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RESEARCH ARTICLE

Novel Framework for Autism Spectrum Disorder Identification and Tailored Education With Effective Data Mining and Ensemble Learning Techniques

FAHIMA HAJJEJ [1], SARRA AYOUNI [1], MANAL ABDULLAH ALOHALI [1], AND MOHAMED MADDEH [2]

[1]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia

[2]College of Applied Computer Science, King Saud University, Riyadh 11451, Saudi Arabia

Corresponding author: Fahima Hajjej (fshajjej@pnu.edu.sa)

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ABSTRACT Autism Spectrum Disorder (ASD) is a neurological condition that significantly affects cognitive abilities, language comprehension, object recognition, interpersonal skills, and communication capabilities. Its primary origin is genetic, and early detection and intervention can mitigate the need for costly medical procedures and lengthy examinations for individuals affected by ASD. Autism Spectrum Disorder is highly diverse, with each affected child being unique. It is often stated that no two autistic children are alike, meaning that what benefits one child may not be suitable for another. An effective teaching approach may be challenging to determine for a child with autism. Two ASD screening datasets of toddlers are merged in this study. The Synthetic Minority Oversampling Technique (SMOTE) method to balance the dataset, followed by feature selection methods. The research introduces a two-phase system: the first phase employs various machine learning models, including an ensemble of random forest and XGBoost classifiers that 94% accurate in ASD identification. In the second phase, the study focuses on identifying appropriate teaching methods for children with ASD by evaluating their physical, verbal, and behavioural performance. This research aims to provide personalized educational approaches for individuals with ASD, harnessing machine learning to enhance precision in addressing their unique needs.

INDEX TERMS Autism spectrum disorder (ASD), autism students learning, SMOTE, multi-model learning, feature engineering.

I. INTRODUCTION

Autism spectrum disorder (ASD) is a developmental disability that affects communication and behaviour and typically appears in early childhood and can last throughout a person's life [1]. The World Health Organization estimates that about 1% of the world's population, or about 75 million people, have ASD [2]. A significant number of children with ASD, about 31%, have an intellectual disability, which can make it difficult for them to learn and function in everyday life [2].

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Nevertheless, the origins of ASD remain uncertain, and there are currently no established medical interventions that prove effective [3]. ASD is a major global health problem that can have a significant impact on individuals, families, and society. An emerging theory is that the atypical behaviours of children with ASD may be caused by the brain's early adaptation to a challenging environment, rather than being a result of ongoing neural damage [4]. Early intervention can help to teach children with autism the skills they need to succeed, and it can also help to reduce the stress and anxiety that families often experience when their child has autism. Previous research has shown that the brain's ability to change and adapt (neural plasticity) declines with age. Early intervention for children with autism can help to improve their language and cognitive abilities before the onset of behavioural problems [5]. Hence, the timely identification of ASD holds substantial importance.

Many of the current methods for ASD detection rely on manual observations, which can be both time-consuming and challenging to implement. As an illustration, consider the Modified Checklist for Autism in Toddlers (M-CHAT), a standardized questionnaire designed for parents. This assessment is typically administered by clinical specialists in carefully controlled clinical settings, and it often requires several hours to complete [6]. So, there is a clear requirement for an intelligent automated detection tool that can enhance the efficiency and ease of the detection process. Numerous physiological and behavioural indicators have proven valuable for detecting ASD in children who are typically developing (TD) [7]. Children diagnosed with ASD exhibit challenges in social interaction, particularly in nonverbal aspects such as replicating eye contact and facial expressions, sharing common attention, engaging in social interactions, and sharing emotions. Extensive literature exists concerning the investigation of eye gaze fixation in children with ASD. The researchers used electroencephalography (EEG) and movement measurements to collect data. The results of these studies suggest that combining machine learning (ML) and eye-tracking technology can help identify unique visual features in people with ASD, which could contribute to autism identification [8]. The use of ML and eye-tracking technology in ASD research has great potential.

By examining patterns in EEG signals, abnormal brain electrical activity related to neurological disorders has been identified. Reference [9] introduced a quantitative method based on EEG data for the automated detection of ASD in TD children, utilizing the area under a second-order difference plot as a distinctive feature. Reference [10] assessed ASD by capturing non-linear attributes from EEG signals. The dataset comprises a total of 73 EEG signals obtained from various patients, with 41 displaying ASD and 32 exhibiting typical neural activity. The researchers explored EEG signals in individuals with ASD by applying the Higuchi Fractal Dimension, demonstrating its effectiveness in assessing the level of nonlinearity within the signals [11]. Reference [12] derived various features, including Autoregressive coefficients, Multifractal wavelet leader estimates, Shannon entropy, and Discrete Fourier Transform coefficients, from the EEG brainwaves of individuals with ASD. They then utilized ML models to classify subjects with ASD and control subjects. Reference [13] applied deep neural network model 2D-DCNN augmented EEG signals.

Children with ASD experience challenges in social interaction, particularly in nonverbal aspects like maintaining eye contact and imitating facial expressions. Students with ASD do not attain similar academic achievements when compared to their peers [14]. Article 26 in the Universal Declaration of Human Rights affirms the right to education for all individuals [15]. Every category of students, including those with disabilities and from minority backgrounds across society, possesses the entitlement to receive an education, which encompasses children with autism spectrum disorder. The education provided to children with autism spectrum disorder is not without its challenges. These students necessitate a unique educational approach and are therefore categorized as having Special Educational Needs (SEN) [16]. Facilitating this specialized education for SEN students is often challenging, primarily because these students face difficulties not only in communication and interaction but also due to the insufficient cooperation between teachers and parents, as well as the scarcity of practical advice and adequate resources to support them. Many studies on autism spectrum disorder rely on extensive statistical analysis. Given that diagnosis is founded on statistical data rather than continuous information, there is potential for some inaccuracies. Consequently, pinpointing their unique educational requirements may also lack precision. However, this can be accomplished more effectively through the use of ML algorithms, which excel at handling extensive datasets with greater precision.

This paper introduces a two-phase system. The first phase is designed to accurately identify autism by processing subjects. While second phase provides in determining the best teaching methods for autistic children. A variety of ML models are applied to classify individual subjects for ASD identification. Multiple features are incorporated to enhance the prediction of each model and compare the results achieved by these selected models in terms of accuracy, precision, recall and F1 score. This paper presents the following primary contributions:

- A Diverse ASD Screening Data for Toddlers dataset is created by merging two datasets of different regions to improve the diversity of the ASD dataset.
- Present a novel ensemble model that amalgamates a random forest (RF) and an XGBoost (XG) classifier, utilizing a voting mechanism to produce the final prediction for autism diagnosis.
- Three feature selection techniques are analyzed in this study including Bi-Directional Elimination (BEFS), Boruta, and ML-based Feature Selection.
- An appropriate teaching approach is recommended by assessing the physical, verbal, and behavioural performance of children with ASD.

