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 daily. 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 demonstration of frequently utilized data sets and 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 to 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.

1. Introduction

Cardiovascular disease (CVD) is a consolidated terminology for conditions affecting heart or blood arteries [1]. A science base organization known as Centers for Disease Control and Prevention (CDC) depits that the leading cause of death among men, women, and individuals from various racial and ethnic backgrounds in the United States is heart disease. [1]. Accordingly, World Health Organization (WHO) declares that 17.9 million people die due to heart disease every year [2]. Unhealthy and processed food, physical sluggishness, usage of nicotine, and excessive alcohol boozing are the major behavioral 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 [2]. 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). [3]. Heart-related illnesses include arrhythmia, myocardial infarction (MI), sometimes known as a heart failure, angina, stroke, heart attack, etc [4, 5]. The

Abbreviations: ECG, electrocardiogram; CVD, Cardiovascular disease; CDC, Centers for Disease Control; CHD, coronary heart disease; MI, myocardial infarction; CAD, coronary artery disease; CHF, congestive heart failure; aVR, augmented Vector Right; aVL, augmented Vector Left; aVF, augmented Vector Foot; DL, Deep Learning; DBN, Deep Belief Network; CNN, Convolutional Neural Network; RNN, Recurrent Neural Network; LSTM, Long-Short Term Memory; GWO, Grey Wolf Optimizer; ABC, Artificial Bee Colony; HLDA-MALO, hybrid linear discriminant analysis with the modified ant lion optimization; GAN, Generative Adversarial Networks; BiLSTM, Bidirectional Long Short Term Memory; KWCNN, Kernel Weight; ARR, Arrhythmia; VHD, valvular heart disease; BBB, Bundle Branch Block; HCM, Hypertrophic cardiomyopathy; DCM, Dilated cardiomyopathy; CPSC, China physiological signal challenge; EMI, Earlier MI; SND, Sinus Node Dysfunction; TIA, Transient Ischemic Attack; SCD, Sudden Cardiac Death; IHD, Ischemic Heart Disease; BIDMC, Beth Israel Deaconess Medical Center; PTB, Physikalisch Technische Bundesanstalt; CUDB, Creighton University Ventricular Tachyarrhythmia Database; MIMIC-II, Multi-Parameter Intelligent Monitoring in Intensive Care II; ML, Machine Learning; SVM, Support Vector Machine; KNN, k Nearest Neighbor; DT, Decision Tree; DGEC, deep genetic ensemble of classifiers; J-RDA, Jaya Algorithm with Red Deer Algorithm; EEMD, Ensemble Empirical Mode Decomposition; LM, local means; PSO, particle swarm optimization; DE, differential evolution; FFNN, Feed Forward Neural Network; RVI, Right ventricular infarction; PVC, premature ventricular contraction; PAC, premature atrial contraction; RBBB, Right Bundle Branch Block; LBBB, Left Bundle Branch Block; APC, Atrial Premature Complexe; APB, Atrial Premature Beat; VEBs, Ventricular Ectopic Beats; AF, atrial fibrillation.

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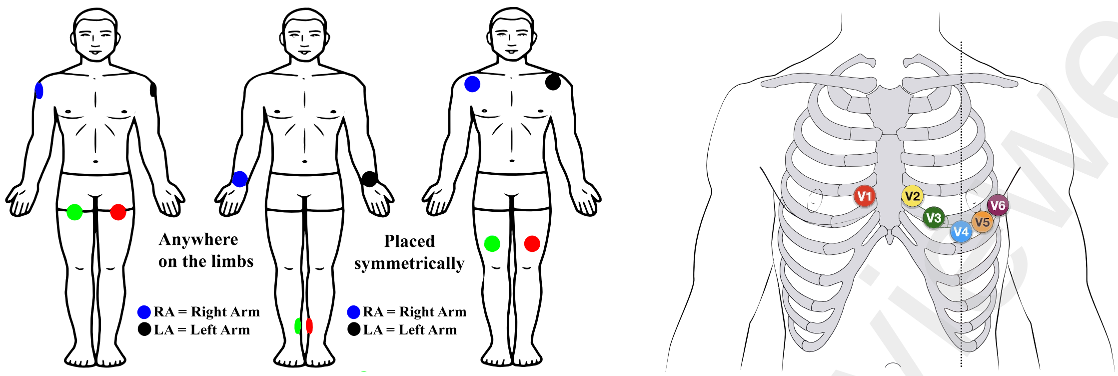
[1] https://www.cdc.gov/heartdisease/facts.htm
[2] https://www.who.int/health-topics/cardiovascular-diseases



(a) Positions for limb leads (b) Positions for precordial leads

Figure 1: Several lead positions

irregularity of the heartbeat known as arrhythmia is linked to a higher risk of blood clots [6, 7, 8]. MI follows when not enough blood reaches a particular area of the heart muscle [3, 9]. The longer it takes for the heart to restore proper blood flow, the greater the harm inflicted on the heart muscle [10]. 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 [10, 11, 12]. This condition is also known as congestive heart failure (CHF) [13, 14].

An ECG is a rapid diagnostic tool that can be utilized to assess the heart's electrical function and rhythm [15, 16]. In this diagnosis, sensors attached to the skin that can detect the electrical impulses that the heart produces with each beat [17, 18, 19]. The signals are recorded by a machine, and a physician evaluates them to determine if there are any irregularities [20]. The 12 ECG leads each reflect a unique 3-D direction of heart action where lead I, II, III, aVF, aVR, aVL, V1, V2, V3, V4, V5, and V6 are the standard ECG leads [21, 22, 23, 24]. However, these leads are classified into two parts such as 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 shown in Figure 1 (b) [25, 26, 27]. Nowadays, detecting heart problems using ECG has become popular due to its reliability and accurate production of signals [28, 29, 30]. 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. 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 [31, 32, 33]. A thorough analysis has been conducted on the automated identification of CAD through the use of ECG signals [34]. 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) [1]. 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 [14, 35, 36, 37]. 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?

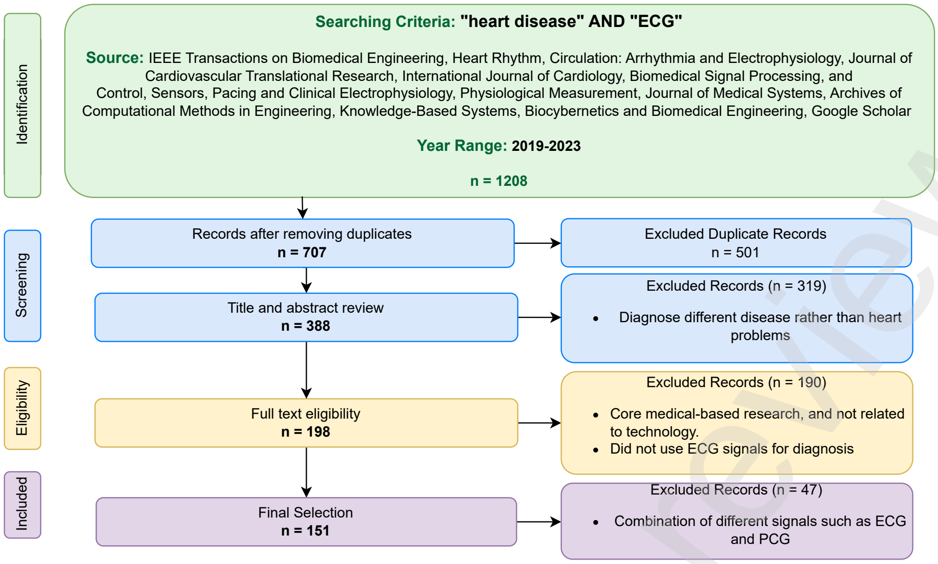


Figure 2: Article search strategy

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. 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 [15, 35, 63, 64]. Moreover, some popular data sets are publicly available for the prediction of different heart problems [38, 13, 3]. Table 1 illustrates the frequently used databases that are utilized for the prediction of several CVDs.

