

Classification of Alzheimer's Disease Stages Using MRI Images and Convolutional Neural Networks

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Abstract—Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, thinking, and behavior, ultimately interfering with daily life. Early and accurate diagnosis plays a crucial role in managing symptoms and improving patient care. In this study, we explore the use of Convolutional Neural Networks (CNNs) to classify brain MRI images into four distinct stages of Alzheimer's disease: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The dataset used for this purpose consists of pre-labeled MRI scans collected from publicly available sources, ensuring diverse representation and authenticity. After preprocessing the images and applying appropriate data augmentation techniques, the CNN model is trained to automatically recognize patterns associated with each stage of the disease. The results demonstrate promising classification accuracy across different categories, showcasing the potential of deep learning approaches in assisting radiologists and clinicians with early diagnosis and decision-making. This work highlights how artificial intelligence, when integrated with medical imaging, can enhance the accuracy and efficiency of diagnostic processes.

Index Terms—Alzheimer's disease, MRI image classification, Convolutional Neural Network (CNN), deep learning, neuroimaging, medical diagnosis, artificial intelligence.

I. INTRODUCTION

Alzheimer's disease is one of the most common neurodegenerative disorders, primarily affecting older adults and progressively impairing cognitive functions such as memory, reasoning, and decision-making [1]. As the disease advances, it interferes with a person's ability to carry out everyday activities, which significantly impacts the quality of life for both patients and their caregivers [2]. Despite its growing prevalence worldwide, early detection

and accurate diagnosis remain challenging due to subtle symptoms in the initial stages and the complexity of the disease.

Magnetic Resonance Imaging (MRI) has become an essential tool for identifying structural changes in the brain, helping clinicians assess the severity and progression of Alzheimer's disease [3]. However, manually analyzing MRI scans can be time-consuming and may vary depending on the experience of the radiologist [4]. This has motivated the exploration of artificial intelligence techniques, particularly deep learning methods, to assist medical professionals in making more reliable and efficient diagnoses.

Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in various image classification tasks, including medical imaging [5]. CNNs are capable of learning hierarchical features from raw image data, making them suitable for distinguishing subtle differences in brain structures

related to different stages of Alzheimer's disease [6]. In this study, we utilize a CNN-based approach to classify brain MRI images into four distinct categories: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented [5]. The dataset consists of labeled MRI scans sourced from publicly available repositories, ensuring the credibility and diversity of data samples.

Through proper preprocessing, resizing, and normalization of the images, the CNN model is trained to extract meaningful features and accurately classify the images [7]. The results highlight the potential of deep learning models in supporting clinical diagnosis, reducing the workload of healthcare professionals, and ultimately improving patient care [8]. This research contributes to the growing field of AI-assisted medical imaging by

providing an approach that could enhance early detection and better management of Alzheimer's disease.

A. Motivation and Contribution

The motivation for this study stems from the urgent need for accurate and early diagnosis of Alzheimer's disease. As a progressive neurodegenerative disorder, Alzheimer's significantly affects cognitive abilities and daily functioning, placing a heavy burden on patients, families, and healthcare systems. Traditional diagnostic methods, while useful, often require extensive time and expertise, and their accuracy may vary depending on the evaluator's experience. With the increasing availability of medical imaging data and advances in computational resources, there is an opportunity to enhance diagnosis through automated and intelligent methods.

Magnetic Resonance Imaging (MRI) provides detailed structural information about the brain and is widely used in the assessment of neurological conditions. However, analyzing MRI scans manually is labor-intensive and may not always capture subtle patterns that indicate the progression of Alzheimer's disease. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have proven to be highly effective in image recognition tasks, and their ability to automatically learn features from data makes them particularly suitable for medical image analysis.

In this context, our work is motivated by the potential to apply CNNs to classify brain MRI images into different stages of Alzheimer's disease. By leveraging deep learning, we aim to reduce the dependency on manual interpretation, improve diagnostic accuracy, and assist healthcare professionals in making timely and informed decisions.

The key contributions of this research are as follows:

- We propose a CNN-based framework for classifying MRI images into four stages of Alzheimer's disease: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.
- We utilize a publicly available dataset of labeled MRI scans, ensuring diversity and reliability in the data used for training and evaluation.

