REVIEW

Review of Computational Techniques for the Analysis of Abnormal Patterns of ECG Signal Provoked by Cardiac Disease

Revathi Jothiramalingam[1], Anitha Jude[2] and Duraisamy Jude Hemanth[2,*]

[1]Kalaignarkarunanidhi Institute of Technology, Coimbatore, 641402, India

[2]Department of ECE, Karunya Institute of Technology and Sciences, Coimbatore, 641114, India

[*]Corresponding Author: Duraisamy Jude Hemanth. Email: judehemanth@karunya.edu

ABSTRACT

The 12-lead ECG aids in the diagnosis of myocardial infarction and is helpful in the prediction of cardiovascular disease complications. It does, though, have certain drawbacks. For other electrocardiographic anomalies such as Left Bundle Branch Block and Left Ventricular Hypertrophy syndrome, the ECG signal with Myocardial Infarction is difficult to interpret. These diseases cause variations in the ST portion of the ECG signal. It reduces the clarity of ECG signals, making it more difficult to diagnose these diseases. As a result, the specialist is misled into making an erroneous diagnosis by using the incorrect therapeutic technique. Based on these concepts, this article reviews the different procedures involved in ECG signal pre-processing, feature extraction, feature selection, and classification techniques to diagnose heart disorders such as Left Ventricular Hypertrophy, Bundle Branch Block, and Myocardial Infarction. It reveals the flaws and benefits in each segment, as well as recommendations for developing more advanced and robust methods for diagnosing these diseases, which will increase the system's accuracy. The current issues and prospective research directions are also addressed.

1 Introduction

ECG signal is one of the greatest initial sources to obtain diagnostic information. In recent research, an effective computational technique has been evolved in processing and analyzing the ECG signal. The major challenging research using the ECG signal is to provide a computational technique based on signal processing to diagnose a heart disease which includes Bundle Branch Block, Left Ventricular Hypertrophy (LVH), and Myocardial Infarction. The ECG with 12 leads helps to diagnose Myocardial Infarction and is useful in predicting complications in cardiovascular disease [1]. However, it has some limitations. The ECG signal with the presence of Myocardial
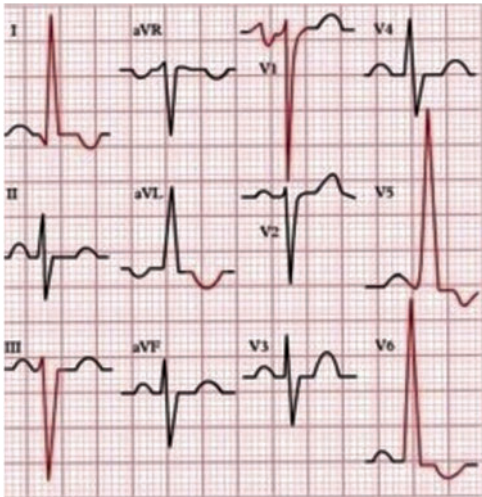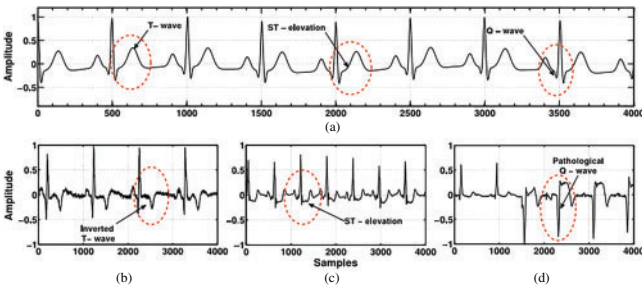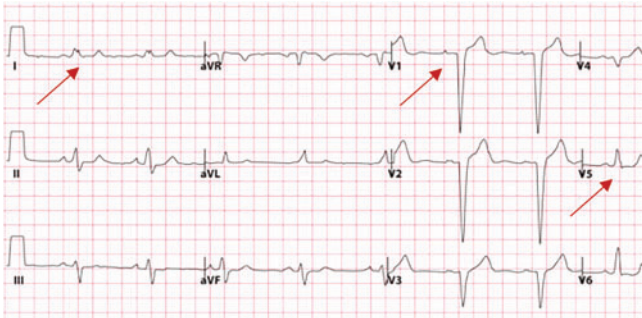
Infarction is difficult to interpret with other electrocardiographic abnormalities such as Left Bundle Branch Block (LBBB) and Left Ventricular Hypertrophy disease [2]. The ECG patterns of Left Bundle Branch Block and Left Ventricular Hypertrophy may resemble the ECG findings related to myocardial Infarction. These patterns decrease the clarity of the ECG signals to detect Myocardial Infarction [2]. Bacharova et al. [3] reported that left ventricular hypertrophy induced modification in the QRS and T pattern, and based on Romhilt-Estes Score, the amplitude of R wave and S wave was greater than 2.0 mV and induced depression in the ST segment. Gubner reported that the sum of the amplitude of the R wave in lead I and S wave in lead III was greater than 25 mV indicated in the LVH. Sokolow Lyon reported that the sum of amplitude of S Wave in V1 lead and R wave in lead V5 caused an increase in voltage by 3.5 mV. Based on Cornell voltage the sum of amplitude of R wave in avL and S wave in V3 was greater than 2.0 mV [3]. Gosse et al. [4] reported that the amplitude of the R wave in lead aVL produced a huge change in the ECG signal for identifying LVH. This approach was simple and cost-effective. Increases in voltage and length of the QRS complex, which are suggestive of a rise in LVM and repolarization changes considered to indicate anomalies in myocardial perfusion, are the most common signs [4]. de la Garza-Salazar et al. [5] reported that the LVH could be diagnosed using ECG and that it was independent of the parameter called ventricular mass. The measurements of ECG parameters were complex and provided a low accuracy for the diagnosis of LVH. Efficient machine learning algorithms were required for the diagnosis of LVH with the highest accuracy [5].

The Electrocardiographic pattern of Left Ventricular Hypertrophy induces a great change in the ST segment and T waves. It shows depression in the ST segment with negative T waves and elevation in the ST segment with positive T waves. This changed pattern may mean that the patient with the ECG signal has a condition that is compatible with Myocardial Infarction [6–8]. The LVH based ECG signal is shown in Fig. 1. An EKG with an R wave in lead I (17 mm) that is greater than 14 mm is seen below. The R wave in lead V5 and/or V6 is about 24 mm, while the S wave in lead V1 is 21 mm. According to Sokolow-Lyon guidelines, the total is 45 mm, which is higher than 35 mm, suggesting left ventricular hypertrophy.

Myocardial Infarction (MI) is the origin of coronary artery disease. It is also known as a heart attack. This is because of the occlusion of any one of the above coronary arteries [9]. The ECG signal with Myocardial Infarction is shown in Fig. 2. It represents the normal ECG signal and the ECG signal with MI. The synthetic ECG [notice Fig. 2a] is only seen for wave morphologies comparison. In a clinical setting, all of the above modifications (Figs. 2b–2d) can be present during an infarction. This demonstrates the importance of evaluating a 12-lead ECG for MI identification and localization.

