Efficient Deep Learning Models For Neuro Degenerative Diseases Detection

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Abstract—The prevalence of neurodegenerative diseases is increasing, posing severe public health risks. Early diagnosis is critical because it allows for timely measures to arrest disease progression. However, delayed diagnosis is typically the result of symptoms appearing gradually. We describe a deep learning-based framework for classifying MRI images of neurodegenerative illnesses, including dementia. We trained and optimized a large number of architectures, such as VGG16, ResNet50, and EfficientNetB0, using a massive dataset of 44,000 MRI images divided into four categories: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. While ResNet50 and EfficientNetB0 obtained 95.5% and 95.6%, respectively, the VGG16 model's overall accuracy was 78%. These results highlight the tremendous potential of deep learning to support neurodegenerative disease detection.

I. INTRODUCTION

Neurodegenerative diseases, particularly Alzheimer's disease, are a serious public health concern due to their rising frequency and a lack of effective treatment options. The World Health Organization (WHO) predicts that over 55 million people worldwide suffer from dementia, which is anticipated to triple by 2050 as the global population ages[1]. Alzheimer's disease is responsible for 60-70% of all dementia cases.

This places a heavy load on healthcare systems, caregivers, and afflicted families alike. Alzheimer's disease must be recognized early and accurately in order to enhance patient outcomes and decrease disease progression with therapy.Automation of the detection and classification of Alzheimer's disease stages could be a game changer, thanks to advances in deep learning and magnetic resonance imaging (MRI), delivering an effective solution to this healthcare challenge. The purpose of this study is to develop an effective classification framework using the most powerful pre-trained convolutional neural networks (CNNs), specifically VGG16, ResNet50, and EfficientNetB0. We expect that by refining these models, we can improve the accuracy and computational efficiency of Alzheimer's disease severity categorization. This research bridges the gap between real-world clinical applications and deep learning methods.

Literature Review

Using the powerful feature extraction and classification capabilities of convolutional neural networks (CNNs), a number of studies have investigated deep learning applications in medical imaging for the detection of neurodegenerative diseases. For example, the Health Science Publishing study [1] demonstrated the effectiveness of transfer learning approaches in diagnosing Alzheimer's disease with high accuracy by using pre-trained CNN models. In the same way, a study that is accessible on ArXiv [2] emphasized the application of DenseNet architectures, which performed better in terms of feature representation than conventional machine learning techniques.

The application of pretrained models, like ResNet50 and VGG16, has been thoroughly studied in relation to Alzheimer's disease detection. To increase classification accuracy, researchers have placed a strong emphasis on optimizing these structures. For instance, Springer [3] showed that optimizing VGG16 produced cutting-edge outcomes in identifying Alzheimer's stages from MRI images. Nonetheless, issues including the requirement for improved generalization and data imbalance have been frequently identified in much research [4, 5]. ScienceDirect [6] suggested sophisticated data augmentation methods, such as flipping, rotation, and intensity modifications, to improve model resilience in order to solve these problems.

Enhancing performance measures for Alzheimer's classification has also been made possible by optimized loss functions. In order to achieve balanced classification results, the Academia.edu study [7] implemented a modified loss function that gave minority class predictions priority. By combining several model outputs, ensemble learning techniques—discussed in Springer [8]—further improved prediction reliability. Current developments go beyond conventional CNN designs. For example, in order to achieve greater temporal feature extraction efficiency, MDPI [9] investigated hybrid models that combined CNNs with recurrent neural networks (RNNs) for sequential MRI data analysis. Additionally, a different MDPI paper [10] presented the idea of lightweight CNNs designed for medical imaging applications with limited resources, guaranteeing real-time performance without compromising accuracy.

All of these results point to the continuous development of deep learning approaches in the diagnosis of neurodegenerative diseases, opening the door to earlier and more accurate detection methods. Convolutional neural networks (CNNs), for example, have shown notable effectiveness in tasks involving feature extraction and picture categorization. The usefulness of pretrained architectures like VGG16, ResNet50, and DenseNet in Alzheimer's detection has been emphasized by recent studies [1, 2].

Previous research has noted challenges such poor generalizability and data imbalance. To address these problems, researchers [3, 4] stress the need of optimizing pretrained models and utilizing cutting-edge data augmentation strategies. Additionally, as mentioned in [5, 6], ensemble learning techniques and efficient loss functions are crucial for improving model performance.

