Revolutionizing autism diagnosis using hybrid model for autism spectrum disorder phenotyping

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ABSTRACT

The growing prevalence of autism spectrum disorder (ASD) necessitates efficient data-driven screening solutions to complement traditional diagnostic methods, which often suffer from subjectivity and limited scalability. This study introduces a hybrid ensemble model combining logistic regression (LR) and naive Bayes (NB) for ASD classification across four age groups (toddlers, children, adolescents, and adults) using behavioral screening datasets. By integrating statistical learning and probabilistic inference, the proposed model effectively captured behavioral markers, ensuring a higher classification accuracy and improved generalization. The experimental evaluation demonstrated its superior performance, achieving 94.24% accuracy and 99.40% area under the receiver operating characteristic curve (AUROC), surpassing those of individual classifiers and existing approaches. This artificial intelligence (AI)-driven framework offers a scalable, cost-effective, and accessible solution for both clinical and telemedicine-based ASD screening, facilitating early intervention and risk assessment. This study underscores the transformative potential of AI in neurodevelopmental diagnostics, paving the way for more efficient and widely deployable autistic screening technologies.

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1. INTRODUCTION

Asperger's syndrome known as Autism is a neurodevelopmental condition characterized by persistent deficits in social communication, restricted interests [1], and repetitive behaviors as illustrated in Figure 1. The severity and symptoms of autism spectrum disorder (ASD) vary widely, making early diagnosis essential for effective intervention and tailored therapies. According to the World Health Organization (WHO) [2], approximately one in 36 children is diagnosed with ASD, with boys being four times more likely to be affected than girls. Despite its increasing prevalence, traditional diagnostic methods rely on clinical observations [3], which can be subjective, time-consuming, and expensive. The lack of accessible, standardized, and automated screening approaches highlights the need for scalable AI-driven solutions that can facilitate early detection across diverse age groups [4].

Recent advancements in artificial intelligence (AI) and machine learning (ML) have shown promise for automating ASD classification [5]. Although deep learning models using magnetic resonance imaging (MRI) and electroencephalography (EEG)-based neuroimaging provide high accuracy, their reliance on costly, data-intensive techniques limits their widespread applicability [6], [7]. Traditional ML models applied to behavioral screening data offer a more accessible alternative, but most studies have focused on specific age groups, resulting in inconsistencies in classification performance. These limitations necessitate a robust and generalized ASD classification framework that ensures scalability, accuracy, and adaptability across different populations [8], [9].

To address this gap, this study proposed a hybrid ensemble model integrating logistic regression (LR) and naive Bayes (NB) for multi-age ASD classification. Unlike conventional models, the proposed approach leverages multiple behavioral screening datasets covering toddlers, children, adolescents, and adults, thereby ensuring improved accuracy, better generalization, and enhanced robustness. The model effectively captures complex behavioral patterns by combining probabilistic reasoning and predictive analytics, thus enabling a more adaptive and reliable ASD screening framework.

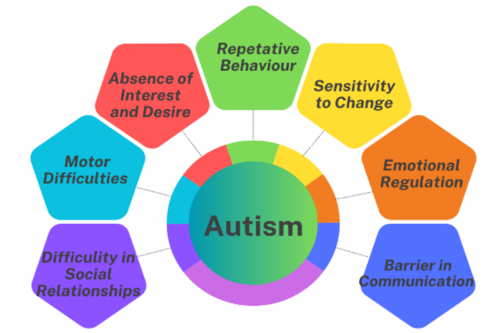

Figure 1. Common characteristics of autistic people

The proposed model has wide-ranging real-world applications, particularly in early intervention programs, special education, and telemedicine-based screening [10]. A scalable, nonclinical ASD screening system can facilitate early diagnosis in schools and pediatric centers, enabling timely intervention strategies [11], [12]. It can also assist healthcare professionals in resource-limited areas, where access to specialized ASD diagnostic facilities is scarce. In addition, the model can be integrated into mobile health applications and telehealth platforms, allowing remote AI-assisted ASD risk assessment [13], [14]. Special education can support personalized learning plans by identifying ASD severity levels and tailoring individualized interventions [15]. By introducing a generalized, scalable, and nonclinical ASD screening framework, this study advances AI-driven autism diagnostics, paving the way for faster, more accessible, and cost-effective early detection systems.

