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Analysis and Classification of Arrhythmia using ECG signals

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Abstract: In medical practices, the ECG plays an important role in diagnosing cardiac arrhythmia. In this paper, a novel method for classification of various types of arrhythmia using morphological and dynamic features is presented. Discrete wavelet transform (DWT) is applied on each heart beat to obtain the morphological features. It provides better time and frequency resolution of the electrocardiogram (ECG) signal. A survey of ECG classification into arrhythmia types is presented in this paper. Early and accurate detection of arrhythmia types is important in detecting heart diseases and finding treatment of a patient. The main purpose of this paper is to design an efficient neural network and also to implement reliable techniques for the classification of various ECG arrhythmia conditions. The obtained accuracy level of arrhythmia detection is 98%, which is the highest rate of performance. The presented approach by GSNN to classify and predict arrhythmia will provide efficient arrhythmia detection as compared to other techniques. The suggested scheme will improve the prediction and classification efficiency.

INTRODUCTION

All over the world at every second there is one death due to the heart attack. Heart illnesses, hypertension and other heart diseases are the main medical issues of the patient and it becoming global problem of human life. This problem can be arises due to the unhealthy life style of people. To design the effective heart monitoring system is the active current research area. There are various devices and application have been proposed for monitoring, recording the heart beats and also to diagnose the heart problems. We are use electrocardiogram (ECG) or the electroencephalograms (EEG) are widely employed for monitoring the health of the patients on the real-time. ECG is a one-dimensional signal that records the electrical activity of the heart, which changes from time-to-time and person-to-person. The ECG signal is enriched with the information of the heart and the cardiovascular system . A single heartbeat comprises of the QRS complex, P wave, and T wave in which each of them denotes a specific task. The P wave indicates the atrial depolarization, QRS complex represents the ventricular depolarization, and the T wave denotes the ventricular repolarization. For the diagnosis of arrhythmia, ECG provides the valuable information including the time interval and the measure of the electrical activity. The time interval pictures the duration of the electrical signal passing through the heart such that one can identify the heartbeat as normal or slow, fast or irregular. The measure of the electrical conductivity ensures the identification of the too large or the overworked parts of the heart . Therefore, a physician can diagnose the arrhythmia using the long-term ECG data recorded with the help of the ECG recording system. The main intention of this work is to perform the accurate classification of the ECG signal in the record to identify the signal as arrhythmia or not to enable the perfect diagnosis by the cardiologist. The proposed method saves time in performing the effective classification. Normally, the shape and the duration of the signal define the scenario of the heart, but errors may occur in case of small variations in the ECG signal when compared to the original signal. Initially, the ECG signal is subjected to feature extraction such that the wave components are identified using the multi-resolution wavelet-based approach. Machine learning technique is implemented and used MIT/BIH data sets to classify the normal and abnormal ECG signals. The classification of ECG signal depends on the characteristics of ECG pattern extraction and the complexity of classification techniques. For efficient result of classification the Support Vector Neural Network (SVNN) is design which is able to classify the ECG signal. The classification is carried out using the SVNN that is trained using the GB algorithm,and the classification is based on the extracted features of the ECG signal. The GB-SVNN is the proposed method of performing the Arrhythmia classification in which the GB optimization algorithm enables the optimal selection of the weights. The contribution of the paper: The GB algorithm is the proposed algorithm formed by the integration of the Genetic algorithm and Bat optimization algorithm for determining the optimal weights for training the SVNN in classifying the arrhythmia classification.

Basic of ECG :

The ECG is a medical diagnostic instrument used to determine the electrical signals and function of the heart rhythms [2]. It is also used for the better understanding the patient state. The ECG signal contain the various beats such as P-Beat, T-Beat, QRS complex and RR interval as shown in Fig. 1. The normal ECG signal of any patient maintain all the parameter of beats such as shape of signal, time interval between the beats, QRS complex and RR interval respectively. Any change in the signal shows the abnormality in functioning of heart. Any abnormality of heart is known as cardiac arrhythmia. Various kinds of ECG system are available for interpretation of arrhythmia; some are based on computer based system in which various machine learning and neural network techniques are applied.

