A WEB-BASED MULTIMODAL SYSTEM FOR EARLY PREDICTION OF AUTISM SPECTRUM DISORDER USING MACHINE AND DEEP LEARNING CONCEPTS

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Abstract: The project introduces a web-based system designed for the early identification of Autism Spectrum Disorder (ASD) by combining facial image analysis with behavioral questionnaire inputs. It serves as a quick and accessible screening solution through the use of multimodal data. Facial features are examined using Convolutional Neural Networks (CNN) to identify patterns associated with autism, while questionnaire responses are evaluated using machine learning techniques such as Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost. Developed using Streamlit, the application enables users to upload facial images and provide behavioral details to receive instant predictions, including risk levels and confidence scores. By merging insights from both image-based and questionnaire-based analyses, the system improves the overall accuracy and dependability of autism risk assessment. It is trained on publicly available datasets that include facial images and behavioral attributes, ensuring a diverse and reliable model. To enhance performance, data preprocessing methods like normalization, data augmentation, and feature scaling are applied. The platform is designed with a simple and intuitive interface, making it accessible even for non-technical users and suitable for preliminary at-home screening. Additionally, its modular architecture allows future expansion, such as incorporating speech or text-based behavioral analysis, making the system adaptable and scalable.

1.PROBLEM STATEMENT

Early detection of Autism Spectrum Disorder (ASD) is crucial for timely intervention, yet it is often delayed due to dependence on traditional clinical assessments that are time-consuming, costly, and not easily accessible to all. Existing screening methods typically rely on limited data sources, such as only behavioral observations or medical evaluations, which restrict their ability to capture the diverse characteristics of autism. Additionally, subtle early signs in children are frequently overlooked, making accurate and timely identification more challenging. These limitations highlight the need for an efficient, accessible, and automated system for early autism screening. This project proposes a web-based application that adopts a multimodal approach by integrating facial image analysis and behavioral questionnaire data. Facial features are analyzed using Convolutional Neural Networks (CNN) to identify patterns associated with ASD, while machine learning models process behavioral responses to assess potential risk. By combining these approaches, the system aims to improve prediction accuracy and reliability compared to traditional single-source methods. The proposed solution enables quick and user-friendly screening, provides real-time risk assessment with confidence scores, and supports early decision-making. It can be effectively used by parents, educators, and healthcare professionals, thereby enhancing accessibility and promoting early awareness and intervention in autism detection.

2.INTRODUCTION

2.1Importance of autism detection.

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects social interaction, communication, and behavior, with a growing number of cases reported globally. Early detection of ASD is essential, as timely intervention can significantly improve cognitive, social, and behavioral development in children. However, many cases remain undiagnosed during the early stages due to lack of awareness, limited access to specialists, and delayed clinical evaluations. An efficient and accessible screening system can play a crucial role in bridging this gap by enabling early identification and supporting informed decision - making for parents, educators, and healthcare professionals.

2.2Challenges in autism detection (subjectivity, accessibility, data limitations).

Despite advancements in medical science, autism detection presents several challenges. Traditional diagnostic methods are often subjective, relying heavily on expert observation and interpretation, which may vary across clinicians. Accessibility is another major concern, especially in remote or underdeveloped regions where specialized healthcare services are limited. Additionally, most existing systems focus on a single type of data, such as only behavioral assessments or medical history, which restricts the overall accuracy of diagnosis. Variability in symptoms, subtle early signs, and the complexity of behavioral patterns further complicate early detection. These factors highlight the need for an automated, reliable, and multimodal approach.

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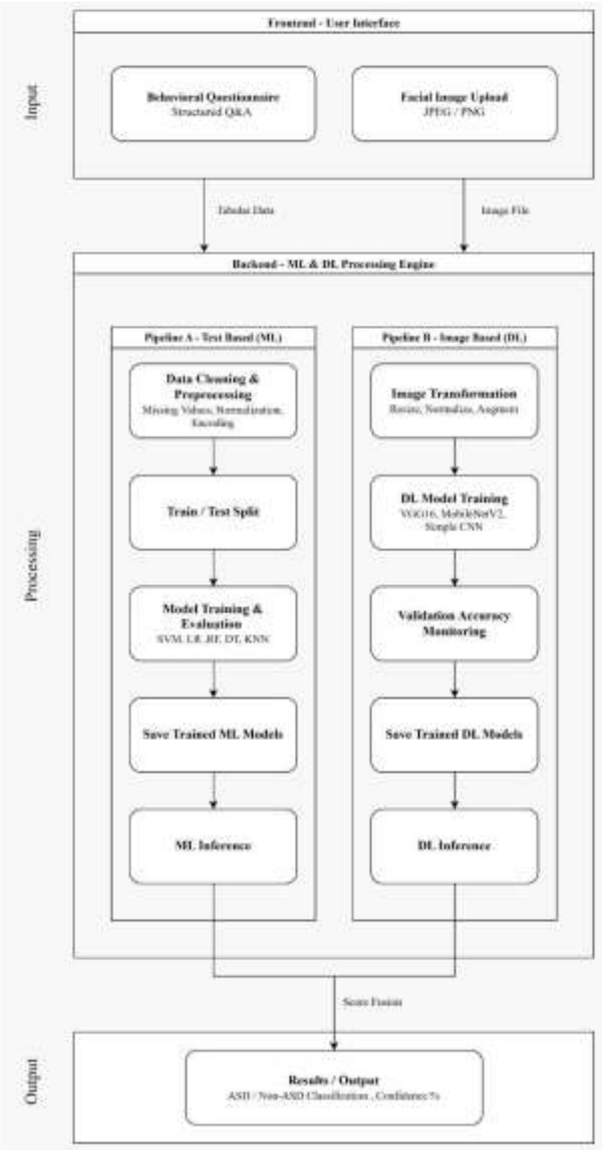
2.3 Objectives.

