Improved Alzheimer's Detection from Brain MRI via Transfer Learning on Pre-Trained Convolutional Deep Models

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Keywords: Alzheimer's Disease (AD), Convolutional Neural Network (CNN), Deep Learning (DL), MCNN, Transfer Learning, Fine-Tuned, FT-VGGNet19, Brain MRI Images.

Abstract: Alzheimer's Disease (AD) presents a major challenge in modern healthcare due to its complex diagnosis and management. Early and accurate detection is essential for improving patient care and enabling timely therapeutic interventions. Research suggests that neurodegenerative changes associated with AD may appear years before clinical symptoms, highlighting the need for advanced diagnostic techniques. This study explores deep learning models for classifying AD stages using MRI scans. Specifically, we propose a Modified Convolutional Neural Network (MCNN) and a fine-tuned VGGNet19 (FT-VGGNet19) architecture. Both models were evaluated on the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, leveraging data augmentation to enhance generalization and mitigate dataset limitations. Experimental results show that data augmentation significantly improves classification performance. The FT-VGGNet19 model achieved the highest accuracy, reaching 90% on the original dataset and 92% with augmented data. This study highlights the strengths of each model for clinical applications, emphasizing the role of optimized deep-learning frameworks in early AD detection. The findings contribute to developing robust and scalable diagnostic systems, offering promising advancements in neurodegenerative disease management.

1 INTRODUCTION

Alzheimer's disease, the most common form of dementia, is a progressive neurodegenerative disorder that typically begins with subtle memory loss and advances to profound cognitive decline, ultimately impairing a person's ability to communicate coherently or interact with their environment. The disease primarily affects brain region responsible for memory, language, and reasoning—such as the hippocampus and cerebral cortex—disrupting neural pathways and compromising an individual's ability to perform routine daily tasks. Current estimates indicate that 1 in 9 adults aged 65 and older lives with Alzheimer's, accounting for approximately 11.4% of individuals in this age group worldwide. Characterized by the accumulation of beta-amyloid plaques and neurofibrillary tau tangles, Alzheimer's remains incurable, though ongoing research seeks to unravel its mechanisms and develop therapies to slow its devastating progression. (Balasundaram et al., 2023). The primary cause of Alzheimer's disease is the abnormal buildup of proteins in the brain, including beta-amyloid plaques and tau tangles, which contribute to brain cell death and the shrinkage of brain tissue. While ongoing research continues to enhance our understanding, there is currently no cure for Alzheimer's. However, medications and lifestyle interventions can help manage symptoms and slow the disease's progression. Medical imaging, particularly Magnetic Resonance Imaging (MRI), plays a crucial role in diagnosing Alzheimer's by providing detailed insights into brain structures and identifying characteristic patterns associated with the condition (Honig and Chin, 2001). Early detection and accurate classification of Alzheimer's disease (AD) are crucial for improving therapeutic outcomes and effectively managing cognitive decline. The challenge lies not only in identifying the con-

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Jallali, M., Mokni, R., Ammar and B.
Improved Alzheimer's Detection from Brain MRI via Transfer Learning on Pre-Trained Convolutional Deep Models.
DOI: 10.5220/0013523000003967
In *Proceedings of the 14th International Conference on Data Science, Technology and Applications (DATA 2025)*, pages 431-438
ISBN: 978-989-758-758-0; ISSN: 2184-285X

dition in its early stages—when symptoms are mild and neurological changes are subtle—but also in systematically categorizing it into distinct stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Precise staging allows clinicians to implement targeted interventions tailored to the severity of the disorder, significantly enhancing patient care and outcomes(Rasmussen and Langerman, 2019). In this context, advanced deep learning methods, particularly those leveraging brain MRI analysis, have proven to be effective tools for detecting early signs of Alzheimer's disease (AD) and monitoring its progression. MRI is widely used due to its unparalleled ability to capture detailed structural features, such as brain atrophy, a hallmark of AD pathology (El-Latif et al., 2023a) (Mokni and Haoues, 2022). The main purpose of this paper is to investigate the application of deep learning models for the early detection of Alzheimer's disease using MRI scans, classifying it into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The key contributions of this work are twofold: (1) the development of a modified CNN architecture (MCNN) tailored specifically for Alzheimer's diagnosis, and (2) the fine-tuning of a pre-trained VGGNet19 model through transfer learning to enhance classification accuracy and performance. These approaches independently highlight the effectiveness of CNN architectural modifications and transfer learning techniques in improving the detection and classification of Alzheimer's disease. The remainder of this paper is structured as follows: Section 2 reviews related work, while Section 3 describes the proposed methodology. Section 4 presents the experimental results, followed by a discussion and comparative evaluation with previous studies in Section 5. Finally, Section 6 concludes the paper and outlines future research directions.

