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Performance of Extreme Learning Machine Kernels in Classifying EEG Signal Pattern of Dyslexic Children in Writing

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Abstract: Dyslexia is a specific learning disability that causes leaners to have difficulties to process letters and number during reading, writing and doing mathematics. Early identification of dyslexic characteristic is crucial so that early intervention given could overcome learner difficulties. A process of writing involves areas in brain learning pathway and motor cortex. This activity could be recorded using electroencephalogram (EEG) non-invasively. Using this information, a study has been conducted to distinguish EEG signal of normal, poor and capable dyslexic children. In this work, EEG signals were recorded from eight channels; C3, C4, P3, P4, FC5, FC6, T7 and T8. The signals were extracted using discrete wavelet transform (DWT) with Daubechies wavelet family order 2, 4, 6 and 8 to acquire beta and theta band features. The coefficient of beta band power and the ratio of theta/beta band power were input features of expert learning machine (ELM) classifier. Four types of kernels namely linear, radial basis function (RBF), polynomial and wavelet were applied as output weight in connecting hidden node and the output node of ELM. Parameters were varied to optimize each kernel to obtain the best classification accuracy. Results show that db2 gives the highest classification performance for all kernel among other Daubechies family. RBF and wavelet kernel yield the highest accuracy at 89% compared with other ELM kernels. This work reveals that ELM with RBF and wavelet kernel together with beta band power and ratio of theta/beta band power extracted from db2 could distinguish normal, poor and dyslexic children during writing.

Keywords: EEG, Dyslexia, ELM, Wavelet, Kernel

1. Introduction

Dyslexia is neurological disorder in some part of brain area processing information, that causes skills to decode word, fluent reading and accurate writing become tough to a learner even though adequate education level appropriate to the age has been received [1]. According to the Malaysian Ministry of Education, the dyslexic learner is categorised as a student who possesses the same or above intelligent quotient level but having severe difficulties in spelling, calculating, reading and writing. Dyslexia Association of Malaysia reported that approximately 10% of school children

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are expected to have dyslexia. While in 2016 other reports revealed that 53,610 children enrolled learning disability program at school with 8.4% of them expected to have dyslexia. The number of dyslexic children enrolled in special program in primary school increase intensely from 577 in 2013 to 5,806 in 2017 [2]. Since the sign of dyslexia in leaner become apparent when they start school which most of learning reading and writing process takes place, early identification of dyslexia is critical as academic content become harder as they grow older. As dyslexic children learn differently, intervention program given at early stage would help them to overcome their disabilities early to match with normal learner.

Brain-based studies to analyse dyslexia used structural and functional connectivity which were implemented previously using an imaging technique such as functional magnetic resonance imaging (fMRI) [3], positron emission tomography (PET) [4] and magnetoencephalography (MEG) [5]. Electroencephalography (EEG) is another popular technique used to detect brain electrical activities due to high temporal resolution where time and frequency domain are preserved, radiation risk-free, cost-effective, portable and less handling procedures. These make EEG fit to be applied in studying learning activity where brain signal activities associated with task currently performed can be recorded using EEG. Numerous studies associate with brain areas related to brain electrical signal connectivity were performed such as in brain-computer interface (BCI) [6], brain disorder [7] and sleep studies [8]. In our work, the detection of brain electrical activities was explored using EEG.

In EEG signal analysis for identifying dyslexia, most of the studies focussed on reading [9][10], not much work concentrated on writing even though writing is also a part of learning disorder for dyslexia. Writing is a complex process involving coordinating between motor skill and cognitive process [11]. Active attention from learner is required during the writing process which stimulates brain area associated with writing. There are several brain areas which are responsible for the ability to write. The first area known as Broca's language area is responsible for expressive language in speaking and writing, while the second area known as Wernicke is responsible for understanding the spoken or written language. Besides that, temporal and parietal areas are also involved in the comprehension of written words and in the program of motor areas to convert visual image into written symbols. All of these appear dominant in the left hemisphere of the brain in a normal learner.

