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# **The Innovation Breakthrough in Digital and Disruptive Era**

# The Effect of Image Size on the Deep Learning Approach for Classifying Covid-19 Pneumonia

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**Abstract.** The scope of this study is related to the classification of covid-19 pneumonia which uses X-ray images of the lungs as input and is then classified into 3 categories, namely normal (healthy), pneumonia, and covid-19 pneumonia. The classification process uses a deep learning approach, which is becoming a trend nowadays because its performance is better than conventional machine learning approaches. The image dataset in this study is a collection of X-ray images of the lungs consisting of 1,525 normal images, 1,525 pneumonia images, and 1,525 Covid-19 pneumonia images. These images vary in size, but all images are larger than 1000x1000 pixels. The large size of the image makes the training time long and the computational resources required are large. Deep learning machines need to reduce the size of the image to make the process more effective. However, changes in image size may affect classification performance. Therefore, we conducted experiments in this study to determine the effect of image size changes on the classification performance of COVID-19 pneumonia using a deep learning approach. We use the Convolutional Neural Network method, which uses 22 layers with 5 convolution layers, for classification. The experimental results show that the size of the input image affects the classification performance of covid-19 pneumonia. This study provides important information that larger image sizes do not always result in better classification performance. In addition, the image size that is too small causes very low classification performance. The performance of the classification of covid-19 pneumonia using the CNN method shows the most optimal results at an input image size of 500x500 pixels.

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## 1 Introduction

Health problems caused by lung disease occur in many countries. Many diseases that arise are caused by disorders of the lungs, one of which is pneumonia [1]. Someone who has pneumonia, their lungs are inflamed due to an infection that causes increased opacity in the lung area [2]. Symptoms that are usually experienced due to disorders of the lungs include fever as the body's response to infection, coughing up phlegm, chest pain, and difficulty breathing. Pneumonia needs to be watched out for, because it is one of the highest causes of death in the world [3]. This disease is also a serious concern in Indonesia, because the number of sufferers reaches 2% of the population and is increasing every year [4].

At the end of 2019 until mid-2023, there was a global pandemic due to the SARS-CoV-2 type corona virus. This virus is highly contagious between humans and attacks the respiratory tract rapidly causing pneumonia [5]. Pneumonia caused by the corona virus which is then called pneumonia covid-19, which has a higher risk compared to other pneumonias, so sufferers need more serious treatment [6].

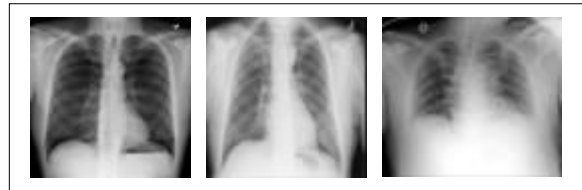
In order to find out whether a person has pneumonia (caused by Covid-19 or other factors) or not (normal / healthy), a doctor or radiologist can make observations of x-ray radiological patterns on X-rays of the lungs [7]. Figure 1 is X-ray images showing lungs with pneumonia (left image), covid-19 pneumonia (middle image), and normal / healthy / not experiencing pneumonia (right image).

**Fig. 1.** X-ray images of the lungs showing normal (left image), pneumonia (middle image), and covid-19 pneumonia (right image)

Many studies have been carried out to obtain important information from X-ray images of the lungs needed for the diagnosis process [8]. This diagnosis is particularly related to the identification of health problems in the lungs, including whether the organ has pneumonia or not.

In the field of computer science, many researchers have developed methods for analyzing x-ray images. In recent years, machine learning approaches, especially deep learning, have become a new trend for solving problems related to image classification, due to their better performance than conventional machine learning approaches. For example, a study tested several trained CNN models for the effective and automated classification of pneumonia [9], with a testing process using lung x-ray image datasets from Kaggle [10]. Another study developed the CNN method by using 4 convolution layers and adding an augmentation process [11]. A study proposes the Light-CNN model which was developed from the SqueezeNet model [12]. The Graph-Knowledge Embedded CNN method was proposed to produce optimal classification performance [13]. A study combining the RetinaNet and Mask R-CNN models to predict pneumonia [14]. While several other studies developed CNN combined with the Extreme Learning Machine (ELM) method [15][16][17][18].

In the deep learning approach for image classification, especially the Convolutional Neural Network (CNN) method and methods developed from the basic CNN model, the image size is reduced from its original size so that the training process involving a



large number of images can be carried out more efficiently. The problem is that determining the ideal image size to get optimal performance is difficult. Various studies use different image sizes. There is no standard image size that can produce the most optimal machine learning performance. Each case has unique characteristics, so the image size used in one case may not necessarily produce the same performance in other cases.