The remainder of the research is structured as follows: In Section II, an overview of existing literature on utilizing ML models to predict ASD is presented. Section III introduces the dataset used in the study, outlines the proposed methodology, presents the ML classifiers employed for the analysis, and describes the evaluation parameters. Section IV presents the experimental results and Section V highlights the outcomes derived from the application of our proposed methodology and assesses their relevance to the research objectives.

Finally, in Section VI, we conclude the study by summarizing key findings and discussing their implications.

II. RELATED WORKS

This section offers insight into earlier ML research relevant to the identification of ASD and the exploration of optimal teaching methods for children with autism. Diverse approaches used to reach significant conclusions are examined and elucidate the specific challenges and limitations associated with machine learning within this domain. Over the past decade, ML techniques have emerged as valuable tools for diagnosing ASD in children.

A. ASD DETECTION

ASD is a neurodevelopmental condition characterized by behavioural and cognitive challenges, typically manifesting in early childhood. ASD has evolved into a global medical challenge, presenting substantial economic and emotional burdens on society. An emerging viewpoint posits that the atypical behaviour observed in children with ASD might be a consequence of early brain adaptation to adverse environmental factors, rather than being solely the result of ongoing neural pathology [17]. Children with ASD struggle with shared attention, eye contact, social interactions, and emotional sharing.

In [18], authors devised an ML algorithm that relied on facial scanning patterns for classification, achieving an 82.51% accuracy in identifying children with ASD. This result provides encouraging support for the potential use of ML algorithms in ASD identification. Reference [19] introduced an ML approach to differentiate between the eye fixations of children with ASD and typically developing (TD) children, achieving an impressive classification accuracy of 84%. These investigations highlight the efficiency and objectivity advantages of ML when contrasted with conventional diagnostic scales. Furthermore, children with ASD exhibit challenges in nonverbal communication skills, including facial expression recognition (FER) and expression imitation, in contrast to their TD peers.

In [20], authors assessed the capacity of children with ASD to mimic the facial expressions of others by examining their facial muscles. The findings indicated that spontaneous expression imitation could serve as a behavioural indicator for identifying children with ASD. Reference [21] created an algorithm for the automatic detection of ASD in individuals with attention-deficit hyperactivity disorder. Their approach utilized facial expression data, employing dynamic deep learning and 3D behaviour analysis. The findings from this study highlight the effectiveness of utilizing facial expression data for ASD detection.

In [22], authors conducted an exploration into the feasibility of using various ML techniques such as Naïve Bayes, Support Vector Machine, Logistic Regression, KNN, Neural Networks, and Convolutional Neural Networks to predict and analyze ASD-related issues in individuals across different age groups: children, adolescents, and adults. They applied these techniques to three distinct non-clinical ASD datasets available from the UCI ML repository. The dataset related to ASD screening in children comprised 292 instances and 21 attributes, the dataset for adult subjects contained 704 instances with 21 attributes, and the dataset for adolescent subjects included 104 instances with 21 attributes. Following the application of various ML techniques, the results strongly indicated that CNN-based prediction models outperformed others on all three datasets,

Another research effort introduces an innovative ML approach known as Rules-ML [23]. This method not only identifies autistic traits in both cases and controls but also provides users with rules that can be utilized by domain experts to gain insights into the factors contributing to the classification outcomes. Empirical findings, derived from the analysis of three datasets sourced from the UCI ML repository, which pertain to children, adolescents, and adults, demonstrate that Rules-ML yields classifiers with superior predictive accuracy, sensitivity, harmonic mean, and specificity compared to alternative ML methods.

In [24], authors conducted a study to investigate the effectiveness of ML algorithms, specifically focusing on linear and quadratic discriminant analysis algorithms, for predicting ASD. They utilized data from the UCI data repository to train and test their ML models. A comprehensive evaluation was carried out, considering metrics such as accuracy, precision, sensitivity, Youden Index, F1 score, and AUC. The results indicated that after fine-tuning hyperparameters, the Quadratic Discriminant Analysis (QDA) algorithm achieved the highest proficiency, with an accuracy of 99.7%.

In [25], authors conducted this study with the aim of improving the detection of ASD traits by reducing data dimensionality and eliminating redundancy within the autism dataset. To achieve this objective, they introduced a novel semi-supervised ML framework known as Clustering-based Autistic Trait Classification (CATC). CATC utilizes a clustering technique and validates classifiers through classification methods. Unlike many ASD screening tools that rely on scoring functions, this method identifies potential autism cases based on their similar traits. The empirical results, obtained from various datasets comprising children, adolescents, and adults, were verified and compared to other commonly used ML classification techniques. The findings demonstrated that CATC provides classifiers with superior predictive accuracy, sensitivity, and specificity compared to other intelligent classification approaches such as Artificial Neural Network (ANN), Random Forest, Random Trees, and Rule Induction.

In [26], authors addressed significant concerns related to autism using ML algorithms. Their emphasis lies in the careful selection of essential autism features to enhance classification accuracy. They highlight the importance of choosing the right features and reducing data dimensionality to yield promising results in the diagnosis of ASD. The authors also point out several issues that can impact accuracy, including imbalanced and insufficient dataset sizes, improper sampling techniques, and feature redundancy.

In [27], authors incorporated both Random Forest CART and Random Forest ID3, conducting an evaluation on a similar dataset before integrating the trained model into a mobile app. In another research, [28] examined 25 ML classifiers using a gathered dataset for ASD and determined that SVM based on Sequential Minimal Optimization (SMO) exhibited superior performance in their experimental setting.

B. BEHAVIORAL ANALYSIS OF ASD CHILDREN

In [29], authors observed that individuals with ASD tend to exhibit inappropriate questioning, spontaneous imitation, a lack of interest in people, difficulties with sharing meals, and repetitive use of objects. In their study, [30] explored warning signs indicative of ASD in participants and noted speech delays, repetitive play patterns with toys, and communication challenges. Additionally, they observed a lack of facial expressions, pretend play, imaginative play, interest in purposefully engaging with peers, comprehension of sarcasm, and awareness of personal space.

According to research by [31], individuals with Asperger syndrome demonstrate inflexible adherence to non-functional routines, repetitive and stereotyped motor behaviours, and limited areas of interest. Reference [32] found that people with ASD tend to engage more easily with those who share similar interests, struggle to initiate and maintain peer relationships, and often prefer social isolation.

In [33], authors investigated symptoms of Pervasive Developmental Disorder-Not Otherwise Specified (PDD-NOS) and observed unusual non-verbal movements, a lack of eye contact during interactions, hyperactivity, hostility, and inappropriate laughter. They identified concerns related to rule-breaking and aggressive behaviour, as well as symptoms of anxiety and depression among individuals with PDD-NOS.

In [34], authors examined symptoms of Childhood Disintegrative Disorder and found that participants displayed limited interests, a lack of imagination, sleep problems, and decreased motor abilities. Reference [35] observed that the diagnosis of autistic disorder can be based on factors such as the first REM (Rapid Eye Movement) delay, muscle twitch density, and rapid eye movement density. Although repetitive behaviours may not always be prominent features of autistic disorder, [36] discovered that younger individuals tended to exhibit repetitive motor and sensory behaviours, whereas older individuals with higher IQ scores demonstrated more complex repetitive behaviours.

