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Classification of Cardiac Arrhythmias Based on Wavelet Transform and Neural Networks

تصنيف اشارة كهربية القلب اعتمادا على تحويلة المويجه والشبكه العصبيه

Submitted in partial fulfillment of the requirement of M.Sc (Honor) Degree in Biomedical Engineering

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List of Abbreviations & Symbols

ECG	Electrocardiographic
MIT-BIH	Massachusetts Institute of Technology/Beth Israel Hospital
N	Normal labeled heartbeat
Sv	Supraventricular ectopic beat
V	Ventricular ectopic beat
F	Fusion beat
Q	unknown beat
AAMI	Association for the Advancement of Medical Instrumentation
WFDB	Wave Form Data Base
AP	Atrial Premature
PVCs	Premature Ventricular Contractions
LBBB	Left Bundle Branch Block
NNWs	Neural Net Works
PRNNW	Pattern Recognition Neural Net Work
SA node	Sinoatrial node
AV node	Atrioventricular node
DWT	Discrete Wavelet Transform
Sym	Symlet
Db	Debauchies
EMG	Elecrtomyogram
IIR	Infinite Impulse Response
FIR	Finite impulse response
r	Radius
k	scale factor

BW	band width
f_x	sampling rate
f_o	centre frequency
θ	Angle of the pole
LPF	Low Pass Filter
HPF	High Pass Filter
S	Original Signal
cA, ca	Coefficient of Approximation
cD	Coefficient of Details
LMS	least mean square
EW	Error derivative of weight
EA	difference between the actual and the desired output
trainlm	Levenberg-Marquardt
MSE	Mean squared normalized error
Sim	Simulate neural network
TP	True positive
TN	True negative
FP	False positive
FN	False negative
PSD	power spectral density

ABSTRACT

Cardiac diseases are one of the most common causes of death, killing millions of people worldwide each year. However, they can be effectively controlled by early diagnosis. Electrocardiograph is the most important and powerful reference tool used to diagnosis and treatment of heart diseases, it represents the electrical activity of the heart and contains vital information about its rhythmic characteristics. This study was built to design computationally efficient models and an intelligent tool for diagnosis of ECG abnormalities with high accuracy while reducing the complexity, cost, and response time of the system and contributing to solve the problem of lacking of physician in rural area. The ECG signals obtained from MIT-BIH database; forty signals used for training and testing. De-noising processing was applied to power line interference and baseline wanders to facilitate accurate detection of features. Symlet wavelet transforms was selected as mother wavelet to feature extraction and pattern recognition Neural Net Works was used as classifier. The extracted features consisted twenty four features, it contain both morphological and statistical features of the signals, and is used as an inputs pattern recognition neural net work with ten hidden neuron layer, which identify normal ECG and four different types of arrhythmias, which are Paced, Atrial Premature, Ventricle Premature contraction and Left Block Bundle Branch.

The performance of the proposed method has been evaluated in terms of accuracy, sensitivity and specificity.

The accuracy of classification for each class are normal class is 100%, paced class is 90%, AP class is 73%, PVC class is 95% and for LBBB class is 100%.

المستخلص

أمراض القلب هي واحدة من أكثر الأسباب شيوعا للوفاة، وقتل الملايين من الناس في جميع أنحاء العالم كل عام. ومع ذلك، فإنها يمكن أن نتحكم بشكل فعال من خلال التشخيص المبكر. اشارة القلب هي أداة مرجعية مهمه وقوية تستخدم لتشخيص وعلاج أمراض القلب وهي تمثل نشاط كهربية القلب وتحتوي على معلومات حيوية عن خصائصه الإيقاعية. بنيت هذه الدراسة على نماذج فعالة حسابيا كوسيلة ذكية لتشخيص إشارات تخطيط القلب بدقة عالية مع تقليل التعقيد والتكلفة وزمن الاستجابة للنظام وتخفيف مشكلة نقص الطبيب في المناطق الريفية.

تم الحصول على إشارات التدريب والاختبار من قاعده بيانات MIT-BIH . وقد اتخذت اربعين اشاره، وتمت معالجتها بازالة التداخل الكهربي و الانحراف من خط الاساس والحصول على اشارة نقيه. تم تطبيق المويجه على الاشارات ومن ثم استخراج معظم الميزات المورفولوجية (الشكلية) والإحصائية من كل الإشارات، وتستخدم هذه الميزات الأربع والعشرين كمدخلات للشبكة العصبية للتعرف على الاشارات الطبيعه واربع امراض مختلفه اخرى. وقد تم تقييم أداء الطريقة المقترحة من حيث الدقة والحساسية والخصوصية و نتائج التجربة وضحت بان النظام المقترح لة القدرة على اعطاء نتائج مقبوله وجيده، ودقة التصنيف كالاتي:

النبضات الطبيعيه100% ، النبضات الغيرمنتظمه90%, تقلصات البطين السابقه لاوانها95%، تقلصات الاذين السابقه لاوانها(غيرناضجه)73% و انسداد حزمه الفرع الشمالي100%

Chapter One

Introduction

1.1 Introduction:

The electrocardiogram, ECG, provides useful information about functioning of heart required for cardiovascular assessment with noninvasive electrodes on the limbs and chest; a typical ECG signal consists of the P-wave, QRS complex, and T-wave. And it's interval. It is usually corrupted with noise from various sources. Therefore, the ECG signal must be clearly represented and filtered to remove all distracting noise and artifacts.

ECG provides valuable information to diagnose heart disorders and the ischemic changes that may occur. The ECG signal provides the following information of a human heart:

- ✓ Heart position and its chamber size.
- ✓ Impulse origin and propagation.
- ✓ Heart rhythm and conduction disturbances
- ✓ Extent and location of myocardial ischemia
- ✓ Changes in electrolyte concentrations
- ✓ Drug effects on the heart

Cardiac arrhythmias divide into two groups, the first group is life threatening and requires immediate therapy with an automatic external defibrillator or an implantable cardioverter defibrillator. The second group is not life threatening but requires sustainability therapy.

ECG signal has two types of features morphological and statistical features. The statistical features include standard deviation, mean and median ….etc. The important morphological features are the QRS complex, the RR interval, the P-R interval, the Q-T interval, the ST segment and the R-wave amplitude.

1.2 Significant of the Study:

ECG analysis is a routine part of any complete medical evaluation, due to the heart's essential role in human health and disease, therefore should be improve and using accuracy method to ease of recording and analyzing the ECG in a noninvasive manner.

1.3 Statement of Problem:

The cardiovascular disease is one of the leading causes of death around the world can be effectively prevented by early diagnosis. While the lacking of physician who is an expert for analysis on ECG signal is one of serious problem especially on rural area. Therefore they need of a system that could analyze the ECG signals properly and with a great accuracy by using intelligent method to relieve this problem.

1.4 Project Objectives:

The main objective of this work is to identify the normal beats from ECG beats so that other beats can be detected as abnormal beats so as to start the early treatment for the problems and many lives could be saved that’s including:

- ✓ Focus and develop the automatic algorithms on computer to analysis of the ECG signals in which the signals are fed into the system and the software extracts the features from ECG signal by using wavelet and feed it to the classifier neural network in which place suffered from the lacking of physician
- ✓ Diagnose and interpret ECG signals accurately, and to less time to start a treatment early.

1.5 Thesis Layout:

The structure of this work is as follows:

Chapter one is the introduction of ECG signals and it also describes the purpose of this work. Chapter two reviews the literature; it involves many topics starting with a comparison, methods of de-noising, and reviews the arrhythmia and methods of detection. Chapter three is theoretical background. Chapter four describes the research methodology. Chapter five displays the results and discussion. Chapter six presents conclusion and future work of the thesis.

Chapter Two

Literature Review

Twenty five papers had been reviewed (from 2009 to 2013), their involved many basic topics as followed comparison between wavelet and Fourier transform, methods of de-noising signals and methods of arrhythmia detection by convention and intelligent methods.

M. Sifuzzaman, M.R. Islam and M.Z. Ali (2009) had compared wavelet transform and Fourier transform, Fourier transform is a powerful tool for analyzing the components of a stationary signal. But it is failed for analyzing the non stationary signal where as wavelet transform allows the components of a non-stationary signal to be analyzed. They found out the main advantage of wavelet transform compared to Fourier transform is that wavelets are well localized in both time and frequency domain whereas the standard Fourier transform is only localized in frequency domain. Wavelets often give a better signal representation using multiresolution analysis. Finally, wavelet transform is a reliable and better technique than that of Fourier transforms technique [1].

Shweta Jain, and M.P. Parsai (2013), they used the DWT, the mother wavelets as its basis function, used for comparative analysis: Debauchies 4 wavelet, Debauchies' 6 wavelet, Symlet 4 wavelet and Symlet 6 wavelet. First of all, the signal file is made readable in MATLAB by using the WFDB toolbox, then the program for removal of different types of noises and detection of "R" wave from the raw ECG data is run. Accuracies and false detection of the 15 ECG wave forms of the detector that uses different mother wavelets as the basis function for

DWT are calculated, and also showed the comparison of Standard Deviations of ECG waveforms using different mother wavelets in DWT. For the purpose of carrying out Pre-processing of ECG waveforms Db4 and Sym4 wavelets show good results but for carrying out Features' Extraction Db6 and Sym6 wavelets show good results.[2]

Neeraj kumar, Imteyaz Ahmad, and Pankaj Rai (2012), had introduced the digital filtering method to cope with the noise artifacts in the ECG signal these artifacts produced by varies sources of either artificial or biological nature. The ECG lead-II signal is taken. The butterworth IIR filter and FIR type1 filters are applied on the ECG signal. The both of them reduce the low and high frequency noise. It is seen that tip of the QRS complex is distorted in case of Butterworth highpass filter of order two. Where as in case of FIR type-1 QRS complex is less modified FIR filter have two important advantages over IIR filter, first they are generated to be stable, even after filter coefficient have been quantized, second they may be easily constrained to have linear phase [3].

Hari Mohan Rai and Anurag Trivedi (2012) had deal with the noise removal of ECG signal using three different wavelet families (Haar, Daubechies and Symlets). The ECG signals to be De-noised is decomposed to the Level 5 and chosen the fourth coefficient for Daubechies and sixth co-efficient for Symlet wavelet because these wavelets show similarity with QRS complexes and energy spectrum is concentrated around low frequencies, and calculated their statistical parameter values for noisy ECG signals and De-noised waveform using wavelet families . Daubechies4 and symlet6 have been used in this work for De- Noising purpose [4].

Dina Kicmerova (2009) focused in measuring of QT intervals. It can be an indicator of the cardiovascular health of the patient and detect any potential abnormalities and focused on modeling of arrhythmias using McSharry's model followed with classification using an artificial neural network. He taken PVC and normal beats to classification, multilayer perceptron was used. The accuracy of it is 93.10% for premature ventricular contractions (PVC) and 96.43% for normal beats. [5]

Himanshu Gothwal, Silky Kedawat, and Rajesh Kumaor (2011) had presented a method to analyze electrocardiogram (ECG) signal, Fast Fourier transforms are used to identify the peaks in the ECG signal and then Neural Networks (NNWs) are applied to identify the diseases. The results obtained have better efficiency then the previously proposed methods [6]. The Short-time Fourier transform (STFT) is time and frequency localized but there are issues with the frequency time resolution, the major draw-back of this STFT is that its time frequency precision is not optimal.

Apoorv Gautam and Maninder Kaur (2012), the proposed paper work aimed to analyze a given ECG by using wavelet transform and to identify the Arrhythmia. Continues wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ. The multi-resolution analysis based on the CWT can enhance small differences when the signal is simultaneously observed at the most appropriate scales [7].
Continuous wavelet analysis is redundant.

Manimegalai.P, Bharathi.P, Dr.K.Thanushkodi (2012), this paper presented a discrete wavelet transform based system for detection and extraction of P wave, QRS complex, and ST segment. The features like amplitude, frequency, energy are extracted from the Electrocardiogram (ECG) to classify them into normal and arrhythmic. The extracted features are given as input to neural network to classify them into normal and arrhythmic. The algorithm was implemented in MATLAB and the same was implemented in real time using Lab VIEW. The above wavelet technique provided less computational time and better accuracy for classification, analysis and characterization of normal and abnormal patterns of ECG. [8] This feature extraction method can be used as a primary measurement tool for automatic and on line disease classification.

