Early Prediction of Autism Spectrum Disorder (ASD) using Machine Learning

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***Abstract*—A multifaceted neuro-developmental disorder, autism spectrum disorder (ASD) is highly disruptive to social interaction, communication, and behavior. Early prediction and intervention are most relevant to improving outcomes. Machine learning techniques for improving auspicious prediction of autism spectrum disorders are investigated through advanced preprocessing, feature selection, and model optimization methods. A structured dataset has been preprocessed from behavioral, developmental, and demographic attributes of 200 children (100 having autism spectrum disorders and 100 non-autistic) from a developmental clinic. Several machine learning algorithms were applied—including Random Forest, XGBoost, AdaBoost, and Support Vector Machines—to train and validate. Among the feature importance analysis, ”Reaction to Daily Routines Changes” and ”Pointing at Desired Objects” were the most significant indicators. The ensemble models manage to reach the top-level accuracy of 95 percent and robustly show its performance through ROC curve and confusion matrix analysis. The work extends previous research and also opens up new horizons in feature engineering and model comparison for effective data-driven ASD diagnostic frameworks.**

***Index Terms*—autism, autism spectrum disorder, machine learning, feature Selection, ASD**

1. INTRODUCTION

Autism spectrum disorder (ASD) is one of the complex neuro-developmental conditions associated with ongoing deficits in social communication, impaired interaction, and restricted, repetitive patterns of behavior [3]. A very large fraction of the population is affected, and meta-analyses in the last few years have estimated the global prevalence to be in the range of 0.7–1.0% in children [17]. The disorder carries considerable individual and societal burdens, affecting education, employment, and health care [4], [7], [17].

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However, early identification of ASD is an important milestone. Even a few years of delay would mean deferred intervention, worsening long-term outcomes. Traditional diagnostic instruments such as clinical observations and ADOS/ADI interviews usually take a long time and often identify ASD only later in childhood [11], [13]. Such cases may be too late for effective early intervention, and many children remain undiagnosed during the critical early developmental window [13].

This diagnostic gap has provided the impetus for seeking automated, data-driven methods for early screening that can highlight ASD risk at younger ages. Recent advances in machine learning (ML) and artificial intelligence show promise in the development of early markers for these disorders. Since ML can extract complex multivariate patterns from large datasets, it complements manual screening by offering faster and potentially more objective evaluations. For instance, large clinical cohorts such as the SPARK genetic study have been subjected to ML algorithms to identify minimal feature sets highly predictive of ASD [10].

Models such as Support Vector Machines (SVM), Random Forest (RF), and gradient-boosted trees (XGBoost) have reliably classified individuals using behavioral and medical features [3], [6]. Deep learning approaches, such as convolutional or recurrent neural networks, have also been successfully applied to high-dimensional datasets including brain imaging and genetic profiles [5], [9], [14]. In particular, ensemble methods that combine different classifiers can offer robustness and accuracy improvements. Bagging and boosting ensembles have been shown to outperform their single-model baselines in multiple ASD prediction studies [1], [8], [18].

All these advances suggest that machine learning, particularly ensemble methods and deep learning approaches, may enable extremely sensitive and specific early ASD screening as never achieved before.

2. RELATED WORK

Various machine learning (ML) approaches have been explored to enhance early diagnosis of Autism Spectrum Disorder (ASD). Traditional classifiers such as Support Vector Machines (SVMs), logistic regression, k-Nearest Neighbors (k-NN), and neural networks have been commonly used on datasets assessing behavior and questionnaire responses. Rasul et al. demonstrated that SVMs and logistic regression performed well on adult and child ASD datasets, with deep learning models achieving over 90 percent accuracy in many cases [11]. On toddler screening data, Alsbakhi et al. showed that a simple neural network was more accurate (94 percent) than SVM (91 percent) and decision trees (87 percent) [5].

