Improved Alzheimer's Disease Diagnosis Enhancing LENET with Extended Layers for Region-Specific MRI Analysis

Hafsaa Tasneem[1], Mohammed Ayaz[2], Mubashir Ansari[3], Aquil Saif[4]
[1]*Assistant Professor Department of CSE-AIML, Lords Institute of Engineering and Technology, Hyderabad, India*
[2,3,4]*BTech Students Department of CSE-AIML, Lords Institute of Engineering and Technology, Hyderabad, India*

***Abstract*—Alzheimer's disease (AD) is a major public health priority. Hippocampus is one of the most affected areas of the brain and is easily accessible as a biomarker using MRI images in machine learning for diagnosing AD. In machine learning, using entire MRI image slices showed lower accuracy for AD classification. We present the select slices method by landmarks on the hippocampus region in MRI images. This study aims to see which views of MRI images have higher accuracy for AD classification. Then, to get the value of three views and categories, we used multiclass classification with the publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset using Resnet50 and LeNet. The models were used in a total dataset of 4,500 MRI slices in three views and categories. Our study demonstrated that the selecting slices performed better than using entire slices in MRI images for AD classification. Our method improves the accuracy of machine learning, and the coronal view showed higher accuracy. This method played a significant role in improving the accuracy of machine learning performance. The results for the coronal view were similar to the medical experts usually used to diagnose AD. We also found that LeNet models became the potential model for AD classification.**

I. INTRODUCTION

Alzheimer's disease (AD) is a major public health priority [1]. Globally, around 44 million people have been diagnosed with AD globally, which may reach 131.5 million people by 2050 [2]. AD is a progressive, neurodegenerative disease that affects elderly people over 65 years old and impacts memory and cognitive function [3]. Although there is no known cure for AD, some medications and treatments can temporarily relieve symptoms or slow down AD progression [4]. Research studies have demonstrated that early AD diagnosis can make a living with the disease easier [3].

In an early AD diagnosis, observing and exploring the deterioration process in the brain regions is important before the progression of the disease. Hippocampus is one of the most affected areas of the brain and is easily accessible as a biomarker of AD [5], [6]. For example, the degeneration of cholinergic circuits in the hippocampus and reduced volume changes in the hippocampus are related to memory loss [5]. In addition, a severe volume reduction of the hippocampus can be easily detected using Magnetic Resonance Imaging (MRI) images and is widely used for diagnosing AD [7]. MRI has become an excellent and valuable tool with a highly effective imagery technique for diagnosing and analyzing structural changes in the brain [8]. Moreover, structural MRI image biomarkers are used in three categories: AD, Mild Cognitive Impairment (MCI), and Normal Control (NC) [9]. Three categories of AD are used to understand subtle changes in disease progression on an MRI image in the early stages of AD [10].

Recently, machine learning models have been developed to diagnose AD based on MRI images [11]. The advances in machine learning have the potential to classify complex patterns from MRI images, and the diagnosis can be finalized in a brief time [12]. For example, a study by Kazemi and Houghten used machine learning models to classify different categories of AD [13]. Other studies showed that cancer detection accuracy is comparable to manual detection. Therefore, machine learning can reduce the time and is expected to perform consistently in large amounts of data at any time. In contrast, manual diagnosis results may be affected by the time to read the MRI images in diagnosing AD. Furthermore, with the advantages, machine learning has become the preferred method for medical image classification [14].

In terms of classification tasks in different AD stages, binary classification is used between two categories to classify AD, such as AD vs. NC, MCI vs. AD, and NC vs. MCI [15]. In comparison, some studies used multiclass classification to classify AD in three categories [16]. The use of multiclass classification can be beneficial in distinguishing the results of three categories of AD because the binary classification consists of only two categories, whereas the multiclass classification consists of more than two categories. Thus, the multiclass classification can help improve the clinical decisions on whether someone will develop the disease through the results of each category to diagnose AD. In order to improve performance for AD classification, several studies have proposed different methods to improve accuracy in machine learning using MRI images for instance, the improvement of MRI image quality to reduce noise [17], the use of segmentation in a specific brain region [18], classification techniques with AdaBoost [19], and slice-based methods [20]. In general, the entire slices of MRI images are composed of 100 to 250 slices [21], [22]. However, Lopez et al. found that classification results improve with several slices rather than using the entire slices [23].

In spite of accuracy improvement for AD classification, there is no detailed information on how to select several slices in MRI images within three views and three categories. For example, in a study by Kang et al., they selected 11 slices based on the highest classification accuracy in coronal view between 1 to 145 slices [24]. Furthermore, getting the information on the biomarker for early AD diagnosis (i.e., hippocampus) in MRI images to select several slices requires medical experts' knowledge and experiences [25], [26]. The medical experts' information can be used as the ground truth in three views and three categories for AD classification. The three views of MRI images are commonly known as axial, coronal, and sagittal [27]. Using three views of MRI images may offer complementary features useful for AD classification. Even though MRI images can provide the landmark of the hippocampus region in three views, medical experts usually require one view, which will be beneficial for diagnosing AD. Thus, the selecting slices method in MRI images can be used for AD diagnosis and provide more computational simplicity than using entire slices. Therefore, we hypothesized that the selecting slices method of MRI images using landmarks in the hippocampus region might improve performance in classifying AD. This study aims to see which views (i.e., axial, coronal, and sagittal) of MRI images yield higher accuracy for AD classification in machine learning. Then, we used multiclass classification on MRI images to get the result in three categories (i.e., AD, MCI, and NC) for AD classification.

1.1 Objective of the Project

Alzheimer's disease (AD) is a major public health priority. Hippocampus is one of the most affected areas of the brain and is easily accessible as a biomarker using MRI images in machine learning for diagnosing AD. In machine learning, using entire MRI image slices showed lower accuracy for AD classification. We present the select slices method by landmarks on the hippocampus region in MRI images. This study aims to see which views of MRI images have higher accuracy for AD classification. Then, to get the value of three views and categories, we used multiclass classification with the publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset using Resnet50 and LeNet. The models were used in a total dataset of 4,500 MRI slices in three views and categories. Our study demonstrated that the selecting slices performed better than using entire slices in MRI images for AD classification. Our method improves the accuracy of machine learning, and the coronal view showed higher accuracy. We also found that LeNet models became the potential model for AD classification.

