Classification Of X-ray COVID-19 Image Using Convolutional Neural Network

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***Abstract*—The current number of coronavirus (COVID-19) infections in Indonesia becomes more and more worrying. According to data on June 11, 2020, the number of infected people in Indonesia has reached 35,295 people. With these consequences, it is considered very important to immediately identify infection in order to stop or minimize the spread of the disease. There have been several ways to detect and diagnose COVID-19, one of which is using X-ray images. This paper examines the use of in-depth features and methods to process two-dimensional data from patients' X-ray images. Convolutional Neural Network (CNN) is a development of Multi-Layer Perceptron (MLP), which is specifically designed to process two-dimensional data or image data. The deep features of the fully connected layer CNN model are extracted and can be immediately classified without the need for any additional techniques. CNN method is used because of its good performance for large datasets that will be used for training and testing. In the classification process, the dataset contains 160 x-ray images and consists of two categories, COVID-19 and normal, that represents a positive or negative classification of Covid-19 infection to a patient. To get the best accuracy of the classification model, the author changed several parameters on CNN, such as the distribution of the dataset and the number of epochs. From the nine models tested, model number 5 and 8 with a dataset ratio of 70:30 and epoch number 30 and 40 respectively, resulted in the best accuracy of 97.91%.**

Keywords—COVID-19, Coronavirus, Classification, X-ray Images, Convolutional Neural Network, Deep Learning.

I. INTRODUCTION

Coronavirus, commonly known as COVID-19, is a type of virus from the subfamily Orthocronavirinae in the family Coronaviridae and the order Nidovirales first appeared in Wuhan, China, in December 2019. The virus is already a severe problem for the world community [1], [2], as its spread expands. Data on August 24, 2020, people who have contracted COVID-19 in the world have reached 23,424,844 people. Coronavirus can cause diseases in humans and animals. In humans, coronavirus causes respiratory tract infections [3]. According to the World Health Organization (WHO), most people infected with the COVID-19 virus will experience mild to moderate respiratory illness and recover without special treatment. In general, several symptoms will occur when a person is infected with COVID-19, including fever, cough, sore throat, headache, muscle pain, and respiratory problems [4]. However, many sufferers also suffer from severe respiratory distress until death. This is a concern for the people of the world, in addition to demographic conditions such as gender and age, and parameters such as temperature and humidity can also affect the prevalence of the disease in the spread of the virus [5], [6].

The people of the world, including Indonesia, have done various ways of anticipating to reduce the spread of coronavirus. One way to do this is to apply rules to limit outdoor activities and require everyone to wear masks. Then another way that can use to detect COVID-19 is through tests. The most common test commonly used to diagnose COVID-19 is using the PCR (Polymerase Chain Reaction) method, commonly referred to as the swab test. However, because the sensitivity of the PCR (Polymerase Chain Reaction) method is low, 60% - 70 % can be done other ways to diagnose the disease early.

After knowing how to diagnose the disease, another problem is that the current COVID-19 test process is difficult due to the lack of available tools to diagnose. Due to the limited availability of COVID-19 testing devices, other diagnostic measures other than PCR (Polymerase Chain Reaction) are necessary because the sensitivity of diagnosing is still less optimal for early diagnosis and more accurate. One of them is to use X-ray imagery [7]. Researchers state that combining clinical imagery features with laboratory results can help in the early detection of COVID-19 [8]–[10]. Because COVID-19 attacks epithelial cells where these cells line our respiratory tract, another way to do this is to analyze a patient's lung health using X-rays. Also, consider that almost every hospital has an x-ray image machine commonly used to diagnose pneumonia, lymph nodes, and pneumonia – it is possible to use this x-ray media to test COVID-19 without a special test kit. However, in the analysis process to diagnose X-ray images requires a radiologist and takes quite a lot of time, which means cutting out time that is invaluable for medical practitioners if a patient is sick. Therefore, automated systems' development to detect and classify COVID-19 using X-rays is necessary to save medical professionals time.

In this study, deep learning proposes for the automatic diagnosis of COVID-19. The deep learning model used in this study is the Convolutional Neural Network (CNN). Convolutional Neural Network (CNN) is a Multi-Layer Perceptron (MLP) development designed to process two-dimensional data or image data. This model will be used to classify the results of x-ray image data. The data prepared in a dataset obtained from Kaggle and Github that is divided into two categories, namely the positive patient's chest x-ray image of COVID-19 and the x-ray image of the patient's healthy chest. This dataset will also train and evaluate the best model by looking for the highest accuracy in classifying COVID-19. This system for detecting and classifying COVID-19 has not been able to replace doctors or medical practitioners' role in making decisions on whether patients are positive or negative from COVID-19. However, the existence of this system, in addition to saving time, can also help facilitate the performance of medical personnel in scoring and diagnosing patients based on the reading of chest

X-rays that have been done by patients. In other words, this study aims to assist health workers and healthcare facilities in dealing with Covid-19 patients, especially regarding the application of scoring that can be used as a filtering tool on the subject of COVID-19.

