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DEEP LEARNING APPROACH FOR PNEUMONIA PREDICTION FROM X-RAYS USING A PRETRAINED DENSENET MODEL

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ABSTRACT

Pneumonia remains a major global health concern, particularly affecting young children and older adults, contributing to significant morbidity and mortality. Traditional diagnostic methods using chest CT scans are time-consuming and prone to errors due to the reliance on manual interpretation. This study investigates the application of DenseNet architectures DenseNet121, DenseNet169, and DenseNet201—for automated pneumonia detection from chest X-ray images. The dataset, obtained from the Guangzhou Women and Children's Medical Center, consists of 5,216 training images and 624 testing images categorized into normal and pneumonia cases. Data augmentation techniques, including rotation, normalization, and shear, were applied to improve training efficiency. The DenseNet models were pre-trained on ImageNet and fine-tuned by adding fully connected layers with 256 neurons and sigmoid activation. The models were trained for 20 epochs using the Adam optimizer and binary cross-entropy loss function. Performance evaluation revealed that DenseNet201 outperformed the other models, achieving a precision of 0.99 and a recall of 0.61 for normal cases (F1-score of 0.75) and a precision of 0.81 with a recall of 0.99 for pneumonia cases (F1-score of 0.89). These findings demonstrate that DenseNet201 provides a reliable and effective solution for automated pneumonia detection, offering improved diagnostic efficiency and accuracy compared to traditional methods.

Keywords*: deep learning, DenseNet, pneumonia prediction, pretrained model.*

I. INTRODUCTION

PNEUMONIA is a major global public health issue, leading to severe illness and death [1], [2]. This respiratory infection, characterized by inflammation of the air sacs in one or both lungs, can result in serious health problems if not promptly and adequately treated [3]. Pneumonia and other lower respiratory infections are a major contributor to global mortality [4]. This is especially accurate for susceptible demographics, such as youngsters aged five and below and senior individuals aged 65 years and above. Pneumonia has a huge impact on global health, affecting millions of people each year and resulting in substantial healthcare burdens and economic expenditures [5], [6].

Pneumonia continues to be the primary infectious cause of death in children, surpassing other serious illnesses like diarrhea and malaria. Every year, millions of children fall victim to this avoidable and curable illness. The significant fatality rate among youngsters serves as a clear indication of the urgent requirement for efficient measures to prevent, detect early, and promptly treat the condition. Pneumonia remains a significant global concern, despite improvements in medical care and the widespread availability of vaccines [7], [8].

The disproportionately high fatality rates in vulnerable groups underscore the critical problem of delayed diagnosis and suboptimal treatment outcomes, highlighting the urgent need for more effective strategies, such as early and precise identification through diagnostic methods like chest X-rays, lung ultrasounds, and molecular diagnostics, to maximize treatment effectiveness and improve patient outcomes [9], [10], [11]. These tools enable healthcare providers to quickly start appropriate therapeutic interventions, ultimately enhancing overall patient care and outcomes.

Historically, pneumonia diagnosis has relied on chest radiography and clinical examinations by skilled radiologists, but these methods can be subjective, often missing early or subtle signs, leading to treatment delays [12], [13]. Factors such as image quality fluctuations, patient placement, equipment limitations, and radiologist fatigue further hinder accurate diagnosis, contributing to the risk of misidentification or delayed therapy [12], [14], [15]. To address these challenges, it is crucial to enhance imaging technology, manage radiologist workload, and standardize protocols for data interpretation, while exploring cost-effective diagnostic methods suitable for resource-limited settings to improve early and accurate detection, ultimately improving patient outcomes [16].

Artificial intelligence (AI) has shown great promise in various industries, especially healthcare, by providing automated systems that offer significant advantages. These advantages include better accuracy in diagnosing conditions, increased efficiency, and the potential to lower healthcare expenses [17]. Convolutional Neural Networks (CNNs) are a type of AI approach that has been highly effective in analyzing images. They are capable of autonomously learning and extracting information from intricate datasets, such as medical imaging data [18], [19], [20].

