بسم الله الرحمن الرحيم

Sudan University of Scienceand Technology

College of Graduate Studies

Classification system for heart sounds based on Random Forests

نظام تصنيف لأصوات القلب بناءاً على الغابات العشوائية

Thesis submitted in partial fulfillment of the requirements for the award of degree of Master of Science in Biomedical Engineering

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الاية

بسم الله الرحمن الرحيم

وَيَسْأَلُونَكَ عَنِ الرُّوحِ ۖ قُلِ الرُّوحُ مِنْ أَمْرِ رَبِّي وَمَا أُوتِيتُم مِّنَ الْعِلْمِ إِلَّا قَلِيلًا

(الاسراء)

Dedication

I dedicate this research with much love and appreciation;

To the candles of my lives.My beloved mother who have always been there for me.

To my father who have always been the brick walls on whom me can learn and depend on forever.

To my love and special one for me..

To my brothers and sister who mean the world to me.To my friends, family, colleagues and teachers in the Past and presents and to everyone that touch my heart.

Acknowledgement

Firstly, thanks to Allah, our creator above for being everything and for giving us the ability and strength to do anything.

I wish to express my deepest gratitude and appreciation for my supervisor for this research *Dr. Mohammed yagoub*for his patience and continuous guidance, advice and supervision through this work.

I would like to extend my gratitude to *Dr.Zeinab Adam*…. for her supports and encouragement for the completion of this research.

Also thank and gratitude to all our teachers who contributed too Ur education and to everyone who helped me in this study.

Abstract

In the last century, cardiovascular illnesses are the first death cause in developed countries. For this reason, many efforts have been made in order to develop sophisticated techniques for the early diagnoses of cardiac disorders. The Phonocardiogram (PCG) signals contain very useful information about the condition of the heart. By analyzing these signals, early detection and diagnosis of heart diseases can be done. It is also very useful in the case of infants, where ECG recording and other techniques are difficult to implement.

In this study, a classification method is proposed to classify normal and abnormal heart sound signals using random forests algorithm.

The proposed framework was applied to a database of 100 heart sound signals which collected from the web site , firstly all the signals were processed using the wavelet technique to eliminate the noise from the signal, features were extracted from the enhanced signals and the most significant features was selected using the RFs Finally The random forests classifier was used to perform the classification process.

The system achieved 93.24% accuracy in distinguishing between normal and abnormal heart sound signals.

المستخلص

في القرن الماضي، والأمراض القلبية الوعائية هي أول سبب للوفاة في البلدان المتقدمة. لهذا السبب، تم بذل العديد من الجهود من أجل تطوير تقنيات متطورة للتشخيص المبكر للاضطرابات القلبية. إشارات تخطيط القلب (بي سي جي) تحتوي على معلومات مفيدة جدا عن حالة القلب. من خلال تحليل هذه الإشارات،الكشف المبكر وتشخيص أمراض القلب يمكن القيام به. كما أنها مفيدة جدا في حالة الرضع، حيث تسجيل تخطيط القلب وغيرها من التقنيات يصعب تنفيذها .

في هذه الدراسة، يتم اقتراح طريقة تصنيف لتصنيف إشارات الصوت الطبيعية وغير الطبيعية للقلب باستخدام خوارزمية الغابات العشوائية.

وقد طبق الإطار المقترح على قاعدة بيانات تضم 100 إشارة صوتية للقلب تم جمعها من موقع الويب، أولا، تمت معالجة جميع الإشارات باستخدام تقنية المويجات لإزالة الضوضاء المرتبطة بالإشارة، و من ثم استخلاص الخصائص من الإشارات المحسنة,أهم الخصائص تم اختيارها باستخدام(ار اف اس), وأخيرا تم استخدام مصنف الغابات العشوائي لأداء عملية التصنيف.

حقق النظام دقة 93.24٪ في التمييز بين إشارات صوت القلب الطبيعية وغير الطبيعية.

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List of Abbreviations

A2 …………………… ……………………....Aortic part.

ADC……………………………………….Analog to Digital Converter.

AI…………………………………………...Artificial Intelligence.

ANN ……………………………………….Artificial Neural Network.

AP ………………………………………… Arterial Pressure.

AV………………………………………….Atrioventricularvalves.

CAD………………………………………..Coronary Artery Disease.

CNN………………………………………..Convolutional Neural Network.

DAC……………………………………….. Digital to Analog Converter.

Db…………………………………………....Debauches.

DSP ……………………………………….. Digital Signal Processing.

DWT ……………………………………… Discrete Wavelet Transform.

ECG……………………………………….. Electrocardiography.

EDV………………………………………..End Diastolic Volume.

ESV…………………………………………...End Systolic Volume.

FFT…………………………………………....Fast Fourier Transform.

HS…………………………………………… Heart Sound.

IDWT……………………………………..... Inverse Discrete Wavelet Transform.

KNN ………………………………………....K-Nearest Neighborhood.

LV…………………………………………….. Left Ventricle.

MFCC………………………………………..Mel Frequency Cepstral Coefficient.

ML…………………………………………....Multi-Layer.

MCU ………………………………………….. Microcontroller Unit.

OOB………………………………………….Out Of Bag.

P2…………………………………………….Pulmonary Part.

PCG…………………………………….........Phonocardiography .

RF…………………………………………….Random Forest.

S1……………………………………………. First Heart Sound.

S2 ……………………………………………Second Heart Sound.

S3……………………………………………. Third Heart Sound.

S4……………………………………………. Fourth Heart Sound.

SNR…………………………………………Signal to Noise Ratio.

THD…………………………………………..Total Harmonic Distortion.

SVM………………………………………….Support Vector Machine.

VP…………………………………………….Ventricular Pressure.

WT……………………………………………Wavelet Transform.

CHAPTER I

Introduction

1.1 General Overview

Heart disease is a major health problem and a leading cause of fatality throughout the world. The treatment can be easier, efficient and economical if the condition is detected early. So it would be very beneficial to detect heart diseases at an early stage. Cardiac disorders can be detected efficiently and economically using auscultation as it requires minimal equipment. Sometimes this is the only available option for diagnosis as in case of primary health care centers, where other high-end instruments for diagnosis are unavailable and also in case of infants where other techniques like ECG are difficult to implement. Conventional auscultation requires extensive training and experience and storage of records for follow ups and future references is not possible[1]. This is the driving force for this study in order to move towards computerized system using for primary diagnosis of heart conditions.

1.2 Significant of the study

Cardiovascular diseases are the single leading cause of death worldwide. Regular heart tests may allow detecting heartbeat irregularities and help to avoid heart complications, greatly increasing the chance of recovery. Because of a fast life pace, the development of non-invasive auto-diagnostic systems, that would allow carrying out a preliminary medical examination at home without doctor participation, becomes the subject of research for many scientists. One of the methods that meets all the standards is phonocardiography (PCG), this technique belongs to a group of methods whose development is particularly needed in self-analysis systems (such as smart stethoscopes). The need to develop efficient methods for self-diagnosis is emphasized in the context of long and lonely expeditions .this kind of solution would allow one for an early detection of pathological health states and commencement of appropriate lifesaving actions[2].

1.3 Problem Statement

The automatic identification of cardiac pathologies by analyzingthe features of heartbeat audio recordings is a challengingproblem due to the variability in patient characteristics,existing noise in recordings and subtle differences betweenheart conditions. The problem becomes particularlydifficult when heart sounds are collected using small mobiledevices, such as digital stethoscopes or smart phones, in diverseenvironments such as hospitals or outdoor populationscreenings. The ability to automatically classify or supportthe classification of heart sounds can greatly contribute tothe spreading of medical care, especially in regions wherethe access to specialized units is difficult.

1.4 Objectives

The objectives of this research are general objective and specific objectives:

1.4.1 General Objective

The main purpose of this research is to design heart sounds classification system in order to provide more accurate results in a fast and easy manner. Hence, this study aims to perform computer-aided heart sound analysis to give support to medical doctors in decision making.

1.4.2 Specific Objectives:

- Design computer system for(processing ,feature extraction and classification of heart sound)
- Classify heart sounds into normal and abnormal cases.
- Improve the accuracy of heart sound classification task.
- Compare the performance and accuracy of the random forest with other machine learning algorithm.

1.5 Methodology

The proposed system consists from five stages as shown in the block diagram below. Heart sound recordings were obtained from the web site, briefly, the database includes 100 recordings of heart sound taken from healthy and cardiac disease patients in both clinical and non-clinical environments, all of them were processed using wavelet technique. A total of 24 features were extracted from the enhanced signals that could have potential to distinguish between the normal and murmur signals. The RF attribute applied on the feature sets to find the most significant features. Finally these features were selected to be used in the classification process using random forests.

Figure (1.1): Block diagram of research methodology.

1.6 Thesis Layout

This research consists of five chapters:

Chapter one is an introduction, chapter two deals of theoretical background and discusses the related literature review .the design and implementation of the classification system was explained in chapter three. The result and discussion were illustrated in chapter four, finally conclusion and recommendations were presented in chapter five.

Chapter II

Theoretical background and related work

2.1 Anatomy and Physiology of the heart

The heart is located in the chest between the lungs behind the sternum and above the diaphragm .it is surrounded by the pericardium .Its size is about that of fit, and its weight is about 250-300g. Its center is located about 1.5cm to the left of the midsagital plane[3]. An overall view is given in figure (2.1).

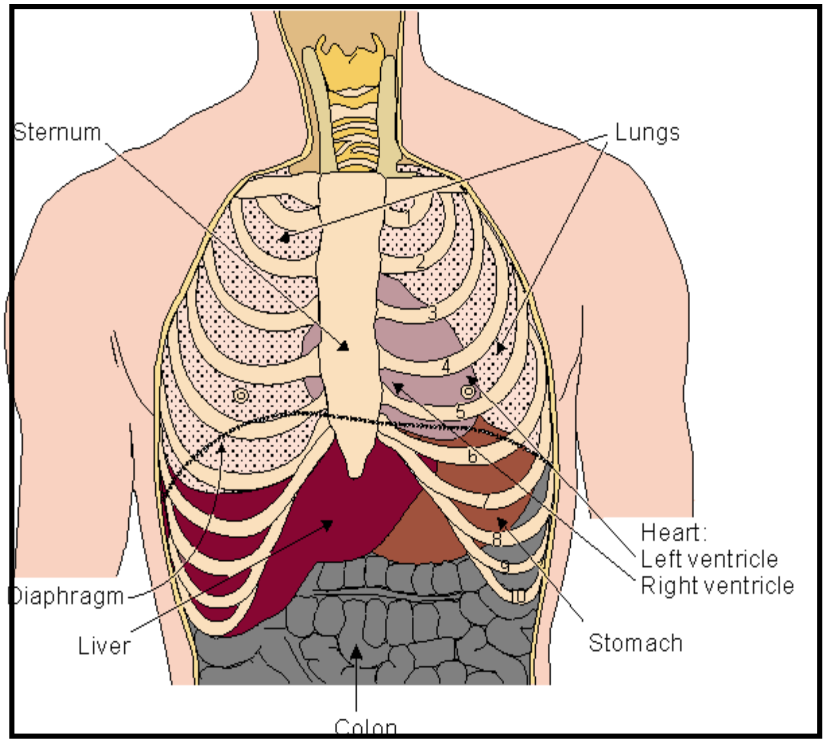


Figure (2.1): Location of the heart[3].

2.1.1 Anatomy of the heart

The walls of the heart are composed of cardiac muscle, called myocardium. It also has striations similar to skeletal muscle. It consists of four compartments: the right and left atria and ventricles. The heart is oriented so that the anterior aspect is the right ventricle while the posterior aspect shows the left atrium as show in the figure (2.2). The left ventricular free wall and the septum are much thicker than the right ventricular wall. This is logical since the left ventricle pumps blood to the systemic circulation, where the pressure is considerably higher than for the pulmonary circulation, which arises from right ventricular outflow. The heart has four valves. Between the right atrium and ventricle lies the tricuspid valve, and between the left atrium and ventricle is the mitral valve. The pulmonary valve lies between the right ventricle and the pulmonary artery, while the aortic valve lies in the outflow tract of the left ventricle (controlling flow to the aorta)[3].

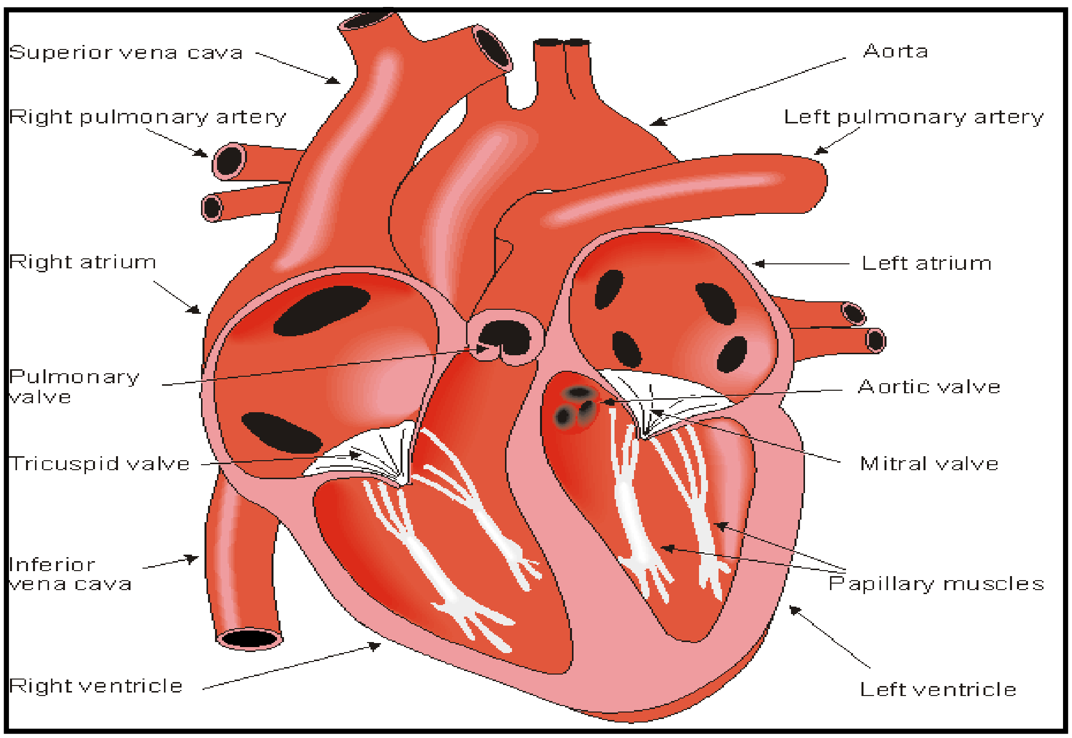


Figure (2.2): the anatomy of the heart and associated valves[3].

The left ventricular free wall and the septum are much thicker than the right ventricular wall. This is logical since the left ventricle pumps blood to the systemic circulation, where the pressure is considerably higher than for the pulmonary circulation, which arises from right ventricular outflow[3].

The cardiac muscle fibers are oriented spirally and are divided into four groups: Two groups of fibers wind around the outside of both ventricles. Beneath these fibers a third group winds around both ventricles. Beneath these fibers a fourth group winds only around the left ventricle. The fact that cardiac muscle cells are oriented more tangentially than radially, and that the resistivity of the muscle is lower in the direction of the fiber has importance in electrocardiography and magnetocardiography[3].figure (2.3) shows the cardiac muscles of the heart.

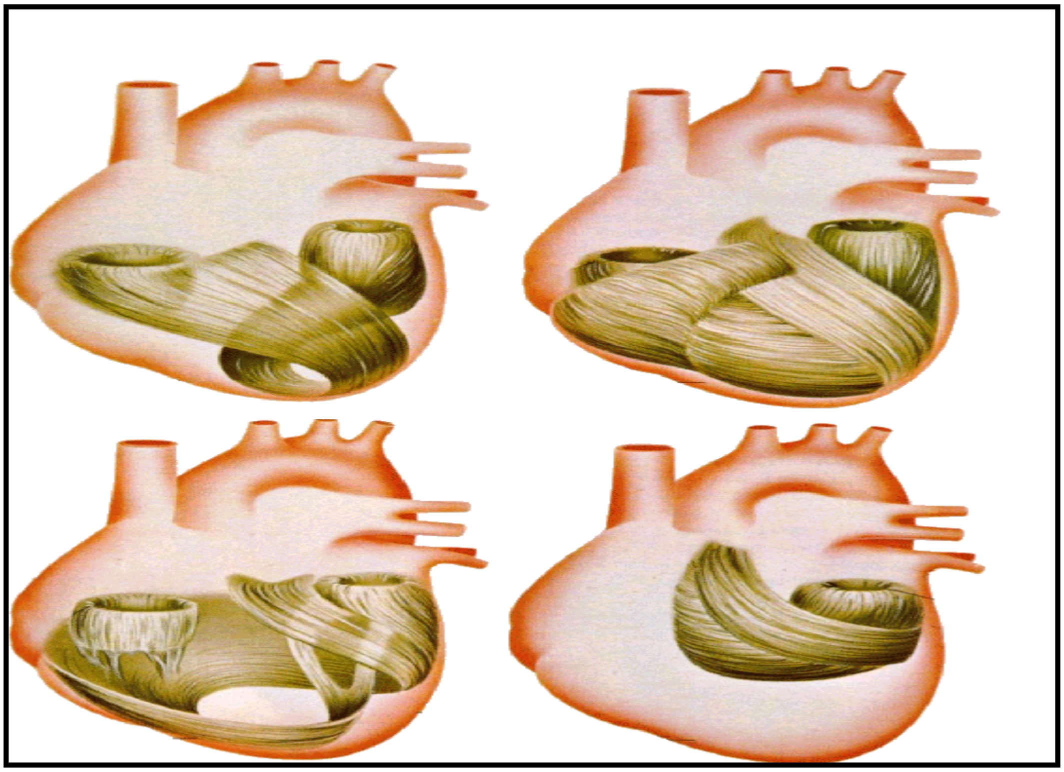


Figure (2.3): muscle fibers of the heart[3].

2.1.2 Physiology of the heart

The human heart consists of four chambers: The left side and the right side each have one **atrium** and one **ventricle**. Each of the upper chambers, the right atrium (plural = atria) and the left atrium, acts as a receiving chamber and contracts to push blood into the lower chambers, the right ventricle and the left ventricle. The ventricles serve as the primary pumping chambers of the heart, propelling blood to the lungs or to the rest of the body[4].

There are two distinct but linked circuits in the human circulation called the pulmonary and systemic circuits. The pulmonary circuit transports blood to and from the lungs, where it picks up oxygen and delivers carbon dioxide for exhalation. The systemic circuit transports oxygenated blood to virtually all of the tissues of the body and returns relatively deoxygenated blood and carbon dioxide to the heart to be sent back to the pulmonary circulation[4].

The right ventricle pumps deoxygenated blood into the pulmonary trunk, which leads toward the lungs and bifurcates into the left and right pulmonary arteries. These vessels in turn branch many times before reaching the pulmonary capillaries, where gas exchange occurs: Carbon dioxide exits the blood and oxygen enters. The pulmonary trunk arteries and their branches are the only arteries in the post-natal body that carry relatively deoxygenated blood. Highly oxygenated blood returning from the pulmonary capillaries in the lungs passes through a series of vessels that join together to form the pulmonary veins—the only post-natal veins in the body that carry highly oxygenated blood. The pulmonary veins conduct blood into the left atrium, which pumps the blood into the left ventricle, which in turn pumps oxygenated blood into the aorta and on to the many branches of the systemic circuit. Eventually, these vessels will lead to the systemic capillaries, where exchange with the tissue fluid and cells of the body occurs. In this case, oxygen and nutrients exit the systemic capillaries to be used by the cells in their metabolic processes, and carbon dioxide and waste products will enter the blood[4].

The blood exiting the systemic capillaries is lower in oxygen concentration than when it entered. The capillaries will ultimately unite to form venues, joining to form ever-larger veins, eventually flowing into the two major systemic veins, the superior vena cava and the inferior vena cava, which return blood to the right atrium. The blood in the superior and inferior venae cava flows into the right atrium, which pumps blood into the right ventricle. This process of blood circulation continues as long as the individual remains alive[4].

