Graphical Abstract

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Highlights

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- Research highlight 1
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Abstract

COVID-19 is a disease caused by the SARS-CoV-2 virus. The virus can cause mild respiratory illness, acute to death. This disease is a challenge for medical staff, especially radiologists to detect patients using chest X-ray results. Nowadays chest X-rays are widely used as imaging modalities because of their little cost and easy operation. However, doctors or radiologists take a long time to analyze the X-ray results of a patient in large quantities. Therefore, solutions are needed to detect patients infected with COVID-19 more efficiently and effectively using a machine learning approach. In previous studies, many researchers used transfer learning to build COVID-19 detection models to handle small datasets. So that the model they produce is large and ineffective when applied to mobile applications. In this study, we used the Convolutional Neural Network (CNN) that we built from scratch so that the resulting model was lighter. We used a dataset available online with a total of 15,153 chest X-rays that were divided into 3 classes namely COVID-19, normal, and viral pneumonia. In addition, we also apply negative transformations and gaussian low pass filters at the image preprocessing stage. Negative transformation techniques are used because they can make the chest X-ray images we use clearer. Negative transformation techniques can turn light pixels dark and vice versa. And gaussian low pass filters are used to eliminate noise. The results of this study showed the CNN model gained good accuracy for the diagnosis of COVID-19 patients with an accuracy of 95 percent on training and testing data.

Keywords: COVID-19, X-ray, Convolutional neural networks, Negative transformation, Gaussian low pass filters

1. Introduction

This section contains an introduction to the research that will be carried out consisting of background, motivation, research problems, objectives, assumptions, constraints and scope of the research.

1.1. Background

Over the last 2 years, the whole world has been struggling with the COVID-19 pandemic. COVID-19 is an infectious disease caused by the acute respiratory syndrome Coronavirus (SARS-CoV-2). On March 2, 2020, Indonesia reported its first confirmed case of COVID-19. Since then the number of cases has continued to increase and spread rapidly in 34 provinces. Symptoms of COVID-19 include fever, cough and difficulty breathing. In more severe cases, the virus can cause pneumonia, acute respiratory distress, and multi-organ failure of the lungs. Based on data compiled by Tempo.co, the total number of COVID-19 cases in October reached 29,254 cases.

Pneumonia is an inflammation of the lungs caused by bacteria, viruses, or fungi [1]. This pneumonia does not only occur in developing countries, but also occurs in developed countries. In Indonesia alone, the pneumonia mortality rate is estimated at 21 (Unicef, 2006). Pneumonia can cause mild to severe symptoms. Some of the symptoms commonly experienced by people with pneumonia are cough with phlegm, fever, and shortness of breath [1]. The symptoms experienced by these patients are similar to the symptoms of patients infected with the COVID-19 virus. There is a need for a way to differentiate between patients infected with pneumonia caused by the COVID-19 virus or those caused by other viruses. This is to minimize the occurrence of misdiagnosis of symptoms experienced by patients.

This is a challenge for medical personnel, especially for radiologists. This is because medical images play an important role in diagnosing patients with COVID-19 symptom [2]. Currently, there are 2 imaging modalities that are widely used to detect COVID-19, namely CT (Computerised Tomography) Scan and also Chest X-ray Radiography [3]. Chest X-ray radiography is more widely used because it has several advantages such as the category of cost that is not too expensive and easy to operate [4].

However, although chest X-ray radiography is more widely used, chest X-ray radiography has a lack of X-ray results. This is because CT Scan has a higher detection sensitivity [4]. In addition, it takes quite a lot of time for a doctor or radiologist to analyze the X-ray results of a patient on a large scale, it is also difficult to identify COVID-19 patients with mild symptoms [5].

1.2. Motivation

Our research was motivated by the work of Hansell which stated that during the COVID-19 pandemic, ground glass patterns were seen at the periphery of the pulmonary vasculature and may be difficult to see visually [6]. Such abnormalities can only be interpreted by a trained radiologist. Given the large number of patients who continue to grow so that more and more x-ray results are produced and the limited number of radiologists, diagnostic methods that are carried out quickly and automatically to diagnose symptoms experienced by patients are urgently needed. Artificial Intelligence has the potential to be a powerful tool to solve problems like this. Previously, due to the lack of availability of public images of COVID-19 patients, studies reporting solutions for the automatic detection of COVID-19 from x-ray images were not widely available. However, recently a small dataset of COVID-19 x-ray images was collected, which enabled AI researchers to train machine learning models to perform automated COVID-19 diagnostics from x-ray images [7].