DenseNet was selected over other deep learning architectures such as ResNet and Inception due to its unique connectivity pattern, which promotes feature reuse and efficient gradient flow [18], [21], [22]. Unlike ResNet, which uses additive identity shortcuts, DenseNet connects each layer to every other layer in a feed-forward fashion, reducing the risk of vanishing gradients and improving parameter efficiency. Compared to Inception, which relies on parallel convolutions with different filter sizes, DenseNet achieves competitive performance with fewer parameters and a more straightforward architecture. These advantages make DenseNet particularly suitable for medical image analysis where subtle features such as pneumonia indicators in chest X-rays require deep but efficient representation learning [23], [24]. Training the model on extensive datasets allows it to identify complex patterns and subtle details in CT images that could indicate pneumonia, thereby improving the accuracy and precision of diagnosis. In addition, the incorporation of AI-powered analysis has the potential to simplify workflow processes, allowing healthcare providers to accelerate treatment decisions and enhance patient outcomes.

This research contributes to the field of AI-assisted healthcare diagnostics by examining how deep learning and pretrained neural networks might be used to diagnose pneumonia[25]. The statement highlights the significant impact that AI technologies can have on transforming healthcare practices. By applying transfer learning techniques with pre-trained models, this study seeks to optimize the model's performance on a diverse range of chest X-ray datasets, allowing it to identify subtle patterns that might be overlooked by human clinicians. It emphasizes the need for thorough validation and integration efforts to guarantee dependable and morally responsible use in real-world medical environments.

With its ability to improve diagnostic accuracy while reducing the cognitive burden on healthcare workers, this innovation enables faster and more accurate decision-making. Additionally, incorporating AI technology into standard clinical workflows has the potential to improve patient outcomes by offering reliable, automated diagnostic assistance, especially in resource-constrained settings. Ultimately, this research seeks to position AI-assisted diagnosis as a critical tool in the fight against pneumonia, with the potential to revolutionize clinical practice and improve the overall quality of healthcare.

II. Related Works

Medical imaging is essential in modern medicine as it offers non-invasive information on anatomical structures and clinical diseases. Traditional imaging techniques like X-ray, computed tomography (CT), and magnetic resonance imaging (MRI) have been fundamental in diagnostic radiology for a long time. They assist clinicians in identifying, describing, and tracking different diseases, including pneumonia[26].

The area of medical imaging has been revolutionized in recent years by the integration of artificial intelligence (AI) techniques, specifically CNNs[27]. CNNs are a specialized category of deep learning models that are primarily built to handle visual input [28]. As a result, they are highly effective for tasks that include image recognition and classification[29]. These networks function by autonomously acquiring representations of features directly from image pixels, hence reducing the requirement for human feature extraction and improving the efficiency and accuracy of image analysis[30].

CNNs are widely used in medical imaging for a variety of purposes, including diagnosis, treatment planning, and prognosis[31]. CNNs have shown significant efficacy in automatically detecting lung

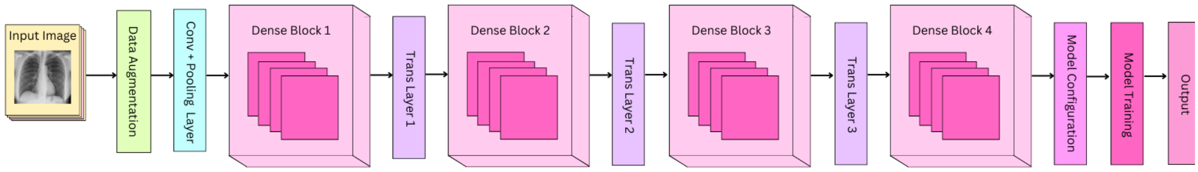

Figure 3. Diagram of the Image Classification Process Using DenseNet

nodules on X-ray, hence assisting in the early diagnosis of lung cancer[32]. Furthermore, CNNs have been utilized in the field of neuroimaging to accurately identify and outline brain tumors on MRI scans. This model can acquire 98% model accuracy at differentiating normal scans and 3 brain tumor type scan [33]. The study on CNNs architectures for COVID-19 diagnosis using CT scans also demonstrated superior performance, achieving an accuracy of 92% and a recall rate of 95%[34].

