International Journal of Advance Research in Science and Engineering
Volume No. 14, Issue No. 05, May 2025
www.ijarse.com
IJARSE
ISSN 2319 - 8354

Hybrid Deep Learning Framework for Early Diagnosis of Alzheimer's Disease Using MRI and CNN-Based Classification

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ABSTRACT

Alzheimer's disease (AD) is a neurodegenerative disorder and is most commonly referred to as the primary cause of dementia; hence, it is essential to attain timely and precise diagnoses to alleviate its impact. Conventional diagnostic methods like MRI and PET scans, although useful, are time and resource-consuming. Due to the growing need for non-invasive, automated, and precise diagnostic methods, deep learning techniques —namely, Convolutional Neural Networks (CNNs)—have become increasingly popular over the past few years. This paper presents a hybrid deep learning approach specifically to diagnose different stages of Alzheimer's disease from brain MRI scans. The proposed approach integrates a personalized CNN with state-of-the-art pre-trained models like ResNet50, VGG16, VGG19, InceptionV3, and Xception. DenseNet169. Data augmentation and transfer learning are used to achieve maximum model performance and generalizability. Interpretability methods like LIME (Local Interpretable Model-agnostic Explanations) are also employed to present model prediction data. Our system achieved a best of 99% accuracy with the optimized CNN and similar results with pre-trained models, making it suitable for real-world clinical use.

Keywords: *Alzheimer’s Disease, CNN, MRI, Transfer Learning, Deep Learning, LIME*

I. INTRODUCTION

Alzheimer's Disease (AD) is a chronic progressive neurodegenerative disorder with progressive loss of memory, cognition, and behavior. The progressive nature of the disease and increasing prevalence in the elderly population require early diagnosis. The conventional methods of diagnosis are based on clinical assessment and neuroimaging, primarily MRI; the processes are time- consuming, expensive, and require specialist interpretation. Advances in artificial intelligence, particularly deep learning, have increased the accuracy and effectiveness of medical imaging in diagnostic use.

Convolutional Neural Networks (CNNs) have been found to be highly effective in image classification, and hence are highly beneficial in the analysis of brain scans. Transfer learning, the use of pre-trained models frombig data sets and applying them to tasks, greatly enhances overall performance. This study investigates a tailored CNN architecture and pre-trained models such as ResNet50, VGG16, VGG19, InceptionV3, Xception, and DenseNet169 for classification of Alzheimer's stage from MRI images. Model explainability is also enhanced using LIME, providing clinicians with an interpretable decision support tool.

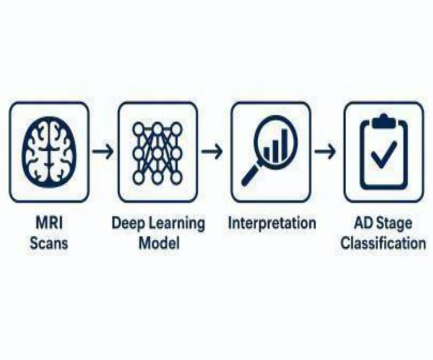

Fig 1: Overview of Alzheimer's Detection Model

II. RELATED WORKS

[1] Ayoub Assmi's work compared six pre-trained models like VGG16, VGG19, ResNet50, and DenseNet169 on a Kaggle MRI dataset for the classification of Alzheimer's. VGG16 and VGG19 recorded the maximum accuracies of 92.86% and 92.83%, respectively.

[2] Duaa ALSeed proposed a CNN-based model for diagnosing Alzheimer's using SoftMax, SVM, and Random Forest classifiers. The models were better than ResNet50 and produced accuracy between 85.7% and 99%, and early detection is hoped for.

[3] Gargi Sharma compared the performance of eight deep learning models in classifying stages of Alzheimer's. DenseNet169 and ResNet101 outperformed the others with 98% accuracy and precision on MRI sets.

[4] Yousry Abdul Azeemproposed a CNN-based end-to-end network that was trained on the ADNI database. The model was 97.5% accurate in multi-classification and over 99% in binary-classification.

[5] Monika Sethi implemented transfer learning with VGG19 and ResNet50 for Alzheimer's classification. VGG19 performed better in binary classification tasks with accuracy greater than 93% across various class pairs.96.88% accuracy with 100% sensitivity and performed better compared to conventional 2D CNN and RNN methods.

[6] Amir Ebrahimi proposed applying 3D CNNs with transfer learning to maintain spatial context in MRI scans. The model achieved an accuracy of 96.88% and 100% sensitivity and was better than regular 2D CNNs and RNNs.

