sensor data.
   - AI-powered anomaly detection to ensure secure transmission from medical devices.
7. **Communication Layer (Edge & Cloud Processing)**
   - Secure 5G/6G communication for DT updates and remote healthcare monitoring.
   - Blockchain and federated learning enable decentralized, privacy-preserving medical AI models.
   - Implements a zero-trust security architecture for healthcare networks.
8. **Processing Layer (AI & DT Simulations)**
   - Uses AI to analyze patient-specific data and generate secure, predictive models.
   - Homomorphic encryption is used for secure AI model training on encrypted health data.
9. **Application Layer (Metaverse Integration)**
   - Includes AR/VR-based immersive training simulations for doctors and students.
   - Enables real-time digital avatars for virtual healthcare consultations.
   - Facilitates remote surgeries through a secure multi-user collaboration framework using DT models.

This multi-layered framework ensures a secure, interoperable, and efficient healthcare system that integrates DT models, Metaverse technologies, and robust security mechanisms to protect patient data and healthcare operations.

3.4.3 Metaverse Applications and Their Limitations in Healthcare

The metaverse application is solely related to healthcare, so establishing a "niche theme" for academics includes teaching, research, training, and the prevention and management of diseases. In recent years, it has developed into a dynamic technology that augments the capabilities of medical students. In addition, patients' health conditions can be immediately monitored at their homes, and the actual world can also be connected with the virtual world through digital twins, a diversified technology [107], [108].

109 The Metaverse has the potential to completely change healthcare by providing realistic consultations, personalized care, and new ways to use technology in the office. But there are many problems with putting it into action. Some traditional healthcare systems might hesitate to adopt these game-changing technologies because they must believe in their vague benefits and know how to achieve them. Also, there are significant cybersecurity risks. Metaverse apps can be hacked, and private patient data could be made public. Even though new technologies like network slicing and blockchain are being used to reduce these risks, people still need to be reassured about how hard it will be to integrate new hardware and ensure robust data security methods are in place [109], [110].

Another big problem is that few have internet access, especially in rural areas. This could make it harder for Metaverse options to be widely used. Immersive experiences in 3D or even 2D environments may strain current infrastructure, making it harder for people to use these new medical tools. While improvements in 5G telecommunications could be answers, setting up infrastructure like small cells as base stations takes much work, especially in places with few people. Getting past these connectivity problems is essential to ensure everyone has equal access to healthcare innovations driven by the Metaverse, especially areas that need more care. The metaverse app is only used for healthcare, giving academics a "niche theme" for education, study, training, and preventing and managing disease. It has become a popular way to help medical students improve their work. Also, patients' health conditions can be directly watched from home, and digital twins, a flexible technology, can connect real life to the virtual world
9 [111], [112]. The global healthcare market in the Metaverse is estimated to be valued at $5.06 billion in 2021. It is expected to reach $71.97 billion by 2030, growing at a compound annual growth rate (CAGR) of 34.8% between 2022 and 2030, based on data spanning the entire Metaverse [113]. Due to the concentration of Metaverse-centric businesses in North America,
9 this region is predicted to outperform others within the above frame. Their robust infrastructure, integration of AR-VR devices, and platforms in the healthcare industry have resulted in increased investment in AR-based goods, applications, and comparable changes to their software and hardware infrastructure [114], [115].

3.5 Dynamic priority scheduling for healthcare digital twin: Case Study

The case study examines a technique for ranking the data transmission order in a healthcare digital twin (HDT) network. The significance of this lies in the fact that data within the network can possess different levels of urgency. This section illustrates that employing a dynamic priority scheduling technique can considerably diminish the average weighted latency (AWL) in the network when compared to conventional scheduling methods such as FCFS (first come, first served). Dynamic priority scheduling ensures the faster delivery of critical data packets, which is particularly important in healthcare situations.

The proposed work analysis is a healthcare digital twin (HDT) network case study focusing on how a dynamic priority-based scheduling technique enhances communication between the physical twin (PT) and virtual twin (VT). Based on the IEEE 802.15.6 Standard, this study
14 categorized data from multiple sources into classes ($L = \{0, 1,..., 7\}$), each of which was given a criticality coefficient. Each data packet's transmission priority was calculated by multiplying its criticality coefficient by the waiting time it had experienced. Different data sizes were considered (ranging from 50 to 100 Kb), and transmission rates for the channels ($K = 10$) between PT and VT were assumed to be evenly distributed. In milliseconds, average weighted latency (AWL) was used to measure performance, with weights allocated to each class. The simulation involved varying the average arrival rate of data packets while comparing first come first served (FCFS) and absolute priority scheduling systems. Priority scheduling dramatically decreased AWL, as Figure 3-8 illustrates. This highlights the significance of a thoughtful scheduling strategy for effective and low-latency PT-VT communications in HDT networks. This strategy ensures timely transmission services while considering packet criticality.

The tactile internet comes into play to enable instant communication between components like VT-to-VT, PT-to-PT, VT-to-PT, and PT-to-VT. It ensures haptic interactions between PT and VT through extremely low delay, robust security, and reliability. Achieving a latency of 1 millisecond is crucial for systems using tactile internet. Cognitive mixed cellular networks can be applied to enhance communication between the physical and virtual realms, meeting this critical low-latency requirement. However, low throughput and underutilization of resources may result from this. Another intriguing avenue is how different technologies, like 5G or 6G cellular networks and distributed machine learning, can be combined to enable tactile internet for HDT modeling. Though it needs to be clarified if 5G/6G can be implemented for HDT, research is now being done on DT solutions for 6G deployment.

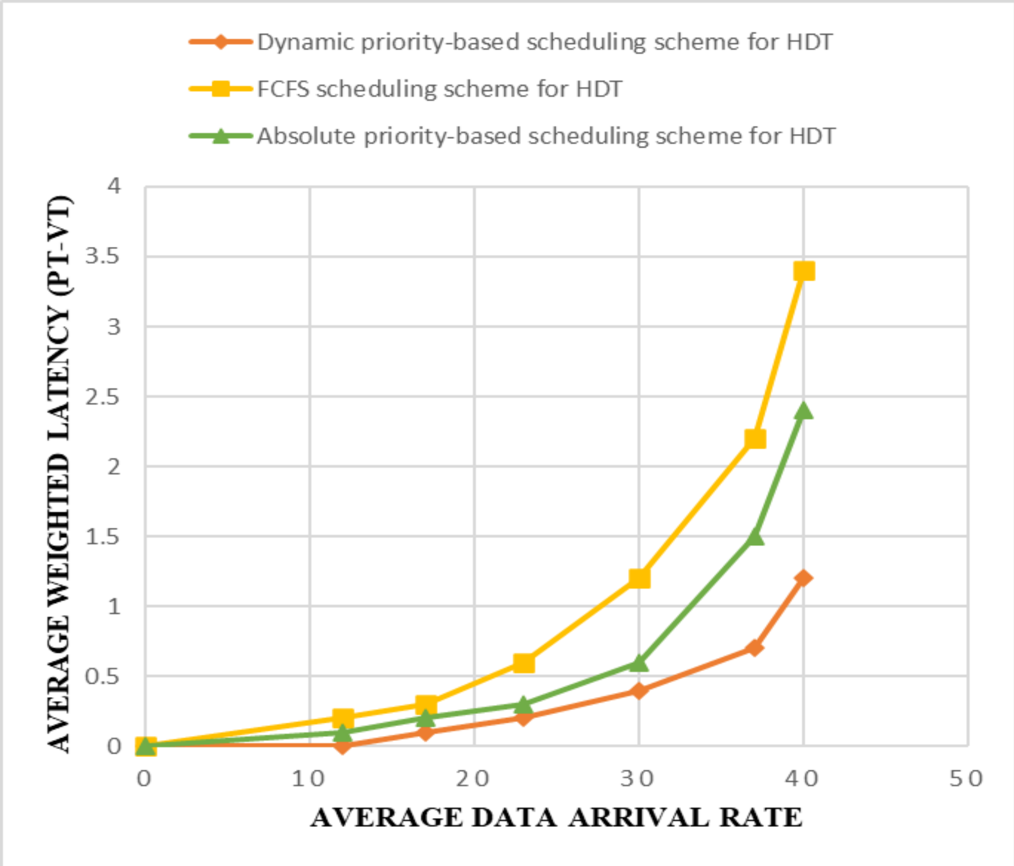


Figure 3-8: PT-VT communications latency network in the HDT

3.6 Conclusion

This research investigates the convergence of Digital Twin (DT) and Metaverse technologies in healthcare, with a focus on their ability to transform medical care, treatment, and research. It suggests a secure DT framework to counter the increasing security threats in healthcare and underscores the need for large-scale IoT data gathering for precise simulations. Through an examination of more than 130 related publications, the research identifies security solutions, technological facilitators, and limitations in DT applications, calling for increased patient privacy and applications in the real world. Applications in DT like virtual organs, genomic medicine, and personalized therapies exhibit its revolutionary influence on healthcare. Nevertheless, effective DT adoption hinges upon policy, regulation, and user support. Good governance will guarantee data privacy, ownership rights, and interoperability, while tough security protocols and clinician education will advance trust and usability. These issues, addressed, will facilitate the adoption of DT on a large scale to ensure ethical implementation, secure cross-border data, and better healthcare delivery.

CHAPTER – 4

DIGITAL TWIN-ENABLED SMART HEALTHCARE SYSTEMS

This chapter explores the integration of Digital Twin (DT) technology in smart healthcare systems, highlighting its role in patient monitoring, disease diagnosis, and treatment optimization. The chapter also presents an AI-driven DT framework for cervical cancer detection, discusses research challenges, and evaluates various machine learning models for improving diagnostic accuracy.

4.1 Introduction

The advancement of digital technologies has significantly transformed the healthcare sector, fostering new possibilities in patient monitoring, diagnostics, and treatment planning. Digital healthcare advancements have led to the development of Digital Twin (DT) technology, which replicates physical entities in virtual space to optimize healthcare operations. The integration of DT in healthcare represents a paradigm shift in how diseases are detected, monitored, and treated, enhancing patient care and medical decision-making. The role of DT in healthcare transformation is profound, as it enables a real-time, data-driven approach to medical treatments. It incorporates artificial intelligence (AI), Internet of Things (IoT), machine learning (ML), and cloud computing to develop a smart healthcare ecosystem. With the increasing prevalence of chronic diseases such as cancer, cardiovascular diseases, and neurological disorders, early diagnosis and intervention are critical to improving survival rates. The integration of DT with AI and deep learning models enhances the accuracy of diagnostics and facilitates personalized treatment.

This study primarily focuses on automated cervical cancer detection using Digital Twin technology. Cervical cancer is one of the most common causes of mortality in women, and early detection remains crucial for its successful treatment. Conventional screening methods, including Pap smears and human papillomavirus (HPV) testing, often suffer from limitations such as subjective interpretation, false negatives, and time-consuming analysis. To address these challenges, this study proposes a Digital Twin-based framework, integrated with AI-driven deep learning models for improved accuracy in cervical cancer diagnosis. This framework merges IoT, data analysis, and deep learning to create a digital copy of patients. This approach gives healthcare experts better tools to manage and improve a patient's health. The research significance and objectives revolve around leveraging DT and AI to enhance the efficiency of cervical cancer detection. This framework aims to reduce misdiagnosis, optimize clinical workflows, and improve patient outcomes by providing an automated, real-time classification system. The study introduces CervixNet, an advanced deep-learning-based classifier that enhances the detection and classification of cervical cancer cells.

Despite significant advancements in cervical cancer prevention and treatment, several research gaps remain. Here are some key areas where research gaps exist and where DT could make a substantial impact:

- ***Early Detection and Diagnosis:*** While Pap smears and human papillomavirus (HPV) tests have improved early detection, there is still room for improvement in accuracy, accessibility, and affordability with intelligent technologies.
- ***Wearable Devices and Biomarkers:*** Exploring the use of wearable devices and sensors for continuous monitoring of biomarkers related to cervical cancer risk. This could provide real-time data for early detection and personalized risk assessment.
- ***Telemedicine and Remote Monitoring:*** Investigating the effectiveness of telemedicine for remote consultations, follow-ups, and patient education. Smart technologies can facilitate virtual interactions between healthcare providers and patients, especially in regions with limited access to healthcare facilities.
- ***Treatment Personalization:*** Research is needed to explore how smart technologies, including genomics and molecular profiling, can contribute to personalized treatment plans for cervical cancer patients. Tailoring treatment based on individual characteristics and tumor profiles can improve outcomes.
- ***Secure Health Data Sharing:*** Addressing the challenges of securely sharing health data among stakeholders. Developing frameworks for ethical and privacy-preserving data sharing is crucial for collaborative research and improved patient outcomes.

Addressing these research gaps and motivation will require interdisciplinary collaboration between healthcare professionals, researchers, and technologists to harness the full potential of smart technologies in cervical cancer care.

4.2 Literature Survey

DT has been recognized as a practical and sustainable technology, particularly
7 in healthcare, since its inception, with the remarkable interest shown by the research community and industry in integrating DTs with healthcare in recent years. This section provides the most relevant research in this domain.

4.2.1 Recent research studies related to cervical cancer cells' segmentation and classification

Plissiti et al. [116] used the SIPaKMeD Pap smear dataset to identify distinct cell features. They employed intensity, texture, and shape-based features to extract these features. Subsequently, they employed the support vector machine (SVM) classifier and achieved an accuracy of 95.35%. A unique technique that uses many pre-trained models to extract deep features was presented by Basak et al. [117]. Principal Component Analysis (PCA) and Grey Wolf Optimizer (GWO) approaches efficiently decrease the feature space's dimensionality. Ramakrishnan et al. [118] presented a two-stage design with a classifier and extracted textural information. Additionally, researchers used DL-based techniques to categorize cervical images. For example, Orhan Yaman et al. [119] suggested a unique pyramid-deep architecture with two stages and used SVM and DarkNet19. DeepCELL, created especially to classify cervical cytology images via several kernels of varying sizes, was presented by the authors in [120], which added to its effective image classification capabilities. In [121] study, cervical cytology images were with 68% accuracy using ViT and DenseNet161. Pascal et al. [122] use many advanced deep-learning algorithms to tackle the problems of data quality and image fluctuation. Using the SIPaKMeD pap-smear dataset, they used over 40 convolutional neural networks (CNN) and 20 ViT-based models. The ViT models performed better with data augmentation and ensemble learning. A unique Conjugated Attention Mechanism and Visual Transformer (CAM-VT) framework is presented in this research [123] for identifying cervical cancer nest images with inadequate supervision. Visual Transformer (VT) integrates Conjugated Attention Mechanism modules, combining global and local feature extraction and ensemble learning to improve identification performance. They reported an accuracy of 88.92% on average using one private dataset. In [124] study, numerous online and offline methods for finding cervical cancer were tested using various data sets. Hybrid methods dealt with segmentation problems and improved feature selection by adding more machine-learning classifiers. Different training methods can obtain the best efficiency, accuracy, memory, and F1 scores. For example, using L1 normalization in regression analysis can lead to 100% accuracy, but it requires a lot of computer power. Medical researchers are investigating computer vision and machine learning to improve [125] cervical cancer screening. Although most infections may not progress to cancer, a negative test result indicates a decreased risk of cervical cancer in the ensuing ten years. It can be challenging to distinguish between high-risk HPV-positive cases requiring urgent care and suitable candidates for colposcopy screening. As a result, scientists have developed an accurate deep-learning algorithm to forecast cancer risk. The author [126] used deep learning and Pap smear images to enhance cancer cell prediction. ResNet50 is a pre-trained CNN model that accurately predicts cancer cells. The goal of this effort is to classify cellular types using incoming photos. Identifying abnormal cellular structures is crucial for early detection and treatment of cervical cancer. The proposed method accurately predicts outcomes across cell types with a success rate of 74.04% over a long period.

4.2.2 Recent research studies related to DT in healthcare

In [127] authors developed DT technology to replicate patient characteristics and behavior in particular environments. DT solutions are becoming more affordable and transforming how healthcare improves lives. For example, DT Solutions can provide global personalized medication. The technology lets doctors cognitively model a patient's optimum treatment using thousands of variables and digital care-backed clinical decision-support tools. DT solutions also assist in investigating diseases like Multiple Sclerosis to improve therapy options and speed up trials. Finally, DT technology can simulate new treatments and speed up vital advances. During the pandemic, medical staff shortages have necessitated faster vaccinations. In [128], authors examined a DT vaccination system in a clinic. The system simulates patients in real-time and generates a dynamic vaccination center. Using the virtual model to identify and fix issues in the natural system improves vaccination efficiency. In [129], authors suggested utilizing generative adversarial networks (GANs) to generate fake photos to anonymize patient data in the health sector and prevent data leaks. GAN systems have been trained to create fake data. According to the study, convolutional neural networks (CNN) may help with dynamic data that requires advanced GAN design. In [25], authors offered relevant studies in this area. The authors' reference model for DT healthcare (DTH) systems uses self-adaptation and autonomic computing to continuously monitor and forecast patient states. They used a motivational scenario for diabetes and chronic disease to support their strategy. No process implementation support was provided. They propose a cloud-based DT system for elderly healthcare. Cloud-DTH [28] It was created by merging the cloud architecture with the first DTH paradigm. This combination aids healthcare system computation and administration. Two case studies demonstrate how the cloud-DTH model enables personalized healthcare. Unfortunately, the case studies lacked performance and result evaluation. Whether AI or machine learning methods were applied in prediction was also yet to be discovered. DT in innovative healthcare systems fails because autonomous machine learning algorithms manage it. Authors [130] Suggest a hospital service management app. IoT devices and discrete-event simulation systems created a hospital DT framework. A predictive decision support model optimized the hospital's services process using real-time data without disrupting everyday operations. Different scenarios were tested using FlexSimHC to determine the methodology's practicality. The proposed model needs to be clarified about DT. The author [50] Presented a DT framework-based intelligent context-aware healthcare system. The applied models are said to forecast cardiac disease accurately. AI and ML are crucial while implementing an electrocardiogram (ECG) classifier to detect heart problems based on different variables. Cardiovascular disease [131] Requires optimal use of preventative drugs, technologies, and therapies. DT can simulate patients to forecast disease and optimize treatment. However, DT development has ethical and implementation issues. Personal DT with actionable insight is explored in [132], and personal digital twin bring IoT, machine learning, and AI closer. Table 4.1 explains all the domains and technologies implemented and researched in cervical cancer and DT.

Table 4.1: Limitations observed from previous research works

Ref.	Year	Domain	Technology Used	Limitations
Karakra et al. [130]	2018	Integrate DES for a hospital DT	DSS, DES, DT, IoT	Real-time data link between virtual and real-life space raises privacy and security concerns about data and creating a realistic virtual world.
Liu et al. [28]	2019	Cloud-based DT system for elderly healthcare	DT, IoT, Cloud Computing	Adoption of the Technology as well as interaction and collaboration issues between machines and services
Goyal et al. [124]	2020	Performance Analysis for Cervical Cancer	Pap smear, ML	Lack of Specific Algorithm and limited explanation of Hybrid Approaches
Piacentino et al. [129]	2020	Anonymization of patient information in the health sector	CNN, DT, GAN	Data organization, especially images. Losses details according to the databases as well as discriminator and generator training time.
Pilati et al. [128]	2020	DT for the vaccination process	DT, IoT, DES	Data safety, problems in real-time and adoption of the Technology.
Mugad et al. [133]	2021	Cervical Cancer Prediction	AI, CNN, DL	AUROC values were considered low Small dataset

Mehmood et al. [134]	2021	Cervical Cancer Prediction	ML, Decision Tree, k-NN	Absence of Information on Dataset and lack of Specific Algorithm
Kaushik et al. [125]	2022	Framework for Predicting Cervical Cancer Risk in Women.	AI, ML, DL	Insufficient Context on Medical Terms and limited context on HPV and Cervical Infections
Subarna et al. [135]	2022	Detecting and classifying cervical cancer photos	CNN, DL	Inadequate Discussion on Potential Limitations of Wavelet Transformations and absence of Performance Metrics
Benedictis et al. [127]	2022	DT for social distancing	DT, 3D Sensors, AI	Patient security and securing medical data
Sahal et al. [25]	2022	Revolutionizing Healthcare with Personal Digital Twins (PDT)	DT, Blockchain, AI	Data quality, connectivity issue between physical and virtual twin as well as technological and privacy challenges

4.3 Proposed Framework

A smart and adaptive DT framework in healthcare is shown in Figure 4-1. Improving patient care and healthcare operations are the main goals for DT applications in healthcare. The suggested DT framework creates a virtual patient replica in three stages by combining data analytics, AI, and IoT devices.

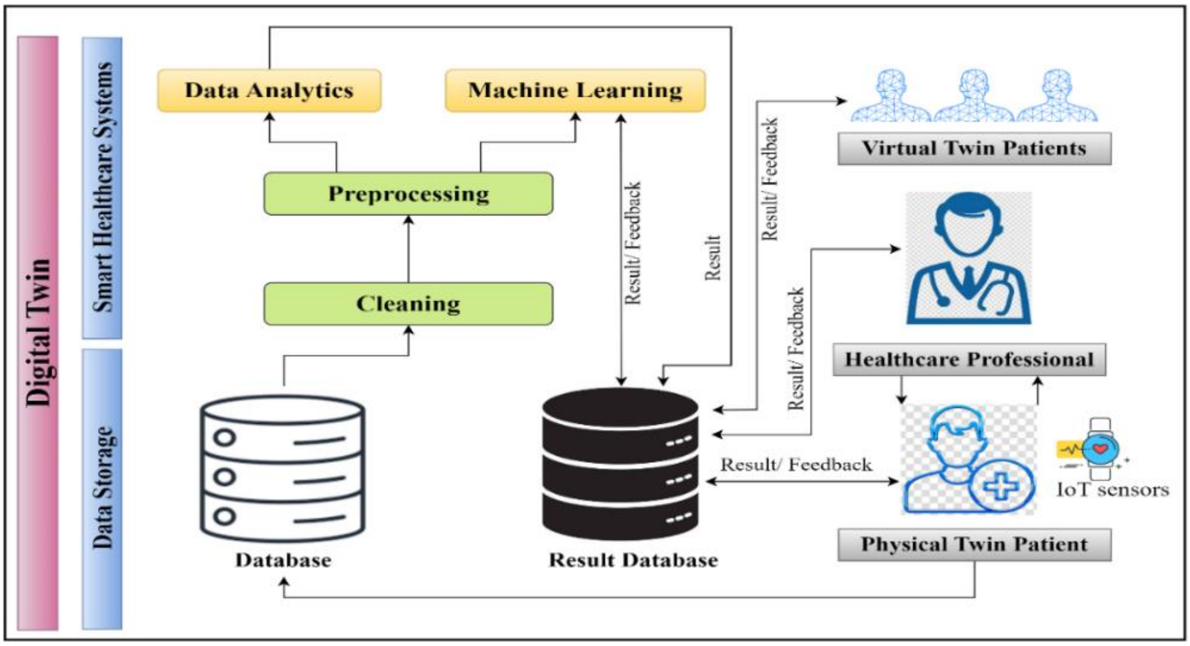


Figure 4-1: Digital Twin Framework

Real-time bodily data is collected from patients via IoT wearable devices equipped with sensors. This data is managed and ready for analysis, as well as different machine learning models by the DT replica. This configuration enables continuous health monitoring, identifying any anomalies early. At that point, medical experts can improve several aspects of healthcare, including treatment recommendations, safe experimentation settings, response tracking, lifestyle designs, and patient-provider communication. This framework has been divided into three stages: (a) data prediction, (b) supervision, and (c) comparison.

