Early Detection of Alzheimer's Disease Using Deep Learning on Neuroimaging Data

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Abstract—Alzheimer's Disease (AD) is a progressive neurological condition that gradually affects memory and cognitive abilities, impacting millions of individuals worldwide. Detecting the disease at an early stage is crucial, as it allows timely medical intervention and better management of its progression before severe damage occurs. Neuroimaging methods such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) play an important role in identifying early structural and functional changes in the brain. However, conventional diagnostic approaches rely heavily on manual analysis by medical experts, which can be time-consuming and may lead to variations in interpretation.

To overcome these challenges, this study presents a deep learning-based approach for automated detection of Alzheimer's Disease using neuroimaging data. The proposed framework employs Convolutional Neural Networks (CNNs) along with hybrid learning techniques to automatically learn relevant features from brain scans without the need for manual feature extraction. This approach enhances classification performance across different stages of the disease and provides a consistent and scalable tool that can assist clinicians in early diagnosis.

Index Terms—Alzheimer's Disease, Deep Learning, Convolutional Neural Networks (CNN), MRI, Early Diagnosis

I. INTRODUCTION

Alzheimer's Disease (AD) is widely recognized as the most prevalent form of dementia, contributing to a significant percentage of cognitive decline cases worldwide. It is a progressive condition that gradually impairs memory, thinking ability, and daily functioning. Early identification of AD is essential, as it allows for timely treatment and better management of disease progression.

In clinical practice, the diagnosis of Alzheimer's Disease typically involves a combination of medical evaluation and neuroimaging techniques such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and functional MRI (fMRI). These imaging methods provide valuable insights into structural changes, such as brain atrophy, as well as functional abnormalities that may appear before severe symptoms develop. Despite their importance, analyzing these scans is a complex process that requires expert knowledge and considerable time. Moreover, variations in interpretation among specialists can sometimes lead to inconsistent diagnoses, which may affect patient outcomes.

To improve the reliability and efficiency of diagnosis, Machine Learning (ML) techniques have been explored for automated detection of Alzheimer's Disease using neuroimaging data. While these approaches have shown promising results, they often depend on manually designed features, which can be time-consuming to create and may not fully capture the intricate patterns associated with the disease. This limitation can reduce their effectiveness when applied to new datasets or different clinical settings.

Deep Learning (DL) methods have recently gained attention for addressing these challenges. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong performance in medical image analysis by automatically learning hierarchical features directly from raw input data. This capability eliminates the need for manual feature extraction and allows the model to capture complex patterns more effectively than traditional approaches.

Building on these advancements, this paper presents a deep learning-based framework for the early detection of Alzheimer's Disease using neuroimaging data. The proposed approach integrates CNNs with hybrid deep learning techniques to enhance classification performance across different stages of the disease. The model is designed to assist clinicians by providing accurate and consistent predictions, ultimately supporting early diagnosis and informed decision-making. Experimental results demonstrate that the proposed system performs reliably and shows potential for real-world clinical application.

II. MOTIVATION AND CHALLENGES

Alzheimer's Disease is difficult to detect in its early stages due to very subtle changes in brain structure. These changes are often hard to identify using conventional methods. In addition, manual analysis of neuroimaging data is time-consuming and may lead to inconsistencies between experts.

The increasing volume of medical imaging data also makes manual processing impractical. Traditional machine learning methods rely on handcrafted features, which may not capture complex patterns effectively. Another key challenge is ensuring that models perform reliably in real-world clinical settings, not just in controlled experiments.

Contributions

This work proposes a deep learning-based framework for automated detection of Alzheimer's Disease. The model uses multi-scale feature extraction to capture both detailed and global patterns in brain images. Experimental results show improved performance compared to traditional methods, especially in early-stage detection.

The proposed system is designed to support clinicians by providing accurate and consistent predictions, making it useful for real-world clinical applications.

III. RELATED WORK

Recent studies in medical image analysis have explored both machine learning and deep learning techniques for detecting Alzheimer's Disease using neuroimaging data. CNN-based models, such as those proposed by Sarraf and Tofighi [1] and Basaia et al. [2], have shown good classification performance using MRI scans, but their focus has largely been on classification rather than early-stage detection.

