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Research paper

A Review of Challenges, Advancements, and AI-Driven Approaches for Mental Disorder ASD and ADHD Detection

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Abstract

Autism Spectrum Disorder (ASD) and attention deficit hyperactivity disorder (ADHD) are neurodevelopmental conditions that frequently co-occur with mental illnesses such as anxiety, depression, schizophrenia, and bipolar disorder. The complexity of these disorders, coupled with overlapping symptoms, presents significant challenges in accurate diagnosis and effective intervention. Traditional diagnostic methods rely on symptom-based assessments, which are often subjective and prone to misdiagnosis or underdiagnosis. In recent years, artificial intelligence (AI) and deep learning have emerged as promising tools for enhancing diagnostic precision by leveraging neuroimaging (MRI, fMRI), speech, and text-based data. This survey provides a comprehensive review of state-of-the-art AI-driven approaches for diagnosing ASD, ADHD, and associated mental illnesses. It explores the integration of multimodal data sources, discusses current challenges in AI-driven mental health assessments, and highlights ethical and privacy concerns. Furthermore, the paper identifies key research gaps, including the need for large-scale multimodal datasets, improved model interpretability, and real-world clinical validation. By bridging the gap between computational intelligence and clinical practice, this survey aims to pave the way for more accurate, scalable, and personalized mental health diagnostics, ultimately improving early detection and treatment outcomes for individuals with ASD, ADHD, and comorbid conditions.

Keywords: *AI-driven Mental Health Diagnosis, Multimodal Neuroimaging Analysis, Deep Learning in Psychiatry, ASD and ADHD Classification, Ethical AI in Mental Healthcare*

1. Introduction

Mental health conditions represent the largest portion of the worldwide disease-related burden. A substantial number of children and adolescents worldwide experience mental health problems, accounting for between 10% and 20%. Diagnosing mental diseases globally requires effective methods for identifying patients. Current mental illness diagnoses, based on symptom-based criteria from the Diagnostic and Statistical Manual of Mental Disorders, are incompatible with acceptable standards of care. The assessment process, which relies on personal observation and subjective decision-making, results in both incorrect and generalized diagnoses of mild conditions, according to recent research [1]. The wide range of prevalence figures concerning adult ASD mental health is attributed to varying research methodologies used in individual studies. These include differences in sampling (e.g., size, bias, and inclusion of clinical samples), challenges in diagnosing individuals with limited communication (e.g., difficulty expressing emotions), and difficulties in distinguishing symptoms of mental illness from ASD symptoms. However, it is widely accepted that mental illness in adults with ASD is more common than in the general population and is associated with long-term negative outcomes. Overrepresentation is evident in neuropsychiatric disorders such as psychotic, mood, anxiety, attention deficit hyperactivity, tic disorders, and catatonia. This overrepresentation, along with the reported rise in ASD prevalence, highlights the importance of general practitioners (GPs) in recognizing and managing mental illness in individuals with ASD [2].

People with autism spectrum disorder experience persistent problems in social interaction, along with inflexible patterns of behavior and restricted interests. Findings on autism prevalence in children vary based on study methods and national contexts but indicate that autism affects approximately 1% of children. Experts recognize a childhood autism prevalence of 1%, even though this figure has increased since the 1970s. The combination of expanded diagnostic services, increased parental and professional awareness, broader diagnostic criteria, and potentially actual prevalence growth likely explains this rise. People with ASD primarily receive services from pediatric providers, despite reported insufficient care for adults with ASD. Key barriers to quality care for adults with ASD include inadequate preparedness among healthcare staff regarding ASD, inconsistent ASD identification by professionals, a lack of dedicated autism mental health resources, and poor interagency communication and coordination [3].

Healthcare practitioners working with adult ASD patients have expressed a need for additional training in providing care to adults with ASD. Research involving 1,580 physicians showed that 23% had never received any dedicated ASD training, demonstrating a lack of understanding and a need for improved education on developmental disabilities throughout medical training. Adults with ASD represent a heterogeneous population; individual skills and challenges vary significantly and are influenced by environmental factors, available supports, and stressors. The prevalence of ASD in adults has been reported to be approximately 1%, which is similar to the rate in children. This article describes mental illness in adults with ASD and outlines specific considerations that general practitioners (GPs) could implement to improve consultations with adults with ASD. Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors [4].

