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Automated Detection of Alzheimer’s Disease

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Abstract: *A computer-aided diagnostic system is developed for the early detection of Alzheimer’s disease by analyzing multimodal brain imaging data using a deep learning–based classification pipeline that integrates 3D structural MRI scans to identify individuals at risk. The approach involves curating and preprocessing a multi-center dataset of co-registered MRI, extracting central brain slices for consistency, normalizing the data, and training a custom 3D convolutional neural network to classify subjects as cognitively normal (CN), having mild cognitive impairment (MCI), or Alzheimer’s disease (AD). By fusing anatomical and molecular imaging, the model captures structural degeneration and amyloid deposition, which are key markers of disease progression. The automated system supports early clinical decision-making, improves diagnostic accuracy, reduces human error, and enhances consistency, while also providing a model interpretation module that highlights influential brain regions for greater transparency. Despite promising results and extendability to real-world clinical or research settings, limitations related to generalizability, cross-dataset validation, and demographic diversity are acknowledged and addressed through the model design and training strategy to enable future improvements*

Keywords: EfficientNetB0, Multimodal Brain Imaging, Alzheimer’s Disease Detection, Deep Learning, MRI Analysis, Medical Diagnostics, Image Preprocessing, 3D Convolutional Neural Network

I. INTRODUCTION

Alzheimer’s disease is a progressive and irreversible neurological disorder that is the most common cause of dementia worldwide. It accounts for nearly two-thirds of all dementia cases and significantly impacts cognitive functioning, memory, and daily activities. The disease typically begins with mild symptoms such as short-term memory loss and gradually progresses to severe cognitive impairment, including difficulties in communication, reasoning, and spatial awareness. As the condition advances, patients may experience behavioral changes, personality shifts, and complete dependency on caregivers. In the final stages, vital bodily functions are affected, leading to death. The duration of the disease varies among individuals, but most patients survive between three to twelve years after diagnosis. The exact cause of Alzheimer’s disease is not fully understood; however, it is believed to result from a combination of genetic, environmental, and lifestyle factors. Genetic predisposition, particularly the presence of the APOE allele, plays a significant role in increasing the risk. Other contributing factors include hypertension, depression, aging, and head injuries. At the biological level, Alzheimer’s disease is characterized by the accumulation of amyloid plaques and neurofibrillary tangles in the brain, which disrupt neuronal communication and lead to cell death. Diagnosis is typically performed using cognitive assessments, clinical evaluations, and neuroimaging techniques such as MRI and PET scans. However, definitive confirmation of the disease is only possible through postmortem examination. Early detection is crucial for effective intervention and management, which has led to increased interest in developing automated diagnostic systems using artificial intelligence and medical imaging technologies.

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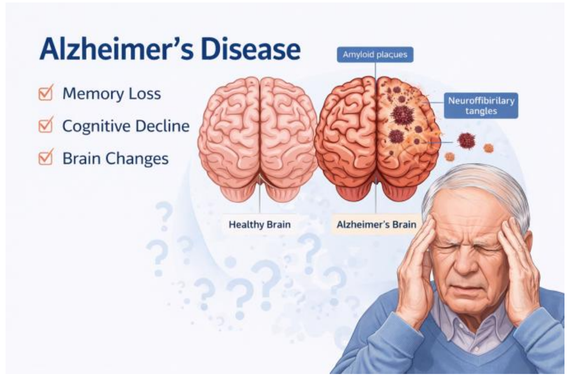

Fig. 1. Visual comparison of a healthy brain and an Alzheimer's-affected brain showing key pathological changes

