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Deep Learning-Based Murmur Detection and Murmur Characteristics Classification from Phonocardiogram

by

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In partial fulfillment of the requirements for the degree of Master of Science in Biomedical Engineering

Supervisor

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Declaration

I, Hafiza Moges Teshager, declare that this thesis is my own work and effort and that I have not submitted it for a degree in any other institution. And all other sources of information used in this work are acknowledged and indicated in the thesis.

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Abstract

CVD is the main cause of death worldwide. The World Heart Federation reported a 20.5 million death from CVD in 2021, by 2030 this number is expected to rise to 23.6 million, and more than 75 percent of CVD death occur in low and middle income nations, as they have less access for equitable health care services. Phonocardiograph (PCG) is an affordable and portable instrument which can record, play back, and provide a visual display for heart sounds. Blood flow that is turbulent may cause the cardiac valves to vibrate enough to produce murmurs, which produces audible heart sounds and abnormal waveforms in the PCG. Most risk factors can be significantly reduced by early diagnosis. Although, PCG signals are useful for detecting heart murmurs it needs a trained medical professional for its interpretation. This study proposes a hierarchical multi-scale convolutional neural network (HMS-Net) based automatic murmur detection and murmur characteristics classification using the publicly available CirCor DigiScope PCG dataset. Previous research studies mainly focus on classifying heart sounds as either murmur vs. normal or detecting a limited type of valvular heart diseases (VHDs) but this study extends it by designing a pipeline that first determines whether a murmur is present or absent; not only these but also it advances the analysis by further classifying five key murmur characteristics: timing, shape, pitch, grade, and quality, which is a significant step beyond traditional binary murmur detection. For the training and evaluation, it adopts the HMS-Net model developed by the winner of the George B. Moody PhysioNet Challenge, with a few important adjustments. In the original work, the dataset included an 'unknown' murmur class due to expert uncertainty to label them as present or absent, so they used a quality assessment method for this class. In this study, the 'unknown' class is excluded, as it does not represent a valid clinical category, so that this study focused on clinically meaningful labels. Additionally, a separate prediction pipeline is designed to detect murmur and simultaneously predict the five characteristics. The core model architecture and preprocessing steps remain unchanged. Each task are trained and evaluated independently using metrics such as accuracy, weighted accuracy, F1 score, AUROC, and AUPRC. The proposed model achieved an accuracy of 93.1%, and F1 score of 86.9% for the murmur detection task. For the murmur characteristic tasks, the model achieved accuracy scores between 74.3% and 81.5%. This goes a step beyond simply detecting whether a murmur is present to identifying the key five murmur characteristics. Identifying these characteristics is very important because it helps to determine the type of VHDs, which makes the model's output more clinically useful. These results are promising, consid-

ering the small data and class imbalance. These results suggest that the proposed system can support early screening to improve patient referrals to specialized care with more detailed murmur information of the patient, which could help to identify the underlying VHDs so that it helps patients to get early diagnosis and timly treatment. It will be very helpful to reduce earlier deaths due to VHDs in resource limited communities.

Keywords: Valvular heart diseases, Murmur detection, Murmur characteristic, Phonocardiograph, Deep-Learning, Classification.

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List of Acronyms

AI	Artificial Intelligence
ALMMO	Autonomous Learning Multiple-Model zero-order
AUPRC	Area Under Precision Recall Curvee
AUROC	Area Under Receiver Operating Characteristics Curve
AV	Atrioventricular
BN	Batch Normalization
CAD	Coronary Artery Disease
CHD	Congenital Heart Disease
CNN	Convolutional Neural Network
CVD	Cardiovascular Disease
DBRes	Dual Bayesian ResNet
DDA	Dual Attention Network
DL	Deep Learning
DNN	Deep Neural Network
FBSE-EWT	Fourier-Bessel Series Expansion based Empirical Wavelet Transform
FN	False Negative
FP	False Posetive
GRU	Gated Recurrent Unit
GTSVM	Growing Time Support Vector Machine
HEF	Hilbert Envelope Features

HMS-Net	Hierarchical Multi-Scale convolutional Neural Network
KNN	K-nearest Neighbors
LSTM	Long Short Term Memory
MFCC	Mel Frequency Cepstral Coefficient
ML	Machine Learning
MTGNN	Moving Time Growing Neural Network
PCG	Phonocardiogram
PDA	Patent Ductus Arteriosus
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSD	Power Spectral Density
RF	Random forest
RHD	Rheumatic Heart Disease
RNN	Recurrent Neural Network
RWNN	Radial Wavelet Neural Network
SA	Sinoatrial
STFT	Short Time Fourier Transform
STGNN	Static Time Growing Neural Network
SVM	Support Vector Machine
TGNN	Time Growing Neural Network
TN	True Negative
TP	True Posetive
VHD	Valvular Heart Disease
ViT	Vision Transform
WHF	World Heart Federation

CHAPTER 1

Introduction

1.1 Background of the Study

The term cardiovascular disease (CVD) is used to describe a broad category of diseases that affect the heart and blood arteries, which includes congenital heart disease (CHD), coronary artery disease (CAD), and valvular heart disease (VHD) [1]. CVD is the main cause of death worldwide [2]. The World Heart Federation (WHF) reported a 20.5 million death from CVD in 2021 [3], by 2030 this number is expected to rise to 23.6 million [4], and more than 75 percent of CVD death occur in low- and middle-income nations [5]. The graph indicating the global CVD deaths reported by WHO (2019), AHA (2020, projected for 2030), and WHF (2021) is shown in Figure 1.1.

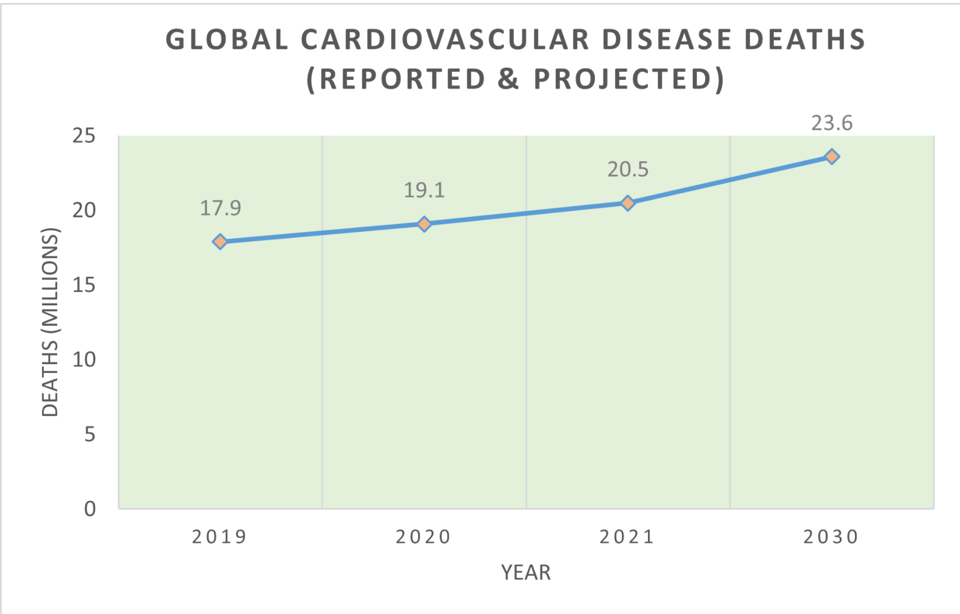


Figure 1.1: Global cardiovascular disease (CVD) deaths reported by WHO (2019), AHA (2020, projected for 2030), and WHF (2021)

People who live in low- and middle-income countries have less access to efficient health care services that provide for their needs, as a result, many people in these countries have late disease identification, leading to earlier death from CVDs [2]. Early therapeutic intervention for one of

CVD which is valvular heart disease (VHD) can be aided by detection of heart murmurs, when diagnosing murmurs, a clinician can use heart sounds as a valuable source [6]. Listening to the heart's sound is known as cardiac auscultation in medical term, the experts listen to the heart's sound using a stethoscope, they listen for sounds by placing the stethoscope on the patient's chest [7]. Although the stethoscope is an affordable, non-invasive instrument for auscultation, it requires an expert to evaluate the results, which restricts its accessibility in environments with limited resources [8]. And the interpretation require a clinician with years of practise and skill, which leads to disagreement among medical professionals, and many of them struggle to differentiate between the abnormal and normal heart sounds [9].

A unique type of sound waveform called a phonocardiogram (PCG) shows the heart sounds' intensity with time. The PCG displays the two primary cardiac sounds, "S1" and "S2," as significant magnitude deflections occurring sequentially, with S1 happening first. They are associated with the "lub" and "dub" sounds that are audible with a stethoscope [10]. The development of digital phonocardiography as a more scientific substitute for cardiac auscultation can record, play back, and provide a visual display for sounds [6]. PCG signals have proven that they are effective in identifying between the normal and abnormal heart sounds, which encourages their use in detecting abnormal heart sounds [11]. The George B. Moody PhysioNet Challenge 2022 released a challenge to identify the heart murmur present, absent, and unknown cases through PCG recordings [8], this shows the PCG importance in detecting heart murmurs.In addition, PCG has proved its ability in determining the cardiac murmur characteristics like; shape, quality, pitch, timing, and grade so that the identification and evaluation of the murmur's characteristics provide useful details in identifying specific valvular heart diseases [12]. The above evidence highlights that deaths due to CVDs are very high and the PCG signal is potential in identifying heart murmurs additional characterizing of the murmur helps to identify the type of valvular diseases, but it needs an expert to evaluate the result, which restricts its access in limited resource environments. This shows that it is very critical to address these diseases urgently by automating the detection to reduce the predicted increase in CVD mortality rates.

1.1.1 CVDs in Ethiopia

In Ethiopia, the prevalence of CVD has been reported from 1% to 24%, with a combined prevalence of 5%, which increases healthcare expenses [13], [14]. While heart disease has various causes, valvular heart disease is the dominant contributor. In Ethiopia, it affects younger populations and reported as a major cause of the overall cardiovascular disease [15], and Rheumatic heart disease (RHD) is a leading cause of the valvular heart disease and it is the most prevalent cardiovascular diseases among patients at Ethiopia's largest public hospital. [16].

RHD is a serious yet preventable diseases which remains to be a major public health issue in many low- and middle-income nations. It is the long-term consequence of rheumatic fever, which in turn develops from untreated or inadequately treated infections caused by a bacterium known as Streptococcus pyogenes, and repeated or severe episodes of rheumatic fever can lead to rheumatic heart disease, which could lead to permanent heart valve damage and can cause serious complications such as heart failure, stroke, and premature death. These infections are most common during childhood, especially in areas where living conditions are poor and access to medical care is limited. Early and effective treatment of the infections with antibiotics can prevent the development of rheumatic fever [17] and this murmur can be identified by cardiac auscultation using a stethoscope. However, to accurately detect and interpret heart murmurs, it requires a trained healthcare professional, and this is a serious challenge in resource-limited areas where medical experts and resources may not be available. This lack of access leads to delayed diagnosis and treatment, which increases the risk of irreversible heart valve damage. This shows that it is very critical to address it by developing an automated and accessible diagnostic tools that can support early detection.

1.1.2 Anatomy of the heart

The heart is an organ that is located in the chest between the lungs, to the left of the center, and it is the component that plays a great role in the circulatory system. It circulates blood throughout the body, by ensuring the supply of oxygen and nutrients to organs and tissues. The heart has different components. we could imagine it as a house, where each part plays a role in its function [18]. In the heart, we find [19]:

- Chambers (Rooms)
- Heart Tissue (Walls)
- Blood vessels (Pipes)
- Valves (gates)
- Electrical conduction system (Electric).

Heart Chambers

The heart has four chambers, two chambers on the right and two chambers on the left. The upper chambers are called the left and right atrium, and the lower are called the left and right ventricles [20]. They work together to keep the blood pump. The right atrium accepts deoxygenated blood from the body through two large veins, the superior and inferior vena cava. Then the blood passes through the tricuspid valve into the right ventricle, then pumps it to the lungs through the pulmonary valve to be oxygenated. When it is oxygenated, it returns to the left atrium via the pulmonary veins. And then, it flows through the mitral valve into the left ventricle. The left ventricle then pumps the oxygenated blood through the aortic valve into the aorta, and sends it to the body [21] [22].

Heart Tissue

The Heart tissue has three different layers, and each have their own functions. The outer layer is called epicardium that serves as a shield for protecting the heart, and the innermost layer is called endocardium, it has a smooth lining for the chambers and valves [20]. The myocardium is the middle layer, and it has strong muscle tissue which are responsible for the heart's contraction and relaxation, and allowing the blood to pump through the body [23].

Blood vessels

Blood flows between the heart and the lungs, and throughout the body, with the help of a network of pipes known as blood vessels. There are three types of blood vessels to serve as pipes for the circulation. Arteries carry oxygenated blood from the heart to different parts of the body, veins transport deoxygenated blood back to the heart and lungs, and capillaries are the tiny vessels where the exchange of oxygenated and deoxygenated blood happens [24].

Heart Valves

The heart has four valves; the tricuspid valve (between the right atrium and right ventricle), pulmonary valve (connecting the right ventricle to the pulmonary artery), mitral valve (between the left atrium and left ventricle), and aortic valve (connecting the left ventricle to the aorta). These valves open in only one direction, by ensuring blood flows the right way and they prevent the backflow of blood [25]. The image for heart chambers and heart valves is shown in Figure 1.2

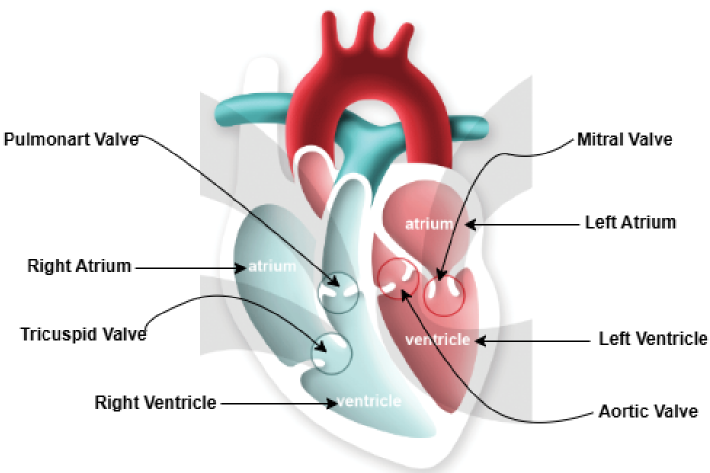


Figure 1.2: Heart valves and heart chambers (image adapted from the Heart Foundation of New Zealand https://www.heartfoundation.org.nz/images/heart-healthcare/public/page-heros/heart-valve-labelled-diagram.gif). (Accessed on January 5, 2025).

Electrical conduction system

The heart has an electrical system that helps it to keep beating in a steady rhythm. This includes the sinoatrial (SA) node, which acts as the heart's natural pacemaker, the atrioventricular (AV) node, the bundle of His, and the Purkinje fibers. These work together to send electrical signals through the heart, by ensuring the atria and ventricles contract in a smooth, and coordinated way [23] [26]. The image for electrical conduction system of the heart is shown in Figure 1.3

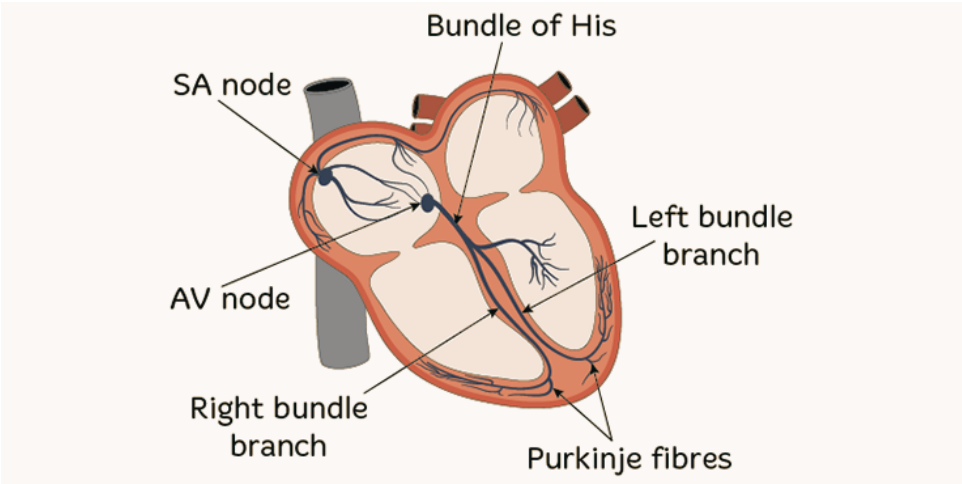


Figure 1.3: Electrical conduction system of the heart, (image adapted from the Heart Foundation of New Zealand https://www.heartfoundation.org.nz/images/heart-healthcare/public/conduction-system.png). (Accessed on January 6, 2025).

1.1.3 Cardiac (Heart) murmur

The heart valves regulate blood flow and make sure it moves in the proper direction. Healthy valves prevent backflow and help maintain a normal heartbeat. A normal heart produces a "lub-dub" sound (S1-S2), the "lub" (S1) occurs when the mitral and tricuspid valves close and it is called systolic sound, and the "dub" (S2) occurs when the aortic and pulmonic valves close, and it is called diastolic sound [27]. The examples in Figure 1.4 were adapted from [28].

