
Artificial Neural Network Application in Classifying the Left Ventricular Function of the Human Heart Using Echocardiography

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Declaration

I, G. A. C. Ranaweera (13020439) hereby certify that this dissertation entitled “Artificial Neural Network Application in Classifying the Left Ventricular Function of the Human Heart Using Echocardiography” is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

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I, N. H. A. P. Samaradiwakara (13020455) hereby certify that this dissertation entitled “Artificial Neural Network Application in Classifying the Left Ventricular Function of the Human Heart Using Echocardiography” is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

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Abstract

The human heart is one of the most important life-giving organs in the human body. According to the World Health Organization (WHO), heart diseases are considered world's number one cause for deaths worldwide. As per the statistics of Ministry of Health of Sri Lanka, the number of heart patients admitted and the annual deaths caused by heart diseases has increased making heart diseases the leading cause of hospital deaths in Sri Lanka as well.

Emergency medicine is the discipline focused on treating patients with urgent medical conditions who are admitted to the Emergency Treatment Unit (ETU) of a hospital. Due to the high number of deaths, the condition of the heart is considered as one of the most critical aspects in emergency medicine. Echocardiography is a widely accepted medical test performed to diagnose the heart condition in non-invasive manner. Generally, the echocardiographic examinations are conducted by acute care physicians who are trained specifically for emergency medicine. Yet there is a chance of them making incorrect decisions due to the lack of clinical experience and expertise in cardiology. Therefore,, an accurate evaluation of the heart condition is highly challenging within the emergency medicine settings.

Left Ventricular (LV) function is a crucial factor when diagnosing the cardiac abnormalities. Several parameters such as LV diameter values and Ejection Fraction are considered to determine whether the patient's LV function is normal or abnormal. Inspired by the recent studies, we carried out several experiments to investigate the possibility of classifying the LV function of the human heart using echocardiography readings. During our study, we considered several image processing and feature extraction methods to extract the important parameters from echocardiography images. The extracted parameters were subjected to train an Artificial Neural Network (ANN) to classify the LV function as normal or abnormal. From our research we obtained a high accuracy for the final result which proves the feasibility of using this methodology to determine the LV heart condition for clinical evaluations.

Keywords: Emergency medicine, Artificial Neural Networks, Image Processing, Echocardiography and Left Ventricular Systolic function

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List of Acronyms

ANN	Artificial Neural Network
EM	Emergency Medicine
ETU	Emergency Treatment Unit
LV	Left Ventricle
LVIDd	Left Ventricular Internal diastolic Diameter
LVIDs	Left Ventricular Internal systolic Diameter
FS	Fractional Shortening
ESV	End Systolic Volume
EDV	End Diastolic Volume
EF	Ejection Fraction
LVEF	Left Ventricular Ejection Fraction
MATLAB	MATrix LABoratory
PSAX	Parasternal Short AXis view
PLAX	Parasternal Long AXis view
AP4C	APical 4 Chamber view
1D	1 Dimensional
2D	2 Dimensional
3D	3 Dimensional
MI	Mitral Insufficiency
HF	Heart Failure
IE	Infective Endocarditis
TTE	Transthoracic Echocardiography
TEE	Transesophageal Echocardiography
GLCM	Grey Level Cooccurrence Matrix
GA	Genetic Algorithm
BP	Back Propagation
DCM	Dilated Cardiomyopathy
HCM	Hypertrophic Cardiomyopathy

Chapter 1 Introduction

1.1 Background to the research

1.1.1 Introduction

Emergency medicine (EM) is the immediate assessment and treatment of patients admitted to Emergency Treatment Units (ETU). This is conducted by Acute Care Physicians who are experts in treating patients in urgent medical conditions. Emergency treatment is significantly essential for patients complaining of a chest pain or stroke because a patient can normally survive only 3-4 minutes after a cardiac arrest.

As per the statistics of Ministry of Health of Sri Lanka [1], the number of heart patients getting admitted to government hospitals has increased to 108,905 in 2014 from 92,107 in 2009. The annual deaths caused by heart diseases also has increased each year. In 2009, 4,856 patients have died due to ischemic heart disease and this number increases to 6346 patients in 2014. The number of patients who died due to ischemic heart diseases is 21.8% of the total deaths in 2014. All these statistics for heart diseases show a continuously increasing trend in each year. The impact of heart disease on human health is further recognizable since it is the leading cause of hospital deaths in Sri Lanka.

Echocardiography is one of the medical tests conducted in emergency medicine to diagnose the condition of the patient's heart [2]. It is a non-invasive medical test where the final conclusion of the examination is highly dependent on the experience and expertise of the medical doctor conducting the test. There are times that the conclusions drawn by an experienced cardiologist (specialist doctor for heart diseases) may also be inaccurate due to various misinterpretations. This emphasizes that there is a comparatively high risk for the lives of patients suffering from heart diseases.

The diagnosis of the heart condition is important when prescribing medicine for patients suffering from other diseases as well. Therefore,, the purpose of this study is to enhance the emergency treatment process of Sri Lanka by providing a methodology to automatically diagnose the heart condition accurately within the least possible time. This would ultimately contribute in saving the lives of thousands of patients where a tick of the clock matters.

1.1.2 Cardiac Dysfunctions

Heart is considered to be the life giving, ever beating muscle which pumps oxygenated blood throughout the human body. The cardiac cycle of the heart composed of two phases called Diastole and Systole. Diastole is the phase at which the cardiac muscle is relaxed allowing blood to flow into the heart chambers. Systole is the phase at which the cardiac muscle is contracted to pump blood out of the heart through the blood vessels. The human heart consists of four chambers with two upper Atria and two lower Ventricles. Out of all chambers inside the heart, Left Ventricle can be considered as the most important since at Ventricular Systole, it pumps oxygenated blood into the aorta whilst generating sufficient blood pressure to circulate blood throughout the body [3]. Due to these reasons, Left Ventricular Systolic function is given high priority when diagnosing the heart condition.

Since the human life depends on the proper functioning of the heart, early detection of heart dysfunctions is of high importance for the controlling of heart diseases. There is a set of aspects that are often analyzed by the experts in evaluating the Left Ventricular heart function. Left Ventricular internal dimensions, Fractional Shortening (FS), End Systolic Volume (ESV), End Diastolic Volume (EDV) and Ejection Fraction (EF) are some of the fundamental parameters that are extracted in both systole and diastole cycles of the human heart [4]. The irregular systolic dysfunction could be caused due to many heart diseases. There are common symptoms for cardiac dysfunctions such as mitral valve regurgitations, myocardial infarction, coronary artery diseases, ventricular hypertrophy and arrhythmia.

It takes a considerable time to examine each heart chamber and valve in both phases of the cardiac cycle for a complete diagnosis of the heart condition using echocardiography. Due to this reason, diagnosing particularly the Left Ventricular Systolic function of the heart could have a significant impact than other areas of concern in emergency medical treatments.

1.1.3 Echocardiography

Echocardiography is considered to be the most prominent method for diagnosing the cardiac disorders due to its non-invasiveness, low cost, simple and efficient techniques in imaging the size, shape and functioning of the heart chambers and valves. Furthermore, it has been shown that non-cardiologists can safely and accurately use echocardiography to assess cardiac function. This method can be used to diagnose dysfunctions of the heart such as abnormal thickening of cardiac muscles, heart valve regurgitations, blood clots inside the heart valves etc.

Echocardiography tests are conducted by applying a gel on the chest of the patient and placing a transducer which emits ultrasound beams. Depending on the placement of the transducer, images of the heart can be obtained in different views. The widely used views by the medical doctors are; Parasternal Short Axis view (PSAX), Parasternal Long Axis view (PLAX), Apical 4-chamber view, Apical 2-chamber view, Apical 5-chamber view and Subcostal view. Each view has its unique uses as they visualize different structures and sections of the heart from different angles [3].

The echocardiography videos can be viewed on the screen in two modes called B-mode and M-mode. B-mode is a 2D image composed of bright dots and the brightness of each dot depends on the amplitude of the returned echo signal. M-mode provides a 1D image and is used for finer measurements since it possesses a higher temporal resolution [5]. This displays the cardiac function and behavior on a given cross section of the heart with respect to the time. Doppler imaging is used to estimate the velocity of blood flow and Tissue Doppler is used to observe the contractions in the cardiac muscles.

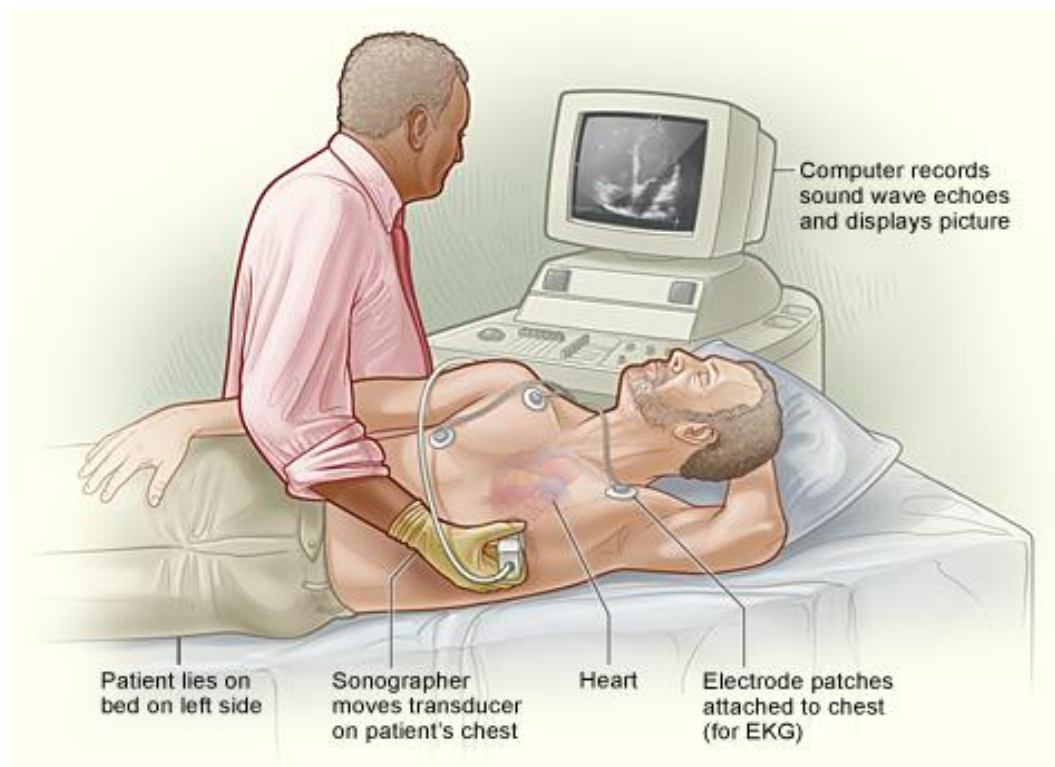


Figure 1.1: Conducting Echocardiography

The doctors can freeze the echocardiography video to observe and measure the parameters from a still image. These extracted parameters are used to predict the heart condition of the patient which requires a considerable time for a complete evaluation. However, most doctors attend to visually estimate and arrive with decisions of the heart based on their long term practical experience and interpreter skills in the field of echocardiography.

1.2 Research Problem and Research Questions

Currently when conducting an echocardiography examination, the doctor needs to select four points on the screen of the M-mode echocardiography image to measure the Left Ventricle Internal End Diastolic Diameter (LVIDd) and Left Ventricle Internal End Systolic Diameter (LVIDs). These 2 diameters are required to calculate the Ejection Fraction (EF) value which is used to determine the condition of the Left Ventricular Systolic function. This is time consuming and these placements vary according to the experience of the doctor. Therefore, if these parameter values can be calculated automatically it will both reduce the time and error in the measurements. Further these measurements values are used in diagnosing the heart condition and this decision depends heavily on the experience of the cardiologist. Therefore, a decision support system giving the final classification of the heart condition would help to increase the accuracy of the final decision of Acute Care Physicians.

By considering the above reasons and the background of the research, the following research questions were selected to be addressed from the research.

Research Question 1: How to reduce the time taken to conduct echocardiography tests for determining the Left Ventricular Systolic function?

Research question 2: How to improve the accuracy of the Acute Care Physician's decision on the Left Ventricular Systolic function?

The final research problem can be summarized as “to find a simple, reproducible methodology to assist Acute Care Physicians in diagnosing the heart condition accurately within a minimum time during emergency medicine”. As the first step in achieving this ultimate intention, the automatic classification of the Left Ventricular Systolic function of the heart as either normal or abnormal would be taken into consideration.

1.3 Justification of the Research

The research is based on the Left Ventricular Systolic function of the heart because Left ventricle is the most important chamber of the heart from which blood is pumped to the whole body [2]. The muscles of the Left Ventricle should contract to create the highest pressure to pump blood into the aorta in order to circulate blood throughout the body. Therefore, Left Ventricular function is the function of the heart which is analyzed in this research to determine the heart condition. The automatic classification of the left Ventricular function of the heart could help to save time in decision making about the overall condition of the heart. The decision making about the Left Ventricular function is conducted frequently in emergency medicine Therefore, this study could have a significant benefit for the emergency medicine field.

1.4 Methodology

The solution will be carried out mainly in three stages. The first stage is image pre-processing. As the initial step, a set of JPEG images will be exported from the echocardiography video. Each image will be subjected to image enhancement techniques (De-noising, Grey scaling, Binarizing) to make them suitable for the digital analysis. In the second stage subsequent to the series of image processing steps, the image will be processed to extract its features to measure the Left Ventricular parameters by which the cardiologists draw conclusions. For this purpose, a feature extraction algorithm will be developed to contrast the myocardial borders of the images in both Diastole and Systole phases.

During the third stage, An Artificial Neural Network (ANN) will be used to classify the heart condition based on the extracted image parameters [6]. The image parameters extracted from both heart patients, normal patients and the cardiologist's recommendations for such data will be used as inputs to train the ANN to distinguish between normal and abnormal Left Ventricular function. During the final stage, another set of echocardiography videos will be used to test the accuracy of the proposed methodology. The output of the trained ANN will be tested against the Cardiologists decision to statistically evaluate the performance of the solution. If the study results could reach higher accuracy level, then it could validate that this methodology can be successfully used in classifying the Left Ventricular function of the human heart as normal or abnormal.

1.5 Delimitations of scope

Since echocardiography is a complex medical test which supports viewing of the heart in different angles, modes and views, it could be used to detect many cardiac dysfunctions. Therefore, it is impractical to consider all these dysfunctions for deriving the decision on the heart condition within the stipulated research schedule. The scope of this research is limited to detecting the condition of Left Ventricular Systolic function using M-mode images taken from Parasternal Long Axis view and Parasternal Short Axis view.

To determine the condition of the heart, many different functions of the heart should be considered. From all of these functions our scope is limited to Left Ventricular Systolic function. It was selected because out of all the dysfunctions which cause heart abnormality, Left Ventricular Systolic dysfunctions are the common dysfunctions. In addition, cardiologists give high priority to it and it is the first thing that a cardiologist checks during an echocardiography test. Systole is the phase of the heart in which pumping of blood occurs through the contraction of cardiac muscles. The other “out of scope” functions that we do not consider in this research are Left Ventricular Diastolic function, Valve functions and Systolic and Diastolic functions of other three heart chambers.

Echocardiography provides viewing of the structure of the heart in several views such as Parasternal Long Axis view, Parasternal Short Axis view, Apical 4-Chamber view and Apical 2-Chamber view. From these views, we have selected Parasternal Long Axis (PLAX) view and Parasternal Short Axis (PSAX) view. This is because PLAX is the most commonly used view to obtain the Left Ventricular dimension measurements and the PSAX view provides the clearest view for detecting the Left Ventricular cavity wall. Left Ventricular cavity wall should be clearly visible for extracting features required to determine the Left Ventricular Systolic function. Even though the other views can be used in different methods they are not considered within our scope as they are not commonly used to give the cardiologist’s final decision.

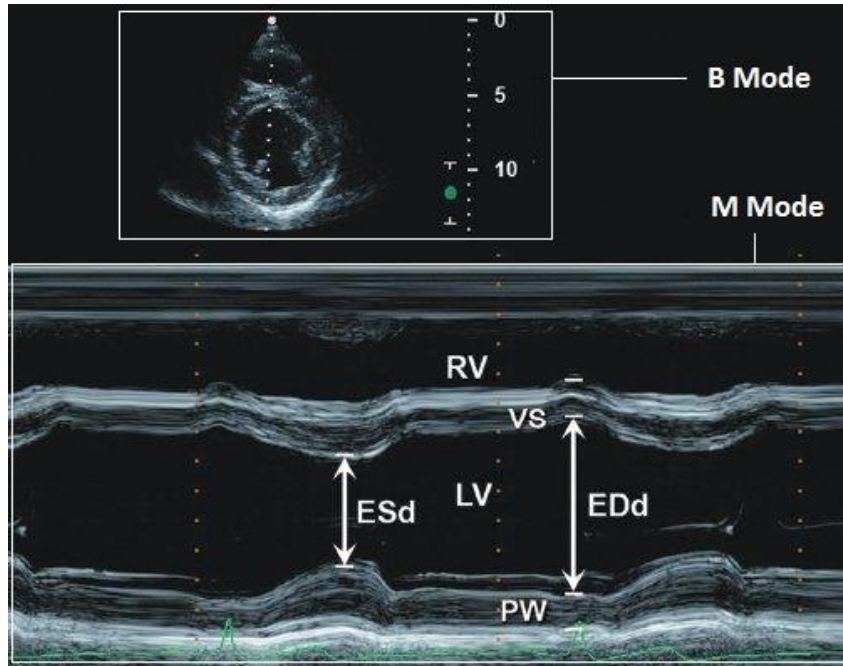


Figure 1.2: B-mode to M-mode conversion

Parasternal Long Axis view can be obtained in M-mode and B-mode (Figure 1-1). M-mode is the 1-D view which is used by cardiologists to measure the Left Ventricular diameters such as LVIDd and LVIDs. B-mode is mostly used to determine the functioning of the heart, for example to check whether the contraction of cardiac muscles, opening and closing of valves occur correctly. Therefore, for conducting the research, M-mode images of the PLAX view were preferred over B-mode images.

1.7 Outline of the Thesis

- Chapter 2 deals with the background of the thesis and the literature review of the study. It provides relevant information regarding Cardiac dysfunctions, Clinical methods for diagnosing cardiac dysfunctions, Echocardiography and Emergency medicine. Further this chapter includes image processing techniques for edge detection in echocardiography images. Moreover, this chapter provides relevant researches on the use of Artificial Neural Networks for cardiac diagnosis and for decision making based on echocardiography.
- Chapter 3 contains a detailed description of research methodology and the research design will be described in this chapter as well.
- Chapter 4 contains the details related to the implementation. The dataset that has being used in the research will be introduced. Additionally, different software, tools and implementations of image processing and machine learning techniques will be discussed. Finally,, the algorithms that were used during implementation for the proposed methodologies will be demonstrated.
- Chapter 5 presents the results of the research using diagrams and confusion matrices to illustrate the results. Afterwards, the results will be discussed in detail for the purpose of evaluating the performance of the ANN implemented in the methodology.
- Chapter 6 provides the conclusion and future work. According to the discussion, the conclusions will be provided with the limitations that became apparent during the progress of the research. Finally,, some potential avenues of investigation will be pointed out along with the work that has to be implemented in the future.

1.8 Conclusion

By introducing the background of the research and the research problem the foundation for the thesis was laid in this chapter. Then the research was justified, definitions were presented, the methodology was briefly described, the thesis was outlined, and the limitations were given. A detailed description of the research will be followed in the proceeding chapters.

Chapter 2 Background & Literature Review

2.1 Introduction

This chapter will provide a detailed description of Cardiac dysfunctions, Clinical methods for diagnosing cardiac dysfunctions, Echocardiography and Emergency medicine. Further this chapter includes image processing techniques for edge detection in echocardiography images. Also studies on the use of Artificial Neural Networks for cardiac diagnosis and for decision making based on echocardiography are included in this chapter. There were several studies for determining the cardiac cycle phase and automated classification of different types of cardiac diseases. Finally, a previous study conducted on automatic classification of Left Ventricular function will be discussed in detail.

2.2 Human Heart

The human heart is a muscular organ located in the thoracic cavity between the lungs, anterior to the back bone and posterior to the sternum. The human heart serves the purpose of pumping of blood to the entire human body. The heart is placed on the left side of the chest and it has a size roughly of a folded fist. The function of the heart is to pump deoxygenated blood collected from various parts of the body into the lungs and to pump oxygenated blood collected from lungs throughout the human body.



Figure 2.1: Location of the human heart

2.2.1 Anatomy of the Human Heart

The heart contains four chambers namely Left Ventricle, Right Ventricle, Left Atrium and Right Atrium. The blood first fills into the two Atria from the veins. Superior Vena Cava and Inferior Vena Cava are connected to the Right Atrium and they bring deoxygenated blood from all parts of the body except lungs. Pulmonary Veins are connected to the Left Atrium and they bring oxygenated blood from the lungs [7].

Left Ventricle is connected to the Aorta which is the main artery that distributes blood throughout the body. Right Ventricle is connected to the Pulmonary Vein which transports deoxygenated blood to the lungs. The two ventricular walls are thicker compared to the atrial walls because they need to be stronger to contract and pump blood away from the heart. Also Left Ventricular walls are more muscular than Right Ventricle since Left Ventricle needs to generate blood pressure that should be sufficient to circulate blood throughout the body.

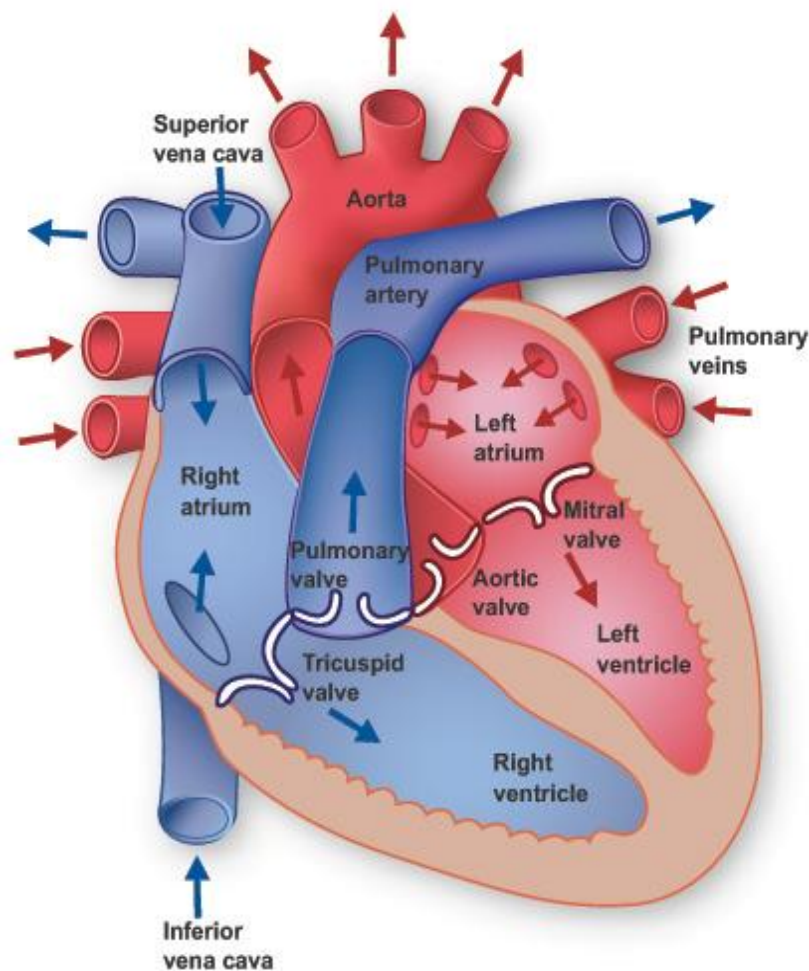


Figure 2.2: Anatomy of human heart

There are several valves present in the heart for preventing blood flowing backwards. Mitral valve is present between the Left Ventricle and the Left Atrium and Tricuspid valve is present between the Right Ventricle and Right Atrium (Figure 2.2). Both Mitral valve and Tricuspid valve are

collectively called Atrioventricular valves. Aortic valve is present at the tip of the Aorta to prevent blood flowing back into the Left Ventricle. Pulmonary valve at the tip of the Pulmonary Artery prevents blood flowing back into the Right Ventricle. Aortic valve and Pulmonary valve are collectively called Semilunar valves because of their shape resembles a crescent moon.

The outermost layer of the heart is called the pericardium which reduces the friction between the heart and the surrounding organs during the heart contractions. The heart wall is made up of three layers of tissues called Epicardium, Myocardium and Endocardium. Epicardium is the outer protective layer lubricating the outside of the heart. Myocardium consists of the middle layer of muscle tissues responsible for the contractions of the heart and it forms the major part of the heart wall. Endocardium is the smooth layer of the heart wall that lines inside of the heart [8].

2.2.2 Cardiac Cycle

The cardiac cycle is the sequence of events that occur during one heartbeat. The normal adult resting heartbeat rate is 60-100 beats per minute. The cardiac cycle consists of two basic phases called Diastole and Systole. Diastole is the period in which all the chamber of the heart are relaxed allowing the blood to fill into the heart from the veins. During Diastole blood flows passively into the two Atria and the Atrioventricular valves are open thereby blood also flows into the two ventricles filling about 75% of the ventricles. During Diastole Semilunar valves kept closed to prevent backflow of blood into the ventricles from the arteries.

At the end of Diastole phase Atrial Systole phase occur. During this phase Atrial walls contract to eject blood into the ventricles through the open Atrioventricular valves. During Atrial Systole semilunar valves remain closed and the ventricles remain in the Diastole phase. At the end of Atrial Systole, the remaining volume of the ventricles get filled with blood [9].

