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Autism Spectrum Disorder Diagnosis through Machine Learning: Techniques, Applications, and Clinical Challenges

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***Abstract*— Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by impairments in social interaction, communication, and repetitive behavioural patterns. The growing demand for ASD in the world has intensified the requirements of early, accurate and scalable diagnostic methods. The standard modes of diagnosis are primarily based on behavioural assessments conducted by experts, which are time-consuming, subjective and often available in settings with low resources. The last several years saw the emergence of promising tools using Machine Learning (ML) and Artificial Intelligence (AI) to support and enhance ASD screening, diagnosis, and analysis with the use of data-driven processes. The review systematically examines previous research in terms of learning paradigms such as supervised learning, unsupervised learning, and deep learning models and the type of diverse data modalities used as behavioral questionnaires, neuroimaging data, eye-tracking signals, and even speech patterns. Furthermore, it highlights significant challenges about ML-based ASD systems, such as a limited data supply, imbalanced classes, and inability to generalize and constraints to the real-world clinical deployment.**

I. Introduction

ASD is a complex neurodevelopment condition which is characterized by persistent difficulties with social interaction, communication, and possibly involving limited or repetitive behavioral patterns. The condition is called a "spectrum" because it has a wide range of variation with symptoms severity, cognitive abilities and functional outcomes among individuals suffering the disorder.

Recent global reports show that prevalence of ASD has been increasing continuously, which has attracted the interest of clinicians, researchers and policymakers towards early diagnosis and appropriate intervention strategies [1,2]. The earliest diagnosis of ASD is essential in enhancing the long-term developmental, behavioural, and social outcomes.

However, the conventional methods of diagnosis practices depend on the clinician, including behavioral assessments like the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R). The tools are considered the gold standard but are time-consuming, solely based on particular expertise and are partially impacted by observer bias and inter-rater variation [3]. Subsequently, delays in the diagnosis are widespread, particularly because the accessibility of trained professionals and other healthcare facilities is low in the regions [4].

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Over the past few years, the fields of Machine Learning (ML) and Artificial Intelligence (AI) have been viewed as potentially effective computational paradigms that could help to address several limitations related to the conventional methods of diagnosing ASD. ML algorithms facilitate automatic learning by means of data and identify non-linear, complicated relationships that could not be easily discovered using traditional statistical tools [5]. The growing accessibility of digital health information and the growth in computational capabilities have further launched the use of AI-based methods in ASD studies [6]. Many different ML/AI approaches have been studied to screen and diagnose ASD with various types of data. Behavioral and questionnaire-based data sets are some of the most popular sources because they are easily obtained and interpreted [7]. Simultaneously, neuroimaging findings, including structural and functional magnetic resonance imaging (MRI and fMRI), have been highly investigated to find neurological biomarkers related to ASD [8].
Also, social visual attention patterns, speech and audio cues indicating language and communication impairments, have shown high-potential in non-invasive and preliminary assessment of ASD [9,10].
Methods of supervised learning, such as Support Vector Machines (SVM), Random Forests, Decision Trees, and Artificial Neural Networks, have demonstrated promising classification results in various research [11,12]. Recently, deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have received interest as they can automatically extract features of high-dimensional data, especially in neuroimaging, and speech-based applications [13]. In spite of these advancements, small sample sizes, imbalance in the datasets, and external validation are reported to significantly limit the generalizability of many reported models [14].
In addition, AI-based ASD systems, in terms of clinical adoption, are limited by issues of model interpretability and ethics as well as a lack of standardized evaluation protocols [15]. Most working ML models act like a black box, and clinicians might not be able to comprehend or depend on how they make decisions. As such, there is an increasing focus on explainable AI and more clinically interpretable models capable of providing insight and not replacement for expert judgments.

II. Methodology of the Literature Review

The method used in this literature review was a systematic and structured review to guarantee full coverage, transparency in methods and transparency of the results.
To ensure that the review process conformed to existing standards of systematic literature review in healthcare and computational research areas, a special focus was made on the studies that use Machine Learning (ML) and Artificial Intelligence (AI) methods to conduct research in Autism Spectrum Disorders (ASD) [16,17].

