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BRIDGING THE GAP: INTEGRATING MACHINE LEARNING INSIGHTS INTO AUTISM DETECTION AND EDUCATION PRACTICES

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Abstract
Autism Spectrum Disorder (ASD) is a lifelong neurodevelopmental condition characterized by atypical communication, social interaction, and sensory processing. Early diagnosis is crucial for improving learning and developmental outcomes, yet traditional methods such as the M-CHAT-R/F are time-intensive and rely heavily on subjective assessment. Recent advances in machine learning (ML) offer promising alternatives by enabling faster, more accurate detection and supporting the design of personalized educational strategies. This review synthesizes current ML-based approaches for ASD detection and intervention, evaluates classifier performance across diverse studies, and highlights future directions for integrating explainable, data-driven models into clinical and educational practice.

Keywords: Autism Spectrum Disorder (ASD); Machine Learning; Early Detection; Personalized Education; Artificial Intelligence

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects communication, social interaction, and adaptability, while often accompanying unique strengths and ways of thinking. It is called a "spectrum" because its severity ranges from mild to severe, and no two individuals experience it in the same way. Major forms once classified under ASD include Asperger's syndrome, Rett syndrome, childhood disintegrative disorder, Kanner's syndrome, and pervasive developmental disorder. Common symptoms, usually evident before age three, include limited eye contact, communication difficulties, hyperactivity, attention deficits, repetitive behaviors, and reduced social responsiveness.

Autism Spectrum Disorder affects around 1% globally, according to estimates from the World Health Organization [1]. In recent years, the global prevalence of autism spectrum disorder (ASD) has shown a noticeable upward trend, drawing increased attention from researchers, healthcare providers, and educators. Figure 1 shows the autism spectrum disorder (ASD) population per 10,000 people across various countries, with Hong Kong having the highest rate (372) and Singapore the lowest (67) [2] and Figure 2 represents the number of children diagnosed with autism spectrum disorder in selected countries (per 100,000) around the world in 2021 [3]. A new study published in *JAMA Network Open* shows that the number of children and adults diagnosed with autism spectrum disorder (ASD) has increased by 175% over a decade [4].

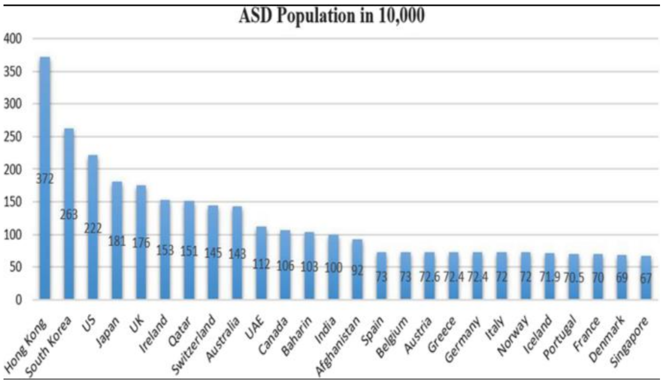

figure 1 asd global population presentation

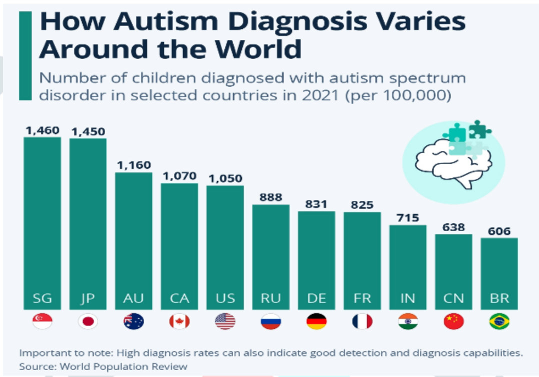

figure 2 asd in selected countries in 2021 (per 100,000)

