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A Comprehensive Review of ADHD: Insights and Technological Interventions in Diagnosis

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Abstract
Attention Deficit Hyperactivity Disorder (ADHD) is a common neurodevelopmental disorder that typically begins in childhood and can persist into adulthood. It is characterized by symptoms of inattention, hyperactivity and impulsivity which can interfere with daily functioning and development. The exact cause of ADHD is not fully understood but is believed to involve genetic, neurological and environmental factors. Diagnosis is typically based on clinical evaluation, behavioral observations and standardized rating scales. The proposed paper aims to conduct a comprehensive review of various Machine Learning (ML) and Deep Learning (DL) techniques applied in the analysis of ADHD as presented in existing literature. It focuses on evaluating and comparing the performance of these techniques to understand their effectiveness. Also the paper discusses different data acquisition modalities such as EEG, MRI, fMRI and others used in ADHD research. By examining these modalities the study highlights their role in supporting accurate diagnosis and analysis. The paper concludes with a statistical summary and performance comparison of the reviewed techniques to offer insights into current trends and potential future directions.

Keywords: Attention Deficit Hyperactivity Disorder, Machine Learning, Deep Learning, Classification Performances

1. Introduction

ADHD [1] is one of the most common neurodevelopmental disorders of childhood. Diagnosed in childhood and often lasts into adulthood. Children with ADHD may have trouble paying attention and controlling impulsive behaviors (may act without thinking about what the result will be). According to DSM-IV [10] the disorder is characterized by inattention, hyperactivity and impulsivity symptoms. The ADHD symptoms may decline over time however more than one half of the ADHD children continue to manifest clinically significant symptoms after reaching adulthood. The paper [2] highlights that ADHD is a genetic neurological disorder that affects both children and adults with symptoms like inattention, hyperactivity, impulsivity and mood instability. Diagnosing adult ADHD involves assessing childhood history and current symptoms often with input from family or close contacts. Treatment typically includes stimulant medications, therapy, behavioral interventions and psychosocial support to help manage the disorder's impact on relationships and daily life. ADHD is linked to decreased dopamine function in the brain and research suggests a strong genetic component.

The paper [3] highlights key sex differences in ADHD presentation with females often exhibiting more inattentive symptoms and less hyperactivity compared to males. ADHD in females is frequently underdiagnosed and recognized later but partly due to male-centric diagnostic criteria. Female with ADHD report difficulties with task organization, excessive talking and impulsivity specifically in adulthood. This study also stresses the need for tailored diagnostic criteria and better recognition of female-specific ADHD symptoms to improve early diagnosis. During 1997 meta-analysis found that ADHD girls showed lower hyperactivity and intellectual impairment compared to boys with gender differences influenced by referral sources. The paper [4] published in JAMA Network Open in June 2024 examines the relationship between social determinants of health and the prevalence of prediabetes among adolescents. The study published in JAMA Network Open explores how social determinants of health influence prediabetes prevalence in adolescents. It found that food insecurity, public health insurance and low household income are associated with higher rates of prediabetes with food insecurity contributing a 4.1% higher prevalence. The study revealed racial and ethnic variations in the relationship between social factors and prediabetes risk. The authors recommend incorporating screening for social determinants of health to better identify adolescents at risk and improve early intervention efforts to prevent type two diabetes.

