TIPTEKNO'24 MEDICAL TECHNOLOGIES CONGRESS
10-12 October 2024
Yasmin Bodrum Resort, Muğla, Türkiye

Diagnosis of Dyslexia using 2D EEG Feature Map and Convolutional Neural Network

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***Abstract*—Neuroscience has been significantly impacted by developments in computational techniques and machine learning algorithms, especially in the early diagnosis and classification of neurological illnesses. This study has been conducted to classify EEG data obtained from theta, alpha, beta1, beta2, and gamma bands to diagnose dyslexic and normal children. In addition to examining the individual classification performances of the data taken from these five bands, the classification success of the set created by combining the data from all bands has also been examined. The well-known models such as AlexNet, GoogleNet, and ResNet18 are compared with the revised version of ResNet18 developed in the study and the classification of handcrafted features with support vector machine (SVM). When the models' performances are compared, it is seen that Revised ResNet18 gives results with the highest accuracy value in all bands except the Gamma band. Additionally, it has been observed that the classification success of handcrafted features is lower than the success of CNN-based models.**

***Index Terms*—Dyslexia, EEG, Deep learning, Machine learning**

I. Introduction

Dyslexia is a neurological disorder that affects people's ability to read, write, and spell, even if they have normal or above-average intelligence [1]. Researchers have suggested several methods for identifying dyslexia indications. These approaches may be generally divided into three categories. Using behavioral symptoms is the first category and these symptoms are used by psychologists to diagnose dyslexia [2], [3]. Using brain imaging methods to depict specific brain behaviors falls under the second category. Several approaches, including electroencephalography (EEG) [4]–[13], and functional magnetic resonance imaging (fMRI) [14] might be employed to display these behaviors. The final category contains eye movement patterns [15].

One common method for evaluating brain behaviors is EEG. A sequence of electrical potential changes that provide information about brain activity is called the electroencephalography (EEG) signal. In this section, the application of EEG in diagnosing dyslexia is examined. In the study of Zainuddin et al. [8], a support vector machine (SVM) is utilized to classify the EEG signals of children recorded while writing words and non-words as normal, poor, and capable dyslexic. By examining the performances of different cross-validation approaches (box constraint and kernel scale), a 91% accuracy rate has been achieved in experiments using EEG data from 33 children (8 normal, 17 poor dyslexics, and 8 capable dyslexics) aged between 7 and 12. Power band features extracted using Discrete Wavelet Transform (DWT) with Daubechies of order 8 (DB8) are normalized and classified with k-nearest neighbor (KNN) in the study [9]. In the experiments in which 21 children (seven of the children are diagnosed as capable dyslexics and four are diagnosed as poor dyslexics, ten are normal children) between the ages of 7 and 12 participate, it is observed that a 100% accuracy rate is achieved when Euclidean distance is used for KNN. The study [10] compares the electroencephalogram (EEG) signal power spectrum density (PSD) of capable and poor dyslexic children during resting and writing activities. Experiments have been conducted using the data from two poor dyslexic children and three capable dyslexic children aged 7 to 11. The results show that capable dyslexics have significantly higher PSD in the frontal right hemispheric locations, while poor dyslexics have higher PSD in the left areas. In the study of Rezvani et al. [11], unlike previous studies, graph analysis of electroencephalographic (EEG) data has been used. Using the phase lag index (PLI), weighted connection matrices have been computed for several frequency bands using EEG resting-state data from 15 normal children and 29 dyslexic children. Weighted connected graphs are obtained using the connectivity matrices. SVM has achieved 95% classification accuracy for local network features across various frequency bands. According to the analysis, it is seen that EEG graph measures provide robust and reliable results in classification. The metrics of activity, mobility, and complexity have been extracted from EEG data collected from 391 children (196 Normal and 195 Dyslexic) and they are classified using three different versions of SVM (Gaussian Kernel (RBF), Polynomial kernel, Sigmoid Kernel) in study [5]. RBF achieves results with 62.4% maximum accuracy. In Zainuddin et al's study [12], the performances of machine learning (ML) algorithms (KNN, SVM, extreme learning machine(ELM)) and a deep learning (DL) model (LSTM) have been compared using EEG signals taken from 54 children (18 poor dyslexic, 18 capable dyslexic and 18 normal) in the relaxed state and different writing states. As