A. Review Design and Protocol

The review was conducted under a multi-stage protocol that entailed identification of the literature, screening, eligibility evaluation and ultimate inclusion. This strategy is consistent with the components of the PRISMA-based systematic review, which are popular in review articles published in various multidisciplinary journals like Heliyon [18]. No quantitative meta-analysis was carried out, but the systematic qualitative synthesis was followed to guarantee uniformity and minimize selection bias.

B. Data Sources and Search Strategy

A review of various major electronic metadata databases was undertaken to include both medical and engineering-oriented literature. The databases incorporated Scopus, Web of Science, IEEE Xplore, PubMed, Science Direct and Google Scholar. These sources were chosen because they index multiple peer-reviewed journals and conference proceedings related to the study of ASD, ML and AI [19].
The search strategy was a mixture of controlled vocabularies as well as free-text terms of ASD, as well as computational intelligence. The main search terms were built based on the Boolean operators as follows:

- (“Autism Spectrum Disorder” OR “Autism” OR “ASD”) AND
- (“Machine Learning” OR “Artificial Intelligence” OR “Deep Learning” OR “Neural Network”) AND
- (“Diagnosis” OR “Detection” OR “Classification” OR “Prediction”)

English-language publications were only searched to facilitate interpretability and consistency. Articles published no earlier than 2013 and no later than 2024 were given preference as they would represent the current methodological improvement and the new methods of AI [20].

C. Inclusion and Exclusion Criteria

Building on objectivity and relevance, the inclusion and exclusion criteria were elaborated before the screening process.

Inclusion criteria:

- Review articles, conference papers and peer-reviewed journal articles
- Research involving the use of ML, AI, or deep learning to screen, diagnose, classify, or predict behaviour of ASD
- Research employing ASD-related data, such as behavioural questionnaires, neuroimaging, eye-tracking, speech or multimodal data.
- Articles with adequate methodological and experimental information.

D. Study Selection and Screening Process

The process of selecting the studies was adapted in several phases. Firstly, all obtained articles were filtered by titles and abstracts, eliminating duplicates and obviously irrelevant articles. Thereafter, all the articles included in the study were reviewed to determine the remaining articles eligibility regarding the aforementioned inclusion and exclusion criteria.

Exclusion criteria:

- Studies not directly related to ASD
- Papers focusing solely on clinical or psychological analysis without computational methods
- Non-peer-reviewed articles, editorials, short communications, theses, and abstracts
- Studies lacking performance evaluation or validation details

These criteria were adopted to ensure methodological robustness and alignment with prior systematic reviews in ASD and ML literature [21,22]. The type of ML model employed, data modality, and the clinical relevance of the proposed approach were given particular attention. At this step, it was possible to exclude studies that had shown no clear methodology, lacked any kind of experiment validation, and those that lacked sufficient relevance to the diagnosis of ASD. This multi-level screening method has been identified to enhance the credibility of systematic reviews in fields of interdisciplinary research [23].

E. Data Extraction and Categorization

For each selected study, relevant information was systematically extracted using a predefined data extraction framework. The extracted attributes included:

- Type of ML or AI algorithm employed
- Learning paradigm (supervised, unsupervised, or deep learning)
- Data modality and dataset characteristics
- Feature extraction and selection techniques
- Performance evaluation metrics
- Reported strengths, limitations, and clinical implications

To help arrange the data extracted, this was sorted into comparative tables and thematic groups to aid the analysis. The methodology helped to identify dominant trends in the methodology and common difficulties in the studies [24].

F. Synthesis and Analysis of Literature

To examine the chosen studies, a thematic synthesis method was used. As opposed to the performance measures in terms of accuracy, the review concentrated on the wider scope of the performance measures that include the data quality, interpretability of the model, the flexibility to generalize and the usability in the real world. Coherent narrative synthesis [25] was used to group studies based on algorithmic category, and data modality [25].

