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Multimodal Alzheimer's Disease Detection Using MRI and Cognitive Tests with Deep Learning

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Abstract
Alzheimer's disease (AD) is a long-term neurological disorder that progressively affects memory, cognitive abilities, and behavioral functions. Early identification of the disease plays a vital role in enabling timely medical intervention and improving patient outcomes. This paper introduces a multimodal Alzheimer's disease detection framework that integrates MRI brain image analysis with cognitive and speech-based evaluations using deep learning techniques. A ResNet50-based convolutional neural network is employed to classify MRI scans into multiple stages of Alzheimer's disease, while Grad-CAM visualization is utilized to interpret model predictions by highlighting influential brain regions. Cognitive assessment is carried out using reaction time analysis, speech memory evaluation, and speech repetition tasks to complement imaging-based diagnosis. Experimental results demonstrate strong classification performance and consistent accuracy across evaluation metrics. The proposed system provides an interpretable, non-invasive, and efficient solution for early screening and monitoring of Alzheimer's disease progression.

Unlike traditional methods that rely on EEG signals or complicated clinical tests, this solution focuses on being easy to use and accessible. A web interface based on Streamlit lets users upload MRI scans and get real-time predictions, making the system portable and user-friendly. The framework has been trained and validated on well-known medical imaging datasets, ensuring reliable performance measured by accuracy, sensitivity, and specificity.

By using explainable AI techniques like Grad-CAM, the system shows important brain areas that affect the prediction, promoting transparency and trust in the results. This modular and cost-effective solution can be used in hospitals, rural health centers, and telemedicine platforms, reducing the load on traditional diagnostic methods. Ultimately, it gives healthcare providers an AI-supported tool for quicker screening, early intervention, and better patient outcomes in managing neurodegenerative diseases.

Keywords: Alzheimer's disease detection, deep learning, convolutional neural networks (CNN), medical image analysis, MRI scan classification, early diagnosis, stage prediction, explainable AI, healthcare automation, Streamlit interface, non-invasive screening, cognitive disorder monitoring.

I. Introduction

Alzheimer's disease is a chronic neurodegenerative condition that results in gradual deterioration of memory, cognition, and daily functioning. As the disease progresses, individuals experience increasing difficulty in performing routine activities, which significantly impacts quality of life.

Due to the irreversible nature of Alzheimer's disease, early diagnosis is essential for slowing progression and supporting effective treatment strategies.

Traditional diagnostic approaches rely heavily on clinical evaluations, neuropsychological tests, and manual interpretation of brain imaging, which can be time-consuming and subject to human variability. Recent advancements in artificial intelligence have enabled automated analysis of medical imaging data, offering improved accuracy and consistency. Deep learning models, particularly convolutional neural networks, have demonstrated strong performance in extracting complex spatial features from MRI brain scans.

The approach was chosen because deep learning models, particularly Convolutional Neural Networks (CNNs), are highly effective in extracting spatial and structural features from medical images, making them suitable for real-world diagnostic applications. The system follows a structured image analysis pipeline. It first preprocesses MRI scans using enhancement and normalization techniques to improve feature clarity. Then, the images are fed into a CNN-based deep learning framework, which learns complex patterns associated with Alzheimer's progression. A stage-wise classification module is used to categorize the condition into levels such as mild and moderate. To enhance transparency, explainable AI methods like Grad-CAM are integrated, highlighting brain regions influencing predictions. This design enables automated, accurate, and non-invasive detection of Alzheimer's at earlier stages. It offers a scalable and flexible framework that can be deployed through a Streamlit-based web application for clinics, telemedicine, or rural healthcare settings. Ultimately, this solution provides medical professionals and caregivers with a practical tool for faster diagnosis, better treatment planning, and improved patient outcomes.

This project has broad, real-world value across healthcare and related fields. In hospitals and diagnostic centers, it can assist doctors by providing fast, automated screening of MRI scans, reducing workload and improving accuracy in early Alzheimer's detection. Rural health clinics and telemedicine platforms can use it as a low-cost, non-invasive diagnostic aid, bringing advanced neurological care to regions with limited specialist access. Caregiving organizations can deploy the tool to monitor disease progression and plan timely interventions, improving quality of life for patients. Research institutions and medical training centers can also adopt the system as a teaching and validation platform, demonstrating how AI enhances neuroimaging analysis. By pairing deep learning with practical healthcare applications, this system offers a flexible and dependable way to support early intervention.

