IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 4, August 2026, pp. 3732~3744
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i4.pp3732-3744 ❒ 3732

Enhancing early detection of autism spectrum disorder through ensemble-based machine learning classifiers

Shabeena Lylath, Laxmi B. Rananavare
Department of Computer Science and Engineering, REVA University, Bengaluru, India

Article Info

Article history:

Received Dec 2, 2024
Revised Jul 13, 2026
Accepted Jul 21, 2026

Keywords:

Autism detection
Autism spectrum disorder
Ensemble-based machine
Healthcare
Learning classifier
Machine learning
Methodology

ABSTRACT

Autism spectrum disorder (ASD) is a developmental disability characterized by significant social, communication, and behavioral challenges. Machine learning is a practical approach for autism detection. The proposed ensemble-based machine learning classifier methodology presented in this study seeks to revolutionize the diagnosis of ASD by harnessing the collective power of various machine learning algorithms. This ensemble approach is designed to enhance diagnostic precision, mitigate the subjectivity associated with traditional diagnostic methods, and accelerate the detection process. This methodology addresses the urgent need for early and accurate ASD identification, enabling timely interventions. Leveraging complex data analysis, it offers deeper diagnostic insights, facilitating informed clinical decisions and advancing ASD research. The methodology's accessibility across healthcare settings marks a significant step forward in making early ASD detection more universally available, showcasing the transformative potential of machine learning in healthcare. In deploying the "ensemble-based machine learning classifier" for ASD diagnosis, this study utilizes an extensive dataset comprising behavioral and medical profiles from diverse demographics, including toddlers, children, adolescents, and adults with ASD. Upon the preliminary analysis, the dataset enables the methodology to learn from a wide array of ASD manifestations, ensuring its robustness and applicability across different age groups and severity levels.

Corresponding Author:

Shabeena Lylath
Department of Computer Science and Engineering, REVA University
Bengaluru, India
Email: shabeenal_12@rediffmail.com

1. INTRODUCTION

A neurodevelopmental illness known as autism spectrum disorder (ASD) usually first appears in early infancy and lasts throughout adulthood [1]. There is evidence of behavioral and communication dysfunction. The World Health Organization (WHO) estimates that 1% of people worldwide are thought to have ASD [2]. Around 75 million people globally are thought to be impacted by ASD. According to research findings, co-occurring intellectual impairment is present in around one-third of people with ASD. The co-occurrence of these illnesses [2], might make it difficult for people to learn new things and carry out daily duties. It is presently apparent that there is a lack of validated therapy strategies to properly manage ASD, and the exact origin of ASD is still mostly unclear [3]. ASD is a common worldwide health concern that can impact individuals, families, and the community as a whole. Recent findings suggest that permanent brain injury is not the cause of the abnormal behaviors seen in children with ASD. Alternatively, these behaviors might be explained as the brain's initial reaction to a stressful event [4].

Early intervention techniques must be put into practice to reduce the stress and worry that families of autistic children frequently experience. The program serves as an instructional tool, giving kids the fundamental information and abilities required for their entire development and success. Age-related decreases in human brain plasticity have been shown in prior studies. The brain's ability to adapt and change is known as neural plasticity. For autistic children, early intervention is advised to improve language and cognitive skills before behavioral problems arise [5]. For this reason, it is critical to diagnose ASD as soon as possible. A typical approach in the diagnosis of ASD is the use of manual observations. The previously mentioned approach can be described as a laborious and time-consuming procedure that could provide difficulties when put into practice. One standardized test that uses a parent-centric method to diagnose autism is the modified checklist for autism in toddlers (M-CHAT). The test usually requires a significant time investment, sometimes spanning many hours. In therapeutic settings that are regulated and overseen, clinical personnel usually provide this. treatment [6]. It takes a sophisticated automated identification technology to improve the process's usability and efficacy.

Children who are typically developing (TD) can be diagnosed with ASD using behavioral and physiological criteria [7]. People who have been diagnosed with ASD find it difficult to socialize. The difficulties include a range of nonverbal elements, including maintaining eye contact and mimicking facial expressions. People could find it difficult to stay focused, engage in social situations, and appropriately express their feelings. There has been a lot of interest in the research on eye gaze fixation in kids with ASD. Electroencephalography (EEG) and mobility tests were employed by the researchers to gather information. The study's conclusions suggest that the use of machine learning in conjunction with eye tracking technology may be able to distinguish between various visual traits in people with ASD. The method outlined in reference [8], [9] could help diagnose autism. There is a lot of promise in using eye tracking and machine learning to study ASD. Because EEG data are essential markers of aberrant brain electrical activity linked to neurological diseases, finding patterns in the data has attracted a lot of attention.

This study aims to provide an automated approach for the diagnosis of ASD in children who are TD. The process makes use of a quantitative approach. This study's methodology makes use of EEG data and concentrates on analyzing the area underneath a second-order difference plot as a factor that sets itself apart. Nonlinear features taken from EEG data were used in the research by the authors in [10] to assess people with ASD. The seventy-three EEG measurements from several participants make up the dataset. Of the participants, forty-one showed signs of ASD, whereas the other thirty-two showed normal brain activity. The EEG data from people with ASD were evaluated by the researchers using the Higuchi fractal dimension approach. Researchers conducted a study that proved the efficacy of this technique in evaluating the nonlinearity of EEG signals [11]. According to Allison *et al.* [12], people with ASD had their EEG brainwaves analyzed to extract different features. Autoregressive coefficients, multifractal wavelet leader estimates, discrete Fourier transform coefficients, and Shannon entropy were among the attributes. Participants in the study were divided into two groups: those who had been officially diagnosed with ASD and those who did not display any specified medical issues (control subjects). To carry out the classification process, machine learning models were used. To improve EEG signals, a deep neural network (DNN) model called the two-dimensional-deep convolution neural network (2D-DCNN) was used in [13].

Social skills development is often difficult for children with ASD, especially when it comes to nonverbal areas like maintaining eye contact and mimicking facial expressions. According to Ali *et al.* [14], people with ASD do not succeed academically to the same extent as their peers without the disease. Every person has an express right to education, as stated in article 26 of the Universal Declaration of Human Rights [15]. Every student has the right to an education, regardless of their financial situation or handicap. Kids with ASD can also benefit from the previously described idea. Educating children diagnosed with ASD has several difficulties. Special educational need (SEN) is the classification given to kids who have been identified as needing a tailored educational approach, as shown in [16]. Encouraging children with SEN to get specialized education can be challenging because of social and communication skills issues, a lack of parent-teacher collaboration, and limited resources and support options. There are several therapeutic modalities available to diagnose ASD in its early phases. When ASD is very likely to occur, the following diagnostic methods are frequently used in clinical settings.

