Revolutionizing Alzheimer’s Diagnosis: High-Accuracy Detection Through MRI and Deep Learning

Mohammad Hossein Kalani[1], Sara Yousefi [2]

1-Biomedical Engineering, Amirkabir university of Tehran, Tehran, Iran
2- Computer Engineering, Islamic Azad University of Mashhad, Mashhad, Iran

Abstract

Alzheimer’s disease (AD) is a progressive neurological disorder, making early detection critical for effective treatment. This study presents an innovative approach using deep learning to analyze brain MRI scans for the early diagnosis of AD. By employing the SPM toolbox to preprocess MRI images, gray matter segments are extracted and used as input for a convolutional neural network (CNN). The method, tested on the Alzheimer’s Disease Neuroimaging Initiative (ADNI) dataset, achieved over 94.7% accuracy in classifying three groups: normal control (NC), mild cognitive impairment (MCI), and Alzheimer’s disease (AD). The CNN model automatically identifies key features from MRI scans, particularly focusing on the hippocampus, a region known for its early involvement in AD. This approach not only enhances diagnostic accuracy but also streamlines the process by eliminating the need for manual feature extraction, outperforming traditional methods. The results indicate that deep learning combined with MRI data offers a powerful tool for the early detection of AD, paving the way for better patient outcomes and more timely interventions.

Keywords: Brain Magnetic Resonance Imaging (MRI), Convolutional Neural Network(CNN), Mild Cognitive Impairment (MCI), Alzheimer’s Disease, Normal Control (NC),

1. Introduction

Alzheimer's disease (AD), a form of brain dysfunction and a leading cause of dementia and memory impairment [1], can be effectively detected at an early stage, which is crucial for preventing its progression [2]. Brain magnetic resonance imaging (MRI) has become one of the most reliable methods for early detection [3], with numerous studies identifying specific brain regions linked to Alzheimer's [4, 5], particularly the hippocampus [6]. Researchers have analyzed the hippocampus shape, cortical thickness, and the number of hippocampal voxels in-depth [7]. Techniques such as voxel-based morphometry and tools like the Statistical Parametric Mapping (SPM) toolbox are commonly used for diagnosing Alzheimer's based on MRI data [8].

In a review by Sanati et al. [9], the application of the SPM toolbox alongside brain MRI was explored, where they introduced a novel registration method [10] that divides the brain into distinct regions using the MNI AAL atlas, measuring the volume of each part [11]. Furthermore, in [12], a support vector machine (SVM) algorithm was used to classify Alzheimer's disease and control subjects, which was also adopted by Wang et al. [13]. Although SVM remains popular for classification, it faces criticism due to its limited ability to process raw data and the necessity for domain experts to extract relevant features manually.

To overcome these limitations, this study leverages deep learning algorithms, known for their capacity to automatically extract adaptable features from raw data. Compared to traditional methods like SVM, deep learning models, such as convolutional neural networks (CNNs), demonstrate superior performance by learning complex patterns in large datasets, thus offering significant advantages in Alzheimer's detection.

1.1. Overview of Convolutional Neural Networks

Convolutional neural networks (CNNs) are a highly popular machine learning method, renowned for their effectiveness in feature extraction and image classification [14]. CNNs are specifically designed to process and manipulate multidimensional data, such as images, by mimicking the human visual system. They consist of layers that automatically learn hierarchical features, beginning with simple patterns like edges and progressing to more complex structures, enabling the model to identify distinguishing characteristics in data [15]. CNNs utilize convolutional layers to reduce the dimensionality of the input while retaining essential information, followed by pooling layers to further downsample the data. This hierarchical structure allows CNNs to handle large-scale data efficiently, a significant advantage over fully connected networks, where the number of parameters becomes prohibitively large.