II. LITERATURE SURVEY

The literature survey highlights significant contributions in the field of Alzheimer's disease detection using clinical assessment tools, medical imaging, and machine learning techniques. Early diagnostic approaches relied on clinical scales such as the Clinical Dementia Rating (CDR), which evaluates cognitive and functional abilities across multiple domains. The introduction of large-scale datasets like the Alzheimer's Disease Neuroimaging Initiative (ADNI) has played a crucial role in advancing research by providing access to standardized MRI, PET, and clinical data. Researchers have increasingly adopted deep learning techniques, particularly Convolutional Neural Networks (CNNs), to automatically extract features from medical images. Studies have shown that CNN-based models outperform traditional machine learning algorithms such as support vector machines and logistic regression in classification tasks. The development of 3D-CNN models marked a significant advancement, as they can capture spatial relationships within volumetric MRI data more effectively than 2D approaches. Multimodal learning approaches that combine MRI and PET data have further improved diagnostic accuracy by integrating structural and functional information. Advanced architectures like ResNet have enabled deeper networks by addressing the vanishing gradient problem, while U-Net has been widely used for precise medical image segmentation. Optimization algorithms such as Adam have improved training efficiency and convergence speed. Additionally, techniques like generative adversarial networks (GANs) have been explored for enhancing image quality and resolution. Overall, the reviewed studies emphasize the growing importance of deep learning and multimodal imaging in Alzheimer's diagnosis. These works provide a strong foundation for developing more accurate and reliable automated diagnostic systems.

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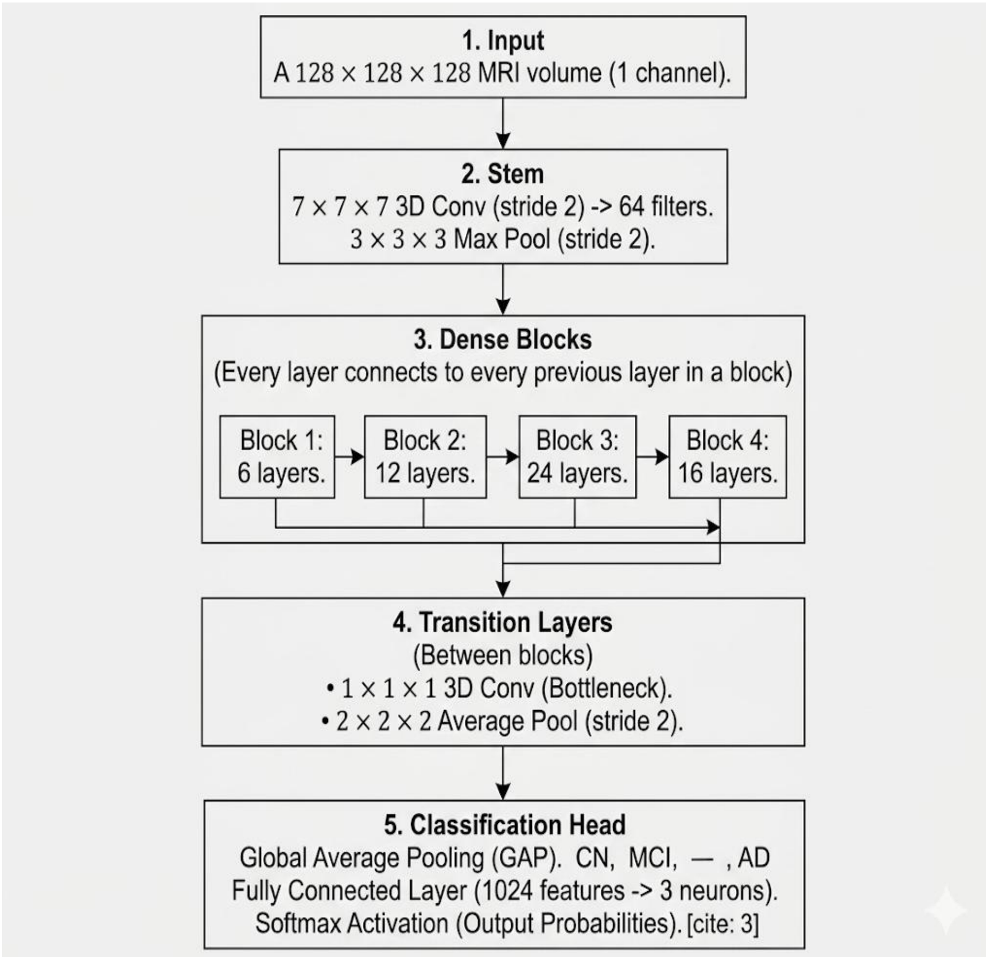

Figure 2: Architecture of Proposed system.