This research is driven by the imperative need to improve ASD diagnosis through machine learning techniques, aiming to surmount the limitations of traditional diagnostic methods that are often subjective and time-consuming. Leveraging machine learning's ability to discern patterns in extensive datasets, this study seeks to develop objective, efficient, and highly accurate diagnostic tools for ASD, addressing the critical window for intervention in early childhood. By bridging the gap between advanced computational methods and practical diagnostic applications, the research endeavors to make early ASD detection more accessible and less dependent on specialized clinical settings. This effort not only advances our scientific understanding of ASD but also offers tangible solutions to enhance early intervention strategies, significantly impacting individuals with ASD and their families by improving life outcomes and integrating technology in solving complex health challenges.

Enhanced diagnostic accuracy: the proposed "ensemble-based machine learning classifier" introduces a cutting-edge diagnostic tool for ASD, leveraging an ensemble of algorithms to achieve superior accuracy and adaptability in detecting the wide range of ASD symptoms. Objective and efficient diagnosis: this methodology streamlines the ASD diagnosis process, significantly reducing reliance on subjective assessments and expediting diagnosis, thus facilitating earlier interventions for individuals with ASD. Data-driven insights and accessibility: by harnessing complex data patterns, the classifier provides deep insights for clinicians and researchers, improving decision-making and broadening access to early ASD detection across diverse healthcare environments.

The research is organized in this paper in 5 sections. Section 1 is the introduction section, which gives a brief overview of ASD. Section 2 gives the literature review. Section 3 describes the proposed methodology. Section 4 gives the performance evaluation of the result in the form of graphs and tables. Finally, section 5 concludes by summarizing the main findings and suggesting future research directions.

2. RELATED WORK

This ASD is a neurodevelopmental disease generally detected throughout early infancy. It is characterized by problems in behavior and cognition. ASD has emerged as a serious medical concern with substantial societal and economic ramifications globally. Based on a growing number of studies, it has been revealed that aberrant behavior in children with ASD may not exclusively be caused by ongoing neurological abnormalities, but also by the early adaptation of the brain to unfavorable environmental factors [17]. Children diagnosed with ASD may encounter difficulty in areas such as shared attention, eye contact, social interactions, and emotional sharing. The user has supplied a reference to a source, represented by the number [18]. The machine learning algorithm was designed to diagnose children with ASD using patterns retrieved from facial scans. The model attained an accuracy of 82.51% in its categorization. This finding promotes the investigation of machine learning algorithms for the identification of ASD. The study successfully obtained a classification accuracy of 84% utilizing a machine learning approach to discriminate between the eye fixations of children with ASD and TD children. The following research gives evidence of the efficacy and impartiality benefits of machine learning as compared to traditional diagnostic scales. Furthermore, as compared to TD youngsters, persons with ASD have difficulty in nonverbal communication abilities, such as expression imitation and facial expression recognition (FER).

The study done by the authors in [18]–[20] employed facial muscle analysis as a tool to test the capacity of children with ASD to copy the facial expressions of others. The findings show that the reproduction of normal facial expressions might serve as a behavioral signal for the diagnosis of children with ASD. A technique was created to automatically diagnose ASD in persons with attention deficit hyperactivity disorder [11]. They built a brand-new semi-supervised machine learning framework called clustering-based autistic trait classification (CATC) to accomplish this aim. Through the application of classification techniques, CATC evaluates classifiers using a clustering strategy. Instead of utilizing score systems like many other ASD screening approaches, this methodology detects likely occurrences of autism based on related traits. The empirical findings, which came from a range of datasets including kids, teenagers, and adults, were validated and contrasted with other widely-used machine learning classification approaches. The results demonstrated that when compared to other intelligent classification approaches like artificial neural networks (ANN), random forest (RF), random trees, and rule induction, CATC gives classifiers with greater projected accuracy, sensitivity, and specificity. Esler *et al.* [16] employed machine learning algorithms to overcome significant autism-related challenges. To increase classification accuracy, they concentrate a major focus on the selective selection of important autism traits. They underline how vital it is to pick the relevant features and limit data complexity to generate optimistic findings when diagnosing ASD. The authors also note a variety of factors that may impair accuracy, such as feature redundancy, inappropriate sampling procedures, and imbalanced and insufficient sample sizes. Coupled RF, classification and regression trees (CART) and RF iterative dichotomiser 3 (ID3), assessing the trained model on a similar dataset before deploying it in a mobile application [17]. In different research, Liu *et al.* [18] looked at 25 machine learning classifiers using a gathered dataset for ASD and found that support vector machine (SVM) based on sequential minimal optimization (SMO) performed better in their test environment.

According to Jiang *et al.* [19], people with ASD have several distinctive traits. Asking inappropriate questions, acting erratically, imitating others spontaneously, displaying a lack of interest in other people, finding it difficult to share meals, and utilizing objects repeatedly are among the behaviors that are noted. Samad *et al.* [20] looked at warning indicators that could point to the existence of ASD in their study. Specific indications of ASD included delayed speech development, repetitive play habits, and communication challenges. It was also noted that there was a lack of facial expression, pretend play, and imaginative play, in addition to a propensity for engaging in active peer interaction, understanding irony, and maintaining personal space. Samad *et al.* [20] show that their study includes the following features: the density of quick eye movements, the density of muscle twitches, and the first delay of rapid eye movement (REM). It has been noted that repetitive behaviors, such as repeating motor and sensory actions, are more common in people with autism, especially in younger age groups. These actions aren't seen as important signs of the illness, either. On the other hand, older people with higher intelligence quotients (IQs) typically display more intricate and sophisticated recurrent behavioral patterns. Even though the aforementioned study showed a considerable increase in the prediction of ASD, the accuracy of academic performance models has not yet achieved its full potential.

Rule-based machine learning (RML) approaches were utilized in [17] to examine the characteristics of ASD. Researchers discovered that applying RML techniques can greatly increase classification models' accuracy in detecting instances of ASD. In a work that was published in [18], the researchers-built prediction models for people of various ages, including adults, adolescents, and children, using the RF and ID3 algorithms. A unique assessment tool that combines the autism diagnostic interview-revised (ADI-R) and autism diagnostic observation schedule (ADOS) machine learning approaches has been proposed [19]. Diverse attribute encoding methods have been utilized to tackle problems associated with irregular data, non-linearity, and insufficient data. Thabtah *et al.* [13] used cognitive computing in conjunction with decision trees (DT), logistic regression (LR), and SVM as prognostic and diagnostic classifiers for ASD. Examining the correlation values between the traits and classes is the aim of this investigation. The current investigation seeks to further earlier studies on the topic [17].

