AN AI-GUIDED MODEL DESIGNED FOR THE TIMELY RECOGNITION OF AUTISM SPECTRUM DISORDERS USING ADVANCED MACHINE LEARNING

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report **"AN AI-GUIDED MODEL DESIGNED FOR THE TIMELY RECOGNITION OF AUTISM SPECTRUM DISORDERS USING ADVANCED MACHINE LEARNING"** is the bonafide work of **"AGNELL J [211420104010], AJEIN MELVIN RAJ A[211420104012], KISHORE KUMAR K [211420104136]"** who carried out the project work under my supervision.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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AGNELL J

AJEIN MELVIN RAJ A

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ABSTRACT

The project introduces a novel and comprehensive framework for predicting the likelihood of Autism Spectrum Disorder (ASD) in children, encompassing a multifaceted approach that incorporates personalized gaming, quizzing, and Magnetic Resonance Imaging (MRI) analysis. The process initiates with participants inputting theirdetails and engaging in specially designed puzzle games aimed at evaluating cognitive abilities and discerning behavioral patterns. Following successful completion, participants progress to a quiz round that specifically targets social interaction and communication skills, providing a more holistic behavioral assessment. Subsequently, the system employs brain MRI images, utilizing the VGG16 algorithm for analysis, to extract features indicative of ASD pathology. By amalgamating the outcomes of behavioral assessments with neuroimaging data, the framework aspires to offer a more nuanced and comprehensive prediction of the likelihood of ASD, providing valuable insights for early detection and intervention. This integrated approach not only enhances theaccuracy of prediction but also underscores the significance of considering both behavioral and neurological factors in understanding and identifying ASD in children.

Keyword: VGG16, Dataset, Framework, Accuracy

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LIST OF ABBREVATIONS

LIST	ABBREVATION
AI	Artificial Intelligence
ASD	Autism Spectrum Disorder
CNN	Computational Neural Network
ML	Machine Learning
MRI	Magnetic Resonance Imaging
VGG16	Visual Geometry Group

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

Autism Spectrum Disorder (ASD) stands as a complex neurodevelopmental condition that poses significant challenges in its early detection, thereby affecting the social and cognitive development of individuals. Early identification of ASD is crucial as it allows for timely interventions and support, ultimately leading to better outcomes for affected individuals and their families. However, the current methods for ASD detection often lack comprehensiveness and may result in delayed diagnosis, hindering the effectiveness of interventions. In response to these challenges, this study proposes a novel approach to enhance early ASD prediction by integrating cutting-edge technology and neuroscience principles. By leveraging advancements in personalized gaming, quizzing techniques, and MRI analysis with the VGG16 algorithm, the aim is to develop a holistic and efficient framework for ASD detection. This innovative approach seeks to address existing gaps in ASD assessment methods, empowering healthcare professionals with the tools needed to provide timely interventions and support for individuals with ASD. Through the integration of multidisciplinary approaches, this study strives to pave the way for improved early detection and intervention strategies, ultimately enhancing the quality of life for individuals living with ASD. In response to the pressing need for more effective and timely identification of Autism Spectrum Disorder (ASD) in children, our project emerges as a pioneering effort to revolutionize early detection methodologies. ASD, a complex neurodevelopmental condition, often presents challenges in timely diagnosis due to its diverse and nuanced manifestations. The motivation behind our project lies in bridging this diagnostic gap by introducing an innovative, integrated framework. By integrating behavioral assessments with neuroimaging data, we aim to provide a more holistic understanding of ASD risk factors, facilitating early intervention and support.

1.2 SCOPE OF THE PROJECT

The scope of this project is broad, covering various crucial aspects related to the detection and early intervention of Autism Spectrum Disorder (ASD). At its core, the project aims to develop a comprehensive assessment tool that offers a nuanced understanding of ASD by integrating personalized gaming and quizzing activities. These activities are meticulously designed to assess cognitive abilities, behavioral patterns, and social interaction skills, providing a holistic perspective on the diverse manifestations of ASD. Unlike traditional behavioral assessments, which may have limitations in capturing the complexities of ASD, the project's approach offers a more thorough and nuanced evaluation. By incorporating personalized gaming and quizzing, the project seeks to uncover subtle nuances and individual differences in behavior and cognition that may indicate ASD. This holistic assessment approach enables a more comprehensive understanding of ASD, allowing for tailored interventions and support strategies. Overall, the project's scope extends beyond conventional methods of ASD assessment, aiming to develop innovative tools and approaches that enhance early detection and intervention efforts. Through the integration of personalized gaming and quizzing activities, the project seeks to revolutionize the way ASD is assessed, ultimately improving outcomes for individuals with ASD and their families. In addition to developing an integrated framework for predicting ASD likelihood, the scope of this project extends to encompass various crucial dimensions. These include rigorous validation and testing of the framework to ensure its accuracy and reliability, as well as designing it to be adaptable and scalable for potential future enhancements. Ethical considerations surrounding data privacy and responsible technology use are also addressed, alongside active collaboration with stakeholders to incorporate their insights and feedback. Moreover, the project aims to promote education and awareness about ASD, facilitate long-term impact assessments, and explore integration opportunities with existing systems. Furthermore, the project endeavors to foster research and innovation in ASD detection and intervention through the sharing of findings and methodologies with the scientific community.

1.3 OBJECTIVE

The foremost aim of this project is to establish an integrated framework capable of forecasting the probability of Autism Spectrum Disorder (ASD) in children, with a pronounced emphasis on early identification and intervention. This objective is pursued through the amalgamation of personalized gaming, quizzing activities, and MRI analysis, all orchestrated to culminate in the creation of a comprehensive assessment tool that transcends conventional behavioral assessments. Specifically, the project endeavors to assess cognitive abilities and behavioral tendencies by engaging participants in interactive puzzle games. These activities are meticulously crafted to not only captivate the participants but also to provide valuable insights into their cognitive functioning, potentially indicative of ASD. Furthermore, the project aims to evaluate social interaction and communication skills through targeted quizzes. By tailoring the quizzes to address key aspects of social communication and interaction characteristic of ASD, the project seeks to glean crucial information about participants' social functioning and potential ASD indicators. In addition to behavioral assessments, the project integrates advanced neuroimaging techniques, utilizing the VGG16 algorithm to analyze MRI images. Through this analysis, the project seeks to extract features from brain imaging data that may serve as biomarkers indicative of ASD pathology. By leveraging cutting-edge technology in this manner, the project aims to enhance the accuracy and precision of ASD prediction, thereby facilitating early intervention and support for affected individuals. In summary, the overarching objectives of the project revolve around the development of an integrated framework for ASD prediction, leveraging personalized gaming, quizzing, and MRI analysis.

1.4 MOTIVATION OF THE PROJECT

The motivation behind this project stems from the imperative need to revolutionize the early detection of Autism Spectrum Disorder (ASD), recognizing its profound impact on individuals' developmental trajectories. Extensive research underscores the pivotal role of timely intervention during early childhood in enhancing outcomes for individuals with ASD, encompassing improvements in social and communication skills, reduction of symptom severity, and fostering greater independence. However, prevailing methods for ASD detection often rely on subjective assessments and may overlook subtle signs of the disorder, resulting in delayed diagnosis and intervention. Consequently, the project is propelled by the urgent necessity to enhance the accuracy, efficiency, and accessibility of ASD detection methods. By converging technology, neuroscience, and clinical practice, this endeavor endeavors to equip healthcare professionals with a comprehensive and dependable predictive tool for identifying ASD at its earliest stages. Ultimately, the project aspires to elevate outcomes and quality of life for individuals with ASD and their families by facilitating timely intervention and support. In addition to the urgent need for improved ASD detection methods, several other factors motivate this project. Firstly, there is a growing recognition of the significant societal and economic burden associated with ASD, including the costs of lifelong care and support services. Addressing ASD detection early can alleviate some of these burdens by enabling timely interventions that may reduce the need for long-term support. Moreover, advancements in technology and neuroscience have opened up new possibilities for more sophisticated and objective methods of ASD assessment. By harnessing these technological advancements, the project aims to leverage innovative approaches that can complement traditional diagnostic tools and provide a more comprehensive evaluation of ASD risk. Furthermore, there is a pressing need to reduce disparities in ASD diagnosis and access to early intervention services, particularly among underserved communities.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

Farhad Abedinzadeh Torghabeh el at. (2024) proposed a novel approach for early ASD diagnosis using scalogram images of EEG signals and a hybrid deep learning architecture. The scalogram images capture both temporal and spectral information, while the deep learning model combines CNN and LSTM layers to analyze spatial and temporal features. Evaluation on a dataset of 34 ASD and 11 normal cases achieves exceptional performance, with accuracies of 93.50% and 92.43% for ASD detection with and without voice, respectively. Results demonstrate the effectiveness of the approach in early ASD diagnosis and highlight the impact of auditory cues on diagnosis.

Anjali Chandra el at. (2023) This paper introduces ASDC-Net, an automated clinical diagnosis system using a CNN for classifying ASD and typical controls (TC) based on rs-fMRI data. The model employs Batch Normalization for accelerated training and utilizes functional connectivity patterns from CC400 brain parcellation atlas. Evaluation on ABIDE dataset shows an accuracy of 76.72%, outperforming state-of-the-art methods. Diagnostic Odd Ratio (DOR) and Matthews Correlation Coefficient (MCC) metrics confirm the effectiveness of the classifier, indicating potential for assisting clinicians in early ASD diagnosis.

Mousumi Bala et al. (2022) discussed on using machine learning to detect autism spectrum disorder (ASD) at earlier stages. Different classifiers were applied to ASD data from toddlers, children, adolescents, and adults. Support Vector Machine (SVM) consistently outperformed other classifiers across all age groups. Evaluation metrics such as predictive accuracy, kappa statistics, and AUROC were used to assess classifier performance. SVM achieved high accuracy rates: 97.82% for toddlers, 99.61% for children, 95.87% for adolescents, and 96.82% for adults.

Daniele Pietrucci et al. (2022) explores the link between gut microbiota and Autism Spectrum Disorder (ASD) using fecal sample sequencing. Despite numerous studies, a consistent dysbiotic profile in ASD patients remains elusive due to technical and external factors. To address this, 959 samples from eight projects were collected, balancing ASD and Healthy Control (HC) groupsThe analysis highlighted the importance of five genera, such as Parasutterella and Alloprevotella. Importantly, ML algorithms could identify common taxonomic features across datasets from different countries, potentially overcoming confounding variables.

Faria Zarin Subah et al. (2021) presented a novel ASD detection method using resting-state fMRI data and four brain atlases. By employing a deep neural network classifier, the model achieves an accuracy of 88%, outperforming existing methods. Sensitivity, F1-score, and AUC confirm its effectiveness, with BASC atlas showing superior classification ability. This approach holds promise for enhancing ASD diagnosis and understanding its neurobiological basis.

Ibrahim Abdulrb Ahmed et al. (2021) discussed about three AI techniques for early ASD diagnosis using eye tracking. ML achieves 99.8% accuracy with FFNNs and ANNs using a hybrid feature extraction method. DL, utilizing pre-trained CNN models like GoogleNet and ResNet-18, achieves 93.6% and 97.6% accuracy respectively. A hybrid approach, combining DL (GoogleNet/ResNet-18) with ML (SVM), further improves accuracy, demonstrating the potential of AI in ASD detection from eye tracking data.

Maraheb Alsuliman et al. (2022) aims to improve early autism diagnosis using machine learning (ML) and optimized feature selection algorithms with PBC and GE data. By employing Gray Wolf Optimization (GWO), Flower Pollination Algorithm (FPA), Bat Algorithms (BA), and Artificial Bee Colony (ABC), informative features are selected to enhance prediction accuracy. Evaluation metrics such as accuracy, F1 score, precision, recall, and AUC validate the effectiveness of the models. The GWO-SVM model achieves high accuracies of 95.66% and 94.34% on PBC and GE datasets, respectively, demonstrating promising results for precise autism prediction.

Ranjani. M et al. (2023) Autism encompasses a range of neurodevelopmental disorders affecting communication and social interaction, often linked to cognitive impairment and slower brain development. Individuals with autism struggle with learning, communication, and adapting to new situations, leading to social isolation. Deep Learning (DL) models, including LSTM, CNN, and MLP, are utilized in healthcare for precise diagnosis. This study employs these models to detect autism from EEG signals, with LSTM demonstrating superior performance in sensitivity, specificity, and accuracy. Implementation is done using Python programming.

Kahina Amara et al. (2022) demonstrated a gesture and voice-based learning framework for children with ASD, leveraging augmented reality (AR) technology to enhance engagement and focus during therapy sessions. The prototype, designed in collaboration with specialists from rehabilitation centers, includes structured activities and AR-based games to promote social interaction and inclusion. A feasibility pilot study involving 18 children with ASD demonstrates significantly higher engagement and concentration compared to non-computer conditions. Preliminary results also indicate improved receptive vocabulary and social interaction, reducing teacher workload while benefiting the children's learning experience.

Chandan Jyoti Kumar et al. (2021) explored automating ASD diagnosis using machine learning techniques on a dataset of 701 samples, integrating AQ-10-Adult and individual characteristics. Two scenarios are considered: one without missing values and another introducing missing values. In the ideal scenario, ANN, SVM, and RF classifiers are trained with RFE feature selection. For real-world data, SVM, RF, Decision Tree, and Logistic Regression with RFE handle missing values. Twelve classification models are generated, with the best-performing models for each scenario evaluated and recommended for ASD diagnosis.

