



Reliable epileptic seizure detection using an improved wavelet neural network

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RESEARCH

Please cite this paper as: Zainuddin Z, La, KH, Ong P. Reliable epileptic seizure detection using an improved wavelet neural network. AMJ 2013, 6, 5, 308-314. <http://doi.org/10.21767/AMJ.2013.1640>

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Abstract

Background

Electroencephalogram (EEG) signal analysis is indispensable in epilepsy diagnosis as it offers valuable insights for locating the abnormal distortions in the brain wave. However, visual interpretation of the massive amounts of EEG signals is time-consuming, and there is often inconsistent judgment between experts.

Aims

This study proposes a novel and reliable seizure detection system, where the statistical features extracted from the discrete wavelet transform are used in conjunction with an improved wavelet neural network (WNN) to identify the occurrence of seizures.

Method

Experimental simulations were carried out on a well-known publicly available dataset, which was kindly provided by the Epilepsy Center, University of Bonn, Germany. The normal and epileptic EEG signals were first pre-processed using the discrete wavelet transform. Subsequently, a set of statistical features was extracted to train a WNNs-based classifier.

Results

The study has two key findings. First, simulation results showed that the proposed improved WNNs-based classifier gave excellent predictive ability, where an overall classification accuracy of 98.87% was obtained. Second, by using the 10th and 90th percentiles of the absolute values

of the wavelet coefficients, a better set of EEG features can be identified from the data, as the outliers are removed before any further downstream analysis.

Conclusion

The obtained high prediction accuracy demonstrated the feasibility of the proposed seizure detection scheme. It suggested the prospective implementation of the proposed method in developing a real time automated epileptic diagnostic system with fast and accurate response that could assist neurologists in the decision making process.

Key Words

Epileptic seizure detection, fuzzy C-means clustering, K-means clustering, type-2 fuzzy C-means clustering, wavelet neural network

What this study adds:

1. EEG is a valuable diagnosis tool in the field of epileptic seizure detection. However, determining the discriminative characteristics that represent the inherent behaviours of the EEG signals properly and distinguishing a transient seizure from background activity accurately still remain a great challenge in epilepsy diagnosis.
 2. The feasibility and effectiveness of using a novel seizure detection paradigm, which pertains to an improved wavelet neural network model, were highlighted in this study.
 3. The classification accuracy obtained demonstrated the practicability of the proposed system in the task of epileptic seizure detection, which may assist and speed up the decision-making process of neurophysiologists in identifying seizure activity correctly.
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Background

Since its inception reported by German neuropsychiatrist Hans Berger in the year 1924, the EEG signals, which record the electrical activity in the brain, have emerged as an essential alternative in diagnosing neurological disorders. By analysing the EEG recordings, inherent information from different physiological states of the brain can be extracted,

which are extremely crucial for epileptic seizure detection since the occurrence of seizure exhibits clear transient abnormalities in the EEG signals. Thus, a warning signal can be initiated in time to avoid any unwanted seizure related accidents and injuries, upon detecting an impending seizure attack. While vital as a ubiquitous tool which supports the general diagnosis of epilepsy, the clinical implementation of EEG is constrained due to the challenges of: (1) Available therapies require long term continuous monitoring of EEG signals. The massive amounts of EEG recordings have to be painstakingly scanned and analyzed visually by neurophysiologists, which is a tedious and time-consuming task. (2) There often is disagreement among different physicians about the analysis of ictal signals.¹ Undoubtedly, an automated diagnostic system that is capable of distinguishing the transient patterns of epileptiform activity from the EEG signals with reliable precision is of great significance.

