Deep Learning Implementation with DenseNet for Alzheimer's Disease Detection in MRI

1st Simeon Yuda Prasetyo
Computer Science Department
School of Computer Science
Bina Nusantara University
Jakarta, Indonesia 11480
simeon.prasetyo@binus.ac.id

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***Abstract*—The challenge posed by Alzheimer's disease (AD) in contemporary healthcare is significant due to its profound impact on cognitive functions. Recent progress in medical imaging and machine learning techniques offers promising avenues for early detection and diagnosis of AD, particularly through analyzing magnetic resonance imaging (MRI) scans. This study addresses the critical need for precise AD detection by optimizing pretrained DenseNet models for AD classification in MRI images. We perform transfer learning and fine-tuning stages on the DenseNet121, DenseNet169, and DenseNet201 architectures to tune the models for AD detection. The model's performance is thoroughly evaluated using comprehensive assessment measures like as accuracy, precision, recall, and F1-score. Our findings demonstrate that DenseNet169 achieves a remarkable accuracy of 99.806%, making it the top performer during the transfer learning phase. Moreover, DenseNet121 and DenseNet201 display competitive performance, showcasing the effectiveness of DenseNet architectures in neuroimaging tasks. These results underscore the potential of pretrained DenseNet models as potent tools for AD detection, providing valuable insights into enhancing diagnostic accuracy and patient care in neuroimaging-based disease diagnosis.**

Keywords—Alzheimer's disease, Deep Learning, DenseNet Models, MRI images, Pretrained

I. Introduction

Alzheimer's disease (AD) presents itself as a significant healthcare concern in modern times, given its substantial influence on cognitive capabilities and overall well-being. AD represents a progressive neurodegenerative condition marked by the deterioration of brain cells, resulting in dementia and the gradual decline of cognitive functions [1]. Memory loss, faulty reasoning, and trouble completing daily tasks on one's own are among the typical signs of AD.

The increasing prevalence and profound societal consequences of Alzheimer's disease highlight the pressing need for research and detection efforts. This condition extends its impact beyond individual patients, affecting families, caregivers, and healthcare systems worldwide. The burden of Alzheimer's disease transcends personal boundaries, influencing emotional, financial, and social dimensions of life.

Alzheimer's disease is a complex disorder with multifactorial etiology, involving various pathological processes such as synaptic dysfunction, neuroinflammation, and protein misfolding [2]. Despite decades of research, the precise mechanisms underlying AD pathogenesis remain incompletely understood, necessitating continued exploration and investigation.

The creation of successful treatment plans requires a thorough understanding of the biology of Alzheimer's disease. Current therapeutic interventions for AD focus primarily on symptom management and disease modification, aiming to slow down disease progression and alleviate cognitive decline [1]. To obtain more meaningful clinical outcomes, however, innovative treatment methods that address the underlying processes of AD pathogenesis are desperately needed.

The societal impact of Alzheimer's disease cannot be overstated. AD is a leading cause of disability and dependency among older adults, significantly impairing individuals' ability to perform daily activities and maintain independence [1]. Moreover, Alzheimer's disease places a substantial burden on caregivers, who often experience high levels of stress, depression, and financial strain [3].

The economic burden of Alzheimer's disease is staggering, with healthcare costs and caregiving expenses reaching billions of dollars annually[4]. The financial strain associated with AD extends beyond direct medical costs, encompassing indirect costs such as lost productivity and income. Furthermore, the projected increase in Alzheimer's disease prevalence in the coming years suggests that the economic burden will continue to escalate, necessitating proactive measures to address this growing crisis [5].

Detecting Alzheimer's disease early is crucial for various reasons. Firstly, it enables timely implementation of interventions to slow disease progression and maintain cognitive function [6]. Second, early detection makes it possible for people and their families to receive support resources, plan ahead, and decide on the best course of care [4]. Finally, early diagnosis makes it easier for people to take part in clinical trials and research studies, which helps to develop new treatments and improve the management of AD.

Advances in medical imaging techniques, particularly magnetic resonance imaging (MRI), have revolutionized the early identification and detection of Alzheimer's disease. Neuroimaging (MRI) offers comprehensive anatomical and functional data about the brain, enabling medical professionals to recognize distinctive neuroimaging biomarkers linked to AD disease [6]. Certain anatomical alterations in the brain, such as cortical thinning and hippocampal atrophy, which are suggestive of Alzheimer's disease, can be identified by the analysis of MRI data [1].

