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Review Article

An Overview of ECG Signal Processing and Analysis Techniques for Categorization of Cardiac Diseases

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Abstract - *An essential diagnostic technique for assessing cardiac health is an Electrocardiogram (ECG). The heart's electrical activity is captured in this recording. The need to share the workload among physicians and relieve pressure on them has led to the development of automatic detection and classification techniques for heart arrhythmias and other abnormalities as the number of heart patients has increased. All detection and classification techniques operate in the following stages: signal preprocessing, which includes denoising, extracting features, and categorising features. Recently, several methods have been used to denoise, extract features, and categorize ECG signals. The preprocessing of the ECG signal is necessary before the extraction phase because numerous noise sources in a medical setting can deteriorate the signal. The present study reviews ECG signal analysis, feature extraction, and denoising techniques. Frequency domain filters adaptive, and Wavelet Transform (WT) based filters are commonly used to denoise ECG signals. For the ultimate classification task, various morphological, temporal, and statistical features, Fourier transform, and wavelet-based coefficients are frequently extracted from the ECG signals. Findings show that deep learning methods are best among the others for the classification task and that hybrid features increase detection efficacy. Most authors have attempted to categorize ECG into five classes. There is scope to identify the features that combine most effectively to provide better performance in categorising more heart diseases. Also, there is a scope for developing a classifier that performs better to classify a more significant number of heart arrhythmias or diseases.*

Keywords - *Analysis, Classification, Deep learning, Feature extraction, Hybrid features.*

1. Introduction

Abnormal cardiac conditions are one of the leading causes of death worldwide, accounting for 30% of all disease-related fatalities [1]. Therefore, these must be diagnosed as soon as possible and treated quickly. As such, devising a rapid, simple, and precise method for recognizing and categorizing various cardiac conditions is invaluable.

Previous researchers have developed systems using various techniques and methods to categorise the ECG signals, and these techniques have been reviewed in this work. Although the developed detecting system's performance is encouraging, more evaluation is necessary to categorize a greater number of cardiac diseases because it has been observed that when one attempts to classify a greater number of cardiac diseases, he or she has to compromise with the system performance in terms of accuracy. Given the wide range of topics covered in the field, the review work has been divided into sections for easier understanding: signal preprocessing; QRS, P and T wave detection; feature extraction and selection; and classification techniques. The stages in categorising cardiac diseases based on ECG are shown in Figure 1 [2]. Pre-processing involves baseline correction, normalization, and eliminating various kinds of noises.

Finding the QRS complex, P and T wave is the second step. Identifying and extracting the features for the categorization is the third stage. Various morphological, statistical, Fast Fourier Transform (FFT) and wavelet based features can be extracted to classify the ECG signals. Various peak and timing information in ECG signals constitute morphological features.

The mean, median, mode and variance of ECG signals constitute statistical features, while in wavelet analysis, the detail and approximation coefficients after the wavelet decomposition of ECG signals at a suitable level will constitute the wavelet features. Fourier coefficients of ECG signals after the FFT of ECG signals can also be selected as features. These features varies with abnormal ECG signals and is the basis for ECG signal categorization.

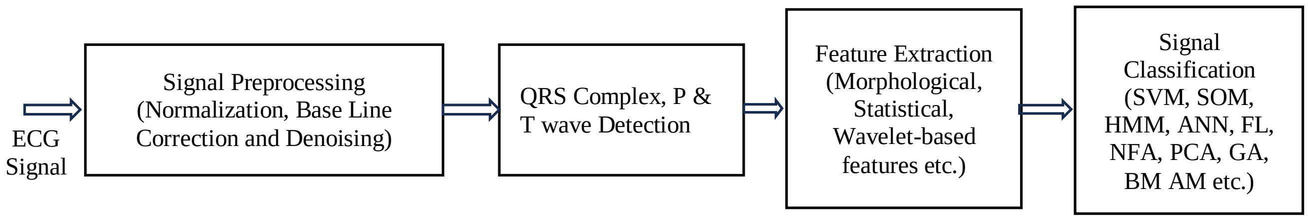

Fig. 1 Steps in the categorization of cardiac diseases

The selected features are fed to the classifier to categorize the ECG signal, constituting the final and fourth steps. Various classifiers generally used are Support Vector Machine (SVM), Self Organising Map (SOM), Hidden Markow Model (HMM), Artificial Neural Network (ANN), Fuzzy Logic (FL), Neuro Fuzzy Approach (NFA), Principal Component Analysis, Genetic Algorithms (GA), Bayesian Method (BM), Autoregressive Model (AM) etc.

This work aims to present pertinent data from studies concerning the enhancement of cardiac disease categorization, with significant contributions from multiple researchers across the globe. Statistical, wavelet and Fast Fourier Transform (FFT) based parameters are frequently extracted from ECG signals in addition to morphological features for the final classification task. As a result, the features that work best for one technique might not work best for another. Predicting the ideal features for a given classifier is impossible due to the unidentified relationships between different features.

Various methods can be applied for ECG classification, including artificial intelligence, deep learning artificial neural networks, and statistical classifiers. This review work is done to find the research gap in cardiac disease categorization using ECG signals.

2. Literature Review

This review examines earlier research on feature extraction, preprocessing, analysis and classification methods for ECG signals.

The preprocessing step involves normalization, baseline correction of the signal, and denoising the signal. Denoising the ECG signal is crucial because noise significantly reduces the recorded ECG's usefulness.

The next step in the classification process is identifying and detecting specific ECG signal features, primarily the QRS, P and T waves and other suitable features.

The classifier in the classification stage receives the features as inputs, containing information about the signals. The feature selection phase aims to identify the minimum feature set necessary to attain satisfactory classification rates. Without training and testing the classifier, developers cannot assess the features' role in the classification process. Thus, repeated attempts are made with different features to train the classifier until a satisfactory level of classification performance is attained. Thus, increasing accuracy and adding new classifiable cardiac conditions should be the aim of ECG signal analysis.

