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Opportunities, Challenges and Future in ADHD Detection using AI-Powered Models: A literature Review

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***Abstract*— Attention Deficit Hyperactive Disorder (ADHD) is a neurodevelopmental condition that can impact individuals of all ages, marked by symptoms such as difficulty focusing excessive activity, and a tendency to act without thinking. Associated with low dopamine levels and reduced metabolic activity in brain regions governing attention and motor control, ADHD diagnosis remains challenging. This review examines deep learning (DL) approaches and diagnostic tools for ADHD detection, emphasizing critical gaps and suggest a new method for improving the accuracy of ADHD detection. Current studies predominantly rely on EEG signals and resting-state fMRI, with limited use of audio data. Promising modalities like MEG and actigraphy remain underexplored, and the scarcity of multimodal datasets weakens model generalizability. Most DL models employ basic architectures like CNNs or ANNs, neglecting advanced, interpretable frameworks that could boost accuracy. Future efforts may emphasize the use of multimodal information and interpretable AI approaches to enhance the precision and trustworthiness of ADHD detection. Moreover, incorporating digital biomarkers and longitudinal datasets can support the development of personalized and clinically relevant diagnostic solutions**

***Index Terms*— Attention Deficit Hyperactive Disorder (ADHD), Electroencephalography, Electro Cardiogram, Magnetic Resonance Imaging.**

I. Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is a mental health condition that typically begins in childhood and can persist into adulthood, affecting about 8% of children and 2–5% of adults. ADHD presents in three main forms: the combined type (the most common), which involves both impulsivity and hyperactivity; the impulsive/hyperactive type (the least common), characterized primarily by impulsive or hyperactive behavior; and the inattentive/distractible type, where individuals are mainly inattentive and easily distracted. Research indicates that imbalances in the neurotransmitter's dopamine and norepinephrine, both crucial for attention and impulse control, are key contributors to ADHD. Additionally, affected individuals often show reduced white and grey matter in brain areas linked to attention and executive function.

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Diagnosis is performed by psychologists or psychiatrists using a combination of medical exams, interviews, surveys, and criteria from the DSM-5. Recently, artificial intelligence (AI) models utilizing neuroimaging data such as EEG and resting-state fMRI have been explored for ADHD detection. This review analyzes 31 significant research papers published from 2023 to June 2025, focusing on current deep learning methods, available datasets, existing challenges, opportunities, and future research directions in ADHD detection.

II. LITERATURE REVIEW

This review is classified into four sections based on the modalities used.

