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Artificial Neural Network versus Support Vector Machine for Classifying the Epileptic Seizure by Using Electroencephalography Signals

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Abstract
In recent years, electroencephalography (EEG) is becoming increasingly crucial in the diagnosis and treatment of mental and brain diseases and abnormalities. The main diagnostic application of EEG is in the case of epilepsy. Thus, it has various benefits and significance in Brain Computer Interface (BCI) system. In this paper, we suggest a novel method which is more efficient in classifying the EEG signal data of epileptic seizure using combination of state-of-the-art feature extraction algorithm, Discrete Wavelet Transforms (DWT) and machine learning technique. The feature would then become inputs to the chosen classifiers. Support Vector Machine (SVM) and Artificial Neural Network (ANN) are used for classification purpose. The performance of the combination of DWT and classifiers was presented and analysed. The result of DWT + SVM achieved the highest classification accuracy up to 83.50%.
Keywords: Electroencephalography; artificial neural networks; support vector machine; discrete wavelet transforms; epilepsy

Introduction
attention of a growing number of researchers. Pattern recognition is one of the fastest and most exciting developing fields and is reflected in developments in numerous fields such as text and document analysis, image processing, computer vision and in neural network. This development is very similar to the development of machine learning. In the last decade, the application of machine learning has experienced dramatic increase due to the many important developments in the underlying techniques and algorithms.

Pattern recognition can also be applied in engineering and numerous scientific disciplines such as multimedia data analysis, bioinformatics, and most recently data science. In addition, human activity recognition is one of the crucial application areas for pattern recognition. The use of modalities such as sound or interactions between people, body movement and posture have made activity recognition become an important advancement. Brain computer interface (BCI) systems aim to detect the users' thought and transform them into input commands that control devices such as prosthesis hand and wheelchair [1]. According to [1], Various BCI systems using EEG signals have been proposed and among them Motor Imagery (MI)-based isine of the most promising.

The main purpose of this study is to analyse and classify the EEG signal data of epileptic seizure. The sample data are divided into two categories, healthy volunteers and epilepsy patients. In this study, the features from both samples are extracted. Then, the classification process is developed by using ANN and SVM. The aim of the study is to evaluate and compare the classification efficiency between ANN and SVM in terms of training time and classification accuracy. Previous work by Qi and Alias [2], showed that the combination of statistical feature extraction method and SVM gained a better result than using ANN and obtained a great performance with classification accuracy of 69.75% and shorter training time. This paper is arranged as follows. The EEG will be presented in Section 2. In the subsequent section, the theory of feature extraction is reviewed followed by concepts of DWT. Section 4 explains the classification stage using ANN and SVM. The experimental analysis and the results obtained are discussed in Section 5. The last section contains conclusions and suggestions for future research work.

Electroencephalography

Recently, the electroencephalography (EEG) has become an effective tool in the diagnosis of seizure such as autism and epilepsy. Meanwhile, a BCI is a direct communication pathway between computer and brain. There are several purposes of EEG device such as capture of neuronal activity around the scalp and measurement of electrical activity that occurs due to movement of eyes, known as electrooculogram (EOG) and movement of the muscles known as electromyogram (EMG) [3]. An electrode is placed in the frontal regions of the scalp to detect the brain wave recognition generated by electric signals. Figure 1 shows an example of depiction of electrode placement in the standard 10-20 systems.