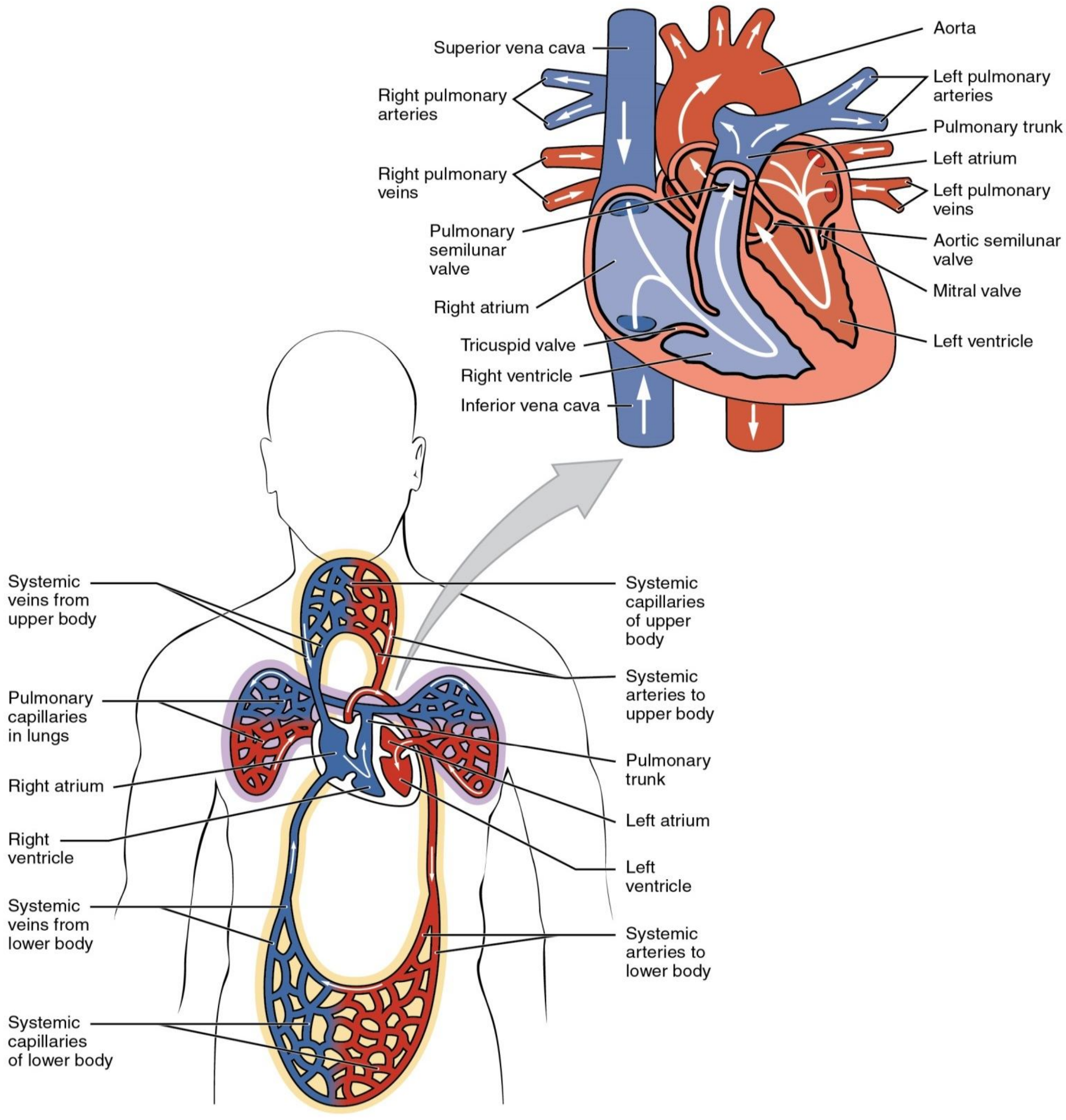


Figure (2.4): Dual System of the Human Blood Circulation[4].

2.2 Cardiac cycle

The period of time that begins with contraction of the atria and ends with ventricular relaxation is known as the cardiac cycle. The period of contraction that the heart undergoes while it pumps blood into circulation is called systole. The period of relaxation that occurs as the chambers fill with blood is called diastole. Both the atria and ventricles undergo systole and diastole, and it is essential that these components be carefully regulated and coordinated to ensure blood is pumped efficiently to the body[5].

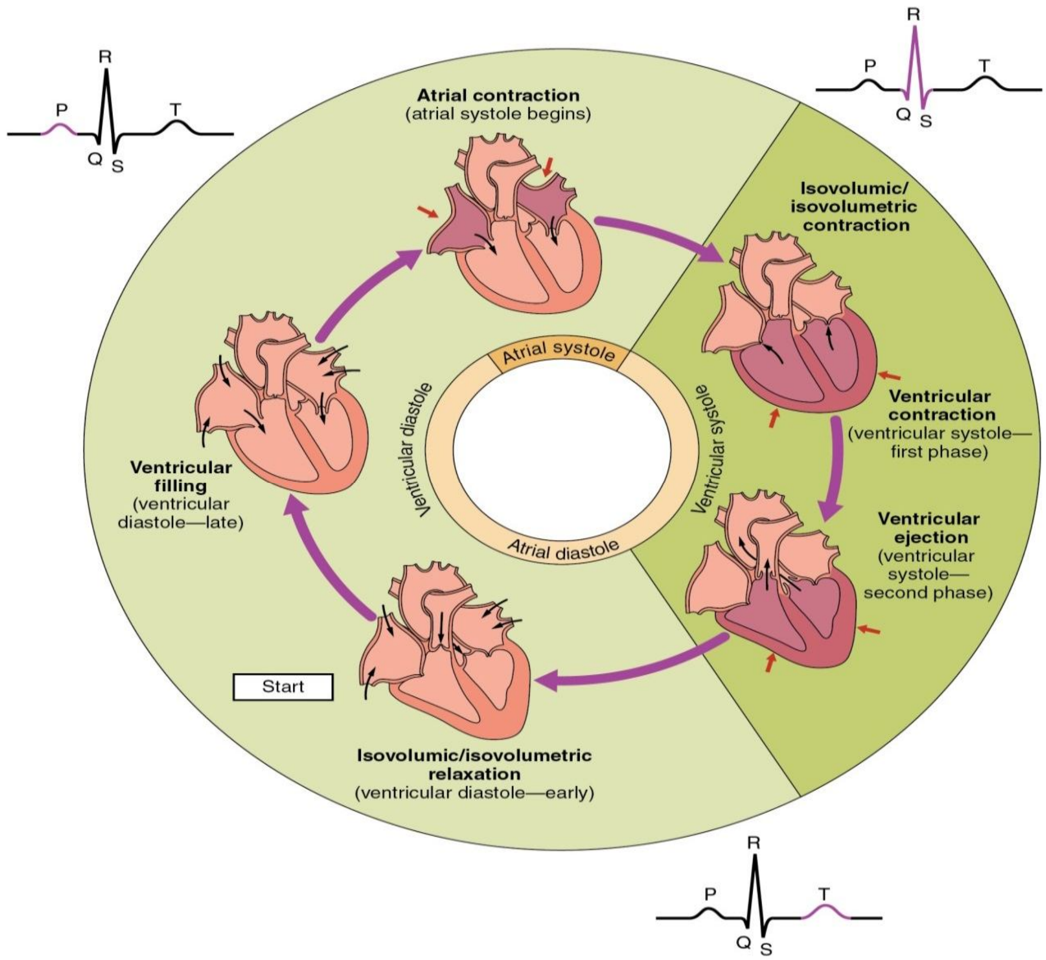


Figure (2.5): Overview of the Cardiac Cycle[5].

2.2.1 Pressures and Flow

Fluids, whether gases or liquids, are materials that flow according to pressure gradients, they move from regions that are higher in pressure to regions that are lower in pressure. Accordingly, when the heart chambers are relaxed (diastole), blood will flow into the atria from the veins, which are higher in pressure. As blood flows into the atria, the pressure will rise, so the blood will initially move passively from the atria into the ventricles. When the action potential triggers the muscles in the atria to contract (atrial systole), the pressure within the atria rises further, pumping blood into the ventricles. During ventricular systole, pressure rises in the ventricles, pumping blood into the pulmonary trunk from the right ventricle and into the aorta from the left ventricle[5].

2.2.2 Phases of the Cardiac Cycle

At the beginning of the cardiac cycle, both the atria and ventricles are relaxed (diastole). Blood is flowing into the right atrium from the superior and inferior venae cavae and the coronary sinus. Blood flows into the left atrium from the four pulmonary veins. The two atrioventricular valves, the tricuspid and mitral valves, are both open, so blood flows unimpeded from the atria and into the ventricles. Approximately 70–80 percent of ventricular filling occurs by this method. The two semilunar valves, the pulmonary and aortic valves, are closed, preventing backflow of blood into the right and left ventricles from the pulmonary trunk on the right and the aorta on the left[5].

2.2.2.1 Atrial Systole and Diastole

Contraction of the atria follows depolarization, represented by the P wave of the ECG. As the atrial muscles contract from the superior portion of the atria toward the atrioventricular septum, pressure rises within the atria and blood is pumped into the ventricles through the open atrioventricular (tricuspid, and mitral or bicuspid) valves. At the start of atrial systole, the ventricles are normally filled with approximately 70–80 percent of their capacity due to inflow during diastole. Atrial contraction, also referred to as the “atrial kick,” contributes the remaining 20–30 percent of filling. Atrial systole lasts approximately 100 ms and ends prior to ventricular systole, as the atrial muscle returns to diastole[5].

2.2.2.2Ventricular Systole

Ventricular systole follows the depolarization of the ventricles and is represented by the QRS complex in the ECG. It may be conveniently divided into two phases, lasting a total of 270 ms. at the end of atrial systole and just prior to atrial contraction; the ventricles contain approximately 130 mL blood in a resting adult in a standing position. This volume is known as the end diastolic volume (EDV) or preload[5].

Initially, as the muscles in the ventricle contract, the pressure of the blood within the chamber rises, but it is not yet high enough to open the semilunar (pulmonary and aortic) valves and be ejected from the heart. However, blood pressure quickly rises above that of the atria that are now relaxed and in diastole. This increase in pressure causes blood to flow back toward the atria, closing the tricuspid and mitral valves. Since blood is not being ejected from the ventricles at this early stage, the volume of blood within the chamber remains constant. Consequently, this initial phase of ventricular systole is known as isovolumic contraction, also called isovolumetric contraction (figure (2.7))[5].

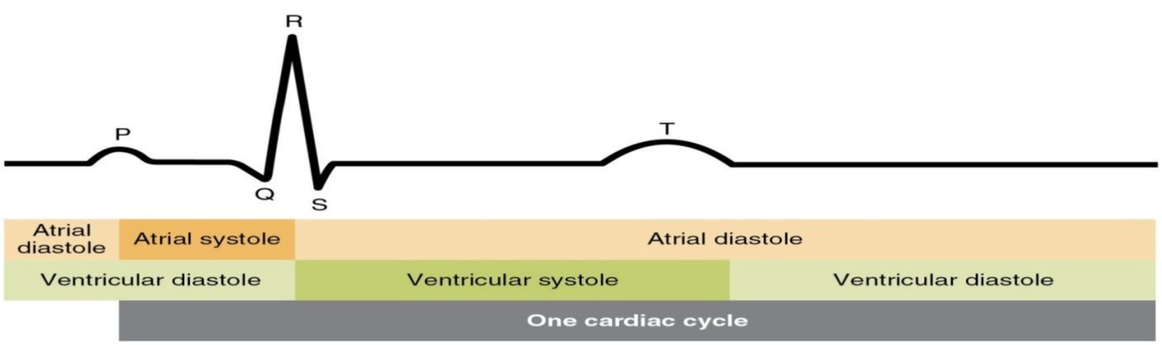
In the second phase of ventricular systole, the ventricular ejection phase, the contraction of the ventricular muscle has raised the pressure within the ventricle to the point that it is greater than the pressures in the pulmonary trunk and the aorta. Blood is pumped from the heart, pushing open the pulmonary and aortic semilunar valves. Pressure generated by the left ventricle will be appreciably greater than the pressure generated by the right ventricle, since the existing pressure in the aorta will be so much higher. Nevertheless, both ventricles pump the same amount of blood. This quantity is referred to as stroke volume. Stroke volume will normally be in the range of 70–80 mL. Since ventricular systole began with an EDV of approximately 130 mL of blood, this means that there is still 50–60 mL of blood remaining in the ventricle following contraction. This volume of blood is known as the end systolic volume (ESV)[5].

2.2.2.3Ventricular Diastole

Ventricular relaxation, or diastole, follows repolarization of the ventricles and is represented by the T wave of the ECG. It too is divided into two distinct phases and lasts approximately 430 ms[5].

During the early phase of ventricular diastole, as the ventricular muscle relaxes, pressure on the remaining blood within the ventricle begins to fall. When pressure within the ventricles drops below pressure in both the pulmonary trunk and aorta, blood flows back toward the heart, producing the dicrotic notch (small dip) seen in blood pressure tracings. The semilunar valves close to prevent backflow into the heart. Since the atrioventricular valves remain closed at this point, there is no change in the volume of blood in the ventricle, so the early phase of ventricular diastole is called the isovolumic ventricular relaxation phase, also called isovolumetric ventricular relaxation phase (figure (2.7))[5].

In the second phase of ventricular diastole, called late ventricular diastole, as the ventricular muscle relaxes, pressure on the blood within the ventricles drops even further. Eventually, it drops below the pressure in the atria. When this occurs, blood flows from the atria into the ventricles, pushing open the tricuspid and mitral valves. As pressure drops within the ventricles, blood flows from the major veins into the relaxed atria and from there into the ventricles. Both chambers are in diastole, the atrioventricular valves are open, and the semilunar valves remain closed and the cardiac cycle is complete[5].



Figures(2.6): Relationship between the Cardiac Cycle and ECG[5].

The overall realashionship between the blood pressure ,electrocardiography and phonocardiography is given in the figure(2.7) below:

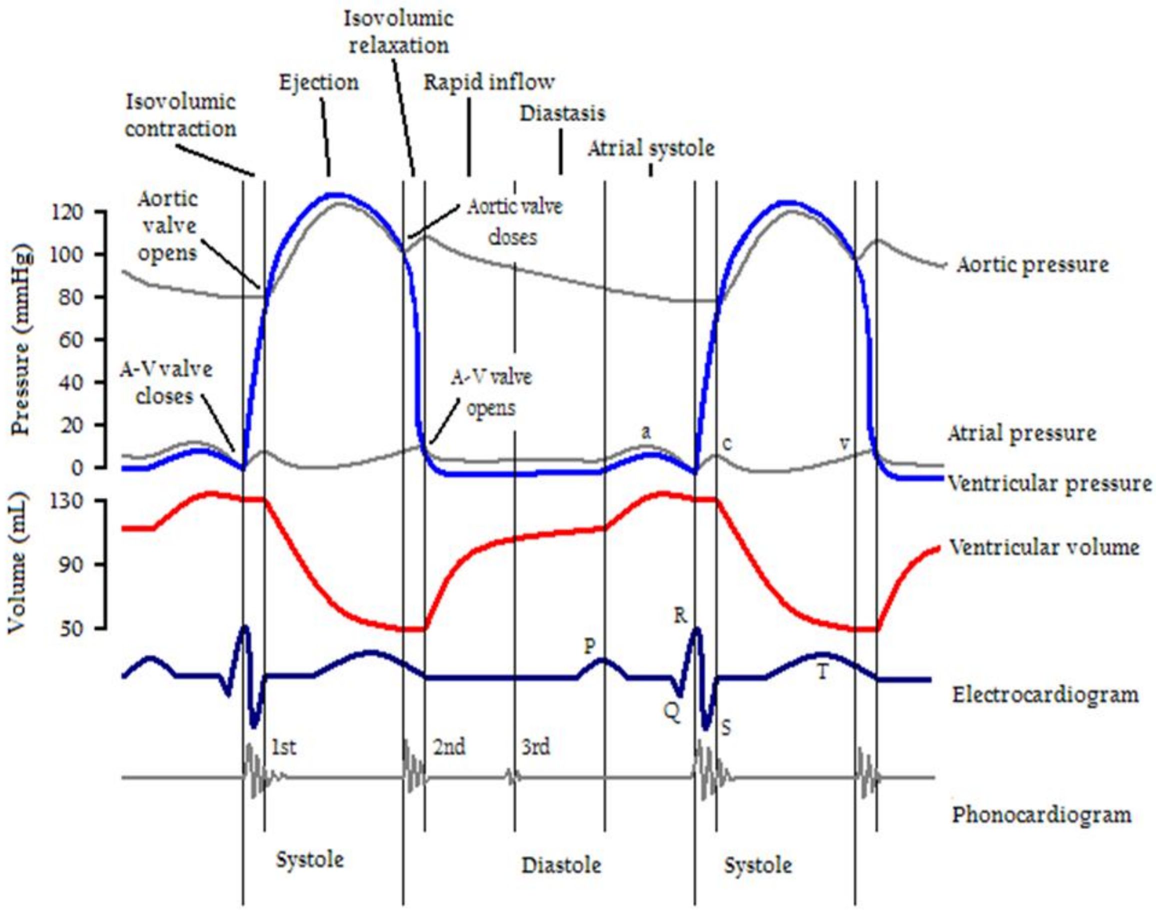


Figure (2.7): Signals of Cardiac Cycle (A) Ventricular Pressure, (B) Ventricular Volume, (C) ECG and (D) PCG (Heart Sounds)[6].

2.3 Heart Sounds

The heart sounds are the noises generated due to mechanical events such as movements of heart wall, closure of walls and due to turbulence and leakage of blood flow .These heart sounds can be used as a primary screening technique for diagnosing different heart disorders. It has been seen that the heart sounds produced by healthy hearts are remarkably identical and abnormal sounds always correlate to specific abnormalities[7].

2.3.1 Locations of cardiac auscultation

In a medical context the heart sound signal is collected from four main regions on the chest wall as demonstrated in figure (2.6). The aortic (A), between the second and third intercostal spaces at the right sternal border ;mitral(M), near the apex of the heart between the fifth and sixth intercostal spaces in the mid-clavicular line; pulmonic (P), between the second and third intercostal spaces at the left sternal border ;and tricuspid (T),between the third ,fourth,fifth,and sixth intercostal space at the left sternal border[8].

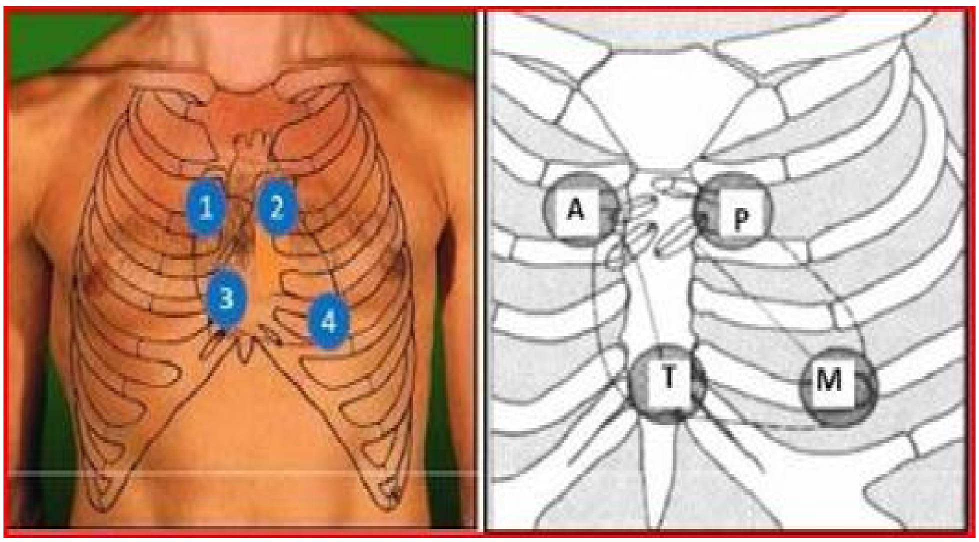


Figure (2.8): Auscultation Sites to Place Stethoscope[8].

2.3.2 Heart Sound Categories

In healthy adults, there are two normal heart sounds often described as a lub and a dub (or dup), that occur in sequence with each heartbeat. These are the first heart sound (S1) and second heart sound (S2), produced by the closing of the atrioventricular valves and semilunar valves, respectively. In addition to these normal sounds, a variety of other sounds may be present including heart murmurs, adventitious sounds, and gallop rhythms S3 and S4[9].

2.3.2.1Primary heart sounds

I. First heart sound (S1)

The first heart sound forms the "lub" of "lub-dub". S1 occurs at the onset of the ventricular contraction during the closure of the AV- valves. It contains a series of low-frequency vibrations, and is usually the longest and loudest component of the PCG signal. The audible sub-components of S1 are those associated with the closure of each of the two AV-valves. S1 lasts for an average period of (100−200) ms and its frequency components lie in the range of (25−45) Hz. It is usually a single component, but may be prominently split with some pathology[10]. These components are the mitral and tricuspid components. The mitral component occurring slightly before the tricuspid one due to earlier occurrence of left ventricular contraction. S1 occurs just right after the QRS complex of the ECG.

II. Second heart sound (S2)

The second heart sound forms the "dub" of "lub-dub". S2 is heard at the end of the ventricular systole, during the closure of the semilunar valves. S2 lasts about 0.12s, with a frequency of 50Hz which is typically higher than S1 in terms of frequency content and shorter in terms of duration. It has aortic and pulmonary sub-components (A2 and P2) corresponding to the aortic part and pulmonary part respectively. Usually A2 and P2 are closed together, but a split S2 can occur if A2 and P2 are just far enough apart that they can be heard as two beats within S2[10]. S2 occurs towards the end of the T wave of the ECG .

2.3.2.2 Extra heart sounds

I. Third heart sound (S3)

S3 – The third heart sound can be heard at diastole, moments after S2. It is believed it is caused by vibrations of the ventricular wall at the rapid filling period. The presence of S3 may be physiological in youths, young adults or athletes, while in elders it is usually related with heart failure and other pathologies. S3 is a low amplitude and low frequency sound whose spectrum is between 25-70 Hz[6].

