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Pneumothorax Detection System in Thoracic Radiography Images Using CNN Method

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Abstract.
Purpose: This research aims to develop an automatic pneumothorax detection system using Convolutional Neural Networks (CNN) to classify thoracic radiography images. By leveraging CNN's effectiveness in identifying medical abnormalities, the system seeks to enhance diagnostic accuracy, reduce evaluation time, and minimize subjective interpretation errors. The output will provide a predicted label of "pneumothorax" or "non-pneumothorax," facilitating faster clinical treatment and improving diagnostic services while supporting radiologists in making more accurate and efficient decisions for this critical condition.
Methods: This research employs an experimental deep learning approach using Convolutional Neural Networks (CNN) to detect pneumothorax in thoracic radiography images. The CNN model is trained on an annotated dataset with preprocessing steps, including zooming, brightness adjustment, flipping and format adjustment, followed by performance evaluation using accuracy, precision, recall, and F1 score metrics.
Result: The results showed that the CNN model detected pneumothorax with 79.59% accuracy, a loss of 1.3056, and 1,092 correct predictions out of 1,372 test data. Precision was 51.12%, recall 78.62%, and F1 score 61.96%, confirming the system's potential, though further optimization is needed.
Novelty: The novelty of this research lies in developing an automated pneumothorax detection system using a CNN architecture, improving diagnostic accuracy and efficiency. Despite high accuracy, precision and recall can be improved. Future research can focus on optimizing the model and applying data augmentation techniques.

Keywords: Pneumothorax, Convolutional neural networks, Computer-aided detection
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INTRODUCTION

Deep learning is a learning method where complex multilayer neural networks automatically represent data by transforming input information into various levels of abstraction [1]. The Convolutional Neural Network (CNN) method is the most effective deep learning model for classifying chest diseases [2]. Therefore, CNN can be applied in the medical field to classify chest diseases, including in Computer-Aided Detection (CAD) systems. In the medical field, deep learning-based Computer-Aided Detection (CAD) assists radiologists in identifying and marking suspicious areas on X-ray or radiographic images [3]. CAD is typically designed to detect radiographic abnormalities, such as lung nodules, pulmonary infiltrates, and pneumothorax, on frontal chest X-rays [4]. Therefore, CAD has the potential to assist doctors in making clinical decisions more accurately, efficiently, and quickly in cases involving pneumothorax [5]. This research developed a Computer-Aided Detection (CAD) system for pneumothorax using a CNN-based classifier to categorize thoracic radiography images.

Several previous studies that serve as references include the first one from E. J. Hwang, J. H. Lee, J. H. Kim, W. H. Lim, J. M. Goo, and C. M. Park [4]. This research aims to evaluate the performance of a deep learning-based Computer-Aided Detection (CAD) system in detecting pneumonia on Chest X-rays (CXR) of patients with a consistent body temperature above 38.3°C and to observe whether CAD can expedite radiologists diagnostics when used as a second reader. The method applied in this research is pure deep learning or deep neural networks.

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In addition, the research by E. Showkatian, M. Salehi, H. Ghaffari, R. Reiazi, and N. Sadeghi [6] aimed to develop and compare a new method for automatically detecting tuberculosis (TB) from thoracic radiography images to improve diagnostic accuracy and reduce errors that may arise in interpreting thoracic radiography image. This research compared the performance of deep learning models with transfer learning techniques using CNN models to train neural networks capable of automatically identifying TB from thoracic radiography images.

The research conducted by P. P. Dalvi, D. R. Edla, and B. R. Purushothama [7] highlights the advantages of the DenseNet-169 model over others such as AlexNet, ResNet-50, VGG-16, and VGG-19 for diagnosing COVID-19 from thoracic radiography image. This study employs transfer learning with a pre-trained DenseNet-169 model and data augmentation techniques to enhance the dataset. It underscores the potential of thoracic radiography images as a cost-effective and efficient alternative for COVID-19 diagnosis, especially given the limitations of RT-PCR testing.

