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Accuracy Enhancement of the Epileptic Seizure Detection in EEG Signals

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Abstract: The detection of epileptic seizures becomes increasingly important because of the widespread of this disease all over the world. Early detection of epileptic seizures helps the patient to manage epilepsy. This paper introduces a detection system for epileptic seizures that implements a Short-Time Fourier Transform (STFT) for denoising the Electroencephalogram (EEG) signal and Wavelet Transform (WT) for features extraction. Four EEG types (i.e Healthy people, Epileptic people during the seizure-free interval (Interictal), Epileptic people during seizure interval (Focal) and Epileptic people during seizure interval (Nonfocal)) are classified by using a Multi-Layer Perceptron Neural Network (MLPNN) classifier. The used dataset was enlarged to be 1050 instead of 500 in the available detection systems. The integration of STFT and WT has an important impact on improving the detection accuracy. The accuracy of the proposed system is 94.4 % which significantly outperforms the previous systems in terms of dataset size and the number of classified EEG signal types.

Keywords: Electroencephalogram, Multi-Layer Perceptron Neural Network, Short Time Fourier Transform, Wavelet Transform

1 Introduction

The human brain is a highly complex structure. Understanding the behavior and dynamics of billions of interconnected neurons of the brain signals requires a knowledge of several signal-processing techniques [1]. Epilepsy is one of the chronic brain diseases which affects approximately 70 million people all over the world. It is responsible for 1% contribution to the global burden of diseases. This contribution increased to be 80% in the developing countries [2]. Epilepsy is equivalent to lung cancer in men and breast cancer in women [3]. Epilepsy is the most common neurological condition in children and the third common disease in adults after Alzheimers and stroke [4].

Early detection of epileptic seizures helps the patient to manage epilepsy. This disease can be visually detected by a specialist diagnosis or automatically by using signal processing knowledge. It is notable that visual detection requires continuous analysis of an expert for few days and it is a time-consuming process. Therefore, using automatic detection and classification of elliptic seizure will reduce the detection time and improve the detection accuracy.

The electroencephalogram (EEG) signal is one of the most promising techniques for clinical investigation of the brain disorders. It is widely used in the detection of epilepsy [5,6,7] because it provides a new neurologic and psychiatric diagnostic tool at the same time. Hans Berger recorded EEG signal for the first time on July 6, 1924. This was during a neurosurgical operation on a 17-year-old boy performed by the neurosurgeon Nikolai Guleke [8].

In this paper, we propose a new detection system of the epileptic seizure using EEG signal for early and accurate detection. Our approach is based on using a short-time Fourier transform (STFT) for removing artifacts from normalized EEG signals [9,10] and extracting features by using Wavelet Transform (WT) [11, 12]. Then, the features are fed into a Feed-Forward, Back-propagation Neural Network (FFBPNN). This network classifies the segment into four classes (i.e. Normal, Interictal, Focal, and Nonfocal). Therefore, the proposed system can detect three epileptic seizure types in addition to normal people. These four detection classes are not previously classified together. The main contributions of this paper are outlined as follows:

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- Using a large dataset of total 1050 record.
- Enhancing the detection accuracy by using a short-time Fourier transform for denoising the signal as well as using Wavelet Transform for feature extraction.
- Detecting four EEG types, which are not addressed together before.
- Achieving early detection of the four classes by using a Forward back-propagation Neural Network.

The remainder of this paper is organized as follows. Section 2 discusses the related work. Section 3 will be devoted to briefly describe the used dataset. Section 4 describes our proposed detection system in details. Section 5 provides the experimental results. Section 6 concludes this paper. Finally, section 7 introduces the future work.

2 Related Work

Several papers addressed the problem of epileptic seizure detection using outdated EEG signals such as [13, 14, 15]. In recent years, EEG Data applications have gained a significant attention as a result of increasingly great research efforts. The researchers try hard to produce more reliable analysis techniques as well as to introduce effective systems that involve the above-mentioned data applications into various aspects of life [16].

