Designing of the Artificial Neural Network Model Trained by Using the Different Learning Algorithms to Classify the Electrocardiographic Signals

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Abstract

An artificial neural network model trained by using various learning algorithms is designed to classify the electrocardiographic signals in this study. The model of artificial neural network is constructed on the structure consisting of a multilayered perceptron based on the feed forward back propagation. A data pool is built by using a dataset consists of 66 electrocardiographic data's taken from the MIT BIH arrhythmia database to perform the training and testing processes of artificial neural network model. The training process of artificial neural network model is performed with 46 electrocardiographic data and then the accuracy of the model is tested via 20 electrocardiographic data. The artificial neural network is trained by 3 different learning algorithms to achieve a robust model. The performance of the learning algorithms used for training the model of the artificial neural network is evaluated according to percentage error. It illustrates that the artificial neural network model trained by Levenberg–Marquardt learning algorithm obtains the better classification result than other learning algorithms. The proposed artificial neural network model can be successfully used to classify the electrocardiographic signals.

Keywords: Artificial neural networks, Electrocardiographic signal, Classification, Learning algorithms.

Elektrokardiyografik Sinyallerin Sınıflandırılması İçin Farklı Öğrenme Algoritmaları Kullanılarak Eğitilmiş Yapay Sinir Ağı Modelinin Tasarlanması

Bu çalışmada elektrokardiyografik sinyalleri sınıflandırmak için çeşitli öğrenme algoritmaları kullanılarak eğitilmiş bir yapay sinir ağı modeli tasarlanmıştır. Yapay sinir ağı modeli, ileri beslemeli geri yayılıma dayalı çok katmanlı bir algılayıcıdan oluşan yapı üzerine kurulmuştur. Yapay sinir ağı modelinde kullanılmak üzere 66 elektrokardiyografik veri kullanılmıştır. Yapay sinir ağı modelinin eğitim süreci 46 adet elektrokardiyografik veri ile gerçekleştirilmekte ve ardından 20 adet elektrokardiyografik veri ile modelin doğruluğu test edilmektedir. Yapay sinir ağı, sağlam bir model elde etmek için 3 farklı öğrenme algoritması ile eğitilmiştir. Yapay sinir ağı modelinin eğitiminde kullanılan öğrenme algoritmalarının performansı hata yüzdesine göre değerlendirilmiştir. Levenberg–Marquardt öğrenme algoritması ile eğitilen yapay sinir ağı modelinin diğer öğrenme algoritmalarına göre daha iyi sınıflandırma sonucu elde ettiğini göstermektedir. Önerilen yapay sinir ağı modeli, elektrokardiyografik sinyalleri sınıflandırmak için başarıyla kullanılabilir.

Anahtar Kelimeler: Yapay sinir ağı, Elektrokardiyografik sinyal, Sınıflandırma, Öğrenme algoritmaları.

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1. Introduction

The aim of the medical signal processing is to obtain medical information consisting of the important data for diagnosis by processing the pure biological signals. The obtained signals can be evaluated, clustered or classified. These classification processes can be used as a decision support system in the medical. In the literature, there are the studies with the classification of ECG signals (Dokur & Olmez 1999, Niwas et al. 2005, Ceylan & Ozbay 2009, Ceylan et al. 2009, Dogan & Korurek. 2009, Kutlu et al. 2009, Dokur 1999, Engin &Kuyucuoglu 2003). In order to generate the datasets used in previous studies, the morphological properties of the ECG data are generally used. In (Dokur 1999), The feature extraction is carried out by applying the discrete Fourier Transform (DFT) and Wavelet Transform (WT) to ECG signal and genetic algorithm and neural networks are used in the classification process of these signals. In another work, the features of ECG signal are obtained by using the wavelet entropy. In the classification step, the statistical method and artificial neural networks are utilized.

In this study, an artificial neural network (ANN) model trained by using various learning algorithms is presented for classifying the ECG signals. An ANN model is trained by using algorithms such as Levenberg–Marquardt (LM), Scaled Conjugate Gradient (SCG), Polak-Ribiére Conjugate Gradient (CGP) etc. the eight learning algorithms are compared against each other in term percentage error and then a benchmark is presented. It is seen that LM becomes prominent as compared to each other for our particular problem. Additionally, the proposed ANN model can be successfully used to classify the ECG signals.

2. Material and Method

The aim of this article is to predict the electrocardiographic signal data using different learning techniques by using the multilayer structure based on feedforward backpropagation on the artificial neural network model. This section consists of two main topics. First, the structure and feature extraction of the electrocardiographic signal data were performed. Then, the data was trained on the artificial neural network model and the classification process was estimated.