Ensemble methods have reported some of the most significant successes in ASD classification. Noor et al. achieved 97.2 percent accuracy using Random Forest, outperforming k-NN and SVM baselines [5]. Jayalakshmi and Geetha developed an AdaBoost model integrated with rough-set feature selection, resulting in enhanced classification performance for adult ASD detection [1]. Twala and Molloy highlighted the superiority of bagging and boosting, demonstrating that ensembles surpassed single classifiers when predicting therapy outcomes in autistic children [18]. Gombar introduced XMAP, a multimodal autism predictor using XGBoost, which achieved high accuracy and interpretability by combining behavioral and synthetic data sources [6].

Deep learning methods have also gained attention. Convolutional Neural Networks (CNNs) have been applied to neuroimaging data (e.g., MRI scans), distinguishing ASD from neurotypical subjects [9]. Hybrid models like CNN–LSTM were utilized on gene expression datasets and outperformed traditional methods due to their ability to capture both spatial and temporal patterns [14]. Though such models require large datasets for optimal performance, they have demonstrated superior predictive capabilities when sufficient data is available.

Feature selection continues to be essential for improving model performance. Chi-square testing and wrapper-based selection techniques are frequently used to identify the most relevant predictors before classification [15]. Furthermore, studies often use 10-fold cross-validation to ensure statistical reliability and avoid overfitting [5]. For example, Alrdees et al. achieved nearly 99 accuracy classification accuracy on toddler datasets using XGBoost combined with chi-square-selected features [15].

The scale and diversity of datasets also play a vital role. Rajagopalan et al. trained models on the SPARK dataset (over 30,000 participants), showing that minimal yet informative features could successfully detect ASD at an early stage [17]. Other large-scale studies, such as those using ABIDE neuroimaging datasets, reinforce that broad and multimodal data sources significantly enhance generalizability [18].

In summary, previous research strongly supports the effectiveness of ensemble learning, deep neural networks, feature selection techniques, and robust validation protocols in developing reliable early-stage ASD prediction systems.

3. DATA COLLECTION PROCESS

In the first place, we are supposed to visit the Children's Hospital Lahore to gather information for this investigation. On getting here, we learned that prior appointment was required for going ahead. After fixing one such appointment with them, we returned back to the hospital entering the administration office, where a clerk handling patient records guided us to Director Medical Education. In our meeting with the director, he suggested the complications involved in data provision owing to privacy issues about the autistic children and hospital reputation. For that reason, we started looking for alternative sources of data collection.

We went to several autism centers in our quest on data acquisition, and from our experience, one of the centers- "Autism Center Pakistan"- which was highly cooperative, required hard copies of our Google Forms, which we did submit. Thereafter, the personnel at this particular center filled in the forms, which finally gave us sample size comprising 100 autistic children. After collecting the hard copies, we entered the data manually in Google Forms to create a soft copy of the collected data. The raw data was converted into a CSV file containing 100 patient records. To address the issue of class imbalance, we fetched data from about 100 healthy children to get an equal weightage of dataset for our study.

The answers obtained for the structured Google Form questionnaire are shown using the bar charts, with each bar chart corresponding with each of the 15 questions asked from the respondents. Each of the bar charts contains the total number of respondents choosing the various alternatives including "Yes", "No", and "Maybe", and further explains each option with distinct legends.

The collected answers given by the participants through the Google Form questionnaire were transformed into a set of bar charts, where each bar graph relates to one of the 15 queries that participants answer. Each bar graph indicates the total number of participants who mostly select among the various options such as Yes, No, Maybe, and clearly distinguished through legends.

