Original Research Paper

Classification of Thoracic X-Ray Images of COVID-19 Patients Using the Convolutional Neutral Network (CNN) Method

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Abstract: Recently, radiology modalities have been widely used to detect COVID-19. Thoracic X-rays and CT scans are the primary radiological tools utilized in the diagnosis and treatment of individuals with COVID-19. In addition, chest CT scans are more accurate and sensitive in early COVID-19 identification. A new problem arises in diagnosing the results of CT scan images of COVID-19 by radiologists or radiology specialists where COVID-19 is difficult to distinguish from pneumonia caused by other viruses and bacteria, so misdiagnosis can occur. Many researchers worldwide have developed computer-aided detection or diagnosis schemes based on medical image processing and machine learning to overcome this challenge. This research focuses on the development of previous studies, where the use of the Convolutional Neural Network (CNN) method to classify Thoracic X-ray Images of COVID-19 Patients is compared with the model developed by Roboflow. Image manipulation techniques applied to this study are pseudo color and the program is Python. This study employs the pseudo color image manipulation technique of the program in Python. This study uses data on patients with confirmed COVID-19 at Andalas University Hospital in 2022. Based on the study's results, a very good CNN Specificity score of 93% was obtained and the perfect Sensitivity score value was produced by the detection method using the Roboflow model, which was 100%. However, the Kappa score for both methods is below the expected threshold of 36-38%. Based on the ROC value, the CNN and Roboflow methods are good for calculating chest X-ray images of COVID-19 and normal patients.

Keywords: Convolutional Neural Network, COVID-19, Early Detection, Roboflow

Introduction

The exploration and application of ionizing radiation, known as medical radiation, commenced with three pivotal discoveries: X-rays by Rontgen (1895), natural radioactivity by Becquerel (1896); Radium by Curie and Sklodowska-Curie (1898); Pospieszny (2019). Since then, radiation has played a crucial role in hindering the progression of therapy and radiology (Fardela and Ashari, 2018). Currently, radiological techniques have been extensively employed for the detection of COVID-19. Among these techniques, thoracic X-rays and CT scans are the predominant modalities for diagnosing and managing COVID-19 patients (Zhao *et al*., 2021; Ismael and Şengür, 2021). Additionally, chest CT scans offer heightened accuracy and sensitivity in the early detection of COVID-19. Only a limited number of studies have explored the utility of ultrasound and PET scans in the diagnosis of COVID-19 (Alhudhaif *et al*., 2021; Aljondi and Alghamdi, 2020).

A novel predicament arises when radiologists or specialists in radiology interpret COVID-19 CT scan images. In these images, distinguishing COVID-19 from pneumonia induced by other viruses and bacteria can prove challenging, potentially leading to misdiagnoses (Dai *et al*., 2020; Lei *et al*., 2020). Complicating matters further are factors such as the blending of anatomical structures surrounding the lungs, the diminutive size of lesions, and varying levels of radiologist experience, all contributing to potential disparities in image interpretation. Consequently, radiologists confront distinct clinical challenges amid the pandemic. To surmount these hurdles, researchers worldwide have devised numerous computer-assisted detection or diagnostic approaches grounded in medical image processing and machine learning (Alafif *et al*., 2021;

Alakus and Turkoglu, 2020; Shorten *et al*., 2021). These endeavors aim to automatically analyze disease attributes and furnish radiologists with valuable decision-support tools, thereby enhancing the precision and efficiency of COVID-19 infected pneumonia detection and diagnosis. These tools either complement radiologist analyses or stand as secondary options (Singh *et al*., 2020; Heidari *et al*., 2020).

This article focuses on the development of previous studies (Hassantabar *et al*., 2020; Chen, 2021; Thakur and Kumar, 2021), which use the Convolutional Neural Network (CNN) method to classify Thoracic X-ray Images of COVID-19 Patients. There are many researchers who have used the CNN method to detect COVID-19. CNN is a type of artificial neural network architecture that is commonly used to process image data and recognize other complex patterns. In 2020 Apostolopoulos and Mpesiana developed a CNN model to detect COVID-19 from lung X-ray images (and Mpesiana, 2020). They claimed that the developed model could help in supporting early diagnosis and accelerate COVID-19 testing efforts. In the same year (Ozturk *et al*., 2020) proposed a CNN-based Deep Transfer Learning (DTL) model to detect COVID-19 from X-ray images. They used pre-trained CNN models, such as VGGNet and ResNet, to obtain robust feature representations from X-ray images (Hemdan *et al*., 2020). Furthermore, Hemdan *et al.* (2020) reported the use of CNN and transfer learning methods. They trained the designed model using X-ray images of patients with COVID-19 and non-COVID-19 indications (Narin *et al.*, 2021).

