Multimodal Image Fusion and Real-Time Alzheimer's Diagnosis using 3D CNN

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Abstract - Alzheimer's disease (AD) is a progressive neurological disorder and the leading cause of dementia, requiring early detection for effective management. This study presents a deep learning-based dual-modality classification model using MRI and PET imaging to differentiate AD from cognitively normal (CN) individuals. The OASIS-3 dataset was used to acquire MRI and PET scans, which were pre-processed and organized into patient-specific folders. The proposed model consists of two convolutional neural networks (CNNs) for feature extraction from MRI and PET images, followed by a fusion layer and fully connected layers for classification. Data augmentation and normalization techniques were applied to improve generalization. The trained model demonstrated the potential of deep learning in neuroimaging-based AD detection, aiding in early diagnosis and clinical decision-making. Future work will focus on optimizing the network architecture and expanding datasets to enhance robustness and reliability.

Keywords: Alzheimer's disease, MRI, PET, deep learning, convolutional neural network, neuroimaging

1. INTRODUCTION

Alzheimer's disease (AD) stands as a worsening brain disorder and the most frequent reason for dementia globally. This condition involves a continuous decline in nerve cells and the connections between them, resulting in worsening cognitive abilities and memory loss. Although the precise origin of AD is still unclear, it is understood that a combination of genetic predispositions, environmental influences, and lifestyle choices plays a role in its development. Currently, there is no way to completely reverse AD, but its symptoms can be managed through the use of medications like cholinesterase inhibitors and memantine, along with cognitive therapy techniques and lifestyle adjustments that include maintaining a nutritious diet, engaging in regular physical activity, and participating in mentally stimulating activities. Identifying AD in its early stages is critically important as it can help to slow down the advancement of the disease and enhance the quality of care provided to patients.

Neuroimaging techniques such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) play a vital role in diagnosing and researching Alzheimer's disease. MRI provides high-resolution structural images, helping detect hippocampal atrophy, white matter abnormalities, and overall brain shrinkage associated with AD. PET scans, using radioactive tracers, enable the identification of amyloid plaques and tau protein accumulation, two hallmark biomarkers of AD. Together, these imaging modalities offer critical insights into both structural and functional changes in the brain, aiding in early detection and monitoring disease progression.

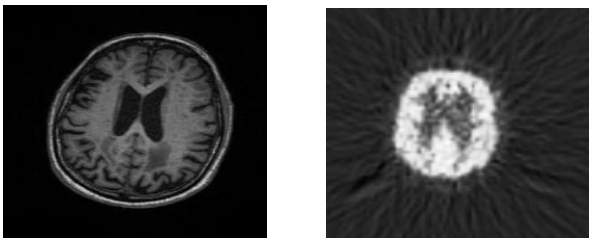

Fig 1. MRI and PET Scans

A useful longitudinal neuroimaging resource is the Open Access Series of Imaging Studies-3 (OASIS-3) dataset, which contains MRI and PET scans from more than 1,500 people in a range of cognitive stages, including AD, mild cognitive impairment (MCI), and cognitively normal (CN).

Considering the intricacy of interpreting these multimodal scans, deep learning methods present a viable strategy for automated and precise AD categorization. In order to improve AD detection, this study suggests a dual-modality deep learning model that combines MRI and PET imaging. Convolutional neural networks (CNNs) are used for feature extraction and classification.

2. LITERATURE REVIEW

Conventional methods for diagnosing Alzheimer's disease involve cognitive assessments like the Mini-Mental State Examination (MMSE) and the Clinical Dementia Rating (CDR), which evaluate memory and logical thinking; however, these typically identify the disease at a later stage. Biomarker analyses using cerebrospinal fluid and blood samples can detect the presence of amyloid-beta and tau proteins, but these procedures are invasive. Neuroimaging techniques are also employed: Magnetic Resonance Imaging (MRI) can show brain shrinkage, and Positron Emission Tomography (PET) can identify alterations in brain metabolism and the accumulation of amyloid plaques. Although these traditional and biomarker methods along with neuroimaging are significant, their interpretation requires specialized expertise, which makes the early and widespread diagnosis of Alzheimer's disease difficult, thus emphasizing the necessity for solutions driven by Artificial Intelligence (AI).