Beyond structural MRI, advanced imaging modalities including as diffusion tensor imaging (DTI) and functional magnetic resonance imaging (fMRI) offer crucial information on the microstructural and functional problems associated with AD [6]. These imaging techniques allow

researchers to investigate connectivity disruptions, white matter abnormalities, and aberrant neural network activity, providing a comprehensive understanding of Alzheimer's disease pathophysiology.

Alzheimer's disease (AD) detection and diagnosis have undergone a radical change because to recent developments in medical imaging and machine learning approaches, especially when it comes to the interpretation of magnetic resonance imaging (MRI) data. These advancements present viable paths for early detection and therapy, which are essential for reducing the incapacitating consequences of AD. A noteworthy addition is made by Lu et al. [7], who presented a useful AD classifier on MRI scans using deep learning and reaching an amazing accuracy of 94.9%. The potential of deep learning algorithms to produce biomarkers of medical grade for integrated diagnostic techniques is highlighted by this breakthrough. Similarly, K et al. [8] demonstrated the effectiveness of utilizing Haralick features and Support Vector Machine (SVM) to classify AD patients from normal controls with an accuracy of 84%, focusing on 2D MRI axial slices. This approach, although relatively straightforward, showcases promising results in differentiating between individuals with AD and healthy subjects.

Furthermore, deep learning methods have demonstrated a great deal of potential in improving the accuracy of AD detection. [9] utilized Segnet, a deep learning model, to achieve a remarkable accuracy of 97% in classifying AD from cross-sectional brain MRI. This highlights the potential of leveraging comprehensive imaging data for accurate and efficient AD diagnosis. Awasthi et al. [10] proposed a novel AD classification technique from brain MRI images, attaining an average accuracy of 92.34%. Their technique shows solid performance in differentiating AD patients from healthy controls by combining a Deep Belief Network (DBN) with Gray Level Co-occurrence Matrix (GLCM) data.

In addition, Muhammed et al. showed that Convolutional Neural Networks (CNNs) are useful for early AD identification, with an accuracy rate of 84.4%. This underscores the value of deep learning methods in improving AD diagnosis and classification. By using brain MRI scans to create a multi-classification model, Kabir et al. were able to beat prior models with an accuracy of over 80% in AD detection. Their findings demonstrate how machine learning techniques can be used to increase the precision of AD diagnosis using MRI data [11], [12].

Additionally, Wu et al. proposed a VGG cascade model for early AD diagnosis based on structured MRI, achieving an accuracy of 90.1%. This model's ability to accurately detect AD at an early stage holds promise for timely intervention and treatment [13]. Ebrahimi et al. introduced transfer learning to 3D ResNet-18 for AD detection on MRI images, attaining an impressive accuracy of 96.88%. This underscores the efficacy of transfer learning in enhancing the performance of deep learning models for AD classification [14]. Finally, with an accuracy improvement of 85.07%, Bian showed the superiority of the ResNet deep learning convolutional network over conventional models. Together, these results demonstrate the tremendous progress made in utilizing deep learning and machine learning methods to improve the precision and effectiveness of AD diagnosis by MRI imaging, eventually enabling early intervention and treatment plans [15].

The main goal of this study is to enhance pretrained DenseNet models, which are initialized with default weights from the ImageNet dataset, for detecting Alzheimer's disease (AD) in MRI images. Specifically, the investigation focuses on DenseNet121, DenseNet169, and DenseNet201 architectures. The study comprises two primary phases: transfer learning and fine-tuning. During the transfer learning phase, pretrained DenseNet models are initialized with weights obtained from the ImageNet dataset and then fine-tuned on the ADNI (Alzheimer's Disease Neuroimaging Initiative) MRI dataset to adapt them to the AD detection task. Subsequently, the fine-tuning phase aims to optimize the models' parameters using the ADNI MRI dataset to further enhance their performance. Important metrics like as accuracy, precision, recall, and F1-score will be used to evaluate each DenseNet variation. This study aims to find the best method for Alzheimer's disease detection in MRI images by carefully contrasting DenseNet topologies and fine-tuning strategies. Finally, the study hopes to significantly advance the development of reliable and effective diagnostic instruments for the early diagnosis of Alzheimer's disease, allowing for prompt intervention and treatment plans.

