Detecting Brain activity in ADHD children and healthy controls using Machine Learning Techniques

Brain activity in ADHD children

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ABSTRACT

This study focuses on Attention Deficit Hyperactivity Disorder (ADHD), a neurodevelopmental disorder that affects both children and adults. Individuals with ADHD often struggle with difficulties related to attention, impulse control, and hyperactivity. To learn more about ADHD, researchers have employed a variety of neuroimaging modalities and analysis techniques over the years. To research brain activity in children with ADHD, this study examines the characteristics of Electroencephalogram (EEG) data using Machine Learning Techniques, which can be a trustworthy diagnostic tool for physicians. After analyzing the EEG data obtained, we can infer from this empirical investigation that the frontal regions of the brain are mostly active and model accuracy is 80% for ADHD classification.

CCS CONCEPTS

• **Applied computing** → Life and medical sciences; Health care information systems; • **Information systems** → Information systems applications; Decision support systems.

KEYWORDS

Attention Deficit Hyperactivity Disorder, Machine learning, Electroencephalography (EEG), Digital Health, Data analytics, Data science

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1 INTRODUCTION

Attention-Deficit/Hyperactivity Disorder (ADHD), is a neurodevelopmental condition that affects both children and adults, impacting their ability to focus, control impulses, and regulate energy levels [1]. To enhance health equity and help individuals with ADHD have a better quality of life, timely diagnosis of ADHD is crucial. Timely intervention enables individuals and their families to understand and navigate the challenges associated with the condition. Diagnosis opens the door to tailored interventions, such as behavioural therapies and, when necessary, medication, optimizing the individual's ability to function in various aspects of life. Moreover, early detection promotes academic and occupational success by addressing specific learning and workplace strategies [2]. Therefore, a timely and accurate diagnosis empowers individuals with ADHD to manage their symptoms effectively, enhancing their overall well-being and quality of life. Recognizing ADHD also diminishes the stigma often attached to behavioural differences, fostering a supportive environment. Left untreated, ADHD can lead to difficulties in relationships, low self-esteem, and an increased risk of other mental health issues [3].

For diagnosis, Electroencephalography (EEG) is a technique for measuring the brain's electrical activity which is commonly used in various neurological and psychological assessments, including ADHD. Using EEG data to diagnose ADHD in children is a topic of ongoing research and exploration [4]. EEG can provide insights into the underlying neural mechanisms and patterns of brain activity that might be associated with ADHD. The objective of our research is to explore brain activities in children with ADHD and healthy controls using EEG data. This helps us in gaining a better understanding of ADHD and supports improving its diagnosis and treatment. Currently, ADHD is diagnosed based on behavioural observations and clinical assessments, which can be subjective. EEG has the potential to provide objective biomarkers of ADHD based on measurable patterns of brain activity [2]. By analyzing EEG data, researchers aim to identify specific brainwave patterns, neural connectivity disruptions, and responses to stimuli that are associated with ADHD. This information can help improve the accuracy and reliability of ADHD diagnosis, track the effects of stimulant medication, explore neurofeedback as a potential treatment option, and personalize treatment approaches based on individual brain activity profiles.

To analyze EEG data, recent developments in Artificial Intelligence (AI) and Machine Learning (ML) plays a crucial role. AI and ML can help us evaluate more features and using different machine learning models, technology can improve the accuracy of the study's results Technology can allow for the exploration of different window sizes, such as 0.5 seconds or 5 seconds, in future studies. This can help enhance accuracy by capturing more comprehensive data. Technology can facilitate the inclusion of a larger sample size in future studies. By collecting data from a larger population, the

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findings can be more generalizable and representative. Technology can enable the integration of EEG data with other neuroimaging techniques, such as functional magnetic resonance imaging (fMRI). This integration can provide complementary information about brain connectivity in children with ADHD, enhancing the understanding of the condition. Therefore, in this research, the attempt is to develop an EEG ML pipeline for ADHD diagnosis and to assess the accuracy of the model in diagnosing ADHD in children. Our objective is to investigate the brain activity of children with ADHD and healthy controls using EEG data. The study aims to analyze the differences in brain activity between the two groups and explore the potential use of EEG data for improving the diagnosis of ADHD. The study also highlights the need for more features and machine learning models, as well as the exploration of different window sizes to improve accuracy. Additionally, the study acknowledges the limitations of a small sample size and the lack of comparison with other neuroimaging techniques.