1.3. Research Problem

The sensitivity level of X-ray results produced by chest X-ray radiographs is not good enough. This is because the general trend seen in patients with symptoms of COVID-19 pneumonia is the presence of ground glass opacification. This ground glass opacification condition makes it difficult to detect COVID-19 using a chest X-ray, especially in patients with low symptoms [5]. This will have an impact on the results of the doctor or radiologist's analysis of the patient. This condition allows errors to occur in the diagnosis based on the patient's X-ray results.

Based on the rise of COVID-19 cases, a doctor and radiologist need a long time to analyze the X-ray results of the patient. Of course this becomes ineffective because it will also have an impact on the speed of handling the patient. Because a doctor will provide treatment according to the patient's diagnosis. To overcome this, artificial intelligence has been developed to assist the work of medical personnel in performing computations based on medical image processing. Including this study, which aims to predict X-ray results of patients identified as COVID-19 faster and more accurately. This was done because in this study it will overcome the uneven gray level in the X-ray distribution at the pre-processing stage, thereby minimizing the error rate in the diagnostic results.

1.4. Assumptions and Constraints

In order for this research to be more directed to the intent and purpose of writing, several problems were carried out. In this study, we only used data in the form of Chest X-Ray images and did not know the age of the patients being diagnosed. In fact, one of the elements that affects the more visible symptoms of Covid-19 is age. In the susceptible age group, although the patient experiences mild symptoms, the lungs tend to be more easily seen. Based on data on the distribution of Covid-19 survivors in the age category, survivors in the vulnerable age group, aged 46-59 years, were most affected by Covid-19. [1]

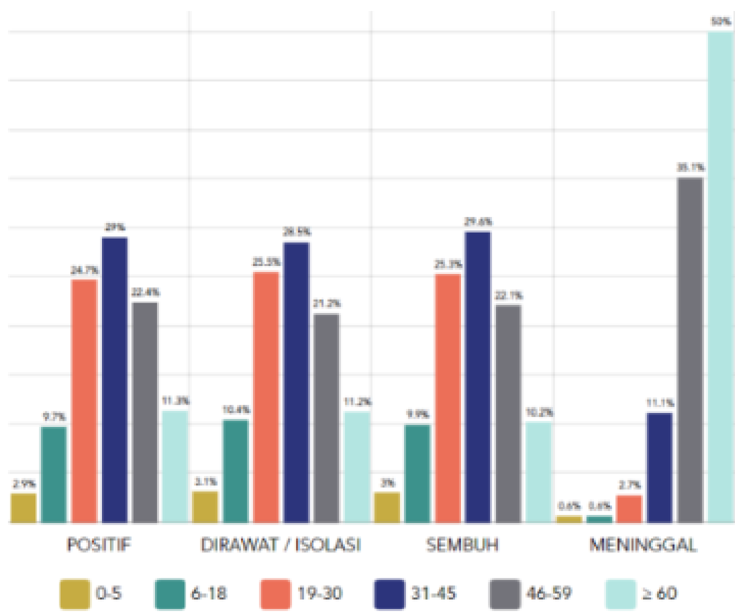

Figure 1: Covid-19 Positive Age Group X-Ray

[1]Covid-19 Positive Age Group X-Ray, available on (https://covid19.go.id/peta-sebaran-covid19)

1.5. Objectives of the Research

1. Predicting patients who are indicated by COVID-19 symptoms automatically quickly and accurately

2. Overcome the uneven gray level effect of the chest image distribution during the segmentation process. This is done to minimize errors in the patient's diagnosis.

3. Make a model with a size that is not large (not using transfer learning), so that the model can be applied to mobile or web displays. The resulting computation can also be faster.

1.6. Scope of Research

This research topic has two approaches in the preprocessing stage of the model. We focused on whether we could increase the gray level produced from the x-ray image so as to overcome the problem of the Ground Glass Opacification condition. In addition, we try not to use transfer learning in the models we use. So, the resulting size is lighter than using transfer learning. We wanted to see if the resulting model could be more accurate than the model using transfer learning.

