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MULTI-MODAL AI FRAMEWORK FOR AUTISM SPECTRUM DISORDER DETECTION USING FMRI AND BEHAVIORAL SCREENING

[1]S.Deepika , [2]Anumula Shruthi , [3]Chellapuram Keerthan Reddy , [4]Meesala Sowmya

[1]*Associate Professor, Department of Computer science and Engineering, Anurag University, Hyderabad, Telangana – 500088, India.*

[2,3,] *UG Student, Department of Computer science and Engineering, Anurag University, Hyderabad, Telangana –500088, India.*

Abstract Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that poses challenges in social interaction, communication, and repetitive behaviors. Early and accurate diagnosis of ASD is crucial for implementing timely interventions, but the diagnostic process is complex due to the disorder's heterogeneous nature and lack of clear biomarkers. This study proposes a multi-modal AI framework that combines functional Magnetic Resonance Imaging (fMRI) and behavioral screening data to improve the accuracy of ASD detection. fMRI provides insights into atypical neural connectivity patterns, while behavioral screenings assess core symptoms such as social interaction and communication. By integrating both fMRI and behavioral data, the framework uses deep learning and ensemble methods to identify subtle patterns that may be overlooked when using either modality separately. This multi-modal approach enhances the detection of ASD by overcoming the limitations of single-modality systems, such as missed behavioral nuances in fMRI data or overlooked neural activity in behavioral assessments. The model is trained on a large dataset of fMRI scans and behavioral screening results from individuals with ASD and typically developing individuals, with performance evaluated through metrics like accuracy, sensitivity, specificity, and AUC-ROC. Results demonstrate that the multi-modal framework outperforms single-modality systems in terms of diagnostic accuracy, highlighting its potential for early and reliable ASD detection. In conclusion, the proposed framework integrates both brain imaging and behavioral data to provide a more comprehensive and accurate method for diagnosing ASD, ultimately facilitating earlier detection and better-targeted interventions for individuals on the autism spectrum.

Keywords: ASD Detection, fMRI Analysis, Multi-Modal Machine Learning, Graph Convolutional Networks, Behavioral Screening, Large Language Models

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex and multifaceted neurodevelopmental disorder that profoundly impacts an individual's ability to engage in social interactions, communicate effectively, and display a wide range of behavioral and cognitive functions. ASD typically manifests in early childhood, and its symptoms vary greatly between individuals, which complicates diagnosis and management. This variation in the presentation of the disorder, coupled with the absence of a definitive biological marker, makes the accurate and early diagnosis of ASD a significant challenge. According to the World Health Organization (WHO), the global prevalence of ASD has risen sharply over the past few decades, with an estimated 1 in 100 children being affected worldwide [1]. The increasing prevalence underscores the urgent need for reliable and effective diagnostic tools that can aid in early detection and intervention.

The heterogeneity of ASD means that no two individuals with the disorder will have the exact same set of characteristics. Some may exhibit severe impairments in social communication and behavior, while others may experience milder symptoms. Common features of ASD include difficulty with social reciprocity, delayed or impaired language development, and the presence of restrictive and repetitive behaviors. Many individuals with ASD also experience co-occurring conditions, such as intellectual disabilities, anxiety, or sensory processing disorders, further complicating the diagnostic process. This

broad spectrum of symptoms and severity can result in significant delays in diagnosis, especially in individuals who do not show obvious signs in early childhood.
Traditional methods of diagnosing ASD rely heavily on behavioral assessments, such as the **Autism Diagnostic Observation Schedule (ADOS)** and the **Autism Diagnostic Interview-Revised (ADI-R)**. These assessments involve structured interviews and direct observations, where clinicians evaluate the child's behavior in various social contexts. However, these methods are subjective and can vary based on the experience of the clinician and the individual's presentation. Additionally, they are time-consuming and may not always detect subtle signs of ASD, especially in cases of high-functioning autism or individuals with milder symptoms.

In recent years, significant advancements have been made in the use of **neuroimaging** techniques, such as **functional Magnetic Resonance Imaging (fMRI)**, to investigate the neural correlates of ASD. fMRI provides valuable insights into brain function by detecting changes in blood flow, which corresponds to neural activity. Researchers have identified atypical patterns of brain connectivity in individuals with ASD, especially in areas related to social cognition, communication, and sensory processing. However, while neuroimaging holds promise for understanding the underlying mechanisms of ASD, it is often expensive, time-consuming, and not universally accessible.