Data Prediction- Internet of Things (IoT) wearable sensors collect patient data at this stage. These sensors deliver real-time body data to monitor health and detect abnormalities. Raw data is briefly saved in a cloud database. After cleaning, preprocessing, and representation, the machine learning classifier trains and forecasts models using given data. These models' results are safely saved in the Result Database, a scalable cloud database. Patients and other system components can use this database for feedback, corrections, and model upgrades.

Supervision- Healthcare professionals, with their knowledge and experience, use result database predictive model outcomes to advise treatments and suggestions. This information improves healthcare when combined with clinical diagnosis and patient monitoring. Regularly updating prediction models with real-time data helps spot body metrics irregularities, monitor them, and intervene. This allows doctors to prescribe the right medicine and improve patients' lifestyles. Professionals can validate results and provide input to optimize the model.

Comparison- DT framework findings from comparable patients can be used to compare the current patient's results to theirs, expanding predictive models with reliable real-life scenarios. This comparison improves model accuracy and helps healthcare practitioners make better decisions. These judgments use real-time data and other patients' past, present, and expected future experiences to simulate, modify, or prevent comparable patient outcomes.

3

4.4 Materials and Methods

The system flow diagram for the suggested cervical cancer screening program is shown in Figure 4-2. Our proposed system has six steps: image acquisition, image enhancement, cell segmentation, feature extraction, feature selection, and classification. For multi-cells, the SIPaKMeD dataset was used during the image acquisition. In the image enhancement process,
144 input Pap smear images were improved to increase the image quality. The next phase was cell segmentation. Feature extraction came next, after segmentation. Distinctive interest points or

features were retrieved throughout the feature extraction process. The CervixNet algorithm was used as a selection technique during the features selection phase. Classification was the last stage. The details of every step have been explained in each subsection.

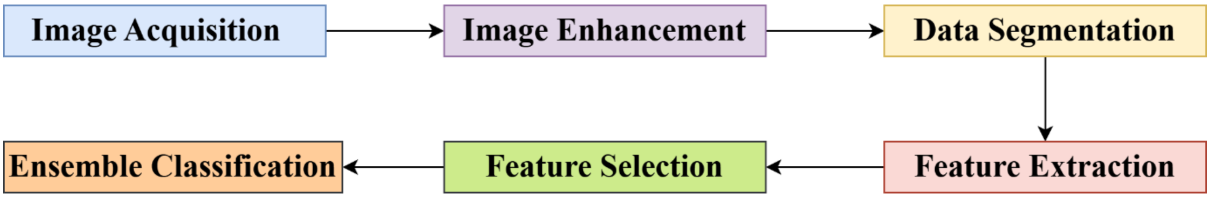


Figure 4-2: Methodology of cervical cancer detection and classification system

4.4.1 Image Acquisition

The SIPaKMeD [116] dataset was used for image acquisition. The SIPaKMeD dataset was used for multi-cell classification. There were 1013 images in the collection, from which 4103 cells could be extracted. The cells were divided into five groups: koilocytotic cells, parabasal cells, metaplastic cells, dyskeratotic cells, and superficial intermediate cells. Table 4.2 contains comprehensive information for each dataset. Figure 4-3 displays the sample pap smear pictures from the SIPaKMeD dataset. Five different types of cells:

- M: parabasal cells
- N: koilocytotic cells
- O: superficial intermediate cells
- S: dyskeratotic cells
- V: metaplastic cells

Table 4.2: Dataset SIPaKMeD

Types	Number of images	Total number of cells
Parabasal cells	116	792
Koilocytotic cells	246	836
Superficial intermediate cells	136	848
Dyskeratotic cells	233	824
Metaplastic cells	282	803
Total images	**1013**	**4103**

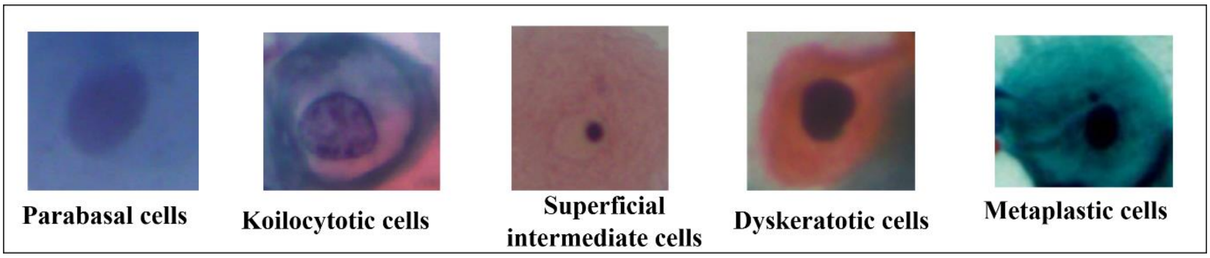


Figure 4-3: Multi-cell images of five classes

4.4.2 Image Enhancement

Sounds or other artifacts may be present in the pap smear images. Noise or contrast may cause pap smear picture quality to decrease. Therefore, we must eliminate noise and artifacts and enhance the image's quality regarding cell contrast. We applied a median filter to the pap smear images to eliminate the noise. Contrast-limited adaptive histogram equalization (CLAHE) [136]. It was used to improve the cell contrast, as shown in Figure 4-4. Compared to low-contrast pictures, high-contrast images made cell segmentation simpler and more accurate.

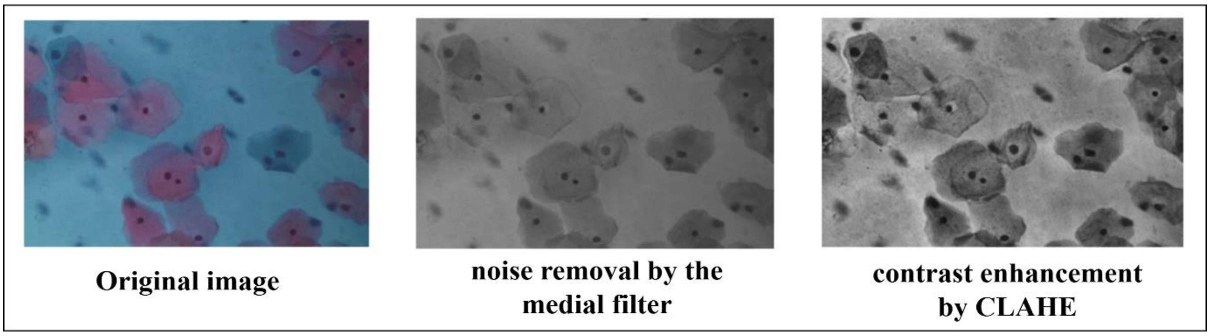


Figure 4-4: Image Enhancement

4.4.3 Data Segmentation

This step aimed to segment the cell's regions from the input images. The cytoplasm and nuclei are crucial elements in the cell area [137]. Cytologists analyze microscope images of cells in a Pap smear screening process, classifying the cells as normal or abnormal depending on their constituent parts' appearance [138]. It follows the same procedure as the automated screening system [139]. The automatic detection method relies heavily on the segmentation of cell components. Segmenting several cells may be challenging due to various issues, such as overlapping or harmful artifacts. For segmentation, we used the marker-controlled watershed technique [140]. To resolve the problem of overlapping border detection and touching cells splitting into individual cells. Over-segmentation is the primary issue with the

80 standard watershed transform. To solve this issue, we used markers [141]. The flowchart of the suggested improved watershed transform method is shown in Figure 4-5.

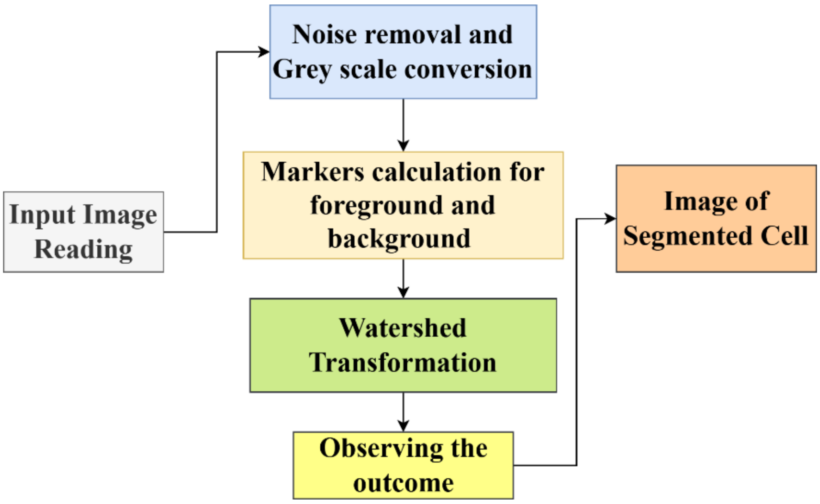


Figure 4-5: Flowchart of watershed transform method

Ten steps were included in our suggested overlapping cells segmentation approach to separate the multi-cell pictures into individual cells, which were then used to extract the cytoplasm and nuclei. Table 4.3 displays a synopsis of each phase.

3 **Table 4.3:** Overlapping cells segmentation approach

Step: 1	Read the color image and convert the grey image
Step: 2	Mark the foreground objects
Step: 3	Compute background objects
Step: 4	Use markers' image that is roughly in the middle of the cells to be segmented
Step: 5	Compute the watershed transform of makers' image
Step: 6	Show the result of detected overlapping cells' regions
Step: 7	Calculate the boundaries of detected regions in the image
Step: 8	Detect areas between the minimum and maximum values for cell regions
Step: 9	Cropping the regions
Step: 10	Classify the regions of the cell into isolated, touching, or overlapped cells

4.4.4 Feature Extraction

The process of extracting features came after the segmentation of the cells. The texture, form, and color characteristics, which were the crucial features, were retrieved at this point. The present study successfully extracted features from the model's global average pooling layer using CervixNet. In this study, a deep learning-based architecture named CervixNet was implemented to extract significant features. Figure 4-6 shows distinct group convolutional layers within the structure's layers.

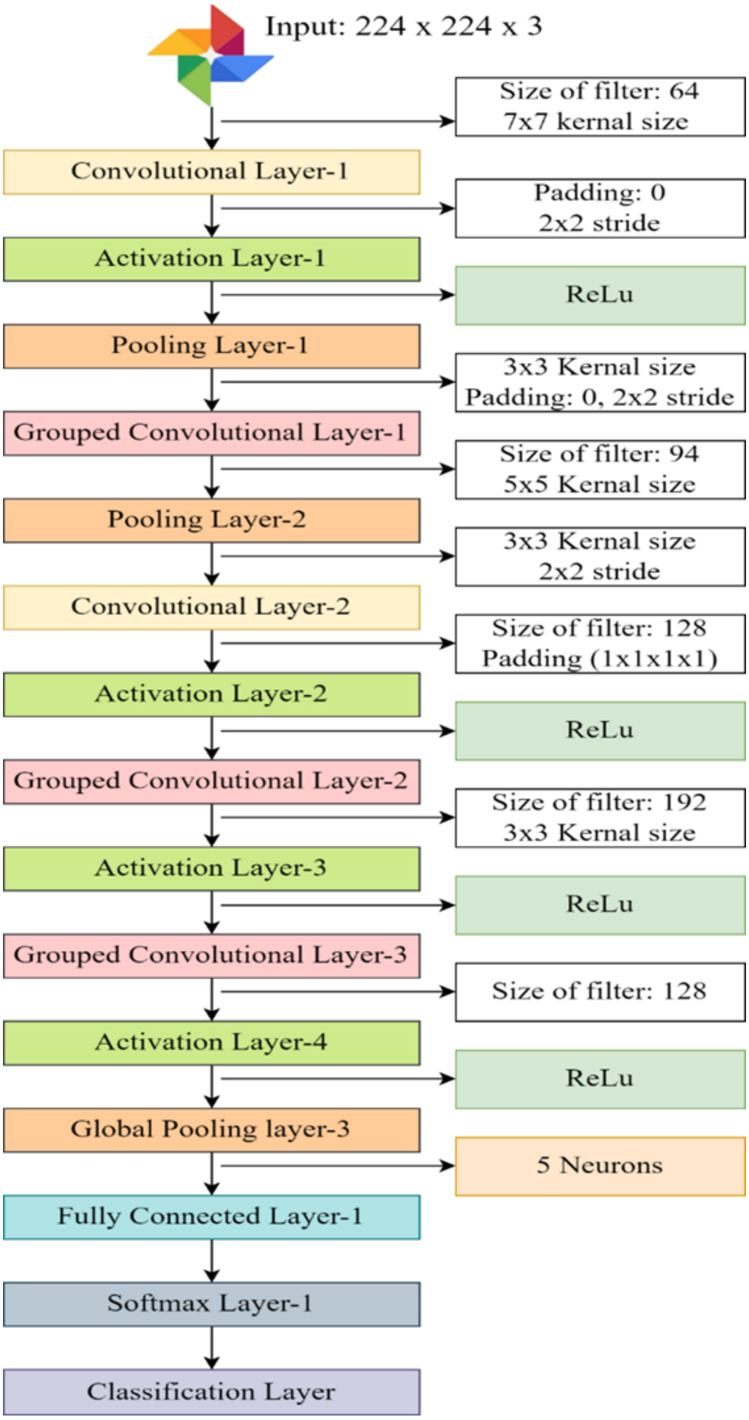


Figure 4-6: Proposed Architecture of CervixNet for feature extraction

The structure starts with a single input node, demonstrated by an image possessing dimensions of 224×224×3. Consequently, the colored image is subjected to a convolutional layer of 64 filters, each possessing a kernel size of 7×7 and a stride of 2×2. The subsequent output is directed to the Rectified Linear Unit (ReLU) layer, which transforms the output from the convolutional layer into either a positive value of +1 or a negative value of −1. To reduce the resolution of the picture features, a 3×3 average pooling layer with 2×2 strides is applied. The resultant output is subsequently put into a two-dimensional grouped convolutional layer. The initial stage of this procedure is to divide the input into separate clusters, which are subsequently tested by applying sliding convolutional filters.

The convolution process is performed in both the horizontal and vertical directions, where the layers of each cluster are merged independently. The present layer utilizes a combination of two separate groups and 94 filters, each having a dimension of 5×5. The padding dimensions for all groups consist of 2 units in each of the four dimensions. The resulting grouping is passed through the ReLU layer and the average pooling layer to achieve down sampling. To obtain additional detailed information, the output is forwarded to an additional convolutional neural network including 128 filters and a kernel size of 3x3, and the padding size is 1x1x1x1x1. After this, the resultant output is directed into the ReLU layer, where it undergoes a mapping procedure to be assigned a value of either +1 or -1. The finding is further processed by the grouped convolutional network, comprising 196 filters and two sets of convolutions. Each set of convolutions employs a kernel size of 3×3. The aggregated outputs of the depth-wise independent channels are transformed using a supplemental ReLU function, resulting in values that range from -1 to +1. The mapping procedure uses two more sets of convolutional layers to enhance accuracy. The layers comprise a collective sum of 128 filters with a kernel size of 3×3. The sampling process is made more accessible by including the global average pooling layer. In conclusion, a fully connected layer with five neurons is added to the output by the number of categories. The Softmax layer subsequently completes the ultimately linked layer.

4.4.5 Feature Selection

The main objectives of using a feature selection approach were to increase the classifier's accuracy and identify the most significant features. The feature selection technique may shorten machine learning algorithms' training times and simplify the classification model. This feature selection technique may improve the effectiveness of training machine learning models by streamlining the underlying classification model. The method known as Independent Principal Component (IPC) Analysis [142] is frequently employed in feature selection. By using linear dimensionality reduction methods, this algorithm efficiently reduces the dimensionality of data, converting it from a higher-dimensional space to a lower-dimensional one. The number of extracted features from CervixNet model was decreased successfully in this work by using IPC, going from 1172 features to the 792 most essential features, as shown in Figure 4-7.

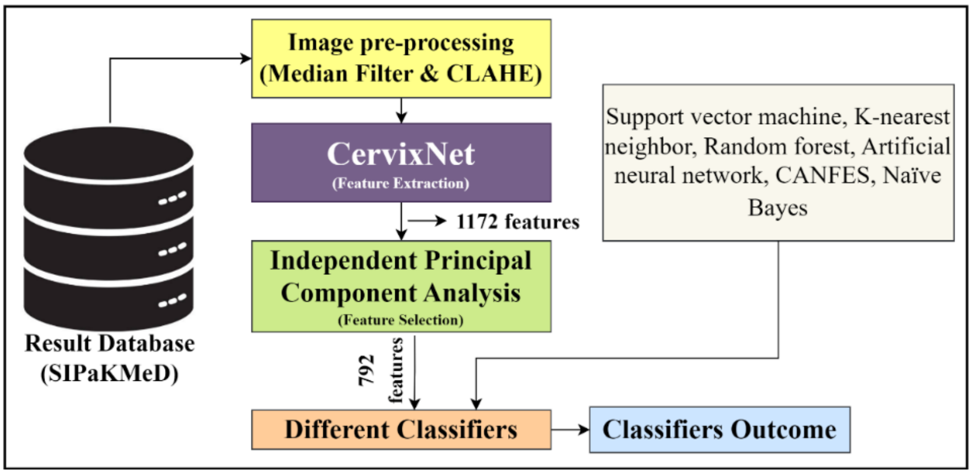


Figure 4-7: Feature extraction and selection

4.4.6 Different Classifiers

To find out which machine learning classifier is the most accurate, the deep learning features of CervixNet are extracted and then sent to several classifiers. The authors employed six machine learning algorithms to determine which works best for cervical cancer detection. These include Artificial Neural Networks (ANN), Support Vector Classification (SVM), Random Forest (RF), k-nearest Neighbor (k-NN), CANFES, and Naive Bayes (NB).

a) **ANN:** The artificial neural network (ANN) is a well-known machine-learning technique [143] that is meant to look like the real neural networks in the brain. ANNs come in many shapes and sizes, and the feedforward neural network is one of the most common types. In this network design, inputs from neurons in the previous layer are processed, and then the weighting factors for each input neuron are sent to the next layer. It is essential to know that the backpropagation method is the most popular way to teach an MLP. They are changing the weights between neurons to improve accuracy. These results show that this model does very well in pattern recognition. The algorithm can quickly adapt to new data sets but may converge slowly to find a locally optimal answer.

87

b) **SVM:** The support vector machine (SVM) is a supervised learning method [144]. That uses training data sets to put things into different groups accurately. Plotting the feature plane provides a visual representation of the training data in the SVM model. This story strongly links important events that stand in for different socioeconomic classes. A curve that occupies the space between the two classes and preserves the maximum distances between each class point and the Support Vector Machine (SVM) can be seen.

c) **RF:** The random forest (RF) classifier [145] comprises several decision trees with a training example set and predictors. The bagging approach selects features at random at each split in the attributes. The trees will continue to develop until they reach a certain depth; at that time, a voting mechanism for the class will be implemented due to the large number of trees produced by the Artificial Neural Networks Classifier.

d) **k-NN:** Supervised k-nearest neighbor (k-NN) [146] Categorization began in 1951. The class of nearby data points determines a category in the above approach. Additionally, the classification results depend on the closest neighbor's pre-determined k-value of 1. At this stage, the k-training samples with the highest similarity to the new sample are picked to determine their category assignment based on their feature vector. Thus, examining the candidate's data's classified classes aligns with the newly calculated vector.

e) **CANFES:** Neural networks (NN) and reduced fuzzy rules were combined to make the CANFES classification method [147]. This also leads to fewer mistakes when the source images are classified. There is one input layer, three or more hidden levels, and one output layer in the CANFES classification design. It is the input layer's job to track how many extracted traits are sent to the hidden layer of the next level. The number of neurons that can be used to build this secret layer is 15. The weights of neurons in the hidden layers of an adaptive neural network are changed based on the traits that were learned from the input. One of the neurons in the output layer makes the output pattern by adding up all the index values from the hidden layer before it.

f) **NB:** A probabilistic model called the Naive Bayes (NB) classifier [148]. Uses a given dataset's frequency and value distribution to forecast probabilities. The approach is based on the idea that the value of the class variable has no bearing on the other variables and emphasizes the application of Bayes' theorem. Since this assumption of independence is rarely valid in practical settings, it is called naive. Nevertheless, the algorithm can rapidly enhance its effectiveness in various regulated classification scenarios.

4.5 Experimental Analysis

46 This section presents the confusion matrix for each model used. Python, Sklearn package, Tensorflow, and Keras were used in the experiment. Other libraries, such as Pandas and Numpy, were also used to help preprocess data. A total of 1013 images from the SIPaKMeD (multi-cell) dataset are utilized to evaluate the efficacy of the proposed technique. From selected images, 4103 cells were chosen and categorized into five categories.

3
- O: superficial intermediate cells
- M: consistent parabasal cells
- V: metaplastic cells
- S: Dyskeratotic cells were present
- N: koilocytotic cells

10 To identify the most effective classification model for cervical cancer detection, six machine learning algorithms were implemented: Support Vector Machine (SVM), Random Forest (RF), 146 k-Nearest Neighbor (k-NN), Artificial Neural Networks (ANN), Naïve Bayes (NB), and CANFES.