Table 1: Diagnosis criteria for pathological conditions using ECG signal

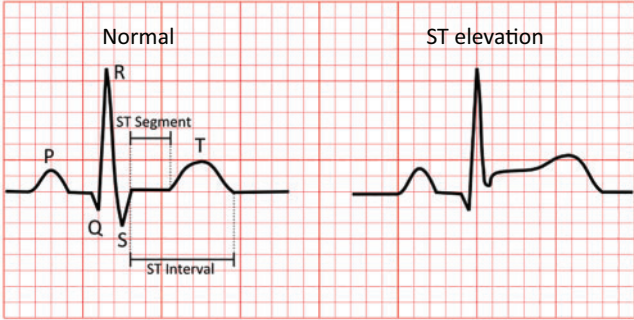| ECG signal with pathological conditions	Criteria to diagnose disease
Figure 1: LVH ECG with various pathological conditions	R wave in lead I-17 mm >14 mm R wave in lead V5 and/or V6 is about 24 mm S wave in lead V1 is 21 mm amplitude of S_{V1}+ amplitude of R_{V5} or $R_{V6} > 3.5$ mV
Figure 2: Normal ECG (a)(b)(c)(d) MI with various pathological conditions [10]	T inversion ≥ 0.1 mV in two contiguous leads down-sloping ST depression > 0.05 mV in two contiguous leads. Prominent R-wave or R/S ratio ≥ 1; Q-wave > 0.1 mV deep
Figure 3: ECG with Left Bundle Branch Block [10]	In leads I, aVL, V5, and V6, the R wave is wide and notched In lead aVL, a small q wave can be present. The ST and T waves are usually in the opposite direction of the QRS effect. Positive T waves in leads with positive QRS are likely normal (positive concordance). In leads with negative QRS (negative concordance), a depressed ST section and/or negative T wave are abnormal.

Table 1 (Continued).

ECG signal with pathological conditions	Criteria to diagnose disease
	Elevation of the ST section at the J-point of more than 0.2 mV in men 40 years of age or older, 0.25 mV or more in men younger than 40 years of age, and 0.15 mV or more in women in leads V2–V3.

Figure 4: Normal and ST-segment Elevation pattern of ECG signal

Another common observation in patients with the ECG signal associated with the LBBB and Myocardial Infarction is revealed that there is a discordance of the ST segment, QRS complex, and T waves. That is, the ECG signal shows ST-segment elevation with negative QRS complexes and depression in the ST segment along with negative T wave and positive QRS complexes [11]. The ECG with LBBB is shown in Fig. 3. Traditional methods to diagnose these diseases are cumbersome. The Electrocardiogram criteria for Left Bundle Branch Block, Left Ventricular Hypertrophy mimics the criteria for the diagnosis of acute Myocardial Infarction. This may lead to a wrong diagnostic and treatment procedure. Fig. 3 represents ECG with Left Bundle Branch Block. In leads I, aVL, V5, and V6, the R wave is wide and notched. The RS pattern can sometimes be shown in leads V5 and V6. In leads I, V5, and V6, there are no q waves. In lead aVL, a small q wave can be present. The ST and T waves are usually in the opposite direction of the QRS effect. Positive T waves in leads with positive QRS are likely normal (positive concordance). In leads with negative QRS (negative concordance), a depressed ST section and/or negative T wave are abnormal. As LBBB progresses, the mean QRS axis can move to the right or left.

The ST segment in the ECG signal pattern indicates the period that occurs between ventricular depolarization and repolarization. The ST segment is the isoelectric part of the ECG signal between the terminal point of the S wave and the starting point of the T wave. The elevation in the ST segment indicates heart abnormalities. Fig. 4 denotes the normal and abnormal ECG signal patterns. This section describes the research work which investigates the heart disease abnormalities that cause changes in the ST-segment pattern of the ECG signal. Tab. 1 indicates diagnosis criteria for pathological conditions using ECG signals.

Noriega et al. [12] evaluated whether the existence of multivessel coronary artery disease (CAD) varied the ST-segment of the ECG signal in patients with acute coronary artery occlusion. It was noticed that both the cases with a single or multivessel CAD had inverse depression in the ST-segment, which was due to the occlusion of the LAD artery. It could lead to a major infarction [12]. Rossello et al. [13] predicted whether QRS and QT duration differentiated between pericarditis and acute myocardial ischemia. It was observed that the elongation of the QRS complex and the reduction in QT interval in the ECG signal was noticed in patients who suffered from acute STEMI but not with pericarditis. A diffuse elevation of the ST segment and an upright divergence of the PR segment with ST-segment depression in lead aVR is common electrocardiogram (ECG) findings in patients with acute pericarditis [13]. Yildirim et al. [14] reported different clinical pieces of evidence that the ECG signal of myocarditis was similar to that of Myocardial Infarction (MI). The reciprocal of the ST-segment elevation was observed in the ECG signal for acute myocarditis cases. It can have a variety of clinical symptoms and can be interpreted as myocardial infarction (MI) because patients typically have chest pain and electrocardiographic changes that are similar to those seen in acute ST-elevation MI [14]. Willemsen et al. [15] analyzed three cases of chest pain. In all these cases, the clinical diagnosis for the general practitioner was unambiguous for conditions such as Acute Coronary Syndrome and light pain in the chest. A General Practioner's ability to distinguish between ACS and less serious sources of chest pain remains a challenge [15]. Coppola et al. [16] reported on various conditions that induced changes in ST-segment Elevation Myocardial Infarction (STEMI). When septal hypertrophy is occurring, the ECG reveals R waves with a high voltage in the anterolateral leads and Q waves in the anterior and inferior leads. The T waves in V2 and V4 are always very deep and inverted, resembling a non-Q AMI [16]. Smith et al. [17] reported that the elevation in ST-segment caused difficulty in differentiating Myocardial infarction from early repolarization of ECG signal. For a variety of causes, it can be impossible to determine the two entities apart. First, although upward ST-segment concavity is typically associated with normal ECG findings, it is also present in 30% to 40% of anterior STEMI (due to occlusion of the left anterior descending artery), particularly early after the onset of symptoms. Furthermore, 30% to 40% of anterior STEMIs have borderline ST-segment elevation [17]. Dodd et al. [18] analyzed Left Bundle Branch Block ECG signal cases with and without Myocardial Infarction and identified variations in the amplitude of QRS complexes, the morphology of ST-segment, and the T waves of ECG signal, and he compared them with modified Sgarbossa criteria to find them perform well against other variations [18]. Pollak et al. [19] reported that the ECG pattern minimized an accurate diagnosis of acute coronary syndrome because of the mystifying ECG patterns of Left Ventricular Hypertrophy, ventricular paced rhythms, and Left Bundle Branch Block. The confound electrocardiographic patterns are those that minimize the electrocardiogram's ability to detect modifications relative to ACS, not because the results resemble STEMI, but because the syndrome obscures the identification of ST-segment elevation [19]. Nable et al. [20] reported that the changes in ST-segment elevation in ECG signal were a key factor for the diagnosis of ST-segment elevation Myocardial Infarction (STEMI). Particularly, this change in ST-segment elevation pattern could also be perceived in the other diseases which included Takotsubo cardiomyopathy, left ventricular hypertrophy, left bundle branch block, and early repolarization [20].

Several efficient algorithms have been evolved for disease identification using the ECG signal. The morphologies of the ECG signal play a vital role in its analysis. Various Signal Processing techniques have been adopted to grasp information from the ECG signal. Various techniques have been investigated to identify the characteristics related to coronary artery disease. The detection of Q, R, S, and T wave amplitudes using signal processing techniques is an important indicator to identify heart diseases.

However, it is troublesome to perceive the differences in the ECG signal to indicate a specific type of heart disease. Hence, an automated heart disease diagnosis system has been devised in the medical field to find a solution to this problem. The data employed in this system are required to be processed and classified accurately. For this purpose, various techniques have been reported in the literature so far.

The statistical diagnostic strategies for predicting cardiac diseases based on ECG signals are summarized in this paper. The technique of ECG signal analysis based on machine learning is explored from preprocessing, feature extraction, feature selection, and classification. End-to-end models for ECG analysis based on deep learning algorithms have been summarized, removing the need for feature extraction using hand-crafted techniques from the analysis process.

