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ANN-based classification of EEG signals using the average power based on rectangle approximation window

***Abstract**. In this study, EEG signals were classified by using the average powers extracted by means of the rectangle approximation window based average power method from the power spectral densities of frequency sub-bands of the signals and two different artificial neural networks (ANNs) which are adaptive neuro-fuzzy inference system (ANFIS) and multilayer perceptron neural network (MLPNN). In order to evaluate their performances together the proposed approach, four different experiments were implemented by using different mixtures of classes. The experiments showed that both classifiers with the proposed approach resulted in satisfactory classification accuracy rates, although the success of MLPNN classifier was a little better than the other.*

***Streszczenie.** W artykule zaprezentowano klasyfikacje sygnału EEG przy wykorzystanoiu widma gęstości mocy w podzakresach częstotliwości oraz sieci neuronowych: adaptacyjnego system neuro-fuzzy ANFIS oraz wielowarstwowego perceptronu MLPNN. (**Klasyfikacja sygnału EEG wykorzystująca sieci neuronowe oraz uśrednioną moc w oknie prostokątnym**)*

Keywords: EEG signals, Rectangle approximation window based average power, Discrete wavelet transform (DWT), Power spectral density (PSD), Artificial neural networks.
Słowa kluczowe: sygnał EEG, sieci neuronowe, transformata falkowa

Introduction

Epilepsy is a critical neurological disease stemming from temporary abnormal discharges of the brain electrical activity and leading to uncontrollable convulsions in the human body, which affects approximately 50 million people worldwide (namely 1–3% of the world's population). Around 90% of these people live in developing countries, and about three fourths of them could not access to the necessary treatment. Therefore, the epilepsy diagnosis and the epileptic seizures detection are very important for the choice of medicine or surgical treatment [1, 2]. The electroencephalography (EEG) signals are generally used for the epilepsy diagnosis and the epileptic seizures detection because they can provide valuable insight into disorders of the brain activity [3]. Although the occurrence of epileptic seizures seems unpredictable, the EEG recordings measured in seizure-free intervals from the epilepsy patients are considered as important components for the diagnosis or prediction process [4-7]. Due to the complex interconnections between billions of neurons, the recorded EEG signals are complex and non-stationary, and they also consist of many sinusoidal components of different frequencies and very large amounts of data. Therefore, the visual analysis of EEG signals is not possible, and automated systems are required for the analysis of EEG signals [2-5, 8-18].

ANNs are widely used in the detection of the class of signal in many biomedical signal analyses because they have better predictive power than signal analysis techniques [9]. Therefore, they provide an important support for the medical diagnostic decision. In a classification system using ANN, first step is related to the feature extraction from the raw data with minimal loss of important information by using numerous different methods such as frequency domain features, time-frequency features, discrete wavelet transform (DWT). In the second step, some statistics over the vectors are used to reduce the dimensionality of these vectors such as mean, maximum, minimum, entropy, and etc. Final step is to apply the feature vectors as inputs to ANNs [10]. Not only the architecture of ANN and but also the training algorithm play key roles to obtain satisfactory results. Although several ANN models with different architectures are used as inference system in the classification of EEG signals, because of their successes in EEG signals classification, multilayer perceptron neural network (MLPNN) [3, 4, 7, 10-12, 19-23] and adaptive neuro-fuzzy inference system (ANFIS) [1, 5, 9, 15] are preferred, in general.

DWT method is the most suitable transform to apply into non-stationary signals like EEG signals, and it has been widely used for analyzing EEG signals since it shows variations in the harmonic amplitude and location in sub-bands of the signals [4-7, 11-18, 22]. DWT provides high-frequency resolution at low frequencies and high-time resolution at higher frequencies. In order to extract the distinguishable features and reduce the dimensionality, although several statistics are used over the coefficients of sub-bands obtained from EEG signals by DWT, the rectangle approximation based average power method is one of the best suited methods [24, 25], But a literature survey leaves the impression that the average method based on rectangle approximation has not been investigated in any detail related to the estimation of the MLPNN and ANFIS accuracy in the classification of EEG signals. Therefore, the aim of this paper is to investigate the impact of this method on the MLPNN and ANFIS accuracy in the classification of EEG signals. For this aim, the feature vectors of EEG signals are extracted from PSDs of sub-bands of the signals by using the rectangle approximation window based average power method, and they are used as the inputs of MLPNN and ANFIS classifiers in different four classification experiments.

