UNIVERSITY OF TURKISH AERONAUTICAL ASSOCIATION
INSTITUTE OF SCIENCE AND TECHNOLOGY

LABVIEW BASED, SIMULATION AND AUTOMATIC ANALYSIS OF ECG SIGNALS USING FPGA.

MASTER THESIS

IHAB AHKAM AL-QARAGHULI

Electrical and Electronics Engineering Department

Master Thesis Program

MAY 2017

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Supervisor: Asst. Prof. Dr. HASSAN SHARABATY

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04.05.2017

IHAB AHKAM AL-QARAGHULI

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List of Symbols

ECG_D	: The FPGA output signal of the ECG diagnosis system
ECG_PR	: The FPGA input port for PR interval feature
ECG_QRS	: The FPGA input port for QRS duration feature
ECG_QT	: The FPGA input port for QT interval feature
ECG_RR	: The FPGA input port for RR duration feature
PR	: The FPGA input signal of the PR interval feature
PR_BMTK	: The MATLAB signal used to read the RR interval from workspace.
QRS	: The FPGA input signal of the QRS duration feature
QRS_BMTK	: The MATLAB signal used to read the QRS duration from workspace.
QT	: The FPGA input signal of the QT interval feature
QT_BMTK	: The MATLAB signal used to read the QT interval from workspace.
RR	: The FPGA input signal of the RR duration feature
RR_BMTK	: The MATLAB signal used to read the RR duration from workspace.
wr	: Clock input signal to FPGA ECG diagnosis system
$UFix$	: Unsigned Fixed number
$d(\boldsymbol{p},\boldsymbol{q})$	: The Manhattan distance between two vectors $\boldsymbol{p}$ and $\boldsymbol{q}$

List of Abbreviations

ADC	: Analogue To Digital Conversion
APB	: Atrial Premature Beat
APC	: Atrial Premature Contractions
AV	: Atrio-Ventricular
ANN	: Artificial Neural Network
B	: Bredycardia
BPM	: Beat Per Minutes
BPNN	: Back Propagation Neural Network
CLB	: Configurable Logic Blocks
DWT	: Discrete Wavelet Transform
ECG	: Electrocardiography
ECG-FE	: Electrocardiogram Feature Extraction
ELM	: Extreme Learning Machine
EMD	: Empirical Mode Decomposition
FDHB	: First Degree Heart Block
FPGA	: Field Programmable Gate Array
HD	: Hamming Distance
HHT	: Hilbert-Huang Transform
HW	: Hardware
HWCOSIM	: Hardware Co-Simulation
ISE	: Integrated Synthesis Environment
JTAG	: Joint Test Action Group
LABVIEW	: Laboratory Virtual Instrument Engineering Workbench
LBBB	: Left Bundle Branch Block
LGL	: Lowen-Ganong Leving Syndrome
MI	: Myocardial Infarction

MIT-BIH	: Arrhythmia Database
MLP	: Multi-Layer Perceptron
N	: Normal
NVG-RAM	: Numeral Weight-Less Neural Network
OVO	: One Versus One
PC	: Personal Computer
PCA	: Principle Component Analysis
PP	: Positive Productivity
QMF	: Quadrature Mirror Filter
RBBB	: Right Bundle Branch Block
RLBB	: Right Or Left Bundle Branch
SA	: Sino-Atrial
Se	: Sensitivity
SG	: System Generator
SOFM	: Self Organization Feature Mapping
SVM	: Support Vector Machine
SP	: Specificity
T	: Techcardia
TD	: Threshold Decision Classifier
U	: Unclassified
UWT	: Un-Decimated Wavelet. Transform
VHDL	: Very High Speed Hardware Description Language
VI	: Virtual Instrument
VIs	: Virtual Instruments
WPW	: Parkinson White Syndrome
XSG	: Xilinx System Generator

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ABSTRACT

LabView based, Simulation and Automatic Analysis of ECG signal using FPGA.

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Master Thesis, Department of Electrical and Electronics Engineering

Thesis Supervisor: Asst. Prof. Dr. HASSAN SHARABATY

May - 2017, 106 pages

Electrocardiography (ECG) is one of the most important things used in medicine, where gives us a lot of information about the electrical system of the heart, and diagnosis the medical condition of the patient suffering from pain in the cheast at lower costs. Heartbeat resulting from ECG will help the doctors to suggest the appropriate treatment for the patient. In our work we built a system to diagnosis of eight different cases of the heart based on the FPGA. The eight cases are the most common ailments affecting the heart which are:(Normal, First Degree Heart Block, Lowen-Ganong Leving syndrome, Myocardial Infraction,Bradycardia, Wolff-Parkinson White syndrome, Right or Left bundle branch,and Techcardia).The ECG diagnose system that were built Consists of three parts which are ECG data acquisition system, feature extraction and decision classifier parts. For Building our diagnostics system, we have been using Lab View biomedical toolkit. In our work we are considered four features which are (PR, QRS, RR, and QT durations)of the ECG. The algorithms that we are used in our work to classifier heart diseases are Threshold Decision(TD) and Numeral Virtual Generalizing Random Access Memory (NVG-RAM) weightless neural network. Simulation results of the two proposed classifiers using MIT-BIH, show that the highest probability of correct classification for the heart conditions identification is achieved by using the NVG-RAM classifier that is 100% followed by the TD classifier which has 98.84% success rate. We use FPGA spartan-3AN XC3S700AN hardware platform to execute Threshold Decision and

NVG-RAM classifiers. This type of FPGA hardware features that faces many restrictions and overcome like speed. The TD classifier 1% utilization of hardware platform slices. While the NVG-RAM classifier utilizes 21% of spartan-3AN XC3S700AN slices. The two executed classifiers have excellent performance in experimental tests, where the overall success rate showed for executed TD and NVG-RAM classifier is 98% and 100%, respectively.

Key words: FPGA, Electrocardiography, LabView.

ÖZET

LabView tabanlı, Simülasyon ve otomatik analizi EKG sinyali Fpga'yı Kullanarak

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Mayıs -2017, 106 sayfa

Elektrokardiyografi (EKG), tıbbın içinde kullanılan ve kalbin elektrik sistemi hakkında çok bilgi veren en önemli şeylerden biridir ve daha düşük masraflarla cheast ağrısı çeken hastanın tıbbi durumunu teşhis eder. EKG'den kaynaklanan kalp atışı, doktorlara hasta için uygun tedaviyi önermesine yardımcı olacaktır. Çalışmamızda, FPGA'ye dayalı sekiz kalp kalbeğinin teşhisine yönelik bir sistem kurduk. Sekiz olgu kalbi etkileyen en yaygın rahatsızlıklar şunlardır: (Normal, Birinci Dereceden Kalp Bloğu, Lowen-Ganong Leving sendromu, miyokardiyal enfeksiyon, Bradikardi, Wolff-Parkinson White sendromu, Sağ veya Sol dal bloğu ve Techcardia). Yapılan EKG teşhis sistemi EKG veri toplama sistemi, öznitelik çıkarımı ve karar sınıflandırıcı parçaları olan üç parçadan oluşur. Teşhis sistemimizi oluşturmak için, Lab View biyomedikal araç setini kullanıyoruz. Çalışmamızda EKG'nin (PR, QRS, RR ve QT süreleri) dört özelliği kabul edilmektedir. Sınıflandırıcı kalp hastalıklarına yönelik çalışmalarımızda kullanılan algoritmalar: Eşik Kararı (TD) ve Sayısal Sanal Genelleştirme Rasgele Erişim Belleği (NVG-RAM) ağırlıksız sinir ağı. MIT-BIH kullanan önerilen iki sınıflandırıcının simülasyon sonuçları, kalp koşulu tanımlamasında doğru sınıflamanın en olası ihtimalinin, 100% olan NVG-RAM sınıflandırıcısını, ardından 98.84% başarı oranına sahip TD sınıflandırıcısını kullanarak elde edildiğini göstermektedir. Eşik Kararı ve NVG-

RAM sınıflandırıcılarını çalıştırmak için FPGA spartan-3AN XC3S700AN donanım platformunu kullanıyoruz. Bu tür FPGA donanım özellikleri birçok kısıtlamayla karşı karşıya ve hızı aşıyor. TD sınıflandırıcısı, donanım dilimlerinin1% 'inden yararlanıyor. NVG-RAM sınıflandırıcısı spartan-3AN XC3S700AN dilimlerinin 21%'ini kullanırken. Uygulanan iki sınıflandırıcı, yürütülmüş TD ve NVG-RAM sınıflandırıcıları için genel başarı oranının sırasıyla 98% ve 100% olduğu deneysel testlerde mükemmel performansa sahiptir.

Anahtar kelimeler: FPGA, Elektrokardiyografi, LabView.

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CHAPTER 1:
1.INTRODUCTION

1.1 Introduction to ECG Diagnostic System

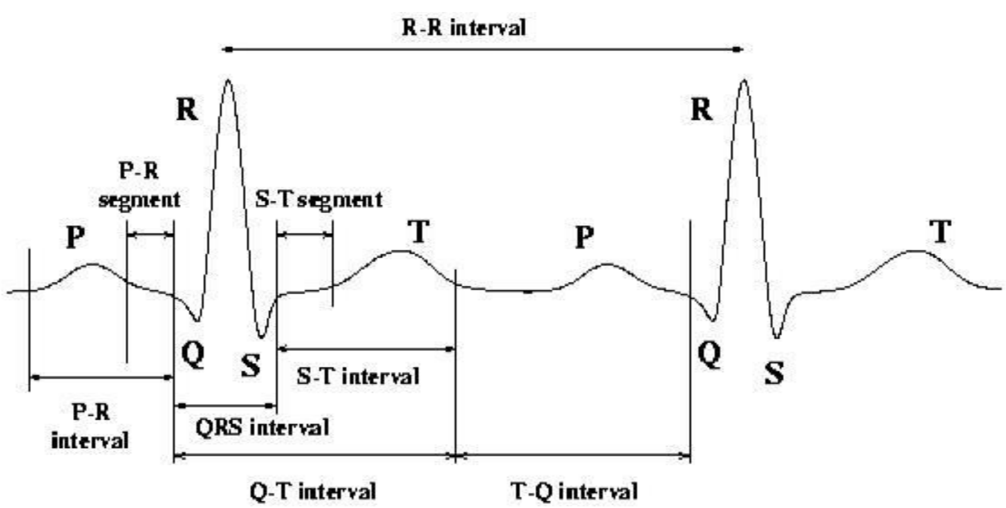
The rise in the rates of the number of people with heart disease, led to an increase in the measurement ECG recordings in hospitals. ECG is one of the most effective devices in the field of medicine it calculates the heart rate then transfer it to signal for display on the monitor or broadsheet. At present, a team of engineers and scientists to exploit the evolution of modern techniques in computer science and engineering of medical devices and electrical engineering to design an intelligent control system by using wearable technology for the purpose of collecting ECG signal. ECG is to record the electrical activity of the heart in detail over a period of time. Knowing these details are very important in the diagnosis of a wide variety of heart diseases that threaten human life. Modern control system is built using cutting-edge technologies in the field of communications to collect the of vital signs of the heart and send it over long-distance [1]. Commercially there are quite a number of monitoring systems available in the market and some of the research proposals classifies these systems proportion of the following features [2].

i) Systems logs only the vital activity of the heart of without analysis, these systems have become from the past.

ii) Systems analysis the signal remotely. Where are here to capture the heart signal and send it via the means of communication to the center for analysis that means, it is not analysis in the same place, which was the signal get.

iii) Systems analyzes at the same time that get the signal.

node characterize with high sensitivity in the composition and characteristics consist from groups of cardiac cells, that produces an electrical current that is the cause of the electric field production. the field is detected at body surface by using differential voltage measurement system. The result of the measurement that taken through electrodes put on the body is known as ECG [3]. Heart resulting signal is too weak (in mv) And it frequency ranges(0.05-100Hz), and the most useful information in the range (0.5-45Hz) [4,5]. The ECG is a graph represent the heart's electric activity over period of time. In natural conditions can be easily predicted in duration, direction, and amplitude of the ECG, this leads to the possibility of evaluating the ECG components and interpretation on the basis of a natural or unnatural. ECG is important to monitor the effect of therapeutic interventions on the heart's response. ECG is a useful tool so the medical person must understand the heart signal analysis. As shown in fig (1.1) we can see an ECG signal with special morphology over a two cardiac cycle Consist of P-wave, QRS complex and a T-wave. Natural ECG signal consists of waves, complexes, segments, and intervals restricted between vertical axis which represents voltage, and horizontal axis which represents time. The beginning and the ending of the single waveforms happening on the baseline. The waveform changes into another waveform when continuity past the baseline. Complex called when two or more waveforms are together. Segment called for the straight line. Interval called for the complex when connected to a segment. If all the ECG tracing over the baseline we described as positive deflections If the contrary the ECG tracing described as negative deflections.



Figure(1.1):The Human ECG signal over Two cardiac cycle [4].

ECG contains important information so understanding and study of the different waves (P, QRS and T), intervals and Amplitudes is an important factor in the diagnosis of heart disease [6]. In medical clinics, automated way to extract the properties of the ECG more logically than the manual method of measuring characteristics at every point at every beat [7], essentially for long ECGs interval. Usefulness of ECG is to identify the different pattern of signal and understanding for the purpose of to design an system to classify these pattern into one of a number of various classes [8]. Cardiologist with expertise can signal heart diagnosis the heart's signal easily just by looking on it.

At present, with the participation of computers in the ECG signal analysis that helped to Relief work for the doctors, where computers used to clarify main parameters in the ECG which help the doctor to do his diagnosis [9]. The real Pattern Recognition of the ECG signal which shown in figure (1.2) Consists of four main parts which are (Preprocessing of the signal, QRS Detection, ECG feature extraction and ECG signal classification) [10].

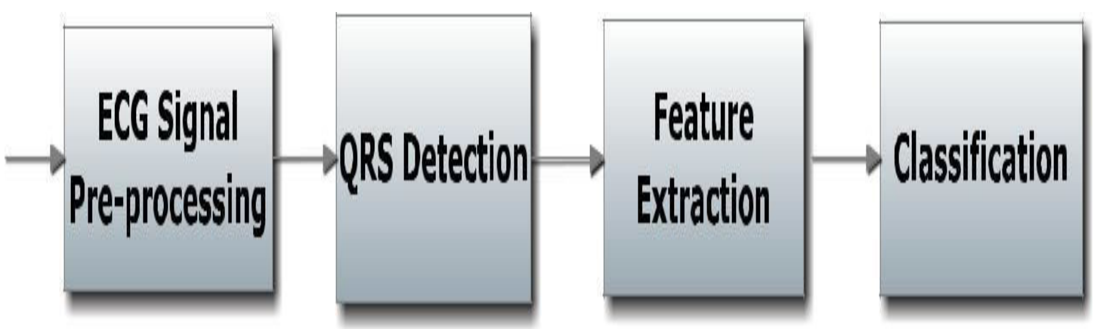


Figure (1.2): Pattern Recognition Steps in ECG.

- The first part is to get the signal. These signals are available on database, which has a wide range of ECG, including abnormal situations. These signals in future we can take them from the person directly
- The second part is to find QRS complex which is the width of the ventricular complex.

- ► Third part identify distinctive set of the signal for the purpose of the classification in the fourth part.
- ► The four ECG's parts pattern recognition will talk about in detail later.

With the development of technological and computer science, which led to the emergence of high-resolution screens are placed on the wrist of people for recording the heart signal. The aim of this thesis is to build a proposed system based classifier on the FPGA., and doing the process of diagnosis with high accuracy.

1.2 Literature Survey

Lately extraction of ECG signal process attracted a good number of scientists and researchers, particularly in the last decade where they propose many modern and advanced technologies competent in this field. this section briefly review some of these works.

Hari Mohan Rai, Anurag Trivedi (2012) [11].

In this paper they utilized discrete wavelet transform and Back Propagation Neural Network(BPNN) for variations from the norm location of the ECG signals. Proposed system used to identify the strange ECG Sample and arrange it into two unique classes (ordinary and irregular). Proposed system used to identify the strange ECG Sample and arrange it into two unique classes (ordinary and irregular). We have utilized MIT-BIH arrhythmia database and picked 45 documents of one moment recording where 25 documents are considered as would be expected class and 20 records of irregular class out of aggregate 48 documents. The components are separate into two classes that are DWT based elements and morphological element of ECG which is a contribution to the classifier. Back Propagation Neural Network is utilized to classify the ECG and the stem execution is measured on the premise of rate precision. The general framework exactness acquired is 97.8 % utilizing (BPNN) classifier.

Maedeh Kiani Sarkaleh and Asadollah Shahbahrami(2012) [12]

In this studies, a specialist framework for Electrocardiography (ECG) arrhythmia compilation is suggested. Discrete wavelet transform is utilized for handling ECG recordings, and extracting several components, and the Multi-Layer Perceptron (MLP) neural system plays out the order assignment. Two sorts of arrhythmias can be recognized by the proposed framework. several recordings of the MIT-BIH arrhythmias database have been utilized for preparing and testing our neural network based classifier. The simulation outcome display the precision of the algorithm is 96.5% utilizing 10 documents including typical and two arrhythmias.

Sambhu D., Umesh A. C.(2013) [13]

In this path, normal and anomalous heartbeats, for example, Left Bundle Branch Block (LBBB), Right Bundle Branch Block(RBBB), Atrial Premature Contractions (APC) and Premature Ventricular Contractions (PVC), Atrial Premature Beat (APB), paced thumps and fusion pulsates are accurately arranged and separated with sufficient levels of exactness. At first the multi determination investigation of ECG signal is done to de-noised and separates 25 features. The mother wavelet utilized for decay was db4. The classification is executed by utilizing OAO (One Against One), SVM (Support Vector Machine). 7 SVM's were prepared and last gathering is finished by most extreme voting. ECG signs are gotten from MIT-BIH database. Tests uncover that the general order exactness is well over 97 % for every one of the classes.

Khalifa Elmansouri, R. Latif and B. Nassiri1and S. Elouaham (2013) [14].

This studies introduces a powerful tool which provides immediate computation for (ECG) signal de-noising where the analysis is carried out in a cardiovascular laboratory. The reduction of noise for the ECG signals is built on the Undecimated Wavelet Transform (UWT) which is an effective technique for corrupted non-stationary noises and has a better capacity on peak detection. The performance shows accurate result for de-noising, beats detection, analysis and diagnosis of heart disorders.

Kirn K. Jembula , G. Srinivasulu And Prasad K.S (2013) [15]

This research proposed ECG diagnosis system based on wavelet transforms algorithm which uses linear Quadrature Mirror Filter (QMF) B-spline wavelet for the detection of QRS –complex feature. This system is work on both offline and online to detect the input ECG signals and hardware implemented using Verilog language and Xilinx FPGA kit respectively.

Raman Yadav, Sharda Vashisth and Ashok K. Salhan(2013)[16].

In this work the design a portable ECG acquisition circuit for real-time monitoring ECG cardiac patients is proposed. This circuit is connected to MATLAB through sound port as a serial interfacing between the ECG acquisition circuit and computer. MATLAB program is responsible for amplifies and filter the input ECG signal.

El H. Elmimoul and Mohammed Karim (2013) [17].

This work utilizes infamous calculation by Pan and Tompkins to remove QRS-complex element. This calculation is equipment actualized in FPGA. Testing this calculation utilizing ECG data set recorded from MIT-BIH arrhythmia information base utilizing MATLAB Simulink with NEX YS2 Digilent Kit. The equipment result demonstrates that the achievement rate is more prominent than 96% for the most pessimistic scenario of ECG tried signal

Nakul Nagpal, Mayuri Chawla and Dr. Daniel Phillips(2014) [18]

This work introduces a features extraction algorithm for (ECG) signal using Huang Hilbert and Wavelet Transform. This system calculates threshold value for the next peak detection cycle by looking at the previous peak. The second step implements this algorithm by using FPGA. FPGA hardware design excess 99% in detection beat. ECG data is taken from standard AF Termination Challenge Database.

Neha Soorma, Jaikaran Singhand Mukesh Tiwari (2014) [19]

A strong mathematical model to extract such useful parameter is used. Here an adaptive mathematical analysis model is Hilbert-Huang Transform (HHT). This new approach, the HHT, is downloaded to analyze the non-linear and non- stationary data. It is unique and different from the existing methods of data analysis and does not require an a priori functional basis. The effectiveness of the proposed scheme is verified through the simulation. HHT and Wavelet Transform have been implemented in this work to extract the features of ECG signal (normal and abnormal).

Rahul Pitale,K. Tajane and J. Umale(2014) [20]

Presented the use of Support Vector Machine (SVM) and Principle Component Analysis (PCA) for better both ECG feature extraction and classification of heart rate. This work shows that combination of the Wavelet Transform and PCA produces a good result of the evaluation of ECG signals.

Sonal Pokharkar and Amit Kulkarni (2015) [21]

In this mission ECG signal analysis are the identification of how quick heart is thumping, whether the musicality of heartbeat is unfaltering or unpredictable and the quality and timing of electrical signals as they go through every part of the heart. This venture endeavors at executing ECG heart-rate calculation in MATLAB and FPGA together. ECG include extraction framework depends on Pan Tompkins' calculation for preprocessing of signal and QRS recognition. The execution of calculation will test against MATLAB normal and approved results in view of the MIT-BIH arrhythmia database (which has been commented on via cardiologists) and ECG database made by utilizing ECG machine HIC 2000, Bio-impedance. Ltd. Outline and execution of ECG feature extraction utilizing VHDL for FPGA based system.

Anjali Deshmukh and Yogendra Gandole (2015) [22]

In this work the proposed method deals with the study and analysis of ECG signal using LabVIEW Biomedical toolkit effectively.