Although all the above-mentioned studies have a significant contribution to predicting ASD and providing improved accuracy, the academic performance prediction models have room for improvement in prediction accuracy.

III. MATERIALS AND METHODS

ASD is indicative of developmental challenges arising from neural variations within the human brain. Professionals in the field believe that multiple factors interact to contribute to ASD. Diagnosing ASD is a complex undertaking because there is no medical test, such as a blood test, available for detection. Physicians typically employ psychological and observational methods, assessing various aspects of a patient's daily routines, to detect signs of ASD.

This section offers an overview of the research, an introduction to the datasets used in autism detection and the determination of optimal teaching methods through the analysis of autistic children's behaviour. It also outlines the study's proposed methodology and the steps taken to implement it. Furthermore, it provides a brief overview of the ML classifiers employed in the study.

A. OVERVIEW

This study comprises two phases. Phase I focuses on the diagnosis of ASD, employing a combination of statistical and ML techniques on an ASD dataset. In the initial preprocessing step, categorical data is converted into a numerical format, and the SMOTE technique is utilized to address dataset imbalance. Subsequently, three feature selection methods are applied to pinpoint the most influential features, enhancing the performance of ML classifiers. The ML models encompass Random Forest (RF), Decision Trees (DT), Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XG), as well as an ensemble of RF and XG for ASD identification during the classification phase. Additionally, a feature ranking analysis is presented to demonstrate the significance of these features. Figure 1 illustrates a graphical representation of the overall process.

Phase II determines the best teaching methods for children with ASD. To achieve this objective, the model must formulate a procedure that takes data as input, processes it, applies ML algorithms and identifies the optimal fit. Figure 2 provides the teaching strategies suggested in this study.

B. DATA

ASD represents a neurodevelopmental condition that incurs significant healthcare expenses, with the potential for substantial cost reduction through early diagnosis. Unfortunately, the prolonged waiting periods for ASD diagnoses and the associated inefficiencies in diagnostic procedures pose challenges. The global rise in ASD cases underscores the urgent necessity for the development of readily deployable and efficient screening methods. Consequently, there is an imminent need for a time-efficient and easily accessible ASD screening tool, aiding healthcare professionals and providing individuals with valuable guidance on whether to seek formal clinical evaluation. Given the escalating prevalence of ASD worldwide, the scarcity of datasets containing behavioural traits poses a considerable obstacle, hindering comprehensive analyses aimed at enhancing the efficiency, sensitivity, specificity, and predictive accuracy of ASD screening.

This study combines two datasets that used Q-Chat-10 questions for data gathering and named it '*Diverse ASD Screening Data for Toddlers*'. Within the Q-Chat-10

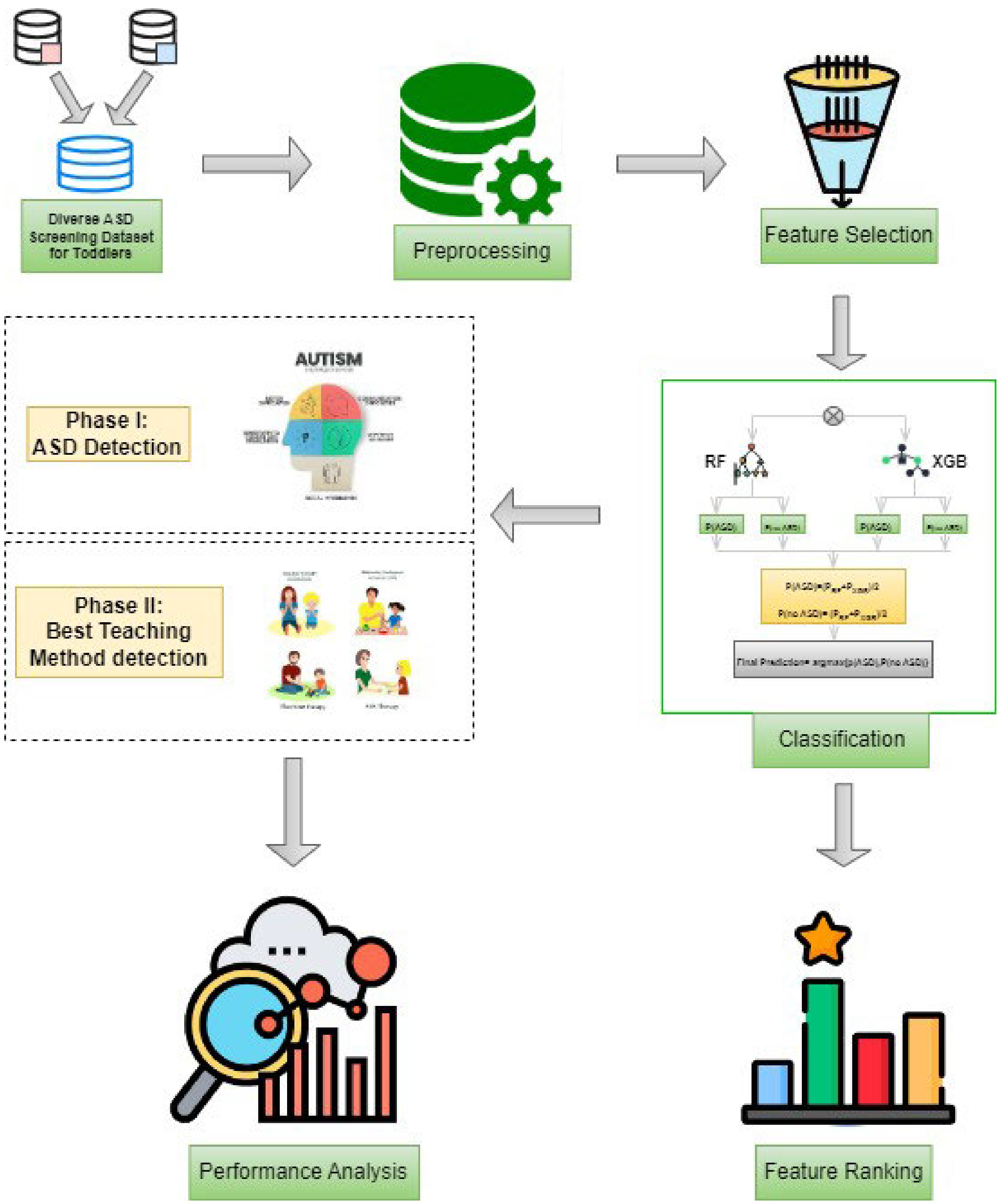

FIGURE 1. **Workflow of proposed methodology.**

questionnaire, responses to items with answer options 'Always,' 'Usually,' 'Sometimes,' 'Rarely,' and 'Never' are transformed into binary values (1 or 0) in the dataset. For questions, 1 to 9 (A1-A9) in the Q-Chat-10, a '1' is assigned to the question if the response was 'Sometimes,' 'Rarely,' or 'Never.' However, for question 10 (A10), a '1' is assigned if the response is 'Always,' 'Usually,' or 'Sometimes.' If a user scores more than 3 points (Q-Chat-10 score) by adding up the scores for all 10 questions, it suggests the presence of potential ASD traits; otherwise, no ASD traits are observed. The complete description is given in Table 1.