Graph (a) shows how the responses relate to whether the child looks at their parent when called by name, one of the important indicators of social behavior. Graph (b) shows whether the child points out things they want, for example toys or snacks. This is again an expression of intent of communication. Graph (c) examines whether the child points at objects to share interest, like pointing at a plane in the sky, which is one of the key signs of joint attention. Graph (d) covers the responses about whether the child looks to the parent's face during play or conversation, denoting social engagement. Graph (e) shows the ability of the child to follow the gaze of another person directed towards some object, inquiring about early social referencing. Graph (f) measures how often the child plays pretend, such as cooking, talking to dolls, or playing pretend with toy cars. Graph (g) tells us to what extent the child comes to comfort other family members who are obviously upset, an important measure for empathy and emotional understanding. Graph (h) represents whether the child gets upset at changes in the daily routine-further indicative of rigidity in behavior. Graph (i) shows whether the child makes use of simple gestures such as waving or pointing, which are considered thr important components of early communication. Graph (j) represents parental suspicion that this child is almost deaf, usually checked owing to poor responses to audible cues. Graph (k) illustrates if the child demanded to listen to the same specific songs repeatedly, indicating possible sensory preferences or fixations. Graph (l) shows if the child reacted strongly to bright lights, very bright colors, or strange sounds within the first year of life, indicating possible sensitivity to sensory overload. Graph (m) shows the age when the child said their first word, grouped into the categories of before nine months, nine to twelve months, one to two years, and after two years, giving some idea of language development milestones. Graph (n) describes how many words the child can say clearly, further quantifying expressive language ability. Graph (o) shows the amount of time a child spends interacting with fellow children in a week, an important feature of socialization abilities.

4. Visualization of Questionnaire Responses

In order to better understand the distribution of responses collected through the Google Form questionnaire, a series of bar charts were generated. Each figure corresponds to one of the 15 questions answered by the participants.

All these graphs provide visual exploration into behavioral, communicative, and sensory attributes all typically associated with the developmental phenomenon of Autism Spectrum Disorders. These visualizations will serve to provide critical insight to early prediction models and further statistical analyses.

Each graph presents visual insights into how different biological, environmental, or developmental factors could relate to presence or absence of Autism Spectrum Disorder in the survey population. These powerful visualizations efficiently summarize the results of questionnaires while laying the groundwork for more diverse statistical and machine learning analyses.

A. INPUT FEATURES

An analysis of two hundred records obtained in this study along-with 15 unique features shows that one hundred children were diagnosed with Autism Spectrum Disorder (ASD), while the other hundred children were healthy (non-ASD). Diagnostic features were gathered with the help of well-structured questionnaires initiated by their parents and caregivers. These questionnaires included information on behavior, development, and demographic data, which are commonly associated with early developmental and behavioral traits concerning ASD. A simple questionnaire comprising a total of 15 questions was made. TABLE I shows the input features of the questionnaire and how the answers are represented

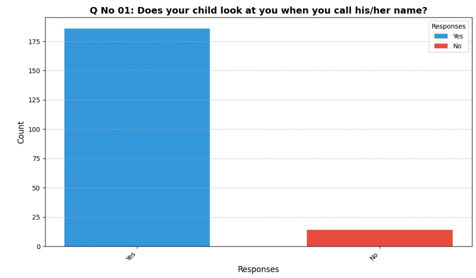

Fig. 1. (a) Does your child look at you when you call his/her name?

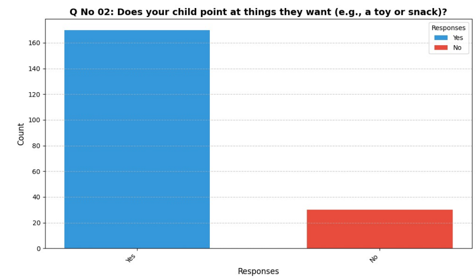

Fig. 2. (b) Does your child point at things they want (e.g., a toy or snack)?

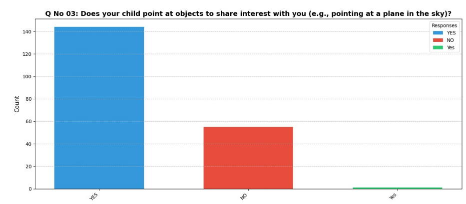

Fig. 3. (c) Does your child point at objects to share interest with you?

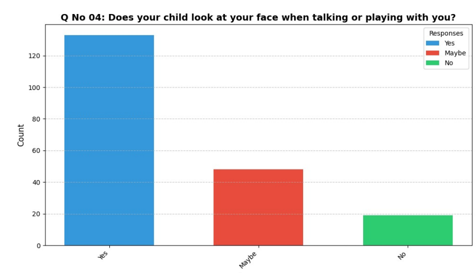

Fig. 4. (d) Does your child look at your face when talking or playing with you?