- In the first phase, ECG signal is acquired which is then followed by filtering the raw ECG Signal to reduce unwanted noises.
- The next phase focuses on extracting the features from the acquired signal and at last visualizing and analyzing the extraction result. Analysis and feature extraction are depending on MIT-BIH database

Shweta H.S.H. Jambukia, V.K. Dabhi and H.B. Prajapati. (2015) [23]

Present a survey of ECG classification into arrhythmia types. Many types classifiers are available for ECG classification. Amongst all classifiers, Artificial Neural Networks (ANNs) have become very popular and most widely used for ECG classification. They discuss the issues involved in ECG classification and presented a detailed survey of preprocessing techniques, ECG databases, feature extraction techniques; ANN based classifiers, and performance measures to address the mentioned issues.

Stalin Subbiah, Subbuthai P, Patro Rajkumar (2015) [24]

They using three classifiers which are Back Propagation Neural Network (BPN), Extreme Learning Machine (ELM), and Support Vector Machine (SVM) for analyzing ECG. They've compared among thems. Using MIT-BIH database to classify the signal into normal and abnormal. Depending on the Specificity (SP), Sensitivity (Se), and Positive Productivity (PP) to evaluate the classifiers. The success rate of each of the (BPN), (ELM), and (SVM) were 64%, 97%, and 73% respectively.

Deepak S and Mrs. Jenitha.A (2015) [25]

By using MIT-BIH database, classify the signal into normal and abnormal by detect and extract QRS-complex using two algorithms which are autocorrelation function and Pan-Tompkins. For simulation they using MATLAB software and hardware they implement these algorithms on FPGA.

L.V.Rajani ,Y.P.Sai,N.Balaji and K.Viswada (2015) [26]

Proposed a simple and reliable Field Programmable Gate Array (FPGA) based ECG Analysis system. The main objectives of the work are; ECG signal enhancement using Empirical Mode Decomposition (EMD) based method and Detection of R peaks which is the first step towards automatic detection of cardiac arrhythmias in ECG signal. The proposed system can detect three different arrhythmias. 94.76% accuracy of the proposed method is achieved in detecting the different heart Arrhythmias correctly by using subset of data records from the MIT-BIH database. The system is implemented using Verilog HDL and Xilinx Spartan 3E FPGA respectively.

1.3 Problem Statement

There are many hardware implementation approaches for ECG monitoring systems. However, the problems of the existing microcontroller based and DSP based medical development kits are that these developments are limited by the speed of clock rate. In addition, these implementation algorithms were built using C++ and

Visual basic... so that its accuracy were inversely proportional with the speed of implementation and speed of delivering the diagnosis. In plus, the used processors were slow so that they have to neglect the low frequency noise, which was affecting the diagnosis efficiency. Also, these programs were complicated and difficult to interface between hardware and software. So our goal is to do designing characterized by simplicity and doing diagnosis with high accuracy

1.4 Aims Of The Thesis.

1.Design and simulate an efficient system for feature extracting.

2. Building an algorithm to carry out the diagnosis.

3.Testing and verifying the performance of the algorithm by using MIT- BIH database and generated ECG signals.

4. Implementation this algorithm in FPGA.

1.5 Main Contributions Of this Work

Medically: using LabView to build the high efficiency diagnose algorithm with high accuracy, and then implementation of this algorithm in the FPGA.

Educationally: using LabView to generate and monitor the heart signal for teaching purposes without need for a person to put an electrode on his body.

1.6 Thesis Outline

This thesis can be arranged into five chapters including this one present as follows:

- Chapter one "INTRODUCTION" is an introduction for literature survey in the proposed work.

- Chapter two "THEORETICAL BACKGROUND" is a theoretical background of the cardiac function, and describe the basic background of the (ECG) signal. In addition, the tools that used to building our system.
- Chapter three "PROPOSED ECG DIADNOSING SYSTEM DESIGN" in this chapter we will describes our design carefully and how we can generate signal.
- Chapter four "SIMULATION RESULTS" in this chapter we will displayed simulation results of our designing system.
- Chapter five "HARDWARE IMPLEMENTATION" will present the Implementation of our designing system on the FPGA and discuss the result.
- Finally, we will conclude our work in chapter six, in addition give some suggestions for future work in this field

.

CHAPTER 2
2.THEORETICAL BACKGROUND

2.1 Introduction

In this section, foundation hypothesis of heart function and electrocardiography are talked about. The instrument of the heart capacity is clarified and the principle wording identified with heart is disclosed to make an establishment for ECG understanding. Besides, the standards of ECG examination are explained by sketching out the principle wording identified with ECG waveforms. As the expectation of this work is to plan and simulate diagnostic system for heart, LabVIEW simulation environment is talked about and the principle parts of the product utilization are highlighted. Two sorts of choice classifiers that used to recognize the heart conditions are examined. At long last, FPGA standards and usage essentials are clarified as it is utilized with respect to the last design execution and testing.

2.2 The Cardiac Function

It is notable that the heart muscle is the focal point of the human cardiovascular system. The human's heart goes about as a pump that makes the blood flows in human's body and subsequently keeping the body alive. Assuming be that as it may, this pump is ceased for reasons unknown, the human will die. Abnormalities in the work of the human heart brings about Signal does not bode well, and give an indication of life risk. Blood course conveys oxygen and supplements that are key to human organs so as to play out their undertakings legitimately. The component of the human heart is controlled by extremely exact electrical system. The electrical system attempts to direct the component of blood dissemination around the cardiovascular system [27]. Any issue in the electrical framework can influence the whole human's body severely. The fundamental assignment of the cardiovascular system is to convey oxygen to every part of the organs of the human's body. The blood goes about as mean of circulating oxygen all through the body, achieving each organ in it. This assignment is refined by a confounded system of vessels, supply routes and vessels that interface the heart to the whole human's body. The human's heart comprises of 4 champers [28]. These champers are in charge of blood pumping around the body. Fig.(2.1) demonstrates a cross segment in the human's heart which gives an unmistakable photo of the four champers. It demonstrates the left and right atria, the left and right ventricles and valves in the blood drift. The atrium goes about as a recipient of blood from all part of the body. The left atrium gets the oxygen rich blood that is started from the lungs, while the atrium chamber gets the oxygen emptied blood that is begun out of body organs. Then again, the ventricles go about as a blood consignor to all accessories of the body. The left ventricle pumps the blood that is rich with oxygen to all parts of the body and organs, while the right ventricle sends the oxygen depleted blood to lungs keeping in mind the end goal to discharge carbon dioxide and ingest crisp oxygen through the lungs. The atria and the ventricles are isolated from each other by a tricuspid valve on the right half of the heart, and the mitral valve on the left half of the heart. when these blood valves are opened, the blood streams from the atria to the ventricles. The ventricles contain much powerful muscles than the atria in light of the fact that their undertaking is pumping blood to the whole body. The capacity of left ventricle is planned by the aortic valve, while the right ventricle is planned by the pulmonary valve [29]. The blood is pumped to the body by the withdrawal of the muscles in the heart. The constriction of the myocardial muscles are started by the possibilities from pacemaker cells that are situated in two ranges in the heart, named as nodes, these are the Sino-Atria (SA) nodes and the Atria-Ventricular (AV) nodes. The cells of the SA pacemaker produce unconstrained activity possibilities 60-80 times for every minute. Be that as it may, these cells are controlled by the thoughtful and parasympathetic nerve framework. The activated of the heartbeat doing by the activity capability of the SA node. In the interim, the AV node starts this activity potential if the SA node neglects to carry out the employment for reasons unknown [30].

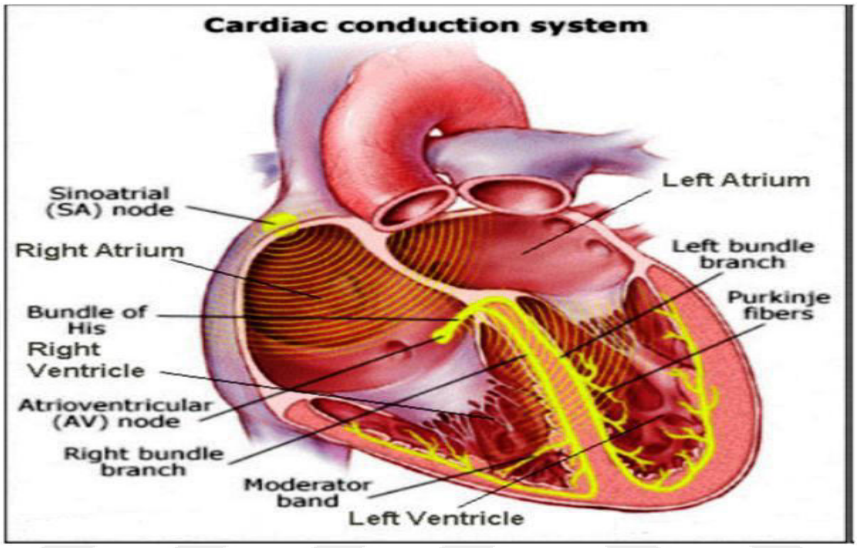


Figure (2.1): The mechanical and electrical components of the heart.[30]

The tissues of the heart subjected to a progression of electrical depolarization re-polarization stages which result in a specific responses of the muscle. Table (2.1) gives a synopsis of these stages. Alluding to Table (2.1), when the SA node is depolarized, the primary phase of the heart beat is started. . The right atrium is loaded with oxygen depleted blood. This blood is begun from the circulatory framework, while the left atrium is loaded with oxygen rich blood that has come back from the pulmonary circulation. The pacemaker of the heart is the SA node which is situated on the back mass of the right atrium. The SA node depolarizes at general interims of time so that a legitimate pacing is guaranteed. The rate of a typical heart is the rate at which the SA node hub transmits beats which is specifically corresponding to the measure of work performed by the heart. At the point when the body makes diligent work, it needs more oxygen rich blood and subsequently the SA node builds the pace to adapt to this necessity [31].

Table(2.1):Stages of cardiac excitation with corresponding ECG representation[30]

Electrical Function	**Mechanical Function**	**Electrical Representation**
1.SA Node emits electrical pulse		
2.Atria depolarize	Atria contract	Start of P Wave
3.Electrical pulse pauses at AV Node	Blood flows to ventricles	End of Wave
4.Pulse travels downs His Bundle to Bundle Branches		Q wave
5.Atria repolarize while ventricles depolarize	Atria relax, Ventricles contract pumping blood to lungs and body	R and S wave
6.Ventricles repolarize	Ventricles relax	T wave

The atria's left and right which frame the upper part of the heart depolarize by the electrical drive from the SA node. This activity of depolarization results in compression of the atria which compels the blood to stream into the ventricles, which is lower part of the heart. The part of electrical flag that compares to this is the P wave. At the point when the compression of the atria is finished they enrapture to inspire prepared to create the following heartbeat. The QRS complex is come about because of the ventricular compression which happens in the meantime as the repolarization of the electrical signal happens. After depolarization of the atria, the depolarization signals unite in the AV node. This node has two essential parts. The first is to interface the electrical flag from the atria to the ventricles, and the second part is to back off the depolarization procedure keeping in mind the end goal to permit the blood to spill out of the atria to the ventricles totally[27]. Electrical depolarization moves to what is called as the His packs from the AV node. The His packs are arranged in the base of the ventricles and they prompt the package branches and afterward to the Parkinje strands. These filaments spread the depolarization motion through the ventricles. Through the ventricular tissue The depolarization signal proliferates quickly which brings about pumping the blood to whatever remains of the body by the muscles of the ventricles. The oxygen depleted blood is pumped by the right ventricle to the pneumonic framework to be oxygenated [30]. The oxygen wealthy blood is boosted by the left ventricle to the circulatory system to outfit the body with oxygen. After depolarization and constriction, the ventricles begin to gather again keeping in mind the end goal to deliver another cycle. The above procedure is repeated rhythmiclly as the length of the heart is working appropriately. As a rule, the typical heart of a sanitary body when in rest is between 60 to 80 beat for each minute. Any glitch in the electrical arrangement of the heart brings about an unpredictable heartbeat which is considered as an unusual case. The variation from the norm of the heart brings about an issue in blood supply to the body. The issues are observed, recorded and investigated by a specialist utilizing an electrocardiogram (ECG) which gives essential certainties about the state of the heart, which could give a legitimate diagnosing of the heart illness.

2.3 ECG or EKG History

The beginning of the Electrocardiogram word is gotten from the Greek words (Electro + Cardio + Gram = ElectroCardioGram), since it is, alludes to electrical action of a Greek (kardio) which implies heart and (gram) for record or chart. The most straightforward importance for the Electrocardiogram is a record of the power on the heart [32]. The Electrocardiogram is one the best innovation in the therapeutic history. It recognizes heart sicknesses and in this manner maintaining a strategic distance from heart assaults. The ECG devise records the electrical beats of the heart and shows as a diagram or a wave following. This can help specialists to analyze heart variations from the norm. The first reasonable ECG was created in 1889 amid and declared in the primary global congress of physiologists. Fig (2.2) demonstrates the first handy ECG machine. The registration of the ECG was maked for a dog's heart by Angus Waller. Prior to that, Alexander Muirhead has gotten a record of a human heart pulse by connecting wires to a patient's wrist when he was conducting his PhD in electrical science [33].

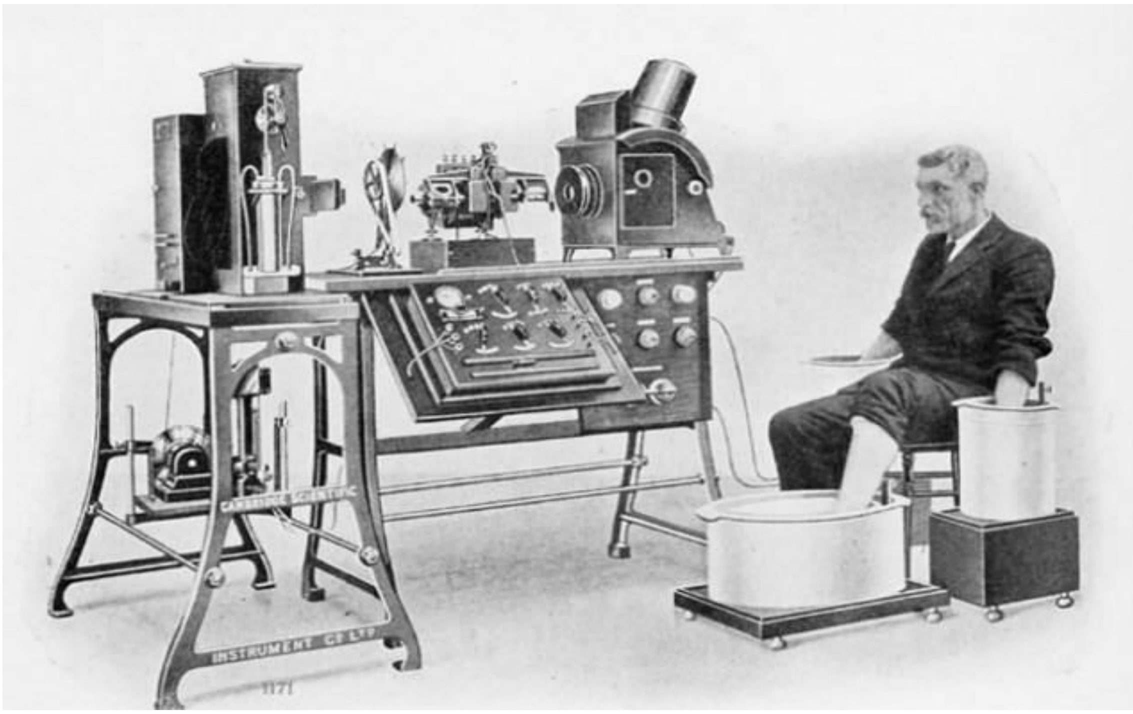


Figure (2.2): The first practical ECG machine[33].

A Dutch specialist, Willem Einthoven (1860-1927) concentrated on the contemplated the way toward creating electrical records of the pulse utilizing probes electrical current. He built up the thoughts of Waller in 1901 by a progression of a model string galvanometer. After two years, Einthoven has achieved an immaculate plan of a useful EKG recorder [34].Einthoven's initial paper in the ECG was registered in 1902 by string galvanometer . On the base is the ECG recorded by the new string galvanometer. On top is the relating recording got with a top notch slender electrometer. In the center is an Einthoven's expectation of the genuine type of the ECG. As it is observed with the string galvanometer, however got from scientific change of the capillary electrometer waveform. Fig.(2.3) demonstrates the first ECG records [34, 35].

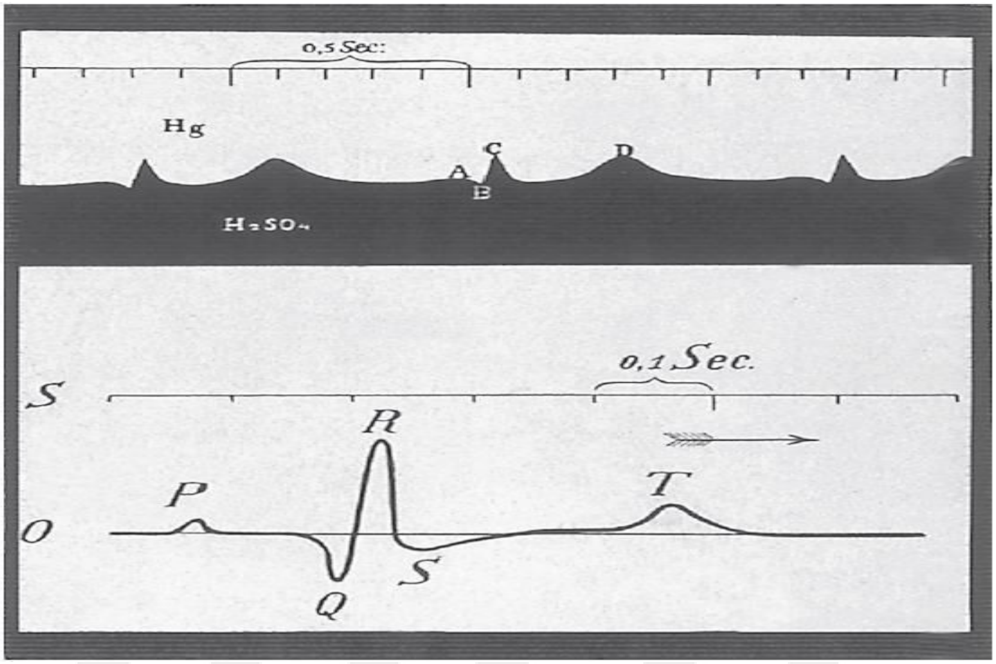


Figure (2.3): Einthoven's first ECG tracings.[34]

The EKG recorder created by Einthoven utilizes a thin bit of wire that goes through electromagnets. This wire is joined to terminals set on the patient's mid-section. The hands of the patients were submerged in salted water shower keeping in mind the end goal to lead electrical heartbeats. The wire was made to marginally tremble with the pulse by the electromagnetic field. The development has possessed the capacity to record the pulse by utilizing a film and a light sparkling on the wire. The quality and the rate of the pulse of a patient were recorded absolutely. The heaviness of the Einthoven's machine was 600 pounds and its size was as the measure of a little room [36]. Despite the fact that the machine was vast it could record heartbeats with outrageous exactness. Einthoven got a US patent on 13 July 1926 for remote signal reception which was the establishment for ECG observing. These days, ECG recorders are little and can be suited on the patient's hand. In any case, it is still in light of the innovation of Einthoven [37]. The comprehension of the ECG history empowers us to bargain successfully with the present. In this manner, by checking on the recorded premise of ECG, may give's a help with their elucidation and in comprehension the relationship between the ECG signals and heart sicknesses. Fig.(2.4) demonstrates the time line of events of historic points in the improvement of ECG [32]

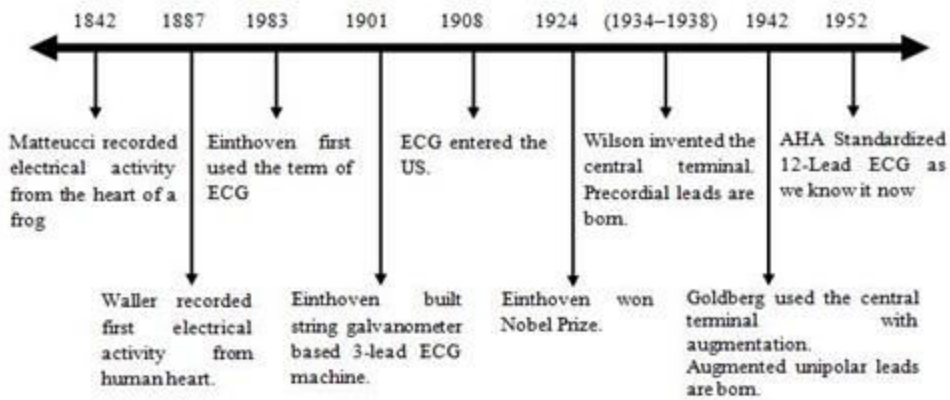


Figure (2.4): Timeline of landmarks in the development of ECG[32]

2.4 Electrocardiography (ECG)

Electrocardiography is a diagram speaking to the movement of the heart over a timeframe. In typical conditions, the following of ECG has an extremely unsurprising abundancy and span. In this way, the different segments of ECG chart can be surveyed as an ordinary or anomalous execution. Electrocardiograph is likewise used to screen heart action when it is under surgery [38]. Electrocardiogram is recorded from a patient utilizing various terminals that are set on the mid-section of the patient. The quantity of these terminals differs from 2 to 14. This relies on upon the part of the heart that required to be centered around. Three basic leads are utilized to interface the electrodes to the ECG recorder. Fig.(2.5) demonstrates these leads (I,II,III) [39]. The Electrocardiogram records the progressions in electrical possibilities between the electrode. This electrical effort is drawn as waveform chart after filtration and expansion.

