AUTISM SPECTRUM DISORDER DETECTION USING MULTIMODAL DATA

A PROJECT REPORT

Submitted by

Kabileshwaran SD - 2021115046

Praveen V - 2021115076

Sumathi K - 2021115112

Harish M - 2021115326

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COLLEGE OF ENGINEERING GUINDY

ANNA UNIVERSITY

CHENNAI 600 025

DEC 2024

ANNA UNIVERSITY

CHENNAI - 600 025

BONAFIDE CERTIFICATE

Certified that this project report titled **"AUTISM SPECTRUM DISORDER DETECTION USING MULTIMODAL DATA"** is the bonafide work of **Kabileshwaran SD (2021115046)** ,**Praveen V (2021115076)**,**Sumathi K (2021115112)**,**Harish M (2021115326)** who carried out project work under my supervision. Certified further that to the best of my knowledge and belief, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on this or any other candidate.

PLACE:CHENNAI
DATE:

Dr. P. VARALAKSHMI
PROFESSOR
PROJECT GUIDE
DEPARTMENT OF IST, CEG
ANNA UNIVERSITY
CHENNAI 600025

COUNTERSIGNED

Dr. S. SWAMYNATHAN
HEAD OF THE DEPARTMENT
DEPARTMENT OF INFORMATION SCIENCE AND TECHNOLOGY
COLLEGE OF ENGINEERING GUINDY
ANNA UNIVERSITY
CHENNAI 600025

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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Kabileshwaran SD - 2021115046
Praveen V - 2021115076
Sumathi K - 2021115112
Harish M - 2021115326

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LIST OF ABBREVIATIONS

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

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 MOTIVATION FOR THE PROJECT

- **Improved Early Detection**: Early detection of Autism Spectrum Disorder (ASD) allows for timely interventions that significantly improve the quality of life for affected individuals. AI models utilizing multimodal data can help reduce diagnostic delays, offering more accurate and faster diagnoses compared to traditional methods.

- **Addressing Diagnostic Limitations**: Traditional diagnostic approaches are subjective and require skilled professionals, which can lead to delays and inconsistencies. Automated tools that integrate multimodal data—such as images, EEG signals, and behavioral assessments—can provide a consistent, objective, and efficient diagnostic solution, especially in underserved areas.

- **Multimodal Insights**: Autism presents in various forms across individuals, making a single data type insufficient for accurate diagnosis. By combining multiple data sources (images, EEG, behavior, and eye-tracking), AI models can generate a more comprehensive and robust prediction of ASD, enhancing diagnostic accuracy.

- **Advancing Research**: AI models offer the potential to advance autism research by identifying new patterns and insights from multimodal data. This can help in understanding the neurological and behavioral aspects of autism, contributing to more effective treatments and therapies.

- **Scalable Solutions**: AI-based tools can be deployed on mobile and web platforms, making autism diagnosis more accessible, especially in low-resource settings. These tools can be used by caregivers and teachers to identify autism early, even in remote areas with limited access to specialists.

- **Personalized Interventions**: Accurate early detection through multimodal analysis can guide personalized interventions. AI-driven tools can help tailor treatments based on individual traits and needs, improving the overall effectiveness of therapies for people with autism.

1.3 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.

1.4 PROBLEM STATEMENT

Despite advancements in research, there is currently no application or tool that effectively integrates multimodal data (such as image data, EEG signals, behavioral assessments like AQ10, and eye-tracking data) to predict ASD in individuals. Existing diagnostic methods primarily rely on isolated data types, and the use of multiple sources of data to improve prediction accuracy remains under-explored.

The lack of a comprehensive tool that combines these diverse data sources prevents a more accurate, holistic, and early diagnosis of autism, which could significantly enhance the effectiveness of intervention strategies. Additionally, existing methods fail to address the complexity and heterogeneity of autism, making it difficult to create a model that works universally across all individuals with ASD.

1.5 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.

1.6 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.

3.2.1 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. The raw data is subjected to various preprocessing steps to make it suitable for feeding it into ML and DL models, improving model efficiency and prediction quality.

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 and improving overall system robustness, generalization, and accuracy.

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.

3.3 TOOLS AND TECHNOLOGIES

1.React.js: A JavaScript library for building user interfaces. React.js is used to develop dynamic and interactive single-page applications (SPA). Its component-based architecture enables the reusability of code, which helps in the efficient rendering of UI components. React's Virtual DOM ensures high performance by minimizing direct manipulation of the real DOM. In this project, React.js is used to create the front end of the autism prediction application, enabling a smooth, user-friendly interface with real-time updates.

2.Tailwind CSS: Tailwind CSS is a utility-first CSS framework that allows for a rapid and flexible approach to styling web applications. It provides a collection of pre-defined classes to control layout, spacing, typography, colors, and other UI elements. Tailwind's approach to styling reduces the need for writing custom CSS, resulting in cleaner code and faster development cycles. It is used in the project to create a responsive and visually appealing frontend that adapts seamlessly across different devices and screen sizes.

3.Node.js: Node.js is a JavaScript runtime built on Chrome's V8 engine that allows developers to run JavaScript on the server side. It is non-blocking and event-driven, making it an excellent choice for building scalable and high-performance backend applications. In this project, Node.js is used to handle client requests and interact with the database efficiently. Its asynchronous nature allows for handling multiple connections simultaneously, ensuring high throughput and low latency in the application.

4.Express.js: Express.js is a minimal and flexible web application framework for Node.js that simplifies the development of server-side applications. It provides robust features for routing, handling HTTP requests, and middleware, allowing developers to build RESTful APIs quickly and effectively. Express is used in this project to implement the backend API that facilitates communication between the frontend and the machine learning models served via Flask. Its modular structure supports the development of scalable and maintainable applications.

5.REST API: Representational State Transfer (REST) is an architectural style for designing networked applications. RESTful APIs use standard HTTP methods (GET, POST, PUT, DELETE) to perform operations on resources. In this project, REST APIs are used to enable communication between the frontend and the backend. The APIs facilitate data exchange and ensure that the machine learning model predictions can be accessed from the frontend application in real-time.

6.Python: Python is the primary language used for implementing machine learning models, data preprocessing, and analysis. It has a rich ecosystem of libraries such as scikit-learn, TensorFlow, Keras, and Pandas, which makes it ideal for building and training machine learning models. Python's versatility allows for rapid prototyping and experimentation, which is crucial for this project, where various machine learning models are trained to predict autism.

7.Flask: Flask is a lightweight Python web framework used to serve machine learning models as APIs. Flask is preferred for its simplicity and flexibility, making it an ideal choice for projects that need to deploy machine learning models without requiring the complexity of a full-fledged web framework. In this project, Flask is used to expose the trained models as HTTP endpoints that the Node.js backend can call to obtain predictions from the machine learning models.

8.Git: Git is a distributed version control system that helps track changes in the source code, allowing multiple developers to collaborate efficiently. It enables branching and merging, which facilitates the development of features in isolation and integrates them seamlessly into the main codebase. Git is an essential tool in the development process of this project, enabling version management, collaboration, and rollback of changes if necessary.

9.GitHub: GitHub is an online platform for hosting Git repositories and collaborating on software development projects. It provides tools for version control, issue tracking, and code review. GitHub allows developers to manage code in a centralized repository, facilitating collaboration between team members.

