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EVALUATION OF ADHD: CLASSIFICATION, TREATMENT STRATEGIES IN PEDIATRIC AND ADOLESCENT POPULATIONS USING MACHINE LEARNING

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ABSTRACT

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder characterized by inattention, impulsivity, and hyperactivity. Despite extensive research, existing diagnostic approaches rely heavily on subjective clinical assessments, leading to misdiagnoses and delayed interventions. Furthermore, conventional treatment strategies lack personalization, often resulting in suboptimal therapeutic outcomes. This study addresses these gaps by leveraging machine learning techniques to enhance ADHD classification and treatment strategies, specifically for pediatric and adolescent populations. Unlike previous studies that primarily focus on symptom-based categorization, our research integrates multi-modal data, including neuroimaging, behavioral assessments, and genetic markers, to improve diagnostic accuracy. A novel hybrid machine learning model is proposed, incorporating convolutional autoencoders and advanced neural architectures to extract discriminative features for precise classification. Additionally, the study explores AI-driven personalized treatment recommendations, optimizing intervention strategies based on patient-specific patterns. The findings of this research contribute to the development of an objective, data-driven framework for ADHD diagnosis and treatment, reducing reliance on subjective evaluation. This work establishes a foundation for future AI-assisted clinical decision-making, ultimately improving patient outcomes and advancing ADHD research.

Keywords: *ADHD, Brainwave, CNN, Cognitive, Disorder*

1. INTRODUCTION

Attention-deficit hyperactivity disorder is a neurological condition predominantly observed in children. It is predominantly linked to a significant prevalence of mental issues, including mood disorders, anxiety, and oppositional defiant disorder (ODD). ADHD predominantly affects 4–12% of school-aged children worldwide. An epidemiological survey indicates that 4–5% of college students experience issues with ADHD. In recent years, the adult population has risen annually [1]. This ailment, known as attention-deficit hyperactivity disorder, was documented over 200 years ago, but in the past 35 years, it has been characterized by varied study and journalism. Over the past decade, it has emerged as the most prevalent condition among children and adults. Table 1 illustrates many aspects of ADHD in children and adolescents.

Clinical usage of a scale allows for the diagnosis of Attention Deficit/Hyperactivity Disorder. During the discussion with the patient and their parents, it is important to note the patient's mental health, the severity of their impairment symptoms, any co-morbidities, and their family medical history [6]. Along with the patient's behavior, the physician monitored his physical and neurological status by watching how the parent and kid interacted [7]. There is a complicated interplay between developmental features, environmental factors, and genetics in attention deficit hyperactivity disorder (ADHD). More than 80% of cases can be helped by these genetic variables. Some commonalities among ADHD diagnostic criteria include the place of study initiation and the quality of the information gathered. Important demographic indicators for Attention Deficit/Hyperactivity Disorder include parents with low levels of education, parents' occupations, the patient's gender, the number of births, and living with a single guardian [8, 9]. There is a clear biological relationship between ADHD and low levels of schooling, and a recent study found that ADHD is associated with delayed maturation of brain regions involved in cognition [10].

Research about the educational environment of children in South Africa is scarce. Regrettably, some physicians argue that Attention Deficit/Hyperactivity Disorder does not warrant hospitalization. The research indicated that several youngsters sought medical care at hospitals, where they were diagnosed with various conditions, including malaria, influenza, common pediatric disorders, and others. Child psychiatrists proficient in diagnosing attention deficit hyperactivity disorder (ADHD) might significantly benefit the community through outpatient pediatric clinics. Consequently, it is crucial to ascertain if the prevalence of ADHD diagnoses in hospitals differs from that in educational institutions; this is an aspect addressed by the study. All significant results are anticipated to exhibit different causal effects, since we see minimal variation in the treatment's impact with or without confounders, and no variations in GPA between scientific responders and non-responders in the placebo group. Besides mitigating academic disparities attributed to ADHD, our findings indicate that a scientific remedy for the condition might substantially influence this domain.

The figure 1 illustration depicts the left and right hemispheres, along with the channels included inside each hemisphere.

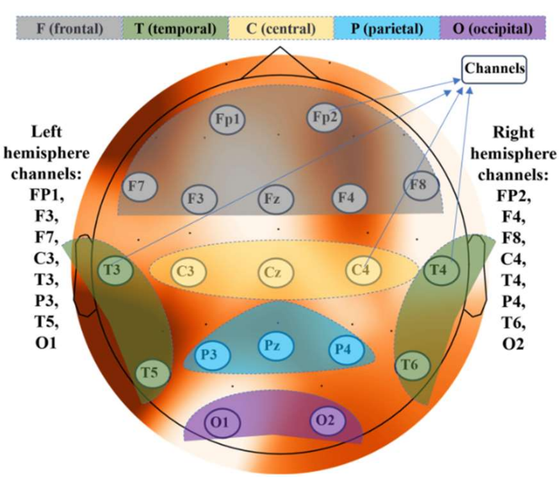

Figure 1: Electrode Placements For EEG In Accordance With The 10–20 Standard Scheme. Diverse Hues Signify Specific Areas And Their Associated Channels.