Continuing in Narin *et al.* (2021) conducted research on the development of the CNN method to detect COVID-19 from lung X-ray images. They used an architectural model ResNet-50 to train and test X-ray image data from COVID-19 patients (Mofrad and Valizadeh, 2023). Proposed the use of 3D CNN for COVID-19 detection from lung CT-scan. They claim that the 3D CNN model is able to produce better performance than the 2D model in identifying signs of COVID-19 infection (Kumar *et al*., 2023). Although in almost all countries the status of COVID-19 from a pandemic has dropped to an endemic, research related to the detection of COVID-19 or abnormalities in the lungs using CNN models is still being carried out by many researchers (Kaya and Gürsoy, 2023; Gulakala *et al*., 2023; Kanjanasurat *et al*., 2023; Akl *et al*., 2023; Hussein *et al*., 2023; Sejuti and Islam, 2023; Liang *et al*., 2021; Oktamuliani *et al*., 2023)

This article reports the development of COVID-19 detection using CNN and Roboflow, the application of the pseudocolour method was carried out in this study. The use of this method is used to improve visualization or contrast in X-ray chest images. In this X-ray image processing, the pseudocolor method will help clarify or visualize areas suspected of being infected with COVID-19. This research is expected to provide an overview of the differences in the use of pseudocolor in CNN and roboflow methods in detecting images of COVID-19 patients. So that proper diagnosis enforcement can be done quickly, precisely, and easily. In addition, the use of excessive contrast media for each examination using the CT-scan modality can be reduced. Another thing is the reduction of repeated radiation exposure to patients can be reduced and of course, the receipt of radiation doses to patients can be reduced as low as possible.

Materials and Methods

This study uses data on patients confirmed with COVID-19 at Andalas University Hospital in 2022. Normal patient images use data from the same hospital. The testing data for the designed system uses patient data that has been confirmed by COVID-19 and patients with normal chest X-ray examinations by radiation specialists. In general, the research stages consist of five stages shown in Fig. 1. Chest X-ray image data of COVID-19 patients and normal patients obtained from the radiology department of the Unand hospital are processed using Python programming.

The first process is to change the DICOM image format to PNG then the image size equalization process is carried out, namely (720×720) pixels. The next process is to perform pseudo-coloring on the original image (colormap_jet). This process is done to increase the contrast so that the information hidden in the image can be observed (Liang *et al*., 2021; Oktamuliani *et al*., 2023). The next process is image augmentation where at this stage the image data is modified, followed by the feature extraction process using the CNN method, and finally, the image classification stage based on the input data. The architecture of this research is presented in Fig. 2.

