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Clinical Assessment Methods for Early Autism Spectrum Disorder in Paediatrics Using Explainable Artificial Intelligence and Quantum Machine Learning

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Abstract: *Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder characterised by persistent social communication difficulties together with restricted and repetitive behavioural patterns. Early and accurate diagnosis is critical for timely intervention,however, traditional clinical assessment methods require extended time and extensive resources while assessment results depend on evaluator judgement. The development of Artificial Intelligence (AI) technologies including Machine Learning (ML) and Deep Learning (DL) has made it possible to automatically identify ASD through the analysis of EEG data and neuroimaging information and eye-tracking results and behavioural signals. The "black-box" characteristics of these models create two main problems which reduce their effectiveness as predictive tools for medical applications. The introduction of Explainable Artificial Intelligence (XAI) techniques, including SHAP, LIME, and Grad-CAM, provides a framework for improving model interpretability and transparency. Quantum Machine Learning (QML) presents two main benefits through its ability to process high-dimensional data while showing improved performance in computational tasks. This review examines the principal datasets, preprocessing techniques, feature extraction methods, and AI-based detection models used in ASD diagnosis.However, researchers continue to study three main problems which include standardised biomarker deficiencies, data variability and clinical validation shortages. The article presents future research paths which will lead to systems that achieve interpretability and robustness while maintaining clinical usability.*

Keywords: *autism spectrum disorder; ASD; quantum machine learning; explainable artificial intelligence; XAI; deep learning; early diagnosis.*

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1. Introduction

Autism Spectrum Disorder (ASD) is a lifelong neurodevelopmental disorder marked by disability in interpersonal interaction, communication difficulties,and restricted or repetitive patterns of behaviour and its worldwide prevalence has increased substantially over the past two decades, raising significant public health concerns and emphasising the importance of early and accurate diagnosis (Chen et al., 2026; Han et al., 2026). Early identification, particularly during infancy and early childhood, enables timely behavioural and educational interventions that can significantly improve cognitive, social, and adaptive outcomes (Said et al., 2026). Current diagnostic practices rely on behavioural observation tools, caregiver interviews, and specialist clinical expertise, including the Autism Diagnostic Observation Schedule (ADOS), the Autism Diagnostic Interview-Revised (ADI-R), and clinical judgement, all of which are time-consuming and require substantial assessment resources (Balaji et al., 2025). The growing access to biomedical signals and neuroimaging data together with behavioural recordings has driven researchers to use artificial intelligence (AI) methods for automated ASD detection (Liu et al., 2025). Machine learning and deep learning (DL) models have achieved considerable success in detecting ASD-related patterns from electroencephalography (EEG) (Baibulova et al., 2025), functional and structural magnetic resonance imaging (fMRI/sMRI) (Bayro & Jeong, 2025), functional near-infrared spectroscopy (fNIRS) (Vidivelli et al., 2025), eye-tracking trajectories (Atlam et al., 2025; Temiz et al., 2025), facial expressions (Gao et al., 2025), speech signals (Moon & Woo, 2025), skeletal motion data (Rajkumar et al., 2025), and physiological signals (Setu, 2025). Data-driven approaches provide objective diagnostic capabilities that can be scaled without substantially increasing costs compared with traditional diagnostic methods (Baydogmus & Demir, 2025).

The 'black-box' characteristics of most AI models create a significant obstacle that prevents their clinical application despite their strong performance metrics (Taneera & Alhajj, 2025). Explainable AI (XAI) techniques are designed to provide human-interpretable explanations for model predictions by identifying salient features, brain regions, temporal segments, or behavioural cues that drive classification outcomes (Sencan & Burak, 2025; Jabbar et al., 2025). ASD detection pipelines now use Shapley Additive Explanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), Gradient-weighted Class Activation Mapping (Grad-CAM), attention visualization, feature importance ranking, and graph-based explainability methods, which have gained increasing adoption in recent years (Baran & Cetin, 2025; Zhang et al., 2025).

Quantum Machine Learning (QML) has introduced new methods that use quantum-enhanced feature spaces to improve brain signal modelling compared with traditional methods. The combination of common spatial patterns and variational quantum circuits in quantum-based models provides effective tools for EEG signal classification through quantum support vector machines and quantum neural networks (QNN) (MacHnaim et al., 2025). The QML-XAI approach may enhance classification accuracy while maintaining computational efficiency and generalization capabilities, thereby supporting the development of advanced intelligent systems for early ASD diagnosis and brain–computer interface applications (Saranya & Menaka, 2025a).

Materials and Methods

This article assesses the advantages and disadvantages of machine learning and deep learning methods used for ASD diagnosis. A keyword-based search was conducted to identify journal articles and conference papers indexed in databases and digital libraries including Scopus, Wiley Online Library, IEEE Xplore, and ScienceDirect. This review paper aims to investigate machine learning techniques together with deep learning model classifiers that are used for ASD diagnosis. This research survey covers AI-based ASD detection studies which were published from 2024 until 2026. The study presents three primary contributions, which include:

1. A complete classification system which organises all ASD diagnostic materials together with their preprocessing techniques and methods to obtain features and all AI techniques used in the field.
2. The examination uses several methods, which include EEG, neuroimaging, eye-tracking, facial expression analysis, behaviour assessment, and multimodal techniques.
3. The article provides a thorough assessment of XAI methods and QML, which demonstrate their value for detecting ASD in clinical settings.

