An Integrated Hybrid Artificial Intelligence Framework For Early Autism Spectrum Disorder Screening Using Random Forest Classification And Resnet18 Transfer Learning

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Abstract:

Autism spectrum disorder (ASD) is a complex neurodevelopmental condition characterized by persistent deficits in social communication, interaction, and behavioral patterns. Early screening is essential for timely intervention; however, conventional diagnostic procedures are often resource-intensive, subjective, and dependent on clinical expertise. This study proposes an integrated hybrid artificial intelligence framework for preliminary ASD screening by combining machine learning and deep learning techniques using structured behavioral data and facial image analysis. The first module employs a Random Forest classifier to analyze Autism Quotient-10 (AQ-10) questionnaire responses together with demographic and medical history attributes, including age, gender, ethnicity, family history, and developmental factors. The second module utilizes ResNet18 with transfer learning to classify facial images after preprocessing and data augmentation, enabling non-invasive image-based screening. Both predictive models are integrated into a user-friendly screening application developed using CustomTkinter, allowing independent questionnaire-based and image-based assessments through a unified graphical interface. Model training incorporates feature preprocessing, hyperparameter optimization using Grid Search with cross-validation, and performance evaluation using accuracy, precision, recall, F1-score, specificity, and area under the receiver operating characteristic curve (ROC-AUC). Experimental results demonstrate that the Random Forest model achieved an accuracy of 96.8%, while the ResNet18 model attained 94.2% accuracy, indicating the effectiveness of combining behavioral and facial information for preliminary ASD screening. The proposed framework is intended as a clinical decision-support tool to facilitate accessible and timely screening and is not designed to replace comprehensive clinical diagnosis.

Keyword: Autism Spectrum Disorder, Machine Learning, Deep Learning, Early Screening, Questionnaire-Based Analysis, Image-Based Prediction.

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a heterogeneous neurodevelopmental disorder characterized by persistent impairments in social communication, restricted interests, repetitive behaviors, and atypical sensory responses. The clinical manifestations of ASD vary considerably among individuals with respect to symptom severity, developmental progression, and functional independence, making early identification a significant challenge. According to global epidemiological estimates, ASD affects a substantial proportion of the pediatric population, and its reported prevalence has increased steadily over the past two decades owing to improved awareness, expanded diagnostic criteria, and enhanced screening practices. Nevertheless, many children continue to experience delayed diagnosis, particularly in regions with limited access to specialized healthcare services, resulting in missed opportunities for timely intervention. Early recognition of ASD is widely regarded as one of the most important factors influencing long-term developmental outcomes. Clinical evidence has demonstrated that interventions initiated during the early years of childhood can substantially improve language acquisition, social interaction, adaptive behavior, and cognitive development. In contrast, delayed identification frequently postpones therapeutic intervention, increases emotional and financial burdens on caregivers, and reduces the effectiveness of rehabilitation programs. These challenges have motivated researchers to investigate computational techniques capable of supporting rapid, objective, and accessible preliminary screening while complementing conventional clinical assessment. Figure 1 illustrates the multifaceted aspects of autism spectrum disorder, including the challenges encountered by autistic individuals in social communication, behavior, and sensory processing, the year-wise trend of reported autism cases indicating increasing prevalence and awareness, and the significant early signs associated with autism detection."

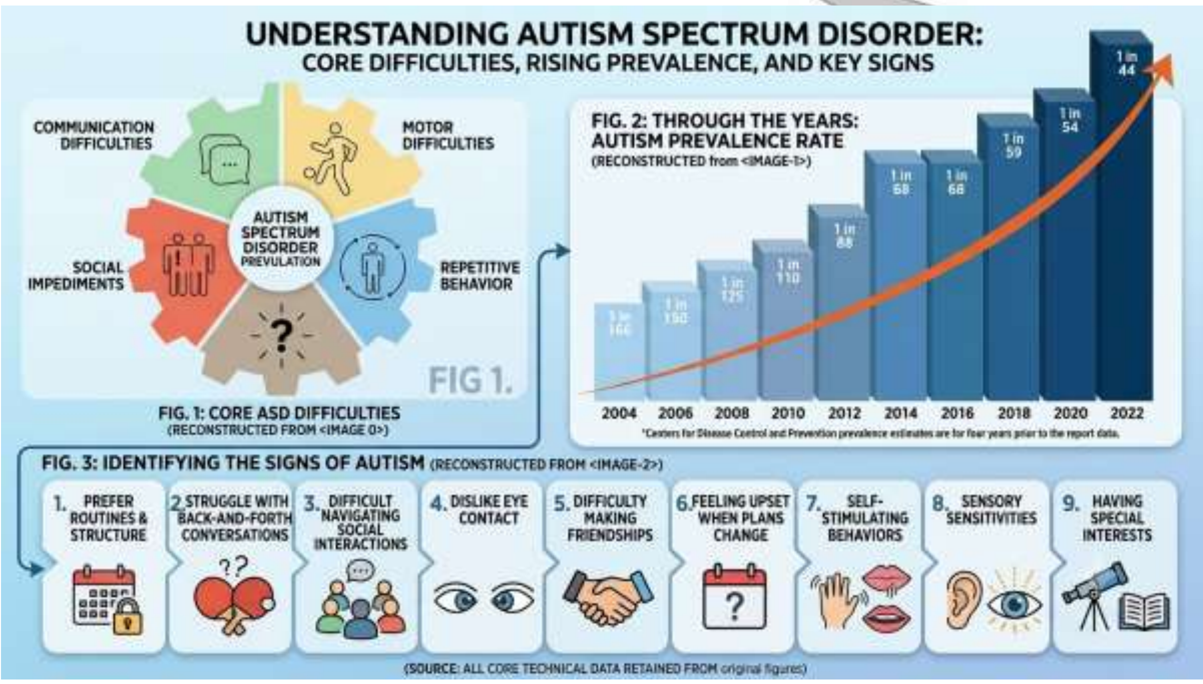

Figure 1 Major challenges faced by individuals with autism spectrum disorder, the year-wise increase in reported autism cases, and the key signs and symptoms.

