Classification of Alzheimer's Disease Stage using Ensemble of Convolution Neural Network on OASIS – 3 datasets

Submitted in partial fulfilment of the requirements for the award of degree of

Bachelor of Technology

In

Electronics and Communication Engineering

Submitted by

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2021-2025

CERTIFICATE

This is to certify that the project work entitled "**Designing a clinical decision support system for Alzheimer's diagnosis on OASIS – 3 datasets**" is a bonafide record of work carried out by **Anirudh Bandi (21ECB0B02), Shrikar Kaveti (21ECB0B21)** submitted to the faculty of the Department of Electronics and Communication Engineering in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Electronics and Communication Engineering at National Institute of Technology, Warangal for the academic year 2024-2025.

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DECLARATION

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

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ACKNOWLEDGEMENT

We wholeheartedly thank our guide **Prof. Dr. K. V. Sridhar**, **Associate Professor**, Department of Electronics and Communication Engineering, for being a source of motivation, constant supervision and invaluable encouragement, and for guiding us with perfection in doing work.

We are grateful to the **Electronics and Communication Engineering Department**, for providing us with all the facilities to carry out this project work.

Table of Contents

Abbreviations

AD – Alzheimer's Disease

MRI – Magnetic Resonance Imaging

CN – Cognitive Normal

MCI – Mild Cognitive Impairment

ADNI – Alzheimer's Disease Neuro-imaging Initiative

OASIS – Open Access Series of Imaging Studies

AIBL – Australian Imaging Biomarkers and Lifestyle Study of Ageing

MIRIAD – Minimal Interval Resonance Imaging in Alzheimer's Disease

CDSS – Clinical Decision Support System

MMSE – Mini-Mental Status Examination

APOE4 – Apolipo-Protein E4 Allele

DL – Deep Learning

CDR – Clinical Dementia Rating

ReLU – Rectified Linear Unit

Abstract

Alzheimer's disease (AD) is the most common neurodegenerative disease, and its early detection is crucial for appropriate treatment. Alzheimer's starts slowly and progressively worsens as the disease advances, symptoms can include problems with language, disorientation, loss of motivation and behavioural issues. Gradually, bodily functions are lost, ultimately leading to death.

This project aims to classify Alzheimer's patients into 4 categories Dementia, Mild Dementia, Very Mild Dementia and Cognitively Normal and predict the patient's clinical dementia ratio (CDR) which can be used to classify the stage of Alzheimer's Disease.

The proposed Model is an Ensembled model, It used both the MRI Data and other medical data of the patient and predict the CDR of the patient. The model proposed is a Functional Model. Therefore, It is more complex compared to the Sequential Model and extract more useful information.

Our Reference Paper had proposed a Binary Classification Ensembled Model, we improved the Model by modifying the layers of the model and made a Multi Categorical Classification Ensembled Model.

The Multi Categorical Classification Model has a training accuracy of 94% for 3500 Training Images and Testing Accuracy of 75% for 400 Images. OASIS-3 Dataset has been used to train the model. OASIS-3 Dataset is the latest MRI dataset with good quality check from Neurologists.

Chapter 1 - Introduction

1.1 Problem Statement

Alzheimer's Disease is a neurodegenerative disease which is caused by degeneration of neurons. Degeneration of Neuron causes the link between the motor nerves and the brain part crucial for the thinking capability of person be damaged. Alzheimer's Disease starts slowly and progressively cause the damage to the neural system. Therefore, Early detection of symptoms of Alzheimer's can be crucial to reduce the symptoms caused by the Alzheimer's.

Magnetic Resonance Imaging (MRI) is used to find the blood flow of the brain and the fat tissue in the brain. There are two types of MRIs – Fat based and Water based. Tw1 Type MRI works based on the water content in the brain where water molecules resonant in the magnetic field produced by the MRI machine. For this project Tw2 Type MRI has been used as Alzheimer's damaged the tissue in the brain. It is clearly visible in the MRI images the change in the tissue caused by the Alzheimer's Disease.

The OASIS-3 Dataset is maintained by the Neuroimaging Tools & Resources Collaboratory which is part of NIH. OASIS – 3 Dataset is the latest MRI dataset quality checked by top neurologist for many patients over several years.

1.2 Objective

1. **OASIS – 3 Dataset preparation,** the classified MRI of patient's data need to be accessed from the NITRC.

2**. Preprocessing of the MRI data** and converting the data into images.

3. Preparing Model and **Training Model** for the Dataset collected.

4. **Training the Model on a GPU** and Storing the Model Weights.

5**. Testing the Mode**l using MRI data unseen by the Model.

1.3 Motivation

Alzheimer's Disease is one of the most common neurodegenerative diseases. Alzheimer's starts slowly and gradually becomes very severe. Early Detection of Alzheimer's can help the patient get better help in the early stages though detection of Alzheimer's is very difficult as the Alzheimer's does not have any specific source and detection of Alzheimer's in the early stages is even difficult for the well trained and experienced neurologists and analysing hundreds of MRI for Alzheimer's can be vary time taking process.

Some of the recent research has suggested the strongest genetic risk factor is from an allele of apolipoprotein E (APOE4). Therefore, we have use both the APOE4 Data and analysis of clinical dementia assessment report along with the MRI data for predicting stage of the Alzheimer's of the patient.

This Model can be help for the neurologist to easily classify the patient and evaluate for early sign of Alzheimer's in the patient.

1.4 Background

1. Alzheimer's Disease

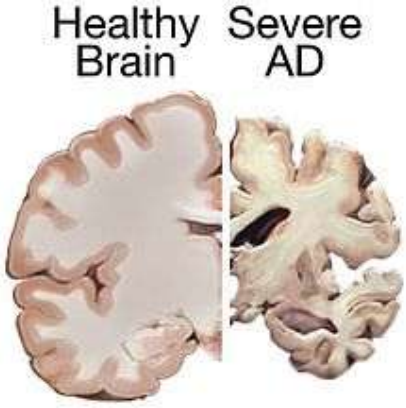

Fig. 1. Difference between the Normal Brain (Left) and Alzheimer's Disease Brain (Right)

Alzheimer's disease is a progressive neurodegenerative disorder that primarily affects memory, thinking, and behaviour. It is the most common cause of dementia, accounting for approximately 60-80% of cases worldwide. Alzheimer's typically develops slowly, with early symptoms such as mild forgetfulness or difficulty finding words, progressing to severe cognitive decline and loss of independence. The disease is characterized by the buildup of abnormal protein deposits in the brain—amyloid plaques and tau tangles—that disrupt communication between neurons and ultimately lead to cell death. While there is currently no cure, treatments and interventions can help manage symptoms and improve quality of life. Ongoing research focuses on early detection, potential therapies, and understanding the underlying causes to slow or prevent the disease.

2. Importance of Early Detection and Classification

Early and accurate classification of Alzheimer's stages is crucial for timely intervention, personalized treatment, and improving patient outcomes. Traditional diagnostic methods, such as cognitive assessments and neuroimaging, can be time-consuming and subject to variability. Therefore, automated and objective tools are needed to support clinicians in diagnosing and tracking disease progression more effectively.

3. Role of Machine Learning

Machine learning (ML) techniques have emerged as powerful tools for analysing complex datasets, including medical images (like MRI scans), biomarkers, and cognitive test results. By training models on these data sources, ML algorithms can identify patterns associated with different stages of Alzheimer's, aiding in classification and prediction. These methods not only enhance diagnostic accuracy but also hold potential for uncovering subtle, early indicators of the disease.

1.5 Applications

1. **Early Detection and Diagnosis**

   ML algorithms can analyse complex datasets—such as MRI scans, PET images, and cerebrospinal fluid biomarkers—to detect subtle patterns indicative of early-stage Alzheimer's. Early diagnosis allows for timely intervention, potentially slowing disease progression through lifestyle changes or medication.

2. **Stage Classification and Progression Monitoring**

   ML models classify Alzheimer's stages (e.g., preclinical, mild cognitive impairment, dementia) based on cognitive and biological markers. Clinicians can track a patient's progression more accurately, enabling personalized treatment plans. Longitudinal data analysis also helps in predicting the transition from one stage to another.

3. **Cognitive Assessment Automation**

   Machine learning can enhance cognitive testing by automating and standardizing assessments. Natural Language Processing (NLP) models, for instance, can analyse speech patterns or written text from patients to detect linguistic markers of cognitive decline.

4. **Image-Based Diagnostics**

   Deep learning models, especially convolutional neural networks (CNNs), analyse neuroimaging data (e.g., MRI, CT, PET scans) to detect structural brain changes. These tools assist radiologists in identifying anomalies that correlate with specific Alzheimer's stages.

