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Autism Spectrum Disorder Prediction Using Hybrid Deep Learning Model and a Recommendation System Application for Autistic Patient

[1]Biplov Paneru, [2]Bishwash Paneru, [3]Krishna Bikram Shah, [4]Awan Shrestha, [5]Ramhari Poudyal and [2]Khem Narayan Poudyal

[1]*Department of Electronics and Communication Engineering, Nepal Engineering College, Pokhara University, Nepal*
[2]*Department of Applied Science and Chemical Engineering, Tribhuvan University, IOE Pulchowk Campus, Nepal*
[3]*Department of Computer Science Engineering, Nepal Engineering College, Pokhara University, Nepal*
[4]*Department of Computer Science and Engineering, Kathmandu University, Nepal*
[5]*Department of Information System Engineering, HIST Engineering College, Purbanchal University, Nepal*

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Corresponding Authors:
Krishna Bikram Shah
Department of Computer Science and Engineering,
Nepal Engineering College,
Pokhara University, Nepal
Email: krishnabs@nec.edu.np

and:

Biplov Paneru
Department of Electronics and Communication Engineering,
Nepal Engineering College,
Pokhara University, Nepal
Email: biplov001@gmail.com

Abstract: The goal of this study is to create machine learning models that use a big dataset to predict Autism Spectrum Disorder (ASD). To achieve optimal performance, a number of algorithms were employed and refined, including Support Vector Machines (SVM), Random Forest, XGBoost, Multi-Layer Perceptron (MLP) and a hybrid model that combines MLP and SVM. To evaluate the durability of the model's performance, the study used cross-validation and hyperparameter tuning techniques. Measures such as memory, accuracy, precision and F1-score have been employed to assess how well the models predict ASD. It's interesting to note that the RBF kernel did quite well in the grid search using the SVM model. All models produced good findings, with test set accuracies ranging from 87-97%. With 97% accuracy on the testing set, the CatBoost algorithm demonstrated excellent performance. Additionally, the hybrid MLP + SVM model demonstrated the potential benefits of combining different approaches by doing well on both the training and testing sets. Additionally, a Flask application was made to provide a straightforward user interface for the machine learning models that were learned. For those with ASD or who are at risk, this application generates predictions based on user input and provides tailored recommendations and interventions. The work highlights the potential for developing useful tools to support ASD diagnosis and intervention, as well as the effectiveness of machine learning techniques in ASD prediction. The robustness and applicability of the existing models may be strengthened by more research and validation on bigger and more varied datasets.

Keywords: Autism Spectrum Disorder, Hyperparameter Tuning, Cross Validation, Flask Application

Introduction

Autism is a neurodevelopmental disorder marked by difficulties with speech and social interaction, as well as by repetitive activities and limited interests (McDonald *et al*., 2018). A range of early-onset, lifelong, neurodevelopmental disorders with complex emerging pathways is known as Autism Spectrum Disorder (ASD) (Newschaffer *et al*., 2007). Autistic children typically exhibit certain features before 3 years old and some may have restricted communication skills by 18-24 months. ASD is diagnosed using the main criteria of social communication impairment and atypical and repetitive sensory-motor activity (Lord *et al*., 2018). ASD is frequently linked to a number of co-occurring illnesses, such as gastrointestinal (GI) issues, immunological disorders and sleep disturbances (Ferina *et al*., 2023). This is a severe developmental condition that is typically identified in children under the age of three (Salari *et al*., 2022). It is a complicated neurodevelopmental disorder that has drawn a lot of attention lately because of its serious effects on

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people's lives, families and society at large, along with its rising prevalence (Reghunathan *et al*., 2024).

It is vital to emphasize that more adults are being evaluated for suspected autism (Huang *et al*., 2020). A frequent neurodevelopmental disorder with a wide variety of symptoms and severity levels is Autism Spectrum Condition (ASD). According to Ramdoss *et al*. (2012) Computer Based Interventions may offer some benefits to improvement of the autistic affected overall visual learning strengths too. Early diagnosis and intervention have a substantial impact on the prognosis and quality of life for people with ASD. ASD is diagnosed using the main criteria of social communication impairment and atypical and repetitive sensory-motor activity (Bottema-Beutel *et al*., 2021). Research shows that maladaptive self-directed behavior can be reduced by increasing adaptive object-directed behavior through structured environments and reinforcement strategies (Horner, 1980). As autism diagnoses increase in frequency, interdisciplinary participation can improve the quality of life and general well-being of those on the spectrum, including adults as well as children (Farooq *et al*., 2023). However, diagnosing ASD can be difficult due to its heterogeneous character and the variety of symptoms among affected individuals. Machine learning approaches have promising opportunities for improving ASD prediction and making targeted suggestions for intervention measures. In the behavioural sciences, machine learning has great promise for improving diagnostic and therapeutic research. It may prove particularly helpful in studies pertaining to the very variable and common syndrome known as an autism spectrum disorder (Bone *et al*., 2015).

