
Jimma University School of Graduate Studies

Jimma Institute of Technology School of Biomedical Engineering

Bioinstrumentation Stream

# ECG Signal Analysis for Automatic Cardiac Abnormality Detection and Classification

A thesis Submitted to the School of Graduate Studies of Jimma University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Biomedical Engineering (Bioinstrumentation Stream)

By:

Ahmed Mohammed

December, 2018

Jimma, Ethiopia


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# Declaration

This research entitled "**ECG Signal Analysis for Automatic Cardiac Abnormality Detection and Classification"** is my original work and has not been presented for a degree in any other university.

**Done By:**

Ahmed Mohammed Abagaro _____ _____

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Dr. Towfik Jemal (PhD) _____ _____

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# Abstract

*Electrocardiogram (ECG), a noninvasive system that is used as a crucial diagnostic tool for cardiovascular diseases. A prepared ECG signal provides indispensable information about the electrophysiology of the heart diseases and cardiovascular changes that may occur. Also it offers valuable information about the functional characteristics of the heart and cardiovascular system.*

*When monitoring ECG for a long period of time about 24 hours it is tedious, so because of that the optical analysis cannot be trusted upon and the possibility of the analyst missing the dynamic information is high. So, computer based investigation and classification of diseases can be very supportive in diagnosis of cardiovascular diseases (CVD).*

*This research was able to develop a system for ECG signal analysis that will analyze the signal with a good, quality and precise feature extraction and classification of ECG wave form to detect diverse heart disease complications.*

*From the literatures, it was point out that the ECG analysis systems established by using hybrid algorithms are too difficult. But, the hybrid techniques that have been applied in the researches yields improved analysis of heart disease classification.*

*This research is implemented using Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) for feature manipulation and Adaptive Neuro Fuzzy Inference System (ANFIS) as a Neuro Fuzzy classifier in classifying Normal, Left Bundle Branch Block(LBBB), paced beat, Right Bundle Branch Block(RBBB) and Supraventricular Contraction(SVC) of ECG signals.*

*The research used physionet database with labelled ECG signals with different cardiac problems. From those data's using DWT it was able to extract around six features and due to inefficiency of the machine processor it was reduced using PCA into five vital feature vectors. Then taking only the detail $D_4$ level decomposition of each signals for calculating the features and feeding into ANFIS classifier it was made possible to attain an overall accuracy of the system about 99.34% with average of 99.36% and 99.84% sensitivity and specificity respectively.*

*Keywords: ANFIS, CVD, DWT, ECG, PCA.*

# Acknowledgment

Firstly I would like to praise ALLAH for everything he has given to me and I take this opportunity to express my sincere gratitude to Dr. Towfik Jemal, Dr. Bheema Lingaiah and Dr. Kinde Anilay for their immense knowledge sharing and valuable guidance during this research. Without them this accomplishment would not have been possible.

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## Table of Contents

# List of table

# List of figures

# Acronym

| | |
|---|---|
| ANFIS | Adaptive Neuro Fuzzy Inference System |
| AR | Autoregressive |
| AV | Atrioventricular |
| BPM | Beats per Minute |
| DCT | Discrete Cosine Transform |
| DWT | Discrete Wavelet Transform |
| ECG | Electrocardiography |
| FIS | Fuzzy Inference System |
| GLM | Generalized Linear Model |
| HPF | High Pass Filter |
| ICU | Intensive Care unit |
| LBBB | Left Bundle Branch Block |
| LPF | Low Pass Filter |
| MATLAB | MATrix LABoratory |
| MLP | Multi-Layer Perceptron |
| MSA | Multi-scale Approximation Analysis |
| NN | Neural Network |
| NSB | Normal Sinus Beats |
| PB | Paced Beats |
| PVC | Premature Ventricular Contraction |
| RBBB | Right Bundle Branch Block |
| RBF | Radial Basis Function |
| SA | Sinoatrial |
| SOM | Self-Organizing Map |
| SVC | Supraventricular contraction |
| SVM | Support Vector Machine |
| WPT | Wavelet Packettree Analysis |
| WT | Wavelet Transform |

# Chapter 1

# 1 Introduction

## 1.1 Background

ECG monitoring is well thought-out as one of the most valuable diagnostic tool in modern medicine. In the critical care setting, the objectives of ECG monitoring range from simple heart rate and basic ECG rhythm reading to the diagnosis of complex cardiac arrhythmias, myocardial ischemia and elongated QT interval [1].

Electrocardiogram (ECG) is a diagnosis tool that accounts the electrical activity of heart recorded by skin electrode. The morphology and heart rate reflects the cardiac health of human heart beat [2]. It is a noninvasive technique that means the signal is measured on the superficial of human body, which is used in classification of the heart diseases [2]. Any sickness of heart rate or rhythm, or change in the morphological pattern, is a sign of cardiac arrhythmia, which could be detected by examination of the recorded ECG waveform. The amplitude and duration of the P-QRS-T wave contains valuable information about the nature of disease afflicting the heart. The electrical wave is due to depolarization and re polarization of Na+ and k + ions in the plasma [2].

In the medical test using ECG, the heart disease detection is based on the different wave signals that seem on the screen during the ECG test. The detection of the pulse is usually detected on the basis of the major in a signal of PQRST of ECG signal. The normal heart beat in a regular rhythm will display the line tracing of the PQRS and T wave looks normal. If there is any clear changes of the PQRST line tracing, it shows that the heart may have a complications. Assessment of overall ECG waveform pattern and shape enables doctors to identify diseases. The ECG remains the humblest noninvasive diagnostic method for various heart diseases.

The ECG signal delivers the following information of a human heart [3]

- heart location and its relative chamber size
- impulse source and propagation
- heart rhythm and conduction turbulences
- degree and location of myocardial ischemia
- variations in electrolyte concentrations

- Medication effects on the heart.

The heart comprises four chambers that is right atrium, left atrium, right ventricle, left ventricle and several atrioventricular and sinoatrial node [2]. The two upper chambers are called the left and right atria, whereas the lower two chambers are called the left and right ventricles. The atria are attached to the ventricles by fibrous, non-conductive tissue that retains the ventricles electrically isolated from the atria. The right atrium plus the right ventricle together form a pump to the circulate blood to the lungs. Oxygen-devoid blood is received through large veins called the superior and inferior vena cava and flows into the right atrium. The right atrium contracts and push blood into the right ventricle, elongating the ventricle and maximizing its pumping (contraction) efficiency. The right ventricle then push the blood to the lungs where the blood is oxygenated. Likewise, the left atrium and the left ventricle together form a pump to circulate oxygen-enriched blood received from the lungs (via the pulmonary veins) to the rest of the body [4].

The mechanical pumping action of the heart effects from electrical activation fronts transversing the cardiac tissue. The heart tissue practices a series of stages of electrical depolarization and repolarization that lead to particular muscle contractions.

The first phase of a heartbeat begins when the sinoatrial (SA) node of the heart depolarizes. During this phase, the right atrium is occupied with oxygen-devoid blood that has returned from the circulatory system and the left atrium is filled with oxygen-rich blood that has returned from the pulmonary circulation. The SA node, situated on the posterior wall of the right atrium, is the pacemaker of the heart, depolarizing at regular time intervals to ensure proper pacing. In a normal heart, the rate at which this node releases pulses is directly correlated to the amount of work that the heart as doing. As the body works harder and requires more oxygen-rich blood, the SA node increases its pace to fulfil the demand [5].

The electrical impulse from the SA node reasons the upper portion of the heart, called the left and right atrium, to depolarize. This depolarization causes the atria to contract forcing the blood from these chambers down into the large lower portion of the heart, called the ventricles. The conforming component of the electrical signal is the P wave. As soon as the atria have completely contracted, they begin to repolarize in training for the next beat. The electrical mark of the repolarization is not discernable in the electrical signal because

it occurs at the same time as the ventricular contraction, which yields the large QRS complex [5].

Following the depolarization of the atria, the depolarizing wave heads signals converge at the atrioventricular (AV) node. The AV node aids two very important purposes. Its first purpose is to link the electrical signal from the atria to the ventricles. The second purpose is to slow the electrical depolarization to allow the blood to completely flow from the atria to the ventricles. The electrical depolarization spreads from the AV node to the His Bundles, which are situated at the base of the ventricles. The His Bundles lead to the bundle branches and then into the purkinje fibers, which quickly spread the depolarizing wave front across both ventricles. This electrical signal moves rapidly across the ventricular tissue producing the muscles of the ventricles to pump the blood to the rest of the body. The right ventricle drives the oxygen-devoid blood to the pulmonary system for oxygenation. The left ventricle pushes the oxygen-rich blood to the circulatory system to carry oxygen to the body. Following the depolarization and contraction, the ventricles start to repolarize to prepare for the next cycle [5].

As long as the heart is working properly, the procedure described above repeats rhythmically with a natural variability. Commonly, the resting heartbeat of a healthy person is about 60-80 BPM [6]. If the electrical system of the heart does not correctly function, the heart's rhythm can become abnormal. This directly disturbs the heart's ability to supply blood to the entire body. To monitor for such difficulties, physicians record and analyze the cardiac electrical signals using the electrocardiogram.

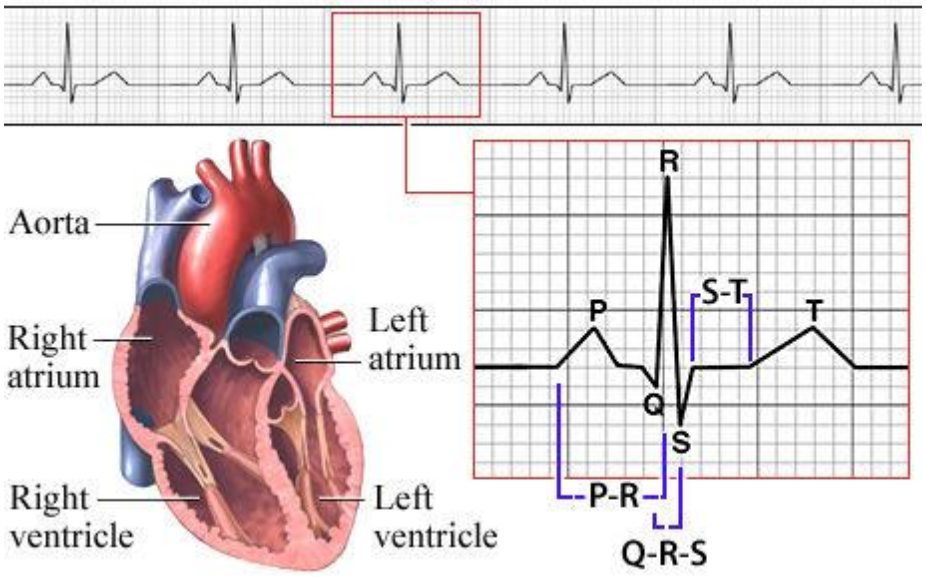


Figure 1. 1 Diagram of the human heart and an example of normal ECG trace [7]

The Electrocardiogram signal is widely utilized as the most imperative tool to study the heart state. The electrical activity of the human heart may be slower, faster or irregular than the normal signal results in circumstance of cardiac arrhythmia. The ECG signals are dynamic in nature, so the disorder of the heart may not act at all times. For correct diagnosis the ECG signal may be observed for distinct hours. This results in a high number of input data and the analysis turns out to be frustrating and time consuming. Due to an extended volume of data, the probability of an analyst to miss data is high. Hence there is a requirement in the diagnosis system to differentiate between the normal and abnormal signals. This assists the cardiologist for easy detection of the arrhythmia. Diverse intelligent systems have been developed for the analysis of the ECG signal.

The research linked to ECG arrhythmias classification is the betterment of the performance of Neuro-fuzzy based classification by the use of Wavelet Transform (WT).For the exact analysis of an ECG signal, feature extraction is very vital to detect the characteristics point and the different time intervals that can be used to detect probable cardiac abnormalities. Most of the times, the ECG signal is either degraded or covered by noise. Wavelet analysis plays a very essential role for the proper classification of the ECG signals as matched to other methods. Wavelet Transform (WT) has the property of Multi-scale Approximation Analysis (MSA) to deliver both time and frequency domain information of the signal. The methods of WT that have been used to observe the signal decomposition into a set of some

primary functions called wavelet. They are gained from a single prototype wavelet by dilations, contraction and shift [8].

Therefore, abundant research work analyzing the ECG signals have been stated for effective diagnosis, the study of ECG pattern and heart rate variability signal may have to be passed out over several hours. Thus, the volume of the data being enormous, the study is boring and time consuming. Naturally, the possibility of the expert missing (or misreading) vital information is high. Therefore, computer based analysis and classification of diseases can be very accommodating in diagnostics. Conventional methods of monitoring and diagnosing electrocardiographic variations rely on detecting the presence of particular signal features by a human observer. Due to large number of patients in intensive care units and the necessity for continuous observation of such conditions, several techniques for automated electrocardiographic variations detection have been developed in the past 10 years to challenge and solve this problem. Such systems work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem [9].

Fuzzy set theory plays a central role in dealing with uncertainty when creating decisions in medical applications. Therefore, fuzzy sets have appealed the rising attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. Neuro-fuzzy systems are fuzzy systems which use artificial neural networks (ANNs) theory in order to define their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems connect the power of the two paradigms: fuzzy logic and ANNs, by utilizing the mathematical assets of ANNs in tuning rule-based fuzzy systems that approximate the way human process information. A specific approach in Neuro-fuzzy expansion is the adaptive Neuro-fuzzy inference System (ANFIS), which has shown substantial results in modeling nonlinear functions. In ANFIS, the membership function parameters are pull out from a data set that describes the system behavior. The ANFIS learns features in the data set and regulates the system parameters according to a given error criterion. Successful applications of ANFIS in biomedical engineering have been reported, for classification and data analysis [9].

Physio Bank database is a big and growing archive of well-characterized digital recordings of physiologic signals and related data for use by the biomedical research community.

Physio Bank at this time includes databases of multipara meter cardiopulmonary, neural, and other biomedical signals from healthy subjects and patients with a range of conditions with major public health implications, including sudden cardiac death, congestive heart failure, epilepsy, gait disorders, sleep apnea, and aging[9].

## 1.2 Problem statement

ECG being a non-stationary signal, the abnormalities may not be periodic and may not display up all the time, but would be noticeable at certain irregular intervals during examination. Also clinical follow-up of ECG can take long hours about 24 hours and can be very tedious in intensive care unit (ICU). For the reason of that visual analysis cannot be trusted upon and the likelihood of the analyst missing the vital data is high. Hence, computer grounded analysis and classification of diseases can be right helpful in diagnosis. Also numerous significant heart cycle movements are also very small and rapid and cannot be trapped by the human vision. Therefore, they need automatic ECG signal analysis with high precision of detection and classification that can give earlier announcement to the physician and patient.

## 1.3 Objectives

### 1.3.1 General objective

Developing automatic ECG signal analysis system with advanced feature extraction and classification method for five cardiac problems with improved level of classification accuracy.

### 1.3.2 Specific objectives

1) To determine the viability of ECG signal and characterization of ECG waveform using different features.
2) To apply DWT for feature extraction of ECG signals and PCA for feature reduction, and also to use ANFIS as a Neuro Fuzzy classifier.
3) To measure the performance of ECG analysis using DWT and ANFIS in classifying the heart disease.

## 1.4 Literature review

A lot of extensive research has been done on renovating ECG signal analysis. For accurate and reliable analysis of ECG signal there are diverse methods of feature extraction and classification techniques that were explored by different researchers. From those

techniques of feature extraction some of them are the discrete and continuous (WT), optimal mother wavelet and Hermitian basis functions. The classification techniques frequently used were fuzzy logic methods, artificial neural network, hidden markov model and SVM.

Joshi D, et. al, on their research try to automate ECG signal analysis system to support the doctor to detect cardiac arrhythmia. They focused on different systems for extracting the convenient features of the ECG signals for use with artificial neural networks. They extract the principal characteristics of the signal by means of the (PCA), DWT and Discrete cosine transform techniques. Subsequently computing signal pre-processing and feature extraction they applied to an ANN MLP. Finally they compared the result with the RBFN and SVM. Discrete cosine transform feature extraction and SVM classifiers yield superior performance compared to others. They point out speed optimization should be considered for future work [10].

Diagnostic system for classification of cardiac arrhythmia from ECG data, using hybrid model of artificial neural network and fuzzy logic was applied. In the proposed paper Mahapatra S, et. al, applied an algorithm based on WPT classifier (for detection of QRS complex) has been employed for the comparative study of automatic real-time ECG data. They stated that amplitude and duration of the typical waves of the ECG can be more accurately obtained using WPT analysis. WPT procedure was used to extract a set of linear (time and frequency domain) characteristics. Next feature extraction using wavelet sub-band energy coefficient they fed it to neuro-fuzzy network for classification. Due to little processing time and advanced accuracy of the hybrid method, they concluded that Neuro-fuzzy network was best for a real-time arrhythmia classification system [8].

Shah MR, et.al, they present a method in which it consists of data pre-processing using the wavelet transform, classification using the Euclidean Distance Classifier. In the study they have used the (DWT) to remove the irregularities in the ECG signal prior to training the neural network and classify via the Euclidean classifier and concluded it was best without comparing with others [11].

Signal V, et. al, proposed a method to analyze ECG signal using features extracted using DWT and classification is done according to various methods like ANN, ANFIS , SVM , & Statistical classifier. Finally they concluded that the overall performance of the system

with ANN is the best classification techniques in terms of accuracy, sensitivity and predictivity [12].

Sambhu D, et. al, are able to extract 25 different features of temporal, morphological and statistical features using DWT and finally classified using SVM executed by using one against one. They endorse that intense computation that might be carried out to do the classification can be tackled by using dimensionality reduction PCA. But they got higher accuracy [13].

Varshney M, et. al, proposed various techniques that where earlier proposed in literature for extracting feature from an ECG Signal and classification into different classes. In addition this paper showed comparative study of methods which are used to check the accuracy of overall system. The suggested schemes were mostly based on ANN, SVM, MLP and morphological descriptor time -frequency distribution. All these techniques and algorithms have their advantages and limitations. Finally the paper concluded that MLP method is best among the rest because it defines the hearts bundle branch which is widely used in the diagnosis [14].

Jambukia SH, et al, conducted survey on different issues in ECG classification, databases available for ECG, different preprocessing techniques available for noise removal, various classifiers available for classification of ECG data, and performance measures for evaluating accuracy of classifier are presented. They mentioned that the preprocessing and feature extraction techniques mostly used are wavelets and algorithms such as Pan-Tompkins algorithm. Among these they recommend one should use algorithm for pre-processing and feature extraction compared to wavelet technique because for extracting features and removing noise using wavelet one should use higher level of decomposition. Moreover, a wavelet technique is more difficult and time consuming. Moreover for classification, researchers have used diverse techniques like different neural networks and SVM. However, it is perceived from survey that neural networks are prone to be good for ECG classification in terms of classification accuracy on training and test datasets [15].

Sahoo JP try to automatically detect cardiac arrhythmia through a novel approach using the properties of Hilbert transform and autocorrelation function. The autocorrelation based process is used to find out the period of one cardiac cycle. The high slope point that means R-peak in ECG signal is recognized from the envelope of Hilbert transform output. And

the adaptive threshold technique is used which helps to separate the R peaks from P-wave and T-wave. The morphological features joined with temporal features of each heartbeat are extracted to deliver better classification accuracy. The feature extraction methodology extracts the features of each heartbeat after automatic detection of R-peak.

The comparative study of ECG beat classifier using multilayer perceptron neural network and radial basis function neural network has prepared for automatic classification of cardiac arrhythmias heartbeats into five classes: normal beats, VEBs, SVEBs, fusion beats and unclassified beats. Finally the result shows MLP neural network succeed higher classification accuracy than RBF neural network on his work [16].

Kamarudin. NHB, proposed the analysis system composed of three major components having the preprocessing, feature extraction using DWT and ANFIS as Neuro fuzzy classier is used to classify about four heart disease from the physionet database with promising classification accuracy. It imply the advantage of hybrid systems over individual systems for future work [17].

A.Mohamed M, et. al, claimed that most of clinically useful information of the ECG signal is found in the time intervals between its successive waves and amplitudes defined by its features. ECG feature extraction algorithm based on Daubechies Wavelet Transform is offered and DB4 Wavelet is nominated due to the similarity of its scaling function to the shape of the ECG signal. R peaks detection is the core of this algorithm's feature extraction. All other primary peaks are extracted with respect to the position of R peaks through creating windows proportional to their normal intervals.

First the ECG signal is smoothed by decomposing and omitting much of the details however keeping the $4^{th}$ level approximation coefficients. The R peaks are then extracted after the down sampled clean ECG signal. This is followed by locating the detected R peaks in the original signal which has allowed positioning other peaks (P, T, Q and S) with reference to the identified R peaks [18].

Elhaj FA, et. al, work on investigating the representation ability of linear and nonlinear features by proposing a combination of such features in order to improve the classification of ECG data. In this study, five types of beat classes of arrhythmia as mentioned by the association for advancement of medical instrumentation are investigated,: non-ectopic

beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F) and unclassifiable and paced beats (U). The representation ability of nonlinear features such as high order statistics and cumulants and nonlinear feature reduction systems such as independent component analysis are joined with linear features, namely, the PCA of DWT coefficients. The features are tested for their ability to differentiate different classes of data using different classifiers, namely, the support vector machine and neural network methods with tenfold cross-validation [19].

## 1.5 Research motivation

Currently science and technology is developing in tremendous way and is putting lots of advancements on medical technology. So it initiates this research to be conducted on the very interesting and sensitive field of area with appropriate technology implementation of latest science.