The introduction of Convolutional Neural Networks (CNNs) in the diagnosis of pneumonia seeks to address these issues by utilizing the advanced machine learning capabilities of these models. Pretrained convolutional neural network (CNN) models, such as DenseNet and ResNet, have been modified and optimized for the specific job of healthcare. This was achieved by training them on extensive datasets of medical images that have been tagged with specific scan information [35].

Recent research has emphasized the capability of CNN-based methods to enhance the identification of pneumonia in many types of medical images, such as X-rays. Furthermore, the implementation of AI-powered algorithms in clinical practice can improve the allocation of healthcare resources and streamline workflow efficiency. This can help reduce diagnostic delays and enhance the overall delivery of healthcare services[36].

III. Research Methods

This section presents a comprehensive methodology aimed at enhancing image classification through deep learning techniques. The approach is systematically divided into five essential phases: Data Collection, Data Augmentation, Model Configuration, Model Training, and Performance Evaluation. Each phase plays a pivotal role in ensuring the model's overall effectiveness, from initial data processing to the final performance evaluation, thereby establishing a robust framework for accurate and reliable image classification. The following diagram provides a visual overview of the methodology, followed by a detailed explanation of each sub-phase.

A. Collection of Data

The dataset utilized in this investigation consists of chest X-ray pictures acquired from the retrospective cohorts of Guangzhou Women and Children’s Medical Center in Guangzhou [37].There are 5216 photos were designated for training consist of 1341 normal samples and 3875 pneumonia samples, while 624 photographs consist of 234 normal samples and 390 pneumonia samples were set aside for testing. The dataset consists of two distinct categories: normal cases and pneumonia cases. Before analysis, all chest X-ray pictures were subjected to a first quality control screening to eliminate scans that were of low quality or illegible. Afterward, two professional physicians independently evaluated the diagnostic grading of these photos. To reduce inconsistencies in grading, a third specialist was enlisted to assess the evaluation set.

B. Data Augmentation

Only the training set underwent data augmentation. The techniques applied included rotation up to 10 degrees, normalization, shear transformations with a range up to 0.1, and the use of nearest fill mode [38]. The validation set was normalized but not subjected to any further augmentation.

C. Model Configuration

The study applies transfer learning using DenseNet-121, DenseNet-169, and DenseNet-201 pre-trained on ImageNet [39] The original fully connected layer was replaced with a 2-neuron layer and softmax activation. All DenseNet backbones were frozen to leverage general visual features [40]. DenseNet variants were chosen for their dense connectivity, which promotes feature reuse and parameter efficiency compared to traditional architectures. However, comparisons with ResNet [41] or EfficientNet [42] could further validate performance claims.

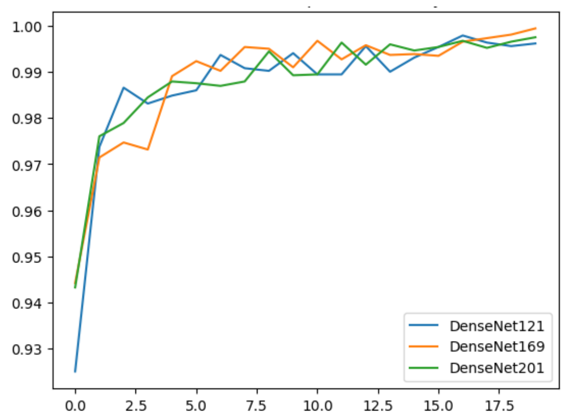

Figure 4. DenseNet accuracy plot of training set

Figure 5. DenseNet accuracy plot of the validation set

D. Model Training Parameters

The training process included the Adam optimizer along with a binary cross-entropy loss function. The models were trained for 20 epochs using a batch size of 32.