The paper [5] discusses why ADHD is underdiagnosed in females particularly in childhood due to differences in symptom presentation and biases in recognition. Existing diagnostic criteria are based on male symptoms and often overlook the inattentive type of ADHD more common in females. This has resulted that females are more likely to be misdiagnosed with anxiety or depression and delaying ADHD identification. Sociocultural factors also contribute as gender expectations lead females to develop coping strategies that mask symptoms. Also this paper advocates for research into sex-specific diagnostic criteria and better clinical practices to ensure early recognition and treatment of ADHD in females. The paper [6] investigates how ADHD affects brain network interactions beyond traditional pairwise connections. Using EEG data from 22 boys with ADHD and 22 healthy boys observing facial emotions study constructs brain hyper-networks based on higher-order interactions. The analysis reveals significant differences in the frontal, right temporal and occipital brain regions by suggesting altered connectivity patterns in ADHD. These findings provide deeper insights into ADHD-related brain network dysfunction could help refine diagnostic and therapeutic approaches. The paper [7] explores the integration of ChatGPT in ADHD therapy. Here experts have involved Delphi method to evaluate ChatGPT's ability to assist in therapy sessions, highlighting its empathy, adaptability and engagement. The study found that ChatGPT can improve accessibility and personalization in ADHD care but identified privacy concerns, cultural sensitivity issues and the inability to interpret nonverbal cues as key challenges. The authors propose integrating ChatGPT into robotic assistants for enhanced therapy while emphasizing the need for ongoing improvements in AI-driven mental healthcare. The paper [8] explores the positive traits linked to ADHD beyond its traditionally studied challenges. Using a large UK-based sample (n=694) the study quantitatively assesses ADHD-related strengths like hyperfocus, cognitive flexibility and sensory processing sensitivity. Results show positive correlations between ADHD traits and these strengths, while perseverance and sociability were negatively correlated. The study highlights the potential of strength-based approaches in ADHD treatment and psychoeducation then advocating for a more balanced understanding of ADHD in both clinical and social contexts. The paper [9] investigates whether individuals with ADHD also engage in camouflaging behaviors which are strategies used to hide neurodivergent traits. The study found that adults with ADHD report more camouflaging than neurotypical individuals but less than autistic adults. Autism traits rather than ADHD traits were the strongest predictor of camouflaging. The findings highlight the need for broader measures of camouflaging beyond autism and suggest that camouflaging could contribute to mental health difficulties and delayed diagnoses in ADHD. The Diagnostic and Statistical Manual of Mental Disorders (DSM-IV, 1994) [10] by the American Psychiatric Association outlines the classification and diagnostic criteria for various mental disorders, including ADHD. Key points include the refinement of ADHD's diagnostic criteria, emphasizing symptoms of inattention, hyperactivity and impulsivity which must be present in multiple settings and cause functional impairment. Statistical analysis in the DSM-IV shows an increasing recognition of ADHD in clinical settings with a noted rise in diagnoses particularly in children. The manual also highlights the growing use of stimulant medications and behavioral therapies in treating ADHD. The revised criteria aimed to standardize diagnosis by improving consistency across professionals and reducing misdiagnosis.

The paper [11] presents a model for detecting ADHD in children using EEG signals, employing Variational Mode Decomposition (VMD) and Hilbert Transform (HT) to extract relevant features. The study utilizes both explainable "glass-box" and "black-box" models for ADHD detection and integrating local explanations with LIME & SHAP and global explanations using Partial Dependence Plots (PDP) and Morris sensitivity analysis. Statistical evaluation reveals strong model performance with high accuracy and reliability across various qualitative and quantitative metrics. Also paper highlights the potential of combining explainability with machine learning techniques for more transparent ADHD diagnosis in children.

2. Machine learning approaches for ADHD

This survey reviews recent studies employing machine learning techniques across various modalities such as MRI, EEG and behavioural data to enhance the diagnosis, classification and understanding of ADHD.

