Automated Detection of Atrial Fibrillation Using Wavelets

Project Report Submitted in Partial Fulfillment of the Requirements for the Degree of

Bachelor of Technology

in

Electronics and Communication Engineering

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CERTIFICATE

This is to certify that the work contained in this report entitled **"Automated Detection of Atrial Fibrillation Using Wavelets"** is submitted by the group members Mr. Harshvardhan Paithane (Roll. No: 16ECE1008), Ms. Mahima Tendulkar (Roll. No: 16ECE1012) and Ms. Sukkhada Joshii (Roll. No: 16ECE1028) to the Department of Electronics and Communication Engineering, National Institute of Technology Goa, for the partial fulfillment of the requirements for the degree of **Bachelor of Technology** in **Electronics and Communication Engineering**.

They have carried out their work under my supervision. This work has not been submitted else-where for the award of any other degree or diploma.

The project work in our opinion, has reached the standard fulfilling of the requirements for the degree of Bachelor of Technology in Electronics and Communication Engineering in accordance with the regulations of the Institute.

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DECLARATION

We Harshvardhan Paithane(16ECE1008), Mahima Tendulkar(16ECE1012) and Sukkhada Joshii(16ECE1028) hereby declare that the project work titled **"Automated Detection of Atrial Fibrillation using Wavelets"** which is being submitted to National Institute of Technology, Goa, Farmagudi, Ponda, in partial fulfillment for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering is a bonafide work carried out by us. The material submitted in this work has not been submitted to any other university or institution for the grant of any degree.

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Abstract

Atrial fibrillation shortened as AF or AFib is a sort of arrhythmia. It is found to be the foremost common among any other cardiac arrhythmia. It leads to different wellbeing related complications and can increment the hazard of heart failure or stroke. It is found especially in hypertensive and elderly patients. Therefore, testing and diagnosing early can reduce the consequences of AF. The aim of the project is to implement an efficient algorithm to automatically detect cardiovascular disease mainly atrial fibrillation by categorizing the dataset that is used, which contains information of different patients and classifying them into either normal rhythm or atrial fibrillation(AF) rhythm on the basis of abnormalities present in the ECG signal. This work is an implementation and extended study of an existing work [1]. The project aims to enhance the generalization ability of the algorithm by training it over multiple datasets. It proposes to achieve the objective of providing such an efficient algorithm by using the concept of wavelet packet transform and correlation function. These concepts are used for for physiological signal analysis and to contrive an efficient feature extraction strategy. The feature set that is constructed is the input to the various classifiers that are being used for the detection. The project also aims to lower the degree of human intervention for the purpose of discovering any form of an anomaly in the human heart, by implementing concepts of machine learning and artificial intelligence in the field of biomedical signal processing. The method is shown to perform well with an accuracy of around 98%+ and a high value of F1 score.

Contents

1 Introduction **1**

1.1 Motivation . . . 2

1.2 Problem description and Objectives . . . 2

2 Background **4**

2.1 Heart . . . 4

2.2 Electrocardiogram (ECG) . . . 5

2.3 Atrial Fibrillation . . . 5

2.4 Wavelet packet transform (WPT) . . . 8

3 Method **10**

3.1 Data Acquisition . . . 11

3.2 Pre-Processing . . . 11

3.2.1 Noise filtering . . . 11

3.2.2 Segmentation . . . 12

3.3 Wavelet Packet Transform . . . 13

3.4 Feature Extraction . . . 15

3.4.1 Features Evaluation . . . 17

3.5 Classification . . . 19

3.6 Performance Evaluation . . . 20

3.6.1 Cross-validation . . . 21

3.6.2 Evaluation metrics . . . 21

4 Results **23**
4.1 Binary classification using MIT-BIH AF Dataset 23
4.2 Binary classification using PhysioNet challenge 2017 Dataset . 24
4.3 Binary classification using PhysioNet challenge 2020 Dataset . 25
4.4 Binary classification for All datasets combined 25
4.5 Parameter Analysis 27

5 Conclusion **28**

6 Future Work **29**

References **30**

List of Figures

2.1 Anatomy of the heart [5]. 5
2.2 A typical one-cycle ECG signal tracing [6]. 6
2.3 Electrical conduction system and ECG signal during normal heartbeat and atrial fibrillation [7]. 7
2.4 WPT decomposition for level l=3 [8]. 9

3.1 The AF detection algorithm framework [1]. 10
3.2 ECG Signal before denoising and after denoising. (MIT-BIH AF dataset record #4015) 12
3.3 A part of a 5-level wavelet packet transform tree [1]. 13
3.4 Plot of the sub-bands $Band_{51}$ and $Band_{52}$ of WPT decomposed NSR signal (top) and AF signal (bottom). (MIT-BIH AF dataset record #4015) 14
3.5 The example of box-plot for W_B in (a)$Band_{51}$ (b)$Band_{52}$ (MIT-BIH AF dataset) 18
3.6 The example of box-plot for H_B in (a)$Band_{51}$ (b)$Band_{52}$ (MIT-BIH AF dataset) 18
3.7 ANN topology in proposed scheme. 20
3.8 A template of the confusion matrix for the binary classification. 22

4.1 ROC curve for the SVM classifier. 26

List of Tables

3.1 p-values of the constructed features for respective dataset. . . 17

4.1 Performance evaluation parameter comparison of the algorithm using MIT-BIH AF dataset with different classifiers. . . 24
4.2 Performance evaluation parameter comparison of the algorithm using PhysioNet Challenge 2017 dataset with different classifiers. 24
4.3 Performance evaluation parameter comparison of the algorithm using PhysioNet Challenge 2020 dataset with different classifiers. 25
4.4 Performance evaluation parameter comparison of the algorithm using all three datasets combined with different classifiers. 26
4.5 Evaluation parameter comparison of the algorithm using different datasets with SVM classifier. 27

Chapter 1

Introduction

Atrial Fibrillation (AF or AFib) is a heart condition that causes abnormal or irregular heart rhythm. It is the most common type among other cardiac arrhythmias. Even though it is not a fatal disease, AF can advance to cardiac complications such as the fall in blood pressure, increased risk of heart failure with the ensuing risk of a heart stroke. Therefore, it is very important to detect AF in order to prevent cardiac threats. Approximately 33.5 million people around the globe were affected by AF in 2010. This estimated number of individuals is expected to grow as the population ages globally. The proportion of strokes associated with AF was found to be 6.6% for ages 50 to 60 years and 36.2% for ages above 80 years [2].

We are living in the 21st century, and the world is going through various changes in different aspects of life. We can take the example of technological evolution, socio-economic changes, environmental changes, etc. We can also agree with the fact that the healthcare sector is also growing at a great pace. But if we look at the latest pandemic caused due to the COVID-19 and its effect, we definitely need to focus more on the healthcare sector in the coming future. As mentioned, there is a lot of research taking place on the issue of detecting such diseases by collecting data of such patients and working on the collected datasets with various methods. Hence, we are aiming to implement a method which will detect atrial fibrillation automatically. This method will save lives of many people, enhance the quality of life of millions of individuals who are at risk, and will help in reducing the socio-economic burden due to AF and such cardiac diseases.