The primary objective of this study is to develop an intelligent and user-friendly web-based system for early autism prediction using multimodal data. The specific objectives include:

- To analyze facial features using Convolutional Neural Networks (CNN)
- To evaluate behavioral questionnaire data using machine learning models such as Logistic Regression, Random Forest, SVM, and XGBoost
- To integrate image-based and data-based predictions for improved accuracy
- To provide real-time risk assessment along with confidence scores
- To design an accessible platform for parents, educators, and healthcare professionals

2.4 Brief overview of our methodology.

The proposed system follows a modular and multimodal approach that combines image analysis and behavioral data processing. Initially, facial images are preprocessed and passed through a CNN model to extract relevant features and predict autism-related patterns. Simultaneously, user-provided behavioral questionnaire responses are processed using classical machine learning algorithms to assess risk levels. The outputs from both models are then combined to generate a final prediction with improved reliability. The system is implemented as a web-based application using Flask and Streamlit, providing an interactive interface for users to upload images or enter data. The results are displayed in real-time, including prediction outcomes and confidence scores. This integrated methodology ensures better performance, scalability, and accessibility for early autism screening.



Proposed System

3. LITERATURE REVIEW / RELATED WORK

Autism Spectrum Disorder (ASD) diagnosis has traditionally relied on behavioral observation and standardized clinical assessments, which are often subjective and time-intensive. In recent years, the integration of machine learning (ML) and artificial intelligence (AI) has emerged as a promising approach for automating and improving the accuracy of early ASD detection. Multiple researchers have contributed to developing data-driven frameworks that utilize behavioral attributes, facial images, and multimodal features to identify autism risk with enhanced precision.

T. Akter et al. [1] introduced a comprehensive study on machine learning-based models for early-stage autism detection, where various algorithms such as Support Vector Machine (SVM), Random Forest, and Decision Tree were trained on behavioral datasets. Their results indicated that ensemble-based techniques performed better in classifying ASD and non-ASD individuals, achieving improved generalization and accuracy. Similarly,

S. R. Dutta et al. [2] designed an ML-assisted diagnostic tool for children, integrating behavioral and developmental data to automate autism assessment. The system effectively reduced manual evaluation time while maintaining diagnostic reliability, proving that ML can support clinicians in large-scale screening.

In parallel, researchers have explored the use of facial image analysis through deep learning to identify autism-related visual traits. M. Beary et al. [3] employed convolutional neural networks (CNNs) for facial recognition and achieved promising accuracy in differentiating ASD children from typically developing peers. Their approach demonstrated that CNNs can extract subtle facial features associated with ASD, supporting the role of computer vision in healthcare diagnostics. F. C. Tamilarasi and J. Shanmugam [4] further expanded on this by designing a CNN-based autism classification model that leveraged image preprocessing and data augmentation to enhance performance. Their work proved that properly optimized CNN architectures can effectively identify developmental disorders with minimal manual intervention.

K. S. Omar et al. [5] conducted a comparative study of traditional machine learning models—Decision Tree, Random Forest, and SVM—on ASD prediction using demographic and behavioral datasets. Their findings revealed that Random Forest outperformed other models in terms of prediction accuracy and robustness, suggesting that ensemble learning can handle the complexity and variability of ASD data. Z. Nazari et al. [6] similarly utilized classical ML methods and emphasized the importance of feature selection, normalization, and cross-validation in improving classification outcomes.

S. M. M. Hasan et al. [7] presented a multi-stage framework that integrated multiple ML algorithms, including Logistic Regression, XGBoost, and Random Forest, to detect early signs of autism. Their hybrid approach combined behavioral features and clinical indicators, leading to improved detection rates and fewer false positives. Meanwhile, M. Elhoseiny et al. [8] perfor med a comparative analysis of pre-trained CNN architectures such as VGG16, ResNet50, and InceptionV3 on facial image datasets for ASD detection. The results demonstrated that transfer learning enhances model efficiency and reduces the need for large labeled datasets, making it feasible for real-world applications.

In another significant contribution, P. Mukherjee et al. [9] evaluated various traditional ML models—including Logistic Regression, Decision Tree, and Support Vector Machine—on structured behavioral datasets. Their study highlighted that data preprocessing, feature engineering, and ensemble integration substantially improve predictive reliability. P. Gyanchandani and G. Shrivastava [10] focused on enhancing ASD diagnosis through advanced data analytics and machine learning, utilizing large-scale datasets to uncover complex relationships between behavioral, facial, and neurological features. Their research emphasized the potential of combining multimodal data sources for holistic and accurate autism detection.

Across the reviewed studies, a clear research trend emerges— hybrid models that integrate both image-based and behavior-based features consistently outperform single-source systems. Deep learning models such as CNNs provide exceptional capability in recognizing non-verbal cues from facial images, while classical ML algorithms excel in analyzing questionnaire-based and structured behavioral data. The synergy between these two modalities leads to higher classification accuracy and greater diagnostic confidence.

Building upon these findings, the proposed project integrates facial image analysis using CNNs with behavioral response evaluation through models like Logistic Regression, Random Forest, SVM, and XGBoost. This multimodal approach aims to deliver a comprehensive, fast, and reliable tool for early ASD screening. By combining the strengths of both visual and behavioral analytics, the system addresses the limitations of existing single-modal models and contributes toward accessible, data-driven early detection of autism in children.

