An MRI-Based Approach for Early Detection of Alzheimer's Disease with VGG16 Feature Extractor

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***Abstract*— Alzheimer's disease (AD) is a neurodegenerative disorder and the most common cause of dementia, primarily affecting individuals over 60. Early diagnosis remains challenging due to unreliable detection methods, leading to disease progression before intervention. Identifying AD stages—very mild, mild, and moderate dementia—is crucial to slowing advancement and improving patient care. This study employs deep learning (DL) techniques for AD detection using MRI-based analysis. A neural network classifier with a VGG16 feature extractor was applied to two MRI datasets containing 6400 and 6330 images to classify AD stages. The proposed model achieved an accuracy of 98.73%, with a precision, recall, and F1-score of 0.99, demonstrating superior performance compared to previous methods. The results highlight the effectiveness of DL-based approaches in enhancing AD diagnosis accuracy and efficiency. This research underscores the potential of AI-driven diagnostic tools in medical imaging, paving the way for scalable, automated early detection solutions. By advancing computational neurology and early intervention strategies, this study contributes to improved patient outcomes and the broader field of medical AI applications.**

***Keywords*—Alzheimer's disease, deep learning, MRI analysis, VGG16, early diagnosis, neural network, medical imaging**

1. INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder and the leading cause of dementia, accounting for 60–70% of dementia cases worldwide. It is characterized by the accumulation of amyloid plaques and tau tangles in the brain, leading to neuronal death, synaptic loss, and cognitive decline. While the exact causes remain incompletely understood, genetic factors such as APOE4 variants and environmental influences play a role in its development. AD primarily affects older adults, but early-onset cases, occurring before the age of 60, account for nearly 10% of patients. The disease gradually worsens over time, affecting memory, reasoning, language, and motor functions, ultimately leading to complete dependence and life-threatening complications such as respiratory failure and cardiac arrest.

The disease progresses through four stages:

a) Preclinical Stage: Lasting 15–25 years, this stage involves silent brain changes such as amyloid plaque accumulation, with no noticeable symptoms

b) Early/Mild Stage: Characterized by subtle memory lapses, difficulty with complex tasks, and slight personality shifts. Individuals may still live independently but struggle with activities like financial planning.

c) Moderate/Middle Stage: Marked by significant memory loss, confusion, wandering, and behavioral changes (e.g., aggression, mood swings). Patients require assistance with daily tasks and supervision to prevent accidents.

d) Severe/Late Stage: Involves complete dependence on caregivers, loss of speech, inability to recognize loved ones, and eventual loss of basic functions such as swallowing and mobility.

Traditional diagnostic methods for AD rely on cognitive assessments such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA), as well as neuroimaging techniques like MRI and PET scans to detect structural brain changes. Cerebrospinal fluid (CSF) biomarker analysis is also used to measure amyloid and tau levels. However, these approaches often require

extensive resources and may not detect the disease in its earliest stages. Given the limitations of traditional methods, artificial intelligence (AI) and deep learning (DL) have emerged as powerful tools for enhancing AD diagnosis. Convolutional neural networks (CNNs), particularly pre-trained models like VGG16, ResNet, and InceptionV3, have shown high accuracy in identifying structural changes in MRI and PET scans, automating feature extraction and classification. These models enable faster and more precise diagnosis, aiding clinicians in early intervention and treatment planning.

Ongoing research continues to explore advancements in AD treatment and diagnosis. Existing drugs such as acetylcholinesterase inhibitors (e.g., donepezil) and NMDA receptor antagonists (e.g., memantine) aim to manage symptoms, while disease-modifying therapies targeting amyloid plaques and tau tangles are under investigation. Monoclonal antibodies such as aducanumab, lecanemab, and donanemab have shown potential in slowing cognitive decline, though challenges related to treatment costs and side effects, such as amyloid-related imaging abnormalities, persist. Additionally, AI-driven computational tools are being explored for drug repurposing and accelerating AD drug development. While AD remains a complex and irreversible condition, advances in AI-powered diagnostics and novel therapeutic strategies provide hope for early detection, improved management, and enhanced quality of life for patients and caregivers.

