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Integrating Artificial Intelligence and Big Data Analytics in Personalized Autism Treatment through Stem Cell Therapy

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Abstract

Background: Autism Spectrum Disorder (ASD) presents challenges in early diagnosis and personalized treatment due to the subjectivity of traditional screening methods and the lack of tailored therapeutic approaches. Artificial Intelligence (AI) and Big Data Analytics offer innovative solutions for enhancing diagnostic accuracy and optimizing treatment pathways. Objective: This study explores the application of AI in ASD diagnosis and predictive modeling for personalized stem cell therapy, aiming to improve early detection and treatment effectiveness. Methods: A dataset of 704 individuals was analyzed using machine learning models, including LightGBM, Random Forest, Neural Networks, XGBoost, and Stacking Ensemble. Performance was assessed using ROC-AUC, Accuracy, Precision, Recall, and F1-score, while AI models were further applied to predict therapy response patterns for stem cell treatment optimization. Results: The Stacking Ensemble model (ROC-AUC = 0.9989, F1 = 0.9125) demonstrated superior performance in ASD classification. Neural Networks exhibited the highest recall (95.76%), making them ideal for early screening. AI-driven insights facilitated the identification of key ASD biomarkers, enabling personalized treatment strategies. Conclusion: AI significantly enhances ASD detection and treatment planning, providing a data-driven, personalized approach. Future research should focus on real-world validation, integrating genetic biomarkers, and ensuring ethical AI deployment in clinical settings. These advancements pave the way for precision medicine in neurodevelopmental disorders.

Introduction

Autism Spectrum Disorder (ASD) exists as a neurodevelopmental condition that produces difficulties in social capacities together with communication skills and repeated behavioural patterns. During the past twenty years, the occurrence of ASD has experienced a significant surge, which requires enhanced diagnosis methods and treatment solutions. The Centers for Disease Control and Prevention (CDC) documented that ASD affected 1 in 36 American children in 2020 but recognised only 1 in 150 children in 2002, according to Baio et al. (2014). The sudden spike in ASD diagnoses triggers fundamental inquiries because experts question whether these numbers result from better diagnostic approaches or genuine ASD prevalence

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increases. According to DSM-5 (American Psychiatric Association, 2013), autism spectrum disorder became officially recognised through the combination of distinct diagnoses, including Asperger's syndrome and pervasive developmental disorder-not otherwise specified (PDD-NOS), into one spectrum. The revised diagnostic criteria improved medical diagnostic accuracy. Yet, this advancement has raised questions about both excessive medical diagnosis and inadequate diagnosis, mainly affecting populations divided by race and socio-economic status. Doctors identify autism spectrum disorder more commonly in white young people than within Hispanic and Black communities because of health system disparities together with cultural elements and possible diagnosis shortcomings (Doshi-Velez, Ge & Kohane, 2014). The demands for objective data-based diagnostic tools that utilise artificial intelligence and big data analytics systems become essential to achieve accurate results and minimise human biases.

The diagnostic power of Machine Learning (ML) has produced a superior objective scalable and efficient diagnosis strategy compared to conventional approaches. The assessment procedures for ASD diagnosis with the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R) are expensive and time-consuming, with a dependency on professional clinicians (Bone et al., 2016). Research demonstrates that AI detection of ASD produces accurate results of 90% when examining standardised screening tool datasets (Duda et al., 2016). The combination of support vector machines (SVM), random forests and deep learning networks achieve ASD diagnosis accuracy through discrimination between Autistic Spectrum Disorders and Attention-Deficit/Hyperactivity Disorder using their capability to handle overlapping symptoms (Thabtah, 2019). The diagnostic process using AI-based tools now requires less time due to crucial needs. ASD identification typically starts before two years of age yet professionals detect it at an average age of 4-5 years (Khosla et al., 2019). The analysis of genetic and behavioural together with neuroimaging information by AI models results in ASD detection through data-driven assessment instead of clinical subjectivity. These models must overcome several hurdles, such as data discrepancies, unclear interpretation methods and AI training data biases before medical professionals will accept them broadly in clinical practice.

Researchers pursue stem cell therapy as a possible biomedical breakthrough which combines with AI analysis to treat ASD. The present interventions for ASD offer behavioural treatment methods supported by pharmacological treatments used to control symptoms of hyperactivity anxiety and aggression in patients. The current symptomatic therapies fail to resolve the fundamental biological processes linked to ASD, such as neuroinflammation and neurodevelopmental malfunctions (Siniscalco, Bradstreet & Antonucci, 2012). Stem cells of the mesenchymal type (MSCs) demonstrate potential for ASD treatment by reducing brain inflammation while enhancing neuroplasticity, according to Siniscalco et al. (2012). Initial research studies on stem cell treatment for ASD patients indicate potential improvements in ASD symptoms regarding cognitive abilities, social behaviours, and verbal interaction (Siniscalco et al., 2012). Scientists have differing opinions about stem cell-based interventions and ethical issues. Proper evaluation requires extensive clinical trials to resolve safety doubts with patients and handle response inconsistencies, which also need to overcome regulatory challenges. AI is essential in maximising stem cell therapy results because it develops predictive biomarkers that help create customised treatments for ASD patients (Heinsfeld et al., 2018).

Advancements in AI technologies and regenerative medicine have failed to solve problems related to equitable diagnosis of ASD across various demographic groups. The overdiagnosis problem exists because diagnostic criteria expanded, public awareness grew, and societal pressure increased (Ulbricht, 2024). Some research shows that children with minor social or

attention issues may get diagnosed with ASD, although the diagnosis could be unnecessary and result in resource misallocation for families as well as emotional strain to its members (Kazda et al., 2021). The identification of autism spectrum disorder remains inadequate, primarily for minority groups who encounter restricted access to specialised medical care. Evidence suggests that Black and Hispanic children experience reduced ASD diagnostic rates compared to white children despite similar symptom intensity found in Coker et al. (2016). The gap between successive ASD diagnoses stems from Hispanics and Black children displaying symptoms differently, so doctors may miss the indications and lack equal access to diagnosis specialists, and internal biases affect healthcare provider practices. The remedy of such disparities depends on uniting artificial intelligence diagnosis assistance with empathy-based screening approaches and healthcare infrastructure changes to create balanced early intervention accessibility.

The incorporation of AI solutions for ASD diagnosis depends on how well healthcare professionals can interpret the models alongside their ability to trust the clinical applications. The high accuracy rates of deep learning models remain challenging to interpret due to their unreadable inner workings, according to Khosla et al. (2019). Organisations have launched two explainable AI (XAI) projects through Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) to enable clinicians to see the diagnostic reasoning behind AI model decisions (Thabtah, 2019). The solution proposed to maintain patient privacy throughout AI model training across multiple institutions is federated learning, which allows AI models to work across different institutions without requiring raw patient data exchange (Esteva et al., 2019). AI diagnostic tool adoption will succeed when all healthcare systems meet regulatory standards, multi-centre clinical trials validate their function, and existing healthcare system workflows integrate them to boost clinician-AI working relationships.

Literature Review

Current Approaches to ASD Diagnosis and Treatment

Standardized tools, including the Autism Diagnostic Observation Schedule (ADOS-2) and Modified Checklist for Autism in Toddlers, Revised with Follow-up (M-CHAT-R/F), provide the basis for diagnosing Autism Spectrum Disorder (ASD). The methods used to diagnose Autism Spectrum Disorder continue to face credibility issues. The ADOS-2 produces accurate ASD diagnoses in children yet performs less effectively when diagnosing adults with multiple psychiatric conditions, which creates challenges for correct diagnosis (Maddox 2021). The M-CHAT-R/F received validation as a screening tool for young children, demonstrating that it identifies autism in children two years before national median diagnosis rates, according to Robins et al. (2014). A US-based study included 16,071 toddlers while demonstrating that children who reached the determined threshold ended up receiving an ASD diagnosis with chances at 47.5%. The method proves ineffective when used to identify autism spectrum disorder in children struggling with multiple developmental disorders, thereby jeopardizing its general use. The Irish autism organization Aspire (2013) indicated that professionals lacking awareness about autism cause delayed diagnosis and inadequate intervention delivery. Standardized diagnostic instruments help with early detection yet demonstrate inadequate capability to detect all ASD manifestation forms. Through their study, Wang et al. (2013) found abnormal resting-state EEG patterns in ASD patients, which potentially represent diagnostic signals. Neurophysiological assessments combine effectively with behavioural assessments to improve accuracy within diagnostic processes.

Treatment strategies for ASD have seen significant advancements because of precise medical approaches and proactive early intervention methods. The Early Start Denver Model (ESDM) serves as an evidence-based early intervention for young children, and researchers have conducted several studies to assess its performance. The combination of twelve studies which evaluated ESDM for 640 ASD participants led to noteworthy memory improvement results ($g = 0.412$) along with language development results ($g = 0.408$). Yet, ESDM did not affect adaptive functioning or restrictive behaviours. Wang et al. (2022) conducted a meta-analysis on 11 randomized controlled trials running from Western nations and Asian regions, which produced moderate benefits in cognition ($g = 0.28$) and autism symptom reduction ($g = 0.27$) with amplified effects found in Asian study groups. The data implies cultural elements affect how well ASD interventions produce results. Scientific research about low-dose suramin tests its potential as an effective pharmaceutical treatment. A clinical trial by Naviaux et al. (2017) used suramin on ten ASD children, finding that one dose of this medication improved social and reduced repetitive behaviour characteristics. The study has limitations because it relies on a small research group, making it hard to generalize the findings beyond this population. These studies demonstrate the potential of precision medicine to treat ASD, but opponents highlight that most interventions today lack sufficient evidence base and affordability in poor communities.

