Improving the Speed and Accuracy of Arrhythmia Classification Based on Morphological Features of ECG Signal

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ABSTRACT:
Electrocardiogram (ECG) signals play a crucial role in determining heart disease. Somehow, by knowing the heart rate on the ECG, one can distinguish the type of arrhythmia and the type of disease. Arrhythmias are a type of heart disease that affects the normal functioning of the heart. The electrical activity of the heart is shown at the peaks of P, QRS, T, and the ST and PR sections. In this study, an effective method for identifying cardiac arrhythmias based on morphological features is presented. The extracted features are classified using SVM and KNN classification and random forest RF. Accuracy, sensitivity, positive predictive rate, negative predictive rate as well as execution time were used to evaluate the proposed method. The results show the superiority of the proposed method.

KEYWORDS: Heart, ECG, Feature Extraction, Morphology, Classification, Evaluation.

1. INTRODUCTION

With the change in people's lifestyles, reduced physical activity and of course obesity, heart disease has become one of the deadliest diseases in recent decades [1], [2]. Since the health and life of people depends to a large extent on the health of heart function and the diagnosis of arrhythmias and dysfunction at the heart level should be done in a short time and also with high accuracy. Anything that disrupts the electrical impulses that cause the heart to contract causes a heart arrhythmia. The heart of a healthy person should beat 60 to 100 times per minute at rest. The more athletic a person is and the healthier his body, the lower his resting heart rate per minute. Olympic champions, for example, have a heart rate of less than 60 beats per minute, and this is because their hearts are more efficient [3]. Some of these arrhythmias are as follows.

- **Tachycardia or rapid arrhythmia**

A rapid arrhythmia (more than 100 beats per minute) is called a tachycardia.

- **Bradycardia or slow arrhythmia**

A slow arrhythmia (slower than 60 beats per minute) is called bradycardia. Sinus node dysfunction, slow heart rate due to abnormal SA node and heart block are types of bradycardia arrhythmias. Cardiac arrhythmias are sometimes classified into two categories according to their origin: ventricular arrhythmias (of ventricular origin) or supraventricular arrhythmias (of upper ventricular or atrial origin).

•Supraventricular arrhythmia

A type of arrhythmia that begins in atrial (upper chambers of the heart). Types of ventricular arrhythmias include: Premature atrial contraction (PAC), Paroxysmal supraventricular tachycardia (PSVT), AV nodal tachycardia (AVNRT), atrial tachycardia, atrial fibrillation, atrial flutter, and Wolff syndrome Parkinson White (WPW).

•Ventricular arrhythmia

This arrhythmia starts in the ventricles (lower chambers of the heart). Types of ventricular arrhythmias include: premature ventricular contractions (PVC), ventricular tachycardia (V-

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tach), ventricular fibrillation (V-fib), and prolonged QT syndrome.

The use of machine learning-based methods has been able to demonstrate its superiority in many areas of medicine, such as the diagnosis of diseases. One of the most dangerous diseases is heart disease, which kills many people every year. It seems that the use of machine learning-based methods can greatly help physicians in diagnosing these diseases. Methods for diagnosing cardiac arrhythmias usually consist of pre-processing, feature extraction, feature vector construction, feature selection, and finally classification training to diagnose the disease [4]. In this study, it is intended to diagnose different types of cardiac arrhythmias with the help of morphological features. In the continuation of this article, it is divided as follows. Section 2 will provide an overview of the research background. Section 3 will present the morphological features and the proposed method. In Section ٤, the proposed method will be evaluated. In Section ٥, the conclusion of the article will be presented