As it was known that heart is very sensitive and our body's vital organ that should be maintained health throughout our daily lives. So it was needed to find a way accurately and precisely differentiate between the cardiac abnormalities.

Since it was the most prominent health problem of this $20^{th}$ century lifestyle. It was found to be mandatory to assist the cardiologist and the physicians in a way that can identify heart diseases without the involvement of specialists.

## 1.6 Scope of the research

In this thesis, ECG signal analysis which is done by DWT for feature extraction, PCA for reducing the feature vectors and classification by ANFIS has been developed. Using MATLAB in this research five heart diseases related to mortality of cardiac patient were classified with very promising overall accuracy of 99.34% for normal, LBBB, RBBB, paced beat, and SVC of ECG signals. Around a 401 data's were studied in the research and from those datasets about 250 were used for training and 151 were used for testing. But this data's are totally patient independent which means the learning data is independent of the testing data.

# Chapter 2

# 2. Cardiovascular system

## 2. Cardiac anatomy and physiology

The heart is a muscular pump that serves two functions used to collect blood from the tissues of the body and pump it to the lungs and to collect blood from the lungs and pump it to all tissues of the body [20].

### 2.1 Cardiac anatomy

Cardiac anatomy includes the location of the heart; the structure of the heart, heart wall, chambers, and valves; and the layout and structure of coronary circulation.

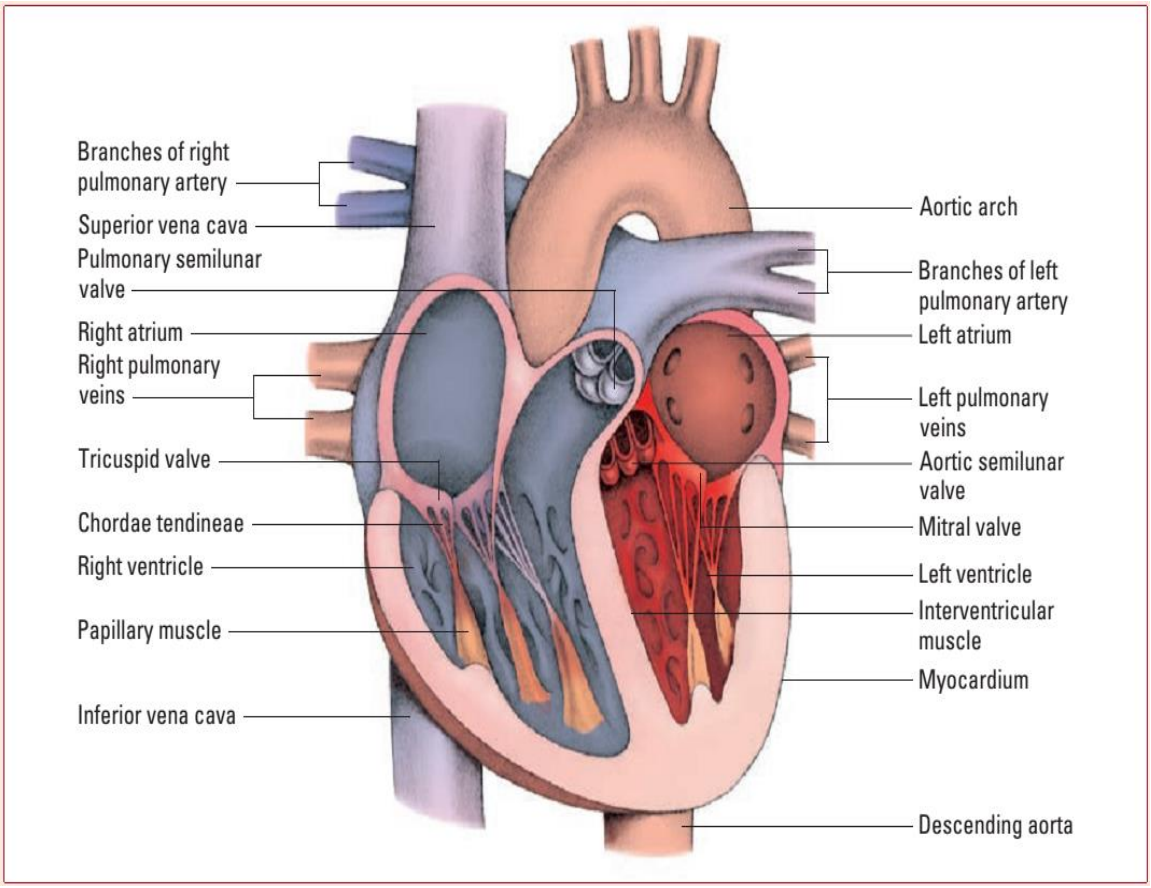


Figure 2. 1The anatomy of a normal heart [3]

#### 2.1.1 Human heart

The heart is a cone-shaped, muscular organ. It's located in the chest, behind the sternum in the mediastinal cavity (or mediastinum), between the lungs, and in front of the spine. The

heart lies tilted in this area like an upside-down triangle. The top of the heart, or its base, lies just below the second rib; the bottom of the heart, or its apex, tilts forward and down, toward the left side of the body, and rests on the diaphragm [3].

### 2.1.2 Layers of the heart wall

The walls of the heart contain three layers: the superficial epicardium; the middle myocardium, which is composed of cardiac muscle; and the inner endocardium. Note that cardiac muscle cells contain intercalated disks that enable the cells to communicate and allow direct transmission of electrical impulses from one cell to another [20].

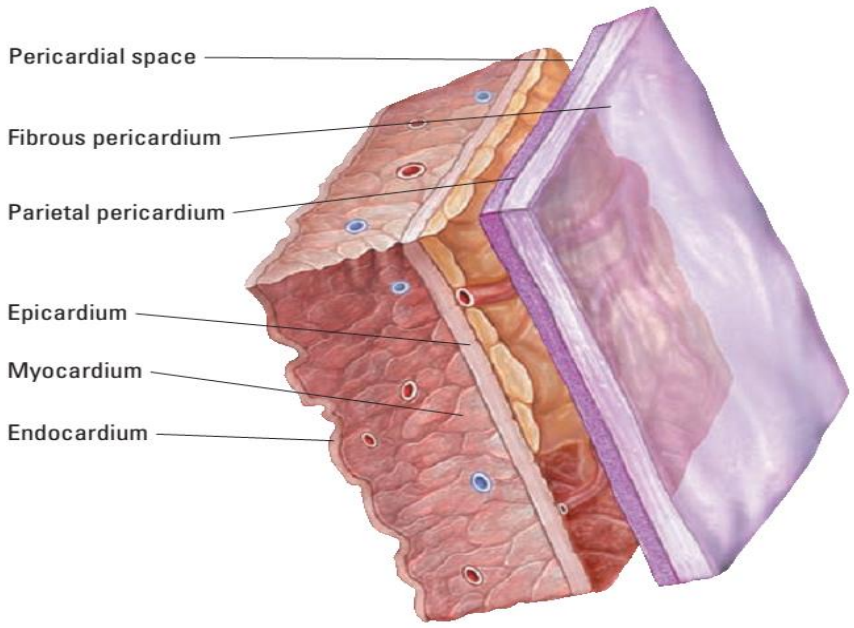


Figure 2. 2 Layers of the heart wall [3]

i. Between the layers of heart wall

The pericardial space separates the visceral and parietal layers and contains 10 to 20 ml of thin, clear pericardial fluid that lubricates the two surfaces and cushions the heart. Excess pericardial fluid, a condition called pericardial effusion, compromises the heart's ability to pump blood.

ii. Inside of the heart

The heart contains four chambers—two atria and two ventricles. The right and left atria serve as volume reservoirs for blood being sent into the ventricles. The right atrium

receives deoxygenated blood returning from the body through the inferior and superior vena cavae and from the heart through the coronary sinus. The left atrium receives oxygenated blood from the lungs through the four pulmonary veins. The interatrial septum divides the chambers and helps them contract. Contraction of the atria forces blood into the ventricles below [3].

### 2.1.3 Pumping chambers

The right and left ventricles serve as the pumping chambers of the heart. The right ventricle receives blood from the right atrium and pumps it through the pulmonary arteries to the lungs, where it picks up oxygen and drops off carbon dioxide. The left ventricle receives oxygenated blood from the left atrium and pumps it through the aorta and then out to the rest of the body. The interventricular septum separates the ventricles and also helps them to pump.

i. One-way valves

The heart contains four valves two atrioventricular valves tricuspid and mitral and two semilunar valves aortic and pulmonic. The valves open and close in response to changes in pressure within the chambers they connect. They serve as one-way doors that keep blood flowing through the heart in a forward direction. When the valves close, they prevent backflow, or regurgitation, of blood from one chamber to another. The closing of the valves creates the heart sounds that are heard through a stethoscope.

The heart pumps by squeezing, compressing and pressurizing the blood which then flows down the pressure gradient. The heart's valves force the blood to go in one direction and prevent backward flow [14].

ii. Cardiac cords

The mitral valve has two cusps, or leaflets, and the tricuspid valve has three. The cusps are anchored to the papillary muscles in the heart wall by fibers called chordae tendineae. These cords work together to prevent the cusps from bulging backward into the atria during ventricular contraction. If damage occurs, blood can flow backward into a chamber, resulting in a heart murmur[3].

iii. Semilunar and Pulmonic valve

The semilunar valves are the pulmonic valve and the aortic valve. These valves are called semilunar because the cusps resemble three half-moons. Because of the high pressures

exerted on the valves, their structure is much simpler than that of the AV valves. They open due to pressure within the ventricles and close due to the back pressure of blood in the pulmonary arteries and aorta, which pushes the cusps closed [3].

### 2.1.4 Blood flow through the heart

Understanding how blood flows through the heart is critical to understanding the heart's overall functions and how changes in electrical activity affect peripheral blood flow. Deoxygenated blood from the body returns to the heart through the inferior and superior vena cavae and empties into the right atrium. From there, blood flows through the tricuspid valve into the right ventricle.

i. Systemic and Pulmonary circulation

The right ventricle pumps blood through the pulmonic valve into the pulmonary arteries and then into the lungs. From the lungs, blood flows through the pulmonary veins and empties into the left atrium, which completes a circuit called pulmonary circulation. When pressure rises to a critical point in the left atrium, the mitral valve opens and blood flows into the left ventricle. The left ventricle contracts and pumps blood through the aortic valve into the aorta, and throughout the body. Blood returns to the right atrium through the veins, completing a circuit called systemic circulation. When valves close, heart sounds are heard [3].

### 2.1.5 Coronary ostium

The coronary ostium, an opening in the aorta that feeds blood to the coronary arteries, is located near the aortic valve. During systole, when the left ventricle is pumping blood through the aorta and the aortic valve is open, the coronary ostium is partially covered. During diastole, when the left ventricle is filling with blood, the aortic valve is closed and the coronary ostium is open, enabling blood to fill the coronary arteries.

i. Right Coronary artery

The right coronary artery, as well as the left coronary artery (also known as the left main artery), originates as a single branch off the ascending aorta from the area known as the sinuses of Valsalva. The right coronary artery supplies blood to the right atrium, the right ventricle, and part of the inferior and posterior surfaces of the left ventricle. In about 50% of the population, the artery also supplies blood to the SA node. The bundle of His and the AV node also receive their blood supply from the right coronary artery

ii. Left Coronary artery

The left coronary artery runs along the surface of the left atrium, where it splits into two major branches, the left anterior descending and the left circumflex arteries. The left anterior descending artery runs down the surface of the left ventricle toward the apex and supplies blood to the anterior wall of the left ventricle, the interventricular septum, the right bundle branch, and the left anterior fasciculus of the left bundle branch.

iii. Circumflex artery

The circumflex artery supplies oxygenated blood to the lateral walls of the left ventricle, the left atrium and, in about half of the population, the SA node. In addition, the circumflex artery supplies blood to the left posterior fasciculus of the left bundle branch. This artery circles the left ventricle and provides blood to the ventricle's posterior portion.

iv. Collateral circulation

When two or more arteries supply the same region, they usually connect through anastomoses, junctions that provide alternative routes of blood flow. This network of smaller arteries, called collateral circulation, provides blood to capillaries that directly feed the heart muscle [3].

### 2.1.6 Veins in the heart

The heart has veins just like other parts of the body. Cardiac veins collect deoxygenated blood from the capillaries of the myocardium. The cardiac veins join to form an enlarged vessel called the coronary sinus, which returns blood to the right atrium, where it continues through the circulation.

The coronary arteries supply the heart with nutrients and oxygen. At the same time, waste products and carbon dioxide must be removed. An extensive network of intercommunicating veins provides venous drainage from the heart. The venous drainage of deoxygenated blood from all tissues is collected in the right atrium; this includes the venous drainage of the heart. Venous drainage of the heart is accomplished through three separate systems: the cardiac venous tributaries, which converge to form the coronary sinus [20].

## 2.2 Cardiac physiology

This discussion of cardiac physiology includes descriptions of the cardiac cycle, how the cardiac muscle is innervated, how the depolarization-repolarization cycle operates, how impulses are conducted, and how abnormal impulses work.

The current approach to understanding cardiac dynamics relies upon movements that adhere to the conventional topographical separation of cardiac muscle into the left ventricle, right ventricle, and septum. Functional analyses have addressed them independently, and this approach has resulted in many suppositions that this report will define and question [19].

### 2.2.1 Cardiac cycle dynamics

During one heartbeat, ventricular diastole (relaxation) and ventricular systole (contraction) occur. During diastole, the ventricles relax, the atria contract, and blood is forced through the open tricuspid and mitral valves. The aortic and pulmonic valves are closed. During systole, the atria relax and fill with blood. The mitral and tricuspid valves are closed. Ventricular pressure raises which forces opening the aortic and pulmonic valves. Then the ventricles contract, and blood flows through the circulatory system.

First, the mitral valve opening during clockwise recoil is caused by the wrap initiating when LV negative dP/pt starts, rather than when a LV pressure falls below left atrial pressure. Second, the entire ventricle does not relax—ongoing strain measurements and sono micrometer crystal recordings confirm outer ascending helical arm contraction. Finally, it produces lengthening that is quantified by MRI, two-dimensional echo, and longitudinal strain recordings. This elongation movement may mirror how a cobra develops an erectile stance before striking [21].

### 2.2.3 Depolarization and Repolarization cycles

As impulses are transmitted, cardiac cells undergo cycles of depolarization and repolarization. Cardiac cells at rest are considered polarized, meaning that no electrical activity takes place. Cell membranes separate different concentrations of ions, such as sodium and potassium, and create a more negative charge inside the cell. This is called the resting potential. After a stimulus occurs, ions cross the cell membrane and cause an action potential, or cell depolarization. When a cell is fully depolarized, it attempts to return to its

resting state in a process called repolarization. Electrical charges in the cell reverse and return to normal. A cycle of depolarization-repolarization consists of five phases 0 through 4. The action potential is represented by a curve that shows voltage changes during the five phases.

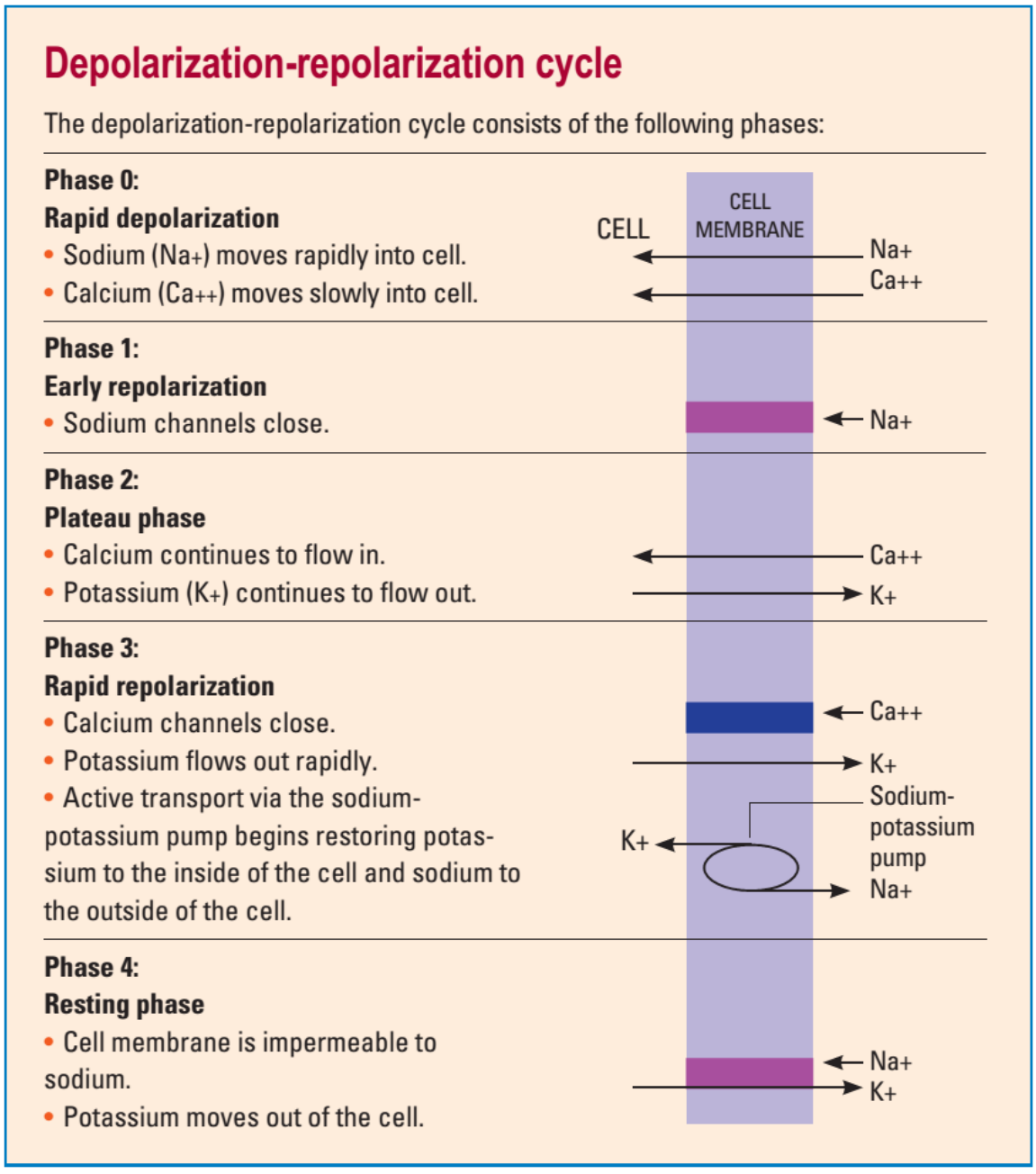


Figure 2. 3 phases of action potential [3]

### 2.2.4 Electrical impulses Pathway through the heart

After depolarization and repolarization occur, the resulting electrical impulse travels through the heart along a pathway called the conduction system. Impulses travel out from the SA node and through inter nodal tracts and Bachmann's bundle to the AV node. From there, they travel through the bundle of His, the bundle branches, and lastly to the Purkinje fibers. Setting the pace The SA node is located in the upper right corner of the right atrium, where the superior vena cava joins the atrial tissue mass. It's the heart's main pacemaker, generating impulses 60 to 100 times per minute. When initiated, the impulses follow a specific path through the heart. They usually can't flow backward because the cells can't respond to a stimulus immediately after depolarization. Specialized fibers propagate electrical impulses throughout the heart's cells, causing the heart to contract.

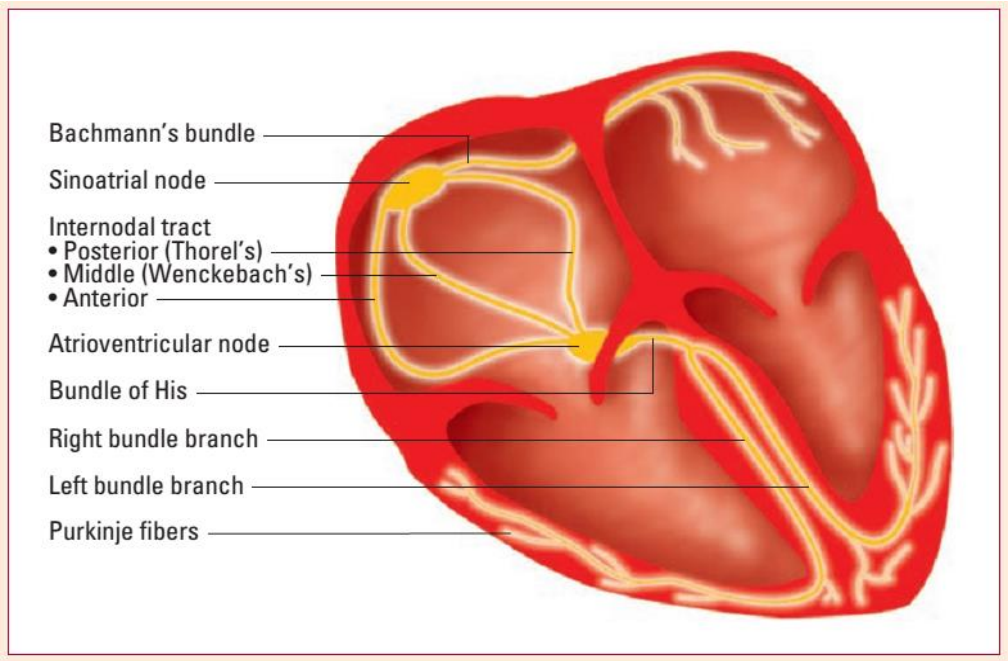


Figure 2. 4 cardiac conduction systems [3]

i. Bachmann's bundle of nerves

Impulses from the SA node next travel through Bachmann's bundle, tracts of tissue extending from the SA node to the left atrium. Impulses are thought to be transmitted throughout the right atrium through the anterior, middle, and posterior inter nodal tracts.

ii. The slow node

The AV node, located in the inferior right atrium near the ostium of the coronary sinus, is responsible for delaying the impulses that reach it. Although the nodal tissue itself has no pacemaker cells, the tissue surrounding it (called junctional tissue) contains pacemaker cells that can fire at a rate of 40 to 60 times per minute.

