Classification of Heart Sounds Associated With Murmur for Automatic Diagnosis of Cardiac Valve Disorders

By

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(Bioinstrumentation)

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DECLARATION

I certify the work which is presented in dissertation entitled "**Classification of heart sounds associated with murmur for automatic diagnosis of cardiac valve disorders** in partial fulfillment of the requirement for the award **of Degree of Master of Science in Biomedical Engineering** submitted to school of Biomedical engineering, Jimma institute of technology is my own work carried under the guidance and supervision of Dr. Towfik Jemal and Dr. Bheema Lingaiah.

The matter contained in this dissertation has not been submitted neither in part nor in full to any other university or institute expect as reported in references.

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ABSTRACT

The heart is one of the vital organs and cardiovascular diseases have been a major cause of deaths in the world. The heart sound is till the primary tool for screening and diagnosing many pathological conditions of the human heart. Abnormal heart sound is one of the precursors of many serious heart diseases; heart failure, coronary artery disease, hypertension, cardiomyopathy, valve defects, arrhythmia. This study concerns only heart valve defects.

Cardiac auscultation is act of listening to heart sounds. Any abnormality in the heart sound indicates some problem in the heart. The abnormality in the heart sounds start appearing much earlier than the symptoms of the disease start showing. In this study, the PCG signal i.e. the digital recording of the heart sounds has been studied and classified into three classes, namely normal signal, murmur signal and extra sound signal. This study focuses on denoising of Phonocardiography signals using selected wavelet families, show superior signal denoising performance due to their properties of multi-resolution, including thresholding techniques, and signal decomposition levels. A total of 15 features from different domain have been extracted and then reduced to 7 features. The features have been selected on the basis of correlation-based feature selection technique. The selected features are used to classify the signal into the pre-defined classes using multi-class SVM classifier.

The performance of our denoising algorithm is evaluated using the signal to noise ratio, percentage root means square difference, and root mean square error. The experiment shows that the level of decomposition, types of wavelets and thresholding techniques are the most important parameters affecting the efficiency of the denoising algorithm. Better SNR values compared with references revealing that the 4th level of decomposition is the optimal level for signal decomposition. The performance of the classification result is evaluated using the parameters accuracy, specificity, and sensitivity. An accuracy of 97.96% is achieved using multiclass SVM classifier. Finally, comparison was done with other related studies to optimize the performance of the proposed algorithm.

Keywords: Auscultation, CFS, Denoising, DWT, Feature extraction, HS, PCG, SVM,

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ACRONYMS

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

Argmax............arguments of the maxima

BW……………Band Width

CART………….Classification Regression Tree

CBFS………….Correlation-Based Feature Selection

Coif……………Coiflets

CPA……………Cepstrum Peak Amplitude

CVD ....Cardiovascular Disorder

Db……………. Daubechies

DR…………….Dynamic Range

DSP…………….Digital Subtraction Phonocardiography

DWT…………..Discrete Wavelet Transform

ECG ……………Electrocardiography

FDR-……………Fisher Discriminant Ratio

FFT……………..Fast Fourier Transform

FR…………….Feature Reduction

HS…………….Heart Sound

IDWT…………..Inverse Discrete Wavelet Transform

LS-SVM………Least Square Support Vector Machine

MATLAB……… Matrix Laboratory

MLP-BP……….Multi-Layer Perceptron Back Propagation

NCD…………Non communicable diseases

PASCAL………..Partnership Among South Carolina Academic Libraries

PCG…………...Phonocardiography

PRD…………Percentage Root means square Difference

PWT…………. Packet Wavelet Transform

RBF…………...Radial Basis Function

RMSE………..Root Mean Square Error

SMOTE ……..Synthetic minority oversampling technique

SNR…………..Signal to Noise Ratio

S1…….……......first heart sound

S2……........….Second heart sound

STFT………….Short Time Fourier Transform

SVM……….....Support Vector Machine

Sym………… Symlets

THD………….Total Harmonic Distortion

WT………….Wavelet Transform

CHAPTER ONE

INTRODUCTION

1.1 Background

Heart disease is the main health problem and a primary cause of fatality all over the world. Phonocardiography, tracing of sounds produced by digital stethoscope, is a tool that leads to valuable information about the heart function and can be a great tool to identify abnormalities and heart disease early. Meanwhile, cardiovascular diseases become one of the leading risk factors for global mortality in modern society. Figure1.1 shows the proportion of non-communicable diseases deaths under the age of 70 years. Cardiovascular diseases are the largest proportion of non-communicable diseases deaths (51.45%), followed by cancers and chronic respiratory diseases. Cardiovascular disorder S (CVD) are the number one cause of death globally and more people die annually from CVDs than from any other causes [1].

All broad indications derived from a range of developing countries indicate an increasing burden imposed by cardiovascular disease [1][2]. Cardiovascular disorders are broad terms that can affect both vasculature and the heart muscle itself. In auscultation technique, a stethoscope is used for heart sound analysis to diagnose the condition of human heart generated by muscle contractions and closure of the heart valves produces vibrations audible as sounds and murmurs, which can be analyzed by qualified cardiologists [3]. The existing of murmur in PCG recording is often related to heart valve disease. Heart diseases include; heart failure, coronary artery disease, hypertension, cardiomyopathy, valve defects, and arrhythmia. This study concerns only heart valve defects. 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.

The heart sounds still the primary tool for screening and diagnosing many pathological conditions of the human heart, which is compound sound of mechanical vibration, and contains different parts of the heart. Conventional auscultation using acoustic stethoscope requires extensive training and experiences of the Physician for proper diagnosis. Moreover, the storage of records for follow-ups and future references is also not possible with conventional auscultation [4]. This is the driving force for this study in order to move towards automatic auscultation using electronic stethoscopes. In this study Phonocardiography will be used for heart condition monitoring which find its roots in auscultation. The method proposed in this study is not a replacement of the other techniques but an early indicator of the problem in order to prevent worsening of the situation. There is difficulty in performing conventional heart sound diagnosis. The main problem is difficulty of obtaining high quality, the differences in hearing sensitivity of each person, vast amount of experience to master heart auscultation skills [3].

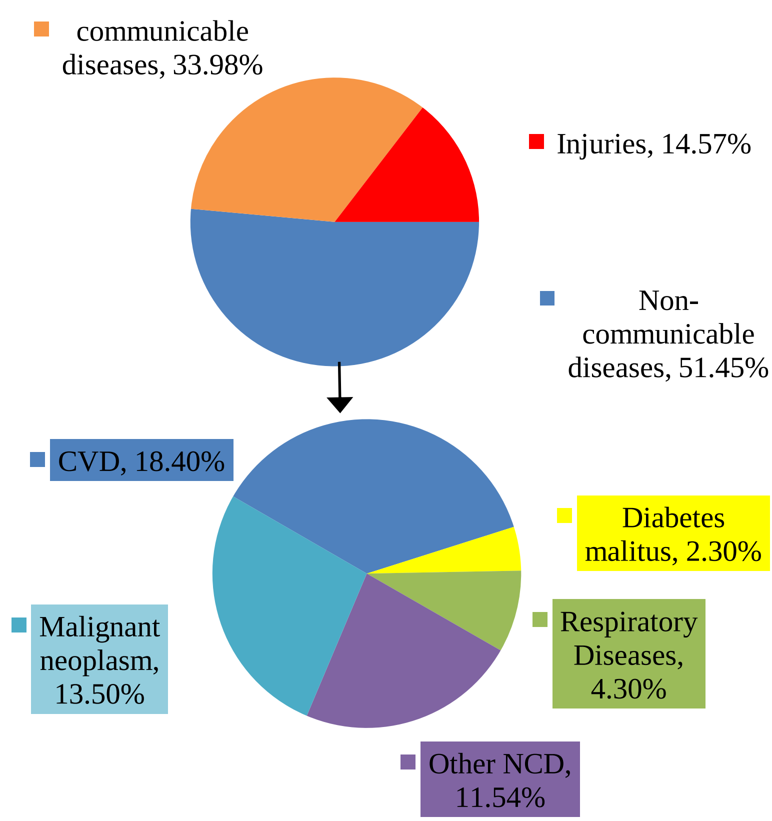

Figure1. 1 Proportion of global deaths under the age 70 years

It is a kind of important means to do research on various physiological signals for the diagnosis and treatment of disease. Thus testing and analysis of heart sound signals in the clinical medicine practice has important application value.

1.2 Statement of Problem

Cardiovascular diseases have been a major cause of deaths in the world. Hearing abnormal heart sound is very difficult, it may be necessary to listen for a long time to each component of the cardiac cycle at each location of auscultation. Artifacts and noises that can visually mask weak heart sounds, differences in hearing sensitivity of individuals, making reliable interpretations, and vast amount of experience to master heart auscultation skills are result of restrictions in classical auscultation techniques [3][5]. Developing how to distinguish the normal sound from the abnormal sounds, including heart murmurs by their frequency information will be a difficult but provocative problem for researchers. Thus, studying automatic detection of heart diseases is an important field of research, as computer-aided intelligent PCG-diagnostic system to obtain an accurate diagnosis of heart disease and to assist clinicians, with appropriate analysis of heart sound is needed.

Various methods were applied to preprocess, extract and classify the heart sounds by the previous researchers. Some of the methods Fourier transform and Different time-frequency representation methods were employed to represent the time frequency information present in the PCG signal, which include short time Fourier transform, wavelet packet transform, wavelet transform. But the Fourier transform is essentially an integral over time. Thus, it lose all information that varies with time and the problem of time and frequency resolution which is the result of the Heisenberg uncertainty principle constitutes a major challenge in the analysis of non-stationary signals [6]. Thus, there is a need to design an automated auscultation diagnosis system that can be helpful to obtain more objective and reliable diagnostic results based on heart sound classifications associated with murmur.

1.3 Objectives

1.3.1 General Objective

The general objective of this thesis is to develop a system for classification of pathological heart sounds associated with murmur for diagnosis of cardiac value disorder by using discrete wavelet transform and multi-class support vector machine learning algorithm.

1.3.2 Specific Objectives

1. To review the most potential heart sound denosing techniques. Particularly from DWT families.
2. To calculate the heart sound feature in different domains. i.e. time domain, frequency domain, and statistical features.
3. To verify and use the best feature selection mechanism for high dimensional data
4. To show SVM classifier is useful for classification of pathological heart sounds associated with murmur based on multiclass SVM.
5. To compare the accuracy level of this system to other previously related works.

1.4 Significance of the Study

The thesis aims to develop a more accurate heart sound classification which has clinical applications. The performance of the method is assessed based on the reference labels provided by the experts. Sensitivity and specificity are two statistical metrics to evaluate the performance of this method, while sensitivity represents the proportion of true positives that are correctly classified and specificity measures the proportion of true negatives results that are correctly classified. Denoising heart sound signals has an excellent ability to inform physicians about heart-related problems. Auscultation has immense potential in detecting heart problems at an early stage. Since auscultation requires tedious and rigorous training and auscultation skills can only be enhanced by experience, which is sometimes missing in the present scenario. This is because the diagnosis of heart diseases these days is completely dependent on modern techniques like echocardiogram and electrocardiography which give a better view of the problem. The abnormalities appear in heart sounds much before the symptoms of pathology start appearing.

So, if the science and art of auscultation are properly used then early detection of heart diseases and proper treatment can be done at an early stage and it would be a great breakthrough as only precautions and also very useful in case of other sophisticated techniques are difficult to implement.

Since PCG signals are an early indicator of heart problems so that before worsening of the problem, proper diagnosis can be done. So, the proposed method is not a replacement of the other techniques but an early indicator of the problem in order to prevent worsening of the situation. In this study, a classification method is proposed to separate normal and abnormal heart sound signals having murmurs without getting into the cumbrous process of segmenting fundamental heart sounds using ECG gating. This study, analyze PCG signals for normal and murmur heart sounds. This paper will have a good potential to help researchers who need to study heart diseases identification based on heart sounds (classifying normal heart sounds from pathological murmur) and also applicable for the development of portable devices.

1.5 Organization of the Thesis

This thesis consists of 6 chapters which have been introduced as follows to get an overview of the study carried out.

Chapter 1 is the introduction. In this chapter, the concept of auscultation has been discussed. Then the concept of phonocardiography has been introduced and discussed in detail. After discussing phonocardiography, objectives and significance of this study have been explained so as to get a better view of the problem. Then the outline of the thesis is given so as to get an overview of this study.

Chapter 2 is The Heart. In this chapter, the importance, structure, and working of the heart have been discussed. The mechanical system of the heart, heart sounds; murmurs and heart defects have been discussed. Some signal processing techniques which are more relevant for HS signal analysis also clearly discussed.

Chapter 3 is literature review. In this chapter, the researches that have been done by various researchers have been discussed. The contributions that have been made by various researchers in their studies on PCG signal have been mentioned. Comparison has also been made for the different methodologies used in various studies which are an input for our studies.

Chapter 4 is materials and methodology. In this chapter software and tools which have been used are mentioned. All the materials used in this research are discussed. The next subsection is dedicated to the methodology of this research. In the methodology section, signal acquisition and preprocessing, followed by feature extraction phase and feature reduction phase. Finally, the classification phase which categorizes the signals into three classes discusses.

Chapter 5 is results and discussion. In which the results obtained using the algorithm are discussed. It tells the rank of selected discreet wavelet families used for preprocessing and about the accuracy of this algorithm. Confusion matrix used to show the accuracy levels of the classifier is also indicated under this chapter.

Chapter 6 is the conclusion and future scope. In this chapter, the conclusion of this study has been mentioned. The improvements that will be done have also been discussed.

CHAPTER TWO

THE HEART

2.1 Importance

The heart is one of the vital organs of the human's body, which pumps blood through the blood vessels by repeated, rhythmic contractions. The importance of this organ can be judged from the fact that heartbeat is considered as the sign of life. If it is not beating the person is declared dead. The function of the heart is to circulate the blood, oxygenated blood is circulated to the body and deoxygenated blood is circulated to the lungs. So, it acts as the pump in order to provide oxygen to the whole body using blood as a medium which is necessary for survival. This oxygen is used by the body to convert carbohydrates of the food into energy which is necessary for proper functioning of the body. Also, it carries waste materials from cells and tissues. The carbon dioxide is collected from cells and the deoxygenated blood is circulated to the lungs for purification. The oxygenated blood is circulated to each and every cell of the body [7].

2.2 Anatomy of the Heart

The heart is contained in the pericardium, a membranous sac consisting of an external layer of dense fibrous tissue and an inner serous layer that surrounds the heart directly [8]. It composes of four chambers and four heart valves. The four chambers of the heart are right atrium, right ventricle, left atrium, and left ventricle.

The upper chambers are thin walled chambers called the right atrium and left atrium and the lower chambers are the right ventricle and left ventricle. The walls of the left ventricle are approximately three times as thick as the right ventricle to withstand high pressures during contractions for pumping blood to the rest of the body [8].

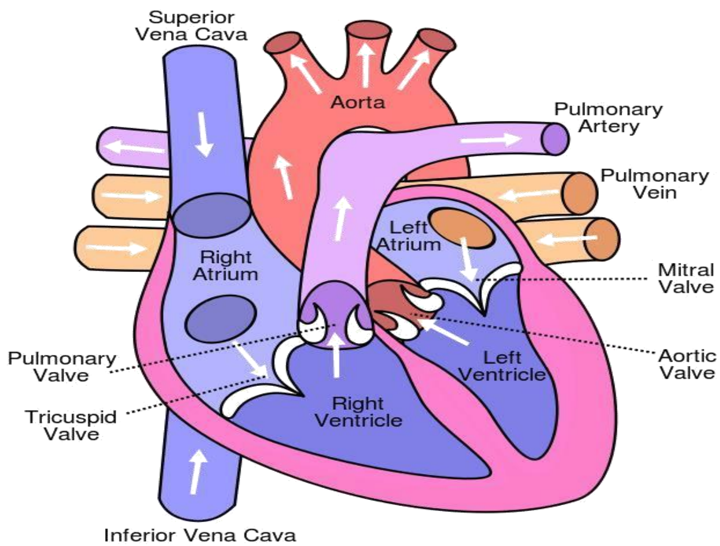

Figure2. 1 Anatomy of human heart [9]

The left atrium is smaller than right atrium. The two sides of the heart are separated by the septum which is the dividing wall of tissue. It also consists of four valves out of which two are atrioventricular valves and two are semilunar valves. These four valves are as follows: mitral or bicuspid valve, tricuspid valve, aortic valve, pulmonary valve. The left atrium is joined to the left ventricle through the mitral valve, which is sometimes called as the bicuspid valve since it consists of two cusps. Similarly, the right atrium is joined to the right ventricle through tricuspid valve [9]. The aortic valve is present between the left ventricle and aorta for one way flow of blood i.e. from the left ventricle to the aorta in order to supply oxygenated blood to the body. Similarly, pulmonary valve is present between the right ventricle and pulmonary artery for unidirectional flow of blood from right ventricle to pulmonary artery which carries deoxygenated blood to lungs for gaseous exchange. Blood enters the right atrium through two main veins: Superior Vena Cava (which takes blood from the body's upper extremities) and Inferior Vena Cava (which takes blood from extremities below the heart) [7].

