VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY
(An Autonomous Institute Affiliated to University of Mumbai)
Department of Computer Engineering

Project Report on

Cognitive Care

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

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University of Mumbai
(AY 2023-24)

VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

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CERTIFICATE

This is to certify that the Mini Project entitled **"Cognitive Care"** is a bonafide work of **Amit Murkalmath (D12C 47)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

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Mini Project Approval

This Mini Project entitled "**Cognitive Care"** by **Amit Murkalmath (47)** is approved for the degree of **Bachelor of Engineering** in **Computer Engineering.**

Examiners

1……………………………………….
(Internal Examiner Name & Sign)

2………………………………………….
(External Examiner name & Sign)

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

This study proposes an innovative approach to tackle Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) by combining medical expertise with modern technology. Through the integration of Health Expertise and Machine Learning (ML), we aim to create a robust software platform for early detection and improved patient recovery. Our method involves analyzing neurological data to uncover patterns crucial for informed decision-making in managing AD and MCI. Additionally, our software incorporates cognitive games tailored for Alzheimer's patients to enhance cognitive functions and engagement, along with a community forum designed for support and shared experiences. Furthermore, we utilize a Convolutional Neural Network (CNN) model for efficient classification of AD, ensuring accurate diagnosis. This research promises to reshape the landscape of cognitive disorder diagnosis and treatment, offering hope for better outcomes for patients and their families.

1.Introduction

1.1 Introduction:

The advancements in medical imaging and machine learning have opened new avenues for the early detection and management of complex neurological conditions such as Alzheimer's disease and Mild Cognitive Impairment (MCI). Magnetic Resonance Imaging (MRI) scans, with their ability to reveal intricate structural details of the brain, have become a valuable resource for comprehending cognitive disorders. This project aims to harness the potential of machine learning to detect Alzheimer's disease and MCI through analysis of MRI scans. Additionally, recognizing the need for comprehensive care, the project also undertakes the development of an innovative recovery algorithm. This synergy of advanced data analysis and recovery algorithm development, the project aspires to significantly impact the early diagnosis and management of cognitive disorders.

1.2 Motivation:

Alzheimer's Disease is a very common disease and it's very rampant and many of the times overlooked by society. Alzheimer's disease (AD) and other forms of dementia are a growing public health problem among the elderly in developing countries, whose aging population is increasing rapidly. Studies say estimated dementia prevalence for adults ages 60+ in India is 7.4%, with significant age and education gradients, sex and urban/rural differences, and cross-state variation. An estimated 8.8 million Indians older than 60 years have dementia. The burden of dementia cases is unevenly distributed across states and subpopulations and may therefore require different levels of local planning and support. These were some of the facts that forced us to realize that it's a grave issue which needs to be addressed and an effective solution needs to be built for the same. Also one of our group members' relatives suffered from the same and the said relative recently passed away. This kind of gave our project a different push and meaning. So we were more than determined to make sure our project reached the masses and served the purpose it was intended to do. Thus, these were some of the points that motivated us to choose this project.

1.3 Problem Definition:

Alzheimer's disease and Mild Cognitive Impairment (MCI) stand as prominent challenges in modern healthcare due to their progressively debilitating impact on cognitive function and quality of life. With the help of technology and advancements in medical imaging the project aims to develop an innovative and user-friendly software solution that can accurately identify individuals with Alzheimer's disease or Mild Cognitive Impairment (MCI) and also provide personalized recovery measures and progress tracking for individuals diagnosed with these conditions.

1.4 Existing System:

The current landscape of Alzheimer's disease (AD) detection research is marked by multifaceted challenges and limitations. Primarily, the scarcity of publicly available large datasets hinders research progress, limiting the availability of labeled datasets crucial for training robust machine learning models. The consequent lack of data affects model accuracy and the comprehensiveness of studies, impeding the development of effective diagnostic tools. Moreover, the issue of class imbalance, characterized by variations in the number of samples across different classes (AD, Mild Cognitive Impairment (MCI), normal), poses a significant challenge to the performance of machine learning algorithms. Addressing these challenges necessitates efforts to expand dataset availability and mitigate class imbalances to improve the reliability of AD detection systems.

Furthermore, transparency and replicability suffer due to the lack of detailed model information, including architecture, training procedures, and hyperparameter settings. This opacity inhibits researchers' ability to verify and build upon existing methodologies, hindering the advancement of the field. Additionally, the restricted use of fusion techniques for integrating information from diverse sources, coupled with an overemphasis on single biomarkers such as medial temporal lobe atrophy (MTA), limits the robustness of AD detection systems. Integrating multiple biomarkers, including cerebrospinal fluid analysis (CSF) and Positron Emission Tomography (PET) imaging, could enhance diagnostic accuracy and reliability. Quality concerns related to poor image quality during pre-processing further jeopardize the accuracy of AD detection, highlighting the need for standardized imaging protocols and rigorous quality control measures. Lastly, the omission of influential factors such as gender, brain size, and age corrections in brain volume calculations undermines diagnostic accuracy and complicates the interpretation of results. Overcoming these challenges requires collaborative efforts to improve dataset availability, enhance transparency in model development, and integrate diverse biomarkers for more accurate and reliable AD detection systems.

1.5 Lacuna in the Existing System:

Despite significant advancements in Alzheimer's disease (AD) detection research, several critical lacunae persist, impeding the development of robust diagnostic tools and hindering progress towards effective treatment and management strategies. One major gap lies in the limited availability of comprehensive datasets for training and testing machine learning models. The scarcity of large-scale, publicly accessible datasets constrains researchers' ability to develop and validate algorithms effectively. This shortage not only hampers the accuracy of AD detection systems but also impedes the generalizability and scalability of research findings. Addressing this lacuna necessitates collaborative efforts to establish standardized datasets encompassing diverse populations, disease stages, and imaging modalities, thereby enabling the development of more robust and widely applicable diagnostic tools.

Moreover, a notable lacuna in the existing system pertains to the lack of holistic approaches integrating multiple biomarkers and clinical data for AD diagnosis. Many current studies focus on isolated biomarkers or imaging modalities, overlooking the potential synergies and complementary information offered by integrating diverse sources of data. For instance, while medial temporal lobe atrophy (MTA) is commonly used as a biomarker in AD detection, its utility can be enhanced by incorporating additional markers such as cerebrospinal fluid (CSF) analysis and positron emission tomography (PET) imaging. By leveraging multimodal datasets and advanced analytical techniques, researchers can gain deeper insights into the complex pathophysiology of AD and develop more accurate and reliable diagnostic algorithms. Bridging this lacuna requires interdisciplinary collaboration among researchers from various fields, including neurology, radiology, bioinformatics, and machine learning, to synergistically leverage diverse data sources and expertise. Additionally, initiatives aimed at standardizing data collection protocols and promoting data sharing across institutions can facilitate the development of comprehensive datasets necessary for advancing AD detection research. Ultimately, addressing these lacunae will be pivotal in enhancing the accuracy, reliability, and clinical utility of AD diagnostic tools, thereby improving patient outcomes and advancing our understanding of this debilitating neurodegenerative disease.

1.6 Relevance of the Project:

Our mini project titled “Cognitive Care” to detect Alzheimers’ Disease overcomes a lot of problems faced by the current system. Our project combines Agile development principles and also aims to give much better results than the existing systems. Our system aims to not only enable intervention and provide detection like other systems but also empower patients on their journey towards cognitive improvement. Through the collaborative efforts of medical expertise, software development, and iterative refinement, we aim to create a meaningful and impactful solution that addresses the complexities of Alzheimer's disease and MCI. And approval from verified and top doctors in the field would give an impetus to our application too. A much simpler and interactive UI would ensure more user participation and superior user experience. Thus, these are some of the main features that sets us apart from the rest of the other systems and how our application contributes to society.

2. Literature Survey

A.Brief Overview of Literature Survey

Performing a literature survey in a research paper is a fundamental step that serves multiple crucial purposes. Firstly, it provides context and background information, allowing readers to comprehend the problem's significance and what has previously been investigated in the field. By thoroughly reviewing existing literature, researchers can pinpoint gaps, inconsistencies, or areas where additional research is required, helping to define their research question and scope. This process also enables researchers to build upon the work of others, advancing the field and demonstrating that their research is a meaningful contribution to an ongoing scholarly conversation. Moreover, it aids in the avoidance of duplicating studies that have already been conducted, emphasizing originality.