Material and Method

EEG Dataset

In this paper, the publicly available dataset in reference [26] is used. The complete dataset consists of five sets (A, B, C, D, and E), and each of them contains 100 single-channel EEG segments of 23.6 s duration. The sets are selected from EEG records after purifying artefacts caused by eye and muscle movements. Sets A (eyes open) and B (eyes closed) are extra-cranially taken from five healthy subjects. Sets C, D, and E are intra-cranially taken from five epilepsy patients. While sets D and C contain the EEG activity measured in seizure-free intervals from epileptic hemisphere and the opposite hemisphere of the brain, respectively, set E only contains the seizure activity. All EEG segments are recorded with the same 128-channel amplifier system, using an average common reference. In this study, EEG signals are normalized into the range of [0, 1] in order to remove extracranial and intracranial amplitude differences. Sample EEG segments taken from sets A, B, C, D, and E are illustrated in Fig. 1.

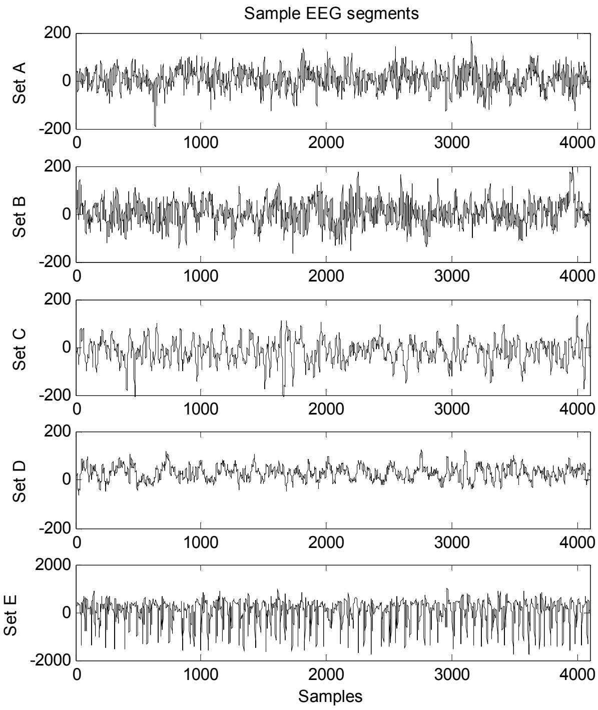

Fig. 1. Sample EEG segments taken from each set

Discrete wavelet transform (DWT)

Discrete wavelet transform (DWT) is an efficient spectral analysis technique used for analyzing non-stationary signals like EEG signals, and illustrates variations in the harmonic amplitude and location. DWT method provides high-frequency resolution at low frequencies and high-time resolution for higher frequencies with the same time and frequency resolution for all frequencies since it uses long time windows at low frequencies and short time windows at high frequencies, leading to good time-frequency localization [14, 15, 27].

The DWT decomposes a signal into a set of sub-bands through consecutive high-pass and low-pass filtering of the time domain signal *f* (Fig. 2).

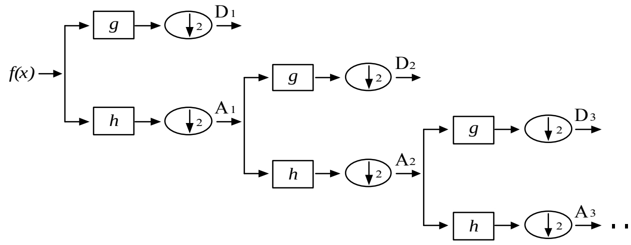

Fig. 2. Sub-band decomposition of a signal by using DWT

The high-pass filter *g* is the discrete mother wavelet function, while the low-pass filter *h* is its mirror version. After first filtering, the down-sampled signals are called first level approximation A_1 and detail coefficients D_1. Then, approximation and detail coefficients of next level are obtained by using the approximation coefficient of the previous level [10].

