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Electroencephalography Representation Learning with Spatiotemporal Reconstruction for Accurate Attention Deficit Hyperactivity Disorder Detection

Yerin Cho[1] and Esther Dettmar[#]

[1]Emma Willard School, USA
[#]Advisor

ABSTRACT

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental condition characterized by persistent patterns of inattention, hyperactivity, and impulsivity that interfere with daily functioning or development. Traditional diagnosis of ADHD often relies on self-report checklists and behavioral assessments, which can be subjective and prone to bias. These methods may overlook subtle neural patterns that are indicative of ADHD which leads to misdiagnosis or delayed intervention. To address these limitations, I propose an Electroencephalography (EEG)-based ADHD screening system utilizing machine learning algorithms. The proposed network takes a set of EEG signals as input and outputs the probability that an individual has ADHD. To enhance accuracy, I introduce a novel EEG representation learning technique to capture the spatiotemporal features of EEG data. The trained network learns to extract rich features from the EEG signals, which significantly improves the accuracy of ADHD detection. Through extensive experiments, the proposed system achieved state-of-the-art performance in screening ADHD, reaching an accuracy of 99%. Additionally, further experiments were conducted to identify which parts of the brain are highly correlated with the screening of ADHD. In conclusion, this research not only validates the effectiveness of the EEG-based system but also contributes to our understanding of ADHD's neurobiological basis.

Introduction

Attention-Deficit Hyperactivity Disorder

Attention Deficit Hyperactivity Disorder (ADHD) is a developmental disorder that encompasses a wide range of symptoms including inattention, hyperactivity, and impulsivity that interfere with the body's functionality. This disorder has significantly high prevalence; specifically, in 2023, 15.5 million US adults were diagnosed with ADHD (Staley 2024), and about 7 million children in the United States were diagnosed with ADHD in 2022 (CDC 2024). The global prevalence of ADHD is about 6-7.5%, suggesting that ADHD is not confined to the US alone (Ayano et al. 2023). Despite its universality, the exact causes are unknown, but environmental and genetic reasons play crucial roles in its development. One crucial environmental factor comes from the advent of the digital era. During the COVID pandemic, as schools adopted online learning methods, adolescents were heavily exposed to electronics and faced hours of screen time (Muppalla et al. 2023). One study highlighted a positive correlation between screen exposure and development of ADHD, implying that the surge of media exposure continuously impacts adolescents worldwide (Liu et al. 2023).

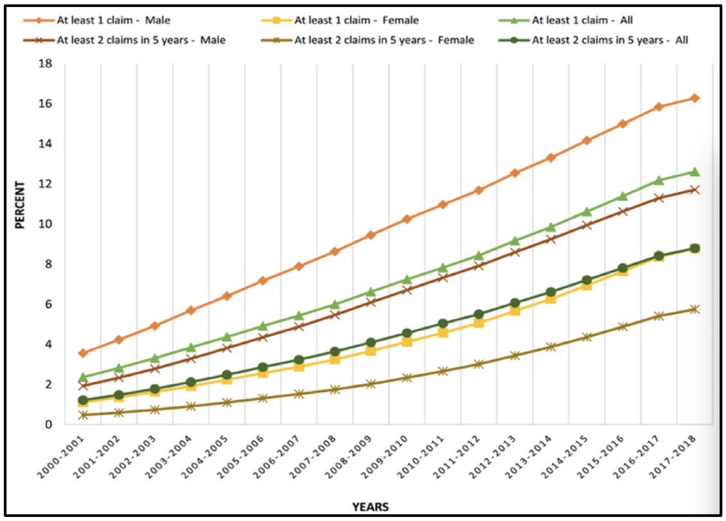

Figure 1. Trend of ADHD prevalence over years (Diallo et al. 2022)

Traditional ADHD Diagnosis Method

Conventional ADHD diagnosis heavily relies on Diagnostic and Statistical Manual -5 (DSM-5), which is a general checklist of ADHD symptoms (CDC 2024). However, since these checklists do not indicate specific biomarkers, they are far from being scientific and objective. Furthermore, experts claim that checking one's symptoms through a checklist may not be an accurate measure (Gopal 2024). The detection of ADHD, thus, involves complex steps, combination of questionnaires and doctoral confirmation, and these processes urge for a different detection approach.