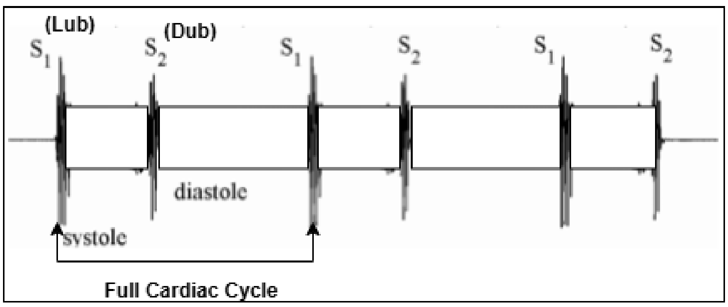


Figure 1.4: An example of a normal heart sound recording, showing the positions of the fundamental heart sounds S1 and S2.

Apart from the fundamental heart sounds S1 and S2, the heart may produce extra sounds called murmurs, which happens due to turbulent blood flow within the heart. This may indicate heart valve problems. Murmurs are often detected during a physical exam using a stethoscope (cardiac auscultation) or confirmed through echocardiography [29]. Heart murmurs are various types and are described using specific characteristics such as timing, grade, shape, quality, and pitch [8].

Murmur Timing

Murmur timing refers to the specific phase of the cardiac cycle during which a heart murmur appears. Murmurs can occur during the systolic phase, the diastolic phase, or span both phases. Based on their occurrence within these phases, murmurs are described as early, mid, late, or holosystolic [30]. The examples in Figure 1.5 were adapted from [28].

- An early systolic murmur is when the murmur begins at the start of systole.
- A mid-systolic murmur is when murmur occurs in the middle of systole.
- A holosystolic murmur is when murmur continues throughout the systole.
- A late systolic murmur is when murmur appears at the end of systole.
- Diastolic murmurs are those that occur during the diastolic phase.

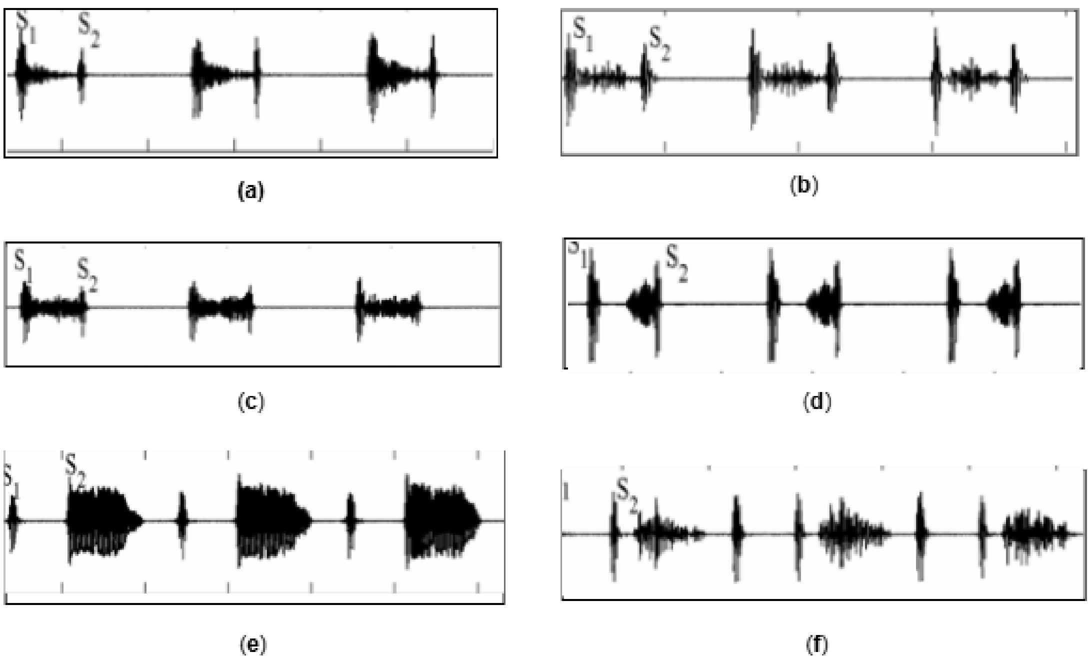


Figure 1.5: An example of murmur timing : (a) early systolic, (b) mid-systolic, (c) holosystolic, (d) late systolic, (e) early diastolic, (f) mid-diastolic.

Murmur Quality

Murmur quality is often the most subjective aspect of murmur characterization. Experts typically describe it like harsh, soft, blowing, vibratory, or musical, this can also reflect the examiner's impression of the murmur's possible cause [31]. In the CirCor DigiScope dataset, murmur quality is presented into three types:

- Musical: It is a quality that arises from harmonic overtones related to the murmur's fundamental sound frequency, giving it a melodic character.
- Blowing: It is described as a "whooping" sound, this quality is often associated with conditions like mitral regurgitation.
- Harsh: It is resulted from turbulent, high-velocity blood flow moving from an area of high pressure to low pressure. This is often linked to more severe or pathological cases [32].

Murmur Shape

The shape of a murmur refers to how its intensity changes throughout the cardiac cycle over time. Some murmurs may gradually increase, reach a peak, and then fade, and others may have a consistent intensity. These variations help in characterizing the murmur and may provide clues about its underlying cause [32]. Murmur shapes are commonly described as follows [30]:

- Crescendo: intensity increases over time.
- Decrescendo: intensity decreases over time.
- Crescendo-decrescendo (Diamond): intensity rises, peaks, and then falls.
- Plateau: intensity remains steady throughout the cycle.

  The examples in Figure 1.6 were adapted from [28].

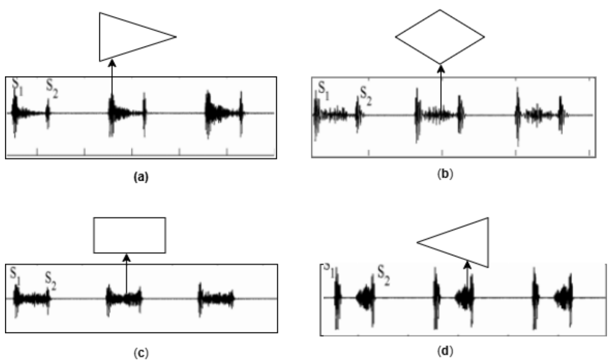


Figure 1.6: An example of murmur shape : (a) decrescendo, (b) diamond, (c) plateau, (d) crescendo.

Murmur Pitch

The pitch of a murmur refers to the frequency of the sound it produces, and it vary depending on the underlying condition. High-pitched murmurs are usually the result of a high-pressure gradient across a small opening such as in cases of a small patent ductus arteriosus or a ventricular septal defect. On the other hand, low-pitched murmurs are often associated with larger defects [31, 32]. Murmur pitch is commonly classified as:

- High: it is a high-frequency murmur, experts use a stethoscope diaphragm for detection.
- Medium: it has a frequency between high and low.
- Low: it is low-frequency murmur, experts use the bell of the stethoscope for better detection.

Murmur Grade

Murmur grade refers to the murmur intensity, or loudness, clinically it is usually assessed using a six-point grading scale, from Grade I (very faint) to Grade VI (extremely loud). Below is described how the murmur can be heard during auscultation [28, 31]:

- Grade I: Barely audible; often heard only in one location and typically requires a quiet room and a calm patient.
- Grade II: Clearly audible and consistently heard throughout the cardiac cycle.
- Grade III: Loud and easily heard across the chest, as loud as normal heart sounds.
- Grade IV: Loud with an associated thrill a vibration felt on the chest wall.
- Grade V: Very loud; can be heard with only part of the stethoscope touching the chest.
- Grade VI: Extremely loud; can be heard even when the stethoscope is slightly lifted.

For cardiac murmur evaluation, it is important to provide a more detailed description of a murmur which includes its quality, pitch, timing, shape, grade, and where it is heard most clearly. When all of these characteristics are considered together, they often help to accurately determine the underlying cause [28] [31]. The diagnostic importance of these murmur characteristics is presented under the section titled Significance in Medical Diagnosis with highlighting the murmur description of some common heart valve diseases.

1.1.4 Cardiac auscultation

Cardiac auscultation is when experts listen to the heart sounds with a stethoscope to assess the cardiovascular status. It's one of the first steps in cardiovascular assessment. While manual stethoscopes are commonly used, they don't have the ability to record or store medical data [29]. Phonocardiography helps overcome the limitations of manual stethoscopes by recording heart sounds throughout the cardiac cycle. This recorded signal, called a phonocardiogram, allows cardiac experts to analyse and visualize the heart's acoustic patterns. The cardiac auscultation remains the primary method for assessing heart function, and using PCG provides both qualitative and quantitative insights into heart murmurs, which significantly helps to distinguish between normal and abnormal heart sounds [33]. The positions for cardiac auscultation are determined by the anatomical locations of the heart valves in relation to the chest wall. Therefore, for cardiac auscultation, the stethoscope should be placed at the following positions, as illustrated in Figure 1.7 and the image were adapted from [12]:

- Aortic valve (1): Second intercostal space at the right sternal border
- Pulmonary valve (2): Second intercostal space at the left sternal border
- Tricuspid valve (3): Left lower sternal border (mid-left)
- Mitral valve (4): Fifth intercostal space at the midclavicular line (also known as the cardiac apex)

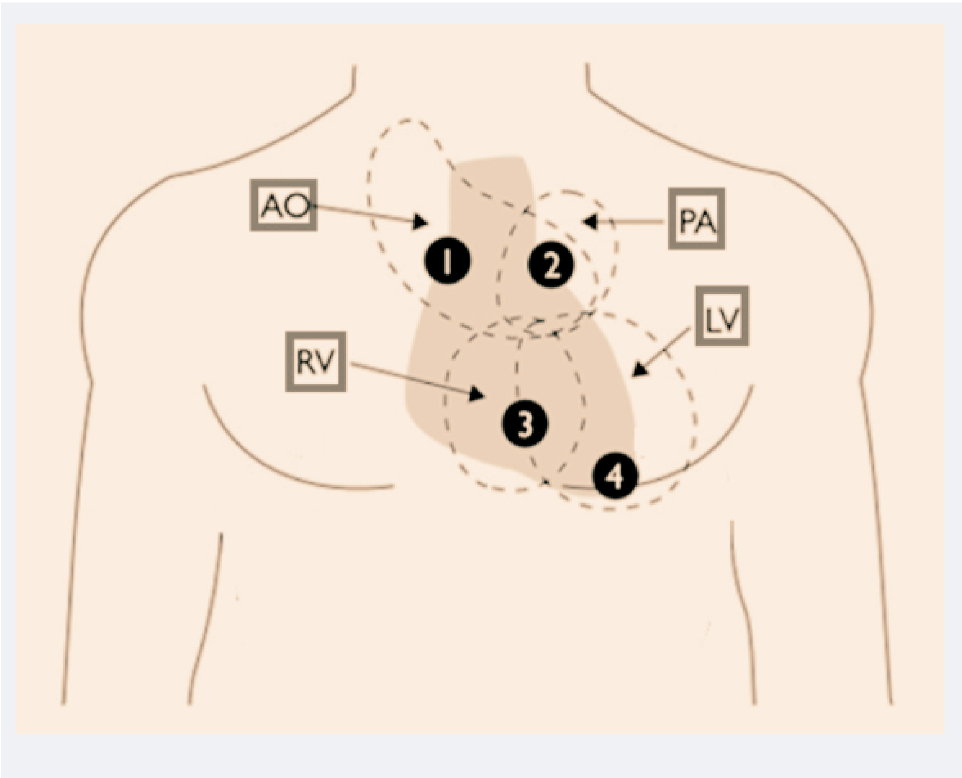


Figure 1.7: Common cardiac auscultation locations. Abbreviations: AO – aortic area; LV – left ventricle; PA – pulmonary area; RV – right ventricle.

1.1.5 Significance in diagnosis

The majority of cardiac murmurs are linked to specific conditions, such as problems in heart valve, failure of the ductus arteriosus to close, and abnormalities in the heart's septum [34]. The characteristics of a heart murmur such as its shape, quality, timing, pitch, grade, can help to indicate the underlying heart condition [35].Auscultation is an important tool in identifying and distinguishing the heart murmur characteristics. The decision to refer a patient to a cardiologist often depends on the skill to describe the murmur and recognizing specific patterns [12].Below is a description of murmurs associated with some common valve diseases.

Aortic stenosis

Aortic stenosis occurs when the aortic valve narrows, restricting blood flow from the heart to the rest of the body. This is often caused by valve calcification, aging, congenital bicuspid aortic valve, or chronic rheumatic heart disease (RHD). During auscultation, it produces a harsh crescendo-decrescendo (diamond-shaped) systolic murmur [12].

Pulmonary stenosis

Pulmonary stenosis is the narrowing of the pulmonary valve. It is often associated with Tetralogy of Fallot but can also be seen in patients with congenital rubella syndrome, Noonan syndrome, or chronic RHD. During auscultation it results in a crescendo-decrescendo (diamond-shaped) systolic ejection murmur [12].

Mitral stenosis

Mitral stenosis occurs when the mitral valve narrows, obstructing blood flow. It is commonly caused by chronic RHD or infectious endocarditis. During auscultation it produces a diastolic murmur [12].

Tricuspid stenosis

Tricuspid stenosis is the narrowing of the tricuspid valve restricting blood flow. It is often caused by infective endocarditis and intravenous medications particularly in conditions like carcinoid syndrome. During auscultation, it produces a diastolic murmur [12].

The image of heart valve disease showing aortic stenosis, pulmonary stenosis, mitral stenosis, and tricuspid stenosis. is shown in Figure 1.8.

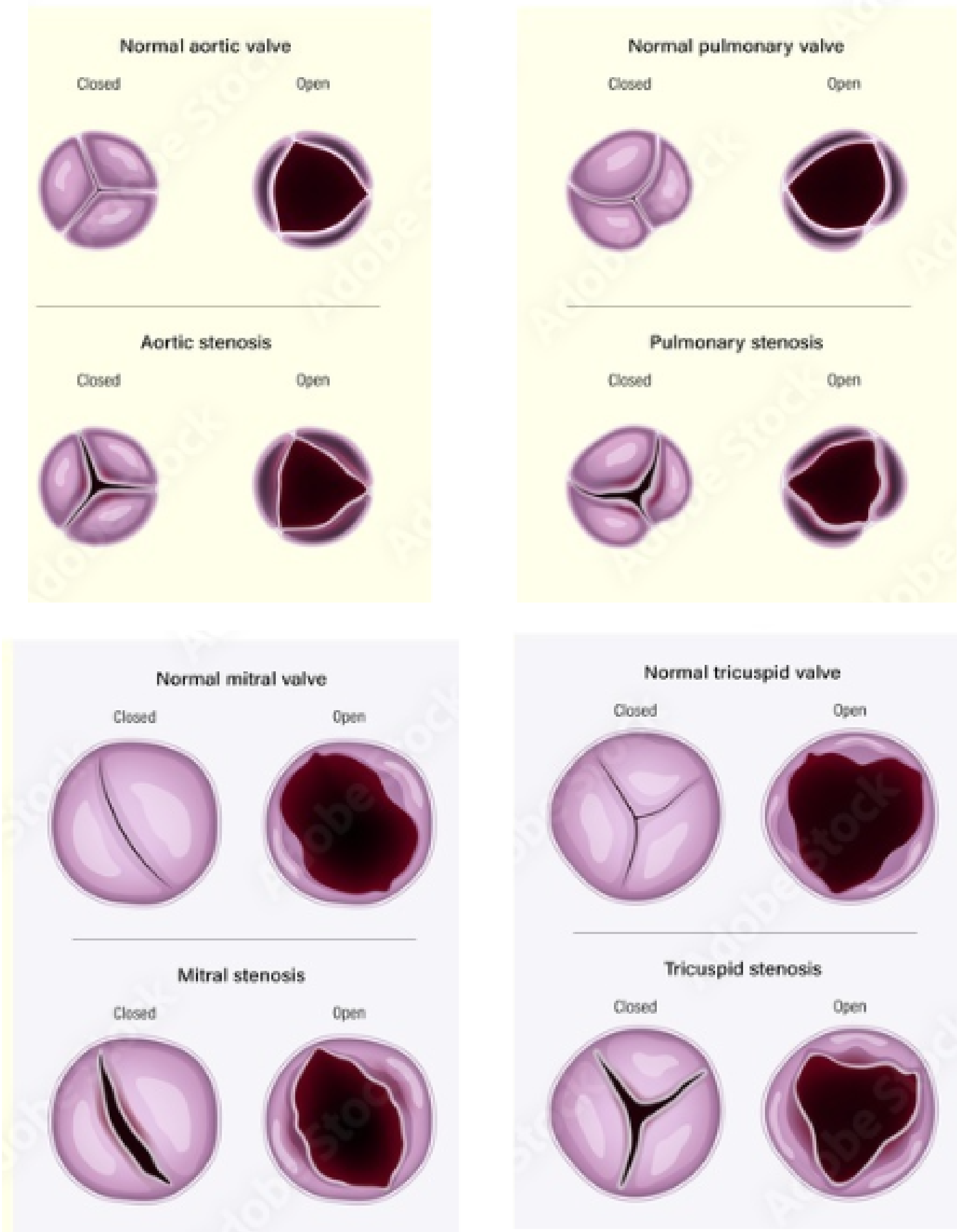


Figure 1.8: Heart valve disease showing aortic stenosis, pulmonary stenosis, mitral stenosis, and tricuspid stenosis. (Image adapted from Adobe Stock: Heart valve disease. Aortic stenosis, Mitral stenosis, Pulmonary ..., available at: https://stock.adobe.com, (Accessed on April 3, 2025).