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 [39, 40, 6, 50]. 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, MIT-BIH Atrial Fibrillation Database (MIT-AFDB), MIT-BIH Malignant Ventricular Ectopy Database (MIT-BIH VFDB), MIT/BIH Sudden Cardiac Death Holter (SCDH), etc [42, 13, 11, 52, 57, 60]. 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. [12, 58, 60]. However, it is observed from the existing literature that researchers are more concerned about detecting different types of arrhythmia disease than others [7, 8, 56]. This is why the arrhythmia data set 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 [41, 60, 65]. After that, MI, CHF, and SCD are also predicted in some research using the MIT-BIH data set [3, 11, 12].

Other heart-related problems such as heart failure, Ischemic Heart Disease (IHD), and abnormal heartbeat are predicted in this field using several popular databases [14, 9, 66]. Hence, Beth Israel Deaconess Medical Center

Table 1
Different types of ECG data sets

Citation	Source of Data	Number of Recordings	Disease Detected
[38]	MIT-BIH arrhythmia	47 subjects: 25 males and 22 females, 4000 ECG Signal	Arrhythmia
[39]	MIT-BIH arrhythmia	N/A	Arrhythmia
[40]	MIT-BIH	47 subjects	Arrhythmia
[13]	(MIT-BIH) ARR database, MIT-BIH Normal, Sinus Rhythm (NSR), and BIDMC CHF database	Total 162 records	CHF, Arrhythmia (ARR)
[3]	PTBDB, MIT-BIH database	48 records	MI
[41]	MIT-BIH Atrial Fibrillation Database	N/A	Atrial Fibrillation (AF)
[14]	RR interval database, BIDMC-CHF database, NSR-RR, Fantasia database, MIT-BIH, NSR database	Total 156 subjects	Heart failure
[42]	MIT-BIH arrhythmia	29 subjects	Arrhythmia
[9]	Self-developed database (ECG Device 'EDAN SERIES-3)	1937 patients data	COVID-19, Abnormal Heartbeat, MI, Previous History of MI, and Normal Person
[6]	MIT-BIH	29 subjects	Arrhythmia
18	Self-developed	43 Patients	IHD
[43]	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
[44]	MIT-BIH arrhythmia and PTB-ECG databases	360 subjects	Heart Disease
[45]	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
[10]	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)
[11]	MIT-BIH-PhysioNet databases	105 subjects	Arrhythmia, CHF, sudden cardiac death (SCD)
[46]	China physiological signal challenge (CPSC) 2018 data set	6877 recordings	9 categories of Arrhythmia

(BIDMC) CHF data set is employed in some studies to detect heart failure [13, 10, 12]. After that, Physikalisch Technische Bundesanstalt (PTB) diagnostic ECG database is utilized in various literature to detect MI, arrhythmia, etc, [3, 43, 49]. 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 [52, 53, 62]. Therefore, these data sets are popularly utilized for a combination of detecting several heart diseases.

Table 1
Different types of ECG data sets (continued)

Citation	Source of Data	Number of Recordings	Disease Detected
[12]	MIT-BIH ARR, MIT-BIH NSR, BIDMC CHF	48 subjects, 18 subjects, 15 subjects	CHF, arrhythmia
[47]	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
[48]	ECG data from wearable sensors	N/A	Arrhythmia
[49]	PTB database	549 ECG records from 290 subjects	MI
[50]	MIT-BIH	48 records	Heartbeats
[7]	MIT-BIH	1800 records	Arrhythmia
[8]	MIT-BIH	48 records from 47 patients	Arrhythmia
[51]	MIT-BIH	47 subjects, 48 recordings	Arrhythmia
[52]	MIT-BIH AFDB, CUDB, MITDB, MIT-BIH VFDB	23 subjects, 35 subjects, 44 subjects, 22 subjects	6 types of arrhythmia
[53]	Fantasia Normal database, European ST-T database, Collected data from IBN-AL-NAFEES Hospital	40 subjects 40 recordings, 78 subjects 88 recordings, 30 subjects 30 recordings	Myocardial ischemia
[54]	Cleveland data set	303 records	Heart Disease
[55]	PTB-XL data set	21,837 records	
[56]	MIT-BIH	25 subjects	AF
[57]	MIT/BIH-SCDH, MIT/BIH-NSR databases	23 subjects, 18 subjects	SCD
[58]	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

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 [38, 3]. 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

Table 1
Different types of ECG data sets (continued)

Citation	Source of Data	Number of Recordings	Disease Detected
[59]	PTB-XL database	21,837 records	CVD
[60]	MIT-BIH Normal Sinus Rhythm (NSR-DB), MIT-BIH Atrial Fibrillation (AF-DB), MIT-BIH Arrhythmia (ARR-DB)	18 records, 23 records, 48 records	AF
[61]	St-Petersburg, BIDMC CHF, PTB Diagnostic	5 subjects 17 records, 15 subjects 15 records, 52 subjects 80 records	CAD, CHF, MI, normal
[62]	MIMIC-II	12,000 instances of 942 patients	Blood Pressure (BP)

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. [38, 42, 49]. 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 [39, 40, 13]. CNN is commonly applied in several studies from DL approaches to detect heart diseases [52, 60]. 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 [38]. 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 [40]. 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 [47]. 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 [39, 13, 3, 48, 50, 12]. CNN-LSTM is a frequently used algorithm among CNN-based hybrid approaches [41, 14, 35, 42]. 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% [3]. Another study suggests an automated diagnosis approach based on Deep CNN and LSTM Architecture (DCNN-LSTM) for diagnosing CHF using ECG signals [14]. 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 (CNN-GWO-ABC) is proposed to detect arrhythmia [48]. 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 [54]. 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 [44, 10, 46]. The performance of these approaches is good but they do not outperform the other approaches in DL [8, 51].

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. [67, 44, 56, 59]. Moreover, a deep genetic ensemble of classifiers (DGEC) is proposed that consists of three layers where SVM is used in every layer [6]. 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, [45, 53]. This study proposes a novel approach for identifying myocardial ischemia using multi-lead long-interval ECG. The method employs Choi-Williams 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 [53]. 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 [49]. 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 [68, 58, 61]. 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 [69]. 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 [70]. The 12-lead ECG is widely used for screening potential cardiac ischemia and is essential for quickly identifying patients who have suffered a heart attack. Healthcare professionals should prioritize the number of leads used for accurate diagnosis and treatment [71].

Every ECG lead represents multiple types of waveforms and the ECG waveform consists of several distinct components that represent different phases of the cardiac cycle. These components include the P wave, QRS complex, and T wave, which are all different types of waves that are important in the interpretation of ECGs. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricular repolarization. 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 [27, 72, 32]. R to R interval, QRS complex are different portions of an ECG signal and these portions are used for identifying different heart problems [73, 74, 75]. However, the majority of the works utilized RR interval for several heart illnesses such as AF, various types of arrhythmias, CAD, etc [74, 76]. Some works have utilized the QRS complex for incorporating the issue [77, 75, 78]. An article has detected RR interval for AF detection using CNN-BiLSTM [73]. 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 [74]. 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 [79]. The only portion of an ECG made up of numerous clustered waves is the QRS complex [80]. The QRS complex consists of Q, R, and S waves and signifies ventricular depolarization. After the QRS complex, the T wave denotes ventricular repolarization. Therefore, the QRS complex is utilized for MI detection in research [81]. 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. Therefore, a comprehensive assessment of P-wave morphology in multiple leads is essential in identifying and diagnosing various types of heart disease related to atrial depolarization abnormalities [83].

