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Research paper

Cardiac Arrhythmia Diagnosis with an Intelligent Algorithm using Chaos Features of Electrocardiogram Signal and Compound Classifier

Elham Zarei , Nasim Barimani, and Gelayol Nazari Golpayegani*

Department of Electrical Engineering,Yadegar-e-Imam Khomeini (RAH) Shahre Rey Branch, Islamic Azad University, Tehran. Iran.

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**Corresponding author: gelayol.nazari@gmail.com (G. Nazari Golpayegani).*

Abstract

Cardiac Arrhythmias are known as one of the most dangerous cardiac diseases. Applying intelligent algorithms in this area, leads to the reduction of the ECG signal processing time by the physician as well as reducing the probable mistakes caused by fatigue of the specialist. The purpose of this work is to introduce an intelligent algorithm for the separation of three cardiac arrhythmias using the chaos features of ECG signal and combining three types of the most common classifiers in these signal's processing area. First, the ECG signals related to the three cardiac arrhythmias of atrial fibrillation, ventricular tachycardia, and post-supra ventricular tachycardia along with the normal cardiac signal from the arrhythmia database of MIT-BIH are gathered. Then the chaos features describing non-linear dynamic of the ECG signal are extracted by calculating the Lyapunov exponent values and signal's fractal dimension. At the end, the compound classifier is used by combining multi-layer perceptron neural network, support vector machine network, and K-Nearest Neighbor. The results obtained are compared with the classifying method based on the features of time-domain and time-frequency domain, as a proof for the efficacy of the chaos features of the ECG signal. Likewise, in order to evaluate the efficacy of the compound classifier, each network is used both as separately and also as combined, and the results are compared. The obtained results show that using the chaos features of ECG signal and the compound classifier can classify cardiac arrhythmias with a 99.1% ± 0.2 accuracy and a 99.6% ± 0.1 sensitivity, and a specificity rate of 99.3% ± 0.1.

1. Introduction

Electrocardiograghy is recording the electrical activity of the heart, which results in a signal that provides precious data related to the function of the cardiovascular system in a way that various cardiac diseases like arrhythmias can be diagnosed from this signal [1-2]. Figure 1 depicts a view of a normal ECG.

The word arrhythmia means the abnormal rhythm of the heart. Atrial Fibrillation Arrhythmia (AF), Ventricular Tachycardia (VT), and Post-Supra Ventricular Tachycardia (PSVT) are of the most common and most dangerous cardiac arrhythmias. In AF arrhythmia, the electrical stimulus does not travel a specific path. This arrhythmia occurs when muscular cells of atrium stimulate and contract chaotically. As a result, they cannot completely pump blood into ventricles. Thus the ventricular pulses occur without following atrium in an irregular way [3]. In VT arrhythmia, the cardiac pulse rate will get over 100 ppm. In this type of arrhythmia, duration and shape of the QRS complex in ECG signal is abnormal [4]. PSVT arrhythmia is considered as one of the emergency conditions of cardiac diseases, in which the pulse rate will get up to 140-220 ppm. The reasons of this arrhythmia are increase in automatic work of atrium, antegrade impulse conduction through AV node, and retrograde impulse conduction through secondary AV path [5].

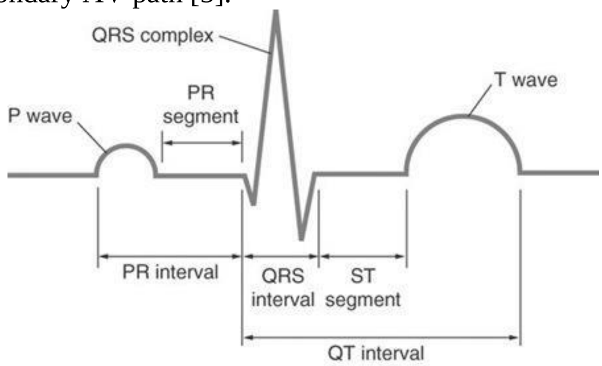


Figure 1. Electrocardiogram signal's waveform. P wave shows atrium contraction, QRS complex shows ventricle contraction, and T wave shows ventricle relaxation.

Since the vital signals like ECG signals are non-stationary signals (meaning that their statistical features vary over time), different reflections of an event might happen in random time scales. Evaluation of these variations in a long duration, from one side has critical information for physicians but is very time-consuming from the other side. In order to reduce the time of ECG signal interpretation and reduce the probable faults arising from fatigue or visual fault of the specialist, designing of intelligent algorithms for ECG signal processing to diagnose cardiac diseases have been of special concern from many years ago. The design of such an intelligent system consists of three stages. In the first stage that is named as the data collection stage, the ECG signals related to various arrhythmias as well as normal ECG signals are collected, and the data will be pre-processed if required, by omitting noises and sampling by a proper frequency. In the second stage that is named as the feature extraction stage, the features that describe the nature of ECG signal in the best way and leads into the best differentiation of cardiac arrhythmias will be extracted. In the third stage that is named as classification, for differentiation and classification of various cardiac arrhythmias with a normal rhythm, a suitable classifier is applied.

Many studies have been done in the area of feature extraction and ECG signal classification for cardiac arrhythmias diagnosis, so far. One of the most important approaches of feature extraction of ECG signals is the feature extraction of time-domain. In the time-domain, the signal is measured as a function of time, and the curve of 'amplitude change over time' is depicted for that. Therefore, in the time domain, the signal will be used in its original format. One of the very important parameters that is extracted from the ECG signal in time-domain, and has an effective application in the diagnosis of cardiac arrhythmias is the time interval of two R peaks. Usually, the statistical parameters of this time interval like average, standard deviation, and mean square of successive distances difference are extracted as the time interval features [6]. Cai *et al*. have developed a real-time arrhythmia classification algorithm using the time-domain features of ECG signals and a Convilutinal Neural Network (CNN), and have obtained the accuracy of 91.5% for 5-classes of cardiac arrhythmia [7]. In the study conducted by them, the non-stationary nature of ECG signals as well as their non-linear dynamics were ignored, and only the linear features of the time domain, which are strongly dependent on the morphology of the signal, were considered.

Some studies have been done on the frequency domain features of the ECG signal. In the frequency approach, the power spectrum of the signal will be estimated. The frequency spectrum of each signal determines that how much frequency exists in that signal. In other words, this shows the amplitude over the frequency curvature. In this domain, by using the Fast Fourier Transmission (FFT) and auto-regression method, the periodic oscillations between two R peaks will be made as quantitative [8-9]. Gowthwal *et al*. have applied fast Fourier transforms to identify the peaks in the ECG signal, and then used neural networks to identify the diseases. They achieved the accuracy of 96.67% by applying a neural network with 7 neurons in the hidden layer [8]. Although they were able to show that features that do not depend on signal morphology are more effective, they still ignore the non-stationary nature of ECG. Also they used only the MLP neural network for classification, and missed the benefits of other classifiers.

Because of the non-stationary nature of ECG signals, using the features of time-frequency domain was the third approach that attracted most researchers. Wavelet transform is one of the most applicable methods of feature extraction in the time-frequency domain. There have been many studies on using wavelet transform for the feature extraction of ECG signals.

