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Exploring the attention process differentiation of attention deficit hyperactivity disorder (ADHD) symptomatic adults using artificial intelligence on electroencephalography (EEG) signals

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Abstract: Attention deficit and hyperactivity disorder (ADHD) onset in childhood and its symptoms can last up till adulthood. Recently, electroencephalography (EEG) has emerged as a tool to investigate the neurophysiological connection of ADHD and the brain. In this study, we investigated the differentiation of attention process of healthy subjects with or without ADHD symptoms under visual continuous performance test (VCPT). In our experiments, artificial neural network (ANN) algorithm achieved 98.4% classification accuracy with 0.98 sensitivity when P2 event related potential (ERP) was used. Additionally, our experimental results showed that fronto-central channels were the most contributing. Overall, we conclude that the attention process of adults with or without ADHD symptoms become a key feature to separate individuals especially in fronto-central regions under VCPT condition. In addition, using P2 ERP component under VCPT task can be a highly accurate approach to investigate EEG signal differentiation on ADHD-symptomatic adults.

Key words: Attention deficit hyperactivity disorder, artificial neural network, support vector machine, electroencephalography, visual continuous performance test

1. Introduction

Attention deficit hyperactivity disorder (ADHD) is a neurological disorder, which onsets in childhood [1]. It affects about 5% of children population all over the world [2]. Although the prevalence of ADHD in adults is not well known, researchers estimate that at least one-third of people are diagnosed with ADHD in their childhood[1].

Nowadays, exploring the effect of ADHD on brain functions with the help of rapidly developing brain imaging systems and machine learning tools has attracted significant attention from researchers. There are several studies about ADHD in children and adults, using functional magnetic resonance imaging (fMRI) [3, 4], single photon emission computerized tomography (SPECT) [5, 6], magnetic resonance imaging (MRI) [7, 8] and electroencephalography (EEG) [9, 10]. Among these techniques, EEG is of great interest due to its low cost and high temporal resolution.

In human brain, neurons show oscillatory activities in delta, theta, alpha, beta, and gamma frequency ranges and EEG signal is a reflection of these oscillatory activities. The electrical activity of the brain can be

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examined both at resting-state and during the processing of sensory or cognitive stimuli [11]. Potentials that are measured in cases where brain activity is triggered by a task are defined as event-related potentials (ERPs). ERPs are reliable indicators of the cognitive processes in the brain and shown to be sensitive to attention-related activities [12, 13].

In the literature, early N1 and P2 components and late P3 component are mostly evaluated in adult studies. Fronto-central N1 is considered as a new component in clue and targeted attention tasks [14]. In fronto-central region, high N1 amplitude is considered as an indicator of increased attention [15]. In 2007, Prox et al. [16] reported considerable difference in N1 wave between ADHD cases and healthy controls. Another study on adults with ADHD indicated an increase in N1 amplitude in the fronto-central region and the finding was associated with increased task-specific attention [17]. P2 wave is a frontally-distributed component associated with the discrimination of stimuli [18] and increase in P2 amplitude after clue is also considered as an increase in attention [19]. In studies with similar to Go/NoGo tasks researchers generally observed an increase in the amplitude of P2 in the fronto-central region of subjects with ADHD [19–21]. P3 wave is associated with inhibition in the fronto-central region and attention in the posterior region [22]. In healthy subjects, the P3 wave occurs in the posterior parietal region, which is formed by cognitive processes with active recognition function [23].

Recently, however, classification of clinically diagnosed adult ADHD patients using EEG signals become a hot topic and researchers have put substantial effort to achieve high accuracies using the state-of-the-art machine learning algorithms. [24–27]. In these studies, researchers mostly utilized visual continuous performance test (VCPT). In general, VCPT is used to obtain quantitative information about the ability to maintain attention over time [28] and it is highly valid test that can objectively measure the ability of concentration on a single long-term task [29]. In 2010, Mueller et al. [24] achieved 92% classification accuracy on VCPT data, using latency measurement features extracted from the independent ERP components. In their later study, they [25] reached 94% classification accuracy, employing latency/amplitude measurements of the ERP components on VCPT data. Tenev et al. [26] focused on four different conditions: eyes-open, eyes-closed, VCPT, and emotional continuous performance test (ECPT). They achieved 72.6% classification accuracy under the eyes-closed condition as their best result. In 2017, Biederman et al. [27] succeeded to reach 0.92 area under the curve (AUC) classification score, using spatio-temporal brain network activation (BNA) features from VCPT data. All of the aforementioned studies employed the support vector machine (SVM) classifier and the most successful results were achieved with radial basis function (RBF) kernel.

Clinically diagnosed subjects generally undergo some medical treatments, and this medication process may affect the EEG signals of the ADHD patients. Hence, comparing the medicated ADHD patients and unmedicated subjects may not be fair due to the variations caused by the medication on EEG signals. In our study, all subjects are healthy and some of them show ADHD symptoms. There is no manipulation on the subject's EEG signals caused by medication. Therefore, our machine learning algorithms explore purely the indicators of ADHD symptoms on EEG signals. In this study, different from the previous studies, unmedicated and undiagnosed healthy adults were employed. We aimed to examine, whether attention processes of adults with ADHD symptoms (we refer to these nonclinical and unmedicated subjects as ADHD+) and without ADHD symptoms (we refer to these nonclinical and unmedicated subjects as ADHD-) differ or not, and identify which ERP components and anatomical brain regions are the most valuable to separate these two groups accurately from EEG signals under VCPT. For the classification purposes, we chose SVM with RBF kernel due to their verified performance in previous EEG studies, and artificial neural network (ANN) algorithm. To investigate anatomical regions which contribute the most to separate two groups, we first chose the most successful classifier and used permutation importance scores [30] detailed in Section 2.5. The healthy subjects with ADHD symptoms were found using the scale developed by Turgay in 1995 [31] as extensively explained in Section 2.1. To measure the sustainability of attention, a VCPT task was applied to the subjects. For the accurate detection of EEG signal differentiation on subjects in VCPT, N1, P2, and P3 ERPs were employed (Details of VCPT task and selected ERPs can be found in Section 2.3).