According to Samad *et al.* [20], there were instances of TD (N = 19) and ASD (N = 11). A correlation-based attribute selection method was applied to ascertain the significance of the qualities. A single dataset was used for the model's assessment, and the comparison's range was constrained. Autism is categorized using the machine learning approach created by the authors of [17]. On the RF algorithm, the model was built. The linear discriminant analysis (LDA) and k-nearest neighbor (KNN) algorithms were used in [16] to diagnose ASD in children between the ages of 4 and 11. Chen *et al.* [17] put out a paradigm for ASD in 2018. Children between the ages of 4 and 11 are the model's target market. The RF classifier is employed. Liu *et al.* [18] looked at how well the DNN could diagnose ASD. Two distinct adult datasets were used in the study. Liu *et al.* [18] created a smartphone application programming interface (API) in 2019 that makes it possible to diagnose ASDs in people of all ages. The technologies RF-CART and RF-ID3 supported the interface. Jiang *et al.* [19] looked at how well several SVM kernels recognized data related to ASD in youngsters. It was discovered that the polynomial kernel performed noticeably better.

In a study that was published in [11], the researchers used four datasets that were associated with ASD to investigate several feature selection techniques. The investigation's conclusions showed that the SVM classifier performed better than other methods in the instance of the repeated incremental pruning to produce error reduction (RIPPER)-based toddler subgroup. When applied to the adult subset using the correlation-based feature selection (CFS) feature selection approach and the child subset using the CFS feature selection method together with the Boruta CFS intersect (BIC) methodology, the SVM classifier showed better performance. Several feature subsets were analyzed by the researchers using the Shapley additive explanations (SHAP) approach. This strategy yielded the highest level of accuracy after evaluating each feature's performance. To categories Parkinson's illness and ASD, Samad *et al.* [20] used ensemble machine learning techniques such as fuzzy KNN, kernel SVM, fuzzy convolution neural network (FCNN), and RF. The leave-one-person-out cross validation (LOPOCV) method is used to validate the categorization findings.

3. METHOD

The proposed methodology outlines a comprehensive approach for developing a machine learning model to predict ASD, starting from data understanding and cleaning, transformation, feature selection, and data processing. It emphasizes the importance of preliminary data analysis, including cleaning and data preparation, to prepare the dataset for modelling. An ensemble classifier model, incorporating various machine learning techniques like extra trees (ET), light gradient-boosting machine (LightGBM), ridge classification, and LDA, is proposed to enhance prediction accuracy. This model leverages multiple classifiers to ensure robustness and utilizes a voting mechanism for prediction aggregation, aiming to improve the overall performance. The process concludes with an evaluation and optimization stage, where models are fine-tuned to achieve optimal results, demonstrating a structured and effective technique for ASD detection through machine learning.

i) Data understanding: this involves assessing the dataset to comprehend its content, structure, and the types of data it includes. This study explore the variables, check the data types, and understand how they correlate with each other.
ii) Data cleaning: this process rectifies issues with the data. Common tasks include handling missing values, correcting typos or inaccuracies, identifying and removing duplicates, and addressing outliers that could skew analysis.
iii) Data transformation: here, the data is manipulated to enhance the analysis. This might involve normalizing or scaling features, encoding categorical variables, creating new features from existing ones, and summarizing or restructuring data to better fit the intended models or analysis.
iv) Feature selection: choosing the features that are most pertinent to the classification task is the main aim of this phase. Association and mutual information may be used in this way to determine which features have a robust association with the outcome variable. Figure 1 depicts proposed workflow for ASD prediction.
v) Data preprocessing: in this phase, the data is pre-processed using a machine learning model. This includes cleaning, formatting the data, filling in the missing values, and normalizing data by evaluating the performance metrics, which are evaluated by calculating the effectiveness of the machine learning model.

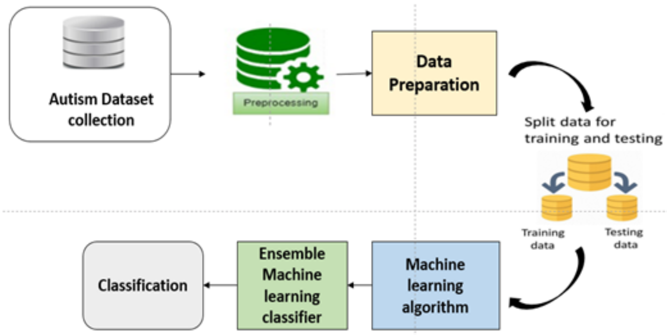

Figure 1. Proposed workflow

The metric used here performs the task it is focused on to do so for the model for which it is used. Wherein the classification models are used for the purpose of evaluating metrics such as accuracy, recall, precision, and F1-score. The proposed model is developed to enhance machine learning algorithms by establishing an autism spectrum detection model capable of classifying autism. Utilizing all the machine learning classifiers in this experiment is essential for ensuring the best results for predicting autism detection. Algorithm 1 shows the algorithm for classification

Algorithm 1. Algorithm for classification
```
Input:   Machine_learning model, Autism_dataset
Step 1:  Start
Step 2:  data <- load Autism_dataset
Step 3:  If data == NaN
           else 0
         Substitute NaN or their. miss_val
Step 4:  Pre-processing
           If target_data = to O
         Substitute O with value zero
           else
         Substitute D with 1
Step 5:  z <- discard {target_data}
Step 6:  a <- target_data
Step 7:  z1,z2,a1,a2 <- split (z,a) data
Step 8:  Model <- train_model using z1 and a1
Step 9:  predict <- test_model using z2 and a2
Step 10: u_z <- data_scaling of z
Step 11: u_z <- data_compress of u_z
Step 12: Apply hyper_parameter tuning
           for each classifier
Step 13: Classifier <- train_model using u_z
```

```
Step 14: Model <- apply_ensemble_classifier using classifier
Step 15: Predict <- cross_validation model
Step 16: Compute performance evaluation metrics
Step 17: End
```

Extra trees are the term used to describe the DT that are produced from the training set. A subset and a partially random cut point are randomly inspected to determine a split rule for the root [21]. Two randomly chosen child nodes break from the parent node. Until the leaf node is reached, each child node is repeated. The ultimate projections are decided by a majority vote. The user decides which of the top features to employ the classifier model considered as the last step, this predicts the decision in case of regression or classification purpose wherein regression involves average prediction on the basis of DT and classification based on tree-based prediction for majority voting. Based on DT, the LightGBM algorithm is a gradient-boosting method. Regression analysis was utilized to classify the data rank. To train and segregate the data from each DT, two methods are available. While the other technique concentrates on the tree's leaves, the first strategy concentrates on the tree's level. Alternatively, to continually separate the leaves and reduce loss, a leaf-wise method is used. LightGBM's tree structure evolves in a leaf-wise fashion, with losses picked and split in each branch according to how much they contribute to the total loss. Faster learning is often a benefit of a tree-based model with a low error rate. The evolution of the LightGBM model is mostly horizontal, preventing overlearning. It has been demonstrated that using huge datasets produces better results.