II. Methodology

A. Experimental Design

This experimental design explains how to use the ADNI dataset to develop and assess deep learning models for Alzheimer's disease identification. Firstly, the dataset is prepared using standard methods, such reducing the size of the pictures to 224 × 224 x 3 pixels. After that, the dataset is divided into three subsets, training, validation, and testing, with percentages of 80%, 10%, and 10%, respectively, to help with efficient model assessment, validation, and training. Pretrained DenseNet models, namely DenseNet121, DenseNet169, and DenseNet201, are then employed for transfer learning. Initially trained on large-scale image datasets, these models are subsequently fine-tuned on the training subset, with adjustments guided by validation subset performance to mitigate overfitting risks.

The testing subset is used to assess the model once it has been trained. In order to assess how successfully the model can distinguish between Alzheimer's disease, mild cognitive impairment, and normal thinking states, metrics such as accuracy, precision, recall, and F1 score are generated. By carefully analyzing each of these criteria, the model that performs best is found, offering important new information about diagnosing Alzheimer's disease and categorizing cognitive states. Those who are interested might view Figure 1, which shows the sequential process from data preparation to model evaluation, as a visual depiction of the workflow used in this experimental design.

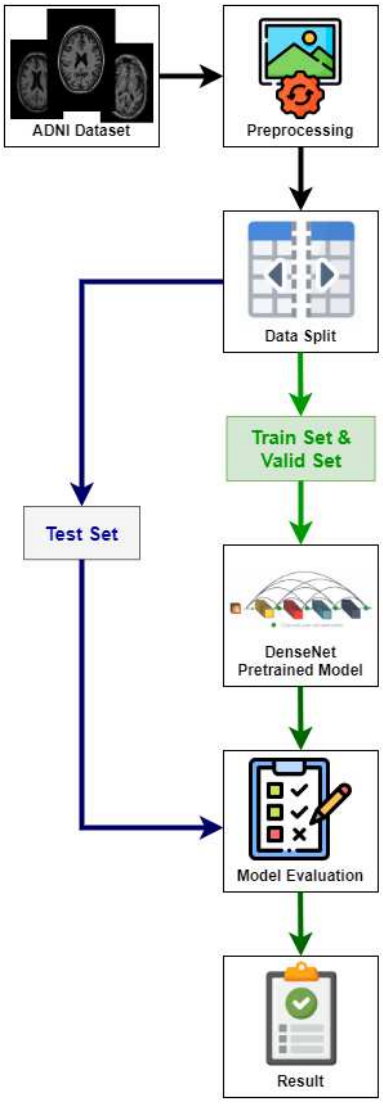

Fig. 1 Experimental Design Workflow

B. ADNI Dataset

The "ADNI Extracted Axial" dataset serves as a pivotal resource for researchers and practitioners in the domains of Alzheimer's disease and neuroimaging. Comprising 5154 meticulously curated 2D axial images sourced from the ADNI baseline dataset on Kaggle [16], this dataset offers a simplified avenue for the implementation of image processing algorithms. With subjects classified into three distinct classes—AD (Alzheimer's Disease), CI (Mild Cognitive Impaired), and CN (Common Normal)—and corresponding image counts of 1124, 2590, and 1440 respectively, the dataset provides a diverse array of images capturing various stages of cognitive impairment.

Researchers can leverage this dataset to advance the diagnosis, treatment, and understanding of Alzheimer's ldisease and related cognitive disorders. By facilitating the development and validation of image processing algorithms, the dataset empowers researchers to enhance diagnostic accuracy and monitor disease progression effectively. Moreover, the dataset's availability on Kaggle encourages collaborative research efforts and knowledge exchange within the scientific community, thereby fostering innovation and expediting breakthroughs in Alzheimer's disease research. For a visual representation of the dataset's contents, interested individuals can refer to Figure 2, which provides exemplary images from the ADNI dataset.