II. **Fourth heart sound (S4)**

The fourth heart sound is a low-pitched sound coincident with late diastolic filling of the ventricle due to atrial contraction. It thus occurs shortly before the first heart sound. Although it is also called the atrial sound, and its production requires an effective atrial contraction, the fourth heart sound is the result of vibrations generated within the ventricle. Commonly, its presence indicates increased resistance to filling of the left or right ventricle because of a reduction in ventricular wall compliance, and it is accompanied by a disproportionate rise in ventricular end-diastolic pressure. In patients with a fourth heart sound, its palpable correlate is often present: a concomitant brief presystolic outward movement of the chest wall[11].

2.3.2.3Abnormal Heart Sounds

I. **Murmurs**

Murmurs are high-frequency, noise-like sounds that are heard between the two major heart sounds during systole or diastole. They are caused by turbulence in the blood flow through narrow cardiac valves or reflow through the atrioventricular valves due to congenital or acquired defects. They can be innocent, but can also indicate certain cardiovascular defects[10].

Murmurs are described as systolic or diastolic according to their timing in the cardiac cycle. Thus, a murmur heard after the first heart sound and before the second is a systolic murmur, and which comes after the second and before the first is a diastolic murmur[12] .

Regurgitation through the mitral valve is by far the most commonly heard murmur, which is sometimes fairly loud to a practiced ear, even though the volume of regurgitant blood flow may be quite small. Yet, though obvious using echocardiography visualization, probably about 20% of cases of mitral regurgitation do not produce an audible murmur[13].

Stenosis of the aortic valve is typically the next most common heart murmur, a systolic ejection murmur. This is more common in older adults or in those individuals having a two, not a three leaflet aortic valve[13].

II. Clicks and Snaps

Are associated with valves opening and indicate abnormalities and heart defects. Opening snaps of the mitral valve or ejection sound of the blood in the aorta may be heard in case of valve disease (stenosis, regurgitation). The opening snap when present, occurs shortly after S2 with the opening of the mitral and tricuspid valves[10]. Clicks are short high pitched sounds, and have three types:

- Ejection click: is the most common click, which occurs shortly after S1 with the opening of the semilunar valves.
- Aortic ejection clicks.
- Pulmonic ejection clicks.[14]

2.3.3 Heart Failure and diseases

Heart failure is Inability of the heart to pump a sufficient amount of blood to metabolizing tissues or the ability to do so only with an increased filling pressure[15].

Heart failure is a syndrome that can be caused by different heart disease:

Coronary artery disease (CAD) causes changes in both structure and function of the blood vessels. Atherosclerotic processes cause an abnormal deposition of lipids in the vessel wall, leukocyte infiltration and vascular inflammation, plaque formation and thickening of the vessel wall. These changes lead to a narrowing of the lumen (i.e., stenosis), which restricts blood flow. There are also subtle, yet functionally important changes that can occur before overt changes in structure are observed. Early in the disease process, the endothelial cells that line the coronary arteries become dysfunctional. Because the endothelium produces important substances such as nitric oxide and prostacyclin that are required for normal coronary function, endothelial dysfunction can lead to coronary vasospasm, impaired relaxation, and formation of blood clots that can partially or completely occlude the vessel.

Hypertension is ‘high blood pressure’. There is higher artery pressure against which the heart should inject.

Cardiomyopathy is a disease of the heart muscle. In most cases, cardiomyopathy causes the heart muscle to become weak.

There are two general types of cardiac valve defects:

Stenosis and insufficiency Valvular stenosis results from a narrowing of the valve orifice that is usually caused by a thickening and increased rigidity of the valve leaflets, often accompanied by calcification. When this occurs, the valve does not open completely as blood flows across it. Valvular insufficiency results from the valve leaflets not completely sealing when the valve is closed so that regurgitation of blood occurs (backward flow of blood) into the proximal chamber.

Arrhythmia is a general term for different rhythm problems, including bradycardia.

2.4 Stethoscopes

The stethoscope is an acoustic medical device for auscultation, or listening to the internal sounds of an animal or human body.

Physicians use a stethoscope as part of a non-invasive examination procedure. Commonly, doctors will listen for sounds of congestion in the lungs and irregular heartbeats. Nurses may also use stethoscope to listen for restored flow during blood pressure checks.

2.4.1 Acoustic stethoscope

For centuries, physicians would literally place their ears directly on a patient's chest or back as part of examination ,a procedure medically called " immediate auscultation ".It was not unusual for doctors to contract communicable disease through such intimate contact which sick patients .In the early 19^{th} century , a young French physician named Rene TheophileHyacinthe Laennec found examining female patient this way to be a little discomforting .In 1816, Dr.Laennec fashioned a cylinder from several sheets of paper and used it to examine a young female patient .He discovered that internal sounds could be insulated and amplified through a tube , making examination less intrusive and easier to interpret[16, 17].

Figure (2.9): Laennec stethoscope [17].

2.4.2 Electronic stethoscope

The heart sound is usually detected by human ear using acoustical stethoscope but this is sometimes not efficient because of the limitations of the human's ear sensitively especially that heart sounds have low frequencies and low intensity, this fact was realized scientists and companies to develop the conventional stethoscope to be more sensitive and that led to inventing the electronic stethoscope.

Listening, or auscultation, has been done with acoustic stethoscopes for almost two hundred years; recently, electronic digital stethoscopes have been developed[18].

Figure (2.10): electronic stethoscope [18].

The goal of a basic digital stethoscope is to have it retain the look and feel of an acoustic stethoscope but to improve listening performance. In addition, high-end digital stethoscopes offer sophisticated capabilities such as audio recording and playback. They also provide data to visually chart results by connecting to an off-instrument display such as a computer monitor. This advanced functionality increases the physician's diagnostic capability. Maintaining the existing acoustic stethoscope form while improving the performance digitally requires the use of small, low-power solutions[18].

The essential elements of a digital stethoscope are the sound transducer, the audio codec electronics, and the speakers. The sound transducer, which converts sound into an analog voltage, is the most critical piece in the chain. It determines the diagnostic quality of the digital stethoscope and ensures a familiar user experience to those accustomed to acoustic stethoscopes[18].

The analog voltage needs to be conditioned and then converted into a digital signal using an audio analog-to-digital converter (ADC) or audio codec. Some digital stethoscopes have noise cancellation that requires a secondary sound transducer or microphone to record the ambient noise so that it can be removed digitally[18].

Once in the digital domain, a microcontroller unit (MCU) or digital signal processor (DSP) performs signal processing, including ambient noise reduction and filtering, to limit the bandwidth to the range for cardiac or pulmonary listening. The processed digital signal is then converted back to analog by an audio digital-to-analog converter (DAC) or audio codec[18].

A headphone or speaker amplifier conditions the audio signal before outputting to a speaker. A single speaker can be used below where the stethoscope tube bifurcates, with the amplified sound traveling through the binaural tubes to the ears. Alternatively, two speakers can be used, with one speaker at the end of each earpiece. The frequency response of the speaker is similar to that of a bass speaker because of the low-frequency sound production needed. Depending on the implementation, one or two speaker amplifiers are used[18].

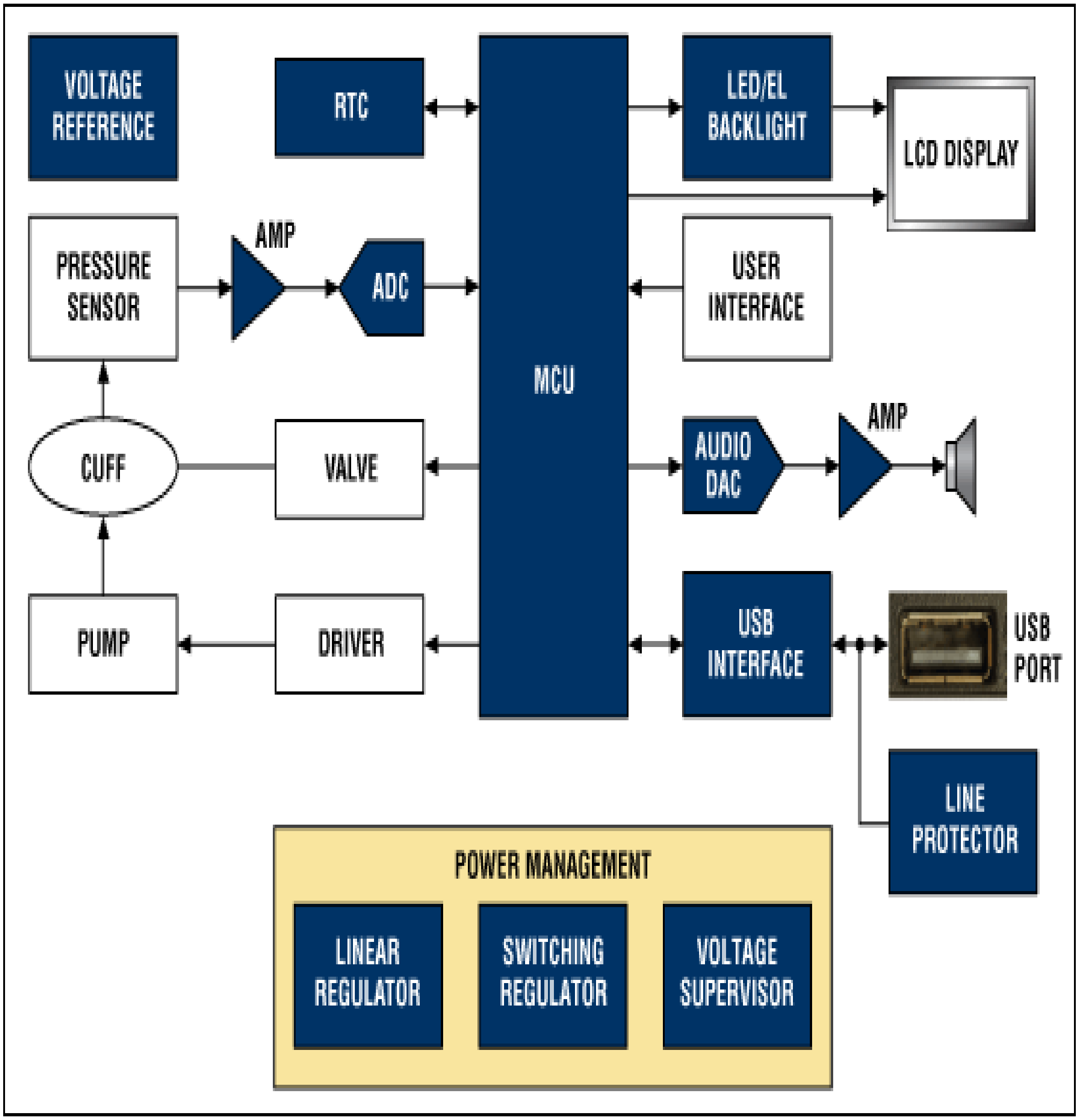


Figure (2.11): block diagram of electronic stethoscope [18].

2.5 Machine learning and artificial intelligence

Machine learning is a subfield of artificial intelligence (AI). The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by people [19].

Although machine learning is a field within computer science, it differs from traditional computational approaches. In traditional computing, algorithms are sets of explicitly programmed instructions used by computers to calculate or problem solve. Machine learning algorithms instead allow for computers to train on data inputs and use statistical analysis in order to output values that fall within a specific range. Because of this, machine learning facilitates computers in building models from sample data in order to automate decision-making processes based on data inputs[19].

2.5.1Machine Learning Methods

In machine learning, tasks are generally classified into broad categories. These categories are based on how learning is received or how feedback on the learning is given to the system developed. Two of the most widely adopted machine learning methods are supervised learning and unsupervised learning[19].

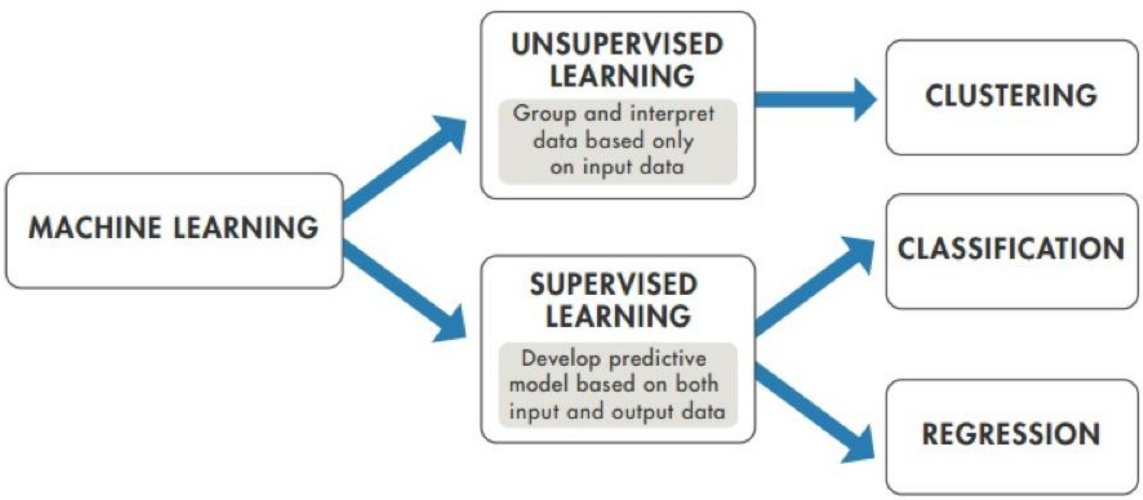


Figure (2.12): machine learning methods [20].

2.5.1.1 Supervised Learning

In supervised learning, the computer is provided with example inputs that are labeled with their desired outputs. The purpose of this method is for the algorithm to be able to “learn” by comparing its actual output with the “taught” outputs to find errors, and modify the model accordingly. Supervised learning therefore uses patterns to predict label values on additional unlabeled data[19].

2.5.1.2 Unsupervised Learning

In unsupervised learning, data is unlabeled, so the learning algorithm is left to find commonalities among its input data. As unlabeled data are more abundant than labeled data, machine learning methods that facilitate unsupervised learning are particularly valuable[19].

The goal of unsupervised learning may be as straightforward as discovering hidden patterns within a dataset, but it may also have a goal of feature learning, which allows the computational machine to automatically discover the representations that are needed to classify raw data[19].

2.5.2 Machine learning tasks

Following are the key machine learning tasks:

- Regression.
- Clustering.
- Multivariate querying.
- Density estimation.
- Dimension reduction.
- Testing and matching.
- Classification.

Regression: Regression tasks mainly deal with estimation of numerical values (continuous variables) .some of the following ML methods could be used for solving regressions problems[21]:

- Kernel regression (Higher accuracy)
- Gaussian process regression (Higher accuracy)
- Regression trees
- Linear regression
- Support vector regression

Clustering: Clustering tasks are all about finding natural groupings of data and a label associated with each of these groupings (clusters). Some of the following are common ML methods[21]:

- Mean-shift (Higher accuracy)
- Hierarchical clustering
- K-means
- Topic models

Multivariate querying: Multivariate querying is about querying or finding similar objects. Some of the following ML methods could be used for such problems[21]:

- Nearest neighbors
- Range search
- Farthest neighbors

Density estimation: Density estimation problems are related with finding likelihood or frequency of objects. In probability and statistics, density estimation is the construction of an estimate, based on observed data, of an unobservable underlying probability density function. Some of the following ML methods could be used for solving density estimation tasks[21]:

- Kernel density estimation (Higher accuracy)
- Mixture of Gaussians
- Density estimation tree

Dimension reduction: Dimension reduction is the process of reducing the number of random variables under consideration, and can be divided into feature selection and feature extraction. Following are some of ML methods that could be used for dimension reduction[21]:

- Manifold learning (Higher accuracy)
- Principal component analysis
- Independent component analysis
- Gaussian graphical models
- Non-negative matrix factorization
- Compressed sensing

Testing and matching: Testing and matching tasks relates to comparing data sets. Following are some of the methods that could be used for such kind of problems[21]:

- Minimum spanning tree
- Bipartite cross-matching
- N-point correlation

Classification: Classification tasks are simply related with predicting a category of a data (discrete variables). Some of the common use cases could be found in the area of healthcare such as whether a person is suffering from a particular disease or not. The ML methods such as following could be applied to solve classification tasks[21]:

- Kernel discriminant analysis (Higher accuracy)
- K-Nearest Neighbors (Higher accuracy)
- Artificial neural networks (ANN) (Higher accuracy)
- Support vector machine (SVM) (Higher accuracy)
- **Random forests (Higher accuracy)**
- Decision trees
- Boosted trees
- Logistic regression
- naive Bayes
- Deep learning

2.6 Random Forests

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees[22].

A Random Forest Classifier consists of a collection of decision tree classifiers where the decision trees are independently distributed random vectors and each tree casts a unit vote for the most popular class for a given input . The general method of random decision forests was first proposed by Ho in 1995, who established that forests of trees splitting with oblique hyperplanes if randomly restricted to be sensitive to only selected feature dimensions, can gain accuracy as they grow without suffering from overtraining . Random forest classifiers use a modified tree learning algorithm in which the concept of bagging is used in tandem with random feature selection . Typically, for a classification problem with p features, features are used in each split. This method displays better performance models than regular decision trees as the variance is decreased without increasing the bias. The average of many trees is not sensitive to noise as opposed to a single tree which is highly sensitive to noise[23].

2.6.1 Random forest algorithm

The random forest algorithm can split into two stages[24]:

- Random forest creation.
- Perform prediction from the created random forest classifier.

2.6.1.1 Random forest creation

The training process of random forests can be described by algorithm as follow[24]:

1. Randomly select “k” features from total “m” features.
   Where k << m
2. Among the “k” features, calculate the node “d” using the best split point.
3. Split the node into daughter nodes using the best split.
4. Repeat 1 to 3 steps until “l” number of nodes has been reached.
5. Build forest by repeating steps 1 to 4 for “n” number times to create “n” number of trees.

The beginning of random forest algorithm starts with randomly selecting “k” features out of total “m” features. Then, using the randomly selected “k” features to find the root node by using the best split approach. The next stage, calculating the daughter nodes using the same best split approach. Then repeating the first 3 stages until form the tree with a root node and having the target as the leaf node. Finally, repeat 1 to 4 stages to create “n” randomly created trees. This randomly created trees form the random forest [24].

2.6.1.2 Random forest prediction:

The following algorithm describes the testing process of the random forests:

1. Takes the test features and use the rules of each randomly created decision tree to predict the outcome and stores the predicted outcome (target)
2. Calculate the votes for each predicted target.
3. Consider the high voted predicted target as the final prediction from the random forest algorithm.

To perform the prediction using the trained random forest algorithm. Need to pass the test features through the rules of each randomly created tree. Each random forest will predict different target (outcome) for the same test feature. Then by considering each predicted target votes will be calculated. This concept of voting is known as **majority voting [24].**

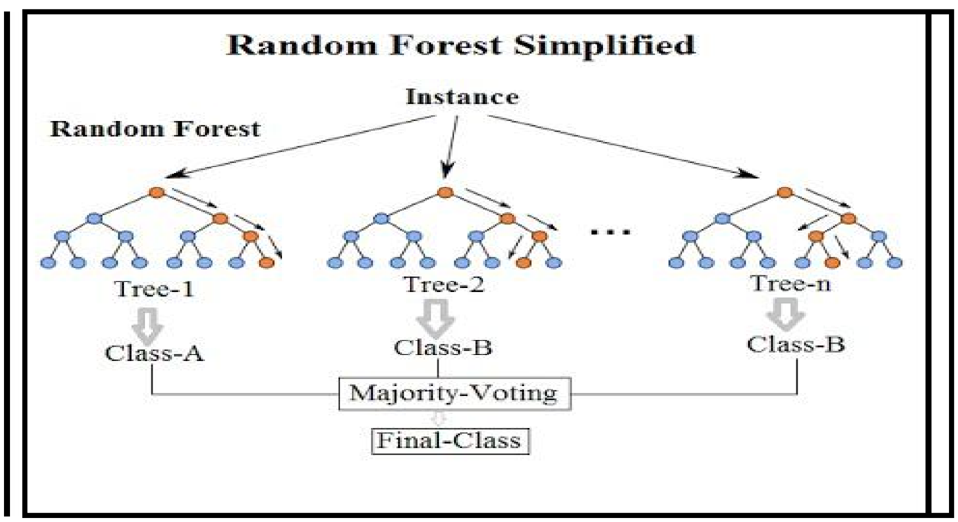


Figure (2.13): random forest classifier [24].

2.6.2 Advantages of random forest algorithm

Below are the advantages of random forest algorithm compared with other classification algorithms.

1. The over fitting problem will never come when we use the random forest algorithm in any classification problem.
2. The same random forest algorithm can be used for both classification and regression task.
3. The random forest algorithm can be used for feature engineering.

Which means identifying the most important features out of the available features from the training dataset [24].

2.7 Related Works

Current research in this field is focused on the development of suitable algorithms, which in the future may lead to development of an intelligent stethoscope. Because of the nature of PCG signals and undesired noise during examination, it is important to divide the diagnosis process into two steps. The first being the processing of original signals aimed to extract features, which would help to distinguish all of the types of signals, and the second associated with the process of signal classification. There were several successful attempts to develop such systems, where the majority of works were focused on the application of techniques based on Artificial Neural Networks (ANN) and Support Vector Machines (SVM).

One of the earliest heart valve disease detection systems based on ANN was developed by Turkoglu, Arslan and Ilkay[25], who used wavelet entropy and short-time Fourier transform to determine specific features of heart signals, consequently obtaining classification accuracy of 94% for normal heart sounds, and 95.9% for pathological ones.