4. METHODOLOGY

4.1.1 Dataset (Description of training/validation sets).

The dataset used in this project consists of two primary data types: facial images and behavioral questionnaire data related to Autism Spectrum Disorder (ASD). The image dataset includes labeled facial images of individuals categorized as ASD and non-ASD, while the behavioral dataset contains structured responses representing social, emotional, and communication patterns. The data is divided into training and validation sets to ensure proper model learning and evaluation. This split helps the models generalize effectively to unseen data and improves prediction reliability.

4.1.2 Preprocessing steps.

To ensure consistency and improve model performance, several preprocessing techniques are applied:

- Facial images are resized to a fixed dimension (e.g., 224 × 224 pixels) to match CNN input requirements.
- Pixel values are normalized to enhance training stability and convergence.
- Data augmentation techniques such as flipping and rotation are applied to increase dataset diversity.
- Behavioral data is cleaned, encoded, and scaled using feature scaling techniques to standardize input values.

Dataset Summary

Data Type	Description	Example
Facial Images	Visual features of individuals	ASD / Non-ASD
Behavioral Data	Questionnaire-based responses	Social & Communication Patterns

4.2 IMAGE-BASED ANALYSIS (CNN)

4.2.1 Detection and feature extraction.

Facial images are processed using a Convolutional Neural Network (CNN) to automatically extract important visual features. The CNN identifies patterns in facial structure and expressions that may be associated with ASD. Feature maps generated through convolution and pooling layers capture both low-level and high-level characteristics.

4.2.2 Model processing.

The extracted features are passed through fully connected layers for classification. The CNN outputs a probability score indicating whether the input image is likely to belong to an ASD or non-ASD category. A threshold is applied to determine the final prediction.

4.2.3 Output generation.

The model produces a classification label along with a confidence score. This output contributes to the final decision-making when combined with behavioral analysis.

4.2.4 Deep Learning Models

Simple CNN - A Custom Convolutional Neural Network (CNN) is a user-defined architecture designed specifically for a given task. It typically consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The model learns hierarchical patterns such as edges, textures, and shapes from input images. Custom CNNs are lightweight and flexible, making them suitable for small datasets and task-specific optimizations.

MobileNetV2 - MobileNetV2 is a lightweight deep learning model designed for efficient image classification, particularly on mobile and embedded devices. It uses depthwise separable convolutions and inverted residual blocks with linear bottlenecks to reduce computational cost while maintaining performance. This architecture minimizes parameters and memory usage, making it suitable for real-time applications. MobileNetV2 balances accuracy and efficiency, which makes it widely used in resource-constrained environments.

VGG16 - VGG16 is a deep convolutional neural network composed of 16 layers with learnable parameters. It uses small 3×3 convolution filters stacked sequentially to capture complex image features while maintaining a simple and uniform architecture. The network includes multiple convolutional layers followed by fully connected layers for classification. Although computationally heavy, VGG16 is effective for feature extraction and transfer learning in various computer vision tasks.

Resnet50 - ResNet50 is a 50-layer deep convolutional neural network that introduces residual learning through skip connections. These shortcut connections allow gradients to flow directly across layers, solving the vanishing gradient problem in deep networks. The model learns residual mappings instead of direct feature transformations, enabling deeper architectures with improved accuracy. ResNet50 is widely used for image classification, feature extraction, and transfer learning due to its strong performance.

4.3 BEHAVIORAL DATA ANALYSIS (ML MODELS)

4.3.1 Model selection.

Behavioral questionnaire data is analyzed using multiple machine learning models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost. These models are chosen for their effectiveness in classification tasks and ability to handle structured data.

4.3.2 Training process.

The models are trained on preprocessed behavioral data using labeled datasets. During training:

Features are fed into the models Predictions are compared with actual labels
Model parameters are updated to minimize error

Evaluation metrics such as accuracy and precision are used to assess performance.

4.3.3 Prediction logic.

Each model generates a prediction score for ASD risk. The outputs can be combined or compared to improve reliability. The final behavioral prediction is then integrated with the image-based result.

4.3.4 Machine Learning Models

Support Vector Machine (SVM) - Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. It works by finding an optimal hyperplane that separates data points from different classes with maximum margin. SVM can handle both linear and non-linear data using kernel functions such as linear, polynomial, and radial basis function (RBF). It is effective in high-dimensional spaces and is widely used for image classification and text categorization.

Logistic Regression - Logistic Regression is a supervised learning algorithm used for binary and multi-class classification problems. It estimates the probability of a class using the sigmoid function, which maps input values to a range between 0 and 1. The model learns the relationship between input features and output labels through maximum likelihood estimation. Logistic regression is simple, interpretable, and performs well for linearly separable datasets.

Random Forest - Random Forest is an ensemble learning method that combines multiple decision trees to improve classification and regression performance. It uses bootstrap sampling and random feature selection to create diverse trees, and predictions are made using majority voting or averaging. This approach reduces overfitting and increases model accuracy. Random Forest is robust to noise and works well with large datasets and high-dimensional features.

Naïve Bayes - Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem with the assumption of feature independence. It calculates the posterior probability of each class given the input features and selects the class with the highest probability. Despite its simplicity, Naive Bayes performs well on large datasets and text classification problems. It is computationally efficient and requires less training data compared to many other algorithms.

Decision Tree - Decision Tree is a supervised learning algorithm that splits data into branches based on feature values to make predictions. It uses criteria such as Gini index or entropy to determine the best splits at each node. The model creates a tree-like structure where leaf nodes represent final decisions. Decision trees are easy to interpret and visualize but may suffer from overfitting if not properly controlled.