In previous studies, some features extracted from EEG signal to find distinguishable feature during writing were power spectrum [12], frequency content [13] and DWT [14]. These features were employed in machine learning with a promising result such as in K-nearest neighbour (KNN) [15] and Support Vector Machine (SVM) [16]. However, no attempts being made yet using ELM to classify dyslexic subject even though it was reported able to produce higher classification accuracy for application in EEG signal analysis such as in emotional recognition[17], epilepsy [18] and BCI [19]. ELM is a feedforward neural network with a single hidden layer proposed by Huang [20]. It works by reducing the processing time required for training a neural network which overcomes the problem of slow learning speed associated with back propagation methods and yields a better performance due to its ability to obtain the smallest training error. The algorithm avoids multiple iterations, generate its random parameter and overcome overfitting problems by empirical risk minimization principle. ELM has been known to be better in generalization, robustness and controllability [21]. However, in limited samples cases, it produced the unsatisfactory result, hence kernel model in ELM is applied to make it more robust and performs better for linearly non-separable samples [22].

This paper describes the performance of ELM with linear, RBF, polynomial and wavelet kernel to achieve the highest classification accuracy with the optimum parameter for normal, poor and capable dyslexic based on EEG signal patterns during writing. In this work beta band power and ratio of the theta/beta band power were extracted using db2, db4, db6 and db8 to act as an input feature vector for the classifier.

2. Research Methodology

The process flow to select the optimum parameter for kernels in EEG signal analysis is shown in Figure 1. This work was carried out in several stages, starting from selection of subject, data collection procedure, EEG signal acquisition, artifacts removal, extraction of features and selection of kernel for optimum classification accuracy.

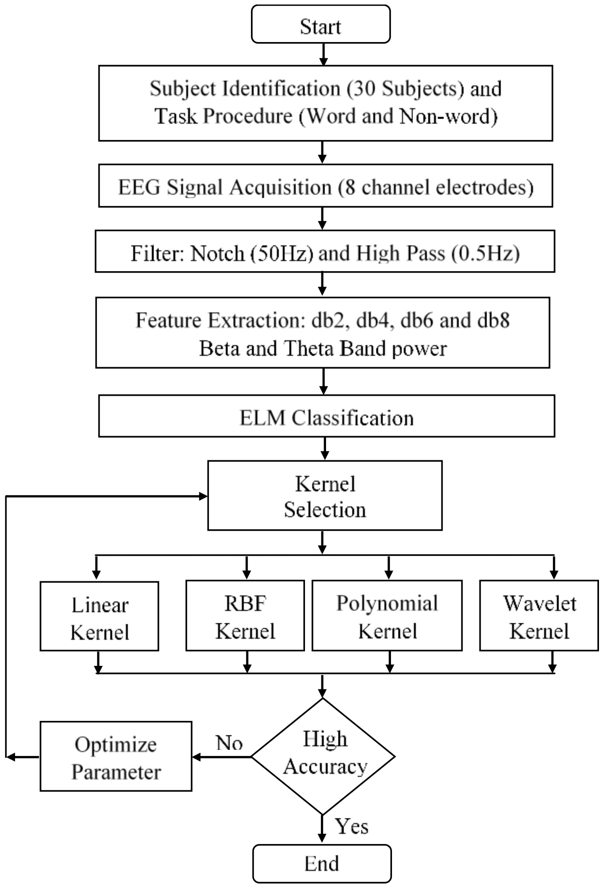

Fig. 1 – Process of classifying EEG signals of normal and dyslexic children

2.1 Subject Identification

In this work, the 30 subjects participated consists of 10 normal subjects, 10 poor dyslexics subjects and 10 capable dyslexic subjects. The characteristics of dyslexia either poor or capable were determined by the assessment carried out with the assistant from the Dyslexia Association of Malaysia. Poor dyslexic is referred to as a subject having difficulty in reading and writing compared with their age group. A capable dyslexic subject is denoted as has the improved capability to read and write. This group of subjects usually already attend the intervention program. During the assessment subjects background, medical history and right and left-hand dominant were recorded to ensure conformity of data with no neurological disorder. Subjects with an aged range between 7 to 12 years old were selected to participate in this work because at this stage, they start receiving formal learning activity at school where the symptom of dyslexia can be clearly seen. Ethical approval in conducting this work was granted from the Research Ethics Committee UiTM. Written informed consent was explained and signed when agreed by the subject's caretaker.