Pooja Bhardwaj, Rahul R Choudhary and Ravindra Dayama (2012), they used automatic detection of cardiac arrhythmia is support vector machine, and using specific computer software for data analysis is LibSVM3.1 for arrhythmia classification in five categories. The dataset used in this study is 3003 arrhythmic beats out of which 2101 beats (70%) are used for training and remaining 902 beats (30%) have been used for testing purpose. only 864 beats are correctly classified. 38 beats are misclassified.[9]

Maedeh Kiani Sarkaleh and Asadollah Shahbahrami (2012) used an expert system for Electrocardiogram (ECG) arrhythmia classification is proposed. Discrete wavelet transform is used for processing ECG recordings, and extracting some features, and the Multi-Layer Perceptron (MLP) neural network performs the classification task. Two types of arrhythmias can be detected by the proposed system. The simulation results show that the classification accuracy of our algorithm was acceptable using 10 files including normal and two arrhythmias. [10]

From the previous studies, this research will focus on using digital filters to preprocessing, and use the wavelet transform in feature extraction because it is mostly consider as powerful tool for analyzing the components of non stationary signal as ECG signals. Then will use neural network to classify signals to normal and abnormal.

Chapter Three

Theoretical Background

3.1 Heart Anatomy:

The heart contains four chambers that two upper chambers are called the left and right atria, while the lower two chambers are called the left and right ventricles. Also contains several atrioventricular and sinoatrial nodes as shown in the figure (3.1).The atria are attached to the ventricles by fibrous, non-conductive tissue that keeps the ventricles electrically isolated from the atria. The right atrium and the right ventricle together form a pump to the circulate blood to the lungs. Oxygen-poor blood is received through large veins called the superior and inferior vena cava and flows into the right atrium.[11]

The right atrium contracts and forces blood into the right ventricle, stretching the ventricle and maximizing its pumping (contraction) efficiency. The right ventricle then pumps the blood to the lungs where the blood is oxygenated. Similarly, the left atrium and the left ventricle together form a pump to circulate oxygen-enriched blood received from the lungs (via the pulmonary veins) to the rest of the body. In heart Sino-atrial (S-A) node spontaneously generates regular electrical impulses, which then spread through the conduction system of the heart and initiate contraction of the myocardium.[11]

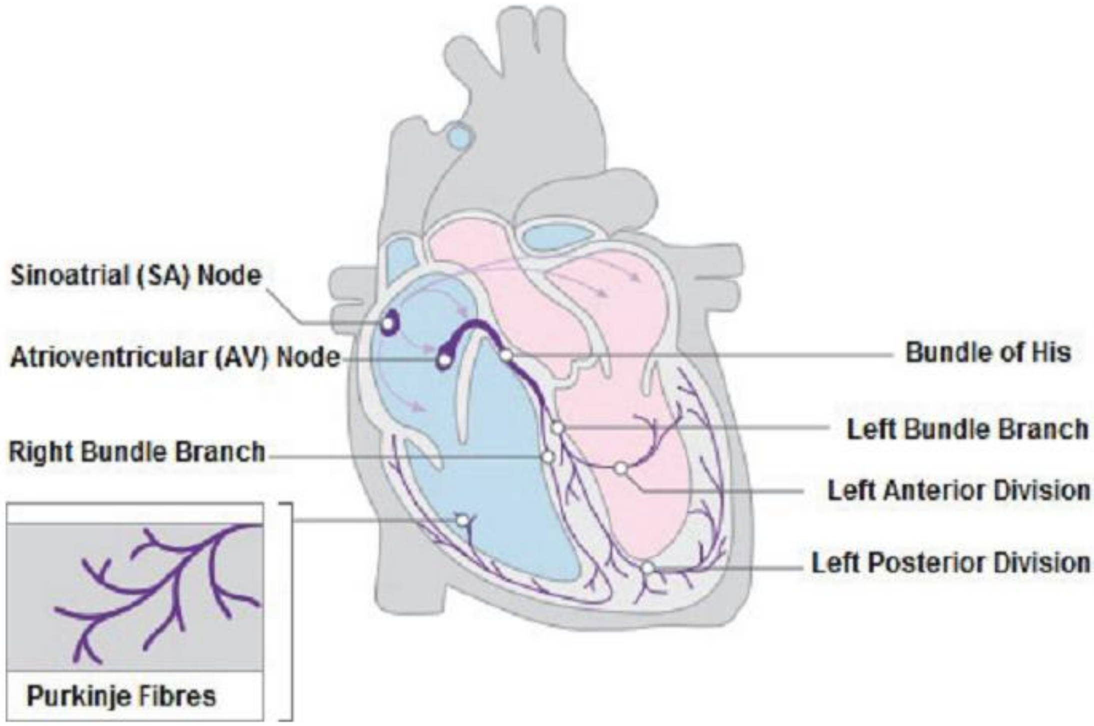

Figure (3.1): the conduction system of the heart

Propagation of an electrical impulse through excitable tissue is achieved through a process called depolarization. Depolarization of the heart muscles collectively generates a strong ionic current. This current flows through the resistive body tissue generating a voltage drop. The magnitude of the voltage drop is sufficiently large to be detected by electrodes attached to the skin. ECGs are thus recordings of voltage drops across the skin caused by ionic current flow generated from myocardial depolarizations. Atrial depolarisation results in the spreading of the electrical impulse through the atrial myocardium and appears as the P-wave. Similarly, ventricular depolarisation results in the spreading of the electrical impulse throughout the ventricular myocardium. [11]

3.2 Electrocardiograph:

It is a machine that records the electrical activity of the heart over time. The ECG allows health professionals to diagnose and monitor various cardiac conditions, including arrhythmias (irregularities of cardiac rhythm) and myocardial damage (such as myocardial infarction). Fundamentally an ECG is a graphic representation of the electrical activity of the heart muscle. When cardiac muscle cells are excited, they produce an electrical impulse lasting approximately 300 ms. [11] The ECG signal has frequency range of 0.05–100 Hz and its dynamic range is 1–10 mV. This is followed shortly by mechanical contraction of the muscle cells. The electrocardiographic deflections are termed P, QRS complex, T and U as in figure (3.2). The P wave represents atrial activation; QRS complex represents ventricular activation or depolarization.

The T wave represents ventricular recovery or re-polarization and the S-T segment, the T wave and the U wave together represent the total duration of ventricular recovery.

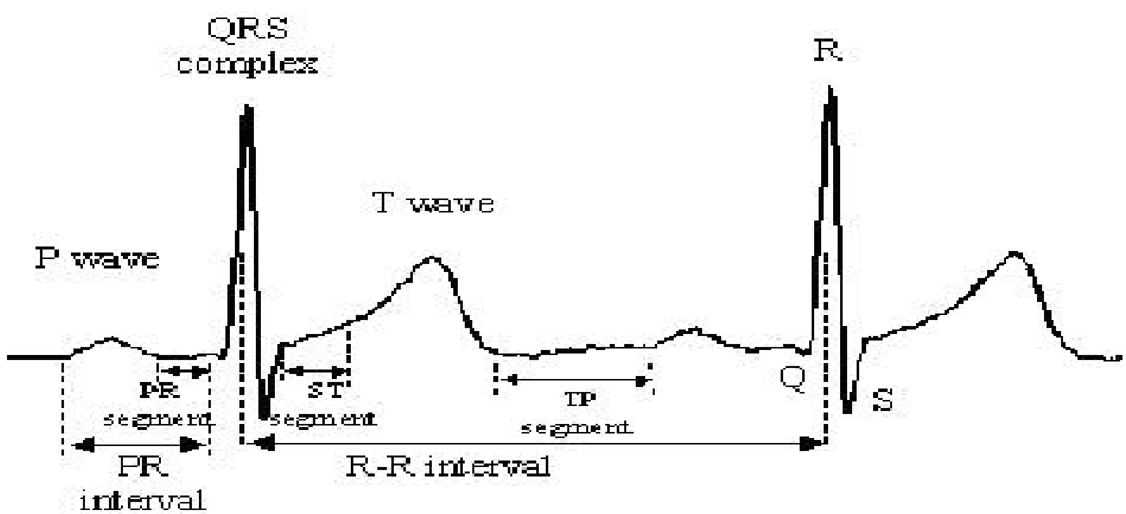

Figure (3.2): Components of the ECG

3.3 Cardiac Arrhythmia:

It is disturbance in the regular rhythmic activity of the heart; Cardiac arrhythmia may be caused by irregular firing patterns from the SA node, abnormal activity from other parts of the heart.

3.3.1 Atrial Arrhythmias:

Atrial arrhythmias originate outside the S-A node but within the atria in the form of electrical impulses. These arrhythmias types are:

(A) Atrial Premature (AP), (B) Atrial tachycardia, (C) Atrial Flutter, (D) Atrial fibrillation.

This project concentrate in Atrial Premature, this arrhythmias results an abnormal P-wave morphology followed by a normal QRS complex and a T-wave. These impulses occur prematurely, before the sinus node depolarizes. AP may occur as a couplet where two AP are generated consecutively. When three or more consecutive PACs occur, the rhythm is considered to be Atrial tachycardia.

3.3.2 Ventricular Arrhythmias:

In this type of arrhythmias, the impulses originate from the ventricles and move outwards to the rest of the heart. In Ventricular arrhythmias, the QRS-complex is wide and bizarre in shape. These arrhythmias types are:

(A) Premature Ventricular Contractions, (B) Ventricular Tachycardia,

(C) Ventricular Fibrillation.

We concentrate in Premature Ventricular Contractions (PVC).In PVC the abnormality is originated from ventricles. PVCs usually do not depolarize the atria or the S-A node and hence the morphology of P-waves maintains their underlying rhythm and occurs at the expected time. PVCs may occur anywhere in the heart beat cycle. PVCs are described as isolated if they occur singly, and as couplets if two consecutive PVCs occur.

3.3.3 Bundle Branch Blocks:

Bundle branch block, cease in the conduction of the impulse from the AV-node to the whole conduction system. In other words there are alterations in the way the lower chambers of the heart are activated. The bundle branches (there is one on the left and one on the right) bring the electrical impulses down from the AV node to the ventricles. Bundle Branch Blocks simply result in the electrical activity spreading from cell to cell. Due to this block there may occur myocardial infarction or cardiac surgery.

The bundle branch block beat is categories into two types. These are Left bundle branch block beat (LBBB) and Right bundle branch block beat (RBBB). In LBBB the left bundle branch will prevent the electrical impulses from the A-V node from depolarizing the left ventricular myocardium in the normal way. When the right bundle branch is blocked, the electrical impulse from the AV node is not able propagate to the conduction network to depolarize the right ventricular myocardium.

3.4 MIT-BIH Database:

The most extensive and freely available collection of ECG waveforms can be found on PhysioNet (the MIT Laboratory for Computation Physiology's Web site), it contains MIT-BIH database. Researchers have used this database to test their various algorithms for arrhythmia detection and classification. It is forty-eight records, each containing two-channel ECG signals for thirty minutes duration selected from 24-hr recordings of forty-seven individuals. Continuous ECG signals are band pass-filtered at 0.1–100 Hz and then digitized at 360 Hz, it have same base name characterizes, but different extensions can be needed. In the directory have three kinds of extensions:

- ✓ An annotation file is (.atr), annotated useful for obtaining impression of content of individual record.
- ✓ A binary file is (.dat), it is contains data.
- ✓ A header file is (.hea), it is contains information about the binary file format variety, the number and type of channels, the lengths, gains, and offsets of the signals, and any other clinical information that is available for the subject.

The recordings divided into two groups, the first group are twenty-five recordings (numbered in the range of 200–234) contain complex ventricular, junctional, and supraventricular arrhythmias which are life-threatening and require immediate therapy with a defibrillator. Detection of these arrhythmias is well researched and successful detectors have been developed with high sensitivity and specificity. The second group, Twenty-three of the recordings (numbered in the range of 100–124) are intended to serve as a representative sample of routine clinical recordings which includes arrhythmias that are not imminently life-threatening but may require therapy to prevent further problems, as shown as in table 3.1.