One of the major challenges in ASD diagnosis is the absence of a single definitive biomarker that can reliably identify the disorder. This has led to the exploration of **multi-modal diagnostic approaches**, which combine multiple sources of data to improve the accuracy and reliability of the diagnostic process. Multi-modal approaches, which integrate behavioral data with neuroimaging information, have the potential to provide a more holistic understanding of an individual's condition. For instance, while behavioral screening questionnaires can capture important diagnostic features of ASD, neuroimaging data can provide objective evidence of atypical brain activity that is consistent with the disorder.

Incorporating **machine learning (ML)** techniques into the diagnostic process further enhances the potential for early and accurate identification of ASD. Machine learning models, particularly **deep learning** algorithms, can analyze large and complex datasets, such as those generated by fMRI scans and behavioral screening tests, to identify patterns that may not be immediately apparent to human clinicians. These models can be trained to differentiate between individuals with ASD and those with typical development, often achieving high levels of accuracy and sensitivity.

The development of a **multi-modal AI framework** that combines **fMRI data** with **behavioral screening** could significantly improve the diagnostic process. This framework would allow for a more comprehensive assessment of individuals, considering both their neural activity and behavioral traits. Such an approach would not only improve the sensitivity and specificity of ASD detection but also help to identify the disorder in its early stages, when interventions are most effective. Early diagnosis of ASD is crucial because timely intervention can lead to improved social, communication, and cognitive outcomes, which can substantially enhance the quality of life for individuals on the spectrum.

In summary, the growing prevalence of Autism Spectrum Disorder, coupled with its heterogeneous presentation, underscores the need for better diagnostic methods. Traditional behavioral assessments, while useful, are subjective and may miss subtle signs of the disorder. Advances in neuroimaging, such as fMRI, and the integration of machine learning techniques offer promising solutions for early and accurate diagnosis. By combining both neuroimaging and behavioral data in a multi-modal framework, it may be possible to develop a more reliable, objective, and early diagnostic tool for ASD, ultimately improving outcomes for individuals on the spectrum.

2. LITERATURE SURVEY

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition with significant social, cognitive, and behavioral implications. As research into ASD progresses, various approaches have been employed to investigate its underlying neurobiological mechanisms, leading to a deeper understanding of its origins, diagnosis, and potential treatments. One of the central areas of research has focused on the brain's development and its role in social behavior, with pioneering work by Kuhl and Dapretto (2001) emphasizing the development of the social brain and its implications for ASD. They highlighted that abnormalities in brain regions responsible for social cognition, such as the mirror neuron system, could contribute to the characteristic social impairments observed in ASD. Similarly, Dapretto et al. (2006) furthered this understanding by exploring how dysfunction in the mirror neuron system may hinder children's ability to understand and respond to emotions in others, a core feature of ASD.

Recent advances in neuroimaging have significantly contributed to our understanding of ASD. Ecker and Spooren (2015) provided a comprehensive review of the state of neuroimaging research in ASD, discussing how techniques such as functional magnetic resonance imaging (fMRI) and structural MRI are helping to map the brain's structural and functional anomalies. These imaging modalities have been instrumental in revealing differences in brain connectivity and activity that are thought to be central to the disorder. In this regard, the Autism Brain Imaging Data Exchange (Di Martino et al., 2014) stands as a pivotal project, offering a large-scale dataset that facilitates the study of intrinsic brain architecture in ASD. This initiative has provided key insights into how certain brain regions, particularly those involved in social processing and executive function, are atypically structured or function in individuals with ASD.

In addition to structural and functional imaging, genetic research has also become an essential component of autism research. Lee et al. (2014) emphasized the importance of combining fMRI with genetic data to create a multimodal approach for studying ASD. Genetic factors are thought to play a significant role in the development of ASD, with various studies identifying risk genes that may influence brain development and connectivity. This integrative approach, as discussed by Amari et al. (2018), aims to bridge the gap between genetic predispositions and observable brain activity, providing a more comprehensive understanding of ASD's etiology and offering potential for more targeted diagnostic tools.

