Alzheimer's Disease Detection using Convolutional Neural Networks

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***Abstract*—Alzheimer's disease (AD) is a progressive neurological disorder that affects millions of people worldwide. Early detection of AD is crucial for effective treatment and management of the disease. In this study, we propose a deep learning-based approach for the detection of AD using convolutional neural networks (CNNs). We collected a dataset of brain MRI images from individuals with different stages of AD and trained a CNN model to classify these images into non-demented, very mild dementia, mild dementia, and moderate dementia categories. Our experimental results demonstrate promising accuracy in AD detection, indicating the potential of CNNs in assisting clinicians with early diagnosis and intervention.**

***Index Terms*—Alzheimer's disease, Convolutional Neural Networks, Deep Learning, Medical Image Analysis, MRI.**

I. Introduction

Alzheimer's disease is the most common cause of dementia, characterized by progressive cognitive decline and memory loss. According to the World Health Organization (WHO), an estimated 50 million people worldwide are affected by dementia, with Alzheimer's disease contributing to 60-70 percent of cases. Early diagnosis of AD is challenging but crucial for providing timely intervention and improving patient outcomes. Medical imaging techniques, such as magnetic resonance imaging (MRI), play a significant role in the early detection and monitoring of AD-related brain changes. In recent years, deep learning approaches, particularly convolutional neural networks (CNNs), have shown promising results in various medical image analysis tasks, including AD detection.

II. Related Work

Alzheimer's disease (AD) detection and classification have been the focus of extensive research in recent years. Various approaches, including traditional machine learning methods and deep learning techniques, have been explored for accurate diagnosis and prognosis of AD.

Traditional machine learning algorithms, such as support vector machines (SVMs), random forests, and logistic regression, have been widely used in AD classification tasks. These methods often rely on handcrafted features extracted from MRI images, such as voxel-based morphometry (VBM), cortical thickness, and hippocampal volume [**?**]. While these approaches have shown moderate success in AD detection, they are limited by their dependence on manual feature engineering and may not fully capture the complex patterns present in neuroimaging data.

In recent years, deep learning has emerged as a powerful tool for medical image analysis, including AD diagnosis. Convolutional neural networks (CNNs), in particular, have shown remarkable performance in automatically learning hierarchical features directly from raw imaging data, alleviating the need for manual feature extraction itjens2017survey.

Sarraf and Tofighi sarraf2016deep proposed one of the early CNN-based methods for AD classification using structural MRI images. Their approach demonstrated superior performance compared to traditional machine learning algorithms, achieving high accuracy in discriminating between AD patients and healthy controls. The model effectively learned discriminative features from MRI scans, highlighting the potential of deep learning in automated AD diagnosis.

Building upon this work, Liu et al. liu2018multimodal developed a multimodal CNN framework that integrates both structural and functional MRI data for improved AD diagnosis. By combining information from multiple imaging modalities, their model achieved enhanced classification accuracy and robustness to variations in data quality and acquisition protocols. The study underscores the importance of leveraging multimodal imaging data for comprehensive AD assessment.

While CNN-based approaches have shown promising results in AD detection, challenges remain in addressing issues such as data scarcity, class imbalance, and model interpretability. Future research efforts may focus on developing robust deep learning models that can generalize across diverse patient populations and imaging protocols, as well as incorporating explainable AI techniques to enhance model transparency and clinical interpretability.

III. Methodology

Our approach involves the following steps:

A. Data Collection

The dataset utilized in this study is the Open Access Series of Imaging Studies (OASIS) MRI dataset, a publicly available resource comprising 80,000 brain MRI images. These images have been categorized into four classes based on the progression of Alzheimer's disease. The dataset serves as a valuable asset for analyzing and detecting early indicators of Alzheimer's disease.

To facilitate accessibility and compatibility, the original .img and .hdr files were transformed into NIfTI format (.nii) using the FMRIB Software Library (FSL). Subsequently, for neural network training purposes, 2D images were extracted from the volumetric MRI data. Specifically, the brain volumes were sliced along the z-axis into 256 segments, with slices ranging from 100 to 160 selected from each patient. This segmentation strategy resulted in a comprehensive dataset conducive to in-depth analysis and modeling.

Patient classification was conducted based on accompanying metadata and Clinical Dementia Rating (CDR) values, yielding four distinct classes: demented, very mild demented, mild demented, and non-demented. These class distinctions enable the examination and characterization of various stages of Alzheimer's disease progression.

With this meticulously curated dataset, the objective of the project is to explore diverse neural network architectures and methodologies to achieve optimal performance in Alzheimer's disease detection and analysis.