The AV node's main function is to delay impulses by 0.04 second to keep the ventricles from contracting too quickly. This delay allows the ventricles to complete their filling phase as the atria contract. It also allows the cardiac muscle to stretch to its fullest for peak cardiac output.

iii. Bundle branch splitting

The bundle of His, a tract of tissue extending into the ventricles next to the interventricular septum, resumes the rapid conduction of the impulse through the ventricles. The bundle eventually divides into the right and left bundle branches. The right bundle branch extends down the right side of the interventricular septum and through the right ventricle. The left bundle branch extends down the left side of the interventricular septum and through the left ventricle. The left bundle branch then splits into two branches, or fasciculi: the left anterior fasciculus, which extends through the anterior portion of the left ventricle, and the left posterior fasciculus, which runs through the lateral and posterior portions of the left ventricle. Impulses travel much faster down the left bundle branch (which feeds the larger, thicker-walled left ventricle) than the right bundle branch (which feeds the smaller, thinner-walled right ventricle). The difference in the conduction speed allows both ventricles to contract simultaneously. The entire network of specialized nervous tissue that extends through the ventricles is known as the His-Purkinje system.

iv. Purkinje fibers

Purkinje fibers extend from the bundle branches into the endocardium, deep into the myocardial tissue. These fibers conduct impulses rapidly through the muscle to assist in its depolarization and contraction. Purkinje fibers can also serve as a pacemaker and are able to discharge impulses at a rate of 20 to 40 times per minute, sometimes even more slowly. Purkinje fibers usually aren't activated as a pacemaker unless conduction through the bundle of His becomes blocked or a higher pacemaker (SA or AV node) doesn't generate an impulse [3].

### 2.2.5 Pacemakers of the heart

Pacemaker cells in lower areas, such as the junctional tissue and the Purkinje fibers, normally remain dormant because they receive impulses from the SA. They initiate an impulse only when they don't receive one from above, such as when the SA node is damaged from a myocardial infarction.

Firing rates illustration shows intrinsic firing rates of pacemaker cells located in three critical areas of the heart

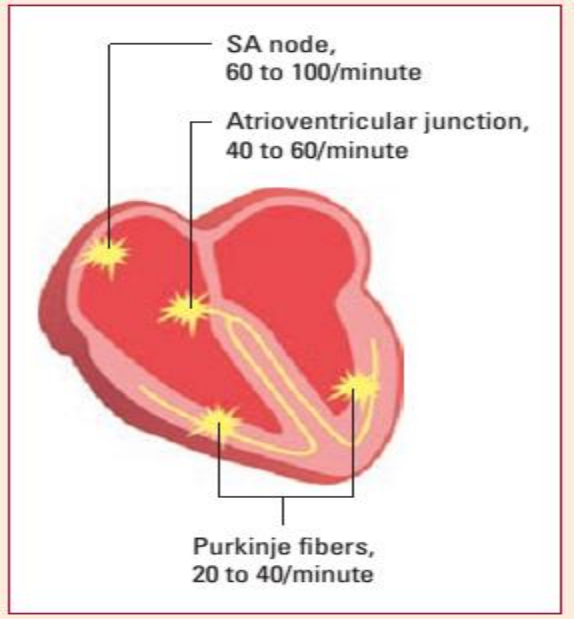


Figure 2. 5 pacemakers of heart [3]

## 2.3 ECG recording

The heart's electrical activity yields currents that radiate through the surrounding tissue to the skin. When electrodes are attached to the skin, they sense those electrical currents and transfer them to an ECG monitor. The currents are then transformed into waveforms that characterize the heart's depolarization repolarization cycle.

Myocardial depolarization occurs when a wave of stimulation passes through the heart and stimulates the heart muscle to contract. Repolarization is the return to the resting state and results in relaxation.

An ECG shows the precise sequence of electrical events occurring in the cardiac cells throughout that process. It allows the nurse to monitor phases of myocardial contraction and to identify rhythm and conduction disturbances. A series of ECGs can be used as a baseline comparison to assess cardiac function [3].

### 2.3.1 ECG leads and planes

To understand electrocardiography, you need to understand leads and planes. Electrodes placed on the skin measure the direction of electrical current discharged by the heart. That current is then transformed into waveforms.

An ECG records information about those waveforms from different views or perspectives. Those perspectives are called leads and planes.

A lead provides a view of the heart's electrical activity between one positive pole and one negative pole. Between the two poles lies an imaginary line representing the lead's axis, a term that refers to the direction of the current moving through the heart.

The direction of the current affects the direction in which the waveform points on an ECG. When no electrical activity occurs or the activity is too weak to measure, the waveform looks like a straight line, called an isoelectric waveform. The direction of the electrical current determines the upward or downward deflection of an electrocardiogram waveform.

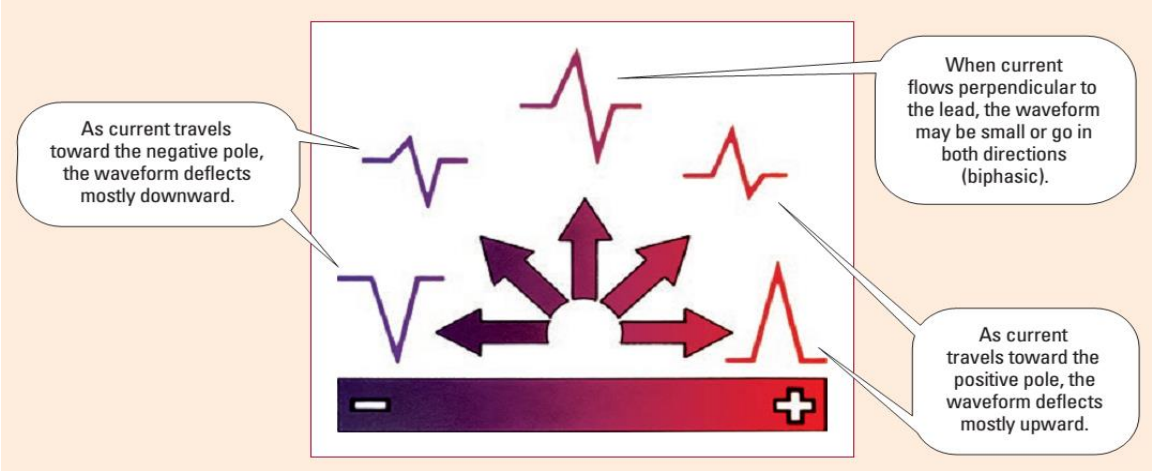


Figure 2. 6 current direction and wave deflection [3]

The term plane refers to a cross-sectional perspective of the heart's electrical activity. The frontal plane, a vertical cut through the middle of the heart, provides an anterior-to-posterior view of electrical activity. The horizontal plane, a transverse cut through the middle of the heart, provides either a superior or an inferior view.

### 2.3.2 Types of ECG recording

The two types of ECG recordings are the 12-lead ECG and a rhythm strip. Both types give valuable information about heart function.

i. The 12-lead ECG

A 12-lead ECG records information from 12 different views of the heart and provides a complete picture of electrical activity. These 12 views are obtained by placing electrodes on the patient's limbs and chest. The limb leads and the chest, or precordial, leads reflect information from the different planes of the heart.

ii. The rhythm strip ECG

A rhythm strip, which can be used to monitor cardiac status, provides information about the heart's electrical activity from one or more leads simultaneously. Chest electrodes pick up the hearts electrical activity for display on the monitor. The monitor also displays heart rate and other measurements and allows for printing strips of cardiac rhythms.

Commonly monitored leads include the bipolar leads I, II, III, V1, V6, MCL1, and MCL6. The initials MCL stand for modified chest lead. These leads are similar to the unipolar leads V1and V6 of the 12-lead ECG. MCL1and MCL6, however, are bipolar leads [3].

### 2.3.3 ECG monitors

The type of ECG monitoring system you'll use hardwire monitoring or telemetry depends on the patient's condition and where you work. Let's look at each system.

i. Hardwire ECG monitoring

With hardwire monitoring the electrodes are connected directly to the cardiac monitor. Most hardwire monitors are mounted permanently on a shelf or wall near the patient's bed. Some monitors are mounted on an I.V. pole for portability, and some may include a defibrillator.

The monitor provides a continuous cardiac rhythm display and transmits the ECG tracing to a console at the nurses' station. Both the monitor and the console have alarms and can print rhythm strips. Hardwire monitors can also track pulse oximetry, blood pressure, hemodynamic measurements, and other parameters through various attachments to the patient.

ii. Telemetry ECG monitoring

Telemetry monitoring is generally used in step-down units and medical-surgical units where patients are permitted more activity. With telemetry monitoring, the patient carries a small, battery powered transmitter that sends electrical signals to another location, where the signals are displayed on a monitor screen. This type of ECG monitoring frees the patient from cumbersome wires and cables associated with hardwire monitoring.

Telemetry monitoring still requires skin electrodes to be placed on the patient's chest. Each electrode is connected by a thin wire to a small transmitter box carried in a pocket or pouch. It's especially useful for detecting arrhythmias that occur with activity or stressful situations. Most systems, however, can monitor heart rate and rhythm only [3].

### 2.3.4 The cardiac rhythm

After the electrodes are in proper position, the monitor is on, and the necessary cables are attached, observe the screen. You should see the patient's ECG waveform. Although some monitoring systems allow you to make adjustments by touching the screen, most require you to manipulate buttons. If the waveform appears too large or too small, change the size by adjusting the gain control. If the waveform appears too high or too low on the screen, adjust the position.

Verify that the monitor detects each heartbeat by comparing the patient's apical rate with the rate displayed on the monitor. Set the upper and lower limits of the heart rate according to your facility's policy and the patient's condition. Heart rate alarms are generally set 10 to 20 beats per minute higher and lower than the patient's heart rate. Monitors with arrhythmia detectors generate a rhythm strip automatically whenever the alarm goes off. Other views of your patient's cardiac rhythm can be obtained by selecting different leads. It is possible to select leads with the lead selector button or switch.

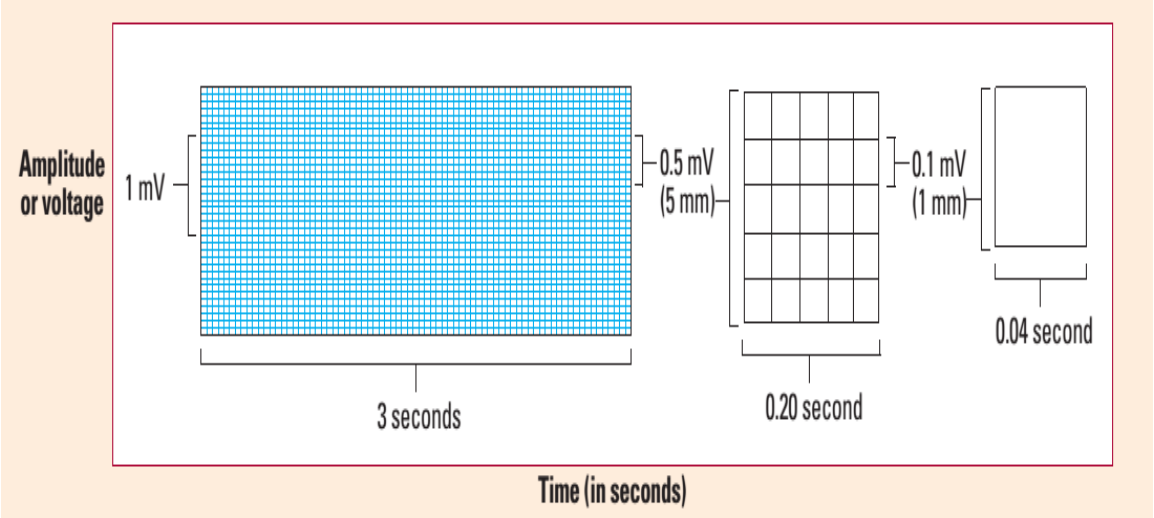


Figure 2. 7 ECG grid [3]

This ECG grid shows the horizontal axis and vertical axis and their respective measurement values.

The horizontal axis of the ECG strip represents time. Each small block equals 0.04 second, and five small blocks form a large block, which equals 0.2 second. This time increment is determined by multiplying 0.04 second (for one small block) by 5, the number of small blocks that compose a large block. Five large blocks equal 1 second (5 × 0.2). When measuring or calculating a patient's heart rate, a 6-second strip consisting of 30 large blocks is usually used.

The ECG strip's vertical axis measures amplitude in millimeters (mm) or electrical voltage in millivolts (mV). Each small block represents 1 mm or 0.1 mV; each large block, 5 mm or 0.5 mV. To determine the amplitude of a wave, segment, or interval, count the number of small blocks from the baseline to the highest or lowest point of the wave, segment, or interval.

### 2.3.5 ECG Monitor problems

For optimal cardiac monitoring, you need to recognize problems that can interfere with obtaining a reliable ECG recording. Causes of interference include artifact from patient movement and poorly placed or poorly functioning equipment.

i. Artifact

Artifact, also called waveform interference, may be seen with excessive movement (somatic tremor). The baseline of the ECG appears wavy, bumpy, or tremulous. Dry electrodes may also cause this problem due to poor contact.

ii. Interference

Electrical interference, also called 60-cycle interference, is caused by electrical power leakage. It may also occur due to interference from other room equipment or improperly grounded equipment. As a result, the lost current pulses at a rate of 60 cycles per second. This interference appears on the ECG as a baseline that's thick and unreadable.

iii. Baseline wandering

A wandering baseline undulates, meaning that all waveforms are present but the baseline isn't stationary. Movement of the chest wall during respiration, poor electrode placement, or poor electrode contact usually causes this problem.

iv. Faulty equipment

Faulty equipment, such as broken lead wires and cables, can also cause monitoring problems.

### 2.3.7 ECG complex

An ECG complex represents the electrical events occurring in one cardiac cycle. A complex consists of five waveforms labeled with the letters P, Q, R, S, and T. The middle three letters Q, R, and S are referred to as a unit, the QRS complex. ECG tracings represent the conduction of electrical impulses from the atria to the ventricles.

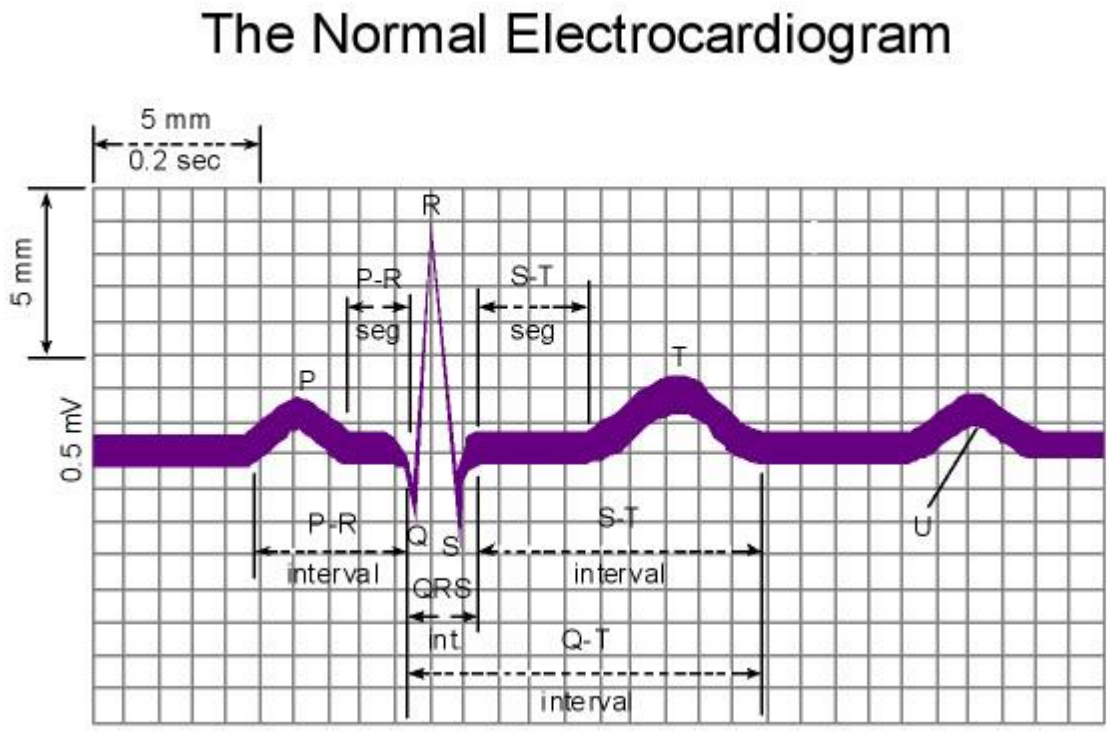


Figure 2. 8 Normal ECG [22]

The P wave is the first component of a normal ECG waveform. It represents atrial depolarization conduction of an electrical impulse through the atria.

The PR interval tracks the atrial impulse from the atria through the AV node, bundle of His, and right and left bundle branches.

The QRS complex follows the P wave and represents depolarization of the ventricles. Immediately after the ventricles depolarize, as represented by the QRS complex, they contract. That contraction ejects blood from the ventricles and pumps it through the arteries, creating a pulse.

Pay special attention to the duration and configuration when evaluating a QRS complex. A normal complex has the following characteristics:

- Location _follows the PR interval

- Amplitude _5 to 30 mm high but differs for each lead used
- Duration _0.06 to 0.10 second, or half of the PR interval. Duration is measured from the beginning of the Q wave to the end of the S wave or from the beginning of the R wave if the Q wave is absent.

Remember that the QRS complex represents intraventricular conduction time. That's why identifying and correctly interpreting it is so crucial. If no P wave appears with the QRS complex, then the impulse may have originated in the ventricles, indicating a ventricular arrhythmia.

The ST segment represents the end of ventricular conduction or depolarization and the beginning of ventricular recovery or repolarization.

The T wave represents ventricular recovery or repolarization.

The QT interval measures ventricular depolarization and repolarization. The length of the QT interval varies according to heart rate. The faster the heart rate, the shorter the QT interval.

The U wave represents the recovery period of the Purkinje or ventricular conduction fibers. It isn't present on every rhythm strip.

## 2.4 Description of cardiac abnormality classes

### 2.4.1 Normal Sinus Heart Rate

The normal heart rate has been measured to be between 60 and 100 beats per minute, although there is some difference with regard to the normal rate in adults. The range (defined by 1$^{st}$ and 99$^{th}$ percentiles) is between 43 and 102 beats per minute in men and between 47 and 103 beats per minute in women. There is also important variability in age in young children. The normal heart rate is 110 to 150 beats per minute in infants, with gradual slowing over the first six years of life [23].

### 2.4.2 Left bundle branch block

Is a pattern seen on the apparent electrocardiogram (ECG), and results when normal electrical activity in the His-Purkinje system is disturbed. The normal sequence of activation is altered dramatically in LBBB, with a resultant characteristic appearance on the ECG.

Left bundle branch block (LBBB) is commonly associated with heart failure. They evaluated the prevalence, incidence, and impact of LBBB on long-term outcome in young

patients with heart failure affected by idiopathic dilated cardiomyopathy (DCM). They found that new-onset of LBBB was associated with an increased risk of all-cause mortality [24].

### 2.4. 3 Paced beat

Once it has been proven that bradycardia or a conduction disorder warrants permanent pacing, the most appropriate pacing mode for the patient must be selected. The choice depends upon the specific abnormality that is existing, since a wide range of pacemaker functions have been established to accommodate specific clinical needs Despite the myriad of clinical situations in which permanent pacing is considered, most management decisions regarding permanent pacemaker implantation are driven by the following clinical factors , the relationship of symptoms with a bradyarrhythmia and the location of the conduction abnormality [25].

### 2.4.4 Right Bundle Branch Block

A pattern seen on the surface electrocardiogram (ECG), and results when normal electrical activity in the His-Purkinje system is interrupted. The prognostic significance of (RBBB) is inconsistent across studies. They aimed to assess the relationship between RBBB (in general population and patients with heart disease) and risk of all-cause mortality, cardiac death, acute myocardial infarction (MI), and heart failure (HF). RBBB is associated with an increased risk of mortality in general population and patients with heart disease [26].

### 2.4.5 Supraventricular tachycardia

Supraventricular tachycardia is an abnormally rapid heart rhythm created above the ventricles, often (but not always) with a narrow QRS complex [27].

# Chapter 3

# 3 ECG signal Feature Extraction and Classification

## 3.1 System Requirement

This research is established by using MATLAB. The ANFIS were also used as classier tools in fuzzy logic toolbox in MATLAB software. MATLAB software is a high-level language and interactive environment that enables to perform computationally intensive tasks faster than with traditional programming languages such as C, and C++. MATLAB codes are also being used because they could read the raw data of ECG signal easily. The input ECG signal are imported from the data files .dat and also the excel file .xls.