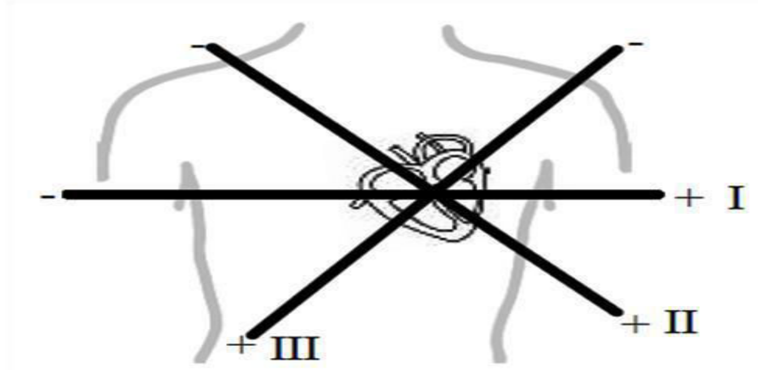


Figure (2.5): Einthoven's triangle showing how leads I, II, and III are recorded.

The ECG is a helpful device utilized as a part of heart variation from the norm location. There are numerous adaptations of the original ECG system. The most understood one is the Twelve-lead ECG system. A standard ECG recorder comprises of 4 limp electrode and in addition 6 chest electrodes. The electrodes and leads screen the action of the heart from twelve places. Six of them are limb- leads and 6 chest leads as appeared in Table (2.2) [40]. Every lead screens the electrical movement of the heart from various edge and has positive and negative parts. Every lead screens a particular bit of the heart contrasting and the potential in the positive terminal associated with that lead.

Table (2.2): Standard ECG system leads.[40]

Standard Leads	**Limb Leads**	**Chest Leads**
Bipolar Leads	**Unipolar Leads**	**Unipolar Leads**
Lead I Lead II Lead III	AVR AVL AVF	V1 V2 V3 V4 V5 V6

The ECG waveform amid a solitary cycle contains a trademark morphology.This comprises of the P-wave, the QRS-complex and the T-wave. An ordinary ECG record makes out of waves, complexes and a voltage variety over an interim of time. The ECG waveform begins and ends at the baseline. It changes to another waveform when it passes the baseline.

2.4.1 The P Wave

The **P wave** represents the contraction of the ateria .The Pwave's term is around 100 msec. while the amplitude as shown in fig (2.6) discounted up to 50-100 μv[41].

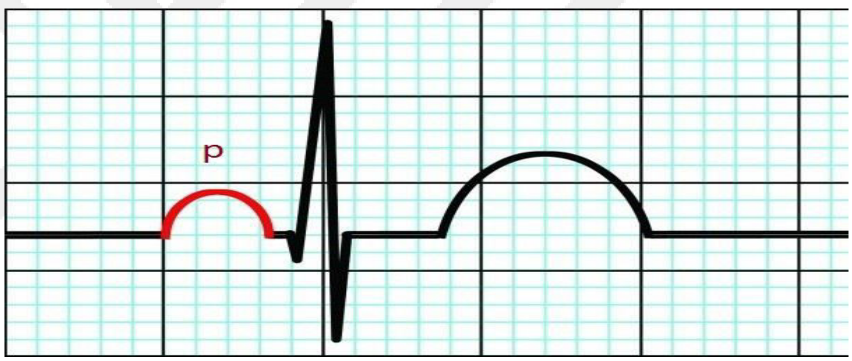
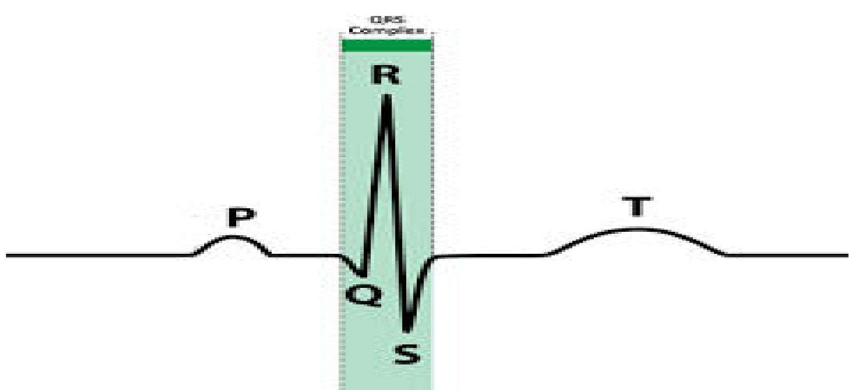


Figure (2.6): Normal P wave[41]

2.4.2 The QRS Complex

It represent the contraction of the ventricles. As shown in fig (2.7) for adults people, it normally lasts 0.06–0.10 s[42].



Figure(2.7): the duration of QRS complex[42]

2.4.3 The T Wave

The T wave represent the expantion (or recovery) of the ventricles. As presented in Fig(2.8) the duration of the T wave about 0.2ms or less in normal cases[42].

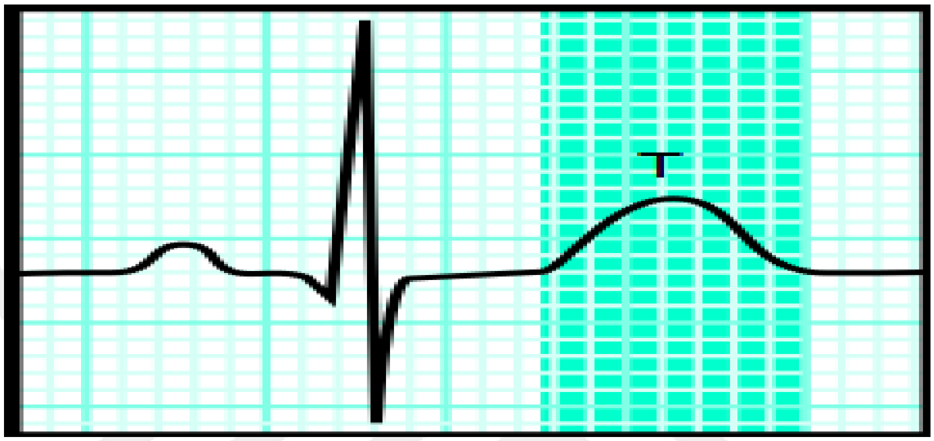


Figure (2.8): Normal T wave[42]

2.4.4 Intervals and Segments

The Intervals and Segments in the ECG as present in fig (2.9) are clarified as follows:

1. The P-R interval: Stretching from the starting of the P-wave to the starting of the QRS complex. This interval naturally measures 0.12-0.20 sec[42].
2. The P-R segment: It limited between the end of the P wave and the starting of the QRS complex.
3. The S-T segment: Illustrates the time between ending of the depolarization and repolarization of the ventricular muscle. In natural values it's about less than 0.12sec[42].
4. The Q-T interval: is measured from the executed of the QRS complex to the end of the T-wave, and its natural duration the Q-T interval about 0.38 sec[42].
5. The R-R interval: is the period between consecutive QRS-complexes which used to calculate heart rate. In normal person it takes time between 0.6-0.1sec[42].

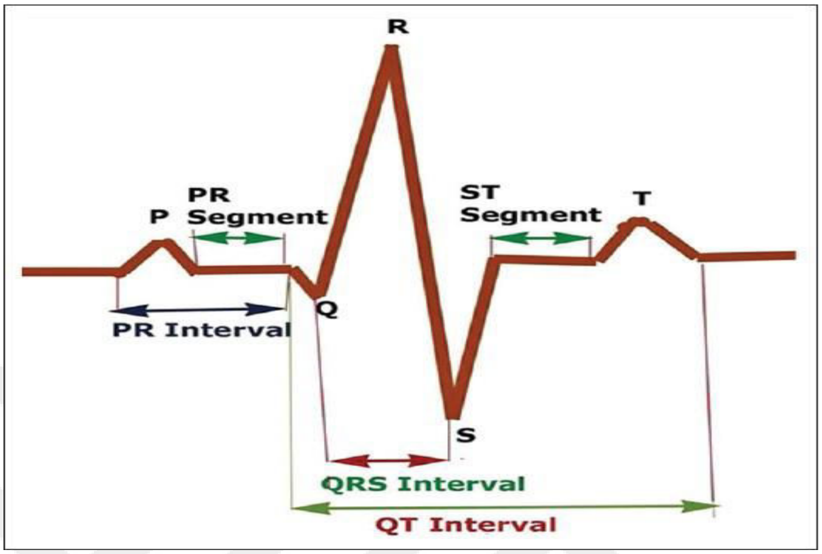


Figure (2.9) The normal electrocardiogram [42].

2.4.5 Heartbeat Measurement:

The naturalist heart, which heartbeat range between 60 t0 80 . For natural man the PR length is under 0.2sec. The length of the QRS Less or equal 0.1sec. The length of the P-wave can't be more than 0.1sec. T-wave's width can in any event be 0.2sec. The R-R range between 0.6 to1sec [42]. Rough estimations of the span of the different waves for ordinary grown-up's heart are appeared in Table (2.3). Rough estimations of the span of the different waves for ordinary grown-up's heart are appeared in Table (2.3).

Table(2.3):Duration of Various waves in normal heart[42].

Parameter	Duration (Sec)
PR interval	0.12-0.20
QT interval	0.30 – 0.40
P wave duration	0.08 – 0.01
QRS duration	0.06 – 0.10

Any alteration in typical morphology of the ECG is utilized to analyze a few sorts of heart variations from the norm. It will be life salvation for individuals with heart issues. Specialists can recognize a specific heart's issue by looking at its EGC. A particular treatment can be given to treat the heart's issue based upon the ECG estimation. The ECG can be separated into various segments and interval. This will lead to be straightforwardly identified the heart conditions. Cutoff points can be put to these interims and components so that any deflection from these breaking points is viewed as an irregularity [43]. In this work the framework utilizes ECG period for analysis of the variation from the norm. We have used these periods (PR, QRS, QT and RR) as appeared in Table (2.3) for the purpose of diagnosis ECG refer to as normal and abnormal. The reason for choosing these periods due to the following reasons:

1. Because of breathing the baseline floats with amplitude around 15%[44].
2. Movement of electrode which are placed on the patient's chest will lead to difference between the skin and the electrodes [45].
3. ECG Amplification differs from instrument to other , because it depends on the manufacturer of the instrument[46].
4.The amplitude o/p voltage that Resulting from the conversion process from analog to digital is not accurate, because it counts on input signal.

2.5 LABVIEW Theory.

Laboratory Virtual Instrument Engineering Workbench (LabView) is programming is utilized for a wide assortment of uses and ventures. LabView is a very profitable improvement environment to make custom applications that interface with real information or signals in fields, for example, science and designing. The net consequence of utilizing an instrument, for example, LabView is that higher quality projects will can be finish in less time with less individuals included. LabView has many application[47] which usually utilized for information obtaining, instrument control, and mechanical computerization on an assortment of working systems (OSs), including Microsoft Windows, different renditions of Unix, Linux, and macOS. By utilize a part of LabView, for programming dialect ,named G, that is a dataflow programming dialect. These execution is dictated by the structure of a graphical square outline (the LabView-source code) the programmer connects different function-nodes by drawing wires[47]. These wires engender factors and any node can execute when all its information get to be accessible. Since this may be the situation for numerous nodes at the same time, G can execute naturally in parallel[48]. Multi-handling and multi-threading equipment is abused naturally by the inherent scheduler, which multiplexes various OS strings over the nodes prepared for execution. In our work we used LabView to built a system to extract the feature from the ECG signal, and to generate ECG signal. LabView programs are called virtual instruments, or VIs, because their appearance and operation imitate physical instruments, such as oscilloscopes and multimeters. Every VI uses functions that manipulate input from the user interface or other sources and display that information or move it to other files or other computers. A VI contains the following three components:

- ► Front panel— Serves as the user interface as shown in fig. (2.10)
- ► Block diagram— Contains the graphical source code that defines the functionality of the VI as shown in fig (2.11)
- ► Icon and connector panel— Identifies the VI so that you can use the VI in another VI.A VI within another VI is called a sub VI. A sub VI corresponds to a subroutine in text-based programming languages.

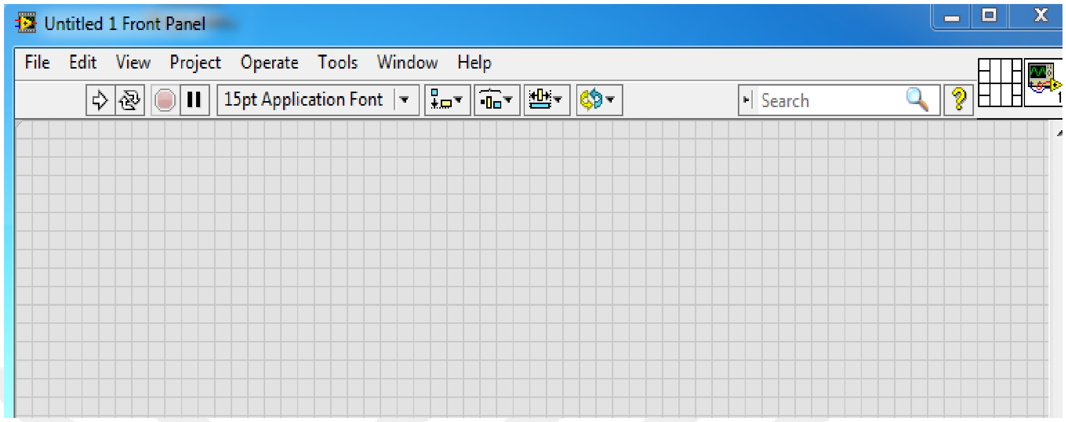


Figure (2.10) Front panel

The front panel is the user interface of the VI. You build the front panel with controls and indicators, which are the interactive input and output terminals of the VI, respectively. Controls are knobs, pushbuttons, dials, and other input devices. Indicators are graphs, LEDs, and other displays. Controls simulate instrument input devices and supply data to the block diagram of the VI. Indicators simulate instrument output devices and display data the block diagram acquires or generates.

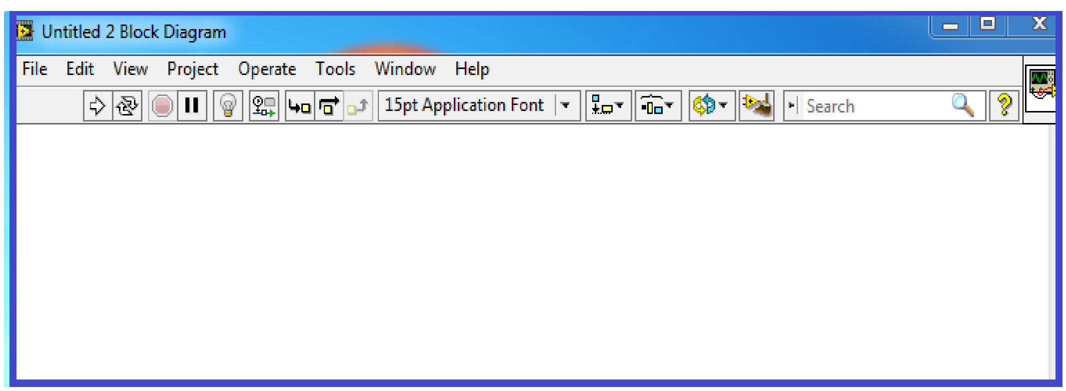


Figure (2.11) Block diagram

After you build the front panel, you add code using graphical representations of functions to control the front panel objects. The block diagram contains this graphical source code. Front panel objects appear as terminals on the block diagram.

Additionally, the block diagram contains functions and structures from built-in LabView VI libraries. Wires connect each of the nodes on the block diagram, including control and indicator terminals, functions, and structures.

2.6 Decision Classifier

After the components are separated from the LabView bundle, they will be connected to the classifier to recognize ECG finding. There are eight sorts of ECG analysis normal, First Degree Heart Block(F.D.H.B), Wolff-Parkinson White Syndrome(W.P.W.S), Right or Left Bundle Branch(R. L.B.B), Myocardial Infarction (M.I) , Lowen-Ganong Leving Syndrome(L.G.L.S), Bradycardia (B) and Techcardia (T). Two sorts of classifiers are proposed in this work. These are threshold decision classifier and NVG-RAM weight-less neural network.

2.6.1 Threshold Decision Classifier

Threshold classifier is one of the fundamental arrangement tools in which choice at every stage is execute by Pre-existing Threshold values. It is here and there called choice tree classifier. In this method, time-request of the components and pre-existing threshold qualities are the better parameters in the execution of the classifier. Subsequently, threshold values and restrict requesting of the picked feature should be selected deliberately to reduce the likelihood of fake classification. The choice depends on two sorts limit examinations: single and multi-threshold correlations. For the single, the classifier pick its choice in view of one pre-existing estimation of threshold. For this manner, the choice will be more dependable because it has one limit is isolates between one class and the others. In any case, in multi threshold correlations, more than one limit of confinement qualities utilized to indicate the choice of the classifier which makes it comparatively less credible because many limits isolate between the required class and the others. Fig.(2.12) shows the boundary between the desired class in red points and the other classes in blue points.

If there should arise an occurrence of one limit, the likelihood of false classification is little in light of the fact that the circles are covered around one limit as delineated in Fig.(2.12-a). While in two limits choice classifier, circles are covered around two limits which makes likelihood of wrong classification higher than in single limit choice classifier as observed in Fig.(2.12-b).

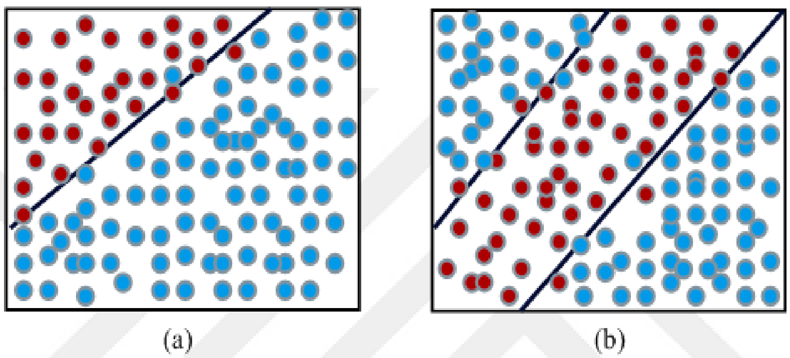


Figure (2.12):Boundary between classes.

2.6.2 Numeral Virtual Generalizing Random Access Memory (NVG-RAM) Weightless Neural Network.

The NVG-RAM is the most straightforward calculation that can be worked by FPGA because of the basic math process utilized as a part of this approach. Also, this classifier can deal with a decimal number rather than binary number utilized as a part of customary VG-RAM. This classifiers's sort enable to be learnt in one shot. The NVG-RAM knowing is simply putting pairs of input/output in RAM. The review phase of this system relies on upon the base less Manhattan distance between obscure pattern and all pairs stored in the RAM. The Manhattan distance is evaluated according to Eq.(2.1) to locate littlest distance. The index of the minimum distance is assigned to the number of the class in output field. The wanted class brought to network output. Fig.(2.13) demonstrates the flowchart of the NVG-RAM [49].

$$d(\boldsymbol{p},\boldsymbol{q}) = \sum_{i=1}^{n} |p_i - q_i| \qquad (2.1)$$

where: $d(\boldsymbol{p},\boldsymbol{q})$is the Manhattan distance between two vectors $\boldsymbol{p}\,,\boldsymbol{q}$, $\boldsymbol{p} = (p_1, p_2, \dots, p_n)$, $\boldsymbol{q} = (q_1, q_2, \dots, q_n)$, and n is the number of elements in each vector. Now and again the FPGA equipment execution of this sort of classifier takes wide slices particularly when the training sets comprises of huge quantities of sets. Consequently, the decreasing of training sets is extremely important to make the equipment stage ready to handle these training sets with saving the execution of the classifier. The minimization training sets algorithm is an intense technique utilized to decrease the training set contingent upon the likeness measure between the comparing components of the vectors in training set as appeared in Fig.(2.14).

