



**CLASSIFICATION OF CARDIAC ARRHYTHMIA USING ANFIS  
CLASSIFIER**



**A PROJECT REPORT**

*Submitted by*

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## **BONAFIDE CERTIFICATE**

Certified that this project report titled “**CLASSIFICATION OF CARDIAC ARRHYTHMIA USING ANFIS CLASSIFIER**” is the bonafide work of **S.SIVASANKARI [Reg. No. 13MCO21]** who carried out the research under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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## ABSTRACT

ECG represents the electrical potential generated by the electrical activity of heart tissue. It is a non-invasive measurement. ECG carries rich diagnostic information. Early detection and effective classification of arrhythmia is essential to provide appropriate treatment for patients. Hence automatic Electrocardiogram (ECG) beat classification is essential for the timely diagnosis of dangerous heart conditions. There are various CardioVascular Disease, such as bradycardia, tachycardia, bundle branch block that are very dangerous to human. These diseases should be classified and predicted using ANFIS classifier.

A good system depends heavily upon the accurate and reliable detection of QRS complex. The ECG samples are taken from MIT-BIH arrhythmia database. From the MIT-BIH arrhythmia database, over 3, 00,000 samples are taken and statistical and morphological features are extracted. The ECG signal is first denoised using Discrete Wavelet Transform, and then features from ECG signal are extracted. Discrete Wavelet Transform is applied and four levels of decomposition is done. Various morphological features such as R amplitude, S amplitude, R interval, T interval, T amplitude ,Q amplitude are extracted. Various statistical features such as mean, standard deviation, minimum, maximum, Energy has been calculated from the fourth level of detail coefficients. Each 1, 00, 00 sample is used for training, testing, checking of the ANFIS classifier. ANFIS classifier uses gbell membership functions and generates 243 rules. These rules use hybrid technique for optimization, and use If-Then rules to classify inputs. The Hybrid algorithm is combination of back-propagation and least squares method to optimize the input parameters. The final output is the weighted average of each rule's input.

Grid Partitioning and Subtractive clustering methods are used to calculate the accuracy, sensitivity, specificity of the four classes. If unknown input is given, the classifier is able to predict the class, and for various other features the output classes are classified.

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## LIST OF ABBREVIATIONS

<b>CVD</b>	Cardio Vascular Disease
<b>ECG</b>	Electro Cardio Gram
<b>MI</b>	Myocardial Infraction
<b>VT</b>	Ventricular Tachycardia
<b>SVT</b>	Supra Ventricular Tachycardia
<b>MIT/BIH</b>	Massachusetts Institute of Technology/Beth Isrel Hospital
<b>ANFIS</b>	Adaptive Neuro Fuzzy Inference System
<b>USPSTF</b>	United States Preventive Services Task Force
<b>IHD</b>	<u>Ischemic Heart Disease</u>
<b>DWT</b>	Discrete Wavelet Transform

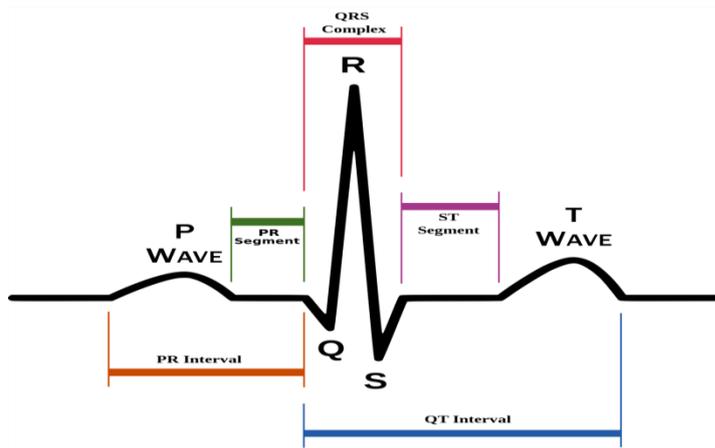
# CHAPTER 1

## INTRODUCTION

### 1.1 ELECTROCARDIOGRAM

An ECG is used to measure the heart's electrical conduction system. It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates into a waveform. The waveform is then used to measure the rate and regularity of heartbeats, as well as the size and position of the chambers, the presence of any damage to the heart, and the effects of drugs or devices used to regulate the heart, such as a pacemaker. Briefly ECG is the representative signal of cardiac physiology, which can be used in diagnosing cardiac disorders.

A typical ECG tracing of the cardiac cycle (heartbeat) consists of a P wave, a QRS complex, a T wave, and a U wave, which is normally invisible in 50 to 75% of ECGs because it is hidden by the T wave and upcoming new P wave. The baseline of the electrocardiogram (the flat horizontal segments) is measured as the portion of the tracing following the T wave and preceding the next P wave and the segment between the P wave and the following QRS complex (PR segment). In a normal healthy heart, the baseline is equivalent to the isoelectric line (0 mV) and represents the periods in the cardiac cycle when there are no currents towards either the positive or negative ends of the ECG leads. However, in a diseased heart, the baseline may be depressed (e.g., cardiac ischaemia) or elevated (e.g., myocardial infarction) relative to the isoelectric line due to injury currents during the TP and PR intervals when the ventricles are at rest. The ST segment typically remains close to the isoelectric line as this is the period when the ventricles are fully depolarised and thus no currents can be in the ECG leads. Since most ECG recordings do not indicate where the 0 mV line is, baseline depression often gives the appearance of an elevation of the ST segment and conversely baseline elevation gives the appearance of depression of the ST segment.

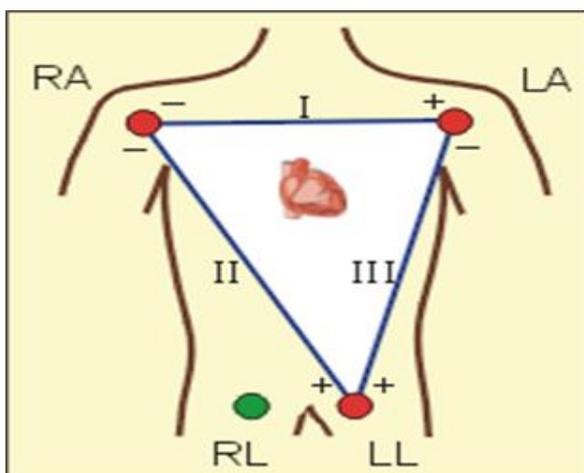


**Figure 1.1 ECG waves**

## 1.2 ECG ACQUISITION

Leads are used to record the ECG signals with 3-12 electrodes. Multi-lead systems with more than 12 electrodes are also available. Recording of the ECG

Leads used: Limb leads are I, II, III, So called because at one time subjects had to literally place arms and legs in buckets of salt water. Each of the leads are bipolar; i.e., it requires two sensors on the skin to make a lead. If one connects a line between two sensors, one has a vector. There will be a positive end at one electrode and negative at the other. The positioning for leads I, II, and III were first given by Einthoven. Form the basis of Einthoven's triangle.



**Figure 1.2 .Leads of ECG**

### Types of ECG Recordings

- Bipolar leads record voltage between electrodes placed on wrists & legs (right

leg is ground)

- Lead I records between right arm & left arm
- Lead II right arm & left leg
- Lead III: left arm & left leg

### **1.3ELEMENTS OF ECG**

#### **RR interval:**

The interval between an R wave and the next R wave; normal resting heart beat is between 60 and 100 bpm.

Duration- 0.6 to 1.2 s.

#### **P wave:**

During normal atrial polarization, the main electrical vector is directed from the SA node towards the AV node and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG.

Duration- 80ms.

#### **QRS complex:**

The QRS complex reflects the rapid depolarization of the right and left ventricles. The ventricles have a large muscle mass compared to the atria, so the QRS complex usually has a much larger amplitude than the P-wave.

Duration -80 ms

#### **ST segment:**

The ST segment connects the QRS complex and the T wave. The ST segment represents the period when the ventricles are depolarized. It is isoelectric

Duration- 80-120ms

**PR interval:**

The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. The PR interval reflects the time the electrical impulse takes to travel from the sinus node through the AV node and entering the ventricles. The PR interval is, therefore, a good estimate of AV node function.

Duration -120-200 ms

**T wave:**

The T wave represents the repolarization of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period.

Duration -160ms

**1.4 CARDIOVASCULAR DISEASE**

**Cardiovascular disease** (also called **heart disease** ) is a class of diseases that involve the heart or blood vessels (arteries, capillaries and veins). Cardiovascular disease (CVD) causes the death of over 17 million people worldwide each year. The cause of CVD is due to heart attacks, strokes, heart valve problems and arrhythmia.

Myocardial Infarction, Premature Ventricular Contraction, Ventricular Tachycardia, Supra Ventricular arrhythmias, ST deviation, Ventricular Fibrillation are the life threatening cardiac disorders. The classification of ECG into these different cardiac diseases is a complex task. Therefore the characteristic shapes of ECG have to be found for the successful classification. By using the magnitude, area and duration typical heart beats are analyzed by using ECG and the PQRST wave properties. Therefore ECG abnormality detection should be reliable in an ECG monitoring system or a defibrillator, if not the patient will lose the chance of treatment. There are hundreds of different types of cardiac arrhythmias like atrial flutter, atrial fibrillation, ventricular flutter, ventricular fibrillation etc.

PVCs are premature heart beats that originate from the ventricles of the heart. They are premature because they occur before the regular heartbeat. This early heart beat can happen in the upper (atria) or lower chamber (ventricles). The pattern is normal beat, the extra beat (PVC), a slight pause then a stronger than a normal beat. The heart is filled

with more blood during the pause following the PVC giving the next beat with extra force. This pattern may occur randomly or at regular intervals. It is caused by an ectopic cardiac pacemaker located in the ventricle. It is characterized by premature and bizarrely shaped QRS complexes usually wider than 120 millisecond on with the width of the ECG. Many studies have shown PVCs, when associated with myocardial infarction, can be linked to mortality. Consequently their immediate detection and treatment is essential for patients with heart diseases. PVCs are performed with MIT-BIH Arrhythmia database.

Ventricular Tachycardia (VT) is a fast heart rhythm that occurs in one of the ventricles of the heart. It has a pulse rate of more than 100 beats per minute. It is a difficult problem for the physicians as it often occurs in life threatening situations. The symptoms of VT are angina, palpitations, shortness of breath etc.

Supra Ventricular Tachycardia (SVT) is also a rapid heart rate with a heart rate above 100 beats per minute. It starts and ends quickly. It originates above the heart's ventricle. It is also called Paroxysmal Supra ventricular Tachycardia. The symptoms of SVT are palpitations, Dizziness etc.

ST Segment depression is determined by measuring the vertical distance between the patient's trace and the isoelectric line. It is a sign of myocardial ischemia. Long term ST is to detect the transient ST segment changes in the ECGs.

Ventricular Fibrillation (VF) is a condition in which there is uncoordinated contraction of the cardiac muscles of the ventricles in the heart, making them quiver rather than contract properly. This condition results in cardiogenic shock and cessation of effective blood circulation. As a consequence, Sudden Cardiac Death (SCD) will result within few minutes.

Bradycardia, also known as bradyarrhythmia, is a slow heart rate, namely, a resting heart rate of under 60 beats per minute (BPM) in adults. It is a type of cardiac arrhythmia. It seldom results in symptoms until the rate drops below 50 BPM. It sometimes results in fatigue, weakness, dizziness, and at very low rates fainting.

During sleep, a slow heartbeat with rates around 40–50 BPM is common, and is considered normal. Highly trained athletes may also have athletic heart syndrome, a very slow resting heart rate that occurs as a sport adaptation and helps prevent tachycardia during training (e.g., professional cyclist Miguel Indurain had a resting heart rate of 28 BPM).

Daniel Green holds the world record for the slowest heartbeat in a healthy human, with a heart rate measured in 2014 of just 26 bpm.

Tachycardia is a heart rate that exceeds the normal range. In general, a resting heart rate over 100 beats per minute is accepted as tachycardia. Tachycardia can be caused by various factors that often are benign. However, tachycardia can be dangerous, depending on the speed and type of rhythm.

