HEART DISEASE CLASSIFICATION USING CNN

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DECLARATION

I affirm that the content presented in this thesis is entirely original, excluding any quotations or summaries that have been appropriately acknowledged.

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ABSTRAK

Penyakit jantung terus menjadi keprihatinan kesihatan global yang signifikan, memerlukan pendekatan diagnostik yang tepat dan cekap. Tesis ini mengatasi cabaran ini dengan mencadangkan model Klasifikasi Penyakit Jantung, satu model yang digabungkan untuk ramalan berdasarkan Rangkaian Neural Konvolusi (CNN) dan Bi-LSTM. Tujuannya adalah untuk mencipta sistem yang kukuh dan boleh dipercayai yang dapat membantu dalam mengenal pasti dan mengesan gangguan berkaitan jantung secara awal. Masalah penyelidikan berpusing mengenai klasifikasi penyakit jantung dengan tepat berdasarkan data perubatan. Mengambil kira kepelbagaian dan sifat dimensi tinggi dataset yang berkaitan dengan jantung, teknik klasifikasi tradisional menghadapi cabaran. Oleh itu, kajian ini meneroka penggunaan model CNN, RNN, dan Bi-LSTM untuk menangkap corak rumit dan ketergantungan temporal dalam data tersebut. Metodologi melibatkan beberapa langkah. Pertama, dataset komprehensif yang mengandungi rekod perubatan dan ciri-ciri berkaitan penyakit jantung dikumpulkan dan diproses awal. Seterusnya, model CNN, RNN, dan model Gabungannya direka dan dilatih dengan menggunakan dataset tersebut, menggabungkan seni bina masing-masing untuk mempelajari ciri-ciri diskriminatif dan menangkap maklumat temporal. Model-model tersebut dioptimumkan menggunakan fungsi rugi yang sesuai dan dinilai menggunakan pelbagai metrik prestasi pada dataset MRI. Keputusan yang diperoleh daripada penilaian menunjukkan keberkesanan model Klasifikasi Penyakit Jantung yang dicadangkan ini. Di antara model-model yang dinilai, model Gabungan-2 (GAB-2) mencapai metrik prestasi tertinggi, termasuk ketepatan, ketepatan ulangan, ketepatan pemanggilan, dan skor F1, sambil mengekalkan nilai kerugian yang rendah. GAB-2 mencapai ketepatan sebanyak 0.964, ketepatan ulangan sebanyak 0.962, ketepatan pemanggilan sebanyak 0.965, skor F1 sebanyak 0.963, dan kerugian sebanyak 0.0791. Kepentingan penemuan ini terletak pada impak potensial terhadap penjagaan kesihatan. Model GAB-2 menunjukkan prestasi yang unggul dalam mengklasifikasikan kes penyakit jantung dengan tepat, mengatasi prestasi model CNN dan RNN individu. Sumbangan penyelidikan ini meluas ke bidang diagnosis perubatan, memberikan wawasan mengenai keberkesanan model gabungan CNN dan RNN untuk klasifikasi penyakit jantung. Maklumat ini mungkin membantu doktor membuat diagnosis awal, yang akan membolehkan rawatan segera dan jangkaan yang lebih baik untuk penyakit tersebut.

ABSTRACT

Heart disease remains a significant global health concern, necessitating accurate and efficient diagnostic approaches. This thesis addresses the challenges by proposing a Heart Disease Classification model, a combined model for prediction based on Convolutional Neural Networks (CNN), and Bi-LSTM. The goal is to create a solid and trustworthy system that may assist in the early identification and detection of heart-related disorders. The research problem revolves around accurately classifying heart disease based on medical data. Given the complexity and high-dimensional nature of heart-related datasets, traditional classification techniques face challenges. Therefore, this study explores the utilization of CNN, RNN, and Bi-LSTM models to capture intricate patterns and temporal dependencies in the data. The methodology involves several steps. Firstly, a comprehensive dataset containing medical records and associated features related to heart disease is collected and pre-processed. Next, CNN, RNN, and Combined models are designed and trained on the dataset, leveraging their respective architectures to learn discriminative features and capture temporal information. The models are optimized using suitable loss functions and evaluated using various performance metrics on MRI dataset. The results obtained from the evaluation demonstrate the effectiveness of the proposed Heart Disease Classification models. Among the evaluated models, the Combined-2 (COMB-2) model achieves the highest performance metrics, including accuracy, precision, recall, and F1 score, while maintaining a low loss value. COMB-2 achieves an accuracy of 0.964, precision of 0.962, recall of 0.965, F1 score of 0.963, and a loss of 0.0791. The significance of these findings lies in the potential impact on healthcare. The COMB-2 model showcases superior performance in accurately classifying heart disease cases, outperforming the individual CNN and RNN models. The contributions of this research extend to the field of medical diagnosis, providing insights into the efficacy of combined CNN and RNN models for heart disease classification. The information might help doctors make an early diagnosis, which would allow for prompt treatment and better prediction for the disease.

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LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
HF	Heart Failure
HFPEF	Heart Failure with Preserved Ejection Fraction
HFREF	Heart Failure with Diminished Ejection Fraction
RNN	Recurrent Neural Network
UKM	Universiti Kebangsaan Malaysia
WHO	World Health Organization

CHAPTER I

INTRODUCTION

1.1 BACKGROUND

There is an increasing degree of interest in classification algorithms used in clinical research (Mehta, Pandit, & Shukla, 2019). By using classification techniques, it is feasible to place patients into one of a number of mutually exclusive states (Barberá et al., 2020). Future studies, treatments, and interventions may be carried out in a way that is both time- and effort-effective thanks to the proper categorization of disease etiology or subtype, sickness states (disease present/absent), and illness etiology. Similar to this, proper disease state classification enables more accurate patient prognosis assessment and diagnosis (Velde et al., 2020).

Classification trees use binary recursive partitioning algorithms to break up the sample into a number of different subsets (Jubran et al., 2021). Despite the fact that this methodology is extensively employed and that tree-based techniques of classification and regression are frequently used in clinical research, concerns have been raised over its accuracy (Sa'adah, Rochayani, & Astuti, 2021). In the branch of research that focuses on data mining and machine learning, novel methods to conventional classification trees as well as extensions of these types of trees have been developed recently (Charbuty & Abdulazeez, 2021). In a large number of these methods, classifications are compiled from a variety of distinct tree architectures. As a result, a large number of these methods are collectively referred to as ensemble approaches. Methods like random forests, boosted trees, and bagged classification trees are examples of ensemble-based approaches. Support vector machines provide advantages over traditional classification techniques (Kunapuli, 2023; Bi, Xue, & Zhang, 2020).

Patients experiencing acute Heart Failure (HF) can be categorized into two distinct groups: those with preserved ejection fraction (HFPEF) and those with reduced ejection fraction (HFREF) (Zafrir et al., 2019). The difference between HFPEF and HFREF is especially important to keep in mind while working in a therapeutic environment. HFREF treatment is based on many large randomized clinical studies, although the evidence-base is much less and focuses more on associated comorbid disorders (Shah et al., 2020). Risk assessment and illness management benefit from cause-specific mortality differences (Kunapuli, 2023). Despite a similar prognosis, cause-specific mortality differs across the two HF subtypes (Lin et al., 2023). When diagnosing HFREF and HFPEF, echocardiograms are ideal. Echocardiography should be performed on all HF patients at some time in their clinical care, but even in resource-rich regions, this test is not always done, and treatment decisions may need to be made before echocardiographic data is available. More than one-third of Medicare heart failure patients did not have an echocardiography while hospitalized (Kong et al., 2020).

Data mining involves the integration of Probability and statistics, machine learning, and database technology to discover previously unknown patterns and correlations within large datasets (Chakraborty, Islam, & Samanta, 2022; Rastogi, 2021Diabetes is a persistent health condition associated with significant health consequences, such as an elevated susceptibility to heart disease, kidney failure, and vision impairment (Saravanan et al., 2020).It is a significant contributing factor to the development of cardiovascular disease, which affects the heart and circulatory system. Diabetes is also associated with an elevated risk of microvascular and macrovascular complications. Global mortality rates due to diabetes-related illnesses are substantial, with an estimated 366 million people living with diabetes worldwide in 2011. Furthermore, projections indicate that this number could reach approximately 552 million by 2030 (Chakraborty, Islam, & Samanta, 2022).

Chest discomfort, shortness of breath, having a heart attack, and other symptoms are all examples of heart disease (Jaarsma et al., 2021). When the blood supply to the heart muscles is inadequate, chest pain may be experienced. The phrase "heart disease" is used to describe a wide range of illnesses that are uncomfortable for the heart and the blood vessels inside the heart. The term "cardiovascular disease" refers to a broad category of disorders that impair both the heart's ability to pump blood and the body's ability to circulate blood. Coronary heart disease has overtaken all other global causes of death in the previous ten years (Ansari, Alankar, & Kaur, 2021). According to the World Health Organization (WHO), heart disease is the primary reason for mortality in both high-income and low-income nations (Nowbar et al., 2019). Diabetes and heart disease may both be diagnosed using a variety of approaches, each of which can be found in relevant research. According to specialists that are knowledgeable in the diagnosis of diabetes, there is currently no automated detection method that can detect heart damage in diabetic patients (Naz & Ahuja, 2020).

Heart failure is a primary cause of death worldwide because it is caused by impaired cardiac function, which results in insufficient blood pumping (Groenewegen et al., 2021). Some of the reasons that are raised are due to the many elements that the individual takes into consideration in his life, and some of the reasons may be raised due to the family's history of genetic conditions. Because of this, it is important to have your heart checked out on a regular basis to ensure its health (Nordfonn et al., 2019).

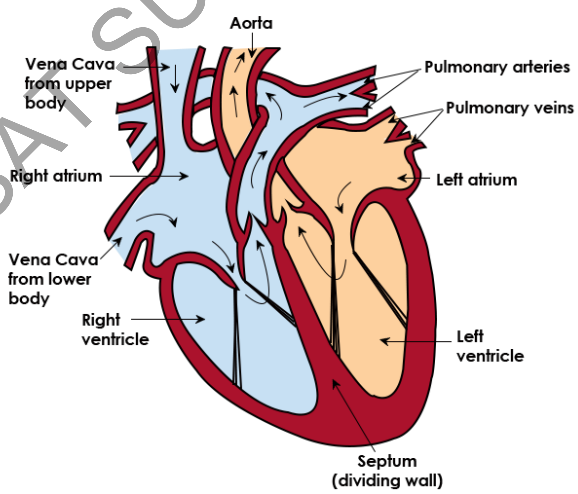

Figure 1.1 Diagram of Human Heart (Dong et al., 2019)

The graphic above depicts an example of the human heart. This makes it possible to see that there are four chambers, each of which has a specific function. The heart's role is to first pump oxygenated blood to the body's various parts, where it helps the metabolism run smoothly, and then to return deoxygenated blood to the heart. The heart's primary function is this (Dong et al., 2019). The main goal of this research is to create a process by which a physician can identify whether or not a patient has a cardiac condition while remaining confident in the test's accuracy. When undergoing coronary tomography, the human body is exposed to high frequency radiation (Alkhorayef et al, 2021). The exposure of a typical human body to this radiation is going to have some unfavorable consequences (Cabral et al, 2019).