1.1 Motivation

Atrial fibrillation, a kind of cardiac arrhythmia may advance to several cardiac complications such as fall in blood pressure, blood clots, risk of heart failure, stroke, other heart diseases. The lives of about 10% of the global population above the age of 75 years is affected by it. As the world population is aging the commonness of AF in the adult population is increasing. A recent study based on prevalence of AF in the globe stated that almost one in four adults will be affected by the AF in the US and Europe [2].

In recent times, the ability of machines and softwares has been improved significantly such that they are able to perform classification, quantification, and identification of the patterns in biomedical signals [3]. Since the global population is aging fast and the healthcare costs are also increasing, there is a need for an automated AF detection method to monitor the health status of patients. It will make life easier for heart patients and improve their conditions. Hence it is important to design and cultivate new methods that will help in detection of atrial fibrillation by performing the analysis of heart rhythm ie. ECG signal.

1.2 Problem description and Objectives

Conventionally, the diagnosis of AF detection is carried out manually by trained physicians by visually inspecting the electrocardiogram (ECG) signals. This makes automated or artificial detection inefficient and pertaining to an individual. The efficiency of AF detection is getting affected due to the huge amount of ECG data [4]. Hence, there is a demanding need for an automated process of AF detection to analyze this huge amount of ECG data and to help forward diagnosis which will reduce the burden on physicians.

The primary objectives of the project are as follows:

- To implement the algorithm for detection of AF using wavelet packet transform and correlation function. It is an implementation of existing work [1].
- To perform the analysis by using different supervised binary classifiers and compare the results.
- Enhancement of the generalization ability of the algorithm by training it over multiple datasets.

Chapter 2

Background

2.1 Heart

The heart is a pumplike muscular organ located slightly left and behind the breastbone. It is hollow inside and around the measure of a clench hand. It capacities by pumping the blood through the circuitry of blood vessels (veins and arteries). The oxygen and nutrients are carried by the pumped blood to the rest of body and carbon dioxide ie. a metabolic body waste to the lungs. The heart is partitioned in two sections: both the upper and lower section comprises two chambers each, left-right atrium and left-right ventricle respectively as shown in Figure 2.1.

A customary electrical motivation is sent by the sinoatrial (SA) node too called the pacemaker of the heart. Due to this impulse the upper heart chambers contract. This impulse then flows to the ventricles through the atrioventricular (AV) node causing them to pump out blood due to its contraction. The right atrium pumps the blood to the right ventricle after it gets it from the veins. After the right ventricle receives the blood it supplies it to the lungs. There it gets mixed with oxygen and then it is received by the left atrium. The left atrium pumps it to the left ventricle which is the most powerful chamber and it supplies it to the whole body [5].

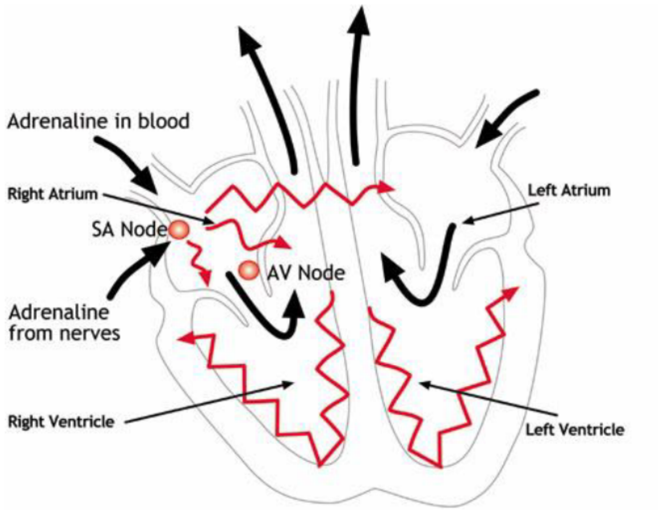


Figure 2.1: Anatomy of the heart [5].

2.2 Electrocardiogram (ECG)

An electrocardiogram (EKG or ECG) is a heart analysis that gauges the rate, rhythm, and depicts the heart's electrical activity. The method of documenting the cardiac electrical action of a patient with the aid of specific electrical sensors over a given time interval is called Electrocardiography. ECG is an important tool that can be used to detect the presence of any sort of cardiac abnormalities or disease with the help of various complex and sophisticated techniques. In the ECG signal, we can observe a repetitive pattern that becomes a part of the collective signals as shown in Figure 2.2 [6].

2.3 Atrial Fibrillation

Atrial fibrillation, shortened as AF or AFib is a kind of heart arrhythmia. It is found to be the most common type of cardiac arrhythmia. It causes quivering or irregular heartbeat. Due to the irregular and rapid electrical stimulus in the atrium, the heartbeats become irregular and accelerated. This ab-

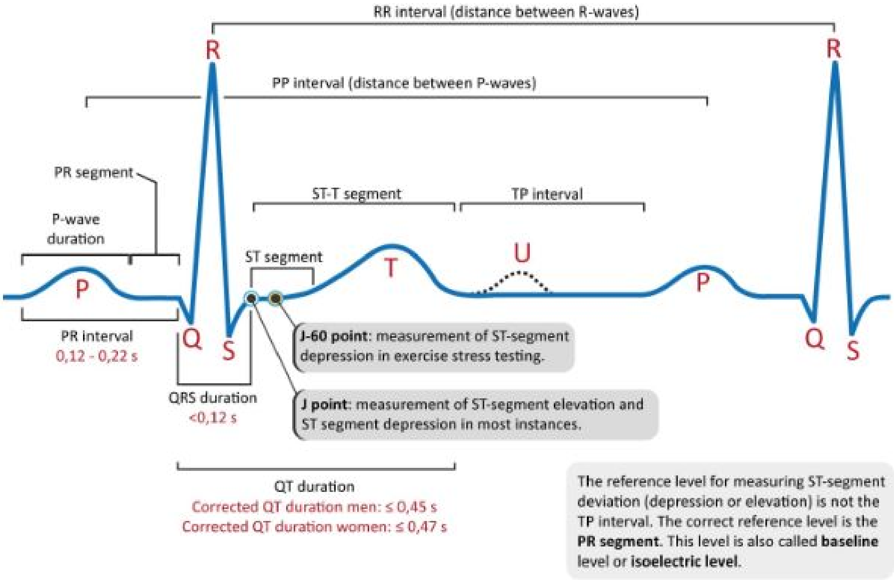


Figure 2.2: A typical one-cycle ECG signal tracing [6].

normal rhythm of the heart can lead to severe heart-related issues like drop in blood pressure, stroke, risk of heart failure, etc. During a regular beat, normal heart contracts and relaxes. But, in atrial fibrillation, two upper chambers of the heart are not in coordination with the two lower chambers. The atria beat irregularly and in a disordered manner (quiver) and is out of coordination with the ventricles of the heart to move blood into the ventricles. Heart palpitations, shortness of breath, and weakness are some symptoms of AF. Conventionally, the diagnosis of AF detection is carried out manually by visual inspection of the ECG signal. The trained physicians observe the ECG signals to diagnose the AF as shown in Figure 2.3. Visual detection is AF is also done by the observing irregularity in the occurrence of R peaks. However, a non-invasive cardiac monitoring technique used to diagnose AF is the absence of P waves on an ECG signal, which is a stronger indicator of AF [7].

