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Lung X-Ray Image Classification Using DenseNet-169 and Bayesian Optimization

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A B S T R A C T

The increasing prevalence of lung diseases caused by infections such as Pneumonia and COVID-19 highlights the urgent need for accurate and efficient early detection methods. This study aims to improve the classification performance of chest X-ray images using the DenseNet-169 deep learning architecture, with a focus on hyperparameter optimization through Bayesian Optimization. The dataset used consists of 3,000 chest X-ray images—1,000 each for Normal, Pneumonia, and COVID-19 classes—sourced from Mendeley Data and split with an 80:20 ratio for training and testing. The baseline DenseNet-169 model initially achieved an accuracy of 96.837%, although slight overfitting was observed. By applying Bayesian Optimization, several key hyperparameters—such as learning rate, number of epochs, batch size, and kernel size—were systematically optimized. The optimized model demonstrated an improved accuracy of 97.33%, with the most notable increase in the recall score of the Normal class, which rose by 3.19% to 97%, effectively reducing the false negative rate for healthy cases. In addition, the final model recorded a precision of 99% and a specificity of 99.50% for the COVID-19 class, indicating a strong discriminative capability in identifying critical conditions. Analysis of the training and validation curves showed good convergence, confirming the effectiveness of the optimization in reducing overfitting and enhancing the model's generalization ability. Overall, the results of this study demonstrate that the application of Bayesian Optimization significantly enhances the performance of DenseNet-169 in chest X-ray image classification. The resulting model is more balanced, robust, and reliable, showing great potential for integration into AI-based automated diagnostic systems in the field of respiratory healthcare.

1. Introduction

The lungs are vital organs in the human respiratory system responsible for the exchange of oxygen and carbon dioxide in the blood [1]. The respiratory tract branches into bronchioles, which are small airways leading to the alveoli. Infections that affect the alveoli are commonly caused by bacteria or viruses. Examples of diseases resulting from such infections include pneumonia and tuberculosis. In addition, the coronavirus that causes COVID-19 is also a pathogen capable of infecting the lungs [2]. Therefore, rapid detection and diagnosis play a crucial role in mitigating the impact of potentially life-threatening diseases and improving patients' quality of life. One of the tools that can support this process is chest X-ray imaging (radiography) [3]. Although chest X-rays are widely used, their interpretation still faces several limitations, such as difficulties in accurately detecting diseases. These limitations may result in delays in diagnosis for both patients and medical professionals. One possible solution to address this issue is the application of machine learning techniques to classify chest X-ray images into specific diagnostic categories [4]. The use of machine learning for chest X-ray image classification has been explored by [5], who applied the backpropagation algorithm as the classification method. In that study, the dataset was divided into 154 images for training data and 41 images for testing data. The results showed a highest accuracy of 87.8%. In addition to machine learning, disease detection in chest X-ray images can also be performed using deep learning approaches. As demonstrated in the study conducted by [2], VGG-16 and DenseNet-169 were used to detect lung diseases, with a total of 7,135 chest X-ray images employed as the dataset. The results showed that the VGG-16 model achieved an accuracy of 86%, with a precision of 87%, recall of 89%, and F1-score of 87%. In contrast, DenseNet-169 achieved higher performance with an accuracy of 91%, precision of 93%, recall of 92%, and F1-score of 92%, making it superior to VGG-16. In addition, a study conducted by [6] implemented the DenseNet-169 architecture to detect COVID-19 from chest X-ray images. This study utilized a pretrained network with transfer learning and employed the Adam optimizer for model optimization. The resulting accuracy reached 96.37%, which was the highest among the compared models, including AlexNet, ResNet-50, VGG-16, and VGG-19. Another study was also conducted by [7], which applied a fine-tuned DenseNet-169 architecture to predict breast cancer metastasis using the FastAI framework and the 1-Cycle Learning Rate Policy approach. The training process was carried out using transfer learning and data augmentation. The evaluation results showed that the model achieved an accuracy of 96.23%, precision of 96.38%, recall of 96.12%, and F1-score of 96.25%, indicating high performance in the automatic detection of breast cancer metastasis. Although promising results have been achieved, studies in the field of deep learning still face several challenges, one of which is determining the optimal architecture and hyperparameters to achieve the best accuracy. While deep learning has shown great potential in data analysis, hyperparameter selection in deep learning models is generally performed manually. This limitation can be addressed through the application of Bayesian Optimization, which serves as a hyperparameter tuning strategy to help identify the best combination and improve model performance [8]. Research on improving accuracy through hyperparameter tuning using Bayesian Optimization has been widely conducted. One such study, conducted by [9], utilized a Convolutional Neural Network (CNN) architecture for feature extraction, followed by Bayesian Optimization to fine tune the hyperparameters effectively. The model achieved an accuracy of 96%, with a dataset split of 80% for training, 10% for validation, and 10% for testing. A similar study by [10] combined CNN based transfer learning with hyperparameter optimization using Bayesian Optimization. The primary focus of this research was on the automated exploration of various hyperparameter combinations. As a result, the best performing model achieved an accuracy of 98.67% with 300 data samples, while the lowest accuracy of 94.74% was obtained with 150 samples. The findings from both studies emphasize that automated optimization approaches can yield high performing models. Based on these challenges, this study adopts a deep learning approach with a specific emphasis on automatic hyperparameter optimization through Bayesian Optimization to improve the accuracy of lung disease detection from chest X-ray images.

