ANALYSIS AND CLASSIFICATION OF HUMAN PHYSIOLOGICAL SIGNALS

A Thesis submitted

in partial fulfillment of the requirements

for the Award of the Degree of

Doctor of Philosophy

in

Electrical Engineering

By

Dinesh Kumar
2K16/PHD/EE/23

Under the Guidance Of

Dr. Mukhtiar Singh
Professor
Department of Electrical Engineering
Delhi Technological University, Delhi 110042

DELHI TECHNOLOGICAL UNIVERSITY,
Shahbad Daulatpur, Bawana Road
Delhi-110042

FEBRUARY-2021

DELHI TECHNOLOGICAL UNIVERSITY
SHAHBAD DAULATPUR, BAWANA ROAD, DELHI-110042
DEPARTMENT OF ELECTRICAL ENGINEERING

CERTIFICATE

This is to certify that the Ph.D. thesis entitled **"Analysis and Classification of Human Physiological Signals"** submitted to the Delhi Technological University, Delhi for the award of Doctor of Philosophy is based on the original research work carried out by me under the supervision of Prof. Mukhtiar Singh, Department of Electrical Engineering, Delhi Technological University, Delhi, India. It is further certified that the work embodied in this thesis has neither partially nor fully submitted to any other university or institution for the award of any degree or diploma.

Dinesh Kumar
(Registration No: 2K16/Ph.D./EE/23)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

Prof. Mukhtiar Singh
(Supervisor)
Professor, EE Dept.

ACKNOWLEDGEMENTS

I wish to express my sincere appreciation to those who have contributed to this thesis and supported me in one way or the other during this amazing journey of my research.

Firstly, I would like to express my sincere gratitude to my Supervisor Prof. Mukhtiar Singh for his continuous support during my Ph.D. study and related research. His patience, motivation, and immense knowledge have been an inspiration and guiding light for me. His guidance helped me in all the time during this research work and writing of this thesis. I could not have imagined having a better Supervisor and mentor than him for my Ph.D study.

Besides my supervisor, I would like to thank Prof. M.M.Tripathi, Prof. Kapil Sharma and Prof. Gitanjali Pandove for helping me wherever required and provided me continuous motivation during my research.

I also want to specially mention about our Present HOD Prof. Uma Nangia and Ex-HOD Prof. Madhusudan Singh and also Prof. Dheeraj Joshi who provided me an opportunity to do research and gave access to the laboratory and research facilities. Without their precious support, it would not be possible to conduct this research.

I thank my seniors & colleagues, Dr. Ashutosh Trivedi, Vivek Raiwani, Abhishek Sinha, Aakash Kumar Seth and Shivam who were always present there with me during my lab work not only for all their help and useful suggestions but also for being there to listen when I needed an ear and also for all the stimulating discussions.

I would especially like to thank our Power Electronics Laboratory staff Late Sh. Vinod Kumar, Ms. Renu, Ms. Vandana and Mr. Raju for their continuous support and help during my research work.

At Last but not the least, I would like to thank my family members, father Sh. Dayal Singh, Mother Smt. Shakuntla Devi, wife Ms. shikha, kids Alina and Diven, and Biomedical Engg. Faculty and staff at DCRUST Murthal Sonipat for supporting me throughout the research period and also in writing this thesis.

Date: **(Dinesh Kumar)**
Place: Delhi

ABSTRACT

Electrocardiogram (ECG) and Electroencephalogram (EEG) are the most important diagnosing tools to analyze the electrical activities of the heart and brain respectively. The heart abnormalities may be diagnosed with the ECG generated signal and are indicated by P, QRS complex, T waves and waves intervals. Whereas, an electroencephalogram (EEG) test is used to identify brain disorders, especially for epilepsy. It records the electrical fields by amplifying voltage differences between electrodes placed on the scalp. The characteristics of these signals keep on changing and have different patterns for different diseases like epilepsy, dementia and during other mental disorders. Since, there is continuous variations in the amplitude, frequency, and waveform intervals due to the noise and artifacts, it is very difficult to extract the accurate features for diagnosing purpose. The accuracy and other performance measures of the diagnosis are the backbone of the decision support system and quality treatment. Different feature extractions techniques and classification methods have been proposed in the literature by various researchers based on the criteria such as underlying learning strategy, application domain, and representation of signals. The ECG and EEG signals are generally processed for extracting diagnostic features using various techniques based on wavelet transform, Artificial Neural Networks, Convolutional Neural Network, Random forest, K-nearest neighbour, Probabilistic Neural Networks, Hidden Markov Model and combination of the other machine learning methods. However, these methods have certain limitations related to accuracy, computation time, and efficiency for large datasets.

The human physiological Signals like ECG, EEG, EMG, ENG, PPG, GSR, etc. are primarily used for diagnosis purposes for various diseases. The proposed work mainly focuses on the ECG and EEG signals where ECG signals are analysed and processed on two different datasets, PTB diagnostic ECG database and MIT-BIH Arrhythmia database from physioNet. Whereas, the study of EEG signals is performed on EEG time series database from Department of Epileptology, University of Bonn, Germany.

The proposed research work using the ECG Signal databases, presented the secured classification model for heart abnormalities and arrhythmia detection. For heart abnormalities like Bundle Branch Block, Dysrhythmia, Cardiomyopathy etc., high security is provided by using improved dictionary matrix compression and bitwise embedding techniques. Further, to improve the classification of ECG signal abnormalities, the modified dynamic classification method is used.

The results of the proposed scheme with performance measures like accuracy, specificity, sensitivity, precision, Jaccard coefficient, and dice co-efficient are compared with the existing techniques for proving efficacy. For Arrhythmia detection, normal and arrhythmia signals waveforms are analysed and their patterns are represented. In this, the automatic method of arrhythmia classification is performed using the proposed Bat-Rider Optimization algorithm-based deep convolutional neural networks (BaROA-based DCNN). The features are fed to the arrhythmia classification module, which classifies the patient as either affected with arrhythmia or normal. The classifier Deep CNN yields an accurate classification and it is an automatic way of classification. The experimentation is performed using the MIT-BIH Arrhythmia Database and the analysis is performed based on the evaluation metrics.

The proposed research work deals with Epileptic seizure detection using the machine learning methods based on EEG Signals. The abnormal electrical disturbances are normally termed as seizure. The improvement of quality treatment is the most essential for epileptic patients. The limitations of existing classification techniques are unknown network duration, having a distributed memory and fault tolerance. So, we need a new framework for detecting cardiac abnormalities and epileptic seizure classification. This work proposed the novel pre-processing technique named as Enhanced Curvelet Transform (ECT) and new hybrid model for feature extraction in epileptic seizure detection. The proposed hybrid model combines the methods of MGT (Modified Graph Theory), NPT (Novel Pattern Transformation), and GLCM feature extraction. Finally, the robust classification technique is achieved by using PCA based Random forest classification. This proposed classification technique had the advantages of high accuracy, minimum overfitting, minimum information loss, and insensitivity to noise. The results of proposed method are analysed by various performance analysis. Another enhancement in this work is proposed to classify the epileptic seizure using neural network based on their frequency waveforms. In this work, the Modified Blackman Bandpass Filter (MBBF) is used for removing the artifacts from the EEG signal. Then the time domain and frequency domain features are retrieved and optimized using Greedy Particle Swarm Optimization. Finally, the classification of seizure is achieved by using the Convolutional Neural Network. The CNN classification utilized to classify the ictal, inter-ictal and healthy classes. Based on the experimental results, it can be observed that the proposed method exhibits enhanced efficiency and accuracy in comparison to other existing techniques.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVATIONS

WHO	-	World Health Organization
ECG	-	Electrocardiogram
PPG	-	Photoplethysmograph
GSR	-	Galvanic Skin Response
EMG	-	Electromyogram
ENG	-	Electronystagmography
GBD	-	Global Burden of Disease
AD	-	Alzheimer's Disease
CVA	-	Cerebro Vascular Accident
EEG	-	Electroencephalogram
BCI	-	Brain-Computer Interface
BMI	-	Brain-Machine Interface
ML	-	Machine Learning
SVM	-	Support Vector Machine
PCA	-	Principle Component Analysis
GA	-	Genetic Algorithm
DT	-	Decision tree
KNN	-	K-Nearest Neighbour
ES	-	Epileptic Seizures
MGT	-	Modified Graph Theory
NPT	-	Novel Pattern Transformation
GLCM	-	Gray Level Co-occurrence Matrix
MBBF	-	Modified Blackman Bandpass Filter
ANN	-	Artificial Neural Network
DWT	-	Discrete Wavelet Transform
NSR	-	Normal Sinus Rhythm
ARR	-	Cardiac Arrhythmia

CHF	-	Congestive Heart Failure
CNN	-	Convolutional Neural Network
SVD	-	Singular Value Decomposition
ZTW	-	Zero Tree Wavelet
RF	-	Random Forest
WPD	-	Wavelet Packet Decomposition
EFA	-	ECG Fragment Alignment
BFO	-	Bacterial Foraging Optimization
PSO	-	Particle Swarm Optimization
SubXPCA)	-	sub-pattern dependent PCA
ICFS	-	Improved Correlation dependent Feature Selection
GST	-	Generalized Stockwell transform
VMD	-	Variational Mode Decomposition
AR	-	Autoregression
IEEG	-	Intracranial Electroencephalogram
GPLVM	-	Gaussian Process Latent Variable Model
FCM	-	Fuzzy CMean clustering
ECoG	-	Electrocorticography
CCEP	-	Cortico-Cortical Evoked Potential
EZ	-	Epileptogenic Zone
FBC	-	Functional brain Connectivity
MFFN	-	Modular Frequency Neural Network
PDC	-	Partial Directed Coherence
GTA	-	Graph Theory Analysis
LNDP	-	Local Neighbour Descriptive Pattern
1D-LGP	-	One-dimensional local gradient pattern
LGS	-	Local Graph Structure
NCA	-	Neighbourhood Component Analysis

RWE	-	Relative wavelet energy
RAPM	-	Raven's Advanced Progressive Metric
LGBP	-	Local Gabor Binary Pattern
OTF	-	Objective Transformation Function
IDFM	-	I-Dimensional Feature Matrix X
PNN	-	Probabilistic Neural Network
DCNN	-	Deep Convolutional Neural Network
ROA	-	Rider Optimization Algorithm
MOBA	-	Multi-Objective Bat Algorithm
BaROA	-	Bat Rider Optimization Algorithm

CHAPTER 1
INTRODUCTION

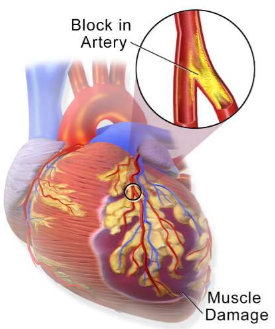
1.1 Cardiac disease

Cardiac disease is a series of health issues worldwide that has a high mortality rate. The WHO estimated 30% of mortality rate due to cardiovascular disease that defines 17.3 million people suffers from this particular disease. Heart defects occur due to blood clots in coronary arteries. It causes the improper pumping of blood. The arteries are diminished, which reduces the supply of oxygen and blood to the heart. The complete artery blockage produces myocardial infarction [1].

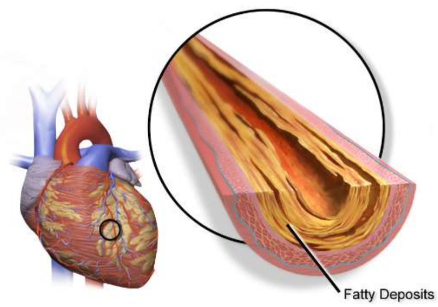
1.1.1 Cardiovascular disease types

The enormous amount of cardiac diseases examined worldwide by the World Health Organization (WHO) are:

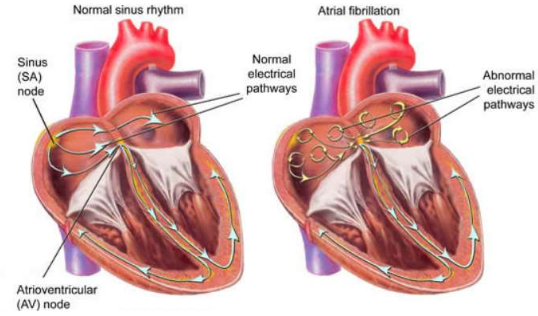
- Myocardial infarction
- Coronary artery disease
- Atrial fibrillation,
- Irregular heart rhythm
- Congenital heart disease
- Heart valve disease
- Cardiomegaly
- Dilated cardiomyopathy



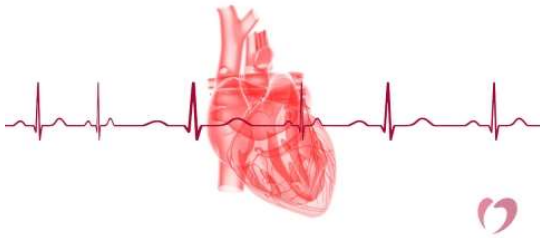
Myocardial infarction



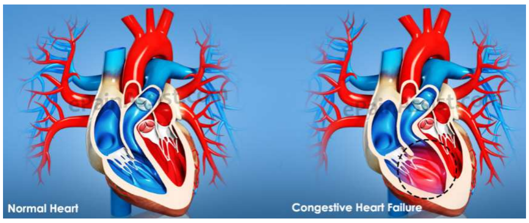
Coronary artery disease



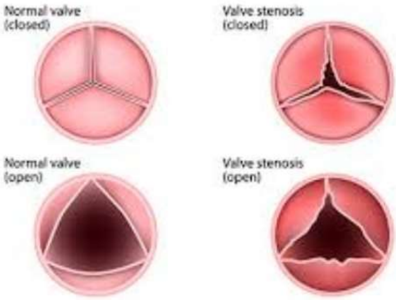
Atrial fibrillation



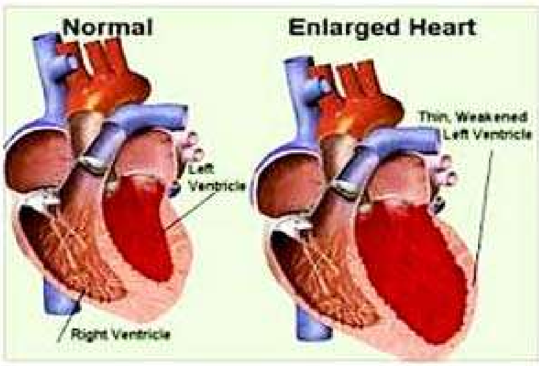
Irregular heart rhythm



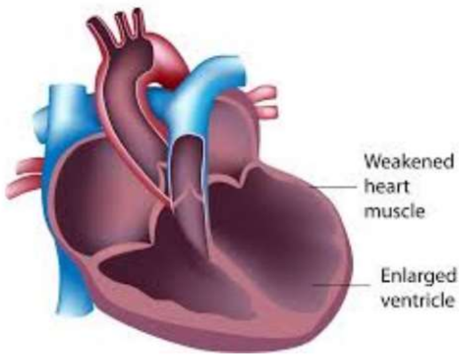
Congenital heart disease



Heart valve disease



Cardiomegaly



Dilated cardiomyopathy

Figure 1.1: Various types of cardiac disease

Figure 1.1 represents the various types of heart abnormalities. Echocardiography is one of the most important methods to diagnose heart disease.

1.1.2 Electrocardiogram (ECG)

The electrocardiogram (ECG) was introduced in 1887 by Augustus Desire Waller. This device records the electrical activity of the heart. This ECG technique has been improved for the diagnosis of cardiac pathologies. This tool determines cardiac arrhythmias by using automatic methods. It utilizes sound waves to generate heart pictures. The understanding of the morphological curve is most important to determine the correct classification of a heartbeat. The ECG of normal pressure consists of P-wave, QRS complex, and T-wave. Generally, ECG records the bandwidth from 0.05 – 150 Hz. The recording consists of 0.04 secs on the horizontal axis with 0.1Mv/mm voltage sensitivity.

Table 1.1: Normal ECG intervals

Wave description	**Interval**
P wave duration	≤ 0.12 seconds
PR interval	0.12 – 0.22 seconds
QRS complex duration	≤ 0.10 seconds
Corrected QT	≤ 0.11 seconds(male) ≤ 0.46(female)

1.1.3 Detection of Arrhythmias

The irregularity or disorder in heart rhythms like abnormal fast heartbeat rate or slow heartbeat rate defines cardiac arrhythmias. These arrhythmias represent the cardiac diseases and indicate the series of heart and circulatory system issues in cardiac deaths. Therefore, the early determination of cardiac arrhythmias in inpatient is the most essential for diagnosing other diseases [2].

The arrhythmias' detection determines heart abnormalities like Bundle Branch Block, Dysrhythmia, Cardiomyopathy, and Myocardial Infarction, etc., in the ECG signal.

1.2 Neurological disorders

Neurological disease is a brain, nerves, spinal cord disorder that occurs due to biochemical, structural, and electrical abnormalities. Various neurological disorders are common and exceptional. Measuring these disorders requires a scrupulous neurological evaluation performed by neuropsychologists and dexterous neurologists [3]. Based on the Global Burden of Disease (GBD), the world health organization examines the 600 types of neurological disorders ranging from migraines to epilepsy. They estimated the disorder scale with more than 1 billion people worldwide. This measure is expected to increase with respect to population rise and may have a severe impact on public health. Interruption of these disorders includes lifestyle changes, physiotherapy, preventive measures, medication, pain management, and neuro-rehabilitation. Some of these disorders' symptoms are loss of sensation, confusion, muscle weakness, poor coordination, paralysis, pain, seizures, and transformed levels of consciousness. Researchers suggest the primary measures of these disorders' seriousness based on mortality statistics, organizations, and countries of disease control programs.

Types of neurological disorders:

a. Parkinson's disease: Generally, the neurologic syndrome results are the failure of neurotransmitter dopamine as a consequence of vascular or inflammatory changes, categorized by the rigidity of movement, rhythmic muscular tremors, festinating, and droopy posture. Lower levels of dopamine have a severe impact on muscle movements.

b. Dementia: Dementia disorder occurs due to intellectual deterioration and other cognitive skills. This severity acts as a drawback in their occupational and social occupation. Alzheimer's Disease is the most common Dementia prevalent that occurs among aged (65 years) people.

c. Stroke: Stroke is called a cerebrovascular accident (CVA) that results in increased brain function loss due to disorder in blood supply. The severe impact is that the brain cells begin to die.

d. Epilepsy: Epilepsy is the chronic neurological disorder of the brain characterized by paroxysmal stereotyped alterations [4]. Chronic non-degenerative neurological disease is the second most brain disorder recognized by neurologists. The WHO estimated that 5.5 million people had Epilepsy in India.

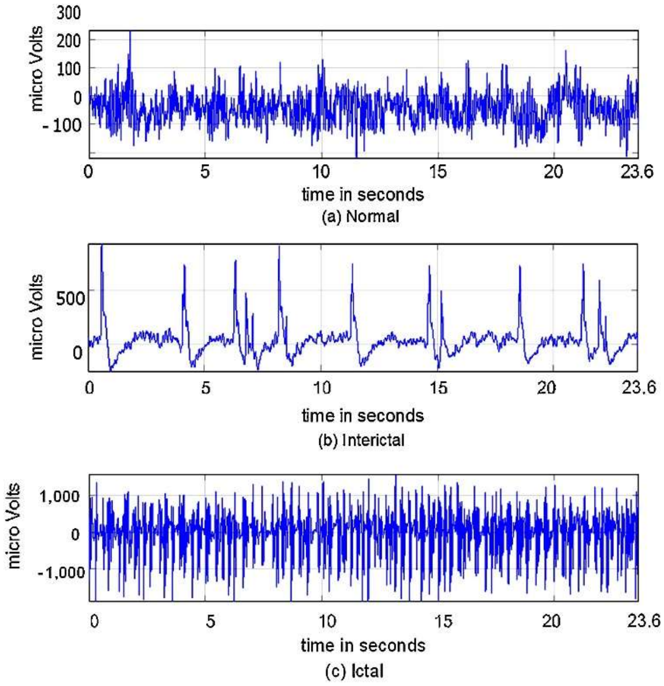


Figure 1.2: Representation of Epilepsy seizure EEG signal [5]

1.2.1 Electroencephalogram (EEG)

The analysis of the electroencephalogram (EEG) described by the German psychiatrist Hans Berger in 1929 provides novel psychiatric and neurologic diagnostic tools without the achievement of psychiatric, neurologic diagnosis and the planning of neurosurgical operative procedures. The introduction of electroencephalography is the advancement of neurologic, neuroscience, and neurosurgical practitioners.

The human brain consists of 10 billion neurons or nerve cells. The neurons of the brain network form a densely parallel information processing system. The neurons and nerve cells take responsibility for processing and transmitting the information by modifying electrical currents' flow through their membranes. It leads to the generation of magnetic and electric fields that should be recorded from the scalp surface. The magnetic fields are examined by placing small electrodes on the scalp. The possible potentials occur among various amplified and recorded electrodes using EEG. The brain potential is categorized into Event potentials and Spontaneous brain potentials. These kinds of electrical activities are recorded by using an electroencephalogram (EEG) machine. The microscopic magnetic fields created by brain neurons are measured by using the Magneto encephalogram (MEG).

1.2.2 Applications of EEG

EEG is used to determine the Seizures by analyzing disorders like Brain Tumour, Epilepsy, Dementia, Stroke, etc. Some modern systems like Brain-Machine Interface (BMI), Human Computer Interaction (HCI), and Brain-Computer Interface (BCI) are used to control and coordinate the prosthetic devices. It also allows patients to communicate their surroundings through the computer and Electrophysiological signals [6].

1.2.3 Electrode placement

Electrodes are tiny metal discs that are made of stainless steel, gold, tin, or silver. The input signals are given through electrodes that are placed on the scalp. EEG records the brain activity that defines the effect of thousands of neurons activity in the brain. The brain activity pattern depends on the fast wave patterns and slow-wave patterns. EEG is mainly used to record brain activities for various diagnosis disorders like epilepsy, dementia, schizophrenia, tumors, etc.

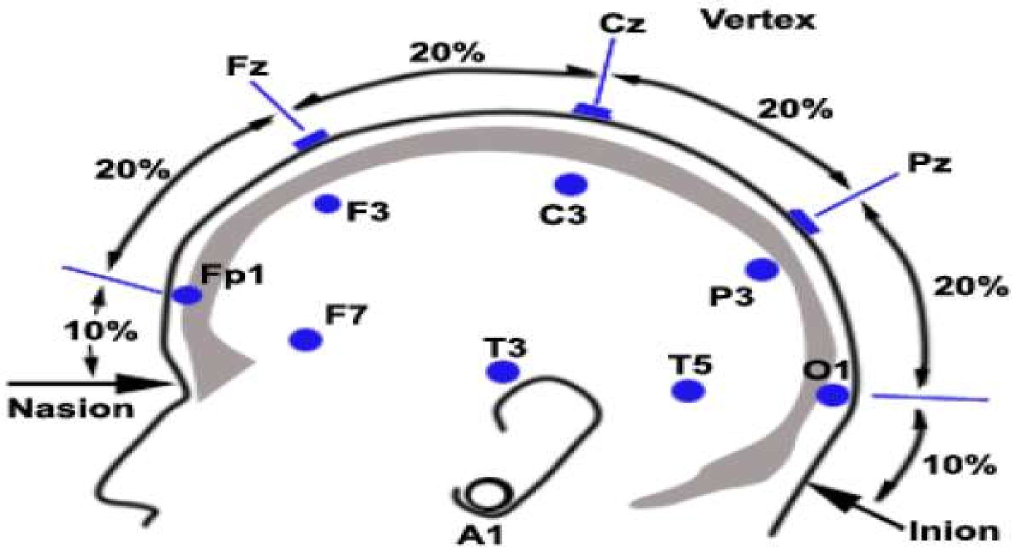


Figure 1.3: Representation of electrode placement [7]

The figure defines the 10-20 electrode placements in overhead view and side view. Each site has a number or letter to identify the location of the hemisphere.

- F – Frontal
- T - Temporal
- C - Central
- P - Parietal
- O - Occipital

The configuration of the reference voltage is defined as the montages. The standard reference point is considered as the one input to the differential amplifier. Every EEG signal is generated by a potential difference among the reference channel and scalp electrode.

1.2.4 Signal Frequencies

The EEG signal waveforms depict the cortical electrical activity. The EEG signal intensity is relatively small, and it is measured in microvolts (µV). Each mental activity or stimulus produced through a particular group of neurons is received, processed, and recorded by an EEG machine.

a. Spontaneous brain potentials

These types of potentials are signals of different frequencies generated through the electrical activities of the brain. The brain frequencies are characterized into Alpha, Beta, Theta, Delta, and Gamma.

Alpha: Alpha represents the 8-13 Hz frequency ranges, and it is seen in head posterior regions when the patient is in relaxing. It arrives when relaxing and closing of eyes, and contributes to constrict with alerting or open eyes by any mental exertion.

Beta: Beta represents the 14-30 Hz frequency ranges. It is also called as fast activity and normal rhythm activity. Generally, it is seen on both hemisphere sides in a symmetrical distribution. Sedative-hypnotic drugs have an impact on this activity.

Delta: Delta represents the 4 Hz of frequency range or below. It has a higher amplitude with lower frequency. It may occur subcortical lesions with deep midline lesions and deep midline lesions.

Theta: Theta represents the 4-7 Hz of frequency ranges, and it is classified as "slow" activity. It is seen as a state of arousal for adults. Excess of theta in adults defines abnormal activity.

Gamma: Gamma represents the 30-100 Hz frequency ranges, and it defines the binding of an enormous neuron collection to perform the motor and cognitive function.

b. Evoked Potentials: The Evoked potentials occur by stimulating the brain's amplitude up to a few hundred times slower than the background EEG.

1.3 Machine learning

In artificial intelligence, learning ability is an essential characteristic. In this field, machine learning examined the computational methods that enhance performance by learning. The focus of machine learning represents technical, cognitive, and theoretical. The technical aim is to automate the process of knowledge acquisition for knowledge-based systems. The cognitive analysis aims to attain human learning at some level. The theoretical analysis considers the learning classification with their scope and demerits [8]. In the healthcare industry, machine learning is used for many applications like to diagnose dermatological disease, female urinary incontinence, thyroid diseases, genes in DNA, predict metabolic and respiratory acidosis, etc.

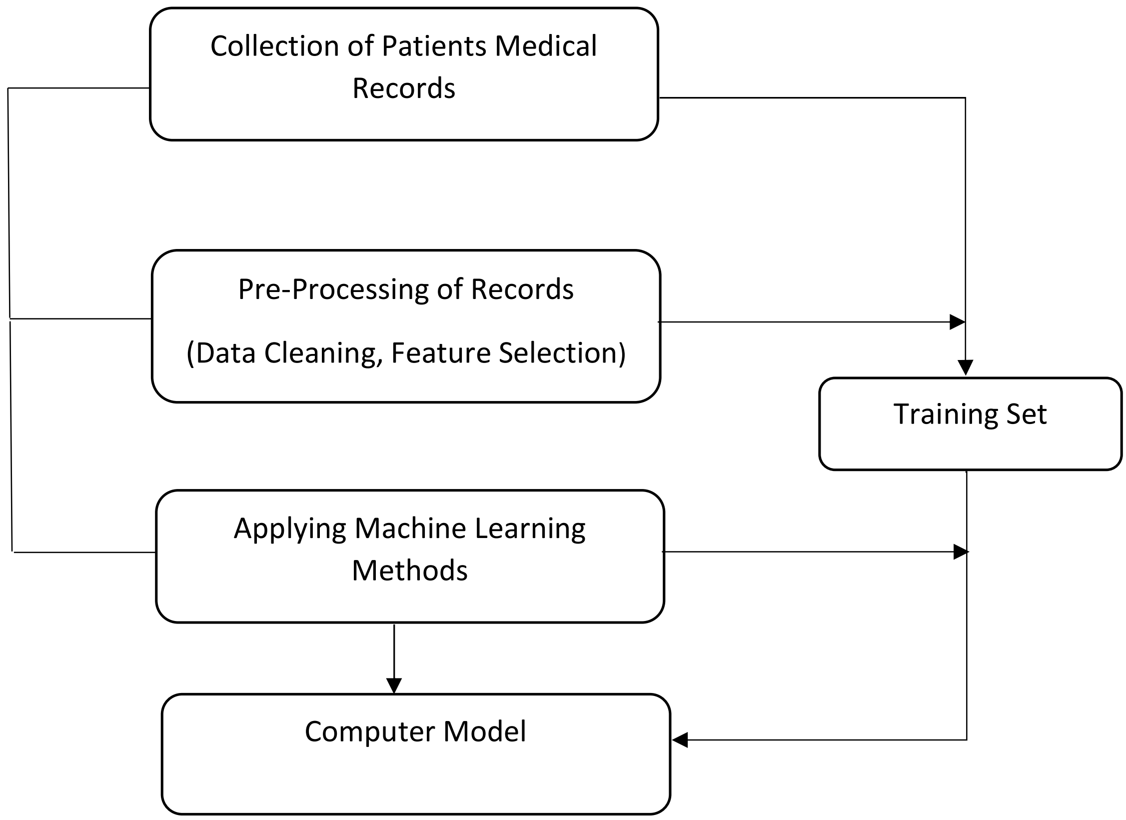


Figure 1.4: Process of machine learning in the healthcare industry [9]

1.3.1 Process of machine learning

The flow of machine learning involves the stages of pre-processing, feature extraction, and classification of disease. The detailed description of these stages is defined as below:

1. **Pre-processing**

The overall process initiates with a specific dataset for pre-processing. The raw dataset of ECG and EEG signal consist of frequency noise, impulsive noise, muscle noise, and respiration. The pre-processing involves the removal of noise present in the signal. Filtering techniques are used for the effective removal of noises. Wavelet transforms utilized the merit function, and it works like Fourier transform. The wavelet transform function localized in both Fourier and real space. Wavelet transform function defined as,

$$\mathrm{F}\ (\mathrm{a}, \mathrm{b}) = \int_{-\infty}^{\infty} f(x)\varphi_{a,b}^{*}(x)dx \tag{1.1}$$

2. **Feature extraction**

Feature extraction involves the removal of irrelevant features in ECG and EEG signals. The important features that are considered useful are temporal, spatial, and textural. The efficient classification is based upon the efficiency of extracted features. The feature extraction process provides a set of features or feature vectors that establishes the image representation. The various features may be categorized as general, local features, pixel-level features, global features, and domain-specific features.

3. **Classification**

The classification system characterizes the input data and target class for the training and testing process. The utilized classifier of input data and target class are provided to the machine learning algorithm to determine the exact decision. It performs the structured and unstructured data to categorize the provided set of data into classes. Training data requires to analyze how the provided input variables are relevant to the class. In the testing process, the input data performs the determination of the target class. Some of the classification problems are handwriting recognition, face detection, speech recognition, document classification, etc. It has the applications of spam filters, disease predictions, document classification, and sentiment analysis.

1.3.2 Heart abnormalities detection in ECG signal using machine learning

Cardiac diseases are one of the common causes of death globally. Most cardiac patients require early prediction and treatment. ECG device is used to monitor the patient's heart condition by recording the heart's electrical activities. Early detection of heart diseases through machine learning programs reduces the mortality rate. Some of the machine learning classifiers are SVM, naïve Bayes, neural networks, decision trees, genetic algorithms, regression, and random forest. The decision tree technique is utilized for retrieving the rules in heart disease prediction. These classification methods are most suitable for medical datasets to determine the heart abnormalities in the ECG signal.

Table 1.2: Machine learning methods for the diagnosis of Cardiac Diseases and Epileptic Seizures

Reference	**Method Name**	**Description**	**Dataset**	**Advantage/ Disadvantage**
{El-Sayed, 2018 #33}	SVM and genetic algorithm	The proposed method solved the congestive heart failure recognition.	CHF2DB	This method yielded 98.79% of accuracy
{Shah, 2017 #34}	PCA and SVM	The suggested method retrieved the heart rate variability signals and employs PCA and SVM on these signals.	Long term STDB	• It yielded 99.2% of accuracy. • This method has not been found

				efficient for large datasets.
{Uyar, 2017 #35}	Neural network and genetic algorithm	This hybrid method diagnosed coronary artery disease.	Z-Alizadeh sani dataset	• This method yielded 93.85% accuracy. • Higher computational time.
[10]	Decision tree	The proposed system has determined the correct decision about the heart disease risk level without classified rules.	WEKA device	86.3% accuracy for the testing phase and 87.3% accuracy for the training phase.
[11]	J48, Naïve Bayes, KNN, SMO	This research has examined the various classifiers for the diagnosis of heart disease.	Existing standard dataset	J48 produced better accuracy compared to other methods.
[12]	SVM classifier	The proposed classification method has been applied to two benchmark datasets to determine the seizures.	CHB-MIT and Bonn University	It yielded the accuracies 92.30% and 99.33% for two benchmark datasets.
[13]	LS-SVM classifier	This research has extracted four features like DCT, DCT-DWT, SVD, and IMF to classify the “ictal” and “inter-ictal” states.	Raw EEG dataset	The proposed method has yielded minimum computational cost.

[14]	Entropy features extraction	This study has involved eight types of entropy features like fuzzy, spectral, Shannon, permutation, sample, approximation, conditional, and correction conditional on the raw dataset.	EEG dataset	It classified “ictal” or “inter-ictal” with 99.50% of accuracy.

1.3.3 Seizure detection in ECG signal using machine learning

Epilepsy is a neurological disorder, and it is difficult to determine it at an early stage. The epilepsy diagnosis is performed by a neurologist using an EEG machine. It is the most convenient and cost-effective method for seizure detection and monitors the patient's brain activity. A seizure is an acute symptom of epilepsy and is categorized based on size pattern spread, regions, and spatio-temporal behavior. The automatic detection of a seizure is attained by establishing the classification framework in machine learning. The obtained data is described as several features for classification. In the training process, the machine learning algorithm generates the appropriate decisions on input data and enhances the desired level of accuracy.

1.3.4 Benefits and Limitations of machine learning (ML)

Benefits:

- ML algorithm gives early detection of many diseases that may reduce the mortality rate.
- These techniques produce a priori probability of disease, and it can save time and cost for patients.
- The ML algorithms extract the hidden patterns from the collected data that lead to the early detection of diseases using new techniques.

Limitations: Machine learning algorithms have a lot of advantages but have some limitations too in some directions, mentioned below:

- The selection of the right feature extraction and classification technique for a particular dataset is a big challenging problem in machine learning.
- Generally, the machine learning algorithm takes a large number of datasets for the training process. The dataset should be unbiased and inclusive of high quality. The dataset collection requires more time.
- The machine learning algorithm takes more time for training and testing to provide the results with high assurance.
- The machine-learning algorithm has a lot of difficulty in estimating the prediction from collected samples.
- The ML algorithm has high error-susceptibility if trained with incorrect or partial data, which may lead to inaccurate results and, thereby, errors in diagnosing a disease.

1.4 Problem identification

Cardiac diseases are the most common reason for death in developing and underdeveloped countries. Early detection of any cardiac abnormalities may reduce the mortality rate. Early detection of any heart abnormality can lead to fast medical treatment. Traditionally, medical decision support systems are introduced to assist clinicians in disease diagnosis. This designed system provides efficient medical diagnostic decisions. The machine learning system helps the decision support systems in decision making with their learning experience. It provides benefits in terms of reducing costs and human resources. This technique enables the early prediction and early diagnosis for proper treatment. Feature extraction and classification are the two most important tasks to the ECG beat recognition process. The efficiency of the classifier mainly depends on the quality of features. Therefore, the informative feature selection and extraction are essential in ECG abnormality detection and seizure classification. Various research studies have utilized advanced classifiers such as deep learning, random forest, and decision trees to determine the ECG signal's heart abnormalities. However, these methods have some disadvantages like,

- The requirement of a large number of decision rules
- High computational time
- Some classifiers are not suitable for large dataset

The prediction and diagnosis of epileptic seizures are the most critical challenge in EEG Signal. An electroencephalogram (EEG) is the conventional method for analyzing the brain's electrical signals and detecting epileptic seizures. The detection of epileptic seizures is required to attain high classification accuracy. Historically, there are various prediction models established to diagnose the state of an epileptic patient. The disadvantages of existing classification techniques are defined as below,

- Unknown network duration
- Having a distributed memory
- Fault tolerance

Therefore, it is required to have a new framework for detecting cardiac abnormalities and epileptic seizure classification.

1.5 Motivation

The proposed work's primary motivation arises from the limitations of the existing methods regarding their effectiveness. Therefore, machine learning and neural network techniques are modified and utilized to determine the various heart abnormalities in the ECG signal and classify the epileptic seizure as ictal or inter-ictal with high efficiencies.

Initially, a heart abnormality detection mechanism has been developed with high security by using improved dictionary matrix compression and bitwise embedding techniques. Then, it classifies the ECG signal abnormalities using an enhanced dynamic classification method.

Secondly, the hybrid feature extraction method is used for Epileptic Seizure Detection. This hybrid method combines the Modified Graph Theory (MGT), Novel Pattern Transformation, and GLCM features, which classify the seizure as ictal or inter-ictal using random forest classification.

Finally, epileptic seizure detection is attained by using a neural network system. The pre-processing is done by using enhanced Curvelet Transform. Then optimization is achieved by Greedy Particle Swarm Optimization. The neural network is then used as an effective classification technique that provides the results as ictal or inter-ictal.

1.6 Contribution

The thesis presents automated ECG abnormalities and EEG Epileptic Signals detection to meet the research objectives using advanced classification algorithms and techniques. The significant contributions of the thesis are summarized below:

I. Dictionary Matrix-based Compression and Bitwise Embedding for ECG signal Classification

- The Dictionary matrix generation is utilized to enhance the compression process of the ECG signal.
- Bitwise embedding mechanism is used to improve the security of the overall process.
- A Modified dynamic classification method is employed to classify the ECG signal abnormalities.

II. Arrhythmia Classification with ECG signals

- Performance measures parameters like accuracy, sensitivity, and specificity are enhanced for ECG Signals Classification.

- The classifier is optimized with the best and latest optimization algorithm to reach the best results.
- The Deep Convolutional Neural Network is employed to achieve the efficient classification of ECG Signals.

III. A Hybrid Feature Extraction model for Epileptic Seizure Detection

- Curvelet Transform is improvised to enhance the pre-processing system.
- A combination of Modified Graph Theory (MGT), Novel Pattern Transformation, and GLCM features is used to achieve the efficient dimensionality reduction or feature extraction process.
- PCA based Random forest classification method is used to improve the classification process.

IV. Extraction of EEG Time and Frequency Domain Features for Classification

- Blackman Bandpass Filter is modified and used to improve the removal of artifacts from the EEG signal.
- The time-domain and feature domain features are extracted to enhance the feature extraction process.
- The Greedy Particle Swarm Optimization is utilized to optimize the extracted features.
- The Convolutional Neural Network is employed to achieve efficient classification.

1.7 Thesis organization

This thesis is organized into six different chapters, including the introduction, conclusion and Future Directions. Chapters are briefly described below:

CHAPTER I: It provides a basic introduction about ECG signals in cardiac disease and EEG signals in seizure disease. And this chapter describes the brief information about the machine learning method to determine cardiac disease and seizure detection. The end of this chapter contains the contribution of the proposed system with an explanation. It defines the problem identification and motivation of the research.

CHAPTER II: It presents the Literature Review of various machine learning methods to detect multiple heart abnormalities in the ECG signal. It also briefly introduces the existing ML techniques to classify the epileptic seizure as ictal or inter-ictal. This chapter discusses various surveys about neural network classification methods. Finally, a catchy summary is also provided.

CHAPTER III: It presents the embedding mechanism for ensuring the security of the overall process. The proposed method of compression, embedding, decompression, de-embedding, and classification techniques has been thoroughly discussed. Simulations results are presented for stating its efficiency, and a brief comparison with the existing methods have been provided to validate its effectiveness.

CHAPTER IV: It presents the automatic arrhythmia classification method using the proposed Bat-Rider Optimization algorithm-based deep convolutional neural networks (BaROA-based DCNN). The experimentation is performed using the MIT-BIH Arrhythmia Database, and the analysis is performed based on the evaluation metrics.

CHAPTER V: It proposes a new hybrid feature extraction for epileptic seizure detection. Here, a detailed description of the proposed pre-processing, feature extraction, and classification methods have been provided. The performance measures are calculated in the result section and compared with various existing methods. At last, a summary has been presented.

CHAPTER VI: It presents the Blackman bandpass filter for removing the artifacts, and different time and frequency domain features are extracted, followed by the classification using a convolutional neural network. Optimization is performed using greedy particle swarm optimization.

CHAPTER VII: This Chapter presents the overall conclusion of the proposed techniques and future work that may be extended for further research using different human physiological databases.

1.8 Summary

The basic introduction of ECG signal in cardiac disease and EEG signal in seizure disease have been provided in this chapter. It also describes the brief information about the machine learning method to determine cardiac disease and seizure detection. The end of this chapter contains the contribution of the proposed systems with a brief explanation. It defines the problem identification and motivation of the research.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

Cardiac diseases around the world are a common cause of death. The ECG signal is the measurement of electric heart activities and plays an essential role in diagnosing heart diseases. Various neurological disorders are relatively common, and it occurs due to the disorders in the brain, spinal cord, and nerves. There are currently numerous machine learning techniques used to determine the heart abnormalities in ECG signals and detect the seizure in EEG signals. This chapter furnishes the literature review on these research areas.

