Alzheimer's Disease Prediction

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I. *Summary/Introduction to the Problem*

Alzheimer's disease (AD) is a progressive, non-reversible neurodegenerative disorder that significantly affects the elderly population, with no current cure available. Early detection is crucial, as it enables more effective symptom management and care planning. Magnetic resonance imaging (MRI) is widely used in AD diagnosis due to its ability to capture detailed brain structures.

The hippocampus plays a key role in episodic and spatial memory, and in Alzheimer's disease (AD), it undergoes shrinkage alongside the cerebral cortex, while the brain's ventricles enlarge. This atrophy leads to cell loss and damages synapses and neuron terminals [1].

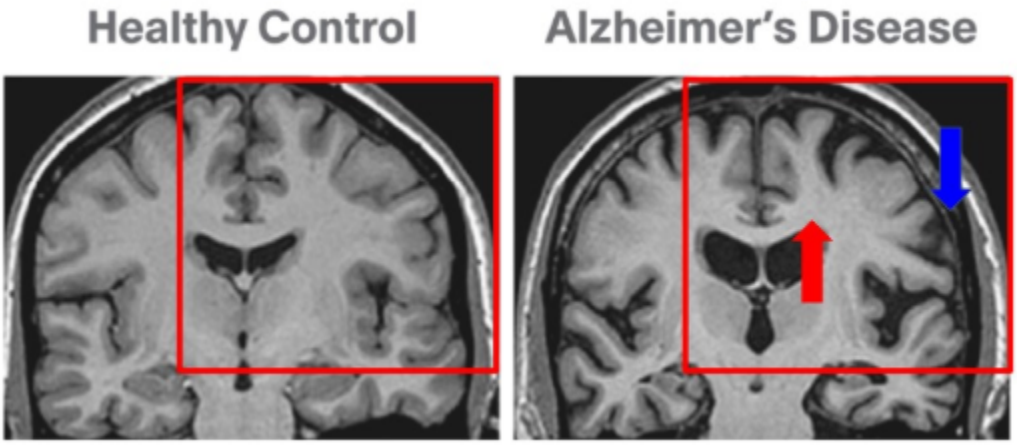

Fig. 1: Difference between healthy control and Alzheimer's Disease [1]

In this project, I address the challenge of classifying Alzheimer's stages using a dataset from the Alzheimer's Disease Neuroimaging Initiative (ADNI) MRI collection (Fig. 2), consisting of over 11,519 brain images [2]. In the project I utilized the Base Model of EfficientNetV2B0 with custom classification layers, and simplified CNN model. The model was trained for multi-class classification to differentiate between four cognitive states: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. The final classification layer contains four neurons with softmax activation to enable multi-class classification across the four Alzheimer's stages. The proposed methods demonstrated promising results, achieving up to 99% training accuracy in multi-class classification.

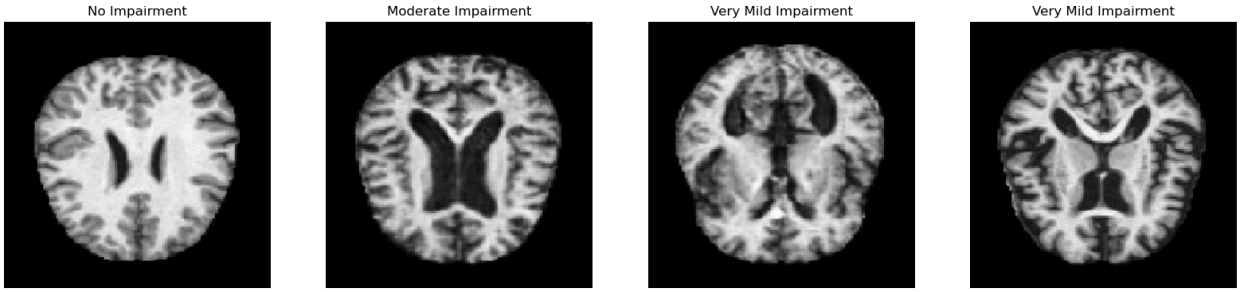

Fig. 2: Sample MRI images from each class in the dataset

II. *Introduction/Position of Our Project in this Context: Our Goals*

The primary objective of this project is to develop and evaluate a deep learning-based classification system capable of identifying four levels of cognitive impairment: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment.