Hamza Sharif et al. (2021) proposed a machine learning framework for ASD detection based on features extracted from corpus callosum and brain volume, achieving high recognition accuracy. Feature selection reduces model complexity by focusing on discriminative capabilities for ASD classification. Additionally, the study explores the potential of deep learning in neuroimaging analysis, employing transfer learning with the pre-trained VGG16 model for ASD classification.

Maraheb Alsuliman et al. (2022) investigates enhancing ASD classification using optimized ML models (GWO-NB, GWO-SVM, etc.) based on PBC and GE data analytics. Four bio-inspired algorithms are employed for feature selection to improve model accuracy. Evaluation metrics including accuracy, F1 score, precision, recall, and AUC demonstrate the effectiveness of the proposed models. Results show high accuracies of 95.66% and 94.34% achieved by the GWO-SVM model on PBC and GE datasets respectively, indicating promising performance for ASD prediction.

2.2 Comparison of Existing Work

Table 2.1 : Comparison of Existing System

S.NO	AUTHOR NAME	TITLE	AIM/SCOPE	METHODOLOGY	DRAWBACK
1.	Farhad Abedinzade Torghabehel at. (2024)	Hybrid deep transfer learning-based early diagnosis of autism spectrum disorder using scalogram representation ofelectroencephalography signals	A new method for early autism diagnosis using EEG images and deep learning, achieving high accuracy and recognizing the importance of auditory cues.	deep learning model combines CNN and LSTM	relatively small dataset size
2.	Anjali Chandra el at. (2023)	ASDC-Net: Optimized Convolutionl Neural Network-Based Automatic Autism Spectrum Disorder ClassificatioN Using rsfMRI Data	ASDC-Net, a system using brain scan data and a CNN to diagnose autism, With high Accuracy (76.72%) on the ABIDE dataset, offering potential support for early ASD diagnosis by clinicians.	Autism Spectrum Disorder Clinical Diagnosis Network."	SDC-Net approach is the lack of external validation on independent datasets beyond the ABIDE dataset

3.	Mousumi Bala	Efficient Machine Learning Models For Early Stage Detection Of AutismSpec trum Disorder	Aimed to use machine learning to find autism earlier in life. They tried different methods on data from toddlers to adults, finding that Support Vector Machine (SVM) worked best, with high accuracy rates across all ages.	Support Vector Machine (SVM) ,AURO C	the lack of explanation regarding the interpretability of the Support Vector Machine (SVM)
4.	Daniele Pietruccial. (2022)	Machine Learning Data Analysis Highlights the Role of Parasutterell a and All oprevotella in Autism Spectrum Di sorders	Explores the link between gut microbiota and Autism Spectrum Disorder (ASD) using fecal sample sequencin g.	"fecal sample sequencing and machine learning analysis ."	introduced by combining data from different projects, which may lead to inconsistencies or inaccuracies
5.	Faria Zarin Subah et al. (2021)	A Deep Learning Approach To Predict Autism Spectrum Disorder Using Multisite Resting-Sta	Presented a novel ASD detection method using resting-state fMRI data and four brain atlases. By employing a deep neural network classifier, the model achieves 88	resting-state fMRI	limited sample size or lack of external validation, which may raise concerns about the robustness and generalizability

6.	Ibrahim Abdulrb Ahmed et al. (2021)	Eye Tracking-Based Diagnosis And Early Detection Of Autism Spectrum Disorder Using Machine Learning And Deep Learning Te chniques	Discussed about three AI techniques for early ASD diagnosis using eye tracking. ML achieves 84.8%accuracy with FFNNs and ANNs using a hybrid feature extraction method	Feedforward Neural Networks,Artificial Neural Network s.	lack of validation on independent datasets or real-world clinical settings
7.	Maraheb Alsuliman et al. (2022)	Efficient Diagnosis of Autism with Optimized Machine Learning Models: An Experimental Analysis on Genetic and Personal Characteristic Datasets	Aims to improve early autism diagnosis using machine learning (ML) and optimized feature selection algorithms with PBC and GE data.	Machine Learning ,Primary Biliary Cholangitis,General Electric	the lack of transparency in the feature selection process
8.	Ranjani. Metal. (2023)	Cognitive Behavior: Identification of Autism Disorder in Individuals Based on EEG Signal Using Neural Netw	Autism encompasses a range of neurodevelopmental disorders affecting communication and social interaction, often linked to	Deep Learning (DL) models, including LSTM, CNN, and MLP	limited explanation or exploration of potential confounding factors or biases in the EEG data collection process

		ork Methods	cognitive impairment and slower brain developmen t.		
9.	Kahina Amara et al. (2022)	AR Computer-Assisted Learning for Children with ASD based on Hand Gesture and Voice Intera ction	Demonstrated a gesture and voice-based learning framework for children with ASD, leveraging augmented reality (AR) technology to enhance engagement and focus during therapy sessions.	Augmented Reality	limited sample size of the feasibility pilot study involving only18children with ASD
10.	Chandan Jyoti Kumar etal. (2021)	The diagnosis of ASD using multiple machine learning tec hniques	Explored automating ASD diagnosis using machine learning techniques on a dataset of 701 samples, integrating AQ-10-Adult and individual.	Machine learning techniques	potential overfitting of the machine learning models to the dataset
11.	Hamza Sharif e tal. (2021)	A Novel Machine Learning Based Framework fordetection of Autism Spectrum Di sorder	Proposed a machine learning framework for ASD detection based on features extracted from corpus callosum and brain volume, achieving recognition	machine learning techniques	limited interpretability of the features extracted from corpus callosum and brain volume

CHAPTER 3
SYSTEM ANALYSIS

3.1 PROBLEM STATEMENT

The challenge of early detection poses significant hurdles for caregivers, educators, and healthcare professionals striving to provide timely support and intervention strategies for individuals with Autism Spectrum Disorder (ASD). Compounding this issue is the heterogeneous nature of ASD symptoms, necessitating a more sophisticated and integrated approach to diagnosis that considers both behavioral and neurological factors. Recognizing the urgent need to address delayed ASD identification, this project endeavors to introduce a multifaceted framework encompassing personalized gaming, quizzing, and MRI analysis. By integrating these diverse methodologies, the project aims to offer a comprehensive understanding of ASD risk factors, thus facilitating early detection and enhancing the prospects for effective interventions and support. Moreover, this initiative aligns with broader efforts to promote inclusivity and accessibility in healthcare by leveraging technology and innovation to overcome barriers to ASD diagnosis and intervention. Through collaborative partnerships with stakeholders and the utilization of cutting-edge technologies, the project seeks to empower caregivers and professionals with the tools and insights necessary to improve outcomes for children on the autism spectrum.

This project addresses the challenges of early ASD detection by proposing a multifaceted framework that integrates personalized gaming, quizzing, and MRI analysis. By considering both behavioral and neurological factors, it aims to provide a comprehensive understanding of ASD risk factors, facilitating early detection and tailored intervention strategies. Aligned with broader efforts to promote inclusivity in healthcare, the project leverages technology and innovation to overcome barriers to ASD diagnosis and intervention.

3.2 AUTISM SPECTRUM DISORDER

Autism Spectrum Disorder (ASD) is a complex developmental condition that typically appears during early childhood and affects social interaction, communication, and behavior. It is characterized by a wide range of symptoms and challenges, which is why it is referred to as a "spectrum" disorder. Individuals with ASD may exhibit difficulties in social interactions, such as understanding and responding to social cues, maintaining eye contact, and forming relationships. They may also have challenges with communication, including difficulty with speech or language development, as well as repetitive behaviors or restricted interests. ASD manifests differently in each individual, ranging from mild to severe symptoms, hence the term "spectrum." Some individuals with ASD may have exceptional abilities in certain areas, such as music, art, or mathematics, while others may require significant support in daily functioning.

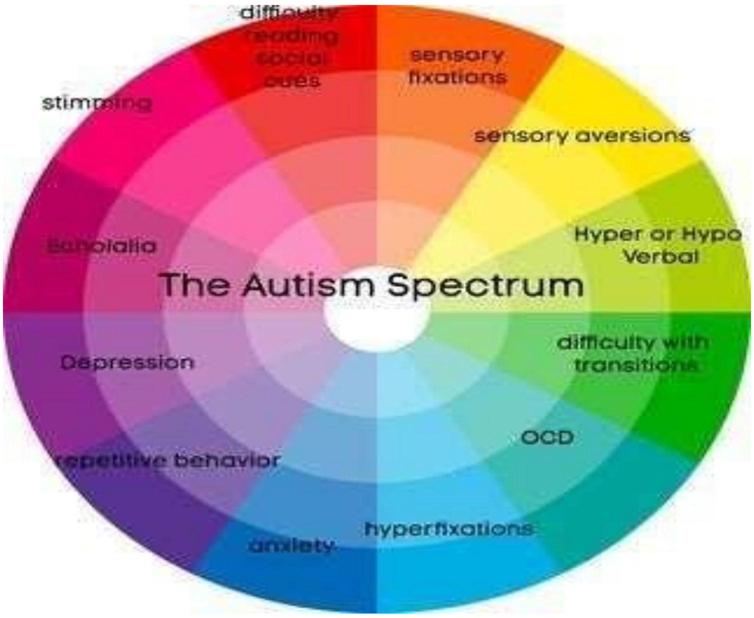


Fig 3.1: Autism Spectrum Wheel

3.3 AUTISM SPECTRUM DISORDER LEVELS

Autism Spectrum Disorder (ASD) is typically characterized by varying levels of severity and support needs, often referred to as "levels" or "degrees" of ASD. These levels are used to describe the extent of support and assistance required by an individual with ASD to function effectively in daily life. The levels are based on the severity of symptoms and the level of impairment in social communication, behavior, and sensory processing.

Fig 3.2: Autism Spectrum Disorder Levels

Level 1: Requiring Support

Individuals with Level 1 ASD require some support in social communication, social interaction, and restricted or repetitive behaviors. They may have difficulty initiating social interactions, maintaining friendships, and adapting to changes in routines. While they may have average or above-average intelligence, they may struggle with understanding social nuances and may need support in certain situations, such as navigating social interactions or managing sensory sensitivities.

Level 2: Requiring Substantial Support

Individuals with Level 2 ASD require more substantial support in social communication, social interaction, and restricted or repetitive behaviors. They may have more pronounced difficulties in social situations, such as difficulty understanding social cues, maintaining conversations, or managing emotions. They may also have more significant challenges in adaptive functioning, such as self-care skills, independent living skills, and managing daily routines. Individuals with Level 2 ASD may benefit from structured interventions and supports to address their specific needs and challenges.

Level 3: Requiring Very Substantial Support

Individuals with Level 3 ASD require very substantial support in social communication, social interaction, and restricted or repetitive behaviors. They may have severe impairments in social communication and interaction, limited verbal communication skills, and significant challenges in adaptive functioning. Individuals with Level 3 ASD may require intensive, individualized interventions and supports to address their complex needs and challenges. They may also have co-occurring intellectual or developmental disabilities that further impact their functioning and require specialized support services.

It's important to note that these levels are descriptive and may change over time as individuals with ASD receive interventions and supports tailored to their specific needs. Additionally, individuals with ASD may have strengths and abilities that are not captured by these levels, and each person's experience with ASD is unique. The levels of ASD are used to guide treatment planning, support services, and interventions to help individuals with ASD reach their full potential and improve their quality of life.

3.4 OVERVIEW OF EXISTING SYSTEM

The existing system for this project is primarily centered on detecting Autism Spectrum Disorder (ASD) solely through facial images. By recognizing the potential of facial features as indicative markers of ASD, the project focuses exclusively on leveraging facial image analysis for accurate and early detection. This targeted approach underscores the significance of facial expressions and features as potential manifestations of ASD traits. By concentrating on facial images, the project aims to streamline the diagnostic process, offering a non- invasive method for ASD detection. This emphasis on facial image-based detection aligns with the overarching goal of providing a more accessible and efficient means of identifying ASD, potentially revolutionizing the landscape of early diagnosis and intervention for individuals on the autism spectrum.. The emphasis on facial image-based detection aligns with the goal of providing a more accessible and efficient means of identifying ASD, potentially revolutionizing the landscape of early diagnosis and intervention for individuals on the autism spectrum.

3.5 DISADVANTAGES

- **Limited Scope:** Face image-based detection may overlook other important indicators of ASD that are not visually apparent, potentially leading to incomplete or inaccurate diagnoses.

- **Cultural and Ethnic Bias:** Facial recognition algorithms may exhibit biases against certain ethnicities or cultural groups, resulting in disparities in diagnosis accuracy and effectiveness across different populations.

- **Accessibility Challenges:** Face image-based detection may pose challenges for individuals with limited access to technology or those who are unable to provide clear facial images due to physical or cognitive impairments, leading to disparities in access to early ASD detection.

CHAPTER 4

SYSTEM ARCHITECTURE

4.1 PROPOSED SYSTEM

The proposed system for this project introduces an innovative approach to Autism Spectrum Disorder (ASD) detection, with facial image analysis serving as its central component. Our system aims to harness advanced computer vision techniques to extract valuable insights from facial features, offering a non- intrusive and efficient method for identifying potential ASD indicators. By deploying cutting-edge algorithms and machine learning models specifically tailored to facial image analysis, our system endeavors to discern subtle patterns and expressions associated with ASD traits. Additionally, the proposed system features a user-friendly interface, facilitating seamless data input and interaction with personalized gaming and quizzes. These interactive elements are strategically designed to complement the facial analysis by capturing cognitive abilities, behavioral patterns, and social interaction skills, thereby enriching the overall assessment process.