2.2 Various existing method for classification of abnormalities in ECG signal

[15] provided a survey of various machine learning methods for the classification of ECG signals. This research presented different classification techniques for arrhythmia types. The accurate and early detection of arrhythmia is a challenge for heart disease detection. Among multiple classifiers, the ANN network becomes the most popular and useful for ECG classification. It presented several pre-processing methods, feature extraction methods, ECG databases, classifiers, and performance measures. Also, this research discussed the issues of ECG classification.

[16] described the survey of various heat disease classification in ECG. The existing ECG based different heartbeat abnormality detection with pre-processing, segmentation, feature description, and learning methods. Additionally, some of the datasets are examined for evaluating the described techniques. In the end, various advantages and disadvantages of these methods have been presented with future challenges.

[17] presented the SVM classification for heart abnormality detection in ECG signals for healthcare applications. This research involves pre-processing and SVM based arrhythmic beat classification that is classified into normal and abnormal. This method achieves low latency and high speed with minimum computational factors. The signal processing scheme has been designed for healthcare systems and mainly focused on removing white noise. For the pre-processing signal, the DWT method has been utilized for HRV feature extraction and machine learning methods to perform the arrhythmic beat classification. This study established the SVM classification using extracted features. The results proved that the suggested method exhibits the best performances in comparison to other classifiers.

[18] described the various machine learning methods for ECG signal classification. Initially, the input signal's pre-processing has been attained by using a high pass, low pass filters, and butter worth filter. It eliminates the high-frequency noises. These filters have been utilized to eliminate the excessive noises from the signal. In the pre-processing of the signal, the peak points are determined by using a peak detection technique. Then features from the signals are extracted using statistical constraints. The classification process has been performed from the feature extraction using the Adaboost algorithm, SVM, naïve Bayes, and ANN that classified the ECG signal dataset as normal or abnormal. The results provide 88% accuracy for SVM, 93% accuracy for Adaboost, 99.7% accuracy for naïve Bayes, and 94% accuracy for ANN classification.

[19] identified the hypertrophic cardiomyopathy in ECG phenotypes with the assistance of machine learning. The ventricular arrhythmia causes cardiac death in hypertrophic cardiomyopathy. The focus of the research is to analyze the various HCM phenotypes concerning ECG computational analysis. This work used the QRS morphology with different QRS patterns.

[20] utilized the ensemble deep residual networks with more attention. This research identified the various abnormalities from 12-lead ECG recordings. Various pre-processing schemes have been employed on ECG signals for augmentation, denoising, and balancing variant classes. The consistency and efficiency of data length and the recordings were reduced to the minimum length. The ECG signals have been utilized for training the DNN that combine this model with an attention mechanism. The ensemble model has been generated according to the trained models to establish the testing set predictions. The suggested method has been examined based on the First China intelligent competition ECG dataset testing using the F1 measure. The experimental results provide a 0.875 F1-score that shows practical performances.

[21] surveyed the various machine learning techniques for ECG data classification. Diabetes, obesity, alcohol consumption, smoking, and other modern lifestyle behaviors are the reasons for cardiac diseases. Machine learning deals with multiple techniques to construct the classification model based on the training sets. Then, performances have been verified using the testing sets. This study provides the existing ML techniques with various perspectives on ECG signal classification. This survey paper may be used for both medical research and computing the automatic diagnosis of cardiac disease. The ML classifiers enhanced the accuracy of early detection to provide better treatment for cardiac patients.

[22] presented the feature selection and machine learning classifiers to determine the cardiac abnormalities in the ECG signal. The feature extraction and ECG data classification are the most important part to identify the cardiac abnormalities. However, accurate classification is a challenging task. This determination evaluates the ECG signal classification into arrhythmia types. The overall process has been examined in the MIT-BIH database that attains optimization and

classification stages. These machine learning methods provide high accuracy with high dimensionality reduction.

[23] detected the heart rhythm abnormality and classification with the assistance of machine learning methods. The study provided the machine learning method for classifying heartbeat irregularity. This particular research focuses on primarily three types of signals:

- Normal Sinus Rhythm (NSR)
- Cardiac Arrhythmia (ARR)
- Congestive Heart Failure (CHF)

The dataset has been prepared from the almost 162 records for research. The collected dataset was segmented into two sets for training and testing. From the overall dataset, 70% has been used for training and 30% for testing purposes. The proposed system involves four stages that are as described below:

1. Collection of Arrhythmia signals and Non- Arrhythmia signals from MIT-BIH dataset
2. Pre-processing of ARR, NSR, and CHF signals
3. Application of the DWT technique for the feature extraction and combination of these features to form a single feature vector.
4. Finally, the extracted features have been utilized for SVM classification to classify the proposed model.

The evaluation results verified that the proposed method, with recall, precision, and f1-score, gives 95.92% accuracy.

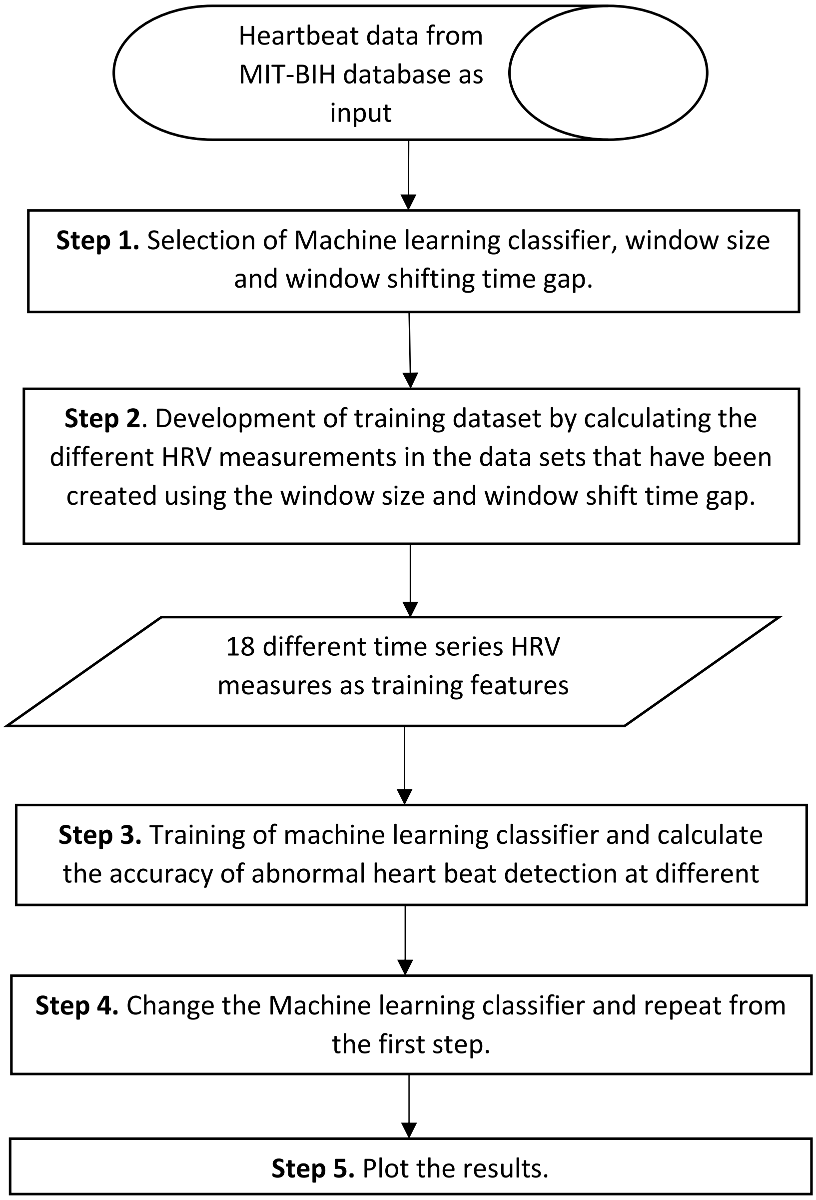


Figure 2.1: Flow of the proposed system in existing system [24]

[25] analyzed the domain invariant heart abnormality by using learnable filter banks. This research described the impact of domain variability in detecting heartbeat sound and provides new strategies to tackle these issues. The enhanced CNN layer with time conventional units and finite impulse response filters have been proposed. The co-efficient has been updated through backpropagation and weighted as a learnable filter bank in the network's front-end. The suggested

method has been applied to multi-domain datasets, and this system exceeds the top-scoring system in the literature to determine the heartbeat abnormality. The estimated performance measures are specificity, sensitivity, and F1-score. The proposed method has attained 11.84% of the increased performance compared to other existing methods. The experimental results have been presented to verify the effectiveness of CNN classification in ECG signals.

[26] utilized the CNN network for arrhythmia detection in long-duration ECG signals. This research introduced the new deep learning concept to classify cardiac arrhythmias with high efficiency. The proposed system has been based on 1000 ECG signal fragments and applied to the MIT-BIH dataset. This research has been designed for the novel 1-D CNN network model. The proposed method has been more fast, efficient, and simple to use and attained 91% overall accuracy in detecting cardiac arrhythmia for 17 disorders.

[27] developed Deep CNN with multi-lead ECG data to classify the Myocardial Infarction (MI). MI is called a heart attack. The ECG signals and blood tests have been utilized for MI diagnoses. However, the increasing amount of blood enzyme measures takes more time after a heart attack. This increased time complexity may suffer the MI diagnosis. This research introduced the CNN network for enhancing the sensitivity and accuracy of over 99% for MI detection on ECG. The suggested deep learning model has been established on the 12-lead ECG signal. The trained CNN model has enhanced the performance with the measures of sensitivity and accuracy.

[28, 29] presented the Genetic Algorithm with Wavelet Kernel Extreme Learning (WKEL) method to classify the ECG signal. The proposed method has been applied to the PTBDB dataset for ECG signal classification. For extracting the features like PR, QRS complex, ST, and QT, the DWT and Pan Tompkins algorithms were used. Then the genetic algorithm has been used to determine the

co-efficient that was utilized in the WKEL algorithm. The results provide 95% accuracy, 80% specificity, and 100% sensitivity to implement a genetic algorithm.

[30] presented the KNN classification with Mel Frequency Cepstral Coefficient feature extraction in ECG signals. The Euclidean distance has been used in the KNN classification using two types of dataset myocardial infarction label and normal label. The K-fold cross-validation has been used to attain efficient results. Based on the experimental results, 13 features have been extracted using MFCC. The results are having 84% accuracy, 85% sensitivity, and 84% specificity.

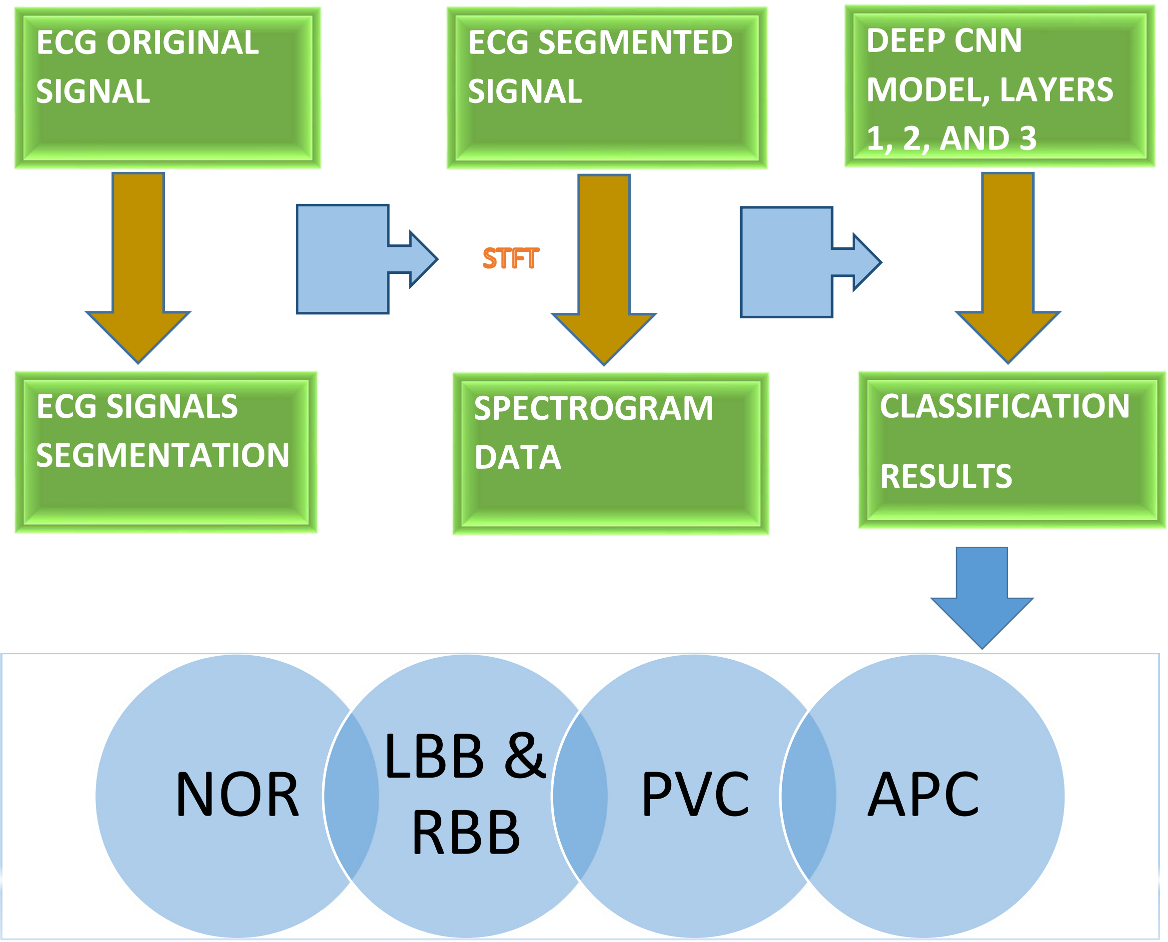


Figure 2.2: Representation of ECG arrhythmia classification using CNN [27]

2.2.1 Compression and embedding mechanisms for heat abnormality detection in ECG signal

[31] presented the hybrid method that combines the Singular Value Decomposition (SVD) and Zero Tree Wavelet (ZTW) technique. This work described the SVD and ZTW with a large amount of ambulatory system for compression. In this system, three various beat segmentation techniques have been used for 2-D array construction with the best correlation of exploitation. The proposed method has been verified on the MIT-BIH arrhythmia record and determined that the proposed method is more efficient in various types of compression of ECG signal having minimum signal distortion for various fidelity assessments. The examination results validate that the proposed method has 24:25:1 of compression ratio, high quality of signal reconstruction, and 1.89% PRD value.

[32] used the wavelet-based watermarking and compression of ECG signals. This research utilized the ECG dataset to determine individual information. The ECG signal is not enough to determine the disease so it requires additional biometric information for authentication and identification. This research integrated the ECG watermarking and compression technique. This watermarking technique enhanced the user's data's reliability and confidentiality, reducing the amount of data. They evaluated the bit error rate, embedding capacity, SNR, CR, Compressed SNR to analyze the proposed method of efficiencies.

[33] evaluated the effective lossless compression technique for ECG signal processing. This research proposed the adaptive linear prediction for lossless compression. The adaptive Golomb-Rice codec technique has been utilized for entropy coding. The combination of these techniques has provided high performances for passed samples. The co-efficient of Golomb-Rice codec and linear prediction generated the self-adjustments of the process. The proposed method has been applied to the MIT-BIH arrhythmia dataset for single-channel

compression and the PTB dataset used for multi-channel compression. These compression schemes have been implemented in the ARM Cortex M4 processor.

[34] explained the incorporation of compression and information hiding for biomedical signals. The watermarking technique performed the quantization-based encryption methods to detect the patient information on ECG signals. Additionally, the hidden information could be retrieved without the original ECG signal. In the compression technique, a threshold-based compression scheme to mitigate the ECG signal has been used to maintain ECG signals' original features. The experimental results validated the proposed method of efficiencies.

[35] utilized the matched filtering on ECG signals for heart rate estimation. This research has used compressive sensing as a minimum complexity of the compression method to monitor ECG signals. The ECG signal derived the beat-to-beat intervals information based on the distance among QRS complexes. Various techniques have been presented for R-peak detection in uncompressed ECG. The signal reconstruction has been performed with complex optimization algorithms that require specific energy consumption. This research addressed the issues of heart rate estimation from ECG recordings. They considered the linear measurements with ECG signals. The QRS locations are evaluated by calculating the correlation of compressed ECG signals in the compressed domain. The experimental results represent the proposed algorithm of effectiveness. This proposed system was used in real-time minimum power applications.

[36] explicated the frequency of localized filter banks to detect the Congestive Heart Failure on ECG signals. The proposed method has been utilized for the automatic diagnosis of CHF in ECG. The proposed system has been verified on four datasets of normal and abnormal CHF classes in ECG signals. Five types of features from wavelet decomposition like Renyi entropy, fuzzy entropy, Higuchi's fractal dimension, Kraskov entropy, and energy has been extracted using the

proposed method. The quadratic SVM method for the training and classification process has been developed. For evaluation, the 10-fold cross-validation method has been used. The proposed method provides 99.6% accuracy, 99.82% sensitivity, and 99.28% specificity. The proposed system offered the advantages of minimum time complexity and minimum error rate with a large amount of ECG signals.

2.2.2 Existing researches using Random forest classifier

[37] utilized the modified random forest classification for heart disease detection on the ECG signal. Various classification methods have been presented in the literature to detect heart diseases. An enhanced RF classifier has been proposed to determine the optimal number of trees with a new simulated annealing algorithm. The proposed method has attempted the objective function to classify the ECG signal. It performs four steps:

- Collection of ECG signal
- Denoising of data
- Feature selection
- Classification using Enhanced Random forest

The overall proposed method has been applied to MIT-BIH and European Physionet ST-T dataset. The evaluation results have proved that the proposed classification method presented 99.62% accuracy based on the trees' determining the optimal number.

[38] presented the random forest classification to classify congestive heart failure. This study evaluated the impact of various machine learning methods using the normal and abnormal classes on long term ECG time series. This research has been categorized as feature extraction and classification. In the feature extraction, the autoregressive burg technique is used to extract the features. In the category,

five various classifiers have been used, such as decision tree, C4.5, SVM, KNN, ANN, and random forest classifier. BIDMC and PTB ECG dataset has been used for the proposed work. The evaluation results have been presented to verify the proposed method's effectiveness in specificity, sensitivity, accuracy, ROC curve, and F-measure.

[39] described the ensemble random forest method with efficient feature selection for heart disease prediction. The heart disease-related information has been taken from the UCI repository. This dataset consists of 1025 instances with 14 attributes. It has sick and non-sick patient's information in the target variable. Classification accuracy, sensitivity, and precision have been identified by using four types of tree-based classification methods such as a random tree, M5P, random forest, and reduced error pruning. All these classification methods have been employed after the completion of the feature extraction process. The proposed system extracted the features by using three methods:

- Recursive features
- Pearson correlation
- Lasso regularization

The proposed three feature selection methods yielded 99% accuracy.

[41] provided the medical decision support system with random forest classification to determine the heart arrhythmia. The proposed RF classification system has attained high performances using 10-fold cross-validation. The proposed method has been applied to MIT-BIH and PICT arrhythmia datasets. This classification method has obtained 99.3% accuracy than the existing C4.5 and CARD methods, which have 98.4% and 98.6% accuracy, respectively. The combination of multiscale PCA denoising, DWT, and RF classification has better performance with a 0.999 ROC curve and a value 0.993 of F-measure.

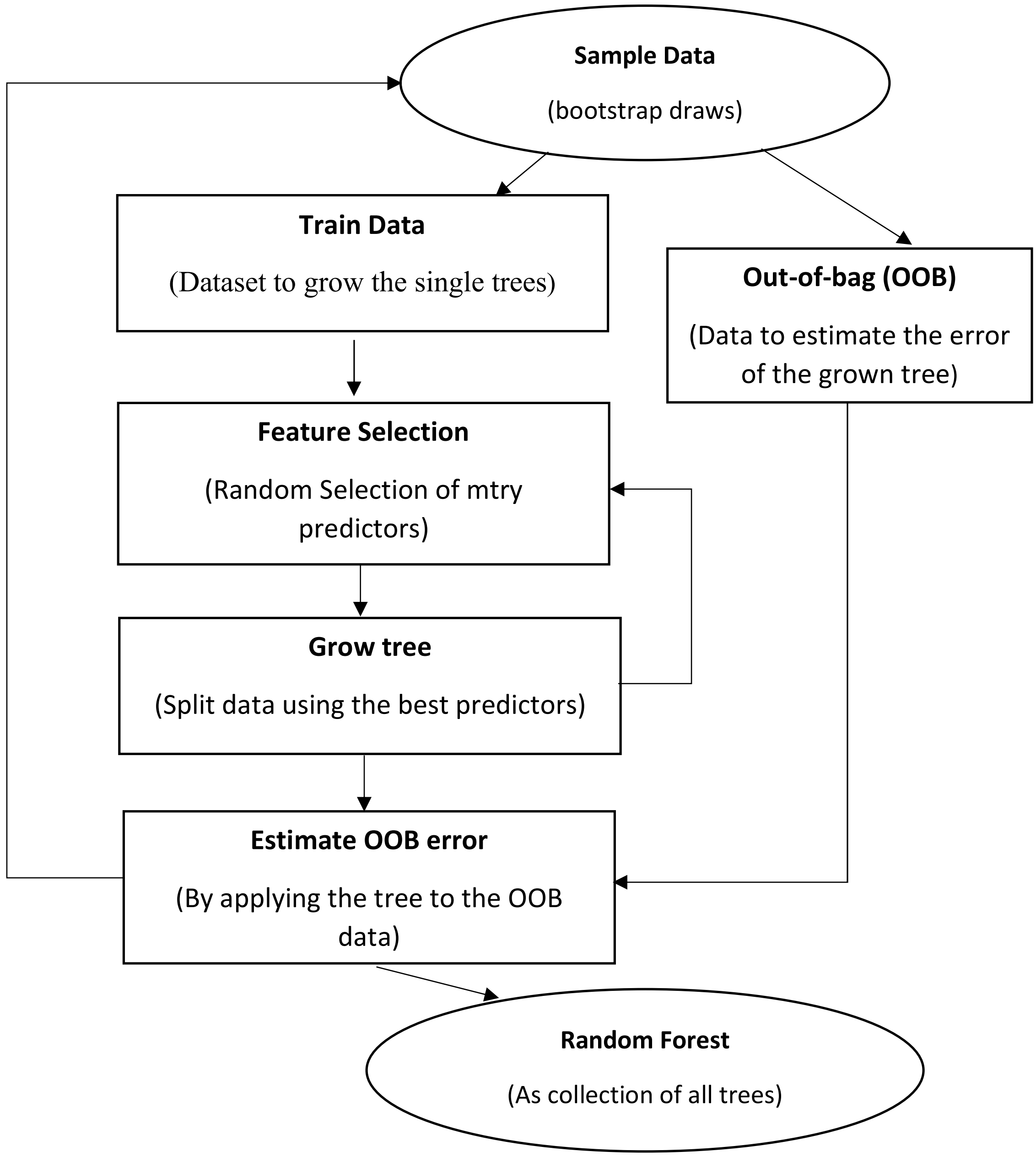


Figure 2.3: Diagnosis of heart disease using RF classifier [40]

[42] analyzed and classified the various heart diseases using machine learning algorithms. This research has presented the Scala language and ML-libs on the Apache Spark structure, consisting of a scalable machine learning library. The ECG signal classification has the challenge of handling the ECG signals

irregularities. Therefore, this study has proposed an effective method for ECG signal classification with high accuracy. In ECG, every heartbeat defines impulse waveforms, which originates from the specialized heart tissues. The classification of heartbeats faced some challenges due to the varied waveforms from person to the person represented by features. Generally, Spark–Scala tools have simplified the usage of various machine learning algorithms. The MIT-BIH dataset has been taken for the evaluation of the proposed method. The spark-scala tool has provided an easy implementation for multiple classifiers like the random forest, decision tree, gradient boosted trees, etc. The experimental results have represented 96.75% accuracy of the proposed method. The multiclass classification has achieved 98% accuracy using GDB and random forest classification.

[43] described the random forest classier with multiple features fusion techniques for arrhythmia classification on the ECG signal. This research has proposed the novel automatic classification technique to enhance the accuracy of classification for arrhythmia. The ECG signal has been utilized pre-processing and denoising process with the help of a wavelet transform. Statistical features such as skewness coefficient, kurtosis coefficient, and variance have been extracted and employed as the RF classifier's input and then compared with SVM and neural network methods. The MIT-BIT dataset consists of 100,647 heartbeats and achieved 99% accuracy, 99% specificity, and 89% sensitivity. Furthermore, the intra-patient and inter-patient schemes have been verified as two classification schemes.

[44] used machine learning techniques to classify in determining the arrhythmia. This research has used the random forest classification for the classification of normal and abnormal signals. The MIT-BIH dataset has been taken for various classification. The proposed classification's efficiency was determined for arrhythmia detection compared with other existing decision tree classifiers and presented 93.4% accuracy.

2.2.3 Existing Principle component analysis technique

[45] described the linear SVM and PCA analysis for automatic detection of an arrhythmia. This research has applied the feature extraction process using a PCA network (PCANet) based on a noisy ECG signal, and the strength of the classification has been enhanced using a linear SVM technique. The experimental results have analyzed the five kinds of imbalanced original and noise-free ECG signals in the MIT-BIH dataset. This dataset has attained the performances of the proposed method with 97% accuracy.

[46] proposed the ECG fragment alignment (EFA) with the PCA network to determine inter and intrapatient coronary artery disease. The proposed PCA network contains 2-convolutional layers and 1-output layer to retrieve the high dimensional abstract features. The proposed EFA method has improved the heartbeats consistency between individuals and high performance in the unbalanced data processing. In the end, the linear SVM has been utilized for the classification of high dimensional features. The experimental results have yielded 99.8% accuracy for dataset A (normal+CAD), 99.9% accuracy for dataset B (normal+CHF), and 99.8% accuracy for dataset C (normal+CAD+CHF).

2.2.4 Existing Hybrid methods

[47] proposed the hybrid model with a genetic algorithm and neural network for efficient decision making. Coronary artery disease has high mortality rates among various heart diseases. Angiography is the most suitable method for CAD diagnosis. However, this method has high costs and side effects. This research has utilized the machine learning model for the diagnosis of CAD disease with high performance. In experimental analysis, the proposed hybrid method has increased neural network performance by 10%, and the genetic algorithm improves the initial weights that have attained better weights for NN. The dataset Z-Alizadeh

Sani has been utilized for the proposed study. The results have 93.8% accuracy, 97% sensitivity, and 92% specificity.

[48] proposed the hybrid ECG classification model with the combination of particle swarm (PSO) and Bacterial Foraging Optimization (BFO). BFO algorithm has been used to tackle the delay of optimum global. The proposed system combines the BFO features and PSO features to determine the abnormal cardiac beat. This research modified the BFO, combined WT, and SVM to validate cardiac arrhythmia detection efficiencies and enhanced the convergence concerning speed and accuracy. The results have been obtained using MI and BBB databases. The combination of BFO-PSO methods with SVM yielded 98.9% accuracy. The proposed method has yielded 99.3% accuracy using the MIT-BIH dataset.

[49] predicted heart disease by using associative classification methods. The research has utilized the Hybrid model with a genetic algorithm and fuzzy logic classification to determine the heat abnormalities at early stages. This hybrid model contained rough sets with feature selection model and fuzzy classification model. Then, the obtained rules have been optimized from fuzzy classifiers by using an adaptive GA algorithm. Features, through the rough set theory [50] and classification through the hybrid classifiers. The experimental results have been evaluated by applying the proposed method to the UCI heart disease dataset. The results have yielded 99.19% accuracy.

2.3 Existing machine learning techniques for Epileptic seizure detection

[51] created a hybrid design for epileptic seizure prediction using GA and PSO to categorize EEG (Electroencephalograms) data. Support Vector Machine (SVM) is a powerful machine learning (ML) method utilized in various applications. Setting of kernel parameter in SVM during the training process creates impacts on the accuracy of classification. This research has used the PSO and GA dependent

techniques to enhance SVM parameters. The proposed SVM has attained a classification accuracy of 99.38% for EEG datasets.

[52] utilized a conventional approach for automatic seizure prediction with the help of Machine Learning methods. Epilepsy is a known nervous system disorder that is characterized as a seizure. Generally, EEG has been utilized to capture the image of brain neural activity to predict epilepsy. The conventional approach has been time-consuming to predict epileptic seizures from the EEG signal. Two main steps of ML are classification and feature extraction. Feature extraction has been utilized to minimize input pattern space by preserving useful features and classifiers to allocate suitable class labels. This research has proposed (Sp-PCA) sub-pattern dependent PCA and (SubXPCA) cross-sub-pattern correlation dependent PCA with SVM for automatic seizure prediction from EEG signals. Here, feature extraction has been done with the use of SubXPCA and SpPCA. These two techniques have been utilized to find a subpattern correlation of EEG signals, which support the right decision. A radial basis kernel has been used for training SVM. Experiments have been conducted on benchmark datasets; Datasets contain 500 EEG signals from the varied scenario. Classification accuracy has been examined with the use of 10-fold cross-validation. The classification result has been presented to verify the proposed work's efficiency.

[53] presented a new technique in which EEG signal dimensionality has been minimized with the help of segmentation technique and mapped to a weighted graph. Generally, Epileptic seizure prediction based on the transform technique is not successful as the signals have non-linear and non-stationary characteristics. Here various ML techniques have been used to classify attributes of the graph. The result has illustrated that usage of graphs has enhanced the quality of predicting epileptic seizures. The proposed technique has indicated abnormalities in the EEG signal that has been complex to predict using existing transformation techniques.

[54] proposed an automatic classification system that has categorized the abnormalities of the EEG signal as Ictal, Interictal, and Healthy. EEG is an electrophysiological technique used to monitor the brain's electrical activity and predict innumerable diseases. One such kind of disease is Epilepsy, which can be predicted by abnormalities in the EEG signal. Automation in the proposed method has been attained by different mining features that consist of numerical data in the transformed domain using the Hilbert and Wavelet method. These features have been utilized to improve differences between the three cases. Experiments have been conducted to examine classifiers' performance concerning performance metrics such as sensitivity, specificity, and accuracy. This automatic classification system has been presented to outperforms other traditional techniques.

[55] utilized the traditional ML technique to highlight the performance of epilepsy seizure prediction task. The EEG dataset used consists of 11,500 attributes and 179 information. One dimensional CNN and ensemble ML techniques like stacking, boosting, and bagging has been implemented. Conventional ML methods like kernel SVM, Naïve Bayes, K-Nearest Neighbour, logistic regression, ridge classifier, extra tree, random forest, and decision tree have been utilized to categorize and detect epilepsy seizure.

Before utilizing the traditional method, the dataset has been pre-processed with Karl Pearson coefficient of correlation to minimize unnecessary attributes. Additionally, prediction’s accuracy and classifier’s classification have been employed using a k-fold cross-validation technique and illustrate an operating receiver characteristic area under the curve for each classifier. Experiments have been conducted to evaluate all ML techniques' performance. It has been found that extra tree bagging classifiers and traditional neural networks have outperformed the other conventional classifiers.

[56] utilized different epileptic seizure prediction algorithms that have been utilized to deal with time-consuming prediction problems. Here, a new automatic seizure prediction method has been proposed. Feature extraction steps have been done with non-linear and linear measures from EEG. The classification practice has been implemented with the help of SVM. Experiments have been conducted with an existing database to differentiate seizure from non-seizure of EEG signals. Results have illustrated high performance for specificity, sensitivity, and accuracy compared to existing techniques.

[57] proposed effective ML techniques to resolve the limitations of the existing techniques. Here, an improved curvelet transform method has been utilized to resolve the drawback of Wavelet and Gabor transformations data loss and unselective orientations. This technique has provided all signal data without data loss of shelter transformation and utilized to pre-process the EEG signal to remove the noise. Then enhanced graph theory, new pattern transformation, and fractional dimension technique have been implemented to extract patterns and features. Feature mining is critical for the compression and classification of a large quantity of EEG signals with the least information. Statistical features have been mined with the standard Gray level co-occurrence matrix method. This technique has computed adjacent sample linear dependency to measure data loss in the transmitted signal efficiently. Then, mined features have been put to Random Forest (RF) classifier to predict and categorize the signal as interictal, ictal, and normal. The simulation has been done to calculate the proposed work's performance, and the result proved the efficiency of the proposed work.

[58] introduced a new analysis technique to predict epileptic seizures from EEG signals with the use of ICFS (Improved Correlation dependent Feature Selection) with RF. The analysis has used ICFS primarily to choose more significant features from entropy dependent features, frequency domain, and time domain.

Experiment results have been presented to verify the effectiveness of the proposed work.

[59] proposed seizure prediction techniques such as RF, SVD (Singular Value Decomposition), and GST (Generalized Stockwell transform). EEG has been converted to a time-frequency matrix with the GST's support, then local and global singular values have been mined by SVD from partitioned and holistic matrices of GST. Consequently, four local parameters have been computed from every vector of local singular values. Lastly, local parameter and global singular value vector have been applied as input to RF for categorization. The final plan of testing EEG has been voted depending on sub-labels received from trained classifiers. Bonn EEG database has been examined with proposed work to find the proposed work's accuracy and presented its effectiveness.

[60] integrated ML and signal processing techniques that have been developed to resolve the time-consuming process of EEG analysis in the existing works. VMD (Variational Mode Decomposition) and AR (Autoregression) dependent quadratic feature mining have been proposed for feature mining, and RF has been implemented to handle three categorization tasks. Raw EEG has been decomposed to a fixed number of (BLIMFs) band-limited intrinsic mode functions using VMD. Then the logarithmic operation has been executed on every BLIMF. Later, optimal AR-dependent quadratic feature mining has been performed on all BLIMF, and then the mined feature vector has been applied as input to RF for categorization. Experimental result on the Bonn epilepsy EEG dataset has presented that the proposed work achieves a good accuracy 97.352% and excels the fixed-order AR-dependent feature mining method. Results have been presented to verify the effectiveness of the proposed work.

[61] introduced a new technique for automatic prediction of seizure depending on iEEG data, which excelled the current seizure prediction technique. The proposed

work has included an ACS (Automatic Channel Selection) engine as a pre-processing step for seizure prediction. RF has been utilized to categorize ictal, interictal, and primary ictal periods of iEEG signals. Here, seizure prediction has been patient-specific and retrospective. iEEG data has been retrieved through Kaggle, and the international epilepsy electrophysiology portal has provided that. The result has proved that the proposed work predicts seizure two times faster than the existing prediction technique.

[62] introduced an automatic epilepsy seizure prediction system for the initial prediction of epilepsy seizure using current communication technology integrated with cloud computing and ML. This design has detected EEG signals from patients' scalps. The EEG signal has been processed with fast Walsh Hadamard transform and high-order spectra-dependent feature mining for mining entropy-dependent features and higher-order statistics. A correlation-dependent feature selection algorithm has been employed to minimize the EEG dataset's dimensionality to manage issues related to the huge volume of data and reduce service delays provided to end-users. RF has been implemented to categorize the EEG signal into three varied seizure stages: ictal, preictal, and normal. The simulation result has proved that RF provides maximum classification accuracy, sensitivity, and specificity and minimizes MSE and training time.

[63] provided a good understanding of how to view the information in EEG signals and has utilized RF to decode EEG signals specifically for numerous illness-stages. Here RF has been integrated with grid search optimization. The feature's dimensionality has been minimized with PCA (Principal Component Analysis). Training parameters have been enhanced using grid search optimization to improve the prediction performance and diagnosis accuracy for three varying levels of epileptic conditions.

The proposed work has categorized 500 samples of EEG data, and numerous cross-validation has been accepted to enhance the modeling accuracy. The area has analyzed the experimental results under the curve, receiver operating characteristic curve, confusion matrix, and accuracy. The proposed model has attained the most efficient classification than the current typical methods. This kind of scheme enhances the quality of life and also reduce the work of neurologist.

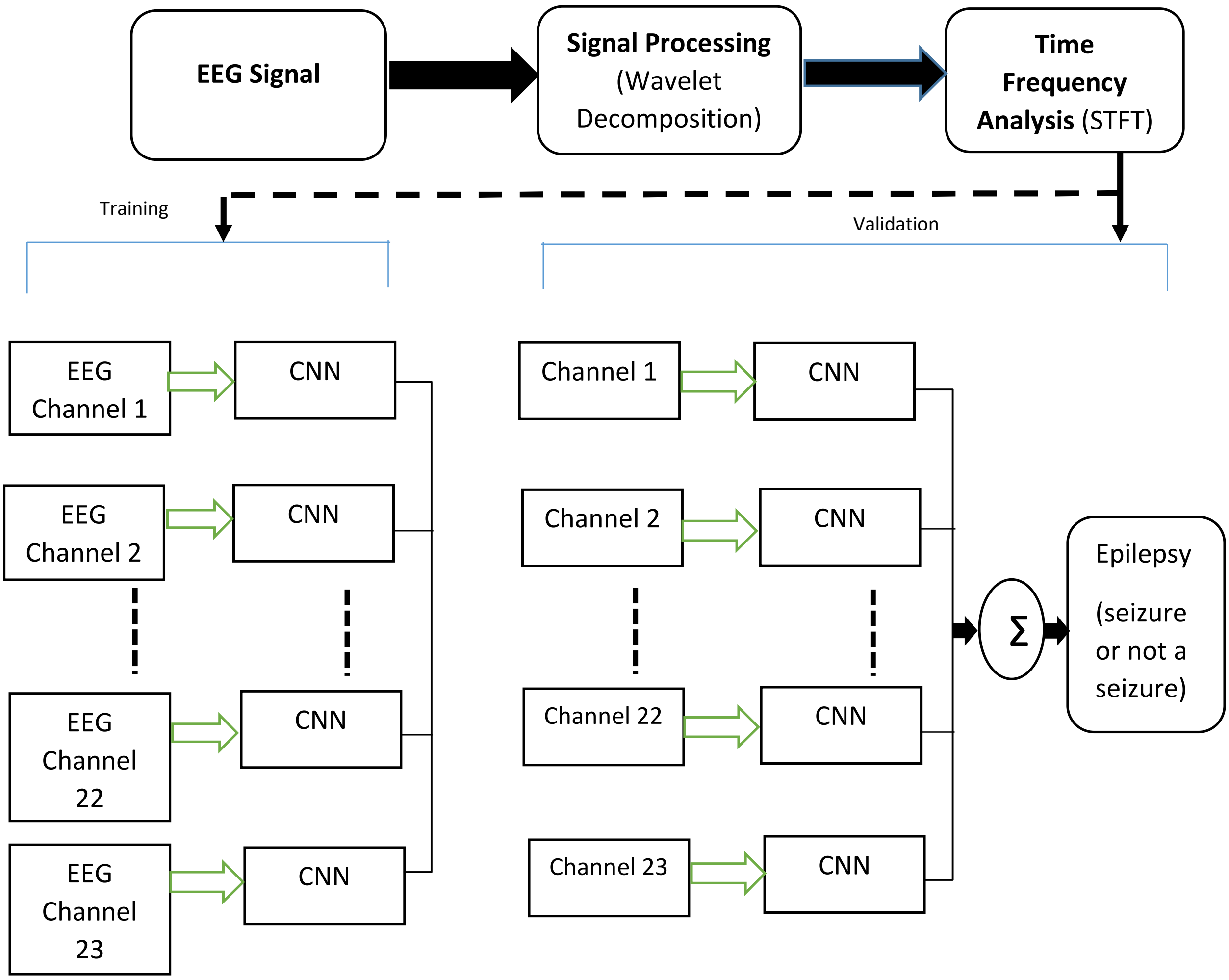


Figure 2.4: Epileptic seizure detection using deep learning

[64] proposed a new automatic epileptic seizure recognition system that has been utilized to resolve the problem of predicting epilepsy by observing EEG signals visually, which takes more time. GPLVM (Gaussian Process Latent Variable

Model) has been utilized to reduce the features by attaining a set of principal features that prominently rejects the "curse of dimensionality." Then supervised classifier (MSVM) has been utilized to categorize epileptic seizures as interictal, ictal, and normal. The experimental result has demonstrated that the proposed work correctly categorizes epileptic seizure in terms of accuracy, (FPR) False Positive Rate, (FNR) False Negative Rate, specificity, and sensitivity. The proposed technique has enhanced classification accuracy up to 2.5 – 12% compared to existing work.

[65] discussed the wireless EEG devices that facilitate ambulatory EEG monitoring while patients in a move of daily activity. This kind of device needs a considerable amount of energy to obtain and encode EEG data and conduct it to the server-side. Generally, three EEG monitoring patterns have been utilized. They are used for transferring of i). real EEG data, ii). compressed EEG data or iii). few EEG features. This research has dealt with how to change the previous pattern to minimize total power consumption over the server-side. The first new module, referred to as MAR (Missing at Random), has been added to the sensor unit. This module has removed a few EEG data points to minimize the quantity of data transmitted and minimize the energy needed to transmit data at the sensor side. Secondly, the data server has been modified to include a new module referred to as EM (Expectation-Maximization), which has been utilized to remove missing EEG data points correctly. The experimental result has illustrated that the proposed work saves 60% of power consumption, ultimately doubling the battery's lifetime.

