

Task-Related and Resting-State EEG Classification of Adult Patients with ADHD Using Machine Learning

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Abstract—Attention-deficit hyperactivity disorder (ADHD) is a prevalent psychological disorder characterized by attention deficits and high impulsivity, impacting both adults and children. This study aims to assess the effectiveness of task-related electroencephalography (EEG) and resting-state EEG in distinguishing adult patients with ADHD from healthy controls. Machine learning techniques are employed to classify the patients' status based on EEG features. The primary objective of this investigation is to determine whether the classification performance of task-based EEG data recorded during a stop-signal task recruiting inhibitory processes outperforms that of resting-state EEG data. We hypothesize that task-based EEG data contains valuable biomarkers related to inhibitory control that can be utilized to detect ADHD, whereas resting-state EEG data does not possess such useful biomarkers.

Index Terms—ADHD, classification, machine learning, electroencephalogram

I. INTRODUCTION

Attention-deficit hyperactivity disorder (ADHD) is a neurodevelopmental disorder that affects a large amount of school-aged children and adults worldwide [1], [2]. The core symptoms of ADHD include inattention, hyperactivity, and impulsivity, which can lead to impairments in academic, social, and occupational functioning [3]. The diagnosis of ADHD is primarily based on clinical assessment and behavioral observations, which can be subjective and prone to biases. Therefore, there is a growing interest in developing objective and reliable biomarkers for the diagnosis and management of ADHD [4].

Electroencephalography (EEG) is a non-invasive and cost-effective tool that measures the electrical activity of the brain and has been widely used in the study of ADHD [5]. EEG recordings can be obtained in different states, including resting state and task-based paradigms. Resting-state EEG measures the spontaneous neural activity of the brain when the participant is at rest, whereas task-based EEG measures the neural activity associated with performing a specific cognitive task [6], [7].

In recent years, machine learning techniques have been applied to EEG data to develop diagnostic and prognostic

models for ADHD [8], [9]. These techniques can identify patterns and features in the EEG data that are associated with ADHD and distinguish individuals with ADHD from healthy controls [10]. However, most studies that have used machine learning techniques for ADHD diagnosis have focused on resting-state EEG data, and the potential of task-based EEG data for improving the accuracy and reliability of ADHD diagnosis has not been fully explored [11].

Therefore, the aim of this paper is to investigate the utility of task-based EEG data for ADHD diagnosis and to compare its performance with that of resting-state EEG data. Specifically, we will use machine learning techniques to develop predictive models for ADHD using both types of EEG data and compare their diagnostic accuracy and reliability. We hypothesize that task-based EEG data will provide better biomarkers for the diagnosis of ADHD and improve the accuracy and reliability of ADHD diagnosis. In this paper, we explore the use of machine learning for ADHD classification on stop signal task EEG signal since multiple studies have suggested a connection between inhibitory control versus ADHD [12].

II. MATERIALS

A. Participants

EEG data were collected at Trinity College Dublin (TCD) by employing a ActiveTwoBiosemi system to collect EEG data from 70 electrodes, with 64 electrodes specifically designated for EEG measurement using the 10 – 5 system [13]. Resting state EEG data were collected from 52 adult individuals diagnosed with ADHD and 98 adult healthy controls, where ADHD participants had a formal diagnosis of ADHD and a T-score higher than 65 on the Conners' Adult ADHD Rating Scale (CAARS), while healthy controls had no formal diagnosis of ADHD and a T-score lower than 65 on CAARS. The stop signal task EEG data were collected from 24 adult individuals diagnosed with ADHD and 78 healthy control adult participants.

B. Experimental Tasks: Resting State and Stop Signal task

Resting state EEG data collection was performed in a quiet and darkened room, with participants seated in front of a computer monitor at a distance of 1.05 meters [13]. The monitor employed a screen resolution of 1024x768 and a refresh rate of 75Hz. Data was collected with participants in both an eye-closed and eye-opened state, however, for the present study, only the eye-closed resting state EEG data was utilized in experiments.

For the stop signal task, participants were presented with left and right arrow stimuli on a computer monitor [14]. They sat in front of the monitor at a standardized distance of 108 cm, with a resolution of 1024x768 pixels and a refresh rate of 75 Hz. The task involved an adaptive event-related Stop Signal Task (SST) lasting approximately 9 minutes. It consisted of 135 Go trials and 45 Stop trials, presented in three blocks of 60 trials. Each trial began with a 1000 ms fixation cross, followed by a 750 ms Go stimulus (arrow pointing left or right). Participants were instructed to respond as quickly as possible by pressing a button corresponding to the arrow direction in Go trials. In Stop trials, an upward-pointing arrow (Stop signal) appeared after the Go stimulus, requiring participants to inhibit their response.