4.2 ADVANTAGES

- **Early detection:** By leveraging advanced technology and neuroscience principles, the proposed system facilitates early detection of ASD, allowing for timely interventions and support.
- **Objective analysis:** The utilization of MRI analysis, coupled with machine learning algorithms like VGG16, offers an objective means of examining neurological markers associated with ASD, enhancing the reliability of predictions.
- **Empowering healthcare professionals:** The proposed system equips healthcare professionals with a reliable and efficient tool for early ASD detection, empowering them to deliver timely interventions and support for individuals with ASD and their families.

4.3 ARCHITECTURE DIAGRAM

An architecture diagram is a graphical representation of a set of concepts that are part of an architecture, including their principles, elements and components.

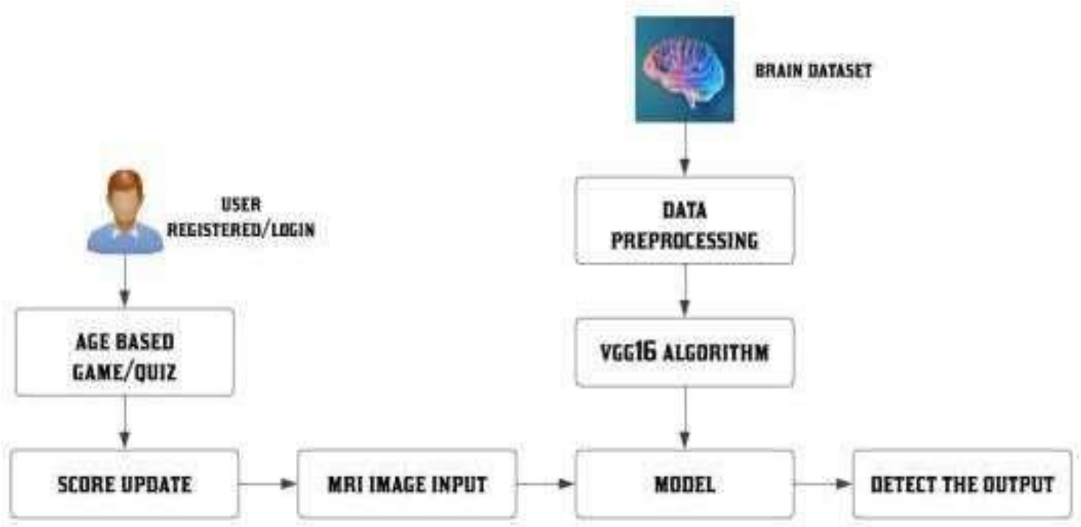


Fig 4.1: Architecture diagram

Facial Image Analysis

Utilizing advanced computer vision techniques for analyzing facial features and expressions, facilitating non-intrusive and efficient ASD detection.

MRI Analysis and Machine Learning

Incorporating MRI analysis and machine learning algorithms like VGG16 for objective examination of neurological markers associated with ASD, enhancing prediction reliability.

4.4 MODULE DESCRIPTIONS

- Exploratory data analytics
- Genesis of VGG16
- Age Based Game /Quiz
- Model Creation
- Autism Detection

4.4.1 EXPLORATORY DATA ANALYSIS

Data preprocessing within this project plays a pivotal role in refining and optimizing the raw sensor data collected from smartphones, making it suitable for analysis and early autism detection. The preprocessing stage encompasses activities such as data cleaning, noise reduction, and feature extraction, ensuring that the data is of high quality and aligned with the requirements of the subsequent algorithms. By effectively preparing the data, we enhance the accuracy and reliability of the analysis, ultimately enabling a more precise assessment of children's behavioral patterns, thus facilitating early ASD detection and intervention. This critical data preprocessing step ensures that the project's algorithms can operate on a robust dataset, contributing to the overarching goal of improving the lives of children with autism by enabling timely support and care.

Enhancing Insights for Early Autism Detection

Within the scope of this project, data preprocessing assumes a pivotal role in refining and optimizing the raw data collected, fostering its suitability for analysis aimed at early autism detection.

Crafting High-Quality Data: A Prelude to Analysis

Data preprocessing serves as the initial step in transforming raw data into a refined form. This involves meticulous data cleaning, noise reduction, and feature extraction procedures. Through these actions, the project ensures that the data maintains a high level of quality, aligning seamlessly with the demands of subsequent analytical processes.

Aligning Integrity with Precision: A Symbiotic Relationship

At its essence, data preprocessing bridges the integrity of the data with the precision required for analysis. By undertaking this essential phase, the project ensures that the data integrity is preserved while harmonizing with the sophisticated analytical methodologies employed.

Optimizing Analysis through Prudent Data Preparation

The efficacy of subsequent analyses hinges on effective data preparation. Through diligent preprocessing, the project optimizes the dataset, thereby enhancing the accuracy and reliability of subsequent analyses. This refinement enables a more nuanced examination of children's behavioral patterns, thereby bolstering the project's capability for early ASD detection and intervention.

Empowering Algorithms with Foundation of Reliability

As the project advances, the significance of data preprocessing becomes increasingly apparent. This crucial step empowers the project's algorithms to operate on a foundation of robust and meticulously processed data. Such data integrity is paramount as it forms the bedrock for achieving the overarching objective of improving the lives of children with autism through timely support and intervention strategies.

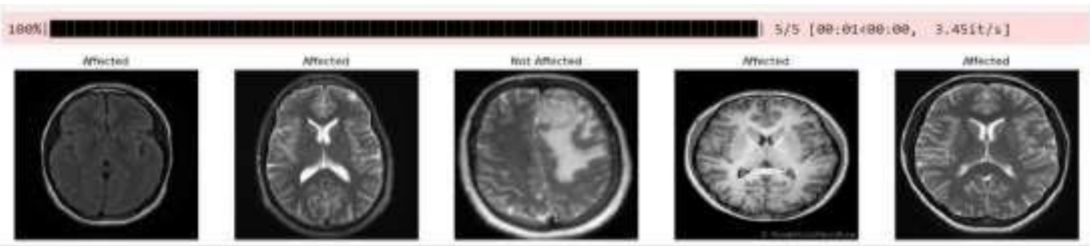


Fig 4.2 Data analysis after pre-processing

4.4.2 GENESIS VGG16 ALGORITHM

The VGG16 algorithm is a remarkable advancement in deep learning and computer vision. It has made its mark by demonstrating its prowess in recognizing complex features in images. With a deep layer learning architecture, VGG16 is well-suited for image recognition tasks, including the critical task of emotion recognition in this project. Its exceptional ability to analyze intricate facial expressions and non-verbal cues facilitates the accurate interpretation of emotions, particularly in children with Autism Spectrum Disorder, where understanding and expressing emotions can be particularly challenging. VGG16 plays a pivotal role in enabling emotional recognition in various contexts and stands as a crucial component in enhancing the emotional well-being and social interactions of individuals with autism.

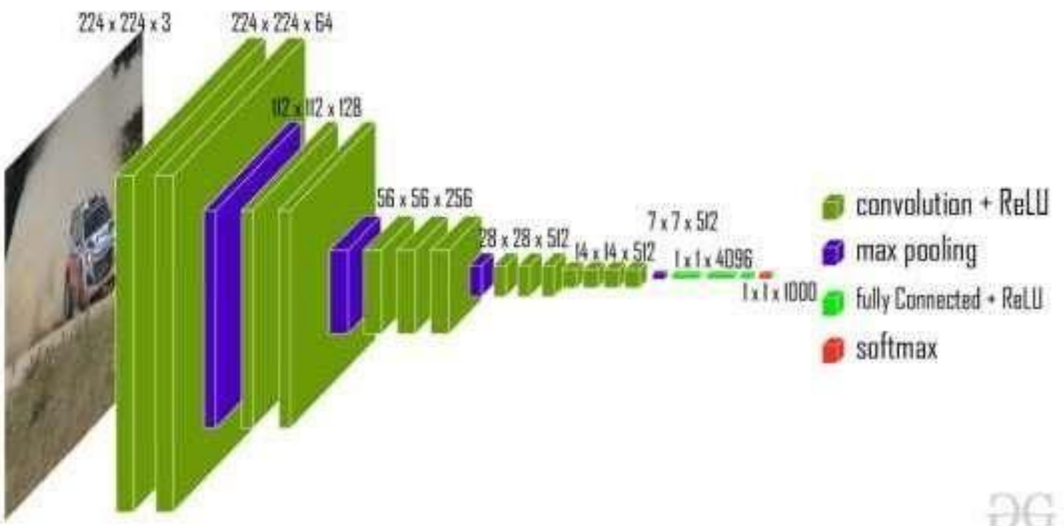


Fig 4.3: VGG16 Architecture

Visual Geometry Group (VGG)

- Background on the Visual Geometry Group at the University of Oxford provides insights into the research environment and expertise that led to the development of VGG16. Understanding the pedigree of the algorithm adds credibility to its application in ASD detection.
- Exploration of the research motivations behind VGG16's development sheds light on

the specific challenges in computer vision that the algorithm aimed to address, potentially including those related to facial recognition and emotion analysis, both pertinent to ASD identification.

ImageNet Challenge

- A comprehensive overview of VGG16's participation in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) underscores its performance and validation in real-world image classification tasks.

- Examination of VGG16's success in the ImageNet Challenge highlights its capability to handle large-scale datasets, which is crucial for training models to recognize diverse facial expressions and emotional cues, particularly relevant for individuals with ASD**.**

Architecture Overview

- Detailed analysis of VGG16's architecture, including its deep layer learning structure, provides insights into how the algorithm processes visual information, enabling robust feature extraction and classification.
- Understanding the specific layers, convolutional filters, and fully connected layers of VGG16 allows for informed decisions regarding its adaptation and fine-tuning for emotion recognition tasks within the ASD detection system.

Simplicity vs. Performance

- Discussion on VGG16's simplicity versus its performance showcases how its relatively straightforward architecture achieved competitive accuracy in image classification tasks compared to more complex models.
- Emphasizing VGG16's balance between model complexity and performance underscores its suitability for deployment in resource-constrained environments, such as those where real-time emotion recognition for ASD detection may occur.

Impact and Legacy

- The influence of VGG16 on subsequent developments in deep learning, its role as a benchmark architecture, and its contribution to advancing computer vision research.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 128)               3211392

