Wavelet Sub-band Energy based ECG Classification

A Dissertation submitted towards the partial fulfilment
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Submitted by

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CERTIFICATE

This is to certify that the dissertation title "**Wavelet subband energy based ECG classifiaction** " submitted by **Mr. Vivek Jain, Roll. No. 2K15/SPD/19**, in partial fulfilment for the award of degree of Master of Technology in

"**Signal Processing and Digital Design (SPDD)",** run by Department of Electronics & Communication Engineering in Delhi Technological University during the year 2015-2017,is a bonafide record of student's own work carried out by him under my supervision and guidance in the academic session 2016-17. To the best of my belief and knowledge the matter embodied in dissertation has not been submitted for the award of any other degree or certificate in this or any other university or institute.

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DECLARATION

I hereby declare that all the information in this document has been obtained and presented in accordance with academic rules and ethical conduct. This report is my own work to the best of my belief and knowledge. I have fully cited all material by others which I have used in my work. It is being submitted for the degree of Master of Technology in Signal Processing & Digital Design at the Delhi Technological University. To the best of my belief and knowledge it has not been submitted before for any degree or examination in any other university.

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ABSTRACT

The electrocardiogram (ECG) is mainly used biological signal in biomedical because it detect the the several cardiac abnormalities Classification of electrocardiogram (ECG) signal play an important role in diagnoses of heart diseases. An accurate ECG classification is a challenging problem.90 This detection and classification of electrocardiogram (ECG) signals is significantly associated to the diagnosis of cardiac abnormalities. In this thesis, a new approach for ECG classification is obtainable using features based on wavelet subband energy coefficients. The ECG signals are decomposed into time-frequency representation with wavelet transform and then wavelet coefficients are used to calculate some statistical parameters. Types of ECG beat considered for the classification are normal beat, paced beat, pre-ventricular contraction, left bundle branch block and right bundle branch block beat. The signals are obtained from the MIT-BIH Arrhythmia database. Multilayer Perceptron Neural Network is use for classification.

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1 INTRODUCTION

1.1 Overview

This chapter contain brief information about the introduction to ECG, principle, working and problem related to Electrocardiogram (ECG) and its analysis. Here we discuss the Electrocardiogram (ECG) analysis problem concerning health issue which inspire the present research. Then presented the problem definitions from the previous studies, the research objectives, scope of the present work and thesis outlines.

1.2 Electrocardiogram (ECG)

Electrocardiogram (ECG) is an analysis of the electrical activity of the heart over a period of time and is recorded by a devce which is connected externally to the body by using the electrode attached to the surface of the skin. The waveform that are produced by this is non-invasive process and are called as Electrocardiogram (ECG).

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

1.3 Principles of ECG

ECG device perceives the minute electrical change on the skin that are caused when the heart muscles depolarizes during each heartbeats thereafter amplifies them.

- E heryart muscles cells have 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 spred 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 waves indicates generally the rhythm of the hearts and weaknesses in different parts of the heart.

- Generally more than 2 electrodes are used for the heart rhythm detection which can be formed into number of pairs such as Right Arm (RA), Left Leg (LL) and Left Arm (LA) electrodes form the 3 pairs, LA + LL+ RA + LL and LA + RA. The outputs from every pairs are called as lead and each leads look from a different angle into the heart. Different types of ECGs recorded include numbers of lead such as "3-lead, 5-lead and 12-lead ECG."

- 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.

1.4 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 ventrices.

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, it becomes ready again to depolarise for the next cardiac cycle

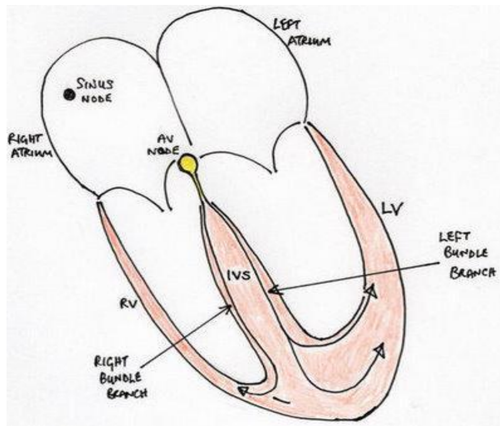

Fig: 1.1 Electropysiology of heart

1.5 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). 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.