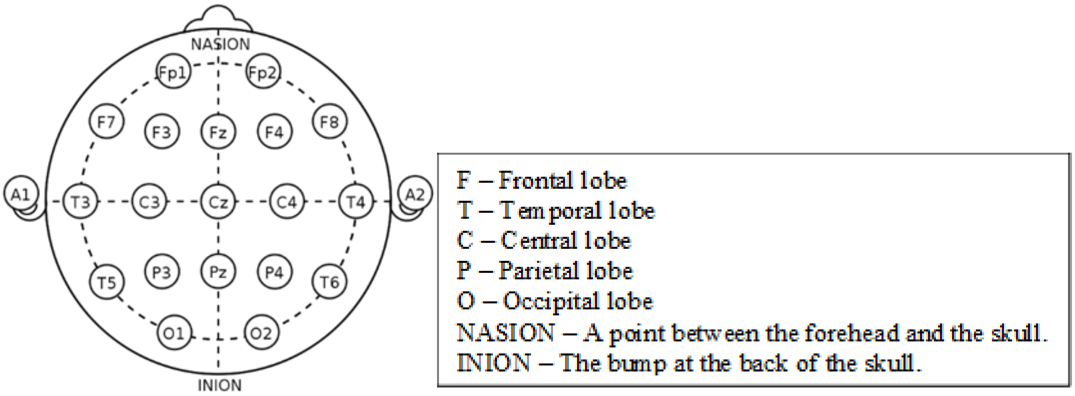

Figure 1 Scheme of the locations of surface electrodes according to the standard 10 – 20 systems.

In view of this, EEG can be used to measure the brain activity such as treatment of mental abnormalities, brain diseases and diagnosis. Therefore, EEG are more effective and affordable healthcare or clinical services. In this study, EEG signal data of epileptic seizure was classified. Epilepsy is one of the neurological disorders of the brain characterized by recurrent seizures. Roughly 1% of the world's population suffers from epilepsy. In addition, the cure for this disorder has not yet been found [4]. Next, the diagnostic category of epilepsy encompasses multiple disorders with varying pathophysiology, aetiologies and outcomes. Moreover, epilepsy is a recurrent and sudden brain malfunction associated with hyper synchronous and activity of the nerve cells. As mentioned by Senthilmurugan *et al.* [5], people have seizures when the electrical signals in the brain misfire. It will cause a communication problem between nerve cells when the brain's normal electrical activity is disrupted by these overactive electrical discharges.

Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a wavelet transform that provides a signal in frequency and time. The wavelets are discretely sampled and efficiently computed. It is a computationally efficient technique and relatively recent for extracting information about non-stationary signals such as audio. This method also improves the pattern recognition rate and can be used to transform image pixels into wavelets. Then, DWT are used for wavelet-based compression and coding. Daubechies, Coiflet and Symmlet are included in several types of wavelet families. A proper wavelet and accurate number of decompositions are important to obtain a good recognition accuracy. Daubechies wavelet is more efficient filter implementation and orthogonality property [6]. In this study, we are using Daubechies wavelet for feature extraction purpose. The DWT was decomposed in two stages, firstly into the convolution of the input signal by the wavelet base and secondly into subsampling process. The convolution is performed by the equations:

$$y_1[n] = y_{low}[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \qquad (1)$$

and

$$y_2[n] = y_{high}[n] = (x * h)[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] \qquad (2)$$

In the above equations, the DWT of an input (signal) $\boldsymbol{x}$ is calculated by passing it through a series of filters. The samples are passed through a low pass filter with impulse response g and h is the impulse response of the high-pass filter. The expression $[n-k]$ corresponds to the delay in the input. Then, $y_1[n]$ and $y_2[n]$ are the outputs of the FIR filters. The outputs give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass filter). The two filter are related to each other. Figure 2 shows the block diagram of filter analysis.

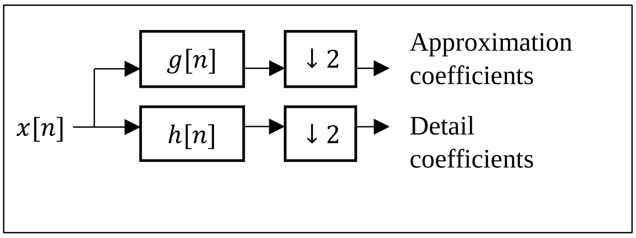

Figure 2 Block diagram of filter analysis.

