

## Artificial intelligence techniques for attention deficit hyperactivity disorder: A systematic review of machine and deep learning methods

Dipendra Kumar Air<sup>1</sup>

<sup>1</sup>Assistant Professor, Central Department of Computer Science & Information Technology, Far Western University, Mahandaranagar, Nepal

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**Corresponding:** Dipendra KUMAR AIR, E-mail: prodipu@gmail.com

### ABSTRACT

The application of Deep Learning (DL) and Machine Learning (ML) methodologies to the investigation and management of Attention Deficit Hyperactivity Disorder (ADHD) represents a significant advancement with broad clinical and research implications. This systematic review analyzes various machine learning and deep learning algorithms, such as Support Vector Machines, k-Nearest Neighbors, Decision Trees, Random Forests, and Convolutional Neural Networks, and their applicability to ADHD research and clinical practice. These computational methods have shown significant usefulness in various areas, including improving diagnostic precision, recognizing different subtypes of ADHD, forecasting treatment outcomes, and revealing neurobiological markers linked to the condition. Utilizing a variety of data sources, such as clinical evaluations, neuroimaging results, genetic data, and environmental influences, machine learning and deep learning methods play a significant role in

clarifying the diversity and fundamental mechanisms of ADHD. Moreover, integrating multi-modal data, longitudinal studies following individuals over time, real-time surveillance systems, and interdisciplinary collaboration are all potential future directions for ML and DL in ADHD research. Furthermore, future research pathways consist of the integration of multimodal datasets, longitudinal analyses, real-time monitoring systems, and strengthened interdisciplinary collaboration. Addressing ethical considerations and ensuring equitable application will be critical for the successful translation of these technologies into routine clinical practice. Overall, ML and DL hold considerable promise for transforming ADHD evaluation and treatment, ushering in a new era of personalized and effective interventions personalized to individual needs.

**Keywords:** Attention Deficit Hyperactivity Disorder (ADHD), Machine Learning (ML), Deep Learning (DL), Diagnosis

### INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental condition characterized by persistent patterns of hyperactivity, impulsivity, and inattention. Although commonly diagnosed in childhood, ADHD often persists into adolescence and adulthood, with symptom expression and impact

varying across developmental stages. Accordingly, this review considers ADHD manifestations in both children and adults. ADHD is one of the most extensively studied neurodevelopmental disorders, alongside schizophrenia, autism spectrum disorder, and epilepsy. It affects approximately 5%–12% of school-aged children worldwide, depending on

diagnostic criteria and study design [1-3]. While numerous associations with potential risk factors have been reported, these relationships do not necessarily imply causation or direct biological significance. The causes of ADHD are complex and involve a combination of genetic factors, interactions between genes and the environment, as well as gene-nutritional influences, epigenetic processes, environmental factors, and psychological stressors. Attention Deficit Hyperactivity illness (ADHD) is a neurobiological disorder marked by recurrent episodes of inattention, impulsivity, and hyperactivity. ADHD affects people of all ages, with most symptoms commonly beginning in infancy and lasting throughout maturity. ADHD has a substantial impact on everyday functioning, academic success, and social interactions, needing proper diagnosis and targeted therapy [4]. Subjective tests, clinical interviews, and standardized behavioral evaluations are common components of traditional ADHD diagnosis techniques. However, these methodologies are susceptible to biases, resulting in under- or excessive diagnosis and inappropriate treatment planning. Furthermore, the variety of ADHD manifestations delays correct categorization and personalized therapeutic techniques. In recent years, Machine Learning (ML) as well as Deep Learning (DL) approaches have transformed ADHD research and management practice. Algorithms for machine learning and deep learning can evaluate massive, multi-modal datasets, including neurological imaging, biological, behavioral, and environmental aspects, to identify convoluted patterns and indicators related to ADHD. ML and DL models have

## LITERATURE SURVEY

Examining the Literature on ADHD Diagnosis along with medical history impulsivity, hyperactivity, and lack of attention are features of ADHD, a common neurodevelopmental disease. Alongside medical history, symptoms such as impulsivity, hyperactivity, and inattention are characteristic of ADHD, which is a prevalent neurodevelopmental disorder. Individuals with this condition, whether children or adults, experience significant challenges in academic, work, and social settings. Given the disorder's inconsistency and the overlap of symptoms with other conditions, an accurate diagnosis is essential for effective treatment. Nonetheless, achieving this can be quite challenging. This literature review outlines current methods, challenges, and advancements in ADHD assessment while also examining the importance of medical history and diagnostic procedures.

W. Te et al. [7] emphasize that assessing a patient's medical history, typical behavioral development, and signs of disorders are all important elements in identifying ADHD. To diagnose ADHD in adults, various diagnostic tools are available, such as the

shown potential in improving diagnosis accuracy, predicting treatment response, and discovering ADHD-related neurobiological markers in children. These computational tools provide for a more thorough knowledge of the underlying processes of ADHD and permit early intervention options suited to individual requirements by combining multiple data sources [5]. Similarly, for adults, machine learning and deep learning approaches may help improve diagnosis accuracy, monitor the intensity of symptoms, and guide treatment choices. These techniques, which draw on longitudinal research and real-world results, may help doctors optimize drug regimens, psychotherapy treatments, and cognitive management measures for people with ADHD. Despite significant advances made possible by machine learning and deep learning in ADHD investigation and therapeutic therapy, some hurdles remain. These include the necessity for big, well-explained information sets, strong validation methods, and the incorporation of computational discoveries into everyday clinical practice. Furthermore, ethical concerns about data privacy, algorithmic prejudice, and fair utilization of technology-enabled therapies must be thoroughly addressed [6]. This comprehensive article aims to offer a complete synopsis of the present state of research on machine learning and deep learning applications for ADHD in adults and kids. By integrating current research and highlighting gaps in understanding, this review aims to define future possibilities for using computational techniques to enhance ADHD evaluation, treatment, and management throughout the lifetime.

