Chapter 1
INTRODUCTION TO ECG

1.0 Overview

In this chapter, brief information about the introduction, principles, working and problems related to ElectroCardioGram (ECG) analysis is presented. This part discusses the ElectroCardioGram (ECG) analysis problems concerning health issue which encourage the present research. Then, the problem definitions from the previous studies, the research objectives, scope of present work and thesis outlines are presented.

1.1 ECG

Electrocardiography (ECG) is an analysis of the electrical activity of the heart over a period of time. It is recorded by a device connected external to the body by using the electrodes attached to the surface of the skin. The waveform produced by this non-invasive process is called as ElectroCardioGram (also ECG).

An ECG is used to measure the rate and regularity of heartbeats, the presence of any abnormality in the heart such as the size and position of the chambers etc. Most of the ECGs are performed for diagnostic and research purposes. There may also be performed on animals, mainly for research applications.

1.2 Principles of ECG

The ECG device perceives the minute electrical changes on the skin that are caused when the heart muscle depolarizes during each heartbeat thereafter amplifies them.

- Each heart muscle cell has a negative charge, during rest position, across its cell membrane called as the membrane potential. Inflow of the positive cations (Na^+ and Ca^{++}) will decrease negative charge to zero called as depolarization. This will activate the contraction mechanism in the cell which produces a wave characterized by the atrium, Sino-Atrial (SA) node, passing through the Atrio-Ventricular (AV) node and then spreading over the ventricles during each heartbeat. This is detected as voltage between the electrodes, as minute rise and fall in the voltage, placed on either sides of the heart which is displayed as a wave. This wave indicates the overall rhythm of the heart and weaknesses in different parts of the heart.

- Usually, more than two electrodes are used for the heart rhythm detection which can be formed into number of pairs such as Left Arm (LA), Right Arm (RA) and Left Leg (LL) electrodes form the three pairs LA+RA, LA+LL, and RA+LL. The output from each pair is called as lead and each lead looks from a different angle into the heart. Different types of ECGs recorded includes number of leads such as 3-lead, 5-lead and 12-lead ECGs.
- Among these all types of ECGs, 12-lead ECG is one of the simple and the common type used. In this process, 12 different types of electrical signals, traditionally printed out as a paper copy, are recorded at approximately the same time. 3- and 5-lead ECGs are the other types of ECGs which may be used but have disadvantages of continuous monitoring, display depends on the equipment used etc.

1.3 Basic Electrophysiology of the Heart

In the heartbeat rhythm generation, the normal cardiac cycle begins with unprompted depolarisation of the sinus node (specialised tissue) placed in the Right Atrium (RA). Then, through the right atrium and across the inter atrial septum, a wave of electrical depolarisation ranges into the left atrium. In the normal heart, atria and ventricles are separated by an electrically inert fibrous ring, so that, from atria to ventricles, only route of transmission of electrical depolarisation is through the atrio-ventricular (AV) node. The AV node provides a short time delay in the electrical signal. Then, the depolarisation wave ranges down the inter-ventricular septum (IVS), via the bundle of right and left branches, into the right and left ventricles.

Hence, under normal cardiac situation, the two ventricles contract simultaneously, which is an important factor in making the cardiac efficiency maximum. Then, myocardium repolarise after complete depolarisation of the heart, before it becomes ready again to depolarise for the next cardiac cycle.

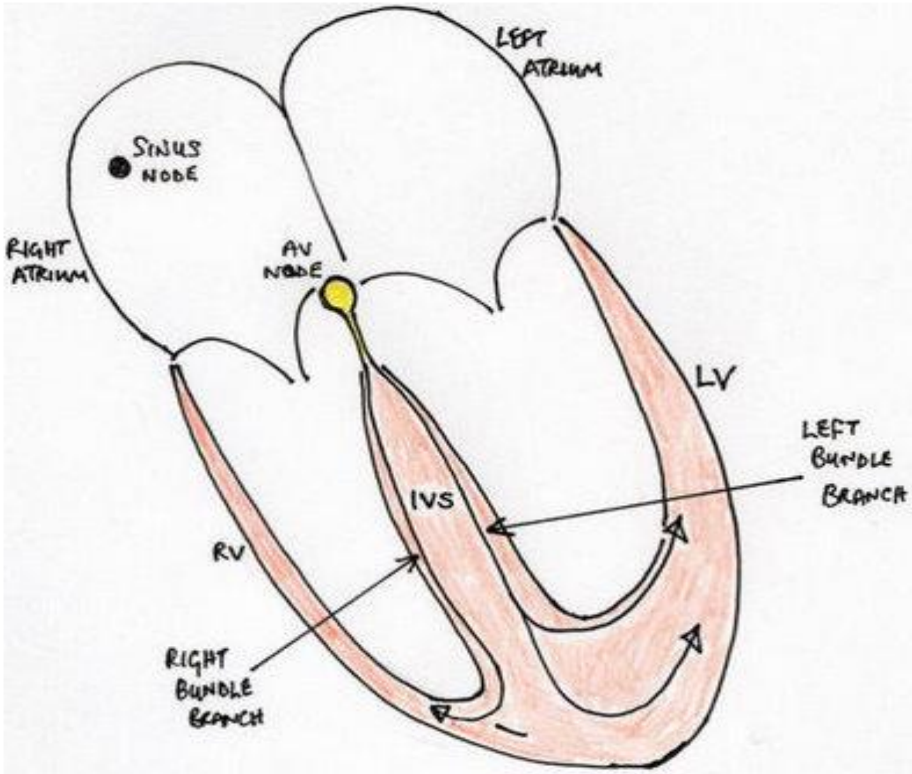

Figure 1.1. Basic electrophysiology of the heart

1.4 Normal ECG

It is already clear that firstly the right atrium is depolarised during normal sinus rhythm which is then followed by the left atrium. Thus, on a normal ECG, the first electrical signal originates from the atria and is known as the P wave (see in Fig.1.2). Even if, generally, there is only one P wave in most leads of an ECG, in fact, the P wave is the sum of the electrical signals superimposed from the two atria.

Then there is a short physiological delay due to the Atrio-Ventricular (AV) node which slows down the electrical depolarisation as it further proceeds towards the ventricles. PR interval is the result of this delay. It is a short span of time during which no electrical activity is observed on the ECG. It is represented by a straight horizontal or isoelectric line.

QRS complex i.e. Largest part of the ECG signal is the consequence of the de-polarisation of the ventricles in the heart and this is because of the greater muscle mass in the ventricles. It is further described as follows:

- Q wave → first initial downward 'negative' deflection

- R wave → upward deflection (crosses the isoelectric line and becomes 'positive')
- S wave → next deflection downwards. It crosses the isoelectric line to become briefly negative before returning to the isoelectric baseline.

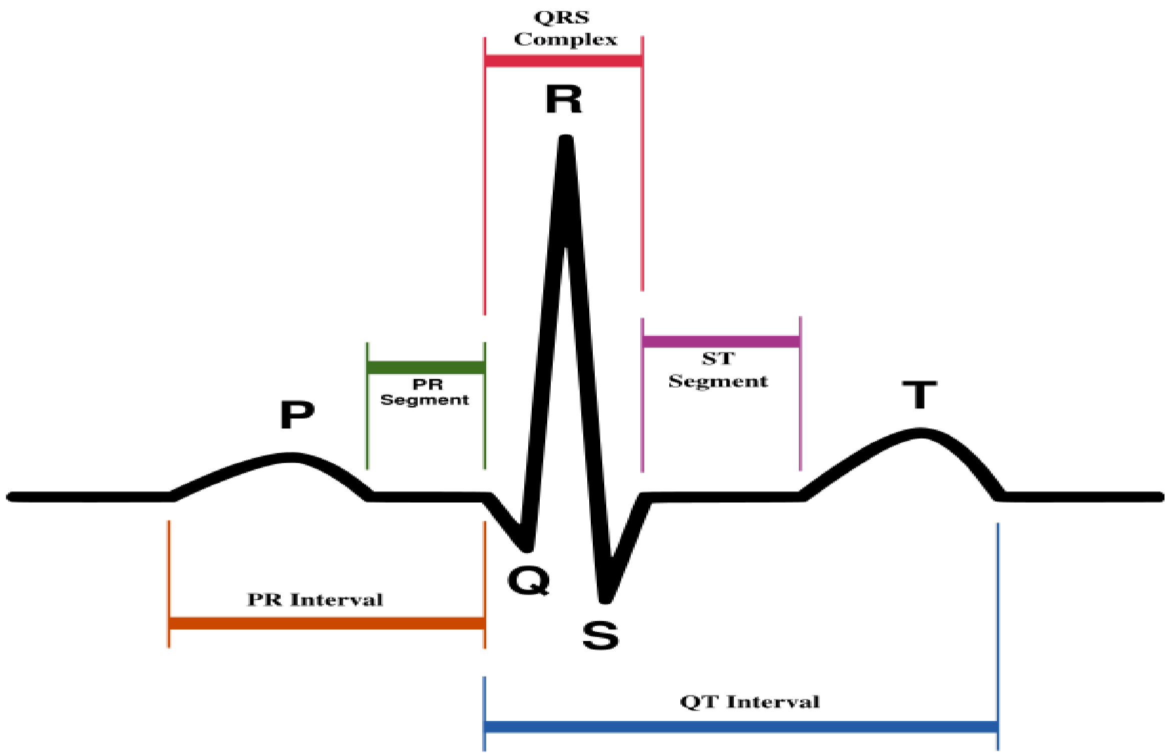

Figure 1.2. Normal ECG pattern

ST segment and T wave in the ECG waveform represents the repolarisation. It is also an electrical signal reflected from the myocardium in the ventricles. Among these, ST segment is isoelectric and the T wave, in most leads, is an upward deflection of the variable amplitude and duration.

1.4.1 Normal Intervals

The P-QRS-T wave recorded on standard paper shows the various phases of electrical depolarisation which allows the time measured, usually, in milliseconds. Normal ranges for such 'intervals' are as follows:

- PR interval → It is measured in the ECG waveform ranging from 120-200 ms starts from the beginning of the P wave and lasts to the first deflection of the QRS complex.
- QRS complex duration → It ranges up to 120 ms and is measured in the ECG waveform from the first QRS complex deflection to the end of QRS complex on the isoelectric line.

- QT interval → It ranges up to 440ms and varies with heart rate. It is slightly longer in females. It is measured from first deflection of QRS complex to end of T wave on the isoelectric line.

1.4.2 Heart rate estimation from the ECG

Standard graph paper permits an approximate estimation of the heart rate (HR) from a graph recording. Every second of the time is portrayed by 250 metric linear unit (5 giant squares) on the horizontal axis. Thus, the amount of enormous squares between every QRS-complex gives the results as:

- 5 - the HR is 60 beats per minute,
- 3 - the HR is 100 per minute and
- 2 - the HR is 150 per minute.

1.5 Abnormal Heartbeats

Any interruption within the heart's electrical system will cause abnormal heartbeats. for instance, AN irregular heartbeat might begin with AN abnormal impulse in an exceedingly a part of the centre aside from the traditional pacemaker (the sinus node). Or the sinus node might develop AN abnormal rate or rhythm. Common causes embrace stress like caffeine, alcohol, tobacco, diet pills and cold and cough medicines. If the heart tissue is broken as a results of non-inheritable cardiovascular disease, like infarction (heart attack) or non-heritable cardiovascular disease the subject (or patient) will be in danger of developing abnormality within the heartbeats or the graphical record signal. Sometimes it should be a disease.

1.5.1 Apnea

Obstructive apnea (intermittent halt of breathing) may be a common downside with major health implications, starting from excessive daytime somnolence to serious internal organ problems. Preventative apnea is related to accrued risks of high pressure level, infarction, and stroke, and with accrued mortality rates. Common place strategies for identification work and quantifying apnea is supported respiration watching, which regularly disturbs or interferes with sleep and is mostly big-ticket. Variety of studies throughout the past fifteen years have hinted at the likelihood of detective work apnea mistreatment options of the ECG. Such approaches are minimally intrusive, cheap, and should be notably well-suited for screening.

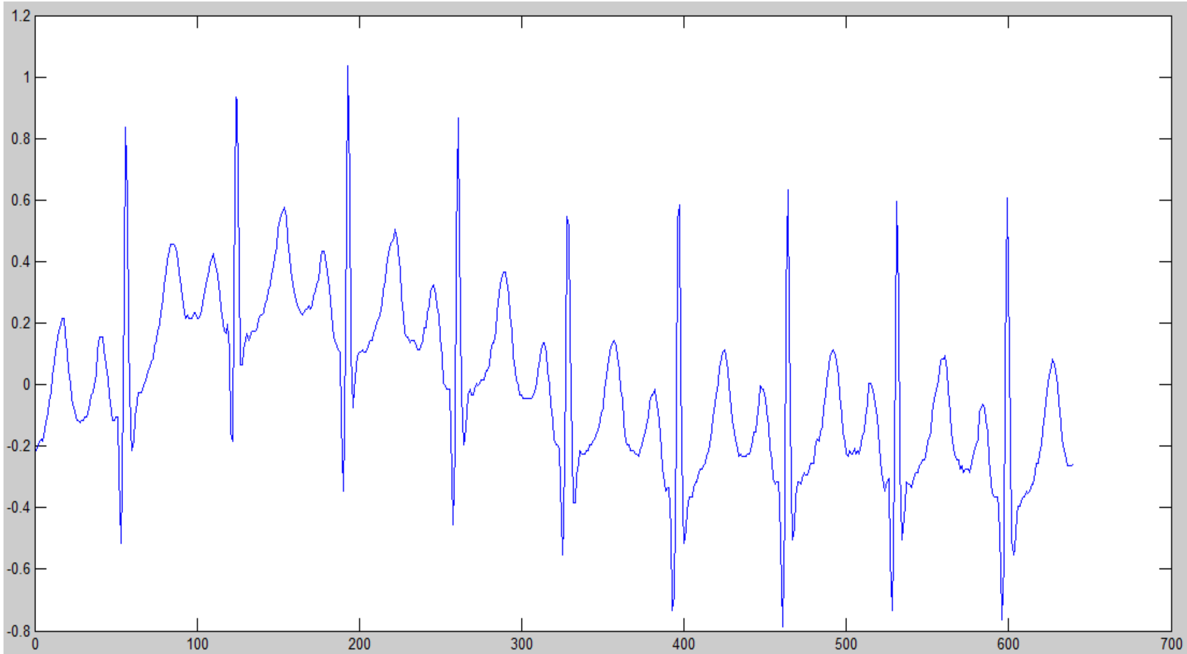

Fig. 1.3. Waveform of Apnea

1.5.2 Ischemia

An ischemia is associate irregular or abnormal heartbeat. ischemia is caused by arteria unwellness, High pressure, Changes within the cardiac muscle (cardiomyopathy), Valve disorders, solution imbalances within the blood, like metallic element or potassium, Injury from a coronary failure, the healing method when surgery, and different medical conditions. The pulse indicates the heart rate, or the amount of times heart beats in a single minute.

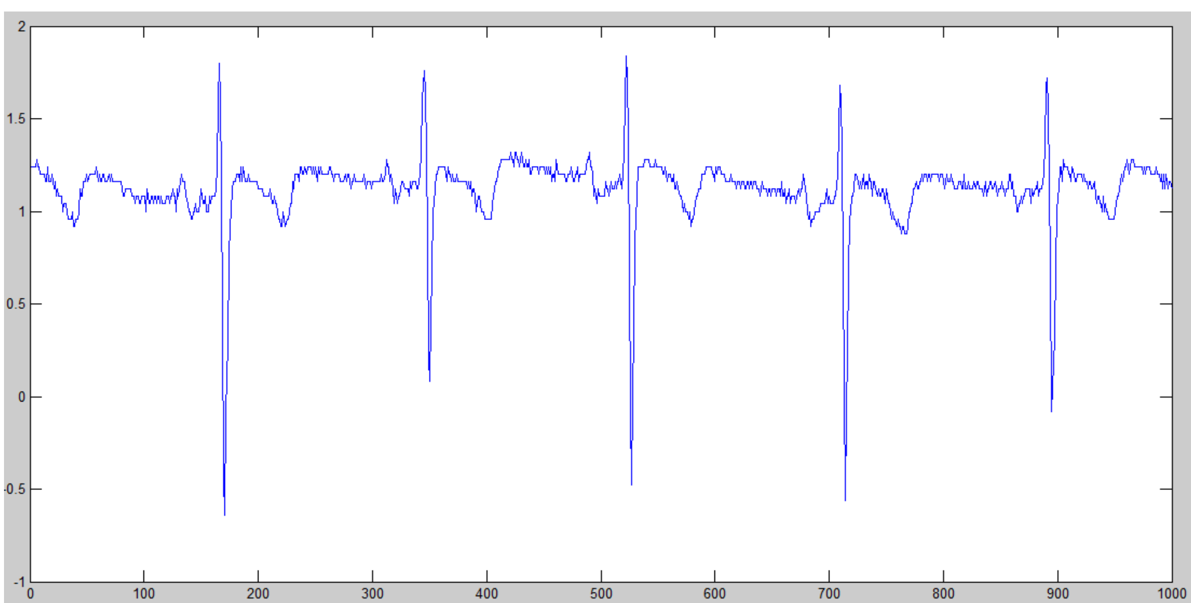

Fig. 1.4. Waveform of Ischemia

Pulse rates vary from person to person. The pulse is slower once the subject is at rest and will increase once exercises, since a lot of oxygen- made blood is required by the body throughout exercise.

1.5.3 Tachycardia

Tachycardias are disorders of cardiac rhythm which can gift with a cardiac arrhythmia. Causes of Tachycardia: Intra-cardiac causes (Ishcaemic cardiopathy, controller cardiopathy, heart disease, cardiomyopathy and nonheritable heart disease) and Extra-cardiac causes (medication, Alcohol, Stimulants e.g. caffeine, Stress, glandular disorder, Infection/Sepsis and Metabolic e.g. hyperkalaemia).