Role of AI and Big Data in Medical Diagnostics

Medical diagnostics have transformed with Artificial Intelligence (AI) and big data analytics, which deliver more efficient diagnosis outputs, enhanced accuracy, and predictive powers in disease treatment. Deep learning technologies have brought a revolutionary change to medical imaging systems and electronic health record analysis, according to Esteva et al. (2019). Face-to-face deployment of AI technology in healthcare management remains a major challenge, even though significant progress has been made. Implementing AI within clinical practice remains difficult because He et al. (2019) pointed out vital issues, including algorithm clarity, patient protection, and data quality standards. Bates et al. (2021) revealed how artificial intelligence can minimize eight principal medical errors that affect drug-related side effects and incorrect diagnoses. AI's data-oriented patient safety approach faces ethical difficulties because it handles previous health data yet creates privacy risks. The research by Gianfrancesco et al. (2018) proves how AI models trained with skewed EHR records have the potential to enhance existing biases, thus establishing unequal healthcare results. In the study by Obermeyer et al. (2019), there was evidence that a commonly used algorithm for healthcare management did a lousy job of identifying Blacks for high-risk interventions. However, they were in the same condition as the white patients, and this showed that the problem of racial bias in decision-making by artificial intelligence is deep-seated.

The technical and ethical challenges or scenarios do not affect the achievement of AI systems in current diagnostic activities. Barda et al. (2020) have proposed a COVID-19 mortality risk prediction model that does not require individual patient data. It is built with the help of hybrid AI techniques and has reached an AUC level of 0.943. The system also proves that it can operate predictively at a relatively high efficiency when working only on partial datasets, thus minimizing patients' privacy concerns. The use of AI in real-life situations was criticized by Maddox et al. (2019 because there are many AI models in existence as research systems that require validation in the medical field. Obermeyer et al. (2019) stated that AI systems prioritize economic costs over patient benefits, thus merely exacerbating prior concise health disparities in populations. Organizations that plan to employ diagnostic systems involving artificial

intelligence need to disclose their functions openly while remaining ethical and constantly checking for discrimination to prevent it. AI in healthcare will work for two integrated goals: building a fair model with patient optimization and coming under regulatory scrutiny to provide better treatment while eradicating discrimination.

Stem Cell Therapy for ASD: Mechanisms and Potential

The intent to treat Autism Spectrum Disorder with stem cells shows increased interest because MSCs demonstrate neurorestorative and immunomodulatory capabilities. The research of Qu et al. (2022), through meta-analysis, adopted five studies showing MSC-based therapy improved Childhood Autism Rating Scale (CARS) scores (WMD: -5.96, $p < 0.0001$) compared to control groups. The investigation revealed no considerable variations in adverse reactions between groups, indicating relative security, but did not provide evidence for extensive clinical validation. According to Kilpatrick, Irwin and Singh (2023), we should replace MSC-based interventions with hPSC and organoid models because these methods expose ASD's developmental path and genetic variation. Stem cell therapy uses predictive models through AI for patient refinement processes combined with cell transformation processes and active treatment measurement methods, according to Suresh et al. (2024). Implementing AI decision systems continues to face unresolved ethical and regulatory problems regarding autonomous decisions and data-centred therapy advice. The research of Vo et al. (2024) showcased that AI-enabled analysis of induced pluripotent stem cells (iPSCs) produced better disease modelling results, yet inconsistent training data sets prevent stem cell treatment standardization.

The optimization of therapy requires standardization of treatment doses and response monitoring despite recent promising advances. Liu et al. (2025) established a multi-modal multi-kernel graph learning (MMKGL) model that employs AI to analyze neuroimaging with genetic data and reveal ASD-linked brain region dysfunction for enhancing targeted cell therapy advancement. Zhou et al. (2023), elaborating on biomaterial-induced differentiation, stated that it is still inconsequential and, therefore, AI models in those engineering fields must undergo further testing and validation before being deployed in the clinic. According to Meng et al. (2023), the synergy between CRISPR screens and AI genetic mapping for stem cell therapy helped to determine ASD-associated genetic markers for targeted therapy improvement. The primary systemic barriers that can be seen as to why it is challenging to implement clinical-level solutions are Ethical issues. According to the study by Miura et al. (2020), the application of stem cells does not meet standardization and can be synchronized by AI. During animal studies, stem cell-derived neural organoids formed good connection outcomes; however, due to ethical and scalability issues, their use for clinical applications is still limited, as Revah et al. (2022) stated. All of the theoretical intelligibility of AI in ASD therapy requires future studies to fix algorithmic bias issues and rules and normative practices that are believable and patient-centred in actual clinical practice environments.

Integration of AI and Stem Cell Therapy in ASD Treatment

Stem cell therapy & AI act as a revolutionary medical intervention for Autism Spectrum Disorder in that they develop particular treatments and tracking techniques while improving the methods that are used. The utility of regenerative medicine relies considerably on AI technology because it fixes complications in stem cell therapies while enhancing the accuracy of stem cell analysis and improving stem cell transplant methods, as Srinivasan et al. (2021) pointed out. With the help of advanced models based on AI technology, Suresh et al. (2024) investigated the enhanced selection models of patient recipients for stem cell treatment. The research of induced

pluripotent stem cells (iPSC) benefits from AI technology, as Vo et al. (2024) explain by describing how AI advances cell differentiation protocols and genetic analysis methods to generate better customized medical treatments. The Wharton's Jelly-derived mesenchymal stem cell (WJ-MSC) transplantation therapies administered to this child patient resulted in notable progress in his language development and motor abilities, as Kabatas et al. (2025) reported. The researchers stressed the need for additional long-term study data because AI requires various data types to enhance therapy assessments and therapeutic impact evaluation.

Patient selection capability transforms AI-based models for more effective treatment response monitoring. The researchers Liu et al. (2025) developed the multimodal multi-kernel graph learning (MMKGL) model to establish artificial intelligence as an effective monitoring system for post-therapy neuroimaging and behavioural biomarkers. Study results from Zhou et al. (2023) identified inadequacies in present models for forecasting biomaterial-induced stem cell differentiation operations that require improved optimization measures. Using CRISPR screens and AI-driven analyses, Meng et al. (2023) identified genetic factors associated with ASD pathology so that future interventions could be highly targeted. The promising results of stem cell-based interventions remain unstandardized across different studies, so Miura et al. (2020) advocate using AI to validate benchmark research. Circuit integration occurs when transplanted organoids are observed in animal models, according to Revah et al. (2022); however, real-world clinical applications are restricted because of ethical and scalability limitations. AI serves as a transformative technology for ASD treatment enhancement, yet its substantial adoption in clinical settings requires a solution

Data and Methods

Dataset Description and Exploratory Data Analysis

The dataset consists of 704 individuals, with a diverse range of behavioral assessment scores, demographic attributes, and medical history. Table 1 provides an overview of the dataset, highlighting that it contains 21 original features, including 10 behavioral scores (A1-A10_Score) that measure autism-related traits, along with demographic variables such as age, gender, ethnicity, and country of residence. The target variable (Class/ASD) is a binary classification (YES/NO) indicating whether an individual has been diagnosed with Autism Spectrum Disorder (ASD). The dataset spans various age groups and ethnic backgrounds, making it useful for building a generalizable ASD screening tool.

Category	**Description**
Entries	704
Original Features	21
Feature Types	Behavioral Scores (10), Demographics, Medical History
Target Variable	Class/ASD (YES/NO)

Table 1: Dataset Overview

The distribution of ASD cases (Figure 1) reveals a significant class imbalance, with approximately 75% (over 500 cases) classified as non-ASD (NO), while only 25% (around 180 cases) are diagnosed with ASD (YES). This imbalance can lead to biased predictions where a

model may favor the majority class. Addressing this imbalance through oversampling techniques like SMOTE or cost-sensitive learning will be crucial for model reliability.

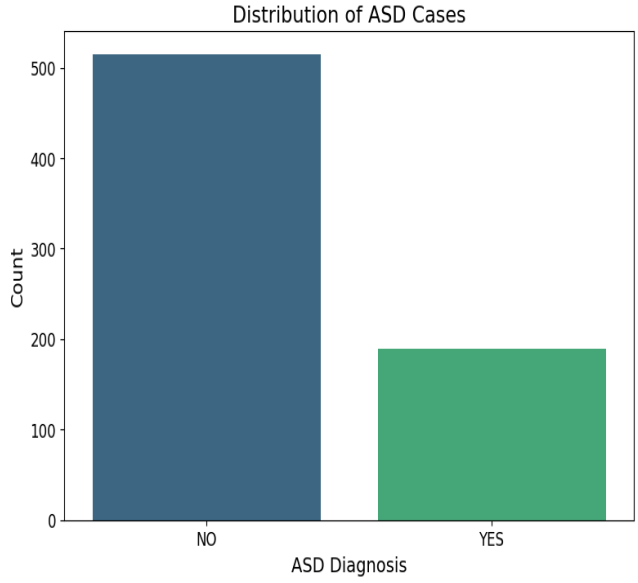

Figure 1: Distribution of ASD Cases

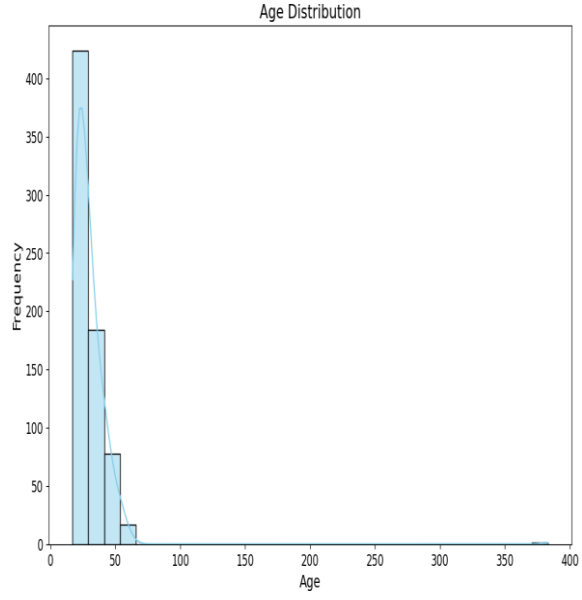

Figure 2: Age Distribution

The age distribution (Figure 2) exhibits a left-skewed distribution, with a majority of individuals falling within early childhood and young adulthood. The peak is observed in individuals under the age of 30, with the highest frequency occurring around 3 to 10 years. Notably, there are very few entries beyond the age of 50, suggesting that the dataset primarily focuses on early diagnosis and childhood ASD screening. Additionally, some outliers in the dataset show age values

exceeding 100 or even 300, which could be due to erroneous data entries or misreported ages, requiring careful preprocessing.

