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Detection of Abnormal Electrocardiograms Based on Various Feature Extraction methods

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ABSTRACT

Electrocardiogram (ECG) is a graphical representation of the electrical activity of the heart obtained by placing various electrodes on specific areas of the subject's body surface. Abnormalities in a patient's ECG signal may indicate cardiac diseases that require immediate medical attention. As a result, detecting an abnormal ECG is critical for the patient's benefit. This work develops a method for classifying ECG signals as normal or abnormal. In this paper, we propose a method for detecting cardiac arrhythmias in electrocardiograms (ECG). In the first stage, the proposal focuses on various feature extractor methods. The Fourier Transform (DFT), Discrete Wavelet Transform (DWT), and Improved complete ensemble empirical mode decomposition with adaptive noise were the feature extraction techniques evaluated (ICEEMDAN). The PCA method is then used to reduce the number of features. Finally, for classification, the Support Vector Machine (SVM) was used, which was trained using the features extracted in the first stage. The proposed models are tested using datasets from MIT-BIH arrhythmia and PTB Diagnostics. The experimental results show that using 3-PCs with the DWT method produces better results than the other methods, which achieve 98.7% in terms of accuracy.
Keywords: Heart disease, Cardiac arrhythmia, ECG, feature extraction, Machine learning, classification.

1. Introduction

The heart is one of the most important organs in the human body, and monitoring of the heart has become a required diagnosis for human health. Electrocardiogram (ECG) data are collected using a non-invasive method that shows the electrical activity of the heart. An abnormal ECG can induce heart disease symptoms such as persistent ventricular tachycardia, low blood pressure, fast atrial fibrillation, and persistent ventricular tachycardia. These diseases are harmful to human life and require immediate treatment (Benjamin et al., 2017).
The ECG signals are thought to be reflective of heart physiology and can be used to diagnose cardiac diseases. Spectral analysis is the most comprehensive approach to display this information (Güler et al., 2005). The goal of ECG analysis is to improve accuracy and include additional heart disorders that may be categorized. The feature extraction stage seeks to identify the minimal collection of characteristics required to obtain acceptable classification rates (Dewangan et al., 2015).
Numerous studies and algorithms have been developed in recent years to characterize ECG heartbeat patterns based on features collected from ECG signals. Fourier transform analysis, for example, provides the signal spectrum or range of frequency amplitudes within the signal; however, Fourier transforms only provide the spectral components and not their temporal correlations. Wavelets can describe a signal's time versus frequency and perform well with non-stationary data . The wavelet transform is a fairly broad approach that can be used in a variety of signal-processing applications (Güler et al., 2005). Moreover, EMD decomposes a signal in the time domain into separate Intrinsic Mode Functions (IMFs) (Huang et al., 1998a). However, other algorithms use morphological features (deChazal et al., 2004), heartbeat temporal intervals (Alexakis et al., 2003), frequency domain features, and multifractal analysis (Ivanov et al., 2009). Biomedical signal processing algorithms require appropriate classifiers to best categorize different ECG signals.
Classification techniques for ECG patterns include linear discriminate analysis, support vector machines (Osowski et al., 2004), artificial neural networks (Fernandez-Delgado et al., 1998), mixture-of-experts algorithms (Yu Hen Hu et al., 1997), and statistical Markov models (Andreao et al., 2006a; Coast et al., 1990). In addition, unsupervised clustering of the ECG signal has been performed using self-organizing maps (Lagerholm et al., 2000).
Many research on the detection of abnormal ECG signals have been published. These methods essentially employ several classifiers to distinguish between abnormal and normal ECG signals. Several of them also classify the ECG using morphological features. The methods for extracting features also differ; however, there are some similarities (Sultan Qurraie et al., 2017) suggested a time-frequency representation-based approach for extracting information for cardiac arrhythmia classification. In heartbeat categorization, the approach demonstrated extraordinarily high accuracy. (Elhaj et al., 2016)

studied the ability of features such as non-linear and linear features and presented a feature combination by improving ECG data classification.