2.3 Physiology

This section is dedicated to the study of the functioning of the heart. The heart function is as a pump. It contracts and relaxes during its functioning as a pump. When the heart contract, blood is forced through the valves, from the atria to the ventricles and eventually out to the body. The two atria mainly act as collecting reservoirs for blood returning to the heart while the two ventricles act as pumps to eject the blood to the body [8].

2.3.1 Normal Physiology

Deoxygenated blood from the body enters the right atrium, passes into the right ventricle and is ejected into the pulmonary artery on the way to the lungs. Oxygenated blood from the lungs re-enter the heart in the left atrium, passes into the left ventricle and is then pumped to the body through the aorta. The blood pressure within a chamber increases as the heart contracts, generating a flow from higher pressure areas towards lower pressure areas. This is the basis of the functioning of the heart. As atria contract, a high pressure is created in the atria which opens the atrioventricular valves and hence blood rushes to ventricles having low-pressure [8].

The heart's job is to pump blood around the body, divided into two major parts: systole and diastole. Systole is defined as a period of contraction of heart muscles, especially the ventricular muscle, at which time the blood is pumped into the pulmonary artery and the aorta. Diastole is the period of dilation of the heart cavities as they fill with blood [8]. During the rapid filling phase (atrial and ventricular diastole), venous blood from the body and from the lungs enters the atria and flows into the ventricles. As the pressure gradient between the atria and the ventricles level out. A final volume of blood is forced into the ventricles by atrial contraction (atrial systole). At the beginning of ventricular systole, all the valves are closed resulting in an isovolumic contraction. When the pressure in the ventricles exceeds the pressure in the blood vessels, the semilunar valves open allowing blood to eject out through the aorta and the pulmonary artery. As the ventricles relax the pressure gradient reverses, the semilunar valves close and a new heart cycle begins [8][10].

2.3.2 Abnormal Physiology

The functioning of the heart can be disrupted because of many reasons. The problem could be genetic or developed with time. Deoxygenated blood from the body enters the right atrium, passes into the right ventricle and is ejected into the pulmonary artery on the way to the lungs. Oxygenated blood from the lungs re-enter the heart in the left atrium, passes into the left ventricle and is then pumped to the body through the aorta. The genetic problem could be that the septum or muscular partitioning of the ventricles could have a hole. So, mixing of blood from left (oxygenated) and a right (deoxygenated) ventricle takes place and hence causes improper functioning of the heart. This is called a septal defect. The non-genetic problem could be due to calcination of valves or due to cholesterol deposition and hence causes thickening of the valves. This impedes the normal blood flow and is a major cause of acquired heart diseases. Leaking valve could also be the reason for heart disease. Sometimes the valves do not close properly and blood leaks back into the atrium [10].

2.4 Mechanical system of heart sound

2.4.1 Physics heart sound

Before studying the heart sounds, it is important to study the basic underlying acoustic phenomenon or the physics of sound. A sound is generated by a vibrating object and propagates as a wave of alternating pressure. The vibrating source sets the particles in motion with the frequency of that tone. Each particle is thus moving around its resting point, but as it pushes nearby particles they are also set in motion and this chain effect results in areas of compression and rarefactions. The alternating areas of compression and rarefaction constitute a pressure wave that moves away from the sound source. These pressure variations can be detected via the mechanical effect they exert on some membrane (the diaphragm of the stethoscope) [11][12].

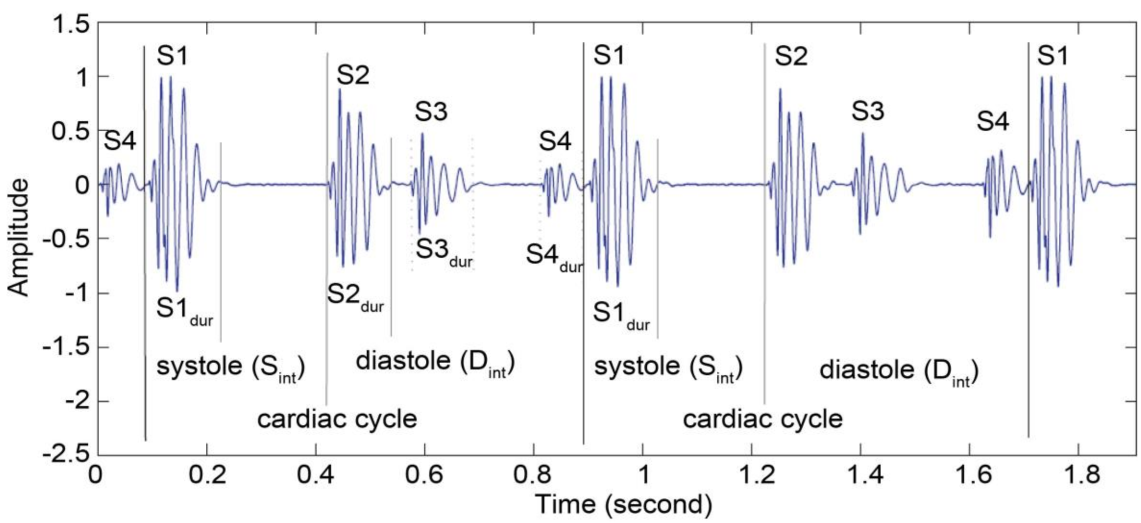

Figure2. 2 PCG heart sound signal

2.5 Heart Murmurs

These are long strings of noise that can't be termed as a single sound is termed as Murmurs. Murmurs are caused by the blood turbulence which is capable of producing a sound that can be heard using a stethoscope. The murmurs can be termed as the indicators to various heart problems [13]. If some extra blood turbulence is created that means the blood is flowing through a few extra small openings, other than just passing through the valves.

About cardiac murmurs, it is widely accepted that the turbulence of cardiac abnormalities causes all murmurs. There are three basic ways that turbulence occurs: the high rate of flow through normal or abnormal orifices, blood flow into a dilated vessel or chamber, and backward flow through an incompetent valve or septal defect. Nevertheless, there are some murmurs which are not pathological.

Innocent heart murmurs are sounds made by the blood circulating through the heart's chambers and valves or blood vessels near the heart or heart valves. There are two cardiac murmurs, which are systolic murmurs and diastolic murmurs. The classification is based on the position of murmur respect to the first heart sound and the second heart sound. Systolic murmurs occur between s_1 and s_2 while diastolic murmurs occur afters_2. Because of the huge abnormalities that can exist in cardiac structures, cardiac murmurs show a large amount of information[14].

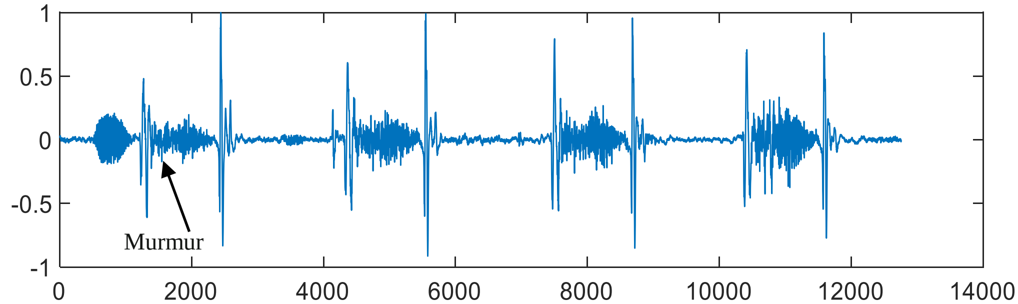

Figure2. 3 PCG signals showing occurrence of murmurs

2.5.1 Causes of Murmurs

The problem causing murmurs could be congenital or developed with time. The congenital problem could be that the septum or muscular partitioning of the ventricles could have a hole. So, mixing of blood from left (oxygenated) and right (deoxygenated) ventricles take place and hence cause improper functioning of the heart. This is called a septal defect. This leaking of blood from small hole present on the septum causes blood turbulence and hence the murmurs.

The non-genetic problem could be due to calcination of valves or due to cholesterol deposition and hence causes thickening of the valves. This impedes the normal blood flow and is a major cause of acquired heart diseases. Leaking valve could also be the reason for heart disease. Sometimes the valves don't close properly and blood leaks back into the atrium. This impedes the normal functioning of the heart. These reasons can also cause blood turbulence and hence the murmurs [14][15].

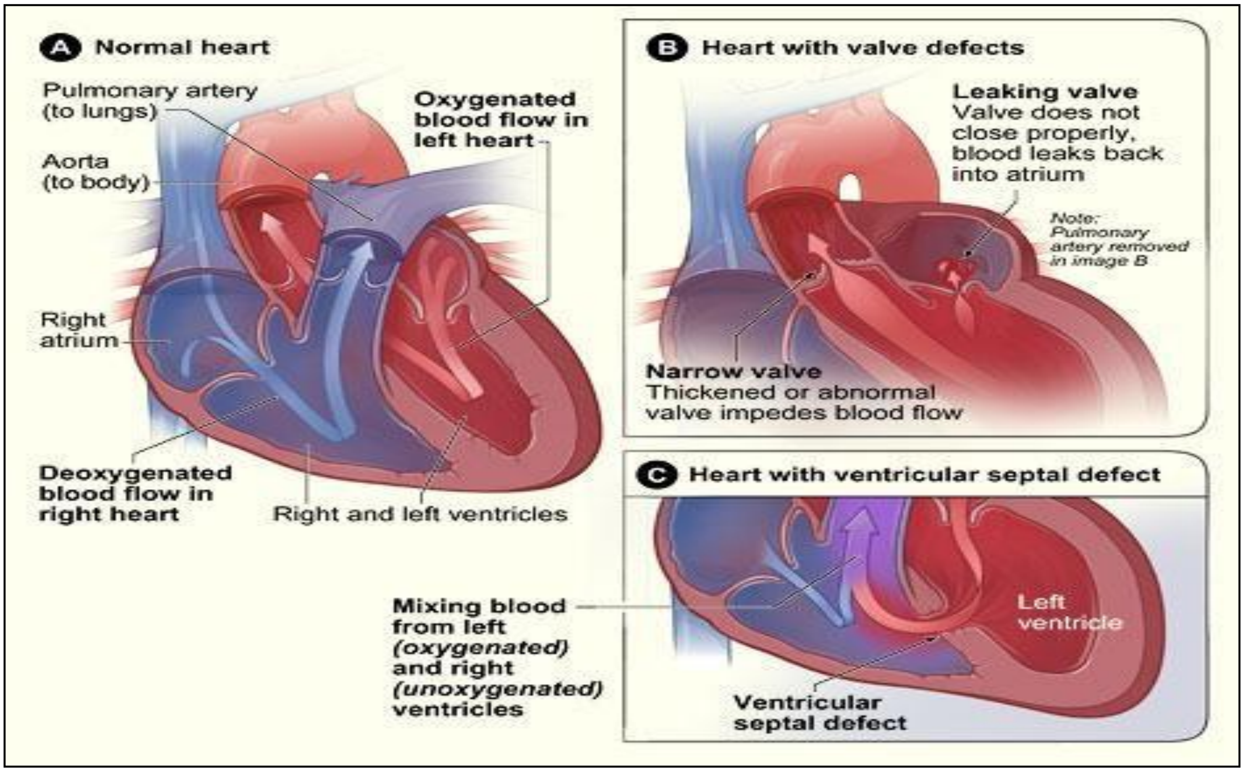

Figure2. 4 Causes of Heart Murmurs [14]

2.4.2 Theories behind the origin of heart sounds

The origin of heart sound studied by two fundamental theories; valvular theory, the heart sound production associated valvular events such as closing and opening with the major audible components of the heart sound and cardio hemic theory, the heart sound production associated vibrations of the entire cardio hemic system: heart cavities, valves and blood.

Nowadays, it is understood that the heart sounds result from the interplay of the dynamic events associated with the contraction and relaxation of the atria and ventricles, as well as the valve movements, and blood flow. Most investigators agree that the sounds are not produced by clapping together of the valve leaflets. Instead, the sudden deceleration of blood flow, resulting from the valve closure, and the tensing of the leaflets to their elastic limits set the entire cardio hemic system into vibration

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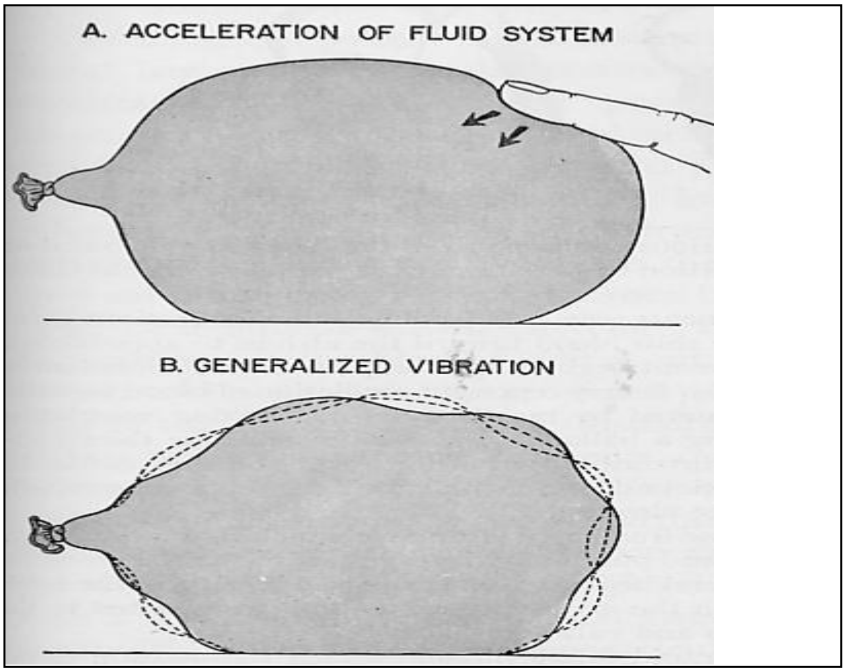

Figure2. 5 Basics of Heart Sounds [16]

The blood flow is normally laminar in nature but when the blood passes through a small opening or has some obstruction in its path then the flow becomes turbulent. That is the reason behind the fact that when blood passes through the valves which are small openings. The blood flow becomes turbulent. Because of this turbulence along with the vibrations caused by the closure of heart valves results in the vibrations of the heart and the blood as an interdependent system. These vibrations according to cardiohemic theory are believed to be the basis of heart sounds. The normal heart sounds are s_1, the heart sound that occurs with ventricular systole and is produced mainly by the closure of the atrioventricular valves. s_2, the heart sound that signifies the beginning of diastole and is caused by the closure of the semilunar valves. s_3, The heart sound that occurs in early diastole and corresponds with the first phase of rapid ventricular filling and s_4, The heart sound occurring in late diastole, corresponding with atrial contraction [17]. The region between $s_1$and s_2 is termed as systole. The region between s_2 and next cycle's s_1 is termed as diastole. Systole is smaller than diastole. Out of these four, the dominant two are $s_1$and s_2 are commonly known as fundamental heart sounds. These two sounds are mainly audible sounds, which are called "lub" and "dub" in common terminology. In medicine, we call the lub sound as s_1 and the dub sound as s_2. The normal heart rates at rest are 60 to 100 beats (“lub dub” s) per minute.

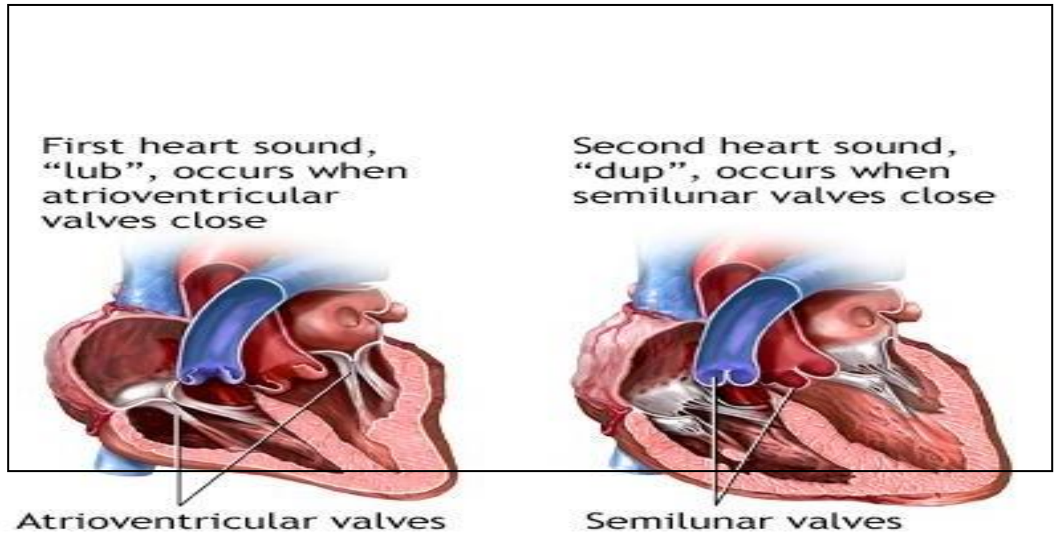

Figure2. 6 Mechanical actions producing Fundamental Heart Sounds [18]

2.6 Auscultation to phonocardiography

Auscultation is basically the act of analyzing sounds in the body that are produced in response to mechanical vibrations generated in the organs. It is an art and science of listening to the heart sounds and properly analyzing them to find the underlying problem. It requires immense experience and practice in order to properly diagnose the problem just by listening to the heart sounds. There are specific areas where the heart sounds are best heard, which are called auscultation sites [19].

