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Early Autism Spectrum Disorder Detection in Toddles Using Machine Learning Algorithms: A Case Study in Rural Area of Bangladesh

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Abstract: Autism Spectrum Disorder (ASD) is a neurological condition that affects a person's behavior and presents challenges in communication, cognition, and social skills. It can be particularly challenging in areas with inadequate education and limited diagnostic facilities. Despite years of research, scientists still face difficulties answering some questions about autism. However, certain common symptoms can help identify the disorder in children between 18 to 24 months old. This research aims to assist people in rural areas of Bangladesh by predicting ASD in children aged 1.50 to 2.00 years based on these symptoms. Following Cohen-Barren's ASD detection criteria, a dataset was collected from three clinics in Madaripur, a district in the western part of Bangladesh. The dataset was cleaned, prepared for machine learning models, and split into 80% for training and 20% for testing. The Logistic Regression achieved the highest accuracy of the eight machine learning algorithms tested and achieved 99.30% accuracy. Although the dataset is small compared to the area's population, future work will include testing more data and developing a web application for broader use.

Keywords: *Autism Spectrum Disorder, Toddles, Madaripur, Machine Learning, Logistic Regression*

Introduction: Bangladesh is a densely populated country with over 170 million people. Despite efforts to improve, the country still faces significant challenges in its public health system, particularly in rural areas with limited access to healthcare. In rural communities, autism spectrum disorder (ASD) is often stigmatized, and treatment options are scarce. For diagnosis, individuals typically need to travel to divisional hospitals. According to a Centers for Disease Control and Prevention (CDC) report published in 2018, 1 in 44 children has ASD in the U.S. In Southeast Asia, 1 in 160 children are affected by ASD, while a report from Bangabandhu Sheikh Mujib Medical University (BSMMU) indicates that in Bangladesh, the rate is 2 out of 1000 [1, 2]. Although ASD symptoms can sometimes be diagnosed after age three, they usually manifest earlier. The condition is more prevalent in boys than girls. While there is no "cure" for ASD, children and their families can benefit from interventions such as speech and language therapy, occupational therapy, and educational support [3]. Therefore, it is crucial to monitor toddlers aged 18 to 24 months for ASD symptoms and ensure accurate early detection. In 2006, the American Academy of Pediatrics recommended that all children be evaluated for autism during their first doctor's appointment, which became standard practice [4]. This led to an increase in autism testing and the identification of previously undiagnosed children, including milder cases [5]. Although advanced diagnostic methods are being developed in other parts of the world, third-world countries like Bangladesh continue to use outdated and often inaccurate methods for ASD testing in toddlers. Even in urban areas such as Madaripur, a semi-urban region in western Bangladesh, better testing methods are not readily available. The predictive model we developed, based on ASD symptoms, aims to address this gap and provide much-needed support for rural communities.

The research is systematically organized into distinct sections. Section two provides a detailed literature review, discussing the scope, limitations, and outcomes of various projects conducted by other researchers. Section three focuses entirely on the research methodology, outlining the steps to complete the study. Section four presents the result analysis, while section five offers the conclusion, summarizing the findings, addressing limitations, and providing recommendations for future work.

Literature Review: In the paper [6], Thabtah F utilized machine learning algorithms with a tool for testing autism, achieving 97% accuracy using support vector machines (SVM). Although the study was conducted in an international context, the dataset was small and imbalanced, consisting of 623 cases, with 612 being autism cases and only 11 non-autism cases. In [7], authors applied various machine learning approaches to detect ASD among children, where Logistic Regression produced the best results. In [8], six different machine-learning techniques were proposed for ASD detection models. The study combined three different datasets: ASD Screening Data for adults (704 instances), ASD Screening Data for children (2,923 instances), and ASD Screening Data for adolescents (104 instances), each containing 21 features. The paper concluded that Convolutional Neural Networks (CNN) provided the highest accuracy (99.53%) for the adult dataset, while Logistic Regression, CNN, and SVM all gave the same top accuracy (98.30%) for the children dataset. For adolescents, SVM proved to be the most accurate, with a prediction accuracy of 96.88%.