II. LITERATURE SURVEY

2.1 The Clinical Use of Structural MRI in Alzheimer Disease

Structural imaging based on magnetic resonance is an integral part of the clinical assessment of patients with suspected Alzheimer dementia. Prospective data on the natural history of change in structural markers from preclinical to overt stages of Alzheimer disease are radically changing how the disease is conceptualized, and will influence its future diagnosis and treatment. Atrophy of medial temporal structures is now considered to be a valid diagnostic marker at the mild cognitive impairment stage. Structural imaging is also included in diagnostic criteria for the most prevalent non-Alzheimer dementias, reflecting its value in differential diagnosis. In addition, rates of whole-brain and hippocampal atrophy are sensitive markers of neurodegeneration, and are increasingly used as outcome measures in trials of potentially disease-modifying therapies. Large multicenter studies are currently investigating the value of other imaging and non-imaging markers as adjuncts to clinical assessment in diagnosis and monitoring of progression. The utility of structural imaging and other markers will be increased by standardization of acquisition and analysis methods, and by development of robust algorithms for automated assessment.

2.2 Impact of New Drugs for Therapeutic Intervention in Alzheimer's Disease

The increases in population ageing and growth are leading to a boosting in the number of people living with dementia, Alzheimer's disease (AD) being the most common cause. In spite of decades of intensive research, no cure for AD has been found yet. However, some treatments that may change disease progression and help control symptoms have been proposed. Beyond the classical hypotheses of AD etiopathogenesis, i.e., amyloid beta peptide (Aβ) accumulation and tau hyperphosphorylation, a trend in attributing a key role to other molecular mechanisms is prompting the study of different therapeutic targets. Hence, drugs designed to modulate inflammation, insulin resistance, synapses, neurogenesis, cardiovascular factors and dysbiosis are shaping a new horizon in AD treatment. Within this frame, an increase in the number of candidate drugs for disease modification treatments is expected, as well as a focus on potential combinatory multidrug strategies. The present review summarizes the latest advances in drugs targeting Aβ and tau as major contributors to AD pathophysiology. In addition, it introduces the most important drugs in clinical studies targeting alternative mechanisms thought to be involved in AD's neurodegenerative process.

2.3 Hippocampus and Its Involvement in Alzheimer's Disease: A Review

Hippocampus is the significant component of the limbic lobe, which is further subdivided into the dentate gyrus and parts of Cornu Ammonis. It is the crucial region for learning and memory; its sub-regions aid in the generation of episodic memory. However, the hippocampus is one of the brain areas affected by Alzheimer's (AD). In the early stages of AD, the hippocampus shows rapid loss of its tissue, which is associated with the functional disconnection with other parts of the brain. In the progression of AD, atrophy of medial temporal and hippocampal regions are the structural markers in magnetic resonance imaging (MRI). Lack of sirtuin (SIRT) expression in the hippocampal neurons will impair cognitive function, including recent memory and spatial learning. Proliferation, differentiation, and migrations are the steps involved in adult neurogenesis. The microglia in the hippocampal region are more immunologically active than the other regions of the brain. Intrinsic factors like hormones, glia, and vascular nourishment are instrumental in the neural stem cell (NSC) functions by maintaining the brain's microenvironment. Along with the intrinsic factors, many extrinsic factors like dietary intake and physical activity may also influence the NSCs. Hence, pro- neurogenic lifestyle could delay neurodegeneration.

2.4 MRI of Hippocampus in Incipient Alzheimer's Disease

Alzheimer's disease (AD) is the most common cause of dementia, yet impossible to diagnose precisely without invasive techniques, particularly at the onset of the disease. Therefore, a reliable diagnostic method is needed. The hippocampus is a part of the mesial temporal lobe memory system, and known to be affected early in the course of AD. Recent development of imaging techniques, particularly magnetic resonance imaging (MRI), has made the evaluation of diminutive brain structures, such as the hippocampus, conceivable. The purpose of this study was to focus on the sensitivity and specificity of different approaches of hippocampal imaging by

MRI, and their applications for the diagnosis of incipient AD. Hippocampal pathology was evaluated by means of linear (interuncal distance, IUD), planimetric (hippocampal area) and volumetric measurements, complete with T2 relaxometry using a 1.5 T imager. The accuracy of hippocampal measurements was compared to that of the amygdala and the frontal lobes. Various procedures for normalization of the data to the head and brain size were compared.

2.5 Prediction of Alzheimer's Disease Dementia with MRI Beyond the Short-Term

Magnetic resonance imaging (MRI) volumetric measures have become a standard tool for the detection of incipient Alzheimer's Disease (AD) dementia in mild cognitive impairment (MCI). Focused on providing an earlier and more accurate diagnosis, sophisticated MRI machine learning algorithms have been developed over the recent years, most of them learning their non-disease patterns from MCI that remained stable over 2–3 years. In this work, we analyzed whether these stable MCI over short-term periods are actually appropriate training examples of non-disease patterns. To this aim, we compared the diagnosis of MCI patients at 2 and 5 years of follow-up and investigated its impact on the predictive performance of baseline volumetric MRI measures primarily involved in AD, i.e., hippocampal and entorhinal cortex volumes. Predictive power was evaluated in terms of the area under the ROC curve (AUC), sensitivity, and specificity in a trial sample of 248 MCI patients followed-up over 5 years.

2.6 Automated Detection, Selection and Classification of Hippocampal Landmark Points for the Diagnosis of Alzheimer's Disease

Alzheimer's disease (AD) is a neurodegenerative, progressive, and irreversible disease that accounts for up to 80% of all dementia cases. AD predominantly affects older adults, and its clinical diagnosis is a challenging evaluation process, with imprecision rates between 12 and 23%. Structural magnetic resonance (MR) imaging has been widely used in studies related to AD because this technique provides images with excellent anatomical details and information about structural changes induced by the disease in the brain. Current studies are focused on detecting AD in its initial stage, i.e., mild cognitive impairment (MCI), since treatments for preventing or delaying the onset of symptoms are more effective when administered at the early stages of the disease. This study proposes a new technique to perform MR image classification in AD diagnosis using discriminative hippocampal point landmarks among the cognitively normal (CN), MCI, and AD populations.