III. METHODOLOGY

A. Overview

In this study, the methodology consists of three main steps: EEG data preprocessing, EEG spectral power extraction, and machine learning modelling (see Figure 1). Two types of data were collected from separate participant groups, and to ensure comparability, all parameters and hyperparameters are kept identical between the two classification experiments. The objective is to assess the potential of task-based EEG data for enhancing ADHD diagnosis accuracy and reliability, compared to resting-state EEG data. The key difference lies in the segmentation approach (Figure 2): resting state EEG data is randomly divided into 2-second segments, while stop signal task EEG data is segmented into 1-second intervals centered around the stimulus signal, with a 0.3-second pre-stimulus and 0.7-second post-stimulus time window selected for each segment.

The preprocessing steps involves filtering and artifact rejection to ensure the quality of the EEG data [15]–[17]. In the spectral power extraction step, the relative spectral power is extracted from 12 frequency bands for 64 EEG channels using the multitaper method. Finally, four machine learning models (Support Vector Machine, K-nearest neighbors, Random Forest, and Elastic Net) are trained and evaluated using nested cross-validation on both resting state and task-based EEG data to compare their diagnostic performance for ADHD. Further details of each experiment stage are elaborated in the following sections.

B. Data Preprocessing

The EEG data are first subjected to re-referencing using the average method. A bandpass filter is applied, spanning

the frequency range of 0-95 Hz. To mitigate the presence of electricity line noise, a notch filter is further employed, with a frequency range of 48-52 Hz. All preprocessing procedures are executed using the MNE library in Python 3.10 [13].

C. Spectral power extraction

In this study, spectral power is extracted from 12 frequency bands spanning 4 Hz each across 64 channels using the multitaper method [18]. The frequency bands are defined as (1,5), (5,9), (9, 13), (13, 17), (17, 21), (21, 25), (25, 29), (29, 33), (33, 37), (37, 41), (41, 45) and (45, 49). Furthermore, a theta-to-beta ratio was calculated for each channel. The resulting feature vector has a dimension of 832.

1) *Resting state EEG data*: 2-second intervals are segmented, and the multitaper method with a Hanning taper is used to extract relative spectral power. The theta-to-beta ratio is determined by comparing the absolute power in the theta band (4 – 8 Hz) to that in the lower beta band (13 – 21 Hz)

2) *Stop signal task EEG data*: for the stop signal task EEG data, 1-second intervals (combining of 0.3 seconds preceding the stimulus and the 0.7 seconds following the stimulus) are created based on the main stimulus, and the multitaper method is applied to calculate absolute and relative power for each frequency band. The theta-to-beta ratio is computed as the ratio of the theta band power to the lower beta band power.

D. Machine learning models

To develop diagnostic models for ADHD using EEG data, four machine learning algorithms were employed in this study: Support Vector Machine (SVM), K-nearest neighbors (KNN), Random Forest (RF), and Elastic Net. These algorithms are chosen because they have been shown to perform well in classification tasks using EEG data [19], [20].

To optimize the performance of the machine learning algorithms, hyperparameter tuning is conducted using a grid search approach. The performance and generalizability of the models for ADHD classification are assessed using a nested cross-validation method. This involves two levels of cross-validation: an outer loop and an inner loop. The outer loop utilizes multiple folds, typically through k-fold cross-validation, where each fold serves as a test set while the model is trained on the remaining folds. The inner loop, within the outer loop, further optimizes the hyperparameters of the models using k-fold cross-validation on the training set of the current outer fold. Different hyperparameter combinations are evaluated, and the best-performing set is selected based on a predefined evaluation metric. The nested cross-validation approach prevents information leakage from the test set during hyperparameter tuning and provides a robust evaluation of the models' generalization capabilities while avoiding overfitting. The final performance of the models is determined by aggregating the results across all outer fold iterations. By employing nested cross-validation, this study ensures a reliable assessment of the models' performance and enhances the validity of the results for ADHD classification using EEG data.

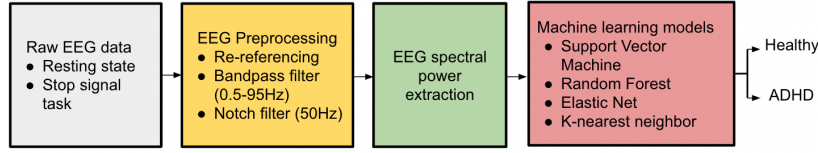
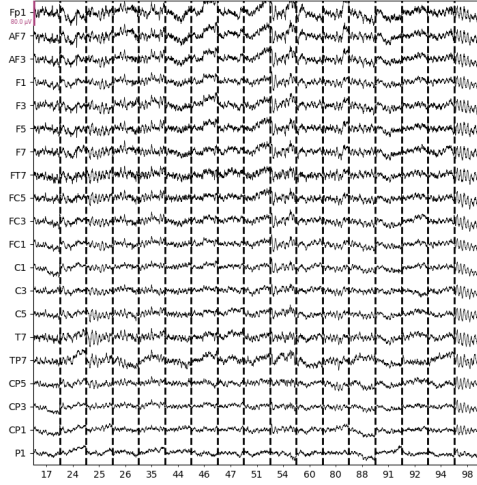
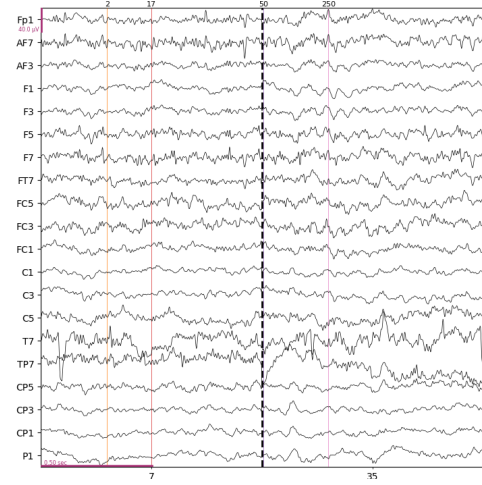


