An AI-Aided Cardiovascular Care Unit for the Classification of Arrhythmias and Cardiac Maladies

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Dedication

Dedicated to:

My Love... Ms. Razia Umar and Mr. Umar Hayat

My Life...Ebraheem, Moosa, Fatimah

My Soulmate... Muhammad Mudasser Ahmad

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I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at Department of Computingat School of Electrical Engineering & Computer Science (SEECS) or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at School of Electrical Engineering & Computer Science (SEECS) or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics which has been acknowledged.

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Umara Umar

Contents

List of Abbreviations

AI Artificial Intelligence

ML Machine Learning

DL Deep Learning

WHO World Health Organization

ECG Electrocardiogram

HR Heart Rate

BP Blood Pressure

SpO2 Saturation of Peripheral Oxygen

CVDs Cardiovascular Diseases

ICU Intensive Care Unit

CCU Cardiac Care Unit

CNN Convolutional Neural Network

DNN Deep Neural Network

SVM Support Vector Machine

DT Decision Tree

RF Random Forest

MIT-BIH Massachusetts Institute of Technology and Beth Israel Hospital

ANN Artificial Neural Network

RNN Recurrent Neural Network

MLP Multilayer Perceptron

RBFNN Radial Basis Function Neural Networks

NN Neural Network

CUDB Creighton University Ventricular Tachyarrhythmia Database

VFDB Malignant Ventricular Arrhythmia Database

PCA Principal component analysis

DWT Discrete Wavelet Transform

CWT Continous Wavelet Transform

PSO Particle Swarm Optimization

TSVM Twin-Support Vector Machine

RBF Radial Basis Function

AAMI Association for the Advancement of Medical Instrumentation

BBNN Block-Based Neural Network

CT Clinical Trials

CAC Coronary Artery Calcium

PNN Probabilistic Neural Network

LSTM Long Short-Term Memory networks

MLPNN-BP Multilayer Perceptron Neural Network-Back Propagation

UCI University of California Irvine Machine Learning Repository

AUC Area under the ROC Curve.

HF Heart Failure

TNMG Telehealth Network of Minas Gerais.

CODE Clinical Outcomes in Digital Electrocardiology

MPA Marine Predators Algorithm

CA Cardiac Amyloidosis

ICA Independent Component Analysis

MRDWT Multiresolution Discrete Wavelet Transform

LBBB Left Bundle Branch Block

RBBB Right Bundle Branch Block

DHCAF Dynamic Heartbeat Classification with Adjusted Features

MCHCNN Multi-Channel Heartbeat Convolution Neural Network

NB Naive Bayes

RBM Restricted Boltzmann Machine

DBN Deep Belief Networks

2D-CNN 2 Dimensional CNN

GRNN General Regression Neural Network

MLII Modified Limb Lead II

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Abstract

Pakistan, like many developing countries, faces several challenges in providing standard healthcare facilities, particularly in less privileged and least developed areas. Cardiovascular diseases (CVDs) are a leading contributor to the reported mortality rate in Pakistan, constituting approximately 30-40 percent of all documented deaths. Unfortunately, the late response in providing specialized health emergency services exacerbates the problem. Cardiologists, who are responsible for providing specialized care to CVD patients, spend a significant amount of time diagnosing the condition, leaving them with less time to focus on treatment, which can be a matter of life and death. To address this issue, an AI-aided system has been proposed that focuses on swift and accurate diagnosis of CVDs and Cardiac Arrhythmias. The system employs an ensemble model that consists of a machine learning (ML) model and a deep learning (DL) model. The proposed ensemble model only takes non-invasive cardiac parameters as an input. The ML model assesses cardiac parameters such as temperature, blood pressure (BP), oxygen saturation (SpO2), and heart rate (HR), while the deep learning model analyzes electrocardiogram (ECG) signals. This combination of cardiac parameters and ECG analysis can provide accurate diagnosis and treatment recommendations in a specific context. To develop a complete cardiac dataset, the ECG dataset from MIT-BIH was extended by using another dataset consisting of temperature, BP, SpO2, and HR. The proposed ensemble paradigm was evaluated by using various evaluation measures including accuracy, F1-score, recall, precision, specificity, and sensitivity. Our findings indicate that the proposed framework outperformed other cutting-edge models for the given cardiac dataset. Moreover, this research promises to predict maximum CVDs and Arrhythmia classes by applying smart AI techniques. Ultimately, the proposed AI-aided system can significantly reduce the workload of cardiologists by enabling them to focus more on treatment rather than diagnosis.

CHAPTER 1

Introduction

This chapter offers a comprehensive exploration of the pertinent backgrounds and fields of knowledge that are relevant to this study. It commences by elucidating the historical context of the issue the research seeks to tackle and the driving factors behind undertaking the study. The problem statement is identified and research objectives are presented, along with the proposed approach to address the identified problem. Additionally, the chapter highlights the key contributions and novelty of the study. Overall, this introduction sets the foundation for the subsequent chapters and provides a clear outline of the research objectives and approach.

1.1 Background

In today's contemporary society, our fast-paced lifestyle and dietary habits have detrimental effects on our health. A rapid increase in the health issues has been observed due to modern lifestyle. Consequently, a remarkable raise in heart diseases has been noticed. AI modeling in healthcare is considered a highly challenging research domain, primarily due to the criticality of acquiring valuable data [3]. The recent surge in AI methodologies has established a robust foundation for a diverse array of applications within the healthcare sector. Artificial Intelligence (AI) is significantly contributing to various aspects of healthcare, such as disease diagnosis/prognosis, pattern recognition, and more cost-effective treatments [6, 7]. Undeniably, AI empowers the system to enhance its cognitive capabilities and achieve more accurate predictions.

The prediction of cardiovascular diseases (CVDs) is a highly discussed and researched topic within the medical industry. AI-based prediction systems have the potential to greatly assist in early disease detection, thereby reducing associated risks. The application of AI in cardiac electrophysiology and automated ECG interpretation is not a new concept, having existed in various forms since the 1970s [1].

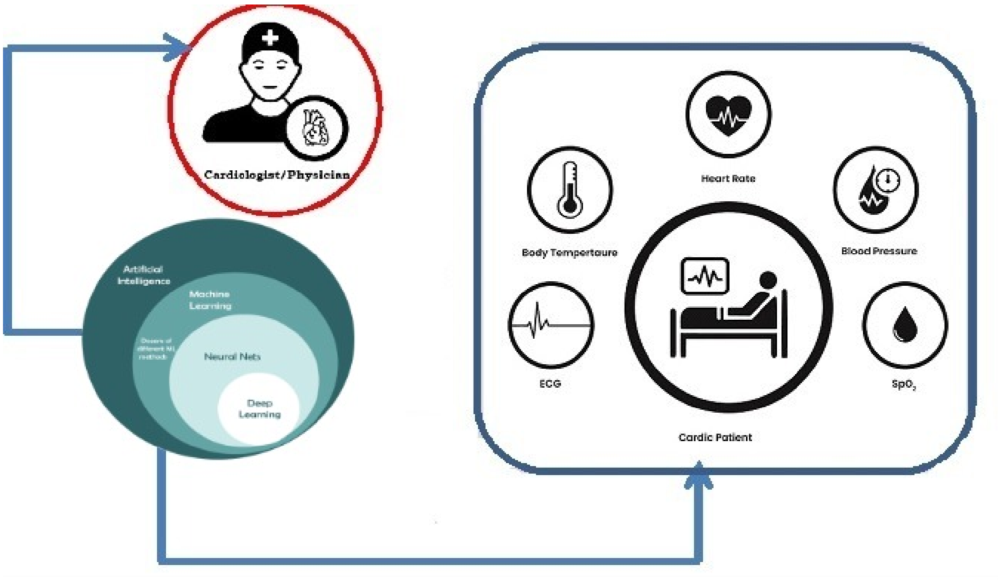

Figure 1.1: AI-based Cardiac Care Unit

Artificial Intelligence (AI) encompasses cognitive functions similar to those of humans, such as perceiving information from the environment and executing actions using algorithms, utilization of pattern matching, cognitive computing, and deep learning in machines (computer systems) aims to accomplish particular goals [39]. Machine Learning (ML), which falls under the umbrella of AI, entails the process of training computers to swiftly, precisely, and effectively analyze extensive datasets through the utilization of intricate computational and statistical algorithms [21]. In the realm of predictive modeling, supervised ML techniques have demonstrated greater success in survival prediction and possess higher prognostic value in contrast to conventional clinical risk scores [31]. Deep Learning (DL), which falls under supervised machine learning, is dependent on neural networks (NN) and automated algorithms that extract meaningful patterns from extensive data collections [32]. In the medical domain, numerous widely adopted deep learning algorithms are utilized, including Artificial Neural Networks (ANN) such as Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNN/ConvNet). It also includes Recurrent Neural Networks (RNN), deep belief networks (DBN), Radial Basis Function Network (RBFN), and deep neural networks (DNN) [39]. Figure 1.1 shows an AI-based cardiac care unit.

Unlike conventional supervised machine learning (ML) techniques, DL models can effectively and automatically learn complex representations of data without the need for manual feature engineering. This makes DL particularly useful for problems involving raw input data that are difficult to manually process and analyze.

One area where DL has demonstrated significant success is in the field of automated electrocardiogram (ECG) interpretation. Early supervised ML methods for ECG analysis relied on manually defined ECG features, such as amplitude, duration, and morphology of specific ECG components. However, these methods were limited in their ability to capture the full complexity of ECG signals, which can contain subtle patterns and relationships that are difficult to extract using hand-crafted features. In contrast, DL models can automatically learn to extract meaningful features from raw ECG data, allowing for more accurate and comprehensive analysis. For example, a modern DL model can be trained to detect sinus rhythm and various arrhythmias directly from raw ECG signals, without the need for manual feature engineering. This approach has been shown to achieve performance that is comparable to, or even exceeds, that of human experts in detecting and diagnosing cardiac abnormalities[29]. ML/DL techniques offer significant advantages in several key domains of cardiac healthcare, encompassing prognostication, diagnostic procedures, categorization, therapeutic interventions, and the optimization of clinical workflows.

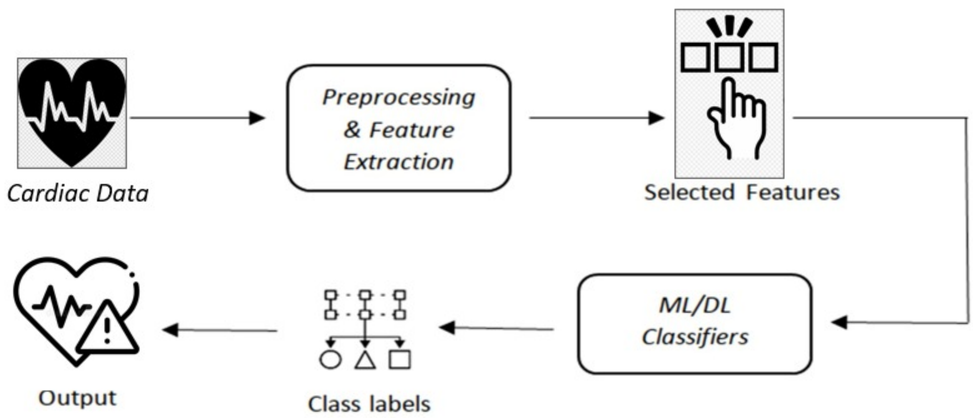

Figure 1.2: AI-based CVD Classification

Utilizing AI, a cardiac system ensures effective monitoring of the physical symptoms [4] experienced by cardiac patients, including temperature, systolic and diastolic blood pressure (BP), Oxygen Saturation (SpO2), Electrocardiogram (ECG), and heart rate (HR) [5]. Furthermore, it seamlessly integrates with relevant environmental factors, enabling comprehensive monitoring without any lapses. Figure 1.2 illustrates AI-based CVD classification. By leveraging the power of AI, the cardiac care framework can provide continuous monitoring and early detection of cardiac abnormalities, enabling timely intervention and treatment. This personalized and proactive approach to cardiac care can significantly improve patient outcomes and reduce the burden on healthcare systems. In summary, AI-based cardiac care frameworks offer a promising solution for pervasive and effective cardiac healthcare, providing personalized and proactive monitoring of physical symptoms and environmental parameters, and ensuring compliance with medicinal and safety standards.

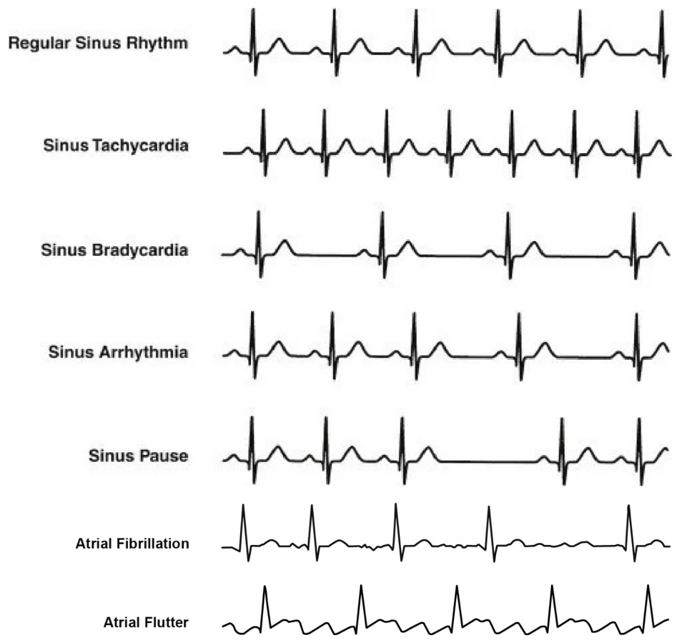

Figure 1.3: Types of Arrhythmia

The Electrocardiogram (ECG) serves as a crucial diagnostic tool in the medical field for detecting various cardiac abnormalities. It captures the cardiac muscle's electrical signals during contraction, and an electrocardiograph is employed to record the patient's ECG. This diagnostic test offers valuable insights into heart rate and rhythm, aiding physicians in identifying potential current or past heart attacks experienced by the patient. Due to its proven reliability, ECG is commonly used as the initial test for assessing heart conditions. It can also detect abnormalities in heart rhythm, known as arrhythmias. ***Arrhythmia*** pertains to irregularities in the pace or pattern of the heart's pulsations. Figure 1.3 illustrates waveforms representing different types of arrhythmias, like atrial fibrillation, atrial flutter, and premature beats. Atrial fibrillation is distinguished by a disorganized, rapid, and unpredictable heart rhythm, with multiple impulses competing to travel through the atria and AV node. Atrial flutter, on the other hand, is a more organized and regular. Atrial arrhythmia arises from the presence of a rapid electrical pathway within the atrium. It is important to analyze and diagnose cardiovascular diseases (CVDs) accurately to reduce associated risks. While CVDs are a significant cause of concern, they can be treated and prevented with appropriate measures [18].

This study targets the impact and utilization of various AI models for ECG analysis along with other vital cardiac parameters. Therefore, one can say that this study is covering the combination of most of the vital parameters for the diagnosis/prognosis of specific heart maladies including different types of Arrhythmia. Physicians have shown substantial interest in the progress made in the domain of computational intelligence, specifically in machine learning (ML) and deep learning models. This has led to the development of integrated, reliable, and powerful methods to elevate the standards of healthcare within the crucial domain of cardiology. While deep learning techniques have gained attention in smart cardiology, it is evident that hybrid approaches are likely to yield more reliable outcomes instead of relying solely on specific AI models.

1.2 Research Motivation

The high prevalence of cardiovascular diseases (CVDs) and their associated mortality rates have been a major concern for healthcare professionals worldwide, including in Pakistan. The World Health Organization (WHO) has confirmed that CVDs are responsible for approximately 80% of sudden deaths, and it is projected that approximately 23.6 million individuals will succumb to mortality due to heart ailments by 2030 [13]. In Pakistan, an estimated 30-40% of all deaths are attributed to CVDs, which amounts the lives of approximately 200,000 individuals annually. According to certain statistics coronary heart disease emerges as the primary contributor to mortality [56]. Despite the advancements in medical science, the diagnosis of CVDs in Pakistan primarily relies on the assessment of physicians. However, the lack of AI-aided cardiac care units in Pakistan prevents doctors from fully exploiting the potential of technology for enhanced diagnosis and treatment of CVDs. Past studies have predominantly focused on analyzing electrocardiogram (ECG) signals and classifying arrhythmias, neglecting other significant cardiac parameters that could contribute to diagnosing various cardiovascular diseases (CVDs). Several studies have predicted five arrhythmia classes using only ECG, including Shadmand et al. [14], Raj et al. [12], Pengfei Li et al. [10], Azariadi et al. [8], Houssein et al. [44], Li et al. [45], and Mohonta et al. [47]. Three arrhythmia classes were predicted in [46]. However, since cardiology is a vast field, it is crucial to explore the impact of other vital indicators in diagnosing CVDs. Hybrid approaches have been investigated in various studies to improve the accuracy of disease detection. As an example, Elhaj et al. [9] presented a hybrid approach for the detection of five arrhythmia classes, while Mathews et al. [22] used a hybrid technique to detect two CVD classes. Rai et al. [25] proposed an innovative hybrid approach for the automated identification of three distinct categories of cardiac arrhythmias Jackins et al. [41] also used a hybrid machine learning approach, combining Naive Bayes (NB) and Random Forest (RF) algorithms for the classification of datasets pertaining to various medical conditions including diabetes, cancer, and coronary heart malady.

Despite some studies attempting to incorporate additional parameters beyond ECG to predict CVDs, their success has been limited [15, 33]. For example, Wolterink et al. [15] put forward a deep learning framework that combined ECG and non-ECG features, but the results were not significantly better than those obtained using ECG alone. Similarly, Subhadra et al. [33] proposed a neural network approach with additional features such as age, gender, and medical history, but the model accuracy was not improved significantly. However, the hybrid model proposed in [36] successfully detected five types of arrhythmia based on both ECG and heart rate (HR), demonstrating that incorporating HR as an additional parameter can improve the accuracy of arrhythmia detection. Additionally, it is also observed that most of the available ECG datasets, like MIT-BIH Arrhythmia Database [49], Challenge ECG dataset [50], PTB Diagnostic ECG Database [51], for predicting cardiovascular diseases (CVDs) do not incorporate other crucial cardiac parameters of the patient, limiting the accuracy and effectiveness of CVD prediction models. Therefore, it is essential to explore the impact of other vital indicators beyond ECG and incorporate them into hybrid approaches to enhance the accuracy of CVD diagnosis.

Unfortunately, there is currently no AI-aided Cardiac Care System available in Pakistan that can assist doctors in making quick and accurate diagnoses. Despite having access to the latest medical machinery [52], [53], such as ECG, ECHO, Angiography, and Angioplasty, we heavily rely on cardiologists for prognostic and diagnostic tasks. This dependency on cardiologists becomes particularly problematic in remote regions with limited access to medical professionals. Thus, the integration of AI in healthcare holds the potential of transforming the diagnosis and treatment of CVDs. AI-based systems can accurately diagnose and classify different types of CVDs, including coronary artery disease, arrhythmias, heart failure, and other unexplored heart maladies. This would significantly reduce the workload of cardiologists and enable them to focus more on treatment and patient care. Moreover, shifting to a ubiquitous healthcare mode [43] could help promote cardiovascular healthcare and reduce the high incidence of sudden deaths due to CVDs.

1.3 Problem Statement

Cardiovascular diseases (CVDs) have a high prevalence and associated mortality rates, making them a significant concern for healthcare professionals worldwide, including in Pakistan. Despite the advancements in medical science, the diagnosis of CVDs in Pakistan primarily relies on the assessment of physicians, and there is a lack of AI-aided cardiac care units in the country. This prevents doctors from fully exploiting the potential of technology for enhanced diagnosis and treatment of CVDs. Additionally, past studies have predominantly focused on analyzing electrocardiogram (ECG) signals and classifying arrhythmias, neglecting other significant cardiac parameters that could contribute to diagnosing various CVDs. Furthermore, most available ECG datasets for predicting CVDs do not incorporate other crucial cardiac parameters of the patient, limiting the accuracy and effectiveness of CVD prediction models. Therefore, the problem addressed in this thesis is the need to develop an AI-aided cardiac care system that incorporates additional vital indicators beyond ECG to accurately diagnose and classify different types of CVDs, including coronary artery disease, arrhythmias, heart failure, and other unexplored heart maladies. This system can significantly reduce the workload of cardiologists and enable them to focus more on treatment and patient care, particularly in remote regions with limited access to medical professionals. Moreover, this thesis proposes exploring the impact of other vital indicators beyond ECG and incorporating them into hybrid approaches to enhance the accuracy of CVD diagnosis. By addressing this problem, this thesis aims to promote cardiovascular healthcare and reduce the high incidence of sudden deaths due to CVDs in Pakistan.

1.4 Research Objectives

The primary goals of the research being conducted are as follows:

- To develop an AI model for a hybrid combination of CCU parameters and ECG analysis.
- To predict maximum number of cardiovascular diseases and arrhythmia classification using appropriate AI techniques.
- To integrate ECG along with other parameters.

- To develop and implement an AI-based cardiac solution in Pakistan for the accurate diagnosis and classification of various cardiovascular diseases. The introduction of such a system has the potential to revolutionize the healthcare industry in Pakistan.

