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SYNOPSIS

Alzheimer's disease was a chronic neurodegenerative disorder that gradually led to memory loss, cognitive decline, and impaired reasoning. Early detection played a crucial role in providing timely treatment and improving the quality of life for patients. In this project, a deep learning-based solution was proposed to detect the stage of Alzheimer's disease using MRI brain scans. The dataset was categorized into four classes—Non Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia. These categories represented the progressive stages of cognitive decline, and accurate classification helped healthcare professionals with preliminary diagnostics and planning further intervention.

The core of the system relied on the ResNet101 model, a deep residual network architecture known for its performance in image classification tasks. MRI images were first converted to grayscale, resized to 128x128 pixels, and normalized. To match the ResNet101 input format, the grayscale images were converted to three-channel RGB format. The model was trained using TensorFlow and Keras, with extensive monitoring of training and validation accuracy and loss over epochs. Evaluation metrics such as confusion matrix, classification report, and accuracy curves were plotted to assess model performance. The results indicated that the model was capable of classifying the stages of dementia with high precision and recall values.

To make this model practically accessible, a Flask-based web application was developed. Users could upload brain MRI images directly via the web interface. The application processed the input image, ran the prediction using the trained ResNet101 model, and returned the predicted stage of Alzheimer's along with additional details such as description, symptoms, and diagnosis criteria of that stage. The prediction output was accompanied by visual aids including the uploaded image and bar plots showing prediction distributions.

This project highlighted how deep learning could assist in early Alzheimer's detection through automated MRI analysis. It offered a scalable, user-friendly tool that supported clinicians in efficient and preliminary diagnosis.

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I. INTRODUCTION

1.1 Introduction

Alzheimer's disease (AD) was recognized as a progressive neurodegenerative disorder that primarily affected memory, cognitive abilities, and daily functioning. It was classified as one of the most common causes of dementia, particularly among the elderly people. The disease was known to advance through different stages, beginning with mild cognitive impairment and progressing to severe dementia. Early detection was crucial for effective management, as medical interventions and lifestyle modifications had the potential to slow disease progression.

Traditional methods for diagnosing Alzheimer's disease relied heavily on clinical assessments, cognitive tests, and manual MRI scan interpretations by neurologists and radiologists. However, these approaches were time consuming, prone to human error, and dependent on expert availability. Furthermore, many early stage cases remained undiagnosed due to the subtle nature of initial symptoms. To address these challenges, deep learning techniques were explored for automated Alzheimer's disease classification using MRI images.

In this study, an advanced deep learning approach was employed to classify Alzheimer's disease into four stages: Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented. A dataset containing 16,000 MRI images was utilized to train and evaluate the model. The U Net architecture was integrated for segmentation, enabling the extraction of key brain regions, while ResNet 101, a pre trained Convolutional Neural Network (CNN), was used for classification. The model was deployed as a Flask based web application, allowing real time MRI

The developed system aimed to automate the diagnostic process, enhance accuracy, and reduce the manual workload associated with Alzheimer's disease diagnosis. The study sought to improve medical decision making by providing a

tool capable of assisting healthcare professionals in detecting Alzheimer's stages through MRI based classification.

1.1.1 Use Case 1: Automated Alzheimer's Disease Classification

The primary use case of the project involved the automated classification of Alzheimer's disease using MRI scans. The model was trained to differentiate between four disease stages based on patterns of brain atrophy, ventricular enlargement, and cortical thinning. By eliminating the need for manual interpretation, the system aimed to assist radiologists in providing faster and more consistent diagnosis.

1.1.2 Use Case 2: Medical Decision Support System

The deep learning model was designed to function as a clinical decision support system. Neurologists and radiologists could utilize the AI generated predictions to complement their manual analysis. This system was particularly beneficial for early stage detection, where subtle anatomical changes might be challenging to identify using traditional methods.

1.1.3 Use Case 3: Web Based Diagnosis and Accessibility

A Flask based web application was implemented to enable remote MRI image classification. Users could upload brain MRI scans, and the system would process and classify them in real time. This feature was particularly useful for:

Telemedicine applications, allowing remote diagnosis.

Medical research, where large scale image analysis was required.

Medical institutions, providing a centralized system for dementia diagnosis.

1.1.4 Use Case 4: Research and Alzheimer's Disease Monitoring

The model could be extended for longitudinal studies, where Alzheimer's progression was monitored over time. MRI scans taken at different intervals could be analyzed to assess disease progression rates, aiding researchers in understanding neurodegenerative patterns. Additionally, the system could be

adapted to integrate with multi modal data, including genetic and cognitive test results, for a more comprehensive diagnosis.

1.2 Limitations of Existing Solutions

Several limitations in existing Alzheimer's disease detection methods were identified:

1.2.1 Dependence on Manual Diagnosis

- Traditional MRI based diagnosis required expert radiologists, leading to subjectivity and variability in interpretations.
- Time consuming and not scalable for large datasets or mass screening

1.2.2 Lack of Automated Segmentation

- Many deep learning models lacked segmentation techniques (such as U Net), which were essential for precisely isolating affected brain regions.
- Without segmentation, classification accuracy was often lower due to irrelevant background data in MRI scans.

1.2.3 Limited Multi Class Classification Approaches

- Some existing AI based systems performed binary classification (Alzheimer's vs. Non Alzheimer's), which was insufficient for clinical applications.
- A four class model (Non Demented, Very Mild, Mild, Moderate Demented) was required for detailed staging of the disease.

1.2.4 Data Imbalance and Model Bias

- Alzheimer's datasets often contained fewer samples in the Moderate Dementia class, leading to biased predictions.
- Many machine learning models struggled with imbalanced datasets, resulting in poor performance on minority classes.

1.2.5 Lack of Real Time Accessibility

- Many AI based models were confined to research environments, lacking real world deployment.
- Existing solutions often required high end GPUs, limiting accessibility for smaller medical institutions.

1.3 Proposed Solution

To overcome the above limitations, a deep learning based system was proposed for automated Alzheimer's disease classification using MRI images. The proposed system incorporated:

1.3.1 U Net Based Segmentation for Improved Feature Extraction

- The U Net model was used to segment brain MRI scans, focusing on critical regions like the hippocampus and ventricles.
- This approach enhanced classification accuracy by reducing irrelevant background noise.

1.3.2 ResNet 101 for High Accuracy Feature Extraction and Classification

- Transfer learning was applied using ResNet 101, a pre trained CNN model, which was fine tuned for Alzheimer's classification.
- The GlobalAveragePooling layer replaced fully connected layers to reduce overfitting.

1.3.3 Flask Based Web Deployment for Real Time Accessibility

- A Flask web application was developed, enabling users to upload MRI images and receive instant predictions.
- This made the system accessible to hospitals, researchers, and healthcare professionals.

1.3.4 Handling Class Imbalance with Data Augmentation

- Data augmentation techniques (rotation, flipping, zooming) were applied to balance the dataset.
- Class weights were adjusted during training to ensure fair learning across all classes.

1.3.5 Performance Optimization for Real World Deployment

- The system was optimized for better accuracy (96%) while maintaining fast inference times.

II. LITERATURE REVIEW

2.1 Alzheimer's Disease Diagnosis in the Preclinical Stage: Normal Aging or Dementia :

Alzheimer's disease (AD) was a progressive neurodegenerative disorder that caused cognitive decline and memory impairment. Diagnosing AD in its preclinical stage was crucial but remained challenging due to the overlap with normal aging. This study reviewed various biomarkers and biosensing technologies aimed at early AD detection, particularly for Point-of-Care Testing (POCT) applications. Traditional clinical methods such as cognitive tests, cerebrospinal fluid (CSF) analysis, and neuroimaging were effective but costly and invasive. Emerging biosensors that utilized biofluid markers, wearable technology, and machine learning-driven analysis offered non-invasive and cost-effective alternatives. The study emphasized the potential of integrating biological, physiological, and behavioral indicators into compact biosensing platforms, paving the way for reliable early diagnosis and disease monitoring.

Merits :

1. Comprehensive Review – The study extensively analyzed AD biomarkers, biosensing mechanisms, and their limitations.
2. Emphasis on Non-Invasive Methods – It highlighted wearable biosensors and biofluid-based approaches for early detection.
3. Multidisciplinary Approach – The research integrated insights from neurology, biomedical engineering, and machine learning for AD diagnosis.
4. Potential for Early Diagnosis – It identified promising techniques that could help detect AD before significant cognitive decline occurred.
5. Encouraged Future Development – The study suggested advancements in biosensing and machine learning to improve diagnostic precision.