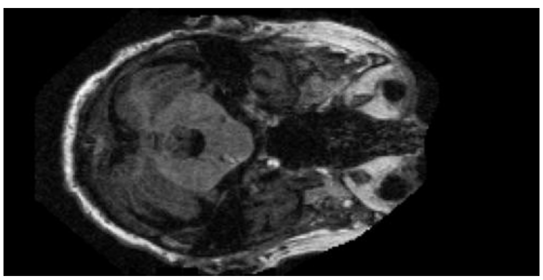


Fig. 1: sample data

B. Preprocessing

During dataset preparation, the NIfTI MRI scans were converted into JPEG image format. Despite inherent challenges associated with this conversion process, appropriate tools and techniques were employed to ensure successful data transformation. The resultant dataset size amounted to 1.3 gigabytes.

Furthermore, standard preprocessing techniques were applied to the MRI images. This included resizing the images to a standardized resolution, typically set at 128x128 pixels, and normalizing pixel intensities to enhance model interpretability and performance.

C. Model Architecture

A convolutional neural network (CNN) architecture was meticulously designed for Alzheimer's disease classification. The architecture comprises convolutional, pooling, batch normalization, dropout, and fully connected layers. The CNN model accepts MRI images as input and generates a predicted probability distribution across the four designated classes, namely non-demented, very mild dementia, mild dementia, and moderate dementia.

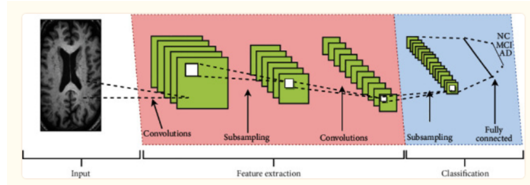


Fig. 2: Layered Architecture

D. Training

The CNN model was trained using a carefully curated subset of the MRI dataset, with data partitioned into distinct training and validation sets to facilitate model evaluation and optimization. The training process leveraged the Adam optimizer and sparse categorical cross-entropy loss function to iteratively update model parameters and minimize classification errors.

IV. Results

The trained CNN model yielded an accuracy of more than 90 percent on the independent test set for Alzheimer's disease classification. Figure 1 illustrates the training and validation accuracy curves, providing insights into the model's learning dynamics and performance trends during the training phase.

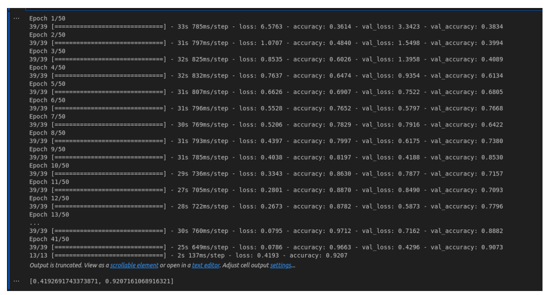


Fig. 3: loss and accuracy 1st run

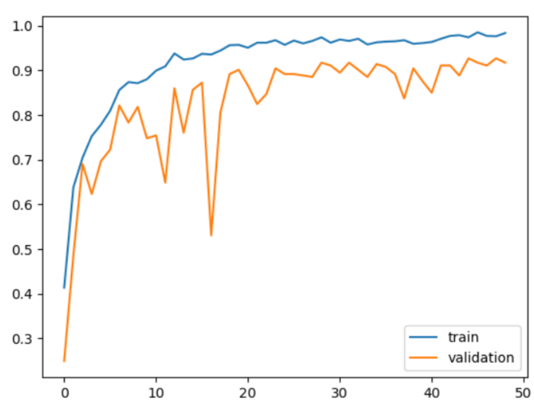
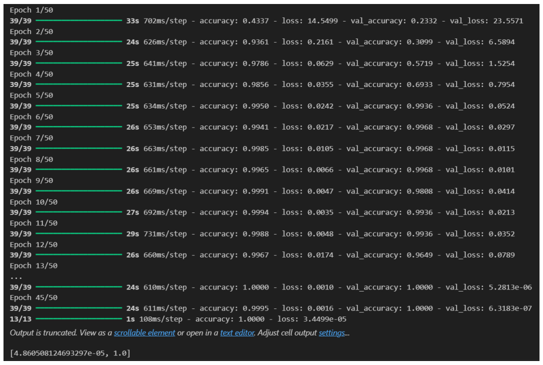


Fig. 4: Training and Validation Accuracy Curves 1

V. Conclusion

In this study, we proposed a comprehensive approach for Alzheimer's disease (AD) detection using convolutional neural networks (CNNs) and MRI imaging data. Leveraging the