1) AUTISTIC SPECTRUM DISORDER SCREENING DATA FOR TODDLERS

The ASD Toddler dataset [37] comprises data obtained from screenings for ASD conducted on toddlers containing key features that can be leveraged for further analysis, particularly in the identification of autistic traits and the refinement of

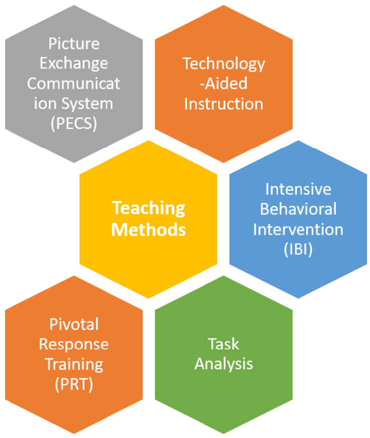

FIGURE 2. **Teaching methods for ASD children.**

ASD case classification. The[1] dataset is available at Kaggle, an online platform of datasets. This dataset encompasses a range of information, including ten behavioural features (Q-Chat-10) along with additional individual characteristics that have demonstrated their effectiveness in distinguishing between ASD cases and control subjects in the field of behavioural science. The dataset contains 1054 instances and 17 columns.

2) ASD SCREENING DATA FOR TODDLERS IN SAUDI ARABIA

This[2] dataset comprises screening information from toddlers aged 12-36 months residing in various regions of Saudi Arabia, differentiating between those with and without Autism Spectrum Disorder (ASD). This data is gathered through an online questionnaire distributed via Google Forms. The questionnaire includes an Arabic translation of the Q-CHAT-10 questions, as well as additional details about the respondents, including their age, gender, geographic region, family history of ASD, and the administrator of the screening test. The dataset contains 506 instances and 17 columns.

C. DATA PREPROCESSING

Categorical data often encompass non-numeric labels or categories, making it imperative to preprocess them into a suitable format for ML models. Label encoding, a widely adopted technique in this context, assigns a unique integer to each category within a feature, thereby facilitating the integration of categorical data into ML workflows.

In this study, label encoding was applied to specific columns (Sr. No. 13-17) within the dataset, transforming categorical features into numeric representations. This preprocessing step was executed with the objective of enhancing the compatibility of the data with a variety of ML algorithms.

[1]https://www.kaggle.com/datasets/fabdelja/autism-screening-for-toddlers

[2]https://www.kaggle.com/datasets/asdpredictioninsaudi/asd-screening-data-for-toddlers-in-saudi-arabia

D. DATA RESAMPLING

Imbalanced datasets, characterized by an uneven distribution of target classes, often necessitate the application of data resampling techniques. Such datasets can pose challenges in classification tasks due to the risk of models exhibiting overfitting to the predominant class. To address this issue, various data resampling methods have been introduced.

Over-sampling is a method that involves augmenting the number of samples in the minority class to match the proportion of the majority class. This augmentation results in a larger dataset, which in turn creates more features for model training, potentially enhancing model accuracy. In this research, we employ the Synthetic Minority Over-sampling Technique (SMOTE) for over-sampling. SMOTE, a cutting-edge approach introduced in [38], was designed to address overfitting issues in imbalanced datasets. SMOTE functions by randomly selecting instances from the minority class and identifying their K-nearest neighbours. Subsequently, new minority class samples are synthesized based on the evaluation of these chosen points using the K-nearest neighbour criteria.

E. FEATURE SELECTION

In ML, effective feature selection is essential for creating high-performing models. Removing redundant and irrelevant features from the original dataset can speed up model training, improve interpretability, and reduce overfitting. In this study, the wrapper method is used for feature selection, as it is well-suited for tailoring the feature set for accurate thyroid disease classification. The selection process is closely linked to the ML algorithm used within the wrapper method. Below, an in-depth explanation of the chosen feature selection techniques and the process of feature selection in ML is provided.

- Bi-Directional Elimination (BEFS) is a feature selection technique that iteratively combines forward and backward selection processes to identify the most relevant subset of features in a dataset. It starts with an empty set and adds features that improve model performance (forward selection) and removes features that don't (backward elimination). This iterative process continues until a stable subset of essential features is obtained. Bi-directional elimination is valuable for efficiently selecting informative features in datasets with large feature spaces, enhancing model interpretability, and improving generalization.
- Boruta is a feature selection method designed for ML and data analysis. It operates by comparing the importance of features in the original dataset with a shuffled version of the same data. Features that consistently show higher importance in the original data are considered important and retained, while less important features are discarded. Boruta is particularly useful for datasets with a mix of relevant and irrelevant features, as it provides a systematic and data-driven approach to feature selection. It helps streamline feature

TABLE 1. Diverse ASD screening data for toddlers dataset features and their description.

Sr no.	Attribute	Description	Type	Count
1	A1	Does your child look at you when you call his/her name?	Categorical	1=879 ,0= 681
2	A2	How easy is it for you to get eye contact with your child?	Categorical	1=720 ,0= 840
3	A3	Does your child point to indicate that s/he wants something?	Categorical	1=682 ,0=878
4	A4	Does your child point to share interest with you?	Categorical	1=806 ,0=754
5	A5	Does your child pretend? (Talk on toy phone, Care for dolls etc.)	Categorical	1=836 ,0= 724
6	A6	A6 Does your child follow where you're looking?	Categorical	1=886 ,0=674
7	A7	If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them?	Categorical	1=965 ,0=595
8	A8	Would you describe your child's first words	Categorical	1=775 ,0=785
9	A9	Does your child use simple gestures? (e.g. wave goodbye)	Categorical	1=791 ,0= 769
10	A10	Does your child stare at nothing with no apparent purpose?	Categorical	1=932 ,0=628
11	Age	It shows the Toddlers age in months	Number	Mean=26.75 , STD= 8.25
12	Score by Q-chat-10	Score by Q-chat-10	Number 1-10	Mean= 5.30 , STD= 2.99
13	Sex	Male or Female	Categorical	Female=668 , Male= 892
14	Ethnicity	List of Regions	Categorical	Al Baha=7, Najran = 9, Tabuk = 18, Jizan = 19, Makkah = 217, Aseer = 13, Northern Borders = 15, Riyadh = 85, Ha'il = 16, Madinah = 23, Eastern = 50, Al Jawf = 12, Qassim = 22, Asian= 299, Black=53, Hispanic =40, Mixed= 8, Middle Eastern= 188 , Native Indian=3 , Pacifica=8 , South Asian=60 , White European= 334, Others= 35.
15	Family member with ASD history	Whether any immediate family member has a PDD	Boolean	Yes= 292, No=1268
16	Who is completing the test	Parent, self, caregiver, medical staff, clinician, etc.	categorical	Family Members= 1435, Others=125
17	Class	ASD Trait	Boolean	Yes=1069 , No=491

engineering, reduce dimensionality, and improve model interpretability while being resilient against overfitting and suitable for various data types.