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a result of the experiments, SVM performed classification with the highest accuracy than others (88.33%). In study [13], 30 children (15 dyslexics, 15 non-dyslexic) who participate in the experiments are asked to perform a visual continuous performance task (VCPT) while EEG signals are recorded. The graph features such as characteristic path length, global efficiency, local efficiency, clustering coefficient, and small-world are extracted from the data and they are classified with a maximum accuracy of 96.7% when KNN is used.

The remainder of the study is structured as follows: The materials and methods used in this study are described in Section II, and the experimental results and discussion are covered in Section IV. The conclusions are mentioned in Section V.

II. Materials and Methods

The 2D EEG feature map and deep learning-based classification of EEG signals captured in both healthy and dyslexic children using Auto Train Brain training technology are provided in the proposed study.

A. Participants and Experimental design

In this study, 32 normally developing (TD) healthy children and 28 dyslexic children voluntarily participated. Children with dyslexia aged 7 to 10 participated in a study at Ankara University Faculty of Medicine. The children in the control group were also healthy and free of recognized illnesses as well as difficulties with reading or writing. With no inclusion/exclusion criteria, the study employed the Auto Train Brain training technology, which is useful for dyslexia at home. This smartphone app uses neurofeedback and multisensory learning techniques to enhance reading comprehension and cognitive abilities in dyslexic individuals, using 14 EEG channels [16], [17].

Raw EEG data was recorded from both the experimental and control groups using the EMOTIV EPOC + headset and EMOTIV PRO software. Artifacts and alias frequencies were eliminated from the data by filtering, and each channel was down-sampled to 128 samples per second. The 10-20 system was used for electrode placement, and 14 EEG channels (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4) and two references were used in the study. After that, the data was divided into theta (θ; 4–8 Hz), alpha (α; 8–12 Hz), beta-1 (β_1; 12–16 Hz), beta-2 (β_2; 16–25 Hz), and gamma (γ; 25–45 Hz) bands for power band analysis [16], [17]. Subband power values for 10 neurofeedback sessions are employed in our investigation for both the TD group and the experimental dyslexia group.

B. 2D EEG Feature Map Organization

To simultaneously combine the spatial, temporal, and frequency features of EEG signals, we create a 2D feature map, as shown in Fig. 1 [18], [19]. 14 channel EEG data are divided into five frequency bands, θ, α, β_1, β_2, and γ, for every neurofeedback session. Thus, for every frequency band and N-EEG channel, we extract Sub-band power-based features and create an N-dimension Sub-band power-based feature vector ($N = 14$). We subsequently transform the N-dimension Sub-band power-based feature vector into a compact 2D map (9×9 matrix) based on the placements of electrodes on the brain to preserve the spatial structural information of the electrode location (Fig.1 (a)). The 2D map of 14-channel estimated sub-band power-based features is shown in Fig.1 (b-left). The colored areas in the matrix represent the normalized subband powers of the relevant channels, while the empty spaces signify that the relevant channel's signals are not being used. The following formulation is used to determine the empty values of the matrix as a function of the point values around them, as stated in the study [20];

$$K_{(i,j)} = \frac{K'_{(i+1,j)} + K'_{(i-1,j)} + K'_{(i,j+1)} + K'_{(i,j-1)}}{M}, \quad (1)$$

where $1 \leq i, j \leq 9$. The features of the empty spaces are represented by the normalized sub-band power-based feature value K, while the surrounding point's normalized sub-band power-based feature value is indicated by K'. The default value of M, which is 1, indicates how many non-zero components there are in the numerator.