(Desai et al., 2015) proposed a system-based approach for computer-aided detection of five types of ECG arrhythmia beats using DWT as a feature to train Support Vector Machine (SVM). In (Pan et al., 2018) For arrhythmia classification, a comprehensive model based on random forest techniques and discrete wavelet was developed. The authors (Kora et al., 2019) The DWT was used to extract features from the ECG signal using ST-segment elevation and inverted T wave logic. (Zubair et al., 2016) suggested the raw data fed a model-based 1D-CNN for classifying ECG signals into some classes that were proposed by the Association for Advancement of Medical Instrumentation (AAMI) and the model. (J. Wang, 2020) developed a model based on 1D CNN and modified the Elman neural network (MENN), which consisted of the 11-layer neural network, and the non-transform ECG signal also fed the model. The purpose of this paper is to categorize ECG signals as normal or abnormal. A three-feature extraction technique for classifying multiple heart diseases from ECG signals has been investigated. DFT, DWT, and ICEEMD methods were used for feature extraction. PCA is then used to reduce the dimensions of these features. Finally, the obtained features are subjected to SVM classification. The remainder of the paper is structured as follows. Section 2 provides a brief overview of the DFT, ICEEMDAN, DWT, PCA, and SVM techniques used in this study. Section 3 goes over the specifics of the proposed method. Section 4 presents the experimental results. Finally, section 5 concludes the study.

2. Background Theory

2.1 The ECG signal characteristics

The ECG analysis, which can be monitored manually or automatically, provides the most important information about the state of the heart (Saechia et al., 2005). A normal cardiac cycle ECG, as shown in Fig.1, has a P wave, QRS complex, T wave, and occasionally a small U wave (Islam et al., 2012). Cardiac arrhythmia is a condition in which the electrical activity of the human heart is abnormal. Manual interpretation of ECG signals requires experience, and it is difficult to detect small changes in the waveform of an ECG signal. Furthermore, because of the various waveforms and variations, the small amplitude (mV) and duration (sec) make automatic interpretation of the ECG signal challenging (Acharya et al., 2017; Diker et al., 2018). As a result, it is necessary to develop a method for classifying ECG signals based on their shapes and characteristics in order to determine whether they indicate a cardiac disease or not (B.R. et al., 2020a). Both approaches to feature extraction and classification are critical to the success of any automatic ECG classification. ECG analysis and classification have numerous applications, including ischemic heart disease, arrhythmia, and myocardial infarction (B.R. et al., 2020b).

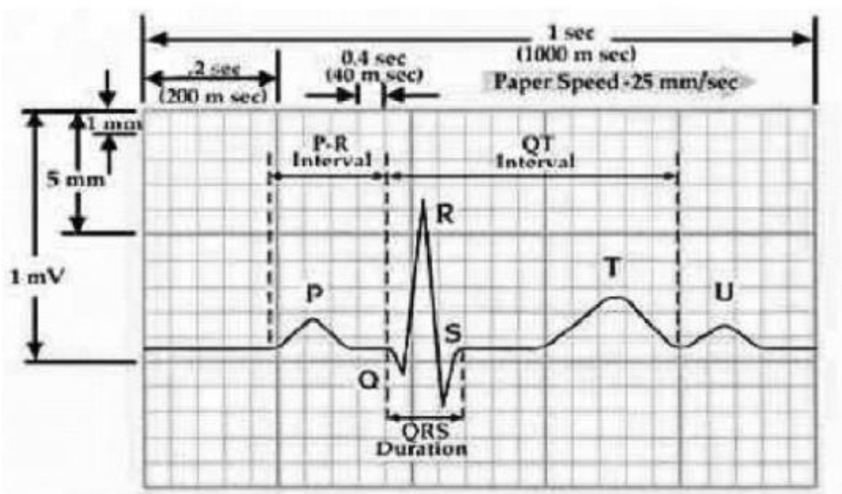

Fig.1 Normal ECG Beats and intervals

2.2 Discrete Fourier Transform (DFT)

The Fourier transform is one of the most important mathematical tools used in digital information processing because it is computationally implementable and can express basic sinusoidal functions (Ersoy, 1994). A key feature of the Fourier Transform is that a function can be completely reconstructed using an inverse process without losing any information. This property enables us to work in the Fourier domain and then return to the function's original domain without losing any information (Gonzalez, n.d.). The advent of digital computers and the development of the Fast Fourier Transform (FFT) algorithm transformed the field of signal processing (E.O. Brigham, n.d.). Fourier transform applications include signal analysis, filtering, reconstruction, and compression, as well as the extraction of characteristics for pattern recognition (Gonzalez, n.d.)

DFT is a technique for acquiring frequency domain information from discrete-time signals. This is commonly used in ultrasound testing problems. DFT in a finite-length discrete-time signal x[n] Calculated by Eq. (1) (Cruz et al., 2017)

$$X\left(e^{\frac{j2\pi k}{N}}\right) = \sum_{n=0}^{N-1} x[n]\, e^{\frac{-j2\pi kn}{N}} \quad 0 \le k \le N-1 \qquad (1)$$

Where j=√1, k is the frequency index, n is the time index, and N is the number of DFT points.