Related Work

By locally preparing two particular ML classifiers, calculated relapse and back vector machine, for the categorization of ASD characteristics and Extreme ASD in both children and grown-ups, the FL approach is utilized for the primary time to analyze extreme ASD in this study. More than 600 records of influenced grown-ups and children from four diverse ASD understanding datasets were accumulated from diverse stores in arrange to extricate highlights. The proposed demonstrated anticipated ASD in grown-ups with 81 curacy and children with 98 curacy (Thabtah, 2017).

ASD issues in children, adolescents and adults were previously predicted and analyzed using a variety of models, including Naïve Bayes, Support Vector Machine, Logistic Regression, KNN, Neural Network and Convolutional Neural Network (Raj and Masood, 2020).

In a study by Horner *et al*. (1980), a mentally disabled kid was placed in an "enriched" setting, maladaptive self-directed conduct was decreased and adaptive object-directed behaviour increased above what was seen in the "enriched" environment alone. This was achieved by the differential reward of adaptive behaviour.

The authors used various models, including SVM, RFC, NB, LR and KNN, to analyze our dataset and create predictive models based on results. The primary goal of their research is to evaluate whether the child is prone to ASD in its early stages, which will help speed up the diagnosis procedure (Vakadkar *et al*., 2021).

They carried out a review examination with two distinctive association estimations and utilized both classic measurable strategies and machine learning methods. The concurrent utilization of factual examination and conventional machine learning approaches moved forward our information of show expectations based on the ghastly or network highlights of a subject's EEG information, whereas moreover approving these forecasts. Altogether, the utilization of machine learning approaches permitted us to find a particular subset of accurately categorized children with ASD, as shown by the inspected EEG parameters (Rogala *et al*., 2023).

This study provides a comprehensive overview of the various machine learning and artificial intelligence algorithms used for ASD diagnosis and prediction in patients of various ages utilizing clinical approaches. This article also focuses on the datasets used to predict autism in individuals, as well as their outcomes, limits and methodological challenges (Damianos *et al*., 2023). Autistic children require the best care, which is behavioural Management therapy, as illustrated in Fig. 1. This study focuses on the development of such informative UI (User Interface design) to provide general information on autism-related care and support methods.

Random forests with transfer learning and deep neural networks achieved ASD classification accuracy of 98.9 and 99.8%, respectively. As a result, the method used in this study demonstrated that machine learning may provide more promising methods for early, objective and accurate ASD categorization than traditional autistic screening methods. Limitations and recommendations for future research are also provided (Boughattas and Jabnoun, 2022).

Fig. 1: Autistic child behavioural illustration

First, the authors took a novel strategy for extracting features from eye fixation, facial expression and EEG data. Then, a hybrid fusion strategy based on a weighted naive Bayes algorithm was described for multimodal data fusion, which achieved a classification accuracy of 87.50%. The results indicate that the machine learning classification approach used in this study is efficient for early diagnosis of ASD. Confusion matrices and graphs show that eye fixation, facial expression and EEG have differing discriminative capacities for detecting ASD versus typically developing children, with EEG potentially being the most discriminative information. The physiological and behavioural data have significant complementary features. Thus, the machine learning approach suggested in this study, which incorporates complementary data, has the potential to enhance classification accuracy considerably (Liao *et al*., 2022).

In this study, the authors describe machine learning techniques for distinguishing between people with ASD and normal people. We utilized data from the ABIDE dataset. Support Vector Machines (SVM), Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) were the three techniques that we assessed. With a 95% accuracy rate, the CNN algorithm produced the best results (Rehman *et al*., 2021).

Previous research has examined a variety of machine-learning approaches for ASD prediction, including feature-based classifiers, deep-learning models and ensemble methods. While some research has found great accuracy in ASD prediction, few have concentrated on integrating recommendation systems to provide individualized care to people with ASD.