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In paper [9], the authors predicted ASD based on complex neural activity. Although the dataset was small, the Support Vector Machine (SVM) achieved an accuracy of 97%. Paper [10] presented a prediction model for Attention Deficit Hyperactivity Disorder (ADHD) using structured and functional MRI data. The researchers found that combining multimodal features yielded the best results, although the improvement over previous studies was minor. In the paper [11], a deep learning approach was employed to classify and detect ASD. The study used pre-trained models such as Xception, VGG19 (Visual Geometry Group Network), and NASNETMobile, with the first model achieving the highest accuracy of 91%, while VGG19 and NASNETMobile produced accuracies of 80% and 78%, respectively. Paper [12] applied a machine learning approach to classify ASD based on behavioral data, with SVM providing the highest accuracy of 97.50%. However, the dataset suffered from over fitting due to the small number of cases. In [13], Al Bannah proposed a smart monitoring system for ASD patients, which screens facial and mental expressions to alert caregivers when needed. A wristband was used to collect real-time data, detecting ASD from images, with the Inception-ResNetV2 model achieving 78.58% accuracy. Finally, the paper [14] analyzed four different datasets (toddler, child, adolescent, and adult) for autism detection, concluding that the Multi-Layer Perceptron (MLP) model provided the best results, achieving 100% accuracy.

Almost all existing datasets are based on first-world countries with access to modern treatments, but there has been limited research focused on urban areas in third-world countries like Bangladesh. Additionally, most datasets target different subjects, such as adults or adolescents, rather than focusing on the most critical period for autism detection: early infancy. The earliest and most crucial time for diagnosing autism is during the toddler stage when symptoms first start to appear. This is why, in this paper, we have chosen toddlers as our primary subject, aiming to create a model that approaches 100% accuracy something that has not been achieved in previous research using real datasets from any urban area.

Research Methodology: The model used in our study on early autism spectrum disorder (ASD) detection in toddlers follows a systematic machine learning (ML) pipeline. It begins with collecting raw data, which is then subjected to a data preprocessing step to prepare the dataset. The dataset is subsequently split into two parts: 80% is used as training data to build the machine learning model, and the remaining 20% is reserved for testing and evaluation. Several ML algorithms are applied during the training phase to create an optimal model. Once the model is developed, hyperparameter tuning is performed to enhance its accuracy and performance. This section outlines the overall research process, including data collection, dataset preparation, and pre-processing. In this study, we consider 8 classifier models. Here is the short model description.

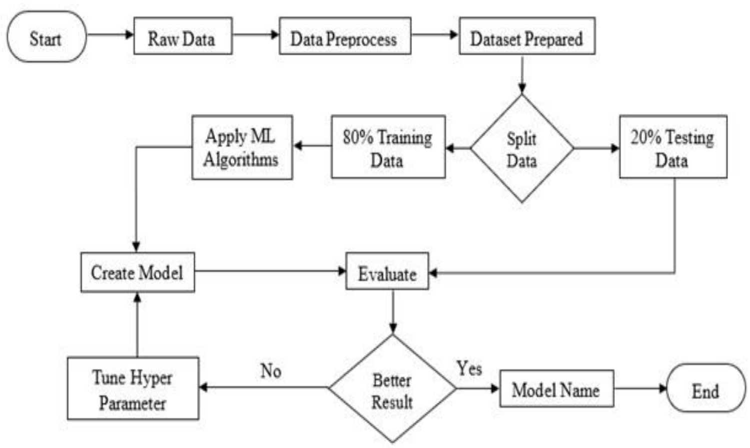

Fig. 1: Model Architecture for Early ASD Detection in Toddlers.

Linear Discriminant Analysis (LDA): Linear Discriminant Analysis (LDA) is a classification technique that seeks to find a linear combination of features that best separates two or more classes. By maximizing the ratio of between-class variance to within-class variance, LDA creates a decision boundary that enhances class separability. It assumes that the data follows a Gaussian distribution and that classes have the same covariance matrix, making it suitable for normally distributed data. LDA is widely used in face recognition, medical diagnosis, and marketing applications to identify and categorize patterns effectively [14].

K-Nearest Neighbors (KNN): K-Nearest Neighbors (KNN) is a simple yet powerful supervised learning algorithm used for classification and regression tasks. It operates by identifying the 'k' closest data points in the feature space to a given query point and making predictions based on the majority class (for classification) or the average value (for regression) of those neighbors [15]. KNN is non-parametric and does not assume any underlying data distribution, making it versatile. However, it can be computationally intensive, particularly with large datasets, since it requires calculating distances between points for each prediction. KNN is widely used in various applications, including recommendation systems and image classification.

