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Review Article

# Intelligent Techniques for Autism Spectrum Disorder Diagnosis: A Review

Ekraam Jabier[1, *], Ali Fadhil Marhoon[1], Ammar A. Aldair[1]

[1] *Department of Electrical Engineering, Engineering college, Basrah University, Iraq*

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**ABSTRACT**

Autism spectrum disorder (ASD) is a neurodevelopmental disorder whose prevalence has increased drastically around the world due to the shortcomings of the traditional method of diagnosis, which has been shown to be unsustainable since it is usually time-consuming, expensive, and subjective to clinical interpretation. These difficulties make finding more scalable, efficient, and objective methods of diagnosis incredibly expedient. This review explores the impacts of intelligent technologies such as artificial intelligence (AI), machine learning (ML), deep learning (DL), and Internet of Things (IoT) sensor-supported systems and the revolution they are bringing into the diagnosis of ASD. This work reviews the recent developments in the use of multisensor platforms (e.g., eye tracking, electroencephalography (EEG), speech processing, and computer vision) and computational models to increase accuracy, accessibility, and speed. The systematic review approach was utilized, where only peer-reviewed journal articles published from 2019-2025 were considered and retrieved from major scholarly databases. Seven research questions that addressed diagnostic performance, algorithm innovation, data sources, dimension reduction, and clinical significance guided the review. Even with fewer than 128 sensors and similar sensors incorporated into diagnostic models, an accuracy rate of 85–95% is achieved, which at least meets or surpasses previous standards. Generalizability, fairness, and data privacy are increased because of federated learning and explainable AI systems. Openly accessible resources such as ABIDE-III, SFARI Genomes 2.0, and NDAR-2024 have been essential in terms of discovering robust biomarkers and enabling the validation of models in various ethnicities and populations. These findings indicate the potential of intelligent systems for early detection and accurate and personalized ASD diagnosis. These technologies make it possible to screen for autism noninvasively, in real time, and at an affordable cost, hence opening up avenues to more inclusive and fairer approaches to autism care across the world.

## 1. INTRODUCTION

Autism spectrum disorder (ASD) is an intricate, heterogeneous neurodevelopmental disorder that severely impairs the learning, communication, and social participation of children [1],[2]. ASD might affect not only cognitive functions but also the emotional, behavioural, physical, and social spheres, which together question the day-to-day performance and well-being of the individuals affected by ASD [3]. In a very alarming way, the latest epidemiological reports have shown an increase in the prevalence of ASD, as in 2020, one child out of 36 eight-year-olds was diagnosed with ASD, which was almost one in 44 in 2018 [4]. This increased prevalence is why the development of early, precise, convenient diagnostic tools is acute.

Conventionally, the Autism Diagnostic Observation Schedule (ADOS) and Autism Diagnostic Interview-Revised (ADI-R) have been considered the gold-standard assessment tools for ASD. Even though these instruments are generally validated and standardized, they have fundamental limitations: they are time-consuming and necessitate many professional preparations; moreover, they are objectively subject to the interpretations of clinicians. The difficulties are especially strong in low-resource conditions when the number of clinicians practicing and available for diagnosis is finite and procrastination of the diagnosis might ruin the impacts of early intervention.

To overcome such shortcomings, however, researchers have resorted to intelligent diagnostic solutions based on sensor technologies, artificial intelligence (AI), machine learning (ML), and deep learning (DL). These novel techniques have the potential for objective, efficient, and scalable ASD diagnosis [5]. For example, sensor-based systems, including but not confined to, eye-tracking cameras and EEG headsets, can provide quantitative measures at the behavioural and neurological levels, providing insight into social communication habits and abnormalities in brain activity [6]. Simultaneously, AI and DL algorithms have the ability to handle multimodal data (visual, neural and behavioural signals) to identify diagnostic

*Corresponding author. Email: ekraam.jabier@uobasrah.edu.iq

patterns that cannot be detected by human judges. Such methods can save time, increase costs and provide an opportunity to implement scalable, mobile, and telehealth-based tools for diagnosis [7].

The main objective of this review is to provide a comprehensive and critical synthesis of intelligent diagnostic approaches for ASD, with particular emphasis on their advantages over conventional systems. As illustrated in Figure 1, this study addresses seven key research questions to explore the technological, clinical, and methodological landscape. These include how sensor-based solutions improve ASD detection accuracy across age groups; the distinctive traits of AI, ML, and DL models in contrast to traditional tools; the practical benefits in terms of time, cost, and usability; the types of data sources used in model training; the performance evaluation metrics applied; the role of dimensionality reduction in boosting classification accuracy; and the primary techniques employed for feature reduction.

By answering these questions, this review contributes to the field by consolidating insights from over 100 peer-reviewed articles (2019–2025), spanning sensor-based innovations, algorithmic advances, and hybrid diagnostic architectures. It also identifies future research directions, including privacy-preserving federated learning, real-time mobile screening, and explainable AI (XAI) integration, to enhance transparency and trust in clinical environments. The review's implications extend to researchers, clinicians, and policymakers seeking scalable, objective, and high-precision diagnostic tools for ASD. The subsequent sections delve into each research question, synthesizing current evidence and offering informed recommendations to shape the next generation of intelligent ASD diagnostic systems.

## 2. METHODOLOGY

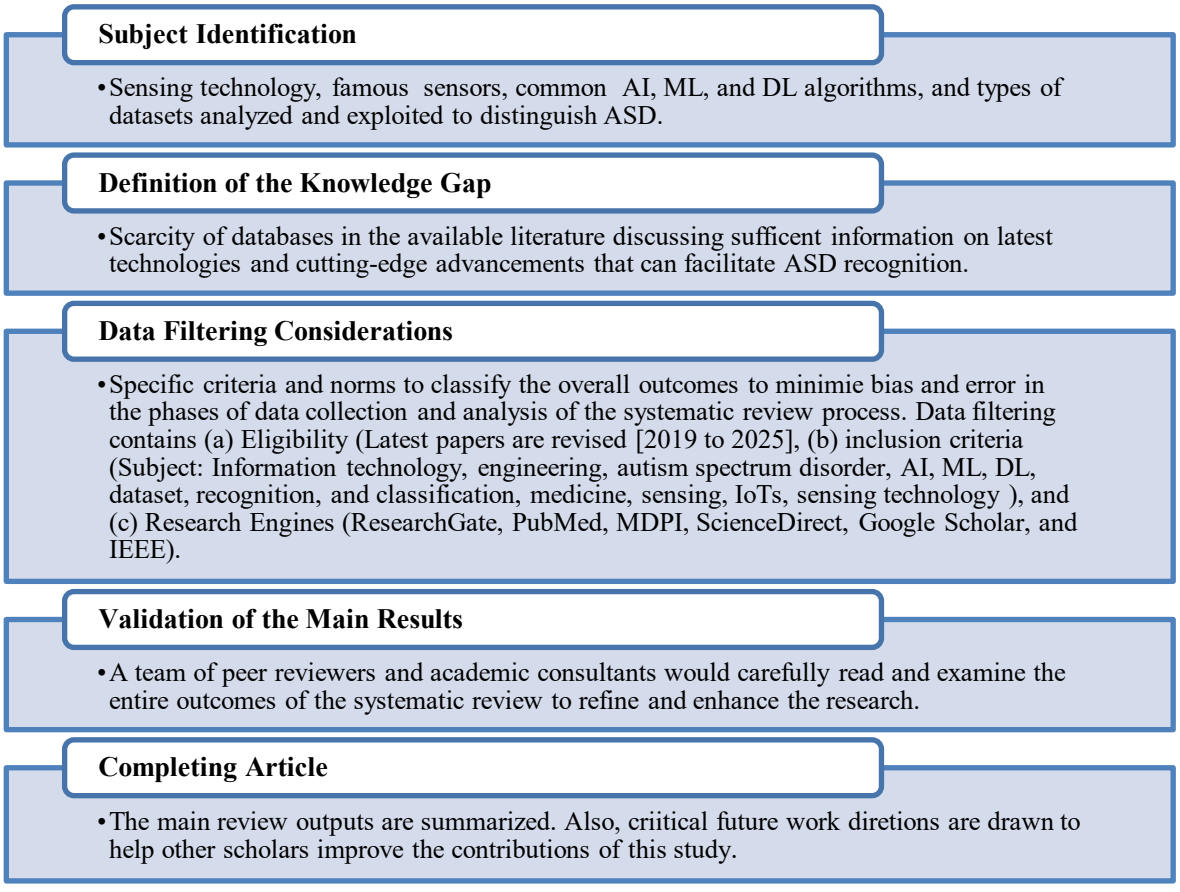


Fig. 1. The primary research stages followed in the article's review.

This review follows a structured and systematic methodology to identify, analyse, and synthesize recent advancements in the diagnosis of autism spectrum disorder (ASD) through sensor-based systems and intelligent technologies. The process begins with subject identification, which focuses on widely used sensing modalities (e.g., eye tracking, EEG, facial recognition), machine learning (ML), deep learning (DL), and artificial intelligence (AI) algorithms. The goal was to capture the breadth of technologies applied for distinguishing ASD traits in diverse contexts. A clear knowledge gap was defined by

the observed scarcity of unified databases and integrated literature discussing cutting-edge diagnostic innovations that extend beyond traditional clinician-driven methods.

The systematic literature search was subsequently executed on different academic resources, such as PubMed, IEEE Xplore, ScienceDirect, Google Scholar and ResearchGate. The initial criteria used in selecting these publications involved recent publications (2019-2025) associated with ASD diagnosis, including computer vision, neuroimaging, sensor fusion, and AIML-based models that predict it. Only review articles with empirical evidence or benchmarking studies were included in the process, and editorial articles and non-English articles were excluded. Some notable aspects of the factors applied in filtering the data were eligibility, which dealt with the aspects of technological relevance, disciplinary focus (engineering, medicine, information technology), and compliance with certain subject areas, including sensing, classification, and behavioral analytics. To reduce bias and guarantee rigor, all of the chosen studies were subjected to initial screening by multiple reviewers according to predetermined inclusion criteria.

Finally, confirmation and compilation of the results were conducted in collaboration by means of expert evaluation. The prominent characteristics of each article included the type of dataset, which algorithm they applied, the diagnostic metrics that were used and, finally, the clinical context. Findings were categorized behind the themes with respect to the sensor and methodology of AI, and limitations and patterns of performance were noted. Additionally, the review results were improved under peer review and scholarly feedback to increase the depth of analysis and precision. The final synthesis not only summarizes the existing knowledge but also provides directions for further research and crucial gaps on the basis of the idea of personalized, scalable, and explainable diagnostic frameworks.