Table (3.1): Set of Analyzed Arrhythmias According to the AAMI Standard

AAMI heartbeat	Description	MIT/BIH heartbeat types
N	Any beat not in the Sv, V, F or Q classes	Normal (N), Left bundle block (LBBB), Right Bundle Branch Block (RBBB), Atrial Escape (AE), Nodal (junctional) escape beat (NE).
Sv	Supraventricular ectopic beat	Atrial Premature(AP), Aberrated Atrial Premature(aAP), Nodal(junctional) Premature(NP), Supraventricular Premature(SP)
V	Ventricular ectopic beat	Premature Ventricular contraction (PVC), and Ventricular escape (VE).
F	Fusion beat	Fusion of ventricular and normal (FVN), Fusion of paced and normal beat(FPN)
Q	Unknown beat	Paced (P), and Unclassifie d (Q).

3.5 ECG Noises:

Noises may disturb the ECG to such an extent that measurements from the original signals are unreliable. The corruption of ECG signal is due to following major noises:

3.5.1 Power line Interferences:

It is varying from country to other, in Sudan 50 Hz and in which database is 60 Hz, it comes from improper grounding [13].

3.5.2 Baseline Drift:

It may be caused in chest-lead ECG signals by coughing or breathing with large movement of the chest, or when an arm or leg is moved in the case of limb-lead ECG acquisition. It can sometimes caused by variations in temperature and bias in the instrumentation and amplifiers. Its frequency range generally bellows 0.5 Hz. [14]

3.5.3 Muscle Contraction (EMG):

Generally muscle contraction is produced due to muscle electrical activity. It is interferences generate rapid fluctuation which is very faster than ECG wave, its frequency content is dc to 10 KHz and duration is 50 ms. [15]

3.5.4 Motion Artifacts:

There are transient baseline changes due to electrode skin impedance with electrode motion. It can generate larger amplitude signal in ECG waveform. The peak amplitude of this artifact is 500 percent of Peak to Peak ECG amplitude and its duration is about 100 – 500 ms. [15]

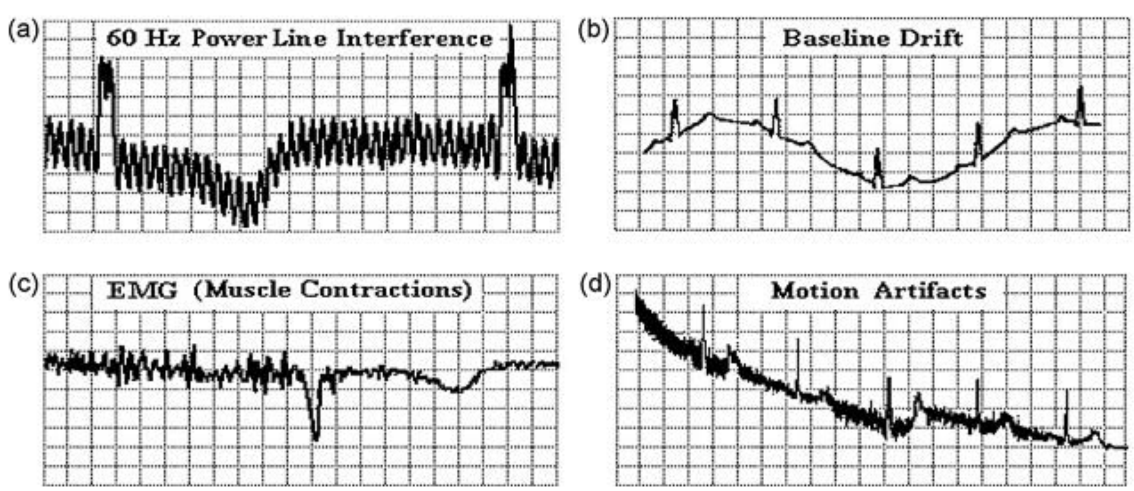

Figure (3.3): Noises of ECG

3.6 Wavelet Transform:

Fourier analysis is as a mathematical technique for transforming our view of the signal from time-based to frequency-based, but it has a serious drawback the time information is lost and it is not suited to detecting characteristics of non stationary signals. In an effort to correct this deficiency, Fourier transform was adapted to analyze only a small section of the signal at a time, a technique called windowing the signal. It's Short-Time Fourier Transform (STFT), maps a signal into a two-dimensional function of time and frequency. However, it can only obtain this information with limited precision, that is determined by the size of the window, the drawback is that once choose a particular size for the time window, that window is the same for all frequencies. Many signals require a more flexible approach one where we can vary the window size to determine more accurately either time or frequency.

Wavelet analysis is a windowing technique with variable-sized regions. It allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. It does use a time-scale region; one major advantage afforded by wavelets is the ability to perform local analysis that is, to analyze a localized area of a larger signal. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. Wavelet analysis can be applied to one-dimensional for signals and two-dimensional for image.

3.6.1 Type of Wavelet Transform:

3.6.1.1 Continuous Wavelet Transform:

It is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ:

$$C\ (scale, position) = \int_{-\infty}^{\infty} f(t)\Psi(scale, position, time)dt \qquad (3.1)\ [7]$$

The ψ ($scale, position, time$), it is defined by

$$\Psi(t)_{a,b} = \frac{1}{\sqrt{|a|}}\ \Psi(\frac{t-b}{a}) \qquad a, b\ \epsilon\ R,\ a \neq 0 \qquad (3.1)\ [1]$$

The parameter a is the scaling parameter, and it measures the degree of compression. The parameter b is the translation parameter which determines the time location of the wavelet. The results of the CWT are many wavelet coefficients, multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal.

3.6.1.2 Discrete Wavelet Transform:

Discrete Wavelet Transform (DWT) has two filters, a low pass filter (LPF) and a high pass filter (HPF).They are used to decompose the signal into different scales. The output coefficients of the LPF are called approximation and output coefficients of the HPF is called Detail. The approximation signal can be sent again to the LPF and HPF of the next level for second-level decomposition; thus can decompose the signal into its different components at different scale levels. In the wavelet analysis the filter decomposes the signal into frequency bands. [16]

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree, as shown in figure (3.5). [17] In the wavelet synthesis the filter reconstructs the decomposed signal back into the original bands. [16] The wavelet has several families Haar, Daubechies, Biorthogonal, Coiflets, symlets, Mexican Hat, Morlet, Meyer, other real and complex wavelet.

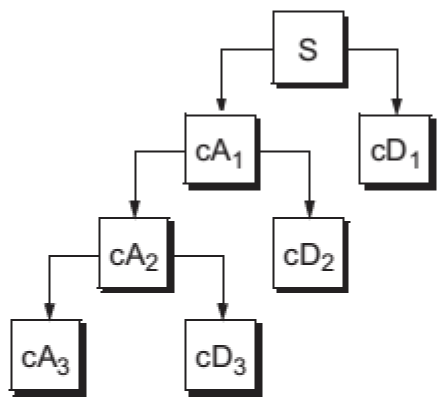

Figure (3.4): Wavelet Decomposition Trees

3.7 Artificial Neural Networks:

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain. It is composed of a large number of highly interconnected processing elements (neurons). It is working in parallel to solve specific problems. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

3.7.1 Architecture of neural networks:

3.7.1.1 Feed-forward networks:

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback. It tends to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition.

3.7.1.2 Feedback networks:

Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their state is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found.

3.7.2 The Learning process:

All learning methods used for adaptive neural networks can be classified into two major categories:

- ✓ **Supervised learning** which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required.
- ✓ **Unsupervised learning** uses no external teacher and is based upon only local information.

The behavior of an ANN depends on both the weights and the input output function (transfer function) that is specified for the units. In order to train a neural network to perform some task, must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. This process called back propagation algorithm.

3.7.3 Advantages of NNWs:

- ✓ Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
- ✓ Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
- ✓ Real Time Operation.
- ✓ Fault Tolerance via Redundant Information Coding.

Chapter Four

Methodology

4.1 Introduction:

Classification of electrocardiograms (ECG) into different disease categories is a complex pattern recognition task. However, the analysis of electrocardiogram signals is the most effective available method for diagnosing cardiac arrhythmias. Computer-based classification of ECGs can provide high accuracy and offer a potential of an affordable cardiac abnormalities mass screening. Successful classification is achieved by finding the characteristic shapes of the ECG that discriminate effectively between the required diagnostic Categories.

Conventionally, a typical heart beat is identified from the ECG and the component waves of the QRS, T, and possibly P waves are characterized using measurements such as magnitude and duration. Also many international datasets using for this purpose but we concentrate in MIT-BIH arrhythmia database used for training and testing of automated classification of ECG signals. This chapter explains all methods followed in this research.

4.2 Block Diagram:

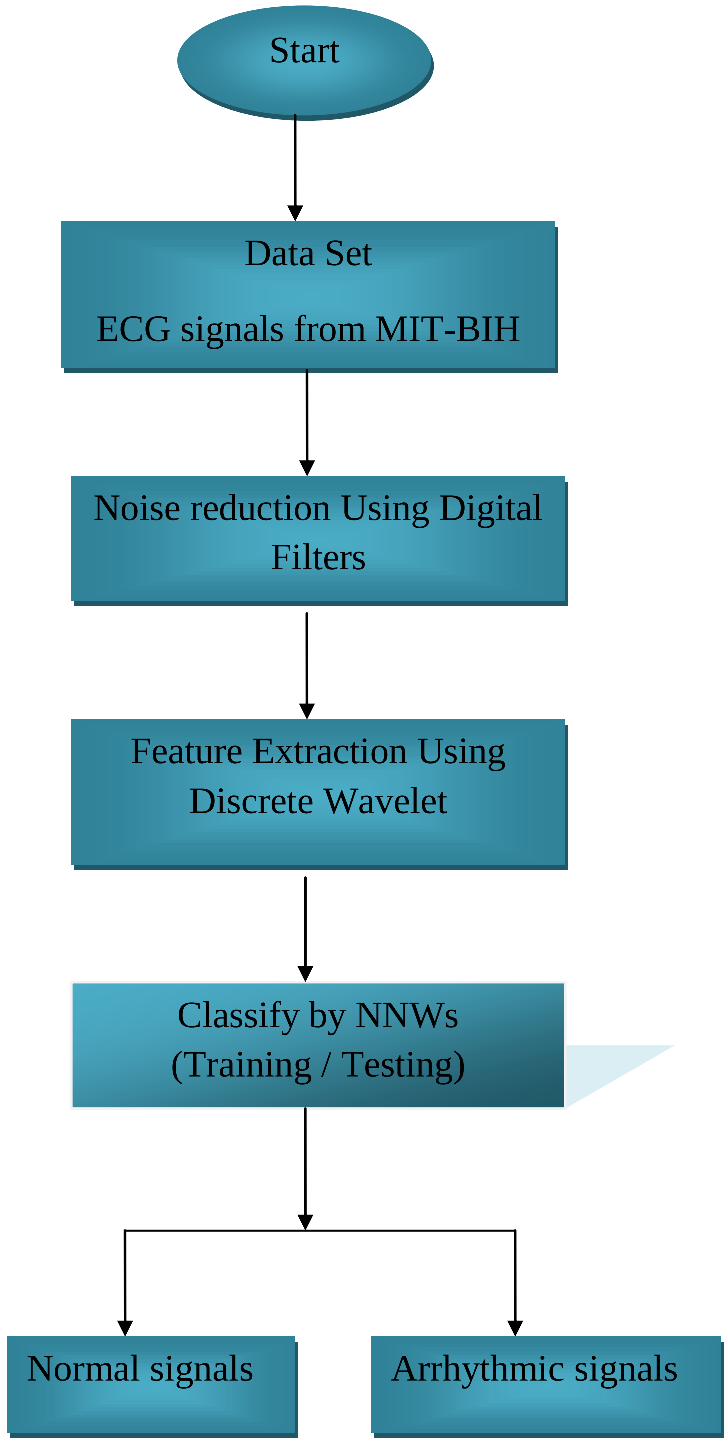

Figure (4.1): Block Diagram of Methodology.

4.2.1 Data Set:

In this research selected forty signals, including normal and other arrhythmia (AP, PVC, LBBB, and Paced), there were for training and testing of NNWs. Read these files in Matlab by using special code.

Table (4.1): A description for forty signals selected from the MIT−BIH Arrhythmia Database.