34 4.5.1 Confusion Matrix

The confusion matrix is a crucial tool for evaluating the performance of classification models 47 by providing detailed insights into their true positive (TP), false positive (FP), true negative (TN), and false negative (FN) rates. The confusion matrices for each classifier are presented in Figures 4-8 to 4-13, corresponding to SVM, RF, k-NN, ANN, NB, and CANFES respectively. 2 A confusion matrix provides a detailed breakdown of how well a model classifies each category of cervical cells:

38
- True Positives (TP): Correctly classified instances of a specific class.
- False Positives (FP): Instances wrongly classified as belonging to a class when they do not.
- True Negatives (TN): Correctly identified instances that do not belong to a specific class.
- False Negatives (FN): Instances that belong to a class but are misclassified.

Each confusion matrix provides a percentage-based representation of the classifier's accuracy across all five cervical cell classes.

4.5.2 Performance of Models

The classification accuracy of the six models was computed, with the following results:

- Support Vector Machine (SVM): 98.9%
- Artificial Neural Networks (ANN): 98.2%
- Random Forest (RF): 91.8%
- k-Nearest Neighbor (k-NN): 97.8%
- Naïve Bayes (NB): 97.5%
- CANFES: 95.9%

The proposed model provides a multi-label classification of input images and uses supervised learning with more training examples via five-fold cross-validation. Testing demonstrates that the suggested classifier outperforms other models in terms of classification accuracy. SVM outperformed all other classifiers, achieving the highest classification accuracy of 98.9%. It demonstrated strong predictive performance across all five classes with minimal misclassification. ANN followed closely with an accuracy of 98.2%, proving effective in distinguishing between normal and abnormal cervical cells. k-NN and NB performed comparably, with accuracies of 97.8% and 97.5% respectively. These classifiers exhibited high classification precision, particularly in detecting metaplastic cells. RF recorded a relatively lower accuracy of 91.8%, indicating that it struggled in correctly identifying certain abnormal cell types. CANFES achieved 95.9% accuracy, but misclassification rates were higher than those of SVM and ANN.

M	217 18.3%	0 0.0%	1 0.1%	0 0.0%	0 0.0%	99.8% 0.2%
N	1 0.1%	247 20.9%	4 0.3%	0 0.0%	1 0.1%	98.6% 1.4%
O	0 0.0%	0 0.0%	271 22.3%	0 0.0%	1 0.1%	99.7% 0.3%
S	1 0.1%	1 0.1%	0 0.0%	261 22.1%	0 0.0%	99.6% 0.4%
V	0 0.0%	3 0.2%	1 0.1%	0 0.0%	221 18.3%	96.9% 3.1%
	99.8% 0.2%	98.1% 1.9%	98.7% 1.3%	98.8% 1.2%	99.5% 0.5%	**98.9%** **1.1%**
	M	**N**	**O**	**S**	**V**	

Figure 4-8: Confusion Matrix SVM

M	211 17.3%	2 0.2%	1 0.1%	5 0.4%	1 0.1%	96.8% 3.2%
N	22 1.8%	210 17.4%	12 1.1%	2 0.2%	7 0.6%	85.2% 14.8%
O	2 0.2%	0 0.0%	261 21.3%	6 0.5%	0 0.0%	94.5% 5.5%
S	20 1.6%	2 0.2%	1 0.1%	240 19.8%	1 0.1%	90.2% 9.8%
V	4 0.3%	9 0.7%	2 0.2%	5 0.4%	197 15.7%	92.3% 7.7%
	91.6% 8.4%	85.6% 14.4%	90.8% 9.2%	97.4% 2.6%	93.6% 6.4%	**91.8%** **8.2%**
	M	**N**	**O**	**S**	**V**	

Figure 4-9: Confusion Matrix RF

M	221 18.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	97.5% 2.5%
N	7 0.6%	243 19.9%	12 0.8%	2 0.3%	0 0.0%	94.7% 5.3%
O	2 0.2%	0 0.0%	273 22.2%	1 0.1%	0 0.0%	97.8% 2.2%
S	5 0.4%	0 0.0%	0 0.0%	251 20.7%	1 0.1%	99.8% 0.2%
V	0 0.0%	4 0.3%	0 0.0%	0 0.0%	212 17.6%	99.5% 0.5%
	97.4% 2.6%	95.5% 4.5%	97.5% 2.5%	99.4% 0.6%	99.3% 0.7%	**97.8% 2.2%**
	M	**N**	**O**	**S**	**V**	

Figure 4-10: Confusion Matrix k-NN

M	221 17.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	99.4% 0.6%
N	6 0.5%	243 19.9%	11 0.9%	2 0.2%	0 0.0%	96.2% 3.8%
O	2 0.2%	0 0.0%	269 22.2%	1 0.1%	0 0.0%	99.5% 0.5%
S	5 0.4%	0 0.0%	0 0.0%	252 20.7%	1 0.1%	98.4% 1.6%
V	0 0.0%	4 0.3%	0 0.0%	0 0.0%	210 17.5%	97.8% 2.2%
	99.4% 0.6%	96.6% 3.4%	99.5% 0.5%	99.1% 0.9%	96.7% 3.3%	**98.2% 1.8%**
	M	**N**	**O**	**S**	**V**	

Figure 4-11: Confusion Matrix ANN

M	223 18.3%	1 0.1%	0 0.0%	0 0.0%	0 0.0%	99.5% 0.5%
N	6 0.4%	240 19.8%	15 1.3%	2 0.2%	0 0.0%	92.1% 8.9%
O	0 0.0%	0 0.0%	271 22.2%	1 0.1%	0 0.0%	99.5% 0.5%
S	5 0.4%	0 0.0%	0 0.0%	251 20.8%	2 0.2%	97.1% 2.9%
V	0 0.0%	7 0.6%	0 0.0%	0 0.0%	211 17.6%	99.5% 0.5%
	98.1% 1.9%	96.2% 3.8%	95.3% 4.7%	98.6% 1.4%	99.5% 0.5%	**97.5% 2.5%**
	M	**N**	**O**	**S**	**V**	

Figure 4-12: Confusion Matrix NB

M	222 17.4%	4 0.3%	1 0.1%	5 0.4%	1 0.1%	98.8% 1.2%
N	22 1.8%	238 17.3%	2 0.2%	12 1.2%	6 0.6%	94.2% 5.8%
O	6 0.5%	0 0.0%	261 21.2%	6 0.5%	2 0.2%	96.1% 4.9%
S	19 1.6%	1 0.1%	1 0.1%	231 19.9%	2 0.2%	95.1% 4.9%
V	2 0.2%	9 0.7%	2 0.2%	5 0.4%	212 15.7%	95.3% 4.7%
	95.1% 4.9%	94.6% 5.4%	95.8% 4.2%	97.4% 2.6%	96.6% 3.4%	**95.9% 4.1%**
	M	**N**	**O**	**S**	**V**	

Figure 4-13: Confusion Matrix CANFES

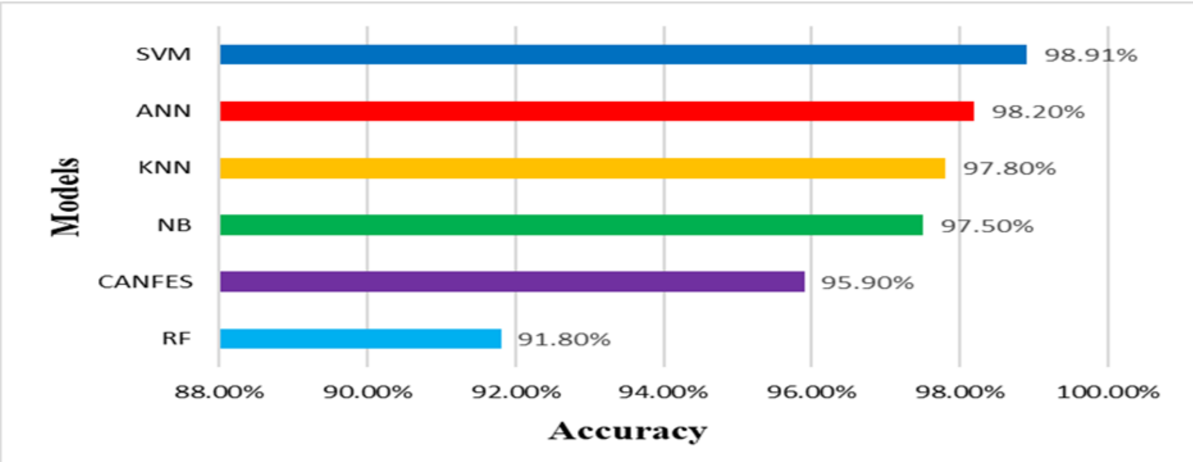


Figure 4-14: Models Accuracy

84

4.5.3 Comparison of Proposed Method with State-of-the-Art Methods

Compared to previous research, the suggested approach produced significant results, obtaining an accuracy level of 98.91% with the same dataset. The current research used an innovative DT framework and CervixNet to improve accuracy, unlike previous studies that relied on traditional methodologies. Furthermore, the model that has been designed is very efficient and reliable. The system's structure is distinguished by its simplicity, uniqueness, and accuracy since it can analyze a new image in milliseconds. The proposed model makes it especially well-suited for medical applications. Table 4.4 compares the proposed model's accuracy to other cutting-edge approaches.

Table 4.4: Accuracy comparison of the proposed method with previously published work with the SIPaKMeD dataset

Ref.	**Year**	**Methods**	**Accuracy**
Lu et al. [149]	2017	DeepPap	93.58%
Plissiti et al. [116]	2018	SVM, CNN	95.35%
Asadi et al. [150]	2020	SVM, QUEST, C&R tree, MLP and RBF	96.60%
Win et al. [151]	2020	Digital Image Processing	94.09%
Chen et al. [152]	2021	CompactVGG	97.80%
Priyanka et al. [153]	2021	CNN, ResNet50	84.40%
Munirathinam et al. [154]	2021	SVM, k-NN	87.30%
Qin et al. [155]	2022	Multi-Task feature fusion model	98.14%
Shinde et al. [156]	2022	DeepCyto	96.81%
Sahoo et al. [157]	2023	Fuzzy rank-based ensemble approach	97.18%
CervixNet with ML classifier Proposed model			**98.91%**

The proposed method significantly improves cervical cancer classification accuracy, setting a new benchmark in the field. The results demonstrate that integrating deep learning with a Digital Twin-based healthcare system leads to superior diagnostic capabilities compared to previous approaches. The accuracy gain of over 5% compared to earlier models highlights the effectiveness of the proposed model, making it a promising solution for automated cervical cancer detection and screening. Future studies can build upon this framework by incorporating more extensive datasets and hybrid AI techniques to further refine diagnostic accuracy.

4.5.4 Challenges

A. **Security and Privacy**: DT system security presents many difficulties. Unauthorized access, abuse, change, or data sharing are inherent risks like any information system. Hackers and other malicious people efficiently target them because of the vast amount of private and sensitive data they maintain. Internet of Things (IoT) devices and sensors add to this complexity since standard security methods often fall short when dealing with these unusual components. The processing of personal user data also raises regulations. Following privacy rules such as the General Data Protection Regulation (GDPR) in Europe or other applicable national requirements is not only required but also significantly complicates the design of DT systems.

B. **Lack of Standardization**: The need for global guidelines for DT causes many problems for the system. Security, privacy, data interchange, interaction protocols, responsibilities, and even physical and virtual world synchronization are all affected. Global standardization would serve as an essential lubricant, promoting DT acceptance and opening the door for quick and extensive deployment.

C. **Handling Multi-sourced and Heterogeneous Data**: DT often ingests data from diverse sources, leading to various data types (structured, unstructured, semi-structured). This data heterogeneity poses challenges for data processing, model evaluation, and training. These challenges directly impact the effectiveness of machine learning models.

4.6 Conclusion

Early diagnosis of cervical cancer greatly enhances prognosis, thereby earning the status of one of the most curable cancers. The current research suggests a Digital Twin (DT)-based automated cervical cancer framework, combining the CervixNet classifier model with machine learning for precise diagnosis. Six machine learning models—ANN, SVM, RF, k-NN, CANFES, and NB—were compared and SVM demonstrated the best accuracy (98.91%). Independent PCA for feature selection decreased 1172 features to 792 for efficient classification. Though computational-intensive, integration of DT promotes enhanced automated diagnostics and screening for better patient outcomes. The focus in future research should be to optimize model effectiveness, real-time processing, and AI innovations for greater scalability and availability in digital health.

CHAPTER -5

SECURING HEALTHCARE IOT WITH DIGITAL TWIN AND AI-DRIVEN INTRUSION DETECTION

This chapter presents a Digital Twin (DT)-enabled security framework for healthcare IoT networks, integrating AI-driven intrusion detection and cryptographic techniques. The study explores the role of DT in cybersecurity, addresses challenges in securing medical IoT devices, and evaluates the effectiveness of blockchain and encryption methods in safeguarding patient data.

5.1 Introduction

98 88 The emergence of Digital Twin (DT) technology has revolutionized healthcare by enabling real-time monitoring, predictive analytics, and personalized treatment. A DT is a virtual replica of a physical entity that continuously updates based on real-world data, allowing for real-time simulations, predictions, and optimizations. The healthcare sector increasingly leverages DT models to enhance patient care, operational efficiency, and clinical decision-making. One of its key applications is in personalized medicine, where patient-specific models allow physicians to simulate treatment plans and predict health outcomes. DTs also facilitate remote patient monitoring by integrating IoT-enabled medical devices and wearable sensors, ensuring continuous health tracking and early detection of abnormalities. Additionally, DTs enhance surgical planning and medical training by providing detailed virtual models for risk-free experimentation and skill development. In medical imaging and diagnostics, DTs augment radiology and pathology by creating interactive 3D models that improve disease detection and diagnostic accuracy. Similarly, in hospital management, DTs optimize resource allocation, workflow automation, and predictive maintenance of medical equipment. However, the integration of DT with IoT-based medical devices has also introduced significant cybersecurity challenges, making data integrity, confidentiality, and system security crucial concerns. Since 19 DT systems rely on continuous data exchange between physical and virtual entities, they are vulnerable to cyber threats such as unauthorized access, data breaches, ransomware attacks, and IoT device exploitation. A secure DT-IoT framework is essential to prevent malicious entities from exploiting vulnerabilities in connected medical devices. Security measures such as authentication mechanisms, secure communication protocols, and encryption techniques can protect DT-enabled IoT networks from data compromise. Additionally, intrusion detection systems (IDS) and anomaly detection models can proactively monitor network traffic to

identify potential cyber threats in real time. AI-powered DT models further strengthen security by simulating cyberattack scenarios, predicting vulnerabilities, and enabling proactive risk mitigation strategies. By analyzing historical attack data and network behavior, DT-based cybersecurity frameworks improve incident response and enhance overall security. Multi-layered security architectures incorporating firewalls, secure access controls, and zero-trust security models provide additional protection for healthcare IoT networks. To further address these security challenges, blockchain and cryptographic techniques have emerged as robust solutions. Blockchain's decentralized and tamper-proof ledger ensures data immutability, transparency, and secure access control, mitigating risks associated with centralized data storage. It eliminates single points of failure, reducing the risk of data breaches and unauthorized modifications while maintaining data integrity through cryptographic hashing. Smart contracts enhance security by automating transactions and enforcing regulatory compliance, such as GDPR and HIPAA. Role-based access control ensures that only authorized stakeholders, including patients, doctors, and administrators, can access specific data. Cryptographic techniques further strengthen security by safeguarding data confidentiality, authentication, and secure communications. Elliptic Curve Cryptography (ECC) offers lightweight encryption ideal for resource-constrained IoT devices, while homomorphic encryption allows computations on encrypted data without decryption, enabling privacy-preserving analytics in DT healthcare applications. Zero-knowledge proofs ensure secure authentication without exposing sensitive information, strengthening patient identity verification. As quantum computing advances, post-quantum cryptographic algorithms are being developed to counter emerging cyber threats. By integrating blockchain with advanced cryptographic mechanisms, healthcare systems can establish a secure, decentralized, and privacy-preserving framework for DT-enabled IoT networks, ensuring safe patient data exchange and a resilient healthcare ecosystem.

By combining blockchain and cryptographic mechanisms, a trustworthy, decentralized, and privacy-preserving framework for DT-enabled IoT healthcare networks can be established, ensuring secure patient data exchange and cyber-resilient healthcare ecosystems. The primary objectives of this study include:

1. Developing a Secure Digital Twin (DT) Framework for Healthcare IoT Networks
    - Establishing a trustworthy DT-IoT model that ensures real-time monitoring, predictive analysis, and cyber resilience.
    - Addressing data security and privacy challenges in healthcare DT applications.

2. Integrating Blockchain and Cryptographic Techniques for Enhanced Security
   - Utilizing blockchain technology for secure patient data management and decentralized access control.
   - Implementing cryptographic techniques such as ECC, homomorphic encryption, and quantum-resistant algorithms to ensure confidentiality and integrity of medical data.
3. Developing an AI-Powered Intrusion Detection System for DT-Enabled IoT Networks
   - 97 Leveraging machine learning-based intrusion detection models to identify and mitigate cyber threats in real-time.
   - Evaluating the effectiveness of anomaly detection, threat intelligence, and automated cybersecurity responses.
4. Validating the Proposed Framework Through Experimental Analysis
   - Implementing proof-of-concept experiments to assess the efficacy of the proposed security model.
   - Comparing results with existing security solutions to demonstrate improvements in accuracy, efficiency, and scalability.

This research aims to bridge the security gap by developing a robust, AI-driven Digital Twin security model, incorporating blockchain for decentralized trust, cryptographic encryption for data confidentiality, and machine learning-based intrusion detection for cyber resilience. The proposed solution will address real-world challenges faced by healthcare organizations, ensuring scalable, secure, and intelligent DT-IoT systems.

5.2 Literature Survey

73 The authors noticed various studies focused on identifying cyberattacks on the Internet of Things (IoT) and Industrial Internet of Things (IIoT) networks as authors investigated recent research. When developing intrusion detection systems for these diverse networks, each research takes a different approach despite having the same objective. A digital-twin method and an open-source UAV ambush dataset were utilized by Benjamin et al. [158] to explore the security of uncrewed ethereal vehicles (UAVs) within the year 2021. Their centralized demonstration, which makes utilization of Machine Learning (ML) and Deep Learning (DL), explores the modern cyber dangers that uncrewed airborne vehicles (UAVs) are up against. Khan et al. [159] describe a new video streaming compression model for IoT settings that uses GANs and fuzzy logic to improve the efficiency of sending multimedia. Their study includes using blockchain to improve security for serverless computing in fog and edge settings, which

gives us strong options for protecting infrastructure [160]. The group also works on managing data from drones using metaheuristic algorithms and blockchain for safe fog settings [161] and looks at the latest developments in IoT security made stronger by blockchain technology [162]. In addition, they suggest a design that uses machine learning to make next-generation radio access networks work better in factories [163] and a way to keep remote sensing data safe in smart towns [164]. These additions make it much easier to use safe and effective technologies in IoT and network systems.

Table 5.1: Literature Review of the most recent studies on Cybersecurity Techniques and Datasets

Ref.	**Year**	**Dataset**	**Techniques**	**Focus**	**Security & Privacy**	**Scalability**
Khraisat et al. [165]	2019	BoT-IoT	SVM, SIDS, and AIDS	Detecting Attacks in IoT Environment,	NO	NO
Alzahrani et al. [166]	2021	NSL-KDD	Decision tree, Random Forest, and Xgboost	Anomaly Detection, SDN Security	NO	NO
Benjamin et al. [167]	2021	open-source UAV attack dataset	ML and DL	UAV modern-cyber threats are explored	YES	NO
Qinghua et al. [168]	2021	SWaT, WADI, BATADAL	GAN	Anomaly Detection for Cyber-Physical Systems	YES	NO
He et. al [169]	2022	CIC-IDS	LSTM	Data Security, Privacy	YES	YES
Ashraf et al. [170]	2022	BoT-IoT	ANN, Federated Learning	Data Privacy	YES	NO
Kumar et al. [171]	2022	BoT-IoT	Blockchain, Xgboost, RF	IDS to detect DDoS attack	YES	NO
Imran et al. [172]	2022	KDD-CUP-99	Deep Autoencoder, SVM	NIDS Effectiveness and Robustness	NO	NO
Seba et al. [173]	2022	Real-Time	Supervised Machine Learning Algorithms	Enhancing ICS Security	YES	NO

Bowen et al. [174]	2023	CIC-IDS, NSL-KDD, IoT-23	Deep Learning Techniques	Handling Imbalanced Datasets	NO	YES
Thakkar et al. [175]	2023	CIC-IDS, NSL-KDD, UNSW-NB-15	Deep Learning, Statistical Feature Selection	Performance Improvement of DNN-based IDS	NO	NO
Swati et al. [176]	2023	BoT-IoT	DL-RF	Securing Digital Twin systems against cyber threats	YES	NO
Huan et al. [177]	2023	UNSW-NB15, CICIDS2017	CNN, BiLSTM, DNN	Cyber-attack behavior identification	YES	NO

Many researchers have found ways to find attacks and strange things happening in networks. One exciting method combines centrality measures with deep learning algorithms, feature extraction, classification strategies, and hierarchical grouping. Every study adds to what we know about Intrusion Detection Systems. The study aims to add to what has already been done by finding the most critical problems from previous research. Table 5.1 shows the issues and restrictions when finding network threats and strange behavior in IoT and IIoT settings. Some of these problems are not enough scalability analysis, not enough work on integrating deep learning models, not having a decentralized storage module, not being able to compare well enough with the latest methods, and not doing enough experiments. The study aims to solve these problems by checking for scalability, comparing with the most up-to-date techniques, using thorough evaluation metrics, and carefully analyzing the results.

5.3 Digital Twin Framework for Secure IoT Networks

Blockchain and artificial intelligence (AI) in intrusion detection systems have received attention in healthcare digital twin technologies. There is still a knowledge vacuum on effectively combining blockchain technology with artificial intelligence (AI) to identify network breaches in the healthcare industry, despite individual studies into AI-driven intrusion detection systems and security protocols. A thorough investigation of their integration is required to design a state-of-the-art framework that can detect and mitigate attacks while protecting data privacy, guaranteeing scalability, and maintaining real-time performance. The literature currently in publication only offers a partial understanding of frameworks that combine blockchain with AI to create effective and dependable intrusion detection systems.