Ridge classifier (RC): RC is the method used in machine learning to examine linear discriminant models. Regularization penalizes the coefficients in a model to stop it from over-fitting. During the training phase, the classifier first treats the issue as a regression, changing the goal values to +1 and -1. LDA: a typical use of the dimensional reduction strategy is in supervised classification problems. For classification, the LDA technique is also employed. To maximize within-class variance and decrease class variation, the LDA method is used. To identify the variables, the method uses a linear combination search technique. It is assured that the best differentiating feature for labels with more than one class is chosen [22].

In (1) to (4) are evaluated as linear coefficients, thereby maximizing the discriminant function. The equations here e represent the linear coefficient θ model, the covariance matrix, and the α shows the average vector function. The machine learning model that is used in the training phase is the model aggregation-based ensemble classifier. Multiple models are used to train the classifier. After receiving the output from each classifier, the classifier forecasted the output class by taking into account the majority vote with the highest score. Ensemble machine learning models frequently use ensemble approaches to aggregate predictions from several independent models. Using the hard voting approach in our study, the class with the most votes is determined by adding together all of the classifiers' predictions. Model aggregation-based ensemble classifiers are used to improve classification robustness and accuracy. There's a chance that some datasets might show an unbalanced breakdown of cases by type. It is crucial to remember that trying to correctly forecast both groups with a single classifier may provide difficulties. The ensemble classifier creates a forecast that is more thorough and precise by combining predictions from several classifiers. Four base classifiers are used in this study's voting ensemble model. The chosen classifier for this system is the ET meta-classifier. Using the whole training input dataset, the basic model was established during the first training of the basic classifiers. The meta-model classifier receives each base model's prediction as an input.

Using the adaptive ensemble classifier helps improve the data's resistance to noise and outliers. Combining the forecasts of outliers and noisy data might lessen their impact. In addition, the application of adaptive voting ensemble classifiers in the detection and assessment of Autism may improve prediction balance, robustness, and accuracy. Algorithm 2 shows pseudocode for the ensemble learning algorithm.

$$b = \theta_1 z_1 + \theta_1 z_1 + \cdots + \theta_f z_f \tag{1}$$

$$u(\theta) = \frac{\theta^v \vartheta_1 - \theta^v \vartheta_2}{\theta^v e \theta} \tag{2}$$

$$U(\theta) = \frac{b_1 - b_2}{b(group_{variance})}$$

$$\theta = E^{-1}(\alpha_1 - \alpha_2) \tag{3}$$

$$E = \frac{1}{(P_1 + P_2)}(P_1 E_1 + P_2 E_2) \tag{4}$$

Algorithm 2. Pseudocode for the ensemble learning

```
Input:   Autism training data
Output:  Ensemble classifsub-trained
Step 1:  Base classifiers = (ET, LGBM, RC, LDA)
         Meta_classifier ET
```

```
Step 2:  Base learner upon applying the data-sub-classifier
Step 3:  For training classifiusing cross validation
           For = <-1 to, … do where (=10)
             θ = ()
Step 4:  Learn the classifier from
           End for
Step 5:  Train_set for Meta_classifier ET
Step 6:  = ()
Step 7:  Return
Step 8:  End
```

This framework outlines a comprehensive machine learning pipeline designed for the analysis and prediction of ASD using ensemble classifiers. Algorithm 3 shows the proposed algorithm. It systematically progresses through seven crucial steps. Figure 2 presents the flowchart of the proposed algorithm.

Algorithm 3. The proposed algorithm

```
Step 1:  Preliminary analysis
         for dataset in [ ASD_Dataset]:
           if dataset.is_available ():
              analyze_dataset_characteristics(dataset)
Step 2:  Data acquisition
         ASD_Data = acquire data ('ASD _Dataset')
         ASD_Data = acquire data('ASD_Dataset')
           combined data = combine datasets(ASD_children_Data, ASD_ Adolescents_Data)
Step 3:  Data pre-processing
         for data in combined data:
           if data. needs conversion ():
              convert_categorical_to_numerical(data)
           if data.is_imbalanced ():
              apply_(data)
Step 4:  Feature Selection
         selected_features = []
           for feature in combined data. features:
              if is_relevant_feature(feature):
                 selected_features. append(feature)
                 apply_feature_selection_methods(feature, methods=[,
                 Extra_Trees_Classifier])
Step 5:  Ensemble_classifier model implementation
         trained_models = {}
           for model in []:
              trained_models[model.name] = train_model(model, selected_features)
Step 6:  Ensemble learning
         ensemble_models = []
           for model in []:
              if model in trained_models:
              ensemble_models.   append(trained_models[model])
              ensemble = create ensemble (ensemble_models, method='soft_voting')
Step 7:  Evaluation and optimization
         for model in [ensemble] + list (trained_models. Values ()):
           evaluate_model_performance(model)
              if model. needs optimization ():
              apply_hyperparameter_tuning(model)
```

Preliminary analysis: the pipeline starts by assessing the availability and characteristics of an ASD dataset. This foundational step ensures a deep understanding of the dataset's structure, quality, and relevance to ASD before proceeding further. Data acquisition: it then moves on to gather ASD-related data, potentially from various sources, to form a rich dataset. This step might include combining data from specific subsets, such as children and adolescents with ASD, to ensure a diverse and comprehensive dataset for analysis. Data pre-processing: the gathered data undergoes critical pre-processing tasks, including the conversion of categorical data into a numerical format for machine learning compatibility and addressing any imbalance within the dataset to prevent biased model predictions. Feature selection: identifying and selecting the most informative features is key to improving model performance. This step employs both manual inspection and automated methods, such as the ET classifier, to determine the most relevant features for ASD prediction.

Ensemble classifier model implementation: various machine learning models are trained on the selected features. This step allows for the flexibility to choose the most appropriate models based on the data's characteristics and the preliminary analysis's insights. Ensemble learning: enhancing the predictive performance by combining the strengths of individual models through an ensemble approach, specifically using soft voting. This method aggregates the predictions of multiple models to make a final prediction, leveraging their collective intelligence for improved accuracy. Evaluation and optimization: the last step involve a thorough evaluation of the performance of both the ensemble and individual models, followed by hyperparameter tuning to optimize their effectiveness. This iterative process ensures that the models are finely tuned for the best possible predictive performance on ASD. Throughout this process, the emphasis is on data preparation, strategic model selection, and continuous refinement of the models. This approach aims to leverage the strengths of ensemble learning to accurately predict ASD, demonstrating a sophisticated and thoughtful application of machine learning techniques to a complex and sensitive medical condition.