Proposed Approach

In order to address lack of scientific rigor in ADHD detection, I developed an objective biomarker for ADHD screening using electroencephalography (EEG). The EEG data that are generated by its electrodes indicates specific parts where the brain was activated or deactivated. The proposed method also tracks for specific time steps, allowing to see how the region activates or deactivates over time. Combining information for specific brain regions and time steps, interpolated topological maps are generated. In order to perform EEG representation learning, a convolutional neural network (CNN) called Encoder compresses all data; subsequently, another CNN Decoder decompresses data and reconstructs all topological maps that highly resemble the actual data. At last, by inserting topological maps into the pretrained CNN, neurodevelopmental disorder classifier network forms, demonstrating one's probability of having a neurodevelopmental disorder. Thus, with a technique that displays high accuracy, this proposed approach serves as an effective biomarker for ADHD.

Method

Preprocessing

The EEG electrodes attached to the brain on specific parts of the brain region dependent on five different locations (frontal, temporal, central, parietal, and occipital) generate data akin to that shown in Figure 2. The proposed method uses specific time steps to analyze brain activity precisely. At each time step, circular topological maps are generated and fitted into squares, generating interpolated topological maps. The topological maps demonstrate the brain's electrical activity and classify sectors into colors: colors near red demonstrate high brain electrical activity, while colors near blue indicate low brain electrical activity. Figure 2 further illustrates the visual representation of the proposed network of an interpolated topological map.

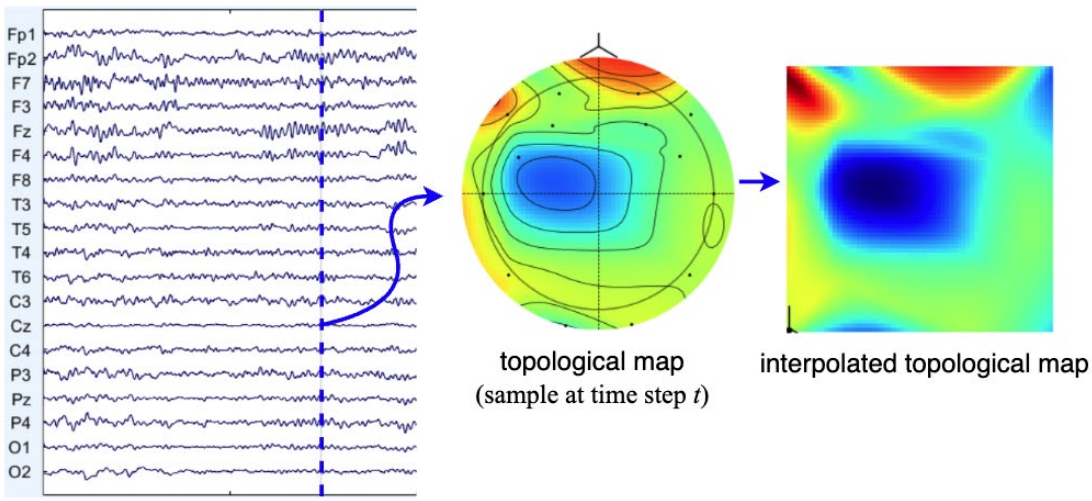

Figure 2. Architecture of the proposed network

EEG Representation Learning

After generating a series of EEG topological maps, the proposed method removes one topological map at a specific time step and replaces it with a null matrix as illustrated in Figure 3.