2.1. The Structure of Ecg Sıgnal

The heart is an important part of the circulatory system in the human body. The small potential values produced by the sinus coronary in the right atrium are taken via the electrodes placed on the breast, arms and legs by using the conductive property of the body. The small potential values are amplified and then printed on the paper. In addition, it is recorded in the memory of the computer systems. The processes of the recording and viewing are called of the electrocardiogram and the device which is performed this process is given the name of the electrocardiograph. In the ECG signal, there is the variation information of the heart electrical potential in terms of the direction, amplitude and time of the signal. The electrocardiogram is the identifying of heartbeat arrhythmia and it is a very important area in the biomedical signal processing. A normal ECG signal is shown in Fig.1. In the ECG signal, there are the waves of named *P*, *Q*, *R*, *S*, *T* and the intervals called of *P–R, QRS*, *S–T*, *QT*, *RR*.

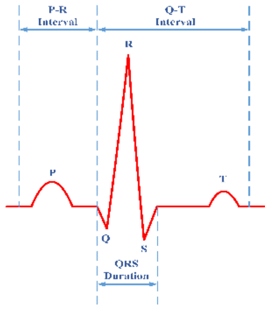

Figure.1. The normal electrocardiographic signal

R point at ECG signal is identified by using the Pan–Tompkins algorithm. The Pan-Tompking algorithm occurs from five steps:band pass filter, differentiator, squarereceptor, sliding window integration, threshold adjustment (Pingale & Daimiwal 2014).

P wave: The first part of this wave is created by the right atrium depolarization of the heart and the second part is also formed by the left atrium depolarization. The width of the *P wave* is smaller than 0.11 second (Ilerigelen & Mutlu 2006).

P–R interval: The interval of the *PR* is obtained by measuring the time of the between the beginning of the *P* wave with the initial of *QRS* duration. This time interval value of adults is normally the between 0.12 and 20 second (Ilerigelen & Mutlu 2006).

QRS duration: *Q* wave represents the first negative wave after *P* wave. In addition, *R* indicates the first positive wave. *S* wave expresses the negative wave existed after *R* wave and it is smaller than 0.04 second. Further, it cannot exceed 25% of total *QRS* time. The time of *QRS* is a maximum of 0.11 second (Ilerigelen & Mutlu 2006).

S–T segment: *ST* segment is called of the range that joints the beginning of the *T* wave with the end of the *QRS* complex. The time of *ST* segment is inversely proportional with the velocity of the heart. The time of *ST* segment is inversely proportional with the velocity of the heart and the value of *ST* can be between 0 and 0.15 second (Ilerigelen & Mutlu 2006).

T wave: *T* wave is the results of ventricular repolarization. The time value of *T* wave for the adults is between of 0.10 and 0.25 second.

RR interval: *RR* interval is the range of between two *R* points.

QT interval: *QT* is calculated by measurement of the time until the end of *T* wave from the beginning of the *QRS* complex. The upper boundary value of the QT interval is 0.44

2.2. Artificial Neural Networks Structure

Artificial neural network (ANN) is developed by getting inspired from the mechanism of the biological neurons, and it is a computation model achieved very high accuracy in computation processes. The network structure of ANN consists of a group artificial neurons that handle info over interconnection. The many different ANN structures are proposed in the literature. Multilayer perceptrons (MLPs) are preferred in this study. Furthermore, the many different learning algorithms can be used for training the network structure of MLPs. The Levenberg–Marquardt (LM), Scaled Conjugate Gradient (SCG), Polak-Ribiére Conjugate Gradient (CGP) learning algorithms are used in the training stage of this study [xxxxx]. The MLPs consist differ layers like input layer, output layer and hidden layer, as shown in Fig. 2.

The neurons in the input layer distribute the input signals xi to neurons in the hidden layer as a buffer area. Each of the neuron j existing in the hidden layer weights them with the strengths of the respective connections w_{ji} from the input layer and then sums up its input signals x_i and computes its output y_j as a function f of the sum, namely

$$y_i=f(\sum w_{ji}x_i) \tag{1}$$

where f(·) can be a simple threshold function, a sigmoid, hyperbolic tangent, a radial basis function, a purelin function etc (Kubat 1999, Jang 1992). The output of neurons in the output layer is computed similarly. A training of the network covers the set of the processes consisting of adjusting the network weights by using one of the available learning algorithms.