A. EEG-based studies

Electroencephalography (EEG) is a brain imaging technique that detects its electrical activity through electrodes on the scalp. It has a high temporal resolution (captures rapid changes in brain activity) but low spatial resolution (precise identification of brain regions). Hasan Alkahtani et al. [4] analysed EEG recordings from 61 ADHD patients and 60 controls, employing LASSO regularization and recursive elimination for feature identification. Various algorithms including CatBoost, Random Forest, Decision Trees, CNN, and LSTM were tested, with CNN achieving 97.75% testing accuracy. Omer Kasim [5] developed a deep learning architecture combining convolution, pooling, bidirectional LSTM, and fully connected layers, utilizing Multitaper and Multivariate Variational Mode Decomposition for feature extraction, achieving 95.54% accuracy. It used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls. Nupur Chugh et al. [6] developed a hybrid LSTM-CNN model trained on EEG data, achieving 98.86% accuracy on ADHD and 98.28% on FOCUS datasets. Md Bayazid Hossain et al. [7] used EEG features like spectral density and entropy, with an SVM RBF kernel reaching a 99.2% cross-validation accuracy. It used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls. Haowei Hue et al. [8] developed SCANet (Selective Channel Attention Network) incorporating attention mechanisms, depth-wise separable connections, and multiscale dual-branch architecture for EEG-based ADHD detection. Gradient-weighted class activation mapping enhanced model interpretability, achieving 99.78% accuracy on Dresden University's dataset and 87.12% on private data. It used - Public dataset (144 children: 44 healthy controls (HC), 52 ADHD patients, and 48 attention deficit disorder) and a Private Dataset (13 patients with ADHD and 11 HC children). Shan Wang et al. [9] compared Random Forest, XGBoost, CatBoost, and LightGBM algorithms on multidimensional EEG features, using SHAP. SHapley Additive Explanation algorithm is used to measure the importance of contributing features to interpret the model CatBoost delivered optimal performance with 99.58% classification accuracy. It used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls. Xu Liu et al. [10] developed a Graph Convolutional Network (GCN) that combines multi-domain EEG features, including time-frequency data from LSTM and CNN, with topological connectivity matrices for ADHD classification, achieving 97.29% and 96.67% accuracy on two datasets. Dataset 1 was gathered be-tween January 2023 and January 2024 at Changchun Sixth Hospital in China. The study included 57 participants in total: 29 children diagnosed with ADHD (17 boys and 12 girls, aged 4–13 years) and 28 healthy control children (20 boys and 8 girls, also aged 4–13 years). Dataset 2 used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls. Ahmed Alhussan et al. [11] introduced the neuroDCT-ICA pre-processing module to remove noise and extract key features, utilizing Rhinofish optimization for feature selection. Their ADHD-Attention Net model attained 98.52% accuracy, with an F-score of 98.26% and specificity of 98.16%. It used a Diagnostic database consisting of 51 ADHD controls and 52 healthy controls and EEG database. Medha Pappula and Syed Muhammed Anwar [12] developed a ResNet-18 CNN model that transformed EEG signals into spectrograms via Continuous Wavelet Transforms, achieving a high precision, recall, and F1 score of 0.9. It used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls.

Javier Sanchis et al. [13] introduced EEG-MSCNet, a multiscale CNN utilizing leave-one-out cross-validation for robustness, attaining an accuracy of 88.42%. It used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls. Md.Maniruzzaman et al. [14] used data from ADHD dataset that was available in IEEE data port. A hybrid selection approach was devised combining SVM and t-test based approaches to select the optimal channels. LASSO logistic regression model was used to extract significant features from the channels selected. Later Gaussian process classification (GPC), random forest, k nearest neighbours, multilayer perceptron, decision tree, and logistic regression were applied for the detection of children with ADHD.GP based classifier achieved an accuracy rate of 97.53 %. It used EEG dataset from IEEE data port which consisted of 61 ADHD patients and 60 healthy controls.

TABLE I. SUMMARY OF STUDIES THAT UTILIZES EEG FOR DIAGNOSIS OF ADHD

Study	Dataset	Key Features	Algorithms	Performance
Hasan Alkahtani et al.	EEG dataset (IEEE data port): 61 ADHD, 60 controls	LASSO regularization, recursive elimination	CatBoost, Random Forest, Decision Trees, CNN, LSTM	CNN-97.75%
Omer Kasim	EEG dataset (IEEE data port): 61 ADHD, 60 controls	Multitaper and Multivariate Variational Mode Decomposition	Deep learning architecture (convolution, pooling, bidirectional LSTM, FC)	Custom DL model-95.54%
Nupur Chugh et al.	ADHD and FOCUS EEG datasets	Hybrid LSTM-CNN	LSTM-CNN hybrid	Hybrid LSTM-CNN - 98.86% (ADHD),98.28% (FOCUS)
Md Bayazid Hossain et al.	EEG dataset (IEEE data port): 61 ADHD, 60 controls	Spectral density and entropy features	SVM with RBF kernel	SVM RBF-99.2%
Haowei Hue et al.	Public (144: 44 HC, 52 ADHD, 48 ADD)	SCANet with attention mechanisms, depth-wise connections, multiscale design	SCANet	SCANet-99.78% (public),87.12% (private) Private (13 ADHD, 11 HC)
Shan Wang et al.	EEG dataset (IEEE data port): 61 ADHD, 60 controls	SHAP for feature importance	Random Forest, XGBoost, CatBoost, LightGBM	CatBoost-99.58%
Xu Liu et al.	Dataset 1: 57 children (29 ADHD, 28 HC)	GCN combining LSTM/CNN time-frequency features + connectivity matrices	Graph Convolutional Network (GCN)	GCN-97.29% (Dataset 1),96.67% (Dataset 2) Dataset 2: IEEE data port
Ahmed Alhussan et al.	Diagnostic DB (51 ADHD, 52 HC) + EEG DB	neuroDCT-ICA pre-processing, Rhinofish optimization	ADHD-Attention Net	ADHD-Attention Net-98.52%
Medha Pappula et al.	EEG dataset (IEEE data port): 61 ADHD, 60 controls	ResNet-18 CNN with Continuous Wavelet Transform spectrograms	ResNet-18 CNN	ResNet-18 CNN-90%
Javier Sanchis et al.	EEG dataset (IEEE data port): 61 ADHD, 60 controls	EEG-MSCNet multiscale CNN with leave-one-out CV	EEG-MSCNet	EEG-MSCNet-88.42%
Md.Maniruzzaman et al.	EEG dataset (IEEE data port): 61 ADHD, 60 controls	Hybrid SVM+ t-test channel selection, LASSO regression	Gaussian Process Classifier, Random Forest, KNN, MLP, Decision Tree, Logistic	Gaussian Process-97.53%