Authors in [9] used Independent Component Analysis (ICA), such as a preprocessing step and STFT, and incorporated them for signal Denoising. This was followed by the feature extraction process based on three parameters, i.e. standard deviation, correlation dimension and Lyapunov exponents. EEG signal classification using Feed-Forward Back-propagation Neural Network (FFBPNN) is compared with Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier. In [17] EEG signal was decomposed into time-frequency representations used discrete WT, Mixture of experts (ME) and Multi-Layer Perceptron Neural Network (MLPNN) structure for classification.

The proposed system in [18] extracted features by using WT sub-band frequencies. These features were used as inputs to MLPNN and ME network. In [19], wavelet decomposition of the EEG was recorded into the sub-band frequencies. Then, these sub-band frequencies were used as an input of a feed-forward neural network trained by the error backpropagation algorithm (FEBANN). The detection method in [20] decomposed EEG signals into time-frequency representations by using WT. The authors used the first-level networks to classify the EEG signals. In addition, the second-level networks were trained by using the outputs of the first-level networks as input data.

Authors in [21] combined the discrete wavelet transform (DWT) with the envelope analysis (EA) method to extract features from the EEG signals. Then, a neural network ensemble (NNE) model is constructed for EEG classification based on the concept of transforming the N-class classification into N-independent 2-class classification. In [22], three different methods for feature extraction were used namely wavelet based entropy, nonlinear, and higher order spectra. Meta classifier with meta learning algorithm Stacking Correspondence Analysis and Nearest Neighbor (SCANN) are used to take the final verdict. The detection method in [23] extracted potential features from the signal by using the Discrete Wavelet Transform (DWT) technique. These features were classified by integrating the best attributes of Artificial Bee Colony (ABC) and radial basis function networks (RBFNNs).

It is noticed that the limitation of the available detection systems requires small EEG database. Moreover, adopting ICA method tends to be helpful in general for EEG analysis, but it has two main disadvantages. Firstly, ICA can be decomposed at most N origins from N data channel while wavelets can decompose data without gaps or overlap. Therefore, the decomposition process is mathematically reversible. Secondly, ICA depends on statistical analysis of the data. Therefore, the result is going to be nonsense if the data amount given to algorithm is not sufficient. In addition, the disadvantage of the Permutation Entropy method is the unequal contribution of the entropies related to each scale to measure the complexity. It is difficult to confirm the weights for each independent scale. In the analysis of EEG data, different measurements are used in recent systems, the results showed that the Wavelet is the most promising technique to extract features from the EEG signals. In this paper, we use WT and NN for EEG signal classification and STFT for denoising the signal. It is noteworthy that using NN classifier to classify four EEG types was not addressed in the previous epileptic seizure diseases detection systems.

Table 1: The Datasets

CLASSES	Train set	Test set	Total
Normal	75	25	100
Interictal	75	25	100
Focal	75	25	100
Nonfocal	700	50	750
Total	925	125	1050

3 Dataset Description

We used the common available dataset that described in [24, 25]. The complete dataset consists of four classes. A large set of standard datasets (1050 cases) were used for training and testing. The former 925 sets were used as training sets, and the latter 125 sets were used as test sets. (Table.1) describes datasets and (Fig.1) shows EEG