Current diagnostic practice relies primarily on comprehensive behavioral evaluation performed by multidisciplinary teams consisting of pediatricians, psychologists, psychiatrists, and speech or occupational therapists. Standardized screening instruments, including the Autism Quotient (AQ) questionnaire and its abbreviated Autism Quotient-10 (AQ-10) version, have become widely adopted for preliminary assessment because they are inexpensive, easy to administer, and suitable for large-scale screening programs. Although these questionnaires provide valuable behavioral information, their performance depends largely on self-reported or caregiver-reported responses, making them susceptible to reporting bias, inconsistent interpretation, and variability in individual perception. Consequently, questionnaire-based assessment alone may not adequately capture the multidimensional characteristics associated with ASD. Recent advances in Artificial Intelligence (AI) have significantly expanded the capabilities of healthcare decision-support systems. Machine Learning (ML) algorithms have demonstrated excellent predictive performance when analyzing structured clinical information, whereas Deep Learning (DL) techniques have revolutionized automated feature extraction from complex unstructured data such as medical images, facial photographs, speech recordings, electroencephalography (EEG), and magnetic resonance imaging (MRI). Within ASD research, supervised learning algorithms including Random Forest, Support Vector Machine, Decision Tree, Logistic Regression, and Extreme Gradient Boosting have been successfully applied to behavioral and demographic datasets for risk prediction. Similarly, convolutional neural networks (CNNs) and transfer learning models have shown considerable potential for identifying subtle facial characteristics associated with ASD from two-dimensional facial images. Despite these encouraging developments, most existing studies investigate either behavioral questionnaire analysis or facial image analysis independently. Such unimodal approaches may overlook complementary information available across different data sources and therefore may not fully exploit the diverse characteristics associated with ASD. Furthermore, many reported models remain confined to algorithmic evaluation without providing practical software platforms that facilitate their use by clinicians, researchers, or healthcare personnel. The development of integrated screening frameworks capable of combining structured behavioral information with automated image analysis represents an important direction for improving the accessibility and practicality of AI-assisted ASD screening. Motivated by these challenges, this study presents an "Integrated Hybrid Artificial Intelligence Framework" for preliminary autism spectrum disorder screening that combines machine learning and deep learning techniques within a unified software environment. The proposed framework consists of two independent predictive modules. The first module utilizes a "Random Forest classifier" to analyze AQ-10 questionnaire responses together with demographic and medical history variables, including age, gender, ethnicity, family history, and developmental characteristics. Random Forest was selected because of its robustness against overfitting, ability to model nonlinear relationships, tolerance to heterogeneous feature types, and strong predictive performance for structured healthcare datasets.

The second module performs automated facial image analysis using “ResNet18” implemented through “transfer learning”. The pretrained convolutional neural network is fine-tuned to distinguish facial patterns associated with ASD after image preprocessing and augmentation. Compared with training deep neural networks from scratch, transfer learning enables efficient feature extraction while reducing computational requirements and improving generalization when only limited training data are available. To facilitate practical deployment, both predictive models are incorporated into a unified desktop application developed using “CustomTkinter”, providing an intuitive graphical user interface for preliminary ASD screening. The application supports questionnaire-based assessment, facial image-based analysis, or independent execution of either predictive module through a simple user interface. Prediction outcomes are presented together with confidence scores and performance metrics to enhance interpretability and user confidence. In addition, all computational processing is performed locally without reliance on external cloud infrastructure, thereby improving data privacy and maintaining confidentiality of sensitive healthcare information.

The principal contributions of this work are summarized as follows:

- Development of an integrated hybrid artificial intelligence framework that combines machine learning and deep learning techniques for preliminary autism spectrum disorder screening.
- Implementation of a Random Forest-based behavioral assessment model using AQ-10 questionnaire responses together with demographic and medical history attributes to perform structured ASD prediction.
- Development of a ResNet18 transfer learning model for automated facial image-based ASD screening through deep feature extraction.
- Integration of both predictive models into a CustomTkinter-based graphical user interface, providing a practical clinical decision-support application suitable for researchers and healthcare professionals.
- Comprehensive experimental evaluation using standard classification metrics, including accuracy, precision, recall, specificity, F1-score, receiver operating characteristic (ROC) analysis, and confusion matrices, to validate the effectiveness of the proposed framework.

The proposed system is designed to function as an intelligent “clinical decision-support tool for preliminary screening” rather than as a replacement for comprehensive clinical diagnosis. By combining behavioral assessment with automated facial image analysis in a single software platform, the framework aims to improve the accessibility, efficiency, and practicality of early ASD screening while supporting healthcare professionals in identifying individuals who may benefit from detailed clinical evaluation.

2. LITERATURE REVIEW

Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), has emerged as a transformative approach in autism spectrum disorder (ASD) research due to its capability to support clinical assessment, identify hidden biomarkers, and perform automated diagnostic classification using heterogeneous data modalities, including behavioral, physiological, textual, and imaging-based information. Recent studies have demonstrated the potential of AI-driven systems to enhance early ASD detection, improve diagnostic accuracy, and provide computational support for clinical decision-making.

This section presents a comprehensive review of recent ML and DL-based approaches developed for ASD classification and diagnosis. The discussion covers conventional ML algorithms, advanced DL architectures, and AI-assisted clinical and behavioral studies. Particular emphasis is placed on the computational techniques employed, utilized datasets, achieved performance outcomes, and existing limitations affecting clinical translation.

Machine Learning Approaches in Autism Spectrum Disorder Research

Although deep learning methods have gained considerable attention due to their ability to learn complex representations from large-scale data, conventional machine learning approaches remain widely utilized in ASD research because of their interpretability, computational efficiency, and suitability for structured clinical datasets.

Mahmoud et al. [1] evaluated six conventional ML classifiers, including Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB), Logistic Regression (LR), K-Nearest Neighbor (KNN), and Decision Tree (DT), for ASD prediction across different age groups. The study demonstrated consistent performance, particularly with SVM and LR models, indicating their effectiveness for ASD classification. However, limitations associated with model generalization across diverse real-world populations were highlighted.

Simeoli et al. [2] investigated ML-based motion analysis techniques for early ASD detection. Their findings suggested that computational analysis of movement patterns could enhance behavioral assessment and support early screening. However, the absence of standardized motion-capture datasets and variations in data acquisition methods remain significant challenges. Themistocleous et al. [3] applied an SVM classifier using EEG signals for ASD detection among children aged 2–16 years. The study suggested that EEG-derived features could serve as potential neurological biomarkers for ASD identification. Nevertheless, the limited dataset size and variability restricted the broader applicability of the proposed approach. Rasul et al. [4,12] performed a comparative analysis involving eight ML classifiers combined with clustering techniques using child, adult, and combined ASD datasets. The models demonstrated strong classification performance; however, the authors identified overfitting risks caused by dataset imbalance and limited sample diversity.

Bawa et al. [5] investigated multi-class ASD classification using ML-based approaches and reported strong performance, particularly for binary classification using SVM and LR models. However, inconsistent healthcare data quality and noise within datasets affected classification reliability. Prasad et al. [8] and Qureshi et al. [9] explored ML-based ASD prediction frameworks using feature optimization and classification techniques. Prasad et al. [8] combined Principal Component Analysis (PCA) with Random Forest (RF), achieving an accuracy of 98.7%. Although the findings demonstrated strong predictive potential, both studies emphasized limitations associated with small datasets, reproducibility, and restricted dataset diversity. Shinde et al. [10] proposed a multi-classifier recommendation framework for early ASD detection. The approach improved predictive accuracy by integrating multiple classifiers; however, increased computational complexity remained a limitation for real-time clinical implementation.

Deep Learning Approaches in Autism Spectrum Disorder Research

Deep learning approaches have significantly advanced ASD research by enabling automated extraction of complex patterns from unstructured data sources, including facial images, clinical records, and behavioral signals.