1.5 Novelty and Contributions

Some significant contributions made by the conducted study are mentioned below:

- A hybrid computational model has been developed to perform an analysis of the maximum non-invasive cardiac parameters (five).
- A novel dataset has been developed consisting of ECG along with other vital cardiac parameters. The inclusion of additional cardiac parameters alongside ECG data in the dataset can potentially enhance the quality and scope of cardiac analyses and aid in the development of improved diagnostic and prognostic models.
- The model has been designed to accommodate a significant number of cardiovascular and non-cardiovascular conditions (seven).
- The model proposed in this study has been employed for the classification of a wide range of cardiovascular diseases (thirteen CVDs) using the novel dataset.

1.6 Research Scope

This study focuses on the impact and utilization of AI models for ECG analysis, as well as other vital non-invasive parameters, in the Cardiac Care Unit. These parameters include temperature, systolic and diastolic blood pressure, oxygen saturation, ECG, and heart rate. Therefore, this study covers a combination of essential parameters for diagnosing and prognosing specific heart conditions, including various types of arrhythmia. However, it does not involve acquiring invasive parameters. Single-lead recordings are used for ECG analysis in our study. In this research study, we specifically address instances of high blood pressure, as it is considered a more life-threatening scenario for cardiovascular patients based on discussions with cardiologists. Additionally, for high and low heartbeats, we treated them as a single case of "abnormal heart rate".

1.7 Thesis Outline

The subsequent chapters of the thesis are organized as follows:

- "Literature Review" explains the work done in AI-aided Cardiac Healthcare from 2016 till 2022. The categorical research done in the field of Cardiac Care by using different Machine Learning and Deep Learning methodologies is presented in intricate detail.
- "Methodology" describes the proposed model for ECG analysis, arrhythmia detection and prognosis/diagnosis of heart maladies using other vital parameters in detail. It also explains different datasets, data pre-processing steps, and development of the Hybrid model.
- "Results & Discussion" elaborates the working of our proposed model by using different graphical representations and evaluation measures.
- "Conclusion" summarises brief description of this research work along with possible tasks that can be carried out in later stages for further research purpose.

The upcoming chapter 2 provides a comprehensive overview and critical analysis of prior studies in this field.

CHAPTER 2

Literature Review

A comprehensive review of the available literature on AI-based cardiac healthcare from 2016 to 2022 is presented in this chapter. Specifically, it examines and compares different machine learning and deep learning models to predict and classify various cardiovascular diseases (CVDs). In Section 2.1, various studies that employ machine learning models for CVDs prediction are discussed, while Section 2.2 focuses on deep learning models. Section 2.3 discusses some hybrid approaches whereas Section 2.4 presents a critical analysis of the past studies in the field of AI-based cardiac care, highlighting their strengths and limitations.

2.1 Machine Learning Models in Predictive Cardiac Care

Machine learning (ML) is a specialized branch of artificial intelligence (AI) that utilizes sophisticated statistical models and advanced computational techniques to facilitate precise and efficient analysis of data. This powerful tool enables computers to perform complex tasks, such as pattern recognition and anomaly detection, with remarkable accuracy and speed.

The study presented in the research conducted by Saxena et al. [13] centers around the development of an Efficient Heart Disease Prediction System using a Decision Tree approach. This system aims to provide valuable assistance to medical professionals by facilitating efficient decision-making based on specific parameters. To train and evaluate the system, the researchers employed a 10-fold technique, attaining an accuracy level of 86.7% during the testing stage and 87.3% during the training stage. The proposed system generates a set of prioritized rules, including Original Rules, Pruned Rules, Rules without duplicates, Classified Rules, Sorted Rules, and Polish, thereby enhancing its overall functionality.

The methodology proposed by Raj et al. [12] introduces a PSO-tuned SVM model for cardiac signal analysis. The study focuses on feature representation using symmetrical features, which leads to improved accuracy. In the category-based assessment scheme, the implemented approach attained an outstanding accuracy of 99.18%, highlighting its remarkable performance. while in the patient-based assessment scheme, it attained an accuracy of 89.10% when assessed using the MIT-BIH arrhythmia dataset. Another study conducted by Li et al. [11] introduces a method that combines wavelet packet entropy (WPE) with random forests (RF) for the categorization of ECG records. The primary emphasis of the research lies in the extraction of distinctive features and the classification process applied in the ECG analysis, employing the publicly available MIT-BIH dataset. Furthermore, Azariadi et al. [8] devised a computational algorithm for the examination and categorization of electrocardiogram data, specifically focused on diagnosing heartbeats, and successfully implemented it on an embedded platform based on the Internet of Things (IoT) technology. The algorithm employed the Discrete Wavelet Transform (DWT) to analyze the ECG and utilized a Support Vector Machine (SVM) for classification. The study reported a remarkable classification accuracy of 98.9%.

In the paper by Sahoo et al. [20], an enhanced algorithm is presented for the feature detection of QRS complex through the utilization of multi-resolution wavelet transform. The objective of this algorithm is to categorise four different kinds of ECG beats: normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), and Paced beats (P). Features extracted from the QRS complex are employed for the classification of cardiac abnormalities. Both a neural network (NN) and a support vector machine (SVM) classifiers are employed to accomplish the classification task. The effectiveness of this framework is assessed using a set of 48 ECG signals extracted from the MIT-BIH arrhythmia dataset. Performance evaluation measures, including sensitivity, specificity, and accuracy, are utilized to assess the algorithm's efficacy. The results demonstrate that the SVM classifier outperforms the NN classifier, with an average accuracy of 98.39% for SVM and 96.67% for NN. The proposed method shows superior performance in detecting ECG arrhythmia beats compared to the NN classifier with extracted parameters.

Nguyen et al. [23] introduced a technique for identifying shockable rhythms utilizing SVM, a machine learning algorithm. The algorithm is trained and tested on publicly available electrocardiogram (ECG) databases. The study incorporates two distinct databases: the Creighton University Ventricular Tachyarrhythmia Database (CUDB) & the MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB). The proposed algorithm was evaluated on the complete database, resulting in an average accuracy of 95.9%, sensitivity of 91.7%, and specificity of

96.8%. Another study conducted by Yang et al. [28] aimed to extract features from noisy ECG signals using the principal component analysis network (PCANet). The classification speed was improved by employing a linear support vector machine (SVM). A set of experiments was carried out on the MIT-BIH arrhythmia dataset, focusing on five categories of imbalanced ECG signals that were also noise-free. The algorithm proposed in the study achieved accuracies of 97.77% and 97.08% for the respective scenarios.

In the paper [26], a method for automated ECG signal classification is proposed. The proposed approach aims to develop a robust classifier model for the categorization of ECG recordings by employing the least-square twin-SVM algorithm and a feature set. The implementation of the classifier involves the utilization of the radial basis function (RBF) kernel. The method's evaluation includes both category-based and personalized schemes, with validation performed on the MIT-BIH ECG dataset. The experimental findings demonstrate notably higher overall accuracy. An accuracy rate of 99.21% was achieved in the category-based approach, while the personalized approach yielded an accuracy rate of 90.08%.

The research article by Raj et al. [37] introduces a novel methodology for real-time monitoring of ECG signals. The proposed methodology uses discrete wavelet transform (DWT) for feature extraction from heartbeats. These extracted features are combined with a Twin Support Vector Machines (TSVM) classifier, fine-tuned using Particle Swarm Optimization (PSO), for accurate recognition. The TSVM classifier demonstrates a significant improvement in speed, outperforming the standard SVM classifier by four times. Additionally, the PSO technique gradually optimizes the classifier parameters, leading to enhanced accuracy. The methodology is validated on the Physionet dataset, comprising 16 categories of ECG signals. When an abnormality is detected, the system generates a warning message as a notification. The proposed platform achieves an impressive overall accuracy of 95.68%, surpassing the performance of previous studies in this field.

2.2 Deep Learning Models in Predictive Cardiac Care

In the past few years, there has been a growing trend of utilizing deep learning models to various aspects of cardiac care, including diagnosis, risk prediction, and treatment planning. The ability of deep learning models to analyze and process large volumes of medical images, ECG signals, and clinical data has shown great potential in improving the accuracy of cardiac disease detection and prediction, as well as optimizing treatment plans. Despite their promising results, deep learning models still face some challenges in the context of cardiac care, such as the lack of sufficient high-quality data and interpretability.

Li et al. [10] implemented a GPU-based heartbeat classification method in their paper. The researchers utilized a parallel DOM (Document Object Model) for extracting heartbeat features and a parallel GRNN (Generalized Regression Neural Network) for classifying the heartbeats. The accuracy achieved on the MIT-BIH dataset, following the AAMI (American Association of Medical Instrumentation) standard, was 95%. When the approach was applied to real patient holter data, the classification accuracy was found to be 88%. In a different study conducted by Shadmand et al. [14], the focus was on classifying ECG heartbeats into five types based on the AAMI recommendation. They utilized a Block-based Neural Network (BBNN) as the classification model, where a feature vector extracted from the ECG signals was utilized as input. Through performance evaluation conducted on the MIT-BIH arrhythmia database, an exceptional classification accuracy of 97% was achieved.

Wolterink et al. [15] they introduced a novel approach for the automated scoring of coronary artery calcium (CAC) in coronary CT angiography. This method leveraged convolutional neural networks (CNN) to accomplish the task. Unlike existing methods that require coronary artery extraction, this approach employed a supervised learning technique to directly detect and measure coronary artery calcium (CAC). The study incorporated cardiac CT examinations from 250 patients, achieving sensitivity of 71% for the developed model. The study discussed in [16] aimed to implement a deep learning (DL) technique that is simple, reliable, and easily applicable for classifying different cardiac conditions. To evaluate the efficacy of the proposed approach, three distinct conditions of ECG waveforms were chosen from the MIT-BIH ECG dataset. The highest achieved accuracy rate for correct recognition reached 98.51%, while the testing phase exhibited an approximate accuracy of 92%.

In the study conducted by Sahoo et al. [19], a method was proposed to detect and extract informative features for the classification of six types of ECG beats collected from the MIT-BIH arrhythmia dataset. The extracted feature set was then subjected to classification using probabilistic neural network (PNN) and radial basis function neural network (RBF-NN) to identify arrhythmia beats. The achieved classification accuracy for the arrhythmia conditions was 99.54% with PNN and 99.89% with RBF-NN. Likewise, Oh et al. [24] proposed an automated approach in their research paper that combined a convolutional neural network (CNN) and long short-term memory (LSTM) for diagnosing five types of arrhythmia in ECG recordings. The uniqueness of their research contribution was the incorporation of ECG segments with varying lengths gathered from the MIT-BIH arrhythmia physiobank dataset. The proposed system demonstrated outstanding classification capabilities in managing data of varying lengths, achieving a remarkable accuracy rate of 98.10% through the implementation of a ten-fold cross-validation methodology.

The study presented by Sannino et al. [27] introduced an approach centered around a Deep Neural Network (DNN) for automatically classifying abnormal ECG beats and distinguishing them from normal beats. The architecture of the DNN encompassed seven hidden layers, with varying numbers of neurons in each layer: 5, 10, 30, 50, 30, 10, and 5. The experiments were carried out utilizing the well-known MIT-BIH arrhythmia dataset. The attained outcomes demonstrated that the implemented DNN achieved the highest accuracy across all datasets, including the training, testing, and complete datasets, with values surpassing 99%.

In the research conducted by Hannun et al. [29], a Deep Neural Network (DNN) was introduced for the purpose of classifying 12 rhythm classes. The dataset used in the study comprised a substantial collection of 91,232 single-lead ECGs obtained from 53,549 patients through ambulatory single-lead ECG recording. This dataset served as a valuable resource for the detection and classification of arrhythmias. The DNN model employed in the research consisted of 34 layers, showcasing a sophisticated architecture. The DNN exhibited promising performance, as evidenced by an average area under the receiver operating characteristic curve (ROC) of 0.97. Moreover, the proposed DNN attained an average F1-score of 0.837, surpassing the average F1 score of 0.780 achieved by cardiologists. Additionally, the DNN demonstrated higher sensitivity compared to the average cardiologists across all arrhythmia classes. It is noteworthy that the proposed model exhibited relatively high complexity.

The research study described in [30] Lin et al. proposed a framework for cardiac disease diagonosis and single-lead ECG analysis. The system comprised an IoT-based hardware on the front-end, sensors, a smart device application interface, a cloud database, and an AI platform utilizing a CNN model for the analysis of abnormal ECG recordings and the diagnosis of four specific types of arrhythmia. The accuracy of the system was reported to be 95.73%. The system was evaluated using the MIT-BIH dataset. In this methodology, the encoded data was accompanied by time stamps and stored on both local mobile devices and a cloud storage server. The system also allowed for the retrieval of a patient's history. However, it should be noted that to improve and train the model, a more extensive dataset from various clinical sources would be required. Additionally, it was acknowledged that certain types of arrhythmia could not be analyzed by this particular system.

The research presented in Subhadra et al. [33] introduced a diagnostic system using a Multilayer Perceptron Neural Network with Back-propagation (MLPNN-BP) as the training algorithm. The goal of this work was to formulate a system capable of predicting five categories of heart diseases. The diagnostic system utilized 14 significant attributes, including blood pressure (BP), ECG readings, glucose levels, cholesterol levels, chest pain, and others, based on relevant medical literature. The proposed system was evaluated and compared with other classification techniques, revealing that it surpassed alternative approaches in the accurate prediction of the heart maladies. The CVD dataset utilized in the research was acquired from the UCI Repository.

Cardiac attack, particularly Myocardial Infarction (MI), is a prevalent cardiac condition characterized by the obstruction of one or more coronary arteries. In the study conducted by Alghamdi et al. [34], an automated framework was introduced for the diagnosis of MI signals within the context of urban healthcare in smart cities. The proposed system utilized a Convolutional Neural Network (CNN) and was tested using the Physikalisch-Technische Bundesanstalt (PTB) standard ECG dataset. The framework achieved a remarkable accuracy of 99.02% in accurately detecting MI signals. The CNN network implemented in the proposed method comprised six convolutional layers, three pooling layers, two fully connected layers, and concluded with one softmax layer, thus totaling 12 layers. Notably, the proposed method demonstrated excellent performance in detecting MI signals even in the presence of noise within the ECG beats.

In the study conducted by Ribeiro et al. [38], a methodology was presented that involved training a Deep Neural Network (DNN) model by utilizing a dataset comprising over 2 million labeled examinations acquired from the Telehealth Network of Minas Gerais (TNMG) as part of the CODE study (Clinical Outcomes in Digital Electrocardiology). The DNN model exhibited excellent performance, outperforming the ability of cardiology resident physicians in accurately detecting and classifying six distinct abnormalities present in 12-lead ECG recordings. The model achieved F1 score exceeding 80% and the specificity above 99%. In Grogan et al. [40], a DNN model was developed for the identification of cardiac amyloidosis (CA) using standard 12-lead electrocardiograms (ECG). In the study, experiments were performed using subsets of single-lead and 6-lead ECG data. The single-lead model with the best performance exhibited an AUC of 0.86 and a precision of 0.78, while the performance of other single leads was comparable. On the other hand, the 6-lead model, specifically utilizing bipolar leads, achieved an AUC of 0.90 and a precision of 0.85. Mehmood et al. [42] proposed a method named Cardio-

Help for heart failure (HF) prediction, employing convolutional neural networks (CNN). The implemented model achieved an accuracy of 97% in HF prediction. These studies collectively demonstrate the effectiveness of DNN models in cardiac diagnosis and prediction, surpassing human performance in certain tasks and showcasing high accuracy levels.

The investigation carried out by Houssein et al. [44] had the objective of automating the enhancement of parameters in Convolutional Neural Networks (CNNs) for the classification of electrocardiogram (ECG) data. The researchers proposed a hybrid model named IMPA-CNN, which integrated an updated version of the Marine Predators algorithm (MPA) with CNN. The CNN paradigm was employed to classify various types of ECG rhythmias, including non-ectopic (N), ventricular ectopic (V), supraventricular ectopic (S), and fusion (F). To evaluate the performance of various optimization approaches, the study conducted experiments using well-known datasets such as the MIT-BIH ECG database, European ST-T dataset, and St. Petersburg INCART dataset. By utilizing the IMPA-CNN hybrid model, the researchers aimed to enhance the accuracy and efficiency of ECG classification tasks, leveraging automated parameter optimization techniques.

The article presented by Li et al. [45] introduced an enhanced deep residual CNN to classify various arrhythmia types. The proposed methodology utilized a CNN architecture consisting of 9 layers. Through experimentation on the MIT-BIH arrhythmia dataset, the proposed system demonstrated significant performance metrics. Notably, it accquired a sensitivity of 94.54%, positive predictive value of 93.33%, and specificity of 80.80% specifically for normal cases. The study classified arrhythmias into 15 classes based on the AAMI standard and grouped them further into 5 parent classes: normal (N), Supraventricular Ectopic beat (SVEB), Ventricular Ectopic beat (VEB), Fusion beat (F), and Unknown beat (Q). The objective was to accurately classify ECG recordings based on these arrhythmia categories using the developed deep residual CNN model.

The research paper presented by the authors in [46] introduced an automated approach for studying cardiac arrhythmias utilizing a 2D-CNN-LSTM model with 20 layers. The proposed methodology involved transforming the 1D ECG signal into 2D Scalogram colored images to create an optimal input for the network. In this hybrid model, the CNN component was leveraged for effective feature engineering, while the LSTM component was utilized for accurate classification. Preliminary results obtained from the MIT-BIH dataset demonstrated the superior efficacy of the proposed paradigm compared to other existing methods. The 2D-CNN-

LSTM model showcased improved performance in terms of efficiency and accuracy in the classification of cardiac arrhythmias. In another study conducted by Mohonta et al. [47], an 8-layer 2D-CNN model was introduced for classifying five types of arrhythmic beats employing ECG measurements from the MIT-BIH arrhythmia dataset. To generate the scalogram of short-length ECG segments, the authors utilized continuous wavelet transform (CWT). The developed model showcased remarkable mean accuracy, sensitivity and specificity with values of 99.65%, 98.87%, and 99.85% respectively.

2.3 Hybrid Models in Predictive Cardiac Care

The application of hybrid AI models in predictive cardiac care has shown promising results in improving patient outcomes. These models combine different Artificial intelligence (AI) approaches like machine learning, deep learning, and rule-based paradigms are utilized to examine vast amounts of data and identify patterns and trends that can be used to predict the risk of cardiac events in patients. In general, the utilization of hybrid AI models within predictive cardiac care holds tremendous potential for a groundbreaking transformation in the approaches to diagnosing and treating cardiovascular conditions thus leading to better patient outcomes and a reduction in healthcare costs.

The research article presented by Elhaj et al. in [9] introduces an effective system for ECG arrhythmia classification. This system combines two unique classifiers, namely SVM-RBF and NN, in a hybrid fashion. A series of experiments conducted on the proposed framework demonstrated that when PCA-DWT, ICA, and HOS models for feature extraction were combined with SVM-RBF and NN, it resulted in equal mean accuracy, sensitivity, and specificity of 98.9%. The study focuses on analyzing five categories of arrhythmia by utilizing the MIT-BIH ECG dataset. In a related work discussed in the article by Mathews et al. [22], a hybrid framework is presented based on the utilization of Restricted Boltzmann Machine (RBM) and deep belief networks (DBN) for the categorization of single-lead ECG recordings. Experimental evaluations on the MIT-BIH dataset reveal that the proposed deep learning framework accquired an accuracy of 93.78% for SVEB beat category and 96.94% for VEB class. The hybrid model demonstrates promising performance in the accurate classification of arrhythmias.

In the research article [25], a novel hybrid technique is introduced for the automatic detection of cardiac arrhythmia. The proposed approach utilizes Multiresolution Discrete Wavelet Transform (MRDWT) for feature extraction, while arrhythmia classification is performed using a

Multilayer Probabilistic Neural Network (MPNN) classifier. By applying this technique to the MIT-BIH arrhythmia dataset, accurate detection of LBBB, RBBB, and normal heartbeats are achieved. The system demonstrates an impressive overall accuracy of 99.07% using the MPNN classifier. This innovative approach shows promising results in the accurate identification of cardiac arrhythmias.

In the research article [36], a comprehensive framework is presented for heartbeat classification, consisting of two modules: Dynamic Heartbeat Classification with Adjusted Features (DHCAF) and Multi-channel Heartbeat Convolution Neural Network (MCHCNN). The DHCAF module utilizes feature engineering techniques, while the MCHCNN module employs a deep-learning approach. The effectiveness of the proposed framework is assessed using the MIT-BIH-AR database, with DHCAF achieving an accuracy of 91.4% and MCHCNN achieving an accuracy of 93%. This model effectively detects and classifies five types of arrhythmia based on ECG signals and heart rate (HR) information. The combined approach of DHCAF and MCHCNN offers a promising solution for accurate heartbeat classification.

The research study [41] explores the application of artificial intelligence in disease classification, specifically using Naive Bayes (NB) and random forest (RF) classification algorithms. The study aims to categorize various disease datasets such as diabetes, coronary heart disease, and cancer, to determine whether a patient is suffering from the respective disease or not. The Bayesian Classification network achieved an accuracy of 82.35%, while the Random Forest model attained an accuracy of 83.85% for the coronary heart disease dataset. This research demonstrates the potential of AI-based classification techniques in accurately diagnosing different diseases.

2.4 Critical Analysis

The critical analysis of the past literature presented in sections 2.1, 2.2, and 2.3 provides insights into the use of various machine learning and deep learning and hybrid techniques in the field of AI-based predictive cardiac care. As indicated in Table 2.1, the comparative analysis of 32 previous studies (from the year 2016 to 2022) highlights the different AI models employed in the detection of various cardiovascular diseases (CVDs) using different cardiac parameters.