Classification of ECG:

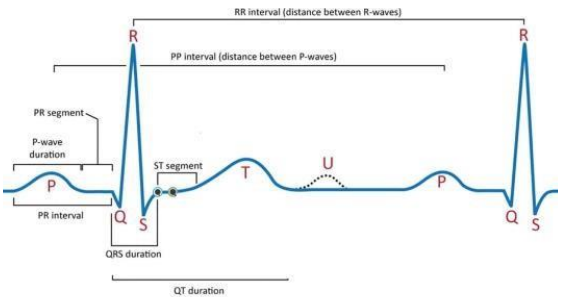
The neural network contains the large number of neurons which are connected to each other to transfer and receives the data simultaneously. Each neuron in the network assigns the weight that represents the state of network and during the learning process each neurons weight must be updated. The proposed model of neural network has fully connected hidden layers for extracting the feature and classifies the arrhythmia abnormalities. We used the general sparsed neural network (GSNN) to decrease the features and reduce the computational time. The feature extraction has different descriptive parameter and data by principle component analysis from the ECG signals. The GSNN is trained and classified based on the feature vectors. In the final result analysis stage used all the MIT-BIH dataset to maintain the effectiveness of the proposed framework. This defines the modules that should be regarded as the design for cost forecasting of a strong neural network model. A commonplace counterfeit neuron as well as the demonstrating of a multi-stage neuron system was represented in Fig. 2. The sign stream from sources of info B1,…, Bn are viewed as unidirectional, shown by bolts to the neuron's yield sign stream (O). The O input for neuron output is provided as:

$$O = f(net) = f\left(\sum_{i=1}^{n} A_i B_i\right)$$

where Ai , Bi are the weight vector and the capacity is f(net) .

Problem statement:

Arrhythmia is a cardiac condition generated by the abnormal electrical activity of the heart, and an electrocardiogram (ECG) is a tool utilized by the cardiologists for determining the arrhythmias or heart abnormalities. Owing to the existence of noise, the non-stationary nature of the ECG signal and the abnormality of the heartbeat, physicians face difficulties in the diagnosis of arrhythmias. Hence, there is a need for computer-aided diagnosis system which can achieve higher recognition accuracy. The arrhythmia classification for detecting the presence or absence of the arrhythmia is based on the analysis of the ECG signal that contains the QRS complex, P wave, and T wave. The shape and duration of the waves, such as PP interval, PR interval, RR interval, QT interval and R peak determine the degree of the problem in the heart and enables in providing the sufficient condition for the diagnosis of the heart diseases. The deformities in the heart rate and the shape of the ECG signal from the normal ECG determines the presence or absence of the arrhythmia. During the classification of the ECG signal by the cardiologist, the errors appear in the classification due to the considerable change in the ECG signals. The duration and the shape of the pure ECG signal.

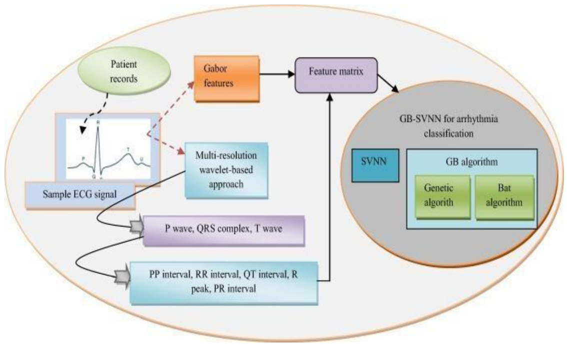


Arrhythmia GB-SVNN: Proposed GB enabled support vector neural network for classification:

The arrhythmia classification gains remarkable importance as the World Health Organization (WHO) reports the death toll of cardiac failures as 17.3 making the available cardiac therapies unsatisfactory and useless specifically, for the aged people suffering from the cardiac diseases. To solve the problem of accurate classification, the classification strategy proposed in this paper is based on the Support Vector Neural Network (SVNN) that performs the supervised classification based on an algorithm (GB) - Genetic algorithm (GA) and Bat algorithm. The proposed method reduces the classification errors for which classification is performed based on the features of the ECG signal that serve as the best solution. The proposed GB-SVNN method of arrhythmia classification is depicted in , and it uses the features of the ECG signal to differentiate the normal signal from the abnormal signal. The main step is the feature extraction that utilizes the PP interval, PR interval, RR interval, QT interval and R peak in the ECG signal along with the other features, such as mean, variance, energy, entropy, standard deviation, skewness, and kurtosis. The GD algorithm trains the SVNN based on the features such that the presence of abnormality is detected. Let us represent the patient records that carry the ECG signal of the individual patients. The patient records are represented as,

$$p=\{p_1,p_2,\ldots,p_k,\ldots,p_n\} \qquad (1)$$

where , n refers to the total number of patients' found in the record. The ECG signal of the k^{th} patient p_k is indicated as E^k . $_{1xu}$



Block diagram of the arrhythmia classification using GB-SVNN.

Results :

This section presents the experimental analysis of the proposed method along with the performance analysis to provide the deep insight of the proposed GB-SVNN. The comparative analysis proves the superiority of the method.

Experimental setup :

The proposed method is implemented in the MATLAB 2015.a environment with the personal computer that operates using 2 GB RAM, Intel core processor, Windows 10 Operating System.

Dataset description :

The dataset used for the analysis and the classification is the MIT-BIH Arrhythmia Database (Moody and Mark, 2001) and The MIT-BIH Normal Sinus Rhythm Database (Goldberger et al., 2000). The MIT-BIH Normal Sinus Rhythm Database (Goldberger et al., 2000) consists of the 18 long-term ECG recordings of the people obtained from the Arrhythmia Laboratory at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). The people considered in the database include 5 men and 13 women aged between 26–45 and 20–50 respectively.

The MIT-BIH Arrhythmia Database (Moody and Mark, 2001) taken from the Boston's Beth Israel Hospital possess the 48 halfhour excerpts of two-channel ambulatory ECG recordings of the 47 persons of the year 1975 and 1979, and the reports are digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range.

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings are chosen at random from a set of 4000 24-h ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be wellrepresented in a small random sample. In our experiment, 18 normal and 48 abnormal files are utilized. In each signal file, normal and arrhythmia beats are utilized.

Competing methods :

The methods taken for comparison includes the KNN, NN (Mitra and Samanta, 2013), Fuzzy Subtractive Clustering (Homaeinezhad et al., 2011), SVNN (Kohli et al., 2010) that enables to prove the effectiveness of the proposed GB-SVNN.

Performance metrics:

Accuracy :

It is the measure of correctness of the detection,

$$\text{Accuracy} = \frac{TN+TP}{TN+TP+FN+FP}$$

where, TP is true positive, TN is a true negative, FN is false negative and FP is false positive.

Sensitivity :

Sensitivity denotes the sharply identified true positives and is given as,

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

Specificity :

The exact true negatives are provided by the specificity and is formulated as,

$$\text{Specificity} = \frac{TN}{TN+FP}$$

Performance analysis based on population size :

The experimentation is performed by considering the 18 normal and 48 arrhythmia classes taken from the MIT-BIH Arrhythmia Database by varying the training percentage of the data from 40 to 80. Initially, 40% of both normal (7 signal files) and abnormal beats (19 signal files) are taken for training and 60% of the both normal (11 signal files) and abnormal beats (29 signal files) are taken for testing. Similarly, for 50%, 60%, 70%, and 80% of the training data, the experimentation is carried out. In this section, the performance analysis using the biomedical + GB-SVNN, statistical + SVNN, and hybrid + GB-SVNN based on the population size 700. For the analysis, three types of the signals are considered including the biomedical, statistical, and the hybrid signals. The rate of accuracy using the biomedical signal is obtained as 0.9519 for 40% of the training data, 0.69 while using statistical signal, and 0.75 while using the hybrid signal that comprises of both the biomedical and the statistical signals. With the increase in the training data, the accuracy of the proposed method using the biomedical, statistical and the hybrid signal is found to increase. Finally, when the training data is 80%, the rate of the accuracy using the biomedical signal, statistical signal, and the hybrid signal is found as 0.9652, 0.9457, and 0.975 respectively. It is concluded that the accuracy of classification using the hybrid signal seems to be higher.