The most common functions of wavelet transform that have been used in these studies are Daubechies, Symlet, and Biorthogonal functions [10-11]. Zaho *et al*. have used both the time-domain and time-frequency domain features of the ECG signals for arrhythmia classification by extracting the wavelet coefficient and AR model coefficient. Then they used a SVM classifier [10]. Although they achieved a high classification accuracy, the non-linear dynamics in the ECG signal was still neglected.

In the recent years, there has raised a lot of interest in using the available techniques in the area of non-linear and chaotic analysis in the study of dynamical behavior of ECG signal. Sabrine *et al*. have applied fractal dimension and artificial neural network to classify cardiac arrhythmia [12]. Also the classification of 7 arrhythmias from ECG signals using the fractal dimension and back- propagation neural network with the accuracy of 98.83% was done by Kiani *et al*. [13]. The strength of their study was the classification of a large number of arrhythmias and the depiction of complexity and self-similarity of the ECG signals by extracting the fractal dimension of this signal. However, no description of Lyapunov exponential values of ECG signal has been provided. The Lyapunov exponent measures the rate of convergence or divergence of two nearby trajectories in state space, so that is one of the most important parameters describing the chaotic behavior of a signal. Casaleggio *et al*. have proved the presence of positive Lyapunov exponent values in the ECG signal, which indicates the occurrence of chaotic behavior in this signal [14].

The purpose of this study is to determine the efficacy of non-linear dynamic scales of ECG signal like with both of Lyapunov exponent and fractal dimension as useful clinical parameters in the cardiac arrhythmias classification. Lyapunov exponent is a quantitative scale for differentiation of various paths based on their sensitive dependence to the initial conditions. There are different algorithms to calculate the fractal dimension. In this work, two common algorithms of Higuchi algorithm and Petrosian have been used, which estimate fractal dimension of vital signals directly from the signal's time series [15-16].

In the field of ECG signals classification, mostly the multi-layer perceptron (MLP), neural networks have been used [17-21]. Karen *et al*. have decreased feature dimensions using the PCA method, and used MLP for the classification in 2021 [22]. Revadas used the three models of the K-Nearest Neighbor, SVM, and Naïve Bayes for data classification in 2021 [23]. Christo *et al*. have decreased feature dimensions using correlation-based feature selection (CFS), and have used neural network with back-propagation learning algorithm for classification in 2019 [24]. Kohli *et al*. have used PCA for decreasing the feature vector's dimension, andused a supportive vector machine as a classifier for 6 classifications in 2011 [25]. Although according to the results of references [17-25], all three types of MLP, SVM, and KNN classifiers have shown good results in the classification of cardiac arrhythmia, in this article, an attempt has been made to somehow by voting between the decisions of all three types of categories, we can achieve better results.

Studies show that combining different classifiers in comparison with applying each of them individually, certainly enhances the precision and accuracy of the classification. Up to now, various algorithms have been introduced for combination of the classifiers. Among these algorithms, we can mention the Majority Vote and the Naïve-Bayes Combination (NB), in which the classifiers are assumed as independent; an assumption that is not always correct. The Behavior Knowledge Space (BKS) algorithm is another method of combining classifiers, which does not require this assumption [26]. In this study, three efficient classifiers have been combined to enhance the performance of the intelligent algorithm of cardiac arrhythmias diagnosis by using Behavior Knowledge Space (BKS). After determining the importance of the discussed topic in this study by reviewing the previous literatures, first the database is introduced in Section 2, and then the research method will be described. The results of this study will be presented and discussed in Section 3. In this section, to approve the efficacy of the introduced feature extraction method of this study, once more, the common features of the time-frequency domain and features of time-domain will be given to the combination of three classifiers, and the classification results will be compared with the obtained results from the applied non-linear dynamic domain features. Also for the efficacy approval of the classifier algorithm used in this research work, the non-linear dynamic domain features have been given to each of the classifiers separately, and the classification results have been compared to the combined classifiers results. At the end, the results of this research work will be concluded in Section 4. The blook-diagram of the proposed method is shown in Figure 2.

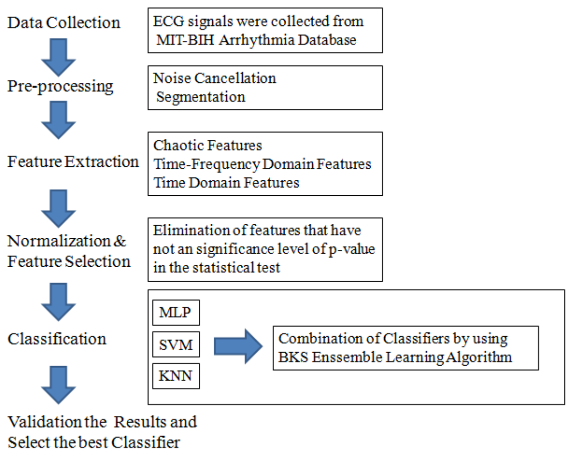


Figure 2. Blook-diagram of proposed method.

2. Materials and Methods

2.1. Data collection

All the required ECG signals have been collected from the MIT-BIH cardiac arrhythmias data bank. This databank consists of various patients records with different cardiac diseases [27-28]. The ECG signals have been recorded from two channels electrocardiogram, and due to the difference in the anatomical characteristics of the people, the leads II and V1 have been used in most of the recordings. Since lead II reveals the health of the heartbeat over time better than other leads, in this research work, only the data recorded for this lead was used for processing.

2.2. Pre-processing

2.2.1. Noise cancellation

Various types of noise and disturbances in the ECG signal strongly affect the visual diagnosis and feature extraction from it. Baseline wander, electrode motion arti-facts, and 60 Hz powerline interference are among these disturbances. The frequency content of the baseline wander is in the range of 0.5 Hz. However, the electrode motion arti-facts mainly occurs in the range from 1 to 10 Hz. Therefore, both of these noises , are low-frequency noises. Hence, to remove these two types of noise, a Butterworth high-pass filter with an order of eight ($N = 8$) and a cut-off frequency of 2 Hz ($fc = 2$Hz) was used. Also, a notch filter with a complex conjugated pair of zeros that lie on the unit circle at ferequency 60 Hz was used to remove the power line noise. The single-lead ECG signal (lead II) has been used, and the noise related to residential electricity, breathing and movement arti-facts has been fully removed.

2.2.2. Segmentation

The duration of recording the ECG signals, which were provided to us for processing from the MIT-BIH database, is 1 minute. Since the sampling frequency of applied signals is 360 Hertz, each recorded signal has 21600 samples, that 20000 of them was used for processing. Each record has an interpretation file consisting the arrhythmia type of that cardiac signal. In this study, three most dangerous cardiac arrhythmias named as Atrial Fibrillation (AF), Ventricular Tachycardia (VF), and Paroxysmal Supraventricular Tachycardia (PSVT) have been considered. 18 signals of each type of these arrhythmias, as well as 18 normal cardiac signals, have been collected from the MIT-BIH databank. Thus totally 72 ECG signals have been provided to process and classify three cardiac arrhythmias and differentiate them from the normal cardiac signal. In Figure 3, 2000 samples of the waveform related to these three arrhythmias have been depicted. A normal resting heart rate for adults ranges from 60 to 100 beats per minute. Thus each heart beat lasts between 0.6s to 1s. Since the sampling frequency of applied signals is 360 Hertz, each heart beat may include between 216 to 360 samples. Therefore, on average, every 256 samples can be considered as one normal heart beat. The segmentation of ECG signals was performed using a moving window of 1000 samples with an overlap of 200 samples. Thus, each ECG signal was divided into 24 pieces of 1000 samples. Therefore, in total, 1728 beats of ECG signals will be provided for the processing.