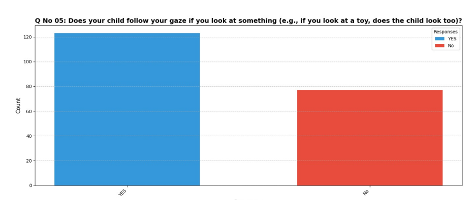

Fig. 5. (e) Does your child follow your gaze if you look at something?

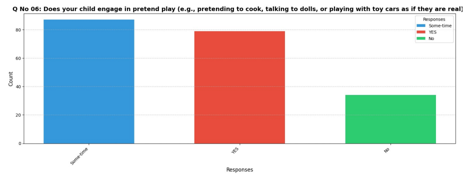

Fig. 6. (f) Does your child engage in pretend play?

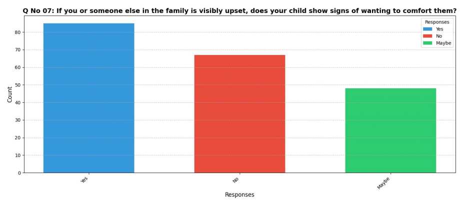

Fig. 7. (g) Does your child comfort others who are visibly upset?

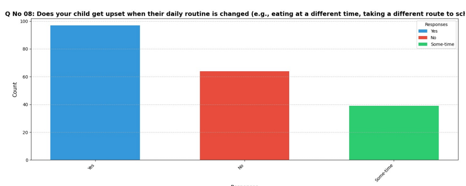

Fig. 8. (h) Does your child get upset when daily routine is changed?

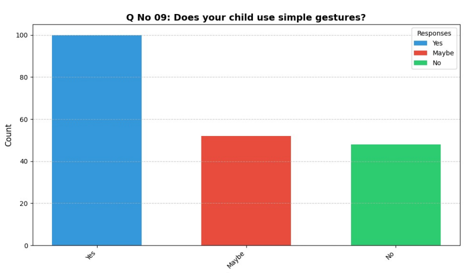

Fig. 9. (i) Does your child use simple gestures?

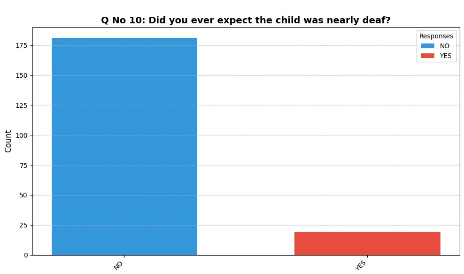

Fig. 10. (j) Did you ever suspect the child was nearly deaf?

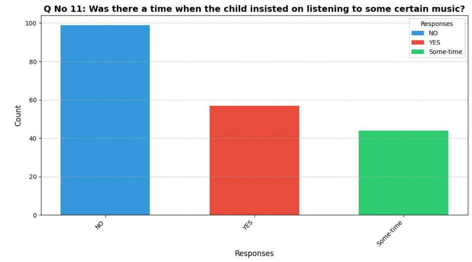

Fig. 11. (k) Was there a time when the child insisted on listening to certain music?

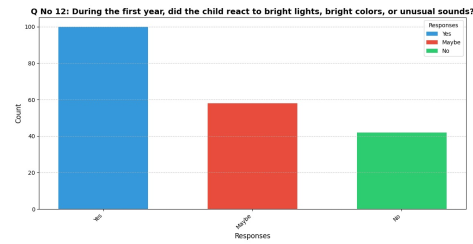

Fig. 12. (l) Did the child react to bright lights, colors, or unusual sounds?

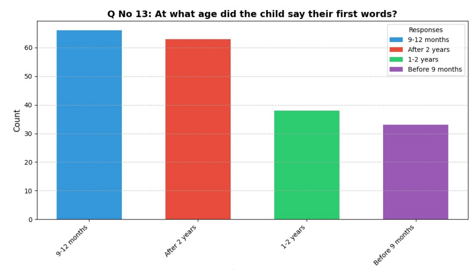

Fig. 13. (m) At what age did the child say their first words?