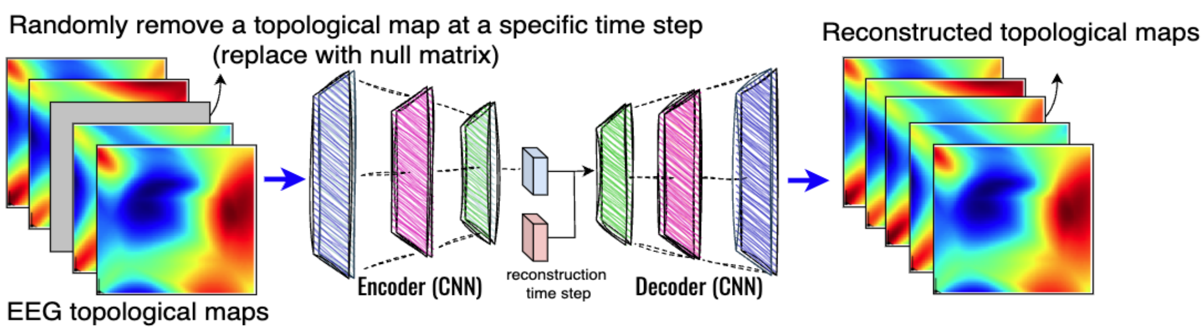

Figure 3. Architecture of the proposed representation learning

Using a convolutional neural network (CNN) called Encoder, the method compresses all data. Subsequently, incorporating reconstruction time step, the CNN finds the removed layer of the map, following with another CNN named Decoder that converts the null matrix into a layer that would be expected at that time step. After these steps, the method creates reconstructed topological maps that resemble the actual EEG data, which is the essential step of EEG representation learning.

Equation 1: Reconstruction loss function

$$L_R = \sum_{t}^{T}\sum_{y}^{Y}\sum_{x}^{X}\left|TM(t,y,x) - \widehat{TM}(t,y,x)\right|_1$$

Equation 1 demonstrates the reconstruction loss function that occurs after the Decoder CNN step to measure how accurately the technique can reconstruct topological maps after going through the encoding and decoding steps.

Equation 2: Weighted reconstruction loss function

$$L_R = \sum_{t}^{T}\sum_{y}^{Y}\sum_{x}^{X}\frac{K_s}{\sigma\sqrt{2\pi}}e^{-\left(\frac{t-t_s}{2\sigma^2}\right)} \times \left|TM(t,y,x) - \widehat{TM}(t,y,x)\right|_1$$

Equation 2 is the weighted reconstruction loss function to balance out errors using standard deviation. In the equation, $\frac{K_S}{\sigma\sqrt{2\pi}}e^{\left(\frac{-t-t_S}{2\sigma^2}\right)}$ is the standard deviation curve. Multiplying the second part of the equation from Equation 1 allows this equation to heavily weigh errors that are far from the expected value and lightly weigh errors that are closer to the expected value to accurately monitor the preciseness of the proposed approach.

Transfer Learning

This chapter explains how to utilize the trained model with the representation learning method described in Chapter 2.2. The encoder of the trained model acts as the foundation for the ADHD screening network, as shown in Figure 4. Instead of training the ADHD screening network from scratch, this transfer learning approach enhances accuracy and speeds up convergence.

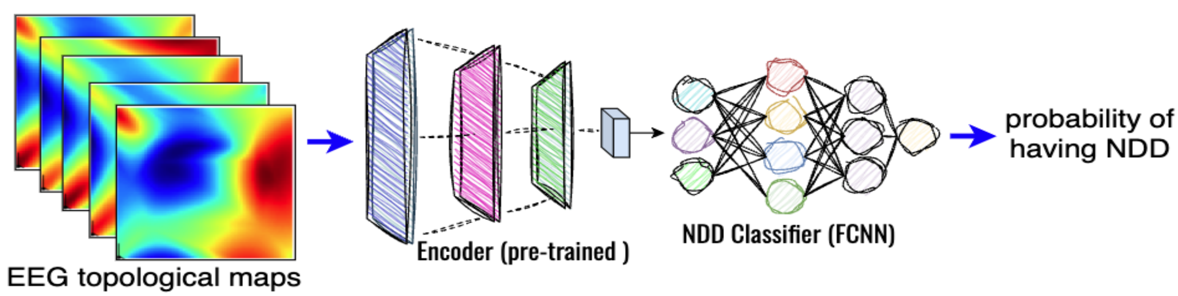

Figure 4. Architecture of the proposed ADHD screening network

To train the ADHD screening network, we used a binary cross-entropy loss function, as detailed in Equation 3.