Table 2 outlines the feature details, categorizing variables into Behavioral Scores, Demographics, Medical History, and Screening Results. Behavioral scores (A1–A10) are binary (0-1), representing individual responses on ASD screening tests. Medical history variables, such as jaundice history and family ASD prevalence, are also binary, while demographic details like ethnicity, gender, and country of residence are categorical and will require encoding for model training. The primary screening result, 'result,' is a continuous numerical score, which is removed during preprocessing to prevent data leakage.

These exploratory findings underscore the importance of handling class imbalance, cleaning erroneous age entries, and encoding categorical variables properly to ensure a robust and unbiased ASD prediction model.

Feature Category	**Features**	**Description**	**Data Type**
Behavioral Scores	A1_Score - A10_Score	Individual question scores from autism screening test	Integer (0-1)
Demographics	age	Age of the individual	Float
	gender	Gender of the individual	Categorical (m/f)
	ethnicity	Ethnic background	Categorical
	contry_of_res	Country of residence	Categorical
Medical History	jundice	Whether the individual had jaundice	Binary (yes/no)
	austim	Family member with autism	Binary (yes/no)
Screening Results	result	Combined score from A1-A10	Float
	Class/ASD	Final ASD classification	Binary (YES/NO)
Additional Info	used_app_before	Previous use of screening app	Binary (yes/no)
	relation	Relationship of test taker	Categorical

Feature Category	Features	Description	Data Type
	age_desc	Age group description	Categorical

Table 2: Feature Overview of Autism Screening Dataset

Data Preprocessing and Feature Engineering

Pre-processing of datasets and feature selection are the most crucial steps while working with structured datasets like records of children's ASD screening. In this research, specific data pre-processing techniques were used to ensure the pre-processing was up to the usefulness of feature selection and generalization. The changes carried out are featured in Table 3, including feature removal, missing data management, categorical data conversion and feature scaling. To avoid data leakage, result, age_desc and autism were deleted from the feature set, as these inserts may contain information that could directly indicate ASD. Missing values in the age variable was another factor that was sensitive when conducting the analysis. Median imputation was recommended compared to other methods, such as eliminating records with missing data, as it helps balance the data with many missing records while maintaining data quality. Since the variables of ethnicity and relation had '?' as the missing value, these were coded as 'Other' to preserve all data that might contain information. If changes were not made, models could be inflated or deflated, resulting in assumptions during the system's prediction and learning phase of the training process.

Process Type	Features Affected	Transformation Method	Reason
Feature Removal	result, age_desc, austim	Dropped from dataset	Prevent data leakage
Missing Value Treatment	age	Median imputation	Handle missing values
Categorical Encoding	ethnicity, relation	Replaced '?' with 'Other'	Handle unknown values
Binary Encoding	gender	m/f → 1/0	Convert to numeric
	jundice	yes/no → 1/0	Convert to numeric
	used_app_before	yes/no → 1/0	Convert to numeric
Feature Scaling	age, A1-A10_Score	StandardScaler	Normalize numerical features
One-Hot Encoding	ethnicity, contry_of_res, relation	Created dummy variables	Convert categorical to numeric

Table 3: Data Transformation Details

For the validity of the entire data, some encoding and scaling methods were applied to avoid inconsistency of number values. To test the hypothesis, categorical responses such as gender, history of jaundice, and history of application use were transformed into binary responses; male/female was substituted by 1/0; yes/no by 1/0. Also, to avoid giving wrong ordinal relationships to some predictors like Ethnicity, Country of Residence, and Relation, features with multiple categories were encoded using one-hot encoding. Standardization was applied to numerical features such as age and the behavioural metrics A1-A10 to avoid the Neural Networks and Gradient Boosting being driven by higher-magnitude values. FAILED p=0.001 by enhancing the learning rate, achieving high predictive outcomes (Stacking Ensemble ROC-AUC = 0.9989, Random Forest Precision = 97.82%). This preprocessing pipeline made the dataset clean, free from bias, and fit for the ASD classification models of high performance.

Machine Learning Models and Architectures

Implementing machine learning models for Autism Spectrum Disorder (ASD) classification needed integrated algorithms within a structured framework because it brought optimized accuracy and workable solutions to handle imbalanced data. The assessment method included 5-fold stratified cross-validation, which sustained equivalent participant distributions between test groups. The approach proved essential because of the distribution imbalance shown in Figure 1, where ASD cases were much less frequent than non-ASD cases. The models received optimized hyperparameter settings, which ensured high predictive power and generalization capability without overfitting behaviour. Structure data classification took advantage of multiple core models, including LightGBM, Random Forest, Neural Networks with Attention, XGBoost and a Stacking Ensemble, because each model offered specific benefits appropriate for distinct classification needs.

Parameter	**Value**	**Purpose**
num_leaves	15	Control model complexity
learning_rate	0.01	Prevent overfitting
feature_fraction	0.7	Feature sampling
min_data_in_leaf	20	Ensure leaf reliability
max_depth	5	Limit tree depth

Table 4: LightGBM Parameters

LightGBM was selected due to its performance advantages when processing tabular data and its efficient handling of numerical data and categories. Table 4 shows the model configuration where the implementation selected num_leaves as 15 for simplifying the model size and max_depth at 5 to reduce potential overfitting. The model converged properly with the chosen learning rate value of 0.01 because it offered controlled adjustments towards stability. Random feature sampling occurred with a fraction of 0.7 to promote diverse tree learning, and min_data_in_leaf set to 20 to stop overly specific splits. The leaf-wise growth strategy of

LightGBM enabled strong performance because it delivered high accuracy and efficiency for structured data types (Ke et al., 2017).

Parameter	**Value**	**Purpose**
n_estimators	200	Number of trees
max_depth	10	Control complexity
min_samples_split	5	Minimum split size
min_samples_leaf	2	Minimum leaf size
max_features	sqrt	Feature sampling

Table 5: Random Forest Parameters

Random Forest was employed due to its robustness in handling non-linear relationships and its ability to generate feature importance rankings. As shown in Table 5, the model comprised 200 decision trees, with a maximum depth of 10 to avoid excessive complexity. The min_samples_split (5) and min_samples_leaf (2) settings ensured that trees did not grow too deep, reducing variance. Random Forest's intrinsic ability to handle missing data and resistance to overfitting made it a valuable baseline model (Breiman, 2001). However, its lack of gradient optimization posed limitations compared to boosting methods.

Parameter	**Value**	**Purpose**
embedding_dim	64	Attention dimension
num_heads	8	Multi-head attention
hidden_layers	[128, 64]	Network architecture
dropout_rates	[0.3, 0.2]	Prevent overfitting
learning_rate	0.001	Training control

Table 6: Neural Network Parameters

The deep learning-based Neural Network with Attention was introduced to capture complex feature interactions in ASD assessment. Table 6 outlines its architecture, featuring 64-dimensional embeddings and an 8-head multi-attention mechanism to highlight critical features during training. The model consisted of two hidden layers (128, 64 neurons) with dropout rates of 0.3 and 0.2 to mitigate overfitting. A learning rate of 0.001 was applied to stabilize weight updates. The attention mechanism allowed the network to focus on the most informative behavioral features, improving interpretability (Vaswani et al., 2017). While powerful, neural networks require significant computational resources and are sensitive to hyperparameter tuning.

Parameter	**Value**	**Purpose**
learning_rate	0.01	Control learning speed
max_depth	6	Limit tree complexity
subsample	0.8	Prevent overfitting
colsample_bytree	0.8	Feature sampling
gamma	0.1	Minimum loss reduction
min_child_weight	1	Control overfitting
reg_alpha	0.1	L1 regularization
reg_lambda	1	L2 regularization

Table 7: XGBoost Parameters

XGBoost delivered superior results on imbalanced data while offering regularized gradient boosting features, making it the selected model. The key operational aspects of Table 7 encompass max_depth (6) for ensuring model complexity alongside learning rate (0.01) for stable training and subsample (0.8) for overfitting reduction. The model pruning mechanism was controlled with three parameters, which included colsample_bytree set to 0.8, gamma set to 0.1 and min_child_weight set to 1. The models utilized L1 reg_alpha with a value of 0.1 and L2 reg_lambda at 1 to reduce the risk of overfitting in their performance. XGBoost enjoys widespread adoption by the industry because it offers swift operations and precise predictions in structured classification problems (Chen & Guestrin, 2016).