2 RELATED WORK

In this section, we summarize and review findings from research studies on Alzheimer's disease detection using deep learning models. Ibrahem M.M. *et al.,* (Madhat et al., 2024)developed an improved method for detecting Alzheimer's disease by combining DenseNet, VGG16, and ensemble learning. They evaluated performance using accuracy, precision, recall, F1-score, and AUC-ROC on preprocessed MRI scans divided into four disease stages. Techniques like transfer learning, fine-tuning, and dropout regularization were used. Using the Alzheimer's Disease Neuroimaging Initiative (ADNI) Dataset, the method achieved The ensemble model reached 94% accuracy, outperforming standalone CNN (90%), VGG19 (89%), and DenseNet (86%), with better precision and recall across all stages, highlighting its promise for early and reliable Alzheimer's diagnosis in clinical practice. This highlights the potential of combining advanced architectures with ensemble strategies to improve early and reliable detection in clinical settings. Araqi & Abbas (Araqi and Abbas, 2022) developed a CNN-based deep learning approach for Alzheimer's detection using brain MRI, achieving 90.83% accuracy. Their findings emphasized the importance of image preprocessing in significantly improving model performance, suggesting that combining data refinement with deep learning enhances early and reliable detection. Ajagbe *et al.,*(Ajagbe et al., 2021) designed a framework for classifying Alzheimer's disease (AD) stages via MRI. Their model achieved 94.5% accuracy in distinguishing AD from normal controls, surpassing traditional diagnostic methods. This underscores the potential of DCNNs for improving early AD detection in clinical settings. Fathi *et al.,* (Fathi et al., 2024) Fathi *et al.,*(Fathi et al., 2024) introduced an ensemble CNN method for early Alzheimer's detection using MRI scans. Tested on the ADNI dataset, their approach reached 91.2% accuracy, demonstrating its reliability for diagnosis. Table 1 provides an overview of past research efforts focused on detecting Alzheimer's disease.

Table 1: Summary of the related works focused on Alzheimer's disease classification.

Proposal	**Used Dataset**	**Method**	**Results**
Ibrahem M.M. *et al.,* (Madhat et al., 2024)	ADNI dataset	CNN VGG16 DenseNet Ensemble learning	90% 89% 86% 94%
Araqi & Abbas (Araqi and Abbas, 2022)	alzheimers-dataset-4-class-of-images	CNN	90.83%
Ajagbe *et al.,*(Ajagbe et al., 2021)	alzheimers-dataset-4-class-of-images	VGG-19	77.66%
Fathi et *al.,* (Fathi et al., 2024)	ADNI Dataset	Ensemble learning CNN	91.2%

3 PROPOSED METHODOLOGY

As highlighted in Section 2, various studies have explored Alzheimer's Disease (AD) diagnosis using deep learning. Some approaches, such as those combining DenseNet, VGG16, and ensemble learning, have demonstrated strong performance but involve complex architectures. Others have employed CNNs, Deep Convolutional Neural Networks (DCNNs), or ensemble learning of multiple CNNs. In contrast, our approach focuses on a modified CNN architecture (MCNN) and a fine-tuned VGGNet19 (FT-VGGNet19), aiming to enhance classification accuracy through architectural modifications and fine-tuning rather than relying on extensive ensemble models. Our approach for classifying Alzheimer's disease (AD), as shown in Figure 1, involves five key steps: (1) Dataset collection (2) Data augmentation, (3) Data preprocessing, (4) Deep learning-based proposed models, and (5) Decision Making to classify AD into four stages.

