Deep Learning Approaches for Alzheimer's Disease Classification Using MRI Images

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Abstract.

1 Introduction

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that affects memory, cognitive function, and daily activities. It is the most common cause of dementia, accounting for approximately 60–80% of cases globally [2]. According to recent statistics, over 50 million people are currently living with AD worldwide, and this number is expected to rise to 152 million by 2050. Early diagnosis of AD is critical to slowing the progression of the disease, enabling timely interventions that improve patients' quality of life.

Magnetic Resonance Imaging (MRI) has become an essential tool for detecting structural brain changes associated with AD. These images reveal subtle differences in brain regions such as the hippocampus and gray matter, which are commonly affected in the early stages of the disease. However, traditional methods for analyzing MRI data rely heavily on manual interpretation and handcrafted feature extraction, which are time-consuming and prone to human error.

The advent of Artificial Intelligence (AI), particularly Deep Learning (DL), has revolutionized medical imaging analysis. Deep learning models, such as Convolutional Neural Networks (CNNs), have demonstrated superior performance in feature extraction and image classification tasks. Techniques like transfer learning and attention mechanisms have further improved diagnostic accuracy, particularly in the presence of limited annotated datasets.

Despite these advancements, challenges remain:

- How can deep learning models achieve robust classification of Alzheimer's and non-Alzheimer's cases using MRI scans?
- What are the limitations of existing approaches, and how can they be addressed?
- What practical value can these models provide to clinicians for supporting early diagnosis in real-world environments?

This study contributes to addressing these challenges by conducting a systematic comparison of Machine Learning (ML) and Deep Learning (DL) techniques.

The focus is on leveraging transfer learning, attention mechanisms, and hybrid approaches to develop accurate and computationally efficient models for AD classification.

2 Related Work

Several studies have explored the use of machine learning and deep learning techniques for the classification of Alzheimer's Disease using MRI data.

Helaly et al. [2] applied transfer learning using pre-trained CNN models, such as VGG19, to classify MRI scans into multiple AD stages. Their work demonstrated the effectiveness of transfer learning in mitigating overfitting when datasets are limited. However, their approach did not explore attention mechanisms, which have been shown to improve feature localization.

Nasir et al. [4] proposed an ensemble learning approach by combining multiple CNN architectures. Their method achieved an accuracy of 90% using majority voting to reduce model variance. While effective, ensemble models often require higher computational resources, which can limit their practicality in clinical settings.

Pandiyaraju et al. [5] introduced a dual-attention-aware CNN architecture to improve classification accuracy. By focusing on critical brain regions like the hippocampus, their model achieved state-of-the-art results with an accuracy of 99.1%. This highlights the potential of attention mechanisms in enhancing the performance of deep learning models.

Jo et al. [6] explored multimodal approaches by combining MRI and PET data. Their use of stacked autoencoders and CNNs achieved accuracies exceeding 98%, demonstrating the benefits of integrating complementary imaging modalities for improved diagnostic performance.

Hybrid approaches combining machine learning and deep learning techniques have also been investigated. Khvostikov et al. [3] utilized structural and diffusion imaging data with feature extraction techniques to improve diagnostic accuracy. However, their work relied heavily on manual feature engineering, which can be time-consuming and prone to errors.

In summary, while existing methods have achieved high accuracy, they face limitations such as high computational demands, reliance on large annotated datasets, and lack of integration into real-world clinical workflows. This study builds upon these contributions by exploring transfer learning, attention mechanisms, and hybrid frameworks to develop a robust and efficient solution for AD classification.

3 Dataset Description

The Alzheimer MRI Disease Classification dataset [1] provides a structured collection of Magnetic Resonance Imaging (MRI) brain scans, categorized into four classes based on varying stages of cognitive impairment. This dataset is highly appropriate for our research as it allows for the evaluation of deep learning and machine learning methods in detecting Alzheimer's Disease (AD) across different levels of severity. By including multiple stages of the disease, the dataset facilitates a more comprehensive analysis, addressing both binary classification (Alzheimer's vs. Non-Alzheimer's) and multi-class classification tasks.

The dataset consists of grayscale 2D MRI images that represent structural brain changes associated with AD progression. Such changes are particularly visible in regions like the hippocampus and gray matter, which are critical for detecting early and subtle signs of the disease. The presence of labeled data makes it suitable for supervised learning techniques, and the class imbalance reflects real-world scenarios, further validating the dataset's applicability in clinical practice.

Figure 1 illustrates sample MRI images from the dataset, showcasing the visual differences across the four classes.

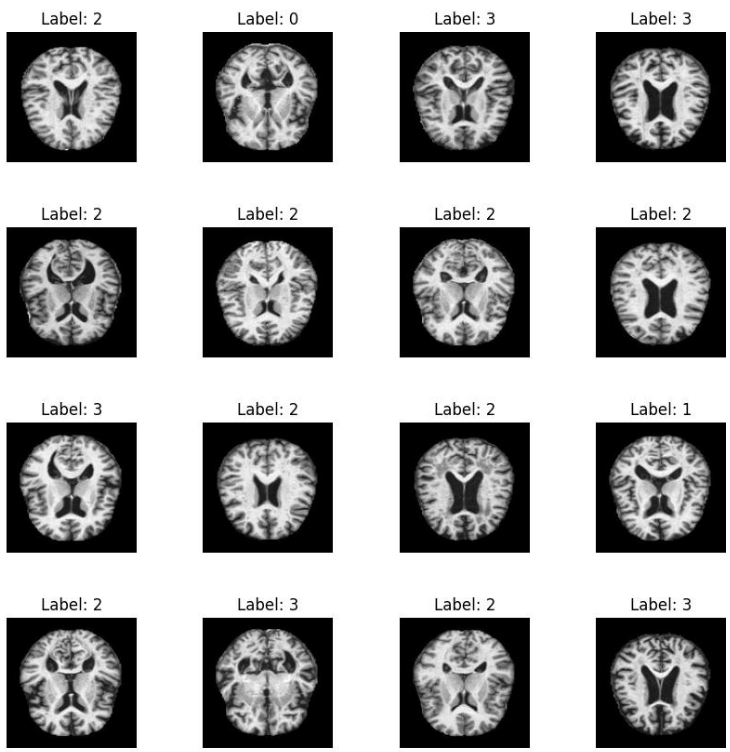

Fig. 1. Sample MRI images from the dataset.

