# Sudan University of Science and Technology

# College of Graduate Study

# Department of Biomedical Engineering


# Adaptive Techniques for Cardiac Arrhythmia Detection by Using Artificial neural Network

# طرق مواءمه للكشف عن دقات القلب غير المنتظمه باستخدام الشبكات العصبيه الاصطناعيه

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


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# Glossary

**AF:** Atrial Fibrillation

**AFL:** Atrial Flutter

**ANN:** Artificial Neural Network

**AUC:** Area under Curve

**CDHMM:** Continuous Density Hidden Markov Model

**CR:** Compression Ratio

**DWT:** Discrete Wavelet Transform

**ECG:** Electrocardiogram

**ED:** Edge Detection

**EBP:** Error Back Propagation

**EMG:** Electromyogram

**FFT:** Fast Fourier Transform

**GLH:** Gray Level Histogram

**HPF:** High Pass Filter

**HR:** Heart Rate

**LDA:** Linear Discernment Analysis

**LPF:** Low Pass Filter

**LVQ:** Learning Vector Quantization

**ME:** Mixture of Experts

**MH:** Military Hospital

**MIT-BIH:** Massachusettes Institute of Technology and Boston's Beth Isral Hospital

**MME:** **Modified Mixture of Experts**

**MNN:** **Modular Neural Network**

**MSE:** **Mean Square Error**

**MV:** **Mean-Variance**

**N:** **Normal Rythm**

**ROC:** **Receiver Operation Characteristics**

**S:** **Supra-Ventricular Arrhythmia**

**SA:** **Sinoatrial Node**

**SNR:** **Signal to Noise Ratio**

**SOM:** **Self Organizing Map**

**WD:** **Wavelet Decomposition**

**WT:** **Wavelet Transform**

**V:** **Premature Ventricular Contraction**

# Dedication

*To the soul of my beloved ones, to my lovely family and wonderful mother.*

# ACKNOWLEDGEMENTS

In the name of ALLAH the most Merciful the most Compassionate, I would like first and foremost give thanks to our LORD for all HE has given us and for it is in his name that we go further.

I am greatly indebted to my supervisor Dr. Zenab Adam Mustafa, who generously shares her knowledge and experience with all her students. I really appreciate her ultimate help, personal concern, patient and objective support.

All my thanks and wishes are extended to all member of the Biomedical Engineering Department, Faculty of Engineering, University of Sudan for Science and Technology for their help and friendly attitude.

# Abstract

95 ECG signals were collected from MIT-BIH Arrhythmia database in Physionet bank in Physionet website. 25 of these samples are said to be abnormal and the rest 70 sample are normal sinus rhythm ECG. These samples were processed to remove baseline wonder and high frequency noise using Fast Fourier Transform and Discrete Wavelet Transform.

The Matlab program was also developed to extract the main feature of the ECG signal during a set period of time. Starting with segmenting the signal into three smaller samples then detecting the R peak knowing that it is the easiest feature to detect because it's the highest peak. The rest of the features were collected easily once R peak is known.

Artificial Neural Network was used in the classification step. The normal signal was given the number 1 while the abnormal sample was 0 in the construction of ANN. All the features were presented in an excel file and used in the development of the ANN. All these data were used in the training of ANN and the results was collected and discussed.

# الخلاصه

95 اشاره رسم قلب كهربيه تم تجميعها من موقع فيزيونت الالكتروني. 25 من هذه الاشارات تعتبر غير طبيعيه وباقي 70 عينه هي عباره عن اشارات ذات ايقاع طبيعي. تم معالجه هذه الاشارات لازاله التشويش والذبذبات ذات التردد العالي باستخدام تقنيتي FFTوDWT

تم تطوير برنامج MATLAB ليقوم ايضا باستخراج المميزات الاساسيه لاشاره رسم القلب خلال فتره زمنيه محدده. بدايه بتقسيم الاشاره الى تلاته عينات اصغر ومن ثم البحث عن القمه Rمع العلم انها اسهل مميزه يتم اكتشافها لانها اعلى قمه. باقي المميزات تم تجميعها بسهوله بمجرد معرفه موقع القمه R.

تم استخدام الشبكات العصبيه في مرحله تصنيف الاشاره. تم اعطاء الاشارات الطبيعيه الرقم 1 والاشارات غير الطبيعيه الرقم 0 في تصميم الشبكه العصبيه. وقد تم تجميع كل المميزات في ملف EXCELليتم استخدامه في انشاء الشبكه العصبيه. كل هذه المعلومات تم استخدامها لتدريب الشبكه و تم تحصيل النتائج ومناقشتها.

# Chapter 1

# 1. INTRODUCTION

## 1.1 General View

Electrocardiogram (ECG) is a diagnosis tool that reported the electrical activity of heart recorded by skin electrode. The morphology and heart rate reflects the cardiac health of human heart beat [1].

Electrocardiogram (ECG), a non-invasive technique is used as a primary diagnostic tool for cardiovascular diseases. Cardiac arrhythmias including heart attack, stroke, and hypertension, is caused by disorders of the heart and blood vessels and is by far the leading cause of death around the world. However, most heart attacks and strokes could be prevented if some method of pre-monitoring and prediagnostic can be provided. In particular, early detection of abnormalities in the function of the heart, called cardiac arrhythmias, can be valuable for the clinicians. The electrocardiogram (ECG) plays an important role in the process of monitoring and preventing cardiac arrhythmias.

The ECG signal provides key information about the electrical activity of the heart. This electrical activity is related to the impulse that travels through the heart, which determines its rate and rhythm. Physicians use this information to diagnose many cardiac disease conditions. The amplitude and duration of the wave contains useful information about the nature of disease afflicting the heart. The electrical wave is due to depolarization and re polarization of Na+ and k- ions in the blood. The ECG signal provides the following information of a human heart:

- Heart position and its relative 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.

ECG does not afford data on cardiac contraction or pumping function [1].

Early ECG systems were just recording the signal by printing it in a paper strip. Slight changes in the amplitude and time of the ECG signal from a predefined pattern have been used routinely to detect the cardiac abnormality. Because of the difficulty to elucidate these changes manually, a computer-aided diagnosis system can help in monitoring the cardiac health status. Computer aided cardiac arrhythmia detection and classification can play an important role in the management of cardiovascular diseases [2].

## 1.2 Problem Statement

The basic complexity and mechanistic and clinical interrelationships of arrhythmias often brings about diagnostic difficulties for treating physicians and primary health care professionals creating frequent misdiagnoses and cross classifications using visual criteria Computerized algorithms can identify cardiac arrhythmias with higher diagnostic accuracy with significant reduction in the cost. Many works reported on arrhythmia beat classification shows that there is a need to improve the classification accuracy when used for huge database. Also most of the methods use complex mathematical features imposing lot of computational burden while evaluating these features [2].

## 1.3 Thesis Objectives

The general objective is to assist the care provider in the diagnosing of cardiac arrhythmia. The specific objective of this research is to develop a highly accurate program for ECG classification as normal and abnormal signals using MATLAB. This program will help the medical staff in diagnosing, treating and preventing of heart problems and therefore reducing the mortality.

## 1.4 Methodology

The thesis methodology is about how to develop a classification software tool for ECG waveform using MATLAB as a programming language and to test the accuracy of this software.

The ECG Classification described in this paper will consist of 4 modules. ECG signals used for the research were obtained from the Physionet Database (Physio Bank). A set of programs from the Physionet was used to import ECG records each of which consists of data file, attribute file and header file in Matlab. Matlab and its Wavelet toolbox were used for ECG signal processing and analysis.

1. Preprocessing Module: The ECG signals were preprocessed by filtering it to remove the baseline wander, the power line interference, and the high frequency noise, hence enhancing the signal quality, and omitting the equipment and the environmental effects.
2. Feature Extraction Module: This module is important in the post processing of ECG readings, because a good set of features will have sufficient discriminative power to facilitate the diagnosis or investigation.
3. Classifier and Optimizer Module.

4. Output module: Gives the performance metrics of the Analyzer and diagnosis result [3].

## 1.5 Thesis Layout

The project thesis consists of six chapters which are:

Chapter one: introduces general view for research, problem statement, objectives and methodology.

Chapter two: literature review

Chapter three: describes theoretical background.

Chapter four: illustrates research methodology.

Chapter five: shows results and their discussions.

Chapter six: includes conclusion and future recommendations.

# Chapter 2

# 2. LITERATURE REVIEW

The first automated ECG programs were developed in the 1970s, when digital ECG machines became possible by third generation digital signal processing boards. Commercial models, such as those developed by Hewlett-Packard, incorporated these programs into clinically used devices.

During the 1980s and 1990s, extensive research was carried out by companies and by university labs in order to improve the accuracy rate, which was not very high in the first models. For this purpose, several signal databases with normal and abnormal ECGs were built by institutions such as MIT and used to test the algorithms and their accuracy [4].

With increase in computational power, sophisticated algorithms have been proposed to improve the prediction accuracy of ECG waveform classification systems. This chapter discusses a variety of techniques proposed earlier in literature for feature extraction, classification and data acquisition of ECG signal.

An approach for effective feature extraction from ECG signal was described in Saxena et al. Their paper deals with an efficient composite method which has been developed for data compression, signal retrieval and feature extraction of ECG signals. They carried out detailed studies and by training different topologies of error-back-propagation (EBP) artificial neural network (ANN) with respect to variations in number of hidden layers and number of elements in each hidden layer, the best topology with two hidden layers and four elements in each hidden layer has been finalized for ECG data compression using a Military Hospital (MH) data base. After signal retrieval from the compressed data, it has been found that

the network not only compresses the data, but also improves the quality of retrieved ECG signal with respect to elimination of high-frequency interference present in the original signal. The compression ratio (CR) in ANN method increases with increase in number of ECG cycles. The features extracted by amplitude, slope and duration criteria from the retrieved signal match with the features of the original signal. The test results at each stage are consistent and reliable and prove beyond doubt that the composite method can be used for efficient data management and feature extraction of ECG signals in many real-time applications [5].

Castro et al. described a wavelet transforms approach for ECG feature extraction. Their paper presented an algorithm, based on the wavelet transform, for feature extraction from an electrocardiograph (ECG) signal and recognition of abnormal heartbeats. A method for choosing an optimal mother wavelet from a set of orthogonal and bi-orthogonal wavelet filter bank by means of the best correlation with the ECG signal was developed. The ECG signal is first denoised by a soft or hard threshold with limitation of 99.99 reconstructs ability and then each PQRST cycle was decomposed into a coefficients vector by the optimal wavelet function. The coefficients, approximations of the last scale level and the details of the all levels, were used for the ECG analyzed. The coefficients of each cycle were divided into three segments, which were related to the P-wave, QRS complex and T-wave, and summed to obtained a features vector of the signal cycles [6].

Alexakis et al. used automatic extraction of both time interval and morphological features, from the Electrocardiogram (ECG) to classify ECGs into normal and arrhythmic. Classification was implemented by artificial neural networks (ANN) and Linear Discriminate Analysis (LDA). The ANN gave more accurate results.

Average training accuracy of the ANN was 85.07% compared with 70.15% on unseen data [7].

Ramli et al. investigate the use of signal analysis technique to extract the important features from the 12 lead system (electrocardiogram) ECG signals. Lead II is chosen for the whole analysis due to it representative characteristics for identifying the common heart diseases. The analysis technique chosen is the cross-correlation analysis. Cross-correlation analysis measures the similarity between the two signals and extracts the information present in the signals. Results show that the parameters signal analysis technique extracted could clearly differentiate between the types of heart diseases analyzed and also for normal heart signal [8].

Tayel and Bouridy together described a technique for ECG image classification by extracting their feature using wavelet transformation and neural networks. Their paper, presents an intelligent diagnosis system for electrocardiogram (ECG) intensity images using artificial neural network (ANN). Features were extracted from many preprocess such as wavelet decomposition (WD), Edge detection (ED), gray level histogram (GLH), Fast Fourier transform (FFT), and Mean-variance (M-V). The ANN supervised feedforward back propagation using adaptive learning rate with momentum term algorithm used as a classifier. The input data to the classifier is very large so, ECG images data were grouped in batches that introduced to ANN classifier. The objective of their paper was to introduce an expert system for ECG diagnosis, more suitable preprocess for the used 63 ECG intensity images, and simplest ANN architecture classifier, depending on the higher accuracy of the classifier related to the extracted input features [9].

Tadejko and Rakowski presented the classification performance of an automatic classifier of the electrocardiogram (ECG) for the detection abnormal beats with

new concept of feature extraction stage. Feature sets were based on ECG morphology and RRintervals. Configuration adopted a Kohonen selforganizing maps (SOM) for analysis of signal features and clustering. In their study, a classifier was developed with SOM and learning vector quantization (LVQ) algorithms using the data from the records recommended by ANSI/AAMI EC57 standard. Their paper compares two strategies for classification of annotated QRS complexes: based on original ECG morphology features and proposed new approach - based on preprocessed ECG morphology features. The mathematical morphology filtering was used for the preprocessing of ECG signal. The performance of the algorithm was evaluated on the MIT-BIH Arrhythmia Database following the AAMI recommendations. Using this method the results of recognition beats either as normal or arrhythmias was improved [10].

Alan and Nikola described chaos theory applied to ECG feature extraction. Several chaos methods, including phase space and attractors, correlation dimension, spatial filling index, central tendency measure and approximate entropy are explained in detail. A new feature extraction environment called ECG Chaos Extractor has been created in order to apply these chaos methods. System model and program functions are presented. Some of the obtained results were listed [11].