Compared to their non-ADHD college counterparts, individuals with ADHD clearly exhibit more instances of off-task behaviors, such as increased rates of gross motor interest and fidgeting [13], poor verbalizations, and a host of others. Figure 1 also shows that compared to girls, boys with ADHD tend to exhibit higher levels of aggressiveness, gross motor activity, and interference. On the other hand, compared to boys, females with ADHD are more likely to approach their teachers for assistance and attention. Previous studies on the application of direct observational techniques include There is at least one student with Attention Deficit/Hyperactivity Disorder (ADHD) in every classroom of twenty to thirty college students, or three to five percent of elementary school-aged children in the US are officially diagnosed with the disorder. [15] In addition, for most people with ADHD, the symptoms continue throughout their formative years and into their minimal formative years [16, 17]. ADHD diagnosis relies heavily on subjective assessments, leading to misdiagnosis and delayed interventions. Existing treatment approaches lack personalization, often resulting in suboptimal outcomes. This study introduces a machine learning-driven framework to enhance diagnostic accuracy and optimize individualized treatment strategies, addressing these critical gaps.

2. LITERATURE REVIEW

Brown, M. R. G., et al[1]created a Neuroimaging-based Classification Advancements in neuroimaging techniques such as functional MRI (fMRI), structural MRI (sMRI), and electroencephalography (EEG) have contributed to ADHD classification. Research by Castellanos et al. (2002) indicated structural brain abnormalities in individuals with ADHD. Further studies using machine learning on neuroimaging data, such as those by Cortese et al. (2012), have improved classification accuracy.

The article [2] discusses how well machine learning categorizes Attention Deficit/Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD), drawing attention to the fact that it has the ability to enhance diagnostic accuracy when contrasted with conventional approaches, which frequently fail to distinguish between these neurodevelopmental diseases in youth. Functional impairments caused by ADHD are difficult to diagnose using conventional methods. Using machine learning to categorize ASD and ADHD is a promising area of research.

Sri Parameswaran, et.al [3] does not address how to categorize ADHD or how to treat it in children and teenagers; rather, it focuses on improving diagnostic processes and treatment results through the use of machine learning models trained on demographic, clinical, and behavioral data. Machine learning may use demographic and behavioral data to make predictions for ADHD. Improves ADHD diagnosis and the ability to forecast treatment success.

Cao, M., et al examines the applications of machine learning in attention-deficit/hyperactivity disorder (ADHD), with a particular emphasis on the behavioral, neurocognitive, and neurobiological components

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involved. Despite the fact that it covers treatment techniques, it emphasizes the need of cautious design owing to the difficulties associated with the interpretability and generalization of machine learning models in the field of ADHD research. An study of the brain processes behind ADHD may be aided by machine learning. Focuses on the behavioral, neuropsychological, and biological variables that contribute to attention-deficit/hyperactivity disorder.

S. Mohan et al, developed a machine learning framework for the categorization of attention-deficit/hyperactivity disorder (ADHD) is presented in this research. The system makes use of 49 key characteristics derived from a dataset consisting of 49 patients. In addition to tackling underdiagnosis via the use of sophisticated decision tree algorithms and feature engineering, it places an emphasis on the significance of correct diagnosis and the effectiveness of therapy. The accuracy of the machine learning framework was 87.7% according to the F1-score. The diagnostic and treatment effectiveness of attention-deficit/hyperactivity disorder (ADHD) are both improved by significant aspects.

The research examines machine learning applications in ADHD, emphasizing behavioral, neurocognitive, and neurobiological variables. Despite the fact that it covers treatment techniques, it emphasizes the need of cautious design owing to the difficulties associated with the interpretability and generalization of machine learning models in the field of ADHD research. An study of the brain processes behind ADHD may be aided by machine learning. focuses on the behavioral, neuropsychological, and biological variables that contribute to attention-deficit/hyperactivity disorder.

Chauhan, N et al, identified the attention-deficit/hyperactivity disorder (ADHD) by using EEG data and machine learning. More specifically, the research focuses on emphasizing the usefulness of several classifiers, including Naive Bayes, in separating ADHD children from healthy controls. However, the paper does not examine treatment techniques. Classification of attention-deficit/hyperactivity disorder (ADHD) based on electroencephalogram (EEG) data. The Naive Bayes classifier attained an accuracy of 84% when considering certain combinations of regions.

Z. Gałuszka, examines several approaches to treating attention-deficit/hyperactivity disorder (ADHD), with a particular focus on a multimodal strategy that integrates pharmacological (both stimulants and non-stimulants) and psychosocial therapies, such as cognitive behavioral therapy. In addition to addressing the difficulties that are associated with gaining access to therapy for pediatric and adolescent populations, it emphasizes the significance of tailored care. The treatment and results of ADHD are improved by using a multimodal strategy. Stimulants have been shown to be very effective, whereas non-stimulants are recommended for patients who are not candidates for stimulation.