Methodology

Dataset

The dataset was taken from Kaggle titled 'The Alzheimer's Disease Multiclass Dataset' contains approximately 44,000 MRI images categorized into four distinct classes based on the severity of Alzheimer's disease. This dataset is intended for use in machine learning model training and testing. All images are skull-stripped and clean of non-brain tissue.

1. VeryMildDemented: 11,200 images
2. MildDemented: 10,000 images
3. ModerateDemented: 10,000 images
4. NonDemented: 12,800 images

Each image is a .JPG file, standardized through resizing and normalization to ensure compatibility with deep learning models.

Model Architectures

VGG16

In our study, the VGG16 model serves as a cornerstone for neurodegenerative disease classification due to its simplicity and depth. Its sequential architecture with 16 weight layers, composed of small 3×3 convolutional kernels, effectively extracts features from MRI images. However, the model exhibited limitations in detecting subtle changes associated with early-stage dementia.The Adam optimizer, with a learning rate of 1e-5, was employed.

ResNet50

ResNet50 with its deeper architecture and innovative residual connections complements the feature extraction. 50 layers enhance deeper feature learning while the residual blocks address the vanishing gradient problem, ensuring effective training. ResNet50 can model complex patterns, it may require enhanced preprocessing techniques or ensemble strategies to match the performance of simpler architectures like VGG16 in this specific application.
EfficientNetB0
EfficientNetB0 introduces a new dimension to our study with its compound scaling technique, balancing depth and width, and resolution to achieve both efficiency. its lightweight architecture and computational efficiency make it an attractive candidate for future exploration. EfficientNetB0's potential to process large-scale medical imaging datasets with fewer parameters could address some of the limitations observed in VGG16 and ResNet50, particularly in terms of scalability and generalizability across diverse datasets.

Training Procedure

Both models were trained using the following configuration:

- Loss Function: Categorical Crossentropy
- Optimizer: Adam
- Batch Size: 32
- Epochs: 25

The dataset was split into 80% for training and 20% for validation. Data augmentation techniques, such as rotation, flipping, and zooming, were applied to improve model generalization.

Results and Discussion

VGG16 Performance

The VGG16 model achieved an overall accuracy of 78.5%. Key classification metrics include:

- MildDemented: Precision = 70.64%, Recall = 89.88%, F1-score = 79.10%
- ModerateDemented: Precision = 99.93%, Recall = 99.61%, F1-score = 99.77%
- NonDemented: Precision = 81.89%, Recall = 66.82%, F1-score = 73.60%
- VeryMildDemented: Precision = 61.66%, Recall = 59.34%, F1-score = 60.48%

ResNet50 Performance

The ResNet50 model achieved an overall accuracy of 95.5%. Key metrics include:

- MildDemented: Precision = 94.82%, Recall = 96.80%, F1-score = 95.80%
- ModerateDemented: Precision = 99.74%, Recall = 99.87%, F1-score = 99.81%
- NonDemented: Precision = 95.88%, Recall = 93.34%, F1-score = 94.59%
- VeryMildDemented: Precision = 92.00%, Recall = 92.89%, F1-score = 92.44%

EfficientNetB0 Performance

The EfficientNetB0 model achieved an overall accuracy of 95.6%. Key metrics include:

- MildDemented: Precision = 94.44%, Recall = 97.97%, F1-score = 96.17%
- ModerateDemented: Precision = 99.87%, Recall = 100.00%, F1-score = 99.94%
- NonDemented: Precision = 94.50%, Recall = 93.65%, F1-score = 94.08%
- VeryMildDemented: Precision = 93.94%, Recall = 91.56%, F1-score = 92.74%

Discussion

The EfficientNetB0 model outperformed VGG16 and ResNet50 in overall accuracy and F1-score. EfficientNetB0 is highly optimized with a compound scaling method that balances depth, width, and resolution, achieving high accuracy with fewer parameters making it effective for handling complex MRI datasets. Its computational efficiency reduces overfitting risks and ensures better generalization even with limited medical imaging data. The model captures both global and local features enabling it to detect subtle patterns indicative of Alzheimer’s while maintaining high classification accuracy across different stages of the disease. Pre-trained EfficientNetB0 models can be fine-tuned for Alzheimer's classification with minimal effort, consistently delivering state-of-the-art performance in medical image analysis.

Conclusion

This study demonstrates the potential of deep learning models for classifying Alzheimer’s disease severity from MRI scans. The EfficientNetB0 model, in particular, achieved promising results, showcasing the efficiency of transfer learning in medical imaging applications. Future work will focus on addressing data imbalance, enhancing feature extraction techniques and exploring ensemble approaches to improve classification accuracy.

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