2. Methods

This study utilizes an open source chest X-ray dataset from Mendeley Data to classify normal, pneumonia, and COVID-19 conditions. The classification is performed using the DenseNet-169 architecture, which is optimized using one of the hyperparameter tuning methods, namely Bayesian Optimization. The research process includes data collection and pre-processing, model development, optimization implementation, training, and model evaluation. All processes were conducted using Google Colab with Python, supported by the TensorFlow and Keras libraries. The overall workflow of the research is illustrated in Figure 1

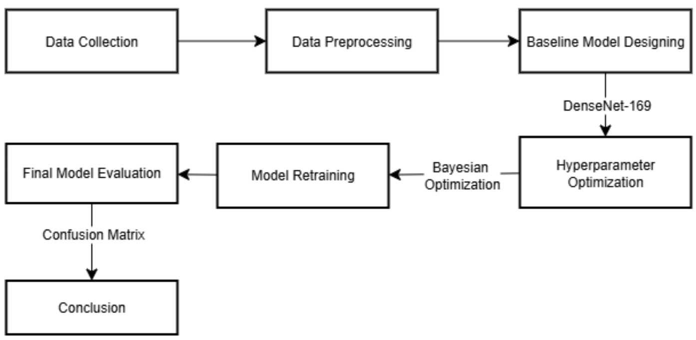

Figure 1. Research Methodology Flowchart

2.1 Data Collection

At this stage, the dataset was collected for use in the study. The dataset was sourced from Mendeley Data [11], titled "*Covid-19-Pneumonia-Normal Chest X-Ray Images*". It consists of three classes: Normal, Pneumonia, and COVID-19, each containing 1,000 chest X-ray images. This dataset was utilized to train and test the model in detecting lung diseases using a deep learning approach. An example of the images used in this study is presented in Figure 2 below:

Figure 2. Normal, Pneumonia, and COVID-19 Chest X-ray Images

2.2 Data *Preprocessing*

In the preprocessing stage, the chest X-ray images were processed to match the input requirements of the DenseNet-169 model, specifically by resizing the images to a format of 224 × 224 pixels [6]. The dataset was then split into an 80:20 ratio, with 80% (2,400 images) used for training data and 20% (600 images) for validation data. This division was intended to comprehensively evaluate the model's performance.