figure 3 signs of autism

Progress has been made significantly in both identifying and educating children with autism spectrum disorder (ASD). There is a substantial amount of scholarly work addressing the identification of ASD based on facial features, behavioral pattens, neuro-imaging, eye gaze fixation, genetic and environmental factors. To improve the efficiency and simplicity of the detection process, various physiological and behavioral indicators have been found to be effective in identifying autism spectrum disorder (ASD) in children with typical developmental patterns [5]. Children with Autism Spectrum Disorder (ASD) often show unique patterns in how they process faces and where they focus their gaze. Extensive research has been conducted on facial expressions and eye tracking technology [6] [7]. **M-CHAT-R/F** (Modified Checklist for Autism in Toddlers, Revised with Follow-Up) which is a two staged parent-reported screening tool is a manual diagnosis and screening method used for ASD identification. It requires manual assessment of the toddler through parents and takes considerable time in controlled clinical setup [8]. It is effectively necessary to find a suitable teaching method for children with autism spectrum disorder (ASD) because every child with ASD has different characteristics and they should have specific education which is appropriate to their needs. Manual observation forms the basis of traditional ASD detection, but this approach is often slow and difficult to standardize. Machine learning algorithms play a crucial role in enhancing the efficiency and easing of the of ASD detection and development of personalized education recommendation process. The study focused on implementation of machine learning in identification of proper education needs of a child with ASD i.e. identifying best teaching method for children [9].

ASD Autism Spectrum Disorder includes a wide range of symptoms, abilities, and challenges that vary from person to person. Several studies have systematically examined the levels of severity of ASD. Children with severe ASD need high support and show very limited social understanding, while those with moderate or mild ASD show improving or advanced social thinking and need less substantial support accordingly. The study mapped the three distinctive levels of severity of ASD using Theory of Mind (TOM) abilities and presented them in the following categories - Level 1: Requiring support (mild), Level 2: Requiring substantial support (moderate) and Level 3: Requiring very substantial support (severe) [10].

TYPES OF AUTISM:

Autism was historically divided into several subtypes, though these are now grouped under Autism Spectrum Disorder (ASD) in the DSM-5:

1. **Kanner's Syndrome:** First identified in 1943, characterized by limited emotional connection, rigid routines, repetitive language use, and unusual attachments. Once considered a distinct and severe form, it is now included within ASD.
2. **Asperger's Syndrome:** Previously classified separately, it represents a milder form of autism with preserved language and cognition but marked social and behavioral challenges. Despite reclassification, the term is still commonly used in clinical and community contexts.
3. **Rett Syndrome:** A rare genetic disorder, almost exclusive to girls, caused by *MECP2* mutations. It initially resembles autism but later shows unique features such as slowed head growth, motor regression, repetitive hand movements, seizures, and cognitive decline.
4. **Childhood Disintegrative Disorder (CDD):** A rare condition involving late-onset and sudden regression in language, play, motor, and self-care skills. It is often accompanied by repetitive behaviors, impaired communication, epilepsy, and anxiety-like symptoms.
5. **Pervasive Developmental Disorder - Not Otherwise Specified (PDD-NOS):** A "catch-all" category formerly used for individuals with autism-like features who did not meet full diagnostic criteria. It included difficulties with social interaction, communication, and adaptability, but was later absorbed into the broader ASD category.

II. LITERATURE REVIEW

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition affecting communication, social interaction, and cognitive processing, with strong genetic influences. Early diagnosis is crucial, as timely interventions improve outcomes and reduce prolonged assessments. Recent studies highlight the role of machine learning (ML) not only in early detection but also in designing personalized teaching strategies tailored to the diverse learning needs of individuals with ASD.