Ubeyli et al. developed automated diagnostic systems employing diverse and composite features for electrocardiogram (ECG) signals were analyzed and their accuracies were determined. Because of the importance of making the right decision, classification procedures classifying the ECG signals with high accuracy were investigated. The classification accuracies of mixture of experts (ME) trained on composite features and modified mixture of experts (MME) trained on diverse features were compared. The inputs of these automated diagnostic systems were composed of diverse or composite features (power levels of the power spectral

density estimates obtained by the eigenvector methods) and were chosen according to the network structures. The conclusions of their study demonstrated that the MME trained on diverse features achieved accuracy rates which were higher than that of the ME trained on composite features [12].

A new wavelet based framework was developed and evaluated for automatic analysis of single lead electrocardiogram (ECG) for application in human recognition by Fatemian et al. Their proposed system utilizes a robust preprocessing stage that enables it to handle noise and outliers so that it was directly applied on the raw ECG signal. Moreover, it was capable of handling ECGs regardless of the heart rate (HR) which renders making presumptions on the individual's stress level unnecessary. One of the novelties of their paper was the design of personalized heartbeat template so that the gallery set consists of only one heartbeat per subject. This substantial reduction of the gallery size decreases the storage requirements of the system significantly. Furthermore, the classification process was speeded up by eliminating the need for dimensionality reduction techniques such as PCA or LDA. Experimental results for identification over PTB and MIT healthy ECG databases indicate a robust subject identification rate of 99.61% using only 2 heartbeats in average for each individual [13].

Pedro et al. was concerned with the classification of ECG pulses by using state of the art Continuous Density Hidden Markov Models (CDHMM‘s). The ECG signal was simultaneously observed at three different level of focus by means of the Wavelet Transform (WT). The types of beat being selected were normal (N), premature ventricular contraction (V) which was often precursor of ventricular arrhythmia, two of the most common class of supra-ventricular arrhythmia (S), named atrial fibrillation (AF), atrial flutter (AFL), and normal rhythm (N). Both MLII and V1 derivations were used. International Journal of Emerging Technology

and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, Volume 2, Issue 1, January 2012) 59 Run time classification errors could be detected at the decoding stage if the classification of each derivation was different. These pulses were selected for a posterior physician analysis. Experimental results were obtained in real data from MIT-BIH Arrhythmia Database and also in data acquired from a developed low-cost Data Acquisition System [14].

Jadhav et al. proposed a new approach for cardiac arrhythmia disease classification. The proposed method uses Modular neural network (MNN) model to classify arrhythmia into normal and abnormal classes. They performed experiments on UCI Arrhythmia data set. Missing attribute values of this data set are replaced by closest column value of the concern class. They constructed neural network model by varying number of hidden layers from one to three and are trained by varying training percentage in data set partitions. Their data set is a good environment to test classifiers as it is incomplete and ambiguous bio-signal data collected from total 452 patient cases. The classification performance is evaluated using six measures; sensitivity, specificity, classification accuracy, mean squared error (MSE), receiver operating characteristics (ROC) and area under curve (AUC). The experimental results presented in their paper show that more than 82.22% testing classification accuracy [15].

# Chapter 3

# 3. THEORATICAL BACKGROUND

This section aims to demonstrate a quick glance into the heart anatomy and physiology, ECG wave's characteristics and a few of cardiac arrhythmias and their waves which is essential to the understanding of the use of diagnostic ECG.

## 3.1 Heart Anatomy

The heart contains four chambers that is right atrium, left atrium, right ventricle, left ventricle and several atrioventricular and sinoatrial node as shown in the Figure 3.1. The two upper chambers are called the left and right atria, while the lower two chambers are called the left and right ventricles. 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. 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 [1].

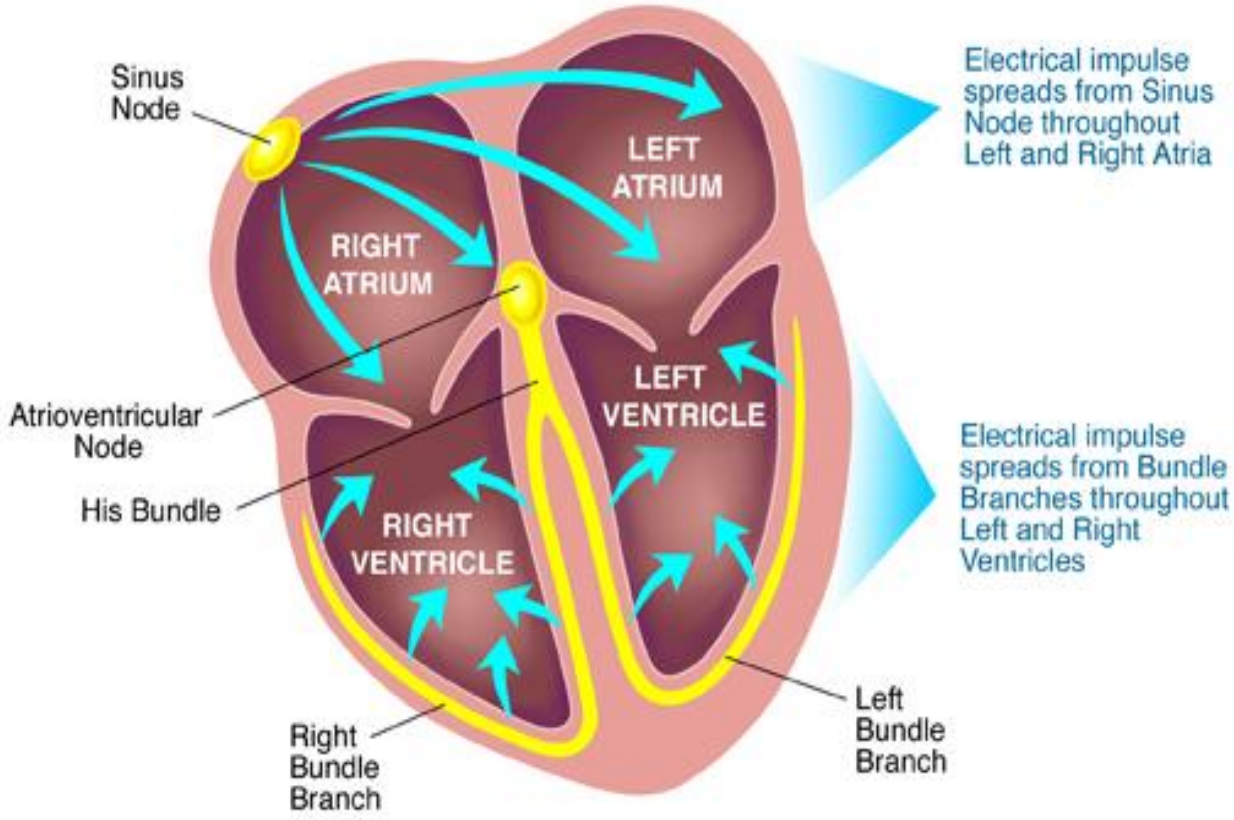


Figure 3.1 the Heart conduction system.

## 3.2 Normal Heart Function and the Electrophysiology of the heart

To fully understand the electrical and mechanical problems that cause arrhythmias and cardiovascular diseases, it is important to understand the electrical and mechanical functions of a normal, healthy heart. A concrete understanding of these differences will provide the information necessary to diagnose, detect, and treat these conditions. Electrical activity in the body drives the mechanical function of the heart. Action potentials are responsible for the contraction of cardiac muscle cells, which is essential for pumping blood through the body. Some cardiac cells,

unlike nerve and skeletal muscle cells are able to generate their own action potentials in order to achieve steady and rhythmic contraction. These cells are known as autorhythmic cardiac cells and work with contractile cardiac cells to pump the heart.

These contractile cells, which make up the majority of cardiac cells, are responsible for heart contraction. Autorhythmic cardiac cells display a pacemaker-like activity; their membrane potential depolarizes after each action potential until they reach threshold and generate another action potential that will cause cardiac contraction.

The autorhythmic cells do not all have the same rate of depolarization. Those cells with the fastest rate of action potential initiations are found on the sinoatrial (SA) node, which is a small region in the right atrial wall. Because the SA node has the fastest rate of action potential initiation, it is known as the pacemaker region of the heart and is known to be the driving force for the rest of the heart. After an action potential is initiated in the SA node, the excitation travels through the remainder of the heart for a full contraction. The action potential first spreads through the atria. The atria must contract before the ventricles can contract, as atrial contraction is responsible for pumping the blood to the ventricles which then contract to pump the blood through the rest of the body. The electrical pathway through which the action potentials follow is demonstrated in Figure 3.2.

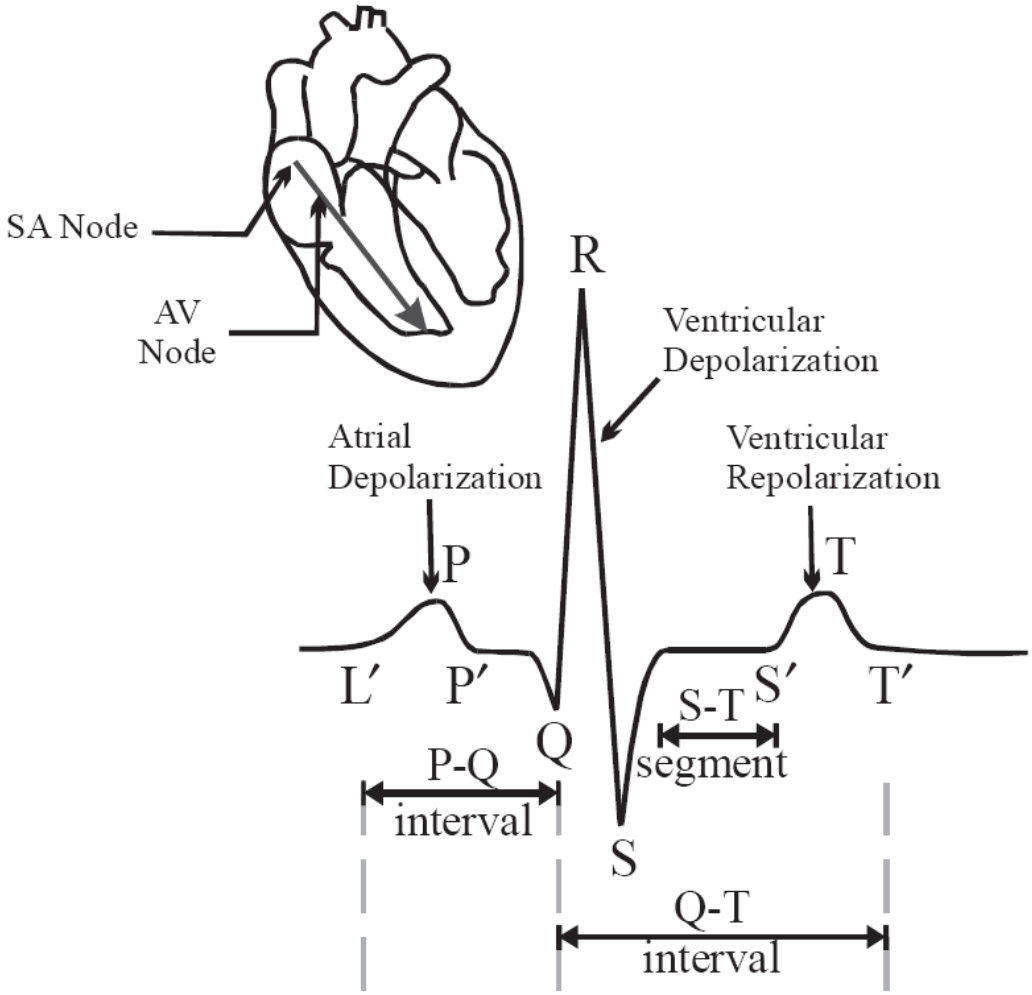


Figure 3.2.Ideal ECG signal. The SA node causes atrial depolarization (P complex). The AV node causes ventricular depolarization (QRS complex). The T complex indicates ventricular repolarization.

An electrocardiogram (ECG) is a recording of this electrical activity of the cardiac cycle. As mentioned, when cardiac muscle cells depolarize and repolarize, electrical currents are generated and spread through the chambers and the tissues that surround the heart. Some of this electricity reaches the surface of the body, and the ECG is able to detect these electrical impulses. An ECG is obtained through electrode placement on a person's skin that detects this electricity and outputs a voltage-time reading. It is important to note that the reading is not a recording of the actual electricity activity of the heart; it is a representation of the

overall spread of electricity during cardiac cell depolarization and repolarization[16].

## 3.3 Electrocardiogram

### 3.3.1 ECG Leads

An electrocardiogram (ECG) is a graphical recording of electrical voltages generated by heart (atrium and ventricle muscles). The measurement is performed by means of patch electrodes placed on the surface of the body. As shown in figure 4 [Goldberger 1999]. The standard ECG has 12 leads: which includes 6- extremity limb lead (3 -bipolar leads, 3 - augmented unipolar leads) and 6 - chest (precordial) leads. A lead is a pair of electrodes (+ve& -ve) placed on the body in designated anatomical locations & connected to an ECG recorde [17].

The six-extremity (limb) leads record voltages from the heart that is directed onto the frontal plane of the body. The extremity leads record six voltage differences from electrodes on the limbs, and each lead has two subgroups, unipolar and bipolar. The extremity leads include:

- Three bipolar extremities lead (I, II, and III). A bipolar lead records the difference between voltages from the heart detected at two extremities. The bipolar extremity leads can be represented by Einthoven's triangle. They are related by the equation II = I + III.

  Einthoven leads:

  Lead I: records potentials between the left and right arm,

  Lead II: between the right arm and left leg, and

  Lead III: those between the left arm and left leg

- Three augmented unipolar extremity leads (aVR, aVL, and aVF). A unipolar lead records voltages at one point relative to zero potential. The unipolar extremity leads can also be represented by a triaxial diagram. They are related by the equation aVR + aVL + aVF = 0.