Detection of heart murmurs using wavelet analysis and artificial neural networks, by N. Andrisevic, K. Ejaz, F.R. Gutierrez, R.A. Flores, They proposed algorithm which consists of three main stages. First; denoising of input data (digital recordings of heart sounds), via Wavelet Packet Analysis. Second; input vector preparation through the use of Principal Component Analysis and block processing. Third; classification of the heart sound using an Artificial Neural Network. Initial testing revealed the intelligent diagnostic system can differentiate between normal healthy heart sounds and abnormal heart sounds (e.g., murmurs), with a specificity of 70.5% and a sensitivity of 64.7% [26].

Wavelet analysis of the PCG signal in combination with homomorphic filtering and K-means clustering method was presented by Gupta et al. (leading to 97% accuracy in distinguishing two abnormal and one normal heart states) [27].

Other works include the use of multivariate matching pursuit to model murmurs and classifying them with a three-layer feed-forward perceptron network with 92.5% of accuracy (distinguishing normal from abnormal heart states) [28] or a combination of detection of characteristic heart features (activity, complexity, mobility and spectral peaks) with ANN, providing a rate of 98% in identification, however able to distinguish only three of them .

Another group of methods employ the SVM as the main classifier. An approach for heart sounds identification presented by Wu et al. ensured 95% of accuracy using wavelet transform to extract the envelope of PCG signals [29]. However, the authors were able to distinguish only normal from abnormal heart states.

The same results were achieved by Jiang and Choi [30] who developed a system for in-home use, however, this system was proven only by a case study.

A diagnosis system based on principle component analysis connected with an adaptive network was developed by Avci and Turkoglu[31]. In this case the system ensured 96% accuracy in classification of normal and 93.1% of two abnormal heart states. Later, Avci improved this system and developed genetic Support Vector Machines, which gave 95% of accuracy.

Classification heart sounds based on the least squares support vector machine, by GurEmreGurak and HarunUguz, which published in International Journal of Innovative during December 2011. In this study, primarily, heart sound signals in numerical format were separated into sub- bands through discrete wavelet transform. Next, the entropy of each sub-band was calculated by using the Shannon entropy algorithm to reduce the dimensionality of the feature vectors with the help of the discrete wavelet transform. The reduced features of three types of heart sound signals were used as input patterns of the least square support vector machines and they were classified least square support vector machines. In the method used, 96.6% of the classification performance was obtained [32].

Tanmay G conducted a study published in IEEE about’’ Machine learning based identification of pathological heart sounds’’[33] he uses Hilbert-envelope and wavelet features to attempt to capture the qualities of the heart sounds that physicians are trained to interpret. And perform a two-step classification of heart sounds into poor quality, normal or abnormal with sensitivity of 0.7958 and specificity of 0.7459.

Jonathan Rubin, Rui Abreu, AnuragGanguli, SaigopalNelaturi , Ion Matei, Kumar Sricharan published a study under the name "Recognizing Abnormal Heart Sounds Using Deep Learning"[34] The work presented applies deep learning to the task of automated cardiac auscultation. they describe an automated heart sound classification algorithm that combines the use of time-frequency heart map representations with a deep convolutional neural network (CNN).the system achieved a final specificity of 0.95, sensitivity of 0.73 and overall score of 0.84.

Chapter III

Methodology

3.1 Introduction

This chapter discusses the method approached to building classification system for heart sound based on random forests, which consist from five stages as shown in figure (3.1) below:

Figure (3.1): research methodology.

3.2 Data Collection

Heart sound recordings were obtained from the website, a collection of 100 data files of heart sounds were collected from medical students and doctors websites [48,49,50] taken from healthy and cardiac disease patients. Heart sound recordings were divided into two types: normal and abnormal heart sounds. The normal recordings were from healthy subjects and the abnormal ones were from patients with different cases (aortic stenosis, atrial fibrillation, aortic regurgitation, mitral fibrillation…etc) .The database consist from 20 normal and 80 abnormal heart sounds.

In implementation, all the data sets were gathered and entered into MATLAB 2016a for processing.

3.3 Pre-Processing

The purpose of this stage is to eliminate and enhance heart sounds, making them easier to segment and identify.

3.3.1 De-noising

High quality signals are essential for correct identification. Unfortunately, the presence of noise in heart sounds signals is inevitable. Even when all background noise is minimized there are always intrinsic sounds impossible to avoid include:

• respiration sounds,

• patient sounds and movements,

• small movements of the stethoscope (friction noise),

• acoustic damping of the bones and tissue, and

• environment background noise.

Therefore, the de-noising stage is extremely important, ensuring elimination of noise and emphasizing relevant sounds [35].

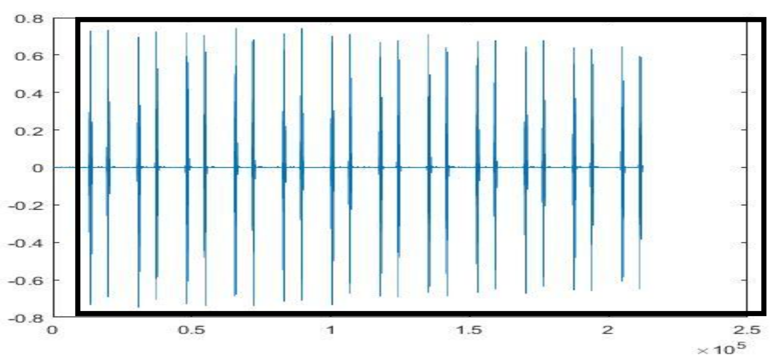


Figure (3.2): Raw heart sound signal .

Due to the overlapping nature of noise with the spectra of the heart sounds signal, simple band pass filtering is not effective for noise reduction. However, decomposing the signal in narrower sub-bandwidths using the wavelet transform enables us to perform the temporal noise reduction for the desired bandwidth sections[14]. The wavelet transform has many advantages over the other methods which include :

a) One of the main advantages of wavelets is that they offer a simultaneous localization in time and frequency domain.

b) The second main advantage of wavelets is that, using fast wavelet transform, it is computationally very fast.

c) Wavelets have the great advantage of being able to separate the fine details in a signal. Very small wavelets can be used to isolate very fine details in a signal, while very large wavelets can identify coarse details.

d) A wavelet transform can be used to decompose a signal into component wavelets.

e) In wavelet theory, it is often possible to obtain a good approximation of the given function f by using only a few coefficients which is the great achievement in compare to Fourier transform.

f) Most of the wavelet coefficients , vanish for large N.

The mother wavelet implemented here is the Debauches wavelet of order 5 (db5) as shown in figure (3.3) .The choice is due to the heart beat signal having most of its energy distributed over a small number of db5 wavelet dimensions (scales), and therefore the coefficients corresponding to the heart beat signal will be large compared to any other noisy signal [36]. The de-noising procedure involves three steps:

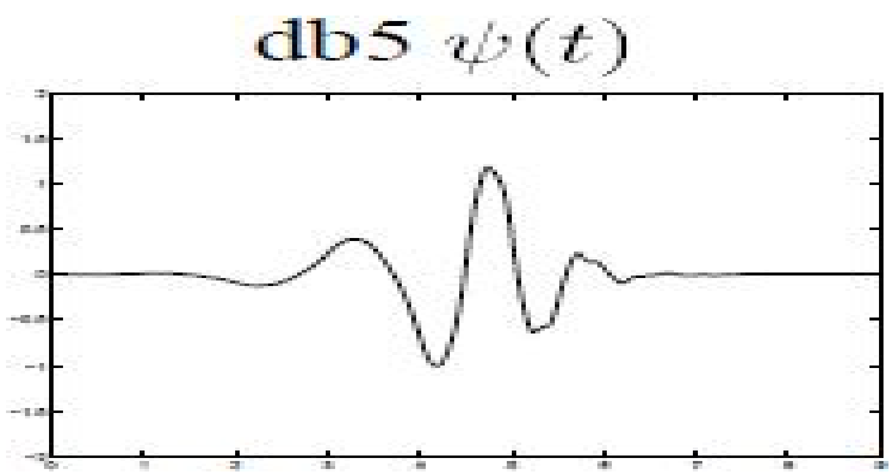


Figure (3.3): Debauches 5 (db5).

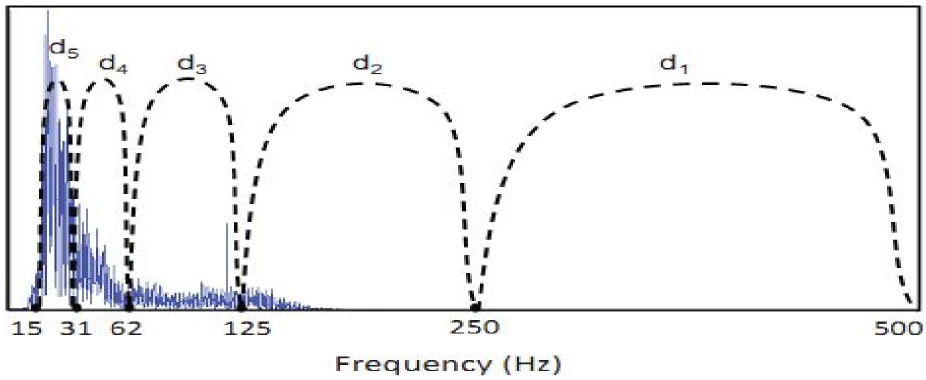


Figure (3.4): Equivalent frequency responses of the DWT, over the heart sounds spectrum.

3.3.1.1 Decomposition

The heart sound in this step is divided into approximations and details, where the approximations represent the slowly changing (low frequency- high scale) features of the signal and details represent the rapidly changing (high frequency– low scale) features of the signal[36].

A decomposition of level 5 with the (db5) wavelet was selected for the decomposition part of the de-noising algorithm.

3.3.1.2 Thresholding detailed coefficients

This step involves thresholding the detailed coefficients of the DWT and then reconstructing the signal with the inverse discrete wavelet transform (IDWT). There are two common methods for thresholding, soft thresholding and hard thresholding. The method chosen is the soft thresholding, where it produces better result than hard thresholding because it sets the elements whose absolute values are lower than the threshold to zero and then the nonzero coefficients remaining are shrunk and set to zero. In the other hand hard thresholding sets the elements whose absolute values are less than the threshold to zero [33].

3.3.1.3 Reconstruction

The last step in the de-noising procedure is to compute the wavelet reconstruction through the summation of the original approximation coefficients of the last level (level5) and the modified detail coefficients of levels 1 to 5 [36].

Each sound was passed through the preprocessing stage. It was threshold and normalized.

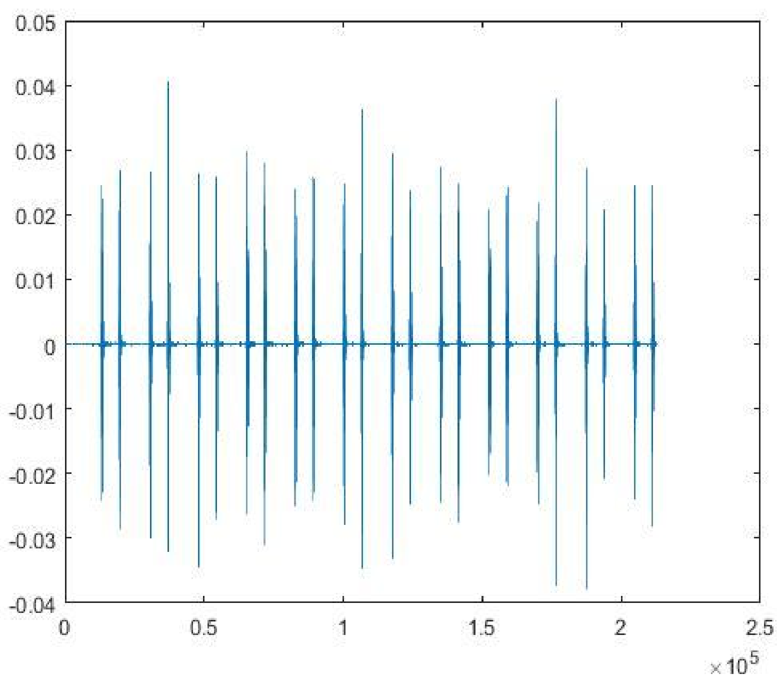


Figure (3.5):De-noised signal.

3.3.2 Segmentation

The purpose of heart sounds segmentation is to separate all the cardiac cycles in a recording so that each can be analyzed individually.

In the implementation, two cycles of heart sound were segmented for further analysis.

3.4 Features Extraction

The feature extraction of HS is the key stage for automatic HS interpretation and diagnosis of heart dysfunction[37].

The extraction of features, which is the process of identifying distinctive properties from a signal, plays a major role in the effective classification of HS. The features can be extracted from the signals in one of the four domains: time domain, frequency domain, statistical domain and time–frequency domain[37]. Some typical feature extraction techniques used in computer-based HS analysis are:

3.4.1 Graphical representation features

In the time domain, heart sounds (HSs) have to be represented graphically; amplitude versus time. However, discriminatory information can be found in the frequency-domain.

3.4.1.1 Spectrogram

Spectrogram is a time-varying spectral representation that plots the variation of spectral density with respect to time. Spectrogram is a two dimensional graph, where horizontal axis represents time and vertical axis represents frequency. A third dimension indicating amplitude of a particular frequency is represented by the intensity or color of each point in the signal [38].

3.4.1.2 Power spectrum

From power and energy prospective, signals can be classified into three broad categories, power signals, energy signals, or both. Heart sound signals also have finite average power and fall into the category of power signals.

3.4.1.3 Scalogram

In signal processing, a **scaleogram** or **scalogram** is a visual method of displaying a wavelet transform. There are 3 axes: x representing time, y representing scale, and z representing coefficient value. The z axis is often shown by varying the colour or brightness.

3.4.1.4 Mel-frequency cepstral coefficients (MFCCs)

Heart sound is an acoustic signal and many techniques used nowadays for human recognition tasks borrow speech recognition techniques. The best and popular choice for feature extraction of acoustic signals is the Mel Frequency Cepstral Coefficients (MFCC) which maps the signal onto a Mel-Scale which is non-linear and mimics the human hearing[39]. MFCC system is still superior to Cepstral Coefficients despite linear filter-banks in the lower frequency range. The idea of using Mel Frequency Cepstral Coefficients (MFCC) as the feature set for a PCG classification system comes from the success of MFCC for speaker identification and because PCG and speech are both acoustic signals[39]. MFCC is based on human hearing perceptions which cannot perceive frequencies over 1Khz. In other words, in MFCC is based on known variation of the human ear’s critical bandwidth with frequency [40].MFCC has two types of filter which are spaced linearly at low frequency below 1000 Hz and logarithmic spacing above 1000Hz[40]. Mel-frequency cepstrum coefficients (MFCC), which are the result of a cosine transform of the real logarithm of the short-term MFCCs are provide more efficient. It includes Mel-frequency wrap-ping and Cepstrum calculation [35].

Mel-Frequency Cepstrum Coefficients (MFCC) are one of the most widespread parametric representation of audio signals (Davis &Mermelstein (1980)). The basic idea of MFCC is the extraction of cepstrum coefficients using a non-linearly spaced filterbank; the filterbank is instead spaced according to the Mel Scale: filters are linearly spaced up to 1 kHz, and then are logarithmically spaced, decreasing detail as the frequency increases. This scale is useful because it takes into account the way we perceive sounds. The relation between the Mel frequency fˆmel and the linear frequency flin is the following[35]:

$$fmel = 2595.\log_{10}\left(\frac{1+flin}{700}\right) \qquad \text{Equ (3.1).}$$

Some heart-sound classification systems use MFCC, while others use a linearly-spaced filterbank. The first step of the algorithm is to compute the FFT of the input signal; the spectrum is then feeded to the filterbank, and the i-thcepstrum coefficient is computed using the following formula:

$$c_{i=\sum_{k=1}^{K} X_k}.\cos\left(i.\left(k-\frac{1}{2}\right).\frac{\pi}{k}\right) \quad i = 0, \ldots, M \qquad \text{Equ(3.2).}$$

Where K is the number of filters in the filter bank, Xk is the log-energy output of the k-th filter and M is the number of coefficients that must be computed [35].

Calculation of MFCC coefficients

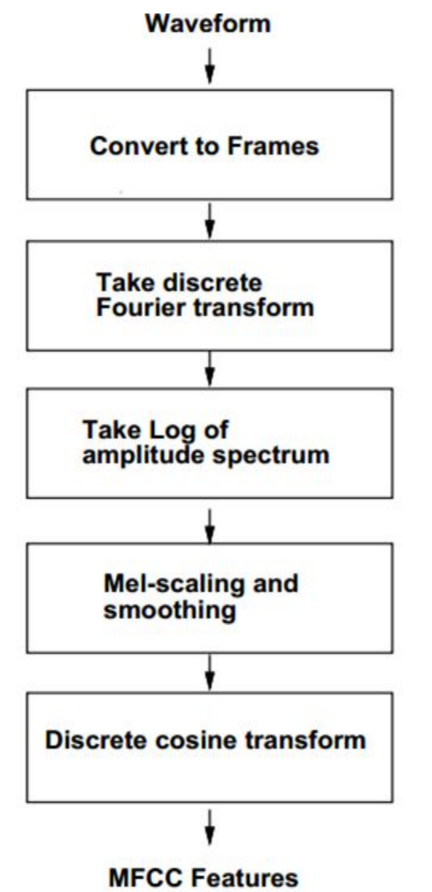


Figure (3.6): Steps of MFCC Calculation's.

In implementation, MFCC was applied for each segment; power spectrum of each coefficient was calculated using this method, and then the coefficients for each point of scale where summed.

3.5.1. Representation of measured and calculated parameters

This study includes 20 measured features for use in the classification process, which include the following:

Table (3.1): Measured Features and their description.

Measured Features	Description
Sum	Return the sum of all values.
Sum of squares	Return the sum of the squares of the values.
Min	Return the minimum of the values.
Max	Return the maximum of the values.
Mean	Returns the arithmetic mean of the values.
RMS	Returns the Root Mean Square of the values.
Variance	Returns the variance based on the values.
Standard Deviation	Returns the standard deviation based on the values.
Mode	Returns the value that appears most often.
Median	Returns the median value of the values.
Skew	Returns the skew of the values.
Kurtosis	Returns the kurtosis of the values.

Total Harmonic Distortion	Returns the total harmonic distortion (THD) in of the real-valued signal. The total harmonic distortion is determined from the fundamental frequency and the first five harmonics using a modified periodogram of the same length as the input signal
Median frequency	Estimates the median normalized frequency, freq, of the power spectrum of a time-domain signal
Mean frequency	estimates the mean normalized frequency, freq, of the power spectrum of a time-domain signal
Correlation coefficients	Returns 1 if there is homogeneity in the signal and -1 if not.
Covariance	Returns the covariance. For a vector of observations, it is the scalar-valued variance.
Entropy	statistical measure of randomness
Zero-crossing rate	The zero-crossing rate is the rate of sign-changes along a signal, the rate at which the signal changes from positive to negative or back

3.5 Features selection

Often in data science there are hundreds or even millions of features and there is a need to create a model that only includes the most important features. This has three benefits. First, make the model more simple to interpret. Second, reduce the variance of the model, and therefore overfitting. Finally, reduce the computational cost (and time) of training a model. The process of identifying only the most relevant features is called "feature selection"[41].

Random Forests are often used for feature selection in a data science workflow. The reason is because the tree-based strategies used by random forests naturally ranks by how well they improve the purity of the node. This mean decrease in impurity over all trees (called gini impurity). Nodes with the greatest decrease in impurity happen at the start of the trees, wile nodes with the least decrease in impurity occur at the end of trees. Thus, by pruning trees below a particular node, we can create a subset of the most important features.

3.5.1. Measurement of Feature Importance Score from a RF

Since each tree is grown from a bagged sample set, it is grown with only two-thirds of the samples, called in-bag samples. About one-third of the samples is left out and these samples are called out-of-bag (OOB) samples[42].

Permutation technique used to measure the importance of features in the prediction, called an out-of-bag importance score. The basic idea for measuring this kind of importance score of features is to compute the difference between the original mean error and the randomly permuted mean error in OOB samples. The method rearranges stochastically all values of the$j$th feature in OOB for each tree and uses the RF model to predict this permuted feature and get the mean error. The aim of this permutation is to eliminate the existing association between the jth feature and Yvalues and then to test the effect of this on the RF model. A feature is considered to be in a strong association if the mean error decreases dramatically[42].

The other kind of feature importance measure can be obtained when the random forest is growing. This is described as follows. At each node t in a decision tree, the split is determined by the decrease in node impurity$\Delta R(t)$. The node impurity $R(t)$ is the gini index. If a subdataset in node t contains samples from c classes, gini (t) is defined as:

$$R(t) = 1 - \sum_{j=1}^{c} p\hat{}_j^2 \qquad \text{Equ(3..3).}$$

Where $p\hat{}_j^2$ is the relative frequency of class j in t.Gini (t) is minimized if the classes t in t are skewed. After splitting t into two child nodest_1 and $t_2$with sample sizes$N_{1(t)}$ and$N_{2(t)}$, the gini index of the split data is defined as:

$$Gini_{split}(t) = \frac{N_1(t)}{N(t)} Gini(t_1) + \frac{N_2(t)}{N(t)} Gini(t_2) \qquad \text{Equ(3.4).}$$

The feature providing smallest $Gini_{split}$ is chosen to split the node. The importance score of feature X_j in a single decision treeT_k is:

$$IS_K(X_j) = \sum_{t \in T_k} \Delta R(t) \qquad \text{Equ(3.5).}$$

And it is computed over all K trees in a random forest, defined as

$$IS(X_j) = \frac{1}{K} \sum_{k=1}^{k} IS_k(X_j) \qquad \text{Equ(3.6).}$$

It is worth noting that a random forest uses in-bag samples to produce a kind of importance measure, called an in-bag importance score. This is the main difference between the in-bag importance score and an out-of-bag measure, which is produced with the decrease of the prediction error using RF in OOB samples. In other words, the in-bag importance score requires less computation time than the out-of-bag measure[42].