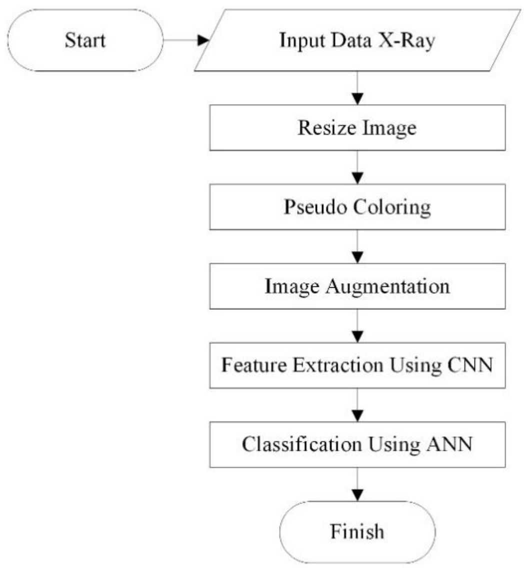

Fig. 1: General research process

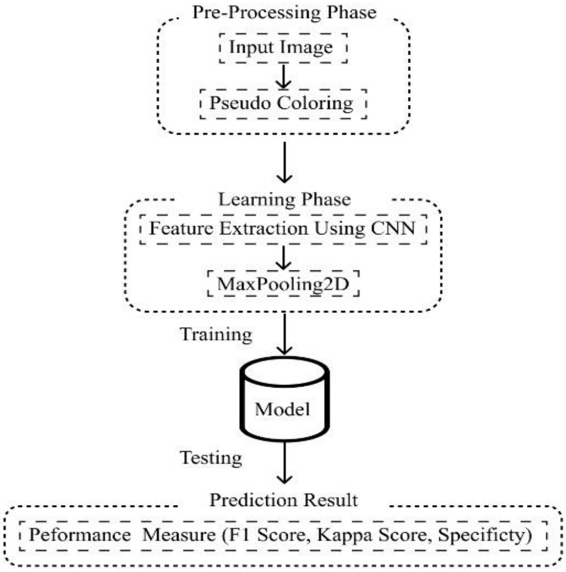

Fig. 2: Architecture diagram of the classification of chest X-ray images of COVID-19 patients using the CNN method

Fig. 2 is the architecture used in this study as well as a more detailed explanation of the process in Fig. 1. In the context of COVID-19 detection, CNN is used to analyze chest X-ray images of COVID-19 patients. The architecture begins with data pre-processing: Image data is prepared before being fed into the CNN model. This includes image size equalization and pseudo-coloring. Next comes the learning phase where the CNN model is built using convolution layers to extract important features from the chest X-ray image of a COVID-19 patient. These convolution layers are followed by other layers such as activation and pooling layers to reduce the dimensionality of the features.

Model training: The CNN model is trained using previously collected image data. The training process involves feeding the model with input images, calculating backward propagation, and adjusting parameters so that the model learns the patterns in the data. Model validation and evaluation: Once the model was trained, it was tested using X-ray image data of COVID-19 patient data that was never recognized by the previously built system. The performance of the model is evaluated using metrics such as Precision Eq. 1, Specificity Eq. 2, Sensitivity Eq. 3, F1-score Eq. 4, and kappa Eq. 5 (Hussein, *et al*., 2024):

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (2)$$

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

$$F1 - Score = 2\times \frac{Precision \times recall}{precision + recall} \quad (4)$$

$$kappa = \frac{(Po - Pe)}{(1 - Pe)} \quad (5)$$

where, Po is the relative observed agreement among raters and Pe is the hypothetical probability of chance agreement. TP represents true positives, TN stands for true negatives, FP corresponds to false positives and FN represents false negatives. The metrics assessing the COVID detection performance in the suggested model include kappa, precision, specificity, sensitivity, and *F1-Score*. A comparison will be drawn between the outcomes of this developed CNN model and the modeling conducted by Roboflow employing the yolov2 architecture. The images utilized are sourced from the same origin and the pseudo-coloring procedure is uniformly executed on Roboflow's platform.

Results and Discussion

Deep Learning (DL) methods, particularly CNN, are effective approaches for representation learning using multilayer neural networks. In this study, patient used in this study for COVID-19 patients and normal patients were 200 data on the results of Chest X-ray images at the Unand Hospital. The testing data used in the study for COVID-19 patients and normal patients is 30 data. The testing data used is taken from the Kaggle COVID-19 radiography database source, presented in Table 1.

A demonstration of the data preprocessing method including pseudo-coloring and dimensional normalization can be seen in Fig. 3. A CNN-based regression framework was used to describe the relationship between radiographic findings and patients' clinical symptoms. The original greyscale images were converted to color images using the pseudo-coloring method and annotated using Python. The scale on the right represents the pixel value range of the image data.

Table 1: Thorax image results of COVID-19 and normal patients

Chest X-ray data types	Train + Val	Test
Positive for COVID-19 (unand hospital)	100	-
Normal (unand hospital)	100	-
Positive COVID-19 (Kaggle)	-	20
Normal (Kaggle)	-	10

