ENHANCING ALZHEIMER'S DIAGNOSIS: MRI ANALYSIS WITH GENERATIVE CHATBOT SUPPORT

A PROJECT REPORT

Submitted by

AMREEN.R [211420243003]

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

PANIMALAR ENGINEERING COLLEGE

(An Autonomous Institution, Affiliated to Anna University, Chennai)

MARCH 2024

PANIMALAR ENGINEERING COLLEGE

(An Autonomous Institution, Affiliated to Anna University, Chennai)

BONAFIDE CERTIFICATE

Certified that this project report **"ENHANCING ALZHEIMER'S DIAGNOSIS: MRI ANALYSIS WITH GENERATIVE CHATBOT SUPPORT"** is the bonafide work of **"AMREEN.R [211420243003]"** who carried out the project work under **Dr. S. CHAKARAVARTHI, M.E., Ph.D.,** supervision.

SIGNATURE	**SIGNATURE**
Dr. S. MALATHI, M.E., Ph.D.	**Dr.S.CHAKARAVARTHI,M.E.,Ph.D.**
HEAD OF THE DEPARTMENT	**PROFESSOR**
DEPARTMENT OF AI&DS,	DEPARTMENT OF AI&DS,
PANIMALAR ENGINEERING COLLEGE,	PANIMALAR ENGINEERING COLLEGE,
NASARATHPETTAI,	NASARATHPETTAI,
POONAMALLEE,	POONAMALLEE,
CHENNAI-600 123.	CHENNAI-600 123.

Certified that the above-mentioned student was examined in End Semester Project Work (AD8811) viva-voice held on___________.

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION BY THE STUDENT

I **AMREEN.R [211420243003],** hereby declare that this project report titled **"ENHANCING ALZHEIMER'S DIAGNOSIS: MRI ANALYSIS WITH GENERATIVE CHATBOT SUPPORT"**, under the guidance of **Dr. S. CHAKARAVARTHI M.E., Ph.D.,** is the original work done by me and I have not plagiarized or submitted to any other degree in any university by me.

AMREEN.R

ACKNOWLEDGEMENT

We would like to express our deep gratitude to our respected Secretary and Correspondent **Dr. P. CHINNADURAI, M.A., Ph.D.** for his kind words and enthusiastic motivation, which inspired us a lot in completing this project.

We express our sincere thanks to our directors **Tmt. C. VIJAYARAJESWARI**, **Dr. C. SAKTHI KUMAR, M.E., Ph.D. and Dr. SARANYASREE SAKTHI KUMAR B.E., M.B.A., Ph.D.,** for providing us with the necessary facilities to undertake this project.

We also express our gratitude to our Principal **Dr. K. MANI, M.E., Ph.D**. who facilitated us in completing the project.

We thank the Head of the AI&DS Department, **Dr. S. MALATHI, M.E., Ph.D.,** for the support extended throughout the project.

We would like to thank my Project Guide **Dr. S. CHAKARAVARTHI M.E., Ph.D.,** and all the faculty members of the Department of AI&DS for their advice and encouragement for the successful completion of the project.

ABSTRACT

Alzheimer's disease is a neurological condition that worsens with time and is characterized by memory loss and a reduction in cognitive function. It is the most prevalent cause of dementia, impacting millions of individuals globally. Alzheimer's disease usually affects elderly folks, however it can also strike younger people on occasion. Diagnostic methods for Alzheimer's disease (AD) frequently combine psychological assessments with neuroimaging modalities like magnetic resonance imaging (MRI). This project extracts complex patterns and aspects of Alzheimer's disease from MRI brain images using deep learning methods. Complex spatial and temporal information is processed using convolutional neural networks. The goal is to develop a robust diagnostic tool for identifying subtle neuroanatomical changes. to augment the diagnostic system's capabilities, a prediction mechanism is incorporated. This mechanism enables the system to anticipate disease progression, empowering healthcare providers to implement proactive management strategies and personalize treatment plans for patients with AD. A generative chatbot interface based on LangChain architecture and driven by the llama2 language model has been introduced to enhance the diagnostic process. This project represents a holistic approach to addressing the challenges posed by Alzheimer's disease, combining cutting-edge technology, innovative interfaces, and predictive analytics to revolutionize diagnosis, management, and patient care. By leveraging deep learning methods, enhancing communication through a generative chatbot interface, and incorporating predictive capabilities and real-time updates, the project aims to significantly improve outcomes for individuals affected by AD and transform the landscape of dementia care.

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Meaning
AD	Alzheimer’s Disease
MRI	Magnetic Resonance Imaging
CNN	convolutional neural networks
CN	Cognitively Normal
MCI	Mild Cognitive Impairment
EMCI	Early Mild Cognitive Impairment
LMCI	Late Mild Cognitive Impairment
MMSE	Mini-Mental State Exam
PET	Positron Emission Tomography
LLM	Large Language Model
ADNI	Alzheimer's Disease Neuroimaging Initiative
NLP	Natural Language Processing
MLP	Multilayer perceptron

CHAPTER 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

Alzheimer's disease is a neurological condition that worsens over time, eventually impairing thinking, memory, and even the capacity to do basic tasks. It is the most frequent cause of dementia, a word used to describe a loss of cognitive skills such as memory, language, and problem-solving that is severe enough to interfere with day-to-day activities. Timely detection, ongoing support, access to current information, and predictive insights are essential components for effective management and care. In response to these critical needs, our project introduces a comprehensive Alzheimer's Care Ecosystem. This ecosystem integrates cutting-edge technologies to provide a holistic approach to Alzheimer's care.

This project combines advanced deep learning techniques, specifically Convolutional Neural Networks (CNNs), for accurate detection of Alzheimer's disease from medical imaging data. Alongside CNN-based detection, we incorporate the assistance of a sophisticated medical chatbot to provide personalized support and information to patients, caregivers, and healthcare professionals. Furthermore, the system offers real-time updates on the latest news and research in Alzheimer's disease, ensuring stakeholders stay informed about developments in the field. Finally, predictive analysis tools are employed to anticipate disease progression and aid in treatment planning.

By combining these elements into a unified platform, our project aims to revolutionize Alzheimer's care by providing comprehensive support, timely information, and proactive management strategies. Through this interdisciplinary approach, we aspire to improve patient outcomes, enhance caregiver support, and contribute to advancements in Alzheimer's research and treatment.

1.1 OVERVIEW

The project aims to develop a comprehensive solution for Alzheimer's disease management, integrating various technological components to enhance early detection, support, and information dissemination. Initially, the project will focus on leveraging deep learning techniques, specifically Convolutional Neural Networks (CNNs), for accurate detection of Alzheimer's disease using structural MRI data. This segment involves training CNN models on a dataset comprising both healthy aging subjects and individuals diagnosed with Alzheimer's disease, followed by thorough evaluation to assess performance metrics. Additionally, the project will include the development of a medical chatbot tailored for Alzheimer's support, providing personalized assistance, information, and guidance to patients, caregivers, and healthcare professionals. Alongside this, a real-time news aggregation system will be implemented to keep stakeholders informed about the latest research findings, treatment options, and news related to Alzheimer's disease. Furthermore, predictive analytics will be employed to anticipate disease progression, enabling proactive treatment planning and management. The integration and deployment phase will involve merging all project components into a unified platform, addressing technical considerations, and ensuring scalability and usability. Through case studies and use cases, the project will showcase the practical applications and effectiveness of each component, followed by a thorough assessment of impact and user feedback analysis. Ultimately, the project aims to contribute to improved Alzheimer's care by providing early detection, personalized support, up-to-date information, and predictive insights, thereby enhancing patient outcomes and advancing research in the field.

1.2 PROBLEM DEFINITION

The need for Alzheimer's detection is paramount given the profound impact of this neurodegenerative disease on individuals, families, and society. Alzheimer's is a progressive condition that gradually impairs cognitive function, memory, and daily living activities, ultimately leading to severe disability and dependency. Early detection of Alzheimer's is crucial as it allows for timely intervention and management strategies to slow disease progression and improve quality of life for affected individuals. Additionally, early diagnosis enables patients and their families to make informed decisions regarding care planning, access support services, and participate in clinical trials for potential treatments. This encompasses a multifaceted approach that incorporates the integration of various data sources, including medical records, imaging studies, genetic information, and cognitive assessments. The overarching goal is to construct predictive models capable of reliably diagnosing Alzheimer's disease at its incipient stages, thus facilitating timely intervention and personalized treatment strategies. Furthermore, the problem statement includes the exploration of novel biomarkers, risk factors, and disease mechanisms through advanced data analytics and machine learning techniques. By addressing these challenges, the aim is to enhance our understanding of Alzheimer's disease, improve early detection rates, and ultimately mitigate its impact on individuals, families, and society as a whole.