2.3. Feature extraction

In this study, to the purpose of applying non-linear dynamics features over the ECG signal and depicting the chaos behaviour of this signal, the values of minimum, maximum, standard deviation, and average of Lyapunov exponent as well as fractal dimension of each segment by using two algorithms of Higuchi and Petrosian were calculated, and were applied as non-linear features of the ECG signal.

2.3.1. Lyapunov exponent

Lyapunov exponent is a quantitative scale for differentiation of different pathways based on their sensitive dependency to the primary conditions. Lyapunov exponents are used to measure the average of the divergent or convergent exponential rate of the close pathways in phase space. If the result of a Lyapunov exponential system is positive, this means that the phase space trajectories, which have started from very close points, will diverge by an increasing exponential rate, and this way the chaotic behaviors can be observed in this system [29].

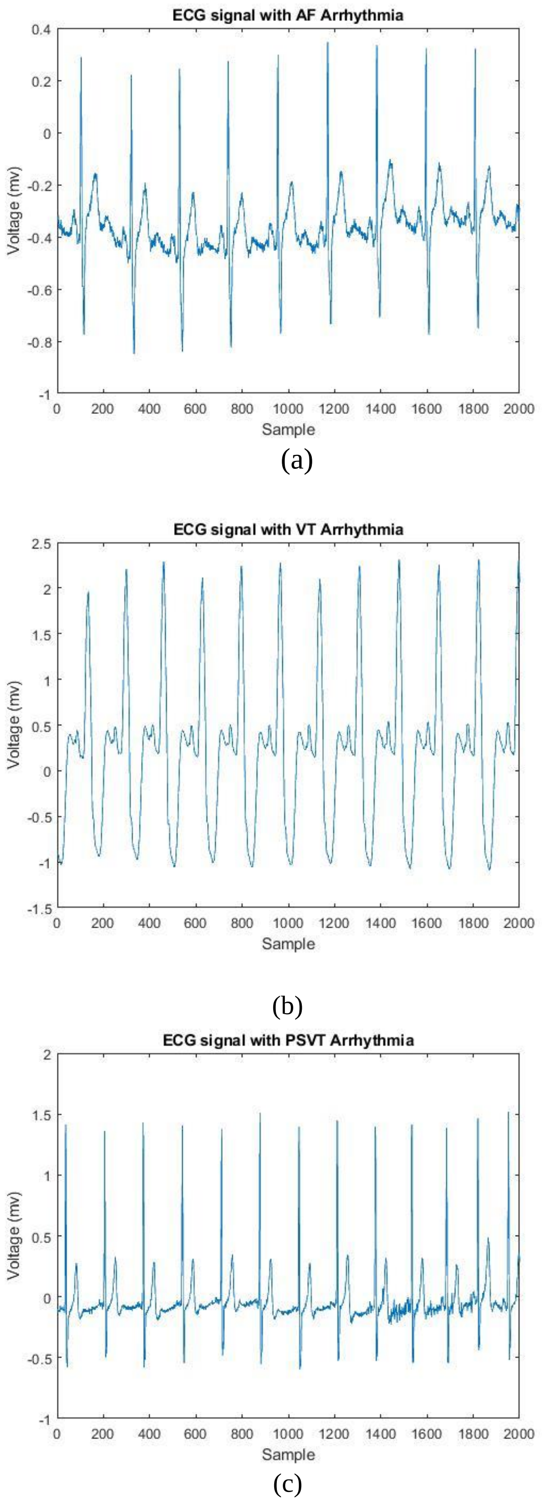


Figure 3. ECG signal waveform consisting of three types of cardiac arrhythmias: A- Atrial Fibrillation (AF), B- Ventricular Tachycardia (VF), and C- Paroxysmal Supraventricular Tachycardia (PSVT).

To calculate the Lyapunov exponent, at first two adjacent points (usually two closest points to each other) are considered in the phase space. The distance between these two points at times of '0' and 't' in 'i' direction is shown with ‖δxi(0) ‖ and ‖δxi(t) ‖, respectively. Then the Lyapunov exponent is calculated by growth rate average of primary distance (λi) and the following equation [30]:

$$\frac{\|\delta xi\,(t)\|}{\|\delta xi\,(0)\|} = \lim_{t\to\infty} 2^{\lambda it} \quad \text{or} \tag{1}$$

$$\lambda_i = \lim_{t\to\infty} \frac{1}{t} \log_2 \frac{\|\delta xi\,(t)\|}{\|\delta xi\,(0)\|}$$

Usually, the Lyapunov exponent is extracted for a signal by two methods: the first method is based on following the time evolution of the points close to each other in mode space [30]. This method only gives an estimation of the biggest Lyapunov exponent. The second method is based on estimation of the local Jacobian matrix, and is able to estimate all Lyapunov exponents [31]. Vectors of all Lyapunov exponents of a system is named the Lyapunov spectrum of that system.

In this study, for each heartbeat, the Lyapunov spectrum consisting of 128 Lyapunov exponents are extracted using the Jacobian matrix method. Then to decrease the dimension of features vector, 4 statistical parameters achieved for Lyapunov exponents related to each segment of ECG signal (including minimum, maximum, average, standard deviation of Lyapunov exponents) are calculated and considered as the features of that segment.

2.3.2. Fractal dimension

Fractal dimension implies the 'not integer' dimension of a geometry with a complicated structure. The fractal dimension is a parameter emphasizing on geometry nature of moving pathways in the mode space of a system, and is used for evaluation of non-linear dynamic and chaotic behaviour occurrence in a signal. In this viewpoint, the system is allowed to move through an appropriate time duration in the attractor. Then the geometry dimension of the attractor is calculated, and then it is evaluated whether the whole phase is covered by the system or not. Indeed, fractal dimensions show the geometry properties of a system's attractor and have high calculation speed [16]. There are different algorithms suggested for the calculation of the fractal dimension of a signal, among which we can mention the Higuchi and Petrosian algorithms.

2.3.2.1. Higuchi algorithm

This algorithm was first introduced in 1988 as an effective algorithm for the measurement of fractal dimension of the incoherent time series. The Higuchi algorithm directly calculates the fractal dimension of time series. By considering X time series as samples of X [1], X [2], …, X [N] , a new time series is made by Equation (2) [16].

$$X_m^k = \begin{Bmatrix} x(m), x(m+k), x(m+2k), \\ ..., x(m + \left[\frac{N-m}{k}\right]k \end{Bmatrix} \quad (2)$$

$$m = 1, 2, ..., k$$

in which, ‘m’ and ‘k’ are whole numbers. ‘m’ shows the primary time value, and ‘k’ shows the incoherent time distance between points (delay). The symbol $\lfloor\frac{N-m}{k}\rfloor$ determines the whole part of $\frac{N-m}{k}$. For each X_m^k , the length $L_m(k)$ is obtained by Equation (3).

$$L_m(k) = \frac{\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left|x(m+ik) - x(m+i-1)k\right| (N-1)}{\left[\frac{N-m}{k}\right]k} \quad (3)$$

In the above relationship, ‘N’ shows samples quantity, and $\frac{(N-1)}{\lfloor\frac{N-m}{k}\rfloor k}$ is the normalization coefficient. For each ‘k’ value, the ‘k’ quantity of the length is obtained. For all-time series that have the same ‘k’ (delay), the average length is calculated as the average of length’s ‘k’. This operation is repeated for k = 1, 2, …, k_{max}, and L(k) is obtained by Equation (4) as the sum of average lengths for each ‘k’.

$$L(k) = \sum_{m=1}^{k} L_m(k) \quad (4)$$

For ‘k’ range, the sum of average lengths is equivalent to K^{-D}, in which ‘D’ is the fractal dimension of Higuchi algorithm. In curvature Ln (L(k)) over Ln($\frac{1}{k}$), the slope of the best line estimated by the least square error method is the fractal dimension.