2.7 Classification of Structural MRI for Detecting Alzheimer's Disease

Alzheimer's Disease (AD) is a pathological form of dementia that degenerates brain structures. AD affects millions of elderly people over the world and the number of people with AD doubles every year. Detecting AD years before the effects of disease using structural magnetic resonance imaging (MRI) of the brain is possible. Neuroimaging features that are extracted from the structural brain MRI can be used to predict AD by revealing disease related patterns. Machine learning techniques can detect AD and predict conversions from mild cognitive impairment (MCI) to AD automatically and successfully by using these neuroimaging features. State-of-the-art machine learning techniques, namely support vector machines (SVM), k-nearest neighbor (kNN) algorithm and backpropagation neural network (BP-NN) are employed to discriminate AD and mild AD from healthy controls. Training hyperparameters of the classifiers are tuned using classification accuracy which is obtained with 5-fold cross validation. Prediction performance of the techniques are compared using accuracy, sensitivity and specificity. Results revealed that AD can be distinguished from healthy controls successfully using multivariate morphological features and machine learning tools. According to the performed experiments SVM is the most successful classifier for detecting AD with classification accuracies up to 82%.

III. SYSTEM ANALYSIS

3.1 Existing System

In the existing system, machine learning algorithms such as Random Forest Algorithm and Naïve Bayes Algorithm are used. By using these machine learning algorithms, the classification accuracy obtained is comparatively less.

Disadvantages of Existing System:

- Less Accuracy
- Inability to handle complex image patterns effectively
- Manual feature extraction required

3.2 Proposed System

In the proposed system, deep learning algorithms such as RCNN, FRCNN, Yolov5, and Yolov6 algorithms are used. By using these algorithms, we can achieve high accuracy. In machine learning, using entire MRI image slices showed lower accuracy for AD classification. We present the select slices method by landmarks on the hippocampus region in MRI images. This study aims to see which views of MRI images have higher accuracy for AD classification.

Advantages of Proposed System:

- High Accuracy
- Automatic feature extraction using deep learning
- Multiclass classification across three AD categories (AD, MCI, NC)
- Computational simplicity by selecting relevant MRI slices

3.3 Functional Requirements

Software Requirements:

- Operating System: Windows 10 (minimum)
- Programming Language: Python 3.7.0
- opencv-python == 4.5.1.48
- keras == 2.3.1
- tensorflow == 1.14.0
- protobuf == 3.16.0
- h5py == 2.10.0
- scikit-learn == 0.22.2. post1
- NumPy, Pandas

Hardware Requirements:

- Processor: Intel i3 (minimum)
- Speed: 1.1 GHz
- RAM: 4 GB (minimum)
- Hard Disk: 500 GB

3.4 Non-Functional Requirements

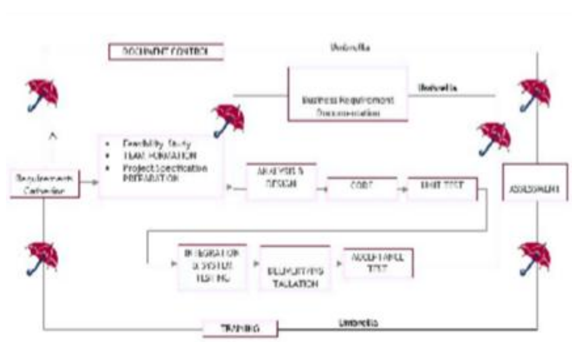
- Usability: Usability is a quality attribute that assesses how easy user interfaces are to use. The word "usability" also refers to methods for improving ease-of-use during the design process.
- Security: The quality or state of being secure freedom from danger, freedom from fear or anxiety, and freedom from the prospect of unauthorized access.
- Readability: Readability is the ease with which a reader can understand a written text.
- Performance: The execution of an action; the fulfillment of a claim, promise, or request; the degree of accuracy and speed of the system.
- Availability: The quality or state of being available trying to improve the availability of affordable healthcare processing.
- Scalability: Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands.

3.5 Process Model SDLC (Umbrella Model)

SDLC stands for Software Development Life Cycle. It is a standard which is used by the software industry to develop good software. The Umbrella Model is adopted for this project as it supports continuous maintenance with no defined endpoint.

Stages in SDLC:

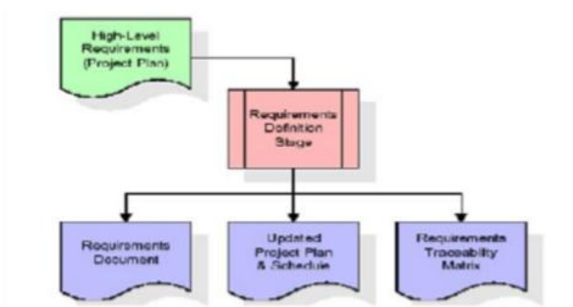
- Requirements Gathering
- Analysis
- Designing
- Coding (Development)
- Testing
- Maintenance



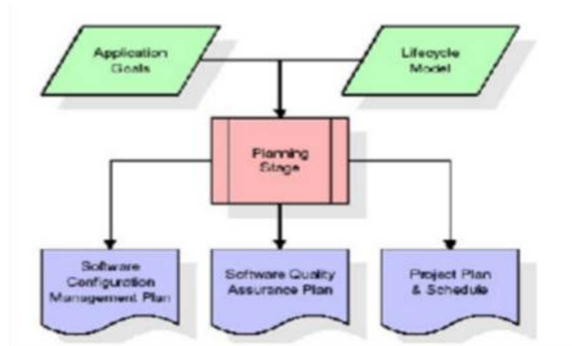
Requirements Gathering Stage:

The requirements gathering process takes as its input the goals identified in the high-level requirements section of the project plan. Each goal will be refined into a set of one or more requirements. These requirements define the major functions of the intended application, define operational data areas and reference data areas, and define the initial data entities. Major functions include critical processes to be managed, as well as mission critical inputs, outputs and reports. A user class hierarchy is developed and associated with these major functions, data areas, and data entities. Each of these definitions is termed a Requirement. Requirements are identified by unique requirement identifiers and, at minimum, contain a requirement title and textual description.

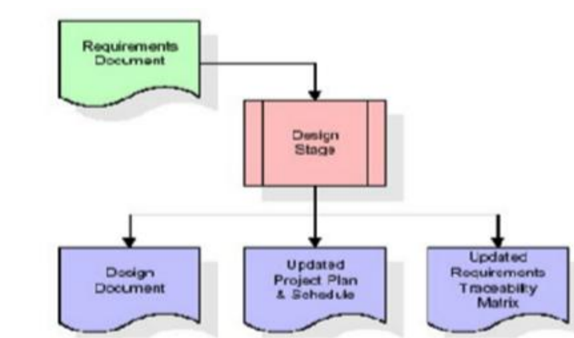
These requirements are fully described in the primary deliverables for this stage: the Requirements Document and the Requirements Traceability Matrix (RTM). The requirements document contains complete descriptions of each requirement, including diagrams and references to external documents as necessary. The RTM shows that the product components developed during each stage of the SDLC are formally connected to the components developed in prior stages.