III. PROPOSED SYSTEM

The proposed system is designed as a comprehensive deep learning–based framework for the automated detection and classification of Alzheimer's disease using structural MRI data. The primary goal of this system is to assist medical professionals in identifying early-stage cognitive decline by analyzing brain structures with high precision. Unlike conventional approaches that depend on manual feature extraction or 2D slice-based analysis, this system utilizes a three-dimensional representation of MRI scans, enabling it to capture spatial relationships across the entire brain volume.

Data Acquisition and Preparation

The system begins with the collection of MRI scans from reliable sources such as publicly available neuroimaging datasets or clinical repositories. These scans often come from multiple centers and may vary in resolution, intensity, and orientation. To address this variability, a robust preprocessing pipeline is implemented. The preprocessing stage includes normalization of pixel intensities, resizing images to a fixed dimension, and removing noise or irrelevant artifacts. These steps ensure that all input data is standardized, thereby improving the consistency and performance of the model during training.

Volumetric Representation of MRI Data

After preprocessing, the MRI scans are converted into a structured three-dimensional format. This transformation preserves the spatial continuity between slices, which is essential for capturing anatomical details of the brain. Unlike 2D models that process individual slices independently, the 3D representation allows the model to analyze the entire brain as a unified structure. This approach significantly enhances the model's ability to detect subtle structural changes associated with neurodegeneration, such as hippocampal shrinkage and cortical thinning.

Architecture of the 3D Convolutional Neural Network

At the core of the system lies a 3D Convolutional Neural Network (3D-CNN), which is specifically designed to process volumetric data. The network consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply 3D filters across the input volume to extract meaningful features. In the initial stages, the model captures low-level features such as edges and textures. As the data flows through deeper layers, it learns more complex and abstract representations that correspond to disease-specific patterns.

Pooling layers are integrated into the architecture to reduce the spatial dimensions of the feature maps. This helps in lowering computational complexity while retaining the most important features. Activation functions, particularly the Rectified Linear Unit (ReLU), introduce non-linearity into the model, enabling it to learn complex relationships between input data and output labels. Additionally, batch normalization is applied after convolutional layers to stabilize the training process and improve convergence speed.

Regularization and Optimization Techniques

To enhance the generalization capability of the model, regularization techniques such as dropout are employed. Dropout randomly disables a fraction of neurons during training, preventing the network from becoming overly dependent on specific features. This reduces the risk of overfitting and improves performance on unseen data. The model is trained using backpropagation, where the error between predicted and actual outputs is minimized using a loss function, typically categorical cross-entropy.

The Adam optimizer is used for updating the network weights due to its efficiency and adaptive learning rate capabilities. It combines the advantages of momentum and gradient-based optimization, allowing faster convergence and stable training. Training is performed over multiple epochs, during which the model gradually learns to differentiate between normal and abnormal brain patterns.

Classification Mechanism

After feature extraction, the learned representations are passed through fully connected layers that perform the final classification. These layers integrate all extracted features and map them to the target classes. The output layer uses a Softmax activation function to generate probability scores for each category. The system classifies MRI scans into three classes: Cognitively Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD). The class with the highest probability is selected as the final prediction.

Performance Evaluation Strategy

To evaluate the effectiveness of the proposed system, various performance metrics are used. Accuracy measures the overall correctness of the model, while precision and recall provide insights into class-specific performance. The F1-score, which is the harmonic mean of precision and recall, is used to assess the balance between these metrics. Confusion matrices are also utilized to visualize classification results and identify misclassifications. These evaluation techniques help in understanding the strengths and limitations of the model.

Integration with Web-Based Interface

To improve usability and accessibility, the trained model is integrated into a web-based application using Flask. This interface allows users to interact with the system without requiring technical expertise. Users can upload MRI scans through a simple web interface, and the backend processes the input, performs necessary preprocessing, and feeds it into the trained model. The prediction result is then displayed on the webpage in an easily understandable format.