3. MATERIALS AND METHODS

It is still unclear what causes attention deficit hyperactivity disorder (ADHD). But there are a lot of things that may go wrong, which could cause it or make symptoms worse for those who already have it. Children with a first-degree relative with ADHD are four to eight times more likely to develop the illness than the general population, which strongly implies a genetic component to the condition [18]. The hereditary component is further shown by studies on twins, which have revealed an astonishing 90% concordance rate for ADHD. Aside from heredity, Table 2 lists the most important environmental causes for attention deficit hyperactivity disorder (ADHD).

Additional research is necessary to fully understand the role of these environmental factors in the development and progression of ADHD [26].

Practical relevance: An all-encompassing approach is required to treat ADHD due to its complex nature. For the best results in managing symptoms and improving functioning overall, it is recommended to combine medication with psychotherapy and psychosocial therapies [7]. In order to identify possible risk factors and customize treatments, doctors must have a thorough understanding of the genesis of ADHD.

Mitigating the prevalence of ADHD in children may be achievable by targeting environmental contaminants or by providing enhanced support to at-risk expectant moms.

A. PATHOPHYSIOLOGY AND GENETICS

The exact pathophysiology of Attention Deficit/Hyperactivity Disorder (ADHD) remains a mystery as its underlying cause is unclear. A wide variety of brain regions and neurotransmitters are impacted by complex neurobiological illnesses such as attention deficit hyperactivity disorder (ADHD). From a biological perspective, the prefrontal cortex is the primary focus and a significant component of the pathology of attention deficit hyperactivity disorder (ADHD), which involves noradrenaline, dopamine, and adrenaline (Figure 2). [27] Unlike adrenaline, which controls focus and alertness, dopamine is essential for learning, motivation, goal-setting, and memory modulation. The frontal subcortical area is where these

two neurotransmitters collaborate, and it's here that attention and memory processing are maintained [28].
Medications that have been effective in treating attention deficit hyperactivity disorder (ADHD) have the potential to alter dopaminergic and noradrenergic neurotransmission in the prefrontal cortex.
Because of the difficulties in executive cognitive functioning that are linked with ADHD, it has been regarded as a condition affecting the "frontal" circuitry. Both adults and children with ADHD have shown diffuse abnormalities in structural imaging tests. The cerebellum, total cerebrum, and the four non-changing cerebral lobes were all shown to be smaller in a comprehensive research conducted by Castellanos and colleagues 55. Adults with and without attention deficit hyperactivity disorder (ADHD) showed smaller ACCs and DLPFCs in a structural MRI research 56. The dorsolateral prefrontal cortex regulates working memory, which includes information retention and processing new information simultaneously. It is believed that these variations explain why people with ADHD struggle with goal-directed and on-task behavior. One of the most important areas of the brain that regulates attention and decision-making is the anterior cingulate cortex (ACC).
Neuroimaging research has identified the impacted brain networks in attention deficit hyperactivity disorder (ADHD), and both stimulant and non-stimulant pharmacotherapies assist in rectifying the underlying neurochemical imbalance (catecholamine). The brain comprises several attention networks, including the ventral, visual, default mode, and frontoparietal networks [31]. Cognitive training may enhance crucial brain networks, potentially improving these deficiencies and overall functioning [32]. Neurofeedback therapy targets EEG irregularities, such as elevated theta waves (along by diminished beta-theta ratios) and excessive cortical sluggishness, which indicate underlying network issues [31, 32]. Research indicates that neurofeedback therapy may enhance the brain's attentional networks. Exercise has been extensively studied due to its many impacts on neurophysiology and neuroplasticity, including an elevation in catecholamine levels in the fronto-striatal region. Advancements in technology have facilitated the development of more focused treatments for ADHD. Technology has enabled mental health providers to decrease the frequency of treatments while concurrently enhancing the flexibility and affordability of treatment delivery, as previously noted [33].
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4. ADHD diagnostic criteria

Effective management of ADHD requires precise therapy; yet, contemporary evidence lacks a validated treatment or diagnostic test for the illness. How can I ascertain this information? The diagnosis of ADHD is contingent upon particular criteria that may be subject to frequent alterations throughout the year [34]. In the last decade, significant discourse has emerged, with several new research suggesting that ADHD is distinctive when seen as a neurological illness.

Recent research indicate that ADHD is most accurately characterized as a neurological disorder, a conclusion that has sparked much discussion over the last decade. Contemporary techniques in genetics, molecular biology, neuropharmacology, and neuroimaging have significantly advanced the field and enhanced our understanding of the biological foundations of ADHD. Nonetheless, no biological marker has shown sufficient sensitivity and specificity for therapeutic use. This remains accurate despite current debates over the potential use of molecular genetics, neuropsychological, neurophysiological, or neuroimaging indications in future ADHD diagnostic systems. The prevailing approach for diagnosing ADHD remains mostly clinical [35].

Currently, there are four primary criteria for diagnosing ADHD. The first two are derived from the criteria outlined in the "Diagnostic and Statistical Manual of Mental Disorders (DSM-IV & V TR)," published by the American Psychiatric Association in its fourth edition. The 10th and 11th editions of the International Classification of Diseases, known as ICD-10 and ICD-11, are accessible [36]. It was created by the World Health Organization. The United Kingdom and many

European countries mostly use ICD-10 and ICD-11, whereas the United States and Africa largely employ DSM-IV and DSM-5 TR.

