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Comparative Analysis of DenseNet Architectures for Lung Cancer Classification Using Histopathologic Images

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Abstract: Lung cancer continues to be one of the most lethal cancers globally, with early and accurate diagnosis being pivotal for improving patient outcomes. This study investigates the effectiveness of three DenseNet architectures namely DenseNet121, DenseNet169, and DenseNet201 in the classification of lung cancer using histopathologic images from the LC25000 dataset, with a specific focus on 15,000 lung images. Comprehensive evaluations were conducted to compare the performance of these models. The results reveal that DenseNet201 achieves superior performance with an accuracy of 99.23%, surpassing DenseNet169 and DenseNet121. This high level of accuracy underscores the potential of DenseNet201 for integration into clinical workflows, offering a robust tool for the early detection and diagnosis of lung cancer. Our findings suggest that deeper DenseNet architectures are particularly well-suited for this task, providing a significant advancement in the use of deep learning for medical image analysis.

Keywords: Lung Cancer Classification, DenseNet Architectures, Histopathological Images, Deep Learning, Medical Imaging

1. INTRODUCTION

Lung cancer remains a leading cause of cancer-related mortality worldwide, accounting for approximately 18% of all cancer deaths. The primary risk factor is tobacco smoking, contributing to the majority of cases. Despite advancements in treatment, lung cancer prognosis remains poor due to late-stage diagnosis. Early detection is critical for improving survival rates and treatment outcomes (Hochhegger et al., 2022; Hatuwal & Thapa, 2020). Histopathologic examination is a crucial method for diagnosing and classifying lung cancer. Traditionally, this process relies on pathologists manually examining tissue slides under a microscope, which is both time-consuming and subject to variability. Digital pathology and artificial intelligence (AI), particularly deep learning, have the potential to revolutionize this field by automating image analysis and providing consistent and accurate results (Gao et al., 2021; Šarić et al., 2019).

Deep learning, especially convolutional neural networks (CNNs), has shown exceptional performance in image classification tasks. CNNs automatically learn and extract features from raw images, making them ideal for complex pattern recognition. In medical imaging, deep learning models can enhance diagnostic accuracy and reduce the workload of pathologists. Studies have demonstrated the potential of deep learning in diagnosing various cancers, including lung cancer (Goodfellow et al., 2016; LeCun et al., 2015). Esteva et al. (2017) successfully applied deep learning to classify skin cancer with accuracy comparable to dermatologists. Similarly, Wang et al. (2018) developed a CNN model to classify lung cancer subtypes from histopathologic images, achieving promising results. These models not only provide accurate diagnoses but also help identify specific histological patterns and molecular markers associated with different lung cancer types.

1.1 DenseNet Architectures

Densely Connected Convolutional Networks (DenseNet) represent a significant advancement in deep learning architectures. Introduced by Huang et al. (2017), DenseNet connects each layer to every other layer, promoting feature reuse and improving gradient flow. This dense connectivity addresses the vanishing gradient problem, enabling the training of deeper models effectively. DenseNet architectures are particularly suited for medical image analysis due to their efficient parameter usage and superior performance (Gao et al., 2021; Šarić et al., 2019). DenseNet121, DenseNet169, and DenseNet201 are variants of this architecture, differing in the number of layers. DenseNet121 comprises 121 layers, DenseNet169 has 169 layers, and DenseNet201 includes 201 layers. The increased depth allows these models to capture complex features, potentially enhancing classification performance. Previous studies have validated the efficacy of DenseNet models in medical imaging tasks such as breast cancer detection and lung nodule classification (Huang et al., 2017).

Detecting lung cancer through histopathologic images involves classifying tissue samples to identify malignant cells. Traditional methods rely on pathologists' expertise to manually interpret these images, which can be time-consuming and prone to variability. Deep learning models offer an automated, standardized approach, reducing pathologists' workload and potentially increasing diagnostic accuracy (Hatuwal & Thapa, 2020). Several studies have explored deep learning for lung cancer detection. Hatuwal and Thapa (2020) used a CNN-based method for detecting lung cancer in histopathologic images, achieving high accuracy. Mohalder et al. (2021) developed a deep learning approach to predict lung cancer from histopathologic images, showcasing AI's potential. These models accurately classify different lung cancer types, including adenocarcinoma, squamous cell carcinoma, and small cell lung carcinoma (Günaydin et al., 2019; Mehmood et al., 2022).