Due to the highly diverse nature of the field of study, the review is separated into three sections: signal preprocessing, extraction of important features and categorization methods. In relation to the work being done now, this review also emphasizes the shortcomings of the current ECG analysis system.

2.1. Signal Preprocessing

Signal pre-processing consists of normalization, baseline correction and denoising of the acquired ECG signal. Any ECG recognition system must, of course, function in a noisy hospital setting. Various kinds of noises typically tamper with the ECG signal. The raw signal must first be processed for a useful outcome because the information is frequently difficult to extract. The noise characteristics vary greatly, as do the sources and types of noise. Removal of the noises is a part of the signal preprocessing stage.

2.1.1. Normalization and Base Line Correction

The ECG signals are normalized using Equation (1) to standardize all the signals to the same level. Conditions like patient movement may sift the signal's baseline from zero, so the signal's baseline is then corrected to zero using Equation (2) after normalization.

$$ECG_{signal} = ECG_{signal} / |(ECG_{signal})_{max}| \quad (1)$$

$$ECG_{signal} = ECG_{signal} - mean(ECG_{signal}) \quad (2)$$

2.1.2. Noise Removal

Usually falling within ± 2 mV, the ECG signal necessitates a recording bandwidth of 0.05 to 100 Hz. Noises generally present in ECG signals are low frequency baseline drift as movement artefacts, 50 Hz interference from the power supply and high frequency muscle noise.

The recording system, instrumentation amplifiers, cables picking up ambient electromagnetic signals, and other factors could all be causing the high frequency noise in an ECG. Interference from electrical supply lines of frequencies 50 (or 60 Hz) and its harmonics can also tamper with the signal.

When coughing or breathing with significant chest movement or when moving an arm or leg during limb-lead ECG acquisition, low-frequency movement artifacts and Baseline Wandering (BLW) can occur in the chest-lead system. EMG may affect the ECG caused by breathing, squirming, or coughing [3].

Haibing et al. (2010) described noises during the ECG signal collection. The typical is Power Line Interference (PLI). 50 Hz and its harmonic frequencies make up the interference frequency. Subsequently, Electromyography (EMG) is a type of muscle tension-induced irregular frequency interference that primarily consists of drive unit signals in the range of 5-10 Hz, surface muscle signals from 0.01 Hz to 500 Hz, and single fiber muscle noise whose range is from 500 Hz to 10 KHz. Finally, there is BLW, which is caused by unwanted electrode contact, variations in skin impedance, breathing, and other bodily movements and occurs in the frequency 0.05 - 2 Hz, which is near the ECG signal's Q wave and ST segment in terms of frequency [4].

ECG signals can be contaminated with several types of noises mentioned in the previous sections and must be removed to classify ECG signals accurately. Time domain, frequency domain, adaptive and wavelet-based filters are mostly used to denoise the ECG signals. Nowadays, adaptive and wavelet-based filters are more popular because of their enhanced performance. Some denoising schemes have been reviewed and reported here.

Thakor and Zhu (1991) proposed several adaptive filter structures for noise reduction and detecting arrhythmias. The adaptive filter effectively reduces noise in the primary input by minimizing the error between the noisy ECG serving as the primary input and either noise or a signal correlating with the ECG serving as the reference input. Different kinds of noises, such as BLW, 50 or 60 Hz PLI, muscle noise, and motion artifact, are effectively eliminated by utilizing different filter structures. The QRS complex's impulse response is obtained by proposing an adaptive recurrent filter structure. The ECG signal to be examined serves as the filter's primary input, and an impulse train corresponding to the QRS complexes serves as its reference input. This technique is used to identify conduction block, atrial fibrillation, paced rhythm, P-wave detection, and premature ventricular complexes, among several arrhythmias [5].

Donoho (1995) proposed a method that involves taking a signal's Discrete Wavelet Transform (DWT) and applying the Inverse DWT (IDWT), after which this transform is sent through a threshold to remove the coefficients that are less than a specific value. This method achieved the SNR at output up to 8.26 [6].

In 2002, Ziarani and Konrad introduced a novel technique to remove PLI from ECG signals. They proposed a technique to extract a desired signal component and track its variations over time. The filters with wavelet analysis theory. The difference between the actual and expected output signals was 0.006324 [11]. Saritha et al. (2008) generated ECG signals by simulation within the MATLAB environment, and wavelet decomposition was performed. The corresponding coefficients at higher scales were eliminated to free ECG signal noise. They concluded that, given the novelty of wavelet transformation as a signal processing technique, more research is needed to improve the wavelet technique's clinical usefulness. This includes examining methodological issues, such as the choice of mother wavelet and scale parameters [12].

Lin and Hu (2008) presented an innovative algorithm for identifying and suppressing PLI as a pre-processing method for the ECG signal. The ability of this innovative algorithm to find PLI in the signal before implementing the suppression algorithm is one of its unique features. If PLI is not found, no PLI suppression action will be taken. Their suggested PLI detector applies an optimal Linear Discriminant Analysis (LDA) algorithm to determine whether PLI is present. PLI suppression is also achieved by developing an effective Recursive Least-Squares (RLS) adaptive notch filter. The algorithm performs better, as evidenced by experimental findings [13].

A new WT based technique to eliminate noise from ECG signals was developed by Qawasmi and Daqrouq (2010). Techniques are evaluated by using different ECG signals in the MATLAB environment. The DWT technique was employed to enhance the ECG signal. When compared to traditional methods, the suggested technique performed well. This technique performs better than Donoho's FIR filter method [14].