3.6 Classification

Random forests (RFs) are a nonparametric method that builds an ensemble model of decision trees from random subsets of features and bagged samples of the training data[42].

Random forest uses the classification results voted from many classification trees. The idea is simple: a single classification tree will obtain a single classification result with a single input vector. However, a random forest grows many classification trees, obtaining multiple results from a single input. Therefore, a random forest will use the majority of votes from all the decision trees to classify data[43] .

3.6.1 Random Forest steps:

- Create the Data.
- Split the Data into Training and Test Sets.
- Train a Random Forest Classifier.
- Identify and Select Most Important Features.
- Create a Data Subset with Only the Most Important Features.
- Train a New Random Forest Classifier Using Only Most Important Features.
- Compare the Accuracy of the Full Feature Classifier To the Limited Feature Classifier.

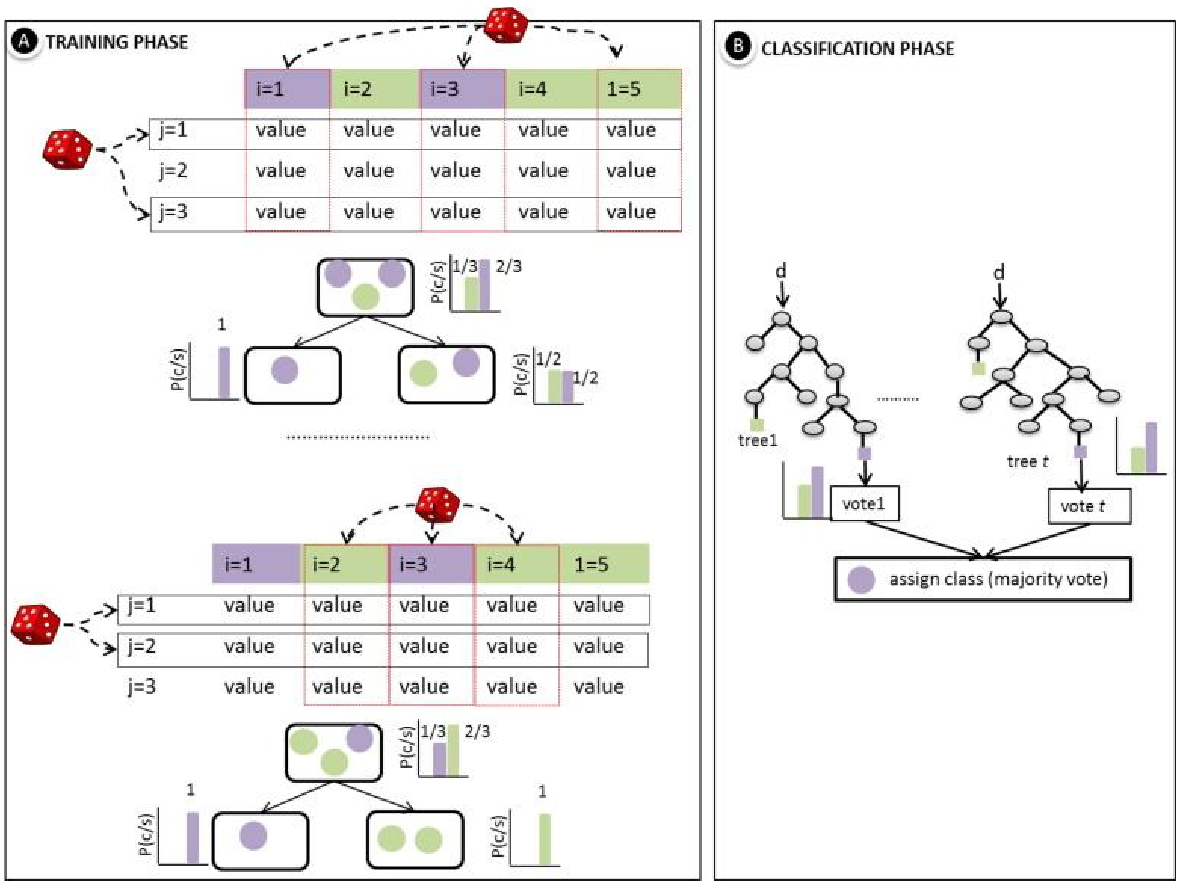
3.6.2 Sampling without replacement

In this method the data is divided into training set and testing set, where the training set must be larger than the testing set for insuring good performance of the system.

3.6.3 Sampling with replacement

When the training set for the current tree is drawn by sampling with replacement, about one-third of the cases are left out of the sample as shown at figure (3.7) below. This oob (out-of-bag) data is used to get a running unbiased estimate of the classification error as trees are added to the forest. It is also used to get estimates of variable importance [44].

After each tree is built, all of the data are run down the tree, and proximities are computed for each pair of cases. If two cases occupy the same terminal node, their proximity is increased by one. At the end of the run, the proximities are normalized by dividing by the number of trees. Proximities are used in replacing missing data, locating outliers, and producing illuminating low-dimensional views of the data [45].



Figure(3.7): sampling with replacement random forests[46].

3.6.4 Random Forest Parameters

Some of the commonly used parameters of random Forest functions are

- x - Random forest formula.
- data - input data frame.
- ntree - number of decision trees to be grown.
- mtry - the number of features used to find the best feature.
- replace- takes True and False and indicates whether to take sample with/without replacement.
- importance - whether independent variable importance in random forest be assessed.

In the implementation the classifier consists from 50 decision tree and the data consists from 100 samples and 20 features .

Due to the limited data used in the classification process so that the data cannot be divided into a training group and a test group, the k folding method was used to solve this problem and to evaluate the performance of the system.

In k-fold cross-validation, the original sample is randomly partitioned into k equal sized subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining $k - 1$ subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds can then be averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. 10-fold cross-validation is commonly used, but in general k remains an unfixed parameter.

Chapter IV

Result and Discussion

4.1 Results

The proposed system has been applied for offline data which collected from the website. A collection of 100 recordings of heart sounds were using for training and testing the system . In preprocessing stage, wavelet transform was applied, and wavelet coefficients are determined by using Daubechies-5 as a mother function, level 5 for each heart sound signal. Then used (soft) thresholding wavelet de-noising .And then extract features graphical and measurable calculated features.These features used in the classification process based on random forest.

4.1.1 Normal & abnormal heart sound

A. Normal Heart sound signal

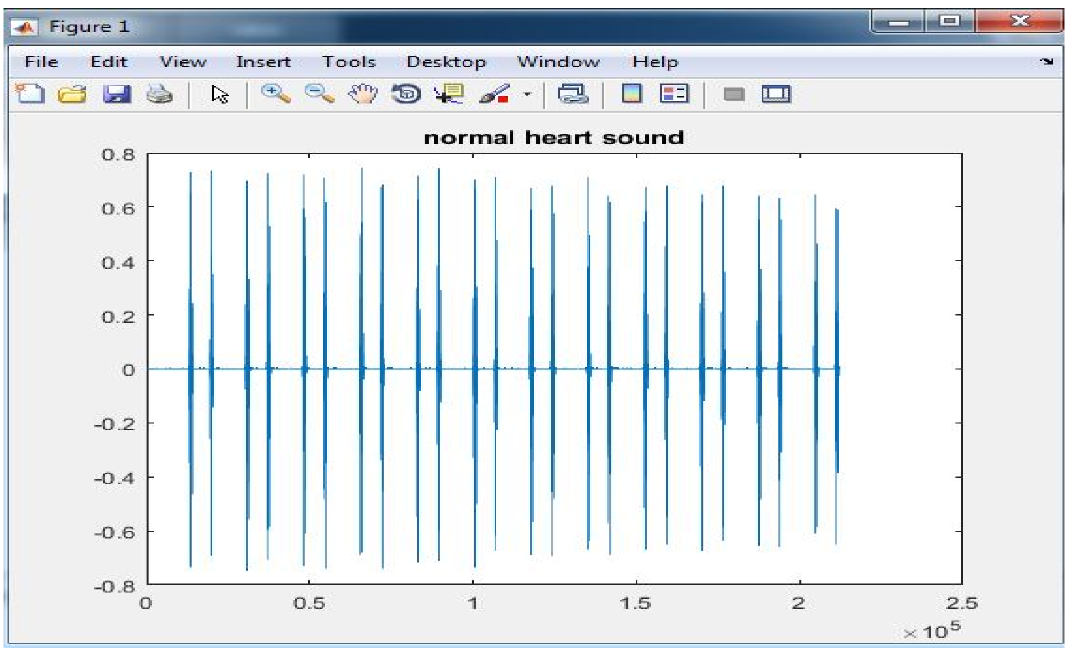


Figure (4.1): Normal heart sound signal.

B. Abnormal Heart sound signal

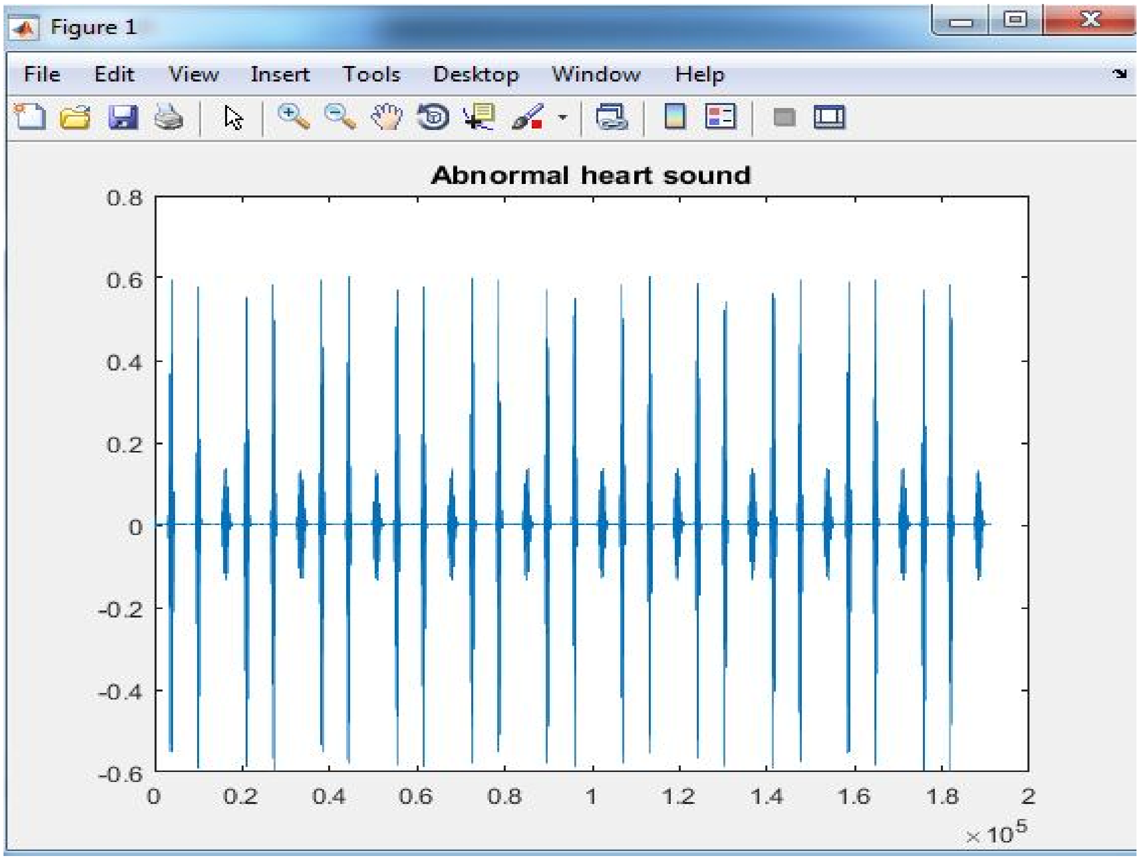


Figure (4.2): Abnormal heart sound signal.

Normal &Abnormal Heart Sound Signal with SNR=10.1896 and 9.1927 respectively .

4.1.2 Pre-processing of heart sound signal

The pre-processing composed of three stages:

- Wavelet Decomposition.
- Wavelet Reconstruction
- De-noising.

4.1.2.1 Wavelet Decomposition

A.Decomposition of normal heart sound

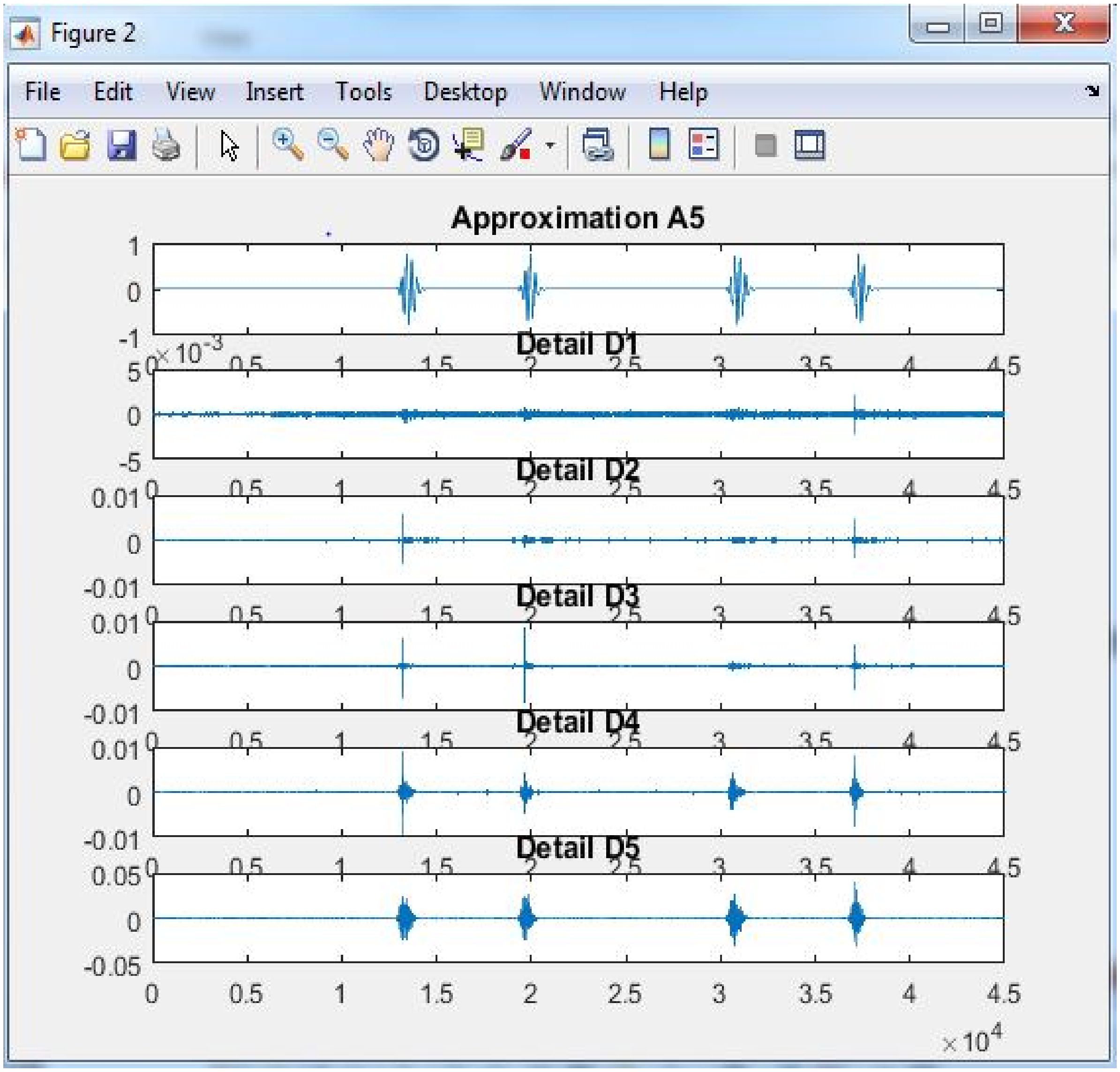


Figure (4.3): wavelet decomposition of normal heart sound.

B. Decomposition of abnormal heart sound

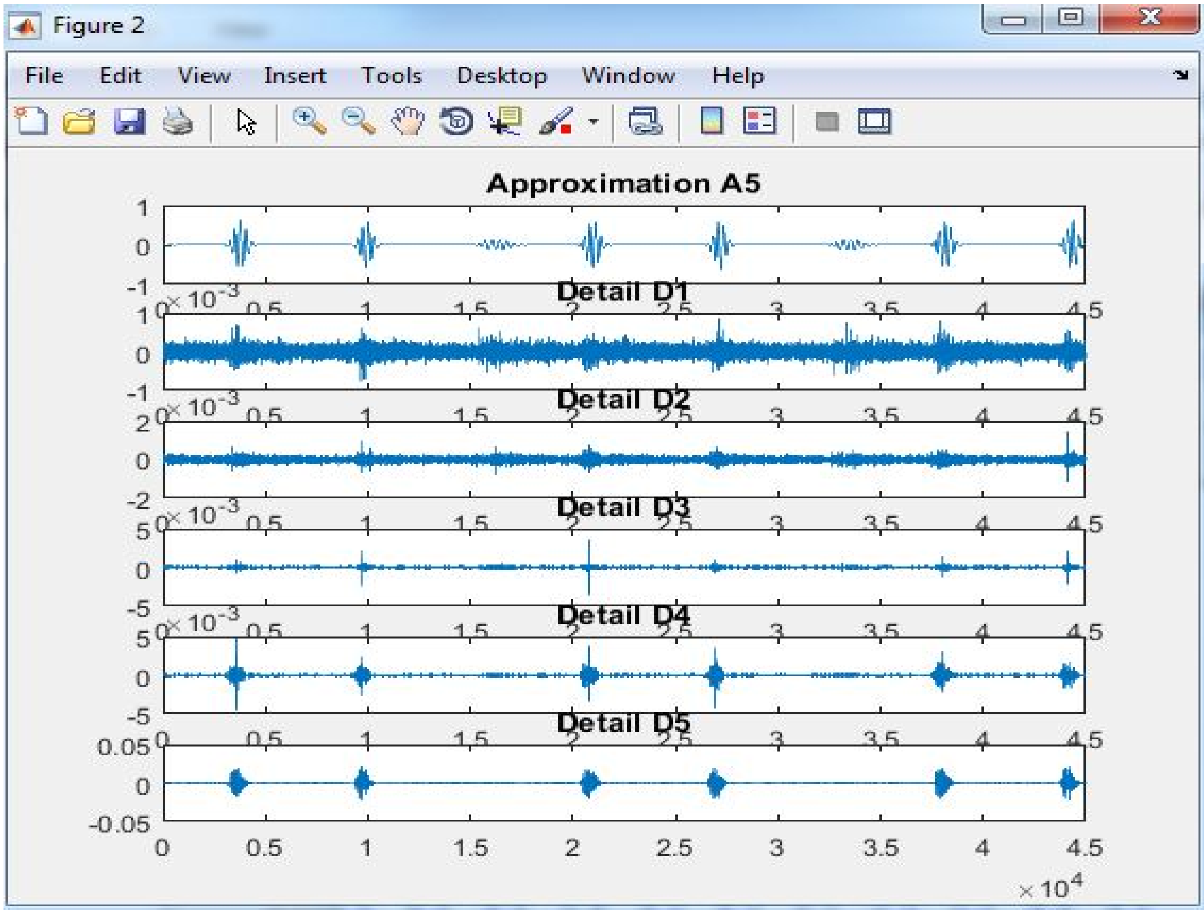


Figure (4.4): decomposition of abnormal heart sound.

In wavelet analysis, a signal is split into an approximation (A) and a detail (D). The approximation is then itself split into a second-level approximation and detail, and the process is repeated. For the above figures the signal was decomposed into 5-level (D1, D2, D3, D4, D5, and A5).