## 3.2 Electrocardiogram Signal Analysis Procedure

The methods presented here are divided into four pieces of steps. Firstly, procedures to identify and annotate of ECG signal for Normal, LBBB, paced beat, RBBB and SVC. Second, a strategy is presented for extracting the feature vectors for each sample of selected heart disease using an algorithm that exploits the coefficient derived from DWT. Third the PCA was applied for feature reduction. Lastly, the procedures of classification process using ANFIS System modeling was applied.

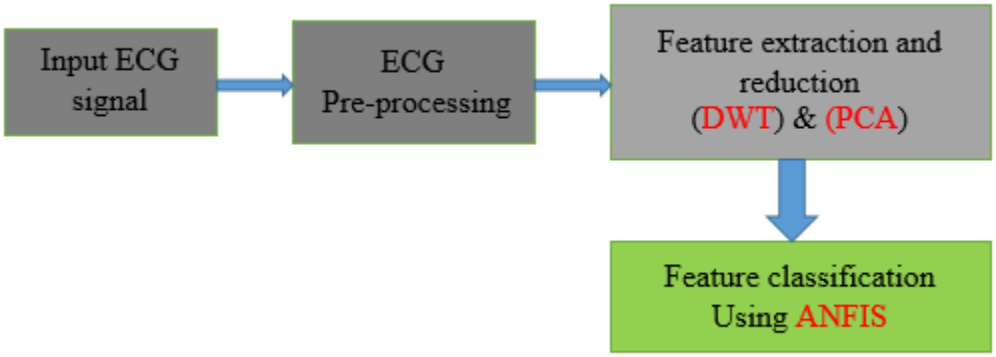


Figure 3. 1 Overall system comprising different phases of ECG signal analaysis

### 3.2.1 Preprocessing

Signal data acquisition is the first step of record and capture data from the patient which is available on physionet database. Data files of the ECG recordings were introduced into MATLAB software where all calculations were carried out. Initially, long series of data

were processed to obtain the discrete wavelet transform of the whole recording of each subject.

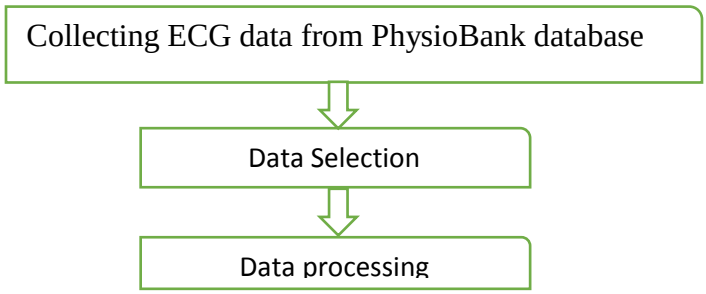


Figure 3. 2 preprocessing step of ECG signal from database

## 3.3 Databases and Data Sources

The ECG signals were taken and documented from the Physio Bank database using MIT-BIH Arrhythmia Database and Intracardiac Atrial Fibrillation Database which are generally accepted as a standard test bench for the assessment of arrhythmia detectors and basic research of cardiac dynamics.

### 3.3.1 Data Selection

Based on Table 3.1, the ECG recordings consist of 401 subjects, 250 data samples were used for training and 151 data samples were used for testing. The samples belong to five categories of cardiac abnormality: Normal, LBBB, paced beat, RBBB and SVC.

Table 3. 1 Sample Data of each ECG Signal

| Signal | Class | Training set | Testing set | Total |
|---|---|---|---|---|
| Normal | 1 | 50 | 31 | 81 |
| LBBB | 2 | 50 | 30 | 80 |
| Paced beat | 3 | 50 | 30 | 80 |
| RBBB | 4 | 50 | 30 | 80 |
| SVC | 5 | 50 | 30 | 80 |
| Total | | 250 | 151 | 401 |

### 3.3.2 Data Processing

The Class 1 consists of 81 normal subjects, Class 2 contains 80 subjects suffering from LBBB, class 3 has 80 subjects suffering from Paced beat, class 4 has 80 subjects suffering

from RBBB and class 5 has 80 subjects suffering supraventricular contraction disease as exposed in Table 3.1 above. This data's were additionally processed using discrete wavelet transform on MATLAB.

## 3.4 Feature extraction

Features extraction is taking out and converting the input data info into a set of features which are called feature vector, by dropping the data representation pattern. The features set will extract the significant information from the input data in order to accomplish the classification task. The transform of a signal is just additional form of representing the signal. It does not alter the information content existing in the signal.

### 3.4.1 What Are Wavelets?

A wavelet is a waveform of partial duration that has an average value of zero. Unlike sinusoids that theoretically range from minus to plus infinity, wavelets have a start and an end. Sinusoids are smooth and expectable and are good at labeling constant-frequency (stationary) signals. Wavelets are irregular, of limited period, and often asymmetrical.

They are better at describing irregularities, pulses, and other events that start and stop inside the signal.

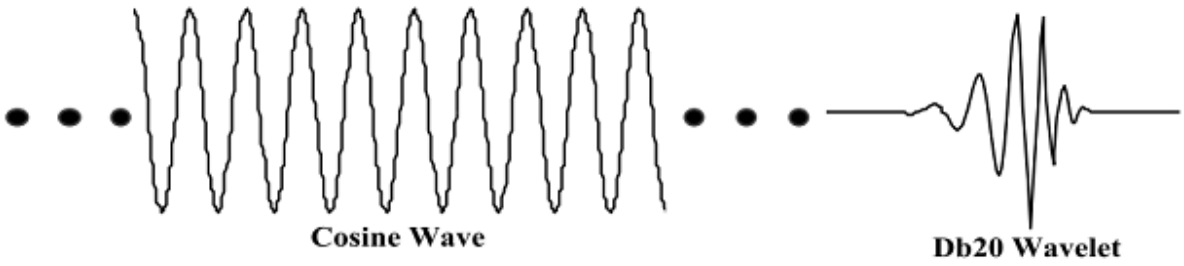


Figure 3. 3 A portion of an infinitely long sinusoid (a cosine wave is shown here) and a finite length wavelet [28]

Notice the sinusoid has an easily visible frequency while the wavelet has a pseudo frequency in that the frequency varies somewhat over the length of the wavelet.

There exists diverse types of wavelets which are corresponding against the shape of the desired signal whose wavelet transform is to be completed. If the wavelet family is close to the wanted physical characteristics of the signal, the particular wavelet family is nominated for use.

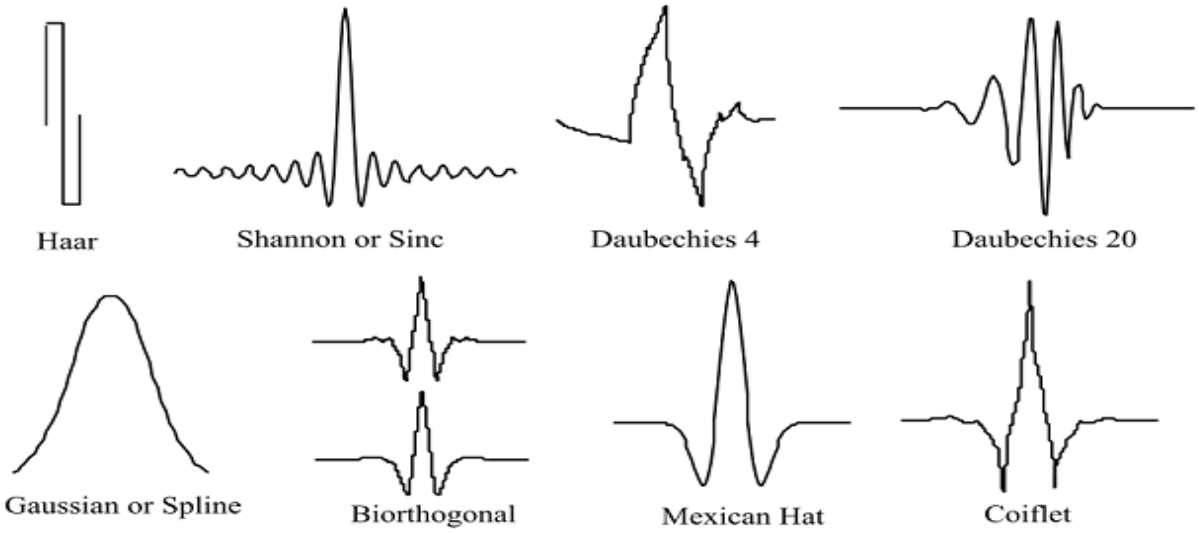


Figure 3. 4 Types of wavelet families [28]

Comparison between Fourier Transform and Continuous Wavelet Transform

Time domain analysis was used in past times to study the features of ECG signals, but due to its inadequacy to describe all the details of ECG features, attention was sidetracked to the frequency representation of a signal. To accomplish this, FFT (Fast Fourier Transform) technique was established which allowed viewing signals in the frequency domain.

FFT decomposes the original signal into the component sinusoids of different frequencies called as spectrum thus permitting manipulation of the transformed data from time to frequency domain, and then by the method of inverse Fourier Transform supports to undergo custom filtering such as abolition of constant frequency noise. In spite of this benefit, FFT doesn't give information about the time that a particular frequency happened.

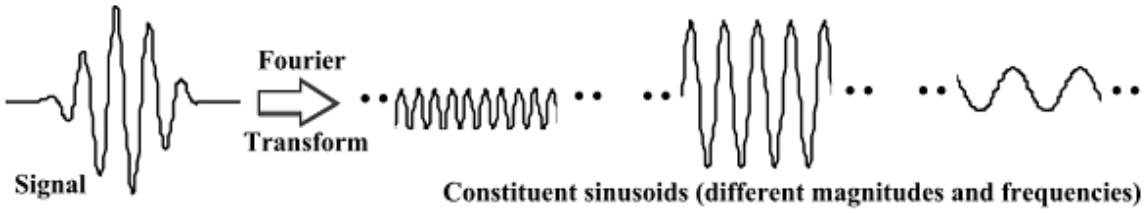


Figure 3. 5 Signal transformed into a number of sinusoids of various sizes and frequencies [28]

Figure 3.6 proves the stretching and shifting process for the continuous wavelet transform. Waveform (B) displays a Db 20 wavelet family of the length of 1/8 second starting at the beginning i.e. t = 0 and finish before 1/4 second. The zero values are stretched to the whole 1 second. The point-by-point assessment with the pulse signal (A) would be very poor obtaining a very small correlation value.

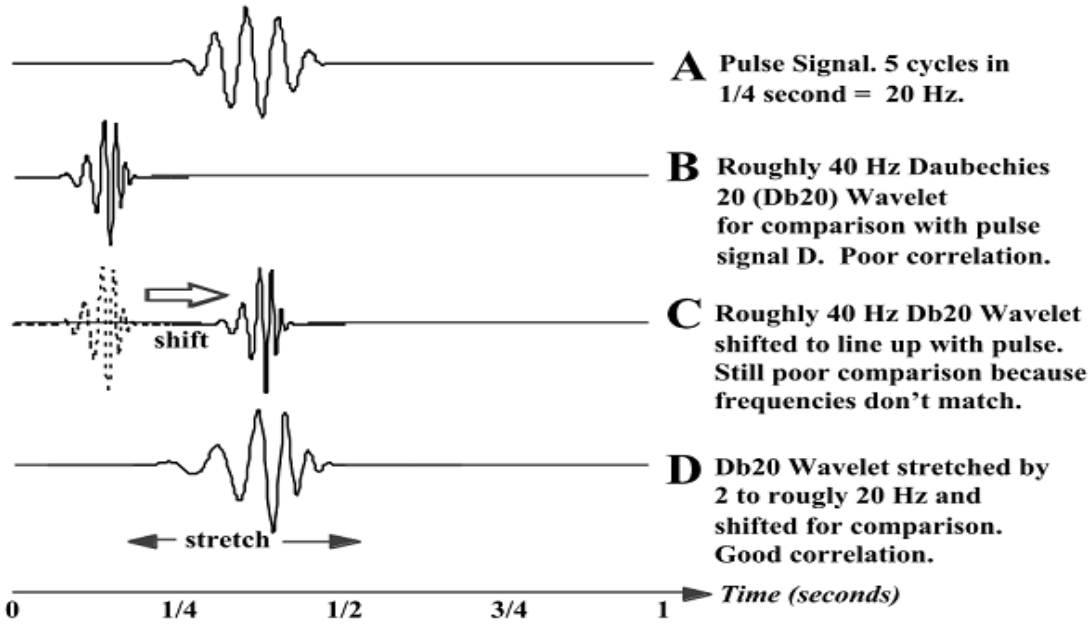


Figure 3. 6 An actual wavelet transform comparing many stretched and shifted wavelets (analysis of wavelets) to the original pulse [28].

The unstretched wavelet is frequently referred to as the mother wavelet. The Db20 wavelet filter we are using here starts out as 20 points long (hence the name) but can be overextended to many more points. An equivalent low pass filter used in the upcoming DWT is regularly called a father wavelet.

Waveform (D) demonstrates the Db20 wavelet stretched to the location where the frequency is almost the similar as the pulse (A) and moved to the right until the peaks and valleys tie up almost perfectly. At these amounts of translating and stretching, we should perfectly get a good comparison and a pronounced correlation value. However, if we extra shift to the right even at this same stretching, it will gradually yield more poor correlations. Further stretching doesn't assist at all because even when lined up, the pulse and the over-stretched wavelet won't be the similar frequency.

In the CWT we have a particular correlation value for every particular shift of the stretched wavelet. The general equation for CWT is a shortcut that shows that the correlation coefficients depend on together the stretching and the shifting of the wavelet, ψ, to match the signal (Xn here) as we have just understood. The equation express that when the dilated and translated wavelet matches the signal the summation will yield a large correlation value.

$$C(\text{stretching, shifting}) = \Sigma Xn\ \psi(\text{stretching, shifting})$$

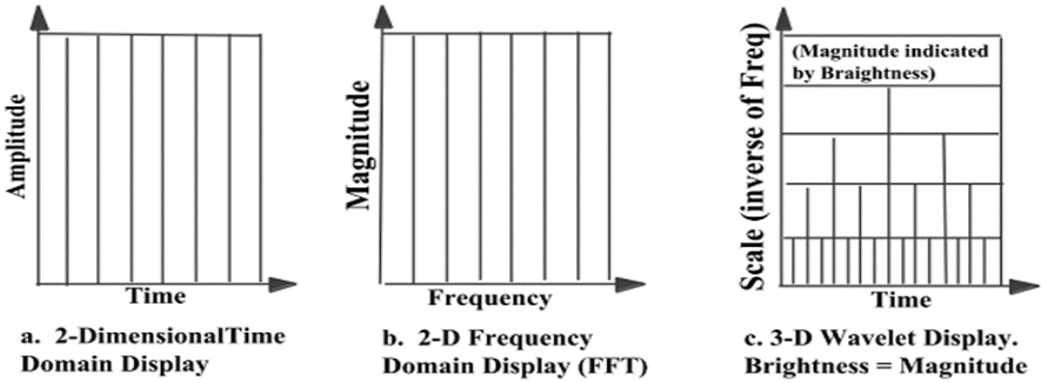


Figure 3. 7 shows a wavelet transform display (c) and how it compares to an ordinary time domain (a) and frequency-domain (b) display [28].

Note that the wavelet display (c) is drawn reversed ("flipped" vertically). In other words the high frequencies are on the bottommost and the lower frequencies are on uppermost. The y axis on most wavelet displays indicate increasing scale (widening of the wavelet) rather than increasing frequency.

### 3.4.2 Advantages of Wavelet Analysis over Traditional Frequency Domain Analysis:

1. By stretching and shifting a wavelet, we are able to match it to the unseen event and thus discover its frequency and location in time. In addition, a specific wavelet shape may tie the event unusually well, also expressing us about the shape of the event. For instance, the Haar wavelet would match a sudden discontinuity while the Db20 would match a chirp signal.

2. A significant advantage of a wavelet transform is that, not like FFT, we can threshold the wavelet coefficients for only portion of the time. Suppose we had a binary signal that had an excessive deal of noise added which altered frequency as time progressed (e. g.

chirp noise). Using a 7-level DWT the noise would act at different times in the different frequency sub-bands which could be threshold at the proper times [28].

### 3.4.3 Wavelet transform

Wavelet theory is the mathematics related with building a model for a signal, system, or procedure. A wavelet is a wave which has its energy focused in time. It has an oscillating wavelike representative but also has the ability to allow concurrent time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying phenomena. WT has a varying window size, being wide at low frequencies and thin at high frequencies, thus leading to a best time-frequency resolution in all frequency ranges.

The Wavelet Transform uses multi-resolution technique by which diverse frequencies are investigated with different resolutions. It is capable of demonstrating signals in different resolutions by dilating and compressing its basis functions. The basis function in wavelet analysis is demarcated by two parameters which are scale and translation. A base function which is mother wavelet is used in wavelet investigation.

For a wavelet of order N, the root function can be denoted by

$$\Psi(\mathrm{n}) = \sum_{j=0}^{N-1}(-1)^j\, c_j(2n + j - N + 1) \dots\dots\dots\dots 1$$

### 3.4.4 Discrete Wavelet Transform

The DWT which is a time-scale depiction of the digital signal is attained using digital filtering techniques, is found to yield a reckless computation of Wavelet Transform. It is easy to implement and assumes dyadic scales and translations in order to decrease the amount of computation time, which results in better competence of calculation.

The DWT which also referred to as decomposition by wavelet filter banks is calculated by consecutive low pass filter and high pass filtering of the discrete time domain signal as the procedure shown graphically on figure 3.8:

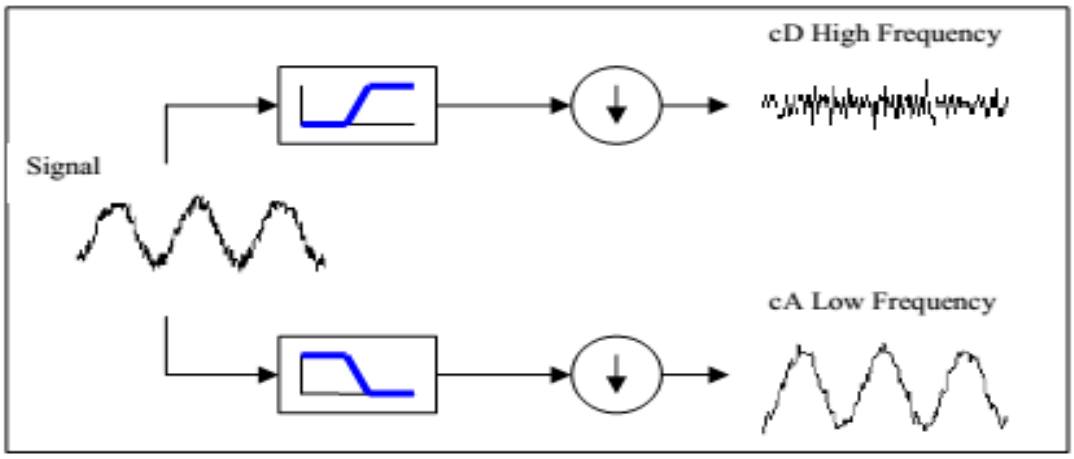


Figure 3. 8 Filter banks signal decomposition

The diverse cutoff frequencies are used for the analysis of the signal at different scales to measure the aggregate of detail information in the signal and the scale is determined by up sampling and down sampling procedure where D and A denoting for details and approximations, while c signifying coefficients. The estimates of the signal are what define its identity while the details only imparts distinction.

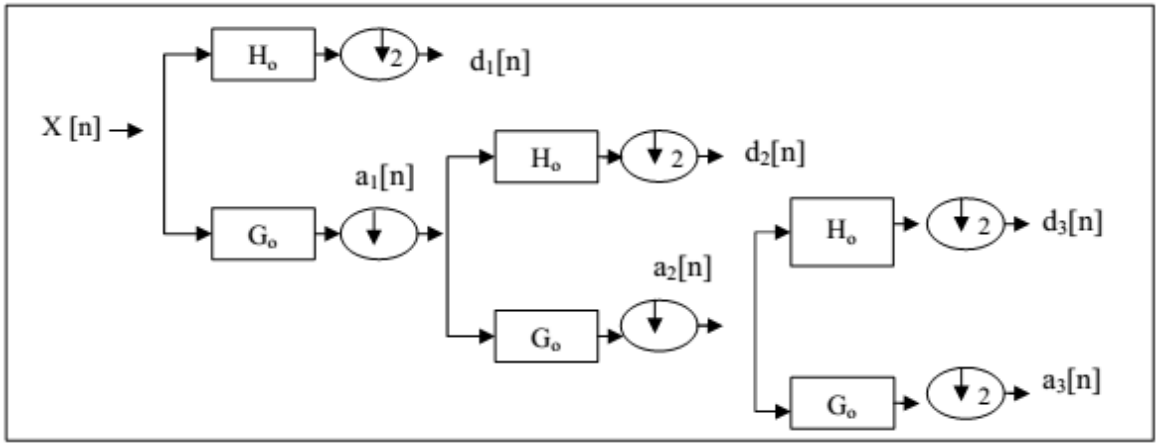


Figure 3. 9 Three-level wavelet decomposition Trees

Figure 3.9 shows that decomposition procedure is iterative. It associates the continuous-time multiresolution to discrete-time filters. The signal is indicated by the sequence input signals x[n], where n is an integer approved through a series of high-pass filters to analyze the high frequencies, and through a series of low-pass filters to examine the low frequencies. Each phase consists of two digital filters and two down samplers by 2

to yield the digitized signal. The low pass filter is symbolized by Go while the high pass filter is symbolized by Ho. At individual level, the high pass filter yields detail information; d[n], whereas the low pass filter related with scaling function yields coarse approximations, a[n]. The down sampled outputs of first high pass filters and low-pass filters deliver the detail, D1 and the approximation, A1. The first approximation, A1 is decomposed over again and this process is continued. The filtering and decimation procedure is continued till the desired level is gotten. The maximum number of levels be determined by on the length of the signal. Only the last level of approximation is save amongst all levels of details, which provides adequate data. The DWT of the original signal is then attained by concatenating all the coefficients, a[n] and d[n], starting from the latest level of decomposition. The signal decomposition can mathematically be stated in equation as:

$$y_{hi}[k] = \sum x[n] \,.\, g[2k - n] \dots\dots\dots\dots\dots 2$$

$$y_{lo}[k] = \sum x\,[n] . h[2k - n] \dots\dots\dots\dots\dots .3$$

With this method, the time resolution becomes randomly good at high frequencies, while the frequency resolution becomes randomly good at low frequencies.