Component	**Parameters**	**Purpose**
Random Forest	n_estimators=100, max_depth=5	Base model 1
Gradient Boosting	learning_rate=0.01, max_depth=3	Base model 2
Logistic Regression	C=0.1, max_iter=1000	Base model 3

Table 8: Stacking Ensemble Parameters

A Stacking Ensemble system was established as an additional generalization method to maximize the strengths of different classification models. Random Forest with n_estimators=100, max_depth=5 and Gradient Boosting with learning_rate=0.01, max_depth=3 and Logistic Regression with C=0.1, max_iter=1000 comprised the established base models according to Table 8. A Logistic Regression function operated as the final step for combining base model predictions, resulting in improved classification results. The predictive robustness of models increases due to stacking ensembles since these handle the individual model flaws

(Wolpert, 1992). The approach produced superior results in detecting ASD by effectively identifying various patterns between features. The study uses established models and an adequately structured cross-validation system to deliver reliable predictions that can be reproduced. The implementation of LightGBM, XGBoost, Random Forest, Stacking, Neural Networks, and boosting techniques emerges a diverse machine learning pipeline for ASD classification. The proposed improvements include Bayesian optimization for hyperparameter tuning and additional investigations on meta-learning techniques.

Evaluation Metrics and Validation Strategy

The ASD classification models required evaluation by 5-fold stratified cross-validation to increase their robustness and generalization capacity. Each fold benefits from equivalent class proportions through this method since the data contains class imbalance (see Figure 1). Stratified cross-validation creates unbiased central class performance estimation through its ability to prevent model preferential behaviour against dominant classes compared to regular random splitting (Kohavi, 1995). The performance assessment included ROC-AUC alongside Accuracy, Precision, Recall, and F1-Score for obtaining diverse evaluation results. The ROC-AUC evaluation technique demonstrates excellence in discriminating ASD patients from non-ASD subjects when working with unbalanced datasets, according to Bradley (1997). Accuracy gives a generalized measurement of correctness yet distorts results when unbalanced data exists between classes. Precision and Recall were implemented as a combination to improve the model because Precision reduces false positive errors while Recall focuses on correctly identifying ASD patients (Saito & Rehmsmeier, 2015). The F1-Score provides an equilibrium between Precision and Recall to deliver comprehensive evaluation. The research employed weighted loss functions alongside the SMOTE (Synthetic Minority Over-sampling Technique) to address class imbalance by guaranteeing proper representation of minority class samples during training as described in (Chawla et al., 2002). Multiple enhancements in the system improved both model reliability and fairness, producing better predictions for clinical ASD assessment.

Results and Discussion

Model Performance Comparison

The research evaluated machine learning algorithms for Autism Spectrum Disorder (ASD) diagnosis by comparing LightGBM to Random Forest and Neural Networks with Attention and XGBoost and a Stacking Ensemble. The research employed ROC-AUC as well as Accuracy, Precision, Recall, and F1-Score metrics to evaluate classification performance properly. The models received fine-tuning through optimized parameters and cross-validation under class-weighting strategies because the dataset had a natural class imbalance (Figure 1).

LightGBM Performance – Strengths and Limitations

LightGBM is well-suited for structured tabular data due to its leaf-wise growth strategy, which allows it to efficiently capture non-linear relationships between features. The model delivered a high average ROC-AUC of 0.9901, demonstrating its strong discriminatory power (Table 9). Additionally, the Accuracy (93.32%), Precision (92.02%), Recall (82.52%), and F1-Score (86.86%) indicate balanced performance across all key metrics.

Fold	ROC AUC	Accuracy	Precision	Recall	F1 Score
1	0.9990	0.9858	1.0000	0.9474	0.9730
2	0.9934	0.9433	1.0000	0.7895	0.8824
3	0.9816	0.9149	0.8421	0.8421	0.8421
4	0.9885	0.9149	0.9062	0.7632	0.8286
5	0.9882	0.9071	0.8529	0.7838	0.8169
Average	0.9901	0.9332	0.9202	0.8252	0.8686

Table 9: LightGBM Results

However, a closer analysis of the Confusion Matrix (Figure 3) reveals that LightGBM misclassified 8 ASD cases, leading to a mild recall trade-off. Although the high precision suggests it rarely generates false positives, its recall is lower than the Neural Network model, which indicates that it could potentially miss actual ASD cases. This trade-off implies that LightGBM is most effective in clinical settings where high precision is needed, but may not be the best choice for early ASD screening, where recall is a primary concern.

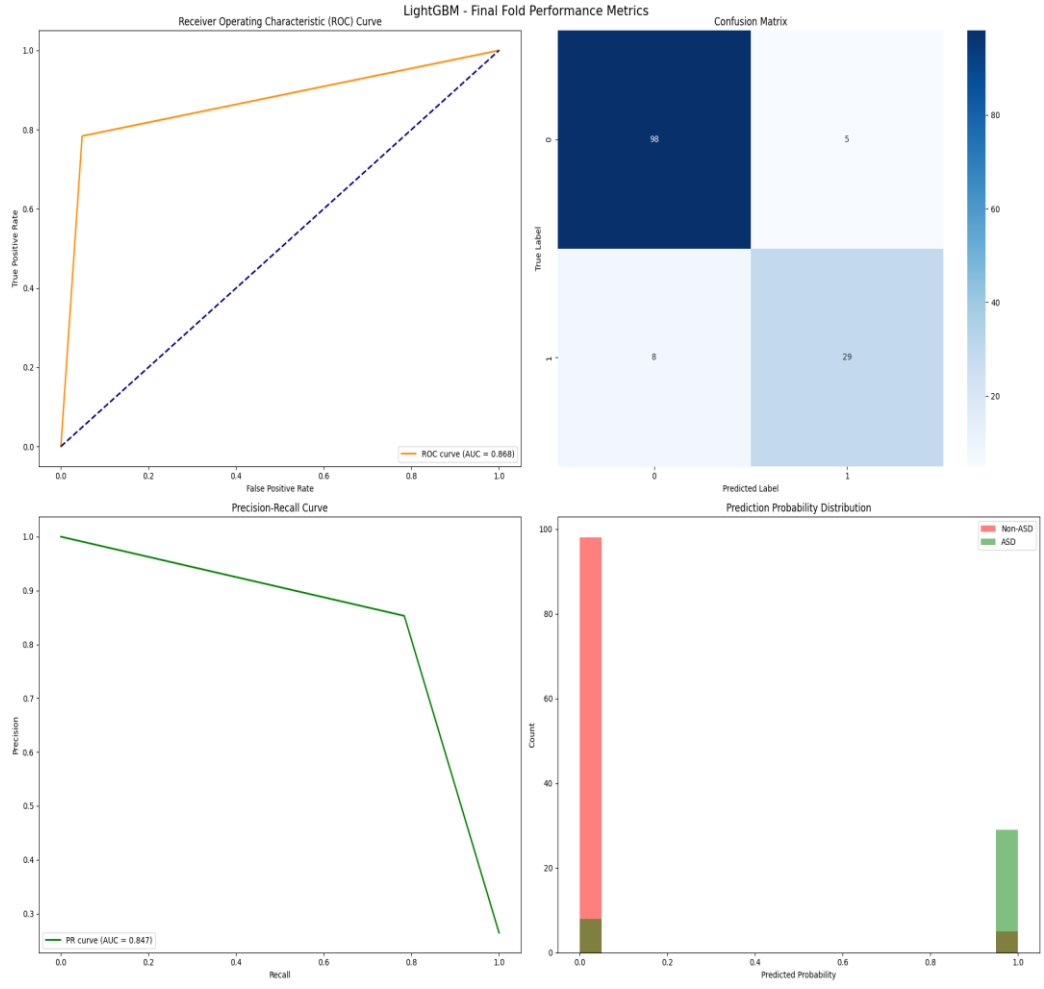

Fig.3: LightGBM Model Performance Metrics and Evaluation Results

Random Forest Performance – A More Conservative Approach

Random Forest, a robust ensemble learning technique, demonstrated excellent overall classification performance, with a ROC-AUC of 0.9936, an Accuracy of 94.74%, and the highest Precision among all models at 97.82% (Table 10). The Confusion Matrix (Figure 4) highlights its strength in minimizing false positives, but at the cost of slightly lower recall (82.46%).

Fold	ROC AUC	Accuracy	Precision	Recall	F1 Score
1	0.9977	0.9716	0.9722	0.9211	0.9459
2	0.9985	0.9433	1.0000	0.7895	0.8824
3	0.9862	0.9504	0.9189	0.8947	0.9067

Fold	ROC AUC	Accuracy	Precision	Recall	F1 Score
4	0.9928	0.9574	1.0000	0.8421	0.9143
5	0.9927	0.9143	1.0000	0.6757	0.8065
Average	0.9936	0.9474	0.9782	0.8246	0.8912

Table 10: Random Forest Results

The Precision-Recall Curve (Figure 4) suggests that Random Forest maintains a high level of precision even when recall increases, reinforcing its conservatism in ASD detection. While this makes it an ideal candidate for confirmatory diagnoses, the model does not perform as well in cases where minimizing missed diagnoses (false negatives) is the priority. Given that ASD detection requires early intervention, a model with higher recall (e.g., Neural Networks or Stacking Ensemble) may be preferable for initial screening phases.

