Classification of Atrial Fibrillation Using Stacked Auto Encoders Neural Networks

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Abstract

In this paper, a combination of deep learning method called stacked auto encoder with the aim of classifying atrial fibrillation (AF) is utilized. An electrocardiogram (ECG) signals from MIT-BIH database are used and spectral, time and non-linear features are extracted from this signal. First extracted features were evaluated using statistical test, analysis of variance (ANOVA) and selected significant features then used for stacked auto encoder as parallel form to classify AF and normal samples. Then, final decision performed using the ensemble averaging method. The average accuracy for classifying AF and normal samples were 95.5%.

Key words: electrocardiogram, atrial fibrillation, stacked auto encoder, non- linear features

1. Introduction

Nowadays the most important reason of death in cardiac patients is cardiac arrhythmia while the current evidences proved that the extraction of information from HRV signals with the aim of detecting and predicting this arrhythmia is possible [1]. Suitable prediction of this arrhythmia leads to preventing it and as a result the necessary actions could be done [2]. Since the VF is the main result of this arrhythmia the thirty-second precognition of VF results in doing indispensable tasks with the purpose of curing it [3]. One of the most important cases of VF is the VT before that and as a result detection of VT leads to detecting VF [4]. In this study another arrhythmia called AF is utilized with the purpose of increasing accuracy. In a study in [1] time-frequency, nonlinear features and the combination of genetic algorithm and neural network are used with the aim of detecting VF and 96.96% accuracy is achieved. In another study in [3] for the prediction emotions in 40 different classes parallel auto encoder technique in a stack manner is utilized and finally high results of separation in emotions are achieved.

2. Data Base

The data base used in this paper are extracted from a general spontaneous Ventricular Tachycardia data base and also a data base related to a competition in 2001 with the purpose of prediction of occurring PAF, which are available in PhysioNet. The prevt data includes 106 records of patients and also prevf data includes 29 records of patients and preAF data are related to 50 records. Moreover, 50 data of healthy human beings are utilized. These data are converted to some signals based upon a set of 1 minute periods, which are exactly occurred 1 minute before happening arrhythmia. The HRV patterns in cardiac preAF signals are derived using Pan & Tamkoins algorithm. Furthermore, features utilized are as follows:

Time-dependent features including (mean_rr,std_rr,nn50,pnn50,tinn) and frequency-dependent features including (vf,hf,vlf), which are indispensable* for creating a matrix with the dimension of 8*235.

3. Collective Deep Learning Model for Identification of Cardiac Arrhythmia

One of the simple tools for learning features with capability to separate high is Auto encoder method. An auto encoder is a type of artificial neural network used to learn efficient data codings in an unsupervised manner. Suppose that training cardiac data are as follows:

$$X = \{x_1,\ x_2, \ldots x_n\}$$

The aim is to representation of input data, which is

Computing in Cardiology 2018; Vol 45 Page 1 ISSN: 2325-887X DOI: 10.22489/CinC.2018.011

performed using optimization of the following formula:

$$\sum_{i=1}^{n} x_i - \delta\left(W_2\left(W_1 x_i\right)\right)^2$$

(1)

Where W_1 and W_2 are the weights of input layer to hidden layer and hidden layer to output layer. Moreover, δ is the activity function of the neural network. This formula using a descending gradient and like neural network is optimized. Also, we equalize the optimization direction of this input-output formula of network. An overview of an auto encoder is shown in Figure 1. In other words, an auto encoder tries to learn an identity function in such a way the inputs of neural network mapped to themselves. After the training of the network is completed, the output of hidden layer is considered as the representation of input data. In other words, whenever an auto encoder is utilized then the last layer is removed and also each input data is mapped to output of hidden layers. As a result of this X is considered as the input data and is represented as follows:

$$X \approx \partial(W_1 X) \qquad (2)$$

An overview of learned features are shown in Figure 2.