The review structure begins with Section 2, which details the datasets used in autism spectrum disorder detection. Section 3 presents the data preprocessing and feature extraction methods and techniques used for ASD detection. Section 4 presents the machine learning and deep learning algorithms that were used to detect ASD. Section 5 extends the survey by introducing performance metrics that researchers use to evaluate both current algorithms and upcoming algorithm designs. Section 6 presents the classification framework for ASD detection. Section 7 highlights the discussion. Section 8 presents the challenges faced by different methods to detect autism spectrum disorder in their respective modalities. Section 9 highlights potential future research directions. The final section concludes the review by emphasising the importance of QML and XAI in early diagnosis of ASD. Figure 1 shows the distribution of reviewed articles across major publishers and digital libraries, including Elsevier, IEEE, Springer, BMC, Wiley, and Tech Science Press. Figure 2 illustrates the proposed QML-based pipeline for autism spectrum disorder detection, involving biomedical and behavioural data processing from raw data acquisition through preprocessing, feature extraction, model learning, and final classification.

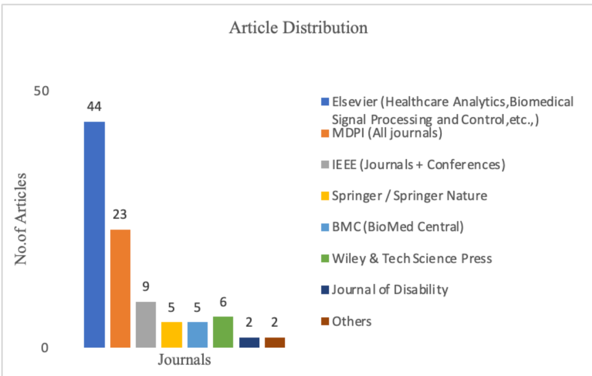

Figure 1. Distribution of reviewed articles across major publishers

2. Datasets Used in Autism Spectrum Disorder Detection

AI-based autism spectrum disorder (ASD) detection systems demonstrate reliable diagnostic performance and generalisability through validation on datasets specifically developed for ASD detection. The current research shows that scientists need dataset transparency and multimodal data and explainable results to solve problems with reproducibility and clinical research implementation. The section provides a complete classification system that uses various data types to show the different datasets used for detecting ASD and their unique attributes and benefits and drawbacks.
Figure 3 illustrates the yearly distribution of dataset modalities, including EEG, MRI, multimodal, and facial datasets, across the reviewed studies.