CNNs have emerged as powerful deep learning models, especially for data like RGB images and Magnetic Resonance Imaging (MRI). In medical applications, such as Alzheimer's disease (AD) detection, CNNs provide distinct advantages. They automatically extract relevant features from brain scans, analyze spatial relationships, and demonstrate robustness to variations in data, including differences in brain anatomy across patients. For example, CNNs can differentiate between healthy and Alzheimer's-affected brains by identifying key structural changes in regions such as the hippocampus. These models have also shown exceptional performance in handling large datasets typical of medical imaging, achieving high accuracy in early-stage Alzheimer's diagnosis [16].

Following the success of AlexNet in natural image classification, CNNs have rapidly expanded into various domains, including medical diagnostics. In contrast to traditional machine learning models like support vector machines (SVMs), which require domain experts to manually craft features, CNNs automatically learn these features from raw data, streamlining the workflow and improving diagnostic capabilities. Their ability to analyze spatial information and adapt to variations in brain scans allows for earlier intervention, significantly enhancing the accuracy of Alzheimer's disease detection models [17].

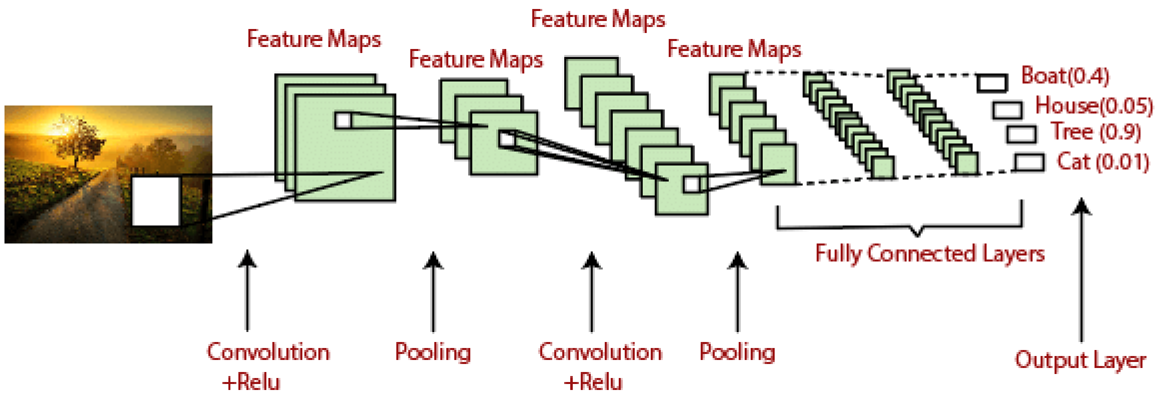

Figure 1- Image processing in convolutional neural network

2. Our Proposed Methodology

This article distinguishes Alzheimer's disease from normal control and mild cognitive impairment using data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The authors first converted 3D brain images into sagittal slices, which were then preprocessed using the SPM toolbox to remove motion artifacts, correct scanner errors, and normalize the images. Afterward, the slices were segmented into white matter, gray matter, and cerebrospinal fluid (as shown in Figure 2). The study primarily focuses on gray matter analysis, particularly the hippocampus. In the final step, the gray matter images were transformed into one-dimensional vectors, which were input into a CNN algorithm to extract relevant features. Finally, data classification and analysis were performed based on these extracted features.