- ML-based Feature selection (MFS) is employed using the Extra Trees Classifier (ETC) is a valuable technique in ML. ETC assesses feature importance by constructing multiple decision trees with random feature subsets, providing a measure of each feature's contribution to predictive performance. It is robust against overfitting, suitable for various data types, and aids in creating more efficient and interpretable ML models. Researchers often use ETC to rank and select the most relevant features, streamlining the model development process and improving model efficiency and accuracy Figure 3 shows the feature importance using the ETC model.

F. MACHINE LEARNING MODELS

In this section, the application of supervised ML models by using the Natural Language Processing Toolkit (NLTK) and Scikit-learn libraries is investigated. Nine distinct ML algorithms are employed. A total of six ML algorithms are utilized, encompassing RF, LR, XG, SGD, SVM, KNN and DT. The implementation of all these models is carried out using the Python programming language. Hyperparameter tuning values are presented in table 2.

Random Forest (RF) [39], an ensemble model built upon decision trees and widely used for classification tasks, achieves high prediction accuracy by combining the outputs of multiple weak learners. It employs the bagging technique to train decision trees, creating bootstrap datasets by randomly subsampling from the original training data. During tree construction, attribute selection is crucial for determining splits in the decision trees. In summary, Random Forest is a powerful ensemble method for classification that leverages decision trees and bagging to make accurate predictions.

A Decision Tree (DT) Classifier [40] is a ML algorithm used for classification tasks. It creates a tree-like structure to make predictions, with each branch representing a feature outcome and each leaf denoting a class label. Decision trees are known for their simplicity, feature importance assessment, and ability to handle both categorical and numerical data. They can be prone to overfitting but offer ways to control it. Decision trees are the basis for ensemble methods and find applications in various fields, offering transparency and interoperability.

Logistic Regression (LR) [41] is a widely used statistical technique in machine learning for binary classification tasks. It models the probability of an event occurring and establishes a linear decision boundary in feature space. This method is prized for its interpretability, making it useful for understanding feature impacts and relationships. Logistic Regression can be regularized to prevent overfitting and extended to handle multiclass classification. It finds applications in diverse fields such as healthcare, marketing, and finance due to its simplicity and effectiveness.

XGBoost (XG) [42]is an influential ML algorithm based on gradient boosting and ensemble learning. It primarily uses decision trees, includes regularization for preventing overfitting, and provides feature importance scores. It is known for its speed and efficiency, can handle missing data, and is widely applicable in various tasks. XGBoost's versatility, scalability, and open-source nature have made it a favoured choice for predictive modelling, particularly in data science competitions and real-world applications.

Support Vector Machines (SVM) [43] are robust and versatile machine learning algorithms. They excel in binary classification by finding a hyperplane that maximizes the margin between two classes. SVM can also handle non-linear problems through kernel functions and is robust to outliers. It can be extended to multi-class classification and regression tasks. SVM models are interpretable and find applications in various fields, but they may face scalability issues with very large datasets.

Gradient Boosting Machine (GBM) [44] is an ensemble learning technique used for classification and regression tasks. It builds a strong predictive model by sequentially training decision trees to correct errors from previous iterations, optimizing a loss function through gradient descent. GBM is known for its high predictive accuracy, feature importance analysis, and ability to handle complex relationships in data. However, it requires careful hyperparameter tuning and can be computationally intensive. Specialized libraries like XGBoost and LightGBM have further enhanced its performance and scalability.

K-Nearest Neighbors (KNN) [45] is an instance-based ML algorithm used for classification and regression. It makes predictions by identifying the K nearest data points from the training set based on a similarity metric. KNN is versatile but requires choosing an appropriate K value and distance metric. It can be computationally expensive, particularly with high-dimensional data, and is suitable for various applications, including recommendation systems and image recognition.

In this study, the proposed approach is designed by integrating soft voting criteria with RF and XG. In soft voting, the outcome with the highest likelihood is recognised as the final result. Algorithm 1 shows how the proposed model works.

Algorithm 1 Ensembling RF and XG

Input: input data $(x, y)_{i=1}^{N}$
M_{RF} = Trained RF
M_{XG} = Trained XG
for $i = 1$ to M **do**
  if $M_{RF} \neq 0$ & $M_{XG} \neq 0$ & $training\_set \neq 0$ **then**
    $P_{RF_1} = M_{RF_1}.probability(class1)$
    $P_{RF_2} = M_{RF_2}.probability(class2)$
    $P_{XG_1} = M_{XG_1}.probability(class1)$
    $P_{XG_2} = M_{XG_2}.probability(class2)$
    Decision function = $max(\frac{1}{n}\sum_{classifier}(Avg(P_{RF_1}, P_{XG_1}), Avg(P_{RF_2}, P_{XG_2})$
  end if
  return final label $\widehat{p}$
end for

The soft voting criteria can be modelled mathematically as: The estimated probability from each individual classifier is blended in a soft voting aggregation procedure to get the final predicted probabilities for the ensemble model. The following is the soft voting aggregation formula:

$$Final\_predicted\_probabilities = (1/n) \times \sum(predicted\_probabilities\_i) \quad (1)$$

where:
Final_predicted_probabilities are the combined predicted probabilities for the ensemble model.
n is the total number of individual classifiers in the ensemble. In our case, it is two.
predicted_probabilities_i represents the predicted probabilities from the $i-th$ individual classifier.

In the soft voting method, the projected probabilities from each classifier are averaged, giving each classifier's contribution equal weight. The ensemble's final prediction is then based on the final anticipated probabilities, often by choosing the class with the highest probability.

TABLE 2. Hyperparameter setting of ML models used in this research work.

Classifiers	Parameters
RF	number of trees=100, random state=25, maximum depth=20
DT	number of trees=100, random state=25, maximum depth=20
LR	solver='lbfgs', penalty='l2'
KNN	number of neighbors=10, algorithm='auto'
SVM	C=1.0, gamma='auto', kernel='rbf'
GBM	number of trees=100, learning rate=0.1, random state=25, maximum depth=20
XGBoost	cat_smooth=10, cat_l2=1.0, tree_method="hist"

G. EVALUATION METRICS

In the assessment of various classifiers on the Diverse ASD Screening Data for Toddlers Dataset, the significance of mathematical metrics comes to the forefront. These metrics serve as essential tools for quantifying the performance of these classifiers. Accuracy, Precision, Recall, and the F1 score are particularly vital in this context.

Accuracy reflects the overall correctness of predictions, giving us a measure of how well a classifier correctly identifies both ASD and non-ASD cases.

Precision delves into the ability of the classifier to precisely identify ASD cases among those it classifies as such, minimizing false positives.

Recall, also known as Sensitivity, gauges the model's effectiveness in identifying all actual ASD cases, reducing false negatives.

