International Journal of Applied Information Systems (IJAIS) – ISSN : 2249-0868
Foundation of Computer Science FCS, Delaware, USA
Volume 13– No. 1, August 2025 – www.ijais.org

Autism Spectrum Disorder: Review of Datasets, Computational Models, and Future Research Directions

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ABSTRACT
Autism spectrum disorder (ASD) is a heterogeneous neurodevelopmental disorder defined by social, communicative, and behavioral difficulties. Early detection is needed to enhance intervention outcomes but is limited by the drawbacks of standard behavioral assessment. Researches are carried out with different dataset that – structured and unstructured. Innovations that involve video games, smart phones are also growing. This review has investigated various ASD detection and intervention methods, integrating evidence from research studies using neuroimaging, behavioral indicators, multimodal physiological information, and machine learning. The summarization provided in work would help any researcher to understand the rudiments of ASD research and its research gaps.

General Terms
Review of Literature – Autism Spectrum Disorder detection using Computational Models

Keywords
Autism, datasets, machine learning, deep learning, feature selection.

1. INTRODUCTION
Autism Spectrum Disorder (ASD) is a condition related to brain development that mainly affects how a person communicates, behaves, and interacts with others [1]. It is a “spectrum” disorder, people with ASD have different symptoms and behaviors. Some of them have only minor difficulties, while others may need support throughout their lives[2]. Due to this wide range of symptoms, diagnosing ASD is not always easy. Effect of this condition is not consistent with people. Some people evolve over a period of time and learn to live independently others require lifelong care taker. Many children and even adults remain undiagnosed for a long time[3]. In many areas, especially rural , people are not aware of ASD, and this leads to late detection, which affects the treatment and support that the individual receive[4]. The process of diagnosis using questionnaire involves both parents and children. A qualitative interview reveals day-to-day activities of the affected person [5]. Many studies do not include racial factors to analyze autism in kids and adult, but it has been proved through literature the ethnicity plays a vital role to show variations in diagnosis procedure. As most of the autism research is not ethnicity centric there is pressing need to look for intersectionality [6]. Behavioral literacy tests use objective data to reveal individual strengths, weaknesses, and potential reactions in workplace or clinical situations. In [7] this procedure is adopted and examined around 31 participants. Participants’ autistic traits are exposed using reaction time. Studies conducted during and after COVID-19 revealed a new autistic trait that challenges the long-held belief that people with autism live in isolation. But actually they were longing to meet their friends to get along during pandemics [8].

Machine Learning Algorithms also known as ML or MLA has improved many diagnosis processes in terms of accuracy. Today most of the health care research is ML based. Machine learning holds significant promise in enhancing the diagnosis of Autism Spectrum Disorder, in terms of speed, objectivity, and scalability. While challenges remain in terms of data quality, model interpretability, and clinical integration, ongoing research is steadily bridging these gaps. As models become more robust and explainable, ML has become an invaluable tool in the early detection and personalized management of ASD

The rising trends in machine learning and deep learning have created new opportunities to address the challenges that exist with autism diagnosis and early detection. Classifiers such as support vector machines, random forests, and decision trees are modeled using ASD children, ASD Adult, ASD adolescent dataset from UCI repository. These models have achieved high accuracy in many studies [9]. Limitation with UCI dataset is its size in terms of instances. Whereas sources viz. ABIDE and KAU have supported machine learning pipelines to identify relavant features - both structural and functional - to ASD. In addition to all pros and cons discussed sample size and population imbalances remain a challenge that limits performance [10].