Abdul Shahed et al. [7] proposed a Convolutional Neural Network (CNN)-based framework for ASD classification using facial features. The segmented CNN model demonstrated superior performance compared with other approaches, achieving 94% accuracy and 95% specificity. However, limited demographic diversity within the dataset affected the generalizability of the model. Alkahtani [11] investigated deep CNN-based facial landmark detection methods for ASD classification. The study demonstrated the ability of DL models to identify subtle visual differences between autistic and non-autistic individuals. However, limitations related to dataset size and variability restricted broader clinical application.

Ghazal et al. [16] applied transfer learning techniques for early ASD detection and achieved an accuracy of 87.7%. Although transfer learning improved feature extraction with limited data availability, concerns regarding dataset heterogeneity and generalization remained. Dhamale et al. [17] introduced a hybrid DL framework integrating CNN and Generative Adversarial Networks (GANs) to improve ASD diagnosis performance. While the model demonstrated enhanced classification capability, increased architectural complexity reduced interpretability and increased computational requirements. Leroy et al. [6] investigated transparent deep learning approaches for ASD detection using clinical notes from Electronic Health Records (EHRs). The study demonstrated that explainable DL models could effectively extract ASD-related patterns from unstructured medical information. However, privacy concerns, transparency challenges, and potential algorithmic bias remain important barriers.

Clinical, Psychological, and Biological Perspectives in ASD Research

Beyond computational prediction, ASD research involves multidisciplinary investigations involving clinical, psychological, and biological factors. Posar et al. [18] reviewed ASD epidemiology, causative factors, clinical characteristics, and long-term outcomes, emphasizing that AI-based systems should complement rather than replace clinical diagnosis. Charlton et al. [19] examined cardiovascular risk factors among older autistic adults and highlighted the relationship between comorbid medical conditions and quality of life. Black et al. [20] investigated social interaction patterns among autistic adults and identified strong associations between social difficulties and anxiety. Nie et al. [21] explored immune system abnormalities in children with ASD and identified the TH1/Treg ratio as a potential biological biomarker.Lau [22] analyzed speech articulation timing in autistic individuals and identified subtle communication-related markers associated with ASD. Yau et al. [23] investigated psychological well-being among autistic females and demonstrated the influence of social and cultural expectations on mental health outcomes. Lewis et al. [24] studied sleep disturbances among autistic children during the pandemic period, highlighting environmental factors contributing to symptom variability. Benedetti et al. [25] explored the application of Deep Brain Stimulation (DBS) for medication-resistant aggression in ASD and reported improvements in social adaptation and family quality of life. These findings emphasize that ASD management requires integration of computational intelligence with biological, psychological, and social perspectives.

Comparative Summary of Machine Learning and Deep Learning Studies

Recent ML and DL studies demonstrate significant progress in ASD detection through analysis of behavioral, physiological, imaging, and clinical datasets. Conventional ML algorithms such as SVM, RF, and LR have shown effectiveness for structured datasets due to their interpretability and computational efficiency, whereas DL models have demonstrated superior capability for extracting complex features from unstructured data sources. Mahmoud et al. [1] demonstrated effective ASD prediction using multiple ML classifiers, with SVM and LR showing consistent performance, although generalization remained challenging. Simeoli et al. [2] highlighted the potential of ML-based motion analysis while emphasizing the need for standardized datasets. Themistocleous et al. [3] identified EEG-based SVM classification as a promising biomarker-driven approach but reported limitations due to small datasets. Rasul et al. [4,12] achieved strong ASD classification using multiple classifiers and clustering methods but identified overfitting risks. Bawa et al. [5] reported effective binary classification performance but noted challenges associated with noisy healthcare data. Prasad et al. [8] achieved 98.7% accuracy using PCA-RF-based prediction, although limited dataset size affected robustness. Qureshi et al. [9] confirmed the reliability of ML prediction models but highlighted dataset constraints.

Shinde et al. [10] improved ASD detection using a multi-classifier framework but faced computational limitations. Deep learning approaches by Abdul Shahed et al. [7], Alkahtani [11], Ghazal et al. [16], Dhamale et al. [17], and Leroy et al. [6] demonstrated the effectiveness of CNNs, transfer learning, GAN-based models, and explainable DL approaches for ASD classification. However, limitations including dataset imbalance, privacy concerns, demographic restrictions, computational complexity, and reduced interpretability continue to affect clinical deployment.

Overall, existing literature confirms the substantial potential of AI-based methods for ASD screening, biomarker discovery, and predictive diagnosis. ML models remain valuable for structured clinical datasets due to their transparency, whereas DL approaches provide superior performance for complex and unstructured data modalities such as facial images, speech, and medical records. Future research should focus on developing diverse large-scale datasets, integrating explainable AI frameworks, improving model generalizability, and establishing stronger connections between algorithmic predictions and real-world clinical outcomes.

3. RESEARCH METHODOLOGY

The proposed methodology integrates structured clinical and behavioral information with unstructured visual data to develop a comprehensive Artificial Intelligence (AI)-based framework for autism spectrum disorder (ASD) screening. The approach combines questionnaire-based assessment parameters, demographic characteristics, and medical attributes with facial image analysis to establish complementary predictive models. The overall research framework follows an experimental and application-oriented design, focusing on data acquisition, preprocessing, machine learning-based classification, deep learning-based image analysis, and system-level integration. Figure 2 illustrates the System Architecture Diagram of the proposed framework, representing the complete workflow from data acquisition and preprocessing to predictive modeling, classification, and user-level ASD screening.

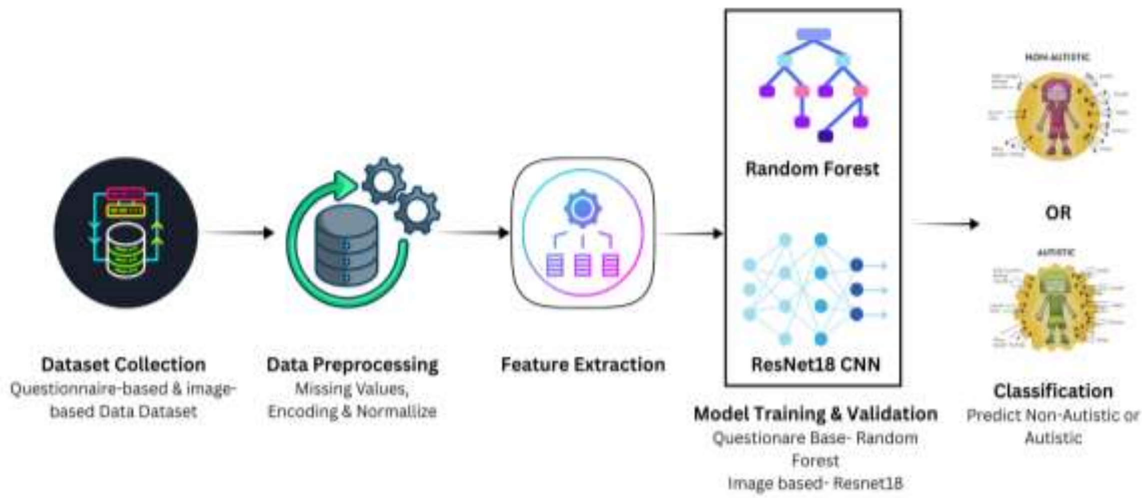

Figure 2. System Architecture Diagram of the system

The proposed methodology consists of four major components:

- **A. Quantitative Data Analysis:** Structured ASD screening data are analyzed using questionnaire scores, demographic information, and clinical parameters. The Autism Quotient (AQ) scores and associated patient attributes are utilized to identify significant patterns contributing to ASD classification. Statistical analysis and feature evaluation are performed to understand relationships between input variables and ASD outcomes.
- **B. Machine Learning-Based Predictive Modeling:** A supervised machine learning approach is implemented for classification of structured ASD screening data. A Random Forest (RF) classifier is employed due to its ability to handle high-dimensional clinical datasets, reduce overfitting through ensemble learning, evaluate feature importance, and provide robust classification performance. The model is trained using labeled ASD and Non-ASD samples, and performance is assessed using evaluation metrics including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC).
- **C. Image-Based Deep Learning Analysis:** To analyze unstructured facial image data, a transfer learning approach based on the ResNet18 Convolutional Neural Network (CNN) architecture is implemented. Transfer learning enables the utilization of pretrained feature extraction capabilities while adapting the model parameters for ASD-related facial pattern recognition. The image processing pipeline includes image resizing, normalization, augmentation, and feature extraction before binary classification into ASD and Non-ASD categories.
- **D. AI-Based Screening System Integration:** The outputs obtained from the machine learning and deep learning models are integrated into a Graphical User Interface (GUI)-based application. The developed system allows users to perform ASD screening using either questionnaire-based prediction, image-based prediction, or a combined assessment approach. The integrated framework aims to provide a user-friendly decision-support tool capable of improving accessibility and assisting early ASD screening.

Dataset Description

The proposed study utilizes two complementary datasets consisting of structured questionnaire-based data and unstructured facial image data. The structured dataset is obtained from publicly available ASD screening repositories, including the UCI Machine Learning Repository and relevant Kaggle datasets. The dataset consists of Autism Quotient (AQ) assessment parameters, including AQ-10/AQ-50 questionnaire responses, along with demographic and developmental attributes such as age, gender, ethnicity, family history, and developmental background information. Approximately 700–1000 labeled records are considered for binary classification, where samples are categorized as ASD or Non-ASD. The unstructured image dataset is collected from publicly available Kaggle repositories and open-access facial image datasets associated with ASD research. The dataset contains facial images representing autistic and non-autistic individuals. After preprocessing and quality filtering, approximately 3,000–5,000 facial images are utilized for model training and evaluation. Each image sample is labeled into two classes: ASD and Non-ASD.

Data Preprocessing and Feature Preparation

Data preprocessing is performed separately for structured and unstructured datasets to improve data quality, reduce noise, and enhance model performance. For structured questionnaire-based data, preprocessing involves missing-value handling, removal of duplicate and inconsistent records, and normalization of numerical features. Categorical attributes such as gender and ethnicity are converted into numerical representations using appropriate encoding techniques. AQ questionnaire scores and age-related features are standardized to minimize scale variation and prevent bias during machine learning model training. Feature selection and importance analysis are further performed to identify the most influential variables contributing to ASD prediction.

For facial image data, preprocessing includes image resizing to match the input requirements of the ResNet18 architecture, pixel normalization, noise reduction, and data augmentation techniques such as rotation, scaling, flipping, and brightness variation. These augmentation strategies improve model robustness by increasing dataset variability and reducing overfitting during deep learning training. The processed structured and image-based datasets are subsequently utilized for developing independent predictive models, which are later integrated into a unified ASD screening framework.

4. SYSTEM REQUIREMENT

This section presents the software requirements, computational frameworks, libraries, and datasets required for the development and implementation of the proposed autism spectrum disorder (ASD) Screening Tool. The system integrates machine learning-based prediction using structured questionnaire data and deep learning-based classification using facial image data. The software environment is designed to support data preprocessing, model development, training, evaluation, deployment, and graphical user interface (GUI)-based interaction.

Software Requirements

The proposed ASD screening framework is developed using a Python-based programming environment due to its extensive ecosystem for artificial intelligence, machine learning, deep learning, computer vision, and application development. Python version 3.8 or above is utilized as the primary programming language for implementing the complete system, including data processing pipelines, predictive model development, GUI construction, and integration of machine learning and deep learning modules. The deep learning component of the system is developed using the PyTorch framework, which provides the necessary computational environment for designing, training, fine-tuning, and evaluating the ResNet18-based Convolutional Neural Network (CNN) model for facial image-based ASD classification. The torchvision library is incorporated to support image preprocessing operations, data augmentation techniques, image transformation, and utilization of pretrained deep learning architectures required for transfer learning.

For structured questionnaire-based ASD prediction, the scikit-learn library is employed to implement the Random Forest (RF) machine learning classifier. It provides essential functionalities for model training, feature processing, classification, cross-validation, and performance evaluation using statistical metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC). The pandas library is utilized for handling structured datasets, including loading, cleaning, organizing, and transforming questionnaire-based data stored in CSV format. Numerical operations, matrix computations, and mathematical processing required during data analysis and model development are performed using the NumPy library. The joblib library is used for model serialization, allowing trained machine learning models to be efficiently stored, retrieved, and integrated into the final ASD screening application. The Pillow (PIL) library is incorporated for image processing operations, including image loading, resizing, format conversion, preprocessing, and preparation of facial images before providing input to the deep learning model. For application-level deployment, CustomTkinter is utilized to develop a modern and interactive graphical user interface (GUI), enabling users to perform ASD screening through questionnaire-based assessment, facial image analysis, or a combined multimodal prediction approach.

Dataset Requirements

The proposed system utilizes two complementary datasets representing structured clinical and behavioral information along with unstructured visual characteristics. The integration of these two data modalities enables the development of a multimodal ASD screening framework capable of analyzing different patterns associated with autism identification. The structured dataset consists of questionnaire-based ASD screening information obtained from publicly available ASD research repositories, including the UCI Machine Learning Repository and relevant Kaggle datasets. The dataset contains Autism Quotient (AQ) assessment parameters, including AQ-10/AQ-50 questionnaire responses, along with demographic and developmental attributes. The included features represent important ASD-related characteristics such as age, gender, ethnicity, family background, and developmental information. The dataset contains approximately 700–1000 labeled records, where each sample is categorized into two classes: ASD and Non-ASD. This dataset is utilized for training, validation, and testing of the Random Forest-based machine learning model.