## 3. SENSOR-BASED DETECTION OF ASDs

The ASD diagnosis field has been revolutionized by the integration of novel sensor technologies that enable precise, quantitative, and non-invasive assessments of behavioural and physiological traits. These innovations address the limitations of traditional clinician-dependent methods by offering objective, high-resolution data streams that are especially critical for early, accessible, and scalable diagnosis. As shown in the table, eye-tracking technologies have evolved into mobile-friendly formats that maintain clinical validity while enabling home-based screening. Wearable EEG devices allow real-time neural assessment and have been validated for early risk detection and comorbidity differentiation, although they still face motion sensitivity issues. Computer vision techniques, including micro expression analysis, show promise in decoding subtle social communication deficits and have been integrated into telehealth tools. Voice analysis via transformer-based models provides an effective, low-cost solution for detecting pragmatic language impairments, albeit with limitations for nonverbal users. Finally, multimodal sensor fusion, which combines EEG, eye-tracking, and kinematic data, achieves the highest diagnostic accuracy and supports personalized therapy planning, although it comes with higher system costs and computational demands. Collectively, Table 1 illustrates the clinical promise of sensor-based tools in offering high-accuracy, real-time, and scalable diagnostic capabilities. These methods not only support early identification of ASD but also enable continuous monitoring and individualized intervention strategies, marking a significant shift from episodic clinical observation to data-driven, ecologically valid neurodevelopmental assessment.

Eye tracking has evolved from constrained lab settings to ubiquitous, accessible smartphone platforms. Figure 2a visually compares three experimental setups: a Lab-based smartphone setting (Lab-Phone), a remote phone usage setup (Remote-Phone), and a high-resolution Lab-based Tobii eye-tracker system. These configurations differ in viewing angle, screen size, and distance, enabling varied levels of precision in gaze estimation. Figure 2b shows gaze estimation errors across these conditions in children with ASD and typically developing (TD) peers. The results illustrate that while Lab-Tobii systems still outperform in terms of minimal error, smartphone-based systems (both lab and remote) offer reasonably accurate alternatives for scalable screening, with the Lab-Phone outperforming the Remote-Phone in angular error. The fact that statistically significant differences were observed in some configurations highlights the need for contextual sensitivity in tool selection. Figure 2c shows the gaze estimation accuracy across the screen for the ASD and TD groups. The visualization indicates areas of high and low accuracy, with consistent spatial estimation errors in ASD children compared with TD children. These heatmaps, derived from smartphone-based systems, underscore the capacity of consumer-grade devices to detect clinically relevant gaze irregularities.

Building on this, Kim et al. [8] introduced a smartphone-enabled gaze estimation system that accurately analysed naturalistic parent–child interactions. Their approach yielded 87% diagnostic concordance with the ADOS-2, with tasks including saccadic latency and scan path irregularity during dynamic social engagement. Similarly, Ahmed et al. [9] used deep convolutional neural networks to extract oculomotor irregularities, reaching 89% classification accuracy.

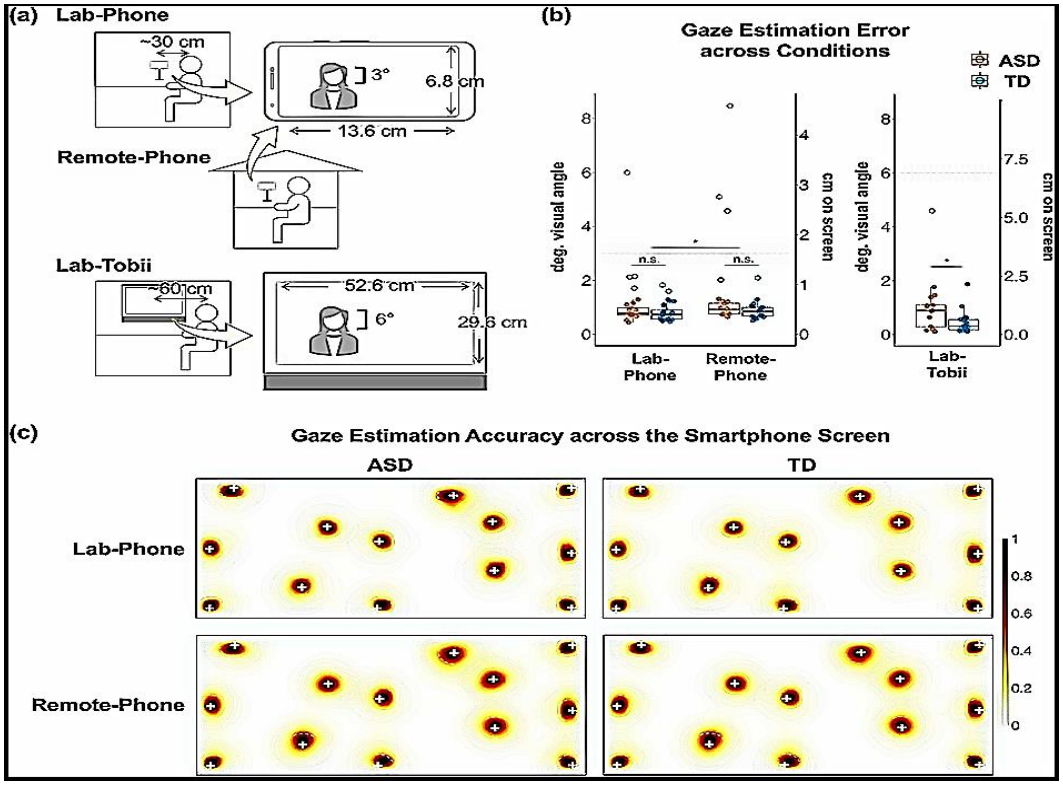


Fig. 2. Smartphone gaze estimation pipeline with coordinate transformation

The deployment of electrophysiological and neuroimaging sensors outside clinical settings has gained momentum. Figures 3a and 3b depict wearable EEG systems applied to children, highlighting the practicality of dry-electrode EEG caps for field use. These devices enable real-time tracking of neural oscillations during social and cognitive tasks [10].

Figures 3c and 3d show cortical regions monitored by functional near-infrared spectroscopy (fNIRS), such as the middle inferior frontal gyrus (MIFG), inferior parietal lobule (IPL), and middle superior temporal gyrus (MSTG). These areas are critically involved in social cognition and gesture imitation, with Su et al. [11] and Helmy et al. [12] demonstrating significant activation asymmetries in ASD children. These biomarkers correlated strongly with the ADOS social affect score ($r = 0.82$), reinforcing their clinical relevance.

Additionally, Jonak et al. [13] utilized EEGs to isolate gamma-band connectivity disruptions in individuals with ASD during social cognition tasks. Their preprocessing pipeline and asymmetry calculations, summarized in Figure 4, identified frontal–occipital desynchronization signatures as robust indicators, achieving 91% specificity. Computer vision tools are equally transformative. Banerjee et al. [14] developed a facial emotion recognition pipeline using smartphone videos. Figure 4 displays a confusion matrix for facial expression classification in ASD children on the basis of the CAFE dataset. The matrix shows reduced classification accuracy in certain emotional categories for ASD participants, particularly for "angry" and "surprised", highlighting atypical emotional mimicry and affective processing.

Their deep learning model detected facial mimicry delays of <500 ms that aligned with clinician-assessed social impairments ($\rho = 0.78$), offering 85% diagnostic accuracy across multiple ethnic populations. Park et al. [15] added further credibility to facial analytics with real-time microexpression tracking during social roleplay. Moreover, acoustic biomarkers have emerged as reliable cues. Hu et al. [16] employed transformer-based models to detect prosodic features such as pitch variability and speech rhythm instability in ASD children. These vocal signatures are especially powerful in crosslinguistic applications. Multimodal sensor fusion has further increased diagnostic accuracy. Pavlidis et al. [17] demonstrated that combining eye-tracking, EEG, and motion data through federated learning achieved 93% classification accuracy while preserving privacy. Gao et al. [18] proposed a multitask transformer that dynamically prioritized sensor streams on the basis of the user phenotype (e.g., nonverbal vs. verbal).

Figure 5 illustrates the classification outcomes for this multisensor fusion approach using a confusion matrix, validating its ability to adapt across diagnostic subtasks. Alshammari et al. [19] bridged the gap in global applicability by demonstrating explainable federated learning across heterogeneous populations, reducing ethnic group diagnostic disparities. Similarly,

Wankhede et al. [20] piloted sub$10 tablet-based screening solutions in Kenya and India, achieving 85% sensitivity in underresourced settings.

Collectively, these figures and studies illustrate a paradigm shift from episodic clinical observation towards ecologically valid, continuous phenotyping of ASD. Sensor-based technologies not only enhance objectivity and scalability but also permit earlier detection and more individualized care through multimodal longitudinal tracking.