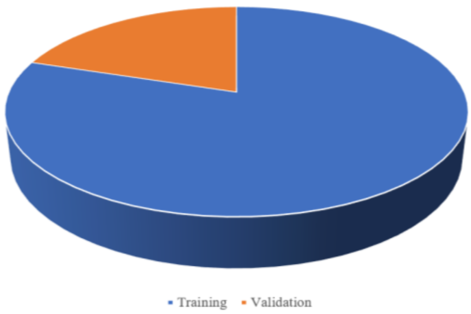

Figure 3. Visualization of Training dan Validation Data Distribution

2.3 Baseline Model Design

The model in this study was developed using the DenseNet-169 architecture. DenseNet-169 is one of the variants of the Dense Convolutional Network (DenseNet) architecture, known for its effectiveness in addressing the vanishing gradient problem, enhancing the flow of information and gradients, and improving parameter efficiency. The main advantage of DenseNet lies in its densely connected layers, where each layer receives inputs not only from the immediate previous layer but also from all preceding layers. This approach allows for more comprehensive feature reuse and greater efficiency in memory and computation [2]. Each convolutional layer in DenseNet consists of three main components: Batch Normalization (BN), Rectified Linear Unit (ReLU), and a convolution operation. Dense blocks are built using a combination of 1 × 1 convolutions followed by 3 × 3 convolutions. In DenseNet-169, the number of 1 × 1 and 3 × 3 convolutional sets in its four dense blocks are 6, 12, 32, and 32, respectively. The first three blocks are followed by transition layers consisting of 1 × 1 convolutions and 2 × 2 average pooling with a stride of 2. The fourth dense block is directly connected to the classification layer.

In total, the architecture contains 6 + 12 + 32 + 32 = 82 convolutional sets, which corresponds to 164 convolutional layers. In addition, there are three transition layers, one initial convolutional layer, and one classification layer, resulting in a total of 169 layers in the architecture. The DenseNet-169 model has a growth rate of 32, indicating the number of new feature maps added by each layer [6]. A visualization of the DenseNet-169 architecture is shown in Figure 4.

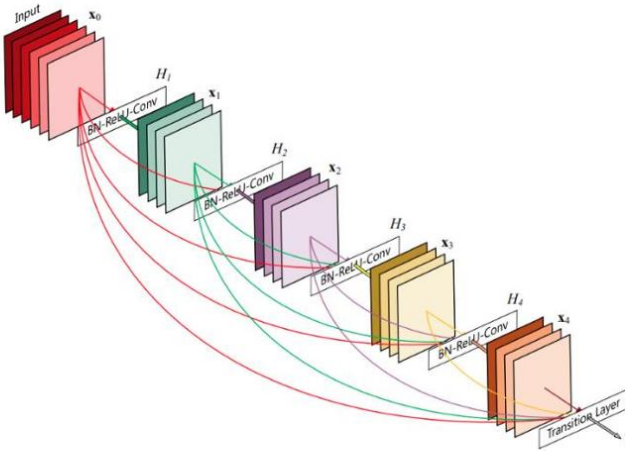

Figure 4. Architecture of DenseNet-169

2.4 Hyperparameter Optimization Using Bayesian Optimization

Hyperparameter tuning is a critical stage in developing machine learning and deep learning models to achieve optimal performance [12]. The process of finding the most effective hyperparameter configuration is known as hyperparameter tuning or hyperparameter optimization (HPO) [13]. Hyperparameters refer to values that must be set manually before training the model. Optimizing these parameters is essential for enhancing the performance of machine learning algorithms, with the aim of identifying the best combination of values that yields optimal results. This process involves experimenting with various hyperparameter configurations and training multiple models to identify the most effective one [14]. HPO aims to systematically and efficiently discover hyperparameter combinations that deliver the best model performance, as opposed to relying on manual methods [15]

Among the various hyperparameter tuning methods, Bayesian Optimization stands out as a leading approach. This method offers a global, gradient-free strategy to locate optimal values with minimal iterations. Bayesian Optimization is applied to automatically identify the optimal parameters for CNNs, with the goal of reducing the time required to obtain an accurate model [14]. As an iterative algorithm commonly used in HPO tasks, Bayesian Optimization (BO**)** selects the next evaluation point based on previously obtained results. BO balances **exploration** (searching new regions) and **e**xploitation (focusing on promising areas) to detect the most likely optimal configurations, while preventing the omission of better solutions in unexplored regions [15].

