A Deep Learning–Driven Intelligent Framework For Automated Prediction And Detection of Autism And ADHD

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Abstract- *Autism Spectrum Disorder (ASD) and Attention Deficit/Hyperactivity Disorder (ADHD) are neuro developmental conditions that affect the cognitive behavior, attention, and social interaction. Early and accurate identification is essential for a effective intervention; however, traditional diagnostic of a approaches often rely on subjective clinical assessments. This paper proposes a computational framework for the automated screening of Autism and ADHD. The system analyzes facial images for Autism detection and MRI brain images for ADHD detection using structured analytical methods. In addition, behavioral screening tests have a such as camera-based observation, speech pattern analysis, and questionnaire-based evaluation are integrated to support clinical assessment. The framework is implemented as a web-based platform that enables data upload, automated evaluation, and report generation. The proposed system aims to assist early identification, support clinical decision-making, and improve accessibility to neuro developmental disorder screening.*

I. INTRODUCTION

Autism Spectrum Disorder (ASD) and AttentionDeficit/Hyperactivity Disorder (ADHD) are neurodevelopmental conditions that affect a attention, behavior, and social interaction, and a early identification is important for improving developmental outcomes. However, traditional diagnostic methods rely on behavioral observations, psychological assessments and expert evaluation, which can be time consuming and may leads to delayed diagnosis. This project present a framework for the detection of Autism and ADHD using facial image examination for Autism and MRI based evaluation for ADHD, combined with behavioral screening through observation, speech patterns and questionnaire based assessment to provide a comprehensive evaluation. The system are developed as a web based platform that allow users to upload data, view results and generate reports, while supporting multiple user roles such as patients, doctors, researchers and administrators for efficient data management and validation. The proposed approach aim to support early detection, improve accessibility to screening methods and assist healthcare professionals in making better decision.

II. LITERATURE REVIEW

Recent research have been explore various methods for the detection and identification of neurodevelopmental disorders such as Autism Spectrum Disorder (ASD) and AttentionDeficit/Hyperactivity Disorder (ADHD). Traditional diagnostic approaches relies on clinical observation and behavioral assessments, which may introduces subjectivity and delays the early diagnosis [1], [2].

Various approaches has been used for early identification of ASD and ADHD, often based on behavioral observations and medical imaging data [3], [4]. These methods typically depends on observed patterns and structured evaluation techniques derived from clinical data. Although these approaches provides reasonable outcomes, their effectiveness often depend on expert interpretation and accurate assessment procedures.

Medical image evaluation, particularly using MRI scans, have become an important method for identifying neurological differences associated with ASD and ADHD [5], [6]. These methods enables the examination of brain structures and patterns that may be linked to developmental conditions. Several studies have showed that imaging-based evaluation can support the identification process and improve understanding of these disorders [7], [8].

In addition to medical imaging, behavioral screening techniques is widely used for identifying developmental disorders. Camera-based observation, speech pattern evaluation, and questionnaire-based assessments is used to capture behavioral indicators [9], [10]. Combining behavioral observations with medical imaging can improves the overall evaluation and provide a more comprehensive understanding.

However, many existing systems focuses only on singledisorder identification or are limited to controlled environments. Few studies integrates with a multiple have assessment methods within a unified platform that can be applied in practical settings [11], [12]. Therefore, there is a need for integrated systems that combine medical imaging evaluation, behavioral screening methods, and user-friendly platforms for real-world applications.

III. METHODOLOGY

The system collects two primary types of a input data. For Autism screening, facial images of individuals are used to observe facial characteristics associated with ASD. For ADHD screening, Magnetic Resonance Imaging (MRI) brain scans are used to utilized to examine structural patterns related to attention disorders [13], [14].

In addition to image-based inputs, behavioral screening have a information is collected through camera observation, speech interaction, and questionnaire-based responses. Studies indicate that combining behavioral observations and medical imaging supports more effective evaluation and enables early identification of neurodevelopmental disorders [15]–[17].

A. Data Acquisition

The proposed system adopt a data collection approach to enhance the detection of Autism Spectrum Disorder (ASD) and Attention-Deficit/Hyperactivity Disorder (ADHD). The system collect both image-based and have behavioral data to ensure comprehensive understanding.