The important auscultation sites are mitral area, the cardiac apex, tricuspid area; the fourth and fifth intercostal space along the left sternal border, aortic area; the second intercostal space along the right sternal border and pulmonic area; the second intercostal space along the left sternal border.

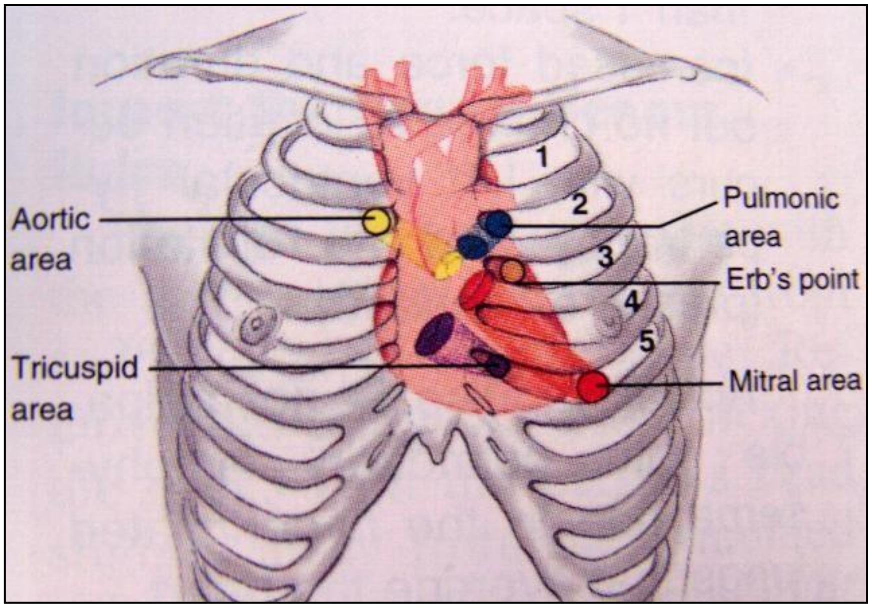

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Figure2. 7 Auscultation Sites [19]

The particular heart sounds are best heard at auscultation sites which are decided on the basis of their area of origin. For example, the low-pitched s_1 is best heard at the mitral auscultation site as it is caused by the closure of mitral and tricuspid valves and shorter duration but louder sound s_2 is caused by aortic and pulmonary valve closure and is best heard over the aortic auscultation area.

2.7 Equipment required for Auscultation

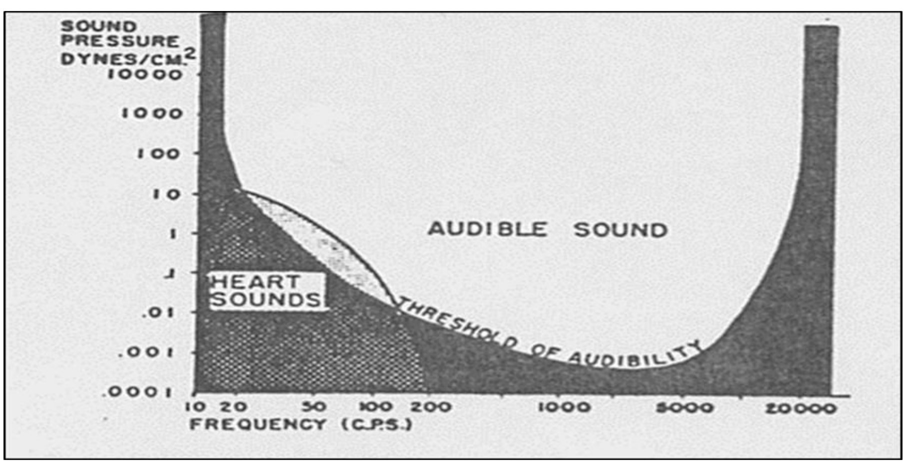

Figure2. 8 Audibility of Heart Sounds [16]

Heart sounds are basically low-frequency low-pitched sounds. As shown in Figure2.8, only a small portion of heart sounds lie in the human audibility range. This means human ears are unable to properly hear these sounds and hence physicians will not be able to analyze the minute details prevalent in order to diagnose the patient properly. So, there is need to amplify these sounds in order to hear and interpret properly.

Figure2. 9 Stethoscope [20]

The stethoscope is an instrument with a chest piece having a diaphragm or a membrane, which when Placed at the proper auscultation site responds to heart sounds by vibrating. This creates a pressure wave which passes through binaural flexible tubing to the ears of the physician. This is acoustic stethoscope. But nowadays electronic stethoscope is used which response to the sound waves identically to conventional acoustic stethoscope with changes in electric field replacing changes in air pressure.

2.8 Features of PCG

As heart sounds and murmurs have very less overlap with human audibility range, the minute details that can be missed during auscultation can be best viewed and taken care of with the help of Phonocardiography. This is because showing heart sounds graphically have nothing to do with audibility range. This helps in better diagnosis with the help of phonocardiography.They are gradually moving towards automatic auscultation, which means software would be sufficient to tell state of heart. This eradicates the limits of immense training and experience of the physician to diagnose the patient properly.

Heart sounds are an early indicator of heart problems. So PCG signal when properly analyzed can lead to cost effective and efficient treatment at early stage. Use of PCG will be extremely beneficial in the case of rural primary health care centers where stethoscope is the only available instrument for diagnosis. Using electronic stethoscope the automatic auscultation would be possible. A dvice from an expert can also be taken by sending PCG signals via electronic media. It is sometimes also the only available option as in the case of infants where implementation of ECG and other techniques cannot be implemented [21]. All these above factors have been an immense driving force in order to work in the field of Phonocardiography.

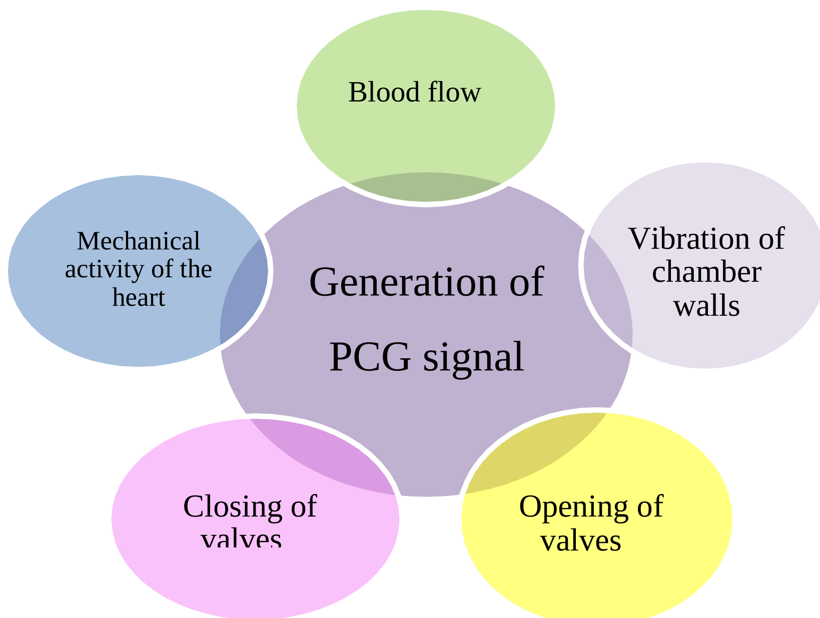

Figure2. 10 Causes of PCG signal generation

2.9 Signal Processing Techniques

Signals carry prodigious amounts of data in which finding important information is more difficult. It is necessary to process the signal in such a way that only a few coefficients reveal the necessary information. In this work, to extract valuable information from heart sound signals an extension of methods based on time-frequency will be investigated. In order to have a successful classification algorithm, it is necessary to understand the basic concepts behind the techniques, which constitutes fundamentals of Fourier theory followed by time-frequency analysis

2.9.1 Fourier analysis

Fourier analysis is useful everywhere in the fields of mathematics and physics because the time-invariant convolution operators are diagonalized. The representation of the Fourier analysis for any energy function *x(t)* which is finite duration is given by the sum of sinusoids $e^{j\omega t}$ as:

$$\mathrm{x(t)} = \frac{1}{2\pi}\int_{-\infty}^{\infty} x(\omega)\, e^{j\omega t} d\omega \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.1$$

The amplitude *x(ω)* for each of the sinusoidal wave function $e^{j\omega t}$ is equal to correlation of $e^{j\omega t}$with *x*, which can also be called as Fourier transform:

$$\mathrm{x(\omega)} = \frac{1}{2\pi}\int_{-\infty}^{\infty} x(\mathrm{t})\, e^{-j\omega t} d\mathrm{t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.2$$

The more regular the function *x(t),* the faster will be the decay of the amplitude $|x(\omega)|$, when the frequency of ω is increased.

These pair of the equation is called a Fourier transform pair. The Fourier transform gives good results as long as the signals are uniformly regular or linearly time-invariant. But when the signals exhibit transient behavior Fourier transform becomes a heavy tool which requires so many coefficients to represent a local event.

The transform only provides information in terms of frequency but loses its time information. Heart sound signals are a kind of signals where an abrupt change, positions of the cardiac events, trends plays an important role in heart signal in the classification of primary components which cannot be detected using Fourier analysis.

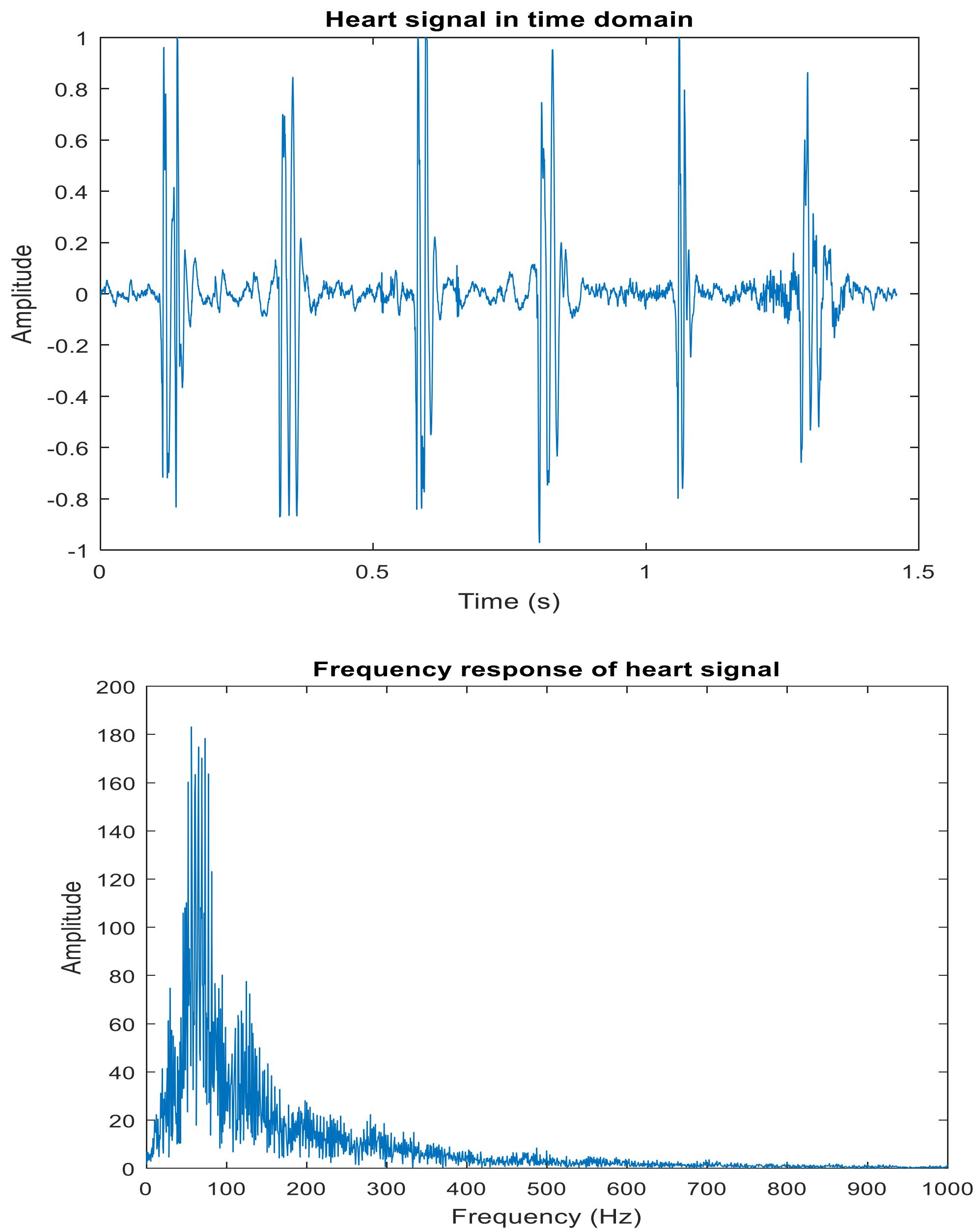

Figure2. 11 Healthy HS signal and its Fourier transform.

2.9.2 Time-Frequency Analysis

In the field of signal processing, time-frequency analysis is one of the study of signal in both time and frequency domains. One dimensional view may not give the required information where both timing and frequency are of much concern. For those cases a transform which gives information in both time and frequency is required leads to the concept of time-frequency analysis. This analysis uses the time localization technique which plays an important role in speech and sound processing. The main issue is to understand how to adapt time-frequency component to signal to process. In this context, the Heisenberg uncertainty principle plays a promising role.

2.9.3 Short time Fourier transforms

It can also be named window Fourier transform. A short time/term Fourier transform (STFT) is constructed by translating a windowed function Ω(t) in both time and frequency domains. The function Ω (t) has a time translation by τ and frequency by α. The analysis is done using Fourier transform by assuming stationary in a finite segment of the signal. The STFT projects x on each of the window function Ω (τ, α)

$$sx((\tau,\alpha) = \int_{-\infty}^{\infty} x(t)\Omega(t-\tau)\, e^{-j\alpha t}dt \ldots\ldots\ldots\ldots\ldots\ldots 2.3$$

The window function Ω *(t)* which is being analyzed is of fixed width. The window is a sliding function which slides along the time axis byτ.

Hence, it is effective as long as the signal doesn't have any variable time-frequency resolutions. The heart sounds on the other side have structures with variable time-frequency resolutions. So STFT can only work for the cases which have constant time-frequency resolutions but not for varying ones. This problem can be handled by the wavelets.

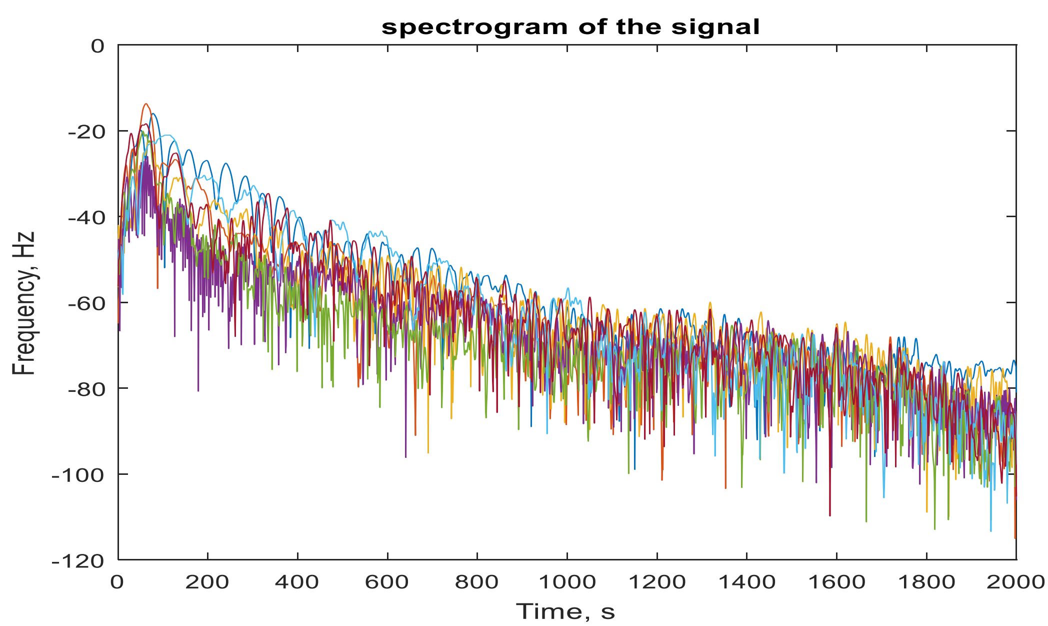

Figure2. 12 STFT for a healthy heart sound using Hamming window of size 512

2.9.4 Wavelet Analysis

Similar to Fourier analysis, wavelets also works to obtain singularity in a signal but wavelets use localized events to represent the signal using only a few coefficients. Unlike STFT, wavelet transform employs a windowing technique which is of variable width. The width variability allows wavelets to work for different frequency resolutions.