This article describes the work reported in various pieces of literature for the diagnosis of cardiac diseases. The structure of the literature review is organized in this chapter as follows: ECG signal database, various pathological-condition-based ECG signals, ECG signal preprocessing, Feature Extraction techniques, and classification techniques. The advantages and disadvantages of various research works are also discussed in detail to identify the appropriate technique to diagnose and differentiate between various cardiac signals indicating heart diseases such as Myocardial Infarction, Bundle Branch Block, and Left Ventricular Hypertrophy. The flow of ECG signal processing technique to diagnose these diseases indicated in Fig. 5
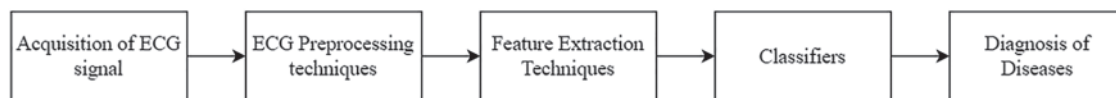

Figure 5: The basic flow of ECG signal processing technique

2 ECG Signal Dataset

The vast majority of research used computational approaches for Ischemic heart disease and myocardial infarction (MI) are detected automatically using publicly available datasets containing ECG waveforms to test the efficacy of their methods. The Physikalisch-Technische Bundesanstalt (PTB), The European ST-T (EST) and MIT-BIH arrhythmia Database as well as others, are all accessible via the Physionet data repository [21]. Fig. 6 indicates the database mainly used for the diagnosis of Myocardial Infarction, Bundle Branch Block, and Left Ventricular Hypertrophy.
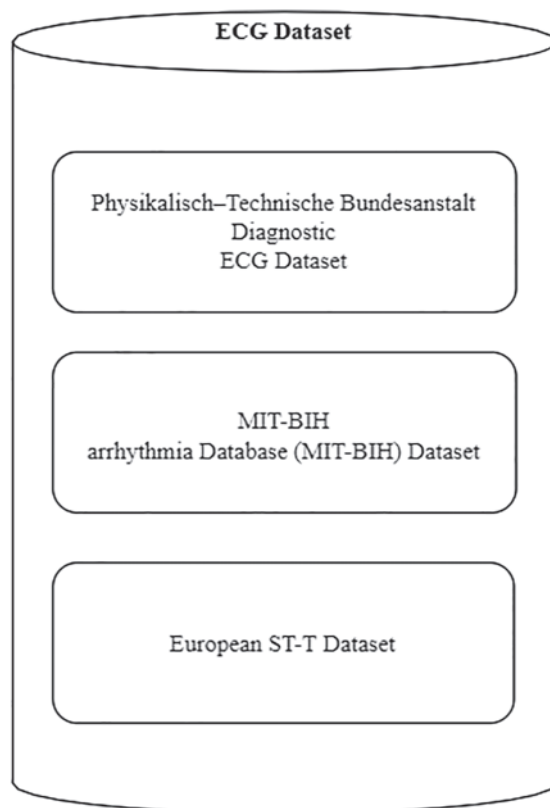
Figure 6: ECG dataset for the diagnosis of myocardial infarction, bundle branch block and left ventricular hypertrophy

2.1 The Physikalisch–Technische Bundesanstalt Diagnostic ECG Dataset

The 549 ECG documents in this dataset were compiled from 290 healthy volunteers and patients with multiple heart disorders. MI, cardiomyopathy/heart failure, bundle branch block (BBB), dysrhythmia, myocardial hypertrophy, valvular heart attack, and myocarditis are among the diseases represented in the dataset. There are 209 males and 81 females in the sample, with an average age of 57.2 years. MI has been annotated in 148 documents in the dataset [22].

2.2 MIT-BIH Arrhythmia Database (MIT-BIH) Dataset

This database is made up of 48 two-lead recordings, each lasting about a half-hour and sampled at 360 Hz. This database provides annotations for both beat class and timing detail, which has been confirmed by an independent expert. Representative beats to be used in the common training details can be found in the first 20 records (100–124). The diseased signal such as Junctional, ventricular, and supraventricular arrhythmias are included in the remaining 24 used documents (200–234) [23].

2.3 European ST-T Dataset

This dataset is designed to aid in the evaluation of ischemia detection algorithms by providing a standard dataset for reporting detection accuracy metrics and benchmarks. A total of 70 men and 8 women, ranging in age from 30 to 84, are included in the study. Of patient has myocardial ischemia, which was confirmed or assumed in the dataset, which includes 367 episodes of

ST-segment changes and 401 episodes of T wave changes. Two of the most revealing ambulatory ECG leads, sampled at 250 Hz, are included in each record [24].

3 ECG Preprocessing

Preprocessing is the preliminary stage involved in the implementation of any proposed approach. ECG signals are commonly affected by noises such as muscle artifacts, electrode motion, powerline interference, and baseline wander [25]. Muscle artifacts are caused by muscle activity. The movement in the position of the electrode introduces an electrode motion [26,27]. Powerline Interference is generally present in the ECG signal that contains a 50/60 Hz sinusoidal signal and harmonics [28]. Baseline wander causes modifications in the baseline of the ECG signal during respiration. These noises could affect the P, Q, R, S, and T segments of the ECG signal, the frequency resolution, and signal quality, and generate amplitudes in the ECG signals that could mimic PQRST waveforms. It made the analysis of the ECG signal more difficult, often misdirecting the physician to make a false diagnosis [29,30]. Hence, the cancelation of these noises present in the ECG signal was an essential task for further processing.

Different techniques have been presented in the literature for removing the noise present in the signal. The adaptive filtering technique based on discrete Wavelet Transform and artificial neural network is applied to the ECG signal, and it shows a significant improvement in Signals to Noise Ratio (SNR). But the disadvantage is that it is restricted to remove only certain types of noises. This technique reduces computational complexity [31]. The hybrid denoising techniques such as Ensemble Empirical Mode Decomposition (EMD) along with Block Least Mean square technique and Discrete Wavelet Transform (DWT) along with Neural Network were investigated and compared with DWT Thresholding method for eliminating the noise present in the signal. These techniques showed better performance than DWT thresholding did [32]. The presence of baseline wanders induced noise within 1 Hz which caused changes in the ST-segment. To reduce the noise Framelet Transform was applied and compared with DWT. The framelet transform showed better performance than DWT did [33]. The wavelet decomposition with level 2 was applied to the ECG signal and it showed that the approximation coefficient was similar to the low-frequency ECG signal. The higher-order decomposition coefficients emerged as the approximation coefficient with distorted ECG signals. So, it minimized the use of Non-Local Means (NLM). The effectiveness of both DWT and NLM was combined and found to be more efficient to remove the noise than other techniques were [34]. The ECG signal processing technique was applied based on Empirical Mode Decomposition (EMD) and the improved approximation envelope method. The Butterworth lowpass filter was implemented before applying it to EMD to eliminate high-frequency noise. This method eliminated the baseline wander and power line interference present in the ECG signal [35]. Jenkal et al. [36] proposed a method to denoise the ECG signal affected by various noises due to EMG signal, high frequency, and power line interferences. This technique depended on the DWT decomposition, and an Adaptive Dual Threshold Filter (ADTF). This technique produced a better result for the noise with higher density [36]. Sharma et al. [37] implemented a wavelet-based technique for the removal of the noise present in the electrocardiogram signal. This technique involved thresholding the coefficients of wavelets at various sub-bands. It was noticed that the utmost energy present in the signal existed in cD4, cD5, and cA5 sub-bands. The noise existed in the lower order sub-bands [37]. AlMahamdy et al. [38] presented various algorithms includes Savitzky-Golay filtering, adaptive filters, and discrete wavelet transform to remove the noise in the ECG signal. The NeighBlock wavelet method outperforms the other techniques. In some mid-range SNRs, however, the RLS and Savitzky-Golay filters work better [38]. Fig. 7 denotes the