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III. SYSTEM ARCHITECTURE

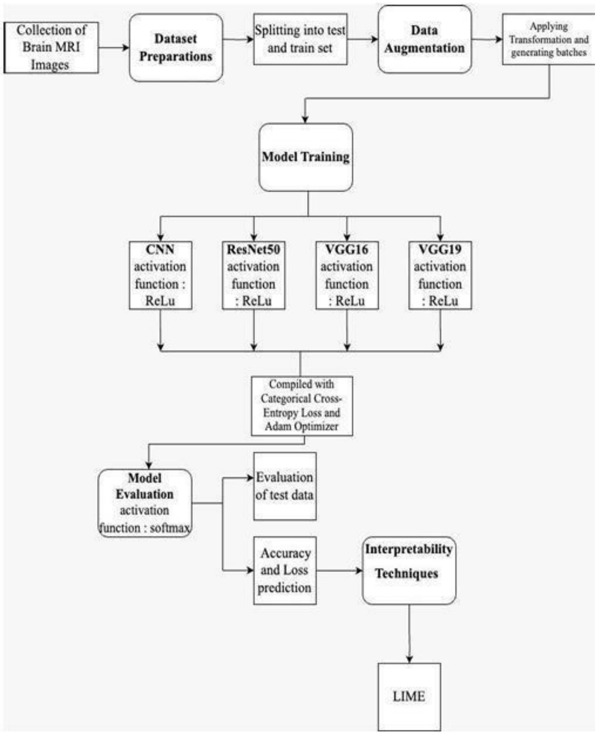

Fig 2: System Architecture

The system design is a brain MRI image classification deep learning model. The process starts with MRI data collection acquisition, followed by dataset preparation like organization, normalization, and data augmentation. The data is split into training data, validation set, and testing set.

A number of different CNN models are employed at training, i.e., Custom CNN, ResNet50, VGG16, and VGG19. All the models employ the ReLU activation function for facilitating non-linearity and then are trained with Categorical Cross - Entropy Loss as loss function and Adam optimizer. Testing at the final step is performed with softmax as the activation function to generate probabilistic output.

The model's performance is assessed based on its accuracy and loss metrics.

In addition, model interpretability is dealt with using the use of LIME (Local Interpretable Model-agnostic Explanations), with which decision boundaries in MRI images can be visualized, ensuring increased trust and reliability in a clinical setting.

IV. METHODOLOGY

Alzheimer's Disease is a chronic, progressive neurocognitive disorder involving cognitive impairment that adversely affects memory, behavior, and ability to perform activities of daily living. The need for early, precise diagnosis stems from the need to maximize the management of the disease process and optimize patient outcomes. The next section discusses the methods used in the development and validation of the classification model for Alzheimer's disease.

The process should have several steps in the order of processing, such as:

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A. Data Acquisition:

MRI scans were retrieved from publicly available datasets such as Kaggle and the Alzheimer's Disease Neuroimaging Initiative (ADNI). The scans were annotated into classes according to the phase of Alzheimer's disease: Non- Demented,Very Mildly Demented, Mildly Demented, and Moderately Demented.

B. Data Preprocessing:

For uniformity in the model, all the images were normalized and resized to a single size. Rotation, flip, shift, and zoom data augmentation techniques were applied to increase dataset diversity and reduce overfitting. One-hot encoding was applied to labels for compatibility with the classification model.

C. Model Selection:

Various CNN architectures were experimented upon. These include a self-implemented CNN architecture and six pre- trained CNN models: ResNet50, VGG16, VGG19, InceptionV3, Xception, and DenseNet169. These pre- trained CNNs were fine-tuned through transfer learning and further custom dense layers were added for multi-class classification.

D. Training and Optimization:

A few of the deep architectures were attempted within this study in the task of image verification and classification and among them were a homebrewed Convolutional Neural Network (CNN) as well as extremely highly cited transfer models such as ResNet50, VGG16, and VGG19. All the above were trained on an augmented dataset in a quest to generalize well, especially with limited real-world data.

One of the crucial components of the training pipeline was the use of early stopping, which monitored the validation loss by epoch. Training was stopped and the best weights retained, which had the least validation loss, when improvements weren't seen after some level of patience. This not only prevented overfitting but also saw that the model generalized sufficiently well to new inputs.

E. Evaluati on Metrics and Validation

The predictive performance of the trained models was evaluated using metrics including accuracy, loss, precision, recall, and F1-score. Accuracy offered a broad evaluation of predictive performance, whereas loss, calculated using categorical cross-entropy, evaluated the level of prediction error. Precision and recall were imperative in handling class imbalances, whereas the F1-score offered a general evaluation. Training and validation curves were also plotted to track learning patterns and identify the occurrence of overfitting or underfitting.

