Combinations of EEG Topographic Feature Maps for the Classification of ADHD

Sude Pehlivan and Onur Akdemir
Dept. of Electrical and Electronics Eng.
Izmir University of Economics
Izmir, TURKEY
sude.pehlivan@ieu.edu.tr

Ozlem Karabiber Cura
Dept. of Biomedical Eng.
Izmir Katip Celebi University
Izmir, TURKEY
ozlem.karabiber@ikcu.edu.tr

Burak Akbuğday and Aydin Akan*
Dept. of Electrical and Electronics Eng.
Izmir University of Economics
Izmir, TURKEY
akan.aydin@ieu.edu.tr

***Abstract*—Attention-Deficit/Hyperactivity Disorder (ADHD) is a common mental disorder affecting both children and adults. It is characterized by issues with concentration, hyperactivity, and impulsivity, which can interfere with everyday duties and interpersonal relationships. Although behavioral studies are utilized to treat the disease, there is no proven method for detecting it. The Electroencephalogram (EEG) is a non-invasive method that monitors electrical activity in the brain and is commonly used to identify neurological and mental illnesses such as ADHD. In this study, the topographic EEG feature maps (EEG-FMs) were obtained from 6 traditional time-domain characteristics known as Hjorth activity, Hjorth mobility, Hjorth complexity, kurtosis, and skewness. The feature maps were concatenated and used as input to Convolutional Neural Network (CNN) model for ADHD classification. To show the efficacy of the recommended approach, EEG data from 15 ADHD individuals and 18 control subjects (CS) were analyzed. The results showed that concatenated EEG-FMs were successful to classify ADHD with up to 99.72% accuracy.**

***Index Terms*—Attention Deficit Hyperactivity Disorder (ADHD), EEG , Feature Map, Convolutional Neural Network (CNN).**

I. Introduction

ADHD (Attention-Deficit/Hyperactivity Disorder) is a neuro-developmental disorder that affects both children and adults. It is characterized by difficulties with attention, hyperactivity, and impulsivity have a significant impact on people's mental health, academic performance, and social connections. Overall, the treatment of ADHD is important for improving the individual's quality of life, reducing the risk of developing other mental health problems, and improving long-term outcomes. [1]–[4]. It is challenging to diagnose ADHD, and incorrect diagnoses are frequently made [1], [2]. Most research employs non-invasive methods to identify ADHD, such as electroencephalography (EEG). EEG signals have been widely used as a reliable, affordable, and non-invasive way to measure brain activity [1], [2], [5].

As of today, a lot of study has been done on calculating the linear and nonlinear aspects of EEG signals to detect ADHD. EEG is a technique used to measure the electrical activity of the brain. There are two main approaches to analyzing EEG data: linear and non-linear. Linear analysis is a conventional method that focuses on measuring the amplitude and frequency of brainwaves in specific frequency bands. Linear methods assume that the brain's electrical activity is generated by linear combinations of independent sources, and therefore only consider the linear relationships between EEG signals. Non-linear analysis, on the other hand, focuses on the non-linear relationships between EEG signals. Non-linear methods assume that the brain's electrical activity is generated by non-linear interactions between neural populations, and therefore consider the non-linear relationships between EEG signals. Prior research on ADHD has relied on the monitoring of EEG signals during various cognitive tasks [4] or at resting state conditions [6]. The most intriguing findings of these investigations were that ADHD patients exhibited increased slow-wave activity, mainly in the theta and delta bands, and decreased fast-wave activity, primarily in the beta band. In investigations to detect ADHD, a number of non-linear metrics have been utilized successfully to glean important data from the EEG. In comparison to the models outlined above, convolutional neural networks (CNN) have the advantage of being able to automatically learn features using a large dataset. To differentiate between ADHD patients and healthy subjects, some researchers [2], [7]–[12] used various deep learning models utilizing EEG data, providing accurate classification results. Recent research has concentrated on using the images obtained from the EEG signal as input in CNN architectures [7], [9], [11] rather than using the raw EEG signal as input [8], [10], [12] because of the crucial importance of the input layer in CNN applications. In the aforementioned ADHD investigations, various methods for producing input images for deep networks utilizing EEG signals are proposed [13]–[15].

