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Support Vector Machine with Theta-Beta Band Power Features Generated from Writing of Dyslexic Children

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Abstract: The classification of dyslexia using EEG requires the detection of subtle differences between groups of children in an environment that are known to be noisy and full of artifacts. It is thus necessary for the feature extraction to improve the classification. The normal and poor dyslexic are found to activate similar areas on the left hemisphere during reading and writing. With only a single feature vector of beta activation, it is difficult to distinguish the difference between the two groups. Our work here aims to examine the classification performance of normal, poor and capable dyslexic with theta-beta band power ratio as an alternative feature vector. EEG signals were recorded from 33 subjects (11 normal, 11 poor and 11 capable dyslexics) during tasks of reading and writing words and non-words. 8 electrode locations (C3, C4, FC5, FC6, P3, P4, T7, T8) on the learning pathway and hypothesized compensatory pathway in capable dyslexic were applied. Theta and beta band power features were extracted using Daubechies, Symlets and Coiflets mother wavelet function with different orders. These are then served as inputs to linear and RBF kernel SVM classifier, where performance is measured by Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) graph. Result shows the highest average AUC is 0.8668 for linear SVM with features extracted from Symlets of order 2, while 0.9838 for RBF kernel SVM with features extracted from Daubechies of order 6. From boxplot, the normal subjects are found to have a lower theta-beta ratio of 2.5:1, as compared to that of poor and capable dyslexic, ranging between 3 to 5, for all the electrodes.

Keywords: Electroencephalograph, dyslexia, wavelet transform, theta-beta band power ratio, support vector machine

1. Introduction

Diagnosis of dyslexia founded on psychological and pedagogical approaches are known to be time consuming and require the service of a skilled therapist. It is a neurological disorder that effects close to 12% of the national population [1]–[3]. Understanding the biological aspect of dyslexia provides the key to unravel its effects on the ability of not only dyslexic children to read or write properly, but also children with intelligent quotient (IQ) of their age. Using electroencephalogram (EEG), the electrical activities of the brain can be recorded and analyzed to give an objective

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neurophysiological assessment to complement the clinical diagnosis, or a screening mechanism to expedite the diagnosis. Early assessment helps the children gain support in time to close the learning gap with their peers. Full potential of the children can only be unleashed, given that the support is based on proper diagnosis and understanding of the underlying learning issues [4], [5]. Records showed that school dropouts stand at 1.36% of the national population in 2017 alone, with dyslexia being the most prevalent cause [6].

Analysis of the brain using EEG works on detecting changes and variations in electrical signals different from the norm. It offers a real time measurement based on strategically placed non-invasive electrodes on the surface of the scalp. In learning related activities, left hemispheric impairment of the Broca and Wernicke areas causes the poor dyslexic to have difficulties in decoding words and then write [7]–[10]. While the same areas are working efficiently in normal children. As shown in Fig. 1, on similar areas of activation, the poor dyslexic made mistakes in their writing, while the normal subject did not. In the case of capable dyslexic, Functional Magnetic Resonance Imaging (fMRI) based studies have shown that the brain compensates the impairment of the left hemisphere with activation of the right hemisphere. This enables them to overcome their learning difficulties and obtain results on par with their age group [11]–[13]. Identification of the neuro learning pathway assists in the localization of electrodes, which could reduce the full recording of 128 locations to a manageable eight. This renders the data acquisition more user-friendly and reduced computation load for post-processing.