[66] discussed MR medical image fusion that plays an essential role in the diagnosis and treatment of disease. NCST, CVT, DWT, and CT are some of the transform domain depending on the image fusion approach, which addresses high complexity and spatial inconsistency. Existing conventional image fusion techniques such as PCA, weighted, Maximum, Minimum, and simple average

have constraints of infused images such as block discontinuities, spectral degradation, noise effects, blurring effects, etc. Curvelet and wavelet image transform have been utilized to resolve these shortcomings to obtain an accurately fused image, improving fusion level.

[67] discussed image classification and segmentation methods. These are considered as two essential steps of image processing. Methods based on clustering play a vital role in the segmentation step of biomedical images, mainly to differentiate cerebrum tumors from MRI brain images, which has been the most challenging task. This research has presented a curvelet transform to extract features for the computerized prediction of abnormalities in MRI brain images. Curvelet transform has been utilized to extract the brain's texture and statistical features using an MRI image. Manual segmentation has been a time-consuming process. Therefore, in this research, Fuzzy C-Means (FCM), AMS, adaptive FCM, and the genetic algorithm have been utilized to extract features with curvelet transform as input. Segmented images act as input for classifiers such as ANFIS, probabilistic neural network, and SVM, which classify input as abnormal and normal.

[68] discussed medical imaging domain that integrates related information and redundancy from numerous medical images to create fused medical images useful for medical examination. Here, a fusion method has been proposed for multimodal medical images depending on curvelet transform and GA. Enhancement of the characteristics of the fusion image has been performed using GA. Proposed work has been tested on numerous medical images and has been compared with current fusion techniques. The results of the proposed work have produced good results compared to other methods.

[69] discussed Epilepsy that is a brain disease that affects all age groups, mainly older and younger people. Up to one-third of patients were medically intractable

and needed surgery. But, the output of epilepsy surgery depends on a precise prediction of EZ (Epileptogenic Zone). CCEP (Cortico-Cortical Evoked Potential) integrated with ECoG (Electrocorticography) monitors humans' brain connectivity and helps clinicians focus on epileptogenic more precisely. The patient has been inserted with subdural grid electrodes, and then electrical stimulation has been given to the cortex for CCEP. Once completing signal pre-processing, three efficient brain networks have been constructed at various spatial scales for the patient. Later, Graph theory has been utilized to examine the topology of epileptic patients' brain networks. From CCEP, the connectivity network has been reconstructed.

Moreover, the response of CCEP has been linked with EZ's position, which has the shortest path length and a high degree of centrality than NEZ. The results have shown that the brain network of people with epilepsy has been asymmetric and contained short-distance connections. NLP and DC have been steady to the distribution of EZ, and these topological parameters have a greater capacity to be utilized to find EZ.

[70] discussed about the Epileptic seizures that have a specific EEG pattern, which facilitates their automatic prediction. Statistical dependence among various brain regions measured by FBC (Functional brain Connectivity). This research has been intended to provide a stable automated seizure prediction technique. A multi-level modular network has been proposed depending on the combination of different EBC classification results at varied frequencies. MENN (Modular Effective Neural Network) has integrated three various EBCs at a particular frequency and has integrated classification results of particular EBCs at seven varied frequencies. The experimental result has concluded that the proposed method provides the best accuracy compared to the other research. Information on structure-relationship among the various region of the brain has been needed to characterize underlying

dynamics. Therefore, a feature dependent on EBC has provided the most reliable automatic seizure prediction method.

[71] proposed two new techniques to categorize semantic vigilance levels using EEG-directed connectivity patterns with their respective graphical network measures. RWTE (Relative Wavelet Transform Entropy), PDC (Partial Directed Coherence), and GTA (Graph Theory Analysis) have been utilized to analyze directed connectivity at four frequency bands. PDC and RWTE have measured the directionality and strength of information flow among EEG nodes. On the other side, the GTA of a complex network has summarized the topological structure. The proposed work has been analyzed with ML classifiers, and experiments have been conducted on nine subjects for 45 minutes.

[72] discussed that the EEG manual prediction has been a time-consuming process, and sometimes it might lead to mistakes. Feature extraction minimizes the input signal's dimension by preserving the most useful features, and classifiers allocate class labels to mine feature vectors. Here two efficient feature extraction methods, such as LNDP (Local Neighbour Descriptive Pattern) and 1D-LGP (one-dimensional local gradient pattern), have been utilized to categorize epileptic EEG signals. ML classifiers such as ANN, DT, SVM, and NN has been used to categorize non-seizure and seizure signals. Here epilepsy benchmark dataset of Bonn has been utilized. Classification performance has been analyzed with 10-fold cross-validation, and the experiment has been repeated 50 times. Eight varying experimental cases have been tested, and in the results, ANN has attained the best classification accuracy compared to other classifiers.

[73] used a new feature mining network depending on LGS (Local Graph Structure) to classify EEG signals. EEG signals have been widely utilized to predict brain disorders like epilepsy. This research has been intended to develop a framework with collections of LGS. DWT (Discrete Wavelet Transform) with

LGS techniques has formed an ensemble feature extraction network. In this proposed framework, 2D-DWT has been used for pooling, and LGS has been used for feature extraction. The proposed work has been experimented on various benchmark datasets and compared with other classifiers, and attained high classification accuracy. The result has depicted the success of the proposed LGS for EEG classification.

[74] proposed a pattern recognition technique that has distinguished EEG signals for various cognitive conditions. Wavelet dependent feature extraction like multi-resolution decomposition and relative wavelet energy (RWE) has been calculated. Extended RWE has been normalized to unit variance and 0 mean and then enhanced using FDR (Fisher's Discriminant Ratio) and PCA. The proposed work has been validated with the EEG dataset using two classifications: i). EEG signal has been noted during complex cognitive tasks using RAPM (Raven's Advanced Progressive Metric) test, ii). EEG signal has been pointed out during the baseline task. Here proposed work has been implemented using ML algorithms like NB, MLP, SVM, and KNN. Proposed work has been executed on a dataset to categorize two cognitive tasks and has attained high classification results of 93.33% accuracy with KNN classifiers. Proposed work output prominently high classification performance with the help of ML classifiers compared to other feature extraction methods.

[75] proposed a new feature extraction technique depending on LGBP (Local Gabor Binary Pattern) and sparse rational decomposition. Channels of EEG records have been decomposed to eight sparse rational components with the use of optimal co-efficient. Then, an enhanced 1D LGBP operator has been utilized monitored by the downsampling of data. The largest LGBP's width has been calculated for eight rational components and 23 channels EEG records. Then, 1 second long EEG epochs have been characterized as 23 * 8 features. Various classifiers have been utilized to assess the proposed feature extraction approach's

efficiency with 25% of every patient's EEG records. The experimental results have been presented to verify the proposed method's effectiveness that excelled the other techniques by attaining better sensitivity and specificity and minimized FAR of 0.35.

[76] discussed feature mining that minimizes image size data by acquiring needful data from the segmented image. From mined features, it's feasible to find abnormal and normal brain MRI. The classification algorithm's reliability has been based on mined features and segmentation methods. In this research, texture features have been mined with the help of (GLCM) Gray level co-occurrence matrix, and shape features have been mined with the use of connected regions. Different tumors have varying features that have been used for the categorization of MR images. Obtained features have been given as input to the classifier for testing and training.

[77] proposed an HTT-dependent GLCM texture feature extraction procedure for the classification of MRI images. The proposed approach has three phases: 1. HTT (Hierarchical Transformation Technique), 2. Texture Feature mining, 3. Classification. The proposed HTT approach has included mathematical operations, bottom-hat morphological operations, disk-shaped mask selection for image enhancement, and pre-processing. An alternate method of HTT-dependent GLCM has been compared with the traditional GLCM texture feature mining technique.

[78] discussed medical-based applications that help laboratories and hospitals know about patients' body condition for further treatment. Ultrasound is a safety technique that has been utilized widely in the healthcare sector with the help of the computer-aided system. But diagnosis might become difficult due to artifacts because of patient mobility and equipment constraints. Few pre-processing techniques have been needed to enhance an image's quality for the segmentation

and classification of pixels. These pixels include information related to images referred to as image features that create a data model for categorization. Therefore, feature mining and selection have been significant stages in the diagnostic system's classification step. Background removal, rotation, interpolation, and cropping have been used as a pre-processing technique to improve an image's quality and made an easy diagnosis. Then GLCM has been utilized to generate statistical texture features. Lastly, acquired features have been minimized to the optimal subset with the use of PCA. The result has illustrated that GLCM with PCA provides high classification accuracy for the ANN classifier.

[79] examined the possibility of predicting seizure with the help of scalp EEG signal. Primarily, the researcher has studied the differentiation between preictal and interictal regions. Secondly, the researcher stated the prediction horizon of detection has been as accurate as feasible. Experiments have been conducted on 204 records of the EEG database. The result has illustrated that i) preictal stage transition occurs almost 10 minutes before seizure onset, ii) Prediction results on the test set have a sensitivity of 87.8% and minimized a false prediction rate of 0.142 FP/h. The result of the proposed work has outperformed the other seizure detection algorithm.

[80] introduced patient-specific epileptic seizure detection technique that lies on CSP (Common spatial pattern) dependent feature extraction of scalp EEG signals. Multichannel EEG signals have been traced and divided into overlapping parts for interictal and preictal intervals. Experiments have been conducted on CHB-MIT databases, which consists of 24 records of patients. The result has depicted that the proposed work attained an average FPR of 0.39 and a sensitivity of 0.89.

[81] utilized CNN to distinguish between scalp EEG and intracranial datasets and introduced general reviewing and patient-specific seizure detection approaches. Short-time Fourier transforms on 30 EEG windows have been used to mine data

from the frequency and time domain. The proposed approach has been utilized with patients of any datasets without the support of manual feature extraction. The proposed method's experimental result has been presented to verify its effectiveness.

[82] discussed the earlier clinical findings to detect seizures from other groups have been advertised in the clinical paper, but fundamental seizure prediction technologies have not been published. The development of this technology has various steps such as: to gather a high-quality database of EEG record, a structured method for the development of the algorithm, monitoring of implantable 16 channel subdural and seizure advisory system. Later preclinical studies have been performed in the canine model, and then the algorithm has been examined with 15 records of patients of two years. The algorithm provides 1. Notification for the high possibility of seizure in 11 out of 14 patients, 2. Notification for the low possibility of seizure in 5 out of 14 patients. Figure 2.5 has illustrated the structure of the Seizure Advisor System (SAS) algorithm. 16 channels rooted iEEG array has provided real-time monitoring. A 3-layer algorithm has been utilized for classification, analysis, and filtering. A combination of 16-channels with six filter options and three analyzer options has given 288 possible features. During training, 16 useful features have been chosen for each patient.

[83] briefed insights from long-term trials of epileptic seizure detection to find research goals for the upcoming decade. Results have included relationships between seizure and spikes, the diurnal structure of seizure activity, and varied seizure populations' co-existence showing unique dynamics. These have caused several previous assumptions in seizure detection studies and recommended an alternative plan to search for an algorithm and provide high clinical utility. Enhancement in analytical methods, especially the deep learning method, have provided promising results.

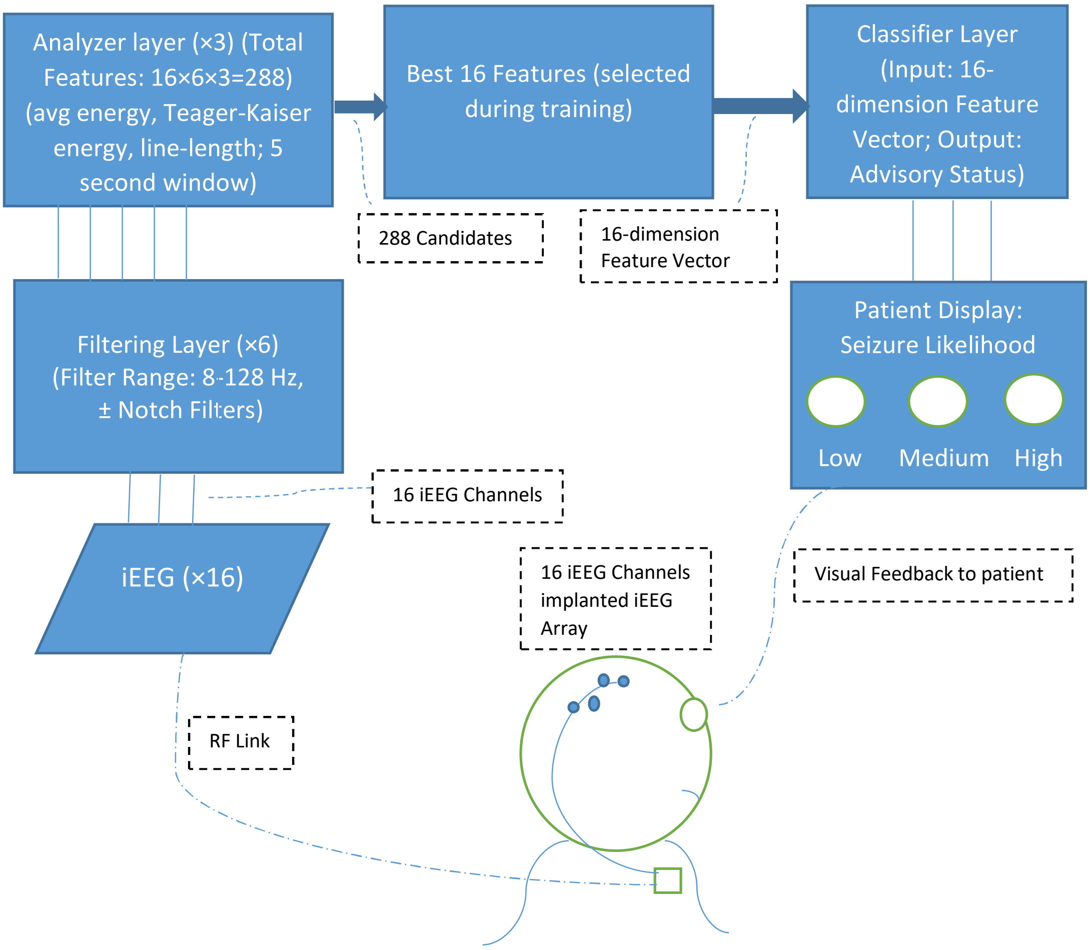


Figure 2.5: Seizure Advisor System [82]

[84] discussed that epilepsy is a burden on the society nowadays because of the high cost of therapy, undetectable and spontaneous seizures, and not exact treatment. Therefore, a fast-neural investigation process is needed to support the diagnosis and determination of epilepsy seizures. Generally, EEG has been utilized to diagnose patients by inspecting the brain's electrical activity related to epilepsy. The proposed approach has various algorithms for feature extraction, energy feature, post-processing with power, and pattern matching. Physiological field features, energy, power, homogeneity, and maxima have been utilized in this proposed design. This design has utilized a real-time patient monitoring system that forwarded the warning messages to the patients before seizure occurrence and

assisted the doctors in making the right decision. This model has yielded an accuracy of 92.66%.

[85] discussed various seizure prediction research that has been performed in the previous decade. The results of these researches have illustrated multiple levels of specificity and sensitivity for therapeutic devices. From these studies, it has been clear that seizure prediction works well with closed-loop seizure control device than seizure advisory device. But still, there have been few queries reported to be resolved for seizure prediction.

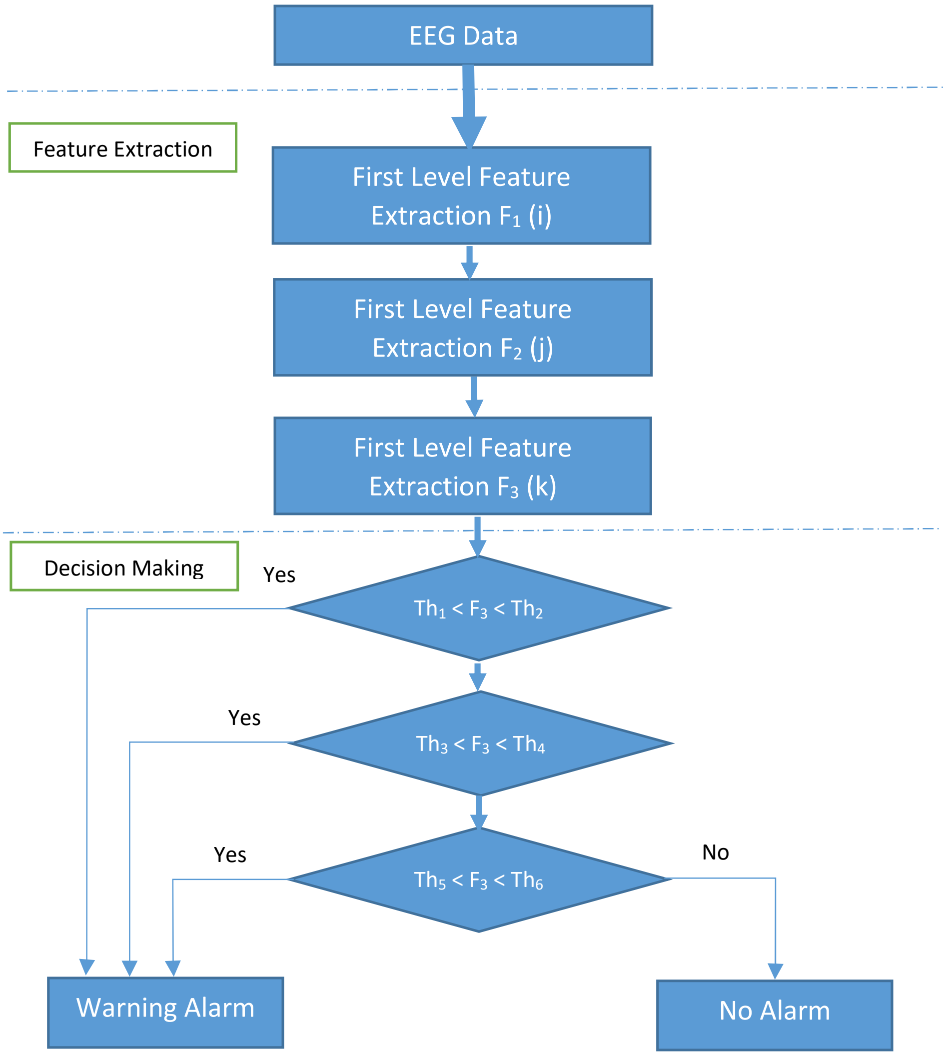


Figure 2.6: Flowchart for epilepsy seizure prediction [86]

[86] proposed a real-time low computational method to detect epileptic seizures and introduced effective hardware for a portable detection system. Three levels of feature extraction have been done to characterize pre-ictal activities of EEG signal. In the 1st level, a line length algorithm has been utilized with the pre-ictal region. Features acquired from 1st levels have been mathematically combined with mined features of 2nd level, and later, line length of 2nd level features has been computed to acquire 3rd level feature. 3rd level information has been compared with already defined threshold levels to decide whether mined characteristics have been related to seizure occurrence or not. Experiments have been conducted with the CHB-MIT database's EEG records, which consist of 19 patients' records. The result has presented that the proposed work achieved a specificity of 88.34%, sensitivity of 90.62%, and accuracy of 88.76%. Figure 2.6 has depicted the flow for predicting epilepsy seizures.

[87] discussed various improvements that have been made on EEG-dependent seizure and epilepsy diagnosis. Numerous new algorithms have been presented, which assist in diagnosing epilepsy with a high degree of accuracy. Recently, the frontier of computational epilepsy has moved towards seizure detection, which has been challenging. While anti-epileptic medication has resulted in patients without a seizure, this kind of medication minimizes the frequency of seizures but cannot control seizures completely. If the seizure has been predicted before clinical manifestation, then treatment has been given by electrical stimulation or implanted device administrating medication or self-administered.

This research has introduced a review of current articles in seizure detection. Technologies utilized for seizure prediction and epilepsy diagnosis have been amended and extended for predicting seizure. This research has concluded with a new idea for seizure detection with ML techniques and especially deep Neural Network ML.

2.4 Survey of various machine learning methods for heart abnormality detection and seizure classification

Reference	Method name	Description	Advantage/Disadvantage
[88]	PNN and wavelet transformation	This research has presented the wavelet transformation for feature extraction and Probabilistic neural network for classification for ECG beat classification.	The PNN classifier has provided six types of ECG features and results show that 99.65% accuracy.
[89]	Wavelet transform	This study has utilized the wavelet transform analysis for QRS complex peak detection. The implementation has been done on MATLAB.	The proposed system has determined the various abnormalities and features with ECG waveforms. It yielded 99.8% accuracy.
[90]	SVM and Extreme learning machine	The proposed method has modified the characterization for singular classification. This method has been applied on the MIT-BIH dataset.	The proposed method has given 89% accuracy.

[91]	Decision tree	The proposed DT model has been considered as popular model for classification. This model has utilized tree learning for the training set.	The proposed model handled uncertain and ambiguity in data.
[92]	SVM and genetic algorithm	In a genetic algorithm, the attribute subsets have been obtained to improve the classification accuracy. The results have been based on the obtained fitness function. This hybrid method has been applied to the UCI dataset.	It provided an enhancement in the classification accuracy than other existing algorithms.
[93]	KNN	This research has described k-nearest neighbor for diagnosis of heart disease	The evaluation results have achieved higher accuracy.
[94]	Artificial Neural Networks	The Feature Subset Selection has been used to reduce the data dimensionality. The combination of KNN	It yielded high accuracy for heart disease diagnosis.

		and FSS method have been used to diagnose heart disease.	
[95]	k-means, genetic algorithm and SVM	The genetic algorithm has been utilized for determining the feature subset and the support vector has been utilized as a classifier for the process of classification.	The proposed method yielded 98.7% accuracy.
[96]	The seizure detection method includes feature classification, extraction, and regularization. Phase Correlation	The undulated global feature has been mined with the help of phase correlation among 2 consecutive epochs of the EEG signals. Likewise, undulated local features have been mined with help of derivation and fluctuation of EEG signal within an epoch.	The proposed approach has yielded high prediction accuracy of 95.4% with reduced FPR
[97]	Automatic seizure classification technique with deep neural	Stack Auto-encoder dependent DNN has been utilized to mine needed structure details from a 3-order	The proposed approach has achieved acceptable classification accuracy for binary classes and 3-classes

	network (DNN) and nonlinear higher-order statistics.	cumulant co-efficient matrix.	of EEG signals with a SoftMax classifier.
[98]	Wavelet Transform, Space Reconstruction method (SSR), fuzzy system and ELM (Extreme Learning Machine)	SSR has been utilized to obtain a phase space trajectory by transmitting the time-space signal into phase space.	The experimental result has been conducted on real-time data to predict seizures. Proposed work included prediction, analysis, and perception of seizure events.
[99]	Field Programmable Gate Array (FPGA), Feed-forward MLP ANN (Multilayer Perceptron ANN), Continuous wavelet transform	FPGA has been utilized to classify seizure with help of MLP-ANN. NN was examined on 822 captured signals from the TUH EEG corpus database.	Attained accuracy of 95.14%. This proposed work acted as a base for modelling (ASIC) application-specific integrated circuit permitting large serial production.

[100]	Multi-objective optimization approach, NSGA (Non-dominated sorting genetic algorithm)	The proposed work has been tested on 24 patients of CHB-MIT datasets.	Result categorized epilepsy seizure with the use of electrodes.
[101]	Continuous Wavelet Transform (CWT), CNN	Acquired 2D frequency-time holograms by using CWT with EEG records. CNN has utilized to study properties of scalogram image	Experiments have been conducted on 5 datasets.
[102]	Wavelet-dependent (EA) envelope analysis, (NNE) Neural network Ensemble, DWT	DWT integrated with EA to mine important features from EEG signals. NNE has been designed in a way to predict epilepsy.	Experimental results have expressed that NNE achieves 98.78% accuracy in predicting epilepsy.
[103]	Imbalanced learning model, DWT, 1DLBP feature	The learning framework has been designed with weakly trained SVM. Under-sampling has been implemented to divide	This model has attained G-mean 97.14% according to epoch-level assessment, event-level sensitivity of 96.67%, and FDR 0.86/h on

	extraction and SVM classifier	imbalanced non-seizure and seizure to multiple balanced subsets	the long-term intracranial database.
[104]	Event-Driven EEG	attained real-time compression and, efficient transmission. In signal processing intelligent event-driven EEG has been utilized.	The experimental result has illustrated that the proposed method achieved 3.3-fold compression and reduced transmission bandwidth. It achieved accuracy 97.5% for mono-class and 96.4% for 3-classes.

2.5 Summary

This Chapter has presented the Literature Review of various machine learning methods for detecting multiple heart abnormalities in the ECG signals. The existing Machine Learning (ML) techniques to classify epileptic seizures as ictal or inter-ictal have been discussed. This Chapter also discussed various surveys about neural network classification methods.

CHAPTER 3

FEATURE EXTRACTION AND CLASSIFICATION OF CARDIAC DISEASES USING PTB DIAGNOSTIC ECG DATABASE

3.1 INTRODUCTION

Cardiac disease is the most dangerous disease in the world. The Electrocardiogram (ECG) acts as an efficient procedure to diagnose cardiac disease. This technique determines the various heart conditions like heart rate variability, heart disorder, etc., that can be diagnosed by applying classification techniques in this ECG signal. Various methods exist to determine and categorize heart diseases as normal or abnormal. In past years, an enormous amount of heart disease detection methods have been developed using ECG that improve classification efficiency. The five basic waves of ECG waveform are defined as P, Q, R, S, T, and U.

The ECG images are remotely sent to the radiology department to integrate their diagnosis reports with images to determine the cardiac disease. The memory space for the repository requires more storage, and it takes time for transmission of images with the increased size of the image. At the same time, the security of these transformed images is more important. The accurate detection of abnormalities is required in the ECG signal to diagnoses heart diseases. Various researches provide various techniques for secured image transmission. This research proposed a new image processing technique to secure ECG signal transmission and classify various abnormalities in this ECG signal. The ECG signal is privately embedded within the dataset to construct the composite signal. This chapter proposed the Dictionary matrix generation-based compression before embedding of the signal. Then the bitwise embedding mechanism is used for the embedding process.

Further, the de-embedding and de-compression process is attained. The classification process is achieved using a modified dynamic classification method to analyze the various abnormalities named Bundle Branch Block, Dysrhythmia, Cardiomyopathy, Myocardial Infarction, etc. The experimental results have been presented to verify the Proposed method's effectiveness compared to the existing techniques such as SVM, RNN, and RF (Random Forest).

3.2 GENERAL PROCESSING OF EEG SIGNAL USING EMBEDDING

Embedding is the information hiding method that hides the presence of communication. The researcher presented various embedding mechanisms, such as LSB embedding, pixel value differencing, optimum pixel adjustment, matrix embedding, and edge concentrated embedding. These methods have been segmented into spatial and frequency domain that helps to achieve high embedding capacity. The important goals of embedding techniques are hiding undetectability, capacity, and robustness. The Hybrid embedding algorithm involves the hybridization of optimum pixel adjustment and matrix embedding algorithm and achieves high embedding capacity and minimum distortion. The efficiencies gained using these algorithms have been presented better than many existing algorithms in several aspects.

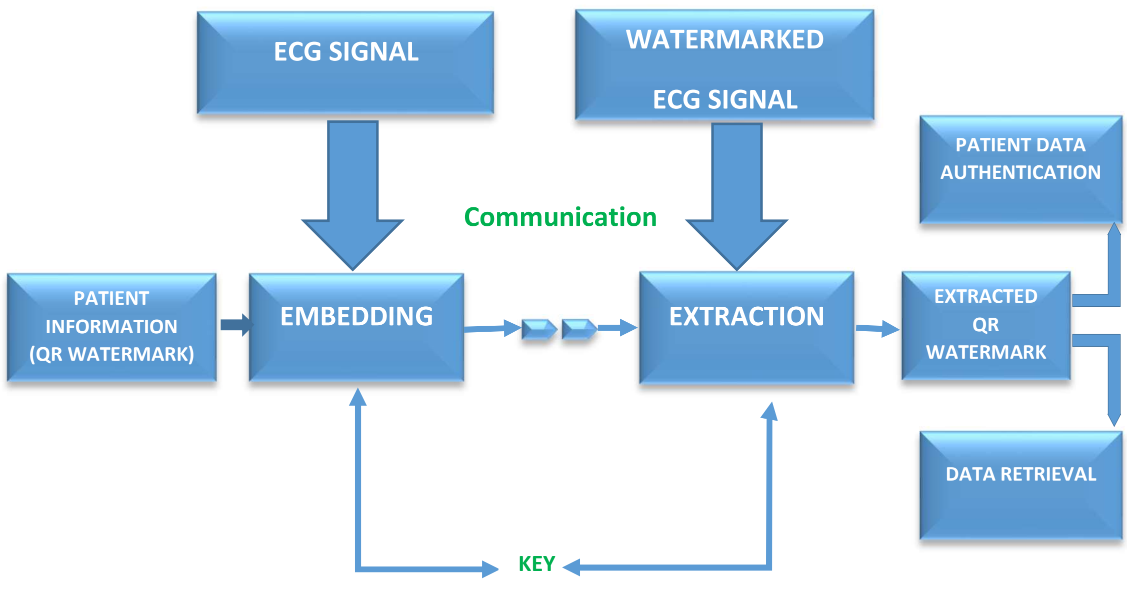


Figure 3.1: General embedding of ECG signal

3.3 OVERALL FLOW OF THE PROPOSED SYSTEM

This section presented a detailed flow of the proposed system for ECG abnormality detection. It involves the following steps:

- Compression
- Embedding process
- De-compression
- De-embedding
- Feature extraction process
- Classification

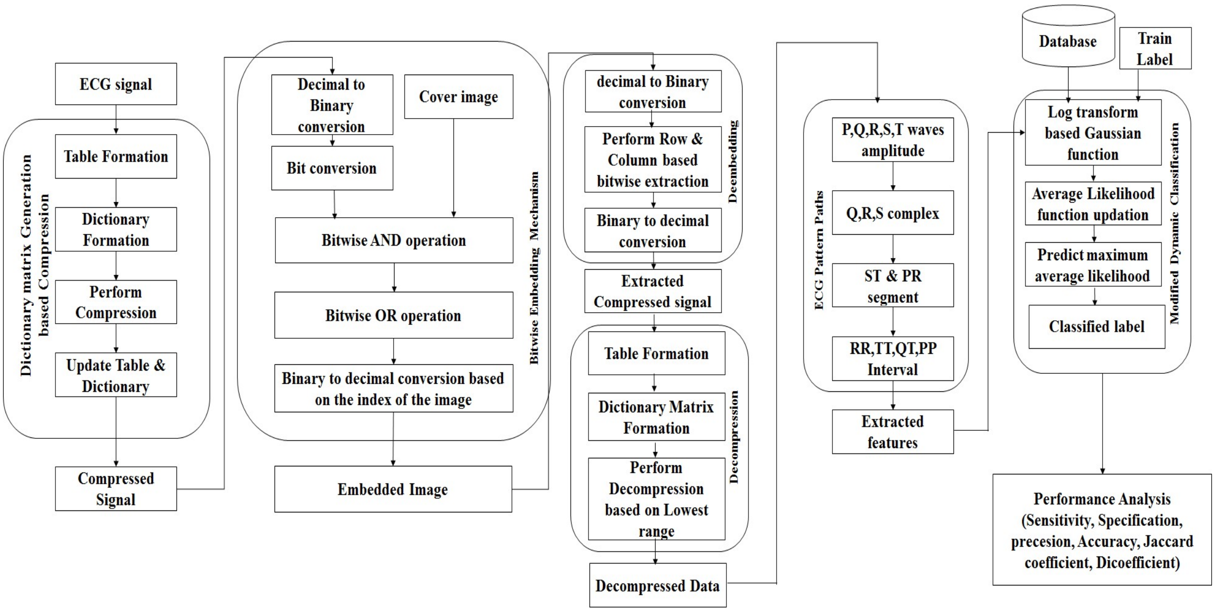


Figure 3.2: Representation of Proposed flow

3.3.1 COMPRESSION

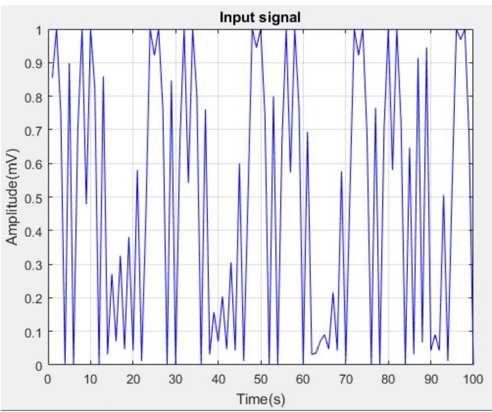
Compression is an essential step in image processing applications that efficiently reduces the data dimensionality and size of the analysis data. It has the robustness for encoding and decoding. It stores and transmits a large amount of information in either a lossy or a lossless way. Various encryption methods have been presented to convert the original image into an encrypted image to ensure security.

However, these encryption schemes provide inefficient security and high data dimensionality.

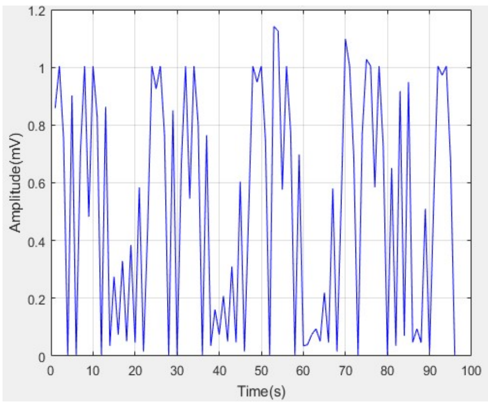
In this work, the new compression technique is proposed to reduce the size of the signal. The proposed compression technique is named Dictionary Matrix Generation (DMG). The DMG technique follows the four stages, such as **table formation, dictionary formation, compression, updating table, and dictionary.**

- Initially, this technique forms the table with the lowest range of attributes, code length, and final code. Then update the most cos-effective range for input data. When the signal information contains a minimum than the threshold's value, it is estimated as 1. Or else, it is estimated as 0.
- Then the dictionary matrix is designed by calculating the data length. The prefix bit, final bit, signal data, and code length are estimated before the process of compression.
- The compression process is attained by validating if the final code value is empty or not.

  Finally, update the table and dictionary values based on this validation.



(a) Input ECG signal



(b) Compressed signal

Figure 3.3: Representation of input ECG signal and compressed signal by applying proposed DMG technique

Figure 3.3 describes the input ECG signal and the compressed signal. The input signal consists of minimum amplitude voltages with noises in high offsets. It also contains the factors of Heart rate, QRS interval, PR interval, ST-segment, and QT interval. In this figure, (b) represents the compressed signal produced by the proposed DMG method.

3.3.2 EMBEDDING

The compressed signal is embedded with the cover image using the assistance of the BE mechanism. This mechanism provides the security of confidential ECG information. The embedded algorithms form the bitwise operations. The embedding procedure is involved in increasing the security level of information. The Bitwise embedding mechanisms involve four stages to enhance the security like Decimal to binary conversion, bitwise AND operation, bitwise OR operation, and binary to decimal conversion based on image index.

- Firstly, the cover image and compressed signal are provided as the input.
- Secondly, convert the compressed signal into a binary format. In this embedding process, the AND and OR operations are involved for entire bits. Then update the obtained value with the index of the image.
- The overall process is repetitive for 8-bit binary data, and the compressed signal attains the embedded image. Once the embedding process is completed with the image, it should be transferred into the specific receiver.
- Finally, the binary format is converted into a decimal format based on the image index to obtain the embedded image.

The embedding image process is mainly used in healthcare applications that transform the embedded image from one hospital to another to maintain privacy.

3.3.3 DE-EMBEDDING AND DECOMPRESSION

In the de-embedding process, the signal is de-embedded for determining the abnormality in the signal. For de-embedding, perform row and column-based bitwise extraction that receives the compressed signal. After receiving the compressed signal, the decompression process is performed with table formation, dictionary matrix formation, updation, and performs the decompression based on the lowest range.

- According to the input data, the minimum value is updated, and the size of the embedded image's compressed data is calculated.
- The de-embedding process is involved in the original image with the 8-bit binary value dimension by zero matrices initialization. The row value is increased as 1 for the first bit of the image.
- When the row value achieves the embedded image of row size, the receiver obtains the data, and the signal attains the de-embedding process using the BE algorithm.
- When the row value is higher than the threshold value for decompressed data, the decoded value is computed. After that, the final code with row values and de-embedded for all the 8bits of the image is updated.
- Then, the binary to decimal conversion for updating the compressed signal is performed. After that, the decompressed signal is allotted with the original signal.

When the output signal's length is minimum than the compressed signal, the dictionary value is updated with zeros' output code. In the end, the signal is decompressed, and the original data is obtained.

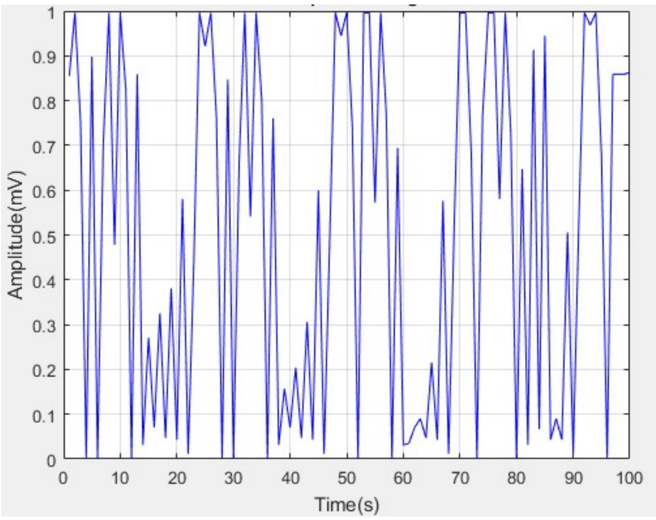


Figure 3.4: Decompressed signal by using BE technique

Figure 3.4 represents the decompressed signal by using the BE technique. After using this compression process and embedding process on ECG signals, it might be transferred to the healthcare system or other central monitoring stations through the internet for classification purposes. The classification accuracy has been validated by using the decompressed signal.

3.3.4 FEATURE EXTRACTION

After receiving the de-compressed signal, the feature extraction process has been performed. Feature extraction defines the extraction of features from images and reduction in the dimensionality of data. The ECG signal's extracted features derive the parameters set that are utilized for the characterizing of the signal. In an ECG signal, each heartbeat represents three events such as P wave, the QRS complex, and the T wave. The decompressed signal features have been extracted in the proposed system using a modified dynamic classification process that includes peak and spectral values. The peak values are most important for feature retrieval from the signal. The peak values vary from patient to patient. The spectral function identifies the various frequency bands of energy content from 0.5 Hz - 9Hz.

Furthermore, the values of the P, Q, R, S, and T waves are calculated for effective classification. The amplitude and interval features of each ECG database are retrieved using the proposed technique. The database contains 126 records that are used for testing. In the proposed system, one document is selected from each diagnostic class for feature extraction.

Table 3.1: Representation of retrieved features using proposed technique for various cardiac diseases (Amplitude in mV and interval in second)

ECG Databases ⟹ / **ECG Parameters** ⇓ **(Amplitude –mV & Interval - second)**	**B_s0451 _re.dat** (B: Bundle Branch Block)	**C_s0456_ re.dat** (C:Cardiomyopathy/Heart Failure)	**D_s0018c re.dat** (D:Dysrhythmia)	**Hes0302 lre.dat** (He:Healthy Controls)	**Hys0390lre .dat** (Hy :Myocardial HyperTrophy)	**Ins0021bre . dat** (In:Myocardial Infarction)	**Ms0509_ re.dat** (M:Myoca-rditis)	**Vs0030_r e. dat** (V:Valvular Heart Disease)
P-Wave Amplitude	0.2941	**0.8980**	0.3020	0.2235	0.3059	0.3098	**0.9608**	**0.9804**
Q-wave Amplitude	0.0353	**0**	0.0157	0.0627	0	**0.0078**	**0.0667**	0.0118
R-wave Amplitude	0.9529	0.9961	0.9882	0.9686	0.9961	0.9882	0.9961	0.8353
S-wave amplitude	0.0118	0.4784	0.3451	0.0353	0.9020	**0**	0.5961	0.0078
T-wave Amplitude	0.1098	**0.9961**	**0.9961**	**0.9725**	**0.9961**	0.6039	**0.9373**	**0.9804**
QRS complex	**0.4000**	0.3000	0.3000	0.3000	0.3000	**0.4000**	0.3000	0.2000
ST segment	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	**0.2000**
PR segment	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.4000	0.3000
RR interval	0.8000	0.7000	0.7000	0.6000	0.8000	0.8000	0.7000	0.9000
TT interval	0.7000	0.7000	0.7000	0.8000	0.8000	0.8000	0.8000	0.8000
QT interval	0.5000	0.4000	0.4000	0.4000	0.4000	**0.5000**	0.4000	0.4000
PP interval	0.8000	0.8000	0.8000	0.7000	0.9000	0.9000	0.8000	0.8000

Table 3.1 represents the extracted features using the proposed technique for various cardiac diseases and healthy controls. In this table, the ECG dataset segmented into B_s0451_re.dat for Bundle Branch Block, C_s0456_re.dat for Cardiomyopathy, D_s0018cre.dat for D: Dysrhythmia, Hes0302lre.dat for Healthy Controls, Hys0390lre.dat for Myocardial Hypertrophy, Ins0021bre.dat for Myocardial Infarction, Ms0509_re.dat for Myocarditis, and Vs0030_re.dat for Valvular Heart Disease.