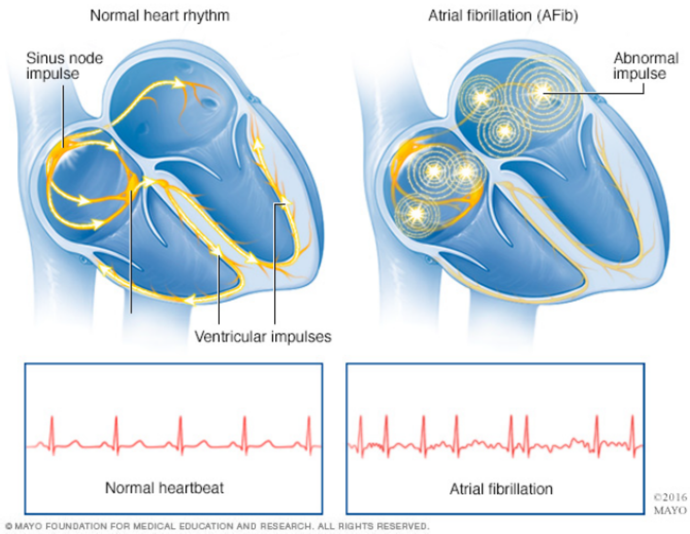


Figure 2.3: Electrical conduction system and ECG signal during normal heartbeat and atrial fibrillation [7].

In addition, sometimes AF cases are asymptomatic, due to which the doctors are not able to diagnose them. So, sometimes they have to depend on the incidental detection of Atrial fibrillation during a physical examination or on the ECG signal. This is quite a challenge for them to go through the ECG recordings manually to find AF episodes. If in some case occurrence of the AF episodes are totally random then a long ECG recording needs to be analyzed. This becomes impractical for doctors. This problem justifies the need for automated atrial fibrillation detection methods, which is important and should be considered. AF can be classified on two bases: the cause or the time period it lasts. Each kind has different treatment [7]: The cause to the condition are also many, some are controllable, some are not. Factors like high blood pressure (BP), diseases related to a heart valve, congenital heart disease, past heart surgery play a big role.

- **Paroxysmal** (holiday heart syndrome): Usually an episode of AF, which lasts maybe for a few minutes or days, but is below the week. In major cases the treatment is not needed.

- **Persistent**: The episode duration is more than a week and medication can be used to stop it. If the treatment or medicines doesn't work, physicians go for the electrical cardioversion, a low-voltage current used to reset the normal rhythm.

- **Permanent**: It is chronic AF, hence cannot be treated. A long term medication to reduce the heart-related complications is prescribed to the patient.

To diagnose AF doctors check signs and symptoms, together with patient's medical history and conduct different kinds of tests such as Electrocardiogram, blood tests, echocardiogram, stress test, chest X-ray, etc

2.4 Wavelet packet transform (WPT)

The wavelet packet transform (WPT) is an efficient method to study and understand non-stationary time series signals such as ECG signals. It performs decomposition of the signal into several independent time-frequency signals called packets. These packets are weighted sums of wavelet base function at different levels. The yield of the signal decayed by WPT in various sub-bands is called wavelet coefficients. These wavelet coefficients exhibit more intrinsic physiological data in the time-frequency space of the signal.

Assuming that the signal *S(t)* is decomposed by WPT, the wavelet coefficients of the signal are given as $d_l^p(t)$ where l is decomposition level and the serial number of node is denoted by p, with $p = 0, 1, \ldots, 2^l - 1$ in the WPT tree. So, we can compute the wavelet coefficients using the following expressions [1]:

$$d_l^{2p}(t) = \sum_{n \in Z} \{h(n).d_{l-1}^{p}(2t-n)\} \tag{2.1}$$

$$d_l^{2p+1}(t) = \sum_{n \in Z} \{g(n).d_{l-1}^{p}(2t-n)\} \tag{2.2}$$

where the low-pass and high-pass filter coefficients are denoted by $h(n)$ and $g(n)$ respectively.

A WPT based signal decomposition process is schematically illustrated in figure 2.4. The number of sub-bands produced by a three-level WPT adds up to 8, where the signal frequency spectrum is divided into eight parts, sub-bands covering one each. The discrete wavelet transform (DWT) gives adjustable time–frequency resolution, but it is affected by the poor resolution within the high-frequency locale. Due to this drawback of DWT, separation of high-frequency transient components becomes challenging. But WPT further breaks down the signal in the high-frequency region and provides the detailed information of the signal by overcoming the limitation of DWT [8].

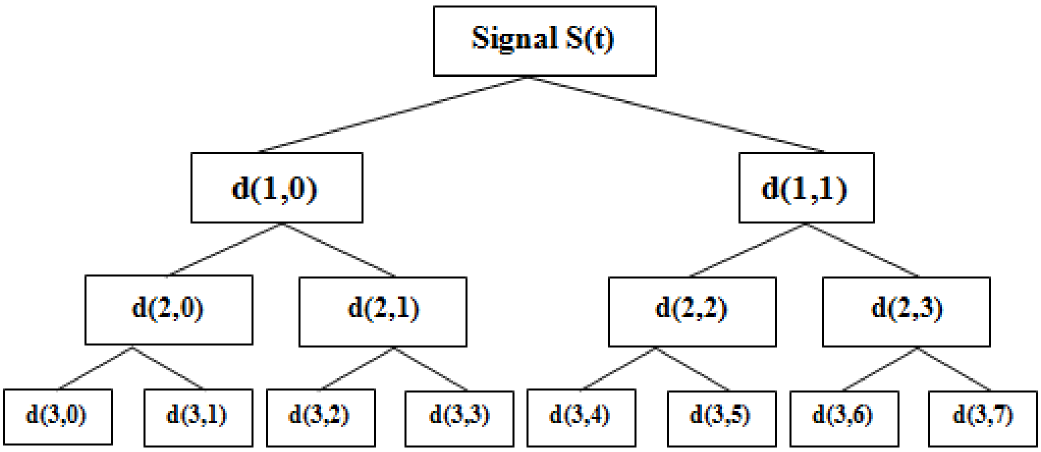


Figure 2.4: WPT decomposition for level l=3 [8].