E. Performance Evaluation

The performance of the model was assessed using commonly used measures like as recall, precision, and F1 score. The evaluation was performed independently on the validation set in order to determine the models' capacity to generalize. The criteria were selected to thoroughly assess the model's capacity to differentiate between normal and pneumonia cases using chest X-ray pictures.

IV. RESULT AND DISCUSSION

In this section, we present and analyze the results of our pneumonia classification models, focusing on DenseNet121, DenseNet169, and DenseNet201. Our analysis delves into two main aspects: model convergence and stability, alongside performance metrics such as accuracy and loss scores. Detailed insights and comparative discussions are provided in the subsequent subsections, highlighting the strengths and weaknesses of each model in achieving accurate and consistent classification results.

A. Model Convergence

The performance of three DenseNet models (DenseNet121, DenseNet169, and DenseNet201) was evaluated on the training set in terms of accuracy and loss, as depicted in the provided plots shown in Figure 2 and Figure 3.

Figure 2 illustrates the accuracy plot of the training set, revealing a consistent improvement in performance across all three models throughout the training epochs. Both DenseNet121 and DenseNet169 exhibit analogous trends, characterized by rapid initial gains in accuracy that subsequently plateau as training progresses. Notably, DenseNet169 demonstrates a slightly more erratic trajectory compared to DenseNet121, although both models generally adhere to a similar performance pattern.

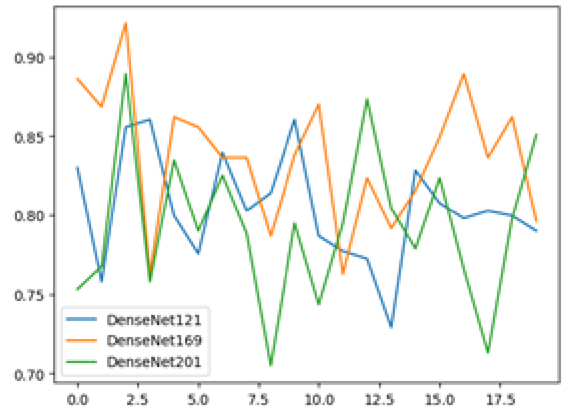

Figure 6. DenseNet loss plot of training set

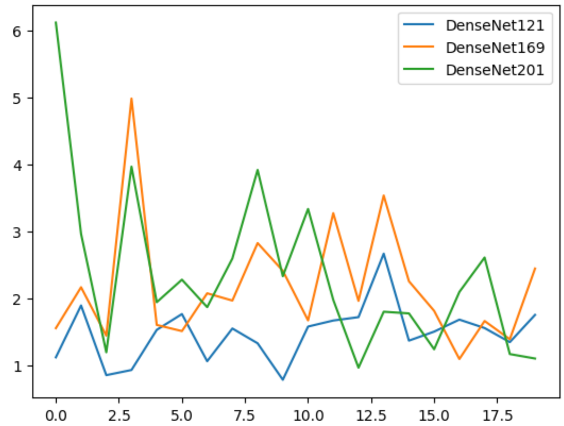

Figure 7. DenseNet loss plot of validation set

In contrast, DenseNet201 consistently maintains a higher accuracy throughout the training process, indicating superior learning capabilities. This model's ability to extract and utilize features effectively contributes to its enhanced performance. By the conclusion of the training period, all models achieve near-perfect accuracy; however, DenseNet201 marginally outperforms its counterparts, underscoring its superior capacity for accurately classifying the training data.

This analysis underscores the effectiveness of DenseNet201 in leveraging its architectural depth to achieve higher classification accuracy, thereby highlighting its potential as a robust model for pneumonia detection tasks. The findings suggest that employing deeper architectures like DenseNet201 may significantly enhance diagnostic precision in clinical applications.

The accuracy plot for the validation set, as shown in Figure 3, illustrates the decrease in error across the training epochs for each model. All models exhibit a sharp decline in loss during the initial epochs, reflecting rapid learning and adaptation. DenseNet121 starts with a higher initial loss but quickly stabilizes at a low level around the 10th epoch. DenseNet169 also shows a significant reduction in loss, albeit with greater fluctuations compared to DenseNet121.