Equation 3: Binary cross entropy loss function

$$L_T = -(\, y \times log_e(\hat{y}) + (1-y) \times log_e(1-\hat{y})\,)$$

Equation 3 is the binary cross entropy loss function. While the cross entropy loss function only calculates how well the CNN generated predictions match with actual data, the binary cross entropy loss function measures the difference between actual and predicted results then penalizes the approach if the difference is large. Thus, a low L_T value represents high accuracy of the proposed approach.

Experimental Results and Discussion

Dataset

The dataset (AI Hub 2024) used in this study comprises 500 samples, evenly divided into a control group (250 samples) and an ADHD group (250 samples). The age distribution of the participants is as follows: 40.27% of the samples are from individuals aged 0-7, 32.93% from individuals aged 7-12, and 26.80% from individuals aged 13-18. To ensure the robustness and generalizability of the proposed EEG-based ADHD screening system, the dataset was split into five groups for 5-fold cross-validation. This approach allows each subset to be used as a validation set once while the remaining four subsets serve as the training set, ensuring that the model's performance is evaluated across all data partitions.

Evaluation Metric

To evaluate the performance of the proposed method, four commonly used metrics in classification tasks were employed: accuracy, recall, precision, and F1-score. Accuracy measures the overall correctness of the model, which indicates the proportion of correct predictions. Recall assesses the model's ability to correctly identify positive instances, while precision evaluates the proportion of true positives among all predicted positives. The F1-score provides a balanced measure of precision and recall, offering a single metric that combines both.

Performance Comparison

The first step of the proposed method involves utilizing Encoder CNNs and comparing both results obtained using EEG representation learning and those from without its usage. By comparing these two results, the effectiveness of the EEG representation learning can be shown. Across three different CNNs of Xception (Fran et al. 2017), ConvNext-50 (Liu et al. 2022), ResNet-152 (He et al. 2016), four different inference metric values are collected.

Table 1. Performance comparison (ablation study)

Architecture	EEG Representation Learning	Accuracy	Precision	Recall	F1-Score
Xception	X	86.95	86.98	86.87	86.92
Xception	O	93.01	93.34	93.41	93.37
ConvNext-50	X	87.93	87.86	87.90	87.87
ConvNext-50	O	94.69	94.54	94.65	94.59
ResNet-152	X	92.14	92.23	92.18	92.20
ResNet-152	O	97.05	97.42	97.14	97.28

The results from Table 1 indicate that without EEG representation learning, all three CNNs show lack of performance compared to results with EEG learning, signifying that the usage of EEG representation learning is quintessential. Furthermore, Figure 5 converts results noted in Table 1 to visualize its data. In conclusion, the highest performing CNN was ResNet-152 with EEG representation learning, having 97.05 accuracy, 97.42 precision, 97.14 recall, and 97.28 F1-Score.

Figure 6 further evaluates ResNet-152's confusion matrix to visualize the performance of the model. Its performance in ADHD patients was 99.31%, and 94.78% for the control group without ADHD. Both values imply that the model accurately detects ADHD.

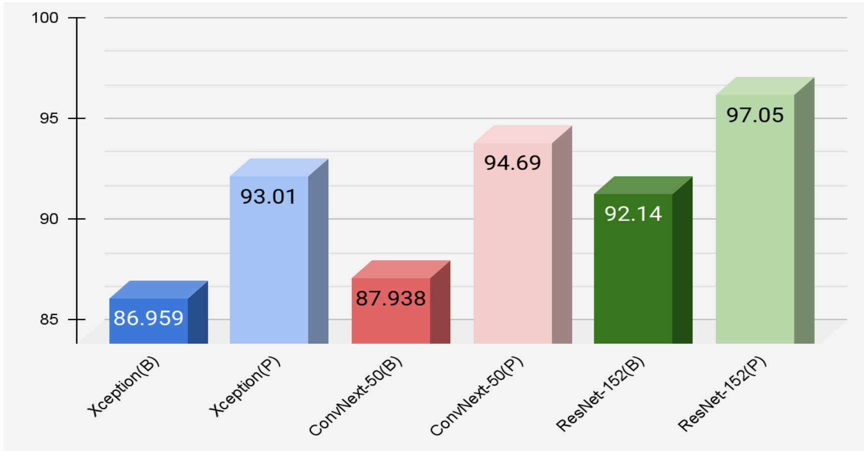

Figure 5. Performance comparison (ablation study)