Adult Self Report Scale, Conner's Adult ADHD Scales, and Brown Attention Scales. Additionally, for a more streamlined evaluation of adult ADHD, the WHO Adult ADHD Self-Report Scale can be employed. Besides diagnostic and follow-up evaluations, clinical interviews, behavioral observations, and assessments of academic, medical, and neurological conditions are vital diagnostic elements. The author stresses that measures of symptoms should not be used alone to diagnose ADHD. The clinical judgment regarding ADHD serves as the foundation for the diagnostic procedure; assessments are meant to complement that. During the interview with the patient's parent, insights about the patient's symptoms, degree of impairment, possible co-occurring conditions, family history, and psychosocial stressors may be uncovered. The behavior of adults, along with the interaction between the adolescent and their parent during pediatric assessments, is observed. Diagnosing ADHD is a complex process that requires a thorough evaluation of the patient's medical history and symptoms, in addition to the use of diagnostic aids. A Singh et al. [8], A comprehensive examination of ADHD in preschoolers is presented in

this research investigation and addresses many aspects of ADHD, such as its neurobiological foundations, complications, and global impact. The research is informed by several conferences and studies concerning ADHD and early childhood learning. The article also examines the impact of ADHD on sleep patterns and the application of functional MRI technology for examining blood flow throughout different brain regions. Additionally, the neuropsychology of ADHD and the correlation between underlying biological mechanisms and ADHD symptoms are investigated in this study. On neuropsychological evaluations, adolescents with ADHD performed less well than control subjects, according to the study. Furthermore, the article examines the worldwide incidence of ADHD among both children and adults, as well as the profound consequences that the disorder has on those affected and their families. S. Salman et al. [9], The operational connectivity-based classification of ADHD utilizing various atlases is described in this study. Using fMRI data, the study intends to develop a computational framework for accurately diagnosing ADHD. Preprocessing of the original data obtained at Peking University in P.R. China was performed using the DPABI instrument. The HELM algorithm was employed for classification, while the LBEM algorithm was utilized for feature extraction. Different timing templates (atlases), such as CC400, CC200, and AAL, were utilized in the study for collecting and analyzing FCs and ROIs. The findings indicate that employing a single hidden layer yields marginally higher precision than utilizing multiple layers. Furthermore, if the dataset size is substantial, the classification model's precision improves as the number of layers that are hidden increases. The proposed method accurately diagnoses ADHD and can be utilized for identifying other neuropsychiatric conditions, according to the study's findings. The suggestions of mathematical models for the precise diagnosis of ADHD alongside additional neuropsychiatric disorders are illuminated in this study.

L. Kazda et al. [10] This work assesses the evidence in favor of and against the excessive diagnosis of ADHD in kids and teens using a thorough scoping review. The review aims to provide focused on patients, evidence-based ADHD evaluation, and therapy in modern healthcare settings. The review follows the PRISMA Extension over Scoping Reviews as well as Joanna Briggs Techniques, discusses the reported rise in ADHD diagnoses as well as the factors influencing the ongoing discussion about excessive diagnosis, and provides important results and implications for the evaluation and treatment of ADHD in kids and teens. CN Dutta et al. [11] The paper addresses how neuroprotection for those with ADHD may be achieved throughout life via phenotype and medication. The review's shortcomings and any

possible biases and methodological variations across the included research are emphasized throughout the publication. According to the research, people with ADHD may have varied brain trajectories throughout their lives, and medication therapy may not necessarily improve overall brain volume or lessen morphological abnormalities in both the white and gray matter. Rather, the medication seems to normalize the anatomy of the ADHD brain by increasing its volume in certain regions, with results that vary with age. The study highlights the complexity of ADHD by pointing out that different neurocognitive endophenotypes mediate networks between genotype and phenotype, which in turn contribute to the disorder's variety of presentations and severity levels. The study also recognizes that more evaluations that are comprehensive are required in the future to further our comprehension of lifelong factors related to the pharmaceutical management of ADHD in adults and children.

B. Vtiello et al. [12], The research offers findings concerning ADHD that are supported by data. The author aims to provide accurate and up-to-date information on ADHD, supported by a substantial and rigorous body of research. They do this by summarizing significant scientific developments over the last 20 years. Eighty writers from 27 different nations on six continents endorsed the author 208 claims concerning ADHD that were backed by actual evidence. The writers identify evidence-based claims concerning ADHD by professional analysis of published high-quality meta-analyses and lengthy investigations. This helps to address the difficulties and issues surrounding diagnosing and treating ADHD. The author anticipate that this thorough analysis will be beneficial and instructive for future ADHD research and therapeutic treatment.

W. MI et al. [13], The primary goal of this work was to provide evidence-based guidelines for assessing, diagnosing, and treating ADHD in young patients. To evaluate the degree of endorsement for each key action statement (KAS), this research highlights the significance of combining an evaluation of the expected balance between benefits and risks with an evidence- quality analysis. The aforementioned recommendation also stresses the importance of patient and family preferences in the effectiveness of treatment and the need to consider them while controlling ADHD. S. Yadav et al. [14], This study thoroughly analyzes how brain circuits and genetic variations contribute to the development of ADHD symptoms. It highlights how crucial it is to comprehend the genetic foundations of ADHD using cutting-edge research in animal models, neuromodulators, and pharmacotherapy. Additionally, this research addresses the impact of genes on alterations in the brain's anatomy, using the **SLC6A3** gene as an example. The report also

examines several research that investigates the connection between hereditary variables and brain function in ADHD. For example, it cites research on how the **SLC6A3** genotype affects brain activity while working memory tasks. It also emphasizes the importance of social contexts that are supportive of altering task performance depending on certain genotypes. The study also includes citations to important investigations in the area, such as the work of Demonte et al. that discovered potential genes linked to ADHD, such as **FOXP2**, **SORCS3**, and **DUSP6**.

D. Pena et al. [15], A thorough analysis of Attention-Deficit/Hyperactivity Disorder Predominantly Inattentive Subtype/Presentation (ADHD-PI) is given in this research. The paper presents translational research and research developments on this significant and sometimes overlooked subgroup of ADHD. The paper addresses how the attentional deficit in ADHD-PI differs from that in other subtypes and how neuropsychological, neurocognitive, and social functioning problems emerge in those who have ADHD-PI.

R. Robberecht et al. [16], Magnesium, iron, zinc, copper, and selenium levels in attention deficit hyperactivity disorder (ADHD) are reviewed in this paper. The article delves into the correlations between these vital elements' concentrations and ADHD symptoms, the techniques used to determine elemental status, and the possible consequences of supplementing. The research further discusses the challenges and conflicting findings regarding whether low ferritin and zinc levels contribute to ADHD symptoms.