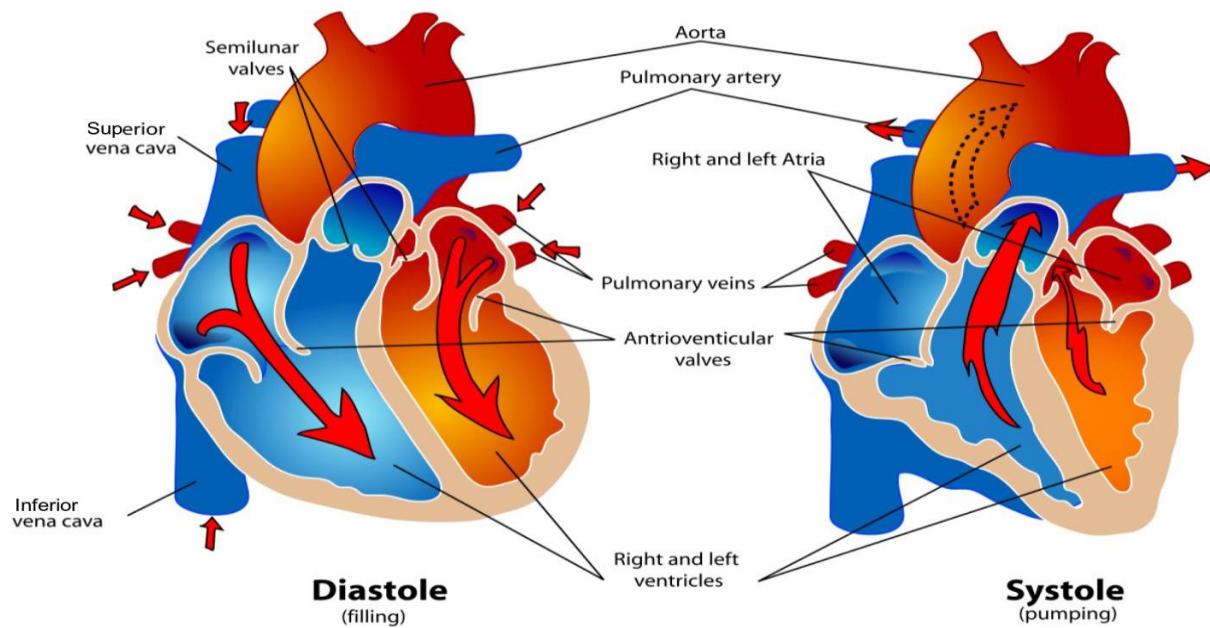


Figure 2.3: Phases of Cardiac Cycle

The final phase of the cardiac cycle is the Ventricular Systole, the period which the Ventricular walls contracts to push the blood away from the heart into the Aorta and Pulmonary Artery. This contraction of the Ventricular muscles forces the semi lunar valves to open to allow blood flow and Atrioventricular valves close to prevent blood flowing back into the atria. At the end of the Ventricular Systole the Ventricular walls again relaxes to enter the Diastole phase thereby the next cardiac cycle commences [10].

2.3 Cardiac Dysfunctions

Cardiac dysfunctions or else in classical terms, Heart failures are caused by a variety of different reasons. Most common heart failures are associated with Left ventricular dysfunctions which causes efficiency reduction in the process of pumping of blood out of the heart by the heart muscle contractions. Cardiac muscle pulse occurs in two distinct, rhythmic cycles called Diastole and Systole which triggers one after the other continuously to assure the correct functioning of blood circulation and oxygenation process of the human body. The dysfunctions and disorders in both dilation and contractile phases can result in congestive heart failures which causes a grave threat for one's life. As such, a good assessment of cardiac cycle and cardiac structure is imperative to diagnose the impairments and symptoms of cardiac dysfunctions.

2.3.1 Left Ventricular Systolic Dysfunction

Systole is the phase at which the Atrial and Ventricular muscle contraction happens. It consists of two phases namely Atrial Systole and Ventricular Systole. Atrial Systole contracts the left and right Atria, allowing the atrial pressure to be increased over the Ventricular pressure and it affects to pump out the remaining arterial blood to Ventricles just before the onset of Ventricular Systole. When the Ventricular Systole occurs, the pressure increases inside the Ventricles make the blood distributed to the lungs and the body via pulmonary artery and aorta respectively. Thus, Systole considered to be the most important phase which keeps the rhythmic behavior and pressure control between the chambers to ensure the correct functioning of the human heart.

In an examination of emergency medical event, dilated Left Ventricle and reduced Ejection Fraction are the prevalent evidences one could diagnose on a heart with Systolic dysfunction. Approximately 50% of the patients with heart failures, predominates the symptoms of left ventricular systolic dysfunction as a low Left ventricular Ejection Fraction (LVEF) [11]. In general terms, Systolic Dysfunction is defined as an LVEF less than 40% [12]. Systolic dysfunction refers to cardiac muscle contraction abnormalities which compromises the blood pumping process to aorta due to the fallen blood pressure generated inside the LV. When the Ventricular contraction happens, both Tricuspid valve and Mitral valve need to close properly due to the pressure difference occurs between Atriums and Ventricles particularly to produce the sufficient stroke pressure to open the aortic valve and thrust the blood into the aorta. Mitral regurgitation or Mitral Insufficiency (MI) is the disorder in which the blood goes back to the Left Atriums when the Left Ventricular Contraction happens. This is a common finding in patients with dilated and ischemic cardiomyopathy who reflect some malfunctions of valve closing mechanism and geometric distortions and of LV [3].

2.3.2 Left Ventricular Diastolic Dysfunction

Left Ventricular Diastolic Dysfunction is one of the causes that could lead to heart failure. Diastolic Dysfunction is the condition at which the ventricular filling is slow or incomplete because the ventricular muscles do not return to its resting state rapidly or completely, to establish the required pressure gradient for the blood to flow from the atrium to the ventricle. The initial Diastolic event is myocardial relaxation which Ventricular pressure falls below Atrial pressure and nearly 80% of the blood poured to the Atriums and then to Ventricles from the main blood vessels namely Inferior Vena Cava, Superior Vena Cava and Pulmonary Veins. When the filling happens, the pressure at Ventricles gradually increases and the blood filling may get restricted to Atriums due to the pressure equivalence between two chambers. The rest of the 30% of volume is pumped to the Right and Left Ventricles through Tricuspid and Mitral valves respectively at the phase at which the Atrium contraction takes place. Hence the malfunctions of this whole process would affect to decrease the blood amount which ought to be filled to the atriums and ventricles after the end of ventricular contraction. Thus, it may reduce the Ejection Fraction (EF), the fraction of stroke volume which pumps from Left Ventricle (LV) to the aorta at end Systolic Phase.

Approximately 30% of the heart patients have normal LV Ejection Fractions but have diastolic dysfunctions [13]. The clinical symptoms do not differ between diastolic dysfunction and systolic dysfunction, however, there is a significant difference in the cardiac structure and function. From this evidence Gaasch and Zile [14] suggested that even though clinical examination cannot distinguish between diastolic dysfunction and systolic dysfunction, it is possible to use echocardiography to distinguish between diastolic dysfunction and systolic dysfunction. Left Ventricular Diastolic Dysfunctions are identified by the presence of an abnormal Doppler pattern for LV filling in echocardiography.

In the early stages of diastolic dysfunction, an abnormal and impaired relaxation pattern of ventricles may be visible. This affects to decrease the early diastolic filling rate due to prolongation of the Ventricular deceleration time and the longer course of time it takes to equilibrate the pressure between Atriums and Ventricles [15].

2.4 Echocardiography

It is obvious that, physical examination alone does not symbolize promising results, due to its limited abilities in diagnosing cardiac characteristics and status in efficient way. Some invasive prognostic methods also take considerable time to characterize the important parameters such as cardiac volume and cardiac output status in an emergency Heart Failure situation. Over the past decades, many techniques have been produced globally to assist in detection and diagnosis of the hemodynamic and morphologic changes in Heart Failure, without the risks and cost of invasive measures. Among them ultrasound scanning is a technique widely used by cardiologists for diagnosing the heart condition.

2.4.1 What are Ultrasound Scans?

An Ultrasound Scan is a medical test that uses high-frequency sound waves to create images of the inside of the body. These sound waves are emitted through an instrument called a “transducer” which picks up the echoes of the waves bouncing back to create moving images on a computer screen to determine the size, shape, and consistency of soft tissues and organs. Most ultrasound scans last between 15 and 45 minutes. These images are interpreted by a medical doctor, radiologist or a sonographer to diagnose and treat patients’ medical conditions. The three main types are:

- External ultrasound scan - the probe is moved over the skin
- Internal ultrasound scan – the probe is inserted into the body
- Endoscopic ultrasound scan – the probe is attached to a long, thin, flexible tube and passed further into the body [16]

The word "ultrasound", in physics, refers to sound with frequencies inaudible to human ear. In diagnostic Sonography, the frequency of sound waves used is between 2 and 18 Megahertz. Even though higher frequencies provide better quality images, they are more readily absorbed by the skin and other tissues. Therefore higher frequency waves cannot penetrate as deeply as lower frequencies. Lower frequencies can penetrate deeper into deeper tissues however the image quality provided is inferior [17].

Although ultrasound waves penetrate through soft tissue and fluids in the body, they bounce back off denser surfaces. For instance, when examining the heart, waves will travel through blood, but much of it will bounce back after hitting heart valves or walls of heart chambers. This varying

shades of gray reflects different densities of the echo received which gives the features of the ultrasound image.

Ultrasound scans are said to be safe and free from side effects since sound waves are used and the patients are not exposed to any sort of radiation. Non-invasiveness, less-expensiveness and creation of images of soft tissues that are not clearly visible in X-rays make ultrasound scans more useful in medical diagnostics.

Recent advancements in ultrasound technology have enabled various types of imaging such as;

- Doppler is used to create images of blood flow through the vessels.
- Bone sonography is used to diagnose osteoporosis.
- Echocardiography is used to image the heart.
- 3D imaging creates a three-dimensional interpretation instead of the traditional two-dimensional images.

Ultrasound scans are performed for diagnosis and treatment in medical procedures. Medical doctors may prescribe an ultrasound scan if the patient is showing symptoms such as pain, swelling which requires an internal view of the body organs. Ultrasound scans are used to view various organs such as; heart, bladder, brain (in infants), eyes, gallbladder, kidneys, liver, ovaries, pancreas, spleen, thyroid, testicles, uterus and blood vessels. [18]

2.4.2 Introduction to Echocardiography

Ultrasound scans in cardiology are specifically called “Echocardiograms”. Echocardiography is widely used globally as a diagnostic tool to examine various cardiac functions in accurate and non-invasive fashion. According to the European heart journal, echocardiography has become the most primarily used diagnostic technique in modern cardiology for the clinical usage of patients with HF [19]. The term ‘Echocardiography’ generally refers to all cardiac ultrasound imaging techniques, which use most comprehensive medical and mathematical modelling of cardiac structures or functions.

Echocardiographic techniques can be used to determine stroke volume, cardiac output, mass, Ejection Fraction (EF) and other important parameters which reflect considerable prognostic value with both symptomatic and asymptomatic patients. These measurements require a sufficient amount of video/image quality and good amount of clinical experience in handling the ultrasound machine to arrive with crucial decisions especially in the emergency HF situations. Small errors in cardiac measurements should be avoided according which otherwise may lead to large errors in diagnosing and decision making.

2.4.3 Echocardiography modes

The modern echocardiography machines image the structure and function of the heart in three basic modes called M-mode, B-mode and Doppler imaging. Each mode has its own advantages and disadvantages. Cardiologists use each mode to serve different assessments depending on the parameters that can be extracted from the mode.

1. M-mode

M-mode is the oldest mode in echocardiography in which the motion of the heart is represented over time. M-mode is a one-dimensional view of the heart and it’s acquired from a 2D image by placing a single scan line along the area of interest in the 2D image. M-mode shows how the structures intersected by the line move towards or away from the line with time.

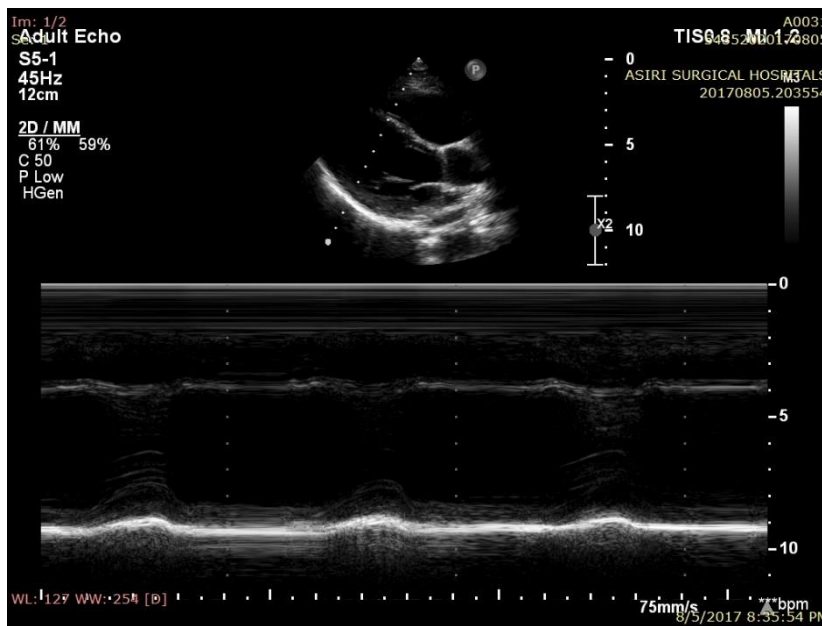


Figure 2.4: M-mode image from the dataset

The main advantage in M-mode images is their superior temporal resolution helps in detecting and recording rapid movements. M-mode data could be acquired at a rate up to 1000 frames per second but it is only 15 to 100 frames per second in B-mode images [5]. Therefore, M-mode is mostly used for assessing fast moving structures such as measuring the dimensions in the heart chambers to calculate parameter values such as Fractional Shortening and Ejection fraction. The disadvantage of M-mode is due to its one-dimensional nature can miss some structures depending on the scan line. Therefore, M-mode images should be obtained with the guidance of two-dimensional images [20].

2. B- mode

B-mode is the default two-dimensional view displayed in an echocardiography machine when it is turned on. In the B-mode the ultrasound echoes reflected from the cardiac interfaces are represented as dots in varying brightness depending on their reflected intensities. The structures that reflect ultrasound signals such as cardiac walls and valves are displayed in white and other areas that do not reflect ultrasound signals such as blood are displayed in black. This helps to distinguish cardiac structures and as mentioned earlier B-mode has a lesser frame rate per second which allows the user to visualize the movement of the cardiac structures clearly.

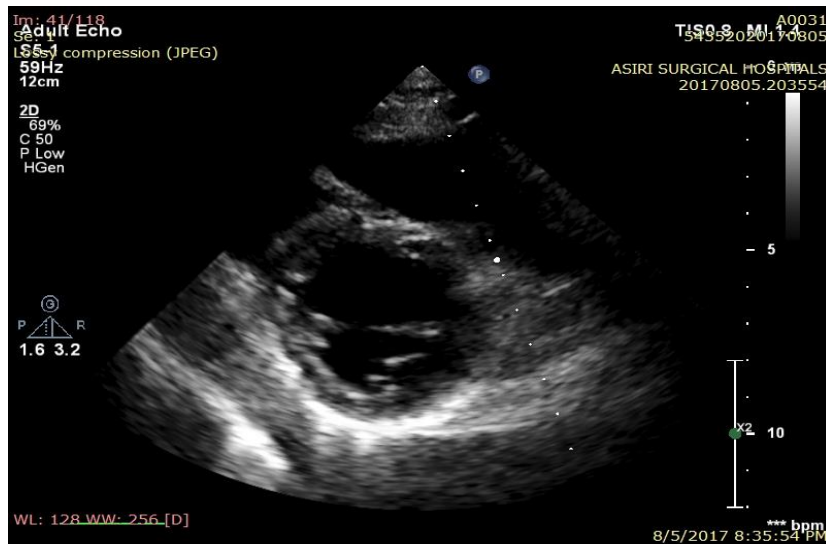


Figure 2.5: B-mode image from the dataset

3. Doppler imaging

Doppler imaging is used to estimate the velocity and direction of the blood flow. In Color Flow Doppler imaging this is done with the use of a color map which is superimposed on the two-dimensional image. The red areas show blood flowing towards the probe and blue areas show blood flowing away from the probe. In addition to Color Flow Doppler imaging there are other types including Continuous wave Doppler, Pulse Wave Doppler and Tissue Doppler for measuring velocities of tissue movement. Doppler imaging is conducted to identify valve regurgitations in the heart since the blood flow depicts the whether the valves properly functions as expected [21].

2.4.4 Echocardiography views

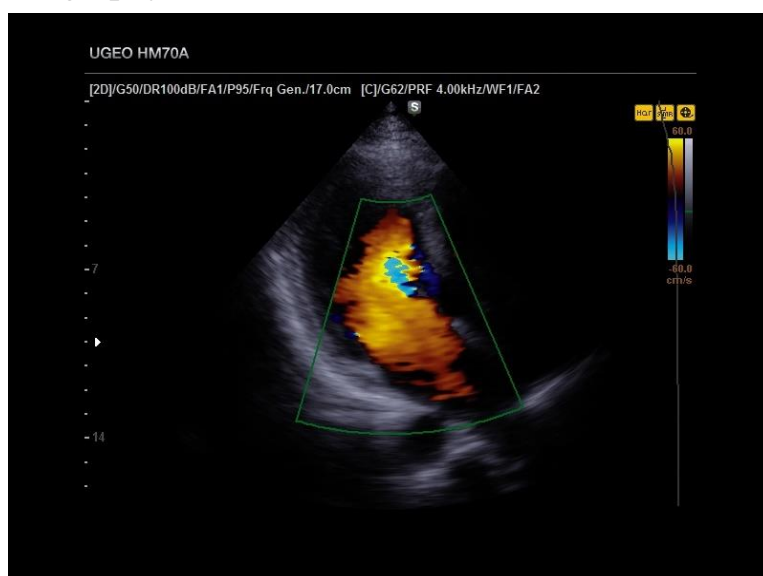


Figure 2.6: Doppler imaging

The echocardiography views differ according to the placing of the transducer on the chest of the patient by the doctor. The transducer should be placed on the chest of the heart so that the emitted ultrasound signals should pass to the heart avoiding the air-filled lungs which act as a barrier for the propagation of the ultrasound signal [22]. Each view gives a different viewing of the heart from different angles thereby the visibility of cardiac structures differs in each view. Therefore, each echocardiography view has a definite purpose when assessing the heart condition. There are many echocardiography views and categorized into four main categories; Parasternal views, Apical views, Suprasternal view and Subcostal view. From all these echocardiography views the following are the echocardiography views used for assessing the Left Ventricular Systolic function of the heart.

1. Parasternal Long Axis view (PLAX)

Parasternal Long Axis view is considered as the best view to measure the thickness of walls and the dimensions of the Left Ventricle. Echocardiography tests normally begin with the PLAX view. For better visualization of the Left Ventricle from PLAX view the transducer needs to be placed between third and fifth intercostal space and adjust it by moving up or down.

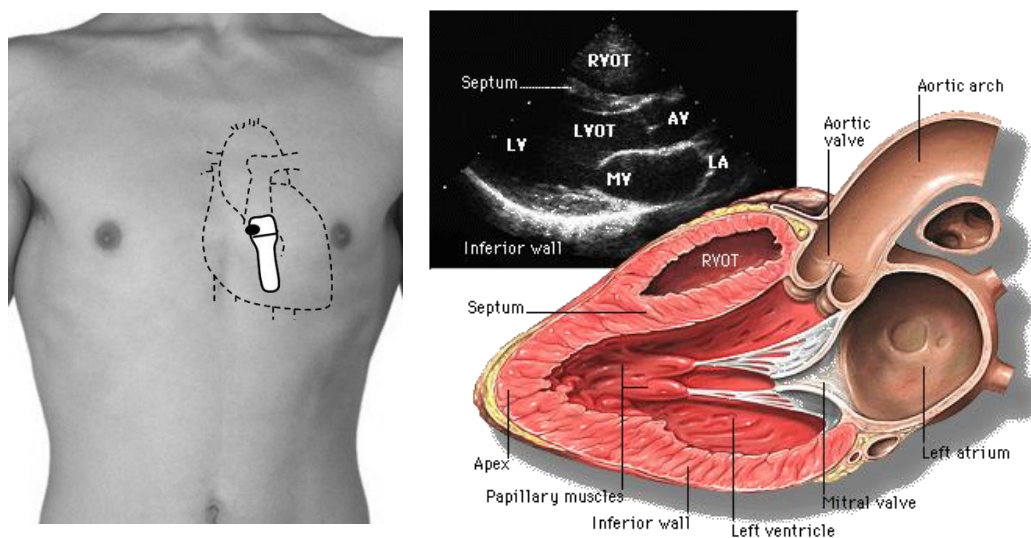


Figure 2.7: Parasternal Long Axis view

In addition to the Left Ventricle other cardiac structure such as Right Ventricle, Mitral valve, Left Atrium, Aortic Valve, Aortic Arch and Interventricular Septum are visible from PLAX view (Figure 2.4). M-mode of PLAX view is used to obtain Left Ventricular dimensions and to calculate Ejection Fraction. A good quality PLAX view should visualize a horizontally oriented septum,

visible aortic and mitral valves but should not visualize the apex of the Left Ventricle and the tricuspid valve [23].

2. Parasternal Short Axis view (PSAX)

Parasternal Short Axis view provides the cross sectional view of the heart by projecting the ultrasound beam from the base to the apex of the heart. The PSAX view is normally taken straight after taking the PLAX view. Therefore, to get the PSAX view the location of the transducer on the chest need not change. To obtain the PSAX view, transducer need to be rotated 90° clockwise by applying a light pressure without sliding it on the chest [24].

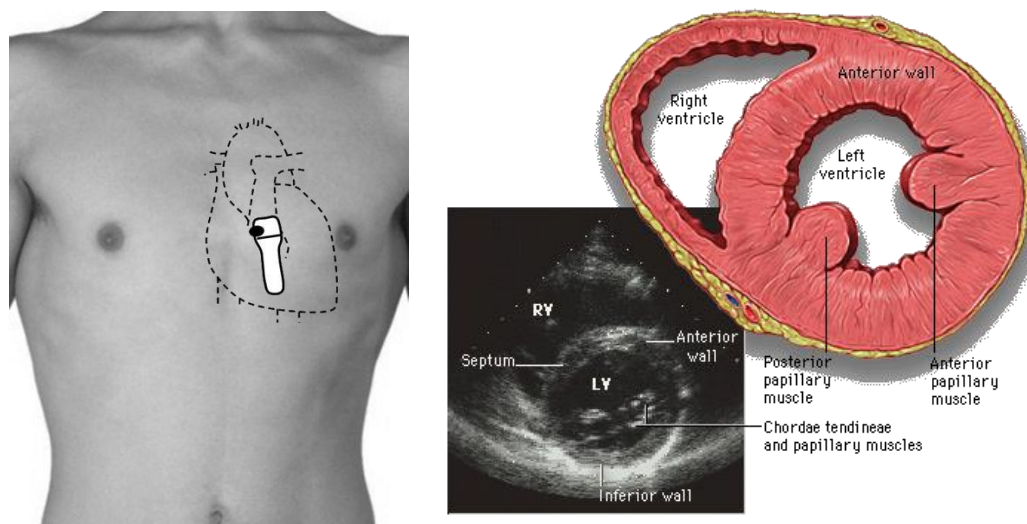


Figure 2.8: Parasternal Short Axis view

In PSAX view there are 3 levels of imaging as Mitral valve level, Mid-papillary level and Aortic level. Mitral valve level gives the cross-sectional view of the Left Ventricle facilitating the assessment of the wall motion of the Left Ventricle. Mid-papillary view gives clear images of the Left Ventricle that can be used for segmental analysis of Left Ventricular wall motion. Aortic level is mostly used to detect abnormalities in aortic valve leaflets. In a good PSAX view the Left Ventricle is in the middle of the screen.

3. Apical 4 chamber view (A4C)

As the name suggests, in Apical 4 chamber view all the main four chambers of the heart (Left Ventricle, Right Ventricle, Left Atrium and Right Atrium) are visible. The transducer placement is at the apex of the heart oriented towards the right shoulder. A4C view is used to assess the function and compare the sizes of each chamber of the heart. Considering the Left Ventricle, A4C view is helpful in assessing the overall function of the heart and the contractility of the Inter Ventricular Septum, apex and lateral walls [25].

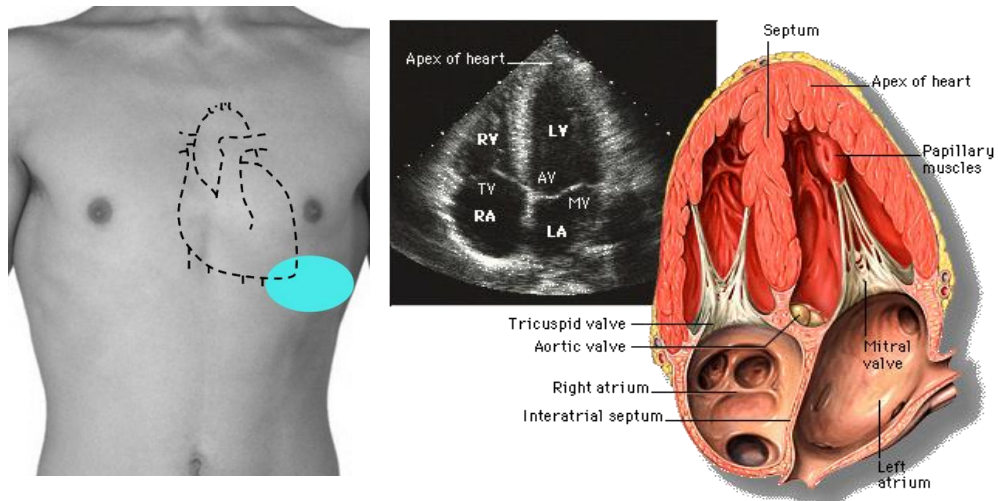


Figure 2.9: Apical 4 chamber view

When assessing the Left Ventricular function A4C view is used in the Simpson's method of calculating the Systolic and Diastolic volumes. In a good visualization by A4C view the apex of the Left Ventricle is close to the probe and full opening and closing of the mitral and tricuspid valves should be visible.