different methods with SNR improvement in decibel. Tab. 2 represents the different denoising techniques using ECG signals.
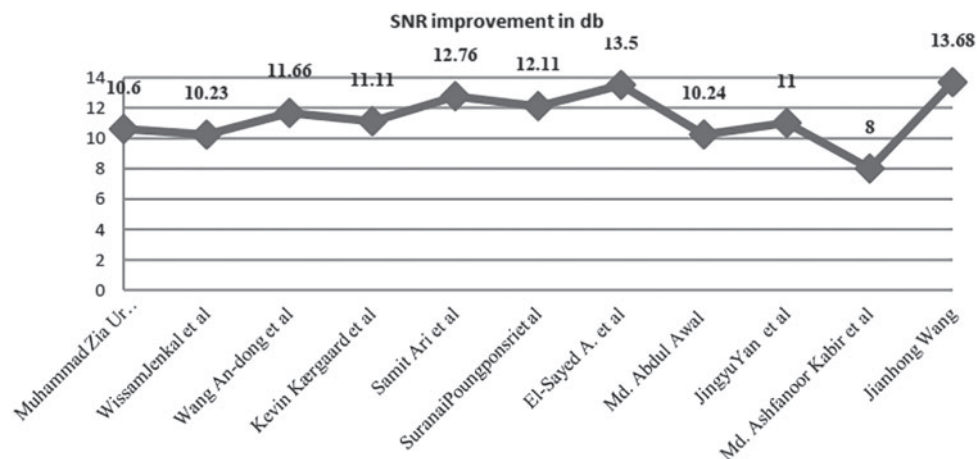

Figure 7: Several methods of SNR improvement in decibel

Table 2: Performance of different denoising techniques

Techniques	SNR in dB
Rahman et al. [39]	10.6
Jenkal et al. [36]	23.29
Wang et al. [40]	11.66
Kaergaard et al. [32]	11.11
Ari et al. [27]	12.76
Poungponsri et al [31]	15.72
El-Dahshan et al. [41]	13.5
Awal et al [42]	10.24
Yan et al. [43]	11
Kabir et al. [44]	8
Wang et al. [45]	13.68

4 Feature Extraction

Feature extraction in the ECG signal is one of the essential processes for classification and different types of features are extracted to describe the ECG signal. The extracted features from ECG signals play a significant role in diagnosing most cardiac diseases, according to Sujan et al. [46] These features include temporal, statistical, and morphological features [47–50]. The feature extraction stage aims to find the simplest number of features that result in acceptable suitable classification rates [51]. It extracts valuable data from ECG signals [52]. Fig. 8 indicates various feature extraction techniques to diagnose MI, BBB, and LVH.
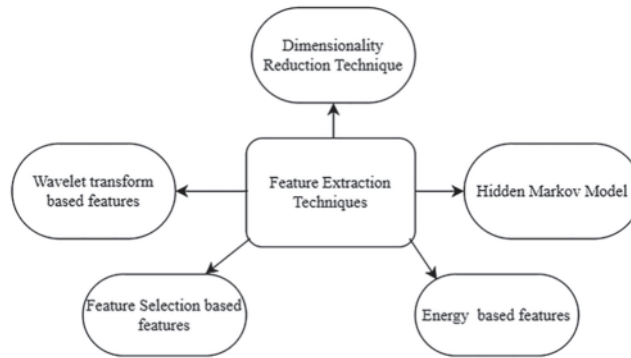
Figure 8: Various feature extraction techniques to diagnose MI, BBB and LVH

4.1 Wavelet Transform Based Features

In several techniques, the temporal features are obtained from the time domain signal. But certain hidden properties cannot be acquired in the time domain signal and do not provide adequate discrimination [53]. Statistical and morphological features can be obtained from both the time and frequency domains. The most popular used time-frequency approach is the wavelet transform [54–58]. This section reviews the wavelet-based research to Diagnose Myocardial Infarction, Bundle Branch Block, and Left Ventricular Hypertrophy.

Non-stationary signals are easily analyzed with DWT [59–63]. The determined DWT coefficients have a compact representation of the signal's energy distribution in time and frequency [64]. As a result, the feature vectors describing the signals were determined using the approximation and detail wavelet coefficients of the ECG signals. Jayachandran et al. [65] applied a Discrete Wavelet Transform to extract morphological features and calculated entropy. It was observed that more entropy value was obtained for normal signal than for MI-based signal. The classification accuracy obtained was 96.1% [65]. The feature extraction technique based on the Discrete Wavelet Transform (DWT) provides superior results [66]. For non-stationary ECG signals, DWT has acceptable scale values and shifting time [66]. Tab. 3 indicates some other papers based on the wavelet transform method.

Table 3: Wavelet transform method-based detection

Author	Database	Method	Comment
Acharya et al. [67]	PTB diagnostic ECG	Discrete wavelet transform, Discrete cosine transform, and Empirical mode decomposition	The advantage was that it was insensitive to the ECG signal noise. This technique was automotive, simple, robust, reliable, and easy to use.
Kumar et al. [68]	PTB diagnostic ECG	Flexible analytic wavelet transform	This technique computes sample entropy and is fed to various classifiers. The Least square SVM performs well than other classifiers.
Arif et al. [69]	PTB diagnostic ECG	Discrete Wavelet Transform	In MI identification, time-domain features perform exceptionally well.

(Continued)

Table 3 (Continued).

Author	Database	Method	Comment
Diker et al. [70]	PTB diagnostic ECG	Discrete wavelet transform and the classification was performed using support vector machine and a genetic algorithm.	The advantage was that there was no derivative information required and it was efficient.
Bhaskar [71]	PTB diagnostic ECG	Pan tompkins algorithm and wavelet Transform	The features are fed to various classifiers. But this technique provides low accuracy when compared to other techniques.
Banerjee et al. [72]	PTB diagnostic ECG	Crosswavelet transform to differentiate normal and inferior MI	It helps to find the similarity between two signals in the frequency domain
Banerjee et al. [73]	PTB diagnostic ECG	wavelet cross-spectrum and wavelet coherence to extract features	The cross-correlation between two time-domain signals is used to determine how close two waveforms are. The continuous wavelet transform is applied to two-time series, and the cross-analysis of the two decompositions reveals localized time and frequency correlations. But the computational complexity is high
Mohsin et al. [74]	PTB diagnostic ECG	Discrete wavelet transform	Rapid computation The amount of dataset used is less for comparison

