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Alzheimer's Disease Identification and Categorization Through Deep and Machine Learning

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Abstract - Alzheimer's disease can be difficult to detect early, which restricts timely diagnosis and treatment options. In this work, we present a practical method for identifying and staging Alzheimer's disease that combines regularly recorded clinical symptoms with brain imaging. By employing explainable artificial intelligence techniques to identify relevant brain regions in addition to significant early warning indicators, the method improves accuracy and offers useful interpretation. In clinical neurology, early and precise identification of Alzheimer's disease (AD), particularly at the Mild Cognitive Impairment (MCI) stage, continues to be a major issue. Although deep learning models have shown remarkable success in diagnosing AD using clinical data and neuroimaging, their opaque nature undermines trust and acceptance in medical settings. This work offers a dual-modal approach that uses explainable AI (XAI) to augment machine learning (ML) and deep learning (DL) models to integrate symptom-based clinical data with magnetic resonance imaging (MRI). Methods: Using clinical and demographic data, four machine learning classifiers—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF)—were trained. Five DL models were used to MRI data for stage-wise classification: CNN, EfficientNetB3, DenseNet-121, ResNet-50, and MobileNetV2. Grad-CAM and SHAP visualizations were used to incorporate interpretability. The results of this study may help with clinical decision-making and provide a flexible foundation for future research to create Alzheimer's detection and staging methods that are more accurate, understandable, and accessible.

Keywords: Alzheimer’s disease, machine learning, deep learning, explainability AI, magnetic resonance imaging, clinical datasets.

INTRODUCTION

The most common cause of dementia is Alzheimer's disease (AD), which gradually impairs cognitive functions like memory, communication, and decision-making. Up to 70% of dementia cases are thought to be caused by AD, a common neurological illness, particularly in older adults. Forgetfulness is common in many disorders, and dementia can be brought on by a variety of different illnesses. One of the most prevalent types of dementia is AD, a neurodegenerative illness that causes mental deterioration and the death of brain nerve cells. A steady decline in cognitive functions like remembering, thinking, and communication is one of the primary indicators of dementia. It affects those who have the illness, as well as their relatives and caregivers, and is more prevalent in the elderly. As the world's population ages, the number of AD cases is expected to rise sharply, posing a significant public health risk. A temporal understanding of cognitive decline can set parameters for novel biomarker-based approaches or AI-based models for early Alzheimer's disease detection. Subsequent research revealed that early hippocampus volume loss could predict diminishing memory and cognitive ability. Using univariate techniques, which only present data in one area at a time, current brain-behavior research has shown univariate relationships between individual brain regions and cognitive decline or clinical severity.

LITERATURE REVIEW

Over the past ten years, there has been a significant evolution in the application of machine learning (ML) in Alzheimer's diagnosis. While AI has now transformed the discipline, it was mostly developed using traditional statistical methods. The ability of deep learning models based on Convolutional Neural Networks (CNNs) to detect the subtle changes in the internal architecture of the brain in the early stages of AD has not been studied, despite the fact that these models have been effectively applied to process MRI data. It is reasonable to assume that employing hybrid models that draw from several data sources will increase accuracy even further. These machine learning methods are particularly good at spotting early structural changes in the brain that do not yet result in clinical symptoms. Deep learning techniques like as Convolutional Neural Networks (CNNs) have shown remarkable performance in diagnosing AD in medical photos.