10.TensorFlow/Keras: TensorFlow is an open-source machine learning framework developed by Google, and Keras is its high-level API for building and training neural networks. TensorFlow is used for training deep learning models such as CNNs for image-based predictions and fully connected networks for integrating multimodal data.

11.scikit-learn: scikit-learn is a machine learning library for Python that provides simple and efficient tools for data mining and data analysis. It includes implementations of various algorithms for classification, regression, clustering, and dimensionality reduction. In this project, scikit-learn is used for building and evaluating traditional machine learning models such as Random Forest, Support Vector Machines (SVM), and others.

12.OpenCV: OpenCV (Open Source Computer Vision Library) is an open-source computer vision and machine learning software library. It is used for real-time computer vision applications and has a wide range of tools for image processing. In this project, OpenCV is used for handling image-based data, including image preprocessing, augmentation, and feature extraction.

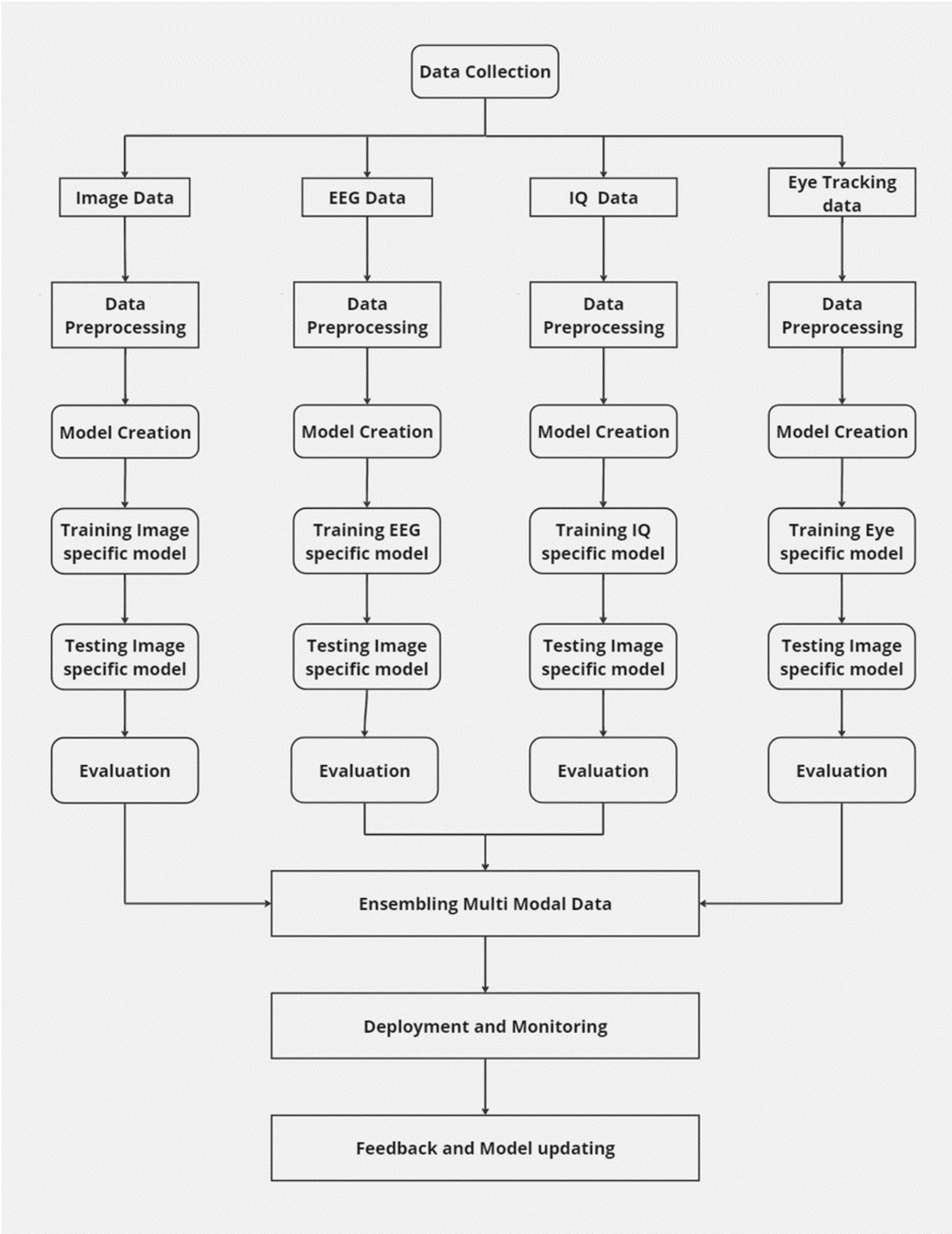

Figure 3.1: System Architecture

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

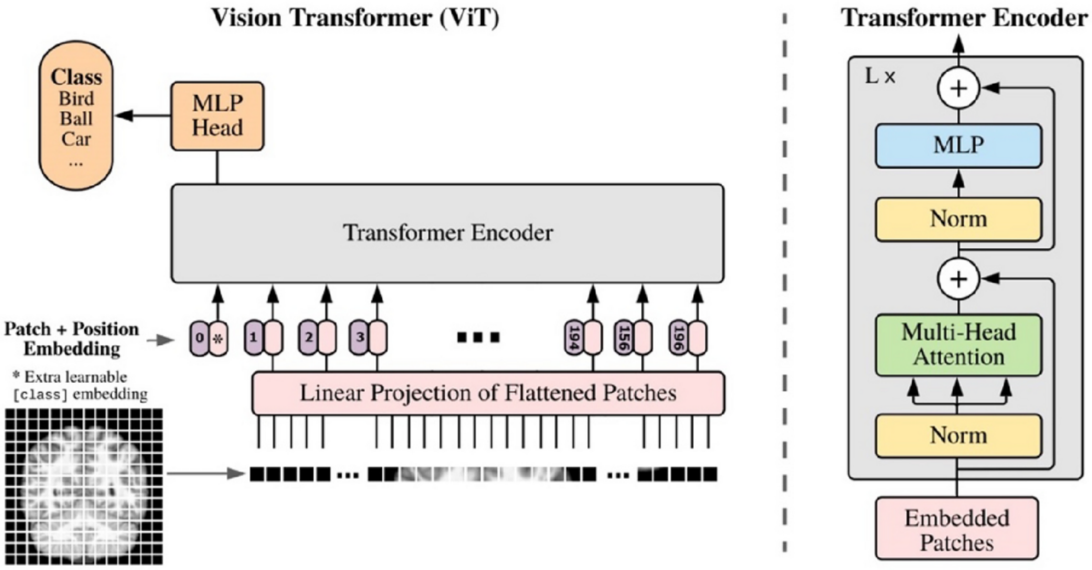

Figure 4.1: ViT Architecture

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.