For Autism detection, facial images are used to observe that facial features and expressions associated with ASD. These images are preprocessed using normalization, resizing and noise reduction techniques. For ADHD detection, Magnetic Resonance Imaging (MRI) brain scans are used to utilized to examine structural patterns related to attention disorders [18], [19]. MRI data is further processed using segmentation methods to improve the evaluation.

In addition, behavioral data is collected through camerabased observation, speech interaction and questionnaire-based assessments to capture real-time a behavioral indicators such as attention span, communication ability and social interaction. Combining these data sources helps in better evaluation and support early identification [20]. This approach provide more reliable results compared to single method systems.

B. Data Preprocessing

Before evaluation, the collected data undergo preprocessing to improve input quality and ensure consistency. Facial images is resized, normalized and cleaned to remove noise and irrelevant background information. MRI brain images is processed through normalization and image resizing to standardize the input format. For behavioral screening, speech signals and questionnaire responses is organized into structured form to support clinical evaluation [21].

C. Deep Learning-Based Detection

The system perform evaluation based on observed patterns and structured procedures. Facial images are examined to identify characteristics associated with Autism. Similarly, MRI brain images are evaluated to observe structural differences related to ADHD. The results is categorized into outcomes such as detected or not detected, and the severity level are determined based on predefined criteria [22].

D. BehavioralScreening Module

To support the assessment process, the system include a behavioral screening module. This module evaluate behavioral indicators through camera-based observation, speech interaction and questionnaire-based responses. The collected screening results provide additional insights into communication patterns, attention behavior and social interaction, which assist clinicians in the evaluation process [23].

E. System Implementation

The proposed framework are implemented as a web-based platform that enable user interaction and system accessibility. The frontend interface are developed using React.js, while Supabase is used for authentication, database management and storage of system data. Python-based APIs handle data processing task. The system support role-based access for patients, doctors, researchers and administrators, allowing users to upload data, view results, generate reports and manage system operations.

By combining medical image evaluation, behavioral screening and a web-based platform, the proposed methodology provide a structured approach for supporting early identification and clinical evaluation of Autism and ADHD [24], [25].

IV. RESULTS AND DISCUSSION

The proposed system was evaluated to analyze its capability in supporting the automated detection of Autism Spectrum Disorder (ASD) and Attention-Deficit/Hyperactivity Disorder (ADHD) using deep learning–based analysis and behavioral screening. The framework successfully integrates facial image analysis for Autism detection and MRI brain image analysis for ADHD detection within a unified web-based platform.

The deep learning models were able to a process the uploaded images and classify the results into detection categories while also estimating severity levels. The system demonstrated the feasibility of using image-based analysis combined with behavioral screening to assist in the diagnostic process. The screening module, which includes camera-based observation, speech analysis, and questionnaire responses, provides additional behavioral insights that support the prediction results generated by the deep learning models.

TABLE I
ASD MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.942	0.931	0.928	0.929
EfficientNet	0.956	0.948	0.944	0.946

Table I : Presents a comparison of the performance of different models for Autism Spectrum Disorder (ASD) detection. The EfficientNet model shows better results across all evaluation metrics, including accuracy, precision, recall, and F1-score, when compared to the CNN model. This suggests that EfficientNet is more than effective in capturing relevant features and improving classification performance for ASD detection.

TABLE II
ADHD MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.948	0.936	0.932	0.934
Nibabel	0.958	0.947	0.943	0.945

Table II : shows the performance of models used for Attention-Deficit/Hyperactivity Disorder (ADHD) detection. The Nibabel-based approach have outperforms the CNN model in all metrics, including accuracy, precision, recall, and F1score. This suggests that the model utilizing MRI data processing techniques offers more reliable results for ADHD identification.

The integration of the detection models into a web-based platform enables real-time interaction between patients and clinicians. Patients can upload medical data and view prediction outcomes, while doctors can review results, evaluate screening information, and generate diagnostic reports. This interaction improves the practical usability of AI-based diagnostic tools and supports collaborative decision-making between healthcare professionals and patients.