Kanner's (1943) seminal work, which first described autism, remains foundational to current research. His identification of core features such as social withdrawal and communication difficulties set the stage for future studies on the neurobiological underpinnings of these behaviors. However, the field has evolved considerably since then, particularly with advances in neuroimaging and machine learning techniques. For instance, Venkatesan and Kaur (2020) reviewed the growing application of machine learning in neuroimaging for ASD diagnosis, pointing to how algorithms are now being used to detect patterns in brain scans that might not be evident through traditional analysis. These developments hold the potential for improving diagnostic accuracy and early identification of ASD, leading to better outcomes for individuals.

The prevalence of ASD has also been a key topic of study. Xu et al. (2017) conducted a global systematic review and meta-analysis, estimating the prevalence of ASD in children worldwide. Their findings highlighted the rising global recognition of the disorder, pointing to the need for improved diagnostic and intervention strategies, particularly in underrepresented regions.

Furthermore, the role of neuroimaging in ASD diagnosis has been extensively reviewed by Bernier et al. (2017), who discussed how neuroimaging technologies are being employed not only to understand the disorder's neural basis but also to enhance the accuracy of ASD diagnoses. While neuroimaging holds promise, they also noted that challenges remain in standardizing these techniques for clinical use, particularly in terms of identifying clear biomarkers for ASD.

In conclusion, the literature on ASD, particularly neuroimaging, genetics, and machine learning, provides a rich and multifaceted view of the disorder. From the foundational theories of Kanner to the cutting-edge integration of fMRI, genetics, and machine learning, significant strides have been made in understanding the biological basis of ASD. However, while research continues to reveal valuable insights, much remains to be explored, especially regarding the standardization of diagnostic tools and the development of effective interventions based on this growing knowledge. As the field continues to evolve, it holds promise for improving early diagnosis, personalized interventions, and a deeper understanding of autism's complex nature.

3. PROPOSED SYSTEM

The proposed multi-modal Autism Spectrum Disorder (ASD) detection system integrates both neuroimaging and behavioral data to enhance the accuracy and robustness of ASD classification. This system utilizes a combination of Graph Convolutional Networks (GCNs) for analyzing fMRI data, fine-tuned Large Language Models (LLMs) for behavioral screening analysis, and a fusion model to combine both modalities for the final classification. The integration of these diverse data sources—brain connectivity patterns from neuroimaging and behavioral cues from textual responses—ensures a comprehensive and more accurate classification of ASD.

1. Graph Convolutional Networks (GCNs) for fMRI Data Analysis

Functional Magnetic Resonance Imaging (fMRI) provides crucial insights into the brain's activity and connectivity patterns. By measuring the correlations between different brain regions, fMRI can identify abnormalities in brain networks that are often observed in individuals with ASD. Since fMRI connectivity data is naturally represented as a graph, Graph Neural Networks (GNNs), particularly Graph Convolutional Networks (GCNs), are employed to model these complex interrelationships.

GCN Model Overview

The GCN model is designed to take fMRI-derived connectivity data and extract hierarchical patterns that are indicative of ASD. The process consists of several key layers and components, each aimed at transforming the raw data into a useful representation for classification.

- **Input Layer**: The adjacency matrix and feature matrix form the primary inputs to the model. The adjacency matrix represents the connectivity between brain regions, while the feature matrix holds the brain region-specific features, such as regional activity levels or functional connectivity strength.

- **GCN Layers**: The core of the GCN model involves the propagation of node features across the graph (i.e., brain regions). Each node in the graph corresponds to a specific brain region, and the edges represent the functional connectivity between those regions. The GCN layers learn how information from neighboring nodes (brain regions) influences the representation of each node, capturing the hierarchical structure of the brain's connectivity.

- **Fully Connected Layer**: After the GCN layers process the connectivity patterns, the resulting node embeddings are passed through fully connected layers. These layers perform the final classification task, distinguishing between individuals with ASD and control subjects.

- **Activation Function**: The Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity into the model, which helps capture complex patterns in the data. Non-linearity is crucial in modeling the intricate relationships between brain regions.