3.1. Neural Network with Sparse Auto encoder

If the dimension or the number of neurons in hidden layer were considered bigger than the input layer and also some restrictions on neurons in hidden layer were considered, then representation of input data would be more interesting. Researchers have always wanted to represent sparse coding of data, which this representation can increase generality and also can enhance discrimination ability of features. Consequently, selecting high number of neurons in hidden layer and changing target function of auto encoder in such a way that forces the hidden layer to active few percent of it neurons leads to achieving sparse representation input data and spare representation input data. Instead of using typical formula for gradient $J(w.b)$ the following formula with some addition is utilized:

$$J_{sparse}(w.b) = J(w.b) + \beta \sum_{j=1}^{s} KL(\rho \parallel \rho_j^{'}) \qquad (3)$$

Where β is the rate of penalty for sparseness and s is the number of neurons in hidden layer. ρ and $\rho_j^{'}$ are the rate of sparseness and average activity of neurons in jth layer. Moreover, the KL is calculated as follows:

$$KL(\rho \parallel \rho_j^{'}) = \rho.\log\frac{\rho}{\rho_j^{'}} + (1-\rho).\log\frac{1-\rho}{1-\rho_j^{'}} \qquad (4)$$

3.2. Neural Network with Stack Auto encoder

Deepening of auto encoder or in other words the addition of number of hidden layers results in increasing the discrimination capability of learned features in such a way that it is said that neurons in first layer can learn time-frequency features separately from cardiac signal. Moreover, neurons in second layer can learn a combination of time-frequency features. If the network deepens appropriately, it will expect that in last layers signals can detect with more separation and classification. It should be mentioned that auto encoder of neurons in each layer are connected to neurons in the next layer, which can be concluded that the number of weights or the learned parameters are very high. As a result, training of weights in network should be performed layer wisely i.e. at the beginning all the raw data are feeding to an auto encoder with a hidden layer. Whenever the network is trained completely, then all the trained data with learned features are represented and this new representation are fed to a typical auto encoder with the purpose of learning in second hidden layer in stack auto encoder . This process is repeated so that the network is deepened suitably. In Figure 2 an example of learning in weights of two-layer network is depicted. In this section the mentioned features are fed to auto encoder input. Using two auto encoder in

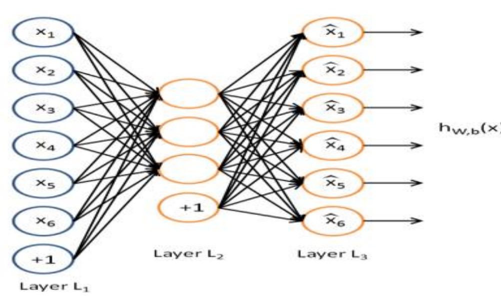

Figure 1: An overview of an auto encoder

subsequent manner 91.4% accuracy is achieved (Figure 3). Moreover, changing the number of hidden layer of network could not cause an obvious difference.

4. Conclusion

In this paper, a combination of deep learning method called stacked auto encoder with the purpose of classifying atrial fibrillation (AF) is utilized. An electrocardiogram (ECG) signals from MIT-BIH database are considered and spectral, time and non-linear features are extracted. First extracted features were evaluated using statistical test, analysis of variance (ANOVA) and selected significant features then used for stacked auto encoder as parallel form to classify AF and normal samples. Final decision performed using the ensemble averaging method. The average accuracy for classifying AF and normal samples were 93.6%. The simulation results depicted the effectiveness of the proposed method.

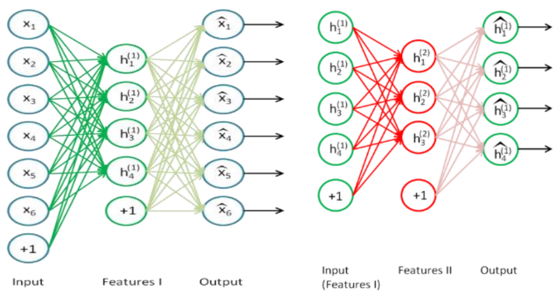

Figure 2: An example of learning in two-layer network

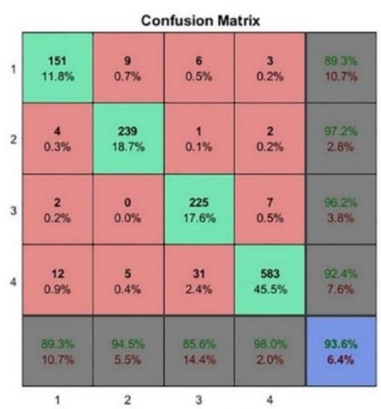

Figure 3: Confusion Matrix for 4 classes of arrhythmia

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