4.2 Feature Selection Based Approaches

The dimension of the feature vector can increase the computational complexity. To overcome this issue, feature selection techniques help to select a feature set with good accuracy. Typically, the feature selection process is intended to provide a method for selecting the features that are suitable for classification optimization [75]. To identify features that are most descriptive for a specific type of disease, a feature selection process is needed [76]. It also helps to improve increase the process of disease detection. The papers which use feature selection techniques are reported in this section. Fig. 9 indicates various feature selection-based techniques to diagnose MI, BBB, and LVH.
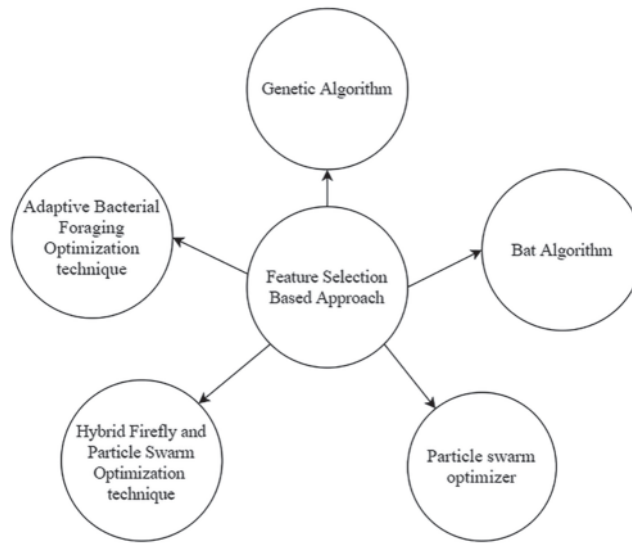
Figure 9: Various feature selection-based techniques to diagnose MI, BBB and LVH

4.2.1 Adaptive Bacterial Foraging Optimization (ABFO) Technique

Many techniques evolved based on the behavior manners of living organisms and have been implemented for finding solutions for real-world practical challenges. The bacterial Foraging optimization technique is one of the populations supported search approach [77–79]. The BFO is a non-gradient problem solved by using E. Coli microorganisms [80]. The operating steps are chemotaxis, Swarming, and reproduction. The movement of E. Coli is based on chemotaxis. This optimization technique helps to extract features from the ECG signal. It minimizes the features by eliminating unnecessary and noisy data. This method is helpful when the gradient of cost function unidentified. The mathematical computation complexity is less in the BFO technique. Bacterial Foraging Optimization with constant step size leads to two issues [81]. The larger step size leads to low precision even though the bacterium attains the optimum point quickly. For the smaller step size, it takes many chemotaxis steps to arrive at the optimal point. Hence, decrease in the convergence rate. Selecting a suitable step size is essential to increase convergence speed and reduce the error to achieve the final optimal value. The adaptive delta modulation helps to select the suitable step size [82]. The detection of BBB using ABFO is compared with the other algorithm which includes GA and BFO. The ABFO shows better result than other techniques.

4.2.2 Hybrid Firefly and Particle Swarm Optimization (FFPSO) Technique

A firefly optimization approach is a newly evolved technique based on the flashing process of fireflies [83]. The fitness function is implemented based on the fluorescence illumination manner of fireflies. Kora et al. [84] presented a Hybrid Bacterial Foraging along with a Particle Swarm Optimization algorithm for the diagnosis of Bundle Branch Block. The time-domain features were extracted from the MIT-BIH database to diagnose Bundle Branch Block. The feature selection approach is based on the combination of particle Swarm and Firefly optimization approach. In this hybrid approach, the position vector of the Firefly approach is adjusted based on the distance between the position of the firefly and the best velocity from previous and global best obtained from PSO. The distance was calculated based on cartesian distance. In this approach, every particle is randomly collected based on the global best in the overall population. The traditional

Firefly Algorithm (FFA) has one drawback: it can get stuck in the local optimum. It is often impossible to get out of that situation. The parameters in the firefly algorithm are set, and there is no mechanism to remember each firefly's previous best situation, so they shift regardless of the previous better solution [84].

4.2.3 Genetic Algorithms

Genetic algorithms are global search approaches that are based on the natural selection and genetics principle. The process starts with a population that is created at random and whose output is assessed using a fitness function [85]. It employs three basic operators known as selection, crossover, and mutation to find an optimized solution [86–88]. Kora et al. [89] implemented a genetic algorithm to obtain the best features. The features were fed to the LMNN classifier for the diagnosis of BBB. This technique achieved an accuracy of 98.9% [89]. Ragheed Allami et al. [90] implemented a Genetic algorithm along with Neural Network (GA-ANN) to extract 19 temporal and 3 morphological features to diagnose Bundle Branch Block. The results of this algorithm were compared with the principal component analysis along with the Neural Network technique. The GA-ANN techniques performed well showing an accuracy of 98% [90].

4.2.4 Bat Algorithm

Bats are the most amazing group of birds [91]. Bats come in over 1200 different varieties [92]. Yang et al. [93] created the Bat Algorithm based on micro-bat behavior. They use echolocation to find their prey. The majority of bats have a highly developed sense of hearing. They make noises that are echoed back to them by insects or other things in their way. The bats can tell how far the insects or objects are from their current location by listening to the echoes. Within a fraction of a second, approximate the size of insects or particles [93]. As it gets closer to the prey, the bat's pulse emission rate raises and loudness reduces. As a result, the Bat Algorithm's optimal points can be chosen based on the bat's pulse emission rate and loudness [94]. Kora et al. [95] presented an Improved Bat algorithm for extracting the best features and applied them as input to the neural network classifier. A good technique consists of high exploration and exploitation ability [94]. Much less exploration and too much exploitation can lead to premature convergence, while too much exploration but not enough exploitation can lead to difficulties in the algorithm's convergence to optimal solutions [96]. But the bat algorithm provides feeble exploration. So, it leads to poor convergence towards global points. This can be overcome by balancing the pulse rate and loudness with the problem dimension. It was noticed that the bat algorithm along with LM NN performed better than other classifiers did to show an accuracy of 98.9% [92].

4.2.5 Particle Swarm Optimizer

Kennedy et al. [97,98] invented the particle swarm optimization method. This is based on the action of a bird [98]. Based on its own and other birds' best flight experience, each particle reaches the optimum velocity. The fitness function is calculated using the inputs of particle coordinate positions as inputs. Sun et al. [99] implemented Multiple Instant Learning algorithms to diagnose Myocardial Ischemia without labeling heartbeats. In this technique, he applied a derivative-based technique and polynomial fitting function to extract features from R, S, T points, and ST segments. Particle Swarm Optimizer was used to cluster the features which were fed to the various classifiers. Its drawback was that the tuning of the input parameter was difficult. But it enhanced the quality of the classification in terms of sensitivity and specificity [99]. The demerits of the PSO technique are that it has been captured into local minima but convergence speed is high but in BFO the convergence speed is low but it's not being captured into local minima.

4.3 Hidden Markov Model

Tang et al. [100] described a hidden Markov model (HMM) for the diagnosis of Myocardial Ischemia. In this work, the time domain signals were documented by the ECG before and during the event of ischemia. Then, the Hidden Markov model was applied for the ischemia diagnosis [100]. Chang et al. [101] extracted features from the ECG signal using the Hidden Markov model. It helps to detect ECG segmentation and a statistical feature called log-likelihood value. In the hidden Markov model, 16 states and 6 states were employed. The 16 states showed better results than the 6 states and the accuracy obtained was 82.5%. The advantage of the proposed system was that the hybrid technique showed better classification accuracy [101].

4.4 Dimensionality Reduction Technique

The ECG signal can be much more detailed if the feature vector has high dimensionality. The cost of computation increases as the volume of data increases. Due to the vast amount of redundant data, some of the features may be associated, resulting in a large number of irrelevant variables, which would have a substantial impact on computational performance [102]. As a result, it is important to eliminate some associated features while enhancing classification accuracy and performance. Data processing becomes much easier and faster as dimensionality is reduced, which improves the efficiency of clustering algorithms with fewer features [103]. PCA (Principal Component Analysis) and ICA (Independent Component Analysis) are dimensionality reduction algorithms. Even if dimensionality reduction is successful, the features extracted before dimensionality reduction are still valuable because they provide the details needed for dimensionality reduction [104]. The processing of principal components includes computing the data's covariance matrix, decomposing it into eigenvalues, sorting the eigenvectors in decreasing order of eigenvalues, and eventually projecting the data into the latest principal component basis by taking the inner product of the actual signals and the sorted eigenvectors. This method reduces the computational complexity of a problem [105]. ICA is a nonlinear dimensionality reduction process to solve the weights. This method implies that the signal being targeted is composed of linearly mixed source components. In this, the data is centered on subtracting the mean and whitened by converting the data distribution into Gaussian. An iterative procedure is used to test the weights. The weight matrix, which contains the source signal weights, can be used to differentiate between ECG beat patterns [106]. This technique is widely used in ECG signal analysis.