In DWT the signals can be characterized by approximations and details. The detail at level j is well-defined as equation:

$$D_j = \sum_{k \subset z} a_{j.k}\, \Psi_{j.k}(t) \dots\dots\dots\dots\dots\dots\dots\dots 4$$

Where, Z is the set of positive integers

Then, the approximation at level J is given as equation:

$$A_i = \sum_{j>J} D_i \dots\dots\dots\dots\dots\dots\dots 5$$

Finally, the signal f (t) can be given by equation:

$$f(t) = A_j = \sum_{j \leq J} D_j \dots\dots\dots\dots\dots 6$$

In DWT where a scaling function is used, which are associated to low-pass and high-pass filters, respectively. The scaling function can be characterized as:

$$\Phi(n) = \sum_{j=0}^{N-1} c_j \, \Phi(2n - j) \dots\dots\dots\dots 7$$

$$\Phi_{j.k}(t) = 2^{j/2}\Phi\left(2^j t - k\right) \dots\dots\dots\dots 8$$

### 3.4.5 DWT Implementation

In this research, feature extraction was directed by applying wavelet analysis techniques to patient data obtained for physionet, thus providing the ECG characteristic point detection capabilities. Since most lately published detectors are created on standard database libraries and limited wave detection, this application is an effort to develop the horizons of current research efforts.

The input selection of feature extraction methods applied in this research has to select fine to make sure which constituents of a inputs best characterize the given configuration of ECG signals. Since the details wavelet coefficients contain a substantial amount of information about the signal, the detail wavelet coefficients of ECG signal of each subject were calculated. The techniques of DWT implementation is described as follow in figure 3.10.

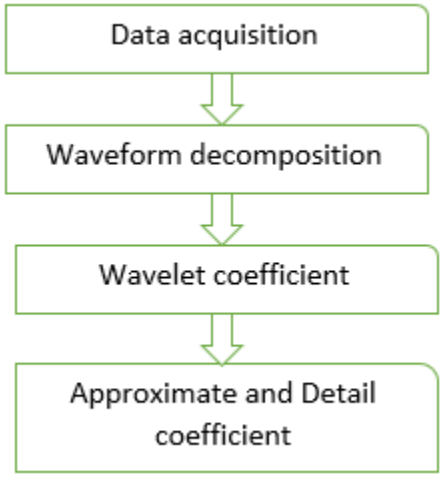


Figure 3. 10 Coefficient extraction techniques

### 3.4.6 Features Extraction Procedures

Collection of appropriate wavelet and the number of decomposition level is very significant in DWT. The levels are selected such that those parts of the signal that relate well with the frequencies essential for classification of the signal are reserved in the wavelet coefficients.

The overall wavelet decomposition of DWT system involves three steps. The outcome of decomposed signal will shows the imperative details and approximation coefficients which characterize the original signal.

The basic form of the procedure follows the steps labelled below.

1) Select a wavelet types.
2) Pick a wavelet name.
3) Select a level N which will calculate the wavelet decomposition of the signal s at level N.

The DWT wavelet types have been selected in this features extraction method and the ECG signals were decomposed into time-frequency demonstrations using single-level one dimensional wavelet decomposition. The wavelet names of Daubechies wavelet filters db4 have been selected and the number of decomposition levels was selected to be 4 as it was done on different researches and yields better outcome seen in this research [18]. It yields better correlation ratio or have good signal to noise ratio after reconstructing from the decomposed signal at level 4. Consequently, the ECG signals were decomposed into the details coefficients $D_1$-$D_4$ and one last approximation coefficient, $A_4$.

The outcome of applying the Daubechies wavelet of order 4 (db4) is more appropriate to detect changes of ECG signal is assessed. The wavelet filter with scaling function more thoroughly similar to the shape of the ECG signal attained better detection. Db wavelet family is similar in shape to ECG signal and their energy spectrums are focused around low frequencies and the signal is approximated by neglecting the signals high frequency components.

The ECG signal and the details for five wavelet scales are schematically shown for improved illustration on figure 3.11.

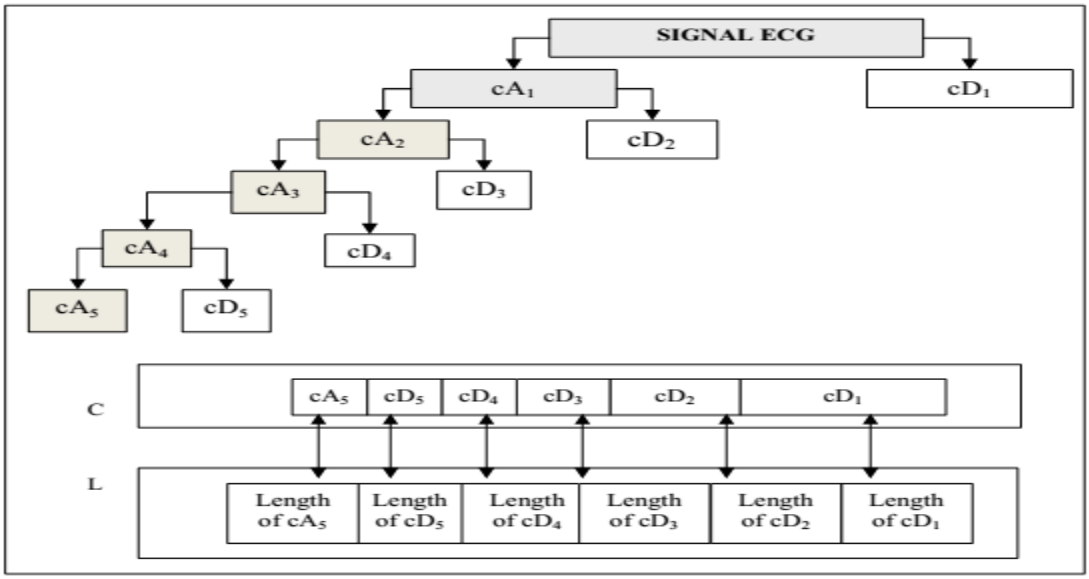


Figure 3. 11 DWT Decomposition Step in ECG Analysis

### 3.4.7 Coefficients Extraction

The computed wavelet coefficients deliver a compact representation that shows the energy spreading of the signal in time and frequency. Therefore, the calculated details and approximation wavelet coefficients of the ECG signal were used as the features vector signify the signals.

In this research, from the unique intervals of ECG signal, six standard measure parameters are used. A signal of 80 discrete data was considered as ECG signals data. For each ECG signals, the detail wavelet coefficients of $4^{th}$ level (80 coefficients) were calculated. In order to decrease the dimensionality of feature vectors, statistics over the set of the wavelet coefficients were used.

The following statistical features were used to characterize the time–frequency dispersal of the ECG signals: The flowchart of the calculated DWT coefficient are shown in Figure 3.12.

1. Energy of the wavelet coefficients of individual ECG signals sample.

2. Max of the wavelet coefficients of individual ECG signals sample.

3. Min of the wavelet coefficients of individual ECG signals sample.

4. Mean of the wavelet coefficients of individual ECG signals sample.

5. Standard deviation of the wavelet coefficients of individual ECG signals sample.

6. Kurtosis of the wavelet coefficients of individual ECG signals sample.

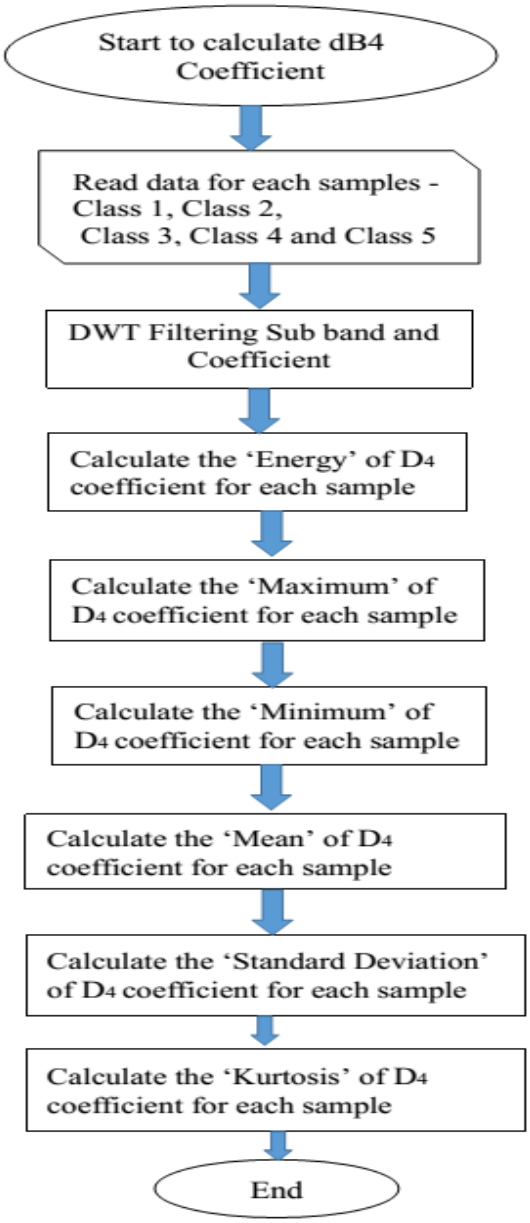


Figure 3. 12 Flowchart of DWT Coefficient Calculation

These features vector which were considered for the $D_4$ frequency band, were used in categorizing the ECG signals as shown in Table 3.2.

Table 3. 2 The extracted features of four exemplary from five classes

| Data set | Feature extracted |
|---|---|
| Normal | Mean |
| | Standard deviation |
| | Maximum amplitude |
| | Minimum amplitude |
| | Energy |
| | Kurtosis |
| Left bundle branch block | Mean |
| | Standard deviation |
| | Maximum amplitude |
| | Minimum amplitude |
| | Energy |
| | Kurtosis |
| Paced beat | Mean |
| | Standard deviation |
| | Maximum amplitude |
| | Minimum amplitude |
| | Energy |
| | Kurtosis |
| Right bundle branch block | Mean |
| | Standard deviation |
| | Maximum amplitude |
| | Minimum amplitude |
| | Energy |
| | Kurtosis |
| Supra ventricular contraction | Mean |
| | Standard deviation |
| | Maximum amplitude |
| | Minimum amplitude |
| | Energy |
| | Kurtosis |

The sub band 4, $D_4$ of details coefficients from the wavelet decomposition assembly has been extracted. These vectors are removed at each scale without scale one, two and three. By disregarding the higher levels of decomposition because it comprises high

frequency details and noise. These details are irrelevant information that will not affect the classification accuracy and signal quality.

This suggests that it is likely to delete information of very minor magnitude in each subspace, producing in much less data information being desired to reconstruct a very noble approximation of the original signal.

Then, the output of the detail coefficients removed from the signal will be demarcated as the input of ANFIS classifier but in advance that we need to apply feature reduction technique of the PCA for reducing the dimension which will be fed to the ANFIS classier. Main idea behind PCA is looking for most precise data representation in a lower dimensional space. PCA conserves largest variances in the data. The fuzzy logic toolbox doesn't bounds the number of inputs. However, the number of inputs may be restricted by the offered memory of your machine. If the number of inputs is too big, or the number of membership functions is too large, then it may also be challenging to analyze the FIS.

Table 3. 3 The eigenvalues difference for different features using PCA

| Eigen values: | | | | | | |
|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | F4 | F5 | F6 |
| Eigen value | 3.139 | 1.468 | 0.923 | 0.201 | 0.174 | 0.095 |
| Variability | 52.318 | 24.464 | 15.379 | 3.357 | 2.906 | 1.576 |
| Cumulative | 52.318 | 76.782 | 92.161 | 95.518 | 98.424 | 100.000 |

From the result of principal component analysis we have seen that the principal features are mean, standard deviation, max amplitude, min amplitude and energy. Finally this feature vectors are fed for the ANFIS for classifying different classes of the cardiac abnormalities.

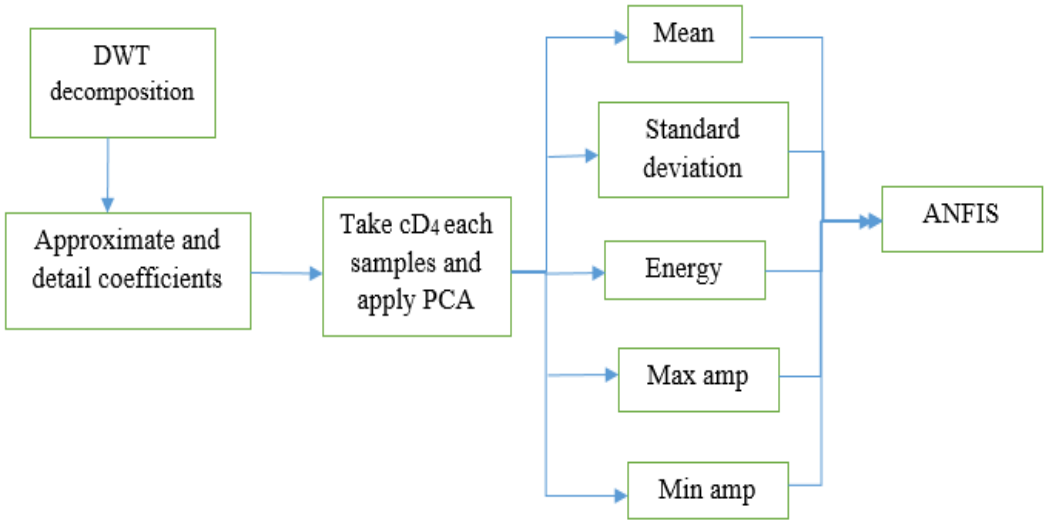


Figure 3. 13 features fed for ANFIS

## 3.5 Classification using Neuro Fuzzy

Decision building of classification was done in two stages: selection of coefficients computing by DWT and the ANFIS classifiers. Five types of ECG beats (Normal, LBBB, paced beat, RBBB and SVC obtained from the PhysioBank databases has been classified by ANFIS classifiers.

### 3.5.1 Neuro Fuzzy Approach

Neuro Fuzzy is a fusion of artificial neural networks and fuzzy logic. Neuro Fuzzy networks are the apprehensions of the functionality of fuzzy systems using neural techniques. Neuro fuzzy network integrates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model involving of a set of IF THEN fuzzy rules as shown in Figure 3.14.

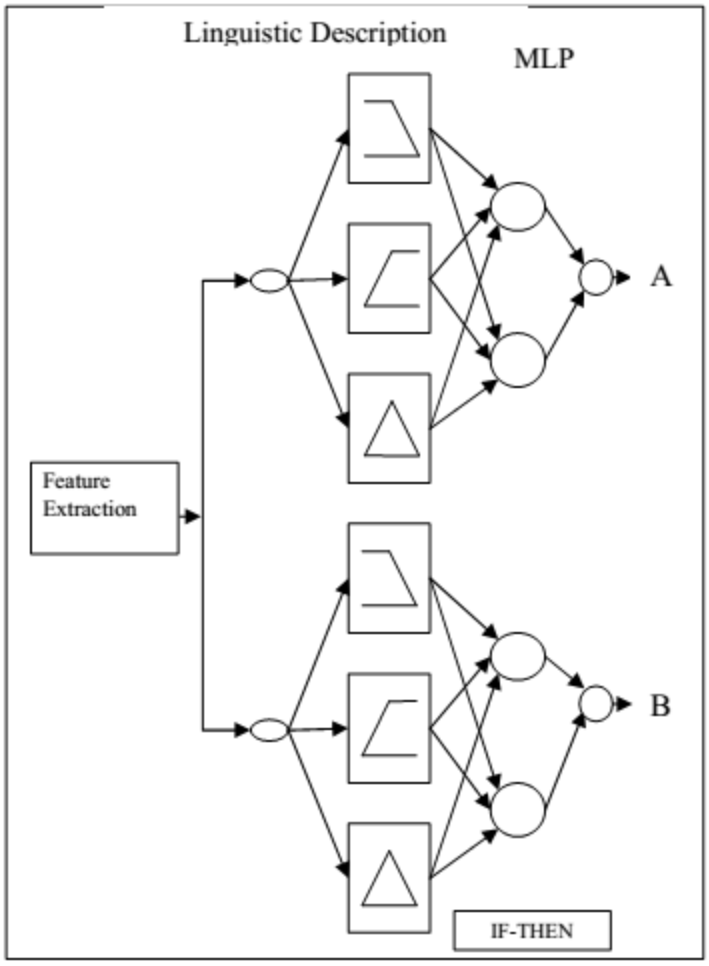


Figure 3. 14 Structure of Feedforward Neuro Fuzzy

The significant part of fuzzy layer is accountable to analyze the dispersal of data and group the data into the diverse membership values. This membership value is given as the input vector to the Multi-Layer Perceptron neural network classifier. The membership value also signify the parameter of each heart beat class.

This research used the output of DWT method as features vector and ANFIS as a Neuro fuzzy classifier for the ECG investigation, because of previous research; the accuracy rates attained by the combined neural network model presented for classification of the ECG beats were to be higher than separate classifier model. The Neuro fuzzy network is also extra tolerant to the noise and less sensitive to the morphological variations of the ECG characteristic and ANFIS also plays an vital role in dealing with uncertainty when making decisions in medical application.

## 3.6 ANFIS Model

ANFIS stands for adaptive Neuro-fuzzy inference system. This technique conveys the learning capabilities of neural networks to fuzzy inference systems. In ANFIS, Takagi sugeno style fuzzy inference system is used. The learning algorithm adjusts the membership functions takagi sugeno type using the training input-output data. The output of each rule can be a linear mixture of input variables. The final output is the weighted average of separate rule's output. The inserted fuzzy system in a neural fuzzy network can self-adjust the parameters of the fuzzy rules using neural network learning algorithms to attain the anticipated results.

The ANFIS learning techniques offer a method for the fuzzy modeling way to learn information about data set, in order to calculate the membership function parameters that best allow the related fuzzy inference system to track the given input output data. ANFIS builds an input-output mapping based on both human understanding (in the form of fuzzy if-then rules) and simulated input output data pairs. It helps as a basis for constructing the set of fuzzy if-then rules with suitable membership functions to generate the input output pairs.

The parameters linked with the membership functions are exposed to change through the learning process. The calculation of these parameters (or their adjustment) is simplified by a gradient vector, which offers a measure of how well the ANFIS is modeling the input output data for a given parameter set. Once the gradient vector is achieved, back propagation or hybrid learning algorithm can be applied in order to correct the parameters. Basic ANFIS structural design has two inputs x and y and one output z is shown in Figure 3.15.

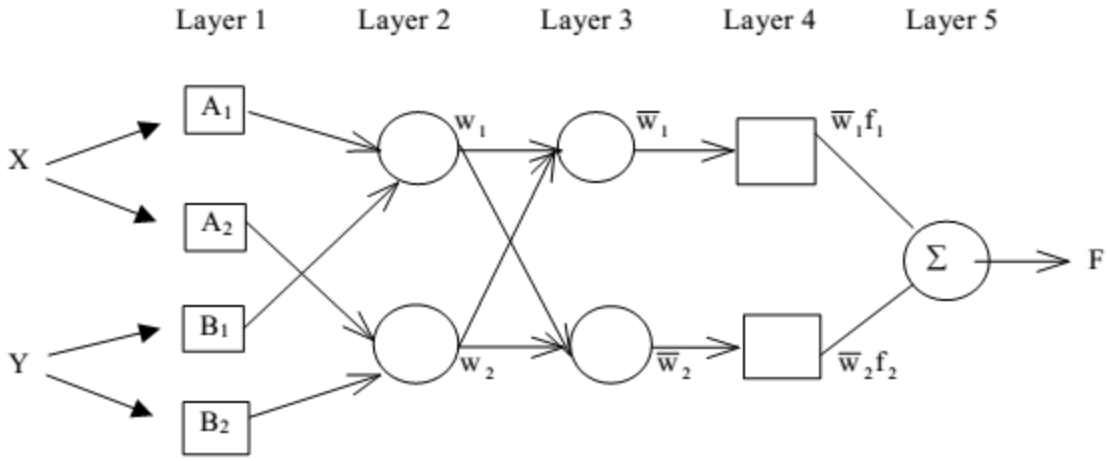


Figure 3. 15 Basic Structure of ANFIS Model

Two Takagi-Sugeno if-then rules are presented in equation as

Rule: if x is $A_1$ and y is $B_1$ then $f_1 = p_1x + q_1y + r_1$……9

Rule: if x is $A_2$ and y is $B_2$ then $f_2 = p_2x + q_2y + r_2$……10

The nodes functions of ANFIS architecture in the similar layer are labeled below:

Layer 1: Every node I in this layer is a square node through a node function as in equation

$$0_{1,\,i} = \mu_{Ai}(x), \text{ for I = 1, 2……11}$$

$$0_{1,\,i} = \mu_{Bi-2}(y), \text{ for I = 3, 4……...12}$$

where x is the input to node I, and Ai(or Bi−2) is a linguistic label (such as "small", "medium", "large") linked with this node. The $0_{1,\,i}$ is the membership function of a fuzzy set Ai and it identifies the degree to which the given input x satisfies the quantifier Ai. Frequently is chosen μAi(x) to gaussmf with max equal to 1 and min equal to 0, such as the generalized gaussmf function in Equation

$$\mu_{Ai}(x) = \frac{1}{1 + \{((x - c_i)/a_i)^2\}^{b_i}} \ldots\ldots\ldots\ldots 13$$

Or the Gaussian function represent in Equation

$$\mu_{Ai}(x) = e^{-((x-c_i)/a_i)^2} \ldots\ldots\ldots\ldots 14$$

Where ai, bi, ci is the parameter set. The membership function for Ai can be any suitable membership function, such as the Bell-shaped, Triangular or Gaussian.