4.2. P-R interval

The PR interval is a crucial measurement in an ECG that reflects the electrical conduction from the atria to the ventricles of the heart [84]. Accurate interpretation of PR interval waves in a 12-lead ECG system is essential in identifying the type of heart disease a patient may have. Specifically, Lead II, Lead III, and aVF are significant leads that provide a view of the inferior wall of the heart, where abnormalities in the PR interval can indicate conduction disturbances. Additionally, leads V1 to V6 offer further insight into the electrical activity of the heart's anterior, lateral, and posterior walls, indicating atrial enlargement or fibrillation [69]. It is important to note that the PR interval can be affected by various heart conditions and medications, highlighting the importance of a comprehensive ECG examination to identify the underlying cause of PR interval waves [85]. Combining multiple leads is usually necessary to make an accurate diagnosis, which is vital in developing an effective treatment plan [69].

4.3. QRS complex

In a research article, the identification of the type of heart disease associated with QRS complex in a 12-lead ECG system [86]. The significant leads for this purpose are V1 to V6, as well as II, III, and aVF. The QRS complex is a representation of ventricular depolarization and its changes can indicate various cardiac conditions such as ventricular hypertrophy, BBB, and MI [87]. To detect right ventricular hypertrophy, leads V1 and V2 are useful, while left ventricular hypertrophy can be indicated by leads V5 and V6. Meanwhile, leads II, III, and aVF can provide information on the inferior wall of the heart, where changes in the QRS complex can indicate blockages or ischemia [88]. Morphology or shape of the QRS complex is also an important factor in identifying heart disease, with a widened QRS complex indicating a BBB, while a narrow QRS complex suggesting a normal conduction pathway [89]. Presence of abnormally deep and wide Q waves may suggest a previous MI [90, 91, 92]. Therefore, an accurate diagnosis and treatment plan require an analysis of a combination of leads and QRS complex morphology.

4.4. R-R interval

A research article examines the utility of a 12-lead ECG system for assessing the electrical activity of the heart [93]. One key aspect of this system is the R-R interval waves, which reflect the time between consecutive R waves and correspond to the ventricular depolarization. Alterations in the R-R interval can serve as indicators of various cardiac conditions, including tachycardia, bradycardia, and arrhythmias. The analysis of the R-R interval can be performed using any of the 12 leads, although lead II and lead V1 are commonly used [94]. Changes in the R-R interval may also indicate heart blocks, such as first-degree AV block, second-degree AV block, and complete heart block. To effectively identify the type of heart disease associated with R-R interval waves, healthcare providers must perform a meticulous analysis of the R-R interval using a combination of leads. The R-R interval serves as a critical component of cardiac function, allowing healthcare providers to accurately diagnose and treat a range of cardiac conditions [95].

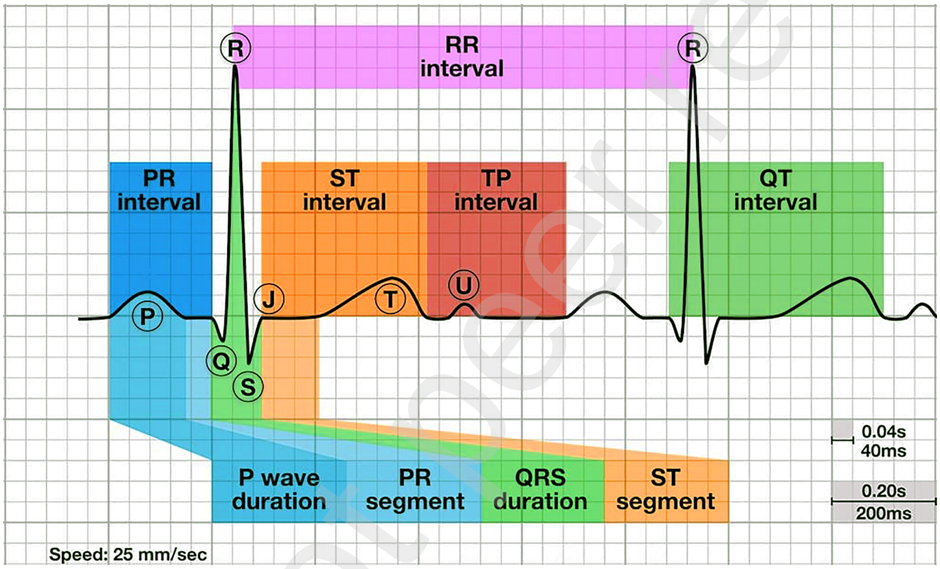
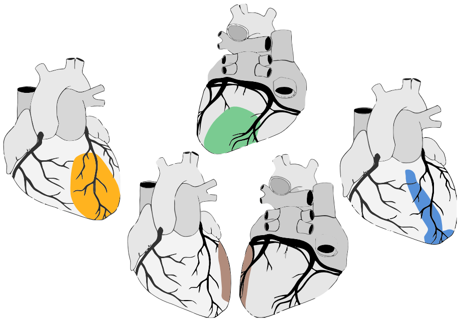


Figure 3: Different types of wave-forms

To summarize, specific leads in a 12-lead ECG system play a significant role in identifying the type of heart disease associated with different types of wave-forms [96]. Each waveform has its own set of significant leads shown in Figure 3. For example, P waves in leads II, III, aVL, and V1 can indicate atrial arrhythmias, while Q waves in leads I, aVL, V5, and V6 can indicate previous MI. There are different cardiac conditions that can be indicated by T waves in leads V2 to V5, ST segment changes in leads II, III, aVF, V1 to V6, and U waves in leads V2 to V5 [97]. Therefore, it is crucial to understand the significance of each waveform and its associated leads in identifying the type of heart disease present and providing appropriate treatment.

The ECG is a valuable tool in diagnosing various heart conditions. Each type of heart disease can cause unique changes in different leads of the 12-lead ECG. For instance, CAD may produce ST-segment depression [98] 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 [99, 100, 101]. 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 [102, 103, 104]. 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.



(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

Figure 4: Cardiac Territory Mapping for Early Detection of Heart Abnormalities

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 [105]. 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 [106, 107, 108]. 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 the left ventricle, such as left ventricular hypertrophy and acute MI [109, 110]. 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 [111, 112]. Finally, the septal leads V1, V2 are placed on the front of the chest and are crucial in detecting abnormalities in the septum [113], 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 [114]. Criteria for RVI include IWMI [115], ST segment elevation greater in lead III than II, ST elevation in V1 (possibly extending to V5 to V6), ST depression [116] 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 [117]. 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 [118, 119, 120, 121, 122]. 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 [123, 124, 125, 126]. 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 [127, 128, 129].

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 are indicative of a disruption in the electrical signals that control the heart's pumping function and are essential for accurate diagnosis [130, 131, 132, 133, 134]. By considering these criteria, medical professionals can identify LBBB and provide appropriate treatment to manage this condition.

APCs (atrial premature complexes) are best visualized in leads II, III, and aVF, which are located in the inferior wall of the heart where the atria are located. APCs can also be seen in other leads [135, 136, 137, 138], such as V1 and V2, but they may be more difficult to distinguish from other abnormalities in those leads. The ECG is a non-invasive diagnostic tool that is commonly used to predict atrial premature beats (APBs). The use of different leads in ECG has been shown to aid in the identification of APBs. Lead II, for instance, is one of the most frequently used leads and measures the electrical activity between the right arm and the left leg, which provides a clear view of the atria. Similarly, the V1 and V2 leads are positioned on the right and left sides of the sternum, respectively, and can detect APBs originating from the right and left atria. The V4-V6 leads, placed on the left side of the chest, are also useful in identifying APBs originating from the left atrium [139, 140, 141]. However, a comprehensive evaluation of a patient's medical history, symptoms, and physical examination is necessary to achieve an accurate diagnosis.

