

An Overview of ECG Arrhythmia Classification Methods

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ABSTRACT

An Electrocardiogram (ECG) is a key detection method employed to examine the electrical activity of heart and to detect cardiac abnormalities and arrhythmias. As the number of patients with cardiac disorders continues to rise, automated ECG analysis and classification methods have been designed to help medical professionals analyze ECG recordings. ECG analysis typically involves several phases, such as signal preprocessing, extraction of relevant features, and classification. Preprocessing is a crucial step, since ECG recordings may include various kinds of noise that can influence the analysis that follows. A range of denoising techniques, such as frequency-domain filters, adaptive filters, and Wavelet Transform (WT) based methods have been studied to enhance the ECG signal's quality. Various feature types, including morphological, statistical, and temporal features, as well as Fourier Transform and wavelet-based features, have likewise been examined for ECG classification. Previous studies have investigated conventional deep learning and machine learning approaches for arrhythmia classification, while hybrid feature-based methods have been examined to provide complementary information from ECG signals. Nevertheless, many existing studies have concentrated on a small number of arrhythmia classes, which makes classification harder as the number of classes grows. Thus, this review surveys existing techniques for ECG signal preprocessing, extraction of relevant features, and classification, and points out areas that warrant further investigation. Drawing on the reviewed literature, a hybrid feature-based approach that uses an LSTM-based classification approach is proposed for multiclass ECG arrhythmia classification. The proposed approach will examine how fiducial, temporal, morphological, statistical, and Wavelet Transform (WT)-based features can be combined, and their potential to improve classification performance and support the classification of a larger number of arrhythmia classes.

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I. INTRODUCTION

Cardiac diseases are among the most common health conditions worldwide. In healthcare, it is of particular importance to identify the disease at an early stage and accurately diagnose it. A routine procedure for recording the heart's electrical activity is an electrocardiogram (ECG). It provides information to identify cardiovascular disease and irregular heartbeats. Given the growing advancements in healthcare technology, researchers have developed several methods to analyse ECG signals and classify arrhythmias automatically. These methods help the doctor in providing analysis of ECG recordings and reducing the challenges that come with manual review.

A variety of approaches have been explored for processing ECG signals and classifying them using signal processing, traditional approaches and deep learning methods. The main steps involved in ECG analysis usually include preparation of the signal, identifying parts of the ECG such as the QRS complex, P wave and T wave, extracting features and selecting the best ones, and classification. These steps are critical because the quality and type of information obtained from an ECG can greatly impact the procedure. Hence, previous studies have explored ways to handle each step to enhance the precision of the automated ECG analysis.

The signal preparation is a key step because ECG recordings may have various types of noise and challenges that can affect the subsequent steps. Common steps include signal normalization, making the start point same and reducing noise from the signal. Several techniques of filtering and wavelets have been studied to minimize the parts that may exist in ECG signals. In the next step, once an ECG signal has been processed it is possible to extract the important points as the QRS complex, the P wave and the T wave. The appearance of the wave shape can then be used at the next stage for extraction of relevant features.

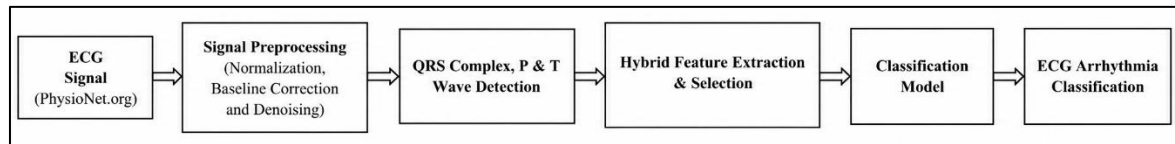


Fig. 1 Stages Involved in Cardiac Disease Classification

Extraction of relevant features is the next step in classifying ECG. Previous studies have investigated a range of ECG features such as waveform morphological features, temporal features related to occurrence of features, numbers that indicate signal characteristics based on Fourier transforms, signal characteristic features based on wavelets and other signal-based features. Features that indicate the shape of the waveform are referred to as features. Features that indicate the time and interval between ECG parts are called temporal features. Features that use numbers can help to indicate a lot about the signal. How it varies. The research also indicates that the use of combinations of different feature types can lead to greater information and potentially better classification than the use of one individual type.

Variety of classification techniques have been used for ECG arrhythmias. Traditional methods that have been reported include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Hidden Markov Models (HMM) decision trees, Bayesian methods and others. In recent times, deep learning methods such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have also been explored for ECG classification. LSTM networks are exceedingly beneficial in sequential data analysis as they are designed to learn from interconnections among sequential data. A study in 2026 on ECG arrhythmia classification reported the use of an LSTM network along with various ECG features that were obtained after the signal preparation and identification of the key points.

The research reviewed here indicates that a variety of ECG classification studies have concentrated on a number of arrhythmia types. A review in 2024 also indicated that classification becomes more challenging as the number of ECG types increases and emphasized the need to identify the features for more arrhythmias. In addition, the differences in data sets, preparation of signal, features used and classification techniques make it difficult to compare studies. Hence, further research is needed to determine the most suitable features and classification methods for classifying types of arrhythmias. Based on these thoughts, this review paper explores the methods used for preparing ECG signals, identifying the points, extracting features, selecting the best features and classification of arrhythmias. A special attention is given to methods that involve combining of features and using deep learning methods using LSTMs. Based on the previous studies, a method is proposed where a variety of ECG features such as the points, timing, appearance of the waveform, numbers and features based on the Wavelet Transform are used as an input to a classifier that uses LSTMs. The proposed work will investigate if this can assist ECG arrhythmia classification and expand the variety of types of arrhythmias that can be classified. The final feature set, number of arrhythmia classes, and experimental configuration will be determined during the implementation and evaluation stage.

II. LITERATURE REVIEW

This review discusses previous works on preprocessing the ECG signal, extraction of features, analysis, and classification methods of ECG signals for cardiac arrhythmia identification and classification.

The first stage of ECG signal processing is normalization, baseline correction, and denoising. Denoising is a significant step since the different types of noise and interference that affect the recorded ECG signal and following processing stages have to be removed.

The next stage is the detection of relevant ECG components, mainly QRS complex, P wave, and T wave, with the extraction of appropriate features in mind.

The purpose of extraction and selection of feature is to identify an appropriate feature set for further ECG classification. Various types of features such as morphological, temporal, statistical, and wavelet-based were explored. Afterward, these features are used by the chosen classifier to distinguish between different cardiac arrhythmias.