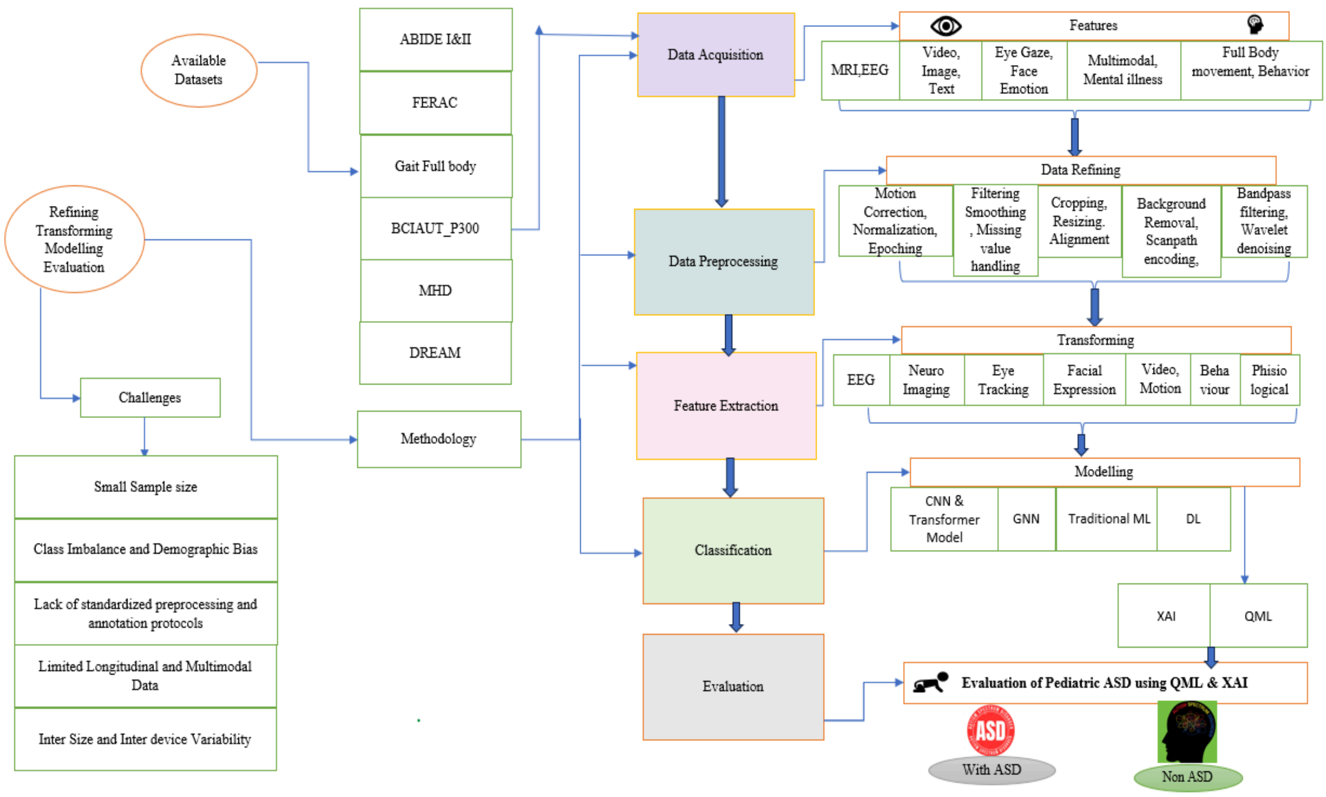

Figure 2. Proposed QML-Based Workflow for ASD Detection

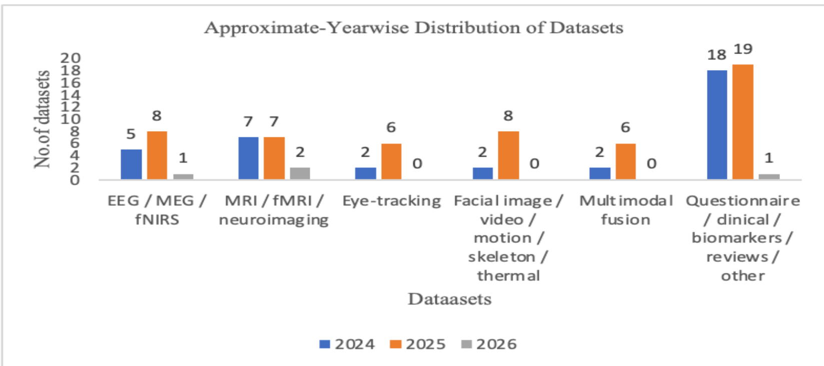

Figure 3. Year-wise distribution of datasets

2.1. Neuroimaging Datasets

Autism Brain Imaging Data Exchange (ABIDE) remains the most widely used public neuroimaging dataset for ASD research. ABIDE I and ABIDE II aggregate resting-state functional MRI (rs-fMRI) and structural MRI (sMRI) data collected from multiple international sites, encompassing thousands of ASD and typically developing (TD) participants across a wide age range. ABIDE variants have been utilised to assess ASD severity and evaluate performance across different research sites according to their respective measurement standards (Arunkumar & Sudhakar Ilango, 2026).

2.2. EEG and Eye-Tracking Datasets

Research on ASD populations has utilized public and semi-public EEG datasets to investigate spectral analysis, functional connectivity, microstates, and nonlinear dynamics (Barik et al., 2024). Some studies use resting-state EEG, while others use task-based EEG recordings that involve auditory and visual and social stimuli (Saranya & Menaka, 2025a). Eye-tracking datasets are used in studies to make a clear distinction between an ASD-diagnosed child and one who has typical development through assessment periods that last less than two minutes (Hudry et al., 2025). The analysis of scanpath trends together with gaze entropy measurements and fixation heatmaps has been applied to train machine learning and deep learning models used for ASD detection (Muniraja Manjunath & Veeramani, 2025).

2.3. Facial Expression and Video-Based Datasets

Facial expression and video-based datasets are used to study stereotypical behaviours , body movements and response-to-name cues through the application of CNNs vision transformers and dual-stream architectures. These datasets support large-scale, non-contact ASD screening; however, several limitations remain, including occlusion issues, variable lighting conditions, subjective annotation practices, and ethical concerns related to privacy protection and informed consent.
Table 1 summarizes the public and clinical datasets used for ASD detection.

Table 1. Public and Clinical Datasets Used for AI-Based ASD Detection

References	Datasets	Dataset type	Source Link
(Arunkumar & Sudhakar Ilango, 2026)	ABIDE	Neuroimaging (rs-fMRI/sMRI)	https://github.com/lsa-pucrs/acerta-abide
(Radočaj & Martinović, 2025)	Facial Emotion Recognition-Autistic Children-FERAC	Face Emotions	https://www.kaggle.com/datasets/rajasreechaiti/ferac-dataset (accessed on 29 August 2025)
(Shin et al., 2025)	Gait Full-Body Dataset	Full-body movement characteristics	https://datadryad.org/dataset/doi:10.5061/dryad.s7h44j150 (accessed on 22 December 2024)
(Vidivelli et al., 2025)	P300-BCI -BCIAUT_P300	EEG - ASD	https://www.kaggle.com/datasets/disbeat/bciaut-p300
(Moon & Woo, 2025)	Kaggle repository: Children Traits	Multimodal	https://www.kaggle.com/datasets/uppulurimadhuri/dataset (accessed on 01 June 2024). https://github.com/johnnyone89/CARE-ASD-Modeling (accessed on 01 June 2024)
(Alutaibi et al., 2025)	ASD Screening	Behaviour	https://www.kaggle.com/datasets/asdpredictioninsaudi/asd-screening-data-for-toddlers-in-saudi-arabia/discussion?sort=undefined https://www.kaggle.com/datasets/faizunnabi/autism-screening
(Pandya et al., 2024)	Pavis Dataset Stanford Home The DREAM Dataset National Database for Autism Research	Video Project-CSV Eye Gaze Text, numeric, image, time series	https://pavis.iit.it/autism-spectrum-disorder-detection-dataset https://healthdata.gov/dataset/National-Database-for-Autism-Research-NDAR-/7ue5-z77y/data

2.4. Behavioural, Motion, Physiological and Multimodal Datasets

The motion capture datasets, together with skeleton-based movement recordings and thermal imaging and physiological signals, which include heart rate and skin temperature measurements, constitute the complete behavioural datasets. Skeleton-based datasets have been used to quantify repetitive movements and posture abnormalities through the application of dual-stream and attention-based deep learning models. Thermal imaging datasets capture emotional regulation and stress response data, which provide additional biological markers for ASD identification (Abhinav Chaitanya et al., 2025; Pope et al., 2025). Multimodal datasets combine different types of data, which include EEG-fMRI and EEG-eye-tracking and facial-behavioural and clinical-questionnaire datasets, enabling comprehensive ASD research because they simultaneously capture complete neurobiological information and behavioural patterns and contextual elements. Multimodal datasets improve diagnostic accuracy and generalisation abilities to a greater extent than unimodal datasets, according to recent research findings (Dcouto & Pradeepkandhasamy, 2024).