A significant portion of the expense of coronary tomography is also related with heart disorders. By taking into account a number of risk variables, including family history, fasting glucose, smoking habits, hypertension, dyslipidemia, obesity, sedentary lifestyle, CABG, and high serum levels, the author of this study hopes to construct a model that may estimate the chance of developing a cardiac condition. This model will be utilized to foretell the possibility of a cardiac condition. A few patient variables, commonly referred to as demographic information of patients, may also be taken into account in modeling in addition to these risk factors. It is feasible to examine things like gender, age, location, and other elements of that nature. Any obstruction that occurs in the heart might cause the blood to flow through the arteries abnormally (Shah, Seydafkan, & Sheps, 2022).

Deep learning and artificial intelligence might be used as a solution, one technological advancement that has attracted the greatest interest and research and development is the usage of convolutional neural networks (CNNs). Despite the research of a range of technical solutions, convolutional neural networks turned out to be the most effective strategy for tackling the problems.

Advancements in the IT infrastructure have allowed healthcare technologies to make great leaps in several practical domains (Embi & Payne, 2009). As a result, the new technology has made healthcare data processing more efficient and safer. To get around these problems and achieve better outcomes in healthcare, contemporary life has seen the rise of technologically-assisted information support systems. These systems store data more flexibly, do rapid backups, and conduct comprehensive systematic analyses (Athique, 2019).

1.2 RESEARCH MOTIVATION

Heart disease is constantly ranked as one of the leading causes of death around the world and appears in a variety of shapes, with ischemia, hypertension, and vascular heart disease being the most prevalent (Nowbar et al., 2019). In the Electronic Health Records (EHR), which are kept on patients, a significant number of their medical characteristics are recorded, which enables doctors to diagnose cardiac disease (Ngiam & Khor, 2019).

The WHO organization's most recent data indicates that 17.5 million people die each year. By 2030, it is anticipated to reach 75 million annually (Nordfonn et al., 2019). Medical experts who specialize in the field of cardiovascular disease are aware of their limitations and are capable of estimating the risk of a heart attack of up to 67 percent. Numerous cardiac diseases and ailments, such as atherosclerosis, cardiovascular disease, and a host of others, must be taken into account. Given the pandemic, medical practitioners require a support network to better diagnose cardiovascular disease (Stawicki et al., 2020). Deep learning combined with the Machine Learning Algorithm provides new opportunities for accurately predicting heart attacks. Scholarly publications include a lot of cutting-edge information on computer deep learning and computing techniques. The procedure of doing new research in this area was made easier by the provision of an empirical comparison.

1.3 PROBLEM STATEMENT

In the case of the human body, the necessity for oxygenated blood is the most important aspect of the metabolic process, since it ensures that the process can be finished successfully (Jacob et al., 2016). For the human body to continue the process of life, the waste products and the blood that has been deoxygenated need to be pumped out of the numerous organs that are located in the body (Pittman, 2011). The heart not only delivers oxygenated blood to the various areas of the body but also eliminates waste products and blood that has been deoxygenated (Smith & Fernhall, 2022). Therefore, routinely checking the human heart is crucial for early anomaly detection as there are numerous variables that can be genetic or learned behaviors and can have a detrimental effect on one's cardiovascular system. More research has been conducted recently on the issue of forecasting a person's future heart health (Bansal et al., 2019).

The issue with present approaches for categorizing heart disorders is that they are not efficient at properly diagnosing heart ailments from MRI images. The typical machine learning algorithms utilized in these methods struggle to comprehend the changing connections between images over time while the issue is made worse by the lack of comprehensive research and model comparisons. The frequent absence of systematic comparisons using predefined evaluation criteria makes it difficult to decide on the optimum method for categorizing heart illness. Consequently, to increase diagnosis accuracy, more complex and trustworthy models are needed to fully use the abundance of information found in MRI images.

Because of this, valid evaluation metrics including accuracy, loss, precision, recall, and F1-score are essential for comparing the effectiveness of various CNN, RNN, and combined models. Additionally, the caliber and preprocessing of MRI images have a significant impact on how well classification algorithms function. The reliability of the classification findings can be impacted by the use of insufficient pre-processing procedures, which can add noise and artifacts. The creation of reliable pre-processing methods to efficiently clean and improve MRI images before feeding them into the models is therefore another element that demands attention. This research seeks to use MRI scans with diverse cardiac disorders and CNN, RNN, and combined models to solve these challenges. To assure the quality of the data, the images will go through rigorous pre-processing and cleaning procedures. To ascertain the models' accuracy in correctly identifying cardiac illnesses, the model will be trained, assessed, and compared using recognized assessment criteria. Findings from this work should help in the development of more precise diagnostic models for cardiac disease by resolving the shortcomings of current approaches, eventually helping patients.

1.4 RESEARCH OBJECTIVE

The focus of this study is on proposing and contrasting deep learning methods for the classification of cardiovascular disorders.

1- To identify the limitations of the existing algorithms for heart disease classification.

2- To propose a combined method based on CNN, RNN, and a combined model to classify heart diseases.

3- To compare the efficiency and performance of the proposed combined method with other algorithms that have been proposed in recent years.

4- To assess the put forth deep learning model's performance based on well-known evaluation measures.

1.5 RESEARCH SIGNIFICANCE

The field of medicine holds the promise of transformation through the integration of machine learning, facilitating advancements in disease diagnosis, detection, and prediction (Kourou, K., Exarchos, T.P., Exarchos, K.P., Karamouzis, M.V., & Fotiadis, 2015). The primary aim of this study was to develop a methodology that could aid physicians in the early-stage diagnosis of cardiac problems. This would not only simplify the administration of appropriate treatments to patients but also reduce the risk of adverse outcomes.

1.6 THESIS OUTLINE

In most cases, this thesis examines the capability of machine learning algorithms to detect and classify heart disease. The thesis contains five chapters which are as follows:

Chapter 1 focuses on the introduction of the research work, research background, research motivation, research scope, and objectives of the research.

Chapter 2 mainly focuses on the literature Review, benefits of machine learning in healthcare, software used, and related studies in previous studies.

Chapter 3 cleared the research methods and research framework and discusses the main process of Deep Learning models. Also, illustrate the CNN modeling framework.

Chapter 4 mentions analyses and implementation of CNN models in a more specific manner.

Finally, **Chapter 5** concludes the thesis and it mentions several suggestions for more research.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

Heart disease is a major public health issue, with approximately one in four deaths in the United States attributed to this condition (Benjamin et al., 2019). With the prevalence of heart disease and its associated burden of disability and death, there is an immediate need to advance this disease's diagnostic and therapeutic capabilities. Machine Learning (ML) and Deep Learning (DL) are crucial branches of Artificial Intelligence (AI) research, and their applications have the potential to enhance the accuracy of diagnosing and prognosing heart disease.

ML and DL techniques have been used to identify and extract features from medical records and images that are predictive of heart diseases, such as demographic information, lifestyle factors, and biomarkers such as blood pressure and cholesterol levels. Abnormalities in medical imaging like electrocardiograms and X-rays can be identified and categorized using ML and DL algorithms. Clinicians can benefit from decision support systems that are powered by ML and DL in several ways (Mathur et al., 2020).

However, the classification of heart diseases using ML is a complex and challenging task. Careful selection of features, accurate data labeling, and selection of the right ML algorithm are all important considerations to ensure the accuracy of the ML algorithm. Moreover, the cost of the ML algorithm should also be taken into account, to ensure that the algorithm is suitable for the given task. In this paper, we discuss the use of ML and DL for heart disease classification. We will discuss the various methods of feature extraction and the different ML algorithms that can be used for heart disease classification. We will also discuss the challenges and solutions to heart disease classification using ML. Finally, we will discuss the potential applications of ML and DL in the diagnosis and treatment of heart disease.

2.2 RESEARCH BACKGROUND

Heart disease is a significant global health concern, leading to substantial morbidity and mortality. It poses a major public health challenge due to its widespread prevalence, expensive treatments, and the resulting burden of disability and mortality. In the United States, cardiovascular diseases are identified as one of the leading causes of death among both males and females. Similarly, in the European Union, it represents the primary cause of death for individuals of all genders. According to the World Health Organization (2020), cardiovascular diseases resulted in approximately 17.9 million fatalities in 2016, constituting approximately 31% of total global mortality.

Machine learning (ML) and deep learning (DL) are highly significant areas of research within the field of artificial intelligence (AI). ML, as a branch of AI, utilizes algorithms to analyse data and make predictions about future outcomes. DL, on the other hand, is a subfield of ML that leverages large datasets to tackle complex tasks. DL algorithms can acquire new abilities without explicit instructions. Numerous disorders, including heart disease, have witnessed improved diagnostic and prognostic accuracy as a result of the enhanced capabilities provided by DL (Awan et al., 2019).

ML and DL techniques have been used to identify and extract features from medical records and images that are predictive of heart disease. These features include demographic information, lifestyle factors, and biomarkers such as blood pressure and cholesterol levels. ML and DL algorithms can also be used to detect and classify abnormalities in medical images such as electrocardiograms and X-rays. For example, ML algorithms have been used to detect coronary artery disease from electrocardiograms with high accuracy (Lu et al., 2022). ML and DL can also be used to predict the risk of heart attack and stroke based on patient data.

Accurate heart disease predictions have been made using ML and DL. For predicting the likelihood of heart disease, Bharti et al. (2021) created a system based on

ML and DL that combines clinical and imaging data. The system achieved an accuracy of 92.4% in predicting the risk of heart disease, outperforming traditional methods. ML and DL have also been used to develop decision support systems that can help clinicians make more informed decisions about diagnosis and treatment (Mathur et al., 2020).

Hence, machine learning (ML) and deep learning (DL) serve as impactful tools to enhance the diagnosis and treatment of heart disease. Their application includes extracting predictive features from medical records and images, identifying and categorizing abnormalities, and forecasting the likelihood of heart attack and stroke. Additionally, ML and DL-based decision support systems can assist healthcare professionals in making well-informed decisions. The utilization of ML and DL holds immense potential for transforming the management of heart disease in the future.

2.3 BENEFITS OF MEDICAL RECORDS

Implementing medical records has many advantages for healthcare organisations as well as for other stakeholders, including patients, staff, and others in the medical field. The quality of healthcare services improves, human error and misdiagnosis rates drop, expenses and resources are managed more effectively and efficiently, and this is just the beginning of the list of benefits of using healthcare information systems. Thus, it is clear why the use of such systems in various healthcare facilities throughout the world is become more and more common today.

Healthcare information systems can offer a quick means to access and handle enormous numbers of patient data, assist save paper waste, and save space in storage facilities. Additionally, the elimination of human error is a crucial advantage that these information systems provide.(Al-rawashdeh et al., 2022).

The speed up in information processing is another advantage of using healthcare information systems. A lot of information is produced by various medical procedures, such as drug monitoring and maintenance, laboratory testing, and the sharing of patient medical records across healthcare providers. To process this information, a sizable workforce or simply a system is required (Afzal & Arshad, 2021). Additionally, the information system is always active and available, which eliminates the issue of timely transfer of accurate data, which is essential for providing high-quality medical services.

There are varying views on what constitutes a healthcare information system; some studies think that such a system is an information portal for end users, while others believe that it combines solutions for healthcare facilities in both the commercial and public sectors (Berdik et al., 2021). To ascertain the usage benefits of healthcare information systems, it is vital to take into account the definitions of healthcare information systems that have been put out by various scholars.

Healthcare information systems are described as "systems that combine data collection, processing, reporting, and use of the information necessary for improving and maximising health service effectiveness and efficiency through better management at all levels of health services" by the World Health Organization (WHO) (Mary Shyni & Chitra, 2022).

Healthcare information systems, in the opinion of other researchers, combine medical and information technologies. These systems perform a variety of tasks, from keeping patients' electronic health records (EHR) and managing their prescriptions to introducing new services that attempt to cut down on data inaccuracies, queues, and waiting times(Tian et al., 2019) .