Saini and Saini (2012) used a Low Pass Filter (LPF) with a cut-off frequency of 100 Hz to eliminate high-frequency noise. By deducting the signal from a low order polynomial, the BLW was eliminated [28]. Martis et al. (2013) used Wavelet based denoising using wavelet db6 [29]. Park and Kang (2014) used a Band-pass filter of 0.1–100 Hz to remove noise [30]. The QRS complex energy was maximised by Rangappa et al. (2018) using a pass-band 4–15 Hz filter. The low-pass and high-pass filters are cascaded to create a band-pass filter, automatically removing higher-frequency artefacts and low-frequency interference [33]. Kiani et al. (2019) used the DWT method proposed by Donoho [6] for fluctuation in the heart, and the BLW removal method proposed by Rai et al. [41] is used [27]. Halemirle and Thippeswamy (2021) used Symmetric scale filters [26] to fix baseline deviations. These authors did not do a denoising performance analysis [26, 27, 28, 29, 33].

Dewangan et al. (2016) used a selective reconstruction process using DWT to remove BLW, 50 Hz PLI, and muscle noise (EMG). EMG, PLI, and BLW noises were eliminated by subtracting the denoised signal at level eight from the denoised signal at level three using the DWT tool in the MATLAB 2009 version. ECG arrhythmia annotated database was used. An average SNR at an output of 7.5 dB was achieved by this method [31]. Many methods have been used to denoise the ECG signals. In the past, various time and frequency domain filters have been used by various authors. The wavelet-based method has recently become more popular due to its time scale property and ability to perform local analyses. The wavelet coefficient graphic shows where the discontinuity occurs exactly in time. The based method is also popular because it can eliminate not only various noises present in the signal but also various important features that contain classification information that can be extracted to categorize the signals. According to a literature review, SNR at output up to 9.07 was attained by [10].

2.2. Detection of QRS Complex, P and T Waves

After the preprocessing step, the next step is extracting significant and valuable features in the ECG signal. P, T waves and QRS complexes distinguish ECG signals. Various peak and timing information constitute morphological features. These morphological features in ECG signals are altered by the diseased heart. Various statistical parameters like mean, median, mode and variance of ECG signals also change in case of various heart abnormalities. In the wavelet domain, various wavelet features change when unusual ECG signals are recorded due to heart abnormalities. So, these features are very useful in categorising or classifying ECG signals. The combination of various morphological, statistical, wavelet or any other features of ECG signals constitutes hybrid features.

ECG signals can easily distinguish p, T waves and QRS complexes. Peak and timing information of various waves present in the ECG are usually manually analyzed by experts or medical professionals [3]. Because there is so much data, manual inspection will be time-consuming and difficult, and there is the possibility that the examiner will overlook crucial information [3]. Because of this, the development of a computer aided device to categorize heart conditions is crucial.

Several techniques were developed to categorise ECG signals based on the various characteristic parameters/features obtained from the ECG. Determining a minimum feature set to attain better performance is the main objective of feature extraction. An analyst cannot determine how well features perform without first training and assessing the classifier. That is why a critical and repeating process is needed to pick features as best as possible, which calls for training several feature sets until a satisfactory level of classification performance is reached [3].

In an ECG, the QRS complex is a significant waveform. The shape and timing of its occurrence reveal a great deal about the current health of the heart. It is frequently utilised in ECG data compression techniques and provides the foundation for automated heart rate calculation because of its unique shape. It also acts as an entrance point for categorising the heart cycle. In this regard, QRS complex detection offers the foundational knowledge to almost all classification systems based on ECG signals.

A real-time QRS detection algorithm was created by Pan and Tompkins (1985) and comprised of Band Pass Filter (BPF), derivative filter, squaring, moving window integration, adaptive thresholding, and search procedures to identify QRS complex. The system can accurately identify QRS complexes using evaluations of digital height, slope and width. An exclusive BPF reduces false positives from different kinds of noises in ECG data. This filtering makes it possible to use low thresholds, which raises detection sensitivity. The algorithm automatically modifies thresholds and parameters regularly to accommodate variations in the ECG, including heart rate and QRS morphology. This approach properly detects 99.3% of the QRS complexes in the 24-hour MIT-BIH annotated database [15].

Daskalov et al. (1998) stated that it has been challenging to automatically detect the beginning and closing points of QRS with a reasonable degree of accuracy. Further small q, r, r9, or s9 waves in many complexes are further exacerbated by the typical presence of PLI, EMG artifacts, and BLW in the actual signal. They proposed a pre-processing technique that ensures precise maintenance of the QRS boundaries, even when significant EMG or PLI is present. Examples of QRS onset and offset point detection are provided, along with a comparison with observer markings, to evaluate the effectiveness of pre-processing and detection consistency [16].

Mahmoodabadi et al. (2005) presented a feature extraction technique that utilised Daubechies wavelets in conjunction with multi-resolution WT. First, the noise is reduced by discarding the associated wavelet coefficients at higher scales in the ECG. The next step is to detect QRS complexes, which are then used to determine the amplitude, beginning and ending of the P and T waves within a single cardiac cycle. P and T waves are more pronounced when details are between 2^4 and 2^8. Lower frequency and high frequency signal ripples are eliminated at these levels. Extremes occurring before and after the identified R peak were P and T peaks. More than 99% and 98% of sensitivity and positive predictivity, respectively, are achieved by this method [17].

WT was used by Sarita et al. (2008) to de-noise ECG signals through the removal of the matching wavelet coefficients at larger scales. P and T wave peaks and their variances were found for each QRS complex once the complexes were identified. Plots of the abnormal signal coefficient and the normal ECG are compared. Various anomalies lead to varying coefficient alterations. They concluded that further research is necessary because WT application in electro cardiology is a relatively new study area (e.g., choice of mother wavelet, scale parameter values) [12].