The wavelet transform is a remarkable mathematical method with the ability to examine the signal simultaneously in time and frequency in a different way from previous mathematical methods. Wavelet analysis has been applied in a wide range of applications: from climate analysis, to signal compression and medical signal analysis. The application of wavelet transform analysis in science and engineering began to increase at the beginning of the 1990s, directly reflecting the interest of the scientific community [22].

Manipulation of the wavelet is into two ways: translation and scaling. Translation is shifting the central portion of wavelet along the time axis; this is done to extract the time information of a signal. In scaling the amplitude and time duration of the wavelet functions are changed to obtain frequency information. Thus, because of the translation and scaling, the wavelet is localized in both time and frequency domain simultaneously.

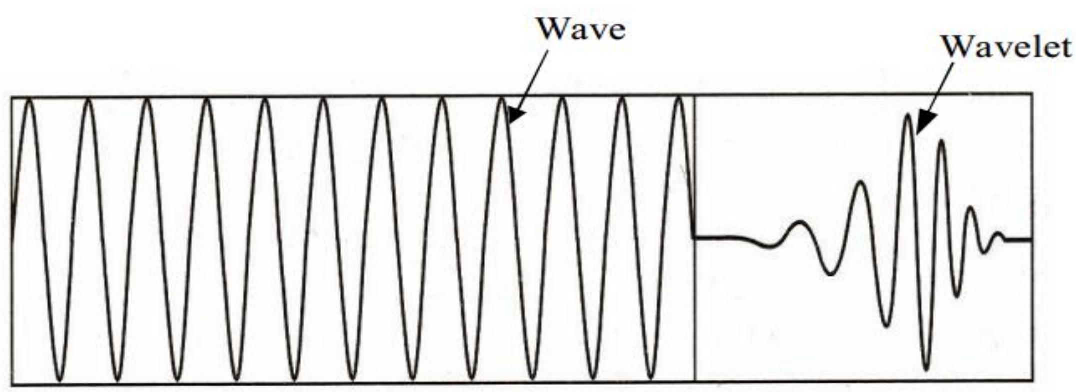

Figure2. 13 Wave and Wavelet

Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. More technically, a wavelet is a mathematical function used to divide a given function into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale.

2.9.4.1 Continuous wavelet transform

Wavelets offer the best representation for non-stationary signals. Here, large amplitude wavelet coefficients can detect and measure short high-frequency variations because of the narrow time localization at high frequencies, so it gives better time resolution and at low frequencies, their time resolution is lower, but they have a better frequency resolution. This modification of time and frequency resolution is adapted to represent sounds with sharp attacks or signals that have much frequency variations. These sharp attacks and high-frequency variations are the exact characteristics of an HS signal.

A wavelet is constructed from a mother wavelet ψ of zero average which is dilated with a scale parameter *s*, and translated by τ :

$$\int_{-\infty}^{\infty} \psi(t)\, dt = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.4$$

The continuous wavelet transform of *x* at any scale *s* and position τ is the projection of *x* on the corresponding wavelet coefficient:

$$wx((\tau\, , s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi^{*}(\frac{t-\tau}{s})\, dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.5$$

It represents one-dimensional signals by highly redundant time-scale coefficients in (τ , *s*) [23]. The scale parameter, *s,* is inversely proportional to the frequency which is defined as $s = \frac{1}{\omega}$, Where *ω* is the frequency in Hertz.

From the wavelet perspective, scaling factor either dilate or compress the wavelet. Larger scales dilate the wavelet which highlights the slow variation activities in the signal and small scales compress the wavelet which retrieves the transient behavior of the signal. The continuous wavelet transform measures the similarity between the signal and the wavelet by continuously translating and scaling the mother wavelet. So to represent the coefficients an infinite number of wavelets are required which increases the redundancy and hence it is impractical. Discrete wavelet transforms works for those cases where redundancy is much concern.

2.9.4.2 Discrete wavelet transform

Continuous wavelet transforms acts as filters in both analysis and synthesis which is called dyadic discretization. Discretization of scale parameter is equivalent to constructing filter banks. In these cases, each wavelet filter bank acts as a bandpass filter which allows only a certain band of frequencies. Dyadic discretization is a process in which the scale parameter of the wavelet is taken as powers of 2 i.e. the translation by a factor of 2 stretches the frequency by a factor of 2 and shifts the frequency component by a factor of 2. Here each filter bank should be non-overlapping with other filter banks. Distinct range of frequencies is covered by each wavelet where each step has a bandwidth reduction by a factor of 2 as shown in Figure2.12.

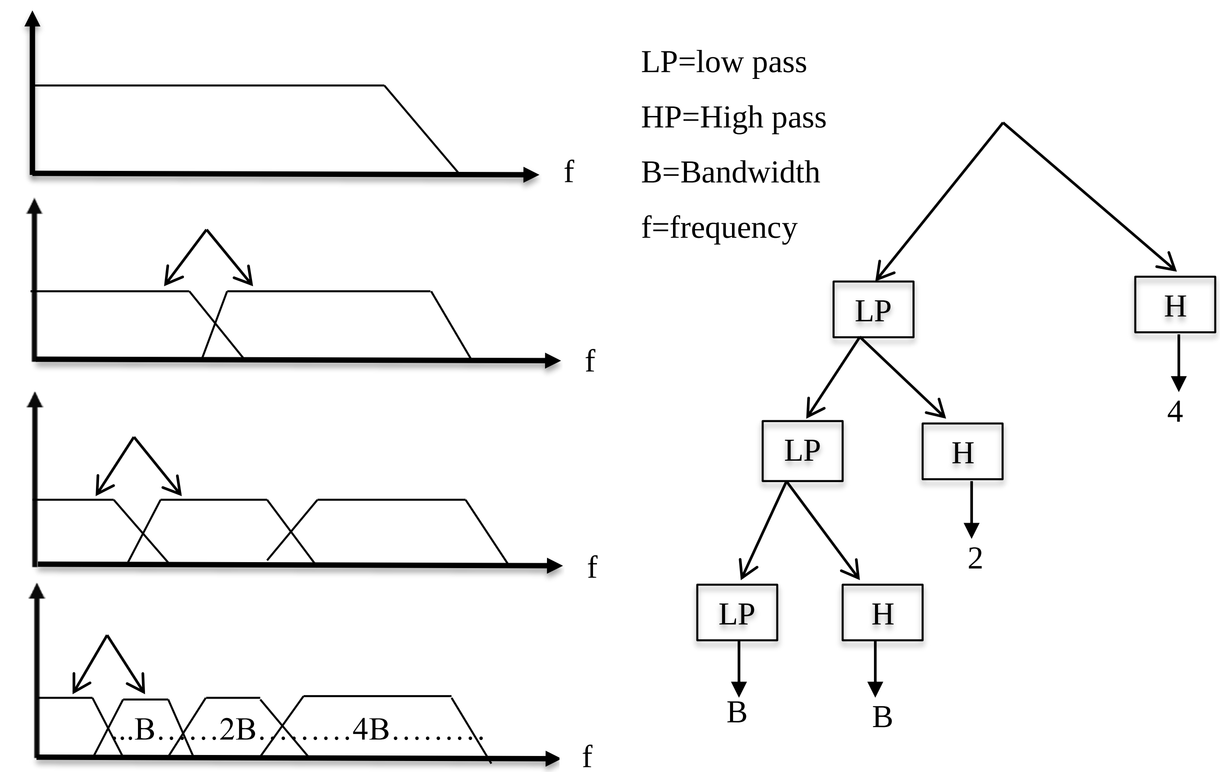

Figure2. 14 Wavelet filter bank

The DWT analyzes the signal by decomposing it into its coarse approximation and its detailed information, which is accomplished by using successive high pass and low pass filtering operations in the frequency domain.

The discrete wavelet transform is a combination of consecutive low pass and high pass filters. Each filter divides the input signal into two half-band frequencies, one-half bands towards low pass filter denoted by H_1 and other half band towards high pass filter denoted by H_0. The low pass filter extracts the lower half of the frequencies which is called as approximation information and high pass filter extracts upper half of the frequencies which is called as detail information.

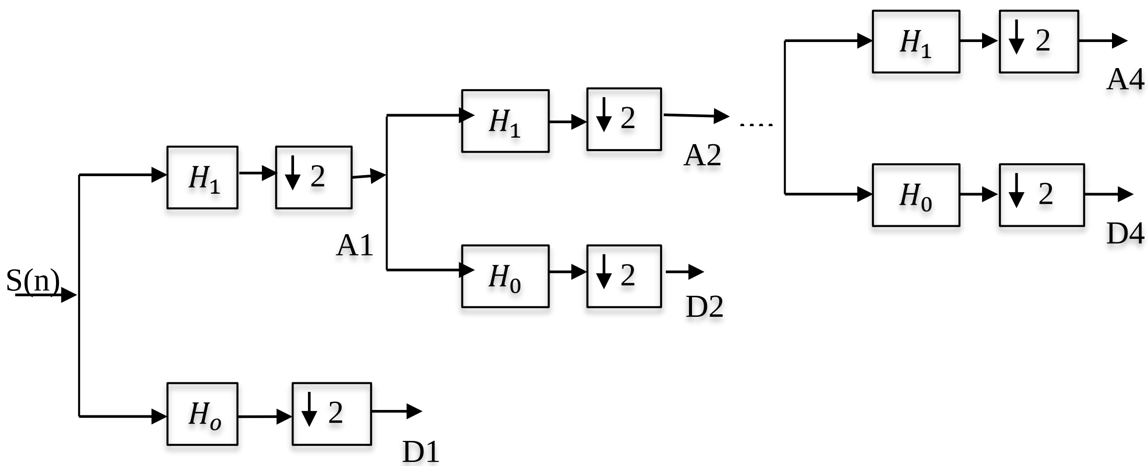

Figure2. 15 Implementation of four level wavelet decomposition.

The expression for one level decomposition is given by the following equation:

$$f_h(k) = \sum_n s(n)h_0(2k - n) \ldots\ldots\ldots 2.6$$

$$f_l(k) = \sum_n s(n)h_1(2k - n) \ldots\ldots\ldots 2.7$$

Where $f_h(k)$ and $f_l(k)$ are the subsampled outputs of both high pass and low pass filters. From the Figure2.15 every decomposition level has a filtering and subsampling blocks in which subsampling is done by a factor of 2. Here each wavelet decomposition level divides the signal into two frequency levels namely, approximation and detail level.

The discrete wavelet transform (DWT) has been widely used in a biomedical signal process for non-stationary signals is used in this research.

CHAPTER THREE

LITERATURE REVIEW

Heart sounds provide valuable information about the health of the heart. Therefore, the invention of stethoscope auscultation is used for diagnosis of heart valve disorders as a primary detection tool. Many researchers have studied PCG signals using various signal processing techniques. Firstly, the pre-processing of heart signals is done. Pre-processing includes normalization, segmentation, and noise removal. After pre-processing features are extracted and used for classification.

Cardiovascular diseases and defects cause changes or additional sounds and murmurs that could be useful in their diagnosis. Many researchers have done various studies in this field and contributed in different ways of studying and classifying heart signals. In this section, related works of different researchers in the area of heart valve diseases identification using heart sound signal processing algorithms would be reviewed.

Emmanuel, B.S. made a review of signal processing techniques for heart sound analysis in clinical diagnosis. This study showed the gaps that exist between contemporary methods of signal analysis of heart sounds associated with a murmur and their applications for clinical diagnosis. The findings of this review paper are: there is a general lack of consensus in research outputs, and inter-patient adaptability of signal processing algorithm is problematic, the process of clinical validation of analysis techniques has not been sufficiently rigorous and as such data integrity and measurement procedures are still in doubt; and the reviewed diagnostic algorithms and systems are too complex and very expensive. As a recommendation, the author argues that the ability to correctly acquire analyses and interpret phonocardiogram (PCG) signals for the improved clinical diagnostic process has become a priority [24].

Devi, A. and Misal, A. made a survey on classifiers used in heart valve disease detection, which gave an insight to the most important feature for the classification problem. The author compare four techniques which give 90% & above accuracy as classifier for heart valve disease detection. The initial survey conducted concerning the exploitation of heart sound signals for detection of heart conditions. Then a comparative study is applied to determine the most effective techniques that are capable of the detection of heart valve disease with a high accuracy. Support vector machine, artificial neural networks algorithms with back propagation network techniques, artificial neural networks algorithms with radial basis function and adaptive neuro-fuzzy inference system classifiers. This gives important ideas that classifier performance depends on Preprocessing, feature selection and dimension of the data [6].

Nabih-Ali, M. et al., proposes methodology how heart diseases can be diagnosed using an intelligent algorithm based on PCG signal analysis. The proposed technique consists of four stages; data acquisition, pre-processing, feature extraction and classification. PASCAL heart sound database is used in this research. The second stage concerns with removing noise and artifacts from the PCG signals. Since the acoustic audio files have varying lengths, between 1 second and 30 seconds, mainly the most information in heart sounds is enclosed in the low-frequency components, having noise in the higher frequencies. But the proposed algorithm uses a small number of PCG records to classify normal and abnormal heart sound and no consideration of extra heart sounds [3].

Cherif.L.H. et al., highlighted the importance of the choice of wavelet analysis for HS signal analysis. The author analyzed the PCG signal using discrete wavelet transform and packet wavelet transform. It was seen that in case of filtering clicks and murmurs DWT is more suited than wavelet packet transform (PWT). If one wants to do filtering of the murmurs such that there is not much distortion of s_1 and s_2 heart sound components, DWT is likely to be used whereas when PWT is applied morphology of internal components are affected much more as compared to when DWT is applied. Various wavelets and their order were used for the analysis and it was concluded that by analyzing wavelet db7 distinction between sounds and various heart can be done easily using DWT or PWT. A qualitative study of systolic and diastolic murmurs and clicks of PCG signals can be carried out more efficiently using DWT but PWT provide better information which gives better comprehension of time-frequency characteristics of heart sounds, internal components, heart murmurs and clicks [25].

Ali Akbari, M. et al., proposed a new analytical technique which he named as Digital Subtraction Phonocardiography (DSP). This technique is based on the principle that the murmurs are random in nature but the Fundamental Heart Sounds (FHS) are deterministic in nature. The difference between the acoustic emissions of two successive heartbeats was simply taken and murmurgram was constructed. It was found that for normal cases the murmurgram should be flat between the FHS but for abnormal cases i.e. heart sounds with murmurs this wasn't the case [26].

Safara F, et al., introduced new entropy to analyze heart sounds and it was shown that it was feasible to use this entropy in the classification of heart sounds and murmurs. The heart sounds considered for classification consisted of one normal heart sound and four common murmurs: Aortic regurgitation, Mitral regurgitation, Aortic stenosis, and Mitral stenosis. To derive various feature vectors the entropy was calculated. Classifications were performed and the accuracy of the generated features was evaluated. The best results were achieved using Bayes Net as a classifier with an accuracy of 96.94%. The results showed that the proposed wavelet packet entropy was effective for heart sounds classification [27].

Singh, M and Cheema, A proposed a new feature called mean12, which is the maximum of the mean in the systolic and diastolic region to classify signal into two classes i.e. normal and murmur signal. 23 features in the time domain, frequency domain, statistical and cepstrum were extracted and only 5 optimal features were selected for classification. Four different classifiers with 5 fold cross validation was used. The classifiers used were Bayes Net, Naïve Bayes, SGD and Logit boost and the accuracies achieved were 91.6%, 93.3%, 91.6%, and 88.3% respectively. Highest accuracy of 93.3% was achieved using the Naïve Bayes classifier [25].