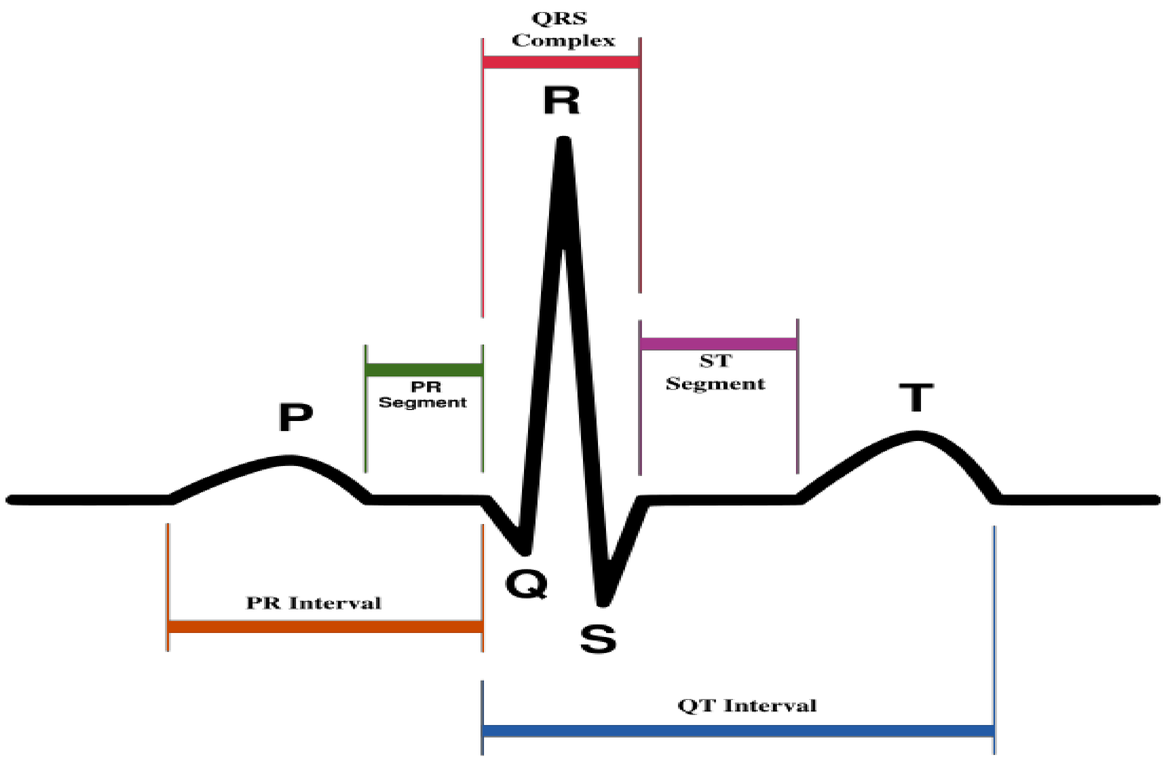

Figure 1.2. Normal ECG pattern

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.

1.5.1 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 start from the beginning of the "P wave" and last to the first deflections of the QRS-complexs.

- 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.

1.5.2 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.

A number of factors change the heart frequency, including:

- the (para) sympathic nervous system.
- The **sympathic system**, e.g. epinephrine, (=adrenalin) increases atrioventricular conduction and contractility (the *fight or flight* reaction.)
- The parasympathic system (nervus vagus,) e.g. acetycholine, decreases the frequency and atrioventricular conduction. The parasympathic system affects mainly the atria.
- Cardiac filling increases the frequency.
- Arrhythmias influence heart rate.

1.6 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.

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.

1.7 Advantages and Disadvantages of ECG

1.7.1 Advantages:

From the ECG tracing, the subsequent info is 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.

1.7.2 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.)

1.8 Research Significance

The ECG analysis systems are the biosignals processing area which involves in the application of the computer science & engineering to be detected & visualize the biological processes. It is necessary tool & information to the studies of diseases to use as a advance technologies to the complicated issues of medical aid that essential to boost the patient living quality and appropriate treatment.