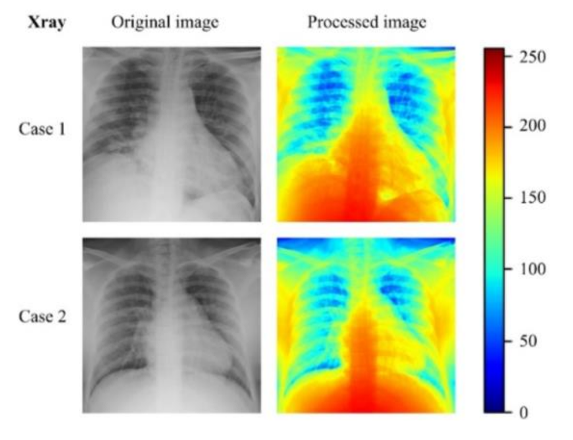

Fig. 3: Demonstration of data prepossessing methods

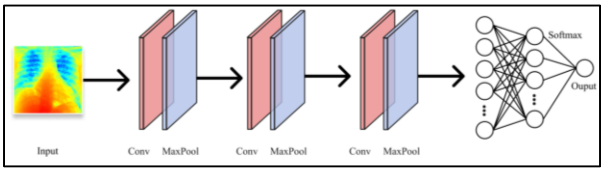

Fig. 4: Classification framework chest X-rays in CNN method

The application of normalization in this research is to reduce the dimensionality of the image. The pseudo-coloring method used is a technique that helps improve medical images for doctors to isolate relevant tissues and group different tissues together.

The next process is feature learning where CNN automatically learns the most relevant features from the input image data (chest X-rays) to identify whether the patient has COVID-19 or not. Basically, the CNN performs hierarchical feature extraction from the chest X-ray image to aid in classification, this process is presented in Fig. 4.

Figure 4 shows the general steps that occur during feature learning on a COVID-19 detection CNN. The chest X-ray image that has been given a pseudo-color feature will undergo a convolution process. At this stage, the CNN uses several filters (kernels) to perform convolution operations on the input image. This convolution process helps detect simple features such as edges, lines, and other patterns from the image. Next activation occurs after the convolution process, an activation function (e.g., ReLU Rectified Linear activation) is applied to deactivate negative values and strengthen relevant features. The next process is pooling where a pooling process (such as max-pooling) is performed to reduce the size of the feature representation and simplify the information found in the convolution stage.

This helps in reducing overfitting and improving generalization. After a series of convolution and pooling layers, the feature representation is converted from a multidimensional matrix to a dimensional vector. The feature vectors are then fed to multiple fully connected layers. These layers act as the final classification to distinguish whether the image indicates COVID-19 or not.

The final layer in the CNN is the output layer, which produces class probabilities (e.g., the probability that the image shows COVID-19 or not). Training and Backpropagation: During training, CNNs use the labeled training data (images with COVID-19 and non-COVID-19 labels) to adjust the weights and biases in each layer to recognize the most relevant features.

Feature learning allows CNNs to automatically find the most informative features from images without any human intervention in defining those features. With this process, CNNs become efficient in identifying COVID-19 from chest X-ray images and are also able to extract features from the images. Other important features that may not be visible to traditional classification methods.

The model validation process is carried out with chest X-ray image data of patients affected by COVID-19 and normal patients. This data was obtained from Kaggel, where 20 chest X-ray image data of patients who indicated COVID-19 and 10 normal chest X-ray image data. Furthermore, this study was compared with the use of other features, namely roboflow as previously described, this comparison data is presented in Table 2.

F1-Score, Kappa score, specificity score, and sensitivity score are evaluation metrics used to measure the performance of the model (CNN). F1-Score is the harmonic mean of precision and sensitivity (Hussein, *et al*., 2024). Precision is the ratio of true positives divided by the total number of positive predictions, while sensitivity is the ratio of true positives divided by the total number of data that are actually positive. F1-Score provides a balance between Precision and sensitivity and can be a better evaluation metric if we have imbalance classes in the data, its formulation is presented in Eq. 4.

The Kappa score measures the extent of agreement between the model predictions and the actual data adjusted for chance probabilities. This metric is useful when the classes in the data have an unbalanced distribution or when the accuracy of the model can be affected by chance. Specificity measures the ability of the model to correctly identify true negatives. mathematically, specificity is calculated as the ratio of true negatives divided by the amount of data that is actually negative.

Recall measures the ability of the model to correctly identify true positives. Mathematically, sensitivity is calculated as the ratio of true positives divided by the number of data that are actually positive. In the context of CNNs and classification tasks, the use of the above metrics is important to evaluate model performance and ensure that the model can accurately recognize the different classes present in the data. Sometimes, depending on the characteristics of the data. These metrics can provide different information about model performance, so they should be used together to get a more complete picture.