Chapter 3

Method

This chapter begins with a description of the framework of the implemented algorithm for AF detection. The data collection procedure along with pre-processing, wavelet packet transform decomposition, feature extraction, and classification. Figure 3.1 shows the framework of the implemented algorithm for AF detection.

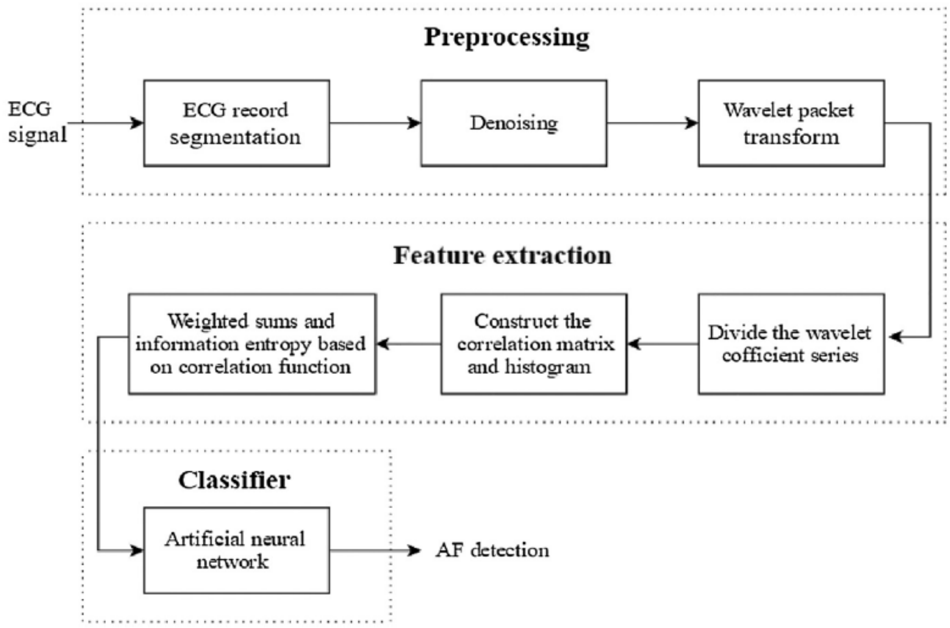


Figure 3.1: The AF detection algorithm framework [1].

3.1 Data Acquisition

A total of three datasets were used to implement the method. MIT-BIH AF Dataset [9], PhysioNet challenge 2017 Dataset, PhysioNet challenge 2020 Dataset [10]. All three databases containing ECG signals are obtained from the PhysioNet website. The database includes arrhythmia dataset, AF dataset, noise stress test dataset, and other datasets and it is publicly available for the people in medical research. The other two datasets also include ECG signals of various patients around the globe. They include a variety of abnormalities which makes them perfect to enhance the generalization ability of the implemented method. The algorithm is trained, validated, and tested on each of them. These datasets are used to validate the genuineness and practicability of the implemented algorithm.

ECG signal files present in MIT-BIH AF Dataset are two-lead ECG sampled at 250 Hz (samples per second), whereas ECG signals present in PhysioNet challenge 2017 dataset are single-lead ECG and are sampled at 300 Hz. ECG signals present in PhysioNet challenge 2020 dataset are 12-lead ECG and are sampled at 500 Hz. In this work, we have used a single lead from each of the datasets to implement the method.

3.2 Pre-Processing

The ECG signal data is pre-processed before it is used for feature extraction. The pre-processing consists of two steps: Segmentation and Noise filtering (Denoising). Noise filtering is carried out first and then the segmentation of the signal is performed. Matlab R2018a was used to perform all the signal processing and analysis of the ECG signals.

3.2.1 Noise filtering

ECG signal is often affected by different noises during its acquisition and transmission. Various noises like Electromyogram (EMG) noise, Baseline

Wander, Channel Noise, and power-line interference, and other AWGN noise [11]. These noisy factors prove to be a hindrance to the features extraction process during ECG analysis.

So we designed and implemented the following filters to remove the noises which were present in the datasets. The 50 Hz notch filter and the 0.3-45 Hz Bandpass filter [12]. The ECG segment before and after it is denoised by the set of filters is illustrated in figure 3.2. We filtered out Baseline wander, 50Hz powerline interference, and electrode motion noise using the mentioned filters.

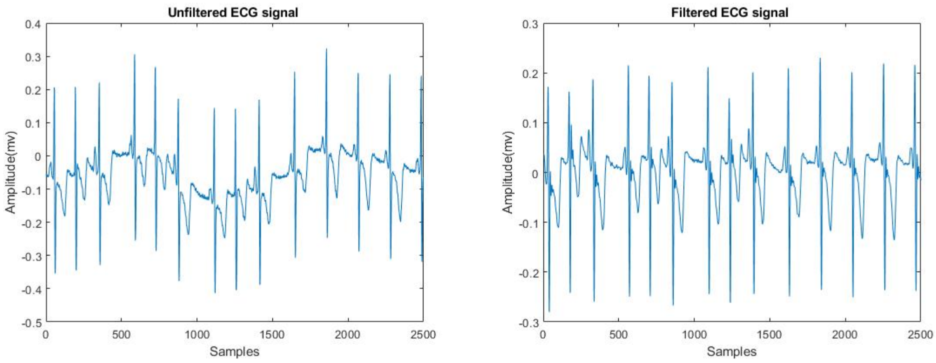


Figure 3.2: ECG Signal before denoising and after denoising. (MIT-BIH AF dataset record #4015)

3.2.2 Segmentation

The procedure of partitioning a signal into numerous sections of a certain estimate is called segmentation. It can be performed with or without using an overlapping window. In this step, ECG records from all three datasets are divided into segments of duration 10 seconds, and the segmentation is done without overlapping the window. These filtered and segmented ECG segments are used to find the WPT coefficients, a pre-requisite step for feature extraction required for binary classification in the next section.

3.3 Wavelet Packet Transform

After ECG records undergo pre-processing, wavelet packet transform is performed on each ECG segment. The segments are decomposed at the level l=5. The figure 3.3 illustrates the WPT decomposition tree.

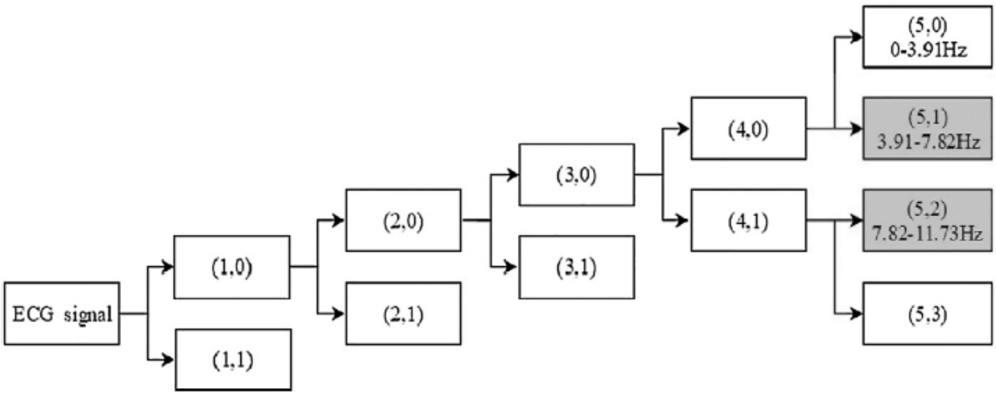


Figure 3.3: A part of a 5-level wavelet packet transform tree [1].