Moreover, the filter output of the low-pass filter in the diagram above is then subsampled by 2 and further processed by passing it again through a new low-pass filter and high-pass filter with half the cut-off frequency of the previous one. The subsampling is calculated, according to:

$$y_3[n] = y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \qquad (3)$$

$$y_4[n] = y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \qquad (4)$$

Figure 3 shows the wavelet decomposition tree. The high frequency components known as detail coefficients, denoted by h are lower importance than low frequency components called approximation coefficient g. This decomposition has halved the time resolution since only half of each filter output characterize the signal. However, each output has half the frequency band of the input, so the frequency resolution has been doubled.

With the subsampling operator ↓

$$(y \downarrow k)[n] = y[kn] \qquad (5)$$

The above summation can be written more concisely.

$$y_{low} = (x * g) \downarrow 2 \qquad (6)$$
$$y_{high} = (x * g) \downarrow 2 \qquad (7)$$

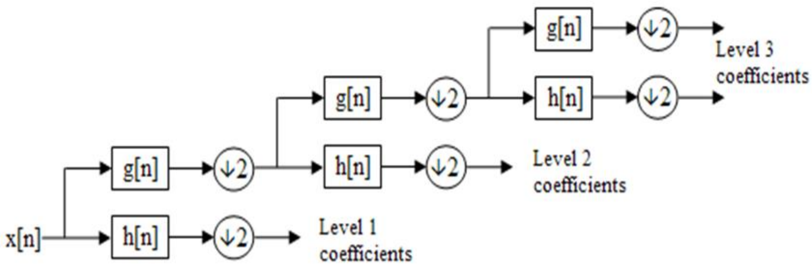

Figure 3 Decomposition Tree of Discrete Wavelet Transform (DWT).

For DWT, the low frequency sequences of the first level become an input to the second stage. Moreover, the half band filters produce signals spanning only half the frequency band at each decomposition level. The decimation and filtering process continued until the desired level is reached. Next, DWT can also decompose low and high frequency components. The low frequency components provide a better recognition accuracy. In previous work, Alsharabi *et al.* [3] investigated the data from EEG signals for the diagnosis of epilepsy based on Shannon entropy, DWT as feature extraction and neural network as classifier. The DWT is used to decompose the EEG signals into several frequency sub-bands while Shannon entropy technique is used to extract the features of EEG signals and as input to FFNN classifiers for classification accuracy.

Classification Module

There are many algorithms that can be used to solve almost any data problem, such as linear regression, logistic regression, SVM, Naive Bayes, Decision Tree and ANN. In this study, ANN and SVM will be used as classification scheme.

Artificial Neural Network

An Artificial Neural Network (ANN) consists of numerous interconnected neurons and every neuron can perform only simple computation [7]. Moreover, the biological neurons are more complicated compared to the architecture of an artificial neuron. ANN is based on a simplified and abstract view of the neuron [8]. It is arranged and connected in layers to form large networks, where the network function will be determined by connections and learning. Note that the connections do not need to be programmed because it only can be formed through learning. Also, according to Graimann *et al.* [9], ANN differs from conventional computing machines that serve to replace and accelerate human brain computation regardless of the network and organization of computer elements. Moreover, ANN are made up of simple elements operating in parallel. It can be constructed in layers connected to one or more hidden layers [7]. Then, each neuron in the hidden layer combines with all neurons in the output layer. The connections between these elements is widely determined. Neural networks will adjust the weight of the connections between these elements. Then, the results are obtained from the output layer.

ANN is proper to solve the complications that arise from ill-defined, complex, high nonlinear, and different variables. In previous work, Liang *et al.* [10] investigated the estimation and prediction of solar radiation by developing the method of ANN. From the study presented by [10], the prediction of solar radiation are more accurate by using ANN compared to conventional model. ANN can be categorized into few types such as FFNN, Radial Basis Function (RBF) Neural Network, and Recurrent Neural Network. According to Moraes *et al.* [8], there are no connections back from the output to the input neurons. Multi-layer Perceptron can be the common type of FFNN [7].