3. Data Preprocessing Techniques and Feature Extraction Methods for Autism Spectrum Disorder Detection

The data preprocessing stage in AI-based autism spectrum disorder detection helps improve signal quality, reduce variability, and enhance feature discriminability, thereby leading to improved model performance and interpretability. The process of feature extraction establishes a crucial bridge between raw biomedical and behavioural and multimodal data, machine learning and deep learning model training through its ability to create usable data representations (Elakkiya & Dejey, 2024; GV et al., 2024; Wang et al., 2024). EEG preprocessing pipelines include artefact removal, filtering, segmentation, and normalisation procedures according to established workflows (Omotehinwa et al., 2024; Saranya & Menaka, 2025a; Singh & Kakkar, 2024; Melinda et al., 2024). EEG feature extraction employs time-domain, frequency-domain, and time–frequency analyses to identify significant neural features (GV et al., 2024). Structural MRI preprocessing pipelines perform four essential tasks: skull stripping, bias field correction, tissue segmentation, and spatial normalisation to standard anatomical templates such as the Montreal Neurological Institute (MNI) space (Bahathiq et al., 2024). The standard preprocessing methods for resting-state fMRI data begin with slice timing correction and head motion correction before researchers apply spatial smoothing and temporal filtering and conduct nuisance signal regression (Ma et al., 2024). ABIDE neuroimaging datasets, which operate across multiple sites, experience major problems because of differences between their sites and their scanning equipment (Liu et al., 2024). Neuroimaging data extraction procedures identify brain region abnormalities which occur in people with autism spectrum disorder.

The standard procedures for extracting features from neuroimaging data include voxel-based morphometry, cortical thickness analysis, and connectivity measurement (Mengi & Malhotra, 2024). The preprocessing stage of eye-tracking transforms raw gaze data into meaningful behavioural patterns while handling missing data and signal noise. Raw gaze data filtering begins with blink and outlier removal, followed by missing sample interpolation (Hudry et al., 2025). To enable cross-participant gaze trajectory comparison, researchers use scanpath normalisation and spatial binning methods, which effectively align gaze data between different participants (Eraslan et al., 2025; Venkatesh et al., 2025).

Eye-tracking systems are used to assess visual attention patterns by analysing how individuals with ASD visually explore their environment. The typical features that scientists measure include the time spent fixating, the number of fixations, the distance moved during saccades, the speed of saccadic movements, the total time spent looking at objects, and the patterns of eye movement between different items and the methods used to compare different eye movement paths. Entropy-based and temporal pattern features, including scanpath trend analysis (STA), gaze entropy, and transition entropy, have demonstrated strong performance in early ASD detection and severity assessment according to recent research findings (Domarecki et al., 2025).

Face detection, alignment, cropping, and resizing through multi-task cascaded convolutional neural networks (MTCNN) and Haar cascades form the core of standard preprocessing procedures (Balasubramani et al., 2025). Data augmentation techniques such as rotation, horizontal flipping, illumination adjustment, and Gaussian noise injection serve two purposes because they improve model performance while solving data shortage problems. The video analysis process begins with frame extraction and temporal sampling and background subtraction and skeleton normalisation before entering model training. Video-based techniques detect spatiotemporal behavioural patterns which relate to ASD symptoms. Skeleton-based features, which include joint position data, joint angle measurements, motion trajectory information, and spatiotemporal coordination results, enable researchers to identify typical stereotypical behaviour patterns and motor abnormalities in individuals with ASD (Banos et al., 2024). Thermal imaging studies analyse facial and peripheral physiological regions to monitor body temperature variations and heat emission patterns associated with emotional states in individuals with ASD (Mohd Salah Aljabiri & Hamdan, 2024).

The process of thermal imaging needs temperature calibration, and it requires noise filtering and the extraction of facial and peripheral physiological areas, which serve emotional regulation purposes, to be completed first before any thermal imaging activities can proceed (Bouchouras & Kotis, 2025). The skeleton-based features enable the detection of repeated motions and symmetric patterns and joint movement coordination (Lecciso et al., 2025). According to recent studies, researchers use deep learning models to extract distinguishing features from both raw and slightly processed data. The combination of CNNs, autoencoders, and recurrent neural networks, together with graph neural networks and transformer networks, produces latent feature embeddings that exceed the performance of manually created features in most ASD detection applications (Wang et al., 2024).

3.1. Preprocessing and Feature Extraction in Multimodal ASD Detection

The process of multimodal ASD detection systems requires additional preprocessing to achieve proper synchronisation between different data streams, which have been collected at separate time intervals and different sampling frequencies. The standard methods for data preparation need these steps, which include temporal alignment, modality-specific normalisation, and feature-level standardisation before performing data fusion (Xie et al., 2024). Multimodal systems can incorporate biological markers such as gut microbiome indicators and neurotransmitter levels to improve ASD prediction models (Bamicha et al., 2024). The multimodal ASD detection systems use attention mechanisms and cross-modal transformers together with explainable fusion strategies to create robust detection systems.

3.2. Preprocessing and Feature Extraction in Explainable AI and Quantum Machine Learning

The combination of excessive filtering and dimensionality reduction techniques diminishes the ability to detect important clinical features. The transparent documentation of all preprocessing methods used in research studies functions as a prerequisite for scientists to create reproducible AI systems that medical professionals can interpret and use to diagnose ASD in patients (Rony et al., 2024). The development of medical features through handcrafted methods, statistical methods, and connectivity-based methods leads to better transparency of results and better understanding of clinical outcomes, whereas deep learning methods need SHAP, Grad-CAM, integrated gradients, and attention visualisation tools to discover their critical decision-making elements and biomarker information. The development of trustworthy and clinically usable AI-based ASD diagnostic systems requires the combination of interpretable feature extraction methods with existing XAI systems (Jeon et al., 2024). Quantum machine learning (QML) preprocessing establishes a systematic method for improving EEG signal quality and feature extraction, which supports autism spectrum disorder (ASD) diagnosis. Signals undergo normalisation before they are divided into fixed-length epochs which match event-related components, especially P300, since these components provide evidence of ASD-related cognitive activities (Turjya & Fawakherji, 2025). The QML process of feature extraction begins with Common Spatial Patterns (CSP) along with time–frequency decomposition and spectral power analysis to create valuable data representations. The combination of classical methods such as principal component analysis and variational quantum circuits in hybrid dimensionality reduction technologies enables the system to maintain essential discriminative features while eliminating duplicate information from the feature set (Saranya & Menaka, 2025b; Turjya & Fawakherji, 2025). Table 2 shows the different preprocessing and feature extraction techniques used in ASD detection.