Scaling function $\varphi_{j,k}(x)$ based on low pass filter and wavelet function $\psi_{j,k}(x)$ based on high pass filter are defined as

(1) $$\varphi_{j,k}(x) = 2^{j/2} h(2^j x - k)$$

(2) $$\psi_{j,k}(x) = 2^{j/2} g(2^j x - k)$$

where x=0,1,2,…,M-1, j=0,1,2,…,J-1, k=0,1,2,…,2^j-1, J equals to $\log_2(M)$ and M is the length of the signal and chosen as 2^J. Sampling rate k and the resolution j specify the positions and the widths on the x axis of functions, respectively [27]. Approximation coefficients $A_i(k)$ and detail coefficients $D_i(k)$ in ith level are described as

(3) $$A_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x).\varphi_{j,k}(x) \right\} \text{ and}$$

$$D_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x).\psi_{j,k}(x) \right\}$$

for k=0,1,2,…, $2^j - 1$.

In this study, EEG signals were decomposed into sub-bands by using the DWT with Daubechies wavelet of order 2 (db2) because it yields well results in the EEG signals classification. The decomposition level was selected as 6 since it provided the highest success of the classifiers for all experiments. Fig. 3 and 4 show the approximate and the detailed coefficients of a healthy segment taken from set A and an epileptic seizure segment taken from set E, respectively.

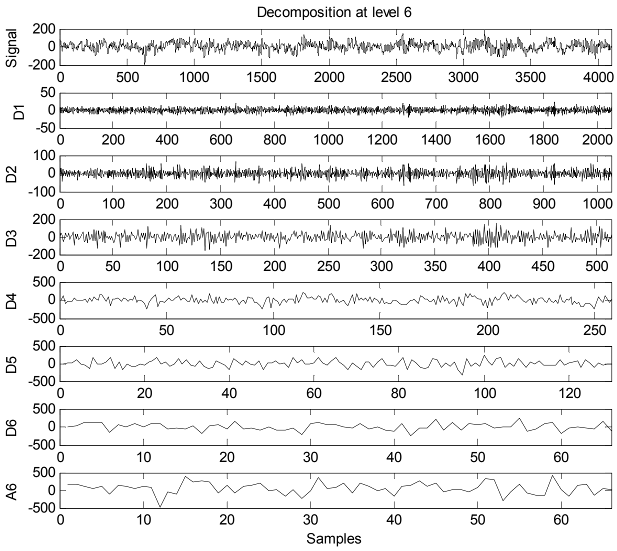

Fig. 3. The approximate and the detailed coefficients of a healthy segment taken from set A

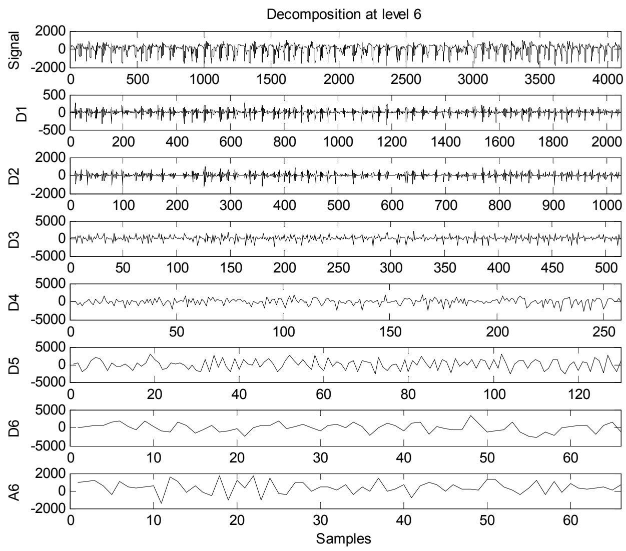

Fig. 4. The approximate and the detailed coefficients of an epileptic seizure segment taken from set E