In recent days novel biomarkers that could supplement behavioural observations are becoming topic of interest. Examining biomarkers viz. gut microbiome profiles, metabolomic signatures, and handwriting-based features are the emerging trends in autism research , though these require more validation before clinical adoption [11]

Applications of pre-trained model and transfer learning are booming, deep learning continues to transform ASD research, particularly in domains involving neuroimaging, video/audio analysis, and multi-sensor data. While CNNs, ResNets, and Autoencoders dominate current applications, MobileNet and E-Net are enabling real-time, accessible diagnostic tools that could improve early detection. The challenge lies in balancing model performance with data availability and interpretability, especially in clinical contexts. Humanoid robots that are implemented using pre-trained models are now deployed for diagnosing autism in kids [12]. As novel screening methods based on home-video recordings [14] is replacing the classical methods, Rule Machine Learning is yet another novel method that is proposed for efficient autism diagnosis procedure for children, adolescents and adults [15].

Mobile gameplay data, and virtual reality–based social training platforms, are replacing classical methods questionnaire or survey among controlled group, which may offer scalable and cost-effective alternatives to traditional assessment. Enhancements in computational techniques are achieved through hybrid models. This review also witnessed such hydrid methods that replace traditional purebreds. Frameworks that combine behavioural, physiological, and neurobiological measures are being considered to better capture the heterogeneity of ASD presentations. These frameworks are in most cases multimodal.

Challenges from classical methods are addressed by using brain scan data like MRI and fMRI from datasets such as ABIDE and KAU [51]. They use machine learning models to find small changes in the brain that are hard to see with human eyes [52]. These models help in finding autism better and faster. But there are some problems with the datasets in which they are sometimes small and don't include people from many backgrounds. Because of that, the models may not work well for everyone. So, even though machine learning is useful, we still need better data and improved models to make it work well in real life.

This work aims to comprehend current evidence on datasets, computational approaches, and emerging technological tools for ASD detection and intervention. It has examined methods, data resources, and reported performance across behavioral, neuroimaging, genetic, and multimodal studies. It has also critically analyzed their strengths, limitations, and directions for future research. It is an easy to interpret review that can support the development of more robust, equitable, and scalable solutions for ASD care in varied contexts.

2. METHODS

This review adopts straightforward methods to extract useful insights from the literature. The methods applied in this study is simple and straight forward. A well-defined eligibility criteria are used. Following this a systematic search strategy, a transparent study selection process, clear data extraction methods are applied. In addition risk-of-bias and quality assessment procedures, and a robust data synthesis approach are analyzed.

2.1 Eligibility Criteria

As mentioned in the earlier sections this review focused on computational, technological, or multimodal approaches. We set up studies focusing on machine learning, signal processing, or data-driven frameworks on behavioral, neuroimaging, electrophysiological (EEG), genetic, or multimodal datasets related to ASD as inclusion criteria. In addition to that studies that discuss benchmark datasets, data collection protocols, or systematic reviews also set as inclusion criteria. Publications that does not discusses performance metrics, purely clinical observational research without computational elements, or reports lacking sufficient methodological transparency comes under exclusion criteria. This review commenced with this clear set eligibility criteria.

2.2 Search Strategy

All research work considered for this review are from major databases, including PubMed, IEEE Xplore, Scopus, Web of Science, and Google Scholar. Search keys were chosen in such a way that the resultant literature exactly matches with the expected one, for example:

("autism" OR "ASD") AND ("detection" OR "diagnosis" OR "intervention") AND ("machine learning" OR "deep learning" OR "EEG" OR "MRI" OR "dataset" OR "biomarker" OR "multimodal")

Synonyms and domain-specific keywords were iteratively refined to maximize coverage. Manual screening of reference lists from key papers supplemented the search.

2.3 Study Selection Process

A two-stage selection process was used. First, titles and abstracts were screened for relevance by two independent reviewers. Full-text screening followed to assess eligibility against inclusion criteria. Discrepancies were resolved through consensus discussions.

2.4 Data Extraction Methods

Data extraction captured study characteristics (e.g., publication year, study population),datasets used (e.g., UCIASD, ABIDE, MMASD+, Engagnition SPARK), Computational techniques (e.g., SVM, CNN, rule-based methods),performance metrics (e..g., accuracy, AUROC, sensitivity), and reported research gaps. Additional details ondataset modalities (EEG, MRI, behavioural video, physiological signals) and their availability were systematically recorded.