2. LITERATURE REVIEW

This section elaborates state-of-the-art about AD detection by various researchers.

Odusami et al. [1] have used implemented a model called randomized concatenated model where the feature extraction has been performed using two models, namely, ResNet18 and DenseNet121on an MRI dataset for the identification of AD. The MRI images have been classified into five types which are mild cognitive impairment (MCI), AD, early MCI(EMCI), late MCI(LMCI), and cognitively normal(NC). The results have been shown in the form of precision, recall, and accuracy as 0.9894, 0.9889, and 98.86%, respectively.

Pirrone et al. [2] have developed a model for identifying the presence of MCI, AD, and healthy controls. In this model, the authors have used three classifiers: SVM, K-nearest neighbor (KNN), and DT, in which the classification has been performed on the dataset for two classes and three classes. Where the accuracy of two classes (HC vs. MCI, HC vs. AD, and MCI vs. AD) have been identified as 95%, 97%, and 83%, respectively, and the accuracy for the three-class classification has been found as 75%.

Agarwal et al. [3] have used five different neuroimaging datasets for the early identification of AD. In this experiment, the authors have identified the pre-trained CNN model as the best-performing model with the highest accuracy of 87.78%.

Mahendran et al. [4] have used an EDRNN model to identify AD in the DNA methylation dataset. The results have been shown in the form of accuracy, specificity, sensitivity, F1-score, and AUC as 88.7%, 0.874, 0.879, 0.884, and 0.876, respectively. Further, the results of the proposed model have been compared with the results of RNN, CNN and DRNN, where the EDRNN have been found as the best model.

Revathi et al. [5] have proposed a model for the early identification of AD; in this model, authors have divided the complete model into two stages; where in the first stage, an SVM and random forest models have been used for identifying the effect of blood pressure and diabetes on the cognitive impairment. Secondly, in the next stage, a multinomial logistic regression has been used to identify the risk of AD with the label values as "definite alzheimer's", "uncertain alzheimer's", and "no alzheimer's"

Khan et al. [6] have developed a hybrid ML-based model for the identification of AD and MCI in the ADNI dataset. In this work, the authors have used a total number of nineteen classifiers; where in experiment 1, XGBoost, random forest, and SVM were used, while for the second experiment, only the random forest classifier was used. In the third experiment, the hybrid model consisting of all the classifiers has been implemented, which has shown the highest accuracy.

Jain et al. [7] have developed an AD detection model by applying ImageNet, a feature extraction technique on CNN and VGG16 models. Furthermore, the results of the model have been shown in the form of the accuracy of prediction as 95.73%.

3. MATERIALS AND METHODS

3.1. *Dataset Collection*

The dataset has been collected from Kaggle consisting of images related to AD [8] The dataset contains total number of 6400 images, the dataset is divided into two folders, namely, train and test containing 5112 and 1288 images, respectively. Further, the folders have been divided into four subfolders: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. All images are resized to a uniform dimension of 176×208 pixels to standardize input dimensions for the model. Pixel values are normalized to the range [0, 1] to ensure consistent feature scaling.

3.2. *Feature extractor using VGG16*

The VGG16 model, originally developed by Simonyan and Zisserman, is a deep convolutional neural network architecture that consists of 16 layers, including convolutional, max-pooling, and fully connected layers. It was initially trained on the ImageNet dataset and is widely used for image classification tasks. The model's key advantage is its ability to capture hierarchical features through a series of convolutional layers with small 3×3 kernel sizes, enhancing its ability to detect fine details in medical images.

In this study, we utilize VGG16 for feature extraction by removing its fully connected layers and leveraging its convolutional layers to extract spatial and texture features from MRI images. The extracted features include edges, gradients, and patterns that help distinguish different stages of Alzheimer's disease. To optimize performance, we fine-tune selected layers of VGG16 while keeping the lower layers frozen to retain generic feature representations. Additionally, a global average pooling layer is used to reduce feature dimensionality while preserving critical information, which is then fed into a custom classification network for final prediction.