5. **Biomarker Analysis**

   ML models can interpret complex patterns in blood or cerebrospinal fluid biomarkers. Multi-omics data (genomics, proteomics) are increasingly used to develop predictive models that identify genetic and biochemical factors associated with disease risk and progression.

6. **Personalized Treatment Recommendations**

   ML models can analyses patient data to recommend personalized therapeutic strategies. By assessing disease stage and individual characteristics, these models help tailor interventions, such as pharmacological treatments, cognitive therapies, or lifestyle modifications.

7. **Clinical Decision Support Systems (CDSS)**

   Integrating ML models into CDSS assists healthcare providers by offering evidence-based insights. These systems analyses patient data in real time, providing diagnostic support and suggesting next steps in care.

8. **Drug Development and Research**

   ML plays a crucial role in identifying potential drug candidates by analyzing large biological datasets and predicting their efficacy. Additionally, ML models can simulate disease progression, helping researchers design more efficient clinical trials.

9. **Remote Monitoring and Telemedicine**

   Machine learning facilitates remote monitoring of Alzheimer's patients through wearable devices and digital assessments. These technologies help detect early signs of cognitive decline and enable remote patient care, particularly important for those with limited access to healthcare facilities.

10. **Public Health and Epidemiology**

    ML models can analyse population-level data to predict trends, identify risk factors, and inform public health strategies. Understanding disease patterns helps in resource allocation and planning preventive interventions.

1.6 Merits

1. **Early Detection and Diagnosis**

   ML models can identify subtle patterns in data (e.g., brain scans, biomarkers) that may not be visible through traditional methods. This enables early detection, allowing timely interventions to slow disease progression.

2. **Enhanced Accuracy and Consistency**

   Compared to human evaluation, ML models reduce variability and subjectivity in diagnosis. They consistently apply the same criteria to classify Alzheimer’s stages, improving reliability.

3. **Efficient Data Processing**

   ML algorithms can process large and complex datasets—such as neuroimaging data or genetic information—much faster than traditional methods, aiding in quicker decision-making.

4. **Multimodal Data Integration**

   Machine learning models can combine different data types (e.g., imaging, genetic, clinical) to provide a more holistic view of the patient’s condition, enhancing classification accuracy.

5. **Non-Invasive Diagnostics**

   ML models analysing speech, cognitive tests, or wearable sensor data provide non-invasive ways to monitor patients, making diagnosis more accessible and comfortable.

6. **Personalized Treatment Plans**

   By analysing individual patient data, ML models help tailor treatment plans to specific needs, improving therapeutic outcomes and quality of life.

7. **Support for Clinical Decision-Making**

   ML-based clinical decision support systems (CDSS) assist healthcare professionals by providing evidence-based recommendations, enhancing the diagnostic process.

8. **Advancements in Research**

   ML models contribute to Alzheimer's research by uncovering new biomarkers, understanding disease mechanisms, and accelerating drug discovery.

1.7 Demerits

1. **Data Quality and Availability**
   ML models require large, high-quality datasets for training. Limited or biased datasets may lead to inaccurate predictions, especially in underrepresented populations.

2. **Interpretability and Transparency**
   Many advanced models, such as deep neural networks, operate as "black boxes," making it difficult to interpret their decision-making processes. This lack of transparency can hinder clinical trust.

3. **Risk of Overfitting**
   Models trained on specific datasets may perform well on training data but fail to generalize to new, unseen data, leading to poor real-world performance.

4. **Ethical and Privacy Concerns**
   Handling sensitive patient data raises ethical issues, particularly regarding data privacy and security. Ensuring compliance with regulations (e.g., HIPAA) is essential but challenging.

5. **Dependence on High-Quality Infrastructure**
   Implementing ML-based systems requires advanced computing resources and specialized expertise, which may not be available in all healthcare settings, especially in low-resource regions.

6. **Limited Generalizability**
   Alzheimer's presentations can vary significantly among individuals. A model trained on one population or dataset may not generalize well to others, leading to misdiagnoses.

7. **Potential Bias**
   Biases in training data (e.g., demographic or socio-economic) can lead to unequal performance across different patient groups, potentially exacerbating health disparities.

8. **Cost of Implementation**
   Developing, training, and deploying ML models can be expensive. Integrating these systems into existing healthcare infrastructure may require substantial investments.

9. **Regulatory Challenges**
   Medical ML applications must meet strict regulatory standards. Obtaining approval for clinical use can be time-consuming and complex, delaying deployment.

10. False Positives/Negatives

Misclassifications (false positives or negatives) can have serious consequences. False positives may cause unnecessary anxiety and treatment, while false negatives can delay critical interventions.

Chapter 2 - Literature Review

Title – Designing a clinical decision support system for Alzheimer's diagnosis on OASIS – 3 dataset
Year – 2022
Type of Publication – Biomedical Signal Processing and Control, Volume 74 (Elvisier)
Authors – Farzaneh Salami, Ali Bozorgi-Amiri, Ghulam Mubashar Hassan, Reza Tavakkali Maghaddam, Amitava Datta

Summary

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that requires accurate detection and classification to facilitate early intervention and improve patient outcomes. Traditional diagnostic methods, such as neuropsychological assessments and manual MRI analysis, are time-consuming and prone to subjectivity. The advent of machine learning (ML) and deep learning (DL) has significantly improved diagnostic capabilities by automating the analysis of complex data, including 3D-MRI scans. Convolutional neural networks (CNNs) such as ResNet, DenseNet, and Inception-v3 have shown promise in extracting intricate features from neuroimaging data, enabling more accurate classification of AD stages—from cognitively normal (CN) to mild cognitive impairment (MCI) and dementia.

Methodology

Various ML models have been applied to Alzheimer's classification, leveraging benchmark datasets like ADNI, OASIS, and AIBL. The OASIS-3 dataset, known for its longitudinal neuroimaging and clinical data, provides a comprehensive resource for model training and evaluation. Previous studies have employed traditional ML techniques, but recent research focuses on deep learning architectures, particularly 3D CNNs, to capture spatial information in brain scans. Ensemble models integrating MRI data with clinical factors such as Mini-Mental State Examination (MMSE) scores and APOE genetic markers have also been explored. These models aim to improve classification accuracy by combining multimodal data, addressing limitations of single-modality approaches.

Conclusion

The integration of machine learning in Alzheimer's stage classification has demonstrated significant potential in enhancing diagnostic accuracy and consistency. CNNs and ensemble models, in particular, have shown the ability to identify subtle patterns in neuroimaging and clinical data, aiding early detection. However, challenges such as data imbalance, interpretability, and generalizability across diverse populations remain. Future research should focus on refining models to better classify intermediate stages like MCI and ensuring robust performance across varied datasets, ultimately supporting more effective clinical decision-making.

Chapter 3 – Workflow

1. Problem Definition and Objective Setting

Objective: Develop a machine learning model to detect and classify Alzheimer's stages (Cognitively Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD)) using the OASIS-3 dataset.

Scope: Determine the classification accuracy and assess model robustness across different patient demographics and data types.

2. Data Collection and Exploration

Source: Download the OASIS-3 dataset, which includes 3D MRI scans and associated clinical data (MMSE scores, APOE genotypes, and CDR scores).

Data Structure: Identify key features:

- MRI scans (3D T1-weighted images)
- Demographic data (age, gender, handedness)
- Clinical scores (MMSE, APOE, CDR)

Exploratory Data Analysis (EDA)

- Understand data distribution and detect any class imbalances.
- Visualize MRI slices to check for variations and anomalies.
- Correlate clinical scores with MRI data to identify potential patterns.

3. Data Preprocessing

Image Preprocessing

- Skull stripping to remove non-brain tissues.
- Intensity normalization and bias correction.
- Align images to a common template.
- Resize MRI scans to a consistent shape (e.g., 176 × 240 pixels).

Clinical Data Preprocessing

- Handle missing values in clinical data (e.g., MMSE and APOE scores).
- Normalize clinical data for integration with image features.

Data Splitting

- Split the dataset into training (60%), validation (20%), and testing (20%) sets.
- Ensure a subject-level split to avoid data leakage from multiple scans of the same patient.

4. Model Development

Ensemble Model

- Integrate MRI data with clinical features (MMSE, APOE) to build an ensemble model.
- Combine outputs from the CNN with a dense neural network processing clinical data.

5. **Model Training and Validation**

Training

- Train models using the training set with appropriate loss functions (e.g., cross-entropy loss).
- Use data augmentation techniques to address class imbalances.