K-Nearest Neighbors - K-Nearest Neighbors (KNN) is a non-parametric supervised learning algorithm used for classification and regression. It works by identifying the k closest data points to a new sample based on distance metrics such as Euclidean distance. The predicted class is determined by majority voting among the nearest neighbors. KNN is simple and effective but computationally expensive for large datasets.

4.4 MULTIMODAL INTEGRATION

4.4.1 Fusion approach.

The system combines predictions from both CNN (image-based) and machine learning models (behavioral data). This fusion enhances overall accuracy by leveraging complementary information from both modalities.

4.4.2 Final prediction.

A combined risk score is generated based on both inputs, along with a confidence level. This provides a more robust and reliable assessment compared to single-input systems.

4.5 WEB APPLICATION IMPLEMENTATION

4.5.1 Interface (Streamlit).

The system is deployed as a web-based application using Streamlit. It provides an intuitive interface where users can upload facial images or enter behavioral responses for analysis.

4.5.2 Visualization and output panels.

The application includes multiple components for user interaction and result display:

Input Panel: Upload image or fill questionnaire Prediction Panel: Displays ASD risk result
Confidence Score Panel: Shows probability of prediction Information Panel: Provides guidance or insights based on results

The user-friendly design ensures accessibility for non-technical users and supports real-time autism screening.

5.1 CNN Model Performance

5.1.1 Image classification accuracy (ASD vs Non-ASD).

The CNN model is evaluated based on its ability to classify facial images into ASD and Non-ASD categories. The performance is influenced by training quality, dataset diversity, and preprocessing techniques. The model achieves reliable accuracy due to feature extraction and pattern recognition capabilities. At optimal training conditions, the model provides balanced predictions with minimal overfitting.

Lower confidence thresholds increase sensitivity but may lead to false positives. Higher thresholds improve precision but may miss subtle cases.
The model performs well on clear facial inputs, while performance may slightly vary with low-quality or noisy images.

5.1.2 Feature extraction reliability.

The CNN effectively captures important facial features such as structure and expression patterns. It shows consistent performance across diverse samples due to normalization and augmentation techniques. However, variations in lighting, pose, and image quality can impact prediction accuracy. Despite this, the model maintains stable performance for most real-world inputs.

5.2 MACHINE LEARNING MODEL PERFORMANCE

5.2.1 Behavioral data classification accuracy.

Machine learning models such as Logistic Regression, Random Forest, SVM, and XGBoost are evaluated for predicting ASD risk based on questionnaire data. All models demonstrate good performance due to the structured and informative nature of the input features. Random Forest, SVM, and XGBoost achieve higher accuracy by effectively capturing complex patterns in the data. However, Logistic Regression is selected as the final model for prediction due to its simplicity, faster computation, and consistent performance. It provides a good balance between accuracy and efficiency, making it suitable for real-time web-based applications.

Model	**Accuracy**
Logistic Regression	**Medium (Selected Model)**
Random Forest	**High**
SVM	**High**
XGBoost	**High**

The use of validation data ensures that models generalize well to unseen behavioral inputs.

5.2.2 Prediction consistency.

The models produce stable predictions when consistent behavioral inputs are provided. Feature scaling and preprocessing improve reliability. Minor variations in responses may slightly affect results, but overall consistency remains high.

5.3 MULTIMODAL SYSTEM PERFORMANCE

5.3.1 Comparative results (CNN vs ML vs Hybrid).

The hybrid system combines predictions from both image-based (CNN) and behavioral (ML) models. Comparative analysis shows:

- CNN performs well when clear facial images are available
- ML models perform strongly on structured behavioral data
- Hybrid system provides the most accurate and reliable results

Model	**Image Input**	**Behavioral Input**	**Overall**
CNN	High	Low	Medium
ML Models	Low	High	Medium
Hybrid	High	High	High

The integration of both modalities reduces individual model limitations and improves overall prediction accuracy.