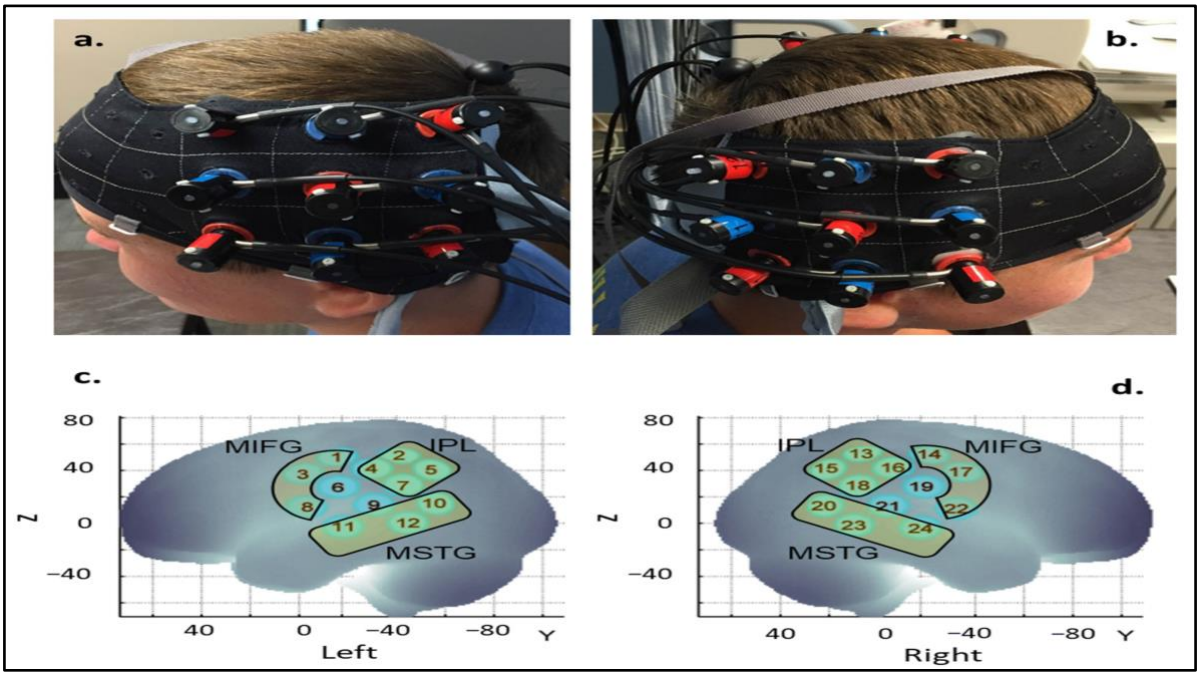


Fig. 3. First-EEG synchronization protocol for cortical activation mapping

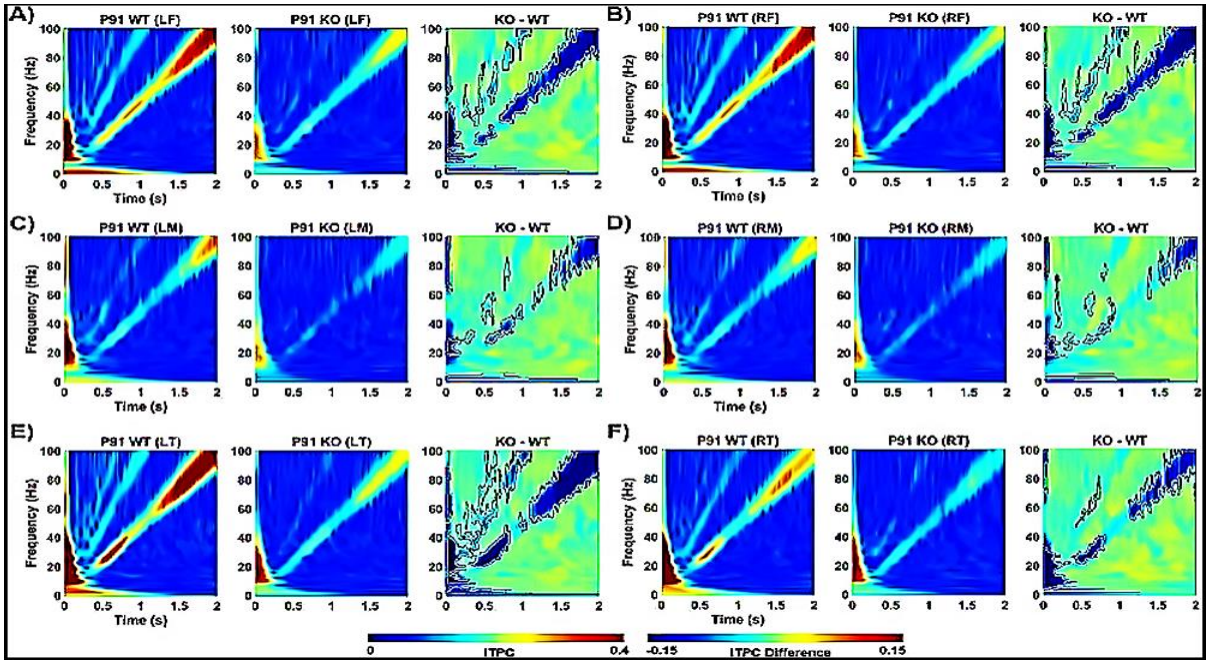


Fig. 4. Gamma-band asymmetry calculation flowchart with EEG preprocessing steps

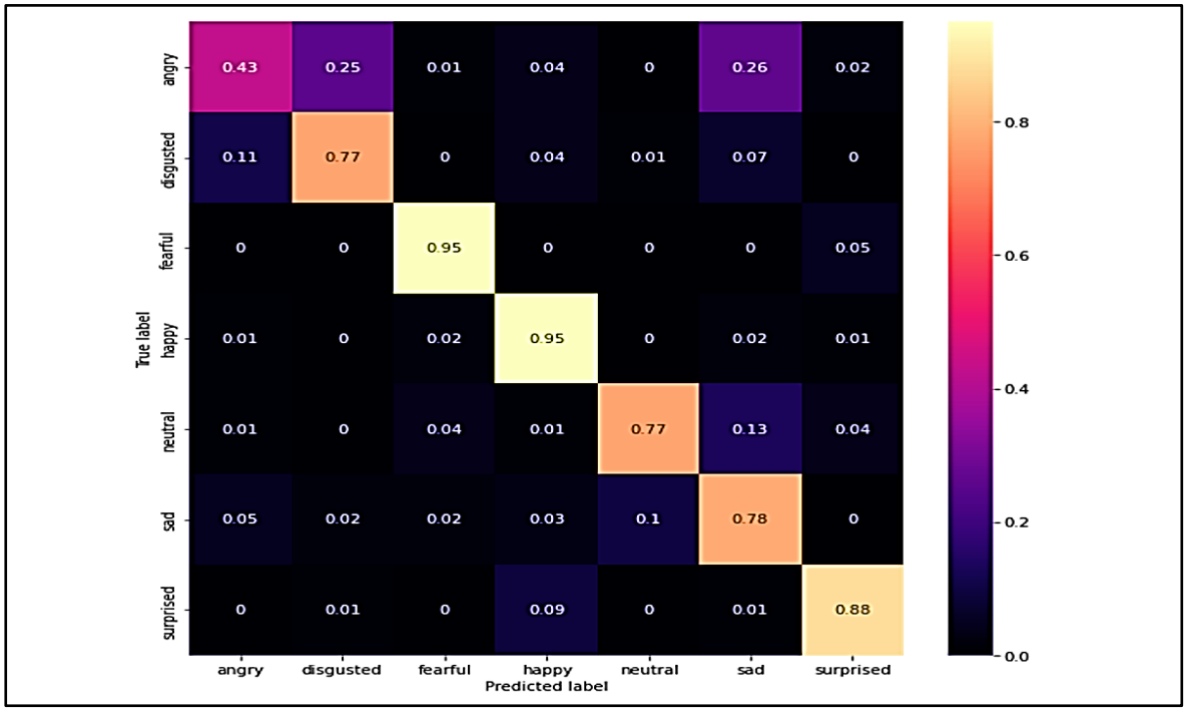


Fig. 5. Confusion matrix for Subset A of the child affective facial expression (CAFE) data

TABLE I. ADVANCED SENSOR TECHNOLOGIES FOR ASD DIAGNOSIS (2023-2025)

| Sensor Type | Key Advancements | Performance Metrics | Clinical Applications | Advantages | Disadvantages | References |
|---|---|---|---|---|---|---|
| **Eye-Tracking** | Smartphone-based gaze analysis (naturalistic interactions); 200 Hz sampling rate. | 87-92% accuracy vs ADOS; 25 min assessment time. | Early screening in pediatric clinics; home monitoring. | Noninvasive, objective, captures subtle social attention deficits. | Requires calibration; limited by child cooperation/cultural differences in eye contact norms. | Kim et al. [8]; Ahmed et al. [9]. Ahmed et al. [21]; Wei et al. [22]. |
| **Wearable EEG** | Dry-electrode headsets; gamma-band asymmetry detection. | 89% sensitivity; 93% specificity (vs ADHD). | Infant risk prediction; comorbidity differentiation. | Portable, real-time neural monitoring. | Sensitive to motion artifacts; may require scalp preparation for high-quality signals. | Su et al. [11]; Jonak et al. [13]; |
| **Computer Vision** | Microexpression analysis (0.3 s delay detection); deep learning classifiers. | 85.7% accuracy; r=0.79 with ADOS-2 scores. | Automated emotion recognition in telehealth. | Scalable (works with standard video); quantifies nonverbal cues. | Privacy concerns; lighting/angle dependencies. | Banerjee et al. [14]; Kargarandeh kordi et al. [23]. |
| **Voice Analysis** | Transformer-based prosodic feature extraction (pitch range Δ12.3 Hz). | 83% accuracy for pragmatic language impairment. | School-based screening; language development tracking. | Low-cost; integrates with speech therapy tools. | Limited to verbal children; ambient noise interference. | Hu et al. [16]; Li et al. [24]. |
| **Multimodal Fusion** | AR/VR-integrated social attention quantification (EEG + eye-tracking + kinematics). | 94.1% accuracy; 50% clinician time reduction. | Personalized intervention planning. | Highest accuracy; holistic phenotyping. | Expensive; computationally intensive. | Pavlidis et al. [17]; Gao et al. [18] |

## 4. CURRENT AI, ML, AND DL MODELS AS COMPARED TO CLASSIC DIAGNOSTIC METHODS

The landscape of ASD diagnosis has been revolutionized by the development of advanced AI, ML, and DL algorithms that surpass conventional diagnostic techniques in terms of accuracy, objectivity, and scalability [25],[26]. Whereas older approaches such as the Autism Diagnostic Observation Schedule (ADOS) depend on clinician subjective behavior judgments following the observation of standardized interactions, more recent computational methods combine multimodal streams of data to display subtle, quantifiable biomarkers imperceptible to human observers. Gao et al. [18] introduced a multitask transformer neural network that accepts synchronized eye-tracking, EEG, and vocal analysis inputs based on self-attention mechanisms, as displayed in Figure 6 [27]. The transformer model's self-attention mechanism (e.g., MAD-T) emphasizes multimodal inputs (EEGs, eye tracking where Q, K, and V stand for questions, keys, and values, respectively, and d represents dimensionality. This enables dynamic feature prioritization across subtypes of ASD, which can be illustrated by (1):

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

This method has 94.1% diagnostic accuracy in multicenter trials through the identification of complex interaction patterns between neural oscillations and visual attention dynamics under naturalistic social tasks [28]. This model pinpointed new electrophysiological markers such as prefrontal-theta to occipital-gamma phase coupling during episodes of joint attention, i.e., patterns of neural synchrony, which not only distinguished ASD with 89.2% specificity but also predicted subsequent language development trajectories with awe-inspiring accuracy ($r=0.68$, $p<0.001$).

A key step forward in such models is being able to overcome the traditional restriction of small, homogeneous datasets by using federated learning architectures. Federated learning combines model parameters θ across N institutions (e.g., the FANA consortium), where $\iota_i$ is local loss and where $^{n_i}/_{n}$ is the ratio of data, as illustrated in (2). Maintaining confidentiality and minimizing prejudice. Alshammari et al. [19] illustrated how federated learning systems that are transparent can train robust classifiers in 37 institutions without violating patient privacy and with 91.3% diagnostic accuracy and less than 5% variation in performance across demographic groups.