In this study, our main contribution is to investigate which brain regions and EEG wave provide the strongest cues of ADHD symptoms that are independent from other comorbidities and medical treatments. To achieve this goal, we first found a highly accurate classifier and observe the permutation importance scores of data from various channels of EEG. To our knowledge, this is the first nonclinical study that uses machine learning to explore the variations of EEG signals sourcing from ADHD symptoms on different regions of the brain.

The rest of the paper is organized as follows: In Section 2, we describe material and methods that we used in our experiments. In Section 3, we present our experimental results. We further elaborate on our results and discuss about the future aspects of our study in Section 4. We draw our conclusions in Section 5.

2. Material and methods

In this section, participant information, EEG recording procedure, preprocessing stage, creation of event related potentials, feature extraction and utilised classifiers are explained in detail.

2.1. Participants

The data used in the study was collected from the study of Kısacık [32]. Data contains a total of 65 adults (34 female and 31 male) 27 of which were grouped as ADHD+ with a mean age around 22.2 ($\pm$ 3.3) and the rest constitutes the ADHD- group with a mean age around 23.0 ($\pm$ 3.6). Inclusion criteria of the participants are as follows:

1. Being from 18 to 30 years old,
2. Being right-handed,
3. Being without any neurological and psychiatric diagnosis, except depression and anxiety disorders in the past,
4. Receiving no diagnosis of neurological or psychiatric disorder in the last six months,
5. Being without any uncorrected refractive error.

Grouping of these healthy (clinically undiagnosed and untreated) subjects was done based on the scale developed by Turgay in 1995 [31]. Validity and reliability of the scale was accomplished by Ercan et al. in 2001 in Turkey [33]. The scale includes three subsections: "attention deficit section" (9 items), "extreme mobility / impulsivity section" (9 items) and "ADHD-related features and problems section" (30 items). In this study, the first two subsections were used to group participants. The subjects with a median score higher than 14 were grouped as ADHD+ (showing ADHD symptoms, mean score = 20.5 ($\pm$ 5.6)) and the rest were grouped as the ADHD- (mean score = 8.8 ($\pm$ 3.2)).

2.2. EEG recordings and preprocessing

The EEG data was collected using brain vision recorder 2.1, Brainamp DC 32-channel EEG-EP system (Brain Products GmbH, Gilching, Germany) and recorded from 30 channels (Fz, F3, F4, F7, F8, FCz, FC3, FC4 , C2, C3, C4, CPz, CP3, CP4, Pz, P3, P4, P7, P8, FT7, FT8, T7, T8, TP7, TP8, TP9, TP10, Oz, Ol, O2) that were placed according to the international 10-20 system. The earlobe was assigned as the reference electrode. Sampling frequency of the data was 1 kHz. Figure 1 shows the representational electrode distributions on a scalp model.

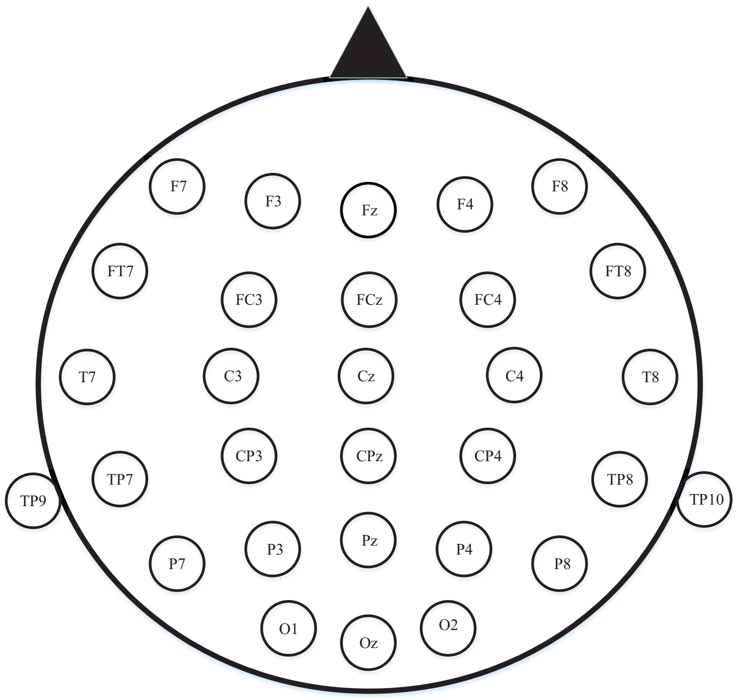


Figure 1. Illustrative EEG electrode placement according to international 10–20 system.

During recordings, the participants were held in an isolated room from sound and electromagnetic field with dim light. The distance of each participant to the center of the screen was set to 114 cm, and the tasks were presented on a 17" monitor. Collected EEG recordings were band-pass filtered with cut-off frequencies at 0.5 and 50 Hz. Slices containing eye movement and muscle artefacts were discarded using brain vision analyser.