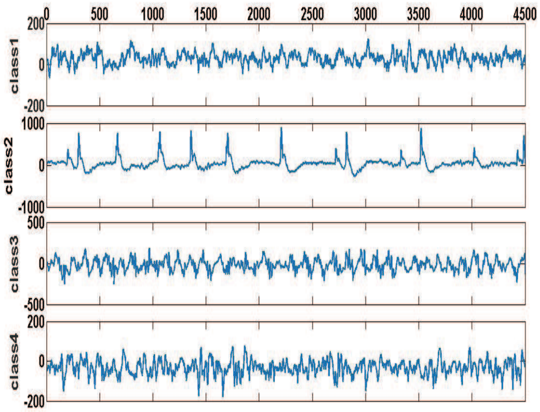

Fig. 1: EEG signals of all CLASSES

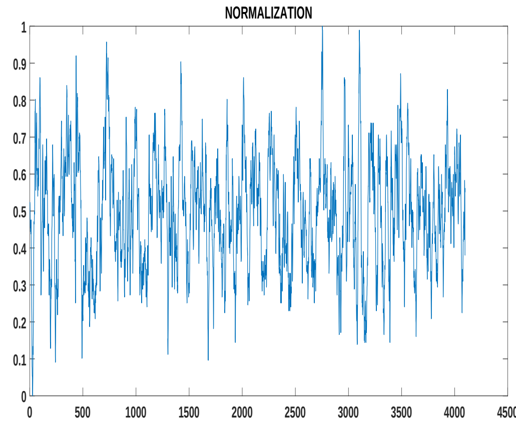

Fig. 3: Original-EEG and Normalization-EEG.

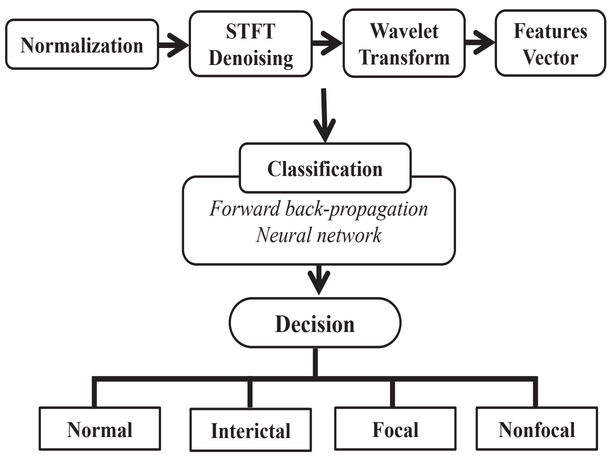

Fig. 2: Block diagram of the proposed scheme for EEG classification

signals of all classes. The frequency of the experimental was adapted to be at one level 173.6 Hz.

4 The Proposed System

In the present work, we use Normalization for making the signal at the same level. Also, we use STFT for denoising the EEG signals. The features are extracted by using WT. The calculation and classification of feature vector are performed by using FFBP. The block diagram of the proposed scheme related to EEG classification is shown in (Fig.2).

4.1 Normalization

Each sample is pre-processed by Normalization. The Normalization process is necessary to standardize all the features to the same level. This makes the calculation simpler. Thus, the template vector will transform to a range between zero and one. (Fig.3) shows ORIGINAL-EEG and Normalization-EEG. All samples are resampled to start at the same value which is used a common average reference with a sampling rate of 173.6 Hz.

4.2 Short Time Fourier Transforms (STFT)

The STFT is widely used for denoising time-dependent signals. Denoising means a removal of noise from a signal. The STFT of a signal consists of the Fourier Transforms that are crossing windowed blocks of the signal. In general, the Fourier Transform is considered a technique for transforming an input signal from time-domain to frequency-domain in which time-information of the signal cant be found after transformation. However, the STFT affords information that is time-frequency plane. Moreover, it consists of the rectangular window used for the purpose of effective signal denoising.

The denoising process consists of three steps. In the first one, the STFT of the noisy signal is calculated. In the Second one, a threshold to the STFT is made and finally the inverse STFT is computed. The spectrogram values less than a specific range are set to zero, known as Thresholding. This result is a perfect reconstruction of the spectrogram. After removing noise, inversing STFT is computed to attain the Denoised signal. (Fig.4) shows the block diagram of denoising performed by STFT [9,26,27].

Denoising in STFT composed of the three following steps:

1.Compute the STFT of the noisy signal

$$P(\tau,\omega) = STFT\{p(\tau)\} \tag{1}$$

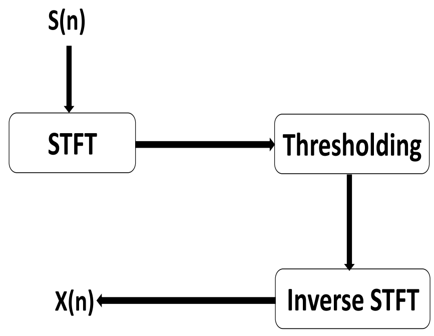

Fig. 4: Block diagram for denoising based on STFT (after [9]).