A. 4.1. DSM-IV-TR criteria

There are mainly three groups into which people are placed according to the DSM-IV-TR criteria.

- 1. Typically hyperactive-impulsive: a youngster who is frequently fidgety and anxious, who is always "on the go," who has trouble sitting still for long periods of time, who acts immaturely, who has no physical boundaries, who acts erratically, and who may have destructive tendencies.
- 2. Mainly distracted: a child with attention issues may display symptoms such as a lack of concentrate on academic duties, difficulty finishing assignments, daydreaming, an overactive imagination, disorganization, and incompetence.
- 3. Type combined: With the youngster displaying both activities. It affects a greater number of youngsters, 60-70%, and is hence the most frequent form of ADHD.

B. 4.2. DSM-V

According to the DSM-V, individuals with ADHD are primarily categorized into

1. Inattentional Symptoms: Six or more inattentional symptoms must be present in children under the age of sixteen, while five or more inattentional symptoms must have endured for a minimum of six months in adults and adolescents aged seventeen and higher. Forgetting things, having problems concentrating, making careless mistakes, and so on are all instances.

2. Signs and Symptoms of Hyperactivity and Impulsivity: In children less than 16, six or more symptoms of hyperactivity-impulsivity must be present, whereas in adults and adolescents older than 17, five or more symptoms must have remained for a minimum of six months. Some indications include tapping or fidgeting often, having trouble sitting still, chatting over others, and answering too fast.

3. Age of Onset: Multiple signs of impulsivity or hyperactivity-inattention must have shown before to the age of twelve.

4. The fourth criterion is that the symptoms must be both long-lasting and impair one's capacity to function in intellectual, social, and occupational settings. The symptoms also do not solely match those of schizophrenia or any other psychotic condition, and they cannot be better defined by any other mental illness [38, 39].

C. ICD-10

The World Health Organization (WHO) use a number of diagnostic tools to identify ADHD, including hyperkinetic disorder, which is characterized by excessive uncontrolled motion and is one of several disorders included in the International Classification of Diseases, 10th Revision (ICD-10). At least six signs pertaining to inattention, three signs pertaining to hyperactivity, and one sign pertaining to impulsivity are required under the current diagnostic paradigm for attention deficit hyperactivity disorder (ADHD). Hyperkinetic disorder and attention deficit hyperactivity disorder have similar diagnostic criteria [40].

A complete diagnosis of Attention Deficit/Hyperactivity Disorder (ADHD) now requires four more criteria. To start, the signs that lead to the impairment must have appeared before the age of seven. Second, these signs need to be visible in several settings, such as at home, in the classroom, and at work. Third, the signs must significantly hinder intellectual, social, or occupational functioning. Fourthly, no mental illness, including schizophrenia, autism, mood disorders, anxiety, dissociative identities, or personality disorders, should provide a better explanation for the symptoms than these [41].

D. ICD-11

The 11th Revision of the International Classification of Diseases (ICD) criteria for Attention-Deficit/Hyperactivity Disorder (ADHD) provide a comprehensive framework for the diagnosis of the disease. An overview of the ADHD ICD-11 criteria may be found below:

1. Attention Deficit and Hyperactivity Disorder—This pattern of behavior hinders functioning or growth and is defined by a minimum of three signs of hyperactivity-impulsivity or inattention.

There must be a minimum of six months of continuous symptoms for this to be considered a diagnosis.

3. Onset and Severity: The symptoms should have begun before the age of 12 and be evident in two or more locations (e.g., home, school, and job). On top of that, symptoms need to make it very difficult to operate socially, intellectually, or professionally [42, 43].

5. MACHINE LEARNING CLASSIFICATION

Following the acquisition of diverse feature channel combinations, the features were used as inputs for six distinct machine learning algorithms: SVM, RF, DT, AdaBoost, Naive Bayes, and LDA. This is a comprehensive explanation of the functioning of each algorithm.

A. Support Vector Machine: SVM is a resilient supervised learning technique used for classification and regression applications. The core premise entails determining an optimum hyperplane that proficiently distinguishes data points of disparate classifications. In binary classification, SVM seeks to identify the hyperplane that optimizes the margin between classes. The data points closest to the hyperplane are termed support vectors and play a crucial role in defining the decision boundary. Support Vector Machines (SVM) adeptly navigate high-dimensional feature spaces and proficiently address non-linearly separable data by using kernel functions.

B. *Decision Tree:* A determination Tree is a multifaceted machine learning method mostly used for classification and regression applications. It works by recursively dividing the data according to feature values to generate a hierarchical structure akin to a tree. At all nodes of the tree, a choice is taken to choose the feature for splitting, aiming to minimize uncertainty within each branch. The tree's leaves represent the ultimate class expectations. Decision Trees can effectively manage both quantitative and categorical characteristics, and their intuitive framework renders them understandable and advantageous for feature selection.