This qualitative synthesis was useful to identify gaps in research, including an imbalance of datasets, absence of external validation and insufficient clinical validation of AI models. The methodology chosen guarantees that the results of this review can give a summary of the current work as well as an evaluation of the current state-of-the-art regarding research on ASD using ML and AI.

III. OVERVIEW OF AUTISM SPECTRUM DISORDER

ASD is a diverse neurodevelopmental disorder with a complex nature and usually shows up in early years of a particular person and continues through the life of an individual's life. It is mainly associated with impairments in social communication and social interaction, and limited, repetitive behavioural, interests and activities. The use of the term spectrum indicates the broad range of symptom severity, cognitive abilities, and adaptive behaviour as exhibited by pre-determined individuals with ASD [26].

Epidemiological reports have indicated that ASD prevalence in the world has considerably increased, and this has been attributed to the increased diagnostic recognition, the generalization of diagnostic criteria, as well as increased screening behaviors [27]. Despite these, the diagnosis of ASD is a difficult process because of its behavioural peculiarities and the lack of clear biological indicators. Clinical diagnosis relies mostly on behavioural observation and developmental history, which means that it is prone to subjectivity and inter-clinician errors [28].

Autism diagnostic scales like the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview -Revised (ADI-R) are commonly considered to be gold standards of ASD assessment. Nonetheless, they incur a lot of training, are both time-consuming and require long periods of observation, which restricts their scaling and reach [29]. Also, there is a high rate of late diagnosis, especially in the poorly- and middle-income countries where specialist healthcare professionals are inaccessible [30].

ASD too is linked with a large number of comorbid conditions, such as attention deficit hyperactivity disorder (ADHD), intellectual disability, anxiety disorders, and epilepsy.

TABLE I

Author	Methods	Dataset Used	Key Results
Ahmed [51]	Hybrid LBP+GLCM with FFNN/ANN, CNN	Eye-tracking scanpath dataset	99.8% accuracy using FFNN/ANN
Raj & Masood [77]	Naïve Bayes, SVM, Logistic Regression, CNN	ASD screening datasets (Adults, Children, Adolescents)	CNN achieved 99.53% (Adults), 98.30% (Children)
Farooq [33]	Federated Learning with SVM	Four public ASD screening datasets	99% accuracy (children)
Awaji [36]	VGG16–MobileNet hybrid CNN	Kaggle ASD facial image dataset	98.8% accuracy, 99.25% AUC
Liu [15]	AE + DNN, CNN, GCN, Ensemble GCN	ABIDE I (NYU subset)	State-of-the-art classification performance
Wen [53]	Graph-based ML (MVS-GCN)	ABIDE, ADNI datasets	Improved ASD classification accuracy
Pietrucci [52]	Random Forest	Public 16S rRNA datasets	70% accuracy
Napolitano [47]	CNN-based neuroimaging analysis	Autism Brain Imaging Data Exchange	High ASD detection accuracy
Cao & Cao [31]	Random Forest	Clinical ASD dataset	High sensitivity and specificity
Megerian [54]	AI-based SaMD (Cognoa)	Proprietary clinical trial data	98.4% sensitivity
Dechsling [55]	ML-based VR systems	ASD intervention dataset	Effective behavioral outcome prediction
Marzouki [44]	ML-assisted clinical framework	Clinical behavioral data	Improved screening reliability
Nisar [48]	ML with genetic biomarkers	SFARI Gene dataset	Effective gene-ASD association learning
Gesi [61]	ML-based diagnostic modeling	Clinical cohort data	Improved diagnostic support
Bougeard [58]	ML classifiers	National health datasets	Improved classification trends
Amorim [76]	ML screening models	Behavioral assessment dataset	Early ASD risk identification
Alrahili [62]	ML-based screening	Caregiver questionnaire data	Improved screening efficiency
Kereszturi [29]	ML-based classification framework	Genetic ASD datasets	Framework-level contribution
Simeoli [18]	CNN-based analysis	Neuroimaging data	Competitive performance
Ding [20]	Ensemble ML	ABIDE & Kaggle datasets	High pooled sensitivity

These comorbidities also make it more difficult to diagnose and plan treatment since similar symptoms might cloud the type of behavioural pattern unique to ASD [31]. Moreover, the path development of ASD differs considerably in relation to age stages, which makes the early detection especially challenging in infancy and the toddler age [32].

