Alzheimer’s disease classification

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1 abstraction

Alzheimer’s disease is a neurodegenerative disorder characterized by progressive cognitive decline. Early diagnosis is critical for patient care and management. In this study, we investigate the application of various deep learning models, including CNN, ResNet, VGG16, and MobileNet, to classify Alzheimer’s disease using a publicly available dataset. We describe the dataset, preprocessing steps, and the methodology used for training and evaluation. The performance of these models is compared in terms of accuracy and computational efficiency. Our findings demonstrate the strengths and limitations of each model in the context of Alzheimer’s disease classification.

Keywords: Alzheimer’s disease, deep learning, convolutional neural networks, ResNet, VGG16, MobileNet, image classification.

2 Introduction

Alzheimer’s disease (AD) is a chronic neurodegenerative disease that affects millions worldwide. Accurate and early diagnosis is crucial for effective management and treatment. Traditional diagnostic methods rely on clinical evaluation and imaging techniques, which can be time-consuming and subjective. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in automating and enhancing the diagnostic process through the analysis of medical images.

In this study, we apply several state-of-the-art deep learning models to an Alzheimer’s dataset to evaluate their performance in classifying AD. The models compared include a simple CNN, ResNet, VGG16, and MobileNet. We aim to identify which model provides the best trade-off between accuracy and computational efficiency for this specific task.

3 related work

Several studies have explored the use of deep learning for Alzheimer's disease classification. Suk et al. [1] used a deep CNN to classify MRI images of Alzheimer's patients, achieving significant improvements over traditional methods. Liu et al. [2] employed ResNet to enhance the feature extraction process, demonstrating superior performance in terms of accuracy. Similarly, VGG16 and MobileNet have been widely used in medical image analysis due to their strong feature extraction capabilities and efficient architectures [3][4].

4 data

The dataset used in this study is the Alzheimer's Dataset, which consists of MRI images labeled as "Non-Demented," "Very Mild Demented," "Mild Demented," and "Moderate Demented." The dataset is split into training and testing sets to evaluate model performance.

Preprocessing Steps:

Data Extraction: The dataset was extracted from a ZIP file and organized into training and testing directories. Image Rescaling: All images were rescaled to a pixel range of [0, 1]. Image Augmentation: Techniques such as horizontal flipping, zooming, and shearing were applied to enhance model generalization. Target Size: All images were resized to 224x224 pixels to match the input size required by the models.

5 methodology

Four deep learning models were employed for the classification task:

CNN: A basic convolutional neural network with several convolutional and pooling layers. ResNet: A Residual Network that uses skip connections to improve training depth and accuracy. VGG16: A deep network with 16 layers, known for its strong performance in image classification tasks. MobileNet: A lightweight model designed for mobile and embedded vision applications, providing a good balance between accuracy and efficiency. All models were trained using the Adam optimizer and categorical cross-entropy loss. Data augmentation was applied during training to prevent overfitting. The models were evaluated based on accuracy and computational efficiency.

6 results

7 conclusion

This study compared the performance of CNN, ResNet, VGG16, and MobileNet models in classifying Alzheimer's disease using MRI images. ResNet achieved the highest accuracy, demonstrating the effectiveness of deep networks with skip connections for medical image analysis. VGG16 also performed well but required longer training times. MobileNet provided a good balance between accuracy and computational efficiency, making it suitable for deployment in resource-constrained environments. Future work will explore the integration of these models into clinical workflows and their performance on larger, more diverse datasets.