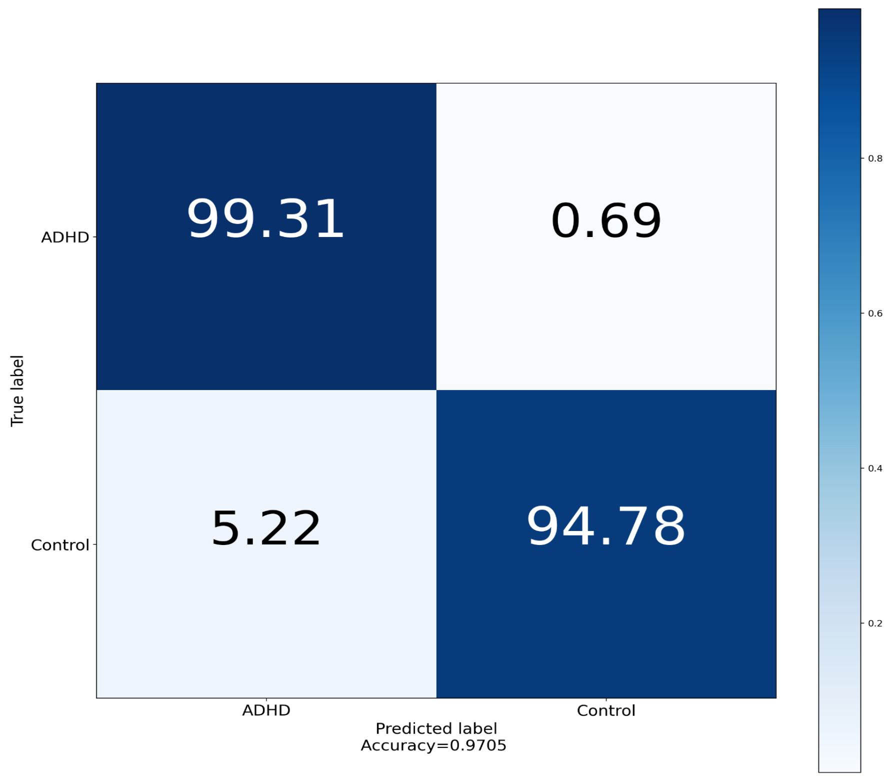

Figure 6. Confusion matrix evaluation (ResNet-152)

Last piece of the experiment comes from data extracted from electrodes attached to specific parts of the four lobes in the brain. Each electrode is attached to corresponding lobes and location, allowing to see where specific parts of the brain change over time steps. Figure 7 demonstrates the overview of electrodes and their locations.