Implementation settings: the proposed ensemble was implemented in Python using the Scikit-learn and LightGBM libraries. The ensemble combines four base learners—ET, LightGBM, RC, and LDA—aggregated through a hard (majority) voting scheme, with the ET classifier also serving as the meta-classifier. Categorical attributes were label-encoded, missing values were imputed, and features were normalized prior to training; the most informative features were selected using the ET feature-importance ranking. Model performance was estimated using 10-fold cross-validation on the publicly available children and adult ASD screening datasets, and reported in terms of accuracy, precision, recall, and F1-score. Default library hyperparameters were used for the base learners unless otherwise stated, ensuring the pipeline can be reproduced by other researchers.

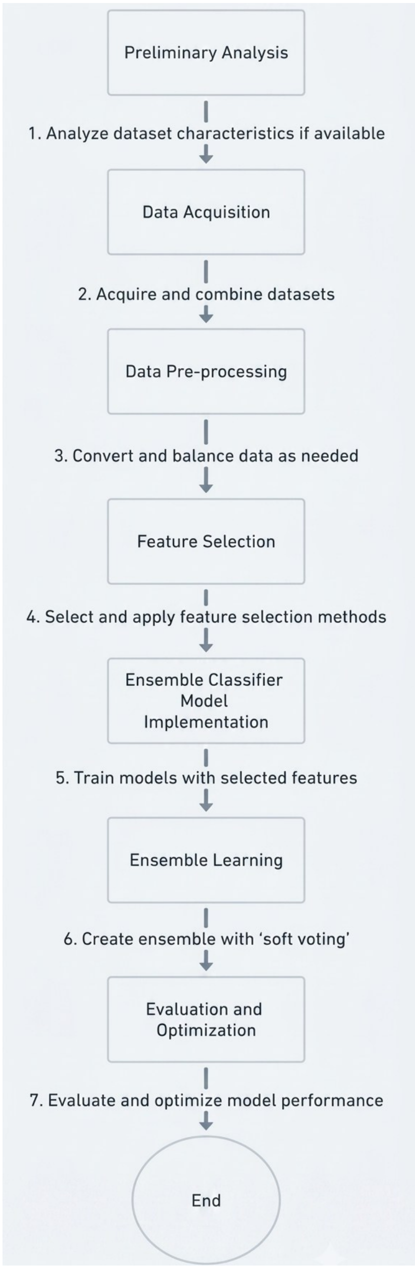

Figure 2. Flowchart of the proposed algorithm

4. PERFORMANCE EVALUATION

The performance evaluation is carried out using the two datasets, the children dataset and the adolescent dataset, wherein the existing state-of-the-art techniques are compared with the proposed model, and the results are given in the form of graphs, as shown in Table 1 and Figure 3. Figure 3(a) presents accuracy, Figure 3(b) presents precision, Figure 3(c) presents recall, and Figure 3(d) presents F1-score. In this study, people with ASD who are divided into two age groups, children and adults, are drawn from two different datasets. A 10-fold cross-validation technique is used to build prediction models using the datasets [23], [24]. In the 10-fold cross-validation training phase, the datasets are split into ten equal-sized groups, or folds, at random. One-fold is reserved for testing in the model-building process, while the remaining nine folds are used for training.

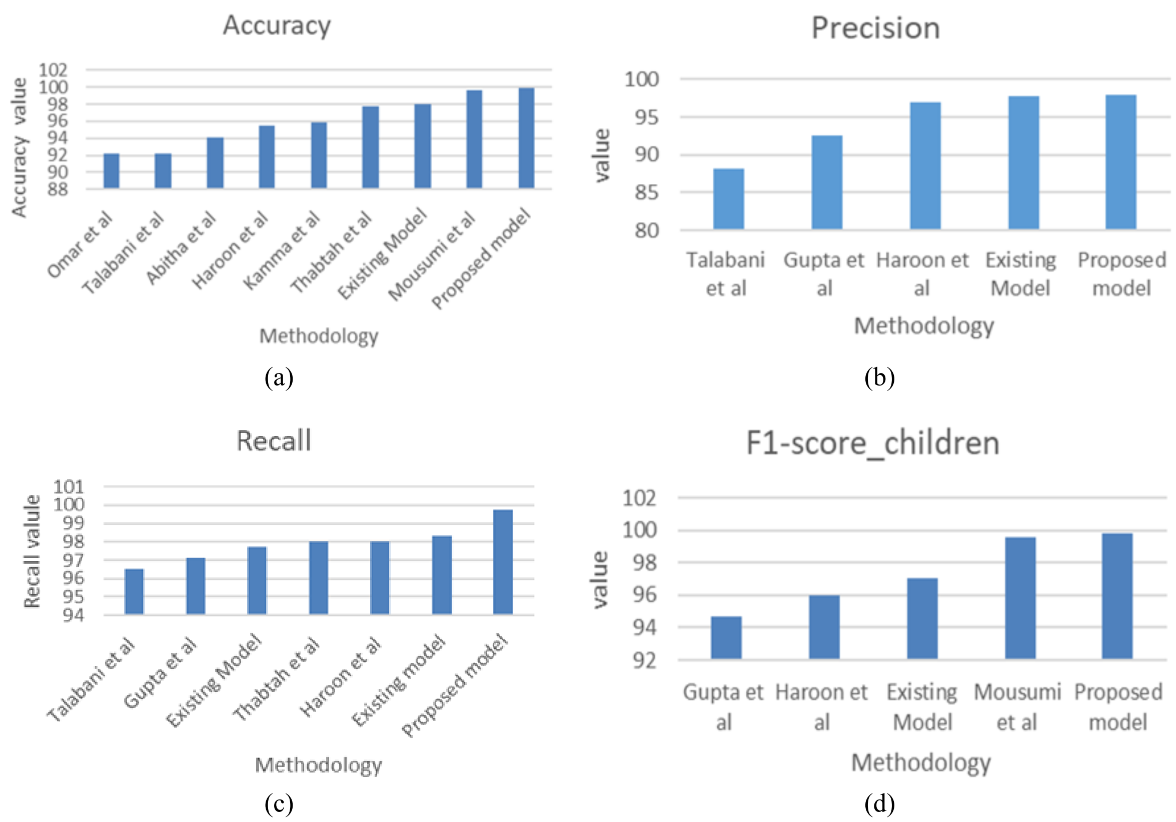

Figure 3. Performance comparison on children dataset: (a) accuracy, (b) precision, (c) recall, and (d) F1-score

The technique is repeated numerous times, particularly 10 times, and the average of those repetitions is used to determine the findings. In this instance, a 10-fold cross-validation technique is used in the process to provide a more widely applicable model. This is a very useful resource when sparse data is present, and overfitting needs to be minimized. Preventing overfitting is accomplished by lowering the variance while creating the model. The lack of adequate samples in the datasets may be the cause of this variance decrease. When holdout validation is used during model development with a fixed test set, overfitting might happen. Overfitting is a phenomenon that can cause variance to rise, making it more difficult for the prediction model to generalize to test data that hasn't been seen before. Several statistical assessment metrics are used to validate the experimental outcomes. Accuracy, precision, recall, F1-score, and receiver operating characteristics (ROC) curve are among metrics [25]–[27].

