

AUTISM SPECTRUM DISORDER

DETECTION USING MULTIMODAL DATA

A PROJECT REPORT

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ABSTRACT

The early and accurate diagnosis of autism spectrum disorder remains a significant challenge in the fields of psychology, neuroscience, and healthcare. Despite the rapid advancements in machine learning, data analysis, and diagnostic tools, many individuals with ASD continue to go undiagnosed or receive late diagnoses, which can hinder their access to timely interventions and support services. This project aims to develop a comprehensive and innovative autism prediction system that harnesses the power of multiple multimodal data sources. These include image data, electroencephalogram (EEG) signals, behavioral assessments, and eye-tracking metrics, all of which contribute valuable insights into the characteristics and indicators of autism. By integrating these diverse modalities into a cohesive framework, the proposed system seeks to significantly enhance both the accuracy and reliability of autism predictions. This multifaceted approach enables a more nuanced understanding of the various factors associated with ASD, thereby facilitating early intervention and tailored support for affected individuals and their families. The project focuses on creating a synergistic model that effectively combines insights derived from each data type, leading to a holistic understanding of autism indicators. To ensure the robustness of the model across various datasets, the project employs advanced techniques for data preprocessing and analysis. By implementing these methods, the project aims to develop a model that can generalize well to new and unseen data, ultimately improving the reliability of autism diagnoses. A key component of this research is the development of a user-friendly graphical interface, created using ReactJS and Flask, which allows users to input and assess different types of data seamlessly. This interface is designed to be accessible to a broader audience, including healthcare professionals, caregivers, educators, and researchers.

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LIST OF ABBREVIATIONS

<i>ASD</i>	Autism Spectrum Disorder
<i>EEG</i>	Electroencephalogram
<i>ET</i>	Eye Tracking
<i>AQ</i>	Autism Quotient
<i>IQ</i>	Intelligence Quotient
<i>ML</i>	Machine Learning
<i>DL</i>	Deep Learning
<i>ABIDE</i>	Autism Brain Imaging Data Exchange
<i>LSTM</i>	Long Short-Term Memory
<i>fMRI</i>	Functional Magnetic Resonance Imaging
<i>CNN</i>	Convolutional Neural Network
<i>AR</i>	Augmented Reality
<i>VR</i>	Virtual Reality
<i>ResNet</i>	Residual Neural Network
<i>NASNet</i>	Neural Architecture Search Network
<i>ViT</i>	Vision Transformer
<i>DeiT</i>	Data-efficient Image Transformers
<i>DAE</i>	Denoising Autoencoder
<i>SVM</i>	Support Vector Machine
<i>IQR</i>	Interquartile Range
<i>KNN</i>	K-Nearest Neighbors
<i>ANN</i>	Artificial Neural Network
<i>DT</i>	Decision Tree
<i>RF</i>	Random Forest
<i>GCN</i>	Graph Convolutional Network
<i>SHAP</i>	SHapley Additive exPlanations
<i>LIME</i>	Local Interpretable Model-agnostic Explanations

<i>PSO</i>	Particle Swarm Optimization
<i>GA</i>	Genetic Algorithm
<i>CSO</i>	Cuckoo Search Optimization
<i>ACO</i>	Ant Colony Optimization
<i>LSO</i>	Lion Search Optimization

CHAPTER 1

INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder that affects an individual's ability to perceive and interact with the world. It primarily impacts communication, social behavior, and cognitive functioning, with symptoms typically becoming apparent in early childhood. Children with ASD often face challenges in social interaction and struggle to understand nonverbal communication. They may exhibit repetitive behaviors and demonstrate a narrow range of interests. These cognitive differences lead to developmental patterns that are distinct from those of typically developing children.

Typically developing children follow more predictable milestones in communication and social skills. In contrast, children with ASD may require specialized interventions to enhance their abilities and improve their quality of life. Figure 1.1 illustrates a typical child with Autism Spectrum Disorder.

Globally, the prevalence of Autism Spectrum Disorder (ASD) is estimated to affect approximately 1 in 100 children, though this figure can vary significantly by region. In countries such as the United States, the prevalence is notably greater, with around 1 in 36 children diagnosed . This increased detection rate can be attributed to comprehensive screening programs and greater societal understanding of autism. In contrast, countries like India report a lower estimated prevalence of about 1 in 68 children. However, this figure may not fully represent the actual number of cases, as many children go undiagnosed due to limited awareness, cultural stigmas surrounding mental health issues, and inadequate access to healthcare services.



Figure 1.1: Autism Spectrum Disorder Children

These disparities in diagnosis underscore the urgent need for enhanced global awareness, effective early diagnostic tools, and accessible intervention strategies to ensure that all children with ASD receive the necessary support. Improved training for healthcare professionals, along with community education programs, can play a pivotal role in recognizing the signs of ASD early on. Figure 1.2 depicts a typically developing child, highlighting the developmental milestones that children with ASD may struggle to achieve. This visual comparison serves to emphasize the importance of early detection and tailored interventions that can facilitate better outcomes for children on the spectrum. By fostering an environment of understanding and support, we can help bridge the gap in diagnosis and intervention, ultimately improving the quality of life for affected children and their families.

Our project aims to address these challenges by developing an efficient and interactive system for the early detection and intervention of ASD using advanced machine learning and deep learning techniques. By analyzing



Figure 1.2: Typically Developed Children

multimodal data, including EEG signals, images, IQ-based questions, and eye-tracking data, we strive to create a more precise model for identifying early signs of ASD. This approach will clarify the differences between children with ASD and typically developing children, allowing for more targeted interventions.

By combining advanced technology with therapeutic support, our goal is to create a holistic and accessible solution for diagnosing and managing ASD, ultimately improving the quality of life for affected children.

1.1 PROBLEMS RELEVANT TO THE RESEARCH

- **Data Complexity and Integration:** The diverse nature of autism necessitates integrating multiple data types such as images, EEG signals, behavioral assessments, and eye-tracking metrics into a unified predictive model. This integration poses challenges in preprocessing and feature extraction, making it difficult to fully leverage the unique insights from each modality.

- **Early Diagnosis and Access to Interventions:** Despite technological advancements, many individuals with autism are still diagnosed late or misdiagnosed, hindering timely access to essential early interventions. Creating an accurate and user-friendly predictive system is crucial for enabling healthcare professionals and caregivers to provide prompt support to those with autism spectrum disorder.

1.2 RESEARCH OBJECTIVES

- **Develop a Multimodal Predictive Model:** Create a predictive model that integrates image data, EEG signals, behavioral assessments, and eye-tracking metrics to accurately identify early signs of autism.
- **Enhance Accessibility to Early Intervention:** Design a user-friendly system that aids in early diagnosis and provides insights to healthcare professionals and caregivers for timely interventions.

1.3 OVERVIEW OF THE PROPOSED SYSTEM

This project focuses on developing a multimodal system for the early detection of Autism Spectrum Disorder (ASD) by analyzing diverse data sources, including EEG signals, images, behavioral assessments, and eye-tracking metrics. The system aims to enhance diagnostic accuracy and facilitate timely interventions through advanced machine learning techniques. Additionally, it incorporates virtual reality modules to provide personalized therapy, supporting children in developing essential social and daily living skills.

1.4 ORGANIZATION OF THE REPORT

This report is organized into 6 chapters, describing each part of the project with detailed illustrations and system design diagrams.

CHAPTER 2: Literature Review reviews existing research, studies, and relevant literature related Autism Spectrum Disorder. Discusses the background, theories, and methodologies used by other researchers

CHAPTER 3: System Design describes the design of the project. Explains the architecture, components, algorithms, and any other technical details.

CHAPTER 4: Implementation provides details about how the project was implemented. Discusses the tools, technologies, programming languages, and frameworks used.

CHAPTER 5: Result and Analysis presents the results of the project. Analyzes the outcomes, compare them with expectations, and discuss any challenges faced during implementation.

CHAPTER 6: Conclusion and Future Work summarizes the findings and draws conclusions. Discusses the significance of your work and its implications

CHAPTER 2

LITERATURE SURVEY

This chapter deals with the existing work carried out in the field of Machine Learning and Deep Learning for Autism Spectrum Disorder. It gives an overview about the challenges in developing the models in the following manner.

2.1 RESEARCH PUBLICATIONS

Autism Spectrum Disorder (ASD) detection has garnered substantial attention in recent years, with multiple studies employing machine learning and deep learning techniques to improve diagnosis accuracy and enhance the understanding of autism's complexities. Study [1] surveyed the rising prevalence of ASD, diagnosing challenges, and EEG-based methods, achieving up to 98.46% accuracy in distinguishing ASD from typically developing children. This reflects a promising application of non-invasive technologies, though the integration of multimodal approaches to create a comprehensive diagnostic framework remains a challenge. Study [2] investigated functional connectivity-based predictions of autism using the ABIDE dataset, applying ComBat harmonization to improve fMRI data accuracy, achieving 71.35% accuracy with neural networks. Despite the improvement, enhancing the accuracy further remains an ongoing challenge, as existing harmonization techniques may still underperform in clinical scenarios. Study [3] focused on gaze patterns in children with ASD compared to typically developing peers, using advanced techniques like LSTM to analyze their gaze in response to emotional faces. The study achieved notable classification results but emphasized the need to improve machine learning models to enhance accuracy, particularly for gaze pattern analysis in emotional face recognition. Study

[4] delved into early ASD detection using video data, such as eye-tracking, facial recognition, and speech analysis. By analyzing small video datasets, this study underscored the potential for earlier diagnosis of ASD in infants, offering a non-invasive alternative to traditional assessments. However, extracting meaningful features from subtle behaviors, especially in infants, posed a significant challenge that could impact the overall efficacy of video-based detection systems.