Fahima Hajjej et al. (2024) developed a two-phase ML framework for early ASD detection and personalized teaching recommendations. Using two toddler screening datasets and SMOTE for imbalance, they compared BEFS, Boruta, and MFS, with MFS (Extra Trees) performing best. The RF-XG ensemble achieved 99.99% accuracy in ASD detection and 99.17% in recommending teaching methods, outperforming multiple existing models and demonstrating strong potential for both diagnosis and individualized support [12]. Zarin Tassnim Zoana et al. proposed an ML approach to recommend effective teaching strategies for autistic children using Naive Bayes, Random Forest, Decision Tree, and KNN. Random Forest achieved the best performance with 98.69% accuracy, 99.10% precision, and 98.48% F1-score, showing strong potential for identifying suitable teaching methods based on individual traits [13]. Suman Raj and Sarfaraz Masood (2020) evaluated Naive Bayes, SVM, LR, KNN, Neural Networks, and CNN across adult, child, and adolescent ASD datasets. CNN outperformed others, achieving 99.53% accuracy for adults, 98.30% for children, and 96.88% for adolescents, highlighting its effectiveness in ASD screening compared to traditional ML methods [14]. Anita Vikram Shinde and Dipti Durgesh Patil (2023) developed a recommender model using classifiers including LR, NB, DT, SVM, RF, and ANN for ASD detection. Both Decision Tree and Random Forest achieved 100% accuracy, underscoring the role of ML in enhancing early diagnosis and improving patient outcomes [15]. Fadi Thabtah et al. (2019) proposed a logistic regression framework for adult and adolescent ASD screening using AQ-10 behavioral features. With feature selection via Information Gain and Chi-square, the model achieved high accuracy, sensitivity, and specificity, offering a practical alternative to genetic datasets for early detection [16]. Said Baadel et al. (2020) introduced the Clustering-based Autistic Trait Classification (CATC) method, integrating clustering with classifiers such as ANN, RF, and Random Tree. CATC-enhanced models outperformed standard approaches, with ANN achieving up to 98% accuracy, demonstrating clustering's value in improving ASD screening [17]. Drishty Sobnath et al. used the MALSEND platform with 270,934 UK graduate records to study employment outcomes for disabled students. Decision Tree and Logistic Regression achieved 96% accuracy in predicting job categories, identifying disability type, institution, and degree classification as key factors [18]. Usama Jabbar et al. (2025) proposed an ML framework for ASD detection across toddlers, children, and adults using KNN, RF, SVM, NB, and MLP with feature selection and hyperparameter tuning. SVM achieved the best performance (98–100% accuracy), while MLP reached 94% on a local child dataset, confirming ML's promise in early ASD diagnosis [19]. Mousumi Bala et al. developed an age-specific ML framework for ASD using multiple feature selection methods and classifiers. SVM consistently outperformed others, reaching 97–99% accuracy across toddler, child, adolescent, and adult subsets, with SHAP used to enhance interpretability of feature importance [20]. S. M. Mahedy Hasan proposed a comprehensive framework evaluating eight classifiers with four scaling techniques across toddler, child, adolescent, and adult datasets. AdaBoost and LDA achieved the best accuracies (97–99%), while feature importance analysis highlighted key ASD indicators, supporting age-inclusive early diagnosis [21]. Charalambos K. Themistocleous et al. developed an NLP-based ASD detection model using narrative and vocabulary data from 68 ASD and 52 typically developing children. Hist Gradient Boosting and XGBoost achieved 96% accuracy, offering a fast, scalable, and non-invasive tool for early ASD identification [22]. V. Balaji and S. Kanaga Suba Raja proposed a deep learning–based framework combining DNN classification with K-means clustering and SGD regression. Despite limited datasets, the model achieved 77–85% accuracy, showing potential as an integrated approach for ASD detection and recommendation [23]. Maryam Aloumi et al. (2018) used classification algorithms to analyze 13 risk factors for autism disorder in Saudi Arabia. The IBk model achieved 80.6% accuracy, with findings highlighting consanguineous marriage, linguistic delays, and abnormal pregnancies as key risk indicators [24]. Sarah A. Alzakari et al. (2024) proposed a two-phase ML framework for toddler ASD detection and personalized teaching recommendations. Using Chi-square feature selection, their LR-SVM ensemble reached 94% detection accuracy and 99.29% accuracy in recommending teaching strategies [25]. Rownak Ara Rasul et al. explored ML and clustering models across children, adult, and combined ASD datasets. SVM and LR achieved 100% accuracy on the children's dataset, while ANN led the combined dataset (94.28%), with clustering methods like spectral clustering identifying key behavioral traits [26]. Suseela Sellamuthu and Sharon Rose proposed a multimodal ML approach using facial images and ADOS scores with CNN-based models. The multimodal concatenation model achieved 97.05% accuracy, demonstrating strong potential for clinical ASD diagnosis [27]. Asma Aldrees et al. designed a two-stage ML framework for early ASD detection and educational strategy recommendation. Using XGBoost with Chi-square features, the model delivered strong performance, though limitations included dataset diversity and computational costs [28]. A personalized learning system was proposed for Rett and Asperger's syndromes, integrating GEP for adaptive content and DCNN for emotion detection. The system achieved 98% accuracy in identifying disengagement and adapted teaching styles dynamically to improve engagement [29]. A study integrated explainable AI (XAI) into ML models for ASD diagnosis using preprocessing, feature selection, and algorithms like SVM, RF, XGBoost, and Neural Networks. XGBoost and NN showed highest performance, while SHAP and LIME enhanced interpretability, supporting clinical adoption [30]. Another study developed an automated ASD prediction model using SVM, RF, NB, LR, and

KNN on behavioral and medical datasets. Logistic Regression performed best, though dataset size limited generalizability, highlighting the need for larger datasets and deep learning approaches [31].