  Unipolar Limb leads:

  aVR Lead: +ve terminal is on the right arm.

  aVL Lead: +ve terminal is on the left arm.

  aVF Lead: +ve terminal is on the left leg.

As a general rule, the P-QRS-T pattern in lead I resembles that in lead aVL. Leads aVR and II usually show reverse patterns. Lead aVF usually resembles lead III. One lead connected to +ve terminal acts as the different electrode, while the other two limbs are connected to the –ve terminal serve as the indifferent (reference) electrode [18].

- The six chest-leads (V1 to V6) record voltages from the heart as directed onto the horizontal plane of the body, from the front and the left side. The chest leads attach to six positions on the chest overlying the 4th and 5th rib spaces as shown in Figure 3.3[19].

  Chest (precordial) leads :

  V1: 4th intercostal space, right sternal edge.

  V2: 4th intercostal space, left sternal edge.

  V3: between the 2nd and 4th electrodes.

  V4: 5th intercostal space in the midclavicular line.

  V5: on 5th rib, anterior axillary line.

  V6: in the midaxillary line.

To make recordings with the chest leads (different electrode), the three limb leads are connected to form an indifferent electrode with high resistances. The chest

leads mainly detect potential vectors directed towards the back. These vectors are hardly detectable in the frontal plane [20]. Since the mean QRS vector is usually directed downwards and towards the left back region, the QRS vectors recorded by leads V1–V3 are usually negative, while those detected by V5 and V6 are positive [18]. In leads V1 and V2, QRS = -ve because, the chest electrode in these leads is nearer to the base of the heart, which is the direction of electronegativity during most of the ventricular depolarization process. In leads V4, V5, V6, QRS = +ve because the chest electrode in these leads is nearer the heart apex, which is the direction of electropositivity during most of depolarization [16].

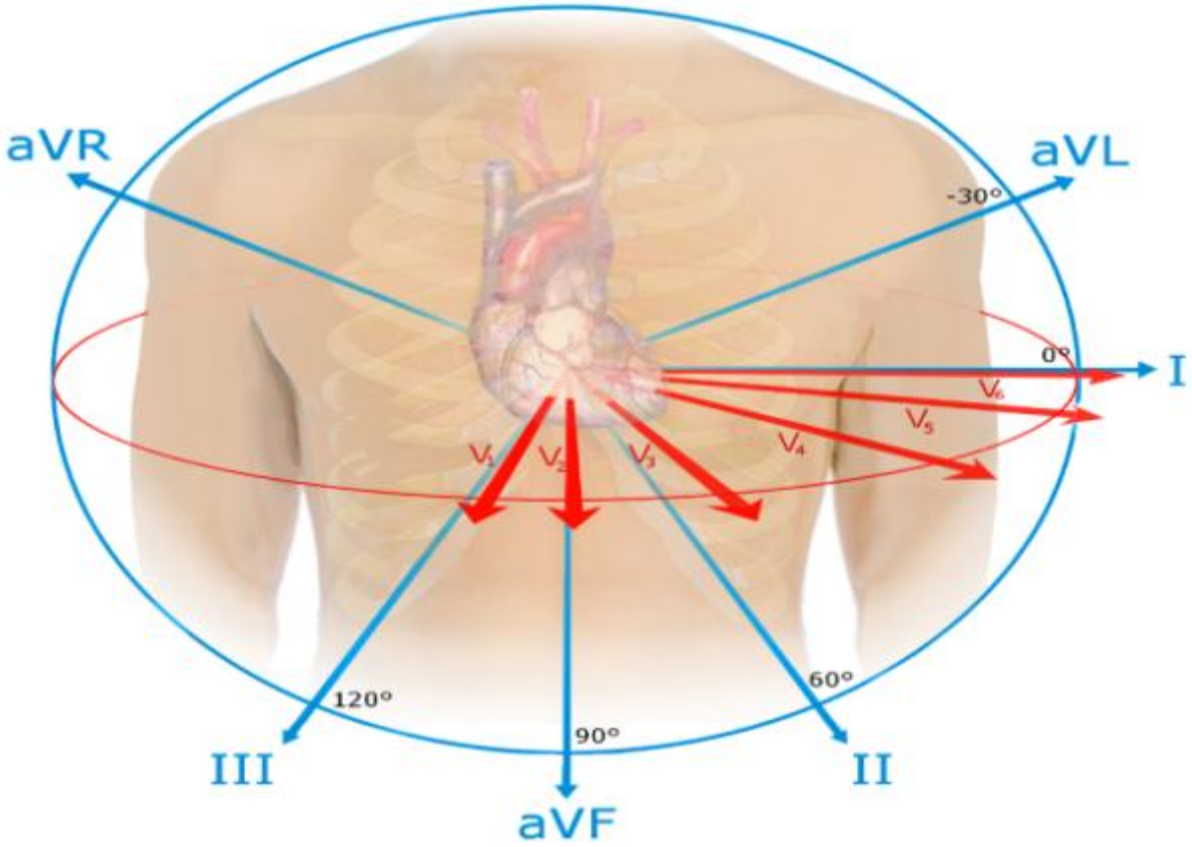


Figure3.3 Twelve ECG leads.

### 3.3.2 Colors in ECG

It's important that you know if you're using a European or American patient cable for monitoring because the colours of the wires will differ as shown below. All references on this page are based on the european (IEC) cable colours.

| **Monitoring cable connections** | | |
|---|---|---|
| Europe | Connect to: | U.S.A. |
| **Red** | Right Arm | **White** |
| **Yellow** | Left Arm | **Black** |
| **Green** | Left Leg | **Red** |
| **Black** | Right Leg | **Green** |
| **White** | Chest | **Brown** |
| **Individual chest leads** | | |
| **White / Red** | C1 / V1 | **Brown / Red** |
| **White / Yellow** | C2 / V2 | **Brown / Yellow** |
| **White / Green** | C3 / V3 | **Brown / Green** |
| **White / Brown** | C4 / V4 | **Brown / Blue** |
| **White / Black** | C5 / V5 | **Brown / Orange** |
| **White / Violet** | C6 / V6 | **Brown / Purple** |

Table3.1 shows the leads color coding.

### 3.3.3 ECG waves and interval

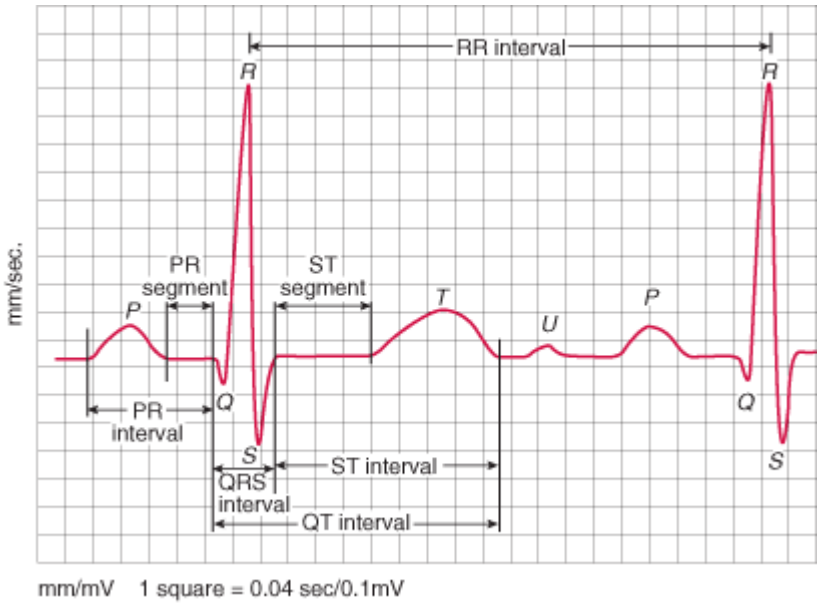


Figure3.4 Schematic representation of normal ECG waveform.

Waves Representation:

- P wave: the amplitude level of this voltage signal wave is low (approximately 1 mV) and represent depolarization and contraction of the right and left atria. A clear P wave before the QRS complex represents sinus rhythm. Absence of P waves may suggest atrial fibrillation, junctional rhythm or ventricular rhythm. It is very difficult to analyze P waves with a high signal-to-noise ratio in ECG signal.
- QRS complex: The QRS complex is the largest voltage deflection of approximately 10-20 mV but may vary in size depending on age, and gender. The voltage amplitude of QRS complex may also give information about the cardiac disease. Duration of the QRS complex indicates the time for the

ventricles to depolarize and may give information about conduction problems in the ventricles such as bundle branch block.

- T wave: Represents ventricular repolarization. Large T waves may represent ischemia, and Hyperkalaemia

| NO. | Features | Amplitude(mA) | Duration(ms) |
|---|---|---|---|
| 1 | 1 P wave | 0.1-0.2 | 60-80 |
| 2 | PR-segment | - | 50-120 |
| 3 | PR-interval | - | 120-200 |
| 4 | QRS complex | 1 | 80-120 |
| 5 | ST-segment | - | 100-120 |
| 6 | T-wave | 0.1-0.3 | 120-160 |
| 7 | ST-interval | - | 320 |
| 8 | RR-interval | - | (0.4-1.2)s |

Table3.2 Amplitude and duration of waves, intervals and segments of ECG signal.

The Table3.2 shows features of P-wave, QRS complex and T wave in maximum amplitude and its duration. According to medical definition, the duration of each RR-interval is about (0.4-1.2)s [1].

### 3.3.4 ECG Noise

Electrocardiogram traces used for identification are obtained using surface electromyography (EMG), where electrodes are placed on the skin in the vicinity of the heart. Potential differences of 1 to 3 mV generated at the body surface by the current sources in the heart are picked up by the electrodes and are amplified in

order to improve the signal to noise ratio (SNR). The ECG waveform is observed on an oscilloscope or is digitized for further processing by a computer (as will be the case for recognition purposes). The digitization process should use a sampling rate of at least 1 kHz to ensure that the ECG trace is of a high enough resolution as required for biometric purposes [21].

ECG measurements may be corrupted by many sorts of noise. The ones of primary interest are:

1. power line interference,
2. electrode contact noise,
3. motion artifacts,
4. EMG noise, and
5. Instrumentation noise [16].

An idealized block diagram of each of these noise sources is shown in Figure2.5. The various noise signals presented in the figure will be characterized in greater detail in this section.

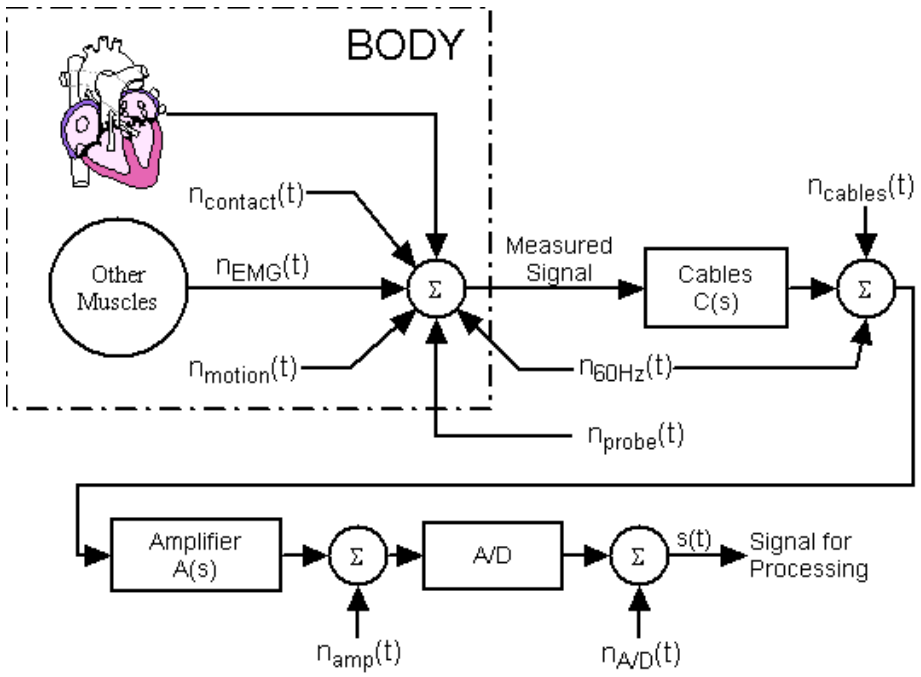


Figure3.5 lock diagram showing the principal noise sources in electrocardiology.

### 3.3.4.1 Power Line Interference

Plotting a Fourier power spectrum of a typical ECG signal Figure3.6 reveals various common ECG frequency components. Several interesting features are readily identifiable:

- The 1.2 Hz heart beat information (approximately 72 beats per minute)
- The 60 Hz power line interference

The remainder of the frequency components represents the subject information (situated between 0.1 Hz and 40 Hz) and contributions of other noise sources.