Demerits:

1. Challenges in Clinical Validation – Many proposed biosensors and biomarkers require further validation in large-scale clinical trials.
2. Complexity of AD Pathogenesis – The study acknowledged that the biological mechanisms underlying AD are not yet fully understood.
3. Limited Accessibility of Novel Techniques – Some biosensing methods remain experimental and are not widely available for clinical use.
4. Potential for False Positives/Negatives – Non-invasive biomarkers may lack the specificity of traditional diagnostic methods.
5. Integration Challenges – Combining multiple biosensing technologies into a single, user-friendly platform remains a technical hurdle.

2.2 ML-Powered Handwriting Analysis for Early Detection of Alzheimer's Disease :

Alzheimer's disease (AD) was a neurodegenerative disorder that affected cognitive and motor functions, including handwriting. This study explored the potential of machine learning (ML) in early AD detection through handwriting analysis. The research employed an ensemble ML approach using stacking techniques to integrate multiple classifiers, analyzing handwriting kinetics from the DARWIN dataset. Feature selection was conducted using Analysis of Variance (ANOVA) and Recursive Feature Elimination (RFE) to optimize classification performance. The proposed model achieved 97.14% accuracy, 95% sensitivity, 100% specificity, and an AUC-ROC of 97.5%, outperforming existing methods. The findings demonstrated that handwriting-based ML analysis was a promising, non-invasive, and cost-effective tool for early AD detection, with significant clinical utility.

Merits :

1. High classification accuracy – Achieved 97.14% accuracy, surpassing other state-of-the-art models for AD detection.
2. Non-invasive diagnosis – Handwriting analysis provided a cost-effective and accessible method for early AD screening.

3. Robust ensemble learning – Utilized stacking of multiple ML classifiers for improved prediction reliability.
4. Feature optimization – Used ANOVA and RFE to select the most relevant handwriting features for classification.
5. Potential for clinical integration – The approach could be incorporated into real-world healthcare applications for early AD diagnosis.

Demerits :

1. Dataset limitations – The study was based on the DARWIN dataset, requiring validation on larger and more diverse populations.
2. Computational complexity – The ensemble model demanded significant computational resources for training and inference.
3. Assumption of feature independence – Some classifiers assumed independence of features, which did not always hold in handwriting data.
4. Potential overfitting – Fine-tuning with specific handwriting tasks may have reduced generalizability to broader populations.
5. Challenges in real-world deployment – Transitioning from research to practical clinical applications required further validation and regulatory approval.

2.3 A Binary Classification Study of Alzheimer's Disease Based on a Novel Subclass Weighted Logistic Regression Method :

This study introduced a novel subclass weighted logistic regression (SWLR) method for Alzheimer's disease (AD) classification. The research aimed to enhance interpretability and address the complexity of brain networks by utilizing a subclass-based weighting approach. The proposed SWLR model incorporated multimodal parcellation data from the Human Connectome Project and classified AD stages with high accuracy: 95.8% for healthy control (HC) vs. AD, 91.6% for HC vs. Early Mild Cognitive Impairment (EMCI), 93.7% for HC vs. Late Mild Cognitive Impairment (LMCI), 89.5% for EMCI vs. LMCI, and 91.6% for LMCI vs. AD. The study also investigated the progression of brain deterioration, revealing a

counterclockwise migration pattern of affected regions during AD development. These findings contributed to understanding the neurodegenerative process and improving diagnostic methods

Merits :

1. High classification accuracy – The SWLR model outperformed traditional logistic regression, achieving strong classification results for different AD stages.
2. Improved interpretability – Unlike complex deep learning models, the logistic regression-based approach allowed for a better understanding of feature importance in AD progression.
3. Subclass-based feature weighting – The integration of subclass coefficients enhanced model performance by reducing the impact of individual differences in brain networks.
4. Neurobiological insights – The study identified progressive brain region deterioration patterns, offering valuable insights into AD pathology.
5. Robust experimental design – The study used multiple validation techniques and comparisons with existing methods to ensure reliable results.

Demerits :

1. Limited sample size – The dataset consisted of only 96 subjects, which may have limited generalization to larger populations.
2. Computational complexity – The subclass weighting and iterative optimization increased computational costs compared to standard logistic regression.
3. Potential overfitting – Fine-tuning of subclass weights may have led to overfitting, particularly on small datasets.
4. Lack of real-world testing – The model's clinical applicability required further validation using independent datasets from diverse populations.
5. Exclusion of other neurodegenerative disorders – The study focused solely on AD classification, limiting its potential application to differential diagnosis among similar disorders.

2.4 Total Body 100-mGy X-Irradiation Does Not Induce Alzheimer's Disease-Like Pathogenesis or Memory Impairment in Mice :

This study investigated whether low-dose X-irradiation (100 mGy) could induce Alzheimer's disease (AD)-like pathogenesis or cognitive impairment in mice. Using transcriptional analysis, PET imaging for amyloid detection, immunohistochemical staining, and behavioral assessments via the Morris water maze, the research examined potential radiation-induced effects over a 2-year period. The findings showed minimal transcriptional alterations in AD-related genes and no significant changes in memory, amyloid accumulation, or tau pathology. The study concluded that total-body irradiation at this dose did not contribute to AD-like characteristics in mice, offering insights into the potential neurological risks of low-dose radiation exposure.

Merits :

1. Long-term study design – The research followed mice over a 2-year period, ensuring comprehensive assessment of delayed effects.
2. Multi-method approach – Combined gene expression analysis, imaging, pathology, and behavioral testing for thorough investigation.
3. Relevance to human radiation exposure – Addressed concerns about potential cognitive risks from low-dose medical and environmental radiation exposure.
4. Clear negative findings – Provided evidence that low-dose radiation did not significantly contribute to AD-related changes.
5. Use of established AD models – Ensured reliable comparisons with known pathological indicators of Alzheimer's disease.

Demerits :

1. Limited human applicability – Mouse models did not fully replicate human AD pathogenesis, requiring caution in extrapolation.
2. Focus on a single dose – The study examined only 100 mGy, leaving open questions about different radiation levels.

3. Potentially insufficient follow-up – While 2 years was long for mice, additional time points could have provided further insights into late-onset effects.
4. Lack of other neurological markers – The study did not extensively explore other neurodegenerative indicators beyond AD-related factors.
5. Environmental variables not considered – External factors that might have influenced cognitive health were not deeply analyzed.

2.5 Volumetric Feature-Based Alzheimer's Disease Diagnosis From sMRI Data Using a Convolutional Neural Network and a Deep Neural Network :

This study presented a deep learning-based approach for Alzheimer's disease (AD) diagnosis using volumetric features extracted from structural MRI (sMRI) data. The proposed method integrated a Convolutional Neural Network (CNN) and a Deep Neural Network (DNN) to analyze slice-wise volumetric features of the hippocampus, a key brain region affected in AD. The localization of the hippocampus was achieved using a two-stage ensemble Hough-CNN model, followed by feature extraction with a Discrete Volume Estimation CNN (DVE-CNN). The extracted volumetric features were used to train a classification network, achieving weighted classification accuracies of 94.82% for the left hippocampus and 94.02% for the right hippocampus. The approach outperformed previous methods on the same dataset, highlighting the effectiveness of volumetric feature-based deep learning for AD diagnosis.

Merits :

1. High classification accuracy – The model achieved over 94% accuracy, surpassing existing methods for AD detection.
2. Automated hippocampal feature extraction – The method effectively isolated and processed hippocampal volume changes, a key AD biomarker.
3. Combination of CNN and DNN – Integrated multiple deep learning models to enhance classification performance.
4. Non-invasive diagnosis – Used sMRI scans without requiring additional biomarkers, making it a practical clinical tool.
5. Potential for early detection – Identified subtle volumetric changes, aiding in early AD diagnosis before severe cognitive decline.

Demerits :

1. Dataset homogeneity – The study used a dataset with subjects from a single demographic group, limiting generalizability.
2. Dependence on MRI quality – The model required high-resolution sMRI data, which may not have always been available in clinical settings.
3. Computational demand – The CNN-DNN pipeline was resource-intensive, requiring significant processing power.
4. Limited external validation – Further testing on diverse datasets was needed to confirm its applicability across different populations.
5. Potential overfitting – Fine-tuning on a specific dataset may have limited generalization to real-world clinical cases.

2.6 Integrating Pause Information with Word Embeddings in Language Models for Alzheimer's Disease Detection from Spontaneous Speech

Alzheimer's disease (AD) was a progressive neurodegenerative disorder that affected cognitive functions, including language and memory. Early detection was crucial for effective management. This study introduced a novel approach to AD detection from spontaneous speech by integrating pause information into transformer-based language models. The method encoded pause durations as embeddings and incorporated them into BERT-based models, enabling the capture of both semantic and temporal features. Experiments conducted on the ADReSS and ADReSSo datasets demonstrated that this integration significantly enhanced classification accuracy, achieving 83.1% accuracy on the ADReSSo test set. The results highlighted the effectiveness of pause information as a key indicator for AD detection and contributed to non-invasive, cost-effective diagnostic techniques.