Tachycardias may be classified as either narrow complex tachycardias (supraventricular tachycardias) or wide complex tachycardias. Narrow and wide refer to the width of the QRS complex on the ECG. Narrow complex tachycardias tend to originate in the atria, while wide complex tachycardias tend to originate in the ventricles. Tachycardias can be further classified as either regular or irregular.

The heart's electrical activity begins in the sinoatrial node (the heart's natural pacemaker), which is situated on the upper right atrium. The impulse travels next through the left and right atria and summates at the atrioventricular node. From the AV node the electrical impulse travels down the Bundle of His and divides into the right and left bundle branches. The right bundle branch contains one fascicle. The left bundle branch subdivides into two fascicles: the left anterior fascicle and the left posterior fascicle. Other sources divide the Left Bundle branch into three (3) fascicles, the left anterior, the left posterior, and the left septal fascicle. The thicker left posterior fascicle bifurcates, with one fascicle being in the septal aspect. Ultimately, the fascicles divide into millions of Purkinje fibres which in turn interdigitise with individual cardiac myocytes, allowing for rapid, coordinated, and synchronous physiologic depolarization of the ventricles.

Using an ECG is a non-invasive technique that is simple to analyze. A patient is attached to few leads and then every single beat is analyzed by the equipment that makes up the ECG. To understand better about ECG, knowledge about the signal outputted by the leads that are analyzing the heart are to be known. Each heart beat signal is analyzed by the ECG. Certain properties help us to determine which cardiac arrhythmias, if any is occurring in the heart. For the arrhythmias in this paper most of them can be analyzed due to differences in the QRS part of the signal. The difference in the heart is determined by the width and height.

### **1.4.1 IMPORTANCE OF CARDIOVASCULAR DISEASE**

Cardiovascular disease (CVD) is a class of diseases that involve the heart or blood vessels. Common CVDs include: ischemic heart disease (IHD), stroke, hypertensive heart disease, rheumatic heart disease (RHD), aortic aneurysms, cardiomyopathy, atrial fibrillation, congenital heart disease, endocarditis, and peripheral artery disease (PAD), among others.

The underlying mechanisms vary depending on the disease in question. IHD, stroke, and PAD involve atherosclerosis. This may be caused by high blood pressure, smoking, diabetes, lack of exercise, obesity, high blood cholesterol, poor diet, and excessive alcohol, among others. High blood pressure results in 13% of CVD deaths, while tobacco results in 9%, diabetes 6%, lack of exercise 6% and obesity 5%. Others such as RHD may follow untreated streptococcal infections of the throat.

It is estimated that 90% of CVD is preventable. Prevention of atherosclerosis is by decreasing risk factors through: healthy eating, exercise, avoidance of tobacco smoke and limiting alcohol intake. Treating high blood pressure and diabetes is also beneficial. Treating people who have strep throat with antibiotics can decrease the risk of RHD. The effect of the use of aspirin in people who are otherwise healthy is of unclear benefit. The USPSTF recommends against its use for prevention in women less than 55 and men less than 45 years old; however, in those who are older it is recommended in some individuals. Treatment of those who have CVD improves outcomes. United States Preventive Services Task Force (USPSTF) is "an independent panel of experts in primary care and prevention that systematically reviews the evidence of effectiveness and develops recommendations for clinical preventive services." The task force, a panel of primary care physicians and epidemiologists, is funded, staffed, and appointed by the U.S. Department of Health and Human Services' Agency for Healthcare Research and Quality

Cardiovascular diseases are the leading cause of death globally. This is true in all areas of the world except Africa. Together they resulted in 17.3 million deaths (31.5%) in 2013 up from 12.3 million (25.8%) in 1990. Deaths, at a given age, from CVD are more common and have been increasing in much of the developing world, while rates have declined in most of the developed world since the 1970s. IHD and stroke account for 80% of CVD deaths in males and 75% of CVD deaths in females. Most cardiovascular disease affects older adults. In the United States 11% of people between 20 and 40 have CVD, while 37% between 40 and

60, 71% of people between 60 and 80, and 85% of people over 80 have CVD.<sup>[10]</sup> The average age of death from IHD in the developed world is around 80 while it is around 68 in the developing world. Disease onset is typically seven to ten years earlier in men as compared to women.

## **1.5 ECG DATABASE**

### **1.5.1 MIT-BIH ARRHYTHMIAS DATABASE**

The MIT/BIH arrhythmia database is used in this study for performance evaluation. The database contains 48 records, each containing two -channel ECG signals for 30 min duration selected from 24-hr recordings of 47 individuals. The subjects were taken from , 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years and the records 201 and 202 came from the same male subject. Each recording includes two leads; the modified limb lead II and one of the modified leads V1, V2, V4 or V5. Continuous ECG signals are bandpassfiltered at 0.1–100 Hz and then digitized at 360 Hz. Twenty-three of the recordings (numbered in the range of 100–124) are intended to serve as a representative sample of routine clinical recordings and 25 recordings (numbered in the range of 200–234) contain complex ventricular, junctional, and supraventricular arrhythmias. The database contains annotation for both timing information and beat class information verified by independent experts[23] .

The source of the ECGs included in the MIT-BIH Arrhythmia Database is a set of over 4000 long-term Holter recordings that were obtained by the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. Approximately 60% of these recordings were obtained from inpatients. The database contains 23 records (numbered from 100 to 124 inclusive with some numbers missing) chosen at random from this set, and 25 records (numbered from 200 to 234 inclusive, again with some numbers missing) selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small random sample of Holter recordings. Each of the 48 records is slightly over 30 minutes long.

The first group is intended to serve as a representative sample of the variety of waveforms and artifact that an arrhythmia detector might encounter in routine clinical use. A table of random numbers was used to select tapes, and then to select half-hour segments of

them. Segments selected in this way were excluded only if neither of the two ECG signals was of adequate quality for analysis by human experts. Records in the second group were chosen to include complex ventricular, junctional, and supraventricular arrhythmias and conduction abnormalities. Several of these records were selected because features of the rhythm, QRS morphology variation, or signal quality may be expected to present significant difficulty to arrhythmia detectors; these records have gained considerable notoriety among database users. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years. (Records 201 and 202 came from the same male subject.)

## CHAPTER 2

### LITERATURE SURVEY

An ECG is used to measure the heart's electrical conduction system. It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates into a waveform. The waveform is then used to measure the rate and regularity of heartbeat as well as the size and position of the chambers, the presence of any damage to the heart and the effect of drugs or devices used to regulate the heart attack such as pacemaker. Briefly ECG is the representative signal of cardiac physiology. Early detection and effective classification of arrhythmia is essential to provide appropriate treatment for patients. Hence automatic ElectroCardioGram (ECG) beat classification is essential for the timely diagnosis of dangerous heart conditions.

#### **[1] Segmentation of Holter ECG waves via analysis of a discrete wavelet-derived multiple skewness-kurtosis based metric.**

A simple mathematical-statistical based metric called Multiple Higher Order Moments (MHOM) is introduced enabling the electrocardiogram (ECG) detection-delineation algorithm to yield acceptable results in the cases of ambulatory Holter ECG including strong noise, motion artifacts, and severe arrhythmia(s). In the MHOM measure, important geometric characteristics such as maximum value to minimum value ratio, area, extent of smoothness or being impulsive and distribution skewness degree (asymmetry), occur. In the proposed method, first three leads of high resolution 24-h Holter data are extracted and pre-processed using Discrete Wavelet Transform (DWT).

#### **[2] Support Vector Machines and Particle Swarm Optimization.**

The use of the SVM approach for classifying ECG signals on account of their superior generalization capability as compared to traditional classification techniques. This capability generally provides them with higher classification accuracies and a lower sensitivity to the curse of dimensionality. The main novelty of this paper is in the proposed PSO-based approach, which aims at optimizing the performances of SVM classifiers in terms of classification accuracy by detecting the best subset of available features and solving the tricky model selection issue. The fact that it is entirely automatic makes it particularly useful and attractive.

### **[3] ECG beat classifier designed by combined neural network model**

The use of combined neural network model to guide model selection for classification of electrocardiogram (ECG) beats. The ECG signals were decomposed into time-frequency representations using discrete wavelet transform and statistical features were calculated to depict their distribution. The first level networks were implemented for ECG beats classification using the statistical features as inputs. To improve diagnostic accuracy, the second level networks were trained using the outputs of the first level networks as input data. Four types of ECG beats (normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat) obtained from the Physio-bank database were classified with the accuracy of 96.94% by the combined neural network.

### **[4] Automatic arrhythmia detection based on time and time—frequency**

An automatic arrhythmia detection system, which is based on heart rate features only. Initially, the RR interval duration signal is extracted from ECG recordings and segmented into small intervals. The analysis is based on both time and time—frequency (t—f) features. Time domain measurements are extracted and several combinations between the obtained features are used for the training of a set of neural networks. Short time Fourier transform and several time—frequency distributions (TFD) are used in the t—f analysis. The features obtained are used for the training of a set of neural networks, one for each distribution. The proposed approach is tested using the MIT-BIH arrhythmia database and satisfactory results are obtained for both sensitivity and specificity (87.5 and 89.5%, respectively, for time domain analysis and 90 and 93%, respectively, for t—f domain analysis).

### **[5] An arrhythmia classification system based on the RR-interval signal**

A three RR-interval sliding window is used in arrhythmic beat classification algorithm. Classification is performed for four categories of beats: normal, premature ventricular contractions, ventricular flutter/fibrillation and 28 heart block. The beat classification is used as input of a knowledge-based deterministic automaton to achieve arrhythmic episode detection and classification. Six rhythm types are classified: ventricular bigeminy, ventricular trigeminy, ventricular couplet, ventricular tachycardia, ventricular flutter/fibrillation and 28 heart block. Results: The method is evaluated by using the MIT-BIH arrhythmia database. The achieved scores indicate high performance: 98% accuracy for

arrhythmic beat classification and 94% accuracy for arrhythmic episode detection and classification.

#### **[6] A robust wavelet-based multi-lead electrocardiogram delineation algorithm**

A robust multi-lead ECG wave detection-delineation algorithm is developed in this study on the basis of discrete wavelet transform (DWT). By applying a new simple approach to a selected scale obtained from DWT, this method is capable of detecting QRS complex, P-wave and T-wave as well as determining parameters such as start time, end time, and wave sign (upward or downward). First, a window with a specific length is slid sample to sample on the selected scale and the curve length in each window is multiplied by the area under the absolute value of the curve. In the next step, a variable thresholding criterion is designed for the resulted signal. The presented algorithm is applied to various databases including MIT-BIH arrhythmia database, European ST-T Database, QT Database, CinC Challenge 2008 Database as well as high resolution Holter data of DAY Hospital. As a result, the average values of sensitivity and positive predictivity  $Se = 99.84\%$  and  $P+ = 99.80\%$  were obtained for the detection of QRS complexes, with the average maximum delineation error of 13.7 ms, 11.3 ms and 14.0 ms for P-wave, QRS complex and T-wave, respectively.

#### **[7]An Intelligent Scoring System and Its Application to Cardiac Arrest Prediction**

Traditional risks core prediction is based on vital signs and clinical assessment. In this paper, we present an intelligent scoring system for the prediction of cardiac arrest within 72 h. The patient population is represented by a set of feature vectors, from which risk scores are derived based on geometric distance calculation and support vector machine. Each feature vector is a combination of heart rate variability (HRV) parameters and vital signs. Performance evaluation is conducted on the leave-one-out cross-validation framework, and receiver operating characteristic, sensitivity, specificity, positive predictive value, and negative predictive value are reported. Experimental results reveal that the proposed scoring system not only achieves satisfactory performance on determining the risk of cardiac arrest within 72 h but also has the ability to generate continuous risk scores rather than a simple binary decision by a traditional classifier. Furthermore, the proposed scoring system works well for both balanced and imbalanced datasets, and the combination of HRV parameters and vital signs shows superiority in prediction to using HRV parameters only or vital signs only.