When the parameters of membership function alters, chosen membership function varies accordingly, thus revealing various forms of membership functions for a fuzzy set Ai. Parameters in this layer are denoted to as "premise parameters".

Layer 2: Every node in this layer is a fixed node labeled as Π, whose output is the product of all received signals defined by Equation

$$0_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y), for\ I = 1,2 \ldots\ldots\ldots\ldots 15$$

Each node output signifies the firing strength of a fuzzy rule

Layer 3: Every node in this layer is a fixed node considered N. The $i^{th}$ node calculates the proportion of the rule's firing strength to the sum of all rules' firing strengths as characterized by equation below

$$0_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, for\ I = 1,2 \ldots\ldots\ldots\ldots\ldots\ldots 16$$

Outputs of this layer are termed "normalized firing strengths"

Layer 4: All node I in this layer is an adaptive node with a node function in equation

$$0_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \ldots\ldots\ldots\ldots\ldots\ldots 17$$

Where $w_i$ stands a normalized firing strength from layer 3 plus {pi, qi, ri} is the parameter set of this node. Parameters in this layer are mentioned to as "consequent parameters".

Layer 5: The particular node in this layer is a fixed node labeled Σ that computes the overall output as the summation of all arriving signals characterize in equation

$$overall\ output = 0_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum i w_i f}{\sum i w_i} \ldots\ldots\ldots\ldots\ldots 18$$

Thus an adaptive network, which is functionally correspondent to the Takagi-Sugeno type fuzzy inference system, has been built.

### 3.6.1 ANFIS Implementation in Classifying Heart Disease

The classification was done using the ANFIS classifiers in Fuzzy Logic Toolbox. ANFIS were trained with the backpropagation gradient descent method in arrangement with the least squares method.

The number of features treated in ANFIS were shown in figure 3.16.

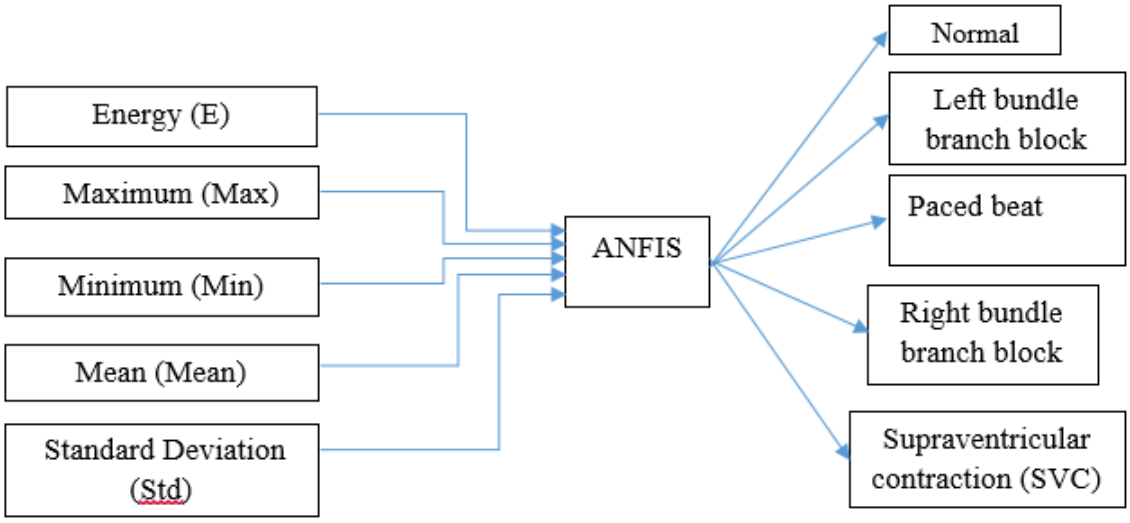


Figure 3. 16 Block Diagram of Heart Disease Classification through ANFIS

The feature vectors that are being calculated from the DWT coefficient are energy, max, min, mean and Standard Deviation were defined as extracted features for ANFIS inputs and normal, LBBB, paced beat, RBBB and SVC are defined as ANFIS outputs.

## 3.7 ECG Signals Dataset

The datasets with target outputs Class 1 (normal), Class 2 ( LBBB), Class 3 (paced beat), class 4 (RBBB) and Class 5 (SVC) was given the target values of 1, 2, 3, 4 and 5 respectively as shown in Table 3.4.

Table 3. 4 Set of heart disease Class

| Heart disease type | Classes |
|---|---|
| Normal | 1 |
| Left bundle branch block | 2 |
| Paced beat | 3 |
| Right bundle branch block | 4 |
| Supraventricular contraction | 5 |

As it is seen on a table 3.4 heart diseases with their labelled classes from the physionet database each having their own characteristic set of different features.

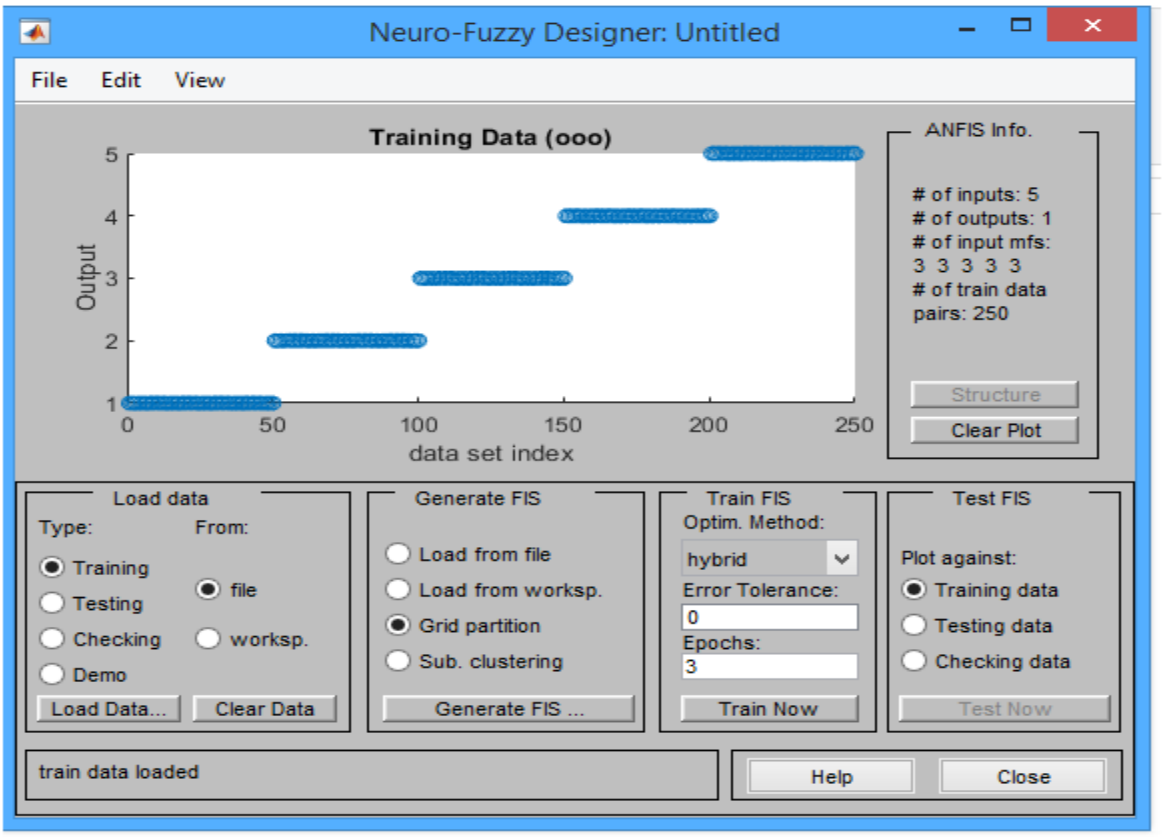


Figure 3. 17 Desired Output Target for each Class with train data loaded GUI

## 3.8 Fuzzy Inference System

ANFIS requisite a predefined network structure and its membership function as well as other parameters can be trained throughout the learning process. The system is initially designed using sugeno FIS. There are two kinds of FIS namely grid partition and subtractive clustering.

The ANFIS grid partition was implemented in this study because this system requisite the number of membership functions for each input. This system uses the gaussmf shaped membership function to describe the fuzzy sets input and Sugeno output membership functions are linear types. In the Layer 1, there are five nodes have been used for each input dimension Xi where i = 1, 2… d and d is the amount of input dimensions. The ANFIS which makes a FIS, whose membership function parameters are tuned using a back propagation algorithm together with a least squares type of method, will permits fuzzy systems to learn from the data that they are modeling. The FIS of heart disease classification is shown in figure 3.18.

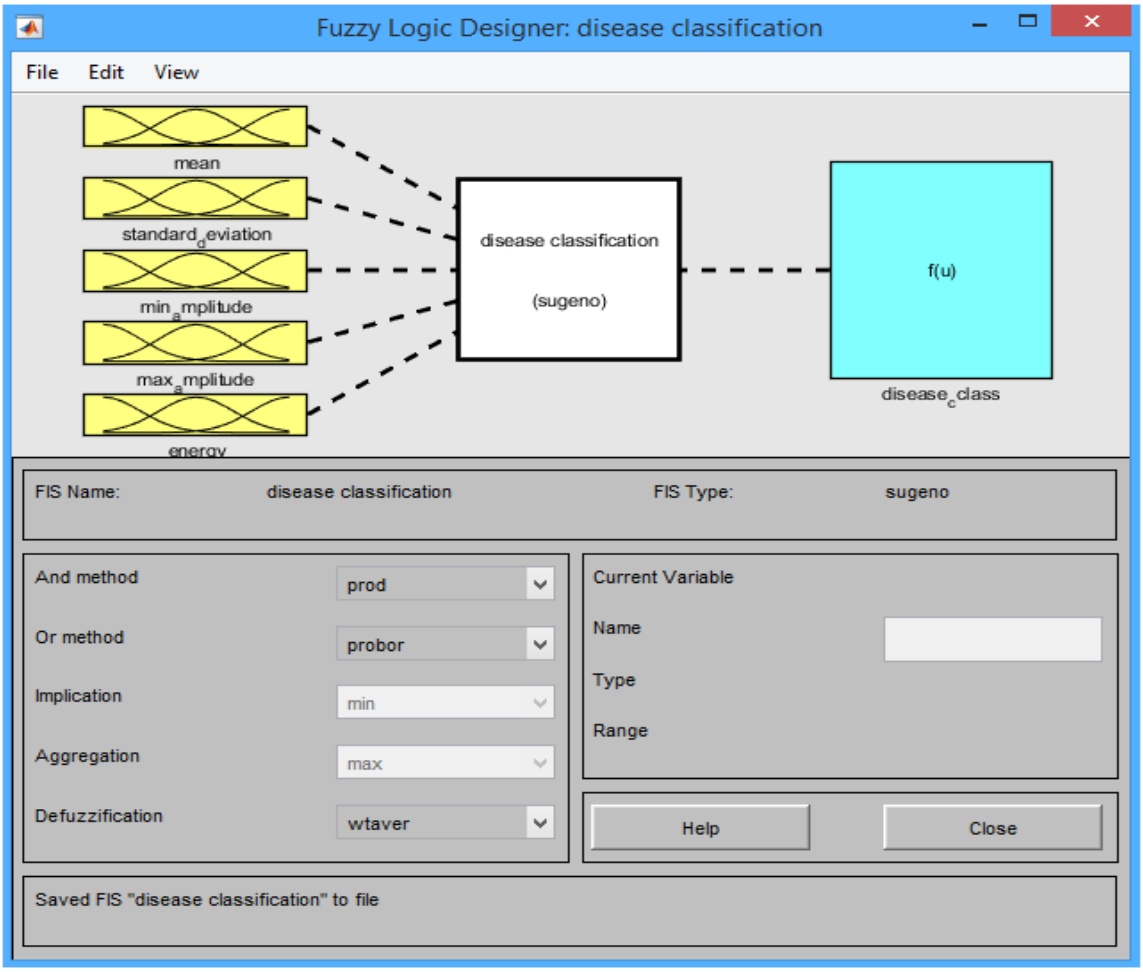


Figure 3. 18 Fuzzy inference system for heart disease classification

Founded on five input-one output systems, the five variables were used which are mean, standard deviation, max, min and energy of DWT coefficients and the output class either

normal, LBBB, paced beat, RBBB, or SVC is taken as the output variable. The input parameters are denoted by fuzzy set or linguistic variables. The membership functions for input variables are shown in figure 3.19.

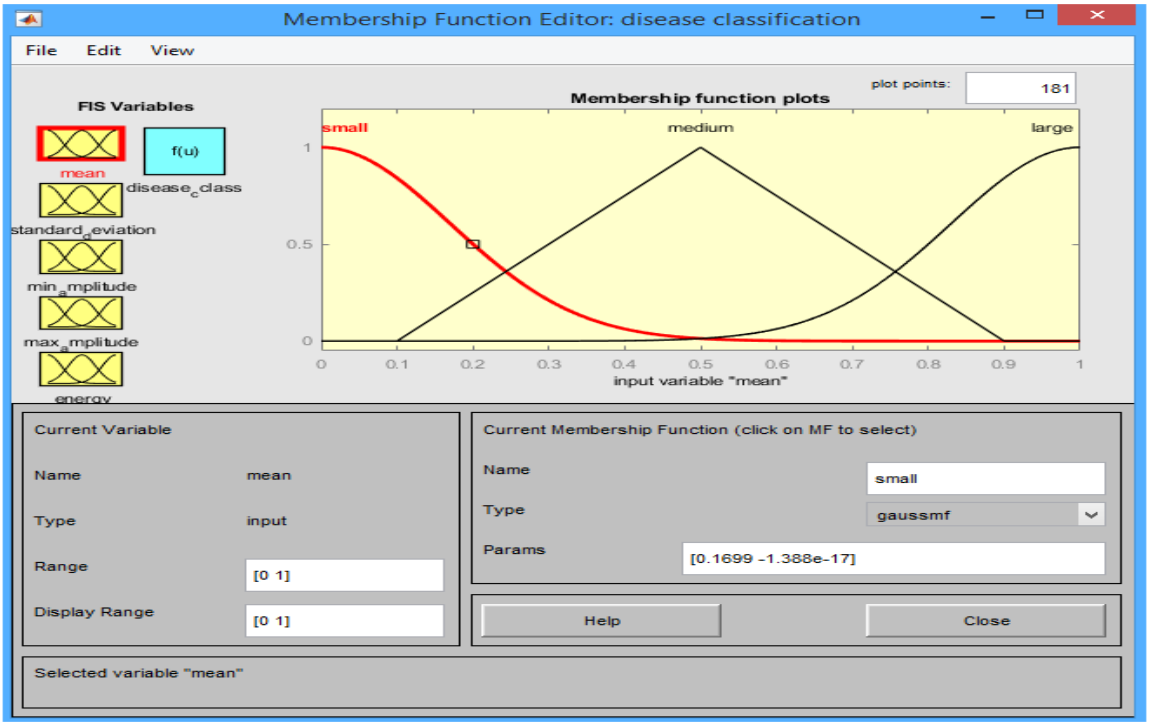


Figure 3. 19 Initial membership functions for mean input dimensions

Based on Figure 3.19, the membership function of each input parameter was separated into three areas, which are, small, medium and large. The inspection of initial and final membership functions indicates that there are substantial changes in the final membership functions of the features.

### 3.8.1 Rule Base Identification

Created on the membership functions, then the fuzzy IF-THEN rules that have a fuzzy antecedent and constant consequence are built. The rule base was formed according to the expert knowledge using MATLAB rule base editor. Built on the three membership function (small, medium, large) that being used in this research, the amount of rule base created by the following equation:

$$a \wedge b = c \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 19$$

Where; a is membership function

b is number of input nodes

c is number of rules output

Consequently, for 3 membership functions and 5 input nodes,

a = 3 membership function, for small, medium and large

b = 5 input nodes, for energy, max, min, mean, standard deviation

a ^ b = c

3 ^ 5 = 243 rules are produced

There are entirely 243 rules nodes are made by the FIS structure. The 243-rule ANFIS structure is shown in Figure 3.20.

There are 5 input nodes for ANFIS structure with 3 inputs of membership functions that handled by 243 rules to classify the desired output of heart disease either in Normal, LBBB, paced beat, RBBB or SVC.

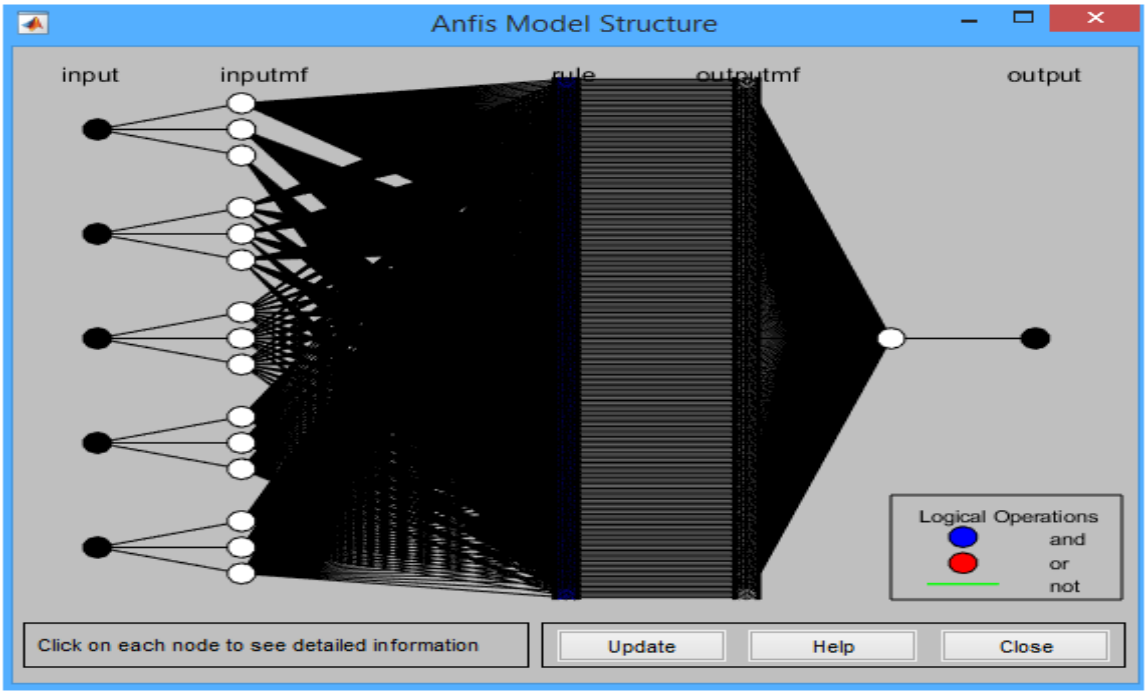


Figure 3. 20 Rule-base of ANFIS Structure

The membership functions in ANFIS fuzzy rule base can be adjusted by hand for each input dimension to improve the FIS output system. The graphical interfaces of fuzzy rules formed in rule based layer are shown in the figure below

The figure below shows the fuzzy rule base and the value of membership functions that characterize the rules regions either in small, medium or large regions. It can be altered to our desired output which is suitable for heart disease characteristic of each class.

By watching the fuzzy rule base tool, it is shown that some features controls the classification result which is some features have more weights in defining which class a data sample belongs to.

