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Exploring the Relationship between Cardiac Disease and Patterns of 12-Lead ECG through Neural Network: A Comprehensive Review

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Abstract: Heart disease is a significant public health concern, affecting a large number of people worldwide every day. With a shortage of qualified cardiologists, particularly in low-income countries, the diagnosis and management of heart disease can be challenging. The electrocardiogram (ECG) is the primary diagnostic tool for heart disease, but interpreting ECG reports requires the expertise of a qualified cardiologist, making it time-consuming and costly. To address this issue, automated ECG signal interpretation is necessary. Hence, this article has made an encyclopedic review of the existing literature. The article includes a demonstration of frequently utilized data sets, tools, and techniques for this domain. Therefore, a framework is proposed based on the observation of existing works. The proposed framework aims to improve the analysis of ECG reports for both cardiologists and non-experts. Our framework considers the 12-lead ECG, the different types of leads, wave patterns, and their relationship with heart disease. The objective is to produce reliable and accurate results while reducing analysis time. The proposed framework is inherent in improve the diagnosis and management of heart disease by enabling a wider range of healthcare providers and individuals to interpret ECG reports. This could lead to earlier detection and treatment of heart disease, which could improve outcomes and save lives.

Keywords: Cardiac Disease, ECG, Machine Learning, Deep Learning, Heart Disease

1. INTRODUCTION

Cardiovascular disease (CVD) is a consolidated term for conditions affecting the heart or blood arteries [72]. A science-based organization known as the Centers for Disease Control and Prevention (CDC) depicts that the leading cause of death among men, women, and individuals from various racial and ethnic backgrounds in the United States is heart disease. Accordingly, the World Health Organization (WHO) declares that 17.9 million people die due to heart disease every year. Unhealthy and processed food, physical sluggishness, usage of nicotine, and excessive alcohol consumption are the major behaviorally threatening elements for heart disease. These risk factors can lead to elevated levels of blood pressure, blood glucose, blood lipids, and being overweight or obese in individuals [1]. The accumulation of fatty substances known as atheroma in the coronary arteries can cause a blockage or disturbance in the blood flow to the heart muscle, which can lead to the development of coronary heart disease (CHD) [101].Heart-related illnesses include arrhythmia, myocardial infarction (MI), sometimes known as heart failure, angina, stroke, heart attack, etc. [40, 126].

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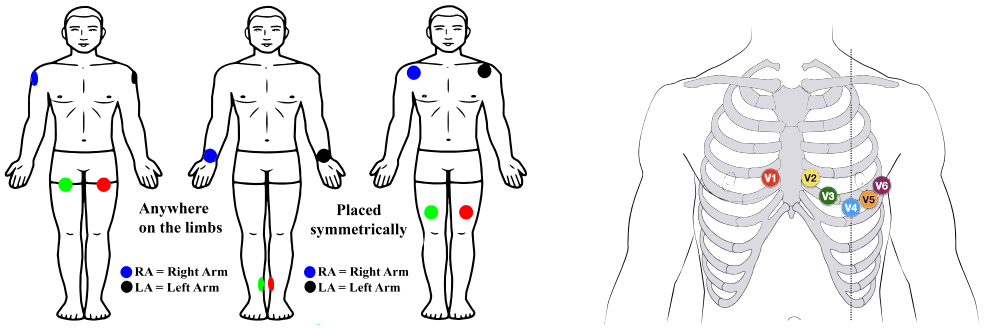
The irregularity of the heartbeat known as arrhythmia is linked to a higher risk of blood clots [97, 109, 133]. MI follows when not enough blood reaches a particular area of the heart muscle [59, 101]. The longer it takes for the heart to restore proper blood flow, the greater the harm inflicted on the heart muscle [26]. Additionally, coronary artery disease (CAD) is the primary cause of heart attacks, while the failure of the heart to effectively pump blood throughout the body is referred to as heart failure, which can result from the heart becoming too stiff or weak [26, 27, 38]. This condition is also known as congestive heart failure (CHF) [28, 67]. An ECG is a rapid diagnostic tool that can be utilized to assess the heart's electrical function and rhythm [114, 150]. In this diagnosis, sensors attached to the skin can detect the electrical impulses that the heart produces with each beat [4, 128]. The signals are recorded by a machine, and a physician evaluates them to determine if there are any irregularities [87]. The 12 ECG leads each reflect a unique 3-D direction of heart action, where leads I, II, III, aVF, aVR, aVL, V1, V2, V3, V4, V5, and V6 are the standard ECG leads [19, 23, 91, 106]. However, these leads are classified into two parts: Leads I, II, III, augmented Vector right (aVR), augmented Vector left (aVL), and augmented Vector foot (aVF) are known as limb leads (Figure 1 (a)), and Leads V1, V2, V3, V4, V5, and V6 are known as precordial leads (Figure 1 (b)) [52, 136, 151]. Nowadays, detecting heart problems using ECG has become popular due to its reliability and accurate production of signals [31, 96, 147]. Detecting heart disease from ECG signals can be a challenging task for medical professionals due to the time required to understand these signals as well as the expense associated with having qualified experts perform this task.



(a) Limb leads positions for ECG (b) Precordial leads position for ECG

Fig. 1. Leads placement for monitoring ECG signals

Therefore, the development of an automated system for detecting heart disease from ECG signals may provide a potential solution to this issue. Several works have been incorporated to detect various CVDs by analyzing ECG signals [20, 99, 124]. A thorough analysis has been conducted on the automated identification of CAD through the use of ECG signals [65]. This study employed sixteen entropy measures to detect distinct latent features from ECG signals obtained from patients with CAD and healthy individuals. In recent years, various methods such as Machine Learning (ML), Deep Learning (DL), and hybrid approaches have been employed for heart disease classification. A review of prior research on the application of DL for ECG diagnosis revealed the use of four standard algorithms: stacked auto-encoders, Deep Belief Network (DBN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) [72]. They conducted a thorough assessment of ECG diagnosis for accomplishing their application, including their advantages and disadvantages. However, most of the research has concentrated on utilizing ECG signals to identify the presence of heart disease [50, 67, 90, 94]. But the working principle of ECG signals and the signal collection procedure of 12 leads of the ECG device are not focal points of the research. Therefore, this research aims to incorporate this issue by answering the following research questions:

• Q1: Which data sets are available to analyze heart rate variance?

• Q2: What is the importance of the automatic classification of heart diseases, and which approaches are utilized to incorporate this issue?
• Q3: What is the relation between heart disease and 12 lead ECG mechanisms and how do they help to predict each distinct heart condition?

1.1. Inclusion and Exclusion Criteria

In this work, some search strategies are applied to find relevant research in this domain. Moreover, this article has analyzed only recent articles to understand the updated and current techniques applied for heart disease detection. In this study, articles that were released between 2019 and 2023 were examined. In addition, we have selected some well-known journals based on ranking and focus on various disease detection, and the medical sector is given more priority to extract the papers.