2.3 Discrete Wavelet Transform (DWT)

Morlet introduced the wavelet transform in the early 1980s, using it to evaluate seismic data (Andreao et al., 2006b). Wavelets, which have numerous applications in mathematics, physics, and digital image processing, are an alternative to classical Fourier algorithms for one and multi-dimensional data analysis and synthesis. The wavelet transform is applicable to both continuous-time and discrete-time signals. For example, The wavelet representation of a discrete signal $x[n]$ consisting of N samples can be computed by convolving X with the Low-Pass Filters (LPF) and High-Pass Filters (HPF) and down-sampling the output signal by 2, so that the two frequency bands each contains N/2 samples. Hence, using mathematical notations, the approximation (low frequency) output, and detail (high frequency) output decomposition level j+1 are computed reactively as follows (Soltani, 2002):

$$A_{j+1}(\mathrm{n}) = \sum_{k=0}^{M-1} LPF(k)\, A_j(2\mathrm{n}-\mathrm{k}) \qquad (2)$$

$$D_{j+1}(\mathrm{n}) = \sum_{k=0}^{M-1} HPF(k)\, A_j(2\mathrm{n}-\mathrm{k}) \qquad (3)$$

Where $A_j(\mathrm{n})$ is the input at level j, M is the number of filter coefficients, $LPF(k)$ is low-pass filters and $HPF(k)$ is high-pass filters.

The basis functions for representing other functions in this technique are wavelets. In the time and frequency domains, these basis functions have limited support. The mother wavelet and a family of wavelets generated by translations and dilations of it are used to perform a multiresolution analysis (Kora et al., 2019). There are several methods for implementing the 2D DWT, including traditional convolution-based and lifting scheme methods. Convolutional algorithms use filtering by multiplying the filter coefficients by the input samples and adding the results. Finite Impulse Response (FIR) filter banks are used to implement these algorithms. The lifting scheme has been proposed for efficient wavelet transform implementation. This approach has three phases, namely: split, predict, and update (Mallat, 1989). At each decomposition level in one-dimensional DWT, the HPF associated with the scaling function produces detailed information related to high-frequency components of the signal, whereas the LPF associated with the scaling function produces coarse approximations related to low-frequency components of the signal. The approximation part can be decomposed iteratively. Figure 2 depicts the process of three-level decomposition. A signal is divided into numerous lower-resolution components. The wavelet decomposition tree is the name given to this operation (Mallat, 1989).

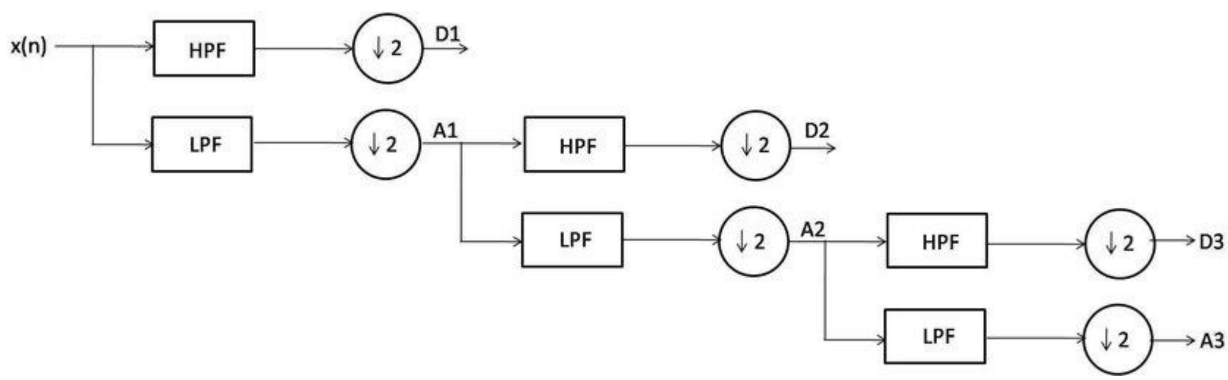

Fig.2 Sub-band decomposition of the DWT implementation.

The literature defines several wavelet families. The most common wavelets are Daubechies wavelets. Daubechies wavelets are used in a variety of applications. In an application, wavelet filters are chosen based on their ability to analyze signals and their shape.