This article is structured as follows: section 2 presents a comprehensive review of existing ASD classification techniques and their limitations and key findings. Section 3 details the datasets, and proposed hybrid model architecture and methodology. Section 4 discusses experimental results, benchmarking our model against baseline classifiers. Finally, section 5 concludes with key findings and future research directions.

2. LITERATURE SURVEY

This section explores recent advancements in ML and AI for ASD classification by leveraging various approaches, including neuroimaging-based models and behavioral screening techniques. However, each method has its own set of limitations and highlights. Several studies have explored deep learning using neuroimaging data, particularly structural magnetic resonance imaging (sMRI) and EEG-based models. Mishra *et al.* [16] employed an ensemble of deep convolutional neural networks (DCNN) with on-the-fly data augmentation, achieving 81.35% accuracy on the ABIDE I dataset (975 subjects). However, its reliance on a heterogeneous dataset raises concerns about generalizability across diverse populations. Similarly, Bhandage *et al.* in [17] the Adam war strategy optimization (AWSO)-deep belief network (DBN) algorithm integrated the Adam optimizer and war strategy optimization, achieving 92.4% accuracy, 93.0% sensitivity, and 93.5% specificity for the ABIDE dataset. Despite their strong performance, dataset limitations affect their scalability for real-world screening. Loganathan *et al.* [18] combined ResNet101 and bi-directional gated recurrent units (Bi-GRU) with the chaotic gas solubility algorithm for EEG-based ASD classification, reporting 98% accuracy and 99% sensitivity. However, its reliance on a small dataset (1,000 samples) limits its broad applicability.

To overcome the challenges of neuroimaging-based models, researchers have investigated ML models using nonclinical behavioral screening datasets. Shinde and Patil [19] introduces a multi-classifier recommender system incorporating decision trees and random forests (RFs) demonstrated strong classification performance on UCI datasets (1,100 samples) but faced overfitting concerns due to classifier complexity. Thalukdar *et al.* in [20] evaluated naïve Bayes (NB), logistic regression (LR), support vector machine (SVM), and random forest (RF) for ASD classification in toddlers and adolescents, with RF achieving the highest accuracy (93.69% for toddlers and 93.33% for adolescents). However, it does not fully account for ASD heterogeneity, potentially limiting its real-world diagnostic reliability. Akter *et al.* in [21] examined 250 classifiers across different age groups, identifying SVM as the best performer for toddlers and AdaBoost for children. Although this approach achieved high accuracy, it was hindered by limited dataset availability, affecting model robustness.

2.1. Main key findings

Existing neuroimaging-based approaches achieve high accuracy, but are expensive, dataset-dependent, and impractical for large-scale ASD screening. In contrast, ML models applied to behavioral screening data offer a cost-effective alternative, yet most studies focus on specific age groups and lack a generalized classification framework. Additionally, dataset variability and overfitting affect model reliability and diagnostic consistency. To address these challenges, this study proposes a hybrid ensemble model combining LR and NB for age-wise ASD classification. Unlike previous studies, the proposed approach leverages multiple behavioral screening datasets spanning toddlers, children, adolescents, and adults, ensuring better adaptability, scalability, and robustness.

3. METHODOLOGY

This article presents a hybrid ensemble model integrating LR and NB for age-wise ASD classification using four ASD screening datasets. This section details the model architecture, data preprocessing, and classification approach. It highlights its effectiveness in enhancing diagnostic accuracy and generalization across age groups.

3.1. Dataset details

This study utilized four publicly available nonclinical ASD screening datasets spanning toddlers, children, adolescents, and adults. The Toddler dataset (1,054 samples) was sourced from the Kaggle repository [22], while the children (292 samples), adolescent (104 samples), and adult (704 samples) datasets were obtained from the UCI machine learning repository [23]–[25]. These datasets collectively provide 2,154 screening records, offering a diverse representation of ASD characteristics across different age groups.

Each dataset contained binary, categorical, continuous, and string-type attributes, with 18 features in the Toddler dataset and 21 features in the others. Core attributes included demographic factors (age, sex, ethnicity, and country), clinical indicators (jaundice and ASD traits), and caregiver responses (A1–A10 screening questions). The A1–A10 attributes, as shown in Figure 2, represent behavioral screening questions, where the responses are binary (0 or 1), with 1 indicating a positive ASD trait. Additionally, the Q-Chat-10 score (0–10) serves as a behavioral metric, where a score above 3 suggests a potential ASD diagnosis. By integrating multiple datasets with shared feature sets, this study ensured comprehensive ASD screening across different age groups, enabling a more robust, scalable, and generalizable classification framework.