It's crucial to acknowledge that while EEG holds promise as a potential diagnostic tool for ADHD, there is still ongoing research to establish its reliability, validity, and clinical utility. The field is continuously evolving, and further studies are needed to refine the methodology and understand how EEG data can best contribute to the diagnosis and management of

ADHD in children. It's important to note that while EEG offers valuable insights into brain activity, it's just one tool in the broader context of understanding and diagnosing ADHD. A comprehensive assessment involving clinical interviews, behavioural observations, and potentially other diagnostic measures is typically required for an accurate diagnosis of ADHD [5] [6] [7].

2 RESEARCH BACKGROUND

EEG can provide insights into the brain's electrical activity patterns. People with ADHD often exhibit different patterns of brain activity compared to those without the disorder [8]. These differences might be observed in specific brain regions and frequency bands. Individuals with ADHD often exhibit neuro-physiological differences in brain activity compared to those without the disorder. EEG allows researchers and clinicians to measure and analyze these differences by recording the electrical signals generated by the brain [8]. ADHD is currently diagnosed based on behavioural observations and clinical assessments, which can be subjective. EEG has the potential to provide objective biomarkers of ADHD that are based on measurable patterns of brain activity. These biomarkers might aid in improving the accuracy and reliability of diagnosis [9]. EEG can capture different types of brainwave patterns, such as alpha, beta, delta, and theta waves. Research has suggested that children with ADHD might exhibit deviations from typical brainwave patterns, particularly in certain frequency bands. ADHD is thought to involve disruptions in neural connectivity and communication between different brain regions. EEG can provide information about functional connectivity and synchronization between brain areas, helping to identify atypical neural interactions associated with the disorder [10]. Children with ADHD often show different neural responses to stimuli, such as tasks requiring sustained attention or inhibitory control. EEG can track these responses in real time, potentially highlighting differences in neural processing and attention regulation. EEG can be used to monitor brain activity in individuals taking stimulant medications for ADHD. These medications can impact brainwave patterns, and EEG can be used to track changes and ensure proper dosing [9]. Neurofeedback is a therapeutic approach that utilizes real-time EEG data to help individuals regulate their brain activity. This technique involves training individuals to modify their brainwave patterns, aiming to improve symptoms associated with conditions like ADHD. Neurofeedback is being explored as a potential treatment option for ADHD, although its effectiveness is still debated and more research is needed [10].

A recent study by [9] highlighted the creation of an EEG ML pipeline for ADHD detection. The model's mean accuracy was 93.2% with training using a dataset of 120 kids. To reduce computing load while retaining accuracy, the study concentrated on employing straightforward EEG linear characteristics and only the first four subbands of EEG. A thorough validation was done to make sure bias and overfitting did not affect the model. The holdout and k-fold cross-validation methods are described in the paper as being used to validate the effectiveness of the ADHD detection classifier. The training set is divided into several folds for training and testing in k-fold cross-validation, as opposed to the holdout technique,
which randomly divides the dataset into training, validation, and test sets. The classifier's accuracy ranged from 92.5% to 94.2% for the test set and from 91.3% to 93.9% for the validation set. After 10-fold cross-validation, it displays the accuracy of the SVM classifier for various PCA variances. For the test set, the accuracy varied from 88.3% to 94.2%. The test's best accuracy, 94.2%, was attained at a variance of 90%, while its lowest accuracy, 84.4%, was at a variance of 97%. For 90%

PCA variance, holdout, and k-fold cross-validation approaches have the maximum accuracy. The holdout method's accuracy is 1% lower than the 10-fold validation methods [9].