1.3 OBJECTIVE

The primary objective of this project is to advance the diagnostic capabilities for Alzheimer's disease (AD) by leveraging cutting-edge technology and methodologies. By utilizing deep learning techniques, particularly convolutional neural networks (CNNs), complex spatial and temporal information inherent in MRI brain images can be effectively processed and analyzed. This approach enables the extraction of subtle neuroanatomical changes associated with AD, thereby facilitating early detection and intervention. Moreover, the integration of a generative chatbot interface, based on LangChain architecture and powered by the llama2 language model, serves to enhance the interaction between users, including physicians and patients, and the diagnostic system. This intuitive interface fosters real-time communication, allowing for the interpretation of diagnostic data and provision of immediate feedback, thereby improving the overall diagnostic process. Furthermore, the incorporation of a prediction mechanism aims to forecast disease progression, enabling proactive management strategies. Additionally, real-time news updates ensure that the diagnostic system remains informed of the latest advancements and findings in AD research, thereby continually enhancing its efficacy and relevance in clinical practice. Overall, this project represents a multidimensional approach to advancing Alzheimer's disease diagnosis, combining state-of-the-art technology with innovative communication interfaces and predictive capabilities to improve patient outcomes and clinical decision-making.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

- **Tetiana Habuza et al. [1]**, The survey explores the use of deep learning in analyzing brain scans and cognitive tests for Alzheimer's disease (AD) detection. It discusses the urgency of AD detection, deep learning's potential in medical imaging analysis, and the role of MRI and cognitive tests in AD diagnosis. It acknowledges limitations like data needs and potential bias.
- **Al Shehri W. [2]**, The study proposes a deep learning-based solution for Alzheimer's disease diagnosis and classification, using DenseNet-169 and ResNet-50 convolutional neural network architectures. The study aims to improve accuracy and efficiency in early detection, as manual diagnosis remains error-prone and time-consuming. The model shows superior performance, demonstrating high accuracy values in training and testing phases. This model offers promise for real-time analysis and classification, contributing to advancements in early diagnosis solutions.
- **Cristina L. Saratxaga et al. [3],** This paper reviews current methods for diagnosing Alzheimer's Disease (AD), focusing on limitations of traditional cognitive tests and the role of Magnetic Resonance Imaging (MRI) in identifying brain abnormalities. It highlights recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), and their potential for AD diagnosis. The review acknowledges challenges like large datasets and potential biases in deep learning algorithms. The aim is to establish the need for improved AD diagnosis and explore deep learning's potential in MRI analysis.
- **Nasir Rahim et al. [4],** The study discusses advancements in Alzheimer's disease diagnosis and prognosis using deep learning techniques, multimodal data fusion, longitudinal analysis, and explainable AI methods. Researchers use datasets like ADNI to develop models that analyze MRI scans to identify patterns associated with AD progression. Longitudinal studies track changes over time, while explainable AI

helps clinicians interpret model predictions. This integrated approach improves early detection and understanding of AD's underlying mechanisms.

- **Yan Zhao et al. [5]**, The study suggests that integrating PET/MR imaging with deep learning (DL) can improve Alzheimer's disease diagnosis and treatment. Despite challenges like data heterogeneity and interpretability, DL has shown potential in improving efficiency and quality of AD imaging. Future research should address these challenges to fully utilize DL's capabilities in improving AD diagnosis, prognosis, and treatment strategies.

- **Naveen Sundar Gnanadesigan et al. [6],** proposed the DC-GC model that is a novel method for identifying candidate genes associated with Alzheimer's disease (AD) using network topology measures and machine learning techniques. This model outperforms existing classifiers like ANN, KNN, SVM, and decision trees in identifying candidate genes. It ranks genes based on their connectivity and physicochemical properties, improving the identification of potential AD-related genes. The model's promising results suggest it can advance our understanding of AD pathogenesis and facilitate the development of targeted therapeutic interventions, thereby improving the development of effective therapies.

- **Zhen Zhao et al. [7],** This paper reviews various machine learning techniques for Alzheimer's disease classification and prediction, including SVM, RF, CNN, Autoencoder, Deep Learning, and Transformer. It discusses feature extractors and input formats, and addresses challenges like class imbalance and data leakage. The review also discusses pre-processing techniques and trade-offs between deep learning and conventional methods. It offers insights for addressing these issues, exploring new techniques, and selecting appropriate input types for optimal AD diagnosis and prediction.

- **Pradnya Borkar et al. [8],** This research aims to develop noninvasive and cost-effective methods for early detection of Alzheimer's disease (AD). By analyzing MRI scans and extracting brain characteristics, a model based on convolutional neural networks and long short-term memory networks is trained. The model outperforms current diagnostic methods, providing high accuracy (99.7%) while remaining noninvasive and cost-effective. This innovative approach contributes to the growing literature on deep learning for early detection and intervention in AD, offering hope for improved patient outcomes.

- **Daichi Shigemizu et al. [9],** The study explores the genetic structure of late-onset Alzheimer's disease (LOAD) using genome-wide association study data from Japanese cohorts. Two distinct groups of LOAD patients were identified: one exhibited risk genes for LOAD development, immune-related genes, and another displayed genes associated with kidney disorders. Impaired kidney function was identified as a potential contributor to LOAD pathogenesis. Researchers developed a prediction model using a deep neural network, providing new insights into LOAD's pathogenic mechanisms.

- **Shangran Qiu et al. [10],** The study explores the genetic structure of late-onset Alzheimer's disease (LOAD) using genome-wide association study data from Japanese cohorts. Two distinct groups of LOAD patients were identified: one exhibited risk genes for LOAD development, immune-related genes, and another displayed genes associated with kidney disorders. Impaired kidney function was identified as a potential contributor to LOAD pathogenesis. Researchers developed a prediction model using a deep neural network, providing new insights into LOAD's pathogenic mechanisms.

CHAPTER 3

SYSTEM ANALYSIS

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing system [1] uses psychophysiological and cognitive tests to detect dementia stages, combining structural data for improved diagnostic accuracy. It investigates brain structure and function, hypothesizing specific features differentiate between disease-related cognitive decline and normal neurocognitive aging. A study involving 287 cognitively normal cases, 646 mild cognitive impairment cases, and 369 Alzheimer's disease cases developed a convolutional neural network-based regression model for predicting cognitive status.

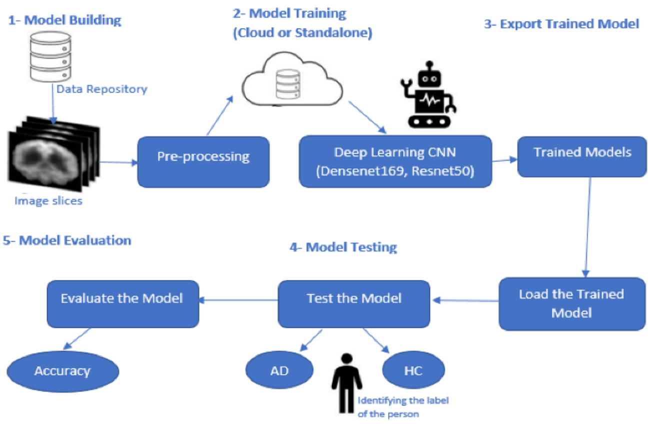

Fig. 3.1 System Architecture for proposed system

Existing systems for Alzheimer's detection [2] and prediction use machine learning and deep learning techniques to analyse complex patterns and biomarkers associated with the disease. These systems use data from neuroimaging, genetic markers, and clinical assessments to predict the risk of Alzheimer's onset or progression. These systems aim to enhance early detection, prognosis, and personalized treatment strategies. However, manual diagnosis is error-prone and time-consuming. This research proposes a deep learning-based solution using DenseNet-169 and ResNet-

50 CNN architectures for the diagnosis and classification of Alzheimer's disease. The model categorizes Alzheimer's into Non-Dementia, Very Mild Dementia, Mild Dementia, and Moderate Dementia stages. DenseNet-169 outperformed in training and testing phases, demonstrating potential for real-time analysis and classification of Alzheimer's disease.

3.2 PROPOSED SYSTEM

- In the proposed system, we are making use of CNNs(Convolutional Neural Networks) Algorithm which are a class of neural network that allow greater extraction of features from the MRI scans.
- CNNs take the data, train the model, and then classify the features automatically for healthier classification.
- The model consists of another model for developing an Alzheimer's prediction system utilizing machine learning techniques trained on the ADNI dataset to forecast cognitive decline based on neuroimaging and clinical data.
- Additionally, the approach gains even more advantages from the usage of chatbots. The implementation of the chatbot makes use of Langchain and Llama2 Algorithm. It enhances its efficacy.

The proposed system is divided into the following modules;

- **Alzheimer Detection:** This module is trained with the dataset that contains various types of MRI scans of the brain, as well as clinical data such as patient history, genetic information, and cognitive assessments. With the help of the model that is trained with CNN can help to classify whether the given MRI scan of the patient is affected with Alzheimer or not.
- **Medical Chatbot:** Developing a medical chatbot for Alzheimer's detection involves collecting and preprocessing medical questions, training a model to understand user queries, building a knowledge base, and integrating a question-answering system. The chatbot provides accurate responses to user questions by

retrieving relevant information from the knowledge base. Continuous testing, evaluation, and maintenance ensure its accuracy and compliance with regulations.

- **Alzheimer Prediction:** Relevant data is collected, including medical records, genetic information, and cognitive assessments. Feature engineering extracts relevant features, followed by training a predictive model deep learning to forecast Alzheimer's disease likelihood. Evaluation with appropriate metrics gauges model performance.
- **Latest News Update:** The Alzheimer's healthcare news update module gathers and presents the latest research findings and developments in Alzheimer's disease from reputable sources, providing healthcare professionals and researchers with timely insights and advancements in the field.