4.1.2.2 Wavelet Reconstruction

A.Reconstruction of normal heart sound

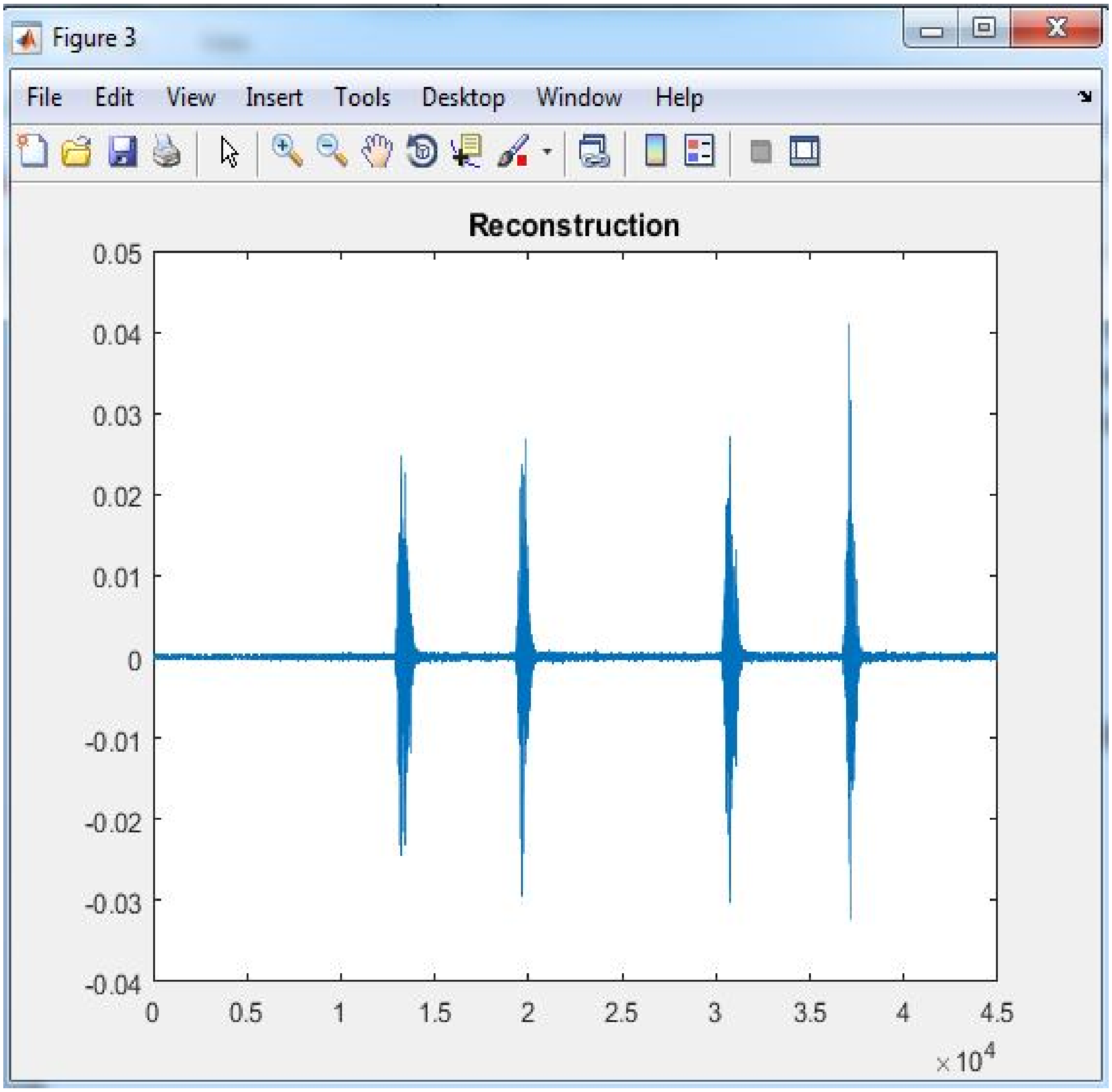


Figure (4.5): reconstruction of normal heart sound.

B.Reconstruction of abnormal heart sound

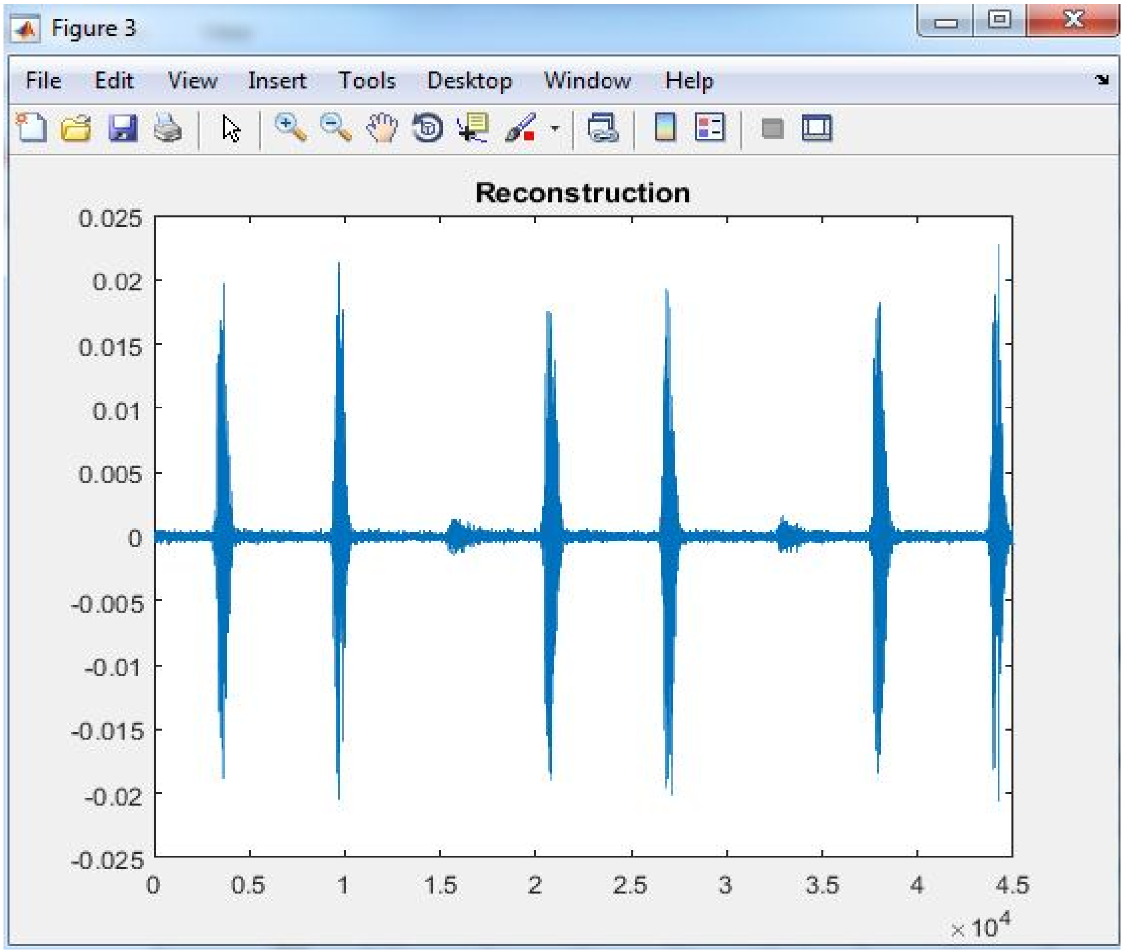


Figure (4.6): reconstruction of abnormal heart sound.

The figures interpret the other half of the wavelet transform, by how those components can be assembled back into the original signal with no loss of information. This process is called reconstruction, or synthesis. The mathematical manipulation that effects synthesis is called the inverse discrete wavelet transform (IDWT). The figures show how to combination wavelet coefficient through the summation of the original approximation coefficients of the last level (level5) and the modified detail coefficients of levels 2 to 5.

4.1.2.3 Thresholding

A.de-noising of normal heart sound signal

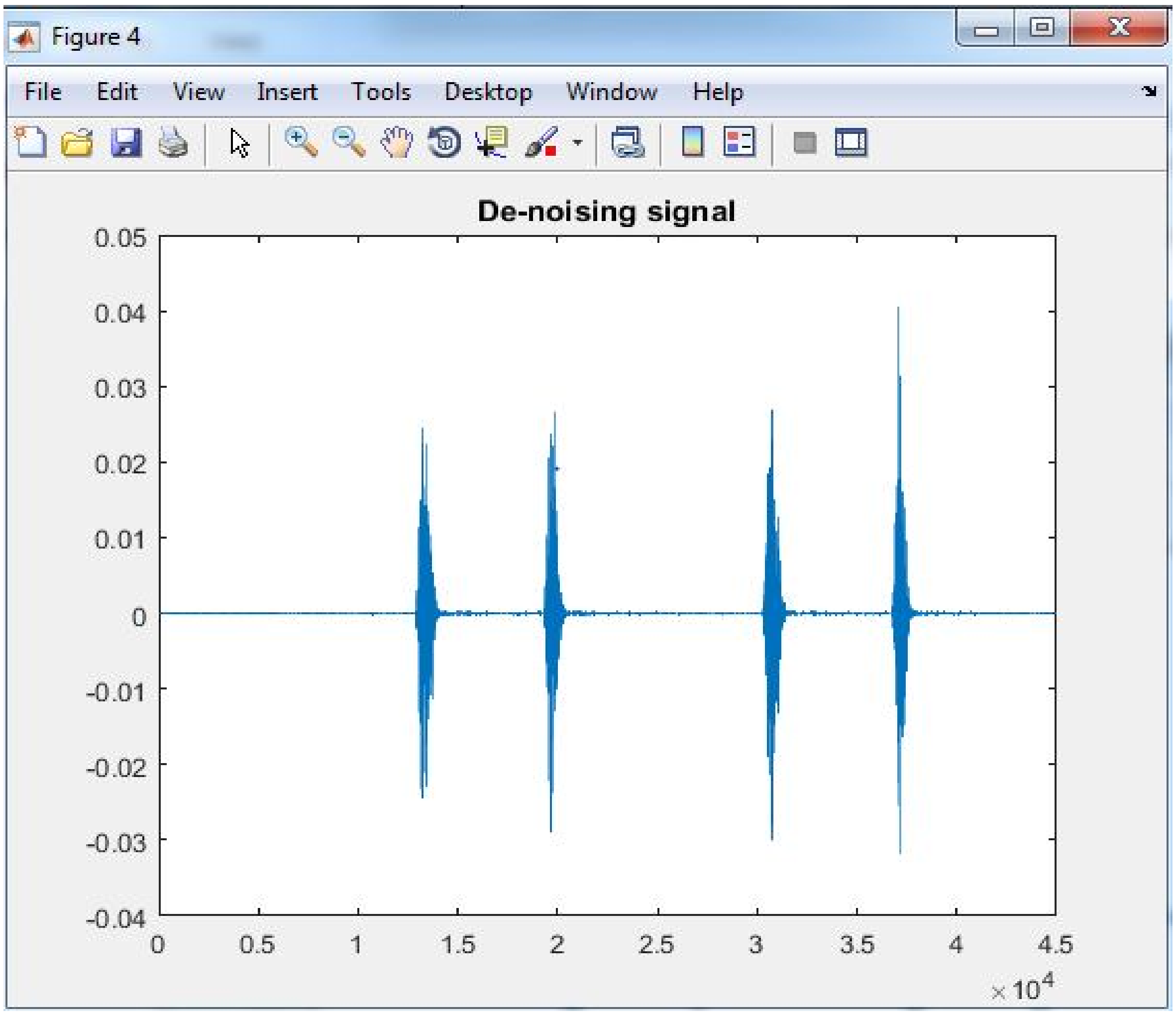


Figure (4.7):de-noised normal heart sound signal.

B. de-noising of abnormal heart sound

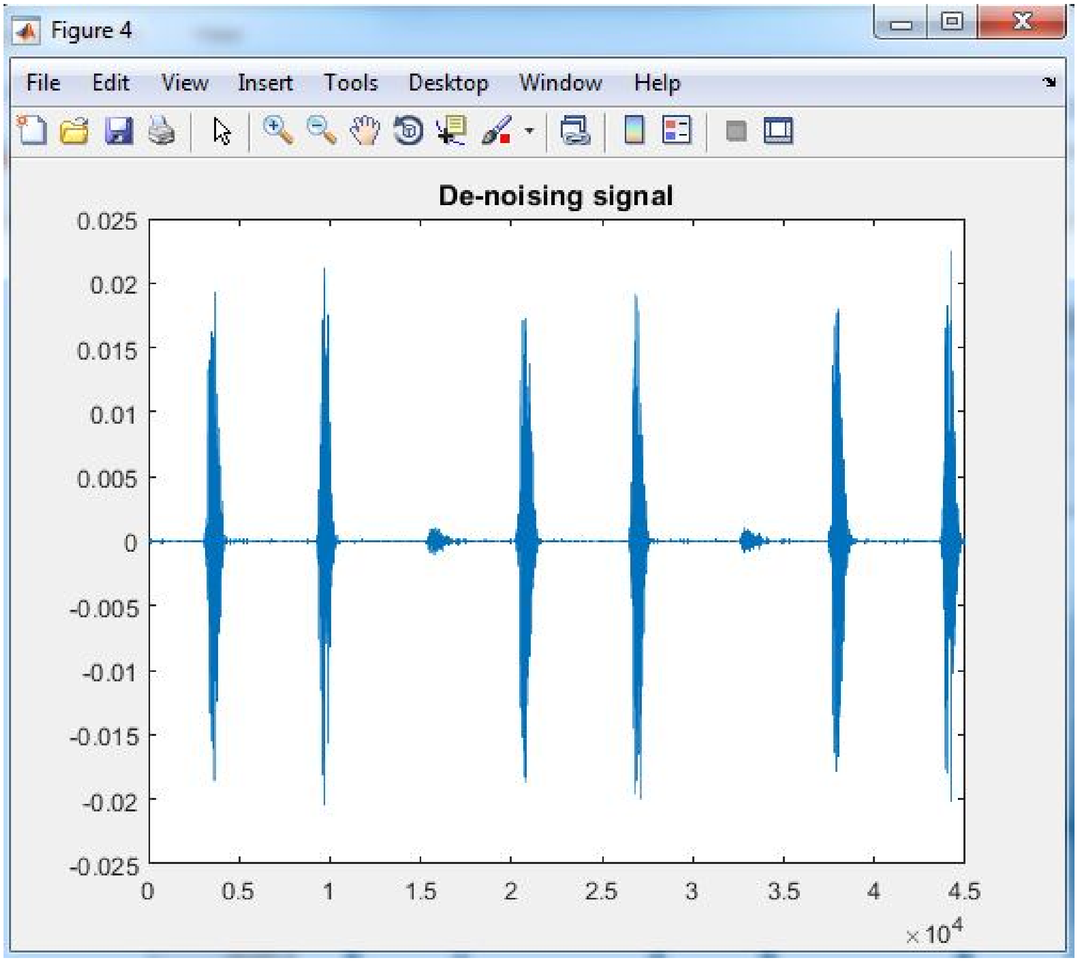


Figure (4.8):de-noised abnormal heart sound signal.

The method chosen here is the soft thresholding, where it produces better result than hard thresholding because it sets the elements whose absolute values are lower than the threshold to zero and then the nonzero coefficients remaining are shrunk and set to zero. This method achieve SNR=16.7085 and 17.0920 for normal and abnormal heart sound signal.

4.1.3 Features extraction

Graphical features

I. Spectrogram

A.Spectogram of normal heart sound

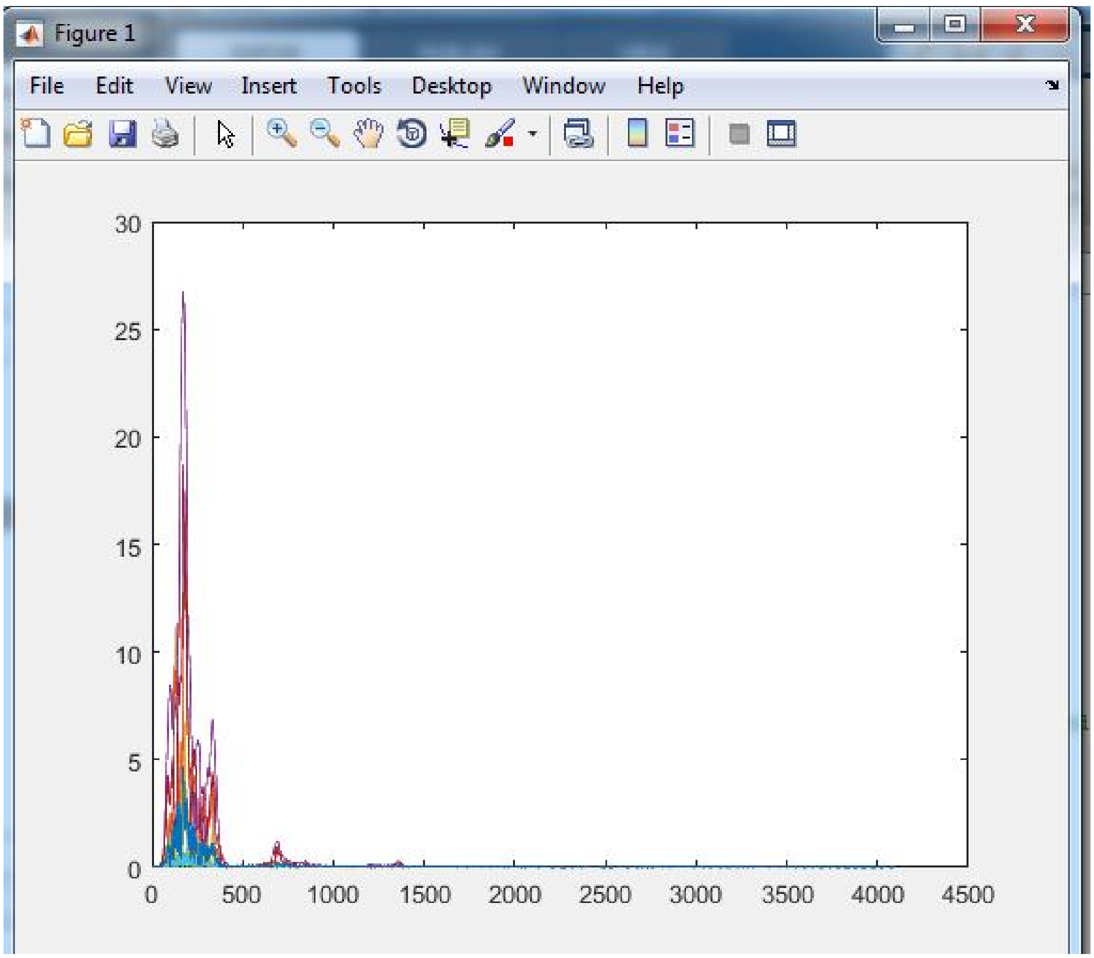


Figure (4.9): spectrogram of normal HSs signal.

B.spectogram of abnormal heart sound signal

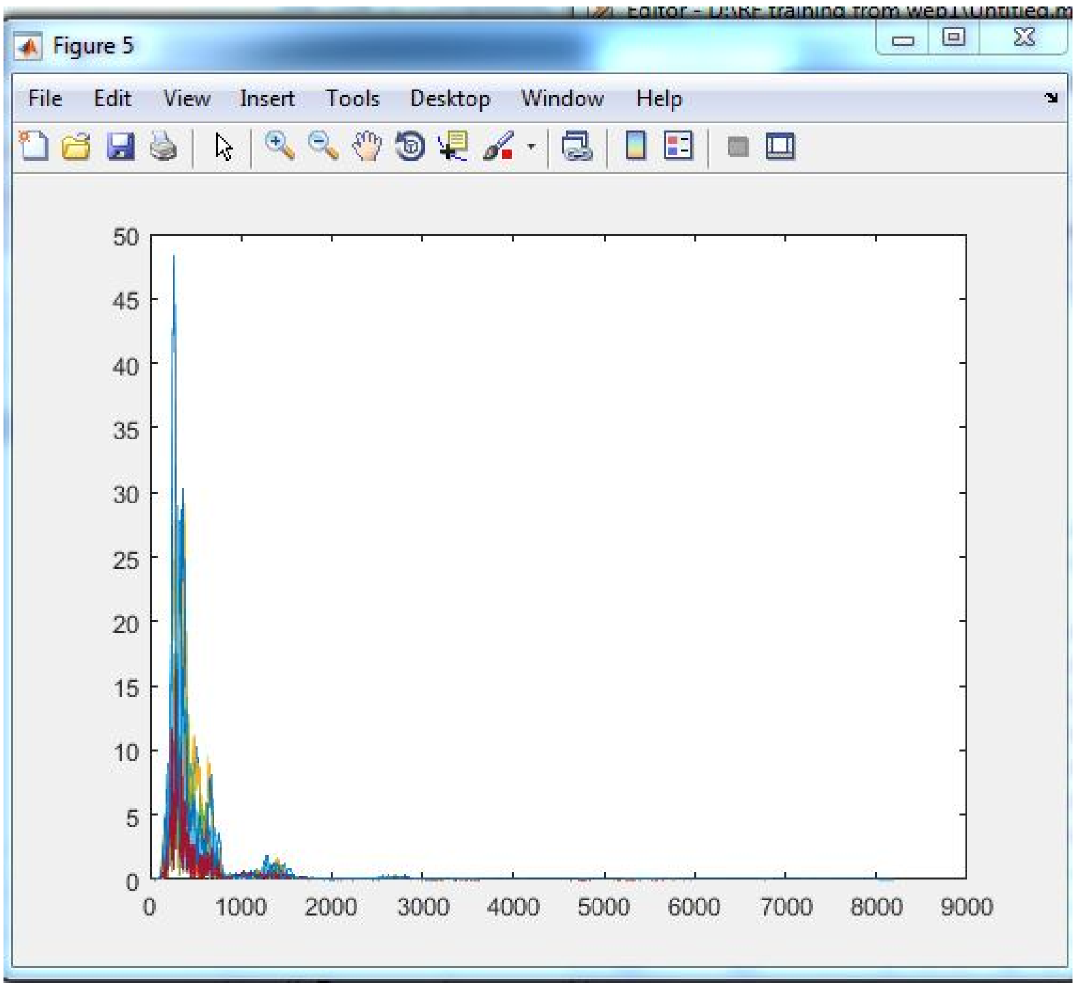


Figure (4.10): spectrogram of abnormal heart sound.