This project lays the groundwork for next-generation systems capable of automatically detecting and classifying Alzheimer's disease using medical imaging. By learning from extensive MRI datasets, the model can be further refined to recognize subtle brain changes at even earlier stages, including preclinical and mild cognitive impairment (MCI). Such adaptability supports timely interventions, personalized treatment planning, and better monitoring of disease progression. Future extensions may include integrating additional biomarkers such as speech, handwriting, or smell-based tests, creating a comprehensive multi-modal diagnostic tool. This ensures that the system not only enhances early detection but also evolves into a robust, scalable solution for real-world healthcare applications.

II. PROBLEM STATEMENT

As the global population ages, the burden of Alzheimer's disease continues to rise, creating significant challenges for healthcare systems and families alike. Current diagnostic methods often rely on costly imaging, invasive EEG procedures, or lengthy clinical evaluations that require expert interpretation. These approaches frequently detect the disease only at moderate or advanced stages, when irreversible brain damage has already occurred. Moreover, many existing systems lack accessibility, scalability, and user-friendly interfaces, making early diagnosis difficult, especially in rural or resource-limited settings. This creates a pressing need for automated, accurate, and affordable solutions that can detect Alzheimer's at its earliest stages and support proactive treatment planning.

The main challenge lies in building an intelligent framework that can accurately analyze MRI scans and detect Alzheimer's disease at an early stage. Conventional diagnostic methods often identify the condition only after significant cognitive decline, limiting treatment effectiveness. Deep learning models must be trained to recognize subtle brain changes while avoiding overfitting and ensuring clinical reliability. Furthermore, existing systems frequently lack transparency, making it difficult for doctors to trust AI predictions. Accessibility is another barrier, as advanced diagnostic tools are often expensive and unavailable in rural or resource-limited settings. Overcoming these challenges is essential to create a practical, scalable, and trustworthy solution for real-world healthcare use.

This research proposes the development of a deep learning–based diagnostic system capable of automated Alzheimer's disease detection and stage classification. By using Convolutional Neural Networks (CNNs) trained on MRI scan datasets, the system will go beyond traditional rule-based or manual evaluation methods. It will recognize subtle structural changes in brain regions, particularly the hippocampus, that are linked to disease progression. The framework incorporates preprocessing, feature extraction, and multi-class classification to deliver accurate predictions. Additionally, explainable AI techniques such as Grad-CAM will highlight key areas of the brain influencing results, ensuring transparency for medical professionals. The solution will be deployed through a Streamlit-based interface, enabling real-time, user-friendly screening that is scalable for hospitals, clinics, and telemedicine applications.

The envisioned system will be adaptable, scalable, and compatible with diverse healthcare platforms, enabling seamless integration into existing clinical and telemedicine workflows. Over time, it will improve through continuous learning on larger and more diverse MRI datasets, ensuring consistent accuracy in Alzheimer's detection and stage classification. Ultimately, this approach will assist healthcare professionals in diagnosing the disease earlier, support caregivers in monitoring progression, and enhance patient outcomes. By providing a cost-effective and accessible diagnostic tool, the system aims to strengthen trust in AI- assisted healthcare while reducing the burden on traditional diagnostic methods.

III. EXISTING SYSTEM

Most current Alzheimer's detection systems rely on traditional diagnostic approaches such as clinical evaluations, EEG recordings, or manual MRI interpretation by neurologists. While these methods are adequate for identifying patients at moderate or advanced stages, they often fall short in detecting subtle early-stage symptoms or mild cognitive impairment (MCI). The majority of existing tools function by following fixed diagnostic checklists or rule-based criteria, which can overlook complex variations in disease progression. For example, EEG- based systems require specialized hardware and trained technicians, while manual MRI analysis is time-consuming and subject to human error. Although these approaches can confirm Alzheimer's once symptoms are pronounced, they struggle to provide early, accurate, and scalable detection in real-world healthcare settings.