In study [5], the focus shifted towards joint attention cycles in children with ASD, a critical factor in social recognition, using techniques like gesture recognition to track cycles. The method demonstrated potential for practical applications, such as joint attention intervention robots, yet the sample size issue posed a significant barrier to improving accuracy and robustness. Study [6] applied a multimodal approach that combined EEG and eye-tracking data, achieving a 10% improvement in classification accuracy for identifying ASD in children. While this demonstrated the potential of integrating multiple data modalities, the real-world applicability of this approach was questioned due to the challenges of robustness across diverse populations. In study [7], researchers explored transfer learning and hybrid deep CNN models for ASD classification using EEG signals, achieving an impressive 96.44% accuracy. The combination of transfer learning with deep CNN significantly enhanced diagnostic capabilities, although there remains room for improvement in feature extraction techniques to maximize classification performance further.

Study [8] explored the feasibility of high-risk ASD identification using video and audio data within the Still-Face Paradigm, a unique approach that achieved 96.39% accuracy using vocal and visual features from infant-caregiver interactions. However, the study highlighted the need for incorporating convolutional neural networks (CNN) and attention networks to improve feature extraction and representation learning from such multimodal

data. Another approach was discussed in study [9], where pre-trained CNN EfficientNet models were employed for facial recognition-based ASD identification in children, demonstrating its applicability in integrating these models into functional websites. This study pointed to the potential of blending facial recognition technology with practical applications, although optimizing model accuracy and key point detection presented ongoing challenges for reliable ASD prediction. Study [10] took a different approach, focusing on hybrid models by combining ResNet-50 and Xception modules for ASD classification in children, leveraging transfer learning to boost accuracy significantly. Although the study demonstrated higher accuracy compared to traditional methods, its generalization limitation was evident, particularly in terms of data variability, suggesting the need for federated learning to improve the model's robustness.

In study [11], a deep convolutional neural network-based detection system was introduced for detecting ASD using facial images, offering a non-invasive screening tool to help parents decide whether further testing was necessary. While this approach showed great promise, real-time data collection and integration remained crucial challenges in improving the system's ability to detect various stages of ASD and enhance overall classification performance. Study [12] highlighted the growing use of augmented reality (AR) and virtual reality (VR) in education, particularly in enhancing the learning experiences of children with ASD. This study demonstrated how immersive technology can positively impact learning outcomes, although language integration and user accessibility remain hurdles that need to be addressed for wider adoption. Finally, study [13] introduced LEARNAUT, an upgraded learning environment and web application for autism management using AR and VR technologies. The study underscored the advantages of making such platforms accessible from any device, offering significant potential for providing personalized therapy for children with ASD. However, therapy integration and the tracking of individual

progress were noted as areas that require further development to provide comprehensive support systems for children and their caregivers.

2.2 CONCLUSION FROM LITERATURE SURVEY

The literature reveals a broad spectrum of methodologies in the detection and diagnosis of autism spectrum disorder, with advancements in EEG, fMRI, video data, eye-tracking, and facial recognition approaches. While several studies report high accuracy, such as EEG-based techniques with 98.46% accuracy [1] and transfer learning with hybrid CNN models achieving 96.44% [7], the challenge of feature extraction and model robustness across diverse populations persists. Techniques like multimodal data integration have shown improvements in classification performance, yet the need for better generalization and real-world applicability remains. Augmented and virtual reality applications also highlight the potential for educational and therapeutic tools for children with ASD, although further work is required to enhance accessibility and language integration.

CHAPTER 3

SYSTEM DESIGN

This system is designed to predict autism by processing multiple types of input data—specifically image, EEG, AQ10 behavioral questionnaire, and eye-tracking data. Each type of input provides unique insights into the characteristics and behaviors associated with autism, offering a comprehensive view of the individual's condition. The architecture is structured to ensure that each data type is handled appropriately, leveraging tailored preprocessing steps in the backend to optimize data quality and readiness before feeding it into machine learning models.

3.1 FRONT-END

The front-end, built using **ReactJS**, provides an intuitive interface that allows users to submit various types of data. Key functions include:

3.1.1 Data Input Form:

- Users can upload **images** for autism prediction through visual analysis.
- **EEG data** can be uploaded as CSV or other formats.
- The **AQ10 questionnaire** is presented as a form with a set of behavioral questions, where users manually enter responses.
- **Eye-tracking data** can be uploaded, typically as a CSV file containing gaze and eye movement information.

3.1.2 Interaction and Selection:

- Users select the type of data they wish to input using radio buttons.
- Progress is displayed, indicating which data modalities have been submitted.
- The system provides easy navigation, allowing users to submit one or multiple types of data.

3.1.3 Results Visualization:

- Once predictions are complete, results for each data type are displayed on a results page.
- Visual feedback includes likelihood scores and classification outcomes for each input modality.

3.2 BACK-END

The back-end is powered by **Flask**, which handles the server-side logic, including routing, data preprocessing, and model integration. The back-end takes the user inputs, preprocesses them, and routes them to the appropriate models for prediction.

- **Routing:** When a user submits data from the front-end, Flask routes the request to the appropriate preprocessing pipeline depending on the type of data submitted.

- **API Integration:** Flask communicates with the models and returns results to the front-end. This communication ensures that once data is processed and predictions are made, results are sent back in real-time.

3.3 DATA PREPROCESSING IN THE BACKEND

Data preprocessing is a critical step in any machine learning or deep learning pipeline, especially in a multi-modal system like autism prediction, which handles diverse data types such as images, EEG signals, behavioral questionnaire responses (AQ10), and eye-tracking data. The goal of preprocessing is to ensure that the raw input data is transformed into a format that is clean, structured, and enriched with relevant features that can maximize the performance and accuracy of the predictive models.

This step is essential because raw data often contains noise, inconsistencies, missing values, and varying formats, all of which can lead to suboptimal model performance if not addressed. The preprocessing stage helps standardize and normalize the data, remove irrelevant or redundant information, extract meaningful features, and ensure that the inputs are in a compatible format for the machine learning (ML) and deep learning (DL) models. These models are highly sensitive to the quality of input data, making preprocessing vital for producing reliable predictions.

For each type of data in autism prediction system, preprocessing is tailored to the specific characteristics of that data, ensuring that the unique challenges posed by each modality are addressed.

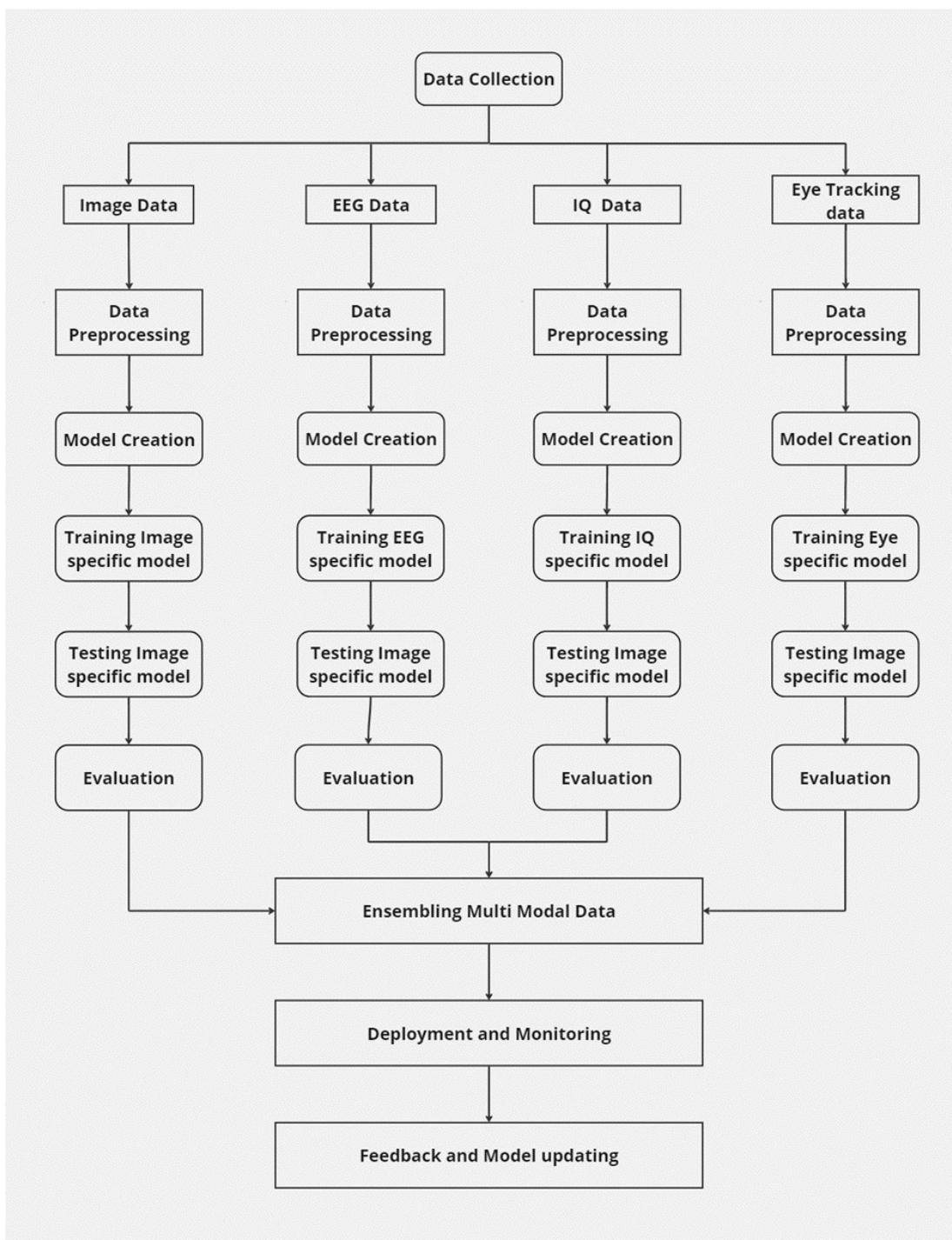


Figure 3.1: System Architecture

CHAPTER 4

IMPLEMENTATION

In this chapter, we will discuss the implementation details of Autism Spectrum Disorder.