The review also lists different classification techniques that have been widely used in ECG signal processing, conventional artificial intelligence, machine learning, and deep learning approaches, among others. From the reviewed articles, it remains a huge challenge to classify a large number of cardiac arrhythmias and select the right set of features for an efficient classifier. Thus, the current project focuses on using LSTM

network with hybrid features including fiducial, temporal, morphological, statistical and Wavelet Transform based features to classify a greater number of cardiac arrhythmia.

2.1. Signal Preprocessing

Preprocessing of the signal for analysis involves various steps, such as normalization, baseline correction, and noise removal from the recorded ECG signal. Recordings of ECG signal are highly susceptible to a number of interferences, and, as a result, they require thorough preprocessing before any further analyses are performed. Clinical ECG signals, in particular, can be affected by a number of disturbances deriving from various sources.

To obtain useful information from the ECG signal, preprocessing of the data and elimination of the diverse noise types from the ECG recording is essential. The major challenge that arises at this stage is that the sources of contamination of the ECG signal by noise can be numerous, and the properties of the noise can be different. Therefore, the mitigation of the effect of the sources of interference and their elimination from the ECG signal is critical before the signal is ready for analysis. Since the main purpose of the current stage is to improve the signal's quality, the importance of this step within the preprocessing of the ECG cannot be overemphasized. As a result, the amount of information that can be retrieved from the clinical ECG will be increased, which is extremely important in medical research. Special significance is associated with preprocessing of ECG data, and one of its major stages is noise reduction.

2.1.1. ECG Signal Preprocessing: Normalization and Baseline Correction

Normalization of the ECG signal are done according to Equation (1) to ensure that the amplitudes of all signals are brought to a common range. The movement of the patient can lift the baseline of the signal, which is not always at zero. To bring the baseline to zero, the equation (2) is applied to normalized signals.

$$\text{ECGsignal} = \text{ECGsignal} / |(\text{ECGsignal})_{\max}| \quad (1)$$

$$\text{ECGsignal} = \text{ECGsignal} - \text{mean}(\text{ECGsignal}) \quad (2)$$

2.1.2. Noise Removal

Usually falling within a range of ± 2 mV, the ECG signal requires a recording bandwidth of 0.05 to 100 Hz. The noises that commonly appear in ECG signals comprise low-frequency baseline drift caused by movement artefacts, 50 Hz interference originating from the power supply, and high-frequency muscle noise.

A number of factors can lead to high-frequency noise in an ECG, such as the recording system, instrumentation amplifiers, cables that pick up ambient electromagnetic signals, and similar sources. Interference from electrical supply lines at 50 (or 60 Hz) and their harmonics can also disrupt signals.

Low-frequency movement artifacts and Baseline Wandering (BLW) can appear in the chest-lead system when a patient coughs or breathes with substantial chest movement, or moves an arm or leg during the acquisition of a limb-lead ECG. Breathing, squirming, or coughing can cause EMG to affect the ECG [3].

Noises occurring during the collection of the ECG signal were described by Haibing et al. (2010). The most common type of interference is firstly, the interference occurs at a frequency of 50 Hz, together with its harmonics. Secondly, Electromyography (EMG) refers to irregular variations in muscle activity that can affect the ECG signal. This interference is made up of drive unit signals beginning at 510 Hz, surface muscle signals spanning 0.01 Hz to 500 Hz, and single fiber muscle noise falling between 500 Hz and 10 KHz. Baseline Wandering (BLW) is the last category of interference. It is the result of poor electrode contact with the skin, changes in skin impedance, breathing, and other physical activities. Its frequency, 0.05 – 2 Hz, is near to that of the Q wave and ST segment of the ECG signal [4].

As outlined in the previous sections, ECG signals may be distorted by various types of noise that need to be eliminated so that the classification of ECG signals can be correctly done. To eliminate noise from ECG

signals, the filters most commonly used are time domain, frequency domain, adaptive and wavelet based ones. Currently, adaptive and wavelet based filters have gained more popularity since their performances have been improved. A number of denoising approaches have been studied and described in this work.

Thakor and Zhu (1991) presented several adaptive filtering configurations that were aimed at noise reduction and arrhythmia detection. By reducing the difference between the noisy ECG, which serves as the primary input, and either the noise or ECG related signal as the reference input, the adaptive filter is found to be very effective to eliminate noise from the primary input. Various filter structures successfully eliminate different types of noise, including BLW, 50 or 60 Hz PLI, muscle noise, and motion artifact. The study proposed an adaptive recurrent filter for obtaining the impulse response of the QRS complex. The main input of the filter is the ECG signal being analyzed, whereas an impulse train that corresponds to the QRS complexes acts as its reference input. Among various arrhythmias, this method is applied for identification of atrial fibrillation, P-wave detection, conduction block, paced rhythm, and premature ventricular complexes [5].

Donoho (1995) put forward a single approach by recommending taking the Discrete Wavelet Transform (DWT) of the signal and then applying Inverse DWT (IDWT). Then his suggestion was to apply a threshold to the result and remove coefficients below a specified value. The approach resulted in the output SNR as high as 8.26 [6].

A new technique aiming to remove PLI from ECG data was presented in 2002 by Ziarani and Konrad [7]. An approach for extracting the desired signal component and following its variation was put forward. The wavelet analysis theory served as the basis for constructing those filters used. By using this method the difference between the target output and the obtained one reached 0.006324 [7].

Simulations of ECG signal were conducted by Saritha et al. (2008) in the MATLAB environment along with the wavelet decomposition where high scale coefficients were omitted in the resulting vector for noise elimination in the ECG signal. These researchers draw a conclusion that further study enhance the clinical performance of wavelet-based approaches since the Wavelet Transform is considered relatively recent signal processing method. More precisely, a variety of the approaches for choosing mother wavelets and scales needs to be considered [12].

A new algorithm was developed to detect and suppress PLI as part of ECG signal preprocessing was put forward by Lin and Hu (2008). One of the key strengths of this innovative algorithm lies in its capacity to detect PLI in the signal prior to the implementation of the suppression algorithm. If PLI goes undetected, no action for PLI suppression will be undertaken. Their proposed PLI detector employs an optimal Linear Discriminant Analysis (LDA) algorithm to identify whether PLI is present. The PLI suppression is also carried out by creating a Recursive Least-Squares (RLS) adaptive notch filter that works effectively. The experimental results show that the algorithm performs better [13].

Qawasmī and Daqrouq (2010) presented their own technique based on weights for removing noise from an ECG signal. They evaluated the proposed methods on various ECG signals using MATLAB environment. To obtain a higher-quality ECG signal, DWT technique was utilized. Their proposed technique was efficient when compared to conventional techniques. The given technique is more effective compared to the Donoho's FIR filter method [14].

