Efficient Deep Learning Models For Alzheimer's Stage Detection Using MRI Images

Fariha Zaman
Department of Computer Science and Engineering
Brac University
Dhaka, Bangladesh
fariha.zaman1@g.bracu.ac.bd

Ayasha Islam
Department of Computer Science and Engineering
BRAC University
Dhaka, Bangladesh
ayasha.islam@g.bracu.ac.bd

Nowrin Sanjana
Department of Computer Science and Engineering
BRAC University
Dhaka, Bangladesh
nowrin.sanjana@g.bracu.ac.bd

Ahanaf Abid Sazid
Department of Computer Science and Engineering
BRAC University
Dhaka, Bangladesh
ahanaf.abid.sazid@g.bracu.ac.bd

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.

Keywords—Neurodegenerative diseases, Alzheimer's disease, dementia classification, deep learning, transfer learning, VGG16, ResNet50,EfficientNetB0MRI image analysis, disease severity detection, medical imaging, early diagnosis, Alzheimer's detection models, large-scale dataset, neural networks.

I. Introduction

Because of their rising incidence and dearth of effective therapies, neurodegenerative diseases—especially Alzheimer's disease represent a serious public health concern. The World Health Organization (WHO) estimates that over 55 million people worldwide suffer from dementia, and as the world's population ages, this figure is predicted to quadruple by 2050[1]. With 60–70% of cases, Alzheimer's disease is the most prevalent type of dementia. Healthcare systems, caregivers, and impacted families are all heavily burdened by this. Alzheimer's disease must be identified early and accurately in order to enhance patient outcomes and decrease the illness's progression through therapies.Automating the detection and classification of Alzheimer's disease stages could be a game-changer thanks to developments in deep learning and magnetic resonance imaging (MRI), offering an effective answer to this healthcare issue. When combined with developments in deep learning, magnetic resonance imaging (MRI) provides a potent method for automating the detection and categorization of Alzheimer's disease stages.

The goal of this research is to create an effective classification framework by utilizing the most advanced pre-trained convolutional neural networks (CNNs), namely VGG16,ResNet50, EfficientNetB0. We hope to increase the accuracy and computational efficiency of Alzheimer's disease severity classification by optimizing these models. This study closes the gap between real-world clinical applications and deep learning approaches.

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 study by Yellu et al. [1] demonstrated the effectiveness of transfer learning approaches in diagnosing Alzheimer's disease with high accuracy by using pre-trained CNN models. Similarly, Li et al. [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, Ji et al. [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]. Techniques such as sophisticated data augmentation methods—including flipping, rotation, and intensity modifications—have been proposed by researchers such as Pandiyaraju et al. [6] to improve model resilience and address these challenges.

Enhancing performance measures for Alzheimer's classification has also been made possible by optimized loss functions. In order to achieve balanced classification results, Anbarasan et al. [7] implemented a modified loss function that gave priority to minority class predictions. By combining several model outputs, ensemble learning techniques—discussed by Rathod and Parmar [8]—further improved prediction reliability. Current developments go beyond conventional CNN designs. For example, Zhang et al.

[9] investigated hybrid models combining CNNs with recurrent neural networks (RNNs) to achieve greater temporal feature extraction efficiency for sequential MRI data analysis. Additionally, Xu et al. [10] presented lightweight CNNs designed for medical imaging applications with limited resources, ensuring 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 image 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 as poor generalizability and data imbalance. To address these problems, researchers [3, 4] stress the need for 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.

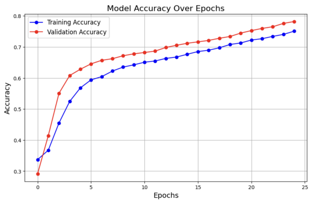
```python
# Function to preprocess a single image
def preprocess_image(image):
    image = image.numpy()  # Convert tensor to numpy array
    # Convert to grayscale
    image = cv2.cvtColor(image, cv2.COLOR_RGB2GRAY)
    # Normalize the image
    image = (image - np.min(image)) / (np.max(image) - np.min(image))
    # Apply CLAHE
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))
    image = clahe.apply(np.uint8(image * 255))
    # Denoise using median blur
    image = cv2.medianBlur(image, 3)
    # Skull stripping (simplified thresholding)
    thresh = cv2.threshold(image, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)[1]
    # Standardize to 3 channels
    image = np.stack((image,) * 3, axis=-1)
    return image
```