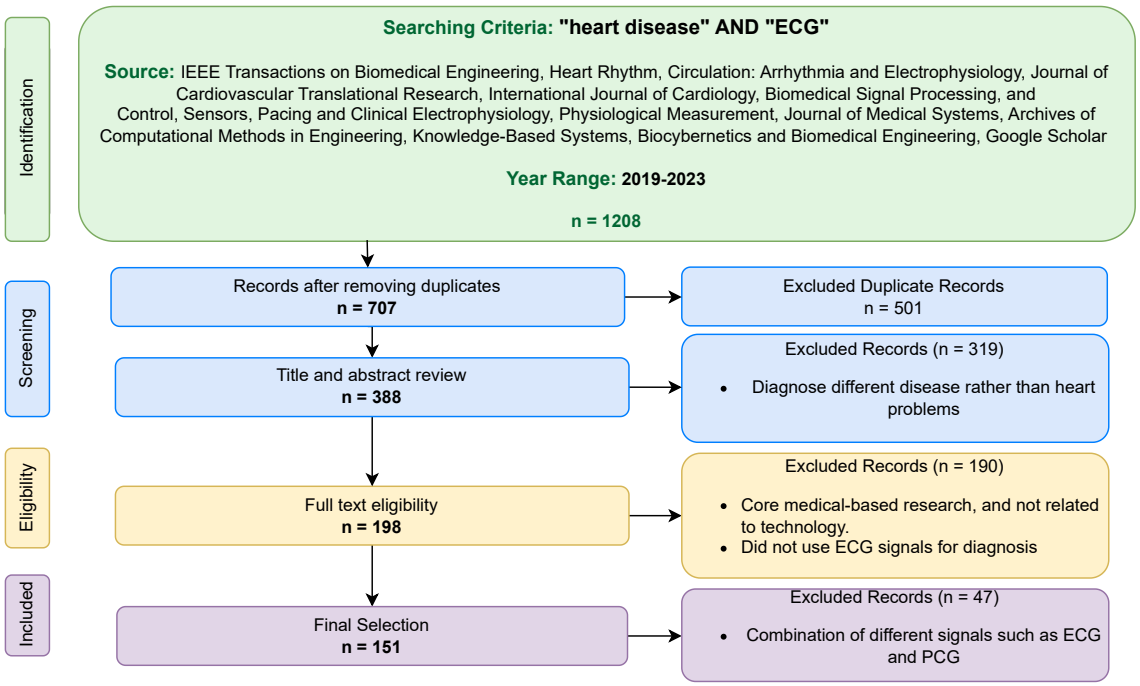


Fig. 2. Article search strategy

The search strategy along with the final list of the articles are illustrated in figure 2. Therefore, this study incorporates the popularly utilized data sets and techniques for various CVD. After that, the relation between heart disease and 12 lead ECG mechanisms has also been incorporated in this study. Finally, a framework has been developed to suggest an executable approach based on the concomitant literature that is described in the Proposed Methodology section.

2. FREQUENTLY USED DATABASES

Data is the fundamental requirement for the detection, analysis, or interpretation of any kind of disease. It is a challenging task to detect disease without any form of information or data. There are several data sets have been built and they are publicly available for disease detection [50, 77, 142, 150]. Moreover, some popular data sets are publicly available for the prediction of different heart problems [8, 28, 101]. Table 1 illustrates the popular data sets used for the detection of arrhythmia, Table 2 refers to the datasets that were used for some

dangerous disease such as MI, heart failure, etc. and Table 3 illustrates the frequently used databases that are utilized for the prediction of several heart problems.

Table 1. Different types of ECG data sets for Arrhythmia

Citation	Source of Data	Number of Recordings	Disease Detected
[8]	MIT-BIH arrhythmia	47 subjects: 25 males and 22 females, 4000 ECG Signal	Arrhythmia
[66]	MIT-BIH arrhythmia	N/A	Arrhythmia
[122]	MIT-BIH	47 subjects	Arrhythmia
[28]	(MIT-BIH) ARR database, MIT-BIH Normal, Sinus Rhythm (NSR), and BIDMC CHF database	Total 162 records	CHF, Arrhythmia (ARR)
[95]	MIT-BIH Atrial Fibrillation Database	N/A	Atrial Fibrillation (AF)
[143]	MIT-BIH arrhythmia	29 subjects	Arrhythmia
[97]	MIT-BIH	29 subjects	Arrhythmia
[116]	Numerical-sultanova, Cleveland, ECG-physioNet, MIT-BIH Arrhythmia data set, PTB Diagnostic ECG Database	N/A, 1190 people, 18,885 patients, 109446 samples, 14552 samples	Arrhythmia
[83]	MIT-BIH Normal Sinus Rhythm, MIT-BIH Arrhythmia, BIDMC CHF database	18 (5 Males, 13 Females), 47 (25 Males, 22 Females), 15 (11 Males, 4 Females)	Arrhythmia, CHF
[38]	MIT-BIH-PhysioNet databases	105 subjects	Arrhythmia, CHF, sudden cardiac death (SCD)
[22]	China physiological signal challenge (CPSC) 2018 data set	6877 recordings	9 categories of Arrhythmia
[27]	MIT-BIH ARR, MIT-BIH NSR, BIDMC CHF	48 subjects, 18 subjects, 15 subjects	CHF, arrhythmia
[55]	ECG data from wearable sensors	N/A	Arrhythmia
[109]	MIT-BIH	1800 records	Arrhythmia
[133]	MIT-BIH	48 records 47 from patients	Arrhythmia
[120]	MIT-BIH	47 subjects, 48 recordings	Arrhythmia
[80]	MIT-BIH AFDB, CUDB, MITDB, MIT-BIH VFDB	23 subjects, 35 subjects, 44 subjects, 22 subjects	6 types of arrhythmia
[141]	MIT-BIH	25 subjects	AF

Table 2. A bunch of ECG data sets for prominent heart problems

Citation	Source of Data	Number of Recordings	Disease Detected
[101]	PTBDB, MIT-BIH database	48 records	MI
[67]	RR interval database, BIDMC-CHF database, NSR-RR, Fantasia database, MIT-BIH, NSR database	Total 156 subjects	Heart failure
[59]	Self-developed database (ECG Device 'EDAN SERIES-3)	1937 patients data	COVID-19, Abnormal Heartbeat, MI, Previous History of MI, and Normal Person
[53]	Self-developed	43 Patients	IHD
[104]	MIT-BIH arrhythmia and PTB-ECG databases	360 subjects	Heart Disease
[26]	PTB diagnostic, BIDMC CHF, St. Petersburg,	236 patient, 15 patient, 7 patient,	MI, Normal (N), CAD, Valvular heart disease (VHD) , Bundle Branch Block (BBB), Hypertrophic cardiomyopathy (HCM), Dilated cardiomyopathy (DCM)
[29]	PTB database	549 ECG records from 290 subjects	MI
[138]	MIT-BIH	48 records	Heartbeats
[44]	Fantasia Normal database, European STT database, Collected data from IBN- AL-NAFEES Hospital	40 subjects 40 recordings, 78 subjects 88 recordings, 30 subjects 30 recordings	Myocardial ischemia
[76]	Cleveland data set	303 records	Heart Disease
[93]	PTB-XL dataset	21,837 records	
[152]	PTB-XL database	21,837 records	CVD
[146]	St-Petersburg, BIDMC CHF, PTB Diagnostic	5 subjects 17 records, 15 subjects 15 records, 52 subjects 80 records	CAD, CHF, MI, normal