Materials

In order to create and assess our hybrid deep learning model for predicting autism spectrum disorder (ASD), we used a number of essential resources and instruments in this study. These resources include the libraries needed for data processing, model training and assessment, as well as the hardware, software and dataset settings.

Dataset

We used a dataset that included clinical assessments, behavioural features and demographic data-all of which are essential for predicting ASD. The following were included in the dataset.

Dimensions: There were 22 columns and 1000 rows in the dataset.

Unique identifiers, AQ scores (A1-A10), age, gender, ethnicity, history of jaundice and autism, place of residence, prior app usage, assessment results, age description, relationship to the person filling out the form and the target variable class/ASD were among the features.

This dataset was used to train, validate and test our models. It is based on the reference (Liao *et al*., 2022).

Hardware

The following computational resources were employed in this study:

1. CPU: Intel Core i7 or a similar model
2. Memory: 16 GB
3. 256 GB SSD for storage
4. GPU: NVIDIA GeForce GTX 1080 or a similar specification to train models more quickly

These hardware specs were sufficient to process the dataset and carry out the calculations required for training and assessing the model.

Software and Libraries

To preprocess the data and develop and assess our machine-learning models, we used a range of software tools and libraries. These included:

1. Python, which served as the main programming language for data processing, model training and assessment; Pandas for data manipulation and preprocessing
2. NumPy for numerical computations; Scikit-learn for machine learning algorithms like SVM, Random Forest and hyperparameter tuning using grid search; CatBoost for CatBoost model implementation
3. XGBoost for XGBoost model
4. Flask for deploying the trained model as a web application

Data Preprocessing

In order to improve our models' performance, we undertook a thorough data preparation, which comprised:

i. Coding categorical variables: Label encoding or one-hot encoding, as applicable, were used to encode the categorical features
ii. Feature scaling: To guarantee that features have a mean of 0 and a standard deviation of 1, they were scaled using standardization
iii. Feature selection: To enhance model performance and lessen overfitting, pertinent characteristics were chosen based on their significance and association with the target variable

Model Evaluation Metrics

Our models were assessed using a range of measures, such as accuracy, precision, recall and F1-score. To guarantee the models' robustness and generalizability, cross-validation was used. These variables were used to compare each model's performance and identify the top model for ASD prediction.

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Methods

We introduce a hybrid deep learning model for ASD prediction that combines the benefits of deep learning and a traditional machine learning approach with the SVM model. To predict ASD, we employ the following techniques: SVM, CatBoost, MLP, MLP + SVM hybrid model, lightGBM, XGBoost and Random Forest. To predict results, behavioural traits, clinical evaluations and demographic information are all used. To enhance the performance of the model, we preprocess the data and choose features relevant to developing the models.

Table 1 Shows the total parameters in our dataset, comprised of 1000 rows and 22 columns consisting of various parameters as features, with 'class ASD' being our target column for the classification of ASD based on those features.

Table 2 Consists of the overview of the dataset with a total of 22 parameters, including class/ASD. The various parameters' relationship with autism spectrum disorder can be obtained and analyzed using the dataset. Age, country of residence, affected with jaundice and ethnicity all have a major role in affecting ASD and various scores are too that are also affecting ASD in the population.

Dataset Description

The dataset provided in Table 2 is based on reference (Liao *et al*., 2022). It includes individual ID, scores for each of the ten items in the Autism spectrum Quotient (AQ) screening tool (A1-A10_score), age of the patient, gender, ethnicity, whether jaundice was present at birth, family history of autism, country of residence, whether the patient has undergone a screening test before, result score for the screening test, age description, relation of the patient who completed it This dataset is intended to aid research and analysis in the field of autism spectrum disorders. There were a total of 801 rows and 22 columns in total dataset we utilized to develop the models and deploy them in the flask application.