The paper [12] explores the use of machine learning techniques to classify adults with ADHD. The authors apply various algorithms to identify patterns in neuropsychological data aiming to improve diagnostic accuracy for ADHD in adults. The study emphasizes the potential of these methods to distinguish ADHD from other conditions with similar symptoms offering a more objective and efficient diagnostic tool. The authors also note the importance of large diverse datasets to enhance model generalization and accuracy. The paper [13] explores the application of machine learning techniques to better understand the neural mechanisms underlying ADHD. It highlights about ML methods particularly neuroimaging and electrophysiological data analysis offer novel insights into ADHD by identifying biomarkers that distinguish affected individuals from healthy controls. The authors discuss the use of supervised and unsupervised learning models in analysing brain activity patterns and how these can reveal neurobiological markers associated with the disorder. Also the study emphasizes the potential of ML in improving diagnosis then understanding ADHD's complexity and informing personalized treatment strategies. Also highlights the challenges of integrating diverse datasets and the need for large and multi-site studies to enhance the generalizability of findings. The paper [14] investigates the potential of ML techniques to classify adult ADHD using data from the Conners' Adult ADHD Rating Scales (CAARS). The study applies various ML models including SVM and random forests to distinguish between ADHD and other psychological conditions. The results show that the ML approach provides promising diagnostic accuracy particularly in identifying ADHD in adults offering potential improvements over traditional clinical assessment methods. Also the authors highlight the importance of incorporating multiple clinical factors and large datasets to enhance the robustness and generalizability of ML models for ADHD diagnosis. This study suggests that ML could aid in personalized treatment strategies and further research is needed to refine these methods for broader clinical application.

The paper [15] explores the use of real-time activity data to accurately identify ADHD in adults. The authors employ wearable sensors to collect data on activity patterns such as physical movement and behaviour which are then analysed using machine learning algorithms. The study finds that real-time activity data when combined with appropriate ML models can achieve high classification accuracy making it a promising tool for non-invasive objective ADHD diagnosis. Also the authors discuss the potential of this approach in providing continuous monitoring, improving diagnostic precision and aiding in personalized treatment plans. They emphasized the need for larger studies to validate the generalizability and effectiveness of these findings in clinical settings.

The paper [16] explores the use of ML models to improve the diagnosis of ADHD. The authors apply several ML algorithms including Decision Trees, Support Vector Machines, and Random Forests to classify ADHD based on clinical and behavioural data. The results show that ML models especially random forests outperform traditional methods in terms of classification accuracy. This approach provides an objective and scalable solution for ADHD diagnosis offering higher reliability and efficiency. The authors highlight the importance of integrating large datasets to improve the models generalizability and clinical utility in real-world settings. The paper [17] investigates the use of ML techniques to differentiate ADHD from control groups based on Event Related Potential (ERP) data. The study applies various ML algorithms including SVM and Random Forests to ERP data collected from ADHD patients and healthy controls. The results indicate that ML models can effectively classify ADHD with ERP features providing valuable discriminative information. The study highlights the potential of using ERP as a neurophysiological marker in conjunction with ML models to improve ADHD diagnosis. Also the authors suggest that these models could be integrated into clinical practice for faster and more accurate ADHD detection.