In their work, which was based on DWT, Sumathi and Sanavullah (2009) decomposed the signal up to level 4, where it was found that the QRS complex was dominating at the approximation level and that R-peak could be determined by locating the points where the amplitude is highest. Adaptive thresholding was employed to remove PVC beats. The performance of db4, Haar, and cubic spline wavelets was compared for R detection. They concluded that the WT using cubic spline wavelet is more suited for this case since it lowers the likelihood of inaccuracy in detecting the QRS complex. In this work, the utility of the WT properties for QRS detection has been investigated, and A new QRS complex detection technique was proposed. Simple detection logic could be used for QRS detection since the adaptive threshold eliminated all relevant noise from the signal. Shorter processing times for prolonged ECG readings are the main benefit of this kind of detection [18].

ECG is an essential tool for learning more about the heart, according to Gautam and Sharma (2010). In ECG signal analysis, the two primary tasks are detecting the QRS complex or R-peak and determining the instantaneous heart rate by calculating the separation between two successive R-peaks. Additional components such as P, Q, S, and T waves can be detected using the window method once the R-peak has been detected. This research describes a reliable QRS complex detection that uses Dyadic Wavelet Transform (DyWT) that outperforms the time-varying shape of the QRS complex and noise. They demonstrated the functionality of the QRS detector using the ECG database of Common Electrocardiography (CSE).

This work proposed a QRS detection technique using DyWT. They discussed the characteristics of the DyWT required for processing ECG signals. Specifically, when a smoothing wavelet is employed, the local maxima of the DyWT are correlated throughout subsequent scales and indicate the existence of a transient. They took advantage of the fact that if the mother wavelet is selected as the first derivative of a smoothing function, the onset of the local maxima of the $|\text{DyWT}|$ of a transitory signal correlates over successive dyadic scales.

The DyWT-based detector's performance was thoroughly evaluated through algorithm testing on a standardised CSE database. These outcomes were also compared with those of popular QRS detection techniques. While no algorithm performed better than the others in all situations, the DyWT-based QRS detector performed comparably better. Strong performance in noise removal and analysing non-stationary ECG data with flexibility are the primary benefits of DyWT over other methods [19].

In 2010, Banerjee and Mitra introduced a DWT algorithm to accurately detect R peaks and determine the QRS complex in an ECG signal. The mother wavelet in this technique was the db6 wavelet. ECG signals were decomposed up to level 10 using WT, and to reduce the noise, and selective reconstruction was employed. To detect the QRS complex, thresholding and the slope inversion approach are employed. The proposed algorithm's time scale feature allows it to distinguish between waves at their occurrence points without interfering with one another. The lowest frequency signal is obtained as the BLW, which is easily correctable. The decomposition of the signal makes it easier to detect relatively high frequency QRS waves. PTB diagnostic database obtained from the Physionet is used to validate the system's performance, and a sensitivity of 99.4% is achieved for ECG recordings [20].

Narayana and Rao (2011) investigated the usefulness of WT and derivative/Pan-Tompkins methods to detect QRS waves in the ECG. The ECG signal can examine the entire heart muscle's anatomical and physiological aspects. ECG signal is imported from the MIT-BIH annotated database in the MATLAB environment to know the performance of these methods in detecting QRS complex in the ECG signal. Their work compared the wavelet-based approach to the derivative-based approach and Pan-Tompkin's algorithms for detecting QRS complex and denoising ECG signals. The wavelet-based algorithm performs better than the other two. The wavelet-based technique has denoised the ECG recordings by deleting the relevant wavelet coefficients at higher scales. Following the detection of QRS complexes, amplitudes of P and T waves and their variations are also found using each complex. They concluded that more research is needed to improve the medical utility of this innovative technique in several methodological areas (e.g., choice of mother wavelet and scale parameter values). Extensive medical trials are required to establish the usefulness of WT for the diagnosis in several disciplines of electro-cardiology [21].

In a 2011 paper, Sasikala and Wahidabanu focused on detecting the P and T waves. Because of its tiny amplitude, determining the location and peak of the P and T waves is difficult. Since WT is a useful tool for analysing transitory signals, it was used in their work to extract various features. The position of the P and T waves is the expected output. For signal categorization, the features' precise locations must be known. The arrhythmia database from MIT-BIH was used to test the method [22].

Detecting QRS complex and P and T waves is important for extracting various morphological features of ECG signals. However, it has been noted from Table 4(b) that when other features are extracted and combined with morphological features, the classification accuracy is significantly improved. So, finding a set of features that can increase classification performance can be a task in the future.

2.3. Feature Selection and Signal Classification

Finding a set of characteristic features that can provide acceptable performance for cardiac disease categorization. Developers cannot assess features' performance before training and testing the classifiers. Consequently, selecting features is a continuous process that requires training by a set of features until the classification system attains a satisfactory performance. Various classifiers generally used are Support Vector Machine (SVM), Self Organizing Map (SOM), Hidden Markow Model (HMM), Artificial Neural Network (ANN), Fuzzy Logic (FL), Neuro Fuzzy Approach (NFA), Principal Component Analysis (PCA), Genetic Algorithms (GA), Bayesian Method (BM), Autoregressive Model (AM) etc.

Doughlas et al. (1990) presented a Hidden Markov Model (HMM)-based method for analysing cardiac arrhythmias. This method classifies ventricular arrhythmias by identifying and analysing the QRS wave and measuring the R-R intervals. A single parametric model is created using the HMM, which integrates statistical and structural information from the ECG data. The challenge of identifying P waves due to their small amplitude in standard ECG signals is addressed by Hidden Markov modelling [23].

Ranjith et al. (2003) detected myocardial ischemia using WT derived from the quadratic spline wavelet. These are associated with the detection of T and P waves. Their techniques show that it has a nominal positive predictivity value and a comparatively higher sensitivity. It can also be readily expanded to identify more irregularities in the ECG. However, the shortcoming of this approach is that it requires more computations than other approaches. This is primarily due to the WT calculation [24].