Mitral regurgitation

Mitral regurgitation occurs when the mitral valve fails to close properly, allowing blood to flow back into the left atrium. In conditions such as degenerative valve disease, chronic RHD, infective endocarditis, or rupture of the chordae tendineae and myocardial infarction. During auscultation it results in a systolic murmur [12].

Aortic regurgitation

Aortic regurgitation is caused by the incomplete closure of the aortic valve, allowing blood to leak back into the left ventricle. It is commonly associated with bicuspid aortic valves, calcified leaflets, and aortic root dilation. During auscultation it results a decrescendo, blowing diastolic murmur [12].

Tricuspid regurgitation

Tricuspid regurgitation occurs when the tricuspid valve does not close properly, allowing blood to flow back into the right atrium. It is often caused by infectious endocarditis or carcinoid syndrome. During auscultation it results a systolic murmur [12].

Mitral valve prolapse

Mitral valve prolapse occurs when the mitral valve leaflets bulge back into the left atrium instead of closing evenly. It is commonly linked to rheumatic heart disease (RHD), idiopathic myxomatous valve degeneration, endocarditis, or congenital conditions like Ebstein's anomaly. During auscultation, it results an early systolic click [12].

Septal defects

Septal defects are congenital abnormalities that create openings in the heart's septum, allowing abnormal blood flow between the heart chambers. These defects can be atrial or ventricular, they are called ”ruptures”. During auscultation, small defects result a loud, harsh quality murmurs [12].

Patent Ductus Arteriosus (PDA)

PDA occurs when a fetal blood vessel fails to close after birth, forming a shunt that allows oxygenated blood to flow back into the pulmonary artery. During auscultation it produces a continuous, “machine-like” murmur [12].

1.1.6 The need for automatic classification

Despite advancements in high-tech cardiac monitoring and imaging systems, cardiac auscultation remains a cost-effective and valuable first-line screening tool. It provides important insights into the mechanical activity of the heart, helping experts detect abnormalities early. The PCG signal captures these heart sounds, allowing for further analysis and diagnosis [36], and it can accelerate treatment or referral when used appropriately, improving the patient's outcome and quality of life. Knowing to perform cardiac auscultation is a complex skill that requires time, practice, and continuous clinical experience. Its use in medical practice in developed countries has declined over time, mainly due to advancements in modern imaging techniques [37]. However, the problem exists in many developing countries, as there is a shortage of both medical resources and trained professionals with an experiance in cardiac auscultation [38]. This calls for the development of an automated cardiac auscultation systems, which can help to solve the gap by providing early detection of heart conditions. These systems can be very useful in resource-limited areas, allowing for earlier identification of patients who need specialized care by refereing them with a more detailed murmur data which can improve the access to timely diagnosis and treatment.

1.2 Statement of the problem

Cardiovascular diseases are a leading cause of death worldwide, yet many of these conditions can be effectively managed or even prevented with early diagnosis and timely treatment [36]. However, in low- and middle-income nations, there is limited access to advanced diagnostic tools and specialized cardiac expertise.

Auscultation, which is the practice of listening to heart sounds using a stethoscope, remains one of the most accessible and cost-effective methods for detecting early signs of heart disease [36]. However, it needs a cardiac expert to accurately interpret heart sounds and identify murmurs. In low- and middle-income countries, where there is a shortage of cardiac experts, many heart problems go undiagnosed or are detected too late leading to complications or even premature death [2].

Some heart disorders present life-threatening symptoms that require urgent intervention within days or weeks. When these conditions are not identified early, the risk is high. Unfortunately, the majority of these deaths occur in low- and middle-income countries due to a lack of advanced diagnostic systems and cardiac experts [5].

To address this need, there is a strong demand for an affordable, automated, and portable solution that can assist in the early detection of cardiac abnormalities using PCG recordings. Many existing studies focus only on detecting whether a heart murmur is present or absent, or on identifying a limited type of VHDs. However, this binary approach is not enough to determine the underlying VHDs, so identifying the specific characteristics of a murmur such as its timing, shape, pitch, grade, and quality is useful for determining the type of VHDs. This calls for an automated tool that not only detects the presence of a murmur but also classifies its key characteristics. This tool would be especially valuable in low and middle-income countries, where access to advanced diagnostic equipment and trained cardiac specialists is limited. By allowing frontline healthcare workers, such as nurses or health extension workers, to perform early screening, it could significantly improve the timely diagnosis and management of VHDs making life-saving assessments more accessible, cost-effective, and practical in resource-limited environments. This work will help to improve patient referrals to specialized care with more detailed information of the patient, and would reduce preventable deaths from cardiovascular diseases like VHDS in resource limited communities.

1.3 Research Objectives

1.3.1 General Objective

The main objective of this thesis is to design a prediction pipeline based on the HMS-Net model that can automatically analyse PCG recordings to detect the presence or absence case of heart murmurs and, if present, classify the key characteristics (timing, shape, pitch, grade, and quality) using the CirCor Digi Scope dataset with the goal to support early screening of VHDs with an approach intended to work on electronic stethoscopes and aims to be accurate and usable by healthcare workers such as nurses or health extension workers, particularly in low- and middle-income countries where access to advanced technologies and cardiac experts is limited.

1.3.2 Specific Objectives

The specific objectives are:

i. To train the HMS-Net model for murmur detection and the five murmur characteristics: timing, shape, pitch, grade, and quality

ii. To achieve more than 84% accuracy in murmur detection task.

iii. To address class imbalance through data augmentation.

iv. To evaluate the performance of the proposed model using accuracy, weighted accuracy, F-measure, AUROC and AUPRC.

v To design a prediction pipeline that receives PCG recordings and simultaneously predicts the murmur and the five murmur characteristics.

1.4 Significance of the thesis

The finding of this study can automatically detect the heart murmur presence or absence case and if the murmur detection outcome is present it automatically generates the murmur's characteristics (quality, shape, grade, timing, and pitch) report, which could help the patient to be referred with a more detailed murmur report to specialised treatment facilities and speed up diagnosis. The use of the proposed automatic technique in this thesis can overcome the drawbacks of lack of cardiac experts who can make cardiac auscultation in resource limited area and the delay in diagnosis. This is important in early screening of heart valve diseases which can be life-threatening in resource limited areas.

1.5 Scope

This study focuses on developing and testing a deep learning model for the detection of heart murmurs and classifying the characteristics. The model is trained and tested using the CirCor Digi Scope dataset which is available in the Physionet dataset. This is currently the largest and the only available dataset that provides the murmur with the characteristics. However, due to the lack of data for the diastolic murmur characteristics it was not included in this study. Additionally, some classes of systolic murmurs were excluded from the study because their sample size was too small to train and test the model.

1.6 Organization of the thesis

This thesis is organized as follows: Chapter 2 discuss the Cardiac murmur and PCG, the deep learning model, and reviews related works. Chapter 3 describes the data sources used, the model selection, the proposed model architecture, the method adaptation and the prediction pipeline in the research. The results and discussions are presented in Chapter 4, followed by conclusions and future works in chapter 5.

CHAPTER 2

Literature Review

2.1 Cardiac (heart) murmur and PCG

Auscultation is the technique of listening to the internal sounds produced by organs and blood vessels in the body, and when it is listening to heart sounds, it is known as cardiac auscultation. For many years, the standard stethoscope has been the tool for this purpose. However, it cannot store, process, or play back sounds, and it cannot provide a visual display of the audio signals [29].

These limitations can be addressed with the electronic stethoscopes. As these devices can capture, store, and play back heart sounds, offering an important improvement in auscultation. Electronic stethoscopes allow for the creation of PCGs which is the graphical representations of heart sound waveforms, it enable visual analysis of the cardiac cycle. This visualization helps to better understand the temporal relationships between the heart's mechanical activity and the corresponding sounds it produces [39].

Analyzing heart sounds is one of the initial and essential steps in evaluating the cardiovascular system. These sounds are acoustic signals generated by the vibrations of heart valves as they open and close during each cardiac cycle, as well as by turbulent blood flow in the arteries. In a PCG, two fundamental heart sounds are observed: the first heart sound (S1), which is caused by the closure of the mitral and tricuspid valves at the start of systole, and the second heart sound (S2), which results from the closure of the aortic and pulmonary valves at the beginning of diastole. The period between S1 and S2 is referred to as the systolic phase, and the interval between S2 and the next S1 is the diastolic phase. During these intervals, abnormal blood flow or turbulent vibrations can generate additional sounds, known as heart murmurs, which appear as irregular waveforms on the PCG [8].

2.2 Deep Learning

Deep learning is a subset of machine learning, and machine learning falls under the category of artificial intelligence (AI). AI is a broader term for a computer program that conduct tasks that typically require human intelligence. The hierarchy is that all machine learning is AI, but not all AI is machine learning, and deep learning is a subset of machine learning [40]

Deep learning uses neural network simulations to learn from datasets and make predictions. It is inspired by the human cerebral cortex, deep learning models showed an ability to learn complex patterns, making it highly effective for tasks such as speech processing, image recognition, and medical diagnostics [41].

While, traditional machine learning is mostly used for solving simpler tasks with small data, and it relies on manually extracting features, deep learning is designed for complex tasks with automatically extracting features. The difference in the two approaches lies in the structure of neural networks: deep learning models have multiple hidden layers, that allow hierarchical feature extraction for an improved representation and learning. The term ”deep” denotes the higher number of hidden layers, each of which extracts and refines different levels of information before reaching at the final output [42].

Convolutional Neural Networks (CNNs) which are mostly used for image and signal processing, Recurrent Neural Networks (RNNs) which are used for sequential data, and the long short term memory (LSTM) are common deep learning models that are used in many studies [43]. More recently, deep learning research has explored emerging models such as transformers for classifying phonocardiogram recordings [44] [45] [46]. Transformers, originally developed for natural language processing, are now being applied to time dependent PCG recordings due to their ability to capture relationships between parts of a signal that are far apart in time or position [47].

The integration of deep learning with PCG data has significantly advanced cardio vascular disease diagnosis. Using spectrogram representation of PCG signal as an input of CNN model, have improved the detection and classification of heart sounds in researches [48]. It has shown high accuracy in classifying PCG signals and We have seen that CNN is utilized in many studies of heart sound diagnosis automation [49] [50] [51] [52].

This study used an HMS-Net model to train and test the murmur detection and characterization tasks. While transformers show promise, they can struggle with time series data especially when there’s not much data available. They sometimes fail to capture detailed time-based patterns, don’t generalize well to new cases, and can be sensitive to changes in the data [47]. And compared to other models like ResNet, the HMS-Net is better suited for heart sound analysis because it captures patterns at different time scales more effectively. Its layered, hierarchical structure allows it to learn both short and long-term dependencies in the PCG signals, leading to better classification performance. This makes HMS-Net a more reliable choice than standard models which receives a single scale input like CNNs or ResNet for detecting complex murmur patterns.

2.3 Related Works

This literature review for related works was conducted based on PRISMA, and two bibliographic databases were used, namely, Science Direct, and IEEE Xplore. The initial search findings using the variety of keyword combinations in the last ten years resulted in a total of 261 papers. The publications were screened to determine their eligibility for inclusion. This process identified duplicates, as well as articles having machine learning and deep learning in their title but unrelated fields to the detection or diagnosis of murmurs or heart valve diseases. To select relevant articles that are within the scope of this study, some screening exclusion criteria were adopted, which finally resulted in 40 selected articles, the flow diagram presenting the process for literature review article selection and filtering is provided in Appendix A. Additionally, related work from Google Scholar was also reviewed. To evaluate the selected studies in PCG classification, a review was conducted with a focus on identifying key gaps relative to the characteristics of an ideal murmur classification system. These desirable features include: high classification accuracy; the ability to not only detect murmurs but also to characterize them in terms of timing, shape, quality, pitch, and grade: comprehensiveness in the classification of valvular heart diseases (VHDs) if it is VHDs classification; and the use of datasets that account for demographic variability and avoid bias.

Table 2.1 and table 2.2 provide the summary of the selected articles, using machine learning and deep learning models to automate the detection of heart murmurs from PCG. Their method, their dataset, and their result with the identified gaps of the publication are reviewed.

Table 2.1: Summary of Machine Learning-Based Studies on Cardiac Sounds

Reference	Model(s) Used	Results	Dataset	Identified Gaps
[53]	SVM	Accuracy: 97.17%, Sensitivity: 93.48%, Specificity: 98.55%	In-house	Dataset Lacks Demographic Variability
[54]	LS-SVM	Accuracy: 99.59%, Sensitivity: 99.59%, Specificity: 99.86%	Aggregated (5 sources)	Lacks Comprehensive VHDs Classification
[55]	GTSVM	Accuracy: 88%, Sensitivity: 86%	In-house	Lacks Murmur Characterization and Dataset Lacks Demographic Variability

Continued on next page

Reference	Model(s) Used	Results	Dataset	Identified Gaps
[56]	RWNN, EKF	No exact metrics reported	In-house	Lacks Comprehensive VHDs Classification and Dataset Lacks Demographic Variability
[57]	SVM, Bayesian	Accuracy: 99.99%	Michigan University	Lacks Comprehensive VHDs Classification
[58]	SVM with thresholding	Accuracy: 100%	In-house, Medical websites	Lacks Comprehensive VHDs Classification
[59]	SVM	Accuracy: 80%	PASCAL	Lacks Murmur Characterization and Has Lower Accuracy
[60]	Composite Classifier	Sensitivity: 98.1%	Public PCG dataset	Lacks Comprehensive VHDs Classification
[61]	KNN, AdaBoost, SVM	Accuracy: 94.04%, Sensitivity: 84.72%, Specificity: 95.30%	PhysioNet 2016, PASCAL	Lacks Comprehensive VHDs Classification
[62]	KNN, SVM	Accuracy: 99.5%, 98.3%	GitHub dataset	Lacks Comprehensive VHDs Classification
[63]	SVM	Accuracy: 99.5%, Precision: 100%	GitHub (Yaseen et al.)	Lacks Comprehensive VHDs Classification
[51]	FBSE-EWT	Accuracy: 98.53%	GitHub dataset	Lacks Comprehensive VHDs Classification
[64]	RF	Accuracy: 99.4%	GitHub, PhysioNet 2016	Lacks Comprehensive VHDs Classification
[65]	RF, AdaBoost	Accuracy: 95.3%, Sensitivity: 94.6%	In-house	Dataset Lacks Demographic Variability
[66]	SVM	Accuracy: 95.39%	PhysioNet 2016	Lacks Murmur Characterization

Table 2.2: Summary of Deep Learning-Based Studies on Cardiac Sounds

Reference	Model(s) Used	Results	Dataset	Identified Gaps
[67]	TGNN	Accuracy: 97.0%, Sensitivity: 98.1%	In-house	Dataset Lacks Demographic Variability and Lacks Comprehensive VHDs Classification
[49]	CNN	Accuracy: 95%	UMichigan, Pascal, PhysioNet	Lacks Murmur Characterization
[68]	STGNN, MTGNN	Accuracy: 82.8%, Sensitivity: 84.2%	In-house	Dataset Lacks Demographic Variability and Lacks Comprehensive VHDs Classification
[69]	ALMMo-0*	Accuracy: 93%, Sensitivity: 90%, Specificity: 95%	PhysioNet	Lacks Murmur Characterization
[70]	RNN, LSTM, GRU	Accuracy: 85% (LSTM best)	PASCAL	Lacks Murmur Characterization
[71]	Deep WaveNet	Accuracy: 98.2%, Sensitivity: 94.0%, Specificity: 99.25%	Public PCG	Lacks Comprehensive VHDs Classification
[72]	CNN, RNN, LSTM	Precision: 90%	Kaggle	Lacks Murmur Characterization
[73]	CNN, BiLSTM	Accuracy: 99.32%, Sensitivity: 98.30%, Specificity: 99.58%	Michigan, PhysioNet 2016	Lacks Comprehensive VHDs Classification
[74]	CNN	No specific metric provided	In-house	Dataset Lacks Demographic Variability
[75]	ConvNet	Accuracy: 96%	Pascal dataset	Lacks Murmur Characterization

Continued on next page

Reference	Model(s) Used	Results	Dataset	Identified Gaps
[50]	1D-CNN	Accuracy: 91-100%	Michigan, Murmur Library, PASCAL	Lacks Murmur Characterization
[76]	HEF	Accuracy: 94.78%, Sensitivity: 87.48%	GitHub, In-house	Lacks Comprehensive VHDs Classification
[77]	MK-ResCNN	Accuracy: 99.73%, Precision: 99.74%	GitHub	Lacks Comprehensive VHDs Classification
[78]	CNN, SVM	Accuracy: 93.45%	PhysioNet 2022	Lacks Murmur Characterization
[79]	Bayesian ResNet, XGBoost	Accuracy: 82%	PhysioNet 2022	Lacks Murmur Characterization
[80]	RNN, LSTM	Accuracy: 99.71% (Pascal), 98.7% (PhysioNet)	Pascal, PhysioNet 2017	Lacks Murmur Characterization
[81]	Cardi-Net, CNN	Accuracy: 98.88%	Public PCG	Lacks Comprehensive VHDs Classification
[82]	DNN	Accuracy: 92.14%	Public PCG	Lacks Comprehensive VHDs Classification
[52]	CNN	Accuracy: 99.04%	GitHub, Kaggle, PhysioNet, PASCAL	Lacks Comprehensive VHDs Classification
[83]	ViT	Accuracy: 99.90%, F1-Score: 99.95%	Not mentioned	Lacks Comprehensive VHDs Classification
[84]	CNN with VGG-19	Accuracy: 97.82%	Pascal	Lacks Murmur Characterization

Continued on next page

Reference	Model(s) Used	Results	Dataset	Identified Gaps
[85]	YAMNet	Accuracy: 99.83%, Sensitivity: 99.59%	GitHub, PhysioNet 2016	Lacks Comprehensive VHDs Classification
[86]	CNN	Accuracy: 99.35%, Sensitivity: 98.84%	Pascal, PhysioNet	Lacks Comprehensive VHDs Classification
[87]	DDA	Accuracy: 97.22%	PhysioNet 2016	Lacks Murmur Characterization
[88]	2D CNN	Accuracy: 98.32%, Sensitivity: 93.07%	GitHub, PhysioNet 2016	Lacks Comprehensive VHDs Classification

Advancements in machine learning and deep learning have significantly improved the automated detection of cardiac murmurs using heart sound records. Many studies have explored different machine learning and deep learning approaches to improve the performance and diagnostic methods.