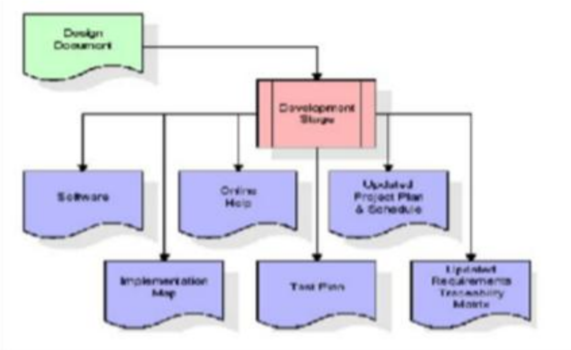
Analysis Stage:
The planning stage establishes a bird's eye view of the intended software product, and uses this to establish the basic project structure, evaluate feasibility and risks associated with the project, and describe appropriate management and technical approaches. The most critical section of the project plan is a listing of high-level product requirements, also referred to as goals. All of the software product requirements to be developed during the requirements definition stage flow from one or more of these goals.



Designing Stage:
The design stage takes as its initial input the requirements identified in the approved requirements document. For each requirement, a set of one or more design elements will be produced as a result of interviews, workshops, and/or prototype efforts. Design elements describe the desired software features in detail, and generally include functional hierarchy diagrams, screen layout diagrams, tables of business rules, business process diagrams, pseudo code, and a complete entity-relationship diagram with a full data dictionary. These design elements are intended to describe the software in sufficient detail that skilled programmers may develop the software with minimal additional input.

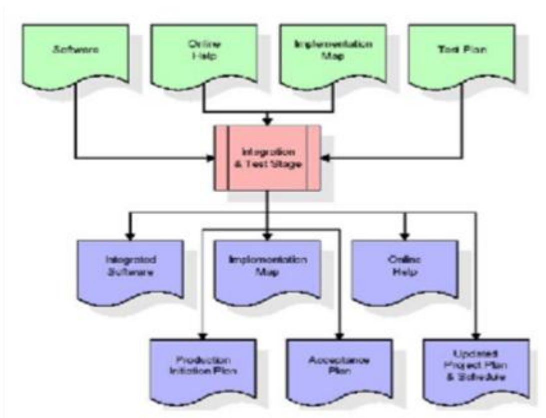


Development (Coding) Stage:
The development stage takes as its primary input the design elements described in the approved design document. For each design element, a set of one or more software artifacts will be produced. Software artifacts include but are not limited to menus, dialogs, and data management forms, data reporting formats, and specialized procedures and functions. Appropriate test cases will be developed for each set of functionally related software artifacts, and an online help system will be developed to guide users in their interactions with the software.



Integration & Test Stage:

During the integration and test stage, the software artifacts, online help, and test data are migrated from the development environment to a separate test environment. At this point, all test cases are run to verify the correctness and completeness of the software. Successful execution of the test suite confirms a robust and complete migration capability. During this stage, reference data is finalized for production use and production users are identified and linked to their appropriate roles.



Maintenance:

The outer rectangle represents maintenance of a project. The maintenance team will start with requirement study, understanding of documentation, after which employees will be assigned work and they will undergo training on their particular assigned category. For this life cycle there is no end — it will be continued so on like an umbrella (no ending point to umbrella sticks).

3.6 Software Requirement Specification (SRS)

3.6.1 Overall Description

A Software Requirements Specification (SRS) is a complete description of the behavior of a system to be developed. It includes a set of use cases that describe all the interactions the users will have with the software. In addition to use cases, the SRS also contains non-functional requirements. Nonfunctional requirements are requirements which impose constraints on the design or implementation (such as performance engineering requirements, quality standards, or design constraints). Projects are subject to three sorts of requirements: Business requirements describe in business terms what must be delivered or accomplished to provide value. Product requirements describe properties of a system or product. Process requirements describe activities performed by the developing organization.

3.6.2 Feasibility Study

Economic Feasibility: A system can be developed technically and that will be used if installed must still be a good investment for the organization. In the economic feasibility, the development cost in creating the system is evaluated against the ultimate benefit derived from the new systems. Financial benefits must equal or exceed the costs. The system is economically feasible as it does not require any additional hardware or software.

Operational Feasibility: Proposed projects are beneficial only if they can be turned out into information systems that will meet the organization's operating requirements. This system is targeted to be in accordance with the above-mentioned issues. The well-planned design would ensure the optimal utilization of the computer resources and would help in the improvement of performance status. Technical Feasibility: The current system developed is technically feasible. It is a user interface for audit workflow. Thus, it provides easy access to the users. The database's purpose is to create, establish and maintain a workflow among various entities in order to facilitate all concerned users in their various capacities or roles. Therefore, it provides the technical guarantee of accuracy, reliability and security.

3.7 External Interface Requirements

User Interface: The user interface of this system is a user-friendly Python Graphical User Interface (GUI).

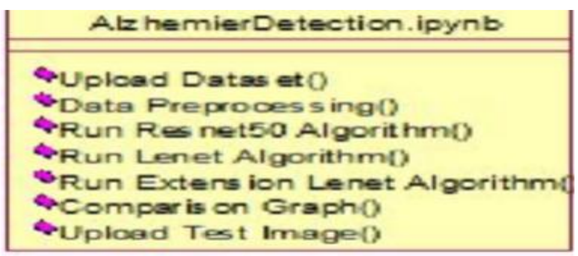
Hardware Interfaces: The interaction between the user and the console is achieved through Python capabilities.

Software Interfaces: The required software is Python 3.7.0.

IV. SYSTEM DESIGN

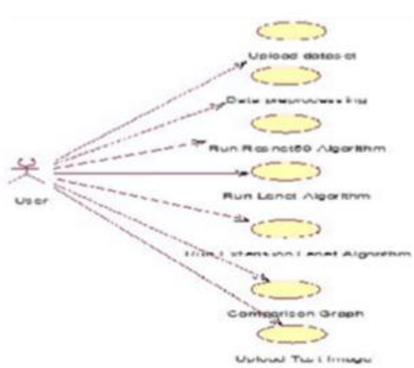
4.1 Class Diagram

The class diagram is the main building block of object-oriented modeling. It is used both for general conceptual modeling of the systematic of the application, and for detailed modeling translating the models into programming code. Class diagrams can also be used for data modeling. The classes in a class diagram represent both the main objects and interactions in the application as well as the classes to be programmed. In the diagram, classes are represented with boxes which contain three parts: the upper part holds the name of the class; the middle part contains the attributes of the class; and the bottom part gives the methods or operations the class can take or undertake.