4.5 Energy Based Features

Liu et al. [107] extracted features from ECG signals collected from the PTB database by fixing an ECG signal with a polynomial function of order 20. The fixed ECG curve was studied based on the Akaike information criterion (AIC), and to obtain a 94.4% accuracy in the diagnosis of Myocardial Infarction (MI) [107]. Sharma et al. [10] reported a technique to Diagnose Myocardial Infarction (MI) from a multi-lead electrocardiogram (ECG). The Multi-scale Energy and Eigenspace (MEES) method was implemented to extract only the relevant clinical components from ECG signal using Eigenvalues [10]. This technique comprises of wavelet transform of ECG signal. The clinical details of an ECG spread in various subbands are based on frequency content. These signals are recomposed with the eigenvalues. Multiscale matrices consist of segmented clinical components from the ECG signal. It helps to identify the MI pathologies [108]. The advantage of this technique was that it did not require the process of segmentation of ST-T complex and the history of the patient [108]. Kumar et al. [109] extracted statistical features which included kurtosis, form factor, and coefficient of variance for the diagnosis of ischemia. The bell curve was obtained from a normal distribution for various conditions of ST-segment which

included normal, elevation, and depression episodes. The statistical features provide low computational complexity. The benefit of this method was that it eliminated noisy beats automatically. It efficiently filtered the desired signals to diagnose ischemia. It showed 97.83% average sensitivity and 97.56% specificity [109].

Kumar et al. [110] reported a technique for the diagnosis of ischemia using an isoelectric energy function that depended on the morphology of the ST segment. The isoelectric function helps to observe the samples that close to the isoelectric line. The value of the isoelectric function raises as an ST-segment exists near the isoelectric level and the value decreases as an ST-segment falls away from the isoelectric line. There were no complex calculations involved in this study. This method helped in the diagnosis of Myocardial Infarction without the knowledge of past references. The limitation of using the isoelectric energy function was that it was not suitable for examining T waves in the ECG signal. It showed 98.12% sensitivity and 98.16% specificity [110]. Sadhukhan et al. [111] extracted morphological and temporal features using the phase distribution pattern based on Fourier Harmonics. The logistic regression and Threshold-based classification rule were applied and obtained an accuracy of 95.6%. The advantage of this technique was that it reduced training time and computational complexity.

5 Classifiers

The performance of the classification is improved by extracting a combination of features mentioned in the previous section [112]. The major issue in the diagnosis of heart disease is that normal ECG signals vary from person to person, and the same disease induces various signs in the ECG signal for different patients. The diagnosis of heart disease using the ECG signal is difficult. Hence, the classification of the ECG signal plays a significant role in the diagnosis of various heart diseases. Many researchers implemented various types of conventional classifiers and artificial Neural Network classifiers for the diagnosis of heart diseases. Different feature extraction and classification techniques have been presented in the literature for obtaining better results from the ECG signal.

5.1 Support Vector Machine Based Classifier

SVM classifier is a supervised learning technique employed for classification or regression [113,114]. A classifier's generalization is better as it minimizes training error while also increasing testing precision for uncertain testing datasets. Because of its generalization capacity, the SVM classifier for a single layer will supervise classification problems [114]. The kernel SVM is based on a statistical learning concept called a non-probabilistic binary-linear classifier [115–117]. In a high-dimensional feature space, this technique is used to formulate a computationally efficient way of learning good separating hyperplanes [118]. The merits of an SVM classifier are highly efficient along with greater accuracy [119]. The kernels are represented in mathematical function supported by kernel function selection [120,121]. The MEES-based extracted features were fed to SVM with linear and kernel function to diagnose Myocardial Infarction, yielding an accuracy of 87.69% and 99%. Han et al. [122] suggested a fusing energy entropy and morphological features diagnose MI. ECG signals are first disintegrated using the maximum overlap discrete wavelet packet transform (MODWPT), and then energy entropy is measured as global features using the decomposed coefficients. As local morphological features, the area, kurtosis coefficient, skewness coefficient, and standard deviation extracted from the QRS wave and ST-T segment of the ECG beat are computed. The best overall result is achieved by using a support vector machine (SVM) with radial basis kernel function and obtained an accuracy of 99.81%. Park et al. [123] implemented a discrete wavelet transform technique to diagnose ischemia. Three elements are

extracted that can be used to distinguish ST episodes from regular episodes: 1) the region between the QRS onset and T-peak points, 2) the normalized and signed sum from the QRS offset to the active zero voltage level, and 3) the slope from the QRS onset to the offset point. These features fed to the SVM classifier and obtained an accuracy of 95.7%. de Lannoy et al. [124] implemented a Wavelet and Independent Component Analysis to extract features and fed to the SVM classifier and obtained an accuracy of 82.47%. Sharma et al. [125] segmented multi-lead electrocardiogram (ECG) signal was decomposed into separate sub-bands using the stationary wavelet transform. The features used are sample entropy, normalized sub-band capacity, log energy entropy, and median slope measured over chosen bands of multi-lead ECG. These features were fed into an SVM classifier, which yielded a 98.84% accuracy.

5.2 KNN Based Classifiers

It is a non-parametric approach employed for regression or classification [126,127]. It is based on the instant learning principle [128]. One of the benefits of the KNN system for classifying objects is that it only involves tuning two parameters: K and the distance metric, to achieve high classification precision. The best choice of K and distance metric for calculating the nearest distance plays a key role in KNN-based implementations. Larger K values generally minimize the impact of noise on classification but leave class boundaries less distinct. The nearest neighbor algorithm is used when the class is estimated to be the class of the closest training sample (i.e., when K = 1). When solving binary classification problems, it's best to make K an odd number to prevent tying votes [129]. When there are many elements in the training set, this classifier is useful in reducing the error of misclassification [130]. A group of "k" features from the training set that is close to the test features is chosen during classification. The distance between vectors was calculated using the Euclidean Distance. The class for the specific data is determined by the most commonly occurring group of the K nearest neighbors [131]. This technique minimizes overlearning and achieves the best results [132]. Don et al. [133] extracted features based on Higuchi's fractal dimension. This method for calculating FD in a discrete-time series is very effective and is less noise-sensitive. The different features extracted in this analysis are FD, spectral entropy, QRS length, kurtosis, QRS amplitude, and mean of the power spectral density. These features were fed to the KNN and GMM classifiers to diagnose ischemia to obtain an accuracy of 99% and 98.24%, respectively [134]. Applied KNN classifier to diagnose MI and obtained an accuracy of 99.31%. The limitation of the KNN classifier was increased memory requirements to hold a training dataset. KNN is a memory-intensive algorithm that has already been labeled as instance-based or memory-based. KNN would take more time to scan all data points, and scanning all data points would necessitate more space for training data storage. This is because KNN is a lazy classifier that memorizes the entire training set without requiring any learning time. To minimize the storage space, Arif et al. [69] implemented a pruning algorithm. The obtained features were fed to the KNN classifier and obtaining 99.97% and 99.99% accuracy, respectively.