2.5 Risk of Bias and Quality Assessment

Studies were assessed for risk of bias using adapted criteria drawn from the QUADAS-2 Framework, including domain-specific aspects relevant to machine learning such as data imbalance, overfitting, validation on external cohorts, and model interpretability. Dataset quality and diversity, including availability of public access and documentation, were also reviewed.

2.6 Data Synthesis Approach

After extracting the methods and datasets from the literature, a narrative synthesis is done and presented through this work. Here a quantitative metrics were reported that are comparable and descriptive comparisons of classification performance were pinpointed, including discussions of cross-validation, reproducibility, and generalizability concerns.

3. RESULTS

Observations through this review are significant and reliable. These insights can be considered for future research works. This result section enumerates datasets employed in recent ASD research, highlighting their sources, sample sizes, modalities, complexity, and availability. Summary of literature is presented in TABLE AI in Appendix section.

3.1 Data set

Datasets play a vital role especially in the fields which involves artificial intelligence. Machine learning (ML) and deep learning (DL) models using UCI_ASD datasets and ABIDE dataset were highly preferred due to its availability. The drawback of these dataset is their size. As concept of big data management is so common today, researcher highly prefer datasets of larger size to come up with high performing ML/DL models. Such datasets found in the literature are MarketScan, ADHD-200, local hospital-based MRI, and even Hebrew speech corpora. One study, for example, leveraged a cohort of 1100 samples for metabolomics research. Table 1 gives details of dataset and its types identified.

3.2 Detection Methods

Early Autism based research used tool like interviews and questionnaire to assess social and behavioral activities of person with potential autistic traits. But these tools are becoming outdated as fields like computer vision are persuading the traditional analysis of neural developmental disorder. Genomic approaches are also has a remarkable progress. Drawing based interpretations are giving interesting facts about autistics traits, microbiome signature, MRI; video-based screening is proofs for research growth in multi-modal machine learning. Recent research explores diverse dataset like handwriting dataset, home-video pipelines, gaming-derived data, virtual reality mediated interventions, and computer-vision based social behaviors quantification and metabolomics biomarker analysis.

Table 1: Dataset, Type and Usage

Category	Dataset	Data Types / Features
Datasets for Machine Learning Model Development and Benchmarking	ABIDE	Structural/functional MRI
	MMASD+	Multimodal signals (behavior, neuroimaging, EEG)
	CALMED	Behavioral and neurophysiological measures
	Video ASD	Video-based behavior features, physiological data, EEG signals
Datasets for Genetic and Epidemiological Studies	NDAR	Clinical-genetic records, linked EEG recordings (some studies)
	SPARK	Large-scale genetic data, associated clinical assessments
Datasets for Behavior or Game-Based Systems	Engagnition	Real-world behavioral data, physiological signals
	Video ASD	Behavioral interaction videos, physiological measurements, EEG-based event-related markers
EEG Features across Datasets	Oddball task EEG recordings	Event-Related Potentials (ERP), Frequency-Domain Features, Inter-Trial Variability, Connectivity Metrics

3.3 Computational Techniques

Advancements in computational techniques have favored clinical diagnosis for rapid solutions. The domain of data science is creating new trends that are unimaginable in the past. The following Table 2 illustrates the machine learning models that are leveraged in ASD research:

Table 2: Overview of Computational Methods

Category	**Earlier Studies**	**Recent Studies**	**Emerging Trends**	**Reference Numbers**
ML Models	SVM, Random Forest	CNN, RNN, multi-class classifiers for ASD subtypes	Graph kernel clustering	[9], [10], [13], [17], [20], [38]
Feature Selection	Boruta	Apriori	Entropy measures (e.g., facial dynamics)	[15], [16], [47]
Techniques	Static classification	Advanced classification	Computer vision–based behavior coding	[43], [45]
Frameworks	Traditional ML pipelines	Deep learning integrated approaches	Intelligent agent dialogue systems, robot-based closed-loop systems	[40], [44], [50]
Research Direction	Algorithm-centered	Hybrid ML/DL	Adaptive, human-centered assistive technologies	[39], [48]

This illustrates a shift from purely static classification to more adaptive, integrated frameworks that blend ML/DL with human-centered assistive technologies

3.4 Performance Metrics

Performance metrics is the one that exhibits the effectiveness of a ML and DL models. Throughout this review it is evident that performance reporting are distinct across each study.