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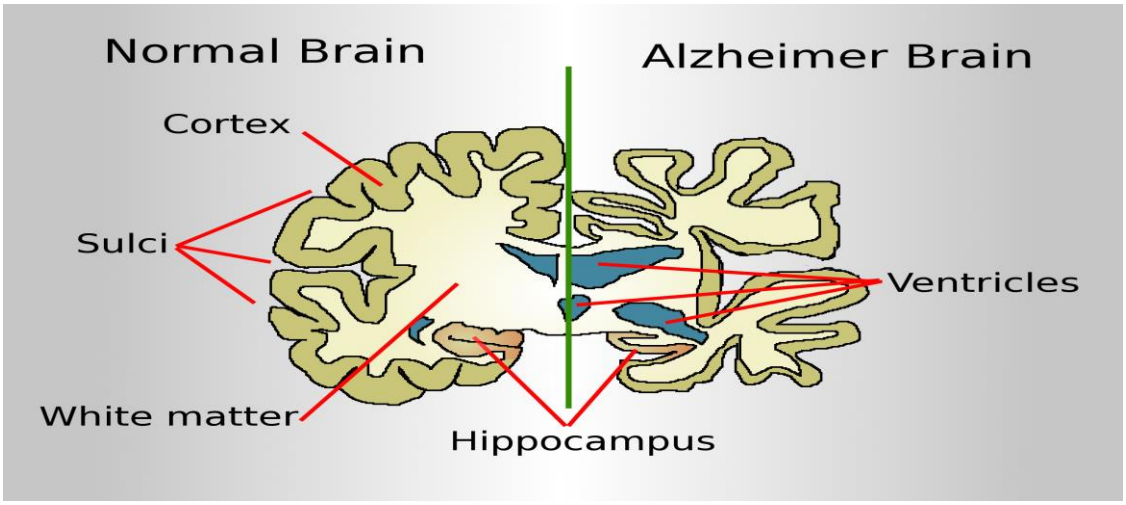
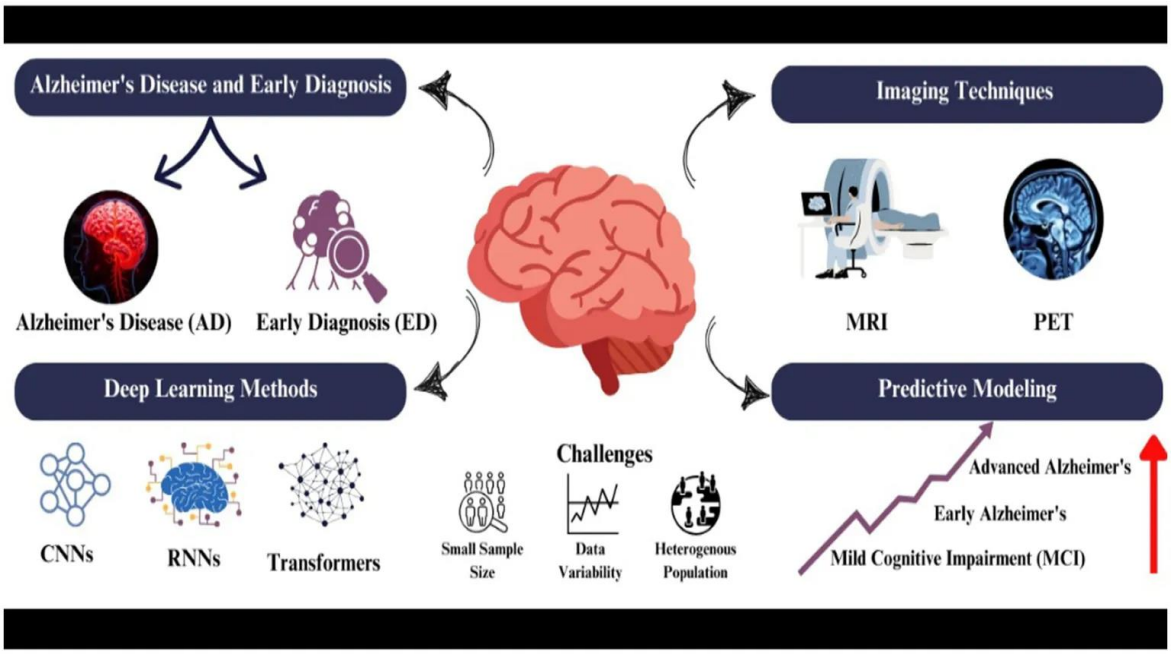
SCOPE OF THE STUDY

The scarcity of annotated multimodal data sources, which are necessary to create reliable and comprehensive models, is one of the present difficulties in Alzheimer's diagnosis. Additionally, they should devise strategies for combining data gathered from several modalities (MRI, genetic data, and clinical assessments) while preserving a sense of the result. Much work needs to be done to confirm that the AI models of Alzheimer's diagnosis are accurate and comprehensible, even if a great deal of uncertainty has been resolved. To achieve better diagnostic performance, future research should focus on strengthening these models and resolving the multimodal data combining problem.