C. *Random Forest:* An ensemble learning method that integrates numerous decision trees to provide resilient predictions. Each tree is created independently using a portion of the data and a random selection of characteristics. Throughout the training phase, each tree recursively divides the data into subsets by evaluating the chosen features. The ultimate prediction is obtained by aggregating the forecasts from each separate tree. Random Forest significantly mitigates overfitting issues and proficiently handles high-dimensional data. Its efficacy is rooted on its precision and ability to discern complex relationships within the data.

D. *AdaBoost*: Aan ensemble learning method that employs many weak learners to construct a robust classifier. It allocates more weights to misclassified data points on each iteration, emphasizing difficult-to-classify samples. In succeeding rounds, it devotes more attention to misclassified occurrences, therefore enhancing the model's forecast accuracy. AdaBoost constructs a robust classifier by an iterative adjustment of sample weights, enabling precise categorization. Its capacity to adjust to diverse data complexity and its potential to enhance model accuracy are significant characteristics.

E. *Naive Bayes*: A probabilistic classification technique derived on Bayes' theorem. It presupposes that characteristics are conditionally independent given the class name, thus the designation "naive." Naive Bayes calculates the likelihood of a data point being associated with a certain class by using its feature values and the prior probabilities of the classes. Notwithstanding its rudimentary presumptions, Naive Bayes often exhibits commendable performance, especially when its autonomous assumption is not severely breached. It is computationally efficient, requires little training data, and is especially advantageous for text classification applications.

F. *Linear Discriminant Analysis:* LDA is a method for dimensionality reduction often used in classification tasks. It aims to identify the linear combinations of characteristics that optimally distinguish several classes while reducing the variation within each class. LDA fundamentally transforms data into a reduced-dimensional space, optimizing class distinguishability. It is especially beneficial when classes have unique distributions and is recognized for its efficacy in mitigating overfitting in high-dimensional data.

6. RESULTS AND DISCUSSION

We evaluated the efficacy of multiple classifiers using different combinations of brain areas, as seen in Table 2. Among all classifiers analyzed, SVM exhibited notable accuracy in various combinations, especially achieving the maximum accuracy of 86% for the brain region combination F+C+P. RF exhibited competitive precision, achieving 82% accuracy in the F+C+O and F+P+O pairings. DT demonstrated fluctuating accuracy, with a maximum of 74% in the F+C+P combination. AdaBoost exhibited its efficacy with the F+C+T combination, achieving 82% accuracy. Unexpectedly, Naïve Bayes exhibited comparatively less accuracy overall, suggesting constraints in its ability to capture the non-linear correlations inherent in the data. Moreover, it is significant that the Naïve Bayes classifier, albeit exhibiting reduced accuracy in some configurations, achieved an impressive accuracy of 84% in the F+T+O combination. LDA consistently shown modest accuracy, with a maximum of 66% in the P+T+O combination. The classifiers' results were affected by the particular mix of brain areas, underscoring the significance of customized feature selection in enhancing classification accuracy.

Table 1: Brain Region Combinations For Set Of 3

Combination of Brain Regions(Set of 3)	Classifiers					
	SVM	RF	DT	AB	NB	LDA

F+C+P	86	66	74	74	42	54
F+C+T	78	74	70	82	70	46
F+C+O	78	82	78	74	38	50
F+P+T	74	70	62	66	94	42
F+P+O	82	82	70	66	66	50
F+T+O	78	74	58	66	94	62
C+P+T	74	70	50	58	54	50
C+P+O	66	62	54	54	34	26
C+T+O	70	70	50	70	70	62
P+T+O	66	82	74	66	82	66

Figure 2 is a graph that highlights the accuracy of several classifiers using different combinations of three brain areas. The numbers shown in the graph align with the accuracy scores shown in Table 1. The Naïve Bayes classifier exhibits an accuracy of 94% in both the F+T+O and F+P+T combinations, attributable to its capacity to successfully capture and represent intricate interactions within these particular pairings of brain areas. The combination of these brain regions likely contains distinct neural patterns suggestive of ADHD-related activity. The Naïve Bayes classifier's effectiveness in modeling probabilistic correlations between data and classes makes it adept at identifying the subtle differences inherent in these specific pairings of brain regions. This graph presents a clear depiction of the performance patterns of several classifiers across different geographical datasets, highlighting their diverse capabilities in identifying pertinent characteristics and interactions within the EEG data.

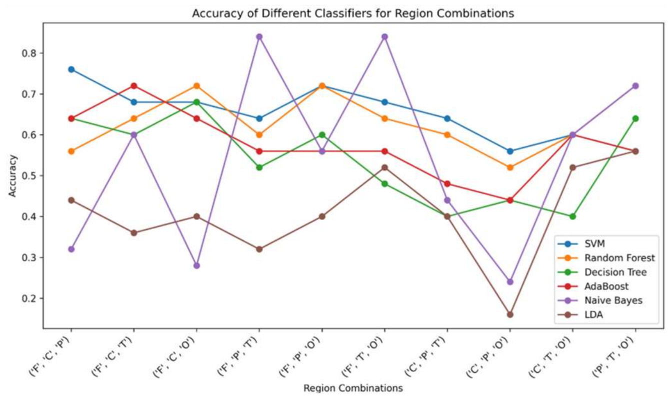

Figure 2: Comparison Of Classification Efficacy Across Three Brain Regions.