2. Background and Related Work

This section provides an overview of X-rays and COVID-19 in general, image pre-processing, evaluation metrics used in COVID-19 using X-ray images prediction, previous approaches to predicting COVID-19 using X-ray images, and a summary.

2.1. X-ray and COVID-19 in general

The first X-ray was discovered by Wilhelm Conrad Röntgen in 1895. X-ray is a medical imaging technique in the form of electromagnetic radiation that doctors use to take pictures of tissues or structures in the patient's body. According to [8] to make radiography, the patient must be positioned with the body part to be imaged located right between the x-ray source and the x-ray detector. When the machine is turned on, the x-ray will spread throughout the body and each tissue will absorb different amounts of x-ray depending on the radiological density it has. When an X-ray passes through the bone, the bone will easily absorb the X-ray resulting in high contrast on the x-ray detector. This is because bones contain calcium and have a higher atomic number when compared to other tissues. Therefore, the results of the radiography of bone structure appear whiter than other tissues on a black background. While when going through an air-filled cavity such as a less radiologically dense lung, X-rays will run more easily. So that the results of radiography on this structure will be displayed in shades of gray. The tool used to detect abnormalities in the lungs is commonly called Chest radiography, or chest X-ray (CXR).

Detection of lung abnormalities using Chest X-ray is widely chosen because the process is relatively fast, easy, has low radiation effects, and is cheaper than using CT scans. From chest X-ray results we can find out the image of normal lungs when the image is not spotted, the texture is smooth, the shape and size of the lungs do not change. While the image of the lungs is abnormal when the image is spotted, the texture is not smooth, the shape and size of the lungs change [9]. Therefore, after the outbreak of COVID-19 disease in 2019, many studies began to be found that attempted to detect COVID-19 by utilizing Chest X-rays. COVID-19 is a disease that was first discovered in Wuhan City, China, in December 2019. COVID-19 can be transmitted through tiny fluid particles that come out of a sufferer's mouth or nose when they cough, sneeze, speak or sing.[2] This terrible disease is caused by the SARS-CoV-2 virus that can cause mild respiratory disease, acute to death in sufferers. With the use of a Chest X-ray can be known whether the patient's lungs are infected with COVID-19 or normal.

2.2. Image Pre-processing

2.2.1. One Point-based Transformation

Single-point operations is an image processing method based on the principle of generating one pixel from an output image based on one pixel of the input image (original). Conversely, the selected operation of this group can cause some information to be lost (if pixels of various values in the original image receive the same value after processing). So from the point of view of the next stage, the objective (that the computer does) of processing, analysis, recognition, and even automatically understanding the image, this operation produces nothing. And this is where single point operations come in handy because by choosing the right gray level (and sometimes also artificial colors), we can make what's recorded in the image more visible.[**?**]

[2]WHO, Coronavirus disease (COVID-19) (https://www.who.int/health-topics/coronavirus, November 10, 2021)

2.2.2. Low Pass and High Pass Filtering of Images

A low-pass filter is a filter that allows a low-frequency signal to pass while weakening the signal above the cut-off frequency. Depending on the design of the filter, the amount of attenuation for each frequency changes. Ideal, Butterworth and Gaussian lowpass filters are three common types of lowpass filters [10]. Low-pass filters, on the other hand, obscure important image components such as edges and lines and reduce image contrast. Although the filter specified by produces the smallest image difference, the smoothing achieved on the textured part of the image is often insufficient. [11] A high-pass filter is a filter to reduce and eliminate low-frequency energy in the spectrum and highlight the edges and details of the image. However, the noise in the image is amplified by this type of filter. On the other hand, high-pass filters promote high spatial frequency and increase contrast in images. In addition, high escape filters are characterized by the presence of a core surrounding the central pixel of the image with a negative value [12]. Because the reflection component contributes more to high frequencies, high-pass filters are used to extract reflection components of the validity level of imagery in homomorphic systems. [13]

2.2.3. Binarization of Medical Images

Binarization is the division of the pixel value of an input image into two-pixel values, such as white for the background and black for the foreground. It is an important component of image processing and the first stage in many document analysis and OCR systems. The majority of Binarization techniques use an intensity value called a threshold to divide the pixel values of the grayscale input image into two classes: background and foreground. Each pixel must be compared to the threshold and assigned to the appropriate class based on the threshold value. As a result, determining the exact threshold value in binarization is a key aspect in producing a successful binary image, and it can be done in two ways: global thresholding or local thresholding.[14]

2.3. The previous approach to predicting COVID-19 using X-ray Images

With the development of technology, the use of Machine learning or ML in the field of health is also increasingly widely applied. ML can be used to analyze structured data such as imaging, genetic, and EP data. In medical applications, ML attempts to group patient traits or infer possible outcomes of the disease [15]. And one of the applications of ML in imaging data is the use of X-rays to diagnose COVID-19 disease.