B.Related Works

Early detection and classification of Alzheimer's disease (AD) is a critical area of research given the progressive nature of the disease and the potential for early intervention to improve patient outcomes. Here's some information on related works in the literature:

1. **Machine Learning Techniques for Early Detection**:Many studies have explored the use of machine learning algorithms for early detection of Alzheimer's disease using various types of data, including neuroimaging data (such as MRI and PET scans), genetic data, and clinical data.Techniques such as support vector machines (SVM), random forests, deep learning, and ensemble methods have been applied to classify patients into Alzheimer's disease, mild cognitive impairment (MCI), and healthy control groups based on biomarkers.
2. **Neuroimaging Biomarkers**:Neuroimaging techniques play a crucial role in the early detection of Alzheimer's disease. Studies have investigated structural changes in the brain, such as hippocampal atrophy and cortical thinning, as potential biomarkers for early diagnosis.Functional MRI (fMRI) studies have also been conducted to analyze functional connectivity patterns in the brain associated with Alzheimer's disease.
3. **Biomarkers in Cerebrospinal Fluid (CSF)**:Analysis of cerebrospinal fluid biomarkers, such as amyloid-beta and tau proteins, has shown promise in the early detection of Alzheimer's disease. Changes in the levels of these biomarkers can

indicate the presence of amyloid plaques and neurofibrillary tangles, which are characteristic pathological features of AD.

4. **Genetic Markers**:Genetic factors play a significant role in the risk of developing Alzheimer's disease. Studies have identified several genetic markers, including the apolipoprotein E (APOE) ε4 allele, as well as variants in genes such as APP, PSEN1, and PSEN2, that are associated with an increased risk of developing AD.Genetic screening and analysis can help identify individuals who may be at higher risk of developing Alzheimer's disease, allowing for early interventions or preventive measures.
5. **Multimodal Approaches**:Recent research has focused on combining multiple modalities of data, such as neuroimaging, genetic, and clinical data, to improve the accuracy of early detection and classification of Alzheimer's disease.Multimodal approaches leverage the complementary information provided by different types of data to better capture the complex and heterogeneous nature of the disease.

2.1 Research Papers Referred

1. **M. Talo, O. Yildirim, U. B. Baloglu, G. Aydin, and U. R. Acharya, "Convolutional neural networks for multi-class brain disease detection using MRI images,"** ***Computerized Medical Imaging and Graphics*****, p. 101673, Oct. 2019, doi: https://doi.org/10.1016/j.compmedimag.2019.101673.**

Abstract :- The importance of early detection of brain disorders and the challenges associated with manual diagnosis using MRI images. To address these challenges, the study employs deep learning models, including AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50, to automatically classify MR images into various disease classes. The research compares their performance and identifies ResNet-50 as the most accurate model, achieving a classification accuracy of 95.23% ± 0.6. The study highlights the potential for this model to be used for testing with a large dataset of MRI images, aiding clinicians in validating their findings after manual examination.

Findings :- Application of convolutional neural networks (CNNs) for the multi-class classification of brain diseases using MRI images. Aim to develop an automated system that can accurately classify brain MRI images into different disease categories, including normal, cerebrovascular, neoplastic, degenerative, and inflammatory diseases. Comparing the performance of different pre-trained CNN models, such as AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50.

2. **S. El-Sappagh et al., “Alzheimer’s disease progression detection model based on an early fusion of cost-effective multimodal data,” Future Generation Computer Systems, vol. 115, pp. 680–699, Feb. 2021, doi: https://doi.org/10.1016/j.future.2020.10.005.**

Abstract :- This study focuses on predicting Alzheimer's disease (AD) progression over 2.5 years. It compares five machine learning algorithms using data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. What makes this research unique is the inclusion of time-series features such as patient comorbidities, cognitive scores, medication history, and demographics, along with semantic preparation of medication and comorbidity text data. The results show that early fusion of these features significantly improves predictive power, with the random forest model performing the best. This study is the first of its kind to explore the role of multimodal time-series data in AD prediction.

Findings :- 4-class classification (CN, sMCI, pMCI, AD).Testing model performance with different datasets. Assessing the importance of features and drug groups.Developing cost-effective models for AD prediction using readily available patient data.

3. **A. De and A. S. Chowdhury, “DTI based Alzheimer’s disease classification with rank modulated fusion of CNNs and random forest,” *Expert Systems with Applications*, vol. 169, p. 114338, May 2021, doi: https://doi.org/10.1016/j.eswa.2020.114338.**

Abstract :- The paper introduces a novel approach for automating the classification of Alzheimer's disease (AD) and related conditions. It uses 3D Diffusion Tensor Imaging (DTI) data, including FA, MD, and EPI intensities. The authors employ Convolutional Neural Networks (CNNs) and a Random Forest Classifier (RFC) for separate training and evaluation. By combining the results using a fusion strategy, they achieve a high classification accuracy of 92.6%. This approach is validated through extensive experiments on the ADNI database, showing its effectiveness in diagnosing AD and related conditions.

Findings :- Classification of Alzheimer's disease using Diffusion Tensor Imaging (DTI) data. Proposed method that combines Convolutional Neural Networks (CNNs) and Random Forest Classifier (RFC) to classify different stages of Alzheimer's disease

4. **M. Rohanian, J. Hough, and M. Purver, "Multi-Modal Fusion with Gating Using Audio, Lexical and Disfluency Features for Alzheimer's Dementia Recognition from Spontaneous Speech," Interspeech 2020, Oct. 2020, doi: https://doi.org/10.21437/interspeech.2020-2721.**

Abstract :- This paper is a submission to the ADReSS challenge, which aims to predict the severity of Alzheimer's Disease using speech data. The authors focus on acoustic and natural language features in spontaneous speech and their connection to Alzheimer's diagnosis and the mini-mental state examination (MMSE) score prediction. They propose a model that uses separate Long Short-Term Memory (LSTM) networks for text and audio data and combines their outputs with a gating mechanism for the final prediction.

Findings :- Study of markers associated with Alzheimer's disease (AD) severity.The document aims to explore lexical markers, disfluency markers (specifically self-repair), and structural markers (with a focus on grammatical fluency) in relation
to AD severity.

5. **X. Zheng, J. Cawood, C. M. Hayre, and S. Wang, "Computer assisted diagnosis of Alzheimer's disease using statistical likelihood-ratio test,"** ***PLOS ONE*****, vol. 18, no. 2, pp. e0279574–e0279574, Feb. 2023, doi: https://doi.org/10.1371/journal.pone.0279574.**

Abstract :- This study employs a statistical likelihood-ratio approach based on signal detection theory. The tool calculates the likelihood ratio using the medial temporal lobe (MTL) volumes obtained from Alzheimer's disease (AD) patients and normal controls (NC). These volume measurements are derived from T1-weighted MRI images using FreeSurfer software. The MRI images come from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, and a separate dataset called Minimal Interval Resonance Imaging in Alzheimer's Disease (MIRIAD) is used for testing. The results show a sensitivity of 89.1% and a specificity of 87.0% for the MIRIAD dataset. These results surpass the performance of the best radiologists, who achieved 85% sensitivity and specificity without using additional patient information.

Findings : - The main focus area of the given paper is the development and validation of a statistical likelihood-ratio procedure for the detection of Alzheimer's disease using MRI T1 weighted images. Specifically, the study focuses on the medial temporal lobe (MTL) volumes of patients with AD and normal controls (NC).

6. **A. Shukla, R. Tiwari, and S. Tiwari, "Review on Alzheimer Disease Detection Methods: Automatic Pipelines and Machine Learning Techniques,"** ***Sci*****, vol. 5, no. 1, p. 13, Mar. 2023, doi: https://doi.org/10.3390/sci5010013.**

Abstract :- Alzheimer's Disease (AD) is becoming increasingly prevalent across the globe, and various diagnostic and detection methods have been developed in recent years. Several techniques are available, including Automatic Pipeline Methods and Machine Learning Methods that utilize Biomarker Methods, Fusion, and Registration for multimodality, to pre-process medical scans. The use of automated pipelines and machine learning systems has proven beneficial in accurately identifying AD and its stages, with a success rate of over 95% for single and binary class classifications. However, there are still challenges in multi-class classification, such as distinguishing between AD and MCI, as well as sub-stages of MCI. The research also emphasizes the significance of using multi-modality approaches for effective validation in detecting AD and its stages.