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 17,926,338
Trainable params: 3,211,650
```

Fig 4.4 Inception of VGG16 Algorithm

4.4.3 AGE BASED GAME/QUIZ

The age-based game/quiz module is a vital component of the machine learning-driven system tailored for early stage identification of Autism Spectrum Disorder (ASD). By creating interactive and engaging activities tailored to different age groups, this module plays a crucial role in assessing cognitive abilities, social interaction, and communication skills relevant to ASD detection. Here's a more detailed exploration of the various aspects of this module:

Personalization

- Besides selecting appropriate themes, content, and difficulty levels, the module also ensures personalization by considering the specific developmental milestones and potential challenges associated with ASD for each age group. This personalized approach enhances the relevance and effectiveness of the games and quizzes in identifying ASD-related traits.
- The module dynamically adjusts the content based on individual progress and responses, ensuring that the activities remain engaging and adaptive to the evolving needs of the participants.

Assessment of Cognitive Abilities

- In addition to assessing cognitive skills such as problem-solving, memory, attention, and logical reasoning, the module incorporates tasks specifically tailored to identify potential cognitive differences associated with ASD across different age groups.
- Tasks are designed to capture subtle variations in cognitive abilities, allowing for early detection of developmental delays or atypical patterns indicative of ASD, thus contributing to the overarching objective of early identification and intervention.

Social Interaction

- Interactive games are strategically designed to promote social engagement and collaboration among participants, mimicking real-world social scenarios. This is crucial for assessing social interaction skills, which are often impaired in individuals with ASD.
- Activities foster opportunities for participants to practice turn-taking, perspective-taking, and cooperative problem-solving, providing valuable insights into their social skills development and potential challenges related to ASD.

Communication Skills

- Quizzes and games within the module incorporate a variety of verbal and non-verbal communication tasks tailored to evaluate expressive and receptive language abilities across different age groups.
- By assessing communication skills through engaging activities, the module helps identify language delays, pragmatic language difficulties, and other communication impairments characteristic of ASD, facilitating early intervention and support.

Varied Content and Difficulty Levels

- The module offers a diverse range of games and quizzes, including matching games, puzzles, trivia quizzes, and role-playing scenarios, with content curated to suit the developmental stage and interests of participants across different age groups.

- Difficulty levels are dynamically adjusted based on individual performance, ensuring that the activities remain appropriately challenging yet achievable, thereby maximizing engagement and accuracy in assessment.

Engagement and Accuracy

- The primary focus of the module is to create activities that not only capture participants' interest but also provide accurate assessments of cognitive, social, and communication skills relevant to ASD detection.
- By incorporating elements of gamification, such as rewards, feedback mechanisms, and interactive interfaces, the module enhances participant engagement while maintaining the rigor and validity of the assessment process.

Fig 4.5 Game (Age 3-8)

Fig 4.6 Game (Age 9-20)

4.4.4 MODEL CREATION

The model creation module focuses on developing a predictive model for assessing the likelihood of Autism Spectrum Disorder (ASD) by integrating behavioral assessment outcomes and neuroimaging data. Leveraging advanced algorithms like VGG16, the module combines information gathered from personalized gaming, quizzing activities, and MRI analysis. The overarching objective is to craft a comprehensive and precise predictive model for the early detection of ASD.

Key Components:

- The module incorporates data obtained from behavioral assessments, including responses from personalized gaming and quizzing activities. These assessments capture various cognitive, social, and communication skills, providing valuable insights into potential indicators of ASD.
- Utilizing neuroimaging techniques such as MRI analysis, the module extracts neurobiological features relevant to ASD diagnosis. This includes examining structural and functional brain characteristics associated with ASD, enhancing the model's predictive capabilities.
- The module employs advanced algorithms like VGG16, renowned for their effectiveness in analyzing image data. VGG16 is utilized to process and extract features from MRI scans or visual stimuli encountered during gaming and quizzing activities, facilitating the integration of neuroimaging and behavioral data.
- The model combines features extracted from behavioral assessments and neuroimaging data using sophisticated fusion techniques. This integration enhances the model's predictive power by capturing a comprehensive range of ASD-related characteristics from multiple modalities.
- Data collected from individuals with and without ASD is utilized to train and validate the predictive model. Rigorous evaluation procedures ensure the model's accuracy, sensitivity, specificity, and generalization capabilities across diverse populations.

Fig 4.7 Uploading of MRI images

4.4.5 AUTISM DETECTION

This aspect of the module involves the cohesive examination of behavioral outcomes derived from gaming and quizzing activities alongside neuroimaging data obtained from MRI scans. By merging these two streams of information, the module achieves a comprehensive assessment of Autism Spectrum Disorder (ASD) likelihood, considering both behavioral and neurobiological factors.

Utilization of Age-Adapted Gaming and Quizzing Metrics:

Scores obtained from age-appropriate gaming and quizzing sessions serve as pivotal metrics for evaluating cognitive, social interaction, and communication skills. These metrics are tailored to the age group of the participants, providing valuable insights into potential indicators of ASD and contributing significantly to the overall assessment.

Integration of MRI Imaging Features:

MRI imaging features play a crucial role in capturing neurobiological markers associated with ASD. By extracting relevant features from MRI scans, the module enhances the depth and accuracy of the detection model, providing valuable insights into the structural and functional aspects of the brain relevant to ASD diagnosis.

Sophisticated Fusion Techniques for Data Integration:

The module employs advanced fusion techniques to seamlessly integrate behavioral and neuroimaging data. Leveraging machine learning algorithms and statistical methods, it synthesizes information from diverse sources, ensuring a comprehensive assessment of ASD likelihood that encompasses both behavioral and neurobiological dimensions.

Machine Learning Algorithms for Pattern Recognition:

State-of-the-art machine learning algorithms are utilized to analyze and process integrated data, identifying patterns and correlations indicative of ASD risk. These algorithms are trained on labeled datasets to distinguish between individuals with and without ASD, facilitating accurate detection and classification.

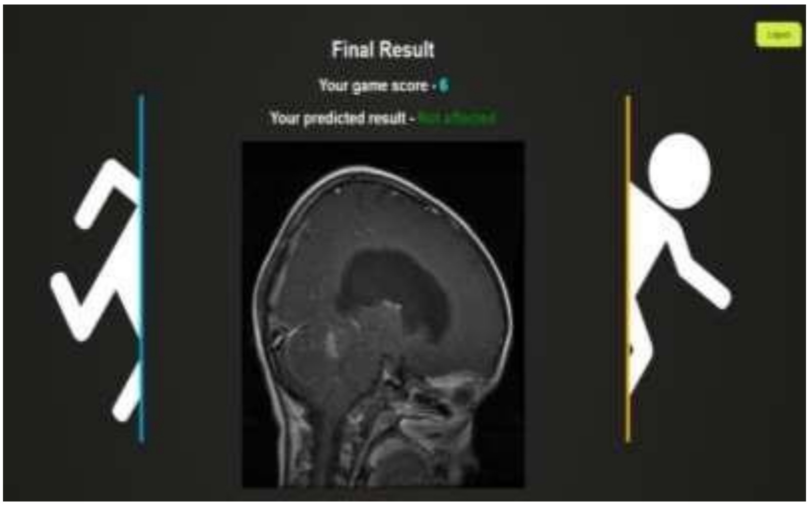


Fig 4.8 Result

4.5 UML DIAGRAMS

4.5.1 USE CASES DIAGRAM

A use case defines the interactions between external actors and the system under consideration to accomplish a goal. Actors must be able to make decisions, but need not be human: "An actor might be a person, a company or organization, a computer program or a computer system — hardware, software, or both

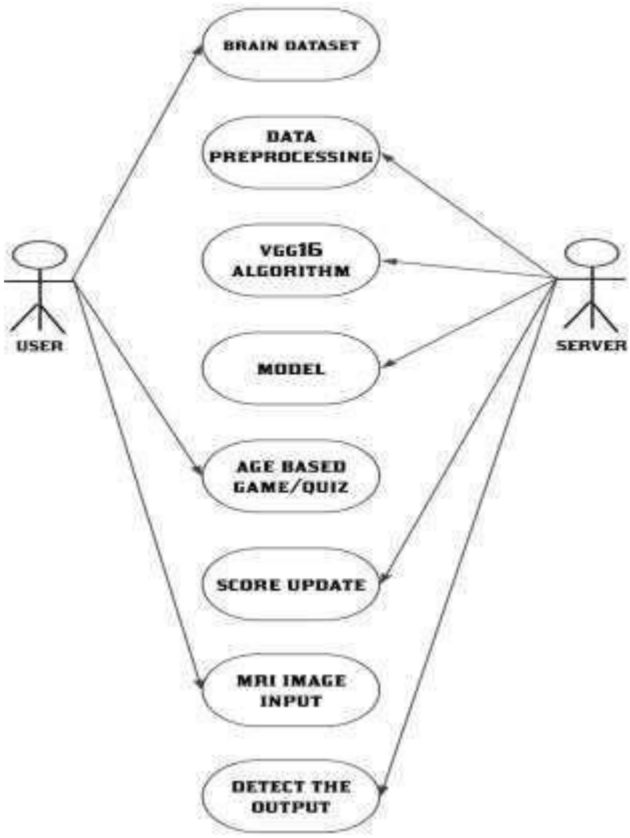


Fig 4.9: Use case diagram

4.5.2 ACTIVITY DIAGRAM

A diagram of the sequence of movements or actions of people or things involved in a complex system or activity and a graphical representation of a computer program in relation to its sequence of functions (as distinct from the data it processes).

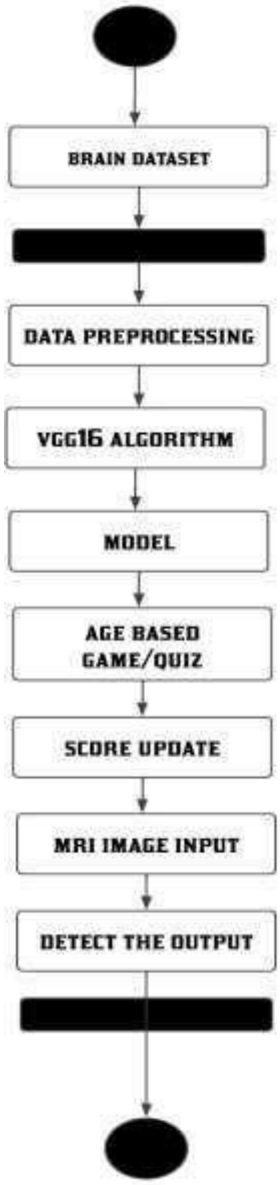


Fig 4.10: Activity diagram

4.5.3 DATA FLOW DIAGRAM (DFD)

DFD represents the data flow of a system or process. It also provides information on each entity's inputs, outputs, and the process itself. There are no loops, control flows, or decision rules in DFD. A flowchart can illustrate specific operations based on the type of data. This graphical application is helpful for facilitating communication between staff members, managers, and users. It is helpful for examining both suggested and current systems.

LEVEL 0

LEVEL 1

LEVEL 2

Fig 4.11: Dataflow diagram

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 INTRODUCTION

System Implementation uses the structure created during architectural design and the results of system analysis to construct system elements that meet the stakeholder requirements and system requirements developed in the early life cycle phases. These system elements are then integrated to for intermediate aggregates and finally the complete system- of-interest.

5.2 SYSTEM CONFIGURATION

5.2.1 HARDWARE SYSTEM CONFIGURATION

Processor	-	I3, i5, i7, AMD
RAM	-	Above 6 GB
Hard Disk	-	500 GB

5.2.2 SOFTWARE SYSTEM CONFIGURATION

Operating System	-	Windows 7/8/10
Front end	-	HTML, CSS
Scripts	-	Python
Tool	-	Python IDLE (3.10 64-bit)

5.3 VGG16 ALGORITHM

In this project, the VGG16 algorithm, a deep convolutional neural network architecture, plays a pivotal role in addressing the challenge of pulmonary disease detection using chest X-ray images. VGG16 is harnessed as a pre-trained model on the ImageNet dataset, exemplifying the power of transfer learning. It serves as a feature extractor, capturing intricate patterns within the images, which are crucial for identifying subtle abnormalities and disease markers. Furthermore, VGG16 takes on the role of classification, categorizing the chest X-ray images as indicative of pulmonary diseases or not. What makes VGG16 particularly valuable in this context is its ability to bridge the gap between diagnostic accuracy and computational efficiency, showcasing that even with limited medical data, it can rival more complex systems. Overall, VGG16's incorporation enriches the project's capabilities, making accurate and accessible pulmonary disease detection a reality, even in data-constrained scenarios.

Table 1: VGG16 Configuration

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

5.4 WORKING OF VGG16 ALGORITHM

The VGG16 algorithm is a deep convolutional neural network (CNN) that is widely used for image classification tasks. Here's a simplified overview of how the VGG16 algorithm works:

1. Input Image

The algorithm takes an input image, typically in the form of a two- dimensional grid of pixel values. In the case of this project, the input image is a medical image, such as a CT scan or a histopathology image of lung tissue.

2. Feature Extraction

VGG16 is composed of multiple convolutional layers stacked on top of each other. These layers are responsible for feature extraction. Each convolutional layer applies a set of learnable filters or kernels to the input image. These filters convolve over the image to detect various features, such as edges, textures, and more complex patterns. As the image passes through these layers, higher-level features are progressively extracted.

3. Pooling Layers

Interspersed between the convolutional layers are pooling layers, typically max-pooling layers. Pooling reduces the spatial dimensions of the feature maps while retaining essential information. It helps in making the network more computationally efficient and robust to variations in the input.

4. Fully Connected Layers