MATERIALS METHODS

In order to accurately classify the stages of Alzheimer's disease (AD), this study suggests a dual-mode diagnostic approach that combines structural neuroimaging via MRI with clinical symptom-related data. The clinical mode shows cognitive test results, memory complaints, early disorientation, age, gender, and education—all variables known to be present in the early stages of AD development.The MRI mode focuses on structural biomarkers including cortical thinning, ventricular enlargement, and hippocampal atrophy, which often happen prior to the onset of obvious clinical symptoms.We utilize cutting-edge DL models (CNN, EfficientNetB3, DenseNet-121, ResNet-50, MobileNetV2) on MRI scans for stage-wise analysis and traditional ML models (KNN, SVM, Decision Tree, Random Forest) on clinical data to investigate these two modes.



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DESCRIPTION OF DATASET

The clinical dataset contains 2149 patients in total: 1061 females and 1088 males, 1389 patients without dementia, and 760 individuals with dementia. Every patient record includes demographic information as well as cognitive characteristics (MMSE scores, memory complaints, disorientation symptoms, and family history of dementia). The 86,437 brain images in the MRI dataset were categorized into four clinical phases based on CDR labeling: normal (67,222), very mild (13,725), mild (5002), and significant dementia (488). All of the MRI scans were preprocessed for skull stripping, intensity normalization, and scaling to 128 × 128 pixels in order to guaranty consistent spatial resolution. This thorough presentation surely improves understanding of the population size and distribution throughout the stages that direct the clinical and imaging evaluations.

AD DETECTION MACHINE LEARNING MODEL

Early detection of Alzheimer's was made possible by the use of a supervised machine learning framework based on more thorough clinical data that included early signs of the illness. A variety of cognitive and demographic variables were included in this data, including age, MMSE scores, memory and disorientation, family history, and other diagnostic criteria. These traits were employed in the two-category classification of Alzheimer's disease and non-Alzheimer's disease because they have been clinically demonstrated to be linked to the development of Alzheimer's disease. An exploratory data analysis (EDA) was carried out by using graphical models to show the distribution of each attribute in order to draw informal conclusions about the dataset. The clinical features were produced for graphical display in the manner described below for this purpose. We used SHAP to improve the interpretability of our Random Forest model, which produced the best results, as well as to assess the impact of each clinical feature on the model's output. The Tree Explainer was designed to operate with Random Forest by performing SHAP computations and optimizing ensemble models. The clinical features were labeled with interpretive care and normalized using a Z-score. The visualization of which clinical variables (MMSE, brain volume, and age) had the greatest predictive impact on Alzheimer's was contextualized at the individual and global levels using this explainability stage as a solid foundation.

AD STAGE DETECTION USING A DEEP LEARNING MODEL

This study offers a deep learning pipeline that uses brain MRI scans to classify AD into four stages: normal, very mild dementia, mild dementia, and moderate dementia. Representative MRI slices of the four classes under study show the progressive structural changes; that is, as the disease advances, hippocampus shrinkage and ventricular enlargement become more noticeable. Deep learning models rely on these visual disparities to distinguish between early and late stages of AD.MRI slices of the brain that reveal the four stages of Alzheimer's disease—normal, very mild dementia, mild dementia, and moderate dementia—as well as the swelling of the ventricles and atrophy of the advancing hippocampus. Custom CNN, EfficientNetB3, ResNet-50, DenseNet-121, and MobileNetV2 are the five deep learning architecture models that were employed and contrasted. They were all carefully selected to achieve a balance between clinical relevance, computational efficiency, and accuracy. With skip connections that maintain flow and prevent the vanishing gradient issue in deeper networks, ResNet-50's deep residual learning was utilized. Its 50-layer architecture allows it to capture both the high-level structural changes and low-level texturing found in the brain.

FINDINGS OF THE STUDY

The results of the suggested dual-modal framework are compared with state-of-the-art methods for Alzheimer's disease classification. The MHAGuideNet architecture With an accuracy of 97.58% on ADNI and 96.02% on OASIS, 2024, a hybrid of a pretrained 3D CNN combined with a 2D CNN and Swin Transformer, outperformed the ViT model. 2024 achieved a 94% accuracy rate on the ADNI dataset. Our approach, which uses CNN for MRI-based stage classification and RF and other models for symptom-based data for Alzheimer's disease identification, obtained an accuracy of 94% for the DL component and 97% for the ML component using the ADD and OASIS datasets. Additionally, our approach enhances interpretability by employing Grad-CAM for CNN and SHAP for RF, while explainability techniques are not included in the MHAGuideNet. This demonstrates that our method offers competitive performance with improved explainability when compared to current SOTA models.