In this study, we use x-ray images of the lungs that vary in size, but all images are larger than 1000 x 1000 pixels. The larger the size of the image causes the training time for machine learning to be longer and the computational resources required are also greater. Thus, the size of the image needs to be reduced so that the training process is more effective. However, changes in image size may affect classification performance. Therefore, we conducted this study to determine the effect of image size changes on the performance of the classification of Covid-19 pneumonia using a deep learning approach. We apply the CNN method as a deep learning approach which contains 22 layers with 5 convolution layers. The classification process was carried out to identify x-ray images of the lungs using 3 categories, namely normal, pneumonia, and covid-19 pneumonia.

We carry out a testing process using various image sizes to determine the effect on the performance of the deep learning approach for pneumonia classification.

## 2 Research Methodology

The deep learning approach in this study uses the Convolutional Neural Network (CNN) method which contains 22 layers. The experiment was carried out using a collection of X-ray images of the lungs [19], which consisted of 1,525 normal lung images, 1,525 pneumonia images, and 1,525 covid-19 pneumonia images.

We apply several test scenarios based on variations in the size of the input image. The measurement metrics that we use are accuracy, precision, recall, and f1 score. The test results for each scenario will be compared to find out which test scenario produces the highest classification performance.

### 2.1 Classification Method

The deep learning approach in this study uses the CNN method. In general, this method includes feature

learning and classification processes. The feature learning architecture consists of convolution layers, activation function, and pooling layers. The process on CNN runs hierarchically, where the output on a convolution layer is used as input on the next convolution layer. While the classification process uses fully-connected layers.

Through the convolution layer, the extraction process is carried out on the image so that the image size becomes smaller. The convolution kernel captures important information from an object in the image. The downsampling process is carried out to reduce the size of the image array while still taking important information. The classification process uses several fully connected layers. This layer includes flatten layer, hidden layer, and output layer. The flatten layer transforms data in the form of multidimensional arrays into one dimension. The hidden layer classifies the image. While the output layer represents the results of the classification.



Fig. 2. CNN architecture in the study

The CNN architecture used in this study, as shown in Figure 2, consists of 22 layers, including 1 input layer, 5 convolutional layers, 5 ReLU (rectified linear activation unit) layers, 5 Maxpool layers, 2 Fully Connected layers, 2 Dropout layers, 1 Softmax layer, and 1 output layer. The dimension values on the convolution layer are 16, 32, 64, 128, 256. The convolution operation on this convolutional layer is the main activity in the CNN method for extracting features from the input image.

## 2.2 Dataset

Experiments in this study used 4,575 X-ray images of the lungs consisting of 1,525 normal lung images, 1,525 pneumonia images, and 1,525 Covid-19 pneumonia images. The specifications for the number of images are shown in table 1. The training process used 3,900 images, including 1,300 normal lung images, 1,300 pneumonia images, and 1,300 Covid-19 pneumonia images. The validation process uses 450 images, including 150 normal lung images, 150 pneumonia images, and 150 Covid-19 pneumonia images. While the training process uses 225 images, including 75 images of normal lungs, 75 images of pneumonia, and 75 images of Covid-19 pneumonia.

Table 1. Image Dataset Specifications

Process	Normal	Pneumonia	Pneumonia Covid-19
Training	1,300	1,300	1,300

Validation	150	150	150
Testing	75	75	75
Number of images	1,525	1,525	1,525

## 2.3 Experiment Scenario

The image dataset used in the experiment varies in size, but all images are larger than 1,000x1,000 pixels. The larger the size of the image makes the training process longer and the computational resources required are also greater. To be more effective, deep learning machines need to reduce the size of the image. However, changes in image size may affect classification performance. Thus, the experiments in this study tested several scenarios based on image size.

Table 2. Experiment Scenario

Scenario	Image Size (pixel)	Performance
1	20x20	Accuracy, Precision, Recall, F1 Score
2	30x30	Accuracy, Precision, Recall, F1 Score
3	50x50	Accuracy, Precision, Recall, F1 Score
4	100x100	Accuracy, Precision, Recall, F1 Score
5	200x200	Accuracy, Precision, Recall, F1 Score
6	300x300	Accuracy, Precision, Recall, F1 Score
7	400x400	Accuracy, Precision, Recall, F1 Score
8	500x500	Accuracy, Precision, Recall, F1 Score
9	600x600	Accuracy, Precision, Recall, F1 Score
10	700x700	Accuracy, Precision, Recall, F1 Score

The test scenario is shown in table 2, where the test was carried out using image sizes of 20x20, 30x30, 50x50, 100x100, 200x200, 300x300, 400x400, 500x500, 600x600 and 700x700 pixels. The testing process is carried out in each scenario to produce the performance of the classification model, in the form of accuracy, precision, recall, and f1 score metrics. The accuracy value is obtained based on the predicted data according to the class compared to the overall data used. The precision value is obtained based on a comparison between the data that fits the class and the data that is predicted to be positive. The recall value is obtained based on the predicted data according to the

class compared to the data according to the class. While the F1 score is calculated based on the comparison value of the average precision and recall.