Herrero et al. (2006) extracted extra spatial information from multichannel electrographic recordings by employing Independent Component Analysis (ICA) and matching pursuits to classify five significant categories of arrhythmias in the MIT-BIH annotated database. The system performs exceptionally well, with sensitivity and specificity for the various categories. They encountered an issue due to the inverted T wave, which hindered the separation of ventricular PBs and PVCs [25].

Two morphological feature extraction techniques using the Hermite basis function and higher order statistics were used by Park et al. (2008). According to their research, the traditional multiclass classification method is less effective than the hierarchical classification method. They compared feature extraction and classification techniques using support vector machines to assess generalisation performance. However, using higher order models increases computing costs and leads to an overfitting issue with generalisation performance. Even with the decrease in accuracy and sensitivity for some classes, they found that their hierarchy-based classification method outperformed the traditional division of the population into multiclass. The hierarchical classification enhanced the mean values of the sensitivity. It was acknowledged that their classification technique may identify multiclass heartbeats even in cases when the distribution of data is not balanced [26].

Sarkaleh and Shahbahrami (2012) used the DWT to extract various features and the Multi-Level Perceptron (MLP) Neural Network (NN) for the classification task. The proposed method can distinguish between 2 types of arrhythmias. The returned feature vector comprises 24 statistics spanning the whole wavelet coefficient range from level one to eight. The characteristics used include each level's variance, as well as minimum and maximum detail coefficients. The overall recognition rate achieved was 96.5% [27].

Four distinct types of arrhythmias were identified and classified using a Back Propagation Neural Network (BPNN) using standard ECG data by Saini and Saini (2012). They used MLP NN selected sigmoid activation function and kept the number of hidden layer neurons to 20. The input layer has 3 fixed neurons, while the output layer has 5 fixed neurons. The three morphological features, Amplitude of R-peak, RR interval, and QRS duration, were used to classify arrhythmias. Achieved sensitivity and accuracy levels of over 95% [28].

Martis et al. (2013) investigated the categorization of five distinct arrhythmias based on the ECG signals in their research. The DWT subbands of the signal were exposed to individual Linear Discriminant Analysis (LDA), PCA, and ICA techniques to decrease dimensionality. The features that were dimensionality-reduced were given into the SVM, NN, and Probabilistic NN (PNN) classifiers to facilitate automated diagnosis. ICA features showed better performance than PCA and LDA. Table 1 displays the average scores for the various parameters when cross-validation of the ten-fold scheme [29].

Table 1. Average score values of parameters (existing)

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

Park and Kang (2014) proposed a new method to classify ECG beats automatically for Holter monitoring. Pan-Tompkin's technique was used for the QRS complex detection and feature extraction, and each beat was classified using a decision tree based on these features. Tests conducted on the arrhythmia database obtained from the MIT-BIH annotated database and the database of own patient show that the accuracy of heartbeat categorization is 94.6% and 99%, respectively. These findings support the efficacy of the proposed work and are on par with results from state-of-the-art systems [30].

Dewangan et al. (2016) classified 6 types of arrhythmias using a feature set of twelve features, including four morphological and eight wavelet features. After decomposing each ECG pulse into eight levels, wavelet features were generated. The variance of the detail coefficients, d1 through d8, was then computed to create a feature set. They categorise 5 different arrhythmias apart from normal beats. The overall average accuracy of the proposed 3-layer feedforward backpropagation neural network approach was 87% [31].

In 2018, Bassiouni et al. proposed a method for categorizing heart arrhythmias. DWT is used to obtain the morphological information of the ECG signal. They used RR interval data as a dynamic feature. The Teager energy operator improves arrhythmias' categorisation by capturing the RR interval's nonlinear dynamics. Following ICA's removal of redundant data from DWT subbands, 12 coefficients are chosen to represent morphological information. Various features are combined to make it hybrid and fed to a NN to categorise signals. With three-fold cross validation, the suggested method raised the class and subject-oriented methods' respective average accuracy to 99.75% and 99.84% [32].

Coronary artery disease may arise from a number of significant cardiac disorders like ischemic heart disease, myocardial infarction and heart failure, according to Rangappa et al. (2018). This work distinguished ECG beats in 5 different classes using a three-stage procedure. The first stage involves finding the peaks in the ECG using the Pan-Tompkins algorithm. The three interval features extracted are merged with higher order ECG statistics in the second phase. In the third stage for the categorization of ECG, the K-Nearest Neighbour (KNN) algorithm is used. The signals were correctly categorised as abnormal or normal using this method. The results demonstrated that the proposed method can achieve up to 98.40% accuracy in signal separation [33].

According to Kiani et al. (2019), the heart's irregular, dynamic, and nonlinear behaviour, extracted from the ECG, depicts the heart's electrical activity. The fractal dimension best represents the ECG signal because it can consider its hidden complexity. BPN and the fractal dimension are used in the analysis of ECG. This article proposes a novel method for accurately diagnosing seven arrhythmias using the fractal dimension. Arrhythmias can be precisely located with this technique. A combination of 5 reliable universal datasets provides a classification utilising the fractal dimension and BPN. The proposed strategy's efficacy is assessed using indices like sensitivity and specificity. It was able to get 96.84% specificity and 99.74% sensitivity. This technique has an accuracy percentage of 98.83 [34].

Dalal et al. (2021) developed a new, reliable technique for rapidly and precisely determining human heart health using ECG signals. DWT is used to eliminate noise, and characteristic features are obtained by using several cumulants. The method is mainly based on the multi-cumulant features obtained from the ECG signals. The Kernel Extreme Learning Machine (KELM) is employed to categorise signals. Genetic Algorithms (GA) are used to optimise the parameters of KELM and multi-cumulants [35]. In 2021, Halemirle et al. developed a classification technique based on hybrid features. It utilises autoregressive modelling, SVD-entropy, dual-tree complex wavelet transforms, and multifractal analysis for feature extraction. From the MIT-BIH annotated database, these features are extracted and fed to KNN, Bayesian Optimized-KNN and Random Forest Classifiers for the classification task. A maximum accuracy of 98.29% is achieved using the random forest classifier. The results substantiate the validity and suitability of the methodology as a tool for identifying cardiac diseases in hospital environments [36].