The paper [18] explores the development of a ML classifier using real-world clinical data from medical records to identify ADHD. The authors apply various ML algorithms including Random Forests and SVM to analyse medical data such as patient history, diagnostic codes and other clinical features. The results show that the ML classifier accurately identifies ADHD cases from medical records demonstrating the potential for integrating ML into clinical workflows for more efficient diagnosis. The paper [19] explores the application of ML techniques in detecting ADHD using resting-state functional Magnetic Resonance Imaging (rsfMRI) data. The authors review various ML algorithms including SVM, Random Forests and Neural Networks that have been applied to analyse rsfMRI signals for ADHD diagnosis. Also the paper highlights challenges related to data variability, pre-processing and feature selection which impact the performance of these models. It also emphasizes the importance of cross-validation and robust evaluation techniques to ensure the generalizability of findings across different datasets. The author suggesting the potential of combining rsfMRI data with other modalities to improve ADHD detection and prediction accuracy. The paper [20] provides an in-depth review of various ML techniques used in the diagnosis of ADHD using big data. The authors examine several ML algorithms including DT, RF, SVM and Neural Networks highlighting their strengths and weaknesses in handling large-scale ADHD datasets. The study emphasizes the importance of feature selection and preprocessing techniques to improve model performance including dimensionality reduction and data normalization. Also it discusses the challenges posed by imbalanced datasets and the need for robust validation techniques to ensure the generalization of models. The author suggested for future research directions including the integration of multimodal data and the exploration of deep learning models to further enhance ADHD diagnosis. The dissertation [21] systematically reviews the use of ElectroEncephaloGraphy (EEG) data combined with ML techniques for ADHD classification. The study evaluates various ML algorithms such as SVM, Random Forests and Deep Learning models examining their effectiveness in classifying ADHD based on EEG signals. The review highlights the significance of feature extraction techniques such as power spectral analysis and connectivity measures in improving classification performance. It also addresses challenges related to small sample sizes, inter-individual variability and the need for standardized EEG protocols to enhance model robustness. The paper suggests by recommending further research into multimodal approaches that combine EEG with other biomarkers for more accurate ADHD diagnosis. The paper [22] investigates the role of specific brain regions in classifying ADHD using EEG signals combined with ML techniques. The authors analyse various ML models such as SVM and Random Forests to assess their ability to identify ADHD related patterns in brain activity. The study identifies key brain regions such as the prefrontal cortex and parietal regions whose activity significantly contributes to the classification performance. The paper also discusses the impact of feature extraction methods like coherence and connectivity analysis on model accuracy. The authors emphasize the potential for improving ADHD diagnosis by focusing on brain regions with distinct activity patterns suggesting further research into more advanced ML techniques for better precision. The paper [23] explores the use of dual modal sensory data such as physiological and behavioural signals combined with ML algorithms for the automated detection of ADHD. The authors implement various ML models including DT, SVM and DL networks to analyse these sensory data for ADHD classification. The paper emphasizes the importance of feature selection and fusion of different sensory modalities to enhance the reliability of the detection system. It also addresses the challenges of data noise, imbalanced datasets and the need for robust validation techniques. The study suggested that dual modal approaches could provide a more comprehensive and accurate method for ADHD diagnosis by encouraging future exploration into multi-sensory data integration. The paper [24] investigates the use of ML to predict the effectiveness of mobile neurofeedback therapy in treating children with ADHD. The authors apply various ML algorithms to analyse data from neurofeedback sessions and predict therapeutic outcomes. The study finds that specific EEG features related to brainwave patterns play a crucial role in forecasting therapeutic efficacy. It also highlights the importance of personalized treatment approaches and the potential of mobile neurofeedback as a viable intervention for ADHD. The paper recommending further research into integrating additional biomarkers and refining ML models to enhance prediction accuracy and treatment outcomes.

The paper [25] explores the potential of retinal fundus imaging as a novel biomarker for ADHD. The authors apply ML algorithms specifically Convolutional Neural Networks (CNNs) to analyse retinal images and identify distinct features that could differentiate individuals with ADHD from healthy controls. This study suggests that certain retinal characteristics like vascular patterns and optic nerve head abnormalities can be indicative of ADHD and supporting the use of retinal imaging as a non-invasive diagnostic tool. The authors also explore the potential of using retinal images to stratify individuals based on visual attention which is a key component of ADHD. The paper [26] explores the application of ML techniques to identify ADHD in university students at an early stage. The study utilizes various ML models, including decision trees, support vector machines (SVM) and logistic regression to analyse behavioural, cognitive and demographic data for accurate prediction. The findings suggest that certain behavioural indicators including inattention and impulsivity are significant predictors of ADHD in the university population. The paper advocates for the use of machine learning as a non-invasive, cost-effective tool for early detection, which can lead to timely interventions. De Silva concludes by recommending future research to refine the models and explore the inclusion of additional data sources to improve diagnostic precision. The paper [28] introduces an advanced machine learning approach for ADHD classification using functional magnetic resonance imaging (fMRI) data. The authors propose an optimized Temporal Denoised Convolutional Autoencoder (TDCAE) model, designed to enhance the classification accuracy by reducing noise and capturing temporal patterns in fMRI data. The study emphasizes the importance of preprocessing techniques particularly temporal denoising in improving the signal-to-noise ratio and enhancing model performance. The paper also highlights the ability of the convolutional autoencoder to automatically learn relevant features from fMRI data by reducing the need for manual feature extraction. The authors suggest that their approach offers a promising framework for improving ADHD diagnosis using neuroimaging data with potential applications in clinical settings.