4.1 IMAGE BASED PREDICTION

4.1.1 Data Description

Autism image dataset consists of 2,950 images that are divided into two categories 1,470 images of autistic individuals (ASD images) and 1,480 images of typically developing individuals (non-ASD images)

This dataset is used to train various deep learning models to predict autism based on image data, with each image labeled as either autistic or non-autistic.

4.1.2 Data Preprocessing

Preprocessing the image data is a critical step to ensure that the input is ready for the deep learning models. The following preprocessing steps are applied:

- a. **Resizing :** Each image is resized to a fixed dimension (e.g., 224x224 pixels) to ensure a uniform input size across all models. Different

models may have different input size requirements, but resizing ensures that all images conform to the necessary input shape.

b. Normalization : Image pixel values, which originally range from 0 to 255, are normalized to a range between 0 and 1 (or -1 to 1) depending on the model requirements. Normalization helps to stabilize and speed up the training process by ensuring that input features are on a consistent scale. This is especially important when using pre-trained models that expect normalized input data.

c. Significance : Normalization ensures that deep learning models can process the images efficiently without running into issues like vanishing gradients. It also helps models interpret the images correctly since pre-trained models (such as those used for transfer learning) are often trained with normalized inputs.

d. Augmentation : Image augmentation techniques, such as random cropping, flipping, and rotation, may be applied to artificially expand the dataset and introduce variety. This helps prevent overfitting and ensures that the model generalizes well to new, unseen data.

e. Conversion to Tensors After resizing and normalization, the images are converted into tensors, which are multi-dimensional arrays that deep learning frameworks (like TensorFlow or PyTorch) can process during model training and inference.

4.1.3 Models Used for Classification

The following models are used to classify images into autistic or non-autistic categories:

1. ResNet (Residual Networks) : ResNet is a deep convolutional neural network that introduced residual connections to tackle the vanishing gradient problem, which occurs in very deep networks. These residual connections allow the model to skip certain layers and "shortcut" the flow of gradients, ensuring effective training even with very deep networks.

Strengths: ResNet is well-suited for feature extraction and classification tasks, as it can capture intricate patterns in images while maintaining computational efficiency.

Variants: Common variants include ResNet-50, ResNet-101, and ResNet-152, with the number indicating the depth of the network.

2. MobileNet : MobileNet is a lightweight convolutional neural network optimized for mobile and embedded applications. It uses depthwise separable convolutions to reduce the number of parameters and computational cost, making it fast and efficient while maintaining high accuracy.

Strengths: MobileNet is ideal for situations where computational resources are limited, such as mobile devices or edge computing, while still achieving good performance.

Variants: MobileNetV1, V2, and V3 are commonly used variants.

3. EfficientNet : EfficientNet is a family of convolutional neural networks that uses a compound scaling method to scale up models in a more efficient way, balancing depth, width, and resolution. It achieves high accuracy with fewer parameters and less computation compared to other architectures.

Strengths: EfficientNet is known for achieving state-of-the-art

accuracy on image classification tasks with significantly fewer resources compared to traditional CNNs.

Variants: EfficientNet comes in multiple sizes, ranging from EfficientNet-B0 (smallest) to EfficientNet-B7 (largest), depending on the computational resources and accuracy requirements.

4. VGG19 : VGG19 is a deep convolutional network with 19 layers. It is known for its simplicity and uniform architecture, consisting of multiple convolutional layers followed by max-pooling layers. VGG networks, despite their depth, use smaller filter sizes (3x3) but have many more layers compared to earlier architectures.

Strengths: VGG19 is effective for image classification tasks and is widely used due to its simplicity. However, it has a large number of parameters, making it computationally expensive.

5. NASNet (Neural Architecture Search Network) : NASNet is a type of convolutional network designed using automated architecture search techniques. Neural architecture search automates the design of the network, optimizing it for both accuracy and efficiency.

Strengths: NASNet is capable of discovering highly optimized architectures that achieve competitive performance on image classification tasks. It can outperform manually designed architectures in some cases.

6. Vision Transformer (ViT) : Vision Transformer (ViT) is a novel approach to image classification that replaces traditional convolutions with transformer-based architectures. Instead of processing the entire image using convolutional layers, ViT divides the image into smaller patches and applies a

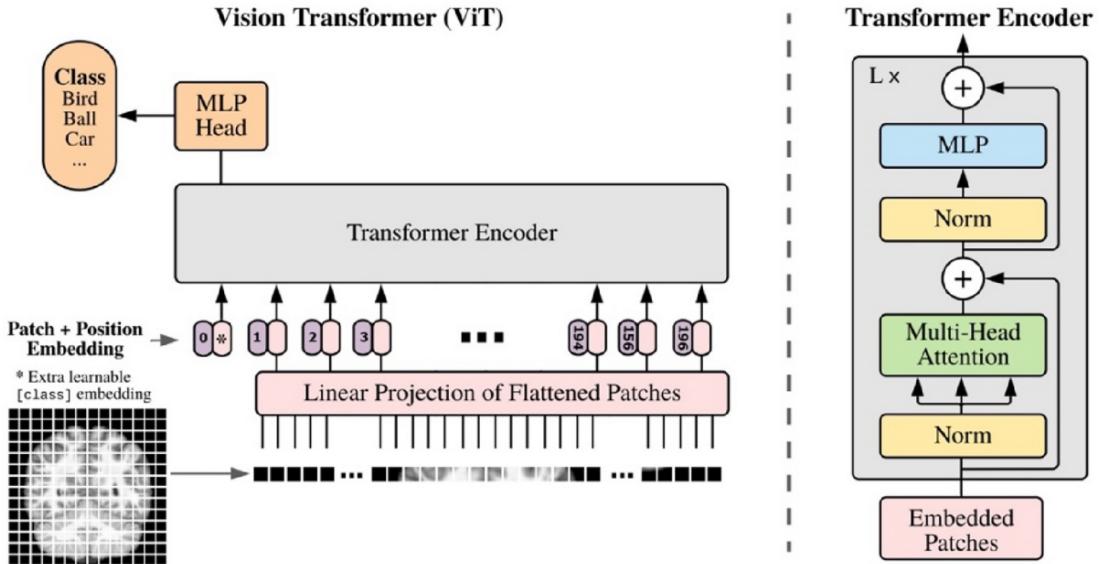


Figure 4.1: ViT Architecture

transformer to model the relationships between these patches.

Strengths: ViT excels at capturing long-range dependencies and patterns in the image, unlike convolutional networks that rely on local feature extraction. ViT has achieved competitive accuracy on image classification tasks, especially when trained with large amounts of data.

7. DeiT (Data-efficient Image Transformer) : DeiT (Data-efficient Image Transformer) is a variant of the Vision Transformer (ViT) that is specifically designed to work efficiently with less training data. While ViT models typically require large datasets to perform well, DeiT introduces techniques such as distillation to train the transformer with fewer data. **Architecture:** DeiT, like ViT, divides the input image into patches, processes each patch using a transformer encoder, and then aggregates the information from all patches to make a classification decision. DeiT leverages a teacher-student training paradigm where a convolutional neural network (CNN) acts as a teacher to guide the transformer, improving its performance on smaller datasets.

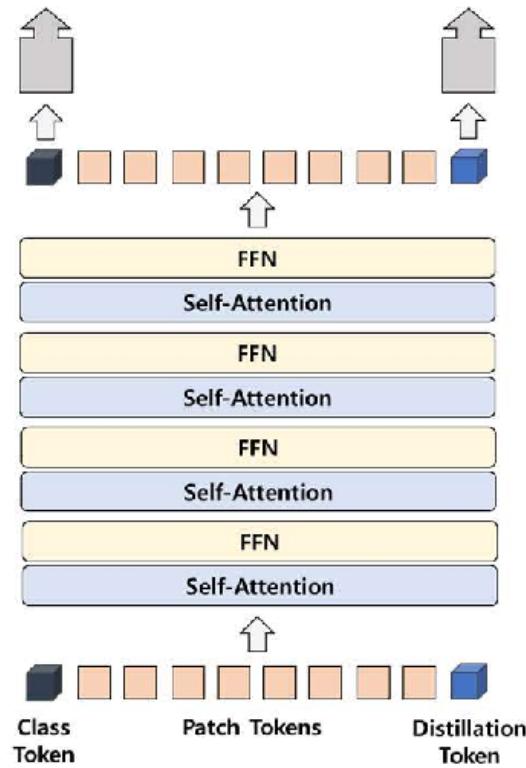


Figure 4.2: DeiT Architecture

Strengths: DeiT is ideal for cases where you do not have a massive dataset but still want to benefit from the power of transformers in image classification. It can match or exceed the performance of traditional CNNs with fewer training examples.