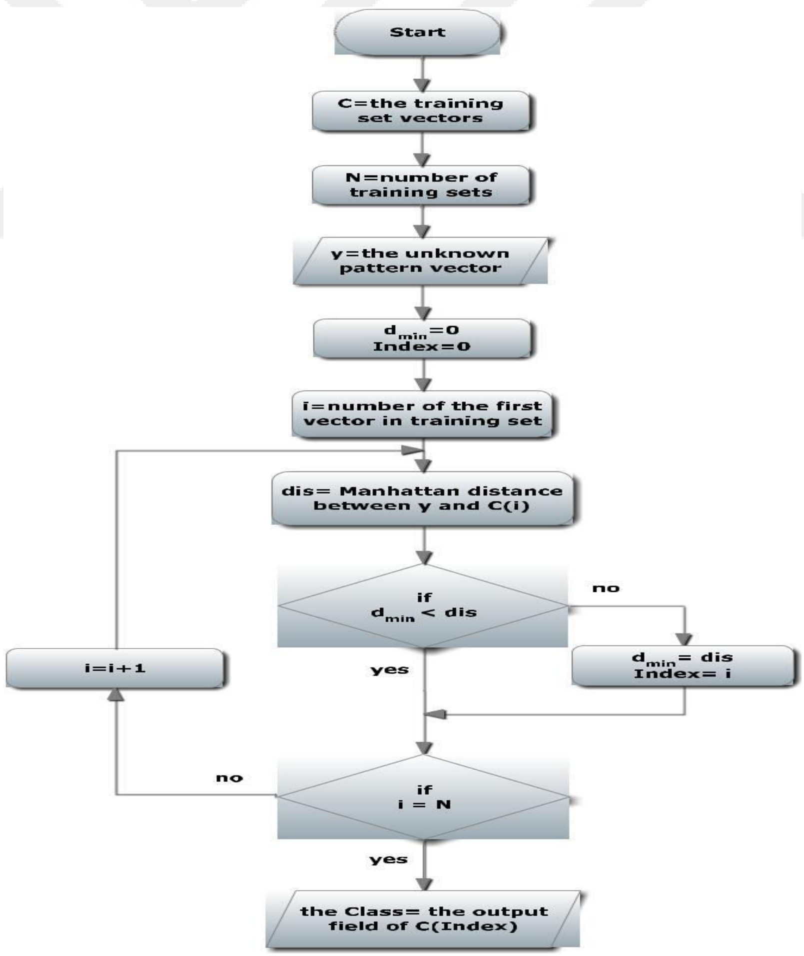


Figure (2.13): Flowchart of the NVG-RAM

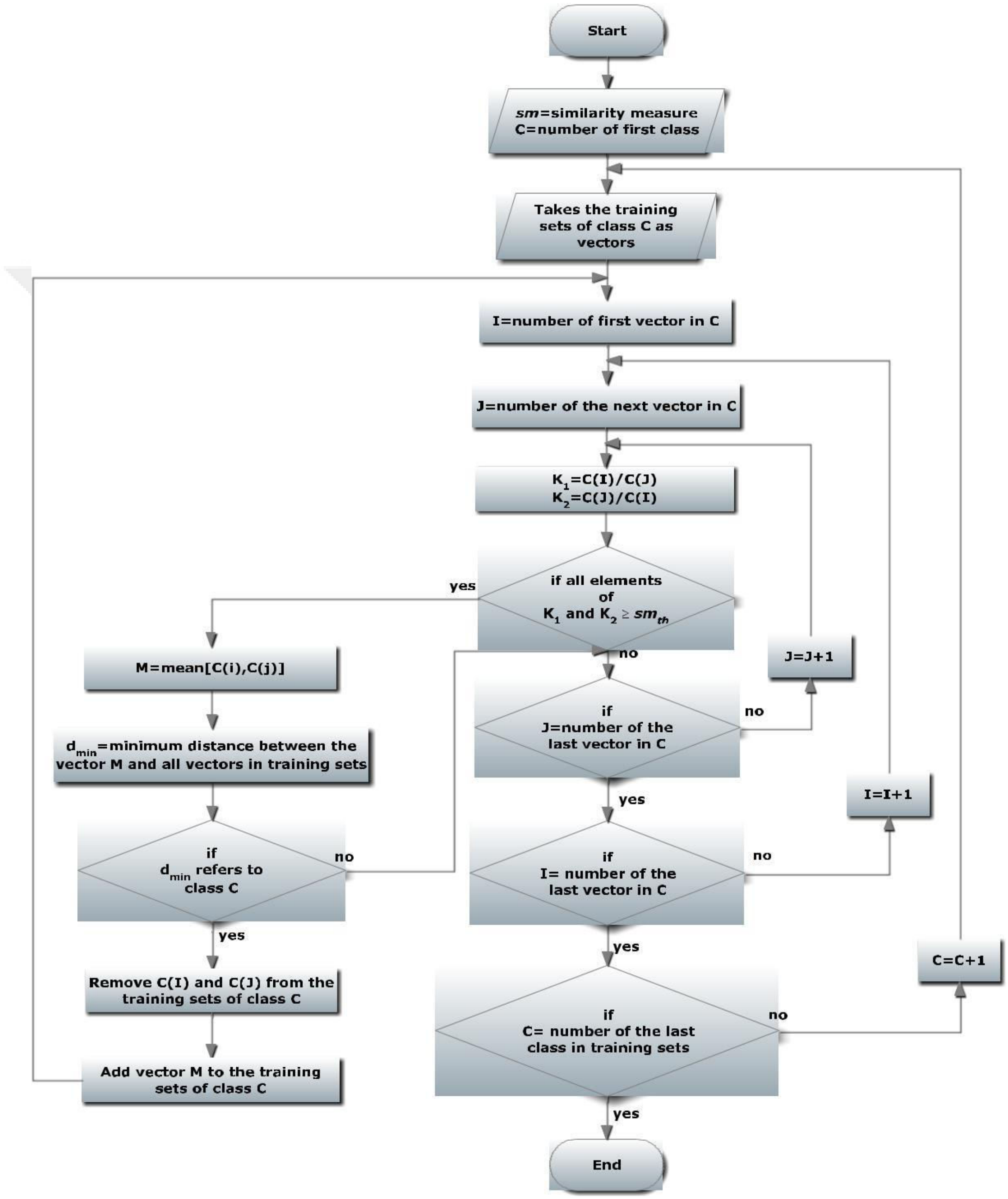


Figure (2.14): Proposed algorithm flowchart .

2.7 Field Programmable Gate Arrays(FPGA)

FPGA are prefabricated silicon devices that can be electrically programmed to become almost any kind of digital circuit or system. They provide a number of computing advantages over fixed function Application-Specific Integrated Circuit (ASIC) technologies such as standard cells: ASICs typically take months to fabricate and cost hundreds of thousands to millions of dollars to obtain the first device; FPGAs are configured in less than a second, and often be reconfigured if a mistake is made, and cost anywhere from a few dollars to a few thousand dollars [50]. FPGA consists of an array of uncommitted Configurable Logic Block (CLB), programmable interconnects and Input Output Blocks (IOBs). FPGA architecture is dominated by programmable interconnects, and CLBs which are relatively simple. This feature makes these devices for more flexible in terms of the range of designs that can be implemented with these devices[51]. Contemporary FPGAs have an on chip presence of higher level embedded memories and embedded functions. Some of them even come with an on chip microprocessor and related peripherals to constitute what are called a complete system on a programmable chip: these devices have one or more personal computer processors embedded within the FPGA logic fabric [51].

2.7.1 FPGA Architectures

In general, the simple FPGA architecture is composed of two dimensional array of flip-flops and logic components blocks with resources for the user to construct as presented in figure 2.15:

- ► Formal logic blocks.
- ► Formal I/O blocks.
- ► Programmable interconnect.

Also, to each one logic block, will be clock circuitry for driving the clock signals and additional logic resources such as ALUs, memory, and decoders might available[52].

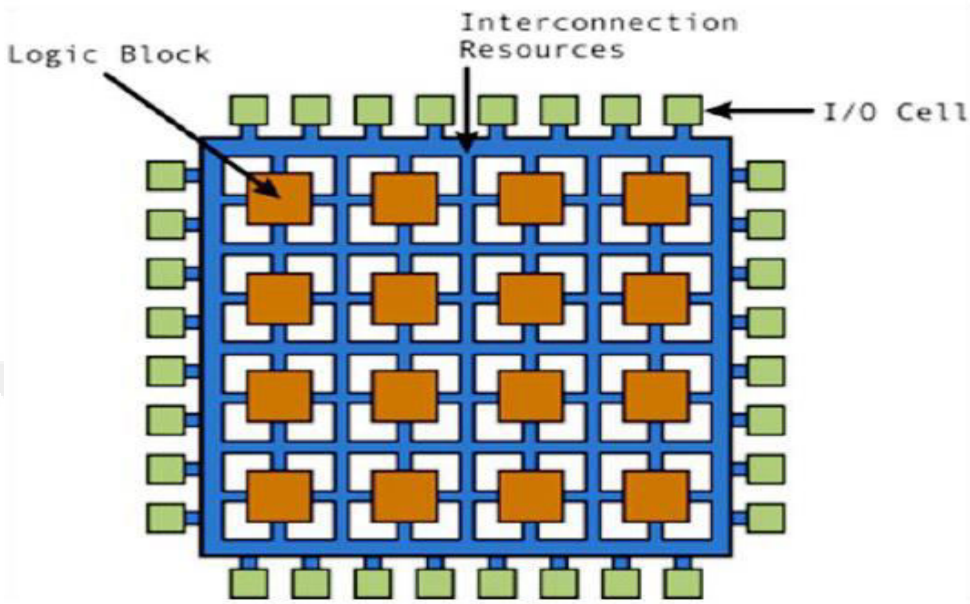


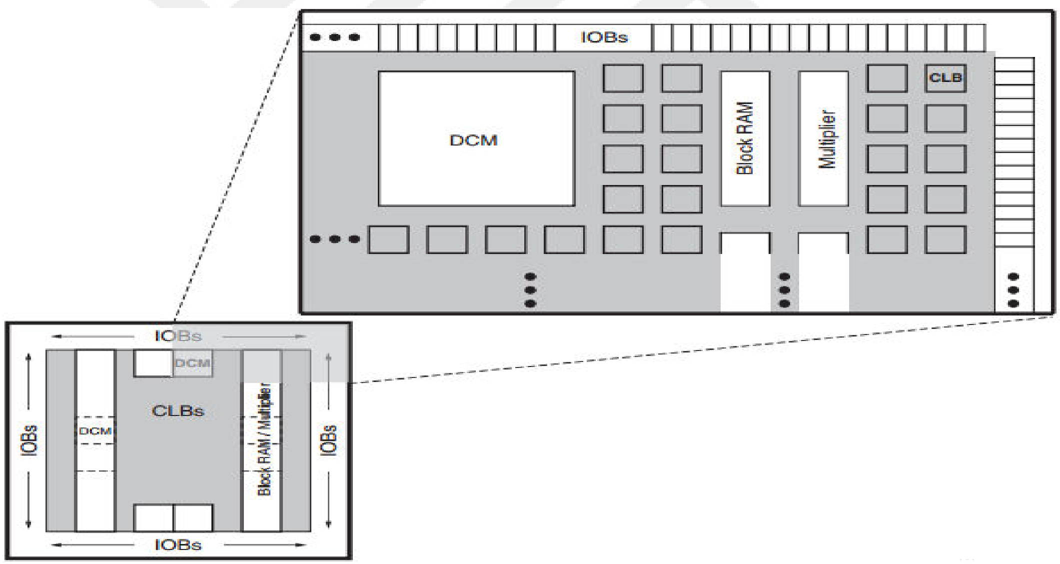
Figure (2.15) FPGA Architecture[52]

2.7.2 Hardware Platforms

The Spartan family, 3AN join the better attributes of leading, low-cost FPGA with technology is of worried across a spacious band of densities. This family join all of the advantages of the Spartan -3 A FPGA family as well as a leader in flash memory configuration system technology and data storage concern. Spartan, including 3AN design is part of the Spartan family extended -3 A, which also includes the Spartan -3 A design including high density Spartan -3 A DSP design including. Interface internal configuration Spartan, 3AN FPGA is a completely self-sufficient, and to increase security design. Family maintains full support to form a state. Spartan, 3AN FPGA is the world's first FPGA with non-volatile multi-playback, support for two or more of the configuration files in a single device, allowing for alternative configurations for field upgrades, and test modes, or multiple system configurations. Gates. This Spartan, 3AN FPGA removes the limitations of conventional FPGA is concerned with the advanced 90 nm. The architecture of Spartan family, 3AN is constituting with five functional features configurable:

1. configurable logic blocks (CLBs)
2. input/output blocks (IOBs)
3. RAM memory block
4. multiplier blocks
5. manager of the digital clock (DCM) blocks.

These elements are arranged as shown in Figure (2.16). Department of IOBs encircles a fixed set of CLBs. The topography of the Spartan family, 3AN rich network of seals that all the functional elements of the interdependence of five, and the transfer of signals between them. Functional for each element has a matrix relevant that provide multiple connections to guide key [53].



Figure(2.16): Spartan-3AN FPGA Architecture [53].

The device that is used in this thesis is XC3S700AN and its features are shown in table (2.4), as noted in this table Kb is equivalent to 1,024 bits. With -4 speed grades, Fig(2.17) show the device.

Table(2.4): Features of XC3S700AN device.

System Gates	700K
Equivalent Logic Cells	13,248
CLBs	1,472
Slices	5,888
Distributed RAM Bits	92Kb
Block RAM Bits	360Kb
Max different I/O pairs	165
Dedicated Multipliers	20
DCMs	8
Maximum User I/O	372

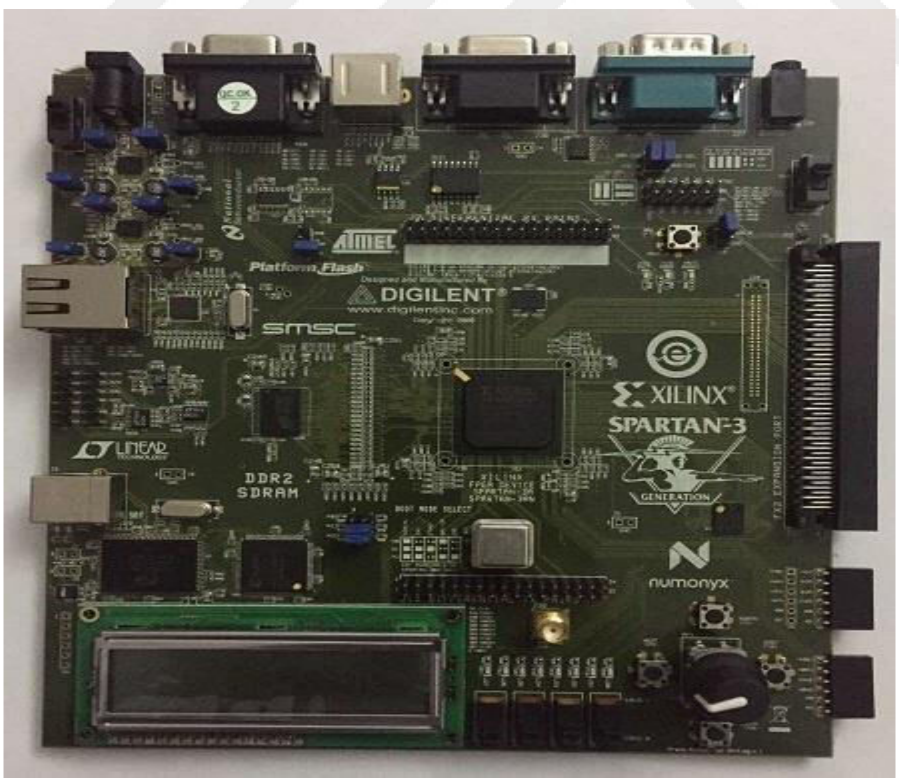


Figure (2.17): Spartan 3AN XC3S700AN

With, VHDL, language we can explain the FPGA hardware functions, and it is necessary a specific software to translate the design into a collected hardware. In this work, we are using an packages of MATLAB, and Xilinx System Generator(XSG) ISE 14.6. We use the Xilinx tool existing in MATLAB for construct the system generator (SG) as expanding block sets of Simulink. After the download steps complete to create the FPGA program, XSG execute this program automatically. SG gives the capability to usefully simulate hardware design MATLAB platform. SG has a black box permits VHDL code to passed into MATLAB/Simulink and co-simulated (Xilinx ISE Simulator). Fig.(2.18). present the initial process of XSG .

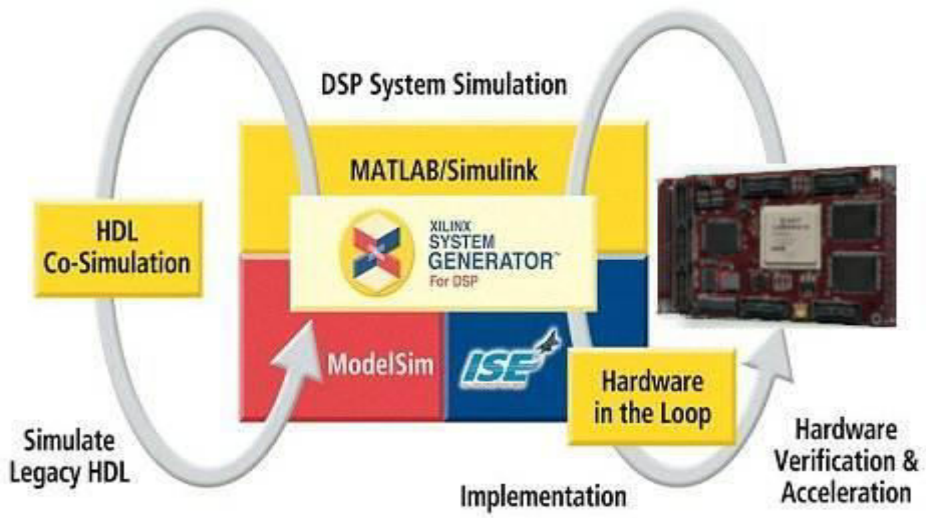


Figure (2.18): Xilinx System generator basic operation

For validate our system on FPGA platform, the Hardware (HW) Co-Simulation timing analysis and simulation prove and perform the system. HW Co-Simulation test by comparing SG supply bit-true - cycle-true consequences (device simulation result with MATLAB simulation result). The Co-Simulation creation bit stream file for XSG designed blocks depend on the core of SG and Xilinx ISE. bit stream will passed into FPGA board in standard connection such as JTAG to lead hardware downloaded (closed connection PC - Xilinx board).

CHAPTER 3:

3. PROPOSED ECG DIAGNOSING SYSTEM DESIGN

3.1 Introduction

In this chapter we will talk about how to generate an ECG signal. In addition, this chapter gives us interested points of the proposed ECG diagnosing designing system. The general format of the system is depicted and the method utilized as a part of the detection of abnormalities is given in detail. Generation ECG signal technique by using LabView is explained. Proposed ECG Features extraction system using LabView package associated with Biomedical Toolkit is built and discussed. In this section two different heart diseases classification procedures are proposed as they are connected to certain ECG parameters utilized as a part of this work. The chapter discusses the use of two classification algorithms, namely Threshold Decision classifier (TD), and one recently devised algorithm, namely, numeral VG-RAM is proposed to classify the heart cases. All these techniques and algorithms have their advantages and limitations. The overall ECG diagnosing system proposed in this work consists of the following stages;

- ► Acquisition ECG data base.
- ► Feature extracting.
- ► Classification of decision making.

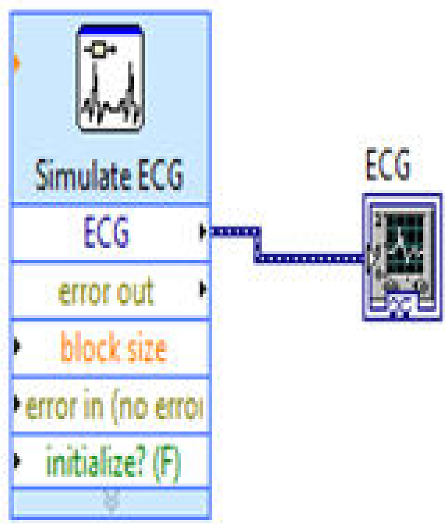
3.2 ECG Generation

The aim of the ECG generation is for teaching purposes. That means it helps to produce the typical ECG waveforms to understand and monitor the heart signal without need for a person to put an electrode on his body. ECG generating signal process is done through LabView software. In our work we will use two methods to generate the ECG signal and which are ECG simulator, and ECG reading methods.

3.2.1 ECG Simulator

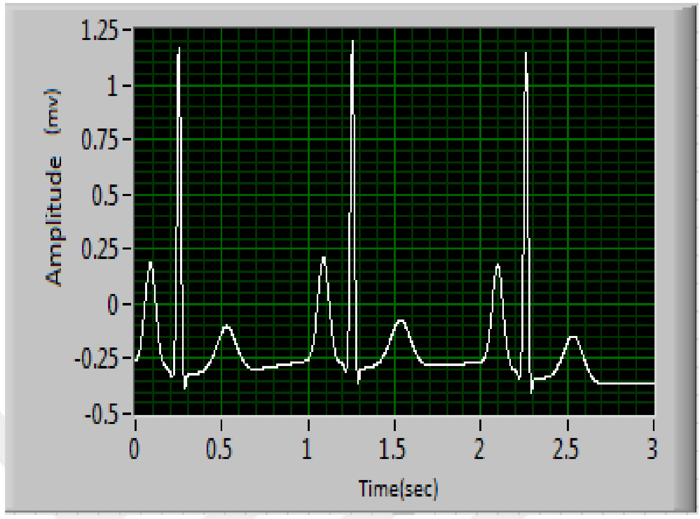
The aim of the ECG simulator is to produce the typical ECG waveforms. This ECG simulator is a LabView based simulator as shown in Fig. (3.1) is able to produce ECG waveform. The use of a simulator has many advantages in the simulation of ECG waveforms.

First one is saving of time and another one is removing the difficulties of taking real ECG signals with invasive and noninvasive methods. The ECG simulator enables us to analyze and study normal and abnormal ECG waveforms without actually using the ECG machine. We can simulate any given ECG waveform using the ECG simulator.



Figure(3.1): ECG simulator

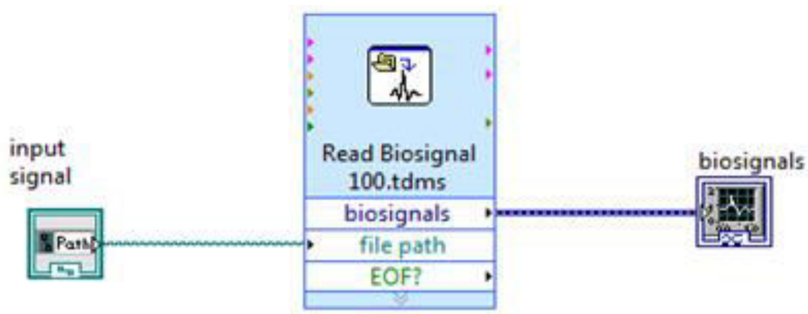
ECG signal is periodic with fundamental frequency determined by the heartbeat. The generated output ECG signal by LabView. The specifications are default for this signal which can be changed according to the user's requirement, for example in Fig(3.2), we take amplitude of P, R, Q, T waves as 0.2mV, 1.18mV, - 0.35mV, -0.1mV respectively while the duration of P-R interval, S-T interval, QRS interval as 0.16s, 0.33s, 0.13s respectively.