In contrast, DenseNet201 consistently achieves the lowest loss throughout the training process, demonstrating superior learning efficiency and stability. Its earlier and lower convergence highlights its robustness and effectiveness, making it a promising model for accurate pneumonia detection. These results underscore the potential of deeper architectures like DenseNet201 to enhance diagnostic performance in clinical applications.

As illustrated in Figure 4, the loss plot for the training set reveals that DenseNet169 consistently achieves the highest accuracy scores throughout the training epochs, frequently surpassing the 0.90 threshold. This performance indicates its superior capability in accurately classifying pneumonia cases. In contrast, DenseNet121 exhibits a more variable accuracy trajectory, attaining high accuracy at certain points but displaying notable fluctuations. This variability suggests that while DenseNet121 can reach elevated accuracy levels, its performance lacks reliability across different epochs.

TABLE 1
DENSENET MODEL PERFORMANCE METRICS

DENSENET MODEL	CLASS		PRECISION	RECALL	F1
DenseNet 121	Normal	0.99	0.44	0.61	Normal
	Pneumonia	0.75	1.00	0.86	Pneumonia
DenseNet 169	Normal	0.99	0.46	0.63	Normal
	Pneumonia	0.76	1.00	0.86	Pneumonia
DenseNet 201	Normal	0.99	0.61	0.75	Normal
	Pneumonia	0.81	0.99	0.89	Pneumonia

DenseNet201, on the other hand, consistently records the lowest accuracy scores, often falling below 0.75. This persistent underperformance highlights its inadequacy in reliably classifying pneumonia cases when compared to the other two models. Overall, these findings underscore the varying effectiveness of each model, with DenseNet169 demonstrating a clear advantage in classification accuracy, while DenseNet201's performance raises concerns regarding its applicability in clinical settings for pneumonia detection.

In Figure 5, the loss plot of the validation set reveals notable differences in the performance of the models across the training epochs. DenseNet121 is distinguished by its relatively low and stable validation loss throughout the epochs, indicating a consistent learning process and strong generalization capabilities. This stability suggests that DenseNet121 effectively adapts to new data while minimizing prediction errors.

Conversely, DenseNet169 exhibits several fluctuations in its loss scores, reflecting a less consistent reduction in prediction errors. Although this model can achieve high accuracy, the variability in its loss trajectory implies that it may not generalize as effectively and could be more susceptible to overfitting during training.

DenseNet201, in contrast, consistently records the highest and most variable loss scores, indicating significant challenges in minimizing prediction errors. This persistent underperformance further corroborates its inadequacy as a reliable model for pneumonia classification compared to its counterparts. Overall, these findings underscore the varying effectiveness of each model, with DenseNet121 demonstrating superior stability and generalization potential for clinical applications in pneumonia detection.

B. Model Performance

The performance of three versions of the DenseNet model (DenseNet121, DenseNet169, and DenseNet201) was evaluated in terms of their precision, recall, and F1-score for detecting normal and pneumonia cases. The models used in this evaluation assessment are the best validation accuracy in the training process. We presented the result in the table below.

Table 1 demonstrates that the DenseNet121 model achieved a precision of 0.99 for normal cases, but its recall was only 0.44, resulting in an F1-score of 0.61. This suggests that although the model has high precision in detecting normal cases, it has a notable deficiency in correctly recognizing a substantial fraction of genuine normal cases. On the other hand, when it comes to pneumonia cases, the model exhibited a precision of 0.75, which is relatively lower, but had a remarkable recall of 1.00, resulting in a high F1-score of 0.86. This indicates that DenseNet121 demonstrates a high level of efficacy in detecting pneumonia patients, albeit with some misclassification of normal cases as pneumonia.