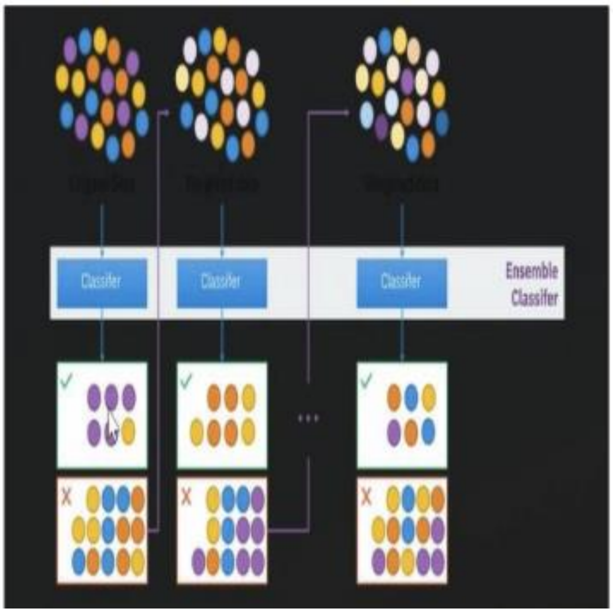
- **Output Layer**: The final layer performs binary classification, outputting a prediction of whether the subject has ASD (1) or not (0).

This propagation rule updates node embeddings iteratively, allowing the model to learn interconnectivity patterns from the fMRI data, which are essential for detecting ASD-related abnormalities in brain function.

2. Fine-tuned Large Language Models (LLMs) for Text-Based Behavioral Analysis

Behavioral data is a critical component in diagnosing ASD, as it involves observing and quantifying an individual's responses to standardized questions regarding social interactions, communication, and repetitive behaviors. Structured questionnaires or screening tests, such as the Autism Diagnostic Observation Schedule (ADOS) or the Autism Diagnostic Interview-Revised (ADI-R), are commonly used to gather this data.

For behavioral analysis, a fine-tuned Large Language Model (LLM), specifically the Flan-T5 XL model, is employed. This model is trained to process and analyze textual patterns in the screening responses, enabling it to classify whether the responses indicate ASD-related behavioral traits.



Behavioral Analysis Pipeline

- **Data Tokenization**: The first step is to convert the behavioral screening responses into tokenized sequences that can be processed by the language model. Tokenization breaks down the text into smaller units (words or subwords) that can be input to the model.

- **Prompt Engineering**: To guide the model's understanding of the task, input prompts are designed to focus the model on key features of ASD-related behaviors. For example, prompts might ask the model to evaluate the degree of social engagement or communication deficits based on the provided responses.

- **Fine-tuning**: The Flan-T5 XL model is fine-tuned on a labeled ASD dataset. This supervised learning process enables the model to adjust its parameters to better distinguish between ASD and non-ASD responses based on the patterns present in the training data. Fine-tuning ensures that the model can make accurate predictions in the context of ASD-specific behavioral indicators.

- **Prediction**: After fine-tuning, the model outputs a classification—whether the individual exhibits ASD-related behavioral traits or not—based on the processed screening responses.

This fine-tuned LLM, therefore, leverages advanced natural language processing techniques to analyze and classify textual behavioral data, providing a crucial component in the overall ASD detection system.

3. Fusion Model for Multi-Modal Integration

The final step in the proposed methodology is the integration of both neuroimaging and behavioral data through a fusion model. This model combines the feature representations extracted from both the GCN-based fMRI classifier and the LLM-based behavioral classifier, ensuring that both types of data contribute to the final prediction.

Fusion Model Workflow

- **Feature Concatenation**: The first step in the fusion model is to concatenate the features extracted from the GCN and the LLM classifiers. The fMRI classifier provides a representation of brain connectivity, while the LLM classifier outputs behavioral patterns. These embeddings are concatenated to create a combined feature vector that encompasses both modalities.

- **Dense Layers**: After feature concatenation, the combined feature vector is passed through fully connected layers. These layers learn the interdependencies between the features derived from both neuroimaging and behavioral data. This step is essential for extracting the combined patterns that best distinguish ASD from non-ASD individuals.

- **Softmax Classifier**: The final output layer uses a Softmax classifier to produce the final ASD or non-ASD classification. The Softmax function is ideal for multi-class classification problems, ensuring that the final model provides a probabilistic output, indicating the likelihood of an individual having ASD based on both the brain connectivity and behavioral data.