Table 2. Pre-processing Techniques and Feature Extraction Methods used in ASD Detection

Data Modality	Preprocessing Techniques	Features	Feature Type	Feature Extraction Methods
EEG (Han et al., 2026)	Band-pass filtering, artefact removal, ICA	Independent Component Analysis	Temporal Patterns	Microstate analysis, CGR
fMRI (Chen et al., 2026)	Motion correction, slice timing, normalisation, Despiking, Band-pass filtering	DPARSF (Data Processing Assistant for Resting State fMRI), SPM	Connectivity	Pearson correlation, graph construction
Facial Images (Radočaj & Martinović, 2025)	Face detection, alignment, cropping	Dlib, MTCNN	Facial Features	Deep CNN features
Video (Shin et al., 2025)	Pose estimation, keypoint extraction	Open Pose, Media Pipe	Skeletal Features	Joint coordinates, angles
rs-fMRI (Luo et al., 2025)	Global signal regression	CONN toolbox	Network Hierarchy	Multi-scale parcellation
fNIRS (Farooq et al., 2025)	Motion artefact correction, baseline removal	Wavelet-based correction	Haemo-dynamic Features	HbO, HbR concentration changes
sMRI (Abu-Doleh et al., 2025)	Bias field correction, tissue segmentation	FreeSurfer	Volumetric Features	Regional volumes, shapes
Proteomics (Tang et al., 2025)	Protein quantification normalisation	Log transformation, quantile	Biomarker Panel	Protein concentrations
Eye-tracking (Eraslan et al., 2025)	Fixation detection, saccade removal	Velocity-based algorithms	Scanpath Features	Trajectory metrics
Motion Data (Mohd Salah Aljabiri & Hamdan, 2024)	Joint smoothing, velocity computation	Savitzky-Golay filtering	Kinematic Features	Joint angles, velocities, trajectories
EEG (P300-based) (Turjya & Fawakherji, 2025)	Quantum Encoding, Filtering, Artefact Removal	Temporal Precision Noise robustness	Quantum Features	Quantum Feature Mapping, Wavelet Transform

4. Machine Learning and Deep Learning Algorithms for Autism Spectrum Disorder Detection

The use of machine learning and deep learning algorithms has become an effective method for detecting autism spectrum disorder symptoms during infancy through accurate diagnostic procedures (Abdelwahab et al., 2024). Traditional ML models remain widely used in ASD research, particularly when datasets are limited in size, computational resources are constrained, or model interpretability is a primary concern (Jayaprakash & Kanimozhiselvi, 2024). Deep learning models possess the capability to extract advanced features from complex datasets, which include images and videos and brain signals, thereby enhancing their ability to classify different types of data (Ding et al., 2024; Zhao et al., 2024). Hybrid models combine multiple DL architectures or integrate ML and DL approaches to exploit complementary strengths (Ashraf et al., 2024). Artificial intelligence development now enables researchers to combine multiple data sources, including eye-tracking signals, neuroimaging data, and textual narratives. The multimodal learning frameworks enable models to detect various autistic behavioural patterns and neurological markers, which results in stronger diagnostic systems (Themistocleous et al., 2024).

Explainable AI and Quantum Machine Learning Models for Autism Spectrum Disorder

Explainability has become a central consideration in ASD detection algorithms to facilitate clinical trust and adoption. Decision trees, rule-based classifiers, and fuzzy inference systems function as interpretable models because they provide built-in transparency. The EASDM model uses deep learning methods that explain predictions to create interpretable results for diagnosing autism spectrum disorder (ASD). Post-hoc XAI techniques, including SHAP, LIME, Grad-CAM, integrated gradients, and attention visualisation, operate as common tools that researchers use to observe essential features, brain areas, and behavioural cues that DL models use to generate predictions (Atlam et al., 2024).

The existence of quantum machine learning (QML) technology creates a new method to identify autism spectrum disorder (ASD) through its ability to process complicated EEG signals from multiple EEG-derived biomarkers. The QSVM–QNN hybrid architecture combines quantum kernel methods with neural learning to identify nonlinear patterns that correspond to atypical brain activity. Quantum state encoding and variational circuits create high-dimensional feature spaces for EEG features that include P300 responses, which improves their ability to distinguish between different types of brain activity (Saranya & Menaka, 2025b; Turjya & Fawakherji, 2025). The latest research on quantum healthcare applications shows that QML technology can enhance medical results through its ability to generalise better while needing less training data and enabling broader use in clinical settings. The combination of quantum-inspired heuristic systems and blockchain technology enables the creation of ASD prediction systems that maintain security and dependability while protecting user privacy (Mazumdar et al., 2024).