2.3.2.2. Petrosian algorithm

Petrosian algorithm is very fast and simple in the calculation of fractal dimension. In this method, the fractal dimension is calculated by Equation (5) [16].

$$D = \frac{\log_{10}^{n}}{\log_{10}^{n} + \log_{10}^{(\frac{n}{n+0.4N_\Delta})}} \quad (5)$$

in which, ‘n’ shows the signal length, and N_Δ is the number of signal’s derivative signs changes. In the incoherent time signal, the signal derivative is equivalent to its consecutive points difference. In this way, for each positive and negative differentiated result, the numbers +1 and -1 are considered, respectively.

2.3.3. Normalization

It is better to perform the normalization operation before many data mining algorithms such as neural networks, SVM, KNN, and KMeans, so that the different dimensions of the features are evaluated fairly by the algorithm, and the effect of one is not greater than the others. In this work, the normalization of the features was done using the $x_{n\_i} = (x_i - \mu_i)/\sigma_i$ relationship, where x_{n_i} represents the i-th normalized feature, x_i, μ_i, and σ_i, respectively, represent the i-th feature, the average, and the standard deviation from the i-th feature. In this way, all features will have a distribution with zero mean and 1 variance.

2.3.4. Feature selection

In this work, instead of selecting the best features, attention was paid to the approach of removing features with an unacceptable significance level ($p > 0.05$), after performing the t-test on the features.

2.4. Classification

2.4.1. Singular classifiers

At the first step, the classification is done by three basic classifiers one by one. These classifiers are multi-layer perceptron (MLP) neural network, Supportive Vector Machine (SVM), and the K-Nearest Neighbor (KNN). In any state, the network input is extracted features of each signal segment, which are used for network training. Also in all three states, 80% of all ECG signal segments are used for network training and 20% of them are used for the network testing. Since we had totally 1728 ECG signal segments, we used 1382 segments for training and 346 segments for testing of each network. The specification of the basic classifiers used in this study are as below:

- Multi-layer perceptron (MLP) with sigmoid tangent activation function and back-propagation learning algorithm. In practice, the number of neurons in MLP neural network’s hidden layer have an important role in the performance of these networks. There has not been any specific guideline according to which we can estimate the number of neurons of the hidden layers of a MLP network. If the neurons quantity is considered low, the network will not have the power of a proper generalization, and on the other hand, high quantity of neurons will lead

to complication and increased time of the network training. Hence, in this study, 40 neurons have been considered by the trial and error method.
- The supportive vector machine with sequential minimal optimization and Gaussian-basis Kernel function by parameter of σ = 0.6 and coefficient of C = 1.
- The algorithm of K-Nearest Neighbor with 5 neighbors, Exhaustive searching methods, and Minkowski distance calculation method.

2.4.2. Combination of classifiers

In the second step, combining these three classifiers using Behavior Knowledge Space (BKS) was done. This method, in fact creates a multi-dimension space, in which each dimension is related to the decision made by each of the classifiers. If the number of classes for classifying is 'M', each classifier will have 'M' selection choice from {1, 2, …, M} for decision-making related to each data. The intersection of decisions made by each classifier (when each has been deployed separately) will occupy one unit of BKS and each unit will summate the input samples of each class. For the current input, the unit that is the intersection of decisions made by classifiers is named the focal unit. As an example, in two-dimensions BKS, if the first classifier recognizes the 'x' sample belonged to the 'i' class and the second classifier recognizes that belonged to the 'j' class, then we will have: e(2) = j, e(1) = i. In this way, unit(i,j) will be single focal. In describing the BKS algorithm that is used for combining 'k' classifiers, the following symbols are defined [32]:

BKS: Behavior Knowledge Space with 'k' dimensions

BKS (*e(1),…,e(k)*): one unit of BSK, in which e(1) is the decision made by the first classifier for 'x' sample and e(k) is the 'k' decision of the classifier on the same sample.

$n_{e(1)\ldots e(k)}$ (m): sum of sample numbers entering to the unit of BKS (*e(1),…,e(k)*), which belongs to the class 'm'.

$T_{e(1)\ldots e(k)}$: total number of samples entering to the unit of BKS (*e(1),…,e(k)*), which is obtained by the following equation [32]:

$$T_{e(1)\ldots e(k)} = \sum_{m=1}^{M} n_{e(1)\ldots e(k)}(m) \tag{6}$$

$R_{e(1)\ldots e(k)}$: the best representative class in the unit of BKS (*e(1), …, e(k)*), which is obtained from the following equation [32]:

$$R_{e(1)\ldots e(k)} = \left\{ j \left| \begin{array}{l} n_{e(1)\ldots e(k)}(j) = \\ \max_{1\le m\le M}\ n_{e(1)\ldots e(k)}(m) \end{array} \right. \right\} \tag{7}$$

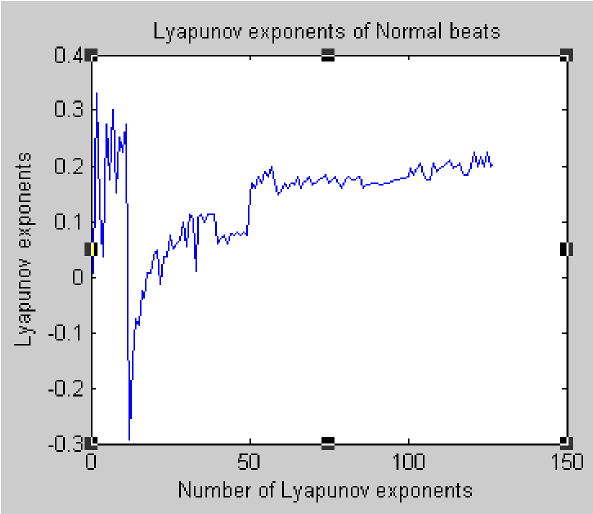
Since the purpose of this study is to combine three types of classifiers for the classification of three cardiac arrhythmias and their separation from the normal cardiac signal, a three-dimensions (k = 3) and four-class (M = 4) BSK algorithm has been employed.

