An Extreme Learning Machine Approach For Detection of Epileptic Seizure

AN EXTREME LEARNING MACHINE APPROACH FOR DETECTION OF EPILECTIC SEIZURE

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Abstract

Irregularities in the electrical activities of the brain can cause epileptic attacks. In the diagnosis and classification of epileptic attacks and epilepsy, data showing the electrical activity of the brain obtained by EEG has an important place. This study presents an EEG classification approach based on the extreme learning machine (ELM). The ELM algorithm is used for the characteristics of single hidden layer feedforward neural network (SLFN). EEG recordings of healthy individuals and individuals who had epileptic attacks were classified by using ELM. As a result of the study, the classification success of the method we applied was found to be 99.67%. It is predicted that the obtained system may be useful in evaluating the pre-diagnosis for physicians.

Keywords: Extreme Learning Machine, Classification, Electroencephalogram, Epileptic Seizure

1. Introduction

The extreme learning machine (ELM) is a learning algorithm applied to single hidden layer feedforward neural networks (SLFNs) [1]. The ELM does not need to adjust the hidden layer weights. The weights between the input layer and the hidden layer are assigned randomly. The weights between the hidden layer and the outputs are calculated analytically [1, 2]. The ELM structure which can output only the local minimums by solving a single linear equation, contains fewer design parameters than conventional neural network-based classifiers [1, 3]. In this way, the learning process of the model is realized very fast. In addition to its ability to learn quickly, ELM is superior to feed-forward networks that learn with conventional back-propagation algorithms in terms of generalization success [1, 4]. Furthermore, offers high performance by minimizing the training errors and norm of output weights for binary classification, multiple classification and regression problems [5].

Classifiers built using the Excessive Learning Machine (ELM), which has superior capabilities such as rapid learning and generalization, are now used in many areas [3, 4, 6, 8].

Transient electrical disorders of the brain cause epilepsy. Sometimes seizures cannot be detected, and sometimes they are confused with migraine and impact events. Approximately one in every hundred people has epileptic attacks in their lives [9, 10]. Although different methods are available for the treatment of epilepsy, these seizures cannot be controlled in 25% of patients [11]. Epilepsy patients may encounter many problems in their social lives. Different tests are performed for the diagnosis of epilepsy. The most important of these is electroencephalography (EEG). EEG is a sign shows the electrical activity in the brain and is a commonly used method [12]. The placement of its electrodes given in Figure 1.

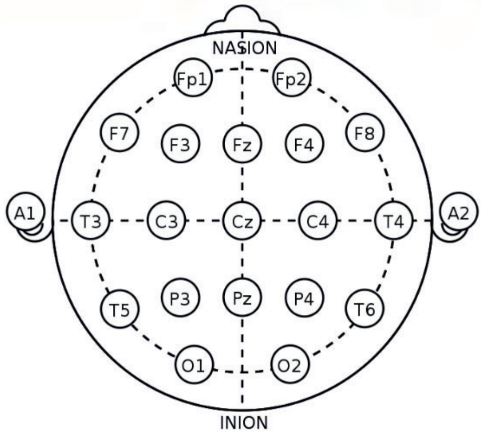

Figure 1. Electrode locations for EEG recording according to the international 10-20 system [13].

Detection of discharges between epilepsy seizures with EEG has an importance in the diagnosis of epilepsy [9, 14]. For this reason, the EEG device is used extensively in neurology clinics for the observation of epileptic attacks. Different classification models have been developed so far due to the complex nature of the epileptic EEG signal [15]. There are two types of abnormal EEG recordings as interictal and ictal in EEG recordings obtained from people suffering from epilepsy. Interictal signals consist of signals between epileptic seizures, while ictal consists of signals obtained during epileptic seizures [14, 16].

Tzallas et al. [17] stated that it is important to detect seizures automatically during long-term EEG recordings in their study. They proposed a method based on time frequency analysis on EEG signals. They used ANN to classify the properties that they obtained. In the model they developed, they have achieved a classification success of 97.72%.

Yıldırım et al. [18] in their study, have presented an automatic pattern recognition system using signs from subjects who is healthy and had epileptic seizures. They obtained spectral information of EEG signals using the Peridogram and Welch methods. The feature vectors they obtained were classified with k nearest neighbor algorithm (k-NN), support vector machine (SVM), extreme learning machine (ELM). They reported that they achieved the best performance with SVM.

Sood et al. [19] used nonlinear features to classify EEG signals and epileptic seizures. They achieved the highest success in the MLPNN classifier with 98.4% in their study.

In this study, to classify epileptic EEG signals obtained in different conditions and from different regions of the brain, extreme learning machine (ELM) that has the advantages of fast learning speed and good generalization performance was used. In this study, it was aimed to detect epileptic attacks by using EEG signals obtained from healthy individuals and individuals having epileptic attacks.