The rectangle approximation window based average power

The power spectral density (PSD) describes how the power of the time series data is distributed with frequency, and it is a very useful tool for identifying oscillatory signals and illustrating their amplitudes and their variations which are strong at frequency ranges [24, 25]. The average power of a random signal $x(t)$ is distributed over some range of frequencies. This distribution $S_x(w)$ over frequency is PSD, and it is non negative. The area under $S_x(w)$ is proportional to the average power in $x(t)$, that is, average power in $x(t)$

$$P = \frac{1}{2\pi}\int_{-\infty}^{\infty} S_X(w)dw \tag{4}$$

where, $S_x(w)$ has units of power/Hz. Mathematically, PSD is the Fourier transform of the autocorrelation sequence of the time series [24]. The integral of PSD over a given frequency band computes the average power in the signal over that frequency band. In a classical Fourier analysis, the power of a signal can be obtained by integrating PSD, which is the square of the Fourier transform's absolute value [24, 25]:

$$F[x(t)] = \int_{-\infty}^{\infty} x(t)e^{-jwt}dt \tag{5}$$

In general, it does not exist, and it is not absolutely integrable. Therefore, the square of the Fourier transform's absolute value ($\left|F[x(t)]\right|^2$) can not be used as power spectrum. The power carried by a defined spectral band can be obtained by integrating PSD along this band. However, the peaks in this spectrum do not reflect the power at a given frequency. The average power method based on rectangle approximation window computes the average power of a signal via a rectangle approximation of the integral of PSD of that signal in a given frequency band, and it can be applied only to PSD of a signal. For this aim, the truncated process can be used as follows:

$$x_T(t) = \begin{cases} x(t), & |t| \le T \\ 0, & |t| > T \end{cases} \tag{6}$$

Truncated process x_T can be represented as

$$x_T(t) = x(t)rect\left(\frac{t}{2T}\right) \tag{7}$$

where, $rect(t/2T)$ is the $2T$ long window, and it is used in approximating PSD of $x_T(t)$ as shown in Fig. 5.

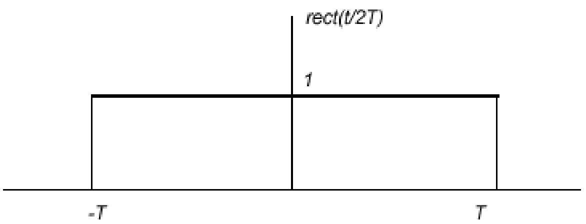

Fig. 5. Rectangular window used in approximating PSD of $x_T(t)$

Signal $x_T(t)$ is absolutely integrable, and, its Fourier transform exists for finite T

$$F_{x_T}(w) = \int_{-\infty}^{\infty} x_T(t)e^{-jwt}dt \tag{8}$$

For every value of w, $F_{x_T}(w)$ is a random variable. According to Parseval's theorem

$$\int_{-T}^{T} \left|x_T(t)\right|^2 dt = \int_{-\infty}^{\infty} \left|x_T(t)\right|^2 dt = \frac{1}{2\pi}\int_{-\infty}^{\infty} \left|F_{x_T}(w)\right|^2 dw \tag{9}$$

The left hand side of Equation (9) is the average power in $x_T(t)$. The average over all $x_T(t)$ functions can be calculated by

$$E\left[\frac{1}{2T}\int_{-T}^{T} \left|x_T(t)\right|^2 dt\right] = E\left[\frac{1}{4\pi T}\int_{-\infty}^{\infty} \left|F_{x_T}(w)\right|^2 dw\right] \tag{10}$$

which leads to

$$\frac{1}{2T}\int_{-T}^{T} E[\left|x_T(t)\right|^2]dt = \frac{1}{4\pi T}\int_{-\infty}^{\infty} E[\left|F_{x_T}(w)\right|^2]dw \tag{11}$$

As $T \to \infty$, the left hand side of Equation (11) is the average power of $x(t)$. So, it can be rewritten

$$Avg\_pwr = \frac{1}{2\pi}\int_{-\infty}^{\infty} \lim_{T\to\infty}\left[\frac{E[\left|F_{x_T}(w)\right|^2]}{2T}\right]dw \tag{12}$$

$$S_X(w) = \lim_{T\to\infty}\left[\frac{E[\left|F_{x_T}(w)\right|^2]}{2T}\right] \tag{13}$$

where, $S_X(w)$ is PSD of the signal $x(t)$, and It has units of power/Hz. The average power in the frequency band (w_1, w_2) can be calculated by