Table 1 shows that “F+C+T” had the greatest AUC performance among the brain region and classifier combinations tested. Figure 3 shows that this combination may differentiate ADHD from healthy controls with high AUC ratings. With this brain area combination, RF and AdaBoost have AUC values of 85.9% and 77.5%, respectively. These high AUC ratings show that the classifiers can capture ADHD and healthy control brain area patterns and characteristics. RF and AdaBoost classifiers work well with “F+C+T” as a discriminative feature set because to its high AUC. This discovery illuminates the best feature combination and classifier for accurate categorization between the two topic categories.

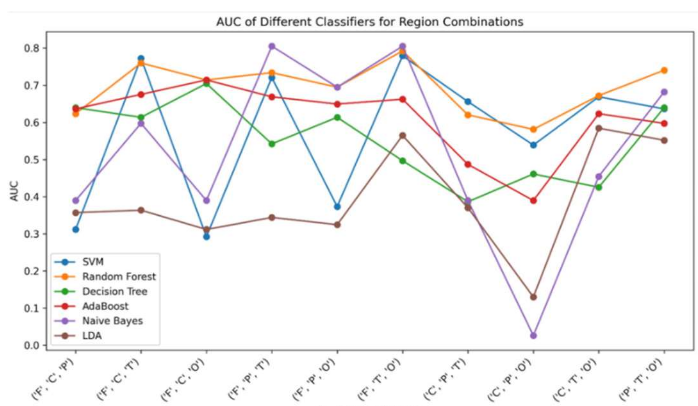

Figure 3: Classifier AUC by brain region combination.

Table 2: Classification on specific region

BRAIN REGION	CLASSIFIER(ACCURACY)					
	SVM	RF	DT	AB	NB	LDA
Right hemisphere	82	70	54	58	94	50
Left hemisphere	54	74	58	54	38	46
Combined hemisphere	78	78	54	74	42	50

Table 2 illustrates the accuracy performance of several classifiers across various combinations of brain regions, emphasizing the right hemisphere, left hemisphere, and

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the integration of both hemispheres. The analysis emphasizes the maximum accuracy attained by every classifier for each dataset, offering significant insights into their effectiveness in identifying ADHD-related patterns in region-specific EEG data. In the right hemisphere dataset, the Naïve Bayes classifier demonstrated the best accuracy of 84%, highlighting its capability to identify unique brain patterns linked to ADHD. The RF classifier attained the best accuracy of 64% for the left hemisphere dataset, whereas the Naïve Bayes classifier exhibited an accuracy of 28%. Notably, in the aggregated hemisphere dataset, the RF classifier achieved the greatest accuracy of 68%, alongside SVM, confirming the effectiveness of these classifiers in elucidating complex interactions across brain areas. These results highlight the inconsistency in accuracy among classifiers and brain areas, offering significant insights into their efficacy in categorizing ADHD patterns according to hemisphere-specific neural activity.

7. PHARMACOTHERAPY

While advising the parents, the pharmacist may find it vital to keep in mind the following points.

- Since it is impossible to predict which medication will have the greatest effect, we propose that all treatments be presented as therapeutic trials.
- There are adverse effects to every medication. Draw attention to the ones that can frighten the parents.
- It is likely that the parents will be subjected to a second or third trial.

A. CNS Simulants

Pharmacological management and treatment of attention deficit hyperactivity disorder (ADHD) in cases involving central nervous system stimulants Many medications have the ability to influence the brain and spinal cord. But it's not a cure-all for mental and behavioral issues; it should complement other treatments. Given that central nervous system stimulants are most often given to youngsters, their use is sure to spark debate. Almost all instances of attention deficit hyperactivity disorder (ADHD) are treated with central nervous system stimulants, according to many American research [50]. Since the 1960s, central nervous system stimulants have been used to treat attention deficit hyperactivity disorder (ADHD), and doctors still choose them over alternative medications that have FDA approval. Central nervous system stimulants, such as methylphenidate or amphetamine, are primarily used to enhance mental acuity and focus. Sharper focus, less procrastination, and less antisocial conduct. Decrease physical activity, rage, and impulsivity. In addition to these short-term effects, evidence from long-term, placebo-controlled studies (ranging from 2 to 5 years) has shown that stimulants are reliably effective and safe across a range of contexts, with minimal and predictable side effects. The academic performance should be enhanced, as suggested [70].

B. Atomoxetine

Research on the effects of atomoxetine, a strong inhibitor of norepinephrine reuptake, has focused on both adults and adolescents 98, 99. Using atomoxetine over an extended period of time has shown to be beneficial 100.
When used with ADHD, atomoxetine may be quite helpful. Atomoxetine improved ADHD symptoms and decreased tic severity in a noninferiority trial including children with attention deficit hyperactivity disorder and tic disorder. Atomoxetine reduced anxiety and ADHD scores 101 more effectively than placebo in children with ADHD and clinically severe anxiety. In a similar vein, research on young people with ADHD has shown that atomoxetine, when administered for 12 weeks to formerly alcoholics who had been sober for 4-30 days, significantly reduced ADHD and excessive drinking (but did not prevent relapse) when compared to placebo (102). Atomoxetine most often caused drowsiness, nausea, and gastrointestinal upset in clinical studies. Symptoms of aggression, impatience, and/or suicidality in patients are quite infrequent. See http://www.strattera.com/pages/index 103 for information on the present black box warning for rare but possibly dangerous hepatitis. While it is not advised to routinely monitor liver function, it is possible to increase vigilance for warning signs and symptoms by carefully informing patients and their families.