Patinder, S. and Pachori, R.M. proposed a new method for classification of heart sound signals. The features which were extracted from the heart beat cycles are reconstructed separately from the heart sounds and murmurs. They used constrained tunable Q-wavelet transform to separate heart sounds and murmurs. The features extracted based on time-domain, tunable Q-wavelet transform and Fourier- Bessel expansion. The features were selected to reduce the obtained feature set and classification was done using least square SVM with various kernel functions. The performance of this method was even validated with publically available datasets. The results were compared with STFT based method when applied to the available dataset. The overall classification accuracy of 94.01% was achieved using the proposed method with the RBF kernel against 93.53% in case of

STFT based method [28]. But the study didn't consider frequency domain features which give valuable information for non-stationary signals.

Plesinger, F. et al., tackle HS analysis using the idea of probability assessment. The algorithm detected heart sounds s_1 and s_2 using amplitude envelopes in the band 15-90 Hz. By using segmentation the averaged shape of s_1 and s_2 pair is computed from amplitude envelopes in five different bands (15-90 Hz; 55-150 Hz; 100-250 Hz; 200-450 Hz; 400-800 Hz). A novel approach of this system is introducing probability assessment as a possible method of machine learning and also indicate its performance is comparable to other machine-learning approaches, but the main limitation lies in distinguish only between two resultant states, while neural network may work with virtually any number of output states. On the other hand training is only semi-automatic and extremely time-consuming [29].

Sujit, N.R. et al., developed a biomedical system for the detection of abnormality in heart and methods to enhance the performance of the system using SMOTE and AdaBoost technique. The back-end classifier to the system developed is Decision Tree using a CART (Classification and Regression Tree), with an overall classification accuracy of 78.33% and sensitivity (alarm accuracy) of 40%. SMOTE and AdaBoost techniques were applied to improve the sensitivity and overall performance. The author recommended it is possible to use these devices as digital stethoscope within the availability of low cost, high-performance mobile phones to detect and analyze the heart sounds by developing an automatic classification of abnormal heart sounds [30]. These reviewed and other related recent literatures are used to conduct this research.

Table3. 1summary of related works

Year	Proposed work	Authors	Methods	Database	Result
2013	Heart Sounds Classification using Feature Extraction of Phonocardiography Signal	Singh M. and Cheema A.	Bayes Net, Naïve Bayes, SGD and Logit boost	PASCAL dataset	93.3% using Bayes classifier
2014	Classification of cardiac sound signals using constrained tunable-Q wavelet transform	. Patinder S. and Pachori, R.M.	tunable Q-wavelet transform (TQWT) least square SVM (LS-SVM)	PASCAL dataset	93.53% accuracy using RBF kernel
2017	heart diseases diagnosis using intelligent algorithm based on PCG signal analysis	Mohammed Nabih-Ali et al.,	• DWT • ANN	PASCAL dataset	95% accuracy using 170 PCG signals
2017	Heart Sound Feature Extraction and Classification using Autoregressive Power Spectral Density (AR-PSD) and Statistics Features	Domy Kristomo et al.	✓ AR-PSD ✓ statistical feature ✓ ANN	Michigan Database	88,89% using 9 signals
2016	Curve fitting, filter bank, and wavelet feature fusion for classification of PCG signals	Imani Maryam et al.,	✓ Maximum likelihood classifier with Gaussian distribution	PASCAL dataset	Accuracy 81.49% 98 PCG signals

2015	murmur-based heart sound feature extraction technique using envelope-morphological analysis	HaoDong Yao, et al	✓ DWT and ANN	PASCAL dataset	Accuracy 96% 60 heart sound signals.
2014	Intelligent Classification of Real Heart Diseases Based on Radial Wavelet Neural Network	Juan. Guillermo.et al	✓ CWT and ANN	✓ PASCAL dataset	Accuracy 76.08% using 17 PCG signals
2013	Heart Sounds Classification using Feature Extraction of Phonocardiography Signal	Mandeep Singh, et al.,	✓ Naïve Bayes Classifier	✓ PASCAL dataset.	Accuracy 93.33% using 60 PCG signals
2016	Improving the performance of cardiac abnormality detection from PCG signal	Sujit, N. R. et al	✓ Regression Tree	✓ PASCAL dataset	Accuracy 78.33% using 266 PCG signals

CHAPTER FOUR
MATERIALS AND METHODOLOGIES

4.1 Materials used

It is known that heart sound signal gives valuable information about the heart condition. The PCG signal is capable of diagnosing various heart diseases at an earlier stage. Therefore, signal processing techniques can be employed to process the PCG signals towards improving the accuracy of diagnosis [31]. For this thesis work two essential materials were employed. A Publically available database for researchers, Partnership among South Carolina Academic Libraries (PASCAL) and MATLAB 2018a was used to develop an algorithm to classify the heart sounds into three classes: normal, murmur and Extra signals.

4.2 Methodology

The methodology used in this study to classify various heart sounds into pre-defined classes consists of five stages: signal acquisition, preprocessing, feature extraction, feature reduction, and classification as shown in the Figure 4.1.

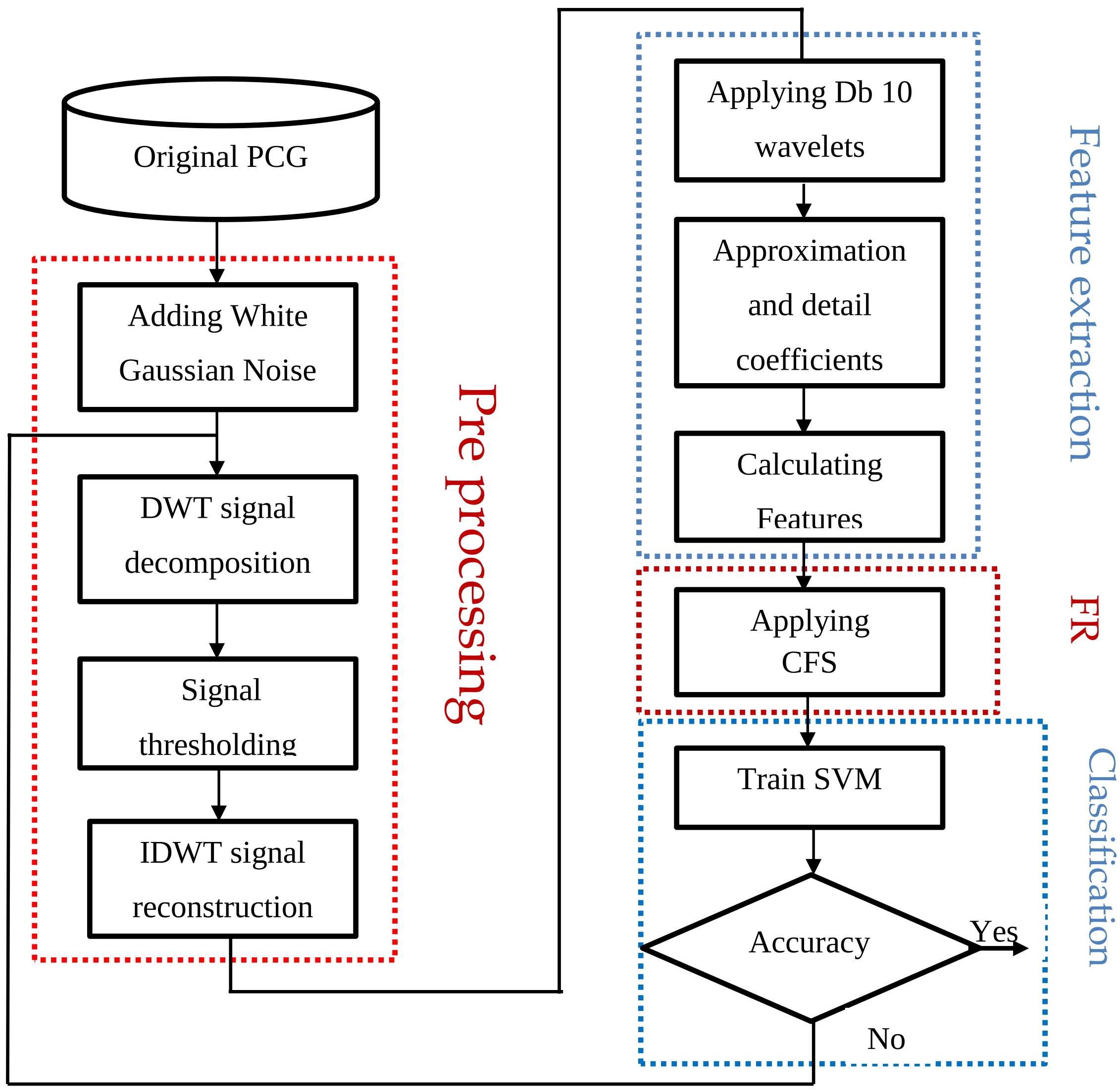

Figure4. 1 Proposed methodology.

4.2.1 Signal Acquisition

The PCG signal acquisition can be done by an electronic stethoscope which response to the sound waves identically to the conventional acoustic stethoscope with the changes in electric field replacing the changes in air pressure. However, for this study an electronic database of PCG signals is taken from PASCAL [32]. The dataset used was taken from a clinical trial in hospitals using the digital stethoscope from adult peoples. In this study, a dataset recorded from Phonocardiograph having 300 signals were used out of which 150 are normal signals, 100 are murmur signals and 50 are extra sound.

4.2.2 Wavelet-based Preprocessing of PCG signals

Heart sound signal is a typical biomedical signal, which is random and has a strong background noise. In the process to collect heart sound signals, it is vulnerable to external acoustic signals and electrical noise interference; in particular, the friction caused by subjects breathing or body movement [33]. The wavelet transform is a time-frequency signal analysis method based on Fourier transforms. It has good localization in both frequency and time domains. The word wavelet mean small wave, the wavelet transform decomposes the signal into one single function, called mother wavelet.

DWT is a linear transformation method that operates on a coefficient vector whose length is an integer power of 2, transforming it to a numerically different vector of the same length. The basic idea of DWT for the signal is splitting into two parts: a high-frequency component and low-frequency component. This splitting process is called signal decomposition. The signal is passed through a series of high-pass filters to analyze the high-frequency components and low-pass filters to analyze the low-frequency components. Filters with different cutoff frequencies are used to analyze the signal at different resolutions [34][35].

Denoising, or noise reduction, is a permanent topic for engineers and applied scientists. The model considered for removing noise is classic: the measured signal X is an additive mixture of an information signal S and a measurement noise R [36].

$$X(t) = S(t) + R(t) \quad \text{……………………………………} 4.1$$

A suitable threshold can separate the noise (incoherent part) from the signal (coherent part). The denoised signal is generated through inverse reconstruction. This procedure is shown in figure 4.2.

Generally, wavelet-based preprocessing of PCG signals procedure precedes three general steps. The first one is decomposition of the signal. This is done by choosing a wavelet at level N and Compute the wavelet decomposition of the signals at level N, Secondly for each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients of the signal. Lastly, reconstruction is done based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

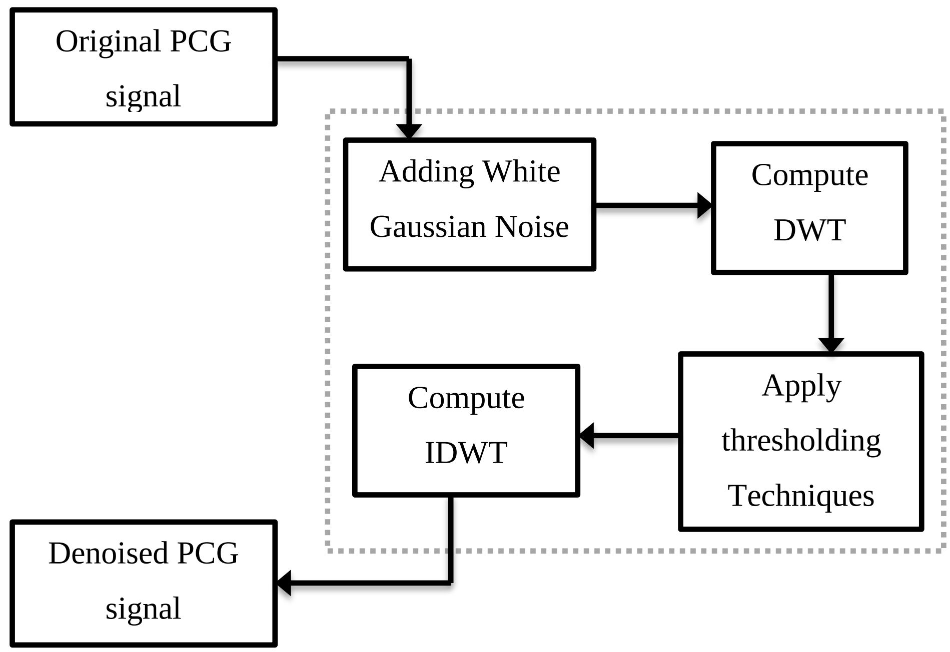

Figure 4. 2 PCG signal denoising procedure

The outputs of the high-pass and low-pass filters are called the DWT coefficients. These DWT coefficients enable reconstruction of the original signal, a process called the inverse discrete wavelet transform.

The main idea of the wavelet denoising algorithm is to obtain the essential components of the signal from the noisy one, then threshold the small coefficients considering them to be pure noise. In this research, four different wavelet families (Daubechies, Symlets, Coiflets and Discrete Meyer) were applied for PCG signal denoising.

There were striking differences in the magnitudes of three classes of signals as shown in Figure 4.3 to 4.5. In normal signals, the amplitude in between peaks was nearly zero but in case of murmur, the amplitude was larger. This helps us to set a threshold value as a Peak is located on the signal. Every peak lies above that value.

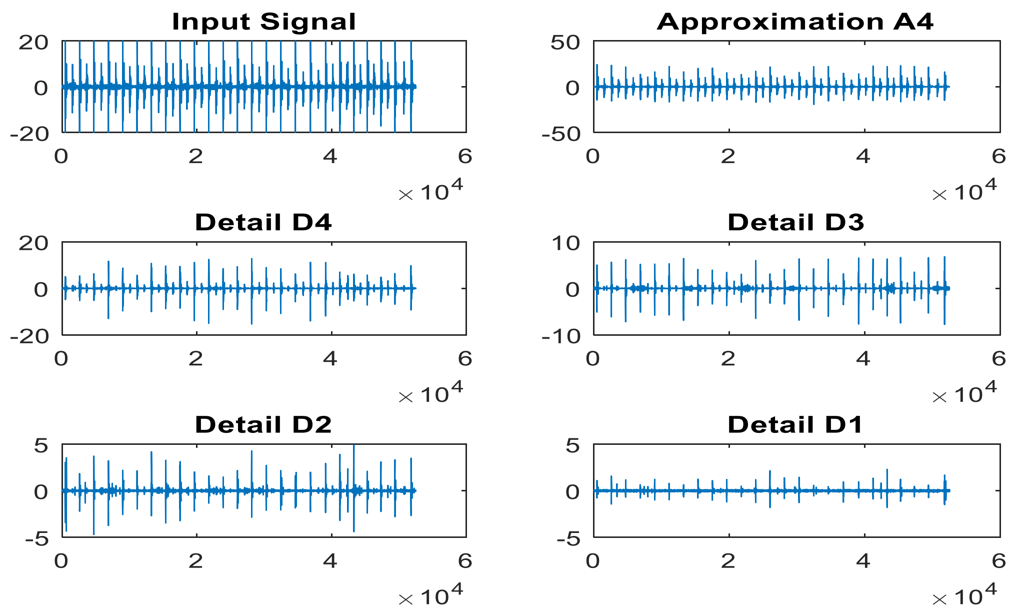

Figure4. 3 Wavelet decomposition for healthy HS signal using Db10 at 4th level

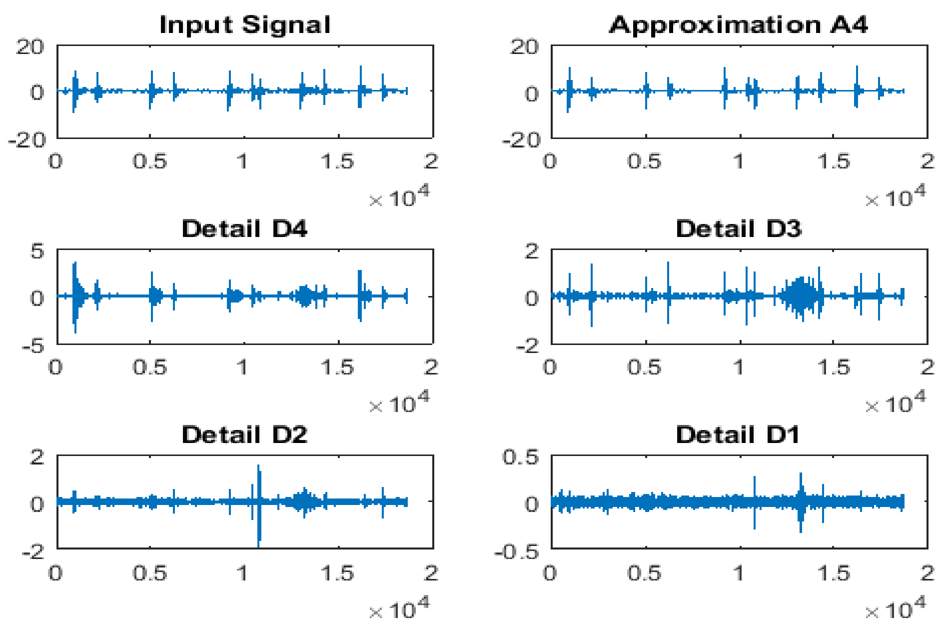

Figure4. 4 Wavelet decomposition for a patient with murmur using Db10 at 4th level