Asmare et al. (2021) [89] proposed a machine learning-based automated Rheumatic heart disease (RHD) screening method, which may be applied outside of a clinical context by non-medically qualified individuals. Heart sound data was gathered from Ethiopia as well as an additional records from an open-access dataset. To accurately describe RHD, thirty-one unique features were extracted. Two nested cross-validation techniques were used to evaluate a support vector machine (SVM) classifier in order to assess the system's generalizability to new subjects. Their result indicated that the f1-score improved as the prevalence rate increased. An f1-score of 96.0 ± 0.9%, and accuracy of 96.2 ± 0.6%, were achieved for regular nested 10-fold cross-validation. At a prevalence rate of 5%, in the imbalanced nested cross-validation it achieved an f1-score of 72.2 ± 0.8%, recall of 92.3 ± 0.4%, precision of 59.2 ± 3.6%, and specificity of 94.8 ± 0.6%. They have got an encouraging result, and it shows that the proposed tool has a high detection rate however, the approach only focuses on detecting Rheumatic heart disease.

Arslan et al. (2022) [64] proposed a method that combines machine learning with traditional time-frequency and deep features for classifying heart valve diseases. They have used five different techniques for extracting the time frequency information and used scalogram images with pre-trained CNN models with Random Forest classification model. They have an impressive 99.4%overall accuracy. They have used two datasets one is Yaseen et al. which is found in GitHub repository and the other is PhysioNet/CinC Challenge 2016, however the classification was limited to aortic stenosis, mitral stenosis, mitral regurgitation, and mitral valve prolapse.

Bathe and Ingale (2022) [78] used machine learning and deep learning models to detect cardiac murmurs. They trained CNN and SVM models using extracted features from audio PCG signals, and classify murmurs into four categories: Healthy, Systolic, Diastolic, and Continuous. Their study showed that using short term Fourier transform (STFT) features with a CNN model achieved the highest accuracy of 93.45% than the other features used in the study. However, their study was limited to detecting four categories of murmurs with no further murmur characterization. They used the publicly available CirCor DigiScope Dataset from PhysioNet.

Krones et al. (2022) [79] presented Dual Bayesian ResNet (DBRes) combined with XGBoost for heart murmur detection and outcome classification. They made the classification in two stages. At first they used spectrogram from PCG recordings as an input for ResNet (DBRes) model and final classification was done by integrating the DBRes output with demographic data of the patient as input for the XGBoost model. Their result showed that this approach improved murmur detection accuracy, achieving 82%. Like Bathe and Ingale's study, they also used the CirCor DigiScope Dataset but focused on detecting murmurs as present, absent, or unknown and determining the clinical outcomes as normal or abnormal.

Khan et al. (2022) [81] proposed Cardi-Net, a deep neural network by combining a power spectrogram with a CNN model for valvular heart diseases classification. The model extracted discriminatory features which are important for the classification by the selection of Power Spectral Density (PSD). Their method achieved a 98.88% accuracy and, they mentioned that their model can be used on low-cost CPUs or cloud-based platforms which makes it to be computationally efficient. However, the classification of the VHDs was limited to aortic stenosis, mitral stenosis, mitral regurgitation, and mitral valve prolapse.

Yujia Xu et al. (2022) [90] are the winners in the 2022 George B. Moody PhysioNet challenge by proposing a hierarchical multi-scale convolutional network (HMS-Net) for heart murmur and clinical outcome classification. They introduced a quality assessment method based on frequency density distribution to relabel the unknown classes which prevents the poor-qualities from affecting the network optimization for murmur classification task. Spectrograms at multiple scales are fed to the hierarchical architecture to capture features at different scales and that helps the model to detect the long and short-term dependencies between features. In HMS-Net, convolutional features from multi-scale spectrograms are extracted at varying depths, larger scales with deeper layers. Additionally, they have integrated patient data in the model for outcome classification task. The preprocessing involves down sampling of the audio signal sampling rate to 2000 Hz for quicker data loading and cropping the audio record length to a 3 second records for the model inputs. They achieved a weighted accuracy of 0.806 on classifying murmur cases. They also used the CirCor DigiScope Dataset but focused on detecting murmurs as present, absent, or unknown and determining the clinical outcomes as normal or abnormal. In their discussion for future works, they suggest removing the unknown segments during data preprocessing to improve the model's performance. While their proposed method is found to be significant for murmur detection, their approach lacks the murmur characteristics classification which is an essential part of the clinical practice of cardiac auscultation. So that our study incorporated their method into our work with modifications to effectively handle the removal of the unknown class in the murmur detection task and further extended the work with the classification of the specific murmur characteristics.

Elola et al. (2023) [91] This study aimed to estimate murmur grades (absent, soft, loud) using multiple PCG recordings collected from a large pediatric population in a low-resource rural area. The study classifies Mel spectrogram representations of PCG recordings by employing an ensemble of 15 convolutional residual neural networks with channel-wise attention mechanisms. The final patient-level murmur grade was determined using a decision rule that considered all estimated labels from available recordings. The model achieved an unweighted sensitivity of 80.4% and an F1-score of 75.8%. The study indicated the potential of automated murmur grading for pre-screening in low-resource settings however, they focused only on classifying the murmur grading character.

Scott et al. (2024) [92] explored machine learning models and CNN for detecting heart murmurs using the Dangerous Heartbeat Dataset. They compared the machine learning algorithms Random Forest, XGBoost, and CatBoost with a CNN model. The dataset is heart sounds with heart beats and heart murmurs. They experimented with classifiers trained on noisy and noise-filtered data. Extracting features using the Librosa Python package, Mel spectrogram was used as input for the CNN model. The best-performing machine learning models achieved up to 77% accuracy, while the CNN model reached a maximum accuracy of 71%. The study highlighted the potential of using machine learning for murmur detection but this study also focuses only in detecting murmur with no further characterization.

Alotaibi et al. (2025) [46] proposed an approach for PCG signal classification using OpenAI's Whisper model, which was originally designed for speech recognition. The study introduced a modified encoder optimized for heart sound characteristics, using a Log-Mel spectrogram pipeline to highlight the unique acoustic properties of PCG signals. The results shows that the adapted model achieved state-of-the-art performance on VHDs classification from existing methods. This research shows the potential of transfer learning from speech recognition to heart sound analysis, which opens new possibilities for improving automated auscultation, however this study is also restricted to classifying four types of VHDs.

These studies collectively show that the potential of deep learning in cardiac diagnosis from PCG, and they demonstrate high accuracy, but they are limited in detecting only murmur or classifying three to four types of VHDs which suggests a need for further classification of murmurs to achieve more comprehensive diagnosis.

2.4 Research Gaps

Despite the advancements in PCG classification using machine learning and deep learning, several gaps has been found across existing studies. Some approaches demonstrate relatively low accuracy, limiting their reliability in real-world screening. A significant number of models focus solely on murmur detection without further classifying its characteristics, which are clinically significant and essential for identifying the underlying type of VHDs. In addition, some studies narrow their scope to classifying a few VHDs, lacking comprehensive classification of various VHDs. Furthermore, commonly used datasets often lack demographic diversity, raising concerns about model generalizability across different populations.

The PhysioNet 2022 dataset was released, which includes annotations for murmur characteristics. So there is an opportunity to extend the existing approaches. However, most studies that used this dataset have only used it for distinguishing murmurs from normal heart sounds or identifying abnormal vs. normal cases. The dataset containes valuable information on murmur characteristics (such as timing, shape, pitch, grade and quality), but there are no studies that have explored or classified these characterstics.

This gap shows the need for a more accurate, more detailed murmur characterization and inclusive PCG classification systems that are better suited for clinical use. Generating a detailed murmur information report in early screening of heart valve diseases in resource limited environment helps the patient to be referred with a more detailed murmur report to specialized treatment facilities and speed up diagnosis.

CHAPTER 3

Methodology

This study introduces a novel pipeline for murmur detection and murmur characteristics classification. For the models training and evaluation, it adopts the model proposed by Yujia Xu et al. [90] who won George B. Moody PhysioNet challenge for murmur detection, with simplifying the murmur detection to a binary classification task by removing the 'unknown' class and further extending this work, with an introduction of a novel pipeline for murmur characteristics classification. Their method is incorporated into the proposed study with some modifications to effectively handle the exclusion of the unknown class and the classification of the specific murmur characteristics. While the original work focused on murmur detection and lacks further murmur characterstics classification, our contribution enables detailed murmur characterstics report.

In this work, we present murmur detection and characterizing, designed to first detect the presence of a murmur and then if detected, further classify the characteristics of the murmur in detail. The murmur detection model performs binary classification (Present or Absent), simplifying prior approaches by removing the "Unknown" class to improve the model's performance. The murmur detection, and the five distinct characteristics classification are trained independently given their unique label distribution: two are binary classifications (timing [Holosystolic or Early-systolic] and quality [Harsh or Blowing]), while the remaining three are multiclass, (shape [Plateau, Decrescendo, or Diamond], pitch [High, Medium, or Low] and grading [I, II or III]). During prediction, it follows a sequential pipeline: the murmur detection model is first, and if the result is murmur present, it further classifies each of the five murmur characteristics. The general architecture of the methodology is shown in Figure 3.1.

The experiments in this study were conducted on a computer with a 12th Gen Intel® Core™ i5-1235U processor (1.30 GHz), 16 GB of RAM, and a 64-bit operating system. The models were implemented and trained using Python. The codes used in this study are provided in Appendix B. To assess performance, several evaluation metrics were used, including accuracy, weighted accuracy, AUROC, AUPRC, and F1-score. Below, the data source, the preprocessing techniques, the model selection, the proposed model architecture, the method adoptation and the prediction pipeline are detailed.

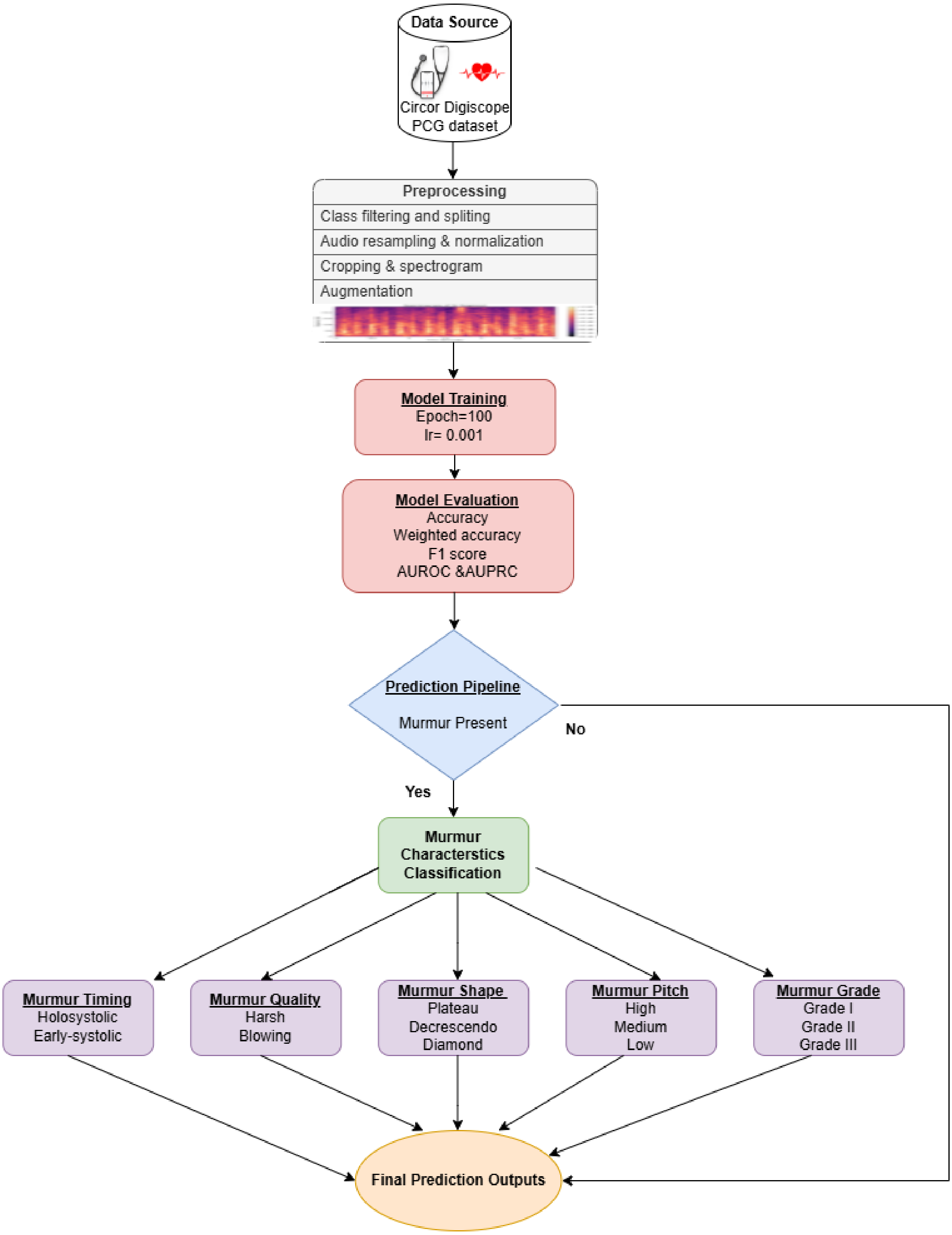


Figure 3.1: General architecture of murmur detection and murmur characteristics classification.

3.1 Data sources

The PCG dataset used in this research study is extracted from the CirCor Digi Scope Dataset which is currently largest heart sound dataset and is available publicly in the Physionet Dataset as part of their annual computing in cardiology challenge. It is the largest paediatric heart sound dataset to date collected from 1,568 patients, and it is the only public dataset where each cardiac murmur has been annotated based on its shape, pitch, grading, timing, and quality. This dataset was collected during two heart screening campaigns in Paraíba, Brazil and was approved by the institution review board of the 5192–Complexo Hospitalar HUOC/PROCAPE [12]. The distribution of CirCor DigiScope dataset is presented in Table 3.1.

Category	Class	Count	Total
Murmur	Absent	1144	1568
	Present	305	
	Low quality	119	
Murmur Timing	Early-systolic	103	314
	Mid-systolic	27	
	Holosystolic	171	
	Late-systolic	3	
	Early-diastolic	8	
	Holodiastolic	1	
	Mid-diastolic	1	
Murmur Pitch	High	75	314
	Medium	94	
	Low	145	
Murmur Grading	Systolic I/VI	176	314
	Systolic II/VI	46	
	Systolic III/VI	82	
	Diastolic I/VI	7	
	Diastolic II/VI	2	
	Diastolic III/VI	1	
Murmur Shape	Crescendo	5	314
	Decrescendo	63	
	Diamond	58	
	Plateau	188	
Murmur Quality	Blowing	145	314
	Harsh	165	
	Musical	4	

Table 3.1: Distribution of the CirCor DigiScope Dataset

The recordings of the CirCor Digi scope dataset were collected from four main auscultation locations: Aortic point, Pulmonary point, Mitral point, Tricuspid point, of the subject. It was captured using a Littmann 3200 stethoscope. Then, they transferred the signals and displayed it in a tablet device. They sampled the signal at 4 kHz with 16-bit resolution and normalized it within the range of $[-1, 1]$. The duration of the phonocardiogram (PCG) recordings is in the range of 5-45 seconds [12].

As we observe from table 3.1, the majority of murmurs (96.8%) occurred during the systolic period, while only a small percentage (3.2%) were detected in the diastolic. Only 60% of the dataset is publicly available, a total of 942 subjects. This paper focuses on murmurs observed at the systolic period, as there is not enough data to classify diastolic murmurs.