Models Used

a. Support vector machines: Support Vector Machine (SVM) is a supervised machine learning algorithm for categorization. It operates by determining which hyperplane best separates distinct classes in the feature space. SVM is effective for high-dimensional data and can handle both linear and non-linear classification problems using various kernels
b. CatBoost: CatBoost is a gradient-boosting library optimized for handling categorical information effectively. It automatically handles categorical variables without the need for extensive preprocessing. CatBoost is well-known for its excellent performance and is frequently used in contests and real-world applications
c. Multi-Layer Perceptron (MLP) is an artificial neural network with numerous layers (neurons). Each node in one layer communicates with every node in the next layer and it processes input and produces output using nonlinear activation functions. MLP is widely utilized in classification and regression tasks
d. XGBoost is an improved and scalable gradient-boosting library. It uses a regularized boosting strategy to avoid overfitting and is well-known for its performance and speed
e. Random forest is an ensemble learning method that creates a large number of decision trees during training and outputs their mode (classification) or mean prediction (regression). It is resistant to overfitting and performs well with high-dimensional data

Model Fine Tuning

Grid search is a strategy for hyperparameter tuning. It involves specifying a set of values for a model's hyperparameters and exhaustively searching through all possible combinations of those values. It uses cross-validation to test each combination and choose the one that performs the best.

Table 1: Dataset parameters content on the training set

Dimension	Number of parameters
Rows	1000
Columns	22

Table 2: Dataset features set used on models training

Feature	Description
ID	Unique identifier
A1_score	Score on AQ1
A2_score	Score on AQ2
A3_score	Score on AQ3
A4_score	Score on AQ4
A5_score	Score on AQ5
A6_score	Score on AQ6
A7_score	Score on AQ7
A8_score	Score on AQ8
A9_score	Score on AQ9
A10_score	Score on AQ10
Age	of the individual
Gender	of the individual
Ethnicity	of the individual
Jaundice	Whether the individual had jaundice (yes/no)
Autism	Whether the individual had autism (yes/no)
Country_of_res	Country of residence of the individual
Used_app_before	Whether the individual had used the app before (yes/no)
Result	of the assessment
Age_desc	Age description of the individual
Relation	of the individual to the person filling out the form (e.g., parent, self)
Class/ASD	Classification of autism spectrum disorder (0 for No, 1 for Yes)

Metrics Utilized

The F1-score is a statistic used to assess the effectiveness of classification models. The harmonic mean of precision and recall is determined as 2*(precision* recall)/(precision + recall). F1-scores range from 0-1, with 1 representing exceptional precision and recall and 0 indicating poor performance:

i. Accuracy is the fraction of correctly classified instances out of all instances
ii. Precision is the proportion of true positive forecasts among all positive predictions
iii. Recall (sensitivity) is the proportion of true positive forecasts among all real positive cases

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall + \frac{TP}{TP + FN} \quad (2)$$

where:

(TP) = True Positives is the number of correctly predicted positive instances
(FP) = False Positives is the number of incorrectly predicted positive instances
(FN) = False Negatives is the number of incorrectly predicted negative instances

The *F1-score* is then calculated as the harmonic mean of precision and *recall*:

$$F1Score + \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

Training Hypermaraters

Table 3 a number of machine learning models were created in our study to predict Autism Spectrum Disorder (ASD) utilizing particular hyperparameters to maximize performance. The following is a quick explanation of the model's hyperparameters.

We utilized the implementation library's default parameters for the Random Forest model. Furthermore, class_weight is set to 'balanced'. By giving minority classes more weight, this parameter helps to address the class imbalance by adjusting the weights inversely proportional to the class frequencies in the input data. Using the Rectified Linear Unit (ReLU) activation function, we set up the Multi-Layer Perceptron (MLP) model with one hidden layer and 100 neurons. Adam was the weight optimization solver, a well-liked stochastic gradient descent technique. To avoid overfitting, we used L2 regularization with an alpha value of 0.0001. 'Auto' was selected for the batch size so the model could figure out the right batch size on its own using the training data. In order to control the step size at each iteration and go toward the loss function's minimum, the learning rate was set to 0.001. For repeatability, we additionally set the random seed to 42 and limited the training to 200 iterations. We utilized the library's default parameters for the XGBoost model. XGBoost is well-known for its effectiveness and performance across a broad range of workloads and the default configurations frequently offer a reliable foundation.

The same hyperparameters that were used for the standalone MLP were also used for the combined MLP + SVM model: one hidden layer with 100 neurons and ReLU activation, Adam solver, L2 regularization with an alpha of 0.0001, batch size 'auto', learning rate of 0.001, maximum iterations of 200 and random seed 42. Before combining the neural network component with the SVM, this arrangement makes sure that it is consistent. The regularization parameter (C), which manages the trade-off between obtaining a low error on the training data and minimizing the model complexity, is set to 1.0 for the Support Vector Machine (SVM) model. For linearly separable data, we employed a linear kernel function. 'Scale' was the gamma parameter, which means it was calculated according to the quantity of features. In order to rectify the class imbalance, we additionally set class_weight to 'balanced' and enabled the probability parameter, which permits the model to produce probability estimates. Default parameters were used for the boost model. Finally, are these parameters useful for enhancing model development.

