

AI-Driven Autism Spectrum Disorder Screening Using LightGBM and Behavioral Analysis

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Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by problems with communication, social interaction, and behavior patterns. Early detection of autism spectrum disorder is crucial for appropriate treatment and positive development. The existing procedures are lengthy and rely on manual assessment. This research work proposes a machine learning solution for the early detection of autism spectrum disorder based on the behavioral data obtained from a questionnaire, along with the demographic features. Different approaches to classification, including Decision Tree, K-Nearest Neighbors (KNN), and Light Gradient Boosting Machine (LightGBM) are tested to select the most efficient method for prediction. LightGBM proves to be the best approach because of its efficiency with structured data. In order to improve model transparency and facilitate decision-making in clinical practice, SHapley Additive exPlanations (SHAP) are incorporated to assess and measure the impact of specific features. The developed model ensures 97% accuracy, 97% precision, 92% recall, and 94% F1-score on the test dataset. The feature importance analysis reveals that the behavioral factors such as communication issues, problems in making eye contact, interaction problems, and repetition are among the important features contributing to the prediction of ASD. By combining high predictive accuracy with transparency, the proposed solution presents a reliable, efficient, and easy-to-use approach for early ASD screening.

Keywords: Autism Spectrum Disorder, Light GBM, Questionnaire-Based Dataset, Behavioral

Analysis, Explainable Artificial Intelligence, SHAP Classification.

1. Introduction

Early disease detection plays a major role in ensuring that the people suffering from ASD experience improved development and quality of life. Early detection of ASD is very important because it ensures that there will be proper intervention through behavioral therapy and appropriate medical treatment, which is very important in getting positive results. Traditional methods of detection of ASD involve clinical evaluation of the patient, behavioral observation of the patient, and also the opinions of the experts in the field. The traditional methods of detecting ASD are quite expensive and time-consuming. In order to mitigate the aforementioned challenges, researchers have started exploring various machine learning methods that can help with the screening and prediction of ASDs. Through the analysis of structured information like behavioral and demographic data, machine learning models can help in detecting any patterns that could be related to ASDs and develop much faster and scalable screening tools. There are different classification algorithms including Decision Trees and KNN for ASD prediction and are proved to be successful.

A major limitation in many of the existing predictive systems is the issue of opaqueness in the process of decision making. For the applications within the healthcare industry, the healthcare professionals need both the prediction outcomes and an insight into the behavior that affects these predictions. Opacity decreases trust and reduces chances of implementation of such systems within the real medical environment.

This study provides an explanation-oriented ML approach for ASD classification through a combination of the behavioral dataset collected by questionnaire with demographic features. The Light Gradient Boosting Machine (Light GBM) is used due to its high efficiency in processing tabular data, quick training procedure, and nonlinear interaction detection between behavioral features. The SHapley Additive exPlanations (SHAP) technique will be applied to enhance interpretability of the prediction by providing a feature-based explanation for each prediction.

The major contributions of this work are summarized as follows:

- Development of an accurate ASD prediction model utilizing LightGBM from the

questionnaire-based behavioral data.

- Implementation of SHAP-based Explainability to determine and measure the importance of each behavioral feature individually.
- Recognition of the main ASD markers including difficulties with social interactions, communicating, making eye contact, and repeating.
- Design of the practical web-based solution for predicting in real time, visualizing results, and managing patient history securely.

2. Related Works

2.1 Traditional ASD Screening Methods

Traditional screening of ASD usually involves clinical assessment, behavioral observation, interviews, and questionnaire forms. Even though these methods are significant for detecting individuals who could benefit from additional testing, they can be costly as well as labor-intensive especially if utilized on a large scale. Modern studies highlight the rising importance of ML in assisting with screening, prediction, and classification of ASD while serving as a supplement to the traditional clinical assessment [1]. The growing use of ML and DL with regard to various sources of data about ASD [2].

Questionnaire-based screening is particularly useful because it gives structured behavioral data which is then analyzed through traditional machine learning techniques. The use of classifiers like SVM, decision trees, and logistic regression in the behavioral dataset of ASD while focusing on the difficulties associated with feature selection, evaluation, and class imbalance [8].

