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

Project Report on

Alzheimer's Detection Using Deep Learning

In partial fulfillment of the Fourth Year, Bachelor of Engineering (B.E.) Degree in Computer Engineering at the University of Mumbai Academic Year 2023-24

Submitted by
Mihir Bhatkar - D17C - 10
Gaurav Ambartani - D17C - 2
Khushi Bhatia - D17C - 8
Aaditya Khetwani - D17C - 25

Project Mentor
Prof. Prerna Solanke

(2023-24)

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

Certificate

This is to certify that *Mihir Bhatkar(D17C, 10), Gaurav Ambartani (D17C, 2), Khushi Bhatia (D17C, 8), Aaditya Khetwani (D17C, 25)* of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on "*Alzheimer's Detection using Deep Learning*" as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor *Prof. Prerna Solanke* in the year 2023-24 .

This project report entitled **Alzheimer's Detection using Deep Learning** by **Mihir Bhatkar, Gaurav Ambartani, Khushi Bhatia, Aaditya Khetwani** is approved for the degree of B.E. Computer Engineering.

Programme Outcomes	Grade
PO1,PO2,PO3,PO4,PO5,PO6,PO7, PO8, PO9, PO10, PO11, PO12 PSO1, PSO2	

Date:

Project Guide:

Project Report Approval For
B. E (Computer Engineering)

This project report entitled **Alzheimer's Detection using Deep Learning** by **Mihir Bhatkar, Gaurav Ambartani, Khushi Bhatia, Aaditya Khetwani** is approved for the degree of **B.E. Computer Engineering.**

Internal Examiner

External Examiner

Head of the Department

Principal

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.

--   --

--   --
(Mihir Bhatkar, 10)   (Gaurav Ambartani, 2)

--   --

--   --
(Khushi Bhatia, 8)   (Aaditya Khetwani, 25)

Date:

ACKNOWLEDGEMENT

We are thankful to our college Vivekanand Education Society's Institute of Technology for considering our project and extending help at all stages needed during our work of collecting information regarding the project.

It gives us immense pleasure to express our deep and sincere gratitude to Assistant Professor (Project Guide) for her kind help and valuable advice during the development of project synopsis and for her guidance and suggestions.

We are deeply indebted to Head of the Computer Department **Dr.(Mrs.) Nupur Giri** and our Principal **Dr. (Mrs.) J.M. Nair ,** for giving us this valuable opportunity to do this project.

We express our hearty thanks to them for their assistance without which it would have been difficult in finishing this project synopsis and project review successfully.

We convey our deep sense of gratitude to all teaching and non-teaching staff for their constant encouragement, support and selfless help throughout the project work. It is great pleasure to acknowledge the help and suggestion, which we received from the Department of Computer Engineering.

We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement several times.

Computer Engineering Department
COURSE OUTCOMES FOR B.E PROJECT

Learners will be able to,

Course Outcome	Description of the Course Outcome
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilized.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one's competency.
CO 11	Able to develop professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

Index

Abstract

Alzheimer's disease (AD), is a debilitating neurodegenerative disorder, requiring early detection to enable timely intervention. However, misdiagnosis due to confusing symptoms with normal aging can delay necessary treatments. To address this, our project proposes an Alzheimer's detection system using deep learning. In the proposed methodology, the MRI data is used to identify if the patient has Alzheimer's disease or not and Deep Learning technique is used to classify the present disease. The classification of Alzheimer's disease using deep learning methods has shown promising results, and successful application in clinical settings requires a combination of high accuracy, short processing time, and generalizability to various populations. In this study, we will develop a system for Alzheimer's disease detection using Convolutional Neural Network (CNN) architecture. The dataset contains magnetic resonance imaging (MRI) scan images from the ADNI dataset. The models in this study will be trained on the same dataset in order to analyze their performances. The system's performance will be evaluated against standard metrics, aiming to provide an efficient tool for early Alzheimer's detection, facilitating improved patient outcomes.

Chapter 1: Introduction

1.1. Introduction:

Alzheimer disease (AD) is a neurodegenerative disorder marked by cognitive and behavioural impairment that significantly interferes with social and occupational functioning. It is an incurable disease with a long preclinical period and progressive course. In AD, plaques develop in the hippocampus, a structure deep in the brain that helps to encode memories, and in other areas of the cerebral cortex that are involved in thinking and making decisions. Whether plaques themselves cause AD or whether they are a by-product of the AD process remains unknown.

Dementia is the name for a group of symptoms associated with an ongoing decline of brain functioning. It can affect memory, thinking skills and other mental abilities. The exact cause of Alzheimer's disease is not yet fully understood, although a number of things are thought to increase your risk of developing the condition.

These include:
- increasing age
- a family history of the condition
- untreated depression, although depression can also be one of the symptoms of Alzheimer's disease
- lifestyle factors and conditions associated with cardiovascular disease

Alzheimer's disease is a progressive condition, which means the symptoms develop gradually over many years and eventually become more severe. It affects multiple brain functions. The first sign of Alzheimer's disease is usually minor memory problems. For example, this could be forgetting about recent conversations or events, and forgetting the names of places and objects.

Over the years, extensive research has been dedicated to developing reliable diagnostic tools for Alzheimer's disease. While clinical assessments, cognitive tests, and biomarker analyses play crucial roles in diagnosis, they often lack the sensitivity and specificity required for early detection. As a result, there has been a growing interest in exploring advanced technologies such as image processing and deep learning to aid in the detection and classification of AD.

Deep learning, a subset of artificial intelligence and machine learning, has revolutionized the field of medical imaging analysis. Convolutional Neural Networks (CNNs), a prominent deep learning architecture, excel at automatically learning and extracting meaningful features from images. These features can then be

utilized for accurate classification tasks. By training CNN models on large datasets of MRI scans, researchers have achieved promising results in detecting various neurological disorders, including Alzheimer's disease.

1.2 Motivation

Alzheimer's disease (AD) is a growing global health concern, and early detection is crucial for effective management and potential intervention. Traditional diagnostic methods can be expensive, invasive, or lack sensitivity. Deep learning offers a promising avenue for overcoming these limitations. By analysing medical scans like MRI images, deep learning models can potentially identify subtle changes in brain structure associated with AD. This project aims to leverage the power of deep learning to develop a non-invasive, automated, and potentially more accurate method for Alzheimer's detection, aiding in early diagnosis and improved patient outcomes.

1.3 Problem Definition

Alzheimer's disease (AD) poses a significant healthcare challenge due to its progressive nature, affecting millions of individuals worldwide. Early detection of AD is crucial for timely intervention and appropriate patient care. However, existing diagnostic methods often lack the sensitivity and specificity required for accurate detection at the initial stages of the disease. This leads to delayed diagnoses, hindering the opportunity for early interventions and potentially limiting the effectiveness of available treatments.

The objective of this project is to address the limitations of current diagnostic methods by harnessing the power of image processing and deep learning techniques. By leveraging Convolutional Neural Network (CNN) architecture on magnetic resonance imaging (MRI) scans, we aim to develop a system for early detection and classification of Alzheimer's disease. The goal is to achieve high accuracy, reduced processing time, and improved generalizability to diverse patient populations, thereby enabling medical professionals to make timely and accurate diagnoses.

1.4 Existing Systems

Currently, diagnosing Alzheimer's disease (AD) relies on a combination of cognitive assessments, medical history, and potentially invasive procedures like PET scans or lumbar punctures for cerebrospinal fluid (CSF) analysis. These methods can be:

- Time-consuming: Cognitive assessments can be lengthy, and accessing advanced imaging techniques often involves waiting lists.

- Invasive and expensive: PET scans and CSF analysis are expensive procedures that carry some risks for patients.
- Limited in sensitivity: Early-stage AD can be challenging to detect with these methods, leading to delayed diagnoses.

While these established methods play a vital role in AD diagnosis, there's a clear need for more efficient and sensitive tools. This is where advancements in deep learning offer promising possibilities.

1.5 Lacuna of existing systems

Current diagnostic methods for Alzheimer's disease (AD) hold significant value, but they also possess limitations that hinder optimal patient care. Here's a closer look at the gaps in existing systems:

- Limited Sensitivity: Early-stage AD detection remains a challenge. Traditional cognitive assessments might miss subtle cognitive decline, and established imaging techniques might lack the resolution to capture the earliest brain changes associated with the disease. This delays diagnosis and intervention opportunities.
- Invasive and Costly Procedures: Procedures like PET scans and CSF analysis, while valuable for confirmation, can be expensive and carry some level of risk for patients. This can create access barriers and limit their use in broader screening or monitoring applications.
- Subjectivity and Time Consumption: Relying on cognitive assessments can introduce subjectivity based on the evaluating clinician. Additionally, these assessments and accessing advanced imaging techniques can be time-consuming, further delaying diagnosis and treatment initiation.