Previous research has mainly focused on the analysis of electrocardiogram (ECG) signals and the classification of arrhythmias, while other significant cardiac parameters have been neglected, which may contribute to the diagnosis of various cardiovascular diseases (CVDs) [48]. In 2016, Shadmand et al. [14] proposed a model for the prediction of five arrhythmia classes, while Raj et al. [12] and Pengfei Li et al. [10] also resulted in the diagnosis of five arrhythmia classes using ECG as an input parameter. Both studies predicted five arrhythmia classes, but Li et al. [11] used a machine learning approach, while Pengfei Li et al. [10] used a deep learning approach. Azariadi et al. [8] resulted in the prediction of two arrhythmia classes, whereas Houssein et al. [44] predicted four classes, and Li et al. [45] and Mohonta et al. [47] successfully predicted five classes. Three arrhythmia classes were predicted in [46]. All of the studies mentioned above used only ECG as an input parameter. Nevertheless, cardiology is a vast field, and it is crucial to explore the impact of other vital indicators in the diagnosis of CVDs.

In the literature, various studies have explored the use of hybrid approaches to improve the accuracy of disease detection. For example, Elhaj et al. [9] used a hybrid approach to detect five arrhythmia classes, while Mathews et al. [22] used a hybrid technique to detect two CVD classes. Rai et al. [25] proposed a novel hybrid technique for the automatic detection of three cardiac arrhythmia classes. Jackins et al. [41] also used a hybrid machine learning approach, combining Naive Bayes (NB) classification and random forest (RF) classification algorithms, to classify several disease datasets including diabetes, coronary heart disease, and cancer.

Although some studies have attempted to incorporate additional parameters beyond ECG to predict CVDs, they have achieved limited success [15, 33]. For instance, Wolterink et al. [15] proposed a deep learning-based framework that combined both ECG and non-ECG features, but the results were not significantly better than those obtained using ECG alone. Similarly, Subhadra et al. [33] used a neural network-based approach with additional features such as age, gender, and medical history, but the accuracy of the model was not significantly improved. On the other hand, the proposed hybrid model in [36] successfully detected five types of arrhythmia based on both ECG and heart rate (HR). The study demonstrated that incorporating HR as an additional parameter can improve the accuracy of arrhythmia detection.

Upon analysis, it is evident that most of the previous studies have focused on arrhythmia detection using electrocardiogram (ECG) analysis on the MIT-BIH dataset. However, there is a lack of research in the use of other cardiac parameters for the detection of heart maladies. Moreover, the critical analysis suggests that hybrid models are sometimes used to improve the accuracy of the AI-based predictive cardiac care system. However, there is a need for more research to explore the use of hybrid models and their potential benefits in the detection of CVDs.

In summary, the analysis of past literature indicates that while there have been advancements in the use of AI-based predictive cardiac care systems, there are still gaps in the research that need to be addressed. Future research should focus on exploring the use of other cardiac parameters and the potential benefits of hybrid models to improve the accuracy of the system.

Table 2.1: Comparative Analysis of Previous Studies

Ref #	Year	AI Methodology	Prognosis / Diagnosis Task	Types of CVDs	Cardiac Parameter/s	Cardiac Dataset	Accuracy
[13]	2016	DT	Heart Disease	N/A	N/A	UCI	86.7%
[14]	2016	BBNN	Arrhythmia	5	ECG	MIT-BIH	97%
[9]	2016	SVM-RBF, NN	Arrhythmia	5	ECG	MIT-BIH	98.9%
[12]	2016	PSO tuned SVM	Arrhythmia	5	ECG	MIT-BIH	89.10%
[10]	2016	GRNN	Arrhythmia	5	ECG	MITBIH	95%
[11]	2016	RF	Arrhythmia	5	ECG	MIT-BIH	94.61%
[8]	2016	SVM	Arrhythmia	2	ECG	CT	98.9%
[15]	2016	Paired-CNN	Coronary Artery Calcification	N/A	CCTA	CT	Sens.=71
[20]	2017	SVM	Arrhythmia	4	ECG	MIT-BIH	98.39%
[19]	2017	RBF-NN	Arrhythmia	6	ECG	MIT-BIH	99.89%
[16]	2017	DL	Arrhythmia	3	ECG	MIT-BIH	92%
[23]	2018	SVM	Arrhythmia	3	ECG	CUDB VFDB	95.9%
[28]	2018	SVM	Arrhythmia	5	ECG	MIT-BIH	97.77%
[26]	2018	Twin LS-SVM	Arrhythmia	16	ECG	MIT-BIH	99.21%
[25]	2018	MPNN	Arrhythmia	3	ECG	MIT-BIH	99.07%
[24]	2018	CNN, LSTM	Arrhythmia	5	ECG	MIT-BIH	98.10%
[27]	2018	DL	Arrhythmia	2	ECG	MIT-BIH	99.68%
[22]	2018	DBN	Arrhythmia	2	ECG	MIT-BIH	93.78%, 96.94%

Table 2.1: *Cont.*

Ref #	Year	AI Methodology	Prognosis / Diagnosis Task	Types of CVDs	Cardiac Parameter/s	Cardiac Dataset	Accuracy
[30]	2019	CNN	Arrhythmia	4	ECG	CT MIT-BIH	94.96% 95.73%
[33]	2019	MPNN-BP	Heart Disease	5	ECG, HR, BP, Glucose, Cholestrol	UCI	94%
[29]	2019	DNN	Arrhythmia	12	ECG	CT	ROC=97 F1=83.7
[34]	2020	CNN	Myocardial Infarction	N/A	ECG	PTB	99.02%
[38]	2020	DNN	Arrhythmia	6	ECG	TNMG	F1=80 Spec. = 99
[37]	2020	TSVM	Arrhythmia	16	ECG	CT MIT-BIH	95.68%
[36]	2020	DHCAF MCHCNN	Arrhythmia	5	ECG, HR	MIT-BIH	91.4% 93%
[40]	2021	AI	Cardiac Amyloidosis	N/A	ECG	MC	90%
[42]	2021	CNN	Heart Failure	N/A	N/A	CT	97%
[41]	2021	RF, NB	Coronary Heart Disease	N/A	N/A	OR	83.85% (RF) 82.35% (NB)
[44]	2022	MPA-CNN	Arrhythmia	4	ECG	MIT-BIH European ST-T St. Petersburg INCART	N/A
[45]	2022	DNN	Arrhythmia	5	ECG	MIT-BIH	88.99%
[46]	2022	2D-CNN-LSTM	Arrhythmia	3	ECG	MIT-BIH	99%

The following chapter, Chapter 3, presents a detailed overview of the proposed research methodology. It outlines the steps that will be taken to ensure the accuracy and validity of the research findings, and highlights the significance of the chosen approach.

CHAPTER 3

Methodology

This chapter involves an in-depth discussion of the characteristics of datasets, techniques, and models used to address the underlying problem. The proposed methodology explains the process of collecting datasets, including the preprocessing steps, feature extraction techniques, and the assembling of cardiac parameters. Furthermore, the chapter also elaborates the use of a hybrid model that combines both Deep Learning and Machine Learning approaches. The frameworks used during the implementation of the hybrid model are also explained in detail, providing a comprehensive understanding of the methodology.

3.1 Sequential Workflow Overview

This section outlines the key stages involved in implementing the research study. The first step is to collect data on five different non-invasive parameters used in cardiac care units (CCUs), which is obtained from two different datasets. Preprocessing steps are then performed on the collected data to clean it, including handling missing data, scaling the data, and removing noise or irrelevant data. The cleaned data is then divided into training and testing subsets with 80:20 ratio, which ensures that the models are trained and tested on different data. For ECG analysis and arrhythmia classification, a deep learning approach is proposed, given the importance of ECG analysis in diagnosing arrhythmias and the effectiveness of deep learning in processing complex medical data. For the other four parameters, machine learning model is used, selected based on the ability to accurately predict these parameters. The final prediction of cardiovascular disease depends on the combined predictions made by both the deep learning and machine learning models, which are then used to make a final diagnosis of the patient's condition.

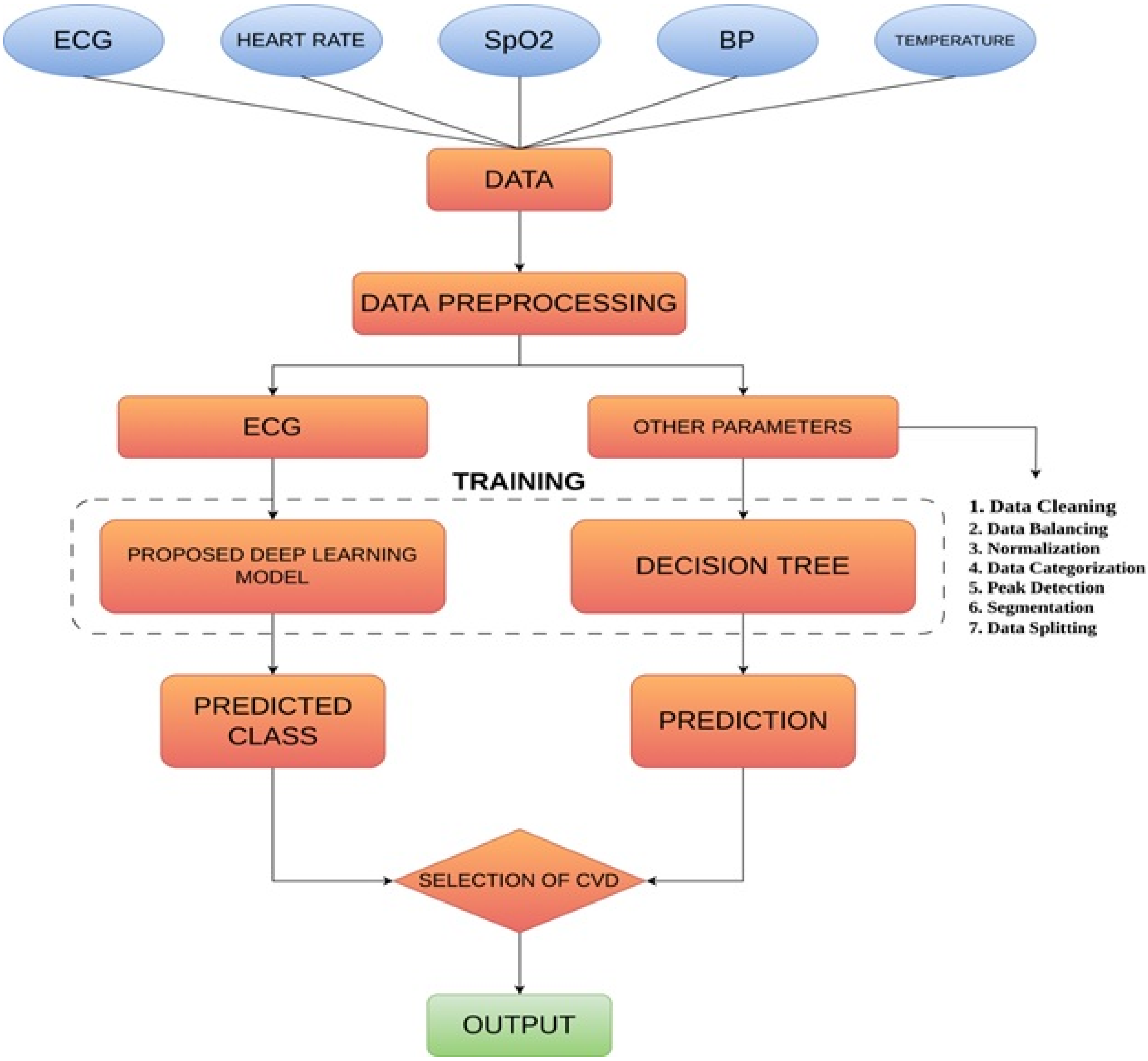

Figure 3.1: Sequential Workflow

The process flowchart offers a holistic depiction of the sequential stages involved in implementing this research, providing a thorough understanding of the procedural steps. The flow diagram in Figure 3.1 helps to visualize the sequence of steps involved in this study, from data collection to final diagnosis, and highlights the critical role played by deep learning and machine learning models in predicting the patient's condition.

3.2 Dataset

In the context of predictive cardiac care, two distinct datasets are utilized, and this section aims to provide a comprehensive explanation of both datasets.

In the proposed model, the CCU parameters are utilized, and their format is presented in Table 3.1. This table provides a comprehensive overview of the specific format that is employed for these parameters within the proposed model.

Table 3.1: Description of CCU Dataset

Dataset	
Attribut Name	**Attribute Description**
ECG	Format: Signal
Temperature (T)	Value0: A (Abnormal) Value1: N (Normal)
Oxygen Saturation (SpO2)	Value0: A (Abnormal) Value1: N (Normal)
Blood Pressure (BP)	Value0: H (High) Value1: L (Low) Value2: N (Normal)
Heart Rate (HR)	Value0: H (High) Value1: L (Low) Value2: N (Normal)
Format of T, SpO2, BP, HR: Numeric	

3.2.1 ECG- Dataset 1

An electrocardiogram (ECG) is a diagnostic procedure to analyze the heart's electrical impulses. This painless and non-invasive test in which small electrodes are affixed on the chest, arms, and legs. These small electrodes are capable of detecting the heart's electrical activity during each heartbeat and record them as waveforms on a graph. Within the ECG waveform, there are discernible elements comprising the P wave, QRS complex, and T wave. The P wave signifies the electrical behavior of the heart's atria, during their contraction phase, which facilitates the movement of blood into the heart's lower chambers called ventricles. The QRS complex refers to the electrical behavior of the ventricles during their contraction, playing a vital role in pumping blood out of the heart. Finally, the T wave represents the electrical recovery of the ventricles preparing for the next pulse. Figure 3.2 represents the typical ECG waveform.

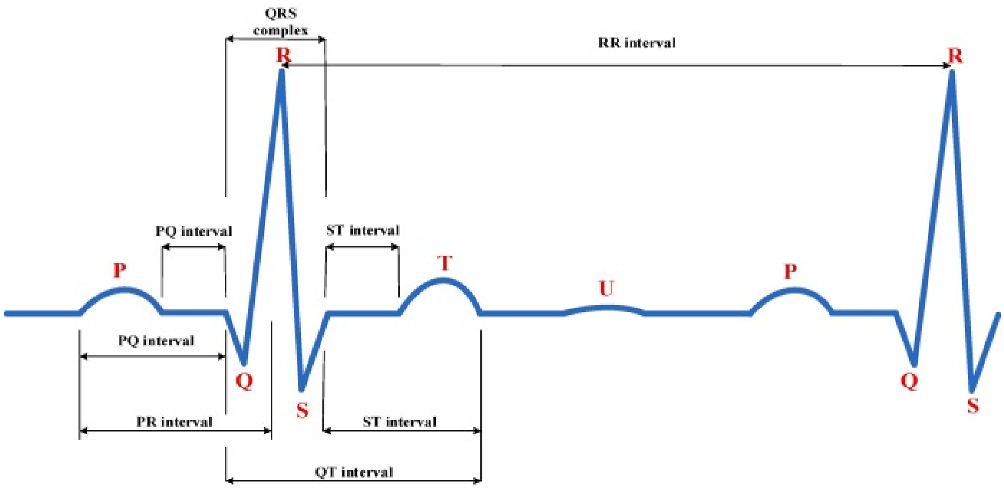

Figure 3.2: Typical ECG-Waveform

[35]

ECG tests are usually used to identify a variety of heart maladies, including arrhythmias, heart attacks, and cardiac arrest etc. By analyzing the patterns and characteristics of the ECG waveform, healthcare professionals can determine whether there are any abnormalities in the electrical behaviour of the heart, and develop appropriate treatment plans.

MIT-BIH dataset is used for the analysis of ECG in our proposed model. The MIT-BIH Arrhythmia dataset [49] is a collection of electrocardiogram (ECG) recordings of patients with various cardiac arrhythmias. It was created by the Massachusetts Institute of Technology (MIT) and Beth Israel Hospital (BIH) and is extensively used for research purposes. The dataset contains 48 records, each of which includes two ECG signals (double-lead) with a duration of 30 minutes. The signals are digitized at a sampling rate of 360 Hz and have 11-bit resolution. The recordings were obtained from patients with a variety of arrhythmia classes, including atrial fibrillation, supraventricular tachycardia, and ventricular tachycardia. The upper signal in most records can be observed as a modified limb lead II (MLII) that is acquired through the affixing of electrodes on chest skin. Whereas, the lower signal is usually a modified lead V1 (though it may sometimes be V2, V5, or in rare cases V4). Typically, normal QRS complexes can be easily identified in the upper signal.

Another ECG dataset is the "Challange ECG Dataset". The objective of the 2017 PhysioNet/CinC Challenge [50] is to promote the creation of computer programs that can categorize a brief electrocardiogram (ECG) single lead recording, lasting between 30 to 60 seconds, based on whether the recording displays regular heart rhythm, atrial fibrillation (AF), a different rhythm, or if the recording is too unclear to classify accurately. As we are utilizing only one lead from the MIT-BIH dataset, we employed two distinct datasets for our testing purposes, namely: 1) the MIT-BIH ECG Dataset, and 2) the Challenge ECG Dataset consisting of a single lead recording. Table 3.2 displays the various arrhythmia classes sourced from the MIT-BIH ECG database used in this research study, as well as the corresponding output labels that are expected to be generated by our proposed model.

Table 3.2: ECG Class Description and Output Labels

Arrhythmia Class	**MIT-BIH Beat Type**	**Output Label**
Normal beat (N)	Normal beat	N
Supraventricular ectopic beat (S)	Atrial premature beat	A
Ventricular ectopic beat (V)	Premature ventricular contraction	V
Fusion beat (F)	Fusion of ventricular and normal beat	F
Paced beat (P)	Paced beat	/
Unknown beat (Q)	Unclassified beat	Q

Preprocessing of ECG-Waveform

Preprocessing is an essential step in analyzing ECG signals, as it can help remove noise and artifacts, enhance the signal quality, and prepare the data for further analysis. Our proposed methodology for analyzing ECG signals involves a set of preprocessing steps which are as follows:

- Peak Detection: Peak detection involves the process of determining peaks or local maxima in the ECG signal. Peak detection is an important preprocessing step because it enables the detection of arrhythmias and other abnormalities in the signal. We used:

  scipy.signal.find_peaks()

  for this purpose. This function is designed to process a one-dimensional array and identify all local maxima by comparing each value with its neighboring elements.

- Segmentation: In this step ECG signals are divided into segments, each representing a single heartbeat consisting of 256 points. The ECG waveform for each subject is 30 minutes long consisting of 660000 samples. We segmented this long signal for each subject into the chunks of 256 points (i.e one complete PQRST wave) after shuffling the 660000 points for all subjects. Segmenting the ECG signal into individual heartbeats is an essential preprocessing step for heart rate variability analysis and arrhythmia detection. Segmented beat is shown in the figure 3.3.

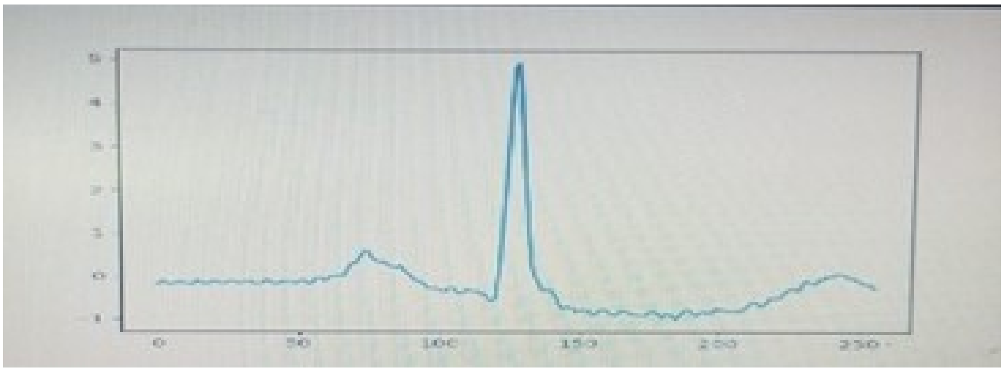

Figure 3.3: ECG Signal Segmentation

- Normalization/Standardization: In normalization/standardization, scaling of the amplitude of the ECG signal is done to a common range. The **sklearn.preprocessing** package provides several common utility functions for this purpose [54].

  sklearn.preprocessing.scale()

  is one of them. It can be used to standardize a dataset along any axis. Thus, each ECG feature has been transformed to have a mean value of 0 and a standard deviation of 1 along x-axis. This is useful for comparing signals from different patients or for comparing signals acquired using different devices.

- Splitting: After the segmentation of the ECG signal we left with 22000 samples. In this step we split the data into training and testing with the ratio of 80:20 i.e. 18000:4000 samples respectively.

  sklearn.model_selection.train_test_split()

  We used sklearn splitter as mentioned above for this purpose. By dividing the dataset in this way, we could ensure that the model was effectively trained and accurately assessed for its predictive capabilities on new, unseen data.

3.2.2 Additional CCU Metrics-Dataset 2

There are many vital invasive and non-invasive cardiac parameters that can be of great help in the diagnosis of various cardiovascular diseases. This research study explores the affect of various non-invasive cardiac parameters in predictive cardiac care along with ECG. In the above section we have already discussed ECG dataset. This section discusses the various non-invasive parameters being used in our proposed methodology.