Figure(3.2): ECG waveform simulated in LabView

3.2.2 Read ECG Signal

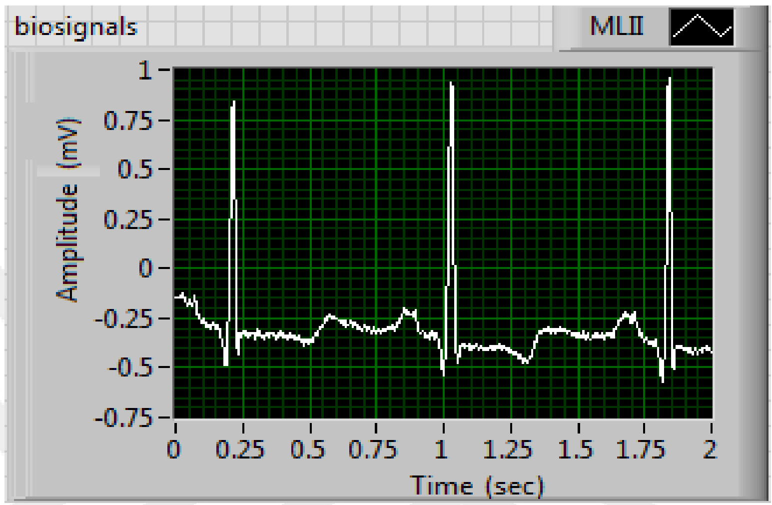
Signal is generated by using the files stored in the calculator and display on the screen. Where the trainee specialist storing cardiac signals for the various people in his computer. The purpose of read the ECG signal is for the examination, diagnosis and clarify cases of natural and non-natural of heart without need a person to take the signal from him. Reading ECG signal doing by using LabView. as shown in Fig.(3.3), we read an ECG file available on MIT-BIH data base.



Figure(3.3) : ECG Reading

The output of the ECG signal as shown in Fig. (3.4). The specifications of the second wave of this signal which include from P, R, Q, T waves as ≈-0.14mV, ≈1mV, ≈-

0.37mV, -0.11mV respectively while the duration of P-R interval, Q-T interval, QRS interval as 0.18s, 0.44s, 0.083s respectively.



Figure(3.4) : ECG Reading output waveform in LabView

3.3 ECG Diagnosing system layout

The development of abnormalities detection which employs data acquisition, feature extracting and classification is constructed in Fig.(3.5). The construction consists of three main parts, namely ECG acquisition, feature extraction and decision classification. The first part, ECG acquisition, captures the ECG signal from ECG database. The second part, feature extraction, is developed to find the ECG features (such as PR, QRS, QT and RR intervals) from the ECG signal. Thirdly, the ECG features are then classified using a one of the classifiers mentioned in chapter 2, namely TD, and NVG-RAM. The output of the classification is a decimal representation, normal or abnormal with seven disease cases.

Figure(3.5): Proposed ECG diagnosing system's elements.

3.4 ECG Database

Two types of ECG database are considered in this work in order to evaluate the performance of the two suggested heart diseases classifiers. The first one is the standard MIT-BIH ECG database which used by most researchers that interest in analysis and diagnosis the ECG signal. Because of the MIT-BIH database does not includes all the heart diseases that considered in this work, a second database is generated using LabView biomedical toolkit to handles all heart cases that should be recognized by proposed ECG diagnosis systems.

3.4.1 MIT-BIH Arrhythmia Database

From the ECG database available at site **www.physionent.org** we taken the ECG data files. Several databases of ECG and other physiological recordings are available for various purposes including the evaluation of ECG analysers. The data obtained from MIT-BIH arrhythmia data base contains 48 half-hour data intervals. The recordings were digitized at 360 samples per second with 11-bit resolution over a 10mv range. By using band pass filter with pass band from 0.1-100 Hz, the analogue signal is filtered to limit analogue to digital converter.

3.4.2 Generated Database

By using LabView biomedical toolkit, The second type of ECG database is generated, This process of generating ECG signals was performed according to the advice of a specialised doctor. Used as a reference the normal ECG. This ECG signal contains features with certain limits. Also, abnormal ECG waveforms which have identified features that belong to one of the heart abnormality cases were used to identify specific cases of heart diseases. The cases are as follows:

- **FDHB: First Degree Heart Block.**
- **WPW: Wolff-Parkinson White syndrome.**
- **LGL: Lowen- Ganong Leving syndrome.**

- ► **RLBB: Right or Left Bundle Branch.**
- ► **MI: Myocardial Infraction.**
- ► **B: Bradycardia.**
- ► **T: Techcardia**

Therefore, to identify normal or abnormal cases, this proposed ECG system employs features. The abnormal cases are related to one of the above abnormality cases. The number of waveforms generated for each one of the normal and the abnormal cases was 50 signals. Also, there are a group of signals that contains additive noise. Hence, the total number of ECG signals is 400.

3.5 Proposed ECG Feature Extracting System

By using LabView package, a proposed system is built to extract the desired ECG features. The package is installed on a personal computer (PC) under Windows7 operating system. The block diagram of the feature extracting system is shown in Fig.(3.6). In this figure the main stages of the ECG processing for feature extracting is laid out. An appearance of the LabView implementation can be seen in Fig.(3.7). The obtained ECG features were exported to MATLAB using MATLAB script function block, as indicated on the left of Fig.(3.6). These features were then processed in the feature classification stage. The sampling rate of the ECG acquisition was 360 Hz.

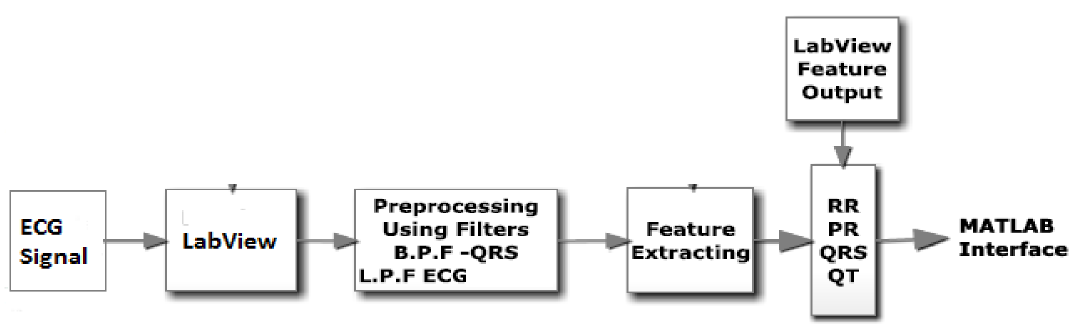
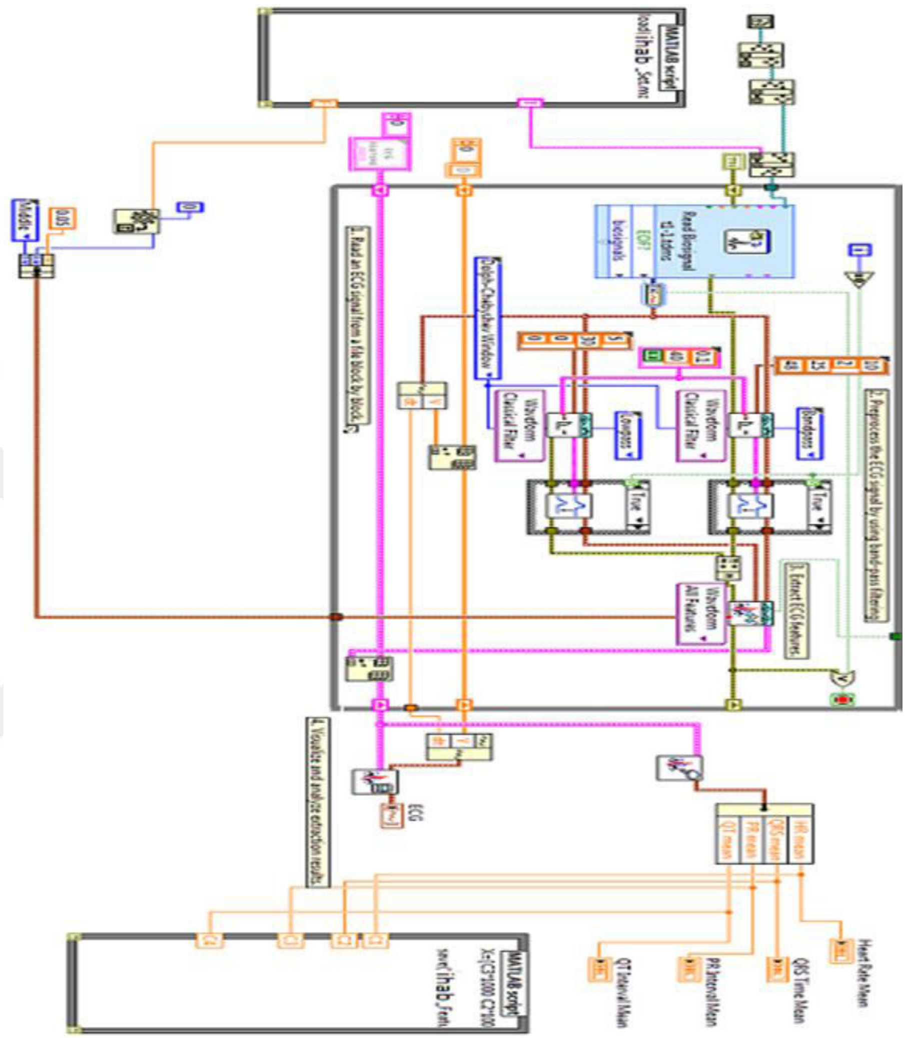


Figure (3.6): Block diagram of the LabView feature extracting implementation



Figure(3.7): Appearance of feature extracting implementation using LabView.

3.5.1 Preprocessing Stage

Two types of filters, band pass and low pass filters contained in this stage. To extracting the QRS complex from the raw ECG waveform, we use the purpose of the band pass filter. And for de-noising the raw ECG signal The second filter which is a low pass filter is used. To extract the required features, namely PR, QRS, QT and RR both outputs from the two filters are used. By using Dolph-Chebyshev window for filter design both filters were designed. It has the best stop-band attenuation, so that the reason for choosing this window type, therefore it has best noise reduction capability than the other types. In other words, the Dolph-Chebyshev filter is less subject to noise than the others. For the specifications of these filters see tables (3.1) and (3.2). Also, for the frequency responses of the filters see Figs.(3.8) and (3.9).

Table (3.1): Specifications of the band pass filter.

Parameter	Descrition
Design method	Dolph - Chebyshev
Order	16
Fstop1	2
Fpass1	10
Fpass2	25
Fstop2	48

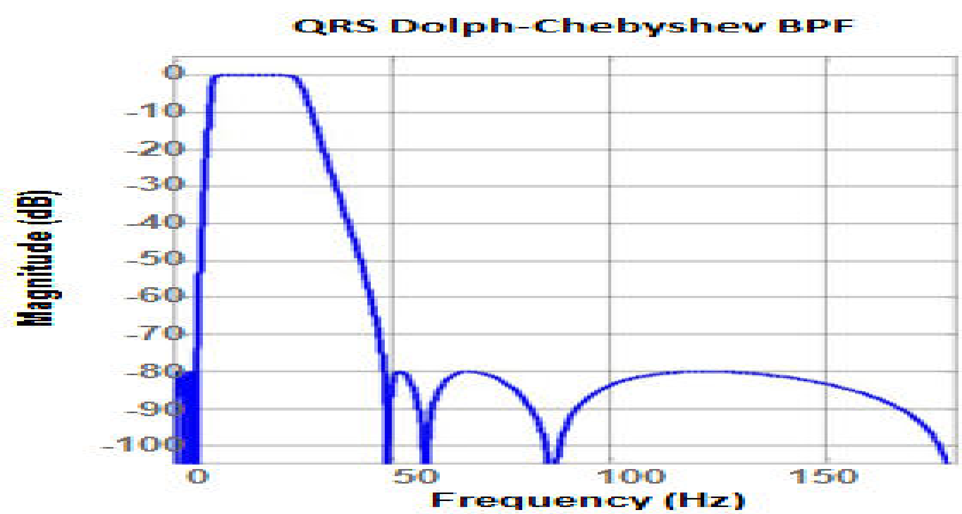


Figure (3.8): Frequency response of band pass filter.

Table (3.2): Specifications of the low pass filter.

Design method	Dolph - Chebyshev
Order	5
Fpass	5
Fstop	30

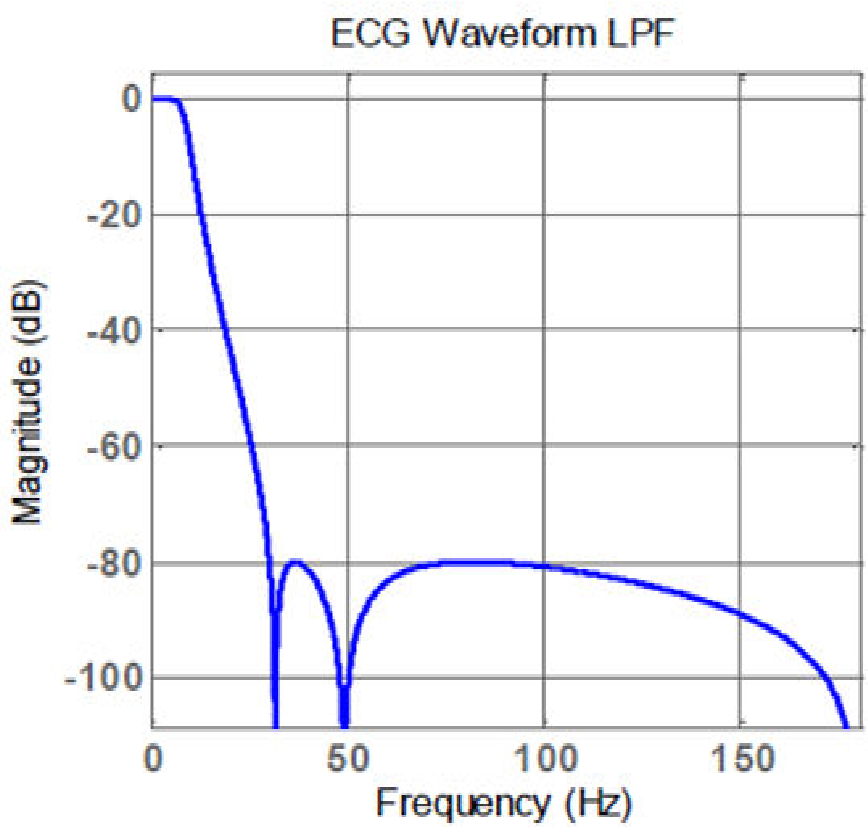


Figure (3.9): Frequency response of low pass filter

To produce a signal with low level of noise we use the purpose of the low pass filter. ECG signal is often contaminated by noise and artifacts that can be within the frequency band of interest and manifest with similar characteristics as the ECG signal itself. In order to extract useful information from the noisy ECG signal, the processes of the raw ECG signal is needed as illustrate in Fig.(3.10). Preprocessing ECG signals is reducing level of noise from the ECG signals. Fig.(3.11) present original and processed ECG signals.

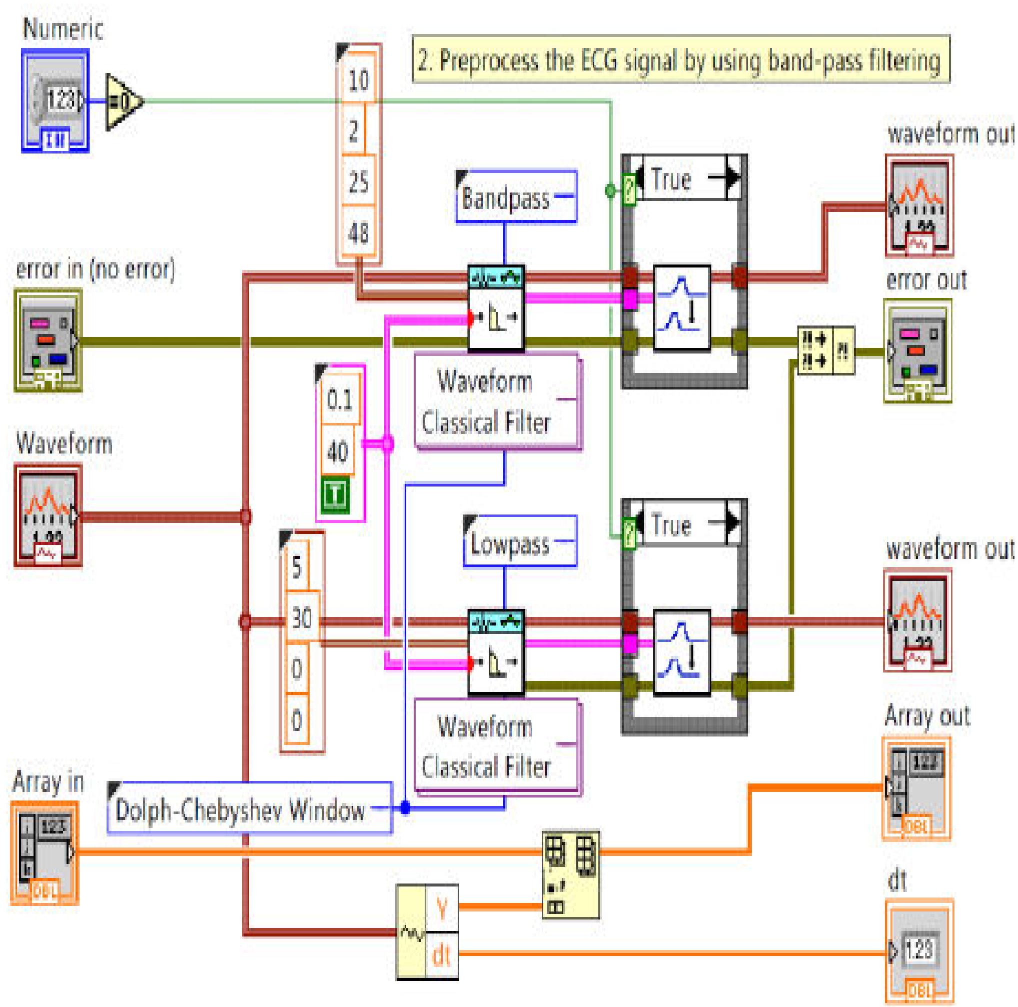


Figure (3.10): Preprocessing stage of the ECG signal

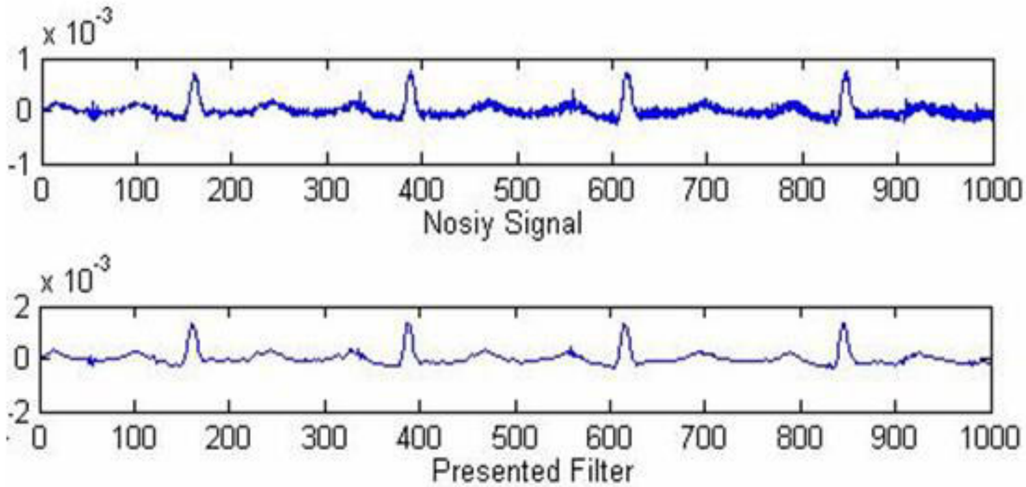


Figure (3.11): Original and signal with low level noised.

3.5.2 Feature Extraction Stage

An important role in diagnosing the cardiac disease are playing by the extracted feature from the ECG signal. In order, it often needs to extract various features from the preprocessed (de-noised) ECG data, such as, PR, QRS, QT and RR intervals to diagnosis the heart diseases by classifier. By using the LabVIEW Biomedical Toolkit includes tools, we can extract the required ECG features that is ECG Feature Extractor (ECG-FE). The ECG-FE detects the QRS waves firstly using the ECG input signal, therefore, depending on the detected QRS the ECG-FE will extract the others features from the raw ECG signal which de-noised by low-pass filter. For the ECG-FE is set to array all features in order to specify the sampling rate of the ECG signal to 360 Hz which is the sampling rate of the signal see Fig.(3.12).

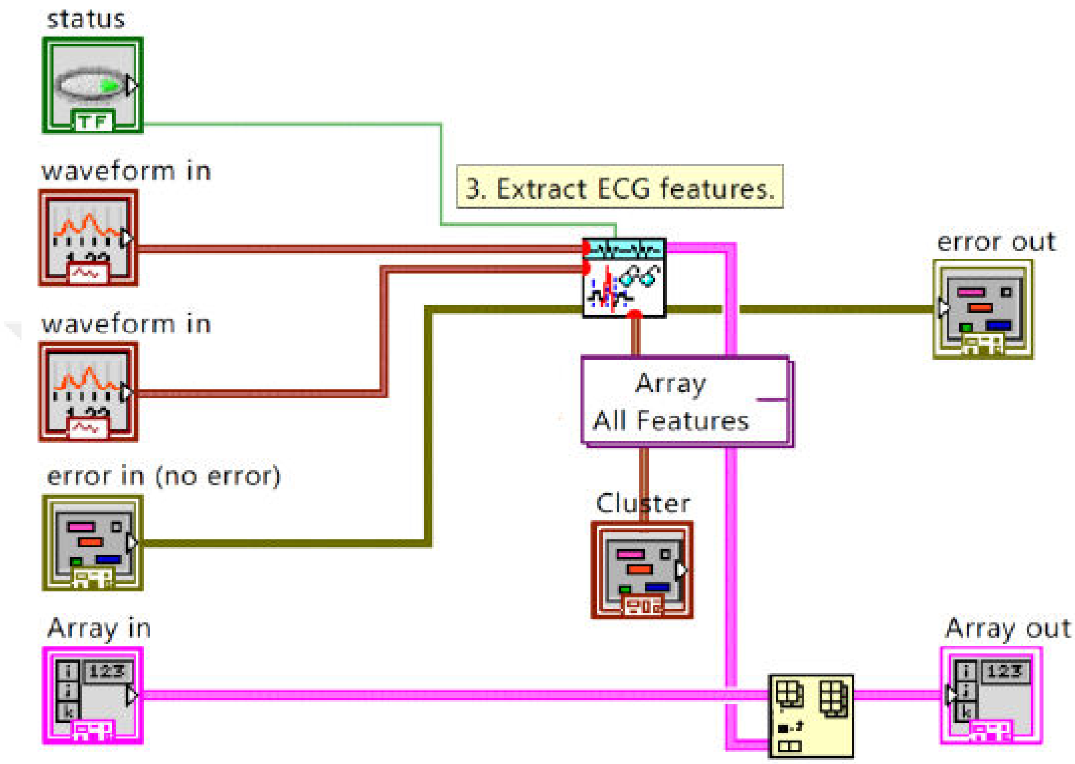


Figure (3.12): Feature extracting stage of LabView appearance .