A multi-layer perceptron (MLP) consisted of three fundamental layers is the most used structure. These three layers are hidden, input and output layers of nodes. Input layers will introduce the model inputs where it receives the input signals from environment. Then, the layers of processing neurons will combine the inputs with weights that are adapted during the learning process and single hidden layer is sufficient in constructing neural nets. Meanwhile, the output layer receives information from hidden layers and transfer answer to the network. In Figure 4 shows the architectural of neuron in ANN.

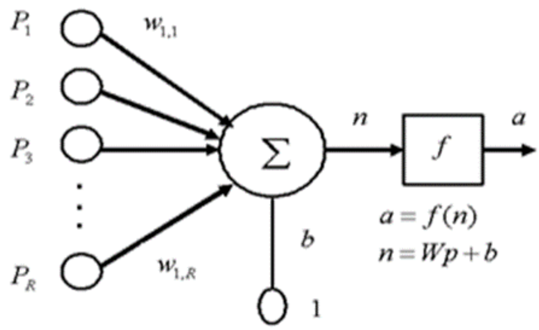

Figure 4 Architectural of neuron in ANN.

From the ANN architecture in Figure 4, the scalar input p is multiplied by the scalar weight w to form wp. Then, the other input 1, is multiplied by a bias b and then passed to the summer. The summer output n, often referred to as the net input, goes into a transfer function f, which produces the scalar neuron output a. f also can be a radial basis function, hyperbolic tangent or sigmoidal.

ANN need to be trained before it used for testing or classification. If p_i are the inputs and w_i are the weight, then the total input to the output neuron I can be calculated by the following summation function:

$$I = w_1 p_1 + w_2 p_2 + \cdots + w_n p_n = \sum_{i=1}^{n} w_i p_i \qquad (8)$$

The result of the summation function is transformed to an output through the activation function, $h_{w,b}(p)$. The output neural network can be obtained as:

$$h_{w,b}(p) = f(W^T p) = f\left(\sum_{i=1}^{n} W_i p_i + b\right) \qquad (9)$$

The weights and biases should be adjusted in order to produce the desired mapping. Therefore, the feature vectors will be applied to adjust its weights, biases, and the variable parameters to capture the relationship between input patterns and outputs. Figure 5 shows MATLAB generated schematic diagram of ANN when DWT is the input. The number of input layers is equivalent to the number of input DWT, while the number of hidden layers is user defined. The number of nodes in output layer must be equivalent to the number of classes, which is two (normal and epilepsy).

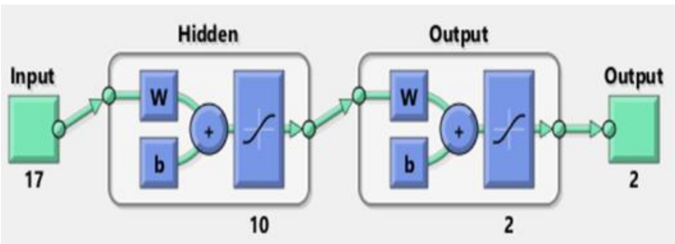

Figure 5 MATLAB Generated Schematic Diagram of ANN when DWT is the input.

Support Vector Machine

Support vector machine (SVM) is a supervised learning technique for knowledge discovery and data mining. They are usually developed for pattern-recognition problem which stems from the framework of statistical learning theory. This statistical learning theory is also called Vapnik-Chervoneskis (VS) theory. Vapnik-Chervoneskis theory is the most successful tool that describes the capacity of learned model accurately. Furthermore, it also describes how to ensure the generalization performance of learning process and shows the ways to construct learning algorithms.