Findings :- The focus area of the paper is on the detection of Alzheimer's disease (AD) using automated pipelines and fusion-based methods. The paper discusses the challenges in multi-class classification, such as distinguishing between AD and mild cognitive impairment (MCI) and sub-stages of MCI. It emphasizes the significance of using multi-modality approaches, including MRI, PET, and CT modalities, for effective validation in detecting AD and its stages. The paper also explores the importance of pre-processing techniques for feature extraction and the use of machine learning and deep learning algorithms in AD detection.

2.2 Inference Drawn

After analyzing the research papers on the detection and classification of Alzheimer's disease and related brain disorders, several key inferences can be drawn:

1. **Use of Advanced Technologies**: The papers highlight the adoption of advanced technologies, including machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), and diffusion tensor imaging (DTI), for the detection and classification of Alzheimer's disease. These technologies offer promising avenues for automating the diagnosis process and improving accuracy.
2. **Multimodal Data Integration**: Many studies emphasize the importance of integrating multimodal data sources, such as MRI images, patient demographics, cognitive scores, medication history, and speech features, to enhance predictive power and diagnostic accuracy. The fusion of diverse data types allows for a more comprehensive understanding of Alzheimer's disease progression.

3. **Early Detection and Progression Monitoring**: The focus is on early detection and progression monitoring of Alzheimer's disease, aiming to identify the disease at its earliest stages and track its advancement over time. Early detection enables timely intervention and treatment, potentially improving patient outcomes and quality of life.
4. **Performance Evaluation and Comparison**: Several studies compare the performance of different algorithms and models, such as CNN architectures (e.g., AlexNet, Vgg-16, ResNet) and machine learning classifiers (e.g., random forest), for disease classification tasks. These comparisons help identify the most effective approaches and guide future research directions.
5. **Clinical Relevance and Validation**: The research emphasizes the clinical relevance of automated diagnostic systems and the importance of validating their findings against manual diagnoses performed by clinicians. Validating automated systems with large datasets and diverse patient populations is crucial for their successful integration into clinical practice.
6. **Challenges and Opportunities**: Despite significant progress, challenges remain in accurately detecting and classifying Alzheimer's disease, particularly in multi-class classification tasks and distinguishing between different disease stages. Addressing these challenges presents opportunities for further research and innovation in the field.

3. Requirement Gathering for the Proposed System

3.1 Introduction to requirement gathering:

In the realm of healthcare, particularly in the context of Alzheimer's disease (AD), the significance of robust requirement gathering cannot be overstated. Our project endeavors to develop a comprehensive application aimed at the detection and management of AD, with a focus on early intervention, cognitive assessment, caregiver support, and overall patient care. To embark on this ambitious journey, it is imperative to lay a strong foundation through meticulous requirement gathering.

The objective is to delineate the key features and functionalities of our proposed application, which stem from a thorough understanding of the needs and challenges faced by AD patients, caregivers, and healthcare providers. By elucidating these requirements, we aim to elucidate the rationale behind each feature and how it contributes to the overarching goal of enhancing AD detection and management.

3.2 Functional Requirements:

Functional requirements delineate the specific functionalities and features that the application must possess to fulfill its intended purpose effectively. In the context of our Alzheimer's disease (AD) detection and management application, the following functional requirements are crucial:

1. Alzheimer's Disease Detection: The primary objective of our application is early detection, a cornerstone in mitigating the impact of AD. Leveraging state-of-the-art technology such as Convolutional Neural Networks (CNNs), we intend to develop a robust algorithm capable of accurately classifying brain MRI images. This feature is not only pivotal in facilitating timely intervention but also in improving diagnostic accuracy, thus paving the way for more effective treatment strategies.

2. Mini-Mental State Examination (MMSE) Integration: Cognitive assessment forms a fundamental aspect of AD management, providing invaluable insights into disease progression and treatment efficacy. By seamlessly integrating the MMSE test, our application enables healthcare providers to conduct regular cognitive assessments, thereby tailoring treatment plans to the specific needs of individual patients.

3. Cognitive Games: Recognizing the importance of cognitive stimulation in AD patients, we propose the incorporation of cognitive games within our application. These games, designed to be engaging and enjoyable, serve as a means to maintain and potentially improve cognitive function. By offering a fun and interactive platform for cognitive stimulation, we aim to enhance the overall quality of life for AD patients.

4. Appointment Booking System: Timely access to healthcare services is paramount in managing AD and addressing emergent health issues. To this end, our application features an intuitive appointment booking system, enabling AD patients and their caregivers to schedule appointments with ease. By streamlining the process of seeking medical help, we aim to ensure that healthcare services are readily accessible when needed.

5. Caregiver Support: Caregivers play a pivotal role in the care of AD patients, often facing myriad challenges along the way. To provide them with the support they need, our application includes a dedicated caregiver support feature. This feature serves as a community platform where caregivers can connect, share experiences, and access valuable resources, thereby enhancing their ability to provide effective care.

6. User-Friendly Interface: Last but not least, we recognize the importance of designing an application that is not only feature-rich but also user-friendly. An intuitive interface ensures that our application is accessible to users of all technological proficiencies, thereby maximizing its utility and impact.

These functional requirements form the backbone of our AD detection and management application, ensuring that it effectively addresses the needs of users and facilitates comprehensive care for AD patients and their caregivers.

3.3 Non-Functional Requirements:

Non-functional requirements specify criteria that are not directly related to the functionality of the system but are essential for ensuring its overall performance, usability, security, and other quality attributes. In the context of our Alzheimer's disease (AD) detection and management application, the following non-functional requirements are crucial:

1. Performance:

- The application must be responsive and capable of handling multiple concurrent users without significant latency.

- Response times for critical functions such as MRI image classification and MMSE administration should be minimal to ensure a seamless user experience.

2. Scalability:

- The application architecture should be designed to scale horizontally to accommodate increasing user loads over time.
- Additional resources (such as servers or computing power) should be provisioned dynamically to support growing user demands.

3. Reliability:

- The application must be highly reliable, with minimal downtime and robust error handling mechanisms in place.
- Data integrity must be ensured through measures such as regular backups and data validation checks.

4. Security:

- Data privacy and confidentiality must be maintained at all times, adhering to relevant regulations such as HIPAA (Health Insurance Portability and Accountability Act).
- Secure authentication and authorization mechanisms should be implemented to prevent unauthorized access to sensitive information.
- Communication between the application and external systems should be encrypted to protect against data breaches.

5. Usability:

- The application interface should be intuitive and easy to navigate, with clear instructions provided for each feature.
- Accessibility features should be implemented to accommodate users with disabilities or impairments.
- The application should support multiple languages to cater to a diverse user base.

6. Compatibility:

- The application should be compatible with a wide range of devices and operating systems, including desktop computers, laptops, tablets, and smartphones.
- Compatibility testing should be conducted to ensure seamless functionality across different platforms and browsers.

7. Maintainability:

- The application codebase should be well-documented and structured to facilitate future updates and maintenance.
- Modular design principles should be employed to enable easy modification or extension of individual components without impacting the overall system.

8. Performance Efficiency:

- The application should optimize resource usage to minimize energy consumption and operational costs.
- Algorithms for MRI image classification and cognitive assessment should be optimized for efficiency to reduce computational overhead.

9. Regulatory Compliance:

- The application must comply with relevant healthcare regulations and standards, including but not limited to GDPR (General Data Protection Regulation) and FDA (Food and Drug Administration) guidelines.
- Regular audits and compliance checks should be conducted to ensure adherence to regulatory requirements.

These non-functional requirements are essential for ensuring the overall effectiveness, reliability, and security of our AD detection and management application, thereby providing a robust platform for improving patient care and support.

3.4.Hardware, Software , Technology and Tools Utilized

Hardware Requirements:

- CPU: A modern multi-core processor (e.gIntel Core i5 or higher, AMD Ryzen 5 or higher) is sufficient for basic machine learning tasks and small datasets.
- RAM: At least 8 GB of RAM is recommended for handling medium-sized datasets and training relatively small models. However, having 16 GB or more will be beneficial for larger datasets and more complex models.
- GPU (Optional): A dedicated graphics processing unit (GPU) is not strictly required, but having one can significantly speed up training times, especially for deep learning models.
- Storage: A solid-state drive (SSD) is recommended for faster data read/write speeds, which can be beneficial when working with large datasets. A capacity of 256 GB or more is preferable to accommodate datasets and model checkpoints.
- Operating System: You can work on machine learning tasks using Windows, macOS, or Linux.

- Python and Libraries: Install Python and essential libraries for machine learning, such as NumPy, pandas, scikit-learn, TensorFlow, PyTorch, or other libraries.