4.2 EEG-Based Prediction

4.2.1 Data Description

The EEG dataset consists of 2,132 samples, each with 2,548 features representing various brain signal measurements. This dataset includes a range of signals such as alpha, beta, theta, and delta waves, recorded during different tasks or conditions related to autism detection.

This EEG data was processed using standard scaling techniques and used to train several machine learning and deep learning models for predicting autism based on the signal data.

4.2.2 Data Preprocessing

EEG data is preprocessed to ensure consistency and proper scaling before model training. The following preprocessing steps are applied:

a. Standard Scaling: The EEG signals are scaled using standard scaling (mean = 0, standard deviation = 1) to ensure the features have a consistent range. This is essential for models like SVM, which are sensitive to the scale of the input data.

b. Handling Missing Data: If there are missing values in the dataset, imputation techniques such as mean imputation or k-nearest neighbor (KNN) imputation are applied to ensure there are no gaps in the data during training.

4.2.3 Models Used for Classification

The following models are employed to classify EEG data into autistic or non-autistic categories:

1. Support Vector Machine (SVM): SVM is a powerful classifier that works by finding the hyperplane that best separates the data into two classes. SVM has been shown to perform well on EEG data due to its ability to handle high-dimensional feature spaces.

2. Decision Tree: Decision Tree is a simple yet effective model that splits the data into branches based on feature values. It is interpretable and fast

but may overfit on complex datasets.

3. Random Forest: Random Forest is an ensemble of decision trees that improves generalization by averaging the predictions of multiple trees. It has shown strong performance on EEG datasets.

4. Convolutional Neural Networks (CNN): CNNs, while traditionally used for image data, can also be adapted for EEG signals by treating the signal as a 2D grid. CNNs are effective at capturing spatial patterns in the data.

5. Long Short-Term Memory (LSTM): LSTM is a type of recurrent neural network (RNN) that is particularly suited for time-series data, making it ideal for sequential EEG data. However, initial tests showed lower accuracy compared to Random Forest.

6. Bidirectional LSTM (Bi-LSTM): Bi-LSTM processes the data in both forward and backward directions, improving the model's ability to capture temporal dependencies. Fine-tuning the Bi-LSTM model yielded significant improvements in accuracy.

7. Denoising Autoencoder: A denoising autoencoder (DAE) is a specialized neural network architecture designed to handle noisy data by learning robust feature representations. Unlike standard autoencoders, a DAE takes corrupted input data, adds noise (such as Gaussian noise), and learns to reconstruct the original, clean data. This ability to handle noisy inputs makes DAEs particularly valuable in tasks like EEG signal processing, where raw data is often contaminated by noise from various sources, including muscle movements, electrical interference, or faulty sensor placements.

In EEG analysis, DAEs help with both feature extraction and anomaly detection by compressing high-dimensional signals into a more compact, denoised representation. The encoder portion of the DAE compresses the input into a lower-dimensional latent space, while the decoder reconstructs the clean signal from this compressed representation. This process allows the network to learn the most important features of the EEG data while discarding irrelevant noise.

The use of early stopping during training ensures that the model doesn't overfit to the noise or irrelevant patterns in the data. This technique halts the training process when the validation performance stops improving, ensuring the model remains generalizable to new, unseen EEG signals. As a result, DAEs are highly effective in improving EEG-based machine learning models.

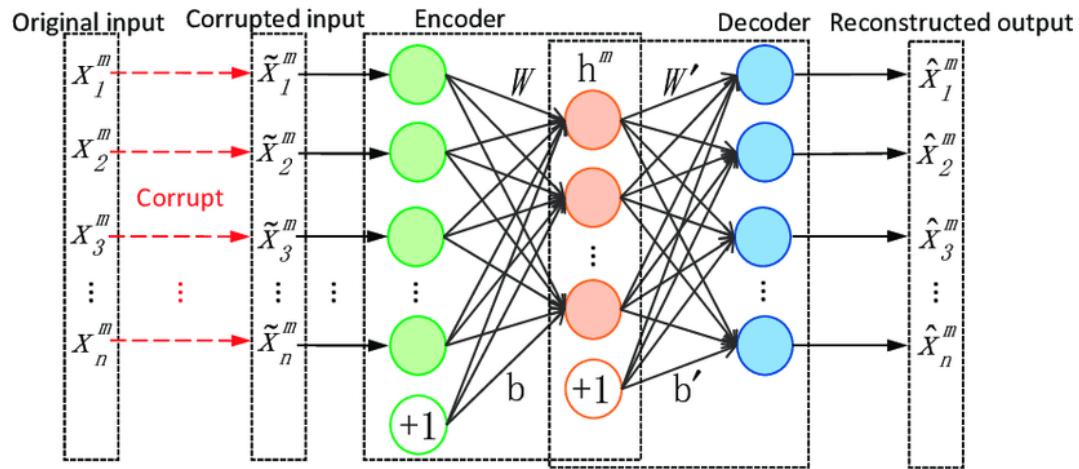


Figure 4.3: Denoising Auto Encoder

8. Complex Neural Network Classifier with Early Stopping: A deeper and more complex neural network architecture was used with early stopping to prevent overfitting. Early stopping halts the training process when the model's performance on the validation set stops improving.

4.3 IQ-Based Prediction

4.3.1 Data Description

The IQ-based dataset consists of 704 samples, each containing responses to 10 questions designed to assess cognitive abilities. The responses are structured to capture various dimensions of intelligence, including reasoning, problem-solving, and verbal comprehension. Each question is formatted to provide clear insights into the respondent's cognitive capabilities, allowing for effective classification of individuals based on their IQ levels.

4.3.2 Data Preprocessing

Preprocessing the IQ dataset is crucial to ensure data integrity and enhance model performance. The following steps were undertaken:

a. Replace Strings with Integers: Categorical responses such as 'YES' and 'NO' were converted into binary integers, where 'YES' corresponds to 1 and 'NO' to 0. Uncertain responses, represented by '?', were standardized to 'Others' to maintain consistency.

b. Correlation Matrix and Feature Selection: A correlation matrix was generated to assess the relationship between each feature and the target variable. Features exhibiting high multicollinearity were identified and reduced to enhance model performance and interpretability.

c. One-Hot Encoding: For categorical features with more than two categories, one-hot encoding was applied. This method converts categorical variables into binary columns, allowing the model to better process non-numeric data.

AQ-10 (Adolescent Version)

Autism Spectrum Quotient (AQ)

A quick referral guide for parents to complete about a teenager aged 12-15 years old with suspected autism who does not have a learning disability.

<i>Please tick one option per question only:</i>		Definitely Agree	Slightly Agree	Slightly Disagree	Definitely Disagree
1	S/he notices patterns in things all the time				
2	S/he usually concentrates more on the whole picture, rather than the small details				
3	In a social group, s/he can easily keep track of several different people's conversations				
4	If there is an interruption, s/he can switch back to what s/he was doing very quickly				
5	S/he frequently finds that s/he doesn't know how to keep a conversation going				
6	S/he is good at social chit-chat				
7	When s/he was younger, s/he used to enjoy playing games involving pretending with other children				
8	S/he finds it difficult to imagine what it would be like to be someone else				
9	S/he finds social situations easy				
10	S/he finds it hard to make new friends				

SCORING: Only 1 point can be scored for each question. Score 1 point for Definitely or Slightly Agree on each items 1, 5, 8 and 10. Score 1 point for Definitely or Slightly Disagree on each of items 2, 3, 4, 6, 7 and 9. If the individual scores **more than 6 out of 10**, consider referring them for a specialist diagnostic assessment.

Figure 4.4: AQ-10 Questions

d. Remove Outliers in Age Using IQR: Outliers in the age column were identified and removed using the Interquartile Range (IQR) method. Values falling outside the range

$$[Q_1 - 1.5 \times \text{IQR}, Q_3 + 1.5 \times \text{IQR}]$$

were considered outliers.

e. Replace NaN Values: Missing values in the age column were filled with 0, indicating unknown or missing ages. This step ensures that the dataset remains complete for analysis.

f. Drop Unwanted Columns: Columns not essential for model training, such as country_of_res, used_app_before, and result, were removed to streamline the dataset.

g. Train-Test Split: Finally, the preprocessed data was split into training and testing sets using a train-test split method, ensuring the models could be effectively evaluated on unseen data.

4.3.3 Models Used for Classification

The following models were trained on the preprocessed IQ dataset:

1. Logistic Regression: Logistic Regression is a fundamental classification algorithm that models the relationship between the binary outcome and one or more predictor variables using a logistic function. It is widely used due to its interpretability and efficiency in binary classification tasks.