A study by Moqadam, Roqaie, et al. [11] investigated the brain networks of control children and ADHD children. To gauge the complexity of brain activity, the researchers collected EEG signals from both groups and extracted the KATZ fractal dimension. They then generated a connection graph by calculating the degree of EEG complexity similarity between various electrodes. They discovered that the number of connections in children with ADHD was noticeably fewer than in control children using a graph coloring method. The study also found that kids with ADHD have significantly fewer connections between the front and posterior areas of their brains. Overall, the findings supported earlier research demonstrating diminished and flawed brain connections in ADHD sufferers. The study's key conclusion is that children with ADHD have much less connection in their brain's neural networks than do children without the disorder. To assess how comparable each electrode's fractal dimensions were, the study used EEG recordings and performed this correlation analysis. The researchers used a graph coloring method to discover that there were considerably fewer brain networks in children with ADHD than in the control group. This indicates that the brains of kids with ADHD may not be functionally connected enough. Between ADHD and control group children, the average number of brain networks was compared. According to the findings, children with ADHD had a mean of 15.4 brain networks, compared to 22.83 for children in the control group.

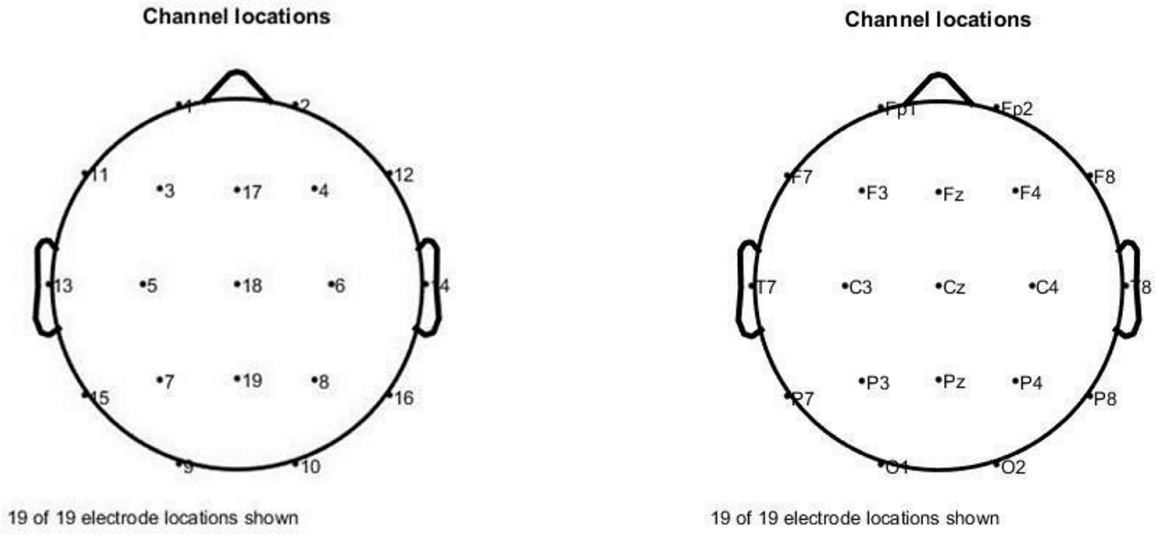

Figure 1: International 10-20 system for EEG electrode locations are depicted by name and number.

This difference was statistically significant (p-value = 0.0026), showing that the number of control children's brain networks was higher than that of ADHD children [11].

The research gap highlighted in this research is to establish the reliability, validity, and clinical utility of EEG as a diagnostic tool for ADHD. While EEG holds promise in identifying individualized brain activity profiles and cognitive performance patterns associated with ADHD symptoms, there is still ongoing research required to refine the methodology and understand how EEG data can best contribute to the diagnosis and management of ADHD in children. Additionally, the interpretation and comparison of EEG indicators across studies can be challenging due to their complexity. Therefore, more studies are needed to address these gaps and enhance our understanding of the role of EEG in ADHD diagnosis.

3 METHODOLOGY

3.1 DATA COLLECTION METHOD:

This empirical study is designed to study the brain activity of ADHD children and healthy controls. The study has 2 classes – each with 30 EEG samples. The 30 ADHD-diagnosed children (boys and girls, aged 7 to 12) were treated with Ritalin for up to 6 months, according to DSM-IV criteria, and the 30 healthy controls (boys and girls, aged 7 to 12) did not have any psychological disorders, epilepsy history, drug abuse, or head injuries. The IEEE data port was used to obtain the dataset for this study [18].