The bandwidth of P-wave and f-wave is majorly concentrated in 4–12 Hz. Hence, they are both considered as low-frequency waves. Therefore for feature extraction, $Band_{51}$ and $Band_{52}$ of WPT decomposition tree are chosen as frequency intervals [1]. An exemplification of the Normal ECG signal and AF ECG signal and their corresponding selected sub-bands are shown in Figure 3.4. The record #4015 from MIT-BIH AF dataset was chosen for the above experiment purpose.

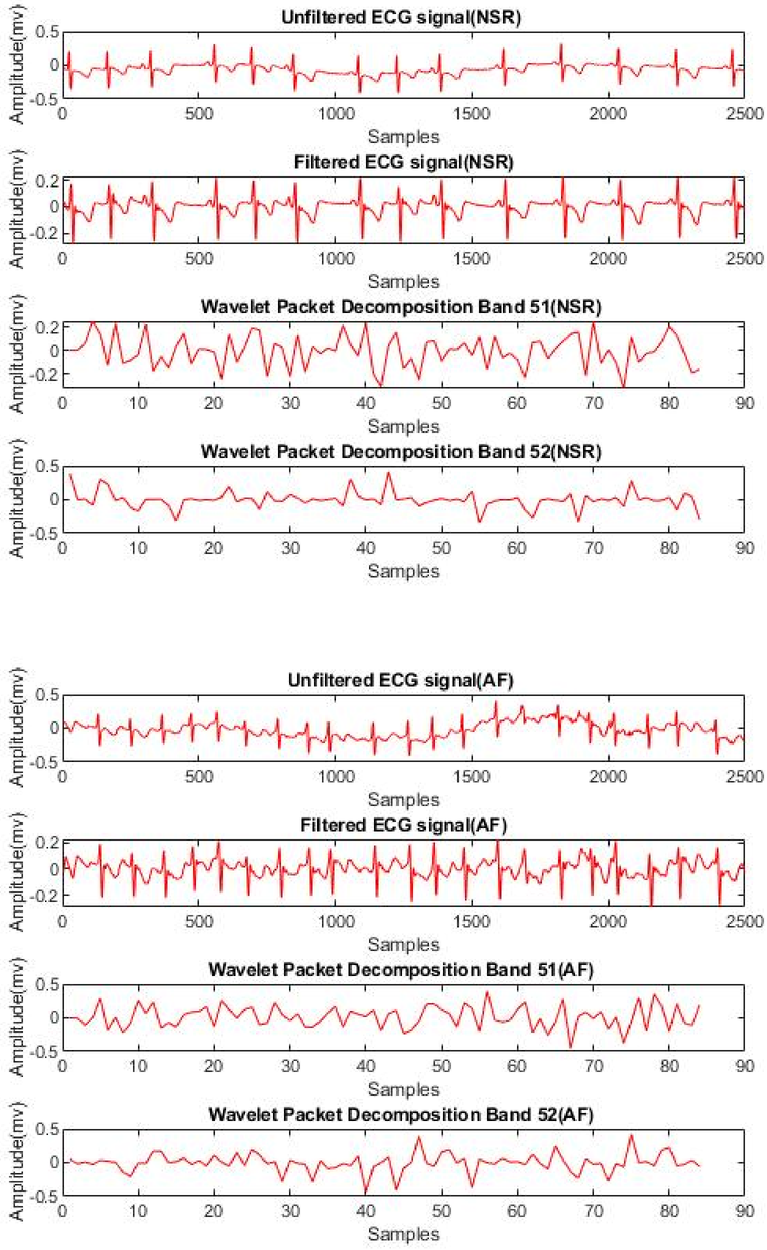


Figure 3.4: Plot of the sub-bands $Band_{51}$ and $Band_{52}$ of WPT decomposed NSR signal (top) and AF signal (bottom). (MIT-BIH AF dataset record #4015)

3.4 Feature Extraction

There are many existing AF detection algorithms in which the features are extracted from the morphological features of ECG signals. Two main features of the ECG signal in AF include the absence of p-waves and RR interval irregularity. In the Afib ECG signal, p-waves are often replaced by f-waves, a fast and disordered fibrillatory waves. All such algorithms involve some pre-processing procedures like detection of R-peak and P-waves, but the algorithm performance is affected if these parameters are not accurately calculated [13]. Hence to avoid this situation, in this work the feature extraction method is based on the correlation between the WPT Coefficients extracted from selected sub-bands ($Band_{51}$ and $Band_{52}$) [1]. It is known that if there is any kind of disorder present in ECG signal the correlation among the coefficients of the wavelet coefficient series will decrease. In any random series, the correlation function has a superior ability to quantify specific characteristics, and because of this property, it is considered for sequential data analysis. The changes in the atrial activity are highlighted due to this property [14]. So the feature set is constructed by calculating the information entropy and weighted sums of selected sub-bands.

The feature extraction steps are explained below:

Step 1. The wavelet coefficients are obtained from the selected sub-bands ($Band_{51}$ and $Band_{52}$) by performing WPT decomposition of filtered ECG segment. The coefficients series is divided into n segments of equal length, and by representing one of the segment as $\bar{d}\left(t_i\right) = \left[d^{(1)}\left(t_i\right), d^{(2)}\left(t_i\right), d^{(3)}\left(t_i\right), \ldots, d^{(m)}\left(t_i\right)\right]$ with $i = 1, 2, 3, 4, \ldots, n$ [1].

Step 2. A correlation matrix is computed with these segments where τ= 0, 1, 2, 3, . . . , n-1, and it is normalized as given below [1]:

$$R_{\bar{d}} = \begin{bmatrix} B_{1,1} & \cdots & B_{1,1+r} & \cdots & B_{1,n} \\ \vdots & & \vdots & & \vdots \\ B_{i,1} & \cdots & B_{i,1+\tau} & \cdots & B_{i,n} \\ \vdots & & \vdots & & \vdots \\ B_{n,1} & \cdots & B_{n,1+\tau} & \cdots & B_{n,n} \end{bmatrix} \tag{3.1}$$

Step 3. The features are extracted from the normalized correlation matrix [1].

$$W_B = \sum_{i=1}^{n} \{B_{i,i+\tau}.n_{i,i+\tau}\} \tag{3.2}$$

$$H_B = -\sum_{i=1}^{n} \{p_{i,i+\tau}.\log p_{i,i+\tau}\} \tag{3.3}$$

where,

$n_{i,i+\tau}$ = Number of $B_{i,i+\tau}$ in a given precision.