2.3. Visual continuous performance test (VCPT) and data preparation

VCPT task contains two visual stimulus called as Go/NoGo paradigm [29]. In this task, participants were informed about the paradigm with the following directions:

1. Look at the focus mark on the screen. When the focus mark disappears the letters (A, B, Y, and X) will be presented.

2. Press the right mouse button, if X follows A (Go task)

3. Do not press button, if Y comes after A, B comes after X, or Y comes after B (NoGo task)

The test consisted of three blocks, each containing 100 stimulus pairs (AX, AY, BX, and BY). In each block, frequencies of the Go/NoGo tasks were arranged as 70% (AX) and 10% (AY, BX, and BY), respectively [29]. In total there were 210 Go and 90 NoGo tasks. The schematic representation of Go/NoGo task is presented in Figure 2. The answers of the VCPT task were given by subject with the index finger of the right hand. EEG recordings were collected continuously during the tasks.

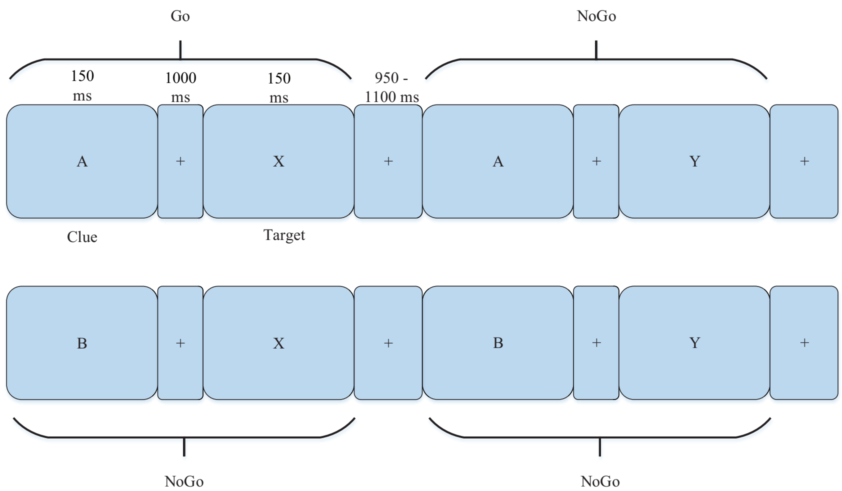


Figure 2. Schematic representation of Go/NoGo task. Top left portion illustrates the target task.

In EEG recordings, event-related potentials (ERPs) were mentioned as key point to measure the visual attention of the subjects [13]. In this study, Go-task based averaged N1, P2, and P3 ERPs were examined to measure differentiation of visual attention between ADHD+ and ADHD- groups. A brief description of relevant ERPs is given as follows:

N1: This is the wave that follows P1 wave. It is an automatic response before attention and is related to the connection between the previous and the new stimulus [34].

P2: This is the first positive wave following the N1 wave which appears approximately 200 ms after the stimulus. It is observed in situations while identifying, differentiating and comparing different stimuli and before the decision has been made [34].

P3: Amplitude of this wave has been reported to be related to sensitivity to the event expectancy, and decision making regarding to the importance of stimulus. Latency and amplitude of this wave is associated with cognitive performance skills [35].

ERPs were chosen in time intervals between 145-185 ms for N1, 220-260 ms for P2, and 335-415 ms for P3 waves [32]. Selection of N1, P2, and P3 waves is presented in Figure 3. To create Go-task based averaged ERPs, artefact-free recordings were divided into slices each of which starts from 200 ms before the trigger and ends 1800 ms after the trigger (Trigger instance corresponds to letter A). Slices of each EEG channel were averaged. Minimum slice number for each participant was determined as 100 for consistency. The final data was created by calculating the mean amplitude values of each electrode group over Go-task based averaged ERPs.

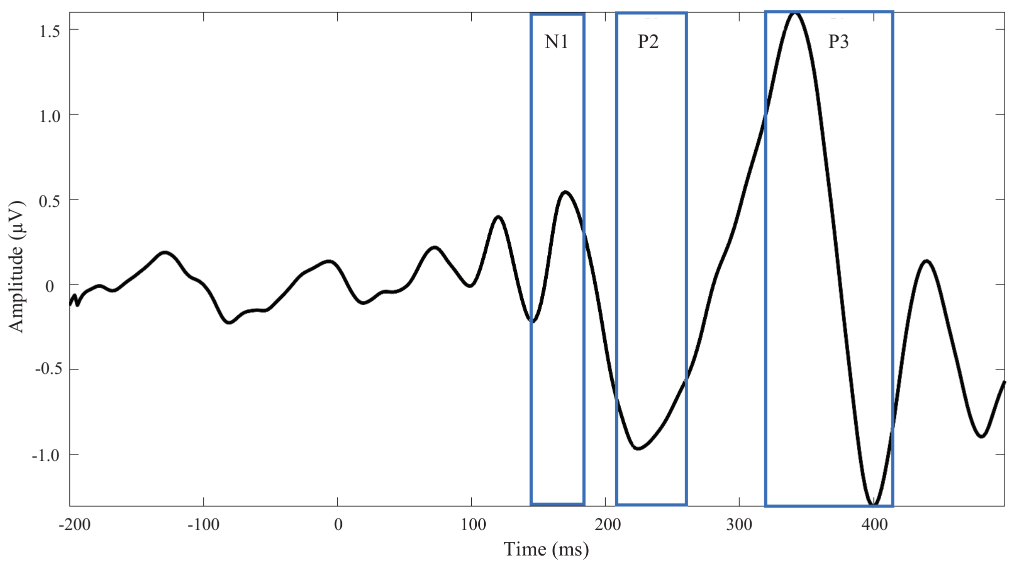


Figure 3. Selection of ERP waves. From left to right N1, P2, and P3 waves.