Low Pass Filter (LPF) having cut-off frequency 100 Hz was utilized by Saini and Saini (2012) for elimination of high frequency noise. Baseline wander (BLW) can be reduced by subtracting a low-order polynomial from the ECG signal [28]. The wavelet based denoising with wavelet db6 was applied by Martis et al. (2013) [29]. A Band-pass filter of 0.1-100 Hz was utilized by Park and Kang (2014) to get rid of noise [30]. By utilizing pass-band 4-15 Hz filter, Rangappa et al. (2018) maximized the energy contained in the QRS complex. A bandpass filter is formed by connecting low-pass and high-pass filters in cascade, which automatically eliminates the high frequency artefacts and low frequency interference [33]. For fluctuation in the heart, Kiani et al. (2019) employed the DWT approach of Donoho [6] along with the BLW removal technique

proposed by Rai et al. [41] is utilized [27]. Symmetric scale filters [36] were employed by Halemirle and Thippeswamy (2021) to correct the deviation at the baseline. No denoising performance analysis was conducted by the authors [26, 27, 28, 29, 33].

An approach was developed by Dewangan et al. (2016) where selective reconstruction process using the DWT, removed the BLW, the 50 Hz PLI and the muscle noise (EMG noise). With the DWT tool available in MATLAB 2009, the EMG, PLI, and BLW noises were removed by subtracting the denoised signal at level eight from the denoised signal at level three. The ECG arrhythmia annotated database was deployed. The approach resulted in an average output SNR of 7.5 dB [31]. To eliminate unwanted noise from ECG signals, number of approaches have been attempted. In the past, various authors have used different time and frequency domain filters. Due to the time-scale property and its ability to provide localized analysis, the wavelet-based approach has become popular in recent times. The plot of the wavelet coefficients describes exactly when the discontinuity takes place. This method is also popular as it is capable of removing not only the different types of noise in the signal, as well as a wide range of significant characteristics with features that can be used to classify the signals. As reported in a review of literature, an output SNR reaching as high as 9.07 was achieved by [10].

2.2. Detection of QRS Complex, P and T Waves

Once the ECG signals have gone through the pre-processing stage, the following stage involves extracting the meaningful and important features present in the ECG signal. The ECG signals are characterized by the P and T waves along with QRS complexes. A variety of peak and timing details comprise the morphological features. When the heart is diseased, the morphological features of ECG signals becomes modified. In presence of different heart abnormalities, various statistical measures such as mean, median, mode and variance of the ECG signals changes. Inside the wavelet domain, numerous wavelet features change when abnormal ECG signals are recorded because of heart abnormalities. Therefore, these kinds of features turn out to be highly useful for categorising or classifying ECG signals. Combining the different morphological, statistical, wavelet, or other features of ECG signals produces what are known as hybrid features.

The P and T waves and the QRS complexes are easily distinguished by ECG signals. Medical professionals or experts usually examine the peak and timing details of the different waves present in the ECG manually [3]. Considering the enormous amount of data, carrying out inspection manually turns out to be time consuming and challenging and individual performing the examination may miss out on vital information [3]. Due to this, creating a computer aided device to categorise heart conditions becomes essential.

Various techniques were created to classify ECG signals by using the different characteristic parameters or features extracted from the ECG. The chief aim of feature extraction is to establish a minimum feature set that guarantees better performance. Without first training and assessing the classifier, an analyst has no way of knowing how well features perform. Thus, the selection of features is of particular importance to realize and constantly adjust. By testing one option against another, you choose the best fit and fine-tune the features to make your classification optimally accurate. It is vital to ensure that the best options are selected and perform their functions to fulfill the purpose of a classification scheme. Thus, the procedure might be time-consuming; however, it is worth the effort since only experimentations can guarantee the best output. You should continue searching for the optimal set of features and fine-tuning them to realize their enhanced performance. [3].

Within the ECG, the QRS complex stands out as a prominent waveform. The shape of this complex and the timing associated with its occurrence provides invaluable insight into the heart's current state of health. Due to the special shape, the QRS complex has one of the most vital roles in different ECG algorithms. For example, it is used during the process of waveform compression to extract the heartbeat interval on its own. It provides a starting point for classifying the heart cycle. Thus, identifying the QRS complex provides the fundamental information on which nearly every ECG signal classification system relies.

Pan and Tompkins (1985) introduced a real-time QRS detection algorithm that includes a band-pass filter (BPF), derivative filtering, signal squaring, moving-window integration, adaptive thresholding, and search

procedures for the identification of QRS complexes. By considering digital height, slope and width, it becomes possible for this system to identify QRS complexes with high accuracy. A dedicated BPF reduces the risk of false positives due to the various noises present in ECG data. Thanks to this filtering, low thresholds can be applied, which raises detection sensitivity. To cope with variations in the ECG, such as QRS morphology and heart rate, the algorithm routinely adjusts thresholds and parameters by itself. Using the 24-hour MIT-BIH annotated database [15], this approach attains a correct detection rate of 99.3% for QRS complexes.

Daskalov et al. (1998) found that reliable automatic detection of the beginning and end of the QRS complex remains challenging. The presence of these interferences (PLI, EMG) often masks the small q, r, r9, or s9 waves of some complexes in the real signal, making it hard to determine their boundaries. To solve this problem and automatically preserve the integrity of the QRS complex despite the presence of significant PLI or EMG, the authors propose a preprocessing stage. The figures show examples of the automatic determination of the beginning and end of the QRS complex and a comparison with manually set markers to evaluate the effect of the described preprocessing method [16].

A feature extraction method based on Daubechies wavelets combined with multi-resolution WT was introduced by Mahmoodabadi et al. (2005). The initial step involves elimination of noise by erasing the corresponding wavelet coefficients found at the higher scales of the ECG. The Detection of QRS complexes follows, which are then utilized to establish the amplitude, the on set and offset of the P and T waves over one cardiac cycle. When the details fall between 24 and 28, the P and T waves appear to be more distinct. Signal ripples at both low and high frequencies are eliminated at these levels. The P and T peaks were the extremes that appeared before and after the located R peak. The results showed that the method provided more than 99% sensitivity and over 98% positive predictivity [17].

Sarita et al. (2008) investigated a WT-based method for denoising ECG signals, in which wavelet coefficients at higher scales were removed. After the QRS complexes had been identified, the peaks of the P and T waves, along with their variances, were determined for each complex. The comparison is made between the plots of coefficients associated with abnormal signals and those corresponding to normal ECG signals. Various anomalies lead to various changes of the coefficients. They got to conclusion that additional study is needed, because applying WT in electro cardiology still is a fairly new field study (such as deciding which mother wavelet to use and selecting appropriate scale parameter value) [12].