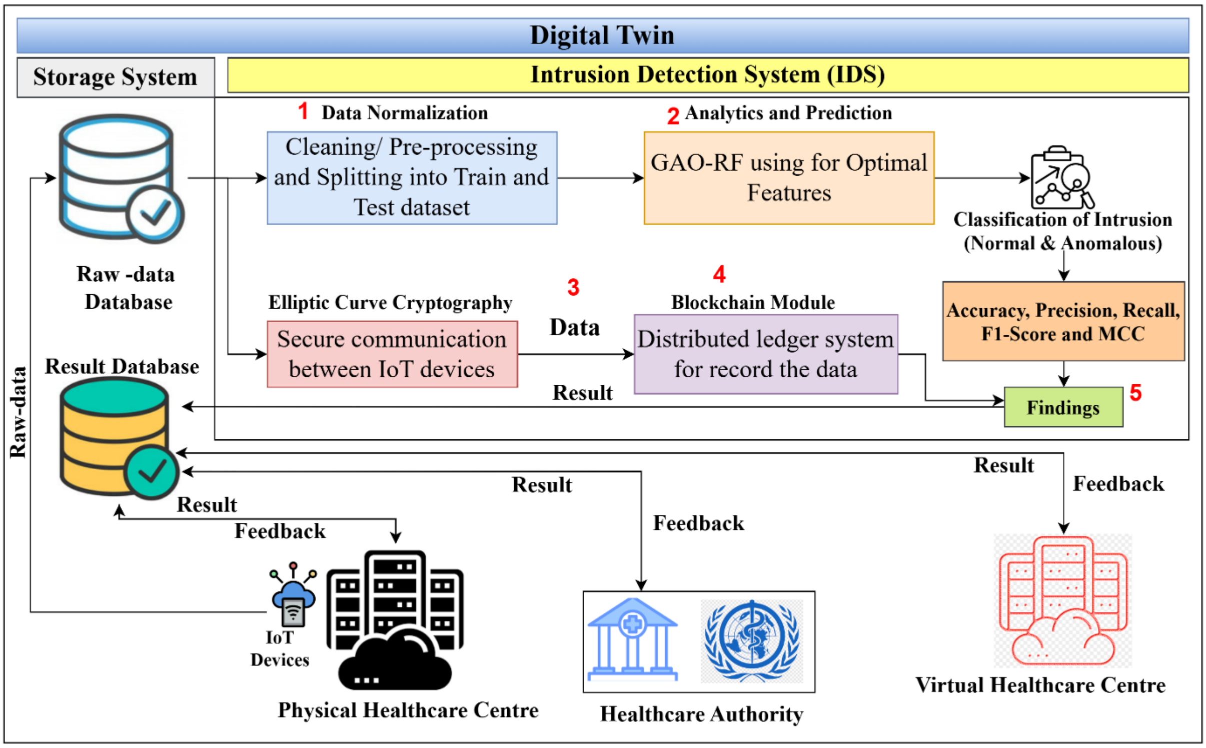


Figure 5-1: System Architecture

Blockchain approaches and optimization techniques are used in constructing Internet of Things (IoT)-based intrusion detection systems in the healthcare industry. Identifying network threats inside healthcare infrastructures is made possible by continuously monitoring IoT devices. The Digital Twin framework for securing IoT transmission using ECC and blockchain is shown in Figure 5-1 and is used in healthcare systems to ensure patient information and streamline workflows. With IoT devices, data analytics, blockchain, and ECC, the proposed DT framework may improve healthcare centers and facilitate efficient collaboration between healthcare authorities. As seen in Figure 5-1, IoT wearable sensors collect and transmit real-time data from patients or healthcare centers. The transmitted data will be cleaned, pre-processed, and converted to utilize for data analytics and prediction. This framework allows for the constant monitoring of data transmission status and the early detection of anomalies. Beginning with a reasonable dataset obtained from IoT devices/sensors separated into bunches, the pre-processing arrangement included normalization, name encoding, and information cleaning. The dataset is at that point isolated into prepare and test sets. The examination and expectation module employments labeled information for patterns indicating interruptions or noxious action. This module employments a wellness function-based developmental calculation to progress highlights, coming about in information visualization and execution assessment measurements expectation. To ensure IoT gadgets and their associations, the information reaction and basic era stage employments Elliptic Curve Cryptography to scramble information and create and trade mystery keys. At long last, despite issues with adaptability, keenness, and assault rates, the blockchain module stores therapeutic information on a cloud-distributed record to protect it from any assaults.

5.4 Materials and Methods

The proposed e-healthcare framework depends on a combination of Elliptic Curve Cryptography (ECC) and blockchain innovation to keep private well-being information secure. Each innovation has its possess qualities that make it valuable for information assurance. ECC is utilized to keep discussions between IoT gadgets in a clinic arranged and secure. Since it can give taller levels of security with smaller key sizes than standard cryptographic strategies, ECC works particularly well in places with constrained assets, like IoT gadgets. ECC makes beyond any doubt that private understanding information remains private whereas it's being sent between gadgets and the Advanced Twin framework by scrambling the information. The independent and unchangeable record in blockchain innovation makes information indeed more secure. A blockchain keeps track of all exchanges that happen with information, such as changes to information, getting to logs, and sharing of understanding data. This makes beyond
30 any doubt that all information trades are clear and can be followed. Once information is recorded on the blockchain, it can't be changed without arranged endorsement. This makes it much less likely that information will be altered. You'll be able to entirely control who can get to and alter blockchain information with savvy contracts. These contracts set strict rules around who can get to and alter information and under what circumstances.

Even with these strong security steps, there are a few things that could go wrong and make data less private:

- Key Management Vulnerabilities: It is very important to handle keys well. A breach can happen when bad habits are used, like sending or storing secret keys without proper security. This risk can be reduced by using safe key management tools and conducting regular checks.
- Smart Contract Vulnerabilities: Smart contracts are used to enforce security rules on the blockchain. It can be broken if it is poorly designed or implemented. It is very important that these contracts are tested thoroughly and have security checks done.

- Endpoint Security: There must be strong physical or virtual security for IoT devices because they can be attacked directly. Endpoint security needs to be improved by using strong login, regular updates, and physical safeguards.
- Scalability and efficiency Problems: As the size of a network grows, it can be hard to find a good balance between security and system efficiency. These problems can be fixed by making the blockchain design better and using strong encryption methods like ECC.
- Quantum Computing Threats: As quantum computing gets better, ECC and other encryption systems may be broken. It is very important to keep up with changes in quantum-resistant security and get ready for future changes.

5.4.1 GAO-RF Proposed Model

To secure IoT and IIoT systems, a new method uses blockchain, genetic algorithms (GA), and the random forest model. Figure 5-2 illustrates the GAO-RF proposed model. Data is encrypted with elliptic curve cryptography (ECC) and stored in blockchain blocks. GA monitors network activity, while real-time datasets help keep the system updated. Data is encrypted with ECC and added to the blockchain for protection against threats. This method strengthens security and helps detect intrusions by combining encryption and machine learning.

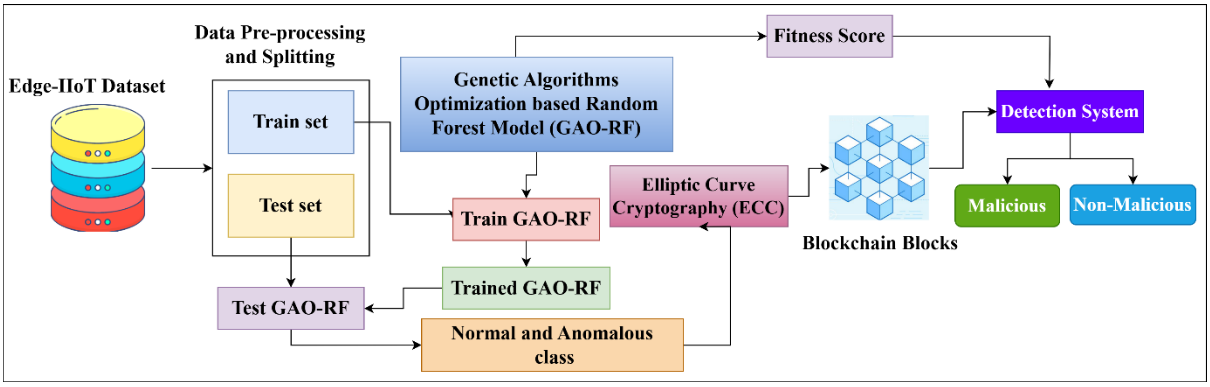


Figure 5-2: GAO-RF Proposed Model

Step 1: Initialization

Initialize a population of genetic algorithms (GA) with random feature subsets:

$$P(t) = \{ F1, F2, \dots, Fn \} \quad (5.1)$$

where P(t) represents the population at generation t, and Fi are the individual feature subsets.

Step 2: Fitness Evaluation

Evaluate each subset using the Random Forest (RF) classifier to determine its fitness based on prediction accuracy:

$$Fitness(Fi) = \frac{1}{\left(1 + Error\left(RF(Fi)\right)\right)} \quad \text{(5.2)}$$

where $Error(RF(Fi))$ is the classification error of the RF model trained with features Fi.

Step 3: Selection

Select feature sets with higher fitness scores for reproduction using tournament selection:

$$F_{selected} = Tournament\left(P(t)\right) \quad \text{(5.3)}$$

where the tournament function selects the best feature set from a randomly sampled subset of the population.

Step 4: Crossover and Mutation

Selected feature sets undergo crossover and mutation to generate new feature sets for the next generation:

$$F_{new} = Crossover(F_{selected}) \quad \text{(5.4)}$$

$$F_{mutated} = Mutation(F_{new}, mu) \quad \text{(5.5)}$$

where mu is the mutation rate, affecting the probability of altering each feature in the feature set.

Step 5: Model Update and Termination

52 Update the population with new feature sets, and iterate the process until a termination criterion is met (often a fixed number of generations or a convergence threshold):

$$P(t+1) = \{F_{mutated}\} \cup \{Best\ of\ P(t)\} \quad \text{(5.6)}$$

$$Terminate\ if\ \max\left(Fitness\left(P(t+1)\right)\right) \geq Threshold \quad \text{(5.7)}$$

This formulation allows the GAO-RF model to systematically optimize the feature selection process, enhancing the effectiveness and reliability of the intrusion detection system.

5.4.2 Dataset (Edge-IIoT)

15 Internet of Things (IoT) and Industrial Internet of Things (IIoT) applications are the focus of the Edge-IIoT [178]. The dataset was developed to train machine learning-based intrusion detection systems in cybersecurity. This dataset contains information from more than ten
20 sensors, including but not limited to temperature and humidity sensors, pH meters, ultrasonic sensors, heart rate sensors, water level detectors, soil moisture sensors, and flame sensors.
16 Edge-IIoT-2022 authors simulated 14 attacks, classifying them into five categories: (i) DoS/DDoS, (ii) Information Gathering, (iii) Man in the Middle (MITM), (iv) Injection, and (v) Malware. We create multi-class intrusion detection systems (IDSs) using the Edge-IIoT-2022 dataset. In this case, there are fifteen classes: 14 classes that represent each attack and one normal class, as shown in Table 5.2. The Edge-IIoT-2022 dataset specifies the data points as vectors of 61 features, of which 43 are numeric, and the other features are nominal and string.
102 *Attack_label* and *Attack_type* are two extra-label features. In the multi-class setup, *Attack_type* is used as the class label. There are a total of 1,176 variables that are included in the dataset, and out of them, 61 features and characteristics indicate significant association. The dataset has a total of 1,909,671 records, consisting of 1,363,998 normal instances and 545,673 instances of attacks. It has been separated into an 80% training set (1,527,736 samples) and a 20% testing set (381,935 samples) for consistent evaluation across 15 distinct classes.

Table 5.2: Types of Cyberattacks in Edge-IIoT

Attacks	**Data Record**
Normal	1,091,198
DDoS_ICMP	54,351
DDoS_UDP	97,253
DDoS_TCP	40,050
DDoS_HTTP	38,835
SQL_Injection	40,661
XSS	12,058
Uploading	29,446
Password	39,946
Backdoor	19,221
Ransomware	7751
Fingerprinting	682
Vulnerable_Scanner	40,021
Port_Scanning	15,982
MITM	286

5.4.3 Elliptic Curve Cryptography (ECC)

Elliptic curve cryptography (ECC) is an exciting and powerful way to protect privacy in a world where digital security constantly changes. This incredible cryptography offers vigorous security, doing so rapidly and efficiently, making it pivotal for keeping advanced communications and exchanges secure. Investigate the world of ECC with us, where the magnificence of elliptic curves meets the necessity for security, marking a paradigm shift in protecting digital spaces. Before information is stored on the blockchain or any other secure storage system, it is encrypted using ECC, ensuring that the data remains secure and confidential, even in the event of unauthorized access. Figure 5-3 illustrates the implementation of ECC in the proposed model. Within blockchain blocks, encrypted data is securely stored. Each block includes a timestamp, cryptographic key, and the data's cryptographic hash. The data is tamper-proof, with access restricted by the cryptographic key, thanks to the blockchain's distributed ledger technology. Since ECC can provide robust security with very small key sizes, it is highly efficient and ideally suited for resource-constrained environments, such as those encountered in Internet of Things (IoT) devices. ECC strength is typically expressed in bits. For example, a 3072-bit RSA key is almost break even in quality to a 256-bit ECC key. This illustrates how compelling ECC is at giving vigorous security with shorter keys.

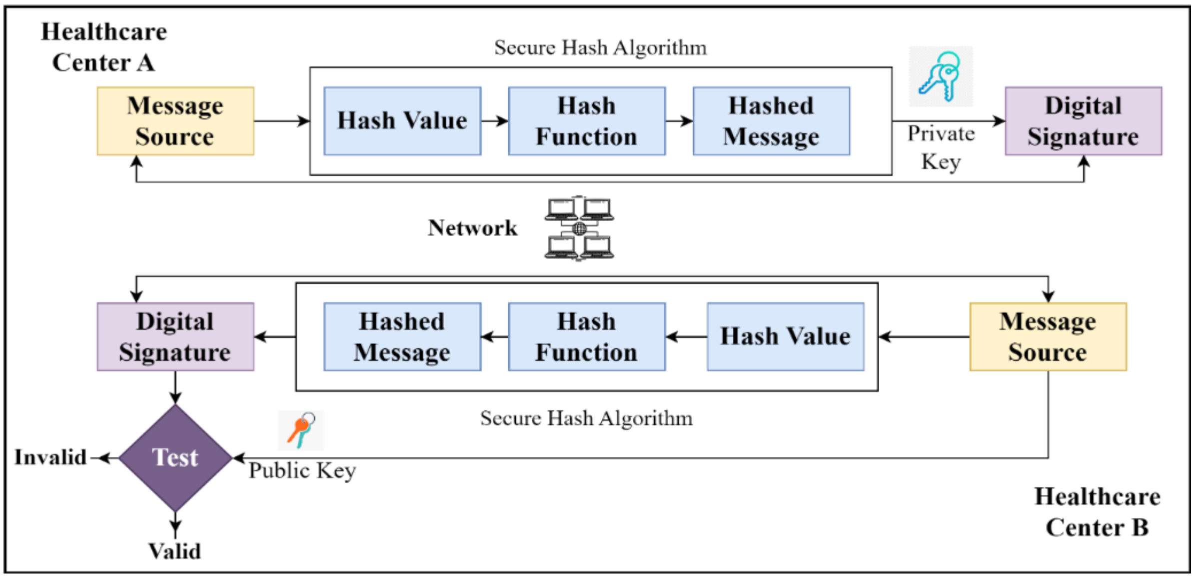


Figure 5-3: Implementation of ECC in the proposed model

Elliptic Curve Cryptography (ECC) is a widely used public-key cryptography algorithm that provides strong security with relatively shorter key lengths compared to other public-key algorithms like RSA. ECC is particularly well-suited for resource-constrained environments, making it popular for securing communications in various applications, including security and privacy.

Step 1: Initialization

- Choose an elliptic curve E defined over a finite field F_P.
- Select a base point G on the curve with prime order n.
- Choose cryptographic parameters for ECC operations.

$$Choose\ E(F_P), G, n$$

$$Choose\ cryptographic\ parameters$$

Step 2: Key Generation

- Each IoT device generates a unique key pair.
- Generate a private key d_i as a cryptographically secure random number.
- Compute the corresponding public key Q_i using scalar multiplication: $Q_i = d_i \times G$.

$$d_i \overset{\$}{\leftarrow} [1, n-1]$$

$$Q_i = d_i \times G \quad \text{(5.8)}$$

Step 3: Secure Communication

- Devices exchange public keys ($Q_i\ and\ Q_j$) Openly.
- Calculate shared secrets (Sij) using private keys and public keys as follows:

  Sender: $S_{ij} = d_i \times Q_j$ .... (5.9)

  Receiver: $S_{ij} = d_j \times Q_i$ .... (5.10)
- Derive a symmetric encryption key from the shared secret for secure data exchange.

Step 4: Data Encryption and Blockchain Integration

- Encrypt the IoT data using the derived symmetric encryption key.
- Prepare data for blockchain storage:
- Create a block with data, a timestamp, and a cryptographic hash of the data.
- Include the public key (K) and digital signature (Sig) for data integrity and authenticity.
- Encrypt the block using ECC, producing the encrypted block ($EncBlock$).

$$C = AES(S_{ij}, IoT\ Data) \quad \text{(5.11)}$$

$$Block = \{C, Timestamp, Hash(Data), K, Sig\} \ldots \ldots \ldots (5.12)$$

$$EncBlock = ECC\_Encrypt(Block) \ldots \ldots \ldots (5.13)$$

5.4.4 Intrusion Detection System (IDS)

Calculation 1 gives more points of interest approximately the usage of RF within the GA. This handle separates datasets A and B into preparing (Atrain, Btrain) and testing (Atest, Btest) sets. A irregular woodland show is initialized and prepared utilizing Atrain and Btrain and learning designs and connections inside the information. The model's execution is at that point assessed on Atest, and in this way, expectations are produced for Btest. At last, a wellness score is computed based on the model's execution on the Btest, giving a quantitative degree of how well the Irregular Woodland show performs on the given assignment. This approach makes a difference survey the model's capacity to generalize to unused information and make precise expectations. The foremost ideal show is one that yields the most elevated precision score.

Algorithm 1: Fitness Function Computation

Input: A, B; the input data frame and output series

Output: Fitness score obtained by the Random Forest model

Step 1: Data Splitting

135 Split data into training and testing sets using a complex stratified split to ensure uniform distribution of classes:

$$A_{train}, A_{test}, B_{train}, B_{test} = split(A, B, test_{size} = 0.3, stratify = B) \ldots \ldots \ldots (5.14)$$

19 This function partitions the dataset into training and testing subsets, maintaining the proportion of classes across them.

Step 2: Model Initialization

Initialize the Random Forest model with a high number of trees and depth to enhance the learning capability:

$$RF = RandomForestClassifier(n\_estimators = 100, \max\_depth = None, random\_state = 42) \ldots \ldots \ldots (5.15)$$

Here, $'n\_estimators'$ represents the number of trees in the forest, 'max_depth' allows the trees to grow until all leaves are pure, and '$random\_state$' ensures reproducibility.

Step 3: Model Fitting

Fit the Random Forest model using the training data with bootstrapping and feature selection:

$$RF.fit(A_{train}, B_{train}) \quad (5.16)$$

This step involves building trees where each tree is trained on a bootstrapped sample of the data, and at each node, a subset of features is randomly selected to determine the split.

Step 4: Model Evaluation and Fitness Computation

Evaluate the model on the testing set and compute the prediction accuracy with a detailed error matrix:

$$predictions = RF.predict(A\_test) \quad (5.17)$$

$$Fitness\ Score = \left(\frac{1}{\left(1 + sum\left(\frac{abs(predictions - B_{test})}{len(B_{test})}\right)\right)} \right) * 100 \quad (5.18)$$

This complex equation for the Fitness Score is an adaptation of the Mean Absolute Error, inversely transformed to reflect higher scores for better performance, normalized to a percentage scale.

The Genetic Algorithm 2 for Feature Selection on the Edge-IIoT dataset begins by initializing a binary-encoded population, each representing a feature subset. The algorithm iteratively evolves the population through crossover and mutation, aiming to improve the fitness of individuals based on a predefined fitness function. The best individual, denoted as Gbest, is updated throughout the process. The evolution loop continues for a specified number of iterations (Mbest), and the selected feature subset is recorded in Elist. The algorithm terminates when reaching a predefined convergence criterion or the maximum number of iterations. The ultimate objective is to identify a subset of features that optimally contribute to the model's performance on the Edge-IIoT dataset.

Algorithm 2: Genetic Algorithm for Feature Selection on Edge-IIoT Dataset

Pre-requisites:

Dataset: *D*, Edge-IIoT Dataset

Feature Names Array: *F*

Target Domain Value: *T*

Empty Feature Subset List: E_{list}

Maximum Iterations (Best Features): M_{best}

Step 1: Initialization

Initialize a population of individuals, where each individual represents a potential solution (i.e., a subset of features):

$P(0) = \{x_1, x_2, \ldots, x_n\}$ .... (5.19)

where $P(t)$ is the population at generation t, and x_i are binary strings where each bit represents the presence (1) or absence (0) of a feature in the dataset.

Step 2: Fitness Evaluation

Evaluate the fitness of each individual using an integral over the data distribution to assess predictive performance:

$f(x_i) = \int Accuracy\big(M(x_i, D)\big)dD$ .... (5.20)

where $M(x_i, D)$ represents the model trained with features xi on dataset D, and Accuracy is the performance metric.

Step 3: Selection

Select individuals for reproduction using tournament selection:

$x_{selected} = Tournament(P(t), f)$ .... (5.21)

where Tournament is a function that selects the individual with the highest fitness from random subsets of the population.

Step 4: Crossover

Apply a crossover operation to generate new offspring from selected individuals:

$x_{offspring} = Crossover(x_{selected})$ .... (5.22)

This function swaps features between pairs of individuals at randomly chosen crossover points.

Step 5: Mutation

Introduce mutations with a small probability to maintain genetic diversity:

$x_{mutated} = Mutation\big(x_{offspring}, mu\big)$ .... (5.23)

where mu represents the mutation rate, determining the probability of a feature being toggled.

Step 6: Update and Termination

Update the population with the new generation and check for termination conditions:

$P(t+1) = x_{mutated} \cup Best\ of\ P(t)$ .... (5.24)

$if\ max\Big(f\big(P(t+1)\big)\Big) > threshold\ or\ t = t_{max}: Terminate$ .... (5.25)

This model outlines a comprehensive genetic algorithm process tailored for optimizing feature selection in an Edge-IIoT dataset, considering the computational and data complexities typical in industrial IoT applications. The GA modified for case study's main stages is shown in Figure 5-4.