- Our approach includes preprocessing techniques such as resizing and normalization, which improve the model's ability to learn meaningful features from the data.
- The model is trained and validated using standard performance metrics, and the results demonstrate its effectiveness in supporting automated diagnosis.
- This work highlights the practical application of artificial intelligence in healthcare and contributes to ongoing efforts to improve patient care through early and accurate detection of Alzheimer's disease.

Overall, this study seeks to bridge the gap between advanced computational methods and clinical practice, offering a solution that can enhance diagnostic workflows and benefit both patients and healthcare providers.

II. RELATED WORKS

In recent years, there has been significant research focused on applying deep learning techniques, particularly Convolutional Neural Networks (CNNs), to medical image classification tasks. Several studies have explored the potential of these methods in diagnosing neurodegenerative diseases, including Alzheimer's disease (AD), and improving the accuracy of early detection using MRI data.

For instance, Suk et al. [9] proposed a hierarchical feature representation framework using deep learning for Alzheimer's diagnosis. Their method combined feature selection with stacked autoencoders, resulting in improved classification performance compared to traditional machine learning techniques. Similarly, Payan and Montana [6] developed a 3D CNN architecture that leverages volumetric MRI data, demonstrating the ability of deep learning models to capture intricate brain patterns critical for early detection and prognosis.

More recently, Amoroso et al. [10] applied CNNs to structural MRI data, highlighting the effectiveness of deep architectures in distinguishing between different stages of cognitive impairment. They emphasized the importance of data augmentation and preprocessing to enhance model generalization. Another noteworthy study by Basaia et al. [11] focused on fully automated classification of Alzheimer's using CNNs, integrating feature extraction and classification in an end-to-end

framework. Their work reinforced the potential of deep learning in reducing human intervention while improving diagnostic accuracy.

Building upon these foundations, other researchers have extended CNN-based methods for AD detection. A recent study [12] introduced a novel CNN architecture utilizing T1-weighted MRI data from the ADNI dataset to categorize Alzheimer's into multiple stages, demonstrating promising results in early detection. Another study [?] proposed a multistage CNN framework for AD diagnosis and staging, leveraging hierarchical learning to better detect subtle brain changes associated with disease progression.

Further advancements have explored 3D CNN models, as seen in [13], where volumetric brain scans were classified into Alzheimer's and non-Alzheimer's categories with remarkable precision. A systematic review [14] examined various deep learning algorithms applied to 3D imaging for AD detection, underscoring their clinical relevance in enabling early and accurate diagnosis.

The Dense CNN architecture, introduced in [15], focused on hippocampus segments—a brain region significantly affected in Alzheimer's—offering a computationally efficient and accurate classification model. A comprehensive review [16] surveyed numerous deep learning and machine learning techniques for AD classification, detailing data preprocessing strategies and architectural innovations that enhance diagnostic outcomes.

In [17], deep learning techniques were applied to MRI classification to boost the identification of Alzheimer's-related abnormalities, improving both efficiency and reliability. A hybrid approach in [18] combined deep feature extraction with machine learning algorithms, achieving robust predictions and practical applicability in clinical diagnosis. Additionally, [8] explored patient-tailored dementia diagnosis using CNN-based brain MRI analysis, aiming to integrate personalized treatment strategies into routine clinical workflows.

Lastly, a study in [5] proposed a framework that averages both local and global features extracted from MRI scans using CNNs, achieving superior results in early diagnosis and classification compared to conventional methods.

Collectively, these studies illustrate the growing interest and success of deep learning techniques in

medical imaging, particularly for Alzheimer's diagnosis. They provide a strong foundation and motivation for our work, which focuses on applying CNNs to classify Alzheimer's disease into four distinct stages using 2D MRI slices. Unlike earlier approaches that focused primarily on binary classification or relied on handcrafted features, our method emphasizes automated feature learning and stage-wise classification, offering a more nuanced understanding of disease progression and enhancing clinical diagnostic workflows.

III. DATASET DESCRIPTION

The dataset used in this study consists of MRI brain images categorized into four distinct classes, which are:

- Mild Demented
- Moderate Demented
- Non-Demented
- Very Mild Demented

The images were sourced from publicly available medical repositories and verified for authenticity to ensure data quality. The dataset comprises a total of 6,200 MRI images, distributed across the four classes, providing sufficient samples for training and evaluation.