B. ECG- based studies

Chui Ping oui et al. [15] presented an explainable Deep learning model which was based on ECG dataset collected from child Guidance clinic from Singapore that consisted of ECG data collected from 45 ADHD, 62 ADHD+CD, and 16 CD patients. The aim of this model was to distinguish between ADHD, ADHD+CD (Conductive disorder) an CD.

Studies reveal that ADHD is usually associated with conductive disorder. The obtained dataset is used to train one dimensional Convolution Neural Network. The model achieved an accuracy of 96.04 %. Medha Wyavaharae et al [16] captured ECG data using a system that was composed of Bio-Amp EXG Pill sensor, an Arduino microprocessor, and graphical user interface (GUI).

The dataset was given as an input to three machine learning algorithms namely K-Nearest Neighbour (KNN), Logistic Regression, and Support Vector Machine (SVM).

TABLE II. SUMMARY OF STUDIES THAT UTILIZES ECG FOR DIAGNOSIS OF ADHD

Study	**Dataset**	**Key Features**	**Model/Architecture**	**Performance**
Chui Ping oui et al	45 ADHD, 62 ADHD+CD, 16 CD patients	Gradient-weighted Class Activation Mapping (Grad-CAM)	1D CNN	96.04%

C. MRI

MohammadHadi Firouzi et al. [17] developed Skip-Vote-Net, a novel deep learning architecture utilizing dynamic connectivity analysis on resting-state fMRI data from the ADHD-200 dataset. The model was evaluated across four classification scenarios: ADHD versus typically developing children using balanced (98% accuracy) and unbalanced data (99% accuracy), ADHD inattentive versus combined subtypes (99.4% accuracy), and three-class classification among typically developing, ADHD inattentive, and ADHD combined groups (98.86% accuracy), demonstrating robust performance across various diagnostic distinctions.

Eman Salah et al. [18] designed Functional magnet resonance imaging with optical amplification for the detection of ADHD. Significant features are extracted using Convolutional neural networks. It utilized ADHD-200 dataset. Three optimization algorithms namely-Maximum adaptive moment estimation (AdaMax), Accelerated Nesterov adaptive moment estimation and Root mean square propagation were used to improve the classification results. RMSprop gave the highest accuracy of 98.33%.

Byunnggun Kim et al. [19] presented a ADHD Diagnosis transformer which extracts important brain spatiotemporal biomarkers from rs-fMRI. Models were evaluated using the data collected from 939 individuals from all sites provided by ADHD 200 competition. The transformer model had 77.78 % accuracy,76.60 specificity,79.22% sensitivity and 79.30 AUC

Nora Fink [20] developed 3D-CNN for detecting ADHD using 3D MRI scans from ADHD-200 dataset.3DCNN architecture and 3DResnet architecture was implemented that came out with an accuracy of 62.64% and 61.54% respectively.