2.5 Model Retraining with Optimized Hyperparameters

After obtaining the optimal hyperparameter combinations through the Bayesian Optimization process, the next step was to retrain the model using the DenseNet-169 architecture. At this stage, the model was trained using the optimized hyperparameters, including learning rate, number of epochs, batch size, and kernel size. During training, loss and accuracy plots were monitored at each epoch to ensure that the model converged stably without overfitting. The purpose of this training process was to build the final model capable of classifying chest X-ray images more effectively, based on the results of the previous hyperparameter tuning.

2.6 Final Model Evaluation

After the model was trained using the training data, its performance was assessed using validation data to measure how well the model performed during training. Subsequently, testing data—consisting of entirely unseen chest X-ray images not involved in either training or validation—was used to evaluate the model’s ability to classify images into the correct categories. All datasets used for training, validation, and testing were kept separate to ensure the validity and accuracy of the evaluation results. During the evaluation phase, a confusion matrix was employed as the primary tool to assess the model's performance. An example of a confusion matrix is shown below [16]:

True label	Predicted label	
	COVID-19	Normal
COVID-19	TP (1952)	FN (27)
Normal	FP (40)	TN (3071)

Figure 5. Example of Confusion Matrix

Where the values are defined as follows:

True Positive (TP) : Positive data correctly predicted by the model
True Negative (TN) : Negative data correctly predicted by the model
False Positive (FP) : Negative data incorrectly predicted as positive
False Negative (FN) : Positive data incorrectly predicted as negative

The evaluation metrics used include accuracy, precision, recall, specificity, and F1-score. These metrics can be calculated using the following formulas [17]:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{4}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

3. Results and Discussion

3.1 Model *Baseline*

The evaluation of the baseline model serves as a crucial step in establishing a performance benchmark prior to implementing more complex optimization techniques. In this study, the baseline model was constructed using the DenseNet-169 architecture. This model was configured with default hyperparameters and trained for 50 epochs. The purpose of this baseline evaluation is to define a reference point for performance before conducting hyperparameter optimization. The results of the DenseNet-169 baseline model evaluation are presented in Table 1 below.

Table 1. Baseline Model Performance Using DenseNet-169

Evaluation Metrics	Normal	Pneumonia	COVID-19
Accuracy	96.83%	96.83%	96.83%
Precision	97%	96%	98%
Recall	94%	97%	98%
Specificity	98.75%	97.75%	98.75%
F1-Score	96%	97%	98%

The analysis of the baseline DenseNet-169 model's performance metrics, as presented in Table 1, demonstrates a highly promising initial result, with an overall accuracy of 96.83%. This high accuracy indicates that DenseNet-169 possesses a strong inherent capability in classifying chest X-ray images into the categories of Normal, Pneumonia, and COVID-19, even prior to the application of Bayesian Optimization. To gain a deeper understanding and visualization of the model's classification patterns, the confusion matrix is shown in Figure 6 below.