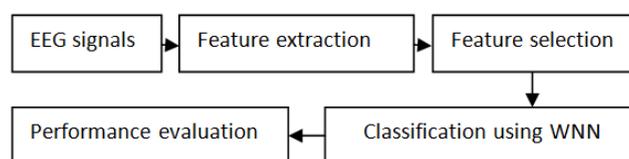
Various efforts have been devoted in the literature in this regard. Generally speaking, a typical epileptic seizure detection process consists of two stages wherein, the inherent information that characterises the different states of the brain electrical activity are first derived from the EEG recordings using some feature extraction techniques, and subsequently, a neural network based classifier is trained based on the obtained features. The discrete wavelet transform (DWT) has gained practical interest in extracting the valuable information embedded in the EEG signals due to its ability to capture precise frequency information at low frequency bands and time information at high frequency bands.²⁻⁵ EEG signals are non-stationary in nature, and they contain high frequency information with short time period and low frequency information with long time period.⁶ Therefore, by analysing the biomedical signals at different time and frequency resolutions, DWT is capable of pre-processing the biomedical signals efficiently in the feature extraction stage. In the second stage of the seizure detection scheme, different artificial neural networks (ANNs) based expert systems have been utilised extensively in the emerging field of epilepsy diagnosis. For instance, the multilayer perceptrons, radial basis function neural networks, support vector machines, probabilistic neural networks, and recurrent neural networks are some of the models that have been reported in literature.^{1,4,7-9} ANNs are powerful mathematical models that are inspired from their biological counterparts – the biological neural networks, which examine how the interconnecting neurons process a massive amount of information at any given time. The utilisation of ANNs in EEG studies is appropriate, due to their capability of finding the underlying relationship between rapid variations in the EEG recordings, in addition

to having the characteristics of fault tolerance, massive parallel processing ability, and adaptive learning capability. The objective of this paper is to present a novel scheme based on an improved WNN model for the optimal classification of epileptic seizures in EEG recordings. The normal as well as the epileptic EEG signals were first pre-processed using the DWT wherein, the signals were decomposed into several frequency sub-bands. Subsequently, a set of statistical features was extracted from each frequency sub-band, and was used as a feature set to train a WNNs-based classifier.

Method

The methodology used in this study is depicted in the block diagram in Figure 1.

Figure 1: Block diagram for the proposed seizure detection scheme



Data acquisition

The EEG signals used in this study were acquired from a publicly available benchmark dataset.¹⁰ The dataset is divided into five sets, labelled set A to E. Each set of the data consists of 100 segments, with each segment being a time series with 4097 data points. Each segment was recorded for 23.6 s at a sampling rate of 173.61 Hz. Each of the five sets was recorded under different circumstances. Both sets A and B were recorded from healthy subjects, with set A recorded with their eyes open whereas set B with their eyes closed. On the other hand, sets C to E were obtained from epileptic patients. Set C and D were recorded during seizure free period, where set C was recorded from the hippocampal formation of the opposite hemisphere of the brain, whereas set D was obtained from within the epileptogenic zone. The last data set, set E, contains ictal data that were recorded when the patients were experiencing seizure. In other words, the first four sets of data, sets A until D, are normal EEG signals, while set E represents epileptic EEG signals.

Feature extraction using discrete wavelet transforms

DWT offers a more flexible time-frequency window function, which narrows when observing high frequency information and widens when analysing low frequency resolution. It is implemented by decomposing the signal into coarse approximation and detail information by using successive low-pass and high-pass filtering. Selecting the appropriate number of decomposition level is important for DWT. For the EEG signal analysis, the number of

decomposition levels can be determined directly, based on their dominant frequency components. The number of levels is chosen in such a way that those parts of the signals which correlate well with the frequencies required for the classification of EEG signals are retained in the wavelet coefficients.¹¹ Since the clinical data used were sampled at 173.61Hz, the DWT using Daubechies wavelet of order 4 (db4), with four decomposition levels was chosen.¹² The db4 is suitable to be used as wavelets of lower order are too coarse to represent the EEG signals, while wavelets of higher order oscillate too wildly.¹³ The four-level wavelet decomposition process will yield a total of five groups of wavelet coefficients, each corresponds to their respective frequency. They are d_1 (43.4-86.8Hz), d_2 (21.7-43.4Hz), d_3 (10.8-21.7Hz), d_4 (5.4-10.8Hz), and a_4 (0-5.4Hz), which correlate with the EEG spectrum that fall within four frequency bands of: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz) and beta (13-22Hz). Subsequently, the statistical features of these decomposition coefficients are extracted, which are:

1. The 90th percentile of the absolute values of the wavelet coefficients.
2. The 10th percentile of the absolute values of the wavelet coefficients.
3. The mean of the absolute values of the wavelet coefficients.
4. The standard deviation of the wavelet coefficients.