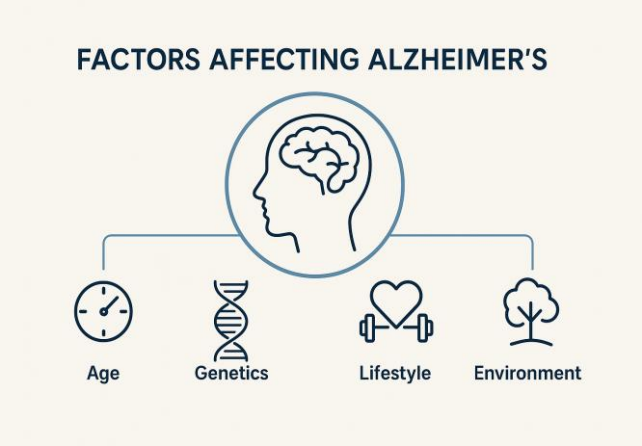

Fig 2. Factors Affecting Alzheimer's

Machine learning (ML) and deep learning (DL) are revolutionizing Alzheimer's diagnosis by facilitating early detection through automated analysis of neuroimaging and clinical data, overcoming the subjectivity and late-stage detection limitations of traditional cognitive tests and biomarker analysis. Artificial Intelligence (AI)-driven models, particularly convolutional neural networks (CNNs), analyze Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scans to identify subtle structural and functional brain changes indicative of Alzheimer's, enhancing diagnostic accuracy beyond human expert capabilities. Multi-modal fusion techniques, integrating MRI for atrophy, PET for metabolic changes, and clinical data for cognitive and genetic factors, offer a more comprehensive assessment, improving the differentiation between Alzheimer's, normal aging, and other neurodegenerative conditions. AI methods enable faster, more consistent diagnoses, reduce reliance on manual interpretation, generalize across diverse populations with large datasets, and support personalized treatment strategies, making deep learning a crucial tool for early intervention, clinical decisions, and advancing Alzheimer's research.

Alzheimer's disease (AD) diagnosis increasingly utilizes diverse datasets and neuroimaging for earlier and more accurate classification. The National Alzheimer's Coordinating Center (NACC) dataset, with its comprehensive clinical records, enables machine learning models like Support Vector Machines (SVM) to achieve high accuracy in AD classification. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, a key benchmark, includes MRI, PET scans, clinical data, and genetics, facilitating multi-modal deep learning to identify biomarkers like hippocampal shrinkage and amyloid plaques. The Augmented Alzheimer's MRI Dataset V2 has trained Convolutional Neural Networks (CNNs) such as EfficientNet-B5 to accurately detect subtle MRI variations. The Open Access Series of Imaging Studies (OASIS-3) dataset allows research on AD progression using longitudinal neuroimaging and cognitive scores. Interpretability is enhanced by techniques like SHAP and LIME, highlighting crucial factors like memory loss and judgment impairment. Advanced deep learning models, including VGG-16, IFRCNN, and 3D CNNs, leverage these datasets for high-accuracy AD stage classification. Multi-modal fusion, integrating MRI, PET, genetics, and cognition, further improves diagnostic precision, demonstrating AI's

potential in AD diagnosis, progression tracking, and personalized treatment.

Detection of Alzheimer's disease (AD) using current AI-based methods has limitations including reliance on single modalities, possible overfitting on particular datasets, and a need for models that are both accurate and clinically relevant. Early, robust diagnosis is difficult with traditional techniques, which also need expert interpretation. By suggesting a dual-modality Convolutional Neural Network (CNN) approach using both Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scans, our work fills these gaps.

