On the use of wavelet neural networks in the task of epileptic seizure detection from electroencephalography signals

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Abstract

This paper investigates the feasibility and effectiveness of wavelet neural networks (WNNs) in the task of epileptic seizure detection. The electroencephalography (EEG) signals were first pre-processed using discrete wavelet transforms (DWTs). This was followed by the feature selection stage, where two sets of four representative summary statistics were computed. The features obtained were fed into the input layer of WNNs. Three different activation functions were used in the hidden nodes of WNNs – Gaussian, Mexican Hat, and Morlet wavelets. A 10-fold cross validation was performed and the performance assessment revealed that the proposed classifiers achieved high overall classification accuracy, which showed the prominence of WNNs in this binary classification task. The best combination to be used was the WNNs that employed Morlet wavelet as the activation function, with Daubechies wavelet of order 4 in the feature extraction stage. The cross comparison done showed that the classification accuracy achieved by WNNs was comparable to those of other artificial intelligence-based classifiers. It was also demonstrated that a classifier would perform better if input features with higher dissimilarity index were used.

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Keywords: EEG signals, epilepsy, epileptic seizure, wavelet neural networks, wavelet transform

1. Introduction

The human brain is a remarkable and highly complex structure. Being part of the central nervous system, this vital organ serves as the control centre for other organ systems of the body by constantly adjusting and regulating its internal mechanisms in response to the rapid changes of the environment. Human beings are gifted with superior cognitive abilities, and it is this hallmark that distinguishes us from other animals on this
planet. An adult human brain weights on average 1.5 kg, and it is estimated that it contains as many as 93 billion neurons and 112 billion non-neuronal cells [1]. Each of these neuron cells is in turn interconnected with each other through more than ten thousand synapses. Taken these facts together, the human brain’s activity is indeed extremely complex and highly dynamic in nature. The neuronal activities, which refer to the passing of information from one neuron to another in the form of electric potentials, are of great interest to neuroscientists as they seek to explain how a collection of individual nerve cells work collaboratively to process a colossal amount of biological data.

Epileptic seizure is a neurological disorder that arises as a consequence of excessive and abnormal firing of electrical signals in the brain. An estimated 50 million people worldwide suffer from this disease [2], making it the second most common neurological disorder, after stroke. The staggering number of patients diagnosed with this disease illustrates the paramount importance of a better diagnosis system to improve the quality of lives of patients. Electroencephalogram (EEG), first introduced by German neurophysiologist Hans Berger in 1924, has been used mainly by neuroscientists in various fields of neurocognitive research and epileptologists in clinical diagnosis. It is a very useful clinical tool that can be used to support general diagnosis of epilepsy.

By analyzing the biomedical signals recorded from EEG, clinicians gain a better understanding about the medical condition of a patient before he or she undergoes a surgery. In general, EEG recordings will be performed a few days prior to surgery to monitor the patient’s condition. However, it is almost impossible for electroencephalographers to scrutinize all the generated signals that have been recorded. Therefore, it is ideal if machines or expert systems can be designed and developed to assist in this matter. Such automated classifiers will not only save medical expenditure, but they can also speed up doctors’ pre-surgical evaluations.

Research in the area of epileptic seizure detection centers around the many techniques employed to extract the useful information embedded in the EEG signals, as well as the different expert systems or classifiers that can be designed to aid in the task of epileptic seizure detection. Researchers employed and incorporated different techniques to analyze the EEG signals. An issue that has been given great attention is the pre-processing stage of the EEG signals because it is of vital importance to use the best technique to extract the useful information embedded in the non-stationary biomedical signals. Among the techniques reported include the Lyapunov exponent [3], multiple signal classification (MUSIC) [4], and approximate entropy (ApEn) [5]. It is noteworthy to mention that the discrete wavelet transform (DWT) is the most popular technique [5-7] because this method is capable of capturing valuable time and frequency information simultaneously.

On the other hand, artificial neural networks (ANNs), support vector machines (SVMs) [8], and decision trees [9] are some of the reported classifiers that have been studied to perform the classification task. Inspired from its biological counterpart, ANNs are powerful mathematical models that mimic the learning mechanisms of neuron cells in the brain. A survey of the literature found that various models of ANNs have been considered and proposed in the task epileptic seizure detection. Among the notable ones include radial basis neural networks (RBNNs) [10], recurrent neural networks (RENs) [11], probabilistic neural networks (PNNs) [3], and wavelet neural networks (WNNs) [6].