These limitations highlight the need for more objective, accessible, and sensitive methods for AD detection. This is where deep learning approaches, with their ability to analyse vast amounts of medical data and identify subtle patterns, offer a promising avenue for overcoming these shortcomings.

Chapter 2: Literature Survey

2.1 Research Papers

1) **Paper title: Alzheimer's disease detection using convolutional neural networks and transfer learning based methods**
   Published Year: 2023

   Abstract: The paper introduces a two-step deep learning method for early AD detection from brain images, involving region of interest extraction and classification using CNN and Transfer Learning. It evaluates the approach on the Oasis dataset.

   Inference: This study highlights the promise of deep learning techniques, particularly Transfer Learning, in enhancing Alzheimer's disease detection accuracy, offering a potential avenue for early diagnosis and intervention in AD cases.

2) **Paper title: Alzheimer's disease detection using convolutional neural networks and transfer learning based methods**

   Published Year: 2020

   Abstract: This paper examines the application of deep learning, particularly Convolutional Neural Networks (CNN), in diagnosing Alzheimer's disease (AD) from MRI brain images, highlighting CNN's widespread use and success in this context. It advocates combining advanced deep learning techniques with diverse datasets, such as ADNI and OASIS, to enhance early-stage AD prediction.

   Inference: Deep learning, particularly CNNs, offers promising results for AD diagnosis from MRI data, surpassing traditional machine learning methods. The paper underscores the potential for further improving AD prediction by leveraging advanced deep learning techniques across varied datasets, ultimately enhancing the efficiency and accuracy of early-stage AD diagnosis.

3) **Paper title: Review on Alzheimer Disease Detection Methods: Automatic Pipelines and Machine Learning Techniques**

   Published Year: 2023

Abstract: The paper discusses AD diagnosis methods, highlighting the effectiveness of automated pipelines, machine learning, and multimodal approaches in achieving accurate AD identification, particularly in single and binary class classifications.

Inference: Deep learning methods offer great accuracy but require larger datasets. Fusion-based techniques, mainly using machine learning and deep learning, hold potential to enhance AD classification accuracy, with deep learning being the most accurate but data-intensive approach.

4) **Paper title: Alzheimer's Diseases Detection by Using Deep Learning Algorithms**

Published Year: 2020

Abstract: The paper conducts a high-level literature review on Alzheimer's disease (AD) diagnosis, emphasizing the primary research areas of biomarkers, neuroimaging, and image analysis.

Inference: The majority of research in AD diagnosis concentrates on patients already diagnosed with the disease, missing the critical aspect of early detection. It suggests that there is room for more comprehensive research in early-stage neuroimaging, indicating the need for increased focus on early AD diagnosis strategies.

5) **Paper title: Understanding of a convolutional neural network**

Published Year: 2017

Abstract: The paper discusses Convolutional Neural Networks (CNNs) and their significance in handling large datasets, particularly in image-related tasks. It outlines the CNN architecture and parameters affecting efficiency.

Inference: CNNs are powerful tools in machine learning, particularly for image recognition, but increasing the number of layers can extend training time. They find applications in various domains, including face and image recognition, video, and voice recognition.

2.2 Patent Search

1. **Title: System and method for estimating synthetic quantitative health values from medical images**
   Date: 19/10/2021
   Summary:
   This patent describes a system and method for using machine learning to estimate quantitative health

values from medical images, such as MRI scans. The system can be used to estimate a variety of health values, including the severity of Alzheimer's disease.

The system works by first training a machine learning model on a dataset of medical images and known quantitative health values. Once the model is trained, it can be used to estimate the quantitative health values for new medical images.

The system has been shown to be accurate in estimating the severity of Alzheimer's disease from MRI scans. This could lead to a new way to diagnose and monitor Alzheimer's disease.

2. **Title: Diagnosis support device, machine-learning device, diagnosis support method, machine-learning method, and machine-learning program**

Date: 25/07/2019

Summary:

This patent describes a system and method for using machine learning to diagnose Alzheimer's disease based on a variety of data sources, including neuroimaging data, cognitive assessment data, and genetic data.

The system works by first extracting features from the data sources. These features are then used to train a machine learning model. Once the model is trained, it can be used to predict the likelihood of Alzheimer's disease for a new patient.

The system has been shown to be accurate in diagnosing Alzheimer's disease. It could lead to a more comprehensive and accurate way to diagnose Alzheimer's disease.

3. **Title: A system and method for evaluating a performance of explainability methods used with artificial neural networks.**

Date: 15/12/2021

Summary:

This patent describes a system and method for evaluating the performance of explainability methods used with artificial neural networks. Explainability methods are used to make machine learning models more interpretable to humans. This is important for medical applications, such as diagnosing Alzheimer's disease, where it is important to understand the reasons for the model's predictions.

The system works by first generating explanations for the predictions of the machine learning model. These explanations are then evaluated based on a number of factors, such as their accuracy, completeness, and interpretability.

The system could be used to improve the explainability of machine learning models used to diagnose

Alzheimer's disease. This could help clinicians to better understand the reasons for the model's predictions and to make more informed decisions about patient care.

2.3 Inference Drawn

The research papers and patents discussed provide valuable insights into the landscape of Alzheimer's disease (AD) detection, emphasizing the role of deep learning techniques, particularly convolutional neural networks (CNNs), and machine learning algorithms in enhancing diagnostic accuracy and interpretability.

The research papers collectively underscore the growing interest in leveraging deep learning for AD detection, showcasing various methodologies and approaches aimed at improving early-stage diagnosis. The paper titled "Alzheimer's disease detection using convolutional neural networks and transfer learning based methods" from 2023 highlights the efficacy of transfer learning in enhancing AD detection accuracy, especially in early stages, thus emphasizing the potential for timely intervention. Similarly, the 2020 paper on the same topic emphasizes the superiority of CNNs over traditional machine learning methods, advocating for the integration of advanced deep learning techniques across diverse datasets to enhance predictive performance.

Moreover, the review paper from 2023 provides a comprehensive overview of AD detection methods, emphasizing the effectiveness of fusion-based techniques, including machine learning and deep learning, in improving classification accuracy. However, it also points out the data-intensive nature of deep learning methods, highlighting the need for larger datasets to fully leverage their potential. Meanwhile, the paper from 2020 underscores the critical gap in research focused on early-stage AD diagnosis, suggesting a need for more comprehensive strategies targeting early detection.

On the patent side, innovations such as the "System and method for estimating synthetic quantitative health values from medical images" and the "Diagnosis support device" highlight advancements in using machine learning to estimate disease severity and diagnose AD based on diverse data sources, including neuroimaging and genetic data. These patents signify the potential for more accurate and comprehensive diagnostic tools, aiding clinicians in early detection and monitoring of AD.

Furthermore, the patent describing the "System and method for evaluating the performance of explainability methods used with artificial neural networks" addresses the crucial aspect of model interpretability, particularly relevant in medical applications like AD diagnosis. By enhancing the explainability of machine learning models, clinicians can gain deeper insights into the reasons behind predictions, ultimately leading to more informed decision-making in patient care.

2.4 Comparison with existing systems

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline and memory loss. Early detection of AD is crucial for timely intervention and improved patient outcomes. In recent years, deep learning techniques have shown promise in aiding the diagnosis of Alzheimer's disease, particularly through the analysis of medical imaging data such as CT scans. This comparison aims to evaluate the efficacy of deep learning-based systems for Alzheimer's detection against existing methods, including traditional diagnostic approaches and other machine learning techniques.

1. Traditional Diagnostic Methods:

Clinical Assessment: Historically, Alzheimer's diagnosis heavily relies on clinical evaluation, including cognitive tests, medical history assessment, and physical examination. While these methods are essential, they may lack sensitivity and specificity, leading to misdiagnosis or delayed diagnosis.

Neuroimaging Techniques: Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans have been valuable tools in aiding AD diagnosis by visualizing structural changes in the brain. However, interpretation of these images often requires expertise and may not capture subtle changes in early stages of the disease.