Other research from B. Park et al. [8] also explores the application of deep learning models for thoracic radiography image analysis. This study compares the performance of a curriculum learning-based model with a baseline model for automatic lung abnormality classification in thoracic radiography images. The results show improved accuracy and reduced loss in detecting thoracic diseases such as nodules, consolidation, interstitial opacity, pleural effusion, and pneumothorax. Overall, this computer-aided diagnostic (CAD) system shows potential for simultaneous detection and classification of multiple disease patterns in thoracic radiography images. However, challenges remain in lesion variation and dataset expansion.

Lastly, in the research by J. Luo, Y. Sun, J. Chi, X. Liao, and C. Xu [9], a deep learning model was developed to assist radiologists in detecting pneumonia caused by COVID-19. The diagnostic results from the deep learning model were compared with those from radiologists. U-Net and ResNet-50 were utilized as the CNN architecture to train the deep learning model on normal patients, community-acquired pneumonia (CAP), and COVID-19 cases.

Based on previous studies, many have explored chest disease detection systems using the CNN method. CNN has proven to be the most effective deep-learning model for classifying lung diseases [2]. However, there are still shortcomings in studies that explicitly examine pneumothorax detection using CNN from thoracic radiography images. Most previous research has focused more on general chest disease detection or other lung diseases, leaving a gap in the specific implementation for pneumothorax. Therefore, this research explicitly develops a CNN-based pneumothorax detection system optimized for analyzing thoracic radiography images to improve the accuracy and efficiency of detecting this condition.

This research aims to design and develop a pneumothorax detection system based on Convolutional Neural Networks (CNN) optimized for chest radiography images. The research is expected to contribute to more accurate and rapid pneumothorax detection, ultimately expediting referral processes, reducing diagnostic delays, and preventing emergencies due to delayed treatment. By designing a CNN architecture specifically for thoracic radiography image analysis, this research also seeks to evaluate the effectiveness and accuracy of the CNN method compared to other approaches previously used for detecting chest diseases. The performance of the proposed system will be measured using key metrics such as accuracy, loss, recall, precision, and F1-score. Accuracy will assess the overall correctness of the model, while recall will measure its ability to identify pneumothorax cases correctly. Precision will indicate the proportion of accurate positive detections, and the F1-score will provide a balanced evaluation of precision and recall. During training, the loss function will also be monitored to ensure the model's convergence and optimal performance.

Through this research, the researcher aims to address several key questions. The first question focuses on how an optimal Convolutional Neural Network (CNN) architecture can be designed to detect pneumothorax in chest radiographs. The second question explores how the CNN model can be effectively trained using a properly annotated radiographic image dataset, ensuring the quality and accuracy of the training process. Finally, the research seeks to evaluate how accurate the CNN method is in detecting pneumothorax compared to other existing methods, providing insights into its relative performance and potential advantages in clinical applications.

The findings of this study will not only demonstrate CNN's advantages in pneumothorax detection but also provide a foundation for future improvements in computer-based detection systems.

METHODS

This research was developed through several stages, including data collection, preprocessing, data partitioning and labelling, augmentation on positive training data, cross-validation, CNN model creation, model training, model testing, and evaluation of the developed model's performance. Figure 1 illustrates the process carried out in this research.