[16] made a prediction related to COVID-19 based on chest X-rays. It aims to diagnose the characteristics of COVID-19 disease automatically and can provide radiologists with valuable decision-making support tools for more accurate and efficient detection and diagnosis in COVID-19 infected patients. The method used in this study is a convolutional neural network (CNN). Where the data will be trained first using these methods. Test results on this study showed the highest accuracy of 0.958.

[17] also made an image classification based on chest X-rays using the technique DeTraC (Decomposition, Transfer, Composition). DeTraC can deal with any irregularities in an image data set by investigating its class boundaries using class decomposition mechanisms. DeTraC can also be used to address problems related to limited annotations of medical images. The results of this study demonstrate DeTraC's ability to detect COVID-19 cases from a comprehensive image data set collected from several hospitals around the world. High accuracy of 0.931 (with 100 percent sensitivity) was achieved by DeTraC in detecting COVID-19 X-ray images of normal and severe cases of the acute respiratory syndrome.

Another study was conducted by [18] by creating a machine learning-based framework for the diagnosis of COVID 19 from chest X-rays. The study aims to improve model performance by performing feature extraction using PCA techniques and analyzing its effects on CNN and Logistic Regression models for automatic diagnosis of COVID-19 from X-ray images. The framework stage starts from a dataset that has been augmented using GAN and normalized its dimensions and then inserted into the PCA to extract features with the most important data information. In this study, researchers only used features with variances 1, 0.99, 0.98, 0.97, 0.96, 0.95, 0.90 and 0.85. After the main feature set of the data set is extracted by the PCA, each set is then used to train the CNN and Logistic Regression models separately. The results showed that the CNN model trained using features with variance 0.99 outperformed other trained models with 100 percent accuracy and training time of 233 ms.

3. Methodology and Formulation

This section will discuss the study design and research framework that we use.

3.1. Methodology

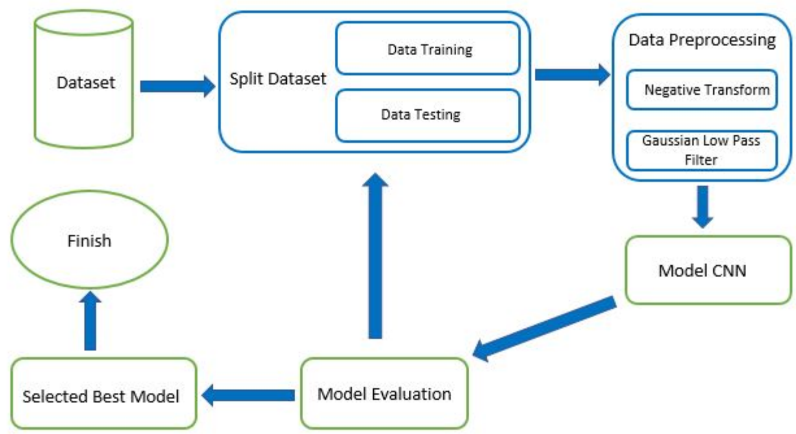

Figure 2: Research Framework

In this research, we use the chest X-ray images dataset available online. From the dataset we got, with a total image of 15.153, the data was first split into 0.80 data training and 0.20 data testing. Then the data is preprocessed using negative transformation and Gaussian Low Pass Filter. Next, we create a model. We tried to create a model using CNN that we built from scratch. In this study, the evaluation model also uses a confusion matrix, to see the value of precision, recall and F1 Score in each predicted class.

3.2. Pre-processing Using Negative Transform and Gaussian Low Pass Filter

In order to improve the results of digital x-ray images, the spatial pixel domain is based on several mathematical filters on the image matrix. This enhancement method is generally divided into 3, point processing method, histogram-based processing method and mask processing method. One of the point processing methods is negative transformation [19]. The negative transformation is meant to highlight X-Ray detail in areas with dark colors.