- Temperature is a critical factor in cardiac care because it can affect both the function of the heart and the body's response to cardiac treatments. In particular, maintaining the body's core temperature within a specific range is essential for ensuring optimal cardiac function and preventing complications during cardiac procedures. For instance, high body temperatures can be problematic in cardiac care. Fever can be a sign of infection or inflammation, both of which can impair cardiac function and increase the risk of complications. In some cases, fever may also be a side effect of certain cardiac medications, such as beta-blockers. Thus, maintaining a stable, healthy body temperature is essential for optimal cardiac function and successful cardiac treatment outcomes. Typically, a healthy adult is regarded to have a normal body temperature of approximately 98.6 degrees Fahrenheit (37 degrees Celsius) when measured orally using a thermometer.

- Oxygen Saturation (SpO2) is a critical measure of cardiac and respiratory function and is commonly used in cardiac care to monitor the oxygen levels in a patient's blood. Oxygen is essential for proper heart and organ function, and a drop in oxygen saturation levels can be a sign of underlying cardiac or respiratory problems. In cardiac care, oxygen saturation levels are typically monitored using a non-invasive device called a pulse oximeter, which measures the percentage of hemoglobin molecules in the blood that are carrying oxygen. Normal oxygen saturation levels are typically between 95 and 100 percent, and levels below 90 percent are generally considered low and may require intervention. Low oxygen levels can be a sign of heart failure, pulmonary embolism, or other serious cardiac conditions.

- Blood Pressure (BP) is an essential measure of cardiac function and is commonly used in predictive cardiac care to assess a patient's risk of developing cardiovascular disease. Elevated blood pressure, known as hypertension, poses a significant risk for heart disease, stroke, and other critical cardiovascular conditions. It has the potential to harm blood vessels and organs over time. The unit to measure blood pressure is mmHg and it consists of two values i.e. for systolic and diastolic pressure. Systolic pressure reflects arterial pressure during heartbeats, while diastolic pressure depicts the pressure between heartbeats when the heart is at rest. Generally, normal blood pressure is considered to be below 120/80 mmHg, while high blood pressure is equal to or higher than 140/90 mmHg.

- Hear Rate (HR) is an important measure of cardiac function and is commonly used in predictive cardiac care to assess a patient's risk of developing cardiovascular disease. Heart rate is referred to the frequency of heartbeats per minute. In adults, the resting heart rate is commonly considered to fall within the range of 60 to 100 beats per minute (bpm). A high resting heart rate is often an indicator of a higher risk of cardiovascular disease, while a lower resting heart rate is generally considered a positive indicator of cardiac health. For example, an elevated heart rate at rest can be a sign of an underlying heart condition such as atrial fibrillation or heart failure, which can increase the risk of stroke or heart attack.

The dataset2 used in this study is a dataset that initially belonged to a disease Sepsis [55]. We used it for the collection of non-invasive parameters relevant to cardiac health care. To ensure the most relevant and informative data for our proposed study, we carefully selected and preprocessed only a subset of the available parameters. This approach allowed us to optimize the dataset for our specific research objectives and minimize any potential confounding variables. The table labeled as 3.3 displays the labels associated with different classes of CVD that are identified based on cardiac parameters other than ECG abnormalities.

Preprocessing of Dataset2:

As previously mentioned, dataset2 was originally intended for sepsis, which meant that preprocessing was necessary to ensure it was suitable for our ML model designed for cardiac care. To

Table 3.3: CVD Class Description and Output Labels

Sr. #	Cardiovascular Disease	Label
1	Normal	Normal
2	Unknown	Unknown
3	Some Other Disease	Some_Other_Dis
4	Respiratory Disease	Repiratory_Dis
5	Less Likely CDV	Less_Likely_CVD
6	Hypertension	Hyper_Tension
7	Hypertension/Some Other Disease	Hyper_Tension_SO1
8	Hypertension/Some Other Disease	Hyper_Tension_SO2
9	Hypertension/Some Other Disease	Hyper_Tension_SO3
10	Mitral Valve Prolapse	Mitral_Valve_Prolapse
11	Valvular Heart Disease with Vegetation	Valular_Heart_Dis_Vegetation
12	Heart Failure	Heart_Failure
13	Tetralogy of Fallot	Tetralogy_Of_Fallot
14	Coarctation of Aorta	Coarctation_Of_Aorta
15	Hypertension	Hyper_Tension_HR1
16	Hypertension	Hyper_Tension_HR2
17	Decompensated Heart Failure	Decompensated_Heart_Failure

accomplish this, we followed a series of preprocessing steps for dataset2, which are as follows:

- Data Cleaning: The first step in preprocessing dataset2 involved identifying and removing incomplete and duplicate records, correcting erroneous data entries, and handling missing data values.

- Data Balancing: This is the process of adjusting the distribution of classes or categories in a dataset so that they are more evenly represented. For example, in dataset 2 we observed that Blood pressure data was primarily skewed in the sepsis data were primarily skewed towards low values. So, we used various techniques for data balancing, such as oversampling, undersampling and generating synthetic data. Data balancing is important in machine learning and predictive data analysis. Datasets with imbalanced distribution can result in models that exhibit bias and demonstrate inadequate performance when it comes to the minority class(es). The skewed dataset initially intended for the Sepsis disease is visually depicted in Figure 3.4. The graph reveals that the occurrence of Low BP is substantially high among patients diagnosed with sepsis. Specifically, the figure indicates a significant frequency of Low BP instances in the dataset, as compared to other medical indicators. The effectiveness of the Data Balancing techniques applied to the dataset is illustrated in Figure 3.5. The graph clearly depicts the successful balancing of the dataset, as the frequencies of the various medical indicators are now evenly distributed. It is evident from the figure that the dataset is now in a balanced form, which is essential for accurate and unbiased analysis.

- Normalization: The next step in preprocessing dataset2 involved normalizing the vital signs, including blood pressure, heart rate, oxygen saturation, and temperature, to a standard range. By standardizing the vital sign data and adjusting for any irregularities, we were able to optimize the dataset for our ML model.

- Data Categorization: In this step, we converted the numeric data of dataset2 into categorical data. This process involved dividing continuous variables into a set of discrete categories or bins based on specific criteria. Categorization is a useful technique for simplifying data, making it easier to analyze and visualize. Since dataset2 contained numerical data, there was a need to convert it into categorical data for the classification of CVDs. By performing data binning, we were able to categorize the data and facilitate the classification of CVDs using our ML model designed for cardiac care. Figure 3.6 shows the binning of continuous data into categorical data.

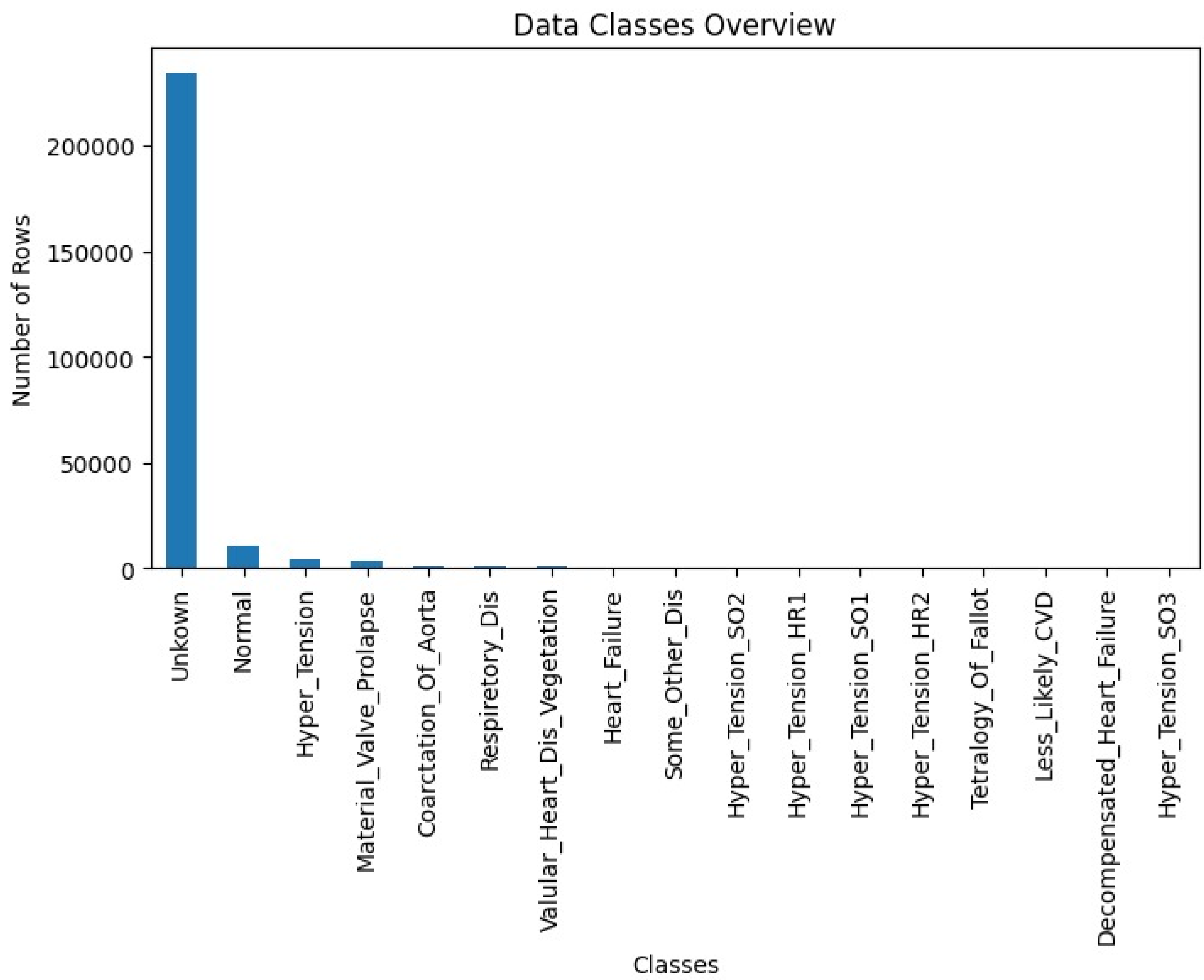

Figure 3.4: Skewed Dataset

- Label Encoding: Label Encoding is a technique used to transform categorical labels into numerical values, enabling them to be processed by machine learning algorithms. By converting labels into a machine-readable format, it allows algorithms to make better sense of the data and perform more effectively. This preprocessing step is particularly valuable when working with structured datasets in supervised learning tasks.

- Data Splitting: To assess the performance of the analysis, we partitioned the dataset2 into separate training and testing subsets. This involved splitting the dataset into two subsets of patient records, with one subset used for training our machine learning model and the other for testing its performance with the ratio of 70:30. This step was crucial in optimizing the accuracy and reliability of our ML model designed for cardiac care.

Oxygen Saturation consists of two labels i.e. Normal (N), and Abnormal (A) based upon certain

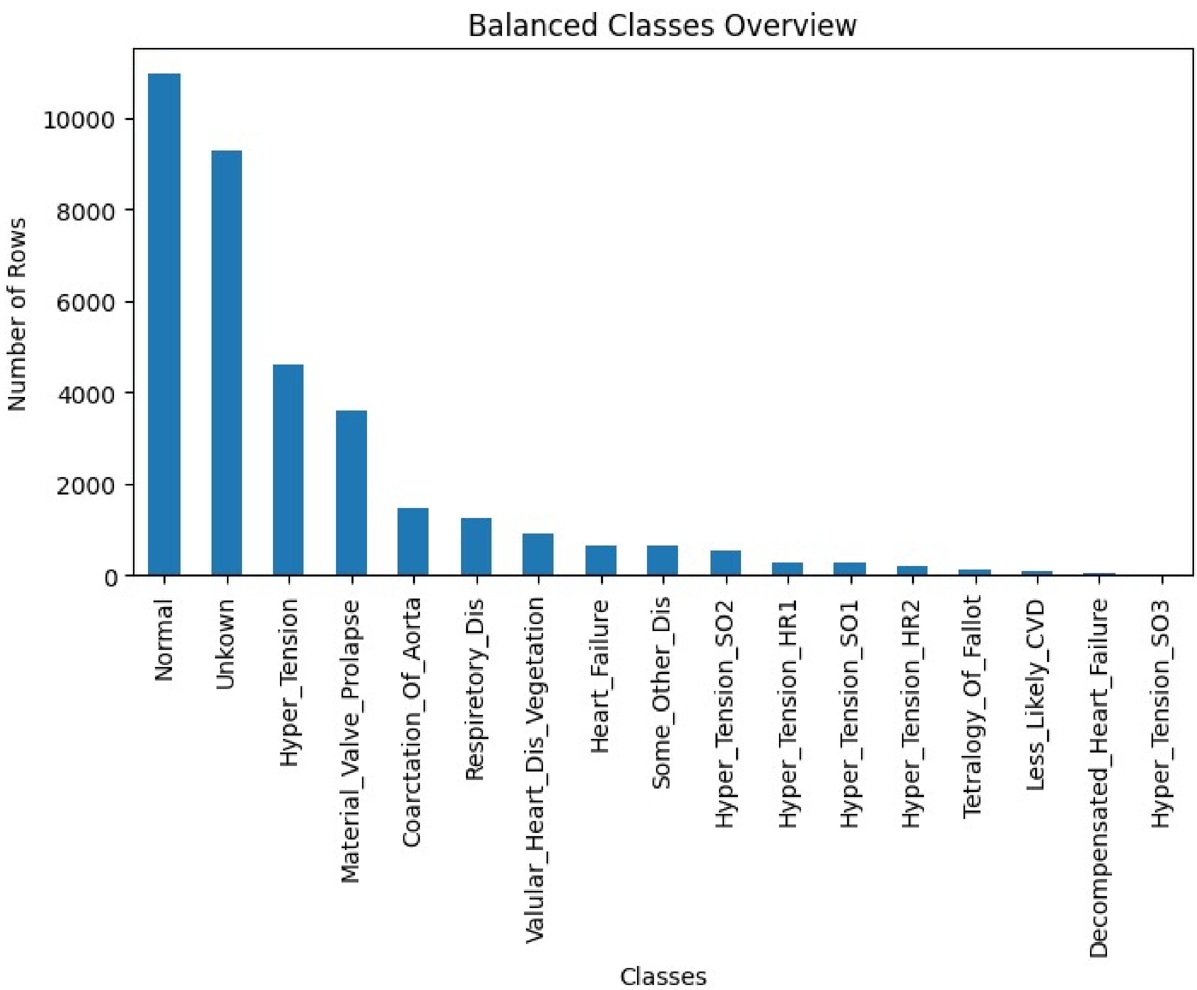

Figure 3.5: Balanced Dataset

ranges as shown in the figure 3.7. Figure 3.8 shows the categorization of "blood pressure" into: Normal (N), High (H), and Low (L). We replaced various numeric ranges of "temperature" with two categories: Normal (N) and Abnormal (A) as shown in the Figure 3.9. Various numeric ranges of "heart rate" were replaced with three categories: Normal (N), High (H), and Low (L) as shown in the Figure 3.10.

3.3 Proposed Model Architecture

Our proposed hybrid model comprises two distinct components: a deep learning model for ECG analysis, and a machine learning model for the analysis of non-invasive cardiac parameters. In the following subsections, we provide a detailed architectural discussion of each model.

	HR	O2Sat	Temp	SBP	DBP
0	N	N	N	H	N
1	N	N	N	N	N
2	N	N	N	N	N
3	N	N	N	N	N
4	N	N	N	N	H
...	...	...	...	...	...
259929	N	A	N	N	L
259930	N	A	N	N	L
259931	N	N	N	N	L
259932	N	A	N	N	L
259933	N	N	N	N	L

259934 rows × 5 columns

Figure 3.6: Categorization of Numeric Data

3.3.1 Deep Learning Model

Deep Convolutional Neural Networks (CNNs) with numerous hidden layers and a vast number of parameters have emerged as the predominant tool in the realm of Deep Learning (DL). The appeal of deep learning paradigms lies in their ability to automate feature engineering. In the context of ECG analysis, these algorithms enable an end-to-end mapping of input signals to various types of arrhythmias and cardiovascular diseases. This deep learning model is specifically designed to analyze ECG data, leveraging the power of neural networks for relevant feature extraction and pattern recognition from the input signal. This model is trained by utilizing a huge dataset of ECG recordings, allowing it to learn complex relationships between different ECG features and the corresponding cardiac conditions.

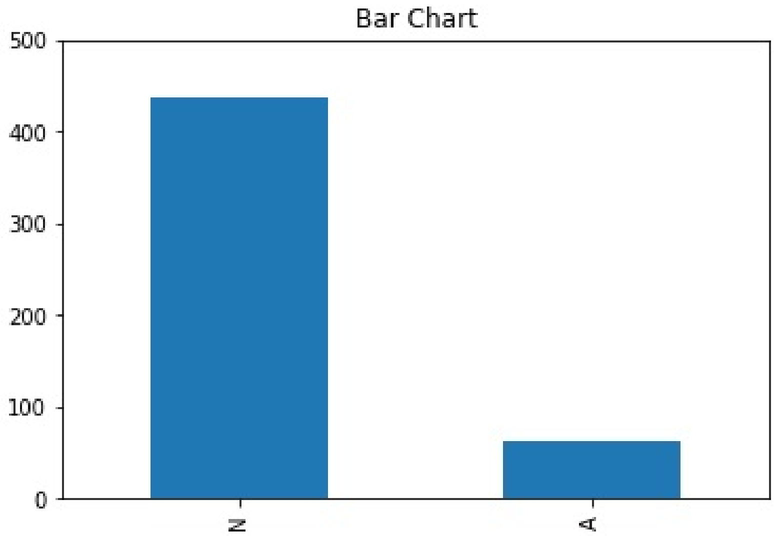

Figure 3.7: Bar Chart for Oxygen Saturation

The primary operations performed by a Deep Neural Network (DNN) include max pooling, convolution, classification, and non-linearity. In the context of this analysis, the DNN is responsible for extracting temporal features and capturing relevant parameters for the classification of various arrhythmias. Figure 3.11 gives the pictorial representation of our proposed DNN architecture.

Now, the details of our proposed DNN architecture are given below:

- Convolution Layer: A 1-D convolutional layer is responsible for applying sliding convolutional filters to a 1-D input. Its purpose is to extract the necessary features and generate a feature map. By moving the filters along the input, the layer performs convolutions by calculating the dot product between the weights and the input, and subsequently adding a bias term. The proposed architecture incorporates five convolutional layers (including one input layer) for this purpose.

- Activation Function: Activation plays a vital role in neural networks, since it helps determine the significance of the information received by a neuron. Its function is to decide whether the received information is valuable or should be disregarded. In this research, the Rectified Linear Unit (ReLU) is employed which is a non linear activation function. ReLU introduces non-linearity by deactivating some of the neurons with the values below zero.

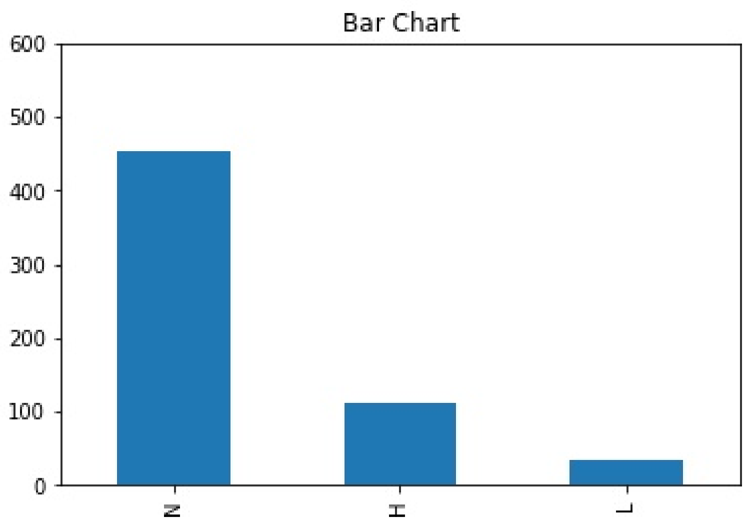

Figure 3.8: Bar Chart for Blood Pressure

$$Y = \text{ReLU}(\sum_{i=1}^{n}(W_i * X_i) + b)$$

where, X are inputs (ECG), W depicts weights and b shows bias whereas Y representing output value. Note that the Σ symbol denotes summation over all the elements of the input vector, and the multiplication of the weight and input vectors is represented by (W*X) and the dot product of W and X is obtained by taking the summation of the element-wise product.

- Batch normalization: The characteristics of the previous layer's parameters can have a substantial influence on the input distribution of the following layer. To address this, batch normalization plays a crucial role by normalizing the output of the preceding layer. It serves as a regularizer to prevent overfitting by estimating the mean and variance of input batches and subsequently normalizing, scaling, and shifting them. This particular study, batch normalization is implemented after applying the activation function. The batch normalization can be calculated as follows:

  For each batch of size m: Compute the batch mean:

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{3.3.1}$$

  Calculate the batch variance:

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2 \tag{3.3.2}$$

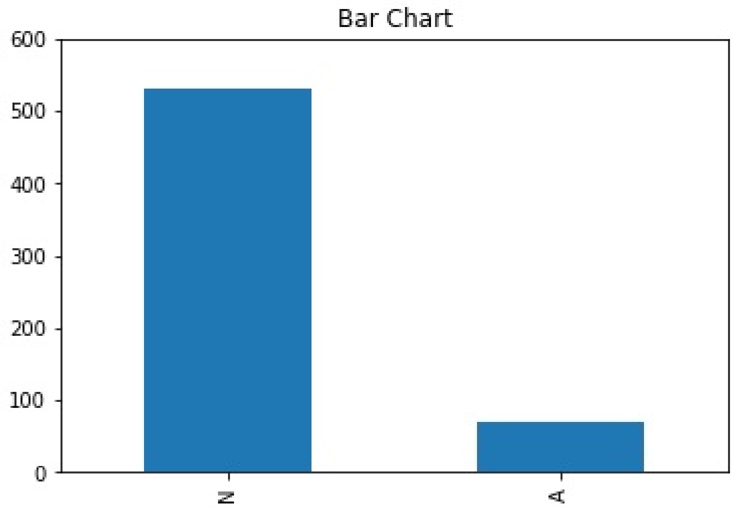

Figure 3.9: Bar Chart for Temperature

Normalize the batch:

$$\hat{x}i = \frac{x_i - \mu B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{3.3.3}$$

Scale and shift the normalized batch using learnable parameters γ and β:

$$y_i = \gamma \hat{x}_i + \beta \tag{3.3.4}$$

where x_i is the input to the i-th neuron in the layer, $\hat{x}i$ is the normalized input, y_i is the output of the i-th neuron after scaling and shifting, μB is the mean of the batch, σ_B^2 is the variance of the batch, ϵ is a small constant (0.001) added for numeric stability, and γ and β are learnable parameters used to scale and shift the normalized input.