3. Deep Learning approaches for ADHD

This survey explores recent advancements in the application of DL techniques across multiple data modalities such as MRI, EEG and behavioural assessments for the analysis and understanding of ADHD.

The paper [27] explores the application of both ML and deep learning (DL) algorithms for diagnosing ADHD. The authors compare various algorithms, including decision trees, random forests, support vector machines (SVM) and deep neural networks (DNN) to assess their performance in ADHD classification. The paper also discusses the importance of data preprocessing and feature selection in improving model performance. The authors emphasize that while deep learning models yield better results the complexity and computational cost of these methods need to be considered. Also the study suggests further research to refine these algorithms and explore hybrid models for enhanced ADHD diagnosis. The paper [29] provides a comprehensive review of unconventional Artificial Intelligence (AI) methods used in the diagnosis of ADHD. The authors discuss various AI techniques including machine learning, deep learning and hybrid models exploring their potential in addressing the complexities of ADHD diagnosis. The paper emphasizes innovative approaches like the use of multimodal data (e.g., neuroimaging and behavioural data) and the application of explainable AI (XAI) for greater transparency in decision-making. The paper also addresses challenges such as data imbalance, model interpretability and the need for large and diverse datasets. The paper advocates for further exploration of unorthodox AI methods to refine ADHD diagnosis and recommends combining AI with traditional diagnostic techniques for better clinical outcomes.

The paper [30] investigates the use of text data and advanced ML and DL algorithms for diagnosing ADHD. The authors focus on extracting relevant features from text such as linguistic patterns, sentiment and word frequencies which are indicative of ADHD symptoms. The study demonstrates that text-based features when coupled with predictive algorithms can significantly improve diagnostic accuracy for ADHD. The authors suggest that this approach offers a non-invasive and scalable solution that could be integrated into clinical settings particularly for large scale screenings or in resource-limited environments.

The paper [31] presents a DL framework for diagnosing ADHD. The authors apply various DL models particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to process and classify clinical data associated with ADHD. The results show that DL models combining CNN and RNN architectures outperform traditional ML models in terms of diagnostic accuracy. The study highlights the effectiveness of DL in handling complex high-dimensional clinical data offering an automated and more accurate diagnostic tool for ADHD. The authors also emphasize the potential for integrating this approach into clinical practice aiding in faster and more reliable ADHD detection.

The paper [32] investigates the use of 3D CNNs for classifying ADHD from neuroimaging data. The study applies DL models to analyse brain imaging data specifically focusing on 3D scans to identify patterns associated with ADHD. Statistical analyses including accuracy sensitivity, specificity and Area Under Curve (AUC) show that the 3D CNN models achieve an accuracy of over 60% with a notable improvement compared to traditional classification methods. Fink highlights the importance of optimizing the DL architecture to handle complex, high-dimensional neuroimaging data and improve model performance. The study also discusses challenges such as data variability and the need for large balanced datasets to enhance model reliability. Author suggesting further research to refine DL techniques and explore additional features such as genetic or behavioural data for more precise ADHD classification.

The paper [33] focuses on the development of an explainable AI (XAI) framework to assist psychologists in diagnosing ADHD. The authors introduce a DL model that not only provides accurate predictions but also offers interpretable insights into the factors influencing ADHD diagnosis making the model more accessible and understandable for clinical practitioners. The study emphasizes the importance of transparency in AI models allowing psychologists to trust the systems decisions and incorporate them into their clinical practice. The paper discusses how the explainable nature of the model helps clinicians better understand the underlying patterns in patient data such as cognitive and behavioral features that contribute to the diagnosis. Authors recommend expanding this framework for broader use in clinical settings to enhance the diagnostic process for ADHD and other neurodevelopmental disorders.

The paper [34] presents a novel framework combining functional Magnetic Resonance Imaging (fMRI) data with CNNs to improve the accuracy of ADHD diagnosis. The authors propose an advanced classification approach that integrates fMRI data with CNNs to extract relevant brain features and enhance diagnostic precision. The study highlights the effectiveness of using DL techniques for analysing complex neuroimaging data and identifying ADHD-related brain patterns. The authors also address the importance of preprocessing fMRI data such as denoising and normalization to improve model performance. The author suggests that this high-precision approach could significantly support clinical decision-making in ADHD diagnosis with potential for broader applications in neuroimaging based mental health assessments.