In [32] Daniela et al. have reported classification accuracies up to 99% on child subsets of the UCI autism dataset, with corresponding AUROC values supporting strong internal performance. Some achieved AUROC scores as high as 0.98 but with weak external validation and low true positive value [20].

CNN-based pipelines gives promising accuracy while game-based and video-based approaches produced AUROC and trupe positive rates ranging from 0.74 to 0.94. Though many studies shows high accuracy they failed with AUROC or F1 scores. This reveals that existence of research gap in ASD research. Table 3 presents the details about the ML and DL algorithms that have given prominent result.

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Volume 13– No. 1, August 2025 – www.ijais.org

3.5 Overall Synthesis

As recent studies that focus on ASD detection has clearly evolved from simple interview based with small size dataset to scalable, multi-modal, and computationally enriched approaches. While advancements in ML and DL have become more popular, consistent large-scale validation and generalizability still remain significant gaps.

New approaches in this field are VR-based interventions, robot-assisted social skills training, and multimodal biomarker fusion including metabolomics. These paradigms offer promising directions for future research. But these novel trends are largely in early deployment stages. As a concluding note to convert these innovative approaches to meet real-world clinical needs, this research area has to prioritize the following: 1. robust datasets 2. transparent reporting of performance metrics 3. community-validated frameworks.

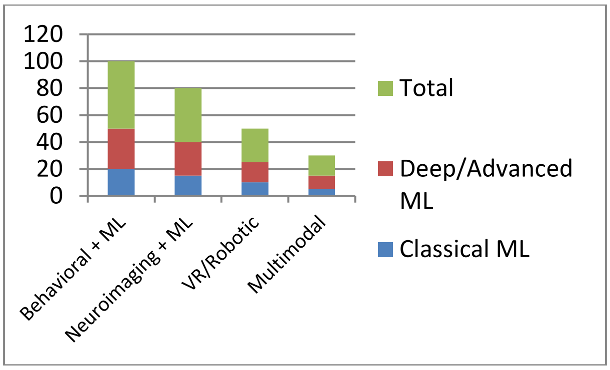

Fig. 1: Detection Methods by Data Type

3.6 Emerging methods in ASD research

Ultimately, 52 studies were analyzed. Emerging trends in Autism Spectrum Disorder Research identified are listed below in Table 4. Human centered robust practices are leads the next level of autism research. Human-in-the-loop strengthens social acceptance as it involves both AI and human care giver inputs. Any research requires secularism; otherwise the solution becomes incompatible for global audience. Ethical cross cultural validations is the methods that need to be adopted for world-class solution for ASD. For early detection capturing biomarkers like facial movements is non-trivial. Smartphone apps are used for low cost interventions.