Table 3: Hyperparameters used for model development

Model	Hyperparameters
Random forest	Default parameters, class_weight = 'balanced'
MLP	Hidden layer: 1 layer with 100 neurons, ReLU activation function Solver: Adam<- - Regularization: L2 (alpha = 0.0001) Batch size: 'auto' -Learning rate: 0.001 -Max iterations: 200 -Random seed: 42
XGBoost	Default parameters
MLP + SVM	Hidden Layer: 1 layer with 100 neurons, ReLU activation function Solver: Adam Regularization: L2 (alpha = 0.0001) Batch size: 'auto' Learning rate: 0.001 Max iterations: 200 Random seed: 42
SVM	Regularization parameter (C): 1.0 Kernel function: Linear Gamma: 'scale' Class weight: 'balanced' Probability: True
CatBoost	Default parameters

Results

Our findings demonstrate that, with a 97% prediction accuracy on the ASD dataset, the CatBoost technique outperforms other methods. To ascertain the efficacy of each algorithm in predicting ASD, we analyze both the hybrid model and its individual performances. Additionally, we use sensitivity analysis and cross-validation to assess the durability of the model.

In addition to ASD prediction, we provide a recommendation system coupled with a Flask application. The recommendation system uses the machine learning model's predictions to provide individualized treatments and interventions for people with ASD. The program provides users with actionable insights and tools to help them address their specific requirements and difficulties.

Flask Application

This Flask application configures a web server to deliver a machine-learning model that generates predictions based on user input. Here's how it operates:

1. Initialization: The Flask application is started with the Flask class from the Flask module.
2. The static URL route is set to/static, which serves static files such as CSS, JavaScript *and* pictures.
3. The trained MLP Classifier model is put into memory via job lib's load function
4. Preprocessing and prediction functions: Preprocess_input: This function prepares the input data before making predictions. Currently, it is a placeholder function that does not conduct any preprocessing. You can modify this method to include preprocessing steps as desired
5. Predict: This function accepts preprocessed input data, makes predictions using the loaded model and provides the results

Routes

Route (home page): When a user accesses the application's root URL, the home function is invoked, displaying the index.html template. This template most likely includes a form where users can enter data for prediction.

Predict' route: This route is configured to receive POST requests containing data from the form submitted on the home page. When a prediction request is sent, the make prediction function is invoked. This function extracts the form's input data, uses the predict function to create a prediction and displays the prediction result in the result.html template.

Running the flask application: Finally, users can start the Flask application with the app. run (debug = True). The debug = True setting enables debug mode, which offers useful debugging information in the event of a mistake and immediately reloads the application when code changes are made.

Users can use a web browser to access the Flask application once it has started executing. They can enter data into the form on the home page, submit it and then obtain predictions on the result page based on the trained machine learning model 83% accuracy was obtained on cross-validation of the SVM model on a testing set 5-fold utilized with a standard deviation of 0.0227.

The mean testing accuracy across all folds is 0.83125, which represents the model's overall average performance across different subsets of the data. The Standard Deviation (SD) of the testing accuracies is 0.022707377655731192, indicating the variability or consistency of the model's performance over folds. This cross-validation accuracy indicates the SVM model's robustness and generalization capabilities. The mean accuracy of 0.83125 indicates that the model correctly predicts the class labels for roughly 83.125% of the cases in the test set. Furthermore, the low standard deviation suggests that the model's performance is constant across diverse subsets of data, which adds to its trustworthiness. The confusion matrix for predictions on the test set was seen as 86% accuracy on the testing set was obtained with the XGBoost classifier algorithm developed on 5-fold stratified validation as shown in Table 4. Similarly, for the MLP classifier, 86% accuracy was obtained on the test set and 94% on the training set after 5-fold cross-validation. Similarly, for the hybrid MLP + SVM model, 95% accuracy was obtained on the training set and 94% on the testing set, which is a great outcome of this research work.

Table 4 testing accuracies over five folds were observed for the Support Vector Machine (SVM) model. For folds 1 through 5, the accuracies were 0.8125, 0.86875, 0.84375, 0.825 and 0.80625, in that order. A calculation yielded a mean testing accuracy of 0.83125 and a Standard Deviation (SD) of 0.022707377655731192. This shows considerable fluctuation between the folds but overall consistent performance.