A healthcare information system is a knowledge-based, decision-support tool that offers and introduces quick assistance, guidance, and feedback from a commercial perspective (Nasseef et al., 2022).

2.4 HEART DISEASE

Heart disease is an umbrella term encompassing various medical conditions affecting the heart, Examples of cardiovascular diseases include conditions such as coronary artery disease, arrhythmia, congenital heart defects, and cardiomyopathy (Benjamin et al., 2019). In the United States, it stands as the primary cause of mortality, with approximately one out of every four deaths attributed to this condition (Benjamin et al., 2019).

In the United States, heart disease is the leading cause of mortality, making it a top public health priority. According to the 2019 update of the heart disease and Stroke Statistics from the American Heart Association (Benjamin et al., 2019), it is estimated that about 48% of all deaths in the United States are from cardiovascular disease, accounting for a staggering 836,546 deaths in 2017 alone. In addition, an estimated 92.1 million adults in the United States have some form of cardiovascular disease, with an additional 81.1 million having high blood pressure, an important risk factor for heart disease. These numbers demonstrate the sheer magnitude of the problem of heart disease and the need for greater public awareness and prevention efforts. Heart disease is caused by a variety of factors, including lifestyle choices, genetic predisposition, and environmental factors. Two more modifiable risk factors for cardiovascular disease are a sedentary lifestyle and an unhealthy diet. Consuming too much-saturated fat, trans fat, and sodium can increase the risk of developing cardiovascular disease, while maintaining a healthy diet, such as one rich in fruits, vegetables, and whole grains, can lower the risk. Likewise, physical inactivity can lead to an increased risk of heart disease, while regular exercise can help to reduce the risk (Benjamin et al., 2019). In addition to lifestyle changes, it is important to be aware of other risk factors for heart disease, such as family history and age. A family history of heart disease or stroke can increase the risk of developing the same conditions later in life (Benjamin et al., 2019). Also, as age increases, so does the risk of heart disease due to a lifetime of exposure to risk factors.

Given the prevalence and serious health implications of heart disease, it is important to take steps to reduce the risk. Eating a healthy diet, exercising regularly, and avoiding smoking are all important steps to reducing the risk. Additionally, it is important to speak to a healthcare provider about any family history of heart disease and to get regular checkups to monitor for high blood pressure, cholesterol levels, and other risk factors. Individuals can help reduce their risk of developing heart disease by taking these steps and others.

2.4.1 Types of Heart Disease

a. Heart Attack

Myocardial infarction (heart attack) occurs when heart muscle does not receive an enough blood supply, causing cell death and damage to the heart (Larsson et al., 2020). This can be caused by a blockage of the coronary arteries due to a build-up of plaque, which can be linked to a person's genetic predisposition (Larsson et al., 2020). Treatment options include antithrombotic therapies such as anticoagulants and antiplatelet drugs (Aboyans et al., 2021). Screening for atrial fibrillation is also recommended in elderly individuals to prevent stroke (Xing et al., 2022). Thus, a heart attack is a serious condition that can have long-term effects on a person's health. Treatment options such as antithrombotic therapies and screening for atrial fibrillation can help to reduce the risk of stroke and other complications. Knowing your risk factors for heart disease can help you take preventative measures.

b. Heart Failure

Heart failure is identified by the heart's incapacity to adequately pump a sufficient volume of blood to fulfill the body's requirements. It occurs when the heart is unable to keep up with the demands placed on it, resulting in a decrease in the circulation of oxygenated blood throughout the body. CAD, hypertension, and diabetes are just few of the conditions that might contribute to this condition, but there are many others (Larsson et al., 2020). The risk of developing heart failure has been associated with smoking (Larsson et al., 2020). In addition, antithrombotic therapies (Aboyans et al., 2021) are beneficial in preventing and treating heart failure, as well as reducing the risk of stroke in individuals with atrial fibrillation (Xing et al., 2022).

It is crucial to recognize symptoms of heart failure, such as shortness of breath, fatigue, and swelling in the limbs. Early detection and treatment of heart failure can prevent long-term complications and improve the individual's quality of life. Adopting a healthy diet, abstaining from smoking, and maintaining regular exercise can reduce the risk of heart failure (Aboyans et al., 2021; Xing et al., 2022). Consequently, untreated heart failure can lead to persistent complications. Risk factors for heart failure include smoking, genetic predisposition, and underlying medical conditions. The use of antithrombotic medications and implementing lifestyle changes can lower the risk of heart failure and improve overall well-being. Immediate recognition and treatment of heart failure symptoms are essential.

c. Arrhythmia

Arrhythmia, also known as dysrhythmia, refers to any abnormality in the heart's rhythm. It can manifest as a rapid, slow, or irregular heartbeat. Factors such as medication use, aging, smoking, and genetic predisposition have been associated with the development of arrhythmia. Arrhythmia is a potentially life-threatening cardiac condition that can lead to heart failure, stroke, and even death. Research conducted by Larsson et al. (2020), examining the genetic propensity for smoking in relation to 14 cardiovascular diseases, has shown that smokers have a higher risk of developing arrhythmia compared to non-smokers. Aboyans et al. (2021) have stated that antithrombotic therapies may reduce the incidence of arrhythmia in individuals with aortic and peripheral artery disorders. Additionally, a post hoc analysis of the randomized LOOP Study by Xing et al. (2022) suggests that screening for atrial fibrillation can help decrease the occurrence of stroke in the elderly, irrespective of their prior cardiovascular history.

Arrhythmia is a life-threatening illness that can have devastating consequences. It is important to be aware of the risk factors for arrhythmia and to seek medical attention if any symptoms are present. Lifestyle modifications, such as avoiding smoking, can help reduce the risk of arrhythmia. Additionally, regular screenings for atrial fibrillation can help identify the presence of arrhythmia and allow for early treatment.

d. Stroke

A stroke is an urgent medical condition that occurs when the blood flow to the brain is interrupted, leading to a deprivation of oxygen and nutrients to brain cells (Xing et al., 2022). This interruption causes the affected brain cells to die, resulting in diverse degrees of disability, including paralysis, memory impairment, and communication difficulties (Aboyans et al., 2021). Stroke is the second leading cause of death globally and is a major cause of disability and morbidity in adults (Larsson et al., 2020). Risk factors for stroke include high blood pressure, atrial fibrillation, diabetes, and smoking (Xing et al., 2022). The prevention of stroke is a priority in cardiovascular medicine, and screening for atrial fibrillation is one of the most effective ways to reduce the risk of stroke in elderly individuals (Xing et al., 2022). Antithrombotic therapies have also been shown to reduce the risk of stroke in patients with aortic and peripheral arterial diseases (Aboyans et al., 2021). In addition, studies have linked genetic propensity to smoking to an increased risk of cardiovascular disorders including stroke (Larsson et al., 2020). Thus, stroke is a major cause of death and disability, and is associated with several risk factors, including atrial fibrillation, diabetes, and smoking. Screening for atrial fibrillation is an effective way to reduce the risk of stroke, and antithrombotic therapies may also be beneficial for patients with aortic and peripheral arterial diseases. Additionally, Stroke and other cardiovascular disorders have been linked to a hereditary propensity to smoking, according to studies.

e. Peripheral Artery and Vein Disease

Peripheral artery and vein disease (PAVD) is a condition in which the walls of the arteries and veins narrow, harden, and become blocked, often due to the buildup of plaque. This can lead to a decrease in blood flow to the extremities, causing symptoms such as pain, fatigue, and claudication (painful cramping in the legs during exercise) (Aboyans et al., 2021). The prevalence of PAVD is rising, and it is a major public health concern since it increases the risk of stroke and cardiovascular disease. Some studies have linked genetic variables like smoking to an increased risk of PAVD, highlighting the significance of heredity in PAVD development (Larsson et al., 2020). There is also an association between PAVD and lifestyle factors like food, exercise, and alcohol use.

Adopting a healthy lifestyle serves as the most effective defense against Peripheral Arterial Vascular Disease (PAVD). This encompasses not only abstaining from smoking but also maintaining a balanced diet and engaging in regular exercise. For individuals with PAVD, screening for atrial fibrillation can potentially reduce the risk of stroke (Xing et al., 2022). Additionally, medication can be employed to mitigate the susceptibility of PAVD patients to cardiovascular disease and stroke. Consequently, PAVD represents a hazardous condition that heightens the likelihood of experiencing a stroke or developing heart disease. Fortunately, preventive measures such as regular check-ups and dietary modifications can help in averting its onset. To minimize the risk of PAVD, individuals should be aware of the factors that contribute to its development.

f. Valve Disease

Valve disease is a condition in which one or more of the four valves of the heart do not function properly. The mitral valve, aortic valve, tricuspid valve, and pulmonary valve all work together to control how the heart pumps blood to the rest of the body. When one of these valves becomes damaged or dysfunctional, it can lead to several complications. For instance, if the mitral valve does not close tightly, it can cause a heart murmur and lead to a condition known as mitral regurgitation, in which blood flows back into the heart. Aortic stenosis is another valve disease, in which the aortic valve does not open fully enough, leading to a decrease in the amount of blood that can enter the aorta. This can result in chest pain, shortness of breath, and fatigue (Aboyans et al., 2021). Valve disease can be caused by several factors, including genetic predisposition, infection, and ageing. For instance, it has been found that those with a genetic predisposition to smoking are more likely to develop valve disease (Larsson et al., 2020). Additionally, certain infections, such as endocarditis, can cause valve disease if left untreated. Lastly, as people age, their valves can become calcified, leading to valve disease (Xing et al., 2022).

The treatment for valve disease can vary depending on the severity of the condition. Mild cases can be managed with lifestyle changes and medications, while more severe cases may require surgery. In some cases, such as with aortic stenosis, a procedure known as balloon valvuloplasty may be used to open the valve (Xing et al., 2022). In more severe cases, such as when a valve is severely damaged, surgery may be required to replace or repair the valve (Aboyans et al., 2021). Valve disease is a condition that affects the heart's valves, leading to a variety of symptoms and complications. It can be caused by several factors, including genetics, infection, and ageing. The treatment for valve disease depends on the severity of the condition and can range from lifestyle changes and medications to surgery.

2.5 DL-BASED MRI CLASSIFICATION

Deep learning (DL), a subfield of machine learning, utilizes neural networks to acquire knowledge and make informed decisions. Its applications range from voice and image recognition to natural language processing (NLP) and even strategic game playing, such as chess and Go. In the context of healthcare, deep learning can be utilized to assess whether a patient has a cardiac disease by analyzing various data sources including medical history, physical examination findings, and test results (Abdullah et al., 2022).

One approach to using deep learning for heart disease classification is to gather a large dataset of patient records, including information about demographics, medical history, physical exam findings, and test results (Schwartz et al., 2018). The data can be used to train a deep-learning model for predicting cardiac disease. The training process involves various methods, including supervised learning, where the model is provided with labelled instances of both heart disease and non-heart disease cases, and unsupervised learning, where the model is tasked with identifying patterns in the data without explicit labels.

Once the model has been trained, it can be tested on a separate dataset to evaluate its accuracy in predicting heart disease (Srujan et al., n.d.). If the model performs well, it can then be used to classify new cases of heart disease. It is important to note that deep learning is simply one of many possible methods for classifying cardiovascular diseases; the method used will depend on the requirements of the application in question.