Research studies demonstrate a strong association between autism and various mental disorders, including anxiety, depression, obsessive-compulsive disorder (OCD), and schizophrenia. This review explores a broad range of established scientific literature on autism spectrum disorder co-occurring with mental health issues to highlight diagnostic challenges, treatment methods, and therapeutic approaches. The research evaluates biological, psychological, and environmental factors affecting this intersection, along with their implications for clinical practice and research. Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition that affects millions of people worldwide, with its prevalence continuing to rise. Individuals with ASD often exhibit communication difficulties and repetitive behaviors as primary symptoms, but many also experience multiple co-occurring mental illnesses. Those diagnosed with anxiety disorders, depression, bipolar disorder, OCD, and schizophrenia face significant challenges in diagnosis and treatment, and their overall quality of life is often compromised [5].

Traditional diagnostic methods fail to recognize overlapping symptoms between autism spectrum disorders and mental health conditions, leading to underestimation or missed diagnoses in autistic patients. Many standard mental health therapies also fail to deliver adequate results for autistic individuals, as they process information differently and display unique sensory responses and communication patterns. There is a critical need to understand the relationship between autism and mental illnesses to develop specialized interventions that improve mental health outcomes based on the needs of autistic individuals.

The mental health condition known as Attention Deficit Hyperactivity Disorder (ADHD) has recently gained more recognition, despite receiving less public attention compared to the previously mentioned conditions. Adults with ADHD often delay essential tasks related to daily life and cognitive work [6]. Brain development issues caused by ADHD lead to significant impairments in social functioning and cognitive abilities. Research has shown that individuals with ADHD face a higher likelihood of divorce and involvement in criminal activity, resulting in arrests, convictions, and even reduced life expectancy.

Medical professionals such as psychiatrists and pediatricians conduct diagnostic assessments to determine whether individuals meet the DSM-5 criteria, which include the presence of five or more symptoms related to inattention and impulsivity/hyperactivity. Diagnosis of ADHD is often significantly delayed due to a global shortage of specialists in these fields. According to statistics from the UK, one psychiatrist serves approximately 100,000 people. The British Broadcasting Corporation (BBC) reports that 1.5 million UK adults have ADHD, but only 120,000 have received a diagnosis, with wait times for an official assessment extending up to seven years.

Adults with ADHD may exhibit irritability, emotional instability, increased activity levels, thoughtfulness, and paranoia—symptoms that overlap with DSM-V criteria for anxiety and bipolar disorder—making diagnosis even more challenging. The subjective nature of ADHD rating scales can lead to inflated perceptions of prevalence among healthcare providers. Recent research indicates that ADHD remains relatively overlooked in adults, despite affecting 7.2% of children and showing a lower prevalence rate of 2.58% among adults worldwide [7]. These components underline the need for screening ADHD in adults to minimize its harmful consequences on personal well-being and communities. Mental disorders highlight the complex nature of mental health data, as they rely on self-disclosure through specific techniques. Machine learning (ML) and deep learning (DL) have introduced a new paradigm for extracting knowledge from complex data over the past decades, and many ML- and DL-based techniques have been developed for healthcare applications, including mental healthcare, with considerable success. Studies specifically utilizing supplemental data for the diagnosis of ADHD include magnetic resonance imaging (MRI), electroencephalography (EEG) [8], and electrocardiograms (ECG). However, since these methods require expert radiologists and specialized equipment such as MRI scanners and EEG helmets, such physiological signals are costly to obtain.

Because of their accessibility, non-invasiveness, and richness of information [9], audio and text modalities have recently attracted growing interest in mental health diagnosis. Unlike physiological signals, human speech conveys not only verbal (linguistic) content, such as words, but also nonverbal (paralinguistic) information, including tone of voice, which is sensitive to subtle changes in the speaker's physiological condition and mental state. Adults with ADHD, for example, often exhibit slight variations in speech output, increased speech rate, and changes in motion rhythm compared to non-ADHD control subjects. Furthermore, as outlined in the DSM-5, individuals with ADHD may demonstrate communication issues such as excessive, inappropriate talking and speaking loudly and rapidly. Nevertheless, several challenges remain in applying ML and DL to mental health detection, including data scarcity, the lack of personality variables, and difficulties in extracting meaningful features from multiple data sources [10]. Figure 1 presents a comparison between Structural MRI (sMRI) and Functional MRI (fMRI), two widely used neuroimaging techniques. sMRI provides high-resolution images that help identify structural abnormalities such as tumors, atrophy, or lesions [3]. The left side (a) displays the anatomical structures of the brain. These images are used to support the diagnosis of neurological diseases and to delineate brain anatomy. In contrast, fMRI scans capture the dynamic functioning of the brain; red hues indicate areas of increased blood flow and neural activity. The application of fMRI plays a critical role in studying neural connectivity, brain function, and mental processes, as it can detect changes in blood oxygen levels. While sMRI focuses on structural aspects, fMRI is primarily used to examine brain function and its associated networks. Table 1 presents the different mental disorders, and this table highlights that while pharmacological approaches typically follow general treatment recommendations, psychological therapies are often preferred or recommended, though evidence for their effectiveness varies across conditions.