Ventricular ectopic beats (VEBs) are abnormal heart rhythms that can be detected using ECG, a widely-used non-invasive diagnostic tool. ECG provides valuable information for predicting VEBs [142, 143, 144], and while each lead in ECG offers important insights, some leads are more sensitive than others in detecting VEBs. Specifically, the V1-V3 leads located on the chest wall are highly sensitive in detecting VEBs originating from the right ventricle, whereas the V4-V6 leads are more sensitive in detecting VEBs originating from the left ventricle. Additionally, lead II can detect abnormal electrical activity in the ventricles, making it useful for predicting VEBs. To accurately diagnose VEBs, a comprehensive analysis of all ECG leads is necessary.

The leads that are most useful for detecting MI are the ones that correspond to the area of the heart that is affected by the blockage of blood flow [145, 146, 147, 148]. For example, if the blockage is in the left anterior descending artery (LAD), which supplies blood to the anterior wall of the left ventricle, leads V1-V4 may show ST-segment elevation, Q waves, and T-wave inversion. If the blockage is in the right coronary artery (RCA), which supplies blood to the inferior wall of the heart, leads II, III, and aVF may show 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 [149, 150]. Additionally, leads V5 and V6 may show a rapid ventricular response due to the irregularity of the atrial activity.

Table 2
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 2 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

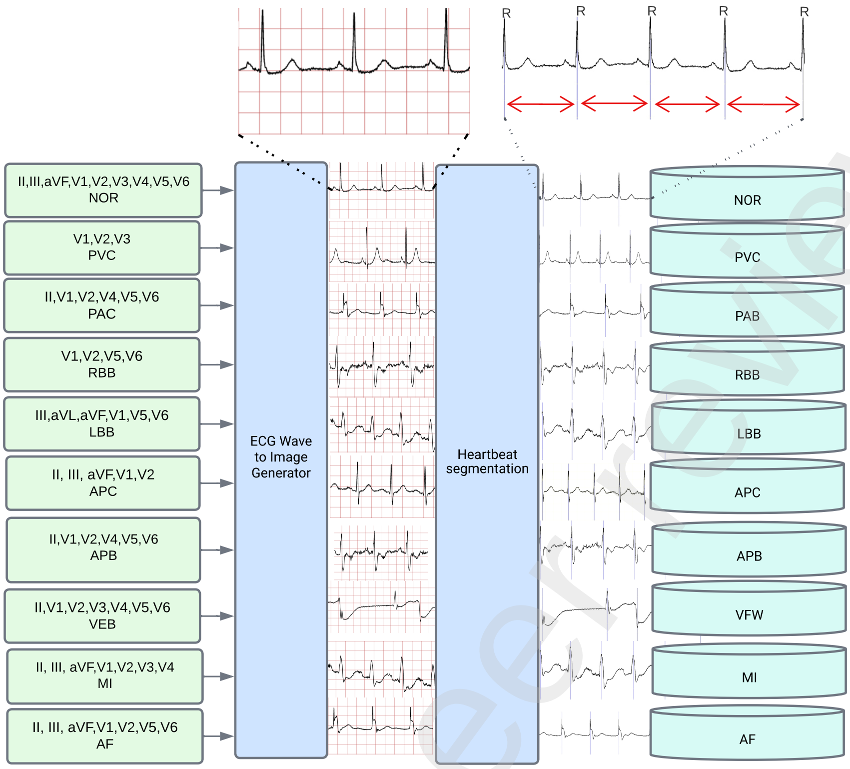


Figure 5: Data set preparation

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 [151]. The Adam optimizer performs well with focal loss.The Adam technique also works efficiently for the high-dimensional data set [152].

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 Pan-Tompkins algorithm. Finally, we split the data set in 70% for training, 20% for testing and 10% for validation purposes.

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

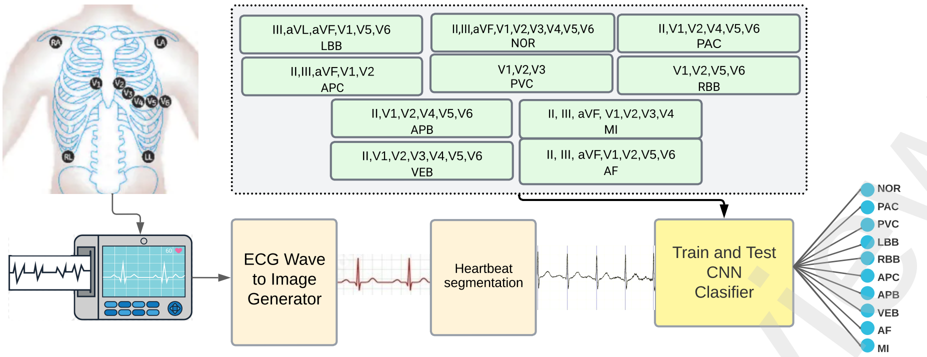


Figure 6: Proposed framework utilizing best classifier

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. 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 transformed 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.

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 3.

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. Additionally, the accuracy metric is almost perfect, with a score of 0.99, suggesting that the model can classify almost all instances accurately. The macro average of precision, recall, and F1-score is 0.98, which demonstrates that the model is consistently performing well across all classes. The weighted average is also high at 0.99, signifying that the model can correctly classify instances

Table 3
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

across all classes with similar high performance. Overall, the findings of this report suggest that the classification model performs well and can accurately classify instances across a wide range of classes, with high precision, recall, and F1-score metrics. This indicates that it can be utilized for automatic classification of ECG reports in real-life medical applications.

8. Conclusion

Heart disease is a major global public health issue, particularly in low-income countries where there is a shortage of qualified cardiologists. The ECG is the primary diagnostic tool for heart disease, but interpreting ECG reports can be time-consuming and costly, requiring the expertise of a qualified cardiologist. To address this issue, automated ECG signal interpretation is necessary, and this article has made a comprehensive review of the existing literature, including popular datasets and tools and techniques for this domain. The MIT-BIH data set, PTB database, BIDMC data set, and PTB data set are popular for the diagnosis of heart disease. These data sets are publicly available and easily accessible. Hence, researchers use them without any complexity. Moreover, CNN, LSTM, BiLSTM, CNN-LSTM, CNN-BiLSTM are widely applied approaches to incorporate the issue of detecting heart disease. Therefore, based on these observations, we have proposed a framework that considers the 12-lead ECG, the different types of leads, wave patterns, and their relationship with heart disease. The proposed framework has the potential to improve the diagnosis and management of heart disease by enabling a wider range of healthcare providers and individuals to interpret ECG reports more reliably and accurately, thus leading to earlier detection and treatment of heart disease and improved outcomes. This study also highlights the significance of utilizing various types of leads in developing a CNN model to minimize unknown pattern complexity. 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.

A. My Appendix

Appendix sections are coded under `\appendix`.

`\printcredits` command is used after appendix sections to list author credit taxonomy contribution roles tagged using `\credit` in frontmatter.

CRediT authorship contribution statement

Abu Sufiun: Conceptualization of this study, Methodology, Software.

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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 daily. 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 demonstration of frequently utilized data sets and 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 to 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.