2. Materials and Methods

In this study, ELM method which provides generalizable performance and does not need parameters according to classical ANN algorithms is used. The proposed method for epileptic seizure prediction consists of five steps. Firstly, healthy and ictal data sets were obtained from the UCI database over the EEG dataset. Segments were formed with 50% overlap on the data set.

Then, to obtain the attributes to be used in the classification, 4th level wavelet coefficients were determined with Discrete Wavelet Transform (DWT). The classification process was performed by using the obtained properties were used as input features for the ELM classification algorithm. Finally, according to the classification results, the decision-making process has been carried out. The flow diagram, which generally describes these steps, is shown in Figure 2.

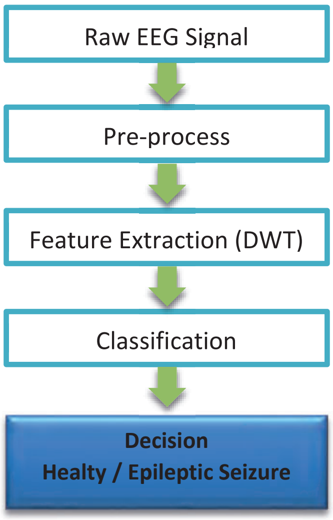

Figure 2. General flow diagram of the proposed method

2.1. EEG Dataset

In this study, the EEG dataset published by Andrzejak et al. [14] was used. The data set contains 100 channels of EEG data sampled at a frequency of 173.61 Hz and divided into 5 different classes: Set A, Set B, Set C, Set D and Set E. Each cluster consists of 100 single-channel EEG data with 4096 samples. In our study, only two of the five different data sets (Set A and Set E) were used. Normal data (Set A); were obtained from five different people who healthy and different ages. Patient (Set E) data were obtained from five different people with epilepsy and different ages [14, 20]. Example signs for clusters used in this study are shown in Figure 3.

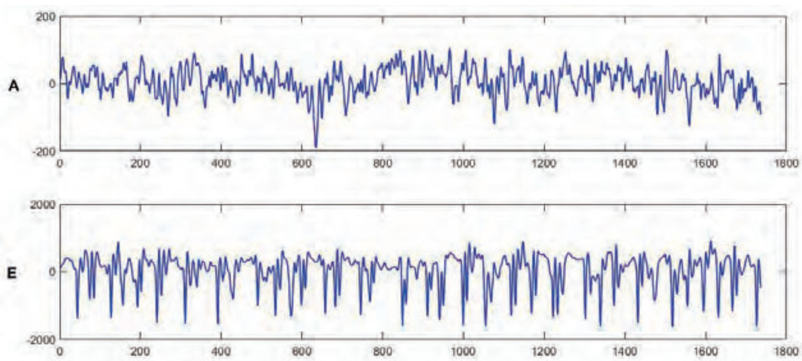

Figure 3. 10-second samples from sets A and E

The signals have transferred to a computer environment after being converted by a 12-bit analog to digital converter. Since the epileptic properties manifest themselves in frequency bands below 30-40 Hz, 0.53-40 Hz bandpass filter is applied to the signals whose spectral range is 0.5-85 Hz [14, 21].

2.2. Discrete Wavelet Transform

Wavelet transform; is a transformation technique that separates data into different frequency components and examines each component with its resolution at that scale. The wavelet transform of a signal, which is a function of time, depends on the frequency and time variables [22]. EEG signals are type of the non-stationary signals. In this study, EEG signals are separated by using DWT according to frequency component and the characteristics of frequency bands are investigated. Since DWT uses a small sized window for high frequencies and a large sized window for low frequencies, it tries to provide optimal resolution in terms of time and frequency [23].

With DWT, the signal is passed through the high-pass filter to analyze the high frequencies in the input signal. The signal is passed through the low pass filter to analyze the low frequencies. As shown in Figure 4, the input signal is indicated by x[n]. Here n is an integer. The low pass filter is indicated by g, while the high pass filter is indicated by h [23, 24].