### 3 Results and Discussion

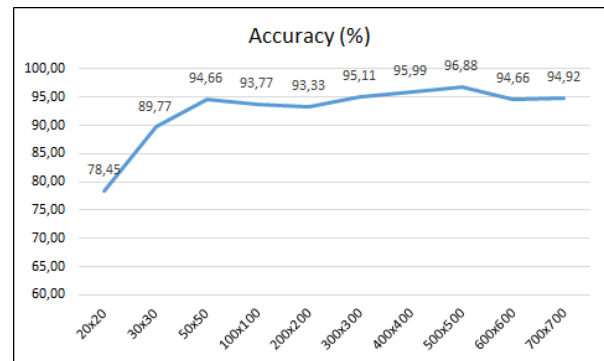
The experimental results in this study are shown in table 3. Each value in the cell in the table shows the performance of the classification method in each test scenario based on image size. The accuracy value is between 0-100 in percent units. While the value of precision, recall, and f1 score ranges from 0 to 1.

**Table 3.** Experimental Results

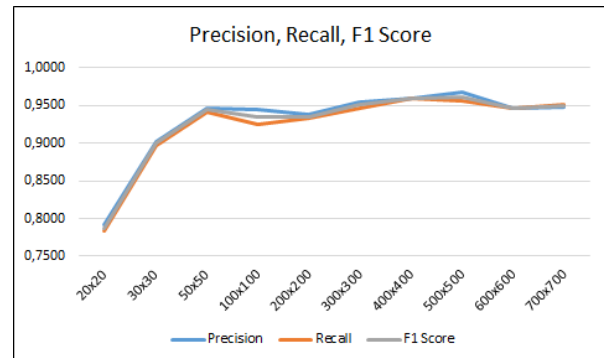
Image Size	Accuracy (%)	Precision	Recall	F1 Score
20x20	78.45	0.7922	0.7831	0.7876
30x30	89.77	0.9017	0.8977	0.8997
50x50	94.66	0.9464	0.9422	0.9443
100x100	93.77	0.9454	0.9244	0.9348
200x200	93.33	0.9375	0.9333	0.9354
300x300	95.11	0.9551	0.9466	0.9508
400x400	95.99	0.9599	0.9599	0.9599
500x500	96.88	0.9684	0.9555	0.9619
600x600	94.66	0.9466	0.9466	0.9466
700x700	94.92	0.9487	0.9516	0.9501

The classification performance shows the best results in the test scenario using 500x500 pixel images, where the accuracy is 96.88%, the precision is 0.9684, the recall is 0.9555, and the f1 score is 0.9619.

A graph showing the trend of accuracy values is shown in figure 3. Classification accuracy is unstable and low at image sizes of less than 50x50 pixels. Classification accuracy is relatively stable at image sizes starting at 50x50 pixels. The accuracy value reaches a relatively optimal value at image size of 300x300 pixels up to 500x500 pixels. At image sizes of 600x600 and 700x700 pixels, the classification performance decreases.



**Fig. 3.** Graph of accuracy values for each image size



**Fig. 4.** Graph of precision, recall, and f1 scores values for each image size

Likewise in other graphs that show a tendency for precision, recall, and f1 score values, as shown in figure 4. Precision, recall, and f1 score classifications are unstable and low at image sizes of less than 50x50 pixels. Precision, recall, and f1 score classification are relatively stable at image sizes starting at 50x50 pixels. Precision, recall, and f1 scores achieve relatively optimal values at image sizes of 300x300 pixels up to 500x500 pixels. At image sizes of 600x600 and 700x700 pixels, the classification performance decreases.

### 4 Conclusion

The experimental results in this study provide important information that larger image sizes do not always result in better classification performance. Image size that is too small causes very low classification performance. Meanwhile, at large image size, it does not guarantee optimal classification performance. In the test scenario that uses 500x500 pixel images, the performance of the Covid-19 pneumonia classification using the CNN deep learning approach shows the most optimal results, where the accuracy is 96.88%, the precision is 0.9684, the recall is 0.9555, and f1 score of 0.9619.

Further studies need to be carried out using other deep learning methods, to find out whether the size of the input image has the same effect as in this study. So that further studies can produce conclusions regarding the ideal input image size for all CNN models and also other methods.

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