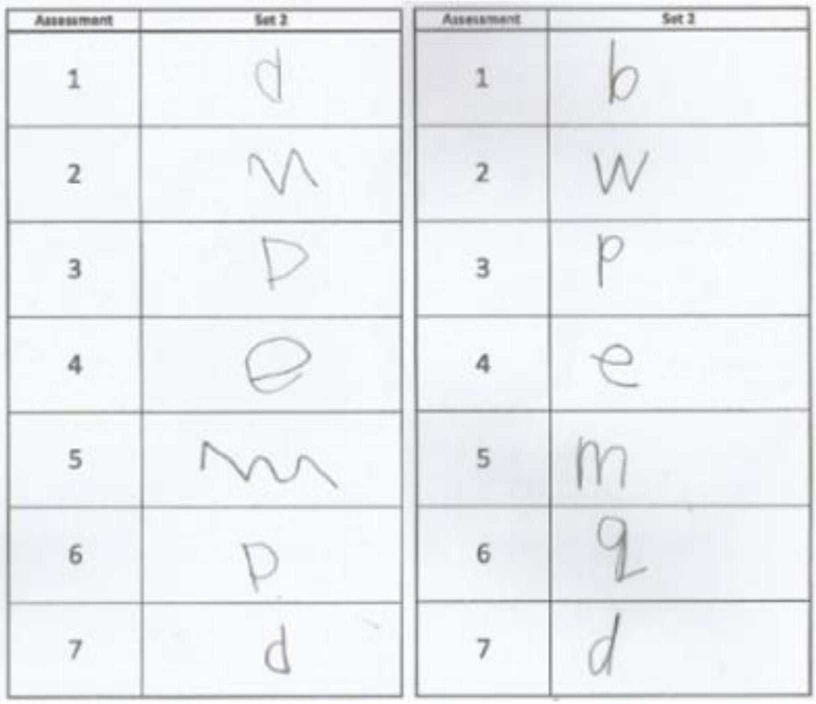

Fig. 1 – Alphabet Writings from a Poor Dyslexic on the Left and Writings from a Normal Subject on the Right

Given advantage of the EEG system, which can provide real time analysis and record without the need for a clinical setting as compared to fMRI, the challenge is to extract significant features from the EEG signals, usually highly coupled with noise and artifacts. These discriminative features could improve accuracy in the classification of normal, poor and capable dyslexic. Wavelet transform is commonly applied in studies related to activities of the brain [14]–[16]. It has the benefit of good time resolution. The EEG feature vectors extracted by it are influenced by selection of the mother wavelet and order of decomposition. Band power is the most widely used technique to extract features from EEG signals, particularly for brain computer interface (BCI) applications [17]. It summarizes the brain activities, where different bands are related to different neuro processes, such as beta is associated with reading and writing. The theta-beta band power ratio indicates the ability to focus. A high theta-beta band power ratio is a sign of a dominant theta, which has a dampening effect on the brain. A ratio of (2:1) is considered status of normal learning, while a ratio higher than (2.5:1) status of anxiety, as a result of struggling in learning. In a meta-analysis study of theta-beta ratio in ADHD, it was concluded that the measurement has prognostic values to evaluate outcome of intervention program or stimulant medication [18]. Five studies in this analysis exhibited a theta-beta ratio of less than 2.5 in normal subjects.

Classification of EEG with algorithms such as SVM, Linear Discriminant Analysis (LDA) and Neural Network (NN) makes way for a brain based assessment or BCI system [19]. With a non-linear kernel, SVM provides an option to best suit the characteristics of EEG features by working them on a higher-dimensional space. Most previous works adopt RBF kernel for SVM, as it offers efficient generalization properties, insensitivity to overtraining and ability to cope with high dimensionality [20]. Performance of SVM was evaluated by Area under the Curve (AUC) of the Receiver Operating Characteristic (ROC) graphs.

Both normal and poor dyslexic tend to activate similar areas on the left hemisphere. By relying only on a single feature vector of beta activation, it is difficult to distinguish the difference between the two groups. Our work here aims to examine the classification performance of normal, poor dyslexic and capable dyslexic subjects with theta-beta band power ratio as an alternative feature vector. Section 2 narrates on subject recruitment, design of tasks, methods to extract features and classify. Section 3 presents results on AUC of ROC graphs from linear and RBF kernel SVM, using features extracted by Daubechies, Symlet and Coiflet wavelets.

