Alzheimer's Disease Detection and Stage Classification Using Deep Learning on MRI Images

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***Abstract*—Alzheimer's Disease (AD) is a progressive neurodegenerative disorder affecting memory and cognitive abilities. This paper presents a deep learning-based Alzheimer's disease detection and stage classification system using MRI images. A ResNet-50 convolutional neural network is used to classify brain MRI scans into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Image preprocessing and augmentation techniques are applied to enhance performance. The trained model is deployed through a Flask-based web application for real-time diagnosis. Experimental results demonstrate high accuracy and robustness, making the system suitable for early Alzheimer's disease detection.**

***Index Terms*—Alzheimer's Disease, Deep Learning, MRI, ResNet-50, CNN.**

I. INTRODUCTION

Alzheimer's disease is one of the most common and severe forms of dementia, affecting millions of individuals worldwide and posing a significant challenge to global healthcare systems. The disease is characterized by the progressive degeneration of brain cells, leading to memory loss, impaired reasoning, behavioral changes, and ultimately loss of independence. With the rapid growth of the aging population, the prevalence of Alzheimer's disease is increasing steadily, making early detection and timely intervention more critical than ever. Early diagnosis plays a vital role in slowing disease progression, improving treatment planning, and enhancing the quality of life for patients and caregivers. However, conventional diagnostic approaches primarily rely on cognitive assessments, neurological examinations, and manual interpretation of neuroimaging data by specialists. These methods are often time-consuming, expensive, subjective, and dependent on expert availability, which limits their scalability and accessibility, especially in resource-constrained environments.

In recent years, advancements in machine learning and deep learning have introduced intelligent and automated solutions for medical image analysis. Deep learning models have the ability to learn hierarchical and complex patterns directly from large-scale medical datasets, reducing human bias and improving diagnostic accuracy. Among these models, convolutional neural networks (CNNs) have demonstrated exceptional performance in image classification and pattern recognition tasks.

Magnetic Resonance Imaging (MRI) is widely used for Alzheimer's disease diagnosis due to its non-invasive nature and ability to capture high-resolution structural details of the brain. MRI scans reveal critical changes in brain regions such as the hippocampus, cerebral cortex, and ventricles, which are strongly associated with different stages of Alzheimer's disease. Leveraging these structural patterns through deep learning enables reliable detection of early-stage cognitive impairment.

This work proposes a deep learning-based Alzheimer's disease detection and stage classification system using the ResNet-50 convolutional neural network architecture. The proposed system integrates image preprocessing, feature extraction, multi-class classification, and web-based deployment to support real-time diagnosis. By classifying MRI images into four stages—Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented—the system aims to assist healthcare professionals in early decision-making and improve clinical outcomes through automated and accurate disease assessment.

II. METHODOLOGY

A. System Overview

The proposed system is an end-to-end deep learning–based approach for the detection and stage classification of Alzheimer's disease using brain MRI images. The system is designed to automatically identify structural abnormalities in the brain that are indicative of Alzheimer's progression. It utilizes publicly available MRI datasets collected from sources such as Kaggle and OASIS for training and evaluation. These datasets contain labeled MRI scans representing different stages of Alzheimer's disease. Each MRI image is processed to remove noise and standardize input dimensions. The processed images are then passed to a pre-trained convolutional neural network. A ResNet-50 architecture is employed for effective feature extraction from MRI scans. The convolutional layers capture high-level spatial and anatomical patterns of the brain. The extracted features are forwarded to fully connected layers for classification. The model classifies the MRI image into four disease stages. These stages include Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented.

B. System Architecture

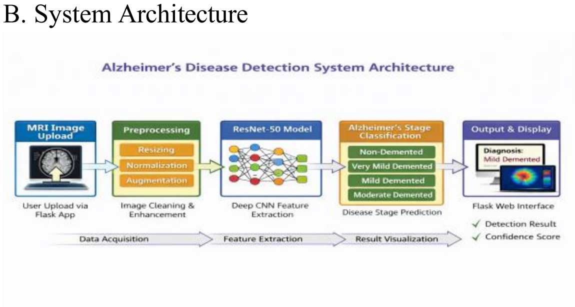

Fig. 1: The system enables users to upload brain MRI images through a Flask-based web interface, where the images are first preprocessed using resizing, normalization, and augmentation techniques. The preprocessed images are then fed into a ResNet-50 convolutional neural network for deep feature extraction and disease stage classification. Based on the learned features, the system detects the Alzheimer's disease stage as Non-Demented, Very Mild Demented, Mild Demented, or Moderate Demented, and displays the detection result along with a confidence score in real time. [1].