Hyperparameter Tuning:

- Optimize hyperparameters (learning rate, batch size, number of layers) using techniques such as grid search or Bayesian optimization.

Validation

- Evaluate performance on the validation set to prevent overfitting.
- Use metrics such as accuracy, precision, recall, F1-score.

6. **Model Evaluation**

Testing

- Evaluate the final model on the unseen test set.

Performance Metrics:

- Calculate and compare key metrics for each class (CN, MCI, AD).
- Analyse confusion matrices to identify misclassification patterns.

Error Analysis:

- Investigate misclassified cases, particularly for challenging MCI detection.

Chapter 4 - Work Done

1. Dataset Acquisition

The dataset used for this project is the **OASIS-3 (Open Access Series of Imaging Studies)**, which contains longitudinal neuroimaging data and clinical assessments for Alzheimer's disease research. The data was downloaded using the wget command-line tool for efficient and automated retrieval.

```
wget --http-user="username" --http-password="password" --auth-no-challenge --no-check-certificate -O data/OAS30002_MR_d2345.zip "https://www.nitrc.org/ir/data/archive/projects/OASIS3/subjects/OAS30002/experiments/OAS30002_MR_d2345/scans/T2w/files?format=zip" &&
```

Explanation

- **wget** - Command-line tool to download files from the internet.
- **--http-user = "username"** - Specifies the HTTP username for authentication.
- **--http-password = "password"** – Specifies the HTTP password associated with the user account.
- **--auth-no-challenge** – This option allows **wget** to send the authentication credentials (username and password) without waiting for a challenge from the server.
- **Use Case** – Useful when the server does not explicitly request authentication before download, but credentials are still required.

Difference Between Tw1 and Tw2 MRI Scans

We used Tw2 MRI Scans for training or our model because It is details the abnormalities in the tissue with more accuracy then the Tw1 MRI Scans as Tw2 used the fats to image the brain.

Magnetic Resonance Imaging (MRI) uses different imaging sequences to capture various tissue characteristics. The two most common sequences are **T1-weighted (T1w)** and **T2-weighted (T2w)** images. Each provides distinct information based on how different tissues respond to magnetic fields and radiofrequency pulses.

Aspect	T1-weighted (T1w) MRI	T2-weighted (T2w) MRI
Signal Basis	Measures the time it takes for protons to realign with the magnetic field (longitudinal relaxation).	Measures the time it takes for protons to lose phase coherence (transverse relaxation).
Appearance of CSF	Dark (low signal intensity)	Bright (high signal intensity)
Appearance of Fat	Bright (high signal intensity)	Intermediate to dark
Appearance of Water	Dark or intermediate	Bright
Gray/White Matter Contrast	White matter appears lighter than gray matter.	Gray matter appears lighter than white matter.
Pathological Detection	Better for structural detail, anatomical information, and identifying fatty tissue.	Better for detecting fluid-related abnormalities, such as edema, tumors, and inflammation.
Clinical Applications	Useful for visualizing normal anatomy, assessing structural abnormalities, and evaluating atrophy.	Useful for identifying lesions, edema, and other pathology involving water content.
Scan Duration	Typically shorter than T2-weighted scans.	Generally longer than T1-weighted scans.

Table. 1. Difference between Tw1 and Tw2 MRI Scans

Examples in Brain Imaging:

- **T1w:** Commonly used to assess brain anatomy, detect tumors, and monitor brain atrophy in conditions like Alzheimer's disease.
- **T2w:** Effective for identifying abnormalities such as multiple sclerosis plaques, brain edema, or cerebrovascular lesions.

T1-weighted and T2-weighted MRI scans complement each other in clinical practice. While T1w images provide detailed anatomical information, T2w images are crucial for detecting pathological changes, especially those involving water content. Combining both sequences offers a comprehensive view of brain structure and pathology.

2. Data Extraction

The downloaded dataset consists of compressed .tar.gz files containing NIfTI (.nii) format neuroimaging data. The files were extracted to organize them for preprocessing.

```
tar -xvzf oasis_dataset.tar.gz -C /path/to/destination/
```

Explanation

- **-x** – Extract the files.
- **-v** – Verbose output to monitor the extraction process.
- **-z** – Handle gzip-compressed files.
- **-f** – Specify the file to extract.

```
# Extraction Code
count = 0

data_files = glob.glob("tw1_data/*.zip")
extraction_file_address = []

for zip_file_name in data_files:
    with zipfile.ZipFile(zip_file_name, mode = "r") as outer_zip:
        # file_name = outer_zip.namelist()[-1]
        print(outer_zip.namelist())
        count += len(outer_zip.namelist()) / 2
```

For Windows, we wrote our own extraction code with python to streamline and do all the processes in a single code.

Output

Extracts the gzip file and collects all the .nii files in a folder for visualization and model training.

```
['OAS30001_MR_d0129/scans/anat3-T1w/resources/BIDS/files/sub-OAS30001_ses-
d0129_run-02_T1w.json', 'OAS30001_MR_d0129/scans/anat3-
T1w/resources/NIFTI/files/sub-OAS30001_ses-d0129_run-02_T1w.nii.gz',
'OAS30001_MR_d0129/scans/anat2-T1w/resources/BIDS/files/sub-OAS30001_ses-
d0129_run-01_T1w.json', 'OAS30001_MR_d0129/scans/anat2-
T1w/resources/NIFTI/files/sub-OAS30001_ses-d0129_run-01_T1w.nii.gz']

['OAS30001_MR_d0757/scans/anat3-T1w/resources/BIDS/files/sub-OAS30001_ses-
d0757_run-02_T1w.json', 'OAS30001_MR_d0757/scans/anat3-
T1w/resources/NIFTI/files/sub-OAS30001_ses-d0757_run-02_T1w.nii.gz',
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d0757_run-01_T1w.json', 'OAS30001_MR_d0757/scans/anat2-
T1w/resources/NIFTI/files/sub-OAS30001_ses-d0757_run-01_T1w.nii.gz']

['OAS30001_MR_d2430/scans/anat4-T1w/resources/BIDS/files/sub-OAS30001_ses-
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OAS30001_ses-d2430_T1w.nii.gz']
['OAS30001_MR_d3132/scans/anat2-T1w/resources/BIDS/files/sub-OAS30001_ses-
d3132_T1w.json', 'OAS30001_MR_d3132/scans/anat2-T1w/resources/NIFTI/files/sub-
OAS30001_ses-d3132_T1w.nii.gz']

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d3746_T1w.json', 'OAS30001_MR_d3746/scans/anat4-T1w/resources/NIFTI/files/sub-
OAS30001_sess-d3746_T1w.nii.gz']

['OAS30001_MR_d4467/scans/anat2-T1w/resources/BIDS/files/sub-OAS30001_sess-
d4467_T1w.json', 'OAS30001_MR_d4467/scans/anat2-T1w/resources/NIFTI/files/sub-
OAS30001_sess-d4467_T1w.nii.gz']

['OAS30002_MR_d0371/scans/anat3-T1w/resources/BIDS/files/sub-OAS30002_ses-
d0371_T1w.json', 'OAS30002_MR_d0371/scans/anat3-T1w/resources/NIFTI/files/sub-
OAS30002_ses-d0371_T1w.nii.gz']
```

3. NIfTI File Conversion to Images

NIfTI (.nii) files represent 3D brain scans and need to be converted into 2D image slices for visualization and processing. The conversion was done using Python with the nibabel and matplotlib libraries.

```
import nibabel as nib
import matplotlib.pyplot as plt
import os

# Load the NIfTI file
nii_file = 'path_to_file/brain_scan.nii'
img = nib.load(nii_file)
data = img.get_fdata()

# Output directory for images
output_dir = 'output_images/'
os.makedirs(output_dir, exist_ok=True)
```

```
# Convert each slice to an image
for i in range(data.shape[2]):  # Loop through slices
    plt.imshow(data[:, :, i], cmap='gray')
    plt.axis('off')
    plt.savefig(f'{output_dir}/slice_{i}.png', bbox_inches='tight')
    plt.close()
```

Nibabel library is a python library for using .nii files and extract additional details about the .nii files such as its origin and other info and MRI 3D Matrix data.