Against these obstacles, there has been an increased desire to find computational and data-based methods that can assist clinicians with objective, scalable, and reproducible diagnostic aids. The emergence of data acquisition tools, like those of digital behavioural assessment, neuroimaging, eye-tracking and speech analysis, has created vast amount of data relevant to ASD that can be computed [33]. This work has preconditioned the use of machine learning and artificial intelligence algorithms in the field of ASD.

IV. MACHINE LEARNING TECHNIQUES FOR ASD DIAGNOSIS

Machine-learning (ML) methods have seen great interest in the field of ASD research because of their capability to analyse high-dimensional data and reveal non-linear relationships. The goal of ML-based methods is to facilitate early screening, enhance the precision of diagnostic results, and discover significant patterns in datasets related to ASD that might not be apparent under a conventional statistical analysis [34].

A. Supervised Learning Approaches

The most popular paradigm of ML applied to diagnose ASD is supervised learning algorithms. Such techniques are based on labelled datasets, i.e., individuals can be diagnosed with ASD or non-ASD. Support Vector Machines (SVM), Random Forests, Decision Trees, Naive Bayes classifiers, and k-nearest neighbor (k-NN) are commonly implemented, supervised models [35].

The SVM-based models have been especially popular as they perform rather well with small samples and high dimensions, as it is prevalent in ASD datasets [36]. Ensemble-based techniques and the use of Random Forests have also shown a good performance because the method can minimize over fitting and enhance the robustness of classification in heterogeneous datasets [37].

ML methods have been implemented in a supervised format using different data modalities, such as behavioural questionnaire data, neuroimaging characteristics, and eye-tracking data. Most of the studies have indicated high classification accuracy, but the performance can differ a lot based on the quality of data sets, the procedures used to select the features, and the techniques used to validate the performance [38].

B. Unsupervised Learning Techniques

Latent structure and subgroups within ASD populations have been examined by using unsupervised learning techniques. Clustering algorithms like k-means, hierarchical, and the Principal Component Analysis (PCA) have been used to determine phenotypes of behavior and neurobiological subtypes in the spectrum of autism [39].

The methods are especially useful when it comes to the problem of ASD heterogeneity, as they are not based on any a priori labels and can bring to light previously undiscovered patterns in the data. Nevertheless, there is a problem with the clinical interpretability of unsupervised findings, and they are usually limited in terms of validation against clinically accepted diagnostic criteria [40].

C. Deep Learning Approaches

Deep learning models as in Fig 1have been receiving more and more interest in the study of ASD over the past few years because of their ability to discover hierarchical representations of features based on raw data automatically. Convolutional Neural Networks (CNNs) have seen intense application in neuroimaging and facial expressions, whereas Recurring Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have found application in the time-dependent sequence data, like speech- or behavior-time-series [41].

The use of deep learning methods has proved better than standard ML models in various studies, especially in cases where data in large amounts is given. But their use in ASD research is frequently limited by a dearth of data, high computing needs, and inability to interpret the model [42]. The fact that the black-box deep learning models are not easily explainable creates further issues in terms of clinical adoption, whereby clinicians need readable and understandable decision-support systems [43].

D. Hybrid and Multimodal Approaches

To overcome the single-modality models' shortcomings, recent research has proposed hybrid and multimodal ML models that consider dynamic combinations of various forms of data, like behavioural data with neuroimaging or speech features. These modalities are meant to enhance diagnostic accuracy by complementing the information reflected by the modalities [44]. Despite the potential, the multimodal systems also come with other problems of data synchronization, feature fusion, and high complexity of models.

V. Deep Learning Approaches in ASD Research

Deep learning, a subfield of machine learning characterized by multi-layered neural network architectures, has gained significant traction in research due to its ability to automatically learn complex feature representations from raw, high-dimensional data.