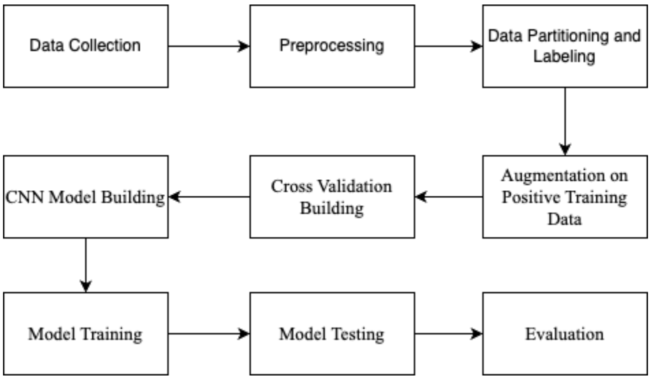


Figure 1. Research methodology flowchart

Data collection

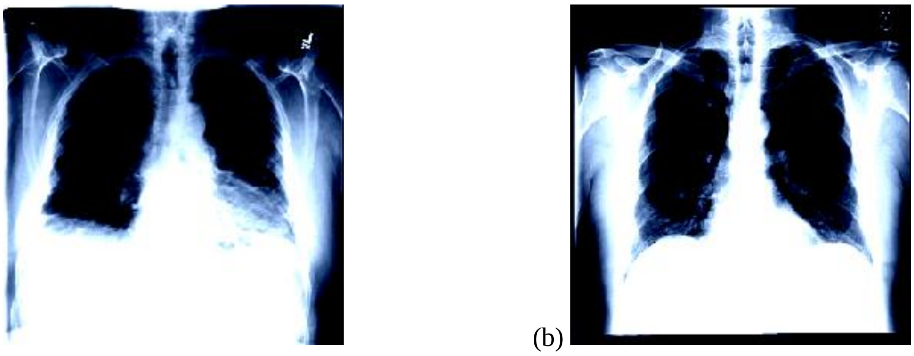
This research used a dataset of digital thoracic radiography images from https://www.kaggle.com/datasets/vbookshelf/pneumothorax-chest-xray-images-and-masks formatted as .png files. The dataset consists of 10.825 images, including 2.379 training images depicting pneumothorax, 7.074 training images without pneumothorax, 290 test images with pneumothorax, and 1.082 test images without pneumothorax.

(a)  (b) 

Figure 2. Pneumothorax (a) and non-pneumothorax (b) sample x-ray images

Preprocessing

Preprocessing is carried out to enhance and modify the image format, making it more compatible with the DenseNet architecture. The preprocessing steps start with resizing the images to 224x224 pixels as A. R. Beeravolu, S. Azam, M. Jonkman, B. Shanmugam, K. Kannoorpatti, and A. Anwar did [10], followed by Min-Max normalization, which adjusts the pixel intensity values within an image to a range of 0 to 1. Min-max normalization is commonly used in image processing due to its straightforward formula, making it suitable for the DenseNet model [11]. The final step is to normalize each channel concerning the ImageNet dataset statistics.



(a) (b)

Figure 3. Pneumothorax (a) and non-pneumothorax (b) sample x-ray images after preprocessing

Data partitioning and labelling

Data partitioning and labelling are performed to separate the dataset based on its purpose and labels, which supports the training and evaluation processes of the model. Proper data partitioning is essential for the success of deep learning [12]. Data partitioning separates the available dataset into three specific subsets: training, validation, and testing [12]. However, this study divided the data into training and testing data. The training data is prepared for training the deep learning model and also serves as validation data because cross-validation will be applied. The testing data is ready to objectively measure the model's performance after training is complete and used to assess the model's ability to make predictions based on unseen data.

Augmentation of positive training data

Data augmentation is a key technique in deep learning that significantly improves model performance and generalization [13]. Data augmentation is used to expand the training dataset to improve CNN's generalization performance and classification accuracy [14]. In this study, transformations such as adjusting brightness, zooming, and flipping of existing data points are converted into new instances with the same labels but different appearances applied to the positive training data to enhance its diversity and help the model generalize better [13]. The transformations included applying zoom-in operations up to 10%, brightness operations up to 30%, and flipping the images horizontally. The model can better capture the essential features required for accurate predictions, mainly when dealing with limited or imbalanced datasets through these techniques.