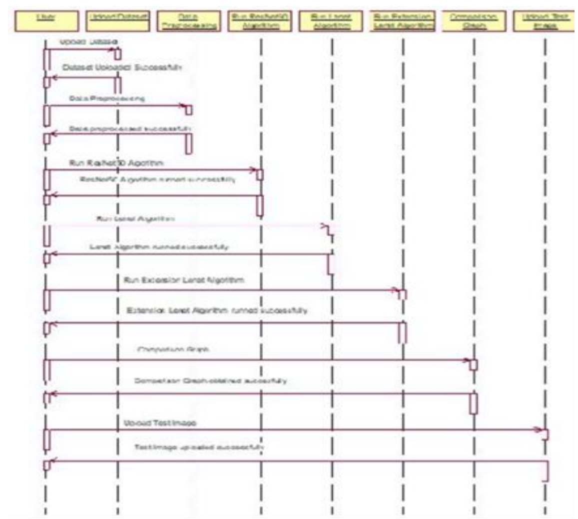
4.2 Use Case Diagram

A use case diagram at its simplest is a representation of a user's interaction with the system and depicts the specifications of a use case. A use case diagram can portray the different types of users of a system and the various ways that they interact with the system. This type of diagram is typically used in conjunction with the textual use case and will often be accompanied by other types of diagrams as well.



4.3 Sequence Diagram

A sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

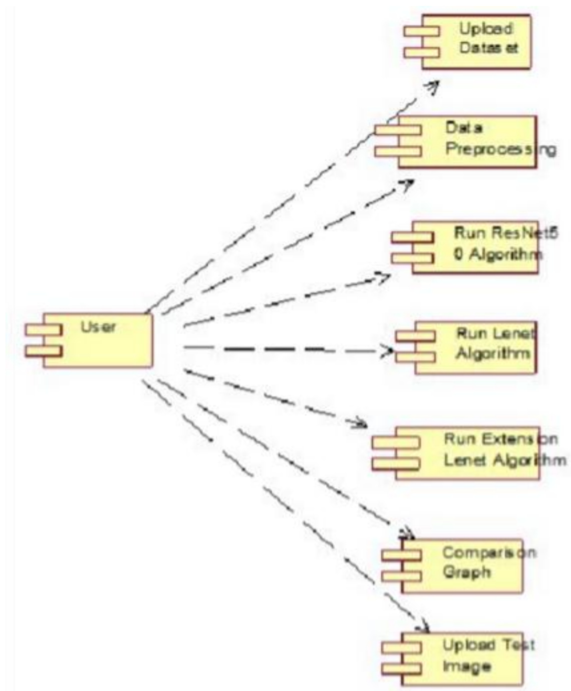


4.4 Collaboration Diagram

A collaboration diagram describes interactions among objects in terms of sequenced messages. Collaboration diagrams represent a combination of information taken from class, sequence, and use case diagrams describing both the static structure and dynamic behavior of a system.

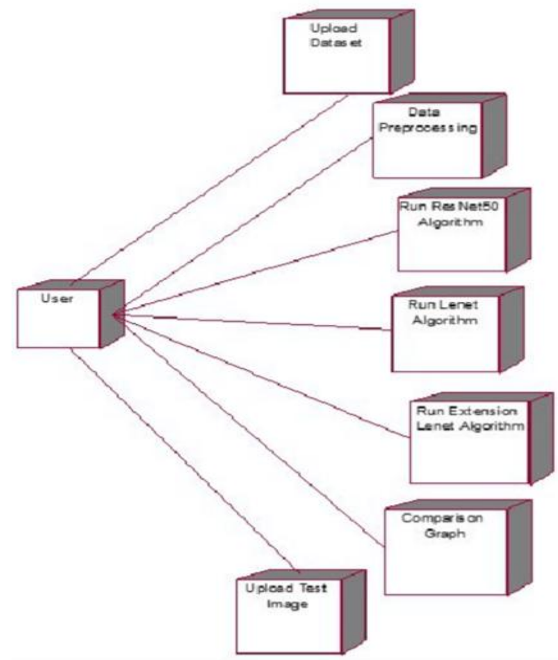
4.5 Component Diagram

In the Unified Modelling Language, a component diagram depicts how components are wired together to form larger components and or software systems. They are used to illustrate the structure of arbitrarily complex systems. Components are wired together by using an assembly connector to connect the required interface of one component with the provided interface of another component. This illustrates the service consumer service provider relationship between the two components.



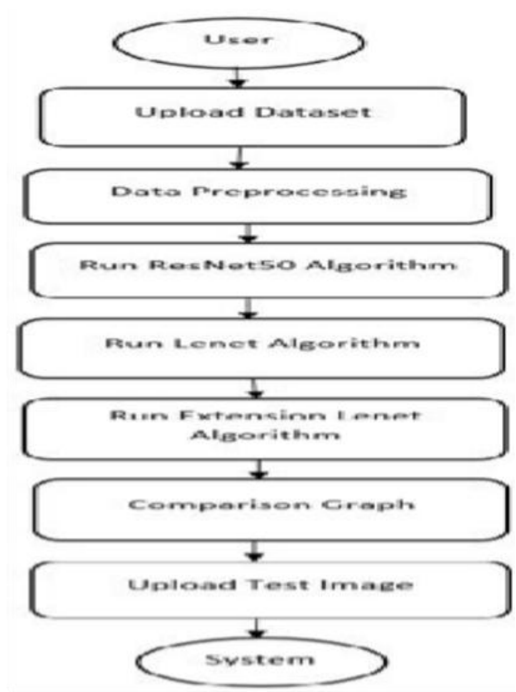
4.6 Deployment Diagram

A deployment diagram in the Unified Modeling Language models the physical deployment of artifacts on nodes. To describe a web site, for example, a deployment diagram would show what hardware components ("nodes") exist (e.g., a web server, an application server, and a database server), what software components ("artifacts") run on each node (e.g., web application, database), and how the different pieces are connected (e.g. JDBC, REST, RMI). The nodes appear as boxes, and the artifacts allocated to each node appear as rectangles within the boxes. A single node in a deployment diagram may conceptually represent multiple physical nodes, such as a cluster of database servers.