The rate of sensitivity using the biomedical signal is obtained as 0.98 for 40% of the training data, 0.6305 while using statistical signal, and 0.81 while using the hybrid signal that comprises of both the biomedical and the statistical signals. With the increase in the training data, the sensitivity of the proposed method using the biomedical, statistical and the hybrid signal is found to increase. Finally, when the training data is 80%, the rate of the sensitivity using the biomedical signal, statistical signal, and the hybrid signal is found as 0.98, 0.97, and 0.99 respectively. It is concluded that the sensitivity of classification using the biomedical signal hybrid to be higher.

The rate of specificity using the biomedical signal is obtained as 0.9284 for 40% of the training data, 0.9189 while using statistical signal, and 0.7168 while using the hybrid signal that comprises of both the biomedical and the statistical signals. With the increase in the training data, the specificity of the proposed method using the biomedical, statistical and the hybrid signal is found to increase. Finally, when the training data is 80%, the rate of the specificity using the biomedical signal, statistical signal, and the hybrid signal is found as 0.9462, 0.9365, and 0.9558 respectively. It is concluded that the specificity of classification using the hybrid signal seems to be higher.

Discussion :

This section presents the comparative analysis of the proposed GB-SVNN method and the existing methods, such as KNN, NN, Fuzzy Subtractive clustering, SVNN based on the performance metrics. The proposed algorithm is simple, flexible, and easy to implement with the ability to solve the nonlinear problems and possess less convergence time.

Comparative analysis based on the performance metrics:

The comparative analysis based on the performance metrics, such as accuracy, sensitivity, and specificity. When the percentage of the training data is 50, the rate of accuracy of the methods KNN, NN, Fuzzy Subtractive clustering, SVNN, and GBSVNN are 0.6842, 0.5, 0.5, 0.7142, and 0.6428 respectively. The accuracy is found to increase with the increase in the training percentage, and this increase is noted for all the methods. However, the proposed GB-SVNN acquires a greater rate of the accuracy. For 90% of the training data, the accuracy rate of the methods, like the KNN, NN, Fuzzy Subtractive clustering, SVNN, and the proposed GB-SVNN are 0.8787, 0.7857, 0.8787, 0.7368, and 0.9696 respectively proving that the proposed GB-SVNN as the effective method of performing arrhythmia classification. The proposed method possesses the capacity to generate more number of solutions so that highly accurate solutions can be determined.