### **[8] Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals**

A new approach for heartbeat classification based on a combination of morphological and dynamic features has been used. Wavelet transform and independent component analysis (ICA) are applied separately to each heartbeat to extract morphological features. In addition, RR interval information is computed to provide dynamic features. These two different types of features are concatenated and a support vector machine classifier is utilized for the classification of heartbeats into one of 16 classes. The procedure is independently applied to the data from two ECG leads and the two decisions are fused for the final classification decision.

### **[9] Adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction**

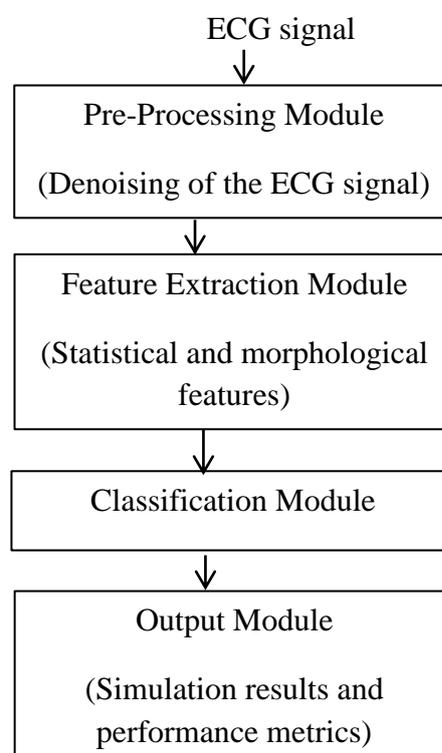
Intelligent computing tools such as artificial neural network (ANN) and fuzzy logic approaches are demonstrated to be competent when applied individually to a variety of problems. Recently, there has been a growing interest in combining both these approaches, and as a result, neuro-fuzzy computing techniques have been evolved. In this study, a new approach based on an adaptive neuro-fuzzy inference system (ANFIS) was presented for epileptic seizure detection. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. Decision making was performed in two stages: feature extractions using the wavelet transform (WT) and the ANFIS trained with the back-propagation gradient descent method in combination with the least squares method. Some conclusions concerning the impacts of features on the detection of epileptic seizures were obtained through analysis of the ANFIS. The results are highly promising, and a comparative analysis suggests that the proposed modeling approach perform ANN model in terms of training performances and classification accuracies. The results confirmed that the proposed ANFIS model has some potential line epileptic seizure detection. The ANFIS model achieved accuracy rates which were higher than that of the stand-alone neural network model.

# CHAPTER 3

## PROPOSED WORK

Classification of ECG signals into different disorders is an important task because the result of this classification determines the health condition of the patients. The treatment is also decided using this result. Hence effective classification is needed to make the system reliable.

### 3.1 FLOW DIAGRAM



**Figure 3.1 Flow diagram**

### 3.2 PRE-PROCESSING MODULE

Considerable attention has been paid to the design of filters for the purpose of removing baseline wander and power-line interference; both types of disturbance imply the design of a narrowband filter. Removal of noise because of muscle activity represents another important filtering problem being much more difficult to handle because of the substantial spectral overlap between the ECG and muscle noise. Muscle noise present in the ECG can, however, be reduced whenever it is appropriate to employ techniques that benefit from the

fact that the ECG is a recurrent signal. For example, ensemble averaging techniques can be successfully applied to time-aligned heartbeats for reduction of muscle noise. The filtering techniques are primarily used for pre-processing of the signal and have as such been implemented in a wide variety of systems for ECG analysis. It should be remembered that filtering of the ECG is contextual and should be performed only when the desired information remains undistorted. This important insight may be exemplified by filtering for the removal of power-line interference.

Removal of baseline wander is required in order to minimize changes in beat morphology that do not have cardiac origin, which is especially important when subtle changes in the “low-frequency” ST segment are analyzed for the diagnosis of ischemia, which may be observed, for example, during the course of a stress test. The frequency content of baseline wander is usually in the range below 0.5Hz; however, increased movement of the body during the latter stages of a stress test further increases the frequency content of baseline wander (see Fig. 2). Patients unable to perform a traditional treadmill or ergometer stress test may still be able to perform a stress test by sitting, running an ergometer by hand, or using a special rowing device. In such cases, baseline wander related to motion of the arms severely distorts the ECG signal. The design of a linear, time-invariant, highpassfilter for removal of baseline wander involves several considerations, of which the most crucial are the choice of filter cut-off frequency and phase response characteristic. The cut-off frequency should obviously be chosen so that the clinical information in the ECG signal remains undistorted while as much as possible of the baseline wander is removed. Hence, it is essential to find the lowest frequency component of the ECG spectrum. In general, the slowest heart rate is considered to define this particular frequency component; the PQRST waveform is attributed to higher frequencies. During bradycardia, the heart rate may drop to approximately 40beats/minute, implying that the lowest frequency contained in the ECG is approximately 0.67Hz . As the heart rate is not perfectly regular but always fluctuates from one beat to the next, it is necessary to choose a slightly lower cut-off frequency such as 0.5Hz. If too high a cut-off frequency is employed, the output of the highpass filter contains an unwanted, oscillatory component that is strongly correlated to the heart rate. In certain situations, baseline wander becomes particularly pronounced at higher heart rates such as during the latter stages of a stress test when the workload increases. Then, it may be advantageous to couple the cut-off frequency to the prevailing heart rate, rather than to the lowest possible heart rate, to further improve base- line removal. Linear filtering with time-

variable cut-off frequency was initially suggested for offline processing of ECG signals and later extended for online use. The other crucial design consideration is related to the properties of the phase response and, consequently, the choice of filter structure. Linear phase filtering is highly desirable in order to prevent phase distortion from altering various wave properties of the cardiac cycle such as the duration of the QRS complex, the ST–T segment level, or the endpoint of the T wave. Discrete wavelet Transform is used to correct the baseline of the ECG signal. First, the raw ECG signal is decomposed using Haar wavelet, and then reconstructed coefficients are calculated using decomposition structure and wavelet. Then the reconstructed coefficients are subtracted from the ECG signal, to eliminate baseline drift.

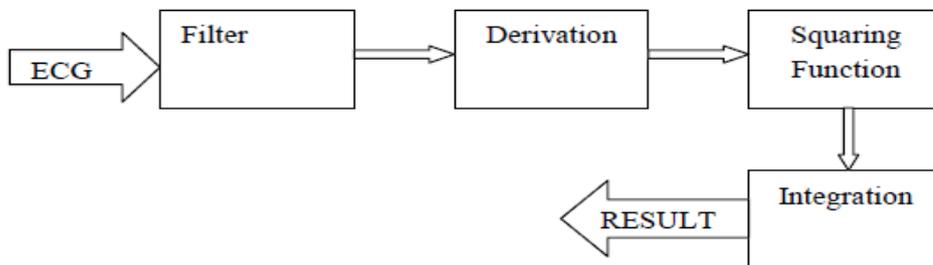
### **3.3 DIFFERENT ECG SEGMENTATION TECHNIQUES**

Electrocardiogram (ECG) introduced into clinical practice more than 100 years ago constitutes a graphical recording of the heart's electrical activity that occurs successively over time. The ECG results determine whether the heart is performing normally or suffering from abnormalities. The recorded ECG is the representation of the depolarization and repolarization of the heart and can diagnose a patient by looking at the characteristics of the traced ECG readings. There are 3 main deflections in an ECG: the P-wave, the QRS complex, and the T-wave. The first upright wave is called the P wave and is normally round in shape and its duration is usually not more than 0.1 second. The QRS complex corresponds to ventricular depolarization.[1] It is normally 0.04 - 0.12 second in duration. Between the P wave and the QRS complex is the PR interval. It represents the time taken by the SA node electrical impulse to travel from its exit out of the SA node to the beginning of ventricular excitation. It is normally 0.1 - 0.2 second in duration. The T wave is another rounded upright wave corresponding to repolarization of the ventricles. Finally, the ST segment is the electric line between the end of the QRS complex and the beginning of the T wave. Additionally, it is useful for epidemiologic studies and screening. The ECG waveforms may differ for the same patient to such extent that they are unlike to each other and at the same time alike for different types of beats. The Wavelets are a powerful tool for the representation and analysis of such physiologic waveforms because a wavelet has finite duration as contrast to Fourier methods based on sinusoids of infinite duration. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem.[4] The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer)

window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions.

### 3.3.1.PAN-TOMPKINS ALGORITHM

Pan and Tompkins detected the fiducial points by finding the highest squared slope during high spectral energy of ECG waves. Based on the observations, the above technique is resulted in more number of fiducial points other than the actual QRS complexes. Two adaptive thresholds are considered and the highest among the two thresholds was chosen to extract QRS complex from the ECG signal and the integration of the ECG signal. A search back algorithm was also applied if no QRS complex candidates were found within a certain time interval. The ECG signal parameters are extracted from the QRS complex, the ST segment, and the statistical characteristics of the signal. [25]The selected parameters are divided into two main categories namely morphological and statistical features. [25]Extractions of morphological features were achieved using signal processing techniques and detection of statistical features was performed by employing mathematical methods.



**Figure 3.2 Pan Tompkins flow diagram**

The Band Pass Filter for QRS detection reduces the noises in the ECG signal by matching the spectrum of the average QRS complex. This attenuates the noises in the ECG signal. Pass band maximizes the QRS energy in the range 5-35Hz.

Differentiation is the standard procedure to find the high slopes that normally distinguish the QRS complex from ECG. Differentiator suppresses the low frequency components like P&T waves of ECG and it provides high gain for QRS complex.

Squaring operation makes the result positive and emphasizes large differences resulting from the QRS complex. The small differences arising from P&T waves are suppressed.

The squared waveform passes through moving window integrator. This window plays a key role in the delineation of ECG wave.

### 3.3.2 WAVELET TRANSFORM

Feature extraction is extracting and converting the input data into a set of features which called feature vector, by reducing the data representation pattern. The features set will extract the relevant information from the input data in-order to perform the classification task. The transform of a signal is just another form of representing the signal. It does not alter the information content present in the signal.

Wavelet theory is the mathematics associated with building a model for a signal, system or process. A wavelet is a wave which has its energy concentrated in time. It has an oscillating wavelike characteristic but also has the ability to allow simultaneous time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying phenomena. WT has a varying window size, [24] being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges. The wavelet transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions. It is capable of representing signals in different resolutions by dilating and compressing in basis functions. The basis function in wavelet analysis is defined by two parameters which are scale and translation. A basis function which is mother wavelet is used in wavelet analysis. For a wavelet of order N, the basis function can be represented in equation

$$\varphi(n) = \sum_{j=0}^{N-1} (-1)^j c_j (2n + j - N + 1) \quad (1)$$

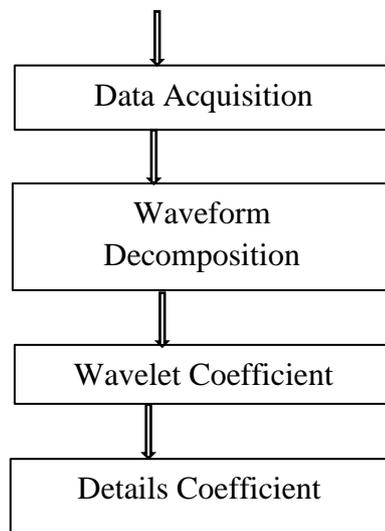
#### 3.3.2.1 DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT), which is a time-scale representation of the digital signal is obtained using digital filtering techniques, is found to yield a fast computation of Wavelet Transform. It is easy to implement and adopts dyadic scales and translations in-order to reduce the amount of computation time, which results in better efficiency of calculation. Various features like statistical and morphological features are extracted. The pre-

processed ECG signal is decomposed using Daubechies wavelet. The wavelet decomposition of DWT procedure involves three steps. The result of decomposed signal will show the important details and approximation coefficients which [24] represents the original signal. The three important steps in DWT are:

- Choosing a wavelet types
- Choosing a wavelet name
- Choosing a level N which will compute the wavelet decomposition of the signal s at level N.