- Max pooling: In this study, max pooling is employed as a technique for reducing the dimensionality or downsampling of input matrices. It involves dividing the input into non-overlapping distinct patches and applying a maximum filter to each sub-region, selecting the highest value within each sub-region.

- Optimization Function: Optimization techniques are used to calculate the weights for your model. They update the weights in the learning process until you reach towards your desired output. We used **Adam** [17] in out architecture.

- Softmax layer: In the context of a multi-class classification task, the softmax layer is utilized to calculate the probability of an event occurring across *n* distinct events. It calculates the probability distribution associated with each desired class within the entire set

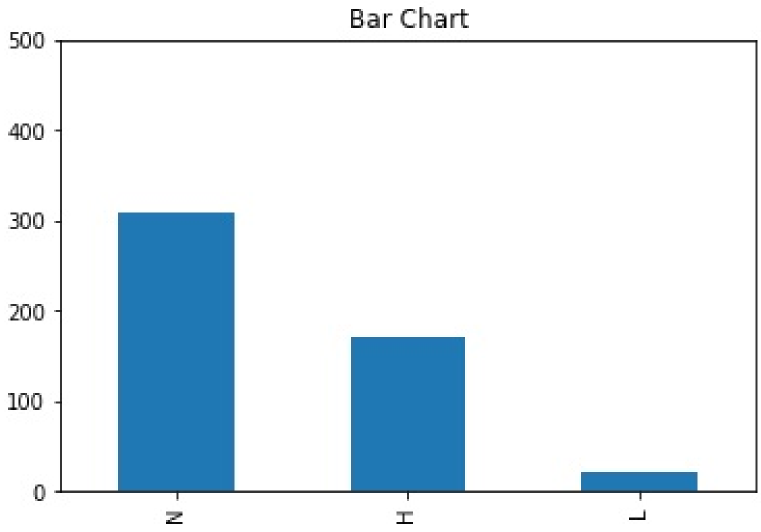

Figure 3.10: Heart Rate Categorization

of classes, assigning values between 0 and 1. These probabilities are subsequently utilized to determine the target class with the highest likelihood for a given input.

- Dense Layer/Classification layer: These are the feed forward neural networks. The first dense layer collects the data from the last convolution Layer to compute the classification and the last dense layer i.e. classification layer provides the final probabilities calculated for each label. In other words, it is used for classifying different categories. The proposed model consists of five dense layers.

- Dropout Regularization: During the training of the model, overfitting is a common challenge that can occur. To address this issue, dropout regularization is employed, which involves randomly deactivating certain nodes within the network and reducing interdependencies among them. In our model, a dropout rate of 50% was applied before the final fully connected layer to mitigate overfitting.

- Cost Function: The cost function evaluates the dissimilarity between the provided test sample and the predicted output, serving as a metric for assessing the proficiency of the neural network. By employing an optimizer function, the cost function is minimized to enhance the network's performance. In the realm of deep learning, various forms of cross-entropy functions are commonly utilized to minimize the cost function and optimize the network's training process. Mathematically, the cost function L can be defined as:

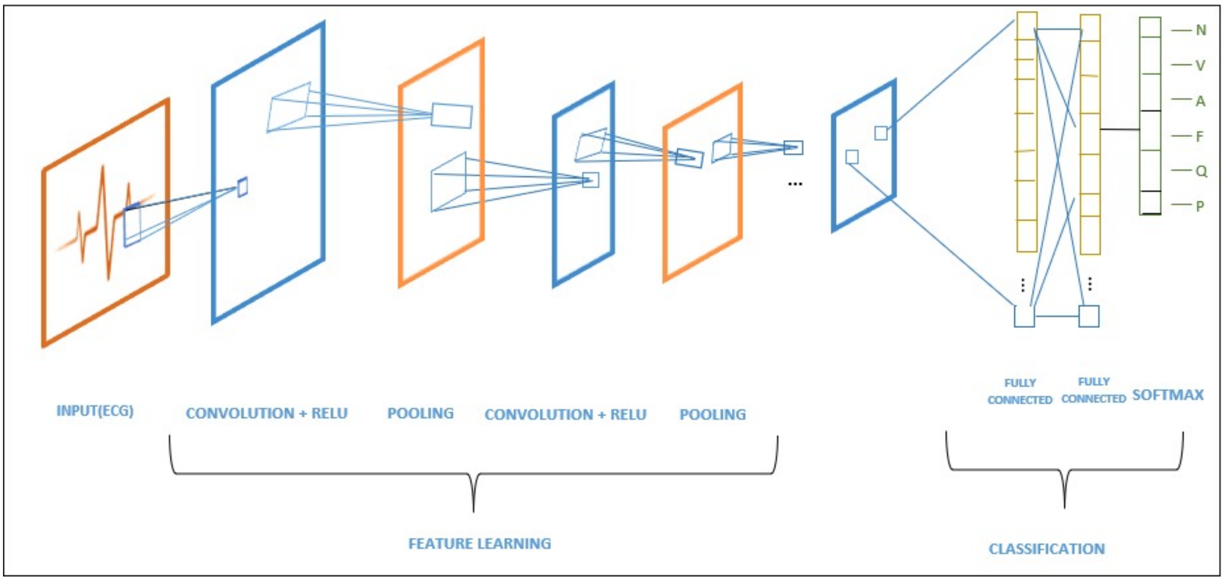

Figure 3.11: Architecture of Proposed DNN

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$

where L is the cross-entropy loss, y is the true label (either 0 or 1), $\hat{y}$ is the predicted label (a value between 0 and 1), and n is the number of examples. In this equation, the first term evaluates the error when 1 is the true label, whereas, the second term measures the error when the true label is 0. The logarithm function is used to penalize the paradigm more severely when the difference is higher between the predicted label and the true label, as the logarithm function grows very quickly as its argument approaches zero. Using an optimizer function (Adam in our case) with a learning rate, we can minimize the cost function.

The specific setup information of the proposed architecture is presented in the table 3.4, elucidating the configuration details:

Figure 3.12 provides the summary of our proposed deep learning architecture.

The next section describes our machine learning model in detail.

Table 3.4: Proposed Architecture Configuration

Convolutional Layers	5 Layers 3 (with 5*5 filters & (128) feature maps 2 (with 3*3 filters & (128) feature maps
Max Pooling	2 (with stride of 1)
Dropout	0.5
Learning Rate	0.001
Training Algorithm	Adam
Activation Function	ReLU
Batch Size	256
Dense Layers	5 Layers (along with one classification layer)
Dataset Distribution	80:20
No. of Epochs	100

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_5 (Conv1D)           (None, 252, 128)          768

 max_pooling1d_2 (MaxPooling  (None, 25, 128)          0
 1D)

 dropout_8 (Dropout)         (None, 25, 128)           0

 conv1d_6 (Conv1D)           (None, 21, 128)           82048

 dropout_9 (Dropout)         (None, 21, 128)           0

 conv1d_7 (Conv1D)           (None, 17, 128)           82048

 dropout_10 (Dropout)        (None, 17, 128)           0

 conv1d_8 (Conv1D)           (None, 15, 128)           49280

 max_pooling1d_3 (MaxPooling  (None, 3, 128)           0
 1D)

 dropout_11 (Dropout)        (None, 3, 128)            0

 conv1d_9 (Conv1D)           (None, 1, 128)            49280

 global_average_pooling1d_1   (None, 128)              0
 (GlobalAveragePooling1D)

 dense_5 (Dense)             (None, 256)               33024

 dropout_12 (Dropout)        (None, 256)               0

 dense_6 (Dense)             (None, 128)               32896

 dropout_13 (Dropout)        (None, 128)               0

 dense_7 (Dense)             (None, 64)                8256

 dropout_14 (Dropout)        (None, 64)                0

 dense_8 (Dense)             (None, 32)                2080

 dropout_15 (Dropout)        (None, 32)                0

 dense_9 (Dense)             (None, 6)                 198

=================================================================
Total params: 339,878
Trainable params: 339,878
Non-trainable params: 0
```

Figure 3.12: Summary of Proposed Architecture

3.3.2 Machine Learning Model

The machine learning model is applied to non-invasive cardiac parameters that are typically measured in a clinical setting, such as blood pressure, heart rate variability, oxygen saturation, and temperature. This model is used to analyze these parameters and predict various cardiac conditions based upon above mentioned parameters. After the preprocessing of the non-invasive parameters as discussed in subsection 3.3.2 the ML model was employed.

We used Decision Tree (DT) for the prediction of various CVDs depending upon non-invasive parameters. Decision trees are a popular and tool in machine learning and data mining. They provide an intuitive and visual representation of decision-making processes and are useful for solving classification and regression problems. Decision trees are well-suited for various applications as they can effectively handle both categorical and numerical data. One notable advantage of decision trees lies in their interpretability, enabling users to comprehend and clarify the inherent decision-making procedure. This ML model is used for the classification of seven CVDs. Furthermore, this model also provides some additional information if the patient is not suffering from any heart malady.

3.3.3 Hybrid Architecture

Based on the factors outlined below, it was necessary to adopt a hybrid model:

- The ECG data and other related parameters were not available for the same patient during the data collection process. This unfortunate circumstance may limit the scope of the analysis and conclusions that can be drawn from the available data.
- Additionally, It is important to highlight that the two datasets employed in this study were not of the same type, namely the ECG dataset and the Sepsis dataset. This difference in dataset types may have implications for the analysis and interpretation of the results.
- The dataset for other medical indicators is relatively straightforward and could be handled using a simple machine learning model. Given the nature of this dataset, it may not require complex algorithms or techniques to yield meaningful insights.

By combining the two models as described in section 3.3.1 and 3.3.2 , our proposed hybrid approach offers a comprehensive and accurate analysis of cardiac health, providing clinicians and researchers with a powerful tool for diagnosis and prognosis.

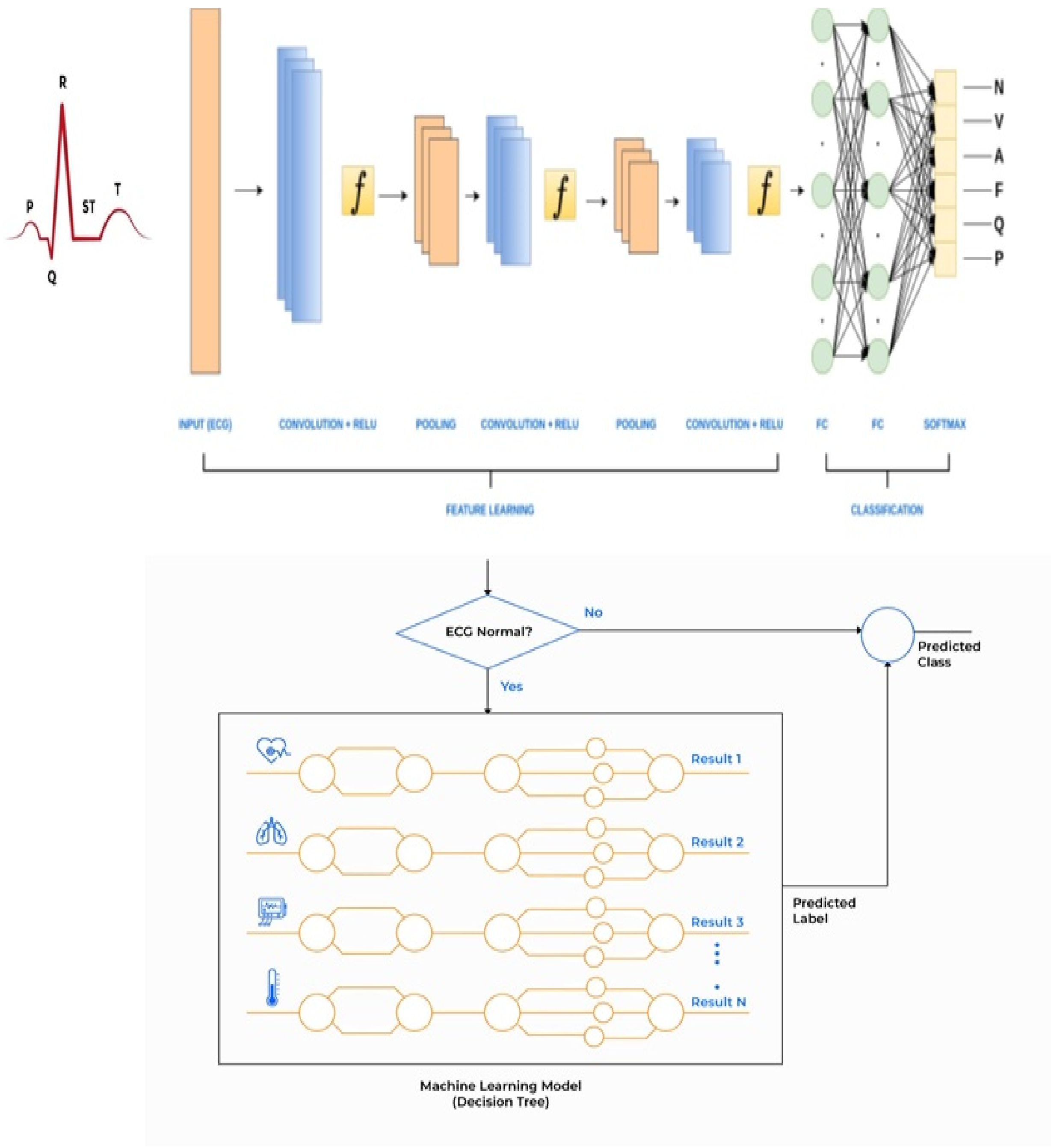

Figure 3.13: Architecture of the Proposed Hybrid Model

Figure 3.13 shows the architecture of our proposed hybrid model. Deep Learning (DL) framework presents the complete working of Arrhythmia classification through 10 layers presented in Table 3.4 and visualized through Figure 3.11. In this study, the ECG waveform sequence data, with dimensions of 256X256, is inputted into a sequence input layer. The input features undergo processing through the first 1-D convolutional layer, which employs 128 filters of size 5X5, with "same" padding and a stride of 1. Convolutional layers 4 & 5 employe 128 filters of size 3X3 with a stride of 1. This convolutional operation generates output data values. Subsequently, the ReLU function is applied to add non-linearity to the output. The ReLU function, represented by Equation (a), assigns values in the range of 0 to 1 and helps in the deactivation of the neurons with values lower than zero. Next hidden layer performs Max Pooling. Here we have taken the pool size =10 with stride 1 for first pooling layer and pool size of 5 with stride 1 for second Max Pooling layer. In addition, the extracted features from five convolutional layers are fed into five fully connected layers to classify the data. To address overfitting, a dropout of 50% is applied, which randomly deactivates nodes during training to enhance generalization. The resulting values are then passed to the final classification layer, functioning similarly to an Artificial Neural Network (ANN). Subsequently, the data is processed by the Softmax activation function, enabling multi-class classification by determining the probability distribution of events among a set of 'n' distinct events. This function assigns probabilities to each target class within the set, with values ranging from 0 to 1. To identify the target class with a higher likelihood, we use these probabilities thus enabling the classification of six different beat types: N, V, A, F, /, and Q as discussed in table 3.2.

Our machine learning model which is a Decision Tree in our case takes four parameters as an input that have already passed through various preprocessing steps. The machine learning model classifies the data into 17 different classes including CVDs and non-CVDs classes. It is capable of predicting 12 classes related to 8 CVDs and 5 other classes. Arrhythmia disorder will be identified by the DNN using ECG. In, case the ECG is normal, the heart abnormality will be predicted by our proposed ML model as described in the figure 3.13. The proposed model exhibits higher recall performance and is characterized by enhanced user-friendliness, making it a favorable option for implementation.

3.4 Evaluation Metrics

In order to quantitatively evaluate the proposed hybrid model, six metrics have been utilized, as suggested by Bengio (1994) [2]. These metrics have been selected for their ability to assess both the machine learning (ML) and deep learning (DL) models. The following section describes each of these metrics in detail:

1. Accuracy: This metric determines the correctly classified samples of the dataset. Accuracy is measured in percentage and is therefore a measure of the overall performance of the model. The formula for accuracy is given below:

$$Accuracy = \frac{\text{True Positives + True Negatives}}{\text{True Positives + True Negatives + False Positives + False Negatives}}$$

2. Precision: This metric measures the number of patients correctly identified by the proposed model, and is therefore an indicator of the model's predictive power. Precision can be calculated by the following formula:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

3. Sensitivity: This metric determines the model's ability to accurately identify the presence of positive cases in the dataset. Equation of Sensitivity is as follows:

$$Sensitivity = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

4. Specificity: This metric is used to measure the model's ability to correctly classify negative samples in the dataset. Mathematically, it can be computed as:

$$Specificity = \frac{\text{True Negatives}}{\text{True Negatives + False Positives}}$$

5. F1-Score: The F1-measure is a commanly employed used metric to assess the effectiveness of a classifier. It serves as a comprehensive measure by combining precision and recall through their harmonic mean. By considering both precision and recall, the F1-score provides a single score that indicates the overall balance between the two metrics. A higher F1-score reflects a better equilibrium between precision and recall in the model's performance. F1-score can be measured as:

$$F1Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}}$$

True positive (TP) refers to the number of correctly diagnosed patients with cardiovascular diseases (CVDs). Conversely, true negative (TN) indicates patients who have been accurately identified as not having CVD. These two measures (TP and TN) signify precise classification. In contrast, false positive (FP) denotes the proportion of patients with wrong classification as having heart malady, while false negative (FN) represents those who have been incorrectly identified as not having CVD. Both FP and FN indicate classification errors. To assess the performance of a classification model in diagnosing cardiovascular disease (CVD), three metrics are commonly employed: accuracy, sensitivity, and specificity. Accuracy quantifies the proportion of accurately classified patients, providing an overall measure of the model's correctness. Sensitivity evaluates the model's ability to correctly identify actual positive patients, capturing the proportion of positive cases correctly detected. Conversely, specificity measures the model's capability to accurately identify actual negative patients, indicating the proportion of negative cases correctly recognized. Together, these metrics offer a comprehensive evaluation of the model's performance in CVD diagnosis. A higher value for all three metrics indicates better classification results. It is important to consider the specific objectives of the classification task when interpreting these metrics. It is essential to prioritize specific objectives, such as identifying all positive patients or minimizing false positives, when interpreting these metrics.

Chapter 4 provides a comprehensive and detailed discussion of the results obtained from various perspectives.

CHAPTER 4

Results and Discussion

In this chapter, we present the insights gained from implementing the approaches discussed in the previous chapter. In Section 4.1, we discuss the significant results obtained from the formulated dataset for non-invasive parameters, including the comparison of different machine learning (ML) models. We also highlight the results for various evaluation measures, as discussed in the previous chapter. Section 4.2 focuses on the results of our proposed deep learning (DL) model for electrocardiogram (ECG) analysis. We present the various results obtained during the tuning of hyper-parameters, for our proposed DL model. Lastly, in Section 4.3, we elaborate on the performance of our proposed model. We also discuss all the above results in this section, which lead to the formation of some significant conclusions.

4.1 Experimental Analysis of Various Machine Learning Models

After formulating and preprocessing the dataset, we divided it into a 70:30 ratio for training and testing. Subsequently, we applied three state-of-the-art machine learning techniques, namely Random Forest, Gradient Boosting, and Decision Tree, to our dataset. To evaluate the performance of the models, we used various metrics discussed in the previous chapter. Based on our analysis, we concluded that the Decision Tree classifier outperformed the other models. Our dataset consists of 17 classes, out of which 12 classes belong to eight cardiovascular diseases (out of which three are overlapping classes). Whereas, the remaining five are associated with other diseases, along with the 'Normal' and 'Unknown' classes. Whereas Figure 4.1 shows the classification summary for the Decision Tree classifier and Figure 4.2 illustrates the sensitivity report. Our dataset yielded an accuracy of 99.9% for the four indicators excluding ECG.

This suggests that our model is highly effective in predicting these four indicators. Overall, our findings demonstrate the effectiveness of the Decision Tree classifier for disease classification, particularly for cardiovascular diseases. These results have important implications for the development of predictive models for disease diagnosis and management.