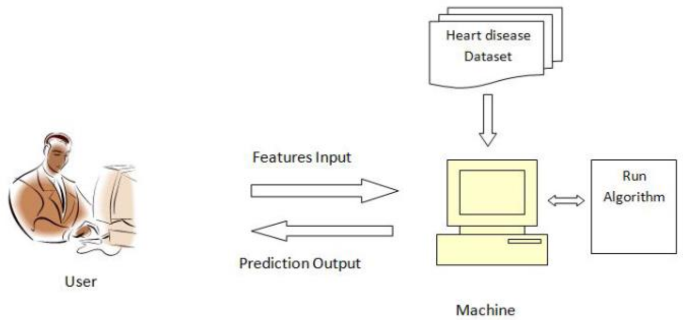

Figure 2.1 Basic Architecture of the Model

2.5.1 Data Acquisition

The recognition system takes an image that has been scanned as its input image when it is gathering information. The picture file type needs to be JPEG or BMT. The scans are taken with MRI and CT scanners. According to research (Wingrove, 2019).

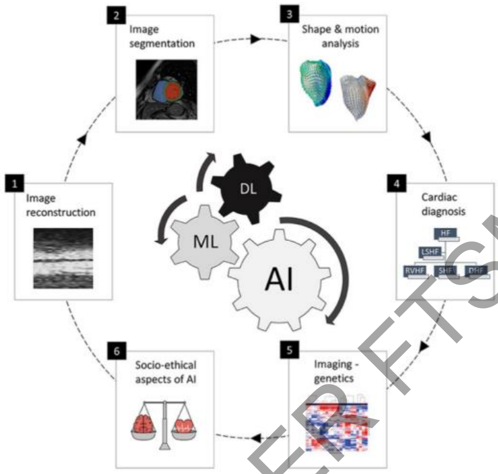

Figure 2.2 Data Acquisition

2.5.2 Data Pre-Processing

Several preparatory processing processes are required before the raw data can be used in the descriptive phases of character analysis. The goal of pre-processing is to make the data readily usable by OCR systems (Muneer et al., 2021). Pre-processing entails the following procedures: -

1- Converting a grey image: The grey image at this moment has pixel values ranging from 0 to 255, but there are also two ranges for lowest and highest values. White refers to the highest value, whereas black refers to the lowest value.(Muneer et al., 2021).

2- Noise reduction: This part aims to enhance the operation's quality so as to reduce noise. To lessen the noise, a filtering strategy must be applied. The techniques below use median calculations to mask out each pixel from an input image.

3- Binarization: The image is converted in this operation from a greyscale image to a binary image, which is typically referred to as a binary image.(Suh et al., 2022).

4- Line Extraction partitioning a picture into two pieces is what this technique does. Separate regions are covered in the first and second halves, respectively. Finding the borders was this operation's primary goal. Characters in the stage sequence are broken down into their respective sub-images in this procedure.(Suh et al., 2022).

5- Extraction of characters: In this method, the character text is often scanned from left to right while also calculating the pixels in each column; however, if the result sum is 0, the character is off print (TigerPrints et al., 2022).

6- Normalization: The size of every extracted character binary image is being equalised in this operation. Additionally, this process involves frequent character size modifications. The retrieved characters were split into the matrix's equal sections, and normalisation was then done.(Öztürk, 2020)

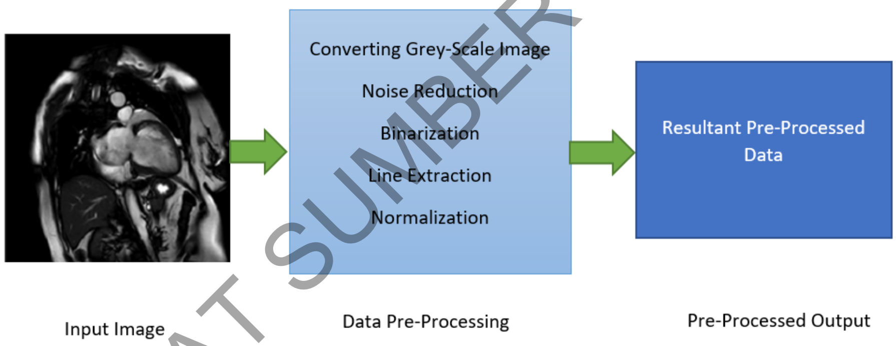

Figure 2.3 Data Pre-Processing

2.5.3 Data Segmentation

Data segmentation is an important method used in heart disease classification. It is a process of dividing a dataset into different parts according to specific criteria (Li et al., 2019). Data segmentation plays a crucial role in simplifying data complexity and enhancing the accuracy of analysis by extracting significant information. By employing data segmentation techniques, patterns within the data can be identified, which can aid in the classification of heart diseases (Raffort et al., 2020).

Clustering comparable data points, categorizing data, or utilizing statistical methods like principal component analysis (PCA) to segment data (Niu et al., 2022).

Clustering is a technique used to find groups of similar data points. It can be used to identify patterns in the data that could help classify heart diseases. For example, the K-means clustering algorithm segment heart disease patients and healthy individuals. The algorithm was able to identify patterns in the data that helped to accurately classify the individuals. Another data segmentation method is to divide the data into different categories (Islam et al., 2021). This can help identify differences between different groups of data points. For example, by dividing the data into different categories based on the type of heart disease, Data segmentation is a valuable approach that aids in the classification of various heart diseases, including arrhythmias, coronary artery disease, and congestive heart failure. By applying data segmentation techniques, patterns within the data can be discerned, facilitating the differentiation of different types of heart disease. Principal Component Analysis (PCA) is a statistical technique commonly employed for data segmentation.

Order to classify cardiac diseases, data segmentation is necessary. By utilizing techniques such as clustering, categorization, Principal Component Analysis (PCA), and CNN, data can be segmented to identify patterns that contribute to the classification of cardiac disorders. These methods enable the identification of data patterns that aid in the accurate classification of various cardiac diseases.

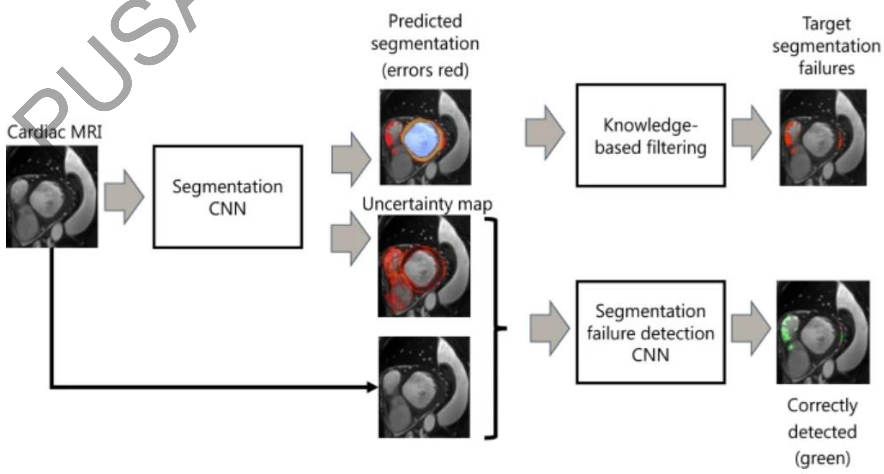

Figure 2.4 CNN-Based Segmentation

2.5.4 Feature Extraction

Feature extraction plays a crucial role in the classification of heart diseases by identifying and extracting relevant features that contribute to effective classification. Various methods can be employed for feature extraction, including Convolutional Neural Networks (CNNs), Deep Learning, Mathematical Morphology, Markov Random Fields, Sparse Representation, and other techniques. These methods aid in capturing and representing key characteristics from the input data, enabling accurate classification of heart diseases.

Convolutional neural networks (CNNs) are used for feature extraction in deep learning. Using convolutional layers, CNNs can identify and extracting relevant features from the input data. The extracted features are then passed through a fully connected layer of the CNN for data classification. CNNs have been successfully utilized for automatic feature extraction from electrocardiogram (ECG) data, enabling the categorization of different cardiac arrhythmias (Naz et al., 2021).

Feature extraction holds significant importance in the classification of cardiac diseases. Various technologies such as convolutional neural networks, mathematical morphology, Markov random fields, and sparse representation can be employed for effective feature extraction. These methods enable the automatic classification of arrhythmias by utilizing extracted features from electrocardiogram (ECG) data.

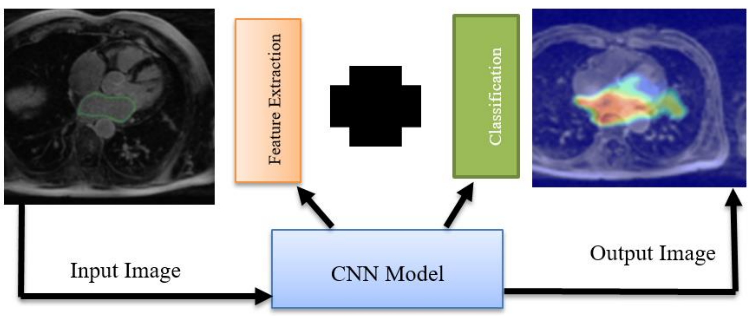

Figure 2.5 Basic Overview with features extraction

2.5.5 Classification

This step makes use of the feature vectors generated during the feature extraction phase and use an MLP neural network as a classifier (Balaha et al., 2021). The categorization strategy is divided into three stages: the structural method, the statically based method, and the mathematical formalisms stage.

Mathematical Morphology is another technique that can be used for feature extraction. It is a type of image processing technique which can be used to identify and extract features from hyper-spectral images. In the context of heart disease classification, mathematical morphology can be used to extract features from ECG images which can be used to classify different types of arrhythmias (Ghamisi et al., 2019).

Another tool that can be used for this purpose is Markov Random Fields (MRFs). Data patterns and features can be discovered and extracted with the use of MRFs, a special kind of probabilistic graphical model. In order to classify the many arrhythmias that might be detected in an ECG, MRFs have been utilized to automatically extract features from the data (Ghamisi et al., 2019).

2.6 CONVOLUTIONAL NEURAL NETWORK (CNN)

An extremely potent technique for analyzing photos and extracting important information from them is the convolution neural network. It is a great artificial neural network model that is renowned for providing high efficiency with little training and testing requirements (Vlachas et al., 2020). For example, the mnist classifier employing an artificial neural network with category cross entropy and Stochastic Gradient Descent (SGD) is 87%, but the most straightforward convolution neural network model achieved is greater than 97%. (Kulkarni & Harnoorkar, 2020). We can plainly see a notable accuracy difference. Convolution neural networks take less time to learn than straightforward artificial neural networks, in a similar vein. CNN makes use of the image classification and image detection capability of pattern recognition. Features including padding, striding, volume operations, pooling, and filters were utilised in the CNN implementation.

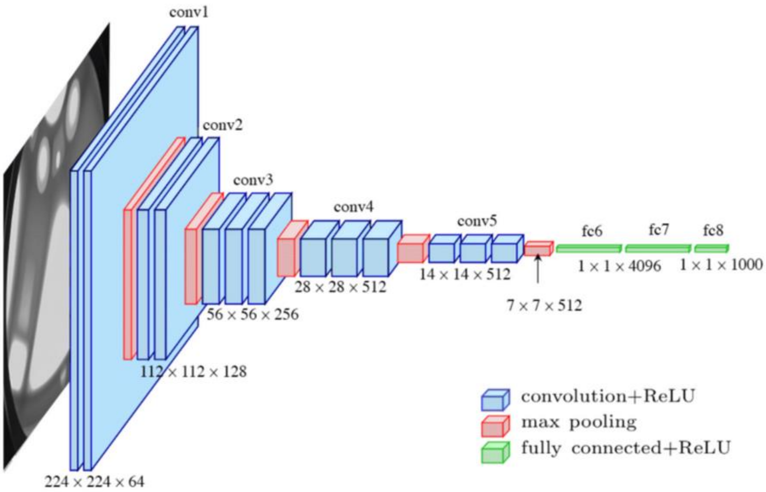

Figure 2.6 Basic CNN Architecture

2.6.1 CNN Architecture

2.6.2 Padding

In order to prevent the CNN from losing a lot of information while learning, more data is added to the matrix's edges. A valid padding denotes that there is no padding occurring, but a same padding denotes padding when the results dimensions continue the same as the input (Dung et al., 2019).