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%



	precision	recall	f1-score	support
MildDemented	0.7064	0.8988	0.7910	1531
ModerateDemented	0.9993	0.9961	0.9977	1543
NonDemented	0.8189	0.6682	0.7360	1902
VeryMildDemented	0.6166	0.5934	0.6048	1648
accuracy			0.7793	6624
macro avg	0.7853	0.7891	0.7824	6624
weighted avg	0.7846	0.7793	0.7770	6624

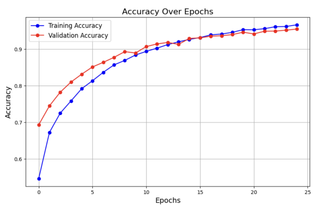
Overall Accuracy: 0.7793

VGG16

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%



	precision	recall	f1-score	support
MildDemented	0.9482	0.9680	0.9580	1531
ModerateDemented	0.9974	0.9987	0.9981	1554
NonDemented	0.9588	0.9334	0.9459	1893
VeryMildDemented	0.9200	0.9289	0.9244	1646
accuracy			0.9556	6624
macro avg	0.9561	0.9573	0.9566	6624
weighted avg	0.9557	0.9556	0.9556	6624

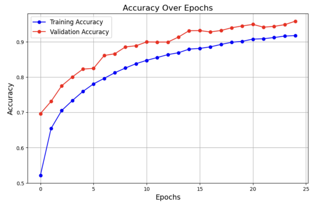
Overall Accuracy: 0.9556

ResNet50

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%



	precision	recall	f1-score	support
MildDemented	0.9444	0.9797	0.9617	1525
ModerateDemented	0.9987	1.0000	0.9994	1549
NonDemented	0.9450	0.9365	0.9408	1891
VeryMildDemented	0.9394	0.9156	0.9274	1659
accuracy			0.9561	6624
macro avg	0.9569	0.9580	0.9573	6624
weighted avg	0.9560	0.9561	0.9559	6624

Overall Accuracy: 0.9561

EfficientNetB0

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.

References

[1] Yellu, R. R., Kukalakunta, Y., & Thunki, P. (2024, May 1). *Deep Learning-Assisted Diagnosis of Alzheimer's Disease from Brain Imaging Data*. https://healthsciencepub.com/index.php/jaihm/article/view/18

[2] Li, S., Qu, H., Dong, X., Dang, B., Zang, H., & Gong, Y. (2024, March 24). *Leveraging Deep Learning and XCeption Architecture for High-Accuracy MRI classification in Alzheimer diagnosis*. arXiv.org. https://arxiv.org/abs/2403.16212

[3] Pradhan, N., Sagar, S., & Singh, A. S. (2023). Analysis of MRI image data for Alzheimer disease detection using deep learning techniques. *Multimedia Tools and Applications*, *83*(6), 17729–17752. https://doi.org/10.1007/s11042-023-16256-2

[4] Hashmi, A., & Barukab, O. (2023). Dementia classification using deep reinforcement learning for early diagnosis. *Applied Sciences*, *13*(3), 1464. https://doi.org/10.3390/app13031464

[5] Helaly, H. A., Badawy, M., & Haikal, A. Y. (2021). Deep learning approach for early detection of Alzheimer's disease. *Cognitive Computation*, *14*(5), 1711–1727. https://doi.org/10.1007/s12559-021-09946-2

[6] Sisodia, P. S., Ameta, G. K., Kumar, Y., & Chaplot, N. (2023). A review of deep transfer learning Approaches for Class-Wise prediction of Alzheimer's Disease using MRI images. *Archives of Computational Methods in Engineering*, *30*(4), 2409–2429. https://doi.org/10.1007/s11831-022-09870-0

[7] Hazarika, R.A.; Maji, A.K.; Kandar, D.; Jasinska, E.; Krejci, P.; Leonowicz, Z.; Jasinski, M. An Approach for Classification of Alzheimer's Disease Using Deep Neural Network and Brain Magnetic Resonance Imaging (MRI). Electronics 2023, 12, 676. https://doi.org/10.3390/electronics12030676

[8] *DEMNET: A deep learning model for early diagnosis of Alzheimer diseases and dementia from MR images*. (2021). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/9459692/

[9] Altinkaya, E., Polat, K., & Barakli, B. (2020). Detection of Alzheimer's Disease and Dementia States Based on Deep Learning from MRI Images: A Comprehensive Review. *Journal of the Institute of Electronics and Computer*, *1*(1), 39–53. https://doi.org/10.33969/jiec.2019.11005

[10] Warren, S. L., & Moustafa, A. A. (2022). Functional magnetic resonance imaging, deep learning, and Alzheimer's disease: A systematic review. *Journal of Neuroimaging*, *33*(1), 5–18. https://doi.org/10.1111/jon.13063