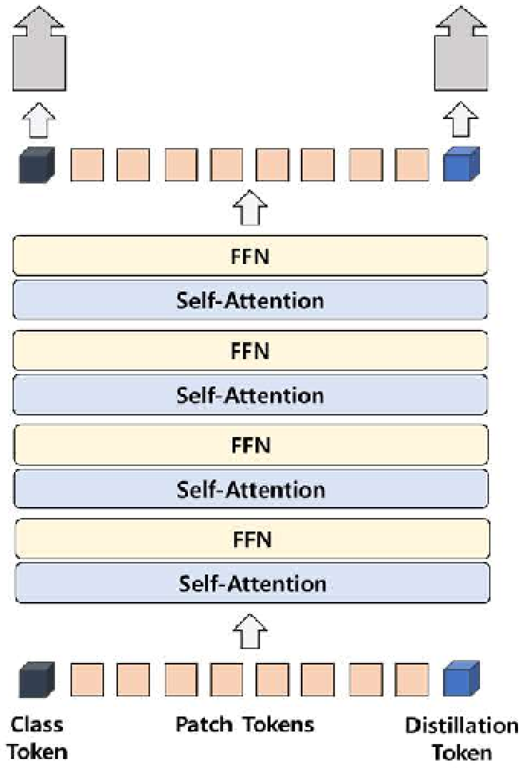

Figure 4.2: DeiT Architecture

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.

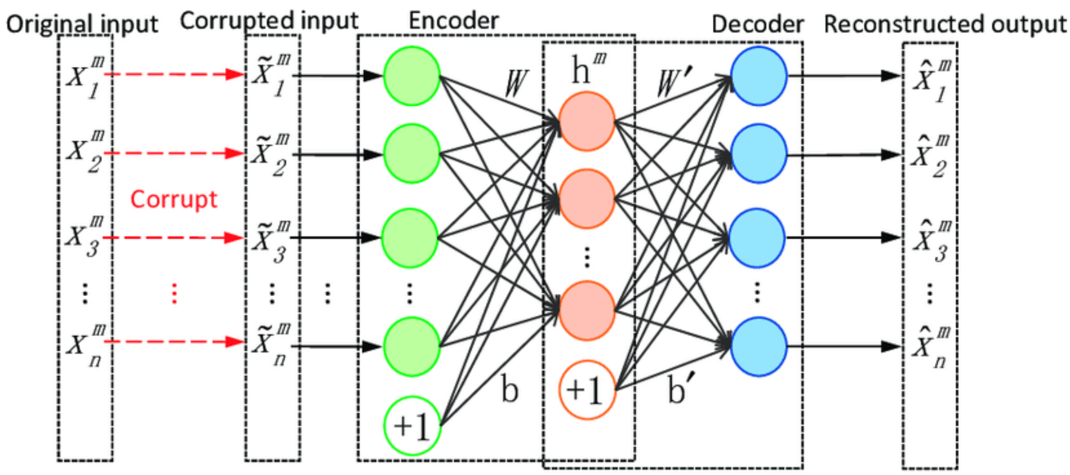

Figure 4.3: Denoising Auto Encoder

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.

NHS
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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.

	Please tick one option per question only:	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 samll details				
3	In a social group, s/he can easily keep track of several different peaople'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 does't know how to keep a conversatioin 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.

CHAPTER 5

RESULTS AND ANALYSIS

The performance achieved for each modalities using different models 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%
ViI	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%