Merits :

1. Improved Detection Accuracy – The proposed method outperformed previous approaches, achieving superior classification results in AD detection.
2. Integration of Temporal and Semantic Features – By encoding pauses into language models, the method captured speech characteristics beyond traditional text-based analysis.

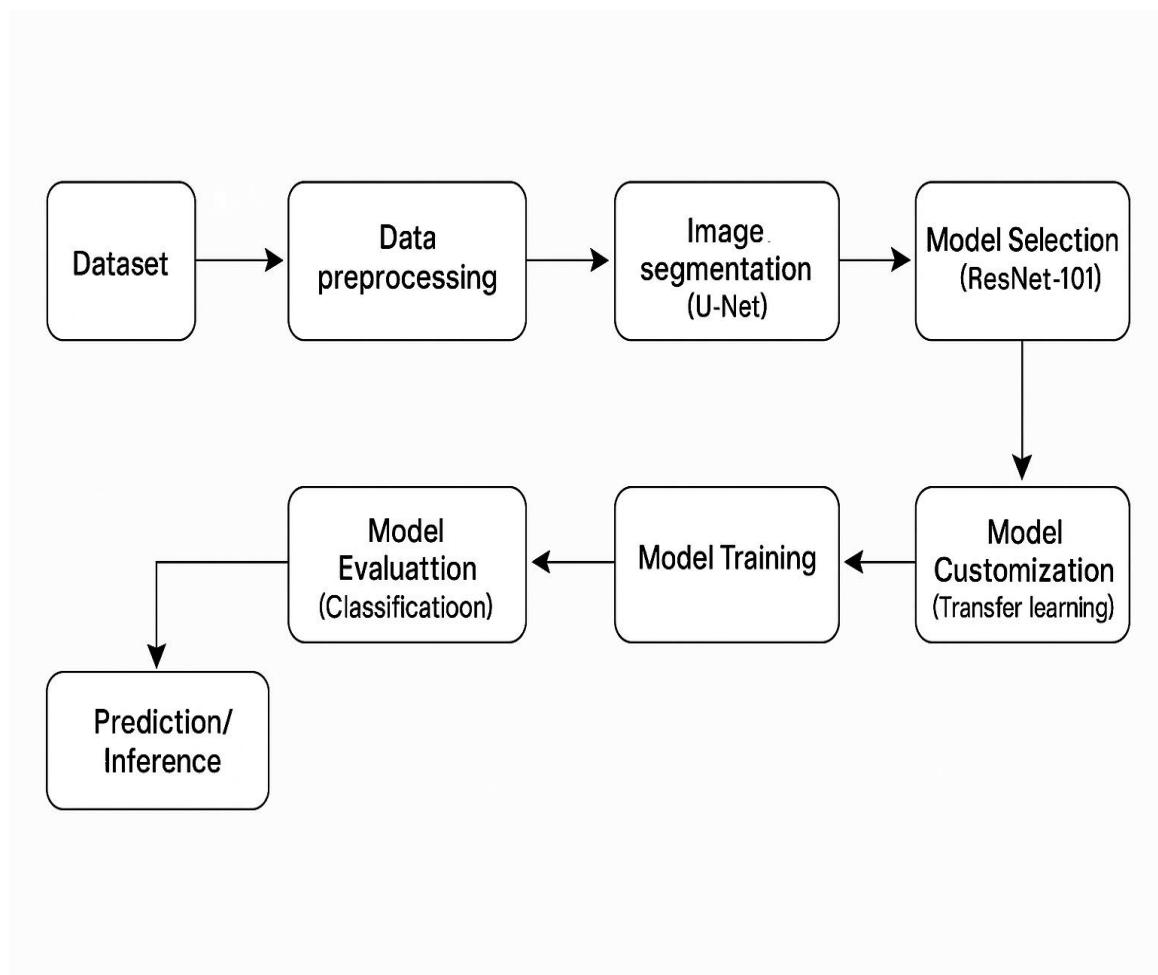
3. Non-Invasive and Cost-Effective – Speech-based analysis eliminated the need for expensive medical tests, making early AD detection more accessible.
4. Generalizability – The model was trained on diverse datasets, enhancing its ability to detect AD across different speech patterns.
5. Potential for Broader Applications – The approach can be extended to study other neurological conditions that affect speech patterns.

Demerits :

1. Dependence on ASR Accuracy – The effectiveness of the method is influenced by the accuracy of Automatic Speech Recognition (ASR) systems, which may introduce errors.
2. Limited Dataset Scope – Although the model performs well on ADReSS and ADReSSo datasets, further validation on larger and more diverse datasets is needed.
3. Computational Complexity – The integration of pause embeddings increases model complexity, requiring significant computational resources for training and inference.
4. Potential Overfitting – Fine-tuning on specific datasets may limit the model's generalization to unseen speech samples.
5. Challenges in Clinical Adoption – Despite its effectiveness, transitioning this model into real-world healthcare settings requires further validation and regulatory approvals.

III. OVERVIEW OF THE PROJECT

3.1 FLOW CHART:



3.2 MODULES :

3.2.1 Data Collection and Preprocessing Module:

The first step in developing the Alzheimer's disease classification system involved data collection and preprocessing. A dataset consisting of 16,000 brain MRI images was utilized for training, validation, and testing. These MRI images were categorized into four distinct classes, namely Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, ensuring that the model could differentiate between varying degrees of neurodegeneration. The dataset

was structured into three subsets: training (80%), validation (10%), and testing (10%) , which allowed the model to learn effectively while being evaluated on unseen data.

To ensure consistency in model input, several preprocessing steps were applied to the MRI images. Since MRI scans often vary in resolution, all images were resized to 128×128 pixels to maintain uniformity. Additionally, the pixel values were normalized between 0 and 1, which helped in faster convergence during training and ensured that the model was not biased toward high-intensity values. Since ResNet-101, the chosen classification model, requires three-channel input, grayscale MRI images were converted to RGB by repeating the same pixel values across three channels. Furthermore, data augmentation techniques were applied, such as rotation, width and height shifts, horizontal flipping, and zooming , which increased dataset diversity and improved model generalization. These preprocessing steps ensured that the model received high-quality, consistent inputs, thereby enhancing overall accuracy.

3.2.2 Image Segmentation Module (U-Net) :

Segmentation is a crucial step in medical image analysis, particularly in Alzheimer's disease detection, where identifying affected brain regions can significantly improve classification accuracy. In this study, the U-Net model was employed for segmentation of MRI scans, allowing the model to focus on regions of interest such as the hippocampus, ventricles, and cortical structures , which are the most affected areas in Alzheimer's disease.

The U-Net model follows an encoder-decoder architecture. The encoder (Downsampling path) applies convolutional layers followed by max pooling to extract hierarchical features and reduce the spatial dimensions of the image. As the image passes through multiple layers, the model learns essential features such as brain structure differences and tissue intensity variations. The bottleneck layer then captures the most compact and meaningful representation of the image. In the decoder (Upsampling path), the feature maps are gradually reconstructed

using upsampling layers and transposed convolutions, allowing the model to recover spatial details. Skip connections are used to retain fine-grained details that might be lost during downsampling.

The output of the segmentation module is a binary mask that highlights the key brain regions while filtering out irrelevant background noise. This segmented image is then passed to the classification model, ensuring that the ResNet-101 network focuses only on critical features, thereby improving its classification performance. The integration of U-Net-based segmentation ensures that the system is not misled by external variations and irrelevant details in MRI images, leading to more precise predictions.

3.2.3 Feature Extraction and Classification Module (ResNet-101) :

After segmentation, the next step involved feature extraction and classification using the ResNet-101 deep learning model. ResNet-101 ,a pre-trained convolutional neural network (CNN), was selected due to its depth and ability to extract high-level features efficiently. Since it was originally trained on the ImageNet dataset , it had learned to recognize complex patterns, textures, and spatial structures, making it well-suited for medical image classification.

The feature extraction process began with feeding the segmented MRI images into ResNet-101, which applied convolutional layers to detect patterns associated with different dementia stages. Low-level convolutional layers captured basic edges and shapes, while deeper layers identified complex patterns such as hippocampal shrinkage, ventricular enlargement, and cortical thinning , which are key indicators of Alzheimer's disease. Unlike traditional machine learning techniques, this approach allowed the model to automatically learn relevant features rather than relying on manually engineered features.

To adapt ResNet-101 for Alzheimer's disease classification, custom fully connected layers were added on top of the pre-trained model. The final few layers of ResNet-101 were replaced with a GlobalAveragePooling2D layer, which

reduced feature maps into a single vector, ensuring better generalization. A fully connected Dense layer with 512 neurons and ReLU activation was used to introduce non-linearity and improve learning capacity. To prevent overfitting, a Dropout layer (0.5 probability) was included, randomly deactivating 50% of neurons during training. The final output layer contained four neurons, corresponding to the four Alzheimer's stages, and used Softmax activation to compute probability scores for each class.