2.4. Classifiers

In this part, we tested two different classifiers: ANN and SVM. For robust performance evaluation, we applied 10 times 10-fold cross-validation for both classifiers. Features were standardized (values are centered around the mean value with a unit standard deviation)before feeding into the classifiers in each fold. 10% of our data (preserving the percentage of samples for each class) were separated as validation data to optimize hyperparameters and were not included in cross-validation process for both classifier.

2.4.1. Support vector machine (SVM)

SVM is a supervised classifier that is commonly used for EEG data classification tasks.This classifier aims to locate a decision boundary with a maximum distance to the nearest samples from different classes. It builds a classifier model, using a given set of features and finds a decision boundary that separates different groups [24]. In this study, RBF kernel was used in SVM and optimum $\mathbb{C}$ (0.1) and γ (0.01) values were determined applying grid search on the validation data.

2.4.2. Artificial neural network (ANN)

ANN was inspired from human brain due to its ability of learning with observation from imprecise or complex data. An ANN consists of an input layer, hidden layers and an output layer. It contains a set of interconnected processing units called as neurons at each layer. Underlying idea of the ANN involves learning the optimum weights inside the network to solve a particular problem based on a set of rules [36].The optimum architecture was found by cooperating with hyper-parameter optimization software Talos [1] with grid search on validation data. According to optimization outcome, we employed an ANN with two hidden layers. Each hidden layer contains 8 neurons. Rectified linear unit (ReLU) function was chosen as the activation function in hidden layers

[1]Autonomio Talos (2019). Computer Software.

and binary cross-entropy was used as the loss function. A total of 400 epochs was applied through the process of learning. Our ANN architecture is shown in Figure 4.

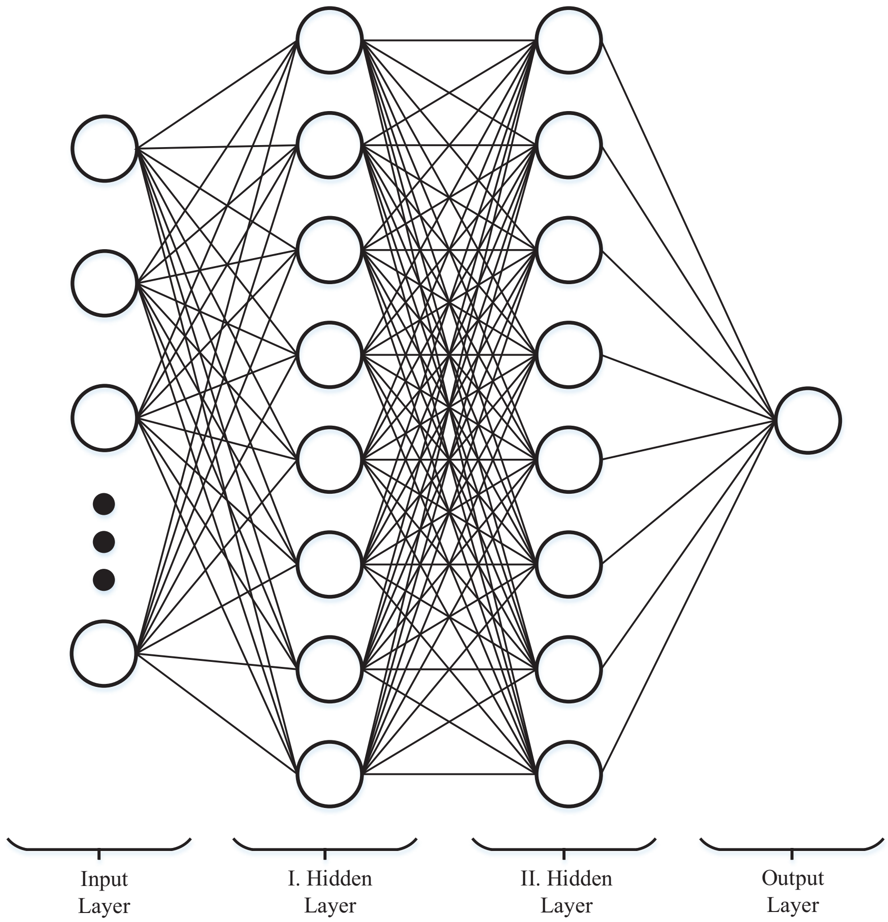


Figure 4. Employed ANN architecture. Each hidden layer contains 8 neurons.

2.5. Permutation feature importance scores

Permutation feature importance score is known as a model evaluation technique and defined as the decrease in a model's performance when a single feature is randomly shuffled [30]. This shuffling process removes the feature/target relation and evaluates the model to see how much the model's performance depends on that particular feature. In the human brain, ERPs change rapidly and have a large spatial distribution. For this reason, ERPs usually recorded from more than one scalp location [39]. In this study, we employed the permutation feature importance scores to explore the EEG channel importance in our experiments.

3. Results

In this section, we present the classification results using VCPT data and channel contributions based on the most successful classifier.