Software Requirements:

Data Collection and Preprocessing:

- Python (version 3.12).
- Data collection (ADNI) - Alzheimer's Disease Neuroimaging Initiative is a complex and unique collection of data, imaging and biospecimens gathered longitudinally from carefully phenotyped subjects.
- Data preprocessing libraries used are Pandas, NumPy for cleaning and organizing data.
- DICOM (Digital Imaging and Communications in Medicine) tool for medical image data.

Machine Learning Frameworks:

- TensorFlow (version 2.13.0): TensorFlow is designed to efficiently handle large-scale computations, making it well-suited for training complex deep learning models on powerful GPUs or distributed computing clusters. PyTorch uses a dynamic computation graph, which allows for more intuitive debugging and flexible model architectures. This makes it easier to work with irregular and varying input data shapes.
- Scikit-learn (version 1.3.0): Scikit-learn offers a rich set of functionalities for data preprocessing, including handling missing values, feature scaling, and encoding categorical variables. This step is essential to prepare the data for modeling.
- Keras (version 3.7.2) : Keras supports building a wide range of neural network architectures, including feedforward networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers. It allows easy customization of layers, activation functions, and optimization algorithms.

Feature Extraction and Selection:

- Libraries for extracting features from medical images (such as CNN-based architectures).
- Feature selection techniques such as Filter method , Wrapper method are used to enhance model efficiency.

Model Development:

- Various ML algorithms (Classification, Regression) to detect Alzheimer's.
- Ensemble methods (Random Forest, Gradient Boosting) for improved accuracy.
- Convolutional Neural Networks (CNNs) or Transformers for temporal data analysis.
- Natural Language Processing (NLP) techniques for processing medical records.

Treatment Suggestions and Recovery:

- Algorithm for suggesting personalized treatment plans based on patient data and medical knowledge.
- Integration of medical guidelines and literature for evidence-based suggestions.

3.5 Constraints:

While developing our Alzheimer's disease (AD) detection and management application, we must navigate certain constraints that could impact the design, development, and implementation process. These constraints encompass various factors:

1. Limited Access to MRI Datasets:

Due to budgetary constraints and accessibility issues, we may have limited access to diverse and large-scale MRI datasets required for training our machine learning models. This constraint could affect the robustness and accuracy of our AD detection model, as it may not be adequately trained on diverse patient populations.

2. Availability of Expertise:

In this, we may have limited access to specialized expertise in fields such as neurology, radiology, and machine learning. This constraint could impact the depth of our understanding of AD and the sophistication of our technical approaches, as we primarily rely on academic resources and self-learning.

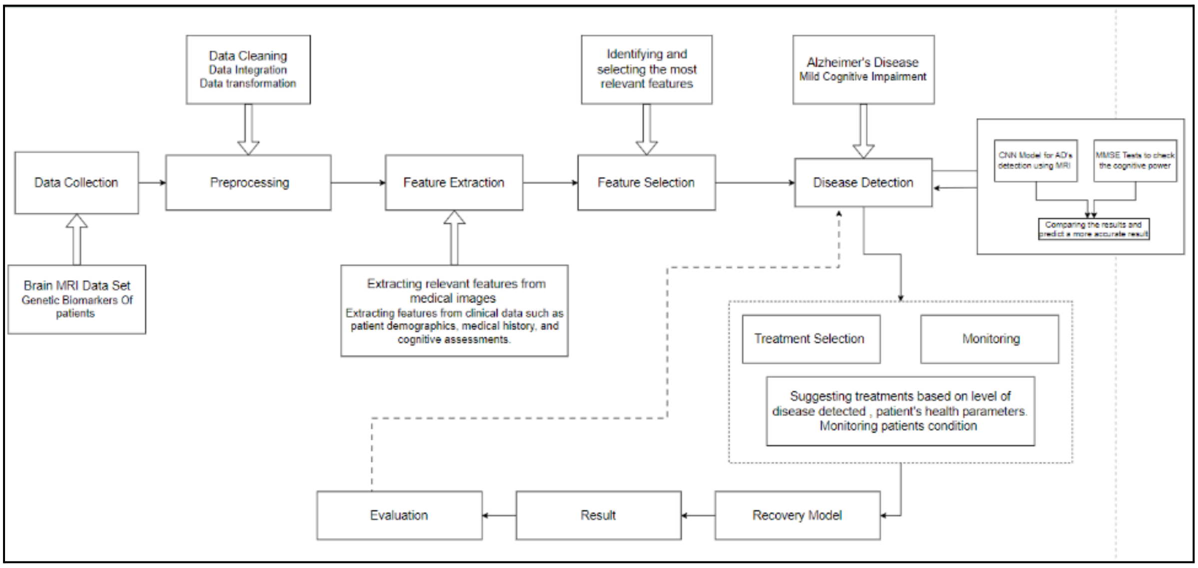
3. Regulatory and Ethical Considerations:

Adhering to ethical guidelines and regulatory requirements, such as patient data privacy laws and institutional review board (IRB) approvals, is paramount in healthcare-related projects. This constraint adds complexity to our project, as we must navigate legal and ethical considerations while conducting research and developing our solution.

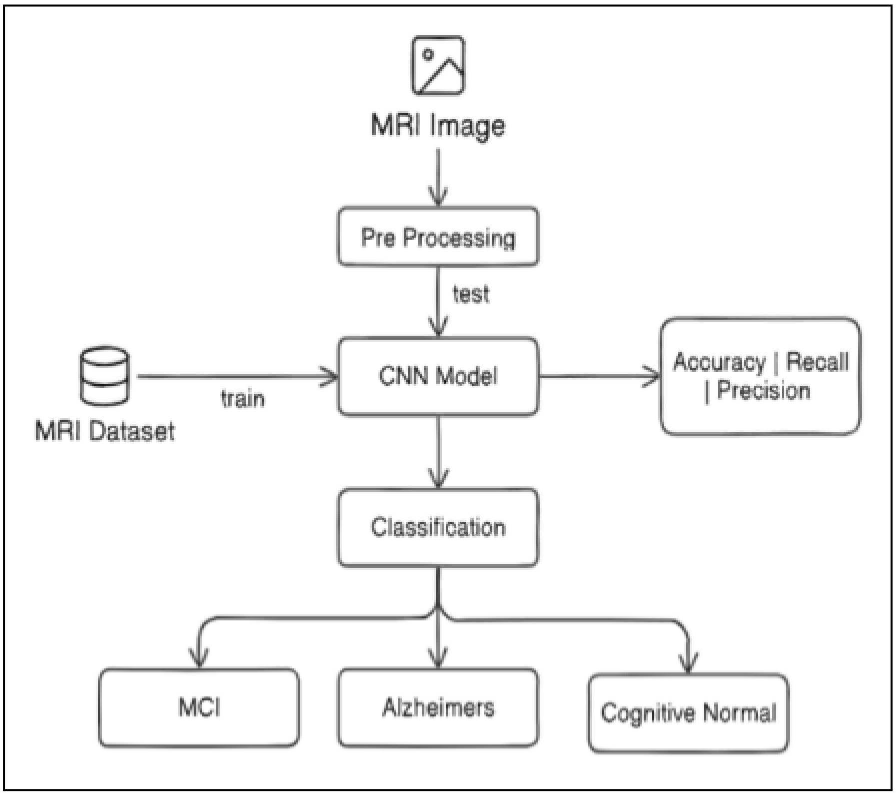
Navigating these constraints requires careful planning, stakeholder engagement, and risk management strategies to mitigate potential impacts on the project's success. By identifying and addressing these constraints proactively, we can effectively manage project risks and ensure the successful development and deployment of our AD detection and management application.

4.Proposed Design

4.1 Block diagram of the system



4.2 Modular design of the system



4.3 Detailed Design

The project architecture described revolves around the development of a Convolutional Neural Network (CNN) model aimed at analyzing Magnetic Resonance Imaging (MRI) scans to detect Alzheimer's disease (AD).

Process Design:

1. **Data Collection and Preprocessing**: Obtain Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) datasets from Kaggle. Preprocess the data to remove noise, handle missing values, and ensure data consistency. Data augmentation techniques are applied to increase the dataset size and diversity.

2. **Feature Extraction**: Extract relevant features from the neurological data, such as brain scans (e.g., MRI images) and patient records. Feature selection techniques may be used to identify the most informative variables.