2. LITERATURE REVIEW

So far, different algorithms have been proposed to classify cardiac arrhythmias. A group of proposed algorithms operate in the time domain. The problem with these algorithms is that they use the electrocardiogram (ECG) ECG signal itself without extracting features to classify cardiac arrhythmias [5,6]. This results in high time costs and moderate accuracy of these methods. Given the above, it can be concluded that feature extraction from the ECG signal is an important step in the classification of cardiac arrhythmias .Various methods are used to extract features from the ECG signal. These include discrete Fourier transform DFT [7], discrete cosine transformation DCT [8], higher order statistical methods such as second, third and fourth order moments [9]. Discrete wavelet transform is also used in various researches to extract features from ECG signal. Discrete wavelet transform is a useful technique for analyzing signal frequency and time. Discrete wavelet transform can accurately estimate rapid signal changes. In [10] three classifications of neural networks, decision trees and Navy Bayes have been used in the diagnosis and prediction of heart disease. In [11] used the support vector machine classification and frequency domain characteristics to diagnose cardiomyopathy and cardiovascular disease. In [12] noted that it is the cause of death from heart disease and has designed a remote ECG recording system to reduce the death rate due to heart disease, which aims to detect cardiac arrhythmias early. In [13] neural networks have been used as a classifier to classify and identify cardiac arrhythmias. In order to reduce the effect of the above training, the reduction of the extracted features in the proposed method has been used. In [14] to extract the heart beat feature has its own properties. In [15] the hidden Markov and spark model in ECG signal analysis is presented. In the proposed method, the HHM hidden Markov model is combined with the Apache spark to increase the speed of signal analysis. In [16] presents a deep neural network DNN with an in-depth training algorithm for classifying features extracted from ECG signals. In [17] used Apache spark features to detect cardiac arrhythmias. The main challenge in diagnosing cardiac arrhythmias is the irregularities in the ECG signal, which is very important for diagnosing the condition. In [18] a new intelligent on-line method for the diagnosis of cardiac arrhythmia is presented. The proposed method includes pre-processing steps of feature extraction and classification. In [19] artificial neural networks have been used to diagnose three types of cardiac arrhythmia, lung disease, and liver disease. The neural network used is a multi-layered perceptron network with a training algorithm for Feed forward back pro propagation, as a result of which patient and healthy diagnosis are separated and identified. In [20] used the spectra obtained by short-time Fourier transform STFT along with convulsive neural networks to investigate the classification of cardiac arrhythmia. In [21] have proposed a non-regulatory method for detecting cardiac arrhythmias in a 12-channel ECG signal based on tensor wavelet transform and 2D Gaussian spectral clustering (high dimensions of ECG data and signals and a large number of variables are among the challenges of ECG signal classification). In [22] used the DEA differential evolution algorithm to optimize the weights of traditional Extremely learning machine (ELM) extreme learning machines and showed the improvement of ELM in cardiac arrhythmia classification using cardiac signals. Feature extraction was performed by discrete wavelet transform in PR period, QT period and ST period and QRs wave. In [23] Cardiac arrhythmia has also been diagnosed as a structural event based on statistical moments and the matrix . In [24] provide a method for identifying and classifying heart disease data. In the proposed method, they improve the PSO particle batch optimization algorithm and then classify it with possible classifications including generalized trees, multilayer neural networks, and support vector machines and possible neural networks. In [25] both in feature extraction and in feature selection, the combination of classifiers in cardiac base classification have been used to diagnose the disease. In [26] Deep Neural Network Ensemble has used clinical data to predict and diagnose heart disease. In [27] convolutional features are used for classification and it is also compared with nonlinear features. In this study, it has been proven that if nonlinear features are combined with convolutional features, the efficiency of accuracy and sensitivity will increase significantly.

3. PROPOSED METHOD

In the previous studies, machine learning based methods have been used in the diagnosis of heart diseases and arrhythmias. Frequency domain characteristics and location domain characteristics were extracted and then, using a classifier, the type of arrhythmia was diagnosed and identified. However, the low accuracy of some methods, and at the same time the low speed of others, has led to the need for fast and, of course, high accuracy methods. In this study, morphological features will be used to improve accuracy.

3.1. Morphological feature extraction

Extracting morphological and visual features from the ECG signal is challenging. Because the frequency of the T-waveform, the ECG baseline and the frequency characteristics are variable. Since the point R is used as a reference in this dissertation, the end of the interval $[t_1,t_2]$ at a signal wavelength is considered to determine T_{end}. The length of the W window, which is •<W <L, will be calculated as Equation 1.

$$L = t_2 - t_1 \quad (1)$$

The area under the T wave will be calculated as Equation 2.

$$A(t) = \int_{t-W}^{t} [s(\tau) - s(t)]d\tau \quad (2)$$

In relation (2) $A(t)$ the area below the signal area t is in the range $[t-W,t]$. $T_{end}(t_2)$will be assumed to maximize the area $A(t)$.

3.2. Block diagram of proposed method

Methods for diagnosing cardiac arrhythmias usually consist of pre-processing, feature extraction, feature vector construction, and finally classification training to diagnose the disease. Fig. 1 shows block diagram of this process. In this research, for the first time, entropy-based features will be used to teach classification. In conventional methods, the feature obtained with the help of classifiers will be classified. Then, with the help of K nearest neighbor, support vector machine SVM classifiers, random forest will be classified. This study attempts to use morphological features in the detection of cardiac arrhythmias in the ECG time signal in five heart beam modes: normal and normal neither beats NOR, left beat black beat and right LBBB black RBBB, PVC and APC. Fig. 1 shows the proposed method with dimension reduction and feature selection.