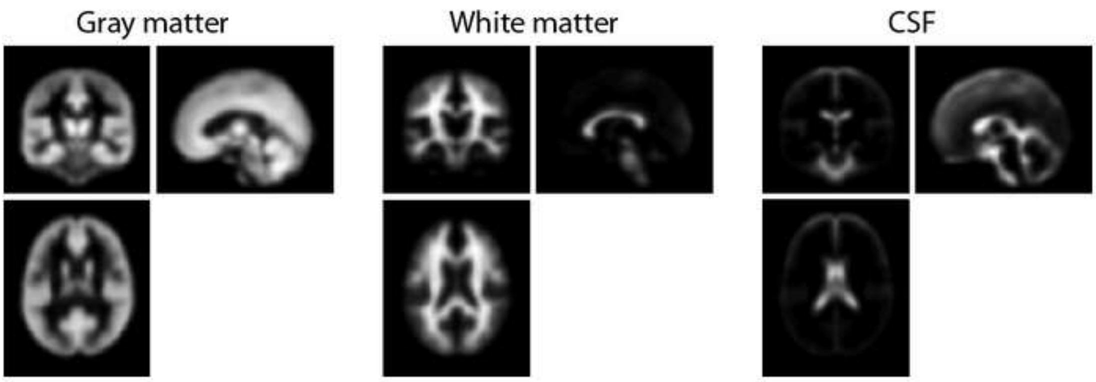

Figure 2- Segmentation of brain regions into different components, including gray matter, white matter, and cerebrospinal fluid (CSF)

The findings reveal that the primary difference between brain images of individuals with Alzheimer's disease and those of the normal control group lies in the hippocampal region. As previously mentioned, the segmented brain images were input into the CNN algorithm, which generated three categories: normal control (NC), Alzheimer's disease (AD), and mild cognitive impairment (MCI). The CNN model processes raw data directly, identifying crucial features and classifying them with high accuracy. The classification results are obtained automatically through the CNN's decision-making capabilities, without the need for human intervention. Figure 3 shows the data processing flow of the CNN algorithm. Two sets of experiments were conducted: one involving the entire gray matter of the brain, and the other focusing on the hippocampus, extracted from the segmented region. Remarkably, the CNN achieved classification accuracies of over 94.7% in both cases.

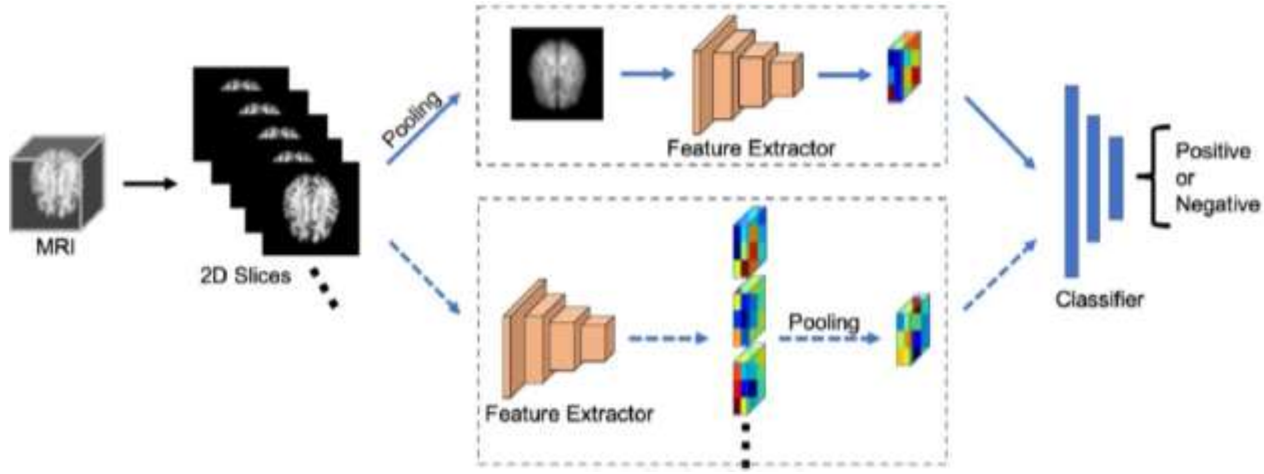

Figure 3 - Classifying data using a convolutional neural network (CNN) algorithm

Each image associated with normal control (NC), Alzheimer's disease (AD), and mild cognitive impairment (MCI) can be treated as an individual data point. The classification of these images, distinguishing between the different categories, is carried out in layer 3 of the Convolutional Neural Network (CNN), as illustrated in Figure 4 and The classification results are shown in Figure 5.