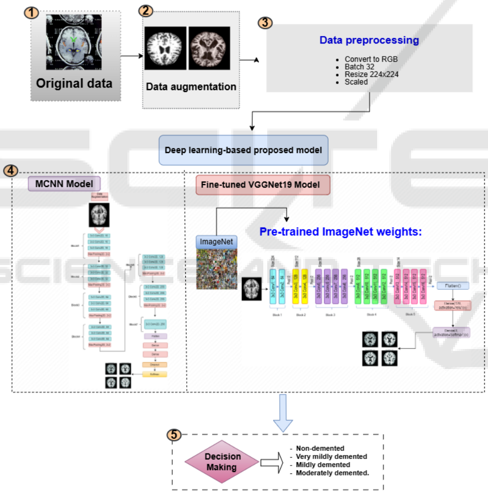

Figure 1: The overview of the proposed Model.

3.1 Dataset Description

We used a publicly available MRI dataset for Alzheimer's disease (AD) (Dubey, 2024), sourced from Kaggle. This dataset includes images from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and contains 6,400 MRI scans split into four categories: mild dementia (896 images), moderate dementia (64 images), non-dementia (3,200 images), and very mild dementia (2,240 images). Examples from the dataset are shown in Figure 2 (El-Latif et al., 2023b).

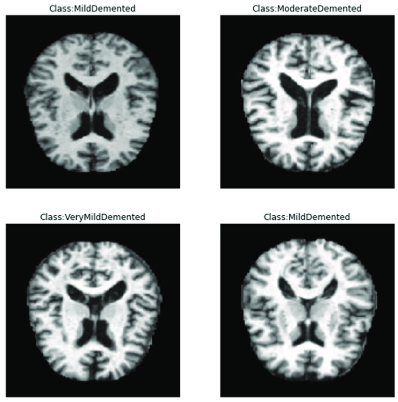

Figure 2: Sample MRI images.

3.2 Dataset Augmentation

Data augmentation is a key technique to improve how well deep learning models classify Alzheimer's disease (AD) using MRI scans. AD datasets are often small due to limited patient availability, which can cause models to overfit and perform poorly on new data. Data augmentation tackles this by artificially expanding the training dataset's size and variety, helping models learn stronger features and generalize better to unseen cases (El-Assy et al., 2024). The original dataset, from Kaggle's open-access platform (Uraninjo, 2024), contains 33,984 MRI scans grouped into four categories: mild dementia (8,960 images), moderate dementia (6,464 images), non-dementia (9,600 images), and very mild dementia (8,960 images). To expand the dataset, we applied image transformations (flipping, rotating...) while keeping key features relevant to Alzheimer's disease intact. The augmentation techniques employed include:

-Rotation: Random rotations within a range of [-20°, 20°] to simulate different head orientations.

-Scaling: Size adjustments were applied to account for MRI dimensional variability.

-Flipping: Horizontal flips were applied to increase dataset variability while preserving the diagnostic features.

-Brightness Adjustment: Variations in brightness were incorporated to simulate the impact of different lighting conditions during the image capture process.

-Zoom Transformation: Images were randomly zoomed within a range of ±20% to simulate variations in scale. Using these augmentation techniques, we expanded the dataset and boosted the performance of our deep learning models in classifying Alzheimer's disease (AD). Figure 3 shows the distribution of Alzheimer's disease categories within the Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

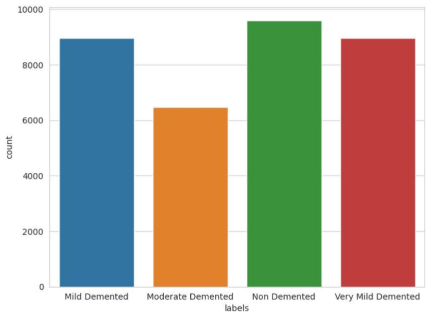

Figure 3: The distribution of Alzheimer's diseases after data augmentation.