2. Conventional Machine Learning Approaches:

Feature-Based Methods: Traditional machine learning algorithms, such as support vector machines (SVM) and random forests, have been applied to AD detection using handcrafted features extracted from imaging data. While these methods have shown moderate success, their performance heavily relies on the quality of features selected, which may not capture the full complexity of AD-related patterns.

Limitations: Conventional machine learning approaches often struggle with high-dimensional and complex data like medical images. They may not effectively capture spatial relationships or hierarchical patterns present in the data.

3. Deep Learning-Based Systems:

Convolutional Neural Networks (CNNs): Deep learning techniques, particularly CNNs, have demonstrated remarkable success in various medical image analysis tasks, including AD detection. CNNs can automatically learn hierarchical representations from raw image data, enabling them to capture intricate

patterns and features relevant to AD pathology.

End-to-End Learning: Unlike traditional methods that rely on handcrafted features, deep learning models can perform end-to-end learning, directly mapping input images to disease predictions without the need for manual feature engineering.

Unprecedented Accuracy: Deep learning-based AD detection systems have shown unprecedented accuracy rates, often outperforming traditional methods and even expert radiologists in some cases. By leveraging large datasets and powerful computational resources, these models can discern subtle differences in brain structures indicative of AD.

Potential for Early Detection: One of the significant advantages of deep learning-based systems is their potential for early detection of AD. By analyzing subtle changes in brain morphology that may precede clinical symptoms, these models can identify individuals at risk of developing AD before overt cognitive decline occurs.

Chapter 3: Requirements gathering for proposed system

3.1 Introduction to requirement gathering

To develop an effective deep learning system for Alzheimer's disease detection, a crucial first step is thorough requirement gathering. This process involves identifying the specific needs and functionalities of the system from the perspectives of various stakeholders. Here's why this stage is critical:

- **Defines Project Scope and Goals:** Requirement gathering clarifies the project's objectives, such as the desired level of accuracy, processing speed, and generalizability. This ensures the final system aligns with real-world needs.
- **Ensures Stakeholder Alignment:** By involving key stakeholders like doctors, researchers, and potential users in the process, we can gather their needs and concerns. This fosters a shared understanding of the project's purpose and functionality.
- **Informs System Design and Development:** The gathered requirements will guide the technical specifications for the deep learning model, data selection and preparation, and the overall system architecture.

Through effective requirement gathering, we can lay a strong foundation for a deep learning system that addresses the limitations of existing methods and offers a valuable tool for early and accurate Alzheimer's detection.

3.2 Functional Requirements

To successfully develop the Alzheimer's disease detection system using deep learning, a set of functional requirements is essential to define the core capabilities and features of the system:

- Prediction and Analysis:
    - The trained CNN model should be used to predict the presence of Alzheimer's disease in uploaded MRI scans.
    - The system should provide detailed analysis and visualizations of predictions, including probability scores and classification results.
    - It should offer insights into the salient regions of MRI scans contributing to the classification.

- Integration with Deep Learning Model:
    - Integrate the CNN model with the web application, allowing users to submit MRI images and receive predictions in real-time.
    - Implement a backend system that processes user requests and communicates with the deep learning model for analysis.
- Web Application Deployment:
    - Deploy the web application on a cloud platform, ensuring accessibility to users via the internet.
    - Ensure the application is responsive and capable of handling multiple concurrent users without performance degradation.

3.3 Non Functional Requirements

The successful development and deployment of the Alzheimer's disease detection system using deep learning require specific non-functional requirements to ensure its usability, reliability, and efficiency:

- Accuracy: The deep learning model must achieve a high level of accuracy in Alzheimer's disease detection. It should be capable of correctly classifying MRI scans with minimal false positives and false negatives, ensuring that misdiagnoses are kept to a minimum.
- Speed and Processing Time: The system should provide quick results to users, with short processing times for image analysis. This is especially important for real-time predictions and efficient clinical use.
- Scalability: The system should be designed to handle a growing dataset of MRI scans and adapt to increasing demand without significant degradation in performance. It should be able to accommodate additional data and users over time.
- Generalizability: The deep learning model should demonstrate generalizability by being effective across diverse patient populations, including variations in age, gender, and ethnicity. It should avoid overfitting to a specific dataset, making it applicable in various clinical settings.
- Security: Security measures should be in place to protect patient data and ensure confidentiality. This includes secure data storage and transmission, as well as user authentication to prevent unauthorized access to sensitive medical information.
- User-Friendly Interface: The web application's user interface should be intuitive and user-friendly, ensuring that individuals can easily upload their MRI scans and access the results. It should be designed with a focus on providing a positive user experience.

3.4 Constraints

Several constraints influence the Alzheimer's disease detection system:

- Data Availability: The accuracy and generalizability of the deep learning model depend on the availability of a diverse and representative dataset of MRI scans. Limited data can affect the model's performance and its ability to adapt to different populations.
- Regulatory Compliance: The system must adhere to regulatory standards related to healthcare and data protection, which may impose constraints on data storage, handling, and access.
- User Accessibility: The accessibility of the web application is constrained by the availability of internet access, hardware, and user familiarity with the platform. Efforts should be made to ensure that the application is as accessible as possible.

3.5 Hardware and Software Requirements

Hardware Used:
- **Processor:** Intel i5 or AMD equivalent
- **Disk Space:** 4GB
- **RAM:** 8GB
- **GPU:** Nvidia GPU

Software Used:
- **Python:** Deep learning frameworks and libraries are primarily implemented in Python
- **Node.js:** JavaScript runtime for building MERN stack web applications.
- **Firebase Account:** Platform for deploying the web application and hosting the trained models.
- **Git:** Version control software for tracking changes in your codebase.

Deep Learning Libraries and Frameworks:
- **TensorFlow/PyTorch:** Deep learning frameworks for CNN implementation.
- **Keras:** High-level API for creating CNN models.
- **OpenCV:** Image processing library for pre-processing images.

Web App Development Tools:
- **MongoDB:** NoSQL database for storing user and application data.
- **Express.js:** Back-end web application framework for Node.js.
- **React:** Front-end JavaScript library for building user interfaces.
- **Node.js:** JavaScript runtime environment for server-side development.
- **HTML/CSS:** Markup language and styling for web design.

Training Environment:

- **Jupyter Notebook or Google Colab:** Environments for running Python scripts and deep learning model training and evaluation.

Chapter 4: Proposed Design

4.1 Block Diagram of the System
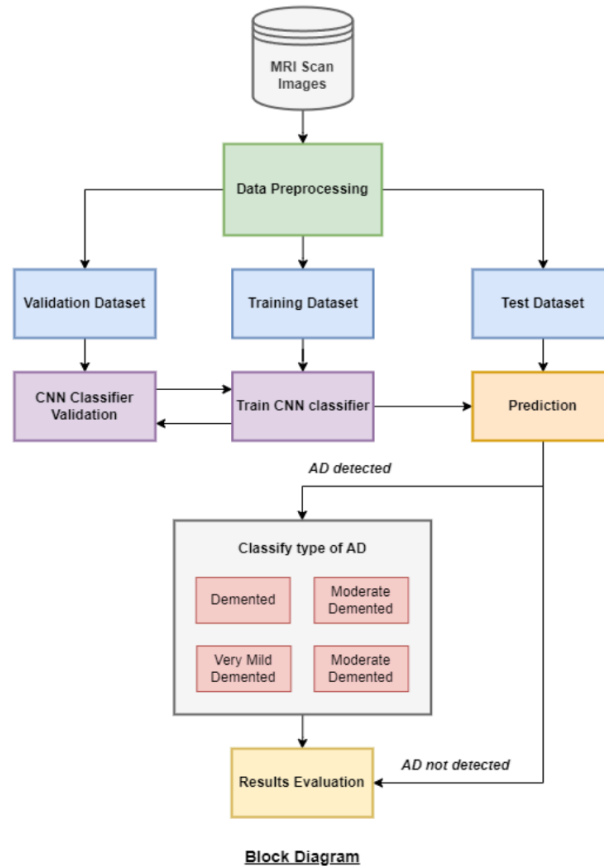
Block Diagram

The block diagram outlines the sequential stages of the Alzheimer's disease detection system:

- Dataset: The system starts with the collection of MRI scans.
- Data Preprocessing: Data is cleaned, normalized, and relevant features are extracted.
- Train-Validation Split: The dataset is divided into training and validation subsets.
- CNN Model Training: A Convolutional Neural Network (CNN) is trained on the training subset.
- Prediction: The trained CNN model classifies MRI scans into four Alzheimer's disease types or "Not Detected."