So the researchs are important as it can be utilized by the other healths 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 recorded the heart condition at the initial 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.

1.9 Research Objective

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 accuracy of the research outputs that makes sured the correct results for the heart problems. Basically the goals of this analysis as follow.

- 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.

1.10 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 ANN and SVM It also discusses MATLAB software of the system

Chapter 4 discusses the features extraction and classification result of ECG analysis using ANN and other 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 ANN and other 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 TWO

LITREATURE REVIEW

2 LITERATURE REVIEW

2.1 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.

2.2 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).

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.

2.3 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 produce 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.

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2.4 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 result. 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.

2.4.1 Artificial Neural Network

Artificial neural network model exploiting morphological classification of heartbeats. The classification of the QRS-complex was the main step in their work to observe Arrhythmia. 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 replies 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.Another advantage is MART'S potency within the multiplication of morphological categories. 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.

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.

2.4.2 Support Vector Machine

S. S. Mehta, and N. S. Lingayat had studied the QRS-complex for the detection of un-wellness 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-

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

Where w is weight and b is bias. After the solution is find out it give rise to a decision function of the for Where, decision function is considered in the form of sgn(($w.x$)+b).

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 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 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.

2.5 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) analyzing 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 yields 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 in feature extraction and classification techniques, it's found that Artificial Neural Network and hybrid ways are one amongst the newest ECG analysis techniques researches significantly in bio-signal 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 THREE