$p_{i,i+\tau}$ = Proportion of $n_{i,i+\tau}$ in total number.

Step 4. The features are assembled as feature set for classifier. We have used K-Nearest Neighbor (KNN), Support vector machine (SVM), and Artificial Neural Network (ANN) learning models for classification.

The correlation function estimation of any two segments is denoted as $\hat{B}_{\bar{d}}(\tau_0)$, which is actually a sequence of numbers with $\tau_0 = 0, \pm1, \pm2, \ldots, \pm(m-1)$, presented as follows [1]:

$$\hat{B}_{\bar{d}}(\tau_0) = \tfrac{1}{m} \sum_{j=1}^{m} \{\bar{d}^{j}(t_i) \,.\bar{d}^{(j+\tau_0)}(t_{i+\tau})\} \tag{3.4}$$

where, $\bar{B}_{i,i+\tau}$ = Mean value of the sequence,

$$\bar{B}_{i,i+\tau} = (\tfrac{1}{2m-1}) \sum_{\tau_0=-(m-1)}^{m-1} \{\hat{B}\bar{d}(\tau_0)\} \tag{3.5}$$

and $B_{i,i+\tau}$ = Normalized value of $\bar{B}_{i,i+\tau}$.

3.4.1 Features Evaluation

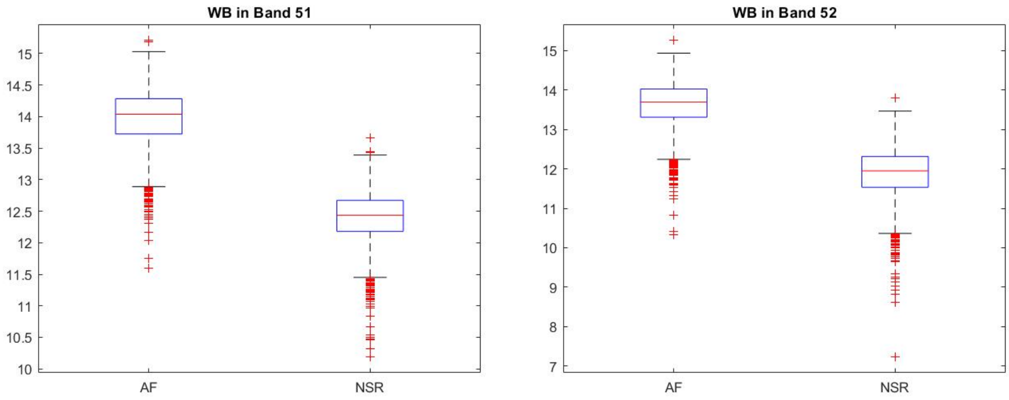
After the feature extraction step, it is important to check if the extracted features are good enough to give input to the classifier model. They can be evaluated by their p-values or box-plots. If the p-value is less than 0.05 then the feature is considered to be reasonable to be used for classification purpose [15]. If not, it is discarded from the feature set. So, to prove the genuineness of the features, the Kruskal–Wallis test was conducted. The p-values obtained after the test for each dataset are given in Table 3.1.

The visual hypothesis testing using box-plots was also executed. The higher classification ability in the selected sub-bands is represented by the box-plots of features. It was useful in proving the significance of the features for the classification. The box-plots for the MIT-BIH AF dataset after the test are shown in Figure 3.5 and 3.6.

The p-values and the box-plots obtained against each dataset suggests that the constructed feature set can be used as an input for the classifier model for automatic detection of AF segments.

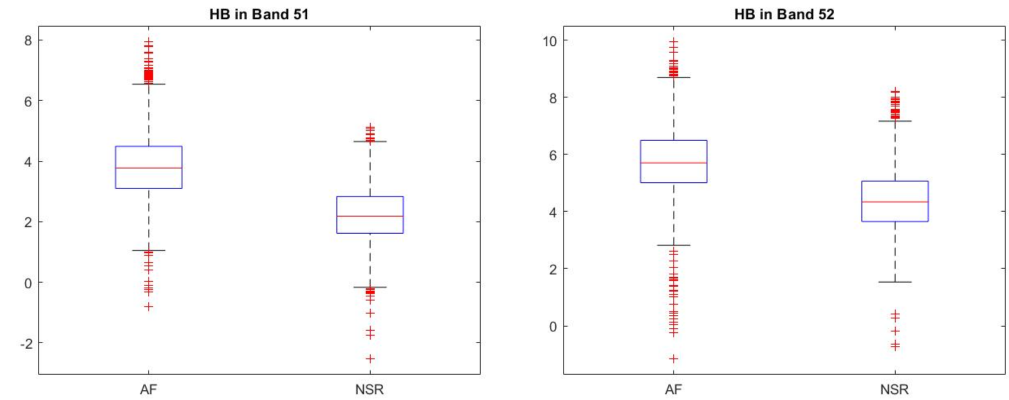
Table 3.1: p-values of the constructed features for respective dataset.

Features	MIT-BIH AF	PNC 2017	PNC 2020
W_B in $Band_{51}$	7.4424e-55	4.6259e-223	1.8753e-31
W_B in $Band_{52}$	9.1575e-60	1.5020e-135	6.4447e-33
H_B in $Band_{51}$	9.3999e-08	6.5043e-145	2.7211e-19
H_B in $Band_{52}$	2.9049e-20	5.9010e-140	5.8739e-15



(a) p-value= 7.4424e-55 (b) p-value= 9.1575e-60

Figure 3.5: The example of box-plot for W_B in (a)$Band_{51}$ (b)$Band_{52}$ (MIT-BIH AF dataset)



(a) p-value= 9.3999e-08 (b) p-value= 2.9049e-20

Figure 3.6: The example of box-plot for H_B in (a)$Band_{51}$ (b)$Band_{52}$ (MIT-BIH AF dataset)

3.5 Classification

To further the study, the algorithm was tested on different types of classification techniques such as ANN, KNN, SVM. For each dataset, all three classifiers were implemented. The default settings were used for training all the classifier models. The obtained results are illustrated in the following chapter. The classifiers that are used perform supervised binary classification by segregating the ECG data into two classes, ie. AFib or NSR.

Support Vector Machine (SVM) A 'Support Vector Machine' abbreviated as SVM is a type of supervised machine learning algorithm commonly preferred for binary classification. It maximizes the limit of separation between two classes in the data by constructing an optimal hyperplane which acts as a decision surface. In this work polynomial type of SVM's like Quadratic and Cubic was found to give better results than other types.

K-Nearest Neighbor (KNN)

KNN is a classification technique that is usually preferred for multi-class classification. It segregates data based on the distance parameter. Based on a specified distance metric, the nearest neighbor search locates all the neighbors or k-nearest neighbors within a specified distance to query data points. In this work, weighted and cosine type of KNN was found to give better results than other variants.