D. Iizarbe et al. [17], Key signs and symptoms used to detect the disease in young people are highlighted in the diagnostic criteria for Attention Deficit/Hyperactivity disease (ADHD) according to the DSM-5 and ICD-10/11. The cause stresses the importance of correct diagnosis and efficient treatment. New insights into the biological and environmental factors that contribute to the onset of attention deficit hyperactivity disorder (ADHD) are explored in this paper's etiology section. It sheds insight into the complicated nature of ADHD by discussing polygenic risk score techniques and the possible significance of uncommon genetic variations in instances. Results from the Neuropsychological Domain show that working memory, time-to-reaction variability, impulse inhibition, intelligence/achievement, planning/organization, and episodic memory are all negatively impacted by ADHD. Furthermore, it stresses how important it is for people with ADHD to have trouble with emotional duties, social tasks, communication, and changing perceptions. When it comes to directing attention deficit hyperactivity disorder (ADHD) in children and

teenagers, therapeutic approaches stress the need for a multimodal strategy. It addresses national and international standards for evaluation and management and stresses the importance of psychoeducation as a therapy pillar. It also mentions the need for more research into genetic markers and biomarkers for Attention Deficit/Hyperactivity Disorder (ADHD) and the difficulties of employing minute effect sizes as diagnostic tools. R. Marticella et al. [18], researchers examined the brain connections between ASD, ADHD, and Theory of Mind (ToM) in people with both disorders and the combined condition. The results showed that prompts needed, length of description, intentionality, and appropriateness were all significantly affected by the condition. All groups showed more intentionality and longer descriptions in the Theory of mind (ToM) condition compared to the Goal-Directed (GD) condition, according to post hoc testing. However, the TD, ASD, and ADHD groups showed lower appropriateness ratings in the ToM condition compared to GD. Furthermore, compared to the GD condition, ToM required more cues. One person with ADHD showed signs of possible difficulty with theory of mind (ToM) in the fMRI test, as seen by their decreased performance on the question-answering phase. Although the ASD group received more prompts than the ADHD and TD groups, they nevertheless managed to produce the shortest ToM descriptions. No significant differences in intention attributions or appropriateness were seen in the out-of-scanner task performance data. The results of this research shed light on the mental operations and brain mechanisms that underlie the theory of mind (ToM) in people with Autism Spectrum Disorder (ASD) and attention deficit hyperactivity disorder (ADHD), which may help in the creation of more specific therapies for these disorders.

SL Regan et al. [19], The eating habits of both ADHD youngsters and their control group counterparts are investigated in this research. According to the research, compared to their control counterparts, children with ADHD ate more processed meals and sweets and less fresh produce and seafood. Compared to their non-ADHD classmates, children with ADHD weighed more and scored worse on intelligence tests. According to the research, dietary changes include cutting down on processed and sugary meals and eating more fish, fruits, and vegetables may help with ADHD symptoms. In addition to conventional pharmaceutical treatments, the research stresses the significance of dietary considerations in the management of ADHD. Dietary therapy may be an effective supplement to conventional treatments for ADHD, according to this study's results, which have significant consequences for healthcare providers, teachers, and parents of children with ADHD.

D. Silva et al. [20], Findings from this research provide light on the genetic and environmental components of rodent attention deficit hyperactivity disorder. In rats, ADHD is contributed to by a polygenic inheritance pattern including several small-effect genes. *Anakkin1, DAT1, LRP5, LRP6, SNAP25, ADGRL3, DRD4, and BAIAP2* are among the risk genes found in rats. Several environmental variables may heighten the incidence of ADHD in rodents. These include lead exposure, secondhand smoke, artificial food colors, acetaminophen during pregnancy, valproic acid during pregnancy, high levels of phthalates, and organophosphate pesticides. Future research in this area is also covered, along with the cognitive and neuroimaging impacts of rodent ADHD. Possible future research directions include studying the role of epigenetics in ADHD, creating gene-environment models, and testing the viability of knockdown models, including two or three combinations of genes.

S. Wigal et al. [21], ADHD is thoroughly covered in this review, which delves into its neurology and treatments. The article discusses how common ADHD is, how to diagnose it, and how to treat it. It also delves into the ways in which the illness affects people in their personal, professional, and academic lives. Additionally, the study delves into the expanding corpus of research and technical developments that enhance our comprehension of the neuroscience behind ADHD. The review's fundamental result is that attention deficit hyperactivity disorder (ADHD) is multifaceted and has diverse effects on people. The evaluation stresses the significance of precise diagnosis and individualized treatment programs that take into account the specific requirements of each patient. Methods for treating ADHD, such as medicine, behavioral therapy, and dietary and lifestyle modifications, are also included in the study. Cao et al. [22], The diagnosis and available treatments for ADHD in preschoolers are discussed in this paper, which is quite helpful. This study focuses on the difficulties of identifying ADHD in preschoolers and offers suggestions for first treatments, such as behavioral therapy and medication. This study delves into the latest findings in the field of ADHD in preschoolers, including topics such as the efficacy of methylphenidate and how co-occurring disorders affect treatment progress. Preschoolers with ADHD should be identified and treated as soon as possible, according to this study, which also includes helpful information for parents and healthcare professionals.

Examining the literature on ADHD diagnosis along with machine learning

People of all ages alike are affected by ADHD, a complicated neurodevelopmental illness characterized by impulsivity, hyperactivity, and lack

of focus. Clinical interviews, behavioral evaluations, and rating scales are the mainstays of conventional ADHD diagnosis procedures; nevertheless, these approaches are subjective and vulnerable to fluctuation. Improving diagnosis accuracy, discovering underlying trends, and developing tailored treatment regimens are all possible outcomes of using Machine Learning (ML) in ADHD research and clinical practice. Key approaches, results, and future prospects are highlighted in this literature review that analyzes the use of ML in diagnosing ADHD.