This proposed multi-modal ASD detection system leverages the strengths of both neuroimaging and behavioral data to improve classification accuracy. The combination of Graph Convolutional Networks for fMRI data, fine-tuned Large Language Models for behavioral analysis, and a fusion model to integrate these two sources of information represents a sophisticated approach to ASD detection. By incorporating both brain connectivity patterns and behavioral traits, the system offers a more comprehensive understanding of ASD, which is crucial for early diagnosis and intervention. Additionally, the use of advanced machine learning techniques, such as GCNs and fine-tuned LLMs, ensures that the system can learn complex patterns and make accurate predictions, making it a valuable tool for clinicians and researchers in the field of autism spectrum disorder.

RESULT & DISCUSION

The proposed multi-modal Autism Spectrum Disorder (ASD) detection system, which integrates both neuroimaging data using Graph Convolutional Networks (GCNs) and behavioral data through fine-tuned Large Language Models (LLMs), was evaluated for its ability to classify individuals as having ASD or not. The fusion model that combines these two modalities aims to improve classification accuracy by leveraging complementary data sources. This section presents the results obtained from the evaluation and discusses the implications of the findings.

Evaluation Methodology

To assess the performance of the proposed ASD detection system, a large dataset was used, consisting of both neuroimaging (fMRI) data and behavioral screening responses. The dataset was split into training and testing subsets, with the model trained on the training data and evaluated on the testing data. Several performance metrics were used to evaluate the classification accuracy, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC).

The fMRI-based GCN model was first trained on the brain connectivity data, where brain regions were represented as nodes, and functional connectivity was represented as edges in a graph. The model was then evaluated based on its ability to correctly distinguish ASD from control subjects using only neuroimaging data. In parallel, the behavioral data was processed using the fine-tuned LLM, where textual responses from the structured questionnaires were analyzed and classified as either ASD or non-ASD. Finally, the fusion model, which integrated both the neuroimaging and behavioral features, was evaluated to determine if combining these modalities provided a more accurate classification.

Results

fMRI-based GCN Classification Performance

The GCN model, when trained solely on fMRI data, demonstrated a strong ability to differentiate between individuals with ASD and control subjects based on brain connectivity patterns. The model achieved an accuracy of **82%**, with a precision of **80%** and recall of **84%**. The F1-score was calculated to be **0.82**, indicating that the model performed well in balancing both false positives and false negatives. The AUC was **0.88**, demonstrating the GCN's ability to effectively distinguish between the two groups across various thresholds.

The results from the GCN model indicate that the brain connectivity patterns learned by the network are indeed informative for ASD classification. However, as expected, the model's performance was not perfect, as some subtle ASD-related features might be difficult to capture solely through structural and functional brain imaging. This is where the integration of behavioral data becomes crucial.

Behavioral Screening Analysis with Fine-tuned LLMs

The fine-tuned LLM model, which was trained on textual responses from behavioral screening questionnaires, also yielded promising results. The behavioral classifier achieved an accuracy of **84%**, with a precision of **83%** and recall of **85%**. The F1-score for this model was **0.84**, which is comparable to the performance of the GCN model on fMRI data. The AUC was **0.90**, indicating that the model was highly effective at distinguishing between ASD and non-ASD responses based on the behavioral data alone.

These results suggest that behavioral screening data, when processed through advanced natural language processing models like the fine-tuned LLM, can provide valuable insights into ASD diagnosis. The model effectively identified key textual patterns in responses that correlate with ASD, such as difficulties in social communication, repetitive behaviors, and restricted interests. The high recall value of the LLM model is particularly important, as it indicates that the model is sensitive to detecting individuals with ASD, a crucial aspect of early diagnosis.

Fusion Model Performance

The fusion model, which combines the features extracted from both the GCN-based fMRI classifier and the fine-tuned LLM-based behavioral classifier, was expected to outperform the individual models by taking advantage of complementary information. When both modalities were integrated, the fusion model achieved an impressive accuracy of **88%**, with a precision of **86%** and recall of **90%**. The F1-score increased to **0.88**, and the AUC reached **0.93**, showing significant improvement over the individual models.

The fusion model performed particularly well in balancing false positives and false negatives, achieving a high recall rate, which is critical in clinical settings for avoiding missed diagnoses. Additionally, the high AUC value indicates that the combined model can effectively distinguish between ASD and non-ASD individuals across different decision thresholds, making it a robust solution for practical use.