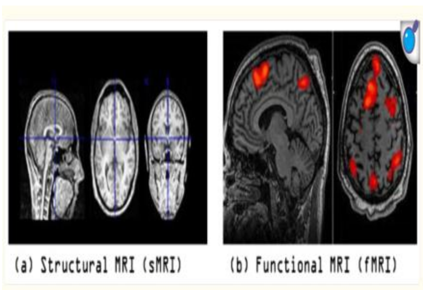

Fig. 1: Difference between structural MRI and functional MRI

Table 1: Survey Table

Mental Illness	Pharmacological Treatment	Psychological Treatment
Anxiety disorders	Psychological therapies are recommended as first-line management	Some evidence for cognitive behavioral therapy (CBT) in treating children and adolescents with autism and anxiety
Depression	Follow general treatment recommendations.	A structured form of psychotherapy, including CBT, is often suggested, but evidence of effectiveness is limited.
	Psychological therapies are first-line for mild depression.	
	SSRIs can treat depression and aggression.	
	Lithium may help if the underlying bipolar disorder is suspected or in cases of high impulsivity and aggression.	
Bipolar disorder	Follow general treatment recommendations.	No clear evidence base, but psycho-education, cognitive, and mindfulness-based therapies may be beneficial.
	Lithium may be useful with mood stabilizers like sodium valproate and carbamazepine.	
	Atypical antipsychotics like quetiapine and olanzapine may be helpful adjuncts.	
Schizophrenia or schizoaffective disorder	Follow general treatment recommendations.	No clear evidence base, but adapted cognitive and rehabilitative approaches may be beneficial.
	Consider heightened sensitivity to side effects and impact on comorbidities.	
	Extra precautions: ability to cooperate with blood tests, consider comorbidities like epilepsy or elevated cardiometabolic risk	
Attention-deficit hyperactivity disorder (ADHD)	Follow general treatment recommendations	
	Treat with caution if comorbidities like tic disorders and anxiety are present.	
Obsessive-compulsive disorder (OCD)	Follow general treatment recommendations	Possible benefits from social skills therapy, individual and family psychotherapy, and behavior therapy, but minimal evidence

1.1 Challenges

1) Data Availability and Quality – A major challenge is the lack of large, high-quality, and diverse datasets for ASD, ADHD, and other mental illnesses. While speech- and text-based mental health data are generally standardized, neuroimaging data (e.g., MRI, fMRI) are expensive to obtain and contribute to inconsistencies in model training and validation.
2) Complexity of Comorbid Conditions – These disorders often occur alongside other mental illnesses such as depression, anxiety, and schizophrenia, making ASD and ADHD particularly difficult to diagnose. Due to overlapping symptoms, AI models struggle to distinguish between conditions, leading to frequent misdiagnoses or underdiagnoses.
3) Generalization and Model Interpretability – AI models trained on specific datasets often fail to generalize across diverse populations due to differences in age, gender, ethnicity, and clinical presentation. Additionally, deep learning models lack transparency, making it difficult for clinicians to trust AI-based diagnostic recommendations.
4) Ethical and Privacy Concerns – Using neuroimaging, speech, and text data for mental health diagnosis raises important concerns about data privacy, security, and informed consent. Ensuring that AI tools protect patient confidentiality remains a significant challenge.
5) Integration with Clinical Practice – AI-assisted diagnostic tools must be effectively integrated into real-world clinical workflows. However, many healthcare professionals lack the training to interpret AI-generated data, and regulatory barriers continue to hinder the widespread adoption of AI-based mental health diagnostics.