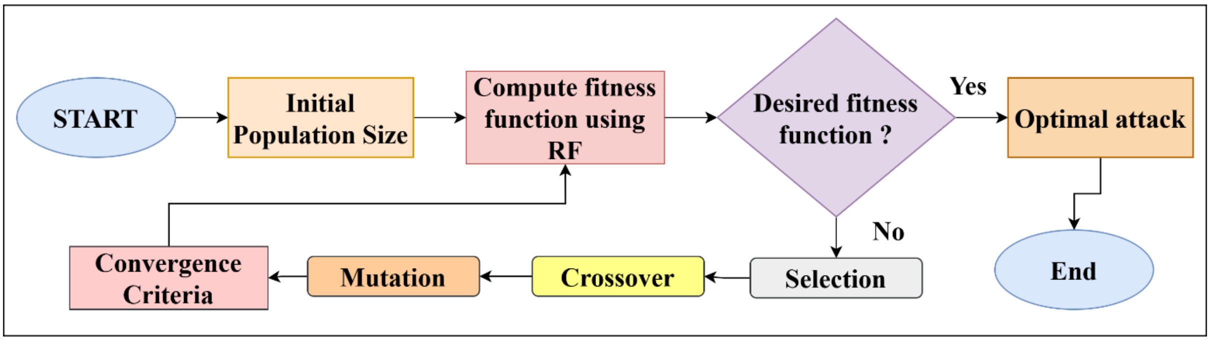


Figure 5-4: Flowchart of GA-fitness function in RF

Combining different methods to improve detection is what hybrid models for better IoT breach detection are all about. A mixed model could combine rule-based systems with machine learning techniques to make a stronger framework. Here is a step-by-step mathematical example of how this kind of mixed model could be set up:

Hybrid Model for IoT Intrusion Detection:

Step 1: Data Collection

Collect data from various IoT devices and sensors:

$D = \{d_1, d_2, \ldots, d_n\}$ ……………………………………………………………….. (5.26)

where D represents the dataset collected, and di represents data points from IoT devices.

Step 2: Data Preprocessing

Normalize and feature-engineer the data to prepare for analysis:

$D_{processed} = f_{preprocess(D)}$ ………………………………………………………….. (5.27)

where $f\_preprocess$ is a function that includes normalization, handling missing values, and feature extraction.

Step 3: Rule-Based Filtering

Apply rule-based filters to quickly eliminate known benign behaviors:

$D_{filtered} = \{d \ in \ D_{processed} \mid rules(d) = true\}$ .... (5.28)

where rules(d) are predefined conditions that data points must satisfy to be considered for further analysis.

Step 4: Feature Selection Using Genetic Algorithm

Optimize feature selection using a genetic algorithm to reduce dimensionality and enhance model performance:

$S = GA\left(D_{filtered}, fitness\right)$ .... (5.29)

where S is the subset of selected features, GA represents the genetic algorithm, and fitness is a function evaluating the effectiveness of the feature subset.

125 **Step 5:** Machine Learning Model Training

Train a machine learning model using the selected features:

$M = train(S, D_{train})$ .... (5.30)

where M is the trained model, and D_{train} is the training subset of $D_{filtered}$.

Step 6: Anomaly Detection

Deploy the model to detect anomalies in new data:

$y_{pred} = M(x_{new}, S)$ .... (5.31)

where y_{pred} is the predicted outcome (anomalous or not), x_{new} is new incoming data, and S is the set of optimized features used by model M.

This six-step approach integrates rule-based filtering and advanced machine learning techniques, optimized by genetic algorithms, to develop a robust system for detecting intrusions in IoT networks. Each step is designed to refine the data and model progressively, focusing on enhancing detection capabilities with accuracy and efficiency.

5.5 Experimental Analysis

This study considered the proficiency of the proposed show for producing Intrusion Detection Systems (IDSs) in IoT gadgets, utilizing the Edge-IIoT dataset. A multi-class test was conducted to classify activity into different assault sorts. For the binary-class situation, the Attack_label highlight was utilized, whereas the Attack_type highlight was utilized for the multi-class situation. The tests were carried out on a portable workstation prepared with an Intel 11th Gen Center i7-4510U CPU processor (2.0 GHz, 4 centers, 8 coherent processors), 16 GB of Smash, and a 64-bit Windows 11 working framework. Python, alongside libraries such as Sklearn, Tensorflow, Keras, Pandas, and Numpy, was utilized for the tests to help in information preprocessing. The proposed show was prepared utilizing 80% of the dataset, with a encourage division to refine the model's hyperparameters. This part come about in a preparing set comprising 80% of the first information and an approval set of 20%. The choice to partition the dataset this way was based on the direction from [179], pointing to adjust the preparing handle and avoid overfitting, as proposed in [180]. This information division procedure was significant for assessing the model's execution dependably and heartily. Six diverse models were created to realize the most noteworthy classification exactness. This segment presents the parameters, execution measurements, and assessment comes about for each show. The utilize of these numerous models was basic to distinguish the best-performing one, guaranteeing a comprehensive evaluation of the proposed IDS's adequacy in identifying different assault sorts in IoT situations.

5.5.1 Confusion Matrix

The disarray lattice may be a visual tool with different assessment parameters. To disentangle, we'll center on the binary-class perplexity network, overlooking the multi-class adaptation, which is an expansion of the same concept. The four assessment measurements are Genuine Positives (TP), Genuine Negatives (TN), Wrong Positives (FP), and Untrue Negatives (FN), outlined in Figure 5-5. The cleared-out inclining speaks to accurately classified information focuses (genuine), whereas the correct inclining appears type-1 (FP) and type-2 (FN) mistakes. This clear portrayal helps in understanding the model's classification execution.

Actual Class		**Predicted Class**	
		Normal	**Anomalous**
	Normal	TN	FP
	Anomalous	FN	TP

Figure 5-5: Binary-class confusion matrix

5.5.2 Performance Evaluation

Accuracy: The concept of accuracy in intrusion detection refers to the efficacy of a model in properly recognizing both positive (intrusion) and negative (non-malicious) occurrences.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \quad (5.32)$$

Table 5.3: Accuracy (%): proposed vs. ML/DL model with different epochs

Epochs	CNN	k-NN	SVM	MLPNN	PNN	GAO-RF
10	95.6	88.3	83.5	97.3	92.4	98.1
20	95.3	87.5	83.4	97.1	92.5	98.1
30	95.4	88.4	84.3	97.8	92.2	98.2
40	95.2	87.9	84.7	97.5	91.9	98.3
50	95.3	88.5	84.5	97.4	92.7	**98.4**

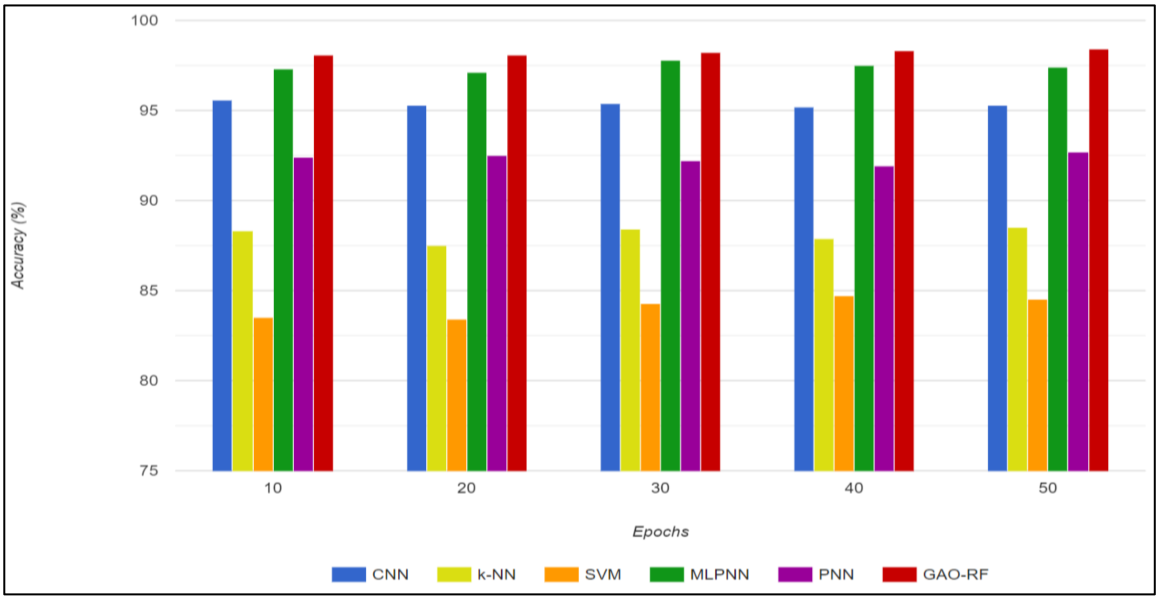


Figure 5-6: Accuracy (%): proposed vs. ML/DL model with different epochs

The proposed GAO-RF model achieved accuracy values of 98.4% for ten epochs, 98.1% for twenty epochs, 98.3% for thirty epochs, 98.2% for forty epochs, and 98.4% for fifty epochs, as shown in Table 5.3 and Figure 5-6. These values were achieved during a short period. In contrast to other models or methods, the model that was presented constantly outperformed them, highlighting the usefulness of the model as well as the solid security that it provides.

101 **Precision:** Precision in intrusion detection measures a model's consistency and repeatability in properly recognizing positive incursions, calculating the percentage of correctly labeled positive events among all positive predictions produced by the model.

$$Precision = \frac{TP}{TP+FP} \times 100 \quad \ldots\ldots\ldots \quad (5.33)$$

Table 5.4: Precision (%): proposed vs. ML/DL model with different epochs

Epochs	CNN	k-NN	SVM	MLPNN	PNN	GAO-RF
10	92.7	87.5	83.4	95.4	91.7	97.5
20	93.4	87.3	83.2	95.4	91.8	97.3
30	92.3	87.1	82.7	95.3	91.6	96.8
40	92.4	87.1	83.2	95.4	92.3	97.4
50	92.1	87.8	82.7	95.1	91.6	**97.3**

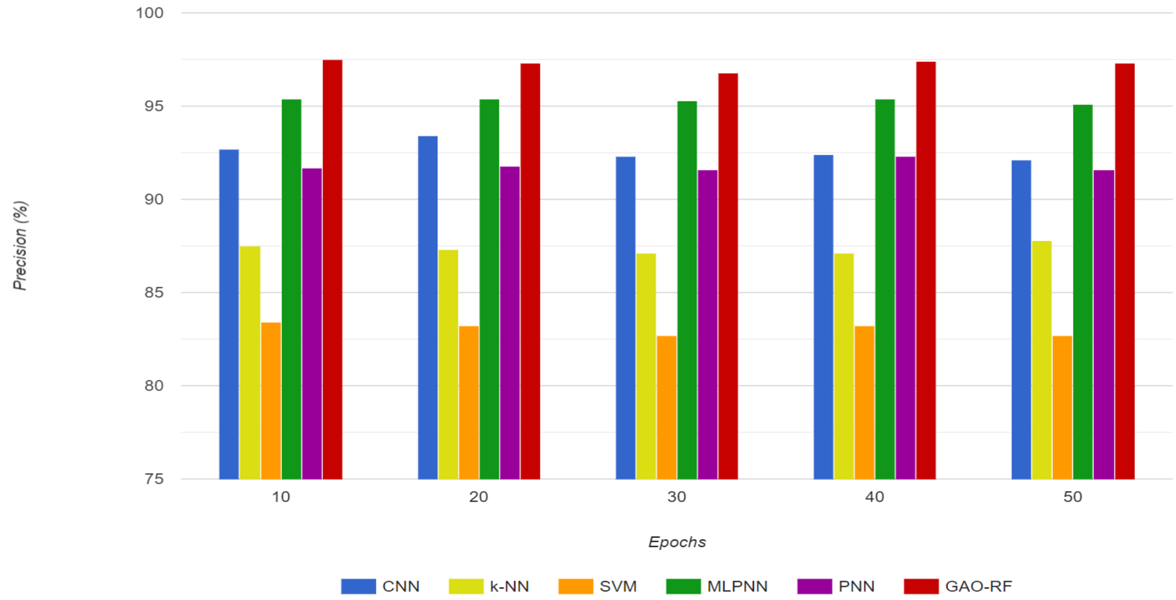


Figure 5-7: Precision (%) proposed vs. ML/DL model with different epochs

The proposed GAO-RF model achieved precision values of 97.5% for ten epochs, 97.3% for twenty epochs, 96.8% for thirty epochs, 97.4% for forty epochs, and 97.3% for fifty epochs, as shown in Table 5.4 and Figure 5-7. These values were achieved during a short period. In contrast to other models or methods, the model that was presented constantly outperformed them, highlighting the usefulness of the model as well as the solid security that it provides.

120 **Recall:** The model's capacity to accurately identify and detect positive network intrusion is evaluated via a recall function. This function computes the proportion of true positives that were accurately expected.

$$Recall = \frac{TP}{TP+FN} \times 100 \quad \ldots\ldots (5.34)$$

Table 5.5: Recall (%): proposed vs. ML/DL model with different epochs

Epochs	CNN	k-NN	SVM	MLPNN	PNN	GAO-RF
10	92.4	86.7	83.4	96.3	89.7	97.5
20	92.5	86.4	83.2	95.2	89.8	97.8
30	92.2	86.5	83.5	96.5	89.5	97.4
40	91.9	86.3	82.7	96.1	89.7	97.3
50	92.7	85.7	83.4	95.9	89.3	**97.4**

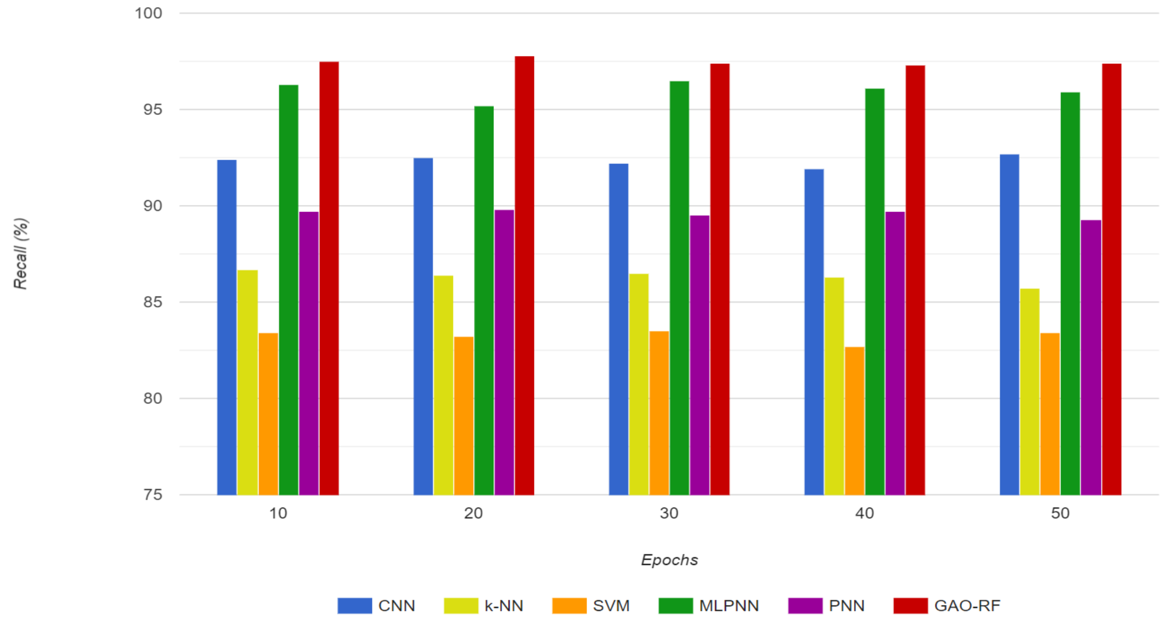


Figure 5-8: Recall (%): proposed vs. ML/DL model with different epochs

The proposed GAO-RF model achieved recall values of 97.5% for ten epochs, 97.8% for twenty epochs, 97.4% for thirty epochs, 97.3% for forty epochs, and 97.4% for fifty epochs, as shown in Table 5.5 and Figure 5-8. These values were achieved during a short period. In contrast to other models or methods, the model that was presented constantly outperformed them, highlighting the usefulness of the model as well as the solid security that it provides.

103 **F1-Score:** The definition of this term is the weight of the harmonic mean of the recall and precision test measures. The calculation is based on recall and precision of measurement to determine how effective intrusion detection is.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad \ldots\ldots (5.35)$$

Table 5.6: F1-Score (%): proposed vs. ML/DL model with different epochs

Epochs	CNN	k-NN	SVM	MLPNN	PNN	GAO-RF
10	92.54	87.09	83.4	95.84	90.68	97.5
20	92.94	86.84	83.2	95.29	90.78	97.54
30	92.24	86.79	83.09	95.89	90.53	97.09
40	92.14	86.69	82.94	95.74	90.98	97.3
50	92.39	86.78	83.04	95.49	90.43	**97.3**

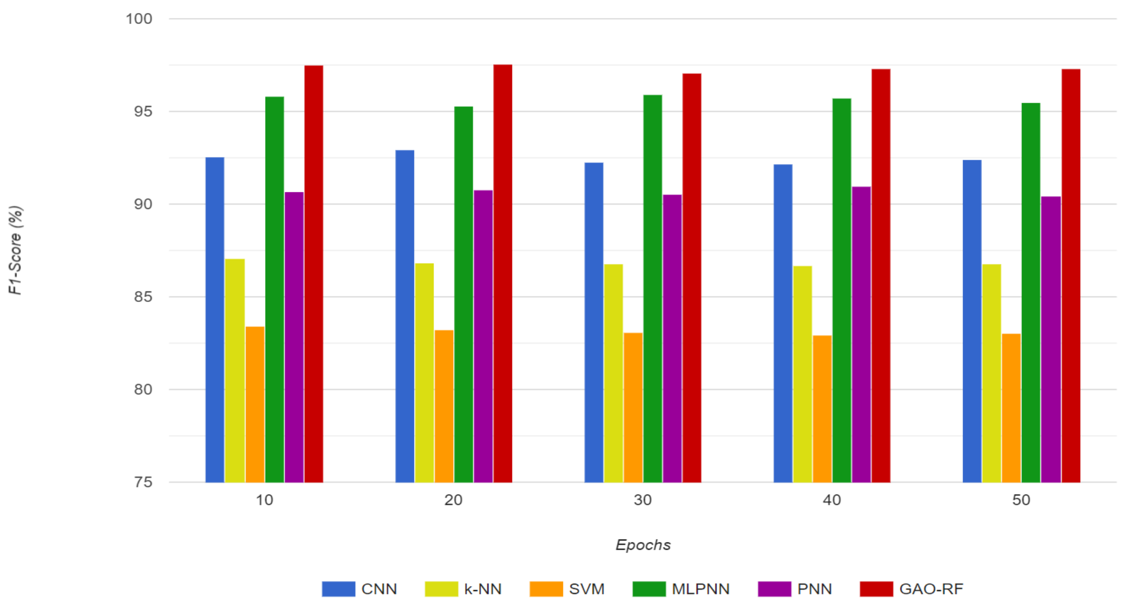


Figure 5-9: F1-Score (%): proposed vs. ML/DL model with different epochs

The proposed GAO-RF model achieved f1-score values of 97.5% for ten epochs, 97.54% for twenty epochs, 97.09% for thirty epochs, 97.3% for forty epochs, and 97.3% for fifty epochs, as shown in Table 5.6 and Figure 5-9. These values were achieved during a short period. In contrast to other models or methods, the model that was presented constantly outperformed them, highlighting the usefulness of the model as well as the solid security that it provides.

Matthews correlation coefficient (MCC): Pearson's correlation coefficient has a discrete case known as the MCC. MCC is a valuable metric for evaluating the reliability of binary classification. The formula determines the worst possible prediction, MCC = -1, while MCC = +1 indicates the best prediction.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad \ldots\ldots\ldots (5.36)$$

Table 5.7: MCC (%): proposed vs. ML/DL model with different epochs

Epochs	CNN	k-NN	SVM	MLPNN	PNN	GAO-RF
10	91.43	86.39	82.34	95.14	91.59	97.27
20	91.84	87.74	83.57	94.29	91.69	97.54
30	91.34	87.69	83.79	95.39	91.67	97.37
40	91.24	87.59	83.64	94.54	91.76	97.57
50	91.29	87.68	83.94	95.39	91.52	**97.69**

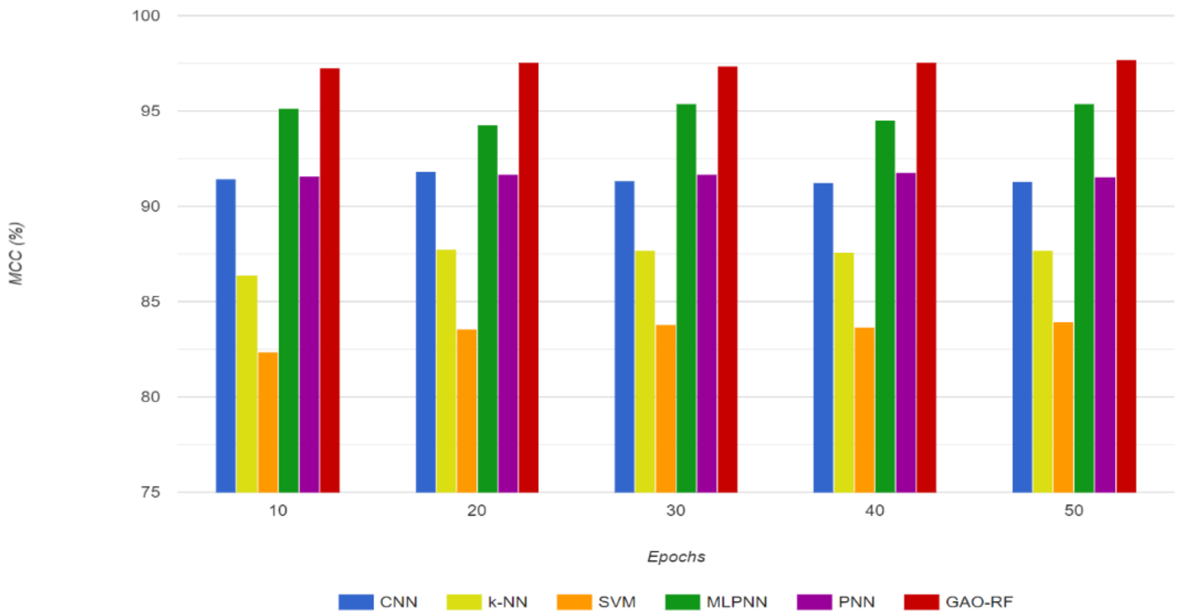


Figure 5-10: MCC (%): proposed vs. ML/DL model with different epochs

The proposed GAO-RF model achieved MCC values of 97.27% for ten epochs, 97.54% for twenty epochs, 97.37% for thirty epochs, 97.57% for forty epochs, and 97.69% for fifty epochs, as shown in Table 5.7 and Figure 5-10. These values were achieved during a short period. In contrast to other models or methods, the model that was presented constantly outperformed them, highlighting the usefulness of the model as well as the solid security that it provides.