Next, a complete EEG feature map of a particular sub-band is produced using a "jet" colormap (Fig.1 (b-middle)). Biharmonic spline interpolation was used to construct 64×64 EEG feature maps to increase the resolution of the 2D EEG feature maps (Fig.1 (b-right)). As a result of all these steps, we create a two-dimensional EEG feature map for the Sub-band power-based features of each frequency band. For example, the EEG feature map of a feedback session for five frequency subbands of a dyslexic patient is shown in Fig.1 (b-right). Regarding the "jet" colormap, an entirely inactive electrode is shown by a dark blue color, whereas active electrodes are indicated by red.

C. Convolutional Neural Network Models

Among the deep learning algorithms, one kind especially made for processing and interpreting visual data is the convolutional neural network (CNN) [21]. It is made up of multiple layers of neurons, each of which processes an input image mathematically. CNNs are frequently utilized in applications including image recognition, object detection, and facial recognition. In this study, four different CNN-based models have been examined: AlexNet [22], GoogleNet [23], ResNet18 [24], and Revised ResNet18. Revised ResNet18 has been created by reducing the filter sizes in ResNet18 by half. For example, the filter size of conv2 in ResNet18 is 64, while it is 32 in revised ResNet18. Similarly, the filter size, which is 128 in the conv3 layer in ResNet18, is 64 in the revised ResNet18. In this way, it is aimed to save time and prevent overfitting.

III. Results and Discussion

The EEG data set from 60 children is divided into a validation set (70%) and a test set (30%). This section includes the

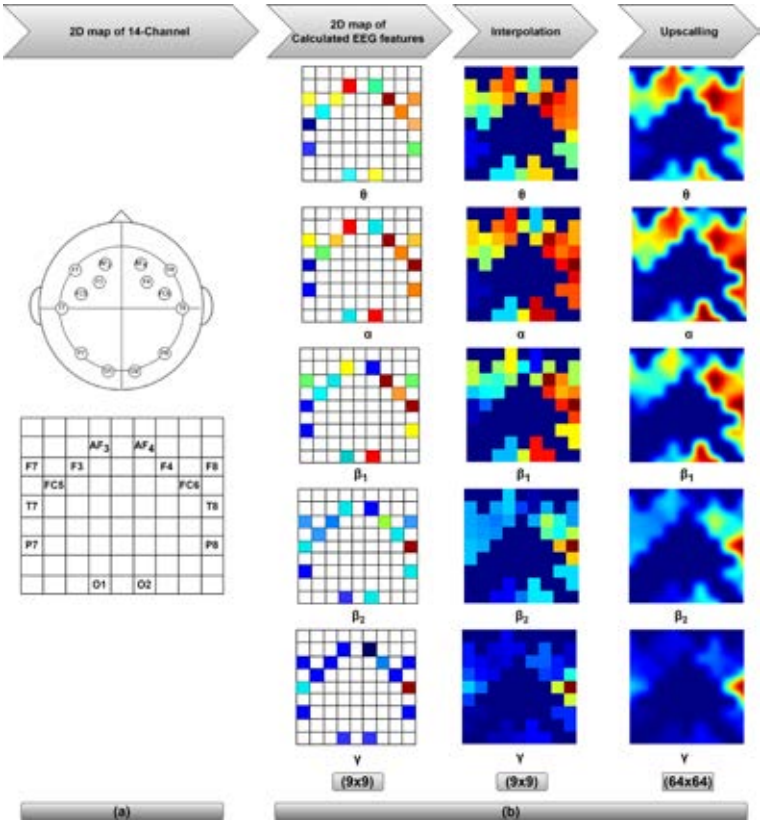


Fig. 1: The 2D EEG Feature Map representation process for Sub-band power-based features.

TABLE I: The classification performances (%) of the models.