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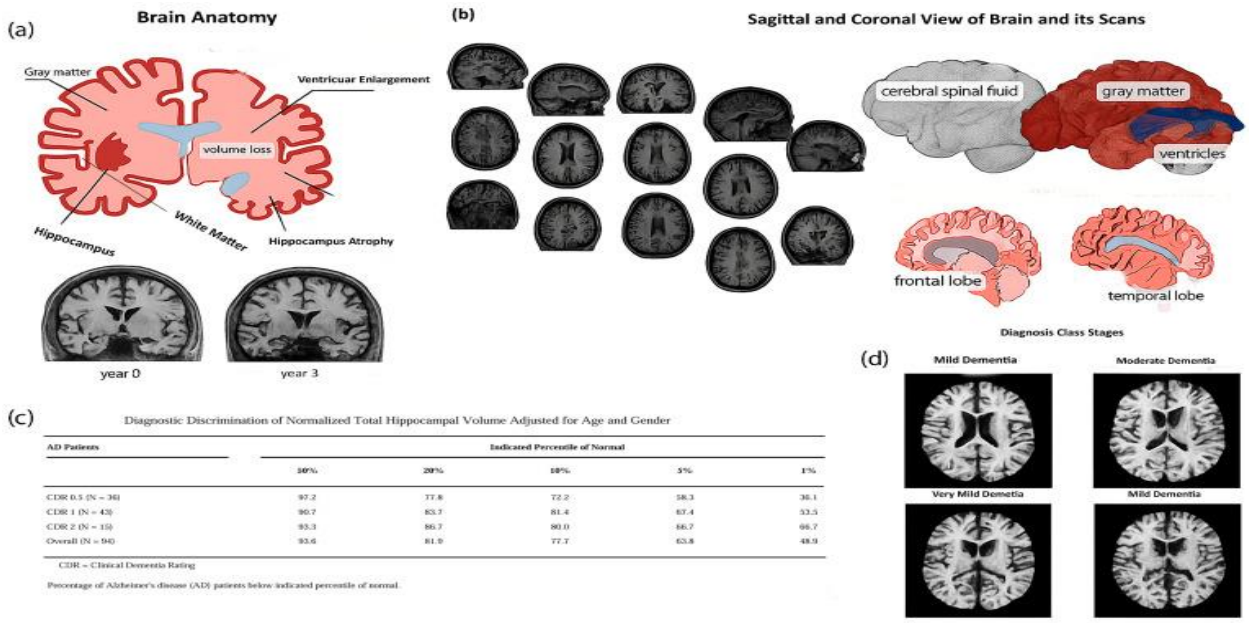

RESEARCH GAP

Compared to big MRI datasets, the clinical sample targeted in this study seemed to be quite small, which would restrict the generalizability. Second, Kaggle and Google Colab provided enough strong computing capacity to train the model; however, high-performance clusters allow for improved hyperparameter optimization. Third, although longitudinal datasets would be more useful in tracking the course of the disease, the framework was also validated using cross-sectional data. By adding more modalities, such as PET pictures, genetic data, or even EEG responses, multimodal pipelines can provide greater diagnostic possibilities in the future. It is anticipated that further advancements in interpretable architectures would provide clinicians with even more comprehensible insights into the decision-making processes. The explainability assessment provided additional evidence for the anatomical and biological importance of the framework.

CONCLUSION

This study introduced a two-mode Alzheimer classification approach that makes use of both MRI-based neuroimaging data and clinical symptom data using both machine learning and deep learning pipelines. By combining these complimentary modalities, the drawbacks of single-source methods were overcome, yielding reliable and clinically understandable diagnostic results. Among the machine learning models examined, Random Forest and Decision Tree performed the best, surpassing 96%. This highlights the superiority of rule-based and ensemble-based classifiers in symptom-driven diagnosis.

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