Table 5 testing accuracies over five folds were observed for the Support Vector Machine (SVM) model. A calculation yielded a mean testing accuracy of 0.83125 and a Standard Deviation (SD) of 0.022707377655731192. This shows considerable fluctuation between the folds but overall consistent performance.

Table 4: SVM accuracies observer over different folds

Fold	Testing accuracy
1	0.8125
2	0.86875
3	0.84375
4	0.825
5	0.80625
	Mean testing accuracy: 0.83125
	SD of testing accuracy: 0.022707377655731192

Table 5: XGBoost accuracies observer over different folds

Fold	Testing accuracy
1	0.875
2	0.89375
3	0.86875
4	0.85
5	0.85625
	Mean testing accuracy: 0.86875
	SD of testing accuracy: 0.01530931089239489

Table 6: MLP + SVM model\s accuracies observer over different folds

Fold	Testing accuracy
1	0.91875
2	0.975
3	0.9625
4	0.9375
5	0.95
	Mean testing accuracy: 0.9487499999999999
	SD of testing accuracy: 0.019525624189766645

Table 7: Hybrid model classification report

Class	Precision	Recall	F1-score	Support
0	1	0.7967	0.8869	123
1	0.5968	1	0.7475	37
Accuracy	-	-	0.8438	160
Macro avg	0.7984	0.8984	0.8172	160
Weighted avg	0.9068	0.8438	0.8546	160

Table 6 out of all the models examined, the combined MLP + SVM model had the best testing accuracy. 0.9487499999999999 was the mean testing accuracy, while 0.019525624189766645 was the standard deviation. This model consistently demonstrated excellent performance, as seen by its low standard deviation and superior mean accuracy.

The classification report for the hybrid model is shown in Table 7, which offers further information about how well it performed. The precision, recall and F1-score for class 0 were 1, 0.7967 and 0.8869, in that order. These measures were 0.5968, 1 and 0.7475 for class 1. With a macro average precision of 0.7984, recall of 0.8984 and an F1-score of 0.8172, the overall accuracy was 0.8438. Recall, F1-score and weighted average precision were 0.9068, 0.8438 and 0.8546, respectively. Although there is space for improvement in class 1's precision, these measures show that the model performs equally well in both classes.

Similarly, 97% on the testing set and 99% accuracy on the training set were obtained by the boosting algorithm. Random forest algorithm gained 100% accuracy on training and 87% on the testing set with a mean testing accuracy of 0.87625 and standard deviation of testing accuracy of 0.010, which is a very good result on 5-fold cross-validation. Overall, every model developed showed a great result in predicting autism spectrum disorder on a given dataset. The classification report of one of the folds is given in the table, which highlights the model's abilities and ensures learning with the help of F1-score, accuracy, precision, etc.

This classification report assesses the hybrid model's ability to identify occurrences of Autism Spectrum Disorder (ASD) based on the features presented. For Class 0, which represents the absence of ASD, the model had a precision of 0.7967, suggesting that over 80% of the predicted Class 0 instances were correct. The recall, or sensitivity, was 0.8869, indicating that the model detected nearly 89% of the real class 0 cases. For class 1, which indicates ASD existence, the precision was lower at 0.5968, implying that around 60% of projected class 1 instances were right. However, the recall was perfect at one, indicating that the model accurately identified all genuine class 1 cases. The model's total accuracy was 0.8438, with a weighted average F1-score of 0.8546, indicating that it performed reasonably well in both classes.

Models Performace Comparision

The bar diagraming Fig. 3 represents the accuracy ratings of multiple machine learning models and gives useful information about their respective effectiveness in predicting Autism Spectrum Disorder (ASD). Each bar in the diagram represents a different model, which includes Support Vector Machines (SVM), random forest, XGBoost, Multi-Layer Perceptron (MLP), a hybrid MLP + SVM model and CatBoost. Notably, the accuracies displayed by these models differ significantly, emphasizing the necessity of adopting an optimal algorithm for ASD prediction.

Among the models tested, CatBoost emerges as the clear winner, with an astonishing 97% accuracy. This result demonstrates the algorithm's robustness and usefulness in detecting complicated patterns in the dataset. In contrast, random forest has a little lower accuracy of 89%, indicating potential limits in dealing with the complexities of the ASD prediction problem.