When the percentage of the training data is 50, the rate of the sensitivity of the methods KNN, NN, Fuzzy Subtractive clustering, SVNN, and GB-SVNN are 0.6175, 0.624, 0.97, 0.637, and 0.6435 respectively. The sensitivity is found to increase with the increase in the training percentage, and this increase is noted for all the methods. Even though the proposed GB-SVNN acquires a lower rate of the sensitivity for 50% of the training data, when compared with the fuzzy subtractive clustering, the sensitivity increases for the increase in the training data and is greater when compared with the fuzzy subtractive clustering. For 90% of the training data, the sensitivity rate of the methods, like the KNN, NN, Fuzzy Subtractive clustering, SVNN, and the proposed GB-SVNN are 0.95, 0.96, 0.97, 0.637, and 0.99 respectively proving that the proposed GB-SVNN as the effective method of performing arrhythmia classification. The proposed algorithm determines the high-quality optimal weights for training the SVNN in performing the optimal classification of the arrhythmia. When the percentage of the training data is 50, the rate of specificity of the methods KNN, NN, Fuzzy Subtractive clustering, SVNN, and GB-SVNN are 0.6, 0.6, 0.5, 0.9, and 0.8 respectively. The specificity is found to increase with the increase in the training percent age, and this increase is noted for all the methods. For the training data as 0.8, the value of the specificity acquired by the proposed GB-SVNN is 0.9473 whereas for the methods, like the KNN, NN, Fuzzy Subtractive clustering, and the SVNN is 0.8947, 0.7142, 0.7894, and 0.9 respectively proving that the proposed method attains a greater specificity. For 90% of the training data, the specificity rate of the methods, like the KNN, NN, Fuzzy Subtractive clustering, SVNN, and the proposed GB-SVNN are 0.9166, 0.875, 0.8333, 0.9, and 0.9583 respectively proving that the proposed GB-SVNN as the effective method of performing arrhythmia classification. The proposed method combines the advantages of both genetic and bat algorithms. The GB optimization algorithm is more advantageous as it possesses the capability of the automatic zooming into the areas where the best solution could be located with the automatic convergence of the best solution and determines the global optimal solution with high-quality.

LITERATURE SURVEY

The ECG plays an important role in diagnosing cardiac arrhythmia. In this paper efficient and most reliable technique is mentioned for the suitable classification of arrhythmia using a general sparsed neural network (GSNN) [2]. The ECG is a medical diagnostic instrument used to determine the electrical signals and function of the heart rhythms [4]. ECG data recorded with the help of the ECG recording system. The morphology of the ECG waveform is interpreted for deciding the heartbeat as the normal sinus rhythm or to the class of arrhythmia [1].The various methods have been developed based on the machine learning approach for intelligent classification model for heart arrhythmia detection. The recent advancement in ECG arrhythmia detection has been proposed using the convolutional neural network techniques [5, 6] and deep neural network [8, 11]. The various researchers have been proposed different methods to various data sets like MIT BIH and obtained enhanced accuracy level in result. Other recent studies proposed a hybrid model based on the various machine learning techniques for classifying the ECG signals in 16 different classes of arrhythmia [12]. heart monitoring system plays vital role to diagnosis the heart arrhythmias problems. In this paper, we developed a model for identify the different heart arrhythmias abnormalities[2]. An approach for heartbeat classification with dynamic rejection thresholds was proposed using QRS morphology, frequency information, AC power of QRS detail coefficients, and RR intervals as features to represent ECG beats [13].Proposed a dictionary learning algorithm for VQ feature extraction in ECG beats classification that utilizes the k-means clustering determined optimally using the k-means++ for developing the dictionaries. The main advantage of the method is that the interference of the dirty data was rejected and the dimension was reduced. Here, the computational burden was greater than the k-means clustering [6]. Utilized a convolutional neural network (CNN) for heartbeat classification. This method improved the efficiency of work for the doctors and reduced the computing cost in the hospital. The major shortcoming is regarding the poor performance of the classification model when accessed practically [8]. The echo state network model was used as classifier of heartbeats and ECG records the two classes using the morphology and uses the extreme learning machine approach, whereas a model based on deep convolutional neural network is proposed for classification of heart signals [2].

CONCLUSION

The proposed method of arrhythmia classification using the GB-SVNN is presented in the paper that uses the GB optimization algorithm to train the SVNN such that the classification by the proposed algorithm is highly accurate. The main source to detect the presence or the absence of the arrhythmia is done by the use of the ECG signal for which the P wave, QRS complex, and the T wave are generated from the required ECG signal. Once the waves are generated, the time interval between the wave, namely the PP interval, PR interval, RR interval, R peak, and the QT interval are determined such these features are used to represent the feature matrix. Along with the time duration of the waves, the Gabor features are used. These features are used in classifying the ECG signal to detect the presence/absence of arrhythmia through the SVNN trained by the GB optimization algorithm. The proposed method overcomes the issues of the existing method through the wider contribution in providing a better-supervised performance.

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