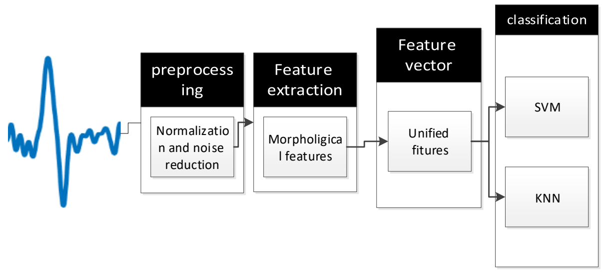

Fig. 1. Block diagram of the proposed method.

A patient-recorded ECG signal is decomposed into 10 IMF intuitive mode functions using the EMD experimental mode analysis algorithm [28]. In these 10 intuitive functions, signal noise is more common in IMF 1 and IMF 2. Baseline distortion is also found in IMF 9 and IMF 10. But other modes have the most information about the ECG signal. The high frequency modes IMF 1 and IMF 2 in this study are eliminated by discrete wavelet transform. But the low frequency noises, IMF 9 and IMF 10, will be eliminated with the help of a middle noise filter. Noise-free ECG signal is then obtained by reconstruction. Fig. 2 shows the preprocessing process.

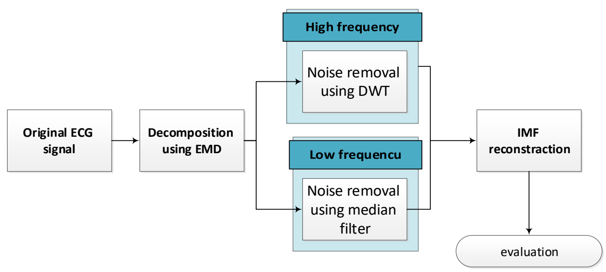

Fig. 2. preprocessing in propose method.

The experimental mode decomposition method is suitable for dealing with data obtained from non-stationary and nonlinear processes. Experimental mode analysis is based on the simple assumption that any data contains intrinsic oscillation modes. Each intrinsic, linear or non-linear mode expresses a simple oscillation, which has the same number of extremes and crosses of zero. In addition, the oscillation is symmetric with respect to the local mean. Each of these oscillating modes is defined by the intrinsic mode function (IMF) which has the following conditions [29].

A) In the primary raw signals, the number of extremes and the number of crossing points must be equal to zero or at most one.
B) At each point, the average value of the top and bottom of the curve is equal to zero.

An IMF expresses a simple oscillation mode as a simple harmonic function, but much more generally: Instead of having a constant amplitude and frequency, the IMF acts as a time function with variable amplitude and frequency.

The steps for obtaining the intrinsic mode function s of a waveform are as follows:
1. At this stage, the local maximum points are connected by a line that passes through all these points and travels the minimum possible path to obtain the top cap of the curve.
2. As in the first step and for the local minimum points, the bottom of the curve is obtained.
3. The average of the top and bottom cover is calculated and its name is put $m(t)$
4 The value of m (t) obtained from the previous step is subtracted from the original waveform to obtain a waveform called $h_1(t)$:

$$h_1(t) = x(t) - m(t) \tag{3}$$

5. If $h_1(t)$ contains both conditions related to the intrinsic mode function, it is known as the first intrinsic mode function of the waveform. Otherwise, $h_{1k}(t)$ is considered as the main function and steps 1 to 4 is repeated on it to get $h_{11}(t)$ as Equation 4:

$$h_{11}(t) = h_1(t) - m_1(t) \tag{4}$$

6. Step 5 is repeated k times and in this case h_1k (t) is known as the first intrinsic function of the waveform *x*(t) (IMF 1). Then it is defined: $c_1 = h_{1k}$
7. c_1 The first intrinsic mode function is reduced from the remaining waveform and its name is called the remainder $r_1(t)$

$$r_1(t) = x(t) - c_1 \tag{5}$$

8. The signal $r_1(t)$ is considered as the main signal and steps 1 to 7 are repeated to obtain two mines of the intrinsic mode function.
9. The above steps are repeated n times to obtain *n* intrinsic mode functions.
10. The above steps stop when r_n becomes a single-frequency signal and no single-frequency component can be extracted. Finally, the input signal is expressed as Equation 6.

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{6}$$

Fig. 3 shows the ECG noise signal as well as the filtered signal afterwards.