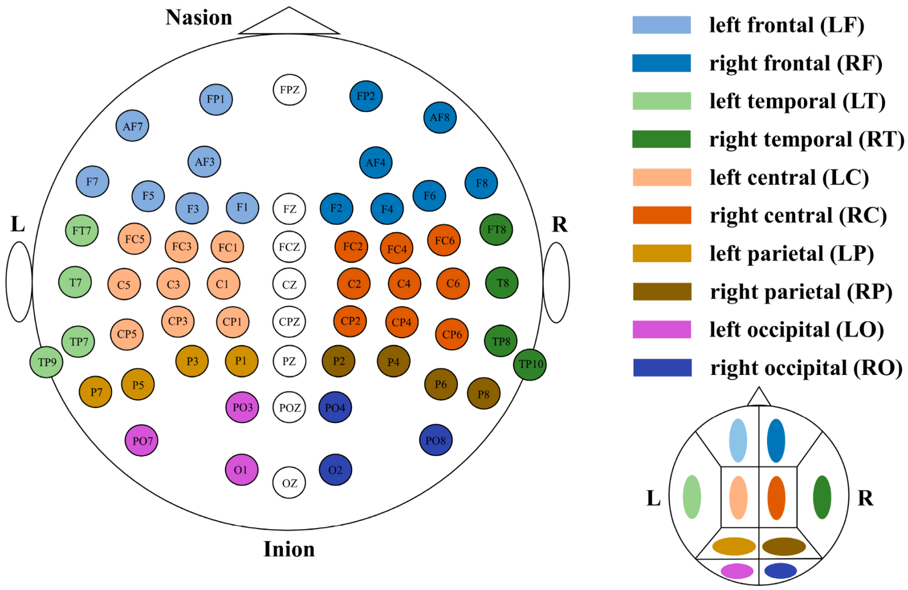

Figure 7. Various parts of human brain

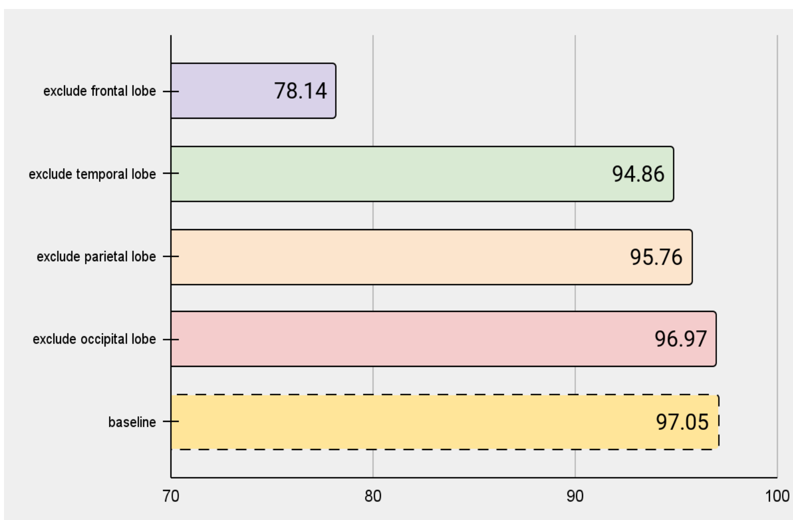

Figure 8. Performance comparison with different EEG setup

In order to see which part of the brain most likely correlates with ADHD detection, experiments to measure accuracy were conducted by excluding a specific lobe every trial. The accuracy values are collected by using ResNet-152's inference metric during this lobe-exclusion experiment. Results shown in Figure 8 demonstrate that the exclusion of the frontal lobe heavily impacts the accuracy of the model, suggesting the frontal lobe activities' high correlation with ADHD.

Table 2. Performance comparison with different EEG setup

Method	Accuracy	Precision	Recall	F1-Score
Exclude frontal lobe	78.14	78.42	78.53	78.47

Exclude temporal lobe	94.86	94.96	94.89	94.92
Exclude parietal lobe	95.76	95.89	95.76	95.82
Exclude occipital lobe	96.97	97.05	96.99	97.01
Baseline	97.05	97.42	97.14	97.28

Table 2 displays inference metric results obtained using ResNet-152 during the lobe-exclusion experiment. Comparing the baseline result of 97.05 accuracy, 97.42 recall, 97.14 precision, and 97.28 F1-Score to that of exclusion of frontal lobe data, the model generated significantly low inference metric values, further solidifying that frontal lobe activity correlates heavily with ADHD detection.

Conclusion

In this research, I proposed a novel approach to detect ADHD using data obtained from EEG and establishing spatio-temporal reconstruction by utilizing machine learning. After generating topological maps, the approach went through encoder and decoder CNNs with reconstruction time step in between to ensure the approach's ability to detect, the fundamental step of EEG training. Implementing this reconstruction representation learning, the experiment results reveal that the highest performing CNN, ResNet-152, generates 97.05% accuracy in detecting ADHD. In addition to developing an approach to detect ADHD, the last piece of the research comes from the brain anatomy driven experiment where the results demonstrate that the frontal lobe has the highest correlation to ADHD. Taken altogether, further development can take place: in order to increase its broad applicability, at different school settings where adolescents need accurate biomarkers to detect ADHD, this technique can be utilized universally.

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