After several convolutional and pooling layers, the feature maps are flattened into a one-dimensional vector. This vector is then passed through fully connected layers, also known as dense layers. These layers perform classification based on the extracted features. The final fully connected layer has as many neurons as there are classes for classification. In this project, the classes represent different types of lung diseases or conditions.

5. SoftMax Activation

The output layer typically uses the SoftMax activation function. SoftMax converts the raw scores (logits) produced by the final fully connected layer into probabilities. Each probability corresponds to the likelihood of the input image belonging to a specific class (e.g., lung cancer or a specific lung condition).

6. Training

Before deployment, the VGG16 algorithm undergoes training on a labeled dataset of medical images. During training, the model adjusts its internal parameters (weights and biases) to minimize the difference between its predicted probabilities and the actual labels. This process, known as backpropagation, is guided by a loss function (e.g., categorical cross-entropy).

7. Inference

During inference or prediction, when a new, unlabeled medical image is presented to the trained VGG16 model, it processes the image through the layers, computes class probabilities using the SoftMax function, and assigns the image to the class with the highest probability.

8. Output

The output of the VGG16 algorithm is the predicted class label for the input medical image, indicating the type of lung disease or condition detected.

In summary, the VGG16 algorithm works by extracting hierarchical features from input medical images through a deep network of convolutional layers, followed by classification using fully connected layers. Its ability to learn complex patterns and its adaptability through fine-tuning make it a valuable tool for image-based classification tasks, including the detection of lung diseases in this project.

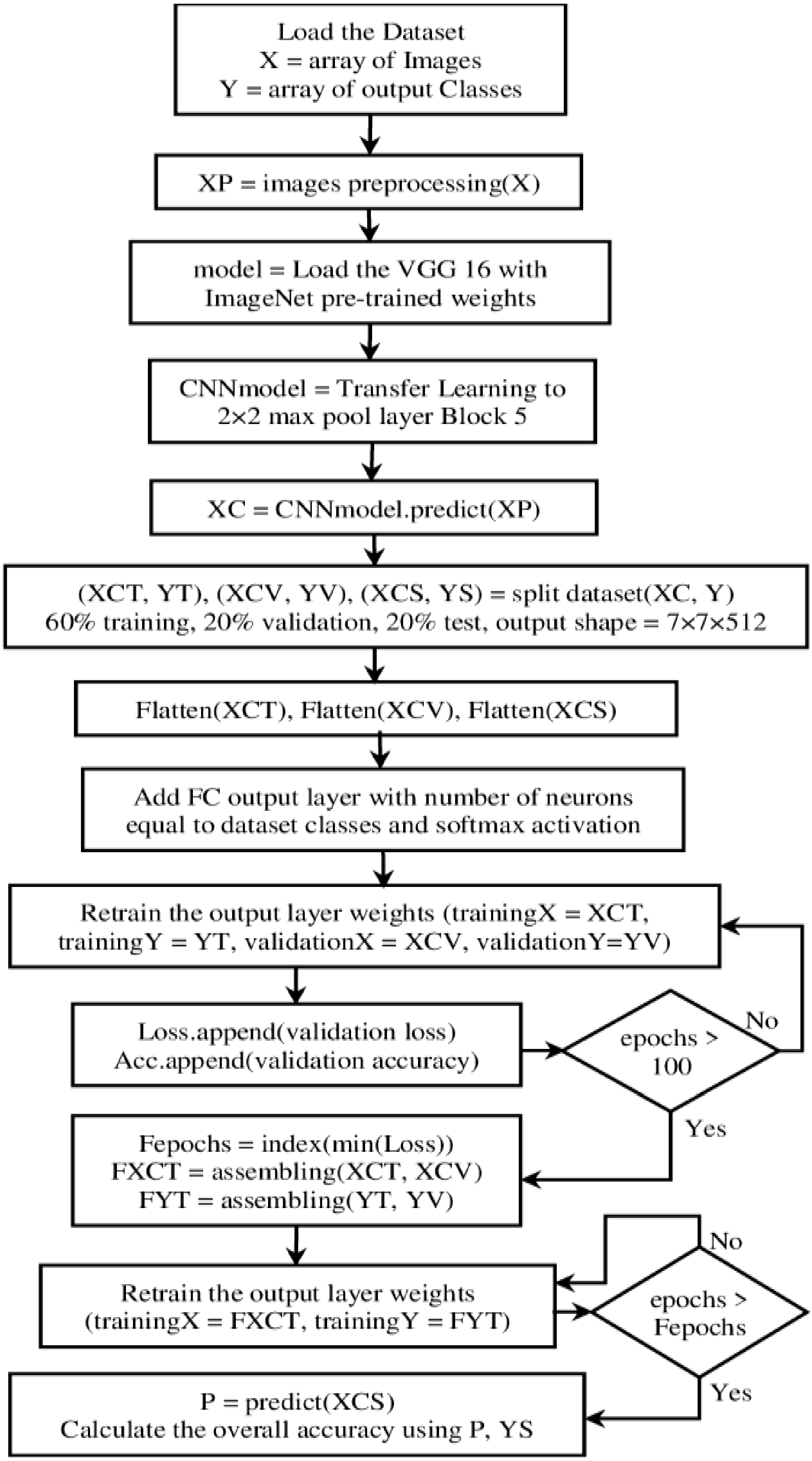


Fig 5.1: Flowchart of VGG16 Algorithm

5.5 PSEUDOCODE FOR VGG16 ALGORITHM

1. Define the VGG16 architecture (omitting specific layer configurations) Initialize VGG16 model
2. Load pre-trained weights (optional) Load pre-trained weights if available
3. Forward pass through the network image = LoadImage()
4. Load the input image

feature_map = ForwardPass(VGG16, image) # Perform feature extraction

5. Flatten the feature map flattened_features = Flatten(feature_map)
6. Fully connected layers for classification

fc1_output = FullyConnectedLayer1(flattened_features)
fc2_output = FullyConnectedLayer2(fc1_output) output_logits = OutputLayer(fc2_output)

7. Apply softmax activation to obtain class probabilities
class_probabilities = Softmax(output_logits)
8. Select the class with the highest probability as the predicted class
predicted_class = argmax(class_probabilities)
9. Output the predicted class label
Output(predicted_class)

5.6 ADVANTAGES OF VGG16 ALGORITHM

- VGG16 is adept at extracting rich and hierarchical features from images. Its deep architecture with multiple convolutional layers captures both low-level and high-level features, making it suitable for recognizing intricate patterns.
- The ability to leverage pre-trained VGG16 models on large-scale datasets like ImageNet provides a head start for new tasks. Transfer learning with VGG16 often requires less training data and can lead to faster convergence.
- The deep architecture of VGG16 allows for visualizing the activations and learned features in various layers, aiding in model interpretability and understanding of what the model is capturing in the data.

CHAPTER 6

RESULT & DISCUSSION

6.1 INTRODUCATION

Look at a picture and find all the faces in it. Focus on each face and be able to understand that even if a face is turned aside or in bad lighting, it is still the same person. Able to pick out unique features of the face that you can use to tell it apart from other people— like how big the eyes are, how long the face is, etc. Compare the unique features of that face to all the people you already know to determine the person’s name and marks attendance with time of entry automatically.

6.2 PERFORMANCE MEASURE AND OPTIMIZATION

6.2.1 INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system.

Input Design considered the following things:

- What data should be given as input?
- How the data should be arranged or coded?
- The dialog to guide the operating personnel in providing input.
- Methods for preparing input validations and steps to follow when error occur.
- Input Design is the process of converting a user-oriented description of the input into a computer-based system.

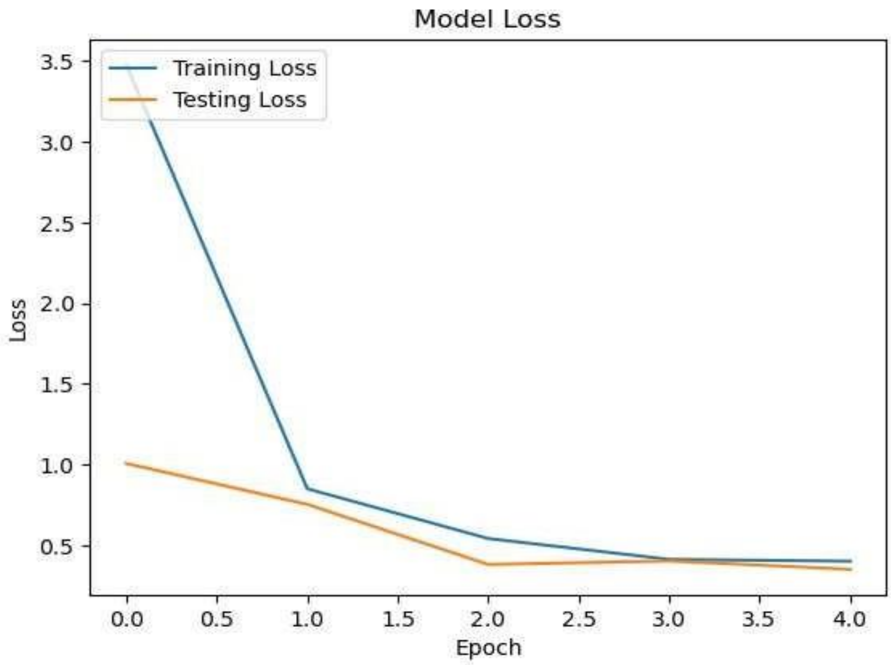


Fig 6.1 Model Loss

6.2.2 OUTPUT DESIGN

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

- Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.

- Select methods for presenting information.

- Create document, report, or other formats that contain information produced by the system. The output form of an information system should accomplish one or more of the following objectives.
- Convey information about past activities, current status or projections of the future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action

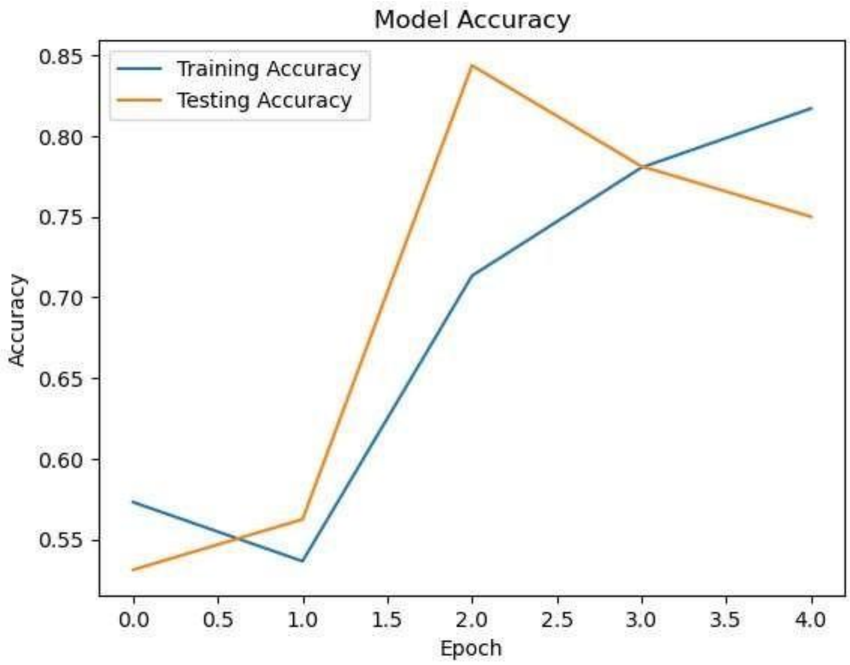


Fig 6.2 Model Accuracy

6.3 SOFTWARE TESTING

6.3.1 WHITE BOX TESTING

White box testing is a software testing method that focuses on an application's internal structure, logic, and coding, rather than its functionality. It's also known as structural, code-based, or glass box testing. White box testing provides a tester with complete knowledge of the application being tested, including access to source code and design documents. This in-depth visibility makes it possible for white box testing to identify issues that are invisible to gray and black box testing.

6.3.2 UNIT TESTING

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

6.3.3 BLACK BOX TESTING

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box you cannot “see” into it. The test provides inputs and responds to outputs without considering how the software works.

6.3.4 FUNCTIONAL TEST

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input : identified classes of valid input must be accepted.

Invalid Input : identified classes of invalid input must be rejected.

Functions : identified functions must be exercised.

6.3.5 INTEGRATION TESTING

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

6.3.6 SYSTEM TESTING

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre- driven process links and integration points.

CHAPTER 7

CONCLUSION & FUTURE ENHANCEMENT

7.1 CONCLUSION

The Integrated Framework for Autism Prediction, incorporating personalized gaming, quizzing, and MRI analysis using the VGG16 algorithm, represents a significant advancement in early ASD detection. Through the seamless integration of multidisciplinary approaches, this framework offers a holistic and efficient solution for predicting ASD likelihood in children. By leveraging personalized gaming and quizzing activities, the framework assesses cognitive abilities, social interaction, and communication skills, providing valuable insights into ASD risk factors. Additionally, MRI analysis using the VGG16 algorithm enables the extraction of features indicative of ASD pathology from brain images, further enhancing the predictive capabilities of the framework. In conclusion, the Integrated Framework for Autism Prediction holds immense potential in revolutionizing the early detection and intervention of ASD. By empowering healthcare professionals with a comprehensive predictive tool, this framework aims to improve outcomes and quality of life for individuals with ASD and their families. The Integrated Framework for Autism Prediction stands as a pivotal advancement in the domain of early Autism Spectrum Disorder (ASD) detection, harnessing a multidisciplinary approach that integrates personalized gaming, quizzing, and MRI analysis using the VGG16 algorithm. This innovative framework offers a comprehensive solution, bridging various facets of ASD assessment to provide a nuanced understanding of ASD likelihood in children. Through the incorporation of personalized gaming and quizzing activities, the framework delves into cognitive abilities, social interaction, and communication skills, capturing subtle nuances that may indicate ASD risk factors. These interactive components not only engage participants but also facilitate the gathering of rich data crucial for accurate assessment. Moreover, the integration of MRI analysis, powered by the VGG16 algorithm, adds a layer of sophistication by extracting features indicative of ASD pathology directly from brain images. This enables a deeper exploration of neurological markers associated with

ASD, further enhancing the framework's predictive capabilities. By providing healthcare professionals with a comprehensive predictive tool grounded in multidisciplinary research, this framework aims to transform outcomes and improve the quality of life for individuals with ASD and their families. Its holistic approach marks a significant milestone in the quest to address the complexities of ASD, paving the way for more effective interventions and support systems.

7.2 FUTURE ENHANCEMENT

To augment the capabilities of the Integrated Framework for Autism Prediction, several feature enhancements can be explored. One avenue involves integrating additional assessment modalities, such as eye-tracking technology or speech analysis, to offer a more comprehensive evaluation of ASD risk factors. These modalities can capture subtle cues and nuances in behavior and communication, further enriching the assessment process. Furthermore, the implementation of advanced machine learning algorithms holds promise in refining the predictive model, enhancing its accuracy and efficiency in identifying ASD likelihood. By leveraging cutting-edge techniques, the framework can adapt and evolve, continuously improving its predictive capabilities. Another key enhancement involves the development of personalized intervention strategies based on individualized assessment results. Tailoring interventions to the specific needs and strengths of each participant can optimize outcomes and support their unique developmental journey. Additionally, incorporating longitudinal data analysis into the framework enables the tracking of changes in behavioral and neurological markers over time. This longitudinal approach facilitates the detection of developmental trajectories and allows for dynamic adjustments to intervention plans as needed. Collaboration with interdisciplinary teams and stakeholders is crucial for validating and refining the framework in diverse clinical settings. By soliciting feedback from healthcare professionals, educators, caregivers, and individuals with ASD, the framework can be iteratively improved to ensure its effectiveness and scalability.

APPENDICES

A.1 SDG GOALS

Goal 3

Ensuring Good Health and Well-being: Target 3.4 focuses on reducing premature deaths caused by non-communicable diseases, which includes mental health conditions such as ASD. This involves raising awareness, improving detection, and enhancing treatment for such conditions.

Goal 4

Providing Quality Education: Target 4.5 aims to guarantee equal access to education and vocational training for vulnerable groups, including people with disabilities like ASD. Detecting ASD early enables timely intervention and support, ultimately improving educational outcomes for affected individuals.

Goal 10

Promoting Reduced Inequalities: Target 10.2 highlights the importance of empowering and socially including all individuals, regardless of their background or status. This entails ensuring that people with ASD have equitable access to healthcare, education, and employment opportunities.

A.2 SOURCE CODE

Test-1.ipynb