Using DWT as a basis for their research, Sumathi and Sanavullah (2009) decomposed the signal up to the level 4 and noticed that the QRS complex appeared in the highest detail on the approximation level. It can be seen that the R-peak can be easily found by finding the maximum amplitude level. PVC beats were removed using an adaptive threshold. For R-peak detection, they compared the performance of the db4, Haar, and cubic spline wavelets. Their conclusion was that the cubic spline wavelet-based WT is more suitable in this case, since it lowers the chance of errors arising during QRS complex detection. Their research examined the ways that properties of the WT could be used for detecting QRS complexes and presented an innovative approach for detecting the QRS complex. Using an adaptive threshold, the unwanted noise components were effectively removed from the signal, so the detection logic was simple enough to suffice for QRS detection purposes. This method has the benefit of reducing processing times for large ECG recordings [18].

Gautam and Sharma (2010) highlighted the importance of ECG in studying the functioning of the heart. In analyzing ECG signals, there are two main aims: detecting QRS complex or R-peak and determining the instantaneous heart rate using the time interval between successive R-peaks. After R-peak detection, the rest components such as P, Q, S, and T-waves can be found out by the window method. This study presents a dependable method for detecting the QRS complex using the Dyadic Wavelet Transform (DyWT), which proves superior in handling both the time-varying morphology of the QRS complex and noise. The accuracy of the QRS detection method was shown by the authors using the ECG database from Common Electrocardiography (CSE).

The study proposed an approach for QRS detection using the Dyadic Wavelet Transform (DyWT). The characteristics of DyWT required to process ECG signals were investigated by them. Using a smoothing

wavelet, transient components can be identified by following the local maxima of the DyWT across successive scales. Their method is based on the observation that selecting the first derivative of a smoothing function as the mother wavelet causes the local maxima of the absolute $|\text{DyWT}|$ of a transient signal to be correlated across successive dyadic scales.

Extensive algorithm testing on a standardized CSE database was carried out to assess the performance of the DyWT-based detector. A comparison of these outcomes with those of commonly used QRS detection methods was also conducted. Although no algorithm outperformed the others in every scenario, the DyWT based QRS detector did relatively better. DyWT offers two key advantages: effective noise reduction and flexibility in analyzing non-stationary ECG signals. [19].

In 2010, Banerjee and Mitra have proposed a DWT based method for precise detection of the R peaks and locate the QRS complex of an ECG signal. In their algorithm the db6 wavelet was employed as a mother wavelet. Using WT the ECG signals were decomposed into level 10 and selective reconstruction was carried out to reduce the noise. Thresholding combined with the slope inversion method is applied to detect the QRS complex. Thanks to its time scale feature the suggested algorithm is able to differentiate the waves at the point of their occurrence, without interfering with each other. The BLW turns out to be the signal with the component occurring at the lowest frequency, which can be corrected relatively easily. Decomposing the signal into its components facilitates the detection of the relatively high frequency QRS waves. The system's performance is evaluated using the PTB diagnostic database obtained from Physionet and for the ECG recordings the sensitivity of 99.4% is achieved [20].

Narayana and Rao (2011) investigated how successful is the performance of the WT and derivative Pan-Tompkins approaches in identifying the QRS waves within the ECG. The structural and functional characteristics of the entire heart muscle can be assessed through an ECG signal. To evaluate the effectiveness of these methods in detecting the QRS complex within the ECG signal, the ECG signal is loaded from the MIT-BIH annotated database in the MATLAB environment. The study compared the performance of the wavelet-based approach with derivative-based and Pan-Tompkins methods for the purposes of QRS complex detection and ECG signal denoising. Compared to the other two, the wavelet-based algorithm provides superior performance. By cancelling out the relevant wavelet coefficients at higher scales, noise in the ECG recordings was reduced through the application of a wavelet-based technique. Once the QRS complexes have been detected, the P- and T-wave amplitudes and their changes are also obtained for each ECG complex. They came up with the conclusion that further investigation is required to enhance the medical value of this novel technique in various methodological aspects (for example, selection of mother wavelet and scale parameter values). To confirm how useful is WT for diagnosis in multiple fields of electro-cardiology, wide-ranging medical trials are needed [21].

In 2011, Sasikala and Wahidabanu carried out a study on detecting P and T waves in ECG signals. Detecting these waves is difficult due to their comparatively low amplitudes. The authors used Wavelet Transform (WT) to extract the relevant signal features, since it is well suited for analyzing transient components. The method was developed to identify the positions of the P and T waves, which are essential for accurate feature identification and for the classification of signals that follows. The proposed approach was assessed using the MIT-BIH Arrhythmia Database [22].

The detection of the QRS complex in addition to the P and T waves is vital in extracting different morphological features of the ECG signals. However, Table 2(b) shows that the classification accuracy increases significantly when additional features are extracted and integrated with the morphological features. Hence, the identification of a feature set that can improve the classification accuracy may be the focus of future work.

2.3. Feature Selection and Signal Classification

Discovering a set of unique attributes that can provide satisfactory performance in the classification of cardiac disease. Prior to training and testing of the classifiers, the developers have no idea of the performance of the features. Thus, feature selection involves trying different combinations of attributes during training and

evaluating their performance until an acceptable level of classification is obtained. Some of the commonly used classifiers are Support Vector Machine (SVM), Artificial Neural Network (ANN), Autoregressive Model (AM), Hidden Markov Model (HMM), Bayesian Method (BM), Fuzzy Logic (FL), Neuro Fuzzy Approach (NFA), Principal Component Analysis (PCA), Self Organizing Map (SOM), Genetic Algorithms (GA), and others.

A Hidden Markov Model (HMM)-based technique for the analysis of cardiac arrhythmias was introduced by Doughlas et al. (1990). By locating and examining the QRS wave and measuring the R-R intervals this approach will classify ventricular arrhythmias. With the use of the HMM, one parametric model is built which combines different types of information, including statistical and structural characteristics of the ECG. Hidden Markov modelling [23] addresses the challenge of detecting P waves stemming from their low amplitude in the ECG signals.

Myocardial ischemia was detected by Ranjith et al. (2003) using a WT obtained from the quadratic spline wavelet. The T and P waves detection is dependent on these. Their methods provided higher sensitivity, although the positive predictivity was relatively lower. The method can also be adapted to detect other irregularities in ECG signals. However, this requires more computation than the competing methods. This stems largely from the computation of the WT [24].