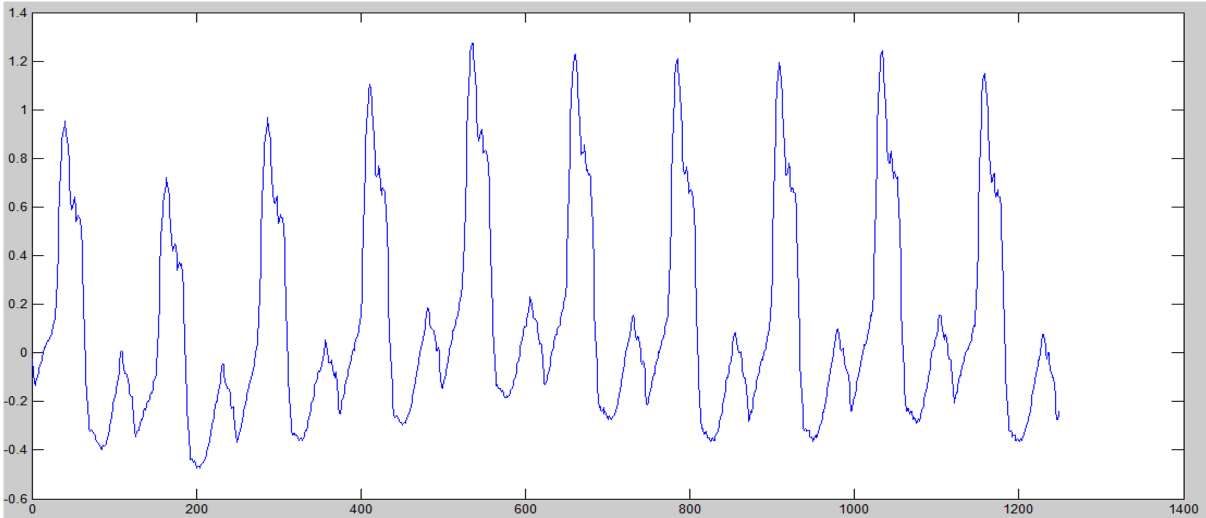

Fig. 1.5. Waveform of Tachycardia

1.6 Advantages and Disadvantages of ECG

1.6.1 Advantages: From the ECG tracing, the subsequent info are often determined:

- the rate
- the cardiac rhythm
- whether there are abnormalities in which the electrical impulse spreads across the heart
- whether there has been a previous coronary failure
- whether there could also be arteria sickness
- whether the heart muscle has become abnormally thickened.

All of these options are doubtless vital. If the graphical record indicates an attack or attainable arteria malady, more testing is commonly done to fully outline the character of the matter and judge on the optimum medical care. These tests typically embody a check and/or internal organ catheterization. If the heart muscle is thickened, an echocardiogram is commonly ordered to seem for attainable control cardiopathy or different structural abnormalities. Changes within the electrical pattern on the graph might offer clues to the reason behind syncopee (fainting), or might indicate underlying internal organ illness.

1.6.2 Disadvantages: The limitations of the ECG are as follows:

- The ECG reveals the heart rate and rhythm solely throughout the time that the ECG is taken. If intermittent heart rhythm abnormalities are present, the ECG is probably going to miss them. ambulant observance is required to record transient Ischemias.
- The ECG will typically be traditional or nearly traditional in patients with unknown arterial blood vessel malady or alternative types of heart condition (false negative results.)

1.7 Research Significance

The ECG analysis system is one of the biosignal processing areas that involve the application of computer science and engineering to detect and visualize the biological processes. It is necessary tools and information to the study of diseases to use advanced technology to the complicated issues of medical aid that essential to boost the patient living quality and appropriate treatment.

This research is important because it can be utilized by the other health care professionals together with physicians, nurses, therapists and technicians to compile information from several technical sources to develop new procedures, or to unravel clinical issues. The EKG analysis system will bring the likelihood to record the heart condition at early stage, that the matter is being onerous interpretation for non-trained individuals. Thus the importance in developing the system that produces this interpretation easier for non-trained individuals and therefore the system might sight the un-wellness with high levels of accuracy as a result of many folks who died is the explanation for heart condition showed no outward symptoms. The results of ECG analysis using the proposed algorithm are able to be used in the patient monitoring system that can be used in a hospital, transport, or emergency response environment.

1.8 Research Objectives

This analysis aims to design associate ElectroCardioGram (ECG) analysis system that may measure the speed and regularity of heartbeats. This method would like a decent quality and accurate of research output to make sure the correct results for the heart problems. Basically the goals of this analysis as follows.

- To verify the viability of ElectroCardioGram (ECG) signal and characterization of ECG wave in classifying the heart illness downside.
- To implement an analysis system for ECG signals mistreatment Principal component Analysis (PCA) and various classifiers.
- To assess the performance of ECG analysis exploiting these strategies that may yield a lot of correct diagnoses in classifying the heart illness.
- To analyze the ECG signal waveform in classifying traditional, Apnea, tachycardia arrhythmia and ischemia of ECG signals.

1.9 Thesis Outline

This thesis is organized in such a way that it provides a continuous and smooth flow of information to the reader, regarding the development and analysis of ECG analysis system. There are total of five major chapters which are subdivided into suitable sections. The major five chapters in this thesis are Introduction, Literature Review, Research Methodology and System Design, Result and Discussion and finally Conclusion and Recommendation of the project. The content of each chapters are outlined as follows.

Chapter 1 is an introduction of the project. This chapter gives brief information about the background, problems of the analysis system and the proposed solution for the ECG analysis system. The overall overview of the project scopes and objectives of the project are also presented in this chapter.

Chapter 2 focuses on the literature review and the methodologies of the previous studies of ECG analysis using the various applications and algorithms of features extraction and classifier are reviewed. This chapter deals with the past and current trends of the ECG analysis study.

Chapter 3 will discuss the research methodology and system design of the project. This chapter explains how the project is organized and the flow of all the project operation part. This chapter discusses about the ECG analysis design and the implementation of PCA with the classifiers named as SVM, ANN, Fuzzy and Neuro-Fuzzy. It also discusses MATLAB software of the system.

Chapter 4 discusses the features extraction and classification result of ECG analysis using PCA and various classifiers used. This part includes the MATLAB software development for the both methods. All discussions that concentrate on the result and performance of the ECG analysis using PCA and various classifiers used are presented. It gives a brief review the correlation of all methods.

Chapter 5 discusses the conclusion and more development of the project. This chapter conjointly presents and describes the issues, limitations and therefore the recommendation for this project and overall graph analysis for the longer term development or modification.

Chapter 2
LITERATURE REVIEW

2.0 Overview

The improvement of ElectroCardioGram (ECG) analysis which is part of bio-signal processing to obtain the heart disease classification has been studied by many researchers from the past decades up to now. Their studies have been carried out through experimental and numerical works. In ECG analysis, the main idea is to make the analysis methods enhancement in the degree of accuracy as classifies the disease. By filling the suitable analysis methods, the heart disease classification can be calculated accurately at a fast rate through the analysis process. Therefore, the past studies of ECG analysis algorithms enhancement are an important topic that should be reviewed. This chapter is aimed at providing some of related information regarding the research carried out pertaining to the improvement of heart disease classification with the important roles played by ECG analysis, from different researchers across the globe.

This literature begins by reviewing some of the previous studies of wireless technology in medical application. It follows by reviewing the studies of heart disease analysis that divided into features extraction and classification techniques. This literature also highlights the limitation of existing ECG analysis system pertaining to current work.

2.1 Heart Disease

In the early 1980s, consistent with the Centres for sickness management and prevention, U.S. (2007), cardiovascular disease is that the leading reason behind death for both women and men nearly within the world and it's conjointly a serious explanation for disability. Within the worldwide, coronary cardiovascular disease kills over seven million folks every year. cardiovascular disease could be a broad term that has many additional specific heart conditions that are Coronary cardiovascular disease, heart failure, Ischemia, myocardiopathy, inherent cardiovascular disease, Peripheral blood vessel sickness (PAD).The most common heart disease is coronary cardiovascular disease, which might cause attack and different serious conditions and therefore the analysis from

PubMed Central Journals (2007) shows that the ischemia is that the most typical explanation for death within the industrial countries. Therefore the earliest identification and treatment exploiting diagnostic procedure (ECG) has been developed to watch the illness signal. Papaloukas et al. (2003) has indicated that the event of appropriate automatic analysis techniques will build this technique terribly effective in supporting the physician's diagnosis and in guiding clinical management.

2.2 ECG Features Extraction Algorithms : A Review of Previous Studies

The ElectroCardioGram (ECG) analysis technique needed the feature extraction and classifier stage. within the previous ElectroCardioGram (ECG) analysis, the feature extraction methods include Discrete Wavelet Transform has been discussed by Thakor et al. (1993), Li et al. (1995) and Clarek (1995), Optimal Mother Wavelet by Castro et al. (2000), Karhunen-Loeve Transform method by Jager (2002), Hermitian Basis functions by Ahmadian et al. (2007) and other features extraction methods by researchers Lin and Chang (1989) and Cuesta-Frau et al. (2002) and other features extraction methods.

Douglas et al. (1990) described an approach to Cardiac Ischemia Analysis Using Hidden Markov Models. This technique classified by detecting and analyzing QRS complex and determining the R-R intervals to determine the ventricular Ischemias. The Hidden Markov approach associates the structural and applied math data of the ElectroCardioGram (ECG) signal in an exceedingly single constant model. The Hidden markov modeling addresses the matter of observing low amplitude P waves in typical ambulant ElectroCardioGram (ECG) recordings. Zigel et al. (2000) conferred the strategy of Synthesis coding in their paper. The synthesis ElectroCardioGram (ECG) compressor algorithmic program relies on analysis by synthesis cryptography, and consists of a beat codebook, long and short-run predictors, and an adaptive residual quantizer. Predetermined distortion level is used in feature extraction of ECG signal. Their algorithmic rule uses an outlined distortion measurement so as to expeditiously encrypt each heartbeat, with minimum bit rate, while maintaining a predetermined distortion level. Their proposed compression algorithms were found to have the best performances at any bit rate as stated in their paper.

Researcher Li et al. (1995) use the Wavelet transforms method including Thakor et al. (1993), Frau et al. (2002), Pretorius and Nel (2002) and Mahmoodabadi et al. (2005) because the results indicated that the DWT-based techniques of feature extraction produces a greater performance. Li et al. (1995) has done the ECG analysis using wavelet transform. This method can distinguish the between the QRS wave and P, T wave. This technique also can distinguish noise, baseline drift and artifacts. Therefore it can illustrate the signal analysis very well and suitable to analyse time-varying waveforms. The DWT is also capable of demonstrating the signals in dissimilar resolutions by dilating and compressing its basis functions as explain by Clarek (1995). Park et al. (2008) applied two morphological feature extraction strategies that are higher-order statistics and Hermite basis functions. Their analysis results showed that stratified classification methodology provides higher performance than the standard multiclass classification methodology. They used the support vector machines to match the feature extraction strategies and classification strategies to judge the generalization performance. However the used of higher order models require a lot of computation value and caused over fitting problem in generalization performance. In term of accuracy, they found that their stratified classification methodology showed much better classification performance than the standard multiclass classification methodology with despite the loss in accuracy and sensitivities bound categories. It united that their classification methodology will distinguish the multiclass heartbeats with the unbalanced information distribution.

Researcher Jager (2002) developed a new approach to feature extraction which is Karhunen Lo`eve transform (KLT) It is a powerful approach to the feature-extraction and form illustration method. It's the answer if the likelihood densities of population for a problem are unknown. The matter concerning this methodology is too sensitive to wheezy pattern of ElectroCardioGram (ECG) signal. According to Ranjith et al. (2003) which used wavelet transforms to detect myocardial ischemia, the wavelet transform is obtained using the quadratic spline wavelet. These correspond to the detection of T wave and P wave. Their strategies shown this technique has a relatively higher sensitivity and nominal positive predictive worth. It's can also be simply extended to notice different abnormalities of the ElectroCardioGram (ECG) signal. But this method also has the limitation that the computations required are higher than those required by other methods. This is mainly because of the calculation of Wavelet Transform.

According to Kadbi et al. (2004) in their paper highlighted those three features for features extraction stage which are time-frequency features, time domain features and statistical feature. These three features are utilized in their project. As a result of these features, it will overcome the restrictions of alternative strategies in classifying multiple sorts of ischemia with high accuracy right away. These strategies are combined with PCA technique to scale back the redundancy caused by the frequency constant within the feature dimension to form certainly the mean of the classification accuracy that can be exaggerated.

Tinati et al. (2006) within the studies used wavelet-transform based search algorithmic program to use the energy of the signal in several scales to isolate baseline wander from the ElectroCardioGram (ECG) signal. They initial take away the artifacts that includes the noise that evoked in ElectroCardioGram (ECG) signals. It is the result from movements of electrodes. The baseline wanders that is thought of as an artefact will have an effect on inaccurate information that is once measured using the ElectroCardioGram (ECG) parameters. In their study of exploiting the bestowed algorithm they can eliminate the baseline drifts from the ElectroCardioGram (ECG) signals while not introducing any deformation to the signal and additionally from losing any clinical info of the signal. Herrero et al. (2006) used the freelance element analysis and matching pursuits for the features extraction for extracting extra spatial features from multichannel medical instrument recordings. It checks for the classification performance of five largest categories of heartbeats within the MITBIH ischemia information that are traditional Sinus Beats, Right and Left Bundle Branch Block, Premature chamber Contraction(PCC) and Paced Beats (PB). The performance of the system is remarkably smart, with specificities and sensitivities for the various categories. They faced the problem as a result of the sophisticated separation between cavum PBs and PCCs due to the inverted T wave. Ahmadian et al. (2007) proposed a new piecewise modeling for approximation of ECG signal using Hermitian Basis. This method uses only the 5th order Hermitian basis functions. This methodology yields to coefficient the approximation error of every segment supporting its importance throughout the ElectroCardioGram (ECG) wave. This methodology shows the error obtained during this methodology is nearly halved as compared with similar non-segmented methodologies. The disadvantage of this methodology may be a tiny error that could mislead the identification.

2.3 ECG Classification Algorithms : A Review of Previous Studies

The pattern recognition of the sort of ElectroCardioGram (ECG) wave, there are completely different solutions bestowed within the literature are projected throughout the last decade and are under analysis. In ECG training and classification analysis stages, maximising the detection level of accuracy is tried by many researchers in many various ways in which like digital signal analysis (Papaloukas et al., 2003) , fuzzy logic ways (Bortolan et al., 1989; Zong and Jiang, 1998; Lei et al., 2002) , Artificial Neural Network (Yang et al., 1997; Silipo and Marchesi, 1998; Pretorius and Nel, 2002; Papaloukas et al., 2002; gao et al., 2004), Hidden Markov Model (Hughes et al., 2003; Graja and Boucher, 2005), Genetic algorithmic program (Goletsis et al., 2004), Support Vector Machines (Osowski et al., 2004), Self- Organizing Map (Lagerholm et al., 2000), Bayesian and different methodology with every approach exhibiting its own benefits and drawbacks. However the foremost recent systems exploit artificial neural networks (Papaloukas et al., 2003) to perform diagnoses since they have great consistency in forming correct results. The performance of the developed detection systems is incredibly promising however they require much more analysis. The automated detection of ElectroCardioGram (ECG) waves is vital to cardiac illness identification. A good performance of an automatic ElectroCardioGram (ECG) analyzing system depends heavily upon the accurate and reliable detection of the illness.

2.3.1 Artificial Neural Network

In [5] they mentioned regarding artificial neural network model exploiting morphological classification of heartbeats. The classification of the QRS-complex was the main step in their work to observe ischemia. They'd really designed a neural network model base on ART. That they had explained the structure and general characteristics, completely different learning capacities that it possesses. They referred to as this new neural network outlet as Multichannel-ART. for every channel, the samples of ElectroCardioGram (ECG) signal they're given as input within the outlet in sure time period and that is therefore used for the detection of position of every QRS-complex then with the assistance of algorithmic rule, it dynamically reply to the characteristics to the input ElectroCardioGram (ECG) signal. During this paper they conjointly realize the specificity and sensitivity and therefore we tend to classify the accuracy of overall system by finding the typical detection rate by the subsequent formula-

Sensitivity specificity

$$ADR = \frac{Sensitivity+Specificity}{2} * 100(\%)$$

Another advantage is MART'S potency within the multiplication of morphological categories. In [6] they use classification of QRS-complex in ElectroCardioGram (ECG) signals exploiting continuous wavelets and neural networks. They uses feedforward neural network for the classification stage with customary back propagation algorithmic program. The three layer feed-forward networks utilizing the BackPropagation (BP) learning algorithmic program had been enforced. During this paper they first of all computed CWT coefficients then noise has been is calculable relying upon the edge value QRS-complex is found then when the classification of QRS-complex the model is trained by exploiting ANN. It can even be trained for traditional and abnormal values of QRS-complex.

In [7], classification of seven totally different parameters of ElectroCardioGram (ECG) signal is 1st computed. At that time they had examined the patients with some diseases exploiting their ECG and an Artificial Neural Networks (ANN) system. The signal is then classified into normal, abnormal and life threatening signals. Then totally different features that are extracted from the ElectroCardioGram (ECG) signal are fed as input to the ANN for classification. The stages employed by N Kannathal, U Rajendra Acharya, Choo Min Lim, PK Sadasivan, and SM Krishnan, includes of 1) preprocessing of the ElectroCardioGram (ECG) signal,2)extraction of characteristic features and 3) classification exploiting ANN techniques. In preprocessing the noise in ElectroCardioGram (ECG) signals is removed utilizing band pass filter and applying the algorithmic program of Van Alste and Schilder (8). In second stages totally different parameters value are extracted. In last the network is trained by the values as neural networks derive their power from massively parallel structure and it's the power to find out from expertise This approach provides a superior performance in terms of accuracy. It’s easier and less complicated to implement and use, because it solely needs the ElectroCardioGram (ECG) signal to see the patients’ states and verify the illness.