Moreover, SVM has a solid theoretical foundation and the classification has performed with greater accuracy than other statistical learning methods. In the work presented by Gupta *et al.* [11], the framework of sleep-staging was proposed. The framework consists of a multi-class SVM classification based on a decision tree approach. The polysomnographic data was used to evaluate the performance of SVM. In addition, forward sequential selection was used as extract feature and k-fold cross validation was applied for classification problem. The classifier that are applied to the data and the features that are extracted achieved an accuracy up to 76.73% [11]. Furthermore, the training of SVM is to find or create an optimal hyperplane that segregates two classes with maximum margin[12]. Figure 6 shows an illustrative example of two different classes of data.

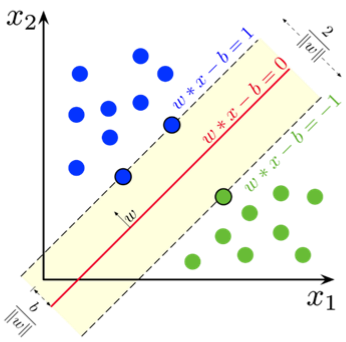

Figure 6 Classification of Data by SVM.

SVM tries to find a boundary that separates the data into two classes, and while doing so it tries to maximise the distance between the nearest data point and the boundary of the classes. From Figure 6, the boundary located in the middle between two classes can be expressed in terms of

$$(\boldsymbol{w}.\ \boldsymbol{x}) + b = 0,\ \ \boldsymbol{w} \in \mathbb{R}\ ,\ b \in \mathbb{R}, \qquad (10)$$

where, $\boldsymbol{w}$ represents the boundary, $\boldsymbol{x}$ represents the input vector of dimension N and b is scalar threshold. The equation for class A and class B respectively are, $(\boldsymbol{w}.\boldsymbol{x}) + b = -1$ and $(\boldsymbol{w}.\boldsymbol{x}) + b = 1$.

According to [13], SVM is a method for the classification of both linear and nonlinear data. The model aims to draw decision boundaries between data points from different classes and separate them with maximum margin. Radial Basis Function (RBF) which is often outperforms other kernel functions in nonlinear classification [14], was chosen as the kernel function to solve the classifier. The complexity of model selection is influenced by the number of hyper parameters. The RBF kernel has less hyper parameters than the polynomial kernel and also has fewer numerical difficulties.

Performance Indicator

Several parameters are computed to evaluate the classification performance such as sensitivity, specificity, and accuracy. Equation (11), (12) and (13) show the formulas for each parameter:

$$Specificity = \left(\frac{TN}{TN + FP}\right) \times 100 \qquad (11)$$

$$Sensitivity = \left(\frac{TP}{FN + TP}\right) \times 100 \qquad (12)$$

$$Accuracy = \left(\frac{TN + TP}{FP + TP + FN + TN}\right) \times 100 \qquad (13)$$

There are several receiver operating characteristics (ROC) parameters that should be considered to measure the performance of classifiers such as true negative (TN), false negative (FN), false positive (FP) and true positive (TP). Specificity and sensitivity are statistical measures of the performance of a binary classification test. Sensitivity can be defined as true positive rate to measure the proportion of actual positives that are correctly identified. Specificity also represents true negative rate to measure the proportion of actual negatives that are correctly identified.

Experimental Results

Dataset

In this study, we worked with the database of healthy volunteers and epilepsy patients. The publicly available EEG database collected from Andrzejak *et al.* [15] at the Epilepsy Centre at the University of Bonn, Germany are used. The EEG dataset contains five sets (named as set A-E). Set A and B consisted of healthy volunteers while set C, D and E consisted of epilepsy patients. In this study, we considered only two different sets which are set B and set E. Each set contained 100 single channel EEG segments of 23.6 seconds duration with sampling rate of 173 Hz.

Set B : normal subjects with open eyes.
Set E : epileptic subjects during seizure intervals.
Set B as "normal signal" and set E as "epileptic signal". Furthermore, all data were recorded using similar EEG data acquisition (128 channel) with an average common reference.