2.2 Task Procedure

Fig. 2 – EEG Signal Recording during writing

In a controlled environment room, the subject was seated with a piece of paper and pencil as shown in Fig 2. A screen in front of subject displayed the word in turn. For each word seen, the subject needs to write one by one in a piece of paper given earlier. Two sets of a word consist of known-word and non-word, were prepared. Known-words are the words that have meaning while non-words are words that mix and match without having any meaning. Familiar word would recall from visual word form area (VWFA) within the occipital-temporal region and any new word for the subject would require decoding through brain learning pathway area. Each set of word contains a letter that poses a problem for a dyslexic.

Five tasks as shown in Table 1 were prepared for this work. Task A was designed to acquire the baseline of EEG signal. Task B and C was intended for recording during writing known-word while Task D and E for non-word.

Table 1 – Writing Tasks

TASK CATEGORY	ACTIVITY
Task A	Relaxes with eye closed for 40 seconds
Task B	Write three known-words
Task C	Write another write three known-words
Task D	Write three non-words
Task E	Write another three non-words

2.3 EEG Signal Acquisition and Pre-Processing

EEG signals were recorded while subject performing tasks using g.Nautilus wireless biosignal acquisition system as shown in Fig 2. Eight channel electrodes were placed on the subject's scalp according to the International 10-20 electrode placement system. These electrode placement are associated with reading and writing and were determined from previous work [23]. On the left side of brain, the signals were recorded from C3, P3, T7 and FC5 along learning pathway while on the right side of brain, the signals were recorded from electrodes C4, P4, T8 and FC6 to detect for an alternative pathway that may exist. Eight channel EEG signals were then sampled at 250Hz with 24-bit resolution. During pre-processing, the unwanted signal from 50Hz power line source were filtered using Notch filter and any Dc offset were removed through high pass filter with cut-off frequency at 0.5Hz. Clean raw EEG signals were saved as .mat files for features extraction and classification using a program written in MATLAB. Table 2 shows the electrode positions on the scalp and function for each area.

Table 2 – Electrode positions used in the work

Area	Left Hemisphere	Right Hemisphere	Function
Parietal Lobe	C3	C4	Sensory motor integration
Wernicle's Area	P3	P4	Recognition of word
Temporal Lobe	T7	T8	Auditory processing of language
Broca's Area	FC5	FC6	Language organization

A total of 960 EEG signals recording were attained from this work. Out of these, 70% is made up for the training dataset and the remaining 30% is for the testing dataset.

2.4 Feature Extraction

EEG signals consist of frequency bands related to its function. These bands were known as delta (δ) band (0.5 to 4Hz) which is associated with deep sleep; theta (θ) band (4-8Hz) that is related to drowsiness or dreaming; alpha (α) band (8-13Hz) indicates relaxation or awareness; beta (β) band (13-30Hz) shows concentration or active attention; and gamma (γ) band (more than 31Hz) is incurred by simultaneous processing of information from different parts of brain. Since all these frequencies were mixed up in one single EEG signal, it needs to be separated according to the frequency band for analysis of brain activity. EEG signal is non-stationary in nature, hence time-frequency scale representation using DWT was employed as it can localize features. Raw EEG signals were decomposed into five frequency sub-bands as shown in Fig 3 using Daubechies mother wavelet with order 2, 4, 6 and 8 to provide smooth EEG signals [24]. Detail coefficients at Level 3 (D3) and Level 5 (D5) were frequency bands of interest in this study. In this work, D3 represents the beta band, state of attention and focus during writing. While D5 represents the theta band, state of dreaming or loss attention.