The main objective of this paper is to investigate on the feasibility of WNNs in the binary classification task of epileptic seizure detection. In this paper, a novel hybrid system was proposed. The EEG signals of interest were first pre-processed using DWT. The method of DWT was chosen because this transform has the superiority of capturing the details of the non-stationary signals. The frequency and abrupt changes in the biomedical signals can be traced and studied effectively using DWT. After the feature extraction stage, a dimensionality reduction stage was performed before the data was fed into the proposed WNNs, with three different activation functions. WNNs were selected as the mathematical models because of their compact architecture and faster learning rate.

It is pertinent to note that the experimental results from scientific and engineering applications are always subjected to outliers. An outlier which deviates markedly from other observations might be attributed to erroneous measurement, sampling error, and non-calibrated equipment. They should be eliminated from the
experimental data before any further downstream analysis. In this work, after the signal feature extraction was accomplished via DWT, four summary statistics, namely maximum, minimum, mean, and standard deviations of the wavelet coefficients from each subband, were derived. In addition, to remove possible outliers that might exist, an additional second set of input feature was proposed, by replacing the maximum and minimum values of the first set of input features with the values of the 90th percentile and 10th percentile, respectively. Eliminating the outliers before the performing the task of epileptic seizure detection is extremely crucial, as the outliers might degrade the classification performance of classifiers.

In short, the contributions of this work are as follows:
(a) A classifier with high predictive accuracy to perform the task of epileptic seizure detection is proposed.
(b) By removing possible outliers that might deteriorate the predictive competence of the classifier, a better and more accurate set of feature representation is obtained.

The remaining of this paper is organized as follows. In Section 2, the outline of the methodology used is given. The results are then presented, followed by some discussion in Section 3. Finally, conclusions are drawn and some future research directions are proposed in Section 4.

2. Methodology

In this work, the EEG signals that were obtained from the benchmark dataset were first pre-processed using DWT (db2 or db4). After the feature extraction stage, the dimension of the data was further reduced through the feature selection stage, where two sets of input feature were considered (set I and II). The obtained featured were then fed into WNNs with varying activation functions (Gaussian, Mexican Hat or Morlet wavelet). Finally, performance evaluation was reported using three statistical measures, namely sensitivity, specificity, and overall classification accuracy. A summary of the methodology used in this research is given in Fig. 1.

![Block diagram for the proposed WNNs](image)

2.1. Data acquisition

The data used in this study was acquired from the publicly available benchmark dataset [12]. A total of five sets of EEG signals, labeled set A until E, were utilized. Each set of data contains 100 segments, where each segment is a time series with 4097 data points.

The data were recorded at a sampling rate of 173.61 Hz for 23.6s. Set A and B were both recorded from healthy volunteers – set A was recorded with their eyes open while set B with their eyes closed. On the other hand, set C until E were obtained from epileptic patients. Set C and set D were recorded during the interictal (seizure free) stage, 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 final set of data, set E, which contains ictal data, was recorded when the patients were experiencing seizure.
2.2. Feature extraction using discrete wavelet transform

A binary classification was considered in this study. Set A until D consist of normal EEG signals while set E represents epileptic EEG signals. In the pre-processing stage, the signals were analyzed using DWT. Two different types of wavelets, namely Daubechies wavelet of order 2 (db2) and order 4 (db4) were considered. A four-level decomposition was employed. At each decomposition level, the signals under study were decomposed into coarse approximation, $a$, and detail information, $d$. The iterated process then yielded the following coefficients with their corresponding frequency: $d_1 (43.4 – 86.8 \text{ Hz})$, $d_2 (21.7 – 43.4 \text{ Hz})$, $d_3 (10.8 – 21.7 \text{ Hz})$, $d_4 (5.4 – 10.8 \text{ Hz})$, and $a_4 (0 – 5.4 \text{ Hz})$.

2.3. Feature selection

After the feature extraction stage, a total of four summary statistics were derived from the generated wavelet coefficients. They are maximum, minimum, and mean of the absolute values of the wavelet coefficients in each subband, and standard deviations of the wavelet coefficients from each subband [13] (referred to as input feature set I). Another set of input feature, termed input feature set II, with slight modification, was also considered. The maximum and minimum values were replaced with the 90th percentile and 10th percentile of the values of the coefficients, respectively. This was done to trim out possible outliers that might present in the data.