1. Introduction

Cardiovascular disease (CVD) is a consolidated terminology for conditions affecting heart or blood arteries [1]. A science base organization known as Centers for Disease Control and Prevention (CDC) depits that the leading cause of death among men, women, and individuals from various racial and ethnic backgrounds in the United States is heart disease. [1]. Accordingly, World Health Organization (WHO) declares that 17.9 million people die due to heart disease every year [2]. Unhealthy and processed food, physical sluggishness, usage of nicotine, and excessive alcohol boozing are the major behavioral 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 [2]. 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). [3]. Heart-related illnesses include arrhythmia, myocardial infarction (MI), sometimes known as a heart failure, angina, stroke, heart attack, etc [4, 5]. The

Abbreviations: ECG, electrocardiogram; CVD, Cardiovascular disease; CDC, Centers for Disease Control; CHD, coronary heart disease; MI, myocardial infarction; CAD, coronary artery disease; CHF, congestive heart failure; aVR, augmented Vector Right; aVL, augmented Vector Left; aVF, augmented Vector Foot; DL, Deep Learning; DBN, Deep Belief Network; CNN, Convolutional Neural Network; RNN, Recurrent Neural Network; LSTM, Long-Short Term Memory; GWO, Grey Wolf Optimizer; ABC, Artificial Bee Colony; HLDA-MALO, hybrid linear discriminant analysis with the modified ant lion optimization; GAN, Generative Adversarial Networks; BiLSTM, Bidirectional Long Short Term Memory; KWCNN, Kernel Weight; ARR, Arrhythmia; VHD, valvular heart disease; BBB, Bundle Branch Block; HCM, Hypertrophic cardiomyopathy; DCM, Dilated cardiomyopathy; CPSC, China physiological signal challenge; EMI, Earlier MI; SND, Sinus Node Dysfunction; TIA, Transient Ischemic Attack; SCD, Sudden Cardiac Death; IHD, Ischemic Heart Disease; BIDMC, Beth Israel Deaconess Medical Center; PTB, Physikalisch Technische Bundesanstalt; CUDB, Creighton University Ventricular Tachyarrhythmia Database; MIMIC-II, Multi-Parameter Intelligent Monitoring in Intensive Care II; ML, Machine Learning; SVM, Support Vector Machine; KNN, k Nearest Neighbor; DT, Decision Tree; DGEC, deep genetic ensemble of classifiers; J-RDA, Jaya Algorithm with Red Deer Algorithm; EEMD, Ensemble Empirical Mode Decomposition; LM, local means; PSO, particle swarm optimization; DE, differential evolution; FFNN, Feed Forward Neural Network; RVI, Right ventricular infarction; PVC, premature ventricular contraction; PAC, premature atrial contraction; RBBB, Right Bundle Branch Block; LBBB, Left Bundle Branch Block; APC, Atrial Premature Complexe; APB, Atrial Premature Beat; VEBs, Ventricular Ectopic Beats; AF, atrial fibrillation.

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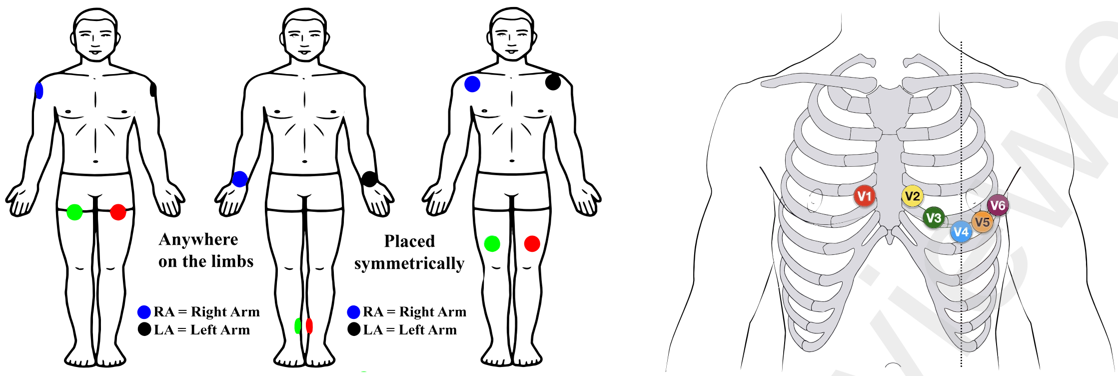
[1] https://www.cdc.gov/heartdisease/facts.htm
[2] https://www.who.int/health-topics/cardiovascular-diseases



(a) Positions for limb leads

(b) Positions for precordial leads

Figure 1: Several lead positions

irregularity of the heartbeat known as arrhythmia is linked to a higher risk of blood clots [6, 7, 8]. MI follows when not enough blood reaches a particular area of the heart muscle [3, 9]. The longer it takes for the heart to restore proper blood flow, the greater the harm inflicted on the heart muscle [10]. 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 [10, 11, 12]. This condition is also known as congestive heart failure (CHF) [13, 14].

An ECG is a rapid diagnostic tool that can be utilized to assess the heart's electrical function and rhythm [15, 16]. In this diagnosis, sensors attached to the skin that can detect the electrical impulses that the heart produces with each beat [17, 18, 19]. The signals are recorded by a machine, and a physician evaluates them to determine if there are any irregularities [20]. The 12 ECG leads each reflect a unique 3-D direction of heart action where lead I, II, III, aVF, aVR, aVL, V1, V2, V3, V4, V5, and V6 are the standard ECG leads [21, 22, 23, 24]. However, these leads are classified into two parts such as 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 shown in Figure 1 (b) [25, 26, 27]. Nowadays, detecting heart problems using ECG has become popular due to its reliability and accurate production of signals [28, 29, 30]. 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. 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 [31, 32, 33]. A thorough analysis has been conducted on the automated identification of CAD through the use of ECG signals [34]. 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) [1]. 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 [14, 35, 36, 37]. 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?

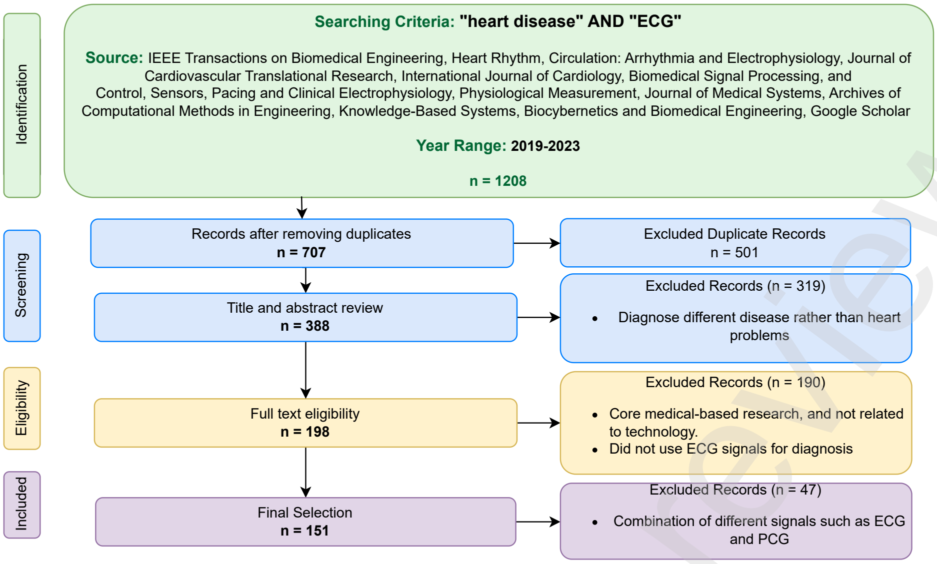


Figure 2: Article search strategy

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. 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 [15, 35, 64, 65]. Moreover, some popular data sets are publicly available for the prediction of different heart problems [38, 13, 3]. Table 1 illustrates the popular data sets used for the detection of arrhythmia, 2 refers to the datasets that were used for some dangerous disease such as MI, heart failure, etc. and 3 illustrate the frequently used databases that are utilized for the prediction of several heart problems.