The F1 score harmonizes both Precision and Recall, offering a balanced evaluation metric that considers the trade-off between these two factors. Together, these metrics provide a comprehensive view of how well classifiers perform on ASD datasets, aiding in the development of accurate diagnostic tools and interventions for individuals within the autism spectrum. The ensuing equations were employed to calculate Accuracy, Precision, Recall, and the F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

In this context, "True Positive (TP)" signifies the correct identification of an ASD sample as having ASD. "True Negative (TN)" represents an accurate prediction of a non-ASD sample as non-ASD. "False Positive (FP)" indicates the erroneous identification of ASD data as non-ASD data. "False Negative (FN)" pertains to non-ASD samples that were mistakenly classified as ASD samples.

IV. RESULTS

Experiments are conducted to predict ASD using a Dell PowerEdge T430 GPU with 2GB of memory. This system is equipped with two Intel Xeon processors, each featuring 8 cores running at a clock speed of 2.4 GHz, and it boasts 32GB of DDR4 RAM. The experimentation took place within the Jupyter Notebook environment, utilizing the Python programming language. For implementing the ML models, this study leveraged the widely-used sci-kit-learn library, renowned for its popularity in the Python ML community.

This study is based on two phases. In phase I, the ASD is predicted using the Diverse ASD Screening Data for Toddlers Dataset. A set of ML classifiers including RF, DT, LR, KNN, SVM, GBM and XG are employed. The dataset is split into training and testing subsets, adhering to an 80:20 ratio, allocating 80% of the data for model training and reserving the remaining 20% for model testing. After that, the models were trained using selected significant features through feature selection techniques. Subsequently, their performance was assessed using a combination of 20% test data. Then, a 10-fold cross-validation approach is applied. In phase II, the best teaching method for children with ASD is detected using ML models using the same settings and dataset as used in phase I.

A. PHASE I

1) MODEL EVALUATION WITH ORIGINAL FEATURES

Table 3 presents the outcomes obtained from ML models utilizing the original feature set. These models demonstrate commendable performance across all evaluation metrics. Notably, tree-based models such as RF, and XG exhibit strong performance, achieving accuracy scores of 0.92. Remarkably, these tree-based ensemble models excel even when working with an original feature set and a large dataset.

Conversely, linear models such as LR and SVM exhibit suboptimal performance due to the constraints imposed by the feature set and dataset type. LR and SVM yield accuracy scores of 0.85 and 0.89 respectively. However, RF-XG stands out as the superior model when evaluated with the original dataset, outperforming all other models with 0.94 value of accuracy, 0.93 value of precision, 0.95 value of recall and 0.94 value of F1 score.

TABLE 3. Experimental results using original features set.

Model	Accuracy	Precision	Recall	F1 Score
RF	0.92	0.94	0.94	0.94
DT	0.90	0.90	0.90	0.90
LR	0.85	0.83	0.82	0.82
KNN	0.91	0.93	0.90	0.91
SVM	0.89	0.91	0.88	0.90
GBM	0.91	0.92	0.90	0.91
XG	0.92	0.93	0.93	0.93
RF-XG	0.94	0.93	0.95	0.94

2) MODEL EVALUATION WITH BI-DIRECTIONAL ELIMINATION

Table 4 illustrates the performance of ML models when employing the Bi-Directional Elimination technique. In comparison to the original features, all models exhibit a decrease in performance with this feature selection technique.

RF and XG achieved the highest accuracy scores of 0.91 and 0.92, respectively, followed closely by RF-XG with an accuracy of 0.92. DT and GBM also demonstrated good performance with accuracy scores of 0.89 and 0.90, respectively. When it comes to Precision, RF-XG outperforms all other models with a score of 0.92, indicating its ability to correctly identify positive cases. In terms of recall, RF-XG and RF stand out with scores of 0.93 and 0.90, respectively, showcasing their effectiveness in capturing all positive instances. Finally, the F1 Score, which balances precision and recall, shows that RF-XG maintains a strong overall performance at 0.92. These results provide valuable insights into the suitability of different ML models for the given task, with RF-XG exhibiting the most promising performance in predicting autism.

TABLE 4. Experimental results using Bi-Directional elimination.

Model	Accuracy	Precision	Recall	F1 Score
RF	0.91	0.90	0.90	0.90
DT	0.89	0.91	0.90	0.90
LR	0.85	0.87	0.89	0.88
KNN	0.84	0.85	0.85	0.85
SVM	0.87	0.88	0.90	0.89
GBM	0.90	0.85	0.87	0.86
XG	0.91	0.90	0.91	0.91
RF-XG	0.92	0.92	0.93	0.92

3) MODEL EVALUATION WITH BORUTA FEATURE SELECTION

The performance of models utilizing the ML feature selection technique is presented in Table 5 This approach demonstrates the significance of models, with Random Forest (RF) achieving the highest accuracy of 0.9889 when employing the Boruta Feature Selection technique. RF-XG surpasses all other models with an Accuracy score of 0.98, demonstrating exceptional predictive capabilities. In terms of Precision, RF-XG maintains a high score of 0.98, indicating its ability to correctly classify positive cases with minimal false positives. When it comes to Recall, RF-XG outperforms all other models with a score of 0.99, showcasing its effectiveness in capturing nearly all positive instances. Finally, the F1 Score, which balances Precision and Recall, highlights RF-XG's strong overall performance at 0.98.

These results reveal that the Boruta feature selection method has led to improved model performance compared to the previous Bi-Directional Elimination method. RF-XG stands out as the top-performing model across multiple metrics, demonstrating its robustness and suitability for the given task. The feature selection process seems to have enhanced the models' ability to make accurate predictions and capture positive instances, leading to higher overall performance scores. The significance of Boruta Feature Selection lies in its ability to select features based on their correlation with the target variable. A higher correlation indicates greater feature importance. This significance of Boruta Feature Selection results in the selection of a concise yet effective feature set for training ML models.

4) MODEL EVALUATION WITH MFS

Table 6 displays the performance of models utilizing the ML-based Feature Selection technique. According to the results, the SVM and LR have shown an improvement in their performance, increasing from an accuracy up to 0.94 and 0.93 respectively. This enhancement is attributed to the selected features rendering the data more linearly separable, thus aiding SVM in establishing a well-defined hyperplane with a substantial margin for effective data classification.

TABLE 5. Experimental results using Boruta features selection.

Model	Accuracy	Precision	Recall	F1 Score
RF	0.95	0.97	0.96	0.97
DT	0.92	0.92	0.92	0.92
LR	0.89	0.89	0.87	0.88
KNN	0.93	0.95	0.94	0.94
SVM	0.90	0.94	0.90	0.92
GBM	0.90	0.93	0.93	0.93
XG	0.96	0.98	0.97	0.97
RF-XG	0.98	0.98	0.99	0.98

The results indicate that the feature selection technique employed in this experiment has further enhanced the models' performance compared to both the Bi-Directional Elimination and Boruta feature selection methods. Notably, RF-XG emerges as the top-performing model across all metrics, achieving an exceptional Accuracy score of 0.99, indicating its superior predictive capability. Its Precision score of 0.99 highlights its ability to classify positive cases with minimal false positives. Additionally, RF-XG's Recall score of 0.99 showcases its effectiveness in capturing nearly all positive instances. The F1 Score, which balances Precision and Recall, reaffirms RF-XG's outstanding overall performance at 0.99.