This study aims to evaluate and compare the performance of three DenseNet architectures namely DenseNet121, DenseNet169, and DenseNet201 in classifying lung cancer from histopathologic images using the LC25000 dataset, focusing on 15,000 lung images. The dataset is split into training, validation, and test sets to ensure robust evaluation. Standard data preprocessing techniques, including resizing, normalization, and data augmentation, are applied to enhance model performance and generalization. Evaluation metrics include accuracy, loss, precision, recall, F1-score, and confusion matrices, providing a comprehensive assessment of

each model's classification capabilities. By analyzing the results, we aim to identify the most effective DenseNet architecture for lung cancer detection and discuss its potential for clinical application.

2. LITERATURE SURVEY

The application of deep learning in medical imaging has significantly transformed the field, offering robust tools for the automatic analysis and classification of medical images. Convolutional neural networks (CNNs), a subset of deep learning, have proven particularly effective in extracting hierarchical features from raw images, which is essential for complex pattern recognition tasks such as disease detection and diagnosis. These models have shown superior performance in various medical imaging applications, including the detection of lung cancer (Gao et al., 2021; Šarić et al., 2019). Esteva et al. (2017) successfully applied deep learning to classify skin cancer with an accuracy comparable to that of dermatologists. Similarly, demonstrated the potential of deep learning in predicting mutations from histopathology images of lung adenocarcinoma, squamous cell carcinoma, and normal lung tissue, highlighting the model's ability to provide accurate diagnoses and identify specific histological patterns and molecular markers associated with different types of lung cancer.

Densely Connected Convolutional Networks (DenseNet) have been a significant advancement in CNN architecture, introduced by Huang et al. (2017). DenseNet is characterized by its dense connectivity pattern, where each layer receives input from all preceding layers and passes its feature maps to all subsequent layers. This architecture promotes feature reuse and mitigates the vanishing gradient problem, enabling the training of very deep networks (Hochhegger et al., 2022). DenseNet architectures, such as DenseNet121, DenseNet169, and DenseNet201, have been particularly effective in medical image analysis. These models differ primarily in the number of layers and have been validated in various studies for their robustness and high accuracy in complex classification tasks. For example, Mehmood et al. (2022) applied DenseNet for malignancy detection in lung and colon histopathology images, demonstrating its potential for accurate and efficient image classification. Lung cancer detection using histopathologic images involves classifying tissue samples to identify malignant cells. Traditional methods rely heavily on the expertise of pathologists, which can lead to variability and potential diagnostic errors. Deep learning models offer an automated approach, providing consistent and accurate classifications (Mohalder et al., 2021, Bushara et al. 2024).

Several studies have highlighted the potential of deep learning in lung cancer detection. Hatuwal and Thapa (2020) used CNNs for the classification of lung cancer from histopathologic images, achieving high accuracy. These models have been effective in distinguishing between various types of lung cancer, including adenocarcinoma, squamous cell carcinoma, and small cell lung carcinoma. In addition to classification, deep learning models have also been used to predict molecular subtypes and treatment responses.. Comparative studies are crucial for understanding the performance of different deep learning architectures. Šarić et al. (2019) compared various CNN-based methods for lung cancer detection in whole slide histopathology images, highlighting the advantages and limitations of each approach. Such studies provide valuable benchmarks and guide the selection of appropriate models for specific tasks AR et al. (2022).

DenseNet variants, such as DenseNet121, DenseNet169, and DenseNet201, have been extensively evaluated in comparative studies. These models differ in the number of layers and their capacity to learn complex patterns from the data. Gao et al. (2021) and Mehmood et al. (2022) have shown that deeper DenseNet models generally perform better in terms of accuracy and robustness, although they may require more computational resources. Recent advancements in deep learning techniques have further improved the accuracy and efficiency of lung cancer detection. For instance, Nazir et al. (2021) discussed the use of self-supervised learning techniques for medical imaging data, which have been shown to enhance model performance. Similarly, Li et al. (2020) developed a framework for automatic lung nodule detection using multi-resolution CT screening images, demonstrating significant improvements in detection accuracy. Moreover, the integration of multimodal data, including genomic and clinical data, with imaging data has shown promise in providing comprehensive diagnostic insights. Studies by Sun et al. (2020) and Xu et al. (2020) have explored the use of multi-view and multimodal deep learning approaches for lung cancer detection, highlighting the potential for more accurate and holistic diagnostic models.