2. Random Forest: Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions. It is robust against overfitting and excels in handling high-dimensional data, making it suitable for this dataset.

3. Support Vector Machine (SVM): SVM is a powerful classifier that identifies the optimal hyperplane that separates data into different classes. It works well in high-dimensional spaces and is effective in cases where the number of dimensions exceeds the number of samples.

4. K-Nearest Neighbors (KNN): KNN is a non-parametric classification algorithm that assigns a class based on the majority class of its nearest neighbors. It is simple and intuitive but can be computationally intensive as the dataset grows.

5. Artificial Neural Network (ANN): ANNs are computational models inspired by the human brain's structure. They consist of interconnected nodes (neurons) organized in layers, allowing them to learn complex relationships in the data.

6. Decision Tree (DT): Decision Trees classify data by creating a model that predicts the value of a target variable based on several input features. The model splits the data into branches based on feature values, making it interpretable and easy to visualize.

7. Extra Trees Classifier: Extra Trees, or Extremely Randomized Trees, is similar to Random Forest but differs in how it builds its trees. It selects a random subset of features at each split and uses random thresholds, leading to increased randomness and often better generalization.

4.4 Eye Tracking Based Prediction

4.4.1 Data Description

The dataset consists of 999,786 rows and 18 columns, including prominent features such as Trial, Stimulus, Export Start Trial Time [ms], Export End Trial Time [ms], Color, Category Group, Gender, Age, and Class.

4.4.2 Data Preprocessing

Preprocessing the ET dataset is crucial to ensure data integrity and enhance model performance. The following steps were undertaken:

- a. Removed Duplicates:** Ensured dataset uniqueness to maintain analysis integrity and avoid skewed results.
- b. Handled Null Values:** Addressed missing values through imputation or removal to improve model quality.
- c. Categorized Features:** Differentiated between discrete, categorical, and continuous variables for tailored analysis and visualization.
- d. Analyzed and Visualized Distributions:** Used visualization techniques to understand variable distributions, identify patterns, and detect anomalies
- e. Label Encoding:** Converted categorical values into numerical format for compatibility with machine learning algorithms.
- f. Removed Outliers:** Identified and handled outliers to enhance

model accuracy and robustness.

g.Box Plot to Check Outliers: Utilized box plots to visualize data spread and detect outliers.

g.Correlation Matrix: Analyzed relationships between continuous variables to inform feature selection and engineering.

4.4.3 Models Used for Classification

The following models were trained on the preprocessed ET dataset:

1. Decision Tree (DT): Decision Trees classify data by splitting it into subsets based on the most significant feature at each node. The tree structure allows for easy interpretation, making it useful for understanding how decisions are made based on feature values.

2. k-Nearest Neighbors (KNN): KNN is a non-parametric, instance-based learning algorithm that classifies data points based on the majority class of their k-nearest neighbors in the feature space. It is simple to implement but computationally expensive for large datasets.

3. Random Forest (RF): Random Forest is an ensemble technique that constructs multiple decision trees and aggregates their predictions. By introducing randomness in both feature selection and bootstrapping, it reduces overfitting and improves model accuracy and robustness.

4. ResNet: ResNet (Residual Networks) is a deep learning model that introduces skip connections (residuals) between layers to address the vanishing gradient problem in very deep networks. This architecture allows

the training of extremely deep models while maintaining high performance in image classification tasks.

5. Long Short-Term Memory (LSTM): LSTMs are a type of recurrent neural network (RNN) capable of learning long-term dependencies in sequential data. Their unique gating mechanism allows them to store and selectively forget information, making them effective for tasks such as time series forecasting and natural language processing.

6. Graph Convolutional Network (GCN): GCNs are neural networks that operate directly on graph-structured data. They perform convolution by aggregating feature information from neighboring nodes in a graph, which allows them to capture both node attributes and the relationships between nodes. This makes GCNs highly effective for tasks like node classification, link prediction, and social network analysis, where data naturally forms a graph structure.

4.5 Optimizers Used for Optimization

The following optimization algorithms were applied to optimize the model Hyper-parameters on the dataset:

1. Particle Swarm Optimization (PSO): Particle Swarm Optimization is an iterative optimization technique inspired by the social behavior of bird flocking. It initializes a group of particles in the search space, which then adjust their positions based on their own experience and that of neighboring particles to find the optimal solution.

2. Genetic Algorithm (GA): The Genetic Algorithm is an evolutionary optimization approach that mimics natural selection. It uses

genetic operations such as selection, crossover, and mutation to evolve a population of candidate solutions over multiple generations, ultimately converging toward an optimal or near-optimal solution.

3. Cuckoo Search (CS): Cuckoo Search is a metaheuristic optimization algorithm inspired by the brood parasitism of certain cuckoo species. The algorithm employs Lévy flights to update candidate solutions, allowing for exploration and exploitation of the search space to find optimal solutions effectively.

4. Differential Evolution (DE): Differential Evolution is a population-based optimization algorithm. It optimizes problems by combining mutation, crossover, and selection operations. The algorithm efficiently explores the search space by mutating candidate solutions based on differences between randomly selected individuals in the population.

5. Ant Colony Optimization (ACO): Ant Colony Optimization is inspired by the foraging behavior of ants. It uses a colony of artificial ants to explore the solution space, where each ant deposits pheromones on paths it travels. Over time, paths with stronger pheromone trails attract more ants, leading to the identification of optimal paths through a process of positive reinforcement.

6. Lion Optimization Algorithm (LOA): Lion Optimization Algorithm is inspired by the social structure and hunting strategies of lions. It simulates lion pride dynamics such as territorial defense, mating, and hunting to find the optimal solution. The algorithm divides the population into prides and nomadic lions, with unique strategies to explore and exploit the search space effectively.

CHAPTER 5

RESULTS AND ANALYSIS

The performance achieved for each modalities are mentioned below

5.1 IMAGE DATA PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score
EfficientNetB4	81%	82.5%	82%	82%
VGG19	82%	79.33%	78%	84.21%
NasNetMobile	69%	71.2%	71.23%	69%
Xception	79.3%	79.01%	80.33%	78.19%
CNN	78.1%	78.3%	79.1%	77.2%
ResNet50	80.4%	80.1%	79.5%	80.3%
MobileNet	78.09%	79.1%	79.1%	76.5%
EfficientNet	83.2%	84.1%	82.3%	80.8%
DeiT Model	84.69%	77.71%	92.42%	84.43%
ViT	71.4%	70.9%	76.5%	71.3%

Table 5.1: Performance Metrics for Different Image Classification Models

5.2 EEG DATA PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score
SVM	97.658%	97.8%	98.3%	98.0%
Decision Tree	94.847%	95.6%	95.6%	95.6%
Random Forest	98.829%	98.8%	98.8%	98.8%
CNN	97.423%	97.5%	99.5%	98.5%
LSTM	98.594%	98.5%	98.8%	98.65%
Autoencoder	92.8%	93.0%	94.2%	93.6%
Complex Neural Network	95.6%	95.6%	96.8%	96.2%
Bi-LSTM (Fine-Tuned)	98.36%	98.36%	98.32%	98.33%
LSTM (PSO optimized)	97.4%	97.7%	94.1%	95.9%
ANN (PSO optimized)	99.1%	99.3%	97.8%	98.5%
LSTM (ACO optimized)	99.3%	99.3%	98.5%	98.9%

Table 5.2: Performance Metrics for Different Models Trained on EEG Data

5.3 AQ10 DATA PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	100%	100%	100%	100%
Random Forest	92.22%	100%	71.05%	83.01%
Support Vector Machine (SVM)	100%	100%	100%	100%
K-Nearest Neighbors (KNN)	91.2%	83.87%	83.87%	83.87%
Artificial Neural Network (ANN)	95.3%	83.33%	96.77%	89.66%
Decision Tree (DT)	91.9%	86.21%	80.65%	83.33%
Extra Trees Classifier	92.9%	100%	74.19%	85.19%
Ann (PSO optimized)	94.69%	95.12%	97.50%	96.30%
Ann (GA optimized)	84.07%	100%	82.00%	90.11%
Ann (CS optimized)	93.81%	100%	92.13%	95.91%

Table 5.3: Performance Metrics for Different Models Trained on IQ Data

5.4 EYE TRACKING DATA PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	98.0%	97.8%	97.8%	97.8%
K-Nearest Neighbors (KNN)	99.725%	99.2%	98.8%	99.0%
Random Forest	99.998%	99.999%	99.999%	99.995%
Long Short-Term Memory (LSTM)	99.962%	99.5%	99.6%	99.65%
ResNet	85.044%	84.0%	85.02%	85.0%
RNN (GA optimized)	99.97%	98.0%	99.02%	97.0%
LSTM (GA optimized)	99.97%	99.2%	98.32%	98.0%