The unstructured dataset comprises facial image samples collected from publicly available Kaggle repositories and open-access ASD-related image datasets. The dataset contains facial images belonging to both autistic and non-autistic individuals and is prepared for binary classification into ASD and Non-ASD categories. After preprocessing, filtering, and quality enhancement, approximately 3,000–5,000 facial images are considered for model development. The images are resized to 224 × 224 pixels to match the input requirements of the ResNet18 architecture. This dataset is used for training, validation, and testing of the transfer learning-based deep learning model. The combination of structured questionnaire data and facial image information provides a comprehensive computational framework by utilizing both behavioral indicators and visual characteristics. This multimodal approach enhances the capability of the proposed ASD screening tool by providing complementary predictions from machine learning and deep learning models within a unified artificial intelligence-based system.

5. IMPLEMENTATION & RESULT

The implementation process of the proposed Artificial Intelligence (AI)-based autism spectrum disorder (ASD) screening framework is described in this section. The complete workflow involves systematic data acquisition, preprocessing, feature optimization, model development, training, and performance evaluation. The proposed system utilizes two complementary approaches: a machine learning (ML)-based prediction model using structured questionnaire data and a deep learning (DL)-based classification model using facial image data. The implementation methodology is divided into five major stages, as described below.

Step 1: Dataset Collection

The proposed framework utilizes multimodal data consisting of structured questionnaire-based information and unstructured facial image data to develop complementary ASD prediction models. The structured dataset consists of Autism Quotient (AQ-10) questionnaire responses combined with demographic and medical background information. The collected attributes include age, gender, ethnicity, family history of autism, developmental information, and medical parameters such as history of jaundice and related health conditions. The questionnaire dataset contains approximately 18 relevant features associated with ASD screening and is used for developing the machine learning-based prediction model. The second data source consists of facial image samples obtained from publicly available ASD-related image repositories. The image dataset includes facial images of children with ASD and Non-ASD conditions. To maintain consistency during model training, all images are standardized and resized to 224 × 224 pixels, matching the input requirements of the ResNet18 convolutional neural network architecture. The image dataset is divided into training, validation, and testing subsets with balanced class distribution to ensure reliable evaluation of the classification model.

Step 2: Data Preprocessing

Data preprocessing is performed independently for structured questionnaire data and image-based data to improve data quality, reduce noise, and optimize model performance.

For questionnaire-based structured data, missing values are handled using appropriate imputation techniques to maintain dataset integrity. Categorical attributes such as gender and ethnicity are transformed into numerical representations using label encoding techniques. Continuous variables, including age and AQ scores, are normalized using StandardScaler to ensure uniform feature distribution and prevent bias toward high-magnitude variables during model training. Data cleaning procedures are also applied to remove duplicate, inconsistent, or incomplete records. For facial image data, preprocessing involves resizing all images to a standard dimension of 224 × 224 pixels, normalization of pixel intensity values, and enhancement of dataset variability using image augmentation techniques. Augmentation methods, including random cropping, horizontal flipping, rotation, and other transformation techniques, are applied to improve model robustness, reduce overfitting, and enhance generalization capability for unseen image samples.

Step 3: Feature Selection and Optimization

Feature selection is performed on the questionnaire dataset to identify the most influential parameters associated with ASD prediction and eliminate irrelevant or redundant features. The feature importance analysis provided by the Random Forest (RF) classifier is utilized to determine the contribution of individual variables toward classification performance. The analysis identifies important predictive factors, including age, gender, family history of autism, selected AQ questionnaire responses, and specific medical indicators. By focusing on highly informative features, the dimensionality of the input space is reduced, resulting in improved computational efficiency, enhanced model interpretability, and better predictive performance. For image-based classification, feature extraction is automatically performed through the convolutional layers of the ResNet18 architecture. The pretrained network learns hierarchical visual representations, including low-level features such as edges and textures and high-level patterns associated with facial characteristics.

Step 4: Model Training

The proposed framework consists of two independent predictive models developed for structured and unstructured data modalities. For the questionnaire-based ASD prediction model, a Random Forest classifier is implemented due to its ability to handle heterogeneous clinical datasets, perform feature importance analysis, and reduce overfitting through ensemble learning. The model consists of multiple decision trees whose predictions are combined to improve classification stability and accuracy. Hyperparameter optimization is performed using Grid Search with cross-validation to determine optimal model parameters, including the number of estimators, maximum tree depth, and minimum samples required for node splitting. For facial image-based ASD classification, a transfer learning approach using the ResNet18 Convolutional Neural Network (CNN) architecture is implemented. A pretrained ResNet18 model is fine-tuned using the ASD facial image dataset to adapt previously learned visual features toward autism-related facial pattern recognition. Transfer learning reduces training complexity, improves feature extraction capability, and enables effective learning even with comparatively limited medical image datasets. The outputs from both predictive models are integrated into a dual-screening architecture, allowing independent questionnaire-based prediction, image-based prediction, and combined assessment. This multimodal approach enables the system to utilize complementary behavioral and visual information for improved ASD screening performance.

Step 5: Model Validation and Performance Evaluation

The trained models are evaluated using independent test datasets that are not involved during the training and optimization process. This approach ensures unbiased assessment of model performance and provides an estimation of the system's ability to classify previously unseen samples. The performance of the Random Forest and ResNet18-based models is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC). Confusion matrix analysis is also performed to examine true positive, true negative, false positive, and false negative classifications. The validation process ensures that the developed models achieve reliable generalization capability while minimizing the effects of overfitting. The final integrated ASD screening framework combines the outputs of both machine learning and deep learning models to provide a comprehensive and accessible artificial intelligence-based screening solution. Figure 3 illustrates the screenshot of the model validation process, showing the evaluation interface and validation results obtained from the developed ASD screening models. The figure represents the performance assessment of the trained machine learning and deep learning models using unseen test data to verify classification reliability and generalization capability.