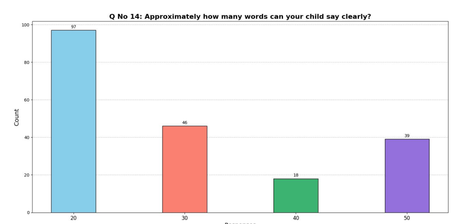

Fig. 14. (n) Approximately how many words can your child say clearly?

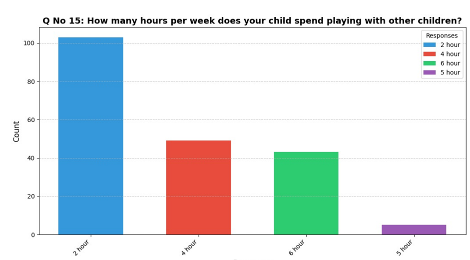

Fig. 15. (o) How many hours per week does your child spend playing with other children?

Such input variables include several categorical and numerical values such as:

- Behavioral manifestations (e.g., response to name, eye contact, sensitivity toward sound or touch)
- Social interaction patterns
- Parameters indicative of language development
- Cognitive responses and observations of daily activities

These 15 attributes help predict potential signs of developing ASD, thus offering a rich feature space suitable for training various machine learning models.

B. DATA ENCODING

Due to the categorical nature of data entries in the dataset (for example – "Yes", "No", and "Maybe"), label encoding was applied to convert all such entries into numerical representations, enabling machine learning algorithms to process the data effectively. Each unique categorical value was assigned a numeric label as follows:

- "Yes" $\rightarrow$ 1
- "No" $\rightarrow$ 0
- "Maybe" or other options $\rightarrow$ Encoded using `LabelEncoder` to ensure consistency across models

This encoding strategy allowed the model to store categorical responses in a numerical form while preserving their distinctions and maintaining logical relationships between responses.

C. DATA PREPROCESSING

Several pre-processing steps were applied to the dataset to prepare it for modeling:

*a) **Missing Values**:* Any missing or blank entries in the dataset were substituted by the mode (most frequent value) of the respective column to maintain consistency across the dataset.

*b) **Feature Scaling**:* To ensure standardization of the feature range, particularly for numerical models and neural networks, normalization was performed using `StandardScaler`. This transformation results in a distribution with zero mean and unit variance:

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where μ is the mean and σ is the standard deviation of the feature values.

*c) **Feature Selection**:* Two complementary methods were employed for feature selection:

- **Chi-square test**: Used to evaluate which features had the strongest statistical association with the target variable.
- **Random Forest Importance**: Features were ranked according to their contribution to decision-making in tree-based models. The highest-scoring features were selected to reduce noise and improve model accuracy.

*d) **Train-Test Split**:* The dataset was partitioned into training and testing subsets using an 80:20 ratio. Stratified sampling was employed to ensure proportional representation of ASD and non-ASD cases in both subsets, maintaining the original class distribution.

5. METHODOLOGIES

Predicting whether a child has Autism Spectrum Disorder (ASD) or not was performed using behavioral, developmental, and demographic parameters collected through questionnaires, employing several supervised machine learning algorithms in this study.

The following machine learning models were used:

- **Logistic Regression:** A linear model used for binary classifications. Logistic Regression estimates the probability that a record belongs to a specific class (ASD or non-ASD) using a logistic function.
- **K-Nearest Neighbors (KNN):** An instance-based, non-parametric learning algorithm that classifies outputs using the majority vote from its nearest neighbors in feature space.
- **Decision Tree:** A tree-structured model that divides the data into parts based on specific feature values. It produces classification outcomes that are highly interpretable and easy to visualize.
- **Random Forest:** An ensemble-based learning technique that builds multiple decision trees during training and aggregates their predictions through majority voting. It reduces overfitting and improves overall performance.
- **Naive Bayes:** A probabilistic classifier based on Bayes's theorem, with a strong assumption that all features are independent. It performs well on high-dimensional datasets.
- **Support Vector Machine (SVM):** A classifier that identifies the best hyperplane to separate different classes in the feature space. Kernel tricks were used to handle non-linear classification problems.
- **AdaBoost Classifier:** An ensemble boosting method that combines outputs of several weak learners into a strong learner by focusing more on misclassified cases from previous rounds.
- **Gradient Boosting Classifier:** Another boosting method that builds models sequentially by minimizing errors, resulting in highly accurate predictions.
- **XGBoost Classifier:** An optimized and scalable version of gradient boosting, widely acclaimed for its speed and superior performance on structured datasets.
- **Artificial Neural Network (ANN):** A deep learning model inspired by the human brain, learning complex patterns as data passes through multiple interconnected neuron-like units (nodes).

Each of these models was trained using the preprocessed dataset. Their performances were evaluated using the following metrics:

- **Accuracy:** Fraction of correctly classified instances out of all instances.
- **Precision:** Fraction of true positive instances among all instances predicted as positive.
- **Recall (Sensitivity):** Fraction of actual positive cases that were correctly predicted as positive.
- **F1-Score:** The harmonic mean of precision and recall, providing a balance between the two.

TABLE I
FEATURES COLLECTED AND THEIR DESCRIPTIONS.

Feature	Type	Description
Q1	String	Does your child look at you when you call his/her name?
Q2	String	Does your child point at things they want (e.g., toy or snack)?
Q3	String	Does your child point at objects to share interest with you?
Q4	String	Does your child look at your face when talking or playing with you?
Q5	String	Does your child follow your gaze if you look at something?
Q6	String	Does your child engage in pretend play?
Q7	String	Does your child comfort someone visibly upset?
Q8	String	Does your child get upset when their daily routine is changed?
Q9	String	Does your child use simple gestures?
Q10	String	Did you ever expect the child was nearly deaf?
Q11	String	Was there a time when the child insisted on listening to certain music?
Q12	String	Did the child react to bright lights, colors, or unusual sounds?
Q13	Categorical (Range)	At what age did the child say their first words?
Q14	Categorical (Range)	Approximately how many words can your child say clearly?
Q15	Categorical (Range)	How many hours per week does your child spend playing with other children?

Confusion matrices were analyzed for each model to observe true positive, true negative, false positive, and false negative rates. Additionally, Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) values were plotted to demonstrate the trade-off between sensitivity and specificity for the classifiers.

This comprehensive analysis helped identify the most accurate and robust models for predicting Autism Spectrum Disorder (ASD).

6. MODEL CONFIGURATIONS

A. Train/Test Split

The set was split into train and test at random and split into 80 and 20, respectively. 80% of the data was used for training machine learning models, while 20% was used for testing and evaluation without the data being labeled. It helps avoid overfitting and provides a realistic estimation of model generalization capabilities.

B. Accuracies Results and Confusion Matrix

All models' accuracies were measured using three validation experiments on which these accuracies are summarized in Table II. From this table, it can be seen that Random Forest, AdaBoost, and XGBoost produced the highest accuracy of 95%, with Logistic Regression and Decision Tree models closely following. Naive Bayes was, on the other hand, relatively poorer.

Moreover, the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for all models are given in Table II as confusion matrices. The Random Forest model had the highest value in the TP and TN categories with the least value FP and FN, representing excellent model strength. In contrast, Naive Bayes reflected a greater number of FP and FN, which reflects its lower strength in prediction than the ensemble models.

C. Feature Selection

Feature selection was done by Chi-Square statistical test and correlation analysis. The figure of Chi-Square was useful in ranking the most important features relevant to an ASD diagnosis. Correlation Matrices were meant for visualization and removal of redundant features. Furthermore, Random Forest feature importance ranking (Figure 17) tried to support that "Q NO 08: Daily Routine Change Upset" and "Q NO 02: Child Pointing at Objects" are also the most important in the data set. Here is the Figure 17 representing important features playing their role in ASD prediction based on their Correlation and Chi square tests.