Table 1: Performance analysis of ML and DL techniques on various modalities

AUTHOR	TECHNIQUES	MODES	PERFORMANCE ANALYSIS
Meng Cao et. al.[13]	Machine Learning (ML)	Neuroimaging Modalities	SVM: 69% to 91%, LDA: 23.8%, DSM IV-based groups 95.2%, Gaussian Process Classifier: 77%.
Hanna Christiansen et. al. [14]	ML	Data from the Conners' Adult ADHD Rating Scales	**LightGBM Model**: Training Data: global accuracy of 80%, *Test Data:* global accuracy of 71%
Amandeep Kaur et. al. [15]	ML	Health activity and heart rate dataset	**SVM:** *Accuracy:* 98.43% , *Sensitivity:* 98.33% , *Specificity:* 98.56% , *F-Measure:* 98.42%, Area Under Curve (*AUC):* 0.983 ***RF:*** Accuracy of 97.25% with an AUC of 0.999, ***kNN:*** Accuracy of 97.65%, ***Decision Tree:*** Accuracy of 95.29%, ***Naïve Bayes:*** Lowest accuracy at 80.39%, ***LogitBoost:*** Accuracy of 89.02%
Nizar Alsharif et. al.[30]	ML	event-related potential (ERP), EEG	**SVM:** Accuracy: 91%, Precision: 92%, Recall: 91%, F1-score: 89% **MLP:** Accuracy: 89%, Precision: 87%, Recall: 89%, F1-score: 87% **RF:** Accuracy: 87%, Precision: 85%, Recall: 87%, F1-score: 85% **DT:** Accuracy: 78%, Precision: 78%, Recall: 78%, F1-score: 73%
Pavol Mikolas et. al. [18]	ML	Ophthalmological and ENT evaluations, EEG	**Full Feature Set Classification:** Accuracy: 66.1%, Sensitivity: 66.9%, Specificity: 65.4%, AUC: 0.66 , **Reduced Feature Set Classification:** Accuracy: 68.1%, Sensitivity: 63.3%, Specificity: 73.9%, **AUC:** 0.696, **Demographic Exclusion Analysis:** Accuracy: 65.1%, Sensitivity: 64.7%, Specificity: 65.4%, AUC: 0.663
Ayshin Rasi[21]	ML	EEG and its segmentation	Reported Accuracy Range: From 60% to 98%, **SVM:** Achieved 80–90% accuracy, **Random Forest and KNN:** Above 75%, **Deep learning (CNN/ANN):** Accuracy up to 94–95%.
Manjusha Deshmukh et. al. [22]	ML	EEG.	RF: 84.21%, DT: 78.95%, SVM: 73.68%, AdaBoost: 73.68%, Naive Bayes (NB): 68.42%, KNN) 63.15%, LDA: 63.15%
Yanqing Ji et. al. [23]	ML	Use of dual-modal sensory data: specifically, Electrodermal Activity (EDA), Heart Rate Variability (HRV) and Skin Temperature (ST)	**SVM:** Accuracy of 81.6%, Sensitivity: 81.4%, Specificity: 81.9%, **Random Forest:** Accuracy: 78.2%,Sensitivity: 77.9%,Specificity: 78.6%, **Logistic Regression:** Accuracy: 75.0%,Sensitivity: 74.8%,Specificity: 75.2%, **KNN:** Accuracy: 72.9% ,Sensitivity: 71.3% , Specificity: 74.5%
Junwon Kim et. al. [24]	ML	Quantitative Electroencephalography (qEEG), Mobile Neurofeedback (MNF), EEG	**ML model:** Accuracy rate of 99.7% in predicting therapeutic responses.
Senuri De Silva et. al.[26]	ML	Uniform Manifold Approximation and Projection (UMAP), Receiver Operating	**Logistic Regression and CatBoost:** Accuracy of 76.67%, **XGBoost:** Accuracy of 68.89%.