5.3 Neural Network-Based Classifier

An artificial neural network (ANN) is a mathematical model that is inspired by biological neurons' establishment and functioning. It is a robust data processing platform that can capture and visualize dynamic input/output relationships [135]. Neural network-based systems [136] can diagnose ischemia diseases more accurately than other current systems, but they cannot provide an interpretation of a diagnosis. The ANN techniques most generally used for the diagnosis of MI, BBB and LVH are Levenberg–Marquardt Neural Network, scaled conjugate gradient method and Resilient Backpropagation Neural network. The best backpropagation network, the

Levenberg–Marquardt Neural Network, is used. The Levenberg–Marquardt optimization method is used to change the weights and bias of this network. It is a simple method for approximating the function [135]. It reduces the nonlinear equation to a minimum and produces numerical performance. The scaled conjugate gradient approach is used to change the weights and biases. The analysis in this system is based on conjugate directions [136]. For each iteration, this approach determines the optimum distance [136,137]. The Resilient Backpropagation Neural network primarily shows the gradient's orientation. It works in a similar way to a backpropagation network, but the weights are modified differently. The weights are determined by resilient propagation based on the sign of partial derivatives obtained in the current and previous iterations [138]. It reduces the influence of partial derivative magnitude. The gradients in the backpropagation network have small magnitudes, resulting in limited weight shifts. It is simple to choose the learning parameter, and it's faster than a backpropagation network [139]. Hopkins et al. [140] designed a Backpropagation Neural Network to diagnose the presence of Left Ventricular Hypertrophy based on clinical information from ECG. This network showed an accuracy of 82%. Liu et al. [141] developed a Backpropagation Neural Network with PCA and without PCA to diagnose LVH. The BPN along with the PCA technique obtained an accuracy of 99.6% and BPN without PCA obtained an accuracy of 98.5%. The advantage of this technique was robust and more accurate production of either real-value or discrete value output. The disadvantages were that it was hard to understand the learning weights, the technique required more domain knowledge, and that it needed more training time [141]. Chaves et al. [142] developed a non-linear Sigmoidal Regression Blocks network which was a feedforward network to diagnose Left Ventricular Hypertrophy. This technique provided flexibility and robustness [142]. To diagnose BBB, a resilient backpropagation algorithm was implemented with 30 and 40 hidden node structures. The Levenberg-Marquardt algorithm was implemented with the 10 hidden nodes and achieved the best result when compared to the resilient backpropagation algorithm. The Polak-Ribiere conjugate gradient algorithm converges 11 times faster than the variable learning rate algorithm. This method lowers the computing complexity [143]. Signal features, rather than the raw signal, were used as the neural network's input vector, which increased the suggested networks' accuracy for both training and testing. Furthermore, by breaking down the classification process into various steps, using multi-stage ANN for ECG signal classification improved the classification process [144]. To diagnose BBB, the feature selection technique along with neural network performs well than conventional technique [144].

5.4 Deep Learning-Based Classification

This paper [145] suggests a novel deep learning-based method for the successful classification of ECG signals. The aim of deep learning, also known as feature learning [146] is to automatically learn a good feature representation from the input data [147–151]. Deep belief networks (DBNs), stacked autoencoder (SAE) [149], and convolutional neural networks (CNNs) [150] are examples of common deep learning architectures [152]. Deep learning has recently shown superior results in many implementations as opposed to shallow architectures [153]. The deep learning approach helps to find out an appropriate feature from the ECG signal. Deep learning has generated benefits in investigating features extracted using a deep neural network. The different layers in the network help to extracts the features from a deep neural network.

Shi et al. [154] reported Convolution Neural networks and long short-term memory Neural networks for the diagnosis of Bundle Branch Block. In this network, features extracted from three inputs using CNN and pooling layers were combined and fed to the LSTM network. A common recurrent neural network is the LSTM [155]. Since it remembers features from the early part

of a series, an LSTM network can learn long-term dependencies [156]. The advantage of this technique was that the features were extracted automatically and combined with implicit features. The heartbeat regions were fully employed as various convolution strides. However, there was a disadvantage because the computational complexity was more and the performance of classes required improvement. It achieved an accuracy of 99.26% [154]. Hu et al. [157] extracted deep features which included Wavelet features, Linear Discriminant Analysis Features, Morphological Features, and statistical features using Deep Neural Network and Bidirectional long short-term memory networks from the multi-lead ECG signal for the diagnosis of Bundle Branch Block to obtain an accuracy of 99.96% [157]. Kwon et al. [158] implemented a Deep Neural Network with 5 hidden layers, Convolutional Neural Network, and an Ensemble Neural Network algorithm to diagnose LVH. The accuracy obtained by these neural networks was 85.2%, 85%, and 86.6% respectively. There were also a few disadvantages to this study. For example, a deep analysis of the characteristics of the P and T waves was required [158]. Tab. 4 indicates the diagnosis of MI based on the deep learning approach.

Table 4: Deep Learning approach

Author	Database	Method	Comment
Reasat et al. [159]	PTB diagnostic ECG	Convolution layer based on Euclidean distance and geometric separability index	This technique provides better performance than Stationary Wavelet Transform
Acharya et al. [160]	PTB diagnostic ECG	Convolutional neural network	It identifies the disease along with the noise
Liu et al. [161]	PTB diagnostic ECG	Multiple-feature-branch convolutional neural network (MFB-CNN)	In this technique, 11 layers are implemented. so computational complexity increased
Baloglu et al. [162]	PTB diagnostic ECG	Convolutional neural network	This technique was able to differentiate between 10 different types of MI and normal ECG signals. The disadvantage was that it was more time-consuming due to a large set of data
Liu et al. [163]	PTB diagnostic ECG	Deep convolution neural network	It does not use manual feature extraction or feature selection, and instead of heartbeat segmentation, it takes three-second ECG signal segments as input.

6 Discussion

This study imparts details of various techniques that are associated with heart disease which induces changes in the ST segment. It describes the performance of each method and provides the scope for further development to explorers. Initially, various signal processing algorithms were implemented to diagnose various heart diseases. Later, different machine learning and deep learning approaches have been proposed to diagnose various diseases. These approaches provide a better result than the conventional techniques.

The various techniques implemented to diagnose Bundle Branch Block, Myocardial infarction, and Left Ventricular Hypertrophy. Most researchers implemented a hybrid technique that involves feature selection and a neural network approach. The feature selection technique along with neural network results shows that convergence speed is high. Generally, the performance of various feature selection and neural network classifiers to diagnose these diseases is nearly 98% accurate. For high-dimensional data, the computation complexity is high in machine learning classifiers. The deep learning approaches extract features implicitly and integrate them. The main disadvantage is higher computational complexity. The existence of a greater number of layers may increase computational time. Several factors may affect the performance of classifiers, which includes several data's in the training set, and the existence of weights and biases in the neural network. Figs. 10–12 show the percentage of accuracy of feature selection, deep learning, and neural network techniques to diagnose. The figures represent that the neural network-based approach provides better results than the feature selection approach along with the conventional classifier.
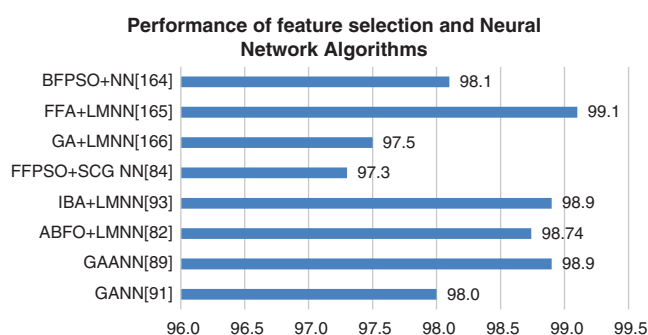