Topic et al. [13] conducted a study with two feature maps topographic and holographic namely TOPO-FM and HOLO-FM. Deep learning (DL) was used as a feature extraction method where all the extracted features were fused afterward. Finally, machine learning algorithms were applied for emotion recognition on DEAP, SEED, DREAMER, and AMIGOS datasets. The topographic and holographic maps were created using nine features namely fractal dimension, Hjorth activity, mobility and complexity, peak-to-peak, root-mean-square, band power, differential entropy, and the power spectral density. The image shape was 200x200x3 and the CNN

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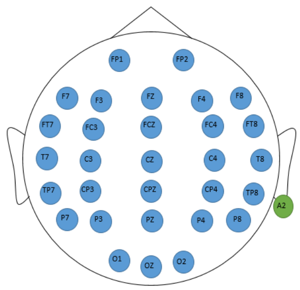
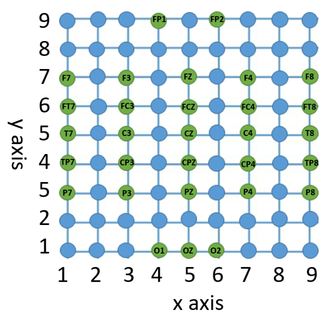


(a)



(b)

Fig. 1: a) 10-20 Electrode System b) 9x9 mapping axis

architecture had 2 convolutional layers with ReLU activation functions where the first convolutional layer was followed by a max pooling layer and the second one with a fully connected layer. The resulting features were fused together and given into Support Vector Machine (SVM) classifier. Results showed that TOPO-FM based classification has a significant success on different datasets and authors stated that the proposed methodology outperformed the studies in the literature [13].

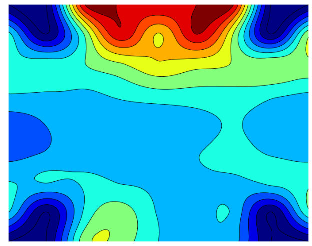
In this study, we aim to develop a fast and automated ADHD classification using concatenated EEG Feature Map (EEG-FM) based input images which are utilized for the training of an advanced CNN-based model.

II. Material and Method

The placements of the EEG electrodes or the EEG topography for a particular EEG segment are typically not taken into account when applying the EEG characteristics. Moreover, deep learning-based methods can be utilized to extract more significant characteristics that exceed hand-crafted, traditional ones [13]–[15]. This work aims to demonstrate the benefits of concatenated EEG feature maps. EEG feature maps represent both spatial and temporal information of each EEG segment. As a result, after computing various linear and non-linear EEG features, feature map images are created. Classification of ADHD patients and CS are performed using a sophisticated CNN-based model.

A. Experimental ADHD Dataset

EEG data are recorded from 15 ADHD patients and 18 CS using the Brain Vision system at the İzmir Katip Çelebi University. The International 10-20 System is a widely used method for placing electrodes on the scalp during EEG recording. It provides a standardized method for electrode placement during EEG recording, which facilitates the comparison of EEG data across studies and allows for the accurate localization of brain activity. Using the International 10-20 system, the utilized EEG signals are recorded from 30 distinct channels (Fp1, Fp2, F7, F8, F3, F4, Fz, FT7, FT8, FC3, FC4, FCz, T3, T4, C3, C4, Cz, TP7, TP8, CP3, CP4, CPz, T5, T6, P3, P4, Pz, O1, O2, Oz). The sampling frequency of the Brain Vision system was 1 kHz. The EEG signal of each participant was recorded for a total of 4 minutes while they are in the open-eyes resting state condition. The Izmir Katip Çelebi University Non-Interventional Clinical Research Ethics Committee granted consent for the gathering of the EEG data utilized in this study on July 11, 2019, under approval number 76.



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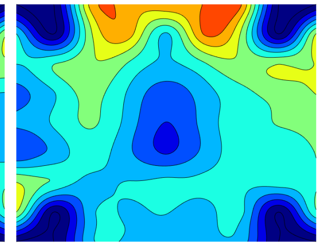

(b)

Fig. 2: Example EEG-FM images of a) CS and b) ADHD subjects

To eliminate power line interference and other disturbances, a Butterworth band-pass filter with a cutoff frequency of $[0.5-50]$ Hz is applied to each channel. Moreover, the EEG data from each channel is separated into 5 s segments.