2.4 Improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN)

Empirical mode decomposition (Huang et al., 1998b) is a data-driven approach for analyzing non-stationary signals. It generates fast and slow oscillation modes known as intrinsic mode functions (IMFs). By adding these IMFs and a monotonic trend, the original signal can be reconstructed. The primary benefit of EMD is its ability to separate stationary and non-stationary components from any complex data set. (Gilles, 2013). Hence, it gained popularity in medical diagnosis (Djemili et al., 2016; Hassan & Hassan Bhuiyan, 2016; K.S. et al., 2017). However, EMD has a serious problem known as "mode mixing," in which information from multiple modes coexists in a single mode. To address this issue, several noise-assisted algorithms have been proposed (Torres et al., 2011; WU & HUANG, 2009). Recently, Colominas et al. (Colominas et al., 2014a) To address the mode mixing problem, ICEEMD, a noise-assisted data analysis method, was proposed. Other advantages of this technique include less residual noise and minimal reconstruction error in the modes, as well as ensuring the algorithm's completeness. According to (Colominas et al., 2014a), This ICEEMD is ideal for processing biomedical signals. The ICEEMDAN algorithm flowchart is shown in Fig.3 (F. Yang et al., 2018)

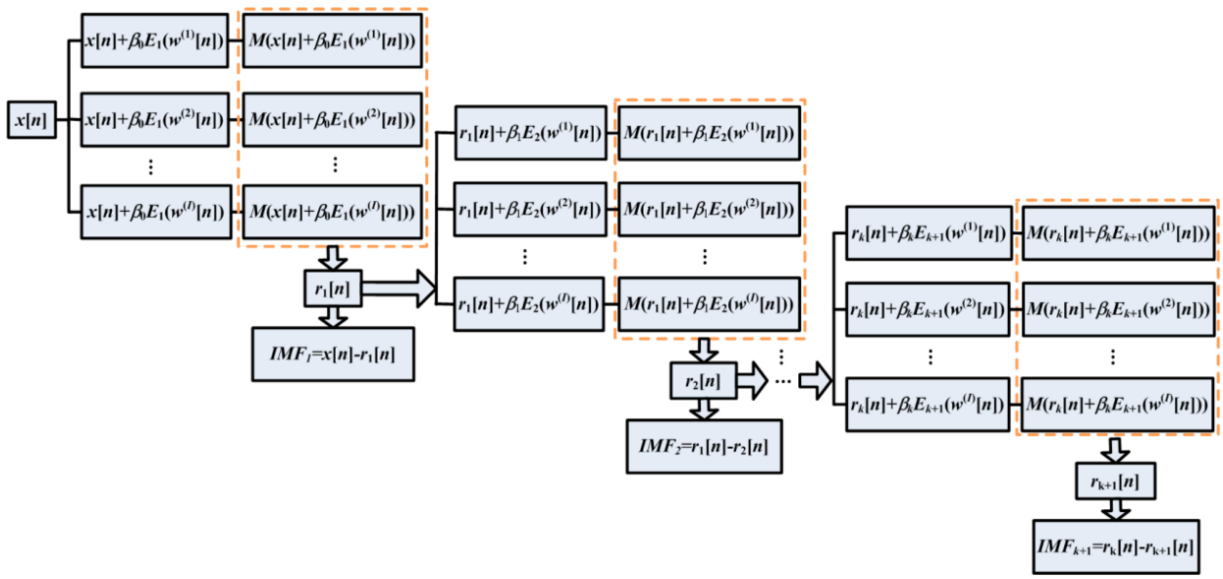

Fig.3 Flowchart of the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) (Z. Wang et al., 2019)

In Fig.3, $E_k(\cdot)$ demonstrates the generation of the k^{th} IMF by EMD, $M(\cdot)$ is used for the calculation of the local mean, and $w^{(i)}$ (i = 1,2, … I) is the white Gaussian noise with zero mean unit variance.

Here β1= Є0σ(r1) is used to obtain the desired SNR at each stage and Є0 = 0.2. The resultant IMFs are more regular and occupy the same scale in the whole period. It provides a better spectral separation. Each IMF contains useful information regarding individual ECG heartbeat.

