Convolutional Neural Network-Based Stage Classification of Alzheimer's Disease Using MRI Scans

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Abstract

A convolutional neural network (CNN) framework is proposed for classifying Alzheimer's disease (AD) stages using high-resolution magnetic resonance imaging (MRI) data. The model is trained on a balanced dataset of approximately 12,000 scans, categorized into Mild Demented (MD), Moderate Demented (MoD), Very Mild Demented (VMD), Non-Demented (ND), and Healthy (H) classes. A comparative analysis of optimizers—including SGD, RMSprop, Adam, and Nadam—was conducted using a fixed learning rate of 0.001, where Adam achieved the highest classification accuracy of 99%. The model effectively differentiates between AD stages, enabling early diagnosis and informing clinical decision-making. Results underscore the critical role of optimizer selection and data diversity in developing robust CNN-based diagnostic tools.

Keywords: Alzheimer's disease, convolutional neural networks, MRI-based classification, Adam optimizer, diagnostic accuracy, neurodegenerative disorders.

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1 Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative condition marked by cognitive decline, memory loss, and behavioural deterioration, primarily affecting the elderly. Its global prevalence is projected to exceed 130 million by 2050, underscoring the critical need for early and accurate diagnostic strategies [1]. The economic burden of delayed AD diagnosis further reinforces the need for timely intervention [10]. From a sociocultural perspective, AD also poses challenges related to identity and caregiving, as noted in contemporary narrative research [11]. Traditional diagnosis, relying on clinical assessment, often fails to detect early-stage AD, delaying timely intervention. Magnetic Resonance Imaging (MRI) offers a non-invasive method for visualising neurodegenerative changes, particularly in regions such as the hippocampus and cortex. Recent studies have shown promise in applying deep learning models, especially Convolutional Neural Networks (CNNs), to MRI data for AD diagnosis [13, 14]. Building on this foundation, this study proposes a CNN-based framework for stage-wise classification of AD using a large, balanced MRI dataset. The model is evaluated using various optimizers, and its performance demonstrates high diagnostic accuracy across five AD progression classes. Assistive software tools designed to stimulate cognitive memory in early-stage AD patients also complement such diagnostic frameworks [2].This approach highlights the role of AI in supporting clinical decision-making and improving early detection of neurodegenerative disorders.

2 Related Work

Recent advances in medical imaging and artificial intelligence have facilitated the development of automated tools for Alzheimer's disease (AD) diagnosis. Basaia et al. [13] employed a CNN model to classify AD from structural MRI data, achieving high accuracy. Similarly, Zhang et al. [14] applied Support Vector Machines (SVMs) on longitudinal MRI scans to differentiate AD from healthy subjects. Rahat et al. [15] explored deep learning models including DeepLabv3 and U-Net for FLAIR-based brain anomaly segmentation, highlighting the importance of architectural choice and data balancing in neuroimaging tasks. Melchiorri et al. [4] underscored the role of neuroinflammation and suggested that integrating imaging with molecular pathways could enhance diagnostic precision.

Additionally, Wang et al. [5] identified urine formaldehyde as a potential early-stage biomarker, reinforcing the value of non-invasive diagnostic approaches. These studies collectively demonstrate the efficacy of AI-driven models and biomarker-informed imaging in improving AD classification. Additionally, emotional and empathy-based assessments have been explored to distinguish AD from other dementia types [3]. Building on these efforts, this study presents a CNN framework trained on a large, multi-stage MRI dataset for accurate and scalable classification of AD progression.

3 Methodology

3.1 Dataset

This study employs a curated dataset of approximately 12,000 high-resolution MRI scans for Alzheimer's disease (AD) classification. The images are categorized into five classes: Mild Demented (MD), Moderate Demented (MoD), Very Mild Demented (VMD), Non-Demented (ND), and Healthy (H), representing various stages of AD progression. Class balance was maintained to prevent model bias and enhance generalization. The high-resolution nature of the scans enables detailed feature extraction, particularly for early-stage detection. The diversity and volume of this dataset provide a strong foundation for training a deep learning model capable of robust stage classification. Representative samples from each class are shown in Fig. 1.