ECG signal



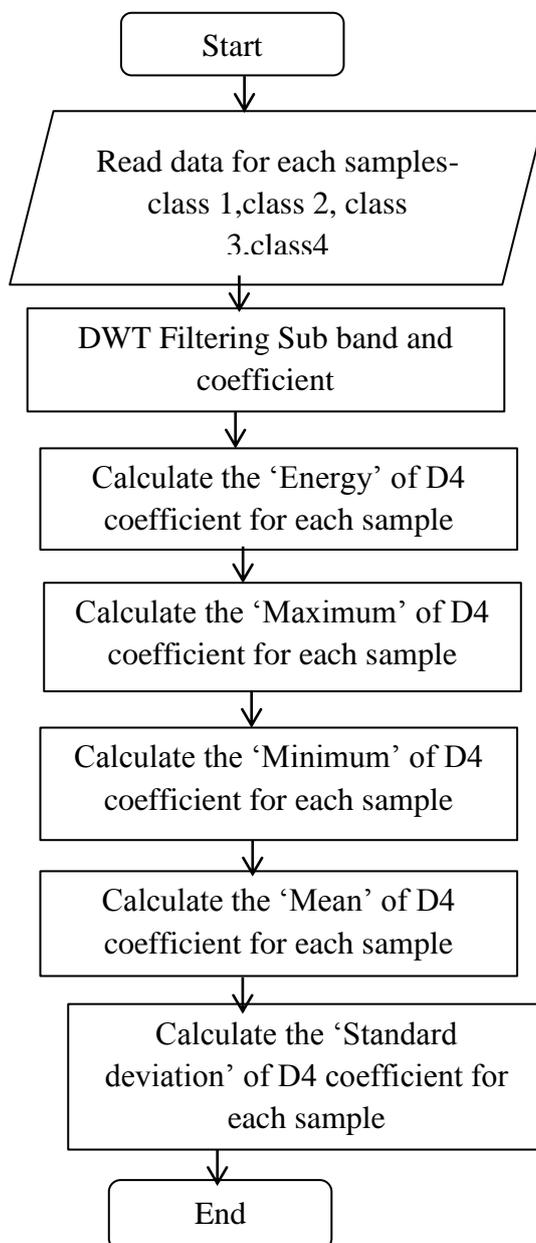
**Figure 3.3 Feature Extraction Techniques**

The wavelet names of Daubechies wavelet filters have been chosen and the number of decomposition levels was chosen to be 4. Thus the ECG signals were decomposed into the details coefficients D1-D4 and one final approximation coefficient A4.

The result of applying the Daubechies wavelet of order 4(db4) which is more suitable to detect changes of ECG signal is evaluated.[24] The wavelet filter with scaling function more closely to the shape of the ECG signal achieved better detection. Db wavelet family is similar in shape to ECG signal and their energy spectrums are concentrated around low frequencies the signal is approximated by omitting the signals high frequency components.

### 3.3.2.2 COEFFICIENTS EXTRACTION

The computed wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency. Therefore the computed details and approximation wavelet coefficients of the ECG signal were used as the feature vector representing the signals. From the original intervals of ECG signal, five standard measures parameters are used. A signal of 3,00000 discrete data was selected as considered ECG signals data. For each ECG signals, the detail wavelet coefficients of fourth level(300000) were computed. The following statistical features were used to represent the time-frequency distribution of the ECG signals.



**Figure 3.4 Flowchart of DWT coefficient calculations**

1. Energy of the wavelet coefficients of each ECG signals sample.
2. Maximum of the wavelet coefficients of each ECG signals sample.
3. Minimum of the wavelet coefficients of each ECG signals sample.
4. Mean of the wavelet coefficients of each ECG signals sample.
5. Standard deviation of the wavelet coefficients of each ECG signals sample.

The Energy of the discrete signal can be calculated using the equation

$$E = \sum_{x=0}^{N-1} \|x(n)\|^2 \quad (2)$$

From the approximation coefficients various morphological features are extracted. In order to compute features from the detected QRS complexes either normal or arrhythmic via the proposed method, first a reliable time center should be obtained for each QRS complex. To find this point, the absolute maximum and the absolute minimum indices of the excerpted DWT dyadic scale 24 using the onset-offset locations of the corresponding QRS complex, are determined. [3] It should be noted that according to comprehensive studies fulfilled in this research, the best time center of each detected QRS complex is the mean of zero-crossing locations of the excerpted DWT.

To make a virtual close-up from each detected QRS complex, a rectangle is built on the complex with following specifications:

- The left-side mid-span of the rectangle is the fiducial location of the QRS complex.
- The Absolute distance of the complex from the fiducial point is the half of the rectangle height.
- The center of rectangle is the time-center of the QRS complex.
- The right-hand abscissa of the rectangle is the distance between QRS time center and its J-location

Thus morphological features are:

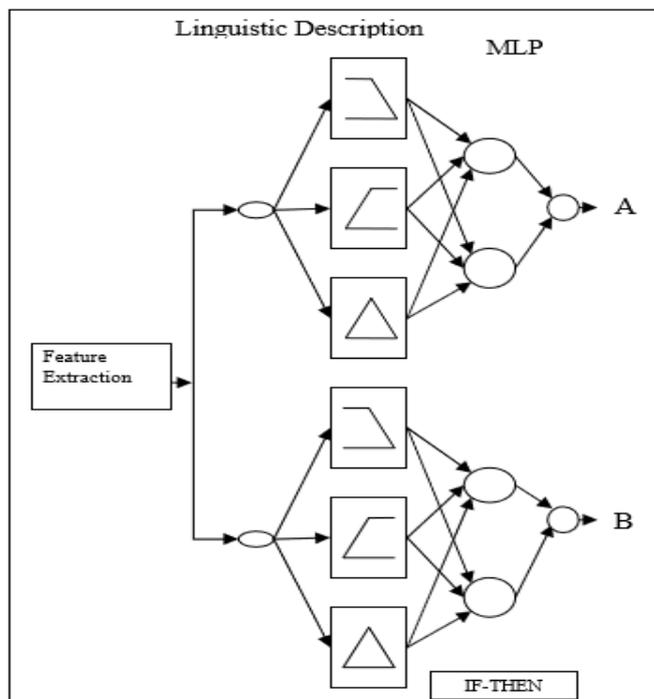
- Q wave interval, amplitude
- R wave interval, amplitude
- S wave interval, amplitude
- T wave interval, amplitude

### 3.4 ANFIS CLASSIFIER

ANFIS is a fuzzy Sugeno model of integration where the final fuzzy inference system is optimized via the ANNs training. ANFIS can be viewed as a class of adaptive networks which are functionally equivalent to fuzzy inference system. It maps inputs through input membership function and associated parameters, and then through output membership function to outputs. ANFIS uses back-propagation or a combination of least square estimation and back-propagation for membership function parameter estimation. The most important point in data classification by ANFIS is designing of fuzzy rules. To solve this problem, several clustering techniques such as fuzzy c-means (FCM), K-means clustering (KMC) and histogram adaptive smoothing (HAS) can be utilized. In this study, subtractive clustering is used in which each cluster represents one independent rule.

#### 3.4.1 NEURO-FUZZY APPROACH

Neuro Fuzzy is a hybrid of artificial neural networks and fuzzy logic. Neuro Fuzzy networks are the realizations of the functionality of fuzzy systems using neural techniques. Neuro Fuzzy Network incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN rules as shown in Figure 3.5



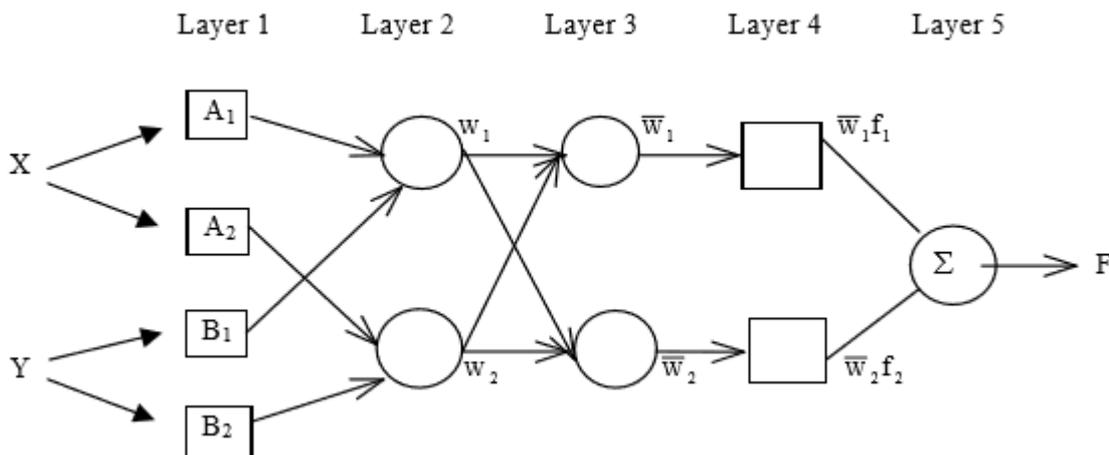
**Figure 3.5 Structure of Feedforward Neuro Fuzzy**

The important part of fuzzy layer, it is responsible to analyze the distribution of data and group the data into the different membership values. This membership value is applied as the input vector to the Multi-Layer Perceptron Neural Network classifier. The membership value also representing the parameter of each heart beat class.

In this project the output of DWT technique as feature vector and ANFIS as a Neuro Fuzzy Classifier for the ECG analysis is used, because the accuracy rates achieved by the combined neural network model presented for classification of the ECG beats is to be higher than the stand alone classifier model.

### 3.4.2 ANFIS MODEL

The ANFIS learning techniques provide a method for the fuzzy modeling procedure to learn information about data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data. ANFIS constructs an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and simulated input output data pairs. It serves as a basis for building the set of fuzzy if then rules with appropriate membership functions to generate the input output pairs.



**Figure 3.6 Basic structure of ANFIS model**

ANFIS gives a powerful tool for data classification.

for example:

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = a_1 x + b_1 y + c_1 \quad (3)$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = a_2 x + b_2 y + c_2 \quad (4)$$

The nodes functions of ANFIS architecture are described below:

Layer 1: Every node I in this layer is a square node with a node function as in equation (5) and equation (6):

$$O_{1,i} = \mu_{A_i}(x), \text{ for } I = 1, 2 \quad (5)$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \text{ for } I = 3, 4 \quad (6)$$

Where  $x$  is the input to node I, and  $A_i$  (or  $B_{i-1}$ ) is a linguistic label (such as “small”, “medium”, “large”) associated with this node. [24] The  $O_{1,i}$  is the membership function of a fuzzy set  $A_i$  and it specifies the degree to which the given input  $x$  satisfies the quantifier  $A_i$ . Usually is chosen  $\mu_{A_i}(x)$  to bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function in equation

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left( \frac{x - c_i}{a_i} \right)^2 \right\}^{b_i}} \quad (7)$$

Where  $a_i, b_i, c_i$  is the parameter set.

Layer 2: Every node in this layer is a fixed node labels as  $\pi$ , whose output is the product of all incoming signals defined by equation below,

$$O_{2,i} = w_i = \mu_{A_i}(x) \mu_{B_i}(y), \text{ for } I=1, 2 \quad (8)$$

Each node output represents the firing strength of a fuzzy rule.

Layer 3: Every node in this layer is a fixed node labelled N. The  $i$ th node calculates the ratio of the rule's firing strength to the sum of all rule's firing strengths as represent by equation below:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \text{ for } I=1, 2 \quad (9)$$

Outputs of this layer are called “normalized firing strengths”.

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

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (10)$$

Where  $\bar{w}_i$  is a normalized firing strength from layer 3 and  $(p_i, q_i, r_i)$  is the parameter set of this node. Parameters in this layer are referred to as “consequent parameters”.