3. **Model Training for AD's detection**: Split the dataset into training, validation, and test sets. Train the CNN model using the training set with a loss function categorical cross-entropy and optimization algorithm. We monitored the model's performance on the validation set to prevent overfitting.

4. **Model Evaluation**: Evaluated the trained CNN model's performance on the test set using metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve (AUC).

5. **Personalized Treatment Recommendation** : We are planning to implement an algorithm to provide personalized treatment recommendations based on the patient's diagnosis and historical data. Use machine learning techniques to analyze treatment response data and tailor recommendations accordingly.

6. **User Interface Development**: We have created a user-friendly interface for clinicians or users to input patient data and view diagnostic results and treatment recommendations.

This algorithm and process design outlines the steps involved in developing a CNN-based software platform for AD and MCI detection, personalized treatment recommendations.

Modular Design:

The project architecture , Revolves around a Convolutional Neural Network (CNN) model designed to analyze Magnetic Resonance Imaging (MRI) scans for the purpose of detecting Alzheimer's disease (AD). The system takes an MRI dataset as input, which includes scans from individuals diagnosed with AD, Mild Cognitive Impairment (MCI), and those who are cognitively normal. Before feeding the scans into the CNN model, a pre-processing stage is crucial. Here, techniques like normalization and segmentation ensure the images are standardized and formatted for optimal analysis by the CNN model.

The pre-processed scans are then fed into the CNN model, which is a deep learning algorithm adept at image analysis. This model is designed to extract features from the MRI scans that are indicative of AD. To achieve this, the CNN model undergoes a training phase where it is presented with MRI scans and their corresponding labels (AD, MCI, or cognitively normal). Through this training, the model learns to identify patterns in the scans that are associated with each label.

Once trained, the model's performance is evaluated on a separate testing set, which consists of MRI scans the model has not encountered before. Metrics like accuracy, recall, and precision are used to assess the model's effectiveness. Finally, the trained and evaluated model can be employed to classify new MRI scans, providing an output classification of AD, MCI, or cognitively normal.

5. Implementation of the Proposed System

5.1 Methodology employed for development

We adopted an Iterative Development Model for our project, chosen for its adaptability and continuous improvement capabilities. This approach involved dividing the project into manageable iterations, beginning with research to identify Alzheimer's disease detection as our focus. A comprehensive literature survey followed, collecting insights from existing research. We then developed the project, implementing features such as the CNN model, cognitive games, appointment booking, and caregiver support. Subsequent iterations incorporated feedback from the reviews, allowing us to refine the project iteratively. This methodology ensured that we could adapt to evolving requirements, resulting in a comprehensive and refined final project.

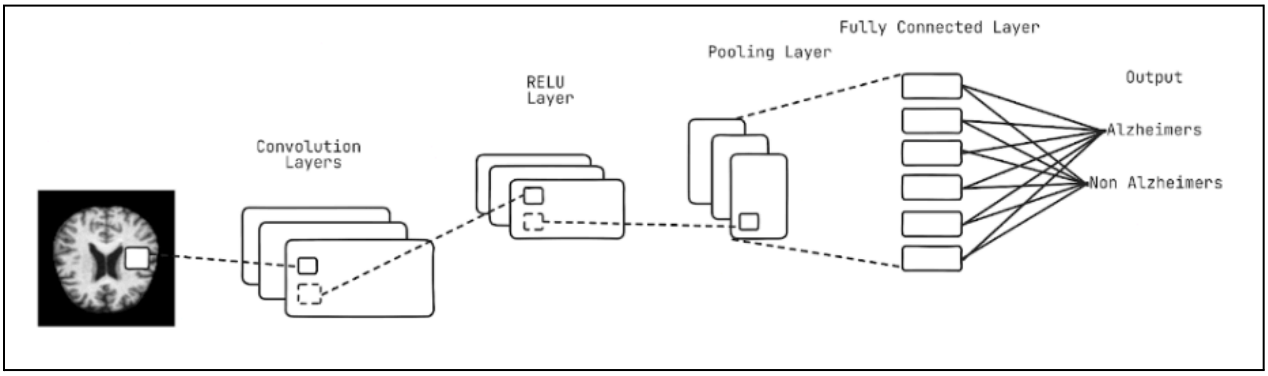
5.2 Algorithm Description

Our Model uses Convolutional Neural Networks to identify the features from the MRI Image And trained the model on a pre-classified Dataset.

Here's a detailed explanation of the CNN algorithm:

1. **Input Layer**: The input to a CNN is typically a multidimensional array, representing an image. For example, a color image might have three channels (Red, Green, Blue), each represented as a 2D array of pixel values.
2. **Convolutional Layer**: The core building block of a CNN is the convolutional layer. This layer applies a set of filters (also called kernels) to the input image. Each filter is a small grid of weights that is convolved with the input image to produce a feature map. The convolution operation involves sliding the filter over the input image, computing element-wise multiplications and summing them up to produce a single value in the feature map.
3. **Activation Function**: After each convolution operation, a non-linear activation function like ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity into the network. This allows the network to learn complex patterns in the data.
4. **Pooling Layer**: Pooling layers are used to reduce the spatial dimensions of the feature maps while retaining important information. Max pooling is a common pooling operation where the maximum value in each local region of the feature map is retained, effectively reducing the size of the feature maps.

5. **Fully Connected Layer**: After several convolutional and pooling layers, the remaining feature maps are flattened into a vector and passed through one or more fully connected layers. These layers perform classification based on the high-level features extracted by the convolutional layers.
6. **Output Layer**: The final fully connected layer produces the output of the network. In a classification task, this layer typically uses a softmax activation function to produce a probability distribution over the classes.
7. **Loss Function**: During training, the output of the network is compared to the ground truth labels using a loss function such as cross-entropy loss. The goal of training is to minimize this loss, typically using optimization techniques like gradient descent.
8. **Backpropagation**: Once the loss is computed, the gradients of the loss with respect to the network parameters are calculated using backpropagation. These gradients are then used to update the parameters of the network through optimization algorithms like stochastic gradient descent (SGD) or Adam.
9. **Training**: The CNN is trained on a labeled dataset using a process called supervised learning. During training, the network learns to extract features from the input images that are relevant for the task at hand (e.g., Alzheimer's detection).
10. **Evaluation**: Once trained, the performance of the CNN is evaluated on a separate test dataset to assess its ability to generalize to unseen data. Metrics such as accuracy, precision, recall, and F1-score are commonly used to evaluate the performance of classification models.



6.Testing of the Proposed System

6.1 Introduction to Testing

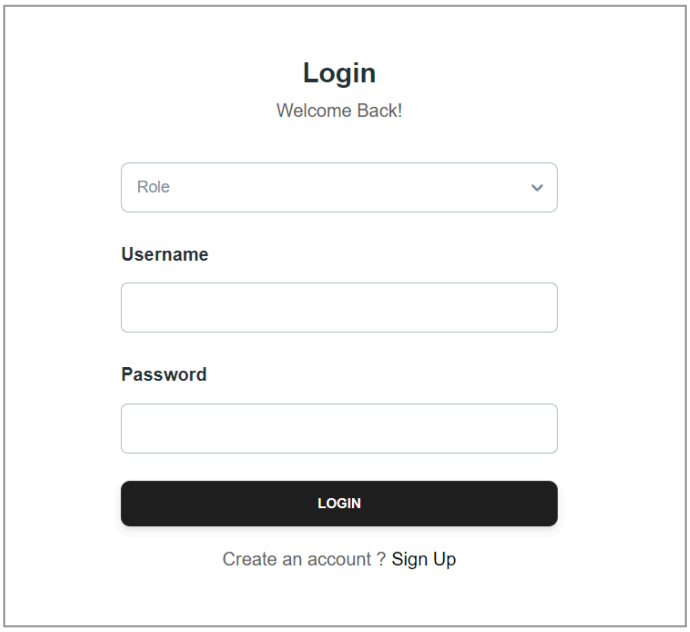
Testing plays a pivotal role in ensuring the effectiveness, reliability, and usability of software applications. In the development of our Alzheimer's disease (AD) detection and management application, testing serves as a crucial phase to validate its functionality and performance. As part of our testing strategy, we have chosen to utilize Selenium, a widely adopted testing framework renowned for its capabilities in automating web application testing.