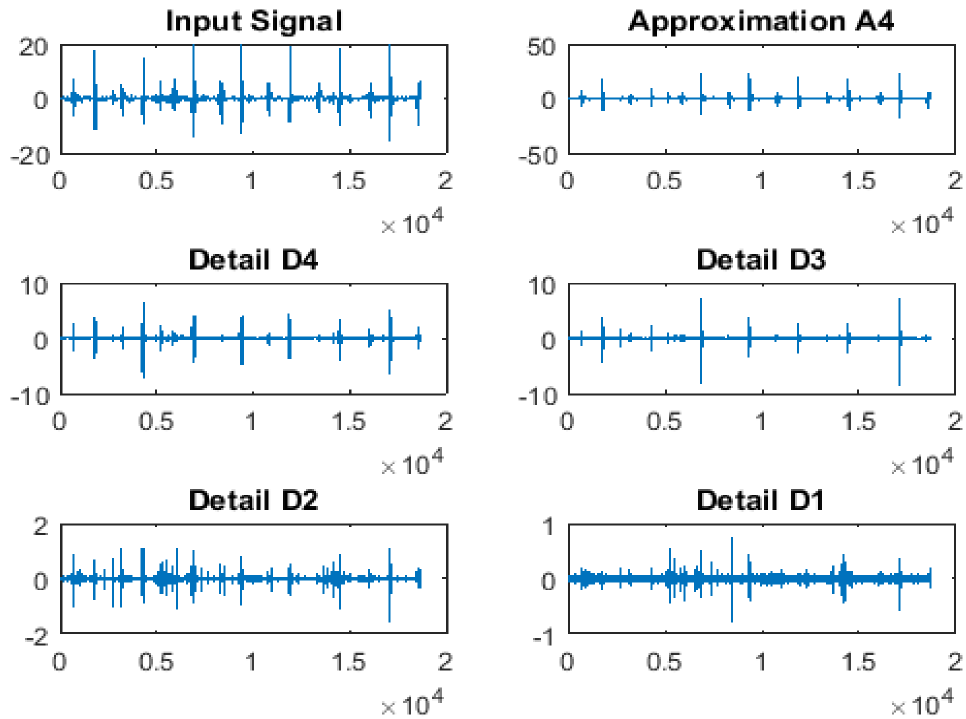

Figure4. 5 Wavelet decomposition for a patient with Extra HS using Db10 at 4th level

For thresholding the two most common methods of thresholding signals, soft and hard are used and also four different threshold selection rules were applied in this work to investigate their performance in signal denoising [34].

- Rigrsure: the threshold is selected using the principle of Stein's unbiased risk estimate (SURE) quadrature loss function.
- Sqtwolog: the threshold is fixed at that yielding minimax performance multiplied by a small factor proportional to log (length(s)), usually $\sqrt{2\mathrm{loglength(s)}}$.
- Heursure: the threshold is selected using a mixture of the first two methods.
- Minimax: the fixed threshold is chosen to yield minimax performance for the mean-square error against an ideal procedure. All of them are included in the MATLAB software toolbox.

Finally, multilevel one-dimensional wavelet reconstruction was done using either a specific wavelet or specific reconstruction filters.

The most suitable way to see the effect of noise added to heart sound signals is to add white Gaussian noise. After the denoising process, the performance can be measured by comparing the denoised signal with the original signal. So many methods have been proposed to measure the performance of denoising algorithms. Numerous studies have been made on heart sound signals containing the desired level of white Gaussian noise to measure the performance of denoising algorithms by calculating the SNR. The SNR is a traditional parameter for measuring the amount of noise present in a signal. The root-mean-square error and percentage root-mean-square difference are also used to evaluate the performance of denoising algorithms [22]. The SNR, RMSE, and PRD can be formulated as follows.

$$\mathrm{SNR}_{db} = 10\log_{1o} \frac{\sum_{n=0}^{N-1} s\,(n)^2}{(s(n)-S'(n)^2)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.2$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}\ (s(n) - s'(n)^2)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.3$$

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=0}^{N-1}\ (s(n)-s'(n)^2)}{\sum_{n=0}^{N-1} s\,(n^2)}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.4$$

Where *s(n)* is the original signal and *s'(n)* is the denoised signal

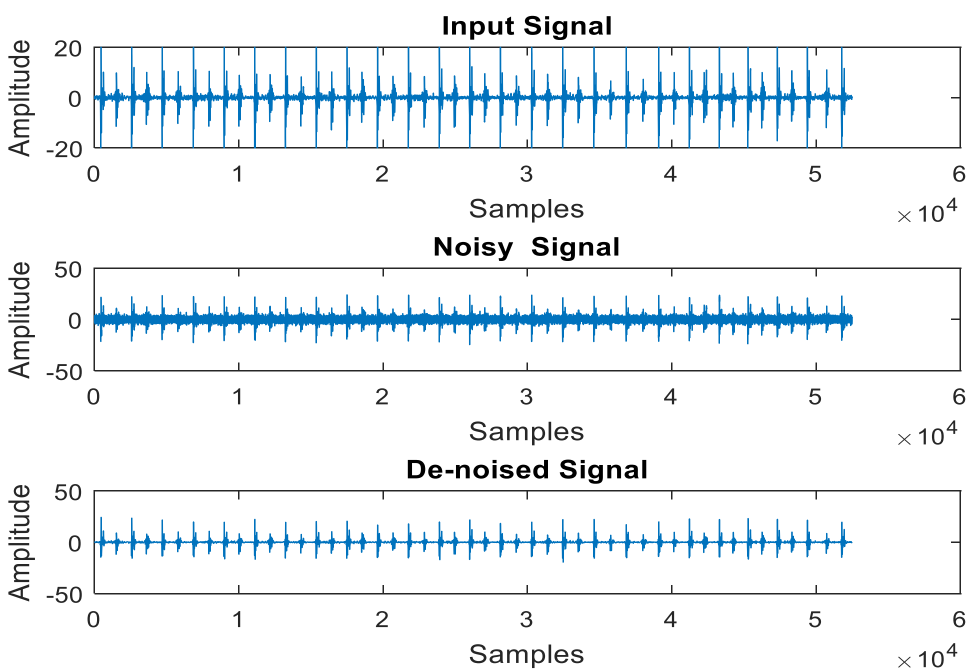

Figure 4. 6 Denoising of healthy PCG signal using Db10 wavelets at 4th level with a soft threshold

4.2.3 Feature Extraction

Any parameter which has the potential to discriminate between different classes is termed as a feature. Various features have been extracted to discriminate between the normal, murmur and extra sound signals. A total of 15 features are extracted in these studies which are of various domains including time domain, frequency domain, and statistical domain. The extracted feature values are recorded and compiled in Microsoft Excel 2010.

The discrete wavelet transform was used to extract characteristics from a signal on various scales proceeding by successive high pass and low pass filtering. The wavelet coefficients are the successive continuation of the approximation and detail coefficients. The basic feature extraction procedure consists of decomposing the signal using DWT into N levels using filtering and decimation to obtain the approximation and detailed coefficients and extracting the features from the DWT coefficients.

Nature is full of non-deterministic (stochastic) processes like the weather, the stock market, speech sound waves. Biomedical signals such as ECG, EEG are also of stochastic nature indicating that an appropriate method for analysis should be used. It turns out that the signal power is distributed differently over frequencies in the case of the pathological murmur than in the case of the physiological murmur [37].

The features extracted from the Inverse discrete wavelet transform of signals are considered useful features for input into classifiers due to their effective time-frequency representation of the non-stationary signal.

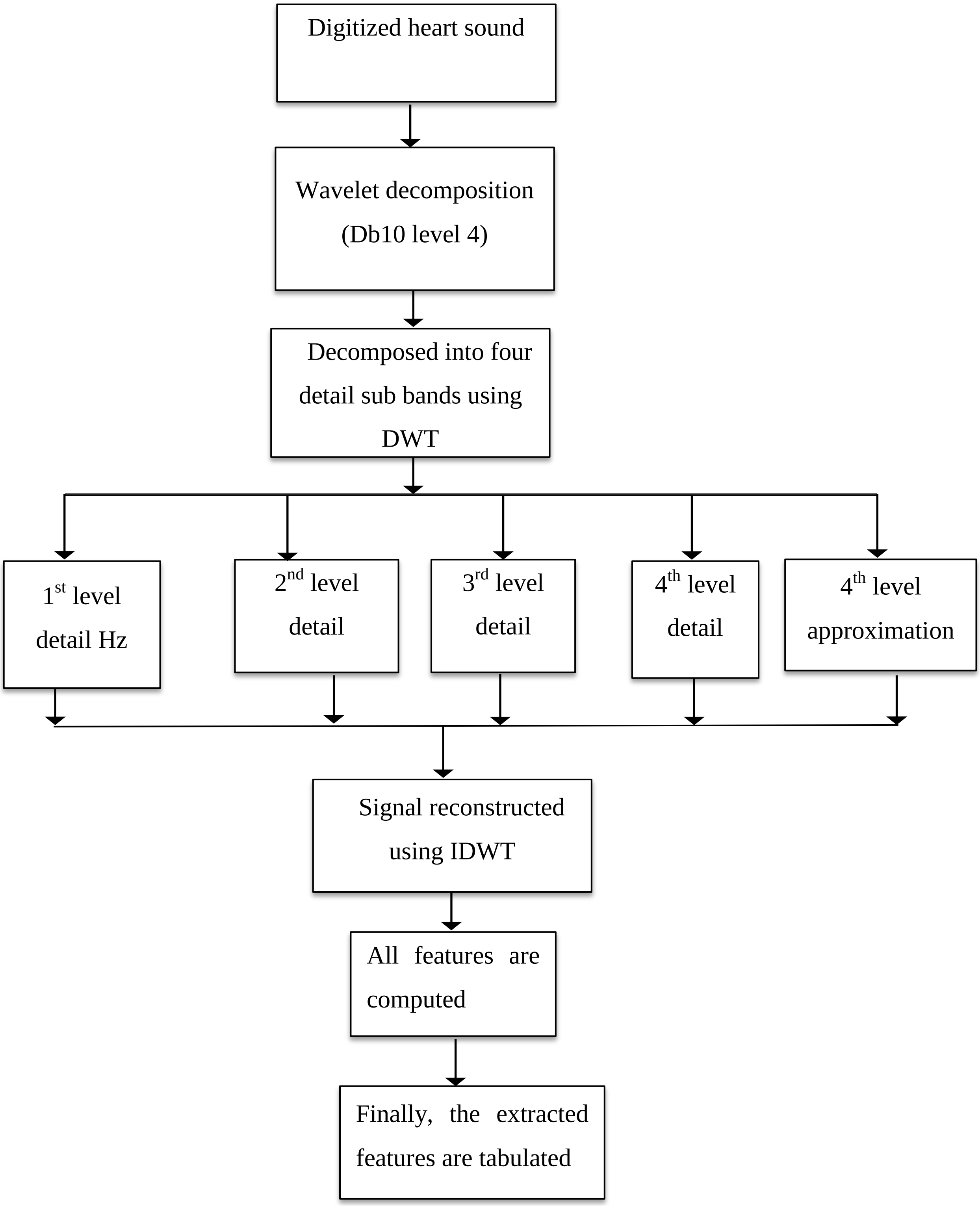

Figure4. 7 Feature extraction process

The various steps involved in the feature extraction algorithm summarized as follows: Step 1: The HS signal decomposed into four detail subbands using discrete wavelet transform. The subbands are high-frequency detail band coefficients and low-frequency approximation band coefficients.

Step 2: The approximation co-efficient are further decomposed using DWT to extract localized information from the subband of detail coefficients. In this work, four levels of decomposition have been done using Daubechies, wavelet (db10).

Step 3: For further analyzing and processing, all the four-level detail band coefficients have been taken.

Step 4: The frequency vector (in radians/sample) is extracted for four detail subbands using periodogram function in Matlab.

Step5: After decomposition signals are reconstructed using IDWT.

Step 6: The features are computed either by using syntax or by implementing the formula. they are mean, variance, standard deviation, kurtosis, skewness, root mean square, total harmonic distortion, bandwidth, dynamic range, maximum amplitude, cepstrum peak amplitude, power, average frequency, maximum frequency, and mid frequency

Step 6: Finally, the extracted features for the three classes of HS signals are tabulated and analyzed for classification. The extracted features from the signal are as below:

Mean: it is nothing but an average value.

Standard deviation: It is defined as the amount of variation in the set of data values.

Variance: a small variance indicates that the data points tend to be very close to the mean and hence to each other, while a high variance indicates that the data points are very spread out around the mean and from each other.

Skewness: is the measure of the asymmetry of the data.

Kurtosis: the Positive value of kurtosis indicates that the signal is peaked and the negative value of kurtosis indicates signal is flat.

Maximum Amplitude: it is the peak value of the amplitude of the signal.

Mid Frequency: it is the frequency value which is obtained when the power spectral density is at the maximum value.

Dynamic Range: it is the ratio of max value to the minimum value in a waveform. Max is the maximum value of the signal.

THD: it is the measurement of the harmonic distortion present in the signal. It is defined as the ratio of the sum of all the powers of harmonic components to the power of fundamental frequency.

Average Frequency: $f_{avg} = \frac{\sum_{i=1}^{n} f_i x p_i}{\sum_{i=1}^{n} p_i}$ …………………………………4.5

Where p is power spectral density, f frequency vector.

Maximum frequency: it is the maximum frequency value of the energy in the spectrum

Power: the feature shows the total power of the signal. The murmur is a higher amplitude signals, is expected to have a higher value of this feature.

Bandwidth: it is the distance between the upper and lower frequencies in a continuous set of frequencies. As murmurs are high in frequency so a higher bandwidth is expected in case of murmur signals from PCG.

Cepstrum Peak Amplitude: the main information is concentrated in the starting of cepstrum and observed the peak values at the start. Hence cepstrum peak amplitude took as a potential feature.

Root Mean Square: it is defined as the root mean square value of the signal. Normal signals should have a lower value for this feature as compared to systolic and diastolic murmur signals.

Table4. 1 List of features extracted for classification

S. No	Feature	Feature Domain	Feature Source
1	Maximum frequency	Frequency	[38]
2	Dynamic range	Frequency	[38]
3	Total Harmonic Distortion	Frequency	[36]
4	Maximum Amplitude	Time	[36]
5	Power	Time	[36]
6	Mean	Statistical	[39]
7	Standard deviation	Statistical	[38]
8	Variance	Statistical	[40]
9	Skewness	Statistical	[40]
10	Kurtosis	Statistical	[40]
11	Root Mean Square	Time	[41]
12	Bandwidth	Frequency	[41]
13	Cepstrum Peak Amplitude	Cepstrum	[42]
14	Mid-frequency	Frequency	
15	Average Frequency	Frequency	

4.2.4 Feature Reduction

In this phase, the redundant and misleading features have to be reduced and only significant features have to be retained for classification. This reduces the computational cost and makes the algorithm time efficient. The final algorithm is to have a minimum number of features and should have maximum accuracy. So, features are ranked and only the best features are used for classification. The selected features have the potential to discriminate between the three classes of signals namely; normal, murmur and extra sound signals.

Best features are selected out of all the extracted features which can do classification with higher accuracy. There are various methods for feature reduction process. Some of them are principal component analysis (PCA), box plot method (BP), fisher's Discriminant Ratio (FDR) and correlation-based feature selection (CFS). Here, in this study CFS algorithm was employed to select the best subsets of relevant features which have been used for classification. Correlation-based heuristic evaluation function has been used to evaluate the ranked of the feature subset [43].

The implementation of CFS is based on three heuristic search strategies: forward selection, backward elimination, and best first. Forward selection begins with no features and greedily adds one feature at a time until no possible single feature addition results in a higher evaluation. Backward elimination begins with the full feature set and greedily removes one feature at a time as long as the evaluation does not degrade. Best first can start with either no features or all features. In the former, the search progresses forward through the search space adding single features; in the latter the search moves backward through the search space deleting single features. To prevent the best first search from exploring the entire feature subset search space, a stopping criterion is imposed. The search will terminate if five consecutive fully expanded subsets show no improvement over the current best subset [44].