3.3 Dataset Preprocessing

This section describes the essential preprocessing steps taken to prepare the data for model training, ensuring efficient learning on a potentially imbalanced dataset. First, all images were turned to RGB color. Next, we bundled them into batches of 32, reshaped them to 224x224 pixels, and scaled their pixel values. For better model performance and generalization, the dataset was split into three subsets: 70% of the data was used for training, 20% for testing, and 10% for validation. This three-way split ensures that the model is evaluated on unseen data, helping to mitigate the risk of overfitting and ensuring that it performs well on new, unseen data.

3.4 Application of Deep Learning-Based Proposed Models

This study explores the application of deep learning-based models for Alzheimer's disease classification, proposing a novel modified Convolutional Neural Network (MCNN) and leveraging transfer learning with pre-trained models. Specifically, we fine-tuned VGGNet19 to develop the FT-VGGNet19 model, optimizing its performance for AD classification.

3.4.1 Modified-CNN

A Convolutional Neural Network (CNN) is a deep learning model specifically designed to process structured grid-like data, such as images. Its architecture typically consists of multiple layers, each serving a distinct purpose: convolutional layers extract meaningful features, pooling layers reduce dimensionality and computational complexity, fully connected layers make high-level decisions, and activation functions introduce non-linearity to enhance learning capabilities. Together, these components enable CNNs to efficiently capture patterns and improve model performance (Awarayi et al., 2024) (Fki et al., 2024). In this study, we propose a novel architecture called Modified-CNN (MCNN), which introduces several enhancements to the standard CNN design. The MCNN consists of seven blocks, with the first six containing four layers each: three Conv2D layers followed by a MaxPooling2D layer. The final block includes an additional Conv2D layer to improve feature extraction. After these blocks, the model is compressed, followed by two fully connected (dense) layers with 512 units each and ReLU activation. A dropout layer with a rate of 0.3 is applied before the final dense layer, which consists of four units and a softmax activation function for classification. Figure 4 provides a detailed overview of the MCNN architecture.

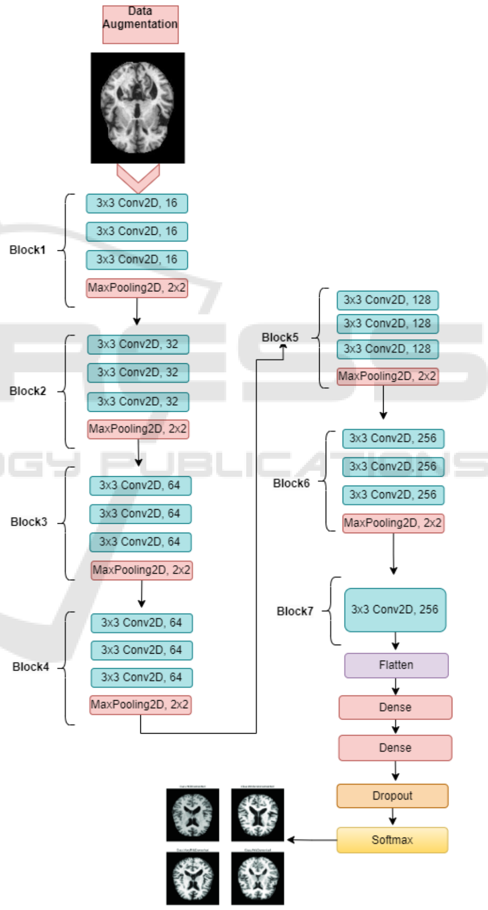

Figure 4: Proposed MCNN Model.

3.4.2 Fine-Tuned VGGNet 19 Model

In this paper, we investigate the use of transfer learning and fine-tuning the pre-trained VGGNet 19 model, called Fine-Tuned VGGNet 19 model (FT-VGGNet 19). Initially, we leverage the VGG19 model, pre-trained on the ImageNet dataset to obtain the trained weights parameters that are used to extract the pertinent features. It consists of 19 layers, including convolutional, pooling, and fully connected layers. The network employs 3×3 convolution filters with small strides to extract features from input images while pooling layers reduce the spatial dimensions of feature maps. The fully connected layers perform object classification, with a softmax output layer handling multi-class classification. In this study, the model's pre-trained weights remain frozen throughout the training process to maintain the integrity of these learned features. After that, we created a transfer learning method by modifying the architecture by firstly flattening, followed by adding a dense layer and introducing a softmax activation function to classify the images into four distinct categories related to Alzheimer's disease. This adjustment effectively tailors the model for Alzheimer's disease image classification. Figure 5 provides a detailed overview of the FT-VGGNet19 architecture.