To illustrate further on this matter, a total of 4 EEG signals were randomly chosen from the data set. The wavelet coefficients were generated from each signal and the $d_4$ coefficients were extracted. As shown in the boxplots in Fig. 2, the outliers are marked individually outside the non-outlier extrema. For the case of input feature I, maximum values, which are actually outliers, have been included. In contrast, if the value of 90th percentile is chosen to replace the maximum value, outliers can be discarded and excluded, which is the case for input feature II.

![Boxplots for four randomly chosen EEG signals that show the outliers for the generated D2 wavelet coefficients](image_url)
2.4. Wavelet neural networks

The data were then fed into the proposed WNNs. WNNs, which were first introduced by Zhang and Benveniste [14], are a variant of ANNs. Due to their capability of rapid identification, analysis of conditions, and diagnosis in real time, ANNs have found a widespread of use in the field of biomedical signal processing; the most prominent ones being speech recognition, cardiology, and neurology [15]. ANNs also demonstrated their feasibility of use in medical diagnosis as they are not affected by several undesirable factors, such as human fatigue, emotional states, and habituation [15].

Specifically, WNNs have been implemented successfully in many biomedical related problems, such as prediction of blood glucose level of diabetic patients [16] and multiclass cancer classification of microarray gene expression profiles [17].

The WNNs proposed consist of three layers – the input layer that receives the input data, the hidden layer that performs the nonlinear mapping, and the output layer that determines the nature or the class of the input data. The mathematical equation that describes the modeling is given by the following equation:

\[
y(x) = \sum_{i=1}^{n} w_{ij} \frac{1}{\sqrt{d}} \psi\left(\frac{x-t}{d}\right)
\]

, where \( y \) is the output, \( n \) is the number of hidden nodes, \( j \) is the number of output nodes, \( w \) is the weight matrix that minimizes the error goal, \( \psi \) is the wavelet function, \( x \) is the input vector, \( t \) is the translation parameters vector, and \( d \) is the dilation parameters vector. Three localized continuous wavelet activation functions were investigated. The three functions are as follows:

(i) Gaussian wavelet, \( \psi_1(t) = -t \cdot \exp\left(-0.5t^2\right) \)  
(ii) Mexican Hat wavelet, \( \psi_2(t) = (1-t^2) \cdot \exp\left(-0.5t^2\right) \)  
(iii) Morlet wavelet, \( \psi_3(t) = \cos(5x) \cdot \exp\left(-0.5t^2\right) \)

The graphical representations of the three functions are shown in Fig. 3.

![Graphical representations of wavelet functions](image-url)
2.5. Learning algorithm

In a typical neural network learning process, the learning phase is divided into two stages. The first stage involves initializing the parameters and defining the activation functions used, while the second stage involves adjusting the weight vectors between the hidden layer and output layer. The training of the WNNs is based on the concept of minimizing a chosen cost function. The cost function used in this study is the mean square error, given by the following formula:

\[ E = \frac{1}{N} \sum_{i=1}^{N} (y_d(n) - y(n))^2 \]  

where \( y_d \) is the desired output value, \( y \) is the output value obtained from the WNNs, and \( N \) is the number of observation.

The simulation for this study was carried out by using the mathematical software MATLAB® version 7.10 (R2010a). The learning algorithm [18] of WNNs, which incorporates the concept of orthogonal least square [19], is described as follows. Starting with no hidden neuron in the hidden layer, the network is first simulated. The error contributed by each of the input vector is calculated. Next, the input vector with the greatest error is identified. Subsequently, the input vector that contributes the most error will be chosen as the next hidden neuron to be added to the hidden layer. Then, the weight vectors that establish the connection between the hidden layer and the output layer are evaluated to minimize the cost function. If the error falls below the specified targeted value, then the network is presented. Otherwise, another hidden neuron will be added and this process repeats until the error falls below the specified targeted value or the maximum number of hidden neuron has been reached. The flow of the learning algorithm is summarized in Fig. 4.

In this paper, the pseudo-inverse learning algorithm with random centre initialization was used. The learning was stopped once the error goal, namely 0.01, was reached. In this study, the number of hidden nodes was determined by the learning algorithm. There was only one output node. If the value of the output was equal to or greater than 0.5, then the value would be reassigned as 1, which implied an epileptic EEG signal. Otherwise, the value would be reassigned as 0, which suggested a normal EEG signal.