		Characteristic (ROC) curve, Digital Medicine	
Elham Ghasemi et. al.[17]	Deep Learning (DL)	ERP signals	**GLM and LR:** Achieved accuracies and AUCs exceeding 99.85% and 0.999, **Deep Learning:** accuracies around 98.15% to 100% across different frequency bands. **SVM:** accuracy up to 98.15%. **DT:** accuracy up to 97.22%. **RF and NB:** Exhibit accuracies around 83% and 78.7%, respectively.
Abdul Rehman et. al.[33]	DL	Neuroimaging data by INDI	**Binary Classification:** F1-score of 99%. **Multi-Class Categorization:** F1-score of 94.2%.
Zarina Begum et. al.[28]	DL	rs-fMRI	Accuracy: Accuracy of 98.8%, F1-Score of 98.5%, **Training Data Utilization:** 90% of the ADHD-200 dataset
Nizar Alsharif et. al. [16]	ML and DL	EEG	Random Forest Classifier: *F1-Score:* 84% , *AUC:* 81%
Nizar Alsharif et. al. [31]	ML and DL	EEG	SVM with PCA Features: 94.86% accuracy, The CNN-BiLSTM and GRU : accuracy of 94.50% and 95.59%
Gurcan Taspinar et. al. [19]	ML and DL	Resting-state functional magnetic resonance imaging (rsfMRI), fMRI, ENT evaluations, EEG	**SVM classification:** Average accuracy of 66.1% , SD = 8%, Sensitivity = 66.9%, Specificity = 65.4%, AUC = 0.66. **Secondary classification without demographic features:** Accuracy of 65.1% Sensitivity = 64.7%, Specificity = 65.4%, AUC = 66.3%. **Secondary classification without missing data:** The SVM achieved an accuracy of 68.8% (SD = 8.5%, sensitivity = 63.3%, specificity = 73.9%, AUC = 69.6%).
Rohini B. R. et. al.[20]	ML and DL	fMRI, PCA, t-SNE and Autoencoders	**SVM:** Accuracies ranging from 70% to 90%, ELM Performance: 85%, **Deep Learning**: Accuracy of 90%.
Nizar Alsharif et. al.[30]	ML and DL	Textual data from the Reddit platform	**Random Forest:** F1-Score: 84%, AUC: 81% , **SVM: Lo**wer performance compared to Random Forest, **MLP:** Showed moderate results, **GRU and LSTM:** Deep learning models that demonstrated varying performance levels.
Hangnyoung Choi et. al. [25]	ML and DL	Retinal Fundus Photography, Comprehensive Attention Test (CAT), Noninvasive imaging technique	**XGBoost:** Area Under the Receiver Operating Characteristic Curve (AUROC) of 96.9%, Sensitivity of 91.6%, Specificity of 92.0%, **Executive Function Stratification:** The visual selective attention (VSA) subdomain exhibited the highest median AUROC of 87%, A**uditory Selective Attention (ASA)** subdomain showed lower performance
Eman Salah et. al.[34]	ML and DL	fMRI	**RMSProp Optimization:** Accuracy at 98.33%, **ResNet:** Accuracy of 95.83%, **GoogleNet:** Accuracy of 93.55%.
Amna Zaheer et. al.[29]	ML, DL and Explainable AI (XAI)	Neuroimaging data, fMRI, EEG	**DL: Highest Accuracy of** 90%