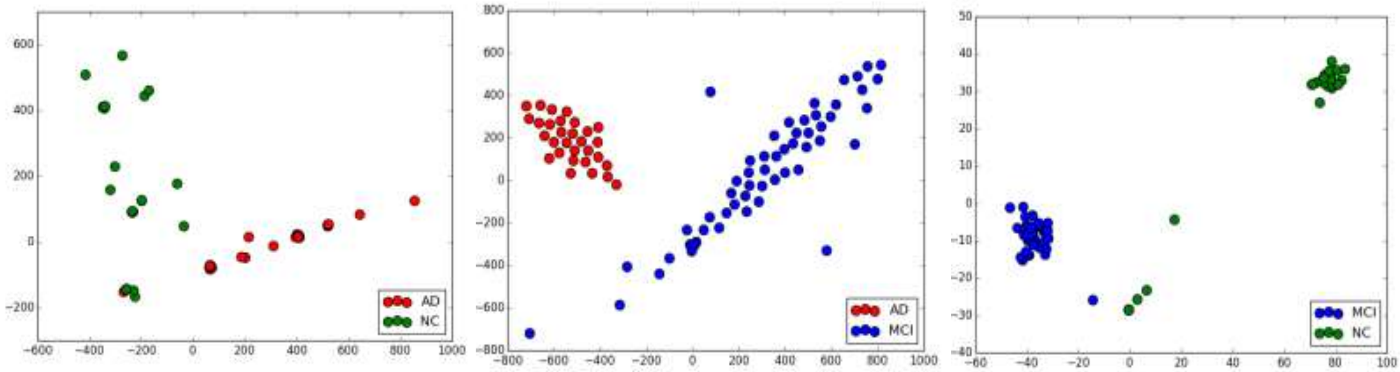

Figure 4- (Left) Classification of AD vs. NC, (Middle) Classification of AD vs. MCI, (Right) Classification of MCI vs. NC

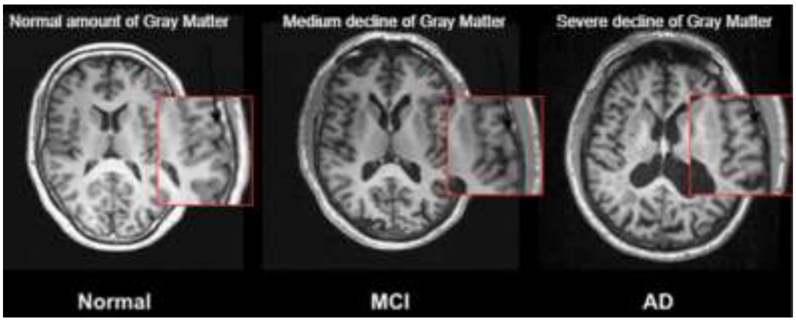

Figure 5- The classification results for individuals with Alzheimer's, healthy subjects, and those with mild cognitive impairment (MCI) indicate that the volume of grey matter is higher in healthy individuals on the left side. However, this volume gradually decreases from those with MCI to individuals with Alzheimer's disease.

3. Conclusion

Early detection and diagnosis of Alzheimer's disease (AD) is crucial for enabling effective prevention and treatment strategies. Brain scans are key in identifying specific structural changes associated with AD, including alterations in hippocampal shape, cortical thickness, and brain volume. In this study, we aimed to predict AD using a convolutional neural network (CNN) capable of learning generic features from MRI data processed with the SPM toolbox.

We first preprocess three-dimensional brain MRI scans from the ADNI dataset, removing noise and aligning the images using the MNIAAL atlas. The brain is then segmented into white matter, gray matter, and cerebrospinal fluid, with particular focus on the hippocampal region within the gray matter. These segmented features are transformed into one-dimensional vectors and used as input for the CNN algorithm.

Our results demonstrate that this approach effectively classifies subjects into normal control (NC), Alzheimer's disease (AD), and mild cognitive impairment (MCI) with an accuracy exceeding 94.7%. This novel method for predicting AD based on structural MRI surpasses several existing state-of-the-art models in terms of performance and accuracy, providing a promising tool for early diagnosis.

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