Real-Time Prediction and Practical Utility

The system is capable of performing real-time predictions, making it suitable for clinical and research applications. The ability to quickly analyze MRI scans and provide accurate classifications can significantly aid in early diagnosis and treatment planning. Additionally, the system can be extended to include visualization tools that highlight important brain regions influencing the prediction, thereby improvng interpretability and trust in the model.

IV. RESULTS AND DISCUSSION

The proposed model was evaluated using standard classification metrics to assess its effectiveness in detecting Alzheimer's disease. The results demonstrate that the model achieved an overall accuracy of 89%, indicating strong performance in distinguishing between different cognitive conditions. For the Cognitively Normal (CN) class, the model achieved high precision, meaning that most predictions labeled as healthy were correct. However, the recall value was slightly lower, suggesting that some healthy cases were misclassified. For the Mild Cognitive Impairment (MCI) class, the model achieved perfect recall, indicating that all MCI cases were correctly identified.

1	Image Data ID	Subject	Group	Sex	Age	Visit	Modality	Description	Type	Format
4	I10269476	941_S_7074	CN	M	72	4_init	MRI	Axial 3D PASL 1500 (Eyes Open) (MSV22)	Original	DCM
6	I11055652	941_S_7051	CN	M	66	4_init	MRI	Axial 3DpCASL 1500 (Eyes Open) (MSV23)	Original	DCM
8	I11128612	941_S_7046	CN	F	74	4_init	MRI	Accelerated Sagittal MPRAGE (MSV21)	Original	DCM
11	I10272111	941_S_6998	CN	M	59	4_init	MRI	Axial 3D PASL 2000 (Eyes Open) (MSV22)	Original	DCM
13	I1295819	941_S_6854	AD	M	86	bl	PET	ADNI3-BRAIN FDG	Original	DCM
14	I1236693	941_S_6803	MCI	F	75	bl	PET	ADNI3-BRAIN FBB	Original	DCM
15	I899022	941_S_6068	MCI	M	76	bl	PET	ADNI3-BRAIN Tau AV1451	Original	DCM
16	I890299	941_S_6058	CN	F	68	bl	PET	ADNI3-BRAIN FBB	Original	DCM

Figure 3: Represent the first 8 rows and all the columns of the dataset.

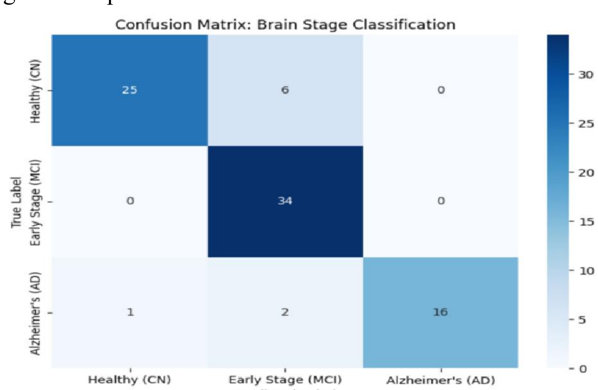

Figure 4: Confusion Matrix

The **macro average F1-score of 0.90** indicates balanced model performance across all classes, while the **weighted average F1-score of 0.89** reflects the overall effectiveness of the model considering the class distribution in the dataset.

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1	Subject_ID	True_Label	AI_Prediction	Correct
2	141_S_6041	Early Stage (MCI)	Early Stage (MCI)	TRUE
3	116_S_4635	Early Stage (MCI)	Early Stage (MCI)	TRUE
4	941_S_6058	Healthy (CN)	Healthy (CN)	TRUE
5	130_S_10214	Early Stage (MCI)	Early Stage (MCI)	TRUE
6	177_S_6328	Healthy (CN)	Healthy (CN)	TRUE
7	941_S_10103	Early Stage (MCI)	Early Stage (MCI)	TRUE
8	381_S_10613	Early Stage (MCI)	Alzheimer's (AD)	FALSE
9	941_S_4365	Healthy (CN)	Early Stage (MCI)	FALSE
10	168_S_6619	Early Stage (MCI)	Healthy (CN)	FALSE