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 [39, 40, 6, 54]. 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, MIT-BIH Atrial Fibrillation Database (MIT-AFDB), MIT-BIH Malignant Ventricular Ectopy Database (MIT-BIH VFDB), MIT/BIH Sudden Cardiac Death Holter (SCDH), etc [42, 13, 11, 48, 61, 49]. 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. [12, 62, 49]. However, it is observed from the existing literature that researchers are more concerned about detecting different types of arrhythmia disease than others [7, 8, 50]. This is why the arrhythmia data set 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 [41, 49, 66]. After that, MI, CHF, and SCD are also predicted in some research using the MIT-BIH data set [3, 11, 12].

Table 1
Different types of ECG data sets for Arrhythmia

Citation	Source of Data	Number of Recordings	Disease Detected
[38]	MIT-BIH arrhythmia	47 subjects: 25 males and 22 females, 4000 ECG Signal	Arrhythmia
[39]	MIT-BIH arrhythmia	N/A	Arrhythmia
[40]	MIT-BIH	47 subjects	Arrhythmia
[13]	(MIT-BIH) ARR database, MIT-BIH Normal, Sinus Rhythm (NSR), and BIDMC CHF database	Total 162 records	CHF, Arrhythmia (ARR)
[41]	MIT-BIH Atrial Fibrillation Database	N/A	Atrial Fibrillation (AF)
[42]	MIT-BIH arrhythmia	29 subjects	Arrhythmia
[6]	MIT-BIH	29 subjects	Arrhythmia
[43]	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
[44]	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
[11]	MIT-BIH-PhysioNet databases	105 subjects	Arrhythmia, CHF, sudden cardiac death (SCD)
[45]	China physiological signal challenge (CPSC) 2018 data set	6877 recordings	9 categories of Arrhythmia
[12]	MIT-BIH ARR, MIT-BIH NSR, BIDMC CHF	48 subjects, 18 subjects, 15 subjects	CHF, arrhythmia
[46]	ECG data from wearable sensors	N/A	Arrhythmia
[7]	MIT-BIH	1800 records	Arrhythmia
[8]	MIT-BIH	48 records from 47 patients	Arrhythmia
[47]	MIT-BIH	47 subjects, 48 recordings	Arrhythmia
[48]	MIT-BIH AFDB, CUDB, MITDB, MIT-BIH VFDB	23 subjects, 35 subjects, 44 subjects, 22 subjects	6 types of arrhythmia
[49]	MIT-BIH Normal Sinus Rhythm (NSR-DB), MIT-BIH Atrial Fibrillation (AF-DB), MIT-BIH Arrhythmia (ARR-DB)	18 records, 23 records, 48 records	AF
[50]	MIT-BIH	25 subjects	AF

Other heart-related problems such as heart failure, Ischemic Heart Disease (IHD), and abnormal heartbeat are predicted in this field using several popular databases [14, 9, 51]. Hence, Beth Israel Deaconess Medical Center (BIDMC) CHF data set is employed in some studies to detect heart failure [13, 10, 12]. After that, Physikalisch Technische Bundesanstalt (PTB) diagnostic ECG database is utilized in various literature to detect MI, arrhythmia, etc, [3, 43, 53]. In spite of that, there are some data sets available employed for the detection of heart problems in

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

Citation	Source of Data	Number of Recordings	Disease Detected
[3]	PTBDB, MIT-BIH database	48 records	MI
[14]	RR interval database, BIDMC-CHF database, NSR-RR, Fantasia database, MIT-BIH, NSR database	Total 156 subjects	Heart failure
[9]	Self-developed database (ECG Device 'EDAN SERIES-3)	1937 patients data	COVID-19, Abnormal Heartbeat, MI, Previous History of MI, and Normal Person
[51]	Self-developed	43 Patients	IHD
[52]	MIT-BIH arrhythmia and PTB-ECG databases	360 subjects	Heart Disease
[10]	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)
[53]	PTB database	549 ECG records from 290 subjects	MI
[54]	MIT-BIH	48 records	Heartbeats
[55]	Fantasia Normal database, European ST-T database, Collected data from IBN-AL-NAFEES Hospital	40 subjects 40 recordings, 78 subjects 88 recordings, 30 subjects 30 recordings	Myocardial ischemia
[56]	Cleveland data set	303 records	Heart Disease
[57]	PTB-XL data set	21,837 records	
[58]	PTB-XL database	21,837 records	CVD
[59]	St-Petersburg, BIDMC CHF, PTB Diagnostic	5 subjects 17 records, 15 subjects 15 records, 52 subjects 80 records	CAD, CHF, MI, normal

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 [48, 55, 63]. 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 [38, 3]. 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. [38, 42, 53]. Among these approaches, some DL algorithms such as CNN, Long-Short Term Memory (LSTM), CNN-LSTM, etc. are widely used in several

Table 3
Detecting multiple heart problems using ECG data

Citation	Source of Data	Number of Recordings	Disease Detected
[60]	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
[61]	MIT/BIH-SCDH, MIT/BIH-NSR databases	23 subjects, 18 subjects	SCD
[62]	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
[63]	MIMIC-II	12,000 instances of 942 patients	Blood Pressure (BP)

applications to identify heart illness [39, 40, 13]. CNN is commonly applied in several studies from DL approaches to detect heart diseases [48, 49]. 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 [38]. 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 [40]. 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 [60]. 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 [39, 13, 3, 46, 54, 12]. CNN-LSTM is a frequently used algorithm among CNN-based hybrid approaches [41, 14, 35, 42]. 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% [3]. Another study suggests an automated diagnosis approach based on Deep CNN and LSTM Architecture (DCNN-LSTM) for diagnosing CHF using ECG signals [14]. 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 (CNN-GWO-ABC) is proposed to detect arrhythmia [46]. 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 [56]. 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 [52, 10, 45]. The performance of these approaches is good but they do not outperform the other approaches in DL [8, 47].

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. [67, 52, 50, 58]. Moreover, a deep genetic ensemble of classifiers (DGEC) is proposed that consists of three layers where SVM is used in every layer [6]. 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, 55]. This study proposes a novel approach for identifying myocardial ischemia using multi-lead long-interval ECG. The method employs Choi-Williams 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 [55]. 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 [53]. 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 [68, 62, 59]. 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 [69]. 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 [70]. The 12-lead ECG is widely used for screening potential cardiac ischemia and is essential for quickly identifying patients who have suffered a heart attack. Healthcare professionals should prioritize the number of leads used for accurate diagnosis and treatment [71].

Every ECG lead represents multiple types of waveforms and the ECG waveform consists of several distinct components that represent different phases of the cardiac cycle. These components include the P wave, QRS complex, and T wave, which are all different types of waves that are important in the interpretation of ECGs. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricular repolarization. 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 [27, 72, 32]. R to R interval, QRS complex are different portions of an ECG signal and these portions are used for identifying different heart problems [73, 74, 75]. However, the majority of the works utilized RR interval for several heart illnesses such as AF, various types of arrhythmias, CAD, etc [74, 76]. Some works have utilized the QRS complex for incorporating the issue [77, 75, 78]. An article has detected RR interval for AF detection using CNN-BiLSTM [73]. 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 [74]. 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 [79]. The only portion of an ECG made up of numerous clustered waves is the QRS complex [80]. The QRS complex consists of Q, R, and S waves and signifies ventricular depolarization. After the QRS complex, the T wave denotes ventricular repolarization. Therefore, the QRS complex is utilized for MI detection in research [81]. 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. Therefore, a comprehensive assessment of P-wave morphology in multiple leads is essential in identifying and diagnosing various types of heart disease related to atrial depolarization abnormalities [83].