Table 3.2: Extracted features for various cardiac diseases

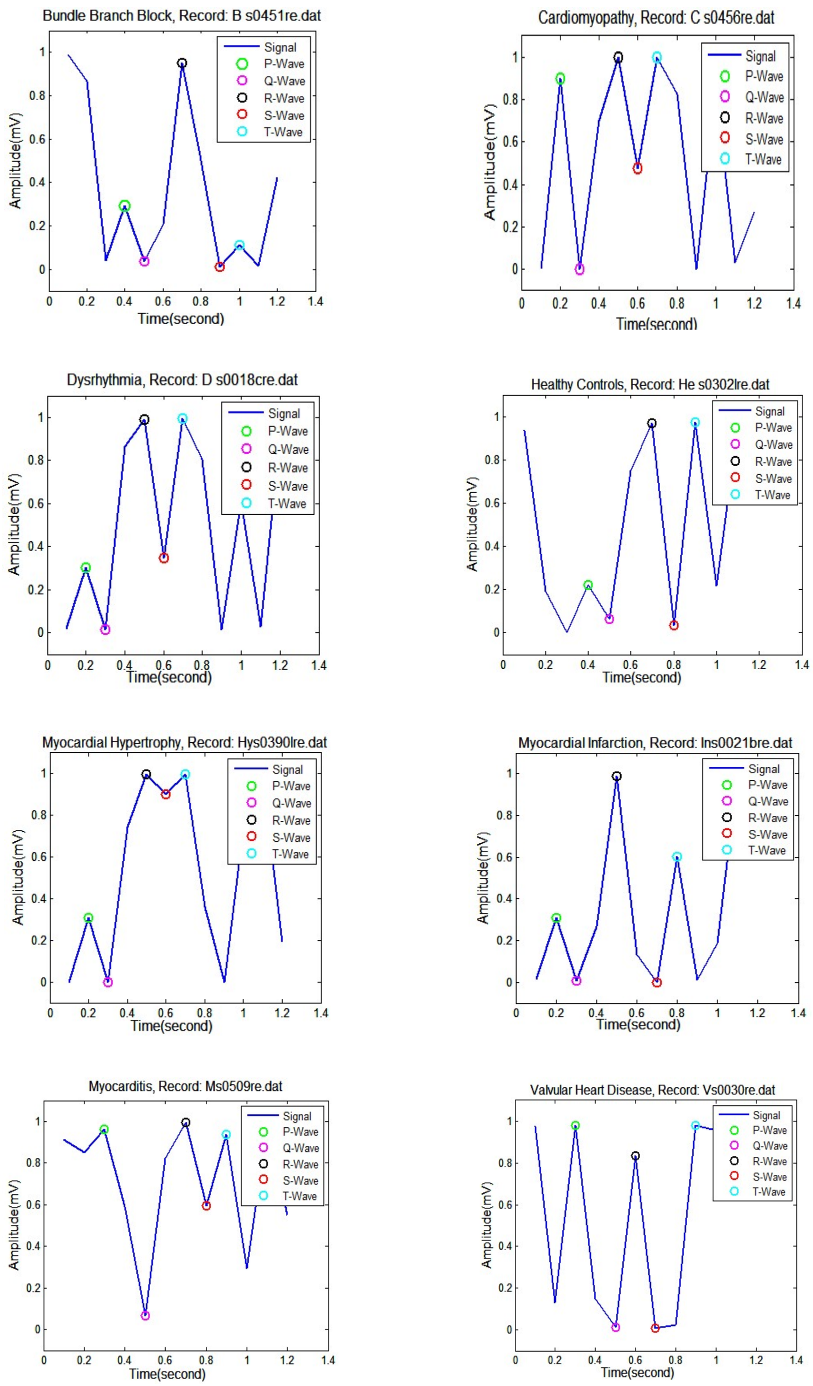


Table 3.2 represents the waveforms of various abnormalities and healthy controls retrieved from ECG databases using the proposed technique. These abnormalities are Dysrhythmia, Bundle Branch Block, Cardiomyopathy, Myocardial Infarction, and Valvular heart disease, etc.

Table 3.3: Characteristic Changes during abnormalities in ECG

Sr. No.	**Diagnostic Classes/ Diseases**	**Characteristic Changes in ECG**
1.	Bundle Branch Block	Prolonged Ventricular depolarization (QRS)
2.	Cardiomyopathy /Heart Failure	QS inferiorly and Tall/ flat/Inverted T waves throughout, Abnormal Q waves
3.	Dysrhythmia	Irregular Heart Rhythms like Tachycardia, Bradycardia, Atrial flutter, Atrial fibrillation, Premature ventricular contractions, Long QT syndrome, Ventricular fibrillation etc.
4.	Healthy Controls	Negligible, ± 5-10% changes may be seen due to artifacts
5.	Myocardial Hypertrophy	Prolonged depolarization (increased R wave peak time) and delayed repolarization (ST and T-wave abnormalities) with associated QRS broadening, ST elevation in V1-3, P wave duration >0.12 sec in leads I and / or II, Tall R waves
6.	Myocardial Infarction	Deep Q wave, ST elevation or depression, Inverted T wave (Ischemia)
7.	Myocarditis	Sinus tachycardia, QRS / QT prolongation, Diffuse T wave inversion, Ventricular arrhythmias, AV conduction defects
8.	Valvular Heart Disease	ST segment depression/elevation, Prolonged P-R Interval

Table 3.3 represents the Characteristic Changes during various abnormalities like Bundle Branch Block, Cardiomyopathy, Dysrhythmia, Healthy Controls, Myocardial Hypertrophy, Myocardial Infarction, Myocarditis, and valvular Heart Disease seen in the ECG.

3.3.5 CLASSIFICATION OF ECG SIGNAL

After feature extraction, the obtained signals have been utilized to determine the various abnormalities like Bundle Branch Block, Dysrhythmia, Cardiomyopathy, and Myocardial Infarction, myocardial hypertrophy, valvular heart disease, and healthy controls, etc. using the proposed MDC algorithm. This proposed method extracts the transformation function to generate the feature space. Larger margins have been utilized to optimize the transformation function. In this technique, randomly initialize the group of transformation parameters for every class. After that, the fitness measurement has been calculated using the training feature vector and initial transformation. Alternatively, the Objective Transformation Function (OTF) has been reduced for each class, and the optimized TF has been used for all training feature vectors. The conditional probability of I-Dimensional Feature Matrix X (IDFM), which belongs to another row vector of IDFM, has been received using the log transform using the Gaussian function. Then determines the average probability and maximum probability value between the classes. Then assign the specific class to the subsequent label. The advantages of this technique are defined as high efficiency, classification accuracy, and minimum complexity. The input as labels, training, and testing features have been provided. Then estimated the column and row of these features. Then, the vector has been evaluated for each test model based on the number of classes. From these vectors, the minimum value and its corresponding index value has been calculated. After that, the classified label has been determined as normal and abnormal signals (Bundle Branch Block, Dysrhythmia, Cardiomyopathy, and Myocardial Infarction, etc.).

3.4 PERFORMANCE MEASURES

This section provides the proposed system's accuracy, specificity, sensitivity, precision, Jaccard coefficient, and dice co-efficiency. The results have been presented to verify the effectiveness of the proposed system compared to the existing classification systems.

3.4.1 Dataset description

PTB diagnostic ECG dataset [105] has been implemented to analyze the proposed method. The dataset comprises 549 records from 290 subjects (aged 17 to 87, mean age 55.5, 81 women, mean 57.2; 209 men, mean period 61.6. In the dataset, each subject is represented by 1 to 5 records.

Table 3.4: Diagnostic classes of cardiac diseases

Diagnostic Classes	**Number of subjects**	**Number of Records used**
Myocardial infarction	148	30
Cardiomyopathy/Heart failure	18	19
Bundle branch block	15	17
Dysrhythmia	14	16
Myocardial hypertrophy	7	7
Valvular heart disease	6	4
Myocarditis	4	4

Healthy controls	52	29

Table 3.4 represents the diagnostic classes of various abnormalities like Bundle Branch Block, Dysrhythmia, Cardiomyopathy, Myocardial Infarction, and healthy controls, etc. which have been utilized in the proposed work.

3.4.2 Accuracy

Accuracy measurement is defined as the standard values, and it is called weight arithmetic mean and inverse precision of the precision value.

The accuracy is calculated by

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3.1}$$

3.4.3 Sensitivity

It is calculated by the positive's ratio and the sum of true positives and false negatives.

The sensitivity is calculated by

$$True\ Positive\ rate = \frac{TP}{TP+FN} \tag{3.2}$$

3.4.4 Specificity

Specificity calculates when the actual state is not existing, the negative classification of abnormalities. And it is represented as a false-positive rate or true negative rate. It is calculated by,

$$Specificity = \frac{TN}{TN+FP} \tag{3.3}$$

3.4.5 Jaccard co-efficient

This measure calculates the similarity among the sets. It is measured by dividing the size of intersection sets union sets.

$$J(A, B) = \frac{A \cap B}{A \cup B} \tag{3.4}$$

3.4.6 Dice Coefficient

Dice co-efficient is calculated by using the measurements of Precision (P) and recall (R). It is calculated by,

$$DSC = 2.\frac{P \times recall}{P + recall} \tag{3.5}$$

Table 3.5: Overall performance of the proposed method for various abnormalities in ECG signal

Performance measures	**Dysrhy-thmia**	**Myocardial infarction**	**Healthy controls**	**Bundle branch block**	**Cardio myopat hy**	**Myocardial infarction**
Accuracy	96.3964	95.4955	95.4955	97.2973	97.2973	95.4955
Sensitivity	87.5	90.3226	92.8571	88.8889	94.4444	90.3226
Specificity	97.8947	97.5	96.3855	98.9247	97.8495	97.5
Precision	87.5	93.3333	89.6552	94.1176	89.4737	93.3333
Dice Coefficient	0.875	0.918	0.9123	0.9143	0.9189	0.918
Jaccard Coefficient	0.7778	0.8485	0.8387	0.8421	0.85	0.8485

Table 3.5 represents the proposed method of overall performance with various performance metrics. In this table, the proposed method has accuracy 96.39%, 87.5%, 97.89%, 87.5%, 0.875%, and 0.778% for Dysrhythmia, and performance measures values for some other abnormalities like Myocardial infarction, Healthy controls, Bundle branch block, etc. are also mentioned.

3.4.7 Signal to noise ratio (SNR)

SNR is described as the signal power ratio to noise power ratio that is defined as,

$$\mathrm{SNR} = 10.\ \log_{10}\left(\frac{p_{\mathrm{signal}}}{p_{\text{Bits received correctly}}\ {}_{\mathrm{noise}}}\right) \tag{3.6}$$

3.4.8 Compression ratio (CR)

CR is represented as the total removed size and deceased center of bottom in cylinder which is divided by the top dead center compressed volume of the piston.

$$\mathrm{CR} = \frac{(\frac{\pi}{4}B^2 S) + V_c}{V_c} \tag{3.7}$$

3.4.9 Root mean square error (RMSE)

RMSE is defined as the measurement of variation between the determined values and observed values from an environment that is calculated by

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{\mathrm{exp},i} - X_{\mathrm{est},i}\right)^2}{n}} \tag{3.8}$$

3.4.10 Bit Error Rate (BER)

BER is described as the bit rate that has associated errors to obtained a total no of bits in transformation.

$$\mathrm{BER} = \frac{\text{Correctly received Bits}}{\text{total bits embedded}} \times 100 \tag{3.9}$$

Table 3.6: Comparative analysis of compression techniques

Compression methods	SNR	CR	RMSE	BER
Golomb-Rice coding	16.628	1.657	0.93	0.92
Huffman coding	27.952	2.932	0.52	0.6621

zero run-length encoding	22.461	1.8798	0.69	0.5664
Proposed method	37.524	4.5511	0.493	0.1514

Table 3.6 represents the comparative analysis of various compression methods named as Golomb-Rice coding [106], Huffman coding [107], and zero run-length encodings [108] with the proposed technique. This representation provides the measures of SNR, CR, RMSE, and BER. The proposed method has 37.54% of SNR, 4.55% of CR, 0.493% of RMSE, and 0.1514% of BER. This analysis validated that the proposed technique has high performance compared to existing techniques.

3.4.11 Percentage RMS Difference (PRD)

PRD is described as the normalized measure that is described as the inexactness among the reconstructed signal and the original signal.

$$\text{PRD} = \left(\frac{\text{rms}_\text{e}}{\text{rms}_\text{v}}\right) \text{x } 100 \tag{3.10}$$

3.4.12 Wavelet based diagnostic distortion (WEDD)

WEDD is measured from the Wavelet coefficients of energy for every band.

$$\text{WEDD} = \sum_{j=0}^{j=L} W_j * PRD_j \tag{3.11}$$

Table 3.7: Comparative analysis of various embedding methods

Embedding methods	SNR	WEDD	PRD
LSB Steganography	38.19	35.42	0.114

Chaotic Map	33.75	31.4	0.135
Proposed	42.36	41.68	0.0996

Table 3.7 represents the comparative analysis of various embedding techniques with the proposed technique. This analysis has been generated from the measures of SNR, PRD, and WEDD.

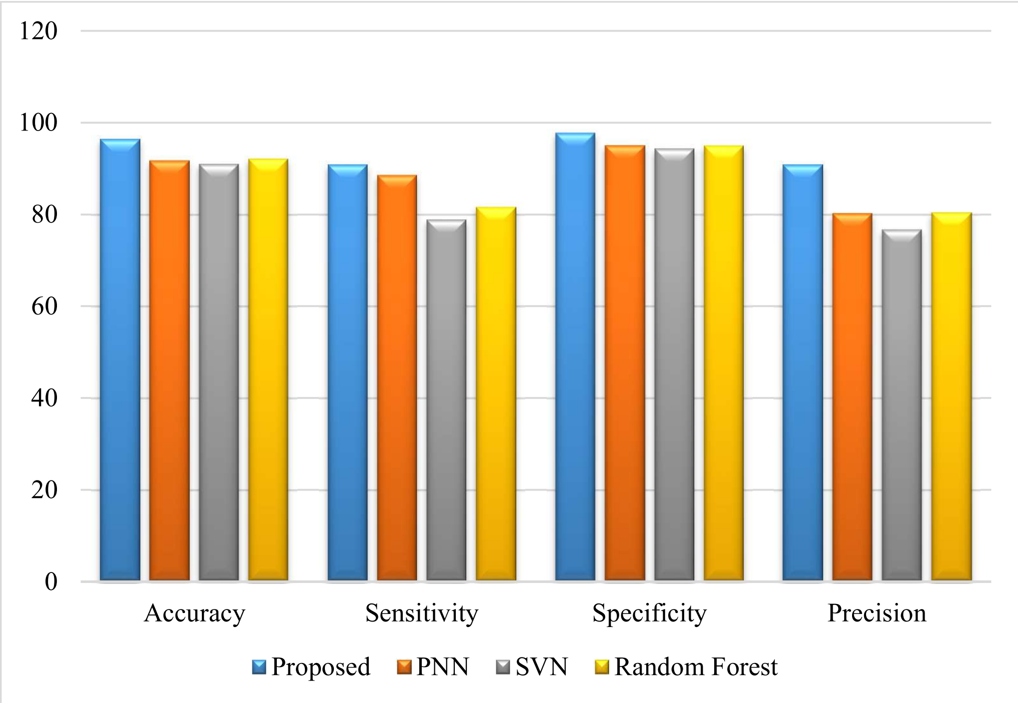


Figure 3.5: Comparative performance analysis of the proposed system with the existing systems

Figure 3.5 described the various performance analysis parameters like accuracy, sensitivity, specificity, and precision for the proposed system compared with some existing systems performances such as SVM, PNN, and RF. The proposed method has presented 96.3964% accuracy, 90.8026% sensitivity, 97.7109% specificity, and 90.816% precision. These results verified that the proposed system has high efficiencies compared to existing systems.

3.4.13 Similarity co-efficient

The similarity level of classification measures has been calculated with the Jaccard coefficient, and Dice coefficient.

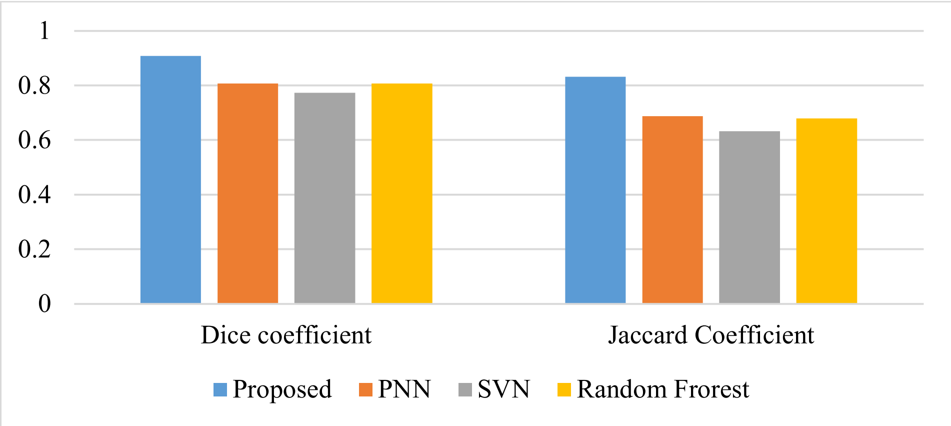


Figure 3.6: Comparison of dice and Jaccard co-efficient values

Figure 3.6 represents the dice and Jaccard co-efficient of proposed and existing methods. The proposed method provides 0.83% of Jaccard co-efficient value and 0.9% of dice co-efficient.

3.4.14 Peak Signal to Noise Ratio (PSNR)

PSNR is described as the ratio between the maximum power of the signal and the power of noise. It analyzes the quality of the image between the compressed image and the input image. The PSNR is measured by,

$$PSNR = 10log_{10}\left(\frac{R^2}{MSE}\right) \tag{3.12}$$

Here, R represents the signal pixel value (max)

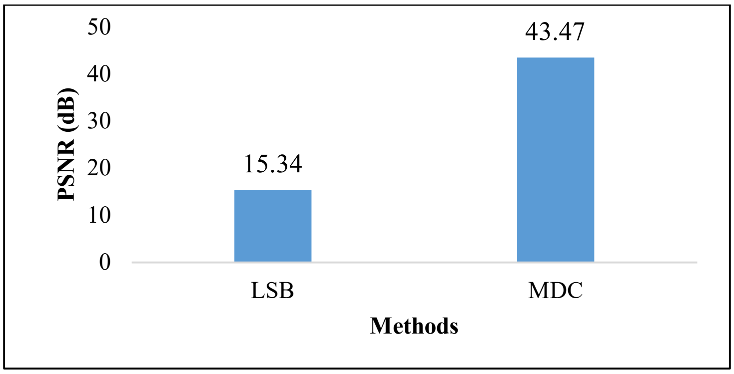


Figure 3.7: Comparison of PSNR measures

Figure 3.7 represents the comparison of PSNR metrics for the proposed MDC method and the existing LSB method. From this statistical analysis, the proposed method has a high PSNR value of 43.47% compared to the existing LSB method.

3.4.15 Confusion matrix

Table 3.8: Confusion matrix of the Proposed method

	Cardiomyopathy/ Heart failure	Bundle branch block	Dysrhythmia	Myocardial infarction	Healthy controls
Cardiomyopathy/ Heart failure	17	0	0	0	1
Bundle branch block	0	16	0	0	2
Dysrhythmia	1	0	14	1	0
Myocardial infarction	0	1	2	28	0
Healthy controls	1	0	0	1	26

Table 3.8 describes the confusion matrix of the proposed method for various cardiac diseases named as Cardiomyopathy, Bundle Branch Block, Dysrhythmia, Myocardial Infarction, and healthy controls.

Table 3.9: Confusion matrix of the PNN method

	Cardiomyopathy/ Heart failure	Bundle branch block	Dysrhythmia	Myocardial infarction	Healthy controls
Cardiomyopathy/ Heart failure	14	0	0	0	0
Bundle branch block	5	17	4	7	7
Dysrhythmia	0	0	12	0	0
Myocardial infarction	0	0	0	23	0
Healthy controls	0	0	0	0	22

Table 3.9 provides the confusion matrix of the existing PNN method for various cardiac abnormalities named as Cardiomyopathy, Bundle Branch Block, Dysrhythmia, Myocardial Infarction, and healthy controls.

Table 3.10: Confusion matrix of the SVM method

	Cardiomyopathy/ Heart failure	Bundle branch block	Dysrhythmia	Myocardial infarction	Healthy controls
Cardiomyopathy/ Heart failure	15	1	0	1	2
Bundle branch block	0	13	0	0	1
Dysrhythmia	1	0	11	2	0
Myocardial infarction	3	1	3	26	5
Healthy controls	0	2	2	1	21

Table 3.10 describes the confusion matrix of the existing SVM method for various cardiac diseases named Cardiomyopathy, Bundle Branch Block, Dysrhythmia, Myocardial Infarction, and healthy controls.

Table 3.11: Confusion matrix of the Random Forest method

	Bundle branch block	Dysrhyth-mia	Cardiomyo-pathy/Heart failure	Healthy controls	Myocar-dial infarction
Cardiomyopathy/ Heart failure	1	0	15	0	1
Bundle branch block	14	0	1	0	1
Dysrhythmia	0	14	0	1	1
Myocardial infarction	0	1	1	2	24
Healthy controls	2	1	2	26	3

Table 3.11 describes the confusion matrix of the existing Random Forest method for various cardiac abnormalities named Bundle Branch Block, Dysrhythmia, Cardiomyopathy, Myocardial Infarction, and healthy controls.

3.5 SUMMARY

This chapter discussed the proposed classification method to determine ECG abnormalities. Here, various existing embedding mechanisms have been discussed. The proposed method's flow has been explained with the steps of compression, embedding, de-compression, de-embedding, feature extraction, and classification using the MDC technique. The results have been presented to prove the proposed method's efficacy by calculating various performance measures like accuracy, sensitivity, specificity, recall, Jaccard, dice co-efficient, SNR, PSNR, RMSE, and CR PRD, and WEDD metrics.

CHAPTER 4

Arrhythmia Classification of ECG database using Deep Convolutional Neural Network

4.1 Introduction

The abnormality in ECG is a major factor that predicts cardiovascular diseases (CVDs) among the old and young population. One of the common diseases is cardiovascular arrhythmia, leading to sudden death in some cases if left untreated. The early warning of the cardiac activity states through real-time monitoring helps the life-saving and cares the health. It is worth noting that the abnormality in the ECG of a person is a discontinuous symptom as the beats corresponding to arrhythmia emerge quickly, limiting the diagnosis of the arrhythmia in hospitals. Additionally, the ECG's traditional monitoring system often links the individuals with the instrument using a signal line. For monitoring, a direct-wired connection is available, whereas the wearable device using the wireless sensors can monitor cardiac activity with no influence on the user's daily life. A tremendous amount of data is being collected daily using the wearable device. The cardiologists engage themselves in detecting the anomaly from the ECG waveform mainly based on the rate of the heartbeats, rhythm, and any variations in the morphological patterns. However, it is not feasible to inspect the individual heartbeat as there are several heartbeats, which raises the inspection's complexity and degrades the clinician's classification accuracy. Heartbeat Classification using ECG seems to be a valuable tool to study cardiac arrhythmia, which appears to be among the biosignal analysis challenges.

Cardiac arrhythmias result is a cause of the change in the heartbeat rate, regularity, conduction or origin of electrical impulses, along with their symptoms ranging from minute palpitations to pain in the chest leading to the fainting of the person and causes death all-of sudden, which is based on the nature and aggressive state of the problem in individuals. Arrhythmia causes a series of heartbeats with abnormal morphology or intervals. Thus, once the acquisition of the signal is made, the significant step is the heartbeat classification.

The automatic heartbeat classification system comprises four parts: signal preprocessing, detection of heartbeats and segmentation, feature extraction, and classification [109]. The features extracted from the data may be morphological features or any characteristic of ECG, heartbeat intervals, independent component analysis (ICA), Hermite polynomials, coefficients generated using the wavelets, and vector cardiogram (VCG) data [110]. Various classification models are used, such as self-mapping, vector support devices (SVMs), partial discrimination, vector quantization learning, neural networks, and powerful learning tools.

Like linear discriminants, the classifiers depend on few assumptions regarding the data, such as linear separability and normal distribution [110]. SVMs are widespread classifiers and, based on the kernel function, and generate the decision regions to attain independent performance in classification corresponding to the linear separability corresponding to the data. Several automatic methods are developed for ECG classification. Various approaches have been employed for automatic ECG classification, like frequency analysis, k-Nearest Neighbour clustering, Artificial Neural Networks, Regression Trees [19], Hidden Markov Models, Support Vector Neural Network, Convolutional Neural Network, and SVM, Probabilistic Neural Networks, and, recurrent NN (RNN). The physiological artifact and noises assess the ECG, which is difficult in the automatic computerized method. Additionally, the variations among the individuals' ECG signals assure the inconsistency of the methods for classifying different subjects. Also, the time-varying dynamics and morphological features of the same individual's ECG signals enhance the automatic assessment method's difficulty

Various limitations are associated with the automatic classification of the heartbeats like computational computing of ECG classification method [110]. The lack of an accurate heart model drags the manual experience in effective decision-making [111]. It is peculiar to note that the application of adequate features with minimal computational complexity causes good quality monitoring while enabling the minimization of the energy consumed [112-113]. Thus, a more generalized system is needed to overcome these issues and limitations.

This research has concentrated on arrhythmia classification using the individuals' ECG signal such that the perfect diagnosis of the patients is initiated. The arrhythmia classification is performed optimally using the deep neural networks, which are tuned optimally with an optimization algorithm. The progressing steps in the arrhythmia classification include feature extraction and feature classification. The wave features are extracted, including the intervals, PP, RR, PR, QT, and R peak. Additionally, the Gabor features are extracted using the Gabor filter. Finally, the wave and Gabor features establish the feature vector for feature classification. Then, the classification has been carried out using the deep neural network named Deep CNN that is trained using the proposed BaROA, and the classification depends on the features acquired from the ECG. The proposed BaROA algorithm is the integration of MOBA and ROA so that the update equation of the bypass rider is interpreted for modification. The BaROA-DCNN classifier performs the arrhythmia classification in which BaROA tunes the Deep CNN classifier optimally.

4.2 Overall flow of the proposed system

The arrhythmia classification is significant research as WHO highlights the death toll of persons with cardiac diseases to be around 17.3 million [114], which insists the conventional cardiac therapies to be useless. More importantly, people with cardiac problems are suffering a lot, requiring an accurate classification strategy. The precise classification is done using the deep CNN, which is optimally tuned using the proposed BaROA. The classification error reduces and thereby, enhancing the accurate detection and the arrhythmia classification using the proposed BA-ROA-deep CNN is depicted in Figure 4.1. Initially, the wave intervals are determined from the ECG signal, which is essential to decide signal abnormalities, symbolizing the presence or absence of arrhythmia.

The Gabor features and the wavelet features are derived along with the wave intervals so that the Gabor, wave, and interval features establish the feature vector. The feature vector has been fed to the classification module where the extracted features have been employed to decide patient to be with arrhythmia or with no arrhythmia. Thus, for arrhythmia classification, deep CNN is employed, which is trained using the proposed BaROA that integrates the MOBA in ROA. The proposed classifier performs the accurate arrhythmia classification using the features from the ECG signal of the individuals. There are two steps, such as feature extraction and arrhythmia classification mentioned in the block diagram, for which initially, the ECG signals are recorded.

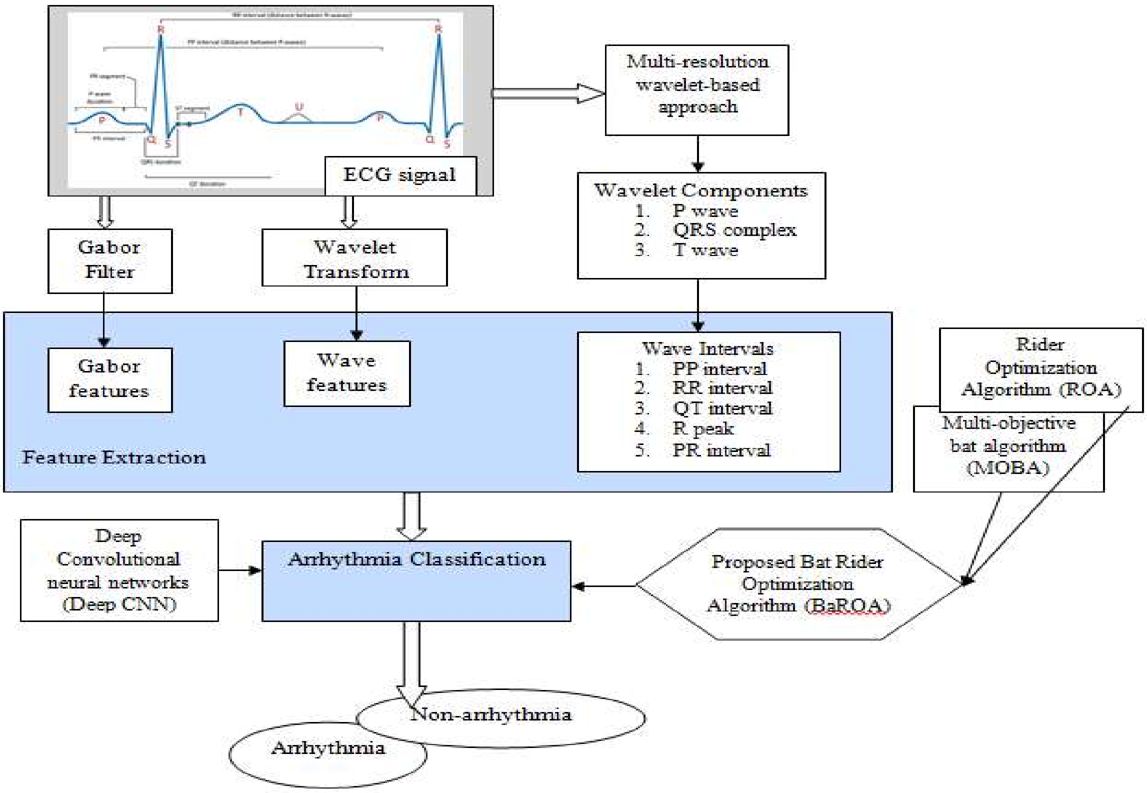


Figure 4.1 Block diagram of arrhythmia classification using BaROA-DeepCNN

4.3 Arrhythmia Classification using the BaROA-based DCNN classifier

The arrhythmia classification is progressed using the BaROA-based DCNN classifier, which integrates the proposed BaROA in the deep CNN classifier. The proposed algorithm determined the classifier's optimal weights, and BaROA is the integration of the standard MOBA [115] in the update rule of ROA [116]. The classifier's significance is that the classification accuracy of the classifier is high due to the compact features acquired from the ECG signal.

a) Deep CNN architecture: The features are fed as input to the Deep CNN, which performs the arrhythmia classification. In deep CNN, there are three layers, such as convolutional (Conv) layers, pooling (POOL) layer, and Fully Connected (FC) layer. Deep CNN differs from normal NN in structure, where one neuron is connected to another, while in deep CNN, a pool of neurons is connected to neurons in successive layers. Each of CNN's deep layers does its job of detecting confinement, sample, and classification features. Figure 4.2 shows the structure of the deep CNN.

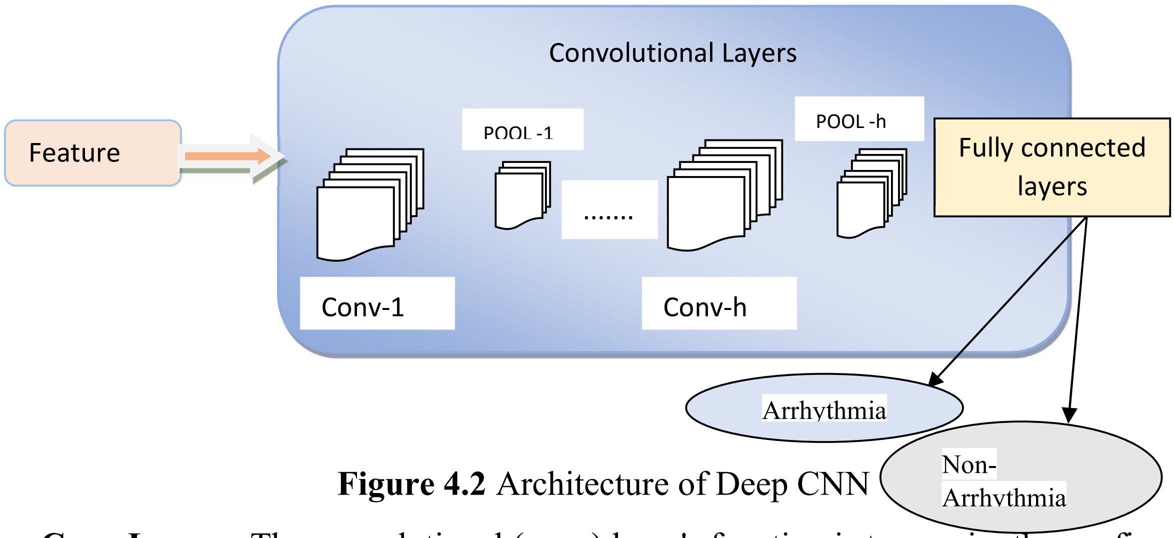


Figure 4.2 Architecture of Deep CNN

Conv Layers: The convolutional (conv) layer's function is to acquire the confine features buried in the input feature vector for which the conv filters are applied to the input. The input features are carried to the next layer through the receptive fields, and the link to the successive layers is enabled with a set of trainable weights. The function of the conv layer is associated with the convolutional operator using which the input data is convoluted with the kernel filter and weights, which are determined optimally using BaROA. The output of each set of the layers with confine features is derived and fed as input to the successive layers of conv units. Let us assume that there are several conv layers in the deep CNN. The number of convolutional layers has been associated with the accuracy of the classification. The accuracy is directly proportional to the total number of the convolutional layers in the deep CNN classifier. The output from the convolutional layer is given by,

$$\left(c_f^a\right)_{P,Q} = \left(B_f^a\right)_{P,Q} + \sum_{d_1=1}^{v_1^{d_1-1}} \sum_{d_2=-v_1^a}^{v_1^a} \sum_{d_3=-v_2^a}^{\kappa_2^a} \left(\chi_{f,d_1}^a\right)_{\upsilon,\tau} * \left(c_{d_1}^{a-1}\right)_{P+d_2,Q+d_3} \tag{4.1}$$

where, $*$ represents the convolutional operator. The conv layer a extracts the local patterns, from the input of the previous conv layer. $\left(c_f^a\right)_{P,Q}$ is the fixed feature map and it marks the output from a^{th} conv layer that is located at, (P,Q). It is peculiar to note that the output from the previous $(a-1)^{th}$ conv layer is the input to a^{th} conv layer. Let us represent the weights of the conv layers that is denoted as, χ_{f,d_1}^a, which represent the weights of a^{th} conv layer and let us indicate the bias of a^{th} conv layer as, B_f^a. Consider that there are h number of conv layers and the notations, such as d_1, d_2, and d_3 denote the feature maps, and feature maps are the output obtained from the individual conv layers through applying the conv filter to the input feature vector. Moreover, the neurons available in the conv layers are organized in 3-dimensions along its width, height, and depth in order to extract the features at all the dimensions. The output from the conv layer is fed to the ReLU layer and the output of the ReLU layer is given as,

$$c_f^a = fn\left(c_f^{a-1}\right) \tag{4.2}$$

The speed of deep CNN to extract the confine features for classification is of greater significance. The ReLU layer extends the ability to deal with a huge number of the layers in the classifier.

POOL layers: The non-parametric layer without any bias or weight is the POOL layer that is said to possess the stable operation.

Fully connected layers: In the FC layer, the classification is carried for which the confined features are acquired from the features using the conv layers. Finally, the classification at FC layer enables the classification of the features to declare the patients with arrhythmia or no arrhythmia. The output of FC layer is denoted as,

$$\left(c_f^a\right) = \delta\, c_f^a \quad with \sum_{d_1=1}^{v_1^{d_1-1}} \sum_{d_2=-v_1^a}^{v_1^a} \sum_{d_3=-v_2^a}^{\kappa_2^a} \left(\chi_{f,d_1}^a\right)_{\upsilon,\tau} * \left(c_{d_1}^{a-1}\right)_{P+d_2,Q+d_3} \tag{4.3}$$

However, the accurate classification of the arrhythmia patients is based on the weights and the biases employed in classification and this measurement and selection are determined using the proposed BaROA.

b) BaROA Proposed Algorithm: The proposed BaROA algorithm is the integration of MOBA into ROA in such a way that the passenger renewal law is amended using the ROA update rating. The proposed BaROA balances the pros and cons of MOBA and ROA and most importantly, the proposed algorithm provides a high level of integration with a good global solution and a high trend towards your local approach to avoidance. On the other hand, diversity of solutions is guaranteed by better integration levels and BaROA's ability to address multiple goals is at work.

Typically, ROA operates on the basis of ideas and concepts, using a new fictional environment, fiction computing, which is a unique computer platform, such as artificial platforms and environmentally inspired platforms. The ROA is based on the characteristics of passenger well-being, in which there are four groups of passengers, such as passer-by, passer-by, attacker and follower. Each passenger shows his or her characteristics and all passengers aim to get to their destination. The best rider is determined by the factor, called the success rate, which should be the maximum for the best rider or leading rider. In addition, it is worth noting that ROA is the end of the use, which operates under a fictional concept. The great importance of ROA is to produce the right global solution, which is free from weight loss and bias. In addition, based on the leading passenger, the position of the other group of four riders renews their positions and the key elements in revitalizing positions include: steering angle, accelerator, gear, and so on. Riders renew their positions depending on the position of the leader and in addition, good performance keeps them away from the slightest avoidance of space to a small local area. This ability to effectively avoid the area is brought about by the invader. On the other hand, ROA has a high level of integration, relying on the world's largest neighbors and the way to integrate is the effort of the one who has taken over. Therefore, positions are updated randomly initially to check the surrounding environment. The person taking the top gets the search space that deserves the level of success and directional guidance which is great, while the follower uses a wide range of space to match the leading rider. It is known that the attacker's search speed is accelerated as the results of various searches. In addition, ROA enables active search. However, the ability to manage multi-purpose work is a major question MOBA plays a major role in. Therefore, combining MOBA and ROA provides a multi-pronged operational management capability. MOBA is appropriately based on the discovery of bats in locating prey. The following are the algorithmic steps of the proposed BaROA:

i) Initialization: As mentioned earlier, there are four groups of riders namely, bypass, overtaker, attacker, and follower, which are initialized as, P_1 , P_2 , P_3 , and P_4 , respectively. According to the rider groups, there are unique features for each group. The bypass rider takes a new path other than the common path, while the follower follows the leader. On the other hand, the over taker overtakes other riders, and the attacker attacks the leader with the aim to win over the leader. However, the aforementioned characteristics of the riders are acquired as a result of the adjustment done on the vehicle parameters. The riding parameters of i^{th} rider include: coordinate angle, steering angle, and position angle that are represented as, $C_{i,j}(t)$, $S_{i,j}(t)$ and $K_{i,j}(t)$. Likewise, the accelerator, gear, and brake of i^{th} rider is denoted as, ω_i , G_i , and β_i , respectively. The gear G_i takes a value between 0 and 4, while the accelerator and gear take a value ranging between 0 and 1.