The implementation of CFS used in the experiments is based on forward selection with an appropriate correlation measure and a heuristic search strategy. CFS's feature subset evaluation function is shown as follows.

$$Ms= \frac{kr_{cf}}{\sqrt{k+k(k-1)r_{ff}}} \qquad 4.6$$

Where Ms= the heuristic "merit" of a feature subset s containing k features

r_{cf} = The mean feature-class correlation (f € s)

r_{ff} = The average feature-feature inter-correlation.

The acceptance of a feature will depend on the extent to which it predicts classes in areas of the instance space not already predicted by other extracted features. CFS calculates feature-feature correlations using forward selection and then searches the feature subset space. The subset with the highest merit (as measured by Equation 4.6) found during the search is used to reduce the dimensionality of the data. It is important to note that the general concept of correlation-based feature selection does not depend on any one module. A more sophisticated method of measuring correlation may make discretization unnecessary. Similarly, any possible search strategy may be used with CFS.

4.2.5 Classification

Support vector machine classifier was originally designed for binary classification problems. However, real-world problems often require the discrimination for more than two categories. Thus, the multi-class pattern recognition has a wide range of applications including optical character recognition, intrusion detection, speech recognition, and bioinformatics [45]. In practice, the multi-class classification problems are commonly decomposed into a series of binary problems such that the standard SVM can be directly applied.

Multiclass SVM aims to designate labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. The dominant approach for doing so is to reduce the single multiclass problem into multiple binary classification problems [45].

Classification of new items for the one-versus-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class. It is important that the output functions be calibrated to produce comparable scores. For the one-versus-one approach, classification is used up by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is raise by one vote, and finally, the class with the most votes determines the instance classification. In this study one-versus-all approach was applied to classify the categories. In one-versus-all multi-classification it is assumed that each class individually separable from all the others. The learning methodologies as shown.

Given a dataset D = $\{x_i, y_i\}$, here the need is to specify a learning algorithm that takes D to construct a function that can predict y given x. finally it find a predictor that does well on the training data and has low generalization error. The input $x^2 < n$ is represented by their feature vectors, whereas the output $y^2\{1,2,\dots,k\}$ is classes which represent domain-specific labels [45].

It decomposes into K binary classification tasks due to class k and constructs a binary classification task as Positive examples (elements of D with label k) and negative examples (all other elements of D). Finally, it trains K binary classifiers w_1,w_2, $\cdots$ w_K

using any learning algorithm to make decision by the winner takes all principles which is argma x_i $w_i^T x$.[46]

From the full dataset, construct three binary classifiers, one for each class as shown in the figure below. The winner takes all predict the right answer, but only the correct label will have a positive score. In this study, this algorithm is selected due to easy to learn, use any binary classifier learning algorithm.

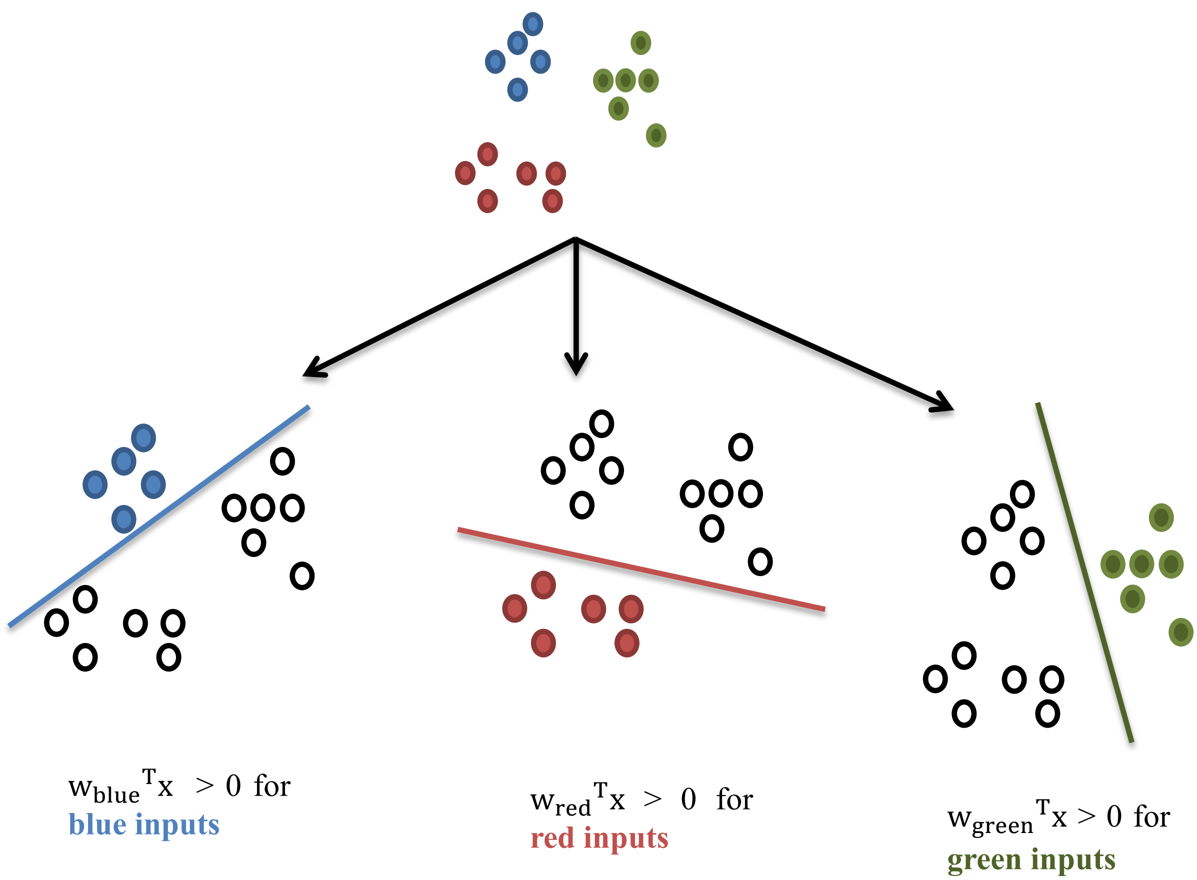

Figure4. 8 Visualizing One-vs.-all multi-classification of support SVM for three classes

CHAPTER FIVE

RESULT AND DISCUSSION

PCG signal has the potential to detect heart diseases at an earlier stage. In this study, the signals have been classified into three classes namely normal signal, murmur and extra sound signal. The results of this study have been compiled below.

5.1 Preprocessing

The developed technique here is to determine most suitable parameters for a wavelet algorithm to denoise heart sound signals with excellent ability to inform physicians about heart-related problems. This is by adding white noise to the original signals and applying different types of wavelet thresholding to remove the noise from the PCG signals, with different thresholding rules (Rigrsure, Sqtwolog, Heursure, and Minimax) to analyzing the resulting denoising performance of PCG signal. After applying a threshold at each level of the original signal, the effects of noise on PCG signals were removed. Finally, the denoised signal was reconstructed using IDWT. The algorithm was tested using the most widely used wavelet families, i.e., Daubechies wavelet family, Symlets wavelet family, Coiflets wavelet family and discrete Meyer wavelet family, The tested PCG signals were contaminated by white noise added at SNR = 5 dB as an initial value to test the performance of the proposed technique for noise elimination.

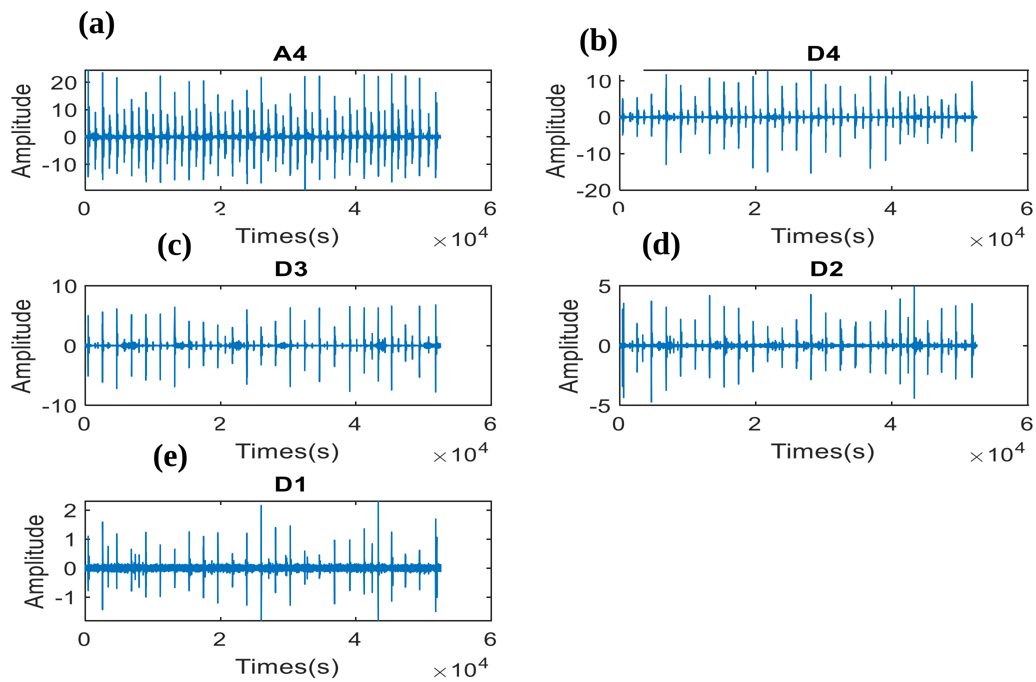

Figure 5. 1 Wavelet coefficients: **a,** approximation coefficient. **b,** denoised detailed coefficient of first level, **c** denoised detailed coefficient of second level, **d** denoised detailed coefficient of third level, **e** denoised detailed coefficient of fourth level.

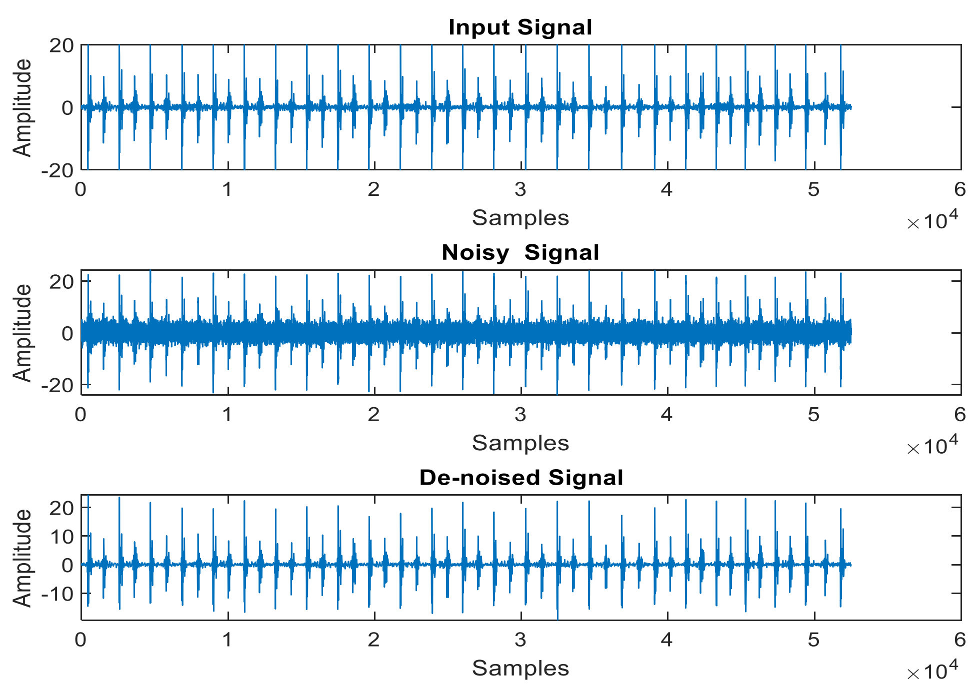

Figure 5. 2 Denoising of PCG signal using Db10 wavelets at 4th level with soft thresholding

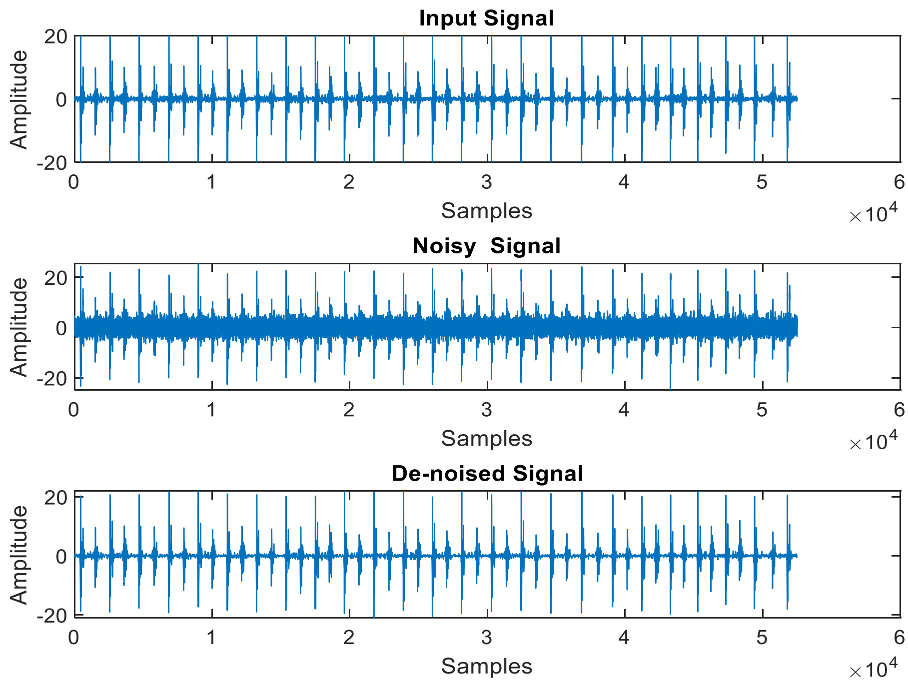

Figure 5. 3 Denoising of PCG signal using Sym6 wavelets at 4th level with soft thresholding

For more convenience, Figure 5.1 shows the wavelet coefficients of the denoised signal, whereas Figure5.2 and 5.3 show the effect of the Sym6 and Db10 wavelets on denoising the normal PCG signal using the 4th level of decomposition. Figure 5.4 shows a histogram comparing the SNR values obtained when using the different wavelet families with soft and hard thresholding. Also, to study the effect of the two thresholding types Table 5.1 presents the SNR results when denoising normal, murmur and extra sound PCG signals using different wavelet families mentioned in Table 5.2.

Table 5. 1 SNR results for denoising PCG signal using different decomposition levels with the Rigrsure threshold selection rule

Wavelet type	Level 3		Level 4		Level 5		Level 6	
	Soft	Hard	Soft	Hard	Soft	Hard	Soft	Hard
Db5	11.0130	10.9492	13.6971	13.7023	14.7013	14.6126	8.6228	8.5790
Db10	10.9935	10.8748	**15.4307**	**15.6019**	13.8640	13.9565	9.0519	9.0421
Sym5	11.0357	11.0521	14.7928	14.2736	13.8969	13.7673	8.7134	8.7020
Sym6	10.9267	10.9575	14.4862	14.3950	13.6277	13.6422	9.2143	9.1888
Coif3	10.9859	10.9606	14.5283	14.5062	13.8659	13.8216	9.0621	9.0716
Coif5	10.9597	11.1185	15.0288	15.0281	13.8573	13.9143	9.1598	9.1339
DM wavelets	11.0522	10.9872	15.2460	15.3563	13.9473	13.7343	9.4293	9.4629

Table 5.1 presents the SNR results using the different wavelet families with different decomposition levels from 3rd to 6th with the Rigrsure threshold selection rule and the two different thresholding types. From Table5.1 it is clear that when choosing the wavelet family, the level of decomposition and thresholding type are important parameters affecting the SNR value. According to the SNR value analysis, the 4th level of decomposition for the discrete Meyer and Db10 wavelets shows the highest SNR values when using the soft and hard thresholding. The SNR values using Db10 are 15.4307 and 15.6019, compared with 15.3563 and 15.2460 when using the discrete Meyer wavelets for soft and hard thresholding respectively.