3. MATERIALS AND METHODS

3.1 Dataset

The LC25000 dataset Aitazaz et al. (2023), specifically focusing on 15,000 histopathologic images related to lung cancer, was utilized for this study. This dataset, which includes a diverse array of histopathologic images, serves as a robust foundation for training and evaluating deep learning models in medical imaging. The lung cancer subset provided sufficient data to train and test the performance of various DenseNet architectures. The sample images are represented in Figure1.

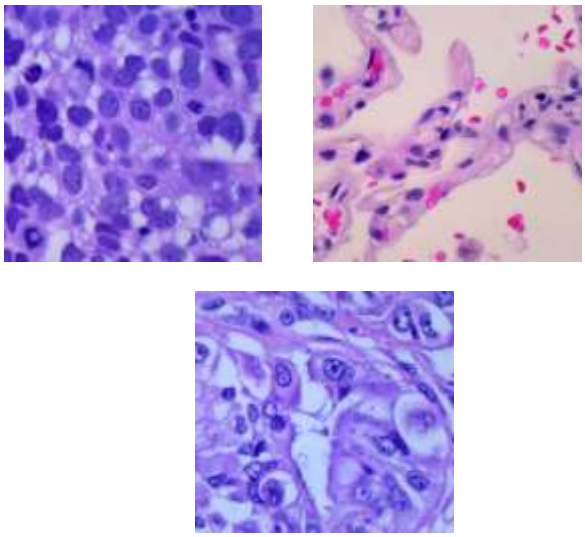

Figure 1: Sample Images from LC25000 datasets. a) Squamous Cell Carcinoma, b) Normal, and c) Adenocarcinoma

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3.2 Data Preprocessing

To prepare the dataset for training, several preprocessing steps were undertaken. The dataset was split into training, validation, and test sets to ensure robust model evaluation. Each image was resized to 224x224 pixels, a standard input size for convolutional neural networks (CNNs). Pixel values were normalized to a range of 0 to 1, facilitating faster convergence during training. Data augmentation techniques, including rotations, flips, and zooms, were applied to the training set to enhance model generalization and prevent overfitting (Simonyan & Zisserman, 2015; Szegedy et al., 2015).

3.3 Model Architectures

Three DenseNet architectures were evaluated: DenseNet121, DenseNet169, and DenseNet201. These architectures differ primarily in their depth and number of layers:

- DenseNet121: This model comprises 121 layers and is the shallowest of the three, balancing performance and computational efficiency.
- DenseNet169: With 169 layers, this model offers a middle ground between complexity and performance.
- DenseNet201: The deepest model with 201 layers, it is designed to capture intricate patterns in the data, albeit with increased computational demands.

Each model was initialized with weights pre-trained on the ImageNet dataset, leveraging transfer learning to improve performance and reduce training time (Huang et al., 2017; Russakovsky et al., 2015.

Figure 2 shows the structure of the proposed DenseNet model for classifying lung cancer. The model starts with an input layer that processes images sized 224x224 pixels with three color channels (RGB). This input layer is followed by three DenseNet blocks, which contain convolutional layers that help extract detailed features from the images. After these blocks, a Global Average Pooling layer reduces the size of the feature maps into a single vector for each map. This vector is then passed to a fully connected layer with 4096 units, allowing the model to learn complex patterns in the data. A dropout layer with a rate of 0.5 is added to prevent overfitting by randomly turning off some neurons during training. Finally, the output layer uses a softmax function to classify the image into one of the lung cancer categories.

3.4 Training Procedure

The models were trained using the Adam optimizer, chosen for its adaptive learning rate capabilities, making it well-suited for complex optimization problems. The categorical