C. Dataset and Preprocessing

The proposed system utilizes publicly available datasets such as the Kaggle Alzheimer's MRI Dataset and the OASIS dataset, which are widely used in Alzheimer's disease research. These datasets contain labeled brain MRI images representing four stages of Alzheimer's disease. The stages include Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Each class reflects progressive structural changes in the brain associated with cognitive decline. The MRI images are collected under varying imaging conditions, improving dataset diversity. Prior to training, all MRI scans undergo a structured preprocessing pipeline. Initially, the images are resized to 224×224 pixels to ensure uniform input dimensions. This resizing makes the images compatible with the ResNet-50 deep learning architecture. Pixel intensity normalization is applied to standardize image values. Normalization improves training stability and model convergence. To reduce overfitting, data augmentation techniques are employed. These include image rotation and horizontal flipping. Augmentation increases dataset size and variability. It also helps the model learn robust and invariant features. The preprocessing steps reduce noise present in raw MRI images. They enhance important anatomical patterns related to Alzheimer's disease. The processed data is divided into training and testing sets. This separation enables unbiased performance evaluation. The four-class classification framework allows detailed stage-wise detection. Overall, effective dataset preparation improves accuracy and generalization of the model.

D. Deep Learning Model Architecture

The proposed system employs the ResNet-50 architecture, which is a deep convolutional neural network consisting of 50 layers designed to address the vanishing gradient problem through residual learning. ResNet-50 introduces skip connections that allow the network to learn identity mappings, enabling stable training even with increased depth. This architecture is particularly effective for medical image analysis due to its ability to capture complex spatial features. A pre-trained ResNet-50 model, originally trained on the ImageNet dataset, is used to leverage transfer learning. Transfer learning allows the model to reuse learned low-level and mid-level features, reducing the need for large training datasets. The convolutional layers of ResNet-50 are frozen to preserve previously learned representations. Freezing layers helps prevent overfitting and reduces computational complexity during training. Freezing layers helps prevent overfitting and reduces computational complexity during training. Custom fully connected layers are added to adapt the model for Alzheimer's disease stage classification. These layers learn task-specific patterns from MRI brain images. A dropout layer is introduced to reduce overfitting by randomly deactivating neurons during training. The output layer uses a softmax activation function for multi-class classification. The model predicts four Alzheimer's disease stages based on probability distributions. Categorical cross-entropy is used as the loss function to measure classification error. This loss function is suitable for multi-class problems. The Adam optimizer is employed for efficient weight updates. Adam combines the benefits of adaptive learning rates and momentum. This results in faster convergence and stable training. The model is trained for multiple epochs with batch processing. Training performance is monitored using accuracy and loss metrics. Validation data is used to assess generalization capability. The architecture balances depth and computational efficiency. It ensures high accuracy while maintaining reasonable training time. Overall, the ResNet-50-based architecture provides a robust and scalable solution for Alzheimer's disease detection.

E. Disease Classification

The trained deep learning model performs Alzheimer's disease classification by analyzing structural patterns extracted from MRI images. Each MRI scan is processed through the ResNet-50 network to obtain discriminative feature representations related to brain atrophy and cognitive decline. These features are passed to fully connected layers that generate probability scores for each disease stage using a softmax activation function. The system classifies the MRI images into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The disease stage corresponding to the highest probability score is selected as the final classification result. This multi-class classification approach enables detailed assessment of disease progression and provides more informative diagnostic output than binary classification systems. The probability-based output allows the system to estimate the confidence level associated with each prediction. Higher confidence scores indicate stronger certainty in the detected disease stage. This information can support clinicians in understanding