Negative transformation also serves to increase white or gray details embedded in dark images [20]. Negative transform is widely used in digital image processing on x-ray results. However, so far there has been no research that specifically uses pre-processing negative transforms in diagnosing the COVID-19 virus. The difference between the results of the x-ray that has been done with a negative transform and the original image from the x-ray without a negative transform can be seen in Figure 3.

In addition to the negative transformation, we apply a Gaussian low-pass filter to remove noise. Gaussian low-pass filter can noise-reduction image [21]. And in our experiment, we using the width of 5 and a height of 5 to generate the blurred image.

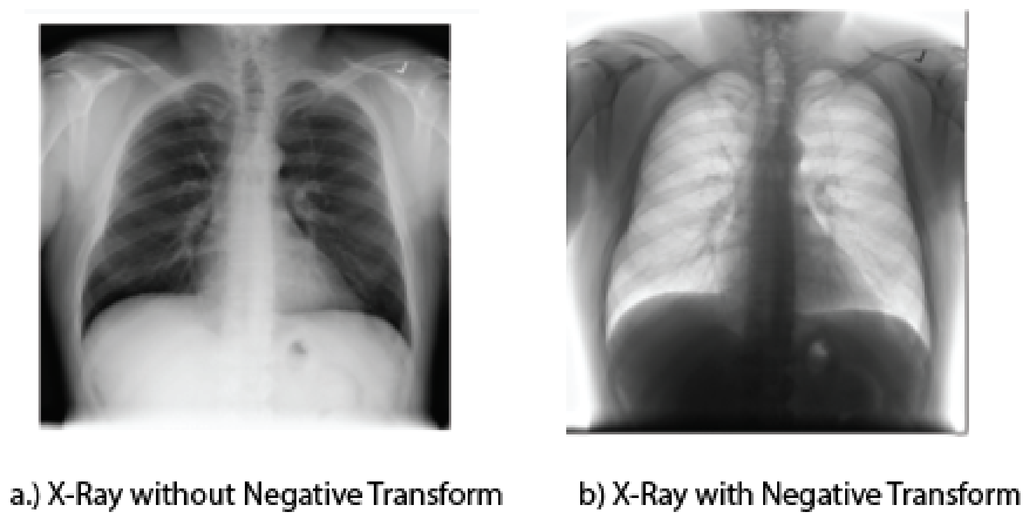

Figure 3. Comparison between X-Ray using Negative Transform and Not Using Negative Transform

3.3. Evaluation Model

In this study, there are three classes as the target of image classification. To evaluate our performance, we use one of the performance evaluations, namely the Confusion Matrix. Confusion Matrix is used to find out the predicted distribution of images in various classes. According to () Confusion Matrix is a visual representation of the performance of the statistical classification model. The Confusion Matrix is a visual representation of the classification model's performance. Table 1 is an overview of the confusion matrix:

	Positive	Negative
Positive	TP	FP
Negative	FN	TN

Table 1 Confusion Matrix

We also adopted Accuracy (ACC), Precision, recall and f1-score as an evaluation of the performance of a model. They are defined as follows.

$$Accuracy = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TN} + \mathrm{FP} + \mathrm{TP} + \mathrm{FN}}$$
$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$
$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$
$$F_1 Score = 2 \times \frac{\text{Precisión} \times \text{Recall}}{\text{Precisión} + \text{Recall}}$$

Where:
TP = Condition where the true value is positive, and the model prediction is positive
FP = Condition where the true value is not positive and the model prediction is positive
TN = Condition where the true value is not positive and the model prediction is not positive
FN = Condition where the true value is positive and the model prediction is not positive

4. Experimental Evaluation

4.1. Dataset

We used Kaggle's Covid-19 Radiography Database data created by Tawsifur Rahman et al[3]. This dataset contains CXR images of COVID, lung opacity, normal, and viral pneumonia patients that have a PNG format with a resolution of 299x299 pixels. The number of samples in the COVID class was 3616 images, the number of samples in the lung opacity class was 6012 images, the number of samples in the normal class was 10192 images and the number of samples in the viral pneumonia class was 1345 images. And to reduce the classes that must be classified, in this study we will only use 3 classes namely COVID, normal, and viral pneumonia classes.