2.3.2 Support Vector Machine

S. S. Mehta, and N. S. Lingayat [2] had studied the QRS-complex for the detection of unwellness and they planned new ways that is accountable for it success specifically, to search out a hyperplane that can divides samples in to classes with the widest margin between them, and therefore the extension of this idea to the next dimensional setting exploiting kernel function to represent a similarity measure thereon setting. in this paper they'd thought-about a collection (x_1,y_1)…………(x_L,y_L).

Then the choice operation is find out with the property-

$$y_i(w.x_i - b) \geq 1, \forall 1 \leq i \leq n \tag{2.1}$$

Where w is weight and b is bias.

After the solution is find out it give rise to a decision function of the form

$$f(x) = \text{sgn}\left[\sum_{i=1}^{l} y_i \alpha_i (x.x_i 0 + b\right] \tag{2.2}$$

Where, decision function is considered in the form of sgn($(w.x)+b)$

α_i = Lagrange multipliers

They used an equivalent idea for the detection of ElectroCardioGram (ECG) signal analysis and ischemia classification. They applied SVM just for the detection of QRS-complex for single lead ElectroCardioGram (ECG) by utilizing LIBSVM software system. LIBSVM is an integrated software system package for support vector classification, regression and distribution estimation. Farid Melgani and Yakoub Bazi [3], projected a completely unique classification system which depends on particle swarm optimisation (PSO) that facilitate to boost the potency of the SVM classifier. to attain sensible performance that had used SVM classifier with kernal filter, they'd optimized the SVM classifier style by finding the most effective worth of the parameters which can modify its discriminant function, and checking for the most effective set of features that are utilized to feed the classifier. They’d additionally used an equivalent technique for multiclass classification. This can be not applicable to morphology and temporal features, sensitivity and specificity. R. Besrour, Z. Lachiri and N. Ellouze, in their paper [4] they work on a brand new methodology for classification of beats which relies on the support vector machine classifier exploiting morphological descriptors and High Order data point utilizing MIT/BIH ischemia dataset. During this paper the truly compute the performance of the classifier used.

In this methodology every QRS beat is separated into two totally different component vectors. The primary component contains 10-morphological descriptor which provides the data of the amplitude, space and specific interval durations. The second component contains 15-sub elements. They had applied the SVM classifier to match the heartbeat classification skills of the two ElectroCardioGram (ECG) feature sets. Therefore during this approach it performed the classification methodology exploiting SVM.

2.3.3 Fuzzy Logic

Zong and Jiang (1998) described the method of fuzzy logic approach single channel ECG beat and rhythm detection. The method summarized and makes use of the medical knowledge and diagnostic rules of cardiologists. Linguistic variables have being used to represent beat features and fuzzy conditional statements perform reasoning. The algorithm can identified rhythms as well as individual beats. This method also handling the beat features and reasoning process is heuristic and seems more reasonable as stated in their paper. It also presented that this method may be of great utility in clinical applications such as multi-parameter patient monitoring systems, where many physiological variables and diagnostic rules exist.

2.3.4 Neuro-Fuzzy Logic

The idea of the ElectroCardioGram (ECG) analysis and classification exploiting the Neuro Fuzzy has been begin around 1990, nevertheless it remains one among the foremost vital indicators of correct cardiovascular disease classification nowadays. The foremost troublesome situation faced by an automatic ElectroCardioGram (ECG) analysis is that the massive variation within the morphologies of ECG waveforms, it happens not just for totally different patients or patient teams however conjointly inside constant patient. Therefore the Neuro Fuzzy is the most fitted technique as a result of it's additional tolerance to morphological variations of the ElectroCardioGram (ECG) waveforms. Scientist Linh et al. (2003) have studied comprehensively on the Neuro8Fuzzy approach to the identification and classification of heart rhythms on the idea of ElectroCardioGram (ECG) waveforms. It uses a new approach for the recognition of heart beat. This project is the resolution for the matter of less sensitivity to the morphological variation of the ElectroCardioGram (ECG). It combining the techniques that are characterization of the QRS -complex of ElectroCardioGram (ECG) by Hermite polynomials and utilizing the coefficients of Hermite kernel enlargement because the features of the method and also the application of the changed neuro-fuzzy TSK network for ElectroCardioGram (ECG) pattern recognition and classification. The performance improvement utilizing planned methodology in Neuro8Fuzzy exploiting autoregressive model coefficients, higher-order cumulant and wavelet transform variances as features by Engin (2004) and Papaloukas et al. (2003) and might solve the matter to observe a lot of cardiovascular disease sorts in high accuracy. The Neuro fuzzy Techniques that refers to the mixture of fuzzy set theory and neural networks with the benefits of each that can handle any reasonable data, numeric, linguistic, logical, imperfect info, resolve conflicts by collaboration and aggregation, self-organizing, self-learning and self-tuning capabilities, no need of previous information of relationships of knowledge, mimic human decision making} process, and quick computation utilizing fuzzy range operations so as to try and do the classification task.

2.4 Summary of the approaches of ECG Analysis Algorithm

Abbrevations used: LDAC-LDA Classifier, MLP-BP-Multilayer Perceptron Back Propagation, NN-Neural Network, FTF-Fourier Transform Features, HB-Heart Beat, NNC-Nearest Neighbour Classifier, WED-Weighted Euclidean Distance, SAECG-Signal Averaged ECG, WDIST-Wavelet DISTance, CCORR-Cross correlation Measure, NC-Nearest Center, BC-Baye's Classifier, WHVD-Wubbler's Heart Vector Distance, NC-Nearest Center, ED-Euclidean Diistance, MRHB-Median of Resampled Heart Beats, CC-Cross

Correlation, DWTMRRS-DWT of Mean R-R Segments, RBFNN-Radial Basis Function Neural Network, GF-Gaussian Fit, RARMA-Residual Auto-Regressive Moving Average, NNC-Nearest Neighbour Classifier, AC-Autocorrelation, WT-Wavelet Transform, HPE-Hermite Polynomial Expansion, SVMLK-SVM Linear Kernel, MANRHB-Mean of Amplitude-Normalized Resampled Heart Beats, DCT-Discrete Cosine Transform

Table.2.1: Summary of the Earlier Proposed Methods

STUDY	TECHNIQUE	ACCURACY
Kyoso and Uchiyama	LDAC	>90%
Palaniappan and Krishnan	MLP-BP + NN	97.6%
Saechia et al.	FTF + MLP-BP + NN	97.15%
Shen	HB + WED + NNC	95.3%
Chan et al.	CCORR + NC	90.8%
Zhang and Wei	PCA + BC	87.4%
Wubbeler et al.	WHVD + NC	98.1%
Chiu et al.	DWT + NC, ED	95.71%
Fatemian and Hatzinakos	MRHB + CC	99.63%
Yao and Wan	DWTMRRS + PCA	91.5%
Boumbarov et al.	PCA + RBFNN	86%
Homer et al.	RARMA + NNC	85.2%
Agrafioti and Hatzinakos	AC + WT + NNC	92.3%
Li and Narayanan	HPE + SVMLK + SVM	98.11%
Lourenco et al.	MANRHB + NC	94.3%
Tawfik et al.	DCT of QRS + MLP-BP + NN	99.09%

2.5 Summary

In the literatures, most researchers have developed the system based on the various techniques and algorithms. Each technique given within the previous project of ElectroCardioGram (ECG) analysis has their benefits and downsides. The performance of the developed detection systems is extremely promising however they require some more analysis. The automated detection of ElectroCardioGram (ECG) waves is vital to internal organ un-wellness identification. A decent performance of an automatic ElectroCardioGram (ECG) analysing system depends heavily upon the accuracy and reliability of the detection of QRS-complex, yet because the T and P waves and most of the researches solely rely upon some illness.

From the literatures, it is indicated that the ECG analysis systems developed by using hybrid algorithms are too complex. But the hybrid techniques that have been implemented in the project recently shown that it yield the better result analysis of heart disease classification. In the systems developed, such technique needs a very precise code in order to achieve good efficiency and accuracy. Therefore, the present work in this thesis is an attempt to simplify and maximize the accuracy of the algorithms.

From the reviewed, there are improvement for ECG analysis in feature extraction and classification techniques, it's found that Aritificial Neural Network and hybrid ways are one amongst the newest ECG analysis techniques researches significantly in biosignal process for medical application that are being carried out by biomedical researchers. Therefore, this type of research is definitely worth for further study. Our analysis primarily aimed to use the chosen algorithms for feature extraction and classification task to boost the results of accuracy and expand the categories of heart condition that may be classified. An ECG analysis system with fast and easily will be developed. This study will be carried out by the simulation works. In the simulation, MATLAB code will be used due to its capability to give good predictions signal processing. This study is expected to be an initial attempt to the development of ECG analysis module.

Chapter 3
PROPOSED METHOD

3.0 Overview

This chapter describes the ElectroCardioGram (ECG) signals analysis modeling by using MATLAB. Here, the methods of analysis are discussed. The analysis system based technique in most ECG analysis was performed in three stages: (1) division of the pre-processing, (2) feature extraction by computation of Principal Component Analysis (PCA) and (3) classification procedures using SVM, ANN, Fuzzy and Neuro-fuzzy classifiers for analysis purposes will be explained. Also, a brief simulation procedure is presented in this chapter.

3.1 Overview of ElectroCardioGram (ECG) Analysis System

The health of a population may be a basic component contributing to progressive sustainable development in all regions of the globe. Nearly all sciences contribute to the requirements of human health and therefore the need of medicines. The development and implementation of science and technology in the medical application tools such as ECG will help to enhance the human healthcare and can assist people to check their health condition with fast and accurate. The invention of the new analysis method of medical instrumentation also can help to improve the efficiency and powerful medical applications.

The ECG analysis is generally exploited for diagnoses of many cardiac diseases, which are the main cause of mortality in developed countries. Biosignal processing techniques such as ECG analysis system offer a powerful tool to simulate the human heart signal. The performance of such detection systems relies heavily on the accuracy and reliability in the detection of the signals, which is necessary to determine the heart disease. The Ischemia and ischemia detection of ECG wave is an important topic. This section explores the ways utilized to collect information for analysis, the isolation of the required information, and also the experiments exploited to analyze the biosignal information.

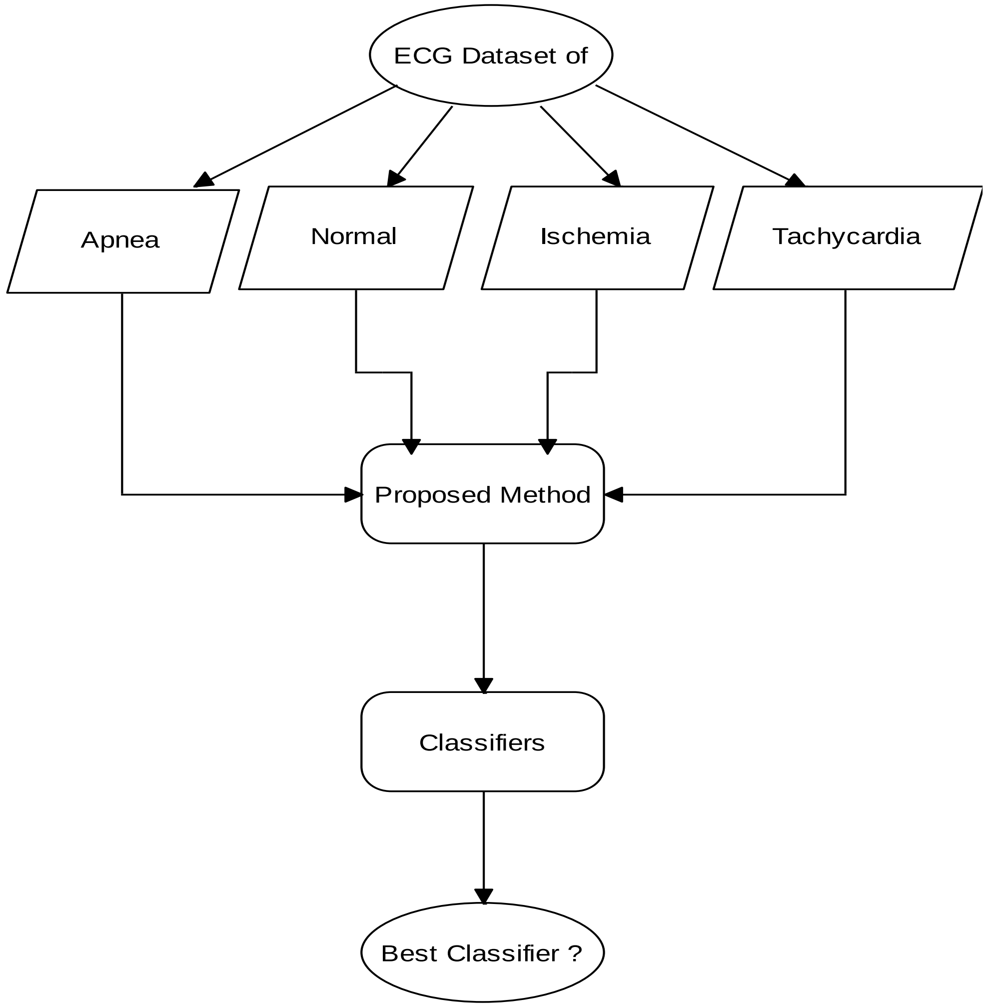

Fig.3.1. Block Diagram

3.2 System Requirement

This project is developed by using MATLAB (MathWorks Inc.) software tool, the numerical computing environment and programming language software for modeling the heart signal in complex algorithms. The Neuro-fuzzy were also used as classier tools within the MATLAB. it's a problem-oriented language that allows to perform computationally intensive tasks quicker than the programming languages like C and C++. This software is among the most commonly used development languages. MATLAB codes also being used because it 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.

3.3 ECG Signal Analysis Procedure

The ways given here are divided into three parts. Firstly, procedures to spot and annotate of ElectroCardioGram (ECG) signal for normal, Apnea, tachycardia and ischemia characteristic. Secondly, a method is given for extracting the features vector for every sample of chosen heart disease exploiting an algorithm named as Principal component Analysis (PCA). Lastly, this part conferred the procedures of classification process using SVM, ANN, Fuzzy and Neuro-fuzzy modeling.

3.3.1 Signal Data Preparation

The ECG recording signals data are partitioning into cardiac cycles, and detection of the main events and intervals in each cycle have been done. The ECG signals which consist of P,Q,R,S and T wave have been detect based on their wave characteristic such as position, amplitude and intervals are shown in Table 3.1. The major features such as the QRS amplitude, R-R intervals, and wave's slope of ECG signal can be used as features to create the mapping structure are also identified.

Table 3.1: Phases in ECG

Section of ECG	Source
P-Wave	Record the electrical activity through the upper heart chambers (Atria Excitation)
QRS- Complex	Record the movement of electrical impulses through the lower heart chambers. (Atria repolarization + Ventricle depolarization)
T-Wave	Corresponds to the period when the lower heart chambers are relaxing electrically and preparing for their next muscle contraction. (Ventricle repolarization)
ST Segment	Corresponds to the time when the ventricle is contracting but no electricity is flowing through it.

3.3.2 Signal Data Characteristics

The characteristic for each sample of heart disease must be studied to make sure the characteristic is correct with the exact characteristics that have been identified by the doctor. The characteristics of each disease are described below.

The standard value of normal signal characteristics for Amplitudes and Durations of ECG Parameters are shown in Table 3.2 and Table 3.3 below.

Table 3.2: Amplitude values for Normal ECG Signal

WAVE	Amplitude
P wave	0.25mV
R wave	1.60mV
Q wave	25% of R wave
T wave	0.1 to 0.5mV

Table 3.3: Duration Values for Normal ECG Signal

WAVE	DURATION
P-R Interval	0.12 to 0.20 sec
Q-T Interval	0.35 to 0.44 sec
S-T Interval	0.05 to 0.15 sec
P Wave Interval	0.11 sec
QRS Interval	0.09 sec

Apnea Ischemia template

- Intermittent halt of breathing
- Due to irregular sleep
- Related to accrued risks of high pressure level

Ischemia template

- Inversion of T wave

- Decrease in amplitude or disappearance of R wave
- Shift of ST segment

Tachycardia Ischemia template

- TachyIschemias are accelerated atrial or ventricular rates that exceed what is considered normal
- Beat too fast
- Regular
- Presence or absence of atrial depolarization (P wave, flutter waves).
- Diagnosis of cardiac Ischemia cannot be considered complete without accounting for atrial activity.

3.4 Principal Component Analysis

PCA is an orthogonal linear transformation. It transfers the data to a new frame of reference such the largest variance of any projection of the information involves lie on the first coordinate (first principal component), the second largest variance lies on the second coordinate (second principal component), and so on. Linear projection method to reduce the number of parameters. Map the data into a space of lower dimensionality.

PCA algorithm:

Let X be an input data set.

Perform the following steps:

- Calculate the mean:

$$u[m]= \frac{1}{N}\sum_{n=1}^{N} X[m,n] \tag{3.1}$$

- Calculate the mean deviation and keep the data in the matrix B[M × N]:

$$B=X-u.\ h, \tag{3.2}$$

where h is a 1 × N row vector of all 1's:

h[n] = 1 for n = 1, …....N

- Find the covariance matrix C:

$$C = B \cdot B^T \tag{3.3}$$

- Find the eigenvectors and eigenvalues of the covariance matrix V^{-1} CV where V is the eigenvectors matrix. D is the diagonal matrix of eigenvalues of C.

$$D[p, q] = \lambda_m \tag{3.4}$$

for p = q = m is the m^{th} eigen value of the covariance matrix C.