The results are evaluated on two datasets, the children and adult dataset for the performance metrics accuracy, F1-score, precision, and recall. The results are shown in the form of a graph and tables. The dataset overview for ASD prediction in children showcases a series of studies, each contributing to the evolving landscape of diagnostic accuracy through machine learning models. Notably, the progression in model performance is evident, culminating in the proposed model, which achieves the highest scores across all metrics: an accuracy of 98.96%, an F1-score of 98.67%, precision at 97.87%, and recall at 98.32%. This indicates a sophisticated model capable of accurately identifying ASD cases with minimal false positives (high precision) and false negatives (high recall), showcasing the potential of advanced algorithms in enhancing ASD diagnostics. Earlier contributions, like Bala *et al.* [1] with an accuracy of 99.61% and an F1-score of 99.6, and Haroon and Padma [28] with balanced precision and recall, set significant benchmarks. However, the proposed model surpasses these through incremental improvements in balancing the precision-recall trade-off, highlighting the continuous refinement and potential of machine learning in contributing to effective, early ASD detection [29]–[32]. Table 1 shows the children dataset.

Table 1. Performance comparison on the children dataset

Reference	Accuracy	F1-score	Precision	Recall
Omar *et al.* [25]	92.26			
Thabtah [26]	97.8			98
Talabani and Avci [27]	92.26		88.09	96.52
Bala *et al*. [1]	99.61	99.6		
Haroon and Padma [28]	95.5	96	97	98
Abitha *et al.* [29]	94.1			
Kamma *et al.* [30]	95.82			
Gupta *et al.* [31]		94.71	92.59	97.09
Existing model [32]	97.95	97.02	96.16	97.72
Proposed model	98.96	98.67	97.87	98.32

This dataset outlines the advancements in machine learning models for a specific application, evidenced by progressively improving metrics across various studies. The proposed model sets a new benchmark with nearly perfect scores: an accuracy of 99.87%, an F1-score of 99.98%, precision at 99.87%, and a recall of 100%. Such high performance indicates an exceptional capability in identifying true positives without increasing false positives or negatives, showcasing a significant leap in predictive accuracy. The journey towards this pinnacle of model performance includes noteworthy milestones, such as Thabtah [26] achieving an almost perfect recall of 99.9% and Bala *et al*. [1] presenting an outstanding balance across all metrics with an accuracy and F1-score close to 100%. The gradual increase in model metrics from earlier studies like [25], [33] to the proposed model highlights the impactful progress in the field, driven by continuous methodological refinements and technological advancements. This evolution reflects a focused effort towards achieving near-perfect model performance, underscoring the potential of current machine learning approaches in reaching unprecedented levels of precision in their applications. The comparative results for the adult dataset are presented in Table 2 and Figure 4. Figure 4(a) presents accuracy, Figure 4(b) presents precision, Figure 4(c) presents recall, and Figure 4(d) presents F1-score.

In the comparison analysis of performance metrics between the existing system and the proposed system for both children and adult datasets, significant improvements are observed across all key metrics, indicating the efficacy of the proposed system. For the children dataset, the proposed system shows an enhancement in accuracy by 1.03%, precision by 1.71%, and recall by 0.61%, with the F1-score seeing a notable rise of 1.7%. This indicates a more accurate and reliable detection of ASD in younger populations. Similarly, the adult dataset comparison reveals substantial improvements, particularly in precision, which jumps by 1.71%, and the F1-score, which increases slightly by 0.77%, while maintaining a perfect recall rate. Accuracy also sees a considerable boost of 0.84%. These improvements underscore the proposed system's capability to provide more precise and dependable diagnoses across different age groups, affirming its potential to significantly impact ASD detection and intervention strategies.

Table 2. Performance metrics on the adult dataset

Reference	Accuracy	F1-score	Precision	Recall
Omar *et al*. [25]	97.1			
Thabtah [26]	99.85			99.9
Shuvo et al. [33]	95.71			85.71
Talabani and Avci [27]	96.91		90.07	96.87
Bala *et al*. [1]	99.82	99.9	99.9	
Abitha *et al.* [29]	98			
Kamma *et al.* [30]	95.82			
Gupta *et al.* [31]		94.26	97.46	91.27
Existing model [32]	99.03	99.11	98.16	100
Proposed model	99.87	99.98	99.87	100