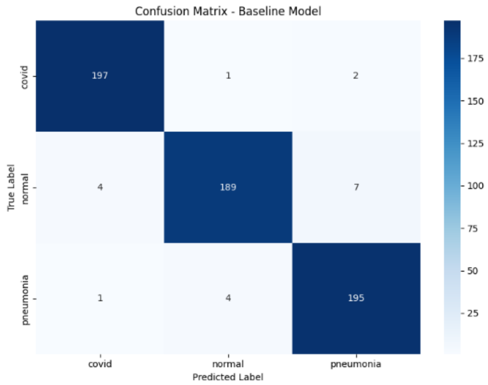

Figure 6. Confusion Matrix of the Baseline Model

For the COVID-19 class, the model demonstrated outstanding performance, with 197 true positives (TP), a very low false negative (FN) count of 3 cases, and a minimal false positive (FP) count of 5 cases. This confirms the model's strong capability in accurately detecting COVID-19 while minimizing diagnostic errors. In the Normal class, 189 TPs were correctly identified. However, there were 11 FNs, which contributed to a slight decrease in recall for this class. Despite this, the model maintained a high precision, with only 5 FPs. As for the Pneumonia class, the model achieved a significant number of 195 TPs, with a low FN count of 5. However, the model also recorded 9 FPs, the highest among the three classes, indicating that some non-pneumonia cases were incorrectly classified as Pneumonia.

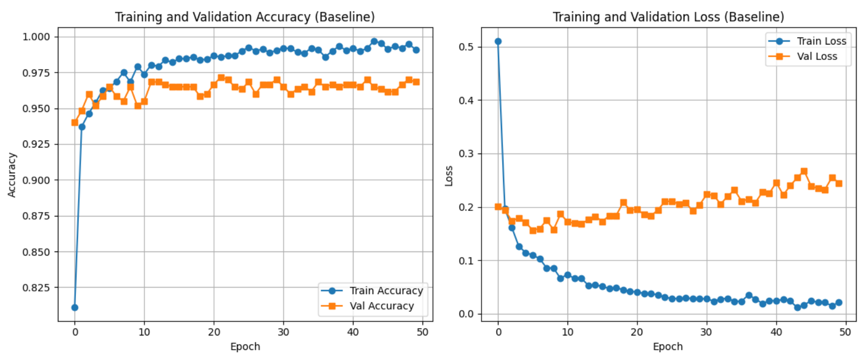

Figure 7. Plot Loss dan Accuracy of the Baseline Model

The visualization of the baseline DenseNet-169 model's loss and accuracy over 50 training epochs, as shown in Figure 7, provides crucial insights into the learning dynamics and potential overfitting. During the early epochs (around 0–10), both plots show a rapid increase in training and validation accuracy, along with a significant decrease in loss, indicating that the model efficiently learned the basic patterns of the data. However, as training progresses, a widening divergence between the training and validation curves becomes apparent. Training accuracy continues to increase and approaches near perfection, while validation accuracy tends to plateau around 0.96–0.97. A similar trend is observed in the loss curves, where the training loss continues to decline steeply, whereas the validation loss flattens or even slightly increases after epoch 20. This divergence is a strong indication of mild overfitting, where the model begins to memorize specific noise from the training data and becomes less effective at generalizing to unseen data. Although the model achieves high overall accuracy, this observation highlights the necessity of the next step—hyperparameter optimization using techniques such as Bayesian Optimization. This aims not only to improve absolute performance metrics but also to address overfitting and enhance the model's generalization capability in a more robust manner.

3.2 Implementation of Bayesian Optimization

After evaluating the baseline model, the next step was to perform hyperparameter tuning (HPO) to improve the performance of the DenseNet-169 model. In this study, HPO was implemented using the Bayesian Optimization method. The search ranges for each optimized hyperparameter were defined based on the previous study conducted by[18], and are presented in table 2.

Table 2. Bayesian Optimization Range

Hyperparameter	Range
Learning Rate	0.00001 – 0.0003
Epochs	200 – 250
Batch Size	1 – 3
Kernel Size	1 - 5

Based on Table 2, the learning rate was optimized within a range of 0.00001 to 0.0003, while the number of training epochs per optimization iteration was set between 200 and 250. The batch size was searched within a range of 1 to 3, and the kernel size of the convolutional layer was optimized between 1 and 5. The Bayesian Optimization process was carried out for five iterations, and the recommended hyperparameter configuration obtained from this process presented in Table 3.