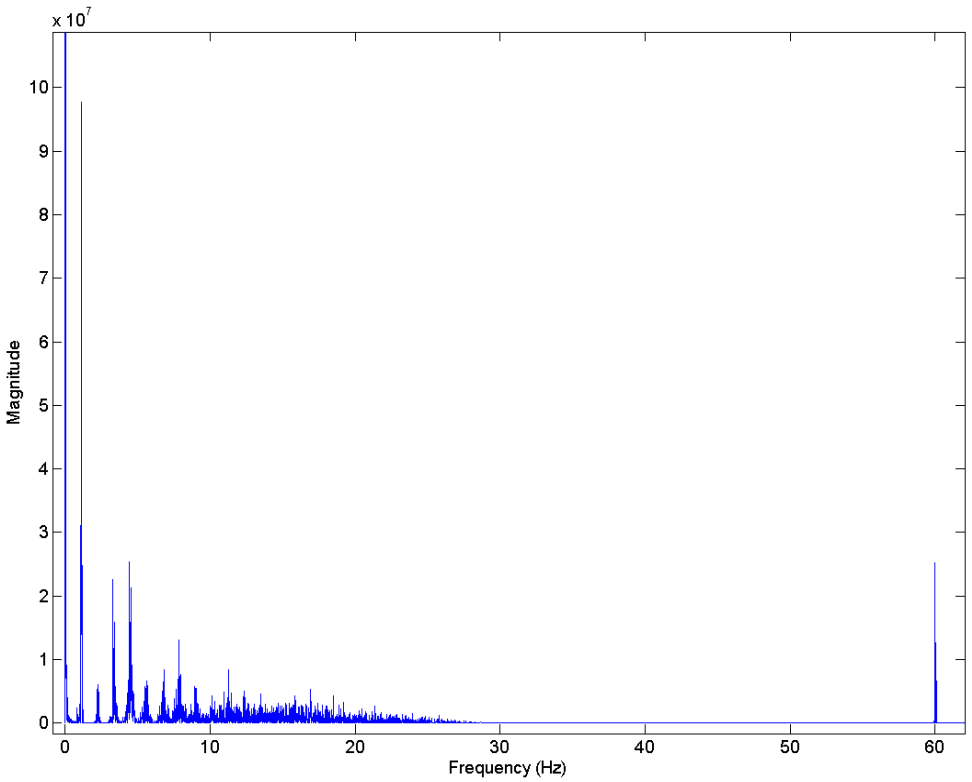


Figure3.6 Fourier power spectrum of an ECG trace. The 60 Hz power line interference and the baseline potential drift noise (at approximately 0 Hz) are identifiable.

Power line interferences contain 60 Hz pickup because of improper grounding. It is indicated as an impulse or spike at 60 Hz/50 Hz harmonics, and will appear as additional spikes at integral multiples of the fundamental frequency. Its frequency content is 60 Hz/50 Hz and its harmonics, amplitude is up to 50 percent of peak-to-peak ECG signal amplitude. A 60 Hz notch filter can be used remove the power line interferences [22].

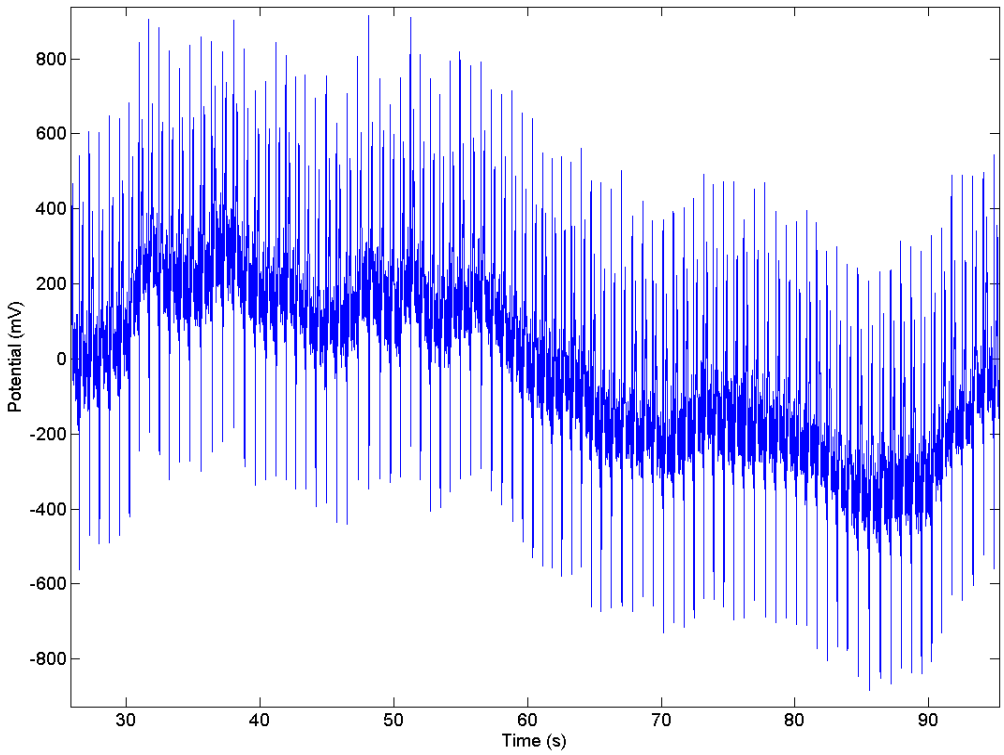


Figure3.7 Seventy seconds of ECG data. The x-axis is time in seconds, and y-axis is the electrical potential in millivolts. A baseline potential drift is present in the ECG trace [23].

### 3.3.4.2 Electrode Contact Noise and Motion Artifacts

Electrode contact noise is caused by variations in the position of the heart with respect to the electrodes and changes in the propagation medium between the heart and the electrodes. This causes sudden changes in the amplitude of the ECG signal, as well as low frequency baseline shifts. In addition, poor conductivity between the electrodes and the skin both reduces the amplitude of the ECG signal and increases the probability of disturbances (by reducing SNR). The underlying mechanism resulting in these baseline disturbances is electrode-skin impedance variation. The larger the electrode-skin impedance, the smaller the relative impedance change needed to cause a major shift in the baseline of the ECG signal. If the skin impedance is extraordinarily high, it may be impossible to detect the

signal features reliably in the presence of body movement. Sudden changes in the skin-electrode impedance induce sharp baseline transients which decay exponentially to the baseline value. This transition may occur only once or rapidly several times in succession [24].

Motion artifacts are transient (but not step) baseline changes caused by electrode motion. The usual causes of motion artifacts are vibrations, movement, or respiration of the subject. The peak amplitude and duration of the artifact are random variables which depend on the variety of unknowns such as the electrode properties, electrolyte properties (if one is used between the electrode and skin), skin impedance, and the movement of the patient [24]. Figure3.8 shows a 70 second segment of a high resolution ECG trace, where the baseline drift varies from approximately -400mV to 400mV. In this ECG signal, the baseline drift occurs at an unusually low frequency (approximately 0.014Hz), and most likely results from very slow changes in the skin-electrode impedance. This noise can also be observed on the Fourier power spectrum in Fig. 8; the large peak nearest to DC is the result of very low frequency base line shifts. The noise artifacts introduced by subject motion are modeled by $n_{motion}(t)$ in Figure3.5.

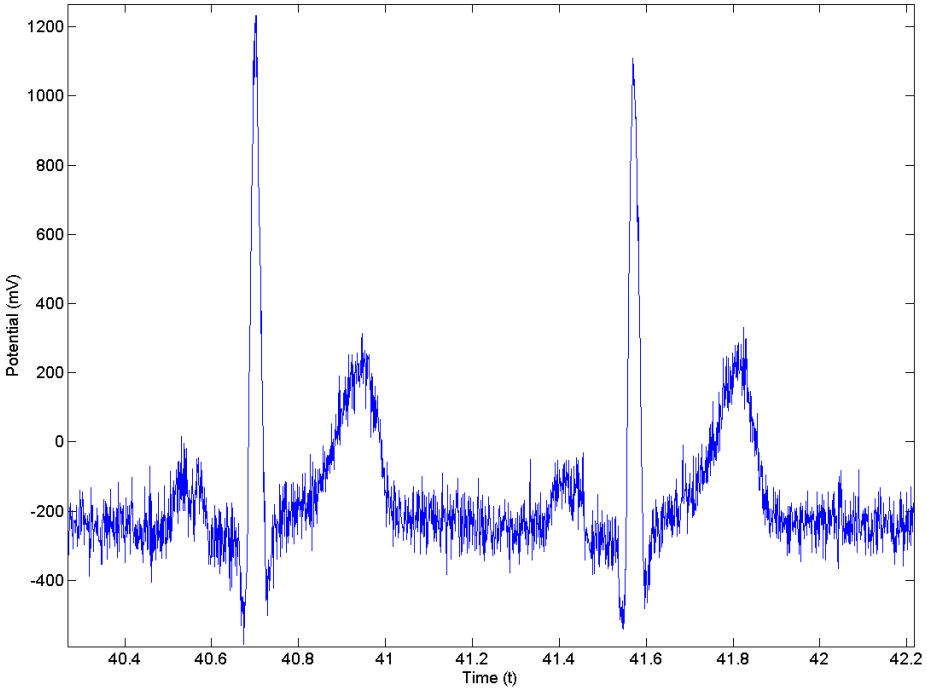


Figure3.8 Two second segment of an ECG trace. The x-axis is time in seconds, and the y-axis is the electrical potential in millivolts. Exact positions of P and T complexes are obscured be presence of EMG noise.

### 3.3.4.3 EMG Noise

EMG noise is caused by the contraction of other muscles besides the heart. When other muscles in the vicinity of the electrodes contract, they generate depolarization and repolarization waves that can also be picked up by the ECG. The extent of the crosstalk depends on the amount of muscular contraction (subject movement), and the quality of the probes.

It is well established that the amplitude of the EMG signal is stochastic (random) in nature and can be reasonably modeled by a Gaussian distribution function [25]. The mean of the noise can be assumed to be zero; however, the variance is dependent on the environmental variables and will change depending on the conditions. Certain studies have shown that the standard deviation of the noise is

typically 10% of the peak-to-peak ECG amplitude [20]. While the actual statistical model is unknown, it should be noted that the electrical activity of muscles during periods of contraction can generate surface potentials comparable to those from the heart, and could completely drown out the desired signal. The effects of typical EMG noise can be observed in the ECG signal, and is particularly problematic in the areas of the P and T complexes. This noise is modeled by $n_{EMG}(t)$ in Figure3.5.

#### 3.3.4.4 Instrumentation Noise

The electrical equipment used in ECG measurements also contributes noise. The major sources of this form of noise are the electrode probes, cables, signal processor/amplifier, and the Analog-to-Digital converter, represented respectively by $n_{probe}(t)$, $n_{cables}(t)$, $n_{amp}(t)$, and $n_{A/D}(t)$ in Figure3.5. Since this form of noise is usually defined by a white Gaussian distribution, adequately represents its effects on the ECG signal. Unfortunately instrumentation noise cannot be eliminated as it is inherent in electronic components, but it can be reduced through higher quality equipment and careful circuit design.

One type of electrical noise is resistor thermal noise (also known as Johnson noise). This noise is produced by the random fluctuations of the electrons due to thermal agitation. The power spectrum of this noise is given by:

$$\overline{V}_n^2 = 4kTR, \qquad (1)$$

Where k is the Boltzmann's constant, T is the temperature, and R is the resistance [26]. This type of noise is generated in the electrodes, in the wire leads connecting electrodes to the amplifier, and in all the resistive electronic components internal to the ECG instrumentation. Since the magnitude of this noise component is

substantial relative to the measured signal, its effects are most noticeable in the electrodes and any other electronic equipment prior to the amplifier.

Another form of noise, called flicker noise, is very important in ECG measurements, due to the low frequency content of ECG data. The actual mechanism that causes this type of noise is not yet understood, but one widely accepted theory is that it is caused by the energy traps which occur between the interfaces of two materials. It is believed that the charge carriers get randomly trapped/released and cause flicker noise. The power spectral density of flicker noise is given by,

$$\overline{V}_{1/f}^{2} = \frac{4kT}{WLC_{ox}f}, \qquad (2)$$

Where k is the Boltzmann's constant, T is the temperature, $C_{ox}$ is the silicon oxide capacitance, WL is the transistor area, and f is the frequency [24]. As the equation suggests, flicker noise is inversely proportional to frequency, indicating that it becomes dominant at lower frequencies. It can be found in any electronic equipment which utilizes bipolar or metal oxide transistors, such as the amplifier used for signal amplification (or more specifically any device which has material junctions).

# Chapter 4
# 4. METHODOLOGY

This chapter introduces the research methodology which is performed using MATLAB to classify ECG signals as normal or abnormal signals. These steps represent only one part of the whole classification system. The program will provide the user with a framework for ECG classification. In this project the ECG signals are collected from Physionet bank (MIT-BIH Arrhythmia Database).

The proposed methodology is depicted in the block diagram in Figure 4.1. Initially ECG Signals are preprocessed for removal of power line noise and high frequency interference. Then deflections in the ECG Signal Q, R, S are identified and through these deflections QRS complex is identified which is a very important feature in identifying arrhythmias. A neural network is trained with 24 dataset containing features of QRS complex, intervals and the Heart Rate.

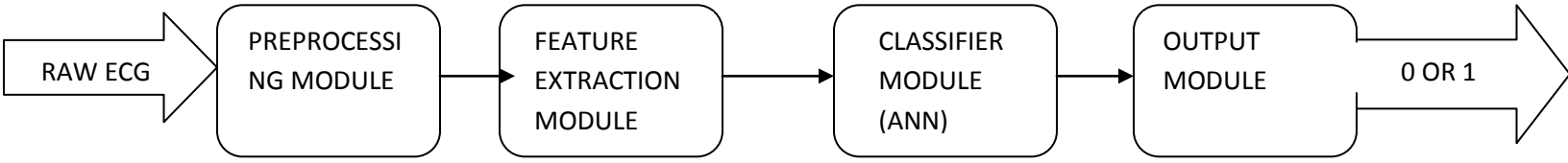


Figure 4.1.: Block diagram of proposed method for ECG classification.

## 4.1 Preprocessing Module:

The main aim of ECG signal preprocessing is to prepare a compact description of the QRS complex, ECG intervals and segment and heart rate, for input to the classification device (Artificial Neural Network) with minimum loss of information.