It is worth mentioning that instead of the usual extrema (maximum and minimum of the wavelet coefficient), the percentiles are selected in this case to remove possible outliers.¹⁴ At the end of the feature extraction stage, a feature vector of length 20 is formed for each EEG signal.

Classification using an improved wavelet neural network

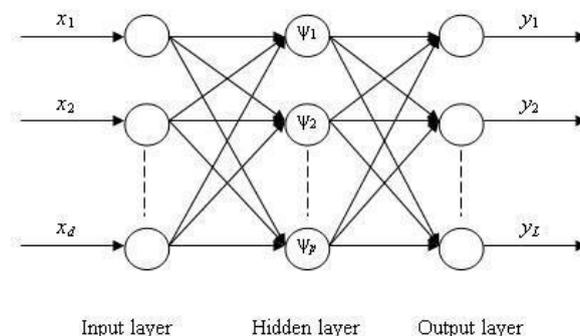
WNNs are feedforward neural networks with three layers – the input layer, the hidden layer, and the output layer.¹⁵ As the name suggests, the input layer receives input values and transmits them to the single hidden layer. The hidden nodes consist of continuous wavelet functions, such as Gaussian wavelet, Mexican Hat wavelet, Morlet wavelet, or Gabor wavelet, which perform the non-linear mapping. The product from this hidden layer will then be sent to the final output layer. Mathematically, a typical WNN is modelled by the following equation:

$$y(\mathbf{x}) = \sum_{i=1}^p w_{ij} \psi \left(\frac{\mathbf{x} - \mathbf{t}_i}{d} \right) + \mathbf{b}, \quad (1)$$

where y is the desired output, $\mathbf{x} \in \mathbb{R}^m$ is the input vector which consists of m numbers, p is the number of hidden neurons, w_{ij} is the weight matrix whose values will be adjusted iteratively during the training phase to minimise

the error goal, ψ is the wavelet activation function, \mathbf{t} is the translation vector, d is the dilation parameter, and \mathbf{b} is the column matrix that contains the bias terms. The network structure is illustrated in Figure 2.

Figure 2: Network architecture of wavelet neural networks



The WNNs are distinct from those of other ANNs in the sense that:¹⁵

- WNNs show relatively faster learning speed owing to the constitution of the fast-decaying localised wavelet activation functions in the hidden layer.
- WNNs preserve the universal approximation property, and they are guaranteed to converge with sufficient training.
- WNNs establish an explicit link between the neural network coefficients and the wavelet transform.
- WNNs achieve the same quality of approximation with a network of reduced size.

Designing a WNN requires the researchers to focus particular attention on several areas. First, a suitable learning algorithm is vital in adjusting the weights between the hidden and output layers so that the network does not converge to the undesirable local minima. Second, a proper choice of activation functions in the hidden nodes is crucial as it has been shown that some functions yield significant better result for certain problems.¹⁶ Third, an appropriate initialisation of the translation and dilation parameters is essential because this will lead to simpler network architecture and higher accuracy.¹⁷

The selection of the translation vectors for WNNs is of paramount importance. An appropriate initialisation of the translation vectors will do a good job of reflecting the essential attributes of the input space, in such a way that the WNNs begin their learning from good starting points and could lead to the optimal solution. Among the notable

proposed approaches are the ones given by the pioneers of WNNs themselves, where the translation vectors are chosen from the points located on the interval of the domain of the function.¹⁵ A dyadic selection scheme realised using the K-means clustering algorithm was also employed.¹⁸ The translation vectors were also obtained from the new input



data.¹⁹ An explicit formula was derived to compute the translation vectors to be used for the proposed composite function WNNs.²⁰ An enhanced fuzzy C-means clustering algorithm, termed modified point symmetry-distance fuzzy C-means (MPSDFCM) algorithm, was proposed to initialise the translation vectors.¹⁷ By incorporating the idea of symmetry similarity measure into the computation, the MPSDFCM algorithm was able to find a set of fewer yet effective translation vectors for the WNNs, which eventually led to superb generalisation ability in microarray study. In short, the utilisation of different novel clustering algorithms in WNNs aims for simpler algorithm complexity and higher classification accuracy from the WNNs.