Decision Tree (DT): Decision Trees (DT) are a popular machine learning algorithm used for both classification and regression tasks. They work by recursively splitting the data into subsets based on feature values, creating a tree-like model of decisions. Each internal node represents a feature test, each branch corresponds to the outcome of the test, and each leaf node represents a class label (for classification) or a continuous value (for regression) [16]. Decision Trees are easy to interpret and visualize, making them accessible for understanding model decisions. However, they can be prone to overfitting, which can be mitigated by techniques such as pruning or using ensemble methods like Random Forests.

Gaussian Naive Bayes (GNB): Gaussian Naive Bayes (GNB) is a probabilistic classification algorithm based on Bayes' Theorem, which assumes that the features follow a normal (Gaussian) distribution. This method is particularly effective for continuous data and works by calculating the posterior probability of each class given the input features. GNB operates under the "naive" assumption that all features are independent of each other, which simplifies the computation and allows for efficient classification [17]. Despite this strong independence assumption, GNB can perform surprisingly well, especially in high-dimensional spaces and scenarios with limited training data.

Support Vector Classifier (SVC): Support Vector Classifier (SVC) is a supervised machine learning algorithm used for binary and multi-class classification [18]. It works by finding the optimal hyperplane that maximally separates data points of different classes in the feature space. The goal of SVC is to maximize the margin between support vectors—data points closest to the hyperplane—ensuring better generalization to unseen data. It is effective in handling high-dimensional spaces and can use kernel functions to deal with non-linear separations.

XGBoost Classifier: XGBoost Classifier is a powerful and efficient machine learning algorithm based on the gradient boosting framework. It builds an ensemble of decision trees sequentially, where each new tree corrects the errors of the previous ones by minimizing a loss function. XGBoost incorporates regularization techniques to prevent overfitting and offers advanced features like parallel processing and tree pruning, making it highly scalable and performant [19]. It is widely used in data science competitions due to its speed and accuracy in handling large datasets.

Logistic Regression (LR): Logistic Regression (LR) is a statistical method used for binary classification problems, where the goal is to model the probability that a given input belongs to a particular class. It uses the logistic function to transform linear combinations of input features into probabilities, ensuring that the output is confined between 0 and 1 [20]. LR estimates the parameters of the model by maximizing the likelihood of observing the given data. Despite its simplicity, it can be very effective and serves as a baseline for many classification tasks, especially in cases where the relationship between features is approximately linear.

Random Forest Regression (RFR): Random Forest Regression (RFR) is an ensemble learning technique that combines multiple decision trees to improve predictive accuracy and control overfitting [21]. It operates by constructing a multitude of decision trees during training and outputting the average prediction from all the trees for regression tasks. By introducing randomness in the selection of data samples and features, RFR enhances model robustness and reduces variance. This approach is particularly effective for handling large datasets with complex relationships, making it widely used in various applications, including finance and healthcare.

Dataset Preparation: The survey was conducted in an Upazila (subunit of a district) of Madaripur district based on the questionnaire developed by [15], meaning the same questions were asked. These researchers designed a quantitative checklist for screening ASD in children aged 18 to 24 months (both male and female). The sample size was 342, meaning we took data from 342 children. Each question in the Q-10 list (refer to Table 1. for questions) has five possible answers, ranging from A to E. For questions 1 to 9, if the responses are C, D, or E, 1 point is assigned. No points are awarded for responses A or B. For question 10, 1 point is given for responses A, B, or C, while no points are assigned for other options. We surveyed three different clinics in Madaripur Sadar Upazila, with parents completing the survey forms with the assistance of physicians.

As ASD is still a stigma in some rural communities in Bangladesh [16], many parents were reluctant to share personal information. Consequently, we did not collect the names of the parents, specific locations, clinic names, or the names of the doctors involved.