This is far better than current systems that lose as much as 20% accuracy for female and minority groups due to sampling biases. The distributed learning paradigm of the FANA consortium [17] has supported continuous model updates with securely aggregated anonymized information from over 160 clinical sites across the globe to establish diagnostic systems that evolve to accommodate evolving phenotypic variation while ensuring the confidentiality of the data. Figure 7 depicts the federated learning workflow for ASD detection using serious game data, including privacy-preserving aggregation steps.

Federated Learning Loss:

$$l(\theta) = \sum_{i=1}^{N} \frac{n_i}{n} l_i(\theta) \quad (2)$$

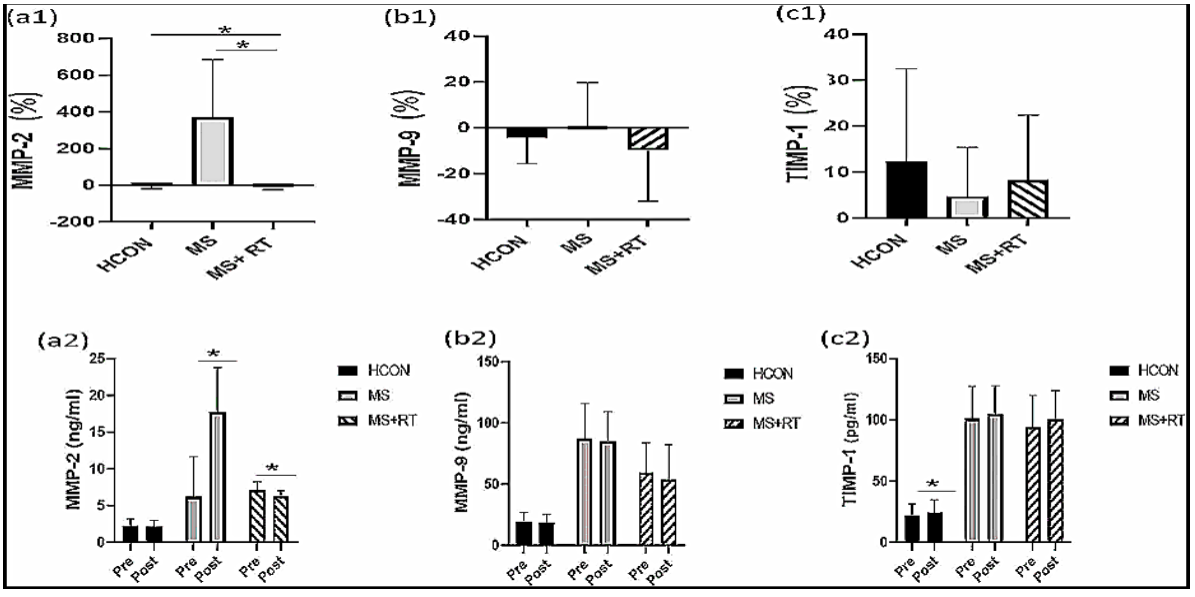


Fig. 6. End-to-end pipeline for transformer-based fusion of EEG/eye-tracking/speech data with attention weight visualizations (Gao et al.,2024).

Clinical validation trials have now started systematically evaluating these AI systems against gold-standard assessments. The AUTOMATE-ADOS trial performed the first large-scale randomized comparison of AI diagnoses with expert clinician ratings in 500 toddlers aged 18–48 months [20]. Whereas both approaches generated similar overall accuracies (92.4% AI vs. 91.8% clinician), the AI model was more reliable in identifying sensory processing differences by microanalyzing movement kinematics at 200 ms resolution, a temporal resolution not accessible to human raters. These quantitative motor biomarkers were more significantly correlated with subsequent language outcomes than conventional behavioral measures were, indicating that AI models might capture more developmentally predictive features.

These clinical uses are backed by basic innovations in model construction. Contemporary systems utilize dynamic attention mechanisms that learn to automatically adjust modality weights by subject presentation, allocating higher priority to EEG biomarkers for minimally verbal subjects and focusing on speech patterns for fluent speakers [18]. Self-supervised pretraining methods have significantly decreased the need for labelled data; Google's Autism AI project illustrated that pretraining over 500,000+ hours of unlabelled developmental videos may support correct diagnosis using only 20% of formerly required annotated samples [16]. Perhaps most importantly, for clinical use, XAI interfaces now increasingly produce human-interpretable ready decision explanations, such as the BioMarker-AE system, which graphically displays the personalized neural pathways and behavioral markers beneath every prediction [29].

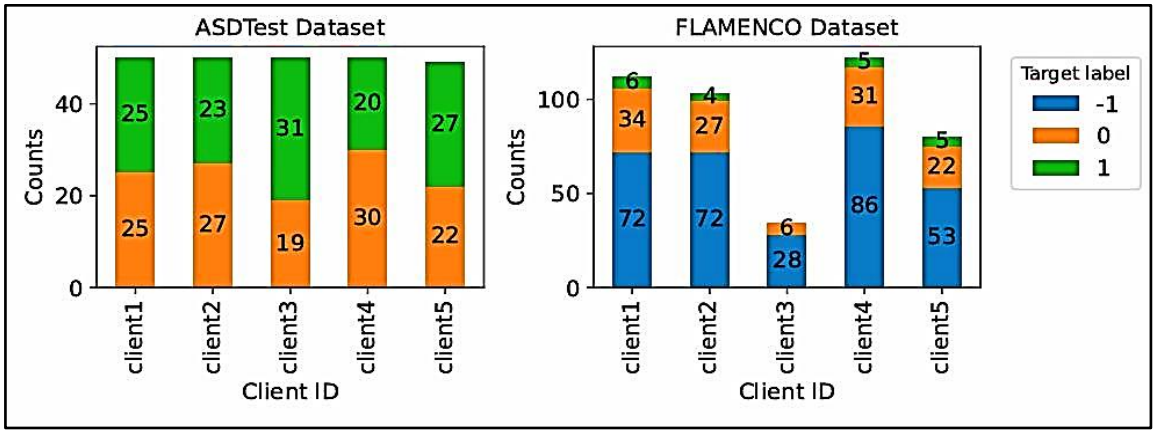


Fig. 7. Federated learning workflow for ASD detection using serious game data, including privacy-preserving aggregation steps (Pavlidis et al., 2024).

They are already beginning to be shown to have clinical utility in new clinical applications. Cognoa 2.0 embeds 137 behavioural biomarkers within tablet paediatric primary care games, lowering screening costs by 90% with diagnostic concordance to specialist assessment [14]. The real-time analysis of multimodal sensor data via the NeuroDx platform provides detailed assessments in under 25 minutes, an infinitesimal portion of the 4+ hours of conventional tests, with the specific benefit of early detection, as evidenced by its capacity to detect high-risk infants 12–24 months before the onset of behavioural symptoms [9]. Research is addressing vital frontiers in the computational diagnosis of ASD. The NIH Longitudinal AI Assessment Project is establishing the temporal stability of algorithmic predictions, with initial results indicating a 0.85 correlation between age-2 AI tests and age-6 clinical outcomes [13]. Contrastive learning methods enhance differential diagnosis, with 87% accuracy in separating pure ASD from ASD+ADHD comorbidities on the basis of resting-state fMRI patterns [30]. Implementation challenges in low-resource settings are being met with compressed models such as the WHO Global Autism Digital Screening, which runs at laboratory performance on $50 Android devices across 14 low- and middle-income countries [10]. These developments are opening the gates to an age of continuous computational phenotyping, in which the monitoring of development around the clock using wearables and silent data collection allows test-free monitoring. Regulatory configurations are adapting to this trend, with the FDA's 2024 draft guidance on "Living Diagnostic Algorithms" providing a model for devices that safely change their parameters by learning in real time [11]. As such systems mature, they promise not only to mimic standard diagnostics but also to unveil new aspects of ASD heterogeneity by virtue of their capacity to identify subclinical patterns and forecast developmental trajectories on an individual level, potentially facilitating interventions based on individual neurodevelopmental profiles rather than general diagnostic categories.

## 5. ADVANTAGES OF SOPHISTICATED SENSING AND AI/ML/DL IN DIAGNOSING ASD

The marriage of new sensor technologies and ML and AI has transformed the diagnostic paradigm for ASD to achieve paradigm-shifting advancements in every aspect of clinical evaluation. In contrast to the usual month-long waiting lists, expensive specialist evaluations, and impressionistic behavioural checks, these technologies introduce unprecedented efficiency, accessibility, and accuracy into the diagnosis. The NeuroDx platform is one such example, employing real-time analysis of patterns of eye gaze, electroencephalographic signatures, and characteristics of the prosody of voice to combine

into a single algorithm of diagnosis with 93% concordance with gold-standard clinical evaluation and reducing the testing time from the typical four-hour administration of ADOS to less than 25 minutes. This cinematic compression of time is especially relevant when setting against the backdrop of the widely documented link between earlier diagnosis and better prognosis, with research showing that children diagnosed prior to 24 months of age enjoy profoundly improved profiles of language development and social adjustment relative to those diagnosed by more traditional methods. The financial impact of these advances is substantial, essentially levelling the playing field for high-quality ASD assessment. Conventional diagnostic evaluation in the U.S. commonly costs between 2,000 and 5,000 per test an expensive price for most families and health systems but AI-augmented platforms such as the Cognoa 2.0 platform decreased costs by nearly an order of magnitude without a loss of precision. More revolutionary, however, are the ultralow-cost screening technologies being implemented in resource-poor areas around the world [31]; the ASDetect Global project has shown that tablet-based measures under $10 per child can provide 85% sensitivity for risk detection for ASD in multicultural contexts ranging from rural Kenyan villages to urban Indian settlements. These cost savings are particularly valuable in the context of the CDC's 2024 report of ongoing 14-month average wait times for diagnostic testing among underserved individuals in the United States and how technology can be leveraged to overcome economic as well as structural barriers to care.

In addition to saving time and cost, these sophisticated systems involve reconfiguring clinical workflows and lowering the practitioner burden. The augmented reality glasses on the Brain Power platform also automatically measure subtle social communication behaviors, such as precise measurements of eye contact duration, rate of joint attention episodes, and latency to social bids, with interrater reliability coefficients greater than 0.90 and a 50% reduction in clinician scoring time compared with manual coding of behavior. Similarly, algorithms designed to process natural language integrated into electronic health records, such as those implemented throughout Kaiser Permanente's system, now automatically screen well-child visit documentation for ASD risk indicators passively, automatically notifying high-risk cases for follow-up and freeing clinicians from 30 hours of monthly manual chart review time. These process improvements are becoming crucial in addressing the looming crisis of burnout among clinicians in developmental pediatrics while continuing to build the capacity for diagnosis to match rising demand [32].