Fig. 1. EEG preprocessing, feature extraction and classification pipeline



(a) The resting state EEG data is segmented into 2-second segments selected at random. Each of these segments is then used to compute the spectral power.



(b) The stop signal task EEG data is divided into segments of 1-second duration (with a 0.3 second time window before the stimulus and a 0.7 second time window after the stimulus).

Fig. 2. EEG data segmentation methods with resting state and stop signal task EEG data

The sklearn library, which is a popular machine learning library in Python, was used for implementing all the models. The evaluation metric used in this study is the Area under the Curve (AUC) score, which measures the ability of the model to distinguish between ADHD and healthy control groups.

IV. RESULTS

A. Classification results

We show in Table I the average AUC score of four algorithms on both resting state and stop signal task EEG data after 100 running times. To evaluate the statistical significance of the comparison in classification performance between task-based and resting state EEG data, a one-sided t-test is employed on the Area Under the Curve (AUC) scores obtained from the classification models. The classification results show that the classification performance of machine learning models was higher when using stop signal task EEG data compared to resting state EEG data. The obtained p-values, all less than 0.05, indicate that the classification performance on stop signal task EEG data is statistically superior to that on resting state EEG data. This result may be attributed to the fact that SST data are task-specific and have a clear stimulus signal that serves as an anchor for data segmentation and these segments may carry useful features for classifying healthy control and ADHD patients. In contrast, resting state EEG data are ran-

TABLE I
CLASSIFICATION RESULTS ON RESTING STATE AND STOP SIGNAL TASK EEG DATA

Algorithms	Resting state EEG	Stop signal task EEG	p-value
SVM	0.523	0.641	3.00e−20
KNN	0.534	0.614	1.49e−07
RF	0.541	0.575	1.00e−04
Elastic Net	0.519	0.642	1.54e−23

domly segmented and may not contain such useful features. Additionally, the spectral power features extracted from SST data may better capture the neural activity related to ADHD, which could improve the accuracy of the machine learning models. However, it is important to note that these findings may be specific to the particular datasets and experimental setup used in this study, and further research is needed to confirm these results.

B. Ablation Study

To further explore the task-based EEG classification performance, we conduct an ablation study by removing the electrodes located close to the motor cortex of the brain including FC3, FC4, C1, C2, C3, C4, C5, C6, CP3, CP4. The ablation study aimed to determine the contribution of these motor-related electrodes in the classification performance

TABLE II
ABLATION STUDY ON STOP SIGNAL TASK EEG DATA

Algorithms	With all 64 electrodes	With removed electrodes
SVM	0.641	0.603
KNN	0.614	0.570
RF	0.575	0.504
Elastic Net	0.642	0.530

of the models [21]–[23]. The results of the ablation study (see Table II) show that removing these electrodes causes a decrease in the classification performance of the models. This suggests that the motor-related electrodes play an important role in the classification of EEG data for ADHD diagnosis, likely due to their involvement in the inhibition processes that are impaired in individuals with ADHD. The findings highlight the importance of carefully selecting the electrodes for EEG data analysis, particularly for tasks involving motor processes. The results of the ablation study, where the classification performance decreases after removing electrodes located close to the motor cortex, provide additional evidence that task-based EEG data may provide more diagnostic information for ADHD than resting state EEG data.

V. CONCLUSION

Our study reveals that the classification performance on stop signal task EEG data surpasses that on resting state EEG data, which suggests that task-based EEG data can offer more effective biomarkers for diagnosing ADHD. As a result, future research can investigate other EEG data collected from different task paradigms to further validate the effectiveness of task-based EEG data for ADHD diagnosis. Additionally, alternative machine learning algorithms, such as deep neural networks, may be explored to enhance the classification performance. AutoML can also be implemented to identify the optimal combination of features and algorithms for classification. Moreover, statistical analysis using between-group analysis methods such as ANOVA can be conducted to determine the contribution of each feature to the differentiation between ADHD and healthy control.

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