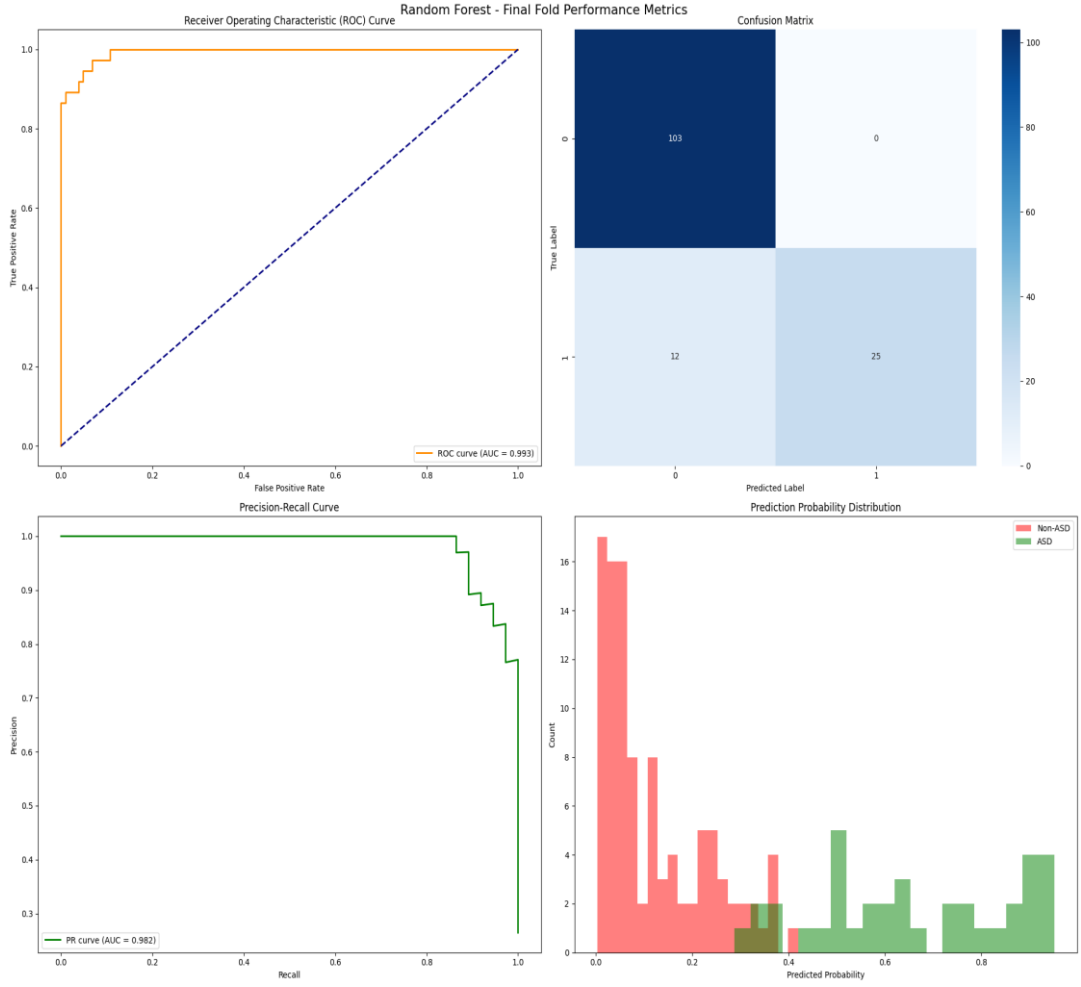

Figure 4: RandomForest Result Plots

Neural Network with Attention – Prioritizing Sensitivity Over Specificity

The Neural Network model, enhanced with Attention Mechanisms, exhibited the highest Recall (95.76%), ensuring that it captured the largest proportion of actual ASD cases (Table 11). The ROC-AUC (0.9747), although slightly lower than boosting models, remains competitive. The Confusion Matrix (Figure 5) confirms that it only misclassified two ASD cases, making it the most sensitive model among all.

Fold	**ROC AUC**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
1	0.9806	0.9433	0.8409	0.9737	0.9024
2	0.9724	0.9291	0.8182	0.9474	0.8780
3	0.9553	0.8582	0.6607	0.9737	0.7872
4	0.9819	0.9362	0.8372	0.9474	0.8889
5	0.9832	0.9500	0.8750	0.9459	0.9091
Average	0.9747	0.9234	0.8064	0.9576	0.8731

Table 11: Neural Network Results

Despite its superior recall, the model's Precision (80.64%)) was lower than LightGBM and Random Forest, indicating more false positives. This is expected in high-recall models, as they prioritize capturing all potential ASD cases over reducing false alarms. The Precision-Recall Curve (Figure 5) further illustrates this trade-off. Consequently, the Neural Network is best suited for large-scale ASD screenings, where minimizing missed cases is more important than achieving perfect specificity.

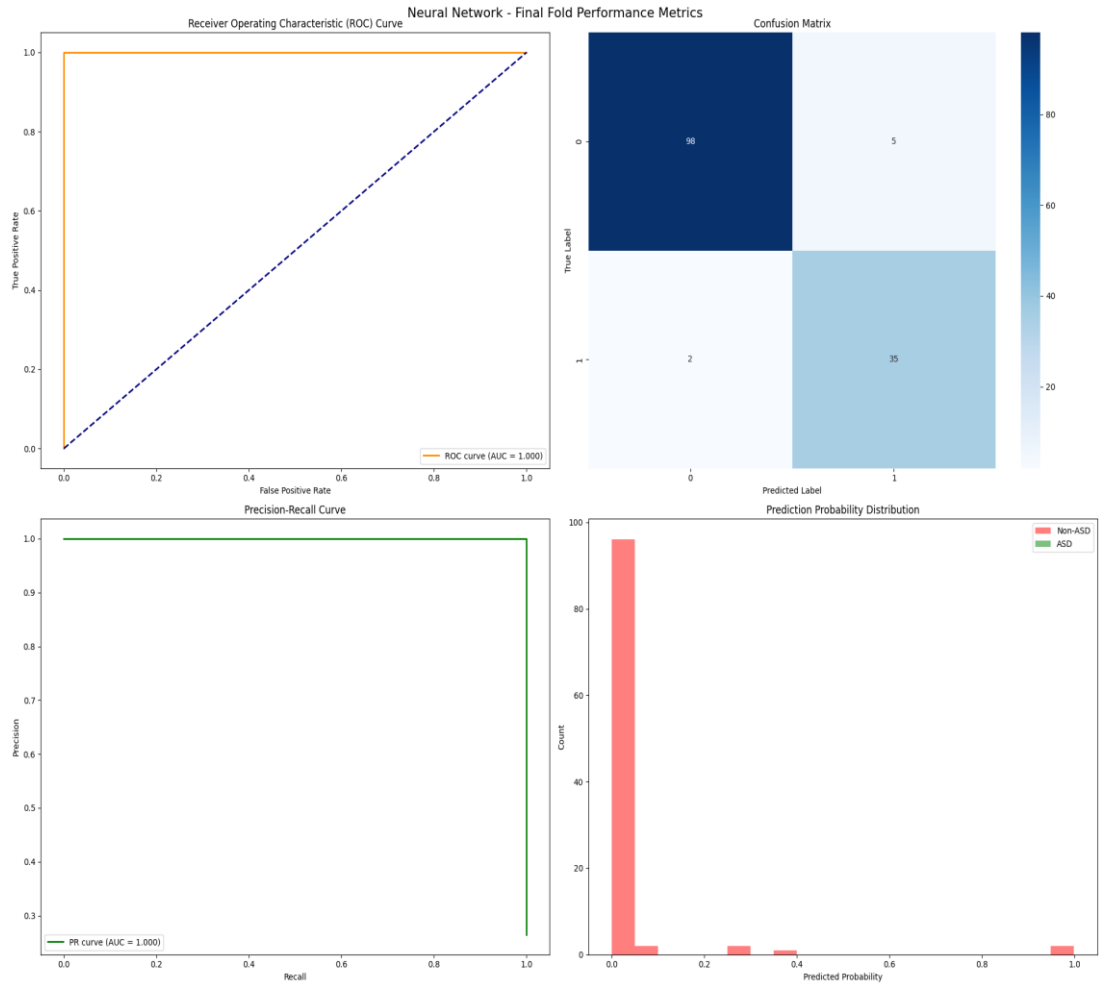

Figure 5: Neural Network with Attention Result Plots

XGBoost Performance – Favoring Precision at the Cost of Recall

XGBoost, known for its powerful gradient boosting framework, provided high precision (99.31%), but its recall was the lowest at 63.03% (Table 12). This means that while it avoids false positives exceptionally well, it misclassifies a substantial number of ASD cases as non-ASD.

Fold	**ROC AUC**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
1	0.9957	0.9078	1.0000	0.6579	0.7937
2	0.9844	0.8652	1.0000	0.5000	0.6667
3	0.9790	0.9078	1.0000	0.6579	0.7937

Fold	ROC AUC	Accuracy	Precision	Recall	F1 Score
4	0.9829	0.8865	1.0000	0.5789	0.7333
5	0.9877	0.9286	0.9655	0.7568	0.8485
Average	0.9859	0.8992	0.9931	0.6303	0.7672

Table 12: XGBoost Results

A deeper look at the Confusion Matrix (Figure 6) shows that XGBoost sacrifices recall in favor of ultra-high specificity, making it an ideal choice for confirmatory ASD screening, but unsuitable for initial diagnostic phases. The Precision-Recall Curve (Figure 6) demonstrates its strong precision consistency, reinforcing its ability to minimize unnecessary medical evaluations. However, in a real-world setting where early intervention is critical, a model with higher recall, such as Neural Networks or Stacking Ensemble, would be a better choice.