- Rearrange the eigenvalues

$$\lambda_1 \geq \lambda_2 \ldots\ldots \geq \lambda_N$$

- Choosing components and forming a feature vector: save the first L columns of V as the M × L matrix W,

$$W[p, q] = V[p, q], \quad \text{for } p = 1, \ldots, M$$
$$q = 1, \ldots, L$$

where $1 \leq L \leq M$.

- Deriving the new data set: The eigenvectors with the maximum eigenvalues are projected into space. This projection results in a vector represented by fewer dimension (L < M) containing the essential coefficients only.

3.5 Classifiers

In classification, a pattern could be a combination of variables {x,w} in which x is the group of observations or characteristics (feature vector) and w is the idea behind the observation (label). The standard of a feature vector is expounded to its ability to discriminate examples from various categories (Figure 3.2).

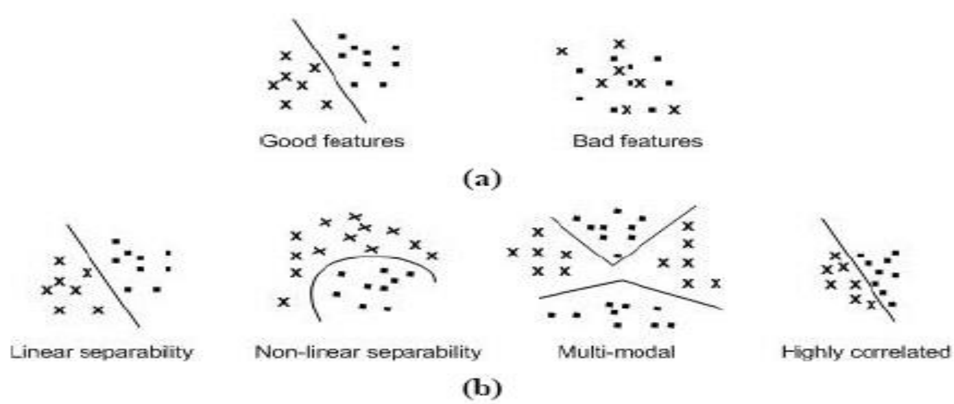

Fig.3.2. Characteristic (feature); a. the distinction between good and poor features, and b. feature properties.

Examples from an equivalent category ought to have similar feature values which includes examples from various categories having different feature values. The goal of a classifier is to partition feature area into class-labeled regions. Borders between the regions are known as the boundaries of decision (Figure 3.3).

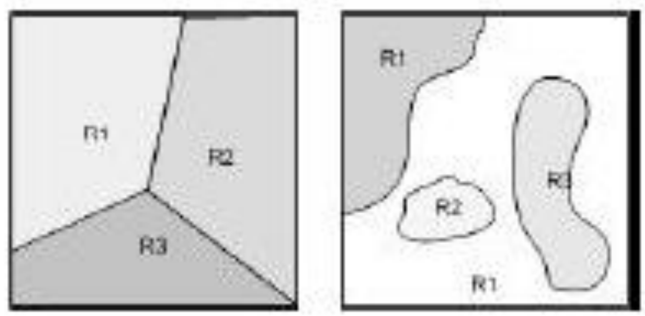

Fig.3.3. Classifier and decision boundaries.

If the characteristics or attributes of a class are known, individual objects might be identified as belonging or not belonging to that class. The objects are assigned to classes by observing patterns of distinguishing characteristics and comparing them to a model member of each class. The task of the classifier component proper of a full system is to use the feature vector provided by the feature extractor to assign the object to a category. Because perfect classification performance is often impossible, a more general task is to determine the probability for each of the possible categories. The abstraction provided by the feature-vector representation of the input data enables the development of a largely domain-independent theory of classification.

The degree of difficulty of the classification problem depends on the variability in the feature values for objects in the same category relative to the difference between feature values for objects in different categories. The variability of feature values for objects in the same category may be due to complexity, and may be due to noise. We define noise in very general terms: any property of the sensed pattern, which is not due to the true underlying model but instead to randomness in the world or the sensors. All nontrivial decision and pattern recognition problems involve noise in some form.

One problem that arises in practice is that it may not always be possible to determine the values of all of the features for a particular input. In our hypothetical system for fish classification, for example, it may not be possible to determine width of the fish because of occlusion by another fish. How should the categorizer compensate? Since our two-feature recognizer never had a single-variable criterion value x* determined in anticipation of the possible absence of a feature, how shall it make the best decision using only the feature present? The naive method of merely assuming that the value of the missing feature is zero or the average of the values for the patterns already seen is provably non-optimal. Likewise, how should we train a classifier or use one when some features are missing?

3.5.1 Support Vector Machine

SVM i.e. Support Vector Machine classifier is utilized for ECG signals classification because of its multi-classification ability in differentiating various classes. SVM is explained using the equations in which margin between the support vectors is to be maximized. For this compute the parameters f, f_0 of the hyperplane so that to:

$$\text{minimize } J(f, f_0) \equiv \frac{1}{2}\|f\|^2 \tag{3.5}$$

subject to equation 2.1.

Clearly, making the norm minimum will makes the margin maximum. This is a nonlinear (quadratic) optimization task subject to a set of linear inequality constraints. Hence, the SVM decision function is expressed as equations

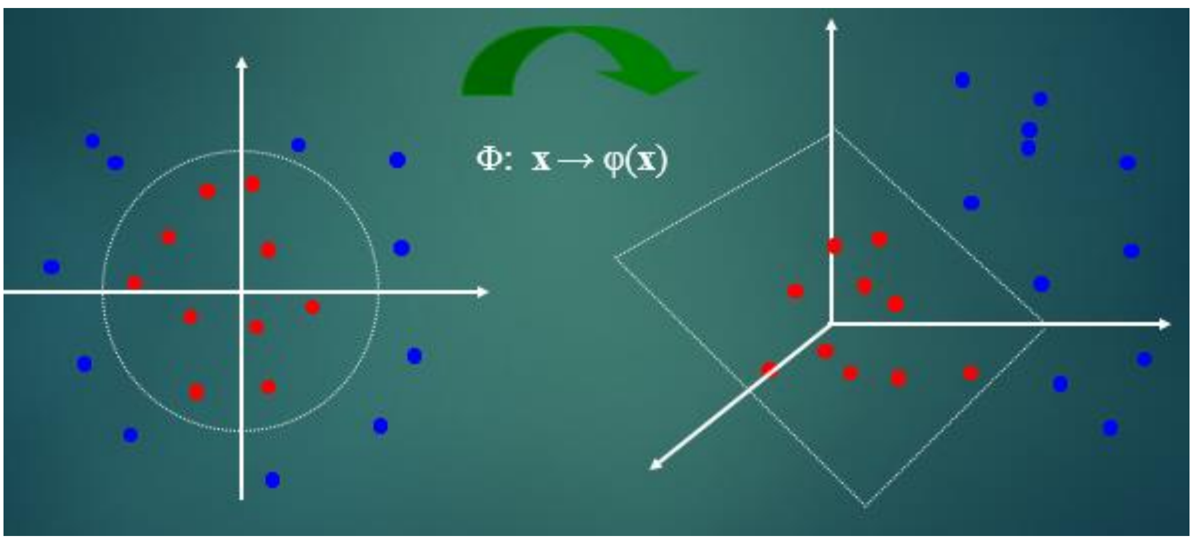

Fig.3.4. Classification using SVM Classifier

$$f = \sum_{i=1}^{N} c_i . z_i . x_i \tag{3.6}$$

$$\sum_{i=1}^{N} c_i . z_i = 0 \tag{3.7}$$

To achieve good performance [16] had used SVM classifier with kernal filter, they had optimized the SVM classifier design by finding the best value of the parameters that will adjust its discriminant function, and checking for the best subset of features that is used to feed the classifier. They had also used the same technique for multiclass classification. SVM doesn't provide good results in classifying different ECG signals and hence, another classifier is used.

3.5.2 Artificial Neural Network

With SVM, ECG classification is also done using Artificial Neural Network (ANN). In this also, train the network first by using some training data. A suitable training algorithm results in an ANN which is capable of generating a non-linear mapping function with the proficiency of demonstrating relationships between given ECG features and cardiac disorders.

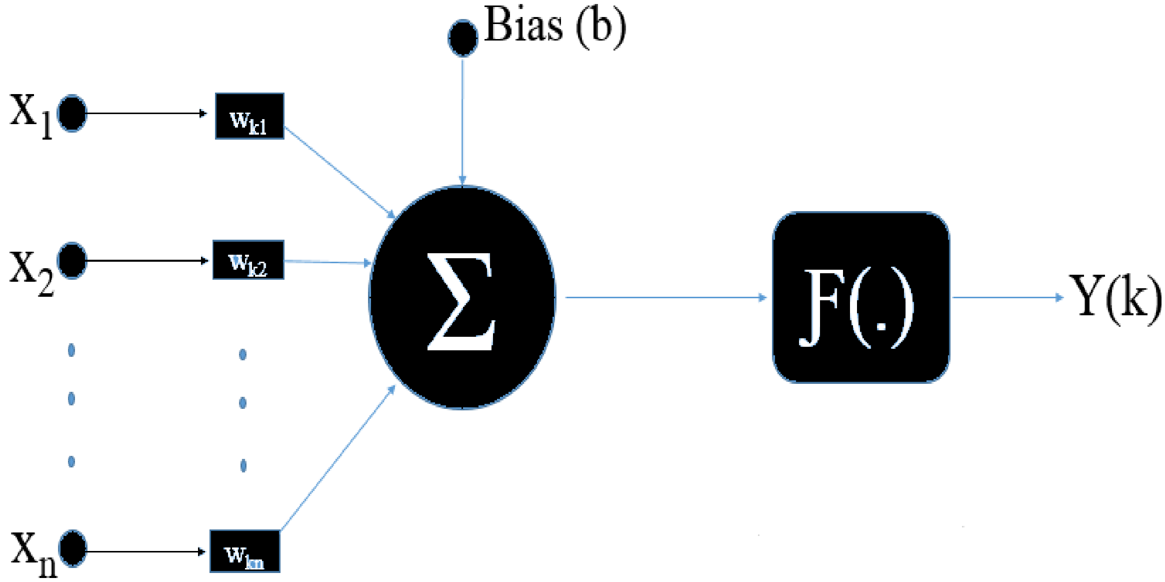

Fig.3.5. Neuron Model

$$u_k = \sum_{j=1}^{n} x_j . w_{kj} \tag{3.8}$$

$$v_k = uk + bk \tag{3.9}$$

A well designed ANN will exhibit good generalization when a correct input output mapping is obtained even when the test input is slightly different from the data used to train the network.

3.5.3 Fuzzy Logic

The Extracted parameters Frequency, variance and Variance is taken into account as input variables to the Fuzzy rule primarily based on choice of method block. Logical thinking System (or FIS) maps an input characteristics to output categories exploiting the fuzzy logic. This system is simple to change a FIS by only including or excluding rules. The fuzzy rules have written for Extracting characteristics to urge results as AWAKE, REM and SWS sample values. Fuzzy Rule primarily based choice for four inputs and one output model is shown in Fig.4.8.

A. Fuzzy Rules

Fuzzy IF- THEN Rule**: "**IF -THEN rule statements are used to create the conditional statements that consist of fuzzy logic. IF - THEN rule assumes the form where A and B are atomic terms explained by fuzzy sets on the ranges (universe of discourse) X and Y, respectively. The premise of the rule 'X is A' is called antecedent, while the conclusion portion of the rule 'Y is B' is called the consequent which makes one rule i.e. 'If X is A then Y is B'. These rules are based on natural language representation and models, which themselves based on fuzzy sets and fuzzy logic" [15].

Fuzzy logic as a tool will be applied to analyze the different stages of EEG classification and check the percentage of correct recognition rate by comparing them with manual readings.

Fuzzy Rule for five input variables and one output variable is defined as few example rules :

a) If (EEG frequency is low) or (EOG standard deviation is high) or (EOG variance is high) or (EMG standard deviation is low) or (EMG variance is low) then (signal is REM).

b) If (EEG frequency is high) or (EOG standard deviation is low) or (EOG variance is low) or (EMG standard deviation is med) or (EMG variance is med) then (signal is SWS).

c) If (EEG frequency is med) or (EOG standard deviation is med) or (EOG variance is med) or (EMG standard deviation is high) or (EMG variance is high) then (signal is AWAKE).

If any one of the Fuzzy Classifier output variable (AWAKE, REM and SWS) is present more number of times in Feature Extracted parameters rule, the Classifier will assign that Fuzzy Classifier output variable to be the final output in the Fuzzy System. The Fuzzy Rule Design is shown in Fig.7

Number of Fuzzy Rules is dependent on number of input variables and their membership functions. In Fuzzy Rule Based Selection model has 5 variables and 3 membership functions.

B. Membership Functions (MF)

A Membership function is a curve that defines how each point in the input space is mapped to a embership value or degree of membership between 0 and 1. The only condition a membership function must really satisfy is that it must vary between 0 and 1.

The Fuzzy Logic Toolbox includes several built in membership function types. The list of membership function types are linear function, Gaussian distribution function, sigmoid curve, straight lines, triangular, trapezoidal and quadratic and cubic polynomial curves. All membership functions have the letters mf at the end of their names.

The selected membership function types are:

a) Triangle: The Triangular membership function name is trimf. It collects more than three points to form a triangle.

b) Trapezoidal: The Trapezoidal membership function name is trapmf. It has a flat top and a truncated triangle curve.

c) Sigmoid: The Sigmoid membership function name is sigmf. It provides asymmetric membership functions.

d) Gaussian: The Gaussian membership function name is gaussmf. It provides smooth and nonzero curve at all points.

3.5.4 Neuro-Fuzzy Logic

Neuro-Fuzzy classifier consists of five layers of nodes out of the five layers, the first and the fourth layers consist of adaptive nodes there are Fuzzification and Defuzzification, while the second, third and fifth layers consist of fixed nodes there are Rule, Normalization, and Summation neuron. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iterations while the fixed nodes are devoid of any parameters. To present the Neuro-Fuzzy classifier, two fuzzy if-then rules based on a first order Sugeno model are considered: [14,15,16]

Rule 1: If (x is A1) and (y is B1) then (f1 = p1x + q1y + r1)

Rule 2: If (x is A2) and (y is B2) then (f2 = p2x + q2y + r2)

where X and Y are predefined membership functions, Ai and Bi are membership values, fi are the outputs and pi, qi, and ri are the consequent parameters that are updated in the forward pass in the learning algorithm. The Neuro-Fuzzy classifier to implement these two rules is shown in Figure.1, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

Layer 1: Fuzzification layer Every node I in the layer 1 is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{A_i}(x), \forall i = 1,2 \tag{3.10}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \forall i = 3,4 \tag{3.11}$$

where x and y is the inputs to node i, where A is a linguistic label (small, large) and where $\mu_{Ai}(x)$, $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function.

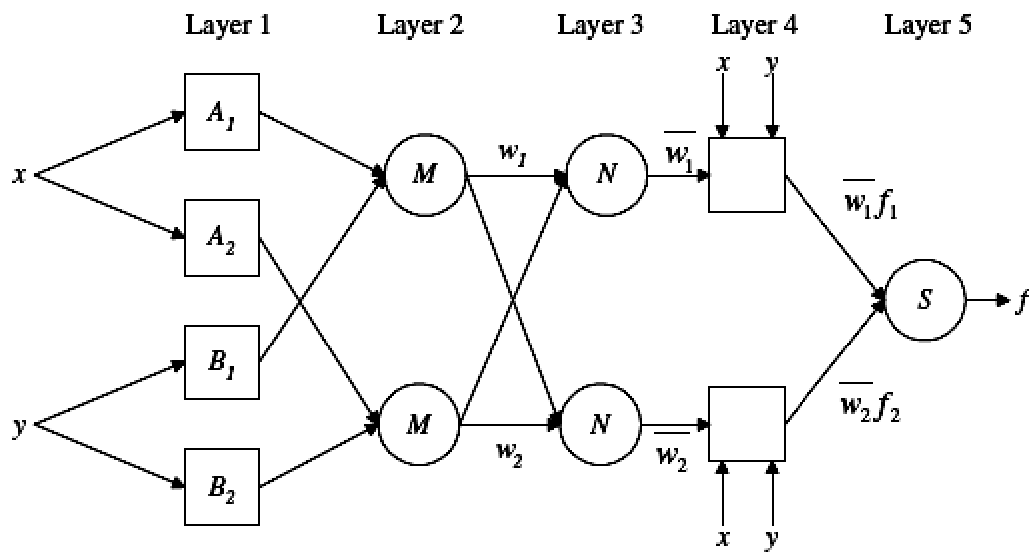

Fig.3.6. Neuro-Fuzzy architecture

Usually we choose $\mu_{Ai}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as:

$$\mu_{A_i}(x) = \frac{1}{1 + \{((x - c_i)/a_i)^2\}^{b_i}} \tag{3.12}$$

where (a_i, b_i and c_i) are the parameters of the membership function. Parameters are referred to as premise parameters.

Layer 2: Rule layer a fixed node whose output is the product of all the incoming signals, The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x).\mu_{B_i}(y), i = 1,2 \tag{3.13}$$

Layer 3: Normalization layer are also fixed node is a circle node.

$$O_i^3 = w_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \tag{3.14}$$

Layer 4: Defuzzification layer an adaptive node with a node the output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial.

$$O_i^4 = w_i . f_i = w_i (p_i x + q_i y + r_i), i = 1,2 \tag{3.15}$$

Layer 5: Summation neuron a fixed node which computes the overall output as the summation of all incoming signals.

$$O_i^5 = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{3.16}$$

3.6 SUMMARY

The methods of analysis are discussed in this section. The analysis system based technique in most ECG analysis was performed in the stages as: (1) Taking the ECG dataset, (2) Calculating the P-QRS-T measures using PCA for the ECG signals and (3) Classification procedures using SVM, ANN, Fuzzy and Neuro-Fuzzy classifiers.