Therefore, the important phases in creating the model include-

- Data collection
- Data pre-processing
- Data exploration and visualization
- Feature scaling
- Splitting the dataset
- Training and testing data
- Model building
- Model deployment

3.2.1. Data collection

The first and foremost step in the process of our model is data collection. Data collection is the process of gathering the data from various sources. For our model, we collect the Alzheimer datasets of two types, that is, ADNI dataset and MRI scans dataset. The ADNI dataset is used for the predicting Alzheimer, which contains the data such as gender, age, demographics, genetic information and cognitive assessment scores, etc. The other dataset contains the MRI scans of people at various stages of Alzheimer. These two datasets are used for both Alzheimer detection and prediction.

3.2.2. Data pre-processing

Data pre-processing is the next stage that follows the data collection procedure. The information gathered in the earlier phase comes from various sources. It may not be in a format that is appropriate for us to work on. A variety of errors—not necessarily errors, such as missing numbers, outliers, redundant data, etc.—may be included. Therefore, handling each of these irregularities that are present in the dataset is required at this point. As a result, the unnecessary columns that essentially reflect the years must be deleted. Moreover, defining the columns for features (x) and goal (y). where y is the output variable, also known as the dependent variable, and X stands for the input variables, also known as the independent variables.

3.2.3. Data exploration and visualization

Data exploration and visualization is a very important step in a model to understand the trends of the data. It basically helps us to make data-driven decisions on our own. Visualization is a key factor which helps us to understand the data in a better way and ultimately increased the productivity and helps us achieve better results. The target variable (y) is the label indicating the clinical diagnosis or cognitive status of each subject, such as Alzheimer's disease, mild cognitive impairment, or healthy control. The model learns to associate patterns in the input features with the corresponding target labels during the training process, enabling it to make predictions on new, unseen data.

The below graphs depcts the relationship between the given parameters-

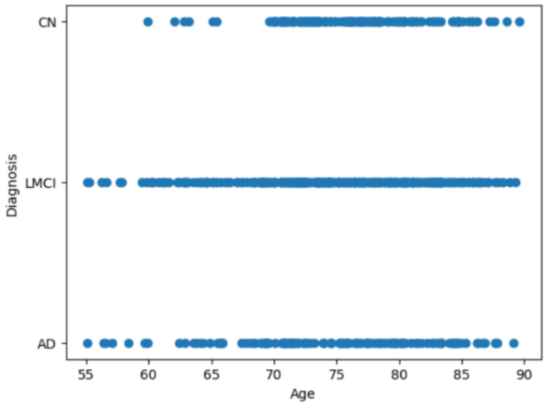

Fig.3.2.3a Relationship between Age and Diagnosis (DX.b1)

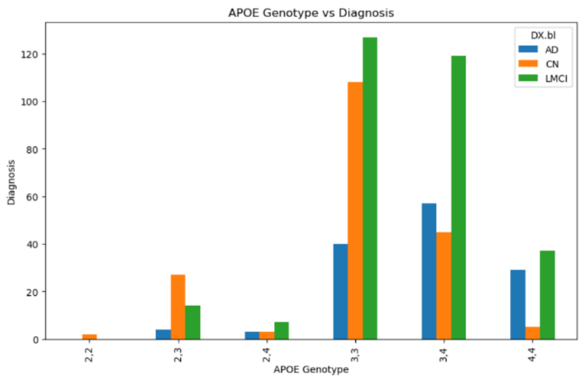

Fig.3.2.3b Relationship between APOE Genotype and Diagnosis (DX.bl)

3.2.4. Feature scaling

Standardizing the range of independent variables in a dataset is known as feature scaling. The Euclidean Distance metric is frequently used by machine learning models to determine the separation between two points in a dataset. For instance, if a column x consistently has larger values than a different column y, then $(x2-x1)^2$ will dominate $(y2-y1)^2$, which implies $(y2-y1)^2$ will be regarded as nonexistent, which is inappropriate. It is for this reason that standardization is required. We will scale the standardizing formula to each of the 20 selected column's observations.

$$Xs = \frac{X - mean}{s.d.}$$

$$Xs = \frac{X - mean}{max - min}$$

$$Xs = \frac{X - min}{\max - min}$$

3.2.5. Training and testing data

The dataset must be split into training and testing datasets as the next stage in the data modeling process. The data can be divided in a variety of ways, for example, by applying ratios like 80:20, 75:25, 70:30, etc. We selected a 70:30 ratio to divide the data for our model, meaning that 70% of the data will be used for training and 30% for evaluating the model's performance.

3.2.6. Model Building

Developing the model is one of our system's most crucial phases. We use a variety of supervised learning methods to model the data after dividing it into training and testing sets. We attempted to use three different techniques to model the data. They are-

- Logistic Regression
- Random Forest Classifier
- MLP Classifier
- Linear Discriminant Analysis
- Gradient Boosting Classifier
- Convolutional Neural Network
- Sequential model

The following sections will provide a description of the aforementioned algorithms and their workflow. The models from all of the previously mentioned models that have been implemented are assessed, and the model with the highest accuracy is chosen to proceed with the deployment process.

3.3 FEASIBILITY STUDY

3.3.1. Social Feasibility

Alzheimer's disease presents global challenges and requires innovative solutions to enhance diagnostic accuracy and address ethical concerns. Deep learning techniques in MRI analysis offer early detection, but concerns about algorithmic bias, patient consent, and data protection persist. Integrating generative chatbots in Alzheimer's diagnosis platforms enhances inclusivity and informed decision-making. Addressing ethical, privacy, and accessibility issues is crucial for maximizing societal benefits. Evaluating the economic feasibility of implementing comprehensive care ecosystems requires careful consideration of various factors.

3.3.2. Economic Feasibility

The Alzheimer's Care Ecosystem, despite its initial investment, offers significant long-term benefits such as improved patient outcomes, reduced healthcare expenses, and enhanced caregiver support. The ecosystem's early detection and integration of advanced technologies like CNN-based detection and predictive analysis improve healthcare delivery efficiency. With growing market demand for innovative Alzheimer's solutions, the ecosystem has the potential to capture a significant market share. Revenue opportunities include subscription-based access, technology licensing, partnerships, and premium services. Overall, the Ecosystem is a promising investment in Alzheimer's care.

3.4 SOFTWARE REQUIREMENT

The software required for our model are-

➢ Operating System: Windows 7/8/10

➢ Language: Python

➢ IDE: VS Code, Google Colab, Jupyter Notebook

3.5 HARDWARE REQUIREMENT

The hardware required for our model are-

➢ Processor: i3 or more

➢ RAM: 4GB or more

CHAPTER 4

DATASETS

CHAPTER 4

DATASETS

Our study aimed to investigate the relationship between Alzheimer's disease progression and various demographic and clinical factors utilizing the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset spanning from 2004 to 2021. We utilized three primary datasets: the clinical dataset, the MRI imaging dataset, and the genetic dataset. The clinical dataset contains approximately 10,000 rows and 100 columns, encompassing variables such as subject ID, age, gender, cognitive scores (e.g., MMSE), diagnosis, and medication history. The MRI imaging dataset includes structural and functional MRI scans from over 2,000 participants, providing information on brain volume, cortical thickness, and connectivity metrics. The genetic dataset consists of genetic markers associated with Alzheimer's disease risk and progression. These datasets were obtained from the ADNI database, a longitudinal multicenter study designed to track the progression of Alzheimer's disease and related disorders. The data were initially provided in CSV format and subsequently transformed into a Pandas dataframe for analysis using Python.

```
data.head(10)
```

	directory.id	Subject	RID	Image.Data.ID	Modality	Visit	Acq.Date	DX.bl	EXAMDATE	AGE	PTGENDER	PTEDUCAT	PTETHCAT
0	4702245ea294ce5d4e9b8a87027dfdf4	011_S_0003	3	32237	MRI	1	09-01-2005	AD	09-12-2005	81.3	Male	18	No Hisp/Latino
1	2e89e352af743597b2368c412e0f6de2	022_S_0004	4	64631	MRI	1	9/22/05	LMCI	11-08-2005	67.5	Male	10	Hisp/Latino
2	90419199306997753de8042f1fd55e38	011_S_0005	5	32246	MRI	1	09-02-2005	CN	09-07-2005	73.7	Male	16	No Hisp/Latino
3	d8d175ffff1e2053e6a18c5df494ccdf	100_S_0006	6	33025	MRI	1	11/15/05	LMCI	11/29/05	80.4	Female	13	No Hisp/Latino
4	986e75b2e604cd44b38feb2188476fb2	011_S_0010	10	32270	MRI	1	11-07-2005	AD	11-10-2005	73.9	Female	12	No Hisp/Latino
5	1b4f75db908c740500a9f46c409b8a30	022_S_0014	14	59375	MRI	1	9/29/05	CN	11-04-2005	78.5	Female	12	Hisp/Latino
6	d48c4a953904db90b35da1a4c06ea373	100_S_0015	15	33066	MRI	1	9/26/05	CN	10/18/05	80.8	Male	18	No Hisp/Latino
7	ff816ae1926d624a1f8de68024959515	011_S_0016	16	32306	MRI	1	9/27/05	CN	10/13/05	65.4	Male	9	No Hisp/Latino
8	089510f9cdcea610b6f294d3b42a9035	067_S_0019	19	45228	MRI	1	10-12-2005	CN	11/23/05	73.1	Female	18	No Hisp/Latino
9	457d28b028ab703eb2cabb3923f6e232	011_S_0021	21	32332	MRI	1	10-10-2005	CN	10/24/05	72.6	Female	18	No Hisp/Latino

Fig 4.1. Dataframe created from the ADNI dataset

Another dataset utilized in our study is the MRI scan dataset obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. This dataset consists of MRI scans collected from participants diagnosed with various cognitive states, including cognitively normal (CN), Alzheimer's disease (AD), mild cognitive impairment (MCI), early mild cognitive impairment (EMCI), and late mild cognitive impairment (LMCI). The source of this dataset is the ADNI database, a longitudinal multicenter study aimed at understanding the progression of Alzheimer's disease. The MRI scan dataset contains approximately 10,000 scans with detailed imaging features extracted, including measures of brain volume, cortical thickness, and white matter integrity. Each scan is associated with demographic information such as age, gender, and clinical assessments. The dataset was initially provided in DICOM format and later transformed into a structured format suitable for analysis. This dataset serves as a valuable resource for studying the neuroanatomical changes associated with Alzheimer's disease progression across different cognitive states.