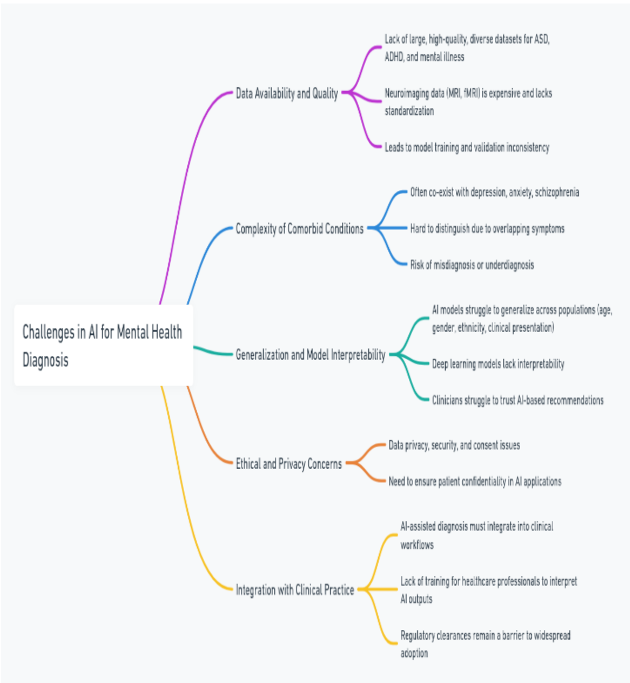

Fig. 2: Challenges Mind Map

2. Related Work

Neuroimaging procedures such as MRI, fMRI, and diffusion tensor imaging (DTI) reveal structural and functional abnormalities in the brains of individuals with ASD, including volumetric differences, connectivity disruptions, and altered brain activity. Jung et al. [19] identified an association between compromised connectivity in the occipital cortex of boys with ASD and the core symptoms and clinical outcomes of the disorder. A strong negative correlation was observed between the tract length of the left cingulum cingulate gyrus and the right uncinate fasciculus and the total score on the Social Communication Questionnaire (SCQ).

2.1 ASD

[11] provided a systematic review of various published papers that used DTI to assess corpus callosum (CC) integrity in individuals with ASD. They observed significant differences between ASD subjects and healthy controls in DTI and tractography measures, suggesting both micro- and macrostructural changes in the CC. These structural changes were also found to be correlated with socio-communicative impairments.[12] reported elevated radial diffusivity (RD) and decreased fractional anisotropy (FA) in both the CC and the internal capsule (IC). Other studies have demonstrated IC connectivity alterations that correlate with DTI changes and core ASD symptoms. Research focusing on language-related tracts, such as the arcuate fasciculus, has shown a significant decrease in FA in ASD subjects compared to individuals with developmental language disorders, helping to differentiate ASD from non-ASD cases. Functional neuroimaging is used to study the functional connectivity and activity of different brain regions. Electroencephalography (EEG) has been employed as a straight-forward method to record brain activity from the scalp, offering high temporal resolution (in milliseconds). Additionally, fMRI measures brain activity by detecting changes in blood-oxygenation-level-dependent (BOLD) signals in response to various stimuli. This four-dimensional (4D) method captures three-dimensional (3D) brain volume repeatedly over time. While fMRI offers high spatial resolution (in millimeters), it has low temporal resolution [13]. This limitation stems from fMRI's inability to capture rapid brain dynamics due to the slow response of the hemodynamic system, often requiring multiple scans over time. Moreover, fMRI is highly sensitive to motion artifacts.fMRI-based methods are typically categorized into two types: event-related or task-based (T-fMRI) and resting-state (rs-fMRI). T-fMRI assesses brain function during specific task performance, whereas rs-fMRI measures brain function in the absence of tasks. Studies have shown that boys with ASD exhibited a non-activated visual striatum, unlike typically developing (TD) boys (Scott-CS, Van Zeeland AA). Furthermore, a study comparing ASD boys and girls found increased activation in the lateral frontal cortex and insula in girls with ASD, suggesting that reduced reward center activation may be a specific feature in boys with ASD [14].[15] extracted DTI-based features such as FA and mean diffusivity (MD) in each region of interest (ROI) to distinguish ASD patients from controls by identifying disease-specific patterns. They also projected ASD severity levels onto clinical scores to support diagnosis. Classification was performed using a nonlinear SVM that employed brain connectivity network features from DTI to detect abnormal functional sub-networks, differentiating ASD subjects from the healthy control (HC) group. Detection was carried out using an SVM-recursive feature elimination (RFE) algorithm.[16] used features extracted from ROI-based white matter (WM) connectivity and DTI measures such as FA, MD, and fiber length. A multi-kernel SVM was applied to discriminate between high-risk and low-risk 6-month-old infants for ASD. The method used was whole-brain fiber clustering analysis with multi-fiber tractography. An SVM classifier was also used to distinguish ASD from HCs.[17] applied graph theory to examine the topology of the white matter network in preschool children with ASD. Nodes and edges were defined based on FA and 90 distinct brain regions. The study found disrupted structural network topology in ASD subjects compared to HCs.[18] Conducted ASD diagnosis using 3D fMRI data from the NYU dataset. The model used the last 50 slices of raw fMRI data as input and was trained using 20 convolutional layers and six max-pooling layers. While few studies have used raw 3D MRI scans for ASD classification, they introduced a 3D-CNN for ASD diagnosis using the 3D MRI ABIDE dataset. A genetic algorithm-based brain masking technique was employed to select brain regions with high discriminative features. The model was trained using a cross-entropy loss function and the Adadelta optimizer, achieving a classification accuracy of 70%.