3. Results and Discussion

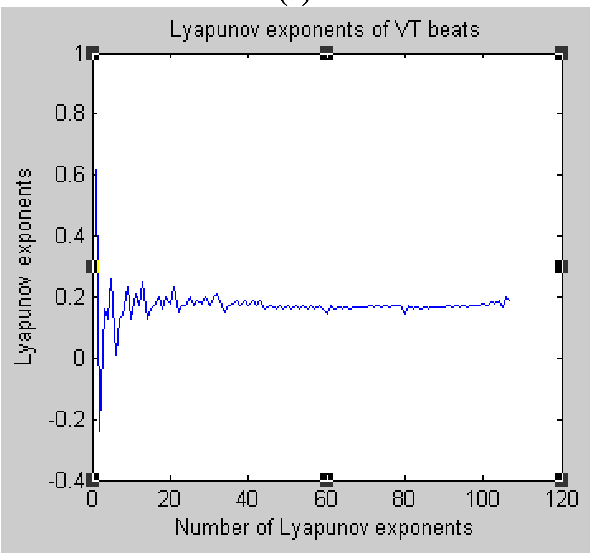
In the first stage, the Lyapunov exponent values were calculated for each ECG signal segment. Since each heart beat contains 256 samples, therefore, for each heartbeat, 128 Lyapunov exponents were extracted. The extracted Lyapunov exponents for one heartbeat of a normal ECG signal, and one heartbeat of an ECG signal with VT arrhythmia have been depicted in Figure 4. As It can be seen in Figure 4, the values obtained for the normal ECG signal are different from those obtained for the ECG signal with VT arrhythmia. The Lyapunov exponent describes how fast a very small gap between two initially closed states grows over time. It can be concluded that the interval in which the Lyapunov power parameter has positive values largely coincides with the interval in which the system exhibits chaotic behaviour and the bifurcation curve becomes bifurcated. Therefore, existence of positive Lyapunov exponents in each signal heartbeat is a proof for chaos behaviour occurrence in both of the normal ECG signal and ECG signals containing arrhythmia. As it can be seen in Figure 4, the ECG signal containing VT arrhythmia has bifurcation very soon and when it enters the chaotic phase; it will remain in this phase. This is while the normal ECG signal will leave the chaotic phase and become bifurcated again some time after the occurrence of chaotic behaviour. Therefore, cardiac signals containing arrhythmia have more continuous chaotic behaviours compared to normal cardiac signals.

Four Lyapunov exponent features obtained for each signal segment in states of 'normal' and 'with AF, VT, and PSVT arrhythmias' have been shown in Table 1.

The Fractal Dimension (FD) is a depictive measure that has been confirmed useful in putting into numbers the complex difficulty or self-similarity of the biomedical signals.



(a)



(b)

Figure 4. Lyapunov exponents obtained for one heartbeat of ECG signal: (a)- Normal, (b)- With VT Arrhythmia.

ECG signal is a self-similar object; consequently, it must have a fractal dimension (FD) that can be obtained through mathematical methods to distinguish and identify apparently particular states of cardiac disease-related conditions. In the second stage, the fractal dimension values of each ECG segment were calculated using the two algorithms of Higuchi and Petrosian. The values calculated with these algorithms for four segments of normal and with AF, VT, and PSVT arrhythmias ECG signals are shown in Table 2.

The results show that the Higuchi algorithm provides the most accurate estimation of fractal dimension in comparison to other fractal dimension calculation methods. The Petrosian algorithm describes the least dynamic range. On the other hand, findings show that the fractal dimension estimated by the Higuchi algorithm will increase by increasing the window length but in the Petrosian method, any impact of window length increase on the estimated fractal dimension were not seen. Also as it can be seen in Table 2, higuchi's fractal dimension obtained from cardiac signals containing arrhythmia is greater than the value obtained for normal cardiac signals. This can confirm the emergence of more complex behaviours in the cardiac signal due to the occurrence of arrhythmia.

Next, in order to keep the features with an acceptable significance level and remove the features for which the p_value > 0.05, the p_value was obtained by the statistical t_test for all six features (respectively, maximum, minimum, average, and standard deviation for the Lyapunov exponents, petrosian coefficient, and Higuchi coefficient). Figure 5 shows the obtained p-value for each feature.

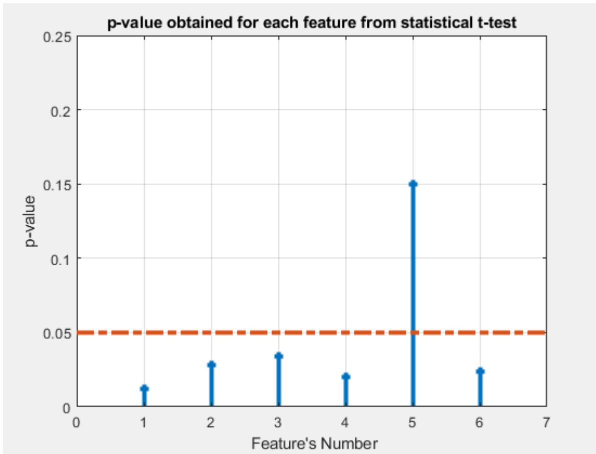


Figure 5. p-value obtained for each chaotic features from statistical t-test.

As Figure 5 shows, $p < 0.05$ was obtained for the features numbers 1, 2, 3, 4, and 6 (i.e. maximum, minimum, average, and standard deviation for the Lyapunov exponents, and Higuchi coefficient); therefore, all these five features are acceptable features from the point of view of t-test statistics. However, for the feature number 5 (i.e. the fractal dimension coefficient with the Petrosian method), the p_value obtained is more than 0.05; therefore, it did not have an acceptable level of significance. This means that this feature is not able to make a good distinction between the classes, and as a result, it is removed in the further processing instructions. In this way, features matrix with 5×1382 dimension was made for 1382 segments of ECG signal by 5 extracted features and was used separately for training of three types of neural networks that were mentioned in section 2-4-1. In this matrix, U_{ij} shows the feature number 'i' of the ECG signal segment number 'j'.

Usually, three indicators of Sensitivity (SE), Specificity (SP) and Accuracy (AC) are used for the evaluation of the classifiers. These indicators are calculated by the following equations [33]:

$$\%SE = \frac{TP}{(TP+FN)}*100 \tag{8}$$

$$\%SP = \frac{TN}{(TN+FP)}*100 \tag{9}$$

$$\%AC = \frac{(TP+TN)}{(TN+FP+FN+TP)}*100 \tag{10}$$

in which, the parameters FP, TP, FN, and TN, respectively, show the number of healthy cases that have been diagnosed false as patient, the number of cases that have been diagnosed true as patient, the number of cases that have been diagnosed false as health, and the number of cases that have been diagnosed true as healthy.

The result of deploying features matrix of non-linear dynamic domain and each classifier of MLP, SVM, and KNN separately, have been depicted in Table 3. The performance of each classifier has been evaluated for 20 times, and the results have been presented as standard deviation ± average (in percentage). As it is shown in Table 3, combining three types of classifiers in this study in comparison to using each one separately could present better results in terms of accuracy, sensitivity, and specificity of the classification.

Since the features of time-frequency domain like wavelet transform features are one of the most common features that have been used so far for classification and diagnosis of cardiac diseases by the researchers in the area of ECG signal processing, in the third stage in order to prove the efficacy of non-linear dynamic domain features, again the time-frequency domain features of ECG signal was extracted and used as the input of each classifier. To this purpose, the coefficients of the Daubechies4 wavelet transform was extracted up to 3 levels of decomposition for each signal segment that we have. This means that ECG signals are decomposed into the details D1–D3, as well as one approximation coefficient A3. These four decomposition are called subbands.