Cross-validation building

Cross-validation (CV) is a set of sampling techniques used to repeatedly divide a dataset into distinct groups for training and testing [15]. The most basic form of cross-validation is k-fold cross-validation, where the data is divided into k parts of approximately equal size [16]. This study divided the training data into five equal parts (folds), as in the study by Z. A. Sejuti and M. S. Islam [17]. The model was trained on four folds while the remaining fold was used for validation, and this process was repeated five times [18]. This approach helps provide a more comprehensive evaluation of the model's performance by ensuring it generalizes well to unseen data [19]. By reducing overfitting, cross-validation enhances the model’s accuracy.

CNN model building

In building the CNN model, hyperparameter tuning was done by selecting optimal values for several key parameters to enhance deep learning performance. Hyperparameters are the parameters that control the training process and structure of a deep learning model [20]. Unlike model parameters learned during training, hyperparameters are determined before training begins and have an essential role in influencing model performance [20]. This research's initial hyperparameter initialization includes a learning rate of 0.001, batch sizes 32, and 20 training epochs. Additionally, the number of Convolutional, Max Pooling, and Fully Connected layers were adjusted. Callbacks such as Early Stopping and Reduce LR were employed to optimize the training process further. Early Stopping halted the training if the model's performance on the validation set did not improve for several epochs, preventing overfitting. Meanwhile, Reduce LR dynamically lowered the learning rate when the validation performance plateaued, allowing the model to converge more efficiently. This tuning process aimed to achieve an efficient and reliable configuration capable of accurately detecting pneumothorax from thoracic radiography images.

This research proposes predicting pneumothorax cases using a CNN with the Denset architecture. Table 1 presents the layers, output shapes, and various parameters of the proposed architecture.

Table 1. Layers of the proposed architecture

Layer Type	Shape
Input Layer	(None, 224, 224, 3)
DenseNet121 (Base Model)	(None, 7, 7, 1024)
Conv2D	(None, 7, 7, 128)
GlobalAveragePooling2D	(None, 128)
Dense	(None, 512)
Dropout	(None, 512)
Dense (Output Layer)	(None, 1)

Model training

At this step, the prepared train dataset is trained using a CNN model with DenseNet architecture based on the hyperparameters defined in the previous phase. The training process is repeated five times (fold) with 50 epochs, following the cross-validation technique set earlier, with a callback for early stopping that monitors 'val_loss', has patience of 4, and restores the best weights when training stops, as well as a callback for reducing the learning rate by a factor of 0.2 when 'val_loss' does not improve, with patience of 2 and a minimum learning rate of 1e-6. After completing the first training, fine-tuning is performed by reducing the learning rate to one-tenth of its original value and training for half the original number of epochs. Model training aims to enable the neural network to learn patterns and features from the training data, allowing it to predict outcomes on new, unseen data accurately.

Model testing

After completing the training in the previous stage, the model is tested on a separate test dataset that the system has not seen before. The results are then used to evaluate the performance of the developed CNN model.

Evaluation

An evaluation of the model's performance was conducted on the built CNN model. This evaluation determines whether the model is optimal or suffers from overfitting or underfitting based on the chosen hyperparameters. Performance evaluation metrics are essential for measuring the accuracy of deep learning models in identifying and classifying pneumothorax disease [21]. The evaluation process in this research includes measuring accuracy, precision, recall, and F1-score. The evaluation process in this research involves measuring accuracy, precision, recall, and F1-score. Each of these metrics provides valuable insights into the model's performance, and we will now delve into a detailed discussion of their definitions and significance in assessing classification outcomes.

Accuracy metrics are the ratio of correct predictions to the total number of predictions [22]. The accuracy calculation formula is presented in Equation (1).

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

Precision metrics are the ratio of true positive predictions compared to the total of true positive and false positive predictions [22]. The precision calculation formula is presented in Equation (2).

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

Recall metrics are the ratio of true positive predictions relative to the total of true positive and false negative predictions [22]. The recall calculation formula is presented in Equation (3).