$$Avg\_pwr = \frac{1}{2\pi}\int_{w_1}^{w_2} S_X(w)dw \tag{14}$$

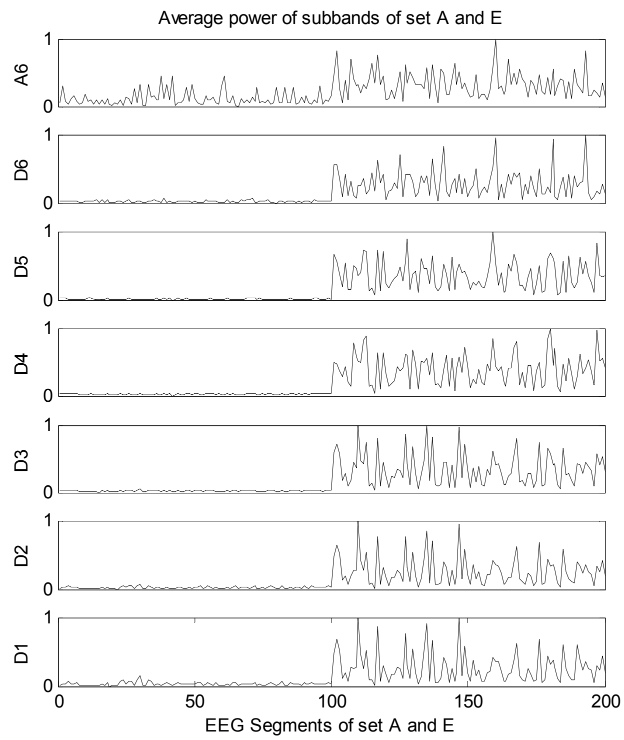

Fig. 6. The average powers of the sub-bands of EEG segments for set A and E

In this study, after EEG signals are decomposed into sub-bands, and the average powers of sub-bands are computed by Equation (14), namely by taking a rectangle approximation of the integral of PSD. Fig. 6 shows the rectangle approximation window based average powers for set A and E.

As seen in Fig. 6, the dissimilarities of the average powers between the segments of different classes (A and E) make the classification more easily.

Classification

Artificial neural networks (ANNs) are usually classifiers composed of large number of simple interconnected elements called neurons which perform a simple numerical computation task [3]. There are different neural network topologies as well as different neurons types. In this paper, MLPNN and ANFIS are used in the classification of EEG signals.

Multilayer perceptron neural network

Multilayer perceptron neural networks (MLPNNs) with two or more layers are the most commonly used feed-forward neural networks due to their fast operation, ease of implementation, smaller training set requirements [4, 19]. The MLPNN consists of three sequential layers: input, hidden and output layers (Fig. 7). The number of neurons of input layer is equal to the number of selected features. Output layer determines the desired output classes. The number of neuron in the output layer depends on the number of desired classes. The intermediate layers may be added to increase the ability of the network and it mostly is useful for nonlinear systems [3]. The hidden layer processes and transmits the input information to the output layer. Although MLPNN can have multiple hidden layers, in general, the MLPNN with one hidden layer is preferred as classifiers. There is no prior knowledge of the number of neurons needed in the hidden layer. Large number of neurons in the hidden layer can increase the computational complexity and processing time. Small amount of neurons can lead to the classification errors.

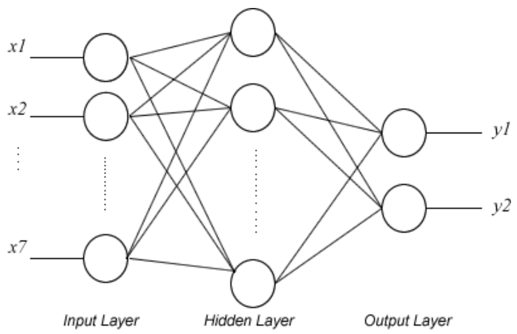

Fig. 7. The structure of MLPNN model

A MLPNN model with insufficient or excessive number of neurons in the hidden layer probably leads to the problems of poor generalization and over-fitting. There is no analytical method for determining the number of neurons in the hidden layer. Therefore, it is only found by trial and error [3, 4, 18, 21]. In the study, a MLPNN model with one hidden layer of 20 hidden neurons was used, its activation function was selected hyperbolic tangent function, and it was trained by the most widely used Levenberg–Marquardt back-propagation algorithm in all experiments [4, 18, 21]. In order to prevent the MLPNN classifiers from the over-fitting, 10-fold cross validation was used, which is one of the most useful methods for generalizing the results of classifiers [3].