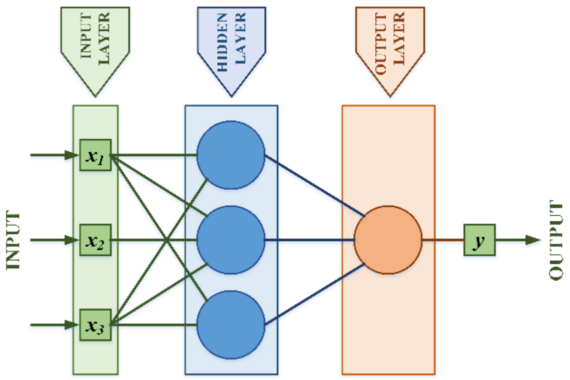

Figure. 2. Artificial neural network architecture based on the multilayer perceptrons

3. Results and Discussion

In this study, the model of the ANN with four layers consisting of the input layer, two hidden layers with twenty–two and twenty–four neurons and the output layer, was used. The ANN model is given in Fig. 3. In the training step, the number of epochs, minimum gradient, momentum parameter (μ), μ increment, μ decrement and maximum were selected as 1000, 1E−7, 0.005, 10, 0.1, 1E10, respectively. Further, tangent sigmoid, tangent sigmoid and purelin function were used in the input layer, a hidden layer, and output layer, respectively.

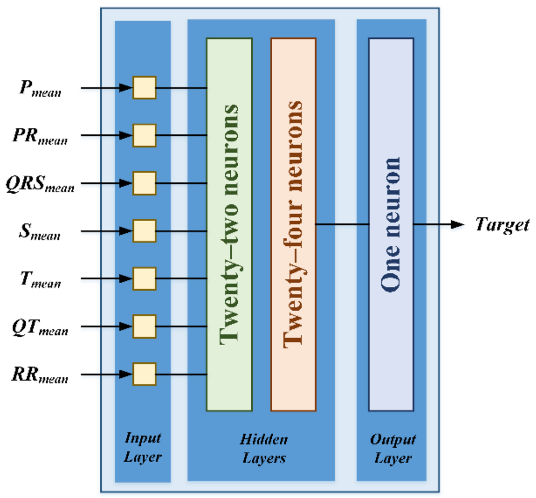

Figure 3. Training process of the artificial neural network model

In the training phase of the ANN model, the parameters of ECG signal (P_{mean}, PR_{mean}, QRS_{mean}, S_{mean}, T_{mean}, QT_{mean}, RR_{mean}) were given as input and respective 1 and 2 values (2 for the healthy humans, 1 for the people having arrhythmia) were introduced as a target to the ANN, as illustrated in Fig.3. According to the relationship between the input and the target, an ANN model was trained to produce the target for each parameter set of ECG signals. While 46 ECG data were used for training process, the samples of 20 ECG were employed in testing process the ANN model. In the training step, the values of the average percentage errors (APE) for the target values predicted via the ANN models trained by LM, SCG and CGP learning algorithms was obtained as 0.94%, 1.78% and 2.21%, respectively. The target and training results are in good agreement. To verify the ANN model, 20 ECG samples, which were not used in training process were used in the testing process. The parameters and target values of the ECG samples for testing process were given in Table I.

Table 1. The parameters and target of the electrocardıographıc samples

	P_{mean}	PR_{mean}	QRS_{mean}	S_{mean}	T_{mean}	QT_{mean}	RR_{mean}	Target
1	4,7349	4,7849	4,8849	5,0749	5,2749	4,9974	0,8746	2,0000
2	4,8476	4,8976	4,9976	5,1198	5,3198	5,0765	0,7826	2,0000
3	4,4841	4,5341	4,6341	4,7689	4,9689	4,7209	1,1573	2,0000
4	4,6865	4,7365	4,8365	4,989	5,189	4,9303	0,6873	2,0000
5	4,6959	4,7459	4,8459	4,9659	5,1659	4,926	0,7452	2,0000
6	4,8318	4,8818	4,9818	5,1024	5,3024	5,06	0,7164	2,0000
7	5,0546	5,1046	5,2046	5,3686	5,5686	5,3043	0,9008	2,0000
8	4,7684	4,8184	4,9184	5,0675	5,2675	5,0105	0,7429	2,0000
9	4,7716	4,8216	4,9216	5,0451	5,2451	5,0009	0,8838	2,0000
10	4,9307	4,9807	5,0807	5,2053	5,4053	5,1605	0,896	2,0000
11	4,615	4,665	4,765	4,8942	5,0942	4,8477	0,763	1,0000
12	4,775	4,825	4,925	5,0562	5,2563	5,0087	1,0639	1,0000
13	4,6948	4,7448	4,8448	4,9668	5,1668	4,9245	0,5082	1,0000
14	4,6354	4,6854	4,7854	4,9035	5,1035	4,8628	0,8944	1,0000
15	4,7409	4,79909	4,8909	5,1002	5,3002	5,0136	0,6309	1,0000
16	5,1567	5,2067	5,3067	5,4614	5,6614	5,404	0,875	1,0000
17	4,6882	4,7382	4,8382	5,0019	5,2019	4,9381	0,6908	1,0000
18	4,7771	4,8271	4,9271	5,0472	5,2472	5,0052	0,7505	1,0000
19	4,8363	4,8863	4,9863	5,1381	5,3381	5,0803	0,6165	1,0000
20	4,8774	4,9274	5,0274	5,1376	5,3376	5,1018	0,7442	1,0000