PROPOSED METHOD

3 PROPOSED METHOD

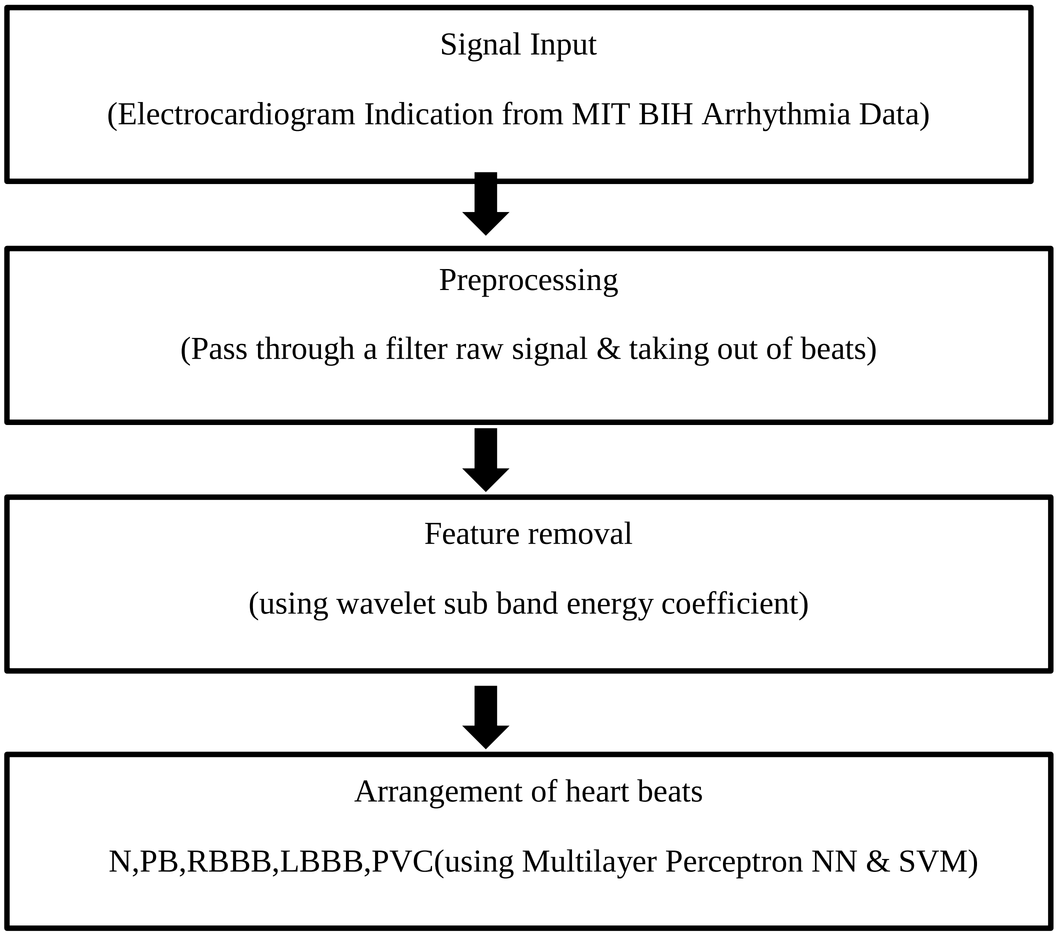
3.1 Overview

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 features based on wavelet sub-band energy coefficients. and (3) classification procedures using SVM, ANN, classifiers for analysis purposes will be explained. Also, a brief simulation procedure is presented in this chapter.

3.2 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. Bio-signal 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 bio-signal information.



Block diagram of the proposed method

3.3 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 .x

3.4 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, Arrhythmia characteristic. Secondly, a method is given for extracting the features vector for every sample of chosen heart disease exploiting an algorithm named as features based on wavelet sub-band energy coefficients. Lastly, this part conferred the procedures of classification process using ANN & SVM.

3.4.1 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.

3.4.2 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

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)

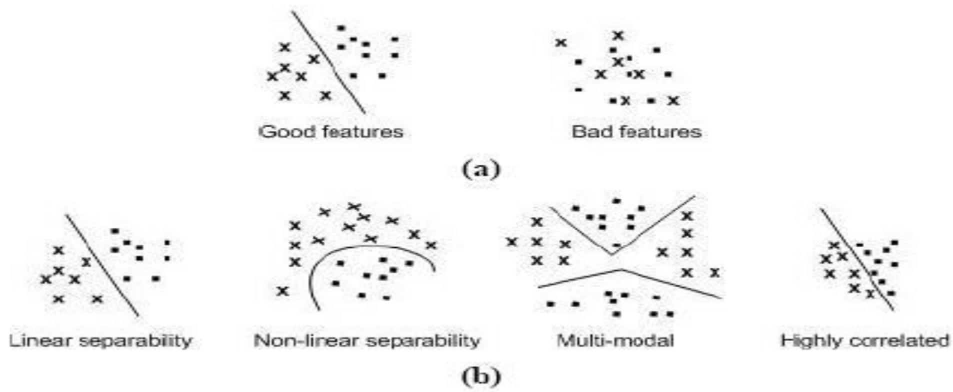


Fig.3.2. Characteristic (feature); a. the distinction between good and poor features, and b. feature properties.

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).

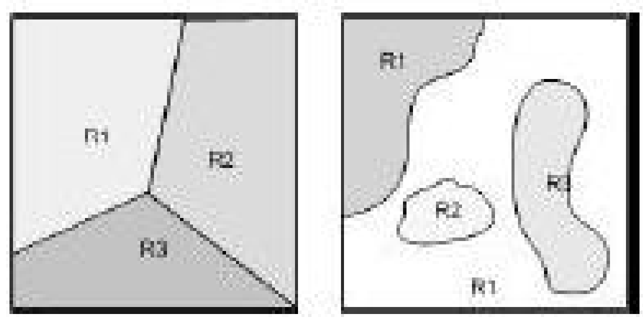


Fig.3.3. Classifier and decision boundaries

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 minimize $J(f, f_0)$.

Clearly, making the norm minimum will make 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

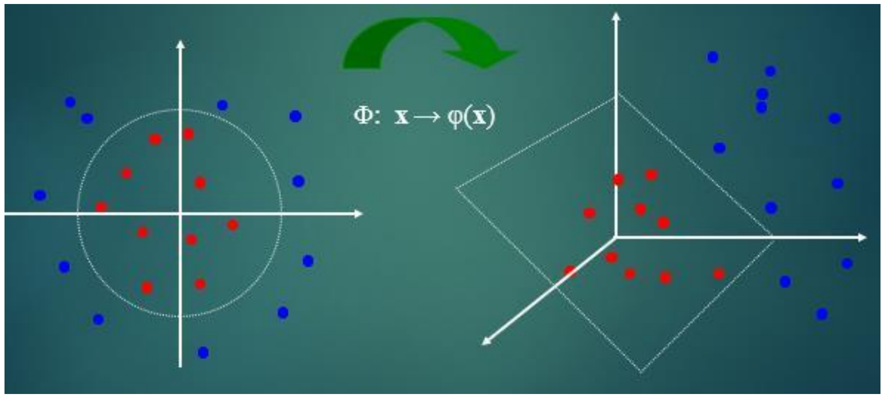


Fig.3.4. Classification using SVM Classifier

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

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

To achieve good performance 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