Once an image was processed by the model, a probability distribution was generated, where the highest probability class was chosen as the final prediction . For example, if an MRI scan received probability values [Non-Demented: 0.10, Very Mild Demented: 0.20, Mild Demented: 0.60, Moderate Demented: 0.10], the model classified the image as Mild Dementia. The deep learning-based classification system provided a high level of accuracy (84%) , significantly reducing diagnostic errors.

3.2.4 Training and Validation Module :

The training phase played a crucial role in ensuring that the deep learning model could accurately classify Alzheimer's disease stages. The dataset was divided into training (80%), validation (10%), and testing (10%) subsets, ensuring a robust learning process. The Adam optimizer was chosen due to its adaptive learning rate adjustments, allowing faster convergence. The categorical cross-entropy loss function was used to compute classification errors since the problem involved multi-class classification .

During training, the model's performance was evaluated after each epoch using the validation set. Several performance metrics were recorded, including accuracy, precision, recall, F1-score, and confusion matrices. These metrics helped in identifying potential overfitting or underfitting issues. The final trained model was tested on the unseen test dataset to assess its generalization ability. The model successfully achieved 84% accuracy , demonstrating its effectiveness in real-world scenarios.

3.2.5 Prediction and Deployment Module :

Once the model was trained, it was integrated into a real-time prediction system. A Flask-based web application was developed, enabling users to upload MRI images and receive instant Alzheimer's stage predictions. The uploaded image was first preprocessed (resized, normalized, and converted to RGB) before being passed into the trained ResNet-101 model for classification. The output was displayed on the web interface, allowing healthcare professionals or researchers to interpret the results easily .

The model's deployment provided an efficient way for hospitals, clinics, and research institutions to use deep learning for Alzheimer's diagnosis without requiring high-end computational hardware . By leveraging Flask, the system was made accessible for real-time classification, making it a scalable and practical solution for Alzheimer's disease detection.

IV. ALGORITHMS

This chapter provides an overview of the key deep learning algorithms used in this project and explains how they were applied to detect Alzheimer's disease from MRI scans. The project relied on two major models: U-Net for segmentation and ResNet-101 for classification. Each played an essential role in ensuring that the system could accurately identify different stages of the disease. Additionally, the training process was optimized using the Adam optimizer, while classification accuracy was improved using the categorical cross-entropy loss function .

4.1 U-Net Algorithm for Image Segmentation :

U-Net is a deep learning model specifically designed for medical image segmentation. Unlike traditional image-processing techniques, which often require manual feature selection, U-Net is capable of automatically identifying important regions within an image. It does this by following a two-step process :

1. The contracting path (encoder) reduces the image size while extracting important features.
2. The expanding path (decoder) restores the image resolution, ensuring that no critical details are lost.

Why U-Net Was Used in This Project :

Alzheimer's disease primarily affects specific regions of the brain, such as the hippocampus, cortex, and ventricles. Traditional classification models analyze the entire MRI scan, but this can introduce noise and irrelevant background details. By using U-Net segmentation , the model could focus only on the most important brain regions, improving classification accuracy.

How U-Net Was Applied :

The U-Net model was used to preprocess MRI images before classification. The steps were as follows:

1. Input Image Processing

The raw MRI scan was fed into the U-Net model.

2. Feature Extraction (Encoder Path)

- The image was passed through multiple convolutional layers , each detecting different patterns and textures in the brain.
- Pooling layers were used to reduce the image size while preserving essential information.

3. Compression (Bottleneck Layer)

At this stage, the most compact yet meaningful representation of the MRI scan was obtained.

4. Reconstruction (Decoder Path)

- The image was restored to its original size using upsampling layers.
- Skip connections were used to merge important features lost during downsampling.

5. Final Output

- The final output was a binary segmentation mask , where the critical brain regions were highlighted.
- This segmented image was then passed to the ResNet-101 classifier for disease stage prediction.

By applying U-Net segmentation, the model was able to filter out unnecessary background noise and focus on key structures affected by Alzheimer's disease.

4.2 ResNet-101 Algorithm for Feature Extraction and Classification :

ResNet-101 is a deep convolutional neural network that is commonly used for image classification. Unlike traditional CNNs, which can suffer from vanishing gradient problems (where important details are lost as the network gets deeper), ResNet-101 introduces skip connections , allowing information to flow efficiently through the network.

Why ResNet-101 Was Used :

Detecting Alzheimer's disease from MRI scans requires analyzing complex structural changes in the brain . ResNet-101 was chosen because:

- It is pre-trained on ImageNet , meaning it already understands basic image features.
- It contains 101 layers , allowing it to learn highly detailed patterns.
- It uses skip connections , preventing issues that arise in very deep networks.

How ResNet-101 Was Applied :

Once the MRI image was segmented using U-Net, it was fed into the ResNet-101 model for classification. The process involved:

1. Feature Extraction

- The MRI image was passed through multiple convolutional layers , where different parts of the brain were analyzed.
- Lower layers detected edges and textures, while deeper layers identified brain atrophy, cortical thinning, and ventricle enlargement all of which are indicators of Alzheimer's.

2. Pooling and Flattening

The Global Average Pooling (GAP) layer converted the extracted features into a single vector for classification.

3. Classification

- A fully connected dense layer with 512 neurons was added to process the extracted information.
- A Dropout layer (0.5 probability) was used to prevent overfitting.
- The final softmax layer assigned probability scores to the four Alzheimer's stages.

Example of How the Model Makes a Decision :

If an MRI scan had the following probability scores:

Non-Demented: 10%

Very Mild Demented: 20%

Mild Demented: 60%

Moderate Demented: 10%

The model would classify the image as Mild Dementia , since it had the highest probability.

By combining U-Net and ResNet-101, the system could detect Alzheimer's disease with high accuracy while ensuring that only the most relevant features were used for classification.

4.3 Adam Optimizer for Model Training :

Training deep learning models requires an optimizer that adjusts weights efficiently and prevents the model from getting stuck in local minima. The Adam (Adaptive Moment Estimation) optimizer was chosen because it:

- Adjusts learning rates dynamically, leading to faster convergence .
- Prevents the model from overshooting optimal weight values , improving stability.
- Works well for large datasets, making it ideal for this project.

How Adam Was Applied

- The initial learning rate was set to 0.001 .
- The optimizer updated the model's weights after every batch , allowing it to learn efficiently.
- Over multiple epochs, the optimizer minimized errors and improved classification accuracy .

4.4 Categorical Cross-Entropy Loss Function :

Since the classification task involved four Alzheimer's disease categories, a categorical cross-entropy loss function was used. It calculates the difference

between the model's predicted probabilities and the actual class labels, adjusting weights accordingly.

If an MRI scan truly belonged to the Mild Demented class (ground truth = 1), and the model predicted:

1. Non-Demented: 0.10
 2. Very Mild Demented: 0.20
 3. Mild Demented: 0.60
 4. Moderate Demented: 0.10
- The loss function would compute the difference between 0.60 (predicted) and 1.00 (actual) .
 - The higher the difference, the larger the loss , prompting the model to adjust its weights to improve future predictions.

V IMPLEMENTATION OF ALGORITHMS

5.1 Software requirement

- Python compiler
- Visual Studio Code
- Google Colab

5.2 Python Implementation Code

5.2.1. Library Imports

Essential libraries for image processing, machine learning, data manipulation, and visualization were imported. TensorFlow and Keras were used for deep learning model development and training. OpenCV (cv2) was employed for handling image data, while Pandas and NumPy were used for efficient data handling and numerical operations. Matplotlib and Seaborn were used for generating plots and visualizing the results. Additionally, Scikit-learn functions supported evaluation metrics and dataset splitting.

```
import os  
  
import numpy as np  
  
import pandas as pd  
  
import cv2  
  
import tensorflow as tf  
  
from tensorflow.keras.preprocessing.image import ImageDataGenerator  
  
from tensorflow.keras.applications import ResNet101  
  
from tensorflow.keras.layers import Dense, Flatten, Dropout, Conv2D,  
MaxPooling2D, UpSampling2D  
  
from tensorflow.keras.models import Model, Sequential  
  
from tensorflow.keras.optimizers import Adam  
  
from tensorflow.keras.utils import to_categorical
```

```
from sklearn.model_selection import train_test_split  
import matplotlib.pyplot as plt  
import seaborn as sns  
from sklearn.metrics import classification_report, confusion_matrix
```