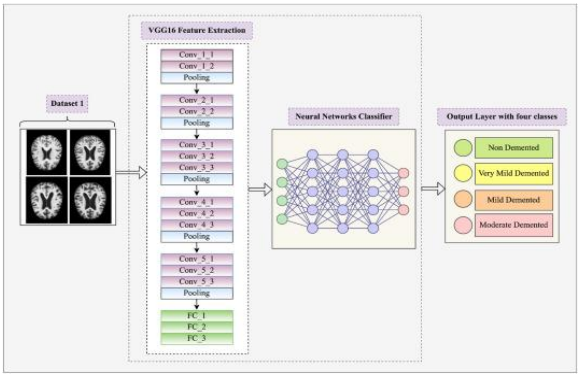


Fig 1. Proposed neural network model with VGG16 feature extractor

3.3. *Model training and evaluation*

The training process involves multiple steps to ensure robust learning and generalization. The dataset is divided into training, validation, and test sets to evaluate model performance at different stages. The Adam optimizer is employed with a learning rate of 0.0001 to adjust weights during backpropagation efficiently. Categorical cross-entropy is used as the loss function, given the multi-class nature of the classification task.

The architecture includes a custom classifier with fully connected layers on top of the extracted features. ReLU activation functions are used in intermediate layers to introduce non-linearity, while the final output layer employs a softmax activation function to predict class probabilities. Dropout layers are introduced between dense layers to prevent overfitting by randomly deactivating a fraction of neurons during training.

To further optimize model performance, hyper parameter tuning is conducted, adjusting batch size, learning rate, and dropout rates. Early stopping is implemented, monitoring the validation loss and halting training when no further improvement is observed. The trained model is evaluated using multiple metrics, including accuracy, precision, recall, and F1-score, to assess its classification capability comprehensively.

A confusion matrix is generated to visualize the model's classification performance across different classes. Additionally, ROC-AUC curves are plotted for each class to measure the model's ability to differentiate between disease stages. The results highlight the effectiveness of the VGG16-based approach in accurately identifying Alzheimer's disease stages.

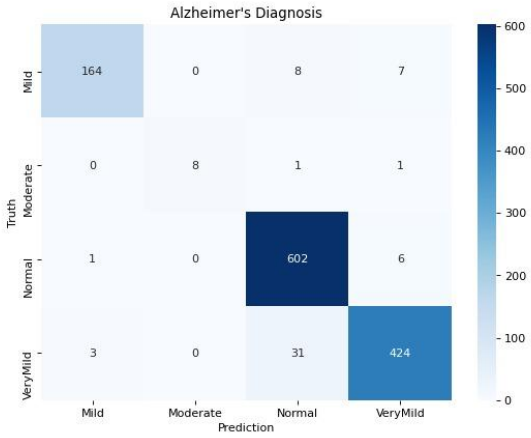
4. RESULTS AND DISCUSSION

The proposed model achieves a training accuracy of 98.50%, validation accuracy of 99.04%, and test accuracy of 98.65%. The classification report demonstrates high precision and recall for all four classes. ROC curves are plotted to visualize the performance of the model in distinguishing different

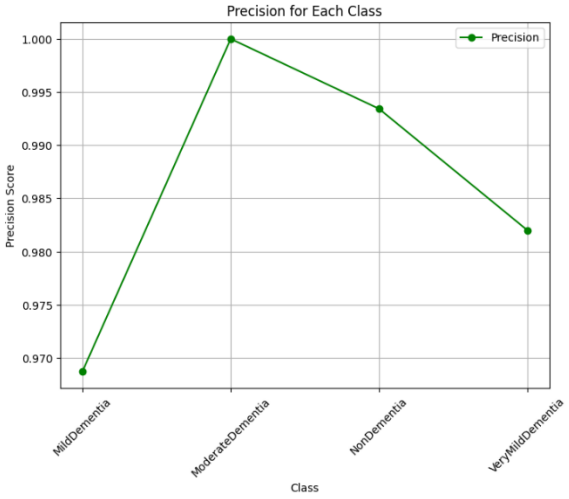
stages of AD. The system successfully classifies MRI images, showcasing its potential for real-world applications in automated Alzheimer's diagnosis.