DenseNet169 displayed comparable patterns. The precision for normal instances remained at 0.99, but the recall showed a little improvement to 0.46, resulting in an F1-score of 0.63. The precision for pneumonia cases was maintained at 0.76, with a recall of 1.00 and an F1-score of 0.86. The marginal increase in recall for normal examples indicates a subtle improvement in the model's capacity to accurately detect normal occurrences in comparison to DenseNet121.

Among the three models, DenseNet201 had the most equitable performance. The model attained a precision of 0.99 for typical scenarios, accompanied by a notably enhanced recall of 0.61, leading to a higher F1 score of 0.75. The precision for pneumonia patients improved to 0.81, while the recall reached 0.99, resulting in an F1-score of 0.89. This suggests that DenseNet201 not only maintained high precision and recall for pneumonia diagnosis but significantly enhanced its recall and overall F1-score for identifying normal cases. The DenseNet201 model demonstrated superior performance in terms of recall and F1-score for both normal and pneumonia cases, indicating its effectiveness as the most optimal model for this classification task.

These findings are consistent with various studies investigating the application of DenseNet in medical imaging. For instance, research on detecting hidden pediatric elbow fractures in X-ray images highlights that the architecture of DenseNet-201 facilitates efficient feature propagation and reuse, leading to improved performance with fewer parameters compared to earlier models[43]. This efficiency represents a notable advancement over traditional convolutional neural networks. Similarly, in the classification of Alzheimer's disease, DenseNet-201 has been recognized for its superior accuracy, reduced computational complexity, and optimized resource utilization, offering a significant advantage over alternative approaches[44]. Furthermore, in the context of predicting anterior slippage of the vertebral lumbar spine, DenseNet-201 has demonstrated comparable or superior performance relative to other models while maintaining a lower parameter count, reinforcing its efficacy in medical image analysis[45].

However, while the DenseNet201 model demonstrated the most balanced performance among the evaluated architectures, its recall and precision metrics suggest important considerations for real-world implementation and future research. The recall rate of 0.61 for normal cases indicates a relatively higher rate of false negatives, meaning some normal cases are misclassified as pneumonia. In clinical applications, this could lead to unnecessary follow-up tests or anxiety for patients. Conversely, its high recall of 0.99 for pneumonia cases suggests a minimal risk of missing pneumonia diagnoses, which is critical in medical imaging applications where early and accurate detection can significantly impact treatment outcomes.

The precision of DenseNet201 for pneumonia (0.81) implies that while most predicted pneumonia cases are correct, some normal cases may still be misclassified as pneumonia. This trade-off between precision and recall must be carefully considered in deployment scenarios, particularly in healthcare, where both false positives and false negatives have significant consequences. Future work should focus on optimizing the model to enhance recall for normal cases without compromising pneumonia detection accuracy. This could involve incorporating advanced loss functions that balance precision and recall, applying data augmentation techniques to improve normal case detection, or integrating ensemble learning to reduce classification errors. Additionally, further research should explore how the DenseNet architecture generalizes across diverse datasets, including different imaging modalities and patient demographics, to improve its robustness in real-world applications.

V. CONCLUSION

This study investigated the performance of three DenseNet models (DenseNet121, DenseNet169, and DenseNet201) in detecting pneumonia through the analysis of CT scans. The findings demonstrate that DenseNet201 surpasses the other two models in terms of precision, recall, and F1-score, specifically in reliably recognizing pneumonia patients while retaining a high level of performance in detecting normal cases. In addition, DenseNet201 exhibited improved learning skills throughout the training phase, attaining higher accuracy and lower loss with increased stability in comparison to DenseNet121 and DenseNet169.

The results emphasize the potential of DenseNet201 as a powerful tool for enhancing pneumonia identification in medical imaging, providing notable benefits compared to conventional approaches. The improved efficiency and dependability of DenseNet201 can enhance the precision and promptness of diagnosis, ultimately resulting in improved patient outcomes and decreased pneumonia-related death rates. Utilizing advanced deep learning models such as DenseNet201 in medical imaging has great potential for improving diagnostic precision and effectiveness in clinical settings. Additional study and clinical validation are recommended to fully comprehend the advantages of these models in real-world healthcare environments.

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