Flask Application Test

The application was utilized by the flask server on the default user localhost server provided by running it. The application GUI developed with HTML and CSS looks, as shown in Fig. 2, that can predict autism on the basis of input features and for better interaction and support from UI buttons and feasible selective options are added for input, as shown in the figure.

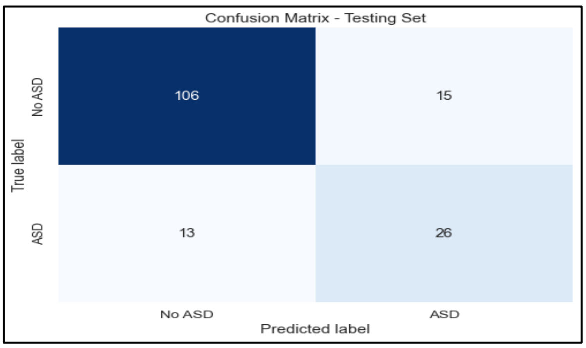

Fig. 2: Model confusion matrix for the classification of classes

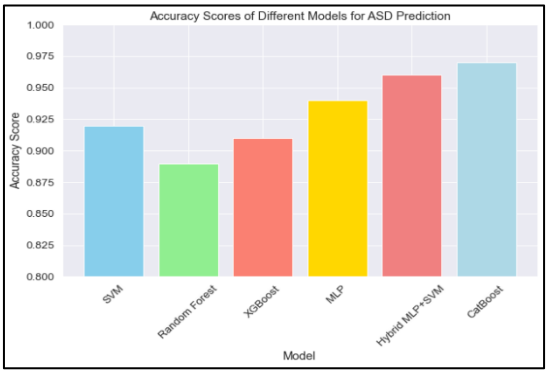

Fig. 3: Developed model accuracies comparison

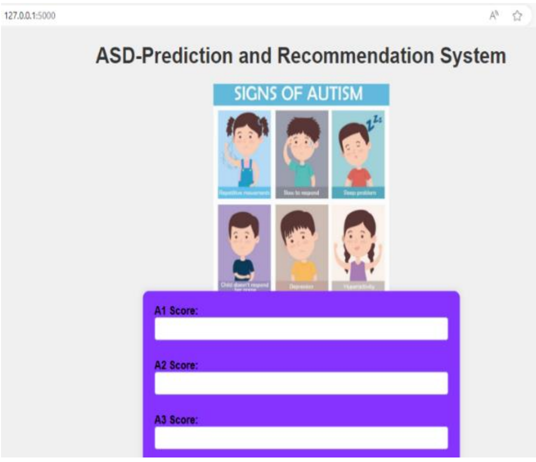

Fig. 4: Autism prediction UI screen on the local server

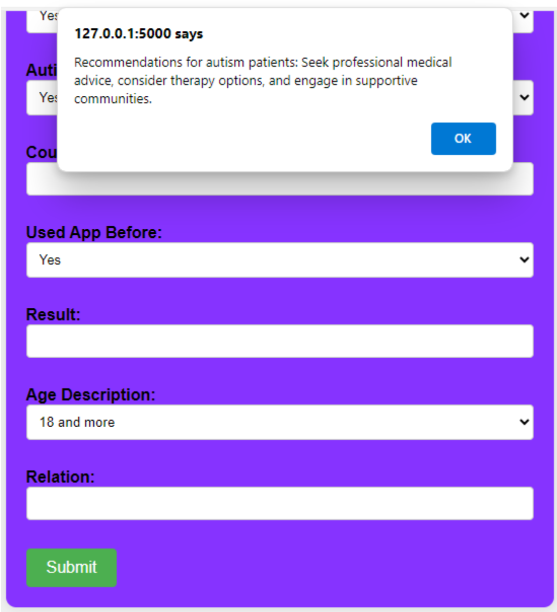

Fig. 5: Autism recommender app screen on the local server

The application, as shown in Fig. 4. was followed with the integration of a recommender system that could make various recommendations to the spectrum disorder detected patients as well as suggest healthy living procedures for those not predicted to ASD disorders. Fig. 5. demonstrates the UI of the application that has different input fields, mainly the parameters for selection (IDs and Score through a selection bar) and other parameters used for training the model can be used for predicting new values using input fields that can accept 'age', 'religion', 'relation' etc., to predict ASD. The UI is made in such a way as to deliver some information to users on ASD and its healing techniques, suggesting proper care and social and behavioural therapies for ASD.