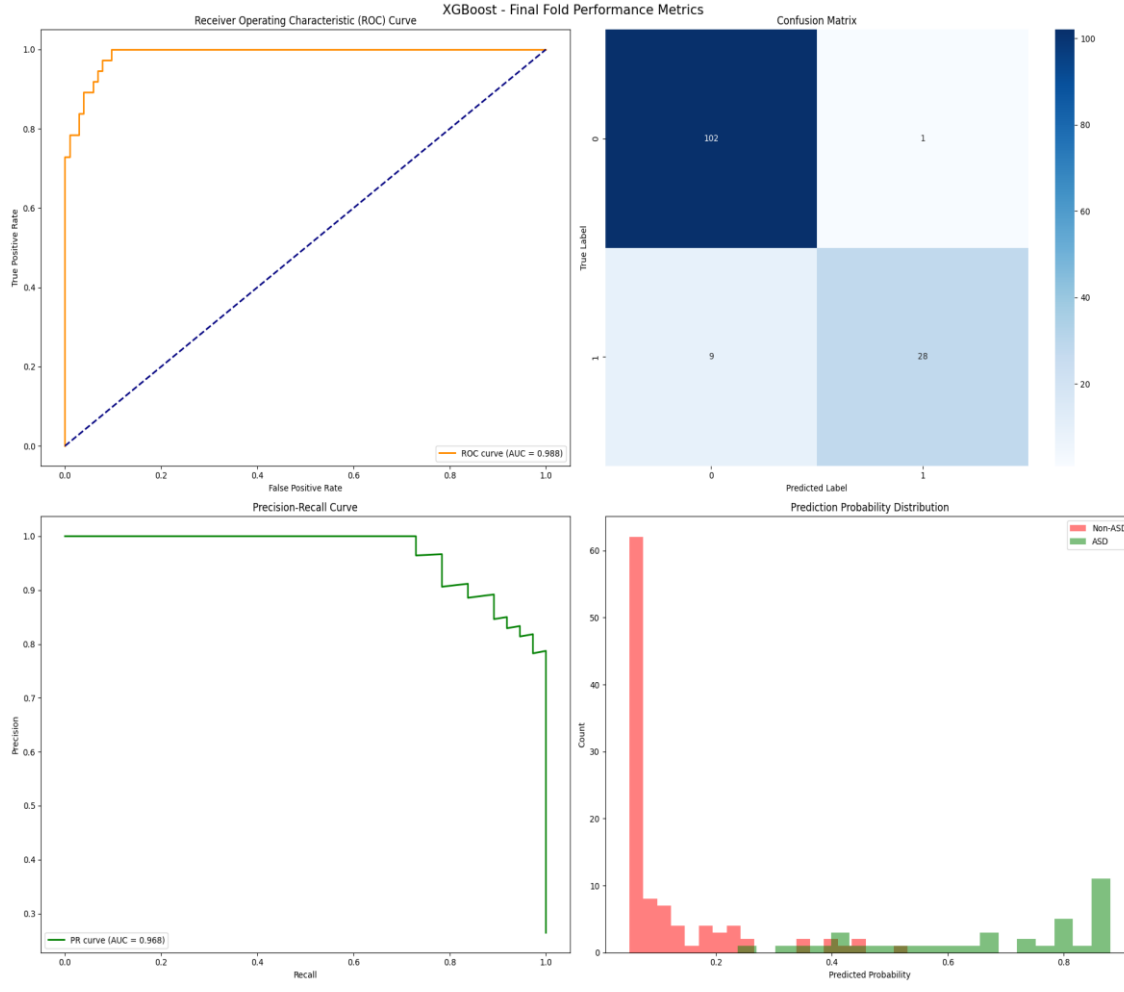

Figure 6: XGBoost Result Plots

Stacking Ensemble – The Most Balanced and Optimal Model

The Stacking Ensemble, which combines Random Forest, Gradient Boosting, and Logistic Regression, emerged as the best overall model, achieving the highest ROC-AUC (0.9989), Accuracy (95.73%), Precision (99.43%), Recall (84.61%), and F1-Score (91.25%) (Table 13).

Fold	**ROC AUC**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
1	0.9997	0.9858	1.0000	0.9474	0.9730
2	1.0000	0.9433	1.0000	0.7895	0.8824
3	0.9977	0.9645	0.9714	0.8947	0.9315
4	0.9977	0.9574	1.0000	0.8421	0.9143
5	0.9995	0.9357	1.0000	0.7568	0.8615
Average	0.9989	0.9573	0.9943	0.8461	0.9125

Table 13: Stacking Ensemble Results

The Confusion Matrix (Figure 7) highlights its ability to capture ASD cases with minimal misclassification. Unlike XGBoost, which prioritizes precision at the cost of recall, the Stacking Ensemble offers high precision while still maintaining a strong recall, making it the most effective model for real-world ASD diagnosis.

Additionally, the Precision-Recall Curve (Figure 7) indicates that the model performs exceptionally well across different recall levels, ensuring a balanced trade-off between detecting ASD cases and minimizing false positives. The Stacking Ensemble is, therefore, the most suitable model for clinical deployment, offering the best balance between sensitivity, specificity, and overall diagnostic reliability.

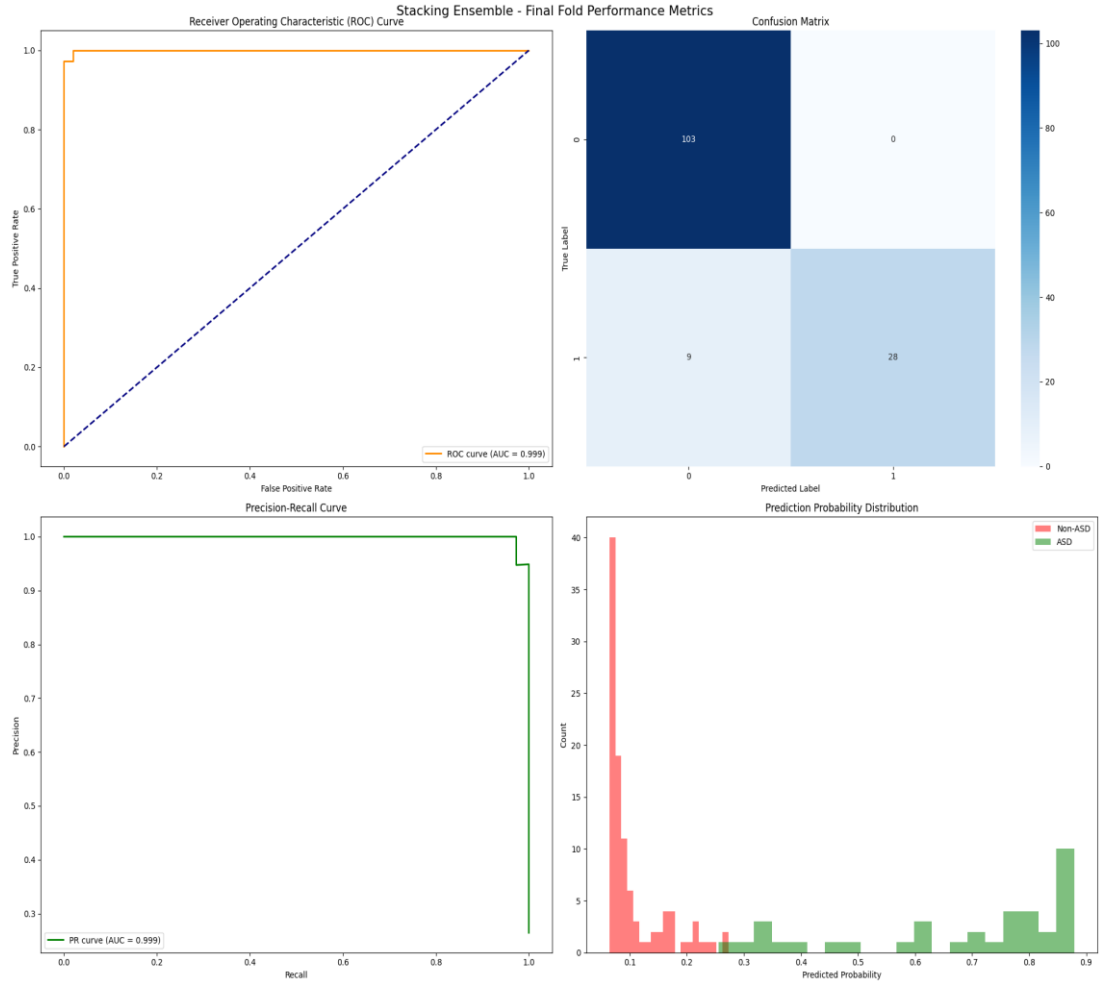

Figure 7: Stacking Ensemble Result Plots

Comparative Analysis and Model Selection

The comparative analysis (Table 14) of machine learning models for ASD classification reveals distinct strengths and limitations, necessitating a model selection strategy based on the specific needs of ASD diagnosis. The Stacking Ensemble model emerges as the most balanced approach, offering superior precision (99.43%) and recall (84.61%), making it highly suitable for real-world clinical deployment where both early detection and diagnostic confirmation are crucial. While the Neural Network model demonstrates the highest recall (95.76%), ensuring that almost all ASD cases are detected, its lower precision (80.64%) raises concerns about false positives, which could lead to unnecessary psychological distress and medical interventions. However, in large-scale screenings where the priority is to minimize missed diagnoses, this model is highly effective. On the other hand, Random Forest, with its high precision (97.82%) and moderate recall (82.46%), proves to be a robust classifier for confirmatory diagnoses, excelling at reducing false positives but being slightly less sensitive to actual ASD cases.