Spectrogram is a two dimensional graph, where horizontal axis represents time and vertical axis represents frequency. A third dimension indicating amplitude of a particular frequency is represented by the intensity or color of each point in the signal.

II. Power spectrum

A.power spectrum of normal heart sound

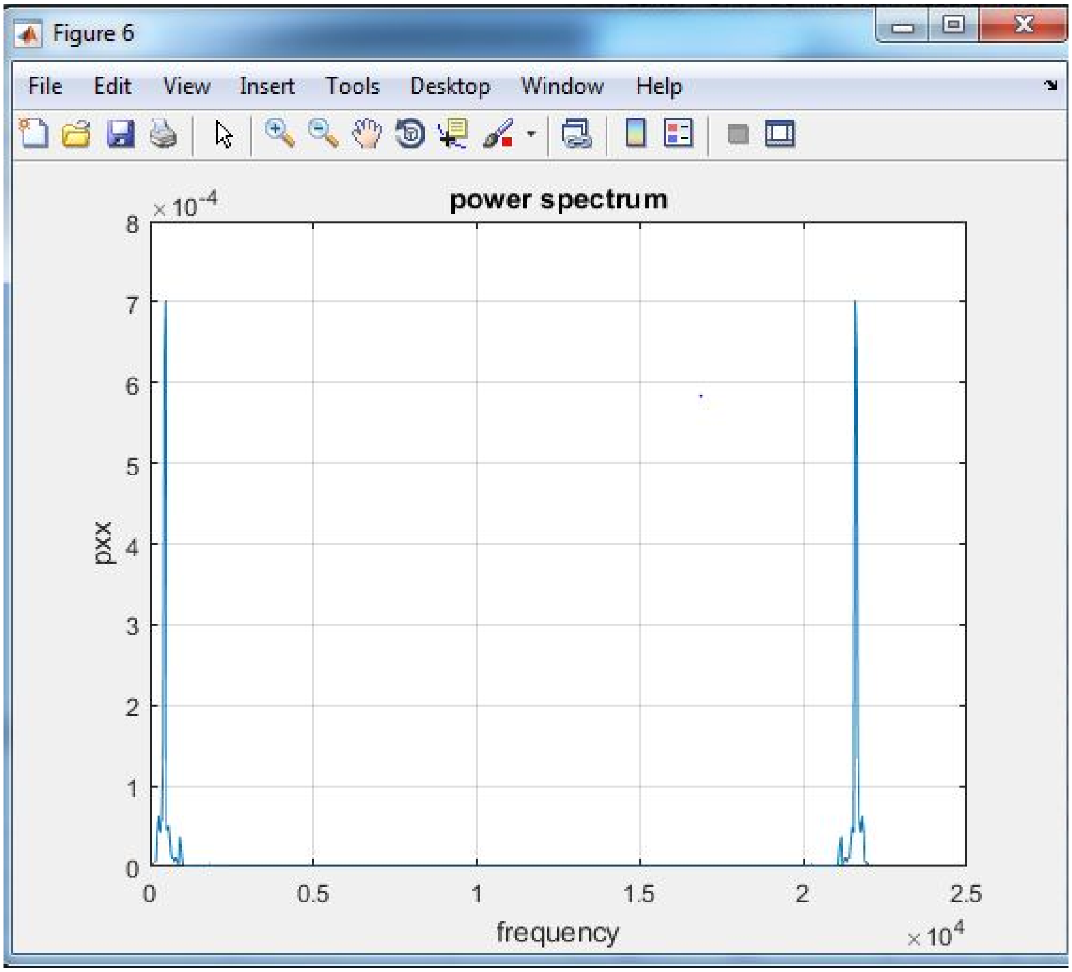


Figure (4.11): Power spectrum of normal heart sound signal.

B.power spectrum of abnormal heart sound

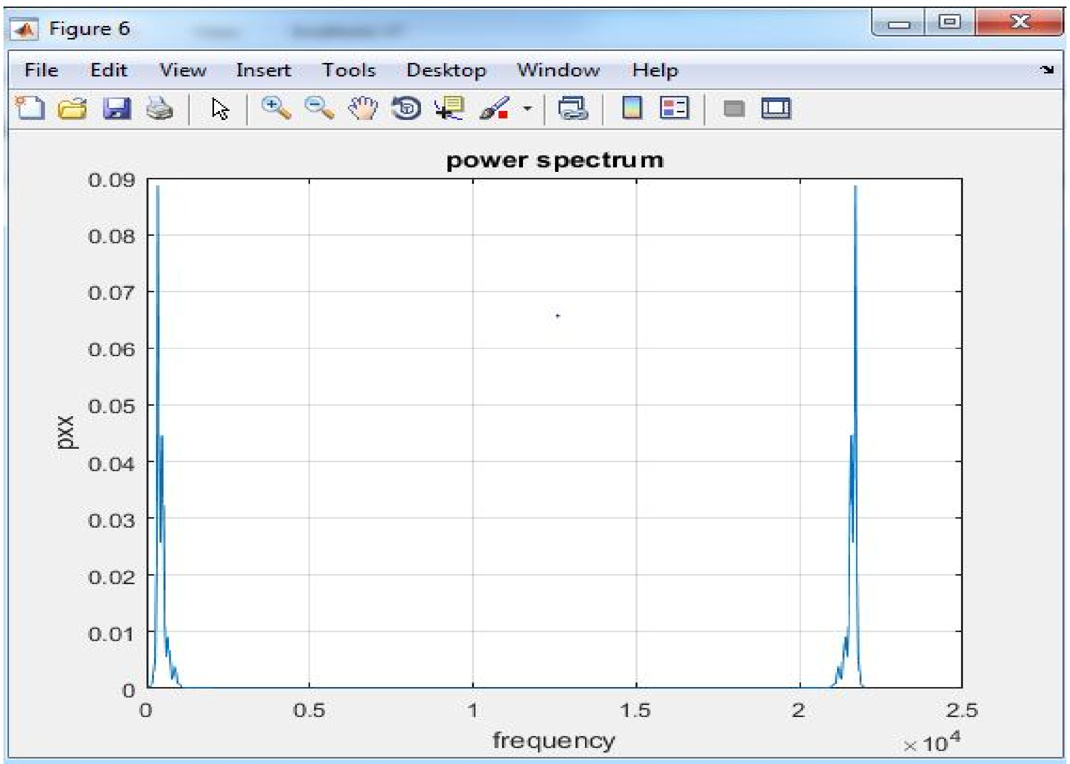


Figure (4.12): Power spectrum of abnormal heart sound signal.

The measurement of energy at the various frequencies, which called Power spectrum density, was extracted for normal &abnormal signal in figures (4.11) and (4.12) above.

III. Scalogram

A.Scalogram of normal HS signal.

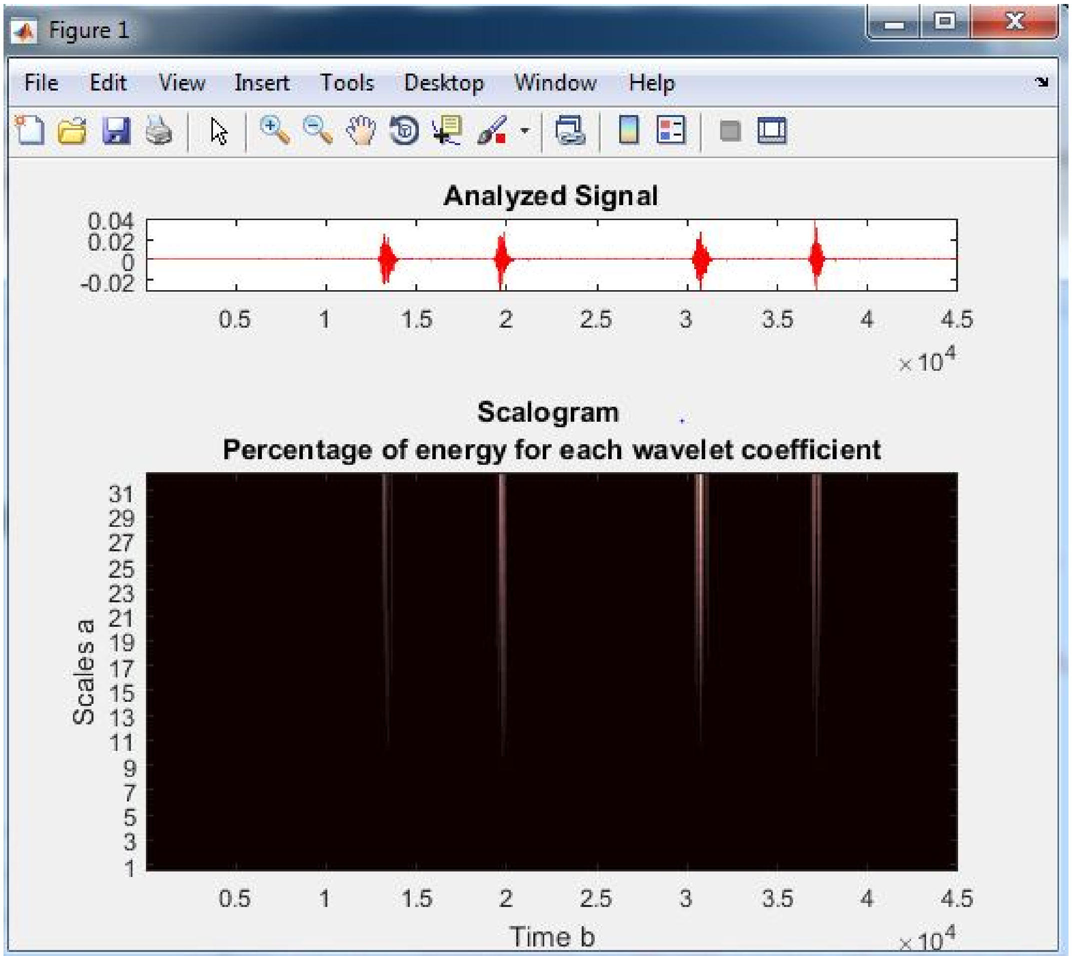


Figure (4.13): Scalogram of normal heart sound signal.

B.Scalogram of abnormal HS signal.

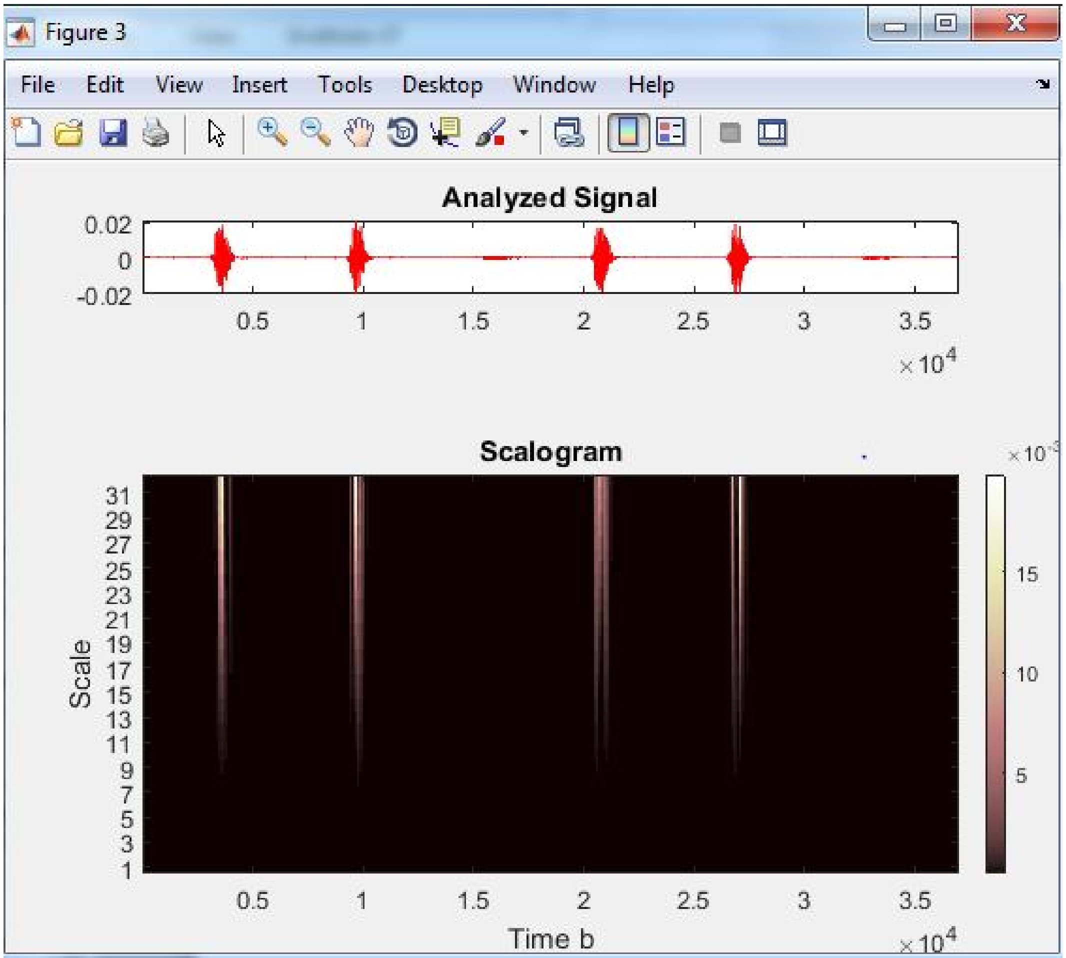
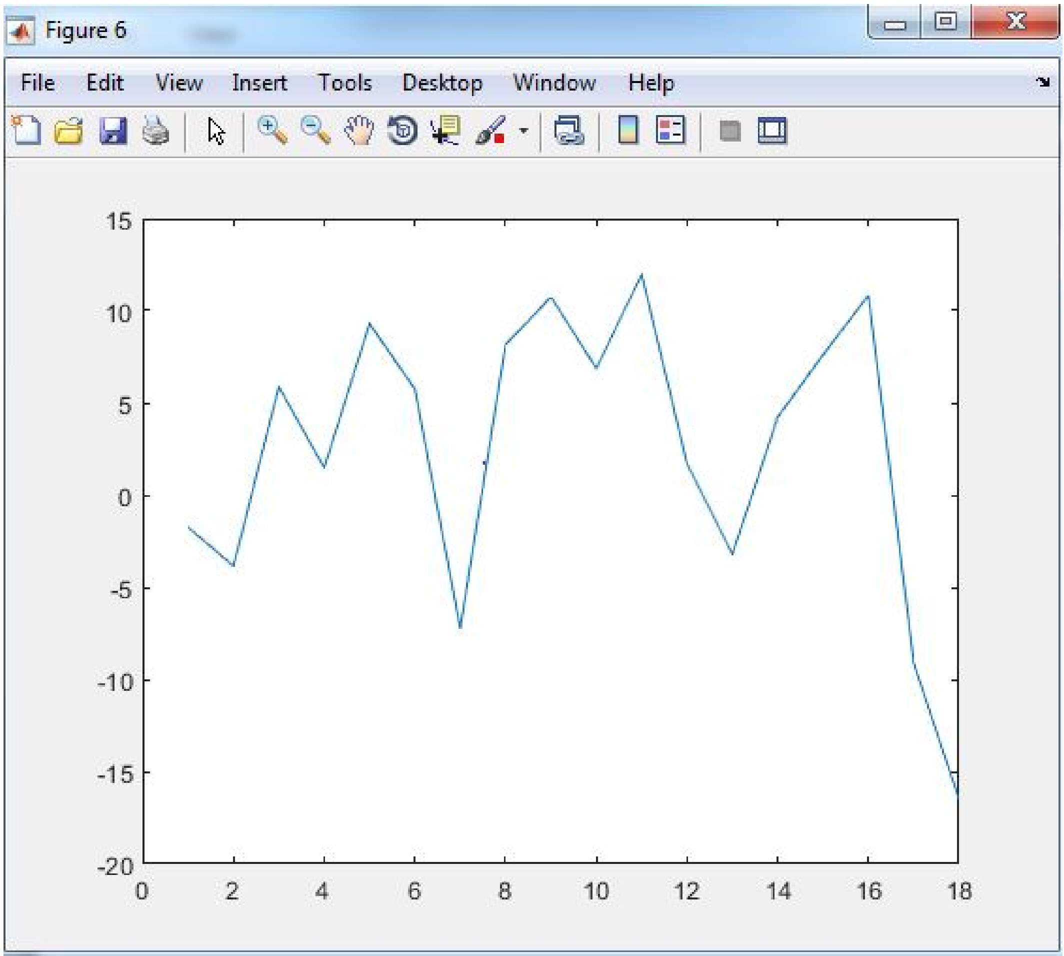


Figure (4.14): Scalogram of abnormal heart sound signal.

The Scalogram shows the percentage energy for each wavelet coefficients. The continuous wavelet transform was applied using the (morlet) as the mother function.

IV. MFCC

A.MFCC of normal heart sound



Figure(4.15):MFCCs for normal heart sound.

B.MFCC of abnormal heart sound

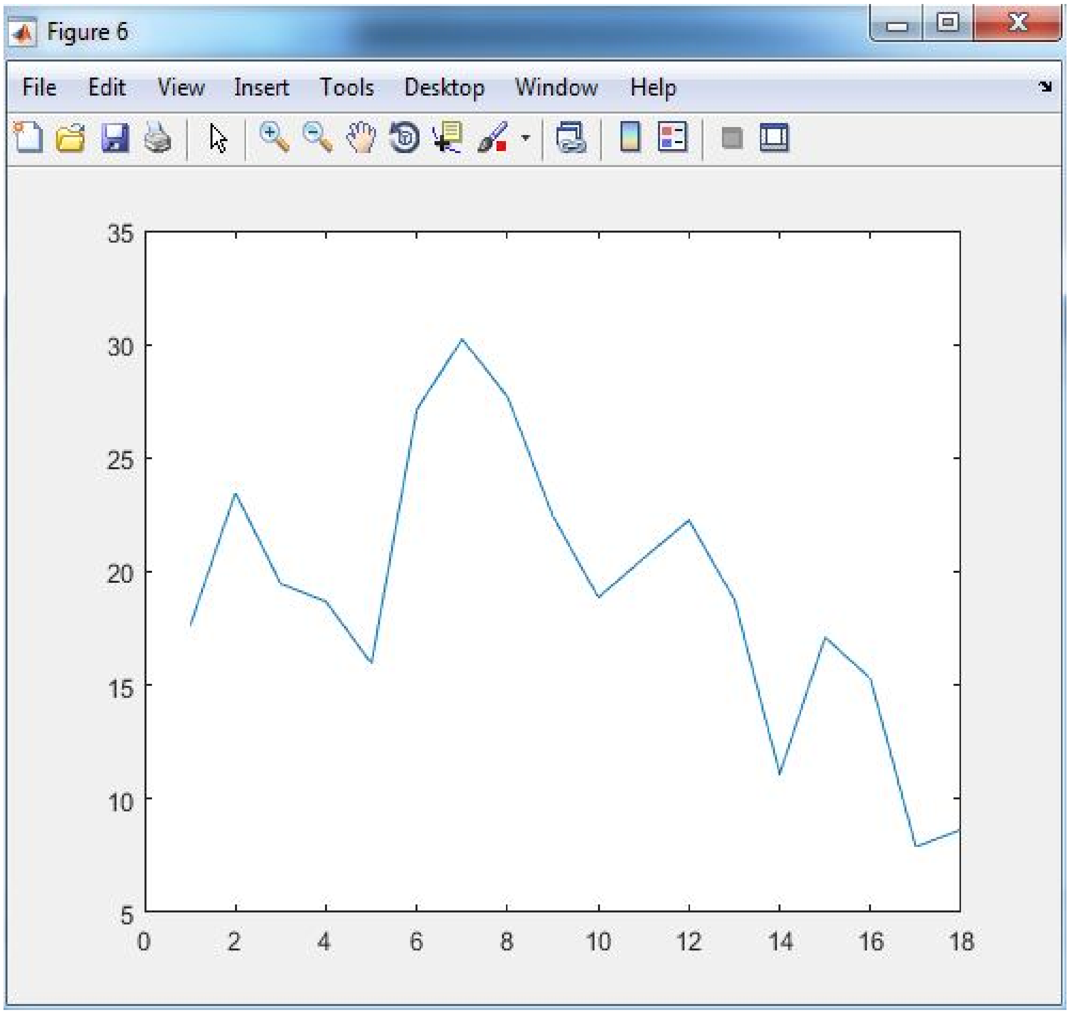


Figure (4.16): MFCCs for abnormal heart sound.

MFCC was applied for each segment; power spectrum of each coefficient was calculated using this method, and then the coefficients for each point of scale where summed .