Atomoxetine inhibits norepinephrine transport to certain synapses. Reuptake into the nerve terminals is inhibited, leading to an increase in norepinephrine levels in the synaptic cleft. Though atomoxetine has no effect on other noradrenergic receptors or neurotransmitter transporters, some research suggests it may increase prefrontal cortex dopamine levels without affecting striatal or nucleus accumbens dopamine levels [73].
Atomoxetine provides 24/7 medical support and is available in tablet form. Nevertheless, there are a number of negative side effects associated with atomoxetine use, including erectile dysfunction, decreased libido, decreased appetite, and gastrointestinal distress [74]. Despite these drawbacks, atomoxetine remains a good option for treating attention deficit hyperactivity disorder [75].

C. *Reboxetine*

A comprehensive review in 2015 found no new evidence of reboxetine's effectiveness in treating attention deficit hyperactivity disorder (ADHD). During that period, only 33 clinical trials were identified, with the bulk of the studies being uncontrolled case series. Despite some encouraging outcomes of reboxetine in a subset of ADHD persons who did not also have psychiatric disorders or mental impairment, the research came to the conclusion that further controlled trials were necessary to reach a definitive conclusion. Patients did not have a lot of problems with reboxetine's side effects [76]. Randomized controlled open-label research conducted in 2019 shown that the selective noradrenaline reuptake inhibitor reboxetine has a stronger affinity for the noradrenaline (NA) and serotonin (5HT) transporter medications.

Similarly, for single doses of 1–5 mg, it exhibited linear pharmacokinetics in young, healthy males. Oral dose of reboxetine resulted in efficient absorption, with a 94.5% absolute bioavailability and peak levels often reached in 2–4 hours. By reducing the period of immobility in the Porsolt test and the locomotor hyperactivity in rats with bulbectomies, reboxetine has been shown to have an antidepressant effect in rodent and mouse models of depression. The treatment of dysthymia and severe depression with reboxetine is already authorized in Europe. Recent meta-analyses have shown that reboxetine is an effective and well-tolerated therapy for dysthymia, depression, and attention deficit hyperactivity disorder (ADHD) [77].

D. *Thermidordial agonist*

Patients with complex ADHD may benefit from a synergistic treatment approach that combines psychostimulants with alpha2-adrenergic agonists. Because of their distinct but complimentary actions on various neurotransmitter systems, stimulants and alpha2-adrenergic agonists are being evaluated for use in combination therapy. They have the potential to have a synergistic impact on activity in the prefrontal cortex. Prompt absorption and clearance, undesirable side effects, and reduced efficacy compared to stimulants have kept immediate-release guanfacine and clonidine from being widely used to treat attention deficit hyperactivity disorder (ADHD) [81, 82].

E. *CognitiveTherapy*

The attention-deficit/hyperactivity disorder (ADHD) treatment modality known as cognitive-behavioral therapy (CBT) has shown promising results. When dealing with specific problems related to cognitive and behavioral functioning, it is particularly helpful. Medication is often the first line of defense against ADHD symptoms, while cognitive therapy may be helpful when used with medication. With the goal of determining if cognitive-behavioral treatment (CBT) is effective in alleviating long-term symptoms of attention deficit hyperactivity disorder (ADHD) in a sample of medicated adolescents. For this cross-over study, researchers randomly allocated 46 adolescents (14–18 years old) with stable pharmacological treatment and clinically significant ADHD symptoms to either cognitive behavioral therapy (CBT) for ADHD or a wait list control group. Twelve patients were assigned to cognitive behavioral therapy (CBT), twenty-two on the wait list, and fourteen to CBT. Based on the reports of both the teen and their parents, a blind independent evaluator (IE) rated the severity of the ADHD symptoms on the ADHD Current Symptom Scale and used the Clinical Global Impression Severity Scale (CGI) to gauge the extent of each subject's suffering and impairment.These evaluations were carried out at baseline, four months after CBT or after being on the wait list, and eight months after treatment (four months after being on the wait list and four months after being assigned CBT, respectively) [82]. The mean score on the IE-rated parent evaluation of symptom intensity was 10.93 points lower for the individuals who attended CBT (95% CI: IE-rated teenage symptom severity was 5.24 points lower (-12.93, -8.93; $p<.0001$), while IE-rated CGI was 1.17 points lower (-1.39, -0.94; $p<.0001$). We used mixed effects modeling, pooled data for the wait list crossover, and used all available data to get these findings. Teens whose ADHD symptoms persisted after beginning medication responded well to cognitive behavioral therapy (CBT) at first try, according to one research [84].