Table 1. Q-CHAT-10 quantitative checklist for autism in toddlers

SL	Questions	A	B	C	D	E
1	Is your child able to follow your gaze?	Many times, a day	A few times a day	A few times a week	Less than once a week	Never
2	When you or another family member appears visibly upset, does your child attempt to offer comfort, such as by stroking their hair or hugging them?	Always	Usually	Sometimes	Rarely	Never
3	How would you describe your child's first words?	Very typical	Quite typical	Slightly Unusual	Very unusual	My child doesn't speak
4	Does your child use basic gestures, like waving goodbye?	Many times a day	A few times a day	A few times a week	Less than once a week	Never
5	Does your child often stare into space without any obvious reason or purpose?	Many times a day	A few times a day	A few times a week	Less than once a week	Never
6	When you call your kid's name, does he or she look at you?	Always	Usually	Sometimes	Rarely	Never
7	How easily do you make eye contact with your child?	Very Easy	Quite easy	Quite difficult	Very difficult	Impossible
8	Does your child point to show that they want something, such as a toy that's out of reach?	Many times, a day	A few times a day	A few times a week	Less than once a week	Never
9	Does your child gesture to share their interest with you by pointing at something they find interesting?	Many times, a day	A few times a day	A few times a week	Less than once a week	Never
10	Does your child play pretend, such as caring for dolls or talking on a toy phone?	Many times, a day	A few times a day	A few times a week	Less than once a week	Never

Data Preprocessing: After collecting the survey data, we prepared the final features, as detailed in the table below. Features 1 to 10 are named using the first letter of each researcher's name who contributed to the Q-10 questions, followed by the corresponding question number. For example, AAB_1 refers to the first question from Allison Auyeung Baron. Initially, the raw dataset comprised 342 rows and 17 columns, with all columns being of the object type. The first 10 columns corresponded to the questions asked in the survey. We removed the 'Timestamp' feature since it did not contribute to the project's objectives. The dataset contained 186 instances labeled 'Yes' for ASD and 156 labeled 'No.' given this distribution, we chose not to attempt any further balancing.

Data Collection Ethics: In rural areas of Bangladesh, there is a significant social stigma surrounding autistic children and their families. Consequently, despite clinics having access to data such as names, addresses, and contact information for each child and their families, we ensured that no identifying information was included to protect their privacy. We adhered to the principles of HIPAA (The Health Insurance Portability and Accountability Act of 1996), collecting only the medical data relevant to enhancing our model's accuracy while refraining from obtaining any details about the children's or their families' identities.

Encoding: Following Cohen-Baron's method, the questions and answer patterns needed to be arranged in a specific order. For questions, AA1 to AA9, the options 'C,' 'D,' and 'E' were assigned a value of '1,' while options 'A' and 'B' were counted as '0.' For question AA10, the options 'A,' 'B,' and 'C' were also assigned a value of '1,' while 'D' and 'E' received a value of '0'. For gender, 'Male' was encoded as '1' and 'Female' as '0.' In the final ASD column, the following condition was applied: if the sum of responses from questions AA1 to AA10 was less than or equal to 3, the ASD value would be recorded as 0 (No/Negative). Conversely, if the sum was greater than 3, the ASD value would be marked as 1 (Yes/Positive). Based on these criteria, I manually encoded the entire set of questions into numerical values for our model.

Train and Test: To build an effective machine learning model with an accurate algorithm, it is essential to allocate the dataset for training and testing purposes. For this process, we utilized the Train Test Split function in Python. We divided the dataset into an 80:20 ratio, a widely used standard for training and testing. This approach aligns with the Pareto principle, which states that 80% of the effects come from 20% of the causes.

Performance Metrics:

Accuracy: Accuracy is a metric used to evaluate the performance of a classification model. It measures the proportion of correctly predicted instances encompassing both true positives and true negatives relative to the total number of instances assessed. While this metric offers a general indication of the model's performance, it may overlook the subtleties of individual classes, particularly in cases of imbalanced datasets.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{eq. 1}$$

In the above formula, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) describe how well the model predicts outcomes. A True Positive occurs when the model correctly identifies a positive instance (when the prediction of ASD is True (1), and that toddler has ASD), while a True Negative is when the model accurately recognizes a negative instance. Conversely, a False Positive, or Type I error, happens when the model incorrectly predicts a positive outcome for a negative case (in our case, the prediction was True, but that toddler had no ASD). A False Negative, or Type II error, occurs when the model misclassifies a positive case as negative (prediction of ASD is False (0), but that child has ASD).

Precision: Precision is the ratio of true positive predictions to the total number of positive predictions (both true and false positives). This metric is particularly useful in scenarios where the cost of false positives is high, as it emphasizes the correctness of positive classifications.