[19] employed an 18-layer ResNet network to extract meaningful representations from fMRI scans using the entire ABIDE dataset. All 2D convolutional layers in the ResNet were replaced with 3D convolutional layers to process the 3D fMRI data. The ResNet was trained from scratch for 30 epochs and achieved a classification accuracy of 73%.[20] Subsequently used a VGG model for ASD diagnosis by modifying the final fully connected layer to perform ASD/TC classification using sMRI data from the ABIDE dataset. The VGG model was trained on a cropped region of the sMRI scan focused on the corpus callosum. During training, the model utilized the softmax activation function and the ADAM optimizer, achieving a classification accuracy of 66%.

Table 2 highlights how diffusion tensor imaging (DTI) and deep learning models are being applied in ASD research, each offering promising insights but with limitations in data requirements, generalizability, and computational complexity.

Table 2: Survey Table

Reference	Method	Findings	Shortcomings
[11]	Systematic review of DTI studies on CC integrity in ASD	Micro- and macro-structural changes in CC correlated with socio-communicative impairments	Lack of standardization in DTI studies makes cross-study comparison difficult
[12]	DTI analysis showing elevated RD and decreased FA in CC and IC	IC connectivity changes correlated with core ASD symptoms	Small sample sizes limit generalizability, and findings may not apply to all ASD populations
[15]	DTI-based feature extraction and classification using nonlinear SVM	SVM-RFE detected abnormal brain sub-networks in ASD	SVM models are sensitive to feature selection and may not generalize well across datasets
[16]	Multi-kernel SVM with ROI-based WM connectivity and DTI features	High discrimination accuracy between ASD high-risk infants and low-risk infants	Multi-kernel SVM requires careful tuning and is computationally expensive
[17]	Graph theory analysis of white-matter networks in ASD preschoolers	Disturbed topology of structural networks in ASD subjects	Graph theory-based approaches depend on predefined network structures, limiting adaptability
[18]	3D-CNN on raw 3D MRI scans from the ABIDE dataset with genetic algorithm masking	3D-CNN achieved 70% classification accuracy using the ABIDE dataset	3D-CNN model performance is constrained by the availability of large labeled MRI datasets
[19]	18-layer ResNet with 3D convolution layers for fMRI-based ASD diagnosis	ResNet model achieved 73% accuracy for fMRI-based ASD classification	ResNet model requires significant computational resources and may suffer from overfitting
[20]	VGG model trained on sMRI corpus callosum data using ADAM optimizer	The VGG model achieved 66% accuracy for sMRI-based ASD classification	The VGG model has lower accuracy compared to other deep learning architectures and struggles with feature extraction

2.2 ADHD

Currently, techniques used for ADHD diagnosis primarily rely on neuroimaging data and physiological markers such as fMRI and EEG. One of the most commonly used brain MRI datasets for automated ADHD identification is the Neuro Bureau ADHD-200 Preprocessed repository (ADHD-200). Although the main objective of this dataset is to identify healthy controls, it includes more control subjects than ADHD patients. Nevertheless, in real-world applications, accurately identifying individuals with ADHD is just as important as correctly classifying healthy individuals.