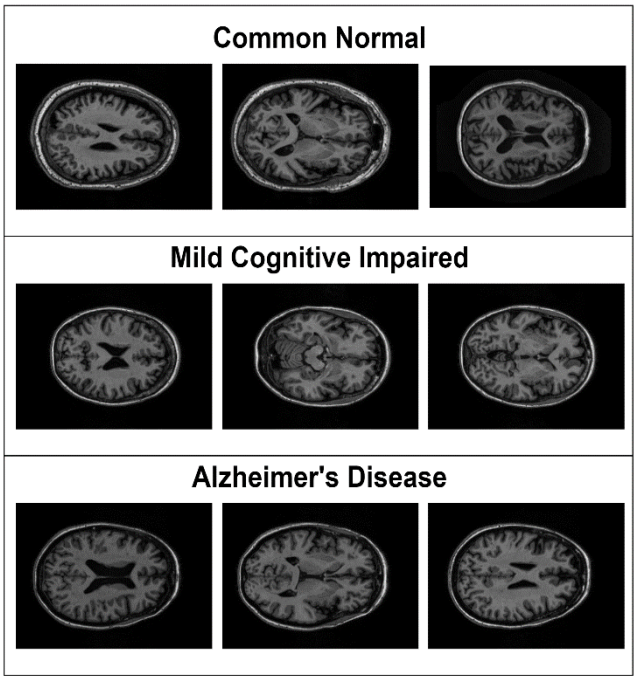

Fig. 2 Example of ADNI Extracted Axial Dataset

C. Convolutional Neural Networks

Convolutional Neural Network (CNN) models that have been pre-trained and rigorously trained on datasets such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) show extraordinary variety and precision in identifying a wide range of everyday objects. These pretrained CNN models may be effectively reused for diverse computer vision applications using transfer learning, avoiding the requirement to develop models from start when confronted with unexpected object identification challenges [17]. CNNs are highly effective in extracting deep features from 2-D data by combining feature extraction and classification into a single, cohesive framework. They also demonstrate strong resilience to both local and geometric changes in images. Convolution, pooling, and output layers—the three central layers of a CNN—work together to obtain feature representations that are hierarchical from the input data. The effectiveness of the CNN is greatly enhanced by this hierarchical learning process in a wide range of computer vision applications [18].

D. DenseNet

DenseNet, short for Dense Convolutional Network, represents a pivotal advancement in convolutional neural network (CNN) architectures, characterized by its dense connectivity patterns. DenseNet establishes direct connections between every layer inside a dense block, in contrast to conventional CNNs where each layer is only connected to the layer after it. Due to the feature reuse that is made possible at various network depths by this dense

connectivity, information moves across the network more effectively. Li et al. emphasized DenseNet's superiority over alternative CNN designs with comparable parameters or FLOPs (floating-point operations) in terms of accuracy and efficiency [19]. This efficiency is crucial for various computer vision tasks, including image classification, object detection, and semantic segmentation, where DenseNet's dense connections contribute to improved gradient flow, thereby facilitating better convergence and learning [20].

Moreover, DenseNet's architecture enables effective feature propagation across multiple layers, making it particularly suitable for tasks requiring high-level feature extraction, such as medical image analysis. Dong et al. (2022) demonstrated DenseNet's efficacy in super-resolution tasks by leveraging its dense connectivity to facilitate feature reuse in a feedforward manner, resulting in state-of-the-art reconstruction accuracy [21]. Due to its capacity to identify complex patterns and minute details in medical images, DenseNet has become a useful tool in the field of medical imaging for pattern recognition, image segmentation, and disease detection [22]. The model can distinguish between complicated patterns linked to a variety of diseases, such as Alzheimer's disease, cancer, and neurological disorders, thanks to DenseNet's thick connections, which encourage feature interactions across various network depths.

Furthermore, DenseNet's dense connectivity promotes efficient information flow and parameter utilization, leading to improved model performance and reduced overfitting. This unique architecture allows DenseNet to achieve state-of-the-art results in various computer vision tasks while maintaining a compact model size. DenseNet's impact extends beyond medical image analysis to domains such as natural language processing, where dense connections have been adapted to enhance the efficiency and effectiveness of transformer-based models. Overall, DenseNet represents a significant advancement in deep learning architectures, offering a versatile and efficient framework for a wide range of applications, from medical imaging to natural language understanding, driven by its dense connectivity and feature reuse mechanisms.