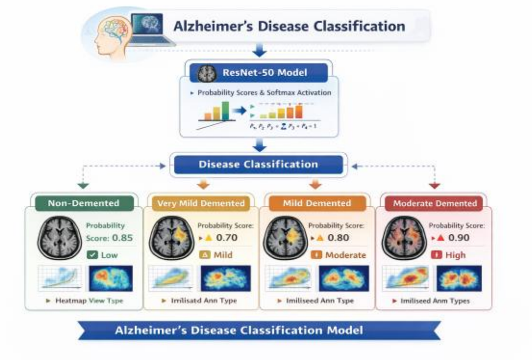

Fig. 2: Disease Classification

the reliability of the classification. The automated classification process minimizes human intervention and reduces diagnostic subjectivity. The system ensures consistent performance across different MRI samples and imaging conditions. Real-time classification enables rapid diagnosis and timely clinical decision-making. The disease classification module enhances early detection and supports effective monitoring of Alzheimer's disease progression.

F. Performance Evaluation and Results

The performance of the proposed Alzheimer's disease detection system was evaluated using standard classification metrics such as accuracy, precision, recall, F1-score, and loss curves, which together provide a comprehensive assessment of the model's predictive capability and reliability. The evaluation was carried out on a held-out test dataset that was not used during training, ensuring unbiased and fair performance measurement. Experimental results demonstrate high classification accuracy across all four Alzheimer's disease stages, with the model consistently distinguishing between Non-Demented and Demented cases with minimal misclassification. Stage-wise performance analysis confirms the model's ability to capture subtle differences between early and advanced stages of the disease. Precision and recall values indicate a low false-positive and false-negative rate, which is particularly important in medical diagnosis to avoid incorrect clinical decisions. The loss curves show smooth convergence during training, reflecting stable learning behavior and effective optimization of model parameters, supported by the use of the Adam optimizer for faster convergence and improved stability. The system generates prediction results within 2–3 seconds per MRI image, making it suitable for real-time clinical support and enabling timely diagnosis and early intervention. Consistent performance across different MRI samples demonstrates strong generalization capability. Visualization techniques such as attention heatmaps were employed to interpret model predictions, highlighting critical brain regions affected by Alzheimer's disease, including the hippocampus and cortical areas. These visual explanations align with known clinical findings, improve model transparency, enhance trust in AI-based medical systems, and validate that predictions are based on meaningful anatomical features.

In addition, the evaluation results indicate that the model performs reliably across varying image conditions and patient samples. The robust performance suggests that the system can adapt well to unseen data in real-world scenarios. The integration of quantitative metrics and visual interpretability provides a balanced assessment of model effectiveness. This comprehensive evaluation framework strengthens the clinical applicability of the proposed system. Overall, the results confirm the practicality and reliability of the approach for supporting Alzheimer's disease diagnosis and staging.

G. Real-Time Deployment Workflow

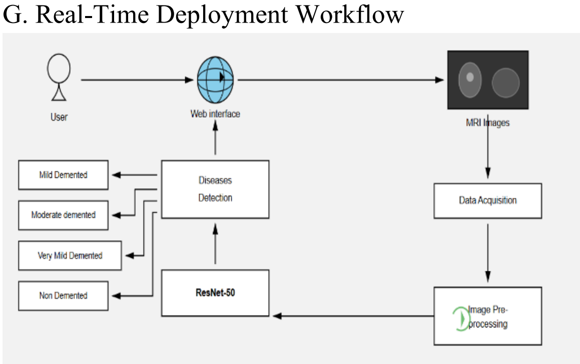

Fig 3: Workflow Diagram

The architecture illustrates an end-to-end Alzheimer's disease detection system that operates through a web-based interface. The process begins when the user interacts with the web interface to upload brain MRI images. These MRI images are first collected through the data acquisition module, which ensures proper input handling. The acquired images are then passed to the image preprocessing stage, where operations such as resizing, normalization, and noise removal are performed. The preprocessed MRI images are fed into the ResNet-50 deep learning model for feature extraction. ResNet-50 analyzes structural patterns within the brain images to identify disease-related characteristics. The extracted features are forwarded to the disease detection module for classification. This module categorizes the MRI scans into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The detected disease stage is then sent back to the web interface. Finally, the system displays the detection result to the user, enabling real-time and accurate Alzheimer's disease assessment.