3. METHODOLOGY

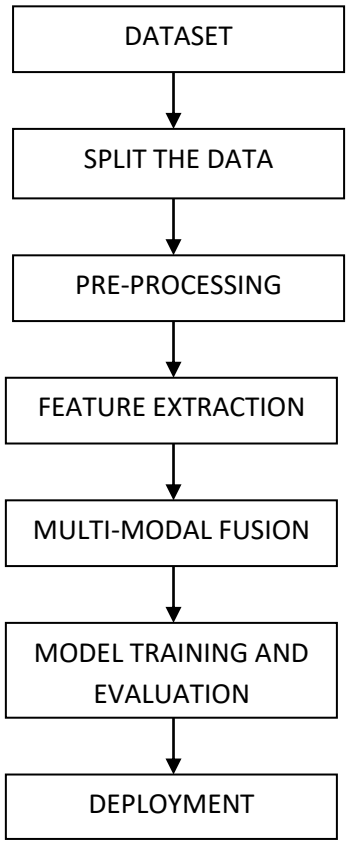

Fig 3. Design Flow

3.1 DATA ACQUISITION AND PRE-PROCESSING

The OASIS-3 repository provided the dataset used in this investigation, which includes patient matched MRI and PET scans. To make sure the ID and session ID matched, the MRI and PET scans were first downloaded in.nii format. Using distinct patient IDs, patient folders were made in order to preserve a structured dataset. Based on the clinical information supplied, the data was divided into two classes: Alzheimer's Disease (AD) and Cognitively Normal (CN). By averaging over the time dimension, PET images that were initially in 4D format were transformed to 3D. The preprocessing technique included scaling to a uniform shape (128×128×128) using cubic interpolation after normalizing to scale pixel intensities between 0 and 1. Zero mean and unit variance were guaranteed by additional standardization. A total of 450 scans were taken. The dataset was then split into training (80%), validation (10%), and testing (10%) subsets, maintaining paired MRI and PET images. This systematic preprocessing ensured data consistency and improved model performance by enhancing feature representation. The entire preprocessing pipeline, including normalization, resizing, and dataset splitting, was automated using Python scripts, ensuring reproducibility and efficiency.

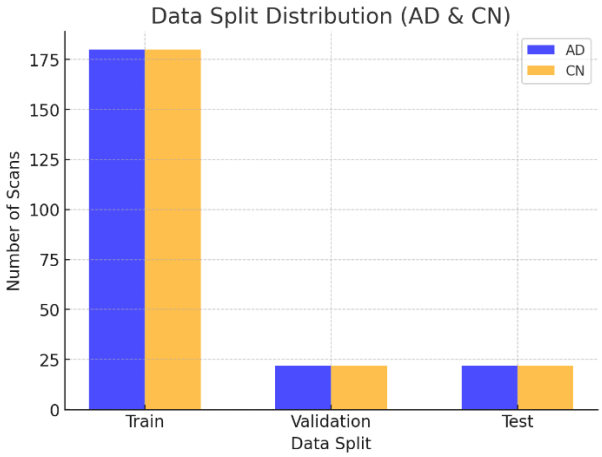

Fig 4. Data Splitting .

3.2 MODEL ARCHITECTURE

The suggested model utilizes a Convolutional Neural Network (CNN) framework that analyzes both MRI and PET scans simultaneously to determine if an individual has Alzheimer's Disease (AD). This framework incorporates two distinct 3D CNN pathways: one specifically designed to pull out features from MRI images, which reflect the brain's structural alterations, and another to extract features from PET images, highlighting metabolic function and the buildup of amyloid plaques. The information gathered by these two pathways is then integrated in a multimodal fusion layer. This combination of data from different sources allows for a more thorough understanding, ultimately improving the accuracy of the classification. Finally, these combined features are processed through fully connected layers, resulting in a classification of the subject as either having Alzheimer's Disease (AD) or being Cognitively Normal (CN). The entire

architecture is designed to effectively learn significant characteristics from the scans, leading to precise diagnoses while also being mindful of the computational resources required.