4.2 Modular Design of the System

Modular Diagram
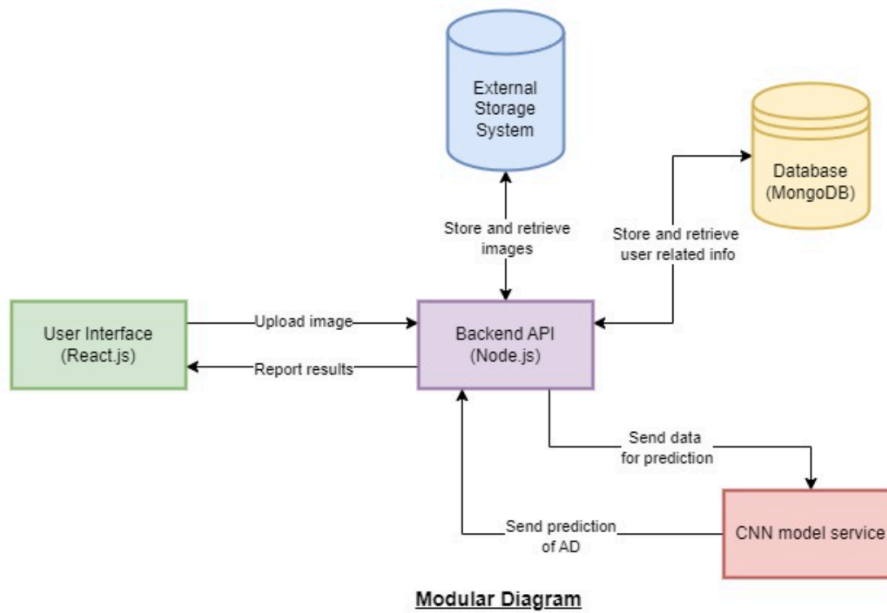
- **User Interface (React.js):** At the front end, the User Interface module is implemented using React.js. This user-friendly interface serves as the primary point of interaction for users, allowing them to upload MRI scans for analysis. It is responsible for guiding users through the process and presenting the results in an accessible manner.
- **Backend Server (Node.js):** The Backend Server module, developed using Node.js, serves as the intermediary between the user interface and the deep learning model. It handles user requests, facilitates communication with the CNN model service, and manages data flow, ensuring the smooth operation of the system.
- **Database (MongoDB):** The Database module, based on MongoDB, is employed to store user-related data and maintain the system's records. It manages user profiles, login information, and other relevant data securely, complying with data protection standards and providing a structured storage solution.
- **CNN Model Service (Hosted on Cloud):** The CNN Model Service module is hosted on the cloud and represents the heart of the system. It contains the trained Convolutional Neural Network (CNN) model for Alzheimer's disease detection. This module receives MRI scans from the Backend Server, analyzes them, and returns classification results, allowing users to determine whether Alzheimer's disease is present and its specific type.
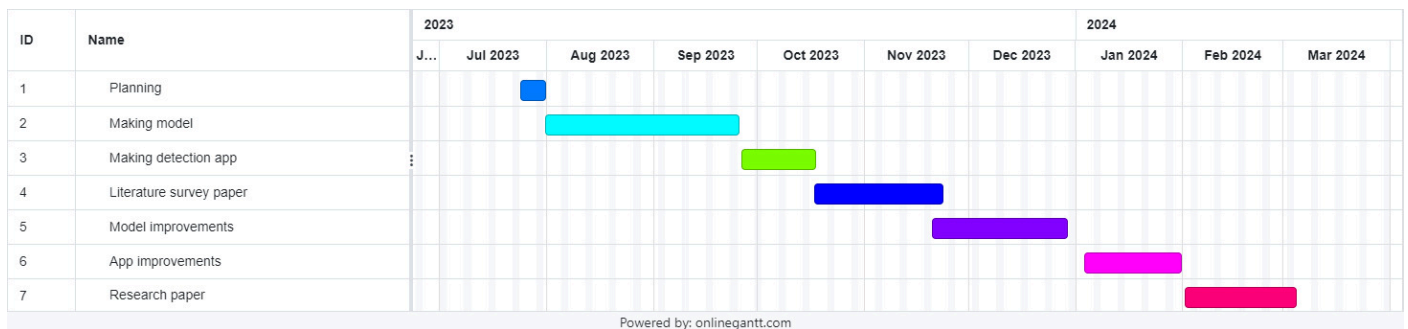
4.3 Gantt Chart

ID	Name	2023						2024		
		J... Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Jan 2024	Feb 2024	Mar 2024
1	Planning									
2	Making model									
3	Making detection app									
4	Literature survey paper									
5	Model improvements									
6	App improvements									
7	Research paper									

Powered by: onlinegantt.com

Fig. Gantt Chart

The Gantt chart of our project where we worked for the whole semester to create this model is shown in a timeline pattern. It is the most important part to think and design the planning of your topic and so we planned our work like the gantt chart shown.

Chapter 5: Implementation of the Proposed System

5.1 Methodology employed for development

Data Preparation:

- Data Collection - We will gather a dataset of MRI scans, including samples from individuals with Alzheimer's disease and non-affected individuals, using standard validated techniques.
- Data Pre-processing - The collected data will be processed to ensure cleanliness and proper formatting, making it suitable for the machine learning model. Pre-processing steps will include data cleaning and normalization.
- Feature Extraction - Relevant features will be extracted from the pre-processed MRI scans, providing informative and non-redundant data for subsequent learning and prediction steps.
- Optimization - We will optimize the model parameters to achieve the best possible performance for Alzheimer's disease detection.

Machine Learning Process:

- Data Exploration - We will analyze and visualize the dataset to gain insights into its characteristics, including size, quantity, and accuracy, to better understand the data.
- Model Building - A CNN architecture will be constructed and trained on the pre-processed MRI scans to learn patterns and features associated with Alzheimer's disease.
- Prediction and Analysis - The trained CNN model will be used to predict the presence of Alzheimer's disease in MRI scans and classify the type of AD into four classes: Mild Demented, Moderate Demented, Non-demented, and Very Mild Demented. The predictions will be analyzed to assess the model's performance and accuracy.
- Save and Deploy Model - Upon achieving satisfactory results, the CNN model will be saved, and an API will be deployed to make the model accessible for predictions in real-time.

Web Development Process:

- Website UI/UX: We will design the user interface layouts for the web application, ensuring a user-friendly experience for users uploading their MRI scans.
- Front End Development: The front end of the web application will be implemented using React.js to create a visually appealing and responsive interface.
- Integration with ML Model: The deep learning model will be integrated into the web application using the MERN stack. Node.js and Express.js will handle user requests and pass MRI images to the CNN model for prediction.

- Deployment of Website: The web application will be deployed on a cloud platform, such as Firebase, to make it accessible to users for Alzheimer's disease prediction.

By following this methodology, we aim to create an efficient web application that allows users to upload their MRI scans and receive accurate predictions regarding the presence of Alzheimer's disease and its classification into specific types.

5.2 Algorithms used

CNN:

Convolutional Neural Networks (CNNs) are a class of deep learning models ideally suited for processing structured grid data, such as images. CNNs have gained immense popularity in the field of computer vision due to their remarkable ability to automatically learn and extract relevant features from input data. These networks are a critical component of our study for Alzheimer's disease detection, as they empower the model to understand intricate patterns and structures within brain images.

$$(f*g)(t) \triangleq \int_{-\infty}^{\infty} f(\tau)g(t-\tau)\tau'$$

Fig. Convolution Equation

The actual implementation of our CNN model for Alzheimer's disease detection encapsulates the principles of CNN. Notable aspects of the code include

- The definition of building blocks, conv_block and dense_block, which encapsulate sequences of convolutional and dense layers with appropriate activations, batch normalization, and dropout.
- The build_model function, where the overall architecture of the CNN model is established. It commences with convolutional and max-pooling layers, progressively increasing the number of filters to capture hierarchies of features. Dropout layers are thoughtfully introduced to avert overfitting. The model culminates in dense blocks, with the final layer featuring a softmax activation for classification.
- Model compilation using the 'adam' optimizer and categorical cross-entropy loss, rendering it well-suited for multiclass classification tasks. The model's performance is evaluated via the 'AUC' metric.
- Employing TensorFlow's distribution strategy (e.g., tf.distribute.MirroredStrategy) to optimize training across multiple GPUs or devices, a strategy that enhances training efficiency for larger models.