The whole results for test samples are given in Table II and Fig. 4. The predicted target values and corresponding percentage errors are tabulated in Table II. It is clearly seen that the predicted results with the ANN models trained by the LM learning algorithm are very close to the target values. The APE values for LM, CGP and SCG learning algorithms is obtained as 1.07%, 2.07% and 2.17%, respectively for the testing stage.

Table 2. Comparison of target, predicted and error values

	Target	*Predicting*			*Error (%)*		
	Values	*LM*	*CGP*	*SCG*	*LM*	*CGP*	*SCG*
1	*2.00*	*2.02*	*1.90*	*2.00*	*1.19*	*5.04*	*0.03*
2	*2.00*	*2.00*	*2.01*	*2.00*	*0.03*	*0.63*	*0.09*
3	*2.00*	*2.04*	*1.86*	*1.95*	*1.94*	*6.92*	*2.55*
4	*2.00*	*2.01*	*2.02*	*1.96*	*0.60*	*0.97*	*2.15*
5	*2.00*	*1.98*	*1.92*	*1.93*	*1.03*	*4.21*	*3.38*
6	*2.00*	*1.98*	*2.03*	*2.03*	*0.92*	*1.61*	*1.26*
7	*2.00*	*2.01*	*1.99*	*1.94*	*0.73*	*0.37*	*3.11*
8	*2.00*	*2.02*	*2.00*	*2.02*	*0.78*	*0.25*	*0.89*
9	*2.00*	*2.00*	*1.99*	*2.00*	*0.16*	*0.55*	*0.13*
10	*2.00*	*2.01*	*2.01*	*1.99*	*0.37*	*0.31*	*0.63*
11	*1.00*	*0.96*	*0.97*	*0.88*	*3.59*	*3.17*	*11.89*
12	*1.00*	*1.00*	*0.99*	*1.00*	*0.44*	*1.18*	*0.21*
13	*1.00*	*1.02*	*1.00*	*1.01*	*2.40*	*0.34*	*0.72*
14	*1.00*	*0.99*	*1.00*	*1.02*	*1.29*	*0.07*	*1.64*
15	*1.00*	*1.00*	*1.00*	*1.02*	*0.11*	*0.11*	*1.53*
16	*1.00*	*1.00*	*1.07*	*1.04*	*0.23*	*6.79*	*4.14*
17	*1.00*	*1.02*	*0.97*	*1.00*	*1.67*	*2.53*	*0.22*
18	*1.00*	*0.99*	*1.02*	*1.07*	*1.08*	*1.68*	*7.30*
19	*1.00*	*0.99*	*1.00*	*1.01*	*0.65*	*0.28*	*1.43*
20	*1.00*	*1.02*	*1.02*	*1.00*	*2.12*	*1.78*	*0.05*
APE					*1.07*	*1.94*	*2.17*

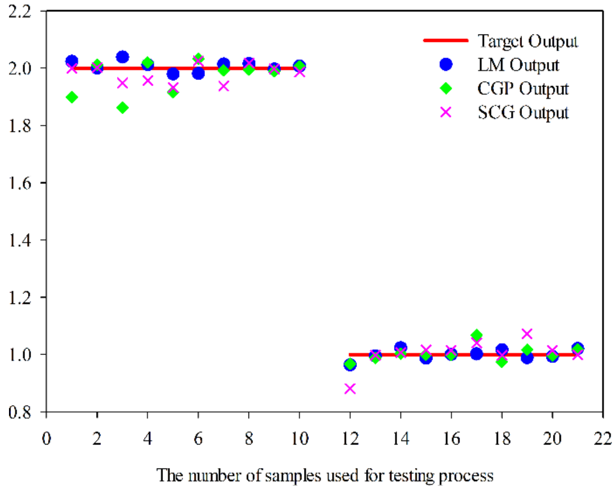

Figure. 4. The comparative results of the predicted and target output for testing samples

4. Conclusions and Recommendations

A comparison of 3 learning algorithms against each other is presented to determine which algorithms are more effective in such nonlinear problem. It is demonstrated that the predicted results agree well with the target results ones; and the learning algorithm of LM comes to fore in this task. The proposed ANN model is able to fast and accurately predict the arrhythmia in the ECG signal if the ANN is properly trained.

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