E. Performance Evaluation

Performance evaluation is essential for describing and assessing a system's effectiveness, especially in classification jobs where measures like accuracy, precision, recall, and F1-score are frequently used. By calculating the ratio of accurate predictions to the entire dataset, accuracy measures the percentage of correctly classified data and effectively separates good from negative examples. Precision gauges how well the model accurately identifies true positive predictions. Recall, on the other hand, assesses the model's accuracy in identifying real positives, which is especially important in situations when there is a significant cost associated with missing positive cases. When addressing imbalanced datasets, the F1-score is particularly useful since it offers a comprehensive evaluation metric by combining precision and recall. This makes it a well-rounded assessment. Together, these metrics offer a comprehensive comprehension of a model's performance across various classification aspects, ensuring a thorough assessment of its efficacy[23], [24], [25] . The formulas for accuracy, precision, recall, and F1 Score are represented in Equations 1 - 4.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-Score} = \frac{2TP}{2TP+FN+FP} \quad (4)$$

III. Results and Discussion

Experimentation unfolded within the Python environment of Google Colab, harnessing the computational prowess of high-performance T4 GPUs coupled with 12.7 GB of RAM to ensure swift and accurate model training and evaluation. This amalgamation of resources facilitated a seamless journey through the intricacies of the project. The process of developing models was made more efficient and successful by utilizing well-known libraries such as Keras and TensorFlow, which provided access to a variety of model architectures and pre-trained weights from ImageNet.

A steadfast adherence to a consistent methodology underscored the experimentation, ensuring uniformity and reliability across all phases. The utilization of the cross-entropy loss function, alongside the standardization of training epochs to 10 and maintaining a batch size of 16, contributed to the robustness of the approach. This meticulous attention to detail laid a sturdy foundation for subsequent analyses and comparisons, fostering confidence in the findings.

The implementation of transfer learning with specific parameters proved instrumental in optimizing model performance. By applying a learning rate of 0.0001 during transfer learning, the pre-trained knowledge was adeptly adapted to the task at hand, enhancing the model's efficacy. Furthermore, a systematic fine-tuning strategy, which involved gradually freezing layers and adjusting the learning rate to 0.00001, further refined the model, enabling it to capture intricate patterns and nuances within the data.

Transparency and reproducibility were paramount throughout the experimentation process, safeguarding the integrity and reliability of the results. Detailed methodologies, encompassing specifics such as batch size and learning rates, were meticulously documented to facilitate reproducibility and transparency. Additionally, the implementation of callbacks for monitoring and control bolstered the transparency and reliability of the experimentation process. Multiple variants of DenseNet models, including DenseNet121, DenseNet169, and DenseNet201, underwent a comprehensive comparison, with the results meticulously presented in Table 1. This presentation not only enhanced clarity but also served as a basis for further analysis and discussion, augmenting the interpretability of the findings.

TABLE I. EXPERIMENTAL RESULTS

Model	Metrics	Phase	
		Transfer Learning	Fine Tuning
DenseNet121	Accuracy	0.99612	0.96505
	Precision	0.99612	0.96565
	Reccal	0.99612	0.96505
	F1 - Score	0.99611	0.96487
DenseNet169	Accuracy	0.99806	0.99223
	Precision	0.99808	0.99238
	Reccal	0.99806	0.99223
	F1 - Score	0.99806	0.99224
DenseNet201	Accuracy	0.99029	0.99417
	Precision	0.99037	0.99419
	Reccal	0.99029	0.99417
	F1 - Score	0.99029	0.99418

The efficacy of pretrained DenseNet models for Alzheimer's Disease identification in MRI images is clarified by the experimental data presented in Table I. DenseNet169 is the best performing model among those that were examined during the transfer learning phase. Its metrics for accuracy, precision, recall, and F1-score are outstanding, coming up at 99.806%, 99.808%, 99.806%, and 99.806%, respectively. This shows that DenseNet169 does not require additional fine-tuning to distinguish between MRI images of Alzheimer's patients and those of healthy individuals. Furthermore, DenseNet121 exhibits competitive performance with an F1-score of 99.611%, accuracy, precision, and recall of 99.612%, 99.612%, and 99.612% during the transfer learning phase. Although DenseNet121's accuracy is marginally lower than DenseNet169's, its strong performance suggests that it may have applications in the identification of Alzheimer's disease.

Additionally, DenseNet201 has encouraging performance, especially at the fine-tuning stage, when it attains an F1-score of 99.418%, recall of 99.417%, accuracy of 99.417%, and precision of 99.419%. DenseNet201 performs much better after fine-tuning, although showing somewhat lower accuracy during the transfer learning phase, highlighting the usefulness of fine-tuning strategies in improving model performance. Together, these results demonstrate the effectiveness of pretrained DenseNet models in detecting Alzheimer's disease and stress the significance of fine-tuning model parameters to maximize diagnostic accuracy in neuroimaging applications.