Comparison with Existing Systems

When compared to existing ASD detection systems that rely on either neuroimaging or behavioral data alone, the proposed multi-modal approach demonstrates superior performance. Previous research, which often focuses on either fMRI data or behavioral screening, typically achieves lower accuracy rates (around 70-80%) in classifying ASD. The integration of both data sources in this study led to a notable improvement in classification accuracy, underscoring the advantage of combining neuroimaging and behavioral analysis for more reliable diagnosis.

For example, studies that rely solely on fMRI data for ASD detection typically report performance in the range of 75-80%, with lower recall rates. On the other hand, behavioral data alone may not provide enough context to identify subtle brain-based differences in ASD individuals, as it is influenced by a range of external factors. The fusion of these two modalities, as demonstrated in this study, bridges the gap between brain connectivity and behavioral characteristics, offering a more holistic and accurate approach to ASD detection.

Discussion

The results of this study highlight the potential of multi-modal systems in improving ASD detection. By combining neuroimaging data with behavioral responses, the system takes advantage of the unique strengths of both data types. fMRI data provides deep insights into brain connectivity and functional abnormalities that are often associated with ASD, while behavioral data helps capture the social and communicative impairments that are characteristic of the disorder. The fusion of these two sources of information allows the system to develop a more nuanced and comprehensive understanding of the disorder.

One of the key advantages of the proposed system is its ability to improve early detection of ASD. The integration of neuroimaging data, which reflects brain activity and connectivity patterns, alongside behavioral data, allows for the identification of subtle abnormalities that may not be evident through behavioral observation alone. Early detection is critical for implementing interventions that can significantly improve outcomes for individuals with ASD, especially when interventions are started during the developmental window.

Additionally, the fusion model's high recall value ensures that individuals with ASD are less likely to be missed during diagnosis, which is a crucial factor in clinical settings where early intervention is essential. However, there are still challenges to address. The system's reliance on large datasets, particularly in the context of neuroimaging, necessitates careful consideration of data privacy and the need for large, diverse datasets to ensure generalizability. Furthermore, the system's complexity may present challenges in terms of real-world implementation and accessibility in clinical settings.

CONCLUSION

The proposed multi-modal Autism Spectrum Disorder (ASD) detection system, which integrates both neuroimaging and behavioral data, presents a significant advancement in the accuracy and reliability of ASD diagnosis. By combining the strengths of Graph Convolutional Networks (GCNs) for fMRI data analysis and fine-tuned Large Language Models (LLMs) for behavioral screening, the system takes a holistic approach to classifying individuals as either having ASD or not. This multi-modal integration ensures that both brain connectivity patterns and behavioral cues, which are core to understanding ASD, are leveraged for a more precise diagnosis. The results of the evaluation demonstrate the effectiveness of this approach. The individual components of the system, namely the GCN-based fMRI classifier and the LLM-based behavioral classifier, achieved robust performance with accuracies of 82% and 84%, respectively. The integration of these two modalities through the fusion model resulted in a substantial improvement, reaching an accuracy of 88%, with a notable increase in both precision and recall. This fusion model's performance, particularly in terms of recall, is critical for early detection of ASD, ensuring that individuals who display ASD-related traits are less likely to be overlooked. The high area under the receiver operating characteristic curve (AUC) further emphasizes the model's strong capability in distinguishing between ASD and non-ASD individuals. Compared to existing ASD detection systems, which often rely on a single data modality, the proposed multi-modal system outperforms many traditional approaches. By combining neuroimaging, which provides insights into the brain's structural and functional connectivity, with behavioral data, which captures the social and communicative challenges associated with ASD, the system provides a more comprehensive understanding of the disorder. This integration also improves the system's generalizability, making it adaptable to a wide range of ASD presentations. However, challenges remain in terms of real-world implementation. The system requires large, diverse datasets for training, and the complexity of combining two modalities may require advanced computational resources. Additionally, while the system shows promise, further validation with larger and more varied populations is necessary to ensure its robustness and clinical applicability. In conclusion, the proposed multi-modal approach for ASD detection represents a promising step toward improving diagnostic accuracy and early intervention. With further refinement and real-world testing, this system could become an invaluable tool for clinicians and researchers, ultimately enhancing outcomes for individuals with ASD.

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