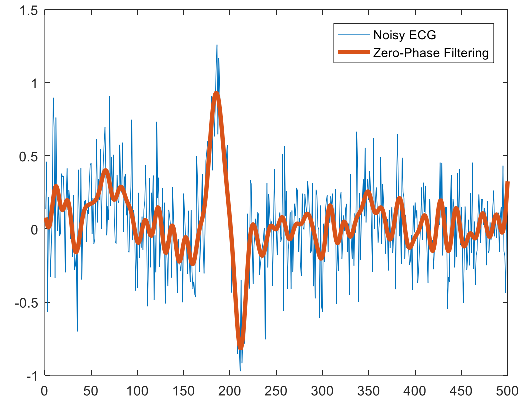

Fig. 3. Noise removed signal in the proposed method.

An ECG signal that has a cardiac arrhythmia consists of parts of the PQRST. In the PQRST waveform, there are PR part, Complex QRS part and ST part. Various methods have been proposed to extract these physical features. The morphological characteristics of P-wave, QRS complex, T-wave and offset value are obtained by this method in [30]. In this dissertation, the method presented in [30] will be used in which the properties related to the peak R to the end of the T wave are calculated. The S wavelength and QRS complex properties will also be calculated.

The number of samples in each signal is 1000000, which should be used for the training process as well as the test. In the proposed method, these signals are divided into 10 equal parts with dimensions of 100000 based on the method presented in [11], of which 7 parts are used for the training process, and the other 3 parts are used for testing.

The window search algorithm method has been used to extract pulses as well as various morphological features. The *R* point is the reference point for the search and will move to the left every 150 milliseconds. In this algorithm, if there is a point, the coordinates of the left end point are recorded. Otherwise the search will end. The right side of point R will then be searched. The search interval will be 150 milliseconds. If successful, the coordinates of this point on the right will be recorded. Otherwise the search will stop. The extraction process will be in Fig. 4.

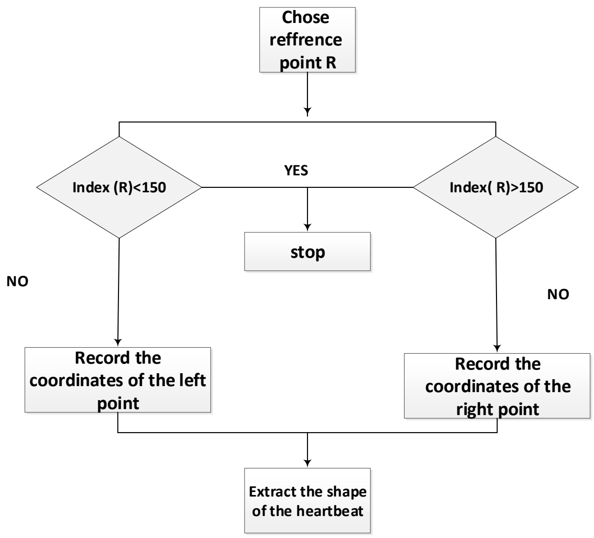

Fig. 4. Block diagram Extraction of morphological features.

Also, in each training sample, in windows with a length of 500 samples, statistical features as well as entropy-based features including sample entropy, approximate entropy and return period entropy will be extracted. These features should be used for the training process as well as the test.

4. EVALUATION CRITERIA

In this section, the results of the simulation of the proposed method to improve the speed and accuracy of the detection of a complete arrhythmia classification algorithm based on the morphological characteristics of the ECG signal will be discussed. Various experiments will be designed to evaluate the proposed method. First, the MIT-BIH database data is classified to the body of the feature selection process, with the help of the SVM and KNN classifiers of the decision tree, and the results will be obtained.

4.1. Evaluation criteria

The proposed method will be simulated on the signals in the MIT-BIH database using the proposed method. Criteria for speed of diagnosis and accuracy will be used in this research. The sensitivity relationship discussed in this study will be calculated with the parameters of Table 1.

Table 1. Diagnosis accuracy parameters.

Parameter symbol	Parameter definition
TP	It is a cardiac arrhythmia and a cardiac arrhythmia has been diagnosed
FN	It is a cardiac arrhythmia and a cardiac arrhythmia has not been diagnosed
FP	It is not a cardiac arrhythmia and a cardiac arrhythmia has been diagnosed
TN	There is no cardiac arrhythmia and no cardiac arrhythmia has been diagnosed

4.2. Equation

Equations 7 to 10 show the calculation of accuracy.

$$\Pr e = \frac{TP + TN}{TP + FN + FP + TN} \tag{7}$$

$$accuracy = \frac{TP + TN}{TP + TN + FPP + FN} \tag{8}$$

$$\text{Negative value rate} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{Posetive value rate} = \frac{TP}{TP + FP} \tag{10}$$

Finally, the tic and toc commands in MATLAB software will be used to calculate the speed of the proposed method and compare it with the basic article method. With this command, the processing time of both methods is calculated and by comparing the calculated times with each other, the speed of the two basic and proposed methods will be compared with each other.