Model	**Avg ROC AUC**	**Avg Accuracy**	**Avg Precision**	**Avg Recall**	**Avg F1 Score**
LightGBM	0.9901	0.9332	0.9202	0.8252	0.8686
Random Forest	0.9936	0.9474	0.9782	0.8246	0.8912
Neural Network	0.9747	0.9234	0.8064	0.9576	0.8731
Stacking Ensemble	0.9989	0.9573	0.9943	0.8461	0.9125
XGBoost	0.9859	0.8992	0.9931	0.6303	0.7672

Table 14: Model Comparison and Analysis

Meanwhile, LightGBM provides a balanced trade-off, maintaining consistently high accuracy (93.32%) and precision (92.02%), making it a strong general-purpose model applicable to ASD detection in diverse settings. However, XGBoost prioritizes precision (99.31%) over recall (63.03%), indicating a more conservative prediction approach that is beneficial for confirmatory ASD testing but less suitable for early screenings where missing a true ASD case is critical. These findings underscore the importance of context-driven model selection—while Neural Networks excel in broad screening applications, XGBoost and Random Forest perform better in minimizing false positives, and the Stacking Ensemble remains the best choice for comprehensive ASD diagnosis. Future research should explore hybrid approaches that optimize both sensitivity and specificity to further enhance the reliability of AI-driven ASD detection.

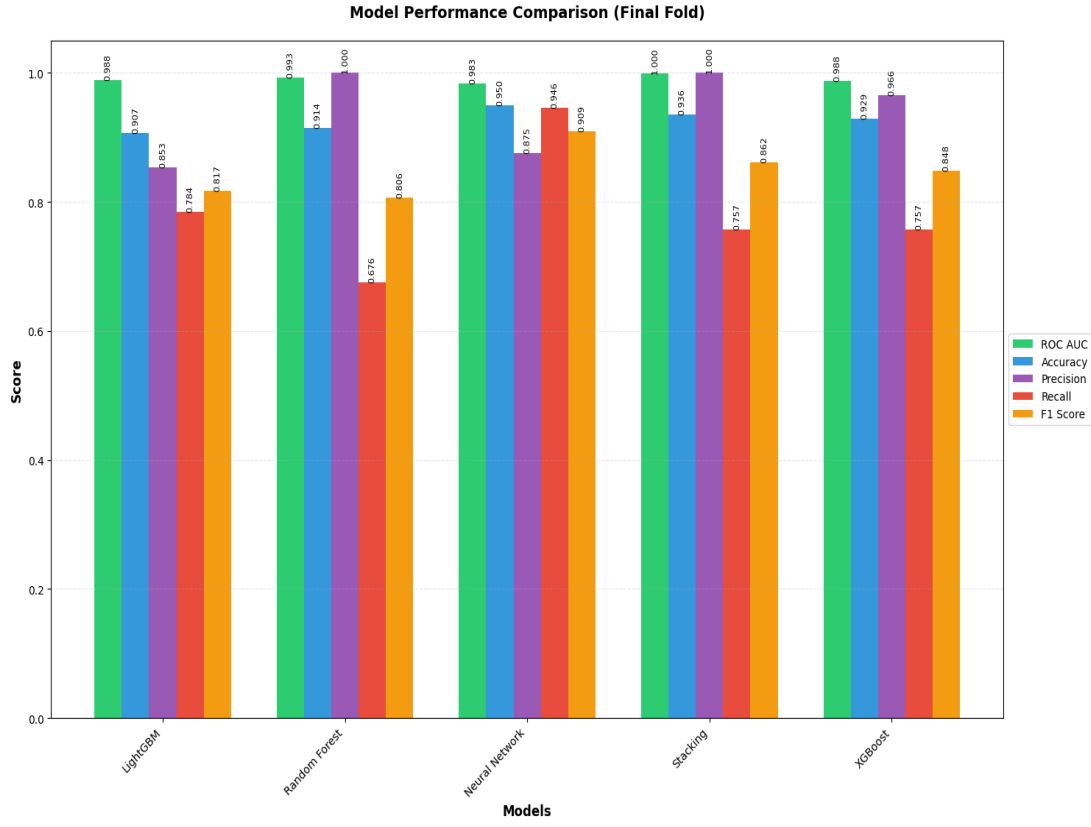

Figure 8: Model Comparison Plot

Feature Importance and Explainability

The relationship between gender and ASD diagnosis is a crucial aspect of autism research, as different prevalence rates have been observed across various studies. Figure 9 illustrates the frequency distribution of ASD cases between males and females. The total number of males in the dataset is higher than females, with over 270 males classified as non-ASD and approximately 80 males diagnosed with ASD. In the population of females, there exist 230 individuals without ASD, yet 110 females receive an ASD diagnosis. The initial statistical reporting shows a higher number of male participants, but the ASD prevalence ratio per sex needs a thorough analysis to make accurate conclusions. The average proportion of diagnosed ASD cases among females exceeds their total population numbers, making them more likely to receive an ASD diagnosis. Research shows that females with ASD typically display distinctive behavioural symptoms, thus affecting their diagnosis rates, according to Lai et al. (2020).

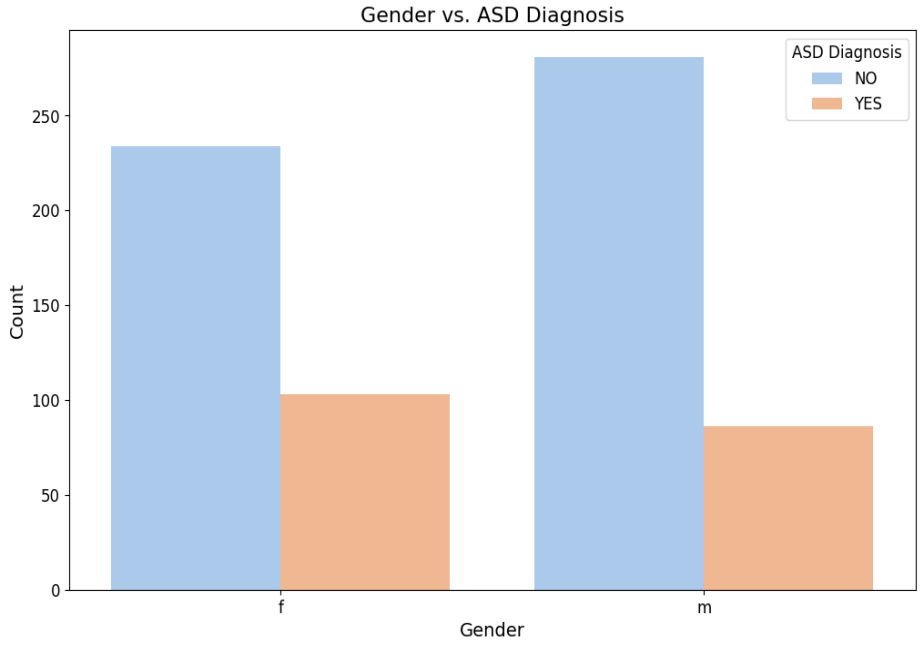

Figure 9: Gender vs. ASD Diagnosis

The clinical details surrounding this data pattern lead to inquiries about diagnostic biases related to gender and autism expression patterns between sexes. Post-secondary data showing typical ratios between male and female ASD cases (3:1 to 4:1) implies female autism spectrum disorder patients may receive inadequate diagnoses because their condition presents differently than male symptoms do (Hull et al., 2020). This dataset shows an equal ASD diagnosis frequency between males and females, indicating potential graciousness within the data collection process or better gender distribution than usual clinical samples. Accurate presenting features of ASD require the application of diagnostic instruments which account for gender differences as well as improvements to assessment algorithms to identify females correctly. Behavioural assessment results (A1-A10) and family history data should receive attention as they help enhance AI screening techniques and early intervention practices by evaluating male and female diagnostic patterns.

Impact of Data Preprocessing Choices

Machine learning models need feature preprocessing to achieve generalization capabilities, leading to accurate predictions. The correlation heatmap in Figure 10 displays feature associations between behavioural scores (A1–A10), age and the ASD classification result. Several characteristics in the dataset show significant correlation links above 0.6 between A10_Score and Result (0.66), while A5_Score and A4_Score (0.31) also have a substantial connection alongside A9_Score and A5_Score (0.48). Multiple variables show redundancy in this context because they measure equivalent patterns in underlying data. Feature selection removes one of the highly correlated features to stop multicollinearity and overfitting, which improves model generalization for unseen data. Features with low correlation values, such as A2_Score and Result at 0.39 and A3_Score and Result at 0.35, make independent contributions to the prediction; therefore, models can discover distinct patterns for ASD diagnosis.