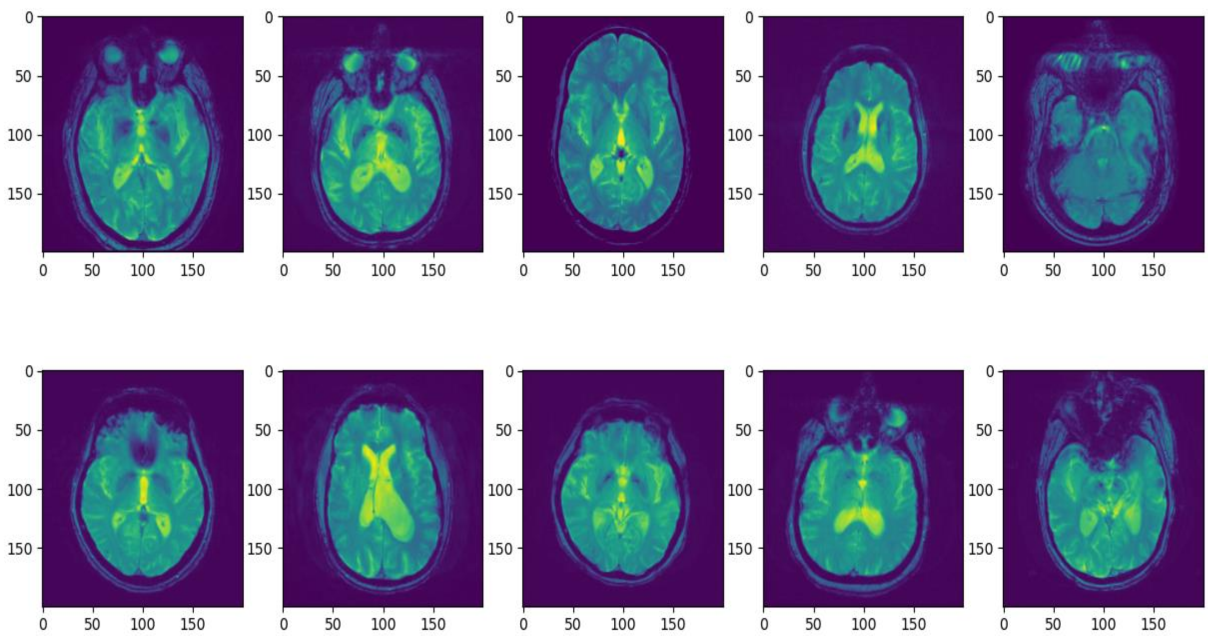

Fig 4.2. Images from the MRI scans dataset

CHAPTER 5

SYSTEM DESIGN

CHAPTER 5

SYSTEM DESIGN

5.1. ER DIAGRAM

Figure 5.1 depicts the relationship between the user, administrator, and the Alzheimer's prediction and detection system. Users input personal data, while the system utilizes pre-trained models to predict Alzheimer's risk. The administrator monitors the process and accesses results, including risk levels and potential indicators, facilitating early intervention strategies.

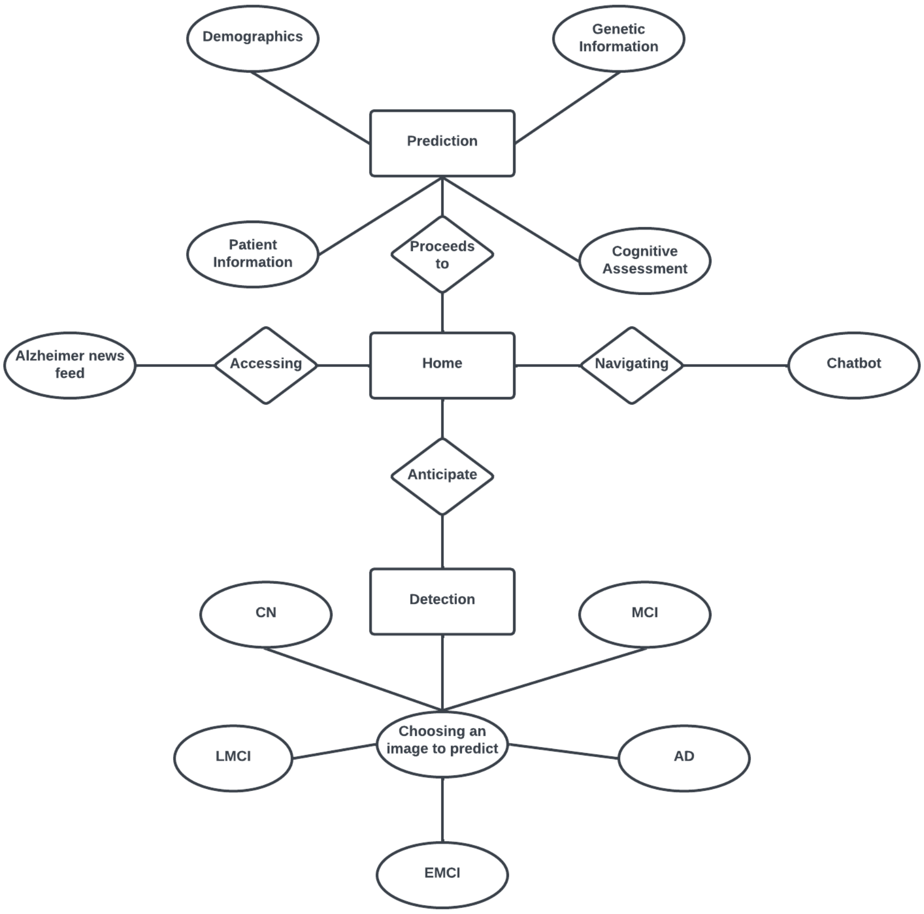

Fig 5.1 System ER diagram

5.2 CLASS DIAGRAM

The following diagram depicts the class diagram of the Alzheimer diagnostic system-

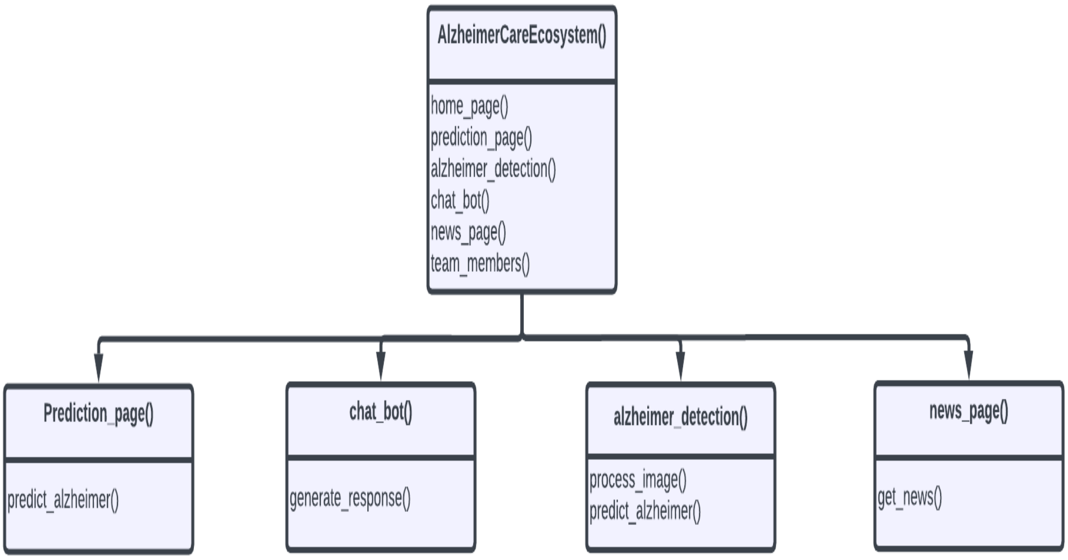

Fig 5.2 Class diagram

Fig 5.2 shows the functions of each class used in our system. The class names here are the home_page, prediction_page, alzheimer_detection, chat_bot, and news_page. Each of the class has its own attributes. The prediction_page predicts the Alzheimer use several characteristics. The alzheimer_detection class checks whether the given MRI scan image of the patient is healthy or not. The generative chatbot system and the real-time news update class are the added advantage to the system.