The proposed ECG-FE firstly detects all beats (R waves) of the input ECG signal. R waves of human ECG usually have a frequency between 10-25Hz. Therefore, by using band-pass filter the R waves can be more obvious and easy for detection. After that, rectifying the ECG signal by performing the absolute and square functions for each sample is very necessary to avoid negative R waves and very large T waves. By comparing the result with estimated threshold the QRS duration and R position can be detected efficiently. Moreover, the R-R interval can be evaluated through the positions of the consecutive R waves. Depending on the R-R interval, the ECG-FE will extract the other features from the raw ECG signal as follows:

- Taking the time elapsed between two successive R waves that contains all other durations.

- Exploring the next highest amplitude that is lower than the amplitude of R from the beginning of R-R interval and assign this amplitude as P wave.
- Taking the differential to the ECG samples that bound the P position and comparing the results with specific threshold to estimate the PR duration.
- Investigating for the next highest amplitude to assign the T wave position.
- Estimating the boundary of QT interval by taking the differential to the ECG samples that surround the T wave to evaluate the end of this wave.

3.5.3 LABVIEW Output Stage

By using LabView, once all the features are extracted, they are stored in MATLAB interface ready for classification stage. Fig.(3.13) present the appearance of the output stage of LabView feature extracting stage. For using classification algorithms, and therefore to identify which one of the heart abnormalities is detected, the MATLAB interface is designed such that the features can be read separately in order to be processed.

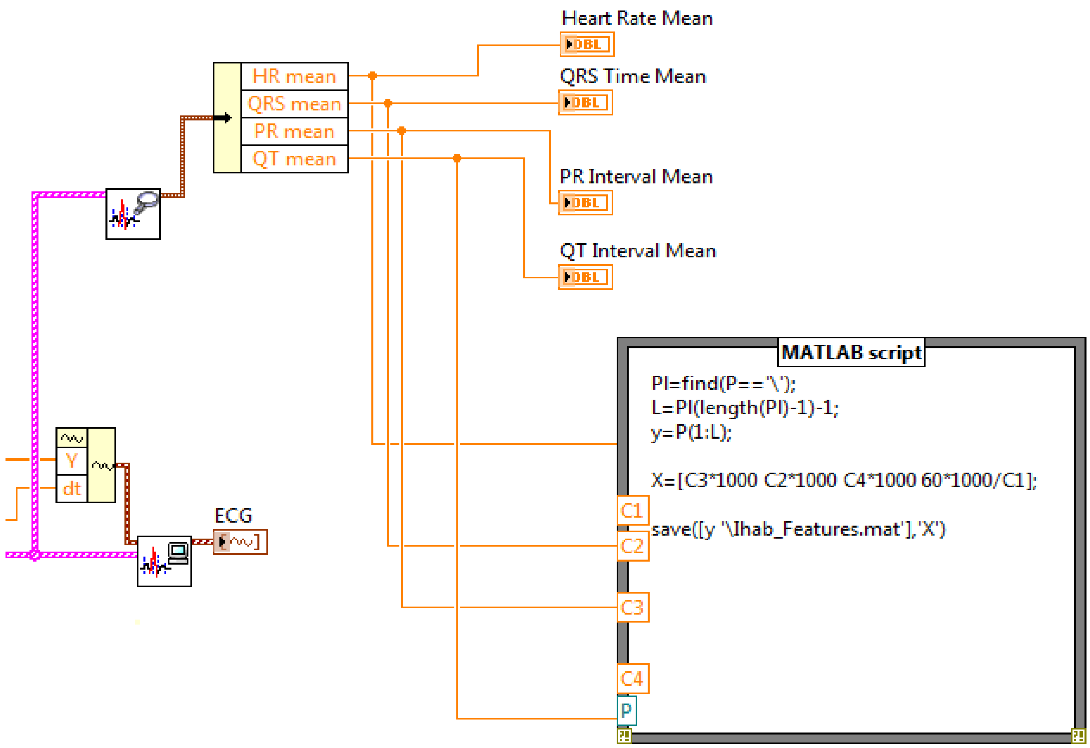


Figure (3.13): Output stage from LabView appearance

3.6 The Proposed Heart Diseases Classifiers

Consisting of many characteristics points, the feature extraction of the ECG signal, can detect the cardiac abnormalities. By using LabView, the ECG signal is obtained and analyzed. The most important parameters of the ECG signal are taken as features by applying the signal analysis technique. To identify the heart disease these features will be used as an input to the classifier. In this work, we suggest two types of decision classifiers to get best probability of strict classification in order, (Threshold decision, based on classical classification algorithms. NVG-RAM, classifier recently devised).

3.7 ECG Diagnosis System Based On Threshold Decision Classifier

We use the ECG extracted features RR, PR, QRS and QT as input to TD classifier. The Threshold classifier makes its decision depending on the boundary values of these features presented in Fig.(3.14). As it can be after the features are extracted, the value of these features is compared with the boundary Threshold values by the classifier. The classifier, at beginning, will perform the following tests:

- ► The case is classified as one of the heart abnormalities cases, if the four features of the input ECG signal exceed the boundary levels of the normal case. Otherwise the classifier will identify this case as normal.
- ► The case will be recognized at the output of the classifier, if the value of extracted ECG features is within the boundaries of the specific case. Otherwise the classifier will identify this case as undefined case.

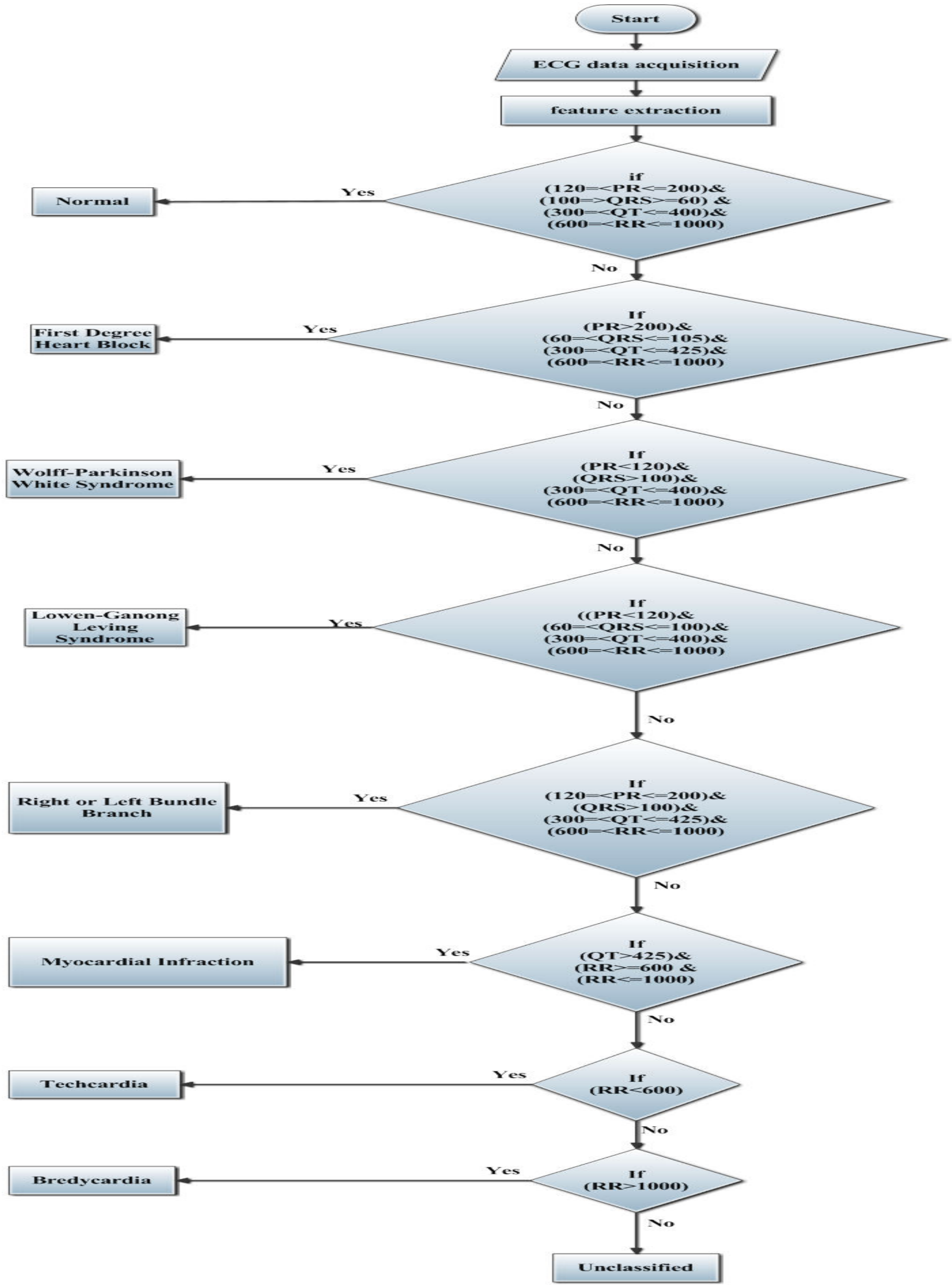


Figure (3.14): Flowchart of proposed ECG diagnosis system based on Threshold Decision classifier.

3.8 Training Sets Of The Neural Network Classifier

To ensure the high performance for the classifier, it is most important process, is the training phase. Many parameters according to the algorithm of suggested classifier witch depending the training phase. However, the main parameters that sharing all networks is the training set. To improving the performance of the neural network, the training set is very effective object. Approximately, all diagnostic situations should having by the training set. There is no standard sets can be adopted to learning the classifiers according to heart diseases considered in this work. Therefore, in this work, the training sets used are created based on the recommendations of the specialized physician in heart as presented in Table (3.3).

Table (3.3): Boundary of ECG durations according to the recommendations of the specialized physician in heart.

Heart situation	PR interval (ms)	QRS interval (ms)	QT interval (ms)	RR interval (ms)
Normal	120 – 200	60 – 100	300 – 400	600 – 1000
FDHB	> 200	60 – 100	300 – 400	600 – 1000
WPW	<100	> 100	300 – 400	600 – 1000
LGL	< 100	60 – 100	300 – 400	600 – 1000
RLBB	120 – 200	> 100	300 – 400	600 – 1000
MI	120 – 200	60 – 100	> 430	600 – 1000
B	120 – 200	60 – 100	300 – 400	< 600
T	120 – 200	60 – 100	300 – 400	> 1000

By using MATLAB and according the situation in Table (3.3), the training sets are generated to handle all states of diseases conditions. For each situation there is a range of intervals, each interval is created with 6 steps to overcome all its values making the number of the vectors of training set for each situation is 1296 vectors. So, ECG training sets for all cases are consisting of 10368 vectors. Each vector contains five fields; the first four fields for the features intervals in millisecond (PR, QRS, QT, and RR) and the last field for the desired heart situation.

3.9 ECG Diagnosis System Based On NVG-RAM Neural Network Classifier

We need eight conditions of heart to be classified by the NVG-RAM network with four durations (PR, QRS, QT and RR) as classifier features. The training set is made to cover all features situations, for all considered heart cases the counter of vectors in the training set is 10368 vectors. Each vector contains five fields; we use the first four fields to storing the duration's values of the features, the fifth field used to contain class number. The RAM of network consists 10368 arrays, each array consists five fields having numbers. (number cells related the number of bits (equivalent binary number features)). In MATLAB simulation, the RAM presented by matrix (two dimension. In MATLAB simulation, the minimizing the number of training sets is not needing because the training set of ECG diagnosis system can be easily build matrix in MATALB. However, there are a reduced number of slices, in FPGA implementation. To reduce the number of training sets, it's important to apply minimization algorithm. Sometimes, the same classification performance produced with similarity measure near unity is the reason to reduce number of training sets. This reduction increases speed of the networks. When the acquisition circuit read the ECG signal, the proposed LabView circuit will read this signal and extract ,from it ,four features. After that, these features executed in to the NVG-RAM classifier searching pairs in training sets for extracting feature based on minimum Manhattan distance, the identifier can diagnose heart case.

CHAPTER 4:
4.SIMULATION RESULTS

4.1 Introduction

This chapter is devoted to the presentation of the simulation results obtained from the proposed ECG diagnosing system. This system is designed and discussed in Chapter 3. The chapter presents the confusion matrices of the two proposed classification namely threshold decision classifier and NVG-RAM. Seven cases of heart abnormalities were identified using these methods. The abnormality cases are FDHB: First Degree Heart Block, WPW: Wolff-Parkinson White syndrome, LGL: Lowen-Ganong Leving syndrome, RLBB: Right or Left Bundle Branch, MI: Myocardial Infraction, B: Bredycardia, T: Techcardia, U: Unclassified. The seven abnormalities are compared to a normal case abbreviated as N. The data are obtained from a standard MIB-HIT data-base as well as data generated based on specialized doctors' recommendations. Results obtained using proposed works are compared with results obtained from two related works. The output of LabVIEW is used as input to two types of classifiers (TD and NVG-RAM). The results of these classifiers are compared to judge the performance of each classifier. The performance is tested and evaluated using two types of databases, the first one is ECG generated data and the second type is obtained from MIT-BIH arrhythmia data base. The results of the proposed work are presented using MATLAB..

4.2 Feature Extraction Testing

The procedure used in testing the proposed ECG diagnosing system depends on the number of heartbeats. This number of heartbeats is taken from MIT-BIH database. The results are compared with two recent journal works. Table (4.1) shows the number of beats comparison of the proposed work with other published work. The proposed system is found to be better that other works regarding the extraction of features. The success rate of the proposed work is 99.62%. While using other techniques, the recognition rate was 99.59% for reference [54] and 99.5% for reference [55]. These results were plotted to show the success more clearly as shown in Fig.(4.1), where Ref.[1] is reference [54] and Ref.[2] is reference [55].

Table(4.1):ECG features extraction system performance comparison

File no.	No.of beat	Current work	[54]	[55]
100	2273	2270	2273	2272
101	1865	1868	1859	1865
102	2187	2185	2187	2186
103	2084	2081	2084	2084
104	2229	2231	2215	2217
105	2572	2606	2546	2498
106	2027	2024	2025	2011
107	2137	2130	2137	2532
109	2532	2527	2532	2532
111	2124	2122	2124	2087
112	2539	2537	2539	2539
113	1795	1793	1792	1794
114	1879	1881	1879	1860
115	1953	1951	1949	1953
116	2412	2393	2388	2381
117	1535	1533	1535	1532
119	1987	1988	1987	1986
121	1863	1859	1861	1861
122	2476	2473	2476	2476
123	1518	1515	1518	1518

124	1619	1614	1619	1609
200	2601	2596	2601	2577
202	2136	2130	1929	2125
205	2656	2652	2656	2651
208	2955	2893	2942	2925
209	3005	3003	3005	3002
210	2650	2588	2641	2618
212	2748	2745	2748	2746
213	3251	3249	3251	3247
214	2262	2256	2257	2250
215	3363	3360	3363	3360
217	2208	2205	2205	2203
220	2048	2045	2048	2048
221	2427	2416	2427	2422
222	2483	2483	2483	2481
223	2605	2601	2604	2594
228	2053	2072	2040	2034
230	2256	2254	2254	2253
232	1780	1788	1762	1778
233	3079	3071	3077	3075
234	2753	2752	2752	2751
Total Pcc		99.62%	99.59%	99.5%

Where PCC is Probability of Correct Classification

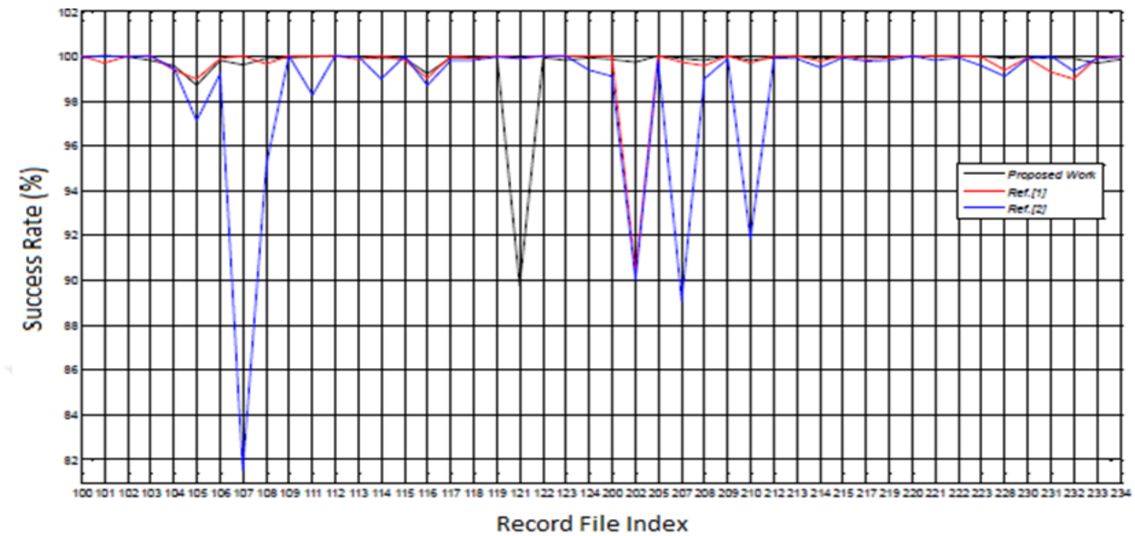


Figure (4.1): Performance comparison of ECG features extraction system.

4.3 System Performance Using MIT-BIH Database

Some of considered heart diseases are found in MIT-BIH database including the normal case. Several ECG signal are selected to be tested by the proposed ECG diagnosis systems depending on the information of each files in this database. Twenty five ECG signals with 30 minutes recording time are used; sixteen files of these signals are normal case while the others include three diseases of heart which are: RLBB, MI and B. Table (4.2) shows the selected 25 records description of MIT-BIH arrhythmia database according to files information found in this database.

Table (4.2): Records distribution of MIT-BIH arrhythmia database.

Heart condition	**Record number**
Normal	100-101-103-105-112-114-116-205-209-210-215-220-221-223-230-234
Right or Left Bundle Branch	109-111-118-200
Myocardial Infraction	107-217-232
Bradycardia	201-202

4.3.1 ECG Diagnosis Performance Based on TD Classifier

The selected twenty five ECG signals from the MIT-BIH are used to evaluate the performance of the proposed heart diseases TD classifier according to boundary threshold levels that specified by the specialized physician in heart. This classifier identify all normal cases only one undefined(205) correctly as shown in Fig.(4.2) in addition to four RLBB , three MI and two B cases successfully. Therefore, the overall probability of correct classification for TD classifier using MIT-BIT as database is 98.4%

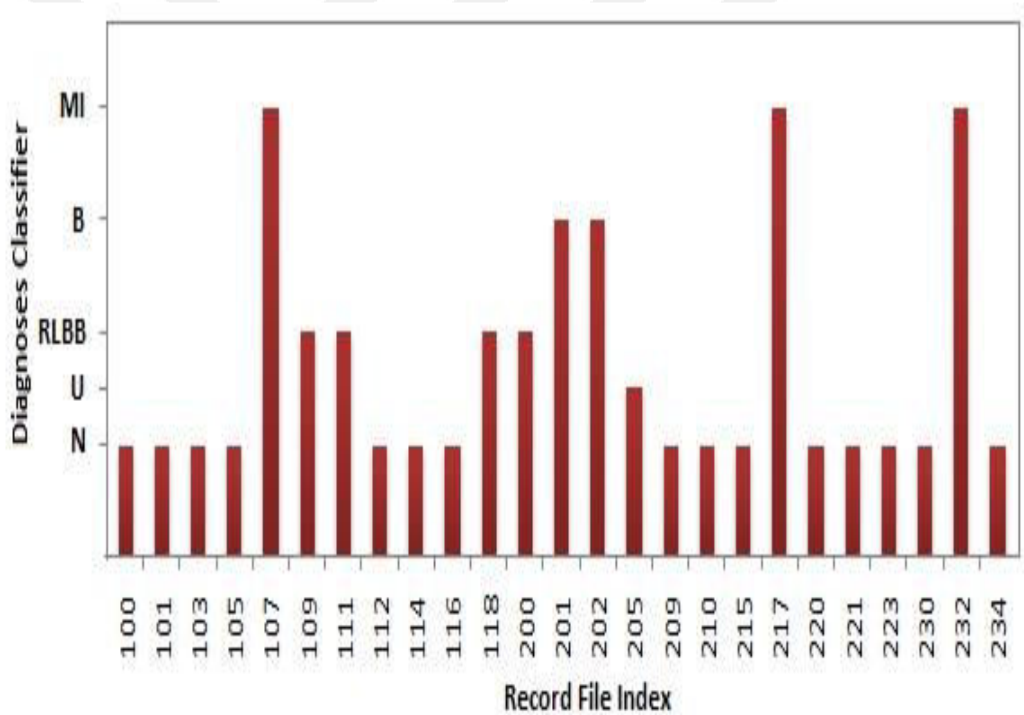


Figure (4.2): Performance of the proposed ECG diagnosis TD classifier using MIT-BIH database

The individual probability of correct classification for each heart disease is using the TD classifier is shown in Table (4.3). The normal only one case is not classified (undefined), RLBB, Myocardial Infraction and Bradycardia heat cases are full classified with 100% success rate.