In this study, the type-2 fuzzy C-means (T2FCM) clustering algorithm²¹ was proposed to initialise the translation vectors of WNNs. Its clustering effectiveness as well as its robustness to noise has motivated the investigation on the feasibility of T2FCM in selecting the translation vectors of the WNNs. For comparison purposes, the use of K-means (KM) and the conventional type-1 fuzzy C-means (FCM-1) algorithms in initialising the WNNs translation vectors were also considered.

Type-2 Fuzzy C-Means Clustering Algorithm

Rhee and Hwang proposed an extension to the conventional FCM-1 clustering algorithm by assigning membership grades to type-1 membership values.²¹ They pointed out that the conventional FCM-1 clustering may result in undesirable clustering when noise exists in the input data. This is because all the data, including the noise, will be assigned to all the available clusters with a membership value. As such, a triangular membership function is proposed, as shown in the following equation:

$$a_{ij} = u_{ij} - \left(\frac{1 - u_{ij}}{2} \right), \tag{2}$$

where u_{ij} and a_{ij} represent the type-1 and type-2 membership values for input j and cluster centre i , respectively. The proposed membership function aims to handle the possible noise that might present in the input data. From equation 2, the new membership value, a_{ij} , is defined as the difference between the old membership value, u_{ij} and the area of the membership function, where the length of the base of each of the triangular function is taken as 1 minus the corresponding membership value obtained from FCM-1.

By introducing a second layer of fuzziness, the T2FCM algorithm's concept still conforms to the conventional FCM-1 method in representing the membership values. To illustrate, it can be noted from equation 2 that a larger

value of FCM-1 value (closer to 1) will yield a larger value of T2FCM value as well. Since the proposed T2FCM algorithm is built upon the conventional FCM-1 algorithm, the formula used to find the cluster centres, c_{ij} , can now be obtained from the following equation that has been modified accordingly, as shown below:

$$c_i = \frac{\sum_{j=1}^N a_{ij} x_j}{\sum_{j=1}^N a_{ij}}, \tag{3}$$

where m is the fuzzifier, which is commonly set to a value of 2. The algorithm for T2FCM is similar to the conventional FCM-1, which aims to minimise the following objective function:

$$J_m(U, V) = \sum_{i=1}^C \sum_{j=1}^N u_{ij}^m \|x_j - c_i\|^2, \tag{4}$$

but it differs in the additional membership function and also the equation that has been modified to update the cluster centres. In general, the algorithm proceeds as follows:

1. Fix the number of centres, C .
2. Initialise the location of the centres, c_i , $i = 1, 2, \dots, C$, randomly.
3. Compute the membership values using the following equation:

$$U = [u_{ij}] = \left[\left(\frac{c \left(\frac{\|x_j - c_i\|}{\|x_j - c^k\|} \right)^{\frac{2}{m-1}}}{\sum_{k=1}^C \left(\frac{\|x_j - c_i\|}{\|x_j - c^k\|} \right)^{\frac{2}{m-1}}} \right)^{-1} \right]. \tag{5}$$