Since 4 features for each segment have been obtained and we have 1382 ECG signals in total, the features matrix with 4 × 1382 dimensions was used as the input once for each classifier individually and once for the combined classifier. Table 4 shows the results for employing the time-frequency features of the ECG signal in the classification of three cardiac arrhythmias and their separation from the normal cardiac rhythm.

By comparing the results shown in Table 3 with those in Table 4, we get that using the non-linear dynamic domain features in comparison to the time-frequency domain, will provide better results in cardiac arrhythmias classification. On the other side, the results in Table 4 confirm that using combination of three different classifiers with the algorithm applied in this study in comparison to using each classifier individually will provide better results in terms of accuracy, sensitivity, and specificity.

Once again, the performance of chaotic features was also compared with time domain features. To extract time domain features, the QRS complex was first revealed by the Pan-Tompkins algorithm [34]. Then a point of the QRS complex was estimated, and by obtaining the maximum absolute value of the signal in each heartbeat, the R wave was extracted from the QRS complex. The intervals between successive R waves are called Heart Rate Variability (HRV) signal, and can be used to extract the time domain features of the ECG signal. In this work, 4 statistical features of HRV signal were extracted as the time domain features of each segment of ECG signals. These 4 statistical features are:

- MNN: the mean of all RR intervals in each segment of the HRV signal,
- SDNN: the standard deviation of all RR intervals in each segment of the HRV signal,
- RMSSD: the root mean square successive difference of intervals in each segment,
- SDSD: the standard deviation of differences between adjacent RR intervals in each segment.

Figure 6 shows a segment of a normal ECG signal along with the HRV signal extracted for it. The values of 4 statistical features obtained from the HRV signal for a segment of a normal ECG signal and a segment of an ECG signal containing AF arrhythmia are shown in Table 5.

Since 4 features for each segment have been obtained and we have 1382 ECG signals in total, the features matrix with 4 × 1382 dimensions was used as the input for the combined classifier. Table 6 shows the results for employing the time-domain features of ECG signal and combined classifier, in the classification of three cardiac arrhythmias and their separation from the normal cardiac rhythm.

Table 1. Statistical parameters calculated for obtained Lyapunov exponents of one segment in 4 ECG signal types.

ECG signal type	Maximum Lyapunov exponents	Minimum Lyapunov exponents	Average of Lyapunov exponents	Standard deviation of Lyapunov exponents
Normal	0.3862	-0.2971	0.1326	0.0914
with AF Arrhythmia	0.5394	-0.0536	0.1839	0.0494
with VT Arrhythmia	0.6192	-0.2379	0.1992	0.0636
with PSVT Arrhythmia	0.7965	0.0273	0.1274	0.0603

Table 2. Fractal dimension values obtained from two algorithms of Higuchi and Petrosian for four different ECG signals.

ECG signal type	Algorithm type of fractal dimesion calculation	Fractal dimesion of segment 1	Fractal dimesion of segment 6	Fractal dimesion of segment 18	Fractal dimesion of segment 24
Normal	Higuchi	0.5373	0.5258	0.5388	0.537
	Petrosian	1.0242	1.0257	1.028	1.0285
with AF Arrhythmia	Higuchi	0.2396	0.2489	0.255	0.2942
	Petrosian	1.0194	1.0202	1.0204	1.0208
with VT Arrhythmia	Higuchi	0.3702	0.4088	0.0981	0.1048
	Petrosian	1.0152	1.0138	1.0146	1.0135
with PSVT Arrhythmia	Higuchi	0.4161	0.395	0.3667	0.3414
	Petrosian	1.0281	1.0292	1.0249	1.0242

Table 3. Classification results using Chaotic features of non-linear dynamic domain and three different classifiers along with combined classifier.

%SE	%SP	%AC	Number of testing data	Classifiers
96.1 ± 0.1	95.8 ± 0.2	95.5 ± 0.4	346	MLP
96.9 ± 0.2	97.1 ± 0.1	96.8 ± 0.3	346	SVM
96.1 ± 0.1	96.2 ± 0.3	95.9 ± 0.1	346	KNN
99.6 ± 0.1	99.3 ± 0.1	99.1 ± 0.2	346	Combination of MLP, SVM, and KNN

Table 4. Results of classification using time-frequency features and three classifiers along with combined classifier.

%SE	%SP	%AC	Number of Testing Data	Classifiers
94.8 ± 0.1	93.9 ± 0.4	94.3 ± 0.2	346	MLP
95.4 ± 0.2	95 ± 0.2	94.9 ± 0.1	346	SVM
95.3 ± 0.3	94.8 ± 0.1	95.1 ± 0.2	346	KNN
96.5 ± 0.1	95.9 ± 0.2	96.3 ± 0.1	346	Combination of MLP, SVM, and KNN

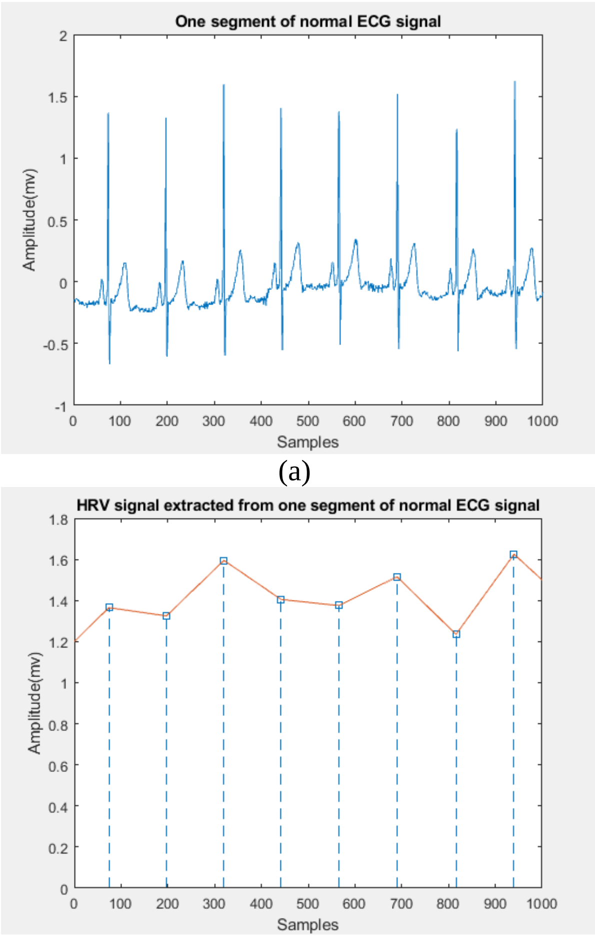
By comparing the results shown in Table 3 with those in Table 6, we get that using the non-linear dynamic domain features in comparison to the time-domain, will provide better results in cardiac arrhythmias classification. Also we found that among the features of three different domains (i.e. chaotic features, time-frequency domain features, and time-domain features), the chaotic and time-domain features, respectively, showed the best and worst results in cardiac arrhythmia classification by combined classifier.