Feature Extraction
Feature extraction is a significant step in pattern recognition-based EEG signal processing. It reduces data dimension and extracts informative parts of data [1]. In this study, DWT was applied as feature extraction. A good recognition accuracy can be obtained by choosing a suitable number of decomposition and the wavelet. Daubechies wavelet has become popular because of its efficient filter implementation and orthogonality property [6]. Daubechies wavelet was chosen to be used in this study. Next, both samples (set B and set E) are consecutively decomposed into detailed and approximation coefficients until the desired input is achieved (eighth level). The number of approximation coefficients obtained at the eighth level is seventeen. Therefore, there are 17 inputs for both classifiers. Figure 7 shows an example of the original and decomposition level coefficient values of set B for channel 1.

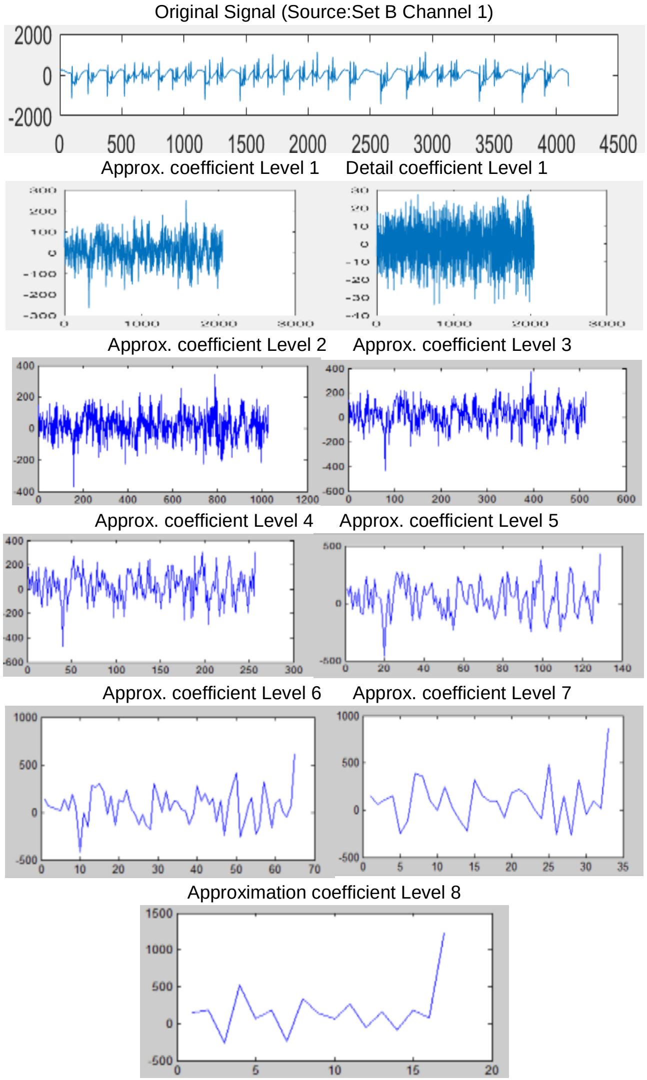

Figure 7 The Original and Eighth Decomposition Level Coefficient Values of Set B for Channel 1

Combination of Discrete Wavelet Transform and ANN

There are 17 feature vectors obtained by using DWT. The feature vector will become the input to the ANN classifier. Next, the database will be split into three sections, 15% for testing, 15% for validation and 70% of the data is used for training. The performance analysis based on error percentage is given in Table 1.

Table 1: The Performance Analysis Based on Error

	Number of Samples, N	Mean Squared Error (MSE)	Percentage Error (% E)
Training	140	$1.15828e^{-1}$	14.29
Validation	30	$1.49325e^{-1}$	16.67
Testing	30	$1.56727e^{-1}$	20.00

By using DWT as the feature extraction tool and ANN as classifier, the overall recognition accuracy obtained is 80% and the duration of training is 1.1410s. The classification accuracy can be calculated by using equation (14). Despite the high accuracy, the mean squared error (MSE) is also increased. This is probably due to the limited number of samples for the neural network to generalize the data and large number of features. Figure 8 shows the confusion matrix of ANN. Confusion matrix is a table that represents the performance of classifiers on a set of test data. In other words, confusion matrix represents prediction results on a classification issue.