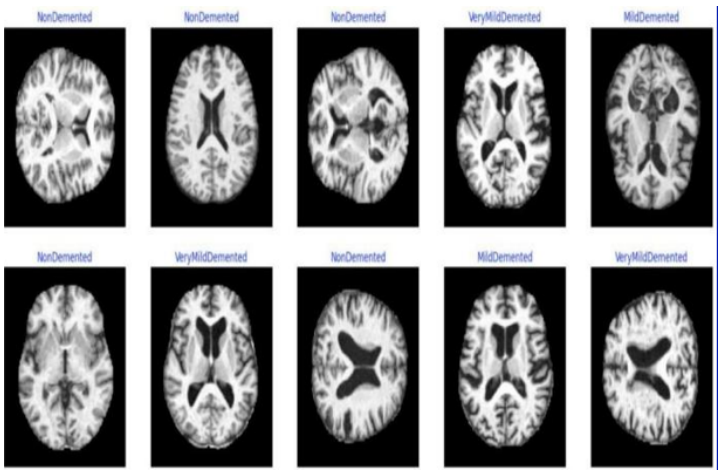

Figure 1 Sample images from the curated MRI dataset used for AD stage classification.

3.2 Image Preprocessing

To enhance model generalization and accuracy, a comprehensive preprocessing pipeline was implemented, incorporating both data augmentation and color-space transformations. Augmentation techniques such as random rotations ($\pm 10^{\circ}$), translations (10%), scaling (0.9–1.1), horizontal flipping, elastic deformation, and brightness/contrast adjustments were applied to simulate anatomical and acquisition variability. Gaussian noise was also introduced to improve robustness against imaging artifacts. This augmentation strategy, visualized in Fig. 2, enriched the dataset without increasing storage.

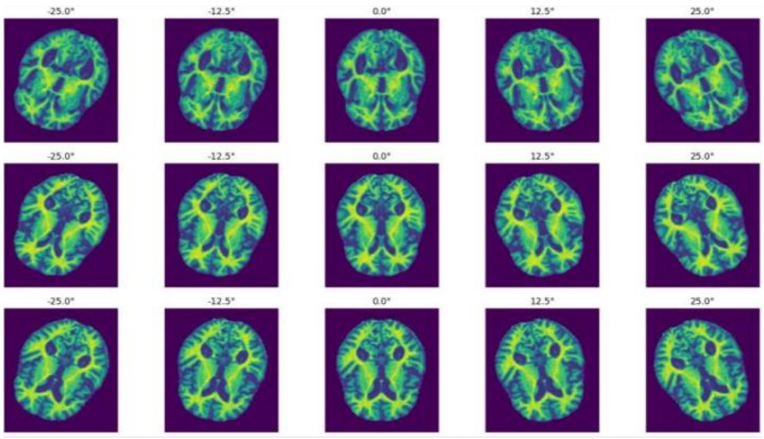

Figure 2 Data augmentation via rotational, translational, and elastic transformations applied to MRI scans.

In parallel, MRI scans were converted to grayscale to emphasize structural features, and further transformed into HSV, LAB, and YCbCr color spaces to enhance contrast and luminance-based feature extraction. These transformations facilitate the detection of subtle pathological patterns relevant to Alzheimer's classification. As illustrated in Fig. 3, multi-space encoding contributed to improved learning of cortical and subcortical abnormalities. This dual preprocessing approach ensured high model sensitivity to AD-specific anatomical variations, particularly in early-stage cases where structural changes are often subtle. Recent advancements in pose-aware 3D deep learning frameworks [12] may further enhance spatial encoding in future AD imaging models.