Layer 5: The single node in this layer is a fixed node labelled  $\in$  that computes the overall output as the summation of all incoming signals in equation (11),

$$\text{Overall output} = O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \quad (11)$$

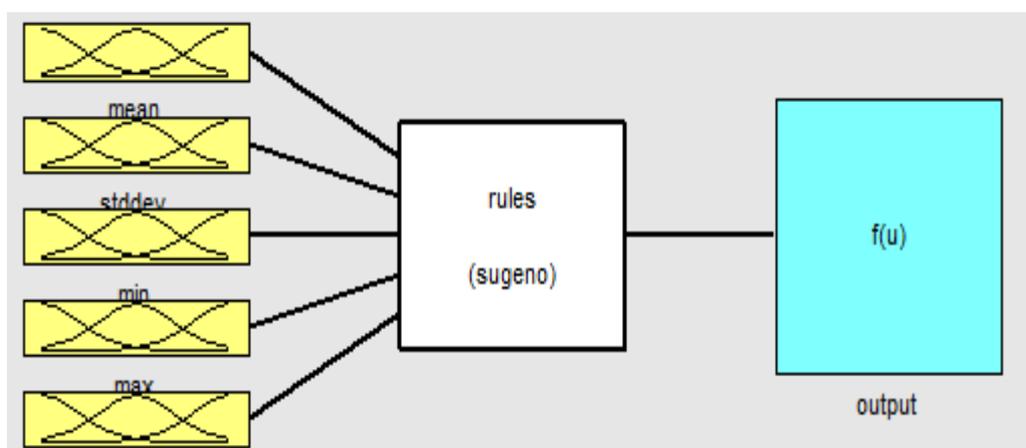
Thus an adaptive network, which is functionally equivalent to the Takagi-Sugeno type fuzzy inference system, has been constructed.

### 3.4.3 GRID PARTITIONING

ANFIS required a predefined network structure and its membership function as well as other parameters can be trained during the learning process.[24]The system is first designed using Sugeno Fuzzy Inference System(FIS).There are two types of FIS namely Grid Partition and Subtractive Clustering.

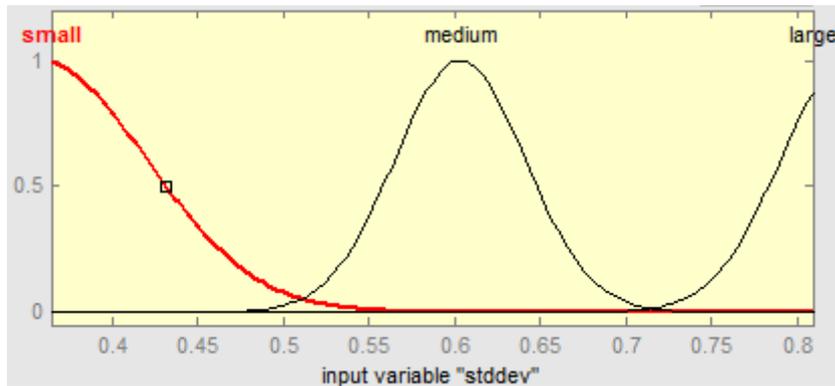
The ANFIS Grid partition requires the number of membership functions for each input.This system uses the gbell shaped membership function to characterize the fuzzy sets input and Sugeno output membership functions as linear types.In the layer 1, there are five nodes have been used for each input dimension  $X_i$  where  $i=1,2 \dots,d$  and  $d$  is the number of input dimensions.

The ANFIS which constructs a FIS,whose membership function parameters are tuned using a back-propagation algorithm in combination with a least squares type of method,which allows fuzzy systems to learn from the data that they are modeling.



**Figure 3.7 Fuzzy inference systems for Heart Disease classification**

The membership functions for input variables are



**Figure 3.8 Initial membership functions**

Based on the above Figure 3.8, the membership function of each input parameter was divided into three regions, which are small, medium and large. The examination of initial and final membership functions indicates that there are considerable changes in the final membership functions of the features.

### 3.4.4 RULE BASE IDENTIFICATION

Based on the membership functions, then the fuzzy IF-THEN rules that have a fuzzy antecedent and constant consequence are constructed. The rule base is created according to the expert knowledge using MATLAB rule base editor. Based on the three membership functions (small, medium, large) that are being used, the number of rules created are given by

$$a^b = c \quad (12)$$

Where;

a is membership function

b is number of input nodes

c is number of rules output

Therefore, for 3 membership functions and 5 input nodes,

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

b=5 input nodes, for energy, maximum, minimum, mean, standard deviation

$$a^b = c$$

$3^5 = 243$  rules are generated.

Rule	Energy	maximum	minimum	mean	Standard deviation	class
1	M	M	S	M	L	1
2	M	M	M	M	L	1
3	L	M	S	M	L	1
4	S	S	M	M	S	2
5	S	M	M	L	S	2
6	S	S	M	M	S	2
7	L	L	S	L	L	3
8	L	L	M	L	L	3
9	L	M	M	L	L	3
10	S	S	L	S	M	4
11	S	S	M	S	M	4
12	M	S	L	S	M	4

**Table. 3.6 Rules created by Expert knowledge**

### 3.4.5 SUBTRACTIVE CLUSTERING

A Data clustering is a process of putting similar data into groups. A clustering algorithm partitions a data set into several groups such that the similarity within a group is larger than among groups. Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction. Clustering techniques are used in conjunction with radial basis function networks or fuzzy modeling primarily to determine initial location for radial basis functions or fuzzy if-then rules. There are different clustering technique such as k-means clustering, fuzzy c-means clustering, mountain clustering and subtractive clustering. If there is no clear idea how many clusters there should be for a given set of data, subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. Consider a collection of  $n$  data points in an  $m$ -dimensional space. Without loss of generality, the data points are assumed to have been normalized within a hypercube. Since each data point is a candidate for cluster centers, a density measure at data point  $x_i$  is defined as:

$$D_j = \sum_{j=1}^n \exp\left(\frac{-\left(\|x_i - x_j\|^2\right)}{\left(\frac{r_a}{2}\right)^2}\right) \quad (13)$$

Where  $r_a$  is a positive constant. Hence a data point will have a high density value if it has many neighboring data points. The radius  $r_a$  defines a neighbourhood; data points outside this radius contribute only slightly to the density measure. After the density measure of each data point has been calculated, the data point with the highest density measure is selected as the first cluster center. Let  $x_{c1}$  be the point selected and  $D_{c1}$  its density measure. Next the density measure for each data point  $x_i$  is revised by the formula 2

$$D_i = D_i - D_{c1} \exp\left(\frac{-\left(\|x_i - x_{c1}\|^2\right)}{\left(\frac{r_b}{2}\right)^2}\right) \quad (14)$$

where  $r_b$  is a positive constant. Therefore, the data points near the first cluster center  $x_{c1}$  will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster center. The constant  $r_b$  defines a neighborhood that has measurable reductions in density measure. The constant  $r_b$  is normally larger than  $r_a$  to prevent closely spaced cluster centers; generally  $r_b$  is equal to 1.5  $r_a$ . After the density measure for each data point is revised, the next cluster center  $x_{c2}$  is selected and all of the density measures for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated. When applying subtractive clustering to a set of input-output data, each of the cluster centers represents a prototype that exhibits certain characteristics of the system to be modeled. These cluster centers would be reasonably used as the centers for the fuzzy rules premise in a zero-order Sugeno fuzzy model, or radial basis functions in a Radial Basis Function Network (RBFN). For instance, assume that the center for the  $i$ -th cluster is  $c_i$  in an  $M$  dimension. The  $c_i$  can be decomposed into two component vectors  $p_i$  and  $q_i$ , where  $p_i$  is the input part and it contains the first  $N$  element of  $c_i$ ;  $q_i$  is the output part and it contains the last  $M - N$  elements of  $c_i$ . Then given an input vector  $x$ , the degree to which fuzzy rule  $i$  is fulfilled is defined by

$$\mu_i = \exp\left(\frac{-\left(\|x - p_i\|^2\right)}{\left(\frac{r_a}{2}\right)^2}\right) \quad (15)$$

This is also the definition of the i-th radial basis function if we adopt the perspective of modeling using RBFNs. [3]Once the premise part (or the radial basis functions) has been determined, the consequent part (or the weights for output unit in an RBFN) can be estimated by the least-squares method. After these procedures are completed, more accuracy can be gained by using gradient descent or other advanced derivative- based optimization schemes for further refinement.

For generating fuzzy inference system, the parameters of subtractive clustering are set as follow: Range of influence=0.5, Squash factor=0.55, Accept ratio=0.5, Reject ratio=0.15. With these parameters, 14 fuzzy rules are obtained. It should be noticed that several parameters such as types of activation functions and several values for NHLN, MEN, Range of influence, Squash factor ,Accept ratio and Reject ratio were examined and were altered based on trying-and-error method and suitable ranges and types were chosen for these parameters.

Subtractive clustering method finds cluster number of the specified input and it assigns membership functions equal to number of clusters.Gbell membership function is used and 14 rules are generated using 5 inputs,1 output.

#### Advantages of the Sugeno Method

- It is computationally efficient.
- It works well with linear techniques (e.g., PID control).
- It works well with optimization and adaptive techniques.
- It has guaranteed continuity of the output surface.
- It is well suited to mathematical analysis.

### 3.5 OUTPUT MODULE

Gives the simulation results and performance metrics of the classifier. Output module diagnoses the Cardiac abnormalities of ECG samples that are considered. The performances of the classifier using various optimizations are expressed in terms of Accuracy, Sensitivity, Positive Predictivity and Specificity.

- **Accuracy-** is the fraction of the total ECG beats correctly classified.

$$= \frac{\text{Number of correct decision cases}}{\text{Total number of cases}} \quad (16)$$

- **Sensitivity**- is the fraction of that specific arrhythmia correctly classified.

$$Se = \frac{TP}{TP+FN} \quad (17)$$

- **Specificity**- is the fraction of correctly classified normal rhythms.

$$Sp = \frac{TN}{TN+FP} \quad (18)$$

- **Positive Predictivity** – is the fraction of correctly classified events in all detected events.

$$+p = \frac{TP}{TP+FP} \quad (19)$$

In these equations TP, TN, FN, FP, and denote true positives, true negatives, false positives and false negatives, respectively. True positives are beats which have been correctly assigned to a certain class whereas false positives are beats which have been incorrectly assigned to that same class. A false negative occurs when a beat should have been assigned to that class but was missed and assigned to another class and true negatives are all the remaining samples that are correctly classified as other classes.

# CHAPTER 4

## MATLAB SOFTWARE

### 4.1 INTRODUCTION

MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. MATLAB can be used for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

### 4.2 KEY FEATURES

- High-level language for technical computing
- Development environment for managing code, files, and data
- Interactive tools for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration
- 2-D and 3-D graphics functions for visualizing data
- Tools for building custom graphical user interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages, such as C, C++, Fortran, Java, COM, and Microsoft® Excel

### 4.3 INTERFACING WITH OTHER LANGUAGES

MATLAB can call functions and subroutines written in the C programming language or Fortran. A wrapper function is created allowing MATLAB data types to be passed and returned. MATLAB libraries (example XML or SQL support) are implemented as wrappers around Java or ActiveX libraries. Calling MATLAB from Java is more complicated, but can

be done with a MATLAB toolbox which is sold separately by Math Works, or using an undocumented mechanism called JMI (Java-to-MATLAB Interface).

#### **4.4 ANFIS TOOLBOX**

##### **4.4.1 MODEL LEARNING AND INFERENCE THROUGH ANFIS**

The neuro-adaptive learning method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. Fuzzy Logic Toolbox software computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. [27] The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS. The `anfis` function can be accessed either from the command line or through the ANFIS Editor GUI. Because the functionality of the command line function `anfis` and the ANFIS Editor GUI is similar, they are used somewhat interchangeably in this discussion, except when specifically describing the GUI.

##### **4.4.2 FIS STRUCTURE AND PARAMETER ADJUSTMENT**

A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs. ANFIS uses either back propagation or a combination of least squares estimation and back-propagation for membership function parameter estimation.

The modeling approach used by ANFIS is similar to many system identification techniques. First, you hypothesize a parameterized model structure (relating inputs to membership functions to rules to outputs to membership functions, and so on). Next, you collect input/output data in a form that will be usable by `anfis` for training. Then use ANFIS

to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion.