5.3.2 Case studies (image-only vs questionnaire-only vs combined). The system is tested under different input scenarios:

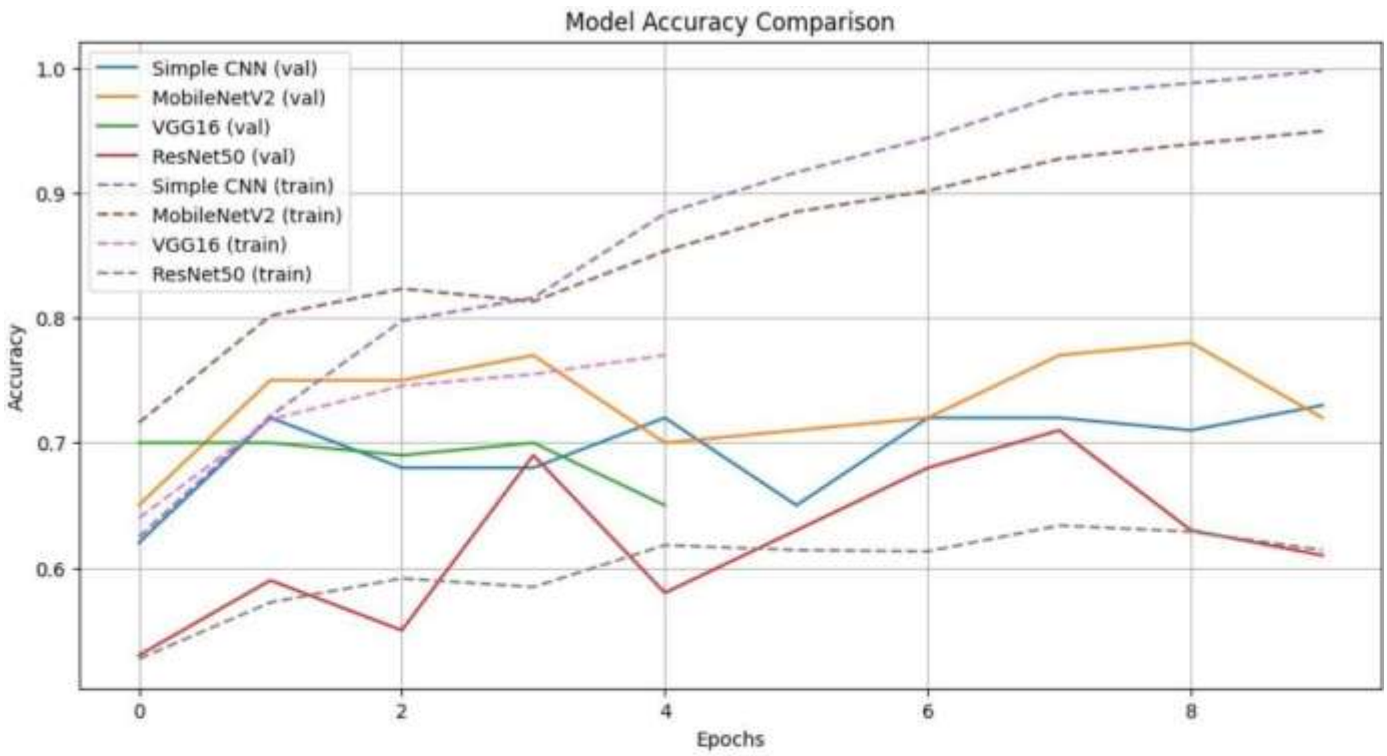
Image-only input: Provides quick results but depends on image quality **Questionnaire-only input:** Stable and reliable but limited to behavioral data **Combined input:** Produces the most accurate and balanced predictions

Input Type	**Performance**	**Observation**
Image Only	Fast	Image dependent
Questionnaire Only	Stable	Limited scope
Combined	Best	High accuracy

The results demonstrate that the multimodal approach enhances robustness, ensures better generalization, and supports effective early autism screening in real-world applications.

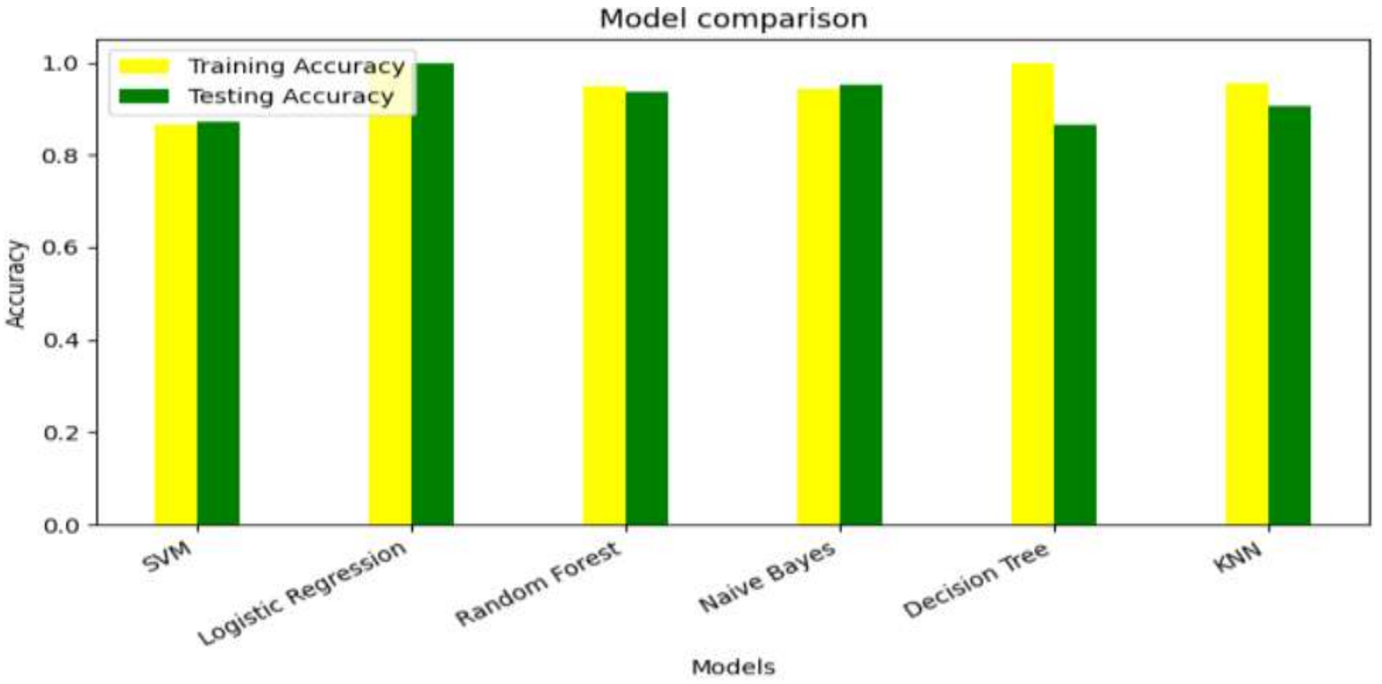
5.4 Visualization Outputs

Model Accuracy Comparison Graph: The figure presents a comparison of training and validation accuracy across multiple CNN architectures over several epochs. The training accuracy for all models shows a consistent upward trend, with the Simple CNN achieving the highest training performance, approaching near-perfect accuracy, followed by MobileNetV2, VGG16, and ResNet50. However, validation accuracy remains lower and more stable, indicating potential overfitting, especially for the Simple CNN where the gap between training and validation accuracy is most pronounced. MobileNetV2 demonstrates relatively balanced performance with moderate improvement in validation accuracy, while VGG16 shows stable but limited gains. ResNet50 exhibits the lowest validation accuracy and slower improvement compared to other models. Overall, the results suggest that although deeper models improve training accuracy, generalization performance varies, with MobileNetV2 providing a better trade-off between training and validation accuracy.