Cohen's kappa statistics (KS): Cohen's kappa statistics (KS) is a performance analysis indicator used in classifier performance analysis. The Kappa statistic determines the agreement between a dataset's expected and actual values.

$$k_s = \frac{p_0 - p_c}{1-p_c} \quad \text{......} \quad (5.37)$$

86

where p_o is the total agreement probability, and p_c is the hypothetical probability of chance agreement.

Table 5.8: KS value (%): proposed vs. ML/DL model with different epochs

Epochs	CNN	k-NN	SVM	MLPNN	PNN	GAO-RF
10	91.54	87.09	88.45	94.84	93.38	96.57
20	91.94	85.84	89.84	94.29	94.58	97.35
30	91.24	88.79	87.69	94.89	94.73	97.67
40	91.14	89.69	88.74	94.74	93.98	96.87
50	91.39	89.78	89.94	94.49	94.83	**97.31**

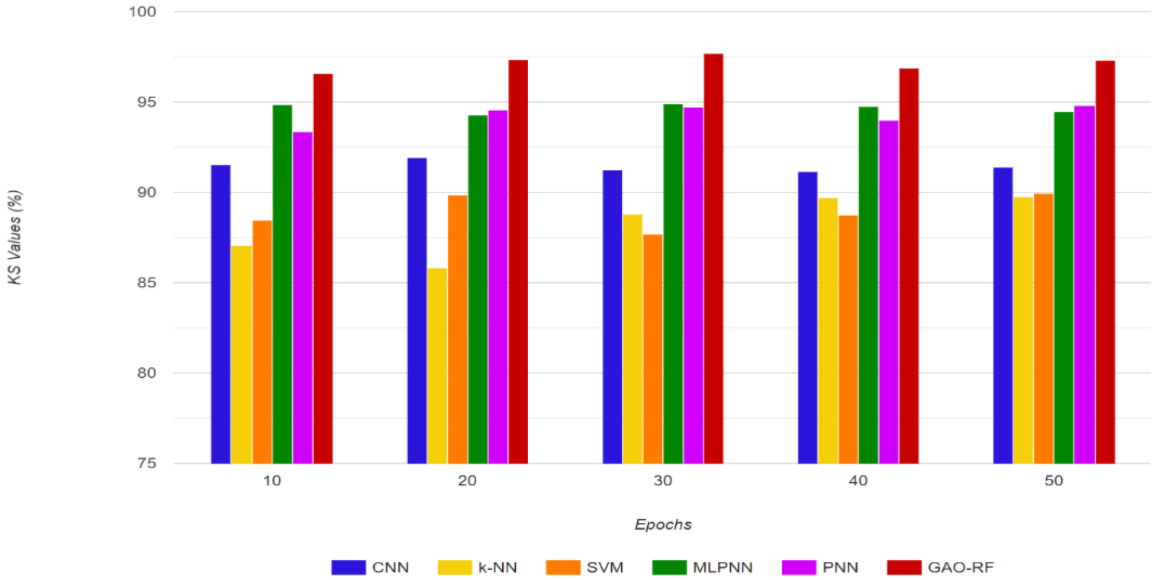


Figure 5-11: KS (%): proposed vs. ML/DL model with different epochs

The proposed GAO-RF model achieved KS values of 96.57% for ten epochs, 97.35% for twenty epochs, 97.67% for thirty epochs, 96.87% for forty epochs, and 97.31% for fifty epochs, as shown in Table 5.8 and Figure 5-11. These values were achieved during a short period. In contrast to other models or methods, the model that was presented constantly outperformed them, highlighting the usefulness of the model as well as the solid security that it provides.

The proposed model performed well in accuracy, precision, recall, and F1 score for detection. To check how effective and efficient model is, we compared it with popular Machine Learning (ML) and Deep Learning (DL) algorithms using the Edge-IIoT dataset. We simulated these algorithms in a Python environment. Table 5.9 and Figure 5-12 show that model outperforms the other algorithms, showing better intrusion detection abilities and proving its effectiveness in spotting intrusions.

Table 5.9: Overall performance evaluation

Models	Accuracy	Precision	Recall	F1-Score	MCC	KS
CNN	95.3	92.1	92.7	92.39	91.29	91.39
k-NN	88.5	87.8	85.7	86.78	87.68	89.78
SVM	84.5	82.7	83.4	83.04	83.94	89.94
MLPNN	97.4	95.1	95.9	95.49	95.39	94.49
PNN	92.7	91.6	89.3	90.43	91.52	94.83
GAO-RF	**98.4**	**97.3**	**97.4**	**97.3**	**97.69**	**97.31**

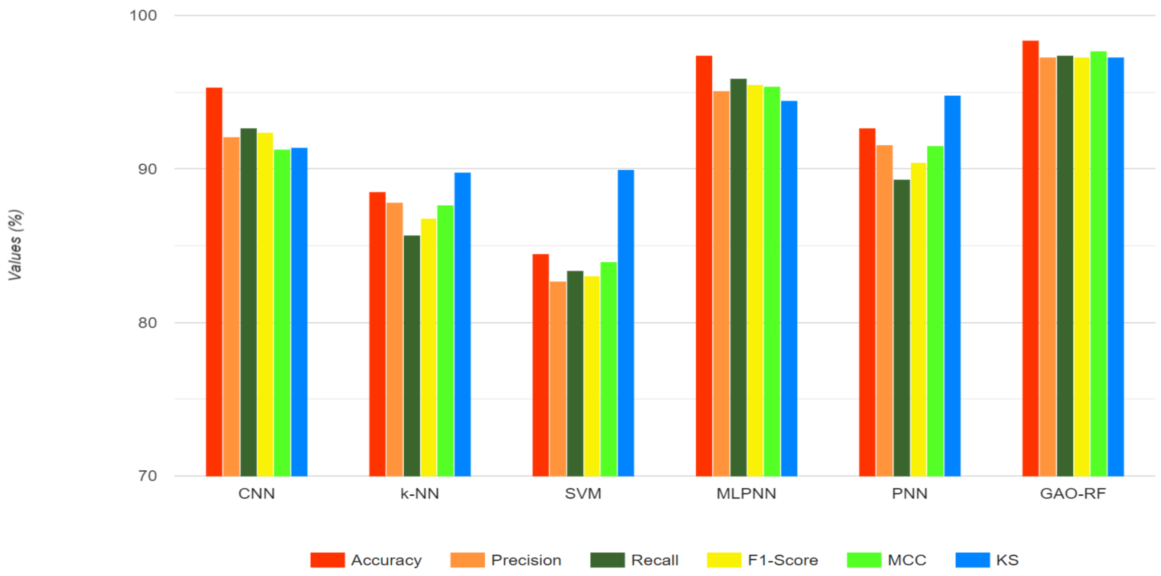


Figure 5-12: Overall Performance of the proposed model

10

5.5.3 Comparison of Proposed Method with State-of-the-Art Methods

Compared to previous research, the suggested approach produced significant results, obtaining an accuracy level of 98.4% with the Edge-IIoT dataset. The current study used an innovative Digital Twin (DT) framework and GAO-RF model to improve accuracy, unlike previous studies that relied on traditional methodologies. This part compares accuracy with some of the most advanced IDSs for IIoT and IoT systems. We focus closely on the datasets used, accuracy metrics, number of classes in the classification task, and models employed, as shown in Table 5.10.

15 116

Table 5.10: Comparison of the proposed method with previously published work

Ref.	Year	Domain	Dataset	Learning Approach	Features	Model	Accuracy (%)
Zolanvari et al. [181]	2019	IoT/ IIoT	WUSTL-IIoT	Centralized	41	RF	99.99
						DT	99.98
						k-NN	99.98
						LR	99.90
						SVM	99.64
						ANN	99.64
						NB	97.48
Koroniotis et al. [182]	2019	IoT	BoT-IoT	Centralized	46	SVM	99.98
						RNN	97.70
						LSTM	98.05
Vaccari et al. [183]	2020	IoT	MQTTset	Centralized	33	RF	99.43
						NN	99.32
Al-Hawawreh et al. [184]	2021	IoT/ IIoT	X-IIoTID	Centralized	59	DT	99.45
						NB	47.08
						k-NN	98.21
						SVM	98.14
						LR	96.61
						DNN	98.39
						GRU	99.46
Ferrag et al. [178]	2022	IoT/ IIoT	Edge-IIoT	Centralized & Federated Learning	61	DT	67.11
						RF	80.83
						SVM	77.61
						k-NN	79.18
						DNN	94.67
						DT	97.80
						NB	98.29
Badawi et al. [185]	2023	IoT/ IIoT	Edge-IIoT	Centralized and Federated Learning	61	J48	92.92
						PART	92.80
						BN	90.86
						AB	86.29
						LB	85.40
						ASC	90.43
Rashid et al. [186]	2023	IoT/ IIoT	Edge-IIoT	Centralized and Federated Learning	61	CNN	93
						RNN	94
Proposed	**2025**	**IoT/IIoT**	**Edge-IIoT**	**Centralized &**	**61**	**CNN**	**95.3**

Model				**Federated Learning**		**k-NN**	**88.5**
						SVM	**84.5**
						MLPNN	**97.4**
						PNN	**92.7**
						GAO-RF	**98.4**

Scalability is very important for the suggested e-healthcare system, especially as more people use it and more IoT devices are included. Combining blockchain and Elliptic Curve Cryptography (ECC), two naturally scalable technologies, this system uses a Digital Twin design. As the network grows, Blockchain's speed stays high because it is not controlled and can handle more transactions without a single point of failure. For example, ECC helps because it offers strong security with smaller key sizes than standard methods. This requires less computing power and works well for expansive networks. The system can also automatically adjust to changes in data trends as more devices connect because it uses a Genetic Algorithm-Optimized Random Forest (GAO-RF) model for intruder detection. Depending on the current network load and user behavior, this model chooses the best features. It can handle a lot of login requests without slowing down or compromising security. It can support a growing network of devices and users easily because it uses advanced cryptography and machine learning methods.

5.6 Conclusion

This chapter assessed a Digital Twin (DT)-based intrusion detection system to improve IoT security in healthcare by combining machine learning (ML), deep learning (DL), and cryptographic methods to protect patient data. The suggested GAO-RF model, which was optimized using a genetic algorithm, exhibited excellent performance by efficiently identifying and countering cyber-attacks. Feature selection minimized computational complexity while preserving accuracy, and training for more than 30 epochs had little improvement. A comparative study indicated that although deep learning models performed better than conventional ML methods, the hybrid GAO-RF model provided a more efficient and scalable solution. In addition to intrusion detection, DT technology provides proactive threat analysis and real-time network monitoring. This study highlights the revolutionary power of DT in cybersecurity and healthcare to provide strong protection against advanced cyber threats.

CHAPTER – 6

DIGITAL TWIN-ENABLED AI FOR MONKEYPOX DETECTION

This chapter presents a Digital Twin (DT)-enabled AI framework for automated monkeypox detection. The study explores the integration of deep learning, IoT, and data analytics to improve diagnostic accuracy and early disease detection. The proposed model, MxSLDNet, is designed to enhance real-time monitoring, optimize healthcare workflows, and support clinical decision-making.

6.1 Introduction

The advancement of Digital Twin (DT) technology has significantly transformed modern healthcare by enabling real-time patient monitoring, predictive diagnostics, and AI-driven decision-making. A Digital Twin is a virtual replica of a physical system that continuously synchronizes with real-world data. In healthcare, it is widely used for disease detection, treatment planning, and personalized monitoring. The integration of Artificial Intelligence (AI) and deep learning into Digital Twin models has greatly improved medical image analysis, especially for detecting infectious diseases such as monkeypox. Monkeypox, a viral zoonotic disease, has raised global concerns due to its outbreak potential, making early and accurate lesion detection crucial for timely diagnosis and prevention. Traditional diagnostic methods struggle to differentiate monkeypox lesions from other skin conditions due to variations in shape, size, and imaging conditions, necessitating automated AI-based solutions. Convolutional Neural Networks (CNNs) have been widely used for medical image classification, offering faster and more objective results than traditional methods. However, existing CNN models demand extensive datasets, high computational power, and lengthy training, making real-time clinical applications impractical. To overcome these limitations, this research introduces the Monkeypox Skin Lesion Detector Network (MxSLDNet), an AI-powered Digital Twin model designed for efficient and accurate lesion detection. Unlike conventional CNN architectures requiring manual preprocessing, MxSLDNet automates classification while maintaining high accuracy, reducing computational demands and making it suitable for real-time diagnosis in clinical and remote healthcare settings. It applies advanced CNN-based feature extraction to distinguish monkeypox lesions from other skin conditions, outperforming models like DenseNet-121 and ResNet-101 while operating efficiently with minimal data and lower processing overhead. Integrating Digital Twin technology with AI-based lesion detection enhances real-time patient monitoring and predictive analytics, creating virtual patient representations that allow healthcare providers to track disease progression and assess treatment effectiveness over time. This data-driven approach supports early intervention and personalized treatment planning, improving patient outcomes. The AI-powered Digital Twin approach also optimizes disease tracking and clinical decision-making, reducing reliance on manual interpretation, which is often time-consuming and subjective. A key challenge in AI-driven medical imaging is acquiring high-quality annotated datasets, particularly for emerging diseases like monkeypox. MxSLDNet addresses this by incorporating data augmentation techniques and specialized transfer learning strategies, enabling effective generalization across different imaging conditions. This enhances its adaptability in real-world clinical scenarios, where variations in lighting, camera quality, and patient skin tone can affect image quality. Additionally, MxSLDNet contributes to advancing AI-driven Digital Twin applications in healthcare by integrating real-time patient data with AI-based lesion classification, facilitating faster, data-driven medical decisions. This is particularly valuable in outbreak situations, where early detection plays a crucial role in public health management. The role of Digital Twin technology in healthcare extends beyond monkeypox detection to applications in chronic disease management, personalized treatment, and intelligent healthcare monitoring systems. By combining deep learning with Digital Twin simulations, this research advances intelligent healthcare models capable of providing automated, real-time diagnostic insights. The proposed MxSLDNet framework bridges the gap between traditional clinical diagnostics and modern AI-powered healthcare solutions, addressing challenges in medical image classification and contributing to more accurate, scalable, and resource-efficient AI-driven healthcare models. As AI-powered healthcare technologies continue to grow in demand, the integration of Digital Twin models with deep learning-based diagnostics is expected to redefine the future of disease detection, patient monitoring, and clinical decision-making. This research lays the foundation for next-generation AI-powered Digital Twin applications, enhancing the efficiency and accessibility of real-time medical diagnostics worldwide. The contributions of this study are as follows:

- Development of the lightweight and storage-efficient MxSLDNet model, specifically designed for detecting monkeypox lesions with high accuracy.
- Integration of MxSLDNet into a Digital Twin framework to facilitate real-time monitoring and improve patient outcomes in resource-limited settings.
- Rigorous comparison with state-of-the-art models, showcasing the superior performance of MxSLDNet in precision, recall, F1-score, and storage requirements.

- Use of the publicly available "Monkeypox Skin Lesion Dataset" to ensure reproducibility and transparency.
- Introduction of a detailed workflow incorporating IoT, machine learning, and cloud storage, enabling efficient health data management.

The integration of Digital Twin, AI, and IoT in Monkeypox detection has the potential to revolutionize infectious disease management. The proposed framework ensures real-time, data-driven diagnostics, early detection, and predictive monitoring, allowing for personalized treatment strategies. The following sections will delve into literature survey, experimental setup, performance evaluation, and real-world applicability of the proposed model.

6.2 Literature Survey

DT has been around for a while now, and it's like a super useful tool, especially in healthcare. Lots of researchers and companies are excited about using DTs in healthcare, and this section will look at the most important research on the topic.

6.2.1 Recent studies of monkeypox lesion detection

Monkeypox is a rare but dangerous virus that has the potential to impact national health significantly. Effective monkeypox treatment and epidemic prevention depend on lesion identification. Recently, deep learning-based algorithms have gained popularity for automating monkeypox lesion detection. A collection of studies has contributed valuable insights into monkeypox lesion detection. This study [187] delved into the realm of CNN-based models, particularly their application in detecting monkeypox lesions, highlighting the potential of deep learning in this context. The authors [188] focused on machine learning, presenting an automated diagnosis model for monkeypox skin lesions and discussing its accuracy and limitations. Authors [189] explored the use of deep neural networks for the early detection of monkeypox outbreaks, emphasizing their efficiency in this critical task. This study [190] surveyed transfer learning, assessing its effectiveness in enhancing monkeypox lesion detection accuracy and comparing it with traditional methods. They [191] offered a review paper, providing an overview of challenges and opportunities associated with monkeypox detection using deep learning methods. This [192] proposed a CNN model for early identification of the monkeypox virus, discussing its potential impact on public health. Authors [193] investigated different machine-learning approaches for classifying monkeypox lesions and assessing their accuracy and robustness. The authors [194] explored the application of transfer learning in monkeypox lesion recognition, highlighting its practicality. This [195] conducted a systematic review, comparing various models for monkeypox detection and summarizing their strengths and weaknesses. This study [196] explored various artificial intelligence techniques for monkeypox virus detection, evaluating their practicality and accuracy. Authors [197] investigated the application of deep learning for monkeypox lesion segmentation, assessing its effectiveness in delineating lesions. This [198] proposed an ensemble learning approach for monkeypox lesion detection, combining multiple models for improved accuracy. This study [199] discussed the challenges and opportunities in monkeypox lesion detection, providing insights into potential future research directions.

6.2.2 Recent research studies related to DT in healthcare

Scientists created something called a Digital Twin (DT), which acts like a computer copy of a real patient [127]. This lets doctors see how a patient would react to different treatments, almost like a test run. It's kind of expensive now, but it's getting cheaper and helping doctors improve people's health in amazing ways. For instance, doctors can use DT to create personalized medication plans [189]. Imagine having medicine designed just for you! This technology is even being used to study diseases like Multiple Sclerosis, which could lead to better treatments and faster research [200]. DT can also be used to try out new treatments virtually, speeding up medical advancements. Remember the staff shortages during the pandemic? DT can help with that too [201]. Researchers studied a system that uses DT to create virtual patients in a clinic, making vaccinations much more efficient [50]. It's like a practice round to find problems before they happen in the real world. Another study looked into a way to protect patient privacy using something called a generative adversarial network (GAN) [129]. This is a system that can create fake data that looks real. They are working on a new system to protect patient privacy [202]. They use fake information instead of real patient data. This way, even if there's a data leak, no one's details get stolen. This system works with a special kind of technology called a convolutional neural network, which helps handle complicated information. The author is also trying to make these systems even smarter. One idea is to make them self-adapting, meaning they can learn and adjust by themselves [28]. This could help monitor patients with long-term illnesses like diabetes. However, figuring out how to make this work in real life needs more research [203]. Another interesting development is a cloud-based system designed especially for taking care of elderly people [130]. This system combines the strengths of both DT (decision tree) and cloud computing, making it easier to handle healthcare information. Studies show this system can create personalized care plans, but more research is needed to see how well it works overall. Using DT in healthcare can be tricky, especially when it comes to managing the complex programs involved [204]. One approach is to create a hospital app that uses real-time information to improve hospital services. This idea has been tested using computer simulations, but researchers need to explain more clearly how DT fits into this system[205]. Overall, DT has the potential to completely change healthcare by allowing doctors to personalize treatments, predict illnesses, and develop new therapies. However, there are still ethical issues and technical challenges to solve before DT can be widely used [206], [207]. In the future, researchers might even create personal DT systems that use artificial intelligence to give you information about your health [208].

Table 6.1: Comparative analyses of existing studies

Ref.	**Training Accuracy**	**Testing Accuracy**	**Training Loss**	**Testing Loss**	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Gulmez [209]	No	No	No	No	Yes	No	Yes	Yes
Ali et al. [191]	No	No	No	No	Yes	Yes	Yes	Yes
Jaradat et al. [197]	No	No	No	No	Yes	Yes	Yes	Yes
Haque et al. [210]	No	No	No	No	Yes	Yes	Yes	Yes
MxSLDNet (Proposed Model)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

A detailed comparison of the numerous parameters used in prior research is presented in Table 6.1. Our study concentrated on the detection of monkeypox lesions, and that comparison is presented in Table 6.1. While each row refers to a particular study, the columns each reflect a distinct assessment statistic. These metrics include accuracy, precision, recall, F1-score, and others. Table 6.1 summarizes the evaluation metrics provided in each of the studies, enabling a complete comparison of the methods applied for performance evaluation. This analysis aims to provide significant insights into the existing literature and emphasize the unique addition that our study has made by combining all of the critical assessment metrics for a complete evaluation of monkeypox lesion detection.

Table 6.2 literature review explores advancements in digital twin technology, AI-based diagnostic models, and innovative approaches for healthcare applications, particularly focusing on monkeypox detection. By analyzing diverse methodologies, datasets, and outcomes, the review highlights significant contributions toward enhancing disease detection, interpretability, and healthcare efficiency.

Table 6.2: Literature Review of the most recent studies

Ref.	Methodology	Dataset	Result	Outcome
Fuller et al. [211]	Explores enabling technologies, and challenges in DT.	General review	Identifies key challenges and opportunities.	Framework for future DT research.
Deebak et al. [212]	Privacy protocol for IoT in healthcare.	Simulation-based	Improved privacy.	Secure smart e-healthcare systems.
Sharma et al. [213]	Digital Twins in Healthcare IoT.	General Exploration	DT aids in precision and monitoring.	Optimized healthcare operations.
Wenham et al. [214]	Public health analysis of monkeypox.	WHO data	Insights into governance.	Policy recommendations for outbreak control.
Ahsan et al. [215]	Deep learning for monkeypox detection.	Monkeypox dataset	High accuracy.	AI-enabled diagnostics.
Glock et al. [216]	Transfer learning for rash detection.	Measles dataset	Effective lesion identification.	Improved clinical workflows.
Agarwal et al. [217]	Efficient CNN model.	Tomato disease dataset	High classification accuracy.	Applications in agricultural disease detection.
Alharbi et al. [195]	Transfer learning with optimization.	Monkeypox dataset	Enhanced precision and recall.	Reliable diagnostic system.
Attallah [198]	Hybrid CNNs with feature selection.	Monkeypox dataset	Improved accuracy.	Efficient detection framework.
Raha et al. [218]	Attention mechanism for monkeypox detection.	Monkeypox dataset	Improved interpretability and accuracy.	Explainable detection framework.
Yasmin et al. [219]	Transfer learning using PoxNet22.	Monkeypox dataset	High classification performance.	Effective disease classification tool.
Ahsan et al. [187]	Interpretable deep learning model.	Monkeypox dataset	High accuracy with explainability.	AI-enabled diagnostic assistance.