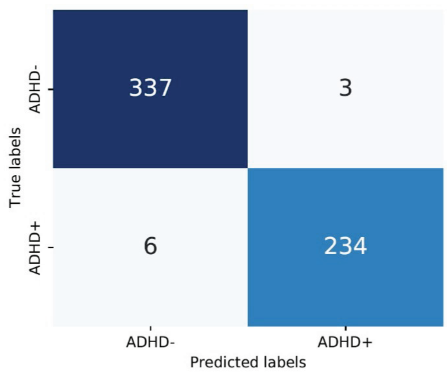
3.1. VCPT classification results

For VCPT data, summed grand-averaged P1, N1, P2 and P3 ERPs were used as feature sets to feed into the classifiers. Table 1 shows the classification results. Confusion matrices of best results with averaged loss of ANN model are presented in Figure 5.

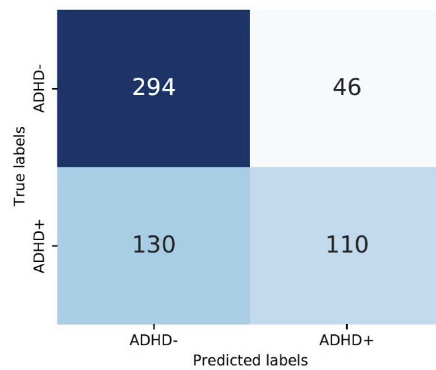
Table 1. Classification results of VCPT data.

Classifier	Feature	Accuracy	Sensitivity	Specificity
ANN	N1	93.1%	0.95	0.92
	P2	98.4%	0.98	0.98
	P3	87.9%	0.87	0.88
SVM	N1	66.3%	0.63	0.67
	P2	69.6%	0.70	0.69
	P3	61.2%	0.53	0.66

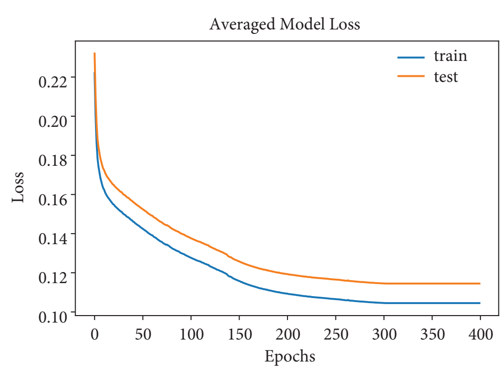
In Table 1, ANN achieved 98.4% accuracy with 0.98 sensitivity, when P2 feature set was used. For the same feature set, SVM achieved 69.6% accuracy with 0.70 sensitivity. Figure 6 shows the ROC curves of the classification results.



(a) Confusion matrix for ANN.



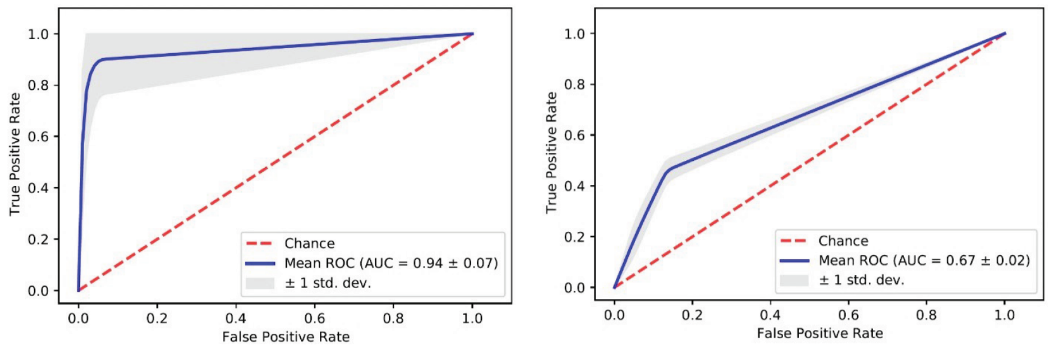
(b) Confusion matrix for SVM.



(c) Averaged Loss for ANN Model.

Figure 5. Confusion matrices for VCPT data and averaged model loss.

ANN model achieved an AUC score of around 0.94 which was almost 0.3 higher than the AUC scores of the best SVM. According to classification results, we inferred that to separate the ADHD+/ADHD- individuals,



(a) ROC Curve of ANN for P2 feature set.

(b) ROC Curve of SVM for P2 feature set.

Figure 6. ROC curves for VCPT data.

using ANN model and P2 feature set is adequate and effective. Considering the ANN model as the baseline model, we visualized the contribution of the features (channels) on classification using permutation importance function [30] in each fold, which calculates the importance scores of features for a given dataset and eventually leads to the brain locations where ADHD symptoms can be effectively classified. Table 2 shows the averaged permutation importance results of each EEG channels for P2 feature set.

Table 2. Averaged permutation feature importance scores.