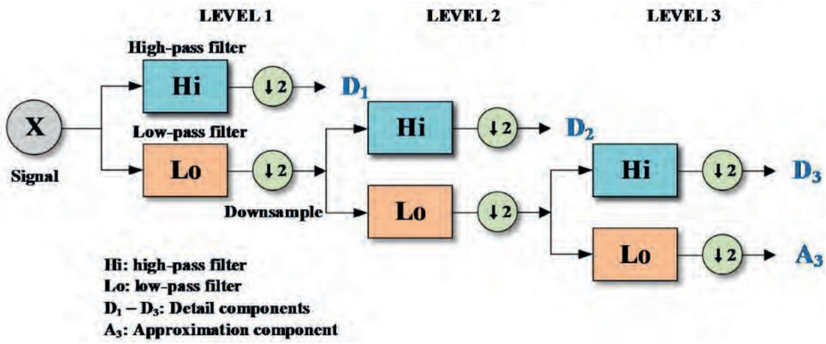

Figure 4. Flow chart for three-level DWT [25]

2.3. Extreme Learning Machine (ELM)

ELM is an effective learning algorithm proposed by Huang et al. for single hidden layer feedforward neural networks [1]. As shown in Figure 5, the ELM model consists of an input layer, a hidden layer and an output layer.

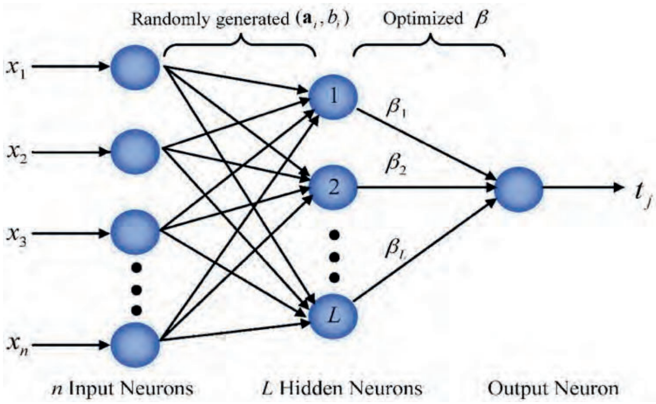

Figure 5. Model structure of extreme learning machine [26]

The output value $y_j \in R^n$ of the ELM network is calculated according to N training samples consisting of $(x_i, t_i) \in R^n \times R^m$ $i = 1,2, \cdots, N$. Here $x_1, x_2, \cdots, x_t$ refers to the property vectors given to the input of the system and y_j refers to the decision vector. The mathematical model of single hidden layer feedforward neural networks which has L number of neurons in its hidden layer is as in Equation (1) [1].

$$\sum_{i=1}^{L} \beta_i g(w_i \cdot x_j + b_i) = O_j \; j = 1 \ldots N \tag{1}$$

Here $w_i = [\omega_{i1}, \omega_{i2}, \ldots, \omega_{in}]$ indicates the input layer weight sequence, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]$ indicates the output weight sequence connected to the hided nerve cell and the exit nerve cells, b_i indicates the threshold values of hidden layer neurons and O_j indicates output vector. $g(.)$ represents the activation function.

In order to maximize the performance of this SLFNs network structure, which is formed in its most basic form, it is accepted that the error could approached the "zero" error value. That is, the desired output and the given output relationship can be expressed as $\sum_{j=1}^{L} \|o_j - y_j\| = 0$. The ELM can be expressed in Equation (2) in a more general expression.

$$\mathbf{H}\beta = \mathbf{Y} \tag{2}$$

H represents the hidden layer output values in this equation and can be expressed in matrix form as shown in Equation (3).

$$\mathbf{H} = \begin{bmatrix} g(\mathbf{w}_1 . \mathbf{x}_1 + b_1) & \cdots & g(\mathbf{w}_L . \mathbf{x}_1 + b_L) \\ \cdots & \cdots & \cdots \\ g(\mathbf{w}_1 . \mathbf{x}_N + b_1) & \cdots & g(\mathbf{w}_L . \mathbf{x}_N + b_L) \end{bmatrix}_{NxL} \tag{3}$$

The β in Equation (4) represents the weight values between the hidden layer and the output layer, and Y represents the output vectors.

$$\beta = \begin{bmatrix} \beta_1^{\mathrm{T}} \\ \ldots \\ \beta_L^{\mathrm{T}} \end{bmatrix}_{Lxm} \quad \text{ve} \quad \mathbf{Y} = \begin{bmatrix} \mathrm{y}_1^{\mathrm{T}} \\ \ldots \\ \mathrm{y}_N^{\mathrm{T}} \end{bmatrix}_{Nxm} \tag{4}$$

According to Moore-Penrose generalized matrix inverse theorem, the representation of a non-square matrix of n×m dimensions of the system given in Equation (2) which provides the smallest norm and least squares solution is as in Equation (5) [1, 3, 27].

$$\beta = \mathbf{H}^{\dagger}\mathbf{Y} \tag{5}$$

Here $\mathbf{H}^{\dagger}$ represents the generalized inverse matrix of the output matrix.