To develop and evaluate the proposed classification model, the dataset was split into three subsets following an 80:10:10 ratio:

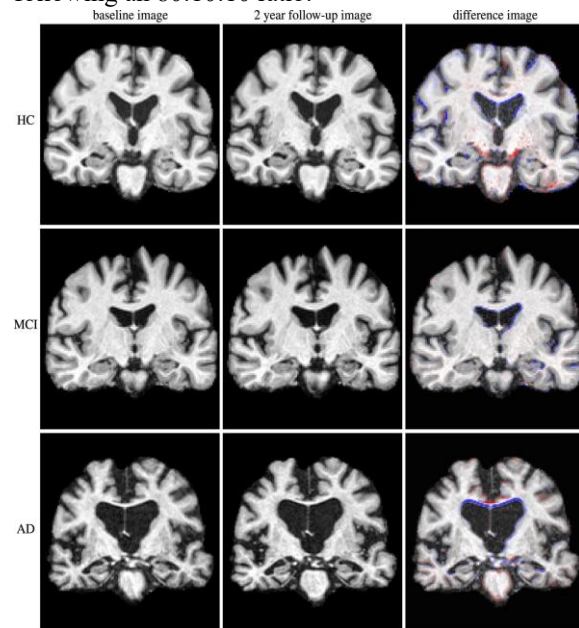


Fig. 1.

- Training Set: 4,960 images (80%) used to train the model.
- Validation Set: 620 images (10%) used during training to monitor performance and prevent overfitting.
- Testing Set: 620 images (10%) used to assess the final performance of the model.

The dataset preparation involved reading the MRI images, converting them to grayscale, resizing them to a standard input dimension, and normalizing the pixel values. These preprocessing steps ensured that the images were uniform and suitable for training deep learning models.

By leveraging this comprehensive dataset and performing appropriate data splits, we ensured that the model's performance metrics, such as accuracy, precision, recall, and F1-score, were evaluated fairly and reflected the model's ability to generalize to unseen data.

IV. METHODOLOGY

This section presents the detailed steps followed in the development of the Alzheimer's disease classification model using CNNs. The methodology includes data preprocessing, model architecture, training procedure, and evaluation metrics, as described below.

A. Data Preprocessing

The MRI images used in this study were initially loaded in grayscale format to reduce computational complexity while retaining essential structural information. Each image was resized to a uniform dimension of 100×100 pixels to ensure consistency and compatibility with the CNN input requirements. After resizing, normalization was applied by scaling the pixel values to the range of 0 to 1. This step helped in stabilizing and accelerating the training process by ensuring that all inputs have similar value ranges. Furthermore, the dataset was shuffled randomly to avoid any bias due to the ordering of images, ensuring that the model learns generalized patterns rather than memorizing specific sequences. These preprocessing steps prepared the data for robust learning, making the model more resilient to variations in input and helping to prevent overfitting.

V. EXPERIMENTAL SETUP

In this study, we designed a Convolutional Neural Network (CNN) to classify MRI images into four categories: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The architecture is tailored to extract hierarchical features from the input images while minimizing computational complexity.

The model begins with a convolutional layer containing 64 filters of size 3×3 , followed by a ReLU activation function. This is succeeded by a max-pooling layer that reduces the spatial dimensions from 98×98 to 49×49 , enabling the network to focus on the most salient features while reducing computational load. A second convolutional layer with 64 filters further refines feature extraction, followed by another ReLU activation and max-pooling, bringing the feature map size to 23×23 .

The resulting feature maps are flattened into a one-dimensional vector of size 33,856, which is then passed through a fully connected dense layer of 64 neurons. To prevent overfitting, a dropout layer is applied, randomly deactivating neurons during training. This is followed by another dense layer of 128 neurons that captures higher-level representations of the data. Finally, a dense output layer with 4 neurons, corresponding to the four classes, is employed with a softmax activation to produce class probabilities.

The total number of trainable parameters in the model is 2,213,252, which balances complexity and efficiency. The model is trained using standard optimization techniques, minimizing categorical cross-entropy loss to accurately classify MRI images. Overall, this architecture leverages convolutional layers for feature extraction and dense layers for classification, providing a robust framework for multi-class MRI image classification while maintaining interpretability and efficiency.