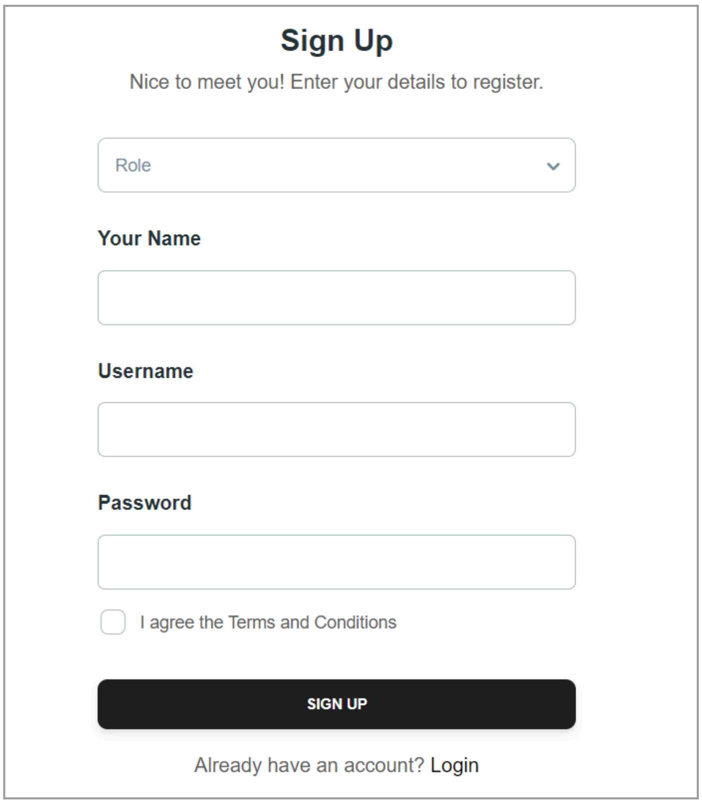
Selenium offers a suite of tools that empower developers to automate testing processes, facilitating thorough evaluation across various browsers and platforms. By harnessing Selenium's automation capabilities, we aim to achieve comprehensive test coverage, ensuring that all critical aspects of our application are thoroughly examined.

This introduction sets the stage for our exploration of testing methodologies and practices employed in the development of our AD detection and management application. Through the utilization of Selenium, we endeavor to streamline our testing processes, enhance efficiency, and deliver a reliable and high-quality solution for AD detection and management.