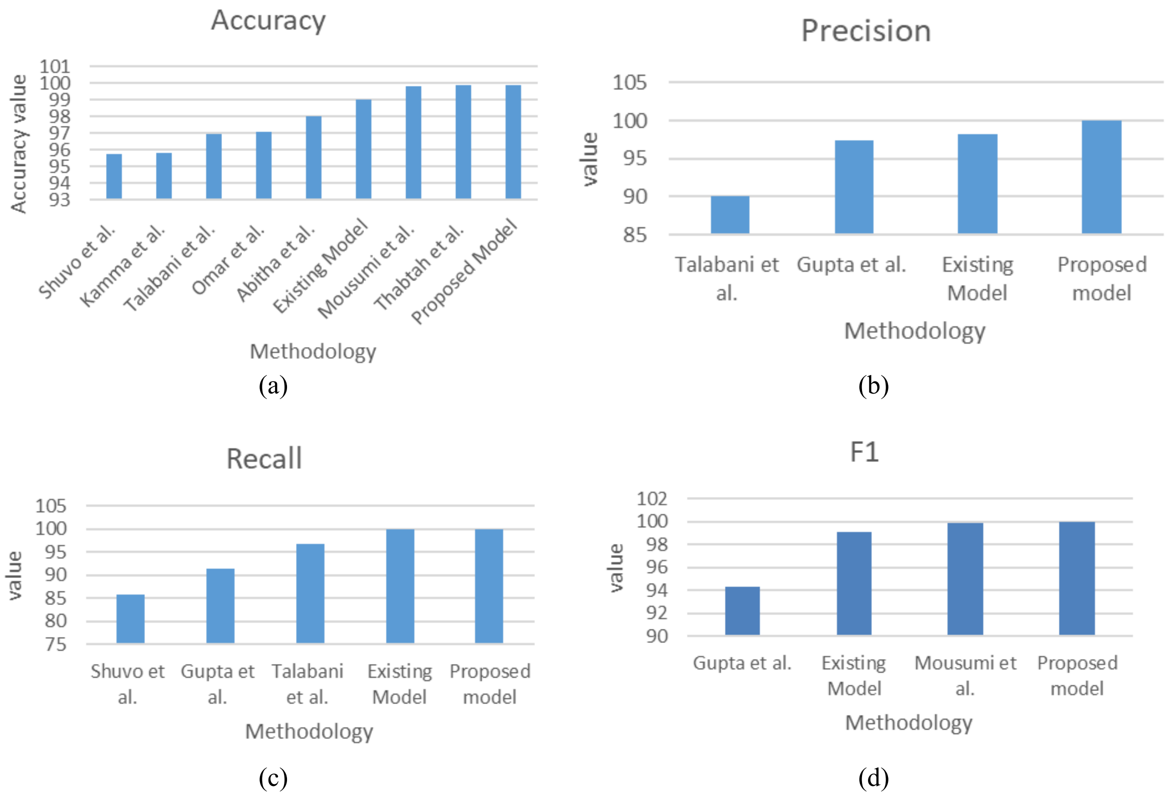

Figure 4. Performance comparison on adult dataset: (a) accuracy, (b) precision, (c) recall, and (d) F1-score

5. CONCLUSION

The development and implementation of the "ensemble-based machine learning classifier" represents a significant advancement in the early detection and diagnosis of ASD. By integrating multiple machine learning algorithms into a cohesive ensemble framework, this study has demonstrated a marked improvement in diagnostic accuracy and efficiency. The methodology's success in handling a comprehensive dataset underscores its potential to adapt to the varied manifestations of ASD across different age groups and developmental stages. Moreover, the approach significantly reduces the subjectivity and time constraints associated with traditional diagnostic methods, offering a scalable and objective tool for healthcare professionals. The insights gained from this research not only enhance clinical practices but also contribute to the broader understanding of ASD, highlighting the indispensable role of machine learning in the future of medical diagnostics. As we move forward, the continued refinement and application of such innovative technologies promise to improve the lives of individuals with ASD and their families, ensuring timely access to interventions and support services.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to all those who have supported and contributed to this research project. In particular, the authors extend their heartfelt thanks to our advisor for his tireless guidance, invaluable insights, and encouragement throughout the research process.

FUNDING INFORMATION

No funding is raised for this research

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Shabeena Lylath	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Laxmi B. Rananavare	✓	✓			✓	✓		✓	✓	✓	✓	✓		

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

CONFLICT OF INTEREST STATEMENT

The author declares that there are no known conflicts of interest associated with this publication. There are no financial or personal relationships that could inappropriately influence or bias the content of this work.

DATA AVAILABILITY

No dataset is utilized in this research.

REFERENCES

[1] M. Bala, M. H. Ali, M. S. Satu, K. F. Hasan, and M. A. Moni, "Efficient machine learning models for early stage detection of autism spectrum disorder," *Algorithms*, vol. 15, no. 5, May 2022, doi: 10.3390/a15050166.

[2] D. Pietrucci *et al.*, "Machine learning data analysis highlights the role of *Parasutterella* and *Alloprevotella* in autism spectrum disorders," *Biomedicines*, vol. 10, no. 8, Aug. 2022, doi: 10.3390/biomedicines10082028.

[3] E. Linstead, R. German, D. Dixon, D. Granpeesheh, M. Novack, and A. Powell, "An application of neural networks to predicting mastery of learning outcomes in the treatment of autism spectrum disorder," in *2015 IEEE 14th International Conference on Machine Learning and Applications*, Dec. 2015, pp. 414–418, doi: 10.1109/ICMLA.2015.214.

[4] J. Amudha and H. Nandakumar, "A fuzzy based eye gaze point estimation approach to study the task behavior in autism spectrum disorder," *Journal of Intelligent & Fuzzy Systems*, vol. 35, no. 2, pp. 1459–1469, Aug. 2018, doi: 10.3233/JIFS-169687.

[5] D. Begum, K. M. Ravikumar, and K. N. Vykuntaraju, "An initiative to classify different neurological disorder in children using multichannel EEG signals," in *2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology*, May 2016, pp. 1563–1566, doi: 10.1109/RTEICT.2016.7808095.

[6] F. Z. Subah, K. Deb, P. K. Dhar, and T. Koshiba, "A deep learning approach to predict autism spectrum disorder using multisite resting-state fMRI," *Applied Sciences*, vol. 11, no. 8, Apr. 2021, doi: 10.3390/app11083636.

[7] K.-F. Kollias, C. K. S.-Delli, P. Sarigiannidis, and G. F. Fragulis, "The contribution of machine learning and eye-tracking technology in autism spectrum disorder research: a systematic review," *Electronics*, vol. 10, no. 23, 2021, doi: 10.3390/electronics10232982.

[8] I. A. Ahmed *et al.*, "Eye tracking-based diagnosis and early detection of autism spectrum disorder using machine learning and deep learning techniques," *Electronics*, vol. 11, no. 4, Feb. 2022, doi: 10.3390/electronics11040530.

[9] P. Sukumaran and K. Govardhanan, "Towards voice based prediction and analysis of emotions in ASD children," *Journal of Intelligent & Fuzzy Systems*, vol. 41, no. 5, pp. 5317–5326, Nov. 2021, doi: 10.3233/JIFS-189854.

[10] S. P. Abirami, G. Kousalya, and R. Karthick, "Identification and exploration of facial expression in children with ASD in a contact less environment," *Journal of Intelligent & Fuzzy Systems*, vol. 36, no. 3, pp. 2033–2042, 2019, doi: 10.3233/JIFS-169915.

[11] M. D. Hossain, M. A. Kabir, A. Anwar, and M. Z. Islam, "Detecting autism spectrum disorder using machine learning techniques," *Health Information Science and Systems*, vol. 9, no. 1, Dec. 2021, doi: 10.1007/s13755-021-00145-9.

[12] C. Allison, B. Auyeung, and S. B.-Cohen, "Toward brief 'red flags' for autism screening: the short autism spectrum quotient and the short quantitative checklist in 1,000 cases and 3,000 controls," *Journal of the American Academy of Child & Adolescent Psychiatry*, vol. 51, no. 2, pp. 202-212.e7, Feb. 2012, doi: 10.1016/j.jaac.2011.11.003.

[13] F. Thabtah, F. Kamalov, and K. Rajab, "A new computational intelligence approach to detect autistic features for autism screening," *International Journal of Medical Informatics*, vol. 117, pp. 112–124, Sep. 2018, doi: 10.1016/j.ijmedinf.2018.06.009.

[14] M. M. Ali, B. K. Paul, K. Ahmed, F. M. Bui, J. M. W. Quinn, and M. A. Moni, "Heart disease prediction using supervised machine learning algorithms: performance analysis and comparison," *Computers in Biology and Medicine*, vol. 136, Sep. 2021, doi: 10.1016/j.compbiomed.2021.104672.