Table 5.4: Performance Metrics for Different Models Trained on ET Data

5.5 VISUAL GUIDE TO WEBSITE FEATURES

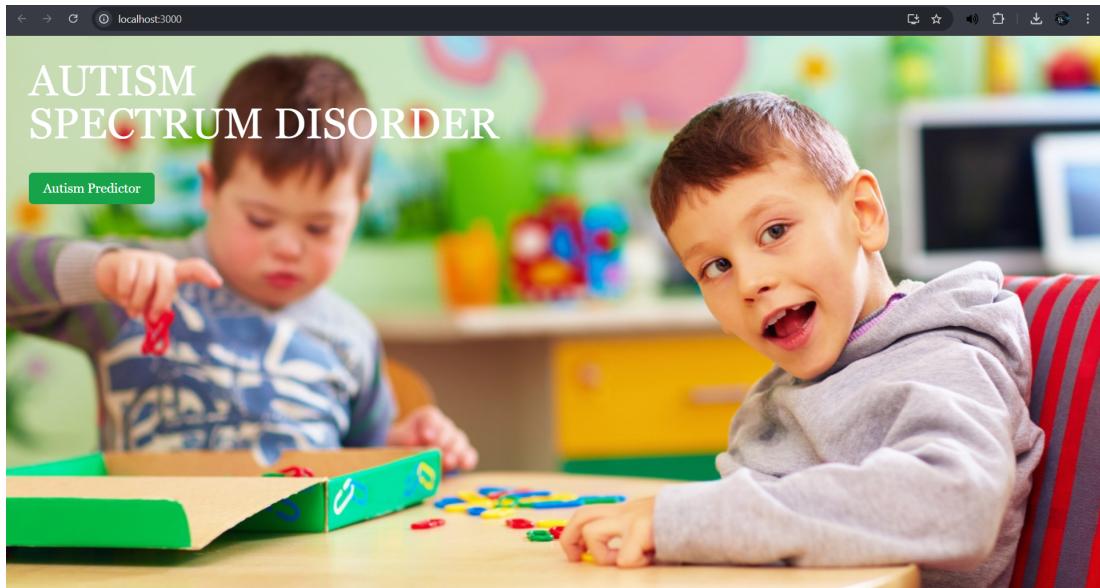


Figure 5.1: Landing Page

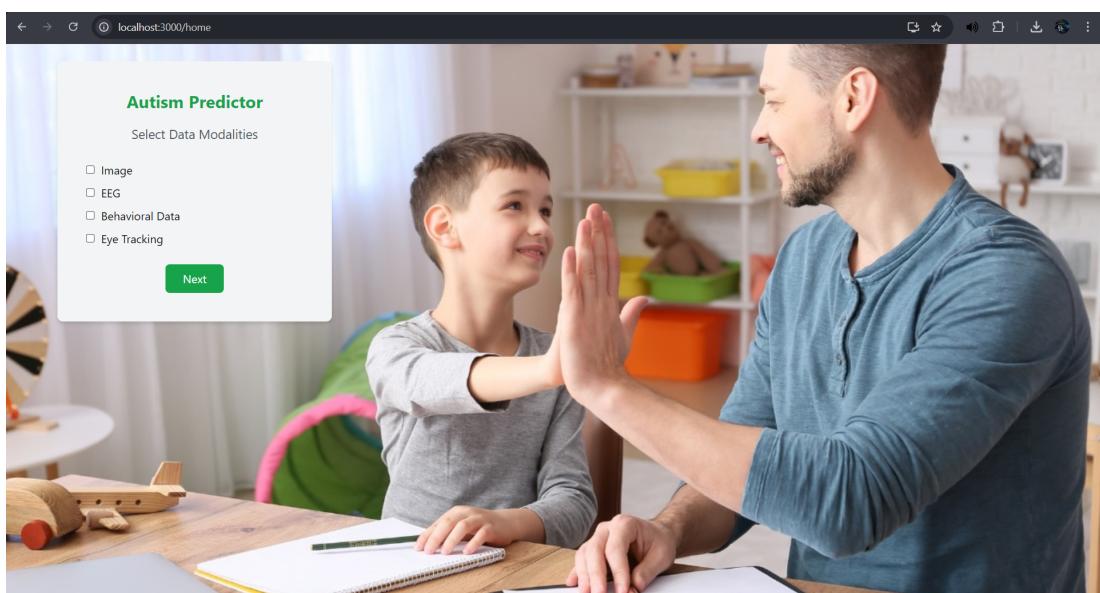


Figure 5.2: Menu Page



Figure 5.3: Image Data Menu selection Interface

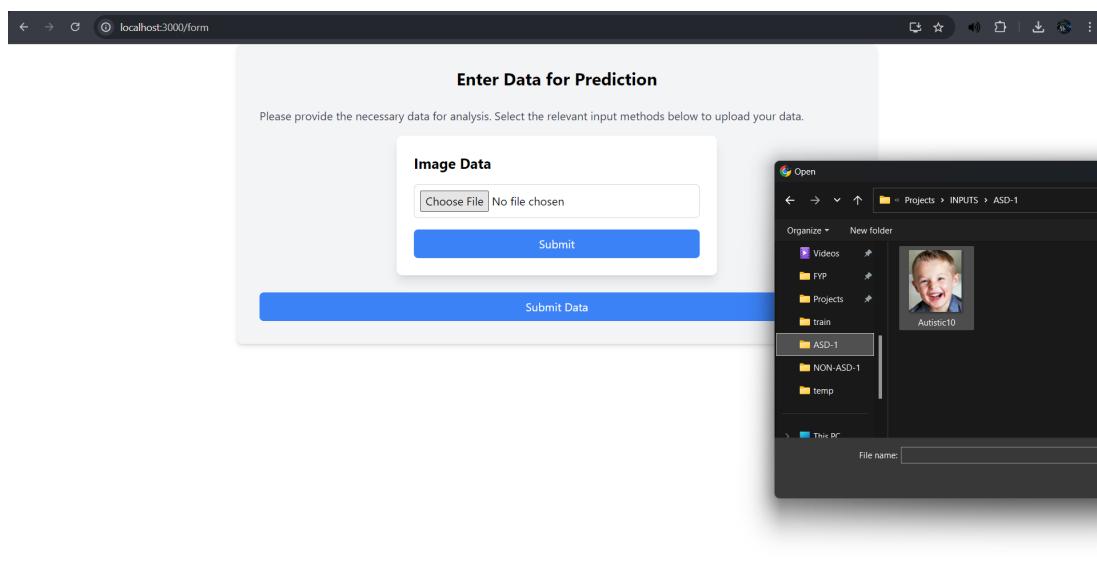


Figure 5.4: Interface for Uploading Eye Tracking Data with Autism Image data

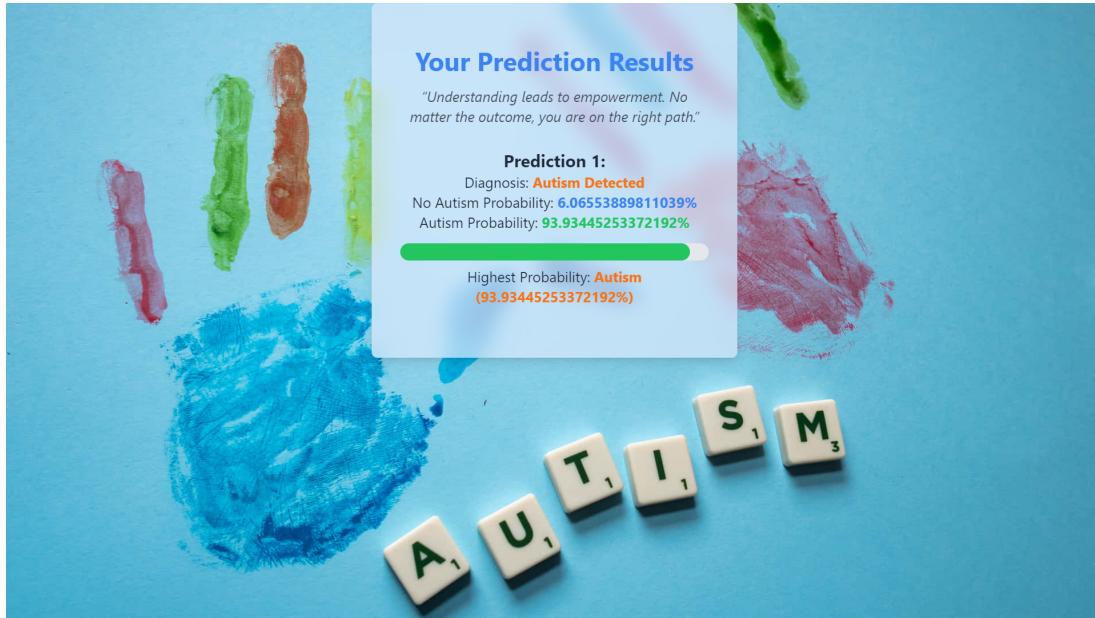


Figure 5.5: Results of Image Data Analysis diagnosing Autism

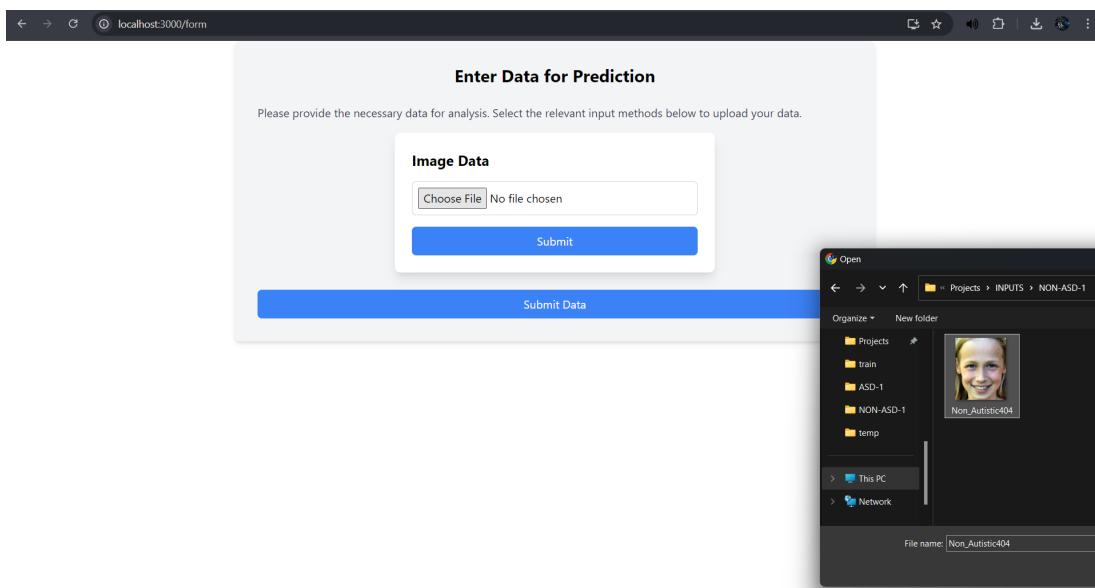