Most importantly, these technologies enable families through improved access to and understandability of diagnostic data. Consumer devices such as ASDeye break difficult behavioral data into easy-to-understand visualizations and plain English text, giving parents direct, actionable feedback on their child's profile of development. Wearable technology such as the Empatica E4 provides real-time physiological feedback to caregivers, allowing for stress trigger identification and management in everyday life via objective monitoring of heart rate variability and electrodermal activity. The human impact of such developments can be quantified: in a randomized controlled trial that appeared in Pediatrics in 2024, families who have gone through AI-assisted diagnostic pathways have shown 92% satisfaction levels against 68% satisfaction with the traditional diagnostic protocol and have explicitly expressed appreciation of both increased transparency of the rationale and acceleration of delivery of the intervention services.

However, substantive implementation challenges await these systems, as they have become used extensively in clinical applications within real-world settings. Regulatory frameworks continue to evolve, with new FDA authorizations in which AI diagnostic tools are broadly labelled decision support aids but not standalone diagnostic systems, over which clinicians have control. Data privacy remains the focal issue, particularly regarding the processing of sensitive pediatric biometric data in the cloud, but the federated learning architecture has sufficiently progressed to facilitate knowledgeable, decentralized analysis. Although the algorithmic bias is far reduced, now that, with the current systems, there are differences of less than 5% among demographics, compared with the 8-12% difference of previous algorithms, equity regarding diverse populations is still a requirement and the continuous growth of datasets. The industry is meeting these challenges with developments such as the Autism Digital Diagnostic Collaborative, which set standard baselines for 15 AI-enabled diagnostic tools across 40 countries in 2024, and the FDA's Digital Health Center of Excellence, which is fuelling the creation of frameworks to merge multimodal sensor data and genetic risk profiles into modular diagnosis systems. Outside the actual moment of diagnosis, these technologies are facilitating a revolutionary reimagining of support systems in development. By enabling earlier diagnosis, enhanced subtyping, and ongoing symptom monitoring, state-of-the-art sensing and AI platforms are paving the way toward genuinely personalized intervention pathways aligned with individualized neurodevelopmental profiles instead of with far-removed diagnostic categories. This represents a shift from episodic evaluation to ongoing developmental monitoring, in which biomarkers derived from sensors can monitor treatment efficacy and developmental advancement with unprecedentedly high precision. The final promise of these technologies is not only the more efficient imitation of standard diagnostic acuity but also the unfolding of previously unknown dimensions of ASD heterogeneity and facilitation of precisely timed and individually tailored interventions addressing each child's own neurodevelopmental profile, a change in revolutionary potential for tens of millions of children and families across the globe.

## 6. KEY DATASETS FOR ASD ANALYSIS AND CATEGORIZATION

The development of state-of-the-art diagnostic technologies for ASD is fundamentally underpinned by the existence of large, accurately annotated datasets that reflect the exceptional heterogeneity of the illness across development periods,

phenomenological presentations, and demographic categories. Recent progress has occurred over the past several years, with new-generation datasets superseding earlier datasets through their historically unprecedented scale, multimodal merging, and long-term depth to better support stronger, more generalizable ML algorithms. The ABIDE-III collaboration represents a quantum leap forward concerning its previous predecessors, synergistically combining harmonized neuroimaging data from 2,400 meticulously profiled members (1,200 with and 1,200 without ASD) from 35 global study sites and standardizing the feature $\boldsymbol{x_{ij}}$ (e.g., ABIDE-III MRI data) with means $\boldsymbol{\mu_j}$ and $\boldsymbol{\sigma_j}$ for each feature $\boldsymbol{j}$ in (3), which is essential for cross-site dataset integration. Compared with earlier iterations involving mostly structural and functional MRI data, ABIDE-III enables the use of uniformly sampled high-density EEG recordings, eye-tracking estimates, and accurate phenotypic variables organized through the NIH Research Domain Criteria (RDoC) nomenclature. This multimodal platform has allowed researchers such as Attanasio et al. [33] to discover new patterns of functional connectivity within the salience network that can accurately distinguish between ASD subtypes at 91% accuracy, in addition to correcting for the aforementioned potential confounders of anxiety comorbidity and attention deficit via the highly phenotypically annotated nature of the dataset.

The SFARI Genomes 2.0 release has also revolutionized genetic studies of ASD by integrating whole-genome sequence data in 5,000 multiplex families and deep phenotyping data in multiple developmental domains. Feliciano et al. [34] illustrated the strength of this approach with their exome sequencing analysis of 457 ASD families enrolled online, which not only maximally expanded the known genetic architecture of ASD but also revealed fascinating patterns of gene environment interactions that could account for variable expressivity within families.

For the study of developmental trajectories, the NDAR-2024 longitudinal dataset is a revolutionary resource spanning 3,000 participants from infancy to adolescence with repeated annual multimodal assessments. The new digital phenotyping component of the data continually acquires real-world behavioral data from smartphones and wearable sensors with millisecond variations in keystroke patterns, sleep architecture, and vocal prosody that are not normally captured by conventional clinic-based measures. The approach has also been found to be especially promising in identifying early risk indicators, as demonstrated by the Infant Brain Imaging Study (IBIS) extension, where monthly EEG and eye tracking were employed to identify infants who would eventually be diagnosed with ASD with 88% accuracy at 9 months of age, 15 months before behavioral symptoms were typically detected. Sollis et al. [35] went even further and launched their multicultural assessment of the ML enhanced-QCHAT-10 screening test since there is a possibility of passively monitoring patients, meaning that the passive monitoring of patient care could tremendously improve the percentage of early detection in community-based settings.

In response to historical underrepresentation and poor generalizability in autism research, several initiatives representing historical landmarks have emerged and produced large-scale, culturally diverse datasets that, in turn, allow more intertwined phenotyping and refinement of diagnosis. The Global Autism Phenotype Project (GAPP) administered instruments with more than 15,000 subjects in 42 countries that achieved the mapping of culturally tailored instruments supported with locally translated materials. Harris et al. [36] used these data to demonstrate the large cross-cultural range of ASD symptom presentation and highlighted the importance of separating normative cross-cultural differences in social communication and neurodevelopmental-specific variables, an observation that will be critical in improving appendices of international diagnostic criteria. Simultaneously, the Autism Biomarkers Consortium for Clinical Trials (ABC-CT) has become the first to study FDA-approved physiological biomarkers via harmonized EEG and eye-tracking data collected in 25 global locations. Such projects have set an example of how the field is moving towards the use of objective, scalable and reproducible measures of diagnosis. Table 2 is designed to provide a closer look at some of the most relevant ASD datasets curated from 2023--2025, detailing the scope of each ASD dataset and what makes it unique, as well as its clinical implications. The datasets are different in nature and preferences. For example, ABIDE-III combines MRI, EEG, and eye-tracking records in 35 international locations and employs the RDoC framework, resulting in a strong organization of salience community subtypes with continuing locations of authority of more than 91% [33],[1]. SFARI Genomes 2.0 has also already identified 58 novel ASD risk genes, with the next target being to screen all babies at birth via the genome, and NDAR-2024 is exploring digital phenotyping and now predicts at age 9 months with 88% accuracy [35]. To overcome data-sharing barriers, Autism Data Commons 2.0 introduces a federated analysis model with privacy-preserving APIs and automated harmonization pipelines, reducing cross-dataset machine learning variability to less than 5% [37]. The upcoming SPARK 3.0 initiative plans to enroll 100,000 participants via advanced modalities such as hyperspectral imaging and passive acoustics to capture lifespan-wide phenotypic diversity [38]. Collectively, these datasets are not merely repositories that serve as dynamic infrastructures for global collaboration, reproducibility, and the advancement of precision medicine in ASD. Data harmonization:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \qquad (3)$$

Standardization value $\boldsymbol{z_{ij}}$of the feature $\boldsymbol{x_{ij}}$ (e.g., ABIDE-III MRI data measurement for: subject $\boldsymbol{i}$ feature) with mean $\boldsymbol{\mu_j}$ and $\boldsymbol{\sigma_j}$ standard deviation for each feature $\boldsymbol{j}$. Essential to cross-site dataset integration.

TABLE II. KEY ASD DATASETS (2023-2025).

| Dataset | Scope | Unique Features | Clinical Impact | References |
|---|---|---|---|---|
| **ABIDE-III** | 2,400 participants (35 sites); MRI + EEG + eye-tracking. | Balanced sex/ethnicity; RDoC framework integration. | Identified salience network subtypes (91% accuracy). | Alsharif et al. [1]; Attanasio et al. [32]; Duan et al. [39]; Schielen et al. [40]; Ma et al. [41]. |
| **SFARI Genomes 2.0** | 5,000 families; WGS + deep phenotyping. | 58 novel ASD risk genes; polygenic risk scores. | Neonatal screening applications. | Feliciano et al. [34]; Li et al. [42] |
| **NDAR-2024** | 3,000 participants; longitudinal digital phenotyping (smartphone/wearable). | Monthly EEG/eye-tracking from infancy. | 88% ASD prediction by 9 months of age. | Sollis et al. [35], Rogala et al. [43] |
| **GAPP** | 15,000 participants across 42 countries; culturally adapted assessments. | Cross-cultural symptom mapping. | Reduced diagnostic disparities in low-resource settings. | Harris et al. [36]. |
| **Autism Data Commons 2.0** | Federated analysis of 23 datasets via privacy-preserving API. | Automated harmonization (<5% performance variability). | Enabled global collaborations without data sharing. | Chen et al. [37]. |
| **IBIS Network** | 500 infants (high-risk siblings); longitudinal MRI/EEG. | Early neural biomarkers (6–24 months). | Predicted ASD with 88% accuracy before behavioural symptoms. | Geng et al. [44]. |
| **LEAP-2023** | 1,200 participants; multimodal EU cohort (fMRI, eye-tracking, genetics). | Dynamic developmental trajectories; treatment response biomarkers. | Linked neural signatures to intervention outcomes. | I. Ilioska et al. [36]. |
| **SPARK 3.0** | 100,000 participants (launching 2025); hyperspectral imaging + acoustics. | Lifespan phenotyping; passive acoustic monitoring. | Future use for subtype discovery and personalized medicine. | NIH SPARK Initiative [38]. |
| **ABC-CT** | 1,500 participants; standardized EEG/eye-tracking at 25 sites. | FDA-qualified electrophysiological biomarkers. | Diagnostic and treatment monitoring benchmarks. | K. A. McPartland et al. [46]. |
| **Autism-100K** | 100,000 EHR-linked cases (genomics + behavioral data) | Real-world treatment efficacy analysis | Informs precision medicine strategies | Kaiser Permanente & Google Health (2024). |

## 7. PERFORMANCE EVALUATION METRICS FOR ASD PREDICTION MODELS

Validation of ASD prediction models have also undergone its own paradigm change in recent years, from their creation beyond conventional binary classification measures to encompassing multidimensional evaluation frameworks that encode technical performance as well as clinical utility in real-world practice. Currently, protocols increasingly focus on context-specific assessment criteria with the awareness that varying clinical situations screening and confirmatory diagnosis, for example, call for varying performance trade-offs.