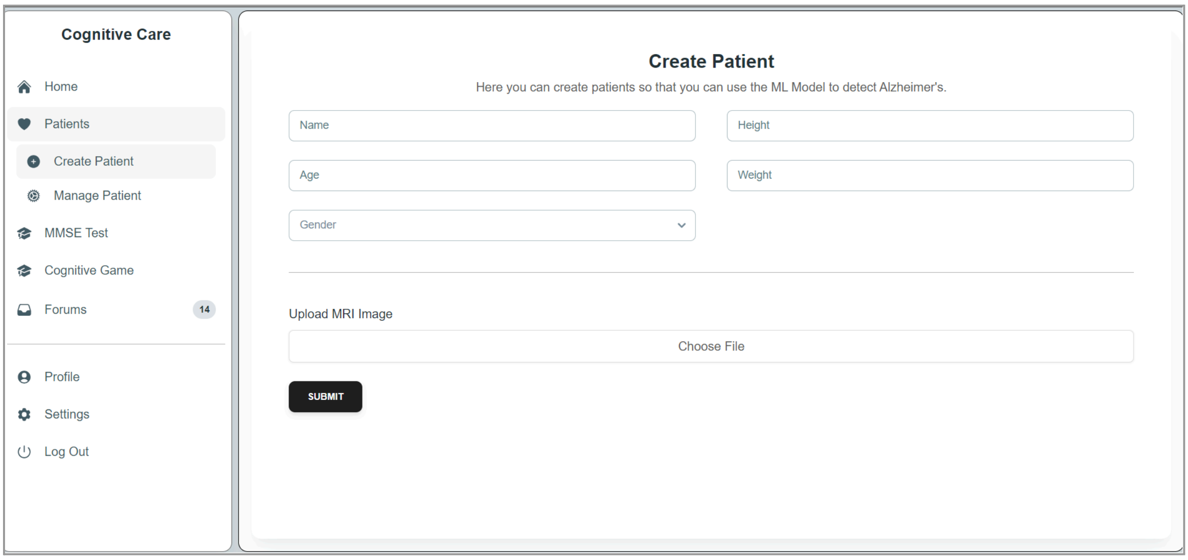
7.Results and Discussion

7.1. Screenshots of User Interface (UI) for the respective module

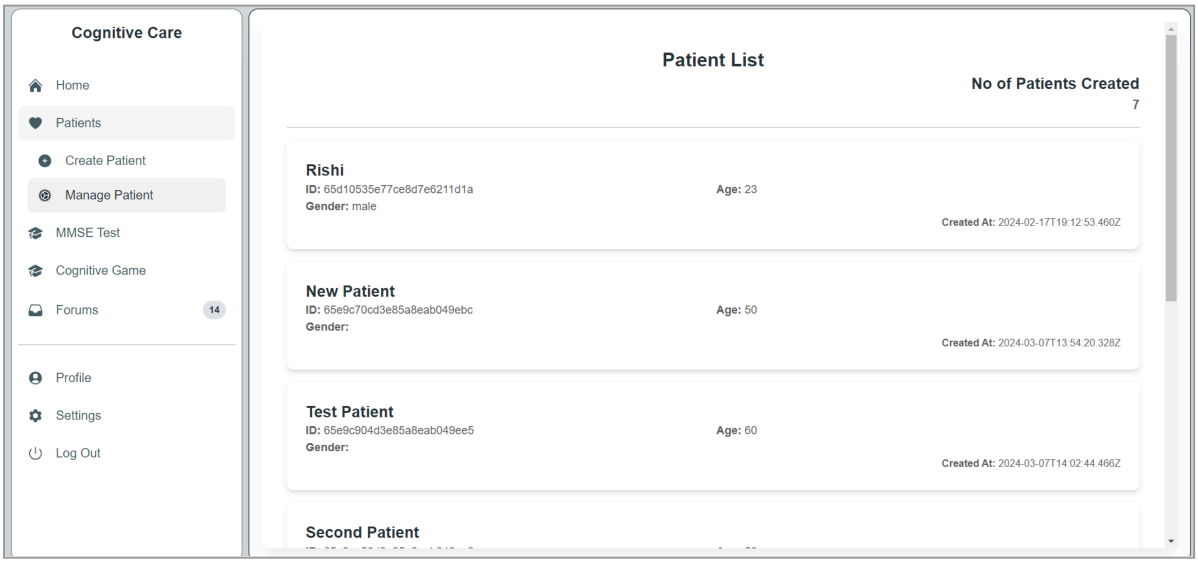




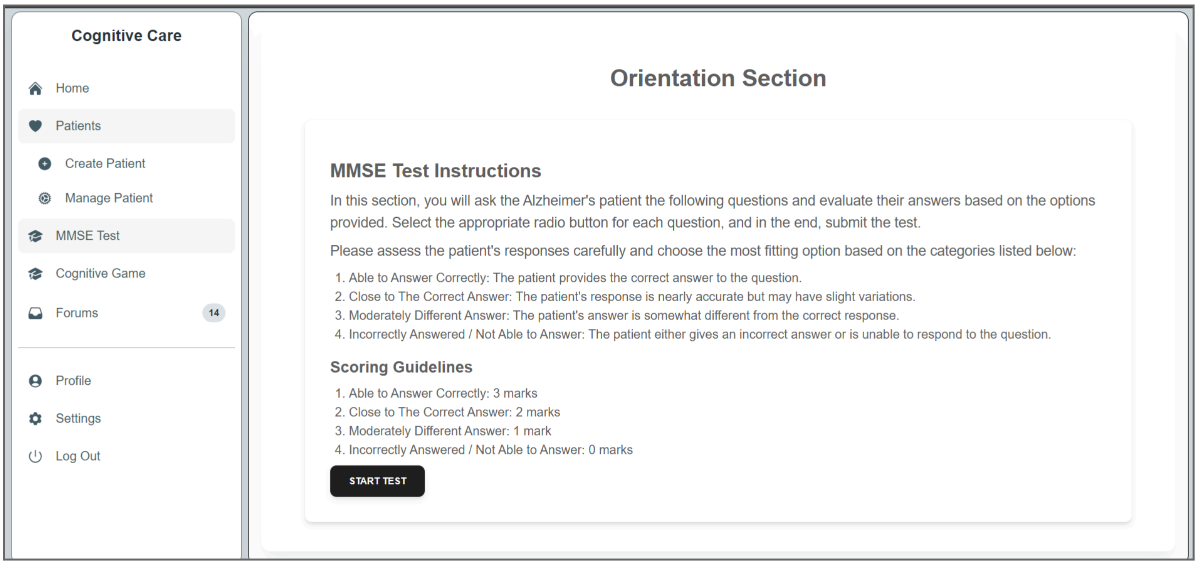
Login & Signup Screen



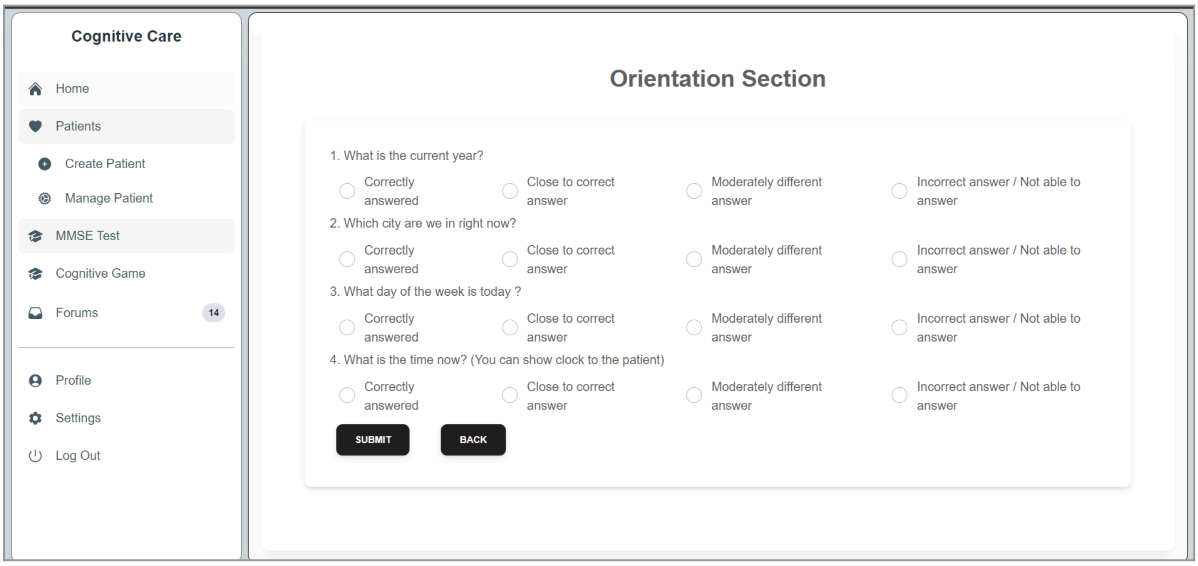
User Dashboard



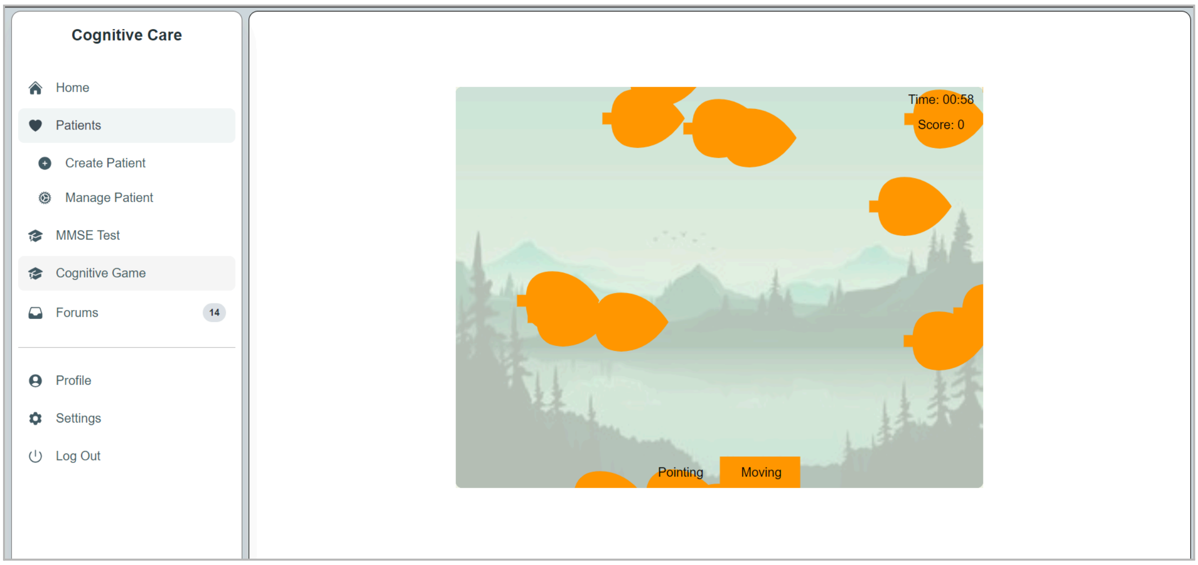
Patient Dashboard



MMSE Test



MMSE Test

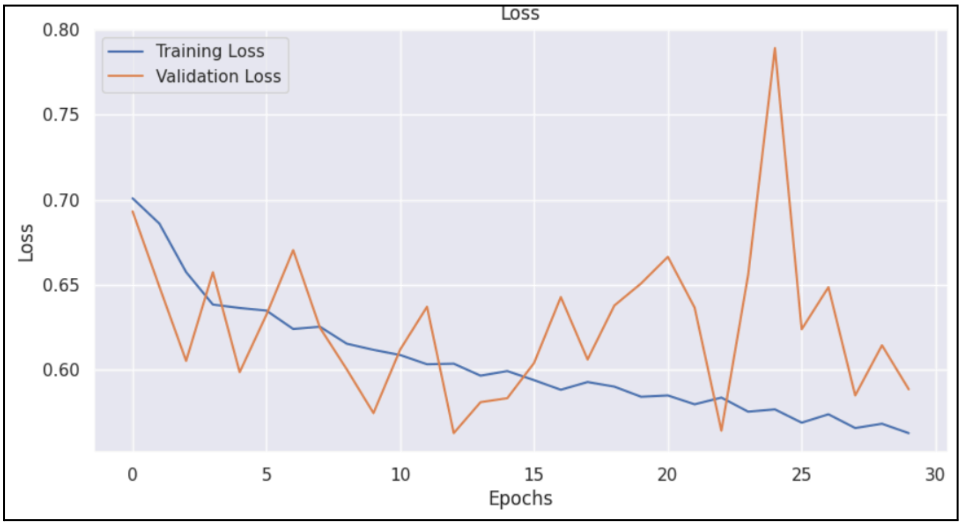


Cognitive Games

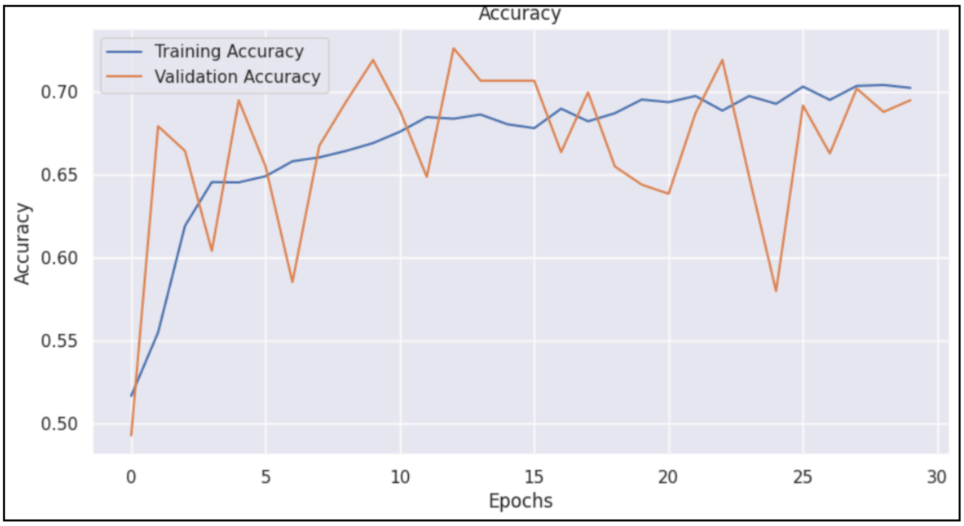
7.2. Performance Evaluation measures

Detection Model Metrics-

1. **Training and Validation Loss**

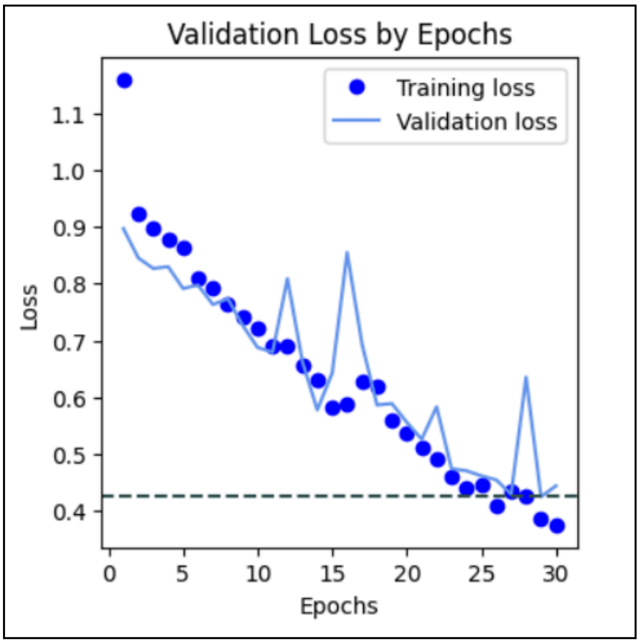


2. **Training and Validation Accuracy**

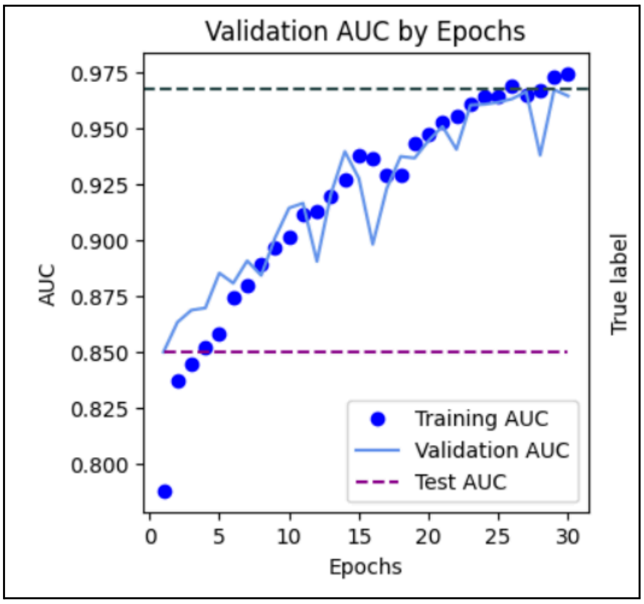


Multi-class Classification Model Using Transfer Learning

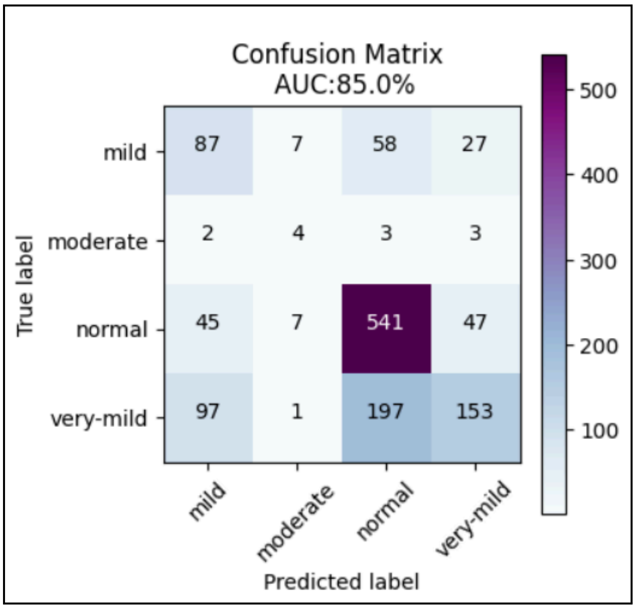
1. **Training and Validation Loss By Epochs**



2. **Training and Validation AUC By Epochs**



3. Training and Validation AUC By Epochs



7.3. Inference drawn

In interpreting the evaluation metrics and formulas provided, several key insights emerge regarding the performance and applicability of our Convolutional Neural Network (CNN) model for Alzheimer's disease detection from MRI scans.

Formulas:

Precision $= \frac{True\ Positive}{True\ Positive + False\ Positive} \rightarrow \frac{TP}{TP + FP}$

Accuracy $= \frac{True\ positives + True\ Negatives}{True\ positives + True\ negatives + False\ positives + False\ negatives} \rightarrow \frac{TP + TN}{TP + TN + FP + FN}$

Recall $= \frac{True\ Positive}{True\ Positive + False\ Negative} \rightarrow \frac{TP}{TP + FN}$

True Positive (TP): The number of correctly identified positive instances by the software.

False Positive (FP): The number of instances that the software incorrectly identifies as positive when they are actually negative.

True negative(TN) :- The Number of outcomes where the model correctly predicts the negative class.

False Negative (FN) :- The Number of outcomes where the model incorrectly predicts the positive class.

```
Confusion Matrix:
[[441 199]
 [441 199]]
Precision: 0.5
Recall: 0.3109375
```

Fig 8: Confusion Matrix value

1. Accuracy and Evaluation Metrics:
    - **Accuracy**: The achieved accuracy of 70.78% demonstrates the model's ability to classify AD and MCI cases correctly.
    - **Precision and Recall**:
2. Confusion Matrix: The confusion matrix is a valuable tool for understanding the distribution of true positive, true negative, false positive, and false negative predictions. It provides insights into the model's strengths and weaknesses.
3. Feature Importance: The importance of different features or layers in the CNN model to identify which aspects of the data had the most significant influence on the classification.
4. Real-World Applicability: The achieved accuracy of 70.78% for early detection of Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI), aligning with the project's goals, offers the potential to enhance the real-world management of cognitive disorders through more timely interventions.

8.Conclusion

8.1 Limitations

In initiating our project on Alzheimer's disease (AD) detection and management, it is crucial to delineate the limitations that may influence our endeavors. Recognizing these constraints from the outset will enable us to strategize effectively and optimize our approach within the confines of our resources and capabilities.