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

The F1-score is the harmonic mean between precision and recall, which measures the balance between the two in a system [22]. The recall calculation formula is presented in Equation (4).

$$\mathrm{F1-Scores} = \frac{2 \text{ x } Presisi \text{ x } Recall}{Presisi + Recall} \tag{4}$$

RESULTS AND DISCUSSIONS

In this section, the results of the experiments and analyses are presented and discussed in detail of the study on the automatic pneumothorax detection system developed using a Convolutional Neural Network (CNN) with DenseNet architecture. Augmentation was applied to the positive samples to balance the dataset and enhance the model's performance on class imbalance. Figure 4 shows the augmented positive training samples.

Figure 4. Training image results after augmentation

The performance of the model was evaluated per fold using cross-validation. The model's accuracy, precision, recall, and F1-score were calculated for each fold to assess its effectiveness in detecting pneumothorax. Table 2 shows the results of the model performance evaluation on various folds.

Table 2. Evaluation of model performance results per fold

Folds	Loss	Accuracy	Precision	Recall	F1 Score
1	0.0049	1.0	0.4837	0.5118	0.4974
2	0.0049	1.0	0.4538	0.4617	0.4577
3	0.0218	0.9979	0.4865	0.5	0.4932
4	0.0033	1.0	0.4805	04644	0.4723
5	0.0344	0.9905	0.4867	0.5185	0.5021

Visualizing the evaluation metrics per fold is included to better understand the model's performance across each fold. This visualization highlights the variations in loss, accuracy, precision, recall, and F1 score, allowing for an in-depth analysis of the model's consistency and effectiveness across different subsets of the data. Figure 5 shows a graph of the training results of our proposed model training.

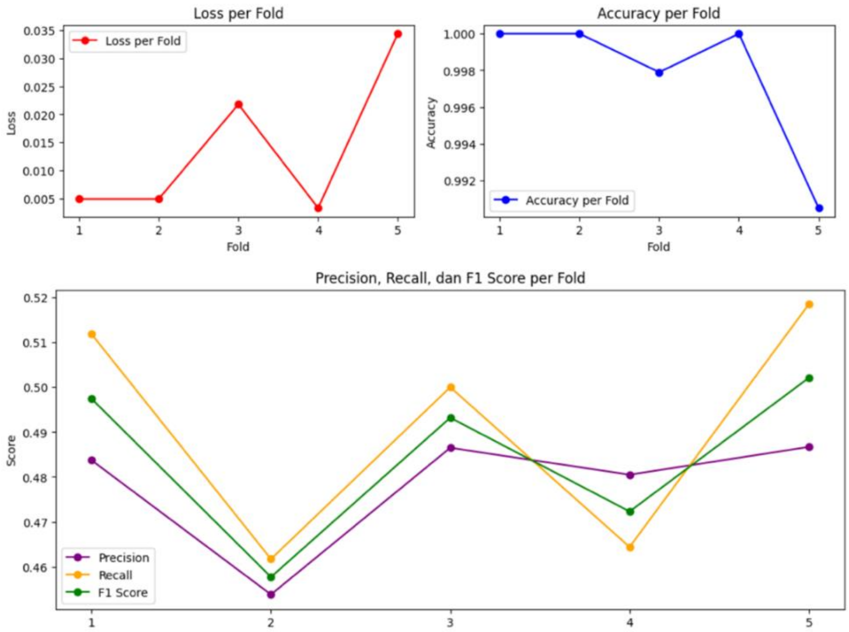


Figure 5. Model training results

Based on the graph, fold 1 achieved the highest scores in accuracy and recall, with an accuracy of 100% and a recall of 51%. The accuracy metric is the number of correct predictions out of the total predictions made [23], and recall, or sensitivity represents the ratio of real positive cases that are accurately predicted as positive [24]. Therefore, the model from fold 1 will be used as the basis for predicting the pneumothorax system.