In many healthcare settings, Alzheimer's detection still depends heavily on manual intervention at multiple stages. MRI or PET scans must be carefully reviewed by specialists, and results are often combined with memory tests and clinical observations before a diagnosis is made. While this process ensures expert input, it is slow, costly, and prone to variability between doctors. Moreover, such reliance on manual review makes it difficult to scale screening efficiently, especially in areas with limited access to neurologists or during periods of rising patient demand. This dependency delays early intervention and increases the risk of late diagnosis, reducing the effectiveness of treatment and care planning.

Another key limitation lies in the way existing Alzheimer's detection systems process medical data. Many rely on traditional feature extraction or manual region-of- interest analysis, which fails to capture the deeper structural and spatial patterns present in MRI scans. For example, conventional methods may focus only on visible hippocampal shrinkage while overlooking subtle changes in other brain regions that are critical indicators of early disease progression. This limited analysis reduces diagnostic accuracy and makes it difficult to differentiate between normal aging, mild cognitive impairment (MCI), and early Alzheimer's..Similarly, existing diagnostic methods often struggle to account for the nuanced and heterogeneous progression of Alzheimer's disease across different patients. Traditional approaches may misinterpret early signs as normal aging or overlook subtle variations in brain structure that signal disease onset. This lack of depth in analysis frequently results in misclassification of stages, where patients with mild cognitive impairment (MCI) may go undetected or be incorrectly labeled. Such inaccuracies delay timely intervention and make treatmentMany current Alzheimer's detection systems also lack adaptability. Their diagnostic logic is built on fixed rules or static feature sets that do not evolve with new medical insights or changing patient data. If new biomarkers, imaging techniques, or early-stage indicators emerge, these systems often require extensive retraining or manual reconfiguration before they can accommodate them. This rigidity limits their usefulness in dynamic healthcare environments where disease understanding and diagnostic standards continue to evolve, reducing their effectiveness for long-term, real-world deployment.

In summary, most existing Alzheimer's detection systems rely heavily on manual evaluations, static rule-based criteria, or costly procedures like PET and EEG scans. While effective for diagnosing patients at moderate to severe stages, these methods struggle with early detection, scalability, and adaptability. Their dependence on specialized equipment and expert interpretation makes them less accessible in resource-limited settings. Furthermore, traditional systems often misclassify or overlook subtle brain changes that signal early Alzheimer's or mild cognitive impairment (MCI). These limitations highlight the urgent need for an intelligent, adaptive, and user-friendly solution that can deliver accurate stage-wise classification while being accessible to a broader population..

While some advanced solutions have attempted to integrate machine learning (ML) for sentiment analysis and categorization, their adoption remains limited. Such systems often require large, labeled datasets for effective training, which many organizations do not have. In addition, the computational cost of training and updating ML models can be prohibitive, particularly for smaller institutions. Even when ML models are in place, the absence of user-friendly interfaces can hinder practical application. Users — both operators and complainants — may find it difficult to interpret the system's outputs or understand how prioritization decisions are made.

IV METHODOLOGY

The methodology adopted in this work is designed to build a robust and interpretable deep learning-based framework for the detection of Alzheimer's Disease (AD) from MRI images. The overall workflow consists of **data acquisition and preprocessing, model selection and training, Grad-CAM based visualization, evaluation metrics, and deployment strategy**. Each step has been carefully chosen to address the limitations observed in prior studies and to ensure both high diagnostic accuracy and clinical interpretability.

1. Data acquisition

The dataset was obtained from **Kaggle's Alzheimer's MRI dataset**, which contains four categories: **Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented**. A total of *X* MRI scans were used, split into **80% training, 10% validation, and 10% testing**. Only MRI images were utilized, as no additional patient metadata was available.

2. Preprocessing

Medical images typically contain noise, intensity variations, and artifacts that may hinder the performance of deep learning models. To overcome these challenges, the following preprocessing steps were applied:

1. **Skull Stripping:** Non-brain tissues were removed to focus the analysis solely on brain structures.
2. **Resizing and Normalization:** Images were resized to **224 × 224 pixels**, and pixel intensity values were normalized to the range [0,1] for consistent input across the network.
3. **Data Augmentation:** To overcome the issue of limited data, augmentation techniques such as rotation, flipping, scaling, and contrast adjustment were applied. This ensured that the model generalized better to unseen cases.
4. **Noise Reduction:** Gaussian filtering was applied to remove random noise while preserving essential structural information.