S. Deverach et al. [23], This article explores the application of machine learning techniques to enhance our understanding of brain processes associated with attention-deficit/hyperactivity disorder. It underscores the importance of machine learning models in creating precise categorization models and tailoring treatment programs to each patient's unique needs, as well as their ability to decipher the intricate interplay between ADHD's many components. In this study, we will look at how to train accurate ADHD classification models using a variety of data sources, such as genetic information, functional connectivity, and morphological characteristics. Additionally, it discusses how to improve the translational potential of neuroimaging in ADHD research by addressing the obstacles related to small sample numbers and the requirement for interpretable models. Furthermore, the study emphasizes the importance of multi-modal machine learning approaches that combine genetic, cognitive, and neuroimaging data to predict ADHD severity and identify structural differences. S. Ortal et al. [24], Using Deep Learning Convolutional Neural Networks, this ground-breaking research identifies unique EEG patterns linked to adult ADHD, which is a huge step forward in the area of ADHD diagnosis. The researchers were able to reach a classification accuracy of  $88\% \pm 1.12\%$  by using machine-learning approaches. This was better than typical neural network models and eliminated the need to manually select EEG parameters. The novel methodology of the research proved that deep learning might be an effective tool for studying EEG patterns, and it also provided mechanistic proof of the pathophysiology that underlies the categorization. The results indicate that compared to healthy controls, individuals with ADHD may exhibit pathophysiological markers such as a drop in alpha band power and an increase in delta-theta band power around 100 ms. The research does note that the dataset is modest, but the proof of concept shows potential for creating objective biomarkers that have real-world therapeutic applications. Insights into the possibilities of modern computational approaches in understanding and managing neurobiological problems are offered by this study, which also marks

a major step forward in the hunt for objective diagnostic tools for adult ADHD. H. Wei et al. [25], The study presents a model that utilizes machine learning and Continuous Performance Test indices to predict ADHD diagnosis outcomes in children aged 6 to 12 years. The research proves that the suggested model is better than the gold standard method, which uses just clinical data. The model outperformed the benchmark by 34% with an accuracy rate of 87%, sensitivity rate of 89%, and specificity rate of 84%. Crucial for distinguishing between normally developing peers and children with ADHD were the CPT total score and control factors (gender, age, time of day, and day of the week). Statistical biases, such as imbalances between levels and within levels, are also addressed in the research by using methods such as the Synthetic Minority Oversampling Technique. The findings indicate that machine learning can enhance the reliability and accuracy of ADHD diagnoses, offering significant implications for pediatric neurology and ADHD treatment. More effective diagnostic and treatment options for ADHD and other cognitive disorders are on the horizon.

L. Wee et al. [26], Automated identification of ADHD and CD using Electrocardiogram (ECG) data is the primary goal of this study's deep neural network model development efforts. Raw electrocardiogram data from 123 individuals diagnosed with mental disorders according to the DSM-IV-TR (Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision) were used in the study. Convolutional layers activated by rectified linear unit (ReLU) functions, dropout layers, and l2 kernel regularizes to avoid overfitting were all part of the model's architecture for the deep neural network. A 64-batch size and 100 epochs were used to train the model. The loss function was sparse categorical cross-entropy, and the optimizer was Adam. In order to rectify the imbalance in the dataset, the research also used weighted loss. The findings showed that the model correctly classified the data, as shown by its high sensitivity and accuracy. Finding a non-invasive and effective way to diagnose ADHD and CD is just one of the many important ways this study might change the face of mental health diagnosis and treatment in the future. M. Esas et al. [27], This review delves into research that used deep learning algorithms to classify ADHD. Improving the quality of life for children diagnosed with Attention Deficit/Hyperactivity Disorder (ADHD) is the ultimate goal of this study. Kids played a game and waited for the robot to explain and show them how it worked; this data set served as the study's backbone. Using RNN-based deep learning algorithms, the data was categorized into three groups: ADHD, ADHD- RISK, and normal. Out of all the RNN models tested, the LSTM-bidirectional model performed the best. Skeletal data collected while children were playing

the game was more useful for ADHD categorization than data collected while they waited, according to the research. This study offers a more precise and time-saving way to diagnose Attention Deficit Hyperactivity Disorder (ADHD), which has consequences for healthcare providers and parents of children with the disorder. Children with attention deficit hyperactivity disorder (ADHD) may benefit from early detection and treatment via the use of deep learning technologies. W. Lee et al. [28] The research presents new hybrid decomposition and deep learning methods for detecting attention deficit hyperactivity disorder (ADHD) in Electroencephalogram (EEG) data. The conventional method of diagnosing ADHD using Electroencephalogram (EEG) data is fraught with difficulties, such as a long processing time and complicated multi-channel recording. Clinical and data-collecting efficiency may be greatly improved by employing fewer EEG channels, according to the research, even if a tiny margin of success rate is sacrificed. With only two channels, Fp1 and F7 were determined to be the most successful in detecting ADHD, with an 88% success rate. Furthermore, the EEG data set showed enhanced classification success after using hybrid decomposition methods, namely RLMD and VMD. More importantly for improving classification success, the results show that RLMD is better than VMD. Using single-channel EEG inputs also reduces algorithm times, which means that ADHD diagnosis might be more practical and efficient, according to the research. Implications for future diagnosis and treatment methods are substantial, as the study sheds light on the possibility of using cutting-edge technologies like deep learning and hybrid decomposition to improve the efficacy and precision of ADHD identification using EEG data.

Trognon et al. [29] An innovative method for diagnosing Attention Deficit/Hyperactivity Disorder (ADHD) and ADHD-RISK in children is detailed in this study. The method involves using a screening game lead by a robot to look for unusual behaviors. A robot moves over a number board in this game, and the goal is for the young player to keep track of the numbers as the robot passes them. Whenever the Wizard of Oz's scarecrow, robot, and lion make an appearance in the game, the young player is prompted to pause and wave their hands. The youngster must remain still and seated in the event that a witch materializes. Researchers employed deep learning algorithms to sort game-playing kids into three categories: normal, ADHD-RISK, and ADHD. Children with ADHD-RISK performed well on the first try, but by the third try, they had become used to the game and were no longer able to focus on it. Insights gained from this study should lead to better methods of diagnosing and treating children with Attention Deficit Hyperactivity Disorder (ADHD),

as well as earlier identification and categorization of the disorder.

D. Zhou et al. [30] This study reveals a DSM-5-based psychometric screening instrument for attention deficit hyperactivity disorder in adults. Participants in the online voluntary aleatory sample were either matched with a control group or given the ADHD scale. In order to maintain participant anonymity, the research only gathered the following information: age, gender, socio-cultural level, diagnosis, and date of completion. After determining which items were most discriminatory, we examined the factorial structure and generated norms using stepwise backward-elimination multiple regression. The screener's discriminant validity was computationally evaluated by training three classification algorithms to compare its performance to those of other scales assessing comorbidities linked with ADHD or not. Since no other questionnaire explicitly measures ADHD behavioral features, the findings demonstrated that the TRAQ10 questionnaire outperformed the other two in terms of accuracy. This differential was statistically significant. M. Wang et al. [31], Based on video long-range EEG data, the study outlined an approach for the diagnosis of ADHD in children using deep learning models. Subjects in the study were youngsters who had just received an ADHD diagnosis. The researchers used the CADWELL video EEG monitoring system in conjunction with the worldwide 10/20 system electrode placement criteria to gather data. Brain wave difference values were standardized as part of the data processing to make sure the dataset was consistent. Researchers in the research suggested analyzing EEG data using deep learning models, such as two-dimensional convolutional neural networks and fully connected neural network models, in order to identify ADHD. By comparing the models' performance on test datasets, the findings reveal that the convolutional neural network model attained a recognition accuracy of approximately 97.7% on the test set and up to 99% on the training set. With an average recognition rate of 92.7%, the fully connected neural network models also demonstrated outstanding accuracy.