Two distinct architectures were tested: 1) a custom sequential CNN model and 2) a simplified EfficientNetV2B0-based model with added dense and dropout layers for regularization and performance enhancement. The project also incorporates data augmentation techniques, careful train-validation-test splitting, and categorical image generators to ensure robustness.

III. *Body and Methodology*

3.1 Dataset/Data Demographics

For this project, I utilized a subset of the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, which provides a large collection of brain MRI scans designed to support research on Alzheimer's disease and related neurodegenerative conditions. The dataset includes structural imaging data alongside clinical and cognitive assessments. It serves as a reliable resource for investigating the progression of Alzheimer's disease and evaluating diagnostic models using imaging-based features.

Dataset comprises 10,240 training images (Fig. 3) and 1,279 testing images (Fig. 4), each labeled with one of four cognitive conditions: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment. These images were evenly distributed across classes in the training set, with 2,560 samples per class, to ensure balanced learning and mitigate bias.

Fig. 3: The Amount of Images in Training Dataset

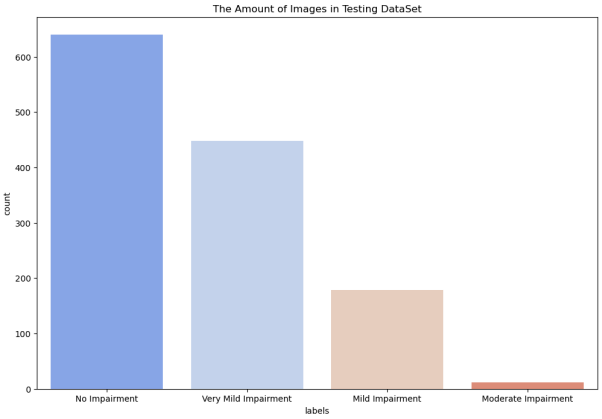

Fig. 4: The Amount of Images in Testing Dataset

To prepare the dataset, images were organized into structured directories and labels were extracted from folder names. The training dataset was further split into training and validation sets (80/20 ratio) using stratified sampling to preserve class proportions. Data augmentation techniques were applied to enhance generalization, and all images were resized to 224×224×3 to fit the input requirements of the deep learning models. The testing dataset, however, remains imbalanced, which is acknowledged as a factor in performance evaluation.

3.2 Proposed Model

The EfficientNetV2B0-based model was implemented using the Keras deep learning framework. The model includes approximately 13.9 million total parameters, of which 13.8 million are trainable. The network begins with the pre-trained EfficientNetV2B0 base (excluding the top layer), followed by a flattening operation, a dense layer with 128 neurons and ReLU activation, a dropout layer (rate = 0.4) to reduce overfitting, and a final dense layer with 4 output neurons using softmax activation for multi-class classification.

To optimize performance and training stability, I compiled the model with the Adamax optimizer using a reduced learning rate of 0.0001 and employed categorical cross-entropy as the loss function, suitable for multi-class classification tasks. The model was evaluated using accuracy as the key metric.

During training, early stopping was implemented with a patience of 4, monitoring validation loss to prevent overfitting and restore the best weights once training plateaued. This regularization technique helps ensure optimal generalization performance on unseen data.