4.1.4 Features selection

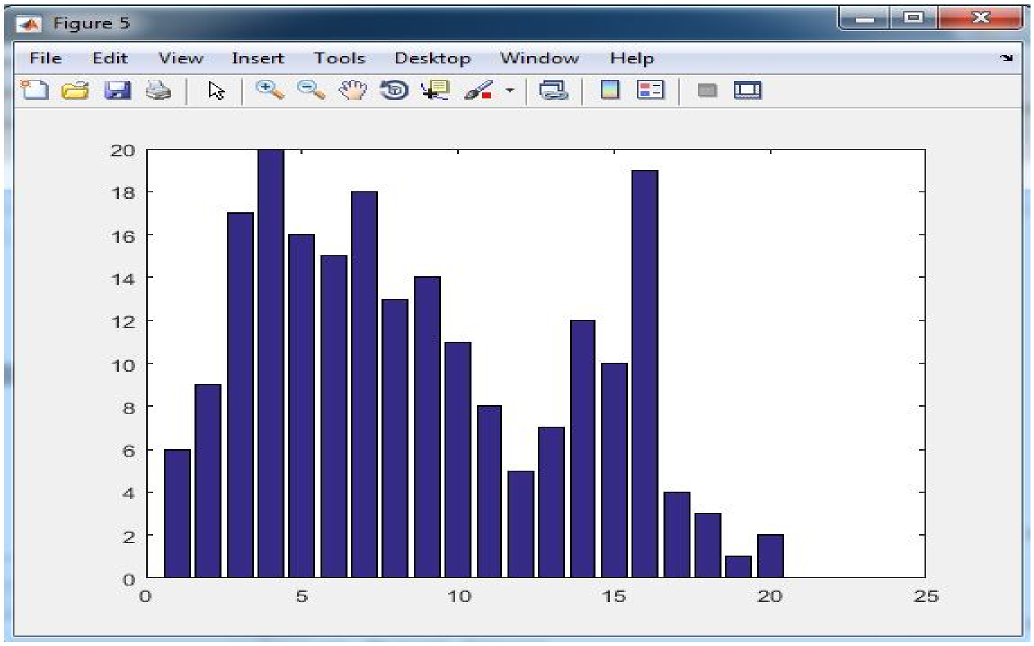


Figure (4.17): Histogram of features importance.

1. Correlation coefficients. 2. Covariance. 3. Maximum. 4. Mean. 5. Median. 6. Minimum.

7. Mode 8. Stander deviation 9.variance. 10. Kurtosis. 11. Skewness. 12. Entropy. 13. rms. 14.sum 15.sumsqr. 16. ZCR. 17. Power. 18. THD 19.meanfrequency. 20. Median frequency.

The above histogram shows the order for every feature was extracted from the signals. The Menfrequency,Medianfrequency, THD ,power,Correation coefficients, Covariance are the most importance features.

4.1.5 Classification

The Random Forest composed from 50 decision trees .the decision tree looks like the figure below :

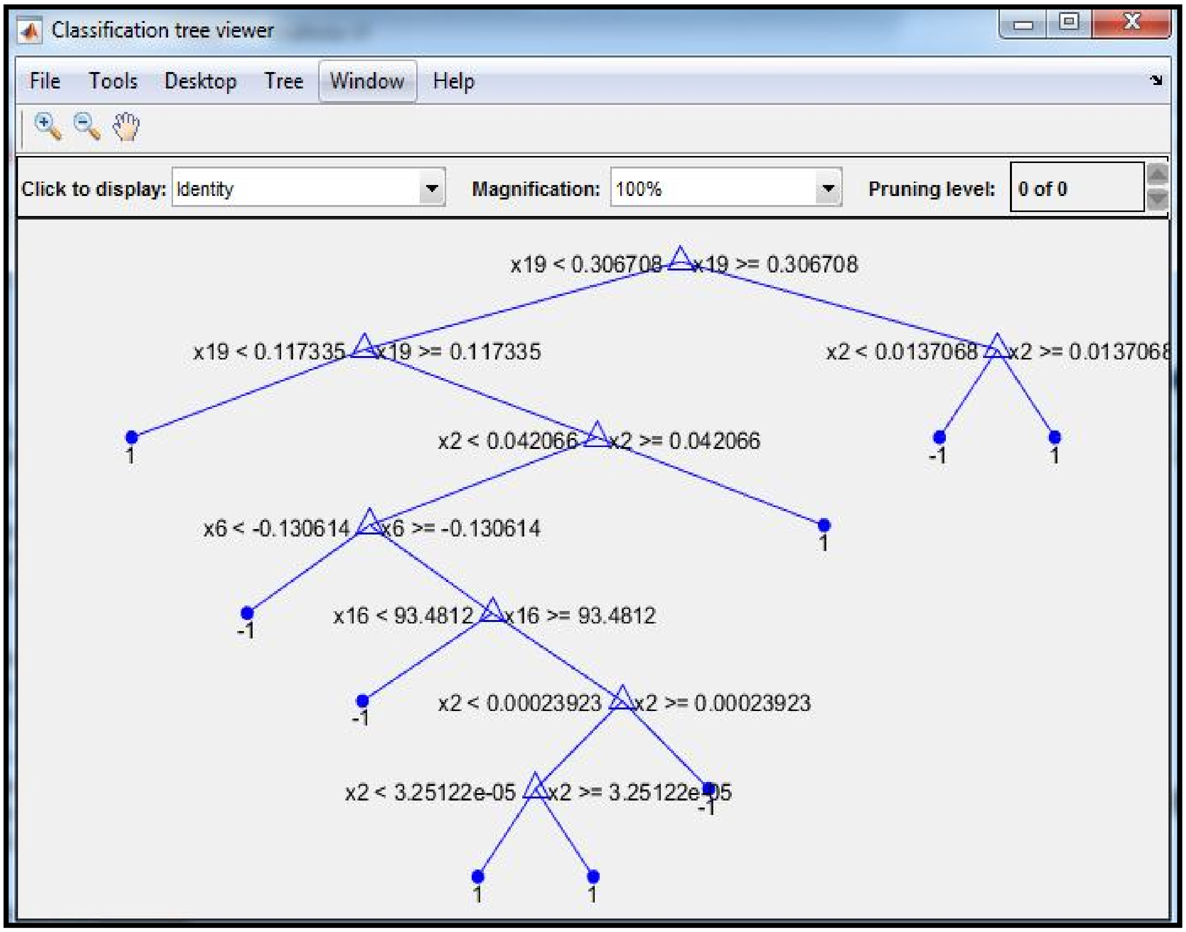
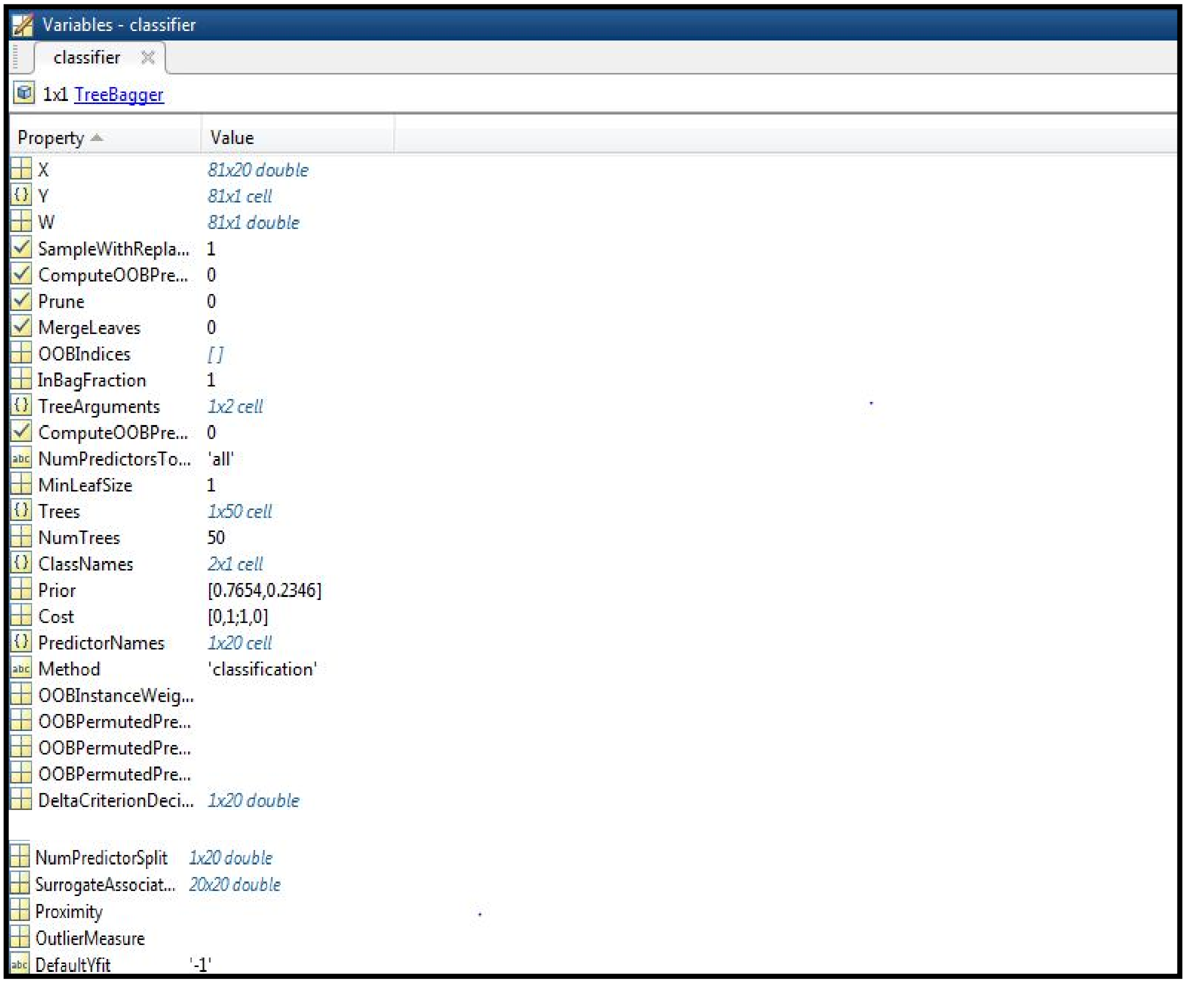


Figure (4.18): Sample of Decision tree from the random forest.

The Random Forests model specifications

The data consists from 100 samples, the training ratio=0.8, so the training data=81 samples and the testing data=19 samples.


Variables - classifier

classifier

1x1 TreeBagger

Property	Value
X	81x20 double
Y	81x1 cell
W	81x1 double
SampleWithRepla...	1
ComputeOOBPre...	0
Prune	0
MergeLeaves	0
OOBIndices	[]
InBagFraction	1
TreeArguments	1x2 cell
ComputeOOBPre...	0
NumPredictorsTo...	'all'
MinLeafSize	1
Trees	1x50 cell
NumTrees	50
ClassNames	2x1 cell
Prior	[0.7654,0.2346]
Cost	[0,1;1,0]
PredictorNames	1x20 cell
Method	'classification'
OOBInstanceWeig...	
OOBPermutedPre...	
OOBPermutedPre...	
OOBPermutedPre...	
DeltaCriterionDeci...	1x20 double
NumPredictorSplit	1x20 double
SurrogateAssociat...	20x20 double
Proximity	
OutlierMeasure	
DefaultYfit	'-1'

Figure (4.19): specifications of the random forest classifier.

The 10 folds accuracy and error rate:

```
Command Window

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 100.000
ErrorRate    = 0.000

Correct rate = 80.000
ErrorRate    = 20.000

Correct rate = 66.667
ErrorRate    = 33.333
```

```
finalRate =

    0.9324

>>
```

The system achieve final accuracy =

(100+100+100+100+100+100+100+100+80+66.66)/10=93.24%.

The classification time=0.105263157 sec.

4.2 Discussion

From literature reviews it was observed, the most recent studies have been applied in off line data.

Wavelet technique has proven its effective in signal processing as well as the method of random forests have advantages over the methods of another machine learning one of them it can be used to know the most important features as well as the classification process.

The random forests method does not need to select the most important features because it arranges the features automatically, the most important features place at the beginning of the decision tree and the less important features at the bottom of the tree .so it used in the process of **features engineering**.

The RF overcomes on the modified decision tree problem which includes:

- Small changes in input data can sometimes lead to large changes in the constructed tree.
- Even data that can be perfectly divided into classes by a hyperplane may require a large decision tree if only simple threshold tests are used.
- inadequacy in applying regression and predicting continuous values
- Possibility of spurious relationships
- Unsuitability for estimation of tasks to predict values of a continuous attribute
- Difficulty in representing functions such as parity or exponential size
- Possibility of duplication with the same sub-tree on different paths
- Limited to one output per attribute, and inability to represent tests that refer to two or more different objects.

The proposed system achieved accuracy of 93.24% for distinguishes between normal and abnormal signals.

Chapter V

Conclusion and Recommendations

5.1 Conclusion

The method proposed in this study is cost efficient as it requires minimal equipment and does not require ECG gating.

The system algorithm has been applied for offline data .In preprocess stage, the signal was filtered from noise, then the graphical and statistical methods were used to analysis the heart sounds and extract features to be applied in classification process, finally the random forests algorithm was used to classify heart sounds into normal and abnormal cases.

The method shown in this study can easily be implemented in the existing electronic stethoscope by interfacing it with the present embedded technology with the accuracy of 93.24%.

The random forests algorithm has proved its effectiveness and its ability to compete with other methods. In the future it can develop and perform well than other machine learning methods

5.2 Recommendations

The recommendations are to:

- Use large and reliable database by using electronic stethoscope.
- Other algorithms can be implemented for feature extraction and classification. The main objective could be to find the best algorithm suitable for heart sound processing.
- Using the graphical features in the classification process to increase the accuracy of the system.
- Improve the classification process by identify the abnormality cases that support the treatment decisions.
- In future, the proposed method can also be implemented in latest mobile phones and can be used for early detection of some common heart diseases.This method would be extremely useful for the developing countries and for rural health management as only the electronic stethoscope with embedded technology is required in this metho

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APPENDIX A

A1: Fourier Transform

The Fourier transform is only able to retrieve the global frequency content of a signal, the time information is lost. It's the most popular transformation, it's decomposes a periodic wave in to its component frequencies.

Defined as:

$$\boldsymbol{X(f) = \int_{-\infty}^{+\infty} x(t).e^{-2\pi jft}} \qquad \textbf{Equ (A.1).}$$

t= time parameter. f= frequency parameter.

Disadvantages:

- Not suitable for transient signals with sharp changes.
- Time information difficult to retrieve.

A2: Short time Fourier transforms:

It's calculates the Fourier transform of a windowed part of the signal and shifts the window over the signal. The short time Fourier transform gives the time-frequency content of a signal with a constant frequency and time resolution due to the fixed window length. This is often not the most desired resolution. For low frequencies often a good frequency resolution is required over a good time resolution. For high frequencies, the time resolution is more important. A multi-resolution analysis becomes possible by using wavelet analysis. The continuous wavelet transform is calculated analogous to the Fourier transform, by the convolution between the signal and analysis function. However the trigonometric analysis functions are replaced by a wavelet function.

Defined as:

$$\boldsymbol{X(t,f) = \int_{-\infty}^{+\infty}[x(t).\omega(t-t')].e^{2\pi jft}dt} \qquad \textbf{Equ (A.2).}$$

APPENDIX B

B1: Wavelet

A wavelet is a short oscillating function which contains both the analysis function and the window. Time information is obtained by shifting the wavelet over the signal. The frequencies are changed by contraction and dilatation of the wavelet function. The continuous wavelet transform retrieves the time-frequency content information with an improved resolution compared to the STFT [42].

B2.Daubechies Wavelets DbN:

This family consist the hear wavelet, db1, which is the simplest and certainly the oldest, it's discontinuous, resembling acquire form.The Hear wavelet is defined by:

$$\boldsymbol{\varphi(x) = 1\ if\ x = \epsilon[0, 0.5], \varphi(x) = -1\ if\ x\epsilon\ [0.5, 1] and\ 0\ if it\ not} :$$

The associated scaling function is the function:

$\boldsymbol{\varphi(x)}$ =1 if x ∈ [0, 1] and 0 if not [42].

Dbnproperaties:

- Symmetric.
- The regularity increase with order.
- The analysis is orthogonal.

B3.Three cases make wavelet the more useful

1- Wavelets constitute a mathematical "zoom" making it possible to simultaneously describe the properties of a signal on several timescales.

2- Wavelets create very simple algorithms that, due to their adaptability, are often more powerful and easy to tune than the traditional methods of functional estimation. The principle consists of calculating the wavelet transform of observations, then astutely modifying the coefficients profiting from their local nature and, finally, inversing the transformation.

3- Wavelets constitute a very competitive method. Due to generally very sparse representations, they make it possible to reduce the volume of information to be coded.

- In 1D the signal is decomposed into two: an approximation and a detail.

B4.Discrete wavelet transform

Discrete wavelet transform (DWT) uses filter banks to perform the wavelet analysis. The discrete wavelet transform decomposes the signal into wavelet coefficients from which the original signal can be reconstructed again. The wavelet coefficients represent the signal in various frequency bands. The coefficients can be processed in several ways, giving the DWT attractive properties over linear filtering [42].

Wavelet Defined as:

$$\boldsymbol{\gamma(s,\tau) = \int f(t)\varphi *_{s,\tau}(t)d(t)} \qquad \textbf{Equ (B.1).}$$

Inverse Wavelet Transform Defined as:

$$\boldsymbol{f(t) = \iint \gamma(s,\tau)\varphi_{s,\tau}(t)d\tau d(s)} \qquad \textbf{Equ (B.2).}$$

All wavelet derived from mother wavelet:

$$\boldsymbol{\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\varphi\left(\frac{t-\tau}{s}\right)} \qquad \textbf{Equ (B.3).}$$

B5.Wavelet Decomposition:

- A single level decomposition puts a signal through 2 complementary low-pass and high-pass filters.
- The output of the low-pass filter gives the approximation (A) coefficients, while the high pass filter gives the detail (D) coefficients.

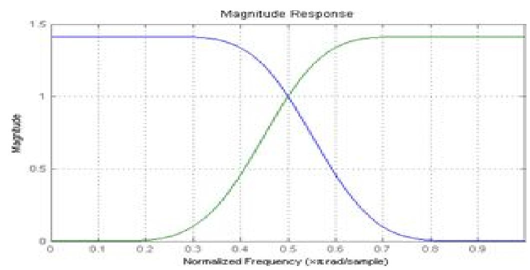

Figure (B.1): low and high pass filter.

B6.Wavelet Reconstruction:

The A and D coefficients can be used to reconstruct the signal perfectly when run through the mirror reconstruction filters of the wavelet family [38].

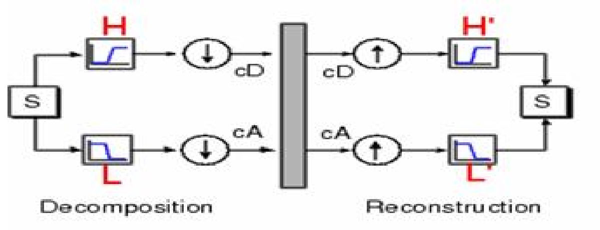

Figure (B.2): decomposition and reconstruction.

The **wavedec ( )** function performs 1D multilevel Discrete Wavelet Transform decomposition of given signal and returns ordered list of coefficients arrays in the form:

[cA_n, cD_n, cD_n-1... cD2, cD1]

Appendix C

Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, decision tree algorithm can be used for solving regression and classification problems too. The general motive of using Decision Tree is to create a training model which can use to predict class or value of target variables by learning decision rules inferred from prior data (training data)[24].

Assumptions while creating Decision Tree

The below are the some of the assumptions while using Decision tree:

- At the beginning, the whole training set is considered as the root.
- Feature values are preferred to be categorical. If the values are continuous then they are discretized prior to building the model.
- Records are distributed recursively on the basis of attribute values.
- Order to placing attributes as root or internal node of the tree is done by using some statistical approach.

The primary challenge in the decision tree implementation is to identify which attributes we need to consider as the root node and each level. Handling this knows the attributes selection. There are different attributes selection measures to identify the attribute which can be considered as the root note at each level[24]. The popular attribute selection measures:

Information gain.

Gini index.

C1.Information Gain

This method tries to estimate the information contained by each attribute. We are going to use some points deducted from information theory. To measure the randomness or uncertainty of a random variable X is defined by **Entropy[24]**.

For a binary classification problem with only two classes, positive and negative class. If all examples are positive or all are negative then entropy will be zero (low). If half of the records are of positive class and half are of negative class then entropy is one (high)[24].

By calculating entropy measure of each attribute we can calculate their information gain. Information Gain calculates the expected reduction in entropy due to sorting on the attribute. Information gain can be calculated[24].

C2.Gini Index

Gini Index is a metric to measure how often a randomly chosen element would be incorrectly identified. It means an attribute with lower gini index should be preferred[24].

C3.Decision Tree Algorithm Advantages and Disadvantages

Advantages:

- Decision Trees are easy to explain. It results in a set of rules.
- It follows the same approach as humans generally follow while making decisions.
- Interpretation of a complex Decision Tree model can be simplified by its visualizations. Even a naive person can understand logic.
- The Number of hyper-parameters to be tuned is almost null.

Disadvantages:

- There is a high probability of overfitting in Decision Tree.
- Generally, it gives low prediction accuracy for a dataset as compared to other machine learning algorithms.
- Information gain in a decision tree with categorical variables gives a biased response for attributes with greater no. of categories.
- Calculations can become complex when there are many class labels.