Output

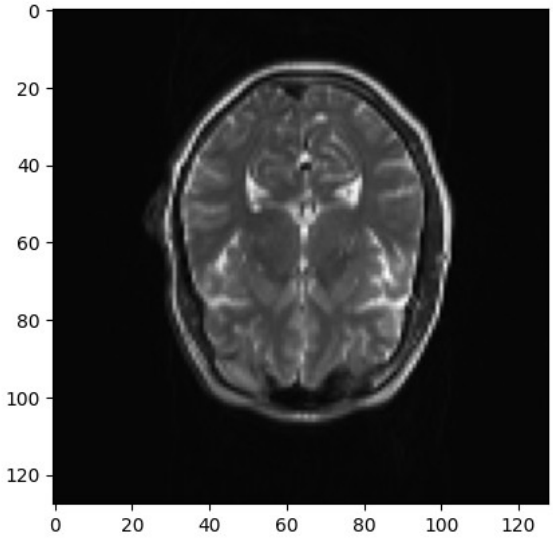

Fig. 2. Output Slice Image of MRI Data from NII Files using Nibabel

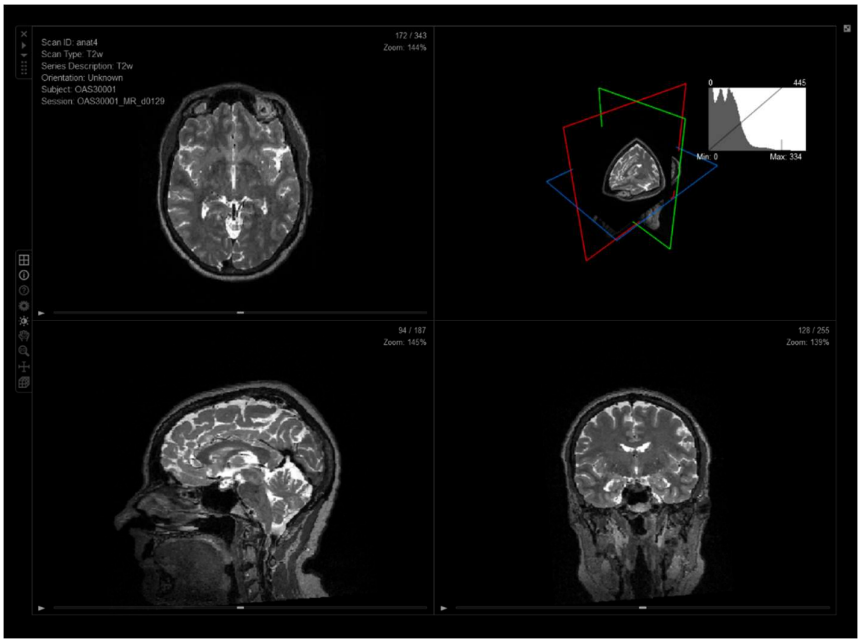

Fig. 3. Visualization of 3D MRI Data from NII Files

This process successfully retrieved and organized the OASIS-3 dataset, converted 3D neuroimaging data into 2D image slices, and prepared the data for the subsequent stages of machine learning model development. This structured workflow ensures reproducibility and facilitates seamless integration with the model training pipeline.

4. Equalization of MRI Data sizes

In the OASIS Dataset, one of the main problems for training the model was that all the 3D MRI data matrices were not of equal size. Generally Resizing a 2D image can be easily done by the Image Libraries available for Python such as CV2 but 3D image data equalization is not possible. Therefore, we sliced the 3D matrix parallel to the mid ridge of the brain. So, we get images of side view of the brain. The Extracted Images are of different size for different NII files which then are equalized using CV2 Resize function with linear interpolation.

```
# 3D MRI Data Equalization Code

for i in nii_files:
    nii_data = nib.load(i).get_fdata()
    nii_data_shape = nii_data.shape

    nii_data_images = []

    (required_x, required_y, required_z) = (88, 120, 5)

    lower_limit_x = int(nii_data_shape[0] / 2) - required_x
    upper_limit_x = int(nii_data_shape[0] / 2) + required_x

    lower_limit_y = int(nii_data_shape[1] / 2) - required_y
    upper_limit_y = int(nii_data_shape[1] / 2) + required_y

    lower_limit_x = int(nii_data_shape[2] / 2) - required_z
    upper_limit_y = int(nii_data_shape[2] / 2) + required_z

    z = int(nii_data_shape[2] / 2)

    print(nii_data[lower_limit_x:upper_limit_x, lower_limit_y:upper_limit_y, z].shape)
```

Output

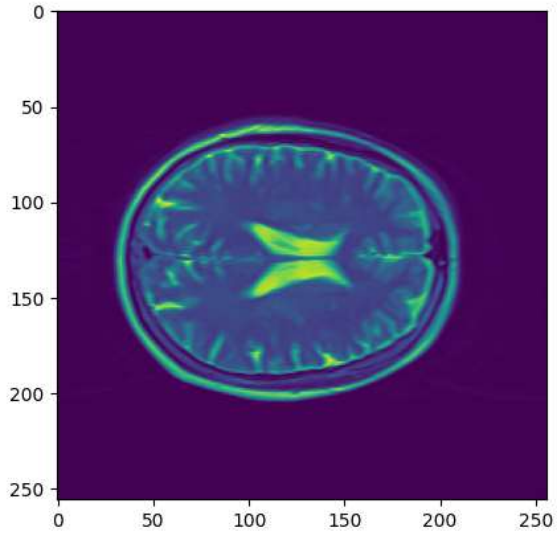

Fig. 4. MRI Sliced Image of size (176, 240) with Highlighting the Tissue

Shape of the NII File	No. of NII Files
(256, 256, 36)	208
(176, 256, 256)	213
(228, 256, 44)	51
(176, 240, 256)	4
(192, 256, 26)	12
(232, 256, 44)	4
(256, 256, 45)	66

Table. 2. Distribution of MRI of different Size in the Dataset

Some Images in the Dataset may not properly align in the Image as the patient may tilt their head or other medical complications may not allow for a aligned MRI Scan. Therefore, Image Data Generator has been used to slightly tilt and zoom in and zoom out the images such that model cannot be overfitted for the dataset.

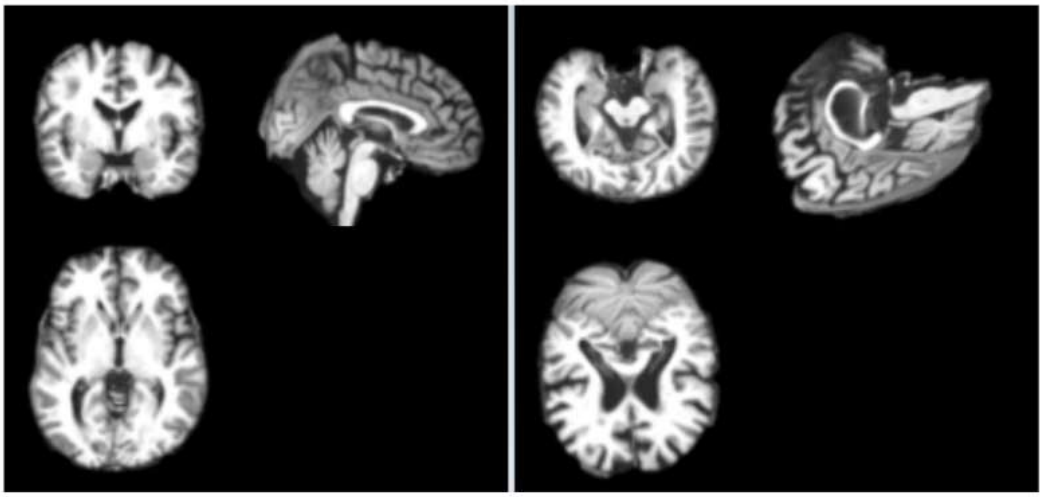

Fig. 5. Example of Correctly Aligned Image (Left) and Incorretly Aligned Image (Right)

5. Model Training

We have prepared two models to compare their accuracy

1. Binary Classification Model
2. Multi Categorical Classification Model

Binary Classification Model

For Detection of Alzheimer's for patient the Binary Classification Model can be used. The Binary Classification Model is Proposed by the Author of the Reference Paper, Proposed Model was a Ensembled model which uses both the MRI Scan Data and Medical Data collected by the Neurologists while examinations of the patient.

Classes in Model – Dementia, Cognitively Normal.

Inputs of the Model are the MRI Scan data from after the Size Equalization process and Medical Data of the patient include APOE4 data and MMSE data of the patient. The model performs has a major difference with and without Additional Medical Data.