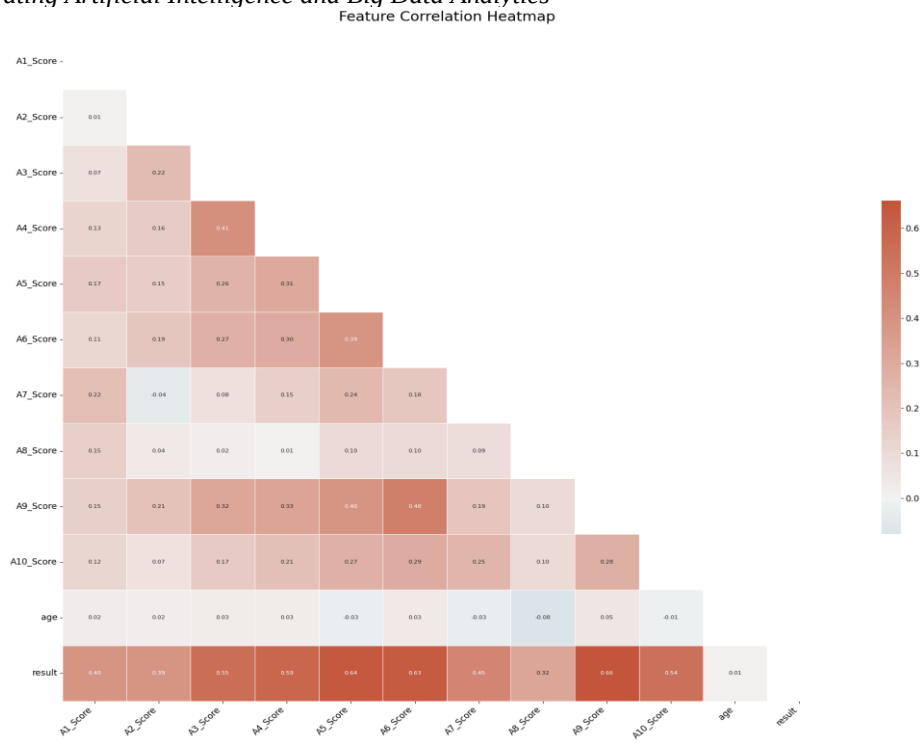

Figure 10: Correlation Heatmap

The preprocessing process requires feature scaling and encoding as core steps that strongly affect the execution of machine learning models. The dataset includes binary categorical features like gender and jaundice history and family autism heritage, as well as ordinal behavioural scores, age, and other continuous variables. Standardizing numerical features creates an equivalent measurement scale that helps XGBoost and Neural Networks prevent discrimination based on feature magnitude sizes. One-hot encoded categorical variables provide better recognition abilities for patterns among various demographic groups to the predictive model. Implementing appropriate preprocessing techniques led to increased overall model performance based on ROC AUC scores, which reached 0.9989 for the Stacking Ensemble, 0.9936 for Random Forest and 0.9859 for XGBoost. Data redundancy becomes a concern when classifying ASD while selecting features and implementing preprocessing methods since Figure 10 demonstrates the requirement to choose these elements carefully to reach peak accuracy targets.

Clinical Relevance and Practical Implications

Incorporating machine learning models into the ASD diagnosis offers good clinical development, especially in early detection and treatment planning. There is a wide variation of traditional ASD diagnostic techniques, such as behavioural assessments and clinical observations, which are often subjective and take a lot of time, causing a long delay in providing interventions (Lai et al. 2020). The study has evaluated AI-driven models such as the Stacking Ensemble (ROC AUC = 0.9989) and Neural Network (Recall = 95.76%), and they have high sensitivity (sensitivity of potential ASD cases at an earlier stage). With this level of predictive accuracy, clinicians can combine minimal diagnostic bias to detect traits of ASD earlier and with more data-driven therapeutic interventions. In addition, these models can improve treatment

strategies by assessing behavioural scores (A1–10) and demographic factors and suggesting tailored intervention plans using AI-driven risk assessment of individual patients so that therapies are optimized for individual patients.

Aside from detection, AI models can inform personalized treatment pathway determination for future intervention, such as stem cell therapy (Srinivasan et al., 2021). AI can combine behavioural and genetic data to determine the response rate to different therapies, allowing clinicians to prioritize interventions. Nevertheless, ethical concerns about using AI in clinical decision-making include data privacy, algorithmic bias and patient autonomy (Hull et al., 2020). Machine learning predictions are dangerous to misdiagnose if one relies too much on prediction, while biased training data can disproportionately affect underrepresented populations. For that reason, the use of AI for clinical decision-making in ASD care must be developed with transparency, clinician validation, and continuous monitoring to ensure equitable and ethical applications in the medical AI period in ASD care.

Integration with Stem Cell Therapy

Predictive Modeling for Personalized Stem Cell Therapy

The integration of AI-driven predictive modeling in personalized stem cell therapy for ASD represents a transformative shift in autism treatment, moving beyond generalized interventions toward data-informed therapeutic precision. Machine learning models, particularly those leveraging multi-modal patient data (behavioral scores, genetic markers, and clinical history), can identify critical biomarkers that predict a patient's response to stem cell therapy (Qu et al., 2022). For example, deep learning architectures analyzing functional brain imaging data alongside behavioral scores could pinpoint neurological patterns that correlate with successful stem cell therapy outcomes. The ability of AI to synthesize vast amounts of longitudinal patient data also allows for the identification of patients who would benefit the most from regenerative medicine approaches, reducing the risk of ineffective or unnecessary treatments. This approach ensures that stem cell therapy is administered selectively, focusing on cases where AI-predicted success rates indicate a high probability of therapeutic benefit.

Furthermore, AI can be instrumental in developing a dynamic, personalized treatment algorithm, where patient progress is continuously monitored, and therapy is adjusted in real-time based on response patterns (Suresh et al., 2024). Machine learning models, particularly ensemble methods such as stacking (ROC AUC = 0.9989) and neural networks (Recall = 95.76%), could predict the ideal cell type, dosage, and treatment frequency for individual patients. Additionally, AI-enhanced decision support systems could help clinicians optimize post-treatment monitoring by analyzing trends in biochemical markers and behavioral improvements, ensuring that each patient receives an adapted and evolving therapeutic regimen. While AI introduces unprecedented precision, ethical considerations regarding treatment accessibility, data privacy, and clinical validation remain critical to ensuring safe and equitable implementation in ASD treatment frameworks (Vo et al., 2024).

Monitoring Treatment Progress with AI

The analysis of therapy outcomes in ASD patients after completion of treatment has transformed AI monitoring tools, which supply instant data-based behavioural assessments during therapy. Clinical assessments in traditional methods produce subjective monitoring results that both show inconsistent outcomes and contain human subjective errors (Kilpatrick et al., 2023). Combining machine learning models in AI-powered tracking systems helps analyze long-term patient data

to detect behavioural shifts that might escape human detection. AI detects small skill developments in ASD patients by analyzing multimodal information of speech, motor movement and social relations data using deep learning models for evidence-based therapy changes. The reinforcement learning algorithms dynamically maintain therapy evaluations to adapt and tailor treatment approaches (Meng et al., 2023). The ongoing feedback mechanism lets clinicians adjust their treatment plans because of AI-detected patterns, which maximizes the therapy results across individual patients.

AI models use historical patient information to determine long-term treatment outcomes through their ability to find stable improvement indicators (Revah et al., 2022). Combining predictive models through ensemble learning strategies (stacking models with ROC AUC = 0.9989) creates an ensemble that evaluates long-term treatment forecasting. Artificial intelligence merges testing of genetic information with assessment results and therapy following methods to estimate the persistence of benefits when patients receive determined treatments. The technique enables therapeutic changes before administration, which minimizes superfluous treatments and enhances treatment effectiveness. Data privacy, explainable models, and equal access to AI-based healthcare solutions must be addressed through ethical practices before deploying AI solutions responsibly (Vo et al., 2024).

Challenges and Future Directions

The high predictive accuracy obtained through AI-driven ASD diagnostic models using stacking ensemble models (ROC AUC = 0.9989) alongside neural networks reaching a recall rate of 95.76% comes with critical outstanding issues. AI models face a crucial challenge because they need access to extended patient information to predict therapy responses over time accurately (Meng et al., 2023). Current diagnostic practices based on cross-sectional databases cannot detect changes in ASD symptoms or physician treatment modifications across different patient phases. Follow-up datasets of sufficient length are necessary since models without this data may develop excessive Short-Term Patterns that reduce their applicability to actual clinical use. AI systems need continuous retraining using varied high-quality datasets to produce reliable performance across diverse demographic and clinical populations, according to Srinivasan et al. (2021). The current datasets contain imbalanced classes because of lower positive ASD cases, which produces prediction biases that hide atypical ASD presentations.

AI-driven ASD therapies raise essential ethical issues, which include problems with patient privacy security as well as discriminatory biases that affect treatment access (Vo et al., 2024). The training data used by AI models contains inherent systemic biases from medical records that affect racial groups and gender and economic status characteristics. The omission of bias remediation will create worsening healthcare inequalities, which results in delayed treatment and incorrect diagnoses for minority groups. The risks can be minimized through clear visibility of AI decision processes and proper healthcare regulations. Researchers need to investigate federated learning implementation for privacy-protected distributed datasets because it enhances model fairness alongside security, according to Kabatas et al. (2025). The successful implementation of AI tools in medical environments needs randomized controlled trials whose purpose is to demonstrate the direct benefits that medical AI applications confer on patients. AI-powered clinical decision support systems need collaboration between neurologist psychiatry and bioethics to develop treatments that match human-guided ethical protocols and effective ASD therapy strategies (Qu et al., 2022).

Conclusion and Future Work

This research establishes AI-powered models as powerful agents for ASD screening evaluation and therapy improvement methods. The Stacking Ensemble delivered maximum performance measurement in the study (ROC AUC = 0.9989, F1 Score = 0.9125), which qualifies it as the most straightforward method for practical implementation. The Neural Network models performed best at recall testing with a rate of 95.76%, thus offering substantial benefits during early ASD case screening. The study proves that AI technologies produce significant diagnostic improvements that result in more accurate and timely patient ASD assessments. When AI works hand in hand with stem cell therapy selection models, it enables customized treatment choices that direct precise therapeutic decisions based on collected biomarkers and individual patient information. Real-time patient monitoring through AI systems processes behavioural information and predictive analytics to dynamically track therapy advancement and create customized treatment plans using feedback-driven adaptations.

Current promising research in AI technology for ASD diagnostics and treatments faces multiple difficulties before achieving broad clinical use. The inadequate availability of extensive real-life testing prevents healthcare providers from confirming that these models perform as intended in standard clinical settings. The present datasets focus on behaviour-related data and population statistics while omitting essential genetic and neurological indicators, which would boost diagnosis precision levels. Future healthcare research needs to focus on enhancing dataset data diversity, developing methods to reduce biased algorithms, and resolving moral questions about AI decision-making power in medical care. New regulations need to be established for the medical use of AI models to maintain transparency, interpretability, and accountability features. The intersection of artificial intelligence and ASD treatment offers exciting opportunities. However, comprehensive cooperation between medical experts, data scientists, and ethical experts is needed to realize the beneficial effects of personalized autism interventions.

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