This review highlights the potential of integrating attention mechanisms, transfer learning, and interpretable AI models in addressing diagnostic challenges. The findings pave the way for scalable and explainable healthcare solutions, offering robust frameworks for improving disease management and public health outcomes.

6.3 Proposed Framework

This study aims to optimize healthcare operations and improve patient care by implementing an innovative and adaptive DT architecture for the healthcare industry. The proposed DT framework integrates data analytics, artificial intelligence (AI), and Internet of Things (IoT) devices to generate a virtual replica of a patient in three stages. IoT wearable devices with sensors are used to gather real-time physiological data from patients, as shown in Figure 6-1. This digital twin then gets this information ready for analysis by powerful computers. By constantly checking a patient's health and looking for anything unusual, this system can help doctors in many ways, from suggesting treatments to figuring out how medications will work and even planning healthy lifestyles for patients to follow. This whole system works in three parts: (a) Data Prediction, (b) Supervision, and (c) Comparison.

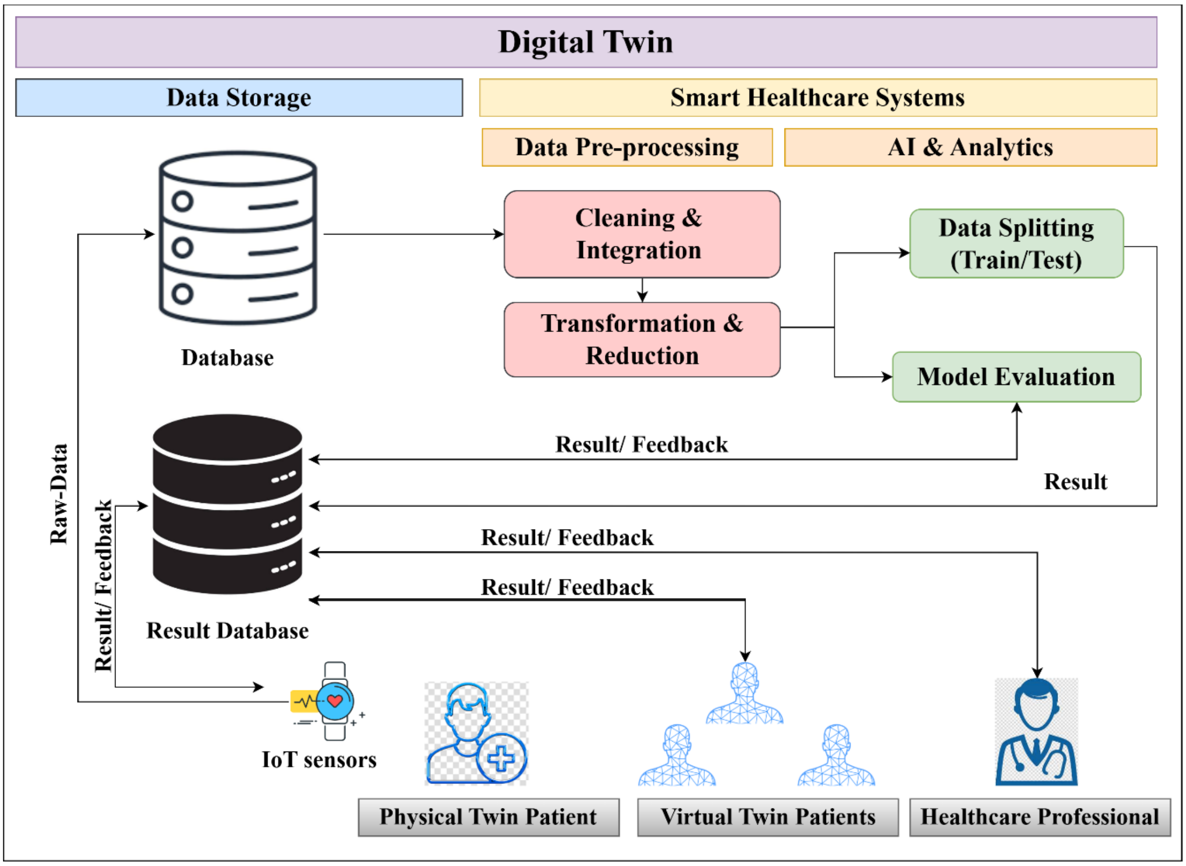


Figure 6-1: Digital Twin Framework for Smart Healthcare Systems

Data Prediction: In this part, the system uses wearable sensors to collect real-time information about a patient's health to see if anything is wrong. This information is then stored in a safe and big online storage space (cloud database) for a short time. Here, the information is cleaned up and made ready for super smart computers (machine learning) to analyze it and predict future health problems. Both patients and other parts of the system can see this information in another safe online storage space (Result Database) so they can add comments, updates, or corrections if needed.

Supervision: Doctors use the information from the prediction models in the Result Database to recommend treatments for patients. This information, along with the doctor's knowledge and keeping track of the patient, helps doctors make better healthcare decisions. Because the information is updated constantly, doctors can find and track problems with a patient's health more easily and take the right steps to fix them. This way, doctors can give patients the right medicine and help them live healthier lives. Doctors can also check the findings from the system and suggest ways to make it work even better.

Comparison: The DT system also makes its predictions more realistic by comparing a patient's information with information from similar patients. This comparison helps the system make more accurate predictions, which in turn helps doctors make better decisions about patient care. These decisions can involve copying, changing, or stopping treatments altogether based on real-time information and the patient's past, present, and predicted future health.

6.4 Materials and Methods

To compare the performance of MxSLDNet to four other models—VGG-19, ResNet-101, DenseNet-121, and EfficientNet-B4—the methodology section of this study talks about how the data was collected, prepared, and pre-processed. It also talks about the architecture of the suggested MxSLDNet model and the evaluation standards that were used. The goals were followed when collecting and processing images of monkeypox skin lesions to make sure quality and consistency. Next, four models that had already been trained—VGG-19, ResNet-101, DenseNet-121, and EfficientNet-B4—were used with transfer learning to make the MxSLDNet convolutional neural network (CNN) model. The next step in finding out how well MxSLDNet worked was to compare its results to models that had already been trained using standard evaluation methods such as F1-Score, accuracy, precision, and recall. Figure 6-2 shows the general steps that were taken to do the study.

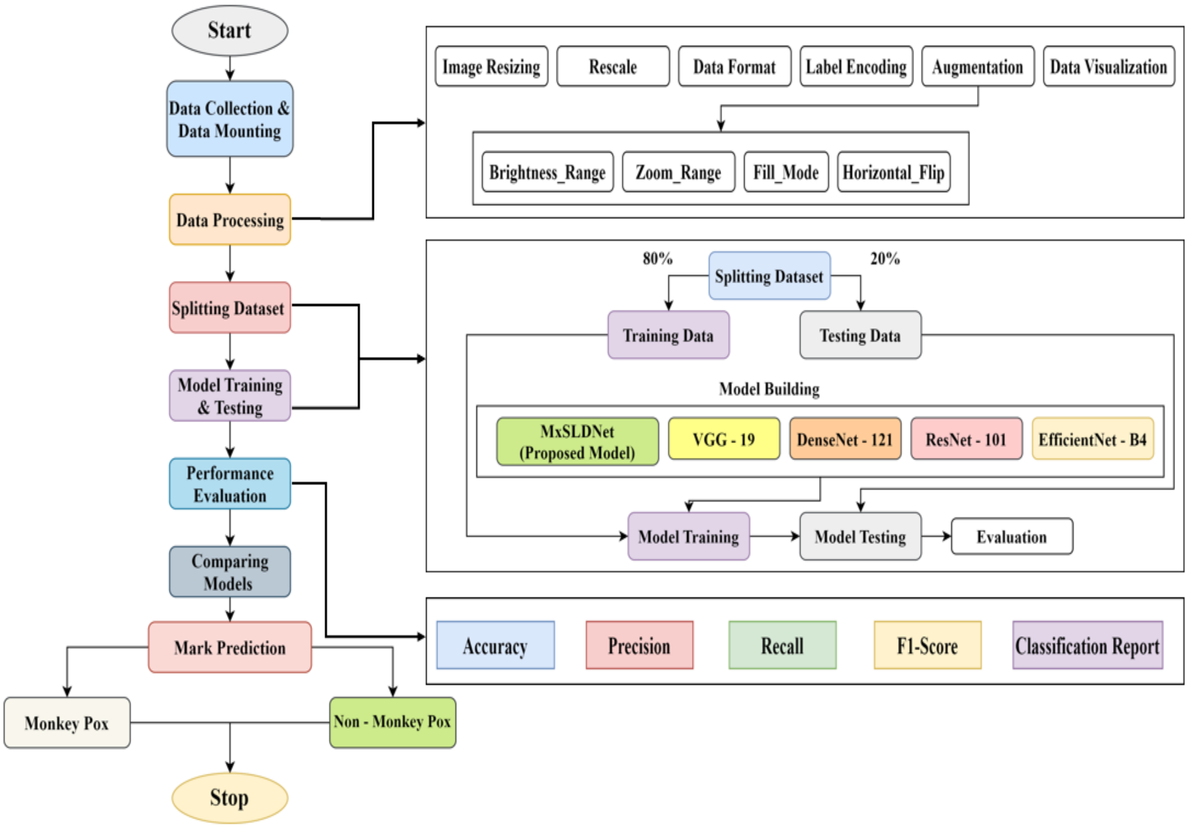


Figure 6-2: Overall Work-flow Diagram

The Digital Twin (DT) framework was implemented to create a virtual replica of patient health parameters using IoT sensors and real-time data streams. The process begins with wearable devices capturing physiological data, such as lesion characteristics and vital signs, which are transmitted to a cloud storage system for preprocessing. Data preprocessing includes normalization, anomaly detection, and noise reduction. The processed data is then fed into the DT, which performs predictive analysis using MxSLDNet. The outputs are stored in a result database accessible to clinicians for diagnostic and treatment planning. A step-by-step breakdown of the framework includes:

- Data Collection: IoT-enabled wearables gather real-time health data.
- Data Preprocessing: Raw data is normalized and cleaned for analysis.
- Digital Twin Modeling: Patient-specific virtual models are updated with incoming data.
- Prediction and Analysis: MxSLDNet classifies lesion images into monkeypox or non-monkeypox categories.
- Clinical Integration: Predictions are visualized for healthcare professionals to support decision-making.

MxSLDNet was selected for its lightweight architecture, optimized specifically for the Monkeypox Skin Lesion Dataset, ensuring superior feature extraction tailored to lesion-specific characteristics. It outperforms models like ResNet-50 and MobileNet-V2 in precision, recall, and F1-score while requiring less computational and storage resources. This makes it ideal for resource-constrained environments and real-time healthcare applications.

6.4.1 Dataset

This study uses the public "Monkeypox Skin Lesion Dataset" [220]. For binary classification, the dataset has the Monkeypox and Non-Monkeypox classes. The Monkeypox class has 1428 skin images. The non-Monkeypox class has 1764 skin images. The detailed data description is shown in Table 6.3.

Table 6.3: Distribution of the monkeypox skin lesion dataset

Class	Augmented Images	Unique Patients	Original Images
Monkeypox	1428	55	102
Non-Monkeypox	1764	107	126
Total	3192	162	228

6.4.2 Data Mounting

This stage mounts a Google Drive Account (GDA) as a virtual drive, similar to a Universal Serial Bus (USB) drive on Windows OS, allowing you to view and access your Drive from Google Co-laboratory. As a result, we uploaded our dataset to Google Drive. Then we imported it into Co-Lab using the Python/glop library, which allows you to read datasets from external folders, and the Python/pandas library, which will enable you to manipulate data in a variety of ways, including data framing, reading, and writing between in-memory data structures.

6.4.3 Data Pre-processing

This phase is essential for the deep learning model since it guarantees that the input data is formatted suitably for training the model, resulting in improved accuracy. During this stage, the data that have been collected are put through a total of six preprocessing activities before being incorporated into the model. The resizing of photos to uniform sizes, the scaling of the pixel value, data format setting, label encoding, data augmentation, and data visualization are all preprocessing processes. Figure 6-4 shows the visualization of the sample image of our dataset. Figure 6-3 shows the in-place augmentation process, and Table 6.4 represents the augmentation parameter [221].

The Monkeypox Skin Lesion Dataset was preprocessed through normalization, data augmentation, and techniques to address class imbalances, ensuring a balanced and high-quality input for model training. Feature selection in MxSLDNet focused on extracting lesion-specific patterns, leveraging convolutional layers for automated feature learning. The choice of features is justified by their relevance to distinguishing monkeypox from other skin conditions. Potential dataset limitations, such as biases in lesion diversity, are acknowledged, with suggestions for expanding the dataset to improve robustness and generalizability.

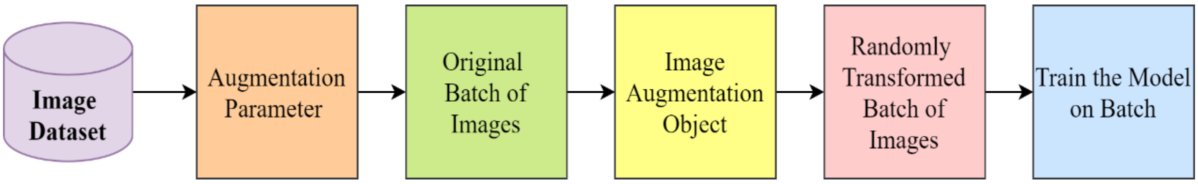


Figure 6-3. Data Augmentation Process

Table 6.4: Augmentation Parameter

S. No.	Type	Value
1.	Zoom Range	0.99 - 1.01
2.	Brightness Range	0.8 - 1.2
3.	Fill Mode	Constant
4.	Horizontal Flip	True

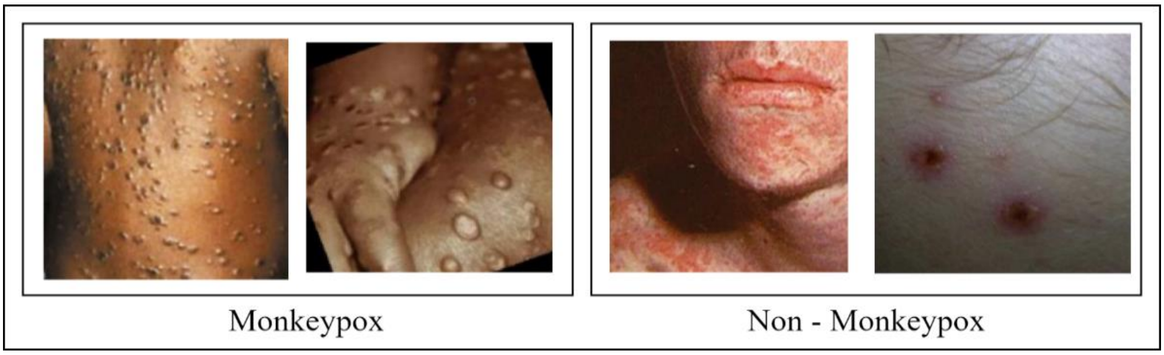


Figure 6-4. Random Image Samples from Dataset

6.4.4 Splitting Dataset

106 To ensure that the model is trained on a section of the data and evaluated on a different
60 portion, the dataset is divided into two sets for training and testing the model.

- Data for training
- Data for testing

We used 80% of the data to train the model, whereas we utilized 20% for testing and validating the model [180]. After analyzing various splitting ratios, we found that 80% and 20% produced higher training and validation accuracy and satisfactory performance metrics.

6.4.5 Model Building

Classifying monkeypox and non-monkeypox lesions is possible using pre-trained models developed to recognize one thousand classes in ImageNet. This study used four pre-trained models: DenseNet-121, Resnet-101, VGG-19, and EfficientNet-B4. Pre-trained architectures require a significant amount of computing time and storage space because of their high number of convolutional layers. To overcome these issues, we suggested a lightweight convolutional network model termed 'MxSLDNet.' The DL network MxSLDNet utilizes a classification-based detection method to retrieve significant information from an input picture and enhances it using layers (convolution, pooling, and dense). Table 6.5 summarizes the models employed in this investigation. Figure 6-5 represents the pipeline of pre-trained and MxSLDNet models.

Table 6.5: Models Summary

Model	Batch Size	Epochs	Loss Function	Details
MxSLDNet	32	15	Binary Cross Entropy	CNN model used for detection of Monkeypox and Non-Monkeypox
VGG-19	32	15	Binary Cross Entropy	CNN model (19 layers) is used for feature extraction and classification.
DenseNet-121	32	15	Binary Cross Entropy	CNN model (121 layers) is used for feature extraction and classification
ResNet-101	32	15	Binary Cross Entropy	CNN model (101 layers) is used for feature extraction and classification
EfficientNet-B4	32	15	Binary Cross Entropy	CNN model used for feature extraction and classification

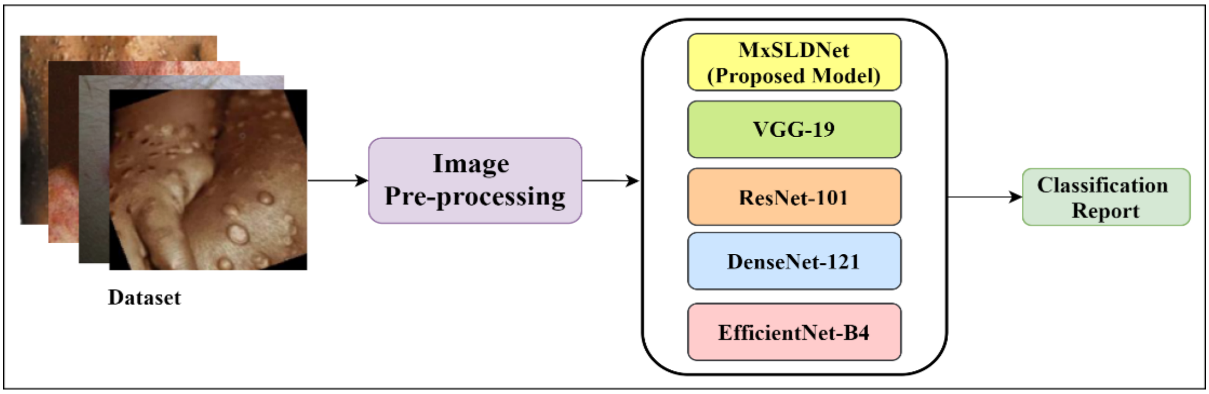


Figure 6-5: Pipeline of pre-trained and MxSLDNet Model

Hyperparameters for the proposed MxSLDNet model.

- No. Of Convolutional Layer - 5
- No. Of Max pooling Layer - 5
- Activation Function - ReLu
- Batch Size – 32
- Optimizer - Adam
- Loss Function - Binary Cross Entropy

A CNN architecture that is built for two-dimensional (2-D) image analysis is the model that we have suggested. This architecture is comprised of five convolutional layers and five max-pooling layers simultaneously. 224x224 input image dimensions are sent to the layer that will receive them. The first convolutional layer has 32 feature kernel filters, all of which have a 3x3 dimension, and the padding function is in the "same" mode. In particular, 64 feature kernel filters make up the second convolutional layer. The padding is set to "same," and the filter size is 3 x 3. The third convolutional layer uses 128 feature mappings with a 3×3 kernel size to perform its functions. The fourth convolutional layer consists of three layers and uses 256 feature maps with a 3×3 kernel size. The neural network's fifth convolutional layer employs 512 feature mappings and a 3x3 kernel size. With a 3x3 kernel size, there are five convolutional layers. These convolutional layers include 512 nodes altogether. Convolutional layers create an output with dimensions of 7×7×512. After each convolutional layer, the ReLU activation function incorporates non-linearity into the model. This is an essential step in learning complicated features and patterns in the input data. Figure 6-6 shows the architecture of the MxSLDNet model.

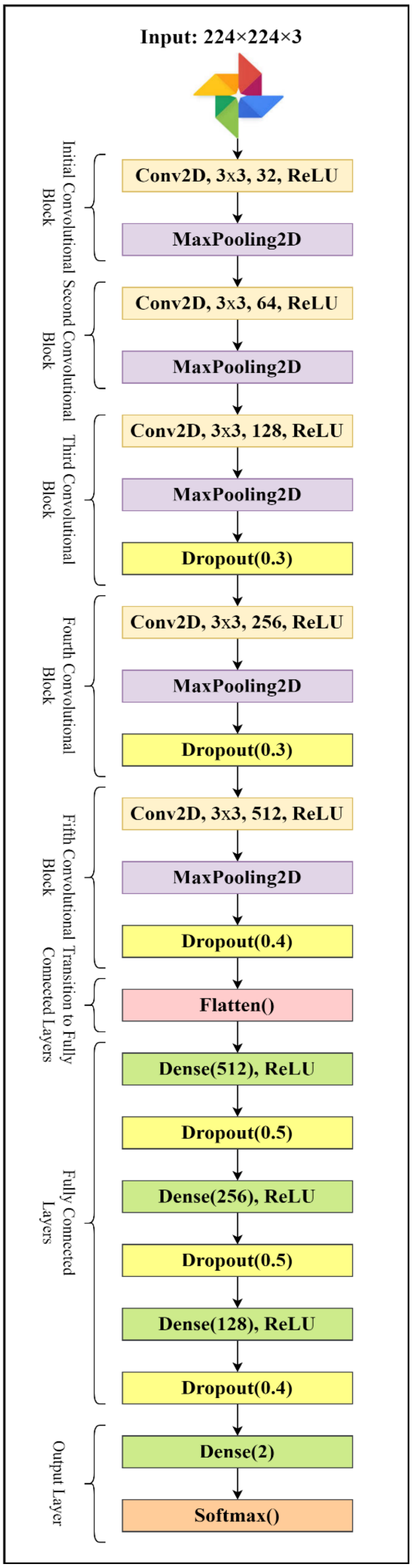


Figure 6-6: Architecture of MxSLDNet Model

6.4.6 Performance Evaluation

Four different evaluation metrics are employed to assess the performance of the proposed method. To compute these metrics, the Confusion Matrix is analyzed. Below is a brief explanation of the Confusion Matrix, Accuracy, Precision, F1-score, and Recall.