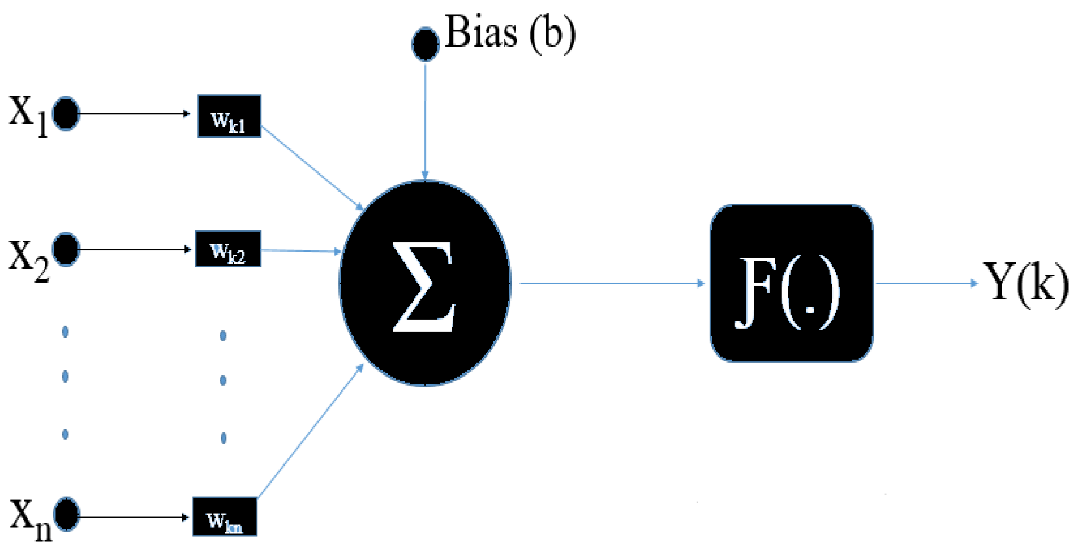


Fig.3.5. Neuron Model

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

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

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.

CHAPTER FOUR
RESULTS & DISCUSSIONS

4.1 Database

We used the MIT-BIH arrhythmia database. A total of five types of signals (normal ECG signal + 4 types of arrhythmia) are considered for the classification. These are:

1. Normal ECG signalPaced beat (PB)
2. Right Bundle Branch Block (RBBB)
3. Left Bundle Branch Block (LBBB)
4. Premature Ventricular Contraction (PVC)

From the MIT-BIH Arrhythmia database following is the table showing different signals for each category:

Hearts-beat Type	**ECG recording containing the respective type of beat**
Normal	101, 103, 200, 213, 221, 234
Paced Beat	102, 104, 107, 217
Left Budle Branch Block	109, 111, 207, 214
Right Bundle Branch Block	118, 124, 212, 231, 232
Premature Ventricu-lar Con-traction	100, 114, 119, 203, 205, 223

4.2 Evaluation metrics

For machine learning applications, accuracy is not an efficient metric for evaluation of the performance. There are certain other metrics are used which are described below:

4.2.1 Confusion matrix

It is a matrix that describes the performance of any classification system. For confusion matrix *C*, any element $C_{i,j}$ will represent the number of observations known to be in group *i* but classified or predicted to be in class *j*. The confusion matrix is a square matrix that show the count value of the true positive, false positive, true negative and false negative.