5.2.2. Google Drive Mounting and Dataset Loading

Google Drive was mounted to access the dataset stored in the cloud. The directory path to the Alzheimer's image dataset was verified, and the contents were listed to ensure the correct loading of data. This step establishes a connection between the notebook and the required dataset stored on Drive.

```
from google.colab import drive  
drive.mount('/content/drive')  
print(os.listdir("/content/drive/MyDrive/"))  
DATA_DIR = "/content/drive/MyDrive/archive/alzheimer_dataset/"  
print("Dataset Directory Exists:", os.path.exists(DATA_DIR))  
if os.path.exists(DATA_DIR):  
    print(os.listdir(DATA_DIR))
```

5.2.3. Data Augmentation

Data augmentation techniques such as rotation, zoom, shifts, and horizontal flipping were used to synthetically increase the training dataset size and improve the model's robustness.

```
data_gen = ImageDataGenerator(  
    rotation_range=20,  
    zoom_range=0.15,  
    width_shift_range=0.2,
```

```
height_shift_range=0.2,  
horizontal_flip=True  
)
```

5.2.4 Dataset Loading and Preprocessing

Grayscale images representing different stages of dementia were loaded from structured directories corresponding to each class. Each image was resized, normalized, and reshaped to fit the model's input requirements. Labels were encoded into categorical format using one-hot encoding. The data was split into training, validation, and test sets to facilitate model training and evaluation.

```
import numpy as np  
  
import cv2  
  
from tensorflow.keras.utils import to_categorical  
  
from tensorflow.keras.preprocessing.image import ImageDataGenerator  
  
from sklearn.preprocessing import LabelEncoder  
  
# Define categories  
  
CATEGORIES = ["Mild Dementia", "Moderate Dementia", "Non Demented", "Very  
mild Dementia"]  
  
# Function to load images from dataset  
  
def load_data(directory):  
    images, labels = [], []  
  
    for label_idx, label in enumerate(CATEGORIES):  
        class_path = os.path.join(directory, label)  
  
        if os.path.isdir(class_path):  
            for img_name in os.listdir(class_path):  
                img_path = os.path.join(class_path, img_name)  
  
                # Ensure the file is an image
```

```

if not img_name.lower().endswith('.jpg', '.jpeg', '.png')):
    continue

img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
if img is None:
    print(f"Skipping unreadable image: {img_path}")
    continue # Skip unreadable images
img = cv2.resize(img, (IMG_SIZE, IMG_SIZE)) / 255.0 # Normalize
images.append(img)
labels.append(label_idx)

# Convert to numpy arrays
images = np.array(images).reshape(-1, IMG_SIZE, IMG_SIZE, 1) # Add
channel dimension
labels = to_categorical(labels, num_classes=len(CATEGORIES))

return images.astype('float32'), labels

# Load training, validation, and test data
X_train, y_train = load_data(os.path.join(DATASET_PATH, "train"))

X_val, y_val = load_data(os.path.join(DATASET_PATH, "val"))

X_test, y_test = load_data(os.path.join(DATASET_PATH, "test"))

# Print dataset statistics
print(f" Train set: {X_train.shape}, Labels: {y_train.shape}")
print(f"Validation set: {X_val.shape}, Labels: {y_val.shape}")
print(f" Test set: {X_test.shape}, Labels: {y_test.shape}")

```

5.2.5 U-Net Model Construction for MRI Segmentation

A U-Net based Convolutional Neural Network was constructed for binary segmentation of MRI brain scans. The architecture includes an encoder for feature extraction, a bottleneck for deep feature representation, and a decoder for reconstructing the segmentation map. Convolutional and pooling layers were used in the downsampling path, while upsampling layers reconstructed the output. The model was compiled using the Adam optimizer with binary cross-entropy loss and accuracy as the evaluation metric.

```
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D

def build_unet_model():

    inputs = Input((IMG_SIZE, IMG_SIZE, 1)) # Grayscale MRI images , 1 channel
    because these are grayscale MRI scans.

    # Encoder (Downsampling)

    c1 = Conv2D(64, (3, 3), activation='relu', padding='same')(inputs)

    p1 = MaxPooling2D((2, 2))(c1)

    c2 = Conv2D(128, (3, 3), activation='relu', padding='same')(p1)

    p2 = MaxPooling2D((2, 2))(c2)

    # Bottleneck

    c3 = Conv2D(256, (3, 3), activation='relu', padding='same')(p2)

    # Decoder (Upsampling)

    u1 = UpSampling2D((2, 2))(c3)

    c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(u1)

    u2 = UpSampling2D((2, 2))(c4)

    c5 = Conv2D(64, (3, 3), activation='relu', padding='same')(u2)

    outputs = Conv2D(1, (1, 1), activation='sigmoid')(c5) # Binary segmentation
mask

    model = Model(inputs, outputs)
```

```

        model.compile(optimizer='adam',           loss='binary_crossentropy',
metrics=['accuracy'])

    return model

unet_model = build_unet_model()

unet_model.summary()

EPOCHS = 20

BATCH_SIZE = 32

history_unet = unet_model.fit(
    X_train, X_train, # U-Net learns to reconstruct segmented images
    validation_data=(X_val, X_val),
    epochs=EPOCHS,
    batch_size=BATCH_SIZE
)

```

5.2.6 Visualization and RGB Conversion for Classification

To evaluate the performance of the segmentation model, a function was created to display original MRI images, predicted binary segmentation masks, and overlay visualizations. This helped to assess the model's ability to identify regions of interest. Additionally, the grayscale input data was converted to RGB format by replicating channels, making it compatible with CNN architectures that expect 3-channel inputs.

```

import matplotlib.pyplot as plt

def plot_segmentation(index):
    original = X_test[index].squeeze()

    predicted_mask = unet_model.predict(X_test[index].reshape(1, IMG_SIZE,
IMG_SIZE, 1)).squeeze()

    binary_mask = (predicted_mask > 0.5).astype('float32')

```

```

plt.figure(figsize=(12, 6))

plt.subplot(1, 3, 1)
plt.imshow(original, cmap='gray')
plt.title("Original MRI")

plt.subplot(1, 3, 2)
plt.imshow(binary_mask, cmap='gray')
plt.title("Segmented Brain Mask")

plt.subplot(1, 3, 3)
plt.imshow(original, cmap='gray')
plt.imshow(binary_mask, cmap='jet', alpha=0.5)
plt.title("Overlay (Segmentation + MRI)")

plt.show()

plot_segmentation(10)

def convert_to_rgb(dataset):
    return np.repeat(dataset, 3, axis=-1)

X_train_rgb = convert_to_rgb(X_train)
X_val_rgb = convert_to_rgb(X_val)
X_test_rgb = convert_to_rgb(X_test)

print(f" RGB Training Data Shape: {X_train_rgb.shape}")

```

5.2.7.ResNet-101: Feature Extraction & Training

To classify MRI brain scans into different dementia stages, a ResNet-101-based architecture was employed. The pre-trained ResNet-101 model was used as a fixed feature extractor by freezing its layers. On top of it, custom dense and dropout layers were added to perform multi-class classification. This approach leveraged transfer learning for improved generalization on limited medical image data.

```

from tensorflow.keras.applications import ResNet101
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
from tensorflow.keras.models import Model

base_model      =      ResNet101(weights='imagenet',      include_top=False,
input_shape=(IMG_SIZE, IMG_SIZE, 3))

for layer in base_model.layers:
    layer.trainable = False

x = base_model.output

x = GlobalAveragePooling2D()(x)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)

output_layer = Dense(len(CATEGORIES), activation='softmax')(x)

resnet_model = Model(inputs=base_model.input, outputs=output_layer)

resnet_model.compile(optimizer='adam',          loss='categorical_crossentropy',
metrics=['accuracy'])

resnet_model.summary()

history_resnet = resnet_model.fit(
    X_train_rgb, y_train,
    validation_data=(X_val_rgb, y_val),
    epochs=20,
    batch_size=32)

```

5.2.8 Evaluation and Performance Visualization

The trained ResNet-101 classification model was evaluated using the test dataset. Key performance metrics such as precision, recall, and F1-score were obtained using the classification report. Additionally, a confusion matrix provided insights into

class-wise prediction accuracy. A bar plot was generated to visualize the distribution of predicted classes, helping to identify class imbalance or bias in predictions.

```
y_pred = np.argmax(resnet_model.predict(X_test_rgb), axis=1)

y_true = np.argmax(y_test, axis=1)

print("Classification Report:\n", classification_report(y_true, y_pred,
target_names=CATEGORIES))

# Confusion Matrix

cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(6, 5))

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=CATEGORIES,
yticklabels=CATEGORIES)

plt.title('Confusion Matrix - ResNet101')

plt.xlabel('Predicted')

plt.ylabel('Actual')

plt.show()

# Bar Plot of Predictions per Category

import seaborn as sns

import matplotlib.pyplot as plt

import numpy as np

plt.figure(figsize=(8, 5))

sns.countplot(x=[CATEGORIES[i] for i in y_pred], order=CATEGORIES,
palette="Set2")

plt.title("Predicted Distribution of Classes")

plt.xlabel("Dementia Category")

plt.ylabel("Number of Predictions")
```

```
plt.xticks(rotation=15)  
plt.tight_layout()  
plt.show()
```