E. Ghasemi et al. [32], This study introduces a novel T-Dependent Neural Network (TDNet) capable of automatically diagnosing ADHD using resting-state functional magnetic resonance imaging (rs-fMRI) data. This approach uses a sliding time window technique to sub-segment rs-fMRI time series, then uses a temporal convolutional network to capture temporal relationships and functional connectivity for each segment. Compared to state-of-the-art methods, TDNet demonstrates superior performance in experimental results on the ADHD-200 dataset. With an average accuracy of 73.2%, the TDNet model outperformed static FC-based methods like as

MLP and CNN. It is crucial to take into account dynamic changes in rs-fMRI data for ADHD detection, since dynamic FC-based models, such as TDNet, shown improved diagnostic performance. This study demonstrates how sophisticated neural network models may be used to enhance the precision and effectiveness of ADHD diagnosis by using neuroimaging data. M. Villa et al. [33], This research set out to use Event-Related Potentials (ERPs) and machine learning models to differentiate between ADHD and other attention deficit hyperactivity disorders. Features were retrieved from several frequency bands in the ERP data set, which included both healthy and ADHD youngsters. There were seven machine learning models used in the technique. These models were Deep Learning (DL), Decision Tree (DT), Generalized Linear Model (GLM), Logistic Regression (LR), and Support Vector Machine (SVM). Tenfold Cross-Validation was used to assess the models, with 70% of the figures being used for training and 30% for testing. According to the results, GLM and LR achieved good accuracy rates across all frequencies. DL, SVM, and DT were tested in the Beta band, Alpha band, and Delta band, respectively. Findings from the research stress the need to combine several factors to improve model accuracy in ADHD diagnosis and the value of using the right algorithms for different kinds of data.

C. Nash et al. [34], Researchers set out to find people who could be suffering from mental health issues by mining Twitter and other social media platforms for signs of mental health in both English and Spanish. After removing irrelevant and spammy tweets, they gathered information from more than 3,200 people in each language. Users with mental health diagnoses and a healthy control group made up the datasets. With the use of n-grams, q-grams, LIWC, and word embeddings, among other linguistic characteristics, ML models were trained on tweet data to carry out both binary and multiclass classification tasks. Both the Spanish and English datasets showed good accuracy from the models, with an AUC of 0.84 and 0.85, respectively. The models were able to accurately identify a considerable amount of positive and negative classes, with an appropriate cut-off point for sensitivity and specificity around 83%. M. Chen et al. [35], The study highlights the significance of big, high-quality datasets for training successful models and examines the applicability of ML techniques in diagnosing ADHD and depression. With 142 participants at the outset, the ADHD-200 dataset contains information on acoustic indicators, gaze direction, posture, facial expressivity, and PHQ-8 scores. If there is an imbalance between the control and patient samples, researchers may utilize incomplete data from this dataset to reduce the impact of bias. Testing accuracy was attained by

utilizing brain Functional Connectivity features processed through an L2,1-Norm Linear Discrimination Analysis model, and various studies have used advanced ML techniques such as decision trees, hybrid AI models, and LightGBM for classification tasks, with accuracy ranging from 80% to 97.6%. Researchers should exercise care when extrapolating results to bigger and more varied populations, despite the fact that some research has produced encouraging outcomes. This is because of worries regarding dataset size and overfitting. C. Tinanhu et al. [36], ADHD detection utilizing brain connectome data was the basis of the study's multichannel deep neural network (mcDNN) model. The ADHD-200 dataset was used for the study. It contains 592 participants' personal characteristic data and resting-state functional MRI scans. The model included information on the individual's age, sex, handedness, and IQ in addition to the brain connectome properties that were retrieved at various spatial scales using various parcellations. With a sensitivity level of 70%, specificity of 84.2%, and accuracy of 78.3% in ADHD classification, the mcDNN model surpassed single-channel deep neural network models.

D. Vall et al. [37] In their study on ML for automatic ADHD diagnosis, the researchers used a dataset that included both structured and unstructured patient records, as well as scores from Sainsbury's Risk Assessment Tool and the QBTest, which objectively measure ADHD symptoms. Using decision tree learning as a focal point, the technique used six well-known ML algorithms to the dataset. Tokenization, lowercase conversion, punctuation removal, stop word deletion, and lemmatization were some of the pre-processing techniques performed on the medical notes. When trained using the primary assessment and risk assessment data, the decision tree algorithm achieved the maximum accuracy of 85.507%, making it the ideal classifier. The decision tree's performance was enhanced to 85.507% after using data from risk assessments. A little drop in accuracy to 79.710% was caused by the inclusion of variables collected from medical notes. The work stresses the significance of using risk assessment data to improve prediction models in clinical practice and the possibility of decision tree algorithms to automate ADHD diagnosis. M. Garcia et al. [38], The researchers in the study on ML for automated ADHD diagnosis used a dataset that included structured and unstructured patient records, together with scores from the QBTest and Sainsbury's Risk Assessment Tool, which objectively quantified symptoms of ADHD. The method used six popular ML techniques on the dataset using decision tree learning at its core. The medical notes underwent several pre-processing procedures, including tokenization, lowercase conversion, punctuation removal, stop

word deletion, and lemmatization. The decision tree algorithm was the best classifier since it trained using data from both the main and risk assessments and reached a maximum accuracy of 85.507%. Utilizing data from risk assessments improved the decision tree's performance to 85.507%. The accuracy was somewhat reduced by including factors derived from medical notes to 79.710%. The study highlights the potential of decision tree algorithms to automate the diagnosis of Attention Deficit Hyperactivity Disorder (ADHD) and the need to use data from risk assessments to enhance prediction models in clinical practice.