Table (4.3): Confusion matrix of The TD classifier using MIT-BIT database

		The output of the classifier								
		N	FDHB	WPW	LGL	RLBB	MI	B	T	U
Actual Cases	N	93.7%	0	0	0	0	0	0	0	0
	RLBB	0	0	0	0	100%	0	0	0	0
	MI	0	0	0	0	0	100%	0	0	0
	B	0	0	0	0	0	0	100%	0	0
	Pcc	98.4%								

4.3.2 ECG Diagnosis Performance Based On NVG-RAM Classifier

The NVG-RAM classifier satisfy 100% overall performance success rate when it tested by the twenty five chosen MIT-BIT record files. sixteen documented normal cases are recognized by this classifier as illustrated in Fig.(4.3), whereas four, three and two of correct identification cases are achieved for RLBB, MI and B heart diseases respectively. Hence, this classifier discriminate all heart conditions that present in MIT-BIT database in perfect form

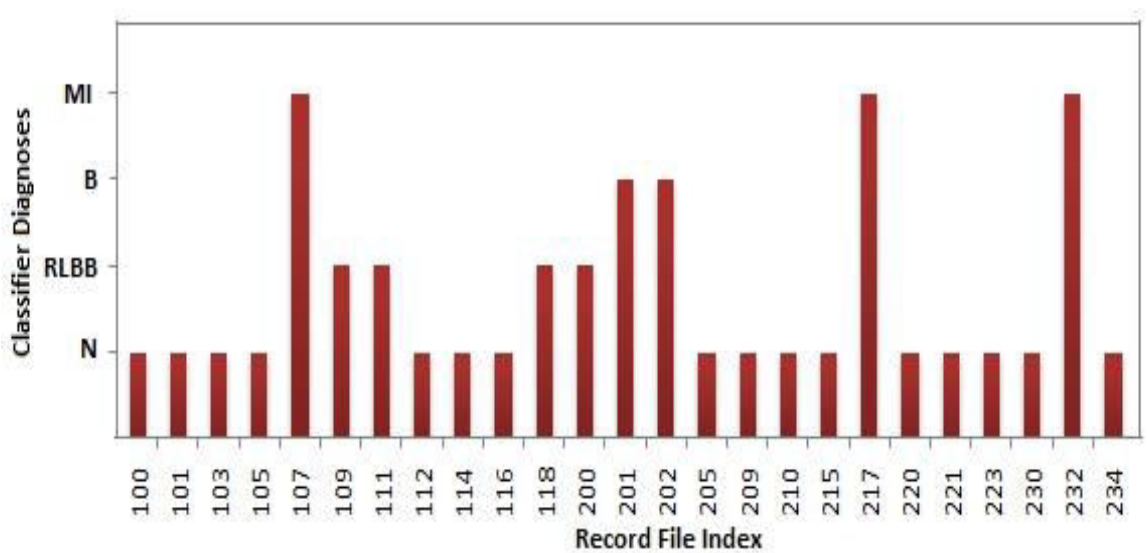


Figure (4.3): Performance of the proposed ECG diagnosis NVG-RAM classifier using MIT-BIH database

Table (4.4) present the confusion matrix of the proposed NVG-RAM classifier using MIT-BIH database. All heart cases are recognized with 100% of probability of correct classification making this type of classifier is the best classifier can be used in ECG diagnosis system. This suggestion is due to the heart condition recognition is deals with human sensitive cases and needs zero tolerance.

Table(4.4):Confusion matrix of the NVG-RAM classifier using MIT-BIH database

		The output of the classifier								
		N	**FDHB**	**WPW**	**LGL**	**RLBB**	**MI**	**B**	**T**	**U**
Actual Cases	**N**	100%	0	0	0	0	0	0	0	0
	RLBB	0	0	0	0	100%	0	0	0	0
	MI	0	0	0	0	0	100%	0	0	0
	B	0	0	0	0	0	0	100%	0	0
	Pcc	100%								

4.4 System Performance Using Generated Database

The best performance evaluation for the two proposed heart diseases classifiers is satisfied when the generated ECG signals are used as testing sets. This is due to this database include all heart cases considered in this work.

4.4.1 ECG Diagnosis Performance Based On TD Classifier

The Threshold decision classifier identifies the 400 cases of generated ECG signals based on the duration of the four extracted features (PR, QRS, QT and RR) as presented in Table (4.5). six cases including the normal case have 100% probability of correct classification, while two ECG signals of the RLBB, and six ECG signals of WPW heart diseases are missed diagnosis. However, the overall performance of this classifier is wonderful where is reach to 98% in addition to this classifier is easy to be implement in hardware.

Table (4.5): Confusion matrix of the threshold decision classifier using generated ECG signals.

		The output of the classifier							
		N	**FDHB**	**WPW**	**LGL**	**RLBB**	**MI**	**T**	**B**
Actual cases	**N**	50	0	0	0	0	0	0	0
	FDHB	0	50	0	0	0	0	0	0
	WPW	0	0	44	0	0	0	0	0
	LGL	0	0	0	50	0	0	0	0
	RLBB	0	0	0	0	48	0	0	0
	MI	0	0	0	0	0	50	0	0
	T	0	0	0	0	0	0	50	0
	B	0	0	0	0	0	0	0	50
	Pcc	98%							

4.4.2 ECG Diagnosis Performance Based On NVG-RAM Classifier

When the generated ECG signals are tested by the proposed NVG-RAM classifier, a perfect performance is presented. All eight heart diseases are full classified with 100% success rate as illustrate in table (4.6). This type of classifier is save to be used for ECG diagnosis because there is no missed classification and has 100% overall probability of correct classification. Moreover, the NVG-RAM classifier is one of the weight-less neural network that can easy to be implemented by FPGA because it need only RAM and simple combinational circuit.

Table(4.6): Confusion matrix of the NVG-RAM classifier using generated ECG signals.

		The output of the classifier							
		N	**FDHB**	**WPW**	**LGL**	**RLBB**	**MI**	**T**	**B**
Actual cases	**N**	50	0	0	0	0	0	0	0
	FDHB	0	50	0	0	0	0	0	0
	WPW	0	0	50	0	0	0	0	0
	LGL	0	0	0	50	0	0	0	0
	RLBB	0	0	0	0	50	0	0	0
	MI	0	0	0	0	0	50	0	0
	T	0	0	0	0	0	0	50	0
	B	0	0	0	0	0	0	0	50
	Pcc	100%							

4.5 Comparison Of The Proposed Classifiers With Previous Works

To evaluate the two classifiers (TD and NVG-RAM classifiers), we let in facing with other classifiers proposed by other works. This facing will be ended under same circumstances in evaluating performance of others classifiers. This is done by using the same database that adopted by previous works which is the MIT-BIH arrhythmia database. The result is appropriate evaluation to be in facing others classifier approaches, each classifier takes different types heart diseases and various numbers records files. The features number and the type of classifier have taken into accounts, which are the most effective parameters that measure the complexity and performance of the classifiers. The overall classification success rate comparison is illustrated in Table (4.7). As it clearly seen from this Table, one of the two propose ECG classifiers have highest recognition rate compared with others previous approaches. Although the number of heart conditions classified by the proposed ECG diagnoses systems is greater than the heart cases used by previous research, the suggested classifiers are superiors the others. Furthermore, the proposed classifiers can be easily hardware implemented with less classification process time to complete the diagnoses operation.

Table (4.7): Probability of correct classification comparison.

Reference No.	**No. of features**	**Type of classifier**	**No. of MIT-BIH record files**	**No. of heart cases**	**Success rate**
[56]	18	MLP	10	6	98.7 %
[57]	25	SVM	24	7	97 %
[58]	64	BPNN	44	2	97.8 %
[59]	24	MLP	10	3	96.5 %
[60]	12	BPNN	Unspecified	4	99.33 %
[61]	Unspecified	SOFM and MLP	7	4	98 %
Proposed work	4	TD	25	8	98.4 %
	4	NVG-RAM	25	8	100%

Where BPNN is Back-Propagation Neural Network and SOFM is self organization feature mapping.

CHAPTER 5:
5. HARDWARE IMPLEMENTATION

5.1 Introduction

The ECG diagnosis system based on NVG-RAM classifier has better performance processing over system based on threshold decision (result in chap 4). The Chapter contain the download of the two classifier and connection at FPGA.VHDL use Xilinx ISE 14.6model, and I/O ports, function blocks, block sets of Xilinx SG in MATLAB/ Simulink to write the ECG diagnosis classifiers. The VHDL source files writen by ISE passed into SG by black box and executed XSG by MATLAB/Simulink.Spartan-3AN XC3S700ANused to download the system for the hardware platform. The hardware features, are a several restrictions in FPGA download of the wanted heart diseases classifiers. Firstly, number of bits per input feature,(large enough to explain the case value, not passing the number of I/O pins hardware board). We use, fixed-array precision of 16 bits with zero bits binary case un-sign number (UFix_16_0) represent the feature value. The resolution of binary result produces perfect precision(resolution about). In addition, the output bits where we conclude the decision of classifier. We use for ECG diagnosis 68 pins I/O pins can be handled by our Spartan-3. An XC3S700AN has 372 bonded I/O. Secondly, massive RAM (big number of training sets).Minimization number of training sets algorithm will be applied to make Spartan-3AN XC3S700AN able to reconcile the classifier.

5.2 FPGA Implementation OF ECG Diagnosis Based On Threshold Decision Classifier

TD download into hardware is simple, depends logical relational process only. The relational process requires small number of FPGA device slice ECG threshold decision classifier performs eight multi-boundary comparisons like presented in section 3.4. These relational comparisons depend on the ECG extracted features (PR, QRS, QT and RR durations) that used to accomplish recognition by this classifier. After the biomedical toolkit is accomplished the features extraction for the acquired real ECG signal, the TD classifier will recognize the diseases of the heart according to the durations of the extracted features. The flowchart of process is presented in fig. (5.1). As demonstrated in figure, ECG_D output signal used to assign type of heart diseases according to Table (5.1). Xilinx Black Box is passing written VHDL code of our TD classifier in to SG presented in fig. (5.2), simulated and implemented by MATLAB/Simulink associative with ISE 14.6. Related limits values of this classifier shown in fig. (5.1).

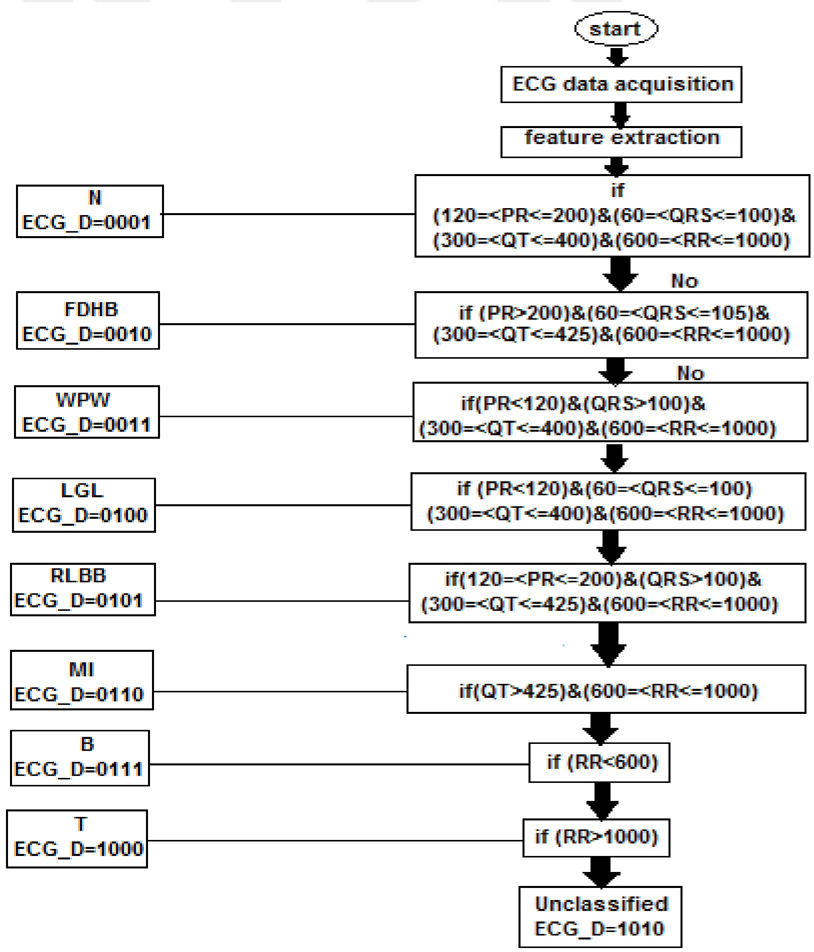


Figure (5.1): Flowchart of proposed ECG diagnosis TD Classifier .

Table (5.1):ECG_D output signal value according to heart diseases

ECG_D	ECG Diagnosis
0000	Features extraction process
0001	Normal
0010	FDHB
0011	WPW
0100	LGL
0101	RLBB
0110	MI
0111	B
1000	T
1001	Undefined

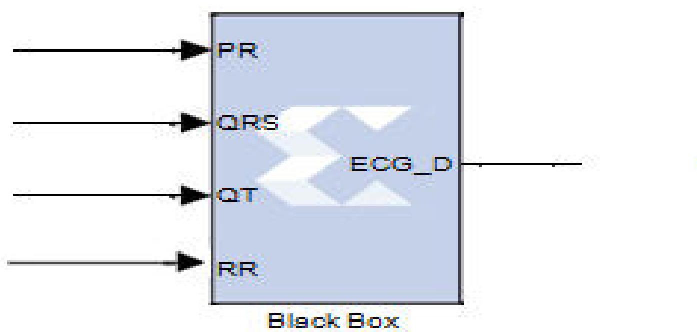


Figure (5.2): ECG diagnosis TD classifier Black Box

Fig.(5.3) present the behavior simulating of this block will fetch input signal when PR input feature is non-zero value that indicates the validity of them. This Box recognizes the diseases of heart when the input features are applied immediately. Deactivated when the biomedical toolkit still run process when PR=0, as viewed in Fig.(5.3). PR alters to non-zero which indicates the features availability, the ECG diagnosis black box execute classification process and assigned type of diseases ECG_D signal.

Figure (5.3): Simulation Behavioral of the proposed ECG diagnosis TD classifier.

FPGA download our TD classifier presented in Fig.(5.4). A source block, 'From Workspace' used to read features extracted by biomedical toolkit form Workspace period series. PR_BMTK, QRS_BMTK, QT_BMTK and RR_BMTK are used to read the value of the ECG signal durations that evaluated by the BMTK and stored in MATLAB workspace. Four Xilinx 'Gateway In' blocks downloaded transform reading data type from workspace to XSG fixed-point (UFix_16_0) the four components of the ECG signal (ECG_PR, ECG_QRS, ECG_QT and ECG_RR). Xilinx 'Gateway Out' (ECG_D) translate the SG from fixed point type to any desired data type to display it.

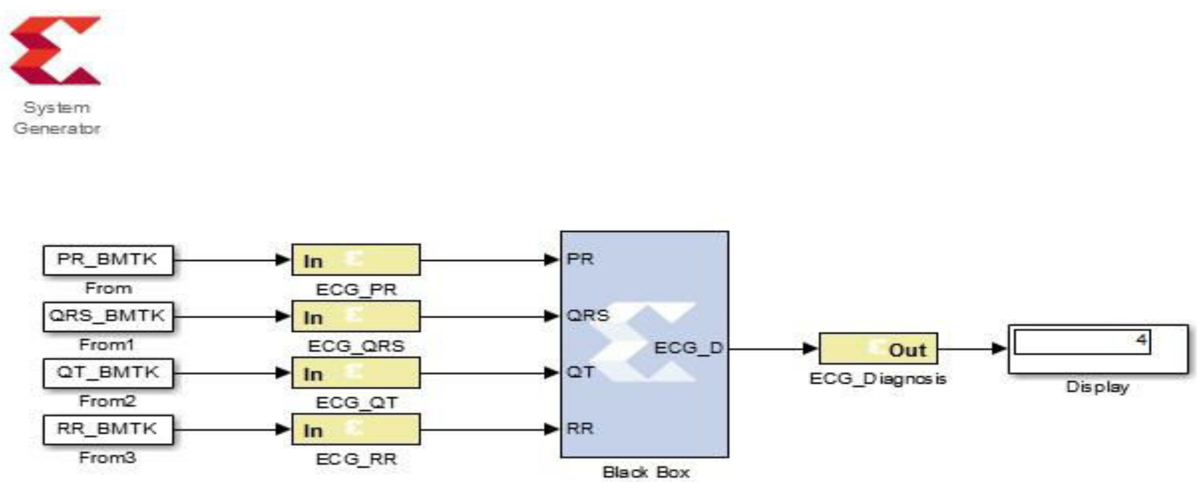
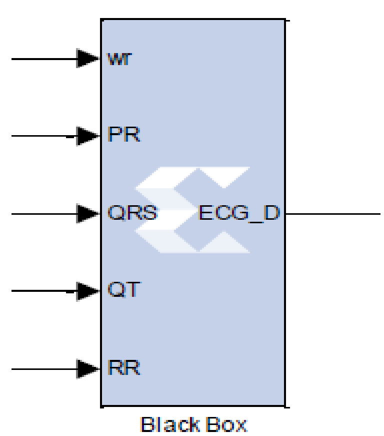


Figure (5.4): ECG diagnosis system based on TD classifier.

5.3 FPGA Implementation Of ECG Diagnosis Based On NVG-RAM Neural Network Classifier

Chapter four computer simulation results present NVG-RAM neural network classifier has better classification performance. It requires a Ram while the minimum Manhattan distance require a basic arithmetic process to be evaluated. The number of training sets is lowered by implementing the training sets minimization algorithm. We use training sets to learn the NVG-RAM classifier consist of 10368 vectors. Each vector contains four features (PR, QRS, QT and RR) and the desired class number. This vectors number of training sets is too large and takes a big number of FPGA device slices in addition to the long processing time that required complete the diagnoses process. Therefore, based on the minimization algorithm the training sets is reduce to 5136 vectors when the similarity measure is 0.95 with 100% of exact classification. However, this number is still large. At 0.90. NVG-RAM classifier is kept 100% and the number of vectors in training set is minimize to 450 which is suitable to be implement by FPGA. The NVG-RAM classifier is activated when the biomedical toolkit is finished ECG input signal, PR signal changed to nonzero value related with four features PR, QRS, QT and RR. Fig.(5.5)present ECG diagnosis passing in SG through Black Box block. When WR signal is activated the heart disease will be assigned to ECG_D output signal as listed in Table (5.2).



Figure(5.5) ECG diagnosis NVG-RAM classifier Black Box.

Table (5.2): ECD_D output signal value according to heart diseases

ECG_D	ECG Diagnosis
0000	Features extraction process
0001	Normal
0010	FDHB
0011	WPW
0100	LGL
0101	RLBB
0110	MI
0111	B
1000	T

The simulating behavior of this block is presented in Fig.(5.6), WR up wanted is 450 clocks to approve ECG diagnosis ECG_D as shown in Fig.(5.7).

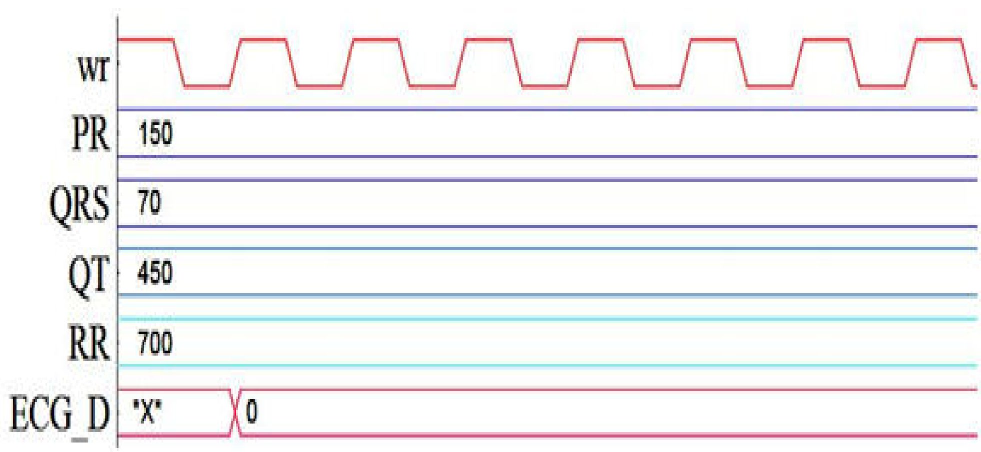


Figure (5.6): Simulation behavioral of applying inputs to the proposed ECG diagnosis NVG-RAM Classifier.

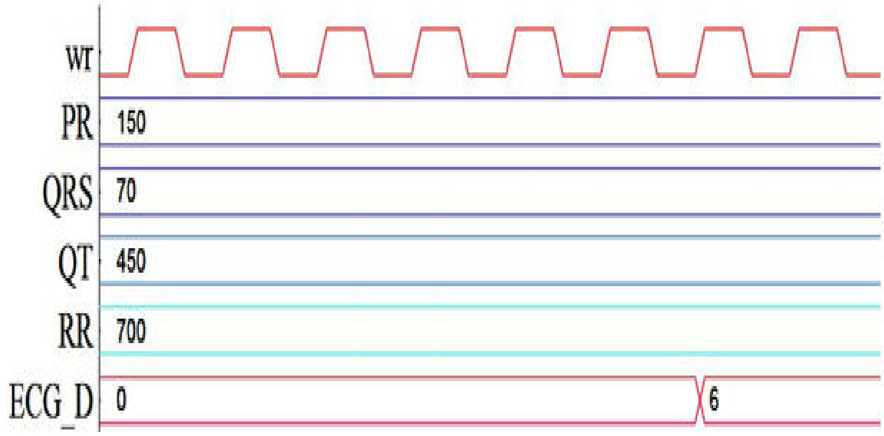


Figure (5.7): Simulation behavioral of the proposed ECG diagnosis .