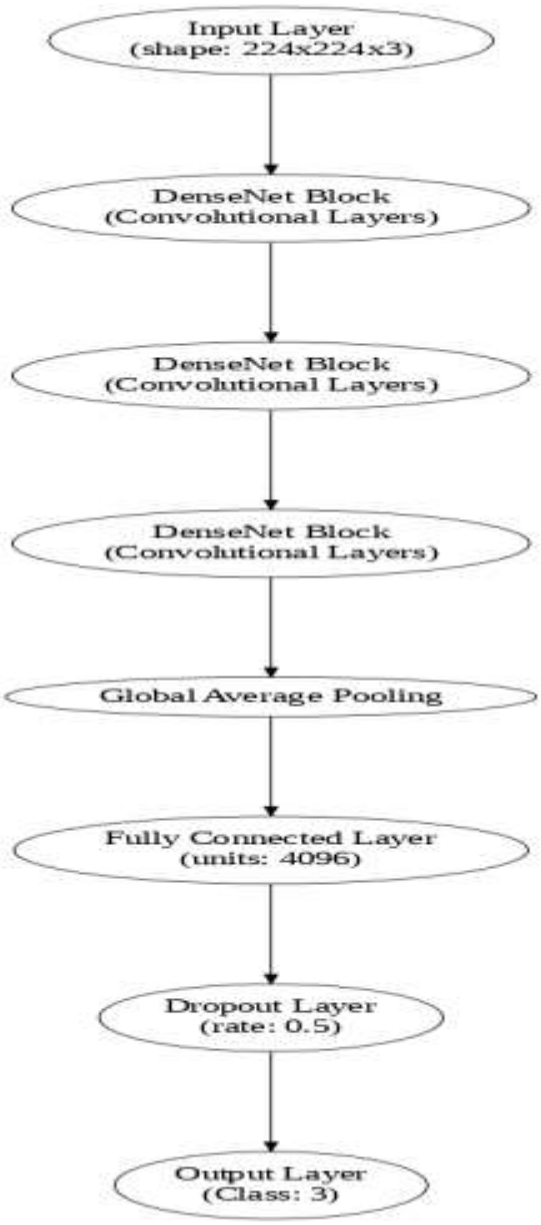

Figure 2: Proposed Densenet Model Architecture for Lung Cancer Classification

crossentropy loss function was employed, appropriate for multi-class classification tasks. Training was conducted with a batch size of 32 over 50 epochs. Early stopping and model checkpointing techniques were used to save the best-performing model and prevent overfitting, based on validation loss (Kingma & Ba, 2015).

3.5 Evaluation Metrics

To comprehensively assess the models, the following metrics were used:

- Accuracy: Measures the proportion of correctly classified instances.

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- Precision: The ratio of true positive predictions to the total predicted positives, reflecting the model's precision in identifying positive cases.
- Recall: The ratio of true positive predictions to all actual positives, indicating the model's sensitivity.
- F1-score: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.
- Confusion Matrix: A detailed performance summary showing true positives, true negatives, false positives, and false negatives.

4. RESULTS AND DISCUSSIONS

In this section, we analyze how well three DenseNet models, namely DenseNet121, DenseNet169, and DenseNet201 performed in classifying lung cancer using the LC 25000 dataset, which includes 15,000 lung images. We used Precision, Recall, F1-Score, and Accuracy to measure how accurately each model identified three different classes of lung cancer Squamous Cell Carcinoma, Normal, and Adenocarcinoma named as Class 1, Class 2, and Class 3 respectively. These metrics help us understand how well the models can distinguish between different types of lung cancer. DenseNet models are known for their ability to handle complex image data by efficiently using all the information in the network, which is especially useful in medical imaging. We carefully evaluated each model's performance to see which one worked best for lung cancer classification. The following discussion compares the results from each model, highlighting important findings and insights. This comparison helps us determine which DenseNet model is most effective for accurate and reliable lung cancer diagnosis, contributing to better automated tools for medical professionals.

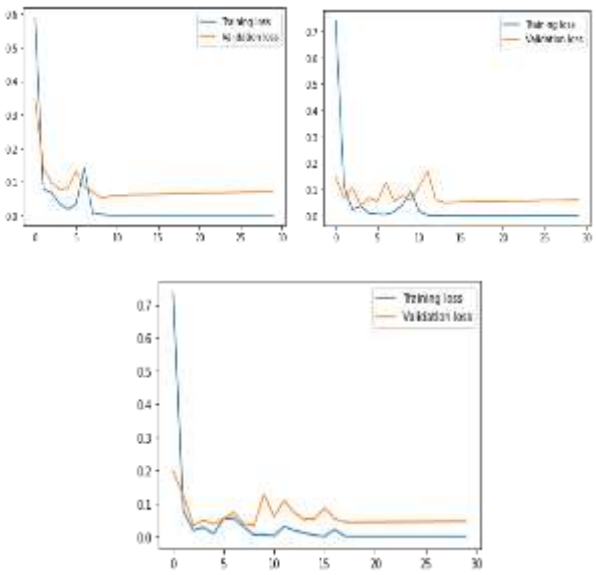

Figure 3: Training and Validation Losses of a) DenseNet121, b) DenseNet169, and c)DenseNet201

Figure 3 illustrates the training and validation losses for the DenseNet121, DenseNet169, and DenseNet201 models. In Figure 3a, DenseNet121 shows a consistent decrease in training loss, with minor fluctuations observed in the validation loss, indicating effective learning with occasional overfitting tendencies. Figure 3b presents DenseNet169, where both training and validation losses exhibit a steady decline with fewer fluctuations compared to DenseNet121, suggesting superior generalization and stability. Figure 3c displays DenseNet201, which demonstrates a smooth and continuous reduction in both training and validation losses, underscoring the model's robust learning capabilities and excellent generalization to unseen data.