Table 3. Detecting multiple heart problems using ECG data

Citation	Source of Data	Number of Recordings	Disease Detected
[39]	MIT-BIH, St. Petersberg, PTB databases	N/A	AV nodal block (AV NB), Acute MI, Atrial fibrilation (AF), CAD, Earlier MI (EMI), Healthy, Sinus Node Dysfunction (SND), Transient Ischemic Attack (TIA), BBB, Cardiomyopathy, Dysrhythmia, Healthy control, MI, Myocarditis, VHD, AFIB, Normal, P, SBR
[125]	MIT/BIH-SCDH, MIT/BIH-NSR databases	23 subjects, 18 subjects	SCD
[15]	MIT-BIH Arrhythmia Database	47 subjects	left bundle branch block (LBBB) beat, right bundle branch block (RBBB) beat, PVC beat, ventricular flutter wave beat, nodal (junctional) escape beat, aberrated atrial premature beat, ventricular escape beat, and normal beat
[74]	MIMIC-II	12,000 instances of 942 patients	Blood Pressure (BP)

Q1: Which data sets are available to analyze heart rate variance?

One of the most popular data sets regarding heart disease is the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) data set [66, 97, 122, 138]. There are various categories of data available in this data set such as the MIT-BIH arrhythmia data set, MIT-BIH Normal Sinus Rhythm (NSR) data set, MIT-BIH-PhysioNet databases, MITBIH Atrial Fibrillation Database (MIT-AFDB), MIT-BIH Malignant Ventricular Ectopy Database (MIT-BIH VFDB), MIT/BIH Sudden Cardiac Death Holter (SCDH), etc [28, 38, 80, 102, 125, 143]. Among them, the MIT-BIH arrhythmia data set is the mostly utilized database and this data set is known by several names such as the MIT-BIH arrhythmia data set, MIT-BIH ARR data set, etc. [15,27,102]. However, it is observed from the existing literature that researchers are more concerned about detecting different types of arrhythmia disease than others [109, 133, 141]. This is why the arrhythmia dataset is popular in this domain for detecting heart problems. Additionally, arrhythmia is also referred to as AF in some articles because AF is a type of arrhythmia [12, 95, 102]. After that, MI, CHF, and SCD are also predicted in some research using the MIT-BIH data set [27, 38, 101]. Other heart-related problems such as heart failure, Ischemic Heart Disease (IHD), and abnormal heartbeat are predicted in this field using several popular databases [53, 59, 67]. Hence, Beth Israel Deaconess Medical Center (BIDMC) CHF data set is employed in some studies to detect heart failure [26–28]. After

that, Physikalisch Technische Bundesanstalt (PTB) diagnostic ECG database is utilized in various literature to detect MI, arrhythmia, etc, [29, 101, 116]. In spite of that, there are some data sets available employed for the detection of heart problems in a few articles. For example, St-Petersburg, Fantasia database, Numerical-sultana, Cleveland, Creighton University Ventricular Tachyarrhythmia Database (CUDB), European ST-T database, Multi-Parameter Intelligent Monitoring in Intensive Care II (MIMIC-II) Waveform database, etc. are utilized in some articles to predict heart disease [44, 74, 80]. Therefore, these data sets are popularly utilized for a combination of detecting several heart diseases.

3. OBSERVATION OF EXISTING APPROACHES

Q2: What is the importance of the automatic classification of heart diseases, and which approaches are utilized to incorporate this issue?
Automatic classification of heart disease can help the cardiologist to save their time and they can operate more patients within a short amount of time. Not only that, automatic diagnosis of heart problems using ECG signals can also help the patients to acknowledge their condition before affected seriously [8, 101]. Therefore, it can also help to diagnose accurately the heart issues since the pre-trained algorithm is trained by the existing database that helps the models to learn the signals specifically. Moreover, the available approaches in different domains are depicted in the subsections below.

3.1. Deep Learning

There are several techniques have been utilized to detect different heart problems in many articles such as ML techniques, DL approaches, Ensemble methods, hybrid approaches, etc. [8, 29, 143]. Among these approaches, some DL algorithms such as CNN, Long-Short Term Memory (LSTM), CNN-LSTM, etc. are widely used in several applications to identify heart illness [28, 66, 122]. CNN is commonly applied in several studies from DL approaches to detect heart diseases [80, 102]. An article introduced a novel neural network architecture based on recent advancements in CNNs as a solution to create self-governing systems for diagnosing heart disease using ECG signals [8]. This research employs 1D convolutional layers and the ReLU activation function, which produces 98.33% accuracy. Alternatively, 1D and 2D CNN models with the same activation function are investigated to construct a robust algorithm capable of effectively classifying the ECG signal in the presence of environmental noise [122]. The 1D CNN and 2D CNN have achieved 97.38% and 99.02% accuracy, respectively. Another article proposed a method for classifying multiple cardiac illnesses using a one-dimensional CNN with a modified ECG signal as input [39]. They applied their method to three distinct data sets where the St. Petersburg data set yielded the best accuracy of 99.71%. Moreover, CNN-based hybrid approaches are also popular in this field for classifying heart disease [27, 28, 55, 66, 101, 138]. CNN-LSTM is a frequently used algorithm among CNN-based hybrid approaches [50, 67, 95, 143]. An automated detection system is proposed for the detection of MI where CNN, CNN-LSTM, and ensemble methods were applied. Among them, CNN-LSTM and ensemble techniques provided high accuracy of 99.9% [101]. Another study suggests an automated diagnosis approach based on Deep CNN and LSTM Architecture (DCNNLSTM) for diagnosing CHF using ECG signals [67]. This approach has performed similarly to the previous work, 99.52%. In this study, CNN is utilized to extract deep features, while LSTM is employed to achieve the goal of detecting CHF using the extracted features. However, another CNN-based hybrid approach known as Grey Wolf Optimizer (GWO) Artificial Bee Colony (ABC) optimization algorithm (CNNGWO-ABC) is proposed to detect arrhythmia [55]. The automatic construction of CNN typology using neuro-evolution has been examined in this work. A unique solution based on the ABC and the GWO has also been developed. The performance of this algorithm is satisfactory but not excellent as compared to the previous study. It showed 94.27% accuracy which is less than

the CNN-LSTM approaches. Another different hybrid strategy is suggested, and it involves a two-stage medical data classification and prediction model [76]. If the results of the initial stage can accurately predict cardiac disease, the second stage may not be necessary. During the first stage, data from medical sensors attached to the patient's body was categorized, while the second stage involved the classification of ECG images to forecast the likelihood of heart disease. To classify sensor data, a hybrid model using Faster R-CNN with SE-ResNet-101 was used, while for ECG image classification, a hybrid approach utilizing linear discriminant analysis with modified ant lion optimization (HLDA-MALO) was employed. Therefore, the performance of this approach is 98.06% in terms of accuracy. Hence, 1D CNN, 2D CNN, and CNN-LSTM are commonly used algorithms in this field for detecting various types of heart diseases. In addition, Generative Adversarial Networks (GAN) and LSTM (GAN-LSTM), Convolutional Capsule Networks, Resnet RNNs (ResRNN), Bidirectional Long Short Term Memory (BiLSTM), Kernel Weight CNN (KWCNN) are also applied in few pieces of literature for heart disease prediction from DL area [22, 26, 104]. The performance of these approaches is good but they do not outperform the other approaches in DL [120,133].