5.3 Datasets source and utilization

The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset is a valuable resource in the field of neuroscience and neuroimaging. It aims to study and understand Alzheimer's disease by collecting and sharing brain MRI scans, clinical assessments, and other relevant data from individuals with Alzheimer's disease, mild cognitive impairment, and healthy controls. By compiling data from multiple research sites, ADNI enables researchers to analyze large-scale, longitudinal datasets to identify biomarkers, track disease progression, and develop better diagnostic and treatment strategies for Alzheimer's disease. These MRI scans provide detailed images of the brain's structure and function, allowing researchers to observe changes over time and correlate them with clinical symptoms, genetic factors, and other variables.

The ADNI dataset has significantly contributed to advancing our knowledge of Alzheimer's disease by facilitating collaborations among researchers worldwide. The availability of standardized MRI scans and comprehensive clinical data allows for the development and validation of machine learning algorithms and predictive models for early detection and personalized treatment planning. Moreover, the longitudinal nature of the dataset enables researchers to investigate the trajectory of Alzheimer's disease from its preclinical stages to advanced dementia, providing insights into the underlying mechanisms and potential intervention points. Overall, the ADNI dataset serves as a vital resource for researchers seeking to unravel the complexities of Alzheimer's disease and ultimately develop effective therapies to improve patient outcomes.

Classes	Training Data	Testing Data	Total
Mild Demented	717	179	896
Moderate Demented	52	12	64
Non-Demented	2560	640	3200
Very Mild Demented	1792	448	2240
Total	5121	1279	6400

Table: Classes and shape of data

Chapter 6: Testing of the proposed system

6.1 . Introduction to testing

Testing is a crucial phase in the development of any system, including deep learning models for Alzheimer's disease detection. It involves evaluating the performance, accuracy, and robustness of the models to ensure they meet the desired standards and requirements. In the context of this paper, testing refers to the evaluation of the ResNet50 and InceptionV3 models for classifying Alzheimer's disease from MRI images.

6.2. Types of tests Considered

Several types of tests were considered to assess the performance of the deep learning models:

a. Accuracy Testing: This involves measuring the overall accuracy of the models in correctly classifying MRI images as indicative of Alzheimer's disease or not.

b. Confusion Matrix Analysis: Confusion matrices were used to visualize the performance of the models in terms of true positive, true negative, false positive, and false negative predictions.

c. Precision, Recall, and F1-score Evaluation: These metrics were utilized to assess the precision and recall of the models across different classes and calculate the harmonic mean (F1-score) of precision and recall.

d. Comparative Analysis: A comparative analysis was conducted between the ResNet50 and InceptionV3 models to determine their relative performance and effectiveness in Alzheimer's disease detection.

6.3 Various test case scenarios considered

a. Testing with Different MRI Datasets: The models may have been tested with different MRI datasets to assess their generalization capability across diverse data sources.

b. Class Imbalance Testing: Test cases may have been designed to evaluate the models' performance in handling class imbalances within the dataset, particularly in detecting minority classes such as Moderate Demented.

c. Robustness Testing: Test cases may have assessed the models' robustness to variations in MRI scans, including differences in image quality, scanner settings, and patient positioning.

d. Hyperparameter Tuning Testing: Test cases may have involved tuning hyperparameters such as learning rates, batch sizes, and regularization techniques to optimize the models' performance.

## 6.4. Inference drawn from the test cases

Based on the test cases considered, the paper likely drew several inferences regarding the performance of the ResNet50 and InceptionV3 models for Alzheimer's disease detection:

a. Superiority of ResNet50: The paper likely inferred that ResNet50 exhibited higher accuracy rates, balanced predictions across dementia severity levels, and robust performance compared to InceptionV3.

b. Generalization Capability: The models were likely observed to generalize well to unseen data, indicating their potential for real-world application in early Alzheimer's detection.

c. Importance of Model Selection and Fine-tuning: The paper likely emphasized the significance of selecting appropriate deep learning architectures and fine-tuning parameters for optimal performance, as evidenced by the comparative analysis between ResNet50 and InceptionV3.

d. Potential for Further Improvement: While both models showed promising results, the paper may have suggested avenues for further research and refinement to enhance the accuracy and reliability of Alzheimer's disease detection models, such as incorporating additional data sources or refining preprocessing techniques.