2.2 Machine Learning Models for ASD Prediction

In recent years, ML has been extensively explored for automation of ASD prediction using behavioral, demographic, medical and background data. An ML architecture was designed by Rajagopalan et al. utilizing a minimal number of medical and background attributes and comparing different algorithms, such as logistic regression, decision tree, random forest, and XGBoost. The paper showed the capability of ML to predict the presence of an individual with high probability of ASD based on a fairly small amount of information as well as the use of the explainable AI to analyze significant predictors [3]. ML and DL approaches, including Naïve

Bayes, SVMs, logistic regression, KNN, neural network, and convolutional neural network, were implemented using open-access ASD screening datasets of children, adolescents, and adults [9].

Similarly, ML Optimizations for ASD Diagnosis utilizing screening datasets and stressed the importance of pre-processing, feature selection, classification, and explainable AI as key aspects of an automated framework to predict ASD [5]. ML framework utilizing structural neuroimaging features especially corpus callosum and intracranial brain volume features by using the ABIDE dataset. Their research proves that ML is also possible in neuroimaging features for ASD diagnosis despite being different from the questionnaire-based screening in terms of data requirement and clinical setting [10].

2.3 Deep Learning and Multimodal Approaches

The application of deep learning techniques has expanded the scope of ASD studies to incorporate functional magnetic resonance imaging (fMRI) in addition to traditional tabular questionnaire data. presented ASD-DiagNet, an approach that combines learning and classification using fMRI data from the Autism Brain Imaging Data Exchange (ABIDE) [6]. Natural Language Processing (NLP) using traditional machine learning and deep learning algorithms to examine the information related to ASD on social media texts. Their research tested decision trees, XGBoost, KNN, recurrent neural networks, LSTM, Bi-LSTM, BERT, and BERTweet, which illustrated the possible use of textual information as another resource for ASD predictions [7].

2.4 Feature Selection and Behavioral Analysis

Feature selection is an important component of ASD prediction because irrelevant, redundant, or highly correlated features can affect model performance and interpretability. Existing ASD research has investigated feature-selection techniques to identify the most informative behavioral and demographic attributes while reducing unnecessary model complexity [8]. Studies using questionnaire-based datasets have also demonstrated that a relatively small set of behavioral characteristics can provide useful information for ASD classification [9]. The UCI Autism Screening Adult dataset used in the present study similarly contains ten behavioral screening scores together with demographic and background variables, making it suitable for structured ML classification. The dataset contains 704 instances and includes A1_Score–A10_Score along with demographic and screening-related attributes.

2.5 Explainable Artificial Intelligence in ASD Screening

Although ML models can provide useful predictive performance, interpretability is particularly important in healthcare applications because users need to understand the factors contributing to a prediction. Recent ASD research has therefore increasingly incorporated explainable AI (XAI) techniques to investigate model behavior and influential predictors [1], [3]. SHapley Additive exPlanations (SHAP) provides a feature-level explanation by quantifying the contribution of individual features to a model prediction. Its application is particularly relevant to tree-based models because it can provide both global feature-importance information and local explanations for individual predictions. Rajagopalan et al., for example, incorporated explainable AI to examine the influence of predictors in their ML-based ASD prediction framework [3].

Overall, the research analysis indicates a lot of potential in the application of ML and DL methods to ASD screening depending on the used data types. However, the current techniques differ significantly in such aspects as data usage, complexity of computations, interpretability, and implementation. Datasets based on questionnaires seem to be an easier option in order to build a screening system. That is why in the current research, the LightGBM algorithm is used for binary ASD classification with structured behavioral and demographic data along with the use of SHAP for explanation of the results at the level of features.

3. Proposed Methodology

3.1 Problem Formulation

In this research work, the proposed system has been designed as a binary classification model that will determine whether a person belongs to ASD or not. With the help of the answers provided in a questionnaire about behavioral patterns along with other demographic information of the individual, a decision regarding whether a person is classified as ASD (1) or Non-ASD (0) is made by the algorithm. For building transparency in the model, SHAP has been used alongside the algorithm.

3.2 Dataset Description

ASD prediction system employs the Autism Screening Adult dataset downloaded from the UCI Machine Learning Repository. This dataset was created by Fadi Thabtah [11] for ASD screening and classification purposes. It includes 704 records with 21 attributes that consist

of ten behavioral features obtained through the questionnaire, demographic features, screening features, and binary target feature showing ASD or not ASD classification. Ten behavioral features obtained from the questionnaire, namely A1_Score to A10_Score, are coded as integers and show answers on the ASD screening questions. Other demographic and background features include age, gender, ethnicity, jaundice, family_pdd, country_of_res, used_app_before, result, age_desc, and relation. The target feature is a class feature which shows the ASD classification.