2.6. K-fold cross validation

In this work, a 10-fold cross validation was adopted to test the robustness of the proposed model. The 100 EEG signals from each set were partitioned into ten disjoint sets – the first nine sets were used as training sets, while the last set was the testing set. The same process was repeated for ten times so that each of the ten data sets can be used as the testing set. A total of ten trials were run and the average values for each performance metric were reported.

2.7. Performance evaluation

The performance of the proposed models was then evaluated using the following three statistical measures:

\[ \text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \]  

(6)
Fig. 4. The flowchart for the learning algorithm of WNNs

START

Initialize network

Feed in data and simulate the network

Compute the error between the input vector and the target value

Identify the input vector that contributes the most error

Assign the input vector that contributes the most error as the hidden neuron

Compute the weight vectors that minimize the cost function

Network error < predefined goal?

END

Yes

No

Specificity = \frac{TN}{TN + FP} \times 100\% \quad (7)

Overall Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \times 100\% \quad (8)

where TP, TN, FP, and FN stand for true positive (an epileptic EEG signal is correctly identified by WNNs as an epileptic signal), true negative (a normal EEG signal is correctly identified by WNNs as a normal signal), false positive (a normal EEG signal is incorrectly identified by WNNs as an epileptic signal), and false negative (an epileptic EEG signal is incorrectly identified by WNNs as a normal signal), respectively.
3. Results and Discussion

3.1. Input and output encoding scheme

Before the wavelet coefficients were being fed into the WNNs, they were re-scaled to [0,1]. This normalization step was performed to prevent attributes with large ranges \( a_i \) and \( d_i \) from outweighing other variables with smaller ranges \( \tilde{a}_i \) and \( \tilde{d}_i \) [20]. The two possible values for the output are 0 and 1, where 0 denotes a normal EEG signal, whereas 1 implies an epileptic EEG signal. During the testing stage, a threshold value of 0.5 was chosen. In other words, any output value that is greater than or equal to 0.5 would be reassigned an output value of 1. Otherwise, it would be reassigned an output value of 0. Mathematically,

\[
\text{output} = \begin{cases} 
0, & \text{if output < 0.5} \\
1, & \text{if output } \geq 0.5. 
\end{cases}
\]  

(9)

3.2. Results and discussion

The results of the binary classification problem, with different parameters setting, were displayed in Table 1.

In this work, it was found that the combination that gave the best overall classification accuracy (98.66%) is the WNNs model that employed Morlet wavelet function and used input feature set II with EEG signal pre-processed using db4.

As shown in the table, when comparing the types of DWT used, it was found that db4 gave slightly better result compared to db2. This corroborated the finding by [21] that db4 is the most suitable wavelet to be used in the task of EEG signals analysis. As stated in [21], the wavelets of lower order are too coarse to represent the EEG signals that have many spikes, while higher order wavelets oscillate too wildly and this characteristic is not desirable as the wavelets cannot represent the EEG signals well.

Also, it was observed that when input feature set II was used, higher overall classification accuracy was obtained. This result showed that the use of 10th percentile and 90th percentile, were indeed, better than the use of minimum and maximum values of the wavelet coefficients. By replacing the two extreme values with percentiles, possible outliers present in the dataset were eliminated to increase the dissimilarity measures between the data points in two distinct groups and as such, result in better overall classification accuracy.

Regarding the use of three different continuous wavelet functions as the activation functions in the hidden nodes of the WNNs, all three wavelet performed efficiently, with overall accuracy ranging from 96.56% to 98.66%. The oscillatory nature of the wavelet functions is able to perform the nonlinear mapping effectively.

It is reported in [22] that the choice of the activation functions used in the hidden nodes of WNNs affects the performance of the approximation capability. When the shape of an activation function resembles the shape of the function to be approximate, the WNN performed better by yielding higher approximation accuracy. The Morlet wavelet function used in this paper is derived from the product of the cosine trigonometric function and the exponential function which contribute to the graph’s oscillatory behaviour. This oscillating shape resembles the shape of the non-stationary EEG signals used in this study.