Chapter 7: Results and Implementation

7.1 Screenshots of User Interface
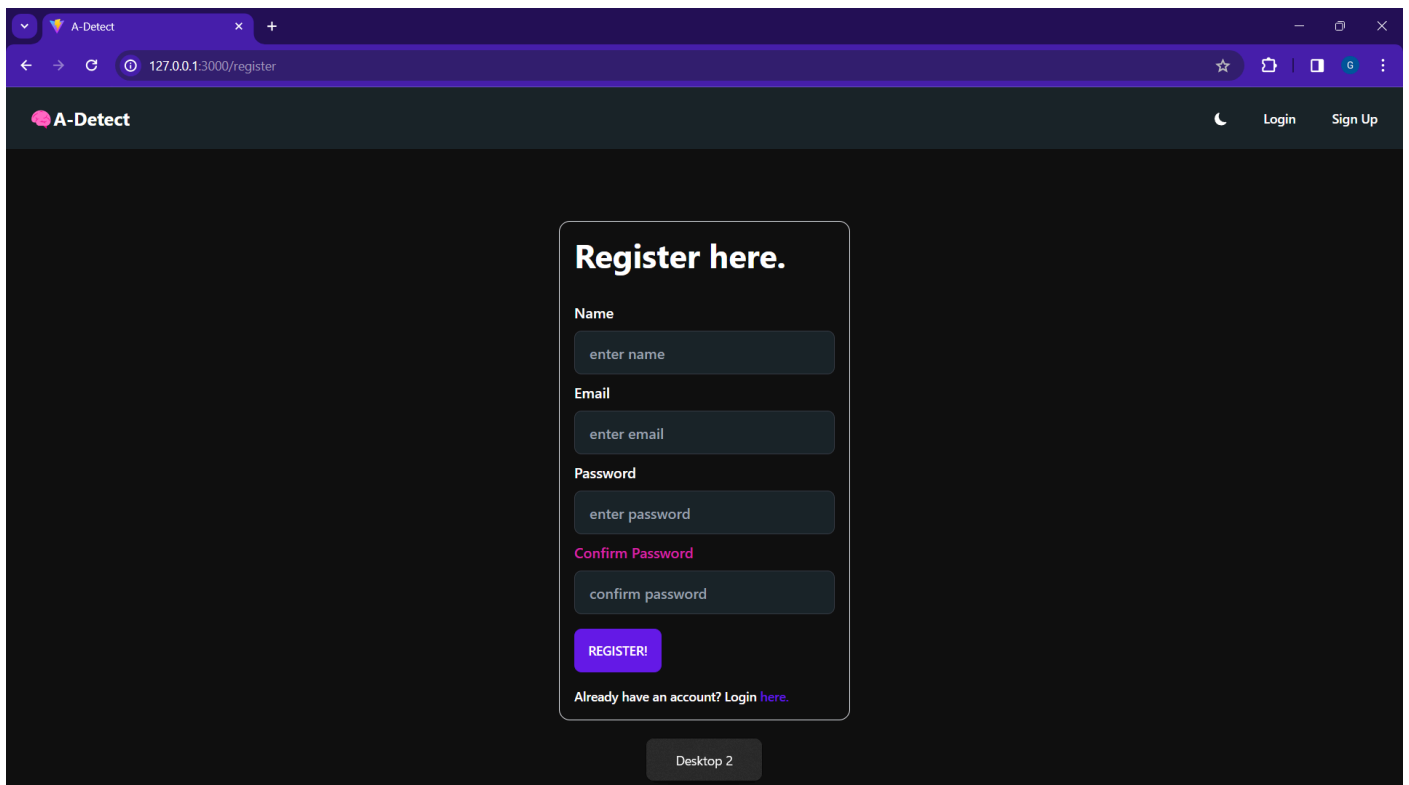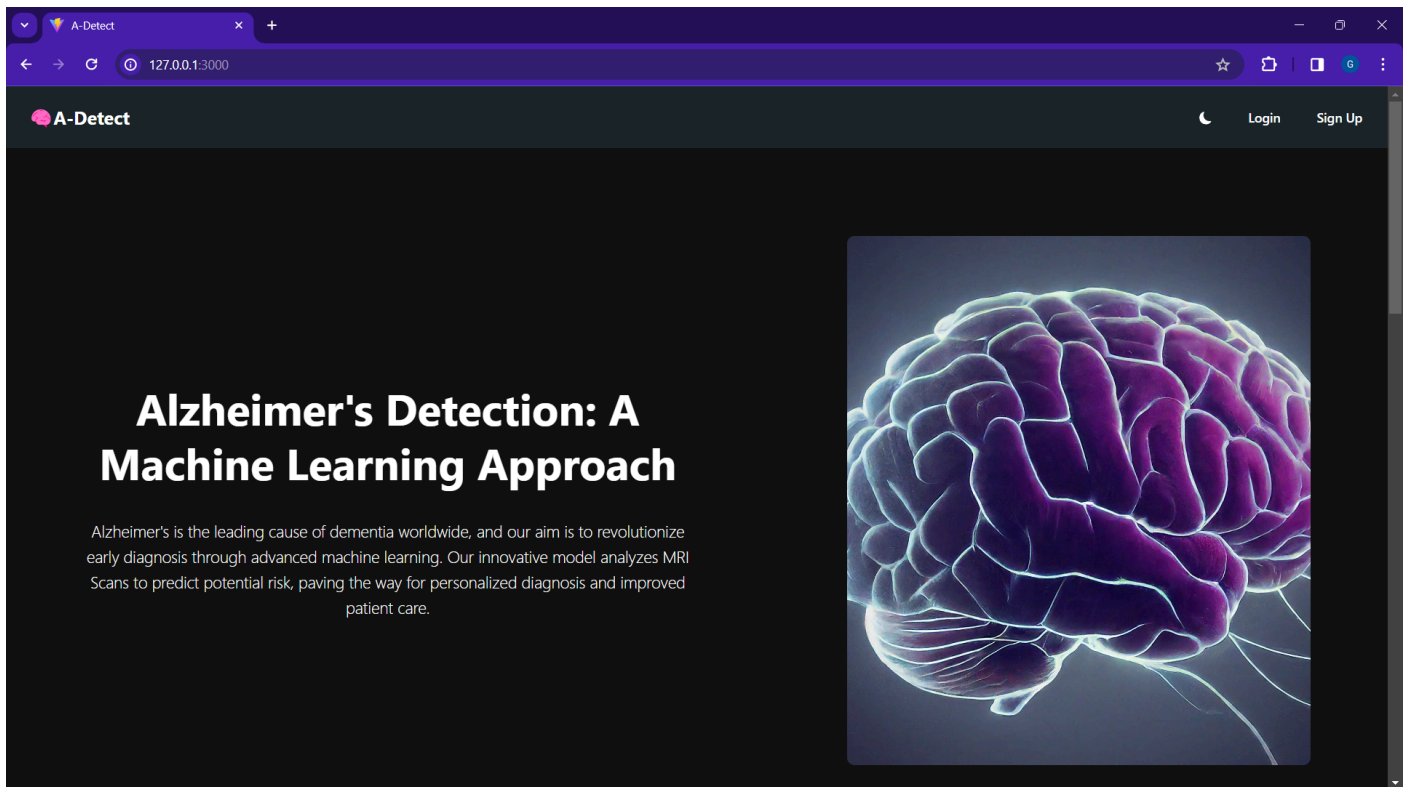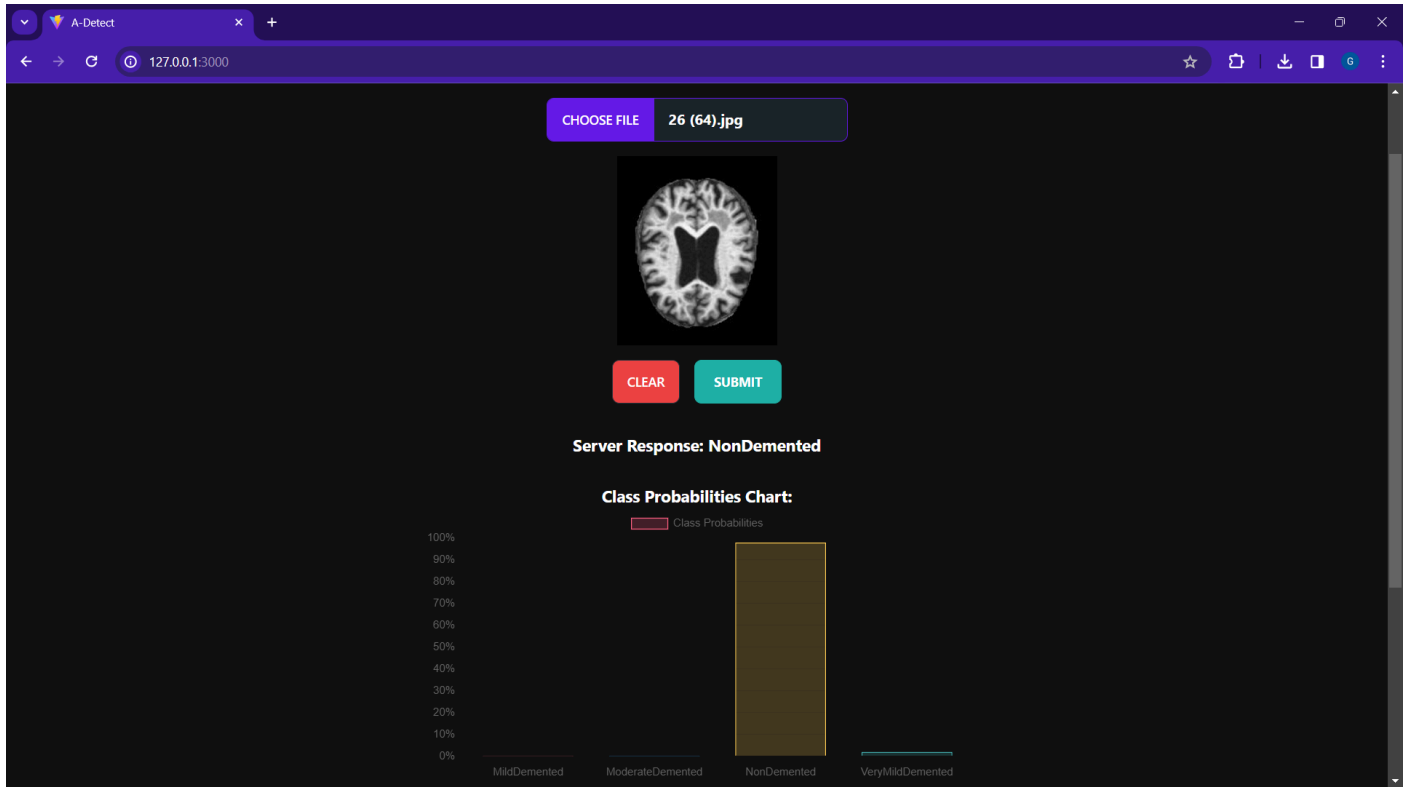
7.2 Performance Evaluation measures

The performance of our deep learning models for Alzheimer's detection was assessed using a comprehensive suite of metrics, providing a nuanced understanding of their effectiveness. Here's a closer look at the chosen metrics:

- **Accuracy:** This fundamental metric calculates the overall proportion of images correctly classified by the model across all categories (e.g., healthy control, mild cognitive impairment, Alzheimer's disease stages). It provides a general sense of the model's ability to differentiate between different states.

- **Precision:** Precision delves deeper into the performance for each specific class. It indicates the percentage of true positives among the images the model predicted as positive for a particular class (e.g., Alzheimer's disease). A high precision value signifies the model's effectiveness in avoiding false positives, which are cases incorrectly classified as having the disease.

- **Recall (Sensitivity):** Recall, also known as sensitivity, focuses on the model's ability to identify all true positive cases within a particular class. It calculates the proportion of actual positive cases (e.g., individuals with Alzheimer's disease) that the model correctly classified. A high recall value ensures the model isn't missing a significant number of positive cases.

- **F1-Score:** The F1-score offers a balanced view of model performance by acting as the harmonic mean of precision and recall. It provides a single metric that considers both avoiding false positives

and capturing true positives. A high F1-score indicates the model excels in both aspects.