In addition to the above stated echocardiography views there are other views that are used by cardiologists in assessing the structure and function of the heart. From them Apical 2 Chamber view is another view that can be used to assess the Left Ventricular function. It is quite similar to the Apical 4 Chamber view but in this view only the Left Ventricle and Left Atrium are visible. Apical 2 Chamber view is also used in Simpson's method to calculate the Ejection Fraction. Also, another small adjustment in the transducer position from the A4C view gives the Apical 5 Chamber view in which the aorta is visualized as the 5th chamber. Therefore, during an echocardiography examination the correct view is selected depending on the requirement.

2.4.5 Clinical Uses of Echocardiography in Diagnosing Cardiac Dysfunctions

Echocardiography has become a widely used clinical method and tool in modern cardiology. Ventricular dimensions, cardiac volumes, wall thicknesses, Fractional Shortening (FS) and Ejection Fraction (EF) are the commonly used echocardiographic measurements in clinical practices. Some of the most common clinical uses of echocardiography are as follows. They are used to evaluate heart murmurs, diagnose heart valve conditions, find changes in the heart structure, assess heart wall motions, assess damages to heart muscle after a heart attack, assess the heart function of the patients with chronic heart diseases, determine fluid collections around the heart, assess and monitor birth defects, monitor blood flow inside the heart, assess damages to heart or major blood vessels due to trauma, assess chest pain and look for blood clots in heart chambers.

However as stated by Zinah R. Hussein et al. [26], the lack of quality in most echocardiography videos, practical complexities and inexperience in the field of echocardiography cause difficulties to Physicians/Radiologists when diagnosing the LV functionalities. In their Study they have proposed a quantitative method to analyse and detect the LV wall motion abnormalities by two-dimensional echocardiography. It was an attempt to estimate the velocities of the different wall segments in LV to find relation between each segment motion using the Optical Flow (OF). Left ventricular wall has a non-uniform thickness, which can be identified as an important parameter to study the regional wall motion function, leading to create high strain and Ejection Fraction (EF) at end diastole [26]. Hence, their work is mainly underlying on the anatomical structure of the Left Ventricular wall in Parasternal Short Axis (PSAX) view as to divide the LV into three segments depending on the major coronary arteries, the Left Anterior Descending (LAD), Left Circumflex Coronary artery (LCX) and the Right Coronary Artery (RCA).

This study is mainly grounded on the hypothesis that, imparity of wall thickness having an association with imparity of velocities of three wall segments. They also stated that, this imparity has a uniform structure in normal wall motion and any deviation from normal could be detected as an abnormal motion. Hence, they have measured, wall thickness from each segments of the LV PSAX images, as a parameter for the study. Further, they have evaluated the velocity of each segment using the popular optical flow model called “Horn and Shunck” and extracted the standard deviation (Std) of each velocity. To distinguish normal and abnormal motion of the three segments, they have computed a ration by dividing the standard deviation of thin segment velocities with the standard deviation of thicker segment velocity. They have taken 42 echocardiography images from both normal and abnormal patients to test their proposed methodology. The velocities were

recorded from each image for one cardiac cycle and the Std of each segment is used to demonstrate the comparison between the three segments. From the results it is observed that the ratios for normal motion are closer to 1.0 while the ratios of abnormal motion are higher or equal to 1.0. Thus, there study has revealed that the anatomical structure of LV can be successfully used to detect and distinguish the normal and abnormal behaviors of LV wall motion to assist in cardiac diagnosis process.

As another clinical use of echocardiography, the feasibility of using echocardiography methodologies to evaluate the patients with Staphylococcus aureus Bacteraemia (SAB) have been investigated by Vance G. Fowler et al. [27]. Among the patients reported with SAB, Infective Endocarditis (IE) is a widely dispersed disease, which causes inflammation in endocardium (inner most membrane of the heart) and heart valves. The latest diagnostic criteria, which is used to assess patients with suspected IE, rely heavily on the echocardiogram due to its difficulty of diagnosis [28]. During their study, 103 consecutive patients were analysed using Transthoracic Echocardiography (TTE) and Transesophageal Echocardiography (TEE) for the purpose of distinguishing the patients with elementary bacteraemia from those with IE.

TTE is the most common, non-invasive type of echocardiogram, which captures a still or moving image of heart by reflected ultrasound beams generated from the transducer placed on the patient's chest area. Conversely TEE uses an electron tube which leads to the heart area orally to make detailed image of the heart and the arteries; [29] however, this is less typically used when good visualization cannot be obtained via TTE. Two-dimensional imaging from multiple tomographic planes and spectral Doppler and colour flow imaging were used in all patients to analyse several malfunctions consistent with IE such as vegetation, abscesses, valvular regurgitation, etc. [27]. Their study findings reveal that the sensitivity of TTE for detecting IE was 32% while achieving a 100% specificity. The addition of TEE helps to boost the sensitivity up to 100% resulting a 99% specificity due to one false positive result. Analysing the study results, they have suggested that secure application of TEE is superior to TTE for the diagnosis of IE to detect serious inter cardiac complications. Therefore, these studies prove the feasibility of using echocardiography to diagnose cardiac dysfunctions.

2.5 Assessment of Left Ventricular Systolic Function using Echocardiography

When conducting echocardiography examinations, the first evaluation conducted is on the Left Ventricular Systolic function. There are different parameters considered when assessing the Left Ventricular Systolic function which includes Ejection Fraction and Fractional Shortening. The doctors use various echocardiography techniques for calculating these parameters and arrive at the final decision regarding the LV Systolic function based on them.

2.5.1 Ejection Fraction

Ejection Fraction is a measurement of the percentage of blood ejected out of the heart in each heart contraction. Left Ventricular Ejection Fraction is defined as the Left Ventricular stroke-volume divided by the End Diastolic volume, multiplied by 100% [30].

$$LVEF = \frac{(LVEDV - LVESV)}{LVEDV} \times 100\%$$

LVEDV - Left Ventricular End-Diastolic volume

LVESV - Left Ventricular End-Systolic volume

LVEF – Left Ventricular Ejection Fraction

As depicted by the definition of LVEF, for calculating the LVEF the volumes inside the Left Ventricular cavity at the end of both Diastole and Systole phases needs to be calculated. They are calculated by measuring the dimensions of the Left Ventricular cavity at the end of each phase and applying them to the following equations.

$$LVESV = \frac{7}{(LVIDs + 2.4)} \times (LVIDs)^3$$

$$LVEDV = \frac{7}{(LVIDd + 2.4)} \times (LVIDd)^3$$

LVIDs - Left Ventricular Internal Systolic Diameter

LVIDd - Left Ventricular Internal Diastolic Diameter

Ejection Fraction is an indirect measure of LV contractility however Ejection Fraction is only one of the measures that could be used to determine the heart condition. Therefore, patients could be having other symptoms of Heart Failure even with having a normal Ejection Fraction [31]. This condition is known as Heart Failure with preserved Left Ventricular function and it could be a result of valve dysfunctions. According to the latest ACCF/AHA guidelines patients with a LVEF more than 50% is classified as having a normal Ejection Fraction, 41% to 49% as borderline cases and less than 40% as abnormal Ejection Fraction [32]. The patients with LV Ejection Fraction of less than 50% is associated with a significant increase in risk of Heart Failure when compared with patients with LV Ejection Fraction of more than 50% [33]. There is no pronounced differences in Ejection Fraction values from international guidelines between males and females or due to ethnic or racial differences [34]. In practical scenarios these guidelines need not be strictly adhered. The final decision of the LV Systolic function is based on the dimensions of the Left Ventricle and the experience of the cardiologist.

2.5.2 Calculation of Ejection Fraction from M-mode

The calculation of Ejection Fraction from the M-mode is conducted from the PLAX view. The M-mode image of PLAX view could be used to measure LVIDs and LVIDd diameters required for calculating Ejection Fraction.

LVIDd is measured by manually placing two points on the position where there is the maximum gap in LV cavity region. LVIDs is measured by placing the minimum gap in LV cavity region

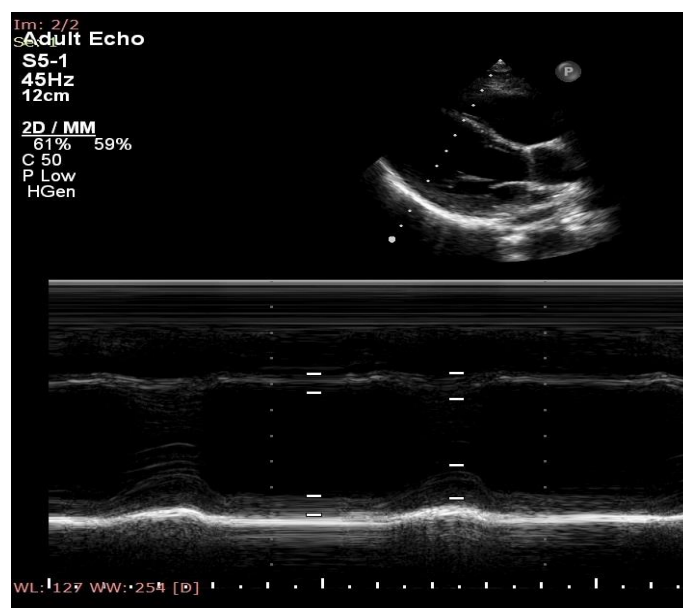


Figure 2.10: Manual placement of points in M-mode

[35]. The manual placement of points on the image requires expertise to produce accurate Ejection Fraction values. After points are selected the diameters are measured and Ejection Fraction will be calculated using the formulae stated in Section 2.5.1.

2.5.3 Calculation of Ejection Fraction from Simpson's method

The calculation of Ejection Fraction from Simpson's method could be from B-mode of both A4C and A2C views. In this method first freeze the image and scroll forwards or backwards until the LV volumes could be observed. The frame at which the LV cavity shows the largest volume represents LVEDV and the frame at which the LV cavity shows the smallest volume represents LVESV [35]. From the echocardiography machine select the points to trace the outline of endocardial points of the Left Ventricle (Figure 2.11). This will result in a formation of an area on the screen and the LV volumes will be calculated. The calculated LVESV and LVEDV values will be used to calculate the Ejection Fraction formula stated in Section 2.5.1.

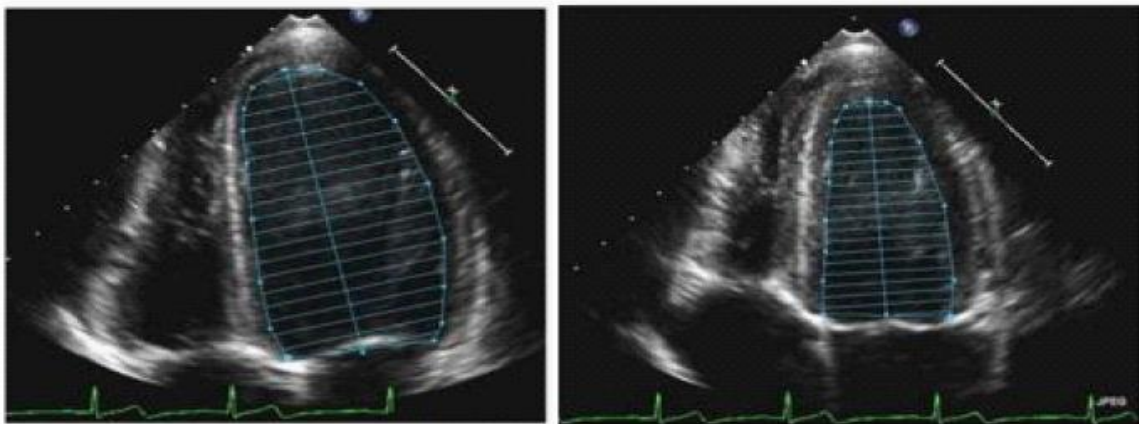


Figure 2.11: Measuring LVESV and LVEDV volumes using Simpson's method

2.5.4 Visual Gestalt of Ejection Fraction

Another method of determining the Ejection Fraction is visual gestalt and it is the method that has the highest dependency on the experience of the cardiologist. In this method an estimation of the Ejection Fraction is done by the cardiologist without taking any measurements [35]. The overall size, contractility, thickness and movements of the LV walls are taken into account when estimating the Ejection Fraction. Although this method could reduce the time taken for echocardiography examination the accuracy of this method is questionable.

2.5.5 Fractional Shortening

Fractional Shortening is the percentage change in the LV diameters from the end of Diastole to the end of Systole. This is used as a measure of the contractility of LV walls. The normal range of fractional Shortening is from 30% to 45%. Fractional Shortening of women is higher compared to men [36].

$$\textit{Fractional Shortening} = \frac{(LVIDd - LVIDs)}{LVIDd} \times 100\%$$

The LVIDd and LVIDs values required to calculate the Fractional Shortening could be measured using the M-mode of PLAX view as described in Section 2.5.2. Fractional Shortening is highly dependent on the accuracy of these diameter measurements and the Fractional Shortening is affected by the presence of regional abnormalities. Also spontaneous respiration or excitement could result in the increase of Fractional Shortening [37]. Therefore, Fractional Shortening need to be used with other parameters for assessing the Left Ventricular Systolic function.

2.6 Emergency Medicine

From the patients admitted to hospitals, there can be patients in critical state who require immediate assessment of their condition. These emergency assessments should be conducted accurately within the least possible time period and it is crucial to provide correct emergency treatments for stabilizing their condition. Emergency Medicine is concerned about handling this process and it is important in reducing the risk of the patient's life before directing him/her for further treatment. Emergency Medicine treatments are conducted in an Emergency Treatment Unit (ETU) by Acute Care Physicians. There is a significant portion of patients who get admitted to hospitals due to diseases related to heart [1] and special attention needs to be given to patients complaining of chest pain or stroke. Also generally Acute Care Physicians assess the condition of the heart before providing emergency treatments to patients. There have been several studies conducted to evaluate the suitability of using echocardiography in emergency medicine.

2.6.1 Impact of using Ultrasonography in Emergency Treatment

The study "Emergency department ultrasonography: Impact on patient management and cost effectiveness" conducted by G.Vairo et al. [38], tried to explore the feasibility and potential advantages of ultrasound scanning by emergency physicians. Their study basically focused on determining the impact of ultrasound scanning by emergency physicians on patient management in the Emergency Department, length of hospital stay, and related cost. They selected 111 patients and divided them into three groups according to symptoms: right hypochondriac region pain (Group A), flank pain (Group B), abdominal pain and hemodynamic instability (Group C). Patients were further divided into three subgroups according to whether they were treated by an emergency physician or a radiologist or did not undergo ultrasonography. For each group the mean length of stay in the emergency treatment unit, the complications rate, the rate at which they returned to the emergency treatment unit for the same pathology (recurrence rate) and the related costs were calculated. Of the 111 patients, 76 received ultrasound scanning, of which 43 were treated by an emergency physician. The results of the study showed that, the length of hospital stay for this group was shorter than that of the other two subgroups. The recurrence rate was highest in the group that did not undergo ultrasonography. The costs were lower for the group that received ultrasound scanning by an emergency physician than for the group treated by a radiologist (Euro 20 vs Euro 38). Therefore,, this study concluded that ultrasound scanning by emergency physicians

can shorten length of hospital stay for emergency patients, reduce recurrence rates for the same pathology and lower patient management costs.

2.6.2 Can Emergency Physicians use Echocardiography to accurately assess Left Ventricular Function?

As mentioned in section 1.3, the assessment regarding the Left Ventricular function is one of the most essential decisions needed for determining the condition of the heart. For assessing the Left Ventricular function many factors need to be considered and the experience of the doctor affects the accuracy of the decision. Therefore, studies focused on Left Ventricular Systolic and Diastolic functions have been conducted to assess whether Emergency Physicians can accurately assess the condition of the heart based on echocardiography images.

Moore et al. [2] have shown that Emergency Physicians with limited training in echocardiography were able to determine the Left Ventricular function of patients admitted to the emergency department with reasonable accuracy. In this study four Emergency Physicians were given training on echocardiography and they were involved in assessing the heart condition of 51 adult patients admitted to the emergency department. These patients were showing symptomatic hypotension and the emergency physicians involved were instructed to classify the left ventricular function as normal, depressed or severely depressed. The basic echocardiographic views such as parasternal long axis (PLAX), parasternal short axis (PSAX), apical four-chamber, apical two-chamber and subcostal view were used for determining the Left Ventricular function and Ejection Fraction. PLAX and PSAX were used to measure the Left Ventricular diameter from M-mode. Volume measurements were made by manual border tracing in Systole and Diastole in both apical four-chamber and apical two-chamber views using the area-length method. Thereafter emergency physicians recorded their quantitative visual estimation of Ejection Fraction and categorized Left Ventricular Fraction into one of three conditions stated. These assessments made by the emergency physicians were reviewed by two cardiologists. The Ejection Fraction data for the cardiologists and emergency physicians were both found to be normally distributed with equal variances. The final decision made by the cardiologist is that there were 22 normal patients, 18 patients moderately depressed and 10 severely depressed Left Ventricular function. The final decision made by the emergency physicians is that 24 normal patients, 16 patients moderately depressed and 10 severely depressed Left Ventricular function. This confirmed that Emergency Physicians trained for echocardiography can determine the Left Ventricular function with reasonably accuracy. Also the researchers have suggested that a five-view echocardiogram with visual

estimation of Left Ventricular Function by an Emergency Physician could be obtained in less than five minutes with reasonable accuracy. Therefore, it's possible for an emergency physician to use echocardiography to determine the Left ventricular Function in emergency settings.

Also in another study conducted by Robert R. Ehrman et al. [39], they have shown that Emergency Physicians with limited additional training in echocardiography are able to accurately identify clinically significant diastolic dysfunctions, using echocardiography. But they have stated that in their study, grading given by the Emergency Physician depicting the level of diastolic dysfunction is only moderately accurate. Therefore, they have suggested that further training is necessary to gain technical skills in order to accurately grade the level of diastolic dysfunction. In this research also the assessment provided by the Emergency Physicians were evaluated against the assessment of a cardiology specialist. 70 patients were taken to the study. Cardiologist's decision was only 62 patients had complete data and from them 21 were normal, 32 having abnormal diastolic function and 9 having indeterminate diastolic function. Emergency Physician's decision was 8 were normal, 36 having abnormal diastolic function and 18 having indeterminate diastolic function. Interpretations of these results (excluding the patients with indeterminate diastolic function) suggested that Emergency Physicians may help to identify patients with undiagnosed diastolic dysfunctions. Also their study has revealed that the agreement between the Emergency Physicians regarding the normal vs abnormal diastolic function was 95% Therefore, suggesting that Emergency Physicians were able to consistently follow a protocol and reach similar conclusions.

These studies theoretically showed that Emergency Physicians could give a reasonably accurate decision on the Left Ventricular function in comparison with cardiologists. Therefore, Emergency Physicians are employed in hospitals to determine the heart condition using echocardiography in Emergency Medicine. But there is an opportunity present for introducing a decision support system for improving the accuracy of Emergency Physician's decision to a level that is similar to that of a cardiologist's decision.

2.7 Image Processing Techniques for Echocardiography Images

To propose a Computer Aided Diagnosis application for decision making using echocardiography, automatic extraction of features from echocardiography images is necessary. Also, poor resolutions and high noise in echocardiography images meant that image processing techniques are required to enhance the quality of the acquired images to enable the extraction of features from echocardiography images. To serve this purpose several algorithms have been proposed from time to time for de-noising and edge detection.

Two new algorithms for Left Ventricular endocardial and epicardial boundary detection in echocardiographic images using Wavelet analysis was introduced by M. R Hassanzadeh, et al. [40]. The first algorithm is a center-based approach in which the Left Ventricular center point is estimated using a fuzzy-based technique and the epicardial and endocardial edge points are searched on radial lines emanating from Left Ventricular center point. There is an assumption in this method stating that the boundary points of Left Ventricle are those with sharpest intensity changes, which can be detected as the global maximum wavelet transform modulus. But this assumption is not valid always because of the presence of artefacts and dropouts in echocardiographic images. In the second algorithm directional gradient with Left Ventricular center point references are computed in all directions using wavelet transform and the images of gradient at different scales are then combined by logical operation to retain only possible boundary points. Boundary points are detected by radial search method and de-noised by wavelet transform. Finally, cubic B-spline approximation method is used to achieve smooth and closed endocardial and epicardial boundaries. Both these algorithms are automatic and they state that they can obtain smoother boundaries from these methods than other methods. Because of the assumption in the first algorithm there could be inaccurate boundary points but this was overcome in the second algorithm. Therefore, they have suggested that the second algorithm could be used to find the most accurate boundary points in echocardiographic images.

J. B. Santos et al. [41] have shown that windows adaptive threshold procedure by Otsu algorithm is more effective for extracting cardiac borders of the Left Ventricle. They have compared windows adaptive threshold procedure against the edge detection on radial lines by the differencing technique. The echocardiography images from the apical four-chamber view was used for this research. Images from all stages of the cardiac cycle was analyzed and it showed that apart from the contour tracing in the mitral valve region in diastolic stage adaptive threshold by Otsu algorithm has a better accuracy. Also, adaptive threshold procedure extract smooth and continuous endocardial boundaries. This method handle problems related to Left Ventricular artefacts better.

They have found that myocardial wall thickness can be extracted easily and the knowledge of Left Ventricular cavity is not necessary for windows adaptive threshold by Otsu algorithm procedure.

Matilda et al. [42] proposed a method to segment the left ventricle area using a region based snake methodology. In their study, a tracking algorithm has been constructed to direct the movement of region based snake while two anchor points are used to determine the path along the edges of the cavity area at different levels of heart contraction. This segmentation of LV area is intended to perform at each frame consecutively over the entire cardiac cycle. A region based snake model is an active contour which inspired in 1987, by Cass [43] introduced as an effort to synthesis the noisy filter response coming from an edge detector. The segmentation of LV is driven by the mathematical and statistical properties of the image data inside and outside the contour. By manually tracking two anchor points in three patients, a prior model has been constructed to guide the movement and direction of the anchor points, particularly to eliminate the tendency of following the cardiac value during the cardiac relaxation. The proposed methodology regarding the segmentation of the LV is obtained by continuously reshaping the contour until an optimal shape and size is obtained [42]. The developed method, which would assist in most ultrasound techniques as a fine remedial to reduce the workload, has shown promising results during their course of study.

In addition to these image processing techniques several other image processing techniques will be discussed along with the studies in the section 2.6. Image preprocessing techniques for image de-noising, image binarizing and edge detection will be discussed with practical applications.

2.8 Artificial Neural Networks (ANN)

Artificial Neural Network is a computational model inspired by biological nervous system. This can be considered as a powerful tool assisting in a wide range of medical applications due to its robust computational abilities. This method is considered as a fine solution to problems which could be complex, indistinct, time consuming or costly when using the traditional decision-making techniques. Most medical applications that use ANNs address classification problems where the domain knowledge in a particular area is weak. In such situations, ANN can be successfully used to provide more accurate and reasonable results after training to perform a particular function by adjusting the values of the connections between elements.

ANN can be trained to observe datasets and identify the patterns of occurring outputs according to the given set of inputs. ANNs can be trained to learn to do tasks without task specific programming. The four types of learning for ANNs are supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. Supervised learning can be achieved by giving the ANN both the input and output patterns until a desirable output is reached for an actual input. Supervised learning is used in the occasions where we know both the inputs and the outputs that we expect but we do not know the relationship between these inputs and outputs. In unsupervised learning only, the inputs are provided to the ANN and it would find the relationships with different inputs to develop a desirable output. Unsupervised learning algorithms are used when we cannot expect a particular output but we suspect that there could be a particular correlation between the inputs. In semi-supervised learning both labeled and unlabeled data are utilized simultaneously for training [44]. Because acquisition of labeled data is more expensive and skilled labor is required, semi-supervised learning is considered as a more practical method in some situations. Reinforcement learning is based on an agent learning on what to do in response to a reward or a punishment with the intention of maximizing the reward the system receives in the long term through trial and error [45].

2.8.1 Use of Artificial Neural Networks for Cardiac Diagnosis

In 2011 Q. K. Al-Shayea [46] has evaluated the possibility of using Artificial Neural Networks in medical diagnosis. In this study a feed-forward back propagation neural network with supervised learning is used as a classifier to distinguish between infected and non-infected patients for acute nephritis disease and another network to distinguish between normal and abnormal hearts for diagnosing heart disease. For diagnosing acute nephritis a two-layer feed-forward network with 6 inputs and 20 sigmoid hidden neurons and linear output neurons was created. For training the Artificial Neural Network a sample dataset from 90 patients were taken and a dataset from 30 patients were taken to test the network. The dataset contained patients' symptoms data prepared by a medical expert. For diagnosing heart diseases, a two layer feed-forward network with 22 inputs and 20 sigmoid hidden neurons and linear output neurons was created. The dataset contained cardiac Single Proton Emission Computed Tomography (SPECT) images. The dataset contained 267 samples, from which 80 samples were used in training the network while 187 samples were used in testing the network. The results obtained by the study showed that the accuracy level of the diagnosis decision given by the ANN is 99% for acute nephritis and 95% for heart disease. It confirmed that a well-trained ANN shows the ability to learn the patterns corresponding to symptoms of the patients and act as a tool for medical diagnosis decision support system.

2.8.2 Use of ANN to Determine the Cardiac Cycle Phase using Echocardiography Images

With the usage of Artificial Neural Networks for cardiac diagnosis, ANNs also have been used for proposing systems that can automatically diagnose the heart condition using echocardiography images. These ANNs can classify the heart functions and diagnose disease conditions based on features extracted from echocardiography images.

Automatically detecting the cardiac cycle phase is the first step in calculating the Diastolic and Systolic volumes. The Diastolic and Systolic volumes are necessary to calculate the Ejection Fraction value which is used to determine the heart condition. Therefore, it's the first step in developing a Computer Aided Application for supporting Emergency Physicians to diagnose the heart condition. Studies have shown that it's possible to use Artificial Neural Networks to

automatically detect the cardiac cycle shown in an echocardiography image without any user intervention.