Figure 5.6: Interface for Uploading Eye Tracking Data with Non Autism Image data

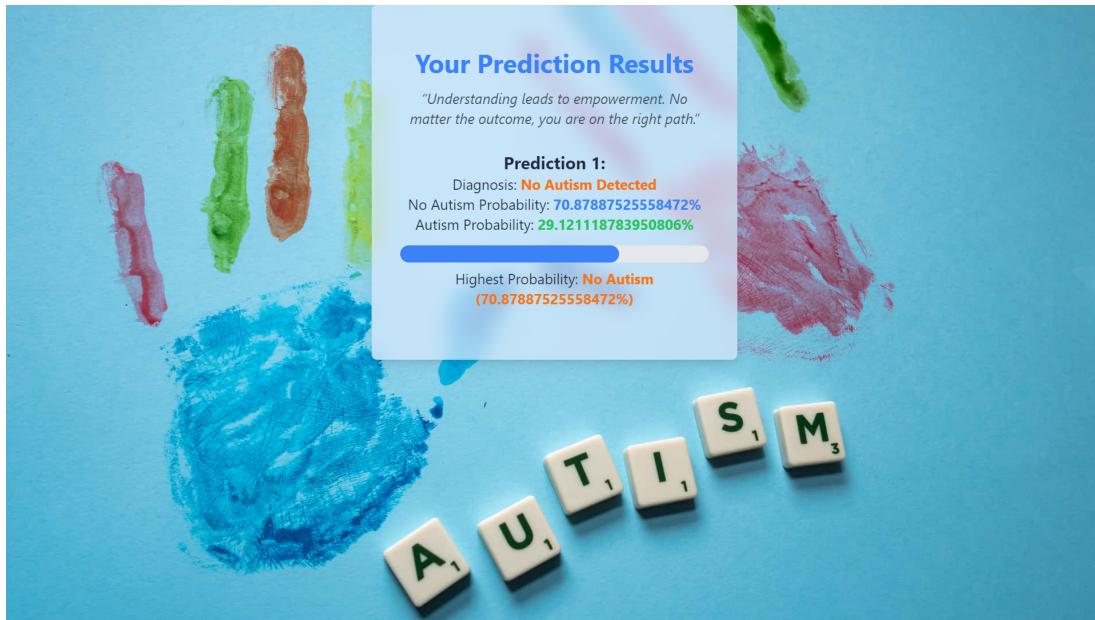


Figure 5.7: Results of Image Data Analysis diagnosing No Autism

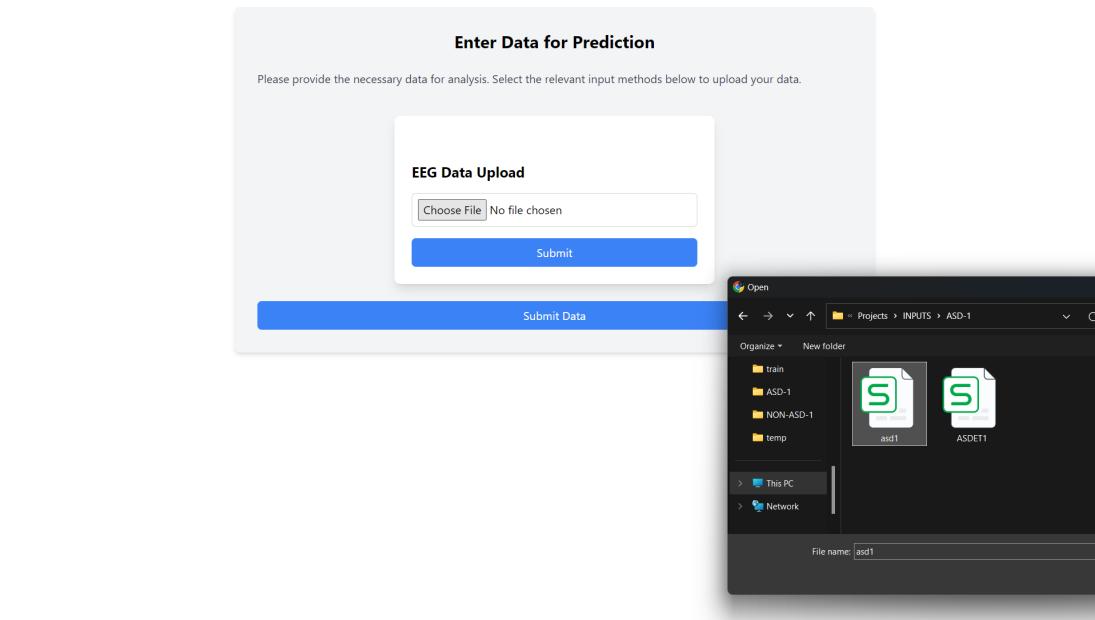


Figure 5.8: EEG file Submission Interface with Autism data

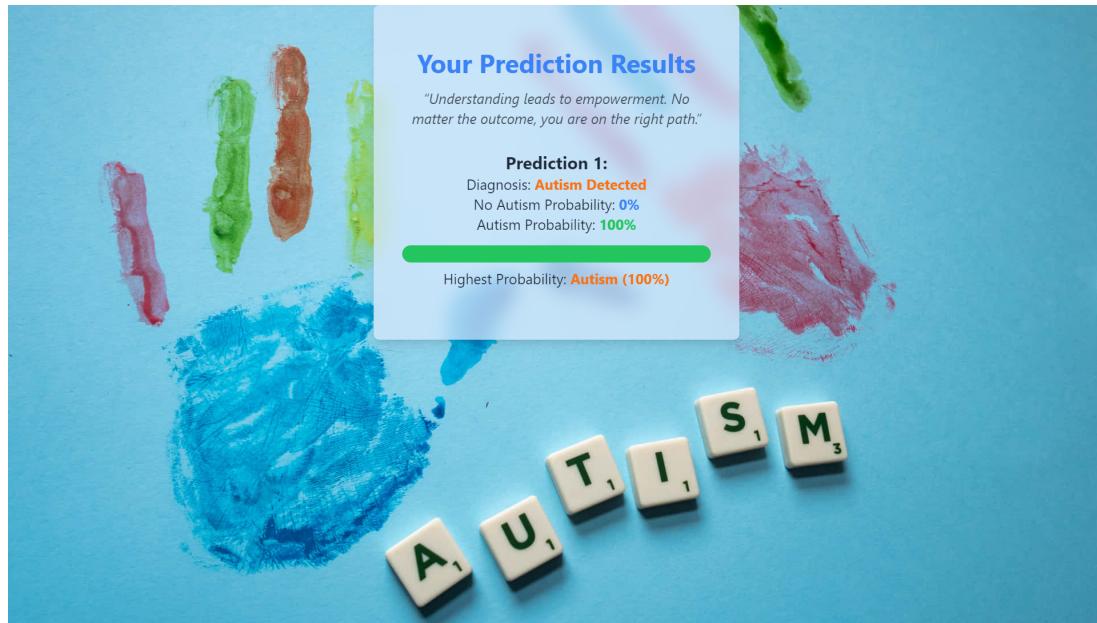


Figure 5.9: Results of EEG Data Analysis diagnosing Autism

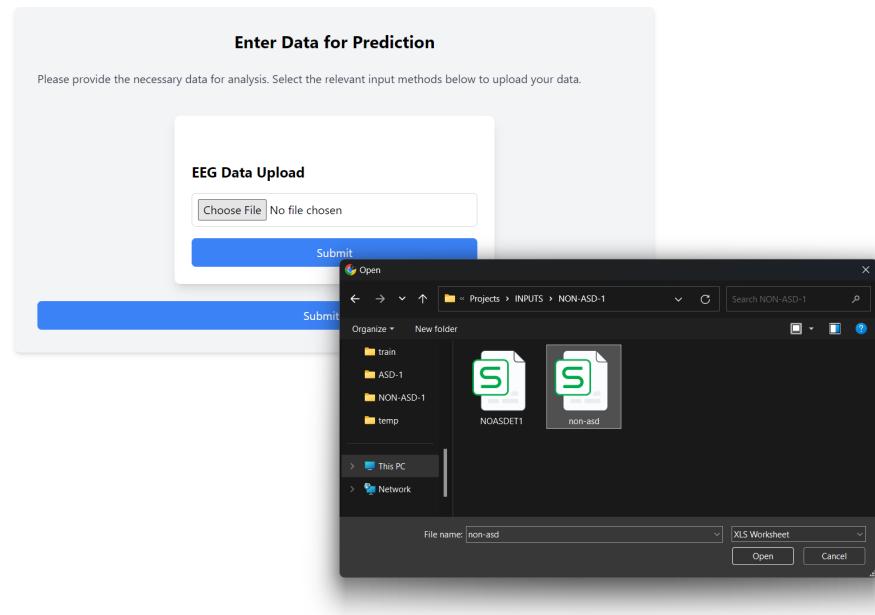


Figure 5.10: EEG file Submission Interface with Non Autism data

Enter Data for Prediction

Please provide the necessary data for analysis. Select the relevant input methods below to upload your data.