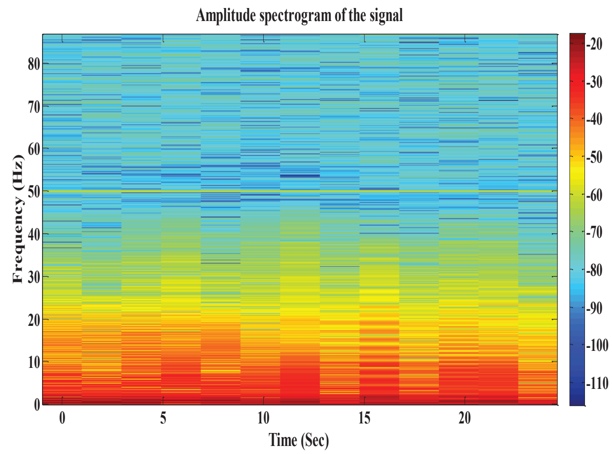

Fig. 5: Spectrogram of the signal using STFT after Thresholding

$$Fd(\tau,\omega) = THR(p(\tau,\omega)) \tag{2}$$

2.Make a threshold on $F(\tau,\omega)$

$$THR(a) = \begin{cases} 0, |a| \leq Threshold \\ a, |a| > Threshold \end{cases} \tag{3}$$

$$Threshold = \frac{\max(orig)mean(orig)}{abs(\min(orig))} \tag{4}$$

Threshold represents the threshold value THR(a), and (orig) represents the original signal. All data values (a) less than threshold are set to zero. Further, the function of the inverse STFT can be used for effectively getting the Denoising signal.

3.Compute the inverse STFT

$$X(n) = STFT^{-1}[Fd(\tau,\omega)] \tag{5}$$

The spectrogram of the signal using STFT after thresholding is shown in (Fig.5)

4.3 Wavelet Transform

The Wavelet is an extension of the classic fourier transform. In some cases, instead of working on a single scale (time or frequency), it can work on a multi-scale basis. Therefore, the multi-scale feature of the WT allows the decomposition of a signal into a number of scales. Each scale is represented by a particular coarseness of the signal under study [28,29,30,31].

In analysis of signals using DWT, is very important to choose a suitable wavelet and a number of levels of decomposition. The Wavelet analysis can represent EEG sub-bands as a weighted sum of shifted and scaled versions of an original wavelet without losing any information or energy. Based on the dominant frequency components of the signal, the number of levels of decomposition is chosen. The procedure of multi-resolution decomposition of a signal x[n] is shown in (Fig.6) [32,33].

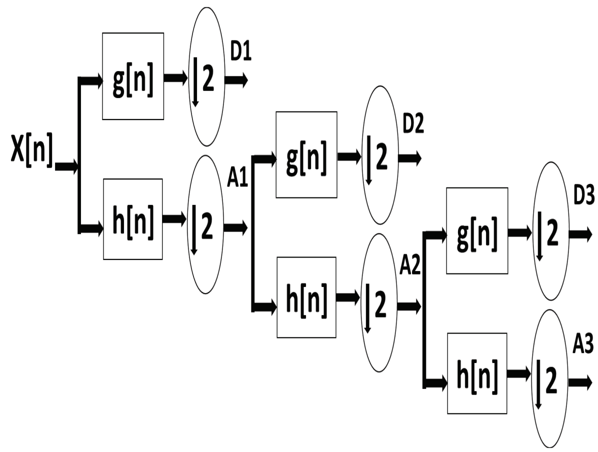

Fig. 6: Subband decomposition of discrete wavelet transform implementation.

In this figure, H represents the Low-Pass Filters (LPF), G represents the High-Pass Filters (HPF), the father wavelet is associated with the LPF, and the wavelet function is associated with the HPF. The decomposition procedure starts by passing a signal through these filters (i.e. HPF and a LPF). The low-frequency components of the time-series are the approximations while the HPF is the details. Then, the filtered signals are decimated by two for computing the approximation at the first level (i.e. A1 and D1 in Fig.6). In the second stage, this procedure is repeated for approximating coefficients. Finally, the decomposed signal is obtained from an expected level. The approximated coefficients and the detail coefficients

Table 2: Different levels of decomposition

Decomposed signal	Frequency range (Hz)
D1	43.4-86.8
D2	21.7-43.4
D3	10.8-21.7
D4	4.5-10.8
D5	2.7-5.4
A5	0-2.7

represent a filtered signal spanning only half of the frequency band at each level. By this decomposition, the frequency resolution is improved since the frequency uncertainty is reduced by half [34,35].