These results demonstrate that the ML-based feature selection technique has significantly improved the models' ability to make accurate predictions and capture positive instances, resulting in a substantial boost in overall performance. RF-XG, in particular, stands out as an excellent choice for the given task due to its consistently high scores across all metrics. This suggests that the feature selection process has identified and retained the most informative features, enabling the models to achieve exceptional results.

TABLE 6. Experimental results using ML feature selection.

Model	Accuracy	Precision	Recall	F1 Score
RF	0.98	0.98	0.97	0.98
DT	0.96	0.96	0.95	0.95
LR	0.93	0.97	0.95	0.96
KNN	0.95	0.96	0.96	0.96
SVM	0.94	0.95	0.97	0.96
GBM	0.94	0.94	0.97	0.95
XG	0.97	0.98	0.98	0.98
RF-XG	0.99	0.99	0.99	0.99

B. FEATURE RANKING

The importance of features is evaluated using ML-based feature selection techniques. Figure 3 provides a visual representation of this analysis, highlighting the relevance of different attributes associated with autism. Remarkably, among the considered characteristics, A8 emerges as the standout feature, demonstrating its pronounced importance in the context of our study. Following closely in significance are A7, A6, A1, and A2, which collectively contribute significantly to the predictive power of our model. These key attributes play pivotal roles in understanding and predicting autism-related outcomes.

On the other end of the spectrum, we find that certain attributes, such as Gender, FM ASD, Region, Age, A4, A10, and others, hold relatively lower importance in our feature selection process. While they may still carry some degree of relevance, their influence on the predictive model is comparatively limited.

This comprehensive analysis not only highlights the critical features but also offers valuable insights into the relative importance of each attribute, aiding in the refinement of our predictive models and the interpretation of autism-related data.

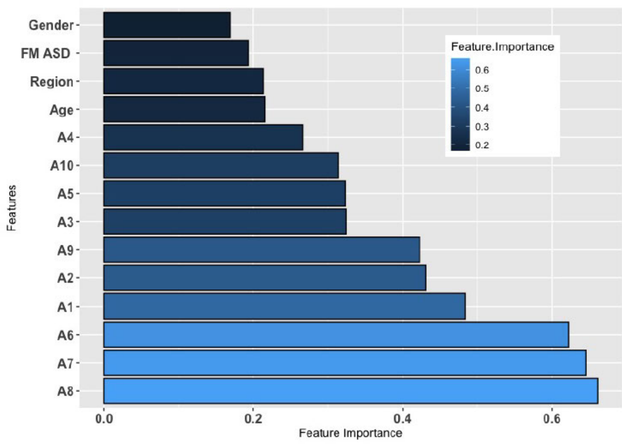

FIGURE 3. Ranking of features using ML feature selection.

C. RESULTS OF K-FOLD CROSS-VALIDATION

To assess the efficacy of the proposed model, this research incorporates k-fold cross-validation. The outcomes of the 10-fold cross-validation are presented in Table 7. The cross-validation results demonstrate that the proposed model achieves an average accuracy score of 0.986. Moreover, the average precision, recall, and F1 score are calculated as 0.987, 0.988, and 0.986, respectively. These results further validate the effectiveness of the proposed model.

TABLE 7. Results of 10-fold cross-validation for the proposed approach.

Fold Number	Accuracy	Precision	Recall	F-Score
Fold-1	0.982	0.985	0.984	0.985
Fold-2	0.984	0.986	0.985	0.986
Fold-3	0.986	0.987	0.986	0.987
Fold-4	0.988	0.989	0.999	0.988
Fold-5	0.989	0.989	0.988	0.988
Fold-6	0.999	0.989	0.989	0.988
Fold-7	0.985	0.989	0.986	0.987
Fold-8	0.987	0.988	0.987	0.988
Fold-9	0.987	0.987	0.988	0.988
Fold-10	0.989	0.989	0.989	0.989
Average	**0.986**	**0.987**	**0.988**	**0.986**

D. PHASE II:

The aim of this study is to employ an ML Algorithm capable of identifying patterns within autistic traits, gender, and other relevant factors associated with autism. The ultimate objective is to predict the most appropriate educational method for each individual. In this phase of the experiment, a new column namely 'Teaching Method' is added to the dataset using the numpy library. This column contains integers ranging from 1 to 6, representing the six specialized teaching methods, and includes the number 0 to indicate that no special education is needed. We assign teaching methods on the basis of the severity of Autistic behaviour. This severity is analyzed on the basis of the Q-Chat-10 score of the dataset which is based on the count of A1-A10 values. The children having a high score are at a high level of severity. These severity levels are presented in figure 4.

High-Level Autistic Children: Pivotal Response Training (PRT): PRT can be effective for high-level autistic children as it focuses on developing pivotal skills such as motivation, initiation, and social communication. It allows for more natural and child-led interactions.

Moderate to High-Level Autistic Children: Technology-Aided Instruction: Technology can be engaging for children with moderate to high-level autism, as it can provide structured and interactive learning experiences. Customized apps and software can be used to target specific skills.

Moderate-Level Autistic Children: Picture Exchange Communication System (PECS): PECS can be valuable for children with moderate autism, providing a visual means of communication that helps bridge language gaps.

Low to Moderate-Level Autistic Children: Task Analysis: Task analysis can break down complex skills into manageable steps, making it suitable for children who need explicit, structured instruction.

Low-Level Autistic Children: Intensive Behavioral Intervention (IBI): IBI is an intensive form of Applied Behavior Analysis (ABA) designed for children with significant developmental delays, including low-level autism.

This phase considers the Teaching methods column as the target class and uses other columns of the dataset for training.

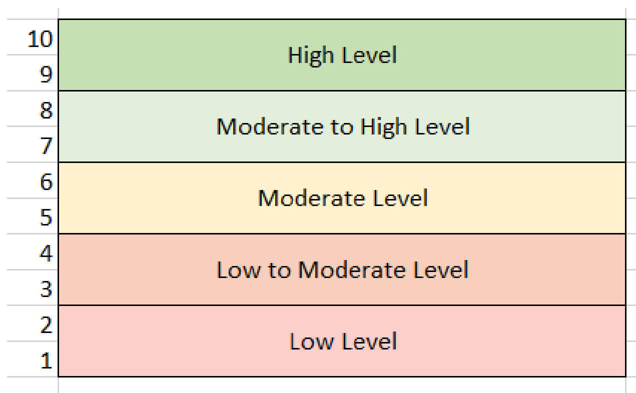

FIGURE 4. Severity levels of autism.

1) MODEL EVALUATION FOR SELECTING BEST TEACHING METHOD FOR CHILDREN WITH ASD

Finally, the predicted values of teaching methods are checked with the values of the testing set to calculate the accuracy of the algorithms. Table 8 presents the results of ML models. The results indicate that these classifiers are being assessed for their ability to recommend the best teaching method for children with ASD based on their predictive performance. Among the models, RF-XG emerges as the top-performing classifier, with an impressive accuracy score of 0.9917, signifying its high level of accuracy in making predictions. RF-XG also demonstrates excellent precision, recall, and F1 scores, all reaching 0.99, suggesting its ability to make precise recommendations while capturing a high percentage of relevant cases.