```
import numpy as np

from tensorflow.keras.preprocessing.image import ImageDataGenerator from

tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Flatten, Dense

from tensorflow.keras.applications.vgg16 import VGG16

IMG_HEIGHT, IMG_WIDTH = 224, 224

train_datagen = ImageDataGenerator(rescale=1/255)

train_generator = train_datagen.flow_from_directory(

    'dataset/train',

    target_size=(IMG_HEIGHT, IMG_WIDTH), batch_size=32,

    classes=['affected', 'not affected'], class_mode='categorical'

)

test_datagen = ImageDataGenerator(rescale=1./255)

test_generator = test_datagen.flow_from_directory(

    'dataset/test',


    target_size=(IMG_HEIGHT, IMG_WIDTH), batch_size=32,

    classes=['affected', 'not affected'], class_mode='categorical'


)

train_dataset = train_datagen.flow_from_directory(directory = r'dataset/train',

                                                  target_size = (224,224),

                                                  class_mode = 'categorical',

                                                  subset = 'training', batch_size

                                                  = 128)

valid_dataset = test_datagen.flow_from_directory(directory = r'dataset/train',
```

```
                                    target_size = (224,224),

                                    class_mode = 'categorical',

                                    subset = 'validation',

                                    batch_size = 128)

import matplotlib.pyplot as plt import

numpy as np

from tqdm import tqdm

fig, ax = plt.subplots(nrows=1, ncols=5, figsize=(20, 20)) for i

in tqdm(range(0, 5)):

  rand1 = np.random.randint(len(train_generator)) batch =

  train_generator[rand1]

  image_batch, label_batch = batch[0], batch[1] rand2

  = np.random.randint(len(image_batch))

  ax[i].imshow(image_batch[rand2]) ax[i].axis('off')


  label = label_batch[rand2] if

  label[0] == 1:

    ax[i].set_title('Not Affected')

  elif label[1] == 1:

    ax[i].set_title('Affected')

plt.show()

base_model = VGG16(weights='imagenet',include_top=False,
```

```
input_shape=(IMG_HEIGHT, IMG_WIDTH, 3))

base_model = VGG16(weights='imagenet', include_top=False,
input_shape=(IMG_HEIGHT, IMG_WIDTH, 3))

for layer in base_model.layers:

 layer.trainable = False

model = Sequential([

    base_model, Flatten(),

    Dense(128, activation='relu'),

    Dense(2, activation='softmax')  # Adjusted to match the number of classes

])

model.summary()

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

try:

    history = model.fit(

        train_generator,
        steps_per_epoch=train_generator.samples // train_generator.batch_size,

        epochs=5,

        validation_data=test_generator, validation_steps=test_generator.samples //

        test_generator.batch_size

    )

    #        Save        the        model

    model.save('model_vgg16.h5')
```

```
except Exception as e: print("Error
    during training:", e)
import matplotlib.pyplot as plt plt.plot(history.history['accuracy'],
label='Training Accuracy') plt.plot(history.history['val_accuracy'],
label='Testing Accuracy')
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc='upper left') plt.show()
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Testing Loss')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')

plt.legend(loc='upper left')
plt.show()
import numpy as np
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
from skimage.io import imshow
from skimage.transform import resize
```

```
# Assuming model and test_dataset are defined elsewhere in your code #

Mapping of class indices to class labels

dic = test_dataset.class_indices


idc = {k: v for v, k in dic.items()} #

Load and preprocess image

img_path = r'Y21.jpg'

img = image.load_img(img_path, target_size=(224, 224))

img_array = image.img_to_array(img)

img_array = img_array / 255.0 # Normalize pixel values

plt.imshow(img_array)

plt.axis('off')

# Expand dimensions to match model input shape

img_array = np.expand_dims(img_array, axis=0) #


Predict using the model

result = model.predict(img_array)

# Determine prediction based on result if

result[0][1] > result[0][0]:

    prediction = "Not affected"

    probability = result[0][1]

else:

    prediction = "afftected"
```

```
   probability = result[0][0]

print("Prediction:", prediction)


print("Probability:", probability)

import numpy as np

from tensorflow.keras.preprocessing import image

import matplotlib.pyplot as plt

from skimage.io import imshow

from skimage.transform import resize

# Assuming model and test_dataset are defined elsewhere in your code #

Mapping of class indices to class labels

dic = test_dataset.class_indices idc

= {k: v for v, k in dic.items()} #

Load and preprocess image

img_path = r'3 no.jpg'

img = image.load_img(img_path, target_size=(224, 224))

img_array = image.img_to_array(img)

img_array = img_array / 255.0 # Normalize pixel values

plt.imshow(img_array)

plt.axis('off')

# Expand dimensions to match model input shape

img_array = np.expand_dims(img_array, axis=0) #
```

Predict using the model

```
result = model.predict(img_array)

# Determine prediction based on result if

result[0][1] > result[0][0]:

    prediction = "Not affected"

    probability = result[0][1]

else:

    prediction = "Affected"

     probability = result[0][0]

print("Prediction:", prediction)

print("Probability:",  probability)
```

app.py

```
from flask import Flask, render_template, request, jsonify,redirect from

flask_cors import CORS  # Import CORS

import sys

import os import

glob import re

import numpy as np

from keras.applications.imagenet_utils import preprocess_input, decode_predictions
from keras.models import load_model

from keras.preprocessing import image

from tensorflow.keras.models import Model, load_model import

numpy as np

import cv2

import os

from glob import glob

from PIL import Image

from skimage import transform

from flask import Flask, redirect, url_for, request, render_template, jsonify from

werkzeug.utils import secure_filename

from gevent.pywsgi import WSGIServer import

sqlite3
```

A.3 SCREENSHOTS

Test-1.ipynb

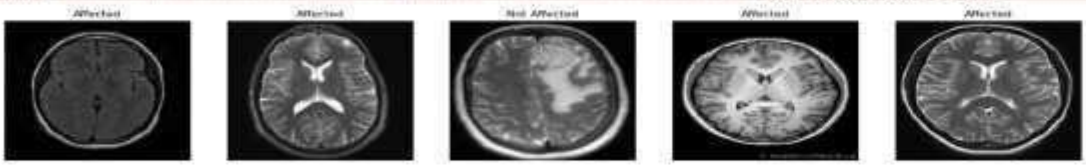
```
In [1]: import numpy as np
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Flatten, Dense
        from tensorflow.keras.applications.vgg16 import VGG16
```

```
In [2]: IMG_HEIGHT, IMG_WIDTH = 224, 224

        train_datagen = ImageDataGenerator(rescale=1/255)
        train_generator = train_datagen.flow_from_directory(
            'dataset/train',
            target_size=(IMG_HEIGHT, IMG_WIDTH),
            batch_size=32,
            classes=['affected', 'not affected'],
            class_mode='categorical'
        )

        test_datagen = ImageDataGenerator(rescale=1./255)
        test_generator = test_datagen.flow_from_directory(
            'dataset/test',
            target_size=(IMG_HEIGHT, IMG_WIDTH),
            batch_size=32,
            classes=['affected', 'not affected'],
            class_mode='categorical'
        )

        Found 196 images belonging to 2 classes.
        Found 46 images belonging to 2 classes.
```

```
In [3]: train_dataset  = train_datagen.flow_from_directory(directory = r'dataset/train',
                                                           target_size = (224,224),
                                                           class_mode = 'categorical',
                                                           subset = 'training',
                                                           batch_size = 128)

        Found 196 images belonging to 2 classes.
```

```
In [4]: valid_dataset = test_datagen.flow_from_directory(directory = r'dataset/train',
                                                          target_size = (224,224),
                                                          class_mode = 'categorical',
                                                          subset = 'validation',
                                                          batch_size = 128)

        Found 0 images belonging to 2 classes.
```

```
In [5]: import matplotlib.pyplot as plt
        import numpy as np
        from tqdm import tqdm

        fig, ax = plt.subplots(nrows=1, ncols=5, figsize=(20, 20))

        for i in tqdm(range(0, 5)):
            rand1 = np.random.randint(len(train_generator))
            batch = train_generator[rand1]
            image_batch, label_batch = batch[0], batch[1]
            rand2 = np.random.randint(len(image_batch))
            ax[i].imshow(image_batch[rand2])
            ax[i].axis('off')
            label = label_batch[rand2]
            if label[0] == 1:
                ax[i].set_title('Not Affected')
            elif label[1] == 1:
                ax[i].set_title('Affected')
        plt.show()

        100%|██████████| 5/5 [00:01<00:00,  3.45it/s]
```



Data Pre-processing

```
In [6]: base_model = VGG16(weights='imagenet', include_top=False, input_shape=(IMG_HEIGHT, IMG_WIDTH, 3))

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kerne
ls_notop.h5
58889256/58889256 [==============================] - 8s 0us/step
```

```
In [8]: base_model = VGG16(weights='imagenet', include_top=False, input_shape=(IMG_HEIGHT, IMG_WIDTH, 3))
        for layer in base_model.layers:
            layer.trainable = False
```

```
In [9]: model = Sequential([
            base_model,
            Flatten(),
            Dense(128, activation='relu'),
            Dense(2, activation='softmax')  # Adjusted to match the number of classes
        ])
```

```
In [10]: model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 128)               3211392

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 17,926,338
Trainable params: 3,211,650
```

```
In [11]: model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

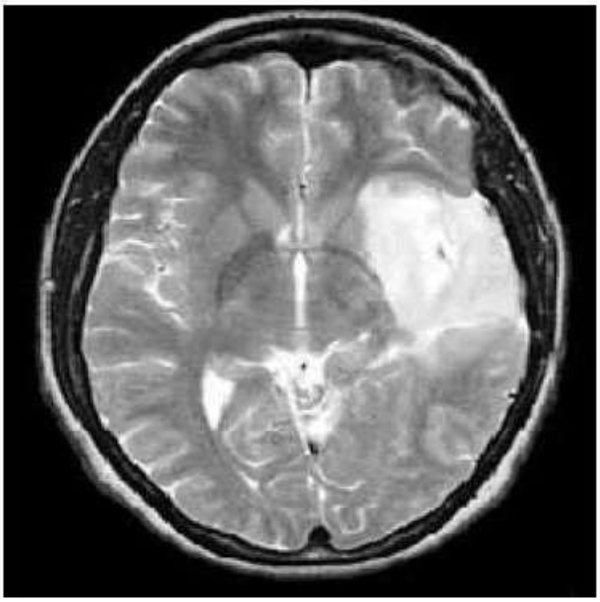
```
In [12]: try:
             history = model.fit(
                 train_generator,
                 steps_per_epoch=train_generator.samples // train_generator.batch_size,
                 epochs=5,
                 validation_data=test_generator,
                 validation_steps=test_generator.samples // test_generator.batch_size
             )

             # Save the model
             model.save('model_vgg16.h5')

         except Exception as e:
             print("Error during training:", e)

Epoch 1/5
6/6 [==============================] - 72s 11s/step - loss: 3.4769 - accuracy: 0.5732 - val_loss: 1.0072 - val_accuracy: 0.5312
Epoch 2/5
6/6 [==============================] - 56s 9s/step - loss: 0.8510 - accuracy: 0.5366 - val_loss: 0.7543 - val_accuracy: 0.5625
Epoch 3/5
6/6 [==============================] - 61s 10s/step - loss: 0.5424 - accuracy: 0.7134 - val_loss: 0.3817 - val_accuracy: 0.8438
Epoch 4/5
6/6 [==============================] - 61s 10s/step - loss: 0.4134 - accuracy: 0.7805 - val_loss: 0.4036 - val_accuracy: 0.7812
Epoch 5/5
6/6 [==============================] - 60s 10s/step - loss: 0.4020 - accuracy: 0.8171 - val_loss: 0.3518 - val_accuracy: 0.7500
```

Installation of VGG16

```
In [21]: import numpy as np
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
from skimage.io import imshow
from skimage.transform import resize

# Assuming model and test_dataset are defined elsewhere in your code

# Mapping of class indices to class labels
dic = test_dataset.class_indices
idc = {k: v for v, k in dic.items()}

# Load and preprocess image
img_path = r'Y21.jpg'
img = image.load_img(img_path, target_size=(224, 224))
img_array = image.img_to_array(img)
img_array = img_array / 255.0  # Normalize pixel values
plt.imshow(img_array)
plt.axis('off')

# Expand dimensions to match model input shape
img_array = np.expand_dims(img_array, axis=0)

# Predict using the model
result = model.predict(img_array)

# Determine prediction based on result
if result[0][1] > result[0][0]:
    prediction = "Not affected"
    probability = result[0][1]
else:
    prediction = "afftected"
    probability = result[0][0]

print("Prediction:", prediction)
print("Probability:", probability)
```

```
1/1 [==============================] - 0s 432ms/step
Prediction: afftected
Probability: 0.639222
```