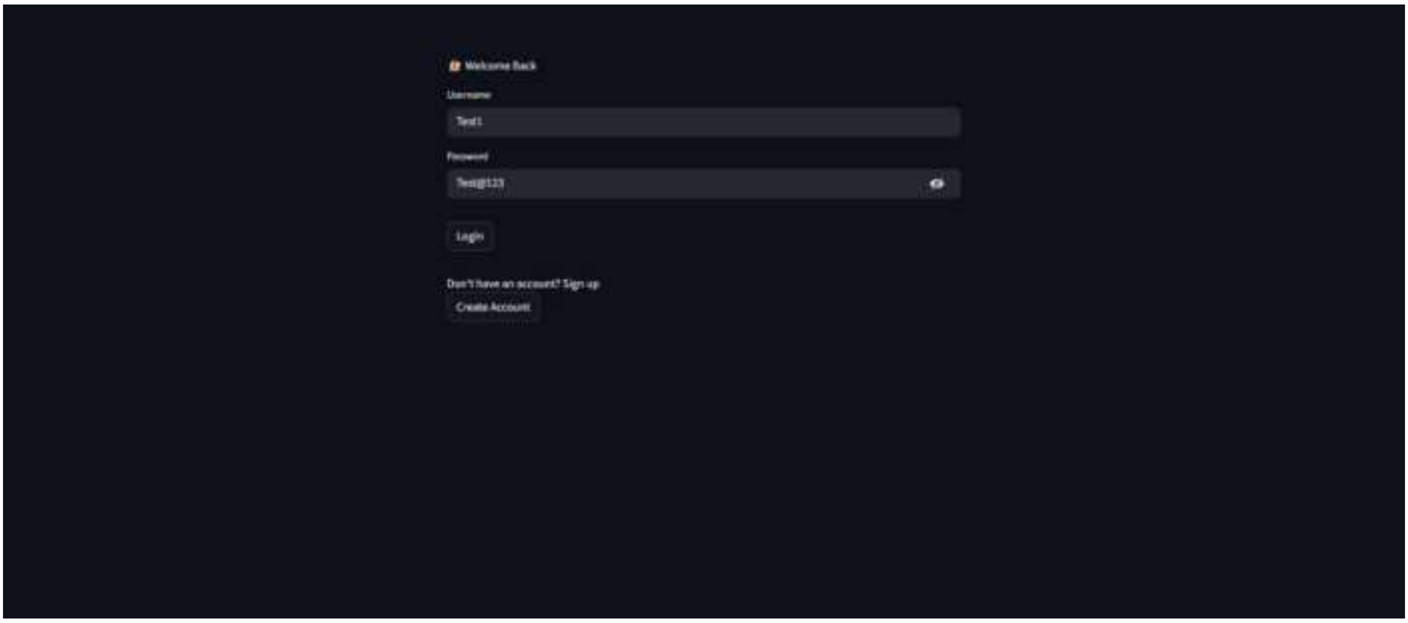
Models Comparison for Image Based Prediction

The image presents a comparative analysis of different machine learning models based on their training and testing accuracy. The models evaluated include SVM, Logistic Regression, Random Forest, Naive Bayes, Decision Tree, and KNN. Logistic Regression achieves the highest and most balanced performance across both training and testing datasets. While Decision Tree shows perfect training accuracy, its lower testing accuracy indicates possible overfitting. Overall, the chart highlights that Logistic Regression provides the most stable and reliable performance, making it suitable for final prediction in the system.