Figure 5: Prediction on test dataset

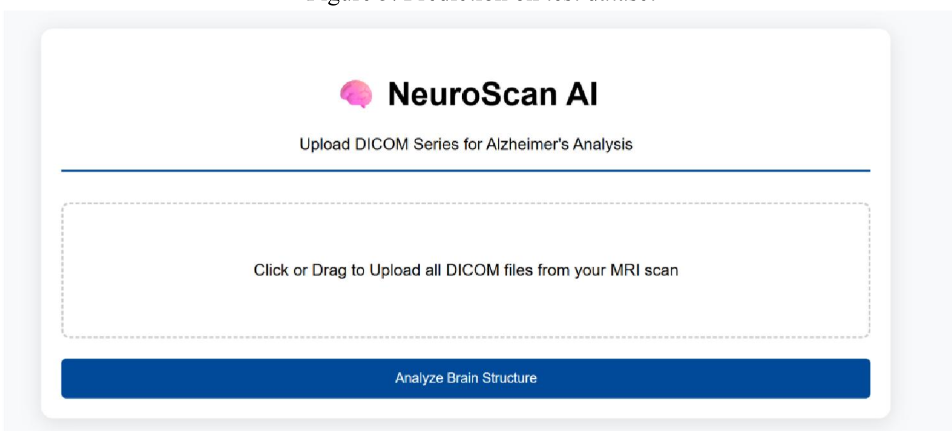

Figure 6: Prediction using Flask Table 1: Performance comparison of algorithm.

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============================================================
 DETAILED PERFORMANCE REPORT
============================================================
                   precision    recall  f1-score   support

     Healthy (CN)       0.96      0.81      0.88        31
Early Stage (MCI)       0.81      1.00      0.89        34
 Alzheimer's (AD)       1.00      0.84      0.91        19

         accuracy                           0.89        84
        macro avg       0.92      0.88      0.90        84
     weighted avg       0.91      0.89      0.89        84
```

This is particularly important because early detection of MCI can help in preventing further disease progression. For the Alzheimer's Disease (AD) class, the model achieved perfect precision, meaning that all predicted AD cases were accurate. The recall was also high, indicating that most AD cases were successfully detected. The macro and weighted average F1-scores further confirm the balanced performance of the model across all classes. Confusion matrices were used to analyze misclassifications and understand model behavior. The results indicate that the model is effective in identifying subtle differences between cognitive stages. Additionally, the integration of the model with a Flask-based web application allows users to upload MRI scans and receive predictions in real time. This enhances the practical usability of the system and makes it accessible to non-technical users. Overall, the results validate the effectiveness of the proposed approach in automated Alzheimer's disease detection.

V. CONCLUSION AND FUTURE WORKS

This study presents a robust and efficient deep learning framework for the classification of Alzheimer's disease using 3D structural MRI data. The use of a 3D Convolutional Neural Network enables the model to capture complex spatial relationships within the brain, leading to improved detection of neurodegenerative patterns. By analyzing full MRI volumes instead of individual slices, the model preserves important anatomical information and enhances classification accuracy. The architecture incorporates advanced techniques such as batch normalization, dropout, and global feature extraction to improve generalization and prevent overfitting. Experimental results demonstrate that the proposed system achieves high accuracy and balanced performance across all classes, making it suitable for real-world applications. The system is flexible and can be extended to handle additional classification tasks or incorporate other imaging modalities. Furthermore, the integration with a Flask-based interface allows for easy deployment and user interaction, enabling healthcare professionals to use the system without technical expertise. Despite its strengths, the study acknowledges limitations such as dataset diversity and generalization across populations. Future work can focus on incorporating larger and more diverse datasets, improving model interpretability, and integrating additional biomarkers for enhanced prediction. Overall, the proposed system represents a significant step toward automated, accurate, and accessible Alzheimer's disease diagnosis.

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