Table 2: Performance indices of the classification framework CNN and Roboflow

Category	CNN	Roboflow
F1-Score	0,5000	0,5882
Kappa score	0,3846	0,3636
Specificity score	0,9333	0,5333
Sensitivity score	0,4000	1,0000

Table 2, the Kappa and specificity values in the CNN method are higher than those in the Roboflow method. This shows the percentage of the ability of an examination to negatively state a sick person (affected by COVID-19) using the CNN method is around 93%, while the percentage using the Roboflow method is 53%. The specificity value is inversely proportional to the sensitivity value. Table 2 shows that the CNN method is well used in detecting normal patients and COVID-19 patients. It is evident that the CNN method is a deep learning architecture that takes an image, applies convolution and unification, and then passes through fully connected layers and activation functions to return the output. The output of the CNN method contains a classification of the content of an image or information about the position of different objects in an image. The CNN method uses the convolution technique.

Convolution is an operation that combines two functions to create a third function that can transform one function into another form of function. At a high level, CNNs are designed to take an image and transform it into a representation that can be understood by a neural network, while retaining the important features that will allow obtaining accurate predictions.

Predicting probabilities for the classification of predictive modeling problems we can use Receiver Operating Characteristic (ROC) curves. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various prediction thresholds. TPR is the percentage of positive data that is correctly predicted as positive by the model, while FPR is the percentage of negative data that is incorrectly predicted as positive by the model. The ROC curve is plotted by varying these thresholds and produces a graph that shows how the model's performance changes at different levels of sensitivity and specificity.

Area Under the Curve (AUC) is a metric calculated from the ROC curve. AUC represents how good the model is at distinguishing between two classes. The higher the AUC value, the better the model is at performing COVID-19 detection.

Using the ROC curve, we can select the optimal threshold to maximize the model's performance in COVID-19 detection. The good results on the ROC curve and the high AUC value indicate that the CNN model has good potential in helping to accurately identify COVID-19 cases based on the given medical data.

Fig. 5, it can be seen that the X-axis is a plot of the false positive rate and the Y-axis is a plot of the true positive rate. ROC curves are used when having an equal number of observations. ROC curves can present an overly optimistic view of the algorithm's performance. Visual interpretation of the ROC plot in the context of an unbalanced dataset may affect its relationship with the reliability of classification performance. If the proportion of positive to negative values changes, then matrices such as accuracy, precision, lift, and F1-Score use values from both columns of the matrix.

The ROC graph is based on the TPR and FPR, that is, each dimension is a strict column ratio, so it does not depend on the class distribution. The results of the research show that the ROC value of CNN is not much different from Roboflow. The ROC value on CNN was obtained at 72% and on Roboflow at 89%. With training data as much as 100 data on patients infected with COVID-19, the ROC value has reached around 80%. If we increase the training data, it is possible that the ROC value obtained will be higher. This limited data is due to the number of patients who indicated COVID-19 at Unand Hospital in mid-2022 has experienced a drastic decline.

Next, the Precision-Recall (PR) curve will be determined which is used to evaluate the performance of the model on the classification of COVID-19 detection using CNN and roboflow. The PR curve provides insight into how well the built model classifies the positive class (in this case, positive detected COVID-19 cases) compared to the negative class (e.g., non-COVID or negative patients). The PR curve results for CNN and Roboflow as a comparison are presented in Fig. 6.