3.2. Machine Learning

ML based algorithms are also explored in some literature to detect heart illness such as Support Vector Machine (SVM), k Nearest Neighbor (KNN), Decision Tree (DT), etc. [104, 129, 141, 152]. Moreover, a deep genetic ensemble of classifiers (DGEC) is proposed that consists of three layers where SVM is used in every layer [97]. The suggested framework comprises an ensemble of three layers (48 + 4 + 1) consisting of 12 classifiers each from the SVM (nu-SVC, RBF), kNN, PNN, and RBFNN + 4 classifiers from the C-SVC and 1 classifier from the C-SVC. This method performs with a 99.37% accuracy rate, which is satisfactory. But the effectiveness of the DGEC system with additional physiologic signals and the improved method was not examined in this study. However, other SVM and fusion SVM models are proposed to detect myocardial ischemia, arrhythmia, and CHF where they have provided 99.09% and 99.06% accuracy respectively [44, 83]. This study proposes a novel approach for identifying myocardial ischemia using multi-lead long-interval ECG. The method employs ChoiWilliams time-frequency distribution to detect changes in the ST and PR segments of the ECG, which are related to ischemic symptoms, to extract ST and PR features [44]. The suggested method is quick, inexpensive, and non-intrusive. Moreover, another ML model known as KNN has been established to detect MI and it showed 99.96% accuracy by single-channel ECG signal [29]. Another study introduced a novel technique for the detection of R-waves and, based on them, the localization of QRS complexes. It was important to evaluate classical classifiers, hence new methods of aggregating ECG signal fragments comprising QRS segments were created. Yet, this model's performance falls short of expectations. It demonstrated a 90.4% accuracy rate for detecting CVD. As a result, using ML algorithms to predict cardiac problems is not widely used. In addition, several different algorithms, including the ridge model, Jaya Algorithm with Red Deer Algorithm (J-RDA), Ensemble Empirical Mode Decomposition (EEMD) with local means (LM) filtering, particle swarm optimization (PSO), differential evolution (DE), and MDD-Net, have been investigated in a few studies [15, 117, 146]. Therefore, since ECG signals are one kind of image related data, ML techniques sometimes cannot process them properly and for that reason DL approaches are utilized in this area.

4. CORRELATION BETWEEN ECG LEADS AND HEART DISEASES

Q3: What is the relation between heart disease and 12 lead ECG mechanisms and how do they help to predict each distinct heart condition?
The 12-lead ECG is vital for detecting and monitoring heart conditions, such as arrhythmia, CHD, and electrolyte imbalances [68]. It records the heart's electrical activity using 10

electrodes placed on the chest, arms, and legs, generating 12 leads. Each lead provides a different view of the heart's activity and is crucial for identifying specific types of heart disease, such as right ventricular infarction (RVI) in leads V1 and V2, and lateral wall infarction in leads V5 and V6 [127]. The 12-lead ECG plays a crucial role in screening for possible cardiac ischemia and rapidly detecting individuals who may have experienced a heart attack. It's imperative for healthcare experts to carefully consider the number of leads employed to ensure precise diagnosis and effective treatment [35]. Each ECG lead conveys a variety of waveform information, and the ECG waveform itself encompasses several distinct elements, each signifying various phases of the cardiac cycle. These elements encompass the P wave, QRS complex, and T wave, each of which represents distinct waveforms with significant relevance in the interpretation of ECGs. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricular re-polarization. Understanding the different types of waves in ECG can help clinicians to diagnose and manage a variety of cardiac conditions. Several works have been incorporated for the detection of various heart problems using ECG signals [84, 124, 136]. R to R interval, QRS complex are different portions of an ECG signal and these portions are used for identifying different heart problems [81, 129, 149]. However, the majority of the works utilized RR interval for several heart illnesses such as AF, various types of arrhythmias, CAD, etc [10, 81]. Some works have utilized the QRS complex for incorporating the issue [86, 135, 149]. An article has detected RR interval for AF detection using CNN-BiLSTM [129]. According to earlier clinical investigations, the Q, R, and S (QRS complex) are three deflections that reflect a single heartbeat. Its timing and structure reveal important details about the heart's condition. Traditional techniques for locating R peaks include wavelet processing, frequency analysis, and digital filters that extract the local maximum value. And R peaks indices have been shown to be important classification indicators for both human and computer-aided categorization. In order to use their model to extract characteristics from pure ECG signals, they would only include R peaks indices in this approach. As a result, they just applied R-R intervals to the original ECG signals in the feature extraction phase to obtain segmentation, and the feature extraction phase will be handled by the model that was used. 0.82 F1 score is achieved by the proposed model in this work. In a different article, the R-Peak Engzee ECG segmentation technique was used to identify and extract features while recording the position, duration, and quantity of R-Peaks [81]. They concentrated on R-R intervals because of the positional invariant nature of CNN layers, the time-dependency of ECG data, and the importance of interval length in ECG interpretation. Therefore, CNN architecture can learn the RR interval data rather than the QRS complex. 91.15% accuracy was achieved by the explainable CNN algorithm for the detection of various arrhythmia in this work. On the contrary, the time domain ECG feature based on Feed Forward Neural Network (FFNN) and CNN provided 91.5% accuracy for the prediction of arrhythmia using the QRS complex [14]. The only portion of an ECG made up of numerous clustered waves is the QRS complex [30]. The QRS complex consists of Q, R, and S waves and signifies ventricular depolarization. After the QRS complex, the T wave denotes ventricular re-polarization. Therefore, the QRS complex is utilized for MI detection in research [21]. They stated that a QRS wider than usual is an indication of BBB and ventricular hypertrophy. For that reason, it is easy to recognize MI by increased R wave amplitude, duration, and high voltage QRS. Using CNN-BiLSTM, they achieved 99.62% accuracy. Therefore, RR interval and QRS complex both are used for the detection of several heart problems and most of them have utilized the CNN algorithm and CNN-based hybrid algorithms for evaluation purposes the performance is similar to each other for both RR interval and QRS complex.