Artificial Neural Network (ANN)

Artificial Neural Network is a type of classification technique based on the principle of neural networks. It is majorly motivated by the function of human brain. The human brain is made up of neurons and neural connections ie. synapses. Each neuron is interconnected to different neurons and neural connections. The computational and signal transferring units of the brain are neurons and synapses respectively. Neural networks are widely used for operations like image classification, market prediction, speech recognition, etc. ANN classifier predicts the output by assigning the input vectors to various categories according to their properties [16].

The neural network structure used in our framework contains three (3) layers ie. input layer, hidden layer, and output layer. The number of neurons or nodes in the input layer was set as four, equivalent to the dimension of the feature vector. Due to the binary classification, the number of neurons or nodes in the output layer was set as two. The hidden node count was set as ten(10). Figure 3.7 shows the ANN topology in proposed scheme. The adaptive learning rate was set to 0.1. Levenberg-Marquardt backpropagation algorithm was used to obtain the best performing model. For the hidden layer, the activation function was set to Sigmoid function and for the output layer, the Softmax function was chosen.

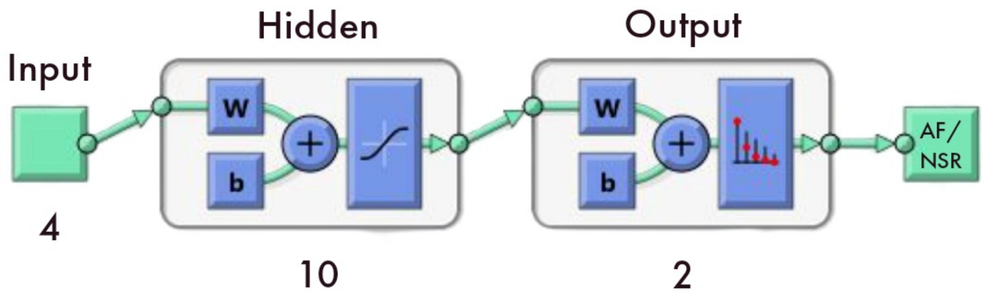


Figure 3.7: ANN topology in proposed scheme.

3.6 Performance Evaluation

A machine learning algorithm is said to be outstanding if it is able to generalize itself and perform well on new and previously unseen samples. A large error will be generated if the model lacks generalization. However, a model can mimic very well with high accuracy if we iterate it many times on the dataset with limited size. But this leads to a situation called overfitting due to lack of generalization. So, to avoid this situation and improve the reliability of the model in an unseen example set, a unique test set is chosen. Usually, it is done by dividing a large dataset into training, validation, and test sets [15].

In this work, all the datasets used are divided into three parts. The proportion was kept as 80% for training and 10% for validation and testing each. During training stage training and validation sets are used. At the final stage, the test set is used for performance evaluation of the model. However, we can take advantage of the idea of cross-validation, if the dataset is limited.

3.6.1 Cross-validation

To enhance the generalization ability of the method, we implemented 10-fold cross validation. This is performed to make sure the conclusive classification performance of the respective classifier [17]. The dataset was divided into 10 parts in a random order, out of which nine were taken as the training set inturn and the remaining one as the test set. The results after each iteration of the experiment were averaged for final classification performance.

3.6.2 Evaluation metrics

To gauge the performance of a classifier, it is always important to have some metrics. The most effective way to scope the implementation of a model is using a table called contingency table or confusion matrix. Some of the metrics like sensitivity (SEN), accuracy (ACC), specificity (SPE), false positive rate (FPR) and error rate (Err) can be calculated using the confusion matrix [18]. The binary classification confusion matrix with positive (afflicted by AF) and negative (not afflicted by AF) classes is a two-by-two table, shown in Figure 3.8.

True Positives (TP): No. of samples correctly classified as AF.

True Negatives (TN): No. of samples correctly classified as non-AF.

False Positives (FP): No. of samples misclassified as AF.

False Negatives (FN): No. of samples misclassified as non-AF.

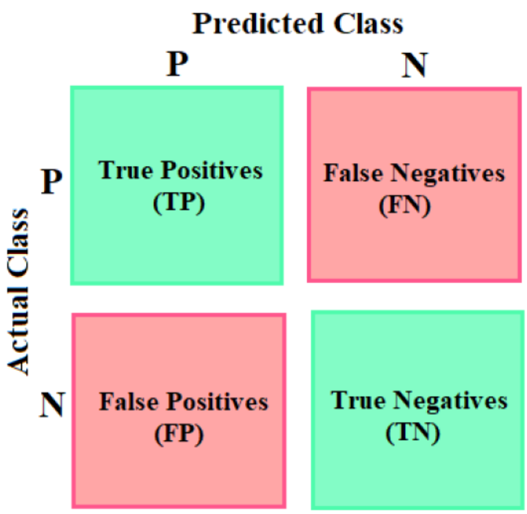


Figure 3.8: A template of the confusion matrix for the binary classification.

In this work, we employed standard metrics that are sensitivity (SEN), specificity (SPE) and accuracy (ACC) to reveal the effectiveness of the classification. The expressions to compute them is given below:

$$\text{SEN} = \frac{TP}{(TP + FN)} \tag{3.6}$$

$$\text{SPE} \ = \frac{TN}{(TN + FP)} \tag{3.7}$$

$$\text{ACC} = \frac{(TP + TN)}{(TP + TN + FN + FP)} \tag{3.8}$$

F1 score: (F measure or F score) It is the weighted average of Precision (PRE) and Recall (REC). Both false positives and negatives are taken into account while calculating F1 score. It is calculated as below:

$$\text{F1 Score} = 2 * (\frac{REC * PRE}{REC + PRE}) \tag{3.9}$$

$$\text{REC} = \text{TP}/(\text{TP} + \text{FN}) \tag{3.10}$$

$$\text{PRE} \ = \text{TP}/(\text{TP} + \text{FP}) \tag{3.11}$$

Chapter 4

Results

The implemented algorithm was tested on different datasets to improve its generalization ability. A total of three datasets were used. The evaluation parameters such as the accuracy, specificity, sensitivity, and F1 score were calculated from the obtained confusion matrix of each dataset against each classifier. The validation performance plot and ROC curve for the SVM classifier model were also illustrated for binary classification using a combined dataset study.

One of the efficient measures of classification performance of the implemented method is the area under the ROC curve (AUC). The higher the area under the ROC curve (AUC) value, the higher is the efficiency of the classification [19].

4.1 Binary classification using MIT-BIH AF Dataset

The algorithm was trained and tested on MIT-BIH AF Dataset. The obtained results are given in this section. Three classifiers were used to perform the classification. Table 4.1 shows the performance evaluation parameter comparison of AF detection results using ANN, KNN, and SVM.