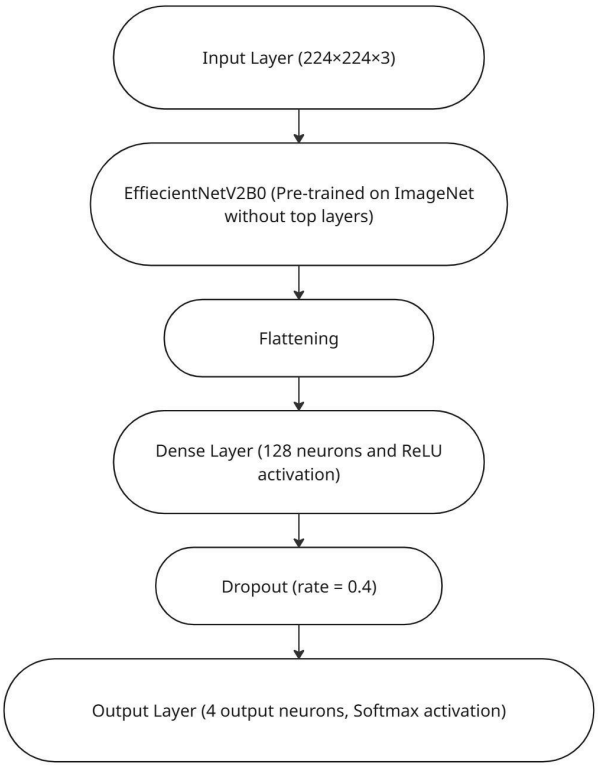

Fig. 5: EfficientNetV2B0 Model Summary

IV. *Experiment Results and Discussion*

4.1 Training and Evaluation Parameters

In this project, I conducted multi-class classification using brain MRI images to identify stages of Alzheimer's disease. The classification task was executed using the EfficientNetV2B0 model, trained on four categories: Mild Impairment, Moderate Impairment, No Impairment, and Very Mild Impairment. The categorical cross-entropy loss function was employed, as defined in equation below:

$$\textbf{Loss} = -\sum \textbf{yi log(pi)}$$

The model was trained for 20 epochs with a batch size of 4. Early stopping with a patience of 4 was applied to prevent overfitting. Figure 6 illustrates the training and validation loss and accuracy curves, respectively, showing good learning behavior with minimal overfitting.

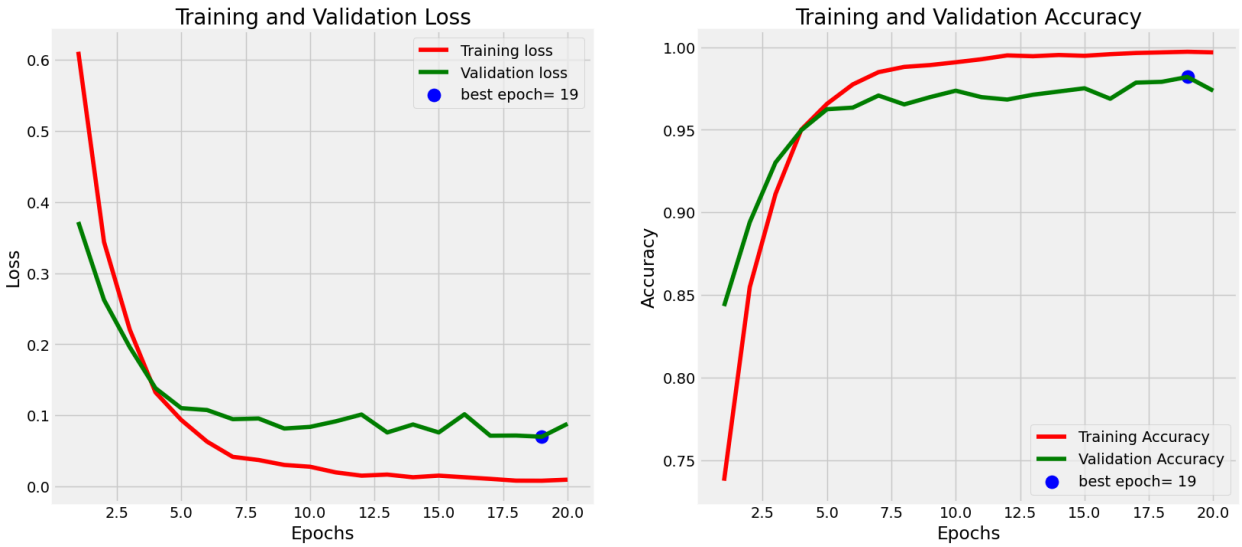

Fig. 6: Model Loss and Accuracy of EfficientNetV2B0

Training achieved a near-perfect accuracy of **99.98%** and loss of **0.0010**, while the validation set achieved **97.36%** accuracy with **0.0880** loss. The test dataset, unseen during training and validation, resulted in a **94.14%** accuracy and **0.2093** loss.

4.2 Experiment Results

The model demonstrates excellent generalization, with strong performance on unseen data. The confusion matrix (Fig. 7) shows the model's predictive strength across all classes. Notably, the model achieved 100% accuracy on Moderate Impairment cases and 98% accuracy on Very Mild Impairment. Only a slight confusion was observed between No Impairment and Very Mild Impairment.