Dorin Bibicu and Luminita Moraru [47] have proved that Artificial Neural Networks can be used to automatically identify the cardiac cycle phase shown in echocardiographic images without manually tracing the boundaries for segmentation process. They have analysed Atrial Diastole and Systole events focusing on the geometric position of the mitral valve to determine the phase of the cardiac cycle. In their research methodology firstly they have conducted image pre-processing to enhance the image for edge detection. The dataset used consisted of 150 images. Fourier Transform and Gaussian Low Pass Filter were used for de-noising the acquired image. The de-noised image was used to automatically obtain a single optimal binarization threshold by using the Otsu's global binarization method. Edge detection in the binarized image was conducted using the Canny edge detector. Then feature extraction was conducted for the pre-processed image. The feature extraction identified the Region of Interest which is the rectangle area consisting the highest number of contour pixels. The extracted features were used as the training dataset for supervised learning procedure of the ANN. They have tested the trained ANN with new echocardiographic images which were not used for supervised training. The ANN was able to successfully classify an echocardiographic image as a Diastolic or Systolic image with a higher accuracy level. The proposed algorithm was implemented as a Computer Aided Diagnosis application for cardiac cycle estimation and it had an execution time of 2 ± 0.3 seconds.

Another similar research methodology conducted by S. Sundaramurthy et al. [48] also prove that Artificial Neural Networks can be used to automatically identify the cardiac cycle phase. The techniques used for image processing and the features extracted for supervised training of the ANN are different. In this research Left Ventricular Systole and Diastole events were analysed focusing the geometric position of the mitral valve to determine the phase of the cardiac cycle. The dataset for the research consisted of 130 images. Image de-noising was carried out using the Median Filter and greythresh function in MATLAB was used for binarizing the de-noised image. Wavelet edge detection has been used for the edge detection in the image. The features extracted from the image to be used for supervised training of the ANN were the mean and Standard Deviation values of all the pixels in the image. The test results obtained after classifying the images using the trained ANN have shown that ANNs can be used to accurately predict the cardiac cycle phase.

2.8.3 Use of ANN for Automated Classification of Cardiac Diseases using Echocardiography Images

To evaluate the feasibility of developing Computer Aided Diagnosis systems there have been researches conducted on using a trained Artificial Neural Network for diagnosing different types of heart diseases from echocardiography images. The automatic classification of the patient's heart as diseased or normal is based on comparing the features extracted from echocardiography images against the anatomical knowledge of the heart and the medical rules described by doctors.

Coronary Artery Disease can be identified using echocardiography images. U. R. Acharya et al. [49] have introduced a methodology to automatically identify patients with Coronary Artery Disease from echocardiography images using an Artificial Neural Network. In this methodology greyscale features were extracted from echocardiography images of coronary artery and they were used to classify patients as normal or as patients suffering from Coronary Artery Disease. In this study 400 images were taken from 30 normal subjects and another 400 images were taken from patients suffering from Coronary Artery Disease. The subtle variations in the images were quantified using greyscale features. Initially 559 features were identified and t-test was used to identify nine features that had more information for better differentiating images. Their proposed methodology is a real-time technique without needing any manual interaction and this can be converted to a software application and installed in any computer at no extra cost. Therefore, in their proposed application once the image is input to the software, the nine features are extracted from the image and they are fed to a Gaussian Mixture Model classifier which outputs the diagnostic decision. The decision whether the patient is having Coronary Artery Disease is based on the HeartIndex value calculated from this technique. If the HeartIndex value is greater than 2.6 patient is suffering from Coronary Artery Disease and otherwise the subject is normal. The accuracy of this technique was proven to be high so it's recommended to be used confidently for clinical purposes to identify Coronary Artery Disease.

A methodology to diagnose heart valve diseases from echocardiography images using an Artificial Neural Network and image processing techniques was presented by Atta Elalfi et al. [50]. They have extracted texture features from echocardiography images and developed an Artificial Neural Network based on a back-propagation algorithm to classify heart valve diseases accurately. The echocardiography images were pre-processed to increase effectiveness of pattern recognition by de-noising with Gaussian filter and image enhancement through Gabor filter. Feature extractions were conducted using a combination of intensity histogram features and Grey Level Co-occurrence Matrix (GLCM). The proposed solution was implemented using MATLAB and supervised

learning was used to train the neural network. They have used a dataset of 120 images belonging to eight different types of heart valve diseases and from them 80 images were used to test the neural network. Performance of the solution was evaluated against precision, recall and accuracy. The results of their research has shown higher accuracy levels for each heart valve disease and an overall accuracy value of 93.75%. This showed that their computer aided diagnosis methodology was suitable for Emergency Physicians or cardiologists to use for diagnosing and classifying heart valve diseases accurately and efficiently from echocardiography images.

Bayesian networks also can be used to classify heart as normal or abnormal. Based on detection and automatic tracking of the endocardium and epicardium of the Left Ventricle M. Qazi et al. [51] have used Bayesian networks to identify the condition of the heart. They have proposed a real-time computer aided diagnosis system to automatically detect wall motion abnormalities from echocardiographic images. Echocardiography images were taken from B mode of apical 4-chamber, apical 2-chamber, parasternal long axis and parasternal short axis views. They have used image processing algorithms that have been already developed by other researchers to detect and track the inner and outer cardiac walls but they have proposed a new methodology for feature selection and classification. The features extracted by them are Velocity features, Circumferential strain features, Radial strain features, Local and Global Simpson Volume features and Segmental Volume features. They have used KS-test for feature selection. KS-test measures the difference between the two histograms of the two classes with respect to all the available features. Only the features at the top of the ranking list given by KS-test are selected for classification. Classification was done using the Bayesian network. 220 images were used to train the network and 125 images were used to test the network. In addition to the 220 images, 2216 cases without images were used only to train the network. Each segment in the Left Ventricular wall was dependent on one of the 6 selected features and classifier performed well for all these segments. Their research could improve the accuracy of diagnosis by assisting Emergency Physicians to interpret wall motion.

Du-Yih Tsai [52] in his research describes a method to automatically classify echocardiographic images using an artificial neural network trained by genetic algorithms (GA's) instead of the Back Propagation (BP). He demonstrated its application by classifying echocardiograms as normal, dilated cardiomyopathy (DCM) and hypertrophic cardiomyopathy (HCM) cases. The data set used included 90 echocardiograms obtained from 45 subjects (2 sample images per subject: an end-systole image and an end-diastole image). The mixture of 45 was made of 23 subjects with a normal heart, 12 with DCM and 10 with HCM. The images used were diagnosed by an experienced physician before the experiment. Each image was digitized by an image scanner at the resolution of 256 X 256 pixels. Since the original echocardiograms have 64 gray levels, the scanned images

were quantized to the same gray levels. Next, Gray-Level Co-occurrence Matrix was generated from each image. From these matrices, 4 features, namely, the angular second moment, contrast, correlation and entropy were extracted and computed. Finally,, an Artificial Neural Network was trained using genetic algorithms. This method showed a faster convergence for obtaining the optimal solution in ANN training. Experiments on different data sets show the superiority of the GA-based method over the back propagation for classification. Although the BP method is efficient for numerical data processing and learning, the calculation is considerably complicated. Also, the method has local minimum issue. This study shows that to overcome issues in Back Propagation, alternative training methods such as genetic algorithm (GA) can be used instead of the BP algorithm.

In another study Micheli-Tzanakou et al. [53] tried to apply ANN to two specific problems in cardiology, namely, diagnosis of echocardiograms for myocardial infarction and prediction of vital status of patients that suffered such. They used ANN to discriminate between normal and infarcted myocardium, by looking at intensity changes of the grey levels in the echocardiogram. The intensities of selected regions were used for training and testing the ANN. In predicting the vital status of patients that have suffered acute myocardial infarction, they used a large database (MIDAS) with follow ups. The ANN trained had two hidden layers with 18 patient variables from the MIDAS dataset as inputs. The ANN was again trained with the feedback algorithm ALOPEX and tested with unknown data. Once an echocardiogram was obtained, it was digitized and saved in a file as a gray scale image (512 x 400). Interest was then selected between the systole and diastole of the cardiac cycle and saved in a different file. The window can be either of a constant size or it can be adaptive (varying) in size. This new file can be enlarged (zoom) for examination of finer details in the image. All image artefacts were filtered out and contrast enhancement was performed. This new image was then saved and served as input to the Neural Network. A traditional 3-layer NN with 300 input nodes (one node for each pixel intensity in the input file), varying number of hidden nodes and two output nodes was used. The output node indicated the status of the patient under testing. A “one” indicates normal and a “zero” an abnormal case. The weights of the connections of ANN were calculated using the optimization algorithms of ALOPEX. One sub-ALOPEX was used for the weights between hidden nodes and input nodes and a second subALOPEX for those from the output to the hidden layer. The ANN was trained with a population of 256 patients some with scars and some normal. It was also tested on known and then on unknown cases. A correspondence of the observed to the predicted probability of being alive at a given time was observed. The categorical classifications (dead or alive) yielded an overall accuracy of 74%.

2.8.4 Use of ANN for Automatic Classification of Left Ventricular Function

As the first step of developing a complete application for automatic classification of the human heart using echocardiography images, automatic classification of the Left Ventricular function could be conducted. B. Thennakoon et al. [54] have investigated the feasibility of applying an Artificial Neural Network for the automatic classification of the left ventricular function as normal or abnormal using echocardiography images. During their study, they have used Left Ventricular horizontal diameter, vertical diameter and Ejection Fraction (EF) as the three numeric parameters used as inputs to train the Artificial Neural Network. These parameters were extracted only from the B-mode of Parasternal Short Axis view. Their trained network was able to identify the state of Left Ventricular function with 95% accuracy. Hence their results showed that a trained ANN can be successfully used as a suitable classifier in medical decision support systems. But they have only used 20 videos for training the ANN and eight videos for testing the ANN. Therefore, they could have improved their performance of the ANN by training it with a larger set of data in order to make solid conclusions. Also they have only conducted image processing experiments on the B-mode images thereby have not considered any M-mode images in their methodology. But M-mode is considered as a better mode for calculating the diameter values of the Left Ventricle because clearer images could be obtained in the M-mode. Therefore, their proposed methodology can be improved by evaluating the possibility of using M-mode images.

2.9 Conclusion

This Literature Review shows that there were continuous researches on using Artificial Neural Networks for automatic classification of heart diseases. The image processing techniques and neural networks training techniques have improved with new studies so that a higher accuracy level could be obtained through the Computer Aided Diagnosis applications which were developed.

Echocardiography is one of the preferred medical tests used to view the heart and its functions. A good assessment of the heart is crucial for the diagnosis of dysfunctions in heart. Left Ventricular Diastolic Dysfunction and Left Ventricular Systolic Dysfunction are considered as the most common causes for heart failures. Emergency Medicine is a crucial aspect in treating patients and

studies have proved that Emergency Physicians with a sufficient training in echocardiography can accurately diagnose the heart condition in emergency situations.

When analysing the literature it is seen that various image processing techniques have been used to extract features from the echocardiography images. The contribution of Artificial Neural Networks in classification of these images based on the extracted features is also significant and it is proved by the accuracy rates shown. Thus it is evident that the combination of image processing techniques and the use of ANN would be able to provide a better solution in automatically classifying the Left Ventricular function of the human heart as normal or abnormal, in order to assist the decision making process of emergency physicians. Hence this initiative would contribute in saving lives of thousands of patients suffering from cardiac dysfunctions.

Chapter 3 Design

3.1 Introduction

This chapter elaborates the proposed solution to address the research questions stated in Section 1.2. Under this chapter, the proposed flow of the research including data acquisition, image pre-processing, feature extraction, feature selection, training and testing the ANN will be described in detail with the reasons for the choice of methods.

3.2 Research Design

The proposed methodology mainly focuses on developing a model which can assist the acute care physicians in diagnosing the heart condition accurately using a simple and reproducible methodology. The research design was carried out in following three experimental stages to address this objective.

- **First Stage:** The echocardiography videos taken from different view angles (PLAX view and PSAX view) were analysed and pre-processed to make them suitable for the digital analysis. Under this experimental stage, certain image conversion, enhancement and de-noising techniques were applied and tested on each sample echocardiography images to see how these methods enhance the image details and features that are used to interpret the cardiac disorders.
- **Second Stage:** The above pre-processed images were subjected to series of image processing steps to address the following three questions,
 - 1) How to identify/isolate the LV cavity from the rest of image details?
 - 2) What method(s) can be employed to detect the accurate position of LV cavity border?
 - 3) Which technique(s) can be used to detect and measure the important parameters out of LV cavity?

In order to address the first problem, a ROI (region of interest) function was developed to isolate the LV cavity region. The second and third concerns were addressed by developing a feature extraction algorithm. This was aimed to extract and calculate the important parameters by which the cardiologists draw some conclusions regarding the heart condition.

- **Third Stage:** Several experiments were conducted to determine the most optimum technique for the classification of LV systolic heart condition. After considering the nature of the

Echocardiography data and the decision making process, an ANN was selected for developing the predictive model. The following questions were considered when developing the ANN.

- 1) Which learning approach, and algorithm is most appropriate for the training process?
- 2) What features can be used for training the ANN?
- 3) Number of neurones and epochs that can be used for training?
- 4) How to evaluate the accuracy and performance of the trained model for the clinical evaluations?

The above questions will be addressed in detail in the proceeding sections of this chapter.

3.3 Echocardiography Data Acquisition

The echocardiography dataset consisting of both, B mode of Parasternal Short Axis (PSAX) view and the M-mode conversion of Parasternal Long Axis (PLAX) view were considered for developing the decision support methodology (Figure 3.1). For initial experiments, sample group of 50 subjects were selected, each having normal or abnormal LV systolic heart conditions. 25 subjects were used for the training purposes and remaining 25 were used for the testing and evaluation purposes.

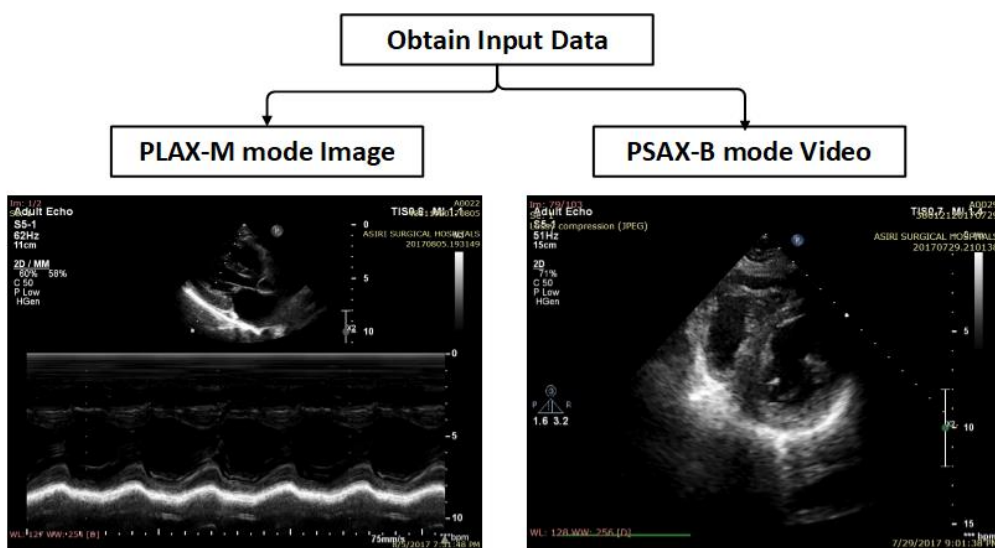


Figure 3.1: The two views considered for the analysis

All data consisting of both PLAX and PSAX view of the heart, with an auto generated cognitive assessment report for each subject. This report consists with manually measured PLAX M-mode readings and the calculated parameters (such as stroke volume, EF etc.) for each heart condition of the subjects (Figure 3.2).

Data acquisition was a little tedious task as there were no online repository of echocardiography

Adult Echocardiography Procedure Report	
Patient Characteristics	
Subject Name:	A0029^^^^
Subject ID:	38012120170729
Exam date:	7/29/2017
Study date:	7/29/2017
Findings	
Finding Site:	Aorta
Measurement Group	
Aortic Root Diameter:	36 mm
Image Mode:	M mode
Aortic Root Diameter:	36 mm
Derivation:	Mean
Selection Status:	Mean value chosen
Image Mode:	M mode
Findings	
Finding Site:	Left Ventricle
Measurement Group	
Interventricular Septum Diastolic Thickness:	8.77 mm
Image Mode:	M mode
Interventricular Septum Diastolic Thickness:	8.77 mm
Derivation:	Mean

Figure 3.2: Adult Echocardiography report from PLAX M-mode readings

videos available for the clinical studies or research purposes. Generally in Sri Lanka, the scanned echocardiography data stores only for one time clinical evaluations; hence will be removed after each usage due to the limited hard drive storage capacity of the echocardiography machines.



Figure 3.3: Philips EPIQ 7C Ultrasound System

Hence, we had to rely on data collected on regular basis as previously stored echocardiography data were not available with the echocardiography machines. Data was obtained from 'EPIQ 7C' model echocardiography machine, manufactured by Philips Medical Systems, located at Asiri Surgical Hospital, Colombo, Sri Lanka (Figure 3.3).

3.4 Data Conversion

The raw data are generally stored in echocardiography machines in ‘DICOM’ (Digital Imaging and Communications in Medicine) format which is a standard for handling, storing, printing, and transmitting information in medical imaging. To analyse the details out of the data set, the “*RadiAnt DICOM Viewer*” software was used to translate image data to .jpg format and video data to .wmv file format from their native DICOM format. Subsequently the data were imported in to ‘*MATLAB*’ software to analyze the details and arrive with clinically imperative decisions.

3.5 Outline of the Research Method

Our proposed methodology composed of two main approaches to provide more accurate and reliable decisions irrespective of different quality constraints of Echocardiography data. The first approach was primarily designed for the good quality PLAX M-mode image data. As discussed under Section 1.3, this method aims to reduce the time taken to arrive at clinical decisions by automating the manual intervention of the current process. According to the proposed methodology, a PLAX-M mode image undergoes following steps to provide a final decision about the LV systolic function of the heart.

- 1) Image Pre-processing
- 2) Image Segmentation to identify the LV cavity area
- 3) Border Detection of the LV
- 4) Feature Extraction
- 5) Feature Classification

During our early experiments, it was understood that, not all PLAX M-mode images were generated with expected quality level sufficient for the quantitative evaluation of LV systolic function. This was mainly because the reverberation artefacts, noise and dropouts inherent when rendering the ultrasound images by real-time ultrasound-based electromechanical waves [19]. Moreover the assumptions made in developing this method (Discussed in Section 3.6) were not always true for all the echocardiography images of PLAX M-mode view. On account of these reasons, a second method was proposed to materialize in cases where the first method applied with PLAX view does not meet the expected image quality needed to recognise the LV cavity region correctly.

The second method was developed targeting the corresponding PSAX B-mode echocardiography video data. Each video should be first converted in to series of images to apply image processing techniques similar to the first method in identifying the LV cavity region. Here the approach used in extracting the cavity features was different as the viewing angle of LV cavity is different to that of PLAX image data. The other importance of employing a second method is the fact that the errors occurred in reading parameters of image frames might be negligible when the final conclusion is derived by the mean value of results retrieved by multiple image frames. Each image frame consists in PSAX-B mode video, should undergo the following phases to arrive with the final conclusion of LV systolic function of the heart.

- 1) Image Pre-processing
- 2) ROI method to identify the LV cavity area
- 3) LV cavity border Detection
- 4) Compute the LV cavity centre
- 5) Feature Extraction and compute important parameters
- 6) Feature Classification

Although the second method demonstrates good ability to measure the important parameters as robust as the first method, it consumes much time to process all video frames and arrive at a decision. Time is a crucial factor when assessing the LV function based on specialist decisions; particularly in emergency medical settings. Hence this method will only be utilised in cases where the first method fails in detecting the correct LV cavity region.

Comparing the two methodologies, each PLAX M-mode image and the PSAX B-mode image frames were subjected to follow the same 1) image pre-processing, 2) Image segmentation 3) border detection methods. However two methods were developed using two distinct feature extraction methodologies to calculate the LVIDs and LVIDd, the parameters by which cardiologists used to interpret the cardiac functionality.

The Figure 3.4 depicts the overall process of the research design. The images obtained from the echocardiography data will mainly undergo three main steps; Image pre-processing, Feature extraction and Feature classification. Each of these steps will be discussed in detail in the next few sections of this chapter.

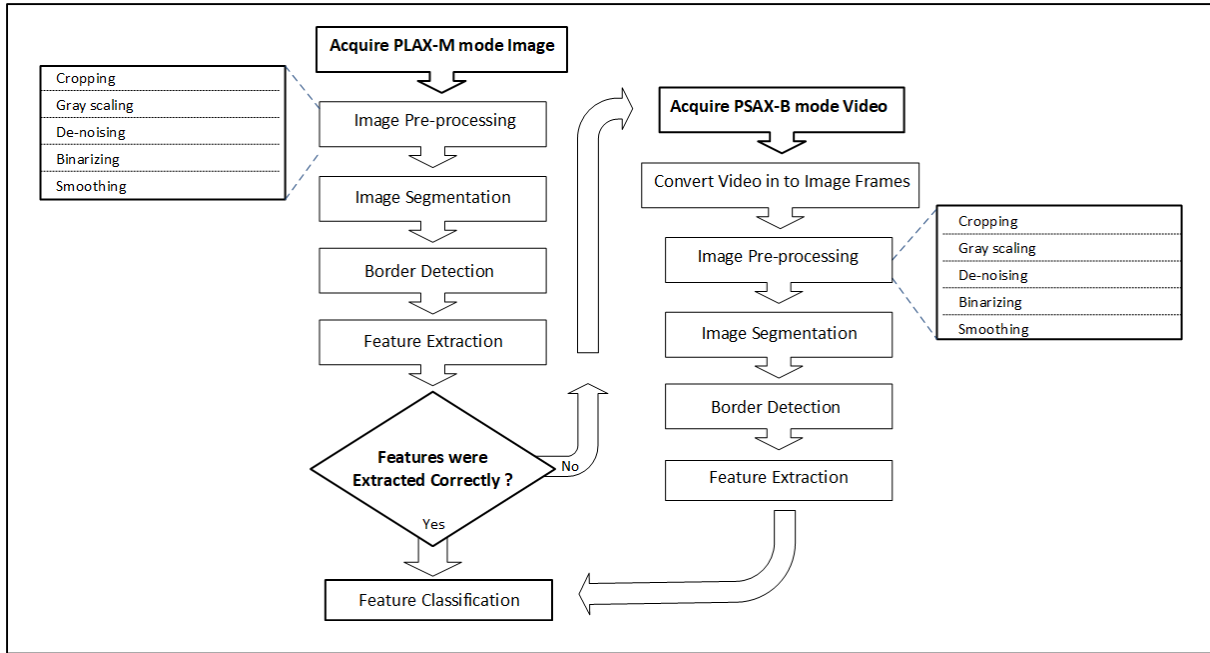


Figure 3.4: Process flow of the research methodology

The proposed method is further detailed in the algorithm below.

Input - Set of echocardiography data (Image/Video)

Output – Classification result for the LV Systolic function with calculated parameters

Begin –

Step 1: Image pre-processing phase

- Crop LV section of the image
- Image Grey-scaling
- Image De-noising
- Image Binarization
- Image Enhancement

Step 2: Border Detection phase

- Apply ROI technique to identify the LV contour
- Applying border detection techniques

Step 3: Feature Extraction phase

- Apply feature extraction techniques on the pre-processed image
- Compute the important parameters (LVIDd, LVIDs)
- Display the final image with identified border and calculated parameters.

Step 4: Feature Classification phase

- Input: Extracted features from echocardiography images
- Processing: Feed-forward ANN is applied for the classification
- Output: Classification of image data (Normal/Abnormal LV function)

End

3.6 Image Pre-processing

Medical images usually contain high noise level and are not clear enough to analyse them digitally. Therefore, image pre-processing is essential in order to eliminate the noise and to improve the quality and clarity of these images. This will make the feature extraction more reliable and accurate. During the first experimental stage, various image enhancement techniques were applied to both PSAX and PLAX echocardiography images using the MATLAB software. These techniques are described in detail below.

3.6.1 Image Cropping

The full screen image/video acquired directly from echocardiography machine contained some unnecessary machine generated details which adds no value to the image analysis (Figure 3.5). Therefore,, all input data were cropped by predefined coordinates to display only the echo image sections.

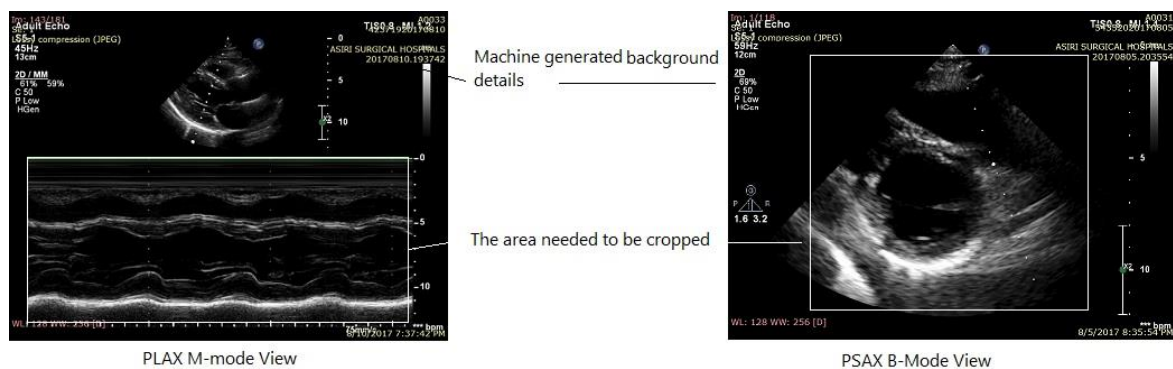


Figure 3.5: Original M-mode and B-mode echo images with the sections to be cropped

3.6.2 Image Grey Scaling

The raw images generated by echocardiography machines were in RGB format with their colour information. An image with three colour channels (Red, Green, and Blue) usually takes three times as long as processing a grayscale image; hence increases the complexity of processing the image details [55]. Besides, to analyse the image details with some important attributes such as sharpness, brightness and contrast, the colour information is not required. Thereby it is important to convert RGB echocardiography images to grayscale by eliminating chrominance information (hue and saturation) while retaining the luminance.