Table 4.1: Performance evaluation parameter comparison of the algorithm using MIT-BIH AF dataset with different classifiers.

	ANN	KNN	SVM
ACC (%)	100	99.44	99.44
SEN (%)	100	99.44	100
SPE (%)	100	99.44	98.90
F1 Score	1.000	0.994	0.994

4.2 Binary classification using PhysioNet challenge 2017 Dataset

The algorithm was trained and tested on PhysioNet challenge 2017 Dataset and the obtained results are given in this section. Table 4.2 shows the performance evaluation parameter comparison of the algorithm using PhysioNet Challenge 2017 dataset with different classifiers.

Table 4.2: Performance evaluation parameter comparison of the algorithm using PhysioNet Challenge 2017 dataset with different classifiers.

	ANN	KNN	SVM
ACC (%)	99.28	99.17	99.27
SEN (%)	98.35	99.33	99.46
SPE (%)	99.54	98.58	98.59
F1 Score	0.983	0.994	0.995

4.3 Binary classification using PhysioNet challenge 2020 Dataset

The algorithm was trained and tested on PhysioNet challenge 2020 Dataset which is available on PhysioNet website. The results obtained are given below. Table 4.3 the performance evaluation parameter comparison of the algorithm using PhysioNet Challenge 2020 dataset with different classifiers.

Table 4.3: Performance evaluation parameter comparison of the algorithm using PhysioNet Challenge 2020 dataset with different classifiers.

	ANN	KNN	SVM
ACC (%)	99.26	98.96	99.15
SEN (%)	99.08	98.50	98.88
SPE (%)	99.44	99.43	99.43
F1 Score	0.992	0.989	0.991

4.4 Binary classification for All datasets combined

After implementing the algorithm on individual dataset we combined all three datasets and used it to train and test the algorithm. The model was trained over 17175 segments, out of which 11935 were NSR and 5240 were AF segments. The performance evaluation parameter comparison of the algorithm using all three datasets combined with different classifiers is shown in Table 4.4. The ROC curve for the SVM classifier model is illustrated in Figure 4.1.

Table 4.4: Performance evaluation parameter comparison of the algorithm using all three datasets combined with different classifiers.

	ANN	KNN	SVM
ACC (%)	98.03	97.78	98.50
SEN (%)	95.05	97.66	98.43
SPE (%)	99.40	98.04	98.39
F1 Score	0.968	0.983	0.988

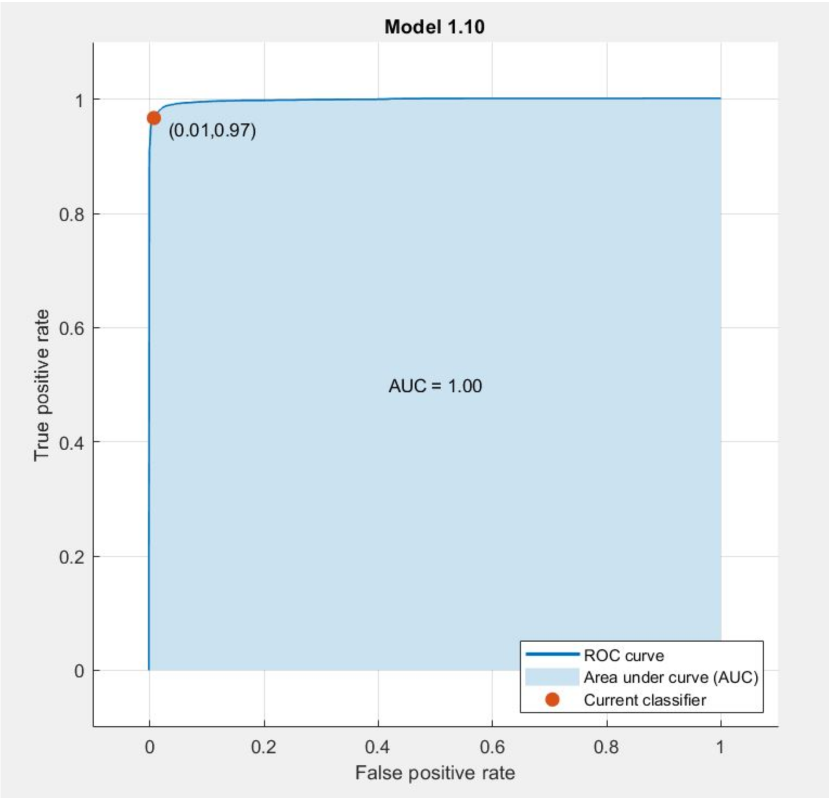


Figure 4.1: ROC curve for the SVM classifier.

4.5 Parameter Analysis

Parameter Analysis for the SVM classifier using different datasets.

It was observed that while ANN gave a better accuracy when the datasets were trained separately, SVM classification was more effective for the generalized approach. Therefore, we chose to closely examine the output of SVM classifier on all datasets. Table 4.5 illustrates the Evaluation parameter comparison of the algorithm using different datasets with SVM classifier.

Table 4.5: Evaluation parameter comparison of the algorithm using different datasets with SVM classifier.

	DS1	DS2	DS3	All Combined
ACC	99.44	99.27	99.15	98.50
SEN	100	99.46	98.88	98.43
SPE	98.90	98.59	99.43	98.39
F1 Score	0.994	0.995	0.991	0.988

Chapter 5

Conclusion

The project is aimed at implementing an efficient algorithm to detect atrial fibrillation using machine learning. This study is an implementation of existing work [1]. The study emphasizes the danger of atrial fibrillation and the need for automated tools that can detect it. It also facilitated in achieving a high detection accuracy.

The algorithm for detection of Atrial Fibrillation was implemented successfully. The generalization ability of the algorithm was improved by implementing it on a larger and more diverse dataset. The SVM classification model gave the highest accuracy of 98.5%. It was observed that while ANN gave a better accuracy when the datasets were trained separately, SVM classification was more effective for the generalized approach.

On our way to achieving so, we learned about electrocardiogram, atrial fibrillation, wavelet packet transform, and gained practical knowledge about biomedical signal processing and, machine learning as well as skills to implement an existing method. We believe that the knowledge and skills that we gained will be useful and will definitely come in handy in the future.

Chapter 6

Future Work

Although the results we are able to get are satisfactory, the implementation can still be improved by training the method using more number of diverse databases with a variety of patients and a variety of cardiac defects. Tasks revolving around machine learning and neural network can be further boosted by using computers having faster processors. The classification can be improved by using deep neural networks like recurrent neural network.

The algorithm could be further simplified by exploring other wavelet transforms in place of wavelet packet transform. Another scope of future work is the detection of other types of arrhythmias such as atrial flutter, paroxysmal tachycardia, and heart-valve related diseases. Further, the algorithm can be improved by deploying it under realistic scenarios and analyzing the results. In the end, the method can be clinically validated in the future and the possibility of implementing a low-cost device can be explored.

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