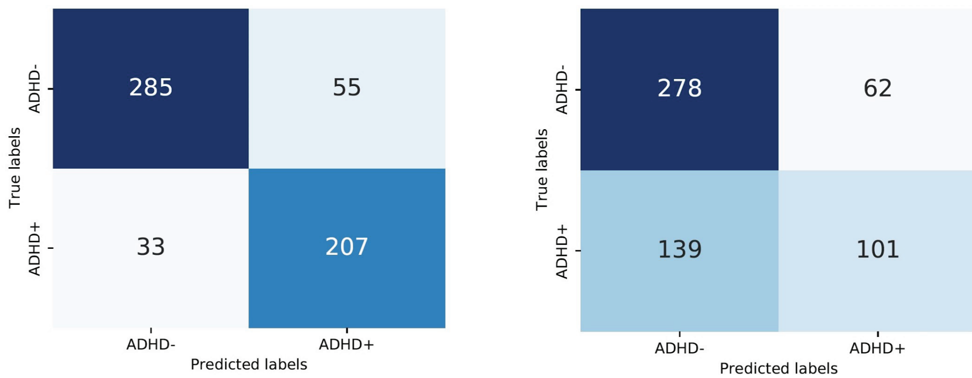
Channel	Scores	Channel	Scores
F3	0.2303 ± 0.0892	Fz	0.0527 ± 0.0295
F4	0.1945 ± 0.0252	T7	0.0402 ± 0.0851
C4	0.1745 ± 0.0203	P3	0.0398 ± 0.0900
C3	0.1441 ± 0.0559	P8	0.0371 ± 0.0202
F7	0.0876 ± 0.0227	P4	0.0362 ± 0.0967
FCz	0.0868 ± 0.0232	P7	0.0336 ± 0.0058
FC3	0.0842 ± 0.0459	T8	0.0311 ± 0.0967
FC4	0.0832 ± 0.0583	Pz	0.0287 ± 0.0274
F8	0.0765 ± 0.0123	O1	0.0267 ± 0.0178
Cz	0.0722 ± 0.0555	TP7	0.0201 ± 0.0414
CPz	0.0699 ± 0.0442	Oz	0.0177 ± 0.0919
CP3	0.0658 ± 0.0060	O2	0.0151 ± 0.0097
CP4	0.0632 ± 0.0680	TP10	0.0131 ± 0.0368
FT7	0.0597 ± 0.0829	TP8	0.0084 ± 0.0501
FT8	0.0548 ± 0.0588	TP9	0.0076 ± 0.0078

As presented in Table 2, top-ten contributions to the classification came from frontal and central channels. Minimum contributions were observed at temporo-parietal and occipital channels. To see the direct contributions of these ten channels we also employed same ANN and SVM models using features of ten channels (named as Reduced). Table 3 shows the classification results and confusion matrices of are presented in Figure 7.

In Table 3, ANN achieved 84.8% accuracy with 0.79 sensitivity and SVM achieved 65.3% accuracy with 0.62 sensitivity. Figure 8 shows the ROC curves of the classification results.

Table 3. Classification results for reduced P2 feature set.

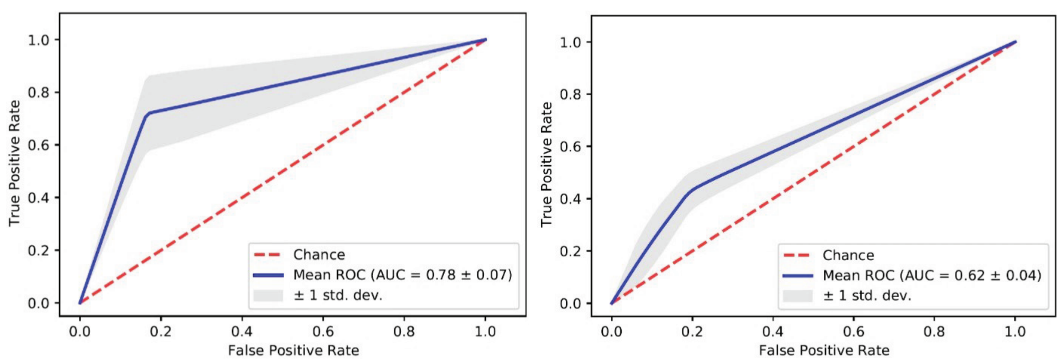
Classifier	Feature	Accuracy	Sensitivity	Specificity
ANN	P2	84.8%	0.79	0.89
SVM	P2	65.3%	0.62	0.66



(a) Confusion matrix for ANN. (b) Confusion matrix for SVM.

Figure 7. Confusion matrices for reduced P2.

ANN model achieved an AUC score of around 0.78 and SVM achieved an AUC score of around 0.62.



(a) ROC Curve of ANN. (b) ROC Curve of SVM.

Figure 8. ROC curves for reduced P2.

4. Discussion

In this work, we aimed to examine whether differentiation of attention processes of adults with ADHD symptoms is a key feature or not to separate them from asymptomatic ones under VCPT task. For this purpose, we employed a commonly-used traditional machine learning algorithm SVM and a deep learning model ANN. The sum of averaged N1, P2 and P3 ERPs from VCPT data were used as input to the classifiers. As depicted in Table 1, ANN algorithm achieved the highest accuracy and sensitivity, when P2 ERP was used. This result showed that under VCPT (especially for P2 ERP), attention processes of ADHD+/ADHD- adults highly differentiate. To understand where this differentiation mostly occurs, we calculated the permutation importance scores. As shown in Table 2, the main contribution or differentiation occurs in frontal and central channels.

In the literature, there are different classification studies on ADHD and Control groups using VCPT Task. Using VCPT, Tenev et al. [26], Mueller et al. [25] and Ghassemi et al. [37] reported 69.2%, 94% and 96% classification accuracies, respectively.In these studies, Mueller et al. [25] used the independent ERP components for the first time and Ghassemi et al. [37] used wavelet-entropy, correlation dimension and Lyapunov exponent to feed their classifiers. Additionally, In 2020, Kaur et al. [40] presented a comparative study and achieved classification accuracies up to 100% under VCPT condition. In this work, different from literature, we used the classification algorithms as a tool to identify EEG signal differentiation on healthy subjects with/without ADHD symptoms under VCPT condition. Our experimental results showed that ANN model achieved 98.4% classification accuracy when P2 ERP used (Table 1) and the attention process of ADHD+/ADHD- subjects provided a distinctive feature to separate these individuals. In Table 2, contributions of EEG channels based on their feature importance scores were presented. Results showed that frontal and central channels can be effective channels for separation of subjects. In Table 3, ANN achieved 84.8% accuracy when only top-ten channels and P2 features were used. This results strongly support the effectiveness of these ten channels, and additionally it showed that other channels also have contributions to achieve higher classification accuracies.