Compared to Y. H. Bhosale and K. S. Patnaik study [25], which utilized ResNet50 for pneumothorax detection, this study employs a DenseNet121-based Convolutional Neural Network. The differences in the architectures, along with variations in dataset and evaluation methods, contribute to distinct performance outcomes. Table 3 presents a detailed comparison of the results from both studies, highlighting key differences in accuracy, precision, recall, and f1 score.

Table 3. Comparison of the results from both studies

Research	Accuracy	Precision	Recall	F1 Score
Y. H. Bhosale and K. S. Patnaik	87.65	44.72	44.44	41.31
Proposed Model	1.00	48.37	51.18	49.74

The next step is to test with a 1372-image thoracic radiography image test dataset, consisting of 290 labelled as pneumothorax and 1082 as non-pneumothorax. The CNN model achieved an accuracy of 79.59% with a loss of 1.3056, correctly predicting 1,092 out of 1,372 test images. Precision was recorded at 51.12%, recall at 78.62%, and the F1 score at 61.96%. Figure 6 shows the graph of the testing results of our proposed model training.

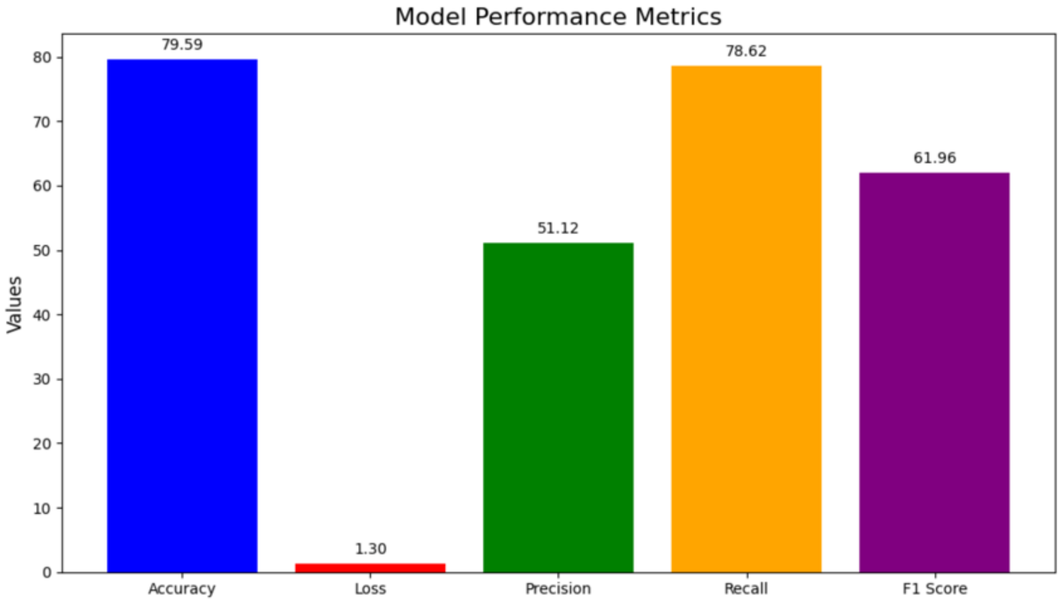


Figure 6. Model testing results

Subsequently, the model was tested on 290 thoracic radiography images, consisting only of positive cases (pneumothorax). The model achieved a loss of 1.2067, an accuracy of 78.62%, a precision of 100%, a recall of 78.62%, and an F1 score of 88.03%. This test highlights the model's ability to identify positive pneumothorax cases effectively, achieving perfect precision and a balanced recall rate. Figure 7 shows the graph of the testing results of our proposed model training on positive data.