### 4.1.1 Used signals

The MIT-BIH arrhythmia database contains number of normal and abnormal ECG signal collected from people with different condition from different gender and ages. This database consists of 48 ECG recordings each recording is 30:06min long. The subjects were 26 men and 22 women. We used 2.5 s of each record in duration. Record contains one signal MLII, sampled at 360 samples per second with millivolts input range.  95 samples were collected, 70 were considered normal sinus rhythm and the rest 25 were abnormal ones. Heart rates are given in beats per minute measured over 3 R-R intervals.

### 4.1.2 Fast Fourier Transform

Removal of baseline wander is required in order to minimize changes in beat morphology that do not have cardiac origin, which is especially important when subtle changes in the „„lowfrequency"" ST segment are analysed for the diagnosis of ischemia, which may be observed, for example, during the course of a stress test. The frequency content of baseline wander is usually in the range below 0.5 Hz; however, increased movement of the body during the latter stages of a stress test further increases the frequency content of baseline wander [27]. In this type of noise FFT was used.

### 4.1.3 Discrete Wavelet Transform

The wavelet transform (WT) is designed to address the problem of non-stationary ECG signals noise removal. It is derived from a single generating function called the mother wavelet by translation and dilation operations. The WT of a signal is the decomposition of the signal over a set of functions obtained after dilation and translation of an analyzing wavelet. The ECG signals which consisting of many data points, can be compressed into a few features by performing spectral analysis of the signals with the WT. These features characterize the behavior of the ECG signals. Using a smaller number of features to represent the ECG signals is particularly important for recognition and diagnostic purposes. The DWT uses two filters, a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into different scales. The output coefficients of the LPF are called approximations while the output coefficients of the HPF are called details. The approximations of the signal are what define its identity while the details only imparts nuance [28].

The procedure of DWT decomposition of an input signals x[n] is schematically shown in Figure4.2. Each stage consists of two digital filters and two down samplers by 2, to produce the digitized signal. The first filter, g[n] is the discrete mother wavelet, which is a high-pass filter, and the second, h[n] is a low-pass filter. The down sampled outputs of first high pass filters and low-pass filters provide the detail D1 and the approximation A1. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is decomposed into many lower resolution components [29]. The use of DWT also includes the removal of high frequency noise that can greatly affect the feature extraction process. This tool allows you to define, level by level, time-dependent (x-axis-dependent) thresholds, and then increase the capability of the de-noising strategies handling non-stationary variance noise. More precisely, the model assumes that the observation is equal to the interesting signal superimposed on noise. The noise variance can vary with time. There are several different variance values on several time intervals. The values as well as the intervals are unknown.

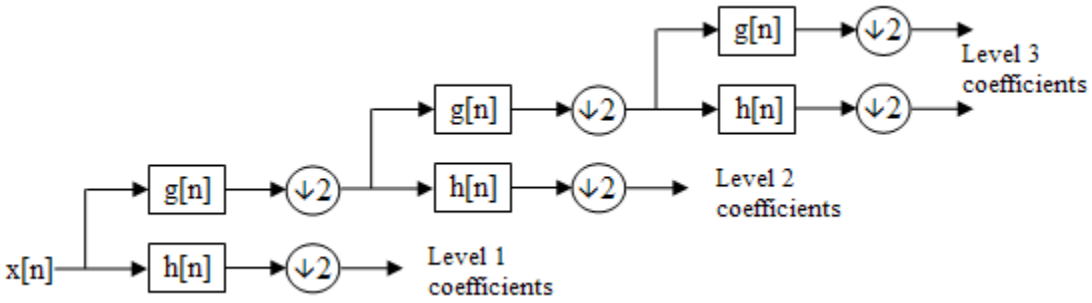


Figure4.2: DWT

### A) Choice of wavelet

To extract a specific event in a signal, the choice of the wavelet becomes important so that the wavelet is adapted to the form of the event to detect. After several tests on various wavelets, our choice was made on the use of the wavelet of ‘’ Daubechies’’ (DB3).

### B) Choice of scales (decomposition level)

The choice of the wavelet makes it possible to choose the levels of scales the most adapted before applying the parameter setting using the selected scales. Concerning the choice of the scales, we used the level of scale 3.

## 4.2 Feature Extraction Module:

### QRS Complex Identification & Feature Extraction

The ECG signals from database were preprocessed for removal of power line noise and high frequency interference. Deflection Identification is then applied to the data thus obtained. Deflection indices found works as input to feature extraction and then neural network is applied to train the system.

## 4.2.1 R Peak Detection

The first stage is the extraction of suitable metrics form the signal of interest. Before these can be extracted from the ECG signal, the Q, R, S deflections in each beat were identified. This is performed with an algorithmic script with the following methodology: The first goal is the detection of the R Peak because once the R-Peak is detected; it can be used to detect the Q and S points easily. Due to the idiosyncratic nature of the QRS complex & the distinctive characteristics of the R peak, this is readily identified even in the most distorted ECG readings. Thus it is used as the basis for ECG feature identification.

The QRS complex is the most striking waveform within the electrocardiogram. Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide mucli information about the current state of the heart. Due to its characteristic shape it serves as the basis for the automated determination of the heart rate, as an entry point for classification schemes of the cardiac cycle. In that sense, QRS detection provides the fundamentals for almost all automated ECG analysis algorithms.

Typical frequency components of a QRS complex range from about 14 to about 25 Hz. Therefore, almost all QRS detection algorithms use a filter stage prior to the

actual detection in order to attenuate other signal components and artifacts, such as P wave, T wave, baseline drift, and incoupling noise. In this thesis a fixed interval thresholding is used to segment the signal into three intervals and the maximum value of each interval was identified as the R peak of this time interval. The values if R peak can be tested by using the equation:

$$Rpeak=max(ecg)*0.6 \qquad (4.1)$$

Where (ecg) is the signal itself. All the point equal and above the Rpeak value are considered when finding the peak as the peak itself or a point near it. The fixed thresholding intervals vary from 1:350, 350:600 and 600:850. It was found after testing that most of the signal can be segmented in this way.

### 4.2.2 P, Q, S and T detection:

After the R peak detection the other key points are easily identified by using the suitable interval thresholding. For the Q detection we used the equations:

$$range=[Rpos-20:Rpos] \qquad (4.2)$$

Where R pos is the position of R peak. After determining the range where Q should exist it can be easily defined as the lowest point there. In the same way the P, S and T is determined.

P point range:

$$range=[Qpos-50:Qpos] \qquad (4.3)$$

S point range:

$$range=[Rpos:Rpos+45] \qquad (4.4)$$

T point range:

$$range=[Spos:Spos+50] \qquad (4.5)$$

Once all the points are determined in position and value other features could be acquired easily such as: RR interval, QRS duration, QT segment and so on.

## 4.3 Classifier and Optimizer Module:

### 4.3.1 ARTIFICIAL NEURAL NETWORKS (ANN)

In modern software implementations of artificial neural network, the approach inspired by biology has more or less been abandoned for a more practical approach based on statistics and signal processing. In some of these systems neural networks or parts of neural networks (such as artificial neurons) are used as components in larger system that combines both adaptive and non-adaptive elements. While the more general approach of such adaptive systems is more suitable for real-world problem solving, it has far less to do with the traditional artificial intelligence connectionist models. What they do, however, have in common is the principle of non-linear, distributed, parallel and local processing and adaptation.

Artificial neural networks have been widely applied in nonlinear signal processing, classification, and optimization. In many applications their performance was shown to be superior to classical linear approaches. The current medical knowledge does not allow any reliable definition of rules to help the traditional automatic system. The self-learning property of neural network allows recovering the feature, which implicitly characterizes the signal. The large variety of topological architectures and learning paradigma makes hard the choice for each problem.

In this thesis artificial neural network tool where used by using the command (nprtool). After preprocessing all of our samples and then extract their feature. All the data collected from this step is presented in two excel sheets. The first represent the target of the ANN: 1 as the normal ECG signals and 0 as the abnormal ones. The second sheet contains 24 ECG features that were used to classify each signal a normal or abnormal. The features hypothesis were first tested and then used in the construction of the network. The 95 signals were divided into: 70% training signals, 15% for testing and 15% as validation. Training signals are presented to the network during training and the network is adjusted according to its error, validation samples used to measure network generalization and to halt training when network generalization stops and testing samples have no effect in training and so provide an independent measure during and after training stops. 20 hidden

layer neurons are used in the end training process were performed and results were collected. The following widows represent the ANN steps for creating ECG classification tool:

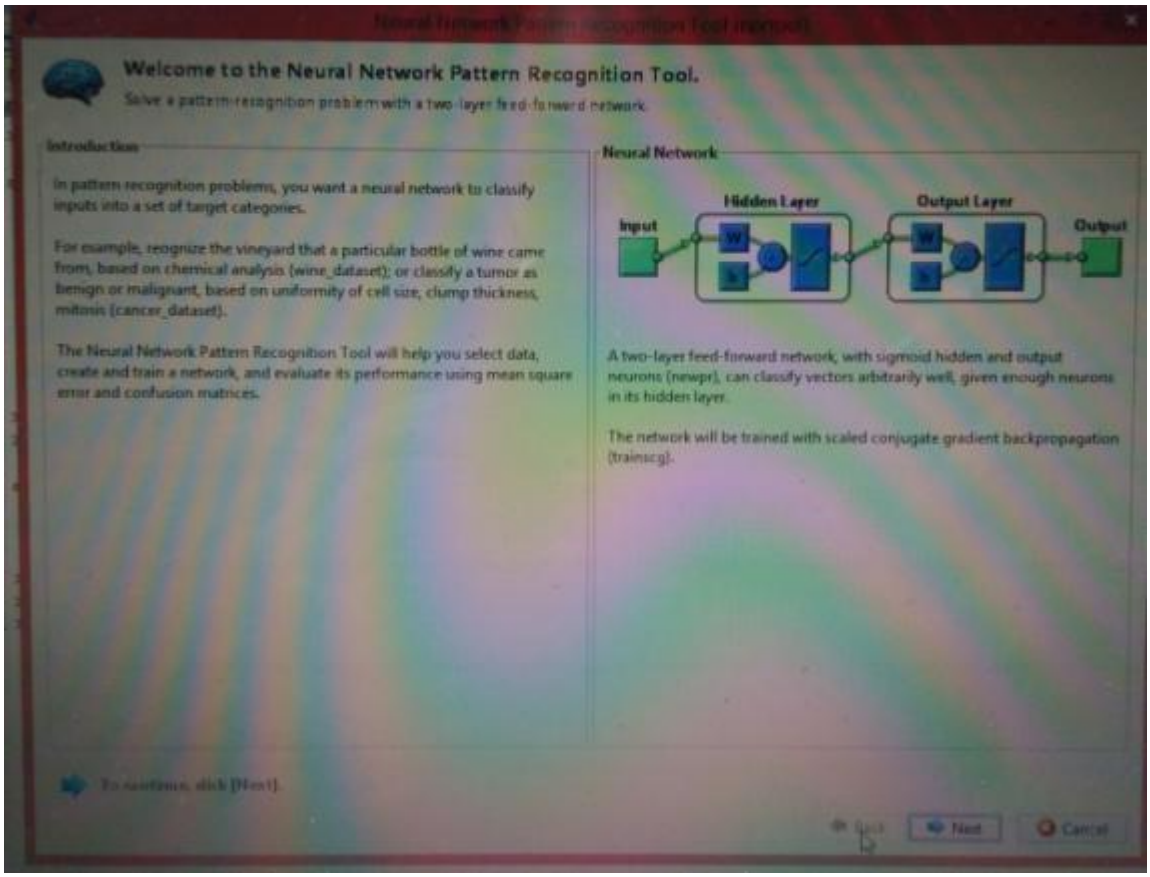


Figure 4.3: The main window of the tool which is open using (nprtool) command

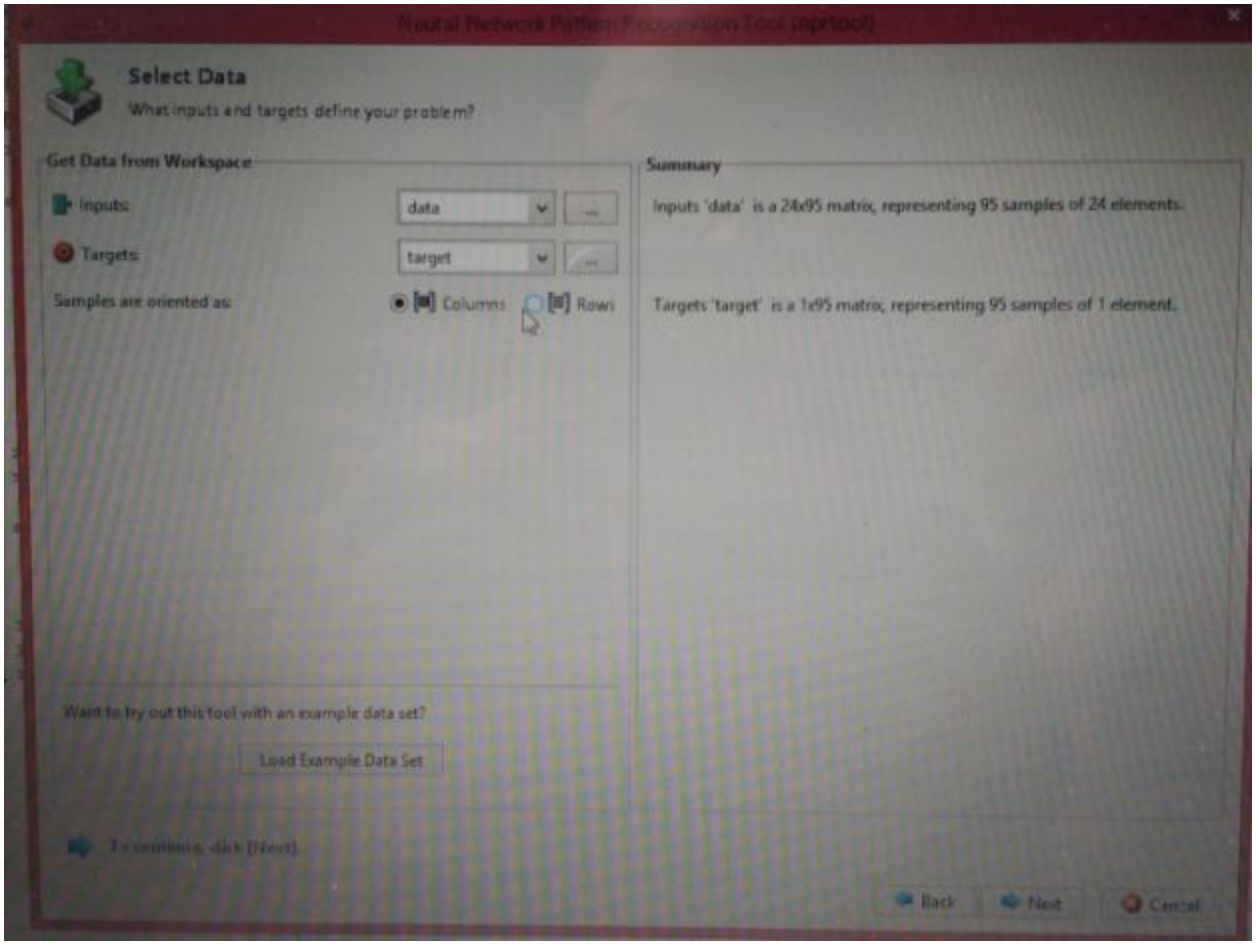

Figure 4.4: widow shows where to input the feature elements and the targets for classifications