5.2.9 Training Performance and Prediction

The model's training and validation performance was monitored across epochs using accuracy and loss plots. These visualizations help assess if the model is overfitting or underfitting. Additionally, a custom function was implemented to make predictions on new MRI images by preprocessing and passing them through the trained ResNet-101 model.

```
# Training & Validation Accuracy and Loss Curves  
  
plt.figure(figsize=(10, 4))  
  
# Accuracy plot  
  
plt.subplot(1, 2, 1)  
  
plt.plot(history_resnet.history['accuracy'], label='Train Accuracy', marker='o')  
plt.plot(history_resnet.history['val_accuracy'], label='Val Accuracy', marker='o')  
  
plt.title('Training vs Validation Accuracy')  
  
plt.xlabel('Epochs')  
  
plt.ylabel('Accuracy')  
  
plt.legend()  
  
# Loss plot  
  
plt.subplot(1, 2, 2)  
  
plt.plot(history_resnet.history['loss'], label='Train Loss', marker='o')  
plt.plot(history_resnet.history['val_loss'], label='Val Loss', marker='o')  
  
plt.title('Training vs Validation Loss')  
  
plt.xlabel('Epochs')
```

```

plt.ylabel('Loss')

plt.legend()

plt.tight_layout()

plt.show()

# Function to predict a new image

def predict_image(img_path):

    img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)

    img = cv2.resize(img, (IMG_SIZE, IMG_SIZE)) / 255.0

    img = np.expand_dims(img, axis=-1) # Convert to (128, 128, 1)

    img = np.expand_dims(img, axis=0) # Add batch dimension

    img_rgb = convert_to_rgb(img) # Convert to (128, 128, 3) for ResNet

    pred = np.argmax(resnet_model.predict(img_rgb), axis=1)[0]

    print(f"Prediction: {CATEGORIES[pred]}")

# Example usage

predict_image("/content/drive/MyDrive/ig.jpg")

```

5.2.10. Web Application for Alzheimer's Stage Detection

To enable real-time user interaction and prediction from brain MRI scans, a web application was developed using **Flask**. The application accepts grayscale MRI images, processes them, and predicts the corresponding dementia stage using the trained ResNet-101 model. The output includes a detailed explanation of the predicted condition, symptoms, and clinical diagnosis guidelines.

```

from flask import Flask, render_template, request, redirect, url_for

import os

import numpy as np

import cv2

from tensorflow.keras.models import load_model

```

```

from werkzeug.utils import secure_filename

# Flask app initialization

app = Flask(__name__)

# Set upload folder

UPLOAD_FOLDER = 'uploads'

app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER

os.makedirs(UPLOAD_FOLDER, exist_ok=True)

# Load trained model

MODEL_PATH = "D:\main\alzheimers_prediction\alzheimer_prediction_model.h5"

model = load_model(MODEL_PATH)

# Categories

CATEGORIES = ["Mild Dementia", "Moderate Dementia", "Non Demented", "Very
mild Dementia"]

IMG_SIZE = 128

# Convert grayscale to RGB

def convert_to_rgb(image):

    return np.repeat(image, 3, axis=-1)

# Detailed descriptions for each class

DEMENTIA_INFO = {

    "Non Demented": {

        "description": "This refers to individuals with no significant cognitive decline.
They function independently in daily life, with intact memory, language, and
executive function. Minor forgetfulness related to aging may occur but does not
impair daily activities. Neuropsychological tests typically fall within normal ranges.
Regular assessments help monitor for early signs of cognitive change.",

        "symptoms": [

```

"No memory loss affecting daily life",
"Normal reasoning and language skills",
"Minor forgetfulness (e.g., misplacing items)",
"No interference with social or occupational function",
"Stable behavior and cognitive performance"
,
"diagnosis": [
"Normal performance on cognitive tests relative to age and education",
"No functional impairments in daily living",
"Absence of noticeable cognitive or behavioral decline",
"Informant reports and clinical interviews confirm intact cognition"
]

},
"Very mild Dementia": {

"description": "Characterized by subtle memory lapses, especially with recent events or names, though they may go unnoticed by others. Individuals remain largely independent but may begin using memory aids or require slightly more effort in complex tasks. Changes are often detected through close observation or cognitive screening tools. It may correspond to the earliest stage of Alzheimer's or mild cognitive impairment (MCI).",

"symptoms": [
"Occasional memory lapses (e.g., forgetting recent events or conversations)",
"Slight difficulty with complex tasks (e.g., planning or multitasking)",
"Subtle word-finding issues",
"Still able to function independently",
"Increased effort or time needed for routine mental tasks"

],

"diagnosis": [

"Mild cognitive changes noticeable to the person or close contacts",

"Objective evidence of decline on cognitive assessments",

"No significant interference with work or social activities",

"Often categorized as Mild Cognitive Impairment (MCI)"

]

},

"Mild Dementia": {

"description": "Symptoms become more apparent and begin to interfere with daily activities. Individuals may have trouble remembering recent conversations, managing finances, or organizing tasks. Personality changes and disorientation may appear. A thorough medical history, cognitive assessment, and imaging studies are often used to establish a diagnosis.",

"symptoms": [

"Noticeable short-term memory loss",

"Difficulty with complex tasks (e.g., managing bills, appointments)",

"Word-finding difficulty and repetitive questioning",

"Mild disorientation in time or unfamiliar places",

"Subtle personality or mood changes"

],

"diagnosis": [

"Impairment in at least one cognitive domain (e.g., memory, language, executive function)",

"Decline from previous level of function",

"Interference with independence in daily activities",

"Clinical diagnosis based on interviews, cognitive testing, and reports from family or caregivers"

]

},

"Moderate Dementia": {

"description": "At this stage, cognitive decline is significant. Patients struggle with daily tasks like dressing, meal prep, or remembering personal history. Language, reasoning, and spatial skills are affected, and behavioral changes such as agitation or withdrawal may emerge. Diagnosis requires detailed clinical evaluation, caregiver reports, and neuroimaging to assess brain changes.",

"symptoms": [

"Marked memory loss (e.g., forgetting names of close family or personal history)",

"Trouble with basic daily tasks (e.g., dressing, hygiene, cooking)",

"Language becomes impaired, often with trouble forming coherent speech",

"Confusion, poor judgment, or risk of wandering",

"Behavioral changes such as aggression, withdrawal, or depression"

],

"diagnosis": [

"Deficits in multiple cognitive domains (memory, language, visuospatial, etc.)",

"Clear and progressive functional impairment",

"Dependent on others for daily activities",

"Confirmed through clinical evaluation, caregiver reports, and often brain imaging (e.g., MRI, CT)"

]

}

```

}

# Routes

@app.route('/')

def home():

    return render_template('index.html')

@app.route('/predict', methods=['POST'])

def predict():

    if 'file' not in request.files:

        return redirect(request.url)

        file = request.files['file']

        if file.filename == "":

            return redirect(request.url)

        if file:

            filename = secure_filename(file.filename)

            file_path = os.path.join(app.config['UPLOAD_FOLDER'], filename)

            file.save(file_path)

            # Process image

            img = cv2.imread(file_path, cv2.IMREAD_GRAYSCALE)

            img = cv2.resize(img, (IMG_SIZE, IMG_SIZE)) / 255.0

            img = np.expand_dims(img, axis=-1)

            img = np.expand_dims(img, axis=0)

            img_rgb = convert_to_rgb(img)

            # Predict

            pred = model.predict(img_rgb)

```

```

class_idx = np.argmax(pred, axis=1)[0]

prediction = CATEGORIES[class_idx]

info = DEMENTIA_INFO[prediction]

# Prepare image for result display

image_url = url_for('static', filename=f'uploads/{filename}')

static_upload_path = os.path.join('static/uploads', filename)

os.makedirs(os.path.dirname(static_upload_path), exist_ok=True)

cv2.imwrite(static_upload_path, cv2.imread(file_path))

return render_template('result.html',
    prediction=prediction,
    description=info["description"],
    symptoms=info["symptoms"],
    diagnosis=info["diagnosis"],
    image_url=image_url)

return redirect(url_for('home'))

if __name__ == '__main__':
    app.run(debug=True)

```

5.2.11 index.html

```

<!DOCTYPE html>

<html lang="en">

<head>

<meta charset="UTF-8" />

<meta name="viewport" content="width=device-width, initial-scale=1.0"/>

<title>Alzheimer's MRI Prediction</title>