The frontal, central, parietal, and occipital regions of the scalp were recorded using an EEG based on 10-20 standard by 19 channels at a sampling rate of 128 Hz, (Fz, Cz, Pz, C3, T3, C4, T4, Fp1, Fp2, F3, F4, F7, F8, P3, P4, T5, T6, O1, O2). Earlobe electrodes A1 and A2 served as the references. The International 10-20 system for EEG electrode locations is depicted in Figure 1 by number and name.

The EEG recording procedure was based on visual attention tasks because visual attention is one of the deficiencies seen in children with ADHD. Children were asked to estimate the number of characters in the image after each one was displayed to them as part of the activity. Each graphic had between 5 and 16 characters, chosen at random, and was large enough for kids to easily see and count the characters to help with visual attention and other mental tasks. After the kid responded, each image was shown instantly and without interruption to provide continuous stimulation during the signal recording. As a result, the child's performance (i.e., response time) determined how long the EEG recording lasted throughout this cognitive visual task. 19 channels of EEG were recorded with a sampling rate of 128 Hz and a resolution of 16 bits during this test.

3.2 DATA ANALYSIS:

3.2.1 Feature selection. Signal Noise Ratio (SNR): All the EEG variables were sorted according to relevance using the Signal Noise Ratio (SNR). The dataset used in the study had 19 electrodes, and as it can be seen from Figure 2, electrode number 17 has the highest rank or power in terms of its significance for classifying or discriminating between two groups of people: those with ADHD and healthy persons. (17-Fz, 19-Pz, 18-Cz, 16-P8, 2-Fp) are the most significant 5 variables. According to the SNR feature selection, the brain's frontal region (Fz) (electrode number 17) using the International 10-20 method (see Figure 1). Therefore, we can infer from this empirical investigation that the frontal regions of the brain are mostly active.

The possibility that anomalies in frontal region activity are related to ADHD symptoms has been raised by research for several reasons. EEG research on the frontal region of the brain in people with ADHD has produced some intriguing results:

The frontal lobes, especially the prefrontal cortex, are in charge of maintaining focus and removing distractions. A frequent ADHD symptom, difficulties in maintaining focused attention, may be exacerbated by altered activity in this area [12]. According to research, people with ADHD may have higher theta (4–7 Hz) and lower beta (13–30 Hz) activity in their frontal lobes. Increased theta activity may be associated with difficulties maintaining attention,

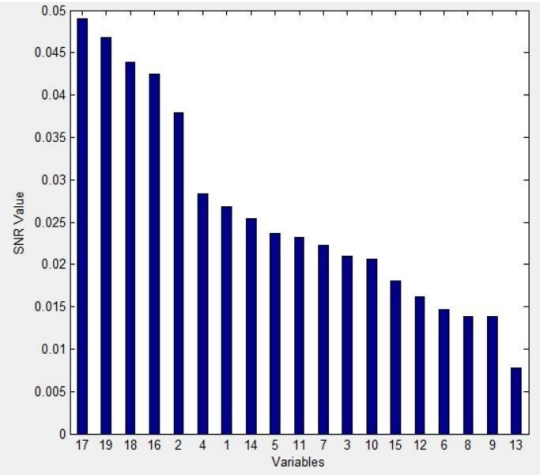

Figure 2: The graph shows the signal-noise ratio calculated for each variable.