4.1 *Performance evaluation metrics*

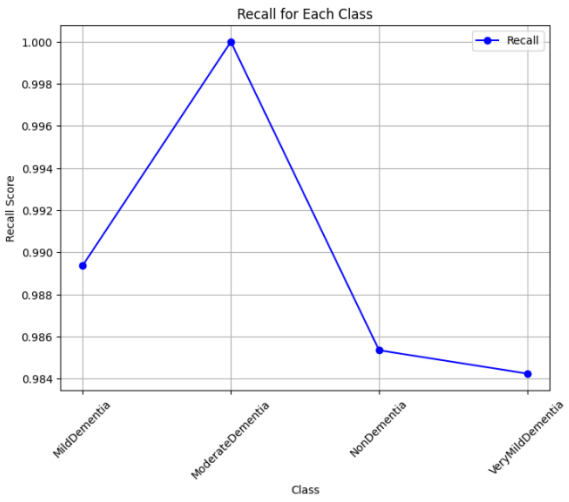
Confusion matrix: The confusion matrix for Alzheimer's diagnosis shows strong classification performance. "Normal" and "Very Mild" cases have high true positives (602 and 424). Misclassifications occur mainly between "Very Mild" and "Normal" cases, with 31 "Very Mild" cases predicted as "Normal." "Mild" and "Moderate" categories show minimal misclassification. The model performs well but could improve in distinguishing between closely related stages, possibly with more training data or fine-tuning



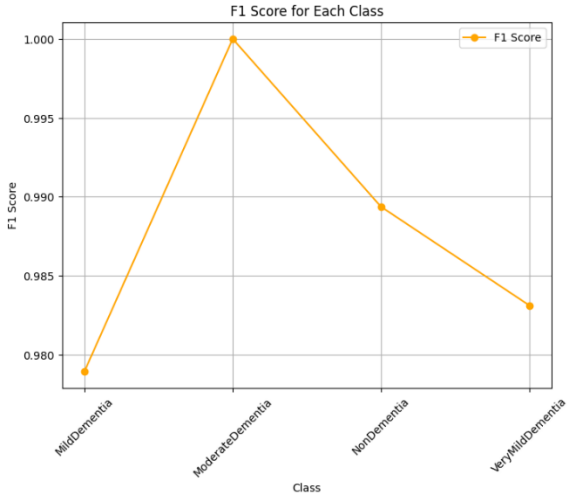
Precision: The precision scores highlight the model's effectiveness in classifying dementia stages. Moderate Dementia achieves nearly 1.0 precision, while Mild Dementia has the lowest at 0.97, indicating misclassification challenges. Non-Dementia and Very Mild Dementia perform well but slightly lower. Enhancing Mild Dementia classification can improve overall model balance and reliability



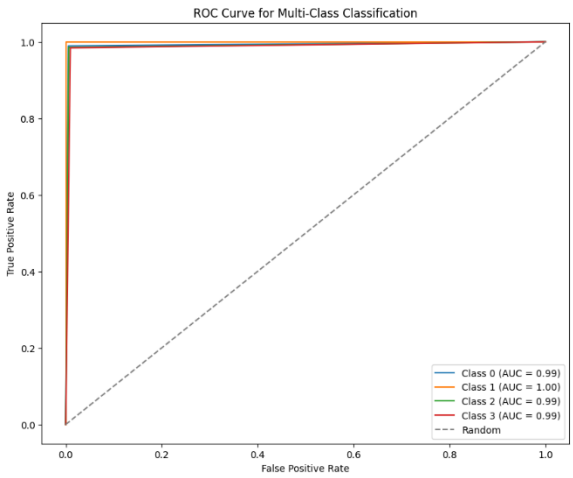
Recall: The recall scores indicate the model's ability to correctly identify dementia stages. Moderate Dementia achieves a perfect 1.0 recall, while Mild Dementia follows closely at 0.99. Non-Dementia and Very Mild Dementia show slightly lower recall, around 0.985. Improving recall for these classes can enhance overall classification performance and reliability