Using ensemble machine learning (ML) classifiers with entropy features extracted from ECG signals, Koh et al. achieved an ADHD identification accuracy of 87.2% [21]. By integrating non-linear features from EEG signals, another method achieved an overall accuracy of 96.05%. Despite these promising results, several limitations remain. First, neuroimaging and EEG data collection are typically restricted to hospital environments or controlled laboratories and require trained professionals. Additionally, collecting data from individuals diagnosed with ADHD is resource-intensive, demanding significant time and financial investment [22]. Furthermore, physiological data often requires extensive preprocessing to reduce dimensionality, eliminate noise, and ensure data cleanliness.

Recognized markers of mental disorders include speech patterns, searching for consistent acoustic biomarkers, a key focus in speech-based mental health diagnosis [23]. Much of the current research involves both conventional hand-crafted features and deep-learned features. Hand-crafted acoustic features have shown correlations with certain mental disorders. For example, reviews have noted that depressed speech is often marked by paralinguistic indicators such as jitter, shimmer, or fluctuations in fundamental frequency. Using features like Mel-Frequency Cepstral Coefficients (MFCC) and short-time energy, researchers have identified depression with models such as Gaussian Mixture Models (GMM) and Support Vector Regression (SVR) [24]. These methods have also been adapted for Alzheimer's Disease (AD) detection by analyzing disfluencies and pause times.

In addition, various low-level descriptor (LLD) feature sets—such as the extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS), IS10 Paralinguistics, and ComParE 2016—have been used for mental health assessment. For instance, [25] achieved an accuracy of 71.34% in detecting Alzheimer's Dementia using eGeMAPS on spontaneous speech data. However, while hand-crafted acoustic features offer insights into speech quality, they may fail to capture task-specific symptoms, often requiring long and complex feature lists that do not always yield optimal results. Custom-designed features can also be challenging to develop, as they must translate clinical concepts into mathematical terms.

To overcome these challenges, the use of pre-trained language models or Automatic Speech Recognition (ASR) systems for deep feature extraction has become increasingly popular. Qin and colleagues optimized speech feature extraction using Wav2Vec2.0, which produced strong results [26]. By combining this with a convolutional neural network and an information fusion approach, they achieved high accuracy in ADHD identification based on speech data. This is particularly relevant, as adults with ADHD have been shown to exhibit disfluencies and poor articulation—although studies focusing specifically on speech markers for ADHD remain limited [27].

Text-based mental health detection systems typically rely on two primary data sources: social media posts and clinical interview transcripts. Platforms like Reddit and Twitter have been used in several studies. For example, [28] compiled a Twitter dataset with manually annotated posts to identify users expressing suicidal thoughts. Allen et al. used semantic analysis of Twitter journal entries to predict symptoms of sadness and intimate partner psychological abuse, while Yates et al. created a depression dataset comprising around 9,000 depressed users and 100,000 controls.

Other studies, such as those by Michelle et al., converted audio recordings into text and conducted comparative analyses of syntactic and semantic structures to detect depression [29]. This approach explores the detection of mental illness through interview transcription and subsequent linguistic analysis. Recently, transformer-based models like BERT have gained attention for their strong performance in capturing subtle linguistic patterns associated with mental disorders. For example, researchers converted voice to text [30] and used a BERT model to successfully distinguish Alzheimer's Disease. However, no known studies have yet applied text-based approaches to ADHD detection, largely due to the lack of ADHD-specific text datasets. This research aims to evaluate whether text data obtained from ADHD clinical interviews—or syntactic and semantic features extracted using a fine-tuned BERT model—can support the identification of ADHD. Table 3 shows the machine learning (ML) and signal-based methods for ADHD and mental illness detection.