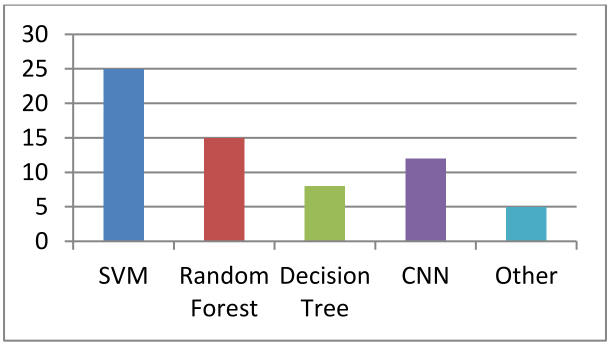

Fig. 2: Frequency of Machine Learning Algorithms used in ASD Detection

4. DISCUSSION

Impactful insights through this review to mention are methods for ASD detection - from machine learning methods to EED-based markers; from social skills training interventions to brain image studies - are expanding. Fig 1 illustrates that behavioral and neuroimaging data are most preferred dataset when ML based solution are derived. Multimodal datasets though becoming famous are not used yet in recent research works. Robotics therapies combined with virtual reality are experimented in 10 literature works. Fig 2 illustrates the most preferred ML algorithm. Support Vector Machines (SVM) tops the list which is followed by Random Forest (RF). In image based diagnosis procedure Convolution Neural Networks (CNN) are preferred. Human in the loop design are preferred for better validation. Employing different sensors are also becoming common in the process of detection. What is missing is that the standards to validate these methods and to test them in real-life settings. Fig 3 shows that while evaluating ML / DL models accuracy is the most likely performance metrics followed by AUROC and F1 score.

The algorithms mentioned in Table 5 serve as critical tools in the feature engineering pipeline of ASD research. Boruta and RFE are suited for complex, high-dimensional datasets where selecting the right features boosts performance. CFS is ideal for fast filtering in more structured or tabular data. RIPPER offers transparent rule-based outputs, making it attractive in clinical diagnostic settings where interpretability is paramount. Chi-Square, and Information Gain provide transparency and statistical grounding. Symmetrical Uncertainty balance relevance and redundancy in structured data. Combining filter, wrapper, and rule-based techniques is often most effective in ASD diagnosis, where the data is heterogeneous, high-dimensional, and sensitive.

It is evident through this study that several recent ASD research are machine learning (ML) based. In terms of accuracy SVM achieved 90%, Random forest and ANN achieved 89% with Ding's dataset. Similarly Logistic regression achieved 97.15% using ABIDE dataset and MLP achieved 100% accuracy with ASD questionnaire dataset.

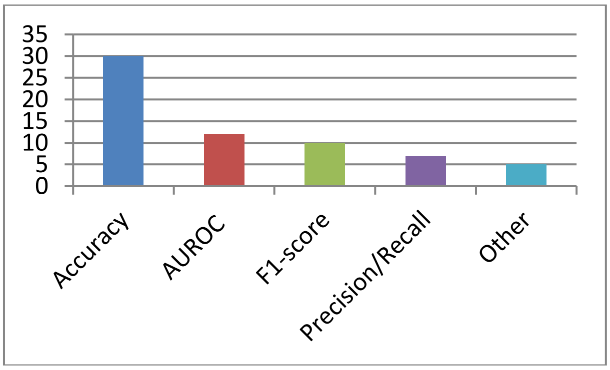

Fig. 3: Performance Metrics Reported Across ASD Studies

Table 3. ML Models and its Performance

Ref. Paper #	ML Model	Accuracy (%)	AUROC	F1 Score	Dataset Used
9	SVM	95–99	0.96–0.99	0.94	UCI ASD, ABIDE
10	Random Forest	92–98	0.94–0.97	0.92	UCI ASD, ABIDE
20	CNN	97–99	0.95–0.98	0.95	ABIDE, gaming data
25	Decision	85–93	0.88–	0.88	UCI

	Trees		0.92		ASD
40	Hybrid AI	91–96	0.90–0.94	0.9	VR/ robot datasets
39	Graph Kernel	87	0.9	0.89	ABIDE graph kernels