3.3 TRAINING AND EVALUATION

The model is trained on the OASIS-3 dataset, using MRI and PET scan pairs labeled as either AD or CN. Data augmentation techniques, such as random rotation, noise addition, and flipping, are applied to improve generalization. The model is trained using the Adam optimizer, with Cross-Entropy Loss as the objective function. A learning rate scheduler is incorporated to adjust the learning rate dynamically based on validation loss. The model is trained for 30 epochs, with early stopping to prevent overfitting if no improvement is observed for 6 or 8 consecutive epochs. Evaluation is performed using training and validation accuracy, to analyze misclassifications. The model achieves a decent classification performance, demonstrating its ability to distinguish between AD and CN subjects effectively.

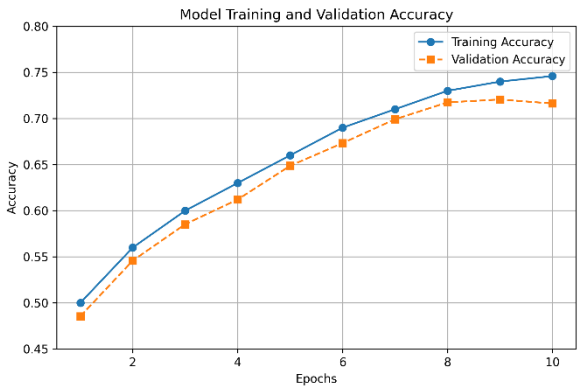

Fig 5. Model accuracy graph

3.4 WEB APPLICATION DEPLOYMENT

To ensure user accessibility, the trained model is deployed as a web-based diagnostic tool. Initially, users are presented with a static login page, a feature that could be enhanced with dynamic database integration in future iterations. Upon successful login, the application, built using Flask as the backend with an interactive web interface, allows users to upload either an MRI or a PET scan as input. Crucially, users must also specify the type of scan being uploaded (MRI or PET). If the selected scan file type does not match the type specified by the user, an "Invalid" message is displayed. Once a valid scan is uploaded and its type is correctly indicated, clicking the "Predict" button triggers preprocessing and inference using the trained model. The resulting prediction, classifying the scan as either Alzheimer's Disease (AD) or Cognitively Normal (CN), is then displayed to the user on the web interface.