Sehirli et al. created an intelligent system in 2021 to classify ECG data using a hybrid machine learning model. They employ 837 ECG segments from 7 classes in the MIT-BIH annotated database for a single lead. The ECG signals are pre-processed to smooth and properly fix the baseline. ECG data containing the Q, R, and S waves are segmented using k-means clustering and local extrema points. Following feature extraction, the measurement parameters are independently computed for each QRS complex. Eight-fold cross validation is used to generate training and test sets. The proposed work classified Cardiovascular Diseases (CVDs) into 7 groups. A hybrid model is created by merging different machine learning models, including naïve bays, SVMs, decision trees, random forests, k-nearest neighbours, and linear and quadratic discriminant analysis. For the CVD classes, the corresponding values are 92.33%, 92.50%, 92.41%, and 0.85 for sensitivity, specificity, accuracy, and MCC [37].

In 2021, Wu et al. used the MIT-BIH annotated database to categorize five arrhythmias by proposing an accurate and efficient 12-layer deep one-dimensional CNN. Wavelet self-adaptive thresholding is used to de-noise the ECG signal. The experimental findings show that the approach presented in this study outperforms random forest, BPNN, and other CNN networks with regard to sensitivity, accuracy, resilience, and anti-noise characteristics. Because of its accurate classification, medical resources are effectively conserved, enhancing medical procedures. The proposed method categorises 5 types of arrhythmias. The proposed CNN network exhibits superior accuracy and robustness compared to previous CNN networks, random forests, and BP neural networks, which is interesting. The classification performance is shown in Table 2, and it is found that the proposed CNN network works remarkably well [38].

Table 2. Average score values of parameters (proposed)

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

Sahoo Santanu et al. (2022) proposed a deep learning method for automatically diagnosing heart arrhythmia using the MIT-BIH annotated database. Different decomposition techniques were used to lower the noise. The multi-domain based on time-frequency characteristics were extracted from the several sub-band coefficients using denoised signals. These generated characteristics were prioritised using Particle Swarm Optimisation (PSO)-based algorithms and the Chi-squared test to find the most informative features for higher classification accuracy. A Deep NN (DNN) could classify five distinct kinds of ECG beats using a ten-fold cross-validation technique and the hybrid features. The Chi-squared selection strategy produced the most accurate and best outcomes, having 99.75% accuracy and 0.14 seconds of computational complexity. The presented technique can be used in hospitals to identify unusual ECG rhythms [39] automatically.

Using ANSI-AAMI standard data, Bhatia et al. (2022) developed a novel Bidirectional Long-Term, Short-Term Memory network (BLSTM) and deep CNN architecture that automatically categorizes ECG into five distinct classes. This hybrid model does not require the extraction of manual features to do end-to-end learning, combining feature extraction and classification. The publicly available MIT-BIH annotated database is used in this experiment. The outcomes were compared with two hybrid deep learning models (Integrated CNN and LSTM and Gated Recurrent Unit and CNN). Furthermore, the model's performance was compared with previous research published in the literature. This database was intentionally oversampled using the SMOTE approach to correct the class imbalance. The hybrid model, created by tenfold cross-validation, is trained using the ECG dataset, which was oversampled and then applied to the real test dataset. According to experimental results, their model outperformed current methods with regard to recall, accuracy, precision, and F-score performance, scoring 91.67%, 94.36%, 98.36%, and 89.4%, respectively [40].

Any ECG categorisation system's effectiveness depends on the reliable and precise detection of various features present in the ECG signal. Most researchers have concentrated on a few specific diseases. It is observed from Table 4(b) that the highest number of heart diseases classified is seven [37].

The latest ECG analysis methodologies rely on hybrid features and deep machine learning methods. The main objective of future research should be to increase the range of cardiac diseases that may be accurately detected. Generally, classification accuracy is reduced when the number of classes of ECG signals is increased. In that case, there is a scope to find features that categorise a greater number of cardiac diseases with excellent classification performance.

3. Methodology

Denoising techniques are summarized in Table 3 (a) and (b) and feature extraction and classification in Table 4 (a) and (b). Wavelet-based denoising is becoming increasingly common, and it works better than filters based on the time domain, frequency domain, or Fourier transform, or Short-Term Fourier transform.

The selection of hybrid features has significantly increased classification accuracy [23-40], with a maximum of 7 classes classified [34]. With deep learning techniques, accuracy levels of above 99% are being attained [39]. Based on these findings, a hybrid strategy is proposed and illustrated in Figure 2. This work will use a deep learning-based classifier, and the classifier's performance will be validated using the MIT-BIH annotated database.

The ECG signals are normalised to bring all features to the same level. Unexpected conditions, like patient movements, may cause the signal baseline to change from zero, so the baseline is adjusted to zero.

For an ECG signal to be accurately classified, noise of various kinds must be eliminated. The MIT-BIH annotated database makes distinguishing between various kinds of noise in certain records possible. Most annotated data show baseline drifting, PLI, and EMG noise. The ECG signal's QRS complex will be de-noised and detected using the DWT property. The windowing technique is used to identify the P and T waves.