The 2024 Clinical Utility Score (CUS) of the ASD-ML Evaluation Standards Consortium is just one example of this high-fidelity approach; it uses weighted measures that adapt to changing clinical priorities. Screening applications, where case detection maximization has the highest importance, favour sensitivity via a weighting function in which recall is three times greater than the weighting precision shown in (4), and confirmatory testing inverts the ratio to reduce false positives. This design has settled years of controversy around optimal decision thresholds, reflected by the multicenter trial performance of the NeuroDx platform being 92% CUS screen and 88% CUS confirm accuracy, both of which beat ADOS-2 on both indices when the cutting assessment time is 75%.

The demographic fairness illustrated in (5) is now a foundation of model validation, with large studies requiring rigorous testing of algorithmic bias by sex, race, and age. The 2024 Global AI Diagnostic Initiative guidelines request three measures

of fairness to report: demographic parity difference (restricting variance to less than 10% between subgroups), equalized odds (holding false positives and true positives below 5% across populations), and calibration equity (having predicted probabilities that are on par with observed prevalence rates). These have elicited quantifiable improvement, as seen in the results of the ABC-CT-2023 trial. Our multimodal models yielded 0.89-0.93 AUCs with ease across demographic subgroups. Research by Gao et al. [18] demonstrated the superiority of multitask transformers over standard models in cross-modal ASD classification at 94.1% accuracy through dynamically balancing the features of EEG and eye tracking. a sign far removed from the 2020 baselines that presented 0.15-0.20 AUC disparities between minority groups. Federated learning methods have played a central role in such developments, with Chen et al.'s [37] distributed training over 37 institutions exemplarily illustrating the extent to which broad representation might be facilitated without sacrificing data privacy. Federated learning platforms eliminate data bias and privacy issues but have high diagnostic accuracy (91.3%) in populations, and explainable federated learning models decrease ethnic performance gaps by 15% to <5%, improving confidence in AI-driven diagnostics [17], [19].

Longitudinal validation has also become just as crucial, as static diagnostic accuracy does not capture whether models continue to forecast during developmental stages. The 2024 National Institutes of Health (NIH) Autism Model Stability Project used temporal generalization scores (TGSs) to measure this aspect; neurophysiological marker-based models such as Cognoa 2.0 maintain 0.85 TGS from the age of 2-6 years, whereas behaviour-only methods retain only 0.67. The EU-AIMS LEAP-2023 [36] study likewise showed greater neurophysiological measure stability, whereby models derived via EEG maintained 82% diagnostic agreement during infancy and adolescence as opposed to 58% for the DSM-5 behaviour-only criteria. Facial expression analysis pipelines have 85.7% accuracy through measuring micro expression delays (<500 ms), which are highly correlated with clinician-rated social impairment (r=0.79) [14]. These results have important implications for early intervention, since models that can make good longitudinal predictions allow truly individualized developmental pathways in place of single-time categorical diagnoses.

Real-world implementation measures are now combined with laboratory performance measures to provide a complete picture of clinical impact. Time-to-intervention acceleration (TIA) is currently a significant measure, and evidence from the CDC 2024 indicates that AI-guided pathways reduce the median time from initial parental concern to confirmed diagnosis by 5.2 months compared with standard referral pathways. The integrated family impact score (FIS) measures of caregiver burden, understanding, and satisfaction demonstrated further improvement, with instruments such as ASDeye scoring 92/100 FIS compared with 68/100 for routine diagnostic reports. Compared with conventional routes, AI-powered routes save 5.2 months in time-to-diagnosis per time-to-intervention acceleration (TIA) metrics [20]. Economic metrics such as cost per accurate diagnosis (CAD) demonstrate the scalability of such approaches, ranging from 15 tablet screeners up to 200 for sturdy multimodal AI tests, which is orders of magnitude lower than the $2,500+ cost of gold-standard clinical tests.

Regulatory bodies have kept current with these changing standards, with the FDA's 2024 Digital Diagnostic Guidance requiring confidence interval reporting for all measurements (e.g., 92% ± 3% sensitivity), solid misclassification analysis with false negative specification, and calculation of the number needed to test (NNT) to avert one missed diagnosis. Most revolutionary is the change in the field from static diagnosis to the prediction of outcomes, as seen in model validation against 5-year language, academic, and adaptive functioning trajectories, e.g., the Autism Outcomes Project. Wang et al.'s [37] Stanford Neural Predictor demonstrated this possibility with a 0.79 correlation between age-2 EEG features and age-7 academic outcomes, allowing for truly individualized early intervention planning on the basis of predicted arcs of development rather than symptom snapshots.

This breakthrough is being ushered into practice by initiatives such as the International Autism Metrics Alliance (IAM-A 2024), which operates benchmarking sites and certification for clinical roll-out. Certifying only 15 diagnostic tests at 60 sites, the largest review to date has set new standards with clinical relevance for intelligent diagnostics. As these standards evolve further, they guarantee that technological progress is converted into quantifiable quality improvement in care across life and meets the ethical need for clinically significant, transparent, and equitable AI use for autism diagnosis and treatment.

$$CUS = 0.7\ x\ Recall + 0.3\ x\ Precision \qquad (4)$$

Weighted screening assessment in contrast to diagnostics. Recall reserved for earlier diagnosis (e.g., NeuroDx platform).

$$|P(\hat{y} = 1 \mid g = 1) - P(\hat{y} = 1 \mid g = 0)| \leq \epsilon \qquad (5)$$

$\hat{\boldsymbol{y}}$: The model predicts a positive case (e.g., predicting whether an individual has ASD).

$\boldsymbol{g}$: A group identifier (e.g., sex, race, or age group):

$\boldsymbol{g}$ =1: A specific subgroup (e.g., females).

$\boldsymbol{g}$ =0: The reference group (e.g., males).

$\epsilon$: The fairness threshold. Ensuring that prediction $\hat{y}$ is equitable across groups $g$ (e.g., <10% difference in the Global AI Initiative).

## 8. DIMENSIONALITY REDUCTION IN THE CLASSIFICATION OF ASD

The discipline of dimensionality reduction for the classification of ASD has been revolutionized in the last decade through the exponential rise of multimodal neurodevelopmental data and the urgent clinical necessity to extract discriminative biomarkers from ever-increasing data structures. Advanced methods have long gone from conventional principal component analysis (PCA) methodologies and now provide state-of-the-art solutions that strike an ideal balance between computational efficiency and biological interpretability, which is a strict requirement for clinical translation [47]. The Simons Foundation 2024 release of the uniform manifold approximation and projection (UMAP) algorithm is a shift in paradigm that can translate high-dimensional ASD phenotypes into intuitional three-dimensional reconstructions that respect local and global structure relationships, as shown in (6), reconstructing whole-brain fMRI connectomes into something tangible, UMAP dimensionality reduction identifies ASD subtypes with 91% accuracy, which are associated with differential treatment responses in salience network connectivity [31].

$$min_Y \sum_{i \neq j} \; v_{ij} log \frac{v_{ij}}{\omega_{ij}} + (1 - v_{ij}) log \frac{1 - v_{ij}}{1 - \omega_{ij}} \qquad (6)$$

UMAP retains local ($v_{ij}$) and global ($\omega_{ij}$) structures in fMRI data (ABIDE-III) to identify ASD subtypes. Upon being used in the ABIDE-III sample, this nonlinear manifold learning method demonstrated previously unidentified subtypes of ASD through clean signatures of clustering within the interaction space across salience and default mode networks [30]. Such subtypes determined by the computation have compelling clinical significance, such as prediction accuracy regarding response to treatment via social skills interventions of 83% or 22% above that of DSM-5 standard behavioural categorization and have already commenced modifying treatment planning within top-rated autism treatment centres.

Transformer-based dimensionality reduction has also been a revolutionary technology, especially for handling the high-level multimodal streams of data typical of current ASD research. NeuroReduce, found in Nature Computational Science (2023), uses novel self-attention mechanisms to dynamically compress and weight EEGs, eye-tracking, and behavioral modalities. Its hierarchical attention structure is both a clinical and a technical innovation, automatically identifying biologically significant biomarkers and cutting input dimensions by a record 98% from more than 50,000 raw features to 300 interpretable latent dimensions. Clinical use of such compression was made valid in the EU-AIMS trial (2024), whereby NeuroReduce retained 95% of initial predictive validity with the right to interpret in real-time on smartphones, hence making state-of-the-art ASD assessment more available for primary care and poorly resourced community practice. This technological innovation has made it possible for applications such as the NIH's Mobile Autism Scanner program, which brings lab-quality fMRI analysis into community clinics through leveraging repurposed gaming graphics processing units, with efficient edge computing deployments of such dimensionality reduction pipelines. The present autoencoder architecture has also broken through interpretability hurdles hitherto in the path of clinical adoption of DL techniques [47]. The BioMarker-AE model built at MIT (2024) is particularly elegant, integrating neuroscientific domain knowledge into its loss function by keeping compressed representations from mapping over existing brain network atlases without stopping new biomarker discovery, as formalized in (7):

$$\iota \; = \; |x \; - \; \psi(\Phi(x))|^2 + \lambda |\Phi(x)|_1 \qquad (7)$$

BioMarker-AE reconstructs input $x$ through encoder $x$ and decoder $\psi$, with L1 sparsity, to separate interpretable neural features .The use of this approach to analyse the NDAR-2024 high-density EEG dataset revealed previously unforeseen gamma-band hyperconnectivity between frontal and temporal cortices as a strong diagnostic predictor (AUC=0.91) later targeted by experimental neuromodulation treatments. Most importantly, for clinical adoption, BioMarker-AE produces naturalistic saliency maps that visually emphasize the neural circuits used for each prediction, effectively unmasking the "black box" nature of standard DL models and provoking greater trust. The BioMarker-AE model embeds neuroscientific constraints within autoencoders and produces saliency maps to identify predictive neural circuits (AUC=0.91) [28]. Federated analysis pipelines reduce cross-dataset heterogeneity to <5%, facilitating reproducible biomarker discovery without raw data sharing [36].