All WTs can be specified in terms of a low-pass filter h, which satisfies the standard quadrature mirror filter condition as follows:

$$H(z)H(z^{-1})+H(-z^{-1})H(-z^{-1})=1 \quad (6)$$

Where H(z) denotes the z-transform of the filter h, its complementary high-pass filter can be defined as follows:

$$G(z)=zH(-z^{-1}) \quad (7)$$

a sequence of filters with increasing length (indexed by i) which can be obtained by

$$\begin{aligned} H_{i-1}(z) &= H(z^{2i})H_i(z) \\ G_{i+1}(z) &= G(z^{2i})H_i(z), \quad i=0,\ldots,I-1 \end{aligned} \quad (8)$$

with the initial condition $H_0(z)=1$. It is expressed as a two-scale relation in time domain.

$$\begin{aligned} h_{i+1}(k) &= [h]\uparrow 2^i h_i(k) \\ g_{i+1}(k) &= [g]\uparrow 2^i h_i(k) \end{aligned} \quad (9)$$

where the subscript $[\,]\uparrow m$ indicates the up sampling by a factor of m and k the equally sampled discrete time. The normalized wavelet and scale basis functions $\phi_{i,1}(k)$, $\psi_{i,1}(k)$ can be defined as follows:

$$\begin{aligned} \phi_{i,l}(k) &= 2^{i/2}h_i(k-2^{il}) \\ \psi_{i,l}(k) &= 2^{i/2}g_i(k-2^{il}) \end{aligned} \quad (10)$$

where the factor $2^{i/2}$ is an inner product normalization, I and l will be the scale parameter and the translation parameter respectively. The discrete wavelet transform (DWT) decomposition can be described as follows:

$$\begin{aligned} a_{(i)}(l) &= x(k)\phi_{i,l}(k) \\ d_{(i)}(l) &= x(k)\psi_{i,l}(k) \end{aligned} \quad (11)$$

where $a_{(i)}(l)$ and $d_{(i)}(l)$ are the approximation coefficients and the detail coefficients at resolution I, respectively.

The Wavelet is a technique, which can be applied to many tasks in a signal processing. The EEG signal is consisting of many data points, which can be compressed into a few parameters. These parameters characterize the behavior of the EEG signal. This feature uses a smaller number of parameters to represent the EEG signal, which is particularly important for recognition and diagnosis purposes. DWT analyzes the signal at different frequency bands with different resolutions. By decomposing the signal into different sub-bands through DWT, the detail wavelet can be obtained [36].

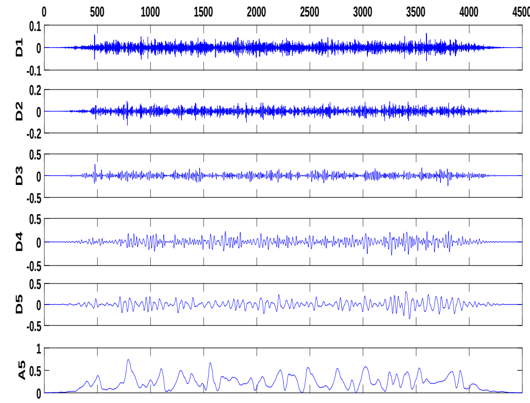

Fig. 7: Approximation (A5) and details (D1-D5) of an epileptic EEG signal

The chosen levels such as those parts of the signal, which correlate well with the frequencies, are retained in the wavelet coefficients. The signals are decomposed into the details D1-D5 and one final approximation is A5 because the EEG signals above 30 Hz do not have any useful frequency components (where the levels were chosen to be 5). (Table.2) shows frequencies corresponding to different levels of decomposition because Daubechies order 4 wavelets with a sampling frequency of 173.6 Hz. These approximated and detailed records are reconstructed from the Daubechies 4 (DB4) wavelet filter as shown in (Fig 7).