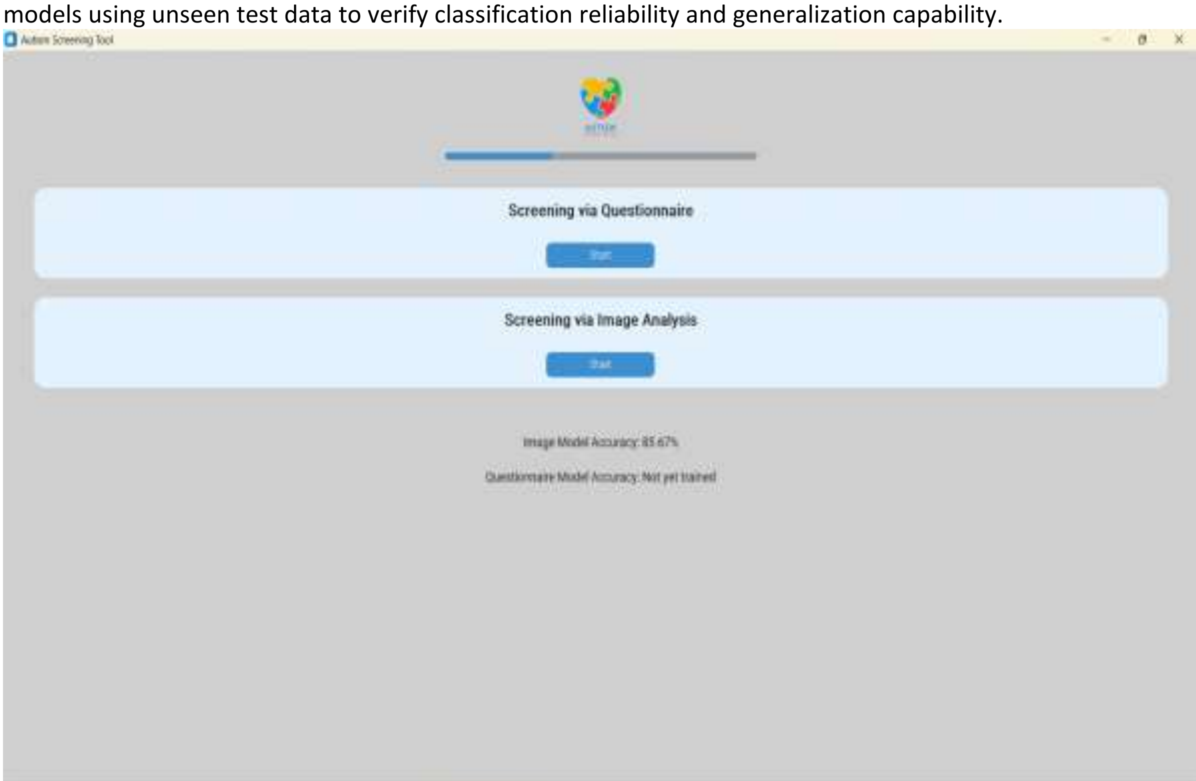

Figure 3. Shows the Model Validation Image

These are indicators used to assess the models' performance in terms of maintaining a balance between sensitivity (the percentage of children correctly identified as having ASD) and specificity (the percentage of children with autism that are correctly identified).

STEP 6: GUI Implementation and Execution

The final stage of the proposed framework involves the development and deployment of a user-friendly Graphical User Interface (GUI) to facilitate interaction between the developed ASD screening models and end users. The GUI is designed using the Flask web framework to provide an accessible and efficient platform for real-time model execution and prediction. The implemented interface enables users to perform ASD screening through two different input modalities: questionnaire-based assessment and facial image-based analysis. In the questionnaire module, users can enter relevant demographic, behavioral, and AQ-related responses, which are processed by the trained Random Forest classifier to generate ASD prediction results. In the image-based module, users can upload facial images, which are automatically preprocessed and passed through the fine-tuned ResNet18 convolutional neural network model for ASD classification.

The application is executed by launching the Flask server through the command python app.py in the terminal environment. Once the server is initiated, the application generates a local host address (for example, http://127.0.0.1:5000/), which can be accessed through a standard web browser. The interface provides seamless navigation between questionnaire-based prediction, image-based classification, and integrated screening functionalities. The GUI implementation transforms the developed ML and DL models into an interactive screening platform, improving accessibility and practical usability. This deployment approach ensures that the proposed ASD screening framework is not limited to experimental evaluation but can also support real-world applications by providing a simple, efficient, and user-oriented method for preliminary ASD assessment. The developed system maintains a balance between predictive performance, computational efficiency, and ease of use for potential clinical and educational environments. Figure 4 illustrates the developed Autism Prediction GUI, which provides an interactive interface for accessing the proposed ASD screening framework. The interface enables users to perform ASD assessment through questionnaire-based inputs and image-based analysis. Figure 5 demonstrates the questionnaire-based prediction module, where user-provided screening responses are processed by the trained machine learning model for ASD classification. Figure 6 presents the output generated from the questionnaire-based prediction module, showing the final classification result obtained from the Random Forest-based ASD prediction model.