Taking the ECG datasets: Dataset for ECG detection is loaded from the MIT-BIH Ischemia database of Physiobank ATM to MATLAB workspace. It is shown below in the Table 3.4.

Table 3.4: Description of dataset used

ECG Signals	Training	Testing	Total
Apnea	18	12	30
Normal	18	12	30
Ischemia	18	12	30
Tachycardia	18	12	30

Computing the P-QRS-T measures using PCA for the ECG signals: For the each and every sample of dataset, PCA algorithm is utilized to measure their P-QRS-T parameter values. In this includes R-peak amplitude, Q, S and T amplitudes with their index values.

Classification using SVM, ANN, Fuzzy and Neuro-Fuzzy classifiers: The Principal Component Analysis of the ECG signals calculated at the second stage are utilized by the classifier to determine the corresponding cardiac conditions. This feature set consists of ECG P-QRS-T measures that should efficiently characterize the variations in the input ECG signals for accurate detection and classification of the ECG. The calculated features will be applied to the classifiers like SVM, ANN, Fuzzy and Neuro-Fuzzy classifiers as training and testing data to classify the ECG signals in their corresponding class.

Chapter 4
RESULTS & DISCUSSION

4.0 Overview

This chapter describes the results of ElectroCardioGram (ECG) signals analysis modeling by using MATLAB. Here, the results of analysis are discussed. The results in ECG analysis includes feature extraction by exploiting Principal Component Analysis (PCA) and then classification results using SVM, ANN, Fuzzy and Neuro-fuzzy classifiers for analysis purposes will be explained. Also, an overall comparison of the results is presented in this chapter.

4.1 ECG Parameters Detection

Now, the ECG signal is used to detect the feature parameters which helps in classifying these different types of ECG signals viz. Normal, Apnea, Tachycardia and Ischemia signals.

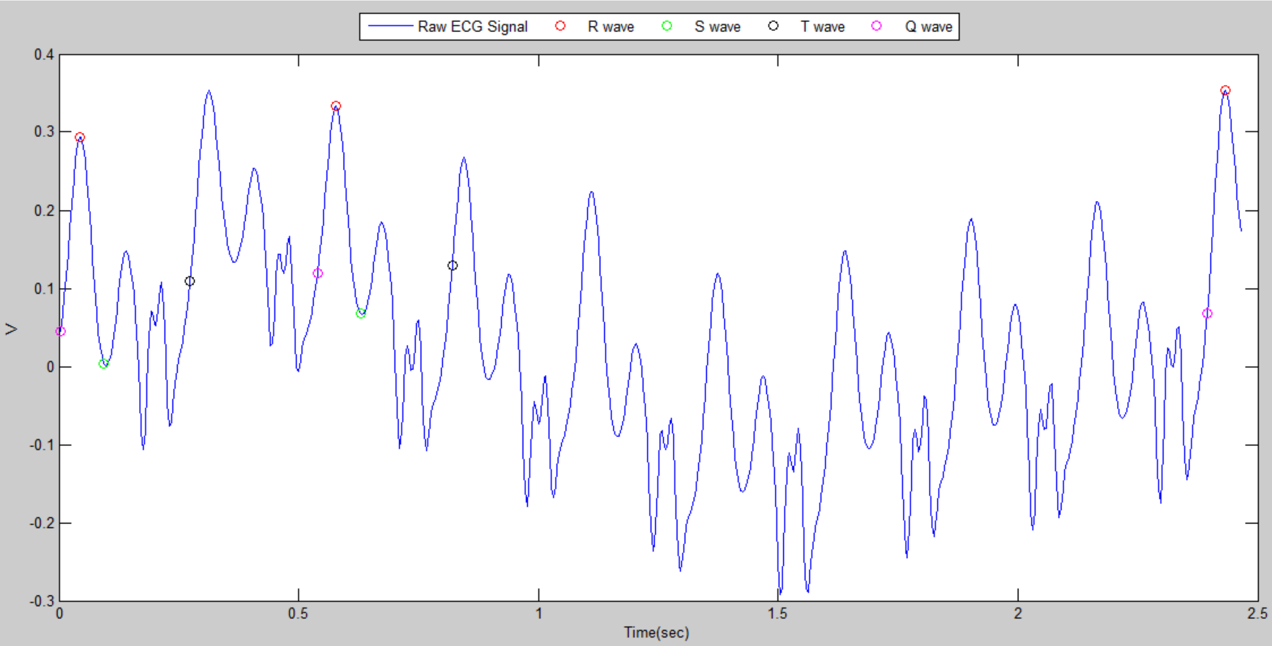

Fig.4.1. Apnea ECG peaks detection

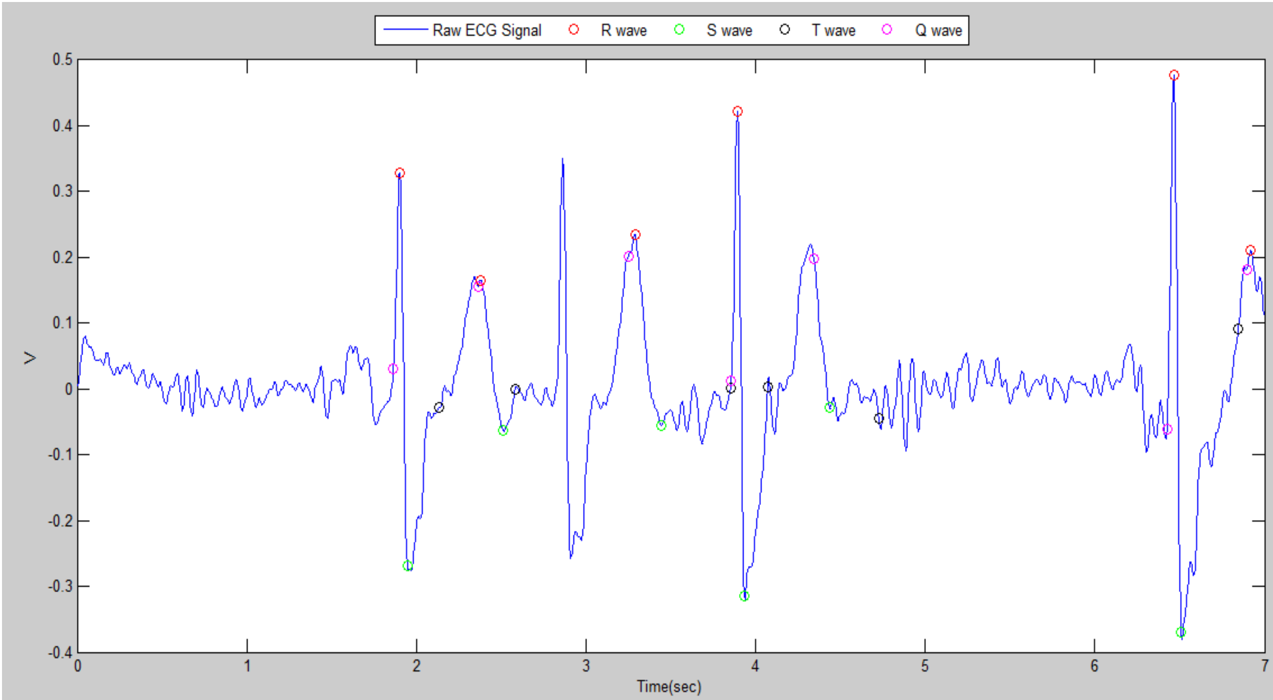

Fig.4.2. Ischemia ECG peaks detection

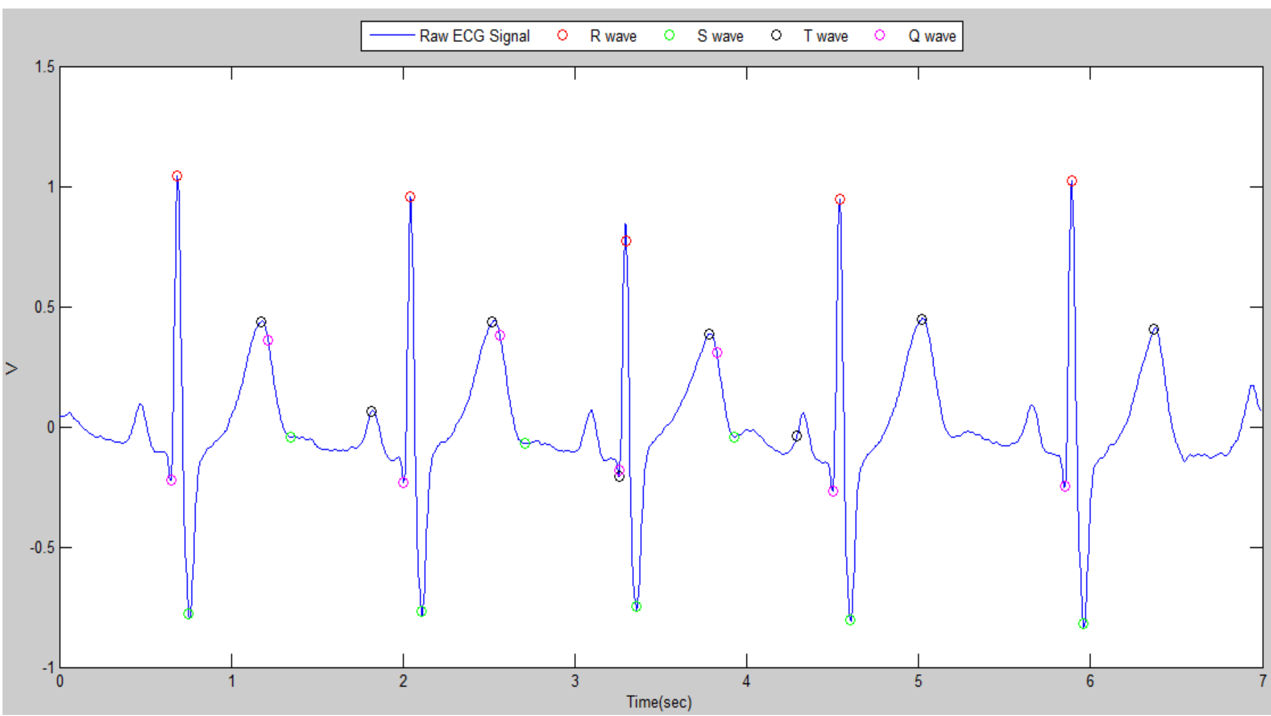

Fig.4.3. Normal ECG peaks detection

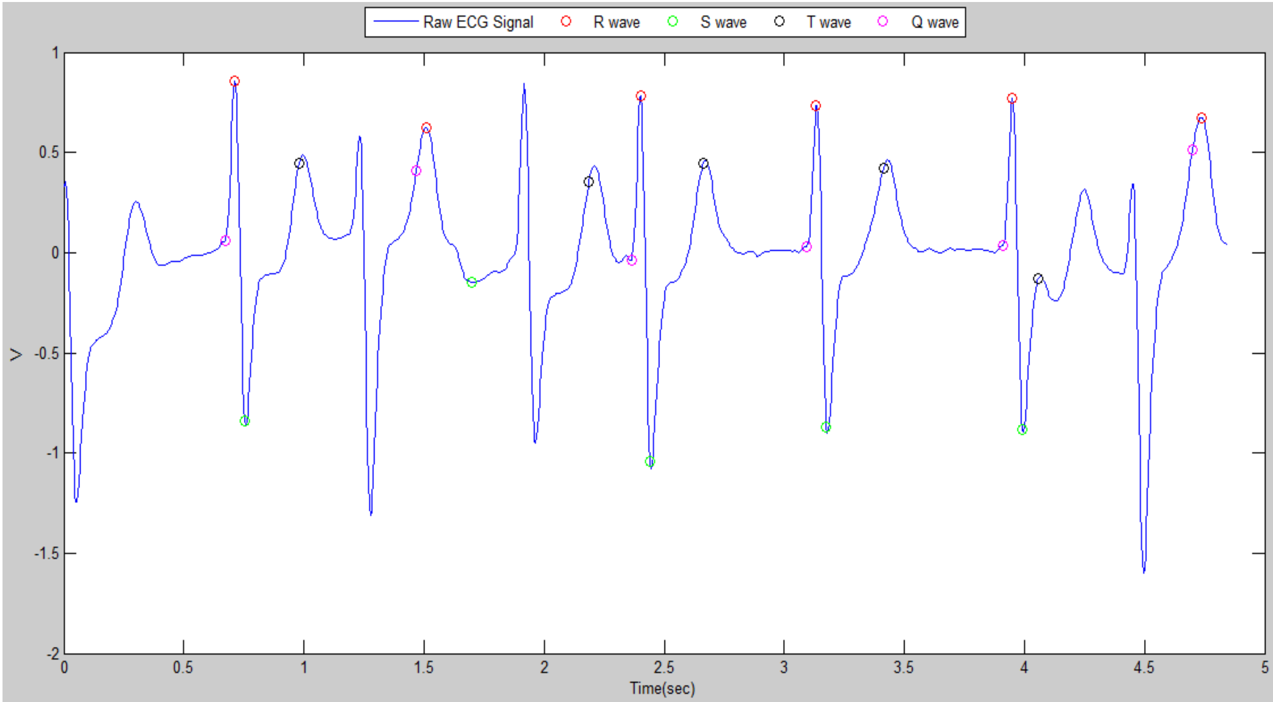

Fig.4.4. Tachycardia ECG peaks detection

In the Fig.4.1-4.4 shows the parameter detection in the ECG signals selected as sample from the datasets. It can be observed from the signals figures that variation among the signals can be observed. And this variation is also shown in the Table 4.1. This table shows the parameter values for the different types of ECG signals used during this project i.e. Apnea, Ischemia, Normal and Tachycardia signals. As feature values, parameters extracted are the amplitudes of Q,R,S and T peaks with their index values which contain their interval values.

Table 4.1: ECG Parameters sample values

ECG	Parameters	Sample values
Apnea	*R_i*	*260.667*
	R_amp	*0.3271*
	S_i	*92.5*
	S_amp	*0.0359*
	T_i	*140*
	T_amp	*0.1194*
	Q_i	*250.667*

	Q_amp	*0.0771*
Ischemia	*R_i*	*1067.6*
	R_amp	*0.2907*
	S_i	*971.667*
	S_amp	*-0.1832*
	T_i	*1033.2*
	T_amp	*0.0040*
	Q_i	*1060.4*
	Q_amp	*0.1028*
Normal	*R_i*	*770*
	R_amp	*0.7243*
	S_i	*792.1250*
	S_amp	*-0.5091*
	T_i	*903.25*
	T_amp	*0.2410*
	Q_i	*763.75*
	Q_amp	*-0.0117*
Tachycardia	*R_i*	*701.5*
	R_amp	*0.7406*
	S_i	*617.6*
	S_amp	*-0.7577*
	T_i	*681.2*
	T_amp	*0.3809*
	Q_i	*691.5*
	Q_amp	*0.1688*

Next in the Fig.4.5 shows is the graph representing the comparison among the feature values extracted using the Principal Component Analysis (PCA) algorithm. And it can be observed from the figure that there is difference among the feature values which can be helpful in the signals classification.

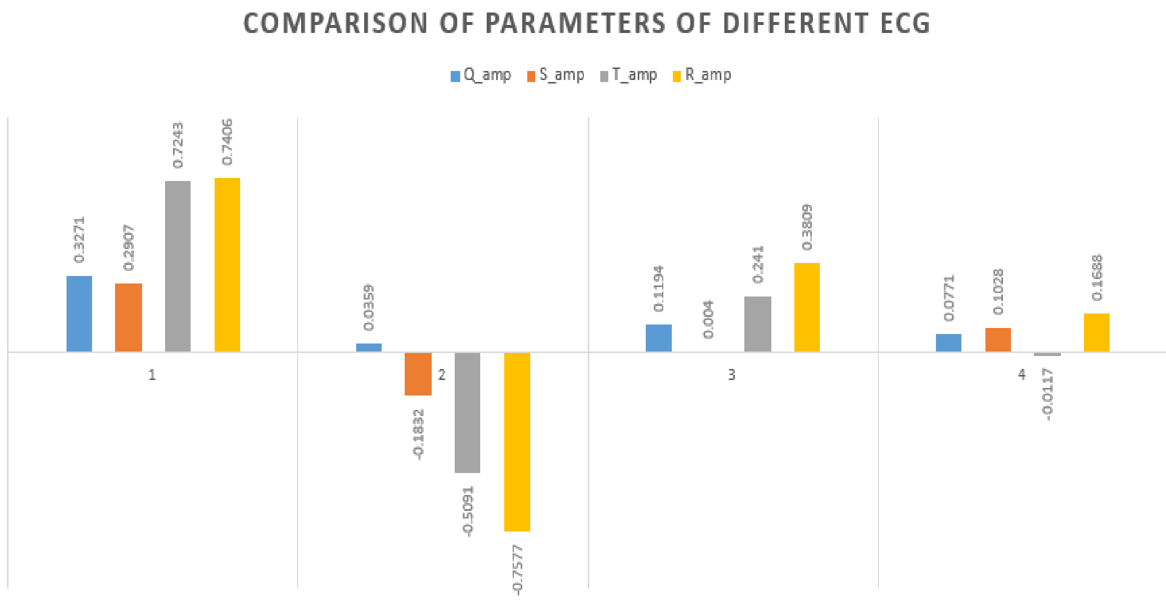

Fig.4.5. Comparison of parameters of different ECGs

4.2 Classification Using SVM

Now, these parameters obtained, are used in the classifiers for the classification of these ECG signals. For the classification, firstly SVM is used. In this classifier, 120 subjects dataset is used in total. Among these, 72 subjects are used to train the SVM and remaining are tested on this trained classifier. The results from the SVM classifier are shown in the Table IV which shows a confusion matrix of the tested dataset. In this table, AP, IS, NR and TC represents Apnea, Ischemia, Normal and Tachycardia respectively.