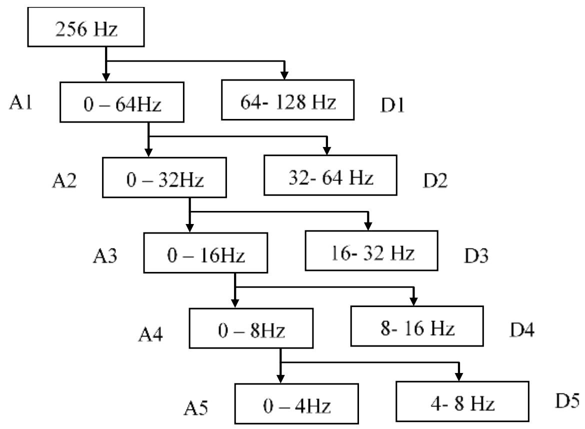

Fig. 3 – Sub-band and frequency range of decomposition level

Power features for reconstructed beta and theta bands were calculated using equation (1) where x is signal values and L is the signal length. The coefficients of beta band power and ratio of theta/beta band power served as the input vector to the classifier.

$$Power = \frac{\sum x^2}{L(x)} \tag{1}$$

2.5 Classifications

ELM is a single hidden layer feedforward (SLFN) neural network based on risk minimization principle that produces fast learning speed and better generalization compare with backpropagation network. This is achieved by initiating randomly, fixing the weights between input and hidden neurons according to a continuous probability density function that bypasses a time-consuming training algorithm. The weights between hidden and output neurons of the SLFN were determined analytically and the only parameter needs to be learned. For N arbitrary distinct samples (x_i, t_i) $\in R^n \times R^m$, standard SLFNs with L hidden nodes and activation function $g(x)$ are mathematically modelled as

$$\sum_{i=1}^{L} \beta_i g(a_i, b_i, x_j) = t_j,\ j = 1,..., N \tag{2}$$

where a_i is the weight factor connecting the ith hidden neuron and the input neuron; b_i is the impact factor of the ith hidden node; β_i is the weight vector connecting the ith hidden node and output node. Equation (2) can be written compactly as (3).

$$H\beta = T \tag{3}$$

where

$$H = \begin{bmatrix} g(a_1,b_1,x_1) \cdots g(a_L,b_L,x_1) \\ \vdots \quad \dots \quad \vdots \\ g(a_1,b_1,x_N) \cdots g(a_L,b_L,x_N) \end{bmatrix}_{N\times L} \tag{4}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N\times m} \tag{5}$$

The ELM is aimed to arrive at the smallest training error and smallest norm of output weights. The least-square solution; $\hat{\beta}$ derived with the minimum norm using (3) to (5) is as follow,

$$\hat{\beta} = H^{\dagger}T \tag{6}$$

where $H^{\dagger}$ is the Moore Penrose generalized inverse of hidden layer output matrix H.

Kernels were employed as output weight and integrated into ELM to obtain better generalization with less user intervention. In this work, the parameters used for each kernel are σ for RBF, n and p for polynomial and b, c and d for wavelet.

Linear Kernel $$K(x,y) = x \times y \quad (7)$$

RBF Kernel $$K(x,y) = \exp\left(\frac{-\|x-y\|^2}{\sigma}\right) \quad (8)$$

Polynomial Kernel $$K(x,y) = \exp(x \times y + n)^p \quad (9)$$

Wavelet Kernel $$K(x,y) = \cos\left(\frac{d\|x-y\|}{c}\right)\exp\left(\frac{-\|x-y\|^2}{b}\right) \quad (10)$$

Table 4 displays pseudocodes prescribing the ELM algorithm for EEG based classification of dyslexic children.

Table 4 - Pseudocodes for ELM classifier

Input:
- A set of training sample (x_i, t_i), $i = 1, 2, \ldots N$
- A set of test sample $\hat{x}$
- Activation function $g(x)$ and kernel parameter

Output:

Predicted label t

Procedure:

Step 1: Assign randomly input weight vector $\boldsymbol{a_i}$, $i = 1, \ldots, L$.

Step 2: Calculate the hidden (kernel) layer output matrix H from $K(x,y)$.