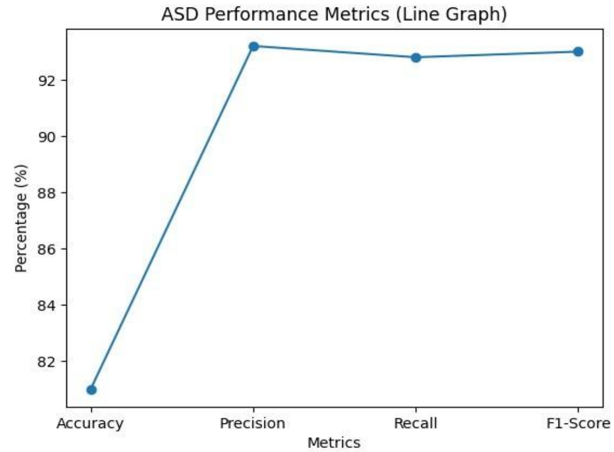

Fig. 1. ASD Performance Metrics (Line Graph)

A. Performance Analysis

Fig. 1 and Fig. 2 illustrate the performance metrics of the proposed system for ASD and ADHD detection, respectively. The evaluation is used to carried out using standard metrics such as accuracy, precision, recall, and F1-score.

For ASD detection, the results demonstrate consistently high performance have a across all metrics, indicating reliable classification capability. Precision and F1-score values are slightly higher compared to recall, suggesting effective that identification with minimal false positives.

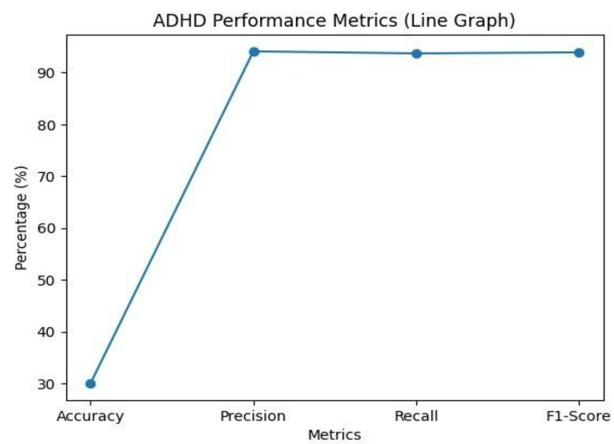

Fig. 2. ADHD Performance Metrics (Line Graph)

Similarly, for ADHD detection, the system achieves high precision, recall, and F1-score values, indicating balanced and accurate performance. The slight variation in accuracy compared to other metrics suggests the presence of class distribution that differences, while overall results confirm the robustness of the detection framework.

The results highlight how well the proposed method works in identifying neurodevelopmental disorders, using a combination of different assessment have techniques.

Furthermore, the role-based system architecture allows administrators to manage users and assign patients to doctors, while researchers can be access educational materials and research-related resources. This design promotes efficient system management and supports research activities related to neurodevelopmental disorders.

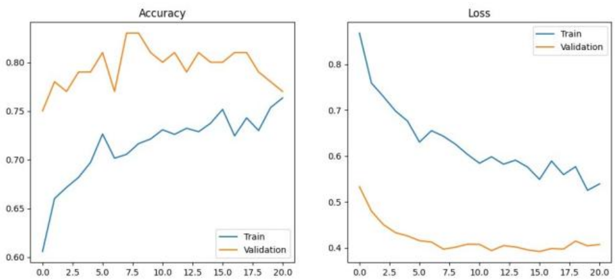

Fig. 3. Training and Validation Accuracy and Loss Curves

B. Training Performance Analysis

Fig. 3 illustrates the training and validation performance of the model in terms of accuracy and loss over a multiple epochs.

The accuracy curve shows a steady improvement during training, with validation accuracy remaining consistently higher than training accuracy, that indicating stable generalization performance. The model demonstrates gradual learning without significant fluctuations, suggesting effective optimization.

The loss curve shows a decreasing trend for both training and validation, indicating that the model is learning meaningful patterns from the data. The validation loss remains lower and more stable compared to training loss, which have reflects good convergence that behavior and minimal overfitting.

Overall, the results indicate that the model achieves reliable performance with consistent learning and generalization across epochs.