Herrero et al. (2006) investigated a method based on Independent Component Analysis (ICA) and matching pursuits for obtaining additional spatial information from multichannel electrographic recordings. The approach was applied to the MIT-BIH Annotated Database for classifying five major arrhythmia categories and showed good sensitivity and specificity. However, the method faced difficulty in distinguishing ventricular PBs from PVCs when inverted T waves were present [25].

Park et al. (2008) employed two techniques for morphological feature extraction based on the Hermite basis function and higher order statistics. The authors discovered that their hierarchical classification approach was more efficient than the standard multi-class strategy. Additionally, they compared support vector machines-based methods of feature extraction and classification in order to evaluate their generalization capability. The authors' approach had a disadvantage that more complex models required higher computational power and tended to overfit the data. Despite lower accuracy and sensitivity for particular classes, the hierarchical approach proved to be more efficient than the conventional multi-class classification method. The mean sensitivity values were improved by the hierarchical classification. It was recognized that their classification method is able to identify multiclass heartbeats even if the data distribution is unbalanced [26].

For the purpose of feature extraction, Sarkaleh and Shahbahrani (2012) employed DWT, while the classification step relied on a Multi-Level Perceptron (MLP) Neural Network (NN). Two distinct kinds of arrhythmias can be distinguished by the method that was proposed. The feature vector that is obtained consists of 24 statistical measures spanning the entire range of the wavelet coefficients from the level one to level eight. Among the characteristics which were used are the variance at each level as well as the minimum and maximum of detail coefficients. A recognition rate of 96.5% was obtained overall [27].

Saini and Saini (2012) implemented a Back Propagation Neural Network (BPNN) technique using the standard database of ECG data to recognize and classify four types of arrhythmia. A Multi Layer Perceptron Network (MLP NN) was used, the sigmoid function was chosen and a hidden layer of 20 neurons was adopted. The input layer consists of 3 constant neurons while that of the output layer consists of 5 fixed neurons. Three morphological features including, the amplitude of R-peak, RR interval and QRS duration were used to classify the arrhythmia. Sensitivity and accuracy levels higher than 95% were recorded [28].

In their study, Martis et al. (2013) investigated how five different arrhythmias can be classified using ECG signals. In order to reduce the dimensionality, the DWT subbands of the signal were separately subjected to Linear Discriminant Analysis (LDA), PCA, and ICA techniques. The dimensionality reduced features were fed to SVM, NN, and Probabilistic NN (PNN) classifiers to facilitate the automated diagnosis process. The ICA

features outperformed both PCA and LDA. Table 1 presents the average values of the different parameters obtained using ten-fold cross-validation [29].

Table 1. Average Values of Existing Parameters

Sensitivity	Specificity	Positive Predictivity	Accuracy
99.97%	99.83%	99.21%	99.28%

A novel classification method was proposed by Park and Kang (2014) to automatically categorize ECG beats during Holter monitoring. QRS complex was detected and features were extracted using the PanTompkin's technique and decision tree classified each beat according to the features. The method was evaluated using the MIT-BIH Arrhythmia Database and the authors' own patient database, and the results showed that heartbeat classification accuracy achieves 94.6% and 99%, respectively. Such results prove the effectiveness of the proposed work and are in accordance with the outcomes reached by state-of-the-art systems [30].

Dewangan et al. (2016) employed a set of twelve features comprising four morphological and eight wavelet-based features for the classification of six different arrhythmias. The features were obtained after each ECG pulse was broken down into eight levels. A feature set was created by calculating the variance of the detail coefficients from d1 to d8. Besides normal beats, they distinguish 5 different arrhythmias. The three-layer feedforward backpropagation neural network proposed in the study obtained an average overall accuracy of 87% [31].

Bassiouni et al. (2018) developed a hybrid feature-based approach for the classification of cardiac arrhythmias. In their method, DWT was used to obtain morphological features from ECG signals, while RR interval information was used to describe the dynamic characteristics of the signal. The Teager Energy Operator helped capture the nonlinear behavior of the RR intervals. To reduce redundant information in the DWT subbands, ICA was applied, and twelve coefficients were retained as morphological features. These features were combined with the other extracted features and supplied to a neural network for arrhythmia classification. The method was evaluated using three-fold cross-validation and achieved average accuracies of 99.75% and 99.84% for the class-oriented and subject-oriented approaches, respectively [32].

Rangappa et al. (2018) proposed a three-stage classification of the ECG beat. The researchers used coronary artery disease in their analysis, which is related to ischemic heart disease, myocardial infarction, and heart failure. In the first stage, they used the Pan-Tompkins algorithm to detect the peaks of the ECG. The second step included combining the three interval features with higher-order ECG statistical features. The final step was to classify the set of features using the K-Nearest Neighbour algorithm. The method demonstrated a good ability to differentiate between normal and abnormal ECG samples with an accuracy of up to 98.40% [33].

Kiani et al. (2019) studied the complex and nonlinear nature of ECG signals for arrhythmia classification. In their approach, fractal dimension was used to capture the complexity of the ECG signal, and the extracted information was classified using a Backpropagation Neural Network (BPN). The method was tested for seven arrhythmia types using five reliable publicly available datasets. It achieved a sensitivity of 99.74%, specificity of 96.84%, and an overall classification accuracy of 98.83% [34].

Dalal et al. (2021) presented a method for assessing heart health from ECG signals with an emphasis on fast and accurate classification. They used DWT to remove noise from the ECG signals and then extracted useful characteristics using several cumulants. The resulting multi-cumulant features were used with a Kernel Extreme Learning Machine (KELM) for classification. Genetic Algorithms (GA) were further used to optimize the KELM parameters and multi-cumulant features [35].

In another study, Halemirle et al. (2021) developed a hybrid feature-based method for ECG classification. Features were extracted using autoregressive modelling, SVD-entropy, dual-tree complex wavelet transforms, and multifractal analysis. The features obtained from the MIT-BIH Annotated Database were then classified using KNN, Bayesian Optimized-KNN, and Rand

Sehirli et al. (2021) developed a hybrid machine learning system for classifying ECG signals. Their study considered a single ECG lead and used 837 ECG segments from seven classes in the MIT-BIH Annotated Database. The signals were first smoothed and corrected for baseline drift. The k-means algorithm and local extrema points were used to identify and segment the QRS complexes containing the Q, R, and S waves. Features were then extracted from these complexes and used to obtain the required measurement parameters. An eight-fold cross-validation scheme was used to prepare the training and testing sets. The hybrid classification system included KNN, decision tree, SVM, Random Forest, Naive Bayes and linear and quadratic discriminant analysis. The reported sensitivity, specificity, accuracy, and MCC were 92.33%, 92.50%, 92.41%, and 0.85, respectively [37].