Step 3: Calculate the output weight vector $\hat{\beta}$

Step 4: Compute the predicted label by equation (11)

For a new test sample $\hat{x}$, the decision function of ELM is given by (11),

$$t = g(\hat{x})\hat{\beta} \quad (11)$$

The overall classification accuracy was calculated using confusion matrix. Sensitivity and specificity were then performed for wavelet with highest accuracy only to show proportion of true positive rate and true negative correctly identified for each group of subjects. The calculation is shown in (12), (13) and (14) where T_n is true negative, T_p is true positive, F_p is false positive and F_p is false negative.

$$Accuracy, Acc = \frac{T_n + T_p}{T_p + T_n + F_p + F_n} \quad (12)$$

$$Sensitivity, Sen = \frac{T_p}{T_p + F_n} \quad (13)$$

$$Specificity, Spe = \frac{T_n}{T_n + F_p} \quad (14)$$

3. Results and Discussions

Table 1 shows the performance of the classifier to classify normal, poor and capable dyslexic children using linear kernel. The highest accuracy was achieved using features from db2 and db6 with 74% accuracy.

Table 1 – Accuracy of ELM with Linear kernel

	Daubechies order			
	db2	**db4**	**db6**	**db8**
Accuracy	0.74	0.69	0.74	0.71

Table 2 displays the overall accuracy of ELM classifier with wavelet kernel when the three variables were tuned to achieve higher accuracy. Each parameter was tuned from 0.00001 to 10000 respectively one by one. It was found that db2 gives the highest classification with 89% accuracy compared to other Daubechies wavelet used in this work, followed by db4 with 86% accuracy and db8 with 80% accuracy. Db6 only manage to get the highest at 69% accuracy.

Table 2 – Accuracy of ELM with Wavelet kernel

b	c	d	Daubechies order			
			db2	*db4*	*db6*	*db8*
0.00001	1	1	0.34	0.34	0.34	0.34
0.0001	1	1	0.37	0.34	0.34	0.34
0.001	1	1	0.63	0.49	0.43	0.49
0.01	1	1	0.80	0.63	0.54	0.57
0.1	1	1	0.77	0.71	0.63	0.66
1	1	1	0.69	0.66	0.63	0.57
10	1	1	0.54	0.43	0.46	0.37
100	1	1	0.49	0.34	0.31	0.29
1000	1	1	0.43	0.31	0.29	0.31
10000	1	1	0.40	0.31	0.29	0.31
1	0.00001	1	0.37	0.37	0.40	0.49
1	0.0001	1	0.37	0.43	0.49	0.37
1	0.001	1	0.57	0.46	0.54	0.29
1	0.01	1	0.51	0.34	0.49	0.31
1	0.1	1	0.43	0.29	0.46	0.54
1	1	1	0.69	0.66	0.63	0.57
1	10	1	0.89	0.83	0.63	0.80
1	100	1	0.89	0.83	0.69	0.80
1	1000	1	0.89	0.83	0.69	0.80
1	10000	1	0.89	0.83	0.69	0.80
1	1	0.00001	0.89	0.83	0.69	0.80
1	1	0.0001	0.89	0.83	0.69	0.80
1	1	0.001	0.89	0.83	0.69	0.80
1	1	0.01	0.89	0.83	0.69	0.80
1	1	0.1	0.89	0.83	0.63	0.80
1	1	1	0.69	0.66	0.63	0.57
1	1	10	0.43	0.29	0.46	0.54
1	1	100	0.51	0.34	0.49	0.31
1	1	1000	0.57	0.46	0.54	0.29
1	1	10000	0.37	0.43	0.49	0.37

Table 3 displays the overall accuracy of ELM classifier with RBF kernel for db2, db4, db6 and db8 when the kernel parameter was tuned within range 10000 to 0.00001 at decrement factor of 10. It can be observed that the accuracy increases to maxima as kernel width decreases until 1 and then it decreases when the kernel parameter continues to decrease. The highest accuracy is achieved by db2 with 89%, db4 at 83% and db8 at 80% when the kernel width set to 1. The db6 only manage to get 71% accuracy at kernel width equal to 10.