Class of signals & Record No.	Age	Gender	Total beat	Sampling (Segmentation)
Normal 115 115	39	female	1953	F=s(1:3600) F=s(7200:10800)
123	63	female	1518	F=s(350:3950)
119	51	female	1987	F=s(628400:632000)
101	75	female	1865	F=s(550:4150)
103	Not recorded	male	2084	F=s(28800:32400)
122	51	male	2476	F=s(64800:68400)
108	87	female	1774	F=s(360000:363600)
Paced 217 217	65	male	2208	F=s(180000:183600) F=s(34660:38260)
107 107	63	male	2137	F=s(46340:49940) F=s(42740:46340)
104 104	66	female	2229	F=s(180360:183960) F=s(17000:20600)
102 102	84	female	2187	F=s(108000:111600) F=s(10800:14400)
AP 222 222	84	female	2483	F=s(75960:79560) F=s(76640:80240)
232 232	76	female	1780	F=s(639200:64280) F=s(10800:14400)
220 220	87	female	2048	F=s(432000:435600) F=s(61200:64800)
209 209	62	male	3005	F=s(642800:646400) F=s(43540:47140)
PVC 208 208	23	female	2955	F=s(68400:72000) F=s(61200:64800)
221 221	83	male	2427	F=s(46800:50400) F= s(1:3600);
223 223	73	male	2605	F= s(1:3600) F=s(360000:363600)

233	57	male	3079	F=s(431640:435240)
119	51	female	1987	F=s(360000:363600)
LBBB 111 111	47	female	2124	F=s(504000:507600) F=s(563000:566600)
109 109	64	male	2532	F=s(75600:79200) F=s(18000:21600)
214 214	53	male	2262	F=s(36250:39850) F=s(108000:111600)
207 207	89	female	2332	F=s(612700:616300) F=s(610000:613600)

4.2.2 Noise Reduction:

In general, the aim of the preprocessing steps is to improve the signal-to-noise ratio (SNR) of the ECG for more accurate analysis to extract useful and accurate features of the signals. In this project concentrated in:

4.2.2.1 Power line interferences:

To remove it used a 60 Hz notch filter, linear filter second order IIR filter and pole-zero replacement. Practically, the pole-zero placement method has good performance when the band pass and band stop filters have very narrow bandwidth requirements.

Design formulas for band stop filters are given in the following equations:

$$r \approx 1 - (WB/fs) * \pi, \text{ good for } 0.9 \leq r < 1 \quad (4.1)$$

$$\theta = \left(\frac{f0}{fs}\right) * 360° \quad (4.2)$$

The scale factor to adjust the band stop filter to have a unit pass band gain is given by:

$$K = \frac{(1-2rcos\theta + r^2)}{(2-2cos\theta)} \tag{4.3}$$

Finally, the transfer functions:

$$H(z) = \frac{K(z-e^{j\theta})(z+e^{-j\theta})}{(z-re^{j\theta})(z-re^{-j\theta})} = \frac{K(z^2-2z\,cos\theta+1)}{(z^2-2rz\,cos\theta+r^2)} \tag{4.4}$$

BW= band width, *fs*= sampling rate, f_o= centre frequency, θ= angle of the pole location. [18]

4.2.2.2 Baseline drifts:

To remove it used a high pass filter, second order and Butterworth with cut-off frequency 0.5 Hz is used at a sampling rate *fs* Hz [14]

4.2.3 Feature Extraction:

To obtain morphology features used wavelet transform, it is a mathematical tool for decomposing a signal into a set of orthogonal waveforms localized both in time and frequency domains. We selected the sym6 as mother wavelet; table (4.2) was shown the general characteristic of sym.

This research used coefficient of approximation ca2, ca3 and ca4 as original signals from each arrhythmia to extract features from them, there are: R-R interval and, R amplitude, also S amplitude, T amplitude, P amplitude, ST segment, QRS duration and QT interval, RS interval we took the minimum and maximum for each one, and statistical features are mean, median, Standard deviation, Variance, corrcoefficient and entropy also power spectral density. Then that made compression between their results to determine which coefficient more suitable for classification of ECG signals.

4.2.4 Classification of Cardiac Arrhythmias:

This project used pattern recognition neural network, there are feed forward networks that can be trained to classify inputs according to target classes. The target data for pattern recognition networks should consist of vectors of all zero values except for a 1 in element i, where i is the class.

4.2.4.1 Data Selection and creation of network:

To creation pattern recognition neural network used input data is 24*20 matrix, representing static data: 20 samples of 24 elements, and target is 5*20 matrix, representing static data: 20 samples of 5 element.

The target were [1; 0; 0 ;0 ;0] for normal, [0; 1; 0; 0; 0] for paced, [0; 0; 1; 0; 0] for AP, [0; 0; 0; 1; 0] for PVC and [0; 0; 0; 0; 1] for LBBB. The samples were matrix columns. And then selected numbers of hidden neurons were 10.

4.2.4.2 Training Phase:

To train used Levenberg-Marquardt (trainlm) as the training function to update the weight and bias values of network. Training multiple times generated different results due to different initial conditions and sampling. Also calculated mean squared normalized error (MSE), it is network performance function.

And then plot confusion matrix to measure of how well the neural network has fit the data. It is plotted across all samples. It shows the percentages of correct and incorrect classifications. Correct classifications are the green squares on the matrices diagonal. Incorrect classifications form the red squares. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). If the network has learned to classify properly, the percentages in the red squares should be very small, indicating few misclassifications.

4.2.4.3 Testing Phase:

To test network used eight samples for each group by y=sim (net, signal).

4.3 Evaluation of performance:

To evaluate of network performance in classification stage we calculated accuracy, sensitivity, specificity by using four values are:

- ✓ *True positives (TP):* It is signals with the characteristic and tested positive.
- ✓ *False negatives (FN):* It is signals with the characteristic and tested negative.
- ✓ *False positives (FP):* It is signals without the characteristic and tested positive.
- ✓ *True negatives (TN):* It is signals without the characteristic and tested negative.

4.3.1 Accuracy or Efficiency:

It is the percentage of test results correctly identified by the test.

$$\text{Accuracy} = (TP+TN)/\ (TP+TN+FP+FN) \qquad (4.4)$$

4.3.2 Sensitivity:

The sensitivity tells us how likely the test is come back positive in someone who has the characteristic.

$$\text{Sensitivity} = \text{divide } TP \text{ by } (TP+FN) \qquad (4.5)$$

4.3.3 Specificity:

It is tells us how likely the test is to come back negative in someone who does not have the characteristic.

$$\text{Specificity} = \text{divide } TN\ /\ (FP+TN) \qquad (4.6)$$

Chapter Five

Results and Discussion

5.1 Introduction:

This research had three steps to obtain the results. The first step included loading, reading signals in Matlab, then noise reduction by used digital filters to eliminate artifact from each signal. The next step was feature extraction. Finally, classify by used neural network to obtain accuracy diagnosis.

5.2 Result of Reading Signals in Matlab and Noise Reduction:

Each case had eight signals loaded and read there by Matlab. In preprocessing used the IIR filter because the filter operation requires a fewer number of computations.

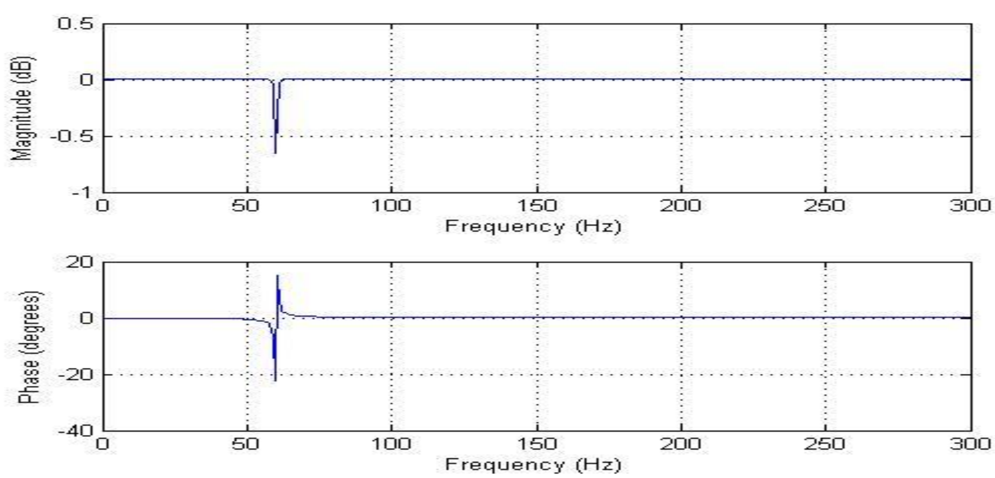

Figure (5.1): Frequency Response of Notch Filter to remove 60Hz

It represented power line interference. We used pole zero replacement method because it simple design equations and it gave us narrow band specifications.

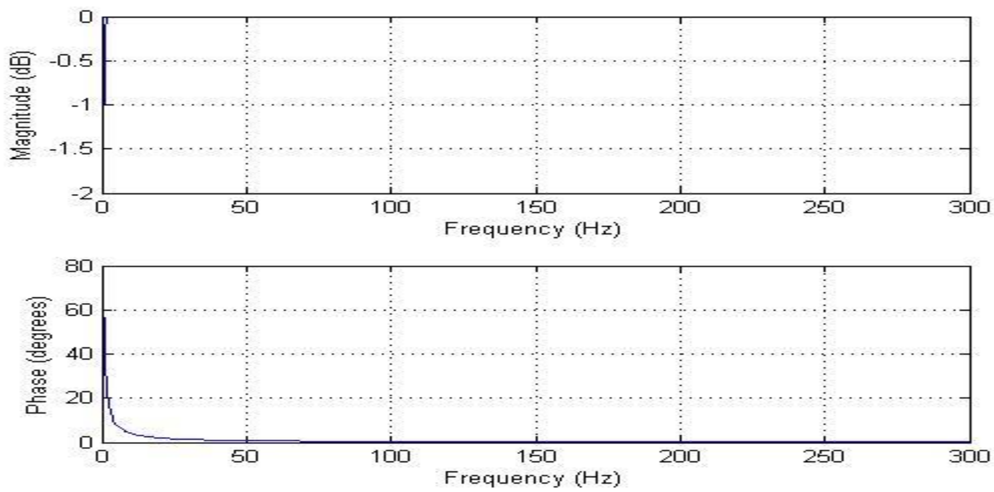

Figure (5.2): Frequency Response of high pass filter

The cut-off frequency 0.5 Hz It represented baseline drift. We used second order Butterworth because it has a short time delay.

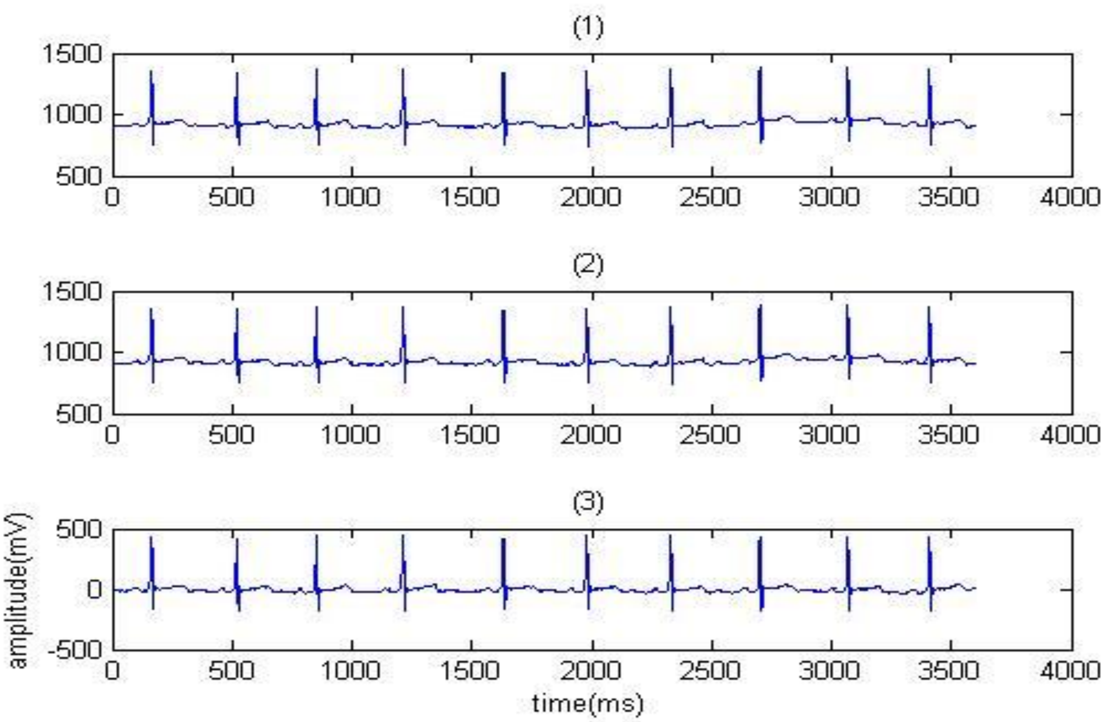

Figure (5.3): ECG Signal after Noise Reduction, Signal 115: (1) the raw ECG, (2) the ECG signal after removed 60Hz and (3) the ECG after removing baseline drift it became in zero line.