Table 3: Survey Table

Reference	Method	Findings	Shortcomings
[21]	Ensemble ML classifiers with entropy characteristics from ECG signals	Achieved ADHD identification accuracy of 87.2%	ECG-based methods are not widely available and require medical-grade devices.
[22]	Integration of non-linear characteristics from EEG signals	Overall accuracy of 96.05% for ADHD detection	EEG methods are expensive and require specialized equipment
[23]	Speech-based analysis using acoustic biomarkers	Paralinguistic markers linked to mental illnesses	Lack of standardized acoustic biomarkers for mental health detection
[24]	Depression identification using MFCC and short-time energy with GMM and SVR	Specific disfluencies and pause times used for AD detection	Hand-crafted features may not generalize well across ADHD cases
[25]	Alzheimer's Dementia Identification Using the eGeMAPS tool	Attained 71.34% accuracy in Alzheimer's Dementia classification	Limited applicability to ADHD diagnosis, as the focus was on dementia
[26]	Speech feature extraction optimized with Wav2Vec2.0	Demonstrated improved speech feature extraction for ADHD detection	Deep-learning-based speech models require large training datasets
[27]	Audio-based characteristics analysis for ADHD identification	Identified poor articulation and speech disfluencies in ADHD adults	Few studies on ADHD-specific speech markers and their diagnostic potential
[28]	Text-based mental health classification using social media posts	Used Reddit/Twitter data for suicide and depression risk assessment	Social media data is noisy and often lacks clinical validation
[29]	Comparative analysis of syntactic and semantic text for depression detection	Text analysis identified linguistic patterns in mental illness diagnosis	Text-based methods require large annotated datasets for high accuracy
[30]	BERT-based model for Alzheimer's detection using transcribed voice data	BERT model successfully distinguished Alzheimer's based on speech-text data	No dedicated ADHD-related text databases are available for training BERT models

3. Research Gap

1) Lack of Large-Scale, High-Quality Multimodal Datasets: Current datasets for ASD, ADHD, and related mental disorders are generally limited, biased, or lack diversity in age, gender, and ethnicity. There is a strong demand for standardized, large-scale, publicly accessible multimodal datasets that include neuroimaging (MRI, fMRI), voice, text, and behavioral data.
2) Limited Generalization of AI Models Across Populations: Many deep learning models are trained on homogeneous or region-specific datasets, resulting in poor generalizability across diverse demographic and clinical populations. Further work is needed to develop AI models that perform reliably across varied populations.
3) Challenges in Differentiating Overlapping Symptoms: ASD and ADHD often co-occur with other disorders such as anxiety, depression, schizophrenia, and bipolar disorder, creating diagnostic complications. AI algorithms struggle to distinguish between overlapping symptoms, increasing the risk of misclassification.
4) Lack of Explainability and Interpretability in AI Models: Deep learning-based diagnostic technologies often function as "black boxes," making it difficult for clinicians to understand how a diagnosis is generated. Explainable artificial intelligence (XAI) models are needed to build trust and improve adoption in clinical settings.
5) Ethical, Privacy, and Bias Concerns in AI-Based Diagnostics: The use of sensitive patient data—such as neuroimaging, voice, and text—raises ethical concerns regarding consent, privacy, and data security. In addition, biases in training datasets may lead to inaccurate or unfair diagnostic outcomes.
6) Limited Integration of Multimodal Data for Diagnosis: Most diagnostic research focuses on a single modality—such as MRI, EEG, or text. Although underexplored, integrating multiple modalities (e.g., neuroimaging, speech patterns, and textual data) has the potential to significantly improve diagnostic accuracy.
7) Lack of Real-World Clinical Validation: Many AI models are tested using retrospective datasets but lack validation in real-world clinical environments. More research is required to evaluate the performance of AI-driven diagnostic systems in hospitals and mental health clinics.
8) Scarcity of Studies on AI-Driven Early Detection and Intervention: Most AI-based studies focus on post-diagnosis analysis rather than early identification of ASD and ADHD, particularly in children. Research into models that can detect early biomarkers and predict mental health risks is still lacking.
9) Inadequate Focus on Speech and Text-Based Mental Health Assessment: While neuroimaging research is widespread, the potential of speech and text analysis for identifying ASD and ADHD is underutilized. Greater attention is needed for natural language processing (NLP) and speech-based AI methods in mental health diagnostics.
10) Challenges in Clinical Adoption and AI Training for Healthcare Professionals: Many medical professionals lack training in artificial intelligence and deep learning-based diagnostic methods. The development of user-friendly AI tools and structured training programs is necessary to support the effective clinical use of AI solutions.