Table 4. Emerging Trends

Ref#	Emerging Trend	Key Features	Future Outlook
[40], [50]	Human-in-the-loop systems	Combines AI with caregivers and therapists to preserve trust and bonding	Expected to strengthen social acceptance
[9], [31], [32]	Multimodal, multi-sensor strategies	Fuses speech, gaze, facial, handwriting, neuroimaging, metabolomics	Improves holistic detection
[20], [25], [49]	Precision subtyping	Matches interventions to ASD subgroups	Supports personalized therapies
[12], [26], [30]	Low-cost, scalable solutions	Smartphone apps, VR, robot therapies	Expands reach to underserved settings
[6], [8], [39]	Ethical and cross-cultural validation	Focus on fairness and inclusivity	Enhances global relevance
[14], [37]	Real-world validation	Shifts from lab to home/community testing	Increases ecological validity
[44], [45], [50]	Dynamic, adaptive interventions	Closed-loop VR and robot-based systems	Supports flexible responses
[46], [47]	Digital phenotyping	Subtle biomarkers (acoustic, facial, movement)	Enables passive early screening
[40], [48], [39]	Human-centered robust practices	Blends computational tools with clinical, equitable frameworks	Guides ASD research over next decade

Table 5. Feature Selection Algorithm

Ref#	Technique
[9]	Boruta CFS(Correlation Feature Selection) RIPPER(Repeated Incremental Pruning to Produce Error Reduction) RFE(Recursive feature elimination)
[10]	CatBoost RFECV(Recursive feature elimination with cross-validation) Boruta GWO(Grey Wolf Optimization)
[16]	Information Gain Ratio, Chi-Square Method. Symmetrical Uncertainty

5. CONCLUSION

According to WHO 1 in 100 children has autism. Autism is a neurological disorder that constitutes various dissimilar conditions hence the name Autism Spectrum Disorder (ASD). ASD detection and treatment using computational techniques is a promising research area that an enthusiast can look upon. Numerous investigations are done with benchmark datasets viz. ABIDE, SPARK, Market Scan. Datasets comes in both structured and unstructured format. Really innovative proposals give rise to novel methods/techniques for the early detection of ASD. Key takeaway from this review are, Autism research is one of the fast growing research areas. There is no single significant reason behind this ASD. Research has been carried out in much different perspective. Diagnosis is done using Questionnaire; EEG signals specifically eye tracking, Gene data, diverse and culturally inclusive datasets are missing, reliable validation methods are missing, affordable tools that work in real-time are not found. ASD research will need to focus on combining strong machine learning systems with fair, clear, and human-centered designs so that these technologies can truly support people with autism and their communities. Table 6 in Appendix –I of this paper presents the detailed summary of the findings through this survey.

6. ACKNOWLEDGMENTS

Our thanks to the management of Prathyusha Engineering College, India towards this research work.

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Appendix - I

Table 6: Summary of Literature

Ref#	ASD Detection Methods	Source of Datasets	Computational Techniques	Performance Metrics	Pros/Cons	Research Gaps
1	Genomic (GWAS) perspectives	Spectrum 10K	None	N/A	Pro: community-informed Con: ethics concerns	Need inclusive, ethical genomic frameworks
2	Music-assisted intervention (RCT)	Local study (27 participants)	None	Social responsiveness	Pro: improved language Con: small sample	Need robust RCT
3	Interpretative Phenomenological Analysis	Local interviews	None	N/A	Pro: female perspectives Con: no predictive models	Screening tools for adult females lacking
4	Qualitative thematic analysis	1248 adult surveys	None	N/A	Pro: lived-experience Con: no computational models	Computational diagnostic support needed
5	Qualitative interviews	31 parents, 25 children	None	N/A	Pro: practical data Con: small sample	Remote ASD detection unexplored
6	Systematic review of inclusion reporting	1013 studies	None	% reporting rates	Pro: equity-oriented Con: no AI use	Diversity-aware ML datasets lacking
7	Behavioral literacy testing	31 participants	None	Reaction time, accuracy	Pro: literacy focus Con: no ML models	Predictive literacy models unexplored
8	Qualitative thematic analysis	144 interviews	None	N/A	Pro: participatory Con: no AI	Models for social withdrawal prediction lacking
9	Questionnaires + feature selection	UCI ASD Repository	SVM, RF, CART, Boruta	Accuracy up to 99%, AUROC	Pro: high accuracy Con: no external validation	Cross-site validation missing
10	Structural MRI biomarkers	ABIDE + KAU datasets	SVM + Grey Wolf Optimizer	Accuracy 71%	Pro: explainable features Con: moderate accuracy	Small MRI datasets, male bias
11	Gut microbiome with 16S rRNA	Two public gut microbiome datasets	SVM, ANN, RF	Accuracy 90%, Sensitivity 96.97%	Pro: novel biomarkers Con: reproducibility issues	Larger diverse validation needed
12	IoT/AI drawing interpretation	Local database	MobileNet, ResNet50, VGG16	Accuracy 56.25%	Pro: innovative; Con: moderate accuracy	Sample size + improved CNN needed
13	Supervised ML review	45 papers reviewed	SVM, DT, RF, text mining	summarized	Pro: broad survey; Con: no new model	Unsupervised methods underused
14	Home video ML	162 videos	LR, SVM, DT	AUC 0.93 (test), 0.86 (validation)	Pro: scalable; Con: rater variability	Need standardization, global data