5.3 Result of Feature Extraction Step:

The features of ECG signal extracted after applying the sym6 at filtered signals, the output signals were decomposed to six levels. Wavelets have the great advantage of being able to separate and isolate the very fine details in a signal and make it easier to analyze. We extracted of approximation coefficients were ca1, ca2, ca3, ca4, ca5 and ca6. The ca2, ca3 and ca4 were used.

The detection of R peak is the first step of feature extraction. The R peak in the signal has the largest amplitude among all the waves, The R peaks were detected at the decomposed signals. The values which are greater than 60% of the max values of the actual signal used as threshold to represent R peaks, according to R peaks the other peaks were detected by using minimum and maximum algorithm. And then calculate the statist

- ✓ **The Result after applied symlet6 at filtered signals:**

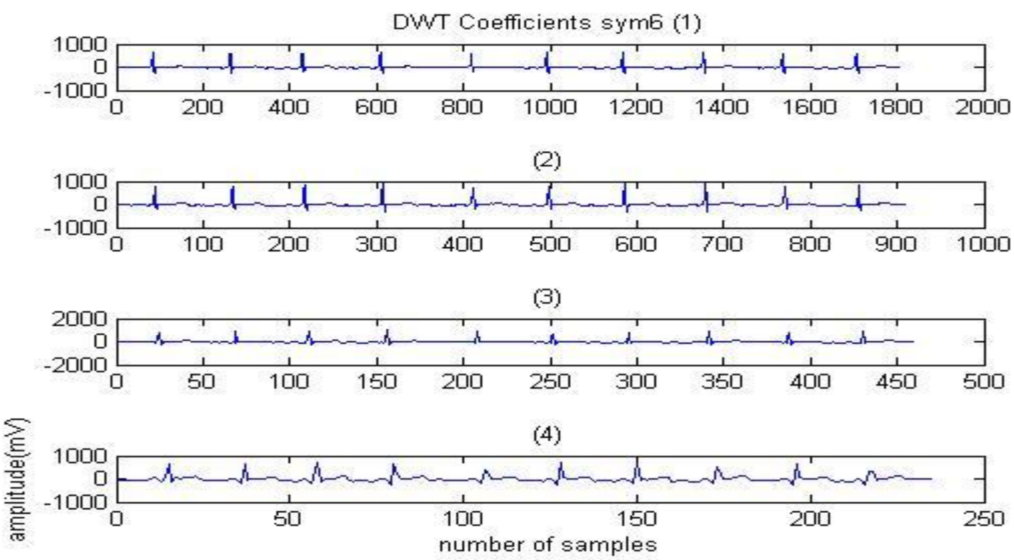

Figure (5.4): Extraction of approximation Coefficients after the Wavelet Transform

In figure (5.4), [1] represented ca1, [2] represented ca2 [3] represented ca3 and [4] represented ca4. There are presented the signals to detect ECG peaks, compute the segments and intervals also calculate the power for each signal.

- ✓ **The Results of Peaks Detection at ca3:**

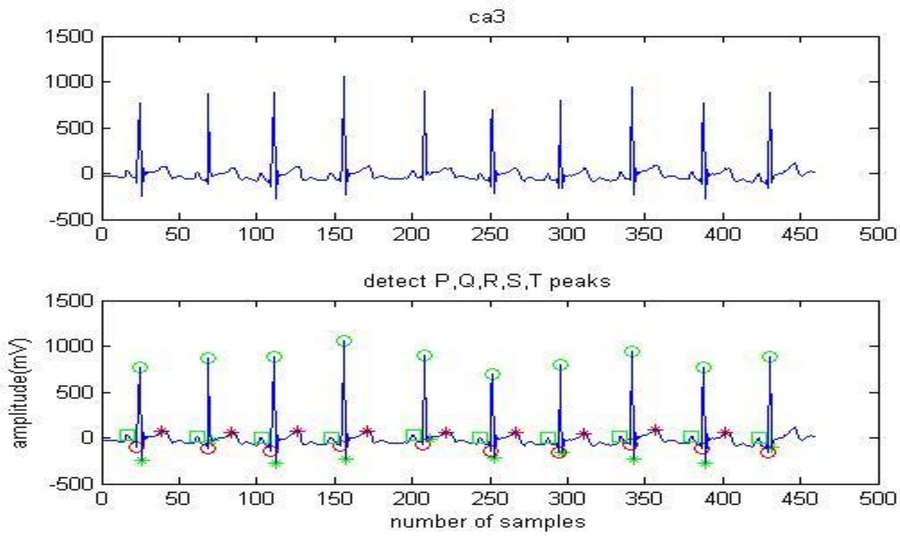

Figure (5.5): Detection for P, Q, R, S, T Peaks. P is Green Square, Q is Red Circle, R is Green circle, S is Green Star and T is Red Star for Normal Beat, Signal 115.

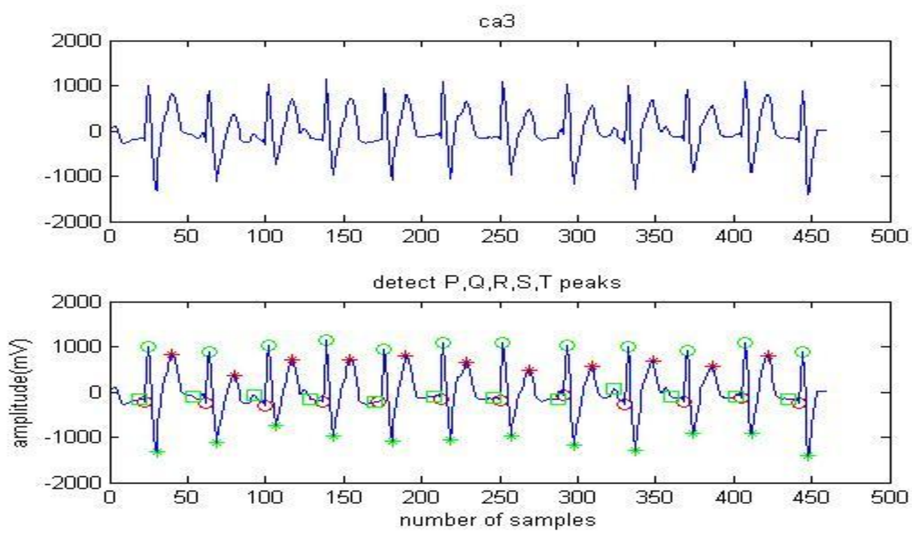

Figure (5.6): Detection for P, Q, R, S, and T Peaks, for Paced Arrhythmia,

Signal 107

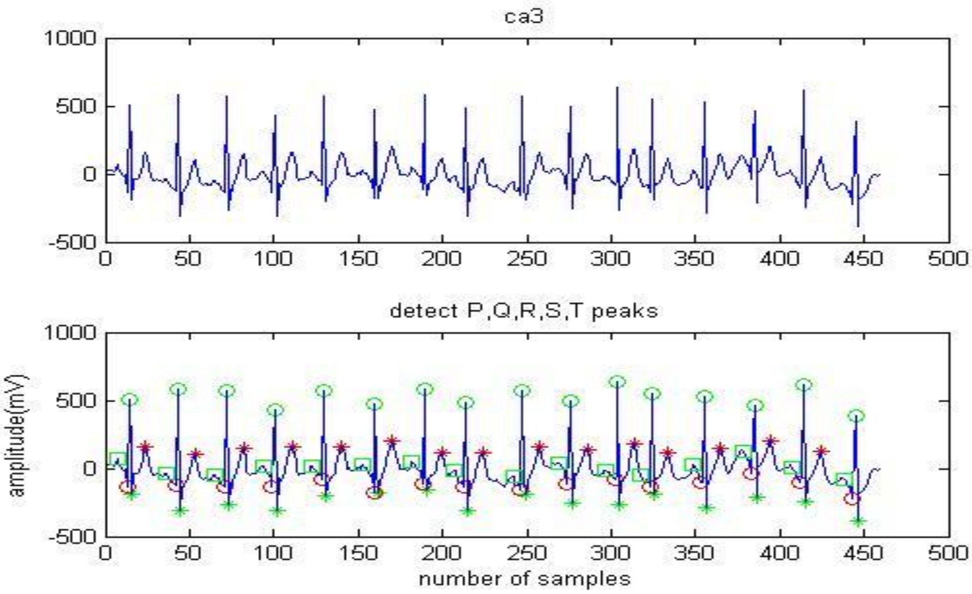

Figure (5.7): Detection for P, Q, R, S, and T Peaks, P is Green Square, Q is Red Circle, R is Green circle, S is Green Star and T is Red Star for AP Arrhythmia, Signal 209.

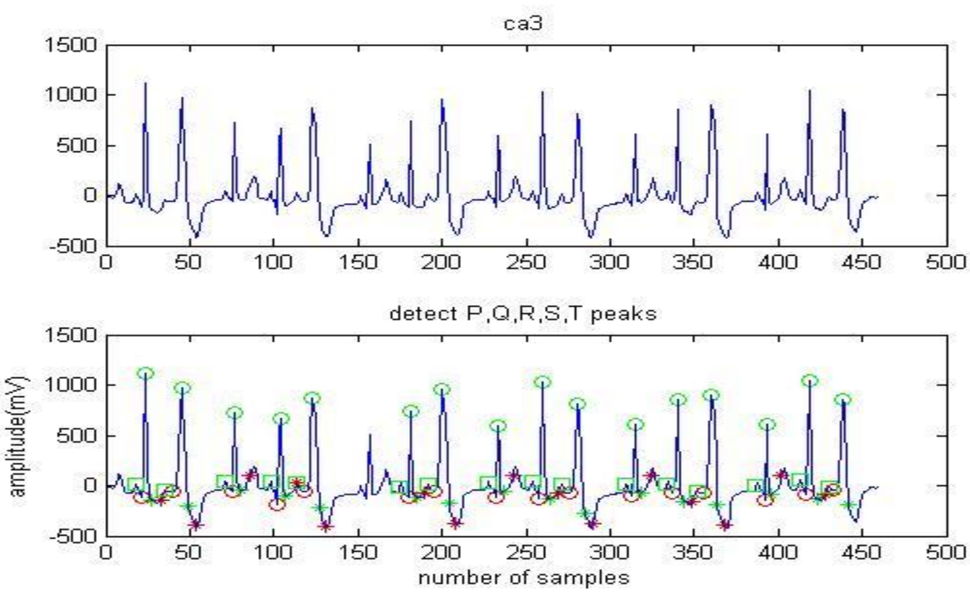

Figure (5.8): Detection for P, Q, R, S, and T Peaks. P is Green Square, Q is Red Circle, R is Green circle, S is Green Star and T is Red Star for PVC Arrhythmia, Signal 208.