Layer Name	Layer	No. of Filters	Kernal Size	Stride
Conv 1	Convolution 2D	32	3 x 3	1
Conv 2	Convolution 2D	32	3 x 3	1
Conv 3	Convolution 2D	32	3 x 3	1
Conv 4	Convolution 2D	32	3 x 3	1

Table. 3. CNN Hyperparameters

Hyperparameters	Value
Stride	1
Padding	same
Activation	ReLU
Neural Network Bias	True
Kernal Initializer	Random (Normal Distribution)
Kernal Regularizes	L2 (Ridge Regression)
Batch Size	1
Epochs	25
Callback	Reduce Learning Rate on Plateau
Optimizer	Adams
Loss Function	Binary Cross Entropy
Model Loss	0.09363958984613419
Model Accuracy	96.52855396270752 %

Table. 4. Network Hyperparameters

Model Architecture

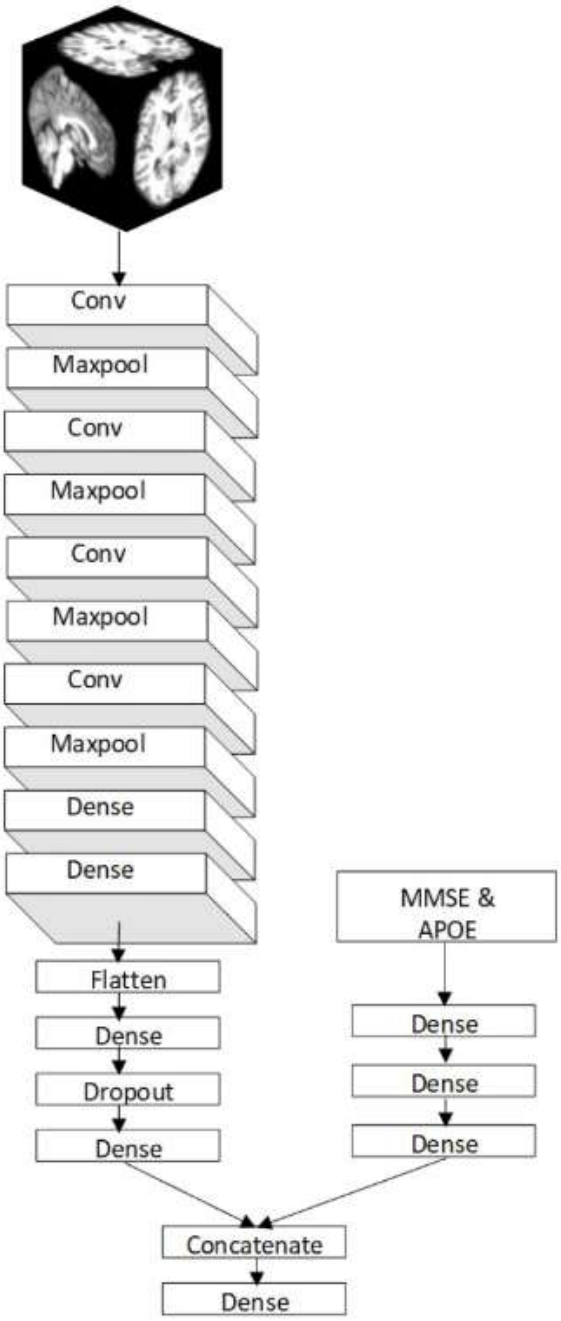

Fig. 6. Model Architecture

Model is created using TensorFlow Library Functional Model, as this is a Ensemble Model a Sequential Model cannot be used to used for two data inputs. Therefore, Functional Model has been used to prepare the model.

The Model has been trained for 3500 MRI Scans and the Model has been tested for 400 Images.

Model uses RMS-Prop for optimization and Binary Cross-Entropy Loss for calculating loss.

Multi Categorical Classification Model

The multi categorical classification model has the same architecture of the binary classification model but the model uses different loss calculation method – Multi Categorical Cross-Entropy Loss.

Classes – Dementia, Mild Dementia, Very Mild Dementia, Cognitively Normal

Input – MRI Scan Data, APOE4 and MMSE Data

Layer (type)	Output Shape	Param #	Connected to
input_image (InputLayer)	(None, 176, 240, 1)	0	-
conv2d (Conv2D)	(None, 176, 240, 32)	320	input_image[0][0]
max_pooling2d (MaxPooling2D)	(None, 88, 120, 32)	0	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 88, 120, 32)	9,248	max_pooling2d[0]…
max_pooling2d_1 (MaxPooling2D)	(None, 44, 60, 32)	0	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 44, 60, 32)	9,248	max_pooling2d_1[…
max_pooling2d_2 (MaxPooling2D)	(None, 22, 30, 32)	0	conv2d_2[0][0]
conv2d_3 (Conv2D)	(None, 22, 30, 32)	9,248	max_pooling2d_2[…
max_pooling2d_3 (MaxPooling2D)	(None, 11, 15, 32)	0	conv2d_3[0][0]
dense (Dense)	(None, 11, 15, 512)	16,896	max_pooling2d_3[…
dense_1 (Dense)	(None, 11, 15, 128)	65,664	dense[0][0]
flatten (Flatten)	(None, 21120)	0	dense_1[0][0]
input_data (InputLayer)	(None, 8)	0	-
dense_2 (Dense)	(None, 64)	1,351,744	flatten[0][0]
dense_4 (Dense)	(None, 16)	144	input_data[0][0]
dropout (Dropout)	(None, 64)	0	dense_2[0][0]
dense_5 (Dense)	(None, 8)	136	dense_4[0][0]
dense_3 (Dense)	(None, 64)	4,160	dropout[0][0]
dense_6 (Dense)	(None, 8)	72	dense_5[0][0]
concatenate (Concatenate)	(None, 72)	0	dense_3[0][0], dense_6[0][0]
dense_7 (Dense)	(None, 4)	292	concatenate[0][0]

Fig. 7. Model Architecture

Layer Name	Layer	No. of Filters	Kernal Size	Stride
Conv 1	Convolution 2D	32	3 x 3	1
Conv 2	Convolution 2D	32	3 x 3	1
Conv 3	Convolution 2D	32	3 x 3	1
Conv 4	Convolution 2D	32	3 x 3	1

Table. 5. CNN Hyperparameters

Hyperparameters	Value
Stride	1
Padding	same
Activation	ReLU
Neural Network Bias	True
Kernal Initializer	Random (Normal Distribution)
Kernal Regularizes	L2 (Ridge Regression)
Batch Size	1
Epochs	25
Callback	Reduce Learning Rate on Plateau
Optimizer	Adams
Loss Function	Binary Cross Entropy
Model Loss	0.18540231883525848
Model Accuracy	94.51287984848022 %

Table. 6. Network Hyperparameters

6. GPU Implementation

For GPU Implementation, the Models have been Implemented on the Laptop GPU – Nvidia RTX 3050 using TensorFlow Library and CUDA Libraries. RTX 3050 has 6 Gb DDR5 Memory and 2560 CUDA Cores with 3rd Generation Tensor cores. The GPU has Nvidia Ampere Architecture and has a power usage rating of 130 W.

Nvidia GPU Specification	Parameters
Model	Nvidia RTX 3060
Cuda Cores	2560
Tensor Cores	3rd Generation
Power Usage	130 Watts

Table. 7. GPU Specification

```
tf.debugging.set_log_device_placement(True)

print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
print(tf.config.experimental.list_logical_devices('GPU'))

sess =
tf.compat.v1.Session(config=tf.compat.v1.ConfigProto(log_device_placement=True))

print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
```

The Above Code is for printing the GPU Session outputs and Memory Allocation for the GPU and other GPU related Data.

7. Model Function Details

1. Model needs to have balance between classification accuracy and computational efficiency.
2. Changes in the Models
   a. All the 2D Convolution layers were changed to 3D Convolution.
   b. Model take 3 Channel Colour Images which is converted into 1 Channel as MRIs are grayscale images.

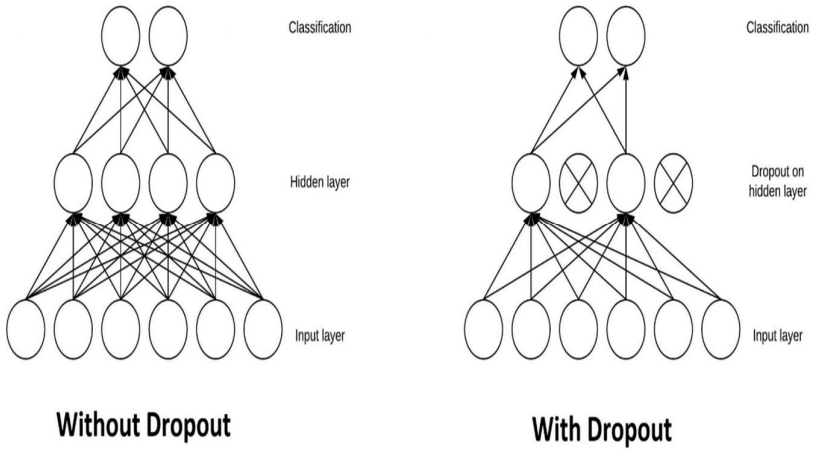

Fig. 8. Dropout Layers

   c. Flatten, Dropout and Dense Layers are added to the Models for avoiding Overfitting of Model for Dataset.