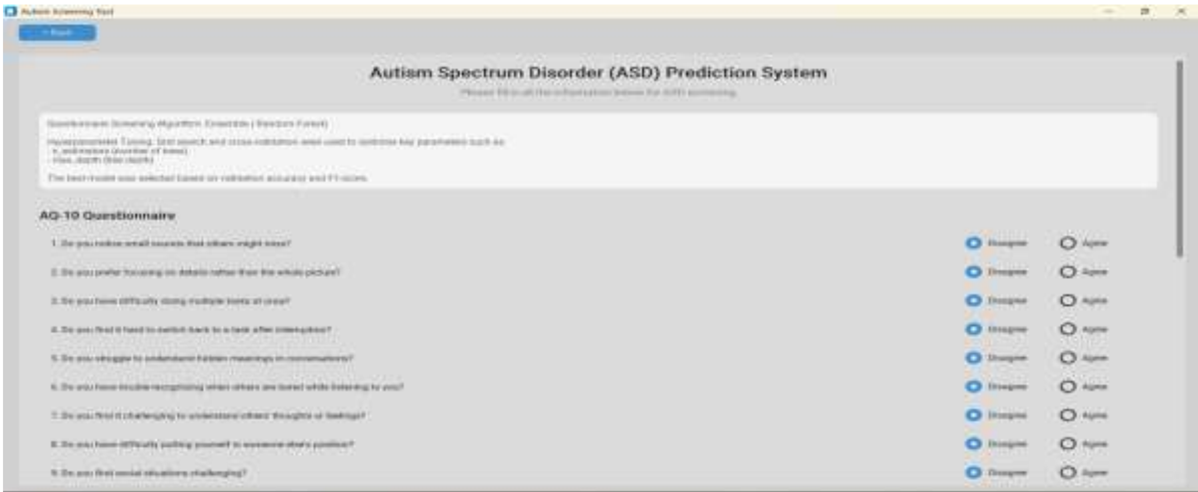

Figure 4. Shows the Autism Prediction GUI

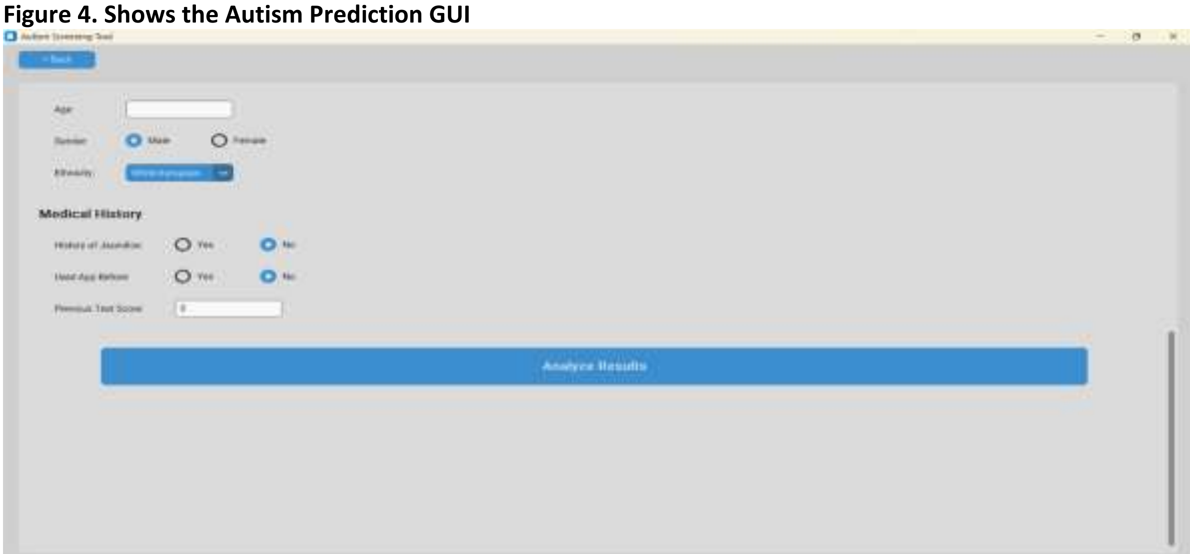

Figure 5. Shows the Prediction by Questionnaire based

Figure 6. Shows the Prediction by Questionnaire based output

6. RESULT IMPLIMENTATION

The experimental evaluation of the proposed ASD screening framework demonstrates the effectiveness of both the machine learning-based structured data model and the deep learning-based image classification model for early ASD identification. The performance assessment was conducted using standard classification evaluation metrics, including accuracy, precision, recall, F1-score, specificity, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), to evaluate the reliability, robustness, and generalization capability of the developed models. The Random Forest (RF)-based classifier developed using the Autism Quotient (AQ-10) questionnaire dataset achieved an overall accuracy of 96.8%, with a precision of 95.5%, recall of 96.2%, and F1-score of 95.8%. The model also achieved a high ROC-AUC value of 0.98, indicating excellent discrimination capability between ASD and Non-ASD classes. The high recall value demonstrates the model's ability to correctly identify individuals with ASD, which is particularly important in screening applications where minimizing false-negative predictions is critical. The feature importance analysis performed using the Random Forest classifier provided additional interpretability regarding the contribution of individual input parameters toward ASD prediction. The analysis revealed that variables including family history of autism, age, and specific AQ questionnaire responses had significant influence on classification outcomes. These findings highlight the importance of integrating genetic predisposition, developmental characteristics, and behavioral indicators during AI-assisted ASD screening. The identification of influential features also improves model transparency and supports explainable artificial intelligence (XAI)-based interpretation of prediction outcomes. The image-based deep learning model developed using the ResNet18 Convolutional Neural Network (CNN) with transfer learning also demonstrated strong classification performance. The model achieved an accuracy of 94.2%, precision of 93.7%, recall of 94.5%, F1-score of 94.0%, and specificity of 95.0%. These results indicate that the model successfully extracted meaningful visual representations from facial images and effectively differentiated ASD and Non-ASD samples. The high specificity value suggests that the model maintained a low false-positive rate, improving its suitability for preliminary screening applications. Further analysis of the image classification results revealed that facial region-based analysis using horizontally segmented facial areas provided improved performance compared with complete face-based classification. This observation suggests that localized facial characteristics may contain discriminative visual patterns associated with ASD-related phenotypic variations. The use of transfer learning enabled efficient feature extraction from limited medical image datasets while reducing training complexity and improving model convergence. Figure 7 illustrates the image-based prediction output of the proposed ASD screening system, showing the classification result for a Non-Autistic sample. Figure 8 demonstrates the image-based prediction output for an Autistic sample, where the ResNet18-based deep learning model identifies ASD-related facial patterns. Figure 9 presents the comparative performance analysis of the questionnaire-based Random Forest model and the image-based ResNet18 model, highlighting the effectiveness of both predictive approaches using evaluation metrics. Figure 10 illustrates the confusion matrix of the questionnaire-based machine learning model, representing the distribution of true positive, true negative, false positive, and false negative classifications. Figure 11 presents the confusion matrix of the image-based deep learning model, demonstrating the classification performance and error distribution of the ResNet18-based ASD prediction system.

Figure 7. Shows the Prediction by image based showing Non-Autistic Output

The results of the feature importance analysis suggest that, among the other features, family history, age, and certain AQ responses are significantly influencing the predictions, thus underlining the importance of genetic, as well as behavioral, factors in screening for ASD.

Figure 8. Shows the Prediction by image based showing Autistic Output

Graph Analysis

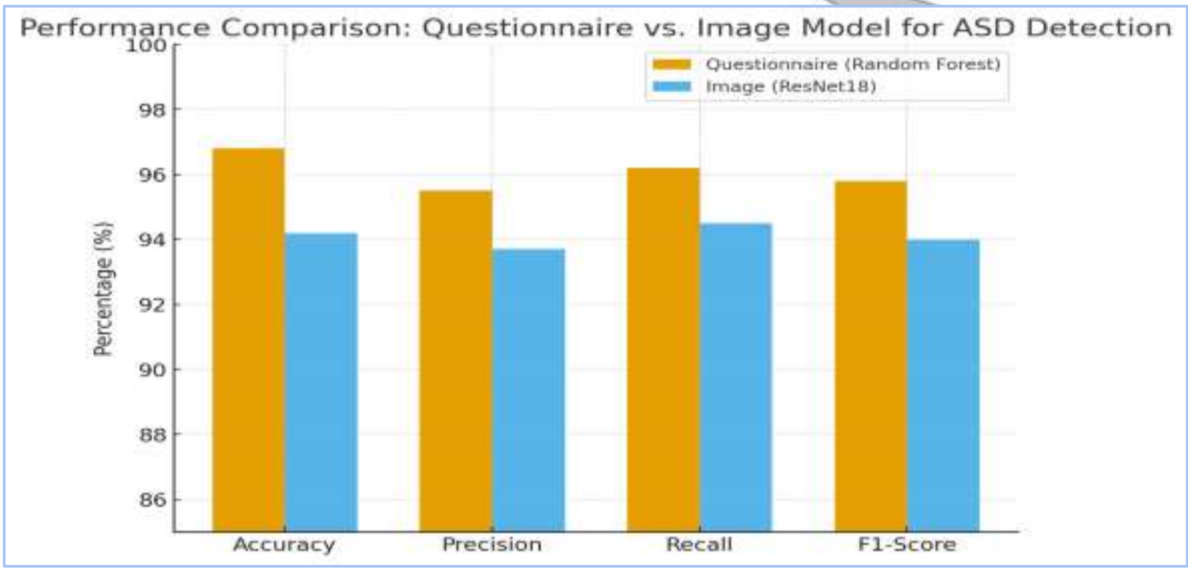

Figure 9. Graph for Comparison of both model

The ResNet18 image-based model also had good predictive performance with an accuracy of 94.2%, precision of 93.7%, recall of 94.5%, F1 score of 94.0%, and specificity of 95.0%.