5. Evaluation Metrics Used in Autism Spectrum Disorder Detection

Evaluation metrics serve as essential tools to evaluate the performance, reliability, and clinical suitability of artificial intelligence systems which detect autism spectrum disorder (Rahman & Hasan, 2025; Alsbakhi et al., 2025). The confusion matrix serves as the primary evaluation method used to assess the performance of classification models, which are applied in ASD detection systems. The matrix consists of four fundamental components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) (Gumusoglu et al., 2025; Kim et al., 2025). The accuracy calculation determines the percentage of correctly classified samples among all tested samples. The metric provides initial performance evaluation for the model but becomes unreliable when the ASD and non-ASD groups have unequal representation (Hoang Reede et al., 2024). The model's capacity to identify ASD patients is evaluated through its sensitivity measurement, which scientists also refer to as "recall" or "true positive rate." The clinical screening process requires this particular medical assessment because low sensitivity increases the likelihood of missing patients who actually have the condition being tested (Arun et al., 2024). The specificity (true negative rate) measures how well the model detects people who do not have ASD. The high specificity of the system decreases both false-positive results and the need for unnecessary clinical referrals (Sharma & Tanwar, 2024). Precision measures the percentage of correct ASD diagnoses among all predicted ASD cases, while the F1 score represents the harmonic mean of precision and sensitivity (Islam et al., 2025). The AUC-ROC test determines how well a model can differentiate between ASD and non-ASD subjects at various classification points. The AUC value increases when a diagnostic test gains more consistent performance and better ability to differentiate between patients who have the condition and those who do not (Ayub et al., 2024).

The common regression-based metrics include mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R^2). The metrics measure prediction accuracy for continuous outcomes, which include symptom severity and developmental scores, and they hold special importance for neuroimaging and multimodal ASD research studies (Mata-Iturralde et al., 2025; Papadopoulos et al., 2024).

5.1. Explainability and QML-Oriented Evaluation Metrics

The evaluation of QML and explainable artificial intelligence (XAI) systems for automated ASD detection requires additional methods which extend beyond predictive accuracy evaluation. The medical field uses saliency maps, attention heatmaps, and graph importance overlays as visualisation-based evaluation methods to assess model performance and improve clinical understanding of model behaviour. The development of AI-based diagnostic tools for ASD requires these explainability-oriented metrics to establish user confidence in their diagnostic capabilities (Tahir et al., 2024; Saranya & Menaka, 2025b). Table 3 and Table 4 analyse the modality-wise approaches of ASD detection with XAI and QML.

Table 3. Modality-Wise ASD Detection Approaches with Explainable Artificial Intelligence (XAI) Techniques

Modality/ References	Key Techniques & Models	Features Extracted	Strengths	Limitations	XAI Techniques	Future Scope
EEG (Baibulova et al., 2025), (Shi et al., 2025), (Zhang et al., 2025), (Lau et al., 2025)	CNN, LSTM, attention-based networks, GNN	Neural synchronisation, spectral power, microstates	Non-invasive, captures temporal dynamics, suitable for infant	Noise sensitivity, inter-subject variability, limited dataset	SHAP, LIME, attention visualisation	Standardised EEG datasets, intrinsically interpretable architecture
fMRI / sMRI (Wang et al., 2025), (Luo et al., 2025), (Zeraati & Davoodi, 2025), (Liu et al., 2024)	GNNs, Residual Graph Transformers; Multi-atlas,	Brain morphology, functional connectivity	High neurobiological insight, accurate prediction	High cost, inter-site variability, accessibility issues	Grad-CAM, Graph explainability, Attention heatmaps	Clinical validation of XAI, large-scale harmonised datasets
Eye-Tracking (Jaradat et al., 2025), (Hudry et al., 2025), (Zhang et al., 2025), (Eraslan et al., 2025)	ML classifiers, CNNs, Scanpath Trend Analysis	Fixation duration, gaze patterns, visual attention	Rapid, non-invasive, suitable for early screening	Sensitive to calibration, age-related variability, experimental setup	SHAP, LIME, permutation feature importance	Large-scale annotated eye-tracking datasets
Facial / Video-Based (Arunkumar & Sudhakar Ilango, 2026), (Asmetha Jeyarani & Senthilkumar, 2025), (Noor et al., 2025), (Ibadi & Lakizadeh, 2025)	CNNs, DenseNet, Vision Transformers, YOLO, Dual-stream networks	Facial expressions, emotion cues, stereotypic movements	Non-invasive, scalable, captures spatiotemporal behaviour	Privacy concerns, annotation challenges, recording variability	Grad-CAM, Attention maps, SHAP for features	Ethical frameworks for facial data, multimodal XAI integration
Multimodal (Atlam et al., 2025),(Moon & Woo, 2025),(Saranya & Menaka, 2025a),(Malik et al., 2025)	Feature-level fusion, Decision-level fusion, Ensemble learning	Combined neurophysiological, behavioural, and facial features	Highest robustness, comprehensive ASD representation	High data collection cost, synchronisation challenges, complex interpretability	Hierarchical Attention, Modality-wise SHAP, Feature attribution maps	Cross-modal explainability, clinically validated XAI evaluation

Table 4. Modality-Wise Approaches with Quantum Machine Learning

Modality/ References	Key Techniques and Models	Features Extracted	QML Techniques Applied	Strengths	Limitations	Future Scope
EEG (Saranya & Menaka, 2025b)	CSP+QSVM	Spatial Features, Variance based EEG patterns	Quantum Kernel Methods, Amplitude Encoding	Improved ASD detection, Strong Spatial discrimination	Preprocessing dependent, Noise Sensitivity	Riemannian features and Magnetoen-cephalography (MEG)
EEG(P300) (Turjya & Fawakherji, 2025)	CNN+QML	Temporal, Spectral, ERP Features	Quantum feature mapping, Hybrid PQCs,	Deep Learning +Quantum Computing	High Computational Cost	Hybrid Transformer Quantum Models
EEG (MacHnaim et al., 2025)	VQC	Quantum Encoding	Linear Layer Mapping	Handles Age Variability	Limited Circuit Interpretability	Deeper Circuit Topologies

6. Classification of ASD Detection Methods

The diagnostic process of ASD requires medical professionals to classify patients into different diagnostic groups which include ASD, typically developing individuals, and various levels of disease severity based on clinical evaluations and diagnostic test results. The existing research work is organised into five independent categories which include data acquisition methods, feature representation techniques, learning paradigm systems, interpretability assessment methods, and data integration approaches. The established taxonomy system together with the proposed hierarchy system provides precise mapping capabilities for newly developed methods which include the QML-XAI framework.