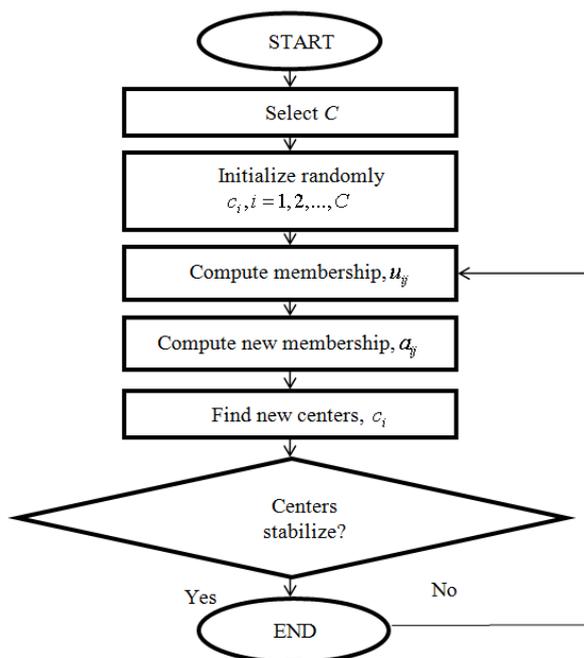
4. Calculate the new membership value, a_{ij} from the values of u_{ij} using equation 2.
5. Update the cluster centres using equation 3.
6. Repeat steps 3-5 until the locations of the centres stabilise.

The algorithm for T2FCM is summarised in the flowchart shown in Figure 3.

K-fold cross validation

In statistical analysis, k -fold cross validation is used to estimate the generalisation performance of classifiers. Excessive training will force the classifiers to memorise the input vectors, while insufficient training will result in poor generalisation when a new input is presented to it. In order to avoid these problems, k -fold cross validation is performed. To implement the k -fold cross validation, the samples are first randomly partitioned into $k > 1$ distinct groups of equal (or approximately equal) size. The first group of samples is selected as the testing data initially, while the remaining groups serve as training data. A performance metric, for instance, the classification accuracy, is then measured.

Figure 3: Clustering algorithm of T2FCM



The process is repeated for k times, and thus, the k -fold cross validation has the advantage of having each of the samples being used for both training and testing. The average of the performance metric from the k iterations is then reported. In this study, k is chosen as 10.

Results

The binary classification task between normal subjects and epileptic patients was realised using the WNNs models. The activation function used in the hidden nodes is the Morlet wavelet function. During the training process, a normal EEG signal was indicated by a single value of 0, while an epileptic EEG signal was labelled with a value of 1. During the testing stage, a threshold value of 0.5 was used, that is, any output from WNNs which is equal to or greater than 0.5 will be reassigned a value of 1; otherwise, it will be reassigned a value of 0. The simulation was carried out using the mathematical software MATLAB® version 7.10 (R2010a). The performance of the proposed WNNs was evaluated using the statistical measures of classification accuracy, sensitivity and specificity. The corresponding classification results between the normal and epileptic EEG signals by using the WNNs-based classifier with different initialisation approaches are listed in Table 1.

In terms of classification accuracy, the translation vectors generated by the conventional KM clustering algorithm gave the poorest result, where an overall accuracy of 94.8% was obtained. The WNNs that used the conventional FCM-1 clustering algorithm reported an overall accuracy of 97.15%. The best performance was obtained by the classifier that

employed the T2FCM algorithm, which yielded an overall classification accuracy of 98.87%.

Table 1: The performance metrics for the binary classification problem

Initialisation methods	Performance metric		
	Sensitivity	Specificity	Accuracy
KM	85.00	97.30	94.80
FCM	93.82	97.92	97.15
T2FCM	94.96	99.43	98.87

Discussion

In the field of medical diagnosis, the unwanted noise and outliers produced from the signals or images need to be handled carefully, as they will affect and skew the results and analysis obtained afterward. In this regard, the concept of fuzziness can be incorporated to deal with these uncertainties. Outliers or noise can be handled more efficiently and higher classification accuracy can be obtained via the introduction of the membership function.

The noise in the biomedical signals used in this work has thus been handled via two different approaches. The first treatment is in the feature selection stage, where the 10th and 90th percentiles of the absolute values of the wavelet coefficients were used instead of the minima and maxima values. The second way is via the T2FCM clustering algorithm used when initialising the translation parameters for the hidden nodes of WNNs. The clustering achieved by T2FCM results in more desirable locations compared to the conventional KM and FCM-1 methods, as reflected in the higher overall classification accuracy.