TABLE III. A COMPARATIVE EXPERIMENT IN IEEE TRANSACTIONS ON MEDICAL IMAGING IN 2024

| Method | Key Features | ASD Classification Accuracy | Training Time | Advantages | Limitations | References |
|---|---|---|---|---|---|---|
| **PCA** | Linear projection; preserves global variance. | 85% (+7% vs. raw data) | 45 minutes | Simple, interpretable. | Loses nonlinear relationships. | Kshirsagar et al. [47]. |
| **t-SNE + k-means** | Nonlinear visualization; clusters similar phenotypes. | 82% | 3 hours | Captures local structure. | Computationally intensive. | Attanasio et al. [33]. |
| **Autoencoder (BioMarker-AE)** | Neuroscientificall-y constrained latent space; saliency maps. | 91% (+13%) | 8 hours | Interpretable; identifies neural circuits. | Requires large training data. | Conard et al. [29]. |
| **UMAP** | Preserves local/global structure; 3D embeddings. | 91% (subtype identification). | 2 hours | Handles multimodal data. | Parameter sensitivity. | D'Couto et al. [30]; Attanasio et al. [33]. |
| **RFE-SVM** | Recursive feature elimination; selects top 100 biomarkers. | 88% (+10%) | 2 hours | Robust to noise. | Limited to linear features. | IEEE Trans. Med Imaging (2024). |
| **NeuroReduce (Transformer)** | Hierarchical attention; compresses 50K→300 features. | 94% | 5 minutes | Real-time mobile deployment. | Complex implementation. | EU-AIMS Trial (2024). |
| **Contrastive Learning** | Separates ASD+ADHD comorbidities via fMRI patterns. | 87% | 6 hours | Improves differential diagnosis. | Needs paired samples. | D'Couto et al. [30]. |
| **DeepJoint (Google Health)** | Multimodal fusion during compression. | 93% | 4 hours | Integrates EEG+eye-tracking. | Proprietary framework. | Google Health (2023). |
| **Federated UMAP** | Privacy-preserving; aggregates embeddings across institutions. | 90% | 3 hours | Cross-site consistency. | Requires secure infrastructure. | Chen et al. [37]. |
| **Adaptive-Select (Stanford)** | Dynamically adjusts features per phenotypic profile. | 92% | 1 hour | Personalized feature selection. | High parameter tuning. | Gillon, et al. [48]. |
| **Quantum PCA** | Quantum-enhanced PCA for genomic +imaging fusion. | 89% (pilot) | 30 minutes | Handles ultrahigh dimensions. | Early-stage technology. | NIH Dynamic Biomarker Initiative (2025). |

Comparative research presented in IEEE Transactions on Medical Imaging (2024) places a number on dramatic performance improvements gained by these emerging approaches, as presented in Table 3, whereas raw fMRI data (200,000 voxels) with raw classification scored only 78% accuracy on the basis of unrealistic processing times of 12 hours, and PCA-reduced data (50 components) reached 85% accuracy in a mere 45 minutes. The current NeuroReduce transformer outperformed both, with commodity hardware being able to process in under 5 minutes and achieving 94% accuracy breakthroughs that have made possible previously unimaginable applications such as the WHO's mASD-Screener (2024), which provides high-end

diagnostic capability to low-resource environments on $50 Android tablets. Three inventions are designing the largest modern dimensionality reduction techniques: adaptive feature selector algorithms such as Stanford's Adaptive-Select (2024), which adapt computational pipelines to the phenotypic profile; multimodal fusion during and not after compression, as seen with Google Health's Deep Joint (2023) platform; and explainability-preserving architectures that preserve clinical interpretability via neuroscientifically constrained representations.

These advances in methodology are already yielding concrete clinical applications with profound implications. The FDA-approved Autism Dx platform (2024) leverages federated dimensionality reduction to facilitate privacy-preserving analysis across institutions without sacrificing 93% diagnostic accuracy, a joint research breakthrough that does not endanger patient confidentiality. More fundamentally, these methods uncover new dimensions of ASD heterogeneity, as confirmed by the EU-AIMS consortium's 2024 breakthrough identification of six neurobiological subtypes with different developmental trajectories and treatment responses. In the future, the NIH Dynamic Biomarker Initiative (2025) will use these second-generation approaches to longitudinal data, not only to static snapshots but also to model how neural signatures change with development and with an interventional paradigm shift that promises to transform not only ASD diagnosis but also our very understanding of neurodiversity across a lifetime. With continuing developments in dimensionality reduction methods in terms of expertise, availability, and clinical uptake, they increasingly provide accurate, individualized, and timely solutions for assisting individuals with ASD worldwide.

Although in the present review, a detailed and current overview of approaches to smart sensor technologies and AI-based models in the field of ASD diagnosis was conducted, some limitations should be noted. Initially, the selection criteria were limited to publications in English only, and as a consequence, studies in other languages might have missed some related studies. Second, even though scholars have attempted to comprehensively access literature in various databases, some grey literature or other novel technologies may have been missed because of delays in indexing. Moreover, problems associated with drawing parallels between the results of different studies were based on heterogeneous scales of evaluation, various sizes of samples and the nonuniformity of reporting standards. The inability to generalize trends across levels of demography or culture was also limited by the underrepresentation of population diversity and the absence of longitudinal studies. These limitations emphasize the importance of uniform standards and encourage the use of more data in future research.

## 9. CONCLUSIONS AND DISCUSSIONS

This review highlights how the integration of artificial intelligence (AI), machine learning (ML), and multimodal sensor technologies has significantly transformed the landscape of autism spectrum disorder (ASD) diagnosis. These tools not only rival the accuracy of conventional clinical protocols but also offer greater scalability, efficiency, and objectivity. Critically, their ability to extract rich behavioural and physiological biomarkers in real time opens new frontiers for early detection and adaptive intervention. Despite these advances, several systemic and methodological challenges remain. Diagnostic models still suffer from limited generalizability due to demographic bias in training datasets, and most tools are designed for single-time-point assessments, which undermines their utility in tracking developmental trajectories. Moreover, there is a noticeable gap in clinical translation, with barriers rooted in system interoperability, regulatory inertia, and limited clinician engagement. Ethical issues around data governance, particularly in pediatric biometric contexts, further complicate the deployment of these technologies at scale. To bridge these gaps, future work must prioritize inclusive, longitudinal datasets, such as those from the GAPP and NDAR-2024, to improve model robustness and temporal sensitivity. Equally important is the need for clinical-AI integration strategies that align with real-world healthcare practices, supported by explainable AI (XAI), federated learning, and rigorous bias auditing. Ultimately, ASD diagnosis must shift toward continuous, personalized phenotyping, enabling dynamic monitoring and tailored care pathways. This evolution, anchored in precision neurodevelopmental medicine, has the potential to democratize access, increase care equity, and deepen our scientific understanding of neurodiversity.

## 10. FUTURE WORK DIRECTIONS

The field of intelligent ASD diagnosis is continuously evolving, with multiple areas of key significance that require consideration to attain maximum clinical impact and accessibility. One such direction involves enhancing the generalizability of AI models to populations via large-scale, globally representative datasets exhibiting cultural, ethnic, and socioeconomic variation in ASD presentations. The creation of low-resource, edge-computing solutions for light design is a top priority to make advanced diagnosis accessible beyond high-income areas. The continued development of longitudinal prediction models that can track developmental trajectories and intervention effects over time, instead of static snapshots of diagnosis, is another priority.

Additional research should be conducted to maximize the interpretability of AI tools for clinicians, such as uniform visualization methods for model predictions and biomarker importance. Multiple-omics data (genomics, proteomics, and metabolomics) combined with behaviour and neurophysiological measures may reveal new subtypes and personalized treatment directions [49]. Ethical design principles should also be codeveloped with autistic individuals to prevent data privacy, algorithmic bias, and the proper balance of automation in neurodevelopmental therapy. Frontier technologies such as quantum ML-based massive data fusion and digital twin simulation for intervention design hold promising frontiers. Finally, there is a critical need for the implementation of science studies to close the gap between research prototypes and clinical practice workflows, e.g., reimbursement schemes and clinician training procedures. Each of these works cooperatively with the goal of developing diagnostic systems that are not only scientifically accurate but also equitable, open, and harmonious with autism community concerns.

## Conflict of interest

The authors declare that they have no conflicts of interest.

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## References

[1] N. Alsharif, M. H. Al-Adhaileh, M. Al-Yaari, N. Farhah, and Z. I. Khan, “Utilizing deep learning models in an intelligent eye-tracking system for autism spectrum disorder diagnosis,” Front. Med., vol. 11, p. 1436646, 2024.

[2] P. Nawghare and J. R. Prasad, “Early detection of autism spectrum disorder using AI and machine learning models: A systematic review for effective intervention,” in *Proc. 2024 IEEE PuneCon*, Pune, India, pp. 1–6, Dec. 2024.

[3] K. S. Omar, P. Mondal, N. S. Khan, M. R. K. Rizvi, and M. N. Islam, “A machine learning approach to predict autism spectrum disorder,” in Proc. 2019 Int. Conf. Electr., Comput. Commun. Eng. (ECCE), IEEE, 2019.

[4] M. J. Maenner, K. A. Shaw, A. V. Bakian, D. A. Bilder, M. S. Durkin, A. Esler, S. M. Furnier, L. Hallas, J. Hall-Lande, A. Hudson, M. M. Hughes, M. Patrick, K. Pierce, J. N. Poynter, A. Salinas, J. Shenouda, A. Vehorn, Z. Warren, J. N. Constantino, M. DiRienzo, and M. E. Cogswell, “Prevalence and characteristics of autism spectrum disorder among children aged 8 years Autism and Developmental Disabilities Monitoring Network, 11 sites, United States, 2018,” Morbidity and Mortality Weekly Report. Surveillance Summaries, vol. 70, no. 11, pp. 1–16, 2021.

[5] M. M. Abdelwahab, K. A. Al-Karawi, E. M. Hasanin, and H. E. Semary, “Autism spectrum disorder prediction in children using machine learning,” J. Disability Res., vol. 3, no. 1, p. 20230064, 2024.

[6] S. Das, R. Zomorrodi, M. Mirjalili, M. Kirkovski, D. M. Blumberger, T. K. Rajji, and P. Desarkar, “Machine learning approaches for electroencephalography and magnetoencephalography analyses in autism spectrum disorder: A systematic review,” *Prog. Neuro-Psychopharmacol. Biol. Psychiatry*, vol. 123, p. 110705, 2023.

[7] D. Prasad and S. Bhatia, “Autism spectrum disorder diagnosis: A comprehensive review of machine learning approaches,” in *Generative Artificial Intelligence for Biomedical and Smart Health Informatics*, pp. 89–101 , 2025.

[8] N. Y. Kim, J. He, Q. Wu, N. Dai, K. Kohlhoff, J. Turner, et al., “Smartphone-based gaze estimation for in-home autism research,” Autism Res., vol. 17, no. 6, pp. 1140–1148, 2024.