15	Rule induction	3 datasets (children to adults)	Rules-ML, Decision Trees, Boosting	higher than baseline	Pro: explainable rules; Con: lacks external validation	No deep learning comparisons
16	ML feature selection review	N/A	SVM, ANN, Apriori, DT	summarized	Pro: thorough; Con: no experiments	Imbalanced data handling gaps
17	sMRI ML review	ABIDE and others	SVM, DL	summarized	Pro: promising; Con: small samples	Standard MRI protocols needed
18	sMRI/fMRI ML survey	ABIDE, ADHD-200	DL (CNN, RNN), SVM	summarized	Pro: multimodal; Con: lacks benchmarks	Benchmark frameworks missing
19	Medical claims ML	MarketScan	LR, RF	AUROC 0.834, specificity 96%	Pro: big data; Con: PPV 20%	Non-US validation missing
20	ASD subclass ML	38,560 records	multi-class classifiers	AUROC 0.86–0.98	Pro: large sample; Con: misclassification 12%	Fine-grained subclass boundaries unexplored
21	Behavioral/clinical	UCI datasets	SVM, RF, KNN	Accuracy 96%	Pro: robust; Con: small sample	Cross-cultural datasets missing
22	Behavioral screening	4 public datasets	DT, SVM, RF, KNN	100% reported	Pro: covers ages; Con: overfitting risk	External validation needed
23	Neuroimaging MRI	ABIDE	VGG16 transfer learning	high (unspecified)	Pro: reduced features; Con: sample limits	Test on multi-center MRI
24	Behavioral questionnaire	Merged ASD datasets	SVM	Accuracy 95%	Pro: standard merge; Con: imbalance risk	Better balanced splits needed
25	Association classification	7 datasets	WCBA, AC	Accuracy 97%	Pro: explainable; Con: rule bloat	Clinical external testing needed
26	Questionnaire ML	Local data	Decision Tree, KNN	not specified	Pro: mobile app prototype; Con: small sample	Pilot studies needed
27	Q-CHAT screening	Q-CHAT local sample	SVM, RF, KNN, LR	highest LR	Pro: simple; Con: missing data	Robust features needed
28	Screening data	UCI datasets	SGD, RF, AdaBoost, CN2	99%+ reported	Pro: age-stratified; Con: overfit risk	External cohort testing missing
29	Handwriting-based	local handwriting	CNN (GoogleNet)	Accuracy 90%, F1 100%	Pro: novel modality; Con: small pilot	Expand handwriting dataset
30	Color-based learning app	local pilot	rule-based	qualitative	Pro: culturally adapted Con: small sample	needs larger validation
31	Behavioral screening	3 UCI datasets	SVM, LR, KNN, CNN	CNN up to 99.5%	Pro: strong accuracy Con: simple features	overfitting risk
32	ML systematic review	26 reviewed studies	SVM, FC, CC200	summary	Pro: comprehensive Con: no new data	feature diversity lacking