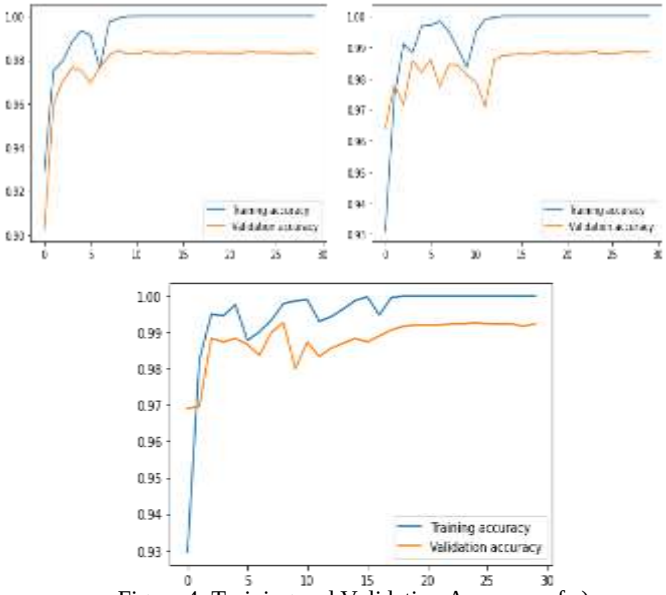

Figure 4: Training and Validation Accuracy of a) DenseNet121, b) DenseNet169, and c) DenseNet201

Figure 4 depicts the training and validation accuracy for the DenseNet121, DenseNet169, and DenseNet201 models. Figure 4a shows DenseNet121 achieving high training accuracy, accompanied by slight oscillations in validation accuracy, indicative of effective learning but some overfitting. Figure 4b illustrates DenseNet169, where both training and validation accuracies increase steadily, with fewer oscillations, reflecting enhanced robustness and generalization compared to DenseNet121.

Figure 4c presents DenseNet201, which exhibits a smooth and continuous increase in both training and validation accuracies, maintaining stability and demonstrating strong generalization capabilities. Collectively, the results indicate that DenseNet169 and DenseNet201 outperform DenseNet121 in terms of stability and generalization, making them more suitable for the lung cancer classification task. Figure 5 displays the confusion matrices for the DenseNet121, DenseNet169, and DenseNet201 models, providing a detailed breakdown of their classification performance across three classes. Figure 5a for DenseNet121 shows mostly accurate predictions but includes some misclassifications, indicating areas for improvement in precision and recall. Figure 5b for

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DenseNet169 highlights improved performance with fewer misclassifications, reflecting higher accuracy and better generalization. Figure 5c for DenseNet201 demonstrates the best classification capabilities, with the highest number of correct predictions and the fewest misclassifications among the three models, underscoring its robustness and reliability in lung cancer classification.