4.4 Feature Vector

In order to promote decreasing the dimension of the extracted feature vectors, statistics over the set of the wavelet coefficients was used [18]. Decomposition coefficients of Wavelet packet were computed by using MATLAB [20]. The following statistical features were used to represent the time-frequency distribution of the EEG signals as follows:

1. Mean: Mean of the absolute values of the coefficients in each sub-band.
2. Std: Standard deviation of the coefficients in each sub-band.

Table 3: Feature vectors for EEG Signals

Class	FX	Wavelet coefficients subbands				
		D1	D2	D3	D4	A4
A	Max	18.0661	38.2277	87.4753	114.5794	226.6854
	Min	2.4964	7.6710	14.4985	16.6438	56.6262
	Mean	3.5353	7.0910	12.4736	16.2452	38.6368
	Std	9.0868	21.0013	38.0271	48.3468	145.1229
B	Max	46.0304	73.5689	87.4753	114.5794	285.5044
	Min	2.4964	7.6710	14.4985	16.6438	56.6262
	Mean	8.9252	11.6432	11.7860	15.9230	38.5408
	Std	16.0793	28.5521	37.1117	38.1324	154.6399
C	Max	48.1285	91.6140	91.2962	114.5794	442.7544
	Min	2.4964	7.6710	14.4985	16.6438	56.6262
	Mean	8.6842	12.6154	13.2590	16.3418	47.0211
	Std	17.4009	30.9473	39.0947	41.4245	163.1753
D	Max	48.1285	91.6140	91.2962	114.5794	442.7544
	Min	2.4964	7.6710	14.4985	16.6438	56.6262
	Mean	6.8305	8.9313	8.5638	13.1701	41.7023
	Std	14.0282	25.7700	35.1935	42.2752	159.0811

3.Max: Max value of the coefficients in each sub-band.
4.Min: Min value of the coefficients in each sub-band.

These features were chosen because they define the statistical distribution of the amplitude vector. (Table.3) shows that sixteen Feature Vectors were used as an input of the Neural Network classifier to classify four classes.

Table 4: The four output target vectors of NN

CLASS	Vector
Class A	[1 0 0 0]
Class B	[0 1 0 0]
Class C	[0 0 1 0]
Class D	[0 0 0 1]

4.5 Neural Network classifier

The theory and design of the Artificial Neural Network (ANN) were significantly developed during the last 20 years. Most of that progress have a direct impact on signal processing. The MLP is by far the most well-known NN. The MLPNN model consists of a feed-forward and layered network of both of McCulloch and Pitts neurons. Each neuron in a MLP has a non-linear Activation Function (AF) that is often continuous and differentiable. Some of the most frequently used AF for MLP include the sigmoid function as well as the hyperbolic tangent function. The weight matrices were chosen as a key step to apply a MLP model.

To get the correct classification percentage, the Back-Propagation Algorithm (BPA))is used. In BPA, the errors are calculated at the output and distributed back through the neural network hidden layers citeMcCulloch,David,Yu. The number of neurons in the output layer is four cases. A target vector is arranged as the desired output for each class. It is a set of Boolean value vectors. This annotated information can be used for designing the target vector and evaluating the classifier performance. The class vectors are shown in (Table.4).

The MLPNN was trained with a BPA. (Fig.8) shows the training performance of neural network architecture 16 neurons in the input layer, 64 neurons in the first hidden layer, 32 neurons in the second hidden layer, 16 neurons in the third hidden layer, 8 neurons in the fourth hidden layer and 4 neurons in the output layer, the numbers of Epochs 559, and a goal was 0.006. The activation function used in the input layer is logsig. The activation function used in output layer is purelin linear function and that of the hidden layer is a hyperbolic tangent sigmoid transfer function. The performance of the classifiers was evaluated by computing the percentages of Sensitivity (SE), Specificity (SP), and Correct Classification (CC). These values give the accuracy of the method, which determines how good a diagnostic test will be to classify the diseased and the non-diseased. The respective definitions are as follows:

- Sensitivity $(Se\%) : [Se = 100TP/(TP+FN)]$ is the fraction of real events that are correctly detected among all real events.
- Specificity $(Sp\%) : [Sp = 100TN/(TN+FP)]$ is the fraction of nonevents that has been correctly rejected.
- Correct classification $(CC\%) : [CC = 100(TP+TN)/(TN+TP+FN+FP)]$ is the classification rate.