The search-space consists of m number of riders and they are represented as,

$$P_{i,j}^{t+1}\,;\,(1 \le i \le m);\,(1 \le j \le r) \tag{4.4}$$

where, r refers to the total coordinates in the search-space. $P_{i,j}^{t+1}$ notate the position of the i^{th} rider in j^{th} dimensional space at time $(t+1)$.

ii)Compute the success rate: The success rate is a factor that finalizes the leading rider. Accordingly, the success rate with the maximal value is declared as the leading rider and, in this paper, the success rate is denoted as, sr , which is nothing but the MSE. It is peculiar to note that the leading rider leads the race and he is the one nearer to the destination and on the other hand, a leading rider is not always supposed to lead the race instead the leading rider changes. Thus, the success rate is evaluated at the end of every iteration.

iii)Position update phase: The rider groups update their position based on the position of the leading rider as follows: The position of the bypass rider is updated as follows:

$$P_{i,j}^{t+1}(R_1)=\alpha\left[P_{j,\varepsilon}^{t} * \delta(j)+P_{j,\lambda}^{t} * (1-\delta(j))\right] \tag{4.5}$$

where, $\delta$and α are the random numbers varying between 0 and 1, $\lambda$and ε specifies the random numbers varying between 1 and m . The dimension of $\delta$is given as, $[1 \times r]$. $P_{i,j}^{t+1}(R_1)$is the position of the bypass rider at the next instant and $P_{j,\varepsilon}^{t}$ is the bypass rider's position at present. The update equation of the bypass rider is modified using MOBA to inherit the proposed BaROA for which the update equation of MOBA is interpreted. The proposed algorithm ensures better search-ability and diversity and in addition, the optimal global convergence is rendered. The standard equation of MOBA is given as,

$$P_{i,j}^{t+1}=P_{i,j}^{t}+v_{i,j}^{t}+\left(P_{i,j}^{t}-P_{best}\right)\gamma_{i,j} \tag{4.6}$$

The above equation is rearranged and rewritten as,

$$P_{i,j}^{t+1} = P_{i,j}^{t} + v_{i,j}^{t} + P_{i,j}^{t} \times \gamma_{i,j} - P_{best} \times \gamma_{i,j} \tag{4.7}$$

$$P_{i,j}^{t} = \frac{1}{1+\gamma_{i,j}} \left[P_{i,j}^{t+1} - v_{i,j}^{t} + P_{best} \times \gamma_{i,j} \right] \tag{4.8}$$

Substitute the equation (4.8) in equation (4.5) for which consider the assumption $\varepsilon = i$ in equation (4.5). Then,

$$P_{i,j}^{t+1}(R_1) = \alpha \left[\frac{\delta(j)}{1+\gamma_{i,j}} \left[P_{i,j}^{t+1} - v_{i,j}^{t} + P_{best} \times \gamma_{i,j} \right] + P_{j,\lambda}^{t} * (1-\delta(j)) \right] \tag{4.9}$$

$$P_{i,j}^{t+1}(R_1) - \frac{\alpha \times \delta(j)}{1+\gamma_{i,j}} \times P_{i,j}^{t+1} = \alpha \left[\frac{\delta(j)}{1+\gamma_{i,j}} \left[-v_{i,j}^{t} + P_{best} \times \gamma_{i,j} \right] + P_{j,\lambda}^{t} * (1-\delta(j)) \right] \tag{4.10}$$

$$P_{i,j}^{t+1}(R_1) \left[1 - \frac{\alpha \times \delta(j)}{1+\gamma_{i,j}} \right] = \alpha \left[\frac{\delta(j)}{1+\gamma_{i,j}} \left[-v_{i,j}^{t} + P_{best} \times \gamma_{i,j} \right] + P_{j,\lambda}^{t} * (1-\delta(j)) \right] \tag{4.11}$$

$$P_{i,j}^{t+1}(R_1) = \left[\frac{1+\gamma_{i,j}}{1+\gamma_{i,j} - \alpha\delta(j)} \right] \left\{ \alpha \left[\frac{\delta(j)}{1+\gamma_{i,j}} \left[-v_{i,j}^{t} + P_{best} \times \gamma_{i,j} \right] + P_{j,\lambda}^{t} * (1-\delta(j)) \right] \right\} \tag{4.12}$$

Thus, equation (4.12) is the update equation of BaROA, which differs from the standard ROA as there are additional optimization factors, like velocity $v_{i,j}^{t}$ and the global best solution of the previous iteration, P_{best}. The additional optimization parameters further enhance the convergence rate and assures global optimal solution. The second group of riders, follower updates their position based on the following equation,

$$P_{i,\ell}^{t+1}(R_2) = L_{V,\ell} + \left[\cos(S_{i,\ell}(t)) * L_{V,\ell} * Y_i(t) \right] \tag{4.13}$$

Let $L_{V,\ell}$ is the position of the leader, L refers to the leading rider, $P_{i,j}^{t+1}(R_2)$ is the position of the follower, and $Y_i(t)$ is the distance travelled by k^{th} rider at instant t. The distance $Y_i(t)$ is measured based on the velocity and off-time and the velocity of i^{th} rider depends on the maximum speed, accelerator, gear, and brake with respect to the vehicle of i^{th} rider. The selection of the co-ordinate selector depends on the on-time probability. On the other hand, **t**he over taker updates the position using the direction indicator, coordinate selector, and success rate. The position of over taker is given as,

$$P_{i,\ell}^{t+1}(R_3) = P_{i,\ell}^{t}(t) + \partial_i(t) * L_{V,\ell} \tag{4.14}$$

where, $P_{i,\ell}^{t}(t)$ is the position of i^{th} rider in ℓ^{th} coordinate and $\partial_i(t)$ is the direction indicator corresponding to i^{th} rider at time t. The direction indicator $\partial_k(t)$ is computed based on the success rate and hence, the formula,

$$\partial_i(t) = \left[\frac{2}{1-\log(SR)}\right] - 1 \tag{4.15}$$

The position of the attacker and follower are similar and hence, the position of the attacker is updated as,

$$P_{i,\ell}^{t+1}(R_4) = L_{V,\ell} + \left[\cos\left(S_{i,\ell}(t)\right)\right] * L_{V,\ell} + Y_i(t) \tag{4.16}$$

iv) Re-evaluate the success rate: The success rate of the riders is recomputed every-time after the rider groups update their positions to signify that the leader is not always the same rider.

v) Update the parameters of the rider: Once the success rate is re-evaluated, the optimization parameters, like the vehicles parameters of the rider, gear, steering angle, accelerator, brake, off-time, and activity counter are updated.

vii)End: The steps are repeated until the destination is met by any of the rider groups, marking the announcement of the winner. Algorithm 1 shows the pseudocode of the proposed BaROA algorithm.

Algorithm 1. BaROA- Pseudo code

BaROA algorithm

```
Input: Rider's position P_{i,ℓ}^{t+1}
Output: Leading rider L_{V,ℓ}
Start
    Initialization
        Rider population and riding parameters
      Position angle K_{i,j}(t)
      Steering angle S_{i,j}(t)
```

Accelerator ω_i

Gear G_i

Coordinate angle $C_{i,j}(t)$

Brake β_i

Compute the success rate

While $t < t_{off}$

For $(i = 1 \ to \ m)$

#Position update phase

eqn. (4.12) for updating the bypass riders' position

Followers' position using eqn. (4.13)

Overtakers' position using eqn. (4.14)

Follow eqn. (4.16) for attacker position update

Ranking the riders with respect to the success rate

Determine the leading rider

Update the Rider parameters

Return $L_{V,\ell}$

$t = t + 1$

End For

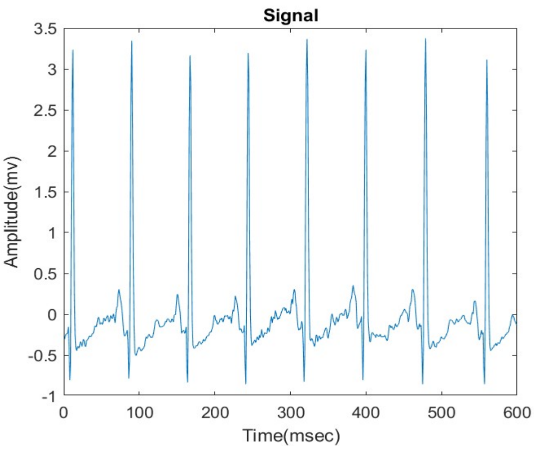
End While

Terminate

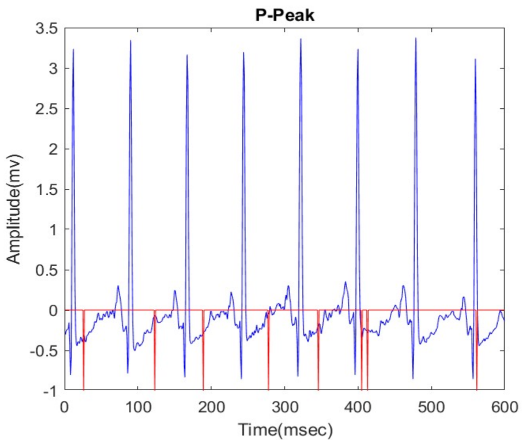
4.4 Experimental analysis

The MIT-BIH Arrhythmia Database [117] is considered for the experimentation, and this database is made available from Boston's Beth Israel Hospital. The database has been prepared by Boston's Beth Israel Hospital from 47 individuals from 1975 to 1979 and digitized at 360 samples per second in a channel such that it carries an 11-bit resolution in the entire10 mV range.

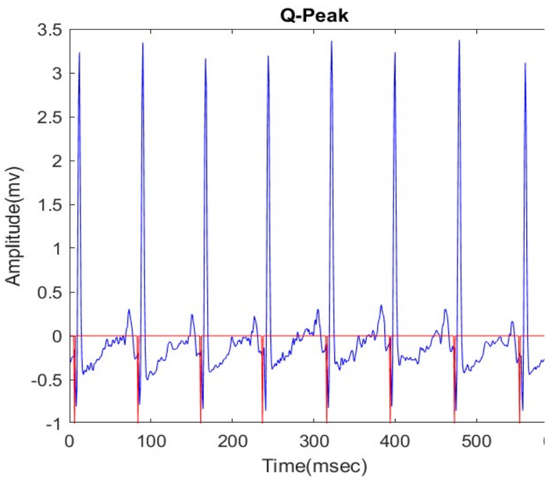
The section presents sample test results where two ECG signals are considered. ECG signs and symptoms associated with arrhythmia are shown in this section. Figures 4.3-4.8 show the test results corresponding to the initial and affected ECG signals of signal 1, signal 2, and signal 3. ECG signal waves corresponding to the first normal ECG signal are shown in numbers 4.3 a) -4.3 f), respectively. A signal associated with associated arrhythmia is shown in Figure 4.4 a) – 4.4 f). Standard 2 signals and three signals are shown in numbers 4.5 a) – 4.5 f) and 4.7 a) - f). Similarly, the affected arrhythmia signals were considered, signal_2 and signal_3, shown in the numbers 4.6 a) -f) and 4.8 a) -f), respectively. Deviations between the initial symptoms and the associated symptoms of arrhythmia are addressed from time to time, which differ between normal and affected symptoms. The time intervals between P, Q, R, S, and T may be longer or less than the typical reporting frequency.



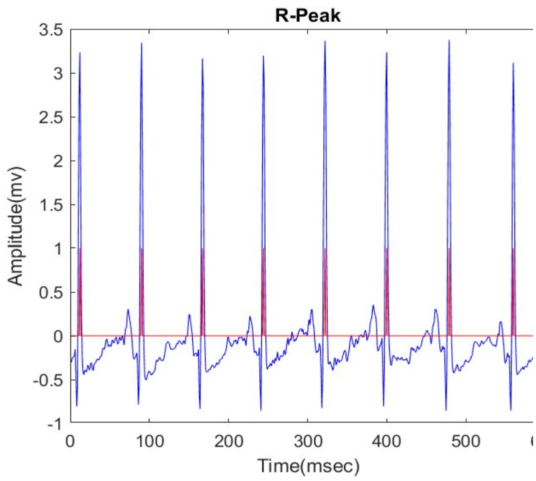
a)



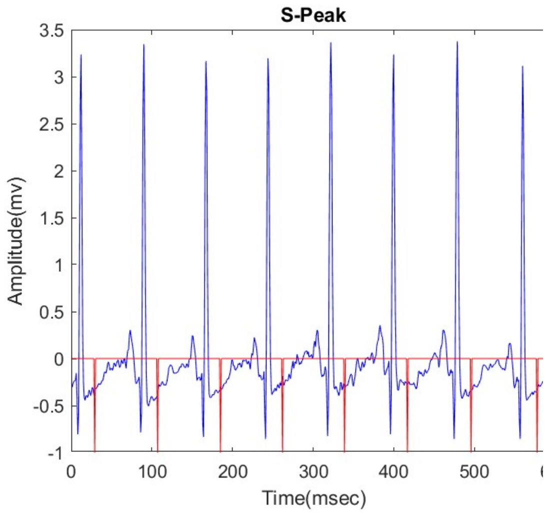
b)



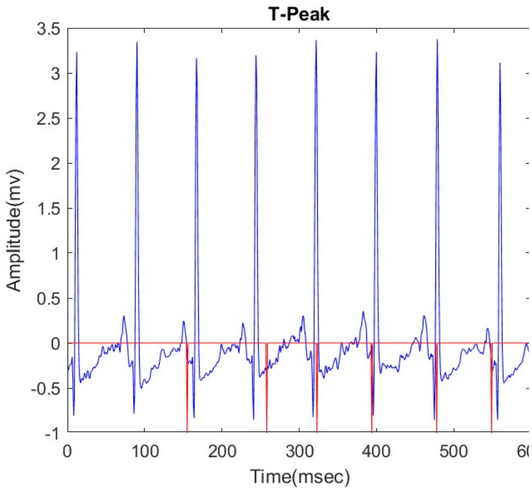
c)



d)

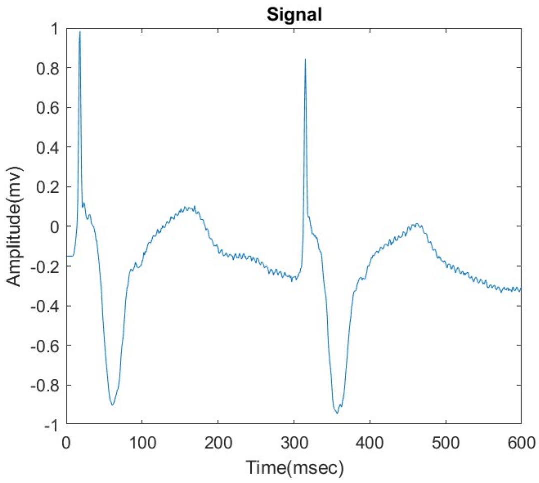


e)

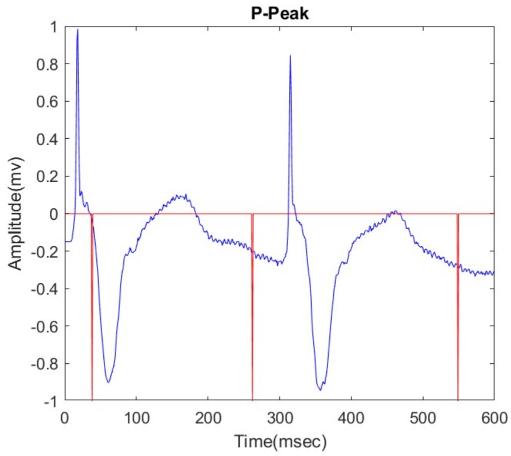


f)

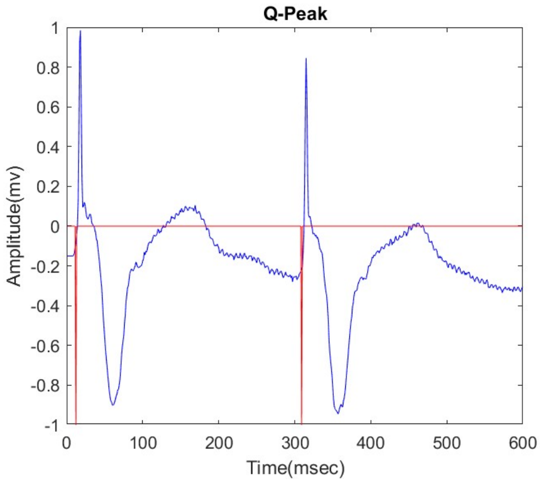
Figure 4.3 Experimental analysis using normal signal-1, a) Original signal_1, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

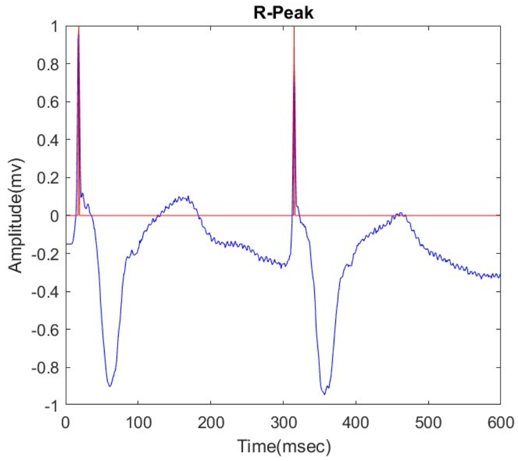


a)

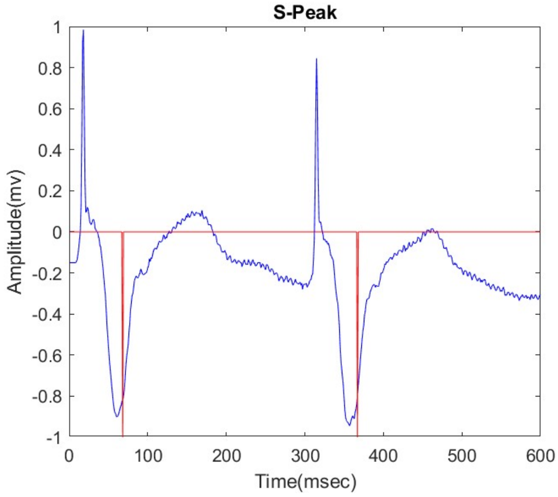


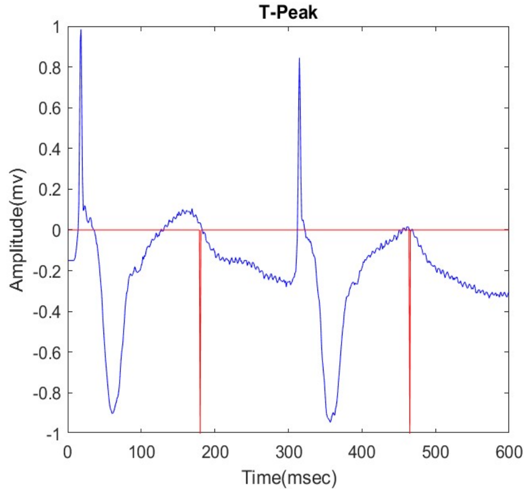
b)





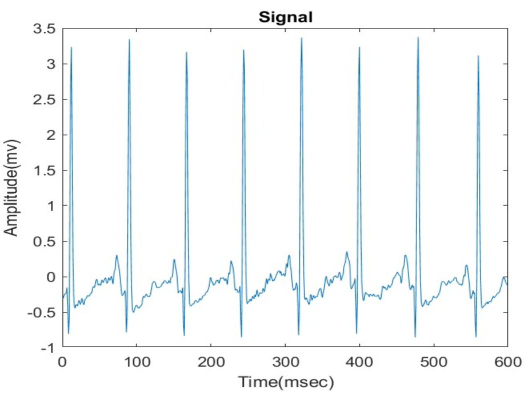
c) d)

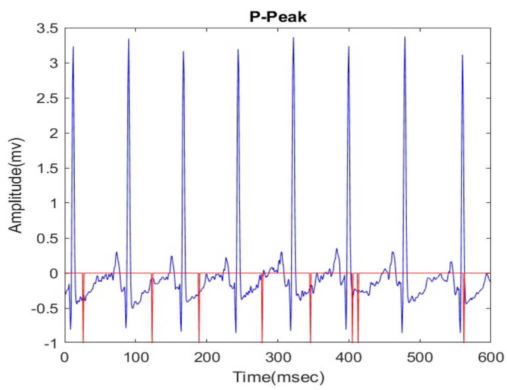




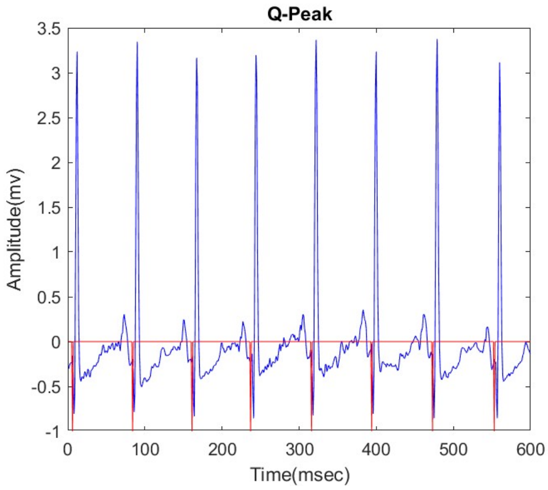
e) f)

Figure 4.4 Signals of the arrhythmia affected ECG signal-1, a) Arrhythmia-affected signal_1, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

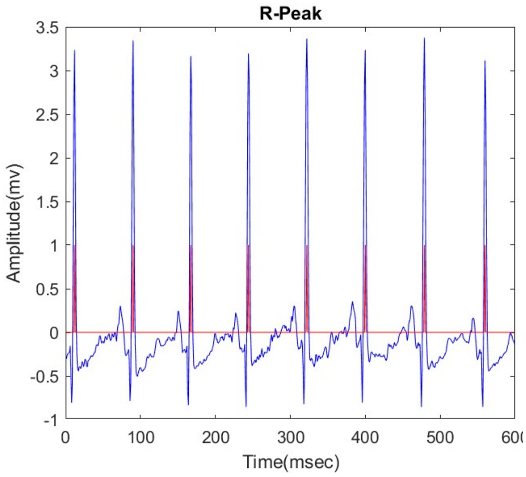




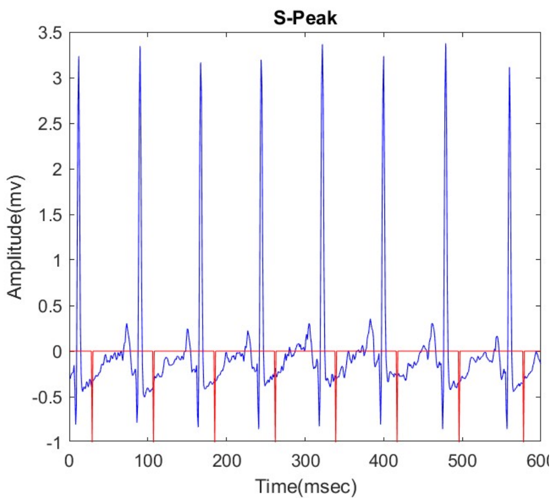
a) b)



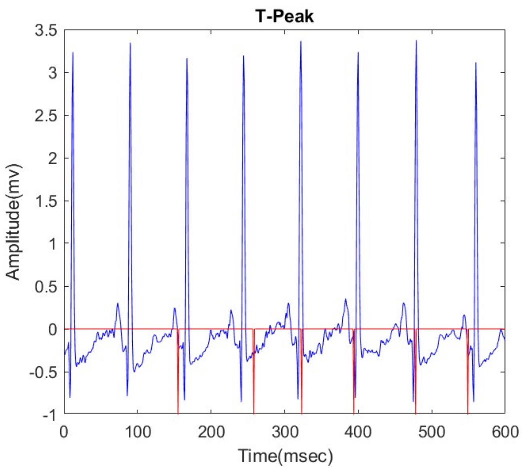
c)



d)

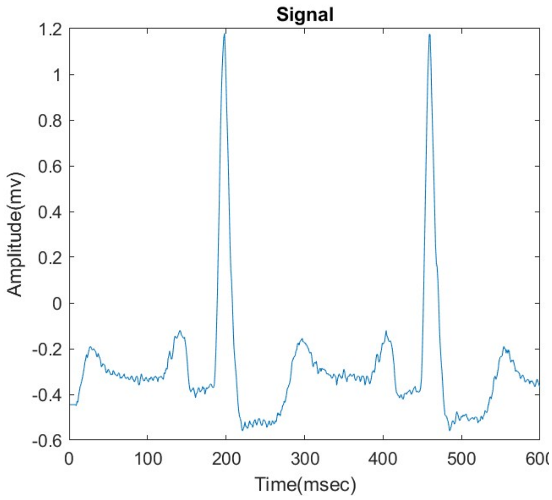


e)

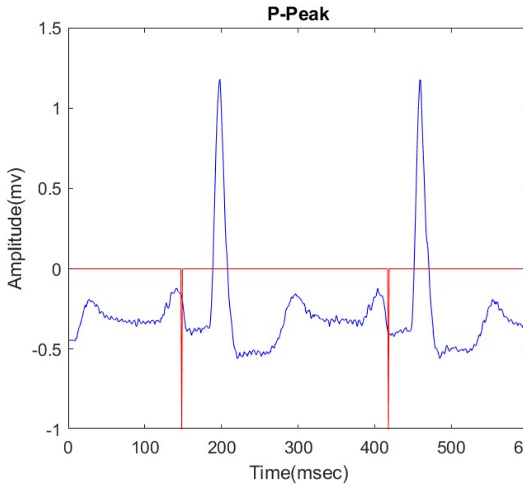


f)

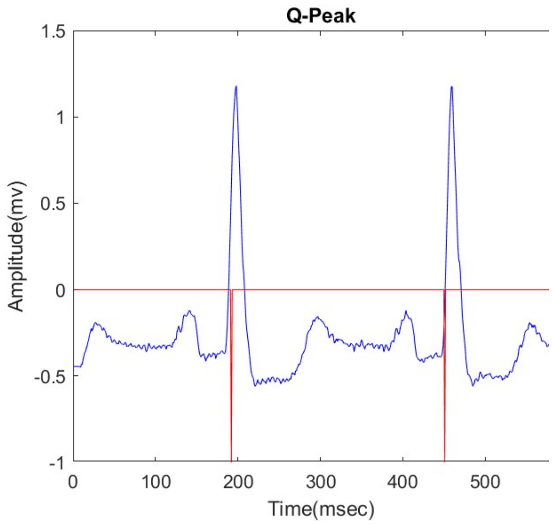
Figure 4.5 Normal ECG signal-2, a) Original signal_2, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak


Signal
Amplitude(mv)
Time(msec)

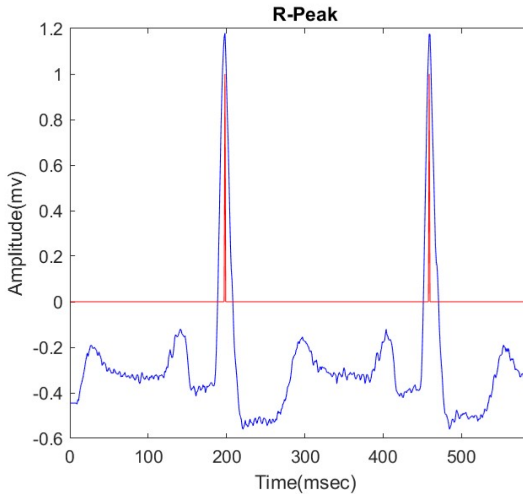
a)


P-Peak
Amplitude(mv)
Time(msec)

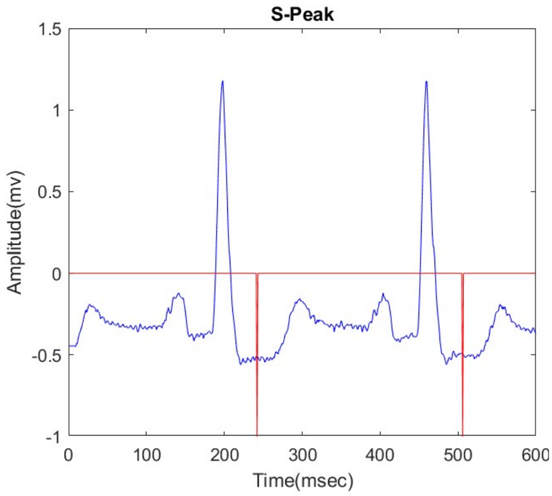
b)


Q-Peak
Amplitude(mv)
Time(msec)

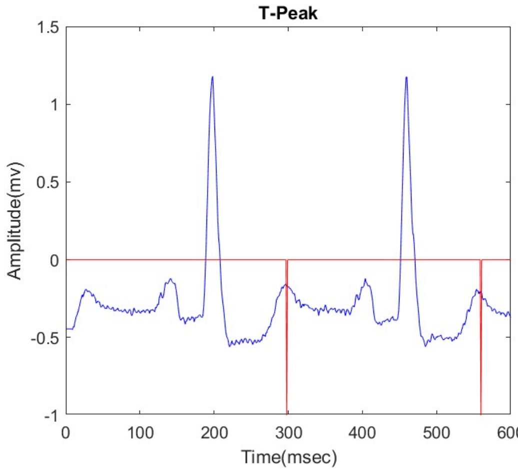
c)


R-Peak
Amplitude(mv)
Time(msec)

d)

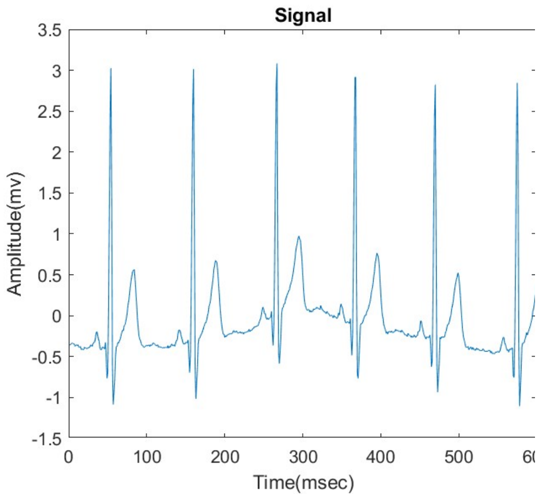


e)

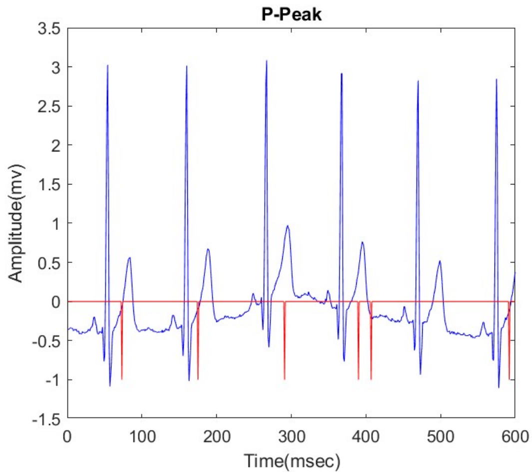


f)

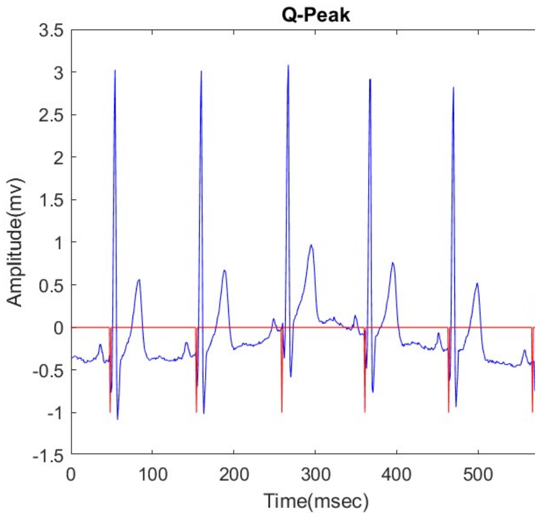
Figure 4.6 Signals of the arrhythmia affected ECG signal-2, a) Arrhythmia-affected signal_2, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak



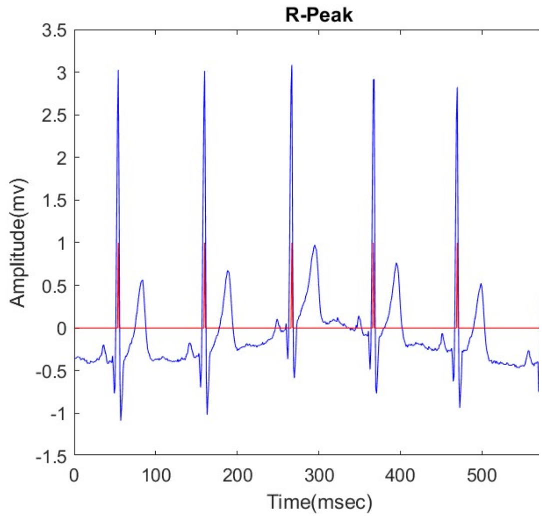
a)



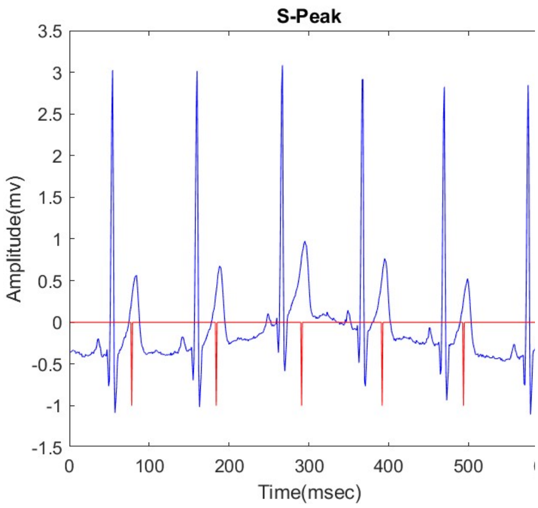
b)



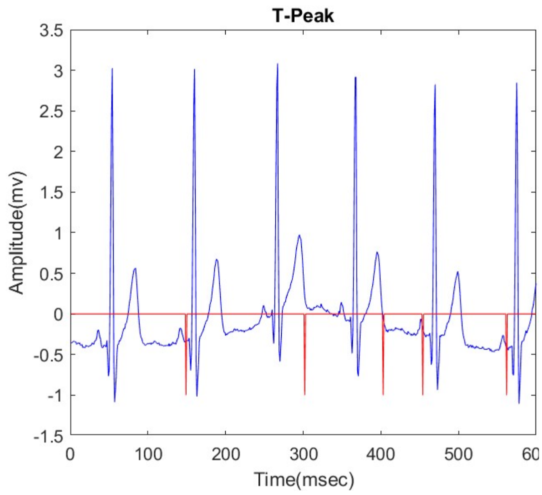
c)



d)

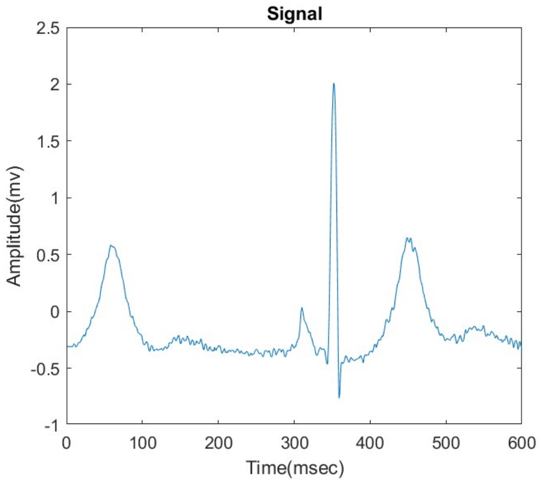


e)

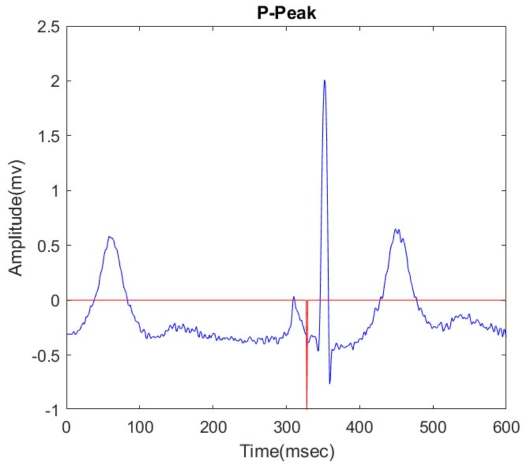


f)

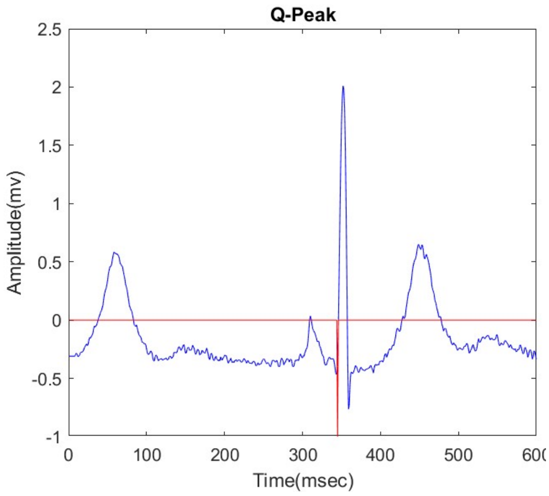
Figure 4.7 Normal ECG signal-3, a) Original signal_3, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak


Signal
Amplitude(mv)
Time(msec)
2.5
2
1.5
1
0.5
0
-0.5
-1
0
100
200
300
400
500
600

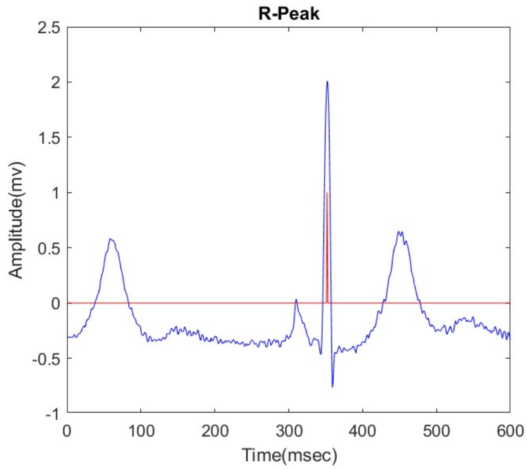
a)


P-Peak
Amplitude(mv)
Time(msec)
2.5
2
1.5
1
0.5
0
-0.5
-1
0
100
200
300
400
500
600

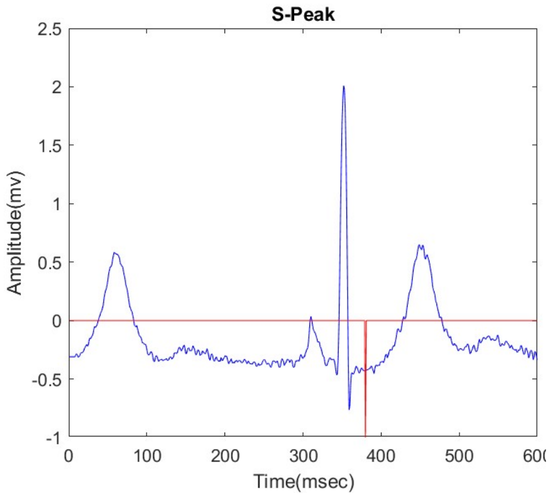
b)


Q-Peak
Amplitude(mv)
Time(msec)
2.5
2
1.5
1
0.5
0
-0.5
-1
0
100
200
300
400
500

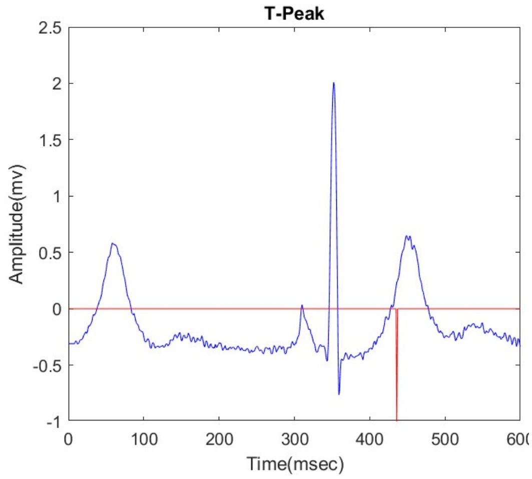
c)


R-Peak
Amplitude(mv)
Time(msec)
2.5
2
1.5
1
0.5
0
-0.5
-1
0
100
200
300
400
500
600

d)



e)

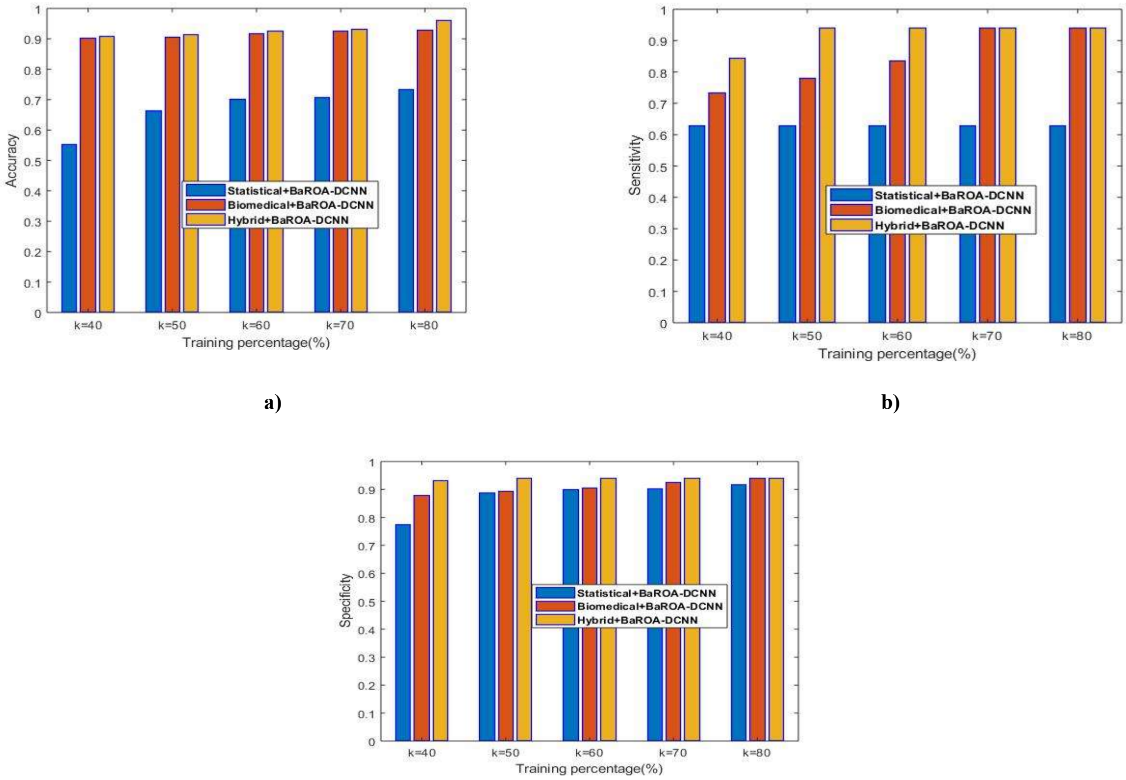


f)

Figure 4.8 Signals of the arrhythmia affected ECG signal-3, a) Arrhythmia-affected signal_3, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

4.5 Performance analysis

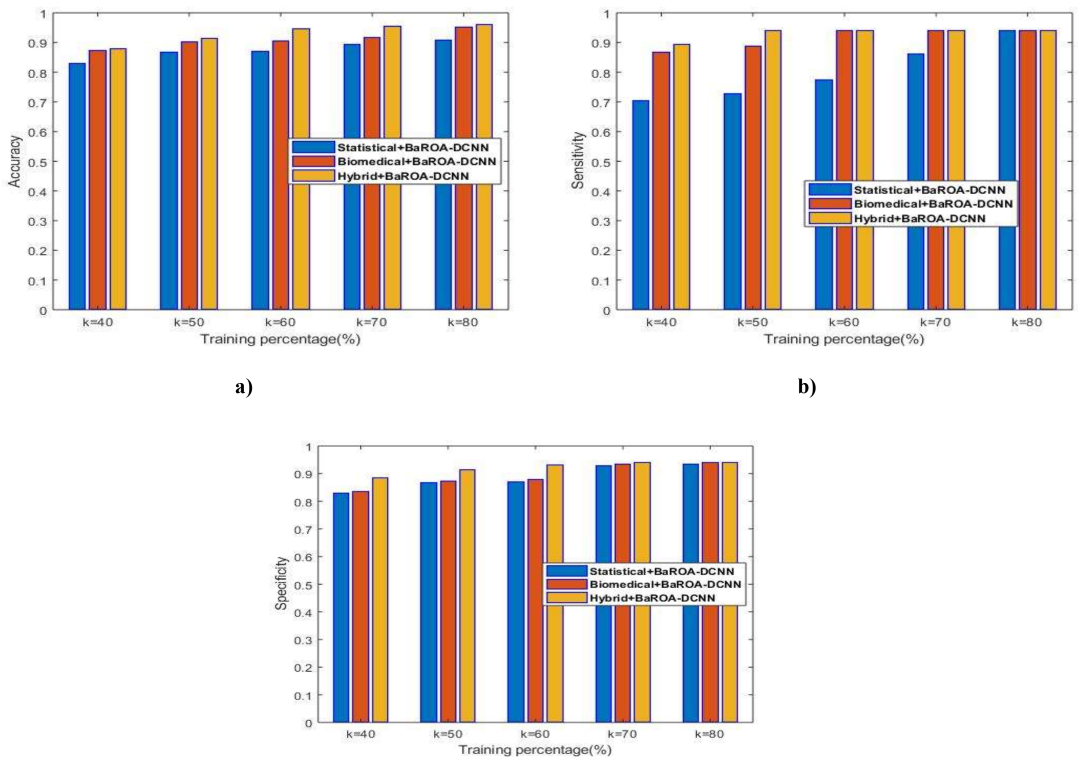
Figure 4.9 depicts the comparative analysis using ECG signal_1. Figure 4.9 a) shows the analysis based on accuracy. When the percentage of training data is 40, the accuracy of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.5531, 0.9009, and 0.9083, respectively. Figure 4.9 b) shows the analysis based on the sensitivity. When the data percentage is 40, the sensitivity of the methods, statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN, is 0.6292, 0.7320, and 0.8434, respectively. Figure 4.9 c) shows the analysis based on specificity. When the training percentage is 40, the specificity of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.7744, 0.8784, and 0.9322, respectively.



a) b) c)

Figure 4.9 Performance analysis using 50 convolutional layers with iteration count as 250, a) accuracy, b) sensitivity, c) specificity

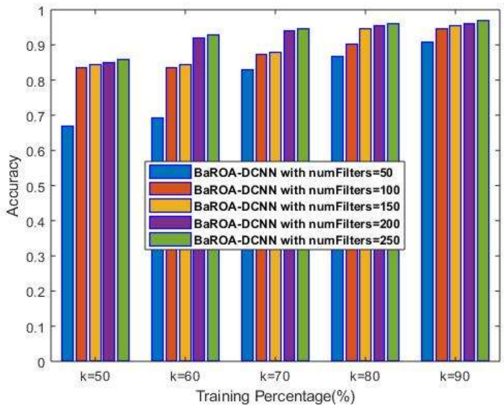
Figure 4.10 depicts the comparative analysis using ECG signal_2. Figure 4.10 a) shows the analysis based on accuracy. When the percentage of training data is 40, the accuracy of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.8297, 0.8733, and 0.8804, respectively. Figure 4.10 b) shows the analysis based on the sensitivity. When the percentage of training data is 40, the sensitivity of the methods, statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN, is 0.7040, 0.8676, and 0.8945, respectively. Figure 4.10 c) shows the analysis based on specificity. When the percentage of training data is 40, the specificity of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.8297, 0.8366, and 0.8856, respectively.