Recall: Also known as Sensitivity or True Positive Rate, measures a model's ability to correctly identify all actual positive instances. It is the proportion of true positive predictions made by the model relative to the total number of actual positives in the dataset. In other words, recall focuses on how well the model can capture all the true positives, making it an essential metric in cases where missing positive instances (false negatives) can have serious consequences.

F1 Score: The F1 Score measures a model's accuracy in binary classification problems (positive/negative). It is also referred to as the harmonic mean of precision and recall, combining both metrics into a single value. The F1 Score balances the trade-off between precision (the accuracy of positive predictions) and recall (the model's ability to identify all actual positives), making it a useful metric when both false positives and false negatives are important. It provides a comprehensive evaluation of a model's performance, especially in situations with imbalanced datasets.

AUC and ROC Curve: The Receiver Operating Characteristic (ROC) Curve is used to evaluate the performance of classification models at various threshold levels. It plots the True Positive Rate (TPR) on the y-axis against the False Positive Rate (FPR) on the x-axis, with both values ranging from 0 to 1. The Area under the Curve (AUC) quantifies the overall ability of the model to distinguish between the classes, with a higher AUC value indicating better performance. The AUC essentially represents the probability that the model will correctly differentiate between positive and negative classes. A value closer to 1 signifies a strong prediction capability, while a value of 0.5 suggests random guessing. Thus, the higher the AUC, the better the model performs in separating class 0 and class 1.

Hyperparameter Tuning for Support Vector Classifier (SVC): The initial results from the classifiers did not meet the desired targets, so hyperparameter tuning was employed on the Support Vector Classifier (SVC), as it responds well to parameter adjustments. To begin the tuning process, we defined the ‘params’ function, which included the key hyperparameters: C (regularization parameter), kernel (type of kernel function), and gamma (kernel coefficient). Next, GridSearchCV is implemented with the SVC model, along with the defined parameters, cross-validation (cv), and verbosity settings. After running the best_params function, the optimal parameters were found to be: {'C': 1.1, 'gamma': 0.1, 'kernel': 'rbf'}. These tuned parameters helped enhance the model's performance.

Result and Discussion:

Exploratory Data Analysis: We asked parents ten questions and collected a few other information. In response to the first question, "Does your child look at you when you call his/her name?” more than 100 of the 186 ‘Yes’ ASD cases reported that their children rarely responded to their names. On the other hand, the 'No' ASD cases generally indicated that their children usually responded when called by their parents, as illustrated in Figure 2. This distinction highlights a significant difference in the behavior of children with ASD compared to those without, in terms of their responsiveness to social cues like name-calling.

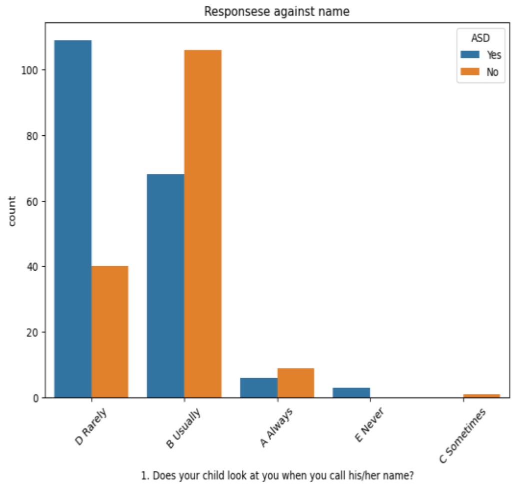

Fig. 2: Response Count of Children to Their Names.

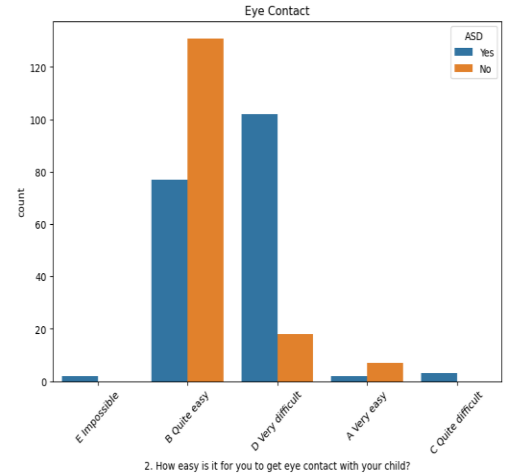

Fig. 3: Frequency of Eye Contact Observed in Participants.