2. Methodology

This Section provides information on the subject population, inclusion and exclusion criteria as well as sampling procedure. The computer-based assessment and its procedures were explained, consisted of three structured learning related tasks to illicit the brain activation response. Methods applied in electrode localization, feature extraction, classification and performance assessment to determine the quality of the chosen feature vectors, were explained.

2.1 Subject Recruitment

11 poor and 11 capable dyslexics whom have been assessed and diagnosed by expert therapists from Dyslexia Association of Malaysia, were recruited. Subjects identified as poor dyslexics are from the beginner class, while capable dyslexic are from the advanced class, having undergone intervention programs and shown improvements in learning. As for the normal group, 11 subjects were recruited based on their current academic standing and the inclusion criterion that no prior history of attending any form of learning assistance program. Table 1 summarizes the group of subjects.

Table 1 – Subject Group Population

Group	Number of Subjects	Age Range	Median*	Standard Deviation*
Normal	11	7 - 12	10.5	1.76
Poor Dyslexic	11	7 - 12	8	2.27
Capable Dyslexic	11	7 - 12	8	1.55

The age of all subjects were limited to 7 to 12, as variation in the EEG signal were observed as the child reading experience increases. The age median for normal subjects stands at 10.5 with a standard deviation of 1.76. Both poor and capable dyslexics has similar age median of 8 with a standard deviation of 2.27 for the former and 1.55 for the latter. Median divides the greater and lesser halves of the age dataset while standard deviation quantifies the amount of spread of the age-dataset. Exclusion criterion includes comorbid features, past history of brain injury, auditory or sight issues, motor development difficulty, under medication and genetic disorder.

2.2 Writing Tasks

EEG recording for all the subjects took place in a controlled environment, to minimize disturbances and distraction. Subjects were seated in front of a 4 by 2 feet computer desk and given an A4 size answering sheet. Firstly, the subjects were instructed to relax with their eyes closed for 40 seconds, to establish the baseline of their EEG. In the second task, the subjects were asked to read and write two sets of words on a computer screen. Complexity of the words was in accordance to their age as shown in Table 2.

Table 2 – Words List for Task 2

Age Group 7 - 8		Age Group 9 - 10		Age Group 11 - 12	
Set 1	Set 2	Set 1	Set 2	Set 1	Set 2
hen	box	chair	smile	bicycle	trousers
cat	mug	face	lunch	water	morning
big	dog	draw	table	drink	together

The third task is similar to the second task, except for the reading and writing of non-words that includes alphabets known to pose difficulties to the dyslexic subjects, i.e. w, e, t, d, b, m, as shown in Table 3.

Table 3 – Words List for Task 3

Age Group 7 - 8		Age Group 9 - 10		Age Group 11 - 12	
Set 1	Set 2	Set 1	Set 2	Set 1	Set 2
szx	cpq	rfld	wrlb	ftecpb	ieacmub
kwl	igo	enug	oqbs	tjupn	pdunjtq
bht	dmr	twms	iltb	dnusz	czwmun

2.3 EEG Acquisition

Here, EEG signals were recorded with g.Nautilus wireless biosignal acquisition system that includes a 16-bit Analog-to-Digital Converter with a sampling frequency of 250Hz. 8 electrode locations (C3, C4, FC5, FC6, P3, P4, T7 and T8) on the 10/20 international system along the left and right hemisphere were selected as shown in Fig. 2. Locations on the left hemisphere are on the learning pathway of Broca and Wernicke. While mirrored locations on the right hemisphere are the compensatory pathway [21]–[23][24].