Adaptive neuro-fuzzy inference system

The ANFIS is a multilayer feed-forward network which takes advantages of the capable of learning of ANNs and the capable of fuzzy reasoning to map an input space to an output space. ANFIS allows the extraction of fuzzy rules from numerical data, adaptively constructs a rule base. Two fuzzy if-then rules based on a first order Sugeno fuzzy model of the ANFIS [28] can be expressed as

$$Rule\ 1: \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1$$

$$Rule\ 2: \text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2$$

where *x* and *y* are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region which is specified by the fuzzy rule, and parameters p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture implementing these two rules is shown in Fig. 8, in which a circle indicates a fixed node, whereas a square indicates an adaptive node [9, 28].

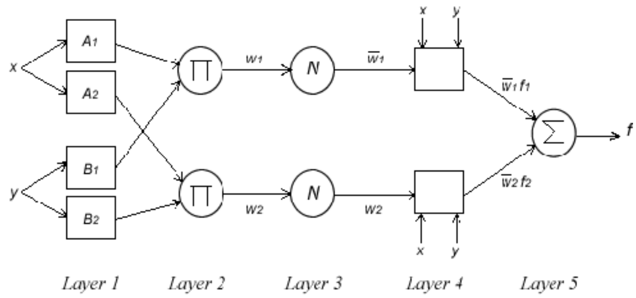

Fig. 8. The structure of ANFIS model

In the first layer, each node generates fuzzy membership grades to which that belongs to the appropriate fuzzy sets by using membership functions. The outputs of this layer are the fuzzy membership grade of the inputs. In the second layer, every node multiplies the incoming signals and sends the product out. The output of each node represents the firing strength of a rule. In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. In the fifth layer, there is only one single fixed node. This single node computes the overall output by summing all the incoming signals.

In this study, the ANFIS was trained by the hybrid learning algorithm which is highly efficient in training the ANFIS [9, 15, 28].

Validity criterion

The following statistical measures were used in order to see the performances of the classification experiments [4, 10, 11, 14, 19]. True Positive (TP) is the number of correctly classified epilepsy patients, True Negative (TN) is the number of correctly classified healthy subjects, False Positive (FP) is the number of incorrectly classified epilepsy patients, and False Negative (FN) is the number of correctly classified healthy subjects. Sensitivity is the proportion of the number of TP decisions to the number of actually positive cases (TP+FN). Specificity is the proportion of the number of TN decisions to the number of actually negative cases (TN+FP). Total correct classification (TCC) is the proportion of the number of correctly classified decisions (TN+TP) to the number of all cases (TN+FN+TP+FP).

Results and discussion

EEG signals were decomposed into sub-bands by using the DWT with Daubechies wavelet of order 2 (db2) The feature vectors were computed by using the average power method based on rectangle approximation window over PSDs of each sub-band of EEG segments with 4096 samples. These features vectors were normalized between 0 and 1, and they were used as the inputs to MLPNN and ANFIS classifiers. Four different experiments were implemented by the classifiers in order to illustrate the performance of the offered approach as follows:

The experiment of A - E classification: Both MLPNN and ANFIS classifiers were trained by the same training dataset which was randomly selected 75 segments from set A (healthy segments with eyes open) and 75 segments from set E (epileptic seizure segments). The trained MLPN and ANFIS classifiers were tested by the same testing dataset consisting of other 25 segments from set A and 25 segments from set E. The testing dataset verified the accuracy of the trained MLPNN and ANFIS classifiers. In this situation, both of them reached to the correct classification success of 100%. Table 1 shows the confusion matrices of the results of two classifications. There is no any misclassification as shown in Table 1.