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%

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%

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

5.5 VISUAL GUIDE TO WEBSITE FEATURES

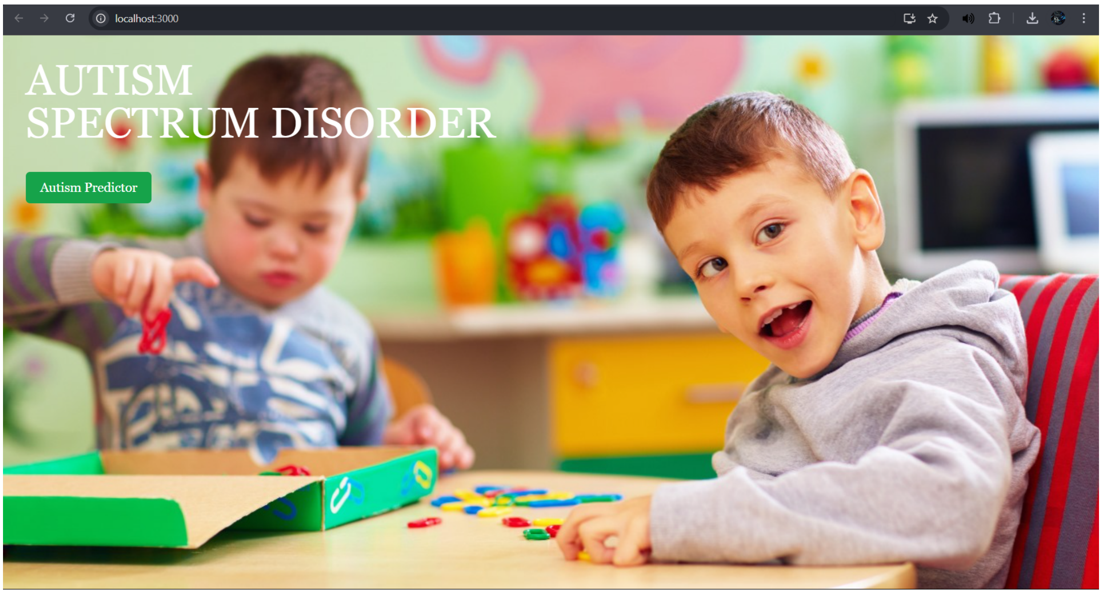

Figure 5.1: Landing Page

Figure 5.2: Menu Page

Figure 5.3: Image Data Menu selection Interface

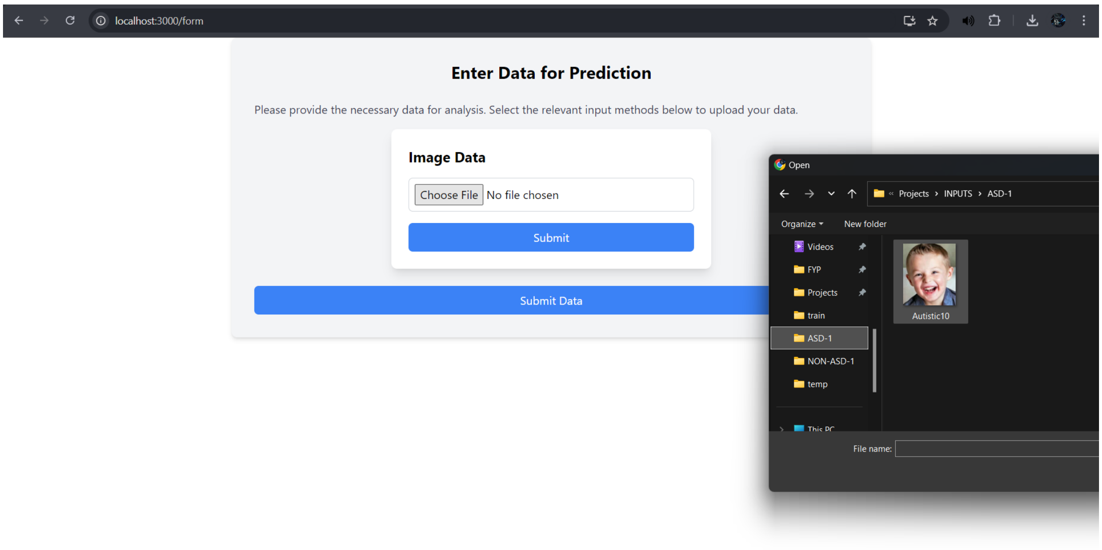

Figure 5.4: Interface for Uploading Eye Tracking Data with Autism Image data

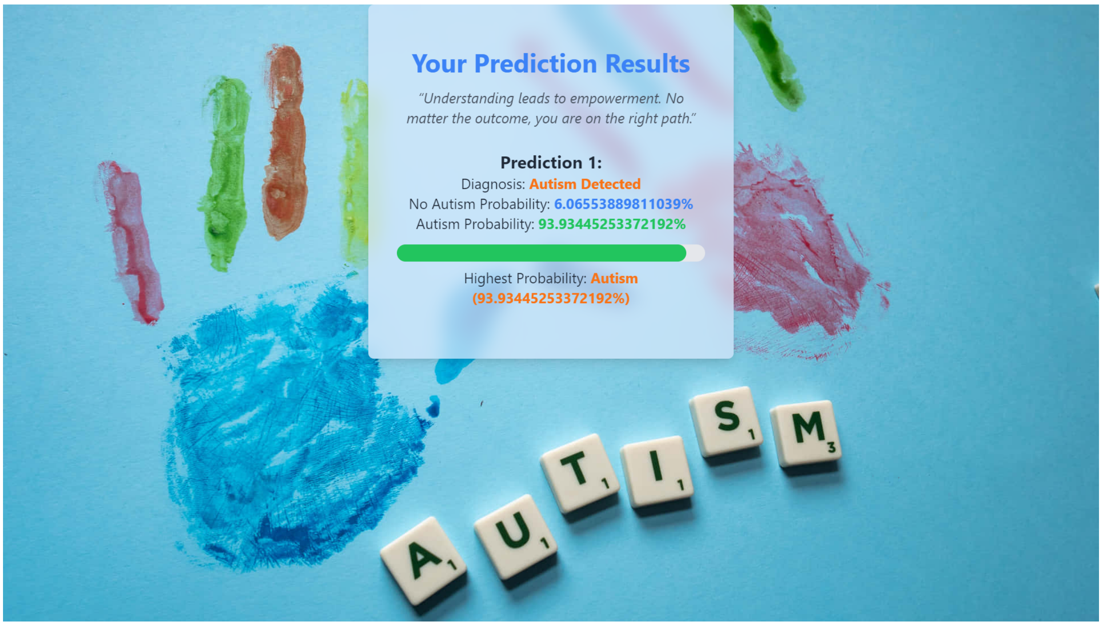

Figure 5.5: Results of Image Data Analysis diagnosing Autism

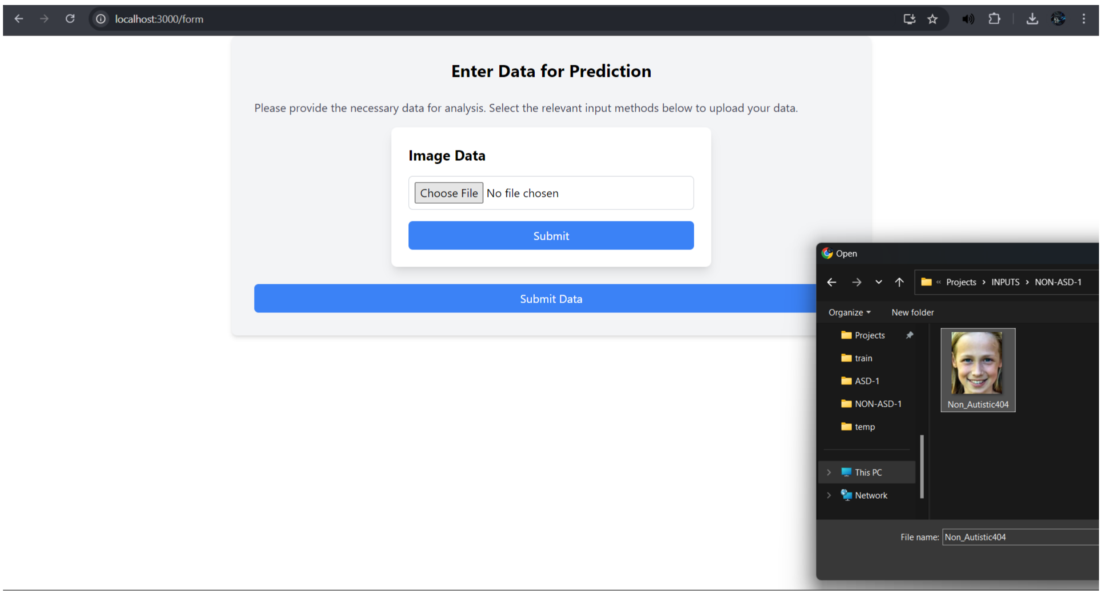

Figure 5.6: Interface for Uploading Eye Tracking Data with Non Autism Image data

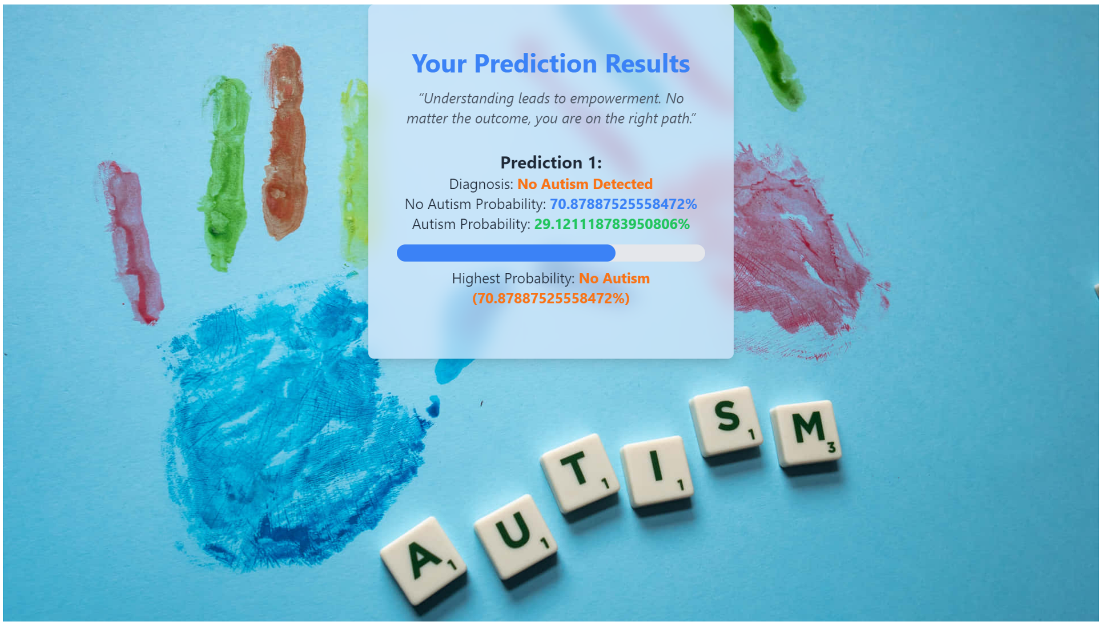

Figure 5.7: Results of Image Data Analysis diagnosing No Autism

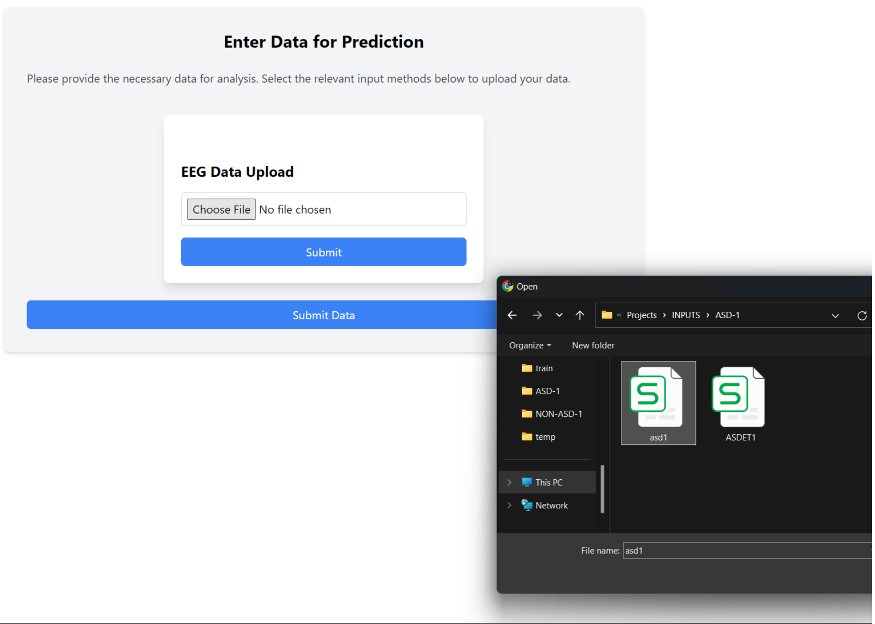

Figure 5.8: EEG file Submission Interface with Autism data

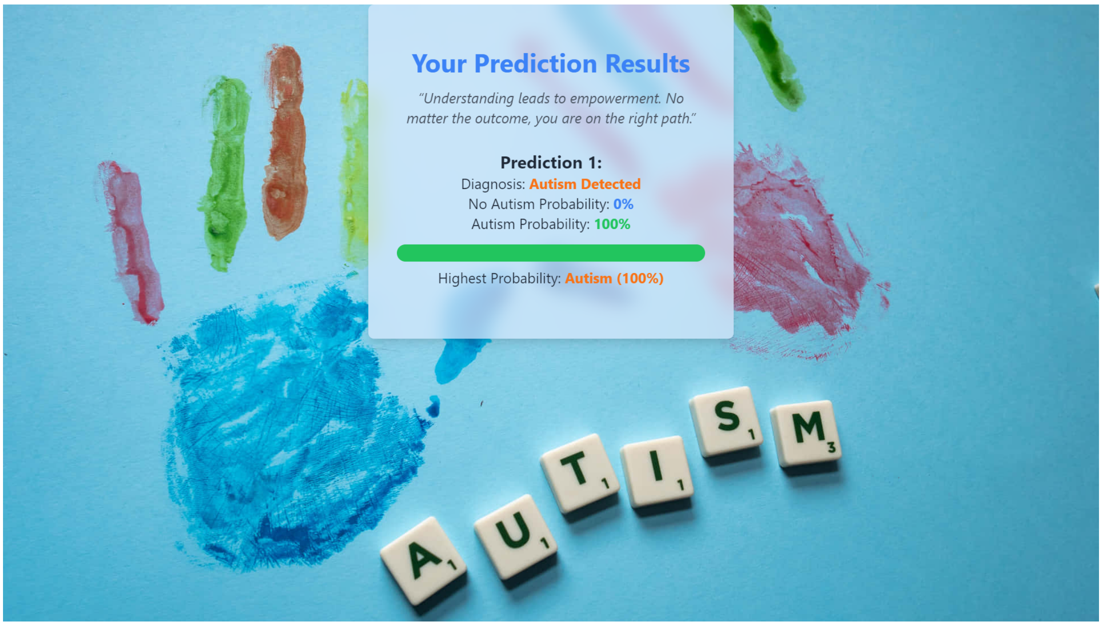

Figure 5.9: Results of EEG Data Analysis diagnosing Autism

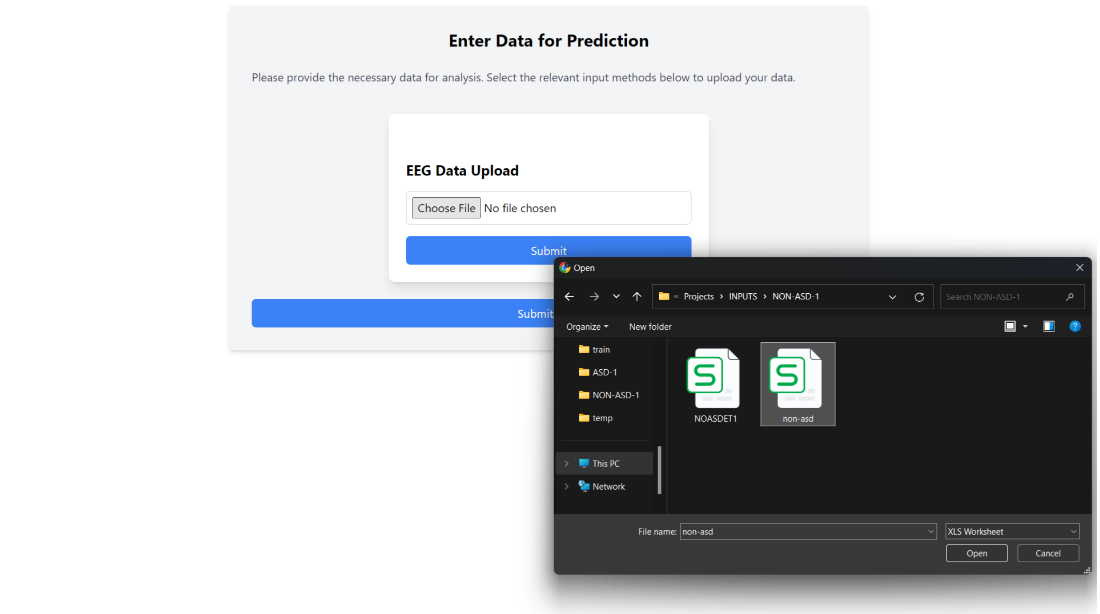

Figure 5.10: EEG file Submission Interface with Non Autism data

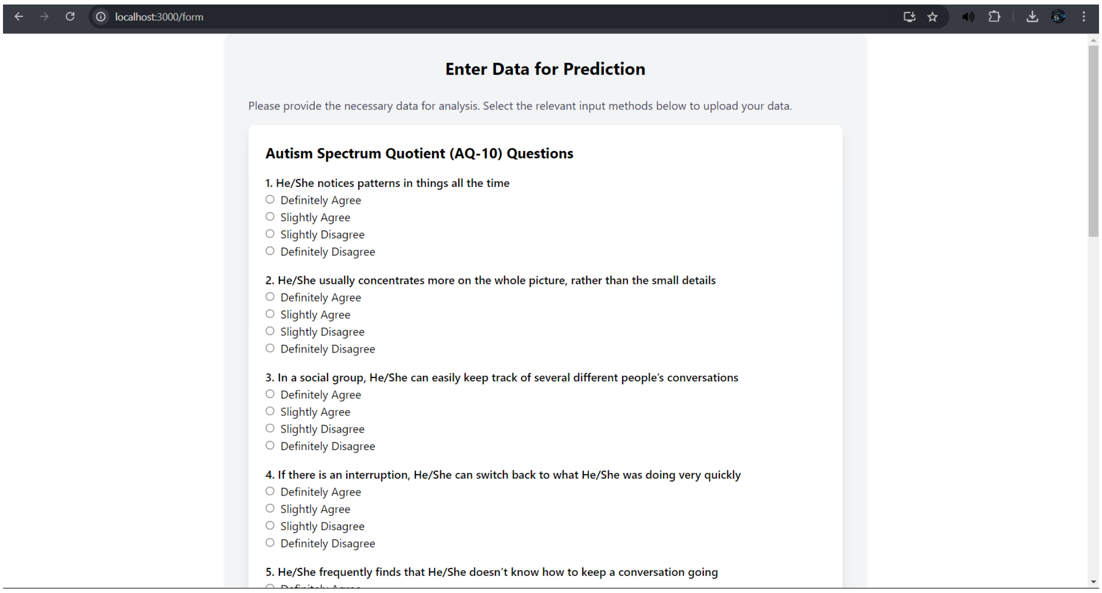

Figure 5.11: AQ10 Questions Submission Interface - i

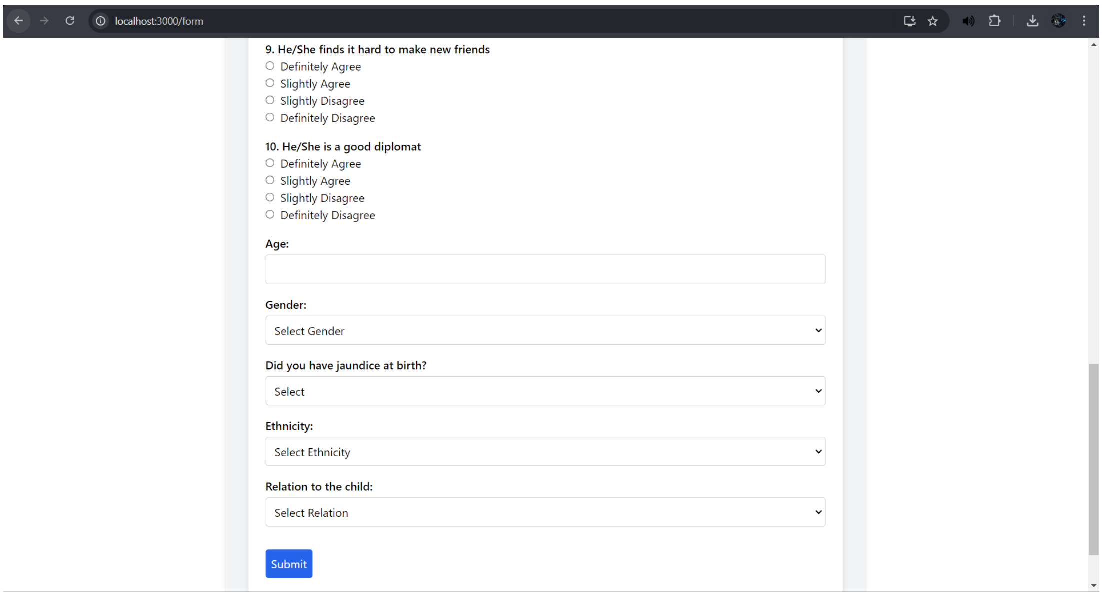

Figure 5.12: AQ10 Questions Submission Interface - ii

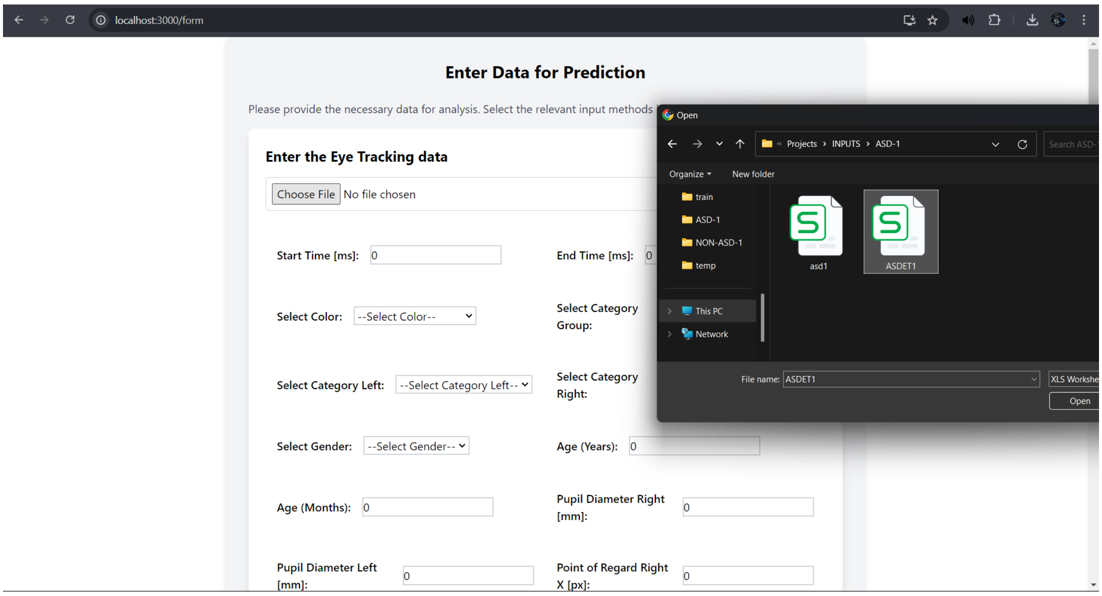