6.1. Classification by Data Acquisition

Direct neurophysiological modalities such as EEG, MRI/fMRI, fNIRS, and MEG capture neural dynamics or structure. The methods deliver objective biomarkers for diagnosing conditions while their diagnostic accuracy depends on expensive equipment needed for complex processes which include artefact removal and brain connectivity estimation. Indirect behavioural modalities based on facial expressions, gaze/eye-tracking, speech, and interaction videos enable non-invasive and scalable screening. The system contains environmental noise problems and subject variability issues, and it suffers from annotation bias.

6.2. Classification by Features

Statistical, spectral, and connectivity-based features enable researchers to interpret data accurately while requiring less data for analysis. These features struggle to identify complex nonlinear relationships. Deep learning models, which include CNNs and LSTMs and transformers and graph neural networks, extract hierarchical data representations from unprocessed input data to achieve high accuracy while incurring higher processing expenses and decreased system transparency (Uddin et al., 2024).

6.3. Classification Based on Modalities

The traditional machine learning methods SVM, Random Forest, and k-NN function as effective baseline methods for small datasets (Rasul et al., 2024). Deep learning models such as CNNs, transformers, and GNNs establish new standards for detecting ASD by modelling spatial–temporal relationships which exist in complex environments. The use of hybrid learning together with multimodal learning systems which include CNN–LSTM and attention-based fusion creates higher system complexity because it improves system robustness and classification performance (Hajjej et al., 2024). Advanced methods such as Quantum Support Vector Machines (QSVM) and Quantum Neural Networks (QNN) use quantum feature space technology to provide improved high-dimensional data representations.

6.4. Classification by Interpretability

The transparent decision-making process used by decision trees and linear models enables better clinical decision-making for physicians yet results in less accurate predictions. The deep neural networks achieve high accuracy rates while their internal workings remain opaque to users. The post-hoc explanation capabilities of SHAP, LIME, and Grad-CAM XAI systems enhance model transparency, which healthcare professionals can use to make medical decisions (Mim et al., 2025).

Single-modality approaches, which include EEG-only and MRI-only methods, present easier implementation, but their limitations prevent complete detection of all ASD traits. Multimodal systems which use EEG and imaging and behavioural data improve diagnostic accuracy and system reliability, and they also face difficulties with data fusion and synchronisation processes.

6.5. QML-XAI Framework

The QML-XAI framework solves the existing problems by using multiple classification dimensions to execute its functions. Quantum feature mapping enables implicit high-capacity representation, which handles complex nonlinear separability challenges. Multimodal data fusion integrates multiple information sources which provide complementary data to the research process (Behera et al., 2026). The proposed framework represents an integrated advancement which integrates implicit learning together with multimodal fusion and explainable decision-making methods. Figure 4 shows how ASD detection methods developed from basic clinical methods to modern artificial intelligence systems. The first methods used statistical analysis and rule-based methods, which were replaced by machine learning systems that operated with manually designed features. Deep learning systems create automatic feature extraction, which is further improved through multimodal and hybrid systems that enhance accuracy. XAI creates a solution to the interpretability problem which exists in advanced machine learning models. The hierarchy reaches its highest point with quantum machine learning, which uses XAI technology to create new methods for classifying ASD in high-dimensional data while maintaining model interpretability.

7. Discussion

The field of AI-based ASD detection has advanced significantly; still, it faces multiple challenges. First, neuroimaging techniques that include MRI and fMRI achieve high spatial resolution. Researchers have to identify a biomarker that can serve as a standardised automated diagnostic tool for ASD detection. EEG-based methods provide high temporal resolution, yet they encounter two major problems, which include vulnerability to noise disturbances and the absence of established standardised methods. The ability of models to predict outcomes for different datasets faces difficulties because of two factors: inter-site differences and the limited number of samples. Most studies show high accuracy results, but the actual performance of these models is evaluated in controlled testing environments, which do not reflect real clinical situations. Explainable AI (XAI) research improves model understanding through current methods, but these methods provide post-hoc explanations instead of creating inherently interpretable models. Quantum Machine Learning (QML) shows potential, but its development remains at an early stage because of insufficient clinical testing. Future research needs to concentrate on creating standardised datasets. The research requires the development of robust validation methods and clinically interpretable models.

8. Challenges and Open Research Gaps in ASD Detection

AI-powered ASD diagnostic systems face limitations that affect reproducibility, generalizability, clinician trust, and widespread implementation in healthcare settings.

The different acquisition methods, which include EEG electrode settings and fMRI scanning parameters, eye-tracking equipment, and experimental procedures, create domain shifts that lower model performance across different settings. Researchers developed advanced deep learning systems that use transformer architectures and graph neural network (GNN) models to achieve exceptional predictive performance; however, these systems maintain their fundamental technical complexity, which prevents clinicians from trusting their results and understanding their inner workings. Post-hoc XAI methods SHAP and LIME and attention visualisation techniques deliver limited model explanations but fail to show a complete match with actual model decision-making processes and causal relationships. The multimodal ASD detection frameworks utilise multiple data sources, which include EEG, neuroimaging, eye-tracking, and facial cues, because these sources provide different temporal resolutions, noise characteristics, and data dimensionality properties. The QML and XAI frameworks, which address ethical considerations and bias issues, require implementation to establish transparent systems that ensure fairness and protect private data while delivering accurate diagnostic results. Current ASD detection pipelines use different preprocessing methods, feature extraction techniques, ML/DL architectures, evaluation metrics, and XAI techniques, which result in research outcomes that researchers cannot reproduce. The development of standardised, end-to-end ASD detection pipelines, including unified preprocessing, feature selection, evaluation, and QML-combined explainability protocols, serves as an essential requirement to achieve reproducible results and standardised testing procedures. The existing lack of databases prevents researchers from creating dependable screening tools, which require age-specific mechanisms to explain results. Early-life ASD detection and intervention planning require age-specific longitudinal datasets that document developmental changes from early life through later periods.