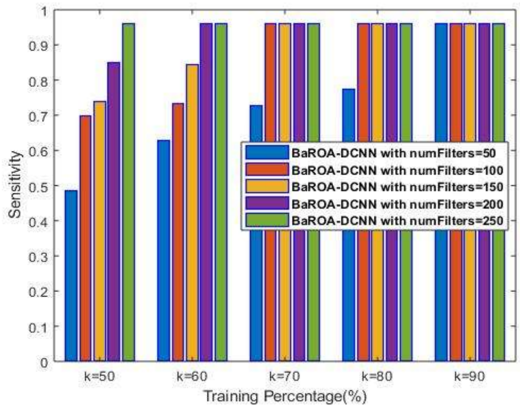
c)

Figure 4.10 Performance analysis using 100 convolutional layers with iteration count as 500, a) accuracy, b) sensitivity, c) specificity

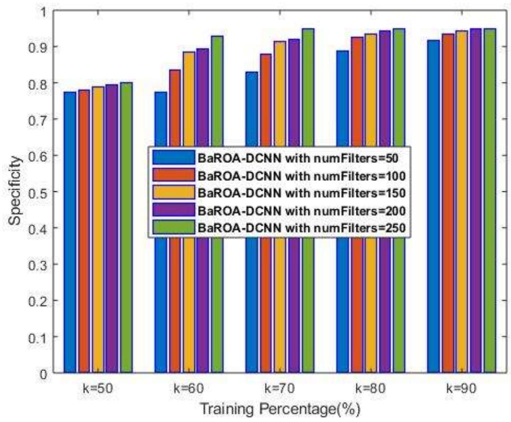
Figure 4.11 demonstrates the comparative analysis using ECG signal_1 with respect to the population size. Figure 4.11 a) shows the analysis based on the accuracy through varying the population size. When the training percentage is 40, the accuracy of BaROA-DCNN with population size 50, 100, 150, 200, and 250 is 0.6702, 0.8366, 0.8434, 0.8503, and 0.8571, respectively. Figure 4.11 b) shows the analysis based on the sensitivity through varying the population size. When the training percentage is 40, the sensitivity of BaROA-DCNN with population size 50, 100, 150, 200, and 250 is0.4840, 0.6971, 0.7380, 0.8503, and 0.9600, respectively. Figure 4.11 c) shows the analysis based on the specificity through varying the population size. When the training percentage is 40, the specificity of BaROA-DCNN with population size 50, 100, 150, 200, and 250 is 0.7744, 0.7808, 0.7872, 0.7936, and 0.8000, respectively.



a)



b)



c)

Figure 4.11. Performance analysis using signal_1 based on the number of filters, a) accuracy, b) sensitivity, c) specificity

4.6 Discussion

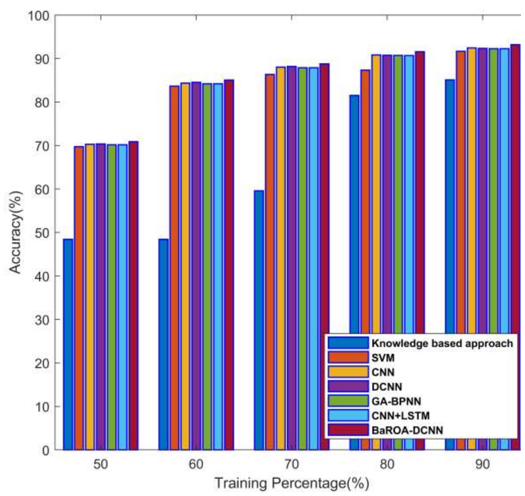
This section elaborates the comparative analysis of the proposed method with the existing methods.

4.6.1 Methods employed for comparative analysis

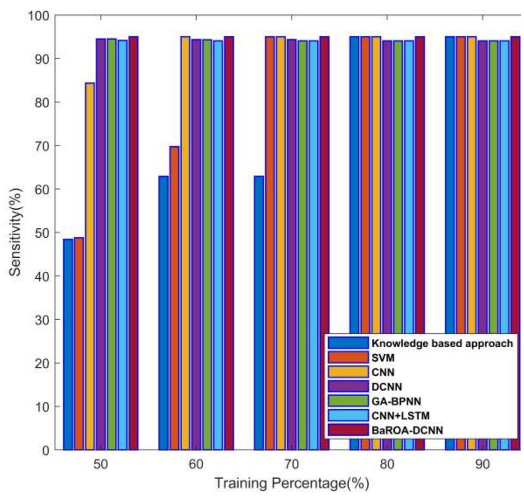
The methods used for comparison include knowledge-based approach [111], Support Vector Machine (SVM) [113], Convolutional Neural Network (CNN) [118], Deep Convolutional Neural Network (DCNN) [119], Genetic Algorithm based Back Propagation Neural Network [120], and convolutional neural network and long short-term memory (CNN+LSTM) [121].

4.6.2 Comparative analysis

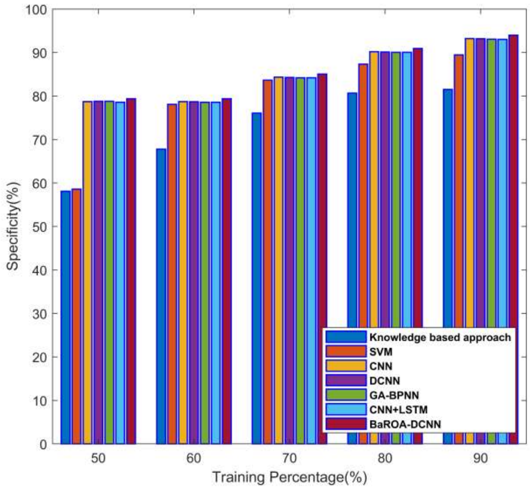
Figure 4.12 shows the comparative analysis using ECG signal_1. Figure 4.12 a) shows the analysis of the accuracy of methods through varying the training data percentage. When the percentage of training data is 50, the accuracy of the knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 48.4%, 83.66%, 84.34%, 84.54%, 84.19%, 84.19%, and 85.03%, respectively. Figure 4.12 b) shows the analysis based on the sensitivity. When the percentage of training data is 50, the sensitivity of the knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 48.4%, 48.8%, 84.34%, 94.52%, 94.51%, 94.16%, and 95%, respectively. Figure 4.12 c) shows the analysis based on specificity. When the percentage of training data is 70, the specificity of knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 76.06%, 83.65%, 84.34%, 84.27%, 84.19%, 84.19%, and 85.03%, respectively.



a)



b)



c)

Figure 4.12 Comparative analysis, a) accuracy, b) sensitivity, c) specificity

4.7 Comparative Discussion

The comparative discussion of the methods has been presented in table 4.1, and best performance occurs for 90% of training data. The accuracy of the proposed BaROA-DCNN is 93.19, which is 8.71%, 1.62%, 0.8%, 0.91%, 0.99%, and 1%, better than the existing methods knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM, respectively. The methods' maximum sensitivity, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 95%, 95%, 95%, 94.05%, 94.05%, 94.05%, and 95%. The performance difference of the proposed BaROA-DCNN over the existing methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM is 13.26%, 4.8%, 0.81%, 0.87%, 0.96%, and 0.99%. Thus, the accuracy, sensitivity, and specificity of the proposed BaROA-DCNN are better than the existing methods, such as the knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM.

Table 4.1 Comparative discussion

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
knowledge-based approach	85.07	95	81.52
SVM	91.68	95	89.47
CNN	92.44	95	93.22
DCNN	92.34	94.05	93.16
GA-BPNN	92.27	94.05	93.08
CNN+LSTM	92.26	94.05	93.05
proposed BaROA-DCNN	**93.19**	**95**	**93.98**

Table 4.2 shows the computational complexity of the proposed BaROA-DCNN, and the existing methods, such as the knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM, in which the proposed system has the minimum computation time of 6.12 sec.

Table 4.2 Computational Complexity

Methods	knowledge-based approach	SVM	CNN	DCNN	GA-BPNN	CNN +LSTM	proposed BaROA-DCNN
Time (Sec)	13.07	11	10.4	9.02	8	7.25	**6.12**

4.8 Summary

The automatic method of arrhythmia classification has been performed using the proposed Bat-Rider Optimization algorithm-based deep convolutional neural networks (BaROA-based DCNN). The classifier Deep CNN yields an accurate classification, and it is an automatic way of classification. The classification accuracy is the benefit of the proposed BaROA in training the classifier. The experimentation has been performed using the MIT-BIH Arrhythmia Database, and the analysis is performed based on the evaluation metrics. The proposed arrhythmia classification method acquired the maximal values of 93.19%, 95%, and 93.98% for accuracy, sensitivity, and specificity.

CHAPTER 5

EPILEPTIC SEIZURE DETECTION USING HYBRID FEATURE EXTRACTION MODEL

5.1 Introduction

Epilepsy is a chronic neurological disorder from which approximately 1% of people suffer. Epileptic seizure detection is achieved by identifying EEG signals. Diagnosis of epileptic seizures has been performed by using EEG records of long duration. These EEG signals consist of noisy, complex, non-linear, and non-stationary. So, the detection of seizures is a challenging task. The machine learning models and classification systems have been utilized to determine epileptic seizures. It classifies the EEG data and determines the seizures with the most relevant patterns that must be satisfied with the effective feature extraction process. Various researches have described machine learning techniques for efficient seizure detection systems. This research provided a new hybrid model for feature extraction in epileptic seizure detection and combined Modified Graph Theory (MGT), Novel Pattern Transformation (NPT), and GLCM feature extraction. This feature extraction process is attained from the proposed pre-processing technique named Enhanced Curvelet Transform (ECT). Finally, the robust classification technique is achieved by using PCA based Random forest classification.

5.1.1 The objective of the research

- To enhance the pre-processing system by using Enhanced Curvelet Transform (ECT).
- To achieve the efficient dimensionality reduction or feature extraction process by using a hybrid model with Modified Graph Theory (MGT), novel pattern transformation, and GLCM features.

- To improve the classification process by using the PCA based Random forest classification.

5.2 Feature extraction

In machine learning, the input pattern is converted into a group of features or feature vectors. The feature extraction process transforms the indiscriminate data into numerical features. The extracted features are utilized to obtain relevant information from the EEG patterns. These should follow important properties like repeatability, distinctiveness, locality, robustness, invariance, and efficiency, thereby performing dimensionality reduction and classification improvement. It considers as an essential factor to achieve a high recognition rate that eliminates redundant and irrelevant features. Features are extracted in time, frequency, and wavelet domains. Some of the important features are topological features, geometrical features, and statistical features.

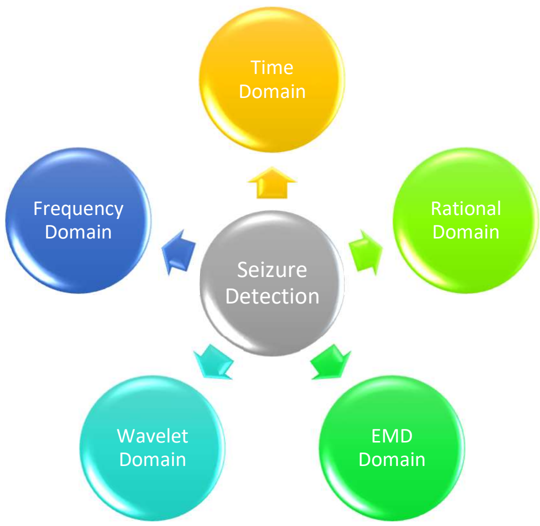


Figure 5.1: Classification of seizure detection techniques [122]

5.3 Classification of epileptic seizure detection using machine learning

In machine learning, the classification system classifies the data item into a single group from predefined groups. The training dataset is utilized to generate the classification model, prediction model, and classification efficiency testing. The training data contains the pair of an input object and the desired object value. The classification process estimates the function of labelled training data. It consists of two types, such as binary classification and multiclass classification problems. In binary classification, two classes are performed. The multiclass classification assigns the objects into multiple classes. Some of the existing classifiers are decision tree, SVM, random forest, naïve Bayes, KNN, etc.

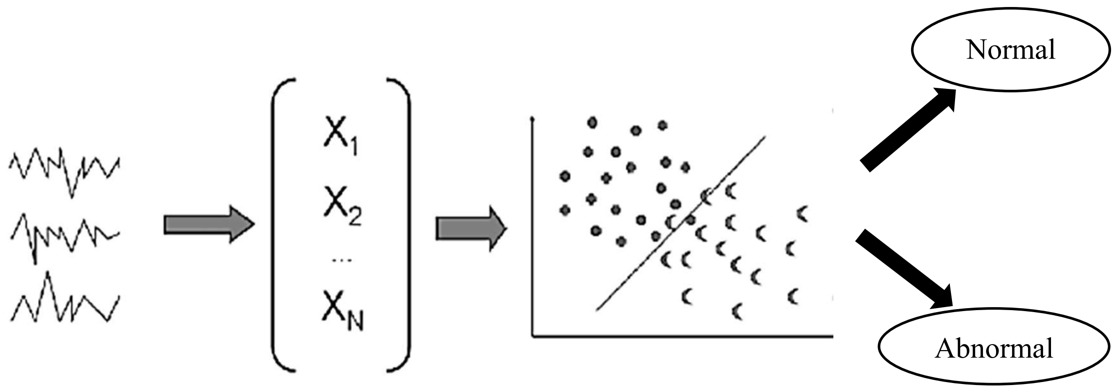


Figure 5.2: Process of Machine learning for the detection of epileptic seizure [123]

5.4 Overall flow of the proposed system

This section describes the proposed flow of the proposed EEG signal classification system. In figure 5.3, the proposed system involves various steps to determine whether the EEG signal is normal or abnormal. These steps are,

- Pre-processing using Enhanced Curvelet Transform
- Feature extraction using a hybrid model
- Classification using Novel Random Forest (NRF) technique

The EEG images are pre-processed from the dataset using the ECT technique that reduces the noises from raw images. Then the features are extracted by using MGT, NPT with fractal dimension, and GLCM techniques. Based on the extracted features, the classification is achieved by the PCA based Random Forest Classifier. It classified the signal as normal or abnormal (interictal or ictal).

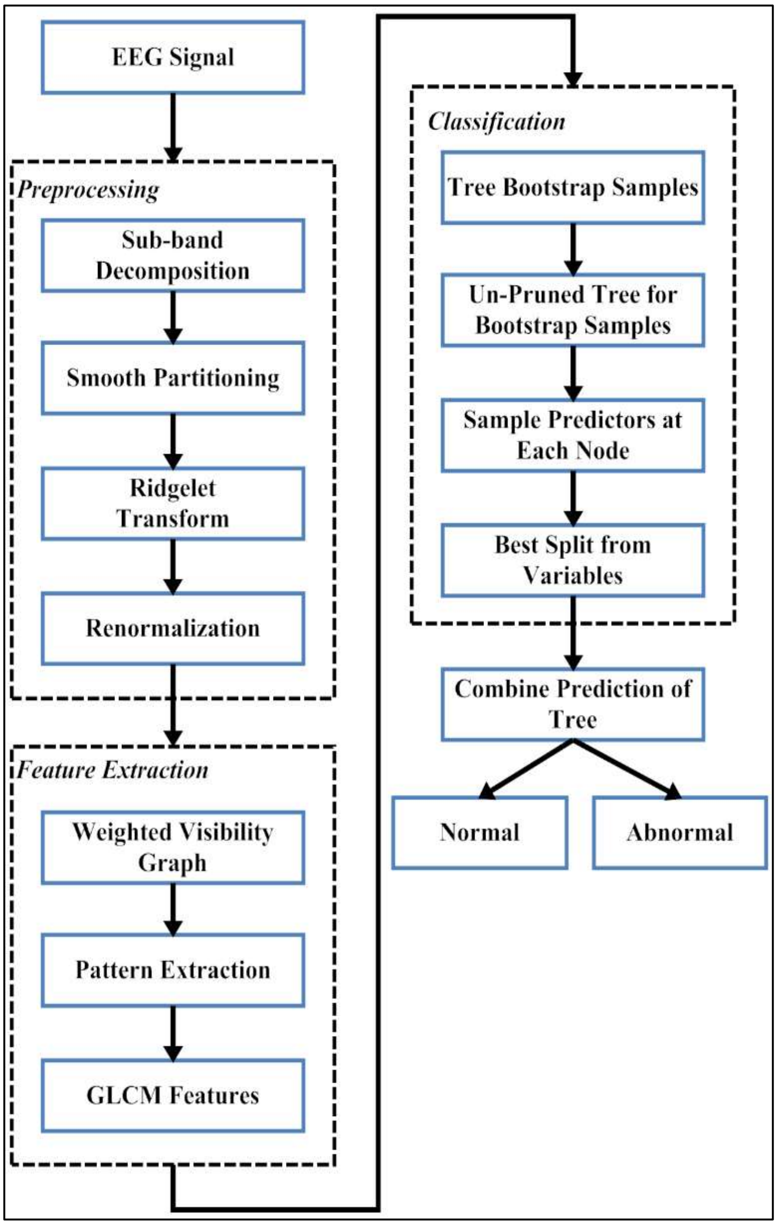


Figure 5.3: Proposed EEG signal classification system

5.4.1 Pre-processing using Enhanced Curvelet Transform (ECT)

From collected raw dataset images, the preprocessing method involves the removal of noises and unwanted factors. The EEG signal consists of noises, spurious content, and outliers. These unnecessary factors must be removed by using denoising and smoothening. The preprocessing process enhances the data quality that involves resampling, filling data gaps, aligning signals, smoothing, removing outliers, and handling non-uniformed signals.

In this research, the **Improved Curvelet Transform** method is used for preprocessing that reduces the memory space without losing information. This process involves various stages such as **decomposition of sub-band, smooth partitioning, ridgelet transformation, and renormalization**. It also reduces the noises and unwanted portions of the signal. The existing Gabor and wavelet transformation methods have the disadvantages of random orientations and information loss. Therefore, this research has proposed a new preprocessing technique named ECT to rectify these issues. It provides a unique representation of data without information loss. It follows the shearlet transformation strategy, where a curve is defined for superposition functioning of different widths and lengths.

- Initially, the image is segmented into curvet sub-bands, and these sub-bands are selected and cascaded to form a Cascaded-curve based on the distinctive curvelet.

$$\Delta_m = \varphi_{2m} * \text{f}, \widehat{\varphi_{2m}}\,(\varepsilon) = \hat{\varphi}\,(2^{-2m}\varepsilon) \tag{5.1}$$

$$\text{f} \rightarrow (P_0 f, \Delta_1 f, \Delta_2 f \,\ldots\ldots) \tag{5.2}$$

  Where Δ_m represents a bandpass filter that is close to (2^{2m}, 2^{2m+2}) frequencies.

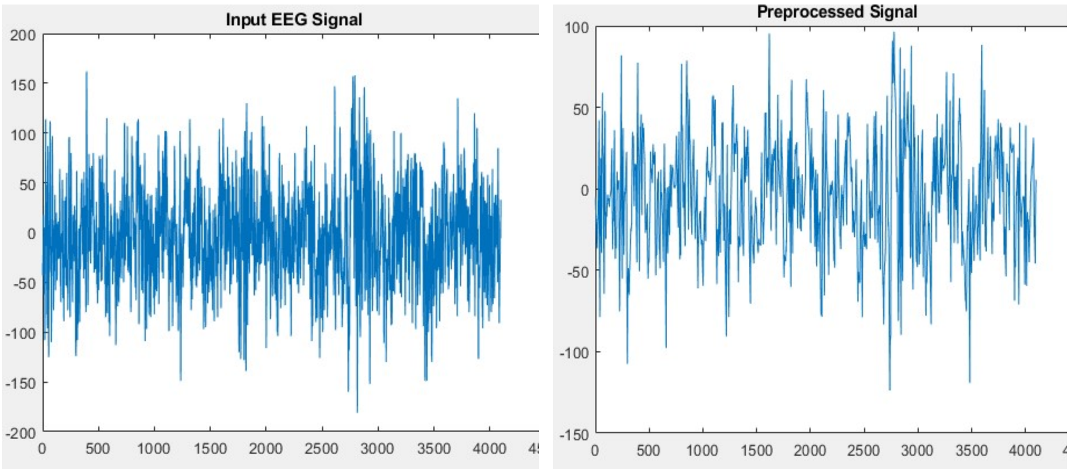
- Then smooth partitioning of phase space is applied to each subband using a ridgelet transform that is localized in frequency and space. The ridgelet packets are represented in the frequency plane with trapezoids.

$$\Delta_m f \rightarrow (w_Q \Delta_m f)_{Q \in Q_m} \tag{5.3}$$

- The generated curvelet entries by ridgelet transform involve the normalization of each sub-bands square into a unit scale.

$$g_Q = \left(T_Q\right)^{-1}\left(w_Q \Delta_m f\right), Q \in Q_m \tag{5.4}$$

- Finally, identified every square and obtained the pre-processed signal with the assistance of shearlet transform. The proposed ECT technique gives the advantages of high efficiency, sparse non-zero coefficients, and sensitivity to directional edges.



(a) (b)

Figure 5.4: Representation of input EEG signal and pre-processed signal by applying ECT technique

Figure 5.4, (a) represents the input EEG signal and (b) represents the pre-processed signal using the proposed ECT technique.

The algorithm I – Enhanced Curvelet Transformation

Input: Input Signal X

Output: Pre-processed Signal

Step 1: Perform wavelet decomposition for obtaining the sub-bands of the image;

$$CA = \frac{1}{\sqrt{m}} \lim_{t \to 1\ to\ size(X)} X(t) * \varphi(t)$$

//Where, the approximate coefficient for the input signal

$$CD = \frac{1}{\sqrt{m}} \lim_{t \to 1\ to\ size(X)} X(t) * \psi(t)$$

//Where, the detailed coefficient for the input signal

$$\varphi(t) = \begin{cases} 1 & 0 \le t < 1 \\ 0 & else \end{cases} \qquad \text{// scaling coefficient}$$

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2 \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & else \end{cases}$$ *// wavelet coefficient*

Step 2: Perform smooth partitioning based on the smooth window,

$$S_p = W_s * CD$$

//Where,S_p- Smooth partitioning results,

W_s– Smooth windowing function

Step 3: Perform renormalization where centering each dyadic square into a unit square;

$$g_Q = T_Q^{-1} h_Q$$

Step 4: Perform Shearlet transform;

Algorithm explanation

In this proposed pre-processing ECT algorithm, the "X" input signal is provided as the input, and wavelet decomposition is attained for dividing sub-images. Then, the approximate value and detailed coefficients for the input signal has been calculated. When computing the coefficients, the scaling and coefficients of wavelet are calculated. Then the smooth partitioning process is involved with the assistance of a smooth window. After that, the renormalization performs on smoothened signals that form the units square. Finally, the shearlet transform is employed to obtain the pre-processed signal.

5.4.2 Feature extraction

The feature extraction process reduces the data dimensionality by using a suitable technique. The features have the input patterns of distinctive properties that assist in differentiating between the input patterns. It converts the large volume of data into the most relevant data with minimum loss of information. The converted features are provided into the classification by considering the image's relevant properties into feature space. In existing, the graph theory is used to extract the most relevant features from the estimated matrix for each subject. This technique can only able to obtain the dynamic properties of time series data and robust to noise. Due to these demerits, the proposed system involves an efficient feature extraction process by using three novel methods such as **MGT, NPT, and GLCM feature extraction**.

5.4.2.1 Modified Graph Theory (MGT)

The Modified Graph Theory (MGT) technique is used for the feature extraction process. This technique effectively differentiates the underlying dynamics through the EEG recordings. For each subject, the correlations among all regions are calculated from time series in the pre-processing stage. In the graph's construction, each data point of time series data is defined as the graph nodes. Then estimate the communication among the nodes according to the distance measures and weight measures. After evaluating the communication between nodes in the graph, the edge weight is calculated among nodes. At this stage, the weight value for vertices and edges with respect to the size of the pre-processed signal has been estimated. After that, the weight value is calculated for the 1st node 2nd node between other nodes. Once the graph construction is completed, the important features are extracted and are used for classification purposes. In this feature extraction process, four features are extracted closeness centrality, graph entropy link density, and amplitude features.

- **Closeness centrality** calculates the mean distance among one vertex to other vertices. It eliminates noisy data. The average closeness centrality calculates the sum of the shortest path length between one node into other nodes in the graph.
- **Link density** measures the ratio of edges among vertices; the undirected graph's maximum density is defined as 1.
- **Graph entropy** is calculated using no vertices, degree distribution, and no connected nodes to a particular node.

- **The signal's amplitude** is measured from no vertices in the graph and the pre-processed signal size.

Finally, these features are combined to construct the group of graph features. Additionally, the fractal dimension features are estimated by considering the Hausdorff distance and synchro squeezing transformation method. The proposed feature extraction technique determines the energy of signals is circulated in 2-D space. It provides the advantages of automatic classification of EEG signal abnormalities.

	1
Link density	35.1900 + 0....
Centrality	5.0459e+03 ...
Graph entropy	-6.7768e+04...
Amplitude	1.9006e+03 ...

Figure 5.5: Extracted features using MGT technique

Algorithm II – Modified Graph Theory Approach

Input: Pre-processed Signal X

Output: extracted features $Graph_{fea}$

Step 1: Estimation of weights for the formed edges and vertices,

n=length (X) //Size of the pre-processed signal

Step 2: Calculate the weight value $W_{ij} =$

$$\lim_{i\to 2:n-1} \lim_{j\to 1:n, j<i} \begin{cases} \sqrt{(\tan^{-1}((X(i)^2 - X(j)^2) * (i-j))) + 1} & if\ X(h) < X(i)\ and\ X(h) < X(j) \\ 0 & else \end{cases}$$

//Where, $X(i)$ *is the first node*

$X(j)$ *is the second node*

$X(h)$ *is the any node between first and second node.*

Step 3: The selection of intermediate node based on the certain criteria, i.e.

$h = k\ \ in \lim_{k\to(j+1)\ to\ n}$, *where k<i*

Step 4: Formed edges, *V(i) and V(j) are connected, edge between these vertices are formed;*

$$E_{ij} = 1$$

$$V_{ij} = [i\ j]$$

//Extracted Features:

Step1: Link Density in Graph for Undirected Graph,

$Edges = size(E_{ij})$ *// Number of formed edges,*

$vertices\ =\ size\ (V_{ij})$ *// Number of formed vertices,*

$$Dense_{graph} = \frac{2 * Edges}{vertices\ (vertices\ - 1)}$$

Step2: Average of Closeness Centrality

For a=1: size (V_{ij})

For b=1: size (V_{ij})

$$Dist(a,b) = \lim_{b \to 1:size\ (V_{ij},1)} \sqrt{(X\left(V_{ij}(a)\right) - X\left(V_{ij}(b)\right))^2}$$

End

$$D\ (a) = \lim_{a \to 1:size\ (V_{ij},1)} \sum_{b=1}^{size\ (V_{ij},1)} Dist(a,b);$$

$$Closeness_{central}(a) = \frac{size(E_{ij})}{D(a)}$$

End

Step3: Graph Entropy

$$Entropy = -\sum_{i=1}^{n} P(i) * \log\left(P(i)\right)$$

// Where,

P - Degree Distribution of graph,

$$P = \frac{n_k}{n}$$

$n_k -$ *number of k connected nodes to the particular node* n^{th} *node;*

n – Number of vertices

Step4: Amplitude of the signal,

$$Amp = X(1{:}n)$$

Step 5: Finally combined the features,

$$Graph_{fea} = \left[Dense_{grap}\ \ Closeness_{central}\ Entropy\ \ Amp\right]$$

5.4.2.2 Novel Pattern Transformation (NPT)

Furthermore, the NPT is used to improve the efficiency of the proposed classification from EEG signals. EEG signals have some unique patterns. So, it is required to transform the local patterns to detect the hidden patterns. In the proposed NPT technique, the wavelets are computed by using shifting parameters and dilations. The patterns are then separately evaluated for alpha, comma, beta, delta, and theta signal waves within specific frequency ranges.

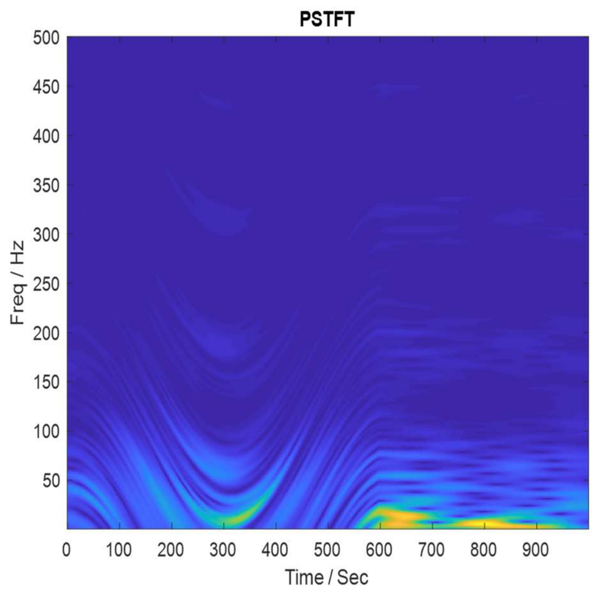


Figure 5.6: Pattern extraction using NPT technique

Algorithm III – Novel Pattern Transformation
Input: Pre-processed Signal X
Output:Extracted pattern features$\text{Pattern}_{\text{fea}}$
Step 1: Wavelets are estimated by dilations and shifting from a single mother wavelet;
$\psi_{a,b}(t) = \frac{1}{\sqrt{x}}\psi(\frac{t-y}{x})$
//Where. x *– Scaling parameter and y- Shifting parameter*
Step 2: Delta:
$$\delta = \psi_{a,b}(fs > 0.5 \,\&\, fs < 4)$$
Step 3: $Theta$:
$$\theta = \psi_{a,b}(fs > 4 \,\&\, fs < 8)$$

Step 4: Alpha:

$$\alpha = \psi_{a,b}(fs > 8 \,\&\, fs < 13)$$

Step 5: Beta:

$$\beta = \psi_{a,b}(fs > 13 \,\&\, fs < 40)$$

Step 6: Gamma:

$$\gamma = \psi_{a,b}(fs > 40 \,\&\, fs < 80)$$

Step 7: Apply GLCM features for the all estimated sub bands, such as Correlation, Energy, Entropy, Homogeneity, Maximum Probability

Correlation:

$\sum_k \frac{(k.l)\, q(k,l) - \mu_x \mu_y}{\sigma_x \sigma_y}$ *//Where, q – signal, k – no of rows and columns;*

Energy:

$$\sum_k \sum_l q(k)^3$$

Entropy:

$$-\sum_k \sum_l q\,(k)\,.\,\log\left((q(k)\right)$$

Homogeneity:

$$\sum_k \sum_l \frac{q(kl)}{1+|k|^2}$$

Maximum Probability:

$$max\ q(k)$$

5.4.2.3 GLCM features

The GLCM features are retrieved with patterns that comprise the properties of **correlation, energy, entropy, homogeneity, and MP - maximum probability**. It is represented as the 2-D histogram of gray levels for pixels segmented by a fixed spatial relationship. The correlation features are obtained with respect to the distance among the data samples through the signals. When the window is correctly ordered, the energy value will be increased. It is used to extract the texture features of the signal. The entropy defines the loss of information in the communicated signal used to measure the signal information. The homogeneity features are retrieved by estimating the feature matrix with the training samples.

	Correlation	energy	entropy	homogeneity	maximum_probability
gamma	-6.8570e-17	106.0412	3.0830	-0.0481	0.7576
beta	-2.8427e-16	30.0115	6.5077	-0.0805	0.2836
alpha	8.6607e-16	1.7491	-0.3816	0.0064	0.0630
theta	0	1.5339	1.4498	-0.0283	0.0505
delta	1.1733e-14	8.6074e-04	7.3802	0.0015	0.0010

Figure 5.7: Extracted GLCM features

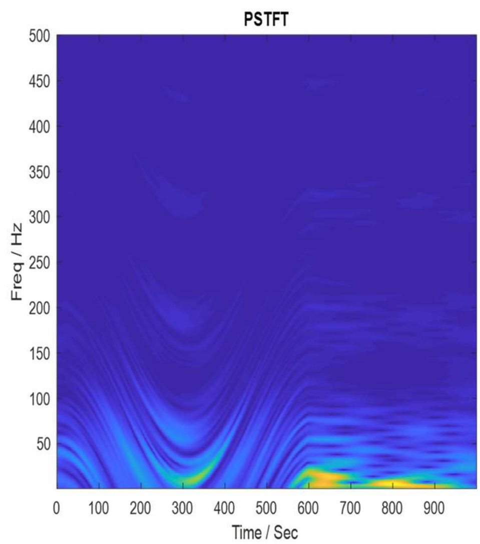
Table 5.1: Output of proposed feature extraction techniques for Inter-ictal and ictal abnormalities

	1
Link density	28.2600 + 0....
Centrality	3.0426e+03 ...
Graph entropy	-1.8769e+04...
Amplitude	-1.0296e+03...

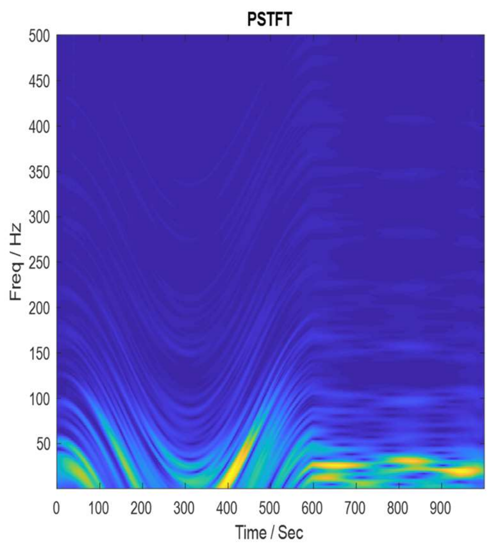
(a) Inter-ictal

	1
Link density	35.4200 + 0....
Centrality	3.5358e+03 ...
Graph entropy	-7.7392e+03...
Amplitude	4.2888e+03 ...

(b) Ictal



(a) Inter-ictal



(b) Ictal

	Correlation	energy	entropy	homogeneity	maximum_p
gamma	-7.7918e-17	141.8576	15.7044	0.1494	
beta	-1.6444e-16	17.1930	-4.5967	-0.1424	
alpha	0	395.6273	37.1104	0.0699	
theta	5.8873e-15	0.2017	5.0563	-0.0013	
delta	5.8362e-15	2.6591e-04	8.2698	3.7116e-04	4

(a) Inter-ictal

	Correlation	energy	entropy	homogeneity	maximum_probabil
gamma	1.7780e-16	126.2718	-2.3357	0.3202	0.64
beta	1.4015e-17	77.2975	7.5848	-0.1351	0.40
alpha	1.9046e-14	0.3504	2.4568	-0.0337	0.03
theta	7.6271e-16	0.0489	4.6090	0.0023	0.01
delta	2.7591e-15	9.9601e-04	7.6422	0.0020	0.00

(b) Ictal

Table 5.1 represents the obtained outputs of proposed feature extraction methods for inter-ictal and ictal.

5.4.3 Classification using Novel Random Forest Classifier

After the feature extraction process from the pre-processed EEG signal, these features involved the classification process. The efficiency of classification mainly depends on the extracted features in the feature extraction process. The classification system determines whether the input features are normal or abnormal based on the training and testing process.

In this research, the classification method is used to determine the EEG signal abnormalities with the combination of Principle Component Analysis (PCA) based Random Forest (PCA-RF) classification. RF classifier is most suitable for signal classification due to the selection of the most relevant features. It generates features from random samples to receive a class label. The RF classifier is constructed by a number of base learners that act as an independent binary tree in a recursive way to determine the variations in predictor value. Also, it provides the decision about classification with respect to obtained votes from all forest trees. This classification is mainly based on the performance of separate trees in the forest. It follows a limit with respect to the number of trees.

The extracted features are then segmented for training and testing. The trained features, test features, and labels are provided as the input. After that, some of the features are selected randomly, and construct the matrix for those features. In each node of the tree, it randomly selects the variables from the training set. Then the PCA technique is used to achieve the group of coefficients and forms the co-variance matrix. This technique works based on the statistical representation of a random variable. It performs the linear mapping of data into lower-dimensional space. The coefficients and top Eigenvectors from the obtained co-variance matrix have been estimated.