Model Functions

1. The Input Image is a 3D cube shape that contains axial, sagittal, and coronal views of the brain.
2. Model Contains Four Convolution and Max-pooling Layers.
3. Convolution Kernal Size (3 x 3)
4. Max-pooling Size (2 x 2)

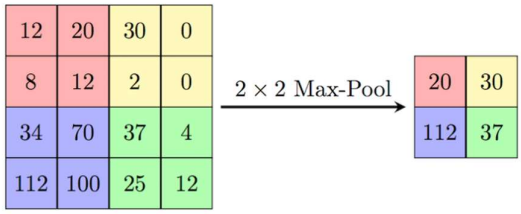

Fig. 9. Max-Pooling Layer

5. 3rd and 4th Layer has Convolution Kernal Size (1 x 1), Bias and activity regularizes to avoid Overfitting for the Dataset.
6. Activation Function (ReLU)

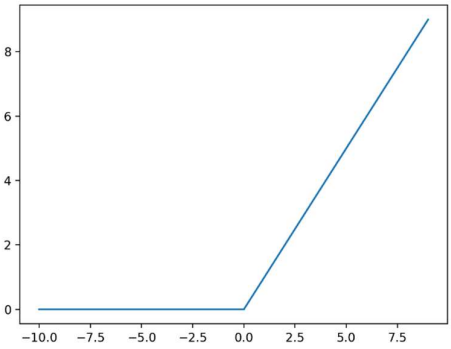

Fig. 10. ReLU Function

7. Finally, Fully Connected Layers with SoftMax layer for finding Probability.

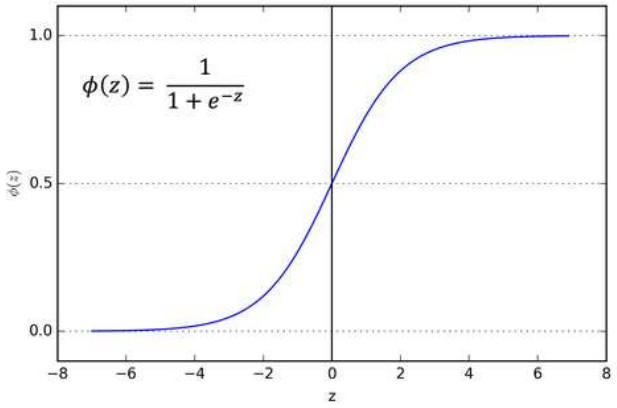

Fig. 11. Sigmoid Function

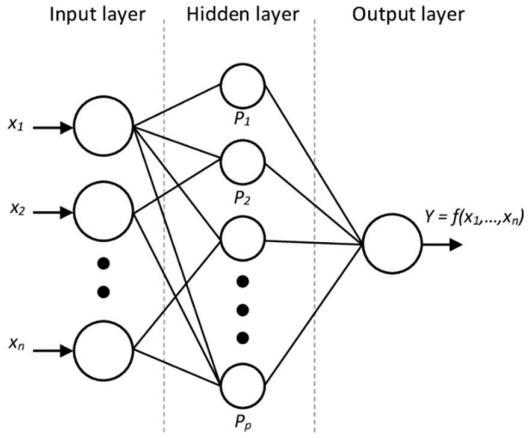

Fig. 12. Dense Layers

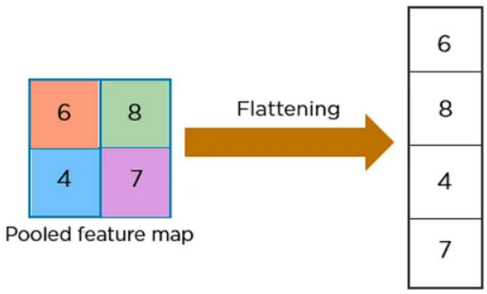

Fig. 13. Flatten Layer

Chapter 5 - Results

OASIS – 3 Dataset has 4000 Images, after Size Equalization and Preprocessing has been divides into three categories – Training Data, Validation Data and Testing Data.

The dataset split has been done by Sci-Kit Learn Library train_test_split function, 80% of the Dataset has been used for Training the Model and 20% has been used for Testing the Model.

Validation Dataset is a small percentage of the Training Dataset used for evaluation the model and updating the model weight for each Epoch.

CDR Value	No. of Patients
2	194
1	126
0.5	127
0	111

Table. 8. Distribution of the CDR values in the Dataset

Model	Time Taken to Train Model
Binary Classification Model	3 Min 3 Sec
Multi Categorical Classification Model	3 Min 30 Sec

Table. 9. Time taken for each Model to Train on GPU

Model	Time Taken to Test Model
Binary Classification Model	82 Sec
Multi Categorical Classification Model	114 Sec

Table. 10. Time Taken for each Model to Test on GPU

Model	Testing Model Accuracy	Testing Model Loss
Binary Classification Model	96.52855396270752 %	0.09363958984613419
Multi Categorical Classification Model	94.51287984848022 %	0.18540231883525848

Table. 11. Models Testing Accuracy and Loss

Binary Classificaition Model

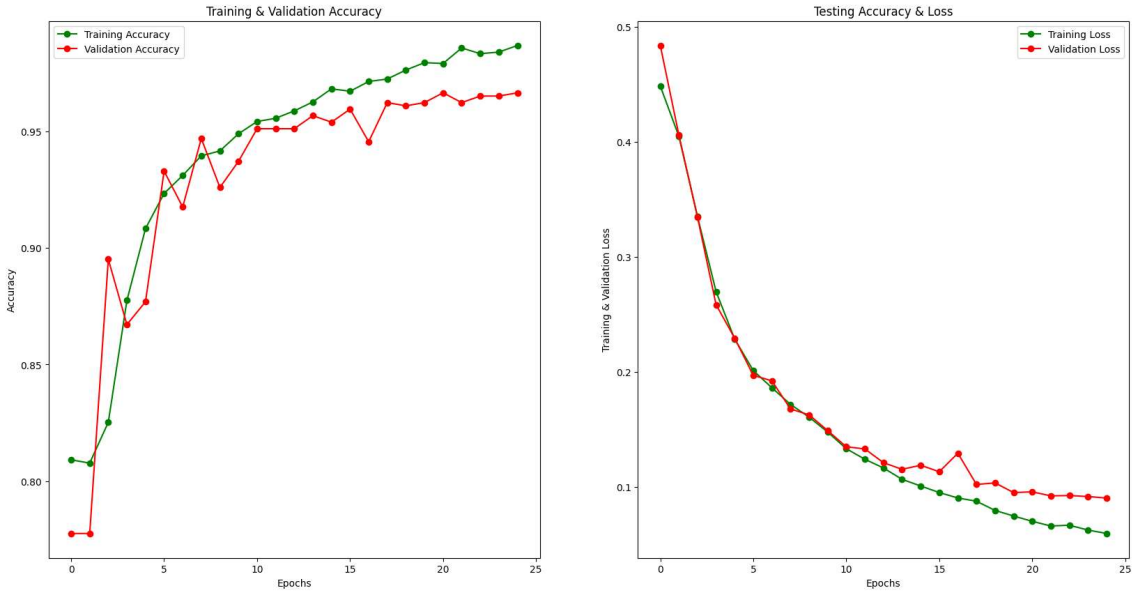

Fig. 14. Model Training Curve

	precision	recall	f1-score	support
Normal (Class 0)	0.91	0.92	0.92	182
Alzheimers (Class 1)	0.98	0.98	0.98	711
accuracy			0.97	893
macro avg	0.95	0.95	0.95	893
weighted avg	0.97	0.97	0.97	893