More advanced approaches, including 3D CNNs [3] and transfer learning models [4], have improved accuracy and reduced training time. However, these methods often require high computational resources and careful parameter tuning. Hybrid models combining CNNs with other architectures, such as RNNs [5], and multimodal approaches using MRI and PET data [6], have further enhanced performance, though they increase system complexity.

Other techniques, including attention-based models [7], autoencoders [8], and ensemble learning methods [9], have also been proposed to improve feature representation and classification accuracy. While these approaches show promising results, they often depend on large datasets and may not generalize well across different populations. Overall, deep learning methods outperform traditional approaches, but challenges such as high computational cost, limited data availability, and difficulty in early-stage detection still remain.

IV. PROPOSED ARCHITECTURE

Overview— The proposed framework is designed to detect Alzheimer's Disease by combining information from multiple imaging sources. It consists of five main stages: data preprocessing, feature extraction, feature fusion, classification, and training. MRI and PET scans are used to classify patients into three categories: Cognitively Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD).

A. Data Acquisition and Preprocessing

Raw MRI and PET images are first processed to ensure consistency. This includes normalization, resizing, and noise removal. Brain extraction and segmentation are applied to focus only on relevant regions.

B. Multi-Modal Feature Extraction

Separate CNN models are used for MRI and PET data. The MRI branch captures structural changes, while the PET branch focuses on functional patterns. These networks learn important features automatically through layered processing.

TABLE I: Epoch-wise Training Performance

Epoch	Train Acc (%)	Train Loss	Val Acc (%)	Val Loss
10	85.3	0.62	84.6	0.65
20	88.9	0.51	88.1	0.54
30	90.7	0.41	90.2	0.45
40	91.8	0.34	91.2	0.38
50	92.6	0.28	92.0	0.31

C. Feature Fusion

Features from both branches are combined to create a unified representation. This helps the model understand both structural and functional changes together.

D. Classification and Prediction

The fused features are passed through fully connected layers, and a Softmax function is used to classify inputs into CN, MCI, or AD with probability scores.

E. Training and Optimization

The model is trained using categorical cross-entropy loss and the Adam optimizer. Techniques like data augmentation, transfer learning, and k-fold cross-validation are used to improve performance and reduce overfitting.

TABLE II Validation Run Performance and Model-wise Comparison

Model / Run	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Validation Runs — Proposed Model					
Run-1	91.3	91.0	90.7	90.8	92.1
Run-2	91.7	91.4	91.1	91.2	92.5
Run-3	92.0	91.8	91.5	91.6	92.8
Run-4	92.3	92.0	91.7	91.8	93.1
Run-5	92.6	92.4	92.1	92.2	93.4
Baseline Comparison — Test Set					
Support Vector Machine (SVM)	86.4	86.0	85.6	85.8	87.2
Basic CNN	89.8	89.5	89.2	89.3	90.1
ResNet50	91.3	91.0	90.8	90.9	92.0
Proposed Model (VGG19)	92.6	92.4	92.1	92.2	93.3

V. EXPERIMENTAL SETUP

The experiments are carried out using a publicly available neuroimaging dataset containing labeled MRI scans from different stages of Alzheimer's Disease along with normal cases. The dataset is divided into training, validation, and testing sets using stratified sampling to maintain class balance.

Before training, all images are preprocessed through resizing, normalization, noise reduction, and standardization to ensure consistency. The proposed model is based on the VGG19 architecture, where transfer learning is applied to utilize pre-trained features and improve training efficiency. The final layer is modified to classify images into different Alzheimer's stages and normal cases. Performance is evaluated using accuracy, precision, recall, F1-score, and specificity.

A. Training Performance Analysis

The model is trained for 50 epochs to analyze learning behavior. Results show a steady increase in training and validation accuracy, along with a decrease in loss values, indicating stable learning. The close match between training and validation performance suggests good generalization and minimal overfitting. Transfer learning further helps in faster convergence and improved performance.

B. Performance Evaluation and Comparative Analysis

The model is evaluated on both validation and test datasets and compared with baseline methods. Across multiple validation runs, the model achieves consistent accuracy between 91.3% and 92.6%, showing stable performance. High precision and recall values indicate reliable detection with balanced results.