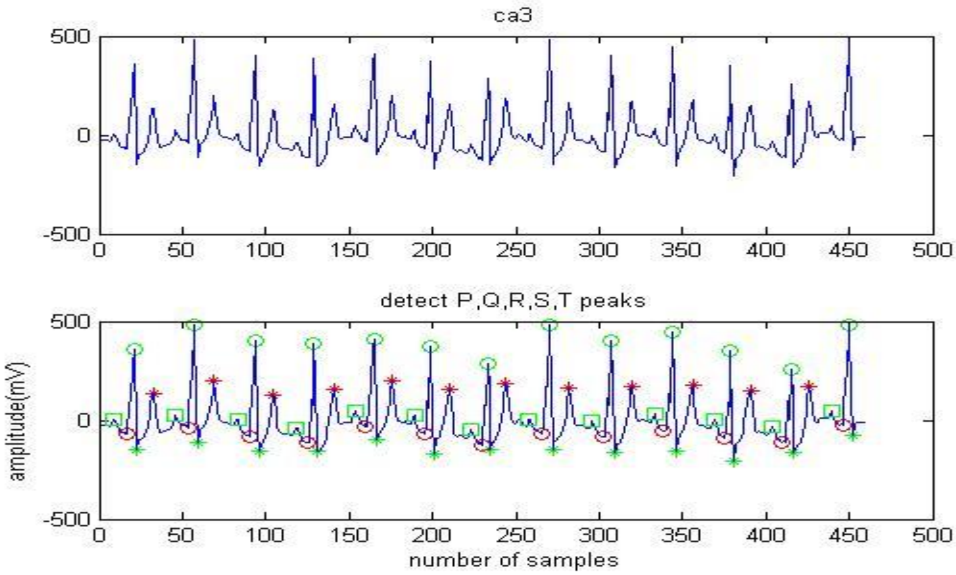

Figure (5.9): Detection for P, Q, R, S, and T Peaks. P is Green Square, Q is Red Circle, R is Green circle, S is Green Star and T is Red Star for LBBB Arrhythmia, Signal 111.

Table (5.1): Results of Minimum values for Features of Signals (ca2)

Signals	R amplitude	R-R interval	ST segment	T amplitude	P amplitude	QRS interval	QT interval	RS segment
Normal 115 115	713 635	83 39	26 13	36 27	-6 -2	7 2	33 16	1028 917
123	726	104	25	124	38	7	23	1056
119	752	82	23	164	-12	4	29	876
101	458.8	78	21	5.6	23.8	6	27	530.9
103	72.7	70	19	121	-13	4	25	826
122	628	73	16	-14	44	10	26	707
108	346.3	92	26	-25.3	83.2	7	34	538
Paced 217 217	430 471	72 70	21 22	282 335	-97 -101	10 9	33 31	1078 1158
107 107	722 680	74 70	18 20	264 369	-151 -170	12 10	32 30	1710 1750
104 104	217.7 151.2	69 38	21 10	26.6 -11.5	-57.7 -28.8	10 9	33 26	512 497.2
102 102	261.9 251.6	70 71	22 19	23.4 11.6	-29.7 -43.7	10 9	34 31	408.9 397.4
AP 222 222	216.7 216.8	68 68	13 13	-26.8 -35.7	37.8 19.3	3 3	17 17	253.8 253.5
232 232	246.9 202.2	65 60	24 22	110.9 70.6	-24.1 -9.4	5 5	29 27	404.6 389.1
220 220	811 660	84 73	25 23	75 23	-9 7	5 4	30 28	1224 1017
209 209	428 418.1	40 53	15 16	72 72.4	-49 -94	4 4	20 20	744 705.1
PVC 208 208	536 477	37 41	13 11	-86 -132	47 -51	8 14	23 26	720 732
221 221	427 497	40 40	13 16	-105 -45	-26 -21	16 12	31 29	560 676
223 223	746 715	64 61	21 11	-117 -99	34 23	7 7	29 20	860 821
233	677	50	17	-121	8	12	31	801
119	732	78	22	134	65	4	29	845
LBBB 111 111	203.6 213.3	69 71	18 17	102.9 99.5	-30.3 -47	13 6	32 24	369.2 355.6
109 109	608 573	61 60	23 22	48 48	44 44	9 9	33 32	899 860
214 214	665 751	62 62	9 13	-21 77	-1 -18	24 15	33 33	841 921
207 207	300.2 299	79 74	15 13	-35.2 -22	-11.4 -50	23 22	40 38	448.1 438

Table (5.2): Results of Maximum values for Features of Signals (ca2)

Signals	**R amplitude**	**R-R interval**	**R-R range**	**ST segment**	**T amplitude**	**P amplitude**	**QRS interval**	**QT interval**	**RS segment**
Normal 115	921	105	811	28	67	20	8	36	1102
115	989	44	374	14	125	61	4	17	1041
123	913	120	780	26	181	70	9	34	1120
119	952	86	835	26	201	88	7	31	980
101	633.6	86	813	21	75.4	89.7	7	28	634.8
103	854	81	763	24	150	16	7	29	904
122	722	82	775	20	75	126	14	31	726
108	0.4176	0.1020	7860	280	284	1284	90	360	5411
Paced 217	568	85	853	24	406	-37	13	36	1130
217	557	80	827	25	447	-1	13	37	1162
107	904	81	764	23	575	26	14	37	1475
107	900	80	840	20	580	90	10	30	1700
104	336.7	78	804	25	131.8	26	14	37	356.6
104	551.3	77	843	26	135.2	109.3	16	41	498
102	349.8	78	817	25	60.7	-6	15	39	392
102	355.1	151	814	26	80.6	4.8	12	36	411.4
AP 222	294.5	82	827	17	29.3	128.6	6	23	298.7
222	294.4	82	751	16	29.1	98	6	20	298.8
232	382.2	70	675	25	124.4	26.8	6	31	509.4
232	307.8	68	714	23	109.3	47.5	7	29	402.3
220	967	87	847	27	126	26	6	33	1262
220	865	78	833	24	74	30	6	29	1074
209	586	67	860	18	146	105	5	23	738
209	545.5	61	852	180	111.8	27.9	5	23	745.6
PVC 208	906	117	829	20	139	39	13	33	940
208	838	78	790	15	171	80	22	35	840
221	575	77	830	17	54	41	20	35	612
221	650	115	826	20	67	47	15	35	690
223	879	70	810	23	-36	94	9	30	925
223	831	66	828	21	-28	69	9	28	880
233	795	53	877	20	-3	135	15	32	800
119	866	83	802	26	167	100	7	31	917
LBBB 111	379.3	74	859	21	140.2	37.9	15	35	777.1
111	405.2	79	817	20	148.9	12.8	10	30	482
109	724	68	830	25	73	82	11	35	974
109	685	67	817	78	68	11	35	35	942
214	882	72	800	13	15	71	26	39	1004
214	869	78	846	16	32	55	21	36	855
207	438.9	135	764	20	-5.3	3.5	27	45	488.6
207	371	137	780	24	2	7	25	48	426

Table (5.3): Results of PSD and Statistical Features of Signals (ca2)

Signals	mean	Median	Standard deviation	Varian	power
Normal 115 115	1 3	-17 -17	116 140	13352 19726	13338 19689
123	0	-24	115	13202	13188
119	-1	-44	139	19242	19222
101	0.9	-13.2	78.5	6156.8	6150.8
103	1	-23	120	14432	14417
122	1	-28	139	19258	19237
108	0.5	-10.8	80.7	6511.2	6504.3
Paced 217 217	1 1	-36 -38	215 231	46068 53416	46020 53359
107 107	-6 0	-68 -60	314 351	98427 11938	9835.6 11925
104 104	0.6 1.4	-4.5 0.2	85.4 99.3	7300.3 9853.2	7292.7 9844.5
102 102	0.3 0.6	-15.5 -16.4	68.4 67.2	4684.3 4519.3	4679.3 4514.8
AP 222 222	-0.1 0.4	-6.8 -3.9	48 47.1	230.7 2218.6	2306.2 2216.3
232 232	-0.4 -8.3	-12.1 -7.9	64.7 67	4192.4 4491	4187.9 4555.2
220 220	0 1	-23 -15	134 120	17854 14510	17834 14495
209 209	-1 0.5	-17 -12.3	103 90.4	10560 8179.7	10549 8171
PVC 208 208	1 1	-36 -30	183 166	33361 27569	33324 27540
221 221	0 0	-22 -20	111 118	12330 13808	12316 13793
223 223	2 1	-22 -24	157 153	24513 23329	24490 23304
233	1	-28	179	32130	32096
119	2	-38	131	17269	17255
LBBB 111 111	0.2 0.2	-15.5 -15.6	77 70.3	5934.7 4935.4	5928.2 4930
109 109	0 2	-22 -25	171 170	29369 28838	29337 28809
214 214	2 1	-19 -22	161 173	25935 29780	25912 29750
207 207	2 -7	12.2 -14	93.4 100	8728.4 10037	8718.8 10075

Table (5.4): Result of Minimum values for Features of Signals ca3

Signals	R amplitude	R-R interval	ST segment	T amplitude	P amplitude	QRS interval	QT interval	RS segment
Normal 115 115	694 635	42 39	11 13	44 27	-5 -2	3 2	15 16	964 917
123	634	52	12	189	64	3	15	984
119	682	41	9	232	88	5	15	823
101	425	38	9	44	32	4	15	527
103	583	35	8	164	-19	3	13	717
122	797	37	8	-29	64	5	14	906
108	479	47	13	-36	111	4	17	742
Paced 217 217	570 570	38 10	11 0	433 -110	-134 -130	5 10	18 10	1429 1550
107 107	880 910	40 40	10 10	370 550	-230 -250	10 10	20 20	2290 2370
104 104	245 191	35 19	10 4	32 -20	-61 -15	6 5	17 16	672 682
102 102	239.7 307.8	34 33	11 8	34.7 14.9	-40.2 -45.2	6 5	17 16	446.7 513.2
AP 222 222	182.4 182.2	33 33	6 6	-39.1 -39.1	38.3 51.9	2 2	11 11	234.2 234.2
232 232	240.2 206.8	32 31	11 11	152.9 114.1	-44.3 -23.9	3 3	4 14	450.9 429.6
220 220	670 565	42 36	12 11	108 68	-41 -6	3 2	15 14	1096 883
209 209	384 287	20 27	8 8	103 98	-83 -13	2 2	11 11	769 596
PVC 208 208	592 519	19 20	4 4	-400 -437	-54 -73	4 4	10 10	873 774
221 221	483 540	21 20	4 4	-302 -317	-39 -36	5 3	10 9	633 725
223 223	920 839	32 31	4 4	-162 -189	45 30	4 4	10 10	1054 970
233	804	25	4	-273	87	5	10	973
119	716	39	5	-82	91	5	10	840
LBBB 111 111	260 293.3	34 36	8 8	125 141	-49 -70.5	5 6	14 14	470 472
109 109	772 742	30 30	12 11	62 72	56 60	5 5	17 17	1168 1134
214 214	899 835	31 31	10 10	-45 -155	3 -18	6 6	16 17	1021 984
207 207	438 390	40 37	5 9	-73 -67	-17 -67	8 9	14 18	619 563

Table (5.5): Result of Maximum values for Features of Signals (ca3)

Signals	R amplitude	R-R interval	R-R range	ST segment	T amplitude	P amplitude	QRS interval	QT interval	RS segment
Normal 115 115	1059 989	52 44	405 374	14 14	89 125	30 61	4 4	17 17	1074 1041
123	1020	60	389	13	250	100	7	20	1143
119	1155	43	417	11	280	147	6	16	1181
101	594	43	406	11	126	115	6	16	652
103	1013	40	381	12	210	17	6	15	1122
122	1006	41	388	10	101	177	6	16	1006
108	584	50	393	14	37	162	7	20	709
Paced 217 217	680 670	73 90	348 430	13 10	565 600	-57 180	8 10	19 20	1470 660
107 107	1140 1170	40 40	420 420	10 10	810 860	70 110	10 10	20 20	1880 2210
104 104	340 720	71 74	402 422	13 13	187 156	-3 130	10 12	21 22	417 646
102 102	359 384.8	39 112	408 369	13 13	83.9 110.4	-2.6 4.4	12 8	22 19	446.9 484
AP 222 222	311.4 311.5	41 41	413 375	9 9	29.8 30	173.1 172.6	6 6	13 13	309.9 310.4
232 232	433 322.4	35 34	337 357	12 13	173.6 154.7	21.1 60	5 6	16 17	577.1 435.2
220 220	1068 986	43 39	423 417	13 13	165 123	25 33	3 3	16 15	1237 1094
209 209	639 571	33 55	431 426	9 10	199 145	124 37	3 3	12 12	798 758
PVC 208 208	1114 1036	58 39	414 396	6 6	105 155	52 126	9 9	14 13	1163 1048
221 221	729 816	39 58	415 413	6 7	-10 -10	76 65	9 9	14 14	666 822
223 223	1180 1103	35 33	405 414	6 6	-114 -103	127 89	9 9	13 13	1241 1142
233	1042	27	439	4	-148	199	7	11	1046
119	1037	42	401	6	-33	149	6	11	1129
LBBB 111 111	482 483.5	37 40	429 409	11 10	201 208.7	47 34.1	8 9	18 18	558 564.1
109 109	948 953	34 33	414 409	12 13	103 102	109 100	9 9	21 21	1279 1283
214 214	1170 1146	36 39	400 423	11 11	22 40	99 64	7 10	18 20	1226 1092
207 207	627 532	68 69	382 390	9 9	-10 2	17 8	12 12	21 21	694 605