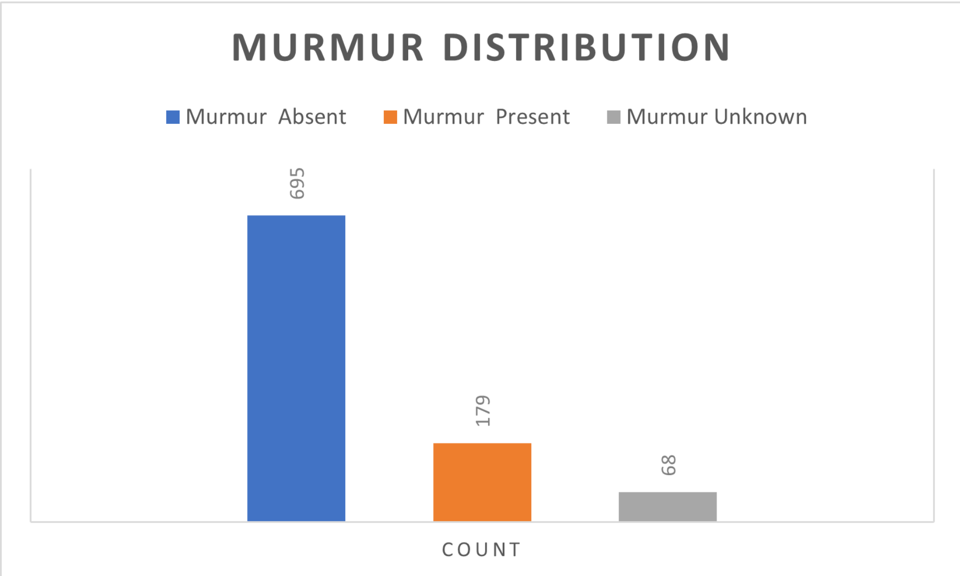


Figure 3.2: Data counts for Murmur distribution

Figure 3.2 presents the distribution of murmur present samples, absent samples and unknown samples in the dataset. The minority of samples belong to the "Unknown." Class, while the majority belongs to “Absent” class.

In this study the Unknown class is removed since, murmur detection is fundamentally binary, positive (murmur present) or negative (murmur absent) the "unknown" class in the dataset exists only because when collecting the data, some signals were low quality, and the annotation was difficult for experts.

Figure 3.3: Data counts for Systolic murmur: shape, quality, grading, timing, and pitch

Figure 3.3 presents the class distributions for systolic murmur characterstics. In the dataset there are only 4 samples of musical class, 2 samples of crescendo class, 1 late-systolic, and 17 mid-systolic samples of classes. These samples are not enough to represent the class in the training and testing of the model, so that they are excluded.

After excluding some classes, this study defines murmur detection as a binary classification: Absent or present, and for the murmur present detected, it defines their systolic murmur characteristics as follows:

- Systolic murmur Shape: Multiclass (Plateau, Decrescendo, or Diamond)
- Systolic murmur Quality: Binary (Harsh or Blowing)
- Systolic murmur Grading: Multiclass (I, II, or III)
- Systolic murmur Timing: Binary (Holosystolic or Early-systolic)
- Systolic murmur Pitch: Multiclass (High, Medium, or Low)

3.2 Model selection

Artificial intelligence (AI) methods provide the potential to automate diagnostic processes, and machine learning is subset of AI, it includes the extraction of features, analysis, selection, and classification. The selection of an appropriate model is very important for effective analysis of PCG signals. Machine learning algorithms using PCG signals are applied for heart sound detection, with different feature extraction approaches and classifiers. However, these machine learning methods have drawbacks, as feature extraction and selection are performed manually. To overcome these limitations of machine learning, researchers are using deep learning algorithms, particularly convolutional neural networks (CNNs) for the classification of cardiac sounds from PCG. These methods provide an automation, without the need for manual feature extraction and feature selection. The model itself extracts hidden features and perform the classification [93].

In this study, deep learning models: Dense Neural Network (DNN) with Mel Frequency Cepstral Coefficients (MFCCs) representaion of the PCG as an input, 2D CNN with spectrogram representaion of the PCG as input and the proposed challenge-winning Hierarchical multiscale convolutional neural network model (HMS-Net) with spectrogram representaion of PCG as an input were evaluated, although, the first two models resulted a good overall accuracy, achieving a total accuracy of more than 80%, the class wise results showed that the present class accuracy achieved less than 60% while the absent class accuracy exceeds 90% and both methods have less than 70% F1 score. This result raises concerns about the use of the first two methods. The proposed challenge-winning model achieved the highest accuracy and F1 score in both overall and class-wise evaluations, so that the challenge-winning model (HMS-Net) is adopted in this study with modifications to effectively handle the exclusion of the unknown class and the classification of the specific murmur characteristics.

3.3 The proposed HMS-Net model

The Hierarchical Multi-Scale Convolutional Neural Network (HMS-Net) enhance PCG classification performance by capturing long short-term dependencies across multiple scales through its hierarchical structure. Figure 3.4 provides an overview of the model's architecture.

The HMS-Net model extracts convolutional features at different depths based on spectrogram scale, larger scales require deeper layers. HMS-Net first extracts feature from multiple scales independently and then fuses them through its hierarchical design that means HMS-Net operates in phases, with each phase progressively increasing in depth to extract features at different scales. At first the sub-networks process Scale 1 and Scale 2 features separately then these features are concatenated along the channel dimension and passed to the next phase. The other sub-network processes Scale 3 features separately, and it is fused with the concatenated features; then the global average pooling is applied to summarize the multi-scale features, followed by a linear layer for classification, and the output depends on the number of classes.

The Structure of the HSM-Net Model is illustrated, with the text inside each box represent the layer parameters. For example, ”3×3 Conv, 512, /2” denotes a convolutional layer with 512 kernels size 3×3 and a stride of 2.

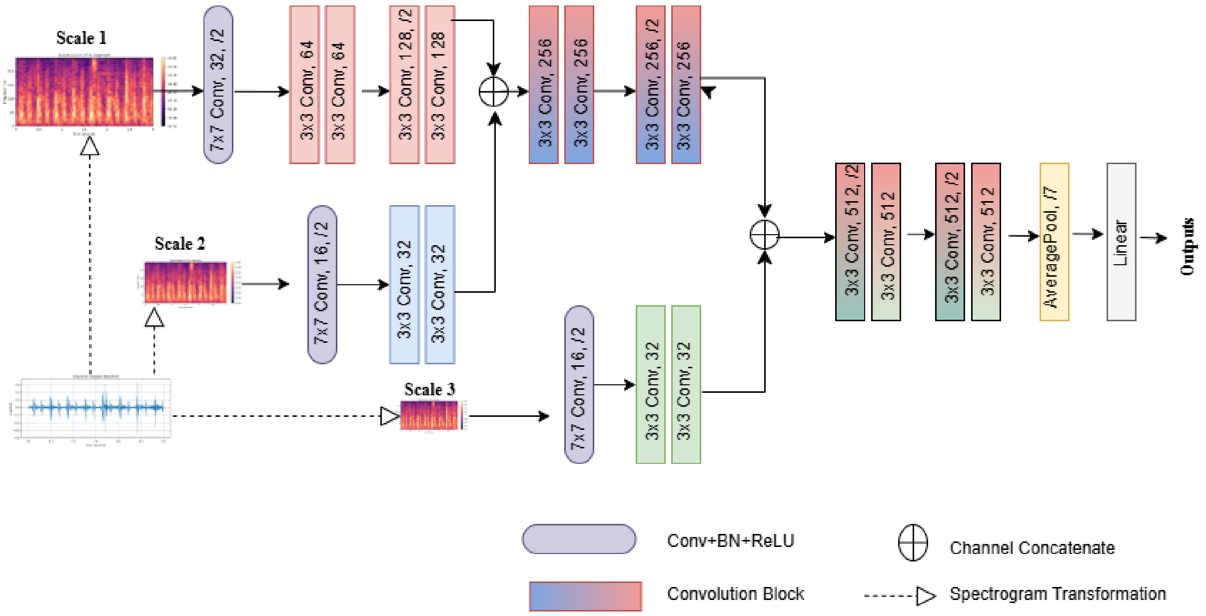


Figure 3.4: The Structure of the HSM-Net Model

The CNN’s receptive fields are fixed for each layer and its size depends on the kernel size and number of layers, however PCG is time dependent signal. Therefore, the multi-scale approach helps to capture features from the time dependent signal. The model processes spectrograms at three different scales to capture features from high-resolution inputs and lower-resolution inputs using independent convolutional pathways. Each scale goes through independent feature extraction before hierarchical fusion at later stages. 7×7 filters at the input ensure broad feature capture in early stages, then 3×3 filters in deeper layers is the standard in CNNs, enabling efficient spatial feature extraction, and the depth progression (32 → 64 → 128 filters) gradually increases representational capacity. These different resolutions, depth, and feature diversity improves the model’s performance compared to single-scale architectures. The network depth overview is presented in Table 3.2.

Stages	Layer Type	Kernel Size	Input Size	Output Size
Scale 1	Conv + BN + ReLU	7×7 / 2	(1, 224, 224)	(32, 112, 112)
	Conv Block (Conv)	3×3 / 1	(32, 112, 112)	(64, 112, 112)
	Conv Block (Conv)	3×3 / 1	(64, 112, 112)	(64, 112, 112)
	Conv Block (Conv)	3×3 / 2	(64, 112, 112)	(128, 56, 56)
	Conv Block (Conv)	3×3 / 1	(128, 56, 56)	(128, 56, 56)
Scale 2	Conv + BN + ReLU	7×7 / 2	(1, 112, 112)	(16, 56, 56)
	Conv Block (Conv)	3×3 / 1	(16, 56, 56)	(32, 56, 56)
	Conv Block (Conv)	3×3 / 1	(32, 56, 56)	(32, 56, 56)
Scale 3	Conv + BN + ReLU	7×7 / 2	(1, 56, 56)	(16, 28, 28)
	Conv Block (Conv)	3×3 / 1	(16, 28, 28)	(32, 28, 28)
	Conv Block (Conv)	3×3 / 1	(32, 28, 28)	(32, 28, 28)
Fusion	Concatenation	-	Concatenate	(160, 56, 56)
	Conv Block (Conv)	3×3 / 1	(160, 56, 56)	(256, 56, 56)
	Conv Block (Conv)	3×3 / 1	(256, 56, 56)	(256, 56, 56)
	Conv Block (Conv)	3×3 / 2	(256, 56, 56)	(256, 28, 28)
	Conv Block (Conv)	3×3 / 1	(256, 28, 28)	(256, 28, 28)
	Concatenation	-	Concatenate	(288, 28, 28)
Deeper Layers	Conv Block (Conv)	3×3 / 2	(288, 28, 28)	(512, 14, 14)
	Conv Block (Conv)	3×3 / 1	(512, 14, 14)	(512, 14, 14)
	Conv Block (Conv)	3×3 / 2	(512, 14, 14)	(512, 7, 7)
	Conv Block (Conv)	3×3 / 1	(512, 7, 7)	(512, 7, 7)
Final Layers	Global Average Pool	7×7	(512, 7, 7)	(512, 1, 1)
	Fully Connected (Linear)	–	(512)	Output Classes

Table 3.2: Network Depth Overview

3.4 Method Adoption

The method proposed by Yujia Xu et al. was considered relevant to our study. So that, we incorporated it into our study with some modifications to better align with our objectives making the murmur detection task binary (“Absent”, and “Present”) and effectively handling the classification of the specific murmur characteristics.

- **Murmur Detection Task**: in the original method by Yujia Xu et al., a quality assessment approach was conducted for the unknown class. However, in this study, the unknown class is excluded, as a result the quality assessment step is unnecessary and not included in this work. While their approach used a multi-class classification, it is modified to a binary classification, so the labels are limited to ”Absent” and ”Present.” Additionally, their method incorporated an additional binary outcome classification, which they integrated into their model. As we do not require this outcome classification in our study, we have not implemented it. Along with these modifications, the mapping of labels is adjusted to focus on the two classes. And then the evaluation function was modified to ensure that the computed metrics correspond to the modified murmur detection task.

- **Murmur Characteristics Classification Task**: for the classification of murmur characteristics, we adopted the methodology to accommodate both binary and multi-class classification tasks. Which means for binary classification tasks, the number of classes was set to 2, and for multi-class classification tasks, the number of classes was set to 3 based on the labels present in the target. Additionally, the target was modified to their corresponding labels. In the original method, the target was ”Murmur” in the characteristic's classification task, it is adjusted to reflect the exact characteristic being classified. For example, if the task is murmur shape classification, the target label is ”Systolic murmur shape.” The label mapping process was also modified to ensure it represents the characteristics classification structure. Additionally, function names and file names were modified to clearly indicate the corresponding tasks. The evaluation function was modified to compute metrics for each target class.

- The preprocessing techniques remain mostly unchanged, except for the data filtering steps to remove the unknown class and other classes in the murmur characteristics classification task. The original method used a custom loss function applicable to both binary and multi-class classification. Since this aligns with our approach, we do not change the custom function similarly, the hyperparameters used for training remain unchanged.

3.5 Preprocessing for Training

The preprocessing for training the proposed model includes several steps to prepare the heart sound recordings for the model input.

3.5.1 Class filtering and splitting

Encountering a limitation in the dataset, as there are underrepresented classes, only the classes with enough numberof samples to represent the class in the training and testing of the model were included. Additionally, the low-quality record, which was introduced as an unknown class in the dataset, was also excluded. After that the dataset was splitted into 80:20 train-test ratio using sklearn model selection and train test split with a fixed $randomstate = 42$. the classes used in this study with their count after filtering are presented in Table 3.3.

Table 3.3: Distribution of classes after filtering

Category	**Classes**	**Distribution**	**Total**
Murmur	Absent	695	874
	Present	179	
Murmur Timing	Early-systolic	59	160
	Holosystolic	101	
Murmur Pitch	High	42	178
	Medium	49	
	Low	87	
Murmur Grading	Systolic I/VI	104	178
	Systolic II/VI	28	
	Systolic III/VI	46	
Murmur Shape	Plateau	111	176
	Decrescendo	34	
	Diamond	31	
Murmur Quality	Blowing	78	174
	Harsh	96	

3.5.2 Audio Resampling

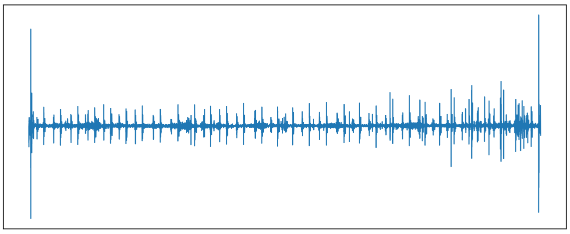
The audio recordings are down sampled to 2000 Hz from their original sampling rate 4000 Hz using SciPy's signal resampling. This helps the data loading to be quicker. Murmur signals ranges from 20-500 HZ [94]. And the Nyquist theorem tells that the sampling frequency must be twice the highest frequency $fs > 2fmax$, to represent the signal accuratly, in that case the murmur-related frequencies are kept, and there is no information loss when resampling it to 2000 Hz.

3.5.3 Z-Score Normalization

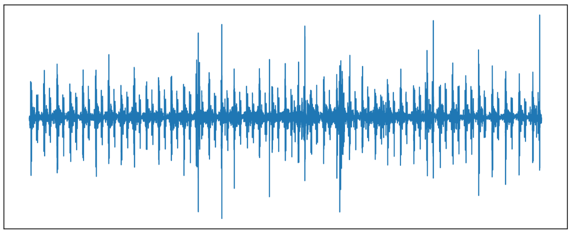
To have a more consistent representation of the signals, a Z score normalization is applied to reduce variations in the data. This adjusts the signals to have a mean $\mu = 0$ and standard deviation $\sigma = 1$ [95].

3.5.4 Audio cropping

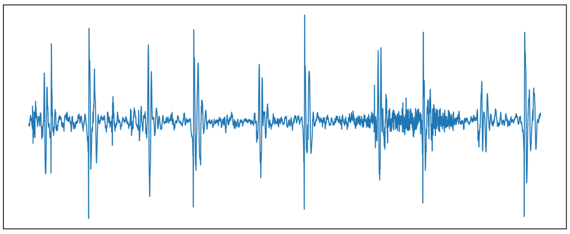
The recording duration differences with recordings ranging from 5 to 45 seconds in the dataset might be taken as one features by the model and impact the classification, so that 3-second segmentation is implemented. Since, the recording S1 lasts approximately 0.1 to 0.16 seconds, and S2 has a duration of around 0.08 to 0.12 seconds [96]. This shows that the whole cardiac cycle has less than 1 second duration; in that case, the information content will not be lost when segmented to a 3-second record. The original and cropped waveforms for both murmur absent and murmur present is shown in Figure 3.5



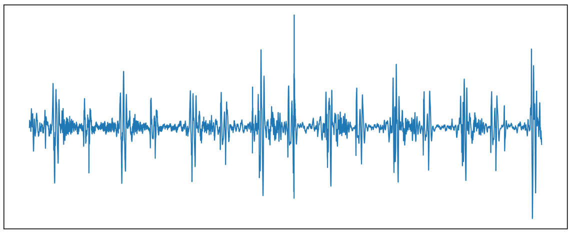
(a) Original Waveform for Murmur Absent



(b) Original Waveform for Murmur Present



(c) 3s Cropped Waveform for Murmur Absent

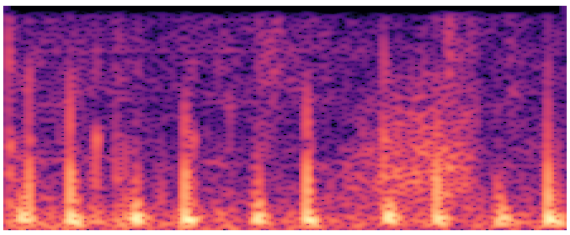


(d) 3s Cropped Waveform for Murmur Present

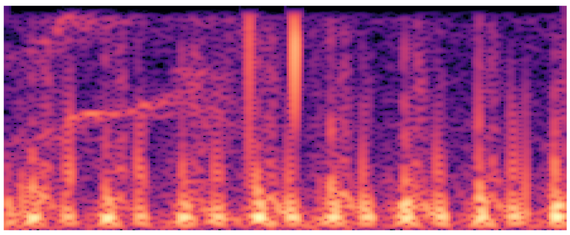
Figure 3.5: Original and Cropped Waveforms of PCG Signal

3.5.5 Spectrogram transformation

In this study the recordings are transformed into spectrograms. Spectrograms are important for deep learning models because they capture detailed information on the signal both in time and frequency domain which improves the model's ability to recognize patterns in the data [97]. The spectrogram representation of the PCG with murmur absent and murmur present is shown in Figure 3.6.