```
print(classification_report(y_test, y_pred, target_names=label_class))
```

```
                               precision    recall  f1-score   support

             Coarctation_Of_Aorta       1.00      1.00      1.00       453
      Decompensated_Heart_Failure       1.00      1.00      1.00        12
                    Heart_Failure       1.00      1.00      1.00       201
                    Hyper_Tension       1.00      1.00      1.00      1343
                Hyper_Tension_HR1       0.99      1.00      0.99        89
                Hyper_Tension_HR2       1.00      1.00      1.00        65
                Hyper_Tension_SO1       1.00      1.00      1.00        87
                Hyper_Tension_SO2       0.99      1.00      0.99       165
                Hyper_Tension_SO3       1.00      1.00      1.00         5
                   Less_Likely_CVD      1.00      1.00      1.00        22
           Material_Valve_Prolapse      1.00      1.00      1.00      1106
                            Normal      1.00      1.00      1.00      3256
                   Respiretory_Dis      1.00      1.00      1.00       362
                    Some_Other_Dis      1.00      1.00      1.00       189
               Tetralogy_Of_Fallot      1.00      1.00      1.00        42
                            Unkown      1.00      1.00      1.00      2849
       Valular_Heart_Dis_Vegetation     1.00      1.00      1.00       272

                          accuracy                          1.00     10518
                         macro avg      1.00      1.00      1.00     10518
                      weighted avg      1.00      1.00      1.00     10518
```

Figure 4.1: Evaluation Results for Decision Tree

Accuracy represents the proportion of correctly classified true positives (TP) and true negatives (TN) among all samples, making it an intuitive measure of classification effectiveness. Sensitivity, on the other hand, quantifies the rate of missed diagnoses, with higher values indicating a lower rate of missed positive cases. Similarly, specificity measures the rate of misdiagnosis, with higher values indicating a lower rate of falsely identified negative cases. When evaluating the performance of a classification model, it is crucial to consider not only accuracy but also sensitivity and specificity. These metrics provide a comprehensive understanding of the model's ability to correctly classify different sample types and can help identify areas for improvement in both the model's design and implementation.

A	B	C	D
	Class_Labels	Decision_Tree	
0	Coarctation_Of_Aorta	1	
1	Decompensated_Heart_Failure	1	
2	Heart_Failure	1	
3	Hyper_Tension	1	
4	Hyper_Tension_HR1	1	
5	Hyper_Tension_HR2	1	
6	Hyper_Tension_SO1	1	
7	Hyper_Tension_SO2	1	
8	Hyper_Tension_SO3	1	
9	Less_Likely_CVD	1	
10	Material_Valve_Prolapse	1	
11	Normal	1	
12	Respiretory_Dis	1	
13	Some_Other_Dis	1	
14	Tetralogy_Of_Fallot	1	
15	Unkown	0.998946999	
16	Valular_Heart_Dis_Vegetation	1	

Figure 4.2: Sensitivity Report for Decision Tree

4.1.1 Analyzing and Comparing the Performance of Machine Learning Models

In this section, a detailed comparison of three machine learning models is presented. The performance of each model is assessed using confusion matrices, which are shown in Figures 4.3, 4.4, and 4.5, for the Decision Tree, Gradient Boost, and Random Forest classifiers, respectively. The results demonstrate that Decision Tree achieved the highest accuracy, with a score of 99.9%, while Random Forest under performed with an accuracy of only 80.1%. These findings provide valuable insights into the effectiveness of each model in predicting the target variable, and can inform future research and decision-making in this field.

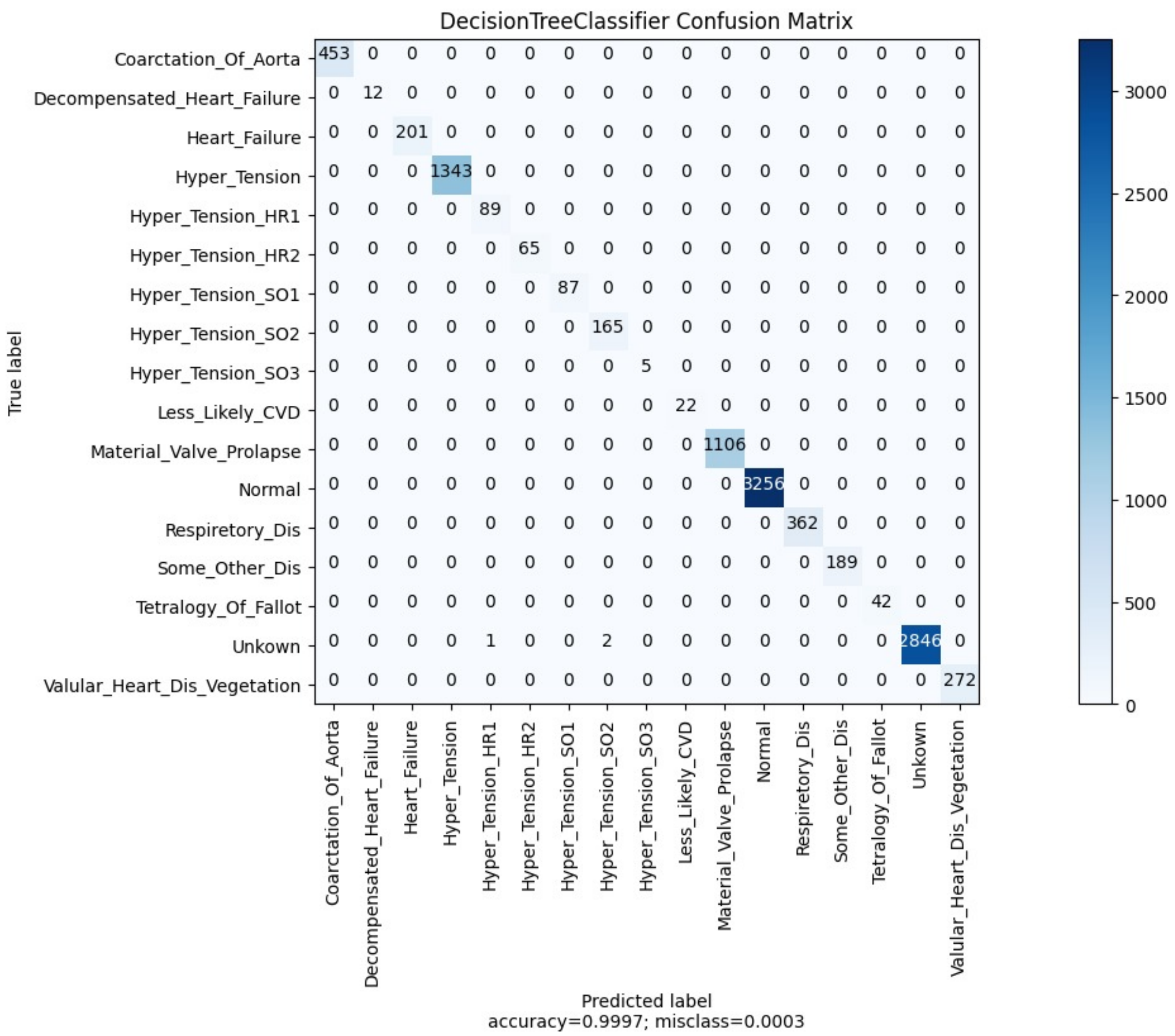

Figure 4.3: Confusion Matrix for Decision Tree

To compare the performance of three machine learning models, namely Decision Tree, Gradient

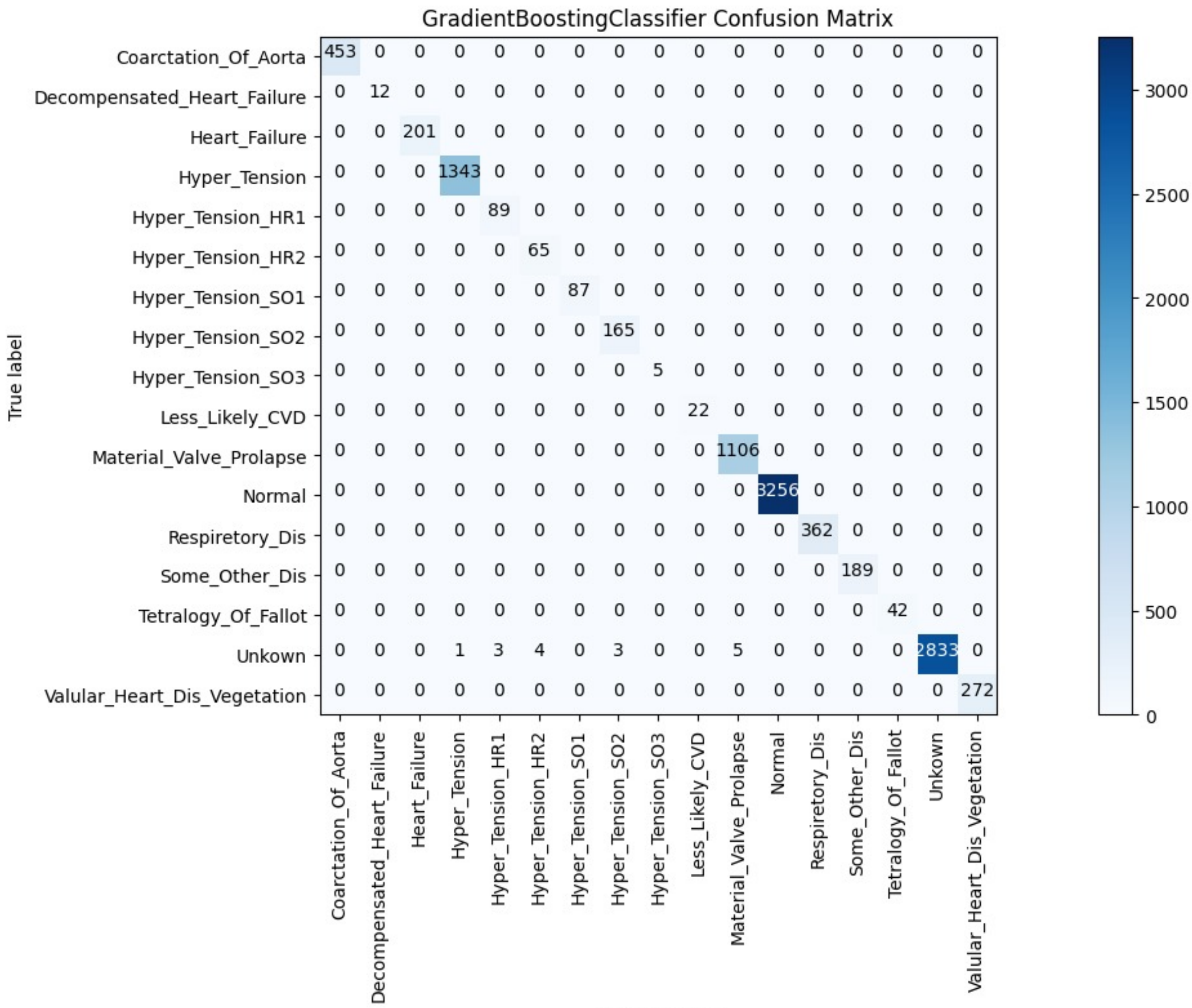

Figure 4.4: Confusion Matrix for Gradient Boost

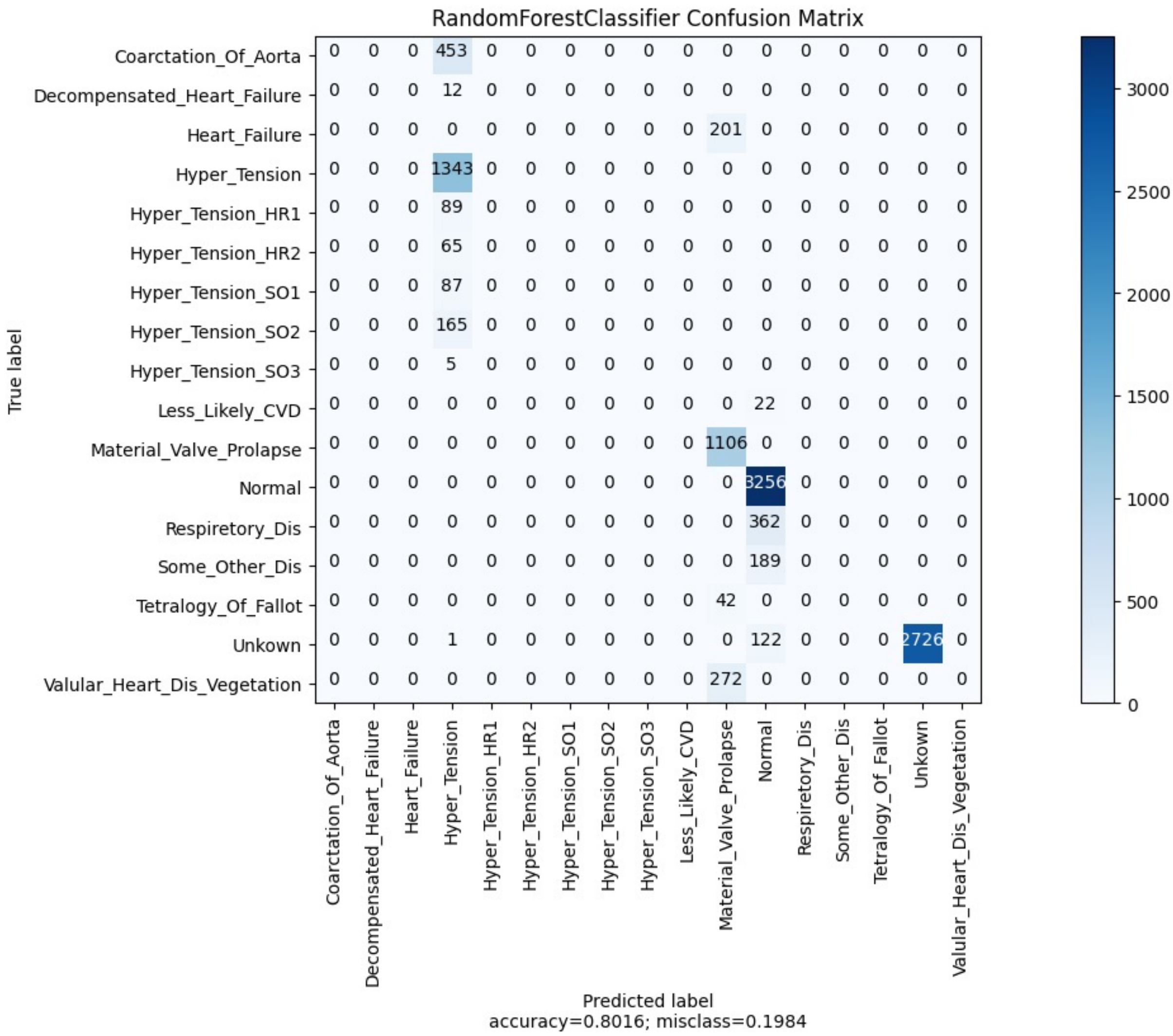

Figure 4.5: Confusion Matrix for Random Forest

Table 4.1: Performance Analysis of Various Machine Learning Algorithms on Dataset

Sr.#	Model	Sensitivity	Specificity	Precision	Accuracy
1	**Decision Tree**	0.999917	0.999977	0.998512	0.999720
2	**Gradient Boosting**	0.999670	0.999906	0.993313	0.998479
3	**Random Forest**	0.232755	0.985529	NaN	0.801578

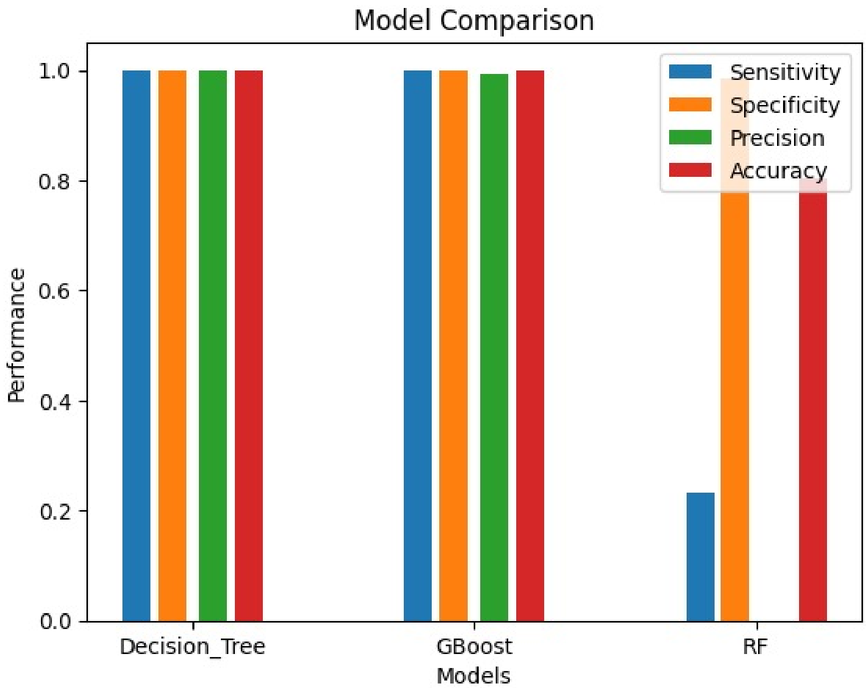

Figure 4.6: Comparison Graph for Three Models

Boosting, and Random Forest in predicting cardiovascular diseases (CVDs), we employed four evaluation metrics, namely precision, accuracy, sensitivity, and specificity.

The results of our analysis are tabulated in Table 4.1 and graphically in Figure 4.6, which displays the mean values of each metric for each classifier. The horizontal axis signifies the different models, whereas the vertical axis represents the evaluation metric values in the graphical representation. Our analysis revealed that model Decision Tree performed significantly better than models Gradient Boost and Random Forest in predicting CVDs. These findings suggest that Decision Tree may be the best choice for predicting CVDs in this context. Figure 4.7 summarizes the "sensitivity" comparison of the three models.

Section 4.2 elaborates the empirical evaluation of the proposed deep learning model.

A	B	C	D	E
	Class_Labels	Decision_Tree	GBoost	RF
0	Coarctation_Of_Aorta	1	1	0
1	Decompensated_Heart_Failure	1	1	0
2	Heart_Failure	1	1	0
3	Hyper_Tension	1	1	1
4	Hyper_Tension_HR1	1	1	0
5	Hyper_Tension_HR2	1	1	0
6	Hyper_Tension_SO1	1	1	0
7	Hyper_Tension_SO2	1	1	0
8	Hyper_Tension_SO3	1	1	0
9	Less_Likely_CVD	1	1	0
10	Material_Valve_Prolapse	1	1	1
11	Normal	1	1	1
12	Respiretory_Dis	1	1	0
13	Some_Other_Dis	1	1	0
14	Tetralogy_Of_Fallot	1	1	0
15	Unkown	0.998946999	0.994383994	0.956826957
16	Valular_Heart_Dis_Vegetation	1	1	0

Figure 4.7: Sensitivity Comparison for Three Models

4.2 Experimental Analysis of the Proposed Deep Learning Model & Findings

To evaluate the efficacy of the DL paradigm we have proposed, an assessment of its performance was conducted for classifying six types of beats. A sequence of experiments was carried out on a particular dataset. We divided the dataset into two portions, by allocating 80% for training purposes and reserving 20% for testing purpose. We varied hyperparameters, including the number of layers, learning rate, and number of epochs, to identify the optimal configuration. After conducting several experiments, we found that a learning rate of 0.001, a batch size of 256, and 100 epochs with a dropout rate of 50% yielded the highest accuracy of 91.59% for classifying the six types of beats using our proposed DL model with 10-layers. Our model achieved a precision of 0.928, F1-score of 0.917, sensitivity of 0.986, and specificity of 0.936, as indicated in Table 4.2. The experimental results provide strong evidence of the efficacy of our proposed DL model in accurately classifying the six kinds of beats, with high accuracy and performance measures. The detailed results are shown in Figure 4.8. Whereas, figure 4.9 shows the training and testing loss.

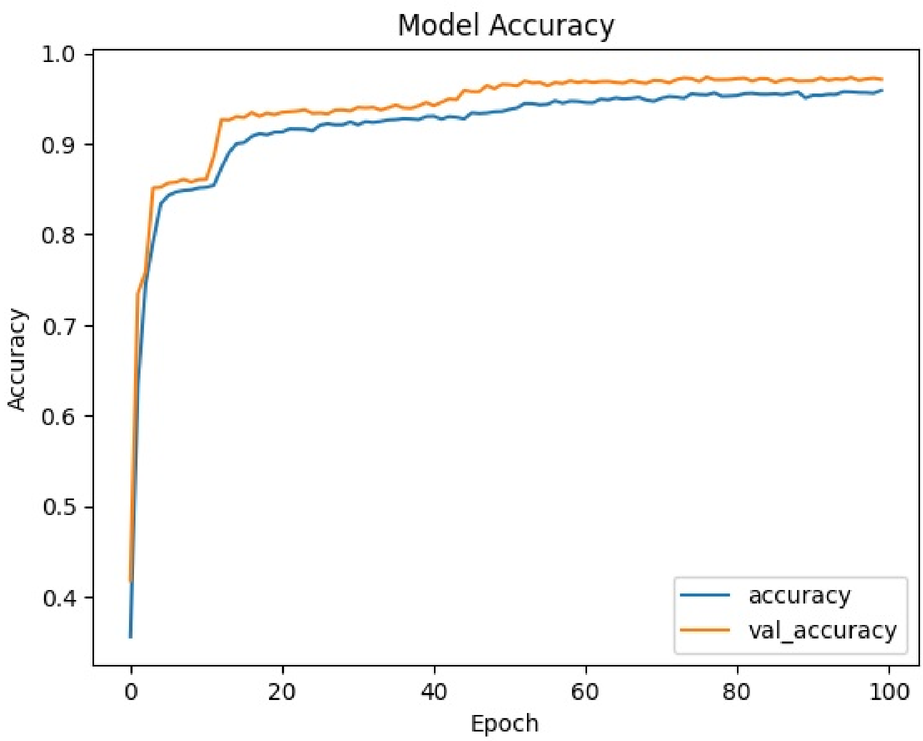

Figure 4.8: Accuracy Graph during Training of the Proposed Model

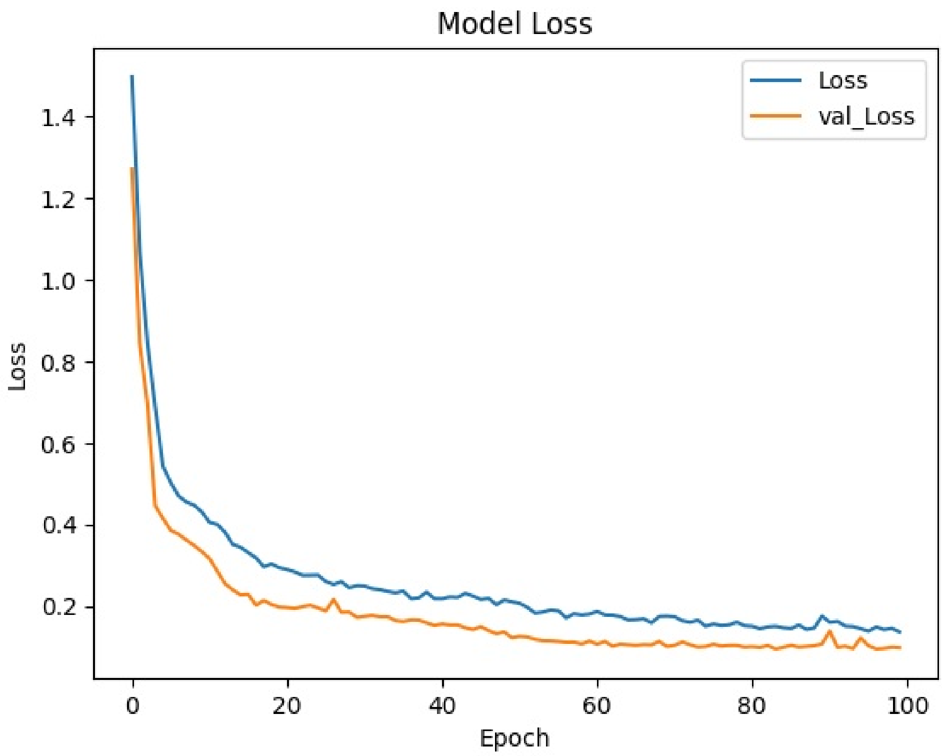

Figure 4.9: Model Loss of the Proposed Model

Table 4.2: Evaluation Metrics for Proposed Model

Proposed Model	Accuracy	Precision	Sensitivity	Specificity	F1-Score
	91.59%	0.928	0.986	0.936	0.917

To check the effectiveness of the proposed paradigm for classifying six types of beats from the MIT-BIH ECG dataset, we constructed a confusion matrix based on the training results. The confusion matrix, presented in Figure 4.10, shows the classification results for each beat type and the number of correct and incorrect classifications.