Unlike traditional ML methods that rely heavily on handcrafted features, deep learning models can capture hierarchical and non-linear patterns, making them particularly suitable for ASD-related data modalities such as neuroimaging, speech signals, facial expressions, and behavioural time-series data [45,46].

A. Convolutional Neural Networks

One of the most popular deep learning models used in ASD studies is Convolutional Neural Networks (CNNs). CNNs have also been used widely on structural and functional magnetic resonance imaging (MRI and fMRI)

data to perform automatic ASD classifications and biomarkers [47]. CNNs are able to learn discriminative features that utilize spatial correlations between imaging data, thus, learning to identify unusual brain connectivity and structural differences in a person with ASD [48].
Several studies have demonstrated that CNN-based models outperform traditional ML approaches when sufficient training data are available.
However, the reliability of these models is often limited by small sample sizes and variability across imaging protocols, which may lead to overfitting and reduced generalizability [49].
Transfer learning and data augmentation tricks have been suggested to reduce these drawbacks, but the success of these methods still depends on the similarity and quality of datasets [50].

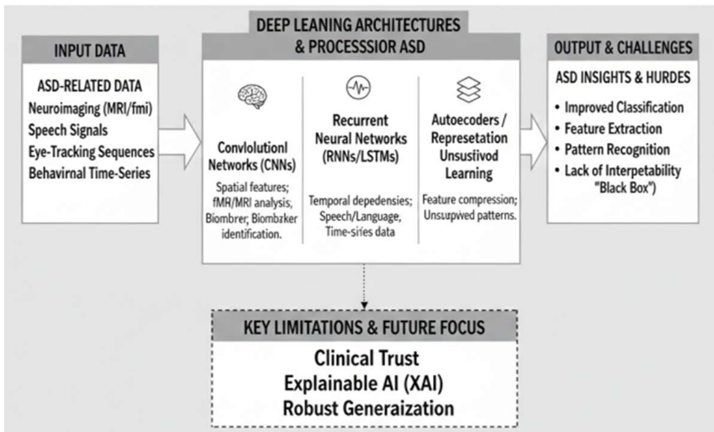

Fig 1. ASD Deep learning Approach

B. Recurrent Neural Networks and Sequential Models

RNNs, particularly LSTM networks, have been employed to model temporal dependencies in ASD-related sequential data. These models are well-suited for analysing speech signals, language development trajectories, eye-tracking sequences, and behavioural time-series data [51].
The results of LSTM-based models have demonstrated encouraging results in learning fine temporal variations of speech prosody, as well as patterns of communication related to ASD, [52]. However, these models demand the meticulously selected datasets and extended sequences that are observed to stabilize their performance. Moreover, interpretability is a vital aspect, with timelike representations trained using RNNs frequently being challenging to decode into clinically relevant aspects [53].

C. Auto encoders and Representation Learning

ASD studies have utilized auto encoders and analogs such as sparse and variational auto encoders to learn features in unsupervised modes and project data onto a reduced dimension. Such models aim to learn small features of intricate data, which can be downstreamly used to classify and cluster data [54].
In neuroimaging research, auto encoders have been used to retrieve latent representations of brain connectionality patterns relating to ASD [55]. Although these methods are useful to extract statistical features efficiently, absence of interpretability and standard validation procedures frequently limits their usefulness in the clinical context [56].

D. Limitations of Deep Learning in ASD Applications

Deep learning approaches have a number of challenges in ASD research despite their potential. The paucity of big data with a lot of annotations is a major limitation of the training and evaluation of the models. Also, deep models are computationally expensive, and they tend to act as black boxes, which creates the issue of transparency, trust and clinical adoption [57]. These restrictions underscore the importance of explicable deep learning architectures and hybrid methods, combining deep models with domain expertise [58].

VI. DATA MODALITIES USED IN ASD STUDIES

The performance of ML and AI-based ASD systems heavily depends on the quality and type of data to be utilized in model development.

The diverse data modalities of ASD have been exploited to support the field of research by covering various dimensions of the disorder. The section discusses the most frequent data sources and how they are relevant to the ML-based ASD assessment.