4.7 Activity Diagram

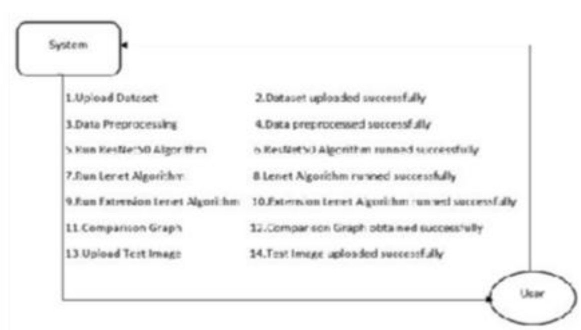
Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flow chart to represent the flow from one activity to another activity. The activity can be described as an operation of the system. So, the control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent.



4.8 Data Flow Diagram

Data flow diagrams illustrate how data is processed by a system in terms of inputs and outputs. Data flow diagrams can be used to provide a clear representation of any business function. The technique starts with an overall picture of the business and continues by analyzing each of the functional areas of interest. This analysis can be carried out in precisely the level of detail required.

As the name suggests, a Data Flow Diagram (DFD) is an illustration that explicates the passage of information in a process. A DFD can be easily drawn using simple symbols. A DFD is a model for constructing and analyzing information processes it illustrates the flow of information in a process depending upon the inputs and outputs. A DFD demonstrates business or technical processes with the support of outside data saved, plus the data flowing from the process to another, and the end results.



V. IMPLEMENTATION

5.1 Python

Python is a general-purpose language. It has a wide range of applications from Web development (like Django and Bottle), scientific and mathematical computing (Orange, SymPy, NumPy) to desktop graphical user interfaces (Pygame, Panda3D). The syntax of the language is clean and the length of the code is relatively short. It is fun to work in Python because it allows you to think about the problem rather than focusing on the syntax.

History of Python:

Python is a fairly old language created by Guido Van Rossum. The design began in the late 1980s and was first released in February 1991. In late 1980s, Guido Van Rossum was working on the Amoeba distributed operating system group. He wanted to use an interpreted language like ABC that could access the Amoeba system calls. So, he decided to create a language that was extensible. This led to the design of a new language which was later named Python adopted from the comedy series "Monty Python's Flying Circus".

Key Features of Python:

- Simple and elegant syntax — easier to learn and read compared to languages like C++ or Java.
- Free and open-source — freely use and distribute Python, even for commercial use.
- Portability — Python programs can move from one platform to another and run without any changes on Windows, Mac OS X, and Linux.
- Extensible and Embeddable — can combine pieces of C/C++ or other languages with Python code for high performance.
- High-level, interpreted language — no need to worry about memory management or garbage collection.
- Large standard libraries — extensive libraries that make a programmer's life much easier.
- Object-oriented — everything in Python is an object, aiding in solving complex problems intuitively.

5.2 Algorithm Implementation

ResNet50 (Pretrained Model):

The pretrained ResNet50 model is used on the Alzheimer's dataset. The model is built with pretrained ImageNet weights and extended with additional Convolutional layers (32 neurons), MaxPooling layers, Flatten layer, Dense layers (256 neurons and softmax output). The model is compiled with the Adam optimizer and categorical cross-entropy loss. Training is done with a batch size of 64 for 5 epochs, with model checkpointing to save the best weights.

LeNet Model:

The LeNet model is defined with Conv2D layers (32 and 48 filters), MaxPool2D layers, Flatten, and Dense layers (256, 84, and output softmax). The model is compiled with Adam optimizer and categorical cross-entropy loss. Training is performed with a batch size of 32 for 5 epochs.

Extension LeNet Model (Proposed):
The extension model enhances the base LeNet architecture by replacing MaxPool2D with MaxPooling2D (pool_size = (2,2)) and adding a Dropout (0.2) layer to remove irrelevant features. The Dropout layer is one of the optimization layers which instructs the model to remove all irrelevant features so that the model trains only on relevant features, thereby improving accuracy. This model achieves the highest accuracy among all three models.

5.3 Dataset Description
The publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset is used. The dataset contains MRI images organized in three view folders: Axial, Coronal, and Sagittal. A total of 5,154 images were found in the dataset. The dataset was split into 80% for training and 20% for testing. Images were resized to 32×32 pixels and normalized (divided by 255) before training. Labels: Axial AD, Coronal MCI, Sagittal NC.

5.4 Performance Metrics
The following metrics are calculated to evaluate model performance: Precision, Recall, F1- Score, and Accuracy. A confusion matrix heatmap is also generated for each algorithm to visualize true vs. predicted classifications.

VI. TESTING

6.1 Implementation and Testing
Implementation is one of the most important tasks in the project. It is the phase in which one has to be cautious because all the efforts undertaken during the project will be very interactive. Implementation is the most crucial stage in achieving a successful system and giving the users confidence that the new system is workable and effective. Each program is tested individually at the time of development using the sample data and has been verified that these programs link together in the way specified in the program specification.

6.2 Testing Strategy
Testing is the process where the test data is prepared and is used for testing the modules individually and later the validation given for the fields. Then the system testing takes place which makes sure that all components of the system properly function as a unit. The test data should be chosen such that it passes through all possible conditions. Actually, testing is the state of implementation which aimed at ensuring that the system works accurately and efficiently before the actual operation commences.

Module Testing:
To locate errors, each module is tested individually. This enables us to detect errors and correct them without affecting any other modules. All the modules are individually tested from bottom up, starting with the smallest and lowest modules and proceeding to the next level. Each module in the system is tested separately. For example, the job classification module is tested separately with different inputs and its approximate execution time is verified.

Integration Testing:
After module testing, the integration testing is applied. When linking the modules there may be chances for errors to occur; these errors are corrected by using this testing. In this system all modules are connected and tested. The testing results are very correct. Thus, the mapping of jobs with resources is done correctly by the system.

Acceptance Testing:
When the user finds no major problems with accuracy, the system passes through a final acceptance test. This test confirms that the system meets the original goals, objectives and requirements established during analysis. Acceptance tests place the final verification on the shoulders of users and management it is finally acceptable and ready for operation.