Table 3. Bayesian Optimization Results

Hyperparameter	Hasil
Learning Rate	0.000010
Epochs	207
Batch Size	2
Kernel Size	3

3.3 Final Model

At this stage, the final DenseNet-169 model has undergone hyperparameter optimization using Bayesian Optimization. The performance of the final model is compared to the baseline model to evaluate the impact of the optimization process on accuracy and the model's generalization capability. Table 4 presents a performance comparison between the baseline model and the final model optimized using Bayesian Optimization. This comparison is essential to assess the effectiveness of the hyperparameter tuning process in enhancing the classification performance of the DenseNet-169 model.

Table 4. Comparison of *Baseline* Model and Final Model Performance

Evaluation Metrics	Class	Baseline Model	Final Model (Bayesian Optimization)	Performance Gain (%)
Accuracy	-	96.83%	97.33%	0.51%
Precision	Normal	97%	96%	-1.03%
	Pneumonia	96%	97%	1.04%

	COVID-19	98%	99%	1.02%
Recall	Normal	94%	97%	3.19%
	Pneumonia	97%	97%	0.00%
	COVID-19	98%	98%	0.00%
Specificity	Normal	98.75%	98.00%	-0.76%
	Pneumonia	97.75%	98.50%	0.77%
	COVID-19	98.75%	99.50%	0.76%
F1-Score	Normal	96%	97%	1.04%
	Pneumonia	97%	97%	0.00%
	COVID-19	98%	98%	0.00%

Hyperparameter optimization using Bayesian Optimization effectively improved the performance of the DenseNet-169 model. The overall model accuracy increased from 96.83% to 97.33%, reflecting a 0.51% improvement, significant considering the already high baseline performance. The most substantial improvement was observed in the recall of the Normal class, which rose by 3.19% to reach 97%. The precision for the COVID-19 class also increased to 99%, significantly enhancing diagnostic reliability. Although there was a slight trade-off in precision and specificity for the Normal class, the optimization process successfully maintained or improved critical metrics for disease classes, most notably, the COVID-19 specificity, which increased to 99.50%. These results indicate that the final model is more balanced, robust, and demonstrates superior discriminative capability.

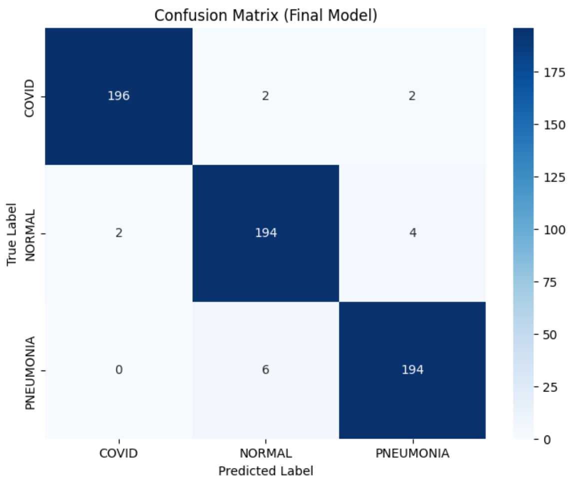

Figure 8. Confusion Matrix of Final Model

The confusion matrix of the final model optimized with Bayesian Optimization, as shown in Figure 8, provides a detailed overview of the classification performance after hyperparameter tuning. This model exhibits improved classification accuracy and error distribution compared to the baseline model. For the COVID-19 class, the model maintained excellent performance with 196 true positives (TP), supported by a low false negative (FN) count of 4 cases and a minimal false positive (FP) count of 2 cases, highlighting its high discriminative capability and outstanding accuracy in detecting COVID-19. The Normal class showed an increase to 194 TPs, with a significant reduction in FNs to just 6 cases. This directly reflects an improvement in recall for the Normal class from 94% to 97%. Meanwhile, the Pneumonia class retained 194 TPs with 0 FNs, meaning that all actual Pneumonia cases were successfully identified. The number of false positives for Pneumonia was 6, slightly higher than in the baseline model; however, this was offset by a notable improvement in detecting actual Normal cases. Overall, the final model's confusion matrix confirms that the optimization process successfully enhanced the model's ability to deliver more balanced and reliable classifications.