3.3 Data Preprocessing

Missing values are handled, duplicates are eliminated, and categorical variables are encoded to numeric values. Splitting of the data into train and test datasets is done at a 80:20 split ratio and stratified sampling 563 records are included in the train dataset and 141 records are included in the test dataset. Test data is only used for the evaluation of the classification accuracy of the models trained. Normalization and balancing of the class imbalance is done when necessary.

3.4 LightGBM Classification Model

The classification is performed using LightGBM, which is the tree-based ensemble learning algorithm that can be applied on structured data. It uses the technique of building multiple decision trees using gradient boosting to achieve better pre-diction accuracy. This algorithm was selected due to the high efficiency, fast training, and complexity handling.

Input data includes ten screening questions on behavior (AQ1–AQ10) along with relevant demographic and background factors that are presented in the Autism Screening Adult dataset. All these features are pre-processed and passed into the trained LightGBM classifier. The result of applying this classifier is the score in the range [0,1] that represents the probability of having ASD. Binary classification is done by setting the 0.50 (50%) threshold on the probability of ASD: if the predicted probability of having ASD is more than 0.50, then it means that this person is suffering from ASD (1); otherwise, this person is Non-ASD (0).

3.5 Explainability Using SHAP

SHAP is applied for the explanation of the predictions that are generated by the LightGBM model. Importance scores are assigned to all the features depending on their significance for the outcome. The features like bad communication, less eye contact, repetitive behaviors, and low social interactions are determined as the significant factors impacting the prediction of ASD.

4. System Architecture and Implementation

The proposed ASD prediction system has been built following a two-tier approach that includes the frontend user interface and the backend processing module. The workflow of the system as shown in Figure.1 comprises various functional modules such as user registration, secure login, data collection on behavior, preprocessing, prediction generation, explanation visualization, data storage in databases, and history management.



Figure 1. Workflow architecture of the proposed ASD prediction system

The front end of the system is designed using HTML, CSS, and Bootstrap for a neat, responsive, and structured web interface. Interaction with the application is done via registration and login pages, which leads to a form for prediction containing demographic information and answers from the behavioral questionnaire. The behavioral questionnaire consists of ten questions, labeled AQ1-AQ10, and it covers important behavioral features of autism spectrum disorder such as communication skills, eye contact, social behavior, emotions, and repetitive actions.

After the completion of the submission process, the collected inputs are sent to the back-end

designed using Flask programming language in Python. The back-end is responsible for user authentication, handling the session management, input pre-processing, machine learning inference process, database management operations, and generating results. Flask works as the core controller which helps in connecting the front end, the prediction system, and the database system. First, the collected inputs are subjected to pre-processing wherein the categorical values are encoded and feature formatting is done in such a way that it matches with the training dataset. Once the inputs are pre-processed, the LightGBM model performs the task of predicting the class of the user, whether he/she falls under the ASD or non-ASD category.

For better interpretability, SHAP has been incorporated into the model. After making the prediction, SHAP values for the specific case will be calculated in order to determine the contribution of each variable in the final prediction. A SHAP plot will then be dynamically drawn using Matplotlib and saved as an image file. The image will be shown on the results page to help users know which behavioral variables had the most impact. All the data related to the prediction such as patient data, question responses, result of prediction, probability score, risk level, and timestamp are saved in the PostgreSQL database. This helps in systematic record keeping and tracking of screening results. Role-based access is supported in the system such that a normal user can see his/her own record of the predictions whereas administrator can see the record of all patients.

5. Experimental Results and Discussion

5.1 Performance Evaluation of the Proposed Model

The performance of the proposed ASD prediction model is assessed using the held-out test dataset after training the model on the pre-processed questionnaire-based behavioral dataset. This dataset is split into train and test datasets in an 80:20 ratio with the use of stratified sampling. This allows for the balance in the distribution of classes among ASD and Non-ASD classes.

LightGBM classifier performance is assessed using various performance measures such as accuracy, precision, recall, and F1 Score. All of these performance measures are very crucial in healthcare-based classification problems as recall is very important because failure to identify ASD-positive cases could result in late diagnosis.

Comparison of the performance of the proposed LightGBM model with various baselines such

as Decision Tree, KNN classifiers. The comparative performance results have been shown in Table I. The confusion matrix and SHAP analysis have been shown in Figure. 2 and Figure. 3 respectively.