Test Case Id	Test Case Name	Test Case Desc.	Test Steps			Test Case Status	Test Priority
			Step	Expected	Actual		
01	Upload Dataset	Verify Dataset is uploaded or not	If Dataset is not uploaded	we cannot do any further operations	we can do further operations	High	High
02	Preprocess Dataset	Verify Preprocess Dataset or not	If Dataset may not Preprocess	we cannot do any further operations	we can do further operations	High	High
03	Run ResNet50 Algorithm	Verify ResNet50 Algorithm runned or not	If ResNet50 Algorithm is not run	we cannot do any further operations	we can do further operations	High	High
04	Run Lenet Algorithm	Verify Lenet Algorithm runned or not	If Lenet Algorithm not Run	We cannot do further operations	We can do further Operations	High	High
05	Run Extension Lenet algorithm	Verify Extension Lenet Algorithm runned or not	If Extension Lenet algorithm not run	We cannot do further operations	We can do further Operations	High	High
06	Comparison Graph	Verify Comparison Graph obtained or not	If Comparison graph is not obtained	We cannot do further operations	We can do further Operations	High	High

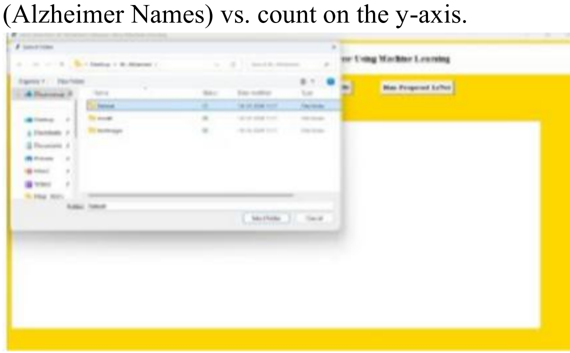
6.3 Test Cases

Test Case Id	Test Case Name	Test Case Desc.	Test Steps	Expected / Actual	Priority
01	Upload Dataset	Verify Dataset is uploaded or not	If Dataset is not uploaded we cannot do any further operations	We can do further operations	High
02	Pre-process Dataset	Verify Pre-process Dataset or not	If Dataset may not Pre-process we cannot do any further operations	We can do further operations	High
03	Run ResNet50 Algorithm	Verify ResNet50 Algorithm runned or not	If ResNet50 Algorithm is not run we cannot do any further operations	We can do further operations	High
04	Run Lenet Algorithm	Verify Lenet Algorithm runned or not	If Lenet Algorithm not Run we cannot do any further operations	We can do further operations	High
05	Run Extension Lenet algorithm	Verify Extension Lenet Algorithm runned or not	If Extension Lenet algorithm not run we cannot do any further operations	We can do further operations	High
06	Comparison Graph	Verify Comparison Graph obtained or not	If Comparison graph is not obtained we cannot do any further operations	We can do further operations	High
07	Upload Test Image	Verify test image uploaded or not	If test image is not uploaded we cannot do any further operations	We can do further operations	High

VII. RESULTS AND SCREENSHOTS

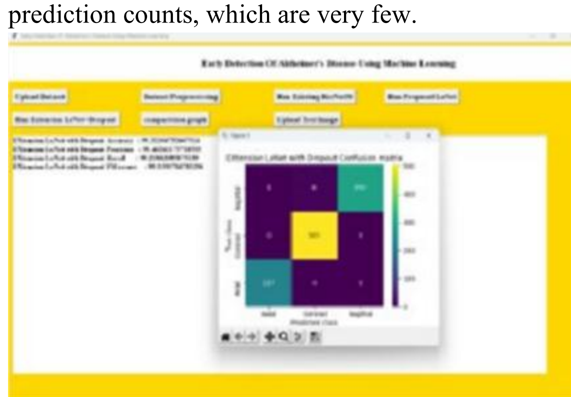
The application is run by clicking on the 'run.bat' file from the file location. The following results were obtained from the system:

Dataset Loading:
The dataset contains 3 folders representing each MRI view region (Axial, Coronal, Sagittal). A total of 5,154 MRI images were loaded from the dataset. The dataset class label graph displays the distribution of images across all three categories on the x-axis (Alzheimer Names) vs. count on the y-axis.

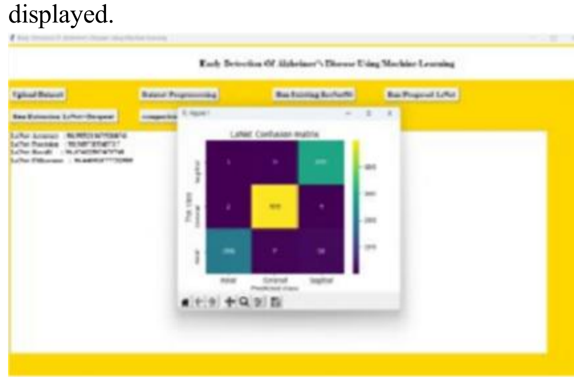


Data Preprocessing:
Images are processed through shuffling, normalization, and splitting into training and testing sets. 80% of images are used for training and 20% for testing.

ResNet50 Results:
The Pretrained ResNet50 model achieved an overall accuracy of 96%. The confusion matrix graph shows x-axis as Predicted Labels and y- axis as True Labels, where different colour boxes represent correct prediction counts and blue boxes represent incorrect prediction counts, which are very few.



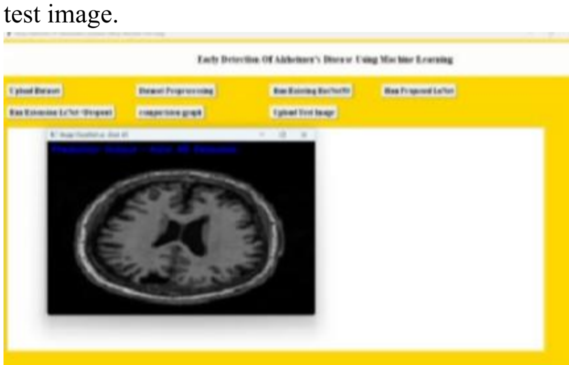
LeNet Results:
The LeNet model achieved an overall accuracy of 97.19%, outperforming the ResNet50 model. Individual class metrics and overall metrics are displayed.



Extension LeNet Results:
The Extension LeNet model with Dropout achieved an overall accuracy of 99.51%, which is the highest among all algorithms tested.

Comparison Graph:
The comparison graph displays the performance of all algorithms in graph format where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars. In all algorithms, the Extension LeNet with Dropout model achieved the highest performance.

Prediction Output:
For a given test image, the system predicts the MRI view category and displays the output (e.g., 'Sagittal NC Detected' or 'Axial AD Detected') overlaid on the test image.



VII. CONCLUSION

Hippocampus is one of the most affected areas of the brain and is easily accessible as a biomarker using MRI images in machine learning for diagnosing AD. In machine learning, using entire MRI image slices showed lower accuracy for AD classification. We presented the select slices method by landmarks on the hippocampus region in MRI images.