3. Results

In this study, it is aimed to classify two different EEG types, which belong to healthy individuals and individuals who had epileptic attacks, with ELM. After obtaining individuals' EEG signals, who are healthy and had epileptic attacks, from raw data, it divided into 5-second segments. As given in Table 1, the EEG signals are subdivided into the detailed sub-bands D1-D4 and finally the A4 sub-band. For the calculation of wavelet coefficients for each segment, 4th level WDT was applied using 2nd order Daubechies (db2) wavelet.

Table 1. Ranges of frequency bands in wavelet decomposition.

Sub-bands	Frequency range (Hz)
D1	43.4-86.8
D2	21.7-43.4
D3	10.8-21.7
D4	5.4-10.8
A4	0-5.4

Statistical properties were applied on the set of wavelet coefficients to reduce the size of the feature vectors obtained after the WDT transformation. Statistical properties including the maximum, minimum, mean and standard deviation of wavelet coefficients in each subband were used to represent the time-frequency distribution of the EEG signals. In total, 20 properties were obtained for each segment.

The classification process performed over the obtained properties by using ELM method. The parameters of the ELM network used are given in Table 2.

Table 2. The learning parameters of ELM network.

Number of Input Layer Neurons	20
Hidden Layer	1
Number of Hidden Layer Neurons	5..200
Output Layer	1
Applied Activation Functions	Hard limit sigmoid, sin, Radial basis, Triangular basis
Learning Algorithm	ELM for single layer feed-forward network

The performance of the ELM network is influenced by the number of neurons in the latent layer and the activation function to be used. Therefore, trials have been performed on different neuron numbers and activation functions. The number of neurons in the hidden layer was obtained by performing trials by increasing one by one, between 5-200 (Figure 6). In order to see the effect of activation function changes, Hard limit sigmoid, sin, Radial basis, Triangular basis activation functions were applied to ELM network. The optimal activation function and the number of neurons were determined according to the training and test performance of the network.

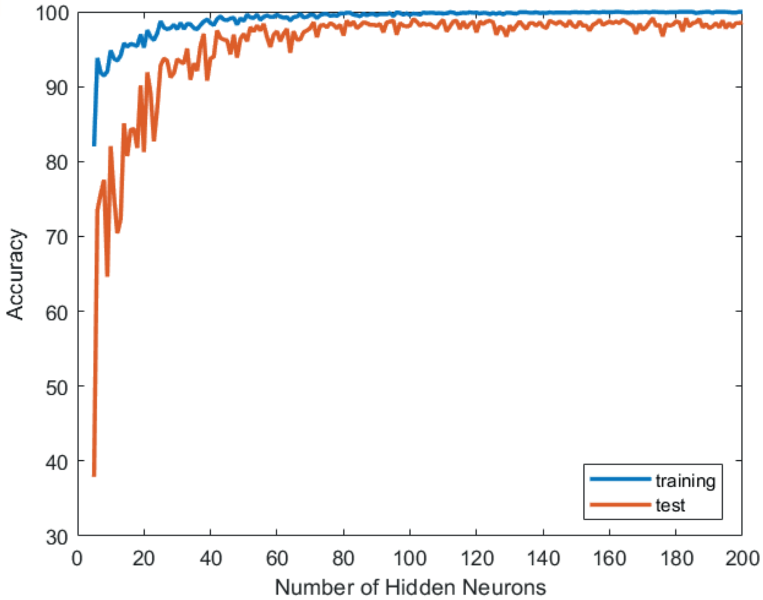

Figure 6. Effect of neuron number change on ELM performance

In this study, the best performance value of the ELM network was obtained in the network structure which has 82 neurons in the hidden layer and has sinus activation function. In the study, 99.67% classification accuracy was obtained. The comparison of this study, which made to classify A and E clusters on the EEG dataset used, with similar studies in the literature is given in Table 3.

Table 3. Seizure detection results of recommended and other methods: For Classes A-E.

Method	*Classifier*	*Training/test*	*Acc.(%)*
Aarabi et al. [28]	BNN	Hold-out (50.00–50.00%)	93.00
Subasi [10]	ME	Hold-out (62.50–37.50%)	94.50
Yuan et al. [29]	ELM	Hold-out (50.00–50.00%)	96.50
Khan et al. [30]	LDA	Hold-out (80.00–20.00%)	91.80
Kumar and Kolekar [31]	SVM	Hold-out (66.67–33.33%)	97.50
Hussein et al. [32]	ESD-LSTM	Hold-out (66.67–33.33%)	100.00
Proposed method	*ELM*	*Hold-out (75.00–25.00%)*	*99.67*

With this study, it is seen that reached the result which can be considered as fast and effective in the diagnosis of epileptic attacks by using the WDT and ELM algorithm in the classification. It is thought the proposed method may be a useful tool for decision-making stage in medical diagnostic systems. Furthermore, the obtained method can be further developed with different EEG clusters and different classification techniques.

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