3.6.3 Image De-noising

Most of the echocardiography images result with some level of noise details caused by unavoidable interferences and disturbances in the ultrasound signals. Salt-and-pepper noise is a form of such noise dispersed as white and black pixels on some echocardiography images (Figure 3.6). As per experimented by many past studies, ‘Gaussian filter’ was applied to blur the image and reduce noise level [6][48][54].

Unlike Gaussian filter, ‘Median filter’ is a non-linear filter which is a common way to reduce noise, while keeping edges of the image relatively sharp [56]. Applying these filters together has shown some promising results to reduce the blur effect of Gaussian filter and keep the optimum contrast level to detect the cavity edges effectively. Hence, the above grey scaled image is subjected to Gaussian and Median Smoothing operations to reduce the noise level and make the dark regions darker and white regions whiter (Figure 3.7b).

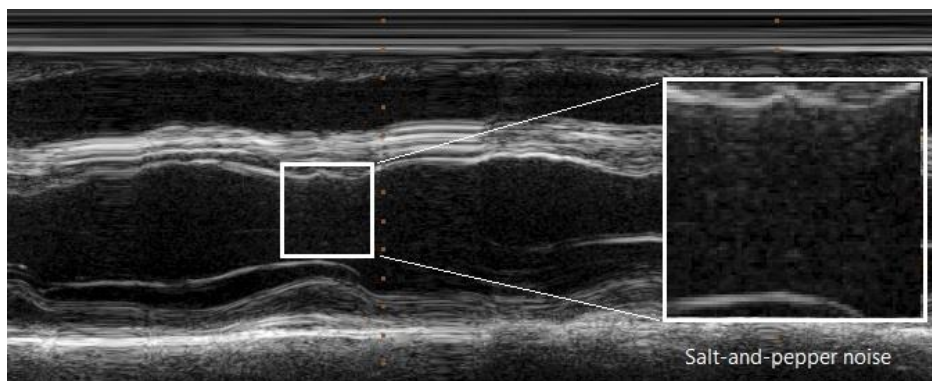


Figure 3.6: Salt and pepper noise inherent in echocardiography images

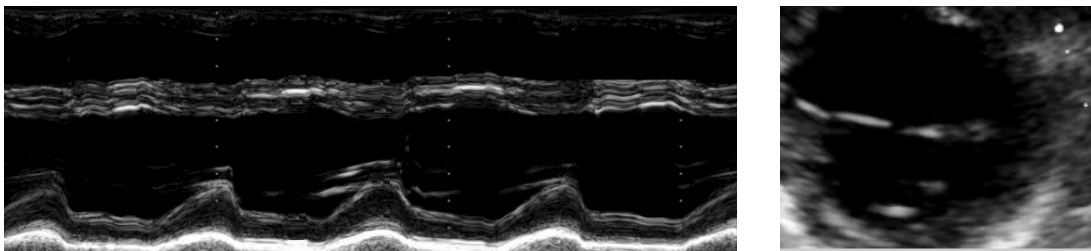
3.6.4 Image Binarization

The complexity of image details can be reduced by the image binarization process. This process converts a detailed pixel image into a binary image which each pixel holds only two possible values, either black or white. This provides the basis for the segmentation process which used to distinguish the heart cavity area (generally represents as darker regions) from the rest of myocardium (Figure 3.7c). After analysing the intensity histogram and the appearance of each tone of the image for plausible image quality constraints, a sensible threshold range for the binarization process was carefully selected. (The binarization function will be discussed in detail under Section 4.4.1).

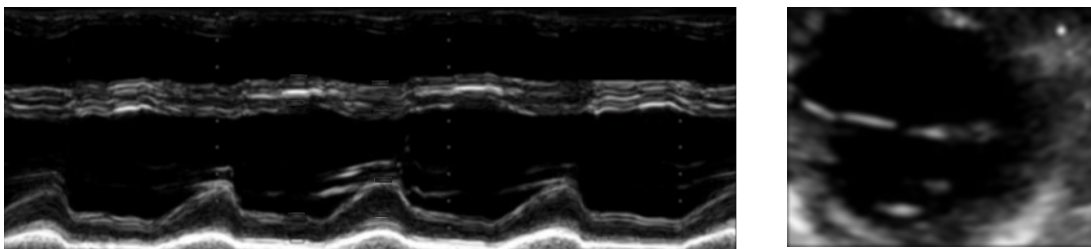
3.6.5 Image Enhancement

Eliminating the unnecessary details which hinder the clear visibility of target regions of the image was important to increase the accuracy of detecting the LV cavity details and to reduce the image processing time. Binarization process usually results in an echocardiography image, leaving many unnecessary speckles and particles. This is due to the detection of LV papillary muscles and valves on images which contaminate the clear view of detecting the LV cavity area properly. As shown on Figure 3.7d, the dark holes surrounded by lighter regions, were filled by a morphological operation applied to the binarized image. (This operation will be discussed in detail under Section 4.4.1).

After retrieving a clear view of the cavity section and cavity border, next step was to remove all the connected components that reside either side of the cavity (generally the particles of inter-ventricular septum and posterior wall) that possess with fewer pixels compared to the cavity region. This aimed to combine together the scattered particles across the large objects and make the image more precise to the border detection (Figure 3.7e).



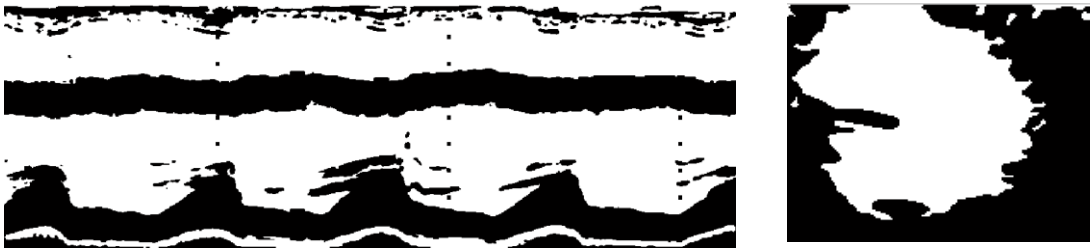
(a) Original PLAX M-mode image (Left) and PSAX B-mode cavity image (Right)



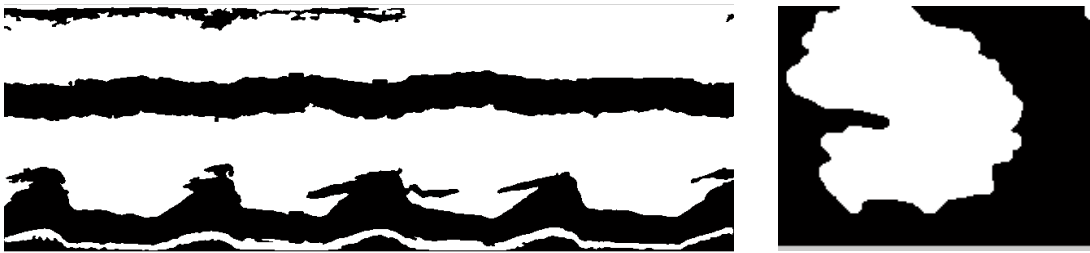
(b) De-noised Image for PLAX M-mode (Left) and PSAX B-mode cavity image (Right)



(c) Binarized image for PLAX M-mode (Left) and PSAX B-mode cavity image (Right)



(d) Filled Image for PLAX M-mode (Left) and PSAX B-mode cavity image (Right)



(e) Smooth Image for PLAX M-mode (Left) and PSAX B-mode cavity image (Right)

Figure 3.7: Steps of image pre-processing

3.7 Border Detection

After going through the above course of actions in pre-processing, yet there were fragments of objects, not referring the LV cavity section (As shown on Fig.3.8, residuals of Right Ventricular cavity areas, posterior wall sections etc.). Hence it was required to isolate the LV contour area before identifying borders of the image. For this task, a LV Region of Interest (ROI) method was employed to produce the most probable pixel region to define the LV cavity area based on the following assumptions.

1. Both upper and lower cavity borders are clearly visible as a continuous pixel area.
2. Left ventricle cavity region is approximately the biggest area which represents most candidate pixels with equal pixel range.



Figure 3.8: The Pre-processed image with LV region of interest (ROI)

Since there was a huge pixel value difference between the cavity region with white pixels and background with black pixels, the cavity border can be identified easily. As per experimented by many of the past studies, several border detection algorithms were considered to trace the cavity boundary [40] [41] [42]. ‘Moore-Neighbor tracing algorithm’ was used to detect the boundaries of the final binary image. It traces the exterior boundaries of objects, as well as boundaries of holes inside these objects, returning a cell array of boundary pixel locations [6] [57]. Those details used to plot the LV cavity border over the original echocardiography image (Figure 3.9).

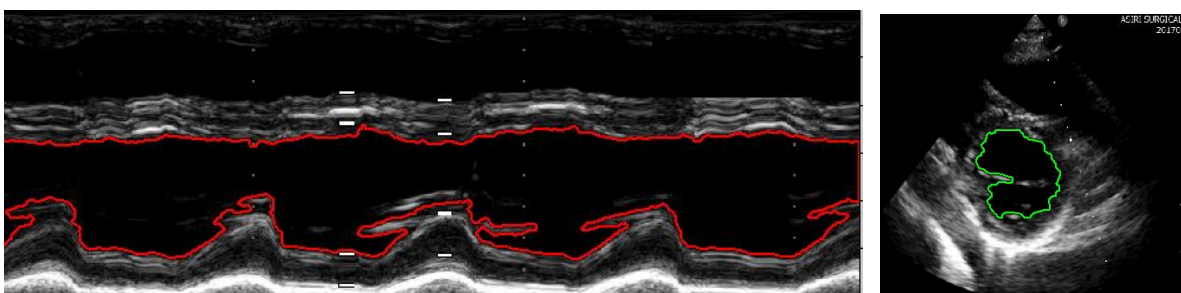


Figure 3.9: Detecting the LV cavity border in both M-mode (Left) and B-mode (Right)

3.8 Feature extraction & Calculation

The sole intention of the feature extraction phase was to identify the LV diameter values for systole and diastole phases. As explained in Section 3.5, two separate methodologies were proposed to evaluate the cardiac LV function based on the quality constraints of input data. Since PLAX M-mode is an image and PSAX B-mode is a video, two separate approaches were used to extract the parameters from two view modes. Below will explain only the feature extraction phases of two methodologies as the above explained image pre-processing, segmentation and border detection approaches were similar for both PLAX and PSAX echocardiography data.

3.8.1 Method-1 for PLAX M-mode view

For PLAX M-mode Echocardiography, the primary intent of feature extraction phase was to determine the maximum vertical diameter (LVIDd) and the minimum vertical diameter (LVIDs) measured between the upper and lower LV cavity borders. As explained in Section 2.4.3, M-mode reflects the time motion display of ultrasound waves along the time axis [58]. Hence y axis pixel columns of image denote the time variable which refer to the time spent in rendering the image. In order to measure the diameter values of LV, it was required to extract all pixel height variances between upper and lower borders. The diameter values thus obtained were plotted on a graph (y axis to denote the diameter and x axis to denote the time) as to make decisions regarding the LV muscle contraction interpreted by the diameter value variance along the time (Figure 3.10).

Followed by the graph, the maximum vertical diameter and the minimum vertical diameters were taken as the LVIDd and LVIDs respectively. As shown by Figure 3.11, the extracted two diameter values were plotted on their corresponding locations on the original M-mode image (The corresponding y axis pixel columns are represented by green vertical line and the measured diameter length between the borders are represented by pink colour). The implementation details of feature extraction algorithm will be discussed in Section 4.4.3.

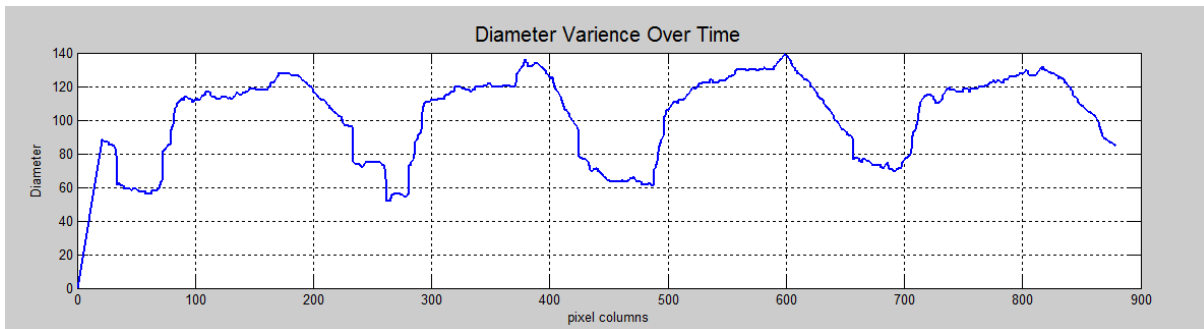


Figure 3.10: Plotting the LV diameter variance along the y axis pixel columns of the image

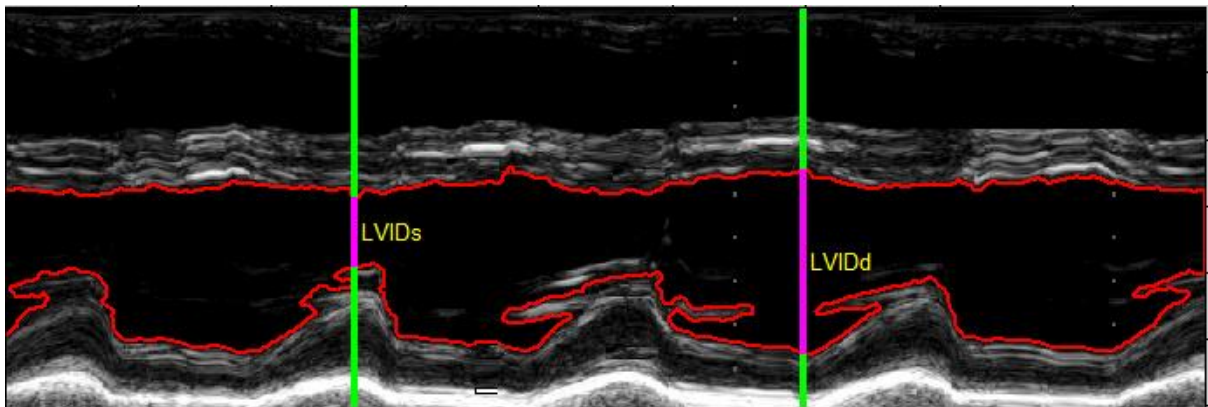


Figure 3.11: Extracting LVIDd and LVIDs from M-mode image

3.8.2 Method-2 for PSAX B-mode view

A separate feature extraction algorithm was developed to calculate the parameters from PSAX B-mode echocardiography videos. Since this is a video, the cavity state changes visible at each and every image frame has to be considered when calculating the parameters (Figure 3.12).

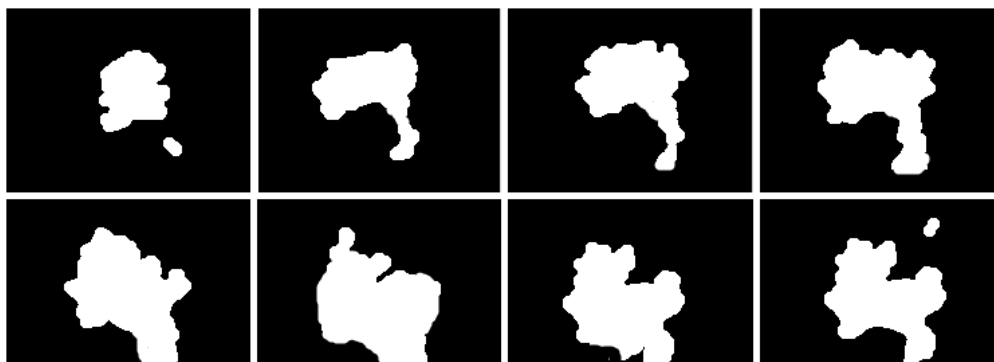


Figure 3.12 Pre-processed image frames of PSAX B-mode LV cavity area captured between systole and diastole states

For a given image frame, the centre point of the LV cavity was identified by averaging the extracted cavity area. Using that as a seed point, it measures the number of pixels up to the cavity border in horizontal and vertical axes. The calculated vertical and horizontal diameters were used to return a mean diameter value for the respective image frame (Figure. 3.13). As the video reads by, the mean diameter values for each image frame was captured and plotted on a graph. Those results were then used to extract the maximum diameter and minimum diameter values that to determine LVIDd and LVIDs respectively (Figure 3.14).

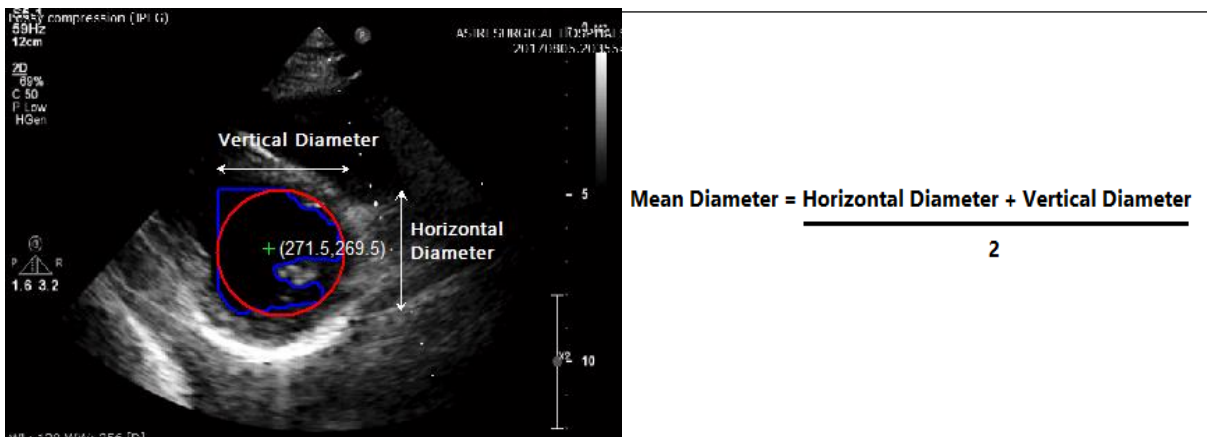


Figure 3.13: Extracting the Cavity Centre (Green cross), Horizontal diameter and Vertical diameter value of PSAX B-mode Image frame

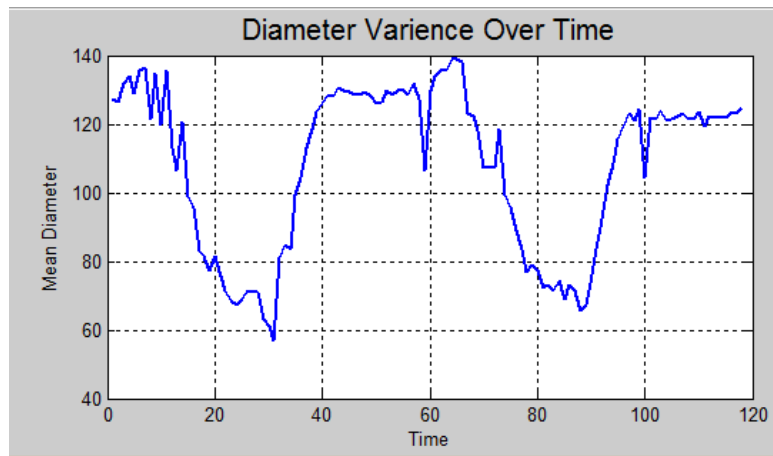


Figure 3.14: Plotting the LV mean diameter variance over the image frames

The calculated LVIDs and LVIDd values from PLAX M-mode view or PSAX B-mode view were then used to calculate the Left ventricular Fractional Shortening, Left Ventricular Systolic volume, Left Ventricular Diastolic volume by the given formulas (Eq. 1, Eq. 2 and Eq. 3). Left Ventricular Ejection Fraction (LVEF) is finally calculated by Eq. 4.

$$LVFS = \frac{LVIDd - LVIDs}{LVIDd} \times 100\% \dots\dots\dots (1)$$

$$LVESV = \frac{7}{(LVIDs + 2.4)} \times (LVIDs)^3 \dots\dots\dots (2)$$

$$LVEDV = \frac{7}{(LVIDd + 2.4)} \times (LVIDd)^3 \dots\dots\dots (3)$$

LVIDs - Left Ventricular Internal Systolic Diameter

LVIDd - Left Ventricular Internal Diastolic Diameter

$$LVEF = \frac{(LVEDV - LVESV)}{LVEDV} \times 100\% \dots\dots\dots (4)$$

LVEDV - Left Ventricular End-Diastolic volume

LVESV - Left Ventricular End-Systolic volume

3.9 Feature Selection

Selecting a suitable subset of features to determine the LV systolic heart function was crucial as the performance of the predictive model depend on them. After considering the clinical importance of each extracted parameters and the recommendations of cardiologists, LVIDd, LVIDs, and LVEF data were considered as inputs for the classification process.

3.10 Training the ANN

As discussed in Section 2.8 of Chapter 2, ANNs have been used successfully in medical diagnosis in numerous previous researches. Moreover, ANNs have shown very high accuracy rates in classifying medical images in past researches. Since ANNs are computer models inspired by biological neural networks where they are able to learn by observing datasets and identifying hidden patterns in them ANN serves as the best solution we can go for in order to classify our images as normal or abnormal while acting like an expert medical doctor.

Since our goal was to use the echocardiography images along with doctor's recommendation for them and train a model which can predict the image category for new images as well, the learning method that was most appropriate in solving such problems in machine learning context was

supervised learning approach. Supervised learning is a type of machine learning approach that uses a known dataset to train a model which can make predictions about a whole new dataset [59]. Here, a dataset which consists of inputs and their respective desired outputs is used to train the ANN. The desired output here is the decision made by the cardiologist (Whether LV function is normal or abnormal).

Feedforward neural networks are mostly used for classification problems in supervised learning when the dataset used is not time dependent and sequential. Also, when considering similar past researches described in Section 2.8 of Chapter 2, feedforward architecture has been widely used for medical diagnosis problems.

Feedforward networks have got its name for a reason. They consist of nodes organized in layers where each node is connected with all the nodes in the previous layer. These connections do not form a cycle and the information travels only in the forward direction inside the network. I.e. they enter through input nodes, then flow through hidden layers and Finally, reach the output layer. Thus they are called “feedforward” networks (Figure 3.15).

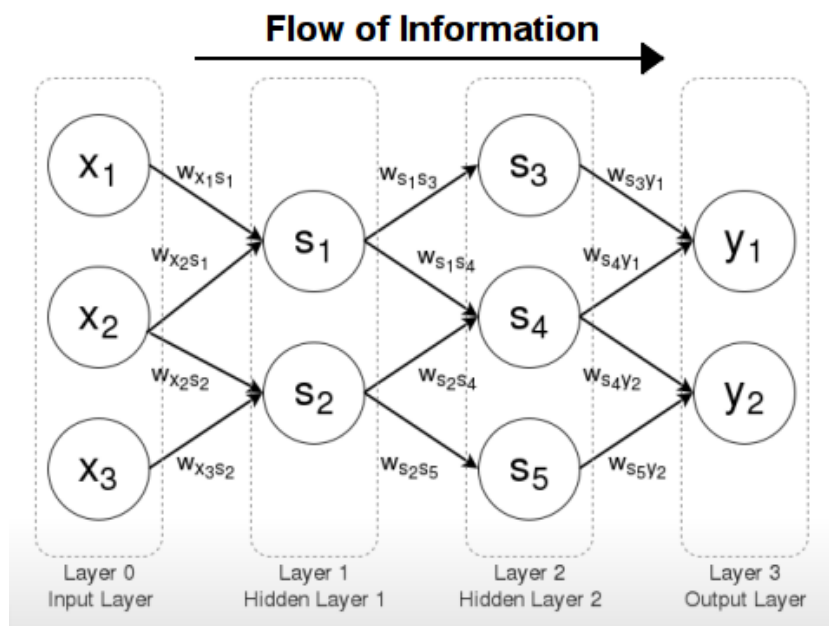


Figure 3.15: Information flow in a feedforward network

The backpropagation algorithm is the most commonly used algorithm with multi-layer feedforward networks. It is a fast algorithm for this type of pattern recognition problems which alters weights and biases dynamically and gives a detailed picture about how the network

behaviour can be changed. Therefore, considering all these factors, we have used a feedforward multilayer neural network with backpropagation algorithm in our research.

As discussed, the classifier was trained using the Back-propagation algorithm mainly due to its proven high accuracy in the previous studies found in the literature.

3.11 Testing the ANN

The constructed ANN was tested with a separate set of echocardiography images obtained from the same machine. The output of the ANN was compared with the recommendation of the cardiologist. The performance of the classifier was evaluated using a Confusion Matrix and a Receiver Operator Characteristic (ROC) curve.

ROC curves are used to visualize, organize and select classifiers based on their performance. In ROC curves, true positive rate (TPR) is plotted against false positive rate (FPR) at various threshold settings (Figure 3.16). TPR is also known as sensitivity and the FPR is known as probability of false alarm or (1-specificity). Each prediction result or instance of a confusion matrix represents one point in the ROC space [60].

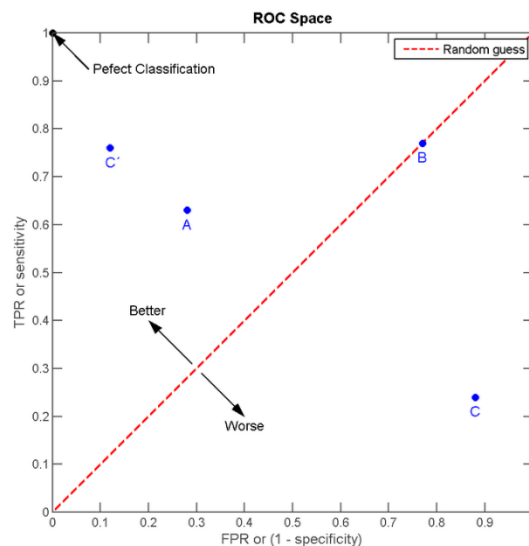


Figure 3.16: ROC Curve

The perfect predictions will result a point in the upper left corner which has the coordinate (0,1). This means that it has 100% sensitivity and 100% specificity. The dotted diagonal in the diagram is where the random guesses would fall. The points that fall above the diagonal represent good classifications and the ones below indicate incorrect classification.