A. Behavioral and Questionnaire-Based Data

One of the most frequently used data modalities in ASD studies is behavioral data obtained with the help of standardized screening tools and questionnaires. Behavioral data, e.g., from instruments like ADOS, ADI-R, and caregiver-reported screening questionnaires, are structured and can be easily manipulated with the help of ML methods [59]. ML models that are trained using data of behavior usually have high classification accuracy because behavioral traits and ASD diagnosis have a strong correlation. But these datasets are all subjective and can be subject to reporting bias and cultural influences, which restricts their applicability to other populations[60].

B. Neuroimaging Data

Neuroimaging (structural MRI, functional MRI (fMRI), diffusion-tensor imaging (DTI), and similar) data have been heavily examined to find neurological biomarkers of ASD. The goals of using ML and deep learning models on the neuroimaging data are to identify abnormal brain structure and connectivity in relation to ASD [61]. Although neuroimaging-based methods provide objective information on the neurobiology of ASD, they have problems concerning large dimensions, noise, and sample size. Besides, the high associated cost and complexity of obtaining imaging limits such methods in real-life screening environments [62].

C. Eye-Tracking and Visual Attention Data

The information on eye-tracking offers quantitative gauge of gaze activity and social visual interest, which has been proven to vary considerably between ASD victims and non-disabled individuals. ML models based on eye-tracking characteristics have proven to have high potential for early screening of ASD, especially among young children [63]. Eye-tracking systems, despite them, need specialized equipment, controlled experiments, which can restrict their prevalence in clinical settings [64].

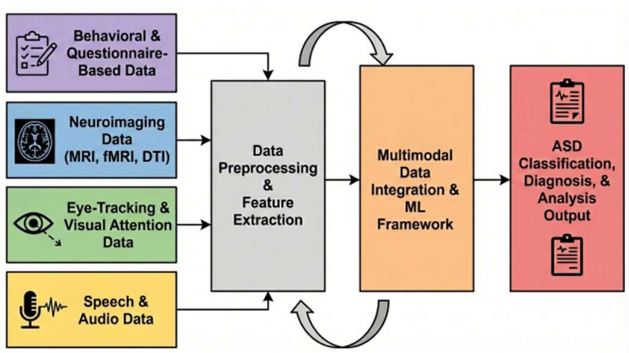

Fig 2. Multimodal Input

D. Speech and Audio Data

Speech and auditory data have been the new non-invasive and less expensive ASD assessment modalities. ML and deep learning models examine characteristics, including pitch, intonation, speech rhythm, and linguistic complexity, to detect ASD-related communication barriers [65].

Despite the high accessibility of speech-based systems, they are subject to environmental distortions, the variability of different languages, and age variations, which require strong preprocessing and normalization methods [66].

E. Multimodal Data Integration

To overcome the limitations of single-modality as in Fig 2 approaches, recent studies have explored multimodal frameworks that integrate behavioral, neuroimaging, speech, and eye-tracking data.

Multimodal ML systems strive to collect complementary information in data sources, resulting in better diagnostic capabilities and strengths [67].

Multimodal integration, however, comes at a price of adding more difficulties in synchronizing data, combining features and a more complex model, which should be carefully considered in order to allow clinical viability[68].

VII. Evaluation Metrics and Validation Strategies

The analysis and diagnosis of Autism Spectrum Disorder (ASD) through machine learning and artificial intelligence models is a significant component of the assessment of the reliability, robustness, and clinical applicability of the models.
Because of the sensitivity of medical decisions, performance measurement is more than a mere simple issue of accuracy effects and needs to be extensively validated with respect to ASD research [69].

A. Performance Evaluation Metrics

The majority of the works use conventional classification measures, such as accuracy, precision, recall, F1-score, sensitivity, and specificity. The accuracy has been often reported because it is simple but it can give incorrect results in case of existing class imbalance that is usually common in the ASD datasets [70]. This is especially relevant to clinical situations because sensitivity and specificity indicate the capability of the model to differentiate those with and without ASD, respectively[71].
The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) has also been popular in assessing classification performance at different thresholds. AUC-based assessment is thought to be more powerful compared to single-threshold measures, particularly when using heterogeneous data [72].