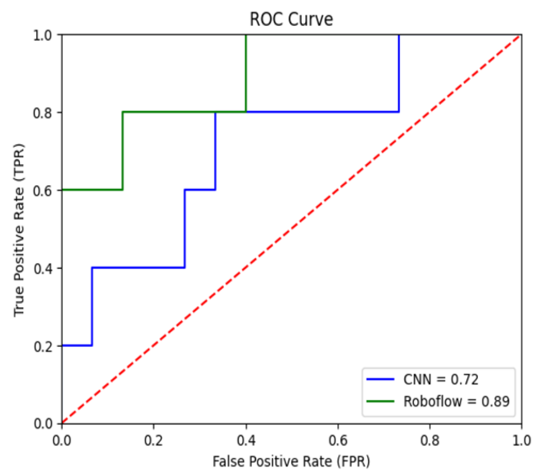

Fig. 5: ROC Curve CNN and Roboflow Methods

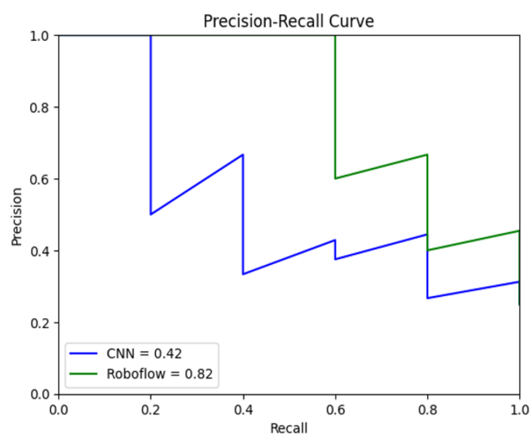

Fig. 6: Precision-recall curves of the CNN and Roboflow methods

Precision is the ratio of the number of true positive COVID-19 cases to the total cases predicted as positive by the model. Precision focuses on how many of the predicted positives are actually true positives. Recall, also known as sensitivity or True Positive Rate (TPR), is the ratio of the number of true positive COVID-19 cases to the total actual COVID-19 cases. Recall focuses on how many positive cases are successfully identified by the model we designed.

There is a trade-off between precision and recall. An increase in recall often results in a decrease in precision and vice versa. This is due to the threshold used to classify the model results as positive or negative. Changing the threshold can affect both precision and recall values.

A PR curve is a curve that plots the precision value on the y-axis and the recall value on the x-axis. On a PR curve, precision values are plotted against recall for different decision thresholds. Area Under the Precision-Recall Curve (AUC-PR) can be used as an evaluation metric for the model. The larger the AUC-PR value, the better the performance of the model in recognizing positive classes with high precision and high recall.

In the task of COVID-19 detection using CNN and Roboflow, interpreting the PR curve will help us understand how our designed model performs in recognizing positive COVID-19 cases and how to set the optimal decision threshold to achieve a balance between precision and recall according to clinical application needs and preferences. Figure 6, it is found that the PR value for CNN is much different from the roboflow model in recognizing chest X-ray images from patients who are indicated by COVID-19 and those who are not indicated. The PR value for CNN is 42% and the roboflow PR is 82%. From these results, it can be said that the model we designed has not been able to meet the standards for COVID-19 classification when compared to the roboflow method. This is thought to be influenced by the limited amount of training data so that when tested with random data obtained from the Kaggle site, the PR value is low. However, this research has been able to provide an illustration that the CNN and Roboflow methods can be developed for the early detection of lung abnormalities. The limitation of this research is that the number of COVID-19 patient images obtained is still limited, namely 100 patients and also 100 negative patients.

Conclusion

Based on the research that has been done, it is obtained that the specificity score value of CNN is very good, namely 93%, and the perfect sensitivity score value produced by the detection method using the Roboflow model, namely 100%. However, the Kappa score value for both methods is below the expected threshold of (36-38)%. Based on the ROC value, it is obtained that the CNN and Roboflow methods are equally good at classifying chest X-ray images of COVID-19 and normal patients, even though the training data value is only 100 data each. However, if we compare with the PR curve value obtained, Roboflow is better than CNN in classifying chest X-ray images of COVID-19 and normal patients with limited data.

The research we conducted refers to research by Liang *et al*. (2021) who used pseudo coloring in the preprocessing process of patient data indicated by COVID-19. The difference is that we try to use less training data, namely 100 data. F1-score obtained from research by Liang *et al.* (2021) was 96.72% with 9143 training data, while this research was able to produce an F1-score of 50.00% using 100 training data. Furthermore, for the Specificity score from the research of Liang *et al*. (2021) of 99.33% with a lot of training data of 9143 data, while the research we conducted with minimal data, namely 100 data, was able to produce a Specificity score of 93.33% (presented in Table 2). The limitation of the research we conducted was that the amount of real training data we obtained from the hospital where this research was conducted was very small, namely 100 data, this was because the number of COVID-19 patients in the hospital at the time of data collection had decreased. For future research, the CNN method can be developed to detect other abnormalities that are difficult to distinguish. We should note that the detection method uses CNN.

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Author’s Contributions

Ramacos Fardela: Conceived and designed the research, collected and/or assembled the data, analyzed and interpreted the data, wrote the article, and approved the final version of the article.

Dian Milvita: Revised the article critically.

Mawanda Almuhayar and Dedi Mardiansyah: Revised and wrote the article critically.

Latifah Aulia Rasyada: Collected and/or assembled the data.

Lukman Mul Hakim: Collected and assembled the data, and revised the article critically.

Ethics

This research has fulfilled the procedure and passed ethical review in the medical field, letter number: LB.02.02/5.7/22/2023.

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