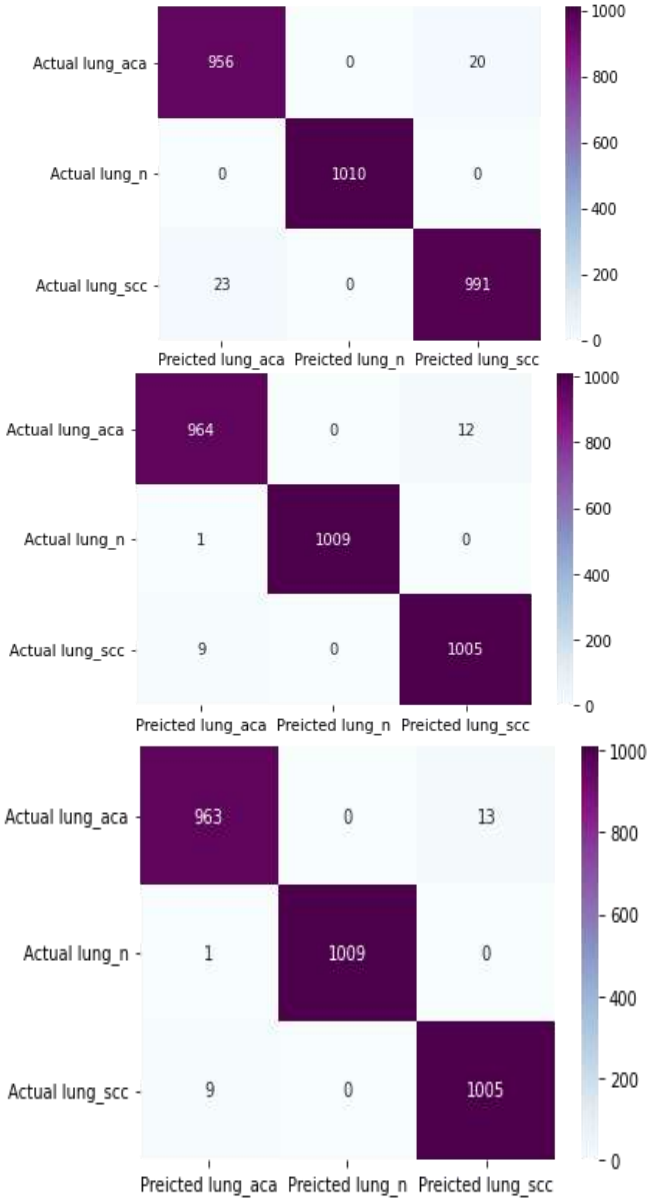

Figure 5 : Confusion Matrices of a) DenseNet121, b) DenseNet169, and c)DenseNet201

The comparative analysis of DenseNet121, DenseNet169, and DenseNet201 architectures for lung cancer classification reveals nuanced performance variations, emphasizing the efficacy of DenseNet169. DenseNet169 achieved the highest accuracy and F1-scores, particularly excelling in Class 1 and Class 3, with precision values of 0.9877 and 0.9911, respectively, and recall values of 0.9907 and 0.9882, respectively is presented in Table 1.

Table 1: Performance Comparison of Three Proposed DenseNet Models

Model	Precision	Recall	F1-Score	Accuracy
DenseNet121 (Class 1)	0.9795	0.9765	0.978	0.9838
DenseNet121 (Class 2)	1.0	1.0	1.0	1.0
DenseNet121 (Class 3)	0.9773	0.9802	0.9788	0.9838
DenseNet169 (Class 1)	0.9877	0.9907	0.9892	0.9934
DenseNet169 (Class 2)	0.999	1.0	0.9995	0.9995
DenseNet169 (Class 3)	0.9911	0.9882	0.9897	0.9949
DenseNet201 (Class 1)	0.9867	0.9907	0.9887	0.9931
DenseNet201 (Class 2)	0.999	1.0	0.9995	0.9995
DenseNet201 (Class 3)	0.9911	0.9872	0.9891	0.9947

The marginally superior performance of DenseNet169 suggests that it effectively balances model complexity and capacity to capture intricate data patterns. DenseNet201, while comparable, exhibits slightly lower recall in Class 3, indicating that additional network depth does not necessarily translate to proportional performance gains. DenseNet121, though robust, is slightly outperformed by the deeper architectures, underscoring the advantage of increased depth in specific classification contexts. All three DenseNet architectures demonstrate high precision and recall for Class 2, with values approaching unity, signifying exceptional reliability in identifying this class. This near-perfect performance highlights the capability of these models to handle clearly defined patterns within the dataset. The study's findings advocate for the continued use and exploration of DenseNet architectures in medical imaging, particularly for tasks requiring high diagnostic accuracy such as lung cancer classification. The observed performance metrics underscore the potential of DenseNet-based models to enhance clinical decision-making, leading to improved diagnostic accuracy and patient outcomes through precise and reliable classification of histopathological images.

5. CONCLUSION

In this study, we evaluated the performance of three DenseNet architectures—DenseNet121, DenseNet169, and DenseNet201—for lung cancer classification using the LC 25000 dataset, focusing on 15,000 lung histopathological images. The models were assessed using key metrics such as Precision, Recall, F1-Score, and Accuracy. Our results demonstrate that all three DenseNet models performed exceptionally well, with DenseNet169 showing the best overall performance, particularly in terms of accuracy and F1-Score across all classes. DenseNet201 also performed comparably, while DenseNet121, although slightly behind the other two, still delivered robust classification results. These findings underscore the effectiveness of DenseNet

architectures in medical image analysis, specifically for lung cancer detection.

Future work can explore integrating advanced data augmentation techniques and transfer learning from other medical imaging datasets to further enhance model performance. Additionally, expanding the dataset and investigating other state-of-the-art architectures, such as EfficientNet or Vision Transformers, could provide deeper insights and improve generalisation

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