Elahe Hosseini et al. [21] leveraged VGG16 to extract 2D features from 3D MRI scans, reducing computational demands while enhancing diagnostic capability. They evaluated four architectures (CNN2D, CNN1D, LSTM, GRU), with the LSTM model integrating clinical data achieving 86% accuracy and 0.9 AUC. Zarina Begum et al [22]. developed an optimized temporal denoised convolutional autoencoder (OTDCAE), combining denoising autoencoders for spatial features and temporal networks for classification. Using the ADHD-200 dataset, their model achieved 98.8% accuracy and 98.5% F-score, demonstrating superior performance.

TABLE III. SUMMARY OF STUDIES THAT UTILIZES MRI FOR DIAGNOSIS OF ADHD

Study	**Dataset**	**Key Features**	**Model/Architecture**	**Performance**
MohammadHadi Firouzi et al.	ADHD-200	Dynamic connectivity analysis of resting-state fMRI	Skip-Vote-Net	- ADHD vs TD (balanced): 98% - ADHD vs TD (unbalanced): 99% - ADHD-I vs ADHD-C: 99.4% - Three-class: 98.86%
Eman Salah et al.	ADHD-200	Feature extraction via CNNs; tested AdaMax, Nesterov, RMSprop optimizers	CNN with optimization algorithms	Highest accuracy: 98.33% (RMSprop)
Byunnggun Kim et al.	ADHD-200 (939 subjects)	CNN-based embedding, local temporal attention, ROI-rank masking	ADHD Diagnosis Transformer	Accuracy: 77.78%
Nora Fink	ADHD-200	3D MRI scan processing	3D-CNN, 3DResNet	Accuracy: 62.64% (3D-CNN) 61.54% (3DResNet)
Elahe Hosseini et al.	ADHD-200	2D feature extraction from 3D MRI; integrated clinical data with LSTM	VGG16 + LSTM/GRU	Accuracy: 86%
Zarina Begum et al.	ADHD-200	Denoising autoencoders for spatial features + temporal networks for classification	OTDCAE	Accuracy: 98.8%

D. Others

ShuangLin Li et al [23] extracted audio data from both ADHD patients and normal controls based on diagnostic interview for ADHD(DIVA) that was conducted in adults. Speech recordings were transcribed using Google Cloud Speech API, and both acoustic and deep learning-based linguistic features were extracted. ADHD classification utilized Support Vector Machines and Logistic Regression. The study involved 22 native English-speaking participants: 10 with an ADHD diagnosis (5 males, 5 females) and 12 healthy controls (8 males, 4 females). A multimodal dataset comprising audio, video, historical data/questionnaires, transcribed text data was constructed after study. With SVM classifier and LOSO Cross validation, eGeMaps with Wav2vec2.0 achieved an accuracy of 77.8% on acoustic feature integrated with text. With LR classifier and LOSO Cross validation, eGeMaps with Wav2vec2.0 achieved an accuracy of 78.3% on acoustic feature integrated with text.MD. Maniruzzaman et al. [24] Handwriting/drawing analysis was explored as a biomarker for detecting ADHD in children with comorbid ASD. Handwriting samples from 29 Japanese children (14 ADHD+ASD, 15 neurotypical) were collected via a digitizing pen tablet. Support Vector machines, Logistic regression, Gaussian

Naïve Bayes, Random Forest, Decision Tree, K-nearest Neighbor, Extra Tree were used, out of which Random Forest achieved 93.01 accuracy.