In literature there are few studies on children using similar Go/NoGo task. In these studies, the amplitude of P2 is reported as increased in the fronto-central region in ADHD patients [20, 38]. Researchers also reported that P2 is not explicit in children and reaches its maximum in the fronto-central region in adulthood [21]. In our work, differentiation of P2 amplitude between ADHD+ and ADHD- groups emerged as an important component and contributions of the channels (from Table 2 and results in Table 3), supported the findings in the literature about fronto-central region in P2 wave.

In literature, however, there is limited information about the P2 wave amplitude differentiation in ADHD patients using attention tasks. This study suggests that, further analysis of P2 wave in ADHD studies would be provide valuable insight for exploring the use of EEG. Our results showed that attention mechanism of ADHD+/ADHD- groups is highly differentiable in fronto-central regions. In addition to this, our results validated the feasibility of using the ERP components as a discriminative method on ADHD studies for unmedicated and undiagnosed healthy subjects.

Preclinical studies are of high value in revealing disease patterns under brain monitoring signals since such signals do not contain any medication-related patterns. To extend our results further, we are planning to extend our EEG data to contain also children (before 18 years old) and apply ANN with ERP components to explore if our results can be expanded for a wider range of population.

5. Conclusion

In this work, we investigated differentiation of EEG signals in healthy adults with ADHD symptoms using classification algorithms under VCPT task. According to our experimental results, ANN algorithm achieved 98.4% classification accuracy when P2 ERP was used. Fronto-central channels contributes the most, providing accuracies up to 85% without the support from other regions. From our results, we conclude that attention process of ADHD symptomatic and asymptomatic adults mostly differentiate in fronto-central regions under VCPT condition and using P2 ERP component of EEG signals of healthy subjects with ADHD symptoms, leads to highly accurate results for EEG signal classification.

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References

[1] Wender P, Wolf Lo, Wasserstein J. Adults with ADHD: An Overview. Annals of the New York Academy of Sciences 2001; 931(1):1-16.

[2] Polanczyk G, De Lima MS, Horta BL, Biederman J, Rohde LA. The worldwide prevalence of ADHD: A systematic review and metaregression analysis. American Journal of Psychiatry 2007; 164: 942-948.

[3] Zang YF, Yong H, Chao-Zhe Z, Qing-Jiu C, Man-Qiu S et al. Altered baseline brain activity in children with ADHD revealed by resting-state functional MRI. Brain and Development 2007; 29: 83-91.

[4] Zang YF, Jin Z, Weng XC, Zhang L, Zeng YW et al. Functional MRI in attention-deficit hyperactivity disorder: Evidence for hypofrontality. Brain and Development 2005; 27: 544-550.

[5] Rohde LA, Roman T, Szobot C, Cunha RD, Hutz MH et al. Dopamine transporter gene, response to methylphenidate and cerebral blood flow in attention-deficit/hyperactivity disorder: A pilot study. Synapse 2003; 48: 87-89.

[6] Szobot C, Roman T, Cunha R, Acton P, Hutz M et al. Brain perfusion and dopaminergic genes in boys with attention-deficit/ hyperactivity disorder. American Journal of Medical Genetics Part B: Neuropsychiatric Genetics 2005; 132 B: 53-58.

[7] Schneider M, Retz W, Coogan A, Thome J, Rösler M. Anatomical and functional brain imaging in adult attention-deficit/ hyperactivity disorder (ADHD) - A neurological view. European archives of psychiatry and clinical neuroscience 2006; 256: i32-41.

[8] Castellanos FX, Lee PP, Sharp W, Jeffries NO,Greenstein DK et al. Developmental trajectories of brain volume abnormalities in children and adolescents with attention-deficit/hyperactivity disorder. Journal of the American Medical Association 2002; 288: 17401748.

[9] Loo SK, Specter E, Smolen A, Hopper C, Teale PD et al. Functional effects of the DAT1 polymorphism on EEG measures in ADHD. Journal of the American Academy of Child and Adolescent Psychiatry 2003; 42: 986-993.

[10] Gevensleben H, Holl B, Albrecht B, Schlamp D, Kratz O et al. Distinct EEG effects related to neurofeedback training in children with ADHD: A randomized controlled trial. International Journal of Psychophysiology 2009; 74: 149–57.

[11] Başar E, Başar-Eroglu C, Karakaş S, Schürmann M. Gamma, alpha, delta, and theta oscillations govern cognitive processes.International Journal of Psychophysiology 2001; 39: 241-248.

[12] Luck SJ, Hillyard SA. Electrophysiological correlates of feature analysis during visual search. Psychophysiology 1994; 31: 291-308.

[13] Başar-Eroglu C, Demiralp T. Event-related theta oscillations: An integrative and comparative approach in the human and animal brain. International Journal of Psychophysiology 2001; 39: 167-195.

[14] Bokura H, Yamaguchi S, Kobayashi S. Electrophysiological correlates for response inhibition in a Go/NoGo task.Clinical Neurophysiology 2001; 112: 2224-232.