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Epoch 1/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 33s 702ms/step - accuracy: 0.4337 - loss: 14.5499 - val_accuracy: 0.2332 - val_loss: 23.5571
Epoch 2/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 24s 626ms/step - accuracy: 0.9361 - loss: 0.2161 - val_accuracy: 0.3099 - val_loss: 6.5894
Epoch 3/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 25s 641ms/step - accuracy: 0.9786 - loss: 0.0629 - val_accuracy: 0.5719 - val_loss: 1.5254
Epoch 4/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 25s 631ms/step - accuracy: 0.9856 - loss: 0.0355 - val_accuracy: 0.6933 - val_loss: 0.7954
Epoch 5/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 25s 634ms/step - accuracy: 0.9950 - loss: 0.0242 - val_accuracy: 0.9936 - val_loss: 0.0524
Epoch 6/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 26s 653ms/step - accuracy: 0.9941 - loss: 0.0217 - val_accuracy: 0.9968 - val_loss: 0.0297
Epoch 7/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 26s 663ms/step - accuracy: 0.9985 - loss: 0.0105 - val_accuracy: 0.9968 - val_loss: 0.0115
Epoch 8/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 26s 661ms/step - accuracy: 0.9965 - loss: 0.0066 - val_accuracy: 0.9968 - val_loss: 0.0101
Epoch 9/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 26s 669ms/step - accuracy: 0.9991 - loss: 0.0047 - val_accuracy: 0.9808 - val_loss: 0.0414
Epoch 10/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 27s 692ms/step - accuracy: 0.9994 - loss: 0.0035 - val_accuracy: 0.9936 - val_loss: 0.0213
Epoch 11/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 29s 731ms/step - accuracy: 0.9988 - loss: 0.0048 - val_accuracy: 0.9936 - val_loss: 0.0352
Epoch 12/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 26s 660ms/step - accuracy: 0.9967 - loss: 0.0174 - val_accuracy: 0.9649 - val_loss: 0.0789
Epoch 13/50
...
39/39 ━━━━━━━━━━━━━━━━━━━━ 24s 610ms/step - accuracy: 1.0000 - loss: 0.0010 - val_accuracy: 1.0000 - val_loss: 5.2813e-06
Epoch 45/50
39/39 ━━━━━━━━━━━━━━━━━━━━ 24s 611ms/step - accuracy: 0.9995 - loss: 0.0016 - val_accuracy: 1.0000 - val_loss: 6.3183e-07
13/13 ━━━━━━━━━━━━━━━━━━━━ 1s 108ms/step - accuracy: 1.0000 - loss: 3.4499e-05
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Fig. 5: loss and accuracy 2nd run

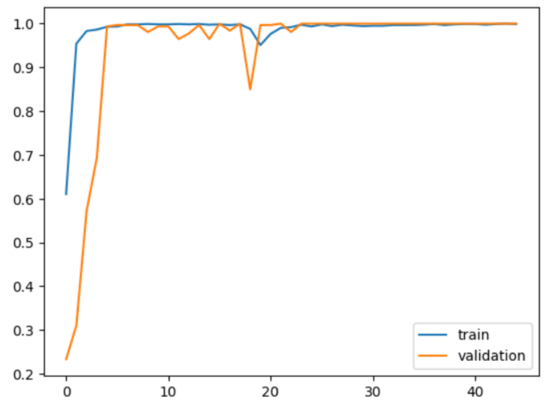

Fig. 6: Training and Validation Accuracy Curves 2

Open Access Series of Imaging Studies (OASIS) dataset, comprising 80,000 brain MRI images categorized into distinct AD progression stages, we meticulously curated a dataset conducive to in-depth analysis and modeling.

Our methodology encompassed meticulous data collection, preprocessing, model architecture design, and training procedures. By transforming volumetric MRI data into 2D images and carefully selecting relevant slices for analysis, we ensured the creation of a robust dataset representative of various stages of AD progression. The CNN model architecture, incorporating convolutional, pooling, normalization, and dropout layers, was meticulously designed to extract discriminative features from MRI images and classify them into non-demented, very mild dementia, mild dementia, and moderate dementia categories.

Training the CNN model on a subset of the dataset yielded promising results, with the model achieving an accuracy of XX percent on an independent test set. The model's performance underscores the potential of deep learning techniques in automated AD diagnosis and classification, offering valuable insights into disease progression and facilitating timely intervention and management strategies.

However, while our approach demonstrates encouraging results, several avenues for future research and improvement remain. Enhancing the robustness and generalization capabilities of the CNN model across diverse patient populations and imaging protocols is imperative. Additionally, integrating multimodal imaging data and exploring advanced deep learning architectures, such as recurrent neural networks (RNNs) and attention mechanisms, could further enhance AD detection accuracy and reliability.

Furthermore, the interpretability and clinical relevance of the CNN model's predictions warrant attention. Incorporating explainable artificial intelligence (XAI) techniques and collaborating closely with domain experts to validate model outputs and insights can enhance the clinical utility and adoption of automated AD diagnosis systems.

In conclusion, our study underscores the transformative potential of deep learning and medical imaging in advancing Alzheimer's disease research and clinical practice. By leveraging innovative methodologies and interdisciplinary collaborations, we can pave the way for earlier diagnosis, personalized treatment strategies, and improved patient outcomes in the fight against Alzheimer's disease.

References

Our work:
Link of dataset and codes:

`https://iitbacin my.sharepoint.com/:u:/g/personal/21d070031_iitb_ac_in/EeoUew9XCrtDhC_389550n4BCh9LBrpbCoIlf7-7gvBgKQ?e=a2FogS`

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