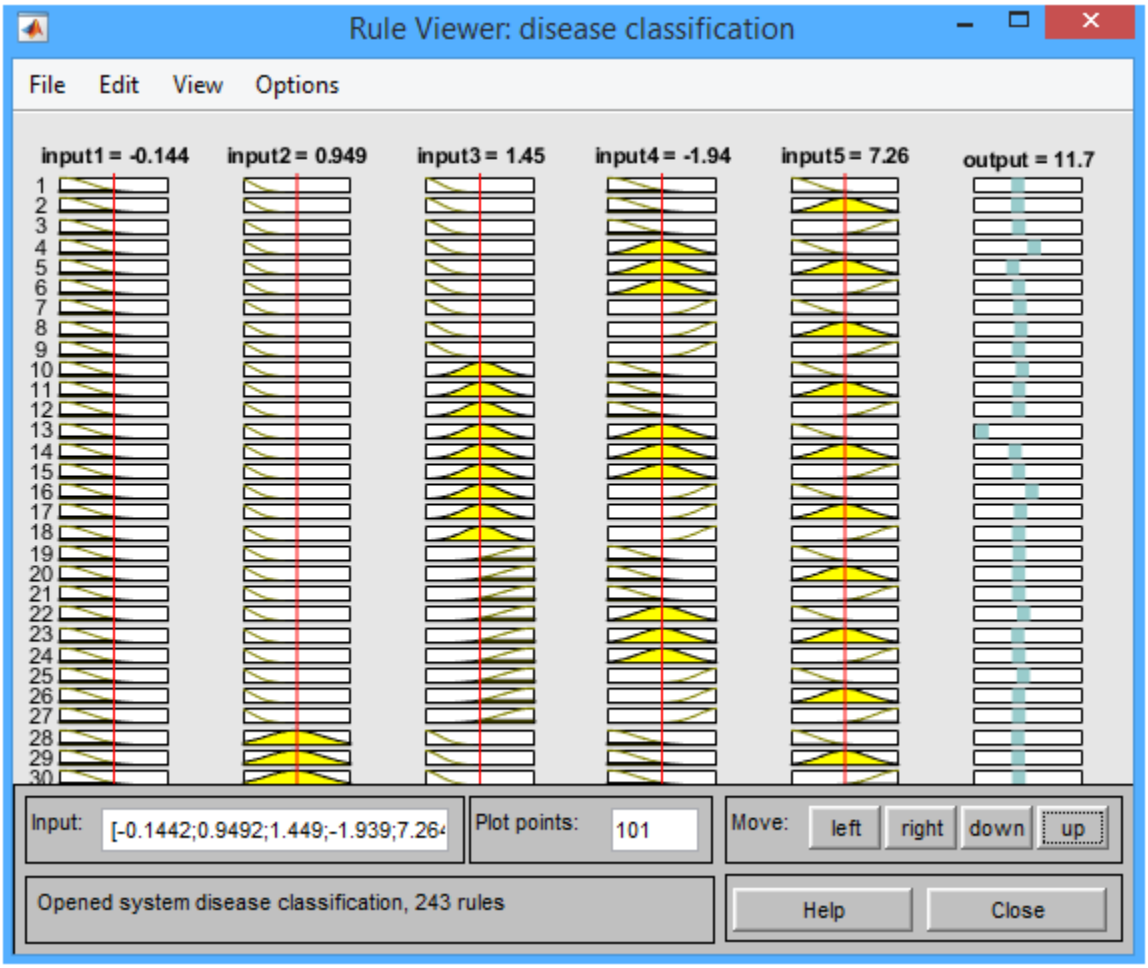


Figure 3. 21 A Fuzzy Rule Base for a Trained 243 ANFIS Rule Base

## 3.10 Datasets used for Training and Testing

The training dataset was used to train the ANFIS model, whereas the testing dataset was used to confirm the accuracy and the efficiency of the trained ANFIS model for classification of the five classes of ECG signals.

In this research, training and testing sets were formed by 401 data samples. The 250 data samples were used for training and 151 data samples were used for testing. The class distribution of the samples in the training and testing data set is summarized in Table 3.5. In order to improve the generalization ability of the ANFIS, training and testing were done by data obtained from different samples.

Table 3. 5 Class Distribution of the data Samples in the Training and Testing Datasets

| Heart disease class | Training set | Testing set | Total |
|---|---|---|---|
| Normal | 50 | 31 | 81 |
| LBBB | 50 | 30 | 80 |
| Paced beat | 50 | 30 | 80 |
| RBBB | 50 | 30 | 80 |
| SVC | 50 | 30 | 80 |
| Total | 250 | 151 | 401 |

All of the features used in the training data have diverse levels of relevancy. So, the final (after training) membership functions with respect to the initial (before training) membership functions of the input parameters were studied. After training, 151 testing data were used to confirm the accuracy of ANFIS model for the detection of heart disease.

# Chapter 4

# Result and Discussion

This ECG signals analysis demo by using MATLAB for the aim of recognition and classification of varies cardiac diseases. So, the methods were explained in detail to detect and classify about five diseases. The planned method have about three stages: (1) The preprocessing and feature extraction using DWT (2) feature selection using PCA (3) classification using ANFIS. Mostly the chapter offer results of simulated data sets from physionet data bases.

## 4.1 The preprocessing and Feature extraction using Discrete Wavelet Transform (DWT)

Before preprocessing the data's were collected from the physionet data base for making it suitable for manipulating with MATLAB software.

On physionet we get data's as we prefer in different formats that gives as full information of all recoded databases under different database names. But one thing here we are facing is the data's labelling inside single data is different for specific sampling time for a single record of patients ECG trace. That means under single record we may got lot of labelling for different cardiac diseases.

In this research the data's of different classes of heart diseases are taken from the Physiobank ATM as a sampled text data for appropriate labelling of the diseases. Then the data's are loaded on the MATLAB and saved as mat format for further processing. So finally each disease with its appropriate labelled data was collected for preprocessing and feature extraction.

As mentioned above the different classes of cardiac diseases were collected in such a way from the physiobank ATM. So they are discussed in detail below.

### 4.1.1 Normal ECG signal

The original normal ECG signal taken from physiobank ATM looks like the figure 4.1.

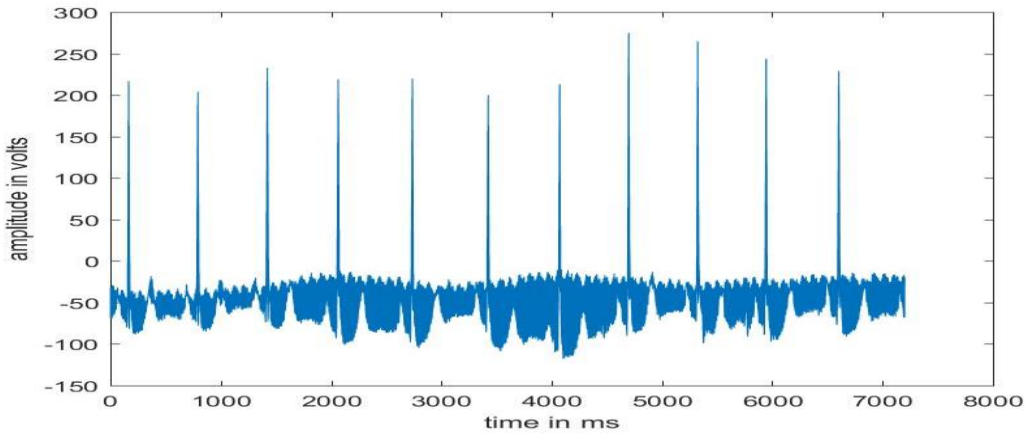


Figure 4. 1 normal ECG signal

For extracting features of normal ECG the DWT decomposition of normal signal into four detail and approximate coefficients of DWT was completed.

The figures 4.2 display the general process of DWT decomposition of normal ECG signal. From this extracted coefficients the research receive only the last level detail coefficient.

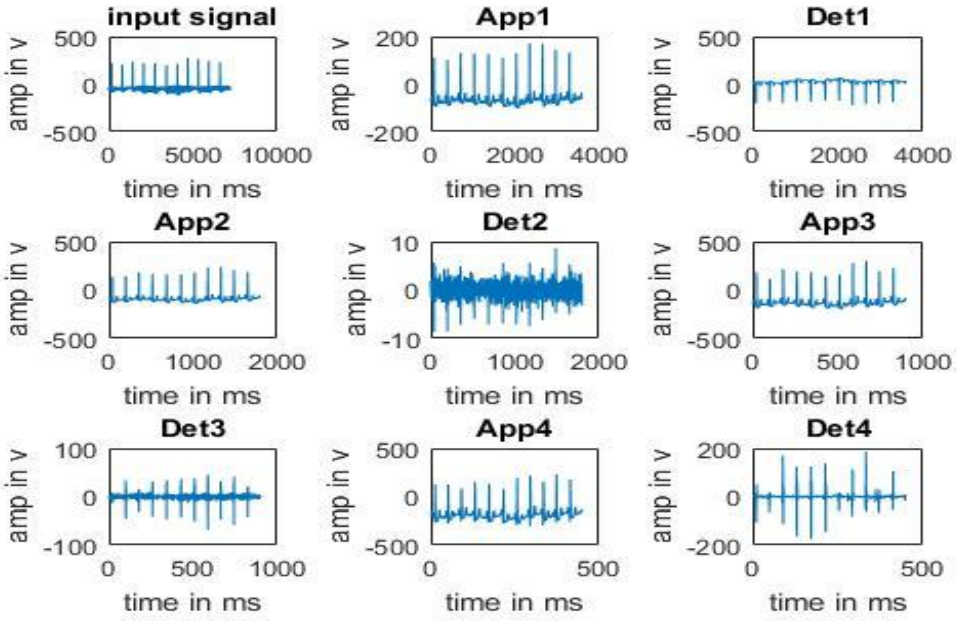


Figure 4. 2 DWT decomposition of normal ECG signal into four level

### 4.1.2 Left bundle branch block

The original left bundle branch block ECG signal taken from physiobank ATM looks like the figure 4.3.

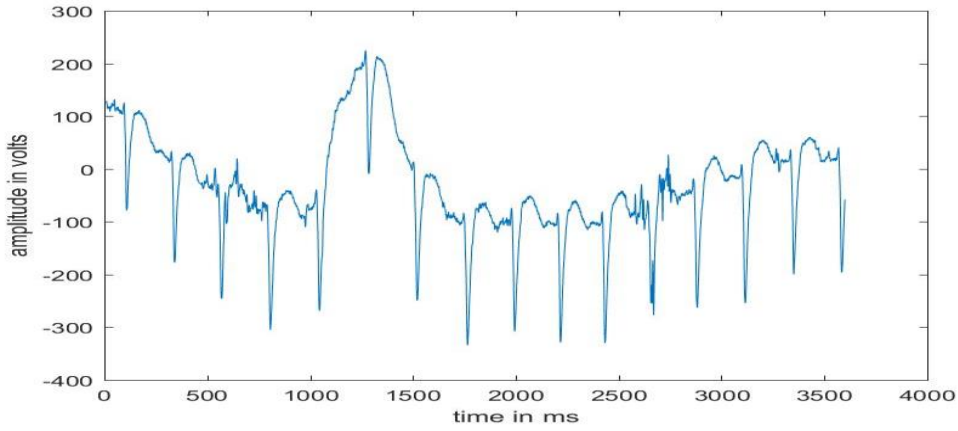


Figure 4. 3 left bundle branch block ECG signal

The figures 4.4 show the complete process of DWT decomposition of left bundle branch block ECG signal. From this extracted coefficients the research receives only the last level detail coefficient.

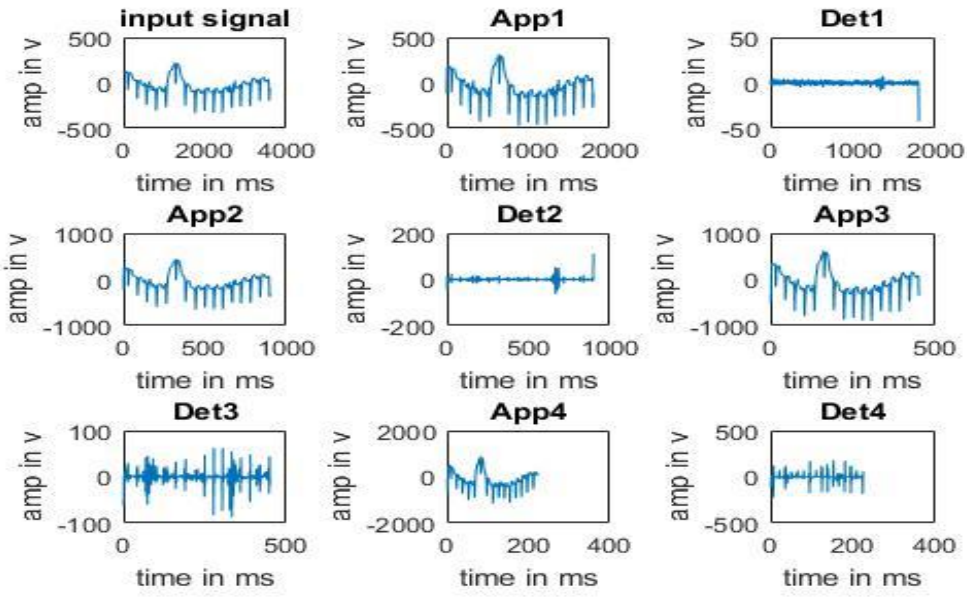


Figure 4. 4 DWT decomposed LBBB ECG signal

### 4.1.3 Paced ECG beats

The original paced beat ECG signal downloaded from physiobank ATM looks like the figure 4.5

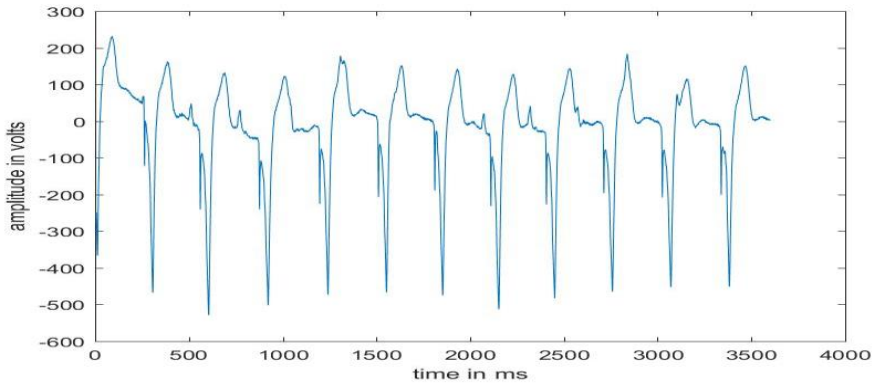


Figure 4. 5 Paced beat ECG signal

The figures 4.6 show the complete process of DWT decomposition of paced beat ECG signal. From this extracted coefficients the system receives only the last level detail coefficient. These last level detail coefficients are then fed to the ANFIS classifier to their appropriate heart disease class.

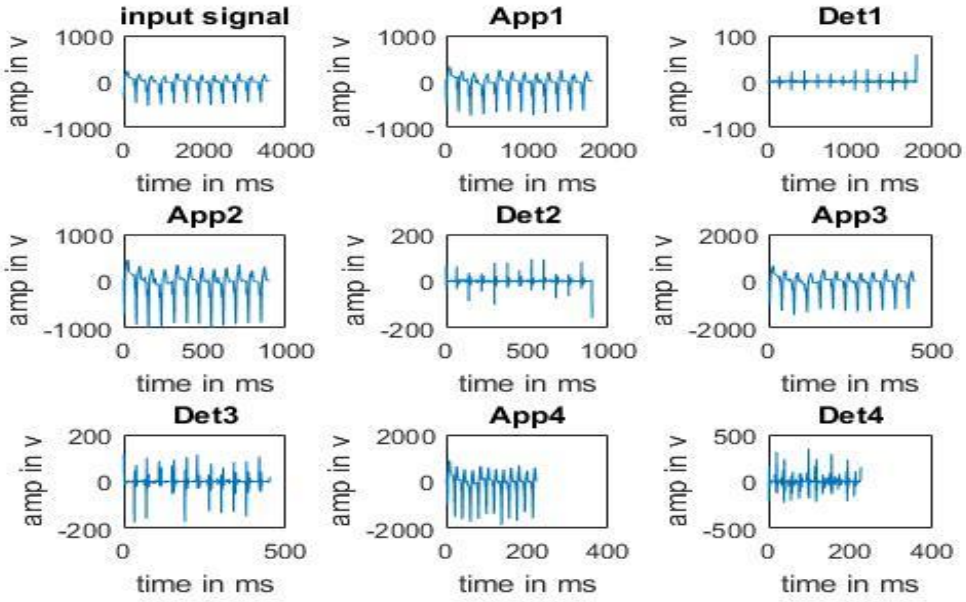


Figure 4. 6 DWT decomposed paced beat ECG signal

### 4.1.4 Right bundle branch block

The original right bundle branch block ECG signal downloaded from physiobank ATM looks like the figure 4.7 when it was plotted on MATLAB.

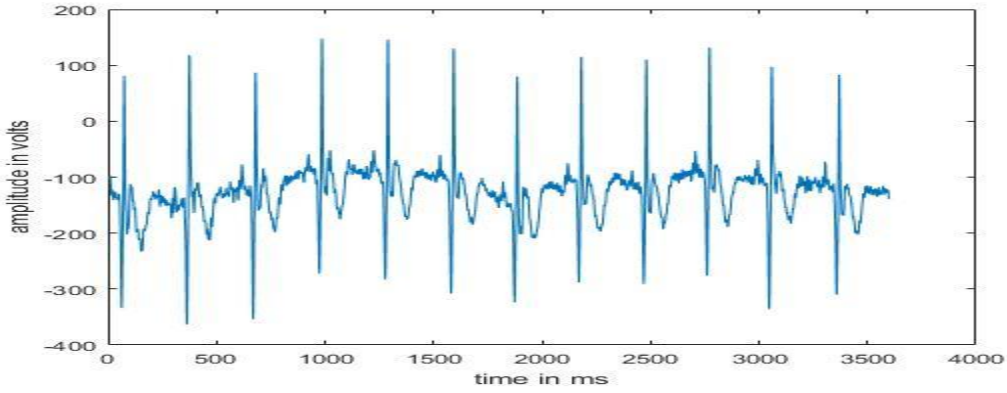


Figure 4. 7 RBBB ECG signal

The figures 4.8 show the overall process of DWT decomposition of right bundle branch block ECG signal. From this extracted coefficients the system takes only the last level detail coefficient. These last level detail coefficients are then fed to the ANFIS classifier to appropriately classify to their heart disease class.

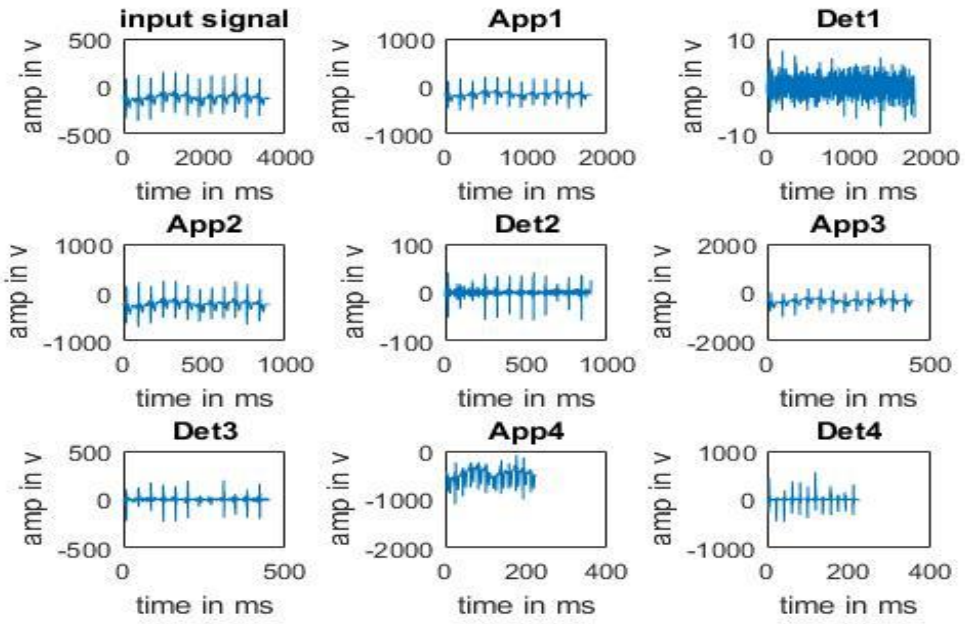


Figure 4. 8 DWT decomposed RBBB ECG signal

### 4.1.5 Supraventricular contraction

The original supra ventricular contraction ECG signal downloaded from physiobank ATM looks like the figure 4.9 when it was plotted on MATLAB.

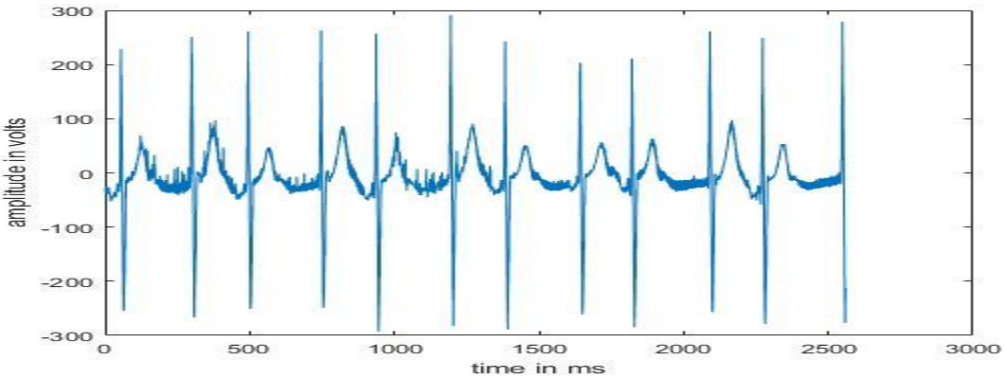


Figure 4. 9 SVC ECG signal

The figures 4.10 show the overall process of DWT decomposition of supraventricular ECG signal. From this extracted coefficients the system receives only the last level detail coefficient. These last level detail coefficients are then fed to the ANFIS classifier to appropriately classify to their heart disease class.