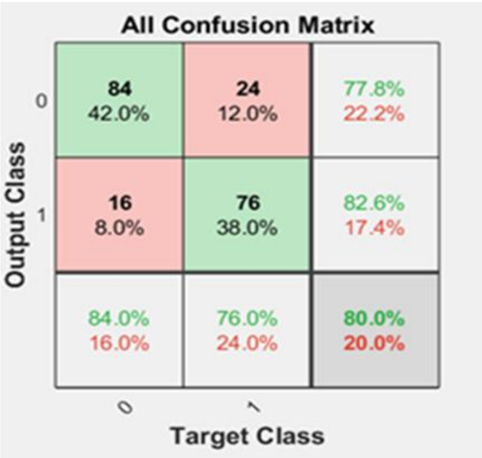

Figure 8 Confusion Matrix Showing Output of Training

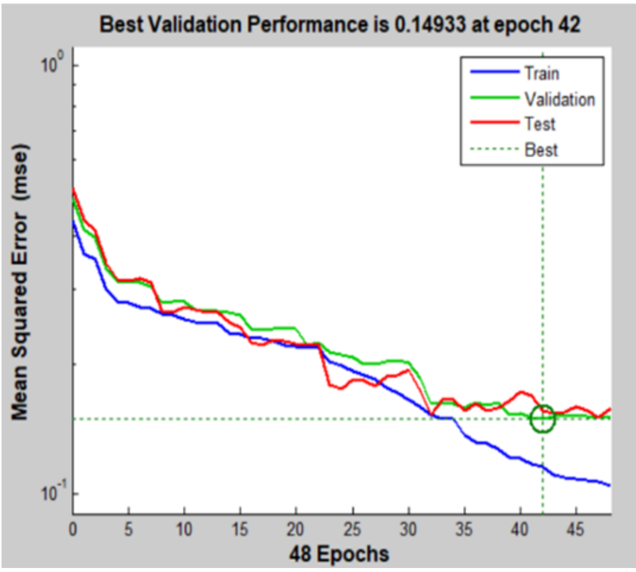

Figure 9 Performance Plot of the Training.

The green box shows the percentage and value of the true class while the red box shows the percentage and value of the false class. The grey box shows the percentage fraction between two classes. Also, Figure 9 shows that best performance is obtained after 48 iterations with the best validation performance obtained at epoch 42 and gradient of 0.0566.

From the confusion matrix of ANN in Figure 8, of the 100 actual normal subjects, the system predicted that 16 were epileptic, and of the 100 that were epileptic, it predicted that 24 were normal. Table 2 shows the detail diagnostic test of ANN as classifier with sensitivity 84.0%, specificity 76.0% and accuracy of 80.0%.

Table 2: The Final Table of Confusion of ANN

		Actual Class		
		Normal	Epilepsy	
Predicted Class	Normal	TP = 84	FP = 24	Positive predictive value =TP/(FP+TP) =77.8%
	Epilepsy	FN = 16	TN = 76	Negative predictive value =TN/(TN+FN) =82.6%
		Sensitivity =TP/(FN+TP) =84.0%	Specificity =TN/(TN+FP) =76.0%	Accuracy =(TN+TP)/(FN+TP+FP+TN) =80.0%

Combination of Discrete Wavelet Transform and SVM

Figure 10 shows the confusion matrix of SVM. The diagonal green box of the table shows the correct predictions while the red box shows incorrect predictions. From the confusion matrix of SVM, the overall classification accuracy refers to the addition of percentage of two true classes which is 83.50% and the duration of training is 1.1210s.