Table (5.6): Result of PSD and Statistical Features of Signals (ca3)

Signals	mean	median	Standard deviation	Varian	Power
Normal 115 115	1 3	-26 -17	147 140	21488 19726	21441 19689
123	0	-33	148	21986	21939
119	-1	-59	187	35066	34990
101	1	-17	102	10416	10395
103	0	-30	158	24990	24935
122	3	-38	195	37973	37899
108	1	-15	112	12537	12510
Paced 217 217	3 0	-52 -50	301 320	90763 104520	90573 104290
107 107	-10 0	-100 -90	440 480	192720 234160	192370 233660
104 104	1 1	-6 0	118 139	13863 19368	13833 19326
102 102	0.5 0.5	-22 -24.7	93.4 91.6	8722.1 8396.7	8703.3 8378.6
AP 222 222	-3 0.5	-11.1 -4.4	62.5 61.1	3903.3 3737.5	3894.9 3729.6
232 232	-7 -13.2	-17.1 -16.5	87.2 91.3	7608.1 8338.4	7592.1 8493.3
220 220	0 1	-32 -22	170 154	28742 23571	28679 23519
209 209	-1 1	-22 -14	135 113	18352 12666	18313 12640
PVC 208 208	1 1	-50 -40	253 231	64256 53234	64117 53119
221 221	0 0	-30 -30	154 163	23848 26538	23797 26480
223 223	2 0	-32 -32	218 212	47461 44782	47363 44684
233	2	-42	251	62858	62726
119	4	-49	170	31893	31836
LBBB 111 111	0 -0.2	-22 -21.2	107 97.1	11425 9424	11400 9403.5
109 109	0 3	-31 -36	241 239	58023 57038	57896 56922
214 214	3 2	-27 -33	226 241	50925 58179	50822 58056
207 207	0 -9	-17 -19	131 142	17243 20026	17205 20061

5.4 Result of classification step:

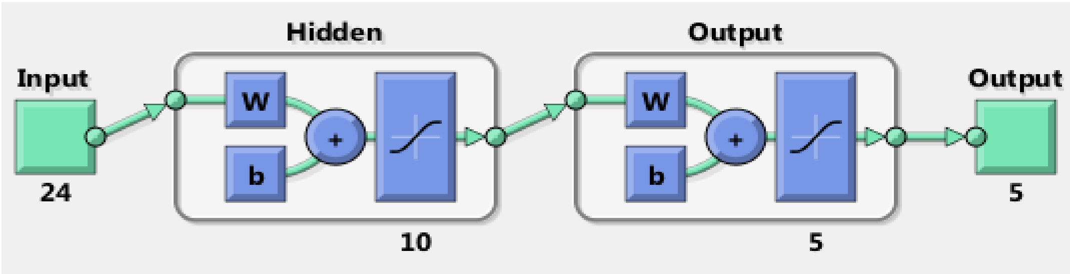

Figure (5.10): Architecture of PRNNW with10 neuron of hidden layers

The twenty four means which feature extracted, there were considered as input for neural networks, ten means number of neurons in hidden layer and five means number of classes.

5.4.1 Training phase:

We did train more than one to obtain good result for fitting data in NNW and save the adjustable weight by using function getx, Weight = getx (net) for using ca2, ca3 and ca4 as original signals.

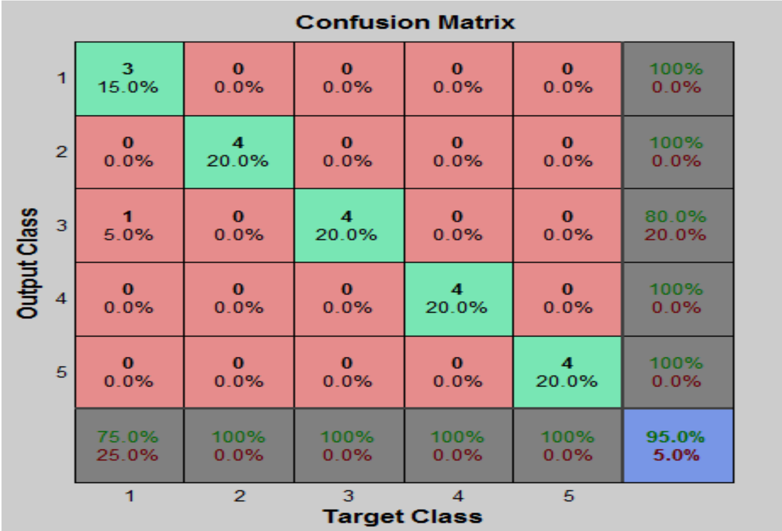

Figure (5.11): Confusion Matrix for ca2.

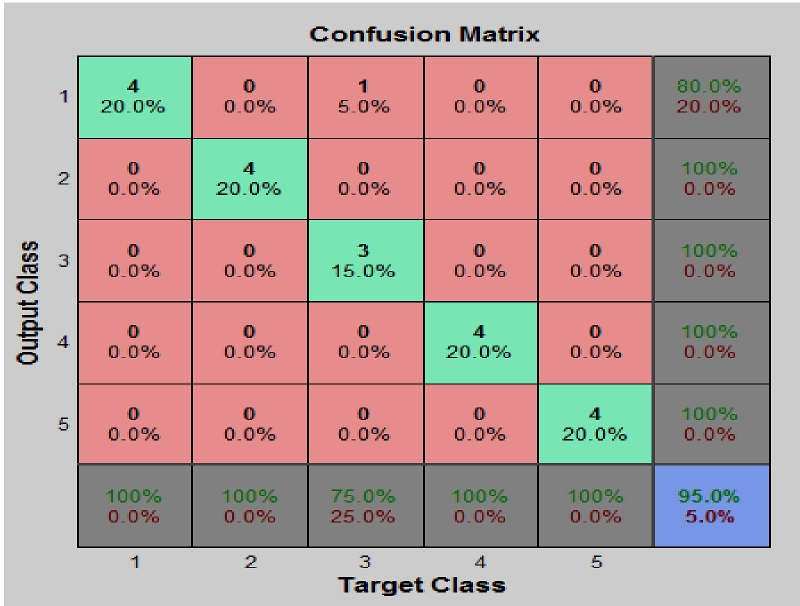

Figure (5.12): Confusion Matrix for ca3.

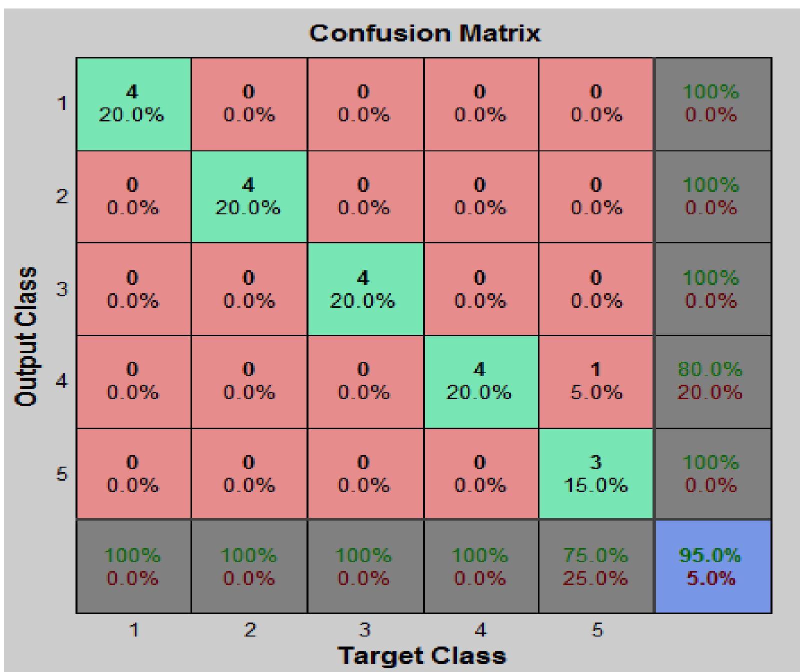

Figure (5.13): Confusion Matrix for ca4.

Figure (5.11), (5.12) and (5.13) shown the total percentage of how fitting data well in pattern recognition network by using ca2, ca3and ca4 respectively, it plotted across all samples. It shown the percentages of correct and incorrect classifications it was noticed the results was same 95%, just different in which class couldn’t detected completely.

By experiment, the obtained results when using training trainlm algorithm. It got the best performance using 10 neurons in the hidden layer. This algorithm is the fastest algorithm compare with other. Also noticed increasing in accuracy and become better when repeat the train, and adjust the weights

5.4.2 Testing phase:

By calling the neural network which used it in training stage and set its weight by using function net= stex (net, weight). We found a result for ca2, ca3 and ca4 and after that made performance evaluation for each one.

Table (5.7): Result of testing phase of PRNNW for ca2

signals	**115**	**123**	**119**	**101**	**115**	**103**	**108**	**122**
Normal	**0.9481** 0.0194 0.0001 0.0009 0.0001	**0.9990** 0.0003 0.2329 0.0000 0.0004	0.0031 0.0000 0.0017 0.1955 0.0256	**0.9984** 0.0000 0.0011 0.0097 0.0005	0.1771 0.0005 0.9302 0.9525 0.0000	0.0002 0.0022 0.9181 0.0067 0.0000	**0.9758** 0.0001 0.0011 0.0000 0.6453	0.0907 0.0000 0.0000 0.0182 0.6056
	217	**107**	**104**	**102**	**102**	**107**	**104**	**217**
Paced	0.0000 **0.9996** 0.0014 0.0001 0.0013	0.0000 **0.9994** 0.0005 0.0003 0.0004	0.0001 **0.9959** 0.0001 0.0013 0.0012	0.0000 **0.2015** 0.0005 0.0415 0.0072	0.8762 0.0074 0.0003 0.9528 0.0002	0.0000 **0.9999** 0.0000 0.0044 0.0437	0.0000 **0.9993** 0.0024 0.0000 0.0026	0.0000 **0.9461** 0.0000 0.4086 0.9157
	222	**232**	**220**	**209**	**232**	**222**	**220**	**209**
AP	0.0068 0.0001 **0.9949** 0.0012 0.0005	0.0015 0.0011 **0.9940** 0.0028 0.0000	0.0011 0.0022 **0.9958** 0.0035 0.0001	0.0000 0.0001 **0.9677** 0.8923 0.0028	0.0002 0.0002 **0.9999** 0.0007 0.0006	0.1373 0.0001 **0.9814** 0.0805 0.0000	0.0246 0.0001 **0.9768** 0.0558 0.0000	0.0001 0.0001 **0.9997** 0.0230 0.0021
	208	**221**	**223**	**233**	**223**	**119**	**208**	**221**
PVC	0.0001 0.0024 0.0001 **1.0000** 0.0000	0.0000 0.0009 0.0000 **0.9993** 0.0007	0.0002 0.0000 0.0015 **0.9992** 0.0003	0.0003 0.0000 0.0000 **0.9789** 0.6336	0.0000 0.0006 0.0565 **0.9931** 0.0347	0.0934 0.0000 0.0045 0.0093 0.0821	0.0007 0.0108 0.0000 **0.9999** 0.0002	0.0001 0.0006 0.0000 **0.9999** 0.0008
	111	**109**	**214**	**270**	**111**	**109**	**207**	**214**
LBBB	0.0015 0.0008 0.0000 0.0000 **0.9932**	0.0001 0.0008 0.0000 0.0019 **0.9977**	0.0009 0.0006 0.0000 0.0017 **0.9987**	0.0017 0.0010 0.0000 0.0023 **0.9979**	0.0003 0.0015 0.9643 0.0076 0.0003	0.0000 0.0014 0.0000 0.0033 **0.9842**	0.0000 0.0006 0.0000 0.0049 **0.9980**	0.0004 0.0019 0.0000 0.9861 0.0658