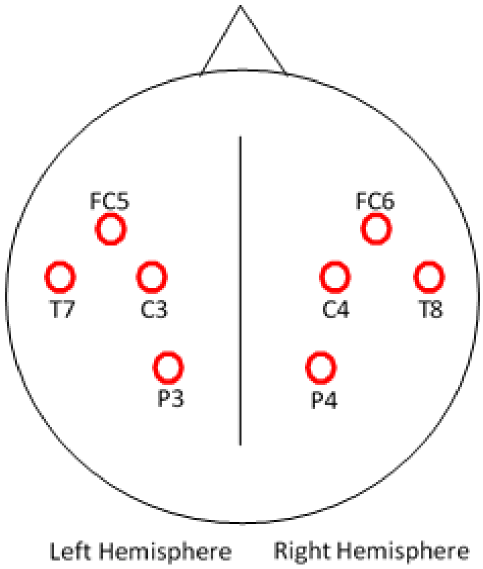

Fig. 2 – Electrode Placement for EEG Recording

Pre-processing of the acquired EEG signal includes a notch filter with a cutoff frequency of 50Hz and a band pass filter with a low cutoff at 0.3Hz to eliminate baseline drift and an upper cutoff of 50Hz to remove high frequency artifacts.

2.4 Feature Extraction

After the pre-processing stage, the initial feature extraction procedure started with the decomposition of the acquired EEG signals with wavelet transform of Daubechies order 8. It was selected based on its orthogonal features and its ability to conserve the resultant signal coefficients to enable an optimal reconstruction of the signal. In addition, it also possessed the capability to highlight and represent changes in the brain activities [25], [26]. From the reconstructed signals, feature vectors of beta and theta band power were calculated as summarized in Fig. 3. Decomposition then was repeated with 2 other mother wavelet functions, Symlets and Coiflets. Orders ranging from 2 to a maximum of 8 in even intervals were applied on Daubechies and Symlets, while order of 2, 4 and 5 were applied on Coiflets.

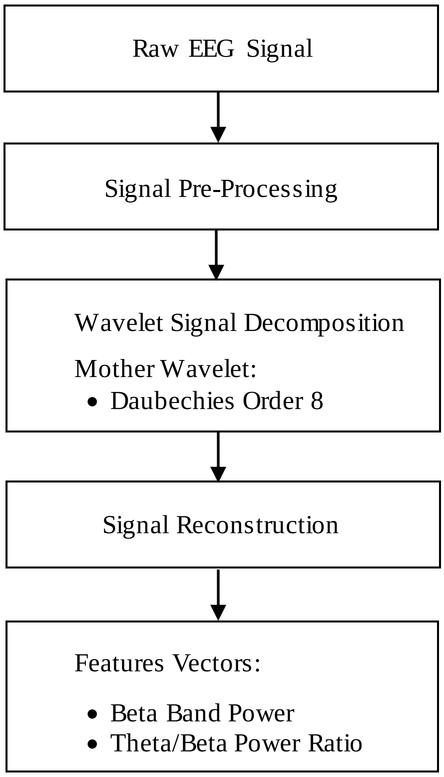

Fig. 3 – Overview of Feature Extraction Procedure

Wavelet decomposes the EEG signals into successive frequency bands by applying a scaling function with a low pass filter (see (1)), followed by down-sampling the signals by half to generate its approximate coefficients. The detail coefficients are computed by applying a high pass filter (see (2)) that was also down-sampled by half. This was repeated for all the levels in the decomposition.

$$Approx1 = H_{\mathrm{low}}[n] = \Sigma k\ h_{low}\ ke^{-jkn} \quad (1)$$
$$Detail1 = H_{\mathrm{high}}[n] = \Sigma k\ h_{high}\ ke^{-jkn} \quad (2)$$

Fig. 4 shows the decomposition of EEG signal into 5 levels of approximate (left side) and detail coefficients (right side) from a sampling frequency of 250Hz.

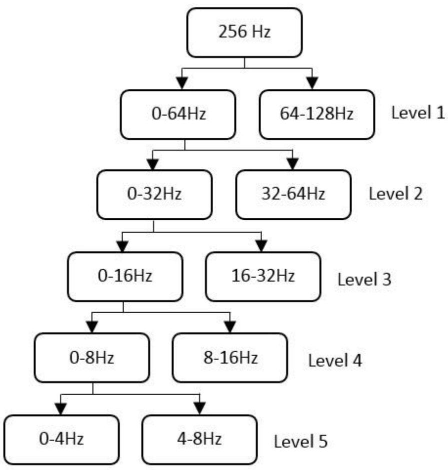

Fig. 4 – Wavelet Decomposition of EEG Signals

Table 4 summarizes the EEG levels of decomposition and its corresponding frequency bands. Beta and theta frequency bands at level 3 and 5 respectively, are the frequency bands of interest.