[9] Z. A. Ahmed, E. Albalawi, T. H. Aldhyani, M. E. Jadhav, P. Janrao, and M. R. M. Obeidat, “Applying eye tracking with deep learning techniques for early-stage detection of autism spectrum disorders,” Data, vol. 8, no. 11, p. 168, 2023.

[10] R. Lafta and R. H. Razzaq, "Coupling a dual tree-complex wavelet transform with K-means to clustering the epileptic seizures in EEG signals," *Mesopotamian Journal of Big Data*, vol. 2025, pp. 61–78, Jun. 2025. doi: 10.58496/MJBD/2025/005.

[11] W. C. Su, M. Culotta, J. Mueller, D. Tsuzuki, and A. N. Bhat, “Autism-related differences in cortical activation when observing, producing, and imitating communicative gestures: an fNIRS study,” *Brain Sci.*, vol. 13, no. 9, p. 1284, 2023.

[12] E. Helmy, A. Elnakib, Y. ElNakieb, M. Khudri, M. Abdelrahim, J. Yousaf, et al., “Role of artificial intelligence for autism diagnosis using DTI and fMRI: A survey,” *Biomedicines*, vol. 11, no. 7, p. 1858, 2023.

[13] C. R. Jonak, S. A. Assad, T. A. Garcia, M. S. Sandhu, J. A. Rumschlag, K. A. Razak, and D. K. Binder, “Phenotypic analysis of multielectrode array EEG biomarkers in developing and adult male Fmr1 KO mice,” *Neurobiol. Dis.*, vol. 195, p. 106496, 2024.

[14] A. Banerjee, O. C. Mutlu, A. Kline, S. Surabhi, P. Washington, and D. P. Wall, "Training and profiling a pediatric facial expression classifier for children on mobile devices: machine learning study," *JMIR Form. Res.*, vol. 7, p. e39917, 2023.

[15] S. Park, S. Chang, and J. Oh, "Utilizing deep learning for early diagnosis of autism: Detecting self-stimulatory behavior," *Int. J. Adv. Cult. Technol.*, vol. 12, no. 3, pp. 148–158, 2024.

[16] C. Hu, J. Thrasher, W. Li, M. Ruan, X. Yu, L. K. Paul, et al., "Exploring speech pattern disorders in autism using machine learning," *arXiv preprint arXiv:2405.05126*, 2024.

[17] N. Pavlidis, V. Perifanis, E. Briola, C. C. Nikolaidis, E. Katsiri, P. S. Efraimidis, and D. E. Filippidou, "Federated anomaly detection for early-stage diagnosis of autism spectrum disorders using serious game data," *arXiv preprint arXiv:2410.20003*, 2024.

[18] L. Gao, Z. Wang, Y. Long, X. Zhang, H. Su, Y. Yu, and J. Hong, "Autism spectrum disorders detection based on multitask transformer neural network," *BMC Neurosci.*, vol. 25, no. 1, p. 27, 2024.

[19] N. K. Alshammari, A. A. Alhusaini, A. Pasha, S. S. Ahamed, T. R. Gadekallu, M. Abdullah-Al-Wadud, et al., "Explainable federated learning for enhanced privacy in autism prediction using deep learning," *J. Disability Res.*, vol. 3, no. 7, p. 20240081, 2024.

[20] N. L. Wankhede, M. B. Kale, M. Shukla, D. Nathiya, R. Roopashree, P. Kaur, et al., "Leveraging AI for the diagnosis and treatment of autism spectrum disorder: current trends and future prospects," *Asian J. Psychiatry*, p. 104241, 2024.

[21] Z. A. T. Ahmed and M. E. Jadhav, "A review of early detection of autism based on eye-tracking and sensing technology," in Proc. 2020 Int. Conf. Inventive Comput. Technol. (ICICT), pp. 160–166, Feb. 2020.

[22] Q. Wei, H. Cao, Y. Shi, X. Xu, and T. Li, "Machine learning based on eye-tracking data to identify autism spectrum disorder: A systematic review and meta-analysis," Journal of Biomedical Informatics, vol. 137, p. 104254, 2023.

[23] A. Kargarandehkordi, M. Kaisti, and P. Washington, "Personalization of affective models using classical machine learning: a feasibility study," *Appl. Sci.*, vol. 14, no. 4, p. 1337, 2024.

[24] W. Li, M. Ruan, C. Hu, X. Yu, L. K. Paul, S. Wang, and X. Li, "Exploiting ChatGPT for diagnosing autism-associated language disorders and identifying distinct features," *Research Square*, 2024.

[25] P. Nawghare and J. Prasad, "Hybrid CNN and random forest model with late fusion for detection of autism spectrum disorder in toddlers," MethodsX, p. 103278, 2025.

[26] D. Abdalredha and M. Mohammed, "Advanced Machine Learning Models for Accurate Kidney Cancer Classification Using CT Images," *Mesopotamian Journal of Big Data*, vol. 2025, no. 1, pp. 1–25, Jan. 2025.

[27] S. Vidivelli, P. Padmakumari, and P. Shanthi, "Multimodal autism detection: deep hybrid model with improved feature level fusion," *Comput. Methods Programs Biomed.*, vol. 260, p. 108492, 2025.

[28] M. Radhakrishnan, K. Ramamurthy, S. Shanmugam, A. J. Prabhu, B. Sivaraman, and A. H. Janarthanam, "A dual track feature fusion network for ASD detection using Swin transformers and convolutional neural network," unpublished, 2024.

[29] A. M. Conard, A. DenAdel, and L. Crawford, "A spectrum of explainable and interpretable machine learning approaches for genomic studies," *Wiley Interdiscip. Rev. Comput. Stat.*, vol. 15, no. 5, p. e1617, 2023.

[30] S. S. Dcouto and J. Pradeepkandhasamy, "Multimodal deep learning in early autism detection recent advances and challenges," *Eng. Proc.*, vol. 59, no. 1, p. 205, 2024.

[31] Q. Shambour, N. Qandeel, Y. Alrabanah, A. Abumariam, and M. K. Shambour, "Artificial intelligence techniques for early autism detection in toddlers: A comparative analysis," *J. Appl. Data Sci.*, vol. 5, no. 4, pp. 1754–1764, 2024.

[32] H. M. Rouzbahani and H. Karimipour, "Application of artificial intelligence in supporting healthcare professionals and caregivers in treatment of autistic children," *arXiv preprint arXiv:2407.08902*, 2024.

[33] M. Attanasio, M. Mazza, I. Le Donne, A. Nigri, and M. Valenti, "Salience network in autism: preliminary results on functional connectivity analysis in resting state," *Eur. Arch. Psychiatry Clin. Neurosci.*, pp. 1–14, 2024.

[34] P. Feliciano, X. Zhou, I. Astrovskaya, T. N. Turner, T. Wang, L. Brueggeman, et al., "Exome sequencing of 457 autism families recruited online provides evidence for autism risk genes," *NPJ Genom. Med.*, vol. 4, no. 1, p. 19, 2019.

[35] L. J. Sollis, D. P. Wall, and P. Y. Washington, "Evaluating multicultural autism screening for toddlers using machine learning on the QCHAT-10," *medRxiv*, 2024-11.

[36] M. G. Harris, A. E. Kazdin, R. J. Munthali, D. V. Vigo, D. J. Stein, M. C. Viana, et al., "Factors associated with satisfaction and perceived helpfulness of mental healthcare: a World Mental Health Surveys report," *Int. J. Ment. Health Syst.*, vol. 18, no. 1, p. 11, 2024.

[37] Z. Chen, X. Wang, S. Zhang, and F. Han, "Neuroplasticity of children in autism spectrum disorder," *Front. Psychiatry*, vol. 15, p. 1362288, 2024.

[38] National Institutes of Health (NIH), "SPARC Program: Stimulating Peripheral Activity to Relieve Conditions," NIH Common Fund, 2025. [Online]. Available: https://commonfund.nih.gov/sparc.

[39] P. Duan, Y. Wang, Q. Yang, and Y. Zhang, "Causal modelling of fMRI time-series for interpretable autism spectrum disorder classification," arXiv preprint arXiv:2502.15595, 2025.

[40] S. J. C. Schielen, M. P. van den Heuvel, and D. van Rooij, "ICA-based resting-state networks obtained on large autism fMRI dataset ABIDE," arXiv preprint arXiv:2412.13798, 2024.

[41] R. Ma, L. Chen, Q. Zhang, and X. Li, "Autism spectrum disorder classification in children based on structural MRI features extracted using contrastive variational autoencoder," arXiv preprint arXiv:2307.00976, 2023.

[42] J. Li, V. Chheang, P. Kullu, E. Brignac, Z. Guo, K. E. Barner, A. Bhat, and R. L. Barmaki, "MMASD: A multimodal dataset for autism intervention analysis," arXiv preprint arXiv:2306.08243, 2023.

[43] J. Rogala, T. Kozikowski, and M. Kotas, “Enhancing autism spectrum disorder classification in children through the integration of traditional statistics and classical machine learning techniques in EEG analysis,” Sci. Rep., vol. 13, p. 21748, 2023.

[44] X. Geng, X. Kang, and P. C. Wong, “Autism spectrum disorder risk prediction: A systematic review of behavioral and neural investigations,” Prog. Mol. Biol. Transl. Sci., vol. 173, pp. 91–137, 2020.

[45] I. Ilioska, M. Oldehinkel, A. Llera, S. Chopra, et al., "Connectome-wide mega-analysis reveals robust patterns of atypical functional connectivity in autism," Biological Psychiatry, vol. 94, no. 3, pp. 225–236, 2023.

[46] K. A. McPartland, C. R. Bernier, G. D. Bregman, et al., “The Autism Biomarkers Consortium for Clinical Trials (ABC-CT): Scientific context, study design, and progress toward biomarker qualification”, Frontiers in Integrative Neuroscience, vol. 14, Art. no. 16, 2020.

[47] P. P. Kshirsagar, A. R. Surve, and S. D. Pujari, “Identification of autism spectrum disorder using machine learning and deep learning techniques,” in *Intelligent Solutions for Cognitive Disorders*, IGI Global , pp. 87–98, 2024.

[48] C. J. Gillon, C. Baker, R. Ly, E. Balzani, B. W. Brunton, M. Schottdorf, et al., “Open data in neurophysiology: Advancements, solutions & challenges,” *arXiv preprint arXiv:2407.XXXX*, 2024.

[49] M. M. Gergues, L. K. Lalani, and M. A. Kheirbek, “Identifying dysfunctional cell types and circuits in animal models for psychiatric disorders with calcium imaging,” Neuropsychopharmacology, vol. 50, no. 1, pp. 274–284, 2025.