The Implementation of the NVG-RAM by FPGA is shown in Fig.(5.8). Our presented recognizer Xilinx 'Gateway in' block that is used for WR signal which represents the system clock.

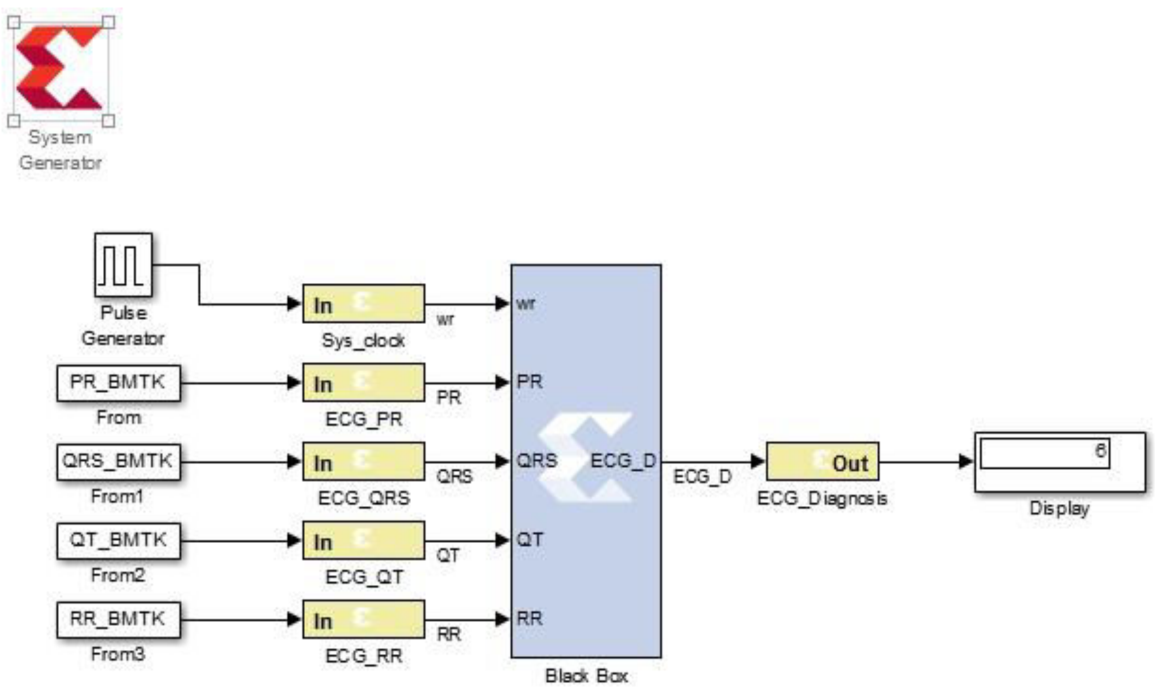


Figure (5.8): ECG diagnosis system based on NVG-RAM classifier.

5.4 FPGA Mapping Of The Proposed Heart Diseases Classifiers

To accomplish the FPGA design flow we need the following four steps and will be done in order;(Design entry, Design synthesis, Design implementation, and Xilinx device programming).The design entry step contains the building for the proposed system with the VHDL files. The design synthesis step includes analyze. Perform FPGA architecture optimization for our proposed system design.(VHDL codes syntax)The design implementation step combine place at time 'Place and Route' process. (input design file- translate process –FPGA hardware – Map process)Xilinx device programming step, insufficient available resources of the Xilinx device is the most limitations of proposed design. (Map process)Table (5.3) present summary of our two classifiers (TD and NVG-RAM) ECG diagnosis system TD takes 1% the hardware device slices. While the NVG-RAM classifier RAM classifier accommodate 21% of 3AN XC3S700AN occupied Slices as it clear in the device utilization summary presented in Table (5.4).

Table (5.3): Device utilization summary of ECG diagnosis proposed system based on TD classifier .

Device Utilization Summary				[-]
Logic Utilization	**Used**	**Available**	**Utilization**	**Note(s)**
Number of 4 input LUTs	72	11,776	1%	
Number of occupied Slices	47	5,888	1%	
Number of Slices containing only related logic	47	47	100%	
Number of Slices containing unrelated logic	0	47	0%	
Total Number of 4 input LUTs	84	11,776	1%	
Number used as logic	72			
Number used as a route-thru	12			
Number of bonded IOBs	68	372	18%	
Average Fanout of Non-Clock Nets	2.14			

Table (5.4): Device utilization summary of ECG diagnosis proposed system based on NVG-RAM classifier

Device Utilization Summary				
Logic Utilization	**Used**	**Available**	**Utilization**	**Note(s)**
Number of Slice Flip Flops	91	11,776	1%	
Number of 4 input LUTs	2,025	11,776	17%	
Number of occupied Slices	1,238	5,888	21%	
Number of Slices containing only related logic	1,238	1,238	100%	
Number of Slices containing unrelated logic	0	1,238	0%	
Total Number of 4 input LUTs	2,115	11,776	17%	
Number used as logic	2,025			
Number used as a route-thru	90			
Number of bonded IOBs	69	372	18%	
Number of BUFGMUXs	1	24	4%	
Average Fanout of Non-Clock Nets	3.37			

According to timing summary, the TD classifier need 16 ns to finish the ECG diagnosis process, while the NVG-RAM classifier with the maximum frequency is 36.94 MHz need 12.81ns to finish the ECG diagnosis process of the heart diseases classifier.

5.5 Hardware Implementation Of The proposed Heart Diseases Classifier On Spartan-3AN XC3S700AN Platform

The ECG diagnosis download, after system design passes through 4 steps. The download configure hardware device according our system design. We use the Xilinx ISE 14.6package into our SG. We use very useful ECG FPGA related. We use JTAG cable connection to configure our ECG diagnosis on FPGA board as present in Fig.(5.9).

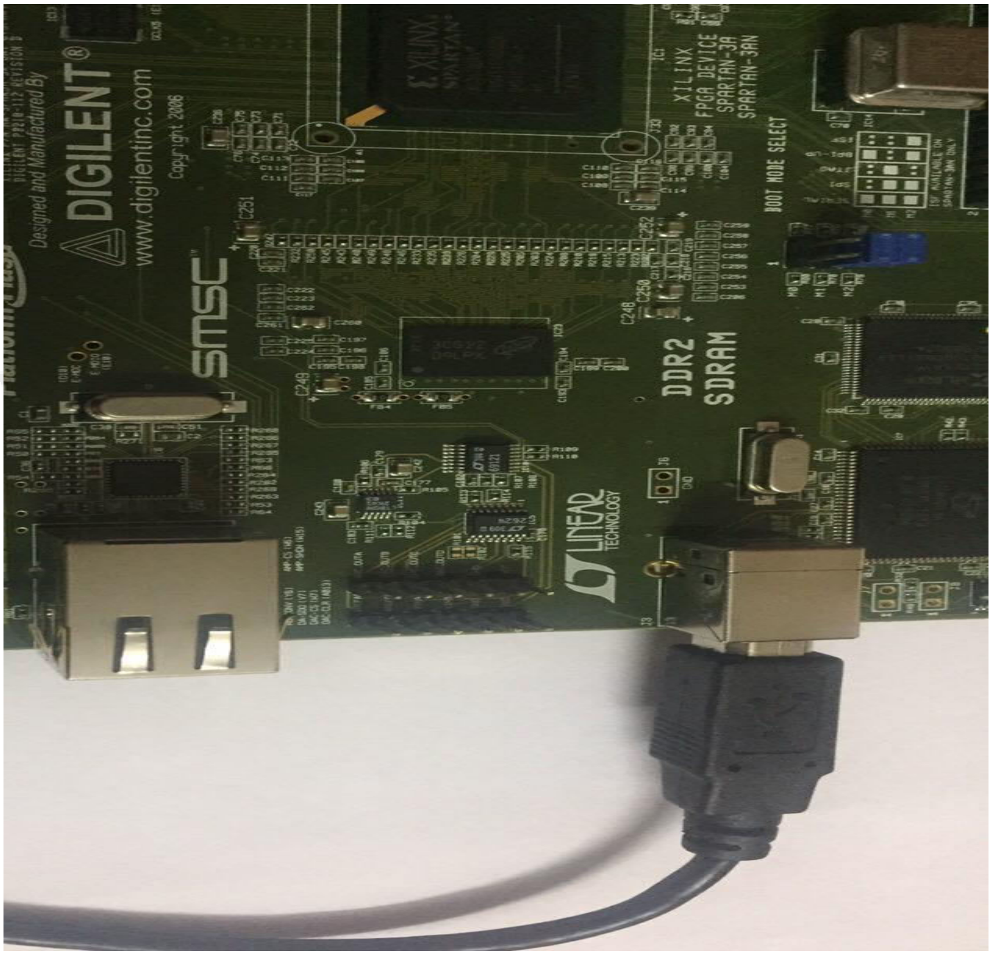


Figure (5.9): JTAG cable connection

As presented in Fig (5.10) the XSG complies our Classifier and produce HW Co-simulation(HWCosim).The Process of diagnosing heart signals are performed by FPGA through JTAG cable as shown in Fig(5.11).

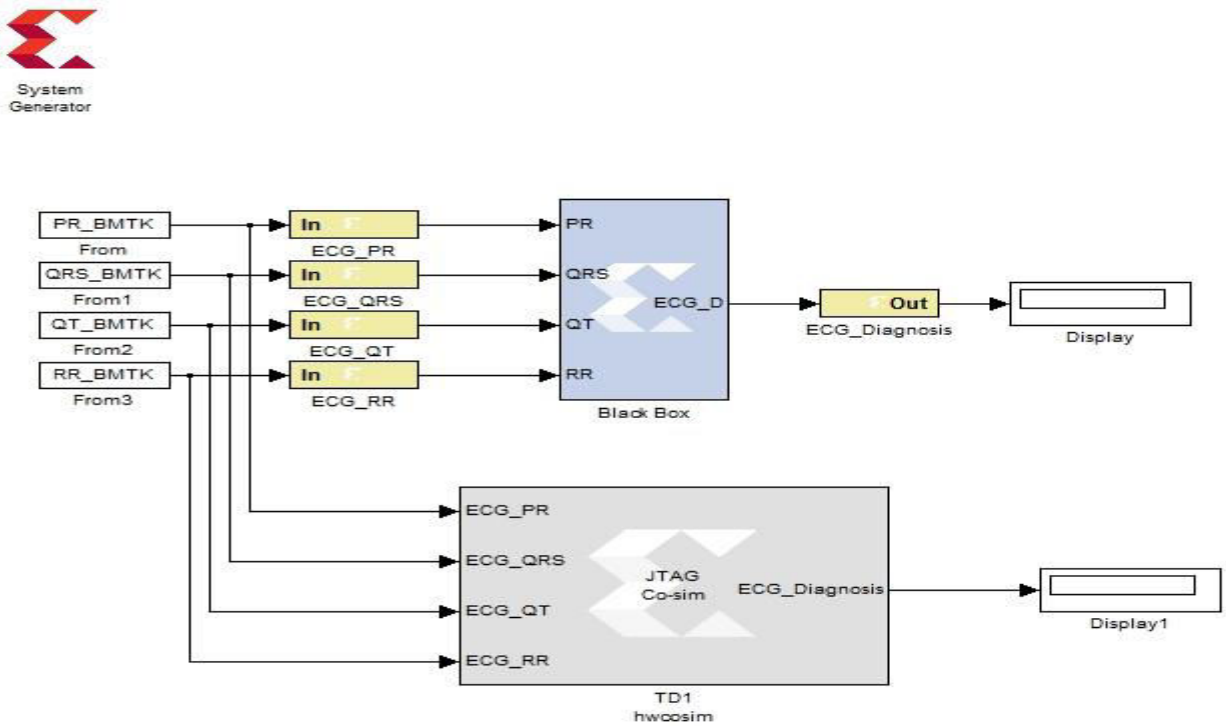


Figure (5.10): ECG diagnosis system with HW Co-simulation

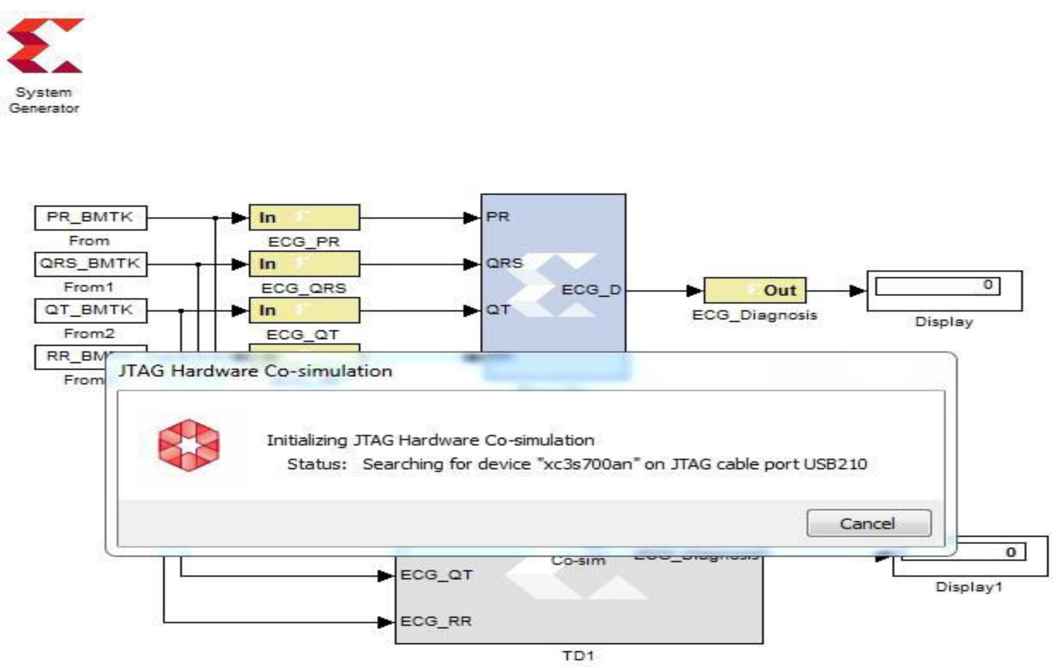


Figure (5.11): Diagnosis of the FPGA though JTAG cable.

Heart Diseases diagnosis will be displayed on pc screen like as Table(5.5).

Table(5.5): Displayed result number according to heart diseases.

ECG-D	**ECG-Diagnosis**
1	Normal
2	FDHP
3	WPW
4	LGL
5	RLBB
6	MI
7	T
8	B
10	Undefined

The Spartan-3AN XC3S700AN and the displaying result number are presented in Figure (5.12).

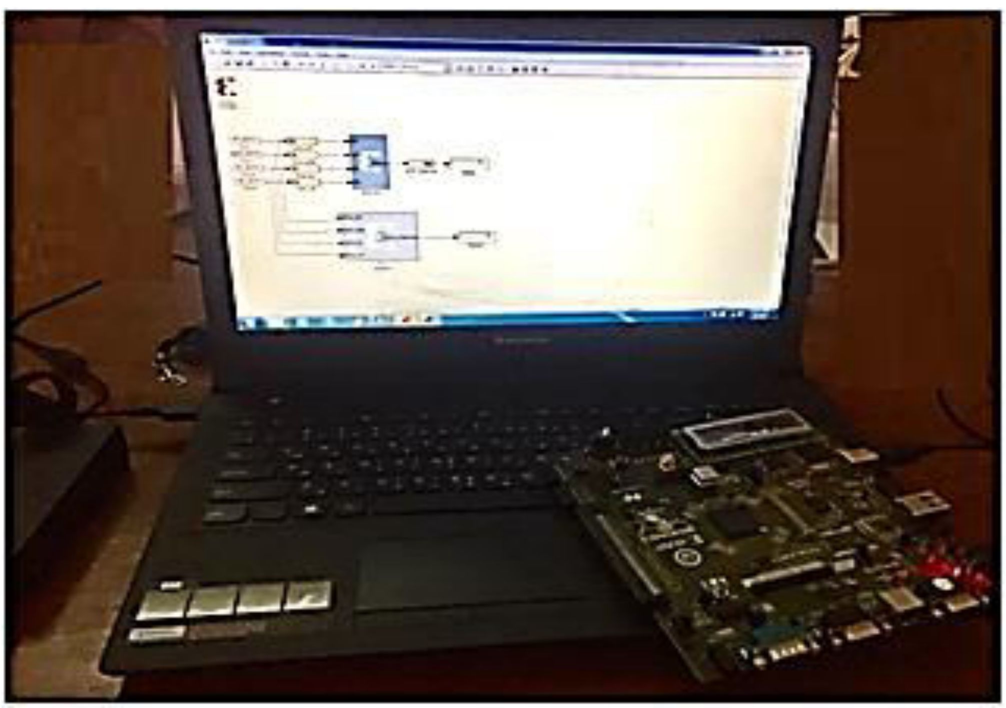


Figure (5.12): Host computer and Spartan-3AN XC3S700AN board Connection

5.6 Hardware Results

To result the ECG diagnosis systems heart diseases classifiers, similar circumstances will be taken. Eight groups of generated ECG signals are used to measure the performance of the hardware classifiers. One of the eight groups is used for normal ECG signal while the others are created to simulate the seven abnormality heart conditions that are considered in this work. Each group consists of fifty ECG signals with 15 s for each. The generated signals are imported to LabView Biomedical toolkit in order to extract the required features (PR, QRS, QT and RR durations). The extracted features are read by MATLAB and send them to the FPGA by JTAG cable.

5.6.1 Hardware Results Of ECG Diagnosis System Based On Threshold Decision Classifier.

Found ECG diagnosis TD eight groups of the ECG generated signal as present in Table (5.6). Most of heart diseases are recognized with 100% of success rate in addition to normal condition, while the two cases of RLBB are classified as MI case due to the confusion when the QRS duration is greater than 100 ms with few milliseconds and the smallest increasing in duration of the QT over its normality, and six cases of WPW are unclassified. The TD 98% which is the same as the simulation result in Chapter four.

Table(5.6): Threshold decision Confusion matrix

		The output of the classifier							
		N	**FDHB**	**WPW**	**LGL**	**RLBB**	**MI**	**T**	**B**
Actual cases	**N**	50	0	0	0	0	0	0	0
	FDHB	0	50	0	0	0	0	0	0
	WPW	0	0	44	0	0	0	0	0
	LGL	0	0	0	50	0	0	0	0

	RLBB	0	0	0	0	48	0	0	0
	MI	0	0	0	0	0	50	0	0
	T	0	0	0	0	0	0	50	0
	B	0	0	0	0	0	0	0	50
	Pcc	98%							

5.6.2 Hardware Results Of ECG Diagnosis System Based On NVG-RAM Classifier.

The NVG-RAM classifier present best performance when analyze the heart diseases as demonstrated in Table (5.7). Although the training sets are minimized from 10368 to 450 vectors to reduce the hardware platform slices, nevertheless most of the generated ECG signals are identified with 100% of correct recognition. The overall success rate of this classifier is 100%. The NVG-RAM. classifier consumes a lot of hardware device slices and has processing time relatively greater than TD classifier, hence the NVG-RAM in ECG diagnosis because it has better performance, but the TD classifier use less hardware requirements and faster process.

Table(5.7): NVG-RAM Confusion matrix.

		The output of the classifier							
		N	**FDHB**	**WPW**	**LGL**	**RLBB**	**MI**	**T**	**B**
Actual cases	**N**	50	0	0	0	0	0	0	0
	FDHB	0	50	0	0	0	0	0	0
	WPW	0	0	50	0	0	0	0	0
	LGL	0	0	0	50	0	0	0	0
	RLBB	0	0	0	0	50	0	0	0
	MI	0	0	0	0	0	50	0	0
	T	0	0	0	0	0	0	50	0
	B	0	0	0	0	0	0	0	50
	Pcc	100%							

CHAPTER 6:
6.CONCLUSIONS AND SUGGESTION FOR FUTURE WORKS

6.1 CONCLUSIONS

According to the proposed ECG diagnosis systems and their results,in this work, ECG diagnosis system based on FPGA has been built., the following conclusions can be listed.

1. The proposed ECG diagnosis system can classified seven abnormality heart conditions in addition to normal case, the abnormality cases are FDHB, WPW, LGL, RLBB, MI, B and T.

2. For resulting ECG. These signal using the proposed extraction system which built by the LabView package associated with Biomedical Toolkit .

3.Two heart diseases classifiers are proposed. one of them classical classification algorithm that is: Threshold Decision. The other one is recently devised algorithm, which is the Numeral VG-RAM RAM weightless neural network.

4.The proposed ECG Features extraction system performance superior the performance of pervious works when tested using the MIT-BIH ECG database where the overall success rate of the proposed system is 99.63%.

5.The simulation results show that, the proposed NVG-RAM classifier has 100% probability of correct classification when the performance of this classifier was evaluated using MIT-BIH and generated database. While the second higher performance is found for TD classifier that reach to 98.4% and 98% for MIT-BIH and generated database respectively.

6. It is present in Table (5.5) that the best one suggested classifiers (NVG-RAM) gave greater classification precision when facing in test similar circumstances.

7.TD utilize1% existing Slices, but NVG-RAM classifier utilize21%.

8. TD classifier need 16 ns ,while the NVG-RAM need 12.81μs to finish the ECG diagnosis process

6.2 Suggestion for future works

1. Built an ECG acquisition circuit module to capture the ECG signal from the human body.

2.Built an ECG database to be used by other researchers.

3. The proposed ECG diagnosis system can be extended to identify more heart diseases.

4. The proposed ECG diagnosis system can be applied for other popular ECG signal database in order to evaluate the performance of this system to prove the generalization validation of it.

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