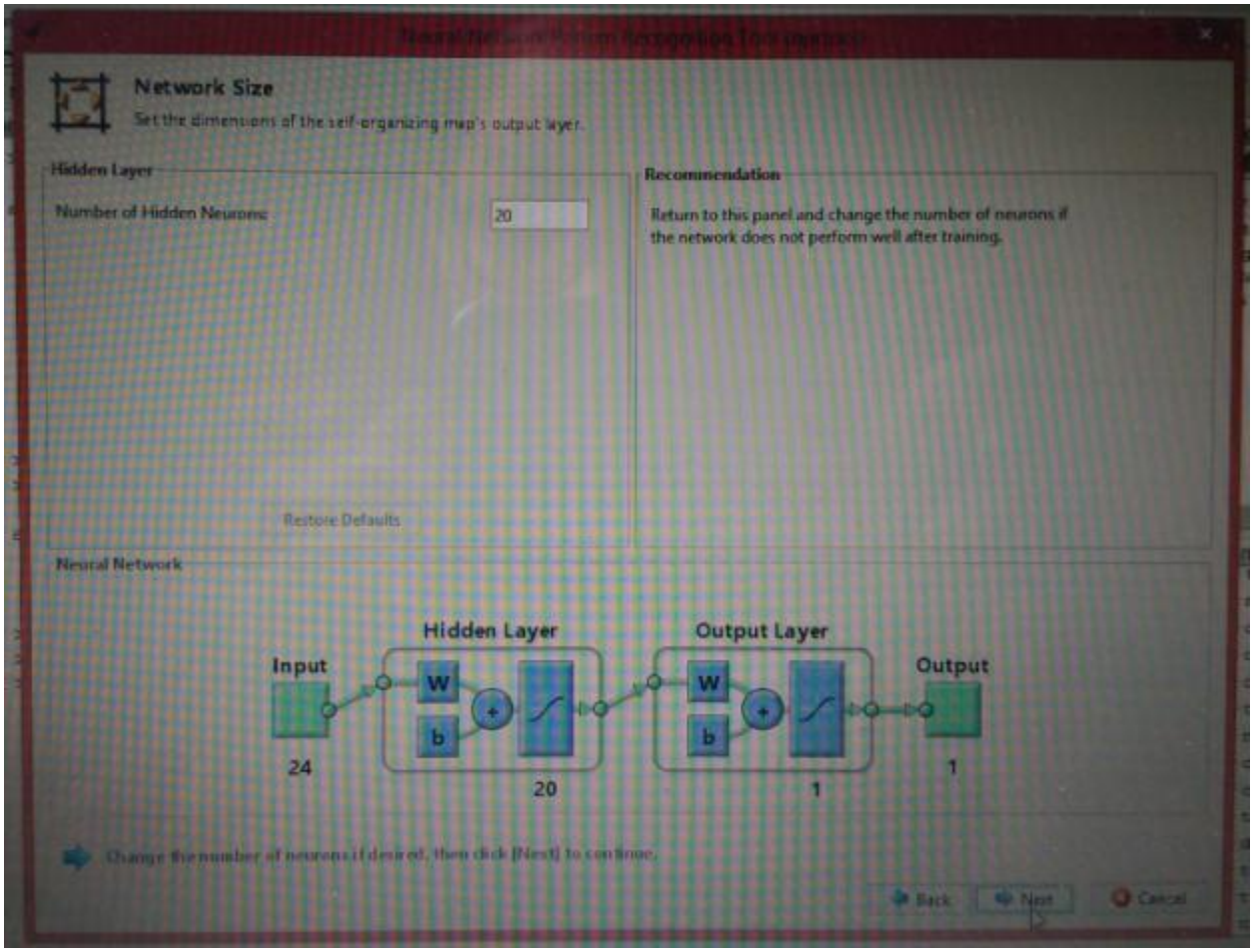

Figure 4.5: 20 neurons in the hidden layer is selected

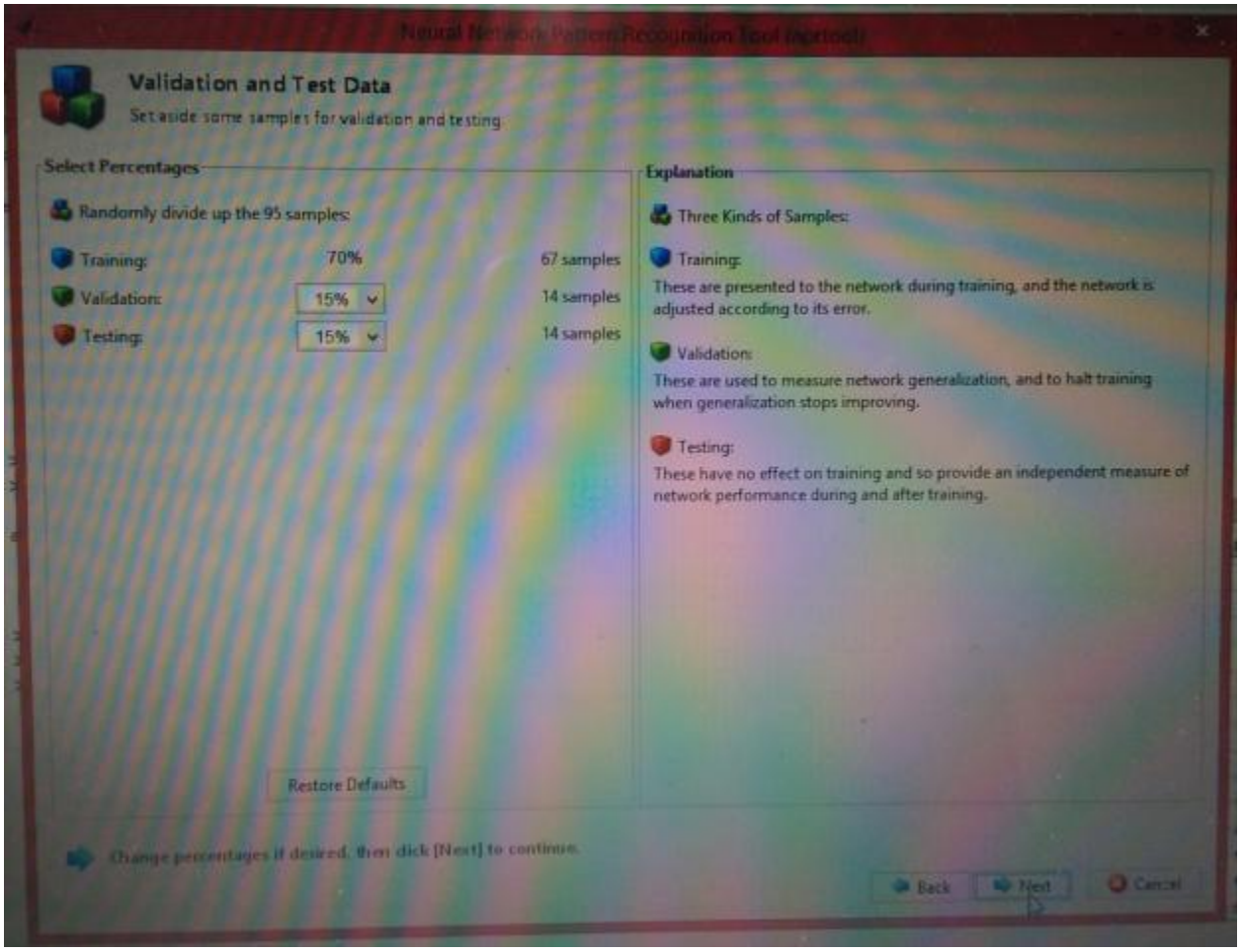

Figure 4.6: then the percentage of the training, testing, and validation samples are selected

After entering all the data required for creating the ANN the next step is to start the training process.


Figure 4.7: training window

After this step results are reviewed and decided whether further training is required or not. The results are discussed in the following chapter.

## 4.4 Output module:

In order to evaluate the classifiers performances, we compute the percentages of Sensitivity, Specificity, Precision and classification rate; defined by the following equations:

The sensibility (SE): SE=TP/(TP+FN)

The precision (PR): PR =TP/(TP+FP)

The specificity (SP): SP=TN/(TN+FP)

Classification percentage (CC): TN+TP/( TN+TP+FN+FP)

Where:

FP = False Positives;

FN = False Negatives;

TP = True Positives;

TN = True Negatives; and

N= FP + FN +TP +TN.

The actual values are presented in the result and discussion chapter.

# Chapter 5
# 5. RESULTS AND DISCUSSION

A software program for ECG classification that has all of its processing steps done on the personal computer (PC) using MATLAB program had been developed.

## 5.1 ECG Data

The ECG data used in this study were obtained from Arrhythmia Database, PHYSIONET website. In this website we found short term (00:10 sec) ECG signals for healthy and sick individuals. Information about each individual health, gender, age and medications used were provided. Also information about the ECG signal itself was found.

## 5.2 Main Windows:

After starting the training progress the Neural Network Training window pop up to show the training in progress which stopped once the validation checks reached 6, as shown in Figure5.1.

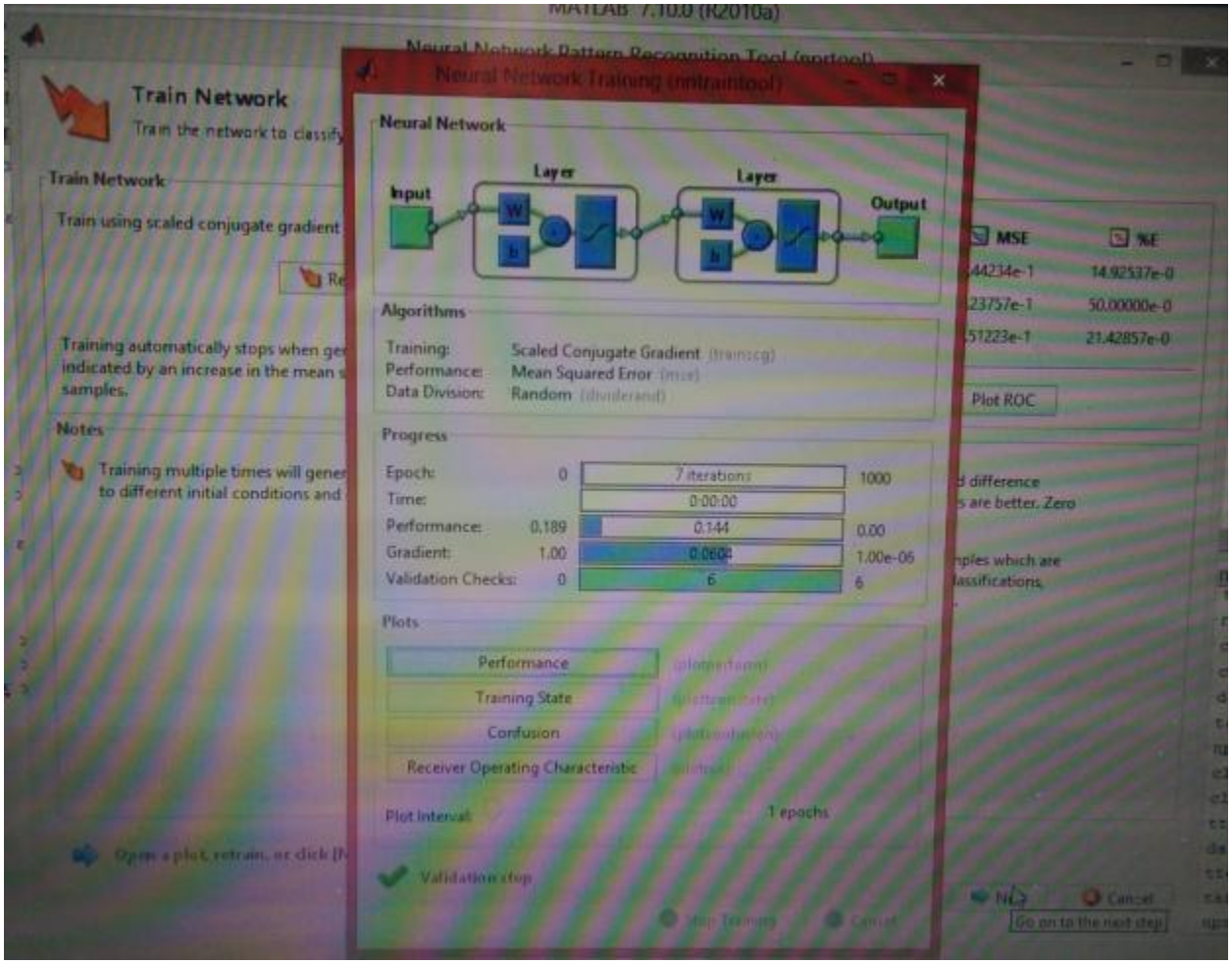

Figure 5.1: Neural Network Training Window (nntaintool)

Confusion matrix as well as ROC graph in the ANN depicts the overall classification rate and accuracy of the network. If the overall classification rate and the accuracy are high, it signifies that the network was successful in correctly classifying the two classes.