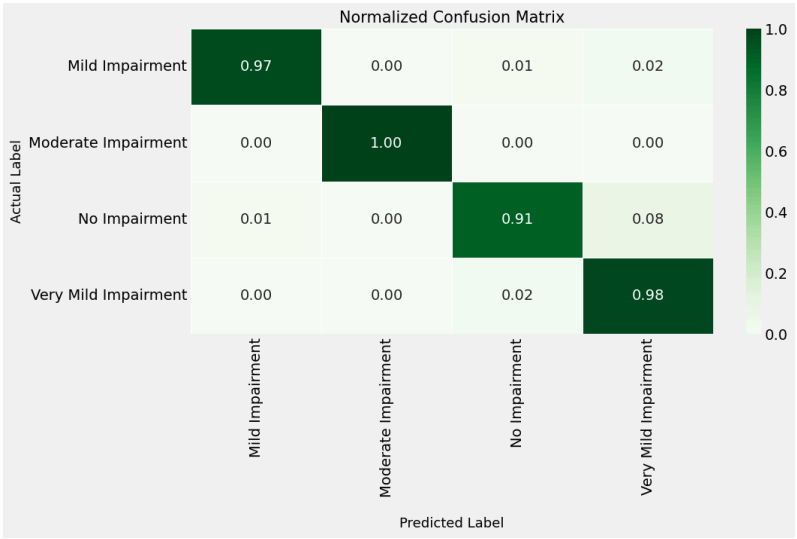

Fig. 7: Confusion Matrix

To provide a more reliable evaluation, especially given the medical context, I calculated the following standard classification metrics [3]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Fig. 8: Standard Classification Metrics [3]

Class	Precision	Recall	F1-score	Support
Mild Impairment	0.96	0.97	0.96	179
Moderate Impairment	1.00	1.00	1.00	12
No Impairment	0.98	0.91	0.94	640
Very Mild Impairment	0.88	0.98	0.93	448
Weighted Average	**0.94**	**0.94**	**0.94**	**1279**

Table 1: Detailed Classification Metrics

Overall test accuracy was **94%**, with macro-averaged precision and recall at **96%**, indicating balanced performance across all classes, including minority ones.

4.3 Discussion

The model shows strong discriminative ability in classifying Alzheimer's stages based on MRI data. The EfficientNetV2B0 architecture proves highly effective, especially in handling class imbalance and extracting relevant spatial features from the input images.

The learning curves suggest that the model is well-regularized, with early stopping effectively avoiding overfitting. However, confusion between No Impairment and Very Mild Impairment cases remains a challenge, likely due to overlapping features in early disease stages.

Future work may involve incorporating clinical metadata or multimodal input to further boost classification precision in borderline cases.

V. *Conclusion*

In this study, I developed and evaluated deep learning models for the classification of Alzheimer's disease stages using structural MRI images from the ADNI dataset. Two architectures were explored: a custom sequential CNN and an EfficientNetV2B0-based model with custom classification layers. My goal was to distinguish between four cognitive conditions: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment.

The EfficientNetV2B0 model demonstrated superior performance, achieving 99.98% training accuracy, 97.36% validation accuracy, and 94.14% test accuracy. Evaluation metrics including precision, recall, and F1-score confirmed the model's robustness across all classes. The learning curves showed stable convergence with minimal overfitting, supported by the use of early stopping and dropout regularization.

In future work, I plan to incorporate larger and more diverse datasets, explore the use of additional imaging modalities, and integrate clinical metadata to further enhance diagnostic precision, particularly for borderline cases such as Very Mild Impairment.

VI. *References*

1. Lili Lang and Ying Wang. Markov model combined with MR diffusion tensor imaging for predicting the onset of Alzheimer's disease (2023). https://www.researchgate.net/publication/375487649_Markov_model_combined_with_MR_diffusion_tensor_imaging_for_predicting_the_onset_of_Alzheimer's_disease
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4. Faizaan Fazal Khan and Goo-Rak Kwon. Comparison and analysis of CNN models to Address Skewed Data Issues in Alzheimer's Diagnosis (2024). https://koreascience.kr/article/JAKO202433843396106.page