**Progressive Deep Learning Optimization for MRI-Based Alzheimer’s Classification Using ResNet Architectures**

1. **Introduction**

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder, with early diagnosis being critical for clinical management and treatment planning. Magnetic Resonance Imaging (MRI) has emerged as a key tool in non-invasive AD detection. However, traditional diagnostic methods often lack the precision and scalability that automated machine learning models offer. In this study, we propose a progressive deep learning pipeline for classifying MRI scans into four Alzheimer’s stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The project systematically evaluates three approaches: (1) a baseline CNN trained on minimally preprocessed images, (2) a fine-tuned ResNet50 model using standard transfer learning strategies, and (3) a custom ResNet50 architecture enhanced by advanced preprocessing techniques.

1. **Materials and Methods**
   1. **Dataset Sampling and Structure**

The dataset, sourced from Kaggle’s “Augmented Alzheimer MRI Dataset V2,” comprises 40,000+ MRI scans labeled into four classes. To ensure class balance and computational manageability, the dataset was sampled into 2,500 images per class, totaling 10,000 images. These were split into training (70%), validation (15%), and test (15%) sets.

* 1. **Baseline CNN Model**

The initial model employed a basic Convolutional Neural Network (CNN) architecture. It consisted of three convolutional layers followed by max-pooling, a flattening layer, and two dense layers with ReLU and Softmax activations. Images were resized and normalized (rescale 1./255) without further preprocessing. The model was trained for five epochs using Adam optimizer and categorical crossentropy.

Results showed poor convergence, with a training accuracy of 28.65%, validation accuracy of 33.90%, and test accuracy of 25.16%. The model overfit early, lacking the representational power to discern between subtle inter-class differences in MRI scans.

* 1. **Fine-Tuned ResNet50**

In the second stage, we implemented a transfer learning approach using the ResNet50 architecture pretrained on ImageNet. The base layers were frozen initially, and a custom classification head was added: a GlobalAveragePooling layer, a dropout layer (0.3), and a dense Softmax output layer. Input images were resized to 224x224 and normalized.

The model was fine-tuned over five epochs with a reduced learning rate of 1e-5. While this approach slightly improved validation performance (val\_accuracy: 34.40%), the test accuracy remained low at 25.11%, revealing that transfer learning without domain-specific tuning or preprocessing was insufficient.

* 1. **Custom ResNet50 with Advanced Preprocessing**

The third stage introduced significant changes to both preprocessing and architecture. The preprocessing pipeline included:

* CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance contrast
* Global histogram equalization to balance intensities
* Z-score normalization to scale pixel distributions

These techniques aimed to reduce noise and standardize the intensity distribution across MRI scans.

A custom ResNet50 model was built with all layers unfrozen for end-to-end training. Additional enhancements included:

* EarlyStopping and ReduceLROnPlateau callbacks
* Mixed precision training for optimized performance
* Dropout (0.5) and L2 regularization to minimize overfitting

This model was trained over 20 epochs, yielding a training accuracy of 99.32%, validation accuracy of 84.70%, and test accuracy of 78.30%. The classification report showed macro F1-score: 0.84 and consistent precision-recall balance across all four classes.

**3. Results**

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| **Stage** | **Model** | **Train Acc** | **Val Acc** | **Test Acc** | **Macro F1** |
| 1 | Baseline CNN | 28.65% | 33.90% | 25.16% | 0.20 |
| 2 | Fine-Tuned ResNet50 | 28.79% | 34.40% | 25.11% | 0.21 |
| 3 | Custom ResNet50 + Adv. Preprocessing | 99.32% | 84.70% | 78.30% | 0.84 |

**4. Discussion** The study highlights the critical importance of tailored preprocessing and architecture adaptation for medical imaging tasks. The baseline CNN failed to capture complex spatial patterns in the MRI scans due to limited depth and lack of normalization. Even with transfer learning, ResNet50 underperformed in the absence of tailored preprocessing. Only after introducing domain-specific enhancements and a custom ResNet pipeline did the model achieve robust performance.

The dramatic leap from Stage 2 to Stage 3 validates that clinical imaging tasks demand more than generic deep learning strategies. Future improvements could include multimodal learning (e.g., combining MRI with PET or clinical scores) and model explainability via Grad-CAM.

**5. Conclusion** This project demonstrates that effective Alzheimer’s stage classification from MRI scans depends on progressive model and pipeline refinement. The custom ResNet50 combined with contrast enhancement and z-score normalization significantly outperformed traditional approaches. The findings support the adoption of domain-specific deep learning pipelines in neuroimaging and provide a scalable framework for future clinical integration.

**References**

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