33	Mobile gameplay	Stanford 83 children	Random Forest	AUROC 0.745	Pro: remote scalable Con: modest AUROC	needs broader validation
34	Exercise outcome prediction	41 ASD children	Random Forest	accuracy 66%	Pro: personalized Con: small cohort	limited to one intervention
35	White matter fiber ML	70 ASD, 79 TDC	tractography + ML	accuracy 78%	Pro: whole-brain Con: moderate performance	needs multimodal fusion
36	AI policy review	N/A	none	N/A	Pro: policy insights Con: no predictive	ASD educational AI frameworks untested
37	Home video ML	local sample	SVM + feature selection	TPR 94%	Pro: interpretable Con: rater-dependent	standard tagging pipelines missing
38	fMRI graph kernel clustering	150 ASD, 137 SZ	graph kernel	not reported	Pro: transdiagnostic Con: no deployment	needs prospective cohort testing
39	VR/AI/robotics review	multiple pilots	summarized	N/A	Pro: innovative Con: early stage	needs long-term RCT
40	Joint attention caregiver-mediated (C3I)	6 dyads	computer-mediated	medium effect size	Pro: caregiver integrated Con: pilot size	needs larger RCT
41	Speech/motor biomarkers	5 ASD, 5 controls	eigenvalue-based ML	not reported explicitly	Pro: multi-domain; Con: tiny sample	scale to broader clinical samples
42	Home-based ABA therapy platform	Romanian pilot	web/mobile app (Unity/RoR)	ISO 9126 QEF	Pro: family-centered Con: early prototype	efficacy in diverse settings
43	Computer vision on mobile	33 toddlers	CV + behavior movies	TPR 94%	Pro: scalable, low cost Con: refinement needed	cross-cultural replication
44	Autonomous social orienting (ASOTS)	10 ASD toddlers, 10 TD infants	gaze tracking + computer system	good tolerance	Pro: autonomous Con: complex hardware	simplification for home use
45	Intelligent agent with collaborative puzzle games	pilot feasibility	dialogue management	qualitative	Pro: engaging Con: pilot only	needs scale-up
46	Speech signal ADOS severity estimation	72 Hebrew children	CNN, DNN, SVR	RMSE 4.65, corr 0.72	Pro: quantitative Con: language specific	test in other languages
47	Facial landmark entropy	436 toddlers	multiscale entropy	higher complexity ASD	Pro: new biomarker Con: lacks external test	complement with other features
48	VR collaboration platform	12 ASD + 12 TD	VR + eye tracking	qualitative	Pro: immersive Con: prototype	needs larger trials
49	Metabolomics biomarker	CAMP 1100 children	metabolomics assays	17% subtype found	Pro: objective Con: partial coverage	expand subtypes

50	Robot-mediated imitation skills	small user studies	RISTA architecture	qualitative	Pro: engaging Con: narrow domain	follow-up studies
51	Visual oddball task	Visual oddball task (checkerboard stimuli) to assess EEG variability	Visual oddball task (checkerboar d stimuli) to assess EEG variability	Visual oddball task (checkerboard stimuli) to assess EEG variability	Visual oddball task (checkerboard stimuli) to assess EEG variability	Visual oddball task (checkerboard stimuli) to assess EEG variability
52	Resting-state EEG features, exploring spectral power, peak alpha frequency, theta/beta ratio, criticality, connectivity (PLV, coherence, wPLI)	Netherlands Autism Register adult cohort (n=186)	Support vector machines, logistic regression (L1/L2), random forest; feature selection with mRMR; nested two-layer cross-validation	Balanced accuracy on test set around 50–56%, nMAE on questionnaire predictions near 1	Pro: robust large sample of intellectually able adults; comprehensive EEG feature set; rigorous cross-validation. Con: low test accuracy, features did not generalize, weak biomarker effect	Need larger, more diverse samples; explore other EEG paradigms (eyes-open, task-based); combine with other modalities (MRI, genetics) to mitigate ASD heterogeneity