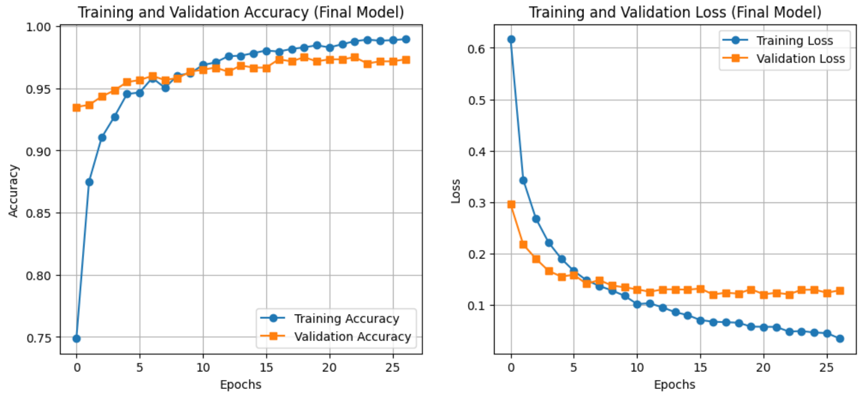

Figure 9. Plot Loss and Accuracy of the Final Model

The visualization of the loss and accuracy trends for the final model, shown in Figure 7, clearly demonstrates the positive impact of hyperparameter optimization. Both curves, Training Accuracy and Validation Accuracy, exhibit consistent and stable improvements. The most striking difference compared to the baseline model is that the Validation Accuracy curve remains very close to the Training Accuracy curve throughout the training process, strongly indicating that the overfitting issue has been significantly mitigated. A similar pattern is observed in the loss plots, where the Validation Loss shows a steady downward trend and remains close to the Training Loss, without the erratic fluctuations seen in the baseline model. This strong convergence and the minimal gap between training and validation performance confirm the effectiveness of Bayesian Optimization in producing a more robust model with superior generalization capability, aligning with the overall improvements observed in the performance metrics.

4. Conclusion

This study investigates the performance improvement of the DenseNet-169 deep learning model in detecting pulmonary diseases (Normal, Pneumonia, and COVID-19) based on chest X-ray images. Considering the importance of early diagnosis in respiratory conditions, the research focuses on hyperparameter optimization using the Bayesian Optimization approach to automatically explore the optimal parameter configurations. The dataset consists of 3,000 RGB chest X-ray images (1,000 images per class), obtained from Mendeley Data, and split into 80% for training and 20% for testing.

Evaluation of the baseline DenseNet-169 model showed a high initial accuracy of 96.837%. However, analysis of the loss and accuracy curves indicated a tendency toward mild overfitting. To address this, hyperparameter optimization was conducted—including learning rate, number of epochs, batch size, and kernel size, within a predefined range based on literature. The optimization process produced a more effective hyperparameter configuration, resulting in a final model accuracy of 97.33%, a 0.51% improvement over the baseline. The most notable enhancement was observed in the recall score for the Normal class, which increased by 3.19% to 97%, effectively reducing the false negative rate for healthy cases. Additionally, the final model demonstrated superior performance in detecting COVID-19 cases, achieving a precision of 99% and specificity of 99.50%, reflecting high discriminative capability and minimal false positives. The training and validation loss curves also indicated strong convergence, signifying that Bayesian Optimization effectively reduced overfitting and enhanced the model's generalization ability.

In conclusion, Bayesian Optimization plays a crucial role in developing a more balanced, robust, and high-performing DenseNet-169 model for multi-class chest X-ray classification. The resulting final model not only demonstrated overall accuracy improvements but also greater precision in distinguishing each disease category, making it a strong candidate as an AI assisted diagnostic tool for early detection of pulmonary diseases.

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