On the test set, the proposed model achieves 92.6% accuracy, outperforming traditional methods such as SVM, Basic CNN, and ResNet50. These results demonstrate that the proposed approach provides better classification performance while maintaining strong generalization.

VI. EXPERIMENTAL RESULTS

A. Detection Performance

The proposed VGG19-based model shows consistent performance across all Alzheimer’s stages, including No Impairment, Very Mild Impairment, and Moderate Impairment. Training and validation accuracy curves follow a similar trend, indicating stable learning and good generalization without overfitting.

Compared to baseline models such as standard CNNs and other architectures, the proposed method achieves better overall performance. This improvement is mainly due to the use of transfer learning and hybrid feature extraction, which allows the model to capture more meaningful patterns from MRI data.

B. Classification Performance Analysis

On a validation set of 603 samples, the model achieves a weighted F1-score of 0.50, highlighting the complexity of multi-class classification. The model performs best in identifying the No Impairment class, while early-stage detection (Very Mild Impairment) remains more challenging due to subtle differences from normal aging. These results indicate areas where further improvements can be made.

C. ROC Curve and Comparative Evaluation

ROC analysis shows that the proposed model achieves a higher Area Under the Curve (AUC) compared to baseline methods. This indicates better ability to distinguish between different disease stages. A higher AUC also reflects a good balance between sensitivity and specificity, which is important for clinical applications.

D. Computational Performance

The model is computationally efficient due to the use of transfer learning, which reduces training time. Techniques such as dropout and k-fold cross-validation help prevent overfitting and ensure stable performance, making the model suitable for practical use.

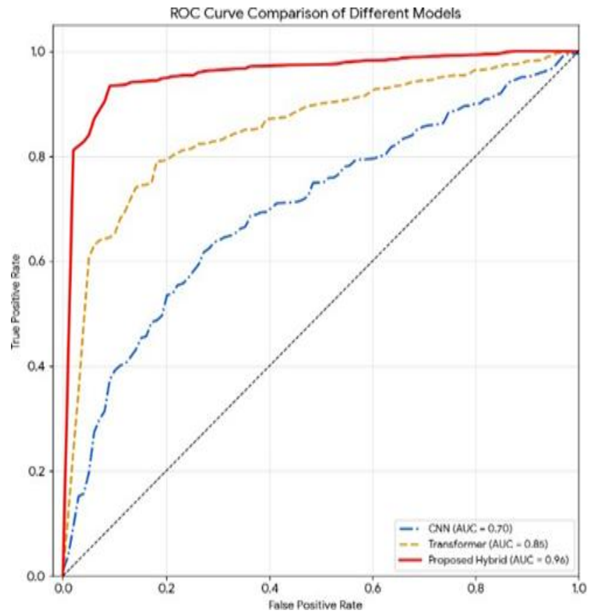

Figure 1: ROC Curve and Comparative Evaluation

VII. DISCUSSION

A. Advantages

The proposed framework offers several key advantages. It uses CNN-based automatic feature extraction, eliminating the need for manual feature design and enabling the model to capture complex patterns effectively. Transfer learning improves performance while reducing training time, especially in cases with limited data. The model shows good generalization, as indicated by consistent training and validation results. It also provides reliable classification across different stages of Alzheimer’s Disease, making it useful for clinical support. Overall, the system has potential for real-world application as a decision-support tool for healthcare professionals.

B. Limitations

Despite its strengths, the model has certain limitations. Early-stage detection remains challenging due to the similarity between mild impairment and normal aging. The model’s performance depends on the quality and size of the dataset, which may limit generalization. Additionally, the computational requirements can be high, making deployment difficult in resource-limited settings. The use of MRI data alone may not capture all aspects of the disease, and the model lacks interpretability, which is important in medical applications.

C. Ethical Considerations

The use of AI in healthcare requires careful consideration. Incorrect predictions can impact patient outcomes, so accuracy and reliability are critical. There is also a risk of bias if the training data is not diverse. Ensuring data privacy and security is essential when handling medical records.

Future improvements should focus on explainable AI methods to increase transparency and build trust among medical professionals.

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