This study aimed to see which views of MRI images have higher accuracy for AD classification. To get the value of three views and categories, we used multiclass classification with the publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset using Resnet50 and LeNet. The models were used in a total dataset of 4,500 MRI slices in three views and categories. Our study demonstrated that the selecting slices method performed better than using entire slices in MRI images for AD classification. Our method improves the accuracy of machine learning, and the coronal view showed higher accuracy. This method played a significant role in improving the accuracy of machine learning performance.

The results for the coronal view were similar to what medical experts usually used to diagnose AD. We also found that LeNet models became the potential model for AD classification, with the Extension LeNet model with Dropout achieving the highest accuracy of 99.51%, demonstrating the effectiveness of deep learning for early detection of Alzheimer's disease.

REFERENCES

[1] Alzheimer’s Association, “2017 Alzheimer’s disease facts and figures,” Alzheimer’s & Dementia, vol. 13, no. 4, pp. 325–373, Apr. 2017, doi: 10.1016/j.jalz.2017.02.001.
[2] K. Alikhan, C. V. Narasimhulu, K. N. Reddy, and R. Fatima, “Machine Learning Model Development based on Brazil’s COVID-19 Dataset,” EBSCOhost, 2022.
[3] G. B. Frisoni, N. C. Fox, C. R. Jack, P. Scheltens, and P. M. Thompson, “The clinical use of structural MRI in Alzheimer disease,” Nature Reviews Neurology, vol. 6, no. 2, pp.

67–77, Feb. 2010, doi: 10.1038/nrneurol.2009.215.

[4] J. Olloquequi, M. Ettcheto, A. Cano, E. Sanchez-López et al., "Impact of new drugs for therapeutic intervention in Alzheimer's disease," Frontiers in Bioscience (Landmark Edition), vol. 27, no. 5, p. 146, 2022, doi: 10.31083/j.fbl2705146.

[5] Y. L. Rao, B. Ganaraja, B. V. Murlimanju, T. Joy, A. Krishnamurthy, and A. Agrawal, "Hippocampus and its involvement in Alzheimer's disease: A review," 3 Biotech, vol. 12, no. 2, pp. 1–10, Feb. 2022, doi: 10.1007/s13205-022-03123-4.

[6] M. Laakso, "MRI of hippocampus in incipient Alzheimer's disease," Ph.D. dissertation, Dept. Neurology, Univ. Kuopio, Kuopio, Finland, 1996.

[7] A. Moscoso, J. Silva-Rodríguez, J. M. Aldrey et al., "Prediction of Alzheimer's disease dementia with MRI beyond the short-term: Implications for the design of predictive models," NeuroImage: Clinical, vol. 23, Art. no. 101837, Jan. 2019, doi: 10.1016/j.nicl.2019.101837.

[8] K. M. Poloni and R. J. Ferrari, "Automated detection, selection and classification of hippocampal landmark points for the diagnosis of Alzheimer's disease," Computer Methods and Programs in Biomedicine, vol. 214, Art. no. 106581, Feb. 2022, doi: 10.1016/j.cmpb.2021.106581.

[9] A. Demirhan, "Classification of structural MRI for detecting Alzheimer's disease," International Journal of Intelligent Systems and Applications in Engineering, vol. 4, no. 1, pp. 195–198, Dec. 2016.

[10] H. Qiao, L. Chen, Z. Ye, and F. Zhu, "Early Alzheimer's disease diagnosis with contrastive loss using paired structural MRIs," Computer Methods and Programs in Biomedicine, vol. 208, Art. no. 106282, Sep. 2021, doi: 10.1016/j.cmpb.2021.106282.

[11] S. Savaş, "Detecting the stages of Alzheimer's disease with pre-trained deep learning architectures," Arabian Journal for Science and Engineering, vol. 47, no. 2, pp. 2201–2218, 2022.

[12] Z. Zhang and E. Sejdić, "Radiological images and machine learning: Trends, perspectives, and prospects," Computers in Biology and Medicine, vol. 108, pp. 354–370, May 2019, doi: 10.1016/j.compbiomed.2019.02.017.

[13] Y. Kazemi and S. Houghten, "A deep learning pipeline to classify different stages of Alzheimer's disease from fMRI data," in Proc. IEEE Conf. Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), May 2018, pp. 1–8, doi: 10.1109/CIBCB.2018.8404980.

[14] S. Gao and D. Lima, "A review of the application of deep learning in the detection of Alzheimer's disease," International Journal of Cognitive Computing in Engineering, vol. 3, pp. 1–8, Jun. 2022, doi: 10.1016/j.ijcce.2021.12.002.

[15] E. Thibeau-Sutre, B. Couvy-Duchesne, D. Dormont, O. Colliot, and N. Burgos, "MRI field strength predicts Alzheimer's disease: A case example of bias in the ADNI dataset," in Proc. IEEE Int. Symp. Biomedical Imaging (ISBI), Mar. 2022, pp. 1–4, doi: 10.1109/ISBI52829.2022.9761504.

[16] M. Raju, V. P. Gopi, and V. S. Anitha, "Multi-class classification of Alzheimer's disease using 3D CNN features and multilayer perceptron," in Proc. Int. Conf. Wireless Communications, Signal Processing and Networking (WiSPNET), Mar. 2021, pp. 368–373, doi: 10.1109/WiSPNET51692.2021.9419393.

[17] V. Sathiyamoorthi et al., "A deep convolutional neural network based computer-aided diagnosis system for the prediction of Alzheimer's disease in MRI images," Measurement, vol. 171, Art. no. 108838, Feb. 2021, doi: 10.1016/j.measurement.2020.108838.

[18] N. Yamanakkanavar, J. Y. Choi, and B. Lee, "MRI segmentation and classification of human brain using deep learning for diagnosis of Alzheimer's disease: A survey," Sensors, vol. 20, no. 11, p. 3243, Jun. 2020, doi: 10.3390/s20113243.

[19] M. Karthiga, S. Sountharrajan, S. Nandhini, and B. S. Kumar, "Machine learning based diagnosis of Alzheimer's disease," in Proc. Int. Conf. Image Processing and Capsule Networks, Springer, 2020, pp. 607–619, doi: 10.1007/978-3-030-51859-2_55.

[20] A. Farooq, S. Anwar, M. Awais, and S.

Rehman, “A deep CNN based multi-class classification of Alzheimer’s disease using MRI,” in Proc. IEEE Int. Conf. Imaging Systems and Techniques (IST), Oct. 2017, pp. 1–6, doi: 10.1109/IST.2017.8261460.