In addition to model evaluation metrics, learning curve in Figure 3 and confusion matrix in Figure 4 plots for DenseNet169 during the transfer learning phase further elucidate the model's performance. The learning curve provides insights into the model's training and validation performance over epochs, depicting how the accuracy and loss evolve during training. On the other hand, the confusion matrix provides a visual depiction of the model's classification performance by displaying the distribution of true positive, true negative, false positive, and false negative predictions. These supplemental visualizations, when combined with quantitative measures, can provide a thorough insight of the model's behavior and diagnostic capabilities.

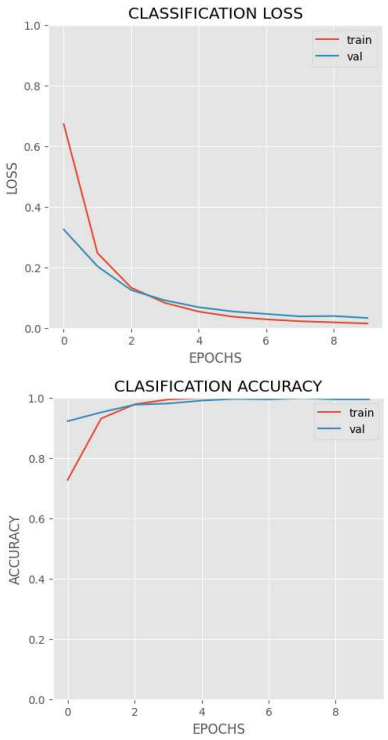

Fig. 3 Learning Curve of DenseNet169 – Transfer Learning

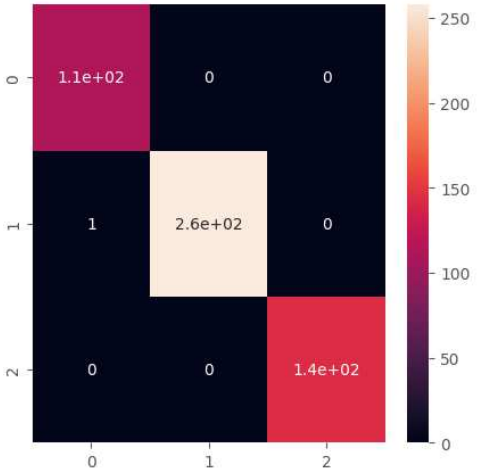

Fig. 4 Confusion Matrix of DenseNet169 – Transfer Learning

In summary, the experimental outcomes demonstrate the potential of pretrained DenseNet models as powerful tools for Alzheimer's Disease detection in MRI images. DenseNet169 emerges as the top performer, showcasing exceptional accuracy and robustness in identifying Alzheimer's-related abnormalities. Additionally, DenseNet121 and DenseNet201 exhibit competitive performance, underscoring the versatility and efficacy of DenseNet architectures in neuroimaging tasks. These results offer valuable insights into the application of deep learning-driven approaches for neurodegenerative disease diagnosis and pave the way for further advancements in diagnostic accuracy and patient care.

IV. Conclusion

The experimental findings underscore the efficacy of pretrained DenseNet models, particularly DenseNet169, in Alzheimer's Disease detection from MRI images. DenseNet169 outperforms other models during the transfer learning phase, achieving remarkable accuracy of 99.806%. This highlights its ability to discern Alzheimer's-related abnormalities with high accuracy without requiring further fine-tuning. Additionally, DenseNet121 and DenseNet201 exhibit competitive performance, showcasing the versatility and effectiveness of DenseNet architectures in neuroimaging tasks. These results not only contribute to the advancement of deep learning-driven approaches for neurodegenerative disease diagnosis but also pave the way for improved diagnostic accuracy and patient care in the field of neuroimaging.

For future work, further exploration could focus on optimizing hyperparameters to enhance the performance of the pretrained DenseNet models in Alzheimer's Disease detection. Specifically, investigating the effects of varying learning rates, batch sizes, and epochs during both transfer learning and fine-tuning phases could provide valuable insights into refining model training strategies. Additionally, exploring ensemble learning techniques by combining multiple DenseNet architectures or integrating domain-specific knowledge into the training process could further improve the models' diagnostic accuracy and robustness. These endeavors would contribute to advancing the state-of-the-art in neuroimaging-based disease diagnosis and bolstering the efficacy of deep learning-driven approaches in clinical settings.

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