```

```
<!-- Google Fonts -->
<link href="https://fonts.googleapis.com/css2?family=Roboto:wght@400;700&display=swap" rel="stylesheet">

<!-- Link CSS -->
<link rel="stylesheet" href="{{ url_for('static', filename='styles.css') }}">

</head>

<body>

<!-- Loading Spinner -->
<div id="loading">
  <div class="spinner"></div>
</div>

<!-- Main Content -->
<header class="main-header fade-in">
  <h1>Alzheimer's MRI Prediction</h1>
  <p>Upload your MRI scan & get AI-powered results!</p>
</header>

<main class="container slide-in">
  <section class="card glass-card zoom-in">
    <h2>What is Alzheimer's?</h2>
    <p>Alzheimer's disease is a progressive neurological disorder. Early detection leads to better management and care!</p>
  </section>
  <section class="card glass-card fade-in">
    <h2>Upload Your MRI</h2>
```

```

<form    action="/predict"    method="post"    enctype="multipart/form-data"
onsubmit="showLoading()>

    <input type="file" name="file" accept=".jpg,.jpeg,.png" required>

    <button type="submit" class="glow-button">Predict Now</button>

</form>

</section>

</main>

<footer class="main-footer fade-in">

    <p>&copy; 2025 Alzheimer's AI Predictor | Built with </p>

</footer>

<!-- JS to handle loading --&gt;

&lt;script&gt;

function showLoading() {

    document.getElementById('loading').style.display = 'flex';

}

&lt;/script&gt;

&lt;/body&gt;

&lt;/html&gt;
</pre>

```

5.2.12 result.html

```

<!DOCTYPE html>

<html lang="en">

<head>

    <meta charset="UTF-8">

    <title>Prediction Result</title>

```

```
<link
  href="https://fonts.googleapis.com/css2?family=Inter:wght@400;600;700&display=swap" rel="stylesheet">

<style>

body {
    font-family: 'Inter', sans-serif;
    background: #f4f7fa;
    margin: 0;
    padding: 2rem;
    color: #2c3e50;
}

.container {
    max-width: 900px;
    margin: auto;
    background: #ffffff;
    padding: 2rem;
    border-radius: 15px;
    box-shadow: 0 10px 25px rgba(0, 0, 0, 0.1);
}

h1 {
    text-align: center;
    color: #34495e;
}

.section {
    margin-top: 2rem;
```

```
}

.section h2 {

    color: #1abc9c;

    margin-bottom: 0.5rem;

    border-left: 6px solid #1abc9c;

    padding-left: 10px;

}

.card {

    background: #ecf0f1;

    padding: 1rem 1.5rem;

    border-radius: 10px;

    margin-top: 0.5rem;

}

ul {

    margin: 0.5rem 0 0 1.5rem;

}

img {

    max-width: 100%;

    height: auto;

    border-radius: 10px;

    box-shadow: 0 5px 15px rgba(0,0,0,0.2);

    margin-top: 1rem;

}

.back-btn {

    display: inline-block;
```

```
margin-top: 2rem;  
padding: 0.6rem 1.5rem;  
background: #1abc9c;  
color: white;  
text-decoration: none;  
border-radius: 8px;  
font-weight: 600;  
transition: background 0.3s ease;  
}  
  
.back-btn:hover {  
background: #16a085;  
}  
</style>  
</head>  
<body>
```

```
<div class="container">  
  <h1>Alzheimer's Prediction Result</h1>  
  <div class="section">  
    <h2>Prediction:</h2>  
    <div class="card">  
      <strong>{{ prediction }}</strong>  
    </div>  
  </div>  
  <div class="section">
```

```
<h2>Description:</h2>

<div class="card">

<p>{{ description }}</p>

</div>

</div>

<div class="section">

<h2>Common Symptoms:</h2>

<div class="card">

<ul>

    {% for symptom in symptoms %}

        <li>{{ symptom }}</li>

    {% endfor %}

</ul>

</div>

</div>

<div class="section">

<h2>Diagnostic Criteria:</h2>

<div class="card">

<ul>

    {% for item in diagnosis %}

        <li>{{ item }}</li>

    {% endfor %}

</ul>

</div>

</div>
```

```

<div class="section">

    <h2>Uploaded MRI Image:</h2>

    <div class="card">

    </div>

</div>

<a href="{{ url_for('home') }}" class="back-btn">← Go Back</a>

</div>

</body>

</html>