4.2.1 Hyperparameter Optimization

We obtained the optimal hyperparameters for training our models by leveraging a maximum test score of 91.59. These hyperparameters included a learning rate of 0.001, 100 epochs, a batch size of 256, a dropout regularization rate of 0.05, and the Adam optimizer. Table 4.3 shows optimised hyperparameters with different test-scores using different activation functions and keeping learning rate and batch size constant.

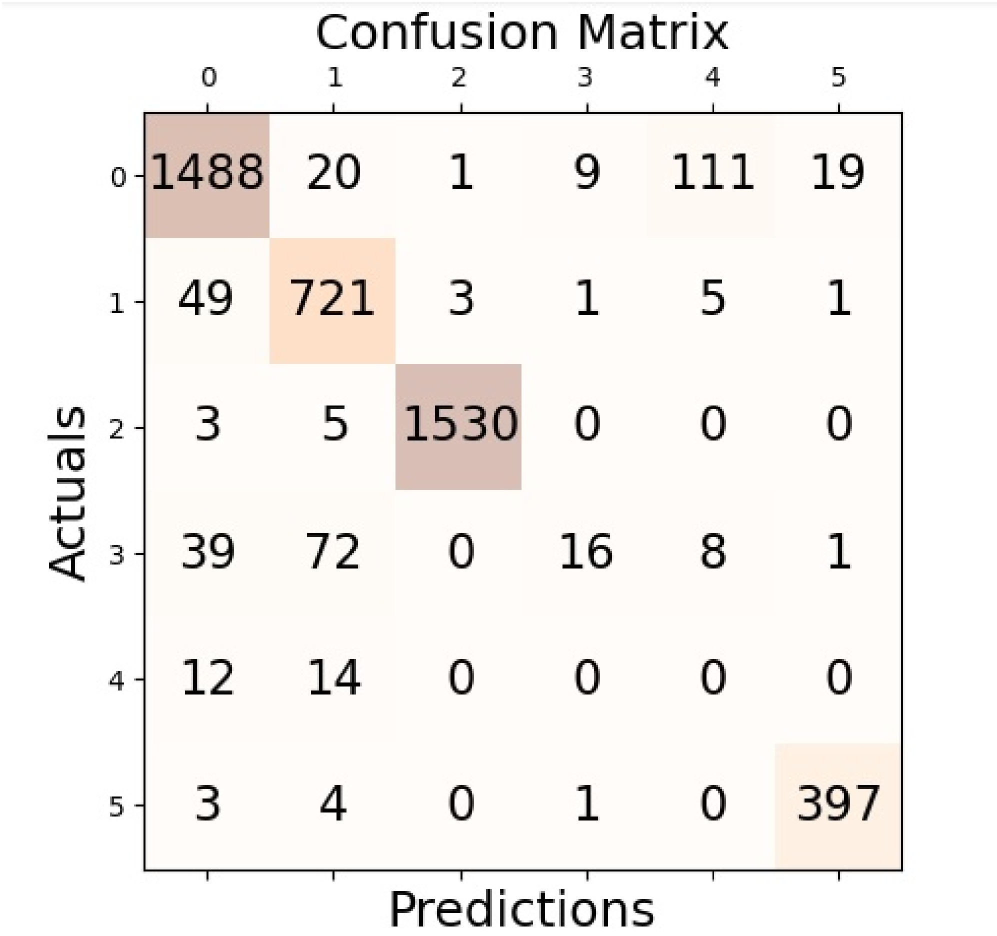

Figure 4.10: Confusion Matrix for the Proposed Model

Here are some accuracy graphs obtained during the hyperparameter tuning process. Each graph is accompanied by a descriptive title that summarizes its experimental details.

Table 4.3: Visualization of Optimal Hyperparameters and Corresponding Test Scores

No. of Layers	Learn-Rate	Batch-Size	Activation-Func	Epochs	Test-Score (%)
7	0.001	256	Relu	40	89.7
7	0.001	256	Leaky Relu	40	85.99
7	0.001	256	Elu	40	87.18
7	0.001	256	Tanh	40	90.29
7	0.001	256	Relu	100	90.65
10	**0.001**	**256**	**Relu**	**100**	**91.59**
10	0.001	256	Leaky Relu	100	90.06
10	0.001	256	Elu	100	85.24
10	0.001	256	Tanh	100	87.53

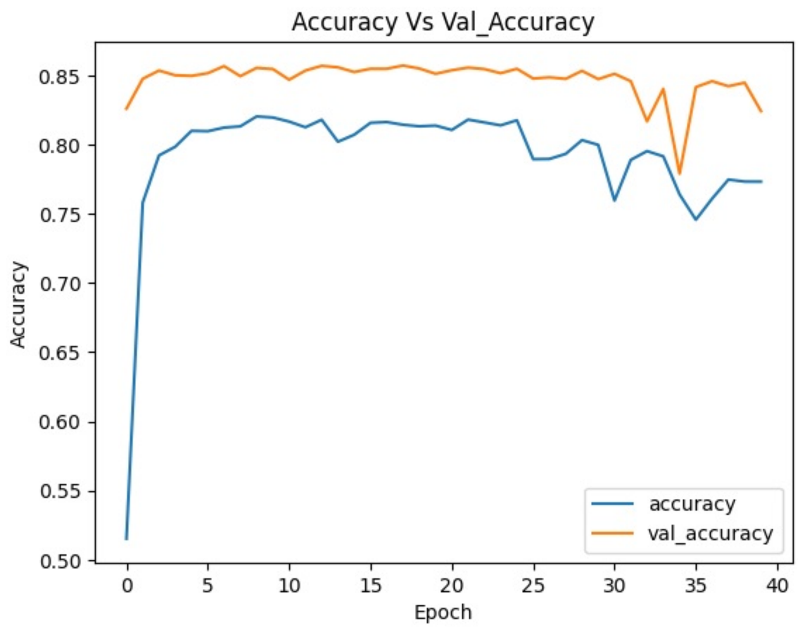

Figure 4.11: Accuracy Graph with Batch Size 256, Epochs 40, and Lr rate 0.01

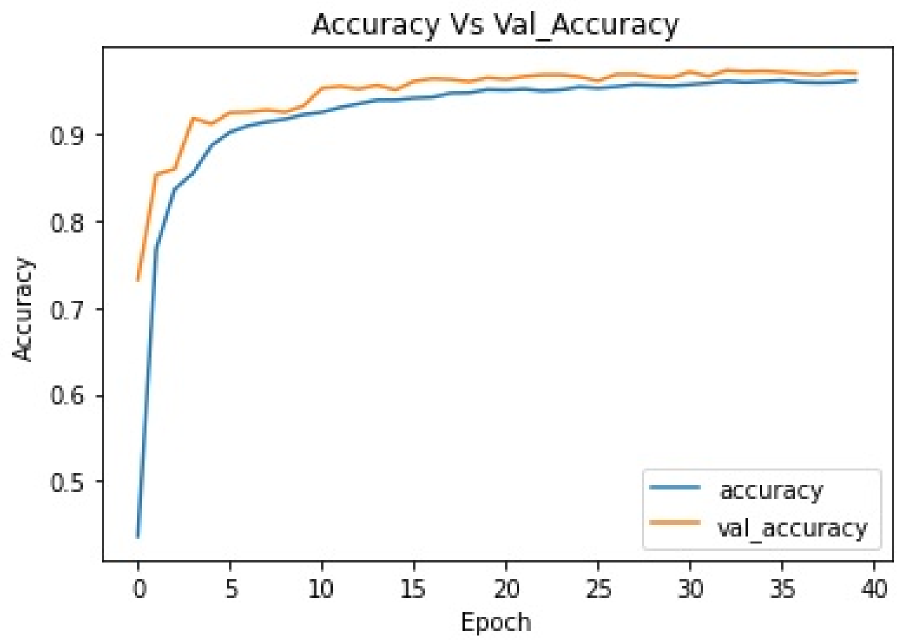

Figure 4.12: Accuracy Graph with Batch Size 256, Epochs 40, and Lr rate 0.001, Acc = 87.1%

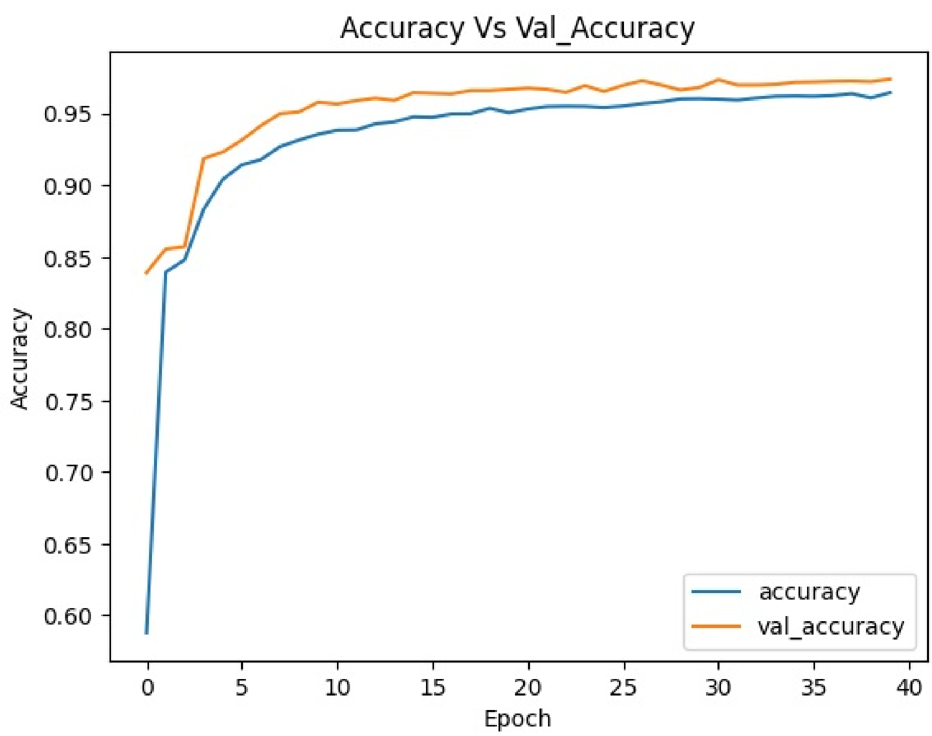

Figure 4.13: Accuracy Graph with Batch Size 128, Epochs 40, and Lr rate 0.001, Acc = 87.6%

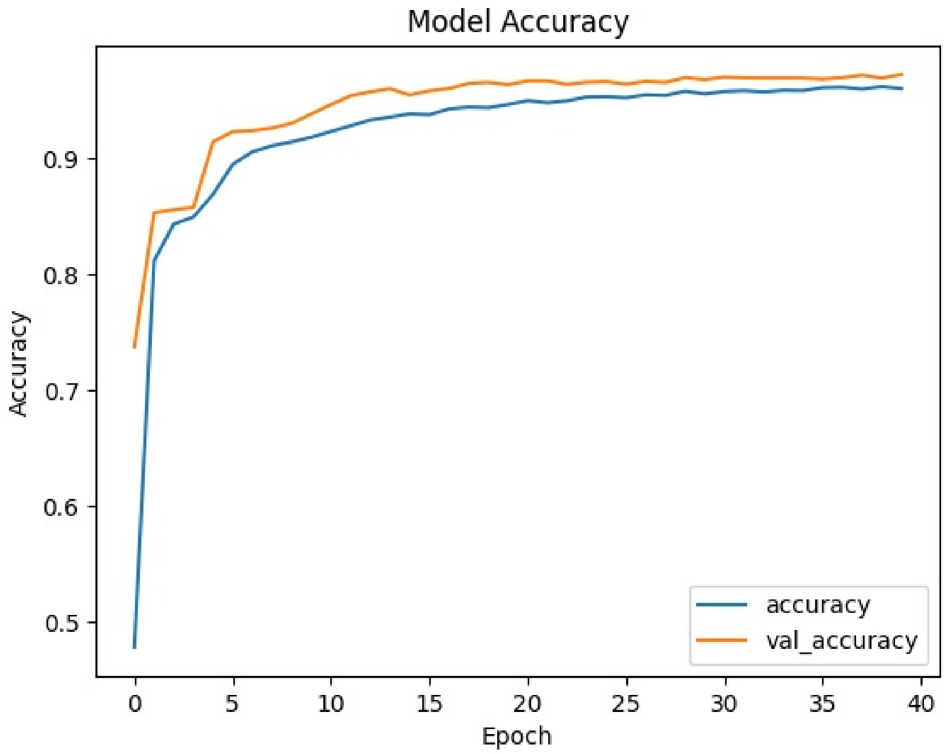

Figure 4.14: Model Accuracy for LeakyRelu with 7 Layers and 40 Epochs

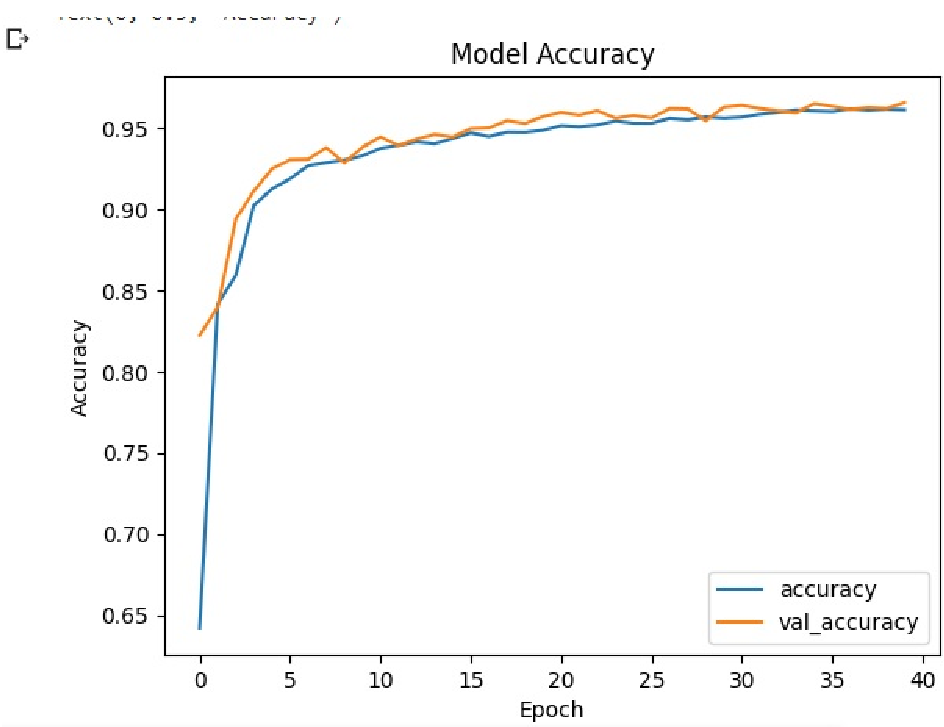

Figure 4.15: Model Accuracy for Elu with 7 Layers and 40 Epochs

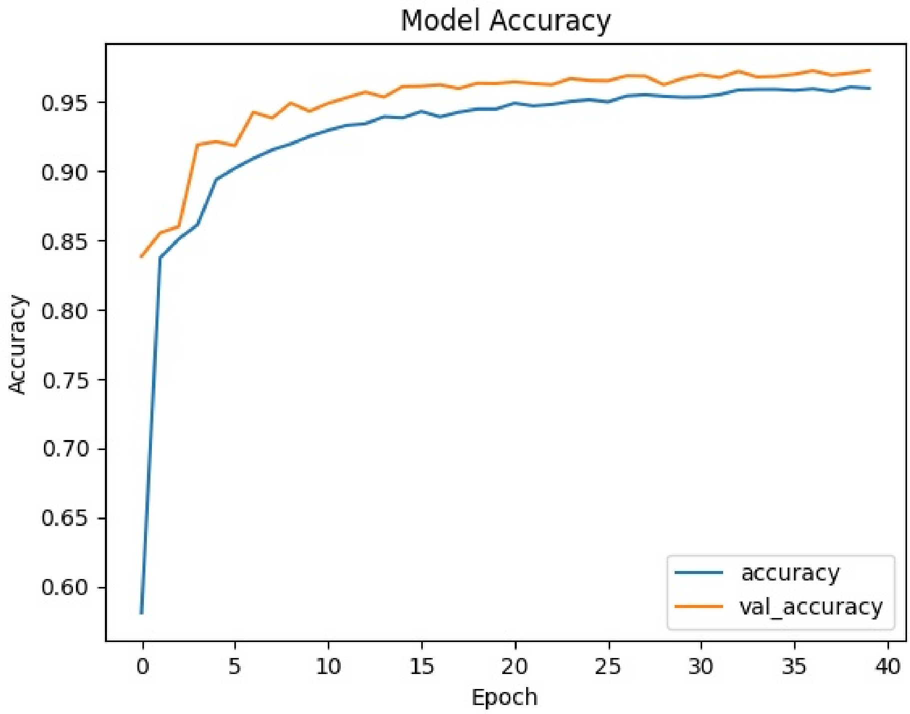

Figure 4.16: Model Accuracy for Tanh with 7 Layers and 40 Epochs

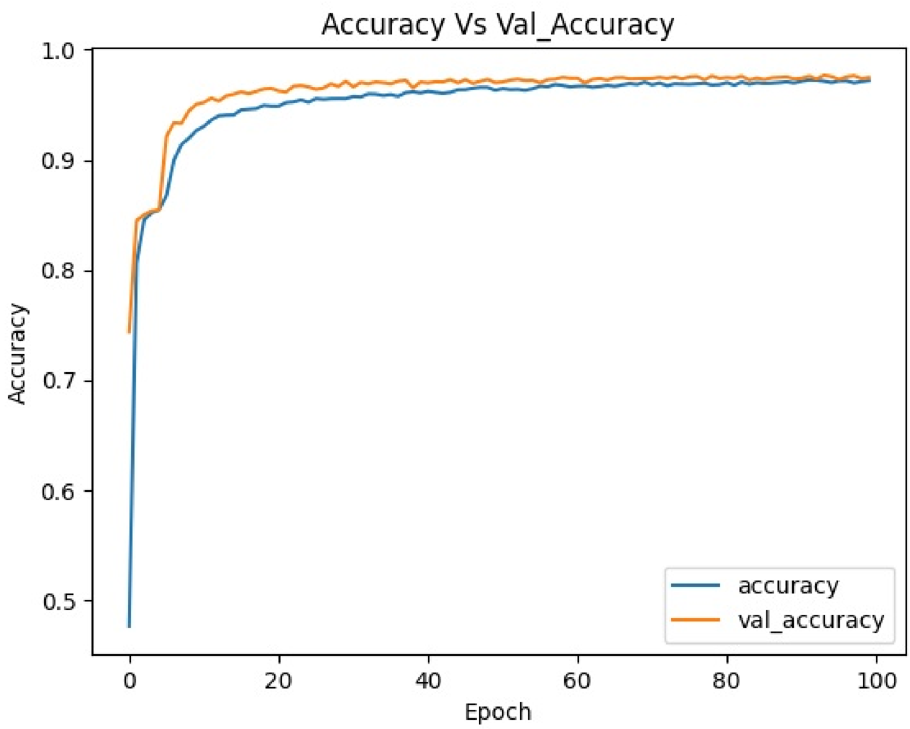

Figure 4.17: Model Accuracy for ReLu with 7 Layers and 100 Epochs

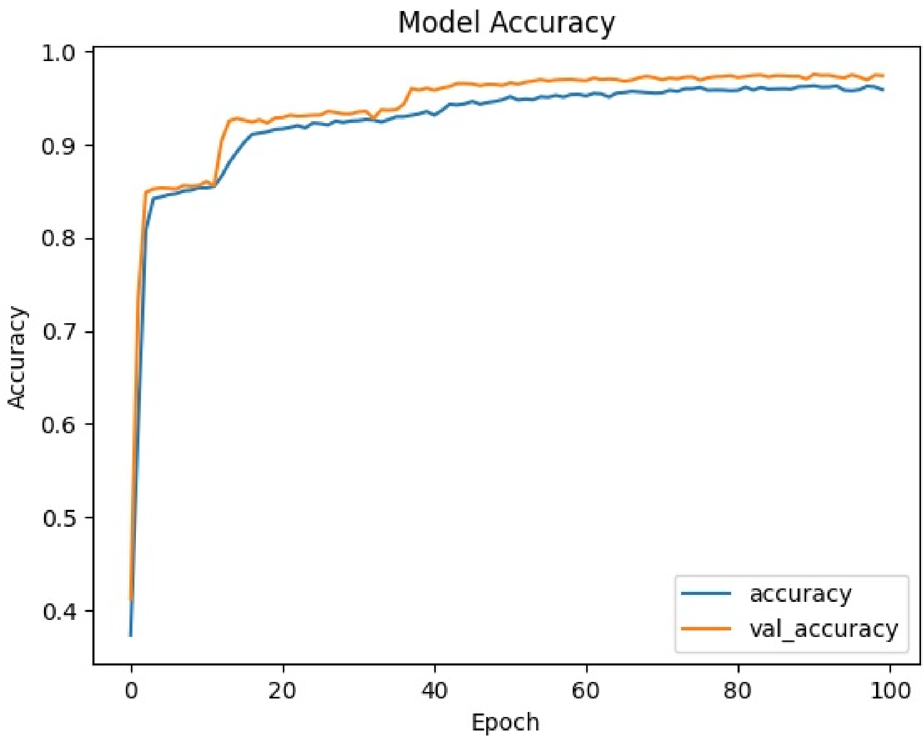

Figure 4.18: Model Accuracy for Leaky Relu with 10 Layers and 100 Epochs

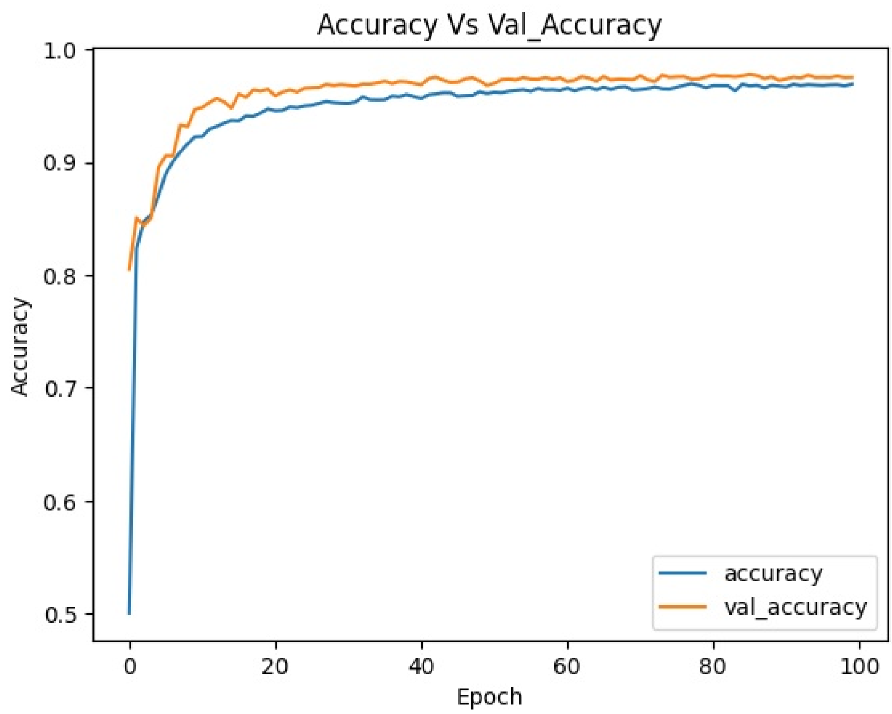

Figure 4.19: Model Accuracy for Elu with 10 Layers and 100 Epochs

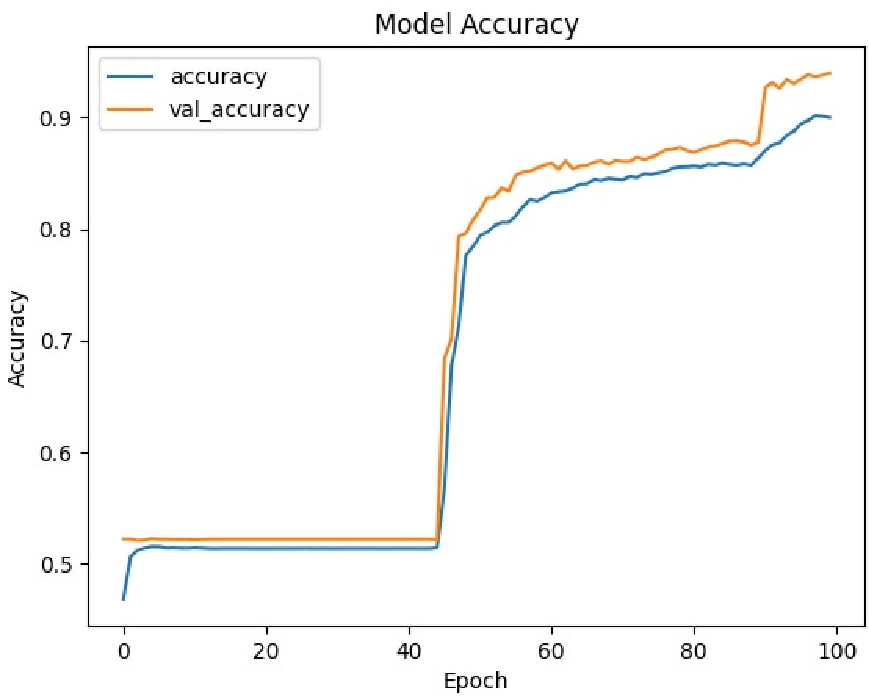

Figure 4.20: Model Accuracy for Tanh with 10 Layers and 100 Epochs

Table 4.4 shows optimised hyperparameters with different test-scores using different layers for varying batch sizes but constant no. of epochs.

Table 4.4: Visualization of Optimized Hyperparameters and Associated Test Scores

Learn-Rate	Batch-Size	No. of Layers	Epochs	Test-Score
0.001	256	7	100	90.65
0.001	128	7	100	90.82
0.001	128	10	100	88.50
0.01	256	10	100	55.68
0.001	**256**	**10**	**100**	**91.59**
0.0001	256	10	100	81.18

4.2.2 Performance Analysis of Various AI Models for ECG Analysis

Various AI- Models were used for the evaluation of ECG analysis. Table 4.5 shows the results obtained from different experiments.

Table 4.5: Performance Analysis of Various AI Models for ECG Analysis

Sr.#	AI Model	Layers	Epochs	Accuracy	Training Database	Testing Database
1	**CNN (1 D)**	4	30	36%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
2	**DNN**	7	40	87%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
3	**DNN**	9	40	89.03%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
4	**DNN**	10	40	90.35%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
5	**DNN**	11	40	89.98%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
6	**DNN**	7	100	90.65%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
7	**DNN**	10	80	90.27%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
8	**DNN**	10	100	91.59%	MITH-BIH (Single lead)	MITH-BIH (Single lead)
9	**DNN**	34	80 (early stopping at 40)	85.04%	MITH-BIH (Single lead)	MITH-BIH (Single lead)

The accuracy graph for the 4-Layer CNN (1 D) with 30 epochs is presented in Figure 4.21. The results indicate a relatively low accuracy rate of 36%. The accuracy graph for the 7-Layer DNN (1 D) with 100 epochs is presented in Figure 4.22. The results indicate an accuracy rate of 90.65%. Whereas the accuracy graph for 10-Layer DNN (1 D) with 100 epochs is presented in Figure 4.8.

Based on the experimental analysis, it can be observed that there is a general trend of increasing accuracy with an increase in the number of epochs and layers. However, it is noteworthy that

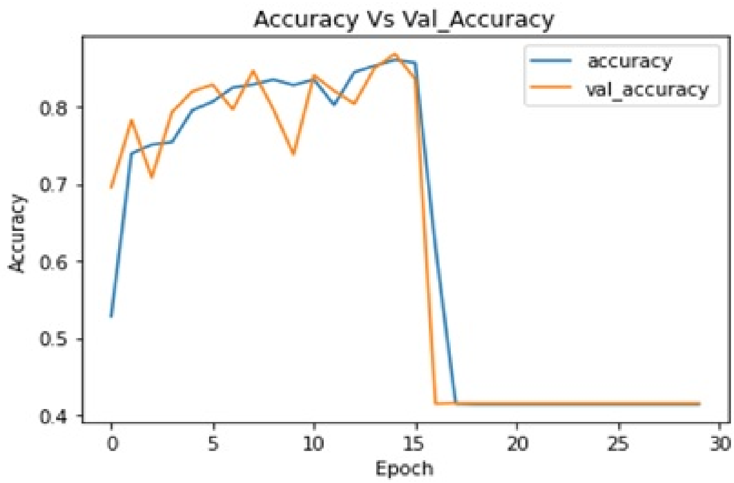

Figure 4.21: Accuracy Graph with Batch Size 256, Epochs 30, and Layers=4

Table 4.6: Results from Proposed Hybrid Model

AI-Model	Non-Invasive Parameter/s	No. of Classes	Accuracy
DNN	**ECG**	**6**	**91.59%**
Decision Tree	**T, BP, SpO2, HR**	**17**	**99.97%**

unnecessarily increasing the complexity of the model by adding more layers may not necessarily lead to a remarkable improvement in accuracy. Therefore, it is essential to achieve a balance between model complexity and accuracy in order to achieve optimal performance.

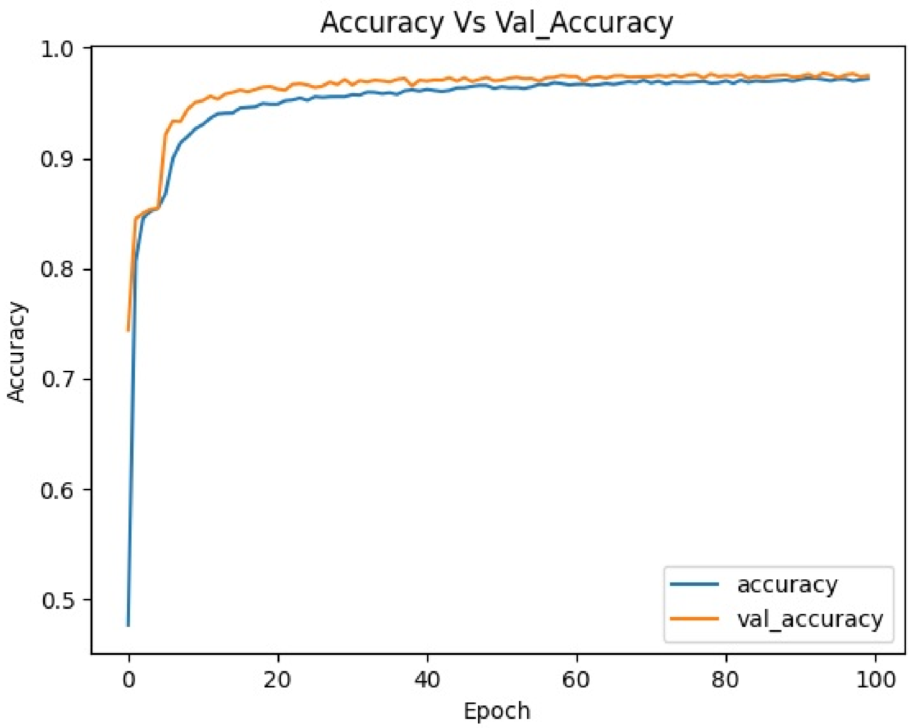

Figure 4.22: Accuracy Graph with Batch Size 256, Epochs 100, and Layers=7

4.2.3 Comparative Analysis with Prior Research Studies

To validate the efficacy of the proposed approach, an investigation was conducted to ascertain its effectiveness. We performed a comparison with existing standard methods, evaluating aspects such as the technique, accuracy, and other statistical parameters, as detailed in Table 4.7. It is noteworthy that our proposed approach demonstrates significant advantages with respect to accuracy and computational cost over other cutting-edge paradigms. This highlights the potential of our implemented approach and suggests that it could be utilized for diagnosing various critical diseases in both CCUs and ICUs.

Table 4.7: Comparison of Proposed Study with Existing State-of-the-Art Models

Study	Year	AI-Model	Database	No. of Classes	Accuracy	Sensitivity	Specificity	F1-Score
[29]	2019	DNN (34-Layers)	CT	12	-	-	-	83.7%
[30]	2019	CNN	MIT-BIH	4	95.73%	-	-	-
[36]	2020	MCHCNN	MIT-BIH	5	93%	-	-	-
[45]	2022	DNN	MIT-BIH	5	88.99%	52.10%	94.75%	-
[46]	2022	2D-CNN-LSTM	MIT-BIH	3	99%	99.33%	98.35%	-
This Study	**2023**	**DNN**	**MIT-BIH**	**6**	**91.59%**	**98.67%**	**93.63%**	**91.7%**

4.3 Discussion

We aimed to devise an optimised ensemble model in this research study which combines a machine learning paradigm with a deep learning framework to enhance the classification performance of arrhythmia and various cardiovascular diseases. Specifically, we used the Decision Tree algorithm for the categorization of 17 classes, including 8 CVD classes, a Normal case, an unknown case and other classes for non-cardiovascular conditions. We created a new dataset by combining non-invasive parameters extracted from Sepsis dataset in addition to our ECG dataset. The performance of various machine learning algorithms was then evaluated on this dataset, and the results are presented in Table 4.1. Our findings indicate that Decision Tree yielded an impressive accuracy of 99.99%, while Gradient Boosting outperformed all other algorithms, achieving an accuracy of 99.96%. In contrast, the Random Forest algorithm performed poorly, exhibiting no precision at all. For the classification of arrhythmia, we employed a deep learning approach using the MITH-BIH single-lead database for ECG analysis. We conducted a series of experiments and performed hyperparameter tuning to optimise our proposed model. The DNN framework was trained with a learning rate of 0.001, a batch size of 256, and 100 epochs. To prevent overfitting, we incorporated 0.5 of dropout regularization, which permitted the retention of only half (50%) of the information for the learning process. Our proposed DL paradigm achieved an accuracy of 91.59%, sensitivity of 98.6%, and specificity of 93.6%, respectively, as reported in Table 