4. Proposed Methodology

The proposed methodology involves a multi-stage framework integrating feature selection, data augmentation, and multimodal fusion for effective classification of individuals with mental disorders. The approach consists of three main components: Evolutionary Algorithm (EA) Based Feature Selection (EAFS), Multioutput Conditional GAN (MCGAN) for data augmentation, and Multiheaded Gating Fusion (MGF) for classification. The expected outcomes include the development of an accurate fMRI-based deep learning model for ASD diagnosis, improving early detection, and identifying distinct neural connectivity patterns. A multi-disorder AI model will be created to diagnose ADHD and other mental disorders using fMRI, identifying both disorder-specific and shared brain activity patterns. Additionally, a multimodal AI model integrating fMRI and sMRI will enhance diagnostic accuracy by combining functional and structural imaging features. These advancements aim to improve mental disorder diagnosis, reduce uncertainty, and provide deeper insights into neurobiological differences for potential clinical applications.

4.1 Motivation and contribution

Autism Spectrum Disorder (ASD), attention deficit hyperactivity disorder (ADHD), and other mental disorders create significant barriers to clinical evaluation and treatment and affect millions of people worldwide. Despite growing awareness, the high comorbidity rates between ASD and ADHD, along with related disorders such as anxiety, depression, bipolar disorder, obsessive-compulsive disorder (OCD), and schizophrenia, present challenges to accurate diagnosis and appropriate treatment planning. Conventional symptom-based diagnostic standards fail to account for overlapping symptoms, often resulting in misdiagnosis, underdiagnosis, and delayed treatment. Additionally, the subjective nature of clinical evaluations, combined with a global shortage of trained professionals, further exacerbates these challenges. Recent advancements in neuroimaging techniques such as MRI and fMRI, along with machine learning-based systems including deep learning, offer promising avenues for improving diagnostic accuracy. These technologies assist in identifying neurobiological markers, support early diagnosis, and guide personalized treatment plans. Furthermore, the integration of speech- and text-based AI models opens up non-invasive ways to explore both cognitive and emotional behavior patterns in individuals with ASD and ADHD. This effort aims to bridge the gap between clinical expertise and computational technologies, ultimately enhancing early diagnosis capabilities, treatment effectiveness, and quality of life for individuals with these psychiatric and neurodevelopmental disorders.

- Comprehensive Review of AI-Based Diagnostics – This survey provides a thorough overview of recent state-of-the-art deep learning and machine learning methods applied to the diagnosis of ASD, ADHD, and comorbid mental disorders, with emphasis on neuroimaging (MRI, fMRI), speech, and text modalities.
- Multimodal Insights for Mental Health Analysis – This research examines the intersection of heterogeneous data sources, such as neuroimaging, speech patterns, and linguistic analysis, to present an integrated perspective on AI-aided mental health assessment, highlighting both benefits and limitations.
- Bridging Clinical and Computational Research – The article identifies key challenges in conventional diagnostic models, presents recent advancements in AI-based approaches, and explores future research directions to improve early detection, personalized intervention, and clinical decision-making for ASD, ADHD, and related conditions.

5. Conclusion

Autism Spectrum Disorder (ASD) and attention deficit hyperactivity disorder (ADHD), which often co-occur with mental illnesses such as anxiety, depression, schizophrenia, and bipolar disorder, complicate diagnosis and treatment. The subjectivity of traditional symptom-based diagnostic systems limits their effectiveness and frequently results in underdiagnosis or misdiagnosis. Advances in artificial intelligence (AI)—particularly in deep learning and machine learning—combined with neuroimaging (MRI, fMRI), voice, and text-based analysis, have created new opportunities to improve diagnostic accuracy. However, major challenges remain: the lack of large-scale, multimodal datasets; limited generalizability of AI models across diverse populations; and ongoing concerns regarding model interpretability, ethical considerations, and integration into therapeutic settings. This study highlights the latest AI-driven approaches for diagnosing ASD, ADHD, and related mental illnesses, identifies critical research gaps, and emphasizes the need for future work focused on explainable AI, multimodal data fusion, and clinical validation in real-world settings. Bridging the gap between AI-driven diagnostics and clinical practice will not only enhance early detection but also enable more personalized and effective treatment plans. Ensuring that AI-based diagnostic tools are reliable and widely accessible will require multidisciplinary collaboration among AI researchers, clinicians, and mental health professionals—ultimately improving the quality of life for individuals with these disorders.

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