Table 4 – EEG Signal Level of Decomposition

Signal Decomposition	Frequency Range (Hz)	Frequency Band
Detail Coefficient Level 1	64-128	Noise
Detail Coefficient Level 2	32-64	Gamma
Detail Coefficient Level 3	16-32	Beta
Detail Coefficient Level 4	8-16	Alpha
Detail Coefficient Level 5	4-8	Theta
Approximate Coefficient Level 5	0-4	Delta

The squared sum of the reconstructed signal (x) at level 3 and 5, divided with the signal length was computed as the frequency band power for both theta and beta as shown in (3).

$$Power = \sum x^2/L(x) \tag{3}$$

2.5 Classification

SVM uses a hyperplane placed in the middle of the gap to classify between different groups of features. The larger the distance of group features from the hyperplane leads to higher accuracy. A non-linear RBF kernel introduces a high dimensional feature space that allows greater separation between different groups, with better performance than a linear SVM. Traditionally a binary classifier, a multiclass SVM with a One-Versus-One approach, in which all possible combination of the paired classifiers is tested, is employed here.

Performance of the SVM was analyzed based on AUC of the ROC graphs. It looks into tradeoff between specificity and sensitivity for the entire range of thresholds and the choice of feature vector inputs. AUC between 0.5 to 1 shows the classifier is acceptable. A value of '1' signifies a perfect classifier, with appropriate feature vectors. While an AUC of less than 0.5 indicates the classifier perform poorly.

3 runs of linear SVM and RBF kernel SVM were executed for all feature vectors extracted from the 3 different mother wavelets and the different orders. Results presented in the following section is the average value of the 3 runs.

3. Results and Discussions

Results in this section are presented in two parts. The first part examines theta-beta band power ratios at all the electrode locations for normal, poor and capable dyslexic. The second part compares performance of linear SVM and RBF kernel SVM with theta-beta band power ratios feature vectors, extracted by 3 different mother wavelets of different orders.

Fig. 5 and Fig. 6 depict boxplot of the EEG theta-beta band power ratios of 33 subjects. The theta-beta band power ratio of poor dyslexic was higher than that of normal and capable dyslexic subjects at all electrode locations. Location T8 and FC5 displays a close median centre between poor and capable dyslexic. In all locations, variability for capable and poor dyslexic was larger than the normal. Outliers at the higher end of the ratio, particularly for poor dyslexic, are hypothesized to contribute to inconsistencies in the classifier results.

Normal subjects were observed to have an average ratio of 1 to 2.5 in all the electrode locations, where the brain is at its most effective in reading and writing tasks. In the case of poor dyslexics, a higher theta-beta band power ratio of 3-5 was recorded at majority of the electrode locations. Higher ratio is a consequence of dominant theta, which signifies slowing of the brain in processing learning tasks, maintaining focus and attention. This was predominantly observed at location P3 of Wernicke and FC5 of Broca, that is known to associate with the learning pathway. For capable dyslexics, the theta-beta band power ratio is rather random, ranges between a minimum average of 2.5 to a maximum average of 4.5, higher than those of the normal. Although the theta values were on the high side, the brain compensontary areas were able to complete the tasks as per the normal.