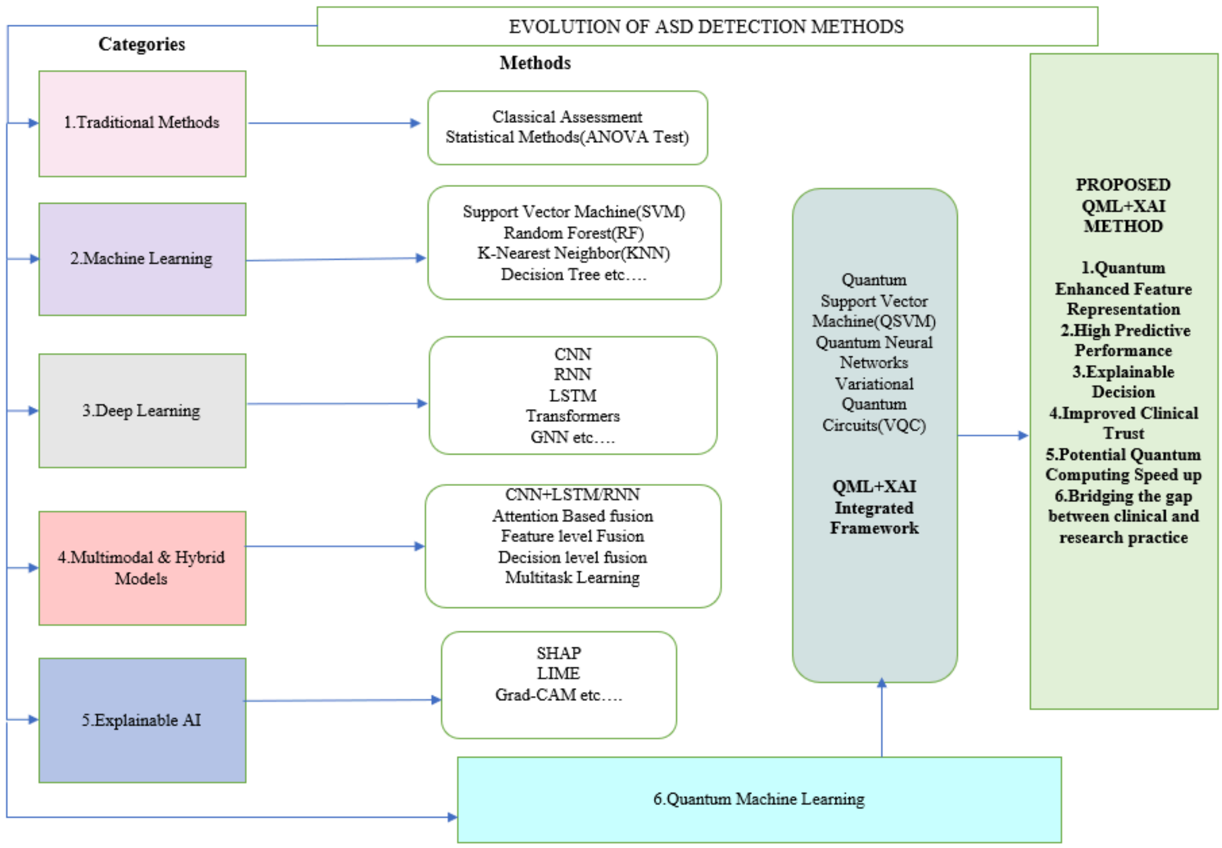

Figure 4. Hierarchical Evolution of ASD

9. Future Directions in ASD Detection Using QML and XAI

Future research directions should aim at building extensive datasets that combine EEG, fMRI, eye-tracking, facial, behavioural, and physiological signals with continuous tracking of developmental changes over time.

Future multimodal frameworks should use modality-wise attribution together with hierarchical attention, causal explainability, and QML methods to measure the contribution of each modality to system performance. Human-centred evaluation frameworks, which need clinician feedback and diagnostic confidence and decision-support effectiveness, should be developed as urgent diagnostic tools.

The expected impact will create a bridge between AI predictions and actual clinical decision-making processes. Future ASD detection systems should use federated learning and differential privacy and fairness-aware optimisation as their foundation to achieve ethical and equitable system deployment.

The expected impact of this system includes three components, which are real-time ASD screening, continuous monitoring capabilities, and explanation-based caregiver support through XAI systems and QML methods.

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10. Conclusion

The research study provided an extensive analysis of autism spectrum disorder (ASD) identification techniques, which included a comprehensive classification system to assess existing detection methods. The review structured existing research through five dimensions, which included data modality, feature representation, learning paradigm, interpretability, and data integration to show how research methods developed over time and which areas of study remain active. The research field has undergone a methodological transition from traditional machine learning methods towards deep learning and multimodal approaches, while hybrid models succeed in delivering both robust performance and broad applicability. The emerging quantum machine learning (QML) methods demonstrate a strong capability to process high-dimensional complex data distributions, but researchers have not yet fully studied this area because of existing hardware and scaling limitations. The QML–XAI framework serves as a solution to existing research gaps because it combines quantum-based feature representation with explainable AI to deliver precise and interpretable results. The framework serves as an advanced solution that current methods cannot address.

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