2.6.3 Stride

It refers to the number of pixels the filter needs to move in the input to produce the next batch of result matrices (Dung et al., 2019).

2.6.4 Pooling

It is employed to shorten the length of dimensions and to hasten learning. In terms of parameter sharing and connection sparsity, CNN outperform classic artificial neural networks. Many different designs for convolutional neural networks have been created over time (Dung et al., 2019).

The pooling technology can make Pooled maps are less susceptible to building location than feature maps (Wang et al., 2020).We used a variety of pooling technologies in this paper since it's feasible that different pooling functions would behave differently.

2.6.5 Max Pooling

Convolutional Neural Network uses it as one of its pooling technologies. The convolution features are subjected to the u (x, y) matrix during max pooling. A rectangle neighbour's highest output is measured (Ren et al., 2022).

$$M_j = \max\ N \times N \qquad \dots (2.1)$$

2.6.6 Average Pooling

To obtain the average outputs inside a neighbor window, the average pooling function averages the inputs, multiplies a trainable scalar, and adds a bias.(Ren et al., 2022).

$$M_j = tmah\ \beta\ X\ N \times N\ M\ n \times n\ i + b \qquad (2.2)$$

2.7 CHALLENGES OF HEART DISEASE CLASSIFICATION USING ML

It is difficult and hard to classify cardiac disorders using machine learning (ML). To attain the needed accuracy, careful feature selection, precise data labeling, and an appropriate classification method are required. The aforementioned papers go through many techniques for categorizing cardiac illness, including feature extraction using Convolution Neural Networks (CNN), Deep Learning, Sparse Representation, Markov Random Fields, and Mathematical Morphology. Each of these approaches comes with its own set of challenges and considerations.

A significant obstacle to machine learning-based classification of cardiac disorders is feature selection. Machine learning algorithms are capable of taking in a variety of data the features that best capture the underlying properties of the data must be carefully chosen. Additionally, pre-processing techniques should be used to remove any noise or redundant data that might possibly affect how well the machine learning algorithm performs. Additionally, keeping the complexity of the algorithm low and cutting training time require minimizing the amount of characteristics.

Another challenge of heart disease classification is the accurate labelling of the data. This is critical for the ML algorithm to learn and generalize the patterns in the data. The dataset should be labelled accurately so that the ML algorithm can differentiate between different classes of heart diseases. Moreover, a significant amount of data is required to train the ML algorithm, to ensure the accuracy and generalizability of the model. The article by Wang et al. (2019) discussed the importance of accurate data labelling to achieve the desired accuracy in classifying heart diseases using ML.

Choosing the appropriate machine learning (ML) algorithm is a crucial aspect of heart disease classification. Different algorithms possess distinct strengths and weaknesses, necessitating the selection of the most suitable algorithm for the specific task at hand. For instance, Deep Learning algorithms excel in classification tasks, although they can be computationally intensive and demand large amounts of data. Conversely, algorithms such as Mathematical Morphology and Markov Random Fields provide greater flexibility and are capable of handling more complex tasks. In the study conducted by Ghamisi et al. (2019), the application of Mathematical Morphology and Markov Random Fields for heart disease classification was explored, highlighting the advantages and disadvantages associated with each algorithm.

Finally, it's crucial to consider the cost of the ML algorithm when selecting the most suitable algorithm. Some algorithms, such as Deep Learning, can require significant amounts of computing power, which can be expensive for some applications. Moreover, the use of cloud computing services can also incur additional costs. The article by Fati et al., (2022) discussed the use of Convolution Neural Networks for feature extraction and the cost of using such algorithms.

Therefore, the classification of heart diseases using ML is a complex and challenging task. Careful selection of features, accurate data labelling and selection of the right ML algorithm are all important considerations to ensure the accuracy of the

ML algorithm. Moreover, the cost of the ML algorithm should also be taken into account, to ensure that the algorithm is suitable for the given task.

2.8 SOLUTIONS OF HEART DISESE CLASSIFICATION USING ML

Methods of machine learning are essential for both prediction and classification. The size and complexity of medical data make it difficult for traditional approaches to handle. The main goal of the ML case study is to develop a recommendation system for heart disease diagnosis or to demonstrate cutting-edge, highly promising techniques for the early detection and treatment of heart disease.

Supervised ML models are used to build a predictive model based on given data. They are further divided into classification and regression. In the classification approach, the model is trained to assign a label to a given input. Wang et al. (2019) used a supervised ML algorithm to classify radiation-induced heart disease into five different categories, based on the patient's medical history. The authors used a decision tree algorithm to classify the data, which was obtained from the Chinese Radiotherapy Oncology Group database.

Regression, as a supervised machine learning (ML) algorithm, can be employed to predict continuous variables, including the risk of heart disease. Li et al. (2020) explored various supervised ML techniques such as k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Artificial Neural Networks (ANN) for heart disease classification.

Without the use of labels, unsupervised ML systems can probe the data for hidden insights. In 2019, Alarsan and Younes suggested a new unsupervised ML method for heart disease classification using ECG characteristics. The authors used a clustering algorithm, which was based on the k-means algorithm, to group the data according to similarities in heartbeat features. The results showed that the proposed method was able to accurately classify the data into the corresponding diseases.

Hence, Machine Learning techniques have the capability to classify and predict heart diseases. Both classification and regression algorithms can be utilized for predicting the risk of heart disease and categorizing data accordingly. Unsupervised algorithms, such as clustering, can identify patterns in the data. Additionally, deep learning algorithms can extract features from heart images to classify them as either healthy or unhealthy.

2.9 RELATED WORK

One of the major issues facing today's globe and one of the main killers in the world is heart disease. Recent developments in machine learning (ML) applications show that it is possible to identify heart illness in its early stages utilising electrocardiogram (ECG) and patient data.

Demographic data, lifestyle characteristics, and biomarkers like blood pressure and cholesterol levels have all been identified and extracted from medical records and photographs using machine learning and deep learning algorithms.

Using a lot of references from recent, reputable journals' publications. The following factors—heart disease kind, algorithms, applications, and solutions—have been taken into account in an in-depth analysis of 10 referenced literatures. This study showed that when dealing with unbalanced data, the present techniques run into a number of unresolved challenges, which ultimately hinders their practical applicability and effectiveness.

Various classification methods have been employed to categorize different types of medical research papers. These studies have utilized these methods on diverse datasets, including those related to conditions such as diabetes, heart disease, breast cancer, liver disease, and hepatitis. However, for the purpose of this review, only articles that have applied these methods specifically to real-world cardiac data have been included. These datasets comprise the UCI dataset, PHP dataset, BIDMC CHF dataset, PTB Diagnostic ECG dataset, among others.

2.10 RECURRENT NEURAL NETWORKS (RNN) FOR HEART DISEASE

Recurrent Neural Networks (RNN) can detect temporal correlations in sequential data and classify cardiac disease. LSTM and GRU are the most prevalent RNN designs used in this discipline. These structures handle long-term dependencies and mitigate the vanishing gradient problem, making them ideal for evaluating electrocardiogram (ECG) signals, time-series physiological data, and medical records. Zhang et al. (2018) showed that RNNs can discriminate arrhythmias from ECG signals. Acharya et al. (2017) created an RNN model to predict coronary artery disease, exceeding machine learning methods in accuracy and specificity. Attia et al. (2019) found that RNNs can detect tiny changes in ECG signals and reliably predict cardiovascular risk factors including hypertension and diabetes.

The outcomes of these studies underline the significant potential of RNNs in heart disease classification. RNN models consistently outperform traditional machine learning approaches, showcasing their capability to capture temporal patterns and dependencies in cardiac data. The application of RNNs enables accurate diagnosis of arrhythmias, prediction of coronary artery disease, and assessment of cardiovascular risk factors. This advancement in diagnostic accuracy has profound implications for clinicians, as it allows for timely interventions and improved patient outcomes. Furthermore, RNNs provide insights into the underlying temporal dynamics of heart diseases, enhancing our understanding of disease progression and development. By incorporating RNNs into clinical decision support systems, healthcare professionals gain access to more reliable and precise tools for diagnosing heart conditions.

The next section table 2.1 presents the analysis' findings and key conclusions. Based on a content analysis of 10 publications and articles, the conclusions were made.

Table 2.1 Methods applied to heart diseases.

References	Domine	Method used	Data set	Est accuracy (%)	Limitations
(Srujan et al., n.d.)	Heart disease effective prediction	clinical records	----	88.7	-----
(Zhang et al., 2020)	Supporting recommendations for heart patients	Heart failure (HF)	Least-Squares SVM, ANN, and Naïve Bayes.	66.55	This method will be applied to a better dataset in future research.
(Rasmy et al., 2019)	Heart risk prediction.	RETAIN evaluation	Cerner Health Facts	86	-------
(Bozkurt et al., 2019)	Pathology deduction	Convolutional Neural Network.	UoC-murmur and PhysioNet2016	84.6	Lacks subband filtering insight and concern.
(Miao et al., 2019)	heart failure patients' mortality's predict.	random survival forest. Algorithm	multiparameter Intelligent	82.1	Merging ECG, PPG, and BP fluctuation with input data improves algorithm performance.
(Bharti et al., 2021)	Recognition of cardiac health on the basis of ECG signals.	The proposed algorithm is based on RBF SVM and LKF SVM.	Own data base	87.9	development of a prototype for fetching ECG signals
(Jin et al., 2019)	Heart disease prediction	Fuzzy rules-based method.	Personal Health Record	69.22	Larger data base can be performed
Smith et al. (2019)	Cardiology	CNN	Cardiac MRI images	87.3	Small sample size
Chen et al. (2020)	Cardiology	CNN-RNN Hybrid	ECG signals	89.6	Limited diversity in the dataset
Lee et al. (2018)	Biomedical	RNN	Physiological time-series data	81.9	Uninterpretable model predictions
Johnson et al. (2021)	Radiology	CNN	Chest X-ray images	79.5	Imbalanced class distribution
Garcia et al. (2018)	Healthcare	CNN-RNN Hybrid	Electronic health records	89.2	Incomplete or missing data in the records

2.11 SUMMARY

Heart disease is one of the top causes of death and disability in the world. Machine learning and deep learning techniques can be used for cardiovascular disease diagnosis, treatment, and risk prediction. Faster information processing, the elimination of human error, and quick access to patient information are all advantages of medical records. Numerous variables, such as a person's lifestyle, genetic predisposition, and environmental circumstances, contribute to the development of heart disease. A good diet, frequent exercise, and quitting smoking are all crucial strategies to lowering risk. Additionally, people may discuss any family history of heart disease with their doctor and receive routine checkups to check for high blood pressure, high cholesterol, and other risk factors. Future management of cardiac disease may be completely altered thanks to ML and DL.