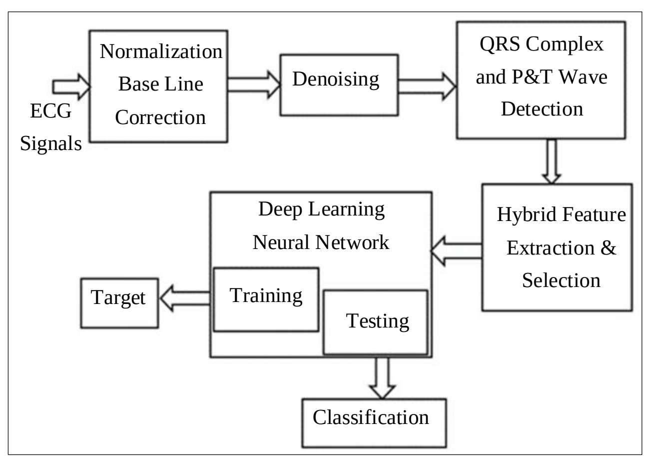

Fig. 2 Illustration of proposed methodology

After the detection of QRS, P, and T waves, the next step in the categorization of ECG signals is to extract various features like temporal, morphological features, fast Fourier transform, WT based coefficients, statistical, entropy, correlation, regression parameters and non-fiducial, fiducial features. Next, as seen in Figure 2, different combinations of these features are chosen to train and test a deep learning neural network to identify and classify different ECG signals.

All deep learning algorithms use different types of multilayer NNs to perform classification tasks. Deep learning algorithms like CNNs have been used by [38, 40], LSTMs by [40], and KNN by [33] to classify ECG signals. Some other deep learning algorithms like Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Transformer Networks, Autoencoders, Deep Belief Networks (DBNs), Deep Q-Networks (DQNs), Variational Autoencoders (VAEs), Graph Neural Networks (GNNs) can be explored in order to classify a greater number of cardiac diseases.

The classifier uses a set of hybrid features to diagnose more than seven heart arrhythmias/diseases based on an ECG signal, which provides sufficient accuracy for multiple classes. The classifier uses hybrid features and can classify more than 7 categories of ECG signals with acceptable multiclass accuracy.

4. Conclusion and Future Scope

Noise, such as PLI and disturbances from the moving recording electrodes, often contaminate biomedical signals. Additionally, biological signals such as EMG and ECGs often interact with one another. In order to extract features and categorize ECG signals, preprocessing of the signal is crucial. In this work, several denoising schemes put forth by different researchers have been reviewed and documented and are shown in Tables 3(a) and 3(b). The popular wavelet-based method provides better results than other methods for denoising ECG signals. Previous researchers have developed systems using various techniques and methods to categorise the ECG signals, and these techniques are summarized in Tables 4(a) and 4(b). Although the performance of the developed detection system is encouraging, more evaluation is necessary to categorize cardiac diseases. From the reviewed literature, it is observed that:

(1) Most writers have utilised WT to reduce noises in the ECG signals.
(2) Since most methodologies have only been tested on smaller data sets, more extensive databases must be used to verify their effectiveness.
(3) Only some arrhythmia classes have been evaluated mostly five in number; all other classes require testing.
(4) The classification accuracy is low for kinds of arrhythmia that are uncommon.

The automated detection of various ECG signal features is crucial for precisely diagnosing heart conditions. Any ECG categorisation system's effectiveness depends on the reliable and precise detection of various features present in the signal. Most researchers have concentrated on a few specific diseases. The latest ECG analysis methodologies rely on hybrid features because they increase parameters' average score values. It can be observed from Table 4(b) that the use of hybrid features and deep machine learning methods provide better average score values for parameters in ECG signal classification. The main objective of future research should be to increase the range of cardiac diseases that may be accurately detected because most researchers have proposed work to classify up to seven different categories of ECG signals.

In future, a secured healthcare monitoring system can be developed for telemetry applications. This system will monitor and classify real-time patient ECG data and ensure patient data privacy using cryptographic techniques.

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Appendix

Table 3(a). Summary of approaches for ECG signal denoising

Authors	Types of Noise in Consideration	Denoising Method Used	Performance of the Denoising Method
Thakor and Zhu (1991)	Baseline wander, 60 Hz PLI, muscle noise, and motion artifact	Several adaptive filter structures for noise cancellation and arrhythmia detection	Better than existing methods
Donoho (1995)	Gaussian random noise	Based on taking Discrete Wavelet Transform (DWT) of a signal, passing this transform through proposed threshold	The SNR at output up to 8.26 was achieved by this method
Ziarani and Konrad (2002)	Power line noise	Developed signal processing algorithm capable of extracting a specified component of a signal and tracking its variations over time	Extremely simple structure which requires a low level of computational resources.
Addison (2005)	Reviewed the scope of WT in mitigating various noises in ECG signals	Wavelet Transform	Reported that the wavelet transform is powerful time- frequency analysis and signal coding tool favored for the interrogation of complex non-stationary signals like ECG.
Tinati et al. (2006)	Baseline wandering	Used Wavelet Transform (WT) based search algorithm to use the energy of the signal in different scales to isolate baseline wander from the ECG signal	Presented algorithm can eliminate baseline drifts from ECG signals without introducing any deformation to the signal and losing any clinical information
Alfaouri and Daqrouq (2008)	Random noise	Used Discrete Wavelet Transform (DWT), db4 wavelet used and proposed a new threshold value	SNR at output up to 9.07 was achieved by this method
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	ECG signal was denoised by removing the corresponding wavelet coefficients at higher scales	Concluded choice of the mother wavelet and the values of the scale parameters require further investigations in order to improve the clinical usefulness