4.1. P-wave

The assessment of P-waves in a 12-lead ECG is a valuable tool for the diagnosis of heart disease [82]. Abnormalities in P-wave morphology, duration, and amplitude can

indicate specific types of heart disease, including atrial enlargement, AF, atrial flutter, atrial tachycardia (one kind of arrhythmia), and WPW syndrome. P-wave abnormalities can be detected in leads II, III, aVF, V1, and V4-6, which are important for the detection of these conditions. The morphology of P-waves in leads II, III can detect right atrial enlargement, while leads V1 and V2 can detect left atrial enlargement. Hence, irregular P-waves are a hallmark of AF. Additionally, P wave abnormalities are also associated with other cardiac conditions, such as atrial flutter, atrial tachycardia, and WPW syndrome. To effectively diagnose different heart diseases associated with atrial depolarization abnormalities, it is crucial to conduct a thorough evaluation of P-wave morphology across multiple leads. This is emphasized in the medical literature as well [118].

4.2. P-R Interval

The PR interval plays a crucial role in an ECG by showing how electricity travels from the atria to the ventricles of the heart [89]. Properly understanding the PR interval's patterns in a 12-lead ECG is vital for diagnosing heart conditions accurately. Specifically, Lead II, Lead III, and aVF provide insights into the heart's lower wall, where PR interval irregularities might signal conduction issues. Furthermore, leads V1 to V6 give us a look at the heart's front, side, and back walls, helping us detect atrial enlargement or fibrillation [68]. Remember, the PR interval can be influenced by various heart conditions and medications. This underscores the need for a comprehensive ECG examination to pinpoint the root cause of PR interval variations [88]. Often, combining data from multiple leads is necessary for an accurate diagnosis, which is critical for crafting an effective treatment plan [68].

4.3. QRS Complex

In a recent research article, we delved into the intricate world of heart disease diagnosis through the examination of the QRS complex within a 12- lead ECG system [139]. Our focus primarily centered on the significant leads V1 to V6, alongside II, III, and aVF. The QRS complex itself serves as a mirror to ventricular depolarization, and its fluctuations can serve as critical indicators for a range of cardiac conditions including ventricular hypertrophy, BBB, and MI [62]. When we set our sights on identifying right ventricular hypertrophy, our trusty companions were none other than leads V1 and V2. Conversely, left ventricular hypertrophy revealed its presence through the ever-reliable leads V5 and V6. Now, for insights into the inferior wall of the heart, leads II, III, and aVF came into play. These diligent leads held the key to uncovering potential blockages or ischemia through changes in the QRS complex [56]. But that's not all; the QRS complex's morphology or shape had a story of its own to tell in the grand scheme of diagnosing heart ailments. A widened QRS complex signaled the presence of a BBB, while a narrow QRS complex hinted at a normal conduction pathway [32]. And let's not forget about those abnormally deep and wide Q waves; they often whispered of a previous MI lurking in the patient's medical history [105, 108, 134]. It goes without saying that an accurate diagnosis and subsequent treatment plan necessitate a meticulous analysis that takes into account a combination of leads and the distinctive morphology of the QRS complex.

4.4. R-R Interval

A research paper delves into the effectiveness of a 12-lead ECG system for evaluating the heart's electrical activity [34]. One crucial element of this system involves the R-R interval waves, which depict the time gap between successive R waves and correlate with ventricular depolarization. Variations in the R-R interval can act as signals for various cardiac issues, encompassing tachycardia, bradycardia, and arrhythmias. When dissecting the R-R interval, healthcare professionals typically use lead II and lead V1 [25], although they may also indicate heart blocks, such as first- degree AV block, second-degree AV block, and complete heart block. To precisely pinpoint the heart disease type linked to R-R interval waves,

healthcare providers must meticulously analyze this interval by examining multiple leads. The R-R interval stands as a crucial component of cardiac functioning, facilitating precise diagnosis and treatment of an array of cardiac ailments [6]. In summary, specific leads within a 12-lead ECG system serve a vital role in discerning the heart disease type associated with various waveforms [85]. Figure 3 illustrates each waveform's significant leads. For instance, P waves in leads II, III, aVL, and V1 can hint at atrial arrhythmias, while Q waves in leads I, aVL, V5, and V6 may suggest a previous myocardial infarction. T waves in leads V2 to V5, ST segment alterations in leads II, III, aVF, V1 to V6, and U waves in leads V2 to V5 can all point to different cardiac conditions [112]. Hence, understanding the importance of each waveform and its corresponding leads plays a pivotal role in identifying the

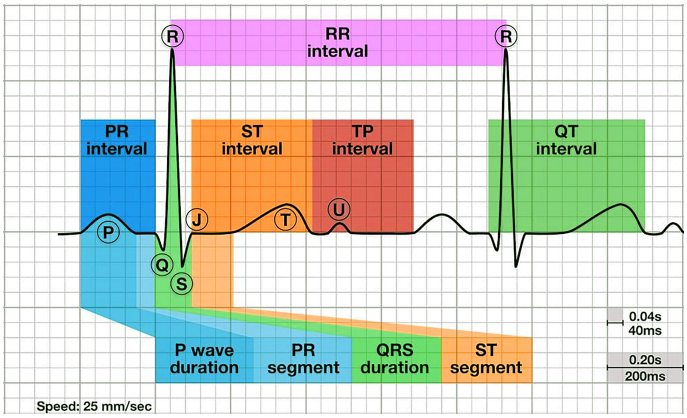


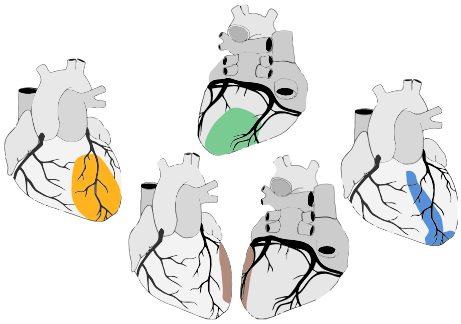
Fig. 3. Different types of wave-forms

prevailing heart disease type and offering suitable treatment. ECGs are invaluable tools for diagnosing various heart conditions, with each type of heart disease manifesting distinct alterations in the different leads of the 12-lead ECG. For instance, CAD may produce ST-segment depression [131] or T-wave inversion in leads II, III, aVF, V4-V6, while a heart attack may cause ST-segment elevation in leads II, III, and aVF (inferior MI) or leads V1-V4 (anterior MI). Heart failure may exhibit non-specific changes like left ventricular hypertrophy or left BBB [46,49,98]. Meanwhile, arrhythmias can produce irregular or abnormal P waves, widened QRS complexes, or absent or abnormal T waves. AF may produce an irregular rhythm, absent P waves, and rapid ventricular response. Other heart conditions, such as heart valve disease, cardiomyopathy, congenital heart defects, pericarditis, and pulmonary hypertension, also cause different ECG changes [36, 51, 121]. It is important to emphasize that only trained healthcare professionals should interpret ECGs and that ECG changes can vary in different individuals and in different stages of the disease.