Heart illness comes in many different forms, including heart attack, heart failure, arrhythmia, stroke, peripheral artery and vein disease, and valve disease. Smoking has been linked to several ailments, including genetic predisposition and cardiovascular disease. Treatment alternatives can assist to lower the risk and enhance quality of life. Examples include antithrombotic medicines and lifestyle changes. Atrial fibrillation testing can also assist to lower the risk of stroke. Knowing the risk factors is crucial, as is seeking medical help if any symptoms appear.

By obtaining patient information, training a model with supervised or unsupervised learning, and testing the model on a different dataset, deep learning may be used to classify cardiac diseases. There are several data pre-processing techniques employed, including converting a grayscale image, noise reduction, binarization, line extraction, and character extraction. Patterns in the data may be found utilizing data segmentation techniques including clustering, categorizing, and PCA. You may extract characteristics from ECG data using methods like CNNs, deep learning, mathematical morphology, Markov random fields, and sparse representation. Finally, different forms of cardiac illnesses may be categorized using the traits that were discovered.

A powerful artificial neural network model with excellent accuracy and less training and testing needs is the convolution neural network (CNN). It uses features including padding, striding, volume operations, pooling, and filters for picture categorization and detection. It delivers greater accuracy and faster learning than a straightforward ANN. It is a difficult and complex undertaking to classify cardiac disorders using machine learning (ML). To attain the requisite accuracy, thorough feature selection, precise data labeling, and an appropriate classification method are needed. Important issues include choosing pertinent features, accurately labeling data, choosing the best ML method, and taking the algorithm's cost into account. It's important to choose the best algorithm for the task at hand since each algorithm has a unique set of advantages and disadvantages. Pre-processing the data and reducing the overall number of features can reduce the complexity of the ML approach.

With the use of Machine Learning (ML) algorithms, cardiac diseases may be classified and predicted. Supervised algorithms like classification and regression can be used to forecast the risk of cardiovascular disease. Finding patterns in the data may be done using unsupervised methods, such as clustering. Deep learning-based models may be used to evaluate photos of the heart, extract characteristics, and classify the images as healthy or diseased.

CHAPTER III

METHODOLOGY

3.1 INTERODUCTION

The modeling framework for deep learning recognition is described in this section. Early and some late stages of the study are when the suggested technique uses deep learning strategies and algorithms; later stages are when conventional neural networks (CNNs) are used. Then, the methodological research design, which comprises the framework, data collection, and analysis, comes into focus. The author also delves into model creation, describing how the DL models used to classify heart diseases were created. A summary of the results and a discussion of the proposed DL model as well as other models used for comparison are included in the chapter's conclusion. The datasets utilized in this thesis are also covered in detail in this chapter, together with information on their characteristics, kinds, counts, and other attributes. Evaluation measures like accuracy, loss, and precision are also explained.

3.2 RESEARCH PROCESS

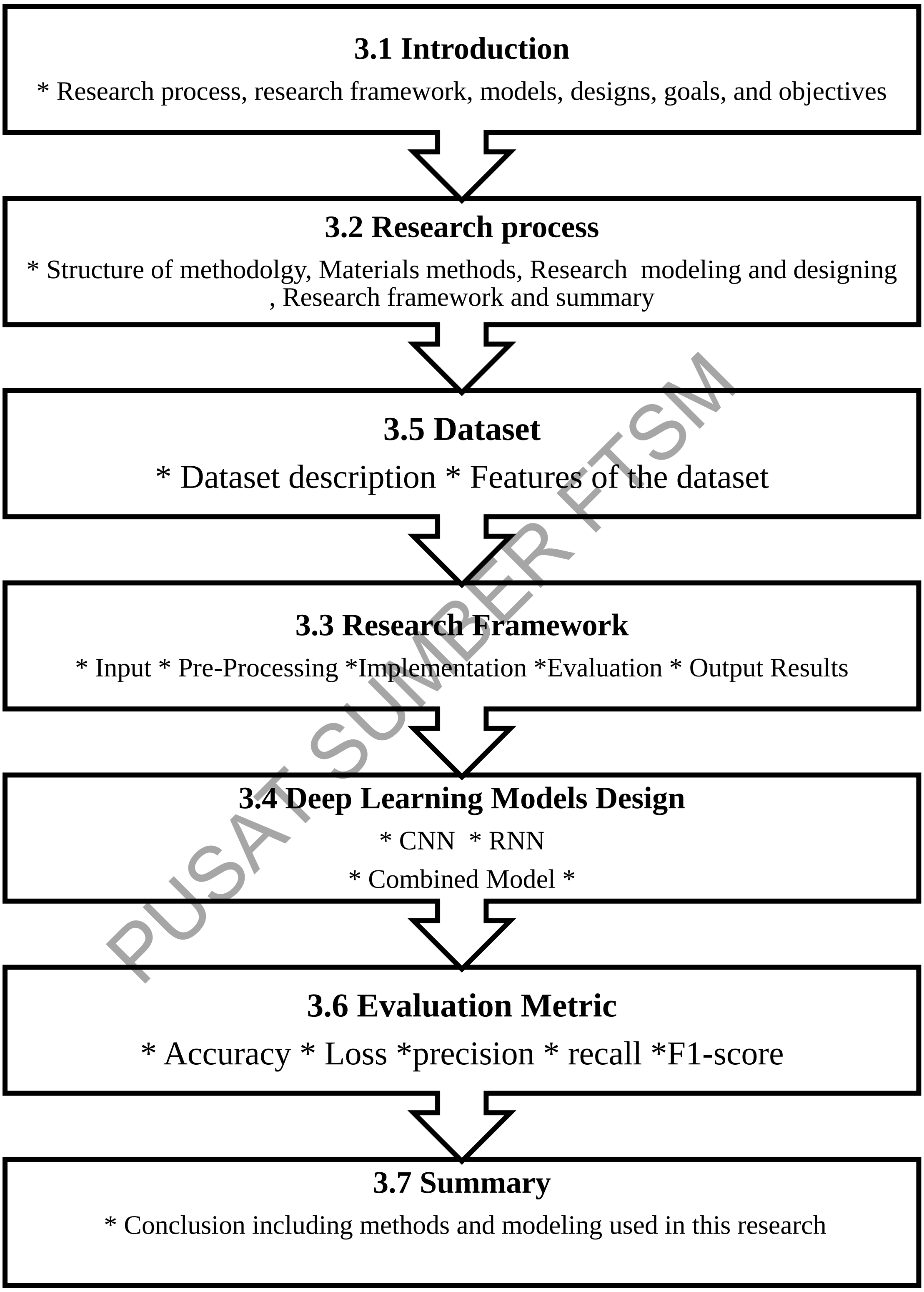

Figure 3.1 Workflow

3.3 DATASET

The Harvard Dataverse (Cardiac MR Center Dataverse) was used for the study's data sources. Public access to the dataset is possible at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/CI3WB6 .

Additionally, there are codes for data reading and the Multi-domain network. The following radial data dimensions are contained in each.mat file: (#slices, #phases, #samples_zero-padded_over-sampled_by2, #radial_views, #coils, real_and_imaginary_components). One dataset, for instance, comprises the following radial data: 1 slice, 25 cardiac phases, 832 samples (including oversampling and zero-padding), and 196, 16, 2 radial data. 16 coils and 196 radial views per frame for genuine and fictional components (as of 2020-08-02).

Body and spine phased-array coils were used throughout the imaging process using a 3T system (MAGNETOM Vida, Siemens Healthcare, Erlangen, Germany). Radial bSSFP cine data were collected from 101 patients and 7 healthy participants, for a total of 108 subjects, participants gave their signed, informed consent for the study team to utilize their cardiac MRI results. With the following imaging parameters:

Table 3.1 Dataset clinical details

Age	**50 ± 17 y**
Sex	72 M, 36 F
Heartbeats	72 ± 15 beats/min
Weight	80.6 ± 18 kg
Repetition time/echo time (TR/TE)	3.06/1.4 ms
Field of view	380 × 380 mm^2
Matrix size	208 x 208
In-plane resolution	1.8 x 1.8 mm^2
Slice thickness	8 mm
Flip angle	48°
Number of channels	16 ± 1
Retrospective ECG-triggering	25 cardiac phases

A mid-ventricular slice was imaged while the patient was holding their breath. Each patient had an average of 196 radial images taken during each cardiac phase, with a breath-hold time of about 14 heartbeats.

This dataset is a valuable resource for researchers and students in the field of heart disease diagnosis and prediction, as it provides a comprehensive set of variables that can be used to develop machine learning or deep learning models for this purpose.

3.4 RESEARCH FRAMEWORK

The following key steps are involved in developing a machine learning model for image processing and computer vision: Pre-processing, training, and assessment are included in these processes. For a model to effectively be developed that can properly evaluate and interpret pictures, it is important to comprehend each of these processes.

Pre-processing is the initial stage in this procedure. The image data is standardized and cleaned at this phase in order to get it ready for future analysis. This helps an image's qualities stand out by reducing noise. On the other hand, noise reduction entails eliminating undesirable fluctuations in the visual data, such as speckles or other sporadic disruptions. Techniques like median filtering and Gaussian smoothing can be used for this. Skeletonization is the process of stripping away all but the centerline of an item from a picture, leaving just a thin, and one-pixel depiction. This is helpful for simplifying an image while maintaining its key components. As the name implies, smoothing entails removing differences from the picture data to make it more regular.

An essential stage in creating an ML model particularly created for image processing jobs is the training phase. The model is built using the pre-processed image data at this point. Extraction of pertinent characteristics from the picture data, such as edges and textures, which function as model inputs, is a fundamental component of training. The model is trained to effectively categorize and interpret photos by exposure to a sizable dataset of countless images, learning to identify patterns and make knowledgeable predictions based on the extracted characteristics. This procedure helps the model to function better and enhances its capacity for efficient image processing and analysis.

Finally, the model's accuracy and reliability are evaluated. This stage involves testing the model on a fresh set of images and comparing its predictions to the actual class labels. The evaluation procedure aids in locating the model's flaws and offers insightful input for enhancing its functionality.

Pre-processing, training, and assessment are processes in creating a machine learning model for image processing. While training is building the model and training it on a sizable collection of pictures, pre-processing entails cleaning and standardizing the image data. Finally, assessment is utilized to assess the model's correctness and dependability.

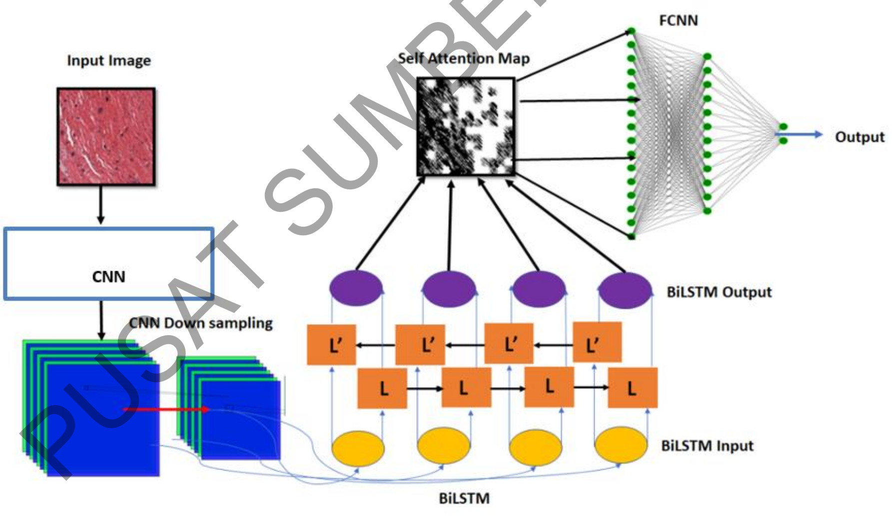

Figure 3.2 Architectural Representation

3.5 MODELS DESIGN

In this section, author provide an overview of the development process for the proposed combined model using CNN and combined model. The creation of each model involved a distinct set of procedures and techniques, which the author will delve into in-depth.