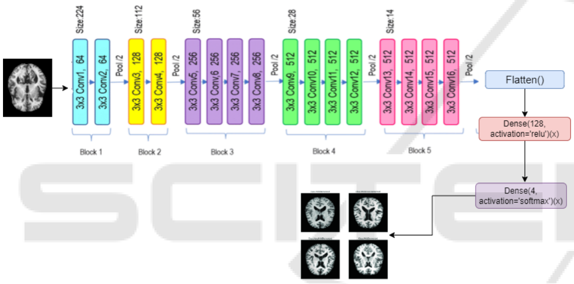

Figure 5: Proposed Fine-Tuned VGGNet19 Model.

4 EXPERIMENTAL RESULTS

In our study, the processing and classification tasks were performed using the Python programming language. The models were trained on Google Colab, leveraging a graphics processing unit (GPU) to enhance computational efficiency. To investigate the contribution of deep learning models in classifying Alzheimer's disease, we conducted several experiments using the proposed models: Modified CNN (MCNN) and Fine-Tuned VGGNet19. Table 2 summarizes the evaluation results for Alzheimer's disease classification, highlighting the impact of different original data methods and augmentation techniques on accuracy and robustness. The results presented in Table2 highlight the impact of data augmentation on the performance of deep learning models for Alzheimer's disease classification. Both the Fine-Tuned VGGNet19 (FT-VGGNet19) and the Modified CNN (MCNN) models demonstrate improved accuracy when trained with data augmentation. Specifically, FT-VGGNet19 achieves an accuracy of 92% with data augmentation compared to 90% without, while MCNN shows a significant improvement from 73% to 90%. Similarly, the F1-score for MCNN improves significantly from 64% to 90% with data augmentation, demonstrating a substantial enhancement in the model's overall classification performance, particularly in balancing precision and recall. These findings emphasize the effectiveness of data augmentation in boosting model robustness and classification performance, particularly for the MCNN model. In this study, we conducted two experiments: the first focused on classifying Alzheimer's disease using the original data, while the second involved applying data augmentation to improve classification performance from MRI images.

4.1 The First Experiment

In this section, a deep learning model was used to classify MRI images into four categories: Mild Demented, Moderately Demented, Non-Demented, and Very Mild Demented, using the original dataset. Model performance was evaluated with a confusion matrix, comparing predicted labels to actual ones (Vengala, 2024) and the training and validation accuracy and curves. Figure 6 presents the results of the confusion matrix for the classification of Alzheimer's diseases according to four categories obtained from MCNN and FT-VGGNet19 using the original dataset. As illustrated in this Figure, FT-VGGNet19 achieved the highest accuracy, outperforming MCNN in terms of classification effectiveness. Diagonal elements indicate correct predictions, while off-diagonal values represent misclassifications. FT-VGGNet19 correctly classifies 161 Non Demented and 122 Very Mild Demented cases, with misclassifications mainly occurring between similar classes. Figure 7 presnts the Training /Validation Accuracy curves results for the classification of Alzheimer's diseases according to four categories obtained from MCNN and FT-VGGNet19 over 15 epochs using the original dataset. Figure 7 (B) tracks training and validation accuracy obtained from FT-VGGNet19 across 15 epochs. A well-trained model shows both curves rising and stabilizing. A divergence where training accuracy increases but validation accuracy stagnates suggests overfitting, while low accuracy in both indicates underfitting. The validation curve is crucial for assessing real-world performance.

Table 2: Evaluation of Alzheimer's Disease Classification Using the Proposed MCNN Model and Fine-Tuned VGGNet19 Models with Data Augmentation Techniques and Original Data.