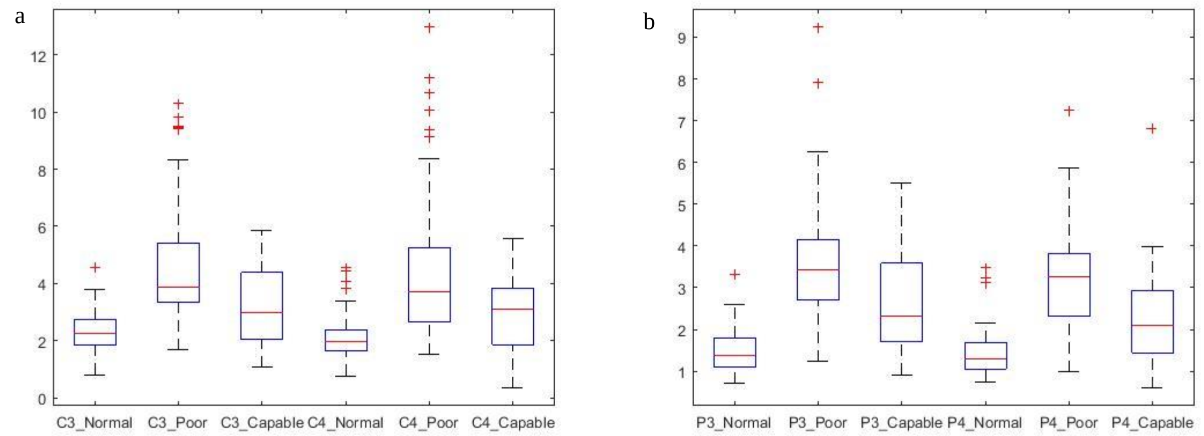

Fig. 5 – (a) Boxplot of Theta-Beta Band Power Ratio at Electrode Locations of C3 and C4; (b) Boxplot of Theta-Beta Band Power Ratio at Electrode Locations of P3 and P4

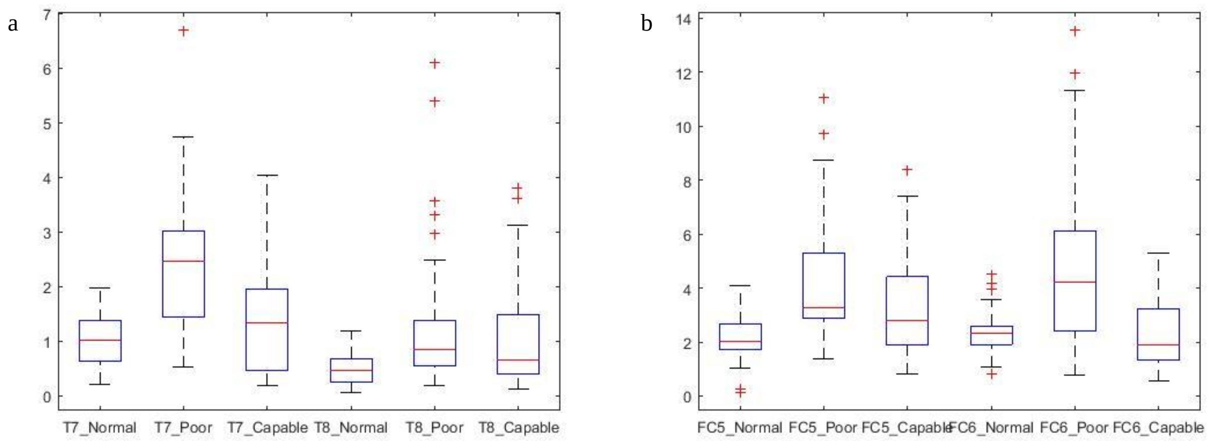

Fig. 6 – (a) Boxplot of Theta-Beta Band Power Ratio at Electrode Locations of T7 and T8; (b) Boxplot of Theta-Beta Band Power Ratio at Electrode Locations of FC5 and FC6

Table 4 summarizes the AUC of ROC graphs for SVM (linear and RBF kernels) with theta-beta band power ratio as the feature input vectors. The AUC values shown here are the average of 3 runs. As a single feature vector, the theta-beta ratio manages to achieve a perfect score of ‘1’ in the first run of RBF kernel for Daubechies order 4 and Symlets order 6 and 8. The results however was not replicated in run 2 and 3, albeit with a commendable value of 0.95 and above in the case of RBF kernel. The highest average AUC of ROC was 0.9838 for RBF kernel SVM combined with Daubechies of order 6 and a much lower average of 0.8668 for linear SVM combined with Symlets of order 2. The above findings merited the inclusion of theta-beta band power ratio as a feature vector in the classification of dyslexia.