The resemblance of the shape of the Morlet wavelet to the oscillating EEG signals might be a possible explanation for the high classification accuracy obtained. However, further empirical and theoretical studies need to be done to confirm this statement, since the work in this paper deals with classification, and not function approximation, as what is being studied in [22].
Table 1. The performance metric obtained using different Daubechies wavelets, input features, and activation functions

<table>
<thead>
<tr>
<th>Daubechies wavelet</th>
<th>Input feature</th>
<th>Performance metric</th>
<th>Activation functions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Sensitivity</td>
<td>Gaussian</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mexican Hat</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Specificity</td>
<td>Morlet</td>
</tr>
<tr>
<td>db2</td>
<td>Set I</td>
<td>93.83 ± 0.84</td>
<td>86.59 ± 1.57</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.05 ± 0.08</td>
<td>99.27 ± 0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>97.20 ± 0.13</td>
<td>96.56 ± 0.25</td>
</tr>
<tr>
<td></td>
<td>Set II</td>
<td>96.03 ± 0.63</td>
<td>89.51 ± 1.79</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.71 ± 0.17</td>
<td>99.50 ± 0.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.14 ± 0.13</td>
<td>97.58 ± 0.26</td>
</tr>
<tr>
<td>db4</td>
<td>Set I</td>
<td>93.82 ± 1.18</td>
<td>81.40 ± 1.80</td>
</tr>
<tr>
<td></td>
<td></td>
<td>97.92 ± 0.27</td>
<td>99.45 ± 0.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td>97.14 ± 0.27</td>
<td>95.88 ± 0.26</td>
</tr>
<tr>
<td></td>
<td>Set II</td>
<td>95.78 ± 0.71</td>
<td>92.26 ± 1.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.83 ± 0.30</td>
<td>99.77 ± 0.18</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.22 ± 0.21</td>
<td>98.26 ± 0.24</td>
</tr>
</tbody>
</table>

3.3. Performance comparison

In this section, a performance comparison was carried out. The classification accuracy obtained by the proposed WNNs was compared with the results from other works by using different artificial intelligence-based classifiers, as shown in Table 2. Each of the binary classification task studied used the same benchmark dataset.

Table 2. Performance comparison of the proposed WNNs with other classifiers

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Feature selection</th>
<th>Classification accuracy</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>Time frequency analysis</td>
<td>97.73</td>
<td>[23]</td>
</tr>
<tr>
<td>MLP</td>
<td>DWT with line length feature</td>
<td>97.77</td>
<td>[24]</td>
</tr>
<tr>
<td>MLP</td>
<td>DWT with k-means algorithm</td>
<td>99.60</td>
<td>[25]</td>
</tr>
<tr>
<td>WNN</td>
<td>DWT</td>
<td>98.66</td>
<td>This work</td>
</tr>
</tbody>
</table>

In [23], the smoothed-Wigner-Ville distribution (SPWVD) was employed as the time frequency analysis to pre-process the EGG signals. A feedforward ANN was then used to classify the signals and an overall classification accuracy of 97.73% was reported.

In [24], DWT coupled with the line length feature was used in the feature extraction stage to analyze the EEG signals before they were fed into the multilayer perceptron (MLP). The classifier managed to achieve an overall classification accuracy of 97.77%.

In [25], the wavelet coefficients obtained from the EEG signals after the DWT were further clustered by using the k-means clustering algorithm. The artificial intelligence-based classifier that was used in the study was MLP. A high overall classification accuracy of 99.60% was obtained.

The use of k-means clustering on the wavelet coefficients in [25] proved to enhance the classification accuracy. It is also noted that while MLP remains a common and popular classifier, it suffers from several drawbacks, such as the time consuming training phase and the use of global activation functions [26]. In contrast, WNNs use localized activation functions. Hence, WNNs serve as an alternative approach.
The proposed WNN model, with DWT in the feature extraction stage, reported an overall classification accuracy of 98.66%, which was comparable to the results obtained by the three aforementioned classifiers.

4. Conclusion

In this paper, WNNs models with varied activation functions and different feature extraction techniques were investigated in the task of epileptic seizure classification. Based on the overall classification accuracy obtained, the Morlet wavelet was found to be the best wavelet function to be used. The db4 was also found to be more suitable to be used compared to db2. By replacing the extreme values of wavelet coefficients with suitable percentiles, the classifiers gave better classification accuracy. The high overall classification accuracy obtained verified the promising potential of the proposed classifier that could assist clinicians in their decision making process. Other neurodegenerative diseases, such as Alzheimer’s and Parkinson’s diseases, can also be studied using the similar methodology and classifiers proposed. The task of epileptic seizure prediction [27] is another interesting task where it requires the classifier to differentiate between pre-ictal and interictal data.

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References