5. MAPPING CARDIAC TERRITORY: ANTERIOR, LATERAL, INFERIOR, AND SEPTAL LEADS FOR HEART ABNORMALITIES

Proper placement and interpretation of leads are critical for accurate diagnosis and management of cardiac conditions. Anterior wall infarction rarely occurs in isolation and is often associated with infarcts of the septum, lateral wall, or both. The anterior wall is represented by leads V3 and V4 [148]. If both the anterior wall and the septum are affected, the infarct changes will appear in leads V1 to V4, known as an anteroseptal acute MI [61, 107, 145].

In cases where the infarct affects both the anterior and lateral walls (anterolateral AMI), changes will appear in V3 to V6 and possibly I and aVL. The lateral leads I, aVL, V5, V6 are placed on the left side of the chest and are essential in detecting abnormalities in



(a) Cardiac territory

I High Lateral	aVR	V1 Septal	V4 Anterior
II Inferior	aVL High Lateral	V2 Septal	V5 Lateral
III Inferior	aVF Inferior	V3 Anterior	V6 Lateral

(b) Specification of cardiac territory mapping

Fig. 4. Cardiac Territory Mapping for Early Detection of Heart Abnormalities

the left ventricle, such as left ventricular hypertrophy and acute MI [60, 73]. The inferior leads II, III, aVF are placed on the lower part of the chest and are helpful in detecting abnormalities in the right ventricle and inferior wall of the left ventricle, including RVI [57, 113]. Finally, the septal leads V1, V2 are placed on the front of the chest and are crucial in detecting abnormalities in the septum [5], such as septal hypertrophy or septal infarction. The appropriate use and interpretation of these leads shown in Figure 4(a) in the 12-lead ECG that can contribute to the accurate diagnosis and management of various cardiac conditions and also the specification for the mapping is illustrated in the Figure 4(b). In the field of electrocardiography, specific leads can be used to diagnose and manage different types of MI. The right-sided leads, which include V4R, V5R, and V6R, can show ST elevation in a right-side infarct. The posterior leads, V7, V8, and V9, are used to diagnose a posterior acute MI [115]. Criteria for RVI include IWMI [2], ST segment elevation

greater in lead III than II, ST elevation in V1 (possibly extending to V5 to V6), ST depression [144] in V2, and more than 1 mm of ST elevation in the right-sided leads (V4R to V6R). Most RVIs occur in conjunction with inferior wall MI [3]. If ST segment elevation is seen in II, III, and aVF, as well as V1, the most probable explanation is an RVI. The treatment of an RVI is very different from that of a left ventricular infarction, and the diagnostic criteria should be carefully considered in treatment decisions.

6. LEAD-SPECIFIC PATTERNS IN DIAGNOSING CARDIAC CONDITIONS

In general, premature ventricular contractions (PVCs) are best visualized in leads V1 to V3, which are located in the right ventricular outflow tract and the septal region of the heart where PVCs often originate [43, 63, 64, 78, 137]. Lead V1 is particularly useful for detecting PVCs because it has a superior view of the right ventricle. PACs (premature atrial contractions) are visualized in Lead II that is one of the most commonly used leads in ECG and can provide valuable information in detecting PACs [9, 11, 37, 100]. PACs are defined as one kind of arrhythmia. Additionally, the V1 lead, positioned at the fourth intercostal space on the right side of the sternum, may be helpful in identifying PACs originating from the right atrium. The V2 lead, positioned at the same location on the left side of the sternum, can help identify PACs originating from the left atrium. Furthermore, the V4-V6 leads, located on the left side of the chest, can also be useful in detecting PACs originating from the left atrium. RBBB is best visualized in leads V1 and V2, which are located in the right ventricular outflow tract where the right bundle branch is located. RBBB can also be seen in leads V5 and V6, which are located in the left lateral aspect of the heart and may show delayed R-wave progression also help to confirm the diagnosis by showing a ”rabbit ears” pattern in the QRS complex [33, 45, 92]. LBBB is properly envisioned in leads V5 and V6, which are located in the left lateral aspect of the heart where the left bundle branch is located. LBBB is a cardiac condition

characterized by the disruption of the electrical signals that regulate the heart's pumping function. In the diagnosis of LBBB, V1 and V6 leads are crucial, being the most important on a standard 12-lead ECG. ECG criteria that suggest the presence of LBBB include a QRS duration greater than or equal to 120 ms, broad and monomorphic R waves in leads I, aVL, and V6, broad and monomorphic S waves in leads III and aVF, an absence or reduction in the size of Q waves in leads V5 and V6, and an rsR' pattern in V1. These electrocardiographic patterns provide crucial insights into disruptions in the heart's 17 electrical signals, which are vital for diagnosing various heart conditions [130–134]. Medical professionals rely on these criteria to identify conditions like LBBB accurately and offer the appropriate treatment. Atrial premature complexes (APCs) become most apparent when looking at leads II, III, and aVF, which are situated on the lower part of the heart, where the atria reside. APCs might also manifest in other leads [17, 18, 42, 71, 123], like V1 and V2, but they can be trickier to distinguish from other irregularities in those leads. The use of different leads in ECG has been useful in recognizing APBs [24, 79, 110, 140]. Lead II, for example, detects electrical activity between the right arm and left leg and provides a clear image of atria function. Similarly, V1 and V2 leads are situated on the right and left sides of the breastbone, and they are capable of detecting atrial premature beats (APBs) from their respective atria. Leads V4-V6, which are positioned on the left side of the chest, are also useful in detecting APBs that originate in the left atrium [13, 54, 103]. Ventricular ectopic beats (VEBs) are abnormal cardiac rhythms that can be diagnosed using an electrocardiogram, a non-invasive diagnostic test that is widely utilized. The ECG gives useful information for predicting VEBs [69, 70, 119]. It's worth mentioning that various ECG leads have a range of sensitivity in identifying VEBs. Leads V1- V3, which are positioned on the chest wall, are more sensitive to detecting VEBs coming from the right ventricle, whereas leads V4-V6 are more adept at detecting VEBs originating from the left ventricle. Lead II can also identify aberrant electrical activity in the ventricles, making it an effective tool for predicting VEBs. A comprehensive study of all ECG leads is required to achieve an accurate diagnosis of VEBs. As established in studies, identifying a myocardial infarction (MI) is mainly reliant on specific cardiac areas impacted by decreased blood flow [16, 47, 48, 75]. For example, if the left anterior descending artery (LAD), which supplies the anterior wall of the left ventricle, is blocked, you may see ST segment elevation, Q waves, and T-wave inversion in leads V1V4. Conversely, if the blockage occurs in the right coronary artery (RCA), which supplies blood to the heart's inferior wall, leads II, III, and aVF could display ST-segment elevation, Q waves, and T-wave inversion. AF is best visualize in leads II, III, and aVF, which are located in the inferior wall of the heart where the atria are located. AF can also be seen in other leads, such as V1 and V2, which may show flutter waves or irregular R-R intervals [7, 111]. Additionally, leads V5 and V6 may show a rapid ventricular response due to the irregularity of the atrial activity.