3.12 Application Overview

Based on the success of the above methodology and the experiments, an application will be developed which yields favourable results to achieve the research questions (Figure 3.17).

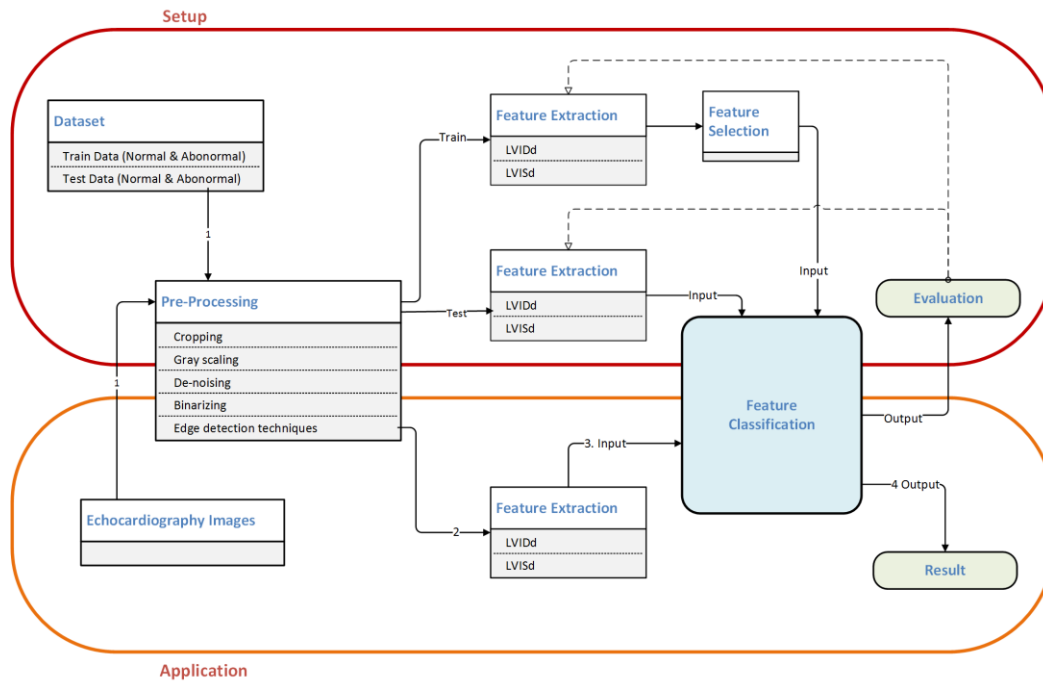


Figure 3.17: Process flow diagram of overall system

The proposed application takes the echocardiography data; either PLAX M-mode image or PSAX B-mode video as inputs. From the given data, it extracts necessary features and compute four parameters; Left Ventricular End Diastolic Volume (LVEDV), Left Ventricular End Systolic Volume (LVESV), Fractional Shortening (FS) and the Ejection Fraction (EF). Subset of these parameters serve as inputs to the ANN, which produces the predicted classification of the input data. Finally, the application will output a report with the calculated parameters and the predicted condition of the Left Ventricular function of the heart as normal or abnormal (Figure 3.18).

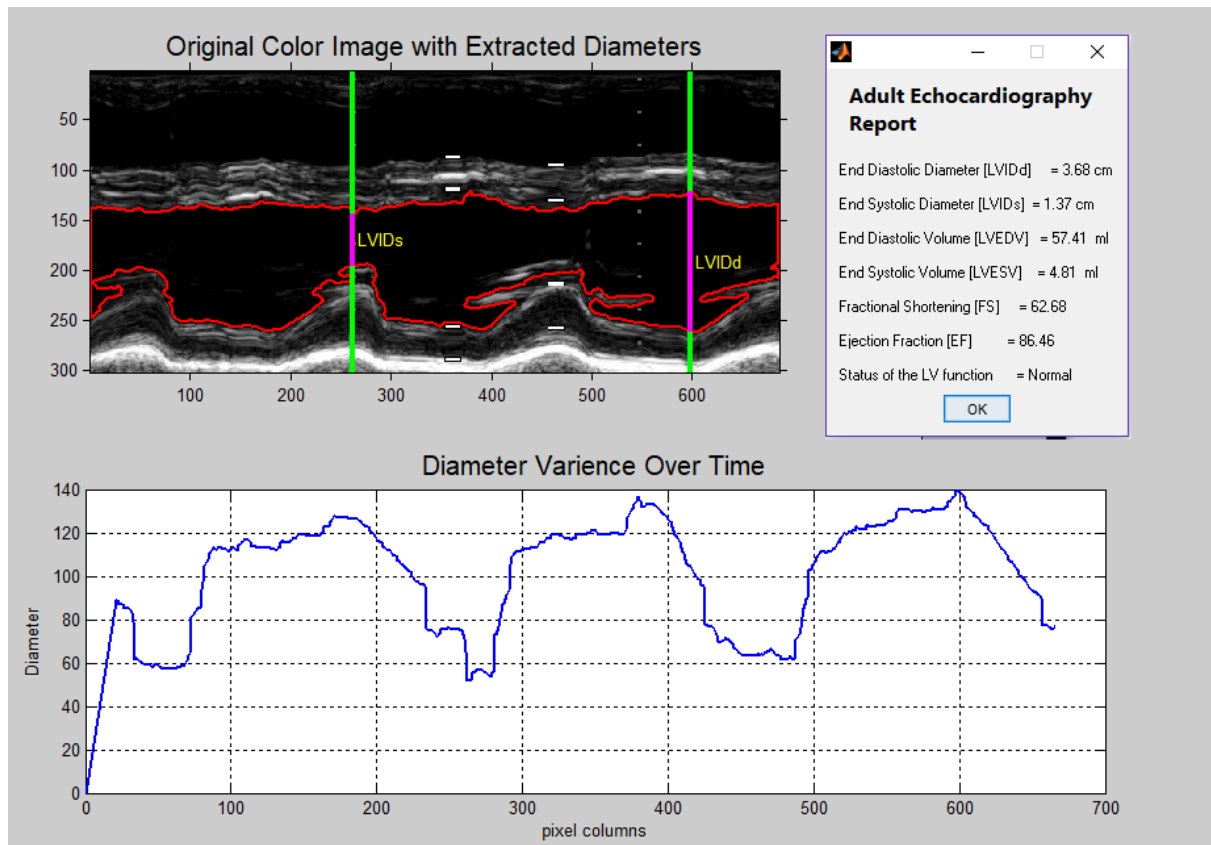


Figure 3.18: Final output of the application

The developed system was further improved by, allowing the user to manually select the region of interest on the original image and evaluate the results based on the selected region. This enhancement showed some promising results for the data which doesn't satisfy the two assumptions made.

3.13 Summary

The main focus of this chapter was to explain the design and methodology of the research. Three stages of research design were described as to answer the research questions. The four main phases in proposed methodology namely, image pre-processing, feature extraction, feature selection, training and testing the ANN were discussed in detail by giving reasons for the selection of every method and technique. The next chapter will discuss about the implementation of the design approaches.

Chapter 4 Implementation

4.1 Introduction

This chapter is focused on the implementation approach for each research stages discussed in Chapter 3. Moreover the tools and techniques used in image pre-processing, feature extraction, feature classification and data representation for two methodologies will be described in detail.

4.2 Selection of Echocardiography Data

The dataset consists of echocardiography videos of both normal and abnormal heart conditions. There were some data which did not satisfy the assumptions made for the proposed methodology. Hence, a subset of 50 original data set was selected for this study; 25 with normal LV function and 25 with abnormal LV function.

Table 4.1: M mode echocardiographic characteristics of different age groups

	Age group (years)			
	All subjects	20–39	40–59	60–81
<i>n</i>	88	25	34	29
Female/male	43/45	13/12	12/22	18/11
Age (years)	51.5	29.9	50.2	71.5
BSA, m ²	1.89 ± 0.2	1.92 ± 0.2	1.96 ± 0.2	1.80 ± 0.2
Heart rate (bpm)	61 ± 8	61 ± 8	60 ± 9	61 ± 9
Systolic BP (mmHg)	127 ± 19	115 ± 12	124 ± 14	142 ± 20‡
Diastolic BP (mmHg)	75 ± 9	69 ± 10	77 ± 6	78 ± 8‡
LVEDD (mm)	50.2 ± 4.7	51.7 ± 3.4	50.5 ± 3.2	48.7 ± 5.1*
FS (%)	36 ± 5	33 ± 4	35 ± 6	38 ± 5†
EF (%)	58 ± 6	58 ± 7	58 ± 6	60 ± 5
IVS (mm)	9.2 ± 1.8	8.2 ± 1.4	9.3 ± 1.6	9.9 ± 2.0‡
LVMI (g/m ²)	87.6 ± 18.6	81.8 ± 17.1	87 ± 16.9	93.5 ± 20.6†
LA (mm)	36.8 ± 5.5	35.3 ± 4.6	34.9 ± 4.2	38.1 ± 6.9†

Mean values ± S.D. BSA=body surface area, bpm=beats per minute, BP=blood pressure, EF=ejection fraction, FS=fraction shortening, LVEDD=left ventricular end diastolic diameter, IVS=intraventricular septum thickness, LVMI=left ventricular mass index, LA=left atrium diameter. Significance levels denote significant correlations with age.

According to the cardiologists, age, gender, region and other demographical factors do not influence largely for the parameters which used for the echocardiographic evaluations. Table 4.1

shows the mean values of cardiac parameters collected for different age categories [61]. Besides, we were not able to collect such data due to the ethical concerns imposed by the hospitals authorities. Therefore,, PLAX M-mode image, PSAX B-mode video, cardiac parameters generated by echocardiography machines and the cardiologist's final decision for each heart condition were collected for each subject.

Finding a good source for collecting data was a crucial requisite since the final results of the proposed methodology was highly dependent on the quality of data. For this study, the data was obtained from the "EPIQ 7C" Philips echocardiography machine of the Asiri Surgical Hospital, Colombo, Sri Lanka.

4.3 MATLAB

MATLAB 8.2, which stands for MATrix LABoratory is a high-level language and interactive environment, particularly useful for analysing data, developing algorithms, or creating models. This programming package is used by millions of researchers and scientists worldwide for their data analysis, visualisation, and mathematical calculations. It consists with number of built-in functions and toolboxes that can be applied for different use cases.

MATLAB Image Processing Toolbox™ provides a set of standard algorithms and workflow applications useful for image processing, optimisation, partial analysis, segmentation, visualization, and algorithm development [62]. Therefore, we have used MATLAB software for the implementation purpose for this research study.

4.4 Method 1- for PLAX M-mode echocardiography Images

4.4.1 Image Pre-processing

As explained in Section 3.5, the echocardiography images need to undergo several pre-processing steps to make the feature extraction task more reliable and accurate. This includes Image enhancement techniques, noise removal and image smoothing techniques. The primary stages applied for the PLAX M-mode images are described in following sub sections with the relevant MATLAB source code for pre-processing. (Listing 4.1)

```

1  %import PLAX image to matlab
2  rgbImage = imread('t1.jpg');
3  imshow(rgbImage);
4
5  % crop the PLAX M-mode section
6  rect = [46 400 898 300];
7  crop = imcrop(rgbImage,rect);
8
9  %grey scale the image
10 grey_scale = rgb2gray(crop);
11
12 %Apply 5*5 Gaussing Blur effect
13 H = fspecial('Gaussian',[5 5],1.5);
14 GaussBlur = imfilter(grey_scale,H);
15
16 % Use a median filter to filter out the noise.
17 Median = medfilt2(GaussBlur);
18
19 %Binarize the image to filter out LV cavity section
20 [rows,columns]=size(Median);
21
22 for i=1:1:rows
23     for j=1:1:columns
24         if (Median(i,j)>10)&&(Median(i,j)<200)
25             Median(i,j) = 0;
26         else
27             Median(i,j) =255;
28         end
29     end
30 end
31
32 % Fill out holes surrounded by dark regions
33 FilledImage = imfill(Median,'holes');
34 % Smoothing the edges/borders of the remaining contour area
35 se = strel('disk',2);
36 contour = imopen(FilledImage, se);

```

Listing 4.1: Image preprocessing source code used in MATLAB

1. Image Grey-scaling

As explained under Section 3.3, converting the row images from RGB to grey scale is important to reduce the complexity of processing the image details with pixel information. Most of the recent studies have shown that grey scaling is important to eliminate the unnecessary colour details to be processed further [6] [54]. The function which used to convert RGB images to grayscale, eliminates the hue and saturation information while retaining the luminance [63].

2. Image De-noising

Ultra sound images are usually generated with higher noise level due to internal and external interferences. Gaussian filtering is a commonly used pre-processing step to improve and smooth the patches and image regions. Hence, the above grey scaled image was subjected to linear Gaussian operation to eliminate the speckle noise and salt-and-pepper noise. The Gaussian function was applied with the smoothing kernel defined as 1.5 according to the equation.

Median filtering is a nonlinear operation often used to reduce the noise, while preserving the sharp edges of the details. This filter operation was applied on the images by replacing the pixel value with the median of 3 by 3 neighbouring pixel values [64]. After applying these filters together, the output image was generated with less noise level without compromising the true edges of the image details. (Figure 4.3b).

3. Image Binarization

Binarization is the process in which converts all pixel data of the image in to binary; either 0 (black) or 1 (white). After analysing the intensity histograms of sample data, it was realised that the pixel details which refer the LV cavity region lie between 0-10 and 200-250 pixel range (Figure 4.1). Considering this fact, the binarization function was developed to convert all the pixels which hold values of range 10 to 200 in to black (pixel value = 0), making the rest of the pixels in to white (pixel value = 255). This function provides the basis for the segmentation process by denoting the LV cavity area in white colour pixels and background in to black colour pixels (Figure 4.3c)

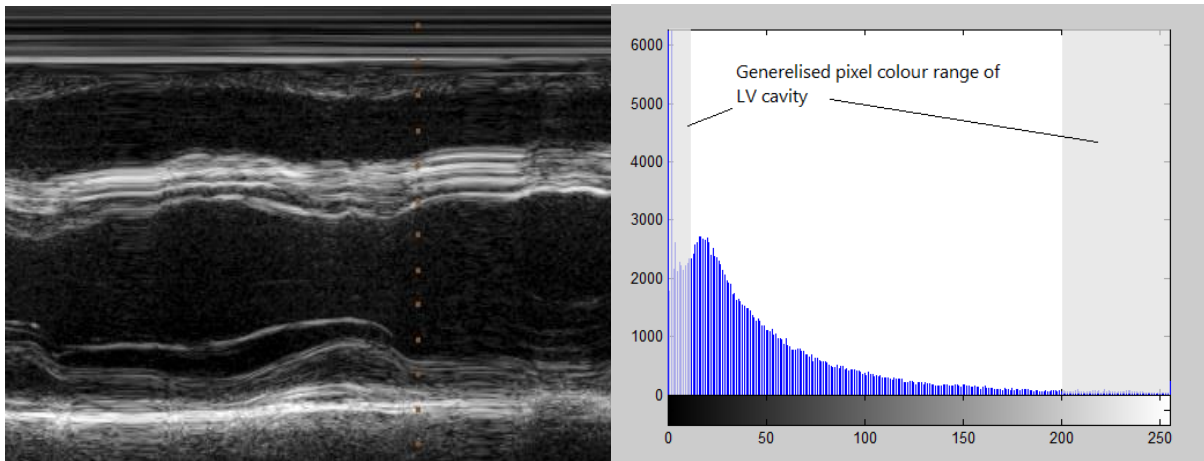


Figure 4.1: A Sample M-mode echo image (left) and the corresponding color histogram (right)

4. ROI Refinement

According to the proposed approach, the primary effort of filtering and isolating the Region of Interest (ROI) was carried out by binarization process. Yet there were many speckles and particles which were not refereeing the LV cavity region, remained in the image. Therefore, those non prominent areas needed to be removed before the border detection phase. MATLAB function *imfill* was used to wipe out such dark regions surrounded by lighter regions [65]. This function uses an algorithm based on morphological reconstruction which fills the holes with the pixel values of neighbouring background (Figure 4.2).

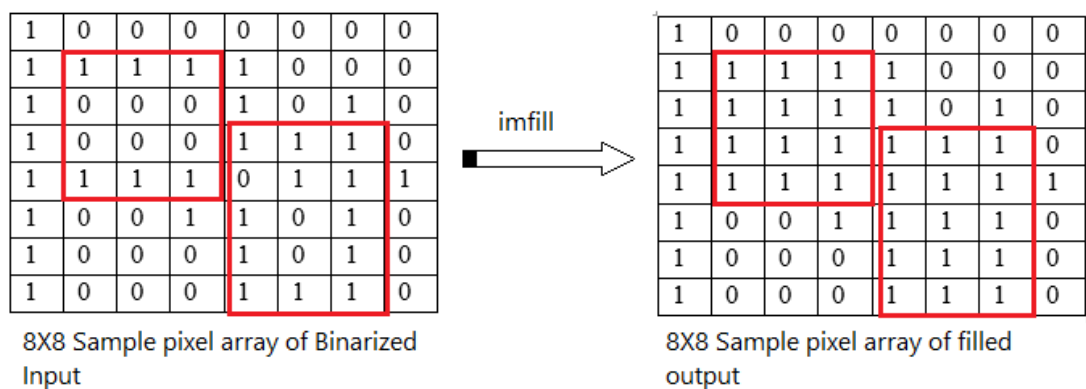


Figure 4.2: Morphological filling operation applied to the binarized image

In order to smooth the borders of the object(s), *imopen* inbuilt function was applied. It performs a morphological opening on the isolated cavity region, returning a quite closed image with a defined Disk-Shaped Structuring. (Figure 4.3d).

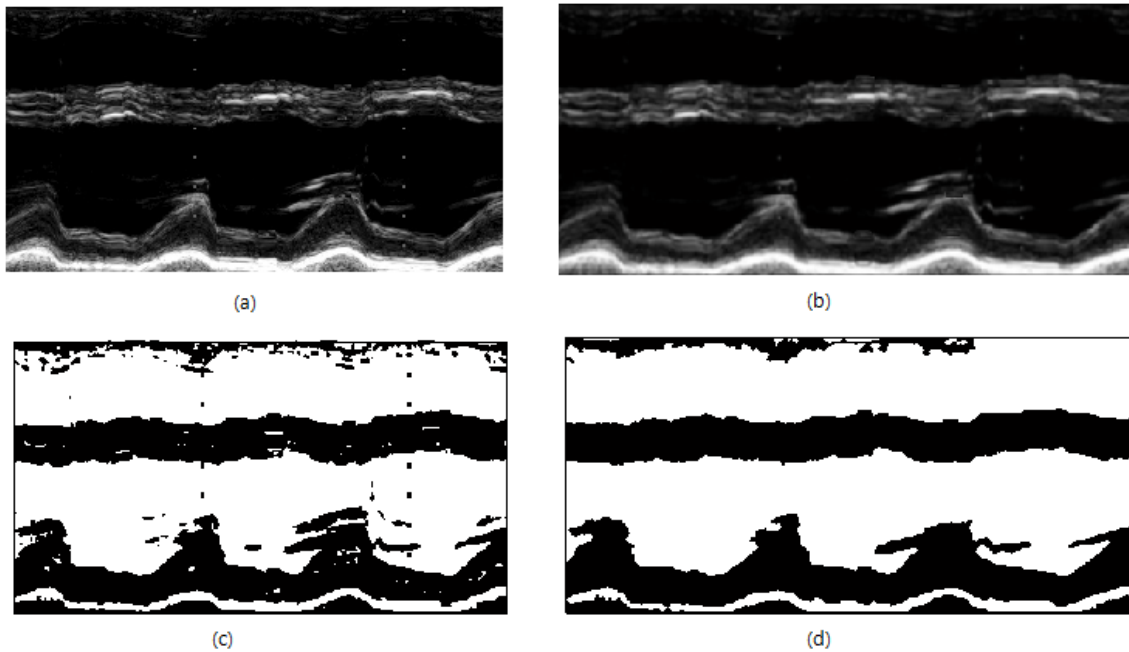


Figure 4.3: Steps of image pre-processing (a) Original PLAX M-mode image. (b) Gaussian Filtered Image. (c) Binarized image for PLAX M-mode. (d) Smooth filled Image.

4.4.2 Border Detection

Border detection plays a major role in detecting and distinguishing the LV cavity region from the residuals presented over the image pre-processing phase. The relevant MATLAB source code for border detection phase is mentioned below (Listing 4.2).

```

1  %Compute the contour area, centroid etc.
2  labeledImage = bwlabel(contour);
3  measurements =
    regionprops(labeledImage,'Area','centroid','orientation');
4
5  % To Find the largest contour area
6  allAreas = [measurements.Area];
7  biggestBlobIndex = find(allAreas == max(allAreas));
8  keeperBlobsImages = ismember(labeledImage, biggestBlobIndex);
9
10 %Display the original colour image.
11 subplot(2, 1, 1);
12 imshow(c, []);
13 axis on;
14 % Enlarge figure to full screen.

```



```

15 set(gcf, 'Units', 'Normalized', 'OuterPosition', [0 0 1 1]);
16
17 hold on; % Prevent plot() from blowing away the image.
18 title('Original Color Image with Extracted Diameters',
    'FontSize',fontSize);
19
20 % Get the border detected and overlay it over the original image.
21 boundaries = bwboundaries(keeperBlobsImages);
22 blobBoundary = boundaries{1};
23 plot(blobBoundary(:,2), blobBoundary(:,1), 'r-', 'LineWidth', 2);
24 hold off;

```

LISTING 4.2: Source code for border detection used in MATLAB

After the image pre-processing stage was completed, MATLAB function called *regionprops* was employed to compute the area of the remaining objects by calculating the number of pixels [66]. When applying the function for isolating the LV cavity from the background details, the assumptions stated at Section 3.7 were considered. According to the second assumption, the object with the biggest area was selected as the LV cavity area.

Since there was a huge pixel value difference between the cavity region with white pixels and background with black pixels, the cavity border was identified by applying the ‘Moore-Neighbor tracing algorithm’. This algorithm was considered as a robust way to trace the boundaries of a given contour area. [57][67]. This algorithm was applied with function MATLAB function *Bwboundaries*. It traces the exterior boundaries of objects, as well as boundaries of holes inside these objects, returning a cell array of boundary pixel locations. Those details were used to plot the LV cavity region over the original echocardiography image (Figure 4.3).

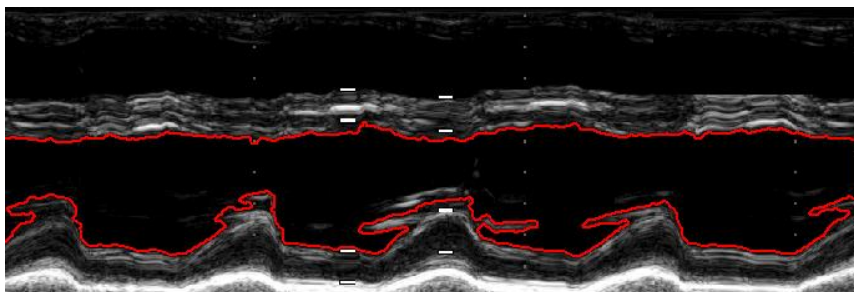


Figure 4.4: Overlaying the detected cavity border over the original PLAX M-mode image

4.3.3 Feature extraction & Calculation

The primary expectation of the feature extraction processes of PLAX M-mode Echocardiography was to calculate the minimum and maximum vertical diameter measured between the upper and lower LV cavity borders. The first task of the feature extraction algorithm was to create a vertical line perpendicular to the upper and lower boundaries. (Fig 4.4 denotes in green vertical line). For each pixel column along the y axis, it identifies the pixel coordinates of top most border and bottom most border location and calculates the vertical pixel length between two borders (Fig 4.4 denotes in pink vertical line).

Repeating the above process for all pixel columns, Finally, it returns the maximum vertical diameter (LVIDd) and the minimum vertical diameter (LVIDs) measured between the upper and lower LV cavity borders. The MATLAB code for feature extraction phase is mentioned below (Listing 4.3)

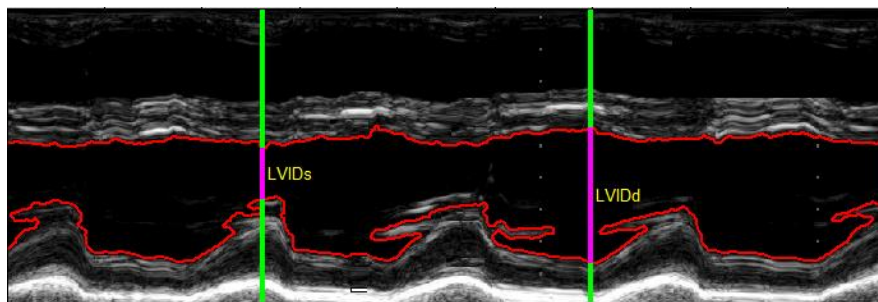


Figure 4.5: Overlaying the detected cavity border over the original PLAX M-mode image

```

1  for k = minx : columns
2
3      y1 = y2 = pixel;
4
5  % Get the profile perpendicular to the midpoint that to measure the
6  % length which first enters and last leaves the object.
7  [cx,cy,c] = improfile(keeperBlobsImages, [y1, y2],[1,columns],
8  1000);
9
10 c(isnan(c)) = 0;
11 firstIndex = find(c, 1, 'first');
12 lastIndex = find(c, 1, 'last');
13
14 % Compute the distance of perpendicular width.
15 perpendicularWidth = sqrt( (cx(firstIndex) - cx(lastIndex)) .^ 2 +
16 (cy(firstIndex) - cy(lastIndex)) .^ 2 );
17
18 % Measuring the longest distance between points.