B. Feature Extraction

Determining the features to be calculated in EEG signals is important for ensuring the accuracy and relevance of the analysis, selecting the appropriate features for the specific application, and reducing the computational burden of the analysis. The choice of features should be based on the research question or clinical application, and should be carefully considered to optimize the effectiveness of the analysis. The EEG signals can be used to extract numerous linear and nonlinear properties in both the time-frequency domain and the frequency domain.

In the proposed study, time-features; Hjorth activity (HA), mobility (HM) and complexity (HC), peak-to-peak (PTP) value, skewness (SKW), and kurtosis (KTS) were used [13], [16]. The Eq. 1, 2 and 3 were utilized to obtain HA, HM, and HC where $Var(z(t))$ is the variance of the signal $z(t)$ and $\frac{dz(t)}{dt}$ is the first derivative of the signal $z(t)$. The SKW and KTS features were calculated using Eq. 4 and Eq. 5,

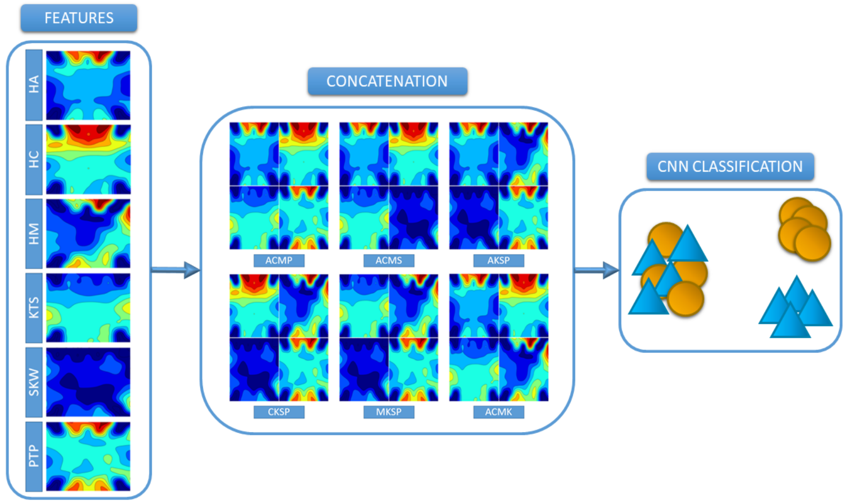

Fig. 3: The flowchart of the proposed approach

respectively where $\bar{z}$) indicates the mean of the signal $z(t)$ [17].

$$HA = Var(z(t)) \tag{1}$$

$$HM = \sqrt{\frac{Var(\frac{dz(t)}{dt})}{Var(z(t))}} \tag{2}$$

$$HC = \frac{HM(\frac{dz(t)}{dt})}{HM(z(t))} \tag{3}$$

$$SKW = \frac{1}{N}\sum_{i=1}^{N}\frac{(z_i - \bar{z})^3}{\sigma^3} \tag{4}$$

$$KTS = \frac{1}{N}\sum_{i=1}^{N}\frac{(z_i - \bar{z})^4}{\sigma^4} \tag{5}$$

The extracted features are mapped into two-dimensional topographical feature maps proposed in [13]–[15] as explained in the following section.

The EEG segments of 5 s in length were used to extract the time domain features for all 30 channels' 48 (4 min x 5 s) segments. 6 features were obtained for each EEG channel and each segment of ADHD patients and CS. The feature vector was then normalized by scaling between 0 and 1, as indicated in Eq. 6, which comprises features computed from EEG segments of both ADHD patients and CS.

$$k_i^{'} = \frac{k_i - k_{min}}{k_{max} - k_{min}} \tag{6}$$

where $k_i^{'}$ denotes the normalized feature value of i^{th} subject, $k_{max}$and k_{min} are the maximum and minimum values of the total feature vector.