Numerous epileptic detection approaches have been implemented in the literature using the same benchmark dataset as in this study. For the sake of performance assessment, a comparison of the results with other state-of-the-art methods reported in the literature was included, as presented in Table 2. As depicted in Table 2, the proposed WNN with T2FCM initialisation approach outperformed the others generally. However, the achieved classification accuracy of 98.87% by the proposed model was inferior to the multilayer perceptrons (MLP) based classifier,²³ which might be attributed to their feature extraction method. Instead of using basic statistical features, the authors used the KM clustering algorithm to find the similarities among the wavelet coefficient, where the obtained probability distribution from the KM was used as the input of the MLP based classifier. A better set of deterministic features might be obtained from this approach, which will be an interesting topic to pursue in future. However, it is pertinent to note



that the MLP based classifiers are subject to slow learning deficiency and getting trapped in local minima easily.

Table 2: Performance comparison of classification accuracy obtained by the proposed WNNs and other approaches reported in the literature

Feature Selection Method	Classifier	Accuracy	References
Time Frequency Analysis	ANNs	97.73	²²
DWT with KM	MLPs	99.60	²³
DWT	MLPs	97.77	²⁴
Approximate Entropy	ANNs	98.27	²⁴
This Work	WNNs	98.87	-

In order to evaluate the statistical significance of the obtained results, statistical test on the difference of the population mean of the overall classification accuracy was performed using *t* distribution. The experiment was run 10 times to get the values of the summary statistics, namely, the mean and the standard deviation of the sample. The 1% significance level, or $\alpha = 0.01$ was tested to check whether there is significant difference between the two population means. Two comparisons were done, namely, between KM and T2FCM, and between FCM and T2FCM. The formula for the test statistics is given by:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{s_{\bar{x}_1 - \bar{x}_2}}, \quad (6)$$

where \bar{x}_1 and \bar{x}_2 are the sample means; μ_1 and μ_2 are the population means; and $s_{\bar{x}_1 - \bar{x}_2}$ is the estimate of the two standard deviations. The critical values of *t* for the two cases were ± 2.947 and ± 2.977 , respectively. On the other hand, the test statistics for the two cases were -16.778 and -6.249, respectively. For both cases, the values of the test statistic obtained fall in the rejection region. So the null hypothesis is rejected and it is concluded that there is significant difference between the classification accuracy obtained using the different initialisation methods, that is, the performance of T2FCM is superior to those of KM and FCM.

Conclusion

In this paper, a novel seizure detection scheme using the improved WNNs with T2FCM initialisation approach was proposed. Based on the overall classification accuracy obtained from the real data on epileptic seizure detection, it was found that the proposed model outperformed the other conventional clustering algorithms, where an overall accuracy of 98.87%, sensitivity of 94.96% and specificity of 99.43% were achieved. The initialisation accomplished via

T2FCM has proven that the algorithm can handle the uncertainty and noise in the EEG signals better than the conventional KM and FCM-1 algorithms. This again suggested the prospective implementation of the proposed method in developing a real time automated epileptic diagnostic system with fast and accurate response that could assist neurologists in their decision making process.