```

```
16 if perpendicularWidth > maxPerpendicularWidth
17     maxPerpendicularWidth = perpendicularWidth;
18     maxPointpx=y1;
19     maxxf=cx(firstIndex);
20     maxx1=cx(lastIndex);
21     maxyf=cy(firstIndex);
22     maxy1=cy(lastIndex);
23 End
24 % Measuring the shortest distance between points.
25 if perpendicularWidth < minPerpendicularWidth
26     minPerpendicularWidth = perpendicularWidth;
27     minPointpx=y2;
28     minxf=cx(firstIndex);
29     minx1=cx(lastIndex);
30     minyf=cy(firstIndex);
31     miny1=cy(lastIndex);
32 End
33     xx(k) = k;
34     yy(k) = perpendicularWidth;
35
36     pixel=pixel+1;
37 end
38 % max diameter inf
39 MaxWidth=maxPerpendicularWidth
40     cx(firstIndex)=maxxf;
41     cx(lastIndex)=maxx1;
42     cy(firstIndex)=maxyf;
43     cy(lastIndex)=maxy1;
44 p = maxPointpx;
```

LISTING 4.3: Source code for feature extraction

4.5 Method 2- for PSAX B-mode echocardiography Images

4.5.1 Image Pre-processing

As explained in Section 3.5, the second method intends to evaluate the LV heart condition in cases where the first method will be unable to detect the LV cavity features correctly. This method uses a 3D ultrasound video of PSAX B-mode view of the heart as input. The video data were converted from DICOM format to .wmv format by using “Radiant Dicom Viewer” software and then imported into MATLAB software for the video processing tasks.

Unlike the first method, the second method needs to process each and every image frame of PSAX B-mode videos to arrive with a clinical evaluation of the LV heart function. Similar to the first method, each image frame of the video was subjected to the same set of image pre-processing steps which were discussed under Section 4.4.1 (Figure 4.5). Source code for the image pre-processing stage is mentioned under LISTING 4.5.

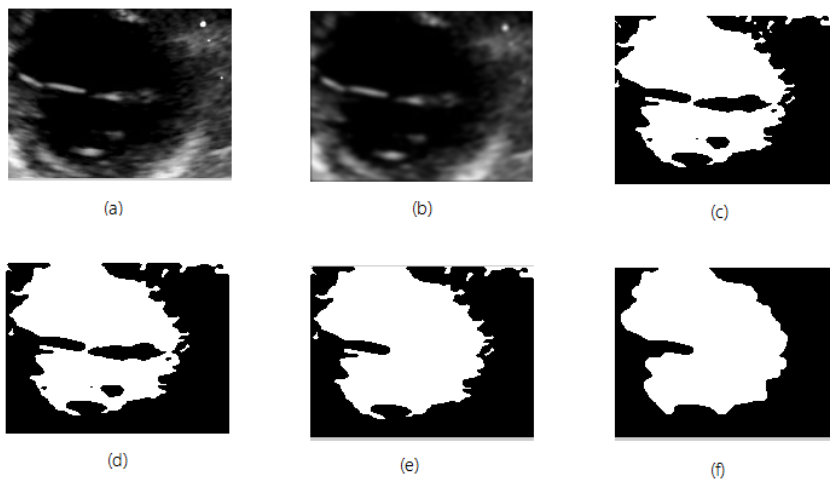


Figure 4.6: Image pre-processing steps for method 2

(a) Original PSAX image frame (b) Gaussian Filtered Image frame (c) Binarized image frame (d) filtered image frame (e) detail filled image frame (f) Smooth filled image frame.

```

1  % import and read the PSAX video
2  obj = VideoReader('MOVIE23.wmv');
3  NumberOfFrames = obj.NumberOfFrames;
4
5  maxdiameter = -inf;
6  mindiameter = inf;
7
8  % extract the features from each image frame
9  for cnt = 1:NumberOfFrames
10 image_frame=read(obj,cnt);
11 if size(image_frame,3)==3
12     image_frame=rgb2gray(image_frame);
13 end
14
15 % crop the the most likely rectangular position of the LV cavity
16 rect = [c1 c2 c3 c4];
17 c = imcrop(image_frame,rect);
18
19 % Apply Gaussian Blur effect
20 H = fspecial('Gaussian',[5 5],1.5);
21 GaussBlur = imfilter(c,H);
22
23 %Binarize the image to filter out LV cavity section
24 [rows,columns]=size(GaussBlur);
25
26 for i=1:1:rows
27     for j=1:1:columns
28         if(GaussBlur(i,j)>10)&&(GaussBlur(i,j)<255)
29             GaussBlur(i,j) = 0;
30         Else
31             GaussBlur(i,j) =255;
32         end
33     end
34 end
35
36 % Eliminate white details which represent less than 0.04% the image)
37 BW3 = bwareaopen(GaussBlur, round(0.0004*numel(GaussBlur)));
38
39 % Fill out holes surrounded by dark regions
40 FilledImage = imfill(BW3,'holes');
41

```

Listing 4.5: Source code for image pre-processing

4.5.2 Border detection

Similar to the first method, the same MATLAB functions were used in detecting the borders. Here the contour region with the biggest area, was filtered assuming it to be the LV cavity section. MATLAB function *bwboundary* was used to plot the cavity border over each every image frame. The source codes for boundary detection phase is mentioned below (Listing 4.6).

```

1. % Tagged objects in BW image
2. Labeled=bwlabel(blob);
3. % Get areas and tracking rectangle
4. out_a=regionprops(Labeled);
5. % Count the number of objects
6. N=size(out_a,1);
7. if N < 1 || isempty(out_a) % Returns if no object in the image
8. solo_cara=[ ];
9. continue
   end
10.
11.     % Select largest area as LV cavity
12.     areas=[out_a.Area];
13.     [area_max, pam]=max(areas);
14.
15.     % Display the original image with cavity border
16.     subplot(121)
17.     imagesc(image_frame);
18.     colormap gray
19.     hold on
20.     title('PLAX-B Mode video with cavity border detection');
21.
22.     % Find the biggest contour area
23.     biggestBlobIndex = find(areas == max(areas));
24.     keeperBlobsImages = ismember(Labeled, biggestBlobIndex);
25.
26.     boundaries = bwboundaries(keeperBlobsImages);
27.     blobBoundary = boundaries{1};
28.     plot(blobBoundary(:,2)+c1, blobBoundary(:,1)+c2, 'b-',
           'LineWidth', 2);

```

Listing 4.6: Source code for border detection

4.5.3 Feature Extraction

A feature extraction algorithm is developed to calculate the parameters from all image frames available at PSAX B-mode echocardiography videos. MATLAB function *regionprops* was employed to identify the centre point of the detected cavity area (Fig. 4.6 Green cross). This function returns the centroid of the contour mass, as x and y coordinates [66]. As explained in Section 3.8.2, the detected cavity centre was used to determine the mean diameter value for the

respective image frame. As the video reads by, the mean diameter values for each image frame was captured and plotted on a graph. Those results were then used to extract the maximum diameter (LVIDd) and minimum diameter (LVIDs) values. The source code for feature extraction function is mentioned under Listing 4.7.

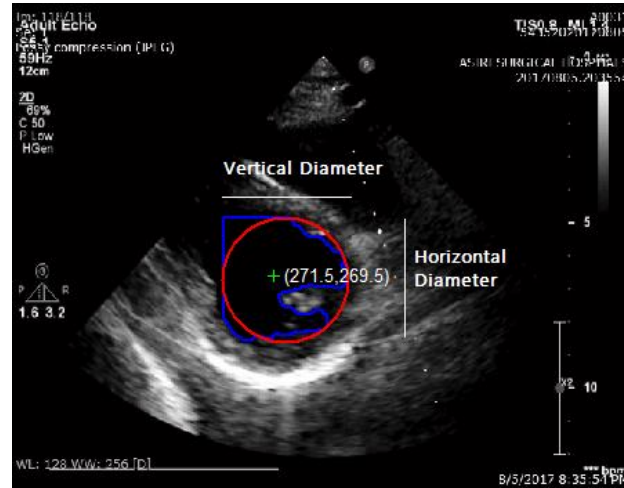


Figure 4.7: Feature extraction of horizontal and vertical diameters from PSAX B-mode image frame

```

1. % identify the center of the LV cavity
2. center=round(out_a(pam).Centroid);
3. X1=center(1);
4. Y2=center(2);
5.
6. X=X1+c1;
7. Y=Y2+c2;
8. % measure the horizontal and verticle diameter for LV cavity
9. out_a(pam);
10.     hd=out_a(pam).BoundingBox(:,3);
11.     vd=out_a(pam).BoundingBox(:,4);
12.
13.     %mean diametr value
14.     mean=(hd+vd)/2;
15.
16.     % Plotting the boundry over LC cavity
17.     circle=[out_a(pam).BoundingBox(:,1)+c1
out_a(pam).BoundingBox(:,2)+c2
18.     out_a(pam).BoundingBox(:,3) out_a(pam).BoundingBox(:,4)];
19.
20.     rectangle('Position',circle,'EdgeColor',[1 0 0],...
21.     'Curvature', [1,1],'LineWidth',2);
22.
23.     % added the cropped x, y values to mark centeroid of the cavity
24.     plot(X,Y,'g+');

```

Listing 4.7: Source code for feature extraction

4.6 Implementing the ANN

The ANN was trained using the neural network pattern recognition tool in MATLAB Neural Network Toolbox. MATLAB provides algorithms, pre-trained models and various applications to create, train, visualize and simulate both shallow and deep neural networks. It is widely used for many neural network applications such as clustering, classification, regression, dimensionality reduction etc. [68].

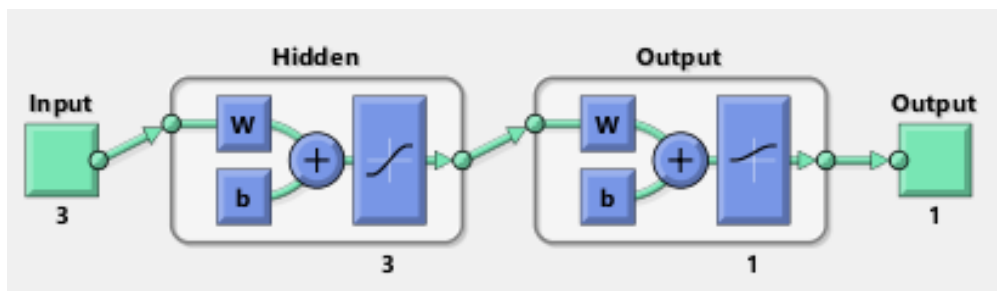


Figure 4.8: Structure of the ANN implemented

The feed-forward ANN with backpropagation algorithm that was constructed is shown in figure 4.8. The network has three layers; input, hidden and output layer. The number of neurons in the input layer is determined by the number of features selected from the extracted features. In this research we have selected three features namely, End Diastolic diameter (LVIDd), End Systolic diameter (LVIDs) and the Ejection Fraction (EF) as inputs to the ANN. The output layer will have two neurons since the images are classified into two classes; normal or abnormal. The number of hidden neurons was determined based on the experiments carried out by gradually altering the number of nodes until the performance of the ANN was optimized.

The backpropagation algorithm used was Scaled Conjugate Gradient (SCG). This algorithm avoids the time-consuming line search. When performing line-search it requires the network response to all the training inputs to be computed many times for each search and this is computationally expensive.

Chapter 5 Results and Evaluation

This chapter is dedicated to the results and the evaluation of the performance of the ANN trained using the data obtained from the Asiri Surgical Hospitals, Colombo. As mentioned in the previous chapter the number of echocardiography images used for the dataset was 50; 25 with normal LV function and 25 with abnormal LV function.

5.1 Purpose of Evaluation

The proposed methodology is intended to be used by the acute care physicians performing emergency medical treatments to particularly diagnose the condition of the human adult heart. The medications and the treatments prescribed by the medical doctors will depend on the decision made based on the Echocardiography test. Therefore,, it is very important to evaluate the accuracy and reliability of the proposed solution.

5.2 Performance Measures

After implementing the ANN using MATLAB, the performance was evaluated using a confusion matrix. Confusion matrices are mostly used to interpret the performance of a classification model [69]. Below is an illustration of a confusion matrix used for a binary classifier.

Table 5.1: Confusion Matrix for a binary classifier

		True Class	
		Positive	Negative
Predicted Class	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

According to our dataset and the classifier,

- True Positives(TP) are normal images correctly classified as normal
- True Negatives(TN) are abnormal images correctly classified as abnormal
- False Positives(FP) are abnormal images incorrectly classified as normal images
- False Negatives(FN) are normal images incorrectly classified as abnormal images

Furthermore, below measures were used to evaluate the performance of the classifier.

Accuracy depicts the overall correctness of the classifier. In other words, it tells us how often the classifier is correct. Accuracy is calculated as;

$$Accuracy = \frac{TP+TN}{TP+TN+TN+FN} \dots\dots\dots(1)$$

Sensitivity (True positive rate or Recall) is another measure which provides how often the classifier correctly predicts positives as positive. It can be calculated as;

$$Sensitivity (TP Rate) = \frac{TP}{TP+FN} \dots\dots\dots(2)$$

Specificity which is the True Negative rate is another measure used when we are more concerned about a particular class than the other in binary classifications. It shows how often the classifier predicts negative when it is actually negative.

$$Specificity (True Negative Rate) = \frac{TN}{TN+FP} \dots\dots\dots(3)$$

Precision says how often the classifier is correct when it predicts positive. It can be calculated as;

$$Precision = \frac{TP}{TP+FP} \dots\dots\dots(4)$$

5.3 Evaluation of the Classifier

The dataset used to train the ANN consisted of 50 echocardiography images; 25 with normal LV function and 25 with abnormal LV function. As explained in sections 3.10 and 4.6, a feedforward neural network with backpropagation algorithm was used. To be more precise, the backpropagation algorithm used was the scaled conjugate gradient algorithm in MATLAB neural network toolbox. Detailed explanations about these algorithms are found in sections 3.10 and 4.6.

The dataset was divided into training set, testing set and the validation set based on the percentages and the numbers shown below;

Table 5.2: Dataset used to train the ANN

Dataset	Number of images	Percentage form total dataset
Training dataset	34 images	70%
Testing dataset	8 images	15%
Validation dataset	8 images	15%

The performance of the classifier was evaluated confusion matrix. The confusion matrix obtained for the overall system is shown below.

Output Class	0	25 50.0%	1 2.0%	96.2% 3.8%
	1	0 0.0%	24 48.0%	100% 0.0%
		100% 0.0%	96.0% 4.0%	98.0% 2.0%
		0	1	
		Target Class		

Figure 5.1: Overall Confusion Matrix

Previously described performance measures were calculated based on the confusion matrix and are shown in the table below.

Table 5.3: Performance measures of the trained classifier

Accuracy	98%
Sensitivity	100%
Specificity	96%
Precision	96.2%

Early stopping method was used to improve the generalization of the network. Since the dataset was divided into three sets namely training, testing and validation, the training of the neural network will take place for sufficient number of epochs until the cross-entropy error of the validation set becomes a minimum. According to the performance graph (Figure 5.2) drawn with epochs against cross-entropy, the minimum cross entropy error is obtained at epoch 5 best validation performance is 0.02912.

Cross entropy error measure was used over the mean squared error measure for the early stopping method due to its suitability in evaluating the quality of neural networks in classification problems [70] [71].

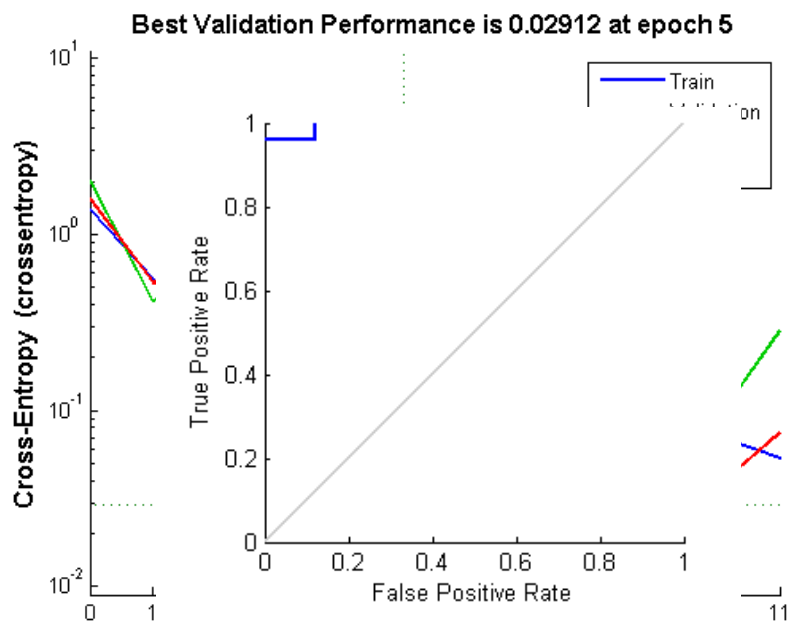


Figure 5.3: ROC curve

Receiver operating characteristic (ROC) curve for the trained classifier is shown in figure 5.3.

Error histogram drawn with instances against errors is shown in figure 5.4.

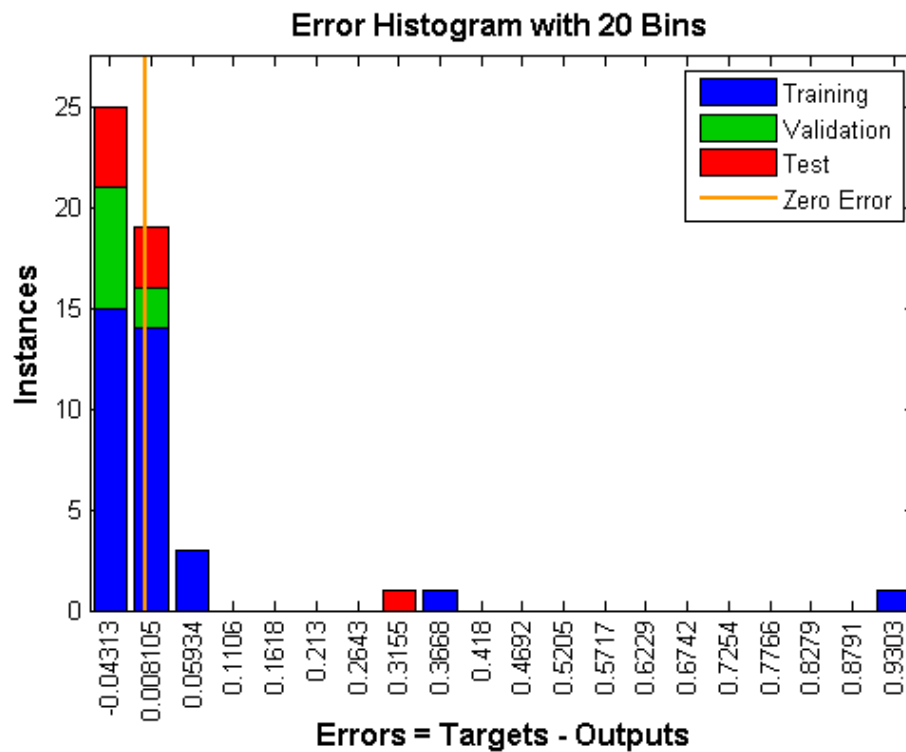


Figure 5.4: Error histogram

A comparison between the output of the classifier and the cardiologist's decision for the test dataset is shown in the Table 5.4 below.

Table 5.4: Comparison of the expected output and classifier output for the test dataset

LVIDd	LVIDs	EF	Expected Output	Classifier Output
1.75	1.20	52.07	Abnormal	Normal
2.85	2.11	45.55	Abnormal	Abnormal
3.29	0.70	95.72	Normal	Abnormal
3.86	2.64	53.43	Normal	Normal
3.82	2.24	66.14	Normal	Normal
3.81	2.98	39.07	Abnormal	Abnormal
3.82	2.25	65.60	Normal	Normal

5.4 Performance Comparison

The results of this methodology cannot be compared with previous other researches since the dataset used in each research is different to one another and there are many factors inherent to the dataset which are contributing towards the final result such as;

- Quality of the images used
- Number of images used
- Image processing techniques used to extract the features

5.5 Summary

This chapter presents the results and the performance evaluation of the ANN implemented. Confusion matrices, ROC curve and the Error histograms were used to analyse the performance of the classifier.

Chapter 6 Discussion

6.1 Discussion

The results obtained suggests that the proposed methodology could classify Left Ventricular Systolic function into normal or abnormal with reasonable accuracy using echocardiography images. Experiments were conducted to extract LV diameter values from two echocardiography views. LVIDd and LVIDs values were successfully extracted from most of the M-mode PLAX images in the dataset. Even though the experiment conducted on B-mode PSAX images produced successful results for some of the videos in the dataset, a significant portion of images failed to produce the expected LVIDd and LVIDs values. Therefore,, the LVIDs, LVIDd and Ejection Fraction values obtained mostly from M-mode PLAX images were considered as inputs to train the ANN.

When collecting echocardiography videos personal details of the patients were not collected because as stated in Chapter 2 factors such as age, gender have a negligible impact on the Ejection Fraction value which is used to determine the LV Systolic function.

The final dataset used for training, evaluating and testing of the ANN was limited to 50 videos which was significantly lower than the initially planned number of videos. The main reason behind this was that we were only able to collect 25 videos with abnormal LV Systolic function within the stipulated time period. Besides we could extract the features only by the images which satisfy the assumptions made when developing the feature extraction algorithm. Therefore,, we decided to limit the number of videos with normal LV Systolic function to 50 to maintain the balance between normal and abnormal videos used to train the ANN.

The final dataset of 50 echocardiography videos were acquired only from the “EPIQ 7C” Philips echocardiography machine of the Asiri Surgical Hospital, Colombo, Sri Lanka. We tried our best to collect echocardiography videos from several sources that uses different models of echocardiography machines. We visited and contacted several resource persons from The National Hospital of Sri Lanka, Sri Jayewardenepura Hospital, Kiribathgoda Base Hospital, Nawaloka Hospital and Ninewells Hospital but a combination of bureaucratic procedures in obtaining ethical clearances and unavailability of sufficient number of videos from patients with abnormal LV Systolic function prevented us from obtaining echocardiography videos from them.

According to the subset of test data given in table 5.4, it is obtrusive that the proposed method does not respond with correct decisions when the input data is significantly deviates from what is trained to be accepted range of normality. Also, there were some contradictive results between the expected output and the system output. All such events could have been resolved, if we could train the ANN with a larger data set with different level of consistency in input parameters.

Sometimes, there were certain misinterpretations occurred by medical practitioners when measuring the features manually (Figure 6.1). Comparing the manually measured features and the system generated features, it is perceived that the developed method is capable of reducing the human errors by interpreting the sharp details which are rather obscure to be observed by naked eye. Also, there were few events pointed by the cardiologists, that the system readings were not taken by the accurate position of LV cavity. Hence, there was always a gap between the cardiologist's diameter readings and the system generated readings compromised by the human errors and the system generated errors (Table 6.1). However, the calculated EF readings were accurate enough to develop an effective classification model.

Considering all these practical issues, the enhanced method which allows the user to determine the area of interest on echo image, yields favorable results to measure LV systolic parameters on the user interested points on M-mode image.

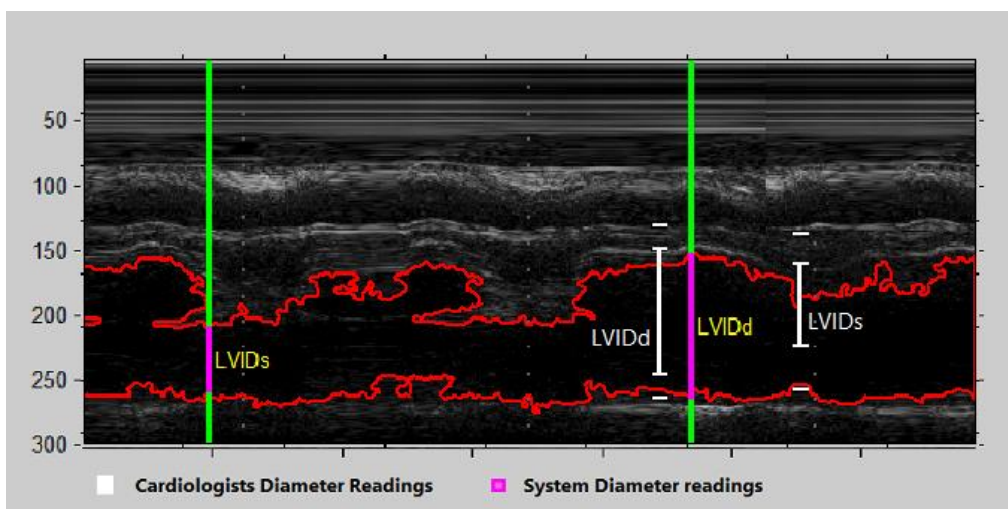


Figure 6.1: Sample M-Mode image with cardiologist's diameter reading and the corresponding system diameter readings

Table 6.1: Comparison of sample cardiologist's readings and system readings of LV parameters

Cardiologist's Readings			System Readings		
LVIDd (cm)	LVIDs (cm)	EF (%)	LVIDd (cm)	LVIDs (cm)	EF (%)
4.49	2.86	66.15	3.82	2.25	72.56
4.73	3.05	64.92	2.80	1.83	69.77
4.84	2.94	70.61	2.57	1.58	74.86
4.79	3.15	63.16	2.63	1.64	76.26
3.32	2.5	50.16	3.01	2.22	46.10

Also, when it comes to medical diagnosis, minimizing false positive errors is crucial. According to our research, false positive errors are the cases where abnormal images are classified as normal images. If this happens, the patients with abnormal LV function will go undiagnosed by the model we have implemented. As shown in confusion matrix presented in figure 5.1 of Chapter 5, the false positives represent only 2% which is a very low amount. If we could collect a larger dataset we could have improved this model further.

Considering all the above positive and negative factors, we can clearly conclude that the proposed methodology reduces the time taken to conduct echocardiography tests significantly by automating the process. Moreover, it addresses the second research question by eliminating human errors that could result due to the lack of expertise of Acute Care Physicians and the critical time factors in the emergency medicine settings.

6.2 Limitations

The following limitations became apparent during the progress of the research and the limitations are listed along with the reasons for its occurrence.