Autism Spectrum Quotient (AQ-10) Questions

1. He/She notices patterns in things all the time
 - Definitely Agree
 - Slightly Agree
 - Slightly Disagree
 - Definitely Disagree
2. He/She usually concentrates more on the whole picture, rather than the small details
 - Definitely Agree
 - Slightly Agree
 - Slightly Disagree
 - Definitely Disagree
3. In a social group, He/She can easily keep track of several different people's conversations
 - Definitely Agree
 - Slightly Agree
 - Slightly Disagree
 - Definitely Disagree
4. If there is an interruption, He/She can switch back to what He/She was doing very quickly
 - Definitely Agree
 - Slightly Agree
 - Slightly Disagree
 - Definitely Disagree
5. He/She frequently finds that He/She doesn't know how to keep a conversation going
 - Definitely Agree
 - Slightly Agree
 - Slightly Disagree
 - Definitely Disagree

Figure 5.11: AQ10 Questions Submission Interface - i

9. He/She finds it hard to make new friends

- Definitely Agree
- Slightly Agree
- Slightly Disagree
- Definitely Disagree

10. He/She is a good diplomat

- Definitely Agree
- Slightly Agree
- Slightly Disagree
- Definitely Disagree

Age:

Gender:

Did you have jaundice at birth?

Ethnicity:

Relation to the child:

Submit

Figure 5.12: AQ10 Questions Submission Interface - ii

Enter Data for Prediction

Please provide the necessary data for analysis. Select the relevant input methods

Enter the Eye Tracking data

Choose File No file chosen

Start Time [ms]: 0 End Time [ms]: 0

Select Color: --Select Color-- Select Category Group:

Select Category Left: --Select Category Left-- Select Category Right:

Select Gender: --Select Gender-- Age (Years): 0

Age (Months): 0 Pupil Diameter Right [mm]: 0

Pupil Diameter Left [mm]: 0 Point of Regard Right X [px]: 0

Figure 5.13: Eye Tracking Data Submission Interface for Autism Prediction

Enter Data for Prediction

Please provide the necessary data for analysis. Select the relevant input methods below to upload your data.

Image Data

Choose File No file chosen

EEG Data Upload

Choose File No file chosen

Submit Data

Figure 5.14: Interface for Uploading EEG and Image data for Autism Prediction

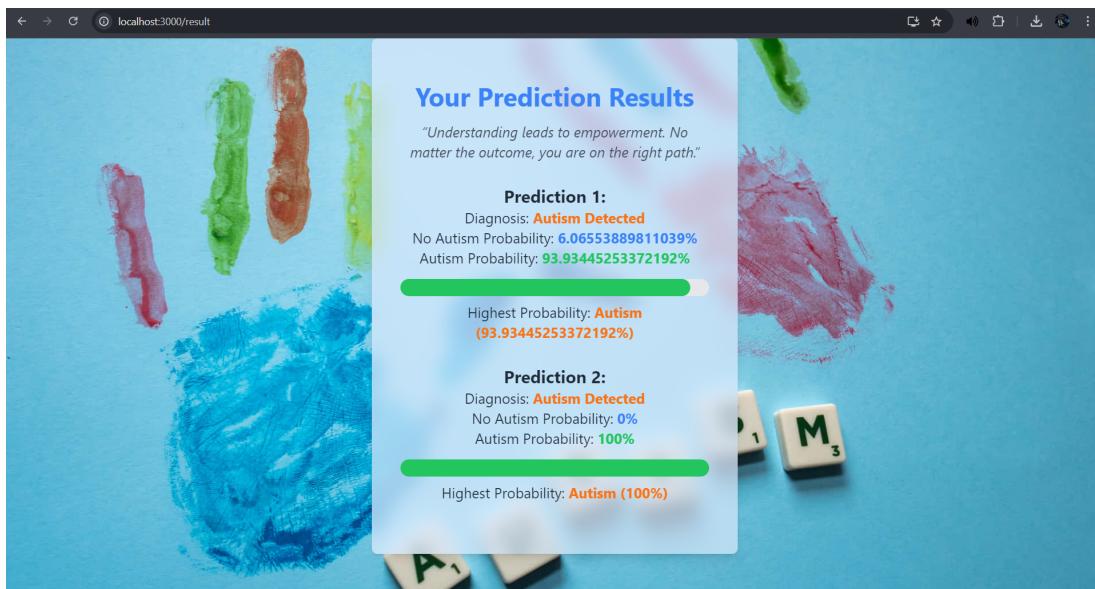


Figure 5.15: Results of EEG and Image Data Analysis diagnosing Autism

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The project focused on autism prediction using multimodal data has made significant strides in addressing one of the most pressing challenges in developmental health—early and accurate diagnosis of Autism Spectrum Disorder (ASD). By combining various data types, such as behavioral, EEG, eye-tracking, and image data, the approach leverages the strengths of multiple sources of information to provide a more comprehensive understanding of autism. This multimodal strategy not only enhances diagnostic accuracy but also reflects the complex, multifaceted nature of ASD, capturing both neurological and behavioral patterns that may be missed when relying on a single data type. The project demonstrates that integrating diverse datasets can lead to a more holistic assessment, improving the likelihood of early intervention and more personalized treatment plans.

Moreover, the inclusion of data augmentation and advanced feature extraction techniques has contributed to the robustness of the system, ensuring that it performs well even with limited or imbalanced datasets. Addressing the issue of class imbalance through methods like data balancing and augmentation helped to create a system that is more reliable across different population groups. These improvements make the system applicable to real-world scenarios, where data is often incomplete, noisy, or unbalanced. Additionally, by focusing on explainable predictions, the project addresses the critical need for transparency in healthcare applications, allowing professionals to trust and validate the results, which is essential when dealing with sensitive conditions like ASD.

The project also delves into the potential therapeutic applications of advanced technologies such as augmented and virtual reality. These technologies have been shown to offer engaging, interactive environments that can be customized for the specific needs of children with autism, aiding in both diagnosis and treatment. The inclusion of such elements makes the system not only diagnostic but also potentially therapeutic, providing a well-rounded approach to managing autism. The emphasis on creating a user-friendly interface further supports this by making the system accessible to both clinicians and caregivers, thus bridging the gap between technology and practical, day-to-day use in managing ASD.

In conclusion, this project represents a significant advancement in the use of technology for autism prediction and management. It highlights the potential of multimodal data integration to create a more accurate, comprehensive, and user-friendly system that can be deployed in real-world settings. By providing earlier and more reliable diagnoses, the project can lead to improved outcomes for children with autism, offering them the opportunity for timely interventions that are critical in shaping their development. The holistic approach to data fusion, combined with a focus on explainability and practical usability, positions this project as a valuable tool for both diagnosis and ongoing care of individuals with ASD, pushing the boundaries of how technology can be utilized in developmental health diagnostics.

6.2 FUTURE WORK

While the current project has achieved significant milestones in autism prediction, there is ample scope for future improvements. One of the major areas for future work is the implementation of **federated learning**. By allowing data to be collected and processed at local devices rather than centralized servers, federated learning can preserve patient privacy and ensure a

more diverse range of data is used to train the models. This approach will help in overcoming the limitations posed by privacy concerns and the unavailability of large, diverse datasets in clinical settings. Models can be trained on distributed data sources from various healthcare centers, improving generalization and robustness across different populations.

Another key area for future work is **real-time data collection and model training**. Currently, the system relies on pre-collected datasets, but to make it more practical for real-world deployment, the integration of real-time data collection from wearable devices, EEG headsets, or eye-tracking systems can be explored. This would allow continuous monitoring of children and provide timely predictions based on live data, which can aid in early detection of behavioral changes and other symptoms associated with ASD. Implementing a real-time feedback loop with continuous learning capabilities would enable the model to adapt and improve as more data becomes available.

Finally, improving the model's interpretability and transparency, particularly for healthcare professionals and caregivers, will be crucial. Incorporating more advanced techniques for explainability, such as SHAP or LIME, alongside real-time predictions, will help make the system more reliable and trustworthy in a clinical setting. This combination of federated learning, real-time data collection, and model interpretability will help advance autism diagnosis and therapy, moving closer to creating a system that can be widely used in real-world applications.

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