Model	Data Augmentation		Original Data	
	FT-VGG-Net19	MCNN	FT-VGG-Net19	MCNN
Accuracy	92%	90%	90%	73%
Precision	91%	91%	92%	83%
Recall	92%	90%	94%	58%
F1 Score	91%	90%	93%	64%

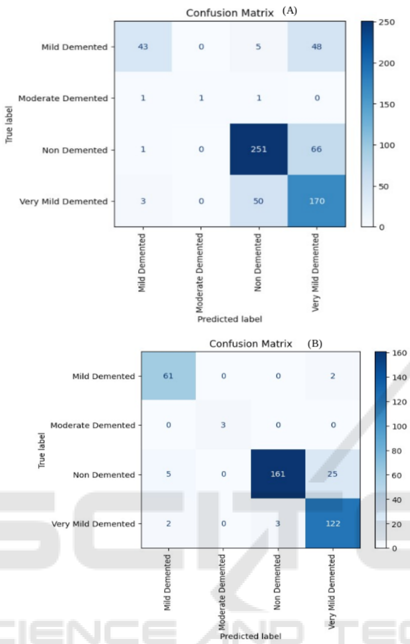

Figure 6: Confusion Matrices obtained by (A) MCNN (B) FT-VGGNet19 with original data.

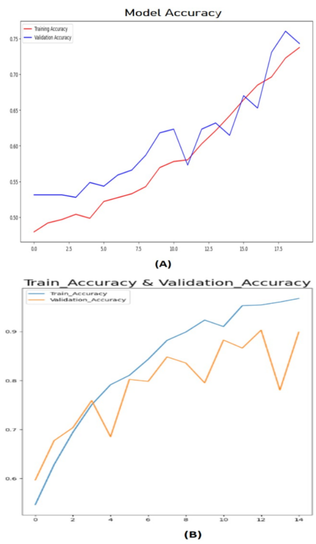

Figure 7: Training and Validation Accuracy curves obtained by (A) MCNN (B) FT-VGGNet19 with original data.

4.2 The Second Experiment

In this section, the proposed MCNN and Pretrained FT-VGGNet19 was implemented to classify MRI scans into four categories: Mild Demented, Moderately Demented, Non-Demented, and Very Mild Demented using the augmented dataset to enhance the model's robustness and generalization. The model's effectiveness was assessed through the confusion matrix, which compares predicted labels with actual ground truth labels and the training and validation accuracy curves.

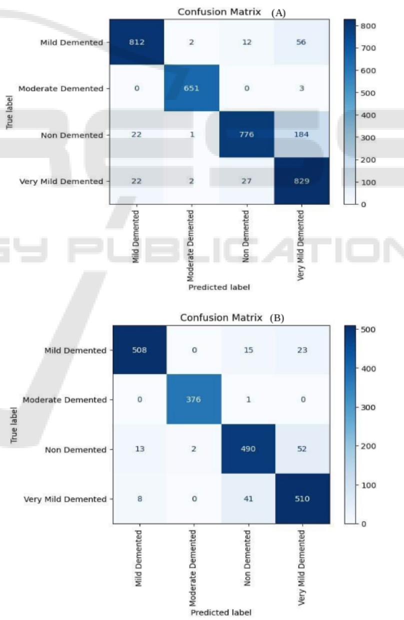

Figure 8: Confusion Matrices obtained by (A) MCNN (B) FT-VGGNet19 with data augmentation.

Figure 8 shows the results of the confusion matrix for the classification of Alzheimer's disease according to four categories obtained from MCNN and FT-VGGNet using the augmented dataset. As shown in this figure, using the augmented dataset, FT-VGGNet19 also achieved the highest accuracy compared to MCNN. FT-VGGNet19 correctly classifies 508 Mild Demented, 376 Moderate Demented,

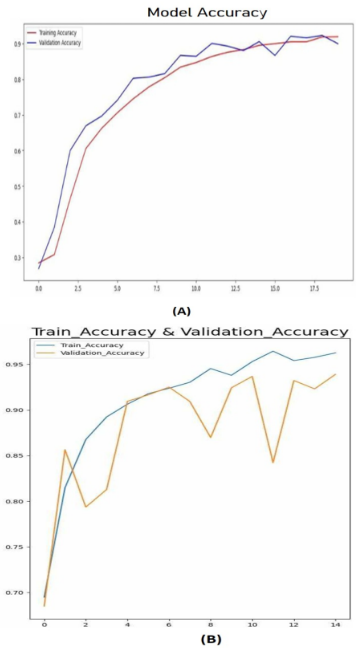

Figure 9: The Training and Validation Accuracy curves obtained by (A) MCNN (B) FT-VGGNet19 with data augmentation.