Figure 5.13: Eye Tracking Data Submission Interface for Autism Prediction

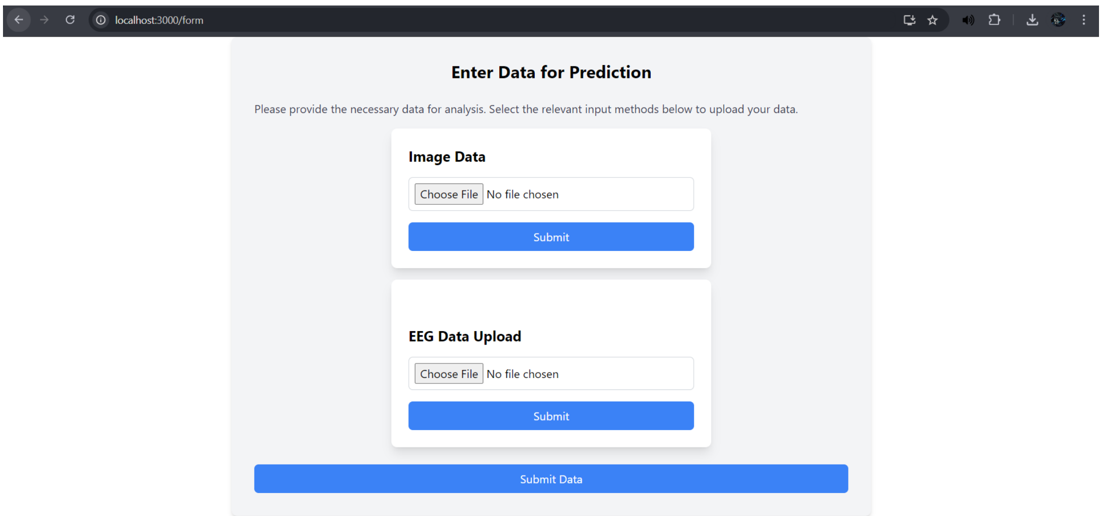

Figure 5.14: Interface for Uploading EEG and Image data for Autism Prediction

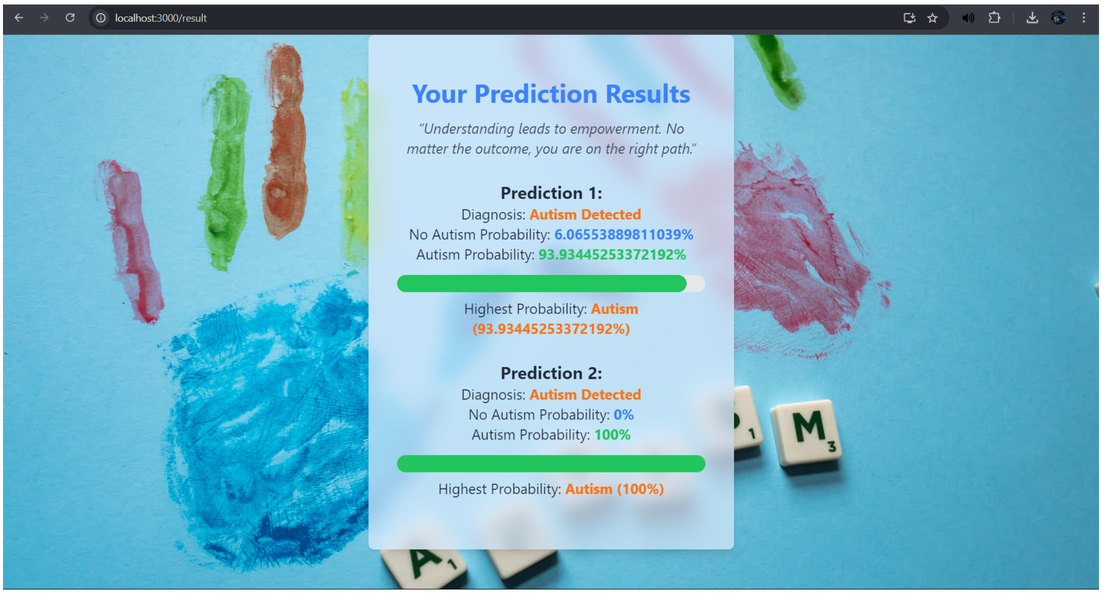

Figure 5.15: Results of EEG and Image Data Analysis diagnosing Autism

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.

REFERENCES

[1] Wanqi Zhang Wei Nie Honghai Liu Zhiyong Wang, Jingjing Liu. Diagnosis and intervention for children with autism spectrum disorder. *A Survey ,IEEE TRANSACTIONS ON COGNITIVE AND DEVELOPMENTAL SYSTEMS, VOL. 14, NO. 3*, 2022.

[2] Arnav Karmarkar Archith Rajan D Rangaprakash Gopikrishna Deshpande Madhura Ingalhalikar, Sumeet Shinde. Functional connectivity-based prediction of autism on site harmonized abide dataset. *IEEE Trans Biomed Eng*, 2021.

[3] Member IEEE Jingsheng Tang Juan Wang Wei Zhou, Minqiang Yang and IEEE Bin Hu , Fellow. Gaze patterns in children with autism spectrum disorder to emotional faces: Scanpath and similarity. *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 32*, 2024.

[4] Alireza Ghahremani. A review on: Autism spectrum disorder detection by machine learning using small video. *3rd International Conference on Intelligent Communication and Computational Techniques (ICCT)*, 2023.