Legend:

- Label 0: Mild Demented

– Label 1: Moderate Demented
– Label 2: Non-Demented
– Label 3: Very Mild Demented

3.1 Data Preprocessing

Before training the models, the dataset underwent the following preprocessing steps:

1. Resizing: All MRI images were resized to 128×128 pixels for uniform input dimensions.
2. Normalization: Pixel values were normalized to the range [0, 1].
3. Augmentation: To address class imbalance, data augmentation techniques such as horizontal flipping, rotation, and scaling were applied to the underrepresented classes.

3.2 Class Distribution

The dataset contains an uneven distribution of images across the four classes, as shown in Figure 2. This distribution highlights the class imbalance, with the 'Non-Demented' class containing the most samples and the 'Moderate Demented' class having the least. To address this imbalance, data augmentation techniques were applied during preprocessing.

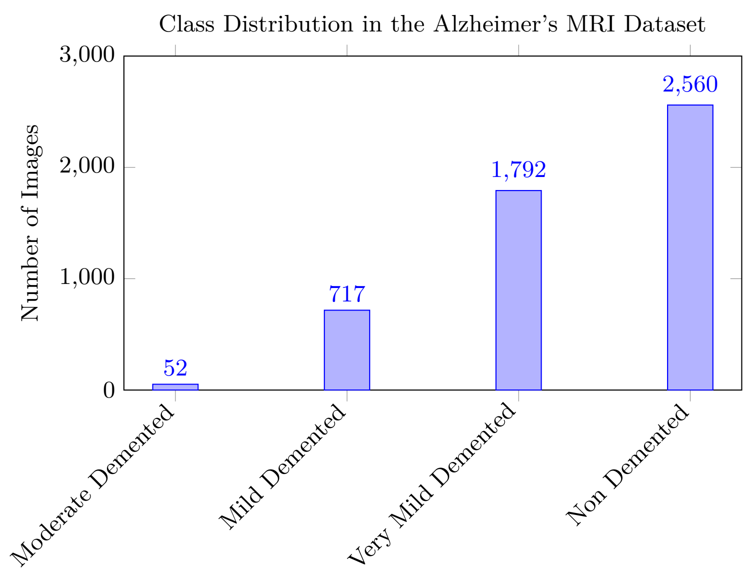

Fig. 2. Distribution of Classes in the Alzheimer's MRI Dataset.

4 Methodology

In this section, we present the analysis methods chosen for Alzheimer's Disease classification using MRI data, the tested settings, the validation strategy employed, and the parameter selection process. The methods selected include Convolutional Neural Networks (CNN) with varying architectures (standard CNN, ResNet, and VGG), as well as Support Vector Machines (SVM) for comparison purposes.

4.1 Convolutional Neural Networks (CNN)

CNNs have proven effective in image classification tasks due to their ability to automatically extract relevant features from images. We employed the following CNN-based architectures:

1. Standard CNN: A baseline CNN architecture consisting of convolutional layers, max-pooling, and fully connected layers. This method serves as a reference point for performance comparison.
2. CNN with ResNet: We utilized a Residual Network (ResNet), which incorporates skip connections to mitigate the vanishing gradient problem and facilitate training of deep networks. ResNet-18 was chosen due to its efficiency in balancing accuracy and computational cost.
3. CNN with VGG: The VGG architecture (specifically VGG-16) was implemented to explore the performance of deeper, uniform convolutional layers. This model is known for its ability to capture fine-grained spatial features in images.

Each CNN model was trained using the following settings:

- Input Dimensions: MRI images were resized to $128 \times 128 \times 1$.
- Activation Function: ReLU (Rectified Linear Unit) was used for non-linear activation.
- Optimizer: Adam optimizer with a learning rate of 1×10^{-4}.
- Loss Function: Categorical Cross-Entropy Loss.
- Batch Size: 32.
- Epochs: 50.

4.2 Support Vector Machines (SVM)

In addition to CNN-based methods, we implemented a Support Vector Machine (SVM) classifier as a traditional machine learning baseline. For SVM, the MRI images were flattened into 1D feature vectors, and a linear kernel was selected for simplicity and interpretability.

The key settings for SVM include:

- Kernel: Linear.
- Regularization Parameter (C): Tested values include $0.1, 1, 10$, with the best value determined using grid search.

4.3 Validation Strategy

To ensure the robustness of the models, we employed a 5-fold cross-validation strategy. The dataset was split into five subsets, with four subsets used for training and one subset for validation. This process was repeated five times, and the results were averaged to minimize variance and overfitting.

4.4 Parameter Selection

The selection of hyperparameters for each method was conducted as follows:

- For CNN models, hyperparameters such as learning rate, batch size, and the number of layers were fine-tuned through empirical testing and grid search.
- For SVM, the regularization parameter C was optimized using grid search with cross-validation.

4.5 Implementation Details

All experiments were conducted using Python and TensorFlow/Keras for deep learning methods. For SVM, we used the Scikit-learn library. The training and testing processes were carried out on Google Colab, leveraging GPU acceleration for CNN models.

References

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