4.3. MIT-BIH database

The ECG database used for this study is the MIT-BIH database. The database includes 18 patients (15 males and 3 females). They are 17 to 82 years old. This data was recorded directly from the hospital. The device for the ratio of these signals is the Holter device. The sampling frequency is 256 Hz. Table 2 shows the specifications of this database [23].

Table 2. MT-BIH database specifications.

Type of arrhythmia	MIT -BIH	MIT-BIH beat
(N) Normal	N-L-R-e-j	Normal beat LBBB RBBB Atrial escape beat
Supraventricul arectopic beat		Nodol premature
Ventricular ectopic beat	a-J-s-V	Nodal
Fusion beat Q Unknown beat	E-F-P-f-U	Merge track specified natural beats Unclassified heart rate

Table 3 shows the classification results for morphological or morphological features. Figure ۵also shows a comparison chart of this simulation and different classifications.

Table 3. Results of simulations using morphological features in percent.

Evaluation criteria	KNN	SVM	RF
Accuracy	94.23	90.10	88.45
Sensitivity	93.85	91.77	89.86
Positive value rate	90.12	89.32	90.88
Negative value rate	92.41	90.52	88.25

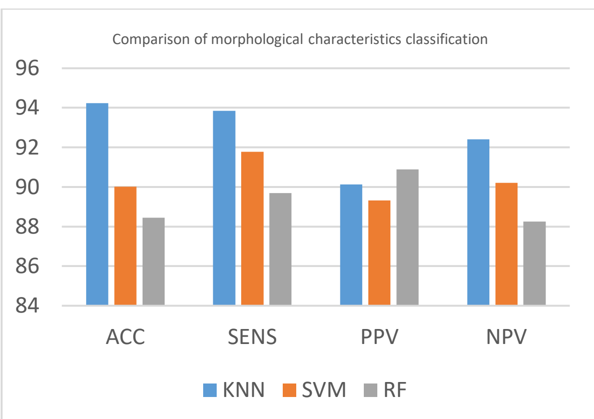

Fig. 5. Comparison of individual classifications in classification using morphological features.

4.4. Comparison with other methods

The proposed method in this study is compared with other studies. These methods include RNN recursive neural networks [31], random forest [32], and deep learning [20]. These methods are among the most common methods that have been used in most studies. The methods used for comparison have used the database of this research. Therefore, it seems that it is possible to have a correct comparison and evaluation of the proposed method. Since the number of training and test data for identifying cardiac arrhythmias varies in each study, the mean accuracy obtained is calculated based on this value. These results are presented in Table 4. As the results of this table show, the proposed method is more accurate than other methods. The database used in all these studies is MIT-BIH.

Table 4. Comparison of the proposed method with other articles in percent.

Method	paper	Arrhythmia	Test set	Average of accuracy
2 D-CNN	[20]	5	1545	98.10
RNN	[31]	4	4900	97.91
RFT	[32]	3	360	94.11
Proposed	-	5	360	98.99

4.5. Comparison of detection time

Comparison of detection time based on the database used is shown in Table 5. The proposed method, after selecting the appropriate features, detects the type of arrhythmia more quickly. The reason for the superiority of the method presented in this research was the selection of appropriate features. In addition to improving accuracy, these features also reduce arrhythmia detection time, which is one of the advantages of the proposed method.

Table 5. Comparison of arrhythmia detection time in the desired methods.

method	paper	Time (second)
Proposed	proposed	0.91
2 D-CNN	[20]	1.41
RNN	[31]	1.23
RFT	[32]	2.51

As can be seen from the results in Table 5, convulsive neural networks require more time to diagnose the type of arrhythmia. While in the evaluated methods, RFT networks have shown poorer results. The proposed RNN recursive neural network method worked without feature selection. Choosing the right feature has improved both accuracy and detection efficiency at the same time.

5. CONCLUSION

In this study, the proposed method in identifying the type of arrhythmia based on morphological features has been investigated. In the proposed method, after the desired features were extracted, they were classified by the support vector machine classification and k nearest neighborhood and random forest 70 % of the data were used for the training set and 30% of the data were used for the test. The proposed method is compared with the methods of RNN [31] recursive neural networks, random forest [32] and also deep learning [20], which shows its superiority both in terms of accuracy and simulation time have given

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