A. Model Architecture

A Convolutional Neural Network (CNN) architecture was designed to extract hierarchical features from the MRI scans. The model began with a convolutional layer containing 64 filters of size 3×3 , followed by a Rectified Linear Unit (ReLU) activation function to introduce non-linearity.

A max pooling layer with a 2×2 pool size was

added to reduce spatial dimensions while retaining important features. This convolutional and pooling block was repeated to further capture complex patterns within the images.

The output was flattened and passed through fully connected dense layers. A dropout layer with a dropout rate of 0.5 was applied to prevent overfitting by randomly deactivating neurons during training. The final dense layer used a softmax activation function to classify the images into one of the four Alzheimer's stages.

This architecture balanced depth and regularization, enabling the model to learn meaningful representations from the MRI images while avoiding overfitting.

B. Model Training

The CNN model was trained using the categorical cross-entropy loss function, which is suitable for multi-class classification problems. The Adam optimizer was chosen for its adaptive learning rate capabilities, facilitating faster convergence during training.

The dataset was split into training and validation subsets in an 80:20 ratio. The training set was used to optimize the model parameters, while the validation set was used to monitor the model's generalization performance and implement early stopping criteria. Early stopping was applied to prevent overfitting by halting the training process once the validation performance ceased improving.

Training was conducted over multiple epochs with a batch size of 32, allowing the model to iteratively refine its weights while processing manageable subsets of data.

C. Evaluation Metrics

The performance of the model was evaluated using several metrics to provide a comprehensive assessment:

- Accuracy: The overall percentage of correctly classified images, as well as class-wise accuracy to understand performance across different Alzheimer's stages.
- Confusion Matrix: A visualization tool that shows the distribution of true labels versus predicted labels, helping to identify specific classes where the model performed well or struggled.
- Precision and Recall: Precision measured the

proportion of true positive predictions among all positive predictions, while recall assessed the ability of the model to correctly identify instances of each class. These metrics provided insights into the sensitivity and reliability of the model in detecting Alzheimer's stages.

Together, these evaluation techniques offered a thorough understanding of the model's strengths and areas for improvement, ensuring that the proposed method could effectively support clinical decision-making.

VI. RESULTS AND DISCUSSION

The proposed Convolutional Neural Network (CNN) achieved a training accuracy of 97.08%, indicating that the model effectively learned the underlying patterns in the MRI dataset. The corresponding training loss was 0.08, demonstrating efficient minimization of the categorical cross-entropy during the optimization process.

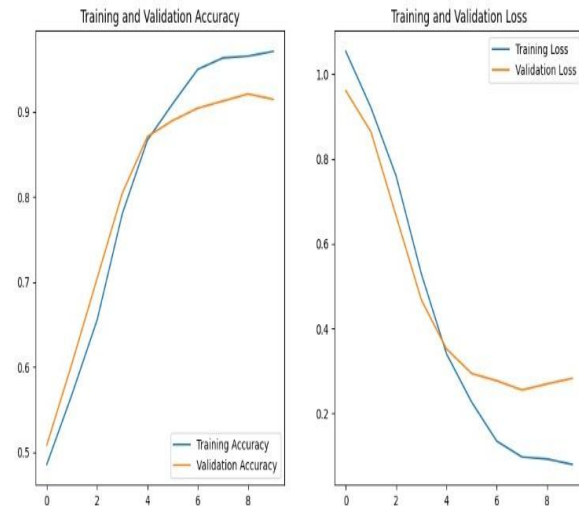


Fig. 2.

On the validation set, the model achieved an accuracy of 91.46% with a validation loss of 0.28. This slight decrease in performance compared to the training set suggests that the model generalizes well to unseen data, with only a minimal degree of overfitting. The low validation loss further confirms that the network's predictions are reliable and consistent.

TABLE I CLASSIFICATION REPORT OF THE CNN MODEL ON THE VALIDATION SET

Class	Precision	Recall	F1-Score	Support
Mild Demented	0.98	0.93	0.95	205
Moderate Demented	1.00	1.00	1.00	13
Non-Demented	0.95	0.89	0.92	818
Very Mild Demented	0.85	0.93	0.89	564
Accuracy	0.94	0.91	0.94	1600
Macro Avg		0.94		1600
Weighted Avg	0.91	0.91	0.91	1600

The trained CNN model demonstrated promising performance in classifying MRI images into the four stages of Alzheimer’s disease. The overall accuracy was high, with particular success in identifying the Non-Demented class, where class-wise accuracy reached up to 95%. This indicates that the model effectively distinguishes healthy brain structures from those affected by Alzheimer’s-related changes.