[5] Haibo Qin Yi Wang Jingxin Deng Huiping Li Jingjing Liu, Zhiyong Wang. Social recognition of joint attention cycles in children with autism spectrum. *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 71, NO. 1*, 2024.

[6] Gaoxiang Ouyang Xiaoli Li Junxia Han, Guoqian Jiang. A multimodal approach for identifying autism spectrum disorders in children using eeg and eye tracking data. *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 30,*, 2022.

[7] Ali Buniya Sawal Hamid Md Ali Noor Kamal Al-Qazzaz, Alaa Aldoori. Transfer learning and hybrid deep convolutionalneural networks models for autism spectrum disorder classification from eeg signals. 2024.

[8] Yuan Zong Nana Qiu Cheng Lu Xilei Zhang Chuangao Tang, Wenming Zheng. Automatic identification of high-risk autism spectrum disorder: A feasibility study using video and audio data under the still-face paradigm. *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 28, NO. 11*, 2020.

[9] Nikitha Anand Rishab Kashyap B S Raghu Bhavana Yadav K, Shreya Vishwas. Automated identification and classification of autism spectrum disorder using behavioural and visual patterns in children. *4th International Conference for Emerging Technology (INCET)*, 2023.

[10] Hema Nikitha N Meghana Nakka Lakshmi Kuruguntla, Madhuri Yadala. Efficient classification of autism in children based on resnet-50 and xception module. *14th International Conference on Computing Communication and Networking Technologies*, 2023.