Fig. 15. Model F Score

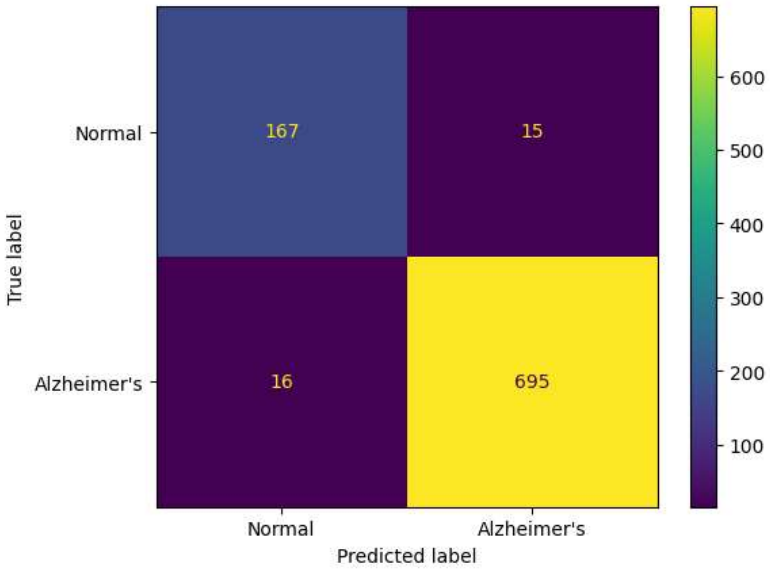

Fig. 16. Confusion Matrix for Testing Images

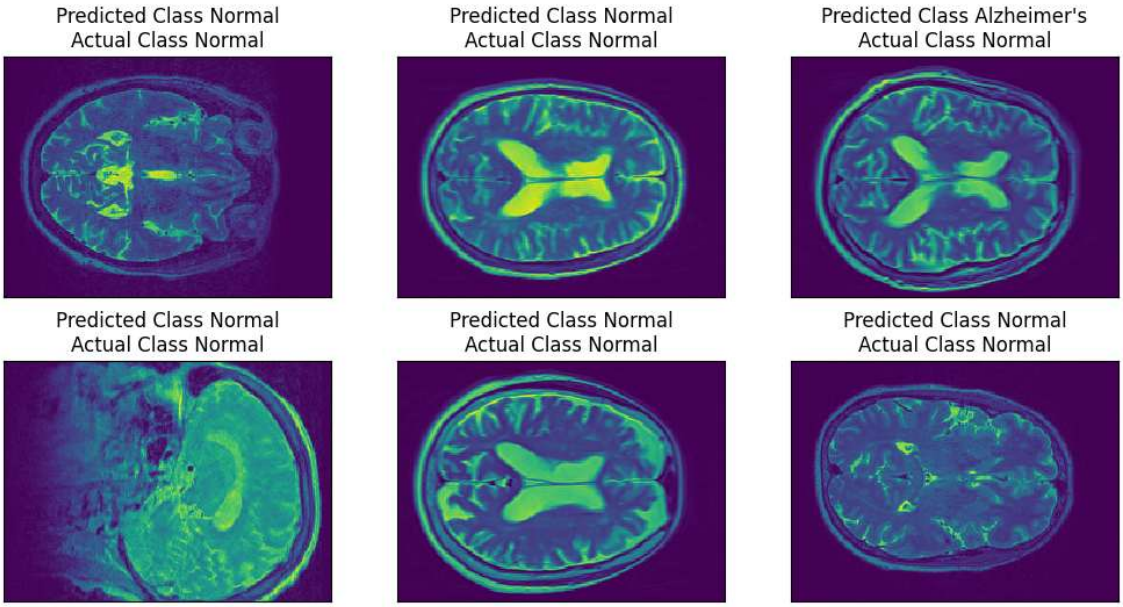

Fig. 17. Correctly Predicted Images

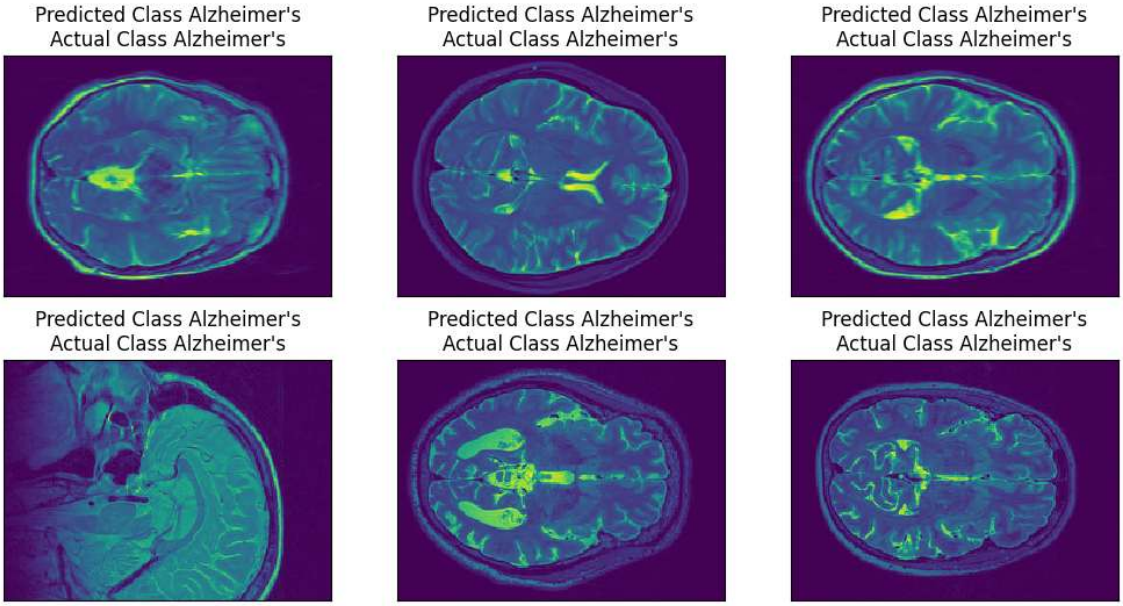

Fig. 18. Incorrectly predicted Images

Multi Categorical Classification Model

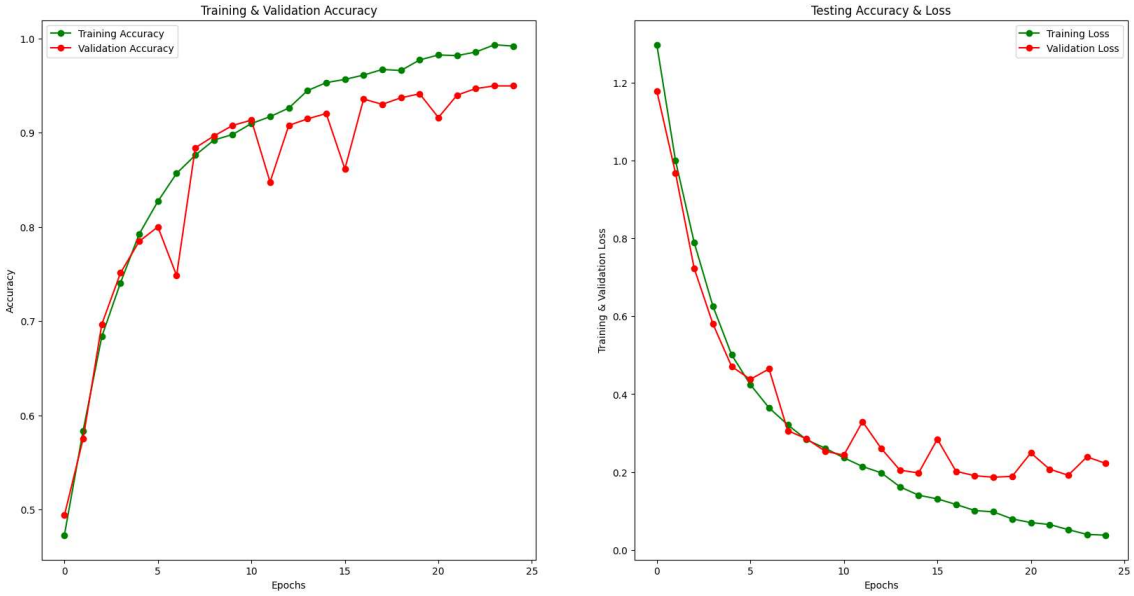

Fig. 19. Model Training Curve

	precision	recall	f1-score	support
Non Dementia (Class 0)	0.92	0.95	0.93	182
Very Mild Dementia (Class 1)	0.95	0.89	0.92	207
Mild Dementia (Class 2)	0.96	0.92	0.94	207
Moderate Dementia (Class 3)	0.95	1.00	0.97	297
accuracy			0.95	893
macro avg	0.94	0.94	0.94	893
weighted avg	0.95	0.95	0.94	893