Studies indicate that an excessive beta frequencies in children with ADHD was believed to cause restlessness, anxiety, distractibility and impulsivity [26]–[29]. It was also speculatively suggested that a high beta was an indication of comorbidity. A theta-beta ratio of lower than ‘1’ is an indication of this scenario. It is envisaged that looking into 2 frequency bands within a location will give a more objective interpretation of activation, as different locations will have an additional variable that had to be taken into account, i.e. contact issues, the strength of the signal, noises, etc.

Table 4 – AUC of ROC Graphs for Linear and RBF Kernel SVM Classifier based on Theta-Beta Ratio from Daubechies (Order 2 to 8), Symlets (Order 2 to 8) and Coiflet (Order 2 to 5)

Run 1	Db-2	Db-4	Db-6	Db-8	Sym-2	Sym-4	Sym-6	Sym-8	Coif-2	Coif-4	Coif-5
Linear	0.7939	0.7433	0.7631	0.7452	0.8006	0.7894	0.7772	0.7554	0.7849	0.7401	0.7285
RBF	0.9987	1.0000	0.9997	0.9984	0.9987	0.9987	1.0000	1.0000	0.9987	0.9997	0.9987
Run 2	Db-2	Db-4	Db-6	Db-8	Sym-2	Sym-4	Sym-6	Sym-8	Coif-2	Coif-4	Coif-5
Linear	0.9092	0.8718	0.8921	0.8782	0.9114	0.8677	0.8772	0.8864	0.8788	0.8810	0.8665
RBF	0.9456	0.9500	0.9582	0.9456	0.9472	0.9411	0.9354	0.9462	0.9491	0.9497	0.9547
Run 3	Db-2	Db-4	Db-6	Db-8	Sym-2	Sym-4	Sym-6	Sym-8	Coif-2	Coif-4	Coif-5
Linear	0.8858	0.8278	0.8731	0.8408	0.8883	0.8434	0.8509	0.8623	0.8652	0.8415	0.8326
RBF	0.9949	0.9911	0.9934	0.9886	0.9949	0.9953	0.9886	0.9870	0.9896	0.9911	0.9892
Average	Db-2	Db-4	Db-6	Db-8	Sym-2	Sym-4	Sym-6	Sym-8	Coif-2	Coif-4	Coif-5
Linear	**0.8629**	0.8143	0.8428	0.8214	**0.8668**	0.8335	0.8351	0.8347	**0.8430**	0.8208	0.8092
RBF	0.9797	0.9804	**0.9838**	0.9775	**0.9803**	0.9784	0.9747	0.9777	0.9791	0.9802	**0.9809**

4. Conclusion

Areas of the brain activated during learning related tasks in normal and poor dyslexic subjects are found similar. Hence, it would be difficult for a single feature vector of beta band power to distinguish between these two groups. Our work here examines if the theta-beta band power ratio is suitable as an alternative feature vector for classification of normal, poor dyslexic and capable dyslexic subjects. Results showed that the ratio is able to distinguish between the 3 groups, even simply by boxplot. The theta-beta band power ratio for normal ranges from 1 to 2.5, capable dyslexic ranges between a minimum average of 2.5 to a maximum average of 4.5 while poor has a ratio of 3 to 5. The ratio displays the amount of engagement by each and every electrode. They also produce a consistently high AUC of ROC graphs, for 3 mother wavelet functions at different orders. The highest average of 0.9838 is attained with RBF kernel SVM with features extracted by Daubechies of order 6. Hence, it can be concluded that theta-beta ratio is suitable to serve as a feature vector for the classification of dyslexia and a high theta-beta ratio of more than 2.5 could be a sign of a learning disorder. Once established, this theta-beta band power ratio may also be useful to the design of a brain based assessment system and protocol for a neurofeedback system, dedicated to dyslexia.

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