B. Validation Techniques

Most studies aim to determine generalizability by employing cross-validation plans which can be either k-fold cross-validation or leave one out validation.
These methods assist in reducing overfitting, especially when there is a small sample ASD dataset [73]. Most researches however only uses internal validation to determine performance, which restricts real-world performance.
The relatively small availability of data and the unavailability of standardized datasets have led to low rates of external validation through independent datasets in modern ASD research.
Lack of cross-site validation lowers the confidence in the robustness of the model and slows the adoption of models into clinical practice [74]. The recent reviews note that it is necessary to develop multi-center and longitudinal validation frameworks to enhance reliability [75].

VIII. Challenges and Limitations

Despite significant progress, several challenges continue to limit the effectiveness and clinical adoption of ML and AI-based ASD assessment systems.

A. Dataset Limitations and Imbalance

One of the most prominent challenges is the scarcity of large, well-annotated datasets. Much ASD data has a small sample size and class imbalance, which adversely affects model training and evaluation [76]. Heterogeneity in data due to variations in acquisition protocols, demographic features and diagnostic criteria also makes it more difficult to generalize the model [77].

B. Overfitting and Lack of Generalization

When using deep learning models on small datasets, high-dimensional data (especially neuroimaging and speech features) are more likely to overfit.
Some studies have indicated high classification accuracy, but such accuracy does not always apply to unseen data [78].

C. Interpretability and Clinical Trust

Complex ML and deep learning models are not interpretable, which becomes a major obstacle to clinical uptake. Numerous AI-based ASD systems turn out to be black boxes, meaning that clinicians cannot comprehend how the model predictions work [79]. This drawback has given rise to an increase in interest in Explainable AI (XAI) techniques that can give clear and understandable support to decisions [80].

D. Ethical and Privacy Concerns

Data related to ASD is usually confidential personal and medical data, bringing up ethical issues of data privacy, consent, and security.
The implementation of AI-based healthcare systems should be accompanied by compliance with the data protection laws and ethical practices [81].

IX. RESEARCH GAPS AND FUTURE DIRECTIONS

Although the use of ML and AI methods has demonstrated promising outcomes in ASD research, there are still several gaps which need to be filled in order to develop the field.

First, there is a need for large-scale, standardized, and publicly accessible datasets that can support robust model training and external validation. Raising the concern that requires joint efforts by institutions and disciplines is fundamental to overcoming the issue of data scarcity and heterogeneity [82].

Second, future research should prioritize explainable and interpretable AI models that can support the clinical decision-making process and foster trust in healthcare specialists. The integration of information-based models with domain knowledge, by which hybrid methods provide a new promising direction [83].

Third, the multimodal and longitudinal analysis represents key opportunities to enhance the accuracy of diagnosis and timely diagnosis. A combination of behavioral, neuroimaging, speech, and physiological research can provide a more comprehensive understanding of ASD [84].

Finally, a possible direction of research in the long-term is the emergent direction of Quantum Machine Learning (QML). Even though it is still in its early stages, over time, QML can provide the computational benefits of high-dimensional ASD data, which should be explored [85].

X. CONCLUSION

The present literature survey will be a good summarization of machine learning and artificial intelligence in the study of Autism Spectrum Disorder. The analysed studies illustrate that ML and AI methods enhance early screening, diagnosis, and awareness of ASD by utilising data-based methods. Although the performance of supervised learning, deep learning, and multimodal systems has been encouraging, issues to do with data quality, generalization, interpretability, and clinical integration remain persistent.

To overcome these limitations, through standardized datasets, explainable models, and well-developed validation approaches are needed to translate AI-based ASD systems into clinical practice. This review is intended to become a reference guide in the future by integrating existing practices and outlining future research opportunities in solving intelligent, reliable, and clinically meaningful ASD assessment solutions.

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