[15] Doallo S, Lorenzo-López L, Vizoso C, Holguín SR, Amenedo E et al. Modulations of the visual N1 component of event-related potentials by central and peripheral cueing. Clinical Neurophysiology 2005; 116: 807-820.

[16] Prox V, Dietrich DE, Zhang Y, Emrich HM, Ohlmeier MD. Attentional processing in adults with ADHD as reflected by event-related potentials. Neuroscience Letters 2007; 419: 236-241.

[17] Karamacoska D, Barry RJ, Steiner GZ, de Blasio FM. Clarifying the sequential processes involved in a cued continuous performance test. Psychophysiology 2015; 52: 67-80.

[18] Kirmizi-Alsan E, Bayraktaroglu Z, Gurvit H, Keskin YH, Emre M et al. Comparative analysis of event-related potentials during Go/NoGo and CPT: Decomposition of electrophysiological markers of response inhibition and sustained attention. Brain Research 2006; 1104: 114-128.

[19] Jonkman LM. The development of preparation, conflict monitoring and inhibition from early childhood to young adulthood; a Go/Nogo ERP study. Brain Research 2006; 1097: 181-193.

[20] Oades RD, Dittmann-Balcar A, Schepker R, Eggers C, Zerbin D. Auditory event-related potentials (ERPs) and mismatch negativity (MMN) in healthy children and those with attention-deficit or tourette/tic symptoms. Biological Psychology 1996; 43: 163-185.

[21] Spronk M, Jonkman LM, Kemner C. Response inhibition and attention processing in 5- to 7-year-old children with and without symptoms of ADHD: An ERP study. Clinical Neurophysiology 2008; 119: 2738-2752.

[22] Bekker E, Kenemans J, Verbaten MN. Electrophysiological correlates of attention, inhibition, sensitivity and bias in a continuous performance task. Clinical Neurophysiology 2004; 115.9: 2001-2013.

[23] Picton TW. The P300 wave of the human event-related potential. Journal of Clinical Neurophysiology 1992; 9: 456-479.

[24] Mueller A, Candrian G, Kropotov JD, Ponomarev VA, Baschera GM. Classification of ADHD patients on the basis of independent ERP components using a machine learning system. Nonlinear Biomedical Physics 2010; 4: 1-12.

[25] Mueller A, Candrian G, Grane VA, Kropotov JD, Ponomarev VA et al. Discriminating between ADHD adults and controls using independent ERP components and a support vector machine: A validation study. Nonlinear Biomedical Physics 2011; 5.

[26] Tenev A, Markovska-Simoska S, Kocarev L, Pop-Jordanov J, Müller A et al. Machine learning approach for classification of ADHD adults. International Journal of Psychophysiology 2014; 93: 162-6.

[27] Biederman J, Hammerness P, Sadeh B, Peremen Z, Amit A et al. Diagnostic utility of brain activity flow patterns analysis in attention deficit hyperactivity disorder. Psychological Medicine 2017; 47: 1259-1270.

[28] Corkum PV, Siegel LS. Is the continuous performance task a valuable research tool for use with children with attention-deficit-hyperactivity-disorder? Journal of Child Psychology and Psychiatry 1993; 34: 1217-1239.

[29] Riccio CA, Reynolds CR, Lowe P, Moore JJ. The continuous performance test: A window on the neural substrates for attention? Archives of Clinical Neuropsychology 2002; 17: 235-272.

[30] Breiman L. Random forests. Machine Learning 2001; 45: 5-32.

[31] Turgay A. Adult Hyperactivity Assessment Scale based on DSM IV (unpublished scale). Integrative Therapy Institute Toronto, Canada, 1995.

[32] Kısacık E. Dikkat eksikliği ve hiperaktivite bozukluğu (DEHB) belirtileri gösteren ve göstermeyen sağlıklı erişkinlerde dikkat süreçlerinin EEG ile incelenmesi. pHD, Ankara Üniversitesi, Ankara, Türkiye, 2018 (in Turkish).

[33] Ercan E, Amado S, Somer O, Çıkoğlu S. Dikkat eksikliği hiperaktivite bozukluğu ve yıkıcı davranım bozuklukları için bir test bataryası geliştirme çabası. Çocuk ve Gençlik Ruh Sağlığı Derg 2001; 8: 132-144 (in Turkish).

[34] Luck S. Ten Simple Rules for Deisgning ERP Experiments. Event-related Potentials a Methods Handbook. London, England:MIT Press, 2005, pp. 17-32.

[35] Holcomb PJ. Automatic and attentional processing: An event-related brain potential analysis of semantic priming. Brain and Language 1988; 35: 66-85.

[36] Chen M, Challita U, Saad W, Yin C, Debbah M. Artificial neural networks-based machine learning for wireless networks: a tutorial. IEEE Communications Surveys and Tutorials 2019; 21: 3039-3071.

[37] Ghassemi F, Hassan M, Tehrani-Doost M, Abootalebi V. Using non-linear features of EEG for ADHD/normal participants' classification. In: Procedia-Social and Behavioral Sciences-4th International Conference of Cognitive Science; Tehran,Iran, 2012; pp. 148-152.

[38] Satterfield JH, Schell AM, Nicholas T. Preferential neural processing of attended stimuli in attention-deficit hyperactivity disorder and normal boys. Psychophysiology 1994; 31: 1-10.

[39] Handy TC. Event-related potentials: A methods handbook. MIT press, 2005

[40] Kaur S, Singh S, Arun P, Kaur D, Bajaj M. Phase space reconstruction of EEG signals for classification of ADHD and control adults. Clinical EEG and Neuroscience. 2020; 51 (2): 102-113.