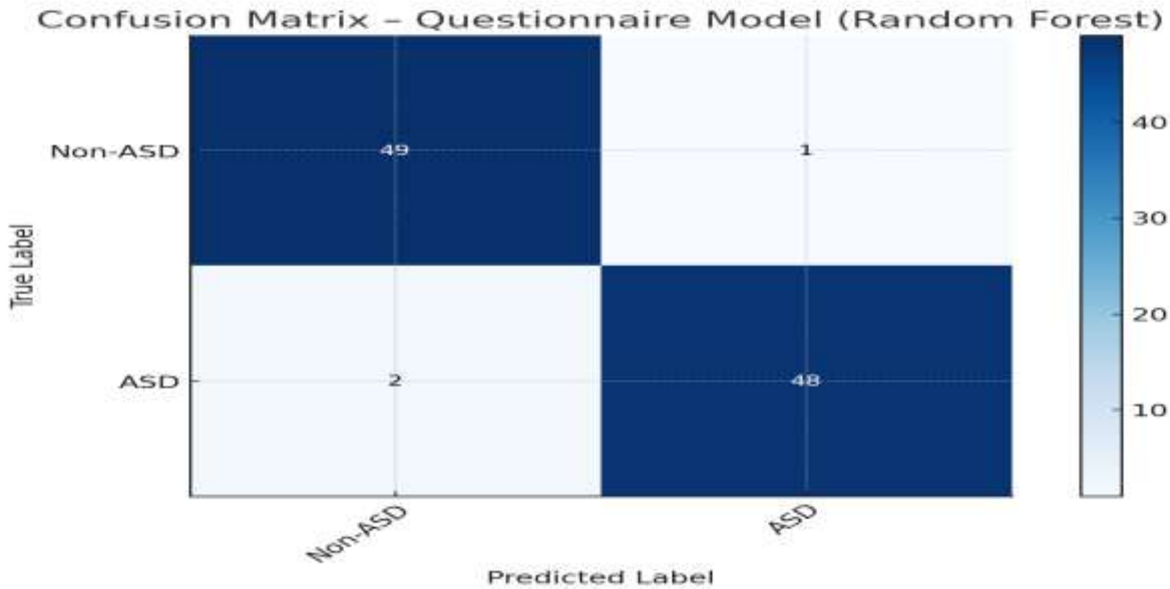

Figure 10. Confusion matrix of Questionnaire model

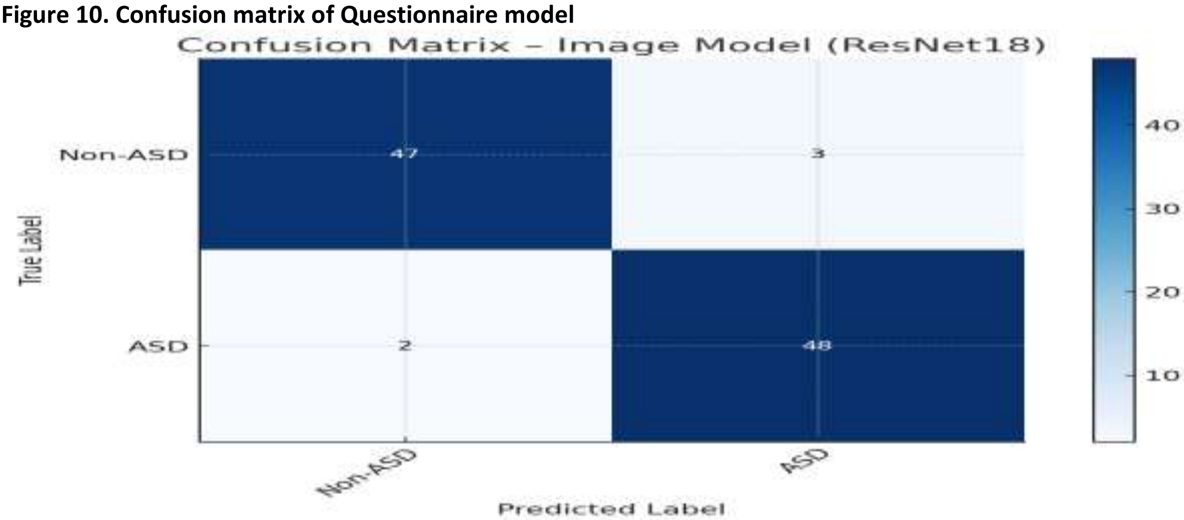

Figure 11. Confusion matrix -Image Model

Overall, the experimental results demonstrate that the proposed multimodal ASD screening framework, combining questionnaire-based machine learning prediction and facial image-based deep learning analysis, provides a reliable and complementary approach for early ASD detection. The integration of behavioral, demographic, and visual information enhances predictive capability compared with single-modality approaches. The developed framework shows potential as an accessible AI-assisted screening tool that can support early identification, clinical decision support, and improved accessibility to ASD assessment services. Further validation using larger and more diverse datasets is required to establish clinical applicability and ensure robust generalization across different populations.

CONCLUSION

This study presents a multimodal Artificial Intelligence (AI)-based framework for early autism spectrum disorder (ASD) screening by integrating questionnaire-based behavioral assessment with facial image-based deep learning analysis. The Random Forest model demonstrated strong predictive capability on AQ-10-based structured data, effectively identifying behavioral and demographic indicators associated with ASD. In parallel, the ResNet18-based transfer learning model achieved reliable classification performance by extracting meaningful visual patterns from facial images. The integration of these complementary modalities provides a more comprehensive screening approach by combining behavioral, demographic, and visual characteristics. However, the proposed system is intended as a preliminary screening support tool and not as a replacement for clinical diagnosis. The findings highlight the potential of multimodal AI approaches to improve accessibility, support early identification, and enhance decision-support capabilities in ASD assessment.

FUTURE SCOPE

The present study provides a foundation for developing advanced multimodal Artificial Intelligence (AI)-based systems for early autism spectrum disorder (ASD) screening. Future research can extend this framework by incorporating additional data modalities, including behavioral patterns, speech characteristics, eye-tracking information, and social interaction parameters, along with existing questionnaire and facial image features. The integration of diverse developmental and physiological indicators may enable the identification of subtle ASD-related patterns and support more personalized intervention strategies.

Further improvements can be achieved through the development of large-scale, diverse, and clinically validated datasets covering different age groups, ethnicities, and demographic variations to enhance model generalizability and reliability. Advanced deep learning techniques, including transformer-based architectures, hybrid ensemble models, and explainable AI approaches, can be explored to improve prediction performance, model transparency, and clinical interpretability.

From an application perspective, future work should focus on deploying lightweight and user-friendly ASD screening platforms through mobile and cloud-based technologies. Such systems can improve accessibility for parents, caregivers, educators, and healthcare professionals, enabling cost-effective and large-scale preliminary screening while supporting early identification and timely clinical intervention.

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