Table 5. Values of 4 statistical features obtained from HRV signal for a segment of a normal ECG signal and a segment of an ECG signal containing AF arrhythmia.

	Normal ECG signal	ECG signal contains AF Arrhuthmia
MNN	52.3750	96.8
SDNN	14.9278	15.5145
RMSSD	123.7209	195.7505
SDSD	1.3801	5.3206

Table 6. Results of classification using time-domain features and combined classifier.

% AC	92.8 ± 0.1
%SP	92.2 ± 0.3
%SE	91.9 ± 0.2



(b)

Figure 6. One segment of normal ECG signal (a) HRV signal extracted for it (b)

4. Conclusion

In this work, an algorithm was presented for the classification of three dangerous cardiac arrhythmias and their separation from the normal cardiac rhythm. This algorithm was designed and implemented on the basis of Lyapunov exponent value extraction and fractal dimension calculation of ECG signal by two algorithms of Higuchi and Petrosian as the chaotic features of signal's non-linear dynamic domain and combination of three classifiers of Multi-Layer Perceptron (MLP), Supportive Vector Machine (SVM), and K-Nearest Neighbour using Behavior Knowledge Space (BKS).

According to the results obtained in the non-linear dynamic domain feature extraction of ECG signal, existence of positive values of Lyapunov exponent confirm the chaotic behaviour occurrence. Also the evaluation results of Higuchi algorithm provides the most accurate results for the fractal dimension of ECG signal. On the other side, Petrosian algorithm is assumed as the simplest and fastest method for the estimation of fractal dimension.

The classification results show that using the normalized non-linear dynamic domain features as the input and using each of the MLP, SVM, and KNN classifiers separately, leads to the cardiac arrhythmias classification with the accuracy of %95.5 ± 0.4, %96.8 ± 0.3, and %95.9 ± 0.1, respectively. When these three classifiers were combined with each other by the BKS algorithm and these chaotic features were used as the input of this combined classifier, the classification was done by the accuracy of %99.1 ± 0.2. This shows that combination of three classifiers comparing to the use of each one separately will lead to better results.

The simulation results also show that using normalized wavelet transform coefficients as the time-frequency domain features and each of MLP, SVM, and KNN classifiers separately leads to the cardiac arrhythmias classification by accuracy of %94.3 ± 0.2, %94.9 ± 0.1, and %95.1 ± 0.2, respectively. This is when using the same features as the input of the combined classifier lead to the accuracy of %96.3 ± 0.1. These results again prove that the combination of three classifiers will lead to more effective performance of classifying algorithm in comparison to when each were used separately.

On the other hand, to prove the efficacy of non-linear dynamic domain features, once, the time-frequency domain features and another time, the time-domain features were extracted for the ECG signals. For this purpose, the wavelet transform coefficients (db4), as the most common features of time-frequency domain of ECG signal, were extracted up to 3 levels of decomposition, and they were normalized, then used as the input for three classifiers as well as the combined classifier. The simulation results showed that when combined classifier with normalized time-frequency features were used, the classification was done with the accuracy of %96.3 ± 0.1. Also 4 statistical parameters of the RR-Intervals that were extracted from HRV signals was applied as the time-domain features of ECG signals. In this case, the classification was done by using combined classifier with the accuracy of %92.8 ± 0.1. This is when using the non-linear dynamic domain features as the input and the combined classifier leads to the accuracy of %99.1 ± 0.2. Hence, we can conclude that the non-linear dynamic domain features like Lyapunov exponent value and fractal dimension not only are able to describe chaotic features (that cannot be observed by any of the time-frequency or time-domain features) in ECG signal but also they can be effectively used as the proper clinical indicators in the field of cardiac arrhythmias classification and their separation from the normal cardiac rhythm. Also comparing the results obtained from using the time-frequency domain and time-domain features showed that the time-frequency features of ECG signals were lead to a better accuracy of classification, and this may be related to the non-stationary nature of biomedical signals.

References

[1] S. Srivasta, and H. Bhardwaj, “ECG Pattern Analysis using Artificial Neural Network,” *SSRG International Journal of Electronics and Communication Engineering (SSRG-IJECE)* , Vol. 7, pp. 1-4, May 2020.

[2] G. Yao, and X. Mao, “Interpretation of Electrocardiogram Heartbeat by CNN and GRU,” *Computational and Mathematical Methods in Medicine*, Vol. **2**, pp. 1-10, 2021.

[3] O. Berenfeld, and J. F. Rodriguez Matas, “Editorial: Atrial Filrillation: Technology for Diagnosis, Monitoring, and traetment,” *Frontiers in Physialogy* , Vol. 13, pp. 1-4, Feb 2022.

[4] W. Schleifer, and K. Sirvathsan, “Ventricular Arrhythmias State of Art,” *Cardiol Clin*, Vol. 31, pp. 595-605, 2012.

[5] N. V. Goonewardane, and Ang S. Kottegoda, “SupperVentricular Tachycardia,” *Journal of Arrhythmia*, Vol. 35, pp. 641-692, 2019.

[6] B. Anuragha, and K. Suresh Kumar, “Classification of cardiac signals using time domain methods,” *ARPN Journal of Engineering and Applied Science*, Vol. 3, pp. 7-12, 2008.

[7] J. Cai, and G. Zhou, “Real-Time Arrhythmia Classification Algorithm using Time-Domain ECG Feature Based on FFNN and CNN,” *Mathematival Problems in Engineering,* Vol. 2021**,** pp. 1-17, 2021.

[8] H. Gothwal, and S. Kedawat, “Cardiac arrhythmia detection in an ECG beat signal using fast Fourier transform and artificial neural network,” *J. Biomedical Science and Engineering*, Vol. 4, pp. 289-296, 2011.

[9] C. H. Lin, “Frequency–domain features for ECG discrimination using gray relational analysis-based classifier,” *Computer & Mathematics with Applications*, Vol. 55, pp. 680-690, 2008.

[10] S. Z. Mahmoodabadi, and A. Ahmadian, “ECG feature extraction using Daubechies wavelets,” *Proceeding of the fifth IASTED international conference on visualization, imaging and image processing., Puerto Vallarta, Mexico.,* IVIP. 2005, pp. 343-348.

[11] Q. Zhao, and L. Zhan, “ECG feature extraction and classification using wavelet transforms and support vector machines,” *International conference on neural networks and brain.,* ICNN&B. 2005, pp. 1086-1092.

[12] B. A. Sabrine, and A. Taoufik, “Arrhythmia Classification Using Fractal Dimensions and Neyral Networks,” *Advances in Intelligent Systems Research,* Vol. 175,pp. 182-187, 2021.

[13] K. Kiani, and F. Maghsoudi, “Classification of 7 Arrhythmias from ECG using Fractal Dimensions,” *J Bioinform Syst Biol*, Vol. 2, pp. 053-065, 2019.

[14] A. Casaleggio, and A. Corana, “Study of the Lyapunov exponents of ECG signals from MIT-BIH database,” *IEEE Conference: Computers in Cardiology., Zaragoza.,* CinC. 1995, pp. 697-800.

[15] O. Gorshkov, and H. Ombao, “Multi-chaotic Analysis of Inter-Beat (R-R) Intervals in Cardiac Signals for Discrimination between Normal and Pathological Classes,” *Entripy*, Vol. 23**,** pp. 1-16, 2021.