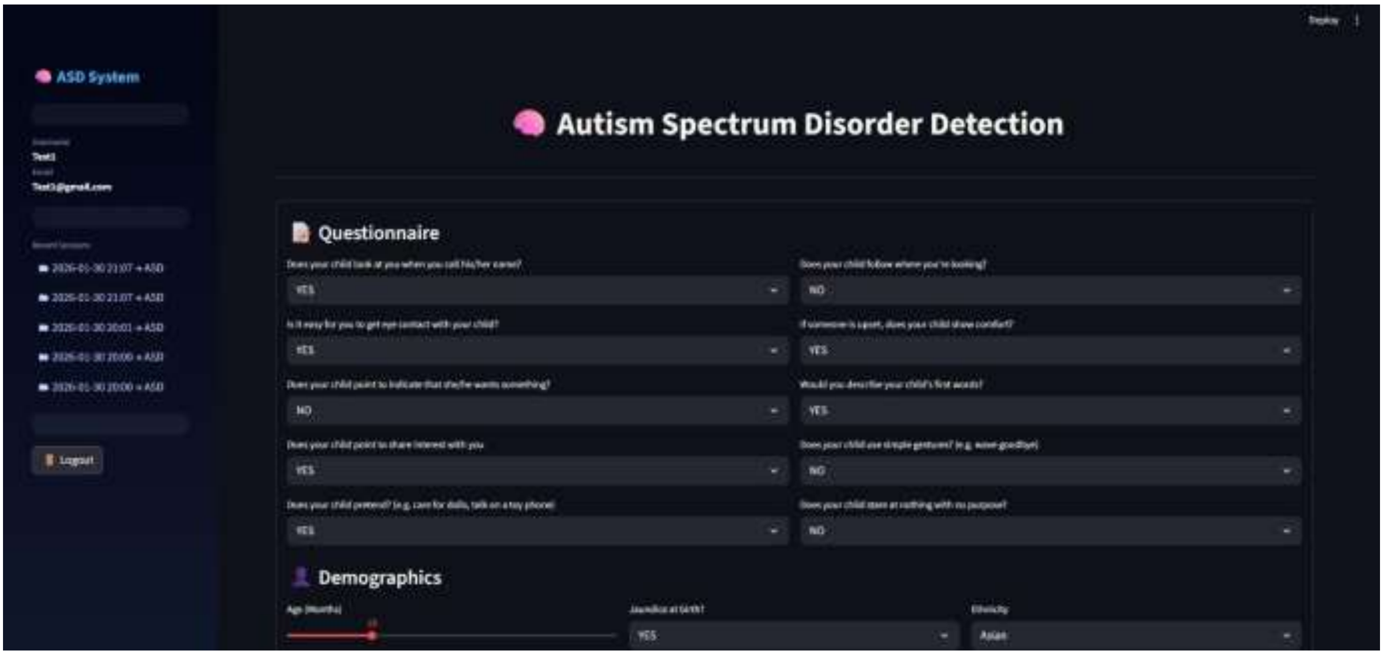
Models Comparison For Questionnaire based prediction

The image shows the login interface of the ASD Detection System. Users can securely access the platform by entering their username and password. The design is clean and minimal, ensuring ease of use for all users. It also includes an option to create a new account for first-time users. The interface focuses on simplicity and accessibility.



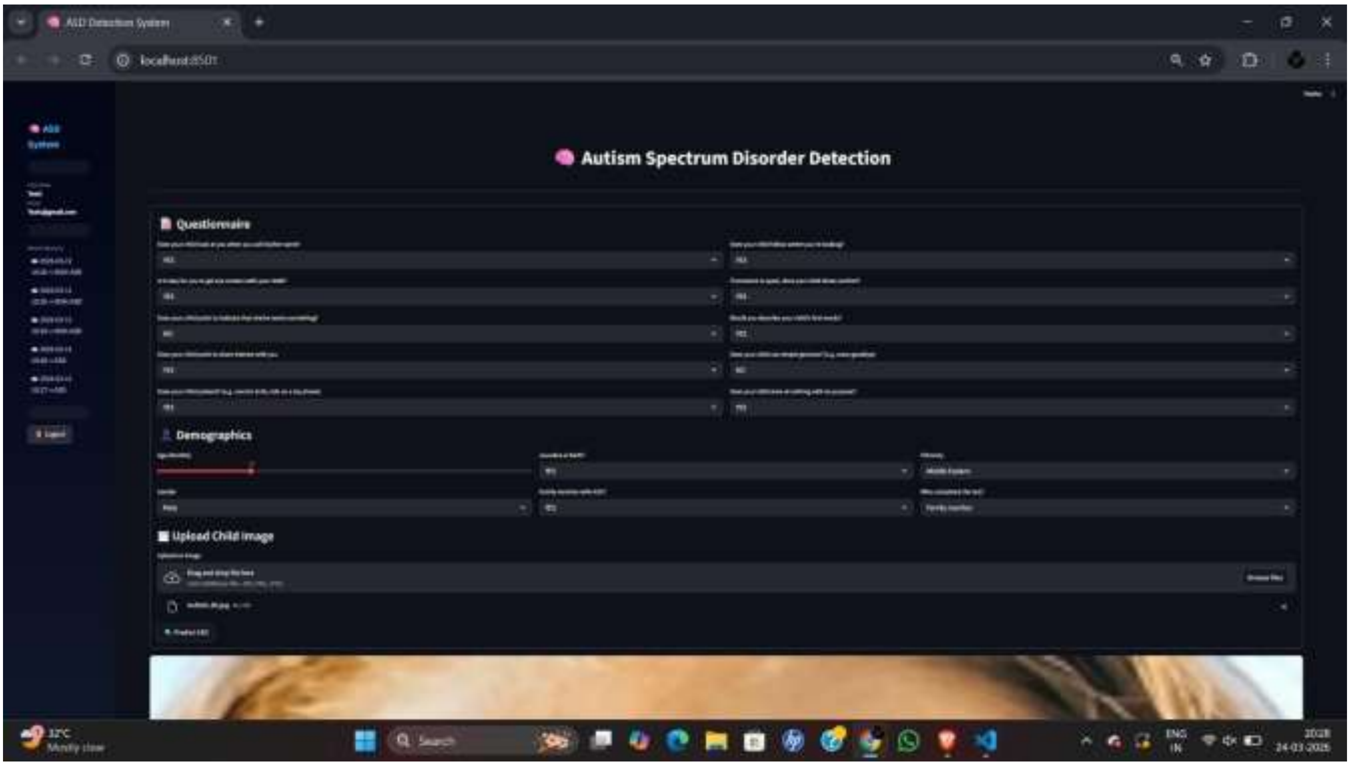
Login Page: User authentication interface allowing users to securely log in or create a new account.

The image displays the main questionnaire section of the system. It includes multiple behavioral questions related to the child's social interaction, communication, and responses. Users can select answers from dropdown menus, making it easy to input data. The layout is well-structured, allowing users to complete the assessment efficiently. It forms a key part of the behavioral data collection process.