Table 4. Best Leads for Visualization of Different Heart Conditions

Heart Condition	**Best Leads for Visualization**
PVCs	V1,V2,V3
PACs	II,V1,V2,V4,V5,V6
RBBB	V1, V2,V5, V6
LBBB	III,aVL,aVF,V1,V5,V6
APCs	II, III, aVF,V1, V2
APBs	II,V1,V2,V4,V5,V6
VEBs	II,V1,V2,V3,V4,V5,V6
MI	II, III, aVF, V1,V2,V3,V4
AF	II, III, aVF,V1, V2, V5, V6

This Table 4 presents a comprehensive list of various heart conditions along with the optimal leads for visualizing each of these conditions. The included heart conditions are

Premature Ventricular Complexes (PVCs), Premature Atrial Complexes (PACs), RBBB, LBBB, APCs, APBs, VEBs, MI, and AF. By providing the best leads for visualization of each condition, this table can contribute to more accurate diagnoses and effective treatments for these conditions.

7. PROPOSED FRAMEWORK: SPECIFIC HEART DISEASE CLASSIFICATION FRAMEWORK

Based on the existing literature, we have found that the mostly used approach for classifying heart problems using ECG signal is CNN. Because, this algorithm is well-known for processing image related data and it is reliable and highest perfomer for predicting heart problems. Therefore, a CNN model DenseNet 201 that is configured using focal loss and Adam optimization. The medical sector often deals with imbalanced data sets, where the normal data set exceeds the disease data set. To address this, we adopt focal loss. Focal loss is effective for imbalance data set [41]. The Adam optimizer performs well with focal loss.The Adam technique also works efficiently for the high-dimensional data set [58]. This research aimed to prepare a data set for heart disease prediction. To accomplish this, we combined multiple data sets which are discussed in the data set section. We have also employed a technique to convert one-dimensional ECG signals into two-dimensional ECG images. This conversion aids in reducing the noise of the ECG signals. The conversion is done using ECG-kit, where we have transformed the ECG signal waves into image format. Next, we split the images into R-R intervals corresponding to one complete cardiac cycle. The resulting images are then stored in separate folders for training and testing, and Lead-Specific Patterns are depicted in Figure 5. The ECG wave-to-image generator is used for this conversion, and the heart bit segmentation is accomplished using the Ecg-kit with the PanTompkins algorithm. Finally, we split the data set in 70% for training, 20% for testing and 10% for validation purposes.

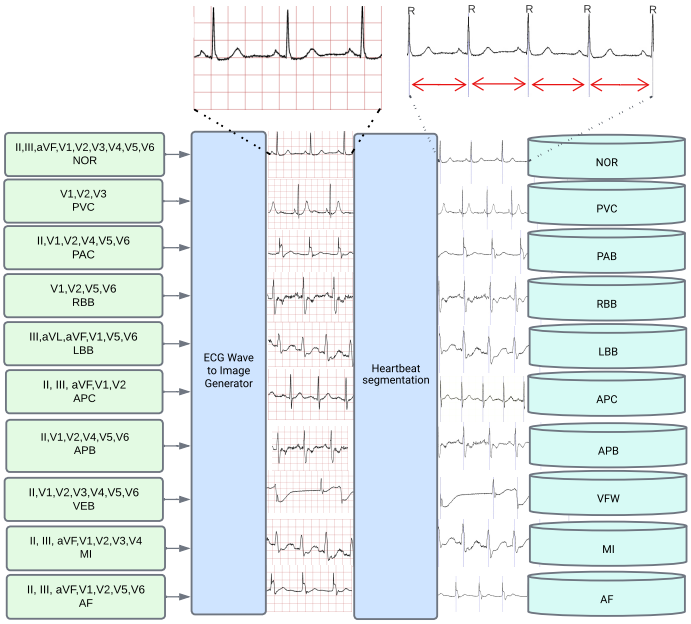


Fig. 5. Data set preparation

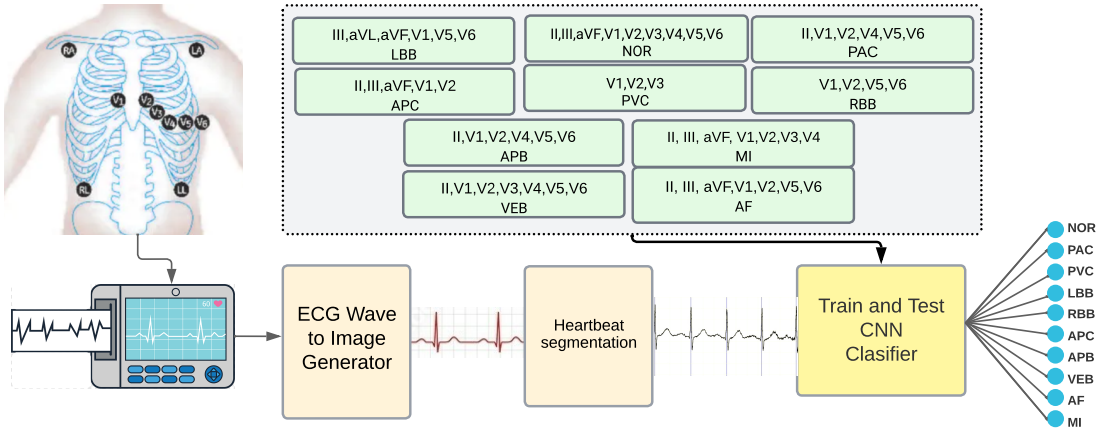


Fig. 6. Proposed framework utilizing best classifier

The ECG-kit is a Python-based toolbox that offers a range of tools for the processing and analysis of ECG signals. The toolkit includes functionalities for beat detection, heart rate variability analysis, ECG signal visualization, and ECG signal processing. A noteworthy feature of ECG-kit is its implementation of the Pan-Tompkins algorithm, a widely used algorithm for detecting the QRS complex in ECG signals. This algorithm utilizes a combination of bandpass filtering, differentiation, squaring, and integration to effectively detect the QRS complex. By leveraging this algorithm, ECG-kit allows users to convert ECG signals into gray scale images, which can be used for further analysis and visualization. In light of the aforementioned background, we suggest a novel DL approach to accurately predict heart disease from ECG signals in real-time scenarios.