Children with ASD often found it challenging to make eye contact, while reciprocal interactions were more commonly observed in the non-ASD group, as shown in Figure 3. This difference underscores a significant characteristic of ASD, where social engagement and nonverbal communication skills, such as eye contact, are typically impaired.

Figure 4 shows that in the survey, over 67 percent of the attendees were male participants, while the number of female participants was only half that amount. Figure 5 illustrates that among the male toddlers, 132 were diagnosed with ASD, compared to 54 female toddlers with the condition.

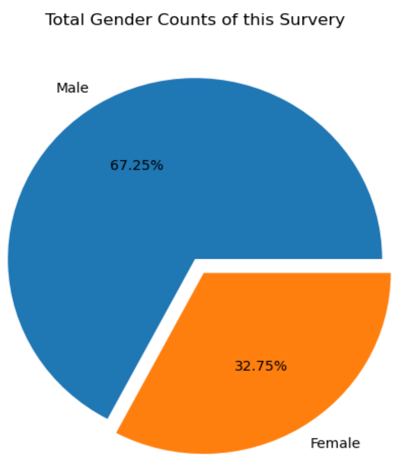

Fig. 4: Distribution of Male and Female Toddlers in the Survey Population.

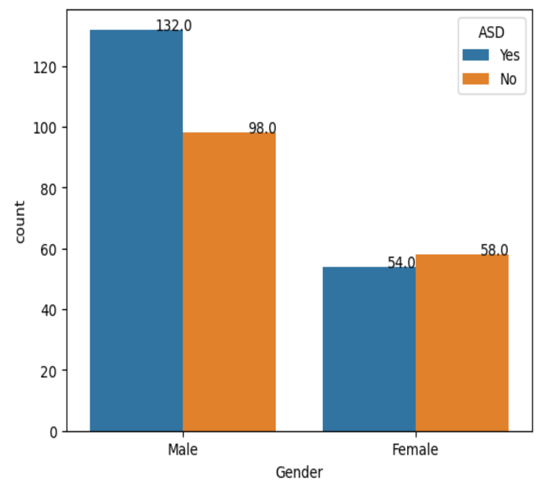

Fig. 5: Distribution of Males and Females Diagnosed with and without ASD.

Table 2, displays the accuracy achieved by various machine learning algorithms. Logistic Regression yielded the highest accuracy at 99.31%, while Linear Discriminant Analysis (LDA) performed less effectively, achieving 81.11%. After hyperparameter tuning using GridSearchCV, the Support Vector Classifier (SVC) reached a performance of 95.65% with a cross-validation (cv) of 10. The Random Forest Algorithm also showed strong performance, achieving 98.24% accuracy following parameter tuning.

Figure 6 demonstrates that the model utilizing the Logistic Regression algorithm accurately predicts all 44 'No' ASD cases and correctly identifies 58 out of the 59 'Yes' ASD cases.

Table 2. Comparison of Algorithm Performance Based on Accuracy

SN	Algorithms (Classifier)	Accuracy (%)
1	Linear Discriminant Analysis (LDA)	81.11
2	K-Nearest Neighbors (KNN)	91.30
3	Decision Tree (DT)	91.30
4	Gaussian Naive Bayes (GNB)	88.40
5	Support Vector Classifier (SVC)	89.81
6	XGBoost Classifier	94.20
7	Logistic Regression (LR)	**99.30**
8	Random Forest Regression (RFR)	**98.24**

This demonstrates the model's high performance in distinguishing between the presence and absence of ASD, effectively capturing the majority of positive cases while maintaining a perfect prediction for negative instances.

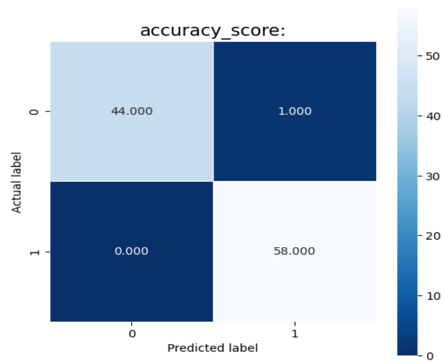

Fig. 6: Confusion Matrix for Logistic Regression Model Performance.