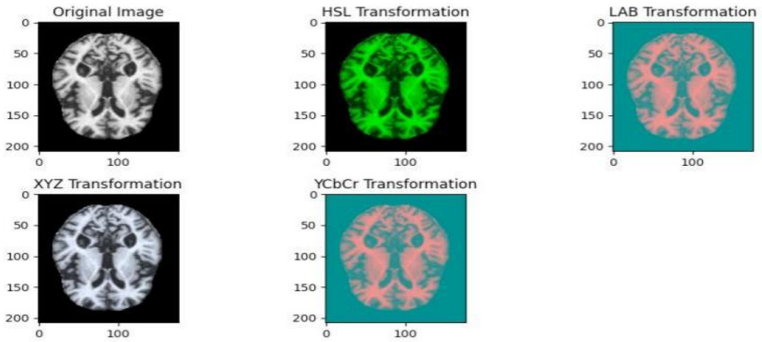

Figure 3 Comparative analysis of color-space transformations used for feature enhancement in MRI-based AD classification.

3.3 Model Architecture

A custom convolutional neural network (CNN) was developed to classify MRI scans into five Alzheimer's disease (AD) stages: Mild Demented, Moderate Demented, Very Mild Demented, Non-Demented, and Healthy. Input images were resized to 150×150 pixels with three channels and normalized via a rescaling layer. The architecture consists of two convolutional blocks, each comprising a convolutional layer with 3×3 filters followed by max pooling. The first block uses 32 filters, and the second uses 64, progressively capturing low-level to abstract spatial features. The extracted features are flattened and passed to a fully connected dense layer with 300 neurons, followed by a dropout layer to mitigate overfitting. The final output layer contains five neurons with softmax activation to predict the respective class probabilities. In total, the model comprises approximately 24.9 million trainable parameters. This architecture is optimized for extracting structural and textural features from MRI data and demonstrates strong potential for stage-wise classification in AD diagnosis.

4 Performance Analysis by Class

The proposed CNN model demonstrated consistently high classification performance across all five categories: Mild Demented, Moderate Demented, Very Mild Demented, Non-Demented, and Healthy. Precision, recall, and F1-scores ranged between 0.98 and 1.00 for all classes, as detailed in Table 1. The best performance was observed in the Moderate Demented and Non-Demented categories, both achieving near-perfect scores.

Very Mild Demented, often challenging due to subtle pathology, was classified with a precision of 0.99 and recall of 0.98, indicating the model's sensitivity to early-stage AD indicators. Healthy controls also yielded high classification accuracy with balanced precision and recall of 0.99. These results confirm the effectiveness of the proposed architecture in distinguishing AD stages and unaffected individuals. The confusion matrix illustrating the class-wise distribution of predictions is shown in Fig. 4, while Fig. 5 compares training and validation accuracy and loss trends across epochs.

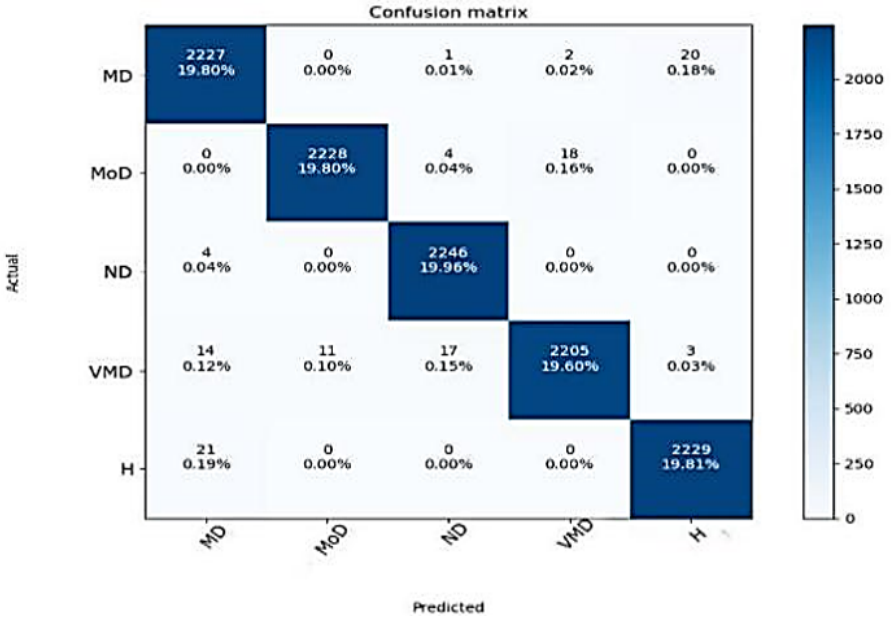

Figure 4 Confusion matrix representing classification performance across all AD stages and the healthy class.