	AlexNet		GoogleNet		ResNet18		Revised ResNet18	
Final Output of	**ACC**	**F1**	**ACC**	**F1**	**ACC**	**F1**	**ACC**	**F1**
Theta	75.60	67.69	68.90	64.99	72.20	72.51	78.90	77.09
Alpha	74.40	74.16	70.00	55.77	76.70	72.75	80.00	79.54
Beta1	74.40	75.77	77.80	76.76	70.00	72.13	81.10	79.04
Beta2	74.40	70.12	76.70	72.00	74.40	75.24	76.70	75.86
Gamma	84.40	84.07	75.60	71.82	75.60	75.56	72.20	68.37
All	84.20	81.91	80.80	79.99	85.30	83.73	88.00	87.15

experimental results performed on the test set. Comparisons have been made using the metrics of accuracy, F1-score, sensitivity, and false discovery rate (FDR).

Accuracy and F1-scores of the four different CNN-based models (AlexNet, GoogleNet, ResNet18, and Revised ResNet18) examined are given in Table I. While Revised ResNet18 provides the best accuracy rates (78.90%, 80.00%, 81.10%, 76.70%, 72.20%, 88.00%, respectively) except the Gamma band, GoogLeNet is the lowest performing model (68.90%, 70%, 77.80%, 76.70%, 75.60%, 80.80%, respectively).

In this study, the classification of handcrafted features with SVM has been also compared with the classification results of CNN-based models. The column chart according to the values of sensitivity and FDR is given in Fig.2. According to this table, the classification of handcrafted features with SVM is less successful than ResNet18 and Revised ResNet18. While a lower sensitivity value is recorded in classification with SVM, a higher FDR value is recorded than most CNN-based models.

The success of the new model, which is based on ResNet18 but created by reducing the filter sizes, is obvious. The accuracy rate of Revised ResNet18, up to 88.00%, is higher than the accuracy rate of RBF used in study [5]. In addition, the maximum accuracy rate reached in the study [12] is also achieved.

Finally, the number of subjects used to create the data set in this study is higher than the number of subjects in many studies in the literature ([8]–[13]). It can be concluded from this that the findings obtained in this study are more reliable.

IV. CONCLUSION

Studies on recorded EEG data to investigate whether dyslexia, a neurological disorder, exists in an individual, have increased considerably in recent years. This study, it is aimed to classify EEG data taken from 14 different channels of 60 children (32 normally developing healthy children and 28

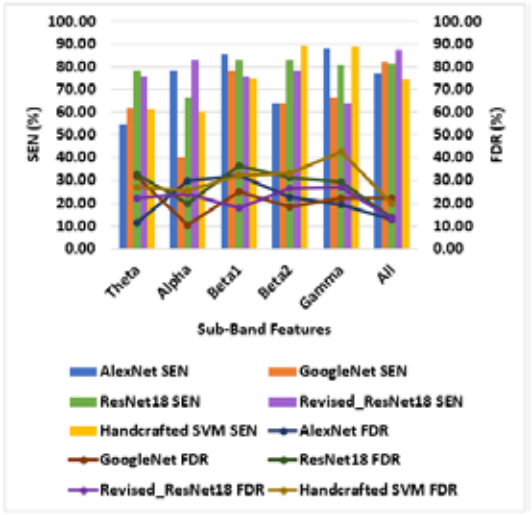


Fig. 2: Comparison of Sensitivity vs. False Discovery Rate.

dyslexic children) using different algorithms. The classification performances of the data from five different bands and the set created by combining data from all bands are investigated. In addition to using known models such as AlexNet, GoogleNet, and ResNet18 in the experiments, a new model (revised ResNet18) has been also developed. On the other hand, the classification of handcrafted features with SVM is tested to see the performance of a classifier different from CNN-based models.

Comparisons are made with four different metrics (accuracy, F1-score, sensitivity, and FDR). To prevent overfitting due to the small number of data, the performance of the revised ResNet18, which is created by reducing the filter sizes by half, has been tested. Reducing the number of filters by half enables the algorithm to be completed in a shorter time. The high performance in a short time of Revised ResNet18 in classification reveals that it is very useful and advantageous. When comparing CNN-based models, the model with the lowest performance was GoogleNet. Additionally, low performance is obtained in classifying handcrafted features with SVM.

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