II. Related Literature

In the development and application of systems to automatically classify, especially in the medical field, it is rapidly growing and gaining popularity by making additional medical practitioners' tools [11]–[13]. Deep learning, an artificial intelligence (AI) research area, enables modelling using input data without the need for manual feature extraction. Deep learning techniques have been widely applied in various medical issues, including claiming and detecting breast cancer [14], classification of skin cancer [15], [16] Then deep learning has also been used to classify diseases in the brain [17]–[19] and detect pneumonia from chest x-ray images [20], [21]. With the development of existing deep learning is also expected to help solve the problem that is classifying COVID-19.

Currently, there has been much research done to try to detect or classify images, especially on COVID-19 issues. The first study to diagnose COVD-19 from chest X-ray images. Research using this deep learning model proposes a model called DCNN. This model consists of four convolutional layers, four pooling layers, one fully Connected layer, and two flatten layers. This model produces 87.3% accuracy for diagnosing COVID-19 [22]. Further research introduced a convoluted network called COVID-Net that serves to detect COVID-19 from chest X-ray images. Researchers also analyzed the COVID-Net model at the prediction-making stage to gain knowledge about factors related to COVID-19 that would expect to help doctors perform initial screening. COVID-Net achieved good accuracy by achieving 93.3% test accuracy [23]. The same subsequent study utilized the Convolutional Neural Network's pre-trained network to automatically detect x-ray images and aimed to assist medical physicians, especially physicians, in the decision-making process related to the diagnosis of COVID-19 patients [24], [25]. The first study, utilizing different convolutional neural network-based models such as ResNet50, InceptionV3, and InceptionResNetV2. This research dataset is 100 data and divided into two categories, namely COVID-19 and Normal. Considering the results obtained, it appears that the ResNet50 model gets the best accuracy results with 98% accuracy. The second investigation, which aims to detect and classify COVID-19, also uses the Convolutional Neural Network (CNN) with five different networks. From the experiment, researchers proposed the MobileNet20 network model as the best network model because it produces 96.78% accuracy. Subsequent research suggested using the Convolutional Neural Network to extract features and coupled with the support vector machine method to classify images from x-rays obtained 95.38% and 93.8% [26], [27].

In this study, after some other research, use it as a reference. We will propose an automated prediction model to classify COVID-19 using convolutional neural network-based models such as the Convolutional Neural Network (CNN) and chest X-ray images. This model is used because from some studies using similar models; it has produced good accuracy performance, also because it is specifically designed to process two-dimensional data or image data and is suitable for extensive data. A dataset of chest X-ray images will describe in the next chapter. The proposed model focuses more on finding the right parameters on a CNN architecture network without using pre-trained models and using additional methods to classify chest X-ray images.

Researchers will change parameters such as epoch and dataset ratios to find the best accuracy of CNN models that design. The model will prove with the dataset used, without adding another classification model. Focusing on an architecture model's parameters alone without trying many pre-trained models can produce good accuracy.

III. Proposed Method

The method used in this study is quantitative. Quantitative methods are methods used to find answers to questions or in numbers mathematically. The research process is also experimental, which is to experiment with the Convolutional Neural Network architecture design on x-ray image detection and evaluate the architectural design results to assess the accuracy of the Convolutional Neural Network architecture.

A. Analysis Process

Process analysis is at a stage where the authors will analyze what processes the CNN model will need to classify COVID-19 correctly. The recommended method for classifying COVID-19 with x-ray images using the first CNN model is to collect image datasets to train CNN models to recognize images according to the categories or labels provided in the data evaluation process. Furthermore, CNN process preparation recommends consisting of the preprocessing stage or the stage at which the dataset will reprocess according to the model's needs, such as resizing the image. To run the experimental process, after the preprocessing scene, the author creates an experiment by changing the epoch parameters and dataset ratios within the CNN architecture and inserted into scenarios with different parameters.