C. The Construction of Topographic EEG Feature Map

The International 10-20 system, given in Fig. 1-a, that is used in the recording stage, was also used to map the normalized feature values of 30 EEG channels on the matrix as shown in Fig. 1-b. In previous studies, a mapping was proposed to accurately map every electrode into a matrix with nine rows and nine columns which is suitable for all EEG dataset with less than 81 electrodes [13]–[15]. Hence, the matrix mapping is adopted for our dataset to obtain EEG Topo-FMs. In the feature matrix, the green points which include the name of the corresponding channel, are filled with normalized feature values. Eq. 7 can be used to represent the values of the missing (blue) points which are empty, as a function of the feature (green) values around them

$$A_{(i,j)} = \frac{A^{'}_{(i+1,j)} + A^{'}_{(i-1,j)} + A^{'}_{(i,j+1)} + A^{'}_{(i,j-1)}}{M}, \quad 0 \le i,j \le 8; \quad (i,j) \in N \tag{7}$$

where A indicates the normalized feature value of the blue point, $A^{'}$ is the normalized value of the point neighboring this point. The default value of K is 1, and it refers to the number of non-zero components in the numerator.

A complete EEG-FM of a particular feature is then formed by interpolating the empty elements of the matrix and applying a "jet" color-map. Finally, the generated color EEG-FM images were stored as "png" images with 684×541 pixel size. The whole procedure of getting EEG-FMs and obtaining the feature images was carried out using MATLAB©2022b. The EEG-FMs obtained using the complexity feature for the first EEG segments of one ADHD patient (right) and one CS (left) are given as an example in Fig. 2. Regarding the "jet" color mapping in the images, the red color designates active electrodes whereas the dark blue color indicates that an electrode is completely inactive. The coordinates for each

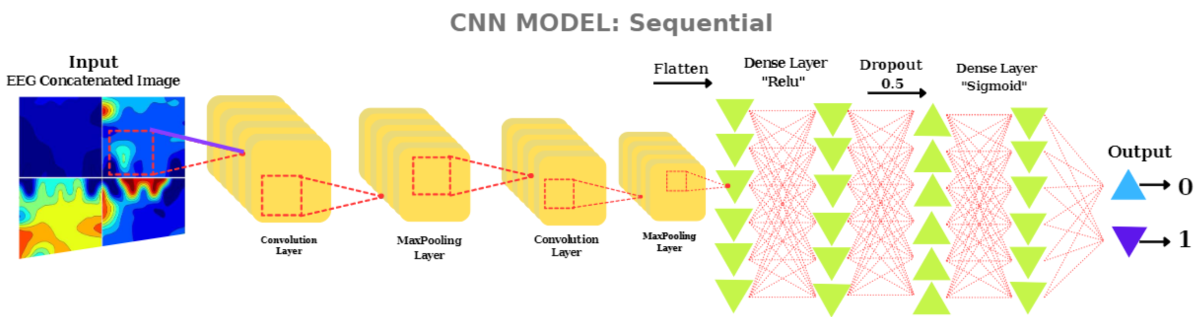

Fig. 4: CNN architecture used in the study

electrode were fixed according to the 10–20 electrode mapping on the 9×9 matrix as shown in Fig. 1-b.

D. Combination of Topographic EEG-FMs

In this study, the topographic EEG-FMs are concatenated and used an augmented input for the classification. This preprocessing is performed before the CNN classification since the number of samples in the dataset highly affects the performance of the CNN model. The augmentation is performed where the quad combination of all 6 features were randomly concatenated into a 2×2 image matrix. Hence, the dataset including 3.656 original EEG-FMs for CS and 2.724 EEG-FMs for ADHD subjects is used to generate 5.484 CS and 4.086 ADHD augmented images. The size of the concatenated images are 1082×1368, however, to be able to compare the results of using single EEG-FMs, the size of the concatenated images are reduced to 684×541.

E. CNN-Based Classification

The process of CNN-based classification of ADHD typically involves the following steps: data acquisition, data preprocessing, feature extraction, training the CNN model, and testing the model.

The proposed CNN architecture includes 2 convolutional layers where each followed by a max-pooling layer. The information of the second max-pooling layer is flattened and sent into a dense layer. Afterward, 50% dropout is applied and the structure is finalized with a dense layer. In convolutional layers, Rectified Linear Unit (ReLU) activation function and a kernel with size 3 are utilized. The last dense layer adopts a sigmoid activation function since the problem is a binary classification. The batch size was 32 and the Adam optimizer is used with a 0.001 learning rate. The CNN architecture is shown in Fig. 4. The concatenation algorithm and CNN classification were performed using Python programming language and the TensorFlow platform.