Table (5.8): Result of testing phase of PRNNW for ca3

Signals	**115**	**123**	**119**	**101**	**115**	**103**	**108**	**122**
Normal	**0.9441** 0.0465 0.0076 0.0027 0.0093	**0.9352** 0.0434 0.0072 0.0009 0.0094	**0.9810** 0.0092 0.0070 0.0201 0.0105	**0.8743** 0.0776 0.0097 0.0002 0.0742	**0.8639** 0.0383 0.0124 0.0001 0.0287	**0.6796** 0.0100 0.0198 0.3194 0.0525	**0.9226** 0.1948 0.0183 0.0001 0.0057	**0.9029** 0.0056 0.0030 0.0015 0.0532
	217	**107**	**104**	**102**	**102**	**107**	**104**	**217**
Paced	0.0105 **0.9740** 0.0024 0.0106 0.0068	0.0309 **0.9760** 0.0247 0.0121 0.0060	0.0170 **0.9911** 0.0027 0.0214 0.0194	0.0091 **0.9868** 0.0010 0.0115 0.1015	0.1172 **0.8764** 0.0727 0.0413 0.0021	0.0020 **0.9613** 0.0009 0.0071 0.2450	0.0001 0.0647 0.0006 0.8132 0.3689	0.0048 0.0335 0.0109 0.1578 0.9516
	222	**232**	**220**	**209**	**232**	**222**	**220**	**209**
AP	0.0399 0.0068 **0.9154** 0.0555 0.0224	0.1972 0.0229 **0.5469** 0.0027 0.0842	0.9156 0.0281 0.0078 0.0097 0.0171	0.0169 0.0068 **0.6524** 0.2083 0.2772	0.0212 0.0050 **0.9972** 0.0418 0.0549	0.0639 0.0025 **0.9803** 0.0379 0.0225	0.7070 0.0075 0.0912 0.0249 0.0419	0.2527 0.0392 0.1954 0.4443 0.0478
	208	**221**	**223**	**233**	**223**	**119**	**208**	**221**
PVC	0.0058 0.0128 0.0010 **0.9992** 0.0067	0.0021 0.0095 0.0074 **0.9943** 0.0246	0.1098 0.0120 0.0004 **0.9624** 0.0048	0.0084 0.0054 0.0058 **0.9945** 0.0106	0.0174 0.0083 0.0016 **0.9913** 0.0104	0.8343 0.0111 0.0002 0.5000 0.0005	0.0044 0.0151 0.0586 **0.9991** 0.0025	0.0001 0.0016 0.0270 **0.9999** 0.0887
	111	**109**	**214**	**270**	**111**	**109**	**207**	**214**
LBBB	0.0159 0.0981 0.0007 0.0090 **0.9269**	0.0154 0.0596 0.0003 0.0031 **0.9628**	0.0413 0.0182 0.0002 0.0040 **0.9590**	0.0067 0.0331 0.0001 0.0274 **0.9471**	0.1507 0.4575 0.0006 0.0042 **0.4789**	0.0204 0.0645 0.0001 0.0026 **0.9701**	0.0014 0.0801 0.0006 0.0465 **0.9813**	0.0034 0.0369 0.0001 0.0190 **0.9929**

Table (5.9): Result of test phasing of PRNNW for ca4

	115	**123**	**119**	**101**	**115**	**103**	**108**	**122**
Normal	**0.7744** 0.0025 0.3913 0.0006 0.1036	**0.7456** 0.0013 0.6200 0.1116 0.0089	**0.9763** 0.0067 0.2155 0.0028 0.0537	**0.9641** 0.0036 0.2632 0.0015 0.0188	0.1617 0.0146 0.0454 0.0017 0.9957	**0.5733** 0.0006 0.5466 0.0642 0.0044	**0.9129** 0.0080 0.0540 0.0013 0.1614	0.3095 0.0076 0.0417 0.2039 0.6836
	217	**107**	**104**	**102**	**102**	**107**	**104**	**217**
Paced	0.0033 **0.9824** 0.0949 0.0021 0.0386	0.0043 **0.9409** 0.0677 0.0032 0.0129	0.0176 **0.9796** 0.0079 0.0037 0.0002	0.0074 **0.9800** 0.0070 0.0127 0.0426	0.6653 0.0055 0.4091 0.0019 0.0158	0.2043 0.0434 0.0027 0.0279 0.9767	0.2043 0.1349 0.0104 0.0029 0.1178	0.0007 **0.9914** 0.0069 0.0087 0.0002
	222	**232**	**220**	**209**	**232**	**222**	**220**	**209**
AP	0.0119 0.0529 **0.8457** 0.0396 0.0006	0.0127 0.0433 **0.8965** 0.0431 0.0008	0.2536 0.0004 **0.6423** 0.0885 0.0047	0.0052 0.0040 **0.8863** 0.0228 0.0125	0.0000 0.9982 0.1225 0.0001 0.0722	0.0199 0.0282 **0.8521** 0.0012 0.0305	0.3583 0.0004 **0.5300** 0.0786 0.0046	0.0730 0.0003 **0.8579** 0.0400 0.0079
	208	**221**	**223**	**233**	**223**	**119**	**208**	**221**
PVC	0.0226 0.0130 0.0000 **0.9780** 0.0035	0.0061 0.0002 0.2176 **0.8914** 0.0105	0.0189 0.0015 0.0410 **0.6547** 0.3637	0.0036 0.0004 0.0914 **0.9081** 0.0630	0.0031 0.0005 0.0576 **0.9309** 0.1576	0.9758 0.0042 0.6111 0.0083 0.0088	0.1720 0.1748 0.0004 0.1038 0.0484	0.0043 0.0002 0.1411 **0.9213** 0.0331
	111	**109**	**214**	**270**	**111**	**109**	**207**	**214**
LBBB	0.0830 0.0949 0.5503 0.0000 **0.8216**	0.3142 0.0084 0.0087 0.0157 **0.7288**	0.0056 0.0009 0.0247 0.8430 0.5076	0.1253 0.0038 0.0233 0.1331 **0.5729**	0.0002 0.0019 0.9233 0.0496 0.0217	0.3121 0.0088 0.0109 0.0292 **0.7366**	0.0000 0.3281 0.4509 0.9220 0.0017	0.0261 0.0025 0.0113 0.4836 **0.8149**

Table (5.7), (5.8) and (5.9) shown the results of testing phases for ca2, ca3 and ca4 respectively**,** we selected the target for each class 1;0;0;0;0 for normal , 0;1;0;0;0 for paced , 0;0;1;0;0 for AP, 0;0;0;1;0 for PVC and 0;0;0;0;1 for LBBB. The result it was near from exactly target and gave us accurate classification and other was so far from its class, it was considered as miss class.

5.5 Result of Performance Evaluation:

The classification performance has been evaluated with three measures Sensitivity, Sensitivity and Accuracy for each class in ca2, ca3 and ca4.

Table (5.10): Performance Evaluation of PRNNW for ca2

Signals	Sensitivity	Specificity	Accuracy
Normal	50%	87.5%	80%
Paced	87.5%	96.9%	95%
AP	100%	100%	100%
PVC	87.5%	96.9%	95%
LBBB	75%	93.75%	90%

Table (5.11): Performance Evaluation of PRNNW for ca3

Signals	Sensitivity	Specificity	Accuracy
Normal	100%	100%	100%
Paced	75%	93.75%	90%
AP	62.5%	90.63%	85%
PVC	87.5%	96.88%	95%
LBBB	100%	100%	100%

Table (5.12): Performance Evaluation of PNRNW for ca4

Signals	Sensitivity	Specificity	Accuracy
Normal	75%	93.75%	90%
Paced	62.5%	90.6%	85%
AP	87.5%	96.88%	95%
PVC	75%	93.75%	90%
LBBB	62.5%	90.6%	85%

When calculated the total of accuracy for ca2, ca3 and ca4 we found were 92%, 94% and 89% respectively. We found ca3 presented better results than other. We represented the accuracy by chart as shown in below.

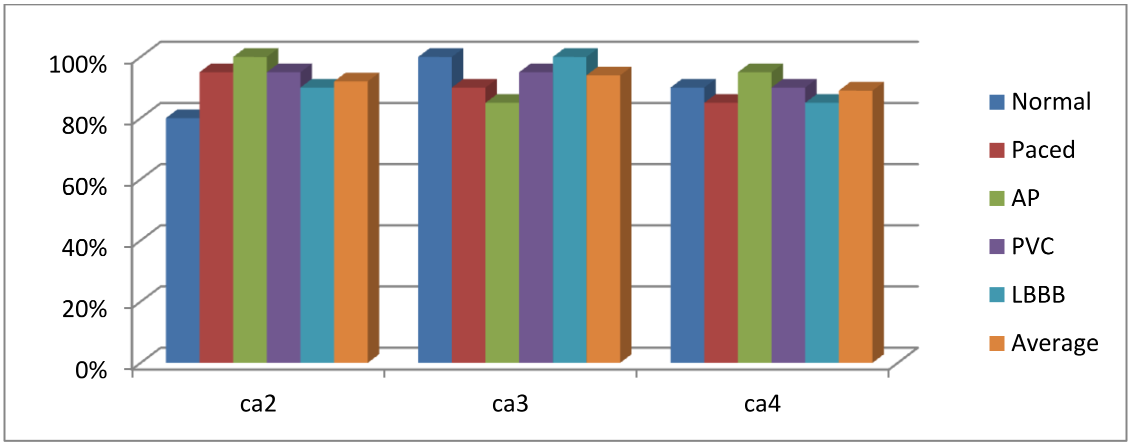

Figure (5.14): Chart of Accuracy for ca2, ca3 and ca4

5.6 Summary of Results and Discussion:

This project made compare between three approximation coefficient after applied sym6, to choice from their which presented the good signals to obtain more accuracy features extraction and classifications by simple algorithm in MATLAB. And made combine between different types of features (morphological & statistical) and also it used special kind of feed forward neural network (pattern recognitions) to classify cardiac arrhythmias into normal and abnormal cases.

In this study the implementation algorithm produced accuracy normal class is 100%, PVC class is 95%, paced class is 90%, AP class is 73%, and for LBBB class is 100%. The percentages of verification results differ on classes of data maybe due to selection and quality of recording signal we noticed the system was a accomplished accuracy more efficient than research of Method for detection and classification in ECG analysis by Dina Kicmerova, he focused in measuring of QT intervals only and He taken PVC and normal beats to classification. The accuracy of it is 93.10% for premature ventricular contractions (PVC) and 96.43% for normal beats.

Chapter Six

Conclusion and Recommendations

6.1 Conclusion:

The ECG signal can be used as a reliable indicator of heart diseases. In this study aimed to identify the characteristics of ECG signals and diagnostic it accurately, to achieved that, the proposed system consists of three phases: the preprocessing phase, the feature extraction phase and the classification phase. In the first phase, notch filter and high pass filter is employed to eliminate the noises from the ECG signals. In the second phase, the DWT is applied on filtered signal and some features from the wavelet coefficients are extracted. In the third phase, the extracted features were used to train PRNNWs as the classifier. The neural network classifier was presented as the diagnostic tool to aid the physician in the analysis of cardiac abnormalities. The implemented algorithms capable of distinguishing five different heart conditions providing very high accuracy that reached to 94% of overall detection rate.

6.2 Recommendations:

The recommendations are to:

- ✓ Increase the quantities of samples and features to increase the accuracy.
- ✓ Compare with different classifiers, and modify the network structure so that it can achieve better classification accuracy.
- ✓ Real time implementation for detecting the cardiac arrhythmias.

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