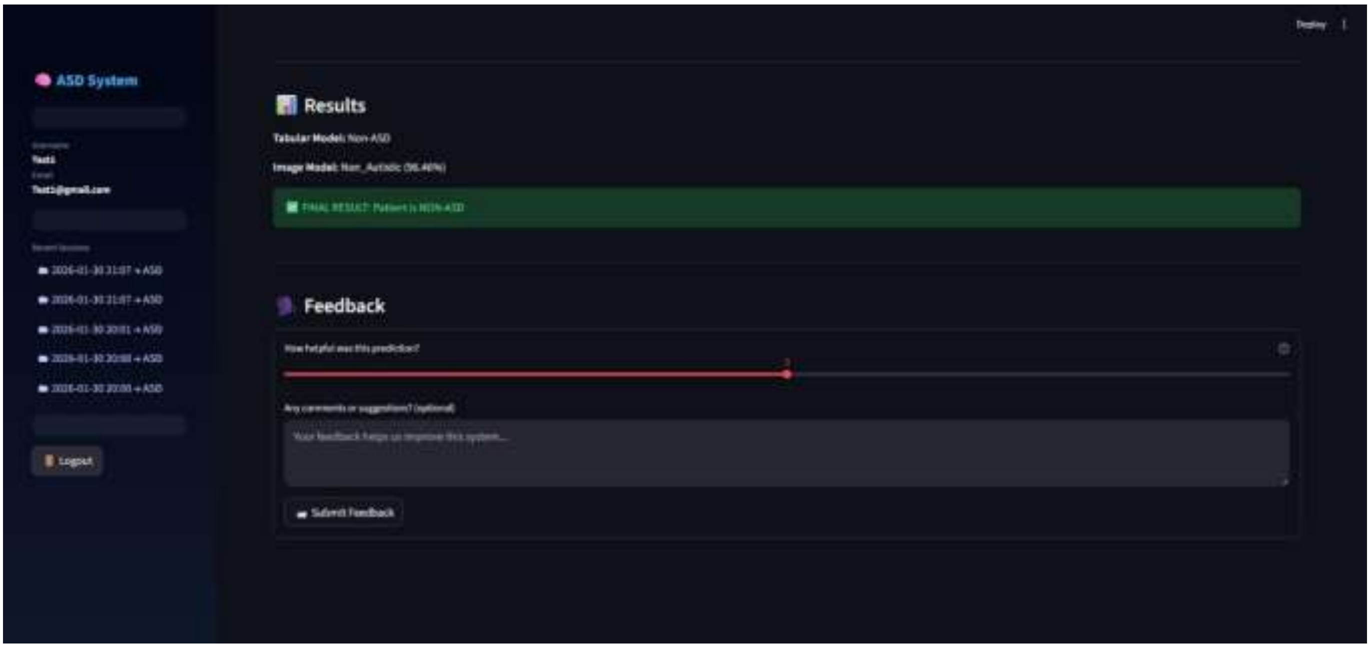
Home Page: Main interface where users input behavioral responses and demographic details for ASD assessment.

The image represents the full input dashboard, including questionnaire, demographic details, and image upload section. Users can enter information such as age, gender, and other relevant attributes. It also provides an option to upload a child' s facial image for analysis. The integrated interface supports multimodal input in a single view. This design improves user experience and streamlines the prediction process.



Input: Screen for entering questionnaire data and uploading a child's facial image for prediction.

The image shows the output screen displaying prediction results. It provides both tabular (behavioral model) and image-based predictions along with confidence scores. The final result is clearly highlighted for easy understanding. Additionally, a feedback section is included where users can rate and provide suggestions. This helps in improving the system based on user input.



Prediction: Displays prediction results from both models along with confidence and allows users to submit feedback.

6. CONCLUSION

6.1.1 Summary of contributions.

This project presents a multimodal autism prediction system that combines facial image analysis using Convolutional Neural Networks (CNN) with behavioral data evaluation using machine learning models. The system integrates image-based and questionnaire-based approaches to provide a more comprehensive and reliable assessment of Autism Spectrum Disorder (ASD) risk. Logistic Regression is used as the primary model for behavioral prediction due to its efficiency and consistent perform ance, while other models are implemented for comparison. The web-based application enables real-time predictions along with confidence scores, offering an accessible and user-friendly platform. This integrated approach addresses the limitations of traditional single-source methods and improves overall prediction accuracy.

6.1.2 Practical applications (healthcare, education, early screening).

The proposed system has significant real-world applications in domains such as healthcare, education, and early childhood development. It can assist healthcare professionals in preliminary screening and support early diagnosis of ASD. Parents can use the platform for initial assessment at home, helping them seek timely medical advice if needed. In educational settings, teachers and counselors can identify children who may require special attention or support. The system enhances awareness and accessibility by providing a quick and easy-to-use screening tool, ultimately contributing to early intervention and better developmental outcomes.

6.1.3 Future scope (multimodal expansion, model improvement, deployment).

The system can be further enhanced by incorporating larger and more diverse datasets to improve model accuracy and generalization. Future improvements may include the integration of additional modalities such as speech analysis, text-based behavioral cues, or video-based observations for more comprehensive assessment. Advanced deep learning architectures and ensemble techniques can also be explored to boost performance. Deployment optimizations such as GPU acceleration and cloud integration can enable faster and scalable real-time predictions. Additionally, incorporating explainable AI techniques can improve transparency and trust in the system's predictions, making it more effective for practical adoption.

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