CHAPTER 6

SYSTEM ARCHITECTURE

CHAPTER 6

SYSTEM ARCHITECTURE

The system architecture diagram of our model is given below-

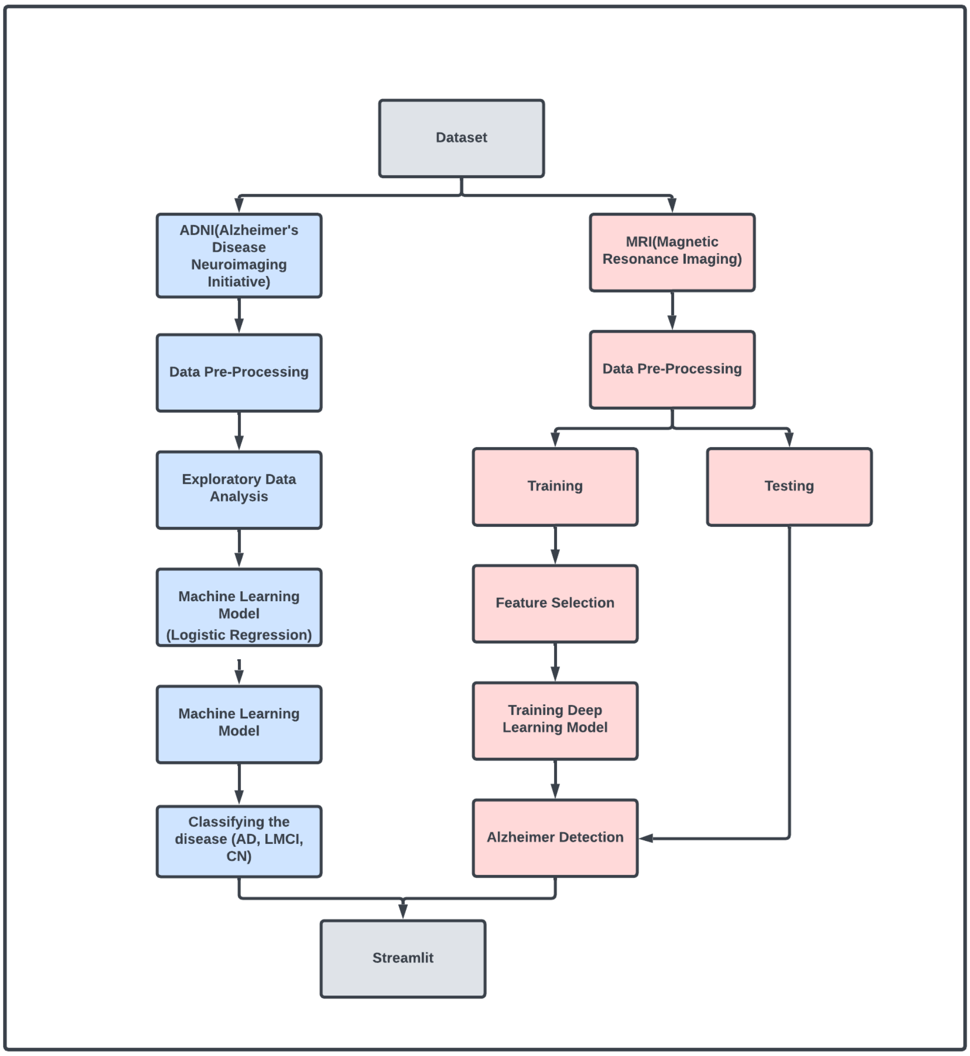

Fig 6.1 System Architecture

Fig 6.1 describes the working of system architecture for Alzheimer Prediction and Detection System. The Alzheimer's prediction and detection system architecture involve a sequential process starting with data collection, followed by pre-processing to clean and standardize the data. Exploration and visualization help understand data characteristics before feature scaling to ensure uniformity. The dataset is then split into training and testing subsets for model training and evaluation. Using machine learning algorithms, the model is built to predict and detect Alzheimer's disease based on the processed data. Finally, the trained model is deployed for practical use in clinical or research settings, aiding in early diagnosis and intervention.

6.1 MODULE DESIGN SPECIFICATION

A). Alzheimer Detection: Leveraging advanced CNN deep learning technology, the proposed Alzheimer detection model utilizes MRI scan images to accurately diagnose whether an individual has Alzheimer's disease or not. The system is designed to process and analyze MRI scans, extracting intricate patterns and features indicative of Alzheimer's pathology. Through extensive training on a diverse dataset comprising both healthy and Alzheimer's affected individuals, the CNN model learns to discern subtle differences in brain structures associated with the disease. The proposed system employs sophisticated image preprocessing techniques to enhance the quality and consistency of input data, ensuring robust performance across varied scan qualities and conditions. Furthermore, the model integrates contemporary deep learning algorithms to effectively capture complex spatial relationships within the brain images, enabling it to achieve high accuracy in Alzheimer's detection. This system holds promise for early diagnosis and intervention, potentially improving patient outcomes and facilitating more targeted therapeutic interventions for individuals at risk of Alzheimer's disease.

B). Generative Chatbot Support: The Generative Alzheimer's Chatbot Support System is designed to provide personalized assistance and support for individuals affected by Alzheimer's disease and their caregivers. Harnessing generative chatbot technology, the system interacts with users in natural language, offering empathetic and informative responses to queries related to Alzheimer's symptoms, treatments, caregiving strategies, and emotional support. The chatbot employs a deep learning-based generative model trained on a diverse corpus of Alzheimer's-related information, ensuring accurate and contextually relevant responses. Additionally, the system integrates sentiment analysis capabilities to gauge the emotional state of users and tailor responses accordingly, offering empathetic and supportive interactions. Through continuous learning and refinement, the chatbot evolves to better understand and address the unique needs and challenges faced by individuals living with Alzheimer's disease and their caregivers. This system aims to provide accessible and reliable support, helping to alleviate stress, improve caregiver well-being, and enhance the overall quality of life for those affected by Alzheimer's disease.

C) Predictive Analysis: The Predictive Analysis System for Alzheimer's Disease integrates a wide array of features, including personal information such as age, gender, and years of education, along with demographics, genetic information, and cognitive assessments, to accurately predict the risk of Alzheimer's disease development in individuals. The system employs advanced machine learning algorithms to analyze and model complex relationships among these diverse features, identifying patterns and risk factors associated with the onset of Alzheimer's disease. Through comprehensive data processing and feature engineering techniques, the system extracts meaningful insights from heterogeneous datasets, enabling it to generate reliable predictions. Additionally, the system utilizes probabilistic modeling approaches to estimate the likelihood of Alzheimer's disease occurrence over time, taking into account longitudinal data and temporal dynamics. By capitalizing on a combination of demographic, genetic, cognitive, and personal information, the Predictive Analysis System offers valuable insights into individualized risk assessment for Alzheimer's disease, empowering healthcare professionals and individuals to proactively manage and mitigate the impact of the disease through personalized interventions and lifestyle modifications.

D) AlzNewsFeed: Alzheimer's News Update System is a comprehensive platform designed to deliver up-to-date news and information related to mental health and Alzheimer's diseases. Leveraging advanced information retrieval and natural language processing techniques, the system continuously monitors a wide range of reputable news sources, medical journals, and research databases for relevant articles, studies, and updates pertaining to mental health conditions and Alzheimer's disease. These sources cover a spectrum of topics, including new treatments, breakthrough research findings, caregiving strategies, and community resources. The system employs sentiment analysis algorithms to assess the tone and sentiment of news articles, helping users identify positive developments and key insights amidst a vast array of information. Additionally, the platform categorizes news updates into easily navigable sections, allowing users to explore specific topics of interest such as Alzheimer's research, mental health awareness initiatives, or caregiver support resources. Through real-time notifications and personalized recommendations, the system ensures that stakeholders stay informed about the latest advancements and trends in mental health and Alzheimer's care, empowering them to make informed decisions and access relevant support services when needed.

6.2 ALGORITHM

The main purpose of this system is to detect and predict the likelihood of Alzheimer's disease in individuals and offer performance analysis. We have employed several supervised learning algorithms tailored for classification problems. These models are thoroughly evaluated, and the model that demonstrates superior performance is chosen for deployment.

6.2.1 Logistic Regression

Logistic regression is a statistical technique used for binary classification tasks, where the outcome variable has two possible outcomes. It models the probability of the binary outcome using predictor variables by fitting a logistic curve to the data. However, it assumes a linear relationship between predictors and the log-odds of the outcome and is limited to binary classification tasks.

The formula for the Logistic Regression is as follows:

$$\boldsymbol{P(Y = 1|X) = \frac{1}{1 + e^{-(\beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn)}}}$$

Where:

- P(Y=1|X) is the probability of the outcome being 1 given the predictor variables X.
- *e* is the base of the natural logarithm.
- β0, β1, β2..., βn are the coefficients of the logistic regression model.
- X1, X2..., Xn are the predictor variables.