Table 4.2: Confusion matrix from SVM

Targets → **Outputs ↓**	**AP**	**IS**	**NR**	**TC**	**Accuracy**
AP	10/12	1/12	1/12	0/12	83.33%
IS	1/12	10/12	1/12	0/12	83.33%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	1/12	2/12	9/12	75%

In the Table 4.2, it can be seen that this classifier doesn't give us a satisfactory results with just 85.4% of accuracy. Hence, for an improvement in the results next classifier is used i.e. ANN.

4.3 Classification Using ANN

ANN applied on the dataset gives the neural network as shown in the Fig. 9 in which 71 subject parameter values are used for the training and 48 for the testing. Fig. 10 gives the output of these ECG datasets classification from Artificial neural network.

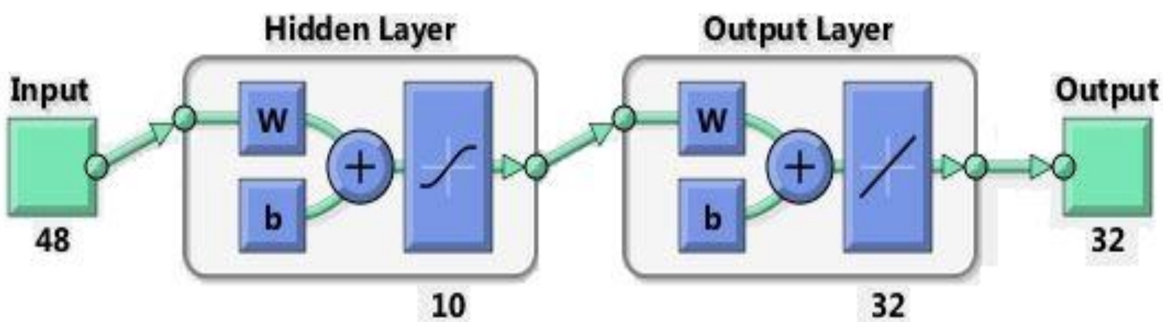

Fig.4.6. Neural Network

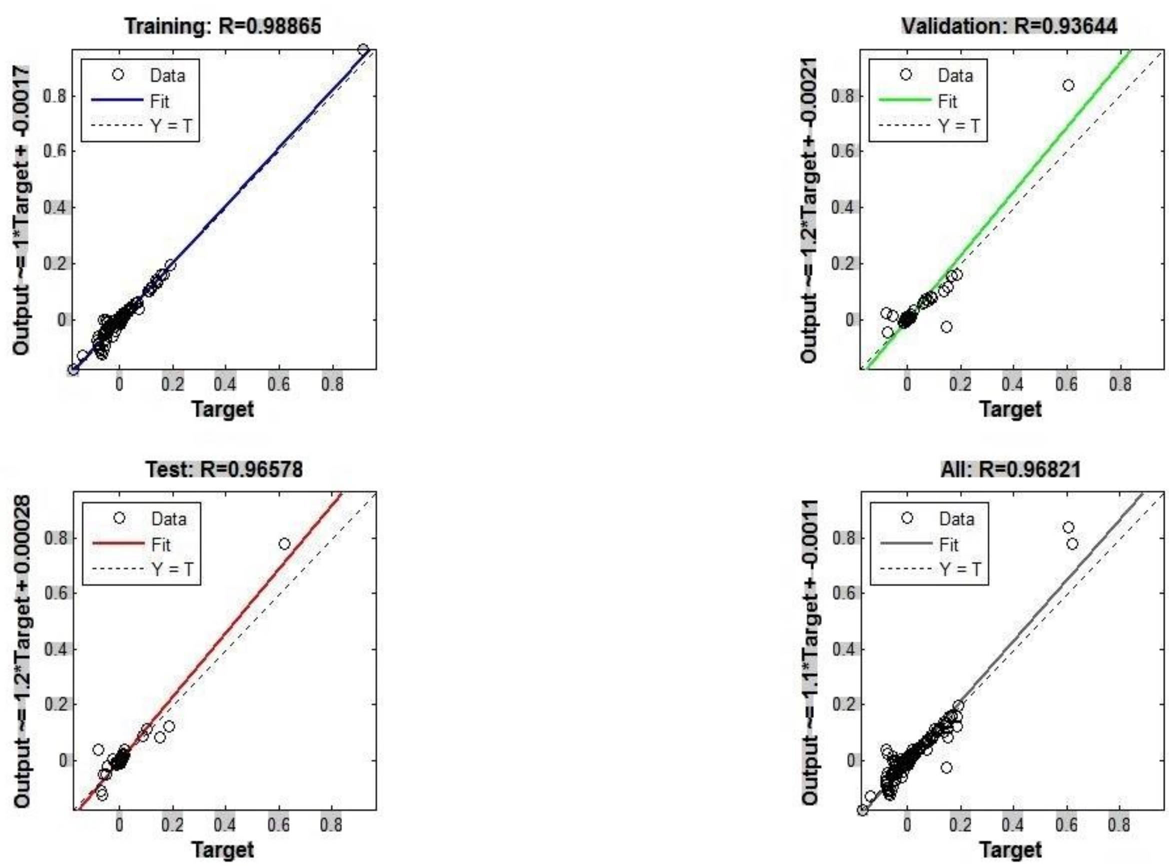

Fig.4.7. Regression plots for ANN

The plots represent the training, validation, and testing data for the ANN. The dashed line in each plot represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. For this, the training data indicates a good fit. The validation and test results also show R values that greater than 0.9. It can be seen in its regression plot in which during training value of R comes out to be 0.989. When testing dataset is applied on this, it produced R=0.966. It also gives a good validation value of 0.936. Then next shown is the Table 4.3 showing the confusion matrix of these ECG signals obtained by classification using this classifier. According to this table, an accuracy of 87.5% is observed which is very good and gives a much better results compared to SVM in which only 85.4% accuracy was observed. Next, Fuzzy-2 is applied on these feature values obtained using these ECG datasets.

Table 4.3: Confusion matrix from ANN

Targets→ **Outputs↓**	**AP**	**IS**	**NR**	**TC**	**Accuracy**
AP	9/12	1/12	0/12	2/12	75%
IS	0/12	11/12	0/12	1/12	91.67%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	1/12	1/12	10/12	83.33%

4.4 Classification Using Fuzzy Logic

Now, the dataset is applied on the Fuzzy logic for the classification purpose. Fig.4.8-4.12 shows the modelling of Fuzzy Logic which helps in the classification of the ECG signal classes. Fig.4.9-10 represents the rule viewer which decides the rules which are used during the classification process. Then the Fig.4.11-12 shows the membership functions for the inputs (Gaussian) and outputs (Triangular) respectively. In the Fig.4.8, a model is shown which gives an idea about the Fuzzy rules that Fuzzy classifier is going to do.

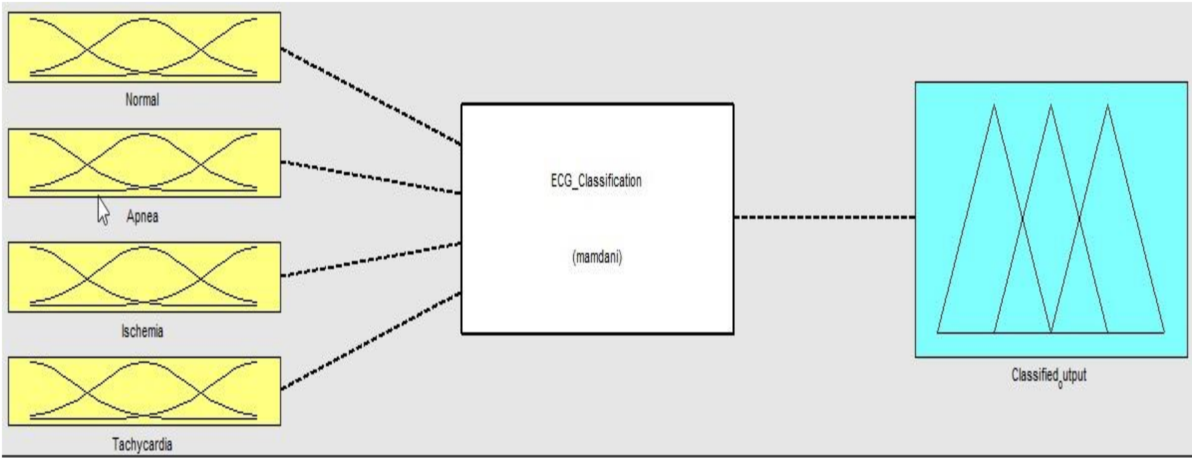

Fig.4.8. Fuzzy Rule Based Model

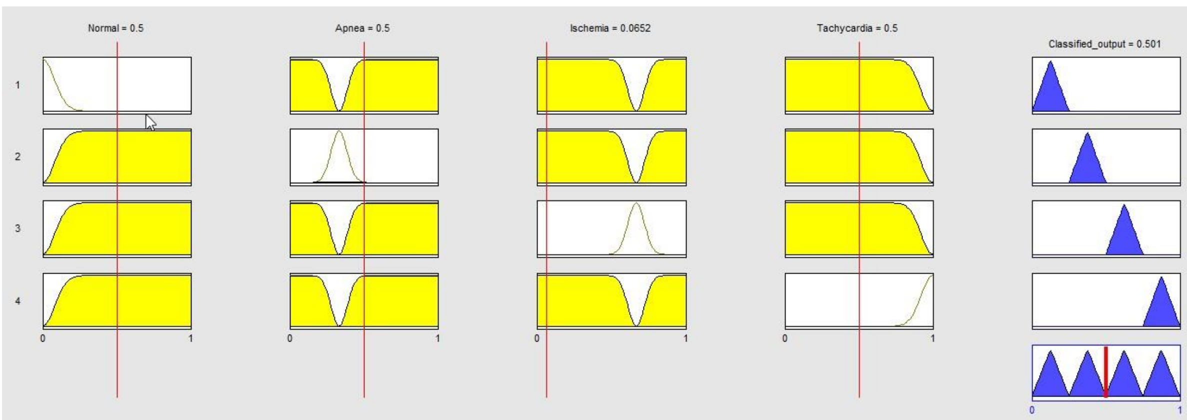

Fig.4.9. Rule viewer

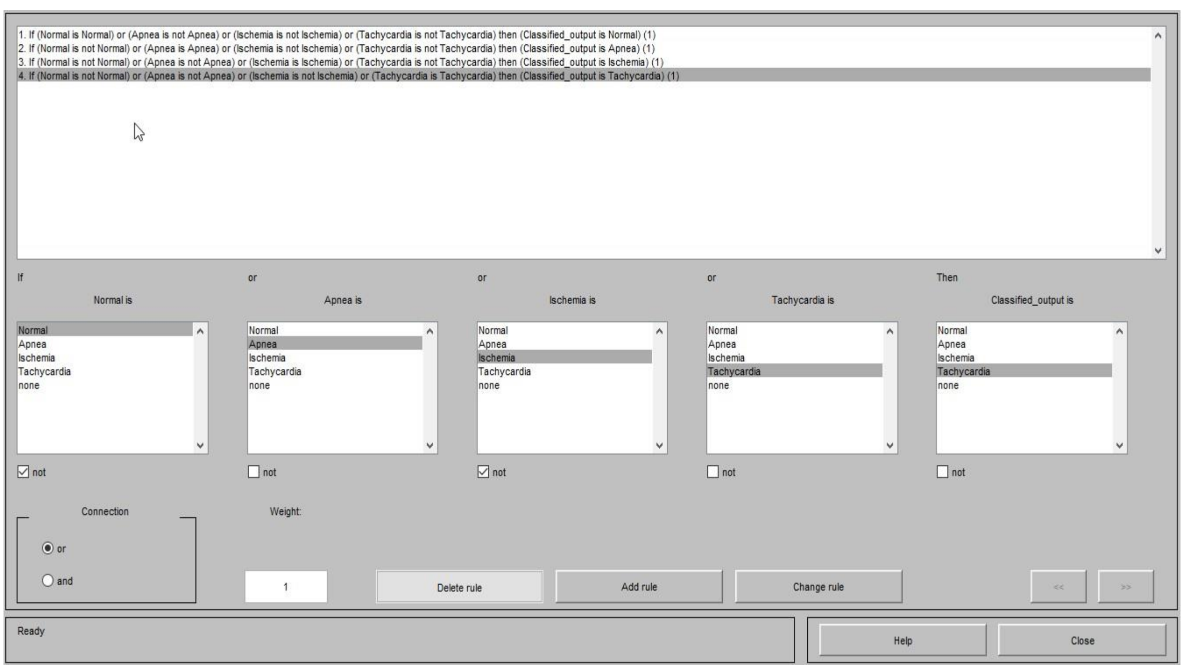

Fig.4.10. Fuzzy Rule Design

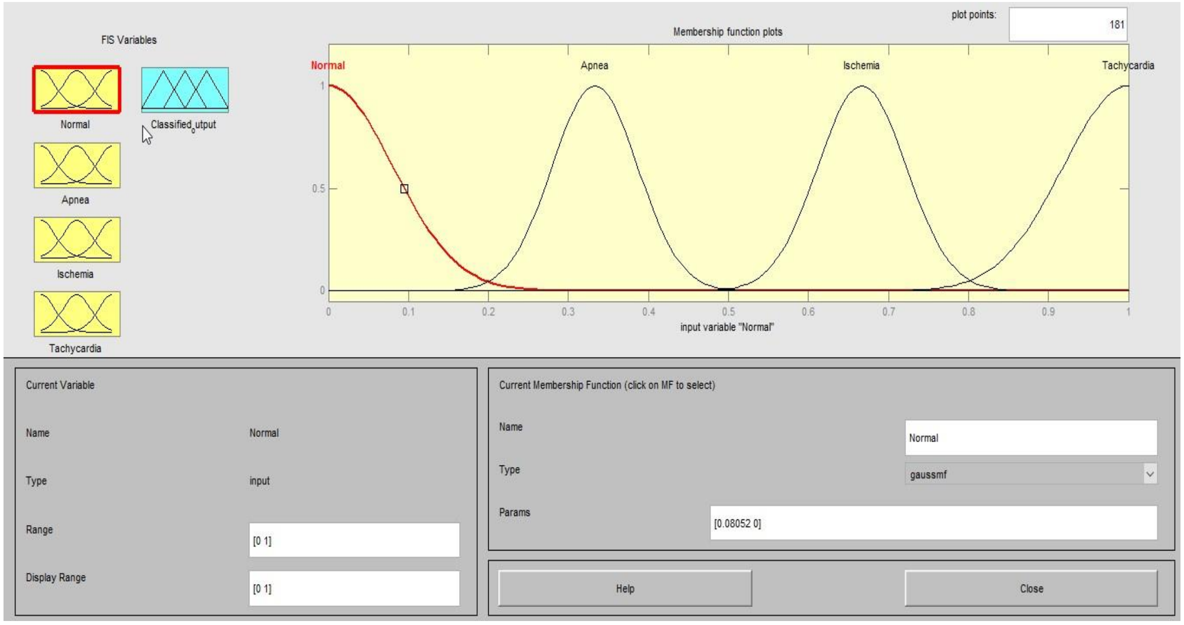

Fig.4.11. Membership_functions for Inputs

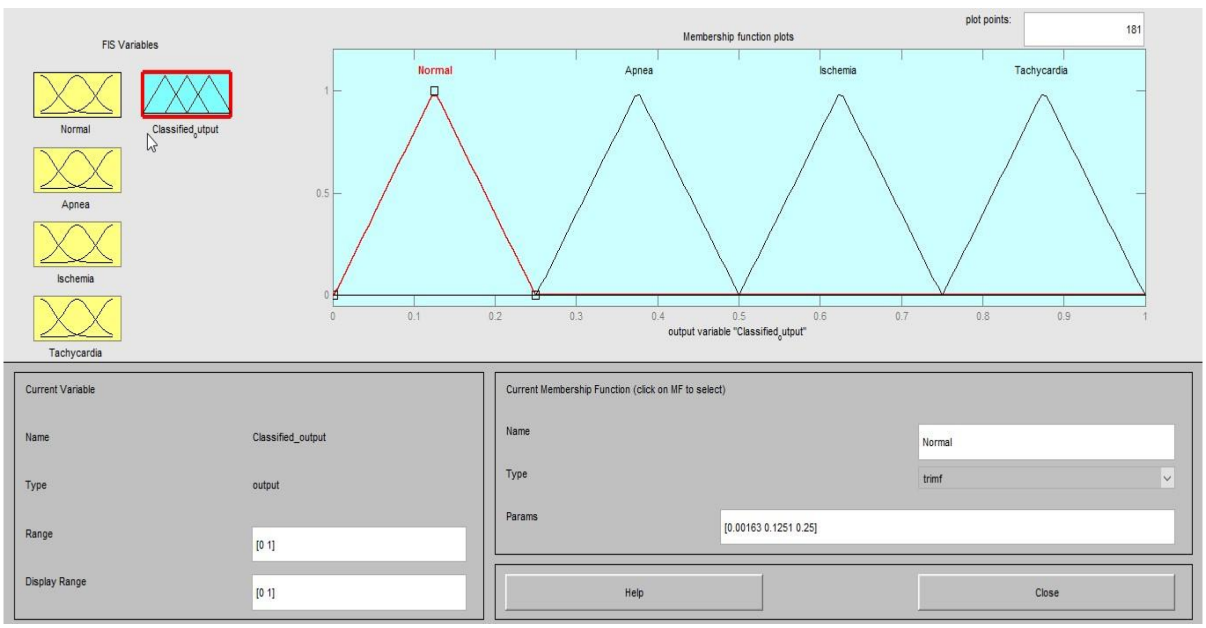

Fig.4.12. Membership Function for Output

In the Table 4.4 shown is the confusion matrix for the Fuzzy classifier. The table shows good accuracy in classifying the different types of ECG signals used during this project. An accuracy of 91.70% is achieved using this classifier. Even now, some signals are mis-classified using this classifiers which is corrected using the hybrid of Neural network and the fuzzy classifiers. Neuro-Fuzzy Classifier.