The Random Forest model achieved the second-highest accuracy at 98.24%. Table 3 presents the classification reports for the two top-performing models from the research. Both models exhibit very high positive prediction rates, with Random Forest at 98% and Logistic Regression at 99%.

Table 3. Classification Report of Logistic Regression and Random Forest

Algorithms	0/1	Precision (%)	Recall (%)	F1 Score (%)
Logistic Regression	0	100	0.98	0.99
	1	0.99	100	0.99
Random Forest	0	100	0.96	0.98
	1	0.97	100	0.98

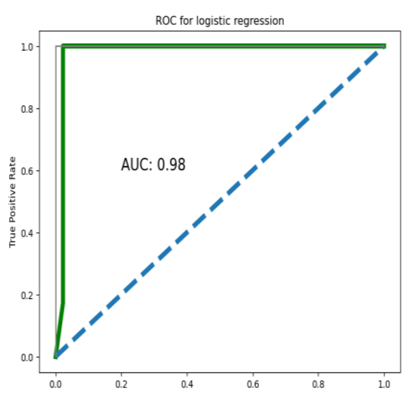

Fig. 7: ROC Curve and AUC Score for Logistic Regression Model.

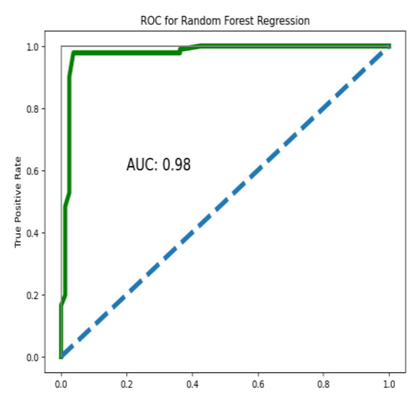

Fig. 8: ROC Curve and AUC Score for Random Forest Model.

Fig. 7 and Fig. 8 display the ROC-AUC curves for these models, which are nearly identical; however, the Logistic Regression model demonstrates a slightly better True Positive Rate. The areas under the curves are comparable for both models. Given that ASD is a highly sensitive condition, maintaining a low False Negative rate is crucial, and our curves indicate that our models perform effectively in this regard.

Conclusion: Autism is a neurological condition that significantly affects an individual's behavior, leading to challenges in communication, cognition, and social interaction. Despite years of research, many questions surrounding autism remain unresolved. However, we have identified several common signs that can indicate the condition in children aged 18 to 24 months. This study aims to predict ASD in 1.50 to 2.00-year-old children based on observed symptoms, providing support for communities in rural Bangladesh, where inadequate educational systems and limited diagnostic resources pose significant challenges. Among nine machine learning algorithms tested, Logistic Regression achieved the highest accuracy at 99.30%. There are several limitations and drawbacks associated with the developed projects. While the data was clean, accurate, and precise, the dataset itself is relatively small, which can affect the reliability of the results. The outcomes of some regression and classification algorithms may vary significantly based on the dataset size. Although Logistic Regression was the leading model, a larger dataset might yield different, potentially more effective algorithms after further tuning and testing. Additionally, the project is currently based on raw code and remains in the beta phase. To make this tool suitable for widespread public use, it is essential to develop a user-friendly interface and enhance accessibility, which the project currently lacks. Several recommendations for future projects of this nature include the following: first, it is crucial to collect more comprehensive and accurate data, similar to this project's approach, to support the needs of data-hungry algorithms. While hyperparameter tuning was performed for the Support Vector Classifier (SVC), there are numerous tuning methods available that could enhance the model's performance. More extensive tuning with a large, high-quality dataset should lead to a more accurate, precise, and robust model suitable for real-world applications.

Author Contributions: H M Mostafizur Rahman conceptualized the research idea and designed the study framework. He contributed to the development of the machine learning models and was responsible for data collection and preprocessing, as well as conducting the initial experiments. Niaz Makhdum and Ahnaf Saif Choudhury contributed to the literature review by identifying relevant works and frameworks. They played a key role in refining the model parameters and performed detailed analyses of the results. Masum Bakaul handled the statistical analysis and evaluation metrics, ensuring the robustness of the findings. Md. Ejharul Haque provided critical insights during the interpretation of the results and was instrumental in revising the manuscript. He ensured that the research adhered to ethical guidelines and contributed significantly to the overall direction of the study.

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