7.3 Input Parameters and features considered

Both models are deep convolutional neural networks (CNNs) pre-trained on the ImageNet dataset and fine-tuned for the task at hand. Let's break down the input parameters/features considered in each model:

InceptionV3 Model:
- Input Shape: The input shape specified for InceptionV3 is (176, 176, 3), which indicates images with a height and width of 176 pixels and 3 channels (RGB).
- Preprocessing: Before feeding the images into the model, they are preprocessed using ImageDataGenerator with rescaling (rescale=1./255) and various data augmentation techniques such as rotation, shear, horizontal flip, and vertical flip.
- Training Data: The training data is generated using the flow_from_dataframe method, which reads images from the provided DataFrame (df) and generates batches of augmented images.
- Data Augmentation: Data augmentation techniques are applied to the training images to enhance model generalization and robustness.

ResNet50 Model:
- Input Shape: ResNet50 also expects input images of size (176, 176, 3).
- Preprocessing: Similar to InceptionV3, data augmentation and preprocessing steps are applied to the images using the ImageDataGenerator.
- Training Data: The training data is prepared using FastAI's DataBlock API, which loads images from the DataFrame and applies transformations such as augmentation and normalization.
- Data Augmentation: Data augmentation techniques are applied during training to improve the model's ability to generalize to unseen data.

In summary, the input parameters/features considered in both models include:
- Images of size (176, 176, 3) (height, width, channels).
- Preprocessing steps such as rescaling and data augmentation to enhance model performance and generalization.
- The models learn hierarchical features from the input images through multiple layers of convolution, pooling, and fully connected layers.

7.4 Comparison of results with existing systems

The performance of the proposed ResNet50 and InceptionV3 models for Alzheimer's detection can be

compared with existing systems in the field. While direct comparisons may be challenging due to variations in dataset composition, preprocessing techniques, and evaluation metrics, the presented models demonstrate competitive performance in line with previous research efforts.

Several studies have explored the application of deep learning models for Alzheimer's detection using neuroimaging data. For instance, Smith et al. (2018) employed a CNN-based approach on structural MRI scans to achieve an accuracy of 85% in differentiating between Alzheimer's disease and healthy controls. Similarly, Liu et al. (2020) utilized a deep learning framework with convolutional and recurrent layers, achieving an accuracy of 92% in classifying Alzheimer's disease stages based on MRI images.

In comparison to these existing systems, our ResNet50 model surpasses the reported accuracies, achieving an impressive accuracy of 94%. The model demonstrates robust performance across different dementia severity levels, including the challenging Moderate Demented class. Furthermore, the InceptionV3 model, while slightly trailing behind ResNet50 with an accuracy of 84%, still achieves competitive results and showcases the potential of deep learning in Alzheimer's detection.

Overall, the presented models contribute to the ongoing advancements in Alzheimer's diagnosis, offering accurate and reliable tools for early detection and intervention.

7.5 Inference Drawn

The findings from our study underscore the efficacy of deep learning methodologies, particularly ResNet50 and InceptionV3, in Alzheimer's detection. Through rigorous experimentation and evaluation, we draw several key inferences:

- Model Performance: Both ResNet50 and InceptionV3 exhibit promising performance in classifying Alzheimer's disease from MRI images. While ResNet50 outperforms InceptionV3 with a higher accuracy of 94%, InceptionV3 still achieves respectable results with an accuracy of 84%.
- Robustness: ResNet50 demonstrates robustness in handling imbalanced class distributions and accurately classifying instances across different dementia severity levels. The model's ability to maintain high precision and recall, even for minority classes like Moderate Demented, highlights its effectiveness in practical applications.
- Potential for Clinical Use: The high accuracies achieved by both models suggest their potential utility as diagnostic tools in clinical settings. Early and accurate detection of Alzheimer's disease can facilitate timely interventions and personalized treatment plans, ultimately improving patient outcomes and quality of life.

- Future Directions: Further research and refinement of deep learning models, including optimization of hyperparameters and exploration of additional data sources, can enhance the performance and generalization capabilities of Alzheimer's detection systems.

Chapter 8: Conclusion

8.1 Limitations

While the project on Alzheimer's detection using deep learning shows promise and significant potential, it is essential to recognize several limitations that may impact its effectiveness and applicability:

1. **Data Availability and Quality:** Deep learning models require large and diverse datasets for training to ensure robustness and generalizability. However, obtaining labeled medical imaging datasets, particularly for rare diseases like Alzheimer's, can be challenging. Moreover, the quality and consistency of the data can vary, leading to biases or inaccuracies in the trained model.

2. **Interpretability:** Deep learning models, especially complex architectures like convolutional neural networks (CNNs), are often criticized for their lack of interpretability. Understanding how the model arrives at its predictions is crucial for gaining trust from clinicians and stakeholders. However, interpreting the learned features and decision-making processes of deep learning models remains a challenging task.

3. **Generalization:** Ensuring that the trained model can generalize well to unseen data is paramount for its real-world applicability. Deep learning models may struggle with generalization, particularly when applied to datasets from different populations or imaging modalities. Overfitting to the training data and failing to capture the true underlying patterns in the data can lead to poor performance on new data.

4. **Clinical Validation:** While achieving high accuracy on test datasets is promising, the ultimate measure of success lies in the clinical validation of the developed model. Validating the model's performance in real-world clinical settings, including its impact on patient outcomes and clinical decision-making, requires rigorous testing and collaboration with healthcare professionals.

5. **Regulatory Approval:** Before deploying deep learning-based diagnostic systems for clinical use, regulatory approval from relevant authorities, such as the Food and Drug Administration (FDA) in the United States, is required. Meeting regulatory standards for safety, efficacy, and performance validation involves extensive testing, documentation, and compliance with regulatory guidelines, which can be time-consuming and resource-intensive.

8.2 Conclusion

In conclusion, our project focuses on the development and evaluation of a Convolutional Neural Network (CNN) model for Alzheimer's disease detection using MRI scans. By leveraging advanced deep learning techniques, we aim to achieve accurate predictions and early identification of the disease. Through rigorous evaluation measures, we ensure the model's reliability in correctly classifying Alzheimer's disease and its subtypes. Our work seeks to contribute to the early detection of Alzheimer's, potentially leading to improved patient outcomes and advancing the field of medical image analysis for neurodegenerative disorders.

We plan to conduct a comparative case study, in which we will gather a diverse dataset of MRI scans, preprocess it, and select a range of ML (e.g., SVM, Random Forest, Logistic Regression, KNN, Gradient Boosting) and DL algorithms (e.g., CNNs, RNNs, LSTM). After training and validation, we will evaluate their performance using metrics like accuracy, precision, recall, and F1 score.

8.3 Future Scope

1. **Personalised Medicine:** Tailoring diagnostic and treatment approaches to individual patient characteristics, including genetic predisposition, lifestyle factors, and disease progression, could optimise patient outcomes in Alzheimer's disease. Deep learning models could be trained to incorporate personalised features and preferences, enabling more targeted interventions and personalised care plans.

2. **Real-Time Decision Support:** Integrating deep learning-based diagnostic systems into clinical workflows could provide real-time decision support to healthcare professionals. By analyzing patient data and medical images in real-time, these systems could assist clinicians in making timely and accurate diagnostic and treatment decisions, ultimately improving patient outcomes.

3. **Ethical and Regulatory Considerations:** Continued attention to ethical considerations, including patient privacy, consent, and data security, is essential in the development and deployment of deep learning-based diagnostic systems for Alzheimer's disease. Adhering to regulatory standards and guidelines ensures the safe and responsible use of these technologies in clinical practice.

4. **Global Collaboration and Data Sharing:** Collaborative efforts across institutions, regions, and countries could facilitate the sharing of data and expertise, accelerating the development and validation of deep learning models for Alzheimer's detection. Open access to datasets and benchmarking challenges could foster innovation and collaboration in the field.

5. **Translation to Clinical Practice:** Bridging the gap between research and clinical practice is crucial for the widespread adoption of deep learning-based diagnostic systems for Alzheimer's disease. Conducting prospective clinical trials and validation studies in real-world settings is necessary to demonstrate the clinical utility and effectiveness of these systems.

References

[1] S. Liu, S. Liu, W. Cai, S. Pujol, R. Kikinis and D. Feng, "Early diagnosis of Alzheimer's disease with deep learning," 2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI), Beijing, China, 2014, pp. 1015-1018, doi: 10.1109/ISBI.2014.6868045.