The application was developed to make predictions with the pkl extension model from MLP trained with proper tuning, as discussed before in the methodology section was integrated into its application. The application could make predictions and make recommendations to the users whom autism spectrum disorder conditions are seen, similarly suggesting healthy living methods for others too.

This program makes predictions based on user input and gives recommendations and interventions specific to people with ASD or those who are at risk. The application's GUI simplifies the interaction and improves the model's usability in real-world applications. The application could suggest to users the potential risks as well as management solutions for autism disorders. The user-friendly flask GUI offers a comprehensive interaction for users and allows for better prediction and use of the model for a real-world novel purpose.

Discussion

Finally, this study attempted to create and test machine learning models for predicting Autism-Spectrum Disorder (ASD) utilizing a large dataset. Several algorithms, including Support Vector Machines (SVM), random forest, XGBoost, Multi-Layer Perceptron (MLP) and a hybrid model combining MLP and SVM, were used and fine-tuned to obtain peak performance. Several behaviour disorders and mental disorders in children and young adults can be found at different ages (Piazza *et al.*, 1996) that shall be addressed with assistive technologies use. Parents are also making use of social media to seek assistance for their children health health-related issues (Frey *et al.*, 2022). The use of social media might have various negative aspects. In order to raise a happy, healthy child and preserve family well-being and emotional resilience, parents of children with autism spectrum disorder (ASD) may find that having a strong peer network and high-quality, freely accessible information is essential (Gibson *et al.*, 2017). A previous study (Ramdoss *et al.*, 2012) has indicated that using computer-based therapies to help people with ASD develop their social and emotional skills is a promising approach. Chemical and environmental exposures can also be one of the underlying factors for autistic children (volk *et al*., 2022), so this field knowledge, too, is one of the vital aspects for parents. Due to the high frequency of gastrointestinal issues in individuals with autism spectrum disorder, scientific advancements are required in many public health fields (Settanni *et al*., 2021). Environmental pollutants are also underlying risks in ASD. It is necessary to focus on environmental health and sustainability to prevent these disorders (Lam *et al*., 2016).

Previously, in a study (Knight *et al*., 2015), findings implied that visual activity plans, particularly when combined with systematic teaching techniques, can support ASD. Research on students with autism (ASD) and the use of mobile digital technologies in education is relatively new. Hence, there is limited evidence of the technology's effectiveness for learning (Ramirez-Duque *et al*., 2019). This system, developed using Flask, offers a very feasible layout and UI screen to users who can early predict the disorders. The new 'normal' established during the COVID-19 pandemic has prompted us to reconsider how persons with special needs, such as those with Autism Spectrum Disorder (ASD), might survive in these unusual circumstances (Ellie Wilson *et al*., 2013). These changing/challenging situations have led us to reconsider the use of telehealth services to improve the quality of life for people with ASD. In the future, we can use the models in mobile version applications and utilize the models on more datasets to minimize the global challenges in the autism field.

Conclusion

The results showed encouraging performance across all models, with accuracies ranging from 87-97% on the test set. On the testing set, the CatBoost algorithm performed particularly well, achieving an impressive 97% accuracy. Furthermore, the hybrid MLP + SVM model performed well on both the training and testing sets, demonstrating the potential advantages of mixing various techniques.

Furthermore, a flask application was created to give a simple interface for using the taught machine learning models. Overall, the study demonstrates the efficacy of machine learning techniques in predicting ASD and emphasizes the possibility of building useful tools for ASD diagnosis and intervention support. Additional research and validation on larger and more diverse datasets could result in more robust models and improved support systems for people with ASD and their caregivers.

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Author’s Contributions

Biplov Paneru: Contributed to the analysis, methodology, software development and model development.

Bishwash Paneru: Contributed to formatting, methodology, software and data curation.

Krishna Bikram Shah: Contributed to data collection, methodology, supervision and data analysis.

Awan Shrestha: Contributed to the literature review. Data collection, methodology, validation and software.

Ramhari Poudyal: Contributed to supervision, data curation.

Khem Narayan Poudyal: Contributed to supervision.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

Conflicts of Interest

On behalf of all authors, the corresponding authors state that there is no conflict of interest.

Use of LLM

This article used Large Language Model (LLM) tools to improve English writing, grammar and punctuation.

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