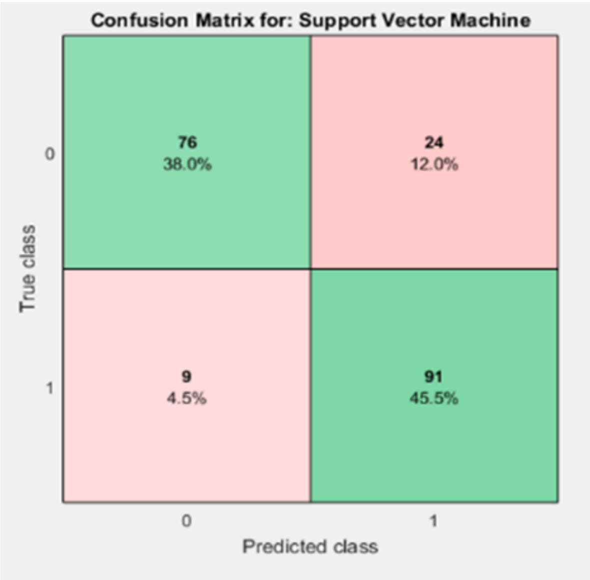

Figure 10 Confusion Matrix for SVM.

From the confusion matrix of SVM in Figure 10, of the 100 actual normal subjects, the system predicted that 9 were epileptic, and of the 100 that were epileptic, it predicted that 24 were normal. Table 3 shows the diagnostic test of SVM as classifier with sensitivity 89.4%, specificity 79.13% and accuracy of 83.50%.

Table 3: The Final Table of Confusion of SVM.

		Actual Class		
		Normal	Epilepsy	
Predicted Class	Normal	TP = 76	FP = 24	Positive predictive value =TP/(FP+TP) =76.0%
	Epilepsy	FN = 9	TN = 91	Negative predictive value =TN/(TN+FN) =91.0%
		Sensitivity =TP/(FN+TP) =89.40%	Specificity =TN/(TN+FP) =79.13%	Accuracy =(TN+TP)/(FN+TP+FP+TN) =83.50%

The filtered data of both samples, healthy volunteers and epileptic patients will be performed by using SVM to identify the classification accuracy and its training time taken.

Comparison between ANN and SVM

The performance of ANN and SVM are evaluated by the whole sets. Performance evaluation and comparison are presented using classification accuracy and training time. Table 4 shows the performance results between ANN and SVM.

Table 4: The Performance Results Between ANN and SVM

Classifier	Overall classification accuracy(%)	Duration for training	Sensitivity	Specificity
ANN	80.0	1.1410	84.0%	76.0%
SVM	83.5	1.1210	89.4%	79.1%

Based on the results in Table 4, under the same features as input, both classifiers produce slightly similar results. SVM is greater than ANN in terms of duration of training and classification rate. Table 4 shows SVM with DWT as the input produces a better result, with accuracy of 83.50% and fairly low training time of 1.1210s.

Conclusion

In this paper, the EEG signal data of epileptic seizure are classified using DWT and two classifiers, ANN and SVM. The performance due to classification accuracy and training time was compared between both classifiers. In previous work presented by Qi and Alias [2], the combination of statistical feature extraction and SVM only achieved the recognition accuracy of 69.75%. The better performance of classification accuracy up to 83.50% is obtained from this study. Moreover, the combination of wavelet transforms feature extraction method and SVM was proved to be superior than using ANN. SVM performs best among current classification techniques, due to its ability to capture non-linearities [13]. In this study, we have used a limited number of samples. The limitation number of samples affect the percentage of accuracy of both classifiers. Therefore, in future research, the number of samples should be increased to increase the recognition rate. Future research will be concentrated on alternate classifiers. Deep Learning, Extreme Learning Machine (ELM) and Genetic algorithm can be performed as an extension of classifiers of this study. `

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