whilst decreased beta activity may be associated with issues with impulse control [9]. Inhibitory control deficits are a key feature of ADHD. The frontal cortex, in particular the prefrontal cortex, has been linked to inhibitory processes, according to EEG investigations. When doing tasks that call for inhibitory control, people with ADHD may exhibit variations in the pattern of activity in these regions. Additionally, the prefrontal cortex is engaged in inhibitory regulation, which aids people in restraining impulsive actions and reactions. If this regulation is weakened as a result of erratic frontal activity, it may contribute to the impulsive and poor decision-making seen in ADHD patients [6]. ADHD frequently has problems with working memory. According to EEG studies, problems updating and storing information in working memory may be related to anomalies in the frontal theta and beta oscillations. For managing and retaining information, working memory is crucial. Working memory functions rely primarily on frontal areas. The prevalent working memory problems in ADHD may be caused by disturbances in frontal activation. Cognitive flexibility, which entails switching between various tasks or mental groups, is a challenge for people with ADHD. Cognitive flexibility is linked to the frontal cortex, especially the anterior cingulate cortex. Inflexibility in people with ADHD may be caused by altered activity in these areas. The ability to switch between various tasks or mental states is known as cognitive flexibility. It is necessary for situational adaptation. The anterior cingulate cortex in particular is a frontal area that is linked to cognitive flexibility. Here, dysregulation could result in rigidity and difficulty planning. Event-related potentials, which are brain reactions to particular events or stimuli, can also be recorded by EEG. The P300 component of ERPs, which is attention-related, has been researched in ADHD. Differential attentional processing may be indicated by variations in the amplitude and latency of these ERPs in the frontal region [12]. Effective neural network synchronization is made possible by the frontal lobes, which help coordinate communication across various brain regions. Different cognitive processes may be impacted by irregular frontal region activity because it may interfere with the timing and coordination of these networks. Infancy and adolescence are crucial developmental years for the frontal lobes. Both the observed anomalies in frontal region activity and the factors that impact its development, including heredity and environmental influences, may be responsible for the symptoms of ADHD [6].

3.2.2 Classification and Cross-Validation. This empirical study has two classes, and we used the Multi-Layer Perceptron (MLP) Machine Learning approach for the classification of EEG data into two classes. We classified the data using Multi-Layer Perceptron (MLP) and I summarized the results of the classification task provided by each of the methods in Figure 3 We used the Leave One Out Cross Validation technique (LOOCV) and K-fold technique for classification tasks. LOOCV means among the sixty samples each time one sample was taken out, so I had fifty-nine remaining samples. The remaining samples were used as the training dataset to train machine learning which showed an accuracy of 80% for class 1 and 50% for class 2 with SNR feature selection of the top 4 variables using MLP. Also, the K–fold cross-validation technique – which showed higher accuracy for class 1 (80%) in both 20-fold and 30-fold techniques with SNR feature selection of the top 4 variables. K-fold cross-validation technique is a simpler form of cross-validation where the dataset is split into different folds for training and testing. It's less computationally intensive but can have higher variance in performance estimates due to the smaller size of the validation set.

The study's primary finding is the creation of an EEG Machine Learning pipeline for ADHD detection. The model's accuracy was 80% after it underwent training using a dataset of 60 kids. The leave-one-out and k-fold cross-validation methods are described in the paper as being used to verify the efficacy of the ADHD diagnosis. The leave-on-out method's accuracy is the same as the K-fold validation methods in this study. But according to Alim et al. [9] the model's accuracy was 93.2% after it underwent training using a sizable dataset of 120 kids, which is being used to validate the effectiveness of the ADHD detection classifier.

Limitations of the study:

1. Need for more features and machine learning models: To improve accuracy, the research suggests evaluating more features and using different machine learning models for comparison of results.
2. Exploration of different window sizes: The research plans to try different window sizes, such as 0.5 s or 5 s, in future studies to further enhance accuracy.
3. Limited Sample Size: The study included a relatively small sample size of 30 children with ADHD and 30 healthy children. This small sample size may limit the generalizability of the findings to a larger population.
4. Lack of Comparison with Other Neuroimaging Techniques: The study focused solely on EEG-based measures of brain connectivity. It did not compare the findings with other neuroimaging techniques such as functional magnetic resonance imaging (fMRI), which could provide complementary information about brain connectivity in children with ADHD.
5. Algorithm Approach: The application of SVM to our EEG dataset encountered critical obstacles. One of the primary issues was the linear separability of the data. We used Multilayer Perceptron (MLP), a type of deep learning model that

CROSS VALIDATION REPORT USING MULTI LAYER PERCEPTRON TECHNIQUES (TOTAL 60 SAMPLES – 2 CLASSES)