III. Results and Discussion

The six extracted features are used to generate concatenated topographic EEG-FMs for the classification of ADHD and healthy subjects using a CNN as summarized in Fig. 3. The performance of the CNN model was analyzed using accuracy, precision, recall, and loss metrics. In Table I, it is shown that the accuracy of the first and last epochs were 89.36% and 99.72%, respectively. The precision increased similarly that in the last epoch, 99.65% can be seen. The recall metric started from 85.39% and increased up to 99.69% which showed that the model identified positives properly. The epoch number was selected on purpose since it was observed that more than 5 epochs resulted in over-fitting on our dataset. The validation accuracy started from 97.46% and ended at 99.48% while the validation loss decreased from 6.64% to 1.54%.

As stated in a study conducted by Chen et al., the DL approach is more successful than the classical SVM classifier to identify ADHD patients. As the input to train the CNN, the connectivity matrix was employed to represent the brain network. After 50 epochs, the suggested framework resulted in an accuracy of 98.17% on the validation data. The results imply that the DL framework's data representation is significant for the performance [7].

In another study, EEG data was transformed into a color picture by assigning each of the three sub-bands (theta, alpha, and beta+low gamma) to one of the RGB channels. After normalization, the data was fed into a CNN model with 13 layers. Results showed 99.06% train accuracy and 97.81%

TABLE I: Results of the CNN Model

Epoch	Training Accuracy	Training Precision	Training Recall	Training Loss	Validation Accuracy	Validation Loss
1	0.8936	0.8923	0.8539	2.2715	0.9746	0.0664
2	0.9852	0.9846	0.9808	0.0426	0.9854	0.0359
3	0.9922	0.9919	0.9899	0.0231	0.9847	0.0403
4	0.9966	0.9968	0.9951	0.0099	0.9892	0.0215
5	0.9972	0.9965	0.9969	0.0061	0.9948	0.0154

TABLE II: COMPARISON OF THE PROPOSED METHOD WITH RECENT STUDIES

Study	Dataset	Approach	Classification	Accuracy
Proposed Study	15 ADHD patients and 18 healthy subjects	Concatenation of Topographic EEG-FMs	CNN	**99.72%**
Moghaddari et al. [9]	31 ADHD patients 30 healthy subjects	θ, α, β, and γ sub-band separation and RGB image creation	Deep CNN	98.48%
Chen et al. [7]	50 ADHD patients 51 healthy subjects	Mutual information Connectivity matrix	Deep CNN	94.67%

validation accuracy were obtained [9]. The comparison of the proposed method to state of art studies is provided in Table II.

In this study, a CNN model with only 2 layers was utilized to eliminate the complexity and run time of the training. It was seen that the suggested model outperformed existing research without being constrained by its small size [9]. Another concern in DL approaches is the number of samples in the dataset. Although the sample size was found to be adequate in this paper, it was observed that the validation accuracy started from a relatively high value. The source of this complication is assumed to be the split ratio of train and validation sets. Fortunately, according to the literature, the relationship between performance metrics can be considered acceptable. Besides, through the epochs, it can be seen that the training accuracy becomes higher than validation accuracy as expected while the loss of both training and validation decreased to an acceptable level.

IV. CONCLUSION

In this study, it is aimed to classify ADHD patients and healthy CS utilizing a 2 layer CNN architecture. Six time-domain features are extracted, and the features are mapped onto topographic feature map images. We propose using a combination of these feature maps by concatenating them into 2×2 augmented images. The overall results showed that the proposed CNN model successfully differentiated ADHD patients and CS. Further research aims to investigate various combinations of EEG-FMs such as arithmetic, geometric averaging, and 3D representations for the augmentation, and increase the CNN model's complexity to improve the performance.

It is important to note that CNN-based ADHD classification is developing field, and further research is needed to adequately examine its utility and reliability in healthcare situations. Overall, CNN-based ADHD classification showed potential as a prospective method of early identification and diagnosis of the disorder, and may possibly lead to more effective treatments in the future.

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