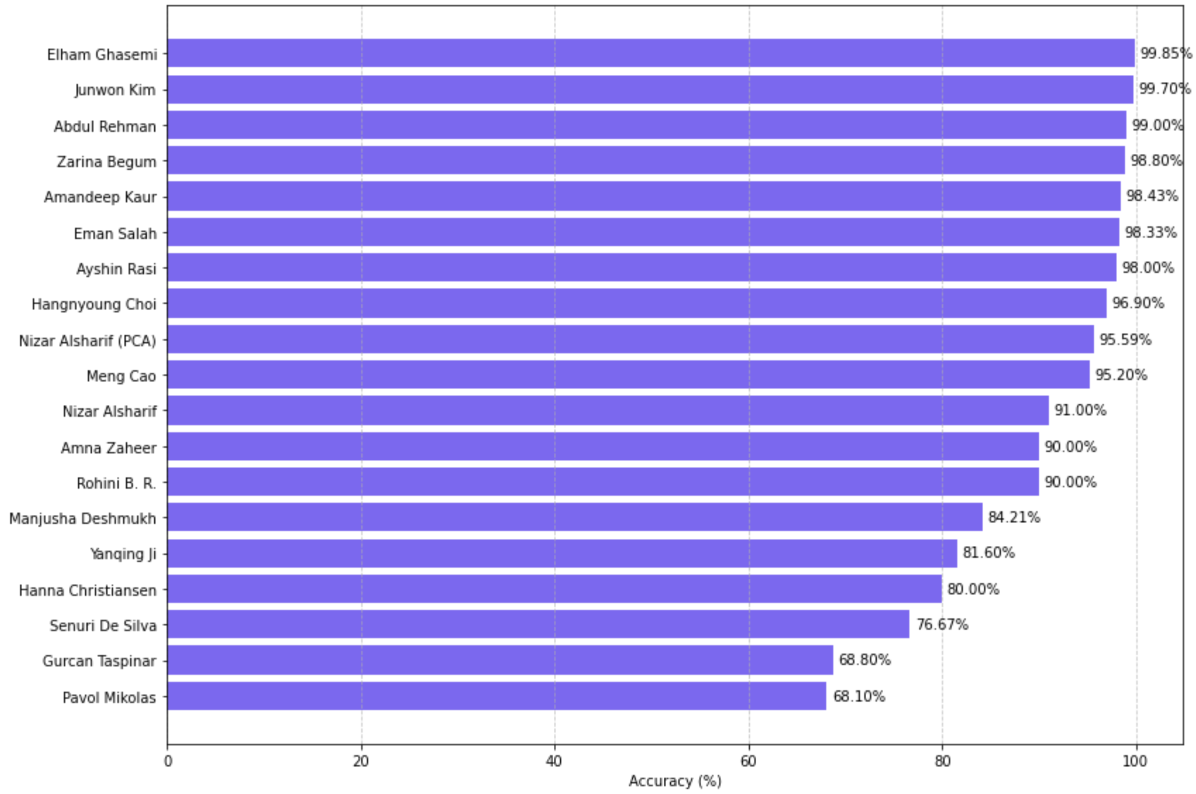

Figure 1: Comparison of proposed models based on maximum accuracy of the classification

Table 1 summarizes the various ML, DL and Hybrid models on ADHD detection along with their performance accuracies. This summary neatly presents the overall development of the computing models corresponding to detection and analysis of ADHD using various modalities. Figure 1 indicates the maximum accuracies of the various ML, DL and Hybrid models proposed by authors from the survey. The bar graph plotting the literatures in order based on accuracies of the proposed models. It also indicating that deep learning model are outperforming comparing machine learning and hybrid models.

Conclusion

This paper presents a thorough review of current research involving the application of ML, DL and Hybrid techniques in the diagnosis and analysis of Attention Deficit Hyperactivity Disorder. Through detailed comparison and evaluation the survey highlights the strengths and limitations of various computational approaches used in conjunction with various data modalities such as EEG, MRI and fMRI. These technologies play a crucial role in enhancing the accuracy and reliability of ADHD diagnosis. The findings from the reviewed literature indicate a clear trend towards Deep Learning models consistently outperform traditional Machine Learning and hybrid methods in terms of classification accuracy and predictive power. This observation underscores the growing importance of DL in advancing ADHD research and supports its continued exploration for more precise and scalable diagnostic tools. The paper concludes by summarizing performance metrics across different models and providing valuable insights that can inform future developments in this evolving field.

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