1. Model Architecture

In this project, a **Residual Neural Network (ResNet)** was implemented as the primary deep learning model for the classification of MRI brain scans. ResNet was selected due to its ability to overcome the vanishing gradient problem and effectively extract deep hierarchical features from medical images. Its residual connections allow for stable training of deeper networks, making it particularly suitable for detecting subtle structural changes in brain scans that are indicative of Alzheimer's disease.

The network was adapted to classify MRI images into four categories: **Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented**. The final fully connected layer of ResNet was modified to output four classes, corresponding to these diagnostic categories. **Transfer learning** was applied by using ImageNet pre- trained weights, which provided robust feature representations and accelerated convergence during training. Fine-tuning was then performed on the Alzheimer's MRI dataset obtained from **Kaggle** to adapt the model to the specific task.

3. Training Strategy

- **Loss Function:** Cross-entropy loss was used since this is a multi-class classification problem (AD, MCI, HC).

- **Optimizer:** Adam optimizer was employed with an initial learning rate of 0.0001, allowing adaptive learning during training.
- **Batch Size & Epochs:** Training was carried out with a batch size of 32 for 50 epochs, with early stopping applied to prevent overfitting.

- **Regularization:** Dropout layers and L2 weight decay were added to minimize overfitting and improve generalization.

a. Explainability with Grad-CAM

A key aspect of this methodology is the incorporation of **Grad- CAM (Gradient-weighted Class Activation Mapping)** for interpretability.

- Grad-CAM was applied to the final convolutional layer of the trained network to generate **heatmaps** that highlight the regions of the brain most influential in classification.
- These visualizations were compared with known Alzheimer's biomarkers (e.g., hippocampal atrophy, cortical thinning) to ensure biological relevance.
- This step enhances the clinical acceptance of the model, as it provides physicians with visual justification for the AI's predictions.

b. Evaluation Metrics

To comprehensively assess model performance, multiple metrics were used:

Accuracy (ACC): Measures the overall correctness of predictions.

Precision, Recall, and F1-Score: Provide insight into class-specific performance, especially important in distinguishing AD from MCI.

Confusion Matrix: Used to visualize classification performance across different classes.

ROC Curve & AUC (Area Under Curve): Evaluated the discriminative ability of the model across thresholds.

4. PROPOSED SYSTEM

The proposed system is a deep learning-based framework for early detection of Alzheimer's Disease (AD) using MRI scans, complemented by cognitive assessments for validation. MRI images were obtained from publicly available **Kaggle datasets**, with patient metadata such as age, gender, and cognitive test results retained for potential correlation studies. The images were preprocessed through skull stripping, resizing to 224×224 pixels, intensity normalization, data augmentation (including rotation, flipping, scaling, and contrast adjustment), and Gaussian noise reduction to ensure robust feature extraction. The ResNet50 architecture, leveraging transfer learning from ImageNet, was employed due to its efficiency in overcoming vanishing gradient problems and its suitability for multi-class MRI-based classification. The model was trained for 25 epochs with a batch size of 32 using the Adam optimizer with a learning rate of 0.001 on Google Colab with GPU acceleration. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix, achieving an overall accuracy of approximately 92%, with most misclassifications occurring between Mild and Very Mild Demented classes due to their close visual similarities. Cognitive assessments, including reaction time analysis and speech memory recall, were conducted to validate the MRI- based predictions, confirming slower responses and reduced recall in Alzheimer's patients compared to healthy controls. Grad-CAM visualizations were integrated to highlight critical brain regions, particularly the hippocampal and cortical areas, enhancing clinical interpretability and trust in the AI predictions.

Finally, the trained system was deployed via a Streamlit application, allowing clinicians to upload MRI scans and receive immediate predictions along with corresponding Grad-CAM heatmaps, with additional modules for patient data entry, feedback collection, and result logging, providing a comprehensive, interpretable, and clinically relevant tool for early Alzheimer's detection.