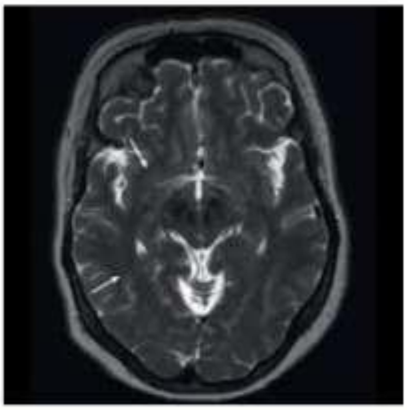

```
1/1 [==============================] - 0s 432ms/step
Prediction: afftected
Probability: 0.639222
```

Separation of 2 classes

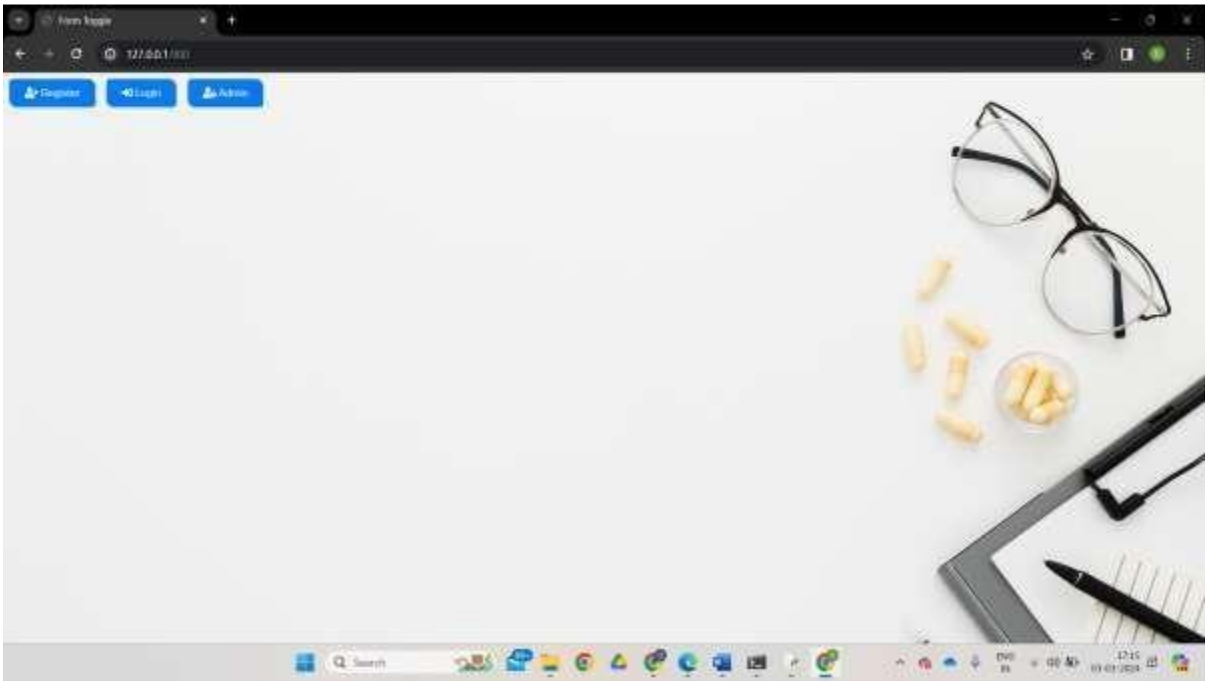
```
In [23]: import numpy as np
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
from skimage.io import imshow
from skimage.transform import resize

# Assuming model and test_dataset are defined elsewhere in your code

# Mapping of class indices to class labels
dic = test_dataset.class_indices
idc = {k: v for v, k in dic.items()}

# Load and preprocess image
img_path = r'3 no.jpg'
img = image.load_img(img_path, target_size=(224, 224))
img_array = image.img_to_array(img)
img_array = img_array / 255.0  # Normalize pixel values
plt.imshow(img_array)
plt.axis('off')

# Expand dimensions to match model input shape
img_array = np.expand_dims(img_array, axis=0)

# Predict using the model
result = model.predict(img_array)

# Determine prediction based on result
if result[0][1] > result[0][0]:
    prediction = "Not affected"
    probability = result[0][1]
else:
    prediction = "Affected"
    probability = result[0][0]

print("Prediction:", prediction)
print("Probability:", probability)
```

```
1/1 [==============================] - 0s 460ms/step
Prediction: Not affected
Probability: 0.8744502
```

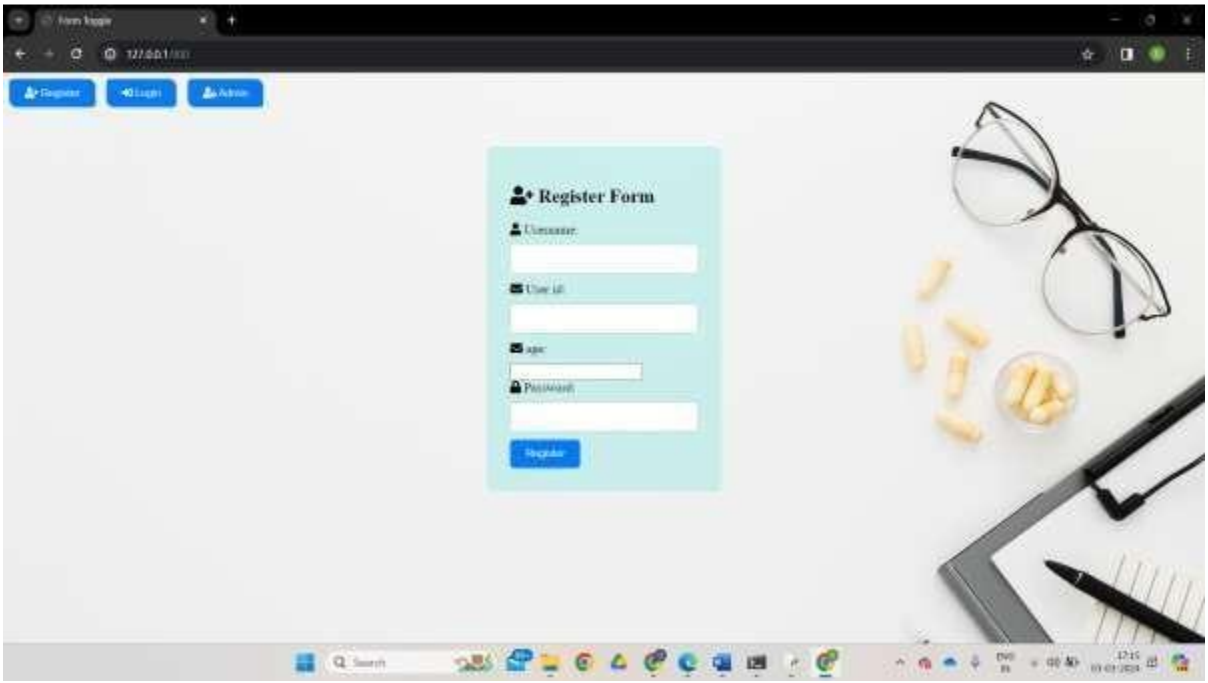


```
In [ ]:
```

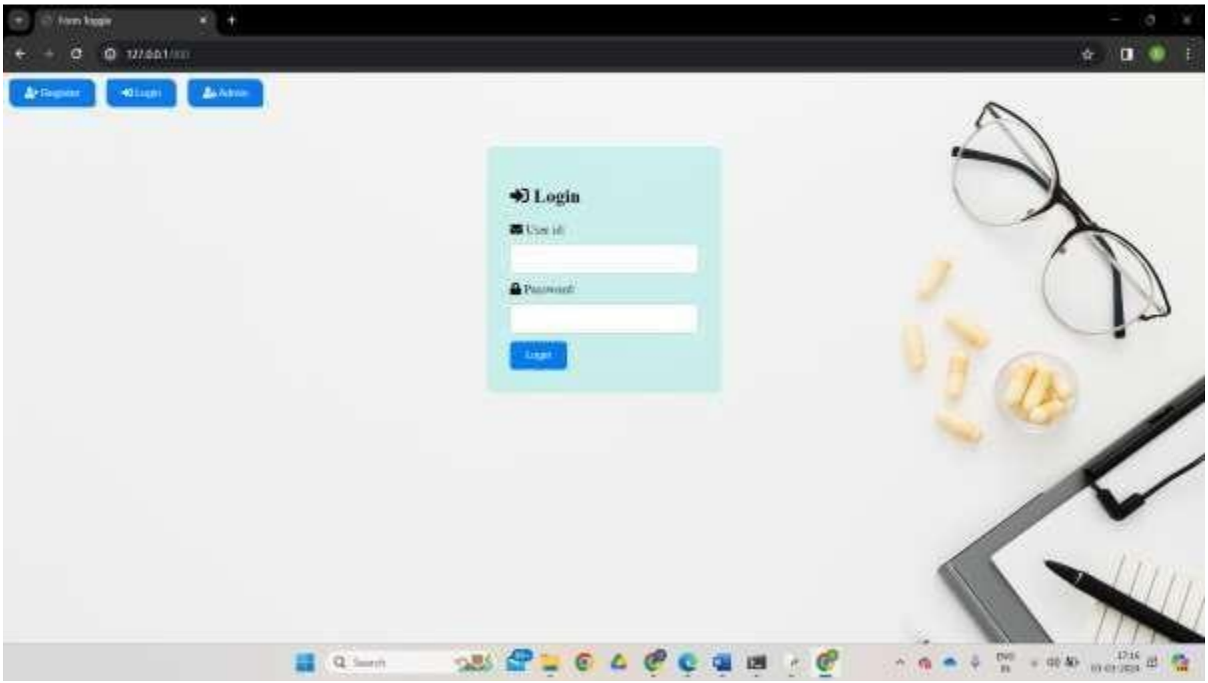
Affected vs Not Affected



Home page



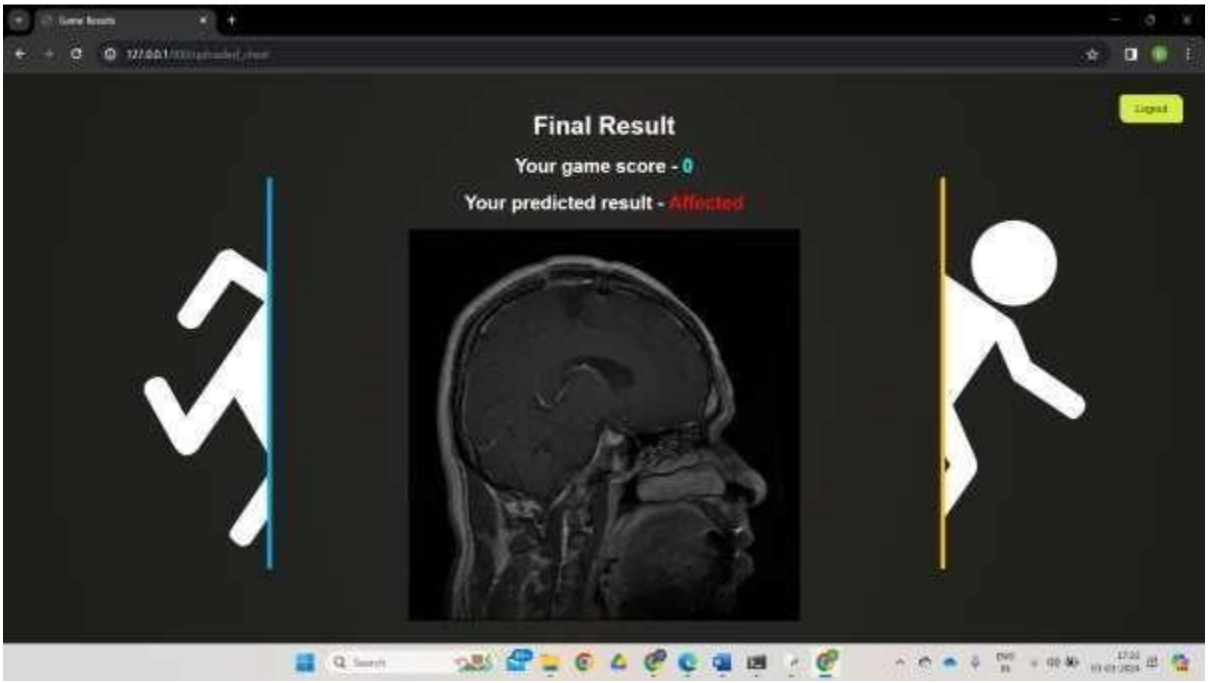
Registration page



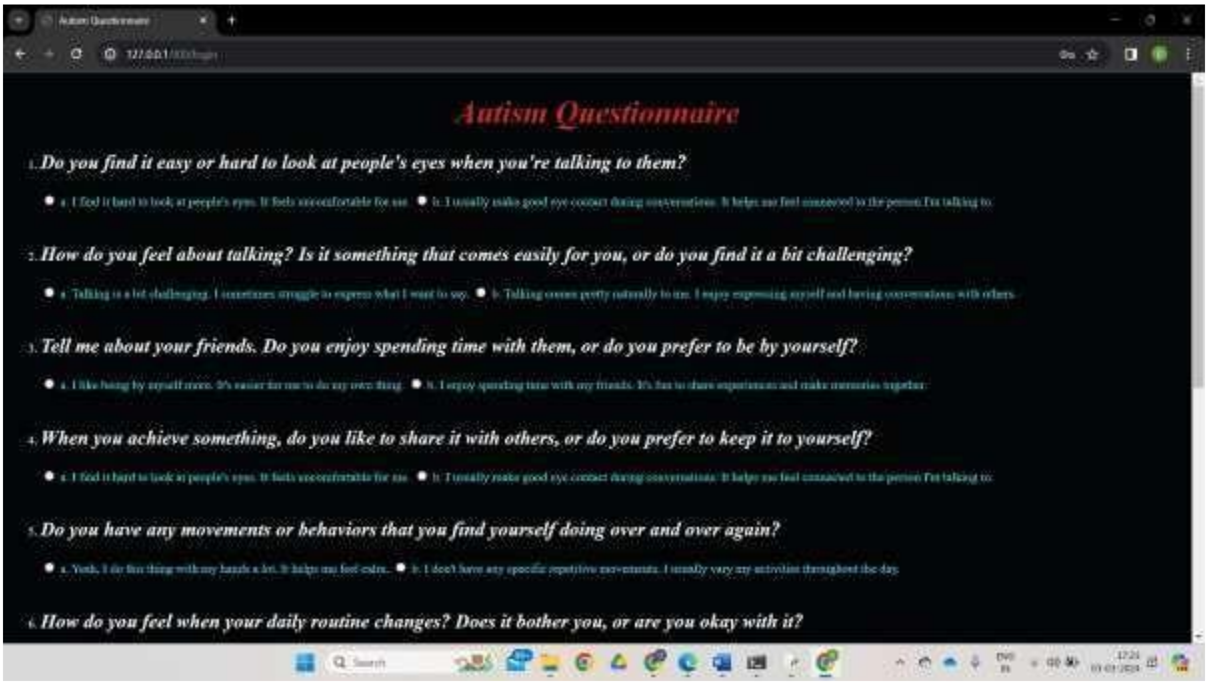
Login Page

Game (3-8)