Table 3 – Accuracy of ELM with RBF kernel

Kernel Parameter, σ	Daubechies order			
	db2	**db4**	**db6**	**db8**
10000	0.69	0.63	0.63	0.66
1000	0.69	0.66	0.63	0.66
100	0.74	0.66	0.63	0.66
10	0.77	0.74	0.71	0.69
1	0.89	0.83	0.69	0.80
0.1	0.83	0.71	0.60	0.69
0.01	0.86	0.61	0.57	0.63
0.001	0.63	0.51	0.46	0.51
0.0001	0.37	0.34	0.34	0.34
0.00001	0.34	0.34	0.34	0.34

Accuracy of classifier using polynomial kernel is shown in Table 4. In this work kernel parameter is polynomial order. The value is set at 2, 3, 4 and 5 were applied to distinguished EEG signal from features extracted using daubieches wavelet. It was found that polynomial order 2 and wavelet db2 gives the highest accuracy with 86% accuracy. 74% accuracy for db4, 66% for db6 and 63% for db8 from polynomial order 5 for highest accuracy.

Table 4 – Accuracy of ELM with Polynomial kernel

Order, *p*	Daubechies order			
	db2	db4	db6	db8
2	0.86	0.71	0.51	0.46
3	0.8	0.69	0.51	0.49
4	0.77	0.66	0.63	0.63
5	0.77	0.74	0.66	0.63

In terms of highest accuracy among all kernels, it was found that db2 gives better performance compared with the rest of the wavelet tested. It also found that db6 accuracy is lower compared with others wavelet due to its insensitivity in detecting normal, poor and capable dyslexic subjects. Hence to calculate sensitivity and specificity, db2 was chosen as it gives better result compared with the rest of Daubechies wavelet order.

Table 5 shows the performance of ELM classifier in terms of sensitivity and specificity obtained from each kernel with the highest accuracy. For normal subjects, RBF and wavelet kernel gives the best classification performance with 92% sensitivity and 87% specificity. Even though the specificity for linear and polynomial attained 100% and 96% respectively, its sensitivity was low with 25% and 67% only. In classifying poor dyslexic subject, ELM manages to achieve 100% sensitivity for linear and polynomial with 91% and 96% specificity respectively which is better than RBF and wavelet kernel with only 83% sensitivity, however, their specificity is 100%. For capable dyslexic subject, all kernels give more than 91% sensitivity except the linear kernel which manages to achieve 100% but its specificity is only 71%.

The results obtained from this study demonstrated that in classifying normal subject, RBF and wavelet are the optimum kernels to be used while for recognizing poor subject, the polynomial kernel is the best. In classifying capable dyslexic subject, RBF and wavelet kernels have very good balanced between sensitivity and specificity even though they could not achieve 100% sensitivity. Therefore, it can be concluded that both RBF and wavelet kernel are the suitable kernels to differentiate EEG signal of normal, poor and capable dyslexic children from writing task.

Table 5 – Performance of ELM Classifier for each Kernel with db2

Group	*Performance*	ELM Kernel			
		Linear	*RBF*	*Polynomial*	*Wavelet*
Normal	Sensitivity	0.25	0.92	0.67	0.92
	Specificity	1.00	0.87	0.96	0.87
Poor	Sensitivity	1.00	0.83	1.00	0.83
	Specificity	0.91	1.00	0.96	1.00
Capable	Sensitivity	1.00	0.91	0.91	0.91
	Specificity	0.71	0.96	0.88	0.96
Overall	Accuracy	0.74	0.89	0.86	0.89

4. Conclusion

In this work ELM classifier was employed to recognize EEG signals of normal, poor and capable dyslexic children during writing word and non-word. EEG signal features were extracted using DWT with Daubechies wavelet order 2, 4, 6 and 8 through beta band power and ratio of theta/beta band power. Linear, RBF, polynomial and wavelet kernels were applied as activation function to determine the optimize parameter for the classifier. Performance evaluation of each kernel was assessed and compared using confusion matrix to determine its accuracy, sensitivity and specificity. Results show that RBF and wavelet kernel with 89% accuracy outperformed polynomial and linear kernel performance. It was also found that features from db2 yield the highest accuracy in determining normal, poor and capable dyslexic subject. This work can be further expanded in examining performance for word task only and non-word task only to see which task would give better accuracy. Other than that, future works would also be focusing on others classifier to find the optimum parameter in differentiating EEG signal pattern of normal, poor and capable dyslexic children.

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