Table 1. The confusion matrices for A - E classification

MLPNN			ANFIS		
Class	A	E	Class	A	E
A	25	0	A	25	0
E	0	25	E	0	25

The experiment of ABCD - E classification: Both MLPNN and ANFIS classifiers were trained by the same training dataset which was randomly selected 300 segments from set ABCD (healthy segments and epileptic seizure free segments together) and 75 segments from set E (epileptic seizure segments). The trained MLPNN and ANFIS classifiers were tested by the same testing dataset consisting of other 100 segments from set ABCD and 25 segments from set E. The testing dataset verified the accuracy of the trained MLPNN and ANFIS classifiers. Both of them reached to the correct classification success of 97.60%. Table 2 shows the confusion matrices of the results of two classifications. Both misclassified only three segments as shown in Table 2.

Table 2. The confusion matrices for ABCD - E classification

MLPNN			ANFIS		
Class	ABCD	E	Class	ABCD	E
ABCD	97	0	ABCD	97	0
E	3	25	E	3	25

The experiment of AB - CD classification: The MLPNN and ANFIS classifiers were trained by the same training dataset which was randomly selected 150 segments from set AB (healthy segments) and 150 segments from set CD (epilepsy segments without seizures). The trained MLPNN and ANFIS classifiers were tested by the same testing dataset consisting of other 50 segments from set AB and 50 segments from set CD. The MLPNN and ANFIS reached to the correct classification success of 100% and 99%, respectively. Table 3 shows the confusion matrices of the results of two classifications. The MLPNN misclassified any segment while the ANFIS misclassified one segment as shown in Table 3.

Table 3. The confusion matrices for AB - CD classification

MLPNN			ANFIS		
Class	AB	CD	Class	AB	CD
AB	50	0	AB	49	0
CD	0	50	CD	1	25

The experiment of AB - CDE classification: The MLPNN and ANFIS classifiers were trained by the same training dataset which was randomly selected 150 segments from set AB (healthy segments) and 225 segments from set CDE (epilepsy segments both with and without seizures). The trained MLPNN and ANFIS was tested by the same testing dataset consisting of other 50 segments from set AB and 75 segments from set CDE. The MLPNN and ANFIS reached to the correct classification success of 97.60% and 98.40%, respectively. Table 4 shows the confusion matrices of the results of two classifications. The MLPNN and ANFIS classifiers totally misclassified only three and two segments, respectively.

Table 4. The confusion matrix for AB - CDE classification

MLPNN			ANFIS		
Class	AB	CDE	Class	AB	CDE
AB	49	2	AB	49	1
CDE	1	73	CD	1	74

The classification statistics of MLPNN and ANFIS models for four different experiments are given in Table 5 and 6.

Table 5. The classification statistics of MLPNN

Experiment Type	MLPNN		
	TCC (%)	Specificity (%)	Sensitivity (%)
A - E	100	100	100
ABCD - E	97.60	97	100
AB - CD	100	100	100
AB - CDE	97.60	98	97.33

Table 6. The classification statistics of ANFIS

Experiment Type	ANFIS		
	TCC (%)	Specificity (%)	Sensitivity (%)
A - E	100	100	100
ABCD - E	97.60	97	100
AB - CD	99	98	100
AB - CDE	98.40	98	98.67

As seen in Table 5 and 6, both classifiers classified ‘healthy’ segments and ‘epileptic seizure’ segments with the accuracy of 100%. On the other hand, MLPNN classifier also classified ‘healthy (AB class)’ segments and ‘epileptic seizure free (CD class)’ segments with the accuracy of 100%. All results showed that both classifiers using the proposed approach resulted in satisfactory classification accuracy rates, although the success of MLPNN classifier was a little better than the other.

Conclusion

In this study, EEG signals were classified by using two different ANN models and the average powers of PSDs of EEG sub-bands. EEG signals were decomposed into sub-bands through the DWT. The powers of PSDs of the obtained sub-bands for each EEG segment were computed by the rectangle approximation window based average power method, and then they were used as the inputs of MLPNN and ANFIS classifiers. Four different experiments were implemented in order to illustrate the performance of the proposed approach in the classifications of EEG signals. All results showed that both classifiers using the proposed approach resulted in satisfactory classification accuracy rates, although the success of MLPNN classifier was a little better than the other.

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