Table 5. ECG Report Heart Disease Classification Metrics

Class	Precision	Recall	F1-score
LBB	0.98	0.98	0.98
NOR	0.99	0.99	0.99
PAC	0.95	0.97	0.96
APC	0.99	0.97	0.98
PVC	0.97	0.98	0.97
RBB	0.99	0.99	0.99
APB	0.96	0.94	0.95
MI	0.97	0.98	0.97
VEB	0.98	0.98	0.98
AF	0.98	0.97	0.98
Accuracy			0.99
Macro Avg	0.98	0.98	0.98
Weighted Avg	0.99	0.99	0.99

Specifically, our proposed method involves utilizing a CNN architecture Densenet-201 to categorize ECG signals into ten distinct classes of heart disease data. To ensure a diverse and comprehensive training data set, we will include unique combinations of lead data for each heart disease class. we use leads V1-V3 for PVCs, leads II,V1,V2,V4,V5,V6 for PACs, leads V1, V2,V5, V6 for RBBB, leads III,aVL,aVF,V1,V5,V6, for LBBB, leads II, III, aVF,V1, V2 for APCs, leads II,V1,V2,V4,V5,V6 for APBs, leads II,V1,V2,V3,V4,V5,V6 for VEBs, leads II, III, aVF, V1-V4 for MI, leads II, III, aVF,V1, V2, V5, V6 for AF, and leads II, III, aVF,

V1-V6 for Normal (NOR). The CNN model will be trained using these segmented images from our proposed data set that precisely classifies each image into its corresponding heart disease class. We will evaluate the proposed model performance using several performance metrics such as precision, accuracy, recall, and F1 score. To demonstrate the effectiveness of our proposed model in real-time scenarios, the proposed model integrates with 12 lead ECG device that produce 12 different types of waveforms. Subsequently the ECG signals will be transform into images using an ECG wave to image generator. Subsequently, the images will be segmented based on the R-R interval through heartbeats segmentation. Moreover, those split ECG images will be processed using the proposed model, and the resulting heart disease predictions will be presented in real-time shown in Figure 6.

Table 6. Implemented model comparison with existing works

Citation	**Dataset Used**	**Proposed Method**	**Model Architecture**	**Accuracy**
[153]	MIT-BIH	High-accuracy ECG heartbeat classification using a CNN	4 convolutional layers and 2 fully connected layers with dropout	99.43%
[154]	MIT-BIH	Deep 2D CNN for ECG arrhythmia classification	Tae Joon Jun et al. [2] Deep 2D CNN for ECG arrhythmia classification MIT-BIH arrhythmia database 4 convolutional layers, 2 max-pooling layers, and 3 fully connected layers with dropout and batch normalization	99.05%
[155]	PTB ECG Database	Deep CNN for automated recognition of MI on ECG signals	5 layers, including convolutional, max pooling, and dropout	99%
[156]	MIT-BIH	Deep CNN	11-layer deep network, normalization using Z-score, and SMOTE for imbalance data	Precision: 98.30%
[157]	AF, VF, ST, and normal dataset	Accurate classification of four ECG patterns using transfer learning	Transfer learning using pre-trained DenseNet with 161 convolutional layers and a linear SVM	97.23%
[122]	MIT-BIH	Accurate classification of ECG signals using a novel 1D and 2D CNN model	Novel 1D and 2D CNN model	1D CNN: 97.38% 2D CNN: 99.02%
Our Study	Lead-specific patterns in diagnosing cardiac conditions dataset	Neural network for 12-lead ECG	DenseNet 201 configured with focal loss and Adam optimization	**99.57%**

However, a major issue encountered in this research was the imbalance in the data set. For example, when considering the lead aVF from the 12-Lead ECG, it was found that this lead could represent any disease. However, certain classes such as NOR, LBB, APC, MI, and AF had pictures of aVF leads, which were not present in other classes such as PVC, PAC, RBB, APB, and VEB. This made it difficult for the model to accurately predict diseases that did not have aVF lead data. Due to the absence of certain types of leads in different types of heart disease classes, the use of 12-Lead ECG data as input for the model resulted in data ambiguity. To mitigate this issue, the research team applied a threshold value of 85%. This meant that if the aVF signal was determined to be PVC, PAC, RBB, APB, or VEB with a confidence level below 85%, the prediction would not be made, and the model would discourage misclassification. Dealing with unknown data is a challenge in this solution, especially in the sensitive medical sector. A promising result was obtained in our research with DenseNet 201, achieving an accuracy of 99.57%. The accuracy is assessed using various metrics such as F1 score, precision, and recall shown in Table 5. Based on the evaluation metrics, the classification model is exhibiting excellent performance. It is achieving high scores for most of the classes, with precision, recall, and F1-score metrics above 0.95 for every class, indicating that the model can accurately classify a substantial portion of instances for each class.

Furthermore, the precision of our metric is nearly flawless, achieving an impressive score of 0.99. This signifies that the model exhibits exceptional accuracy, effectively categorizing almost every instance with precision. When we examine the macro average of precision, recall, and F1-score, we consistently observe a strong performance at 0.98 across all classes, underscoring the model's consistent and reliable performance. Even the weighted average remains notably high at 0.99, emphasizing the model's capability to correctly classify instances across a diverse array of classes, maintaining consistently high performance levels. A comparison with the existing models has been incorporated in Table 6 that shows the efficiency of our proposed model. In summation, the results presented in this report unequivocally demonstrate the model's proficiency in accurately classifying instances spanning a wide spectrum of categories, featuring exceptional precision, recall, and F1-score metrics. This compelling performance lends itself to practical utilization in real-world medical applications for the automated classification of ECG reports.

8. CONCLUSION

Heart disease stands as a pressing global public health concern, with a particularly pronounced impact on low-income countries where the scarcity of qualified cardiologists exacerbates the problem. Electrocardiography (ECG) serves as the primary diagnostic tool for heart ailments, yet the process of interpreting ECG reports proves to be both time-consuming and financially burdensome, demanding the expertise of a certified cardiologist. To confront this challenge, the imperative of automated ECG signal interpretation emerges. This article, in response, conducts a comprehensive examination of the existing literature, encompassing popular datasets, tools, and techniques within this domain. Noteworthy datasets such as the MIT-BIH dataset, the PTB database, the BIDMC dataset, and the PTB dataset have gained prominence in the realm of heart disease diagnosis. These datasets are available to the public and easily accessible, simplifying their utilization for researchers. Furthermore, various methodologies like Convolutional neural Networks (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and hybrid models like CNN-LSTM and CNN-BiLSTM have emerged as widely adopted approaches to addressing the heart disease detection challenge. In light of these observations, we propose a comprehensive framework that takes into account the 12-lead ECG, diverse lead types, waveform patterns, and their interrelation with heart diseases. This proposed framework holds substantial promise for enhancing the diagnosis and management of heart ailments. It empowers a broader spectrum of healthcare providers and individuals to decipher ECG reports with greater reliability and

accuracy. This, in turn, facilitates earlier detection and treatment of heart diseases, ultimately leading to improved patient outcomes. Furthermore, this study underscores the importance of incorporating various types of leads when developing a CNN model, aiming to simplify the intricacies of detecting unknown patterns in the context of heart disease diagnosis. The proposed framework and observations from the existing works contribute significantly to the field of ECG analysis and can aid in the development of more accurate diagnostic tools for detecting heart diseases. Therefore, we recommend further research to validate and refine our proposed framework, which is based on the existing literature, to improve automated ECG signal interpretation and ultimately contribute to better heart disease management.

9. DISCLAIMER

This research work is an extension of the undergraduate thesis submitted at Daffodil International University, Dhaka, Bangladesh.

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