490 Non-Demented, and 510 Very Mild Demented cases, with misclassifications mainly occurring between similar classes.

Figure 9 illustrates the training and validation accuracy curves for Alzheimer's disease classification into four categories using MCNN and FT-VGGNet19 over 15 epochs with the augmented dataset. Specifically, Figure 9 (B) depicts the accuracy trends for the proposed FT-VGGNet19 model.

A well-trained model exhibits steadily increasing and stabilizing curves, indicating effective learning. However, if the validation accuracy plateaus with noticeable fluctuations while the training accuracy continues to rise, it suggests overfitting.

5 DISCUSSION AND COMPARATIVE EVALUATION

This section presents the results of classifying Alzheimer's disease into four categories—non-demented, very mildly demented, mildly demented, and moderately demented—using various architectures. We modified a basic CNN and fine-tuned a pre-trained VGGNet19, evaluating them on both original and augmented datasets. As shown in Table 2, data augmentation had a significant positive impact.

The FT-VGGNet19 maintained high performance across both datasets, while the modified CNN benefited most from augmentation. These results highlight the value of data augmentation, especially for custom architectures when data is limited. To the best of our knowledge, no prior work has been conducted using augmented data for Alzheimer's disease classification with this dataset. Therefore, we compare our results with previous studies that used the same original dataset. Table 3 highlights the effectiveness of our proposed model in classifying Alzheimer's disease compared to previous studies, including those by Ajagbe et al. (Ajagbe et al., 2021) and Araqi & Abbas (Araqi and Abbas, 2022), which were conducted on the original Alzheimer's dataset (4-class classification). As illustrated in Table 3, our model achieved an accuracy of 90%, outperforming Ajagbe et al. (Ajagbe et al., 2021) (77.66%) with an improvement of 12.34%, and yielding comparable results to Araqi & Abbas (Araqi and Abbas, 2022) (90.83%).

Table 3: Comparative analysis of proposed work with previous works.

Authors	**Datasets**	**Models**	**Accuracy (%)**
Proposed	alzheimers-dataset-4-class-of-images	FT-VGGNet19	90%
	Augmented Alzheimer MRI Dataset	FT-VGGNet19	92%
Ajagbe. *et al.*, (Ajagbe et al., 2021)	alzheimers-dataset-4-class-of-images	VGG-19	77.66%
Ibrahem M.M. *et al.*, (Madhat et al., 2024)	MRI dataset	CNN VGG16 DenseNet Ensemble	90% 89% 86% 94%
Araqi & Abbas (Araqi and Abbas, 2022)	alzheimers-dataset-4-class-of-images	CNN	90.83%

6 CONCLUSION AND FUTURE WORK

Alzheimer's disease (AD) is a major neurodegenerative disorder, where early diagnosis is crucial for effective intervention. Traditional diagnostic methods rely on clinical expertise, which can lead to delays and inconsistencies. Advances in deep learning, particularly in medical imaging, have significantly improved diagnostic accuracy using brain MRI scans. This study proposes a modified CNN (MCNN) and a fine-tuned VGGNet19 (FT-VGGNet19) for classifying Alzheimer's disease into four categories—non-demented, very mildly demented, mildly demented, and moderately demented, evaluating both on original and augmented datasets. The FT-VGGNet19 consistently maintained high performance, achieving 92% accuracy with data augmentation and 90% without. In contrast, the MCNN benefited significantly from augmentation, demonstrating notable improvement. Additionally, we assessed the models using precision, recall, and F1-score, further validating their effectiveness. Overall, this study underscores the potential of deep learning in improving AD diagnosis through MRI analysis. Future work will explore advanced augmentation techniques and explainable AI frameworks to enhance model interpretability and clinical applicability.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the Ministry of Higher Education and Scientific Research of Tunisia under grant agreement number LR11ES48.

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