(a) Spectrogram Representation of PCG Signal with Murmur Absent



(b) Spectrogram Representation of PCG Signal with Murmur Present

Figure 3.6: Spectrogram Representation of The PCG Signals

Following the approach of Yujia Xu et al. the spectrogram inputs are generated in three scales by varying the key parameters; FFT size(nfft), window length and hop length and the spectrogram parameters in this study are adopted with the same value they proposed (Scale 1 Spectrogram Shape: (1, 224, 223), Half scale Spectrogram Shape: (1, 112, 112), and Quarter scale Spectrogram Shape: (1, 56, 56)).

3.5.6 Data Augmentation and Model training

Frequency masking and time masking are used as data augmentation techniques by slightly changing spectrograms. It works by randomly hiding parts of the frequency and time axes. This helps the model to be more robust and perform better and it has been highly effective, achieving top results on well-known speech recognition [98]. In this study, frequency masking with randomly removing up to 20 frequency bins with a 50% probability and time masking with randomly removing up to 40 time frames with a 50% probability are applied as proposed by Yujia Xu et al.

The model training uses the AdamW optimizer, with a maximum of 100 epochs. The initial learning rate is set to 0.001, and if the training loss does not improve for five consecutive epochs, the learning rate is reduced by a factor of 0.1. The model is trained using a cross-entropy loss function with 0.1 label smoothing.

3.6 Prediction Pipeline

After training and evaluating the dataset with the proposed method, the prediction pipeline is designed. Each trained models are saved with ".pth" extension (format for saving trained models). The pipeline process follows an approach of first detecting cardiac murmurs and further classifying the characteristics.

3.6.1 Input: Audio File

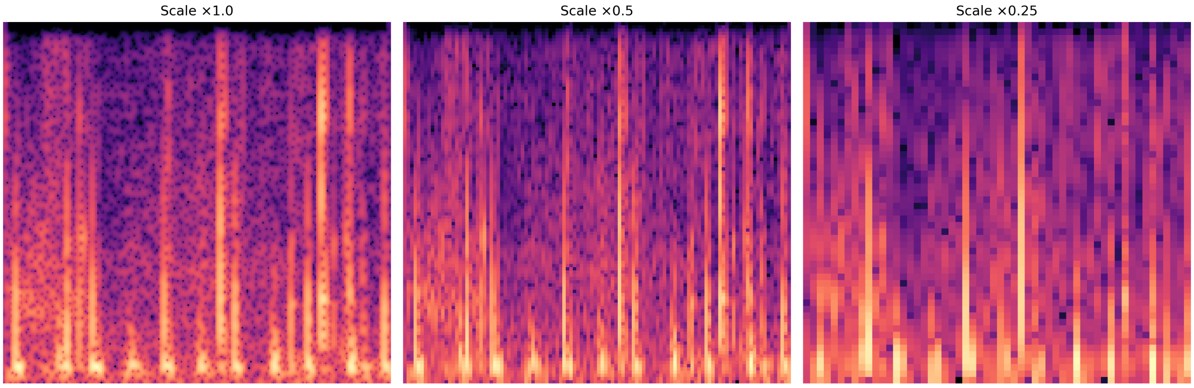
The prediction pipeline starts by taking an audio recording of cardiac sounds in a wave format as an input. The file is read with extracting both the signal and its sampling frequency.

3.6.2 Preprocessing the Audio Signal

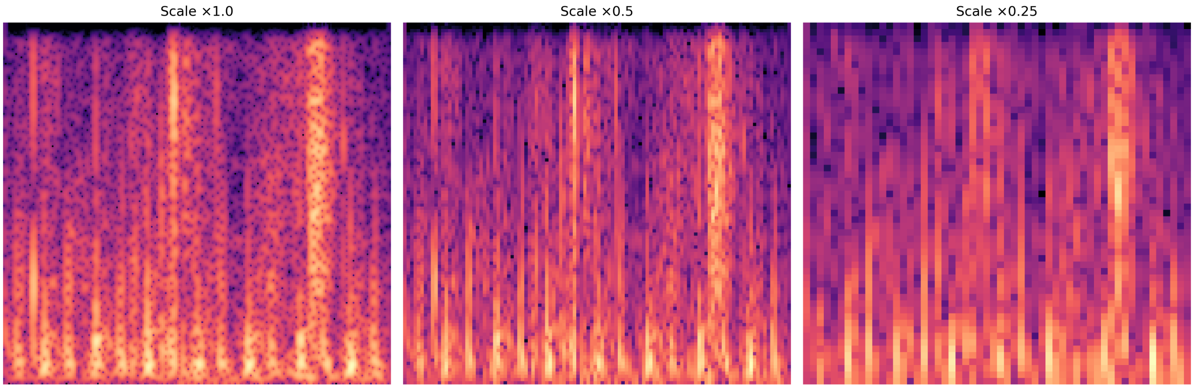
For prediction, the signal passes through a preprocessor that processes the signal into an appropriate format for the trained model (HMS-Net). The multi-scaled PCG model inputs for murmur absent and murmur present is shown in Figure 3.7. The preprocessing for model input involves:

- Resampling the signal to a fixed frequency of 2000 Hz.

- Generating multi-scale spectrograms.



(a) Multi-Scaled PCG Signals of Murmur Absent



(b) Multi-Scaled PCG Signals of Murmur Present

Figure 3.7: Examples of Multi-Scaled PCG Signals for The Model Input

3.6.3 Model Loading

The trained models are loaded for the classification. Its architecture is loaded from a pre-trained checkpoint stored as a .pth file:

- Murmur detection: ”murmur_classifier.pth”
- Systolic murmur timing classification: ”timing_classifier.pth”
- Systolic murmur quality classification: ”quality_classifier.pth”
- Systolic murmur shape classification: ”shape_classifier.pth”
- Systolic murmur pitch classification: ”pitch_classifier.pth”
- Systolic murmur grading classification: ”grading_classifier.pth”

3.6.4 Classification Steps

After loading the trained models, the pipeline for classification starts:

- **Murmur Presence Prediction:** The first step is determining whether a murmur is Present or Absent. This is performed by feeding the audio to the murmur_classifier.pth model. If this results murmur present, then the pipeline predicts the characterstics as follow:
- **Murmur Timing Classification:**The timing_classifier.pth model classifies murmurs as:
  - Holosystolic
  - Early-systolic
- **Murmur Quality Classification:** The quality_classifier.pth model classifies murmurs as:
  - Blowing
  - Harsh
- **Murmur Shape Classification:** The shape_classifier.pth model classifies murmurs as:
  - Diamond
  - Plateau
  - Decrescendo
- **Murmur Pitch Classification:** The pitch_classifier.pth model classifies murmurs as:
  - Low
  - Medium
  - High
- **Murmur Grading Classification:** The grading_classifier.pth model classifies murmurs as:
  - I/VI
  - II/VI
  - III/VI

3.6.5 Final Prediction Output

The prediction pipeline is structured to return the murmur characteristics classification if only the first result is murmur present otherwise it returns “No murmur found - further analysis not performed”. For murmur present result, each classifier returns the corresponding predicted murmur characteristic.

CHAPTER 4

Results and Discussion

This chapter presents the results of the murmur detection task and the murmur characterization classification task, and each task is evaluated independently and then discusses the outcomes and mentions the limitation of the study. Table 4.1 presents the 80:20 train-test data split counts.

Table 4.1: Training and testing data distribution for each classification task.

Classification Task	Total Data Count	Training Data Count	Test Data Count
Murmur classification	874	699	175
Murmur timing classification	160	128	32
Murmur quality classification	174	139	35
Murmur shape classification	176	140	36
Murmur pitch classification	178	142	36
Murmur grade classification	178	142	36

4.1 Evaluation Metrics

When using a classification model, evaluating how well it performs is very important to see how accurate and reliable the model is. To measure a classification model, different evaluation metrics are used. Commonly used metrics include accuracy, precision, recall, and F1-score. In medical, additional metrics such as sensitivity, specificity, and AUROC are widely applied [99]. The other tool is the AUPRC. As one metric may not show the model performance in detail, it is important to evaluate the model with different evaluation metrics.

Performance metrics can be applied to both binary and multiclass classification tasks. The calculation is straightforward for binary classification, but additional methods are used when working with multiclass. The averaging methods include micro, macro, and weighted averaging. Micro-averaging aggregates the contributions of all classes to compute an overall metric, treating each prediction equally. Macro averaging calculates the metric independently for each class and then takes the average, treating all classes equally. Weighted averaging is similar to macro, but it accounts for the number of instances in each class and gives more importance to larger classes. For AUROC and AUPRC in multiclass tasks, two main approaches are commonly used. The one-vs-one method which calculates the metric for each possible pair of classes and then averages the results. The one-vs-rest method computes the metric for each class against all others combined and averages the results [100]. In this study, the macro averaging and the one-vs-rest approach were used for evaluating the multiclass classification tasks. The following section presents the metrics used in this study in detail.

4.1.1 Accuracy

Accuracy is the most commonly used metric to evaluate the performance of a classification model. It measures the overall correctness of the model by calculating the proportion of correctly predicted samples out of the total number of samples. The formula is shown in Equation 1:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where :

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN= False Negatives

While accuracy is commonly used to see how well a model performs, it doesn't always give the full picture it can be misleading. When having imbalanced datasets a model can achieve high accuracy by predicting most samples as the majority class and failing to correctly detect the minority class.

4.1.2 Weighted Accuracy

In the CirCor DigiScope Challenge, a weighted accuracy metric was introduced to evaluate classification performance that better reflects clinical priorities and class imbalances. Unlike the accuracy, which treats the misclassifications equally, the weighted accuracy which is based on the confusion matrix, rewards the correctly predicted minority class. In this research, we adopt the CirCor challenge's weighted accuracy metric and optimize the weights for each task based on their class distribution.

To better understand the weighted accuracy used, it is better to define the confusion matrix. It is a table that compares the model's predictions with the actual class labels. For a classification task with N classes, NxN table where:

- Rows represent the true (actual) classes.
- Columns represent the predicted classes.

Table 4.2: Example of a 2x2 Confusion Matrix

		Predicted	
		Positive	**Negative**
Actual	**Positive**	TP	FN
	Negative	FP	TN

The weighted accuracy is computed using a confusion matrix and a weight matrix, both of shape NxN and the formula is shown in Equation 2:

$$\text{Weighted Accuracy} = \frac{\text{trace}(W \cdot M)}{\sum W \cdot M} \tag{2}$$

Where :

- W is the weight matrix.
- M is the confusion matrix.
- The Numerator = total weighted correct predictions (diagonal)
- The Denominator = total weighted predictions (correct + incorrect)

The minority class are set to be 1.5 more important than the majority 3:2 ratio of weights to handle the class imbalance without being aggressive and still care about majority class performance.

4.1.3 F1 Score

The harmonic mean of precision and recall is called F1 score. It provides a balance between recall and precision, it is an important metric when there is a need to balance the precision and recall. First let's see what precision and recall are to better understand the F1 score:

Precision: It is the proportion of correctly predicted positive samples out of all samples predicted as positive, this is a very helpful metric to measure the model's ability in avoiding false positives. The formula is shown in Equation 3:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

Where

- TP = True Positives
- FP = False Positives

Recall: it is the measure of sensitivity or true positive rate. It is the proportion of correctly predicted positive samples out of all true positive samples. This is helpful to measure model's ability in finding the positive samples. The formula is shown in Equation 4:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

Where:

- TP = True Positives
- FN= False Negatives

The F1 score formula is presented in equation 5

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

4.1.4 AUROC

It is the area under the receiver operating characteristics (ROC) curve, which plots the recall (True Positive Rate) against the False Positive Rate at different thresholds, it provides a measure of the model's ability in discriminating between classes, regardless of the classification threshold and it is insensitive to class imbalance. The formula for the true positive rate is presented in Equation 4 above and the false positive rate formula is presented in Equation 6:

$$\text{False Positive Rate} = \frac{FP}{FP + TN} \tag{6}$$

Where:

- FP = False Positives
- TN = True Negatives

4.1.5 AUPRC

It is the area under the precision recall (PR) curve. The PR curve plots precision against recall (True Positive Rate). This is useful for measuring the model performance when focusing on the positive class (when the positive class is more important or the minor class). It is calculated by integrating the precision-recall curve and it is sensitive to class imbalance.

4.2 Evaluation results

The evaluation result section presents the evaluation results of the model for the murmur classification task and each of the murmur characteristic tasks, where each task's performance is assessed using accuracy, Weighted accuracy F1 score, AUROC, and AUPRC. The results provide insight into the model's ability to distinguish between the murmur present and absent classes while highlighting the murmur characteristics classifications are challenged by data limitations.

4.2.1 Murmur Detection Result

The result of the evaluation metrics for murmur detection task is presented in Figure 4.1 and in Table 4.3.

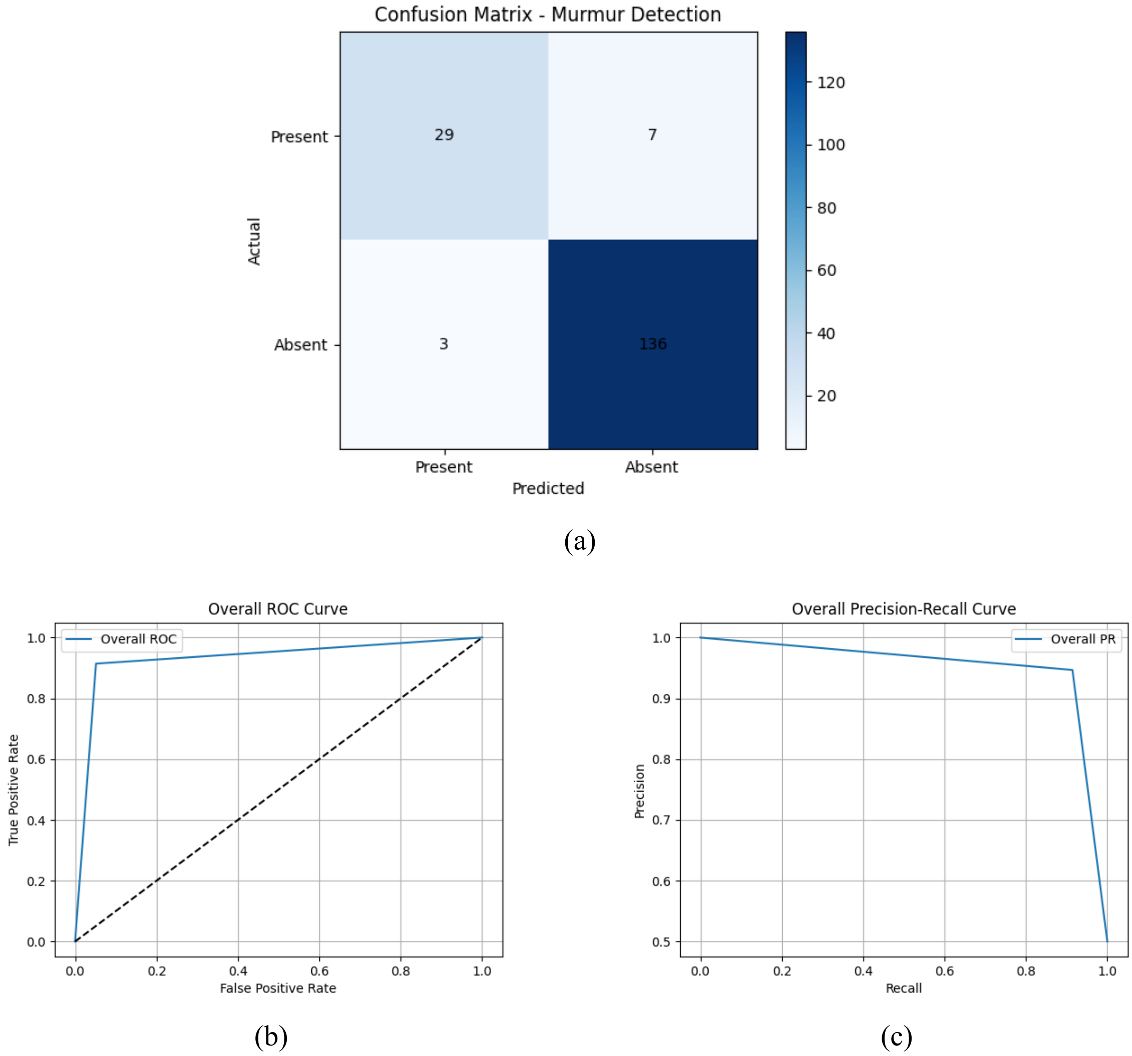


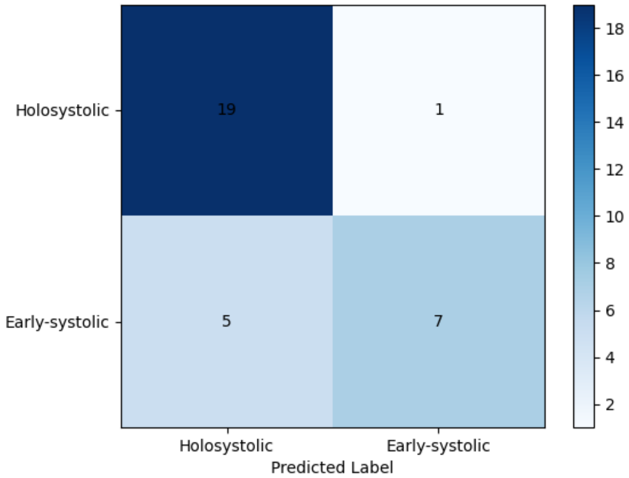
Figure 4.1: Murmur classification Evaluation result: (a) Confusion matrix, (b) The ROC curve, (c) The PR curve.