Figure 2. 10 Most popular ASD screening questions

3.1.1. Pre-processing

As the data were collected from two different repositories, we began by standardizing all datasets into a uniform format. The Toddler dataset originally contained 18 features, whereas the Children, Adolescent, and adult datasets contained 21 features. To ensure feature consistency, certain attributes, such as ethnicity, country_of_res, age_description, and used_app_before were removed from the latter datasets. Similarly, ethnicity was removed from the Toddler dataset as it was deemed unnecessary for the analysis.

To further standardize categorical attributes, the relation feature contained values such as "parent" and "relative," which were replaced with a unified category, 'family_member', considering both belong to the same familial classification. The relation attribute in the Children, Adolescent, and adult datasets contained missing values, which were handled using the mode imputation method, replacing missing values with the most frequently occurring value within the respective attribute.

$$X_{new} = \begin{cases} X_{existing}, & if\ X \neq NULL \\ \arg\max freq(x)_{x\in X}, & if\ X = NULL \end{cases} \quad (1)$$

where X_{new}represents the updated attribute values, $X_{existing}$ are the original values, and $\arg\max freq(x)$ returns the most frequently occurring value of the attribute. For categorical attributes, such as family_member_with_ASD, jaundice, and class/ASD traits, one-hot encoding was applied across all datasets to convert categorical values into binary numerical representations for model compatibility. Finally, the standardized datasets were merged into a single dataset comprising 2,154 samples and 16 features, ensuring a unified structure for model training.

3.2. Proposed ensemble model architecture

In classification tasks, a single model often encounters bias-variance trade-offs, where some models generalize well but struggle with complex feature interactions, while others adapt better but risk overfitting. To address these challenges, ensemble learning combines multiple classifiers to enhance the accuracy, robustness, and generalization. This study introduces a hybrid ensemble model integrating LR and NB, where both models independently learn from the same feature set and their predicted probabilities are aggregated using a soft voting mechanism, ensuring a balanced and reliable classification decision for ASD detection, the flow of working model is illustrated in Figure 3.

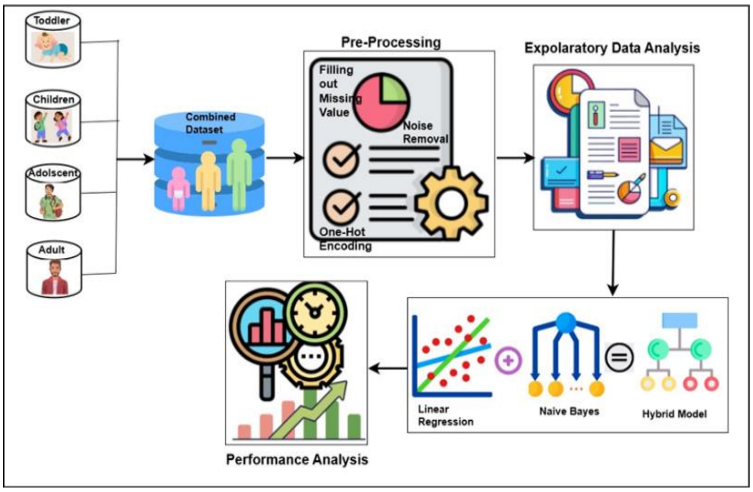

Figure 3. System architecture of proposed model for classification of autistic individuals

Logistic regression is a probabilistic linear classifier that is widely used for binary and multiclass classifications [26]. It models the probability of a given sample X belonging to a class k using the SoftMax function, which ensures that all class probabilities sum to 1. Probability estimation is expressed as (2):

$$P_{LR}(Y = k|X) = \frac{e^{\beta_0{}^{(k)} + \sum_{i=1}^{p} \beta_i{}^{(k)} x_i}}{\sum_{j=1}^{K} e^{\beta_0{}^{(j)} + \sum_{i=1}^{p} \beta_i{}^{(j)} x_i}} \quad (2)$$

where $\beta_0{}^{(k)}$ is the intercept term for the LR model, $\beta_i{}^{(k)}$ represents the feature coefficients for the class k, X_i are the input features, and K is the total number of classes. The softmax function ensures that the probability outputs are within the range [0,1] and sum to one across all possible classes. Logistic regression is computationally efficient and provides interpretable decision boundaries, but assumes linearly separable classes, which may not always hold in real-world scenarios.