2.5 Principle Components Analysis (PCA)

Principal Component Analysis (PCA) is a statistical method for identifying the principal components denoted as a linear combination, analyzing multivariable relationships, and explaining overall changes with several components (Jolliffe, n.d.). PCA can be used to reduce dimensionality in a data set by retaining the data set's characteristics that contribute the most to its variance and by retaining lower-order principal components, which frequently contain the most important aspects of the data (Framework & Analysis, n.d.). For a data matrix XT, with zero empirical means (the distribution's empirical mean has been subtracted from the data set), where each row represents a different repetition of the experiment and each column contains the results from a specific type of data (Zhang et al., 2010), the PCA transformation is given by (2):

$$Y^T = X^T W = V \sum T \tag{4}$$

Where the matrix Σ is an m-by-n diagonal matrix with non-negative real numbers on the diagonal and the n × n matrix V is the matrix of eigenvectors of XTX.

2.6 Least Square-Support Vector Machine (LSVM)

Support Vector Machine (SVM) is a highly nonlinear and single-layered network with high generalization ability that can correctly classify unseen patterns (Cristianini & Shawe-Taylor, 2000). The classifier, unlike other classifiers, minimizes structural risk rather than empirical risk. It simultaneously maximizes the distance between the patterns and the class separating hyperplanes to discriminate between patterns belonging to different classes. In general, nonlinearly separable patterns in the given feature space are projected into a high dimensional space where the features are assumed to be linearly separable and classification is performed. The kernel trick is the name given to this technique. Kernels that are commonly used are linear, quadratic, polynomial of order 3, and radial basis function (RBF) kernels. In the current study, a modification of the original SVM known as the Least Square SVM (LS-SVM) is used (Suykens & Vandewalle, 1999).

3. The Proposed Method

In this section, first, we will present a brief overview of our proposed method using three different methods each time for classifying multiple heart diseases from ECG signals, and in the consecutive sections, we present the details of every step. In this paper, instead of working with the raw ECG signal, a modified ECG signal is processed with different feature extraction methods including, DFT, DWT, and ICEEMD with the PCA method. SVM is used for heart disease classification based on the modified ECG signal.

3.1 Feature Extraction Methods

3.1.1 Discrete Fourier Transformation (DFT)

The discrete Fourier transformation was applied to each heartbeat (DFT). The resulting sequence contains both real and imaginary elements (Poularikas, 2018). Not all components are required as feature vectors and those components with higher energy contribution have been selected. Further, only the real part of the components can be used. PCA has been applied to reduce the dimension of the feature vector. In this work, only four PCs (features) were used from 187 features. Further, it is found that when the components are more than 5, they do not contribute much to the accuracy of the classifier. Therefore, we have selected 4 significant components to train an SVM with these coefficients as inputs and the category of the heartbeat as output.

3.1.2 Discrete Wavelet Transform (DWT)

DWT was used to decompose ECG signals in this step. First, only normal ECG signals are chosen. The detail coefficients and approximation coefficients were extracted after they were decomposed into three levels using Daubechies wavelets of order 2 ('db2'). There are numerous wavelet filters that can be applied to a signal. The Daubechies wavelet family is similar in shape to QRS complexes, and their energy spectra are concentrated around low frequencies, which is why this type is used. The ECG signals were decomposed into details (cD1-cD3) and approximation using three levels of decomposition (cA1-cA3). As the level increased in DWT, the number of features for details and approximations decreased. Level 1 of DWT analysis divides the signal into cD1 (94 features) and cA1 (94 features) (94 features). Then, in level 2, cA1 is decomposed into cD2 (47 features) and cA2 (47 features). Furthermore, in level 3, cA2 decomposes into cD3 (24 features) and cA3 (24 features). Three levels are considered in this work to test our method. Following that, a feature reduction step is applied to features to reduce their dimensions using the PCA. The number of features used is equal to the number of PCs extracted using the largest eigenvectors (Mahajan et al., 2011). This work considers a different number of principal components (PCs). Finally, the SVM algorithm was applied to the extracted features for classification.

3.1.3 Improved complete ensemble empirical mode decomposition (ICEEMDAN)

We can infer from experiments (Rajesh & Dhuli, 2018), that ECG heartbeat groups are nonlinear, non-Gaussian, and non-stationary. As a result, it is worthwhile to extract features from the nonlinear decomposition method that can reveal the implicit (nonlinear, non-stationary) information from ECG signals. ICEEMD is an ECG segment adaptive nonlinear decomposition method. It provides oscillatory modes that reveal subtle information in non-stationary signals generated by nonlinear systems (Colominas et al., 2014b). The feature vector is formed in this work by summing the first three and five intrinsic mode functions (IMFs) for each signal. In the other words, for each ECG signal which has (187) features, only three and five features were used for each experiment respectively. Finally, the extracted features are passed to the SVM algorithm for classification purposes.