Z. Zhang et al. [39], Using a countrywide deep learning technique and registry data from more than 200,000 people in Sweden, this research sought to predict the emergence of attention-deficit/hyperactivity disorder (ADHD) in children and adolescents. Preprocessing operations on the dataset included managing features with strong correlation, deleting features with near-zero variance, and dividing the data into training and testing strata. Multiple ML models were trained and tested using various measures, including AUC, balanced accuracy, AUPRC, and logistic regression, random forest, gradient boosting, XGBoost, Naïve Bayes, and deep neural network. In the testing set, the deep neural network model achieved the most area under the curve (0.753), making it the top performer. Having a parent with a criminal record, being male, having a relative with attention deficit hyperactivity disorder (ADHD), the amount of failed academic courses, and speech or learning difficulties were the top five factors affecting the categorization. Researchers showed that machine learning might be useful for predicting when attention deficit hyperactivity disorder (ADHD) will first appear in children and teenagers by mining registration data.

M. Valstar et al. [40], To diagnose disorders like ADHD, ASD, PD, MDD, and SCZ, researchers conducted a scoping review of studies using ML and DL AI methods in MRI disease classification in humans. The datasets included structural magnetic resonance imaging (T1-w), Functional Magnetic Resonance Imaging (fMRI), diffusion tensor imaging (DTI), and resting-state functional magnetic resonance imaging (rs-fMRI) images. A variety of approaches were used, including Generative Adversarial Networks (GANs), Support Vector Machines (SVMs), and Random Forests (RFs). Depending on the condition and the particular AI algorithm used, the models' accuracy ranged from 62.7% to 100% across tests. As a whole, the use of AI to MRI categorization has shown encouraging results in enhancing the precision and efficacy of diagnoses for a range of mental and neurological disorders, demonstrating how AI has the ability to transform the way neurology and psychiatry

approach patient treatment. Table 1 shows the different methodologies with accuracy, Sensitivity, and Specificity of the model

**Table 1.** Comparison of different research published over the ADHD-200 dataset

Classification Techniques	Methodology	Accuracy (%)	Sensitivity (%)	Specificity (%)
Convolutional Neural Network (CNN)	Feature Extraction with Seed-based Correlation [55]	85.36	72.8	66.24
	EMI-MI Multi-instance Learning Algorithm [56]	70.4	-	-
	4D-CNN Sigmoid Classifier [57]	71.13	73.2	69.7
Support Vector Machine (SVM)	Functional Connectivity Network with Multi-Dimensional Scaling [58]	73.55	75	72.73
	Discriminate Subnetwork Selection [59]	94.91	93.22	96.94
	Feature selection with functional connectivity matrices using neural network [60]	73.3	-	-
	Bi-objective optimization [61]	81.08	-	-
K-Nearest Neighbour (kNN)	J-Extended Frobenius Norms [63]	81	66	87
Decision Tree	Non-negative Matrix Factorizing [64]	66.8	76.2	50.60
Random Forest Classifier	3D fMRI segmentation [65]	75.46	-	-
Convolutional- GRU	Spatio-temporal feature extraction with nested residual convolutional Denoising Autoencoding [62]	72.44	70.15	74.16

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## Assessment and evaluation types for Attention Deficit Hyperactivity Disorder (ADHD)

The standard method for evaluating ADHD is to conduct a battery of tests designed to collect detailed information about the symptoms, functioning, and possible causes of the disorder. Common forms of testing for attention deficit hyperactivity disorder include:

**Interviews in a clinical setting:** A crucial part of the evaluation procedure is conducting clinical interviews with the person who is believed to have Attention Deficit/Hyperactivity Disorder (ADHD), in addition to their parents, instructors, or other pertinent persons. These interviews collect data on the patient's present symptoms, their effect on everyday functioning, and their developmental history.

**Observations of behavior:** One way to learn about a person's attention, activity level, and impulsivity is to watch how they behave in different environments, including at home, school, or when doing prescribed activities.

**Behavior rating scales:** To measure and evaluate the severity of ADHD symptoms, standardized rating scales may be filled out by the person, their parents or instructors. The Vanderbilt ADHD Diagnostic Parent and Teacher Rating Scales, the ADHD Rating Scale, and the Conner's Rating Scales are a few examples.

**Evaluation of the brain:** Attention, memory, processing speed, and executive functioning are some of the cognitive skills that neuropsychological evaluations look at. Some examples of such tests include CPTs (Continuous Performance Tests), sustained attention tests, and response inhibition tests.

**Evaluations of mental health:** Psychological evaluations may be carried out to gauge emotional regulation, co-occurring disorders (such as depression or anxiety), and general psychological and social well-being. Beyond only looking at ADHD symptoms, these tests may provide a fuller picture of the person's abilities and areas for improvement.

**Health examination:** To identify and exclude any medical issues or drugs that might cause or worsen symptoms of Attention Deficit Hyperactivity Disorder (ADHD), a comprehensive medical assessment is necessary. This includes a physical exam as well as a review of medical history. If further underlying medical problems are detected, it may also include neuroimaging investigations or laboratory testing.

**Computerized tests:** Cognitive measurements of attention, impulsivity, and sustained attention may be objectively measured using computerized tests like the Continuous Performance Test (CPT) and the

Test of Variables of Attention (TOVA). Clinical observations and self-report measurements may be supplemented by these tests.

**Functional Assessments:** These tests measure how ADHD symptoms affect many parts of people's lives, such as how they do in school, with their friends and family, at work, and with basic self-care. Improving Attention Deficit Hyperactivity Disorder (ADHD) diagnosis, understanding, and treatment with the use of machine learning

The symptoms of Attention Deficit Hyperactivity Disorder (ADHD), which include impulsivity, restlessness, and lack of focus, may affect many areas of a person's life and continue into adulthood. The variability of ADHD symptoms and their overlap with other illnesses make diagnosis and management of the disorder a challenging task, notwithstanding the high incidence and substantial burden of ADHD. Advances in machine learning (ML) have opened up exciting new possibilities for better understanding attention deficit hyperactivity disorder (ADHD), making more accurate diagnoses, and creating individualized treatments <sup>[46]</sup>. Machine learning is a subfield of AI that focuses on creating algorithms that computers can use to understand data, find patterns, and make judgments or predictions without human intervention or programming. When applied to attention deficit hyperactivity disorder (ADHD), ML methods may sift through massive, diverse datasets, including clinical evaluations, MRI images, genetic markers, behavioral notes, and environmental variables. Machine learning (ML) algorithms are able to find patterns and correlations that would not be obvious using more conventional methods of analysis by drawing on these many data sources.