These formulas will contain the following contractions. TP refers to the number of true positives. TN refers to the number of true negatives. FN refers to the number of false negatives. FP refers to the number of

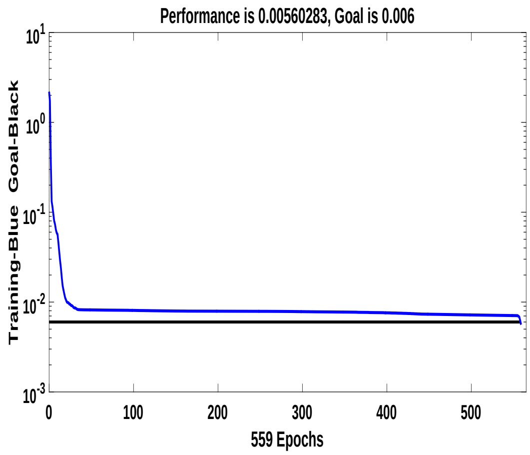

Fig. 8: Training performance of the neural network.

Table 5: Training dataset results

Class	Train	A	B	C	D	Unk
A	75	71	0	1	1	2
B	75	0	74	0	1	0
C	75	1	0	70	1	3
D	700	0	0	0	700	0

Table 6: Testing dataset results

Class	Test	A	B	C	D	Unk
A	25	21	0	0	0	4
B	25	0	23	0	0	2
C	25	0	0	25	0	0
D	50	0	0	0	49	1

Table 7: Sensitivity and Specificity

Class	Test Set	T P	T N	F P	F N
A	25	0	21	4	0
B	25	23	0	0	2
C	25	25	0	0	0
D	50	49	0	0	1

Table 8: Comparative results of different methods

Method	Dataset	Accuracy
STFT-WT-MLPNN	1050	94.4%
ICA-STFT-MLPNN [9]	500	96%
WT-MLPNN [17]	300	84.83%
WT-MLPNN [18]	500	94.5%
WT-FEBANN [19]	500	91%
WT-MLPNN [20]	500	94.83%

false positives. All the above-mentioned true positives are appropriately defined below. For example, TP classifies Disease as Disease. FP classifies Normal as Disease. TN classifies Normal as Normal. FN classifies Disease as Normal.

5 Experimental Results and Discussion

There are many parameters can be selected to obtain better results in ANN. For the most common case, these parameters are as follows:

- The number of hidden layer.
- Type of transfer function.
- Training epoch number.
- Weights and bias.

(Table.5) shows Training datasets, and (Table.6) shows Testing datasets.

The whole dataset is divided into two groups, which are training dataset and testing dataset. Training dataset aims at training the network. Whereas, testing dataset aims at checking the effectiveness of the classifier. The training dataset consists of 925 and the testing dataset consists of 125.

In (Table .5) Class A, 71 datasets are classified correctly and 4 datasets are misclassified, Class B, 74 datasets are classified correctly and 1 dataset is misclassified, Class C, 70 datasets are classified correctly and 5 datasets are misclassified, Class D, 700 dataset are classified correctly. In (Table .6) Class A, 21 dataset are classified correctly and 4 dataset are misclassified, Class B, 23 datasets are classified correctly and 2 datasets are misclassified, Class C, 25 datasets are classified correctly, Class D, 49 datasets are classified correctly, and 1 dataset is misclassified. Furthermore, (Table .7) represents the Sensitivity, and Specificity. According to this table, it is clear that Sensitivity= 97%, Specificity= 84%, and the Correct Classification= 94.4%.