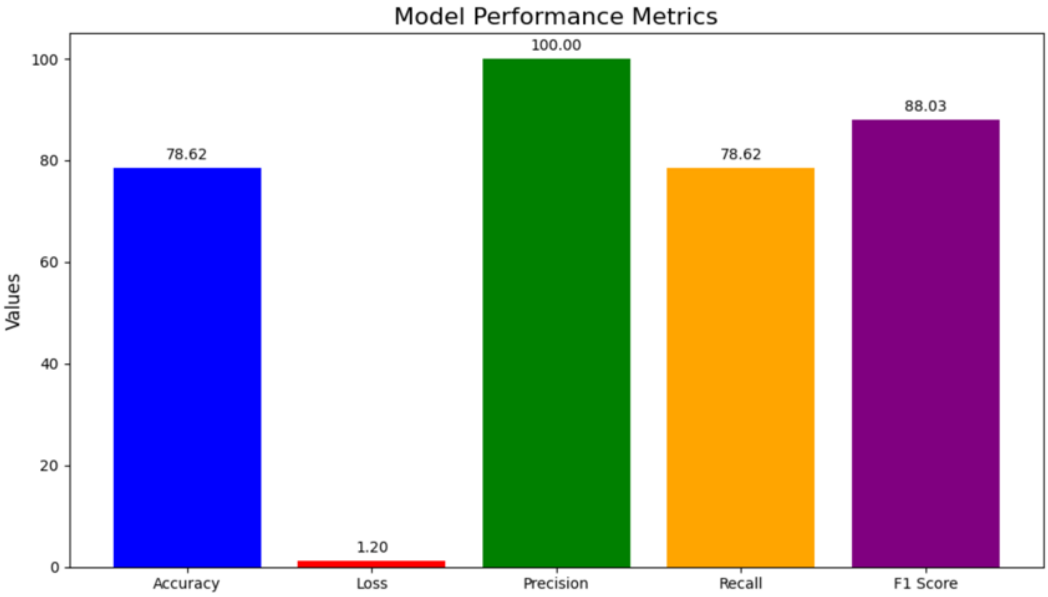


Figure 7. Model training results on positive data

The test data is distinct from the training data that was previously used. It was never included in any part of the training process, ensuring no overlap. The test data has been specifically prepared separately, starting from the pre-processing stage, to evaluate the model's performance on unseen cases.

Validation was also carried out by two radiology specialist doctors who expertise in thoracic radiology. The two doctors validated the model's prediction results using 100 randomly selected images from 1372. Based on the assessment of the first doctor by Dr. Bambang Satoto, MD, MH and the second doctor by Adhikamika Aripriandari, MD, the prediction results from the randomly taken model test data showed an accuracy rate of 72% when compared to manual diagnosis. Both doctors provided positive feedback regarding the model's ability to recognize pneumothorax patterns on chest radiographs.

Based on the evaluation results, the proposed model performs reasonably well in predicting pneumothorax cases using radiology images. However, model optimization is necessary to improve the recall score. Further enhancements could involve tuning hyperparameters using methods such as grid search or random search or increasing the diversity of training data. These approaches would allow the model to generalize and improve its performance on unseen data, potentially leading to more accurate predictions.

CONCLUSION

This paper presents a method for detecting pneumothorax in thoracic radiography image using a convolutional neural network model based on DenseNet121. The research includes data collection, image preprocessing (normalization), data partitioning and labeling, CNN model training with cross-validation, model testing, and evaluation. The results show that the model achieved an accuracy of 79.59% with a loss of 1.3056, correctly predicting 1,092 out of 1,372 test images. The precision was 51.12%, recall was 78.62%, and the F1 score was 61.96%. These findings indicate that the DenseNet121-based CNN model can effectively detect pneumothorax in thoracic radiography image. However, the model's precision remains relatively low, suggesting that further improvements are needed to reduce false positives. Future research could explore using advanced data augmentation techniques, hyperparameter tuning, or a combination of multiple deep learning architectures to enhance the model's performance, particularly in improving precision and reducing false optimistic predictions.

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