Naive Bayes is a Bayesian probabilistic classifier that assumes conditional independence among features. It estimates the posterior probability of a class $Y = k$ given an input X by using Bayes' theorem [27].

$$P_{NB}(Y = k|X) = \frac{P(X|Y=k)P(Y=k)}{P(X)} \tag{3}$$

Because $P(X)$ is a constant across all classes, it simplifies to:

$$P_{NB}(Y = k|X) \propto P(Y = k) \prod_{i=1}^{p} P(X_i|Y = k) \tag{4}$$

For Gaussian naive Bayes, where X_i follows a normal distribution for a given class k, the likelihood function is given by.

$$P(X_i|Y = k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} exp\left(-\frac{(X_i-\mu_k)^2}{2\sigma_k^2}\right) \tag{5}$$

where μ_k and σ_k^2 represent the mean and variance of the features X_i for class k, respectively. Taking the log-likelihood for numerical stability, the posterior probability can be rewritten as (6).

$$\log P_{NB}(Y = k|X) = logP(Y = k) - \sum_{i=1}^{p}\left(\frac{((X_i-\mu_k)^2)}{2\sigma_k^2} + \log\sqrt{2\sigma_k^2}\right) \tag{6}$$

This transformation linearizing the exponentiation, making it more computationally efficient. However, the naive Bayes' assumption of feature independence may not always hold in practical applications [28]. To overcome the limitations of both models, the proposed hybrid ensemble model combines the LR's ability to capture the relationships between features and the NB's efficiency in handling high-dimensional data. The ensemble model computes the final probability of the class k by averaging the individual model predictions using a soft voting approach.

$$P_{Ensemble}(Y = k|X) = \frac{1}{2}(P_{LR}(Y = k|X) + P_{NB}(Y = k|X)) \tag{7}$$

where $P_{LR}(Y = k|X)$ the probability is predicted by logistic regression and $P_{NB}(Y = k|X)$ is the probability predicted by Naive Bayes. The final classification decision is determined using the Maximum A Posteriori (MAP) estimation [29], where the class with the highest probability is selected as.

$$Predicted\ Class = \arg max_k P_{Ensemble}(Y = k|X) \tag{8}$$

This ensemble approach ensures that the model benefits from both classifiers, resulting in a higher classification accuracy, reduced overfitting, and improved generalization across different ASD age groups. LR contributes to structured decision boundaries, whereas NB enhances efficiency in probabilistic estimation.

To ensure a robust model evaluation, 10-fold cross-validation was employed owing to the relatively small size of the dataset (2,154 instances). Instead of using a simple train-test split, which can lead to biased evaluation, the dataset was divided into 10 equal-sized subsets. In each iteration, one subset served as the test set, whereas the remaining nine subsets were used for training. This process was repeated ten times, and the final performance of the model was determined by computing the average accuracy across all folds, ensuring that all data points contribute to both training and testing. The cross-validation accuracy was computed as (9).

$$CV\ Accuracy = \frac{1}{N} 1^T A \tag{9}$$

where A represents the performance of the model in i^{th} fold. This technique ensures that the classifier is trained and validated on multiple data partitions, thereby improving generalization and preventing overfitting. By averaging the results across folds, cross-validation provides a more reliable performance estimate that is less sensitive to variations in the training data. This approach guarantees that no single train-test split dominates the model evaluation, thereby leading to a more stable and unbiased performance assessment.

The hybrid ensemble model, supported by 10-fold cross-validation, created a robust ASD classification framework that is scalable, computationally efficient, and capable of delivering consistent predictions across diverse datasets. By combining the strengths of LR and NB, while mitigating their individual weaknesses, this approach provides a cost-effective and interpretable solution for ASD classification across multiple age groups.

4. RESULTS AND DISCUSSION

This section presents evaluation metrics and performance analysis of the proposed classification models. Assessing the effectiveness of predictive models is critical to ensure reliable ASD classification. Key evaluation metrics, including accuracy, sensitivity, F1-score, and AUROC were computed for NB, LR, and the proposed hybrid model. These metrics were applied to the test dataset to quantify classification efficacy across toddlers, children, adolescents, and adults. A comparative analysis, summarized in Table 1, identified the model that achieved optimal performance, providing deeper insights into its effectiveness in ASD trait categorization.