4.2. In our study, we also explored the impact of various activation functions to determine the efficacy of our proposed model, as outlined in Table 4.3. Our findings indicate that the Rectified Linear Unit (ReLU) activation function produced the optimum results, while the model's accuracy was least with the Elu function for 10 layers. Moreover, we observed that by increasing the number of epochs, the proposed model's performance improved further. In this thesis, we offer a comprehensive analysis of the efficacy and outcomes of the implemented deep learning and machine learning techniques for electrocardiogram (ECG) analysis and other non-invasive parameters respectively. The findings are presented in Table 4.6. Furthermore, we compare our proposed study with some existing techniques, and the comparison results are presented in Table 4.7. One of the key contributions of our work is the collective diagnosis of 13 cardiovascular diseases (including 5 arrhythmia classes), made possible through the combined use of the machine learning and deep learning approaches. The proposed hybrid model holds the potential to augment the precision of disease detection, which is mandatory for timely and effective treatment.

The concluding chapter 5 of this thesis presents a comprehensive summary of our research findings and provides recommendations for future research directions

CHAPTER 5

Conclusion

The final chapter of this dissertation serves as a succinct yet comprehensive synthesis of the research conducted, emphasizing its significant contributions to the field of study. Additionally, this section addresses the challenges encountered throughout the investigation, delves into potential avenues for future research, and recognizes the limitations that persist in the present work.

5.1 Summary

As per the guidelines of the World Health Organization (WHO), cardiac diseases account for around 80% of sudden deaths. By the year 2030, an estimated 23.6 million individuals are projected to experience fatalities attributable to cardiovascular conditions. In Pakistan, CVDs are responsible for 30-40% of all deaths, with coronary heart disease being the leading cause, resulting in approximately 200,000 deaths per year, equivalent to 12 people dying every hour due to heart attack. Unhealthy diet, physical inactivity, tobacco use, and hypertension are some of the risk factors for these diseases. AI technology holds the immense potential to revolutionize the identification and treatment of cardiovascular ailments, leading to better care services, improved quality of life, and cost-effective systems. By using AI-based systems, healthcare professionals can accurately diagnose and classify various types of CVDs, such as coronary artery disease, arrhythmias, and heart failure, reducing the workload of cardiologists and allowing them to focus more on patient care. Additionally, promoting cardiovascular healthcare is crucial to reduce the incidence of sudden deaths due to heart diseases. An AI-aided system has been proposed to address the issue of swift and accurate diagnosis of Cardiovascular Diseases (CVDs) and Cardiac

Arrhythmias. The system employs an ensemble model consisting of a machine learning (ML) model and a deep learning (DL) model, which take non-invasive cardiac parameters as input. The ML model assesses parameters like blood pressure, temperature, oxygen saturation, and heart rate, while the DL model analyzes electrocardiogram signals. This combination provides accurate diagnosis and treatment recommendations. A complete cardiac dataset was developed by extending the ECG dataset from MIT-BIH with another dataset of temperature, BP, SpO2, and HR. The proposed framework outperformed various other cutting-edge models for the given cardiac dataset, as evaluated by various measures. This research promises to predict maximum CVDs and Arrhythmia classes by applying smart AI techniques, which can potentially save lives by enabling instant and accurate diagnosis. The proposed ensemble model can be used in various healthcare settings to improve the diagnosis and treatment of CVDs and related conditions, ultimately reducing the workload of cardiologists and allowing them to focus more on treatment.

5.2 Contributions

Some significant contributions made by the conducted study are mentioned below:

- A hybrid computational model has been developed to perform an analysis of the maximum non-invasive cardiac parameters (five).
- A novel dataset has been developed consisting of ECG along with other vital cardiac parameters. The inclusion of additional cardiac parameters alongside ECG data in the dataset can potentially enhance the quality and scope of cardiac analyses and aid in the development of improved diagnostic and prognostic models.
- The model has been designed to cater a large variety of cardiovascular and non-cardiovascular conditions (seven).
- The model proposed in this study has been employed for the classification of a wide range of cardiovascular diseases (thirteen CVDs) using the novel dataset.

5.3 Challenges

The following are the challenges that were encountered during the execution of this research.

- An adequate dataset comprising both ECG data and essential non-invasive cardiac parameters from the same patients was not readily accessible. Such a dataset is essential for effectively conducting tasks like arrhythmia classification and predicting other cardiovascular diseases.
- Due to the formulation of the BP data from the 'Sepsis' dataset, the data was found to be skewed, presenting a challenge that necessitated data cleaning and balancing.
- The training of our model was conducted utilizing a single-lead of MIT-BIH ECG dataset, which was challenging due to the dataset's double lead nature. Despite this, we successfully trained the model to accurately predict ECG signals using only one lead. To test the model's performance, we evaluated it on the "Challenge" dataset, which also comprises single lead ECG recordings.

5.4 Future Recommendations

There are opportunities for improvement in this study in terms of:

- This research study has the potential to be beneficial for the investigation and analysis of EEG signals in the future.
- To enhance accessibility and user-friendliness, it is possible to save the AI model on a cloud platform and create a web interface that can be easily accessed by end-users in the future.
- The proposed model has the potential to be integrated into a real-time environment which would enhance the ubiquitous access to healthcare, particularly in rural areas.

5.5 Limitations

There are few limitations associated with this study.

- The dataset we used in our study consists of single-lead ECG recordings, which offer a narrower signal scope compared to the more extensive information available in a standard 12-lead ECG. It remains uncertain whether our algorithm's performance would exhibit similar results when applied to 12-lead ECGs.

- Although our study is restricted to non-invasive parameters, a comprehensive smart cardiac system can be developed by integrating other vital invasive cardiac parameters such as glucose, cholesterol, etc. within an advanced Cardiac Care Unit (CCU). By adding these attributes we can obtain a more comprehensive assessment of the patient's cardiovascular health.

- The hybrid approach of our proposed study may not be necessary when cardiac parameters are available for a single patient, and a single AI model can be used instead. This could potentially simplify the model and reduce computational complexity. Further research is needed to explore the feasibility and effectiveness of using a single AI model in this context, and to assess its performance in comparison to the hybrid model.

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