- The freezing of the echocardiography video should be done manually to obtain the still image for conducting image processing. The reason for this was when a still image is taken it displays only 3 cardiac cycles and we need to determine which cardiac cycle's/ heart beat's visual representation is clearer out of all shown in the video. Therefore,, it's more appropriate to manually determine when to freeze the video rather than automatically getting a frame for image processing. This means that the Acute care physician who conducts the echocardiography test should freeze the video once a clear cardiac cycle is visible as usual and this still image can be used to extract accurate parameters.
- The number of echocardiography videos taken as the dataset for the research had to be limited to only 50 videos which is lower than the amount which was planned initially. The accuracy of the study could have been increased with the use of a larger dataset.

Chapter 7 Conclusion

7.1 Conclusion

This thesis presents a simple reproducible methodology for automatically classifying the Left Ventricular Systolic function of the human heart using echocardiography. As a first step in building a decision support system for classifying the human heart, a methodology was developed using ANN to classify the Left Ventricular function of the human heart. The Left Ventricular Systolic function was selected because it has a higher impact on the overall condition of the heart.

In Emergency Medicine echocardiography tests are conducted to determine the condition of a patient's heart before treatment is given to the patient. Emergency medicine is focused on treating the patients admitted to the Emergency Treatment Unit (ETU) in order to stabilize their condition from critical state. Once the emergency treatments are conducted by Acute Care physicians the patient is directed to a specialist or specialized unit for further treatment. It's critical to determine the heart condition of the patient who is in emergency condition and there can be situations where there are no records about the patient's medical history. Therefore,, an accurate decision of the heart condition should be taken within minimum amount of time during emergency medicine.

The medical doctors utilize both B-mode and M-mode views displayed in echocardiography machines to make decisions about the Left Ventricular Systolic function. The final decision on the Left Ventricular function is taken based on the Left Ventricular End Systolic diameter (LVIDs), Left Ventricular End Diastolic diameter (LVIDd) and Ejection fraction. The accuracy of this decision is dependent on the experience of the doctor. Therefore,, in this research a methodology is introduced to assist decision making by Acute Care Physicians who are not specialized in cardiology.

To implement the proposed methodology a dataset of 50 echocardiography videos were acquired from the "EPIQ 7C" Philips echocardiography machine of the Asiri Surgical Hospital, Colombo, Sri Lanka. The cardiologist's decision on each video in the dataset was also obtained. The echocardiography videos are saved in the DICOM format. Therefore,, RadiAnt DICOM viewer was used to export images in .jpeg format. B-mode images of Parasternal Short Axis (PSAX) view and M-mode images of Parasternal Long (PLAX) view were exported.

Several image pre-processing techniques were applied to both PSAX B-mode and PLAX M-mode images. Several MATLAB functions, de-noising filters and binarizing techniques were utilized to finalize the image pre-processing methodology. Border detection was carried out using MATLAB functions for extracting the features from the images. Two different algorithms were developed for B-mode PSAX and M-mode PLAX images respectively. Feature extraction algorithm was developed to calculate pixel height along the borders to determine the maximum vertical diameter (LVIDd) and the minimum vertical diameter (LVIDs) in PLAX M-mode images and the diameter variances along the time was plotted on a graph to abstract a mean value of LVIDd and LVIDs for all the systole and diastole cycles appeared on the image. For extracting features from PSAX B-mode images, number of pixels up to the cavity border in horizontal and vertical axis was measured and the mean diameter values for each image frame was captured and plotted on a graph to extract the maximum and minimum diameter values for determining LVIDd and LVIDs respectively.

The Ejection Fraction was calculated using the extracted LVIDs and LVIDd values of PSAX B-mode and PLAX M-mode images by teicholz formula. The values of LVIDs, LVIDd and Ejection fraction were used as input parameters for the Artificial Neural Network. The ANN was trained using supervised learning by giving the cardiologist's decision as the expected output.

The ANN classifies the heart as normal or abnormal. Finally,, classification results got 100% of sensitivity 96% of specificity and 98% of accuracy.

Considering accuracy, sensitivity and specificity of above methodology this study has realized a reliable outcome for the final decision on the Left Ventricular Systolic function. This showed that an accurate decision could be obtained using this methodology within a less period of time. Therefore,, the proposed Artificial Neural Network based methodology will be helpful for the decision-making purposes of Acute Care Physicians in emergency settings.

7.2 Contribution of the research

We have successfully addressed our research questions stated in Chapter 1 of this thesis and these achievements of the objectives depict the contribution of our research.

Research Question 1: How to reduce the time taken to conduct echocardiography tests for determining the Left Ventricular Systolic function?

To reduce the time taken for conducting echocardiography tests, this study has eliminated the manual selection of points in the screen by the doctor. The image processing techniques utilized are capable of automatically identifying these points needed to calculate the diameter values of the Left Ventricular function. Therefore, the time taken for conducting the echocardiography test could be reduced. Also since the proposed methodology provides the classification of the Left Ventricular Systolic function as normal or abnormal it would serve as a decision support system. This helps to save time taken for final decision making during emergency settings.

Research question 2: How to improve the accuracy of the Acute Care Physician's decision on the Left Ventricular Systolic function?

This question was answered with the implementation of the ANN to classify the Left Ventricular Systolic function according to the parameters extracted from the echocardiography images. The developed ANN showed a significant accuracy value and Therefore, this ANN can be recommended to be used by Acute Care Physicians to support decision making on the Left Ventricular Systolic function. Also, manual placing of points on the echocardiography images is eliminated which results in the consistency and accuracy of measurements from echocardiography images.

7.3 Implications for further research

The following opportunities can be suggested for future researchers to improve this methodology.

- This study focused on images taken from B-mode of Parasternal Short Axis view and M-mode of Parasternal Long Axis view. Even though these two are the most common views for determining the Left Ventricular function other echocardiography views can be analyzed to further improve the accuracy of the methodology. Especially Apical 4-chamber view can be utilized to calculate the Ejection fraction using Simpson's method.
- The ANN developed can be improved by fine tuning. For this purpose, increase the number of echocardiography videos utilized as the dataset for training the ANN.
- Currently the developed application runs on Windows environment using MATLAB. Therefore,, a study on the compatibility of introducing a technique to embed this functionality to an echocardiography machine will be useful to improve the performance of the application.
- This research methodology could be extended to other heart functions and especially to similar functions like Right Ventricular Systolic function.
- The proposed methodology for extracting values from B-mode images of PSAX view could be fine-tuned to improve it to produce reliable methods and use it as an alternative method in finding LV dimension measurement from echocardiography images.
- With the researches already done to evaluate the feasibility of using ANN to identify some of other types of cardiac dysfunctions, a study could be done to evaluate the feasibility of combining all these methodologies to develop a single ANN application to classify the human heart. This could be used as a decision support system to identify the overall condition of the heart.

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Appendix A: Code Listings

Method 1- for PLAX M-mode echocardiography Images

```

1     % profile on
2
3     % Clean up and initialization
4     clc; % Clear the command window.
5     close all; % Close all figures (except those of imtool.)
6     imtool close all; % Close all imtool figures.
7     clear; % Erase all existing variables.
8     workspace; % Make sure the workspace panel is showing.
9     fontSize = 15;
10
11    % Read in the color echo image.
12    folder = 'E:\Research\ml\day 1';
13    baseFileName = 't1.jpg';
14    fullFileName = fullfile(folder, baseFileName);
15    % Get the full filename, with path prepended.
16    fullFileName = fullfile(folder, baseFileName);
17    if ~exist(fullFileName, 'file')
18    % Didn't find it there. Check the search path for it.
19    fullFileName = baseFileName; % No path this time.
20    if ~exist(fullFileName, 'file')
21    % Still didn't find it. Alert user.
22    errorMessage = sprintf('Error: %s does not exist.',
fullFileName);
23    uiwait(warndlg(errorMessage));
24    return;
25    end
26    end
27
28    %import PLAX image to matlab
29    rgbImage = imread('t1.jpg');
30    imtool(rgbImage);
31
32    % crop the PLAX M-mode section
33    rect = [46 400 898 300];
34    crop = imcrop(rgbImage,rect);
35
36    %grey scale the image
37    grey_scale = rgb2gray(crop);
38
39    %Apply 5*5 Gaussing Blur effect
40    H = fspecial('Gaussian',[5 5],1.5);
41    GaussBlur = imfilter(grey_scale,H);
42
43    %Binarize the image to filter out LV cavity section

```

```

44     [rows,columns]=size(GaussBlur);
45
46     for i=1:1:rows
47         for j=1:1:columns
48             if(GaussBlur(i,j)>10)&&(GaussBlur(i,j)<200)
49                 GaussBlur(i,j) = 0;
50             else
51                 GaussBlur(i,j) =255;
52             end
53         end
54     end
55
56     % Eliminate (white) details less than 0.01 > 0.004 > 0.001 of
the image (in many cases this ignores the cavity if 10%)
57     BW3 = bwareaopen(GaussBlur, round(0.0004*numel(GaussBlur)));
58     % subplot(2,2,2);
59     % imshow(BW3); %binary image
60     % axis on;
61     % title('Less Noised Image', 'FontSize',fontSize);
62
63
64
65     % Fill out holes surrounded by dark regions
66     FilledImage = imfill(BW3, 'holes');
67
68     % Eliminate white details which represent less than 4% of the
entire image
69     blob = bwareaopen(FilledImage, round(0.004*numel(FilledImage)));
70
71     % Smoothing the border line of the remaining contour area
72     se = strel('disk',2);
73     contour = imopen(blob, se);
74
75     %Compute the contour area, centerioid etc.
76     labeledImage = bwlabel(contour);
77     measurements = regionprops(labeledImage, 'Area', 'MajorAxisLength'
, 'MinorAxisLength', 'centroid', 'orientation');
78
79
80     % To Find the largest contour area
81     allAreas = [measurements.Area];
82     biggestBlobIndex = find(allAreas == max(allAreas));
83     keeperBlobsImages = ismember(labeledImage, biggestBlobIndex);
84
85     %Display the original color image.
86     subplot(2, 1, 1);
87     imshow(c, []);
88     axis on;
89     % Enlarge figure to full screen.
90     set(gcf, 'Units', 'Normalized', 'OuterPosition', [0 0 1 1]);
91

```



```

92     hold on; % Prevent plot() from blowing away the image.
93     title('Original Color Image with Extracted Diameters',
'FontSize',fontSize);
94
95     % Get borders detected and overlay it over the original image.
96     boundaries = bwboundaries(keeperBlobsImages);
97     blobBoundary = boundaries{1};
98     plot(blobBoundary(:,2), blobBoundary(:,1), 'r-', 'LineWidth',
2);
99     hold off;
100
101     %% max(x) length of blob **
102     x = blobBoundary(:, 2); % x = columns.
103     y = blobBoundary(:, 1); % y = rows.
104
105     % Bolbwidth = measurements(biggestBlobIndex).MajorAxisLength
106     maxx = max(x);
107     minx = min(x);
108
109     BolbwidthX= maxx-minx
110     columns
111
112     if BolbwidthX < columns
113
114         columns = maxx-20;
115         minx = minx+20;
116     end
117
118     %% loop for calculating max and min diameters
119     pixel=minx;
120     maxPerpendicularWidth = -inf;
121     minPerpendicularWidth = inf;
122     maxPointpx=0;
123     maxxf=0;
124     maxx1=0;
125     maxyf=0;
126     maxyl=0;
127     for k = minx : columns
128
129         % Use point slope formula (y-ym) = slope * (x - xm) to get
points
130         y1 = pixel;
131         y2 = pixel;
132
133         % Get the profile perpendicular to the midpoint so we can
find out when if first enters and last leaves the object.
134         [cx,cy,c] = improfile(keeperBlobsImages, [y1,
y2],[1,columns], 1000);
135         % Get rid of NAN's that occur when the line's endpoints go
above or below the image.

```

```

136     c(isnan(c)) = 0;
137     firstIndex = find(c, 1, 'first');
138     lastIndex = find(c, 1, 'last');
139
140     % Compute the distance of that perpendicular width.
141     perpendicularWidth = sqrt( (cx(firstIndex) - cx(lastIndex))
.^ 2 + (cy(firstIndex) - cy(lastIndex)) .^ 2 );
142
143     if perpendicularWidth > maxPerpendicularWidth
144         maxPerpendicularWidth = perpendicularWidth;
145         maxPointpx=y1;
146         maxxf=cx(firstIndex);
147         maxx1=cx(lastIndex);
148         maxyf=cy(firstIndex);
149         maxy1=cy(lastIndex);
150     end
151
152     if perpendicularWidth < minPerpendicularWidth
153         minPerpendicularWidth = perpendicularWidth;
154         minPointpx=y2;
155         minxf=cx(firstIndex);
156         minx1=cx(lastIndex);
157         minyf=cy(firstIndex);
158         miny1=cy(lastIndex);
159     end
160
161     % Get the average perpendicular width. This will
approximately be the area divided by the longest length.
162     %averageWidth = measurements(blobIndex).Area / maxDistance;
163
164     % This blocks the loop when partially identified
165     xx(k) = k;
166     yy(k) = perpendicularWidth;
167
168     pixel=pixel+1;
169 end
170 % max diameter inf
171 MaxWidth=maxPerpendicularWidth
172     cx(firstIndex)=maxxf;
173     cx(lastIndex)=maxx1;
174     cy(firstIndex)=maxyf;
175     cy(lastIndex)=maxy1;
176
177 p = maxPointpx;
178
179 %min diameter inf
180 MinWidth=minPerpendicularWidth
181     qx(firstIndex)=minxf;
182     qx(lastIndex)=minx1;
183     qy(firstIndex)=minyf;

```

```

184             qy(lastIndex)=minyl;
185
186     q = minPointpx;
187
188     % Plot the boundary over the gray scale image from initial for
loop no
189
190     %     subplot(2, 2, 3);
191     %     plot(x, y, 'y-', 'LineWidth', 1.5);
192     % For this blob, put a line between the points farthest away
from each other.
193     %line([x(index1), x(index2)], [y(index1), y(index2)],
'Color', 'r', 'LineWidth', 3);
194
195     % plot(xMidPoint, yMidPoint, 'r*', 'MarkerSize', 15,
'LineWidth', 2);
196     % Plot max perpendicular line. Make it green across the
whole image but magenta inside the blob.
197     line([p, p],[1,columns], 'Color', 'g', 'LineWidth', 3);
198     line([cx(firstIndex), cx(lastIndex)], [cy(firstIndex),
cy(lastIndex)], 'Color', 'm', 'LineWidth', 3);
199
200     % Plot min perpendicular line. Make it green across the
whole image but magenta inside the blob.
201     line([q, q],[1,columns], 'Color', 'g', 'LineWidth', 3);
202     line([qx(firstIndex), qx(lastIndex)], [qy(firstIndex),
qy(lastIndex)], 'Color', 'm', 'LineWidth', 3);
203
204     %label LVIDd
205
206     message = sprintf(' LVIDd');
207     text([cx(firstIndex)+
cx(lastIndex)]/2,[cy(firstIndex)+cy(lastIndex)]/2, message, 'Color',
'y');
208
209     %label LVIDs
210
211     messaged = sprintf(' LVIDs');
212     text([qx(firstIndex)+
qx(lastIndex)]/2,[qy(firstIndex)+qy(lastIndex)]/2, messaged, 'Color',
'y');
213
214
215     % plotting the diameter variene over the x pixel axis
216     subplot(2, 1, 2);
217
218     idxmin = find(yy == max(yy));
219     idxmax = find(yy == min(yy));
220     plot(xx, yy, '-', 'LineWidth',2), grid on

```

```

221         title('Diameter Variance Over Time', 'FontSize',
fontSize);
222         xlabel('pixel columns'), ylabel('Diameter');
223
224     %End Systolic Diameter
225     ESD = MinWidth;
226
227     %End Systolic Volume
228     ESV = 7/(ESD + 2.4)*(ESD)*(ESD)*(ESD);
229
230     %End Diastolic Volume
231     EDV = 7/(EDD + 2.4)*(EDD)*(EDD)*(EDD);
232
233     %Fraction Shortening
234     ES = (EDD-ESD)/EDD * 100;
235
236     %Ejection Fraction
237     EF = (EDV-ESV)/EDV * 100;
238     %-----
-----
239
240     % Tell user the results.
241     message = sprintf('End Diastolic Diameter #1 (px) =
%.2f\n',EDDmax);
242     message = sprintf('%s\nEnd Diastolic Diameter #2 (px) =
%.2f\n',message, EDD);
243     message = sprintf('%s\nEnd Systolic Diameter (px) =
%.2f\n',message, ESD);
244     message = sprintf('%s\nEnd Diastolic Volume (ml) =
%.2f\n',message, EDV);
245     message = sprintf('%s\nEnd Systolic Volume (ml) =
%.2f\n',message, ESV);
246     message = sprintf('%s\nFractional Shortening = %.2f\n',message,
ES);
247     message = sprintf('%s\nEjection Fraction = %.2f\n',message, EF);
248     uiwait(msgbox(message));
249
250     fprintf('%s\n', message);
251
252     hold off;
253     % close(hFig);

```

Method 2- for PSAX B-mode echocardiography Images

```

1   % Clean up and initialization
2   % % % clc; % Clear the command window.
3   clc;
4   close all; % Close all figures (except those of imtool.)
5   imtool close all; % Close all imtool figures.
6   clear; % Erase all existing variables.
7   workspace; % Make sure the workspace panel is showing.
8   fontSize = 15;
9
10  c1=218.5;
11  c2=211.5;
12  c3=184;
13  c4=140;
14
15
16  % import and read the PSAX video
17  obj = VideoReader('MOVIE23.wmv');
18  NumberOfFrames = obj.NumberOfFrames;
19
20  maxdiameter = -inf;
21  mindiameter = inf;
22
23  % extract the features from each image frame
24  for cnt = 1:NumberOfFrames
25      image_frame=read(obj,cnt);
26      if size(image_frame,3)==3
27          image_frame=rgb2gray(image_frame);
28      end
29
30  % crop the most likely rectangular position of the LV cavity
31  rect = [c1 c2 c3 c4];
32  c = imcrop(image_frame,rect);
33
34  % Apply Gaussian Blur effect
35  H = fspecial('Gaussian',[5 5],1.5);
36  GaussBlur = imfilter(c,H);
37
38  %Binarize the image to filter out LV cavity section
39  [rows,columns]=size(GaussBlur);
40
41  for i=1:1:rows
42      for j=1:1:columns
43          if(GaussBlur(i,j)>10)&&(GaussBlur(i,j)<255)
44              GaussBlur(i,j) = 0;
45          else
46              GaussBlur(i,j) =255;
47          end

```

```

48     end
49 end
50
51 % Eliminate white details which represent less than 0.04% of the
entire image)
52 BW3 = bwareaopen(GaussBlur, round(0.0004*numel(GaussBlur)));
53
54 % Fill out holes surrounded by dark regions
55 FilledImage = imfill(BW3,'holes');
56
57 % Eliminate white details which represent less than 4% of the
entire image)
58 blo = bwareaopen(FilledImage, round(0.004*numel(FilledImage)));
59
60 % Smoothing the border line of the remaining contour area
61 se = strel('disk',5);
62 blob = imopen(FilledImage, se);
63
64 %% detecting the boundry %%
65
66 % Tagged objects in BW image
67 Labeled=bwlabel(blob);
68 % Get areas and tracking rectangle
69 out_a=regionprops(Labeled);
70 % Count the number of objects
71 N=size(out_a,1);
72 if N < 1 || isempty(out_a) % Returns if no object in the
image
73     solo_cara=[ ];
74     continue
75 end
76
77 % Select larger area
78 areas=[out_a.Area];
79 [area_max, pam]=max(areas);
80
81 %% the image to be shown
82 subplot(121)
83 imagesc(image_frame);
84 colormap gray
85 hold on
86 title('PLAX-B Mode video with cavity border detection',
'FontSize',fontSize);
87 % Enlarge figure to full screen.
88 set(gcf, 'Units', 'Normalized', 'OuterPosition', [0 0 1 1]);
89
90 % Find the biggest contour area
91 biggestBlobIndex = find(areas == max(areas));
92 keeperBlobsImages = ismember(L, biggestBlobIndex);
93

```

```

94     boundaries = bwboundaries(keeperBlobsImages);
95     blobBoundary = boundaries{1};
96     plot(blobBoundary(:,2)+c1, blobBoundary(:,1)+c2, 'b-',
'LineWidth', 2);
97
98     %% *****Plotting *****
99
100    % identify the center of the LV cavity
101    center=round(out_a(pam).Centroid);
102    X1=center(1);
103    Y2=center(2);
104
105    X=X1+c1;
106    Y=Y2+c2;
107
108    % measure the horizontal and verticle diameter for LV cavity
109    out_a(pam);
110    hd=out_a(pam).BoundingBox(:,3);
111    vd=out_a(pam).BoundingBox(:,4);
112
113    %mean diametr value
114    mean=(hd+vd)/2;
115
116    % Plotting the boundry over LC cavity
117    circle=[out_a(pam).BoundingBox(:,1)+c1
out_a(pam).BoundingBox(:,2)+c2
118    out_a(pam).BoundingBox(:,3)   out_a(pam).BoundingBox(:,4)];
119
120    rectangle('Position',circle,'EdgeColor',[1 0 0],...
121    'Curvature', [1,1],'LineWidth',2);
122
123    % added the cropped x, y values to mark centeroid of the
cavity
124    plot(X,Y,'g+');
125
126    %% ROI crop for the subsequent images *
127
128    text(X+10,Y,['(',num2str(X),',',num2str(Y),')'],'Color',[1 1
129    1]);
130
131    xx(cnt) = cnt;
132    yy(cnt) = mean;
133
134    subplot(122)
135
136    idxmin = find(yy == max(yy));
137    idxmax = find(yy == min(yy));
138    plot(xx, yy,'-', 'LineWidth',2), grid on
139    title('Diameter Varience Over Time', 'FontSize',
fontSize);

```

```

139         xlabel('Time'), ylabel('Mean Diameter');
140         set(gcf, 'Units', 'Normalized', 'OuterPosition', [0 0 1
141 1]);
142         if mean > maxdiameter
143             maxdiameter = mean;
144         end
145
146         if mean < mindiameter
147             mindiameter = mean;
148         end
149
150         hold off
151         % --
152         drawnow;
153     end
154
155     maxdiameter
156     mindiameter
157
158     ESD = mindiameter;
159
160     %End Diastolic Diameter
161     EDD = maxdiameter;
162
163     %End Systolic Volume
164     ESV = 7/(ESD + 2.4)*(ESD)*(ESD)*(ESD);
165
166     %End Systolic Volume
167     EDV = 7/(EDD + 2.4)*(EDD)*(EDD)*(EDD);
168
169     %Fraction Shortening
170     ES = (EDD-ESD)/EDD * 100;
171
172     %Ejection Fraction
173     EF = (EDV-ESV)/EDV * 100;
174     %-----
175     -----
176
177     % Tell user the results.
178     message = sprintf('End Diastolic Diameter (px) = %.2f\n',EDD);
179     message = sprintf('%s\nEnd Systolic Diameter (px) =
%.2f\n',message, ESD);
180     message = sprintf('%s\nEnd Diastolic Volume (ml) =
%.2f\n',message, EDV);
181     message = sprintf('%s\nEnd Systolic Volume (ml) =
%.2f\n',message, ESV);
182     message = sprintf('%s\nFractional Shortening = %.2f\n',message,
ES);

```



```
183 message = sprintf('%s\nEjection Fraction = %.2f\n',message, EF);
184 uiwait(msgbox(message));
185
186 fprintf('%s\n', message);
```

ANN Implementation

```

1
2   % This script assumes these variables are defined:
3   %
4   %   Inputs0x2D1 - input data.
5   %   Outputs0x2D1 - target data.
6
7   x = Inputs0x2D1';
8   t = Outputs0x2D1';
9
10  % Create a Pattern Recognition Network
11  hiddenLayerSize = 3;
12  net = patternnet(hiddenLayerSize);
13
14  % Choose Input and Output Pre/Post-Processing Functions
15  net.input.processFcns = {'removeconstantrows','mapminmax'};
16  net.output.processFcns = {'removeconstantrows','mapminmax'};
17
18
19  % Setup Division of Data for Training, Validation, Testing
20  net.divideFcn = 'dividerand'; % Divide data randomly
21  net.divideMode = 'sample'; % Divide up every sample
22  net.divideParam.trainRatio = 70/100;
23  net.divideParam.valRatio = 15/100;
24  net.divideParam.testRatio = 15/100;
25
26
27  net.trainFcn = 'trainscg'; % Scaled conjugate gradient
28
29  % Choose a Performance Function
30  net.performFcn = 'crossentropy'; % Cross-entropy
31
32  % Choose Plot Functions
33  net.plotFcns = {'plotperform','plottrainstate','ploterrhist',
...
34    'plotregression','plotfit'};
35
36
37  % Train the Network
38  [net,tr] = train(net,x,t);
39
40  % Test the Network
41  y = net(x);
42  e = gsubtract(t,y);
43  tind = vec2ind(t);
44  yind = vec2ind(y);
45  percentErrors = sum(tind ~= yind)/numel(tind);
46  performance = perform(net,t,y)

```

```
47
48 % Recalculate Training, Validation and Test Performance
49 trainTargets = t .* tr.trainMask{1};
50 valTargets = t .* tr.valMask{1};
51 testTargets = t .* tr.testMask{1};
52 trainPerformance = perform(net,trainTargets,y)
53 valPerformance = perform(net,valTargets,y)
54 testPerformance = perform(net,testTargets,y)
55
56 % View the Network
57 view(net)
58
59 % Plots
60 % Uncomment these lines to enable various plots.
61 %figure, plotperform(tr)
62 %figure, plottrainstate(tr)
63 %figure, plotconfusion(t,y)
64 %figure, plotroc(t,y)
65 %figure, ploterrhist(e)
66
67 % Deployment
68 % Change the (false) values to (true) to enable the following
code blocks.
69 if (false)
70     % Generate MATLAB function for neural network for application
deployment
71     genFunction(net,'myNeuralNetworkFunction');
72     y = myNeuralNetworkFunction(x);
73 end
74 if (false)
75     % Generate a matrix-only MATLAB function for neural network
code
76     % generation with MATLAB Coder tools.
77     genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
78     y = myNeuralNetworkFunction(x);
79 end
80 if (false)
81     % Generate a Simulink diagram for simulation or deployment
with.
82     % Simulink Coder tools.
83     gensim(net);
84 end
```