Fig. 20. Model F Score

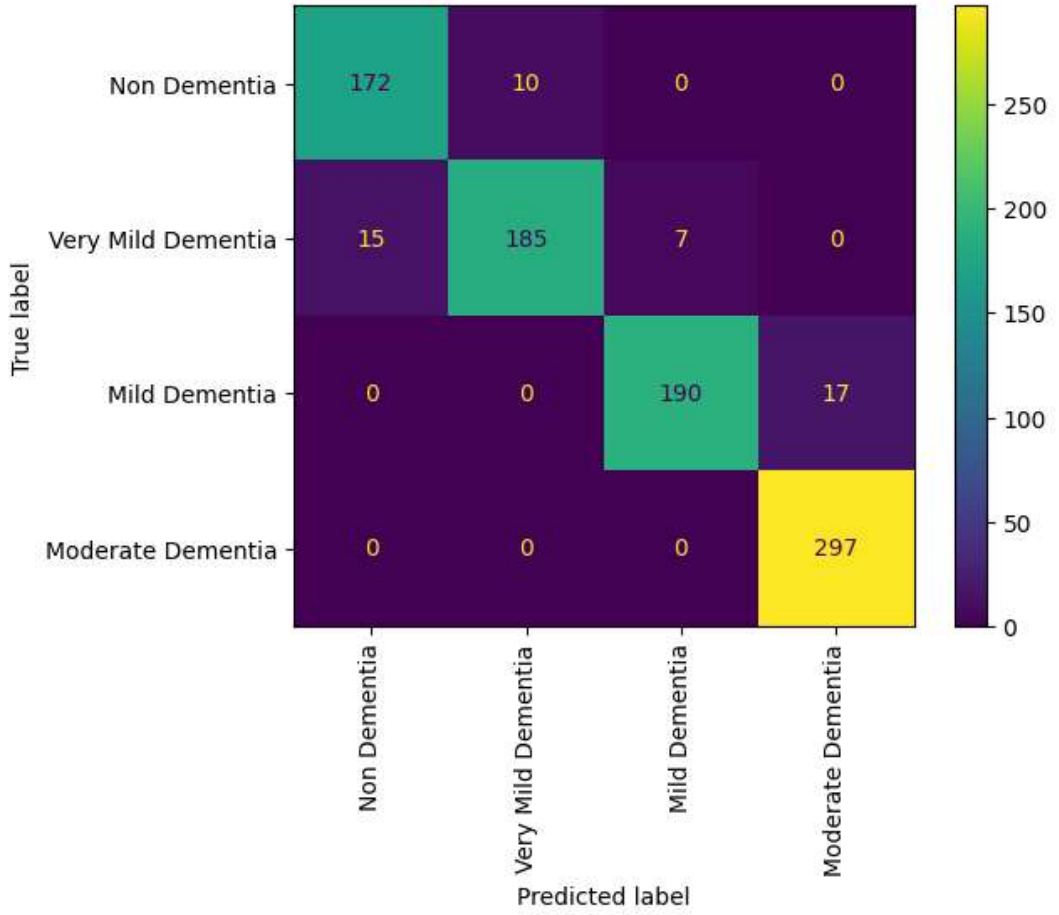

Fig. 21. Confusion Matrix for Testing Images

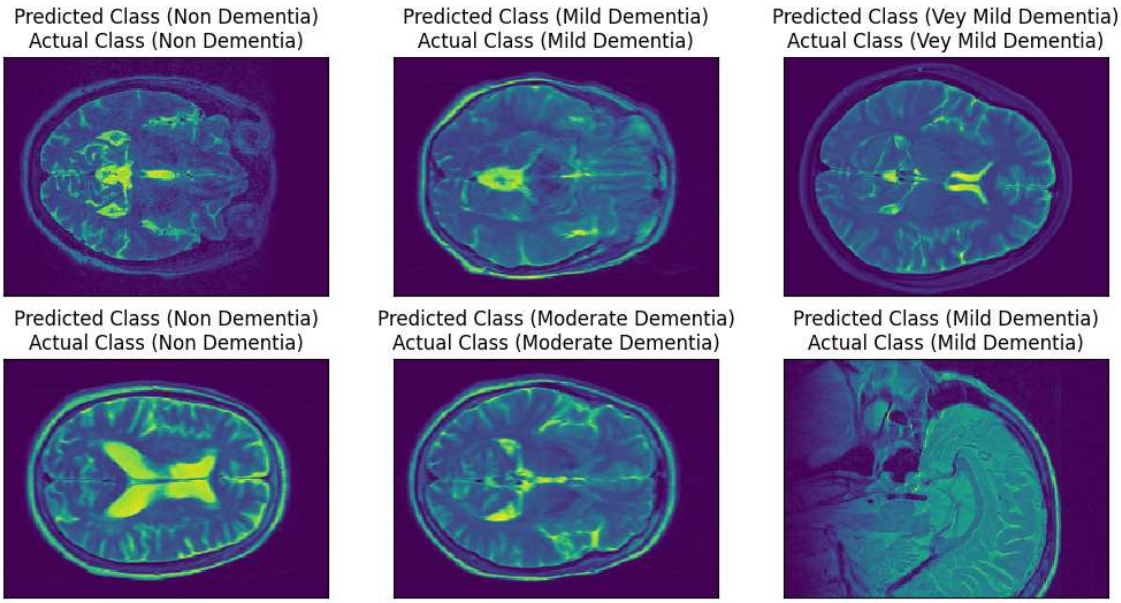

Fig. 22. Correctly Predicted Images

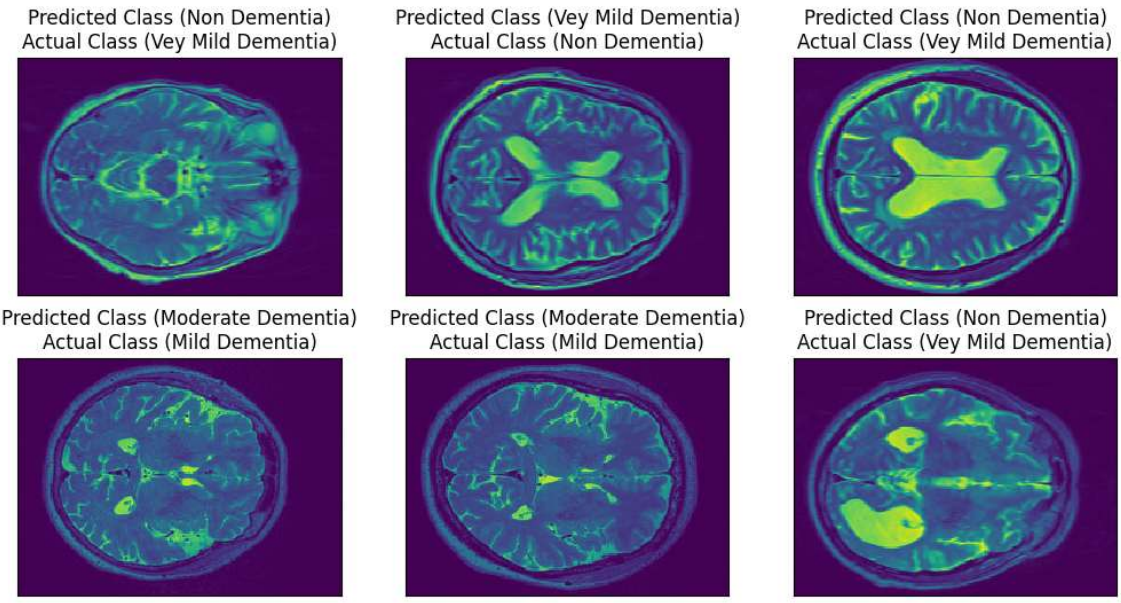

Fig. 23. Incorrectly Predicted Images

Chapter 6 - References

[1] 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.

[2] A. Amrutesh, G. B. C G, A. A, A. R. KP and G. S, "Alzheimer's Disease Prediction using Machine Learning and Transfer Learning Models," 2022 6th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, India, 2022, pp. 1-6, doi: 10.1109/CSITSS57437.2022.10026365.

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[4] Farzaneh Salami, Ali Bozorgi-Amiri, Ghulam Mubashar Hassan, Reza Tavakkoli-Moghaddam, Amitava Datta, Designing a clinical decision support system for Alzheimer’s diagnosis on OASIS-3 data set, Biomedical Signal Processing and Control, Volume 74, 2022, 103527, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2022.103527.

[5] A. Manimuthu, P. Peter Jose, E. Gangadevi, U. U. Kumar and M. D. Anandaraj, "Prediction of Alzheimer’S Disease from Magnetic Resonance Images (MRI)," 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 2024, pp. 631-635, doi: 10.1109/IC2PCT60090.2024.10486545.