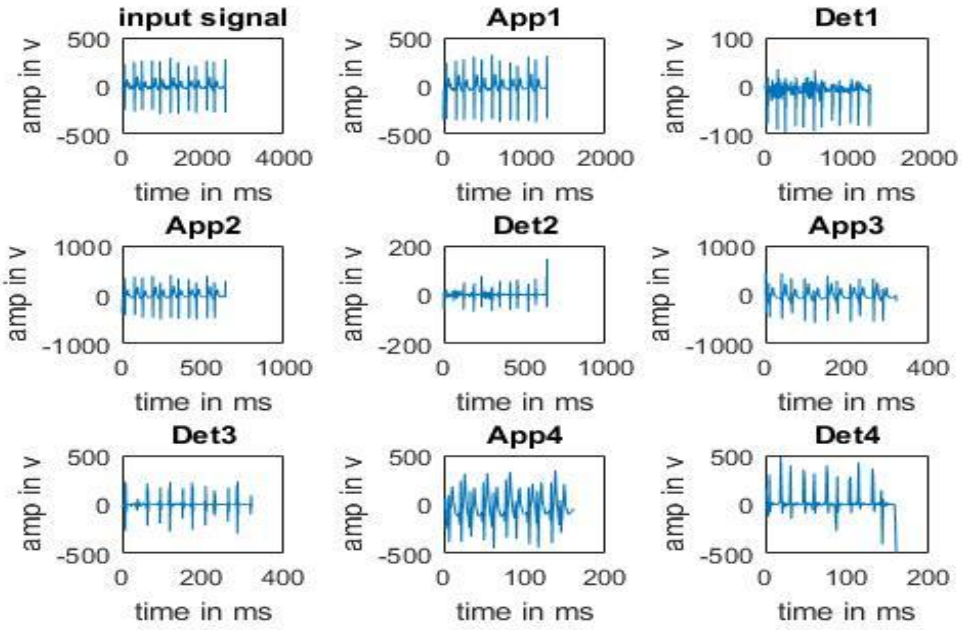


Figure 4. 10 DWT decomposed SVC ECG signal

### 4.1.2 DWT Feature Vectors

From the Table 4.1, the 25 feature vectors are extracted from five classes of ECG signal were calculated from the D4 frequency band and shows the difference between them, therefore, they are useful parameters in classifying the ECG signals.

Table 4. 1 Features Extracted from Five Classes

| Dataset | Extracted features | DWT Coefficient D4 sub band |
|---|---|---|
| Normal | Mean | -0.014992584 |
| | Standard deviation | 0.120873705 |
| | Max amplitude | 0.18843191 |
| | Min amplitude | -0.502181054 |
| | Energy | 0.252185811 |
| Left bundle branch block | Mean | -0.068358022 |
| | Standard deviation | 0.405353691 |
| | Max amplitude | 0.592484745 |
| | Min amplitude | -1.401518641 |
| | Energy | 1.964254502 |
| Paced beat | Mean | 0.125162933 |
| | Standard deviation | 0.691765213 |
| | Max amplitude | 2.220861202 |
| | Min amplitude | -0.940985618 |
| | Energy | 4.932224477 |
| Right bundle branch block | Mean | -0.048380204 |
| | Standard deviation | 0.340067297 |
| | Max amplitude | 0.573133351 |
| | Min amplitude | -1.164976607 |
| | Energy | 1.357170495 |
| Supraventricular contraction | Mean | -0.489420072 |
| | Standard deviation | 0.97787963 |
| | Max amplitude | 0.618437515 |
| | Min amplitude | -1.746853362 |
| | Energy | 3.051496668 |

The DWT feature coefficients extracted from each ECG signal showing the different value for 401 samples for the training and testing datasets. This all features coefficients were used by ANFIS classifier as inputs in MATLAB.

## 4.2 Classification using ANFIS

ECG signals classified using the mixture of DWT features vectors and ANFIS. ANFIS was taught with the backpropagation gradient descent method in mixture with the least squares method has been prepared. The hybrid algorithm is consist of least squares method (forward pass) is used to optimize the resulting parameters with the premise parameters stable and the gradient descent method (backward pass) is used to regulate optimally the premise parameters corresponding to the fuzzy sets in the input domain. When the optimal consequent parameters are originate, the backward pass starts instantly. The output of the ANFIS is measured by employing the consequential parameters found in the forward pass. The output error is used to train the premise parameters by means of a standard backpropagation algorithm.

The present research established that the wavelet coefficients are the features that well illustrate the ECG signals and the ANFIS trained on these features achieved high classification accuracies. In classification, the aim is to allocate the input patterns to one of five classes, usually symbolized by outputs restricted to lie in the range from 1 to 5, so that they represent the probability of the class membership. While the classification is passed out, the explicit pattern is given to specific class according to the distinguishing features that represent the ECG signal.

In this study, training and testing data sets were formed by 401 data samples. The 250 data samples were used for training and 151 data samples were used for testing. The training dataset was used to train the ANFIS, while the testing dataset was used to prove the accuracy and the efficiency of the trained ANFIS model for the detection of heart disease patients.

The ANFIS used 250 training data in 70 training periods and the step size for parameter variation had an initial value of 0.290725. At the end of 70 training epochs, the network error convergence curve of ANFIS had the final error convergence value of 0.007252.

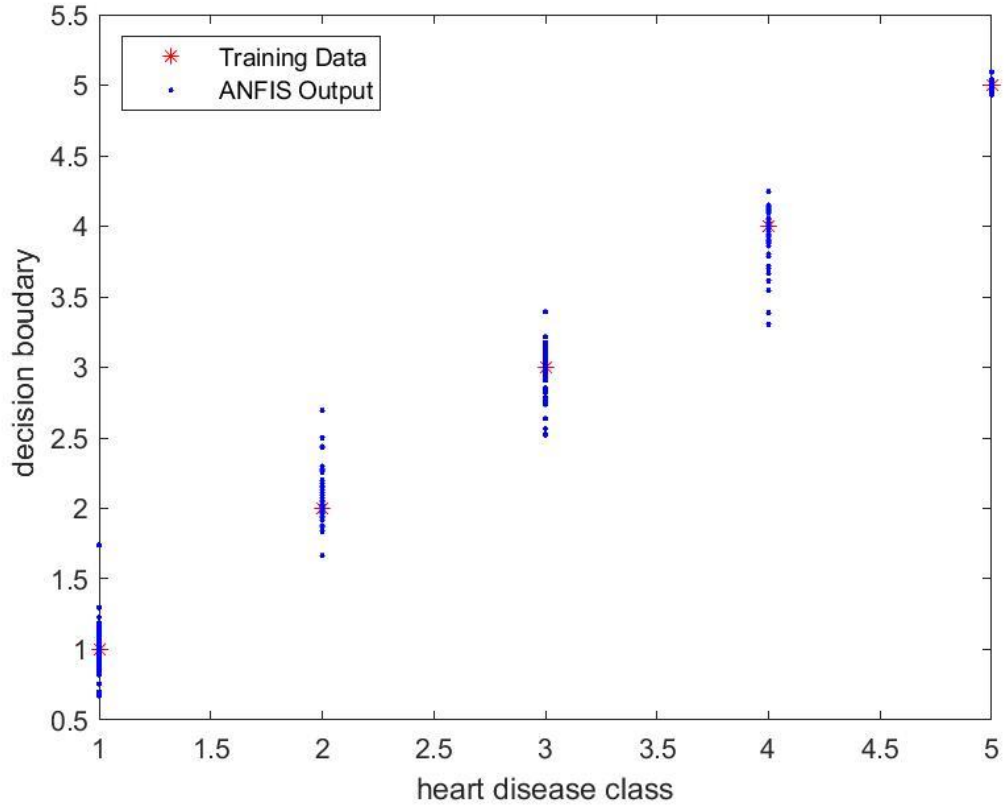


Figure 4. 11 ANFIS Training Performance for training dataset

Table 4. 2 Statistics of Heart Disease Classification of testing dataset

| Heart disease type | Class | Correctly Classified | Misclassified |
|---|---|---|---|
| Normal | 1 | 31 | 1 |
| Left bundle branch block | 2 | 30 | 0 |
| Paced beat | 3 | 30 | 0 |
| Right bundle branch block | 4 | 30 | 0 |
| Supraventricular contraction | 5 | 30 | 0 |
| Total | | 150 | 1 |

The statistic of heart disease classification according to performance of ANFIS the classes also shown in bar chart as percentage demonstrated in Figure 4.12.

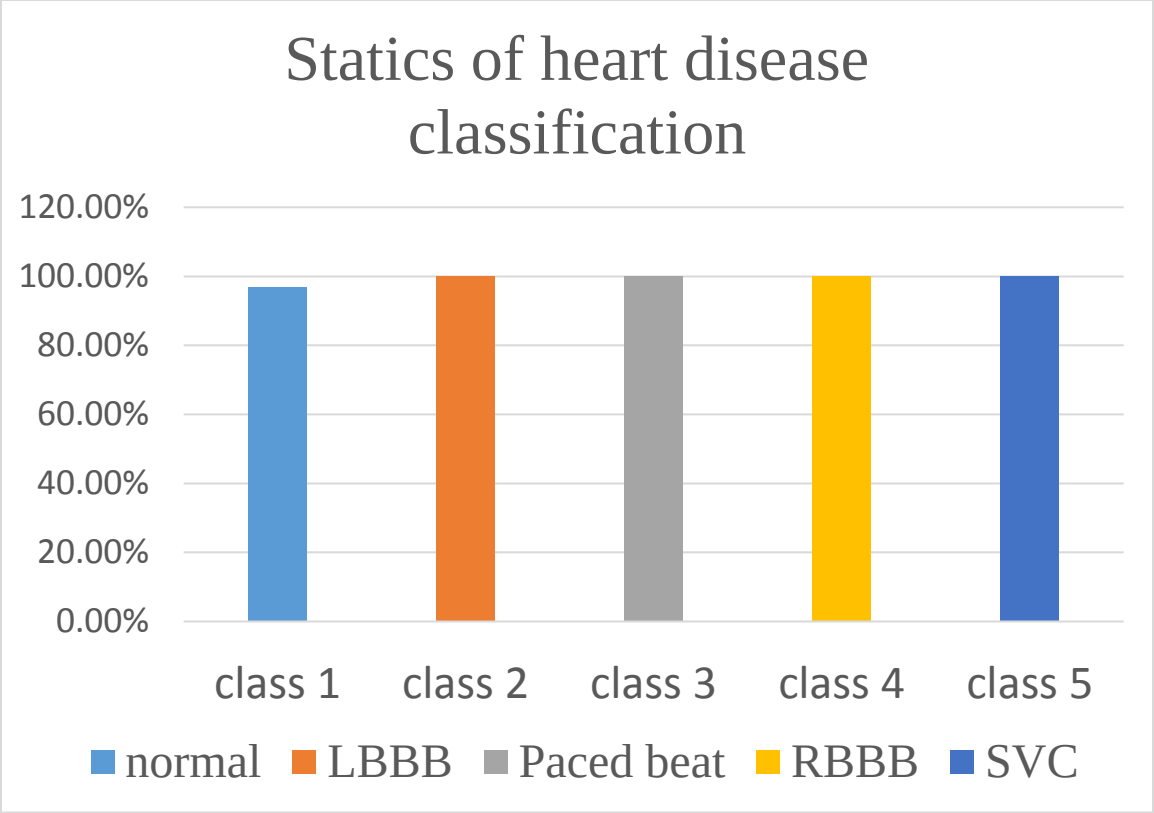


Figure 4. 12 Statistic of Heart Disease Classification according to Class

Table and Figure explain the correctly classified and misclassified data samples of heart disease for individual classes. 30 samples from Class 1 were classified correctly and 1 data sample is incorrect classified. For class 2, 3, 4 and class 5 each having 30 samples is classified correctly and no samples are misclassified for testing dataset. The ANFIS classified 5 classes of heart disease having 151 testing data samples.

The figure below demonstrate the ANFIS output performance of the testing dataset. As it was a hybrid of both neural network and fuzzy logic the output is fuzzy output in the limit across decision boundary (midpoint) among the consecutive classes.

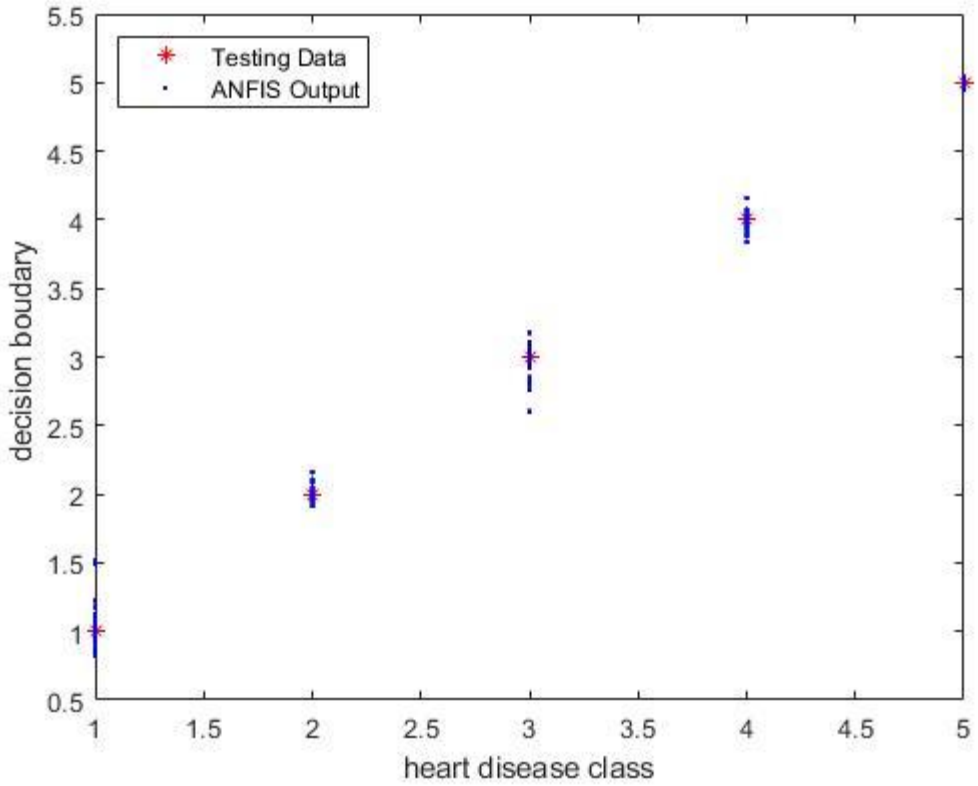


Figure 4. 13 ANFIS output testing performance

The confusion matrix in Table 4 below clarify the classification results of the ANFIS model used for classification of the ECG signals. This matrix can prompt the presence with which an ECG signal is misclassified as another. The confusion matrix is demarcated by predicted classification on the rows and convinced network outputs on the columns.

Table 4. 3 ANFIS Testing Performance

| Confusion matrix | | | | | |
|---|---|---|---|---|---|
| Desired output | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 |
| Class 1 | 30 | 0 | 0 | 0 | 0 |
| Class 2 | 1 | 30 | 0 | 0 | 0 |
| Class 3 | 0 | 0 | 30 | 0 | 0 |
| Class 4 | 0 | 0 | 0 | 30 | 0 |
| Class 5 | 0 | 0 | 0 | 0 | 30 |

According to the confusion matrix, 1 Normal signal from Class 1 was misclassified by the ANFIS model as LBBB signal from Class 2. The rest LBBB, paced beats, RBBB and SVC signals from class 2, class 3, class 4 and class 5 were classified correctly.

## 4.3 Performance Analysis

The classification performance of the proposed ANFIS model was determined by the calculation of statistical factors such as sensitivity, specificity and accuracy as follows.

Table 4. 4 Classification performance of ANFIS

| ECG datasets | Statistical parameters | | |
|---|---|---|---|
| | Sensitivity (%) | Specificity (%) | Total classification accuracy (%) |
| Normal | 96.8 | 100 | 99.34 |
| LBBB | 100 | 99.2 | |
| Paced beat | 100 | 100 | |
| RBBB | 100 | 100 | |
| SVC | 100 | 100 | |

Table shows the classification accuracy firm by ANFIS model. The overall classification accuracy determined by ANFIS model was 99.34%. The classification specificity rate of Normal, LBBB, paced beat, RBBB and SVC signals offered by ANFIS system are 100%, 99.2%, 100%, 100% and 100% respectively. As seen from the Table 4, the ANFIS classified Normal, LBBB, paced beat, RBBB and SVC signals with the classification sensitivity of 96.8%, 100%, 100%, 100% and 100%, respectively.

### 4.3.1 Calculation of Sensitivity and Specificity

i. Normal Signal

$$sensitivity = \frac{Number\ of\ correctly\ classified\ Normal}{Number\ of\ total\ Normal\ signals}$$

$$= \frac{Tp}{TP+Fp}$$

$$= \left(\frac{30}{31}\right) \times 100\% = 96.8$$

$$specificity = \frac{Number\ of\ correct\ classified\ heart\ disease}{Numberof\ total\ heart\ disease}$$

$$= \frac{TN}{TN+FP}$$

$$= \frac{30+30+30+30}{30+30+30+30} \times 100\% = 100$$

ii. LBBB signal

$$sensitivity = \frac{Number\ of\ correctly\ classified\ Normal}{Number\ of\ total\ Normal\ signals}$$

$$= \frac{TP}{TP+FP}$$

$$= \frac{30}{30} \times 100\% = 100$$

$$specificity = \frac{Number\ of\ correct\ classified\ heart\ disease}{Numberof\ total\ heart\ disease}$$

$$= \frac{TN}{TN+FP}$$

$$= \frac{30+30+30+30}{30+30+30+30+1} \times 100\% = 99.2$$

iii. Paced beat signal

$$sensitivity = \frac{Number\ of\ correctly\ classified\ Normal}{Number\ of\ total\ Normal\ signals}$$

$$= \frac{TP}{TP+FP}$$

$$= \frac{30}{30} \times 100\% = 100$$

$$specificity = \frac{Number\ of\ correct\ classified\ heart\ disease}{Numberof\ total\ heart\ disease}$$

$$= \frac{TN}{TN+FP}$$

$$= \frac{30+30+30+30}{30+30+30+30} \times 100\% = 100$$

iv. RBBB signal

$$sensitivity = \frac{Number\ of\ correctly\ classified\ Normal}{Number\ of\ total\ Normal\ signals}$$

$$= \frac{TP}{TP + FP}$$

$$= \frac{30}{30} \times 100\% = 100$$

$$specificity = \frac{Number\ of\ correct\ classified\ heart\ disease}{Numberof\ total\ heart\ disease}$$

$$= \frac{TN}{TN + FP}$$

$$= \frac{30 + 30 + 30 + 30}{30 + 30 + 30 + 30} \times 100\% = 100$$

v. SVC signal

$$sensitivity = \frac{Number\ of\ correctly\ classified\ Normal}{Number\ of\ total\ Normal\ signals}$$

$$= \frac{TP}{TP + FP}$$

$$= \frac{30}{30} \times 100\% = 100$$

$$specificity = \frac{Number\ of\ correct\ classified\ heart\ disease}{Numberof\ total\ heart\ disease}$$

$$= \frac{TN}{TN + FP}$$

$$= \frac{30 + 30 + 30 + 30}{30 + 30 + 30 + 30} \times 100\% = 100$$

### 4.3.2 Total Classification Accuracy

$$Total\ classification\ accuracy = \frac{number\ of\ correctly\ classified\ class}{Total\ numbers\ of\ testing\ data}$$

$$= \left(\frac{150}{151}\right) \times 100\% = 99.34\%$$

In the research, the ANFIS algorithm revealed significant outcomes of the accuracy of the classification which are above 95%.The accuracy rates obtained are highly promising and suggest that adaptive neuro fuzzy approach is realistic in heart disease detection. So ANFIS classification system is an outstanding system for predicting and classifying heart diseases.

# Chapter 5
# Conclusion and Recommendation

## 5.1 Conclusion and Outcomes of the Research

The heart is an organ which pumps blood to the body and the lung for the circulation of oxygen and nutrients. ECG was one of the conventional diagnostic tool by which the physicians are able to detect different heart disease using it. As it was known ECG displays the electrical activity of the heart when it contract and dilate during blood circulation.

This research is an attempt to suggest a solution applying the hybrid algorithm to decide an optimum ECG classification scheme designed for the medical environment in our country, where technological progresses have seen modifications to many aspects of the daily lives of person, but there is still a substantial gap between the existing solutions and the necessities in the medical field. The method offers an analysis system that is capable to classify the certain heart disease.

The research was able to confirm that DWT feature extraction is the robust and up to date method of feature extraction nowadays. The PCA is implemented to reduce the feature vectors from six to five indicating that we can able to extract a lot of extra features and can optimize using this technique.

The proposed method in this research was able to classify five classes with total classification accuracy rate up to 99.34%, sensitivity rate are 96.8%, 100%, 100%, 100% and 100%, for normal, LBBB, paced beat, RBBB and SVC class respectively. Also, the specificity rate that attained in classifying the normal, LBBB, paced beat, RBBB and SVC class are 100%, 99.2%, 100%, 100% and 100%, respectively. The ANFIS model offered in this study verify that it accomplished the higher rates of classification accuracy attaining its objectives set earlier.

## 5.2 Research limitations and problems

i. Problem of getting real data or problem of not applying on the real situation.
ii. As the number of input nodes used in ANFIS model amplified will cause increasing of the number of rules, and make the system out of memory so that it will disturb the time to run the sample data used in the training process of the ANFIS system.

## 5.3 Recommendations for future work

i. By automating the ECG monitoring procedure, the most updated information for all patients are readily available at all times and avoids the delayed actions.

ii. The features of ECG analysis can be prolonged to include other features by using an enhanced and other hybrid algorithms to evaluate and select features which are suitable for many types of heart disease detection.

iii. By using advanced and better computers it can be extended to classify many heart diseases with one system by adding features and using best hybrid algorithms.

iv. If this system was able to be implemented on smartphones by finding or developing specific applications they would improve the capacity of monitoring of patients to high level.

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