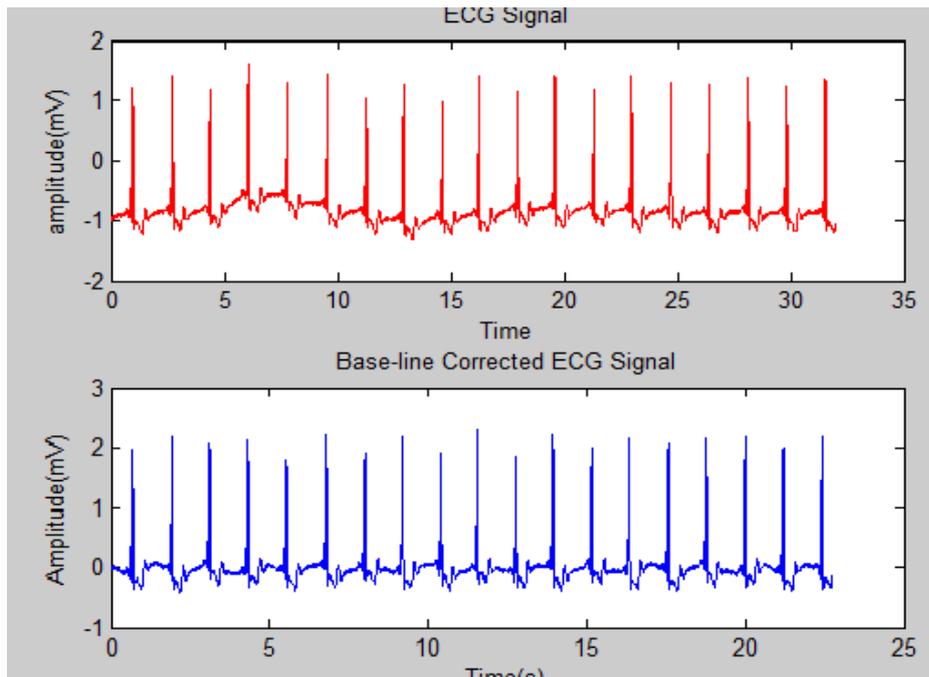
In general, this type of modeling works well if the training data presented to anfis for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. [27]In some cases however, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. In such situations, model validation is helpful.

## CHAPTER 5

### RESULTS AND DISCUSSION

#### 5.1 PRE PROCESSING

First the input ECG signal is pre-processed using discrete wavelet transform and noise is removed from the ECG signal.



**Figure 5.1 Base-line corrected ECG signal**

The ECG signal has some baseline drifts and noise artifacts, during the time of recording. DWT is used to remove the baseline drift and noise artifacts.

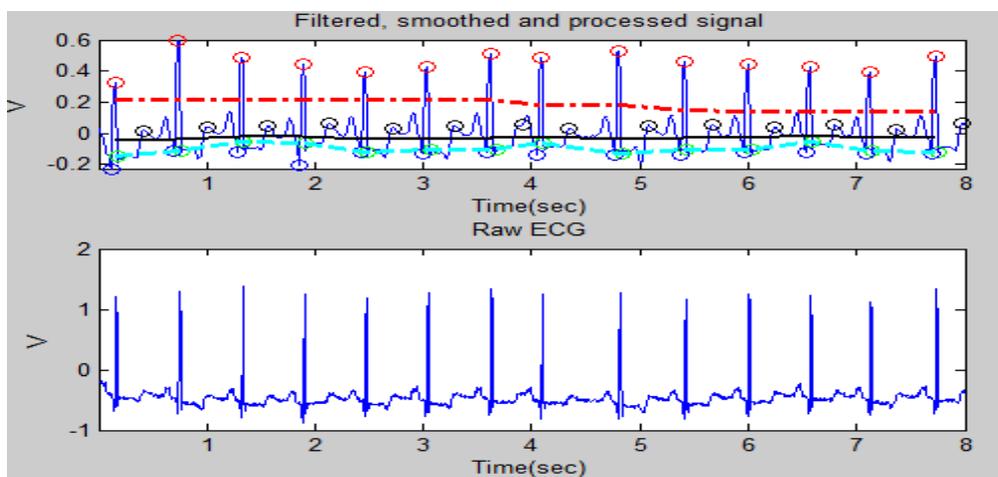
After baseline correction various features like statistical and morphological features are extracted.

#### 5.2 FEATURE EXTRACTION

After baseline correction, statistical features like mean standard deviation, minimum, maximum, standard deviation, Energy are calculated using DWT.

Record no	Mean	Standard deviation	minimum	Maximum	Energy
100	0.0124	0.4282	-1.6537	2.4337	0.1832
102	-0.0594	0.8091	-3.5554	4.6291	0.6570
	-0.0133	0.6419	-3.0113	3.9431	0.4114
106	-0.0023	0.3646	-2.6533	1.2688	0.1327

**Table 5.1** Statistic features for Testing.

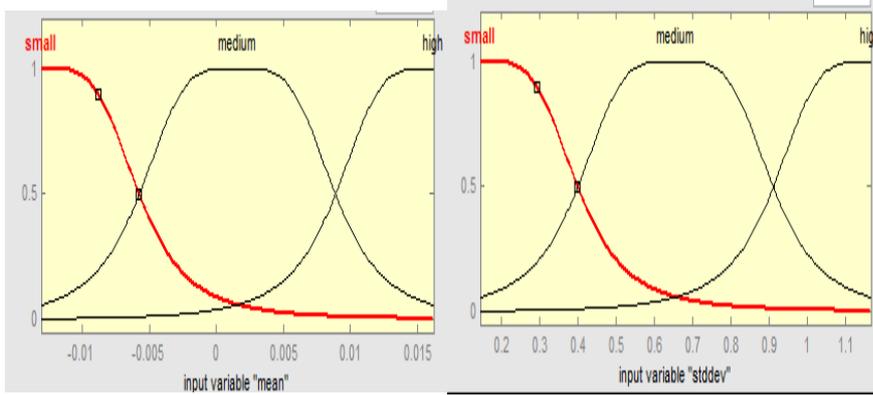


**Figure 5.2** Morphological features extraction

The Figure 5.2 shows that the various features are extracted using DWT ,using four levels of decomposition.

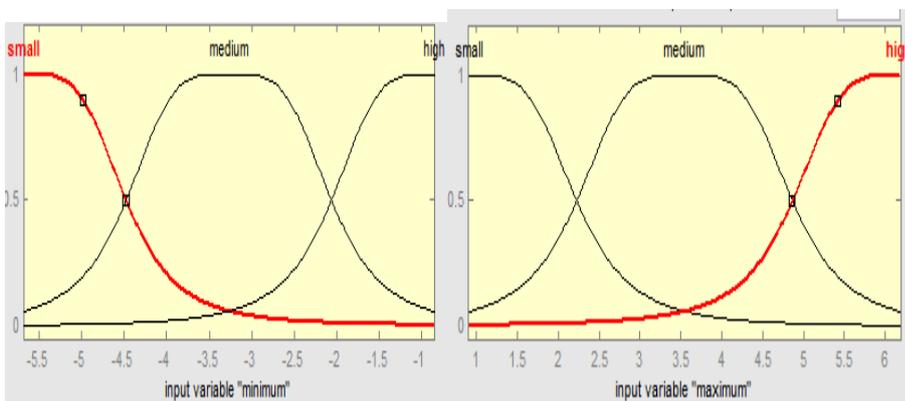
### 5.3 CLASSIFICATION USING ANFIS CLASSIFIER

There are five statistical features are selected and three membership functions are used.The three membership functions are named small,medium ,high. The membership functions before training are shown below in Figure 5.2 (a),(b),(c),(d).



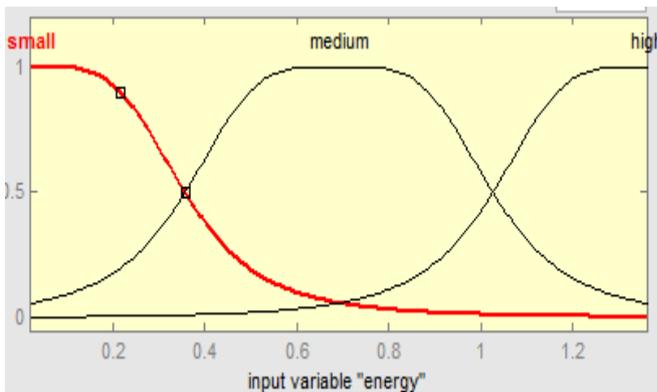
**Figure 5.3 (a) Mean coefficients**

**Figure 5.3 (b) stddev coefficients**



**Figure 5.3 (c) Minimum coefficients**

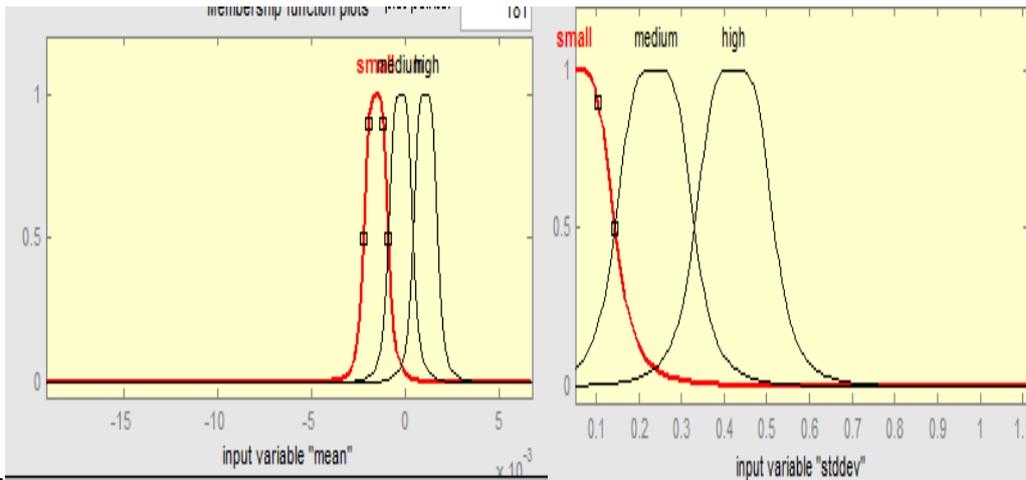
**Figure 5.3 (d) Maximum coefficients**



**Figure 5.3 (e) Energy coefficients**

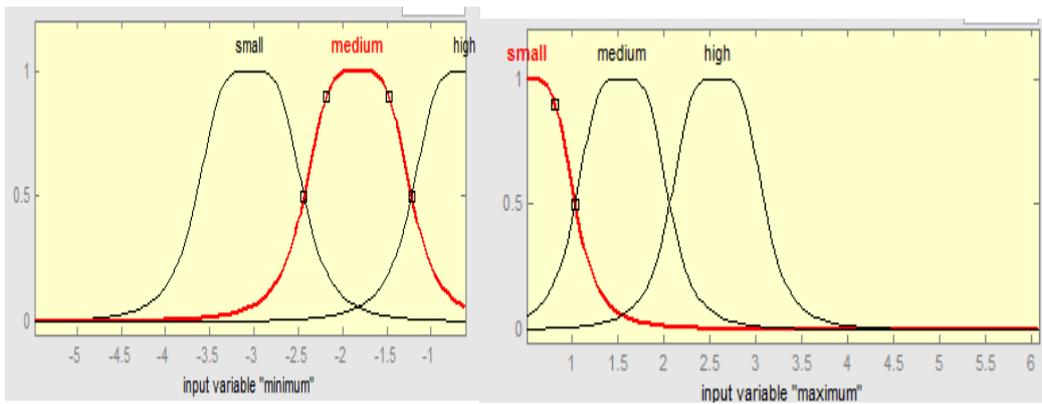
Classification of the statistic features using grid partitioning is shown below