Confusion Matrix: The Matrix summarizes a classification model's performance through a tabular representation. It displays True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values, comparing predicted and actual target values. This matrix highlights the counts of correctly and incorrectly classified instances, providing insights into the model's accuracy. TP and TN represent correctly classified instances, while FP and FN represent misclassified instances. In the matrix, TP and TN are on the diagonal, while FP and FN are on the off-diagonal cells. Table 6.6 shows the actual class labels in the rows and the predicted class labels in the columns.

Table 6.6: Confusion Matrix of Monkeypox and Non-Monkeypox lesion

		Predicted Class	
		Monkeypox	Non-Monkeypox
Actual Class	Monkeypox	*TP*	*FN*
	Non-Monkeypox	*FP*	*TN*

Accuracy: Accuracy measures how effectively a classification model correctly predicts class labels. It is calculated by dividing the number of correctly predicted instances by the total number of cases, then multiplying by 100 to get a percentage. High accuracy indicates that the model correctly predicts all labels (Monkeypox and Non-Monkeypox). For example, a model with 70% accuracy correctly predicts 70 out of 100 instances

Precision: Precision is the proportion of true positive predictions among all positive predictions made by the model. It is calculated by dividing the number of true positives by the sum of true positives and false positives, focusing on Type I errors. A high precision value indicates few false positives.

Recall: Recall quantifies the number of true positive cases the model correctly identifies. With an emphasis on Type II errors, it is computed by dividing the number of true positives by the total of true positives and false negatives. A model with a high recall value effectively detects most positive cases, reducing the number of false negatives.

F1-Score: The F1-score computes the harmonic mean of precision and recall to incorporate both into a single metric. It ranges from 0 to 1, with a high F1-score signifying superior model performance and a balance between precision and recall. The optimal performance is indicated by an F1-score of 1.

These metrics collectively provide a comprehensive evaluation of the model's performance.

6.5 Experimental Analysis

This section presents the findings obtained from training and testing several different models on a dataset used to detect monkeypox. Measures such as confusion matrix, classification reports, precision, recall, and F1-scores were utilized to assess the performance of the models.

6.5.1 Accuracy and Loss Analysis

The author employed data augmentation techniques to avoid overfitting and increase the dataset size during training. This was done to deal with the small quantity of photographs available on Kaggle. We recorded the accuracy and loss metrics for every algorithm after 30 training epochs were finished. Table 6.7, which shows the training and validation accuracy attained by running the suggested model four times for thirty epochs, offers a trustworthy assessment of the model's performance. This provides a reliable evaluation mechanism and lessens the effects of chance. When the MxSLDNet model was being trained, it achieved an average training accuracy of 97.91% and an average validation accuracy of 94.35%. Because this consistency holds across runs, it emphasizes the necessity of performing numerous assessments to evaluate the model's performance precisely. A comparison of the training and validation accuracies and losses for each model is presented in Table 6.8. With a training accuracy of 96.77% and a loss of 0.0799, the model we suggested, MxSLDNet, demonstrated exceptional performance. Its validation accuracy was obtained at 95.42%, with a loss of 0.1174. Other models, such as VGG-19, DenseNet-121, ResNet-101, and EfficientNet-B4, exhibited lower accuracy and loss levels during the training and validation phases as shown in Table 6.8. Due to the complete nature of this comparison, it is possible to evaluate and pick the most effective model for the correct detection of monkeypox lesions.

Table 6.7: Multiple Training accuracy and Testing accuracy for the MxSLDNet Model

Experiment	Epoch	Training Accuracy	Loss	Testing Accuracy	Loss
1	30	98.72	0.0812	94.72	0.1267
2	30	96.54	0.0932	92.76	0.1245
3	30	98.53	0.0851	95.26	0.1853
4	30	97.87	0.0731	94.67	0.1327

Table 6.8: Evaluation of accuracy and loss for each model during training and validation

Model Name	Training Accuracy	Loss	Testing Accuracy	Loss
VGG-19	85.65	0.3412	87.71	0.3364
DenseNet-121	87.46	0.4513	85.58	0.3177
ResNet-101	78.62	0.5227	72.12	0.5448
EfficientNet-B4	81.37	0.3027	80.47	0.3327
MxSLDNet (Proposed Model)	96.77	0.0799	95.42	0.1174

6.5.2 Classification Report Analysis

94 The classification report provides detailed precision, recall, and F1 scores for each class, which helps us evaluate the performance of the MxSLDNet model. Table 6.9 shows these scores for all models used in this study, including VGG-19, DenseNet-121, ResNet-101, EfficientNet-B4, and our proposed MxSLDNet model. For each class (Monkeypox and Non-Monkeypox), the report includes:

- *Precision:* The percentage of correct positive predictions. For DenseNet121, the precision for Monkeypox is 0.86, meaning 86% of samples classified as Monkeypox were correct.
- *Recall:* The percentage of actual positives correctly identified. DenseNet121 has a recall of 0.82 for Monkeypox, meaning it correctly identified 82% of actual Monkeypox cases.
- *F1-score:* A balanced measure of precision and recall. DenseNet121 has an F1-score of 0.83 for Monkeypox.

Similar metrics for the non-Monkeypox class and other models like ResNet-101, EfficientNet-B4, and VGG-19 are provided. Our MxSLDNet model shows superior
48 performance with high precision, recall, and F1-score values of 0.96, 0.95, and 0.95, respectively, indicating high accuracy in detecting monkeypox lesions. This classification

report allows for a comprehensive comparison of model performance, helping us identify the most effective model for accurate monkeypox lesion detection.

Table 6.9: Comparative classification performance analysis of our proposed model vs pre-trained model

Model Name	Patient Status	Precision	Recall	F1-Score
VGG-19	Monkeypox (0)	0.86	0.80	0.79
	Non-Monkeypox (1)	0.81	0.87	0.83
DenseNet-121	Monkeypox (0)	0.86	0.82	0.83
	Non-Monkeypox (1)	0.67	0.76	0.71
ResNet-101	Monkeypox (0)	0.86	0.78	0.81
	Non-Monkeypox (1)	0.81	0.85	0.82
EfficientNet-B4	Monkeypox (0)	0.83	0.82	0.82
	Non-Monkeypox (1)	0.81	0.81	0.81
MxSLDNet (Proposed Model)	Monkeypox (0)	0.96	0.95	0.95
	Non-Monkeypox (1)	0.96	0.95	0.95

6.5.3 Confusion Matrix of MxSLDNet Model

A practical method for assessing classification models is to use a confusion matrix. This confusion matrix displays the number of samples correctly and incorrectly identified for every class. The confusion matrix for our suggested MxSLDNet model is shown in Figure 6-7. A total of 320 test photos are assessed here. True Positive indicates the frequency with which the model classifies monkeypox correctly. Similarly, True Negative suggests that the model can accurately identify non-monkeypox cases as non-monkeypox cases. Figure 6-7 shows that 148 photos are correctly classified as non-monkeypox (True Negative) and 157 photographs as monkeypox (True positive) by the MxSLDNet model. Figure 6-7 shows that, out of 320 photos, our model successfully identified 305. Conversely, false positives indicate that the model mistakenly classified non-monkeypox cases as monkeypox. On the other hand, false negatives show cases in which the model incorrectly diagnoses monkeypox as something else. Additionally, we can see that 8 photos of monkeypox were mistakenly labeled as false negatives, and 7 images of non-monkeypox were mistakenly classed as false positives. It demonstrates that our method, with high true positives and true negatives, can successfully identify patients with monkeypox.

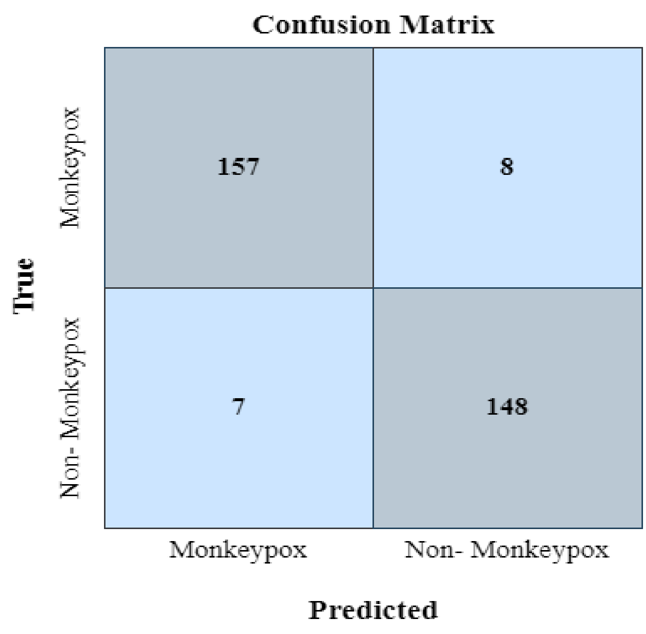


Figure 6-7: Confusion Matrix of MxSLDNet Model

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6.5.4 Comparison of Proposed Method with State-of-the-Art Methods

Within this section, the authors provide a complete analysis comparing the performance of our proposed MxSLDNet model with that of previously pre-trained models. Our evaluation of the models utilized key parameters like accuracy, precision, recall, and F1-score.

Table 6.10 shows that MxSLDNet effectively recognizes positive cases correctly, with the highest achievable precision score of 0.96. The MxSLDNet recall score of 0.95 indicates high reliability when identifying monkeypox images. Additionally, it was demonstrated that the model's F1-score—a measure of recall and precision—reached 0.95, indicating a better balance between the two metrics than pre-trained models. Given that the MxSLDNet accuracy score was 0.95, likely, most instances were correctly classified. MxSLDNet is the most accurate model for identifying monkeypox lesions, consistently outperforming the other models on all metrics. Higher values indicate better performance, and MxSLDNet consistently beats its
39 rivals. To enhance the explainability of the results, Grad-CAM (Gradient-weighted Class Activation Mapping) was employed to visualize the regions of input images that significantly influenced the model's predictions. These heatmaps highlight critical features in monkeypox
119 lesions, providing insights into the decision-making process of the MxSLDNet model. This interpretability ensures clinicians and researchers can trust the model's predictions, facilitating its adoption in real-world healthcare applications by demonstrating a clear and transparent
95 rationale behind the results. k-fold cross-validation (with k=5) was conducted to validate the

robustness of the proposed MxSLDNet model. The results showed consistent performance across all folds, with an average accuracy of 95.42%, precision of 0.96, recall of 0.95, and F1-score of 0.95. This approach ensured that the model's evaluation was not biased by a particular data split, providing stronger evidence of its reliability and generalization capability for monkeypox lesion detection. Table 6.11 and Table 6.12 compares our MxSLDNet model's accuracy with other models that use the Monkeypox Skin Lesion Dataset (MSLD). MxSLDNet outperformed other models, with an accuracy of 95.67%, compared to other models, with accuracy ratings ranging from 63% to 94%. This illustrates the remarkable performance of MxSLDNet in accurately identifying and categorizing monkeypox lesions.

Table 6.10: Overall Performance of our proposed Model vs. pre-trained model

Model Name	Accuracy	Precision	Recall	F1-Score
VGG-19	0.82	0.83	0.82	0.82
ResNet-101	0.84	0.85	0.84	0.84
DenseNet-121	0.81	0.86	0.85	0.85
EfficientNet-B4	0.78	0.79	0.78	0.78
MxSLDNet (Proposed Model)	0.95	0.96	0.95	0.95

Table-6.11: Comparison of proposed work with existing work w.r.t. various evaluation parameters

Ref.	Accuracy	Precision	Recall	F1-Score
MxSLDNet (Proposed)	95.67%	0.96	0.95	0.95
A. D. Raha et al. [218]	93.45%	0.94	0.92	0.93
F. Yasmin et al. [222]	91.67%	0.92	0.9	0.91
M. M. Ahsan et al. [223]	92.78%	0.93	0.91	0.92

Table 6.12: Result Analysis of existing study with the proposed system

Ref.	Year	Datasets	Methods	Accuracy
Ali et al. [191]	2022	MSLD	VGG-16	81.48
			ResNet-50	82.96
			Inception-V3	74.07
			Ensemble	79.26
			MobileNet-V2	91.13
Irmak et al. [224]	2022	MSLD	MobileNet-V2	91.37
			VGG-16	83.62
			VGG-19	77.58

Jaradat et al. [197]	2023	MSLD	EfficientNet-B3	63
			VGG-19	91
			VGG-16	89
			ResNet-50	78
			MobileNet-V2	94
Sahin et al. [225]	2022	MSLD	ResNet-18	73.33
			GoogleNet	77.78
			EfficientNet-B0	91.11
			NasnetMobile	86.67
			ShuffleNet	80.00
			MobileNet-V2	91.11
Almufareh et al. [196]	2023	MSLD	Inception-V3	93.33
			ResNet-50	88.89
			MobileNet-V2	88.89
			EfficientNet-B4	88.89
Dwivedi et al. [226]	2022	MSLD	ResNet-50	84
			EfficientNet-B3	87
			EfficientNet-B7	77
Aydin et al. [227]	2022	MSLD	DesNet-121	72
			ResNet-50	75
			Xception	73
			EfficientNet-B3	82
			EfficientNet-B7	90
Proposed Work	**2024**	**MSLD**	VGG-19	82
			ResNet-101	84
			DenseNet-121	81
			EfficientNet-B4	78
			MxSLDNet (Proposed Model)	**95**

Based on the study's findings, it is clear that the development and evaluation of the MxSLDNet model have resulted in significant advancements in the detection of monkeypox lesions. Our findings consistently demonstrate that the MxSLDNet model is superior to other pre-trained architectures that are commonly used, such as VGG-19, ResNet-101, DenseNet-121, and EfficientNet-B4. This is shown by the fact that we place a strong emphasis on key performance indicators such as accuracy, precision, recall, and F1-score. When distinguishing monkeypox lesions from digitized skin lesion photographs, our model consistently obtains outstanding training and validation accuracies, demonstrating its robustness and reliability. This is shown by rigorous validation and many runs of the model. Furthermore, confusion matrices indicate that the model can effectively differentiate between positive and negative occurrences. Because they give medical personnel a powerful instrument for early detection and intervention in cases of monkeypox, these findings have substantial implications for managing diseases. As a result, this makes it possible to promptly administer treatment and containment measures, which helps reduce the spread of the disease.

The MxSLDNet model is a forward-thinking and innovative advancement in detecting monkeypox lesions. It makes numerous applications that can potentially have a substantial impact available. Initially, it makes it possible to detect and diagnose monkeypox lesions at an earlier stage. This helps in the timely intervention and treatment of the disease, reducing the danger of the disease progressing and being transmitted to other people. In healthcare settings, this non-invasive element is especially advantageous because it decreases physical contact between patients and healthcare personnel. As a result, the likelihood that a disease may be transmitted from one individual to another is reduced. In addition to improving clinical decision-making, the model enhances diagnostic accuracy and therapy outcomes. The provision of automated lesion identification and classification fulfills this objective. In addition, implementing this technology into public health surveillance systems offers the potential to facilitate the early detection of epidemics, the monitoring of epidemiological trends, and the creation of focused intervention approaches. The MxSLDNet model may affect businesses involved in disease surveillance, pharmaceutical research, public health policy, and the healthcare industry. Attempts to create cures and vaccines, as well as decisions regarding policy for disease control and prevention, could be significantly aided by this information. In summary, implementing the MxSLDNet concept can dramatically improve healthcare delivery, the efforts to manage disease, and the outcomes of public health programs undertaken worldwide.

6.6 Conclusion

This work presents MxSLDNet, a machine learning-based Digital Twin (DT) architecture for reliable Monkeypox detection, with the help of IoT-enabled real-time data harvesting and deep learning for instant diagnosis. Experimental findings demonstrate MxSLDNet performs better compared to pre-trained models such as VGG-19, ResNet-101, and EfficientNet-B4, substantially decreasing false negatives and enhancing disease tracking. The robustness of the model was established by using classification reports and confusion matrix assessments. Challenges like scalability, security, and interoperability still exist and need to be addressed through additional research in blockchain-based security and edge AI for real-time processing. This research validates the prospect of AI-driven DT applications for preventing infectious diseases, with subsequent research directed toward scaling digital healthcare innovations.

CHAPTER 7

CONCLUSION

This chapter summarizes the research contributions in Digital Twin Healthcare (DTH), highlighting key achievements, model evaluations, and security frameworks. The study demonstrates the potential of DTH in predictive diagnostics, real-time patient monitoring, and cybersecurity. Future directions for scalability, Edge AI integration, and 6G-enabled healthcare innovations are also discussed.

2.7 Introduction

The advancements in digital healthcare have paved the way for groundbreaking innovations, with Digital Twin Healthcare (DTH) emerging as a transformative paradigm. This research has systematically addressed the development, implementation, and evaluation of a DTH model by integrating deep learning architectures, blockchain security mechanisms, and advanced data transmission frameworks. The culmination of this work presents a robust, scalable, and efficient model designed to enhance predictive healthcare, patient monitoring, and data security. The objectives laid out at the beginning of this research have been comprehensively achieved through the following key contributions.

2.8 Achievements of Research Objectives

Objective 1: Development of a Digital Twin Healthcare (DTH) Model

One of the core objectives of this study was to develop an innovative DTH model that integrates real-time patient data, artificial intelligence, and secure communication channels. The research successfully conceptualized and implemented a digital twin system that can replicate patient health conditions, predict disease progression, and assist medical professionals in personalized treatment planning. The developed DTH model utilizes machine learning algorithms and convolutional neural networks (CNNs) to improve the accuracy of disease diagnosis. In particular, the CervixNet model for cervical cancer detection and the Monkeypox Skin Lesion Detector Network (MxSLDNet) exemplify the potential of DTH in predictive diagnostics. The
29 implementation of digital twins in healthcare ensures real-time monitoring of patients, thereby improving treatment outcomes and reducing manual intervention errors.

Furthermore, the research highlights the role of digital twins in bridging the gap between the physical and digital healthcare environments. By simulating patient-specific conditions and integrating real-time IoT-based health monitoring, the proposed DTH model demonstrates its capability to enhance remote patient management, early disease detection, and precision medicine. These findings strongly validate the feasibility and effectiveness of digital twins in modern healthcare applications.

Objective 2: Design of a Framework for Data Transmission between Physical and Digital Systems

A critical challenge in DTH implementation is ensuring a seamless and secure data flow between physical entities (patients, medical devices) and their digital counterparts. This research introduced a novel framework that integrates blockchain technology with elliptic curve cryptography (ECC) to safeguard healthcare data from cyber threats. The proposed framework addresses key concerns related to data integrity, patient privacy, and real-time accessibility. The integration of a blockchain-based encryption mechanism ensures that patient data transmitted between physical sensors and digital twins remain tamper-proof and confidential. The research findings demonstrate that the proposed approach outperforms conventional security models by significantly reducing vulnerability to cyberattacks and unauthorized access. Additionally, the Genetic Algorithm-Optimized Random Forest (GAO-RF) model has been employed to enhance intrusion detection, further strengthening the security infrastructure of the DTH system.

Moreover, the proposed framework provides an efficient data transmission mechanism that minimizes latency while maintaining high accuracy in healthcare diagnostics. The use of IoT-enabled healthcare sensors for real-time data collection and transmission ensures that digital twin models are continuously updated with the latest patient information. This connectivity is crucial for implementing proactive healthcare strategies, enabling early intervention in critical medical conditions.

Objective 3: Evaluation of the Proposed Model Against Existing Deep Learning Architectures

99 To validate the efficiency and effectiveness of the proposed DTH model, rigorous comparative analyses were conducted against existing deep learning architectures. The research compared the performance of the developed models with well-established architectures such as VGG-19,

DenseNet-121, EfficientNet-B4, and ResNet-101. The results indicated that the proposed models consistently outperformed conventional deep learning networks in terms of classification accuracy, precision, recall, and computational efficiency.

The CervixNet model for cervical cancer detection achieved an outstanding classification accuracy of 98.91%, outperforming traditional approaches that rely on manual cytological examination. Similarly, the MxSLDNet framework for monkeypox lesion detection demonstrated superior predictive performance while requiring significantly less storage space than other deep learning models. The success of these models underscores the potential of digital twin technology in enhancing the accuracy and efficiency of disease detection.

Additionally, the research introduced an anomaly detection framework using digital twin technology for cybersecurity in IoT-enabled healthcare networks. The integration of blockchain, ECC, and deep learning significantly enhanced intrusion detection rates, making the DTH model more robust and resilient against cyber threats.

2.9 Future Directions

1. Scalability and Real-World Deployment

   - The proposed model needs to be tested on larger, multi-center datasets to ensure its effectiveness in diverse healthcare settings.
   - Future research should explore cloud-based Digital Twin platforms for large-scale implementation.

2. Integration with Edge AI and Federated Learning

   - Implementing Edge AI will enable real-time, low-latency diagnosis without relying on centralized servers.
   - Federated Learning can enhance privacy preservation, allowing collaborative model training without compromising sensitive patient data.

3. Optimization for 6G and Smart Healthcare Systems

   - The adoption of 6G wireless networks could further enhance data transmission speeds and expand connectivity for IoT-enabled Digital Twin systems.

- Future studies should explore intelligent healthcare systems integrating AI, Digital Twins, and Extended Reality (XR) for immersive patient monitoring.

This research has successfully developed, implemented, and validated a Digital Twin Healthcare model that integrates deep learning, blockchain security, and real-time data transmission frameworks. The proposed models have demonstrated superior accuracy and efficiency in disease detection, outperforming traditional architectures. By ensuring secure and seamless data flow between physical and digital systems, the research has set a strong foundation for the future of intelligent, predictive, and secure healthcare solutions.

Digital Twin Healthcare stands as a promising frontier in medical science, revolutionizing patient care by offering precise diagnostics, real-time monitoring, and proactive treatment strategies. As technology advances, the further refinement of DTH models will play a pivotal role in shaping the future of healthcare, making it more accessible, personalized, and resilient. The insights gained from this research pave the way for continued innovation, driving the evolution of healthcare into a more intelligent, interconnected, and patient-centric ecosystem.

Page 128 of 144 - Integrity Submission Submission ID trn:oid:::27535:87273600

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