[16] R. Esteller, and G. Vachtsevanos, “A comparison of waveform fractal dimension algorithms,” *IEEE Transactions on circuits and systems-I: Fundamental theory and applications*, Vol. 48, pp. 177-183, 2001.

[17] G. Jaiswal, and R. Paul, “Artificial neural network for ECG classification,” *Recent Research in Science and Technology*, Vol. 6, pp. 36-38, 2014.

[18] J. Fornari, and J. Pelaze, “Bundle Branch Blocks Classification via ECG using MLP Neural Networks,” *Foundations and Applications of Intelligent Systems*, Vol. 213, pp. 547-561, 2014.

[19] A. Ebrahimzadeh, and M. Safarnehad, “Classification of ECG signals using Hermite functions and MLP neural networks,” *Journal of AI and Data Mining*, Vol. 4 (1), pp. 55-65, 2016.

[20] A. Sahedin, Ah. Zakernejad, S. Faridi, M. Javadi, and R. Ebrahimpour, “A Trainable Neural Network Ensemble for ECG Beat Classification,” *International Journal of Biomedical and Biological Engineering*, Vol. 4 (9), pp. 479-485. 2010.

[21] M. Engin, and S. Demirag, “Fuzzy-hybrid neural network based ECG beat recognition using three different types of feature sets,” *Cardiovascular Engineering: An International Journal*, Vol. 3 (2), pp. 71-80, 2013.

[22] A. karen, and E. andres, “Classification models for heart disease prediction using feature selection and PCA,” *Informatics in Medicine Unlocked*, Vol. 19, pp. 1-11, 2021.

[23] R. M. Revadas, “Cardiac Arrhythmia Classification using SVM, KNN and NAIVE BAYES Algorythms,” *International Research Journal of Engineering and Technology (IRJET)*, Vol. 5, pp. 3937-3941, May 2021.

[24] V. R. Elgin Christo, H. Khanna Nehemiah, B. Minu, and A. Kannan, "Correlation-based Ensemble Feature Selection using Bioinspired Algorithms and Classification using Back-propagation Neural Network," *Computational and Mathematical Methods in Medicine*, Vol. 7, pp. 1-17, Sep 2019.

[25] N. Kohli, and N. K. Verma, “Arrhythmia classification using SVM with selected features,” *International Journal of Engineering, Science and Technology*, Vol. 3, pp. 122-131, 2011.

[26] L. I. Kuncheva, and J. C. Bezdek, “Decision Templates for Multiple Classifier Fusion: An Experimental Comparison,” *Pattern Recognition,* Vol. 34, pp. 299-314, 2001.

[27] G. B. Moody, and R. G. Mark, “The impact of the MIT-BIH Arrhythmia Database,” *IEEE Engineering in Medicine and Biology Magazine*, Vol. 20**,** pp. 45-50, 2001.

[28] MIT-BIH Arrhythmia PhysioNet, Available: https://www.physionet.org/physiobank/database.

[29] H. D. Abarbanel, and R. Brown, “Lyapunov exponents in chaotic systems: their importance ad their evaluation using observed data,” *International journal of modern physics B,* Vol. 5**,** pp. 1347-1375, 1991.

[30] J. P. Eckmann, and S. O. Kamphorst, “Lyapunov exponents from time series,” *Physical Review A*, Vol. 34, pp. 4971-4979, 1986.

[31] M. Sano, and Y. Sawada, “Measurement of the Lyapunov spectrum from a chaotic time series,” *Physical Review Letters*, Vol. 55, pp. 1082-1085, 1988.

[32] YS. Hung, and CY Suen, “The behavior – knowledge Space method for Combination of Multi Classifiers,” *IEEE Society Conference on Computer Vision and Pattern Recognition., New York.,* CVPR. 1993, pp. 347-387.

[33] I. Kaur, R. Rajini, and A. Marwaha, “ECG Signal Analysis and Arrhythmia Detection Using Wavelet Transform,” *J. Inst. Eng. India Ser. B.,* Vol. 97, pp. 499-507, Dec. 2016.

[34] J. Pan, and W. J. Tompkins, “A real time QRS detection algorithm,” *IEEE Transaction on Biomedical Engineering.,* Vol. 32, pp. 230-236, 1985.

تشخیص آریتمی قلبی توسط یک الگوریتم خوشمند با استفاده از ویژگی‌های آشوبگونه سیگنال الکتروکاردیوگرام و طبقه‌بند ترکیبی

الهام زارعی، نسیم بریمانی و گلایول نظری گلپایگانی*

گروه مهندسی برق، واحد یادگار امام خمینی (ره) شهرری، دانشگاه آزاد اسلامی، تهران، ایران.

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چکیده:

آریتمی‌های قلبی از خطرناکترین بیماری‌های قلبی هستند. لذا بکارگیری یک الگوریتم هوشمند برای تشخیص این بیماری می‌تواند منجر به کاهش زمان مورد نیاز و همچنین کاهش خطای احتمالی پزشک در تشخیص شود. هدف از این مطالعه، ارائه یک الگوریتم هوشمند برای جداسازی سه نوع آریتمی قلبی از ریتم نرمال قلب با استفاده از ویژگی‌های آشوبگونه سیگنال الکتروکاردیوگرام و ترکیب سه نوع از رایجترین طبقه‌بندها در این حوزه است. برای این منظور ابتدا سیگنالهای الکتروکاردیوگرام مربوط به سه نوع آریتمی فیبریلاسیون دهلیزی، تاکی‌کاردی بطنی و تاکی‌کاردی حمله‌ایی فوق بطنی و همچنین سیگنال قلبی نرمال از پایگاه داده MIT-BIH جمع‌آوری می‌شود. سپس با محاسبه نمایی لیاپانوف و بعدفرکتال سیگنالهای جمع‌آوری شده، ویژگیهای آشوبگونه ایی که بیانگر دینامیک غیرخطی موجود در سیگنال الکتروکاردیوگرام هستند، استخراج می‌شود. در نهایت با ترکیب سه نوع طبقه‌بند شبکه عصبی پرسپترون چند لایه، شبکه ماشین بردار پشتیبان و شبکه k تا نزدیکترین همسایه توسط الگوریتم ماشین‌شورایی، عمل طبقه‌بندی انجام می‌شود. برای اثبات کارآیی ویژگی‌های آشوبگونه، بار دیگر عمل طبقه‌بندی با استخراج ویژگی‌های حوزه زمان- فرکانس و ویژگی‌های حوزه زمان، انجام شده و نتایج، با آنچه با بکارگیری ویژگی‌های آشوبگونه بدست آمده، مقایسه می‌شود. نتایج شبیه‌سازی نشان داد با بکارگیری ویژگی‌های آشوبگونه و طبقه‌بند ترکیبی می‌توان طبقه‌بندی آریتمی‌های قلبی را با دقت $0.2 \pm 99.1\%$ و حساسیت $0.1 \pm 99.6\%$ و میزان اختصاصی بودن $0.1 \pm 99.3\%$ انجام داد.

کلمات کلیدی: نمایی لیاپانوف، بعد فرکتال، شبکه عصبی پرسپترون چندلایه، شبکه ماشین بردار پشتیبان، سیگنال الکتروکاردیوگرام.