table 1 prominent work in the field of asd

Sr. No.	Year	Paper Title	Author	Methods Used
1	2024	Novel Framework for Autism Spectrum Disorder Identification and Tailored Education with Effective Data Mining and Ensemble Learning Techniques	Fahima Hajjej and Others	RF, DT, LR, KNN, SVM, GBM, XG and RF-XG
2	2022	Application of Machine Learning in Identification of Best Teaching Method for Children with Autism Spectrum Disorder	Zarin Tassnim Zoana and others	Naive Bayes, Random Forest, Decision Tree, and K-Nearest Neighbors
3	2020	Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques	Suman Raj, Sarfaraz Masood	Naive Bayes, Support Vector Machine, Logistic Regression, K-Nearest Neighbors, Neural Networks, and Convolutional Neural Networks
4	2023	A Multi-Classifier-Based Recommender System for Early Autism Spectrum Disorder Detection using Machine Learning	Anita Vikram Shinde and Dipti Durgesh Patil	Logistic Regression, Naive Bayes, Decision Tree, Support Vector Machine, Random Forest, and Artificial Neural Network
5	2022	A Machine Learning Framework for Early-Stage Detection of Autism Spectrum Disorders	S. M. Mahedy Hasan and others	AdaBoost (AB), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Gaussian Naïve Bayes (GNB), Logistic Regression (LR), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA)
6	2024	Autism Detection in Children: Integrating Machine Learning and Natural Language Processing in Narrative Analysis	Charalambos K. Themistocleous and others	Hist Gradient Boosting, XGBoost, Decision Trees, and Gradient Boosting
7	2022	Recommendation Learning System Model for Children with Autism	V. Balaji and S. Kanaga Suba Raja	Deep Neural Network (DNN), K-means clustering, and Stochastic Gradient Descent (SGD) regressor.
8	2024	Early detection of autism spectrum disorder using explainable AI and optimized teaching strategies	Sarah A. Alzakari and others	Logistic Regression, Support Vector Machine (SVM), and their ensemble (LR-SVM)
9	2024	Data-centric automated approach to predict autism spectrum disorder based on	Asma Aldrees and others	Logistic Regression, Random Forest, SVM, ANN, KNN, Naïve Bayes, XGBoost 2.0

		selective features and explainable artificial intelligence		
10	2025	Recommendation learning management system for autism using deep convolutional neural networks and gene expression programming	Tholkapiyan. M and others	Gene Expression Programming (GEP) and Deep Convolutional Neural Networks (DCNN);

III. SYSTEM DEVELOPMENT

Autism, or autism spectrum disorder, is a developmental condition affecting the brain, often noticeable in early childhood but sometimes diagnosed later. It involves challenges in social interaction, communication, and flexibility in activities, along with atypical responses to sensory input. Abilities and support needs vary widely—some individuals live independently, while others require lifelong care. Autism can influence education, employment, and family life, with societal attitudes and available services playing a key role in overall quality of life [32]. The system development process is structured into two phases: **Phase I** involves the diagnosis of ASD using a combination of statistical methods and machine learning techniques on an ASD dataset. During preprocessing, categorical variables are converted into numerical form, and the SMOTE technique is applied to address class imbalance. The selected algorithms are trained on the refined dataset to develop the diagnostic model. **Phase II** focuses on identifying the most effective teaching methods for children with ASD, based on the insights gained from the diagnostic phase. Figure 1 illustrates a graphical representation of the overall process.