[3] Kaggle, Covid-19 Radiography Database (https://www.kaggle.com/tawsifurrahman/covid19-radiography-database?select=COVID-19$_{R}adiography_{D}ataset, November 10, 2021$)

Class Name	Total sample
COVID	3616
Normal	10192
Viral pneumonia	1345
Total data	15.153

Table 2 Dataset Infomation

4.2. Experimental Design

In this study, we conducted an experiment by applying a negative transformation preprocessing and also a Gaussian Low Pass Filter to diagnose Covid-19 disease. We also use various optimization parameters to improve the accuracy results obtained and prevent overfitting. Overfitting is a fundamental problem in machine learning that can prevent our model from perfectly generalizing the model until it matches the observed data on the training data, as well as the test data. Overfitting is the most serious problem in CNN training [22]. Therefore, an appropriate model is needed to deal with this problem. We use several layers in building a CNN model, such as Conv2D, Maxpooling2D, Dense and Dropout. In each Conv2D layer we choose to use activation relu and activation softmax on the Dense layer. From this model, it produces a total parameter of 836,611. In this CNN model, we use a loss function, namely categorical crossentropy, because we will perform diagnostics in 3 different classes. The complete architecture of our model can be seen in figure 4.

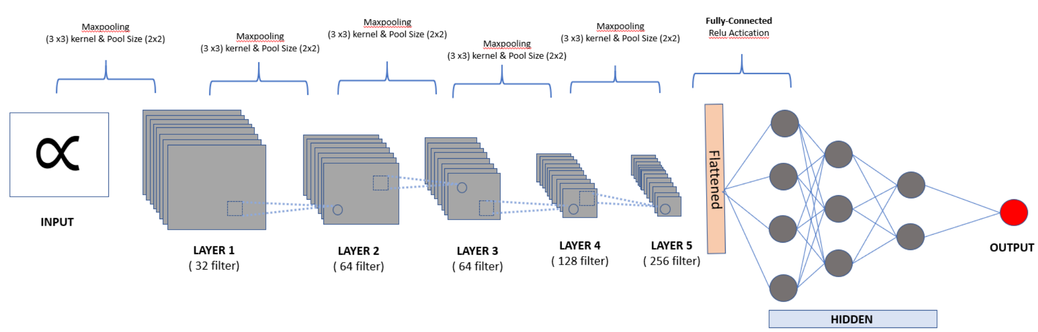

Figure 4. Model Architecture

4.3. Result and Analysis

In this study, chest X-ray imagery was used to predict COVID-19. This study also used 3 classes as predictions, namely class COVID-19, Normal, and Viral Pneumonia. Some popular gray image preprocessing techniques such as Negative transform and gaussian low pass filter also applied to chest X-ray images. Then by using CNN as a model, where this algorithm is the State of The Art of image classification is expected to be able to provide good performance in predicting COVID-19. Performance results can be seen in Table 3.

	Precision	Recall	f1-score	Support
COVID	0.95	0.89	0.92	724
Normal	0.96	0.98	0.97	2039
Viral Pneumonia	0.94	0.93	0.93	269
Avg/Total	0.95	0.933	0.94	3032
Accuracy				0.95

Table 3 Classification Report

Can be seen the results of table 3, using Negative transform and GLPF as image preprocessing technique and also CNN as a deep learning model obtained results of 95 percent accuracy with an average precision of 95 percent, recall 93.3 percent, and f1-score 94 percent with a total data test of 3032. Based on these results, the techniques used in this study are considered quite effective and also have good performance, although the image dataset is not spread in balance, the model can produce excellent performance.

5. Conclusion

We conducted this study to find how to detect COVID-19 based on chest X-ray images quickly and efficiently using a machine learning approach. We've managed to make that model with CNN that we built from scratch. We also apply negative transformation and Gaussian low pass filters as image preprocessing. The technique used in our study is quite effective and has good performance and accuracy. In the test data, the accuracy of our model managed to achieve a value of 95 percent, recall is 93.3 percent, and f1-score is 94 percent. From these results, the model created in this study was expected to help medical staff, especially radiology, to save time in analyzing patient x-ray results. The patient's diagnosis process can also be faster and remain accurate because machine learning models can analyze a lot of data stably in a short time and can also reduce human errors. In addition, we can reduce the workload of radiologists too.

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