[11] Sheela Gowr Oswalt Manoj K Kalaivani Sajeev Ram Arumugam, Sankar Ganesh Karuppasamy. A deep convolutional neural network based detection system for autism spectrum disorder in facial images. *Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 2021.

[12] Hrithik S Hotagi S. Ajitha, Shonit Aric T. Augmented reality applications for special kids. *2022 4th International Conference on Circuits, Control, Communication and Computing (I4C)*, 2022.

[13] M. J. Maenner et al. Prevalence and characteristics of autism spectrum disorder among children aged 8 years–autism and developmental disabilities monitoring network, 11 sites, united states, 2018. *MMWR Surveill. Summaries*, 70, 2018.

[14] L. Zwaigenbaum and M. Penner. Autism spectrum disorder: Advances in diagnosis and evaluation. *BMJ*, 361, May 2018.

[15] C. Lord et al. Autism spectrum disorder. *Nature Rev. Disease Primers*, 6, 2020.

[16] W. Zheng et al. Multi-feature based network revealing the structural abnormalities in autism spectrum disorder. *IEEE Trans. Affect. Comput.*, 12, Jul 2021.

[17] A. Klin. Biomarkers in autism spectrum disorder: Challenges, advances, and the need for biomarkers of relevance to public health. *Focus*, 16, Apr 2018.