- Data Availability:
  Access to sufficient and diverse MRI datasets for training the machine learning model may be limited. Without access to a wide range of data, the model's performance and generalizability could be compromised, potentially affecting the accuracy of AD detection.
- Expertise and Resources:
  As a college project, there may be limitations in terms of expertise and resources available for developing and implementing advanced machine learning algorithms and healthcare applications. This could impact the sophistication and robustness of the solution compared to what could be achieved with access to more specialized resources.

Acknowledging and addressing these limitations transparently throughout our project journey demonstrates our commitment to integrity and thoroughness in our research and development efforts. By embracing these challenges as opportunities for growth and innovation, we aim to deliver a project report that not only highlights our achievements but also provides insights into the complexities of tackling AD detection and management.

8.2 Conclusion

Our project, titled "Cognitive Care," presents a significant advancement in the early detection and personalized management of Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). With an achieved accuracy of 78%, our software marks a promising step towards improving AD and MCI detection. However, the full realization of our project aims to deliver a groundbreaking software solution that not only facilitates early detection but also offers personalized recovery assessment and progress tracking. By leveraging advanced data analysis techniques and machine learning-driven predictions, our software has the potential to revolutionize the management of cognitive disorders, ultimately enhancing patient outcomes and contributing to our understanding of cognitive recovery.

Through the integration of Agile development principles and a focus on surpassing existing systems, our project, "Cognitive Care," distinguishes itself by empowering patients on their journey towards cognitive improvement. Our collaborative efforts involving medical expertise, software development, and iterative refinement have resulted in a solution that addresses the complexities of AD and MCI. Moving forward, approval from verified and top doctors in the field will provide further validation and impetus to our application. Additionally, we recognize the importance of a simpler and more interactive user interface to ensure greater user participation and superior user experience. These features, along with our commitment to societal impact, set our application apart and highlight its significance in advancing the field of cognitive disorder management. Future research could focus on refining the software further and exploring additional avenues for enhancing patient care and outcomes in cognitive disorders.

8.3 Future Scope

This project achieves all the functionalities it aimed to achieve in the first place. One of the paths we can explore is using a multi model approach to detect Alzheimer’s and provide a much more comprehensive result by incorporating all the results from various models used. We can also use a transfer learning model to predict and classify Alzeimers for the patients. So these are some directions our project could be moved in.

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