Table 4.3: Performance Metrics results for the Murmur classification

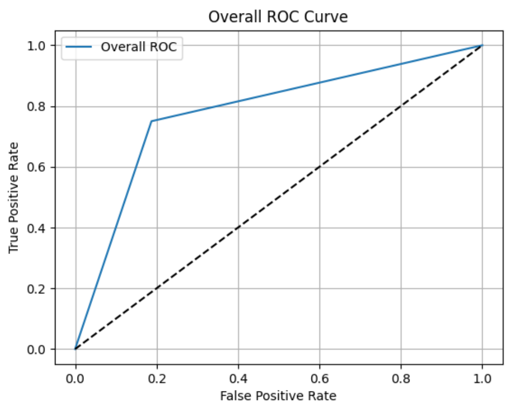
Metric	**Value**
Accuracy	0.931
Weighted Accuracy	0.973
F1-Score	0.869
AUROC	0.859
AUPRC	0.816

4.2.2 Murmur Timing Classification Result

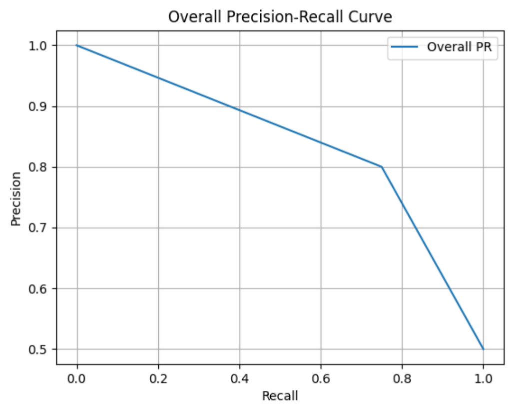
The result of the evaluation metrics for murmur timing task is presented in Figure 4.2 and in Table 4.4.



(a)



(b)



(c)

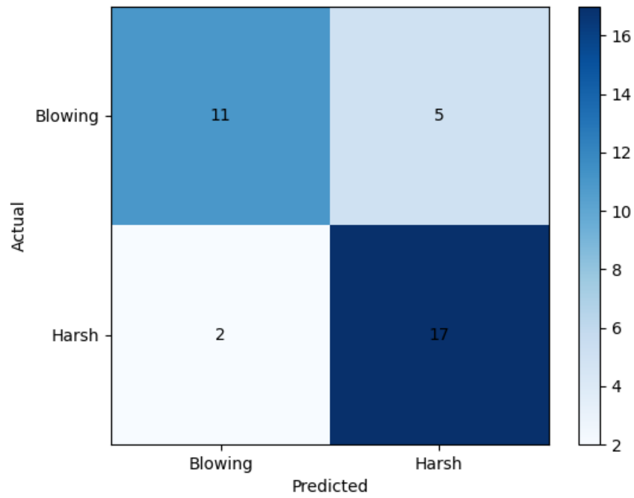
Figure 4.2: Murmur Timing classification Evaluation result: (a) Confusion matrix, (b) The ROC curve, (c) The PR curve.

Table 4.4: Performance Metrics Results for Murmur Timing Classification

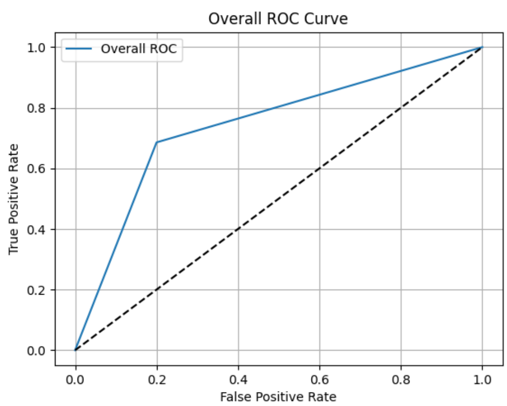
Metric	**Value**
Accuracy	0.781
Weighted Accuracy	0.908
F1-Score	0.755
AUROC	0.742
AUPRC	0.709

4.2.3 Murmur Quality Classification Result

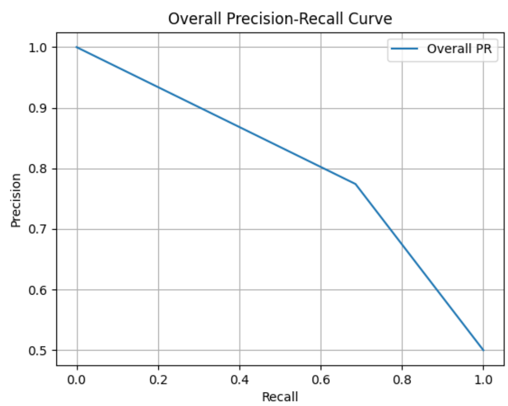
The result of the evaluation metrics for murmur quality task is presented in Figure 4.3 and in Table 4.5.



(a)



(b)



(c)

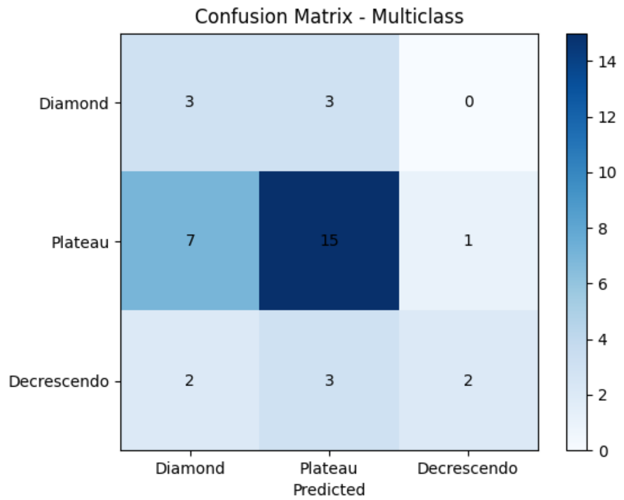
Figure 4.3: Murmur Quality classification Evaluation result: (a) Confusion matrix, (b) The ROC curve, (c) The PR curve.

Table 4.5: Performance Metrics Results for Murmur Quality Classification

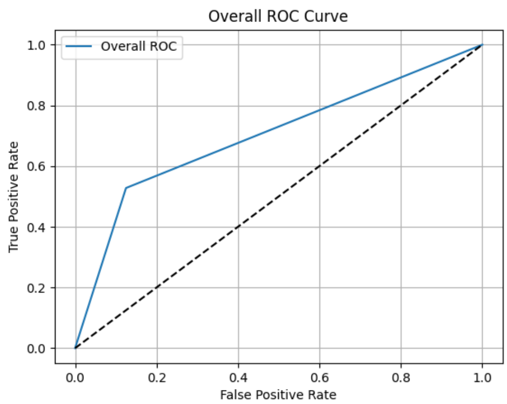
Metric	**Value**
Accuracy	0.743
Weighted Accuracy	0.905
F1-Score	0.695
AUROC	0.729
AUPRC	0.673

4.2.4 Murmur Shape Classification Result

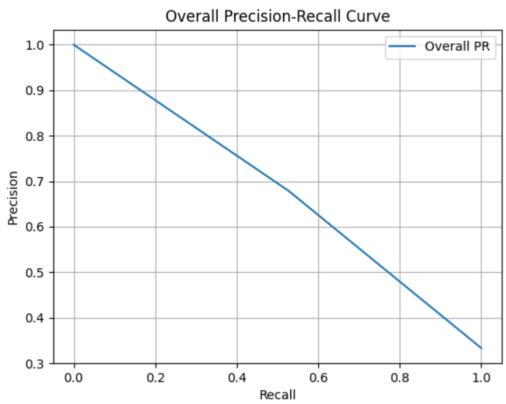
The result of the evaluation metrics for murmur shape task is presented in Figure 4.4 and in Table 4.6.



(a)



(b)



(c)

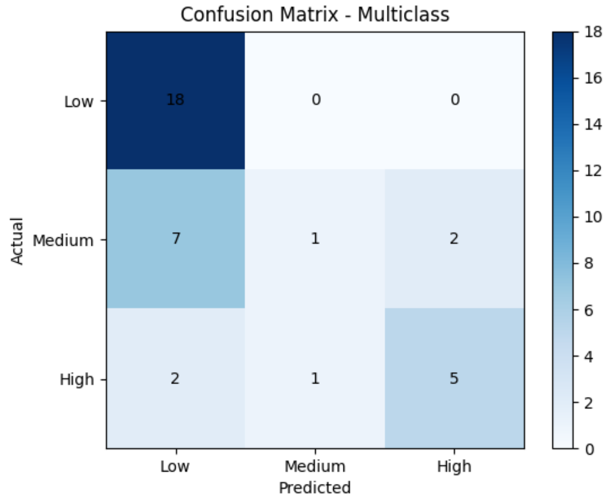
Figure 4.4: Murmur Shape classification Evaluation result: (a) Confusion matrix, (b) The ROC curve, (c) The PR curve.

Table 4.6: Performance Metrics Results for Murmur Shape Classification

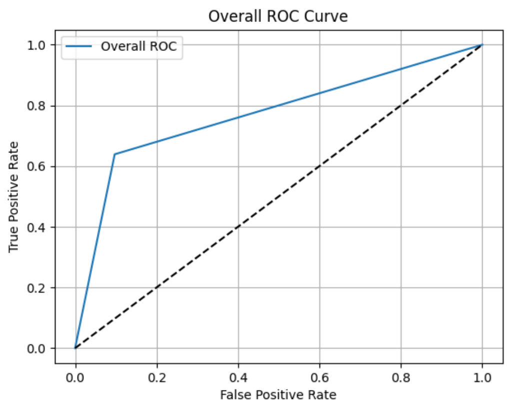
Metric	**Value**
Accuracy	0.759
Weighted Accuracy	0.738
F1-Score	0.494
AUROC	0.618
AUPRC	0.432

4.2.5 Murmur Pitch Classification Result

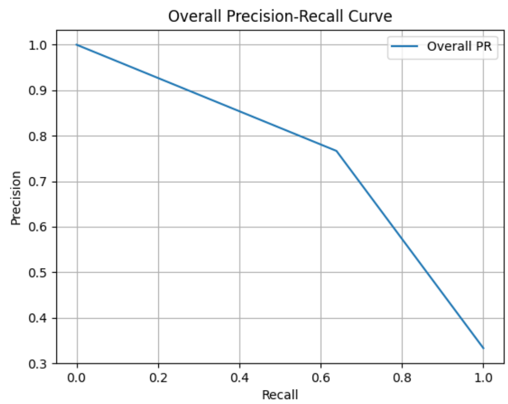
The result of the evaluation metrics for murmur pitch task is presented in Figure 4.5 and in Table 4.7.



(a)



(b)



(c)

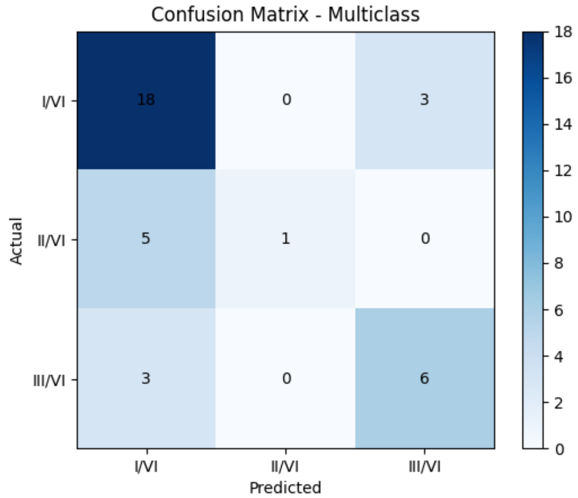
Figure 4.5: Murmur Pitch classification Evaluation result: (a) Confusion matrix, (b) The ROC curve, (c) The PR curve.

Table 4.7: Performance Metrics Results for Murmur Pitch Classification

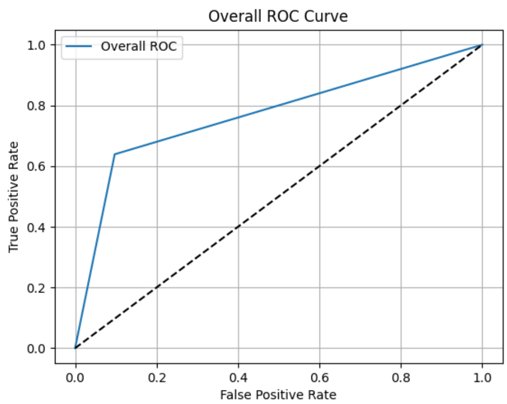
Metric	**Value**
Accuracy	0.815
Weighted Accuracy	0.818
F1-Score	0.568
AUROC	0.723
AUPRC	0.541

4.2.6 Murmur Grade Classification Result

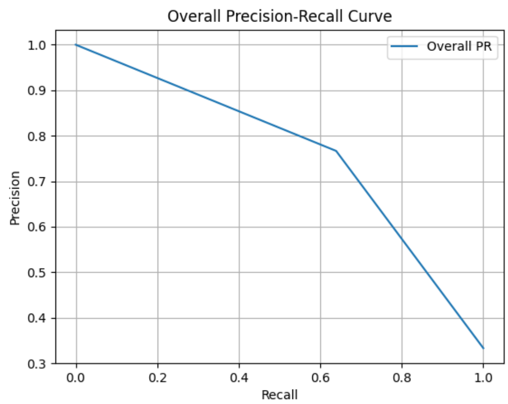
The result of the evaluation metrics for murmur grade task is presented in Figure 4.6 and in Table 4.8.



(a)



(b)



(c)

Figure 4.6: Murmur Grade classification Evaluation result: (a) Confusion matrix, (b) The ROC curve, (c) The PR curve.

Table 4.8: Performance Metrics Results for Murmur Grade Classification

Metric	**Value**
Accuracy	0.815
Weighted Accuracy	0.838
F1-Score	0.578
AUROC	0.703
AUPRC	0.527

4.2.7 Final Prediction Output Results

Example of final prediction output of the proposed method for both murmur present and murmur absent results are presented in Figure 4.7, showing the prediction results of the 5 murmur characteristics for murmur predicted as present and ”No murmur found further analysis not performed” message for murmur predicted as absent.

```
"Predicted Result": {
    "Murmur": "Present",
    "Murmur Timing": "Holosystolic",
    "Murmur Quality": "Blowing",
    "Murmur Shape": "Diamond",
    "Murmur Pitch": "High",
    "Murmur Grade": "III/VI"
```

(a)

```
"Predicted Result": {
    "Murmur": "Absent",
    "Message": "No murmur found - further analysis not performed"
}
```

(b)

Figure 4.7: Example of the final predicted outputs of the method: (a) Murmur Present is predicted, (b) Murmur Absent is predicted.

4.3 Discussion

This study introduces deep learning-based system for the murmur detection and additionally for the murmur characteristics classification. The murmur detection using different machine learning and deep learning models has been proposed in previous studies, but detailed murmur characteristics (timing, quality, shape, pitch, and grade) classification is a novel contribution.

An automated system for generating a detailed murmur information in early screening of heart valve diseases in resource limited areas will help the patient to be referred with a more detailed murmur report to specialized treatment facilities and speed up the diagnosis. The graph presenting the classification performance of each task for comparison is shown in Figure 4.8.