[18] Z. Zhao, H. Tang, X. Zhang, X. Qu, X. Hu, and J. Lu. Classification of children with autism and typical development using eye-tracking data from face-to-face conversations: Machine learning model development and performance evaluation. *J. Med. Internet Res.*, 23, Aug 2021.

[19] C. Tang et al. Automatic identification of high-risk autism spectrum disorder: A feasibility study using video and audio data under the still-face paradigm. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 28, Nov. 2020.

[20] M. E. Minissi, I. A. C. Giglioli, F. Mantovani, and M. A. Raya. Assessment of the autism spectrum disorder based on machine learning and social visual attention: A systematic review. *J. Autism Develop. Disorders*, 52, May 2022.

[21] M. Startsev and M. Dorr. Classifying autism spectrum disorder based on scanpaths and saliency. In *Proc. IEEE Int. Conf. Multimedia Expo Workshops (ICMEW)*, July 2019.

[22] J. Li, Y. Zhong, J. Han, G. Ouyang, X. Li, and H. Liu. Classifying asd children with lstm based on raw videos. *Neurocomputing*, May 2020.

[23] R. Carette, M. Elbattah, F. Cilia, G. Dequen, J.-L. Guérin, and J. Bosche. Learning to predict autism spectrum disorder based on the visual patterns of eye-tracking scanpaths. In *Proc. 12th Int. Joint Conf. Biomed. Eng. Syst. Technol.*, 2019.

[24] C. Wu, S. Liaqat, S.-C. Cheung, C.-N. Chuah, and S. Ozonoff. Predicting autism diagnosis using image with fixations and synthetic saccade patterns. In *Proc. IEEE Int. Conf. Multimedia Expo Workshops (ICMEW)*, July 2019.

[25] T. Falck-Ytter, S. Bölte, and G. Gredebäck. Eye tracking in early autism research. *J. Neurodevelopmental Disorders*, 5, Dec. 2013.

[26] M. Plitt, K. A. Barnes, and A. Martin. Functional connectivity classification of autism identifies highly predictive brain features but falls short of biomarker standards. *NeuroImage, Clin.*, 7, Jan. 2015.

[27] B. Yamagata et al. Machine learning approach to identify a resting-state functional connectivity pattern serving as an endophenotype of autism spectrum disorder. *Brain Imag. Behav.*, Oct. 2018.

[28] W. Liu, M. Li, and L. Yi. Identifying children with autism spectrum disorder based on their face processing abnormality: A machine learning framework. *Autism Res.*, 9, Aug. 2016.

[29] G. Wan, X. Kong, B. Sun, et al. Applying eye tracking to identify autism spectrum disorder in children. *J. Autism Developmental Disorders*, 49, Jan. 2019.

[30] A. Crippa, C. Salvatore, P. Perego, et al. Use of machine learning to identify children with autism and their motor abnormalities. *J. Autism Developmental Disorders*, 45, Jul. 2015.

[31] B. Li, A. Sharma, J. Meng, et al. Applying machine learning to identify autistic adults using imitation: An exploratory study. *PLoS ONE*, 12, Aug. 2017. Art. no. e0182652.

[32] A. Anzulewicz, K. Sobota, and J. T. Delafield-Butt. Toward the autism motor signature: Gesture patterns during smart tablet gameplay identify children with autism. *Sci. Rep.*, 6, Aug. 2016. Art. no. 31107.

[33] G. Xu, L. Strathearn, B. Liu, and W. Bao. Prevalence of autism spectrum disorder among us children and adolescents, 2014–2016. *Jama*, 319, 2018.

[34] Z.-A. Huang, Z. Zhu, C. H. Yau, and K. C. Tan. Identifying autism spectrum disorder from resting-state fmri using deep belief network. *IEEE Trans. Neural Netw. Learn. Syst.*, 32, Jul. 2021.

[35] H. C. Hazlett et al. Early brain development in infants at high risk for autism spectrum disorder. *Nature*, 542, 2017.

[36] X. Wen Q. Li H. Zhang, R. Li and X. Wu. Altered time-frequency feature in default mode network of autism based on improved hilbert–huang transform. *IEEE Journal of Biomedical and Health Informatics*, 25(2):485–492, Feb. 2020.

[37] K. Mutou M. Kikuchi, Y. Yoshimura and Y. Minabe. Magnetoencephalography in the study of children with autism spectrum disorder. *Psychiatry and Clinical Neurosciences*, 70(2):74–88, Feb. 2016.

[38] J. Han et al. Development of brain network in children with autism from early childhood to late childhood. *Neuroscience*, 367:134–146, Dec. 2017.

[39] C. Aldrich T.-M. Heunis and P. J. De Vries. Recent advances in resting-state electroencephalography biomarkers for autism spectrum disorder—a review of methodological and clinical challenges. *Pediatric Neurology*, 61:28–37, Aug. 2016.

[40] T. Takahashi et al. Enhanced brain signal variability in children with autism spectrum disorder during early childhood. *Human Brain Mapping*, 37(3):1038–1050, Mar. 2016.

[41] T. Wadhera and D. Kakkar. Social cognition and functional brain network in autism spectrum disorder: Insights from eeg graph-theoretic measures. *Biomedical Signal Processing and Control*, 67:Art. no. 102556, May. 2021.

[42] M. Baygin et al. Automated asd detection using hybrid deep lightweight features extracted from eeg signals. *Computers in Biology and Medicine*, 134:Art. no. 104548, Jul. 2021.

[43] J. Liu . Tan, K. Xu and H. Liu. A trend on autism spectrum disorder research: Eye tracking-eeg correlative analytics. *IEEE Transactions on Cognitive and Developmental Systems*, Aug. 2021. Early access, doi: 10.1109/TCDS.2021.3102646.

[44] S. Eraslan Y. Yesilada V. Yaneva, L. A. Ha and R. Mitkov. Detecting high-functioning autism in adults using eye tracking and machine learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(6):1254–1261, Jun. 2020.

[45] J. Song Z. Niu J. Kang, X. Han and X. Li. The identification of children with autism spectrum disorder by svm approach on eeg and eye-tracking data. *Computers in Biology and Medicine*, 120:Art. no. 103722, May. 2020.

[46] Y. Tang S. Zhang, D. Chen and L. Zhang. Children asd evaluation through joint analysis of eeg and eye-tracking recordings with graph convolution network. *Frontiers in Human Neuroscience*, 15:Art. no. 651349, May. 2021.

[47] B. A. Cociu et al. Multimodal functional and structural brain connectivity analysis in autism: A preliminary integrated approach with eeg, fmri, and dti. *IEEE Transactions on Cognitive and Developmental Systems*, 10(2):213–226, Jun. 2018.

[48] L. E. Mash et al. Atypical relationships between spontaneous eeg and fmri activity in autism. *Brain Connectivity*, 10(1):18–28, Feb. 2020.

[49] H. M. O'Leary H. Tager-Flusberg A. R. Levin, K. J. Varcin and C. A. Nelson. Eeg power at 3 months in infants at high familial risk for autism. *Journal of Neurodevelopmental Disorders*, 9(1):p. 34, Dec. 2017.

[50] S Srinithi Sheeba Rachel, C Buvana. Learnaut - upgraded learning environment and web application for autism environment using ar-vr. 2023.