Table 1. Performance comparison of classification models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree [7]	61	56	99	72
KNN [9]	95	97	96	96
LightGBM (Proposed)	97	97	92	94

From the results, the LightGBM model outperforms all the other models when it comes to accuracy. This is because the LightGBM model can capture the nonlinearity among features and also work effectively with structured behavior data.

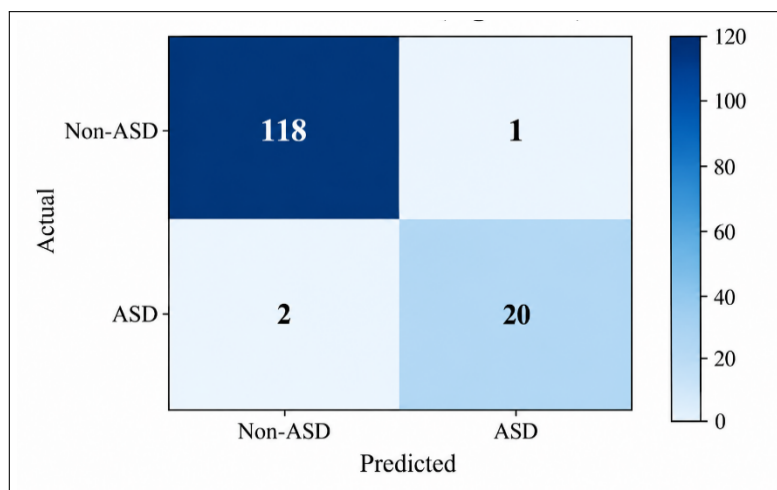


Figure 2. Confusion matrix of LightGBM model

The confusion matrix illustrates that the model correctly identifies most ASD and Non-ASD cases with only a small number of misclassifications. The confusion matrix evaluates the LightGBM model by comparing the actual ASD/Non-ASD classes with the predicted classes. It identifies correct predictions and misclassifications, providing a clear view of model performance.

5.2 SHAP Feature Importance Analysis

SHAP-based analysis is performed to determine the most significant features that contribute towards ASD prediction. Behavioral factors like inadequate communication skills, less eye

contact, repetition, emotional response, and social interaction always seem to be the most significant factors for predicting ASD. This is consistent with the clinical perspective on autism-based behavioral characteristics.

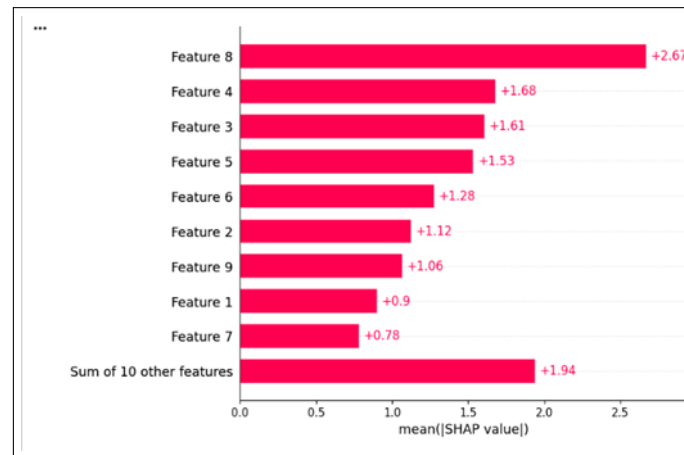


Figure 3. SHAP global feature importance analysis for ASD prediction

The features with positive SHAP value increase the chances of autism spectrum disorder classification, while the features with negative SHAP value decrease the chances. In this way, the interpretability of the model can be carried out both globally and locally. For each individual prediction, SHAP provides the information of why a particular patient is considered high or low risk.

5.3 Dashboard

The dashboard acts as the output interface of the proposed ASD screening system, allowing a user to visualize the way the screening based on a questionnaire is performed and explained on a single screen. On the left side, there is the screening form where a user needs to provide demographic information about himself, including his name, age, gender, family history, and medical history. In addition, a user needs to provide answers to the ten questions about his behavior (AQ1 through AQ10), answering them either 'Yes' or 'No' in a similar manner to what was mentioned in the description of the dataset in the paper. Pressing "Run prediction" button will give us the probability of being ASD in the suggested model shown in Figure. 4.