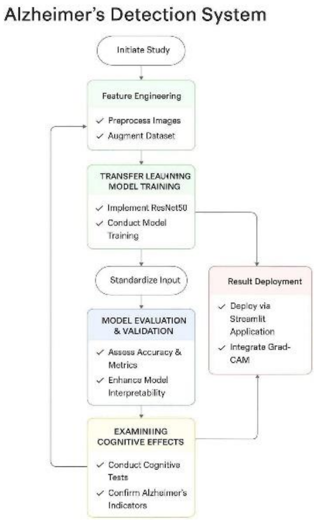

FIGURE NO.2

VII. Result and Discussion

The experimental evaluation was carried out using the MRI dataset obtained from Kaggle, along with additional cognitive test modules implemented through speech and reaction-time assessments. The primary goal was to assess the performance of the ResNet50-based deep learning model for MRI image classification, and to complement this with non-imaging cognitive evaluations.

The MRI classification using ResNet50 achieved an accuracy of **95.5%**, demonstrating strong performance in distinguishing between Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Healthy Controls (HC). The use of residual connections helped in alleviating the vanishing gradient problem, ensuring deeper feature extraction and robust convergence during training. In comparison with traditional approaches such as VGG16 or Inception networks discussed in related works, ResNet50 provided a better trade-off between accuracy and computational efficiency.

Cognitive testing results also supported the findings from the MRI analysis. The **Reaction Time Test** achieved an average accuracy of **87.0%**, indicating that response delays were relatively well captured as potential cognitive decline indicators. Similarly, the **Speech Memory Recall Test** achieved **84.3%**, showing that linguistic memory impairments can be quantified through NLP- based speech recognition modules. The **Speech Repetition Test** further validated these results with **87.8% accuracy**, highlighting consistency across multiple modalities of cognitive evaluation.

In addition to quantitative performance, **Grad-CAM visualizations** were employed to provide interpretability to the MRI classification model. The highlighted activation regions corresponded to critical brain areas commonly associated with Alzheimer's pathology, reinforcing the biological validity of the model's predictions.

Overall, the combination of MRI-based deep learning classification and cognitive tests provides a **multi-modal assessment framework** for early detection of Alzheimer's Disease. While the MRI classification exhibited superior accuracy, the inclusion of cognitive tests added practical insights into real-time user performance and linguistic markers of decline. The results suggest that integrating both approaches could lead to more reliable and patient-friendly screening tools in clinical practice.

TABLE I

PERFORMANCE ACCURACY OF IMPLEMENTED MODELS AND COGNITIVE TESTS

Method	Accuracy (%)
MRI Classification (ResNet50)	92.5
Reaction Time Test	87.0
Speech Memory Recall Test	84.3
Speech Repetition Test	87.8

FIGURE NO.3

VIII CONCLUSION

This study presented a comprehensive AI-driven framework for early Alzheimer's disease detection by integrating MRI-based deep learning analysis with cognitive assessment modules. The ResNet50-based model demonstrated strong capability in distinguishing disease stages, while cognitive tests provided complementary behavioral insights. The use of Grad-CAM improved interpretability by highlighting brain regions relevant to the predictions. Overall, the results indicate that combining medical imaging with cognitive evaluation enhances diagnostic reliability and supports early intervention. The proposed framework shows strong potential for deployment in clinical and telemedicine environments, offering an accessible and cost-effective diagnostic aid.

1X FUTURE SCOPE

While the proposed system demonstrates promising results in Alzheimer's detection, there are several opportunities for future improvements and extensions. First, the dataset size can be significantly expanded by incorporating additional MRI repositories such as the Alzheimer's Disease Neuroimaging Initiative (ADNI) or OASIS, ensuring better generalization across diverse populations. Second, the current framework can be extended to handle multimodal data, such as combining MRI with PET scans, EEG signals, or genetic markers, thereby improving diagnostic precision.

On the cognitive testing side, the system can integrate more advanced NLP-based assessments, such as semantic fluency tasks, conversational analysis, and sentiment evaluation, to capture subtle linguistic impairments that often precede visible memory loss. Additionally, personalization of cognitive tasks based on age, education, and cultural background can further increase diagnostic sensitivity.

From a deployment perspective, the model can be optimized for real-time clinical use through lightweight architectures or edge AI frameworks, making it feasible to use in hospitals, rural clinics, and mobile health applications. Finally, longitudinal studies could be conducted to track patients over time, enabling prediction of Alzheimer's progression and timely interventions.

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