References

1. Tang Y, Durand DM. A tunable support vector machine assembly classifier for epileptic seizure detection. *Expert Syst Appl.* 2012; 39:3925-38.
2. Ebrahimpour R, Babakhani K, Arani SAAA, Masoudnia S. Epileptic seizure detection using a neural network ensemble method and wavelet transform. *Neural Netw World.* 2012; 22:291-310.
3. Guo L, Rivero D, Pazos A. Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks. *J Neurosci Meth.* 2010; 193:156-63.
4. Ubeyli ED. Combined neural network model employing wavelet coefficients for EEG signals classification. *Digit Signal Process.* 2009; 19:297-308.
5. Zandi AS, Javidan M, Dumont GA, Tafreshi R. Automated real-time epileptic seizure detection in scalp EEG recordings using an algorithm based on wavelet packet transform. *IEEE T Bio-Med Eng.* 2010; 57:1639-51.
6. Subasi A, Gursoy MI. EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Syst Appl.* 2010; 37:8659-66.
7. Gandhi TK, Chakraborty P, Roy GG, Panigrahi BK. Discrete harmony search based expert model for epileptic seizure detection in electroencephalography. *Expert Syst Appl.* 2012; 39:4055-62.
8. Kumar SP, Sriraam N, Benakop PG, Jinaga BC. Entropies based detection of epileptic seizures with artificial neural network classifiers. *Expert Syst Appl.* 2010; 37:3284-91.
9. Naghsh-Nilchi AR, Aghashahi M. Epilepsy seizure detection using eigen-system spectral estimation and multiple layer perceptron neural network. *Biomed Signal Proces.* 2010; 5:147-57.
10. Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P, Elger CE. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Phys Rev E.* 2001; 64.
11. Subasi A. EEG signal classification using wavelet feature extraction and a mixture of expert model. *Expert Syst Appl.* 2007; 32:1084-93.



12. Ubeyli ED. Wavelet/mixture of experts network structure for EEG signals classification. *Expert Syst Appl.* 2008; 34:1954-62
13. Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. *J Neurosci Meth.* 2003; 123:69-87.
14. Kandaswamy A, Kumar CS, Ramanathan RP, Jayaraman S, Malmurugan N. Neural classification of lung sounds using wavelet coefficients. *Comput Biol Med.* 2004; 34:523-37.
15. Zhang QG, Benveniste A. Wavelet Networks. *IEEE T Neural Networ.* 1992; 3:889-98.
16. Zainuddin Z, Ong P. Modified wavelet neural network in function approximation and its application in prediction of time-series pollution data. *Appl Soft Comput.* 2011; 11:4866-74
17. Zainuddin Z, Ong P. Reliable multiclass cancer classification of microarray gene expression profiles using an improved wavelet neural network. *Expert Syst Appl.* 2011; 38:13711-22.
18. Hwang K, Mandayam S, Udpa SS, Udpa L, Lord W, Atzal M. Characterization of gas pipeline inspection signals using wavelet basis function neural networks. *NDT and E Int.* 2000; 33:531-45.
19. Lin CJ. Nonlinear systems control using self-constructing wavelet networks. *Appl Soft Comput.* 2009; 9:71-9.
20. Cao JW, Lin ZP, Huang GB. Composite function wavelet neural networks with extreme learning machine. *Neurocomputing.* 2010; 73:1405-16.
21. Rhee FCH, Hwang C. A type-2 fuzzy C-means clustering algorithm. *Proceedings of the 20th IEEE FUZZ Conference; July 25-28, 2001; Vancouver, Canada2001.* p. 1926-9.
22. Tzallas AT, Tsipouras MG, Fotiadis DI. Automatic seizure detection based on time-frequency analysis and artificial neural networks. *Comput Intell Neurosci.* 2007; 2007:1-13.
23. Orhan U, Hekim M, Ozer M. EEG signals classification using the K-means clustering and a multilayer perceptron neural network model. *Expert Syst Appl.* 2011; 38:13475-81.
24. Guo L, Rivero D, Dorado J, Rabunal JR, Pazos A. Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks. *J Neurosci Meth.* 2010; 191:101-9.

Higher Education, Malaysia under the FRGS research grant scheme and Universiti Sains Malaysia under the USM Fellowship Scheme. The third author is grateful to Universiti Sains Malaysia, which supplied a generous Post-Doctoral Fellowship and made it possible to undertake this research.

PEER REVIEW

Not commissioned. Externally peer reviewed.

CONFLICTS OF INTEREST

The authors declare that they have no competing interests.

ACKNOWLEDGEMENTS

The authors acknowledge the dataset provided by Ralph Andrzejak from the Epileptic Center, University of Bonn, Germany. The authors also gratefully acknowledge the generous financial support provided by The Ministry of