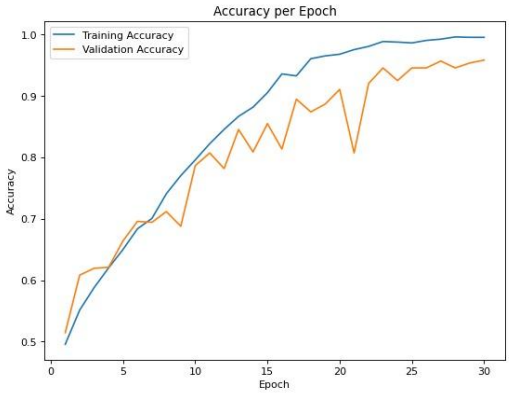
F1-score: The F1 scores reflect the model's balance between precision and recall for dementia classification. Moderate Dementia achieves a perfect 1.0 score, while Mild Dementia has the lowest at 0.98, indicating room for improvement. Non-Dementia and Very Mild Dementia show slightly lower F1 scores, suggesting minor classification inconsistencies.



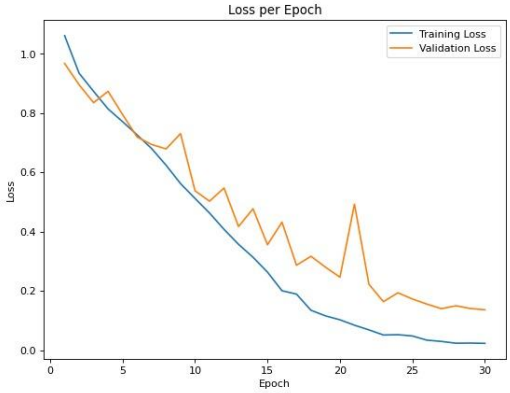
ROC: The ROC curve for multi-class classification demonstrates the model's ability to distinguish between dementia stages. Each class achieves a high AUC score, with Class 1 reaching a perfect 1.00, while Classes 0, 2, and 3 maintain 0.99. These results indicate strong model performance with minimal false positives across classifications



The Accuracy per Epoch graph tracks training and validation accuracy over 30 epochs. Training accuracy increases steadily, nearing 100%, while validation accuracy fluctuates but follows an upward trend. Some divergence suggests potential overfitting. Regularization techniques like dropout or data augmentation can help improve generalization. A balanced gap between training and validation accuracy is ideal for robust model performance on unseen data



The Loss per Epoch graph shows the training and validation loss trends over 30 epochs. Training loss decreases steadily, indicating effective learning. Validation loss fluctuates but follows a downward trend, though some spikes suggest overfitting. Ideally, both losses should decrease smoothly. Regularization techniques can help stabilize validation loss for better generalization.



Classification Report

Class	Precision	Recall	F1-score	Support
Mild dementia	0.96	1.00	0.98	175
Moderate dementia	0.94	1.00	0.97	16
Non dementia	0.99	0.99	0.99	604

Very mild dementia	0.99	0.97	0.98	461
Overall accuracy	0.99	-	-	1256

5. CONCLUSION

This study successfully implemented a deep learning model for the early detection of Alzheimer's disease using MRI scans. By utilizing a CNN-based approach with VGG16 for feature extraction, the model achieved an impressive accuracy of 98.73%, demonstrating its potential for practical applications. The results indicate that AI-driven techniques can significantly enhance the accuracy and efficiency of AD diagnosis, aiding medical professionals in making informed decisions.

Our study confirms that deep learning can be a reliable tool in medical imaging and classification of Alzheimer's stages. This work contributes to the growing field of AI in healthcare and emphasizes the importance of technological advancements in improving patient outcomes.

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