An important use of ML in the field of attention deficit hyperactivity disorder (ADHD) is to improve the precision of diagnostic tests. The subjective nature of the evaluations and behavioral observations used in traditional ADHD diagnosis criteria makes them vulnerable to bias and inter-evaluator variability. On the other hand, ML algorithms may combine data from several sources to create prediction models that can accurately differentiate between neurotypical controls and persons with ADHD <sup>[47]</sup>. These models aid in the more accurate and objective diagnosis of attention deficit hyperactivity disorder (ADHD) by spotting trends in behavioral traits, neuroimaging biomarkers, and genetic predispositions. To further address the disorder's variety, ML approaches make it easier to identify different subtypes of ADHD. It is tough to find strategies that are beneficial for everyone with ADHD since the symptoms, comorbidities, and reactions to therapy may vary greatly. Machine learning algorithms may simplify this mess by grouping people into subsets defined by

common traits like genetic markers, cognitive profiles, or the intensity of symptoms. Through the identification of these subtypes, medical professionals may personalize treatment plans to address certain areas of symptoms and underlying causes, ultimately leading to better therapeutic results. Individuals with ADHD may benefit greatly from individualized therapy guided by ML, which also helps in predicting treatment response. In order to find out what makes pharmacological or behavioral treatments work, ML algorithms look at long-term data on symptoms, medication adherence, and treatment results. To better meet the requirements of each patient, physicians might customize treatment programs by modifying pharmaceutical doses, therapy modes, or environmental adjustments. Machine learning also makes it easier to find genetic variations linked to attention deficit hyperactivity disorder (ADHD) as well as structural and functional brain imaging indicators. Finding these biomarkers will allow researchers to create objective metrics for diagnosis, prognosis, and therapy monitoring, which will improve the accuracy of clinical decision-making by decreasing the need for subjective evaluations. Finally, there is great hope that machine learning may improve patient outcomes and deepen our knowledge of attention deficit hyperactivity disorder (ADHD) in clinical treatment and research [48-52]. More effective, tailored treatments for attention deficit hyperactivity disorder (ADHD) may be developed if researchers and doctors use machine learning (ML) algorithms to sift through large datasets, spot trends, and forecast future results. There is great promise for ML to transform ADHD diagnosis, treatment, and management as our understanding of the disorder grows and new technologies become available.

#### Support Vector Machine (SVM) in ADHD

Research on ADHD has made growing use of SVM, a robust ML technique. Because of its versatility as a supervised learning approach, support vector machines (SVMs) are ideal for evaluating large datasets in search of patterns related to attention deficit hyperactivity disorder (ADHD) diagnosis, subtyping, and treatment efficacy. Researchers have shown that support vector machines (SVMs) may improve diagnosis accuracy for attention deficit hyperactivity disorder (ADHD) by differentiating neurotypical controls from those with the disorder using a variety of factors, such as genetic markers, neuroimaging data, and behavioral evaluations. Support vector machines (SVMs) [41] improve classification accuracy by correctly identifying nonlinear connections and optimally separating classes by transforming input data into a higher-dimensional space using a kernel function. By grouping people with similar symptoms, cognitive profiles, or neurobiological markers into homogenous

subtypes, support vector machines (SVMs) have also been used to detect different forms of attention deficit hyperactivity disorder (ADHD). Clinicians may target certain symptom domains and underlying processes with tailored treatment methods using this subtyping technique. The result is more individualized and effective therapies. Furthermore, support vector machines have been used to forecast how well people with attention deficit hyperactivity disorder (ADHD) would respond to medication. To help doctors optimize pharmaceutical regimens and guide tailored treatment plans, support vector machines (SVMs) analyze longitudinal data on symptom trajectories, medication adherence, and treatment outcomes to discover predictors of favorable treatment response. The Support Vector Machine shows potential as a useful resource for ADHD studies and clinical practice, shedding light on diagnostic subtyping, therapy optimization, and diagnostic categorization; it also helps to enhance personalized medicine methods for ADHD management.

#### K-Nearest Neighbors (KNN) in ADHD

An adaptable machine learning technique, K-Nearest Neighbors (KNN) has shown potential in the study of Attention Deficit Hyperactivity Disorder (ADHD). When it comes to evaluating varied datasets and finding patterns related to ADHD diagnosis, subtyping, and treatment response, KNN is the way to go. It's a basic supervised learning algorithm that works well for classification and regression tasks. Researchers have used KNN to improve the accuracy of ADHD diagnoses by sorting patients into neurotypical and ADHD categories using a variety of factors, such as results from neuroimaging studies, behavioral evaluations, and neuropsychological testing [42]. For local pattern capture and nonlinear relationship management, this technique shines because it finds a new data point's class by looking at its closest neighbors' classes in the feature space. In addition, KNN has been used to classify ADHD patients into different subtypes by aggregating them into groups with shared symptoms, cognitive abilities, or neurobiological markers. In order to develop more effective and individualized treatments for ADHD, this clustering method may be used to identify subgroups of patients with similar symptoms. KNN has been used to forecast how well behavioral treatments would work for people with ADHD. Clinicians may use KNN to better personalize treatment regimens and optimize therapeutic results by examining longitudinal data on symptom intensity, treatment adherence, and functional outcomes to uncover predictors of favorable treatment response. As a whole, K-Nearest Neighbors is a great tool for ADHD studies and clinical practice since it helps with diagnosis, finding subtypes, and finding the best way to treat the

disorder. It holds great promise for the advancement of customized medicine approaches to ADHD therapy because to its simplicity, adaptability, and capacity to detect local trends.