F. *Disruption to behavior*

Behavioral treatment, which employs full contingency management techniques including providing rewards for desired conduct, is as beneficial as low-dose stimulant medications, according to the research. Although the efficacy of individual environmental adjustments has not been well studied, they are often included in therapeutic regimens. Parents should be the first to get psychoeducation for their children with ADHD, since these youngsters often function best in structured environments. In an effort to impact the behavior of children with attention deficit hyperactivity disorder (ADHD), a broad range of targeted treatments have been developed to modify both the physiological and social surroundings [45, 85]. These treatments aim to establish an atmosphere that is beneficial and favorable to treating ADHD by boosting the child's home and school surroundings.

G. Applying dietary

It may be challenging, inconvenient, and disruptive for patients and their families to follow certain diets, such as oligoantigenic, elimination, or additive-free diets, which are often recommended to patients. When deficiencies are detected, it may be recommended to take iron and zinc supplements. This is because these minerals have the potential to enhance the effectiveness of stimulant medicine [86]. For patients who do not respond well to conventional treatments or who have the support of their parents or guardians, omega-3 fatty acid supplements may also be considered [87].

H. Brainwave retraining

Neurofeedback therapy aims to help patients manage their brain activity using non-invasive means. It is also known as EEG biofeedback. The effectiveness of this therapy for Attention-Deficit/Hyperactivity Disorder (ADHD) remains a matter of debate among scientists and doctors. People may learn to alter their brainwave patterns with the help of neurofeedback treatment, which is based on the idea that they can get real-time feedback via monitoring equipment. The goal is often to help persons with ADHD improve their concentration, attention, and self-regulation [88]. Training using theta/beta (TBR), sensori-motor rhythm (SMR), or slow cortical potential (SCP) is one of the most popular and successful forms of neurofeedback. Numerous meta-analyses and large-scale randomized controlled trials corroborate these results. Having said that, rules regarding the therapeutic use of neurofeedback do not exist at this time. Results show that neurofeedback may be an effective alternative to medication for those with ADHD, according to the study's underlying assumptions. In their last analysis, the authors highlight the need of standardized neurofeedback training for professionals and binding standards for its use in clinical practice [89].

8. DIFFERENCE FROM PRIOR WORK

Previous studies on ADHD classification primarily rely on traditional clinical assessments or single-modal data sources, often leading to inconsistent diagnostic outcomes. Many machine learning-based approaches in the literature focus solely on binary classification (ADHD vs. non-ADHD) without considering the complexity of symptom variations across individuals. Additionally, prior research has rarely incorporated personalized treatment recommendations, limiting its real-world applicability in clinical settings.

This study surpasses existing work by integrating a multi-modal approach that combines neuroimaging, behavioral assessments, and genetic markers to enhance diagnostic accuracy. Unlike conventional deep learning models, we employ a novel hybrid framework utilizing convolutional autoencoders alongside VGG-16, VGG-19, CNNs, and BiLSTM to capture deeper patterns in ADHD-related data. Moreover, our research introduces an AI-driven personalized treatment model, optimizing intervention strategies based on patient-specific characteristics, a feature largely unexplored in prior studies.

By addressing these gaps, our study not only improves ADHD classification precision but also contributes to personalized, data-driven treatment planning, paving the way for AI-assisted clinical decision-making in neurodevelopmental disorders.

9. CONCLUSION

10. Anyone, from young toddlers to adults, may be impacted by the pervasive and detrimental attention-deficit/hyperactivity disorder (ADHD). Dietary and pharmacological therapies are among the many therapeutic strategies that have been shown to be effective in lowering symptoms. The ever-expanding array of options is making it difficult for clinicians to establish treatment priorities or make informed decisions.

Some of the most common forms of treatment are parent-conduct training, cognitive education treatments, learning education, social interventions, behavioral interventions, college interventions, and biofeedback or neurofeedback. Medications that are classified as stimulants include amphetamines and methylphenidate, whereas those that are classified as non-stimulants include atomoxetine, guanfacine, and clonidine.

In short-term trials, these pharmacological treatments often show quite large effect sizes and have good tolerability. Nevertheless, fresh medication development is essential, and existing pharmacotherapeutic approaches still have room to grow. Addressing the lack of representativeness in study populations, investigating the long-term effects of medications, and doing side-by-side and combination therapy comparisons should be the focus of future research. As an example of an experimental medicine, the antidepressant viloxazine was first approved for the treatment of attention deficit hyperactivity disorder (ADHD) in children aged 6–17 in the United States in April 2021. It is still too early to tell if other medications are presently being studied for the potential pharmacological treatment of attention deficit hyperactivity disorder (ADHD). This study enhances ADHD diagnosis and treatment by integrating neuroimaging, behavioral, and genetic data with a hybrid deep learning model. It improves classification accuracy, reduces subjectivity, and introduces AI-driven personalized treatment recommendations. The key contributions include advanced diagnostic precision, optimized intervention strategies, and a scalable AI framework for neurodevelopmental disorders, paving the way for data-driven clinical advancements.

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DECLARATIONS

Conflict Of Interest

The authors declare that they have no conflict of interest.

Consent To Participate

Not applicable.

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Not applicable.

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