3.5.1 CNN-1 & CNN-2

The Convolutional Neural Networks are the specific type of deep learning algorithm that draws inspiration from the structure of the human visual cortex (Sahu & Dash, 2021). While CNNs are predominantly employed for tasks such as image classification and recognition, their versatility enables their application to diverse data types, including audio and text (Pouyanfar et al., 2018). In a typical CNN architecture, multiple convolutional and pooling layers are employed to process and compress the input data, with one or more fully connected layers generating the final prediction (Krizhevsky et al., 2017). Convolutional and pooling layers extract localized features from the input data, which are subsequently employed for classification by the fully connected layers (Liu et al., 2015).

Figure 3.3 general architecture of CNN

The architecture of a Convolutional Neural Network (CNN) can be broadly divided into four main parts:

Convolutional layers: Local characteristics are extracted from the input data via numerous filters used by this layer. The filters iteratively multiply elements of the incoming data by themselves and generate feature maps. After that, the feature maps are sent on to the subsequent layer (Keren & Schuller, 2019).

Pooling layers: The feature maps can be down-sampled and their spatial dimensions reduced using pooling layers without losing any useful information. The most used pooling strategy is max pooling (Gholamalinezhad & Khosravi, 2020).

Activation layers: In order to boost the network's representational capability, activation functions like ReLU and sigmoid are applied element-wise to the feature maps (Chadha & Schwung, 2019).

Fully connected layers: CNNs classify using one or more fully connected layers. These layers multiply feature maps from previous layers by a matrix and activate a softmax activation function to get the final output (Basha et al., 2020).

The number of layers, the number of filters in each layer, the size of the filters, and the choice of activation function are some of the hyperparameters that can be adjusted to optimize the performance of a CNN for a specific task (Aszemi & Dominic, 2019).

3.5.2 Combined Model (BiLSTM + CNN)

Researchers created a hybrid model that combines CNNs and LSTMs to take advantage of their strengths (Eapen et al., 2019). This hybrid model combines the strengths of bidirectional LSTMs in handling sequential input and CNNs in extracting visual features (Ullah et al., 2017). By processing sequences in both forward and backward directions, the bidirectional LSTM enables a deeper understanding of sequence data (Muneer et al., 2021). The hybrid model proves to be effective in tackling image classification problems that require spatial and temporal information processing, making it suitable for applications such as video categorization and image captioning.

In order to extract useful characteristics from an input image, a hybrid model combining a Convolutional Neural Network (CNN) and a Bidirectional Long Short-Term Memory (LSTM) commonly employs a succession of convolutional and pooling layers (Jamil et al., 2021). The sequential processing of these features by a bidirectional LSTM network is then used to capture the temporal relationships between the features (J. Zhang & Peng, 2020). In order to boost the model's precision, a bidirectional LSTM network may analyse the sequence input in both directions.

This type of hybrid model is particularly useful for tasks that require a combination of spatial and temporal information processing, such as video classification or image captioning. In video classification, for example, the CNN can extract features from individual frames, while the bidirectional LSTM network can capture the temporal relationships between frames to classify the entire video (Muneer and Fati et al., 2020).

In image captioning, the CNN can extract features from the image, while the bidirectional LSTM network can generate a descriptive sentence based on these features (H. Lu et al., 2021). The bidirectional LSTM network can also use the context of previously generated words to inform the generation of the next word (Santhanam, 2020).

Overall, the hybrid model that combines CNN with bidirectional LSTM offers the benefits of both networks, making it a powerful deep learning architecture for tasks that require both spatial and temporal information processing.

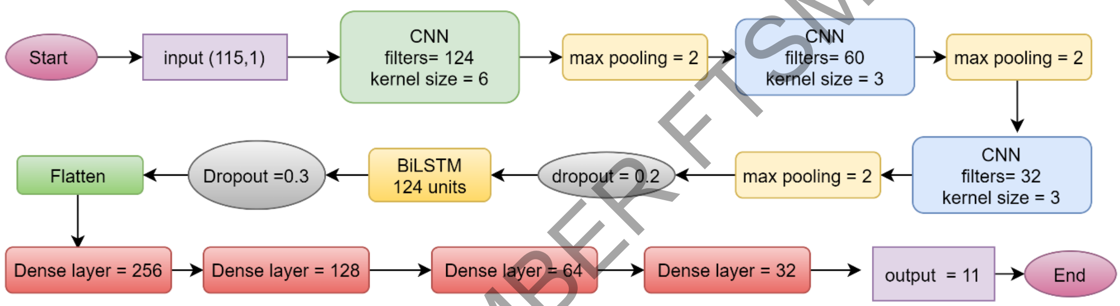

Figure 3.4 BiLSTM-CNN architecture

Instead of only employing one or the other, the author took an innovative method and combined CNN and BiLSTM in a single model. The first step in implementing BiLSTM is duplicating the network's first recurrent layer. This creates a layered structure with two recurrent layers. Then, the initial sequence must be fed into the first layer, while the second layer receives a mirror image of the initial sequence. Multiple investigations support the hypothesis that combining CNN and RNN yields superior results to either method working alone (Lu et al., 2019). Figures 9 and 10 depict the basic framework of the BiLSTM + CNN. To avoid overfitting, the author used a three-layer CNN architecture in this study, with a max-pooling layer added after each. In addition, the author employed a BiLSTM layer comprised of 64 and 128 units.

3.5.3 Recurrent Neural Networks (RNNs)

Artificial neural networks of the Recurrent Neural Network (RNN) variety were developed with the express purpose of handling sequential input. An RNN's ability to remember and use data from earlier inputs is made possible by a recurrent connection built into the network's architecture. RNNs are very helpful for tasks like natural language processing, speech recognition, time-series analysis, and in the context of your research, heart disease classification, because of their ability to capture sequential dependencies. The input layer, the hidden layer, and the output layer are the three fundamental building blocks of a recurrent neural network. Here's a quick rundown of what each part does:

1- Input Layer: The input layer receives sequential input data, such as time-series measurements, ECG signals, or other relevant features related to heart diseases. Each input in the sequence is typically represented as a vector or a time step.

2- Hidden Layer: The hidden layer is the core component of an RNN. It maintains a hidden state or memory that is updated at each time step. The hidden state retains information from previous inputs and influences the processing of future inputs. It allows the RNN to capture the context and temporal dependencies in the sequential data. In traditional RNNs, the unseen reality is computed at each time step based on the current input and the prior concealed state.

3- Output Layer: The output layer produces predictions or classifications based on the processed information from the hidden layer. It can have different configurations depending on the specific task.

For heart disease classification, it might be a binary output indicating being there or absence of a specific condition or a multi-class output representing different types of heart diseases.

3.6 EVALUATION

Evaluation metrics in machine learning play a crucial role in measuring the performance of a model on a given dataset (Abdar et al., 2021). These metrics provide insights into how well a model is able to make predictions and how it can be improved. Metrics for success are best selected in relation to the situation at hand and the model employed (Moraffah et al., 2020).

Accuracy is commonly employed as a measure of success when evaluating classification tasks. It quantifies the proportion of correctly predicted samples and serves as a straightforward metric for assessing the effectiveness of a model (Tharwat, 2021). In addition to accuracy, classification models are often assessed using precision, recall, and F1 score (Chicco & Jurman, 2020). Precision measures the ratio of correct predictions to the total number of positive predictions, while recall evaluates this ratio relative to the total number of positive samples. The F1 score provides a balanced assessment, incorporating both precision and recall (Kulkarni et al., 2020).

For binary classification problems, ROC curves and AUC are popular evaluation metrics. The AUC assesses the overall performance of a binary classifier, while the ROC curve compares the true positive rate to the false positive rate (Hodson, 2022).

3.6.1 Accuracy

Accuracy is a widely utilized evaluation metric in the field of machine learning, especially for classification tasks. It calculates the ratio of correctly classified samples to the total number of samples, offering a straightforward means of gauging model effectiveness (Muneer & Fati, 2020).

For example, if a model is trained on a dataset with 100 samples, and it correctly classifies 90 of them, the accuracy of the model is 90%. The accuracy metric provides an overall evaluation of how well the model is performing and can be useful in comparing different models (Kynkäänniemi et al., 2019).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{\text{Total number of predictions}} \quad \dots (3.1)$$

$$Accuracy = \frac{True\ Positives + \text{True Negative}}{(True\ Positives + \text{True Negative} + False\ Positives + False\ Negative)} \quad \dots (3.2)$$

Accuracy is not necessarily the greatest metric for model performance. In some cases, a model with high accuracy might still have a large number of false positive or false negative predictions, which can be a problem in certain applications. In certain circumstances, precision, recall, or F1 score may better assess model performance.

Overall, accuracy is a useful evaluation metric in machine learning, but it should be used with caution and in conjunction with other metrics that provide a more comprehensive evaluation of model performance.

3.6.2 Loss

In the field of machine learning, the concept of "loss" pertains to the disparity between the anticipated and observed outcomes obtained from analysing a specific set of input data. Loss is alternatively referred to as "cost" or "objective function" (Zhang et al., 2021). The objective during model training is to minimize the loss, aiming to make the model's predictions as closely aligned with the actual outputs as possible (Samaniego et al., 2020)

The problem domain and the chosen model dictate the optimal loss function (Martinez & Stiefelhagen, 2019). For regression issues, a frequent loss function is the mean squared error (MSE), while for classification problems, the cross-entropy loss is often employed (L. Wu et al., 2018).

Throughout the training process, the loss function acts as a feedback mechanism to direct the optimization of model parameters. In order to minimise the loss, the optimizer makes adjustments to the model parameters. Adjusting the model's parameters over time reduces the loss and improves the accuracy of its predictions (Berghout & Benbouzid, 2022).

$$\mathbf{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad \ldots(3.3)$$

Loss plays a vital role in machine learning as it serves as a means to assess the performance of a model and guide the optimization of its parameters (Shi & Weninger, 2019). Through the minimization of loss, practitioners can enhance the accuracy of their models and attain superior outcomes for their specific applications (Krishnan & Tickoo, 2020).

3.6.3 Precision

Precision is a metric used in machine learning to evaluate the performance of a binary classifier. Accuracy is a metric that quantifies the ratio of correctly predicted positive instances (True Positives) to the total number of positive predictions made by the classifier (True Positives + False Positives) (Chicco & Jurman, 2020).

Precision is a measure of the accuracy of positive predictions, and is defined as:

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \quad \ldots(3.4)$$

When the accuracy value is high, the classifier demonstrates minimal errors in its predictions, while a low accuracy value indicates a higher number of mistakes made by the classifier. In domains such as medical diagnosis or fraud detection, where false positive predictions can have significant consequences, the significance of accuracy is underscored (Muneer et al., 2020).

When the accuracy of a classifier is high, it implies that the number of errors in its predictions is minimal. On the other hand, a low accuracy value suggests that the classifier is prone to making a greater number of mistakes. This becomes particularly crucial in fields like medical diagnosis or fraud detection, where the ramifications of false positive predictions can be substantial. Therefore, accuracy assumes great importance in such applications (Muneer et al., 2020).

3.6.4 Recall

Machine learning uses recall to evaluate binary classifiers. It calculates the ratio of valid positive predictions (True Positives) to actual positive instances (True Positives + False Negatives) in the data (Muneer et al., 2020).