4.2. P-R interval

The PR interval is a crucial measurement in an ECG that reflects the electrical conduction from the atria to the ventricles of the heart [84]. Accurate interpretation of PR interval waves in a 12-lead ECG system is essential in identifying the type of heart disease a patient may have. Specifically, Lead II, Lead III, and aVF are significant leads that provide a view of the inferior wall of the heart, where abnormalities in the PR interval can indicate conduction disturbances. Additionally, leads V1 to V6 offer further insight into the electrical activity of the heart's anterior, lateral, and posterior walls, indicating atrial enlargement or fibrillation [69]. It is important to note that the PR interval can be affected by various heart conditions and medications, highlighting the importance of a comprehensive ECG examination to identify the underlying cause of PR interval waves [85]. Combining multiple leads is usually necessary to make an accurate diagnosis, which is vital in developing an effective treatment plan [69].

4.3. QRS complex

In a research article, the identification of the type of heart disease associated with QRS complex in a 12-lead ECG system [86]. The significant leads for this purpose are V1 to V6, as well as II, III, and aVF. The QRS complex is a representation of ventricular depolarization and its changes can indicate various cardiac conditions such as ventricular hypertrophy, BBB, and MI [87]. To detect right ventricular hypertrophy, leads V1 and V2 are useful, while left ventricular hypertrophy can be indicated by leads V5 and V6. Meanwhile, leads II, III, and aVF can provide information on the inferior wall of the heart, where changes in the QRS complex can indicate blockages or ischemia

[88]. Morphology or shape of the QRS complex is also an important factor in identifying heart disease, with a widened QRS complex indicating a BBB, while a narrow QRS complex suggesting a normal conduction pathway [89]. Presence of abnormally deep and wide Q waves may suggest a previous MI [90, 91, 92]. Therefore, an accurate diagnosis and treatment plan require an analysis of a combination of leads and QRS complex morphology.

4.4. R-R interval

A research article examines the utility of a 12-lead ECG system for assessing the electrical activity of the heart [93]. One key aspect of this system is the R-R interval waves, which reflect the time between consecutive R waves and correspond to the ventricular depolarization. Alterations in the R-R interval can serve as indicators of various cardiac conditions, including tachycardia, bradycardia, and arrhythmias. The analysis of the R-R interval can be performed using any of the 12 leads, although lead II and lead V1 are commonly used [94]. Changes in the R-R interval may also indicate heart blocks, such as first-degree AV block, second-degree AV block, and complete heart block. To effectively identify the type of heart disease associated with R-R interval waves, healthcare providers must perform a meticulous analysis of the R-R interval using a combination of leads. The R-R interval serves as a critical component of cardiac function, allowing healthcare providers to accurately diagnose and treat a range of cardiac conditions [95].

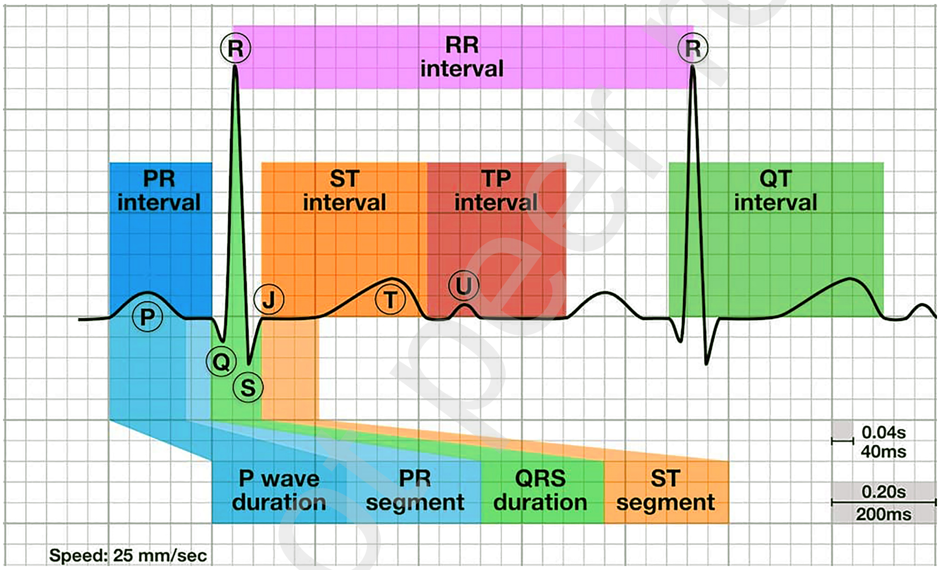
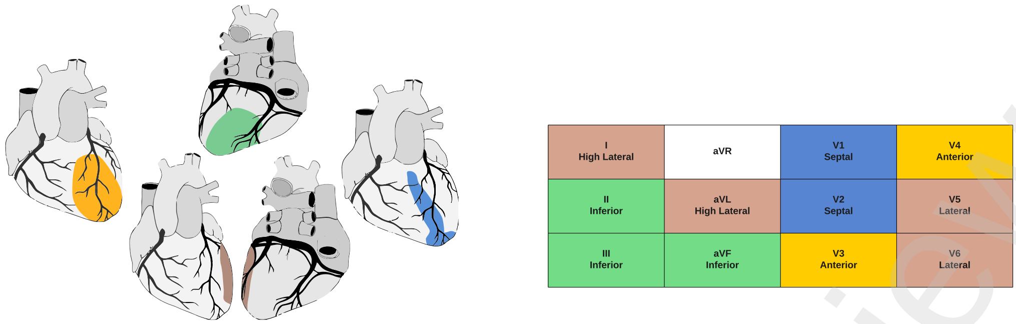


Figure 3: Different types of wave-forms

To summarize, specific leads in a 12-lead ECG system play a significant role in identifying the type of heart disease associated with different types of wave-forms [96]. Each waveform has its own set of significant leads shown in Figure 3. For example, P waves in leads II, III, aVL, and V1 can indicate atrial arrhythmias, while Q waves in leads I, aVL, V5, and V6 can indicate previous MI. There are different cardiac conditions that can be indicated by T waves in leads V2 to V5, ST segment changes in leads II, III, aVF, V1 to V6, and U waves in leads V2 to V5 [97]. Therefore, it is crucial to understand the significance of each waveform and its associated leads in identifying the type of heart disease present and providing appropriate treatment.

The ECG is a valuable tool in diagnosing various heart conditions. Each type of heart disease can cause unique changes in different leads of the 12-lead ECG. For instance, CAD may produce ST-segment depression [98] 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 [99, 100, 101]. 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 [102, 103, 104]. 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.



(a) Cardiac territory (b) Specification of cardiac territory mapping

Figure 4: Cardiac Territory Mapping for Early Detection of Heart Abnormalities

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 [105]. 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 [106, 107, 108]. 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 the left ventricle, such as left ventricular hypertrophy and acute MI [109, 110]. 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 [111, 112]. Finally, the septal leads V1, V2 are placed on the front of the chest and are crucial in detecting abnormalities in the septum [113], 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 [114]. Criteria for RVI include IWMI [115], ST segment elevation greater in lead III than II, ST elevation in V1 (possibly extending to V5 to V6), ST depression [116] 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 [117]. 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 [118, 119, 120, 121, 122]. 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 [123, 124, 125, 126]. 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 [127, 128, 129].