D. ROC Curve Analysis

Receiver Operating Characteristic (ROC) curves were created for each classifier to evaluate model discriminative power. The SVM showed the highest AUC score of 0.97 regarding differentiating the two phenomena referred to as ASD and non-ASD. Other ensemble methods, including Random Forest, AdaBoost, and XGBoost, have also shown high AUC values that endorse their robustness and predictive power. Figure 16 shows ROC curve based on model's performances

7. RESULTS AND DISCUSSION

A. Model Accuracies

When the Random Forest, AdaBoost, and XGBoost were compared, they scored closer by showing accuracy towards 95%. Logistic Regression and SVM followed, each achieving above 90% accuracy. Simpler models such as Naive Bayes recorded reduced accuracy at about 75%. Thus, the accuracy indicates how well ensemble methods work much more than the individual classifiers do. Table III compares the three validations on accuracy.

B. Analysis of Confusion Matrix

The confusion matrix result in Table II also provides among-the-other insight of models' performance. Random Forest achieved the greatest number of true positives and true negatives along with false positives and false negatives to be few, indicating reliability. AdaBoost and XGBoost also showed some minor misclassifications. On the other hand, Naive Bayes generated misclassifications at a comparatively higher level, confirming less predictive strength on this dataset.

TABLE II
ALGORITHMS AND THEIR RESPECTIVE VALUES OF THE CONFUSION MATRICES USING SELECTKBEST TECHNIQUE CONSISTING OF TRUE POSITIVE (TP), FALSE NEGATIVE (FN), FALSE POSITIVE (FP) AND TRUE NEGATIVE (TN) VALUES.

Algorithms	**TP**	**TN**	**FP**	**FN**
Random Forest	18	20	2	0
Naive Bayes	14	16	6	4
SVM	17	19	3	1
ANN	17	20	2	1
Decision Tree	17	20	2	1
KNN	17	19	3	1
Logistic Regression	16	21	1	2
AdaBoost	17	21	1	1
Gradient Boosting	17	21	1	1
XGBoost	17	21	1	1

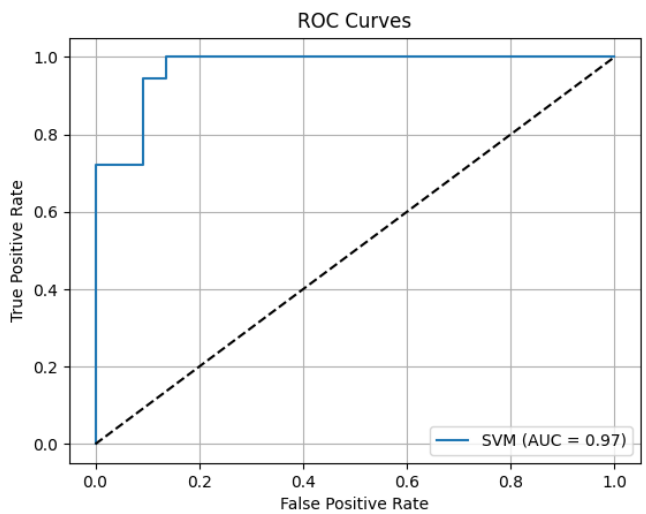

Fig. 16. ROC curve based on model's performances

TABLE III
ALGORITHMS WITH THEIR RESPECTIVE ACCURACIES.

Algorithms	**A**	**B**	**C**
Logistic Regression	92.5	92.5	92.5
Random Forest	95.0	95.0	92.5
KNN	90.0	90.0	90.0
Decision Tree	92.5	90.0	90.0
SVM	90.0	90.0	90.0
Naive Bayes	75.0	75.0	75.0
ANN	93.0	95.0	95.0
AdaBoost	95.0	95.0	95.0
Gradient Boosting	95.0	93.0	93.0
XGBoost	95.0	95.0	95.0

C. Analysis with ROC Curve

In effect, the ROC curve analysis had proven that the highest AUC achieved by using the Support Vector Machine (SVM) model is 0.97, which indicates that the model was very sensitive and specific. Random Forest, AdaBoost, and XGBoost provided a good ROC, emphasizing their discriminating ability. These results reinforce the strength of ensemble methods and SVM for the purposes of ASD prediction.