Table 4.4: Confusion matrix from Fuzzy

Targets→ / Outputs↓	AP	IS	NR	TC	Accuracy
AP	10/12	0/12	0/12	2/12	83.33%
IS	0/12	11/12	0/12	1/12	91.67%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	0/12	1/12	11/12	91.67%

Therefore, next classifier used is the Neuro-Fuzzy classifier for the classification of different types of ECG signals.

4.5 Classification Using Neuro-Fuzzy Logic

Neuro-Fuzzy Logic is applied on the ECG signals according to the structure shown in the Fig.4.13. This is a Neuro-Fuzzy structure. It is a multi-layer neural network with fuzzy rules inbuilt in it. In this, Fuzzy rules are used in the hidden layer of the Neural Network and hence, named as Neuro-Fuzzy Classifier.

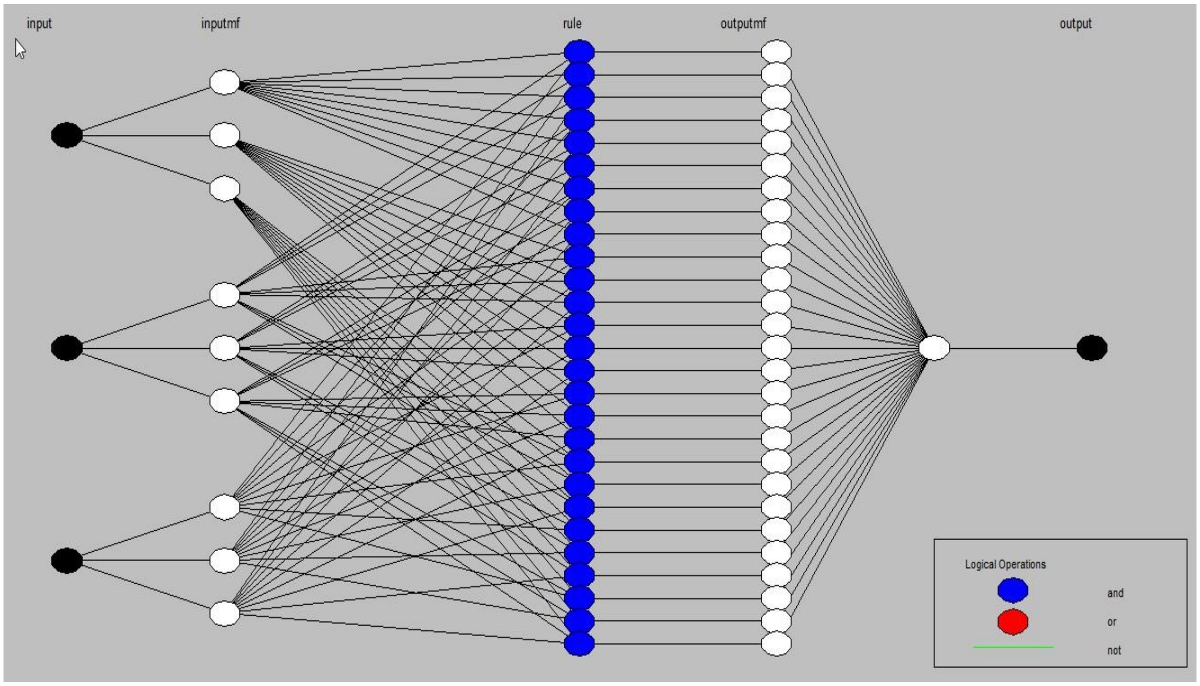

Fig.4.13. Neuro-Fuzzy Structure

Now, in Fig.4.14-16, shows about the training data that how it will look during training (Fig.4.14), after training (Fig.4.15) and the error comes during training (Fig.4.16).

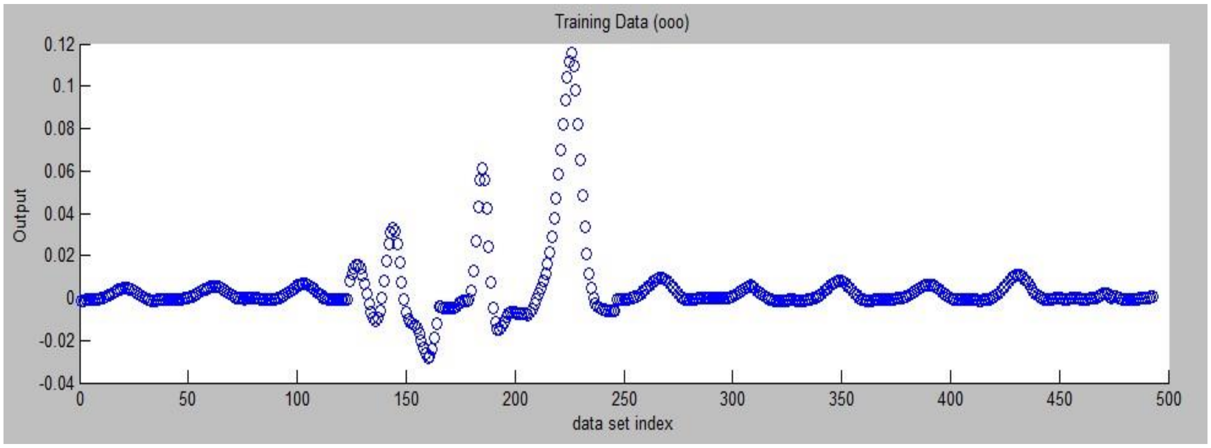

Fig.4.14. Training data

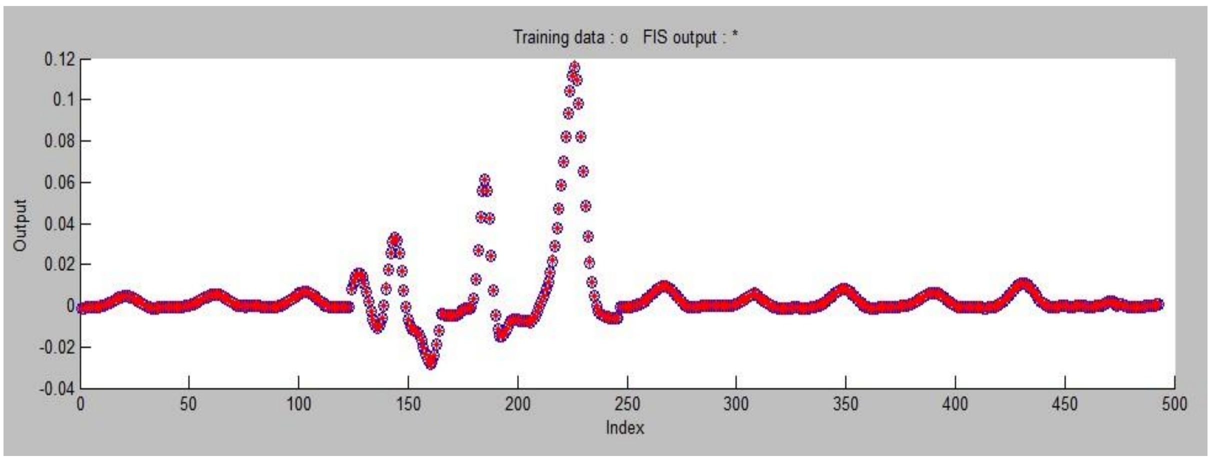

Fig.4.15. Trained data

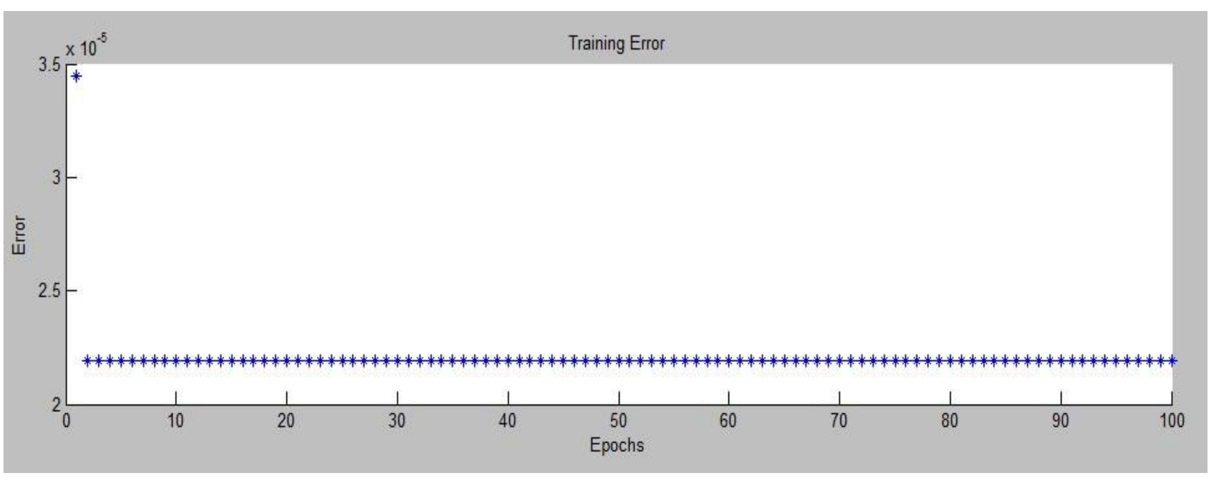

Fig.4.16. Training error

Then next figures shows about testing using the Neuro-Fuzzy classifier. Among these figures, Fig.4.17-18 shows the testing data and testing results. And, Fig.4.19 represents the rule viewer which are made using the Fuzzy logic in this classifier.

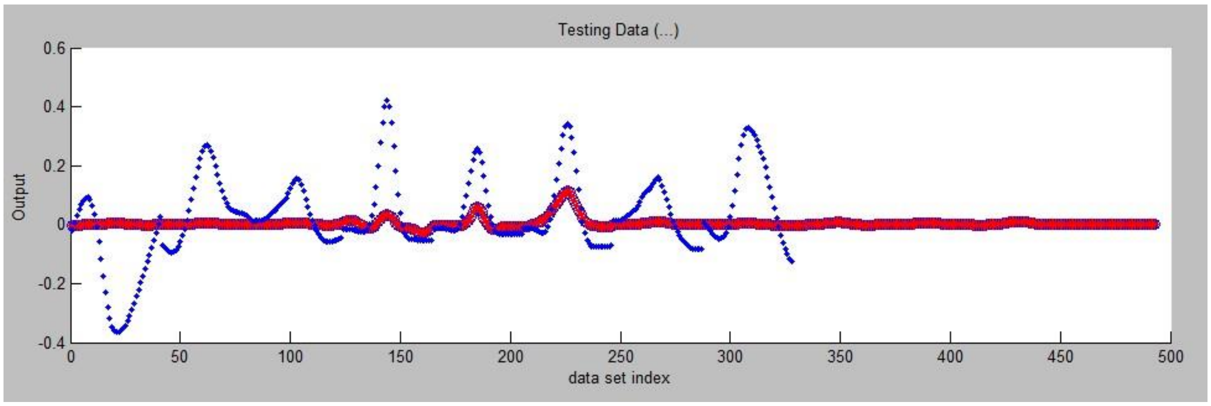

Fig.4.17. Testing data

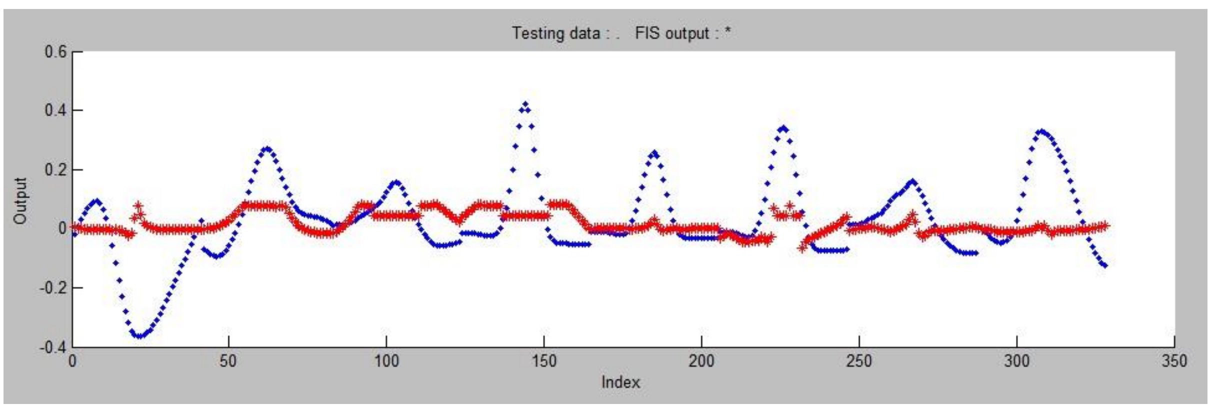

Fig.4.18. Testing results

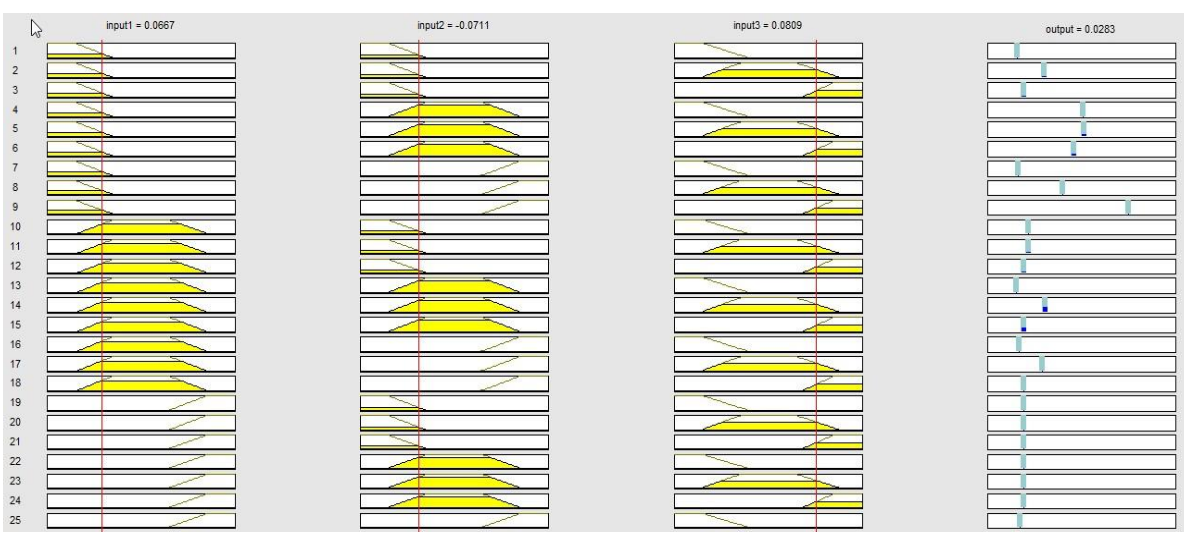

Fig.4.19. Neuro-Fuzzy rules

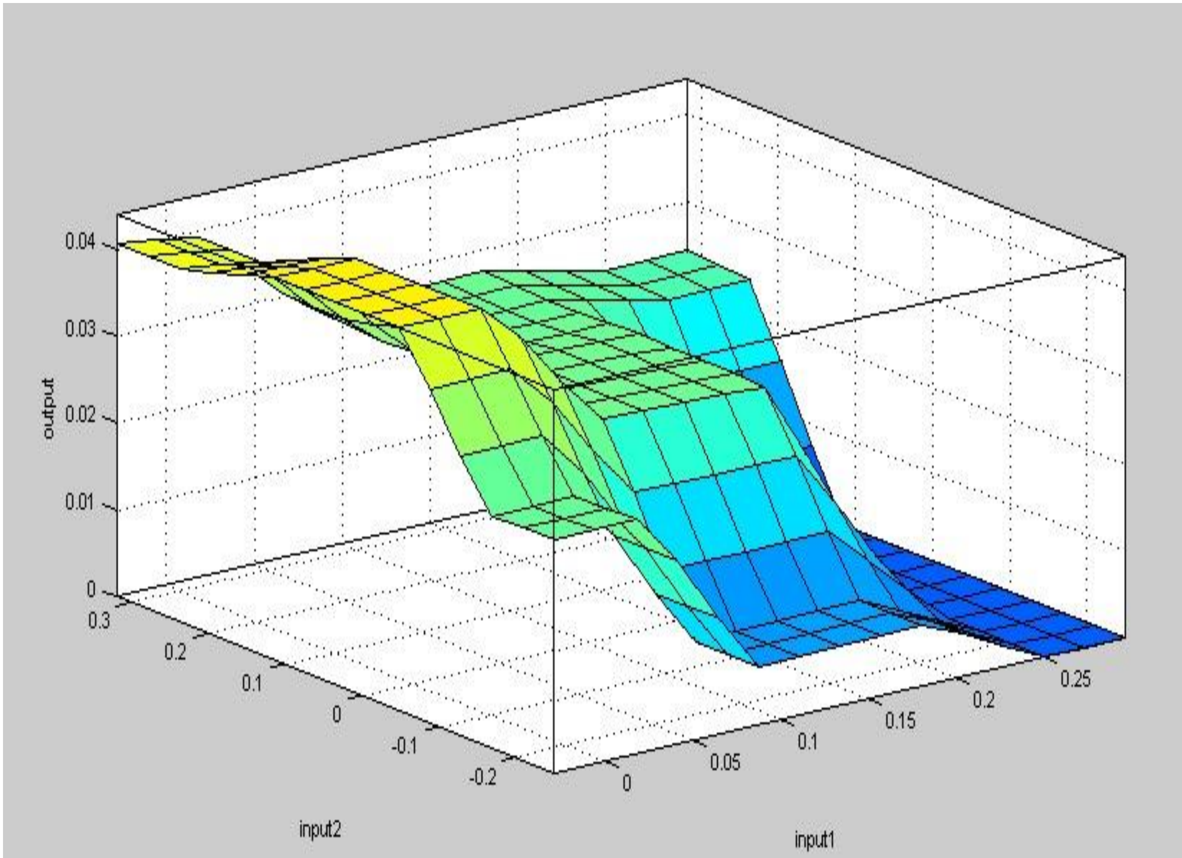

Fig.4.20. Neuro-Fuzzy Surface viewer

Fig.4.20 represents the surface viewer of the classification results obtained from the Neuro-Fuzzy classifier. Then next, in Table 4.5, confusion matrix is shown showing the classification using Neuro-Fuzzy classifier. And it can be seen from the table that only 1-1 signals (AP and IS) are misclassified in the other classes but all other signals are accurately classified using this classifier.