These results are crucial in the context of selecting the best teaching method for children with ASD, as they highlight the classifiers' effectiveness in making accurate and reliable recommendations. RF-XG, in particular, appears to be the most suitable model for this task due to its consistently high scores across all evaluation metrics. This information can be valuable for educators and professionals working with children with ASD, as it helps them make informed decisions about teaching methods that can have a significant impact on the children's learning and development.

TABLE 8. Experimental results of classifiers for selecting best teaching method for children with ASD.

Model	Accuracy	Precision	Recall	F1 Score
RF	0.9899	0.98	0.98	0.98
DT	0.9241	0.92	0.92	0.92
LR	0.8991	0.89	0.89	0.89
KNN	0.9434	0.94	0.94	0.94
SVM	0.8521	0.85	0.84	0.85
GBM	0.9430	0.95	0.96	0.96
XG	0.9721	0.97	0.97	0.97
RF-XG	0.9917	0.99	0.99	0.99

V. DISCUSSION

Numerous investigations have explored ASD datasets; however, the accuracy of ASD prediction models still requires substantial enhancement. This study undertook the task of gathering ASD datasets and addressing class imbalance by employing the SMOTE method. Subsequently, a range of classifiers, including RF, DT, LR, KNN,SVM, GBM, XG and RF-XG are applied for ASD detection and selecting the best teaching methods for children with ASD. Following that, three feature selection techniques are employed including BiEFS, Boruta, and MFS feature selection. Finally, RF-XG in combination with MFS outperformed other approaches enhanced the efficiency of ASD detection and performed well in detecting the best teaching method for children with ASD.

The study findings unveil a range of pivotal and pertinent features for the early diagnosis of ASD. Notably, A8, A7, A6, and A1 emerged as the most critical attributes according to the ML model's perspective. This comprehensive investigation underscores the sufficiency of key attributes in ASD recognition, promising effective applications in ASD diagnosis and selecting the best teaching methods for children with ASD.

A. PERFORMANCE COMPARISON WITH STATE-OF-THE-ART APPROACHES

The proposed model is compared with relevant prior research findings in Table 9. It's worth noting that a majority of previous studies primarily utilized small ASD datasets. For instance, [46] employed feature transformation techniques and achieved impressive results, with a maximum accuracy of 98.77%. In another study, [47] utilized feature selection methods, attaining top scores in accuracy score of 97.82%. [48] implemented a feature transformation approach that yielded the highest accuracy of 99.25%. A recent study [49] has achieved 99.85% of accuracy in ASD detection.

The proposed approach introduced in the current study incorporates feature selection and leverages a combination of Random Forest and XGBoost (RF-XG) with MFS (ML-based Feature selection). This approach achieved an exceptional accuracy rate of 99.99%. This result suggests that the proposed method surpasses the performance of the state-of-the-art studies, making it a significant and promising contribution to the ASD Detection task.

TABLE 9. Performance comparison with state-of-the-art studies.

Reference	Feature Selection	Approach	Accuracy
[46]	No	LR	98.77%
[47]	Yes	SVM, AdaBoost, Glmboost	97.82%
[48]	No	AdaBoost , LDA	99.25%
[49]	Yes	AdaBoost	99.85%
Proposed	Yes	RF-XG with MFS	99.99%

VI. CONCLUSION AND FUTURE WORK

Autism Spectrum Disorder (ASD) is a complex neurological condition that can have a profound impact on cognitive functions, including language comprehension, object recognition, interpersonal skills, and communication. Although ASD is primarily genetic, early detection and intervention can help to reduce the need for expensive medical procedures and lengthy diagnostic processes. One of the key challenges after detecting ASD is finding practical teaching approaches. This is because ASD is a highly diverse spectrum, and each child with ASD has a unique set of characteristics and needs. It is widely acknowledged that no two autistic children are alike, which underscores the individuality of their experiences and requirements.

This study merged two ASD screening datasets for toddlers and used the SMOTE method to balance the dataset. The study then employed rigorous feature selection techniques to develop a two-phase system. In the first phase, a variety of ML models, including an ensemble of random forest and XGBoost classifiers, were used to accurately identify ASD. In the second phase, the study focused on identifying tailored teaching methods for children with ASD by evaluating their physical, verbal, and behavioral performance. The overall goal of this study was to contribute to the development of personalized educational strategies for individuals with ASD by using ML to improve the precision of addressing their distinct and diverse needs.

As our understanding of ASD and the capabilities of ML advance, we move closer to providing more effective support and interventions for individuals on the autism spectrum. The individuality of each child with ASD remains at the forefront, and our quest to identify optimal teaching methods is a dynamic and ongoing journey in the field of autism research and education. The future work directions of this research problem is to make use of more complicated and real-world data with transfer learning models to make a more genuine approach to this problem.

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FAHIMA HAJJEJ received the Ph.D. degree in computer science from the Faculty of Sciences of Sfax, in 2017. She is currently an Assistant Professor with the Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University (PNU), Saudi Arabia. She is also a member of the Research Laboratory in Technologies of Information and Communication and Electrical Engineering (LaTICE). Her research interests include the modeling concepts of e-learning, e-assessment, the integration of formal and semi-formal methods, data science, and big data.

SARRA AYOUNI received the M.S. degree from the Faculty of Sciences of Tunis (FST) and the Ph.D. degree in computer science from the University of Montpellier 2, France. She is currently an Assistant Professor with the Department of Information Systems, College of Computer and Information Sciences (CCIS), Princess Nourah bint Abdulrahman University (PNU), where she is also a Coordinator of Distance Education. Her main research interests include data science, artificial intelligence, fuzzy datamining, and e-learning.

MANAL ABDULLAH ALOHALI received the Ph.D. degree in computer science from the University of Plymouth, U.K. She is currently an Assistant Professor with the Information Systems Department, College of Computer and Information Sciences (CCIS), Princess Nourah bint Abdulrahman University (PNU), Saudi Arabia. She is also the Dean of CCIS. Her research interests include information systems, machine learning, and cyber security. She received the PNU Research Excellence Award.

MOHAMED MADDEH received the Ph.D. degree in computer science from the National School of Computer Sciences of Tunis (ENSI), in 2013. He was an Assistant Professor in computer science with the Higher Institute of Finance and Taxation of Sousse (ISFF). He was an Analyst and Data Base Administrator with the Ministry of Social Affairs, from 2003 to 2009. He served in many administrative positions with King Saud University. He was a Coordinator of the web and computer certification (moodle) in collaboration with the Virtual University of Tunis (UVT). He was the Head of the Department of Law and Finance, ISFF, in 2014. He is currently an Assistant Professor with King Saud University. His main research interests include the fields of software engineering and model driven engineering. He was a member of the Scientific Committee of ISFF, in 2011. He was also a Treasurer of the Tunisian Association of Artificial Intelligence (ATIA).