Additionally, the classifier matrix is generated with a training set for further process. Based on the testing features, the normal and abnormal features are evaluated for all existing classes. The predicted class's high counts are received as a classified label that includes normal or abnormal (ictal or interictal) based on the estimated value. This proposed classification technique has the advantages of high accuracy, minimum overfitting, minimum information loss, and insensitivity to noise.

Algorithm IV –PCA based Random Forest Classification

Input: Trained features $Train_{fea}(m\ X\ n\ matrix)$, *Test features* $Test_{fea}$*and Label* $L\ (1\ X\ m\ matrix)$

Output: Classified output Cl

Step 1: Let take random samples, G.

Step 2: Construct a subset of features set by splitting the Feature set i.e. $Train_{fea}$

Step 3: At each split, consider only 'K' features from the entire set of features $Train_{fea}$, *which are picked randomly,*

$X_s = \lim_{s \to 1:K:n} Train_{fea}(:, s: s + K - 1)$ *//Take every K set of matrix values from* $Train_{fea}$;

Step 4: Apply PCA on X to obtain coefficients Co which is in a matrix format.

Perform covariance matrix,

$$cov = \frac{1}{K} X_s {X_s}^T$$

Estimate the top d eigenvectors from the estimated covariance matrix,

U= $cov(diag(1: d))$

Finally, compute the coefficients Co using the following equation,

$$Co = U^T X_s$$

Step 5: Build classifier matrix B as the training set,

$$B^K = \lim_{s \to 1:K:n} [X_s \, Co]$$

// Classification Phase:

Step 6: Estimate votes for all available classes based on test features:

$V_j = \frac{1}{n} \sum_{i=1}^{n} B_j^K(i) * Test_{fea}(i)$

//Where, j-number of class, i-number of feature dimension and V_j – estimated votes each available class.

B_j^K- Classifier matrix for the certain images which belong to the j^{th} class;

Step 7: Finally obtain the predicted class which having high votes;

$$Cl = L(\operatorname*{argmax}_j V_j)$$

5.5 Results and Discussion

This section describes the proposed method results with accuracy, sensitivity, specificity, precision, recall, f-measure, and Jaccard. The proposed technique has been applied to the dataset to analyze the proposed system efficacy.

5.5.1 Dataset description

In this research, the dataset [124] is utilized that obtains from Bonn University. This dataset consists of five subgroups of signals. Each subgroup contains 100 EEG recordings in a 23.6s period. The sampling rate of data defines 173.61 Hz.

SET A	Z.zip	With Z000.txt-Z100.txt	(564kB)
SET B	O.zip	With O000.txt-O100.txt	(611kB)
SET C	N.zip	With N000.txt-N100.txt	(560kB)
SET D	F.zip	With F000.txt-F100.txt	(569kB)
SET E	S.zip	With S000.txt-S100.txt	(747kB)

Figure 5.8: Representation of proposed dataset segments

Each set contains ZIP-file with100 TXT-files. Each file consists of 4096 samples of one EEG time series.

5.5.2 Performance analysis

The proposed method's performance analysis is measured with accuracy, sensitivity, specificity, precision, recall, F-score, and Jaccard coefficient. In the previous chapter, the mathematical formulas for each performance measure have been estimated.

5.5.2.1 Accuracy, Sensitivity, and Specificity

In this section, the proposed method of performance measures with existing methods such as SVM-RLS, SVM-MRBF [125], SVM-MRBF & MPSO, SVM-SRBF, ATFFWT-LSSVM [126], and TQWT based multiscale KNN [127] have been compared. These measurements were analyzed based on the various data segments in a dataset like S-Z, S-F, S-N, and S-NF.

Table 5.2: Comparison of proposed method performance measures with existing methods based on segments

Segments	Performance metrics	SVM-RLS	TQWT based multiscale KNN entropy	SVM-MRBF	ATFFWT-LSSVM	SVM-MRBF MPSO	SVM-SRBF	Proposed method
S-Z	Sensitivity	95.40	-	99.20	-	100	98.80	100
	Specificity	97.80	-	95.00	-	100	98.80	100
	Accuracy	96.60	99.50	97.10	99	100	98.80	100
S-F	Sensitivity	94.40	-	96.40	-	96.80	93.60	98
	Specificity	96.60	-	95.70	-	97.20	97.80	98

	Accuracy	95.20	98	96.05	98.50	97.60	95.70	98
S-N	Sensitivity	98	-	94.70	-	99.60	94.60	99
	Specificity	100	-	95.80	-	100	100	99
	Accuracy	99	100	95.25	100	99.8	97.30	99
S-NF	Sensitivity	97.40	-	94	-	98	97	98.66
	Specificity	96.70	-	97.95	-	99.10	97.10	98.50
	Accuracy	96.93	99	96.93	99.20	98.73	97.07	98.50

Table 5.2 represents the comparison of proposed method performance measures with existing methods based on segments. The proposed method provides sensitivity, specificity, accuracy parameters, 100 % for the S-Z segment, 98% for the S-F segment, and 99% for the S-N segment. For the S-NF segment, the proposed method gives 98.66% sensitivity, 98.50% specificity, and 98.50% accuracy.

These results proved that the proposed method has high performance compared to other methods. It provides more efficiencies in the S-Z segment in the dataset.

5.5.2.2 Precision and Recall

The precision and recall measures of the proposed system are considered for SVM-RLS, SVM-MRBF, SVM-MRBF & MPSO, SVM-SRBF, ATFFWT-LSSVM, and TQWT based multiscale KNN segments.

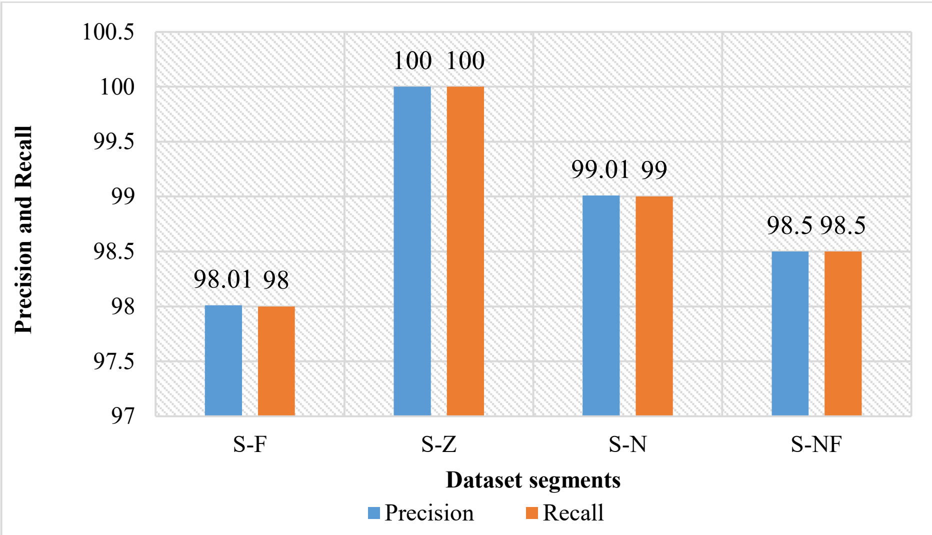


Figure 5.9: Precision and Recall values of the Proposed method

Figure 5.9 represents the proposed method's precision and recall values for the various segments in the dataset. This suggested technique provides 98.01% precision for the S-F segment, 100% precision for the S-Z segment, 99% precision for the S-N segment, and 98.5% precision for the S-NF segment. It gives 98% of recall for the S-F segment, 100% recall for the S-Z segment, 99% of recall for the S-N segment, and 98.5% recall for the S-NF segment.

5.5.2.3 F-measure and Jaccard Coefficient

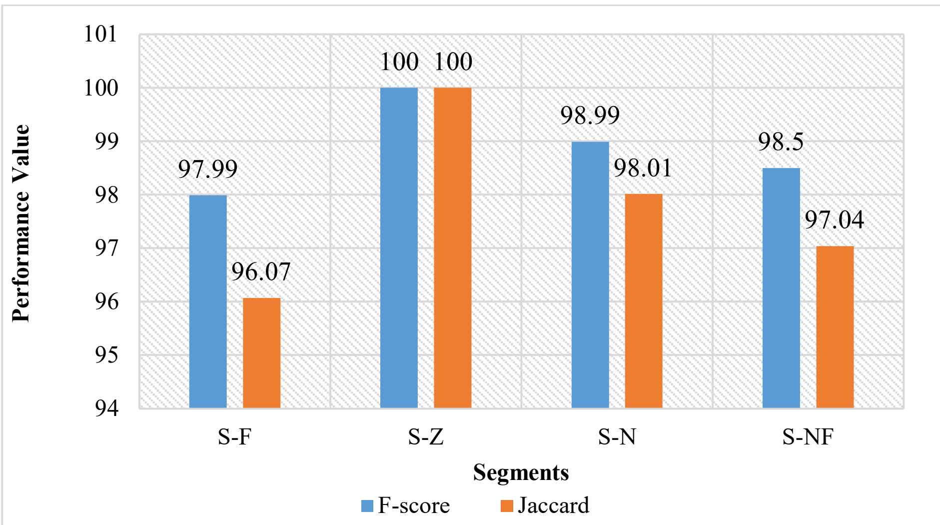


Figure 5.10: F-score and Jaccard coefficients for the Proposed method

Figure 5.10 describes the statistical results of the proposed method F-score and Jaccard coefficient. This proposed technique provides 97.9% F-score for the S-F segment, 100% F-score for the S-Z segment, 98.9% F-score for S-N segment, and 98.5% F-score for the S-NF segment. It gives 96.7% Jaccard for the S-F segment, 100% Jaccard for the S-Z segment, 98.1% Jaccard for the S-N segment, and 97.04% Jaccard for the S-NF segment.

These statistical analyses verified that the proposed method have high efficiencies for the S-Z segment in the dataset.

5.5.2.4 Overall performance

This section provides the results of the proposed classification technique for healthy, Ictal, and Interictal classes.

Table 5.3: Performance measures of the Proposed method for various classes

Performance metrics	Healthy	Ictal abnormal	Interictal abnormal
Specificity	100	99.5	99
Accuracy	99.8	99.2	99
Sensitivity	99.5	98	99
Recall	99.5	98	99
Precision	100	98	98.5075
Jaccard	99.5	96.0784	97.5369
F1-Score	99.7494	98	98.7531

Table 5.3 represents the proposed method's performance measures for healthy, ictal, and inter-ictal classes. This technique has 99.8% accuracy, 100% specificity, 99.5% sensitivity, 99.5% specificity, 100% precision, 99.5% recall, 99.7% F-score, and 99.5% Jaccard for healthy EEG signals. It provides 99.2% accuracy, 99.5% specificity, 98% sensitivity, 98% precision, 98% recall, 98% F-score, and

96% Jaccard for ictal signals. This technique gives 99% accuracy, 99% specificity, 99% sensitivity, 98.5% precision, 99% of recall, 98.7% F-score, and 97.5% Jaccard for inter-ictal signals.

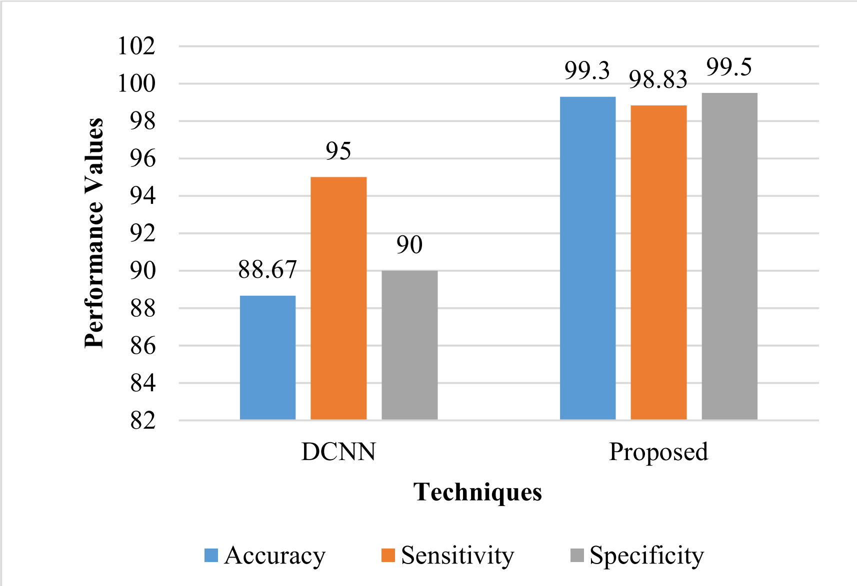


Figure 5.11: Comparison of proposed technique performance with existing DCNN technique

In the figure 5.11, the performance of the proposed method is compared with the existing DCNN technique. The DCNN method provides 88% accuracy, 95% sensitivity, and 90% specificity, and the proposed method gives 99.3% accuracy, 98.83% sensitivity, and 99.5% specificity. From this statistical analysis, the proposed method has 8% increased performance compared to the existing method.

Table 5.4: Comparison of the proposed method with the existing statistical pattern algorithm

Class type	**Accuracy**		**Specificity**		**Sensitivity**	
	Statistical pattern algorithm	**Proposed algorithm**	**Statistical pattern algorithm**	**Proposed algorithm**	**Statistical pattern algorithm**	**Proposed algorithm**
Healthy	99	99.8	100	100	100	99.5

Ictal abnormal	Nil	99.2	99.99	99.5	98	98
Interictal abnormal	Nil	99	99.99	99	98	99

Table 5.4 describes the comparison of the proposed method with the existing statistical pattern algorithm. From this table, it has been analyzed that the proposed method has high performances compared to the statistical pattern algorithm.

Table 5.5: Performance comparison of the proposed feature extraction technique with the existing feature extraction techniques

Feature extraction techniques	**Accuracy**	**Specificity**	**Sensitivity**
TQWT and Kraskov entropy	97.95	98.07	97.68
CWT, HOS, and textures	96	97	96.9
WT-Quadratic	98.7	99	98
MFDFA	99.6	Nil	99.7
Proposed method	99.3	99.5	98.83

Table 5.5 describes the various existing feature extraction techniques that are compared with the proposed technique. The proposed hybrid model provides 99.3% accuracy, 99.5% specificity, and 98.83% sensitivity. From this table, it has been analyzed that the proposed feature extraction method has high performances compared to other methods such as TQWT and Kraskov entropy, CWT, HOS and textures, WT-Quadratic, and MFDFA.

5.6 Summary

In this chapter, the basic definitions of feature extraction classification for Epileptic seizure detection have been described. This chapter has discussed the proposed hybrid feature extraction method for the effective detection of Epileptic seizures that combines the Modified Graph Theory (MGT), Novel Pattern Transformation (NPT), and GLCM feature extraction. The proposed pre-processing technique, named Enhanced Curvelet Transform (ECT), has been implemented. Finally, the classification technique has been achieved by using PCA based Random forest classification. The experimental results have proved the efficacy of the proposed system by comparing it with various existing methods.

CHAPTER 6

EPILEPTIC SEIZURE DETECTION USING CNN

6.1 Introduction

Epilepsy seizure is an abnormal brain disorder. People can suffer from this disorder due to misunderstanding, fear, and missing of self-confidence. Epilepsy forces people into obscurity, and they suffer misery in their lives [128]. The EEG signal acts as the support system for the diagnosis of Epilepsy seizures [129]. Machine learning techniques are used in different perspectives to differentiate the EEG pattern. The deep learning concept enhanced the detection of seizures based on neural network classification. The research's main purpose is to determine the appropriate features that should be provided to a neural network for attaining the best performances. The selection of an appropriate classifier is the most essential for EEG signal classification.

This research proposed the Modified Blackman Bandpass Filter (MBBF) for removing the artifacts from the EEG signal. The time and frequency domain features are retrieved and then optimized using Greedy Particle Swarm Optimization. Finally, the classification of seizure has been achieved by using the Convolutional Neural Network.

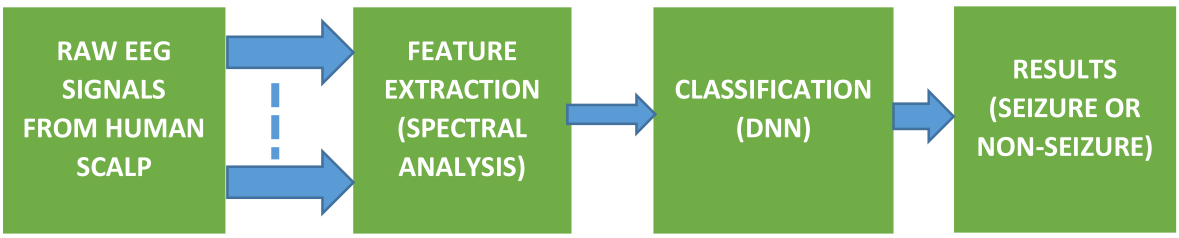


Figure 6.1: Detection of Epileptic seizure using Neural Network [130]

6.2 Time and frequency domain features in EEG signal

The time-frequency domain representation is used for the localization of EEG signal both in time and frequency domains, and it can be done using the Wavelet Transform (WT). In the EEG waveform, time-domain features are measured from signal amplitude values obtained through the recording [131]. The time-domain features are variance, mean, skewness, standard deviation, Mean Absolute Deviation, Kurtosis, Waveform Length, Williston Amplitude, and Slope Sign Change. The frequency domains are Median Frequency, Mean Frequency (MF), and Signal to Noise Ratio (SNR), Power Spectrum Deformation (PSD), and Signal to Motion Artifact Ratio (SMAR).

6.3 Overall flow of the proposed system

The proposed Epileptic seizure detection by pattern prediction is based on the time and frequency domain analysis. The proposed system involves various stages that are defined as below,

- Removal of artifacts using Modified Blackman Bandpass Filter (MBBF)
- Feature extraction based on time-domain features and frequency domain features
- Feature optimization using Greedy Particle Swarm Optimization – GPSO
- Classification of seizure using CNN – Convolutional Neural Network

Initially, the raw dataset has been used for the overall proposed system to detect the seizure. The Modified Blackman Bandpass Filter (MBBF) has been utilized to suppress the other frequency signals than predefined frequencies. This MBBF filter differentiates the frequency ranges and the passage of signal in specific frequencies where the filter reduces the outside ranged signal. Then extracts the time domain features and frequency domain features for efficient determination of epileptic seizure classification. The extracted time domain features are Mean variable of Square Root (MSR), Absolute variable of the Summation of Square root (ASS), mean absolute value (MAV), waveform length (WL), Absolute Summation value of exponential root (ASE), zero crossings (ZC), auto-regressive coefficients (AR), Willison Amplitude (WAMP), slope sign changes, and Root Mean Square (RMS). The frequency-domain features are Maximum Amplitude, Mean Frequency, Median Frequency, Power Spectrum deformation, and Spectrum Moment. Then estimated features are optimized using Greedy Particle Swarm Optimization (GPSO) to select the best optimal features. These obtained optimal features involve the classification process using the Convolutional Neural network (CNN). The convolutional layer for the training process based on labels and extracted features has been updated in the CNN network. In the classification stage, the severity of the detected epilepsy has been classified.

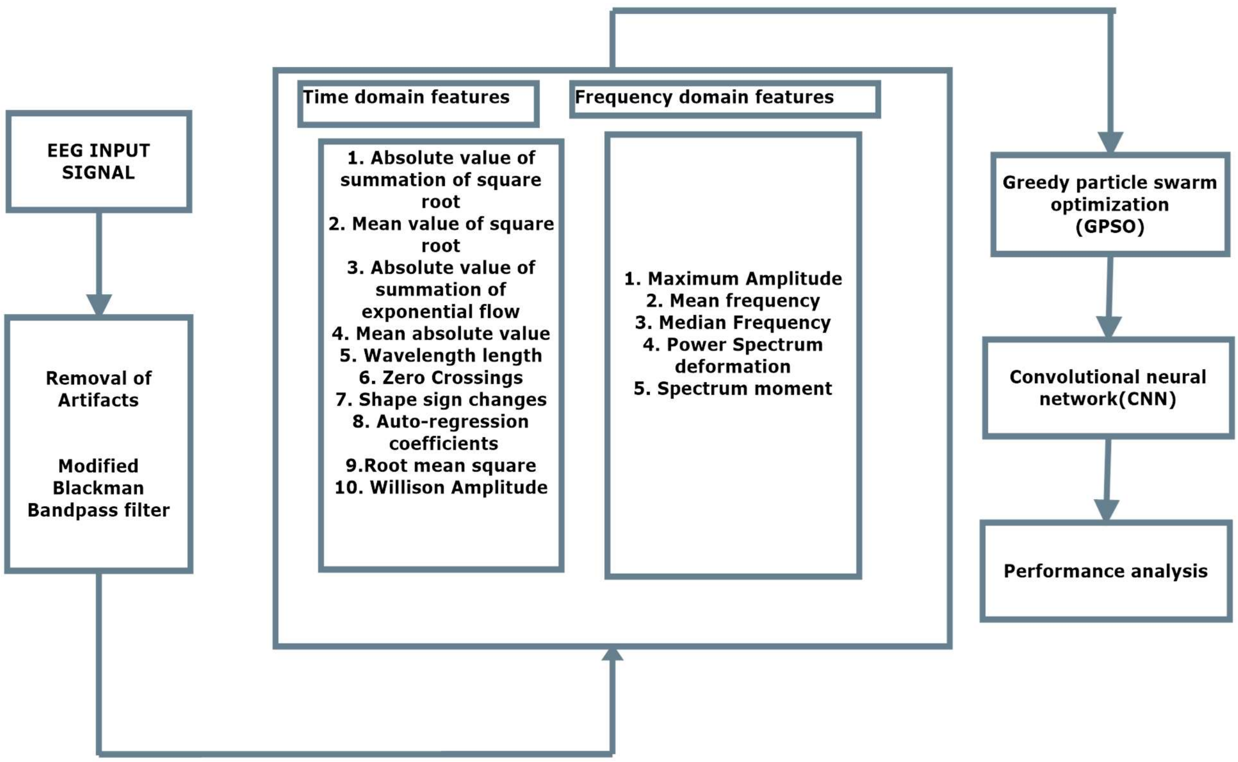


Figure 6.2: The proposed flow of Epileptic seizure detection

Figure 6.2 represents the proposed flow of epileptic seizure detection with various stages. The detailed description of these stages is described below.

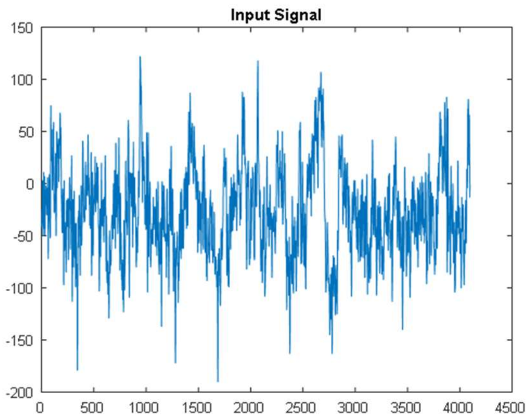
6.3.1 Artifacts removal using Modified Blackman Bandpass Filter (MBBF)

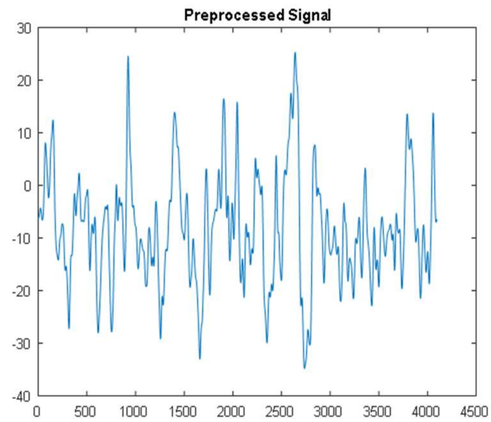
The bandpass filter has been utilized to filter out the specific frequencies within a particular range of frequencies. In the proposed system, the EEG signal is considered as an input signal for the filtering process. Various window functions are used to eliminate the noises from the input signal, such as hamming windows, handing windows, and Blackman windows. Among these methods, the Blackman window provides more benefits by providing better stopband attenuation. In the window function method, the leakage is discrete in different ways according to specific applications. The Blackman window provides the highest stopband ripple (74 dB down) compared to the hamming window in the FIR filter's output.

The equation defines the Blackman window function,

$$W\ (m)=0.42-0.5\cos\ (2\pi mN-1)+0.08(4\pi mN-1),\ \text{where, } m=0,\ 1,\ M-1 \qquad (6.1)$$

In this proposed system, the Modified Blackman Bandpass Filter (MBBF) has been utilized to suppress the other frequency signals than predefined frequencies. The bandpass filters are used to differentiate the frequency ranges. It passes and attenuates the signal in specific frequencies.





(a) **(b)**

Figure 6.3: Representation of input signal and pre-processed signal using the proposed technique

6.3.2 Time-domain features and frequency domain features extraction

After removing the noises using the MBBP filter, the EEG signal has been utilized for the feature extraction process. The feature extraction involves dimensionality reduction from a large amount of input dataset. In the feature extraction process, the spectral features, spatial features, and temporal features have been extracted. The time-domain features involve the calculation of ASS, MSR, Absolute Value of Summation of Exponential flow (ASE), Mean Absolute Variable (MAV), waveform Length, zero crossings, modifications of shape sign, auto-regression coefficients, RMS, and Willison amplitude.

The absolute value of summation of square roots is calculated by,

$$\text{ASS} = \left|\sum_{k=1}^{n}(x_k)^{1/2}\right| \tag{6.2}$$

Mean value square root can be expressed by,

$$\text{MSR} = \frac{1}{n}\sum_{k=1}^{n}(x_k)^{1/2} \tag{6.3}$$

Absolute Value of Summation of Exponential value is estimated by,

$$\text{AVSE} = \left|\frac{\sum_{k=1}^{n}(x_k)^{exp}}{n}\right| \tag{6.4}$$

Mean Absolute Value can be calculated by,

$$\text{MAV} = \frac{\sum|X - \mu|}{K} \tag{6.5}$$

The amplitude of the rectified EEG signal can be expressed by,

$$\text{exp} = \begin{cases} 0.50 & if\ (k\ \geq 0.25 * k \quad n \leq 0.75) \\ 0.75 & Otherwise \end{cases} \tag{6.6}$$

The frequency-domain features like maximum amplitude, mean frequency, power spectrum deformation, median frequency, and spectrum moment have been retrieved. The time-domain feature extraction is not only possible for transient and non-stationary characteristics of the EEG signal. The frequency-domain features should be retrieved with fundamental characteristics of EEG. When obtaining the continuous frequency on the EEG waveform, it consists of the central rhythms of frequency like theta, beta, gamma, and Delta, similar to various brain functions, states, and pathologies.

Healthy:

Absolute Value of the Summation of Square Root (ASS)	7.0766e+03
Mean Value of the Square Root (MSR)	1.5066
Absolute Value of the Summation of the Exponential Root (ASE)	1.8246
Mean Absolute Value (MAV)	6.5056
Waveform Length (WL)	246.1464
Zero Crossing	76
Slope Sign Change (SSC)	182
Auto-Regressive Coefficients (AR)	-0.3308
Root Mean Square (RMS)	0.5430
Wilson Amplitude (WAMP)	2043

Figure 6.4: Representation of time-domain features for Healthy Signals

	1
Maximum Amplitude	24.7663
Mean Frequency	8.4973e+03
Median Frequency	0.0325
Power Spectrum Deformation	-3.2031e+03

Figure 6.5: Representation of frequency domain features for Healthy Signals

Interictal:

Absolute Value of the Summation of Square Root (ASS)	1.1653e+04
Mean Value of the Square Root (MSR)	0.5973
Absolute Value of the Summation of the Exponential Root (ASE)	4.9285
Mean Absolute Value (MAV)	13.3298
Waveform Length (WL)	238.8708
Zero Crossing	52
Slope Sign Change (SSC)	146
Auto-Regressive Coefficients (AR)	-0.3284
Root Mean Square (RMS)	0.7278
Wilson Amplitude (WAMP)	1871

Figure 6.6: Representation of time-domain features for Interictal Signals

	1
Maximum Amplitude	31.3704
Mean Frequency	-3.9897e+04
Median Frequency	0.0212
Power Spectrum Deformation	-3.2031e+03

Figure 6.7: Representation of frequency domain features for Interictal Signals

Ictal:

Absolute Value of the Summation of Square Root (ASS)	1.7329e+04
Mean Value of the Square Root (MSR)	3.1375
Absolute Value of the Summation of the Exponential Root (ASE)	6.0361
Mean Absolute Value (MAV)	41.5786
Waveform Length (WL)	3.2913e+03
Zero Crossing	174
Slope Sign Change (SSC)	204
Auto-Regressive Coefficients (AR)	-0.3324
Root Mean Square (RMS)	6.0308
Wilson Amplitude (WAMP)	3962

Figure 6.8: Representation of time-domain features for Ictal Signals

	1
Maximum Amplitude	145.0774
Mean Frequency	1.6044e+04
Median Frequency	0.1052
Power Spectrum Deformation	-3.2031e+03

Figure 6.9: Representation of frequency domain features for Ictal Signals

6.3.3 Greedy Particle swarm optimization

After time and frequency domain features extraction, the greedy strategy determines the improved solution in the immediate neighborhood of the current solution. The proposed greedy PSO optimization involves the optimization of extracted features by choosing the best features among them. This technique improves the candidate solution through the optimization of the problem. The position solved the particle issues through the population of a candidate solution, and the particles move on the particle's location and velocity. The modification of the agent position is achieved by the velocity and position information. The particle movement influences the best local position. But the best-known search space that determines the best position could have been relied on by everyone. The greedy strategy involves where the objective function is considered, and it should be optimized at the corresponding point. At every step, the greedy choices are generated in a greedy algorithm to enhance the objective function. Bird flocking optimizes the specific objective function. Every agent recognizes the best value as gbest and pbest. Each agent modifies its position using the below information,

- Current velocity
- Current position
- Distance among current position and pbest
- Distance among current position and gbest

The time and frequency domain feature extraction has been declared to complete the greedy system to improve the optimal solutions' efficiency. The best solution from the best solutions of particles has been obtained using the proposed Greedy PSO technique. This technique has been most suitable for optimizing problems towards making a better solution over updating the particle's position and velocity. This algorithm provides the advantage of fast runtime.

Algorithm: 1 Greedy Particle Swarm Optimization

Input: Ex_c **-** Sequences of extracted features

Output:Op_dOptimization data

Procedure:

S, the Size of the total sequences of extract features

Initialize the decision variable $nvar_c$)

Initialize $decision\ matrix$ (var_c)

Maximum iteration (max_{iter})

To set the lower and upper bound variables,

vel_{min}=-10

vel_{max}=10

Let population size pop_{num} =length (Ex_c)

Let initialize the greedy_PSO parameters,

Inertia weight wt=1

Let inertia weight damping ration wt_{damp} =0.99

To find velocity limits,

vel_{max}=0.1*(vel_{max}-vel_{min})

vel_{min}=-vel_{max}

for i=1:pop_{num}

Let initialize position, value, velocity and best value,

To find the particle value(ρ_{value})

ρ_{value} (i).position=(Ex_c(i)), Let initialize velocity,

ρ_{value} (i).velocity=$zeros(var_c)$,

Let evaluation greedy process,

end

for i=1:max_{iter}

for i=1:pop_{num}

Clustered extraction from the sequences

Say S= (er_c)size

For i=1 to S

Let input data=$er_{c\,i,j}$

$An_{d(i,j)}$=$\left(\sqrt{er_{c\,i}} - \sqrt{er_{c\,j}}\right)^2$-$\left(\sqrt{er_{c\,j}} - \sqrt{er_{c\,i}}\right)^2$

End

Let v_f=$x_i - x_j/t$ // ant velocity initialization

Let r_{nd}= choose random numbers

Estimate p_s=function (An_d, r_{nd})

For i=1 to 255

Update the velocity

Let the velocity limits

ρ_{value}= wt*(ρ_{value}. velocity)+rand($nvar_c$)*ρ_{value}. position+ rand($nvar_c$)

For k=1-$r_{nd} - 1$

p_s=($r_{nd(i,k)} + r_{nd(i,k+1)}$)- (($r_{nd(i,k+1)} + r_{nd(i,k+1)}$))+$r_{nd}$

v_f=ω($r_{nd} - 1$)*$v_f(r_{nd}) - An_d/p_s(\sqrt{r_{nd}})$

End

End

Update An_d values,

Update the position,

Objective function obj_n

Op_d=$obj_n(An_d)$

Best value=mean (p_s)

Fitness value f_{fn}

If $f_{fn} < p_s$

Op_d=f_{fn}

End

6.3.4 Classification using Convolutional Neural Network (CNN)

The CNN classifier has been applied to EEG signals due to its effectiveness and extensive usage to predict the seizure. This network is interconnected with neurons, and it takes responsibility for the processing of information and signals.

The CNN network estimates the non-linear and linear dependencies between input and output data. The overall network links with neurons from one layer to another, composed of every single neuron. In a network, the weights are defined as neurons' strength and are activated during the training and testing process.

Like traditional perceptron NN, the CNN network is multi-layered and consists of the input layer, output layer, and many hidden layers. The hidden layer has been comprised of pooling layers, convolutional layers, and fully connected layers. In the CNN layer, the convolution operation has been used as an input and transmitted to the ensuring segment. In each neuron, the convolution adversaries respond to visual provocations. The networks include global and local pooling layers. The output of a one-layer neuron is combined with the next neuron. The average value is obtained from the previous layer that consists of the individual group of mean pooling. The CNN classifier provides the more efficient for high dimensional data analysis. In the CNN network, the parameter sharing scheme is utilized to mitigate the no parameters, spatial size of the representation, computation in-network, and quantity of parameters. The design of the pooling layer mitigates the control overfitting.

A. Convolutional layer

The convolutional layer reduces the dimensionality and performs convolution on the image into the matrix. The convolutional layer consists of the 64 feature maps into the input layer through 3*3 kernels. It includes the kernels that slide over EEG signals diagonally.

$$Y_k = \sum_{n=0}^{N-1} Z_n h_{k-n} \tag{6.7}$$

The kernel combines the matrix with input EEG signal and stride. Then controls the degree to which the filter integrates the diagonal input signals.

B. Pooling layer

The pooling layer reduces the number of parameters and maintains important information through downsampling or subsampling. Max pooling obtains the highest element from the rectified feature map. Then the output neurons are reduced based on the feature map. In a feature map, the sum of all elements is called sum pooling.

C. Fully connected layer

It obtains the filled association towards the complete activations through other layers. The feature map matrices are converted into vector form. Then combine these features to form a model.

D. Activation layer

Finally, the activation function classifies the output in the activation layer. The output obtains from the class using the activation function. The classification output is attained by sigmoid and tanh activation.

Tanh activation Function

$$\mathrm{A} = 1 - (z * z) \tag{6.8}$$

Sigmoid Activation Function:

$$A = z * (1 - z) \tag{6.9}$$

z represents $Features\ values$

Algorithm 2: Convolutional Neural Network
Input: optimized Sequences f_{fn} **Output: C**lassified output **Procedure:** C the Size of the Total sequences for classification. N_l=3 // no. of layer N_r=1 // no of runs Let N_s //no of samples Let N_f //no of features Initialize $Training\ Set\ Size\ (t_{\phi c})$ and $testing\ Set\ size\ (t_{\Psi c})$ // 80 % training and 20% testing From the sequences, the features were extracted and create a table of features set Letf_{fn} be the feature set extracted Let initialize CNN parameters, Let batch_size =1 No of the epochs=1 Let Lb_s be the labels corresponding to the selected features Let N_c be the no of identified classes Load f_{fn} // optimized data For i=1 to N_l Split F_{fs}into Ʈ   For j=1 to Ʈ To Find back_propagation_cnn,

```
For i=1:size(t_Ψc)
N_l.f_fn = t_Ψc(i,:)
End
For i=2:N_l
Layer=i
  If N_l(i)=t_Ψc(i,:)
Val=N_l(i)*t_Ψc(i,:)
****Convolutional layer*********
  For j=1:length(Val)
  Z=0;
For k=1: length(Val)
  Kk=kk+1;
Val=N_l(i − 1)*t_Ψc(k)
Val1=N_l(i)*t_Ψc(k(;,:,1))
End
End
End
**********Pooling Layer*************
  For j=1:length(Val)
  h=N_l(i)*t_Ψc(i,:)+N_l(i − 1)*t_Ψc(k)
For k=1: length(Val)
  Kk=kk+1;
Val=N_l(i − 1)*t_Ψc(k)
Val1=N_l(i)*t_Ψc(k(;,:,1))
End
End
End
************Fully connected Layer
```

```
For j=1:length(Val)
 h=N_l(i)*t_Ψc(i-1)+N_l(i-1)*t_Ψc(k-1)
For k=1: length(Val)
 Kk=kk+1;
Val=N_l(i-1)*t_Ψc(k)
Val1=N_l(i)*t_Ψc(k(;,:,1))
End
End
End
**************Activation Layer*********
 For j=1:length(Val)
 h=N_l(i)*t_Ψc(i-1)+N_l(i-1)*t_Ψc(k-1)
For k=1: length(Val)
 Kk=kk+1;
Val=N_l(i-1)*t_Ψc(k)
Val1=N_l(i)*t_Ψc(k(;,:,1))
End
End
 Let f_fn is to be feature in F_fs(i,j)
        Eliminate the subset values Ʈ from F_fs
            Let T_CLF train (f_fn, Lb_s)
               Train out T_out=sim(T_CLF, T_in)
D_pro=mapminmax( T_out,1)  // decision profile
R_sort=sort( T_out) //rank level
  Let compute accuracy
Switch case 2
     Compute Trained T_CLF
Let R_sort=sort( T_out) //rank level
```

Switch case 3

Trained T_{CLF} estimates f_{fn}

Let R_{sort}=sort(T_{out}) //rank level

Let accuracy = mean(T_{CLF} ,1)

$T_{CLF} = \sum_i T_{out} / {R_{sort}}^2$

$cnt_i = \Sigma(f_{fn})$ in belonging to $samples\ N_s$

End

Compute Total count as $Cnt_T = \sum_{i=1}^{N} cnt_i$

Estimate probabilistic Components

For i=1 toN_c

$P_{comp}(i) = cnt_i/Cnt_T$

End

End

Algorithm explanation

In this method, the optimized sequences are f_{fn} and it initializes the training and testing set size. The features are extracted from sequences and generated from the list of feature sets. Then initialize the CNN parameter and determined the backpropagation. There are multiple layers like pooling layer, fully connected layer, convolutional layer, and the activation layer used to obtain the classified output with the assistance of sigmoid function and tanh (Fnandri mam Function).

6.4 Results and Discussion

This section represents the proposed method of various performance measures such as specificity, accuracy, sensitivity, F score, recall precision, and the Jaccard coefficient that determines the EEG signal's seizure with high efficiency. The proposed method was applied to the same dataset [124], and it consists of five kinds of EEG datasets (from Set A to Set E). Each dataset contains 100 single channels with a duration of 23.6s.

6.4.1 Performance analysis

The proposed method's performance analysis has been evaluated, and the evaluation formula has been described in the previous chapter.

6.4.1.1. Performance analysis for healthy, Interictal and ictal

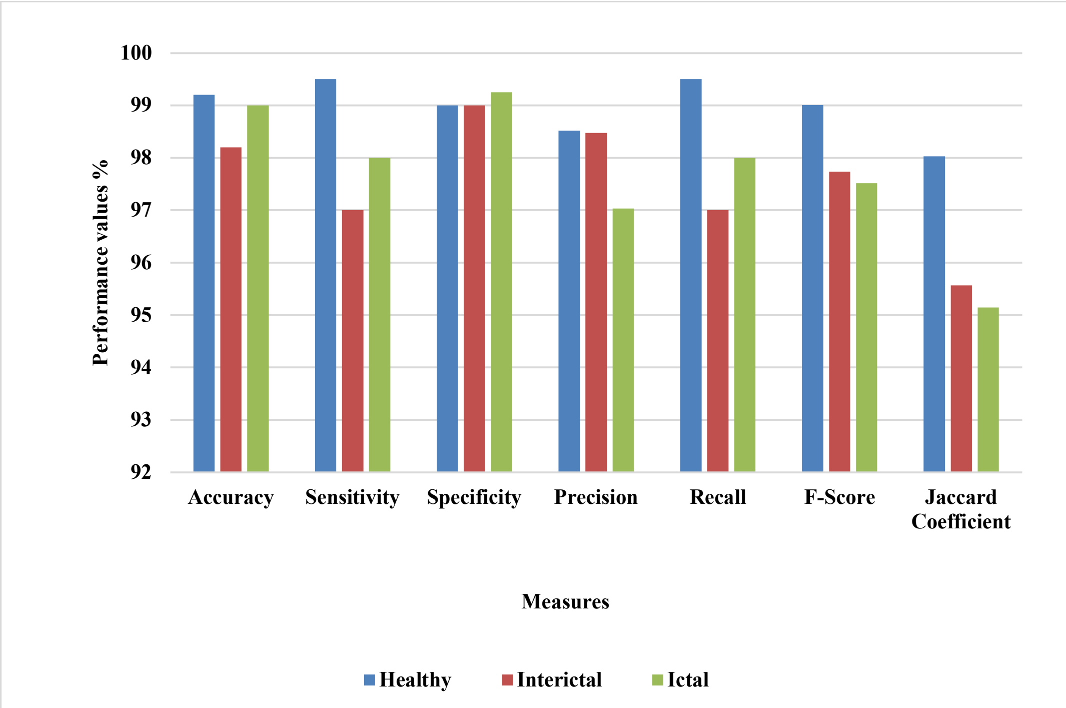


Figure 6.10: Performance measures of the proposed method for seizure classification

Figure 6.10 represents the proposed method's various performance measures for the classification of the seizure (Healthy, Inter-ictal, and Ictal). In this analysis, the healthy classification provides 99.2% accuracy, 99.5% sensitivity, 99.9% specificity, 98% precision, 99.5% recall, 99% f-score, and 98% Jaccard coefficient. The inter-ictal classification gives 98.2% accuracy, 97% sensitivity, 99% specificity, 98% precision, 97% recall, 97% f-score, and 95% Jaccard coefficient. The Ictal classification provides 99% accuracy, 98% sensitivity, 99% specificity, 98% precision, 97% recall, 97.7% f-score, and 95% Jaccard coefficient. From this analysis, it has been identified that the proposed classification method yielded better accuracy for healthy signals as compared to other abnormalities.