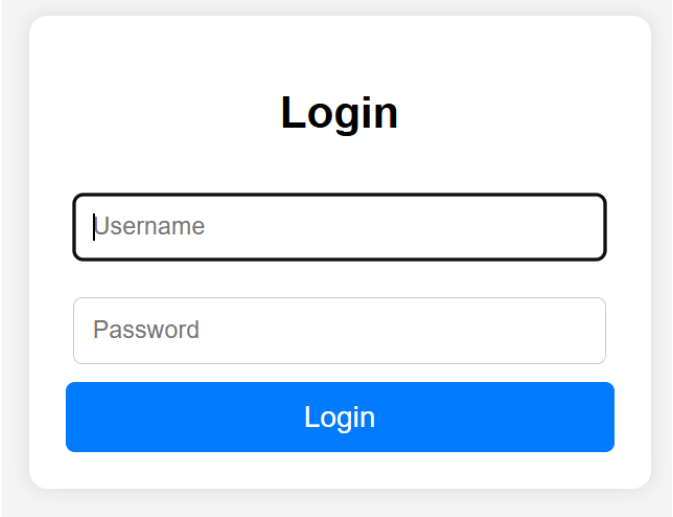

Fig 6. Login page

3.5 RESULT

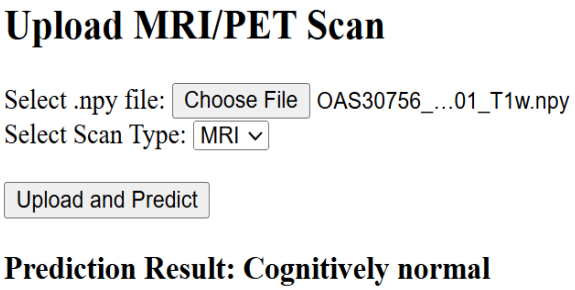

Fig 7.1 Result

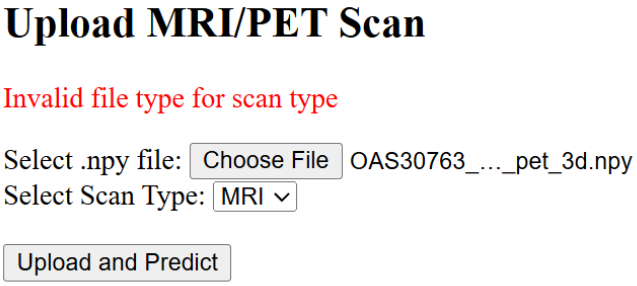

Fig 7.2 Result Invalid case

4. FUTURE SCOPE

The project's future scope can be expanded in a variety of ways to improve Alzheimer's diagnosis accuracy,

efficiency, and real-time capabilities. One significant breakthrough could be the use of more complex deep learning models, such as Transformer-based architectures or hybrid CNN-RNN models, to collect both spatial and sequential information from MRI and PET images. Furthermore, expanding the dataset and incorporating more diverse data from numerous sources might aid in minimizing bias and enhancing generalization. The study could also be expanded to categorize Alzheimer's into multiple phases, such as Mild Cognitive Impairment (MCI) and severe dementia, rather than merely binary categorization.

A significant future enhancement involves optimizing the model for immediate use on edge computing devices such as NVIDIA Jetson or on cloud-based healthcare platforms. This would enable medical professionals to utilize the model efficiently, eliminating the requirement for powerful, expensive computer systems. Moreover, the system could be integrated into a user-friendly web or mobile application, enabling doctors to upload brain scans and promptly receive diagnostic predictions accompanied by explainability tools like heatmaps that visually highlight impacted brain areas. Lastly, incorporating additional imaging types like CT scans or integrating genetic information could lead to more dependable and accurate diagnoses, aiding in earlier detection and improved treatment strategies.

5. CONCLUSIONS

In this study, two deep learning models were developed for Alzheimer’s disease classification using MRI and PET scans. The first model utilized raw .nii format MRI and PET scans, achieving an accuracy of 75%, while the second model converted .nii files into 2D image slices, selecting 150 slices per MRI scan and 85 slices per PET scan, ultimately reaching an accuracy of 98%. Although the slice-based approach significantly improved classification accuracy, the .nii-based model remains more efficient in preserving volumetric data and should be further optimized.

During the course of this research, several challenges were encountered. PET scans require substantial storage space, leading to computational limitations, especially on a Windows laptop without a GPU, where RAM constraints posed a major hurdle. This necessitated a shift from TensorFlow to PyTorch for better memory management, particularly when implementing 3D CNN models. Additionally, while the OASIS-3 dataset offers valuable longitudinal data, handling such datasets requires meticulous preprocessing to ensure consistency and reliability. Another critical challenge is the limited availability of PET scan datasets, as only a few publicly accessible datasets provide PET imaging for Alzheimer’s research, restricting the ability to develop more generalized models.

Despite achieving high accuracy, Alzheimer's disease remains a progressive neurodegenerative disorder that requires early and precise diagnosis. Given its irreversible nature and lack of a cure, integrating additional imaging modalities—such as fMRI, DTI, or CT scans—could enhance the robustness of deep learning-based diagnostic systems. Future work should focus on optimizing 3D CNN models for efficiency, expanding dataset diversity, and leveraging multimodal fusion techniques to develop a more comprehensive and clinically viable Alzheimer’s detection framework

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