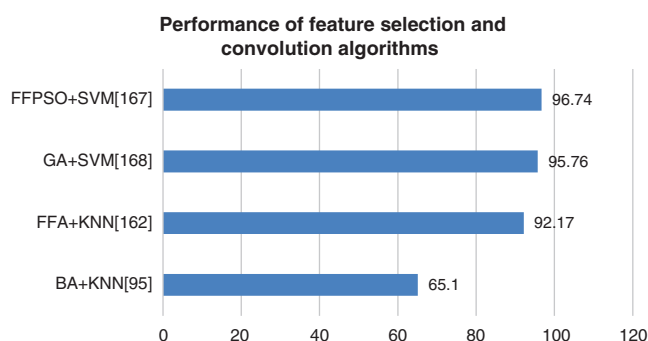**Figure 10:** Performance of feature selection and neural network algorithms

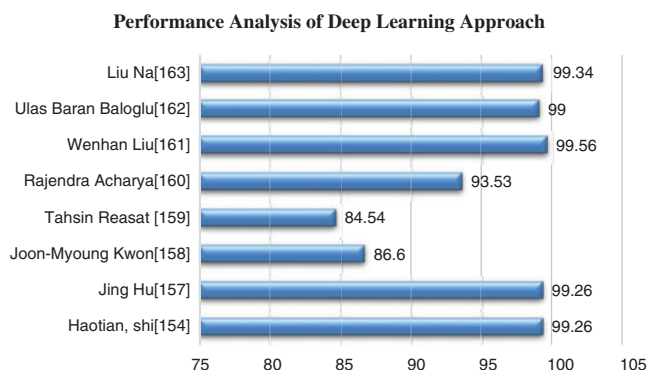**Figure 11:** Performance of feature selection and conventional algorithm

Figure 12: Performance analysis of Deep Learning approach

Previous research on the diagnosis of these heart diseases was based on statistical and mor-phological features, wavelet transform, neural networks, and deep learning approaches. The deep learning approach requires huge data for analysis. It leads to time consumption and computational complexity. Tab. 7 indicates the shortcomings and advantages of various features to diagnose these diseases. Only very few researches have been implemented in the diagnosis of LVH. Most researchers proposed neural network approaches to diagnose LVH [135]. The method does not necessitate any advanced knowledge of the ST section. The estimated features can be used for automated LVH labeling, reducing the need for manual annotation and allowing for faster LVH diagnosis. The limitations are that it requires more computational time.

Tab. 5 indicates the performance analysis to diagnose these heart diseases using the MIT-BIH dataset. The PTB diagnostic database is used widely to diagnose Myocardial Infarction, Bundle Branch Block, and Left Ventricular Hypertrophy. Tab. 6 indicates the classification analysis of these heart diseases based on ResNet and VGGNet. This article benefits researchers to seek various hybrid approaches to differentiate these diseases.

Table 5: Comparative analysis of various methods using MIT-BIH database

Author	Database	Method	Percentage of accuracy
Sharma et al. [169]	MIT-BIH	QRS complex and obtained five statistical features and fed them to KNN classifier	99.05%
Allami et al. [90]	MIT-BIH	Genetic algorithm along with Neural Network	98%
Hao et al. [170]	MIT-BIH	multiple-feature from magnitude-squared coherence	98.9%
Ceylan et al. [171]	MIT-BIH	Backpropagation algorithm with Mexican hat	99.2%
Vedavathi et al. [172]	MIT-BIH	Discrete wavelet transform with SVM classifier	98.46%

(Continued)

Table 5 (Continued).

Author	Database	Method	Percentage of accuracy
Zhu Li et al. [173]	MIT-BIH	Residual convolutional neural network	99.06%
Haroon et al. [174]	MIT-BIH	Residual neural network and VGG Network	ResNet-50 = 83% VGG-16-99%
Hu et al. [175]	MIT-BIH	Deep residual network	78.58%

Table 6: Classification result analysis based on ResNet and VGG Net

Author	Database	Method	Percentage of accuracy
Han et al. [176]	PTB	Multi-lead residual neural network	95.49
Gopika et al. [177]	PTB	Deep residual CNN	99
Jafarian et al. [178]	PTB	Deep residual CNN	98
López-Espejo et al. [179]	PTB	Deep residual learning with dilated convolutions	99.99
Alghamdi et al. [180]	PTB	VGG-Net model	99.02
Diker et al. [181]	PTB	VGG-16	76.47
		ResNet-18	83.35

Table 7: Merits and demerits of various techniques

Type of features	Advantages	Disadvantages
Statistical	Does not involve complex calculations Does not require prior information on the ST-segment	Difficult to develop model properties of ECG signal. Not suitable for non-stationary signals
Morphological	Techniques that depend on morphological features rely on accurate results	Difficult to analyze the morphology of waveforms due to the presence of noise Extracting morphology of ST-segment and QRS wave is complex and modifiable

(Continued)

Table 7 (Continued).

Type of features	Advantages	Disadvantages
Statistical	Does not involve complex calculations	Difficult to develop model properties of ECG signal
	Does not require prior information on the ST-segment	Not suitable for non-stationary signals
Morphological	Techniques that depend on morphological features rely on accurate results	Difficult to analyze the morphology of waveforms due to the presence of noise
		Extracting morphology of ST-segment and QRS wave is complex and modifiable
Feature Selection based MI	Speed is high, memory space low, high reliability	Adjusting input parameter is difficult
	Minimal possibility to make decisions based on noise	
Wavelet transform	Supports both time and frequency domain dimensions	Features extracted based on wavelet transform are difficult to implement in hardware platforms because of complexity
	Apply different mother wavelets for different ECG pattern	
Hidden Markov model	Capable to detect low amplitude waveforms	It accomplishes better average statistics in ischemic detection but not suitable for non-ischemic detection
	Automatically assess the model parameters from the training dataset	
Deep learning	This model automatically acquires distinctive features from the dataset and attempts to match the results with the desired output	More network size and training complexity
		Network training was slow when nodes that exist in the hidden layer increases. It indicates no progress in the performance
	It doesn't require feature extraction and selection techniques	Huge data required
	Denoising is not an essential	

7 Conclusion and Future Scope

This paper describes the overview of heart diseases that induce changes in the ST segment of the ECG signal. The process of analysis of ECG signal is reviewed in different sections which include diagnosis of Myocardial Infarction, Bundle Branch Block, and Left Ventricular Hypertrophy. Left Bundle Branch Block and Left Ventricular Hypertrophy are two similar conditions. Since patients normally complain of chest pain and the electrocardiographic changes mimic those seen in acute ST-elevation MI, it is called a myocardial infarction (MI). It has the potential to

mislead the diagnostic process. A General Practitioner's task is made more difficult by the fact that distinguishing between Acute Coronary Syndrome and less serious causes of chest pain. The majority of scientific work is focused on the automatic diagnosis of Myocardial Infarction using ECG signal, with a few works based on the automatic diagnosis of Left Ventricular Hypertrophy using ECG signal. Several issues with the automated classification of these diseases have been posed by researchers. The MIT-BIH and PTB diagnostic databases are used to present results in the literature. The limited number of databases available is a significant impediment to progress in research based on the fully automated classification of these diseases in ECG. To enhance the observed performance, some investigators used hybrid approaches. This is further described in various subsections such as different signal processing and classification techniques. Signal processing and classification techniques for the diagnosis of Myocardial infarctions in specific positions of coronary arteries in the heart, such as Left Anterior Descending Artery (Anterior position), Left Circumflex (Lateral position), and Right Coronary Artery (Inferior and Posterior position), can be investigated. Another essential direction is the investigation of these heart diseases using hybrid approaches.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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