The graph for logistic regression is as follows-

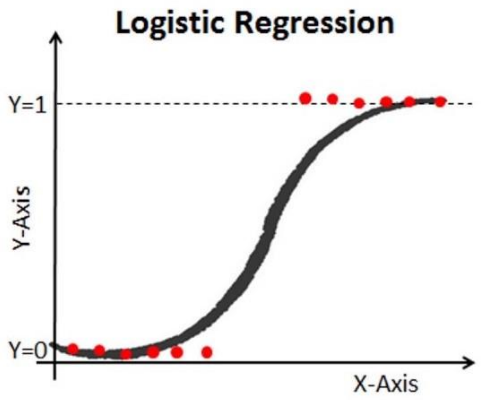

Fig. 6.2.1: Logistic Regression

Steps in Linear Regression:

1. Load and preprocess the data.
2. Splitting the data.
3. Define the logistic regression model and its parameters.
4. Train the model.
5. Evaluate the model.
6. Tweak the model's parameters.
7. Make predictions on new, unseen data.

6.2.2 Ridge Classifier

Ridge Classifier is a linear classification algorithm that extends the concept of linear regression to classification problems. Similar to linear regression, it assumes a linear relationship between the input features and the target variable, but it's applied to classification tasks rather than regression tasks.

Steps in Ridge Classifier:

1. Data Loading and Preprocessing.
2. Data Splitting.
3. Ridge Classifier Model Definition.
4. Model training and model evaluation.
5. Parameter tuning.
6. Prediction on new data.

CHAPTER 7

EVALUATION METRICS

CHAPTER 7
EVALUATION METRICS

The performance of our model was assessed using a number of metrics for evaluation. This section discusses common evaluation metrics.

7.1 Confusion Matrix

The metrices contains four values namely True Positive, True Negative, False Positive and False Negative where-

True Positive (TP) =Observation is positive, and is predicted to be positive. False Negative (FN) = Observation is positive, but is predicted negative.

True Negative (TN) = Observation is negative, and is predicted to be negative. False Positive (FP) =Observation is negative, but is predicted positive.

The confusion matrix for the Logistic Regression model can be given as-

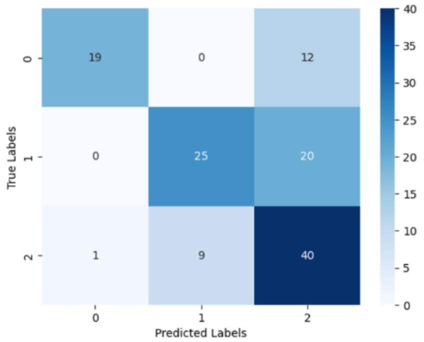

Fig. 7.1a: Confusion matrix for Logistic Regression

The confusion matrix for the Ridge Classifier model can be given as-

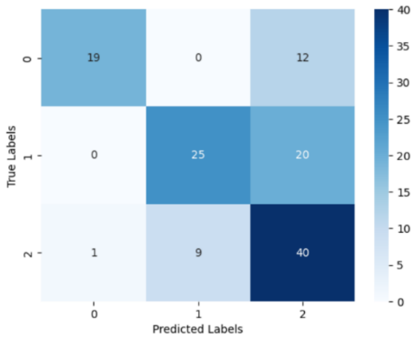

Fig 7.1b: Confusion matrix for Ridge Classifier

7.2 Accuracy

The accuracy of a model can be calculation by the given formula:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

7.3 Recall

Recall is simply defined as the total number of correctly classified positive observations divided by the total number of positive classifications.

Recall can be calculated as:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

7.4 Precision

Precision can be defined as the total number of correctly classified positive observations divided by the total number of predicted positive observations.

Precision can be calculated as

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

7.5 F1 Score

The F1 score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance, especially when dealing with imbalanced datasets where one class is much more frequent than the other.

F1 Score can be calculated using the following formula

$$\boldsymbol{F1} = \boldsymbol{2}.\frac{\boldsymbol{Precision\ X\ Recall}}{\boldsymbol{Precision + Recall}}$$

CHAPTER 8

SYSTEM IMPLEMENTATION

CHAPTER 8

SYSTEM IMPLEMENTATION

8.1 SAMPLE CODE

Module: Alzheimer Detection

 # import opencv

```
import cv2
```

 # store list

```
images = []
lables = []
```

AD Patient Brain Scan with PreProcessing of the Image

```
for i in range(1, 172):
    img = cv2.imread(f"C:\\Alzheimer-Disease-Prediction-master\\Alzheimers-ADNI\\train\\Final AD JPEG\\AD ({i}).jpg")
    gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
    gray = gray/255
    gray = cv2.resize(gray,(200, 200))
    images.append(gray)
    lables.append(0)  # AD
```

 # Sample Images

```
import matplotlib.pyplot as plt
plt.figure(figsize = (15,15))
for i in range(20):
    plt.subplot(4, 5, i + 1)
```

```
    plt.imshow(images[10 + i*3])
plt.show()
```

 # Shape of the Images

```
print(f"Shape of each image is = {images[1000].shape}")
```

 # Convert The List into Array Format #

```
import numpy as np
train_feature = np.array(images)
lables = np.array(lables)
```

Display Array Shape

```
print(f"image dataset shape = {train_feature.shape}")
print(f"lable dataset shape = {lables.shape}")
```

 # # Deep Learning CNN Model Architecture

 # MODEL ARCHITECTURE

```
import keras
import tensorflow
from tensorflow.keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
```

 # ONE NOT ENCODING

```
train_target = to_categorical(lables)
```

 # MODEL LAYERS

```
model=Sequential()
```

 # Convolutional Layers

```
model.add(Conv2D(25, kernel_size = (3,3), strides = (1,1), padding = 'same', activation
= 'relu', input_shape = (200, 200, 1)))
```

```
model.add(Conv2D(75, kernel_size = (3,3), strides = (1,1), padding = 'same', activation = 'relu'))
model.add(MaxPooling2D(pool_size = (2,2)))
model.add(Flatten())
model.add(Dense(500,activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(250,activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(100,activation='relu'))
model.add(Dense(5,activation='softmax'))
model.summary()
```

 # MODEL COMPILE

 # Function to predict Alzheimer's

```
def predict_alzheimer(image):
    processed_img = preprocess_image(image)
    prediction = model.predict(processed_img)
    class_label = np.argmax(prediction)
    if class_label == 0:
        return "AD (Alzheimer's Disease)"
    elif class_label == 1:
        return "CN (Cognitively Normal)"
    elif class_label == 2:
        return "EMCI (Early Mild Cognitive Impairment)"
    elif class_label == 3:
        return "LMCI (Late Mild Cognitive Impairment)"
    elif class_label == 4:
        return "MCI (Mild Cognitive Impairment)"
```

```python
# Main function for Streamlit app
def main():
    st.title("Alzheimer's Disease Prediction")
    st.write("Upload an image to predict the result")

    # File uploader
    uploaded_file = st.file_uploader("Choose an image...", type=["jpg", "jpeg"])

    if uploaded_file is not None:
        # Display uploaded image
        image = np.array(bytearray(uploaded_file.read()), dtype=np.uint8)
        st.image(image, caption='Uploaded Image', use_column_width=True)

        # Predict result
        result = predict_alzheimer(image)
        st.write("Predicted class:", result)

if __name__ == "__main__":
    main()
```

CHAPTER 9

SYSTEM TESTING

CHAPTER 9

SYSTEM TESTING

In this chapter, the results are checked for inputs provided by the user.

9.1 ALZHEIMER DETECTION SYSTEM

[1] Input
Upload an image (CN image)

[1] Output
Predicted Class: Cognitively Normal

9.2 ALZHEIMER PREDICTION SYSTEM

[2] Input
Age: 65
Gender: Male
Years of Education: 20
Ethnicity: Hisp/Latino
Race Category: White
APOE Allele Type: APOE4_0
APOE4 Genotype: 2,2
Imputed Genotype: True
MSME Score: 25

[2] Output
Detected Class: Late Mild Cognitive Impairment (LMCI)

CHAPTER 10

RESULTS AND DISCUSSIONS

CHAPTER 10

RESULTS AND DISCUSSION

10.1 RESULTS AND DISCUSSIONS

In this study, logistic regression was employed to predict the presence or absence of Alzheimer's disease based on a comprehensive set of features including patient information, demographics, ethnicity, and genetic information.

	Precision	Recall	F1-score	Support
0	0.81	0.85	0.83	20
1	0.91	0.88	0.89	33
Accuracy			0.87	53
Macro avg	0.86	0.86	0.86	53
Weighted avg	0.87	0.87	0.87	53

Table 10.1: Classification report for Logistic Regression

The above table represents the accuracy report for the Logistic Regression model. The model achieved an accuracy of 87%, indicating a substantial level of predictive capability. This suggests that the variables included in the model are informative in distinguishing between individuals with and without Alzheimer's disease.

Our approach involved the utilization of a Convolutional Neural Network (CNN) model, constructed using the Keras deep learning API, to analyze and classify brain images associated with Alzheimer's disease progression. We preprocessed the images using OpenCV, a computer vision library, to enhance their quality and extract relevant features. Subsequently, we employed scikit-learn, a machine learning library, to split the dataset into training and testing sets, ensuring robust evaluation of the model's performance.

Upon rigorous evaluation, our model demonstrated exceptional accuracy in classifying different stages of cognitive impairment, achieving an impressive accuracy score of 98%. This signifies the model's ability to accurately discern subtle variations in brain imaging patterns indicative of Alzheimer's disease progression.