Yichun Li et al. [25] introduced a novel hyperactivity assessment system using the first real-world multimodal ADHD dataset (M-ADHD). By analyzing motion patterns from RGB videos, this non-invasive method detects ADHD traits with superior accuracy and AUC scores compared to existing approaches. The dataset includes five male and five female ADHD subjects and eight male and four female neurotypical controls. 3D CNN was used here. The proposed method achieved an accuracy of 95.5%

TABLE IV. SUMMARY OF STUDIES THAT UTILIZES OTHER DATASET FOR DIAGNOSIS OF ADHD

Study	Modality	Dataset	Key Features/Techniques	Performance
ShuangLin Li et al.	Audio/text analysis	22 adults (10 ADHD/12 control)	Acoustic features + Wav2vec2.0 text embeddings	SVM -77,8% Logistic Regression-78.3%
MD. Maniruzzaman et al.	Handwriting analysis	29 children (14 ADHD+ASD/15 NT)	Digitizing pen tablet kinematic data	Random Forest (best among 7 classifiers)-93.01%
Yichun Li et al.	Video motion analysis	22 adults (10 ADHD/12 control)	3D CNN for RGB video motion patterns	Custom 3D CNN architecture-95.5%

III. DISCUSSION

Attention-deficit/hyperactivity disorder (ADHD) is a chronic condition impacting millions of children and frequently persisting into adult life. Individuals with ADHD commonly experience a combination of persistent difficulties, such as challenges with maintaining focus, excessive activity levels, and impulsive behaviors. In this paper 31 prominent research studies from various scientific repositories from 2023 to May 2025 have been reviewed.

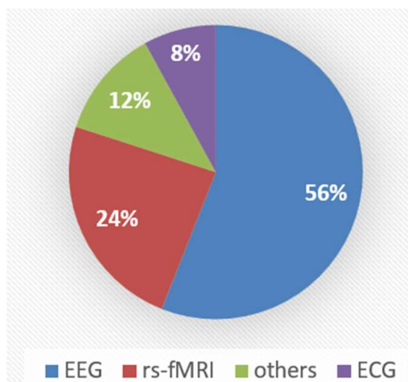

Figure 1. Distribution of studies based on dataset

As we can see, most of the research papers have used EEG signals. The second most used dataset is rs-fMRI. ECG dataset has been used only in very few research studies. Oregon ADHD-1000 dataset, MEG signals and actigraphy is not explored. Audio data, handwriting and raw RGB videos are used rarely in the last two years.

Excellent results are provided by physiological signals like EEG and ECG but using small dataset. From Table 1 out of 14 research studies on EEG signal 7 research studies used EEG dataset from IEEE data port. It consisted of 61 ADHD patients and 60 healthy controls. Some research studies have applied both ML algorithm and DL algorithms on EEG dataset where DL models outperformed the ML models. Out of 14 research studies using EEG dataset, DL models gave excellent results. LSTM while using a limited dataset [4] achieved an accuracy of 97.75 Another remarkable model is LSTM-CNN [6] which achieved an accuracy of 98.86% accuracy on ADHD and 98.28% on FOCUS datasets. ADHD-Attention Net [11] attained an accuracy of 98.56% while SCANet [8] attained an accuracy of 99.52%. The use of ECG signals in research studies has been quite limited over the last two years. When trained on ECG datasets, deep learning models demonstrated high accuracy. Six research studies used rs-fMRI and utilized DL models for ADHD detection. Functional magnet resonance imaging with optical amplification along with optimization algorithm root mean square propagation gave the highest accuracy of 98.33% [17]. Using the ADHD-200 dataset, OTDCAE model achieved 98.8% accuracy and 98.5% F-score, demonstrating superior performance [22]. Many research studies utilized other modalities like audio data, handwriting and motion patterns and utilized basic machine learning algorithms. The Oregon ADHD-1000 dataset is a comprehensive longitudinal repository containing multi-modal MRI scans, cognitive assessments, genetic data, and clinical records. No research studies in past two years have utilized this dataset.