The model for murmur detection achieved a high accuracy of 93.1%, with a weighted accuracy of 97.3%. The weighted accuracy is higher than the standard accuracy because the correct predictions of the present class are given more weight considering the lower representation of the present class in the dataset and to reflect that missing a murmur is more harmful than a false positive result in pre-screening. When we look at the confusion matrix, we see that the instances of an actual present class predicted as absent is higher than an actual absent class predicted as present. This is due the number of absent class data used for training was 4 times higher than the number of present class data, we can see that this imbalance made the model to predict most samples as the majority class. Despite this, the F1 score of 86.9% indicates that the model maintains a good balance between precision and recall, making it a reliable. In terms of AUROC and AUPRC, the model achieved a high AUROC of 0.859 and a slightly lower AUPRC of 0.816. This is expected in imbalanced datasets. AUROC assesses the model’s ability to rank positive samples higher than negatives, regardless of threshold, and is insensitive to class imbalance. But AUPRC focuses on the performance for the positive class and is more affected by false

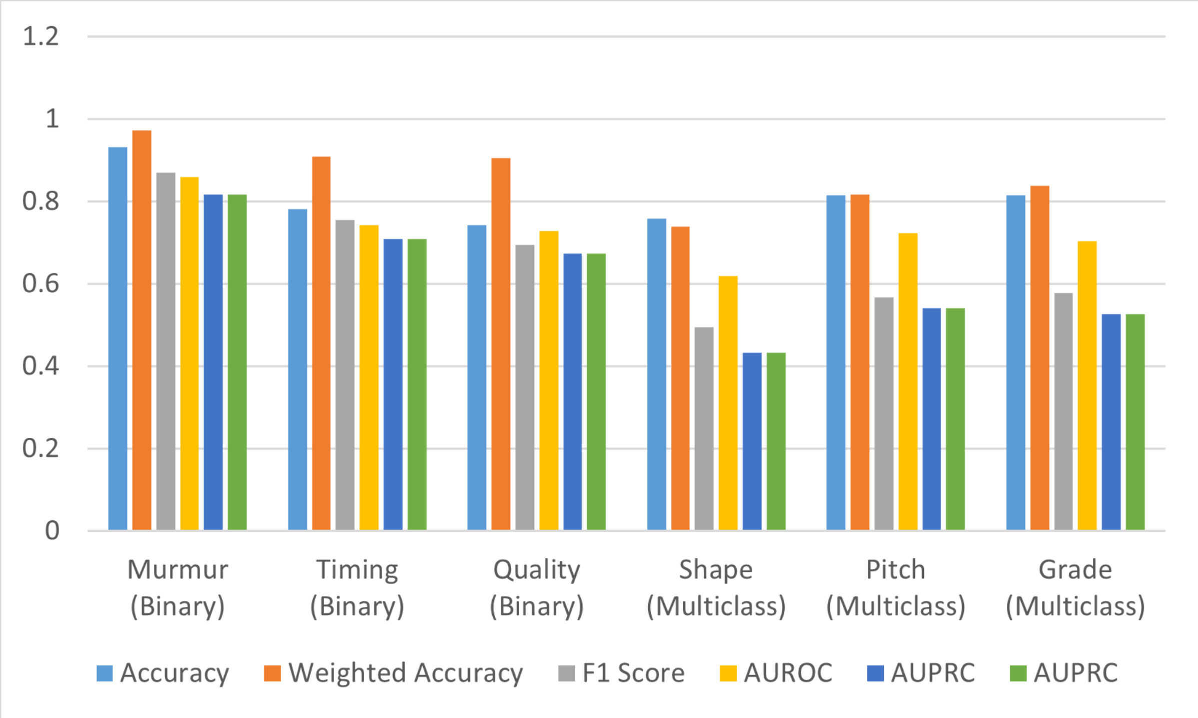


Figure 4.8: Graphical representation of classification performance for murmur and the murmur characterstics tasks.

positives. So, the observed difference between AUROC and AUPRC in this study indicates the challenge of precisely identifying the minority (present) class, even though the overall performance remains strong. In conclusion, the murmur detection (present/ absent) showed high accuracy and reliable precision-recall balance. Compared to previous works such as the 83.78% accuracy reported by Yujia Xu et al. for murmur detection including the "unknown" class and the 82% accuracy by Krones et al. using the same CirCor DigiScope dataset our model showed an improved accuracy. This shows that our approach to the murmur detection with removing the "unknown" class has improved the model's performance.

Each murmur characteristic was evaluated separately. The model's performance for murmur timing showed moderate accuracy but higher weighted accuracy. The higher weighted accuracy is resulted from the model being rewarded more for correctly predicting the minority early-systolic class. This indicates that applying weights to the minority classes was beneficial. From the confusion matrix we can see that the number of an actual early-systolic class predicted as holosystolic is higher than an actual holosystolic class predicted as early-systolic, that is because the number of holosystolic class data used for training was almost 2 times higher than the number of early-systolic class data, This imbalance led the model to predict most samples as holosystolic. Despite this, the moderate F1 score suggests that the model maintained a moderate balance between precision and recall. As the murmur detection, here also we see that a high AUROC score, and the AUPRC was relatively lower, which is expected in imbalance dataset. Therefore, the observed gap between AUROC and AUPRC shows the model's relative difficulty in precisely identifying the minority (early-systolic) class.

The murmur quality classification model also showed moderate accuracy and higher weighted accuracy. The higher weighted accuracy is due to the weight given to the correctly predicted minority blowing class. From the confusion matrix, we can see that the number of an actual blowing class predicted as harsh is higher than an actual harsh class predicted as blowing, that is because the number of harsh class data used for training was higher than the blowing class data, The imbalance in class counts with harsh being majority led the model to predict harsh more. Again, despite this, the moderate F1 score shows a good prediction balance. The AUROC remained high, but AUPRC was lower, as expected. Here we see that a little lower performance than the performance of the murmur timing which suggest that the model is better at detecting timing classes than quality classes this could be because timing is when the murmur occurs within the cardiac cycle and it is an objective characteristic and clearer when a murmur starts and ends which could result relatively easier for a model to learn from the time-frequency representations (spectrograms).

For murmur shape, the model achieved moderate accuracy, but this time, the weighted accuracy was actually lower than the accuracy. Even though weights were given to correctly predicted minority diamond and decrescendo classes than the majority plateau class, the result shows that giving weight for these classes not benefited as the plateau class count is still much higher. The confusion matrix shows that the number of diamond and decrescendo murmurs misclassified as plateau was nearly the same to the actual diamond and crescendo predicted correctly, this is could be due to the number of plateau class data used for training was 3 times higher than the diamond and decrescendo class data, we can see that this imbalance made the model to predict most samples as plateau. The F1 score dropped as a result of its multiclass nature and class imbalance (111, 34, 31). Here also we see that a high AUROC score, and the AUPRC was relatively lower, which is expected given the plateau class is more represented.

The model performed for murmur pitch classification, with good accuracy and a weighted accuracy very close to the accuracy. Although weight was given to the minority medium pitch and high pitch classes, it didn't result in higher weighted accuracy as the low pitch class count is still much higher. The confusion matrix shows that medium pitch murmurs were misclassified as either low pitch or high pitch murmur than its correct prediction, this could be due to the medium pitch lies in between low and high, and its features may overlap with both and low and high pitches are at the extremes and easier to differentiate than medium. We can see that no misclassified low pitch classes as this low pitch class is the majority class and it gets easier for the model to differentiate this class. A moderate AUROC, the F1 score and AUPRC has dropped which suggest that the model is struggling to predict the minority class due to the small and imbalanced data. Here we can see that murmur pitch has a little better performance than murmur shape which suggest that the model is better at detecting pitch classes than shape classes.

The model's performance for murmur grade was almost similar to the pitch performance. It achieved good accuracy and higher weighted accuracy, showing that giving more weight to the minority classes helped. A moderate AUROC, and low F1 score and AUPRC were resulted, showing that predicting the minority classes remains to be the challenge. From the confusion matrix, we see that grade II murmurs were misclassified as either grade I or grade III. This could be the same reason given to murmur pitch which is because grade II lies between grade I and grade III and its features may overlap with both. On the other hand, it shows that the model predicts most of the grade I class correctly due to its class number is higher than the other two classes.

The results indicate that the model performance is high for the murmur detection in each metrics evaluated. This is due to the murmur detection task has higher training and testing data counts than the number of data used for training and testing of each murmur characteristics. From the murmur characteristics tasks the murmur timing and murmur quality show promising results which suggests that the model performance is good on binary classes tasks, while having relatively lower performance on the multiclass tasks like murmur shape, murmur pitch, and murmur grade.

The achieved murmur detection task accuracy of 93.1% shows the model's potential to be used as a reliable screening tool, especially in low- and middle-income countries with limited access to advanced technologies and cardiologists. For example, in our country Ethiopia, rural parts healthcare is often delivered by non-cardiac expert such as nurses or health extension workers, a cost effective and automated tool like this can play a critical role in early detection of VHDs, and reducing missed or delayed diagnoses.

For murmur characteristic classification, the model achieved accuracies ranging from 74.3% to 81.5%, which, are promising, but they are lower than murmur detection task performance. This can be attributed to small class samples in the dataset for example, the grade II class in murmur grade has only 28 samples and diamond class from murmur shape contains only 31 samples, making it difficult for the model to learn true patterns or variability within that class and leading to poor performance on unseen data.

Compared to single scale input CNN models, the HMS-Net architecture offers an advantage due to its hierarchical multi-scale input structure, which enables better capture of both short-term and long-term features in PCG signals. PCG is a time dependent signal so using different multi scale input instead of single scale input has improved the model's performance. Additionally, while traditional machine learning methods, such as SVM, are computationally efficient and easier to interpret, they rely on manually extracted features which may fail to capture the complex and non-linear patterns present in real-world cardiac sounds. In contrast, deep learning models like HMS-Net has more computational cost, but they learn features directly from the data, which enables them to capture features that are essential for detecting and characterizing heart murmurs. This makes the additional computational cost justifiable.

The proposed system is designed with a goal to support valvular heart diseases screening in low-resource settings. Although not yet deployed, the HMS-Net model is based on a convolutional architecture that can be optimized for real-time inference. With further engineering, the model could be integrated into portable electronic stethoscopes powered by devices like Raspberry Pi or similar platforms. Which would enable use by healthcare workers such as nurses or health extension workers in low resource settings. Future work will focus on optimizing the model for lightweight deployment (e.g. quantization) and clinical validation through a pilot study at Cardiac Center Ethiopia, assessing usability and performance in real-world screening environments.

Overall, the proposed approach in this study where murmur detection and each murmur characteristic classification task are trained and evaluated independently, then combined in pipeline for prediction is the objective of the study and it is a novel approach. Even though a small and imbalanced dataset is used, the performance results are promising, which suggests that with more data and better class balance, higher performance can be achieved. The use of the proposed approach will help to address the shortage of skilled cardiac experts and the automated generating of detailed murmur reports will be very important for early screening of life-threatening heart valve diseases in resource limited areas.

4.4 Limitations of the Study

The dataset used in this study is CirCor DigiScope dataset. This is currently the largest and only publicly available dataset that provides murmur with detailed murmur characteristics. However, the dataset does not have enough data for diastolic murmurs. As a result, when we refer to murmur characteristics in this work, we are referring to systolic murmurs. Additionally, in the systolic murmur, some classes are removed as a result of limited sample sizes for training and testing, the ”Musical” class under murmur quality, the ”Crescendo” class under murmur shape, and both ”Mid-systolic” and ”Late-systolic” under murmur timing were removed. In the systolic murmur chraracterstics, the small imbalanced data has challenged the performance of the model, these limitations indicate the need for larger and balanced datasets for the automatic classification of the characteristics of all types of heart murmurs.

CHAPTER 5

Conclusion and future works

5.1 Conclusion

The objective of this thesis was to use PCG recordings to automatically detect the presence or absence cases of murmurs, and further identify the characteristics of the murmur using deep learning. This study was motivated by reports showing that cardiovascular diseases (CVDs) are high with the three-quarters of the death occurring in low- and middle-income nations. While phonocardiogram (PCG) has great potential for identifying heart murmurs, resource-limited areas does not have access to trained cardiac experts. The public release of the CirCor DigiScope dataset that includes murmur with detailed murmur characteristics labels further motivated us to work on the problem. The proposed pipeline first detects the presence of a murmur and, if murmur is detected, it proceeds to classify five different murmur characteristics: timing, quality, shape, pitch, and grade.

The training and evaluation are done for each murmur and murmur characteristic tasks independently, the result shows that excluding unknown classes label from murmur detection task has improved model performance. This work not only improved the accuracy of the murmur detection but it also introduced a novel further five murmur characteristics classification of the detected murmurs a way which is not seen in existing research. Even though the dataset is small and imbalanced, the model showed a promising result. The study has some limitations as there are no other datasets that has murmur characteristic labels other than the CirCor dataset, and it lacks diastolic murmur characteristics, and some systolic data classes have very few samples which was not enough to train and test, so that they were excluded in this work. In future work, if additional datasets become available the work can be extended for both systolic and diastolic murmur types with improving the performance.

Overall, this thesis introduced a novel approach to automate cardiac auscultation with more detailed murmur diagnosis report and shows promising result on PCG data, which can be used as a tool for early screening of heart diseases in low resource healthcare areas.

5.2 Contribution

This study shows that removing the unknown class which is not recognized clinically in murmur diagnosis as murmur diagnosis is present or absent, improved model performance compared to previously reported results which have used the unknown class. Additionally, the study introduces a novel approach that further extends the murmur detection to include 5 main and different murmur characteristics classification for a more detailed automatic diagnostic report of murmur.

5.3 Future works

As this study focused only on systolic murmurs as a result of the absence of diastolic murmur data in the CirCor DigiScope dataset. Additionally, the performance of the current model is limited by the number of samples in some classes and some classes from systolic murmur characteristics were removed as a result of insufficient data. If future datasets provide enough and balanced dataset that have both systolic and diastolic murmur including the murmur characteristics the method can be extended:

- To support both systolic and diastolic murmur characterization report.
- To include the previously removed murmur characteristic classes for more comprehensive classification.
- With exploring other new models and optimization methods to improve performance.
- With applying it in real-world applications with deploying the model on tools like electronic stethoscope.

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Appendix

A Appendix A: Flow diagram of the process of the litrature review based on PRISMA

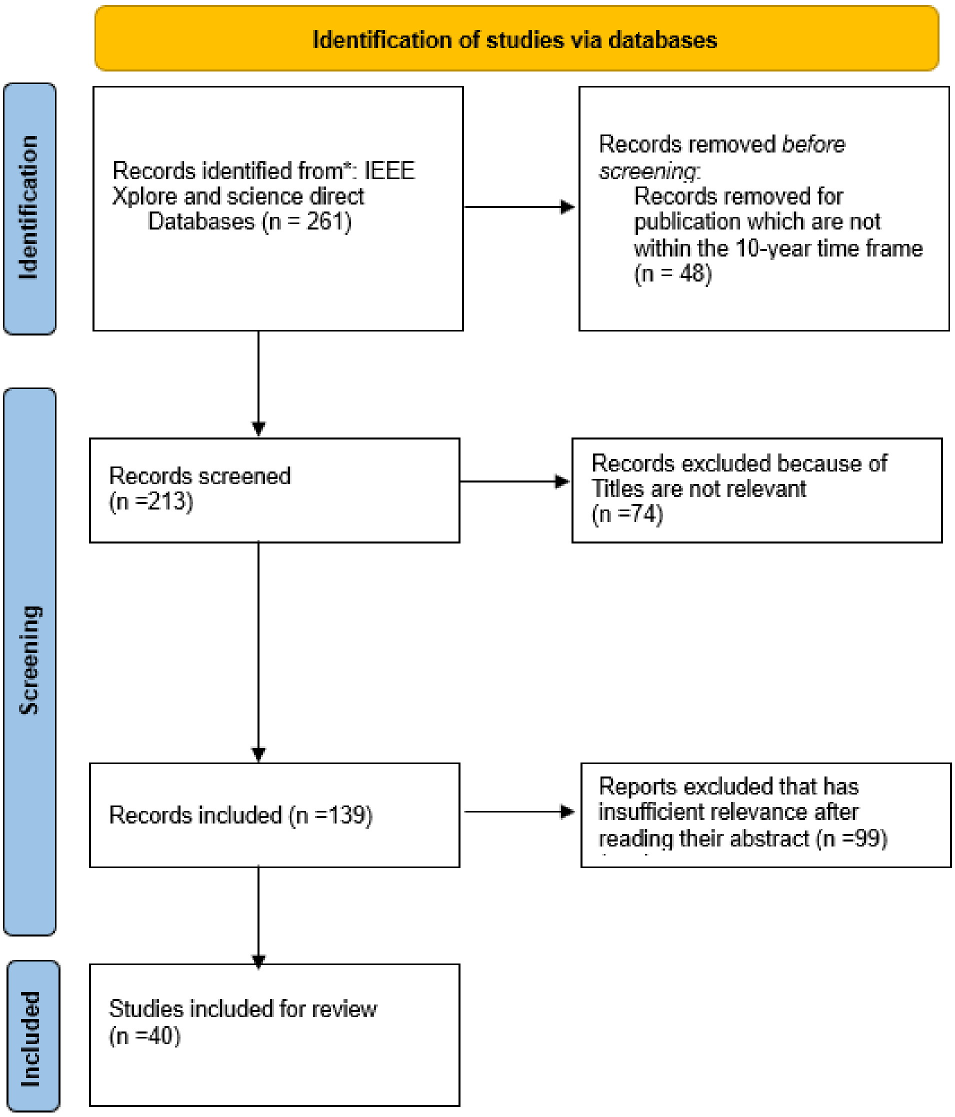

Figure 1: Scientific review PRISMA based flow diagram presenting the process for literature review article selection and filtering.

B Appendix B:Codes

The code used for experiments in this thesis are posted on GitHub; the murmur detection task, each classification task and the prediction pipeline. The repositories are as follows:

- Murmur-classification: github.com/Hafi96/murmur-classification.git
- Murmur-timing-classification: github.com/Hafi96/murmur-timing-classification.git
- Murmur-quality-classification: github.com/Hafi96/Murmur-quality-classification.git
- Murmur-shape-classification: github.com/Hafi96/murmur-Shape-classification.git
- Murmur-pitch-classification: github.com/Hafi96/murmur-pitch-classification.git
- Murmur-grade-classification: github.com/Hafi96/murmur-grading-classification.git
- The Pipeline (Murmur-Detection-and-Murmur-Characteristics-Classification): github.com/Hafi96/Murmur-Detection-and-Murmur-Characteristics-Classification.git