Table 3(b). Summary of approaches for ECG signal denoising

Authors	Types of Noise in Consideration	Denoising Method Used	Performance of the Denoising Method
Lin and Hu (2008)	Power-line interference	Employs an optimal Linear Discriminant Analysis (LDA) algorithm to make a decision for the PLI presence. An efficient Recursive Least- Squares (RLS) adaptive notch filter 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 coefficients and FIR filter
Dewangan et al. (2016	Baseline wander. 50 Hz PLI, muscle noise	Method adopted DWT	Average SNR at output 7.5 dB was achieved
Saini and Saini (2012)	BL W and noise of > 100 Hz	A low pass filter with cut-off frequency 100 Hz was used. The BL W was removed by subtracting the signal from a low order polynomial.	Denoising performance analysis not done, but classifier achieved 95% sensitivity and accuracy
Martis et al. (2013)	Noise present in signals of MIT- BIH arrhythmia database	Wavelet based denoising using wavelet db6	Denoising performance analysis not done, classifier achieved 99.28% accuracy
Park and Kang (2014)	Noise present in signals of MIT- BIH arrhythmia database	Band-pass filtered at 0.1-100 Hz	Denoising performance analysis not done, classifier achieved 94.6% accuracy
Rangappa et al. (2018)	BL W. muscle noise. 60Hz interference, and interference in T- wave	Pass-band 4-15 Hz is used for maximizing the QRS complex energy. The low-pass and high- pass filters are cascaded to form Band-pass filter where the low-frequency interference and higher frequency artifacts removed automatically.	Denoising performance analysis not done, classifier achieved 98.40% accuracy
Kiani et al. (2019)	Fluctuations in the heart muscle whose frequency is above 150 Hz. is removed, BLW.	DWT method proposed by Donoho [6] for fluctuation in the heart and for BLW removal method proposed by Rai et al. [41] are used	Denoising performance analysis not done, classifier achieved 98.83% accuracy
Halemirle and Thippeswamy (2021)	System interaction and baseline wandering	Symmetric scale filters and denoising operations were used to correct baseline deviations	Denoising performance analysis not done, classifier achieved 98.29% accuracy

Table 4(a). Summary of approaches for feature extraction and ECG signal classification

Authors	Types of Noise in Consideration	Denoising Method Used	Heart Abnormalities Detected	Performance of the Denoising Method
Pan and Tompkins (1985)	QRS complex	A real time QRS detection algorithm which included band pass filter, differentiator, squaring operation, moving window integration and adaptive thresholding and search procedures	TO	Algorithm correctly detects 99.3 percent of the QRS complexes
Daskalov et al. (1998)	QRS boundaries	Proposed a pre-processing method guaranteeing accurate preservation of the QRS boundaries	THAT	Preserves the QRS boundaries even in the presence of 50 Hz and EMG noise of considerable amplitude
Mahmoodabadi et al. (2005)	QRS complex and peaks of the individual waves, including onset and offset of the P and T waves	Developed feature extraction system based on multi-resolution wavelet transform using Daubechies wavelets	THAT	QRS detector achieved sensitivity of 99.18% ± 2.75 and a positive predictivity of 98% ± 4.45
Sumathi and Sanavullah (2009)	QRS detection	Based on DWT, decomposed the signal up to level 4 where ORS complex was found to be dominant at that level of approximation and R-peak is detected by finding the points of highest amplitude	THAT	It consumes less time for long duration ECG signal for QRS detection
Gautam and Sharma (2010)	QRS. P & T wave detection	Dyadic Wavelet Transforms (DyWT)	THAT	The main advantages of the DyWT over existing techniques are its robust noise performance and its flexibility in analysing non-stationary ECG data
Banerjee and Mitra (2010)	QRS complex	DWT where db6 wavelet was selected as mother wavelet	THAT	Sensitivity of 99.4%
Narayana and Rao (2011)	QRS complex	Derivative based/Pan-Tompkins/wavelet transform based algorithms	THAT	Concluded that the Choice of the mother wavelet, values of the scale parameters will require further investigations
Sasikala and Wahidabanu (2011)	Detection of the P and T wave	Wavelet Transform	THAT	Average sensitivity is 99.89%
Sarkaleh et al. (2012)	Used detail coefficients obtained by eight level decomposition of ECG signal	Multi-Level Perceptron (MLP) Neural Network (NN)	2 classes	Recognition rate 96.5%

Table 4(b). Summary of approaches for feature extraction and ECG signal classification

Authors	Features Extracted	Extraction Method / Classification Technique	Heart Abnormalities Detected	Performance of the Classifier
Saini and Saini (2012)	3 morphological features	Artificial neural network	4 classes	Sensitivity and accuracy 95%
Martis et al. (2013)	Dimensionalities reduced features obtained after DWT of the ECG signal	Support Vector Machine (SVM), Neural Network (NN) and Probabilistic Neural Network (PNN)	5 classes	Accuracy 99.28%
Park and Kang (2014)	QRS complex, P wave	Decision tree	2 classes	Accuracy 94.6
Dewangan et al. (2016	4 morphological features and 8 wavelet features (R peak, QRS duration. PR interval and RR intervals as morphological features and variance of detail coefficients d_1-ds after 8 level decomposition as wavelet features)	Three-layer Feed forward Back Propagation Neural Network	6 classes	Average accuracy 87%
Rangappa et al. (2018)	Pan-Tompkin's algorithm (PTA) is used for detecting the peaks in ECG signals. Extraction of three interval features combined with ECG higher order statistics.	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.. Dual-Tree Complex Wavelet Transform (DTCWT). SVD- Entropy. Autoregressive modelling, and Multifractal analysis-based feature extraction	Random Forest Classifier. K-Nearest Neighbor's (KNN), and Bayesian Optimized-KNN classifiers	5 classes	Highest accuracy achieved in random forest classifier is 98.29%
Wu et al. (2021)	Hybrid features	1D CNN	5 classes	Accuracy 97.41%
Santanu et al. (2022)	DWT. EMD and VMD are used to de-noise the ECG signal. The time-frequency based multi-domain features are extracted from the various coefficients of the sub-bands from de-noised signals along with RR intervals.	A deep learning approach	5 classes	Accuracy of 99.75%