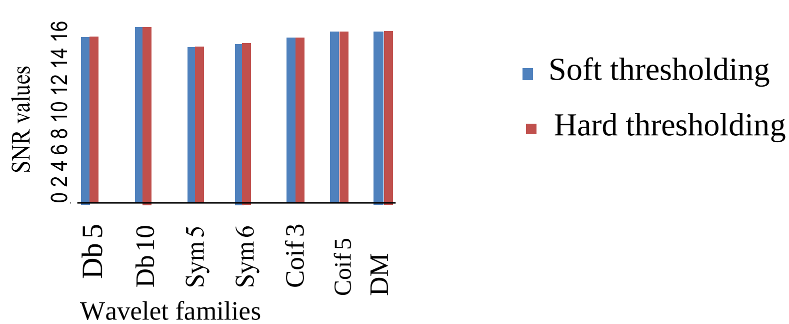

Figure 5. 4 Comparison of SNR values obtained using different wavelet families with soft and hard thresholding

Figure 5.4 shows a histogram comparing the SNR values obtained when using the different wavelet families with soft and hard thresholding. The effect of Db10 wavelets on denoising the PCG signal using the 4th level of decomposition gives a better SNR values. Thus Db10 wavelet of 4th level decomposition is used for this thesis preprocessing analysis. To study the effect of the four thresholding rules, several experiments are done using selected wavelet families. Table5.2 presents the performance in terms of SNR, RMSE, and PRD when denoising normal, murmur and extra sound PCG signals using the optimal parameters mentioned the Table 5.2.

Table5. 2SNR, RMSE, and PRD values for some heart sound signals using the 4th level of decomposition with the four threshold selection rules and soft thresholding

Thresholding type	Soft											
Wavelet function	Db10											
Threshold rules	Heursure			Rigrsure			Minimax			Sqtwolog		
Threshold parameters	SNR	RMSE	PRD %	SNR	RMSE	PRD %	SNR	RMSE	PRD %	SNR	RMSE	PRD %
Normal	14.957	0.011	17.9	14.97	0.011	17.85	15.07	0.011	17.7	15	0.011	17.89
Murmur	7.9908	0.013	39.9	7.912	0.013	40.22	7.969	0.013	40	7.97	0.013	39.96
Extra HS	13.03	0.04	22.3	13.07	0.04	22.2	12.99	0.04	22.4	11.7	0.04	22.08

Here, the Rigrsure and Sqtwolog selection rules perform better than the others as show in Table 5.4. Rigrsure shows the maximum performance for all the wavelet families. These results show that the proposed algorithm using the Db10 families at the 4th level of decomposition gave the maximum SNR, RMSE, and PRD values. It is known that it is difficult to analyze PCG signals in the time domain. Therefore, PCG signals in the frequency domain were provide in Figure5.5. Figure 5.5 presents spectrograms for the noisy and denoised PCG signals to show the clarity of the heart sound components obtained after applying the proposed denoising algorithm. In the denoised PCG signal spectrogram, the heart sounds are clear.

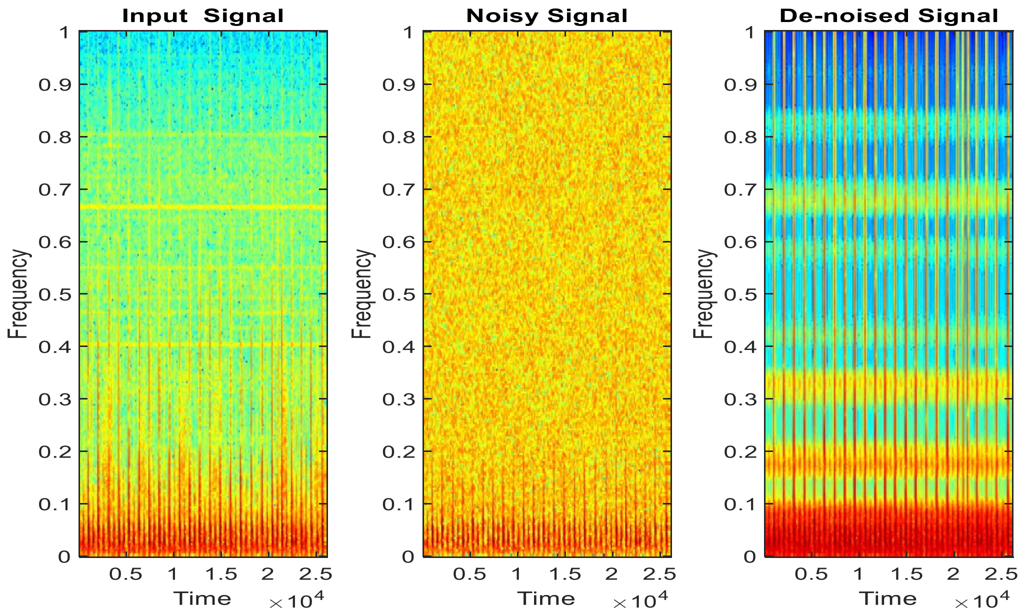

Figure5. 5 PCG signals spectrograms:

5.2 Feature extraction

This is a step where a certain signal is expressed in its statistical parameters. Features have been extracted in different domains i.e. time domain, frequency domain, and statistical domain. A total of 15 features have been extracted for 300 signals, and also new features mid frequency and average frequency is also introduced in this study.

Several MATLAB built-in function and formulas are used to calculate 15 features. A sample of the feature extracted in this study is shown in the Figure5.6. The figure represents numerical values of sample signals for all features during feature extraction.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Max. freq	DR	THD	BW	Mid.fred	Avg.freq	mean	power	STD	Kurtosis	skewnes	CPA	RMS	Variance	Max.Amp
2	9.710361	0.649455	-6.2742	66.34329	0.097599	0.575704	0.210152	0.022353	0.05757	0.438661	10.43866	68.96654	11.37413	0.854101	35.96157
3	6.561411	0.60911	-15.4207	66.36132	0.354222	0.990755	0.001842	0.077956	0.009908	0.489187	7.489187	9.109991	1.652372	1.011047	17.98685
4	3.02497	0.800861	-18.696	72.963	0.284856	0.210755	0.257507	0.023643	0.021076	0.177285	1.177285	3.784069	15.41107	0.555178	14.75305
5	0.378772	0.648952	-9.058	66.70106	0.787414	1.148588	0.003908	0.011784	0.148588	0.042938	4.042938	0.522478	1.418418	12.86578	9.297725
6	6.882193	0.638549	-12.0064	63.61417	0.765588	4.046076	0.002528	0.038699	0.046076	0.059742	0.059742	10.04743	31.37524	10.94282	22.72731
7	0.189229	0.667914	2.325798	39.0691	0.96297	6.022236	0.002017	0.001645	0.022236	0.00107	0.107001	0.538643	1.393107	0.719207	11.37425
8	22.54157	0.626098	-18.9453	72.03716	0.617503	7.023083	0.06817	0.011238	0.023083	0.263369	0.263369	28.51786	1.331374	0.894924	19.8791
9	4.485239	0.779442	-25.6497	64.79631	0.91723	9.002198	0.001097	0.00592	0.002198	0.053982	0.053982	6.402698	1.326002	67.86501	17.76764
10	48.01115	0.7976	-11.8545	66.58533	0.706427	9.004944	0.169254	0.033245	0.004944	0.061772	0.61772	66.39919	61.34692	0.799798	33.27715
11	3.535288	0.882507	-9.60723	69.86353	0.465703	1.056826	0.09259	0.029396	0.056826	0.052285	0.522848	4.628389	1.349068	0.920772	20.76636
12	2.840806	0.736804	-9.04204	69.24951	0.756879	0.030933	0.003308	0.035992	0.030933	0.142304	0.423041	3.755267	1.474203	0.885682	21.14575
13	22.82153	0.780333	-11.7979	69.88368	0.109929	0.114449	0.011856	0.063711	0.114449	0.572721	0.572721	29.84575	34.64729	230.8936	26.81523
14	19.9525	0.770141	-14.1894	62.46078	0.068784	0.025569	0.020961	0.017324	0.025569	0.864356	0.864356	29.98402	30.46299	230.7886	17.37111
15	30.80609	0.879231	-15.7883	64.94162	0.279019	0.053342	0.224955	0.124427	0.053342	0.236259	0.236259	43.9808	0.463501	0.869077	25.21594
16	2.482793	0.61936	-7.88612	62.01422	0.356985	0.009577	0.010935	0.242124	0.009577	0.150661	0.150661	3.770502	0.634297	0.821523	18.61469
17	0.160516	0.65226	-6.42961	46.89157	0.583322	0.012049	0.045703	0.142401	0.012049	0.206026	0.206026	0.399515	1.685966	670.772	9.960936
18	282.2477	0.838609	-8.02961	71.13041	0.572603	0.105087	0.020234	0.059145	0.105087	0.129258	0.129258	362.2973	1.315497	0.801658	37.30863
19	4.970222	0.673388	-2.88543	67.51933	0.939506	0.015385	0.006386	0.024504	0.015385	0.003934	0.003934	6.763563	1.367015	0.76699	16.02516
20	0.178216	0.707984	-4.75491	73.66441	0.160207	0.035836	0.017508	0.105318	0.035836	0.046744	0.046744	0.220452	1.429888	0.843613	7.306384
21	1.646139	0.716423	-2.85567	74.18721	0.984928	0.00535	0.003602	0.000872	0.00535	0.003487	0.003487	2.024702	1.449562	87.89178	14.06754
22	0.239148	0.611574	-14.3126	68.94305	0.795362	0.02371	0.010458	0.006261	0.02371	0.107528	0.107528	0.317615	1.235587	0.798897	7.066959
23	0.442582	0.816946	-15.6929	69.98015	0.337919	0.032043	0.011058	0.601959	0.032043	0.005399	0.539927	0.577926	11.36404	84.81554	7.504363
24	0.458572	0.681915	-8.27796	71.37866	0.502692	0.047506	0.035347	0.084411	0.047506	0.058431	0.058431	0.586397	1.296245	67.85596	6.330116
25	163.8777	0.725691	-11.4905	66.12171	0.925007	0.00467	0.002429	0.013762	0.00467	0.050286	0.050286	228.1417	1.264016	2020.944	33.31352

Figure5. 6 sample of extracted features

5.3 Feature reduction

The features which are extracted in the feature extraction phase are then reduced to a few features which are further used for classification. This is done in order to reduce the dimensionality, redundancy and computational load. The features that have been reduced using CFS and those selected features with higher CFS value as shown in the Table5.3. After applying CFS out of the total feature, only seven features have been selected.

Table5. 3 List of Selected Features for Classification

S.no	Feature	Feature domain
1	Mean	Statistical
2	Standard deviation	Statistical
3	RMS	Time
4	Dynamic range	Frequency
5	Peak Amplitude	Time
6	Total power	Time
7	Peak frequency	Frequency

Selection of only a few significant features reduces the curse of dimensionality and the computational time. This means that by simply evaluating the value of signal for the above features, classification of three types of signals can be done.

5.4 Classification

The classification is done using the set of selected feature values. The feature set is divided into a training set consisting of 202 signals and a test set consisting of 98 signals. The test samples are given as input first and classification is done according to the algorithm. The output of the algorithm is the class of the signal. The accuracy is then calculated according to how many test signals are classified correctly and confusion matrix has also been made according to the classification of test samples. An accuracy of 97.96% was achieved using this algorithm.

5.2.1 Confusion matrix

The confusion matrix is the visualization of the performance of an algorithm. It reports the number of false positives, false negatives, true positives, and true negatives. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. Hence, by using the confusion matrix the performance parameters accuracy, sensitivity, and specificity can be calculated in order to properly analyze the efficiency of the algorithm.

Table5. 4 Accuracy, Sensitivity and Specificity Parameters from Confusion Matrix

Parameter	**Formula**
Accuracy	TP+TN/TP+TN+FP+FN
Sensitivity	TP/TP+FP
Specificity	TN/TN+FN

In this study, 300 heart sound signals were used and divided into 202 signals (100 normal signals 70 murmur signals and 32 extra sound signals) for training and 98 signals (50 normal signals and 30 murmur signals and 18 extra sound signals) for testing. As shown in Table 5.5 out of the 50 normal signals 49 were classified correctly and 1 normal signal were classified wrongly as murmur signal. Out of 18 extra sound signals, 17 were classified correctly as extra sound signals and 1 extra sound signal were classified as normal signal. All the 30 murmur signals were classified correctly.

Table5. 5 Confusion matrix for classification using multiclass SVM algorithm.

<table>
<tr><td colspan="2" rowspan="2">Actual Class
Predicted Class</td><td rowspan="2">Normal</td><td rowspan="2">Murmur</td><td rowspan="2">Extra sound</td><td colspan="2">Total (100%)</td></tr>
<tr><td>Correctly</td><td>Incorrectly</td></tr>
<tr><td colspan="2">Normal</td><td>49</td><td>1</td><td>0</td><td>98%</td><td>2%</td></tr>
<tr><td colspan="2">Murmur</td><td>0</td><td>30</td><td>0</td><td>100%</td><td>0%</td></tr>
<tr><td colspan="2">Extra sound</td><td>1</td><td>0</td><td>17</td><td>94.4%</td><td>5.6%</td></tr>
<tr><td rowspan="2">Total (%)</td><td>Correctly</td><td>98%</td><td>96.8%</td><td>100%</td><td colspan="2" rowspan="2">97.96%
2.04%</td></tr>
<tr><td>Incorrectly</td><td>2%</td><td>3.2%</td><td>0%</td></tr>
</table>

The 98%, 100%, and 94.4% were the classification performance of a developed system for normal, murmur and extra sound classes respectively.1 signal (2%) from normal and 1 signal(5.6%) from extra sound class were misclassified into murmur and normal respectively and all of the murmur classes were correctly classified.

Table5. 6 values of measuring performance parameter

Parameters	Types of Heart sound			Total Number
	Normal	Murmur	Extra	
Number of signals used for testing	50	30	18	98
True positive	-	30	17	47
True Negative	49	-	-	49
False positive	1	-	-	1
False negative	-	-	1	1

The overall accuracy of the developed algorithm were 97.96% with Sensitivity of 97.92 % and Specificity of 98.0%, which gives better classification performance of a system when it compare with the previous conducted researches as summarized in the Table 5.7.

Table 5. 7 Comparison between the proposed methodology and previous proposed methodologies.

Author	Database	Methods	Result
Mandeep Singh (2013)	PASCAL dataset	Naïve Bayes classifier	Accuracy 93.33%
Elsa Ferreira (2013)	PASCAL dataset	Decision tree classification algorithm	Accuracy 72.76.33%
N. R. Sujit (2016)	PASCAL dataset	Regression Tree	Accuracy 78.33%
Zichun Tong (2015)	PASCAL dataset	Hilbert Transform + SVM	Accuracy 90.5%
Nabih-Ali (2017)	PASCAL dataset	DWT and ANN	Accuracy 97%
The proposed System	PASCAL dataset	DWT and SVM	Accuracy 97.96%

Finally, the proposed algorithm results compared with the previous methodologies results to see the efficiency of the proposed methodology. From the Table 5.2, it is clear that the proposed algorithm reached better classification accuracy than the compared studies, which leads to more reliable diagnosis from previous studies. To conclude, this developed algorithm is fully automated and robust enough for the classification of the three classes of heart sound signals.

CHATER SIX

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In this thesis, an attempt was made to study and analyze the characteristic features of PCG for detection of heart valve diseases. The algorithms proposed in this study were time efficient, simple, and require only PCG as input signal unlike other methods which require ECG gating.

PCG signals are capable of indicating the heart problem at an earlier stage which can be very useful in preventing fatality due to heart problems. Research in this area can be very helpful for easy and earlier diagnosis of various heart diseases.

The thesis presents the application of the wavelet transform method to PCG signal analysis. Comparison of the results obtained using different wavelet families reveals the resolution differences among them. Since the noise level is one of the most important parameters in wavelet denoising, it was examined at different levels and the Db10 wavelets at the 4th level of decomposition give the maximum SNR and minimum RMSE for HS.

In this thesis, the PCG signal were studied and classified into three classes, namely normal signal, systolic murmur signal, diastolic murmur signal. Many features in time, frequency and statistical domains have been extracted and the best features were selected for the classification using Multi SVM. Two new features mid-frequency and average frequency were introduced in this study for classification of the PCG signals. Finally using 7 optimal features and Multi SVM classifier an accuracy of 97.96% were achieved and thus can lead to a more reliable diagnosis.

The proposed algorithm for murmur detection is useful to detect mainly the valve-related diseases and other congenital abnormalities.

6.2 Future Scope

The proposed method can also be implemented using the latest mobile phones with the applications which can work as electronic stethoscope or phonocardiogram which can be used for detecting any abnormalities at an earlier stage.

In future research, the research work intend to generalize the algorithm to determine the most suitable parameters for real noisy PCG signals by studying all wavelet families. The accuracy of the presented algorithms can be further increased by incorporating Artificial Intelligence techniques or other hybrid classifiers on a larger dataset.

The case of continuous murmur and types of murmur signal has not been included in this study. So it can be included for classification in further studies.

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