4. EXPERIMENT RESULTS

4.1 Database

The proposed method is evaluated on MIT-BIH Arrhythmia Database (George B. Moody & R.G. Mark, n.d.). It was used to train and test the created classifier model. This standard database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects between 1975 and 1979. Each channel contains 360 samples per second with an 11-bit resolution over a 10mV range.

4.2 Evaluation

Two metrics are used to assess the performance of the abnormality detection method: accuracy and F1-Score. These measures are derived from the confusion matrix, where True Positives (TP) represent the number of times the classifier correctly predicts a heartbeat without arrhythmia, i.e. Normal. False Negatives (FN) represent the total number of normal heartbeats misclassified as arrhythmic, whereas False Positives (FP) represent the number of arrhythmic heartbeats classified as Normal. Finally, True Negative (TN) quantifies the number of correctly predicted arrhythmic heartbeats. The two metrics' equations are as follows:

$$AR = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$F1 - Score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{6}$$

The Accuracy Rate (AR) is the percentage of correctly predicted heartbeats out of all heartbeats analyzed. The F-score is the harmonic mean of the recall and precision values for the given class. The dataset is divided into train and test parts to test the performance of the proposed method. The experiments were run on a personal computer. Python was used to write the feature extractors and classifiers.

4.3 Results and Discussion

SVM was used to determine whether the ECG signal was normal or abnormal. The transformed data obtained from the above-mentioned techniques was used to train the SVM in various experiments. The output is defined by 0's and 1's, so the classifier understands that normal data corresponds to 0 and abnormal data corresponds to 1. The classification data is divided into 70% training and 30% testing. The experiments in DWT and DFT show that a different number of PCs can produce different results. In other words, the higher the value of the PCs, the greater the accuracy. Following several investigations, the best number of PCs is chosen to construct the classification model using SVM. Tables 1 and 2 represent the obtained results in terms of AR and F-score using DFT, DWT, and ICEEMDAN methods with SVM. The best rate of AR and F-score were obtained with the DWT method for both experiments. Slightly lower results were achieved when using (3-IMFs and 5-IMFs) with the ICEEMDAN method. However, regarding the DFT method, lower results were obtained when using only 3 and 5 PCs. As shown in Table 1, the lowest execution time was obtained using DFT. On the other hand, ICEEMDAN takes the highest execution time as compared to the other two methods.

TABLE 1. PERFORMANCE OF THE PROPOSED METHOD using 3 Features

Feature Extraction Method	AR	F-score	Execution Time (sec)
DFT	88.8 %	85.5 %	15.12
DWT	98.7 %	98.3 %	93.29
ICEEMDAN	97 %	97.1 %	94.64

TABLE 2. PERFORMANCE OF THE PROPOSED METHOD using 5 Features

Feature Extraction Method	AR	F-score	Execution Time (sec)
DFT	95.3 %	94.1 %	6.64
DWT	98.4 %	97.3 %	93.07
ICEEMDAN	97.2 %	96.5 %	94.09

4.4 Comparison

Table 3 summarizes the comparative study of existing work and the proposed method's performance. The experiments were also performed on the MIT-BIH arrhythmia dataset. As can be seen in Table 3, our proposed method has high performance compared to some other work proposed in the literature for ECG arrhythmias classification.

TABLE 3. THE COMPARISON OF THE PROPOSED METHOD WITH EXISTING WORKS.

Authors	AR
(Leite & Moreno, 2018)	90.6
(Venkatesan et al., 2018)	96 %
(W. Yang et al., 2019)	95.2 %
(Ullah et al., 2021)	97.3 %
(Reddy et al., 2022)	98.2 %
Proposed Method	98.7 %

5. Conclusion

This paper detects abnormal ECG via three strategies based on DFT, DWT, ICEEMDAN, PCA, and SVM. The first and second strategies (DFT and DWT) used PCA and SVM for feature extraction, feature reduction, and classification, respectively, whereas the third strategy employs ICEEMDAN and SVM as the classifier. The ECG data used in this study is from the MIT-BIH database. The results show that using only three features (DWT with PCA and SVM) could achieve an average accuracy of 98.7%. Meanwhile, when using (5) features, (DFT with PCA and SVM) and (ICEEMDAN and SVM) achieved accuracy of 95.3% and 97.2%, respectively.

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