The output on the right side appears in the form of layers. There is a circular gauge indicating the probability as a percentage, color-coded according to risk level; green for low, amber for moderate, and red for high. Alongside this, the user interface indicates if the patient is classified

as ASD or Non-ASD using a cut-off point of 50 percent, together with an explanation. Below this layer is a bar chart, similar to SHAP, listing the top eight features in terms of influence, with red bars indicating factors increasing the probability of ASD and teal bars reducing the probability of ASD, along with their numerical contributions. Suggested action items like consultation with the clinician ends the results page. At the bottom end of the page, there is a table containing details of all the runs conducted including timestamp, patient, age, result, probability, risk level and top contributing factor to reflect record management using PostgreSQL.

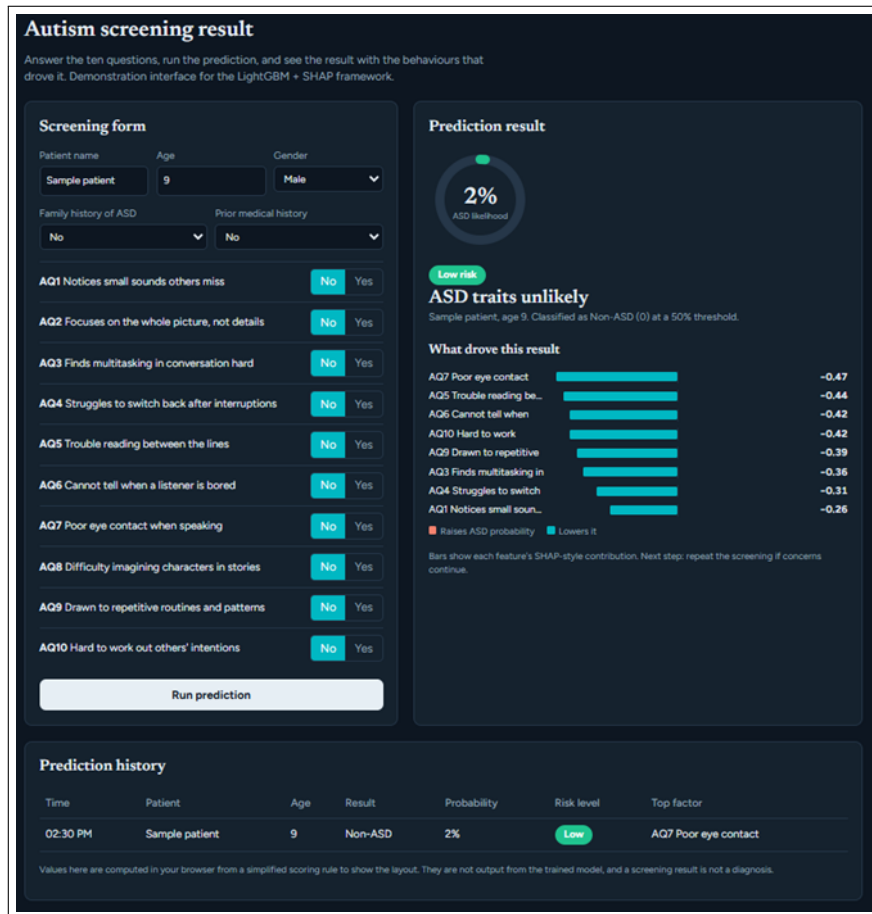


Figure 4. ASD screening dashboard

The experimental results show that the proposed architecture effectively integrates predictive capability with explainable artificial intelligence. LightGBM shows excellent classification capabilities in the case of structured questionnaire-based behavioral data, whereas SHAP improves explainability by explicitly showing the contribution of features.

6. Conclusion and Future Scope

This research presents the machine learning methods for early screening of Autism Spectrum Disorder based on behavioral and demographic data. From the experiment, it is evident that the LightGBM model has achieved the highest accuracy of 97%, proving that this method is very useful for predicting the cases of ASD based on the structured questionnaire information. The use of SHAP also improved the interpretability of the model as the contributions of each feature to the predictions have been estimated and visualized. The implemented web application is used for the real-time screening, visualization, and secure handling of results. Further development of the presented approach is possible by considering early childhood screening, multimodal data (speech, face expressions, eye tracking, clinical data), and multi-class severity prediction. The future research could focus on deep learning techniques, hybrid approaches, and neural networks, along with attention mechanisms and other hybrid systems where deep learning is integrated with gradient boosting. Combining structured questionnaire data with image, audio, or video information could increase the applicability of the system in ASD detection systems.

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