6.4.1.2 Performance analysis for S-Z, S-F, S-N, S-ZNF

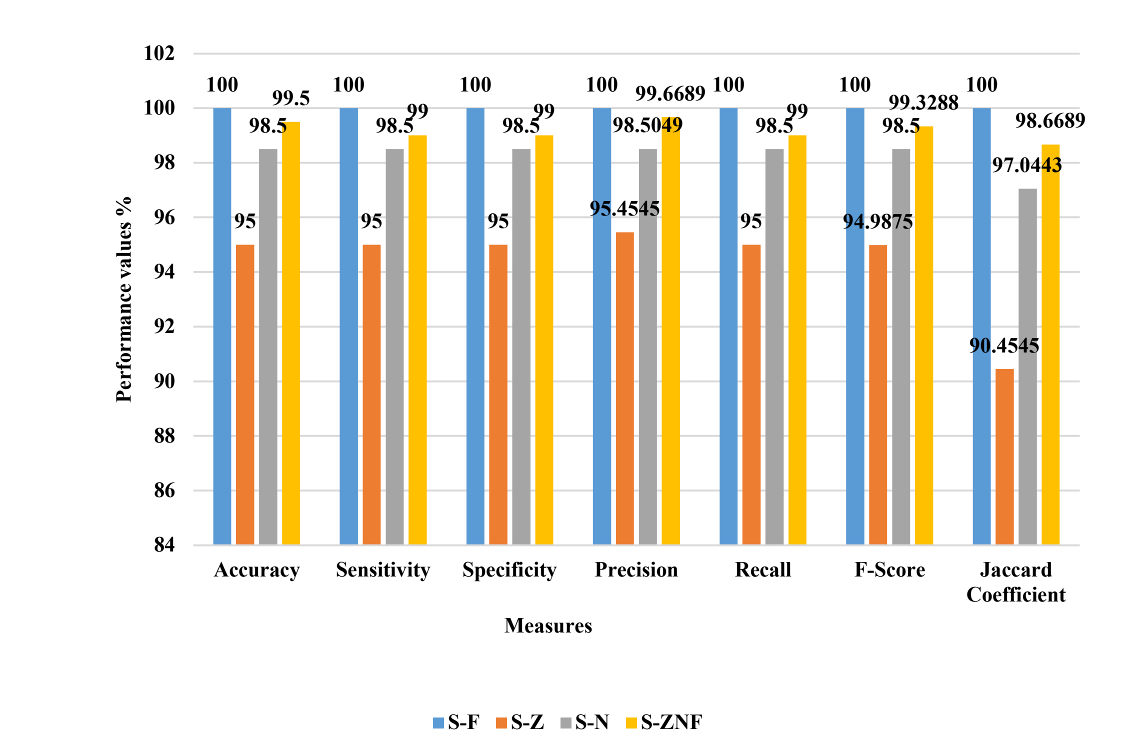


Figure 6.11: Performance measures of the proposed method for S-Z, S-F, S-N, S-ZNF

Figure 6.11 represents the proposed method's various performance measures for S-Z, S-F, S-N, and S-ZNF segments. In this graph, the proposed method have 100% accuracy, specificity, sensitivity, recall, precision, f-score, and Jaccard coefficient for S-F segment, 95% accuracy, specificity, sensitivity, recall, precision, f-score, 90% Jaccard coefficient for S-Z segment, 98.5% accuracy, sensitivity, specificity, precision, recall, f-score, 97% Jaccard coefficient for S-N segment and 99% accuracy, specificity, sensitivity, recall, precision, f-score, and Jaccard coefficient for S-ZNF segment. The proposed classification method has yielded high efficiencies for the S-ZNF segment compared to other segments from this analysis.

6.4.1.3 Comparative analysis

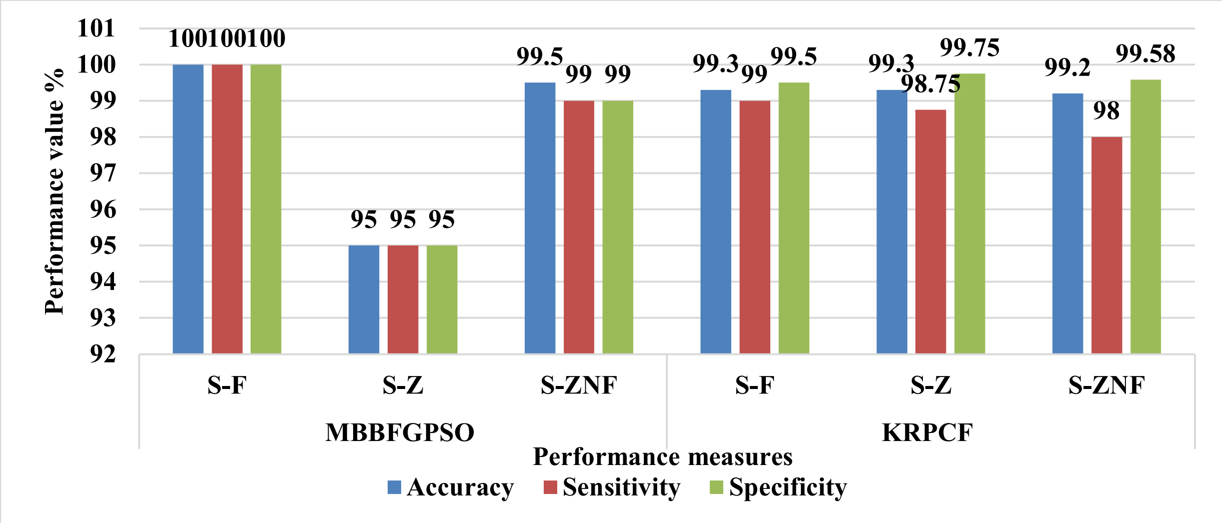


Figure 6.12: Comparison of Performance measures evaluation for the proposed and existing method

Figure 6.12 compares the existing method KRPCF (kernel robust probabilistic collaborative function) with the proposed method. The existing method provides 99.3% accuracy, 99% sensitivity, and 99.5% specificity for S-F segment, 99.3% accuracy, 98.75% sensitivity, 99.75% specificity for S-Z segment, and 99.2% accuracy, 98% sensitivity, 99.58% specificity for S-ZNF segment. The accuracy of the proposed method for the S-F value is higher than the existing technique. The sensitivity of the proposed technique for S-F, S-Z, and S-ZNF is 100, 95, 99, respectively, which looks better than the existing KRPCF technique 99, 98.75, 98. These results have validated the proposed method's efficacy compared to the existing method.

6.5 Summary

This chapter has discussed the time and frequency domain features in EEG signals. The proposed method MBBF-GPSO has been used for seizure detection in EEG signals, and CNN has been utilized to classify the ictal, inter-ictal, and healthy classes of EEG signals. The experimental results have proved the efficacy of the proposed method with the values of various performance measures.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

In this thesis, the secured cardiac abnormality detection is introduced using the ECG signal databases. To enhance the compression process of the ECG signal, the Dictionary matrix generation is utilized and security is introduced by using bitwise embedding mechanism. The detection of ECG cardiac abnormalities like Bundle Branch Block, Dysrhythmia, Cardiomyopathy etc. have been achieved by using modified dynamic classification method. The results of the proposed techniques with performance measures like accuracy, specificity, sensitivity, precision, Jaccard coefficient, and dice co-efficient have been thoroughly presented and a brief comparison with other existing techniques have been provided. Here, it can be easily observed that the proposed method outperforms other methods in terms of improved efficiency and accuracy using PTB diagnostic ECG dataset. Further, an automatic method of arrhythmia classification using the proposed Bat-Rider Optimization algorithm-based deep convolutional neural networks (BaROA-based DCNN) is proposed. The experimentation is performed using the MIT-BIH Arrhythmia Database and the analysis is performed based on the evaluation metrics.

For epileptic Seizure signals detection using university of Bonn database, the hybrid feature extraction method and convolutional neural networks methods have been used. In the first proposed system, the pre-processing system have been attained by using improved Curvelet Transform. To achieve the efficient dimensionality reduction or feature extraction process by using a hybrid model with the combination of Modified Graph Theory (MGT), Novel Pattern Transformation, and GLCM features. The classification process has been achieved by using the PCA based Random forest classification. The proposed method of performance measures for the classes of healthy, ictal, and inter-ictal. The proposed method gives 99.3% accuracy, 98.83% of sensitivity, and 99.5% of specificity. From this statistical analysis, the proposed method has 8% increased performances compared to the existing method. In the Second proposed system, the epileptic seizure detection is attained by using a neural network system. The pre-processing is done by using enhanced Curvelet Transform. To optimize the extracted features, the Greedy Particle Swarm Optimization is utilized. Then the neural network is used as an effective classification technique that provides the results as ictal or inter-ictal. The performance measures of the proposed method are evaluated for S-Z, S-F, S-N, S-ZNF segments. In these results, the S-F segment provides 100% accuracy, specificity, sensitivity, recall, precision, f-score, and Jaccard coefficient. The S-Z segment gives 95% accuracy, specificity, sensitivity, recall, precision, f-score, and 90% of the Jaccard coefficient. The S-N segment provides 98.5% accuracy, sensitivity, specificity, precision, recall, f-score, and 97% of the Jaccard coefficient. The S-ZNF segment provides 99% accuracy, specificity, sensitivity, recall, precision, f-score, and Jaccard coefficient. From these results, it has been verified that the proposed method gives high performances for S-ZNF segment as compared than other methods. In comparative analysis, a brief comparison has been provided with the existing KRPCF (Kernel Robust Probabilistic Collaborative Function) method.

7.2 FUTURE WORK

This work determined heart abnormalities in ECG signal and classified the seizure detection in EEG signal with the advantages of enhanced security, high classification accuracy and minimum computational time. This work may be extended to the other human physiological databases like for EMG, ENG, EOG, ERG, GSR, PPG, etc. Efforts to work on patterns on these databases can be work out further with some other advanced level algorithms.

REFERENCES

[1] R. J. P. Princy, S. Parthasarathy, P. S. H. Jose, A. R. Lakshminarayanan, and S. Jeganathan, "Prediction of Cardiac Disease using Supervised Machine Learning Algorithms," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2020, pp. 570-575.

[2] L. Vindhya, P. A. Beliray, C. R. Sravani, and D. Divya, "Prediction of Heart Disease Using Machine Learning Techniques," *International Journal of Research in Engineering, Science and Management,* vol. 3, pp. 325-326, 2020.

[3] V. Hachinski and M. R. Azarpazhooh, "Stroke is a burdensome but preventable brain disorder," *The Lancet. Neurology,* vol. 15, p. 892, 2016.

[4] Z. Lasefr, S. S. V. Ayyalasomayajula, and K. Elleithy, "Epilepsy seizure detection using EEG signals," in *2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*, 2017, pp. 162-167.

[5] R. Ebrahimpour, K. Babakhan, S. A. A. A. Arani, and S. Masoudnia, "Epileptic seizure detection using a neural network ensemble method and wavelet transform," *Neural Network World,* vol. 22, p. 291, 2012.

[6] E. E. Barcelon, W.-H. Cho, S. B. Jun, and S. J. Lee, "Brain microglial activation in chronic pain-associated affective disorder," *Frontiers in Neuroscience,* vol. 13, p. 213, 2019.

[7] R. Roy, A. Konar, and D. Tibarewala, "CONTROL OF ARTIFICIAL LIMB USING EEG & EMG-A REVIEW," *Escuela de Biosciencias e Ingenierías de la Universidad de Jadavpur, Kolkata,* 2011.

[8] M. Nilashi, O. bin Ibrahim, H. Ahmadi, and L. Shahmoradi, "An analytical method for diseases prediction using machine learning techniques," *Computers & Chemical Engineering,* vol. 106, pp. 212-223, 2017.

[9] R. Bhardwaj, A. R. Nambiar, and D. Dutta, "A study of machine learning in healthcare," in *2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC)*, 2017, pp. 236-241.

[10] K. Saxena and R. Sharma, "Efficient heart disease prediction system," *Procedia Computer Science,* vol. 85, pp. 962-969, 2016.

[11] B. Bahrami and M. H. Shirvani, "Prediction and Diagnosis of Heart Disease by Data Mining Techniques," *Journal of Multidisciplinary Engineering Science and Technology (JMEST),* vol. 2, pp. 164-168, 2015.

[12] D. Chen, S. Wan, J. Xiang, and F. S. Bao, "A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG," *PloS one,* vol. 12, p. e0173138, 2017.

[13] R. Hussein, M. Elgendi, Z. J. Wang, and R. K. Ward, "Robust detection of epileptic seizures based on L1-penalized robust regression of EEG signals," *Expert Systems with Applications,* vol. 104, pp. 153-167, 2018.

[14] S. Chen, X. Zhang, L. Chen, and Z. Yang, "Automatic diagnosis of epileptic seizure in electroencephalography signals using nonlinear dynamics features," *IEEE Access,* vol. 7, pp. 61046-61056, 2019.

[15] S. H. Jambukia, V. K. Dabhi, and H. B. Prajapati, "Classification of ECG signals using machine learning techniques: A survey," in *2015 International Conference on Advances in Computer Engineering and Applications*, 2015, pp. 714-721.

[16] E. J. d. S. Luz, W. R. Schwartz, G. Cámara-Chávez, and D. Menotti, "ECG-based heartbeat classification for arrhythmia detection: A survey," *Computer methods and programs in biomedicine,* vol. 127, pp. 144-164, 2016.

[17] C. Venkatesan, P. Karthigaikumar, A. Paul, S. Satheeskumaran, and R. Kumar, "ECG signal preprocessing and SVM classifier-based abnormality detection in remote healthcare applications," *IEEE Access,* vol. 6, pp. 9767-9773, 2018.

[18] S. Celin and K. Vasanth, "ECG signal classification using various machine learning techniques," *Journal of medical systems,* vol. 42, p. 241, 2018.

[19] A. Lyon, R. Ariga, A. Mincholé, M. Mahmod, E. Ormondroyd, P. Laguna*, et al.*, "Distinct ECG phenotypes identified in hypertrophic cardiomyopathy using machine learning associate with arrhythmic risk markers," *Frontiers in physiology,* vol. 9, p. 213, 2018.

[20] Y. Liu, R. He, K. Wang, Q. Li, Q. Sun, N. Zhao*, et al.*, "Automatic detection of ECG abnormalities by using an ensemble of deep residual networks with attention," in *Machine learning and medical engineering for cardiovascular health and intravascular imaging and computer assisted stenting*, ed: Springer, 2019, pp. 88-95.

[21] S. Thiyagarajan and T. Chakravarthy, "A Survey on ECG Data Classification Using Machine Learning Approaches," 2019.

[22] M. G. Shankar and C. G. Babu, "An exploration of ECG signal feature selection and classification using machine learning techniques," *Int. J. Innovative Technol. Exploring Eng. Regul,* p. 9, 2020.

[23] C. U. Kumari, R. Ankita, T. Pavani, N. A. Vignesh, N. T. Varma, M. A. Manzar*, et al.*, "Heart Rhythm Abnormality Detection and Classification using Machine Learning Technique," in *2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184)*, 2020, pp. 580-584.

[24] P. Vyas and D. Pandit, "Heartbeat Abnormality Detection using Machine Learning Models and Rate Variability (HRV) Data," 2018.

[25] A. I. Humayun, S. Ghaffarzadegan, M. I. Ansari, Z. Feng, and T. Hasan, "Towards Domain Invariant Heart Sound Abnormality Detection using Learnable Filterbanks," *IEEE Journal of Biomedical and Health Informatics,* 2020.

[26] U. B. Baloglu, M. Talo, O. Yildirim, R. San Tan, and U. R. Acharya, "Classification of myocardial infarction with multi-lead ECG signals and deep CNN," *Pattern Recognition Letters,* vol. 122, pp. 23-30, 2019.

[27] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals," *Information Sciences,* vol. 415, pp. 190-198, 2017.

[28] M. Zubair, J. Kim, and C. Yoon, "An automated ECG beat classification system using convolutional neural networks," in *2016 6th international conference on IT convergence and security (ICITCS)*, 2016, pp. 1-5.

[29] A. Diker, D. Avci, E. Avci, and M. Gedikpinar, "A new technique for ECG signal classification genetic algorithm Wavelet Kernel extreme learning machine," *Optik,* vol. 180, pp. 46-55, 2019.

[30] S. A. A. Yusuf and R. Hidayat, "MFCC feature extraction and KNN classification in ECG signals," in *2019 6th International Conference on Information Technology, Computer and Electrical Engineering (ICITACEE)*, 2019, pp. 1-5.

[31] R. Kumar, A. Kumar, and G. K. Singh, "Hybrid method based on singular value decomposition and embedded zero tree wavelet technique for ECG signal compression," *Computer methods and programs in biomedicine,* vol. 129, pp. 135-148, 2016.

[32] K.-K. Tseng, X. He, W.-M. Kung, S.-T. Chen, M. Liao, and H.-N. Huang, "Wavelet-based watermarking and compression for ECG signals with verification evaluation," *Sensors,* vol. 14, pp. 3721-3736, 2014.

[33] T.-H. Tsai and F.-L. Tsai, "Efficient lossless compression scheme for multi-channel ECG signal processing," *Biomedical Signal Processing and Control,* vol. 59, p. 101879, 2020.

[34] Y.-H. Hu, Y.-H. Li, and M. Zhao, "Integration of information hiding and compression for biomedical signals," *Journal of Internet Technology,* vol. 20, pp. 975-982, 2019.

[35] G. Da Poian, C. J. Rozell, R. Bernardini, R. Rinaldo, and G. D. Clifford, "Matched filtering for heart rate estimation on compressive sensing ECG measurements," *IEEE Transactions on Biomedical Engineering,* vol. 65, pp. 1349-1358, 2017.

[36] A. A. Bhurane, M. Sharma, R. San-Tan, and U. R. Acharya, "An efficient detection of congestive heart failure using frequency localized filter banks for the diagnosis with ECG signals," *Cognitive Systems Research,* vol. 55, pp. 82-94, 2019.

[37] N. Sihem, S. Bitam, and A. Mellouk, "An enhanced random forest for cardiac diseases identification based on ECG signal," in *2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC)*, 2018, pp. 1339-1344.

[38] Z. Masetic and A. Subasi, "Congestive heart failure detection using random forest classifier," *Computer methods and programs in biomedicine,* vol. 130, pp. 54-64, 2016.

[39] D. C. YADAV and S. PAL, "Prediction of Heart Disease Using Feature Selection and Random Forest Ensemble Method," *International Journal of Pharmaceutical Research,* vol. 12, 2020.

[40] P. Patil and S. Kinariwala, "Automated Diagnosis of Heart Disease using Random Forest Algorithm," *International Journal of Advance Research, Ideas and Innovations in Technology. https://github. com/mbbrigitte/Predicting_heart_disease_UCI/blob/master/heartdisease_UCI. Rmd,* 2017.

[41] E. Alickovic and A. Subasi, "Medical decision support system for diagnosis of heart arrhythmia using DWT and random forests classifier," *Journal of medical systems,* vol. 40, p. 108, 2016.

[42] F. I. Alarsan and M. Younes, "Analysis and classification of heart diseases using heartbeat features and machine learning algorithms," *Journal of Big Data,* vol. 6, pp. 1-15, 2019.

[43] Z. Wang, H. Li, C. Han, S. Wang, and L. Shi, "Arrhythmia Classification Based on Multiple Features Fusion and Random Forest Using ECG," *Journal of Medical Imaging and Health Informatics,* vol. 9, pp. 1645-1654, 2019.

[44] R. R. Janghel and S. kumar Pandey, "Classification and Detection of Arrhythmia in ECG Signal Using Machine Learning Techniques," in *2019 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, 2019, pp. 101-104.

[45] W. Yang, Y. Si, D. Wang, and B. Guo, "Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine," *Computers in biology and medicine,* vol. 101, pp. 22-32, 2018.

[46] W. Yang, Y. Si, D. Wang, G. Zhang, X. Liu, and L. Li, "Automated intra-patient and inter-patient coronary artery disease and congestive heart failure detection using EFAP-Net," *Knowledge-Based Systems,* p. 106083, 2020.

[47] Z. Arabasadi, R. Alizadehsani, M. Roshanzamir, H. Moosaei, and A. A. Yarifard, "Computer aided decision making for heart disease detection using hybrid neural network-Genetic algorithm," *Computer methods and programs in biomedicine,* vol. 141, pp. 19-26, 2017.

[48] P. Kora, A. Abraham, and K. Meenakshi, "Heart disease detection using hybrid of bacterial foraging and particle swarm optimization," *Evolving Systems,* vol. 11, pp. 15-28, 2020.

[49] R. P. Cherian, "Weight Optimized Neural Network for Heart Disease Prediction using Hybrid Lion plus Particle Swarm Algorithm," *Journal of Biomedical Informatics,* p. 103543, 2020.

[50] G. T. Reddy, M. P. K. Reddy, K. Lakshmanna, D. S. Rajput, R. Kaluri, and G. Srivastava, "Hybrid genetic algorithm and a fuzzy logic classifier for heart disease diagnosis," *Evolutionary Intelligence,* vol. 13, pp. 185-196, 2020.

[51] A. Subasi, J. Kevric, and M. A. Canbaz, "Epileptic seizure detection using hybrid machine learning methods," *Neural Computing and Applications,* vol. 31, pp. 317-325, 2019.

[52] A. K. Jaiswal and H. Banka, "Epileptic seizure detection in EEG signal using machine learning techniques," *Australasian physical & engineering sciences in medicine,* vol. 41, pp. 81-94, 2018.

[53] F. S. Miften, M. Diykh, S. Abdulla, and J. H. Green, "Epileptic Seizures Detection Based on Non-linear Characteristics Coupled with Machine Learning Techniques," 2020.

[54] A. Anugraha, E. Vinotha, R. Anusha, S. Giridhar, and K. Narasimhan, "A machine learning application for epileptic seizure detection," in *2017 International Conference on Computational Intelligence in Data Science (ICCIDS)*, 2017, pp. 1-4.

[55] R. Sahu, S. R. Dash, L. A. Cacha, R. R. Poznanski, and S. Parida, "Epileptic seizure detection: a comparative study between deep and traditional machine learning techniques," *Journal of Integrative Neuroscience,* vol. 19, pp. 1-9, 2020.

[56] C. Mahjoub, R. L. B. Jeannès, T. Lajnef, and A. Kachouri, "Epileptic seizure detection on EEG signals using machine learning techniques and advanced preprocessing methods," *Biomedical Engineering/Biomedizinische Technik,* vol. 65, pp. 33-50, 2020.

[57] D. K. Atal and M. Singh, "A hybrid feature extraction and machine learning approaches for epileptic seizure detection," *Multidimensional Systems and Signal Processing,* pp. 1-23, 2019.

[58] M. Mursalin, Y. Zhang, Y. Chen, and N. V. Chawla, "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier," *Neurocomputing,* vol. 241, pp. 204-214, 2017.

[59] T. Zhang, W. Chen, and M. Li, "Generalized Stockwell transform and SVD-based epileptic seizure detection in EEG using random forest," *Biocybernetics and Biomedical Engineering,* vol. 38, pp. 519-534, 2018.

[60] T. Zhang, W. Chen, and M. Li, "AR based quadratic feature extraction in the VMD domain for the automated seizure detection of EEG using random forest classifier," *Biomedical Signal Processing and Control,* vol. 31, pp. 550-559, 2017.

[61] N. D. Truong, L. Kuhlmann, M. R. Bonyadi, J. Yang, A. Faulks, and O. Kavehei, "Supervised learning in automatic channel selection for epileptic seizure detection," *Expert Systems with Applications,* vol. 86, pp. 199-207, 2017.

[62] K. Singh and J. Malhotra, "IoT and cloud computing based automatic epileptic seizure detection using HOS features based random forest classification," *Journal of Ambient Intelligence and Humanized Computing,* pp. 1-16, 2019.

[63] X. Wang, G. Gong, N. Li, and S. Qiu, "Detection analysis of epileptic EEG using a novel random forest model combined with grid search optimization," *Frontiers in human neuroscience,* vol. 13, p. 52, 2019.

[64] R. Sharma and K. Chopra, "EEG-based epileptic seizure detection using GPLV model and multi support vector machine," *Journal of Information and Optimization Sciences,* vol. 41, pp. 143-161, 2020.

[65] R. Hussein and R. Ward, "Energy-efficient EEG monitoring systems for wireless epileptic seizure detection," in *Energy Efficiency of Medical Devices and Healthcare Applications*, ed: Elsevier, 2020, pp. 69-85.

[66] P. A. Hagargi and D. Shubhangi, "Brain tumor MR image fusion using most dominant features extraction from wavelet and curvelet transforms," *Brain,* vol. 5, pp. 33-38, 2018.

[67] P. M. Krishnammal and S. S. Raja, "Medical image segmentation using fast discrete curvelet transform and classification methods for MRI brain images," *Multimedia Tools and Applications,* pp. 1-24, 2019.

[68] M. Arif and G. Wang, "Fast curvelet transform through genetic algorithm for multimodal medical image fusion," *Soft Computing,* vol. 24, pp. 1815-1836, 2020.

[69] C. Zhao, Y. Liang, C. Li, R. Gao, J. Wei, R. Zuo*, et al.*, "Localization of Epileptogenic Zone Based on Cortico-Cortical Evoked Potential (CCEP): A Feature Extraction and Graph Theory Approach," *Frontiers in neuroinformatics,* vol. 13, p. 31, 2019.

[70] B. Akbarian and A. Erfanian, "A framework for seizure detection using effective connectivity, graph theory, and multi-level modular network," *Biomedical Signal Processing and Control,* vol. 59, p. 101878, 2020.

[71] F. M. Al-Shargie, O. Hassanin, U. Tariq, and H. Al-Nashash, "EEG-Based Semantic Vigilance Level Classification Using Directed Connectivity Patterns and Graph Theory Analysis," *IEEE Access,* vol. 8, pp. 115941-115956, 2020.

[72] A. K. Jaiswal and H. Banka, "Local pattern transformation based feature extraction techniques for classification of epileptic EEG signals," *Biomedical Signal Processing and Control,* vol. 34, pp. 81-92, 2017.

[73] T. Tuncer, S. Dogan, F. Ertam, and A. Subasi, "A novel ensemble local graph structure based feature extraction network for EEG signal analysis," *Biomedical Signal Processing and Control,* vol. 61, p. 102006, 2020.

[74] H. U. Amin, W. Mumtaz, A. R. Subhani, M. N. M. Saad, and A. S. Malik, "Classification of EEG signals based on pattern recognition approach," *Frontiers in computational neuroscience,* vol. 11, p. 103, 2017.

[75] K. Samiee, P. Kovács, and M. Gabbouj, "Epileptic seizure detection in long-term EEG records using sparse rational decomposition and local Gabor binary patterns feature extraction," *Knowledge-Based Systems,* vol. 118, pp. 228-240, 2017.

[76] S. K. PS and V. Dharun, "Extraction of texture features using GLCM and shape features using connected regions," *International Journal of Engineering and Technology,* 2016.

[77] R. Usha and K. Perumal, "SVM classification of brain images from MRI scans using morphological transformation and GLCM texture features," *International journal of computational systems engineering,* vol. 5, pp. 18-23, 2019.

[78] D. Kumar, "Feature Extraction and Selection of kidney Ultrasound Images Using GLCM and PCA," *Procedia Computer Science,* vol. 167, pp. 1722-1731, 2020.

[79] H. Khan, L. Marcuse, M. Fields, K. Swann, and B. Yener, "Focal onset seizure prediction using convolutional networks," *IEEE Transactions on Biomedical Engineering,* vol. 65, pp. 2109-2118, 2017.

[80] T. N. Alotaiby, S. A. Alshebeili, F. M. Alotaibi, and S. R. Alrshoud, "Epileptic seizure prediction using CSP and LDA for scalp EEG signals," *Computational intelligence and neuroscience,* vol. 2017, 2017.

[81] N. D. Truong, A. D. Nguyen, L. Kuhlmann, M. R. Bonyadi, J. Yang, S. Ippolito*, et al.*, "Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram," *Neural Networks,* vol. 105, pp. 104-111, 2018.

[82] D. J. DiLorenzo, K. W. Leyde, and D. Kaplan, "Neural state monitoring in the treatment of epilepsy: Seizure prediction—conceptualization to first-in-man study," *Brain sciences,* vol. 9, p. 156, 2019.

[83] D. R. Freestone, P. J. Karoly, and M. J. Cook, "A forward-looking review of seizure prediction," *Current opinion in neurology,* vol. 30, pp. 167-173, 2017.

[84] K. Das, D. Daschakladar, P. P. Roy, A. Chatterjee, and S. P. Saha, "Epileptic seizure prediction by the detection of seizure waveform from the pre-ictal phase of EEG signal," *Biomedical Signal Processing and Control,* vol. 57, p. 101720, 2020.

[85] K. Gadhoumi, J.-M. Lina, F. Mormann, and J. Gotman, "Seizure prediction for therapeutic devices: A review," *Journal of neuroscience methods,* vol. 260, pp. 270-282, 2016.

[86] H. Sadeghzadeh, H. Hosseini-Nejad, and S. Salehi, "Real-time epileptic seizure prediction based on online monitoring of pre-ictal features," *Medical & biological engineering & computing,* vol. 57, pp. 2461-2469, 2019.

[87] U. R. Acharya, Y. Hagiwara, and H. Adeli, "Automated seizure prediction," *Epilepsy & Behavior,* vol. 88, pp. 251-261, 2018.

[88] Z. Li, D. Zhou, L. Wan, J. Li, and W. Mou, "Heartbeat classification using deep residual convolutional neural network from 2-lead electrocardiogram," *Journal of Electrocardiology,* vol. 58, pp. 105-112, 2020.

[89] S. K. Mohapatra and M. N. Mohanty, "Arrhythmia Detection Using a Radial Basis Function Network With Wavelet Features," *International Journal of Knowledge-Based Organizations (IJKBO),* vol. 10, pp. 48-56, 2020.

[90] S. S. Yadav, S. M. Jadhav, R. G. Bonde, and S. T. Chaudhari, "Automated Cardiac Disease Diagnosis Using Support Vector Machine," in *2020 3rd International Conference on Communication System, Computing and IT Applications (CSCITA)*, 2020, pp. 56-61.

[91] M. M. Ghiasi, S. Zendehboudi, and A. A. Mohsenipour, "Decision tree-based diagnosis of coronary artery disease: CART model," *Computer Methods and Programs in Biomedicine,* vol. 192, p. 105400, 2020.

[92] S. Bhatia, P. Prakash, and G. Pillai, "SVM based decision support system for heart disease classification with integer-coded genetic algorithm to select critical features," in *Proceedings of the world congress on engineering and computer science*, 2008, pp. 34-38.

[93] M. Shouman, T. Turner, and R. Stocker, "Applying k-nearest neighbour in diagnosing heart disease patients," *International Journal of Information and Education Technology,* vol. 2, pp. 220-223, 2012.

[94] A. Khemphila and V. Boonjing, "Heart disease classification using neural network and feature selection," in *2011 21st International Conference on Systems Engineering*, 2011, pp. 406-409.

[95] S. Iftikhar, K. Fatima, A. Rehman, A. S. Almazyad, and T. Saba, "An evolution based hybrid approach for heart diseases classification and associated risk factors identification," 2017.

[96] M. Z. Parvez and M. Paul, "Seizure prediction using undulated global and local features," *IEEE Transactions on Biomedical Engineering,* vol. 64, pp. 208-217, 2016.

[97] R. Sharma, R. B. Pachori, and P. Sircar, "Seizures classification based on higher order statistics and deep neural network," *Biomedical Signal Processing and Control,* vol. 59, p. 101921, 2020.

[98] S. S. Kumar and N. Kasthuri, "EEG seizure classification based on exploiting phase space reconstruction and extreme learning," *Cluster Computing,* vol. 22, pp. 11477-11487, 2019.

[99] R. Sarić, D. Jokić, N. Beganović, L. G. Pokvić, and A. Badnjević, "FPGA-based real-time epileptic seizure classification using Artificial Neural Network," *Biomedical Signal Processing and Control,* vol. 62, p. 102106, 2020.

[100] L. A. Moctezuma and M. Molinas, "EEG Channel-selection method for epileptic-seizure classification based on multi-objective optimization," *Frontiers in Neuroscience,* vol. 14, p. 593, 2020.

[101] Ö. Türk and M. S. Özerdem, "Epilepsy detection by using scalogram based convolutional neural network from EEG signals," *Brain sciences,* vol. 9, p. 115, 2019.

[102] M. Li, W. Chen, and T. Zhang, "Classification of epilepsy EEG signals using DWT-based envelope analysis and neural network ensemble," *Biomedical Signal Processing and Control,* vol. 31, pp. 357-365, 2017.

[103] C. Sun, H. Cui, W. Zhou, W. Nie, X. Wang, and Q. Yuan, "Epileptic seizure detection with eeg textural features and imbalanced classification based on easyensemble learning," *International journal of neural systems,* vol. 29, p. 1950021, 2019.

[104] S. Mian Qaisar and A. Subasi, "Effective epileptic seizure detection based on the event-driven processing and machine learning for mobile healthcare," *Journal of Ambient Intelligence and Humanized Computing,* pp. 1-13, 2020.

[105] *The PTB Diagnostic ECG Database*, Available: https://www.physionet.org/physiobank/database/ptbdb/

[106] T.-H. Tsai and W.-T. Kuo, "An efficient ECG lossless compression system for embedded platforms with telemedicine applications," *IEEE Access,* vol. 6, pp. 42207-42215, 2018.

[107] O. Yildirim, R. San Tan, and U. R. Acharya, "An efficient compression of ECG signals using deep convolutional autoencoders," *Cognitive Systems Research,* vol. 52, pp. 198-211, 2018.

[108] C. K. Jha and M. H. Kolekar, "ECG data compression algorithm for tele-monitoring of cardiac patients," *International Journal of Telemedicine and Clinical Practices,* vol. 2, pp. 31-41, 2017.

[109] Saurabh Pal, MadhuchhandaMitra, " Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method", Measurement, vol.43, no.2, pp.255-261, February 2010.

[110] Bo Hjorth, “EEG analysis based on time domain properties”, Electroencephalography and Clinical Neurophysiology, vol.29, no.3, pp.306-310, September 1970. [109] Bo Hjorth, “EEG analysis based on time domain properties”, Electroencephalography and Clinical Neurophysiology, vol.29, no.3, pp.306-310, September 1970.

[111] TomásTeijeiro, Paulo Félix, JesúsPresedo, and Daniel Castro, "Heartbeat Classification Using Abstract Features From the Abductive Interpretation of the ECG", IEEE Journal of Biomedical and Health Informatics, vol.22 , no.2 , pp.409 - 420, March 2018.

[112] João Paulo R.R. Leite and Robson L. Moreno, " Heartbeat classification with low computational cost using Hjorth parameters", IET Signal Processing, vol.12 , no.4 , pp.431 - 438, 6 June 2018.

[113] Sandeep Raj and Kailash Chandra Ray, "ECG Signal Analysis Using DCT-Based DOST and PSO Optimized SVM", IEEE Transactions on Instrumentation and Measurement, vol.66 , No.3, pp.470-478, March 2017.

[114] Saurabh Pal, MadhuchhandaMitra, " Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method", Measurement, vol.43, no.2, pp.255-261, February 2010.

[115] Xin-She Yang, "Bat Algorithm for Multi-objective Optimisation", International Journal of Bio-Inspired Computation, Vol.3, No.5, pp.267-274, March 2012.

[116] D. Binu ; B. S Kariyappa, "RideNN: A New Rider Optimization Algorithm-Based Neural Network for Fault Diagnosis in Analog Circuits", IEEE Transactions on Instrumentation and Measurement, pp.1-25, 2018.

[117] MIT-BIH Arrhythmia Database, "https://physionet.org/physiobank/database/mitdb/ ".

[118] XiaolongZhai and Chung Tin , "Automated ECG Classification Using Dual Heartbeat Coupling Based on Convolutional Neural Network ", IEEE Access, vol.6, pp.27465 - 27472, 08 May 2018.

[119] U. Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, Muhammad Adam, Arkadiusz Gertych, and Tan Ru San, "A deep convolutional neural network model to classify heartbeats", Computers in Biology and Medicine, vol. 89, pp. 389-396, 2017.

[120] Hongqiang Li, Danyang Yuan, Xiangdong Ma, Dianyin Cui, and Lu Cao, "Genetic algorithm for the optimization of features and neural networks in ECG signals classification", vol. 7, 2017.

[121] Shu Lih Oh, Eddie Y K Ng, Ru San Tan, and U. Rajendra Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length Heart beats", Computers in Biology and Medicine, vol. 102, pp. 278-287, 2018.

[122] Y. Paul, "Various epileptic seizure detection techniques using biomedical signals: a review," *Brain informatics,* vol. 5, p. 6, 2018.

[123] M. L. M. i. BCI, "Machine Learning Methodologies in BCI," 2020.

[124] *EEG time series*. Available: http://epileptologiebonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3

[125] Y. Li, X.-D. Wang, M.-L. Luo, K. Li, X.-F. Yang, and Q. Guo, "Epileptic seizure classification of EEGs using time–frequency analysis based multiscale radial basis functions," *IEEE journal of biomedical and health informatics,* vol. 22, pp. 386-397, 2018.

[126] M. Sharma, R. B. Pachori, and U. R. Acharya, "A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension," *Pattern Recognition Letters,* vol. 94, pp. 172-179, 2017.

[127] A. Bhattacharyya, R. Pachori, A. Upadhyay, and U. Acharya, "Tunable-Q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals," *Applied Sciences,* vol. 7, p. 385, 2017.

[128] M. A. Issaka, A. S. Dabye, and L. Gueye, "Localization of epileptic seizure with an approach based on the PSD with an autoregressive model," *arXiv preprint arXiv:1506.00947,* 2015.

[129] C. Kamath, "A new approach to detect epileptic seizures in electroencephalograms using teager energy," *ISRN Biomedical Engineering,* vol. 2013, 2013.

[130] J. Birjandtalab, M. Heydarzadeh, and M. Nourani, "Automated EEG-based epileptic seizure detection using deep neural networks," in *2017 IEEE International Conference on Healthcare Informatics (ICHI)*, 2017, pp. 552-555.

[131] C. Altın and O. Er, "Comparison of different time and frequency domain feature extraction methods on elbow gesture's EMG," *European journal of interdisciplinary studies,* vol. 2, pp. 35-44, 2016.

LIST OF PUBLICATIONS

1. Dinesh Kumar Atal and Mukhtiar Singh, "*A dictionary matrix generation-based compression and bitwise embedding mechanisms for ECG signal classification*", Springer International journal of Multimedia Tools and Applications- Impact Factor: 2.313. SCI-Expanded Indexed, *Multimed Tools Appl* **79,** 13139–13159 (2020). https://doi.org/10.1007/s11042-020-08671-6.

2. Dinesh Kumar Atal and Mukhtiar Singh, "*Arrhythmia Classification with ECG signals based on the Optimization-Enabled Deep Convolutional Neural Network*", Elsevier journal of Computer methods and programs in Biomedicine, June 2020. Impact Factor-3.632. SCI Indexed. https://doi.org/10.1016/j.cmpb.2020.105607.

3. Dinesh Kumar Atal and Mukhtiar Singh, "*A Hybrid feature extraction and machine learning approaches for epileptic Seizure Detection*", Springer International journal of Multidimensional Systems and Signal Processing. Impact Factor- 1.810. SCI Indexed, *Multidim Syst Sign Process* **31,** 503–525 (2020). https://doi.org/10.1007/s11045-019-00673-4.

4. Dinesh Kumar Atal and Mukhtiar Singh, "*A study on Electrocardiogram analysis and classification methods"* International Cloud Conference (ICC-2020, August 8-9, 2020) at Baba Masthnath University (BMU), Rohtak, Haryana.

5. Dinesh Kumar Atal and Mukhtiar Singh, "*Characteristics study of normal & epileptic EEG signals*" International Cloud Conference (ICC-2020, August 8-9, 2020) at Baba Masthnath University (BMU), Rohtak, Haryana.

6. Dinesh Kumar Atal and Mukhtiar Singh, "*Extraction of EEG Time and Frequency Domain Features for Classification Using CNN*", Communicated in Springer International journal of Medical & Biological Engineering & Computing.