After training the network for sufficient number of epochs till the network is perfectly trained having low MSE and less misclassifications, confusion matrix and ROC graph were plotted to measure the true positive rate, that is, sensitivity, true negative rate, that is, specificity, false positive rate, false negative rate, and accuracy of the network

Analysis of ROC graph and confusion matrix of the trained network are generally more than enough for evaluating the designed neural network classifier's accuracy.

There is an additional option to test network on more data and then decide the quality of the network's performance.


Figure 5.2: confusion window

The confusion matrix for training, testing and validation samples and the three data combined is shown in the above Figure5.2. The network output is very accurate, is seen by the high number of correct responses in the green square and the low number of incorrect responses in the red squares. The lower right blue squares

illustrate the overall accuracies. The first row represented by the 1 is the normal signals making the number in the green box the true positive rate (TP) and the number in the red box is the false positive rate (FP). While the second row represented by 2 is the abnormal signal making the number in green is the true negative rate (TN) and in red is the false negative rate (FN).

Due to low accuracy value resulted in the first training process, a retraining is performed again and results are obtained as shown in Figure5.3 and 5.4 below

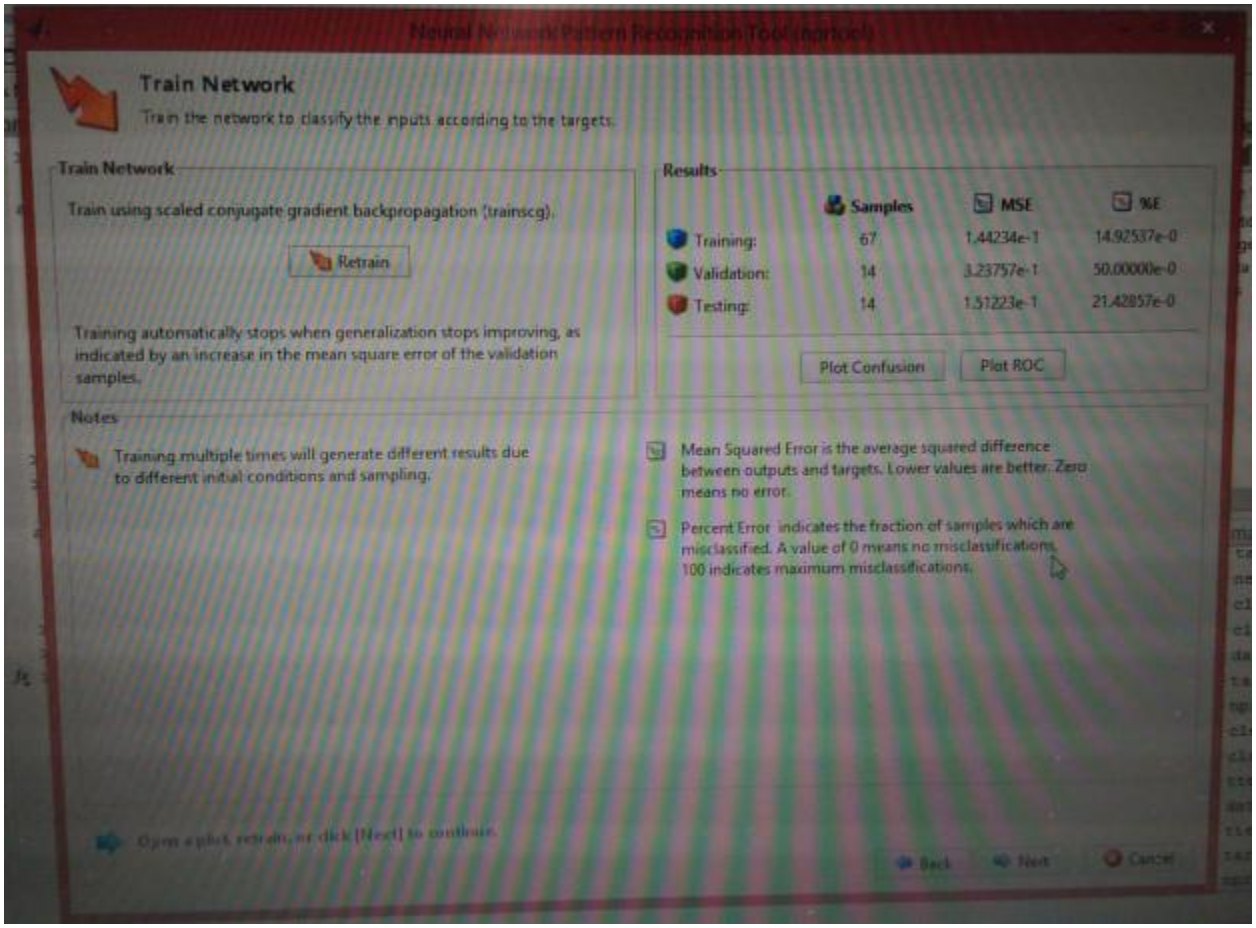


Figure 5.3: retraining window


Figure 5.4: second confusion window

Table5.1 below gives a better interpretation to the above figures 5.2 and 5.4. As one can see an increase in the ANN accuracy is noticed and that's the essential goal on the retraining process, to give the ANN to learn from previous errors.

| % | Accuracy (ACC) | Sensitivity (SE) | Specificity (SP) | False positive rate | False negative rate | misclassification |
|---|---|---|---|---|---|---|
| First: all confusion matrix | 89.5% | 95.7% | 72% | 28% | 4.3% | 10.5% |
| Second: all confusion matrix after retraining | 92.6% | 94.3% | 88% | 12% | 5.7% | 7.4% |

Table5.1 display of the ANN efficiency after training and retraining

Calculation:

**First training:** 89.5% accuracy which is the correct number of correctly classified cases and is found in the blue box in the confusion matrix and can be calculated by adding the true positive and true negative values and divide the by the number of sample collected from the confusion matrix in Figure5.2.
ACC= (TP+TN)/(TP+TN+FP+FN)=(67+18)/(67+18+7+3)=89.5%

Also the sensitivity which is the true normal signal classification ratio and calculated by
SE=TP/(TP+FN)=(67)/(67+3)=95.7%

And the Specificity which is the true abnormal signal classification ratio and equal
SP=TN/(TN+FP)=18/(18+7)=72%

**Second retraining:** 92.6% accuracy, SP= 88% and SE=94.3% which were calculated the same way

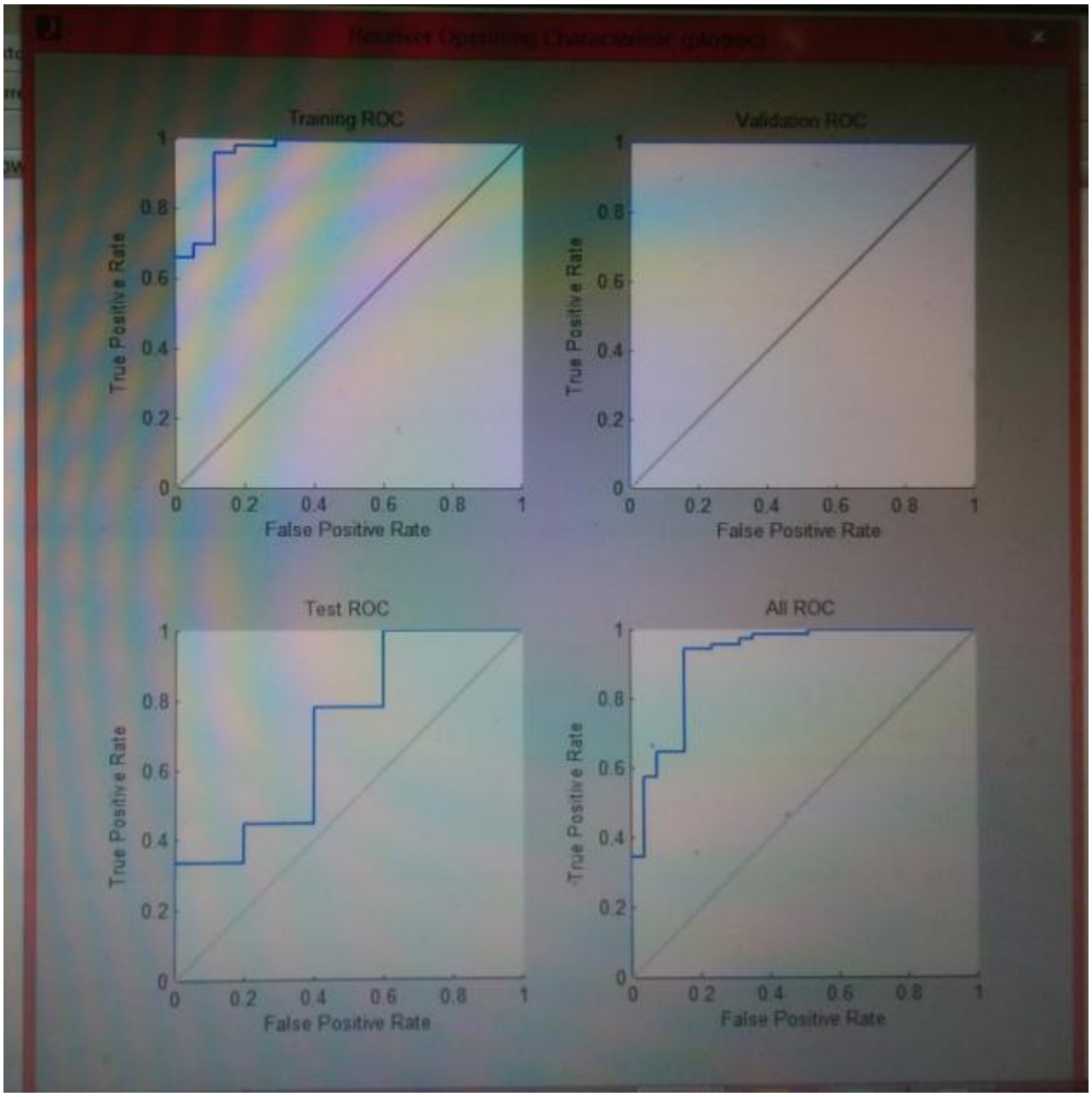


Figure5.5 Receiver Operating Characteristics (plotroc)(ROC)

In the above figure the colored line in each axis represent the ROC curves. The ROC curve is a plot of the true positive rate (sensitivity) versus the false positive rate (1-specificity) as the threshold is varied. A perfect test would show points in the upper-left corner with 100% sensitivity and 100% specificity. For this problem the network in training and validation samples performed well, therefore the all ROC curve did relatively well.

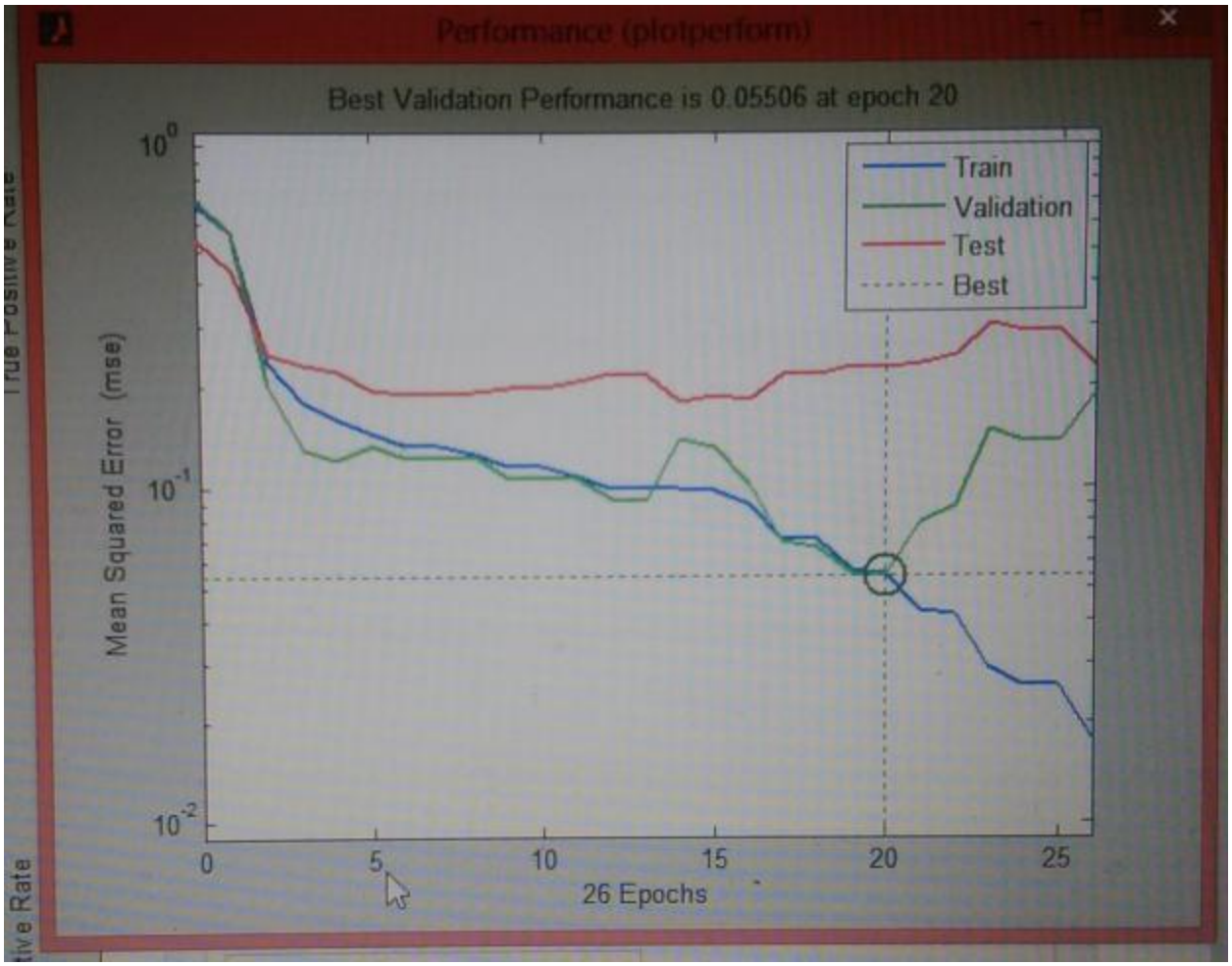


Figure5.6 Performance (plotperform)