Applying the MIT-BIH annotated database, Wu et al. proposed an accurate and efficient 12-layer deep one-dimensional CNN in 2021 to classify the five types of arrhythmia. Removal of noise from the ECG signal is performed using wavelet selfadaptive thresholding. The results of the experiments demonstrate that, compared with random forest, BPNN, and other CNN networks, the proposed method is more sensitive, accurate, robust, and has better noise resistance. The medical resources are saved due to the high accuracy of the proposed CNN network, enhancing medical procedures. Five sorts of arrhythmia are categorized using the proposed method. Notably, the proposed CNN network is more accurate and robust than previous random forests, BP neural networks, and CNN networks. Table 2 exhibits the classification performance, and it can be observed that the proposed CNN network has an excellent result [38].

Table 2. Average values of proposed parameters

Sensitivity	Specificity	Positive Predictivity	Accuracy
97.05%	99.35%	97.21%	97.41%

Sahoo Santanu et al., (2022) introduced an automatic deep learning method for the detection of cardiac arrhythmia using the MIT-BIH database. Different decomposition methods were used to reduce the noise present in the signal, and multi-domain time-frequency was obtained using the various sub-band coefficients from the denoised signals. The ranking of features was performed using the PSO-based algorithms with the Chi-squared test to select the best features for obtaining enhanced classification accuracy. Using ten-fold cross-validation with the hybrid features, a Deep Neural Network (DNN) classifier classified five different types of ECG beats. Among the evaluated feature selection methods, Chi-squared selection provided the best classification accuracy, reaching 99.75% with a computational time of 0.14 seconds. The authors suggested that the proposed method could be used in hospitals for detecting abnormal ECG rhythms [39].

Mishra et al. [42] discuss various methods and techniques used to process and analyze ECG signals for classifying cardiac diseases. In their review, the main steps of ECG analysis were considered, including preprocessing of the ECG signal, detection of the QRS complex and P and T waves, extraction of relevant features, and classification. The preprocessing stage includes signal normalization, baseline correction, and denoising procedures. The review covers various sets of morphological, temporal, statistical, frequency domain, and wavelet-based features of ECG applicable for classification tasks. The review also reports that combining different types of features along with morphological features can improve a classifier's performance, whereas the choice of an optimal and discriminative feature set remains a challenging issue.

Mishra et al. [43] suggested a deep long short-term memory network for classifying cardiac arrhythmia using hybrid features. The authors used the MIT-BIH arrhythmia database and applied normalization, baseline wandering removal, noise reduction, and fiducial-point detection to preprocess the ECG data. Then, they extracted morphological, temporal, statistical, and wavelet-based features from the signals. The combination of features that yielded the best results included three morphological, three temporal, eight wavelet, and three statistical features for a total of 17. The best-performing hybrid feature set consisted of 17 features, including three morphological, three temporal, eight wavelet-based, and three statistical features. These features were used to develop a deeper Long Short-Term Memory (LSTM) network for ECG beat classification.

An automatic categorization of the ECG signals into the class has been a goal of many researchers. Bhatia et al. [35] proposed a new architecture in 2022 which consists of Bidirectional Long-Term, Short-Term Memory (BLSTM) Network to extract the feature and CNN deep to classify them. Unlike conventional studies, the authors applied an end-to-end approach to extract and classify features simultaneously. The results were obtained from MIT-BIH annotated database as a public database. The effectiveness of the proposed model was compared to a previously published two different hybrid deep learning models and a set of references from literature. The authors also utilized the SMOTE method to equalize minority and majority classes by oversampling the former ones. The study developed a hybrid model and tested it using ten-fold cross-validation. The model was trained on resampled data set and tested on a test set to evaluate its performance. As a result, the values of F-score, recall, precision, and accuracy were 89.4%, 91.67%, 98.36%, and 94.36% respectively, indicating that the proposed architecture achieved promising results and showed better performance than methods reported in earlier studies. The current study proved the significance of applying a deep learning model for automatic classification of ECG signals for healthcare and medical industries. The study was conducted using BLSTM and CNN networks which yielded high precision and accuracy, making the model a good candidate for further research and application.

The ability to understand how to design a system that can categorize the ECG signals correctly is crucial. The features mentioned in Table 2 (b) can be found in ECG database and extracted from ECG signal with a specific lead in consideration. The features are related to the existence of specific human health disorders. From the information in reference [37], it can be observed that not more than seven heart diseases can be detected using the ECG. Therefore, it is vital to consider the critical features to use in the identification model to ensure effective diagnosis and classification of heart diseases.

Recently ECG analysis methodologies have been exploring hybrid features and deep learning approaches. Thus, one important research direction would be to broaden the range of arrhythmia classes that can be classified accurately. In general, classifications are becoming more difficult as the number of ECG classes increases. Therefore, there is room for finding appropriate feature combinations and developing effective classification methods for accurately classifying a higher number of cardiac arrhythmias.

III. METHODOLOGY

Noise removal approaches are discussed briefly in Table 1(a) and 1(b), and methods used for extraction of feature and classification are summarized in Table 2(a) and 2(b). Wavelet-based denoising has been widely investigated for ECG signal processing due to its ability to address different types of signal disturbances. Previous works have also investigated the utilization of hybrid features for improving the performance of ECG classification. Based on the above observations, a hybrid feature-based approach with a deep learning classifier will be investigated in the present work.

The ECG signals will first be normalized to bring the data values to a common level. Due to patient movements and other factors during ECG recording, the baseline of the signal may shift. Therefore, baseline correction will be considered to reduce baseline variations prior to further processing.

To support accurate ECG arrhythmia classification, different types of noise contained in the ECG recordings should be eliminated prior to further analysis. After preprocessing, the QRS complex will be detected, followed by recognition of the P and T waves. The detected fiducial points will be utilized for subsequent feature extraction.

After detecting the QRS complex, P wave, and T wave, extraction of different types of features from the ECG signal can be done. These may include fiducial, temporal, morphological, statistical, wavelet-based, and other appropriate features. Combining different groups of features can provide complementary information and may be investigated for improving multiclass ECG arrhythmia classification.

Previous works have utilized different deep learning and machine learning algorithms for ECG classification, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and other neural-network-based approaches. LSTM networks are suitable for sequential data and have therefore been

investigated classification of ECG. In the proposed approach, different ECG signal features will be combined to form a hybrid feature set, which will be investigated with an LSTM-based classification model for multiclass ECG arrhythmia classification.