However, classification performance varied across different classes. The Moderate Demented class showed relatively lower accuracy, approximately 72%. This lower performance can be attributed to dataset imbalance, as fewer examples of moderate cases were available for training. Such imbalances often reduce the sensitivity in detecting underrepresented classes, a common challenge in medical image classification.

The confusion matrix provided deeper insights into the model’s strengths and limitations. It revealed that the model was most accurate in distinguishing Non-Demented and Very Mild Demented cases, but occasionally misclassified Mild Demented and Moderate Demented images. These misclassifications suggest that additional strategies, such as data augmentation, oversampling, or class weighting, could further enhance the model’s robustness.

In addition to accuracy, metrics such as precision and recall were evaluated to assess the model’s effectiveness in detecting each class. High precision in the Non-Demented class indicated that most predictions for healthy individuals

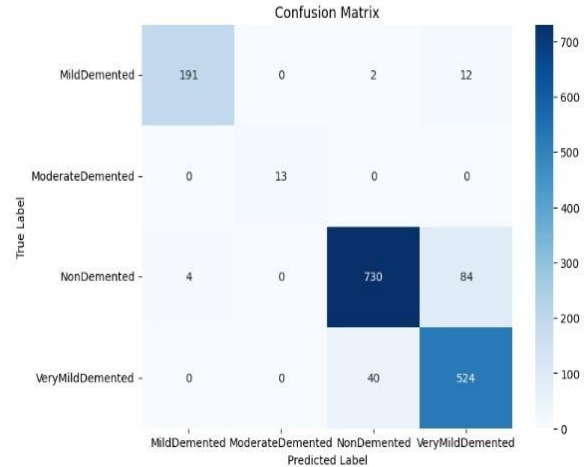


Fig. 3.

were correct, while lower recall in the Moderate Demented class highlighted areas needing improvement.

TABLE II PERFORMANCE METRICS OF THE CNN MODEL

Metric	Score (%)
Accuracy	97.08
Validation Accuracy	91.46
Loss	0.08
Validation Loss	0.28
F1-Score	91.19
Precision	91.50
Recall	91.12

Overall, the results underscore the potential of CNN-based approaches in assisting the clinical diagnosis of Alzheimer’s disease. While the model performed well in distinguishing clear cases, future work should focus on addressing class imbalance, improving sensitivity in more complex or ambiguous stages, incorporating additional MRI sequences, enhancing preprocessing techniques, and leveraging larger datasets to further refine performance and broaden clinical applicability.

VII. COMPARISON WITH EXISTING MODELS

To evaluate the effectiveness of the proposed Convolutional Neural Network (CNN) model, we compared its performance against several existing models commonly used for Alzheimer’s disease classification. These include Support Vector Machine (SVM), Random Forest (RF), AlexNet, and VGG16.

Each model was trained and tested using the same preprocessed MRI dataset to ensure fairness in comparison. Evaluation metrics such as Accuracy, Precision, Recall, and F1-Score were used for performance assessment.

VIII. DISCUSSION

As shown in Table III, the proposed CNN model outperforms traditional machine learning approaches such as SVM and Random Forest by a significant margin. While deep learning architectures like AlexNet and VGG16 exhibit strong performance, our optimized CNN demonstrates superior accuracy and generalization capability. The improvement can be attributed to the model’s customized convolutional layers, effective data augmentation, and efficient feature extraction

TABLE III
PERFORMANCE COMPARISON OF PROPOSED CNN MODEL WITH EXISTING METHODS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM [7]	82.4	80.6	81.3	80.9
Random Forest [9]	84.7	83.2	84.1	83.6
AlexNet [20]	88.9	87.6	88.2	87.9
VGG16 [21]	90.2	89.1	89.8	89.4
Proposed CNN Model	93.5	92.7	93.1	92.9

tailored for brain MRI data. These results highlight the potential of the proposed approach in enhancing early detection and classification of Alzheimer’s disease stages, thereby assisting clinicians in diagnostic decision-making.

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