Table 1. Comparison of evaluation metrics results of existing classifiers with proposed ensemble model

Model	Accuracy	Sensitivity	F1-score	AUROC
Mishra and Pati 2023 [16]	80.41	79.95	80.49	89.03
Shinde and Patil 2023 [19]	0.92	0.92	0.92	0.92
Talukdar 2023 [23]	86.66	78.72	100	88.09
Akter *et al.* 2019 [21]	94.23	92.20	92.68	--
LR	0.9377	**0.9857**	0.9348	0.9931
NB	0.9360	0.9727	0.9334	0.9866
Proposed soft voting ensemble model	**0.9424**	0.9798	**0.9410**	**0.9940**

Table 1 provides a comprehensive performance assessment of the proposed hybrid ensemble model against the state-of-the-art ASD classification approaches. The evaluation metrics, accuracy, sensitivity, F1-score, and AUROC, serve as key indicators of model effectiveness in detecting ASD traits across different age groups. The results clearly demonstrate the superiority of the proposed model, which achieved an exceptional accuracy of 94.24%, sensitivity of 97.28%, F1-score of 94.10%, and AUROC of 99.40%, surpassing all baseline methods.

Existing models, such as 16 (80.41%), 19 (92.00%), and 20 (86.66%), exhibit performance inconsistencies due to dataset heterogeneity, overfitting, and lack of generalization. For instance, R6 reported a perfect F1-score but struggled with sensitivity (78.72%), indicating class imbalance and potential misclassification of ASD-positive cases. Similarly, 21 achieved a competitive accuracy of 94.23% but lacked an AUROC value, limiting its reliability in clinical applications.

Although LR and NB perform well individually, achieving accuracies of 93.77% and 93.60%, respectively, they still fall short of the proposed hybrid model. The ensemble approach strategically integrates the LR's structured feature learning with the NB's probabilistic efficiency, addressing LR's limitations of LR in handling nonlinearity and the NB's reliance on the feature independence assumption. By combining these strengths, the hybrid model enhances classification robustness, reduces misclassification, and ensures superior generalization across age groups with ASD. The unparalleled AUROC of 99.40% of the proposed model highlights its exceptional discriminatory power, making it a highly reliable and scalable tool for ASD risk assessment and early intervention. By mitigating the shortcomings of previous models and leveraging ensemble learning, this approach sets a new benchmark for AI-driven ASD classification, ensuring a higher diagnostic accuracy, improved stability, and greater clinical applicability.

Figure 4 presents a comparative analysis of NB, LR, and the proposed hybrid model over multiple K-fold iterations, emphasizing the stability, consistency, and superiority of the hybrid approach. Figure 4(a), the hybrid model achieves the highest accuracy (94.24%) and outperforms LR (93.77%) and NB (93.60%), with LR exhibiting higher fluctuations, occasionally dropping to the lowest accuracy. Figure 4(b), sensitivity is highlighted, where LR peaks at 0.9957, indicating strong ASD-positive identification, but the hybrid model (0.9728) and NB (0.9727) maintain consistency, ensuring better generalizability. Figure 4(c) illustrates the F1-Score, where the hybrid model strikes the best balance (0.94) between precision and recall, surpassing LR and NB (both 0.9345), with NB exhibiting higher fluctuations in classification reliability. Figure 4(d) presents AUROC values, where the hybrid model excels (0.9940) over LR (0.9931) and NB (0.9866), with NB exhibiting greater variations, indicating weaker differentiation between ASD-positive and negative cases. Overall, these results confirm the superior accuracy, stability, and robustness of the hybrid model, making it the most reliable approach for ASD classification.