The figure mentioned before shows the performance of each the sample categories. As seen here the validation and train sample both did their best performance at some point, on the other hand the test samples did not performed as well as they should

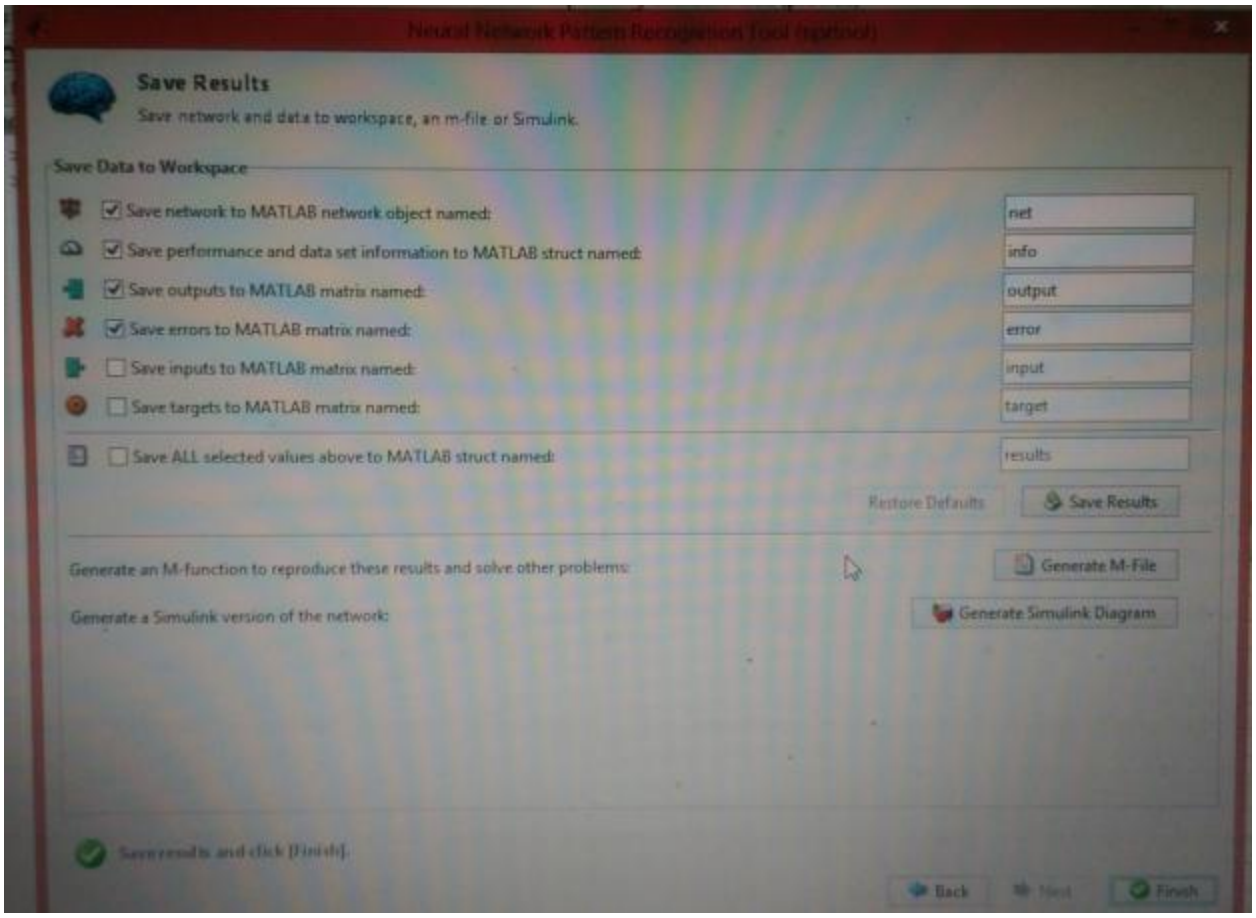

Figure5.7 Neural Network Pattern Recognition Tool

In the above window the network is saved as an M-file in the workshope for further testing,

# Chapter 6
# 6. Conclusion AND Future Works

## 6.1 Conclusion

A matlab program for ECG processing and classification is presented. The project succeeded in developing a program which provides ECG de-noising , feature extraction and classification as normal and abnormal sample. We used segmented samples which were obtain from the internet , also In this thesis we used simple matlab programming language in the feature detecting step and finally created the ANN using the (nprtool) for easier understanding of who the ANN works.

## 6.2 Future Works

The tool can be developed by adding:

1- A more adaptive technique instead of the fixed interval thresholding to help deal with all kind of arrhythmia and increase the ANN generalization.
2- Increase the number of samples used in the construction of the ANN.
3- Detect the type of the arrhythmia itself and by increasing the detection features.

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# APPENDIX 1: MATLAB code

```
%baseline drift
fresult=fft(x1);
fresult(1: round(length(fresult)*5/360))=0;
fresult(end- round(length(fresult)*5/360) : end)=0;
corrected=real(ifft(fresult));
%figure,plot(corrected)
m=corrected;
%decompose the ecg signal%
[C,L]=wavedec(m,3,'db1');
cA3 = appcoef(C,L,'db1',3);
cD3 = detcoef(C,L,3);
cD2 = detcoef(C,L,2);
cD1 = detcoef(C,L,1);
%Reconstruct the level 3 approximation and detail from C%
A3 = wrcoef('a',C,L,'db1',3);
D1 = wrcoef('d',C,L,'db1',1);
D2 = wrcoef('d',C,L,'db1',2);
D3 = wrcoef('d',C,L,'db1',3);
%denosing the signal%
[thr,sorh,keepapp] = ddencmp('den','wv',m);
clean = wdencmp('gbl',C,L,'db1',3,thr,sorh,keepapp);
figure,plot(clean)
%first peak
%r detection
clean1=clean(1:350);
m=max(clean1);
rpos1=find(clean1==m);
Rmax1=m;
rpos1=mean(rpos1);
Rpos1=ceil(rpos1);
%Q,P detection
range=[Rpos1-20:Rpos1];
Qmax1=min(clean1(range));
qpos1=find(clean1==Qmax1);
qpos1=mean(qpos1);
Qpos1=ceil(qpos1);
range=[Qpos1-50:Qpos1];
Pmax1=max(clean1(range));
ppos1=find(clean1==Pmax1);
ppos1=mean(ppos1);
Ppos1=ceil(ppos1);
%S,T detection
range=[Rpos1:Rpos1+45];
Smax1=min(clean(range));
spos1=find(clean==Smax1);
spos1=mean(spos1);
Spos1=ceil(spos1);
range=[Spos1:Spos1+50];
Tmax1=max(clean(range));
tpos1=find(clean==Tmax1);
tpos1=mean(tpos1);
Tpos1=ceil(tpos1);
STinterval1=Tpos1-Spos1;
PRinterval1=Rpos1-Ppos1;
```

```
QRSduration1=Spos1-Qpos1;
QTinterval1=Tpos1-Qpos1;
%second peak
%r detection
clean2=clean(350:600);
n=max(clean2);
rpos2=find(clean2==n);
Rmax2=n;
rpos2=mean(rpos2);
Rpos2=ceil(rpos2);
Rpos2=Rpos2+350;
%Q,P detection
range=[Rpos2-20:Rpos2];
Qmax2=min(clean(range));
qpos2=find(clean==Qmax2);
qpos2=mean(qpos2);
Qpos2=ceil(qpos2);
range=[Qpos2-50:Qpos2];
Pmax2=max(clean(range));
ppos2=find(clean==Pmax2);
ppos2=mean(ppos2);
Ppos2=ceil(ppos2);
%S,T detection
range=[Rpos2:Rpos2+45];
Smax2=min(clean(range));
spos2=find(clean==Smax2);
spos2=mean(spos2);
Spos2=ceil(spos2);
range=[Spos2:Spos2+50];
Tmax2=max(clean(range));
tpos2=find(clean==Tmax2);
tpos2=mean(tpos2);
Tpos2=ceil(tpos2);
STinterval2=Tpos2-Spos2;
PRinterval2=Rpos2-Ppos2;
QRSduration2=Spos2-Qpos2;
QTinterval2=Tpos2-Qpos2;
%third peak
%r detection
clean3=clean(550:850);
h=max(clean3);
rpos3=find(clean3==h);
Rmax3=h;
rpos3=mean(rpos3);
Rpos3=ceil(rpos3);
Rpos3=Rpos3+550;
%Q,P detection
range=[Rpos3-20:Rpos3];
Qmax3=min(clean(range));
qpos3=find(clean==Qmax3);
qpos3=mean(qpos3);
Qpos3=ceil(qpos3);
range=[Qpos3-50:Qpos3];
Pmax3=max(clean(range));
ppos3=find(clean==Pmax3);
ppos3=mean(ppos3);
Ppos3=ceil(ppos3);
```

```
%S,T detection
range=[Rpos3:Rpos3+45];
Smax3=min(clean(range));
spos3=find(clean==Smax3);
spos3=mean(spos3);
Spos3=ceil(spos3);
range=[Spos3:Spos3+50];
Tmax3=max(clean(range));
tpos3=find(clean==Tmax3);
tpos3=mean(tpos3);
Tpos3=ceil(tpos3);
STinterval3=Tpos3-Spos3;
PRinterval3=Rpos3-Ppos3;
QRSduration3=Spos3-Qpos3;
QTinterval3=Tpos3-Qpos3;
RR1=Rpos2-Rpos1;
RR2=Rpos3-Rpos2;
%find rate
r=max(clean)*0.6;
r1=find(clean>=r);
x1r=zeros(length(x1),1);
rr=clean(r1);
rrdiff=diff(rr);
rrdiff_logical=rrdiff<0;
rrpeak=diff(rrdiff_logical)==1;
p=sum(rrpeak);
numberofpeaks=p;
    n=length(x1);
    m=n*0.0027;
    duration_second=n/360;
    duration_minutes=duration_second/60;
    bpm=p/duration_minutes;
    BPM=ceil(bpm);
  %results in mV and Sec
  fs=360
    BPM
   Rpeak1=(1024-Rmax1)/200
    Rpos1=Rpos1/fs;
   Rpeak2=(1024-Rmax2)/200
    Rpos2=Rpos2/fs;
   Rpeak3=(1024-Rmax3)/200
    Rpos3=Rpos3/fs ;
   RRinterval1=RR1/fs
   RRinterval2=RR2/fs
   %%%%%%%%%%%%%%
   Qpeak1=-(1024+Qmax1)/200
    Qpos1=Qpos1/fs;
   Qpeak2=-(1024+Qmax2)/200
    Qpos2=Qpos2/fs;
   Qpeak3=-(1024+Qmax3)/200
    Qpos3=Qpos3/fs;
    %%%%%%%%%%%%
   Ppeak1=(1024-Pmax1)/200
    Ppos1=Ppos1/fs ;
   Ppeak2=(1024-Pmax2)/200
    Ppos2=Ppos2/fs;
   Ppeak3=(1024-Pmax3)/200
```

```
 Ppos3=Ppos3/fs ;
 %%%%%%%%%%%%%
Speak1=-(1024+Smax1)/200
 Spos1=Spos1/fs;
Speak2=-(1024+Smax2)/200
 Spos2=Spos2/fs;
Speak3=-(1024+Smax3)/200
 Spos3=Spos3/fs;
 %%%%%%%%%%%%
Tpeak1=(1024-Tmax1)/200
 Tpos1=Tpos1/fs ;
Tpeak2=(1024-Tmax2)/200
 Tpos2=Tpos2/fs;
Tpeak3=(1024-Tmax3)/200
 Tpos3=Tpos3/fs ;
%%%%%%%%%%
PRinterval1=PRinterval1/fs
PRinterval2=PRinterval2/fs
PRinterval3=PRinterval3/fs
%%%%%%%%%%%
QRSduration1=QRSduration1/fs
QRSduration2=QRSduration2/fs
QRSduration3=QRSduration3/fs
%%%%%%%%%%%
QTinterval1=QTinterval1/fs
QTinterval2=QTinterval2/fs
QTinterval3=QTinterval3/fs
%%%%%%%%%%%%
STinterval1=STinterval1/fs
STinterval2=STinterval2/fs
STinterval3=STinterval3/fs
```