IV. Proposed Methodology

The proposed framework aims to enhance the diagnostic precision of Attention-Deficit/Hyperactivity Disorder (ADHD) and support individualized therapeutic interventions. This study utilizes the Oregon ADHD-1000 dataset—a longitudinal, multi-modal resource comprising structural and functional MRI scans, cognitive assessments, genetic markers, and clinical profiles collected over a 12-year period. The investigation introduces a hybrid deep learning architecture that integrates convolutional neural networks (CNNs) for spatial feature extraction from neuroimaging data, transformer-based encoders for modeling temporal dependencies within longitudinal measures, and attention mechanisms for adaptive multi-modal feature fusion. This design improves diagnostic accuracy by capturing complex neurodevelopmental trajectories and cross-modal associations. Furthermore, the learned embeddings are employed within a recommendation module to personalize pharmacological treatments, such as methylphenidate or atomoxetine, according to each patient's unique neurobiological and behavioural profile.

A. Dataset Description

The Oregon ADHD-1000 dataset includes approximately 1,000 participants, encompassing both children diagnosed with ADHD and neurotypical control subjects. Data collection spans 12 years, providing a rich longitudinal perspective on the disorder's developmental course. The multi-modal data comprise structural MRI (sMRI) and functional MRI (fMRI) scans, enabling detailed analyses of neuroanatomical organization and functional connectivity. Complementary cognitive measures—such as IQ and memory assessments—further characterize cognitive function. Genetic data, represented by single nucleotide polymorphism (SNP) markers, facilitate exploration of heritable risk factors, while detailed clinical records document comorbid conditions and medication histories, supporting individualized treatment modeling.

B. Proposed Model Architecture

The proposed architecture consists of three primary components. First, a Convolutional Neural Network (CNN) module processes sMRI and fMRI volumes through sequences of 3D convolutions, batch normalization, ReLU activations, and max pooling layers to extract spatial representations. Next, a Transformer module models temporal dynamics across longitudinal data by encoding time-series embeddings of cognitive, imaging, and clinical features, incorporating positional encodings and multi-head self-attention to preserve sequential structure and detect developmental trends. Finally, an attention-based fusion mechanism assigns optimal importance to features from each modality using cross-attention, effectively merging spatial, temporal, and clinical information. This integrated approach provides a comprehensive representation of ADHD progression, enabling more accurate and interpretable diagnostic modeling.

V. Conclusion

Deep learning approaches have led to notable progress in the diagnosis and management of ADHD, representing a significant advancement compared to conventional methods. A major obstacle was the limited availability of multimodal datasets, which reduced the effectiveness of deep learning methods in diagnosing ADHD [28]. The reviewed studies show that Deep Learning models generally achieve better results than traditional Machine Learning and hybrid approaches, especially in classification accuracy and predictive power. This highlights the increasing significance of Deep Learning in ADHD research and suggests it should be further investigated to develop more accurate and widely applicable diagnostic tools [31].

Future research should focus on the following areas:

Multimodal Data Integration and Large-Scale Clinical Validation: Researchers should work on gathering and using data from different sources—like EEG, MRI, clinical symptoms, and wearable sensors—together. This will help make AI models for ADHD diagnosis stronger and more reliable. It's also important to test these AI models on large groups of people in real-world situations. This will make sure the models work well for everyone.

Development and Optimization of Smartwatch-Compatible Models: Advancing AI and deep learning models that are compatible with smartwatches and other wearable devices, enabling continuous, non-invasive monitoring and early detection of ADHD symptoms in daily life.

Interpretability and Transparency of AI Models: Making AI algorithms easier to understand is important so doctors can trust and use them in their work. This means creating ways for clinicians to see how the models make decisions and to know which information is most important for diagnosis.
Personalized Treatment Strategies: Leveraging AI to analyse individual patient data and tailor treatment plans, thereby improving outcomes and reducing the risk of overdiagnosis or underdiagnosis.
Addressing Heterogeneity and Sample Biases: It is important for research to include people of different ages, genders, races, and cognitive abilities. This helps reduce bias and makes AI diagnostic tools more useful in real clinical settings.
Integration with Traditional Diagnostic Approaches: Combining AI-driven methods with existing clinical assessments to enhance diagnostic accuracy, efficiency, and effectiveness, while maintaining a patient-centered approach.
These directions will help advance the field toward more objective, reliable, and clinically actionable AI applications for ADHD.

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