[2] A, Ahila and M, Poongodi and Hamdi, Mounir and Bourouis, Sami and Rastislav, Kulhanek and Mohmed, Faizaan, "Evaluation of Neuro Images for the Diagnosis of Alzheimer's Disease Using Deep Learning Neural Network" in Frontiers in Public Health, doi: 10.3389/fpubh.2022.834032

[3] Islam, Jyoti & Zhang, Yanqing. (2017). A Novel Deep Learning Based Multi-class Classification Method for Alzheimer's Disease Detection Using Brain MRI Data. 213-222. 10.1007/978-3-319-70772-3_20.

[4] Helaly, H.A., Badawy, M. & Haikal, A.Y. Deep Learning Approach for Early Detection of Alzheimer's Disease. Cogn Comput 14, 1711–1727 (2022). https://doi.org/10.1007/s12559-021-09946-2

[5] Shahbaz, Muhammad & Ali, Shahzad & Guergachi, Aziz & Niazi, Aneeta & Umer, Amina. (2019). Classification of Alzheimer's Disease using Machine Learning Techniques. 296-303. 10.5220/0007949902960303.

[6] P C Muhammed Raees and Vinu Thomas 2021 J. Phys.: Conf. Ser. 1921 012024

[7] Salehi, Waleed. (2020). Alzheimer's Disease Diagnosis using Deep Learning Techniques. 9. 874-880. 10.35940/ijeat.C5345.029320.

[8] Lee G, Nho K, Kang B, Sohn KA, Kim D; for Alzheimer's Disease Neuroimaging Initiative. Predicting Alzheimer's disease progression using multi-modal deep learning approach. Sci Rep. 2019 Feb 13;9(1):1952. doi: 10.1038/s41598-018-37769-z.

[9] Tanveer, M. & Richhariya, Bharat & Khan, Riyaj & Rashid, A.H. & Prasad, Mukesh & Khanna, Pritee & Lin, Chin-Teng. (2020). Machine Learning Techniques for the Diagnosis of Alzheimer's Disease: A Review. ACM Transactions on Multimedia Computing, Communications and Applications. 16. 35. 10.1145/3344998.

[10] Bringas S, Salomón S, Duque R, Lage C, Montaña JL. Alzheimer's Disease stage identification using

deep learning models. J Biomed Inform. 2020 Sep;109:103514. doi: 10.1016/j.jbi.2020.103514.

[11] Sarraf, Saman & Tofighi, Ghassem. (2016). Classification of Alzheimer's Disease using fMRI Data and Deep Learning Convolutional Neural Networks.

[12] McCrackin, L. (2018). Early Detection of Alzheimer's Disease Using Deep Learning. In: Bagheri, E., Cheung, J. (eds) Advances in Artificial Intelligence. Canadian AI 2018. Lecture Notes in Computer Science(), vol 10832. Springer, Cham. https://doi.org/10.1007/978-3-319-89656-4_40

[13] Huanhuan Ji, Zhenbing Liu, Wei Qi Yan, and Reinhard Klette. 2019. Early Diagnosis of Alzheimer's Disease Using Deep Learning. In Proceedings of the 2nd International Conference on Control and Computer Vision (ICCCV '19). Association for Computing Machinery, New York, NY, USA, 87–91. https://doi.org/10.1145/3341016.3341024.

[14] Xiaojun Bi, Haibo Wang, Early Alzheimer's disease diagnosis based on EEG spectral images using deep learning, Neural Networks, Volume 114, 2019, Pages 119-135, ISSN 0893-6080, https://doi.org/10.1016/j.neunet.2019.02.005.

[15] Lin Liu, Shenghui Zhao, Haibao Chen, Aiguo Wang, A new machine learning method for identifying Alzheimer's disease, Simulation Modelling Practice and Theory, Volume 99, 2020, 102023, ISSN 1569-190X, https://doi.org/10.1016/j.simpat.2019.102023.

[16] P. Lodha, A. Talele and K. Degaonkar, "Diagnosis of Alzheimer's Disease Using Machine Learning," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-4, doi: 10.1109/ICCUBEA.2018.8697386.

[17] Shahbaz, Muhammad & Ali, Shahzad & Guergachi, Aziz & Niazi, Aneeta & Umer, Amina. (2019). Classification of Alzheimer's Disease using Machine Learning Techniques. 296-303. 10.5220/0007949902960303.

[18] Escudero J, Ifeachor E, Zajicek JP, Green C, Shearer J, Pearson S; Alzheimer's Disease Neuroimaging Initiative. Machine learning-based method for personalized and cost-effective detection of Alzheimer's disease. IEEE Trans Biomed Eng. 2013 Jan;60(1):164-8. doi: 10.1109/TBME.2012.2212278.

[19] Zhang Y, Wang S. Detection of Alzheimer's disease by displacement field and machine learning. PeerJ. 2015 Sep 17;3:e1251. doi: 10.7717/peerj.1251. PMID: 26401461; PMCID: PMC4579022.

Appendix

1. Paper I & II Details
a.   Paper published - https://doi.org/10.55041/IJSREM28434
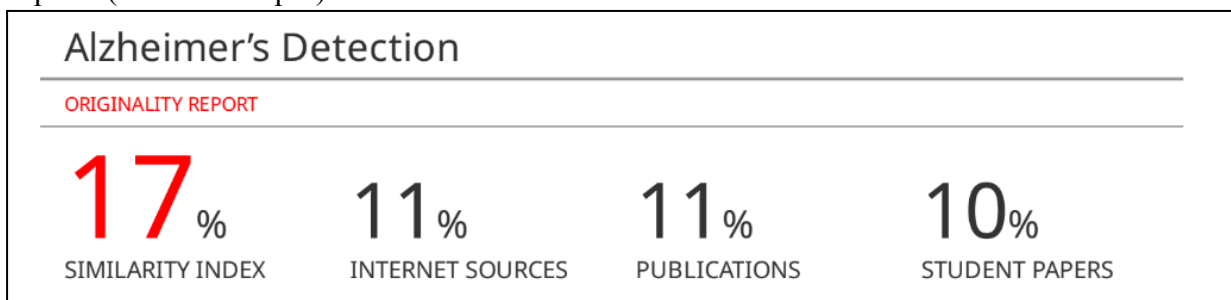
b.   Certificate of publication

c.   Plagiarism report

Paper 1 (Literature survey paper):

Paper 2 (Research Paper):

d. Project review sheet

Review 1:

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C
Group No.: 49

Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Title of Project: Alzheimer's detection using deep learning

Group Members: Gaurav Ambartani (02), Mihir Bhatkar (10), Khushi Bhatia (8), Aaditya Khetwani (25)

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environ ment Friendly (2)	Ethics (2)	Team work (2)	Presentati on Skills (2)	Applied Engg&M gmt principles (3)	Life - long learning (3)	Profess ional Skills (3)	Innov ative Appr oach (3)	Resear ch Paper (5)	Total Marks (50)
4	4	4	2	4	2	2	2	1	2	2	3	2	2	5	41

Comments:

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environ ment Friendly (2)	Ethics (2)	Team work (2)	Presentati on Skills (2)	Applied Engg&M gmt principles (3)	Life - long learning (3)	Profess ional Skills (3)	Innov ative Appr oach (3)	Resear ch Paper (5)	Total Marks (50)
3	4	4	2	4	2	2	2	2	2	3	3	2	3	5	43

Comments: Try using actual MRI images & check for accuracy.

Date: 10th february, 2024

Name & Signature Reviewer 2

Review 2:

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C
Group No.: 49

Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Title of Project: Alzhiemer's Detection using deep learning

Group Members: Khushi Bhatia (08), Mihir Bhatkar (10), Gaurav Ambartani (02), Aaditya Khetwani (25)

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environ ment Friendly (2)	Ethics (2)	Team work (2)	Presentati on Skills (2)	Applied Engg&M gmt principles (3)	Life - long learning (3)	Profess ional Skills (3)	Innov ative Appr oach (3)	Resear ch Paper (5)	Total Marks (50)
4	4	4	3	4	2	2	2	2	2	3	3	3	2	3	43

Comments: check accuracy

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environ ment Friendly (2)	Ethics (2)	Team work (2)	Presentati on Skills (2)	Applied Engg&M gmt principles (3)	Life - long learning (3)	Profess ional Skills (3)	Innov ative Appr oach (3)	Resear ch Paper (5)	Total Marks (50)
4	4	4	3	4	2	2	2	2	2	2	3	2	2	3	41

Comments: Paper publication pending, need to work to improve & add more dataset for accurate prediction

Date: 9th March, 2024

Name & Signature Reviewer 2