#### Decision Tree in ADHD

Research on ADHD has shown that the popular machine learning method Decision Tree is useful. For the purpose of evaluating complicated datasets and identifying relevant patterns associated with ADHD diagnosis, subtyping, and treatment response, Decision Trees—which are supervised learning models are well-suited. By using a variety of characteristics, such as behavioral evaluations, neuropsychological tests, and neuroimaging data, Decision Trees have improved the diagnosis accuracy of ADHD research by grouping people into neurotypical and ADHD categories. Recursively, Decision Trees divide the feature space into subsets, with the goal of increasing the homogeneity of the target variable within each subset. Through this procedure, decision criteria that properly categorize patients into different diagnostic categories may be discovered. Moreover, Decision Trees have been used to discover ADHD subtypes by dividing the ADHD population into comparable subgroups according to shared neurobiological markers, cognitive performance, or symptom profiles [43]. Decision Trees help in subgroup identification, allowing for the creation of individualized treatment plans and treatments. Decision trees have also found use in the prediction of treatment response in ADHD patients, especially in the context of pharmaceutical treatments. Decision Trees help doctors choose the best course of therapy for their patients by examining longitudinal data on symptom intensity, treatment adherence, and functional results; this data is then used to find predictors of favorable treatment response. All things considered, Decision Trees are a great resource for ADHD studies and clinical practice because of the information they provide on subtype identification, diagnostic categorization, and treatment optimization. A potential method to advance personalized medicine techniques in ADHD care, they are interpretable, can handle nonlinear interactions, and can record complicated decision rules.

#### Random Forest Classifier in ADHD

The Random Forest Classifier, an ensemble learning method based on decision trees, serves as a powerful tool in ADHD research. In order to analyze complicated datasets and get useful insights about ADHD subtyping, treatment efficacy, and diagnosis, Random Forests are ideal supervised learning models because of their versatility and their ability to handle classification problems with high-dimensional and heterogeneous data. Researchers studying attention

deficit hyperactivity disorder (ADHD) have used Random Forest Classifier to better categorize patients into neurotypical and ADHD groups using a variety of characteristics gleaned from neuroimaging, behavioral evaluations, and neuropsychological testing [44]. Random Forests provide trustworthy classification results by reducing the likelihood of overfitting and improving generalization performance by integrating the forecasts of several decision trees trained on separate data subsets. In addition, Random Forests have shown promise in the identification of ADHD subtypes by the division of the ADHD population into similar subgroups defined by common features including neurobiological markers, cognitive performance, or symptom profiles. Random Forests enable the identification of significant subgroups within the ADHD population by using the combined knowledge of several decision trees, which capture complicated interactions and nonlinear linkages in the data. Random Forest Classifier has been used to forecast how well ADHD treatments, especially pharmaceutical ones, would work for certain people. Clinicians may better meet the requirements of their patients by using Random Forests to analyze longitudinal data on symptom intensity, treatment adherence, and functional outcomes. This data can then be used to find predictors of favorable therapy response. When it comes to diagnosing ADHD, identifying subtypes, and optimizing therapy, Random Forest Classifier is an invaluable tool in both clinical practice and research. A potential way to improve personalized medicine techniques in ADHD care is to handle high-dimensional and diverse data, reduce overfitting, and capture complicated interactions [54].

#### Convolution Neural Network (CNN) in ADHD

In the field of ADHD research, Convolutional Neural Networks (CNNs) have become an innovative tool, especially for analyzing neuroimaging data. Convolutional neural networks (CNNs) are a kind of deep learning model that successfully extracts spatial characteristics from photos and other high-dimensional data by modeling their architecture after the visual cortex in the brain. Attention Deficit Hyperactivity Disorder (ADHD) is characterized by minor functional and neuroanatomical abnormalities, and CNNs have the ability to detect these abnormalities. Neuroimaging studies have used CNNs to distinguish between neurotypical controls and those with ADHD by revealing unique patterns of brain anatomy and function. Convolutional neural networks (CNNs) may automatically learn discriminative characteristics that indicate changes in brain morphology, connectivity, and activation patterns associated to attention deficit hyperactivity disorder (ADHD) by evaluating structural and Functional Magnetic Resonance Imaging (fMRI) Data

Including Diffusion Tensor Imaging (DTI). To supplement current clinical evaluations, this allows for the creation of objective biomarkers for the diagnosis and prognosis of attention deficit hyperactivity disorder (ADHD) [45]. In addition, Convolutional Neural Networks (CNNs) categorize people with ADHD into similar groups according to common patterns of brain abnormalities, which helps in identifying subtypes of ADHD based on neuroimaging. These models are able to extract unique subgroups of ADHD patients by capitalizing on the hierarchical structure of Convolutional Neural Network (CNN) architectures to represent intricate spatial correlations in neuroimaging data. As this subtyping technique allows for customized therapies targeting distinct neurobiological profiles associated with ADHD, it has implications for individualized treatment planning. Convolutional Neural Networks (CNNs) have shown potential in using pre-treatment neuroimaging data to forecast therapy efficacy in ADHD patients. Convolutional neural networks (CNNs) allow doctors to choose the best treatments for their patients by examining baseline brain imaging data [53] and finding neural predictors of treatment success. All things considered, convolutional neural networks (CNNs) are a potent tool for expanding our knowledge of the neurobiological bases of attention deficit hyperactivity disorder (ADHD), which in turn allows for more accurate diagnosis, subtype identification, and individualized treatment plans based on the specific brain-based traits of each patient.

## CONCLUSION

There has been a significant leap forward with far-reaching consequences in our understanding of ADHD and its treatment thanks to the use of ML and DL approaches. From improving diagnostic accuracy and identifying unique ADHD subtypes to predicting treatment response and directing individualized therapies, these computational techniques have shown their worth in several fields. A wide variety of ML and DL methods, such as Support Vector

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6. Future work in applying ML and DL to the study and treatment of attention deficit hyperactivity disorder (ADHD) shows great potential for new developments in this area. Research and clinical practice related to this might greatly benefit from using Deep Learning (DL) and Machine Learning (ML) approaches in the future. One potential approach is integrating multi-modal data from several sources, such as neuroimaging, genetics, behavior, and the environment. By bringing these domains together, we can learn more about the causes, variations, and effects of ADHD, which can help us create better prediction models and tailor our interventions to each individual's needs. To understand the ever-changing nature of attention deficit hyperactivity disorder (ADHD) and to find factors that may predict its long-term effects, longitudinal studies that follow the same people over time are essential. By allowing for continuous evaluation of symptoms and medication adherence in real-world situations, real-time monitoring systems using wearable devices and digital biomarkers have the potential to transform ADHD therapy completely. To make progress in the area and successfully use discoveries in clinical practice, it will be crucial for academics, physicians, data scientists, and tech developers to work together across disciplines. To guarantee the fair and responsible use of ML and DL technologies in ADHD treatment, it is crucial to address data privacy, equity, and ethical concerns.
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## CONFLICT OF INTEREST:

The author declare no competing interests.

## HUMAN PARTICIPANTS AND/OR ANIMALS

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