The resulted classification accuracy is greater than 94% of all classes. The characteristics of the training set are very important to achieve high classification accuracy. The comparison of different approaches used for Detection in EEG Signals is presented in (Table .8). In this paper, the proposed system is represented by STFT-WT-MLPNN. The accuracy achieved in the approach WT-MLPNN, which is presented in [17], is 84.83% while 94.5% detection rate is achieved in [18]. Although they use the same techniques for feature extraction and classification, the result is not equal. This is due to the difference in the amount of the used dataset. The accuracy in WT-FEBANN system [19] is 91%, while in the approach WT-MLPNN 20] [20] 94.83%. Accuracy achieved in the approach ICA-STFT-MLPNN [9] is 96%, which is slightly higher than the accuracy achieved for other systems. This is mainly due to the fact that the ICA-STFT-MLPNN system used heavy computations to increase the accuracy. In fact, this leads to high complexity, which is not applicable in medical field.

It is notable from (Table .8) that the previous detection systems achieved classification accuracy from 84% to 96% for the dataset from 300 to 500. Whereas, our proposed system achieved 94.4% detection accuracy for 1050 dataset. In addition, the proposed system achieved this detection accuracy of four EEG types [i.e. Healthy people, Epileptic people during a seizure-free interval, Epileptic people during seizure interval (focal), and Epileptic people during seizure interval (Nonfocal)]. These four EEG types are not addressed together in the previous systems. The proposed system is not only important for providing an automatic procedure that addresses all available features in a specific way and makes a decision based on these data but also it allows insight into the severity of the brain state. This method guarantees a trustworthy computerized methodology for proper EEG signal classification and better decision making for epileptic seizure diagnosis. Perhaps, the wavelet neural network classification can be used as a key appliance of diagnostic decision support to help physicians in the treatment of epileptic patients.

This current study shows the significance of EEG signal feature extraction. It shows how this step has a great influence on the whole detection accuracy of the system. The detection rate rests on the technique that used for the signal extraction, the consistency of this technique for the extracted EEG signal features and the probability of fusing between two datasets and classification by using MLPNN. The development of these systems can considerably develop the way of diagnosing epilepsy patients.

6 Conclusion

This paper presents a new system for EEG classification by using the soft computing techniques. Initially, it shows the application of short-time Fourier transform for Denoising the signal throughout computing the STFT of the noisy signal. At that point, it elaborates the adoption of a threshold for the STFT and computing the inverse STFT. To extract the features, the Wavelet Transform is used via decomposing the signals into six EEG sub-bands i.e. D1-D5 and A5. Time-frequency analysis can be properly achieved by Wavelet transform and STFT because these methods result simultaneous time and frequency localization. To conclude, there are four ECG signal types. The first one is Data of Healthy people. The second one is Epileptic people during seizure-free interval. The third one is Epileptic people during seizure interval (Focal). The fourth and last one is Epileptic people during seizure interval (Nonfocal).

All these four ECG signal types are classified by using the Neural Network classifier. In the current experiments, we employ a large set of total (1050) datasets and combination between two databases. Likewise, for the purposes of training and testing, we used nearly about 925 datasets and 125 datasets respectively. We found that the accuracy of the proposed system was 94.4% which significantly outperform the previous methods in terms of dataset size and EEG signals types.

7 Future Work

The outcome of this study contributes to create a further evidence of the advanced seizure. The future work may be devoted to show some further advances in performance. It may explore other ways to extract discriminatory features from the EEG signals. It may consider other directions of research such as the evaluation of adjustment settings related to different parameter. In addition, more advanced classification algorithms and techniques may be considered together with Fuzzy methods. This will benefit to foresee the initial signs of a seizure. It is noteworthy to investigate the continuous long-term EEG recordings of several hours for one subject in the future work. Moreover, implementing the methodology based on using real-time signals and free online dataset will enhance the detection accuracy.

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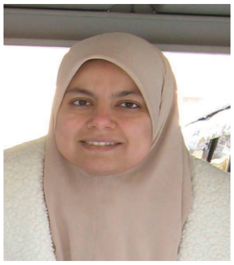

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