5 Results and Analysis

The CNN model achieved high performance across all Alzheimer's disease (AD) stages, with precision, recall, and F1-scores ranging from 0.98 to 1.00.

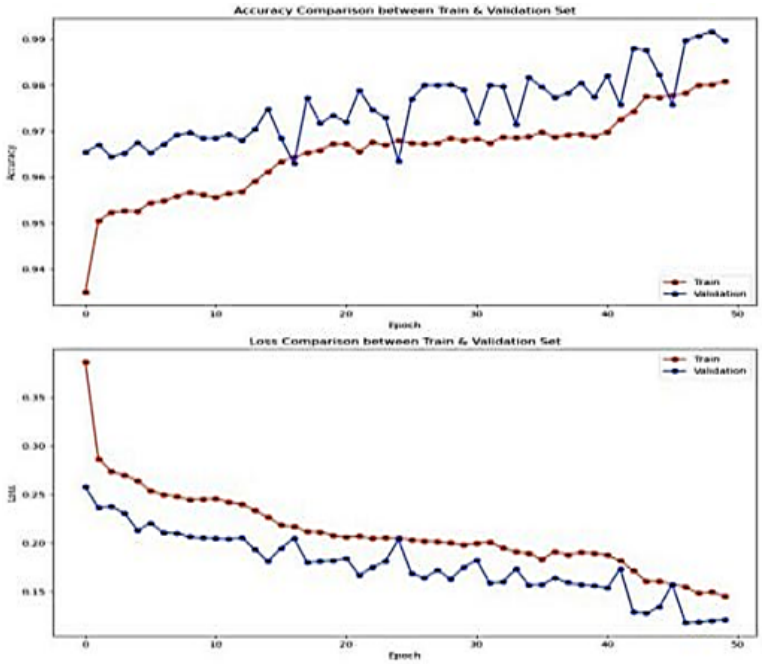

Figure 5 (A) Accuracy comparison between training and validation sets. (B) Loss comparison between training and validation sets.

Table 1 summarizes the detailed classification metrics for each category. These results validate the model's robustness in distinguishing between multiple stages of AD and healthy controls.

Table 1 Classification report of the CNN model across all categories.

Class	**Precision**	**Recall**	**F1-score**	**Support**
Mild Demented (0)	0.98	0.99	0.99	2250
Moderate Demented (1)	1.00	0.99	0.99	2250
Non-Demented (2)	0.99	1.00	0.99	2250
Very Mild Demented (3)	0.99	0.98	0.99	2250
Healthy (4)	0.99	0.99	0.99	2250
Accuracy			0.99	11250
Macro avg	0.99	0.99	0.99	11250
Weighted avg	0.99	0.99	0.99	11250

The Adam optimizer with a learning rate of 0.001 was found to be the most effective among the tested optimizers (SGD, RMSprop, Nadam), yielding an overall classification accuracy of 99%.

The integration of color-space transformations and aggressive data augmentation contributed significantly to this performance by enhancing feature discrimination and reducing overfitting. These findings support the viability of CNN-based MRI analysis as a diagnostic aid for early detection and progression monitoring of AD. The methodology demonstrated here may be generalized to other neuroimaging-based classification tasks in clinical decision support systems.

6 Conclusion

This study presents a CNN-based framework for multi-stage classification of Alzheimer's disease (AD) using MRI data. The model integrates convolutional layers, data augmentation, and color-space transformations to achieve a classification accuracy of 99% across five diagnostic categories. Among the evaluated optimizers, Adam with a learning rate of 0.001 demonstrated superior performance. The results highlight the potential of deep learning in supporting early and accurate AD diagnosis through non-invasive imaging. The proposed methodology offers a scalable, data-driven approach that may be extended to other neurodegenerative conditions. Future work will explore the integration of transfer learning to reduce training time and improve generalization, particularly across diverse demographic groups. Embedding this model into clinical decision-support systems could further enable early intervention and longitudinal patient monitoring in real-world healthcare settings.

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Biography

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