In the proposed project, hybrid ECG features comprising fiducial, temporal, morphological, statistical, and Wavelet Transform (WT)-based features will be investigated as inputs to the classification model. The proposed work will explore the potential of combining complementary ECG features with LSTM-based learning to improve classification performance and support the classification of a larger number of cardiac arrhythmia classes.

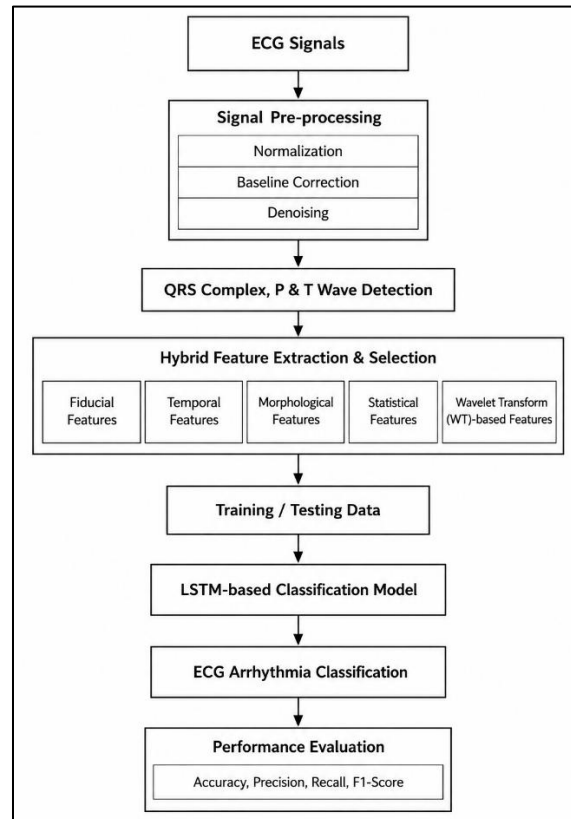


Fig. 2 Illustration of proposed methodology

IV. CONCLUSION AND FUTURE SCOPE

Unwanted components such as Power Line Interference (PLI) and disturbances caused by the movement of recording electrodes can affect ECG signals. Physiological signals such as Electromyographic (EMG) activity may also interfere with ECG recordings. Therefore, preprocessing is an important step before extraction of feature and classification of ECG arrhythmias. In this study, different denoising techniques reported in previous studies have been examined and summarized in Tables 1(a) and 1(b). Wavelet-based methods have been widely investigated for ECG denoising. Previous studies have also used different deep learning, signal processing and machine learning techniques for ECG classification, as summarized in Tables 2(a) and 2(b). From the reviewed literature, the following observations can be made:

- (1) Wavelet Transform (WT) has been widely used for reducing noise in ECG signals.
- (2) Many existing methods have been evaluated using relatively limited datasets. Therefore, larger and more diverse datasets are needed to further examine their effectiveness.
- (3) Most studies have considered a limited number of arrhythmia classes, and classification of a wider range of arrhythmias needs further investigation.
- (4) Classification performance is generally lower for uncommon arrhythmia classes compared with more frequently occurring classes.

The reliable detection and selection of ECG features are important for effective arrhythmia classification. The reviewed studies show that different feature types provide different information from ECG signals. Combining different feature types has therefore been investigated to provide complementary information for classification. Deep learning methods, including LSTM-based approaches, have also been explored for ECG classification. Overall, the reviewed literature shows that there is still scope for investigating suitable combinations of ECG features and effective classification approaches for a larger number of arrhythmia classes.

Based on these observations, the present review proposes further investigation of a hybrid feature-based approach with an LSTM-based classification model. Fiducial, temporal, morphological, statistical, and Wavelet Transform (WT)-based features will be considered as possible complementary feature groups. The proposed work will investigate suitable feature combinations and the use of LSTM-based learning for multiclass ECG arrhythmia classification. The final feature set, number of arrhythmia classes, dataset, and experimental configuration will be determined during the implementation and evaluation stage.

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Appendix I

Table 1(a). Overview of ECG Signal Denoising Approaches

Authors	Types of Noise Considered	Denoising Method Used	Performance of the Denoising Method
Thakor and Zhu (1991)	Baseline wander, muscle noise, motion artifact and 60 Hz PLI	Several adaptive filter structures for noise cancellation and arrhythmia detection	Better than existing methods
Donoho (1995)	Gaussian random noise	The approach is based on applying the Discrete Wavelet Transform (DWT) to the signal, followed by thresholding using the proposed threshold.	This method achieved an output SNR of up to 8.26.
Ziarani and Konrad (2002)	Power line noise	Developed a signal processing algorithm for extracting a specific component of a signal and monitoring its changes over time.	The approach is simple to implement and requires limited computational resources.
Addison (2005)	Examined the use of WT for reducing different types of noise in ECG signals.	Wavelet Transform	The study reported that Wavelet Transform (WT) is well suited for time-frequency analysis and signal coding of complex, non-stationary signals such as ECG.
Tinati et al. (2006)	Baseline wandering	Applied a Wavelet Transform (WT)-based search algorithm that uses signal energy at different scales to separate baseline wander from the ECG signal.	The algorithm was able to reduce baseline drift in ECG signals without distorting the waveform or removing clinically relevant information.
Alfaouri and Daqrouq (2008)	Random noise	Applied the Discrete Wavelet Transform (DWT) using the db4 wavelet and introduced a new threshold value.	The approach resulted in an output SNR of up to 9.07.
Zhang and Ge (2008)	Random noise	Used wavelet based adaptive filters	Provides better result than Donoho's method
Saritha et al. (2008)	Noise generated by simulation	Wavelet coefficients at higher scales were removed to reduce noise in the ECG signal	The study concluded that further investigation is needed to determine suitable mother wavelets and scale parameters to improve clinical usefulness.

Table 1(b). Overview of ECG Signal Denoising Approaches

Authors	Types of Noise Considered	Denoising Method Used	Performance of the Denoising Method
Lin and Hu (2008)	Power-line interference	An optimal Linear Discriminant Analysis (LDA) algorithm was used to determine the presence of Power Line Interference (PLI), while an efficient Recursive Least-Squares (RLS) adaptive notch filter was developed for PLI suppression	Easy to implement and computationally efficient
Qawasmi and Daqrouq (2010)	Noise signals generated by simulation	Method adopted DWT	Better performance than Donoho's discrete wavelet thresholding and FIR filtering methods
Dewangan et al. (2016)	Baseline wander. 50 Hz PLI, muscle noise	Method adopted DWT	The approach resulted in an average output SNR of 7.5 dB.