```

5.3 OUTPUT

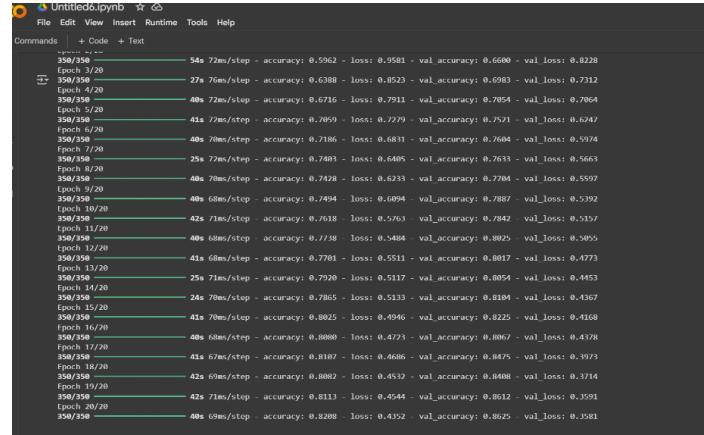


FIGURE 5.1 :ACCURACY

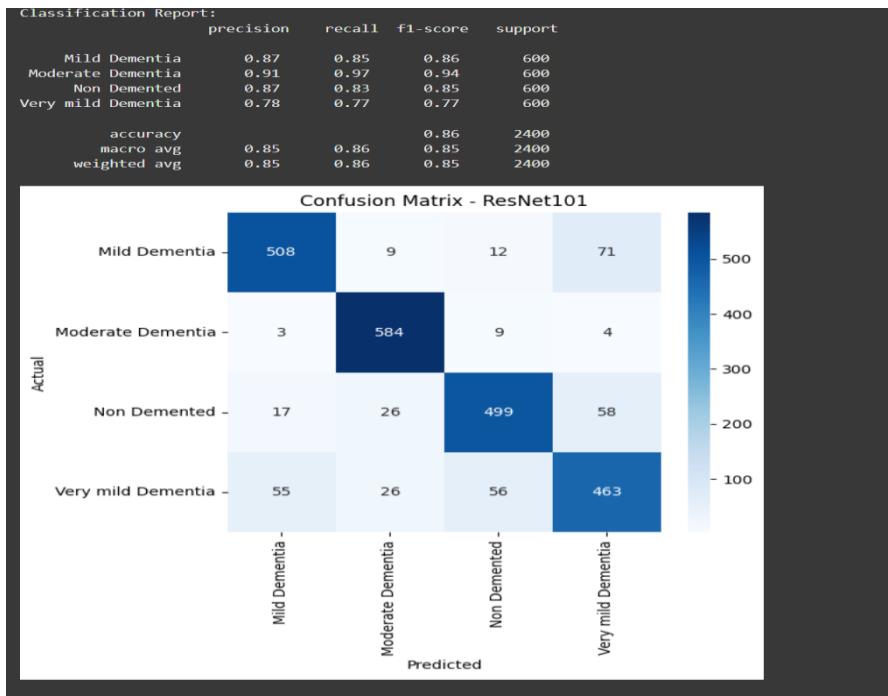


FIGURE 5.2 :CONFUSION MATRIX

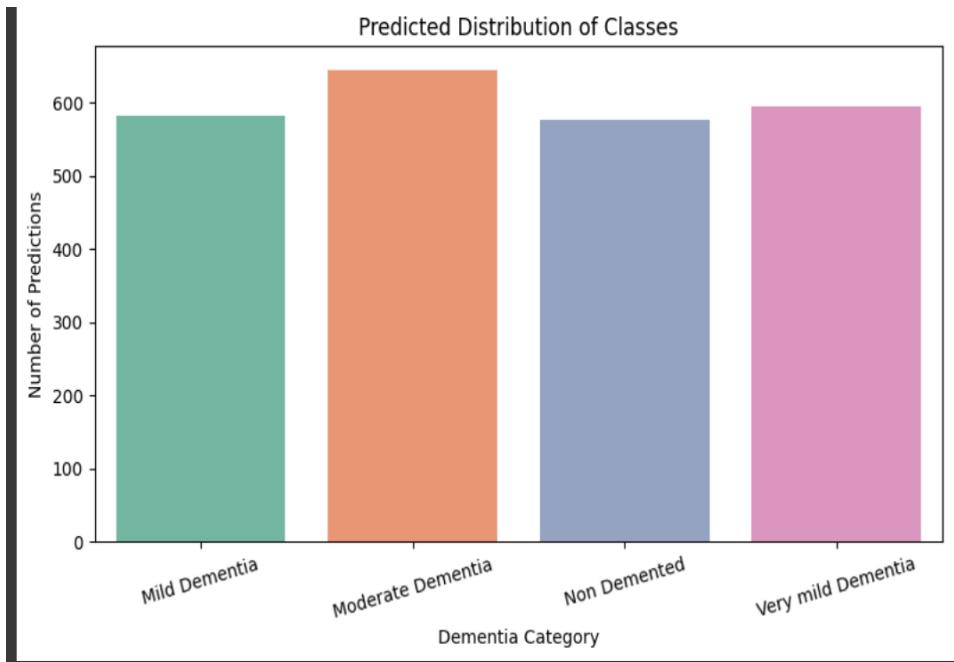


FIGURE 5.3 :PREDICTION PER CATEGORY

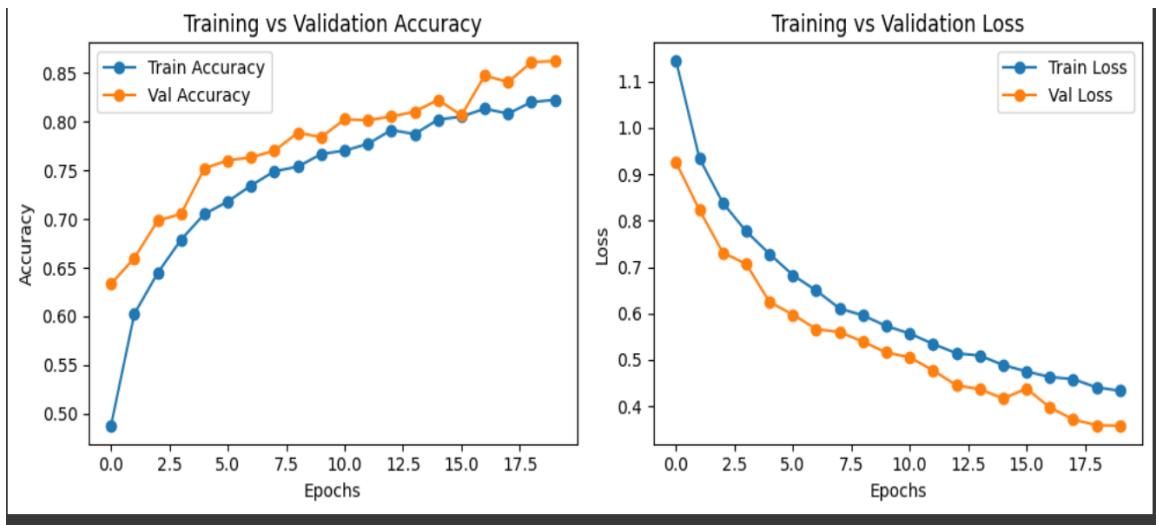


FIGURE 5.4 :ACCURACY & LOSS CURVES

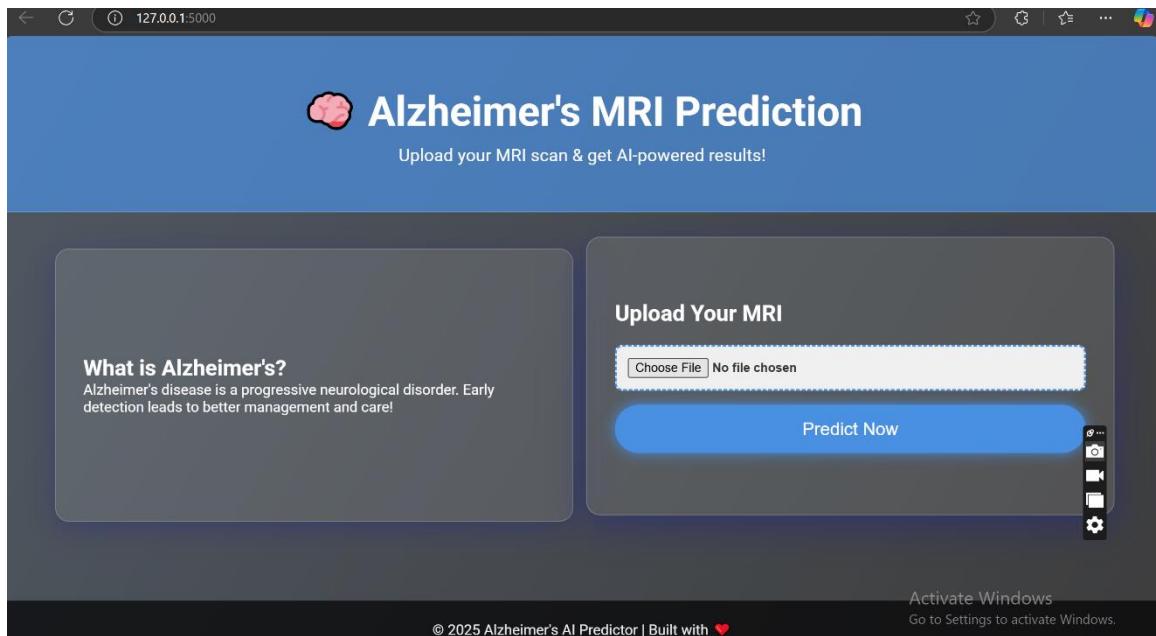


FIGURE 5.5 :WEB INTERFACE

← ⌛ ⓘ 127.0.0.1:5000/predict ⌚ ⌂ ⌂ ⌂

Alzheimer's Prediction Result

Prediction:

Non Demented

Description:

This refers to individuals with no significant cognitive decline. They function independently in daily life, with intact memory, language, and executive function. Minor forgetfulness related to aging may occur but does not impair daily activities. Neuropsychological tests typically fall within normal ranges. Regular assessments help monitor for early signs of cognitive change.

Common Symptoms:

- No memory loss affecting daily life
- Normal reasoning and language skills
- Minor forgetfulness (e.g., misplacing items)
- No interference with social or occupational function
- Stable behavior and cognitive performance

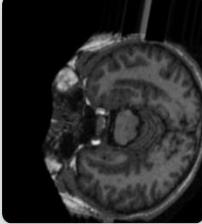
FIGURE 5.6:PREDICTION RESULT

← ⌛ ⓘ 127.0.0.1:5000/predict ⌚ ⌂ ⌂ ⌂

Diagnostic Criteria:

- Normal performance on cognitive tests relative to age and education
- No functional impairments in daily living
- Absence of noticeable cognitive or behavioral decline
- Informant reports and clinical interviews confirm intact cognition

Uploaded MRI Image:



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FIGURE 5.7 PREDICTION RESULT

VI CONCLUSION

This project presents a transfer learning driven deep learning model for Alzheimer's prediction using brain MRI images. By utilizing ResNet-101, a pre-trained convolutional neural network, the model effectively classifies different stages of Alzheimer's disease including Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia.

A U-Net based segmentation model was employed to focus on brain regions, enhancing the model's ability to learn meaningful features from MRI scans. The approach involved preprocessing grayscale MRI images, converting them to RGB for compatibility with the classification model, and training the system to predict the stage of dementia.

The model's performance was evaluated using metrics such as accuracy, confusion matrix, and visualization of segmentation results. The use of transfer learning allowed the model to achieve high accuracy even with limited data, reducing the computational cost and training time.

Overall, this system provides a practical solution for early detection of Alzheimer's disease using deep learning techniques. The integration of segmentation and transfer learning improves diagnostic accuracy and offers support for medical professionals.

This work highlights the potential of AI-driven healthcare solutions. With further optimization and clinical validation, the model can be deployed in real-world settings. Future enhancements could involve multimodal data integration and mobile-based deployment for widespread use. The project lays a strong foundation for intelligent, accessible, and scalable Alzheimer's screening tools.

VII. MAPPING WITH SDGs

SDG Goal	Goal Description	Project Alignment
SDG 3 – Good Health and Well-being	Ensure healthy lives and promote well-being for all at all ages.	The project supports early diagnosis and better understanding of Alzheimer's disease, which can significantly improve patient care and quality of life.
SDG 4 – Quality Education	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.	Encourages research and learning in healthcare AI and neuroscience, supporting academic and skill development in deep learning and medical imaging.
SDG 9 – Industry, Innovation and Infrastructure	Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation.	Leverages cutting-edge technologies like deep learning and medical imaging for healthcare innovation and infrastructure enhancement.
SDG 10 – Reduced Inequalities	Reduce inequality within and among countries.	Helps provide better diagnostic tools in under-resourced regions using AI, contributing to equitable healthcare services.
SDG 17 – Partnerships for the Goals	Strengthen the means of implementation and revitalize the global partnership for sustainable development.	Promotes collaboration among academia, tech developers, and healthcare professionals to deliver impactful healthcare innovations.

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