IV. RESULTS

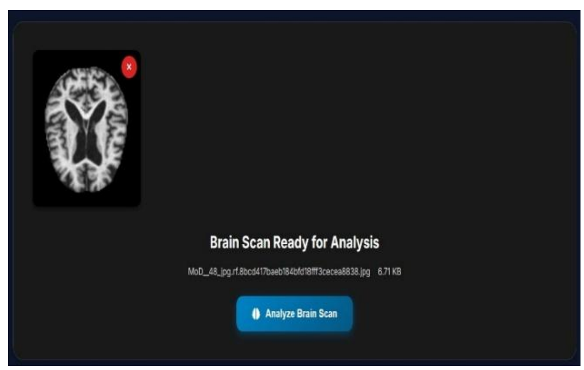

Fig 4 : MRI Image Upload

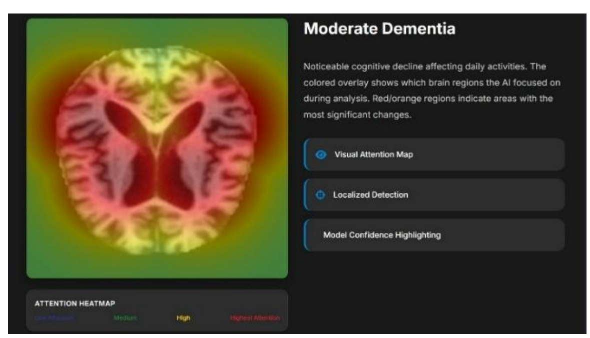

Fig 5 : Stage Detection

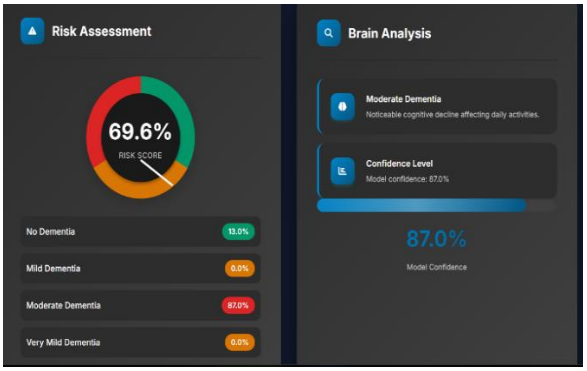

Fig 6: Risk Score And Brain Analysis

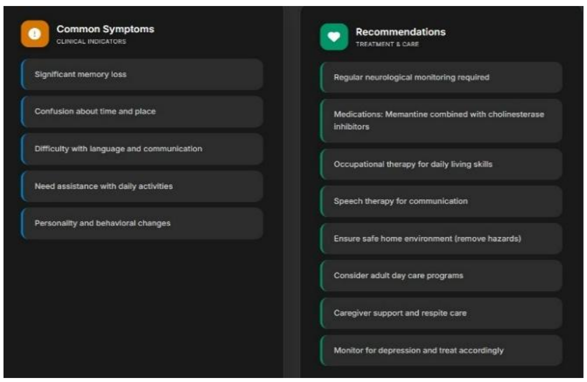

Fig 7: Common Symptoms And Recommendations

V. CONCLUSION

This paper presents a robust deep learning–based system for the detection and stage classification of Alzheimer's disease using brain MRI images. By integrating the ResNet-50 architecture with effective preprocessing techniques, the system achieves high accuracy and reliable classification across different disease stages. The use of transfer learning reduces training complexity while preserving strong feature extraction capabilities. Deployment through a Flask-based web application enables real-time interaction and result visualization, making the system practical for clinical and research use. The automated approach minimizes human intervention and supports early diagnosis of Alzheimer's disease. The system's ability to classify multiple stages provides valuable insight into disease progression. Visualization tools further enhance interpretability and clinical trust. The results highlight the effectiveness of deep learning in medical image analysis. The proposed framework demonstrates scalability and real-world applicability. Future enhancements can further improve diagnostic accuracy and clinical acceptance.

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