The membership functions for five features after training are shown below



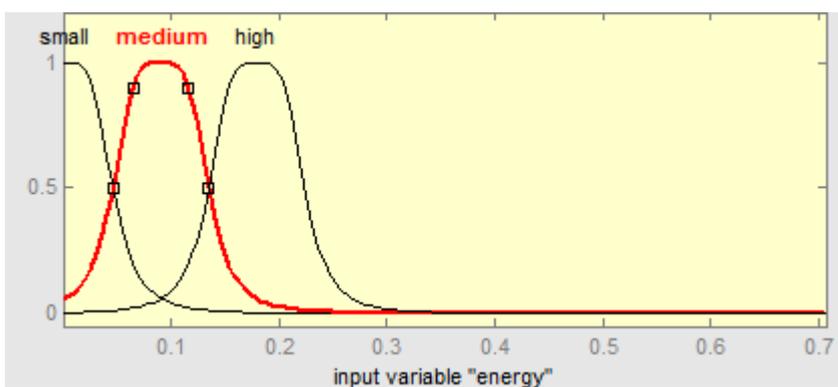
**Figure 5.4 (a) mean coefficients coefficients**

**Figure 5.4(b) standard deviation**

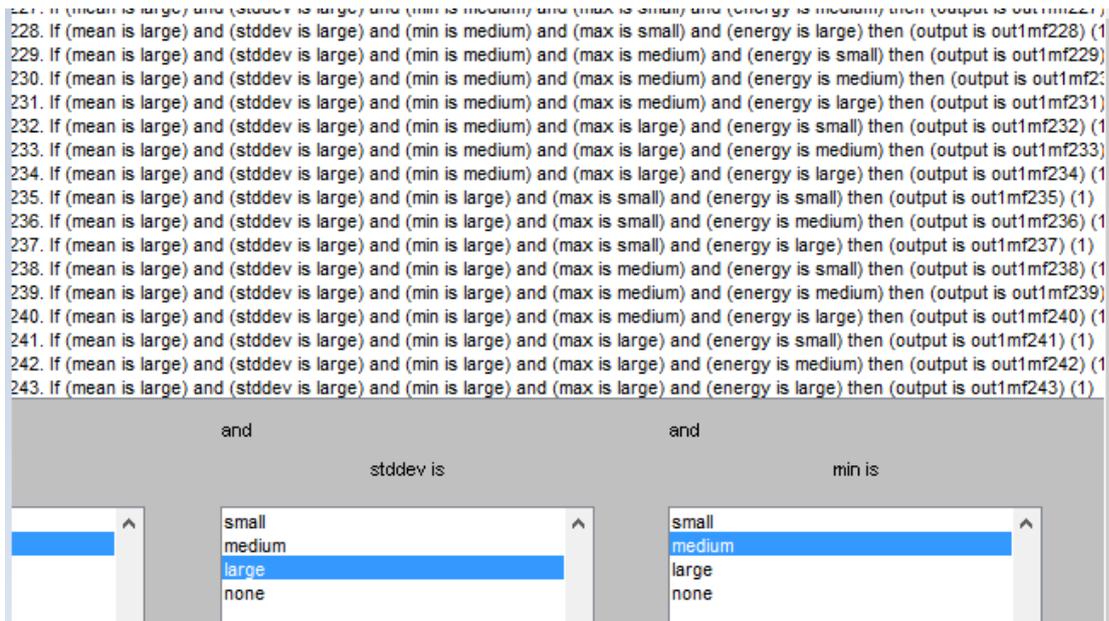


**Figure 5.4(c) minimum coefficients**

**Figure 5.4(d) maximum coefficients**



**Figure 5.4(e) Energy coefficients**



**Figure 5.5** Rules generated using grid partitioning

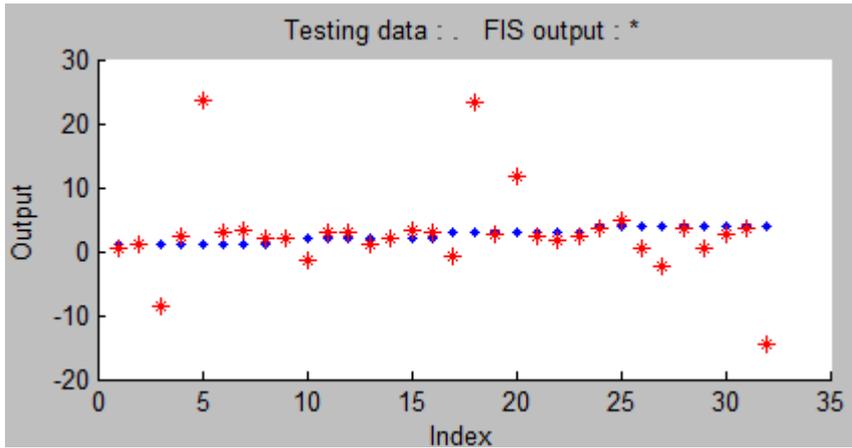
These are the 243 rules generated using ANFIS using Grid partitioning method. There are five inputs and single output. The final output is the weighted average of each rule's input.

### 5.3.1 ANFIS CLASSIFIER FOR STATISTICAL FEATURES



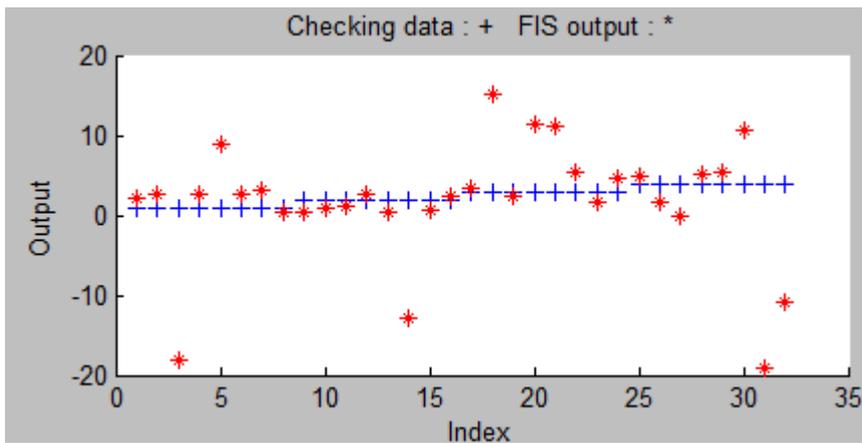
**Figure 5.6** Training data

The Figure 5.5 shows that the ANFIS output in asterisk marks, are correctly classified into four classes.



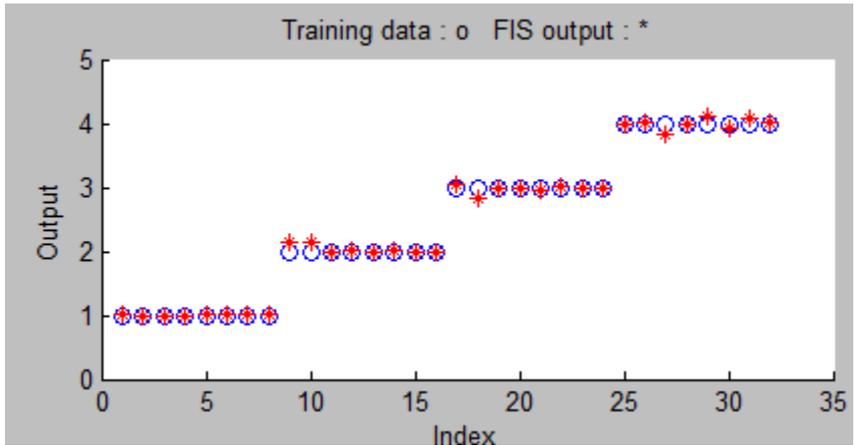
**Figure 5.7 Testing data**

The figure 5.6 shows the testing data ,where the asterisk marks are the output of ANFIS classifier, that starts to overfit with the target classes.



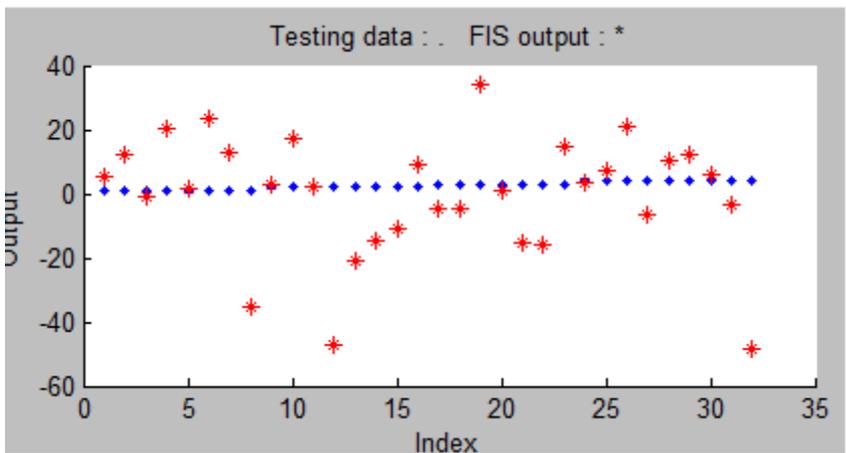
**Figure 5.8 Checking data**

The Figure 5.8 shows the checking data validation model,that overfits with training output.



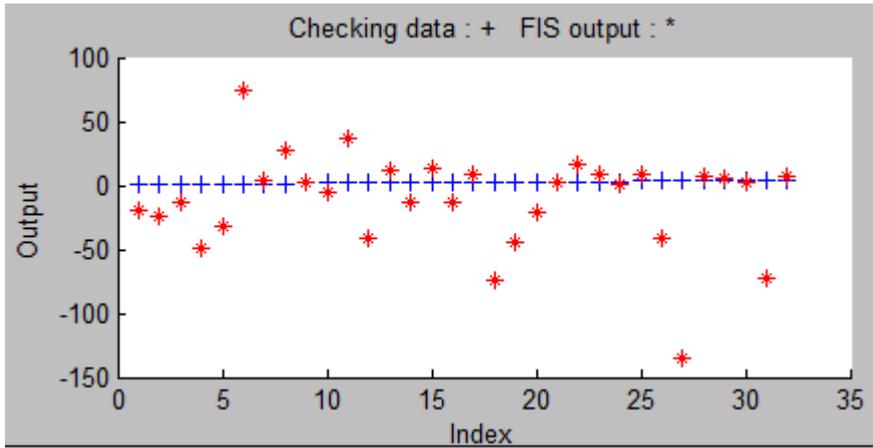
**Figure 5.9 Training data using subtractive clustering**

The subtractive clustering technique ,generates clusters and depending on the cluster calculates the number of membership functions. Figure 5.9 shows the target of classes 1,2,3,4 and the ANFIS output.



**Figure 5.10 Testing data using subtractive clustering**

1,00,000 samples are taken for testing and tested using subtractive clustering.



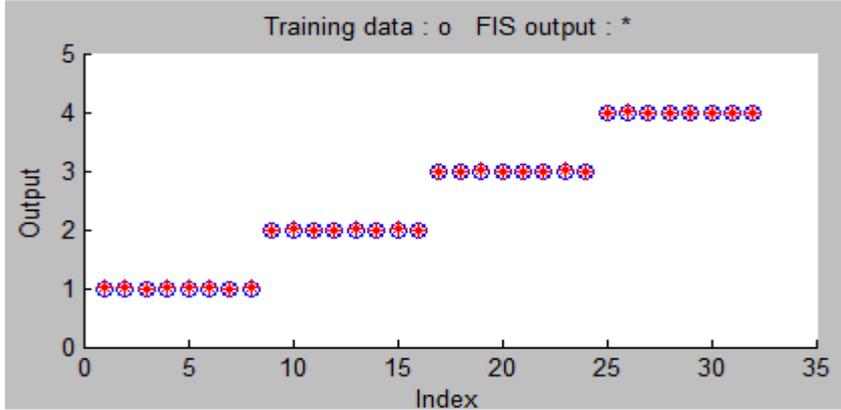
**Figure 5.11 Checking data using subtractive clustering**

The checking data given by asterisk mark,denots the ANFIS output,that gives the result of classification.