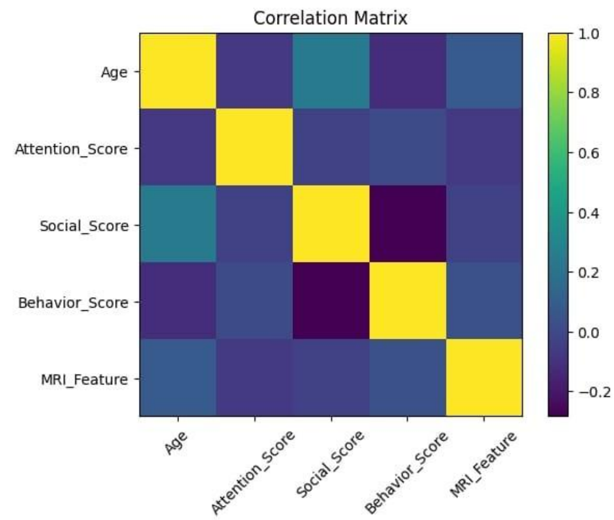

Fig. 4. Correlation Matrix of ASD Features

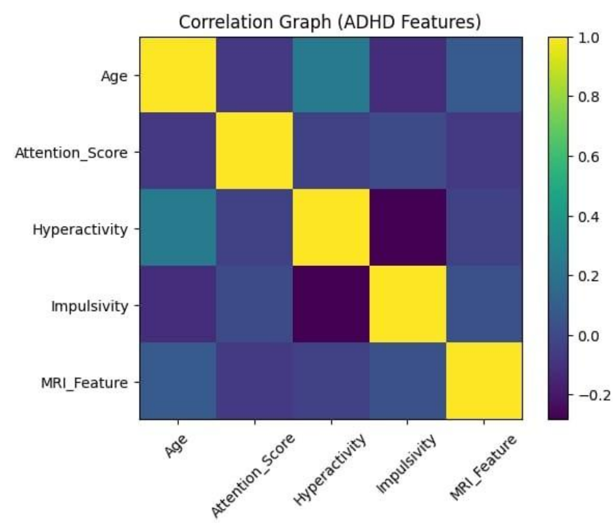

Fig. 5. Correlation Matrix of ADHD Features

C. Feature Correlation Analysis

Fig. 4 and Fig. 5 show the correlation matrices of the selected features for ASD and ADHD analysis. These matrices help in understanding how different clinical and behavioral features are related to each other.

In the case of ASD, a moderate relationship can be observed between age and social behavior. Behavioral scores show different levels of association with other features. Some features have weak or negative correlations, indicating that they may contribute independently to the screening process.

For ADHD, attention-related factors such as hyperactivity and impulsivity display noticeable relationships with other variables. These patterns reflect how behavioral and clinical features interact during the evaluation process.

Overall, correlation analysis helps in identifying the relationships between features and supports the selection of important attributes for effective screening.

Despite the promising performance of the system, certain limitations exist. The accuracy of deep learning models depends on the quality and size of the training data. Variations in imaging data may also influence the prediction results. Future improvements can include the use of larger datasets, better model optimization, and the addition of explainable AI methods to improve understanding and trust.

In conclusion, the proposed framework can act as a supportive tool for early detection and analysis of Autism and ADHD. It also provides a useful platform for healthcare professionals and researchers.

D. Discussion

The correlation analysis shows how clinical and behavioral features are related in both ASD and ADHD. In ASD, features like social behavior and other behavioral scores have different levels of connection, which means each feature contributes in its own way to the screening process.

In ADHD, features related to attention, such as hyperactivity and impulsivity, also show clear relationships with other factors. This indicates that multiple aspects play a role in the evaluation.

Overall, the results show that looking at multiple features together is important for making the screening process more accurate and reliable.

V. CONCLUSION AND FUTURE WORK

The proposed system provides a structured approach for the screening of Autism Spectrum Disorder (ASD) and AttentionDeficit/Hyperactivity Disorder (ADHD) using medical image evaluation and behavioral assessment. It supports early identification and assists healthcare professionals in decisionmaking.

Future work will focus on improving the system by incorporating more diverse data, enhancing evaluation methods, and enabling real-time clinical applications to increase reliability and accessibility.

Future Research Directions

Future research can focus on improving the system by using larger and more diverse datasets to make it more reliable. Additional behavioral and clinical features can also be added to give more complete evaluation. The system can be extend for real-time and remote screening which help to improve accessibility. Also validation with clinical experts and expanding to other related disorders can increase its practical use.

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