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 are indicative of a disruption in the electrical signals that control the heart's pumping function and are essential for accurate diagnosis [130, 131, 132, 133, 134]. By considering these criteria, medical professionals can identify LBBB and provide appropriate treatment to manage this condition.

APCs (atrial premature complexes) are best visualized in leads II, III, and aVF, which are located in the inferior wall of the heart where the atria are located. APCs can also be seen in other leads [135, 136, 137, 138], such as V1 and V2, but they may be more difficult to distinguish from other abnormalities in those leads. The ECG is a non-invasive diagnostic tool that is commonly used to predict atrial premature beats (APBs). The use of different leads in ECG has been shown to aid in the identification of APBs. Lead II, for instance, is one of the most frequently used leads and measures the electrical activity between the right arm and the left leg, which provides a clear view of the atria. Similarly, the V1 and V2 leads are positioned on the right and left sides of the sternum, respectively, and can detect APBs originating from the right and left atria. The V4-V6 leads, placed on the left side of the chest, are also useful in identifying APBs originating from the left atrium [139, 140, 141]. However, a comprehensive evaluation of a patient's medical history, symptoms, and physical examination is necessary to achieve an accurate diagnosis.

Ventricular ectopic beats (VEBs) are abnormal heart rhythms that can be detected using ECG, a widely-used non-invasive diagnostic tool. ECG provides valuable information for predicting VEBs [142, 143, 144], and while each lead in ECG offers important insights, some leads are more sensitive than others in detecting VEBs. Specifically, the V1-V3 leads located on the chest wall are highly sensitive in detecting VEBs originating from the right ventricle, whereas the V4-V6 leads are more sensitive in detecting VEBs originating from the left ventricle. Additionally, lead II can detect abnormal electrical activity in the ventricles, making it useful for predicting VEBs. To accurately diagnose VEBs, a comprehensive analysis of all ECG leads is necessary.

The leads that are most useful for detecting MI are the ones that correspond to the area of the heart that is affected by the blockage of blood flow [145, 146, 147, 148]. For example, if the blockage is in the left anterior descending artery (LAD), which supplies blood to the anterior wall of the left ventricle, leads V1-V4 may show ST-segment elevation, Q waves, and T-wave inversion. If the blockage is in the right coronary artery (RCA), which supplies blood to the inferior wall of the heart, leads II, III, and aVF may show 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 [149, 150]. 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

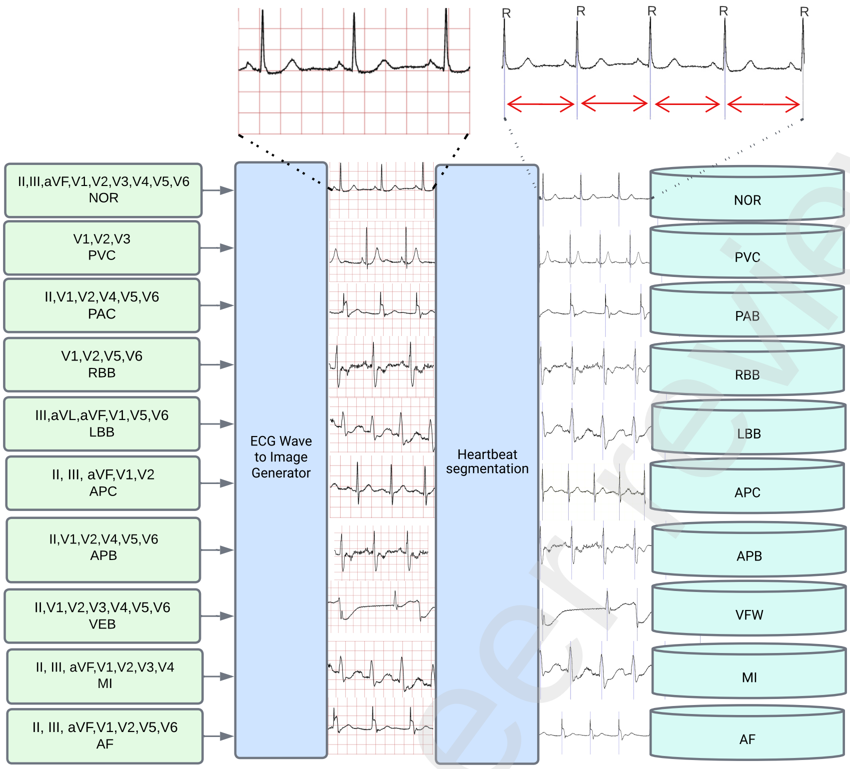


Figure 5: Data set preparation

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 [151]. The Adam optimizer performs well with focal loss.The Adam technique also works efficiently for the high-dimensional data set [152].

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 Pan-Tompkins algorithm. Finally, we split the data set in 70% for training, 20% for testing and 10% for validation purposes.

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

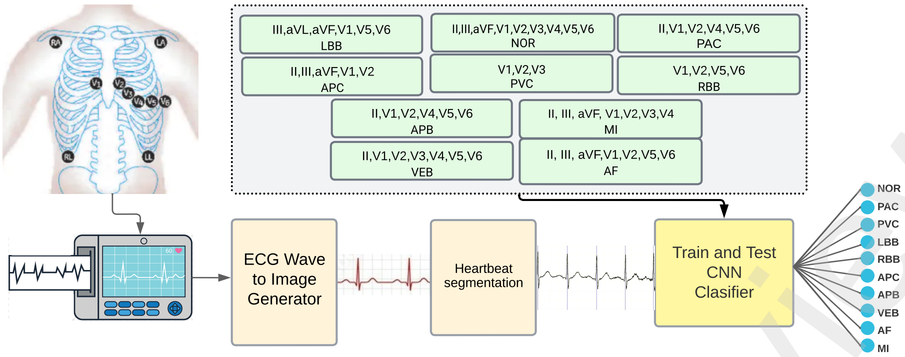


Figure 6: Proposed framework utilizing best classifier

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. 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 transformed 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.

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. Additionally, the accuracy metric is almost perfect, with a score of 0.99, suggesting that the model can classify almost all instances accurately. The macro average of precision, recall, and F1-score is 0.98, which demonstrates that the model is consistently performing well across all classes. The weighted average is also high at 0.99, signifying that the model can correctly classify instances

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

across all classes with similar high performance. Overall, the findings of this report suggest that the classification model performs well and can accurately classify instances across a wide range of classes, with high precision, recall, and F1-score metrics. This indicates that it can be utilized for automatic classification of ECG reports in real-life medical applications.

8. Conclusion

Heart disease is a major global public health issue, particularly in low-income countries where there is a shortage of qualified cardiologists. The ECG is the primary diagnostic tool for heart disease, but interpreting ECG reports can be time-consuming and costly, requiring the expertise of a qualified cardiologist. To address this issue, automated ECG signal interpretation is necessary, and this article has made a comprehensive review of the existing literature, including popular datasets and tools and techniques for this domain. The MIT-BIH data set, PTB database, BIDMC data set, and PTB data set are popular for the diagnosis of heart disease. These data sets are publicly available and easily accessible. Hence, researchers use them without any complexity. Moreover, CNN, LSTM, BiLSTM, CNN-LSTM, CNN-BiLSTM are widely applied approaches to incorporate the issue of detecting heart disease. Therefore, based on these observations, we have proposed a framework that considers the 12-lead ECG, the different types of leads, wave patterns, and their relationship with heart disease. The proposed framework has the potential to improve the diagnosis and management of heart disease by enabling a wider range of healthcare providers and individuals to interpret ECG reports more reliably and accurately, thus leading to earlier detection and treatment of heart disease and improved outcomes. This study also highlights the significance of utilizing various types of leads in developing a CNN model to minimize unknown pattern complexity. 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.

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