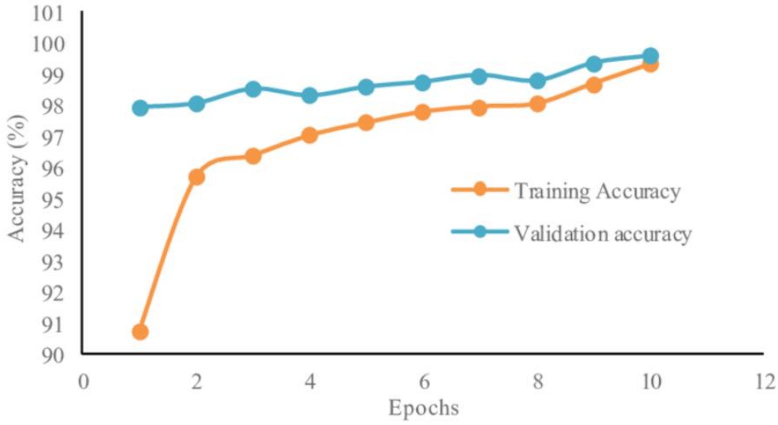

Fig 10.1: Training accuracy and validation accuracy graph of CNN.

The high accuracy achieved in classifying Alzheimer's disease progression underscores the efficacy of our machine learning approach. By leveraging advanced computational techniques, we have developed a robust tool for early detection and staging of Alzheimer's disease, facilitating timely intervention and personalized care for affected individuals. The ability to accurately identify individuals at different stages of cognitive impairment holds significant implications for clinical practice, enabling healthcare professionals to initiate appropriate treatment strategies and support services tailored to the specific needs of patients.

GenAI models are evaluated using four datasets: ARC, HellaSwag, MMLU, and TruthfulQA. Each dataset has a 25-shot evaluation setup, with rankings determined by calculating average performance across different levels. This comprehensive approach provides a holistic understanding of models' capabilities.

The following table is the accuracy report of the chatbot-

Model	Avg	ARC	HS	MMLU	TQA
Shining Valiant 1.2	74.17	72.95	87.88	70.97	64.88
Llama 2	67.35	67.32	87.33	69.83	44.92
Llama 2 Chat	66.80	64.59	85.88	63.91	52.80

Table 10.2: Accuracy table for Generative chatbot support

CHAPTER 11

CONCLUSION

CHAPTER 11

CONCLUSION

11.1 CONCLUSION

The Enhanced Alzheimer’s diagnosis system is an advanced solution that transformed the Alzheimer detection system at early stage and manages it. It contains modern technologies such as Convolutional Neural Networks (CNN), Generative Chatbot Support, Logistic Regression and Real-time news update mechanism. The system used CNN model to detect the presence of AD or varying stages of cognitive impairment of individuals with the help of MRI scan results. This benefits the healthcare professional to quickly identify any minute changes in the brain structure. The prediction system which is developed using the machine learning model gets the data from the user and predicts the status of the patients in terms of AD. The Generative Chatbot Support System offers a personalized assistance for the patients, caregivers, family members, etc. The Generative Chatbot Support System, powered by LLAMA2, LLM, and LangChain, offers personalized assistance for patients, caregivers, family members, and others. LLAMA2, LLM, and LangChain are such vital parts of the system's framework that are considered to be the drivers for the provision of the right information and resources that will be tailored towards the needs and preferences of each individual. Additionally, the real-time news update module helps the user to find the advances made in the contemporary world. The integration of this system helps both the patients and the doctors to plan the treatment at the early state, ultimately enhancing patient outcomes and quality of life.

11.2 FUTURE WORK

Future enhancements for the Comprehensive Alzheimer's Care Ecosystem could involve incorporating additional machine learning techniques to improve the accuracy of CNN-based detection, expanding the capabilities of the medical chatbot support system to offer more personalized assistance, integrating more comprehensive real-time news updates on Alzheimer's research and treatment options, and refining predictive analysis algorithms to enhance early intervention strategies. Additionally, exploring avenues to incorporate sensor data and wearable technology for continuous monitoring of patients' cognitive and physical health could further enrich the ecosystem's capabilities in providing comprehensive care and support for individuals affected by Alzheimer's disease.

CHAPTER 12

APPENDICES

CHAPTER 12

APPENDICES

A.1 Sample Screens

Screen Shot of Home Page:

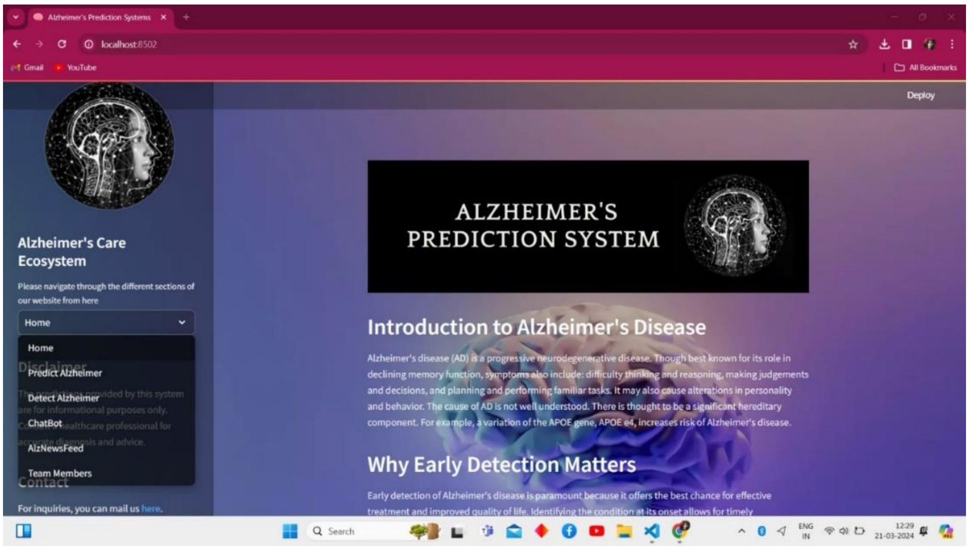

Figure A.1: Screen Shot of Home Page

Screenshot of Alzheimer Detection page:

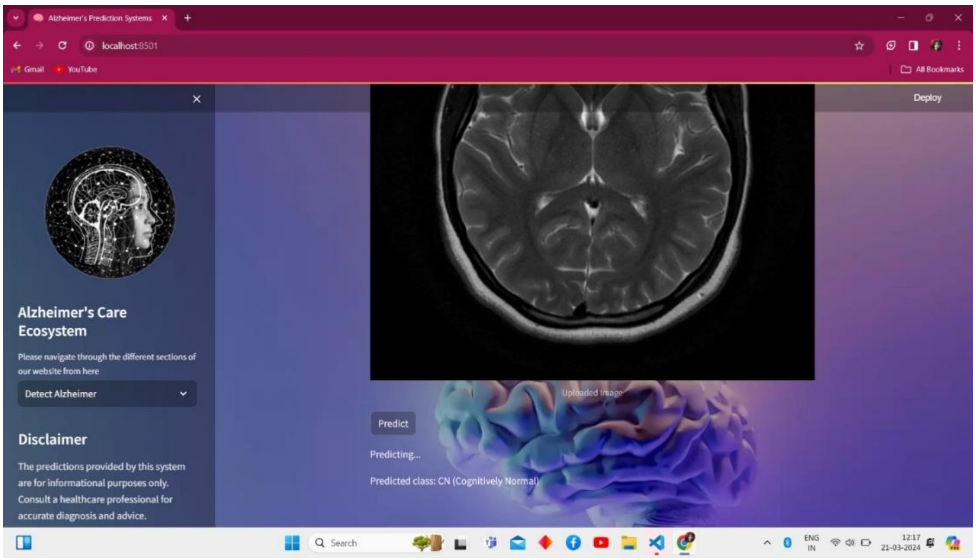

Figure A.1: Screen Shot of Alzheimer Detection System

Screenshot of Alzheimer Prediction page:

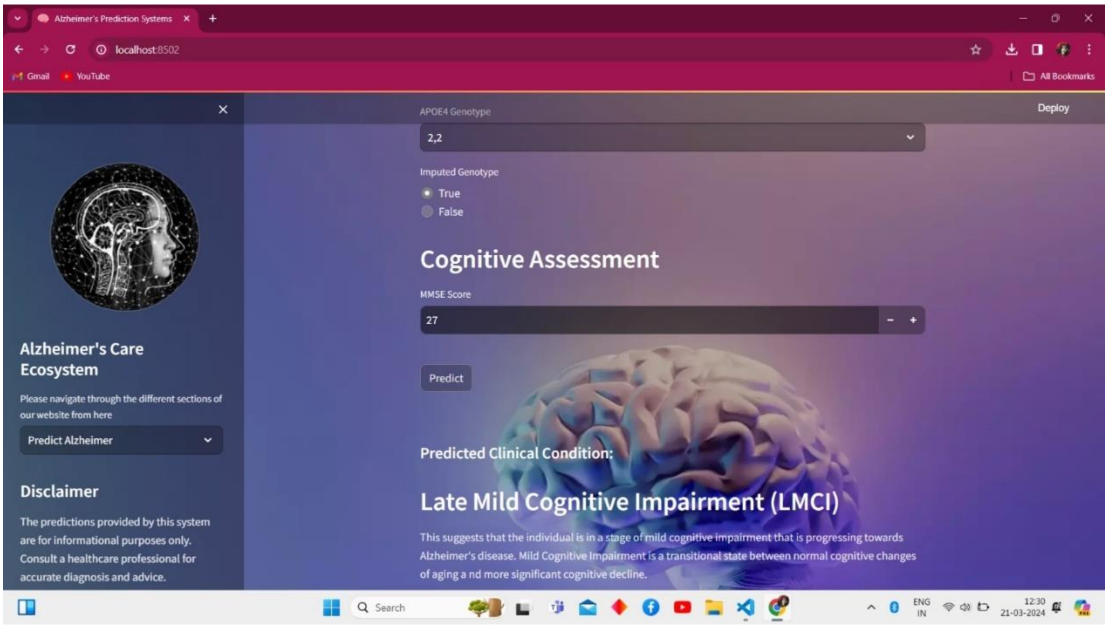

Figure A.1: Screen Shot of Alzheimer Prediction System

Screenshot of chatbot page:

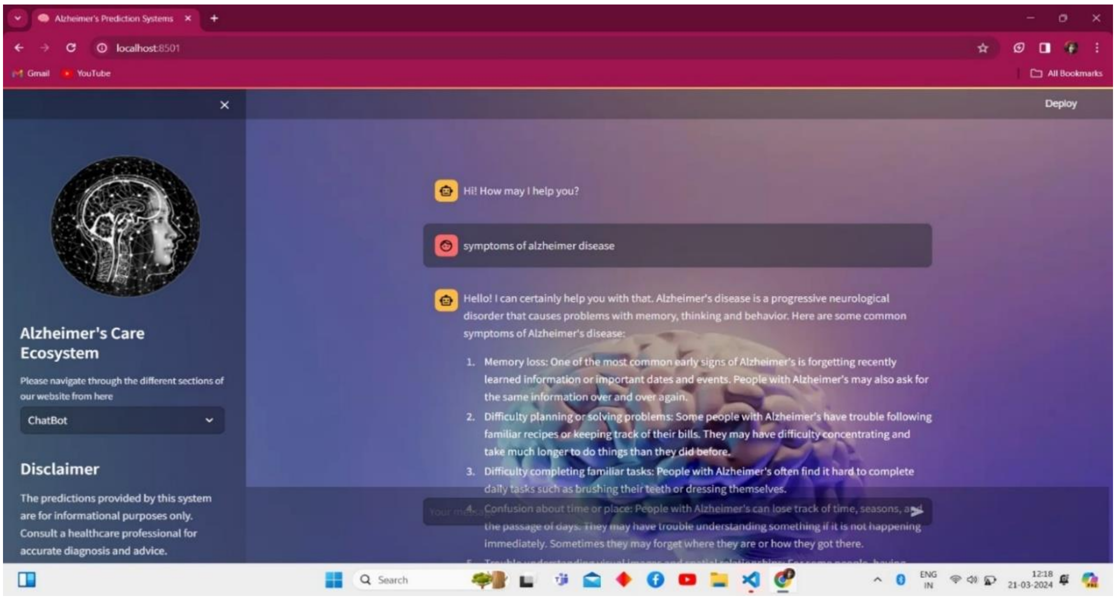

Figure A.1: Screen Shot of Generative Chatbot

Screen Shot of AlzNewsFeed:

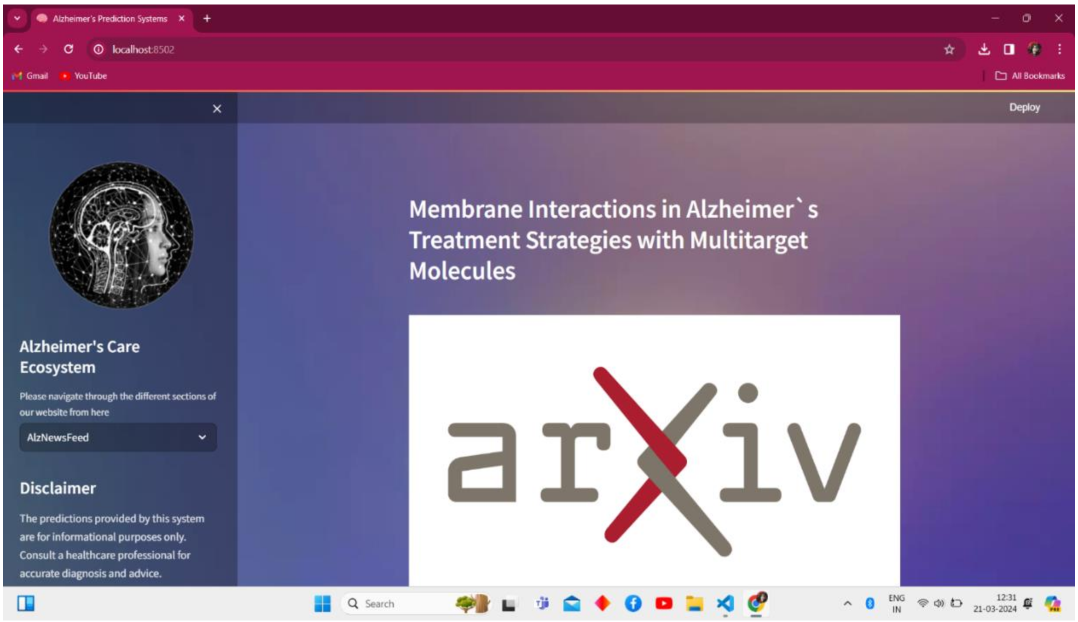

Figure A.1: Screen Shot of Real-time news update

CHAPTER 13

REFERENCES

CHAPTER 13

REFERENCES

1. Tetiana Habuza, Nazar Zaki, Elfadil A. Mohamed, Yauhen Statsenko, “Deviation From Model of Normal Aging in Alzheimer’s Disease: Application of Deep Learning to Structural MRI Data and Cognitive Tests”, IEEE Access (Volume: 10), DOI: 10.1109/ACCESS.2022.3174601
2. Al Shehri W. 2022. Alzheimer’s disease diagnosis and classification using deep learning techniques. PeerJ Computer Science,DOI: 10.7717/peerj-cs.1177
3. Cristina L. Saratxaga, Iratxe Moya, Artzai Picón, Marina Acosta, Aitor Moreno-Fernandez-de-Leceta, Estibaliz Garrote and Arantza Bereciartua-Perez, “MRI Deep Learning-Based Solution for Alzheimer’s Disease Prediction”, https://doi.org/10.3390/jpm11090902
4. Nasir Rahim, Shaker El-Sappagh, Sajid Ali, Khan Muhammad, Javier Del Ser, Tamer Abuhmed, “Prediction of Alzheimer's progression based on multimodal Deep-Learning-based fusion and visual Explainability of time-series data”, https://doi.org/10.1016/j.inffus.2022.11.028
5. Yan Zhao, Qianrui Guo, Yukun Zhang, Jia Zheng, Yang Yang, Xuemei Du, Hongbo Feng and Shuo Zhang, “Application of Deep Learning for Prediction of Alzheimer’s Disease in PET/MR Imaging”, Bioengineering 2023, 10(10), 1120; https://doi.org/10.3390/bioengineering10101120
6. Naveen Sundar Gnanadesigan, Narmadha Dhanasegar, Manjula Devi Ramasamy, Suresh Muthusamy, Om Prava Mishra, Ganesh Kumar Pugalendhi, Suma Christal Mary Sundararajan & Ashokkumar Ravindaran, “An integrated network topology and deep learning model for prediction of Alzheimer disease candidate genes”, Application of soft computing, Published: 15 May 2023, Volume 27, pages 14189–14203, (2023)
7. Zhen Zhao, Joon Huang Chuah, Khin Wee Lai, Chee-Onn Chow, Munkhjargal Gochoo, Samiappan Dhanalakshmi, Na Wang, Wei Bao, Xiang Wu,

"Conventional machine learning and deep learning in Alzheimer's disease diagnosis using neuroimaging: A review", Front. Comput. Neurosci, https://doi.org/10.3389/fncom.2023.1038636

8. Pradnya Borkar, Vishal Ashok Wankhede, Deepak T. Mane, Suresh Limkar, J. V. N. Ramesh & Samir N. Ajani, "Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals", Focus, Published: 09 June 2023, https://doi.org/10.1007/s00500-023-08615-w
9. Daichi Shigemizu, Shintaro Akiyama, Mutsumi Suganuma, Motoki Furutani, Akiko Yamakawa, Yukiko Nakano, Kouichi Ozaki & Shumpei Niida, "Classification and deep-learning–based prediction of Alzheimer disease subtypes by using genomic data", Translational Psychiatry volume 13, Article number: 232 (2023)
10. Shangran Qiu, Prajakta S Joshi, Matthew I Miller, Chonghua Xue, Xiao Zhou, Cody Karjadi, Gary H Chang, Anant S Joshi, Brigid Dwyer, Shuhan Zhu, "Development and validation of an interpretable deep learning framework for Alzheimer's disease classification", Brain, Volume 143, Issue 6, June 2020, Pages 1920–1933, https://doi.org/10.1093/brain/awaa137
11. E. Mggdadi, A. Al-Aiad, M. S. Al-Ayyad and A. Darabseh, "Prediction Alzheimer's disease from MRI images using deep learning," 2021 12th International Conference on Information and Communication Systems (ICICS), Valencia, Spain, 2021, pp. 120-125, doi: 10.1109/ICICS52457.2021.9464543