D. Feature Importance

Chi-Square test and Random Forest importance analysis revealed "Reaction to Daily Routine Changes" and "Pointing at Desired Objects" as the most significant predictors of autism spectrum disorder (ASD). They matched the known behavioral indicators of ASD, which were critical for the proper performance of the model. Concentrating on the important features increased model accuracy.

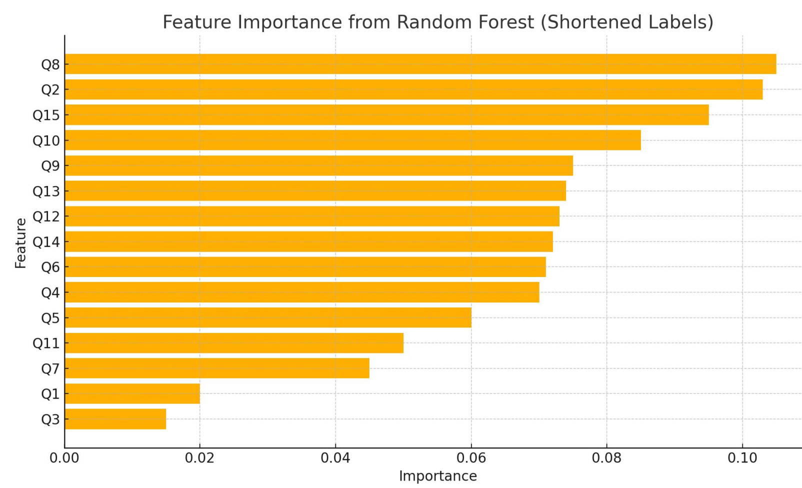

Fig. 17. Feature Importance Plot for ASD Prediction showing features as Question 1 to Question 15.

E. Best Model Selection

Random Forest, AdaBoost, and XGBoost are recommended for the early prediction of ASD based on combined results from accuracy scores, confusion matrices, ROC curves, and feature importance analyses. SVM is another strong alternative as it yields almost the same performance. Ensemble learning techniques have been proven to be better than simpler methods in all the cases described and have thus proved their robustness and reliability in real-world applications for ASD detection.

8. CONCLUSION

After visualizing the data and evaluating our models, we put forth the following observations based on the accuracy and performance of our models:

- Random Forest, AdaBoost, and XGBoost models achieved the highest accuracy of 95% for predicting ASD.

- Behavioral features like "Reaction to Daily Routine Changes" and "Pointing at Desired Objects" were the most significant indicators of ASD.
- Ensemble learning models outperformed simpler models like Naive Bayes, indicating that combining multiple weak learners leads to stronger predictive performance.
- Support Vector Machine (SVM) also showed excellent performance, achieving the highest AUC (0.97) among all models.
- Feature selection techniques (Chi-Square Test and Random Forest Importance) helped in enhancing model accuracy by removing irrelevant features.
- Data pre-processing steps like handling missing values, normalization, and label encoding played a critical role in improving model efficiency.
- Early prediction using machine learning can support faster diagnosis and early intervention strategies for ASD.

9. Limitations and Future Considerations

Nevertheless, notwithstanding the promise of results, current ASD-predictor models have their own limitations and constraints. Most of the models rely on samples that are either small or narrow in terms of demographics, which holds a bearing on generalization. The input of a single modality such as behavioral questionnaires may lack the inclusion of biological signals, paramount genetic or neuro-imaging signals. Some real-world problems that confront model reliability include class imbalance, missing values, and noise. With high levels of complexity, the lack of interpretability of models may subsequently dilute clinical confidence in their predictions. Looking further, a concerted research effort emphasizing diverse, multi-site datasets that can accommodate multi-modal input while adopting explainable AI approaches that allow traceability of their predictions has become urgent. It is meaningless without external validation and application in real-world implementation studies to help translate these models into clinical applications.

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