Table 4.5: Confusion matrix from Neuro-Fuzzy

Targets → **Outputs ↓**	**AP**	**IS**	**NR**	**TC**	**Accuracy**
AP	11/12	1/12	0/12	0/12	91.67%
IS	1/12	11/12	0/12	0/12	91.67%
NR	0/12	0/12	12/12	0/12	100%
TC	0/12	0/12	0/12	12/12	100%

4.6 Comparison of All the Classifiers Used

Then in Table 4.6 shown is the comparison of all these classifiers used during this research and it is perceived from the table that Neuro-Fuzzy classifier used gives the best results**.**

Table 4.6: Comparison of four classifiers

Classifier Name	**Accuracy(%)**
SVM	85.4
ANN	87.5
Fuzzy	91.70
Neuro-Fuzzy	95.83

4.7 Summary

Table 4.7: Comparison of proposed method of ECG classification with other methods

REFERENCE	**METHODS USED**	**ACCURACY**
Proposed Method	***Neuro-Fuzzy***	***95.83%***
Chiu et al.[18]	Nearest center	95.71%
Palaniappan and	Neural Network	94.6%
Yao and Wan[19]	Low Match Score (LMS)	91.5%
Homer et al.[20]	kNN	85.2%
Odinaka et al.[21]	Generative Model Classifier	76.9%

Now Table 4.7 displays the comparison of the best method that Neuro-Fuzzy comes out from this research with the earlier methods that have already been used for the ECG classifications using some other techniques i.e. other than the method which is used during this work.

Chapter 5
CONCLUSION & FUTURE SCOPE

5.0) Overview

This chapter discussed overall process and outcomes of ElectroCardioGram (ECG) Analysis using Principal component analysis and various classifiers including the facing problems and project limitation during the projects.

5.1) Conclusion

This thesis is an endeavour to suggest a solution utilizing the hybrids algorithms and to determine an optimum ECG classification scheme designed for the medical environment, where technological advancements have seen changes to many aspects of the daily lives, but there is still a significant gap between the existing solutions and the needs in the medical field. This system provides an analysis system that is capable to identify the certain heart disease.

This analysis system is composed of three major components. Based on the pre-processing stage, it is responsible for gathering the database for patient from MIT- BIH Arrhythmia database. This stage have been done by dividing each element of the heart disease phase into Normal signal, Apnea signal, Tachycardia signal, and Ischemia signal. The signals are successfully evaluated and processed. The data gathered from the selected databases are connected to MATLAB software where the data are processed.

The second part of the analysis system is based on applying Principal Component Analysis (PCA) theories. This takes PCA algorithm as a medium to process the patient data. These features provide significant information regarding the analysis of possible heart diseases. The data are successfully can be extracted from 48 subjects of patients signal in classifying the Normal signal, Apnea signal, Tachycardia signal and Ischemia signal.

Finally, the last part of this system involve various classifiers such as SVM, ANN, Fuzzy and Neuro-fuzzy classifiers in classifying the heart disease where the decision of heart disease is made based on the extracted features processed by Principal Component Analysis algorithm. Neuro-fuzzy classifier plays an important role and gives the best results in dealing with uncertainty when making decisions in medical application. The ability to learn how to determine results from the sample data is its biggest asset. In Neuro-fuzzy classifiers, the membership function parameters are extracted from dataset that describes the behavior of the ECG signals. Neuro-fuzzy classifier was used to detect ECG changes while the P-QRS-T parameters are defined as its inputs. The Neuro-fuzzy classifier presented in this study was trained with the back-propagation gradient descent method combining with the least squares method. Neuro-fuzzy classifier is able to get total classification accuracy rate up to 95.83% compared to 91.70% with fuzzy, 87.50% with ANN and 85.40% with SVM for classifying Normal, Apnea, Tachycardia and Ischemia class. The Neuro-fuzzy classifier model presented in this study prove that it achieved the higher rates of classification accuracy.

5.2) Limitation and Problems

There are many types of heart disease which their ECG signals vary closely in amplitude and time duration and represent the expected disease. So the signals must be understood and recognize clearly to make sure the signals are not misclassified.

The increasing of input nodes will also cause the networks to learn more complex functions and relatively increase the number of training epochs to complete the learning process until the root mean square error close into zero error rates.

5.3) Future Work

- There are large number of patients present in intensive care units and hence, the need for continuous observation is also required. The current technology development can help to develop the automated ECG monitoring system that allows the system for continuous heart signal monitoring capabilities. By automating the ECG monitoring process, the most updated information for all patients are made available at all times and avoided the delays treatments. It is also can intended to give support to the current health care environments.

- The characteristics of the wave features for the ECG analysis can be extended to the other form by using a better or other hybrid algorithms to evaluate the selected features which suitable for many types of heart disease detection.
- The quality of accuracy, sensitivity and specificity of ECG analysis can be improved by adding more input databases in the training samples , so that the system are able to learn more and train the system to identify the signal accurately.
- The diagnostic accuracy of Neuro-fuzzy classifier model which combined the neural network adaptive capabilities and the fuzzy logic qualitative approach also can be improve by combining several Neuro-fuzzy classifier in input data training stage.
- The performance of accuracy and training time for classifying the heart disease of ECG analysis systems that widely done in MATLAB software can be improved by embeds the system in the Field Programmable Logic Arithmetic (FPGA). In the code development, more accurate algorithms rates should be used.

REFERENCES

1. S. Graja and J.M. Boucher, (2005) “Hidden Markov Tree Model Applied to ECG Delineation”, IEEE Transactions on Instrumentation and Measurement, vol. 54, no. 6.
2. Ahmadian, S. Karimifard, H. Sadoughi and M. Abdoli, (2007) “An Efficient Piecewise Modeling of ECG Signals Based on Hermitian Basis Functions”, in Proc. IEEE EMBS, pp. 3180-3183.
3. V. Sharmila, E. HariKrishna, K.N. Reddy, K.A. Reddy, (2013) “A New Method for Enhancement of ECG Signals Using Cumulant Based AR Modeling”, Proc. Of IEEE Conference on Information and Communication Technologies.
4. Liang-Yu Shyu, Ying-Hsuan Wu, and Weichih Hu, (2004) “Using Wavelet Transform and Fuzzy Neural Network for VPC Detection From the Holter ECG”, Ieee Transactions On Biomedical Engineering, Vol. 51, No. 7.
5. Shivajirao M. Jadhavl, Sanjay L. Nalbalwar, Ashok A. Ghatol, (2010) “ECG Arrhythmia Classification using Modular Neural Network Model”.
6. Manab Kumar Das, Dipak Kumar Ghosh and Samit Ari, (2013) “Electrocardiogram (ECG) Signal Classification using S-transform, Genetic Algorithm and Neural Network”, IEEE 1st International Conference on Condition Assessment Techniques in Electrical Systems.
7. Argyro Kampouraki, George Manis, and Christophoros Nikou, (2009) “Heartbeat Time Series Classification With Support Vector Machines”, Ieee Transactions On Information Technology In Biomedicine, Vol. 13, No. 4.
8. Shwetha Edla, Narayan Kovvali, and Antonia Papandreou-Suppappola, (2014) “Electrocardiogram Signal Modeling With Adaptive Parameter Estimation Using Sequential Bayesian Methods”, Ieee Transactions On Signal Processing, Vol. 62, No. 10.
9. I.A. Hameed, C.G. Sorensen, O. Green, (2011) “Building an intelligent controller using simple genetic type-2 fuzzy logic system”. ‘Fuzzy controllers, theory and applications’, ed. Grigorie, L. ISBN:978-953-307-543-3, pp. 148–162.
10. Kartik Audhkhasi, Osonde Osoba, Bart Kosko, (2013) “Noise Benefits in Backpropagation and Deep Bidirectional Pre-training”.

11. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, (2015) “Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition”, Ieee Transactions On Pattern Analysis And Machine Intelligence, Vol. 37, No. 9.
12. Chia-Feng Juang and Po-Hsuan Wang, (2015) “An Interval Type-2 Neural Fuzzy Classifier Learned”.
13. Databases webpage on Physionet (2012). [Online]. Available: http://www.physionet.org/physiobank/.
14. R Kapoor and R. Gupta, (2015) "Morphological mapping for non-linear dimensionality reduction," in Computer Vision, IET, vol.9, no.2, pp.226-233.
15. V. Sharmila1, E. HariKrishna, K. Nagarjuna Reddy, K. Ashoka Reddy, (2013) “A New Method for Enhancement of ECG Signals Using Cumulant Based AR Modeling”, Proceedings of IEEE Conference on Information and Communication Technologies.
16. R. J. Martis, U. R. Acharya, A. K. Ray, C. Chakraborty , (2011) “Application of higher order cumulants to ECG signals for the cardiac health diagnosis”, Engineering in Medicine and Biology Society, EMBC, Annual International Conference of the IEEE.
17. Ayman Rabee and Imad Barhumi, (2012) “Ecg Signal Classification Using Support Vector Machine Based On Wavelet Multiresolution Analysis”, 11th International Conference on Information Sciences, Signal Processing and Their Applications.
18. R. Palaniappan and S. M. Krishnun, (2004) “Identifying individuals using ECG beats,” in Proc. Int. Conf. Signal Processing and Communications, pp. 569–572.
19. C.-C. Chiu, C.-M. Chuang, and C.-Y. Hsu, (2008) “A novel personal identity verification approach using a discrete wavelet transform of the ECG signal,” in Proc. 2nd Int. Conf. Multimedia and Ubiquitous Engineering, Busan, Korea.
20. J. Yao and Y. Wan, (2008) “A wavelet method for biometric identification using wearable ECG sensors,” in Proc. 5th Int. Summer School and Symp. Medical Devices and Biosensors, (ISSS-MDBS 2008), pp. 297–300.
21. M. Homer, J. M. Irvine, and S. Wendelken, (2009) “A model-based approach to human identification using ECG,” in Proc. SPIE, Orlando, FL, vol. 7306.
22. I. Odinaka, P.-H. Lai, A. D. Kaplan, J. A. O’Sullivan, E. J. Sirevaag, S. D.

Kristjansson, A. K. Sheffield, and J. W. Rohrbaugh, (2010) “ECG biometrics: A robust short-time frequency analysis,” in Proc. IEEE Int. Workshop Information Forensics and Security (WIFS), pp. 1–6.

23. Jang, J.S.R., Sun, C.T. and Mizutani, E. (1997) Neuro Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. United States of America: Prentice-Hall.
24. Mitra, S.K. (2006) Digital Signal Processing: A Computer-Based Approach. New York: McGraw-Hill.
25. Proakis, J.G. and Manolakis D.G. (2007) Digital Signal Processing: Principles, Algorithms and Application. New Jersey: Prentice-Hall.
26. Ahmadian, A., Karimifard, S., Sadoughi, H. and Abdoli, M. 2007, ‘An Efficient Piecewise Modeling of ECG Signals Based on Hermitian Basis Functions’, Proceedings of the 29th Annual International Conference of the IEEE EMBS, Lyon, France, pp. 3180-3183.
27. Bortolan, G., Degani, R. and Pedrycz, W. 1989, ‘A Fuzzy Pattern Matching Technique for Diagnostic ECG Classification’, In IEEE Proceeding.
28. Burges, C.J.C. 1998, ‘A Tutorial on Support Vector Machines for Pattern Recognition", Data Mining and Knowledge Discovery’, vol. 2, pp. 121-167.
29. Castro, B., Kogan, D. and Geva, A.B. 2000, ‘ECG Feature Extraction Using Optimal Mother Wavelet’, Proceeding IEEE Convention of the Electrical and Electronic Engineering, Tel-Aviv, Israel, pp. 346-350.
30. Chrysostomas L.Nikias,Athina P.Petropulu, “Higher order spectral Analysis: A Non Linear Signal Processing FrameWork”, Prentice Hall, 1993.
31. Douglas, A.C., Stern, R.M., Cano, G.G. and Briller, S.A. 1990, ‘An Approach to Cardiac Arrhythmia Analysis Using Hidden Markov Models’, IEEE Transactions of Biomedical Engineering, vol. 37, no. 9.
32. Frau, C.D., Cortes, J.C., Garcia, A.G. and Novak, D. 2002, ‘Feature Extraction Methods Applied to the Clustering of Electrocardiographic Signals: A Comparative Study’, Proceedings of the 16th Annual International Conference on Pattern Recognition vol. 3, pp. 30961.

33. Gao, D., Madden, M., Schukat, M., Chambers, D. and Lyons, G. 2004, ‘Arrhythmia Identification from ECG Signals with a Neural Network Classifier Based on a Bayesian Framework’, Department of Information Technology, National University of Ireland.
34. Goletsis, Y., Papaloukas, C., Fotiadis, D.I., Likas, A. and Michalis, A.K. 2004, ‘Automated Ischemic Beat Classification Using Genetic Algorithms and Multicriteria Decision Analysis’, IEEE Transactions of Biomedical Engineering.
35. Graja, S. and Boucher, J.M. 2005, ‘Hidden Markov Tree Model Applied to ECG Delineation’, IEEE Transactions on Instrumentation and Measurement, vol. 54, no. 6.
36. Heden, B., Ohlsson, M., Edenbrandt, L. and Rittner, R. 1995, ‘Artificial Neural Networks for Recognition of Electrocardiographic Lead Reversal’, University Hospital Sweden.
37. Hu, Y.H., Palreddy, S. and Tompkins, W. 1997, ‘A Patient Adaptable ECG Beat Classifier Using A Mixture of Experts Approach’, IEEE Transactions of Biomedical Engineering, vol 44, pp. 891-900.
38. Hughes,N.P., Tarassenko, L. and Roberts, S.J. 2003, ‘Markov Models for Automated ECG Interval Analysis’.
39. Jager F. 2002, ‘Feature Extraction and Shape Representation of Ambulatory ElectroCardioGram (ECG) Using the Karhunen-Lo`eve Transform’, Electrotechnical Review, Ljubljana, Slovenija.
40. Lagerholm, M., Peterson, C., Braccini, G., Edenbrandt, L. and Sornmo, L. 2000, ‘Clustering ECG Complexes Using Hermite Functions and Self-Organizing Maps’, IEEE Transactions of Biomedical Engineering, vol. 47, no. 7.
41. Li, C., Zheng C. and Tai, C. 1995, ‘Detection of ECG Characteristic Points Using Wavelet Transforms’, IEEE Transactions of Biomedical Engineering, vol. 42, no. 1.
42. Lin, K. and Chang, W.H. 1989, ‘QRS Feature Extraction Using Linear Prediction’, In IEEE Transactions of Biomedical Engineering vol. 36, no. 10, pp. 1050–1055.
43. Minami, K., Nakajima, H. and Toyoshima, T. 1999, ‘Real-Time Discrimination of Ventricular Tachyarrhythmia with Fourier-Transform Neural Network’, IEEE Transactions of Biomedical Engineering, vol 46.

44. Moraes, J.C.T.B., Seixas, M.O., Vilani, F.N. and Costa, E.V. 2002, 'A Real Time QRS Complex Classification Method Using Mahalanobis Distance', Computer Cardiogi.
45. Osowski, S., Hoai, L.T. and Markiewicz, T. 2004, 'Support Vector Machine Based Expert System for Reliable Heart Beat Recognition', IEEE Transactions of Biomedical Engineering, vol. 51, no. 4.
46. Papaloukas, C., Fotiadis, D. I., Likas, A. and Michalis, LK. 2002, 'An Ischemia Detection Method Based On Artificial Neural Networks', Artificial Intelligence in Medicine, vol 24, issue 2, pp. 167-178.
47. Papaloukas, C., Fotiadis, D.I., Likas, A. and Michalis, L.K. 2003, 'Automated Methods for Ischemia Detection in Long-Duration ECGs', Cardiovascular Reviews and Reports, vol. 24, no. 6, pp. 313-319.
48. Pretorius, L.C. and Nel, C. 2002, 'Feature Extraction from ECG for Classification By Artificial Neural Network', In Fifth Annual IEEE Symposium on Computer-Based Medical Systems , pp. 639-647.
49. Silipo R. and Marchesi, C. 1998, 'Artificial Neural Networks for Automatic ECG Analysis', IEEE Transactions on Signal Processing, vol. 46, no. 5.
50. Yang, M.Y., Hu, W.C. and Shyu, L.Y. 1997, 'ECG Events Detection and Classification Using Wavelet and Neural Networks',In Proceeding of the Annual Conference of the IEEE Engineering in Medicine and Biology Society, vol. 1, pp 289–292.
51. Zong, W. and Jiang, D. 1998, 'Automated ECG Rhythm Analysis Using Fuzzy Reasoning, In IEEE Conference of Computers in Cardiology, pp. 69872.