Methods	Class	Without Feature selection	With Feature (SNR) selection
Overall classification accuracy – Leave one out Cross validation Method	Class 1 (ADHD Children)	56.67	80
	Class 2 (Healthy Children)	47.7	50
Overall classification accuracy – 20-Fold Cross validation method	Class 1 (ADHD Children)	63.33	80
	Class 2 (Healthy Children)	30	43.3
Overall classification accuracy – 30-Fold Cross validation method	Class 1 (ADHD Children)	63.33	80
	Class 2 (Healthy Children)	33.33	47

Figure 3: Cross-validation report.

offers several advantages for EEG data analysis. Unlike SVM, MLP is inherently designed to capture complex, non-linear relationships through its deep architecture and multiple layers of non-linear processing units. This capability makes MLP particularly suited for modelling the intricate patterns present in EEG signals, which are often reflective of non-linear brain dynamics.

4 RESULTS

Early diagnosis is important to avert consequences because ADHD is the most prevalent disorder in children. In this study, we describe a machine-learning method for detecting children with ADHD using an MLP applied to a dataset that is openly accessible (19-channel EEG data from 60 subjects) and found the model accuracy is 80% for ADHD classification. By studying the EEG (Electroencephalography) electrode data, we also concluded that people with ADHD (Attention-Deficit/Hyperactivity Disorder) have greater activity in the frontal area of the brain. Since the frontal lobes are essential for a variety of cognitive processes known as executive functions, research into frontal area brain activity in ADHD is important. All of these abilities are typically compromised in people with ADHD, including attention, inhibition, working memory, cognitive flexibility, and decision-making.

5 CONCLUSIONS

It's vital to remember that while EEG results can be insightful into the brain activity patterns connected to ADHD, they are not diagnostic on their own. Multiple factors, including hereditary, environmental, and neurological ones, contribute to the complexity of ADHD. The brain mechanisms underlying the symptoms of ADHD are revealed by EEG research, providing a piece of the puzzle. Overall, combining EEG data with other assessment techniques, such as behavioural evaluations and clinical interviews, can help us gain a deeper knowledge of ADHD and perhaps even help us build more precise interventions and therapies.

It's critical to stress that ADHD is a complicated condition with numerous underlying causes, and research into the connection between frontal area brain activity and ADHD is ongoing. Although abnormalities in frontal activity appear to be linked to symptoms of ADHD, they are probably a component of a larger network of interrelated brain regions and circuits that contribute to the condition. Overall, research on frontal region activity in ADHD sheds light on the brain basis of the condition, aiding researchers and clinicians in better understanding its causes and possibly paving the way for more specialized therapies and treatments.

The use of EEG data to improve ADHD diagnosis has been an active area of study. The goal of EEG-based approaches is to offer objective and neurophysiological markers that can help with the identification and comprehension of ADHD. The following are some noteworthy developments and trends in this area:

To create diagnostic models for ADHD, machine learning methods such as support vector machines, random forests, and deep learning have been applied to EEG data. These models can possibly distinguish between people with ADHD and neurotypical people by learning patterns in the EEG signals linked to ADHD

[5] [13]. Researchers are concentrating on locating particular EEG signal characteristics of ADHD. Event-related potentials (ERPs), connection measurements, and spectral power in various frequency bands are a few examples of these properties. The most pertinent EEG features for an ADHD diagnosis can be found with the aid of sophisticated feature selection algorithms [14]. A more thorough understanding of brain function and structure in ADHD can be obtained by combining EEG data with other neuroimaging modalities (such as fMRI or structural MRI). The goal of multimodal techniques is to collect further data and improve identification precision [15]. Improvements in EEG analysis enable more specialized evaluations. Because ADHD is a heterogeneous condition with a wide range of symptom patterns, this is essential. Individualized EEG indicators may help determine treatment plans and forecast patient outcomes [16]. EEG-based neurofeedback training is becoming more popular as a possible ADHD treatment. People get immediate input on their brain activity and develop the ability to self-regulate it. This method alters brain activity patterns to improve self-control and symptoms of ADHD [17].

Despite the promise of these developments, EEG-based diagnostic methods for ADHD are still not frequently applied in clinical settings. Their dependability, sensitivity, and specificity must be established by ongoing research and validation. The proper use of EEG data in the diagnosis and treatment of ADHD also requires ethical considerations and standardization.

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