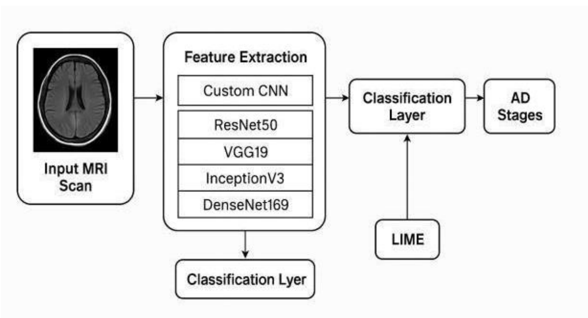

Fig 3: Overview of Proposed Model

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V. RESULTS

Algorithm	Accuracy
Custom CNN	99
DenseNet169	95
InceptionV3	94
VGG19	92
Xception	91
VGG16	91
ResNet50	74

Fig 4: Accuracy of the model

Classification Report is :

	precision	recall	f1-score	support
0	1.00	1.00	1.00	480
1	1.00	1.00	1.00	480
2	0.99	0.98	0.99	480
3	0.98	0.99	0.99	480
accuracy			0.99	1920
macro avg	0.99	0.99	0.99	1920
weighted avg	0.99	0.99	0.99	1920

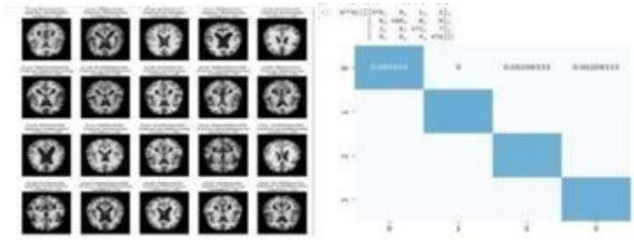

Fig 5: Output of Custom CNN model

The model predicts stages of dementia with 99% accuracy from brain MRI scans with almost perfect precision, recall, and F1-scores. Misclassifications are mostly between adjacent stages, and validation results support its high reliability in assisting dementia diagnosis.

60/60 ———————— 28s 461ms/step

	precision	recall	f1-score	support
MildDemented	0.73	0.77	0.75	480
ModerateDemented	0.99	1.00	1.00	480
NonDemented	0.76	0.60	0.67	480
VeryMildDemented	0.57	0.65	0.61	480
accuracy			0.76	1920
macro avg	0.76	0.76	0.76	1920
weighted avg	0.76	0.76	0.76	1920

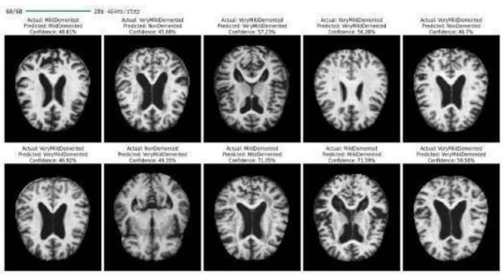

Fig 6: Output of ResNet50 model

The model had an accuracy of 76%, performing exceptionally well with the Moderate Demented class (F1-score: 1.0), but performing poorly with Very Mild Demented and Non demented classes. Misclassifications were common among these very close stages.

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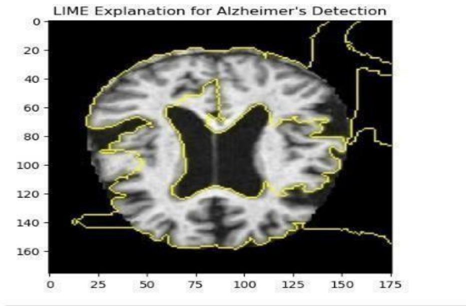

Fig 7 : LIME

The LIME visualization emphasizes important brain regions impacting the model's Alzheimer's predictions, especially regions with structural alterations. These explainable features demonstrate the model is making decisions based on medically important patterns.

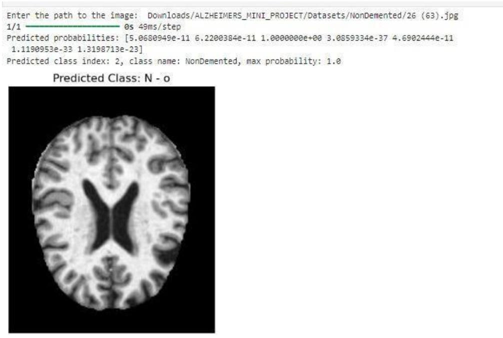

Fig 8 : New dataset passed to test the models knowledge

The model was sure that its prediction is that the brain scan is of a Non Demented person with 100% probability. The model is highly sure that there is no sign of Alzheimer's in this MRI scan.

CONCLUSION & FUTURE WORK

The goal of the current research was to create an early diagnosis system of Alzheimer's disease based on deep learning from brain MRI scans. Different CNN models like an in-house model and pre-trained models like ResNet50, VGG16, VGG19, InceptionV3, Xception, and DenseNet169 were experimented with.

Task-specific architecture of the tailor-made CNN achieved the best accuracy of 99%, which is a testament to the superiority of task-specific architectures. DenseNet169 and InceptionV3 were good, while ResNet50 achieved comparatively lower scores of 74%. LIME was used for interpretability and provided transparency to the model's predictions.

Finally, task-specific CNNs and models like DenseNet169 offer robust solutions to Alzheimer's classification problems. Future research can investigate 3D CNNs, heterogeneous data sets, and ensemble techniques to offer more accurate outcomes. Use of longitudinal imaging data can also allow for more accurate disease progression tracking. Integration with electronic health records and clinical metadata can offer more accurate predictions. Cloud deployment would make it real-time available to clinicians. Emphasis on light models can also allow for mobile and off-line diagnostic tools.

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