Recall is a measure of the completeness of positive predictions, and is defined as:

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \quad \ldots(3.5)$$

A high recall number implies that the classifier is able to properly identify most of the positive cases in the data, whereas a low recall value shows that the classifier is missing many of the positive instances. Recall is especially critical in situations where false negatives have substantial effects, such as spam filtering or cancer diagnosis (Podder et al., 2021) (Podder et al., 2021).

Like precision, recall should not be used as the sole metric for evaluating classifier performance. The F1-score finds a happy medium between accuracy and recall. It is the harmonic mean of the two measures.

3.6.5 F1-score

The F1-score balances precision and recall in machine learning binary classifiers. Precision-recall harmonic mean (Grandini et al., 2020).

The F1-score is a single value that go over the precision and recall of a classifier into a single metric, and is defined as:

$$F1 - score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \quad \ldots(3.6)$$

The F1-score is especially useful when the positive class is rare, or when there is a severe imbalance in the distribution of positive and negative instances in the data. In such cases, precision or recall alone may not be a good indicator of classifier performance, and the F1-score provides a more balanced evaluation of classifier performance (Li et al., 2019).

3.6.6 Contributions and Implications of the Study

The primary contribution of this research lies in the creation and assessment of deep learning models specifically designed for the classification of MRI data. The findings of the proposed study indicate that integrating CNN and RNN architectures can enhance the performance of these models, resulting in improved accuracy when categorizing MRI dataset as either normal or diseased.

Medical image analysis stands to benefit greatly from the conducted research. MRI data are a common diagnostic tool in clinical settings, and accurate and efficient classification of these images can improve patient outcomes by enabling early detection and treatment of diseases. The deep learning models developed in this study have the potential to assist radiologists and clinicians in the diagnosis of chest diseases, especially in resource-limited settings where access to specialized medical personnel is limited.

3.7 SUMMARY

The author discusses in detail the necessary conditions for putting the suggested paradigm into practice in this chapter. How to build and apply the model, as well as what elements will affect it and how to deal with them. Additionally, dataset is explained and also provides the whole files information of the MRI data in the dataset section. This chapter discusses and analyzes all of these significant pieces of information. The chapter also discusses the characteristics, kinds, counts, and assessment metrics of the datasets utilized in the thesis, including accuracy, loss, and precision. Several hyper-parameters, including the number of layers, the number of filters inside each layer, the size of the filters, and the choice of activation functions, may be changed to improve the performance of a CNN.

This type of deep learning architecture combines the best of both models by using a bidirectional LSTM for sequential data processing and modeling and a CNN for extracting visual features. As a summary, this chapter discusses the datasets utilized in the thesis as well as the assessment measures. It also describes the methods and models employed in the research.

CHAPTER IV

RESULTS AND DISCUSSION

4.1 INTRODUCTION

The proposed technique of a combination model for heart disease diagnosis utilizing MR imaging is discussed and evaluated by the author in this chapter. Prior to being input into the models, the images were cleaned and subjected to conventional pre-processing and assessment metrics like accuracy, loss, precision, recall, and f1-score. The author summarizes the research objectives, hypotheses, methodology, and methods for gathering and analyzing data at the beginning of this chapter. The study's findings are then presented by the author along with tables and statistical analysis. Finally, discuss the study's weaknesses and offer recommendations for more research in this field.

4.2 RESULTS AND ANALYSIS

This study tested and compared machine learning models for heart disease diagnosis using MRI data. The proposed work is implemented in Python 3.10 enabled Keras and Tesorflow packages and other mandatory libraries such as matplotlib, pandas. The majority of this section is dedicated to discussing data pre-processing and cleaning, as well as the creation and testing of the models.

4.2.1 Data Pre-processing and Cleaning

To ensure high-quality input for the machine learning models, the MRI data were cleaned and processed to eliminate noise and other artefacts prior to training. The photos were preprocessed by converted to grayscale and having their pixel values normalized to fall within the range 0-1. Additionally, both manual and automatic techniques were used to segment the pictures to obtain the region of interest (ROI) encompassing the heart.

The cleaning process involved removing any images with artifacts, such as motion or breathing artifacts, and ensuring that the remaining images were properly labeled as normal or diseased. As a dataset were acquired in 101 patients and 7 healthy subjects (108 total subjects) images were randomly divided into training (87 subjects) and testing (21 subjects) subsets.

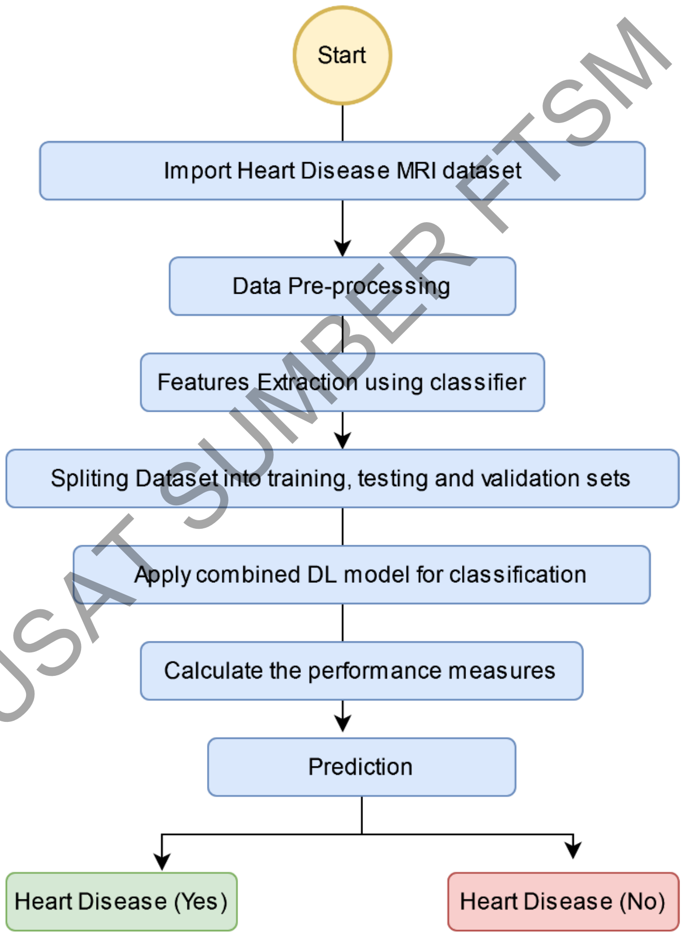

Figure 4.1 Flow chart of proposed model

The data was divided into three sets: a training set, a validation set, and a testing set after going through the appropriate cleaning and pre-processing stages. The validation and testing sets each included 10% of the data, leaving the training set with 80%. To tweak hyper-parameters and reduce over-fitting, the models were trained using the training set and then fine-tuned and optimized using the validation set. Testing the models on the testing set allows to determine how well they performed overall.

Table 4.1 Characteristics of the Preprocessed and Cleaned Dataset

Total	Training set	Testing set	Validation set
	80%	10%	10%

Overall, assuring the quality of the data and enhancing the precision of the models required the pre-processing and cleaning of the data. The photos' dimensionality was reduced and any unnecessary characteristics were removed thanks to the uniform size, grayscale conversion, and normalization, which also made sure that the pixel values were scaled consistently. For effective model training and assessment, the segmentation made sure that the clean pictures were correctly labeled.

4.2.2 Model Evaluation

In this section, the author discusses and analysis the combined model evaluation for detecting heart disease from MRI dataset. The author trained and evaluated each model on the pre-processed and cleaned dataset described in Section 4.2.1.

a. CNN Models

The author developed two CNN models for this study. The first model, CNN-1, consisted of three convolutional layers with kernel sizes of 3x3, followed by three max pooling layers with a pool size of 2x2.

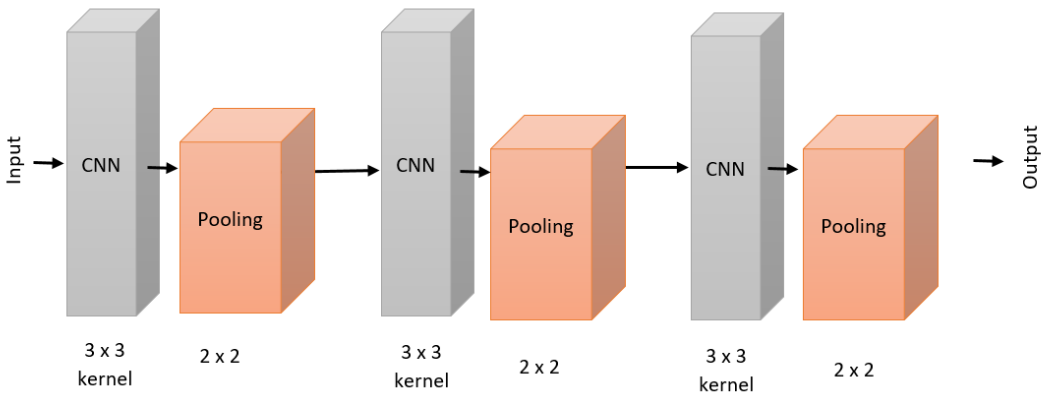

Figure 4.2 CNN-1 Model

The second model, CNN-2, consisted of five convolutional layers with kernel sizes ranging from 3x3 to 5x5, followed by two max pooling layers with a pool size of 2x2. The overall architecture of CNN-2 is the same as CNN-1 just the number of layers and kernel size is changed. Table 4.2 shows the performance metrics of the CNN models. Both models achieved high accuracy, with CNN-2 slightly outperforming CNN-1. However, the precision and recall scores of both models were relatively low, indicating that they were not as effective in correctly identifying diseased cases as they were incorrectly identifying healthy cases. The F1 scores of the models were also relatively low, indicating a trade-off between precision and recall.

Table 4.2 Performance Metrics of CNN Models Testing set.

Model	Accuracy	Precision	Recall	F1 Score	Loss
CNN-1	0.83	0.74	0.66	0.70	0.65
CNN-2	0.85	0.77	0.69	0.72	0.63

b. RNN Models

In proposed study, the author created two RNN models. The first model, RNN-1, comprised of two LSTM layers, each containing 64 units, followed by a dense layer with a sigmoid activation function.

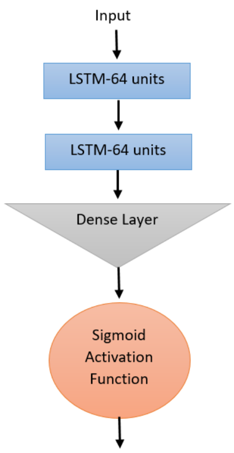

Figure 4.3 RNN-1

The second model, RNN-2, included three LSTM layers with 64, 128, and 256 units, respectively, followed by a dense layer with a sigmoid activation function.

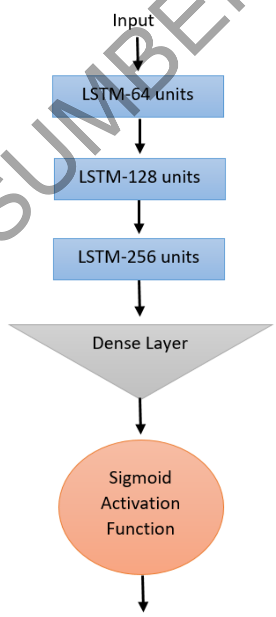

Figure 4.4 RNN-2

Table 4.3 shows the performance metrics of the RNN models. Both models achieved high accuracy, with RNN-2 outperforming RNN-1. However, like the CNN models, the precision and recall scores of both RNN models were relatively low. The F1 scores of the models were also relatively low, indicating a trade-off between precision and recall.