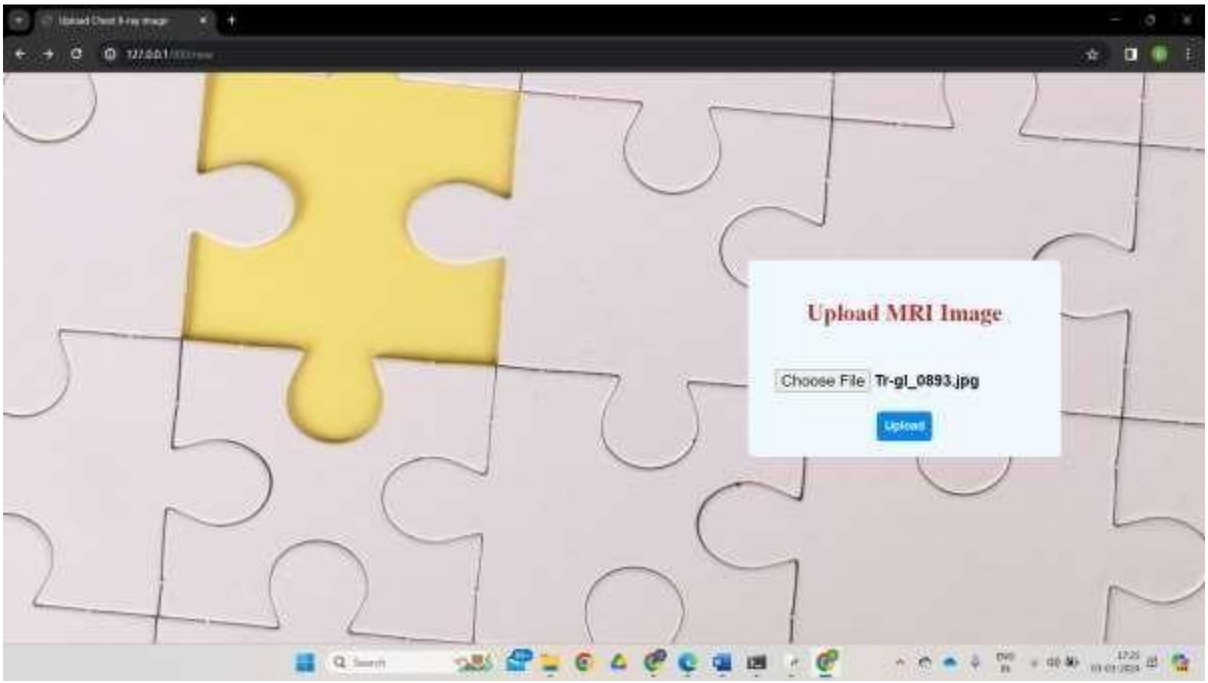
Game (3-8)



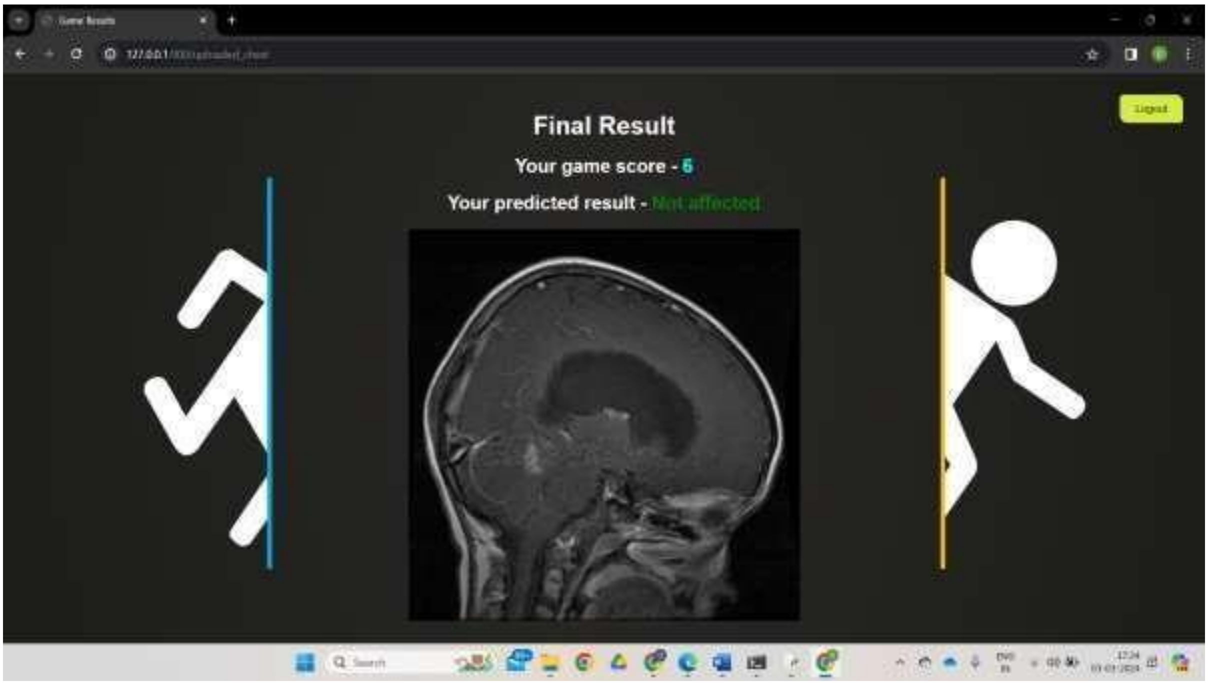
Result for the above game



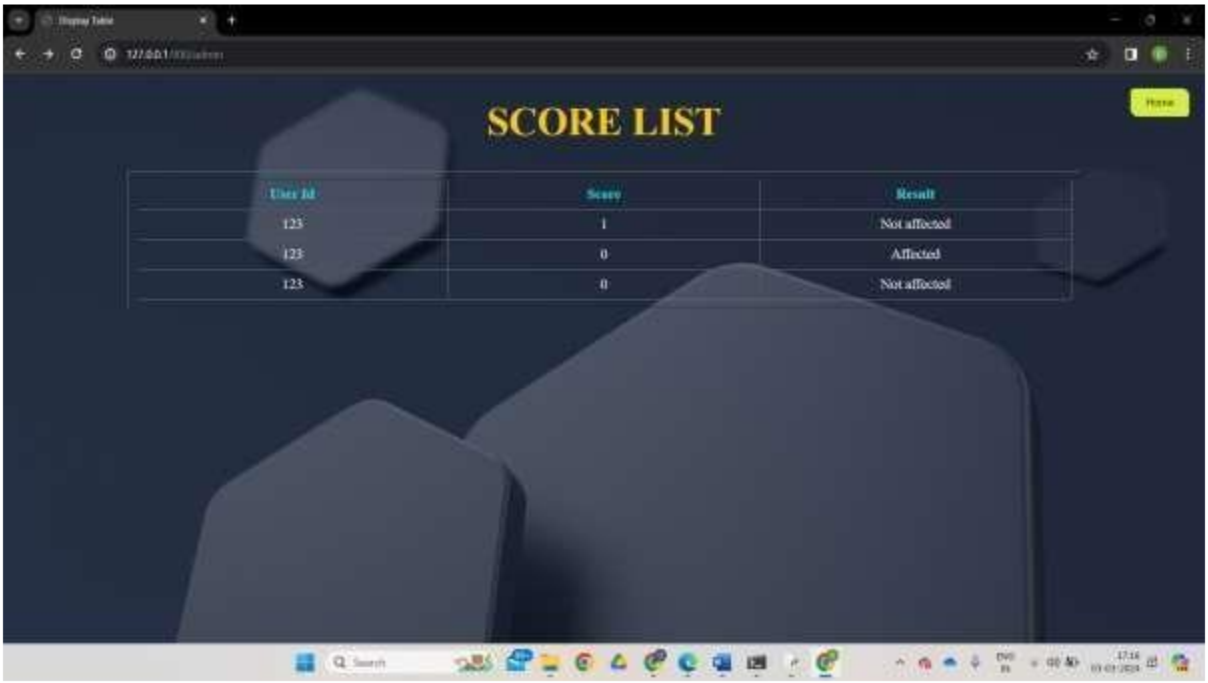
Game (9-20)



Uploading of MRI images

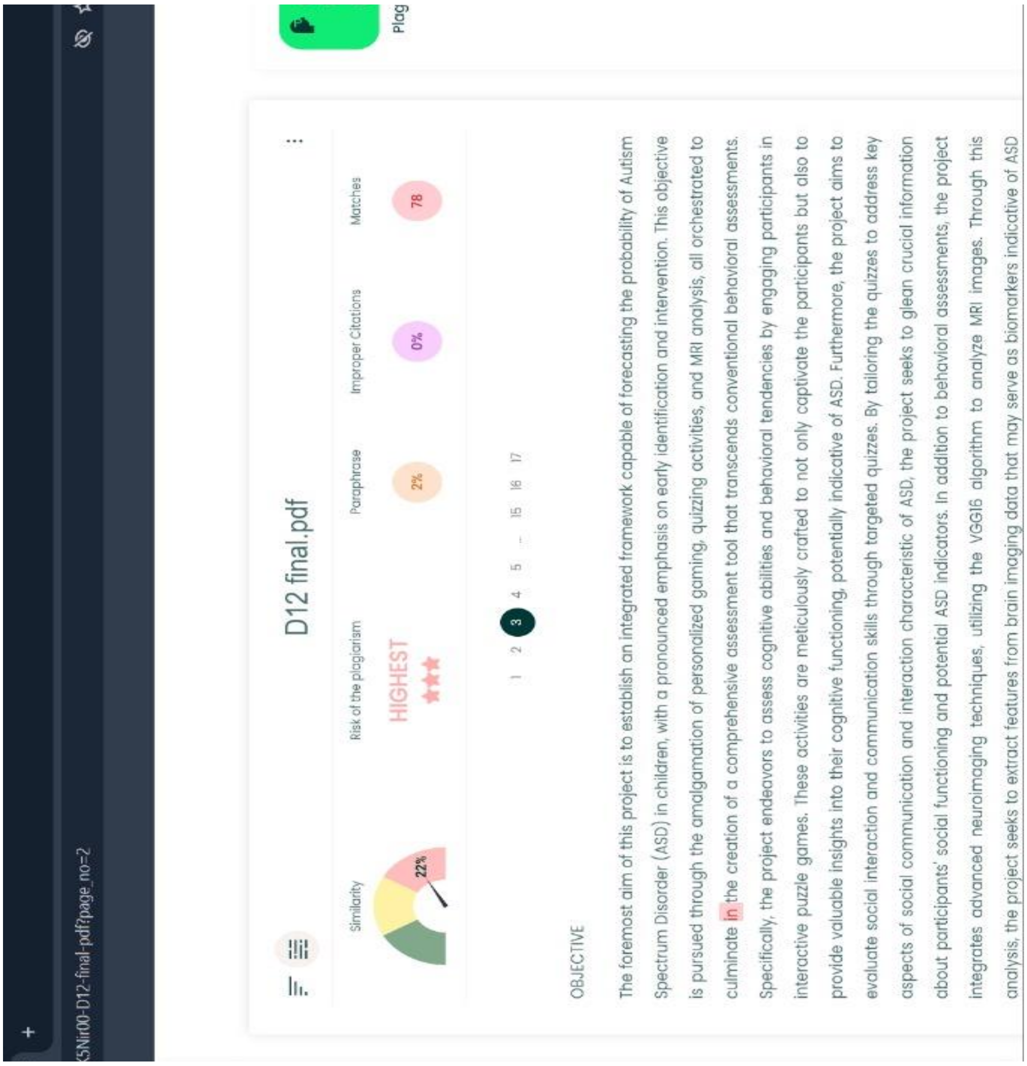


Result



Dataset

A.4 PLAGIARISM REPORT



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