[15] E. Dritsas and M. Trigka, "Stroke risk prediction with machine learning techniques," *Sensors*, vol. 22, no. 13, Jun. 2022, doi: 10.3390/s22134670.

[16] A. N. Esler *et al.*, "Patterns of special education eligibility and age of first autism spectrum disorder (ASD) identification among US children with ASD," *Journal of Autism and Developmental Disorders*, vol. 53, no. 5, pp. 1739–1754, May 2023, doi: 10.1007/s10803-022-05475-5.

[17] Y. Chen *et al.*, "The relationship between motor development and social adaptability in autism spectrum disorder," *Frontiers in Psychiatry*, vol. 13, Nov. 2022, doi: 10.3389/fpsyt.2022.1044848.

[18] W. Liu, M. Li, and L. Yi, "Identifying children with autism spectrum disorder based on their face processing abnormality: a machine learning framework," *Autism Research*, vol. 9, no. 8, pp. 888–898, Aug. 2016, doi: 10.1002/aur.1615.

[19] M. Jiang, S. M. Francis, D. Srishyla, C. Conelea, Q. Zhao, and S. Jacob, "Classifying individuals with ASD through facial emotion recognition and eye-tracking," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Jul. 2019, pp. 6063–6068, doi: 10.1109/EMBC.2019.8857005.

[20] M. D. Samad, N. Diawara, J. L. Bobzien, J. W. Harrington, M. A. Witherow, and K. M. Iftekharuddin, "A feasibility study of autism behavioral markers in spontaneous facial, visual, and hand movement response data," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 2, pp. 353–361, Feb. 2018, doi: 10.1109/TNSRE.2017.2768482.

[21] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Machine Learning*, vol. 63, no. 1, pp. 3–42, Apr. 2006, doi: 10.1007/s10994-006-6226-1.

[22] A. Tharwat, T. Gaber, A. Ibrahim, and A. E. Hassanien, "Linear discriminant analysis: a detailed tutorial," *AI Communications*, vol. 30, no. 2, pp. 169–190, May 2017, doi: 10.3233/AIC-170729.

[23] V. Yaneva, L. A. Ha, S. Eraslan, Y. Yesilada, and R. Mitkov, "Detecting high-functioning autism in adults using eye tracking and machine learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 6, pp. 1254–1261, Jun. 2020, doi: 10.1109/TNSRE.2020.2991675.

[24] H. Fang, L. Fan, and J.-N. Hwang, "Auxiliary diagnostic method for early autism spectrum disorder based on eye movement data analysis," in *2021 IEEE 7th International Conference on Cloud Computing and Intelligent Systems*, Nov. 2021, pp. 72–77, doi: 10.1109/CCIS53392.2021.9754665.

[25] K. S. Omar, P. Mondal, N. S. Khan, M. R. K. Rizvi, and M. N. Islam, "A machine learning approach to predict autism spectrum disorder," in *2019 International Conference on Electrical, Computer and Communication Engineering*, Feb. 2019, pp. 1–6, doi: 10.1109/ECACE.2019.8679454.

[26] F. Thabtah, "Machine learning in autistic spectrum disorder behavioral research: a review and ways forward," *Informatics for Health and Social Care*, vol. 44, no. 3, pp. 278–297, Jul. 2019, doi: 10.1080/17538157.2017.1399132.

[27] H. Talabani and E. Avci, "Performance comparison of SVM kernel types on child autism disease database," in *2018 International Conference on Artificial Intelligence and Data Processing*, Sep. 2018, pp. 1–5, doi: 10.1109/IDAP.2018.8620924.

[28] A. S. Haroon and T. Padma, "An ensemble classification and binomial cumulative based PCA for diagnosis of parkinson's disease and autism spectrum disorder," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 1, pp. 216–231, Jan. 2024, doi: 10.1007/s13198-022-01699-x.

[29] R. Abitha, S. M. Vennila, and I. M. Zaheer, "Evolutionary multi-objective optimization of artificial neural network for classification of autism spectrum disorder screening," *The Journal of Supercomputing*, vol. 78, no. 9, pp. 11640–11656, Jun. 2022, doi: 10.1007/s11227-021-04268-4.

[30] S. P. Kamma, S. Bano, G. L. Niharika, G. S. Chilukuri, and D. Ghanta, "Cost-effective and efficient detection of autism from screening test data using light gradient boosting machine," in *Intelligent Sustainable Systems*, Singapore: Springer, 2022, pp. 777–789, doi: 10.1007/978-981-16-2422-3_61.

[31] U. Gupta, D. Gupta, and U. Agarwal, "Analysis of randomization-based approaches for autism spectrum disorder," in *Pattern Recognition and Data Analysis with Applications*, Singapore: Springer, 2022, pp. 701–713, doi: 10.1007/978-981-19-1520-8_57.

[32] S. M. M. Hasan, M. P. Uddin, M. A. Mamun, M. I. Sharif, A. Ulhaq, and G. Krishnamoorthy, "A machine learning framework for early-stage detection of autism spectrum disorders," *IEEE Access*, vol. 11, pp. 15038–15057, 2023, doi: 10.1109/ACCESS.2022.3232490.

[33] S. B. Shuvo, J. Ghosh, and A. S. Oyshi, "A data mining based approach to predict autism spectrum disorder considering behavioral attributes," in *2019 10th International Conference on Computing, Communication and Networking Technologies*, Jul. 2019, pp. 1–5, doi: 10.1109/ICCCNT45670.2019.8944905.

BIOGRAPHIES OF AUTHORS

Shabeena Lylath is currently working as an assistant professor in HKBK College of Engineering, Bengaluru, India. She earned his Bachelor of Engineering degree in Information Science and Engineering from Channabasaveshwara Institute of Technology, Tumkur, India, in 2005. She obtained her master's degree in M.Tech. (Computer Science and Engineering) from Akshaya Institute of Technology, Tumkur, India, in 2015. Currently, she is a research scholar at REVA University doing her Ph.D. in the Department of Computer Science and Engineering. She has an experience of 10 years in teaching Computer Science and Engineering. Her areas of interest are artificial intelligence and machine learning. She can be contacted at email: shabeenal_12@rediffmail.com.

Dr Laxmi B. Rananavare is currently working as an associate professor in Department of Computer Science and Engineering, REVA University, Bengaluru, India. She has vast experience of more than 30 years in teaching Computer Science and Engineering. Her research interests are: artificial intelligence, machine learning, and natural language processing. She is involved in research on applications of artificial intelligence. She has published many papers in national and international conferences and journals. She can be contacted at email: laxmib.rananavare@reva.edu.in.