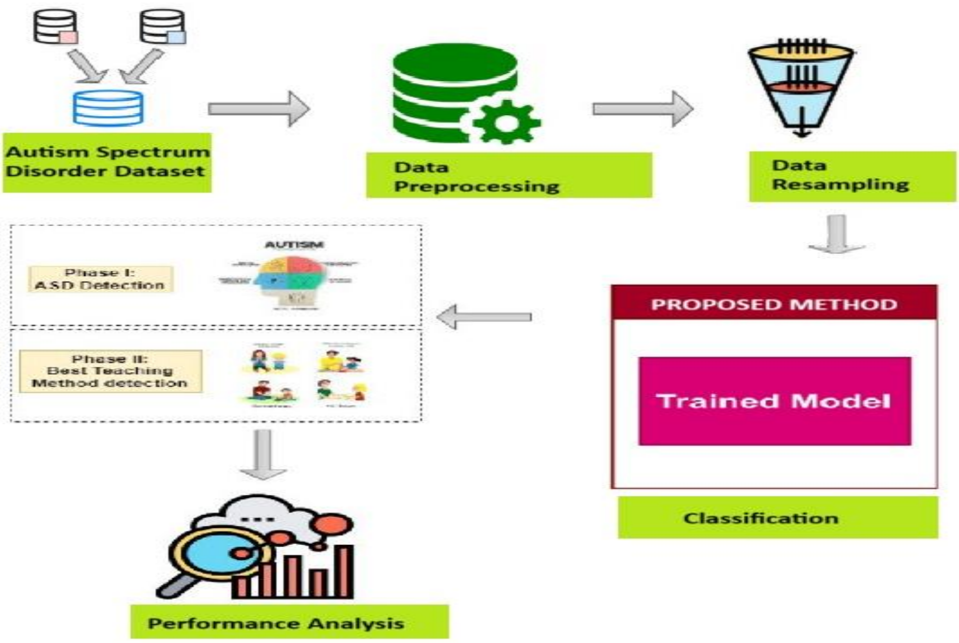

Figure 4 Workflow of Process

MACHINE LEARNING MODELS

This section outlines the application of supervised machine learning (ML) models, implemented with the Natural Language Toolkit (NLTK) and Scikit-learn. The algorithms reviewed include Random Forest (RF), Logistic Regression (LR), XGBoost (XG), Gradient Boosting Machine (GBM), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Neural Networks (NNs).

Random Forest (RF): An ensemble method that builds multiple decision trees on random data subsets and combines results to improve accuracy, handle high-dimensional data, and reduce overfitting. It is robust in managing noise and missing values [33].

Logistic Regression (LR): A statistical model widely used in medicine for binary classification (e.g., ASD vs. non-ASD). It can incorporate multiple predictors, manage both categorical and continuous variables, and assess interactions while ensuring good model fit [34].

XGBoost (XG): A highly efficient implementation of gradient boosting. It uses decision trees with added regularization to reduce overfitting, provides feature importance scores, handles missing values, and is valued for its scalability and predictive performance [35].

Support Vector Machine (SVM): Strong in binary classification tasks, SVM finds the optimal hyperplane separating data points. Kernel functions enable it to model non-linear problems, while extensions allow multi-class and regression applications. Although robust, SVM can struggle with very large datasets [36].

Gradient Boosting Machine (GBM): An ensemble method that sequentially builds trees, each correcting the errors of the previous ones. GBM achieves high accuracy and effectively captures complex data patterns but requires careful tuning and is computationally costly. Variants like XGBoost and LightGBM address these challenges [37].

K-Nearest Neighbors (KNN): A simple, intuitive algorithm for classification and regression. It predicts outcomes based on the closest *k* training samples using distance metrics. While flexible, performance depends on the choice of *k* and distance measure, and computation can be intensive with larger, high-dimensional data [38].

Neural Networks (NNs): Inspired by the human brain, NNs capture complex, non-linear patterns and are widely applied in healthcare and education. Toteja and Bajpai (2024) consolidated 3,043 behavioral records into seven teaching categories, testing four ML models (KNN, MLP, RF, and DT). The Multi-Layer Perceptron (MLP) achieved the highest accuracy (99.3%), highlighting NN potential in developing tailored education strategies for children with ASD [39].

IV. CONCLUSION

This review highlights the growing role of machine learning in advancing both the early detection of Autism Spectrum Disorder (ASD) and the development of personalized educational strategies. Across the studies reviewed, models such as Random Forest, Support Vector Machine, Logistic Regression, XGBoost, and Neural Networks consistently achieved high accuracy, often above 95%, underscoring the promise of data-driven approaches for timely diagnosis and tailored teaching.

However, important challenges remain. Many studies rely on small or non-diverse datasets, limiting generalizability. Feature selection often struggles to capture complex, non-linear patterns, and real-world implementation in clinical or educational settings is still limited. Issues of interpretability, scalability, and the integration of multimodal data such as behavioral, linguistic, and image-based features must be addressed to ensure robust and practical adoption.

Building on the insights gained from this literature review, our future research will be directed toward addressing the identified gaps by developing a robust machine learning framework. In particular, we aim to explore a combination of algorithms that balance interpretability and predictive power. This hybrid model may include advanced ensemble methods such as Gradient Boosting Machine (GBM), LightGBM, CatBoost, and Extra Trees (Extremely Randomized Trees), XGBoost along with an algorithm like Logistic Regression (LR), Linear Regression, Naïve Bayes (NB), Linear Discriminant Analysis (LDA), -Nearest Neighbors (KNN), Decision Trees (DT), Random Forest (RF), Support Vector Machine (SVM with RBF kernel).Through this hybrid approach, we intend to enhance diagnostic accuracy and provide more effective personalized education strategies for individuals with Autism Spectrum Disorder (ASD).

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