	Class 1	Class 2	Class 3	Class 4
Class 1	4	2	0	0
Class 2	0	7	0	0
Class 3	0	0	4	0
Class 4	0	0	1	4

**Table 5.2 Confusion matrix for statistical features**

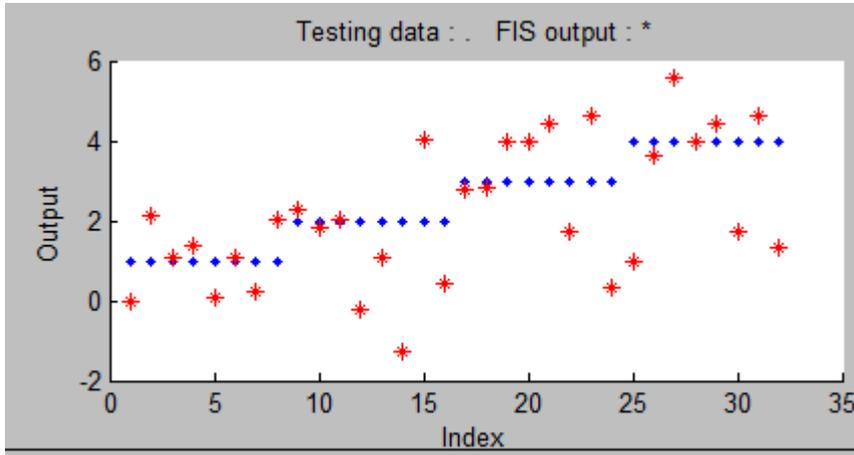
**5.3.2ANFIS CLASSIFIER FOR MORPHOLOGICAL FEATURES**



**Figure 5.12 Training data using grid partitioning**

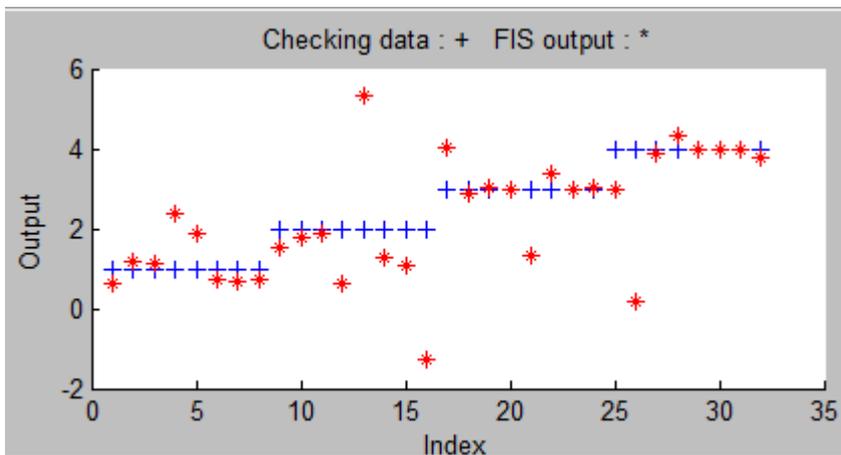
Various morphological features such as R amplitude,Q amplitude ,S amplitude, T amplitude ,R wave interval ,T wave interval are taken and classified using ANFIS

classifier. The Figure 5.12 shows the training data and ANFIS output generated using If-Then rules are shown.



**Figure 5.13 Testing data**

The 1,00,00 samples are taken and statistical features for 1,00,000 samples are classified using ANFIS classifier. The features are tested with ANFIS classifier using ANFIS classifier.

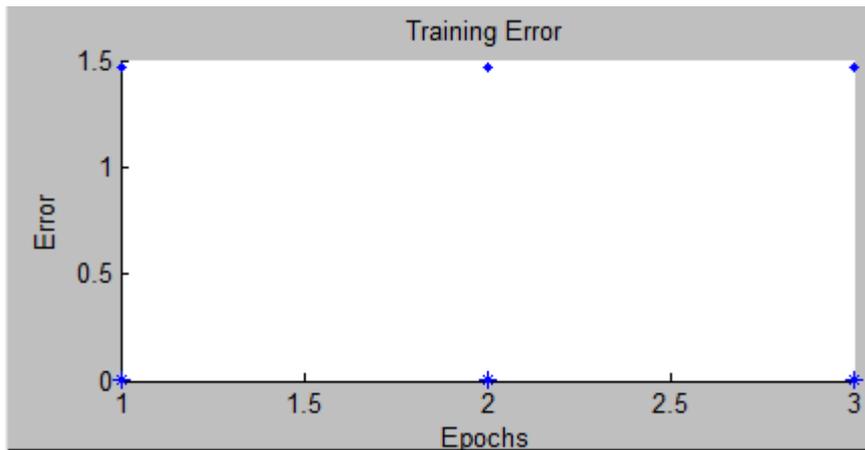


**Figure 5.14 Checking data**

The 1,00,000 samples are checked and ANFIS output for four classes normal, bradycardia, Tachycardia. Bundle branch block is shown in Figure 5.14

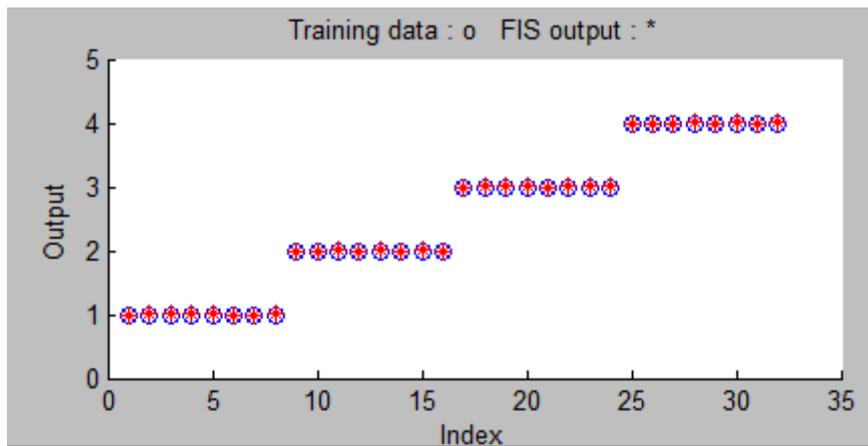
	Class1	Class2	Class 3	Class 4
Class1	6	2	0	0
Class 2	4	3	0	0
Class3	1	0	7	0
Class 4	1	0	3	5

**Table5.3 Confusion matrix for morphological features**



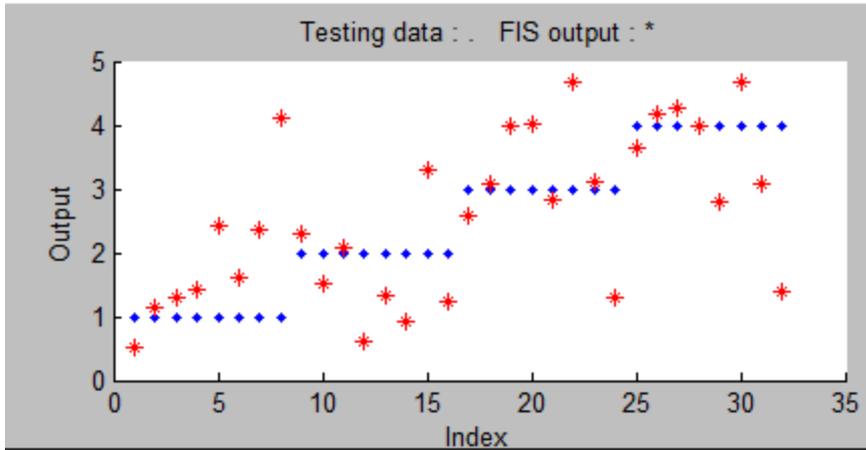
**Figure 5.15 Training error**

The Figure 5.15 shows that average training error is reduced and hence hybrid method is best technique for optimization.



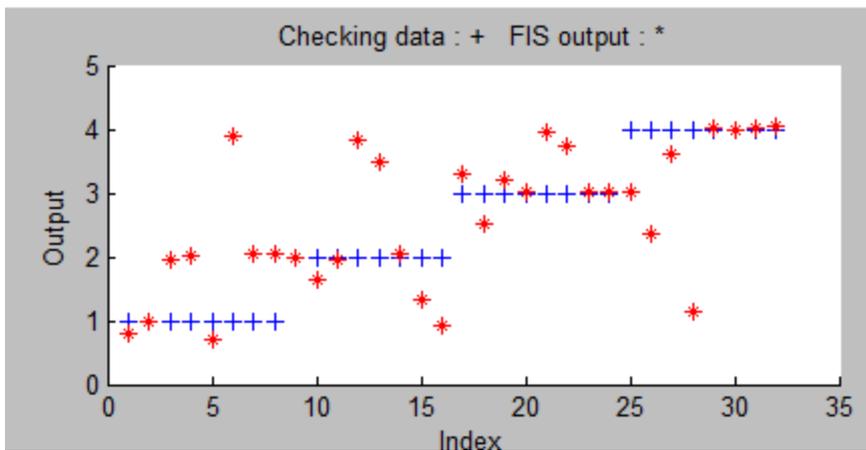
**Figure 5.16 Training data using subtractive clustering**

The training data is classified using subtractive clustering technique and it classified all the four classes.



**Figure 5.17 Testing data using subtractive clustering**

The testing data is checked ,and it shows deviations compare to training data,and starts to overfit.



**Figure 5.18 Checking data using subtractive clustering**

Classes	Sensitivity	Specificity
1	100%	88%
2	77%	86%
3	80%	90%
4	100%	90%

**Table 5.4 Performance measures of statistical features**

Overall Accuracy=82%

Classes	Sensitivity	Specififcity
1	75%	92%
2	57%	96%
3	88%	88%
4	62%	85%

**Table 5.5 Performance measures of morphological features**

Overall Accuracy= 70%

Thus when compared to morphological features ,statistical features give high overall accuracy,using Grid Partitioning technique.Thus ANFIS classifier produces better result for classification of various diseases,and predict unknown class if unknown input is given to the classifier.

<b>Existing method</b>	<b>Proposed method</b>
<b>Automatic arrhythmia detection based on time and time—frequency analysis of heart rate variability-Markos G. Tsipouras, Dimitrios I. Fotiadis, 2004</b>	
sensitivity -87.5 and 89.5%	Sensitivity-100% -normal class and 100%-Tachycardia class
Specifificiy-96%	Specififcity-96%-Bradycardia class 2-(using morphological features)

**Table 5.6 Comparison of Existing and proposed method**

## CHAPTER 6

### CONCLUSION AND FUTURE WORK

In this project, Sugeno type ANFIS classifier is designed and tested for morphological features and statistical features. An accuracy of 80% is obtained using Grid partitioning which is higher than the performance of Subtractive Clustering (72%). The sensitivity of normal class and bundle branch block is classified with 100% sensitivity with ANFIS classifier. Thus the ANFIS classifier successfully classifies the four classes: normal, bradycardia, tachycardia, bundle branch block (class 1, class 2, class 3, class 4) of normal and cardiac arrhythmia patient records. If other than this class of patient record is given to the classifier it predicts that record as class 0.

In the future work, both statistical and morphological features are fused and can be given to the classifier. ANFIS Mamdani model can be used for classifying various kinds of features and the performance measures can also be compared. The characteristics of the wave features for the ECG analysis can be extended to other forms by using a better or other hybrid algorithms to evaluate the selected features which are suitable for many types of heart disease detection. The diagnostic accuracy of ANFIS model, which combined the neural network adaptive capabilities and the fuzzy logic qualitative approach can also be improved by combining several ANFIS classifiers in input data training stage.

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## **LIST OF PUBLICATIONS**

### **Conferences**

- Presented a paper titled "Feature Extraction and Classification of arrhythmia using ANFIS classifier" in 2<sup>nd</sup> IEEE International Conference on Innovations in Information, Embedded and Communication systems (ICIIECS'15) on 19<sup>th</sup> & 20<sup>th</sup> March 2015, organized by Karpagam College of Engineering, Coimbatore.
- Presented a paper titled "Classification of Cardiac Arrhythmia using ANFIS classifier" in IEEE International Conference on Engineering and Technology (ICETECH'15) on 20<sup>th</sup> March, 2015, organized by Rathinam Technical Campus, Coimbatore.

### **Journal**

- Paper titled, "Feature Extraction and Classification of arrhythmia using ANFIS classifier" has been selected for the journal International Journal of Applied Engineering Research (IJAER).