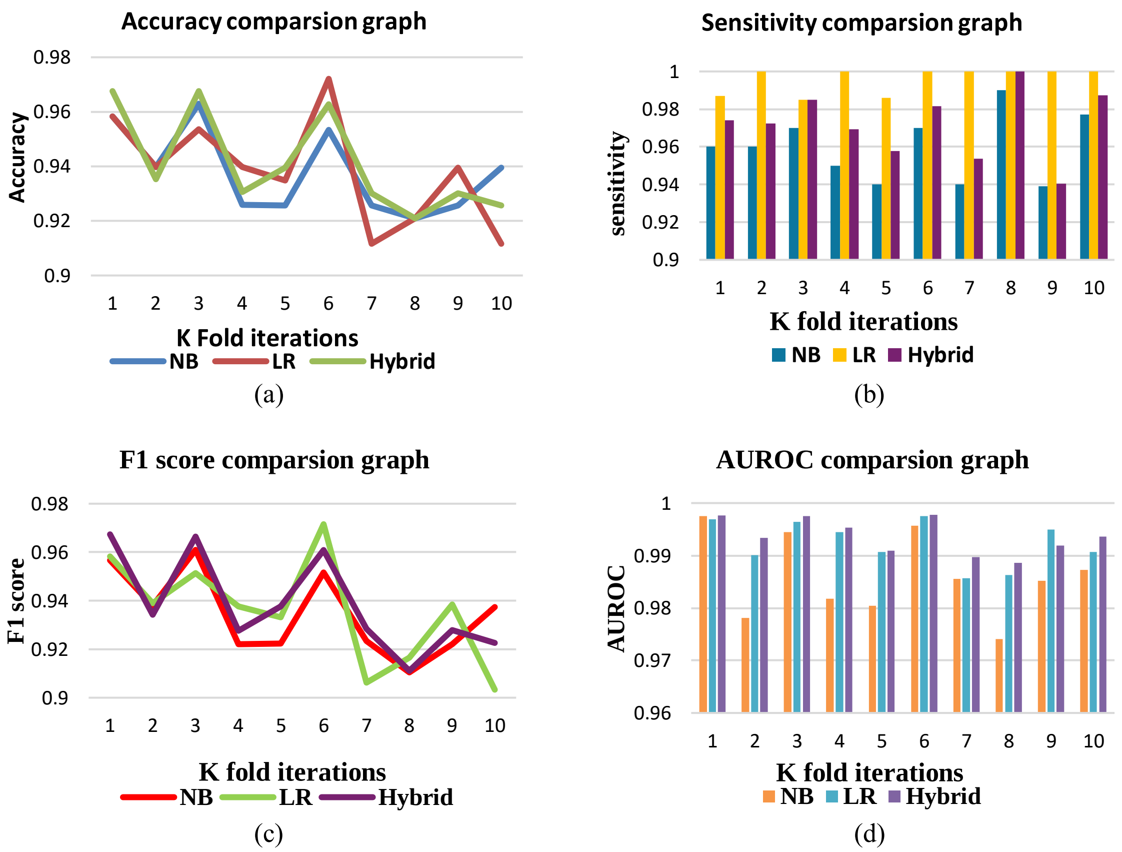

Figure 4. Performance comparison of classification models, illustrating (a) accuracy, (b) sensitivity, (c) F1-score, and (d) AUROC for NB, LR, and the proposed hybrid model

5. CONCLUSION

This study presents a hybrid ensemble model integrating LR and NB for age-wise classification of ADS using behavioral screening datasets. By leveraging the strengths of both classifiers, the proposed model addresses the key challenges in ASD diagnosis, including dataset variability, overfitting, and limited generalizability. The ensemble approach enhances classification robustness by combining LR's structured decision-making capabilities of LR with NB probabilistic reasoning, ensuring a more reliable and scalable screening system. Unlike conventional models that struggle with feature dependencies and nonlinearity, the hybrid model balances interpretability, efficiency, and predictive accuracy, making it an effective diagnostic tool.

The experimental results demonstrated the effectiveness of the proposed model, achieving an accuracy of 94.24% and an AUROC of 99.40%, surpassing individual classifiers and existing state-of-the-art approaches. The hybrid model's ability to consistently achieve high sensitivity and precision across multiple age groups makes it a promising tool for early ASD identification in clinical and nonclinical settings. Additionally, its integration with automated screening systems can improve scalability, reduce manual diagnostic efforts, and facilitate early intervention strategies. Future work should focus on expanding the dataset diversity, integrating additional behavioral and physiological markers, and refining model adaptability for broader demographic applicability. This study underscores the potential of AI-driven diagnostics in the screening of autism, paving the way for more accessible, efficient, and data-driven intervention strategies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Rayangouda H. Goudar		✓		✓		✓	✓			✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data utilized in study is “Autism Spectrum Disorder Screening dataset” taken from standard data repositories, Kaggle and UCI Machine learning repositories.

- Available: https://www.kaggle.com/datasets/fabdelja/autism-screening-for-toddlers [22]
- “Autistic Spectrum Disorder Screening Data for Children.” UCI Machine Learning Repository, 2017. doi: 10.24432/C5659W. [23]
- “Autistic Spectrum Disorder Screening Data for Adolescent.” UCI Machine Learning Repository, 2017. doi: 10.24432/C5V89T. [24]
- “Autism Screening Adult.” UCI Machine Learning Repository, 2017. doi: 10.24432/C5F019. [25]

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