Consider the case of simple binary classification where only two classes exist: positive class denoted by P and negative class denoted by N. Confusion matrix for this case can be shown as below:

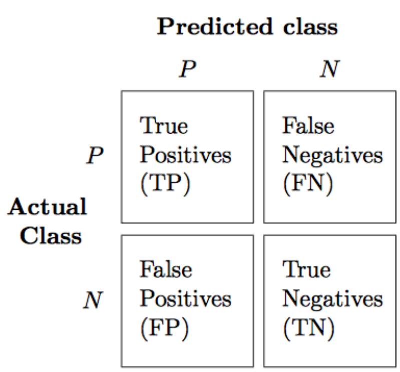


Figure 4.2: Confusion matrix

Note:

For multiclass classification problem, as like the case here, the value of TP, TN, FP and FN can be extracted from the confusion matrix as below:

- For any class, total number of examples will be the sum of the corresponding row (*i.e.* TP + FN)
- For any class, total number of FN will be the sum of values in the corresponding row (excluding TP) while FP will be the sum of values in the corresponding column (excluding TP)

- For any class, total number of TN will be the sum of rows and columns (excluding the row and column corresponding to that class)

4.2.2 Precision

It denotes the fraction of prediction which actually have positive class out of the total positive predicted classifications.

$$PRE = \frac{True\ Positives}{Predicted\ Positives} = \frac{TP}{TP + FP}$$

4.2.3 Recall

It denotes that of all the samples having positive class, what fraction correctly classified as positive class.

$$REC = \frac{True\ Positives}{Actual\ Positives} = \frac{TP}{TP + FN}$$

4.2.4 F1-score

For any classifier, precision and recall should be high. But both the precision and recall can't be high at the same time. Thus, another parameter is used for the analysis called F1-score.

$$F1 = 2\frac{PRE\ \times REC}{PRE + REC}$$

Value of F1-score lies in the range 0 to 1.

4.2.5 Accuracy

It is defined as the ratio of number of correct predictions to the total number of predictions.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

4.3 Results

We used two classifiers, Neural Networks and SVM for the classification of the above mentioned five types of arrhythmias. Different results obtained from these methods are as mentioned below:

4.3.1 Classification using Neural Network

4.3.1.1 Confusion matrix

	N	**PB**	**LBBB**	**RBBB**	**PVC**
N	**0.86**	0.04	0.03	0.01	0.08
PB	0.02	**0.91**	0.03	0.03	0.01
LBBB	0.00	0.01	**0.96**	0.03	0.00
RBBB	0.05	0.02	0.04	**0.89**	0.00
PVC	0.07	0.09	0.01	0.02	**0.81**

4.3.1.2 Precision, Recall and F1-score

	Precision	**Recall**	**F1-score**
N	0.860	0.860	0.860
PB	0.850	0.910	0.878
LBBB	0.897	0.960	0.923
RBBB	0.908	0.890	0.899
PVC	0.900	0.810	0.852

Accuracy calculated from the above-mentioned formula is: **88.6%**

4.3.2 Classification using SVM

4.3.2.1 Confusion matrix

	N	**PB**	**LBBB**	**RBBB**	**PVC**
N	**0.92**	0.02	0.00	0.00	0.06
PB	0.01	**0.97**	0.01	0.01	0.00
LBBB	0.00	0.00	**0.95**	0.03	0.02
RBBB	0.02	0.01	0.06	**0.89**	0.02
PVC	0.03	0.00	0.01	0.00	**0.96**

4.3.2.2 Precision, Recall and F1-score

	Precision	**Recall**	**F1-score**
N	0.938	0.920	0.928
PB	0.970	0.970	0.970
LBBB	0.922	0.950	0.935
RBBB	0.956	0.890	0.921
PVC	0.905	0.960	0.932

Accuracy calculated from the above-mentioned formula is: **93.8%.**

CHAPTER FIVE

CONCLUSION & FUTURE WORK

5 CONCLUSION & FUTURE SCOPE

5.1 Overview

This chapter discussed overall process and outcomes of ElectrocardioGram (ECG) Analysis using features based on wavelet sub-band energy coefficients. ANN and other classifiers including the facing problems and project limitation during the projects.

5.2 Conclusion

This thesis is an endeavor 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 has been done by dividing each element of the heart disease phase into Normal signal, Arrhythmia 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 features based on wavelet sub-band energy coefficients. These features provide significant information regarding the analysis of possible heart diseases. Finally, the last part of this system involve various classifiers such as SVM, ANN classifiers in classifying the heart disease where the decision of heart disease is made

5.3 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.

5.4 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 sample, so that the system are able to learn more and train the system to identify the signal accurately.
- 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.

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