Saini and Saini (2012)	BLW and noise of > 100 Hz	A low-pass filter with a cutoff frequency of 100 Hz was applied, while baseline wander (BLW) was removed by subtracting a low-order polynomial from the signal	Denoising performance was not evaluated, while the classifier achieved 95% sensitivity and accuracy.
Martis et al. (2013)	Noise present in the ECG signals from the MIT-BIH Arrhythmia Database	Wavelet based denoising using wavelet db6	Denoising performance was not evaluated, while the classifier achieved an accuracy of 99.28%.
Park and Kang (2014)	Noise present in the ECG signals from the MIT-BIH Arrhythmia Database	Band-pass filtered at 0.1- 100 Hz	Denoising performance was not evaluated, while the classifier achieved an accuracy of 94.6%.
Rangappa et al. (2018)	60Hz interference, BLW, interference in T- wave, and muscle noise	A passband of 4–15 Hz was used to enhance the energy of the QRS complex. Low-pass and high-pass filters were cascaded to form a band-pass filter, which automatically reduced low-frequency interference and high-frequency artifacts.	Denoising performance was not evaluated, while the classifier achieved an accuracy of 98.40%.
Kiani et al. (2019)	High-frequency fluctuations above 150 Hz caused by cardiac muscle activity were removed, along with baseline wander (BLW).	Donoho's DWT-based method [6] was used to analyze heart-rate fluctuations, while the baseline wander (BLW) removal method proposed by Rai et al. [41] was also applied.	Denoising performance was not evaluated, while the classifier achieved an accuracy of 98.83%.
Halemirle and Thippeswamy (2021)	System interaction and baseline wandering	Symmetric-scale filtering was combined with denoising operations to minimize baseline deviations.	Denoising performance was not evaluated, while the classifier achieved an accuracy of 98.29%.

Table 2(a). Summary of Methods for ECG Feature Extraction and Classification

Authors	Features Extracted	Extraction Method / Classification Technique	Detected Cardiac Abnormalities	Classifier Performance
Pan and Tompkins (1985)	QRS complex	A real-time QRS detection algorithm was developed using a band-pass filter, differentiator, squaring operation, moving-window integration, adaptive thresholding, and search procedures.	Not Reported	The algorithm achieved a QRS detection rate of 99.3%.
Daskalov et al. (1998)	QRS boundaries	Proposed a preprocessing method designed to preserve the QRS complex accurately.	Not Reported	The method maintains the QRS boundaries effectively under considerable 50 Hz and EMG noise.
Mahmoodabadi et al. (2005)	QRS complex and peaks of the individual waves, including onset and offset of the P and T waves	A feature extraction system was developed using multi-resolution Wavelet Transform with Daubechies wavelets.	Not Reported	The QRS detection method obtained a sensitivity of $99.18\% \pm 2.75$, with a positive predictivity of $98\% \pm 4.45$.
Sumathi and Sanavullah (2009)	QRS detection	The signal was decomposed up to level 4 using DWT, where the QRS complex was found to be dominant in the approximation component, and the R-peaks were detected by identifying the maximum amplitude points.	Not Reported	It requires less processing time for QRS detection in long-duration ECG signals.
Gautam and Sharma (2010)	QRS. P & T wave detection	Dyadic Wavelet Transforms (DyWT)	Not Reported	DyWT offers two major advantages: robust noise performance and flexibility in analyzing non-stationary ECG data.

Banerjee and Mitra (2010)	QRS complex	DWT where db6 wavelet was selected as mother wavelet	Not Reported	Sensitivity of 99.4%
Narayana and Rao (2011)	QRS complex	Derivative based/Pan-Tompkins/wavelet transform based algorithms	Not Reported	It was concluded that further investigation is required to identify suitable mother wavelets and scale parameter values.
Sasikala and Wahidabanu (2011)	Detection of the P and T wave	Wavelet Transform	Not Reported	Average sensitivity is 99.89%
Sarkaleh et al. (2012)	Applied the detail coefficients derived from an eight-level decomposition of the ECG signal.	Multi-Level Perceptron (MLP) Neural Network (NN)	2 classes	Recognition rate 96.5%

Table 2(b). Summary of Methods for ECG Feature Extraction and Classification

Authors	Features Extracted	Extraction Method / Classification Technique	Detected Cardiac Abnormalities	Classifier Performance
Saini and Saini (2012)	3 morphological features	Artificial neural network	4 classes	Sensitivity and accuracy 95%
Martis et al. (2013)	Reduced-dimensionality features were obtained from the ECG signal using DWT	Probabilistic Neural Network (PNN), Neural Network (NN) and Support Vector Machine (SVM)	5 classes	Accuracy 99.28%
Park and Kang (2014)	QRS complex, P wave	Decision tree	2 classes	Accuracy 94.6%
Dewangan et al. (2016)	The feature set consisted of 4 morphological features (R-peak, QRS duration, PR interval, and RR interval) and 8 wavelet features calculated from the variance of detail coefficients d_1 – d_8 obtained through 8 level decomposition.	Three-layer Feed forward Back Propagation Neural Network	6 classes	Average accuracy 87%
Rangappa et al. (2018)	The Pan–Tompkins Algorithm (PTA) was used to detect peaks in the ECG signals, followed by the extraction of three interval features along with higher-order statistical features	K-Nearest Neighbor (KNN) technique	5 types of ECG beats	Accuracy 98.40%
Kiani et al. (2019)	Hybrid Features	Back Propagation neural network	7 classes	Accuracy 98.83%
Halemirle et al. (2021)	Hybrid features i.e. DualTree Complex Wavelet Transform (DTCWT). SVD- Entropy. Autoregressive modelling, and Multifractional analysis- based feature extraction	K-Nearest Neighbor's (KNN), Random Forest Classifier, and Bayesian OptimizedKNN classifiers	5 classes	The Random Forest classifier achieved the highest accuracy of 98.29%.
Wu et al. (2021)	Hybrid features	1D CNN	5 classes	Accuracy 97.41%
Santanu et al. (2022)	DWT, EMD, and VMD techniques were applied for ECG signal denoising. The resulting sub-band coefficients were used to extract time-frequency features from different domains, together with RR interval features.	Deep learning approach	5 classes	Accuracy of 99.75%
Mishra et al. (2026)	17 hybrid features	LSTM network	7 classes	Accuracy: 99.41%; Precision: 99.43%; Recall: 99.44%; F-score: 99.45%