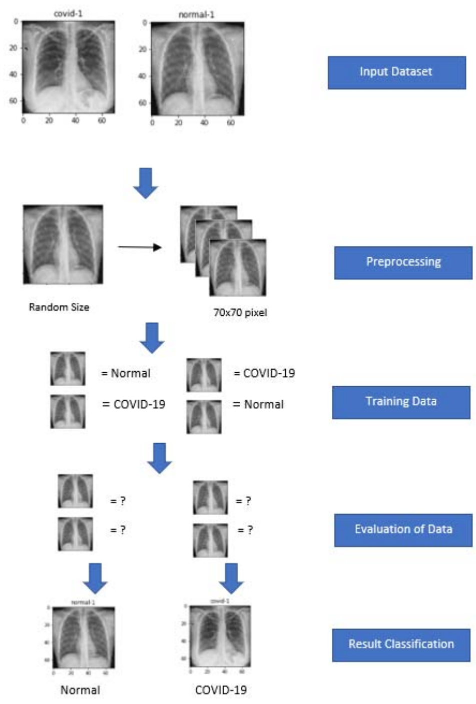

Fig. 1. Classification Process

The next step is to train the data, this stage aims to allow the CNN model to learn by recognizing x-ray images and distinguishing x-ray images based on the category created and the latter is the evaluation of the data, where the model will test with an x-ray image dataset without being labeled the x-ray image. The more models correctly claim the image, the better it will be. These stages will be explained more fully in the next section, for the complete classification process that we see in the Fig. 1:

B. Dataset

In this study, x-ray images were obtained from two different sources that would later use to diagnose and classify COVID-19. The first dataset used in the study was obtained from the Github repository Dr. Joseph Cohen, a postdoctoral fellow at the University of Montreal [28]. The repository consists of images from several categories such as x-ray images of patients with acute respiratory distress syndrome (ARDS), Middle East respiratory syndrome (MERS), severe acute respiratory syndrome (SARS), and COVID-19. The total dataset is 312 images in various categories because the research focuses only on COVID-19, so the dataset is pre-selected and only takes x-ray image datasets with the COVID-19 category with a total of 160 images. The second dataset is a dataset of normal chest x-ray images collected from the repository, Kaggle, an x-ray pneumonia data containing pneumonia labels, and normal [29]. A researcher took data with the category of normal chest x-rays only. The study will use a normal chest x-ray image that amounts to the same amount as images x-ray COVID-19, which is 160 images to be more optimal.

The datasets used will be labeled as COVID-19 with a total of 160 images and normal with a dataset of 160 images. All pictures of the data set will be resized to 70 x 70 pixels and likened to jpg and RGB-type extensions. For more information about data sets, see table 1:

TABLE I. DETAIL DATASET

Samples	Number	Repository
X-ray Image COVID-19	160	Github's repository Dr. Joseph Cohen
X-ray Image Normal	160	Github chest x-ray Images (Pneumonia)
Total	320	

Here are Fig. 2 and Fig. 3, COVID-19 X-ray images, and normal X-ray images

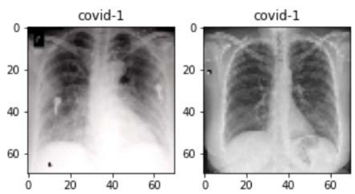

Fig. 2. X-ray image COVID-19

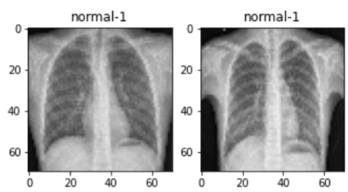

Fig. 3. X-ray image normal

C. Analysis Process CNN

This section will explain the process that the CNN model will take. The process will start from data preparation or preprocessing, scenario creation to training process from the dataset that has been obtained before. The first process to done to run this CNN model is preprocessing. The purpose of preprocessing is to maximize performance when the training and testing process carry out. After the dataset was created and labeled in this study, the next preprocessing process is done by resizing the image (resize). All images from both label categories change to 70x70 pixels. The second process to done is scenario creation. As explained earlier, this study will propose a model that focuses on the parameters of CNN architecture and does not use pre-trained models. Because this study is experimental, researchers will try to change CNN's architectural model's parameter, searching for the best model accuracy. Researchers will try to create nine different scenario models on the number of epochs and dataset ratios used to find the best architecture for classifying images. Epoch is the number of iterations at the training stage at which models will train to recognize image datasets with pre-defined categories. Then the dataset ratio is how much of a share of the number of datasets will use for training and testing. The parameters to be changed and tested are epochs of 20, 30, and 40 in size, and the dataset ratio will change to 80:20, 70:30, and 60:40. The following detailed scenario that will try to find the best accuracy value will display in table 2:

TABLE II. DETAIL OF SCENARIO

Scenario	Epoch	Dataset Ratio
CNN 1	20	80:20
CNN 2	20	70:30
CNN 3	20	60:40
CNN 4	30	80:20
CNN 5	30	70:30
CNN 6	30	60:40
CNN 7	40	80:20
CNN 8	40	70:30
CNN 9	40	60:40

The third stage is data training. This process is the stage at which models will be trained and taught to get to know COVID-19 x-ray images and normal x-ray images. To be at the test stage, this model can adequately classify with images according to the label or category that has given. The training process will also use parameters set in scenarios where epochs and ratios will put in table 2.

D. CNN Classification Model

CNN proposed a classification model previously train to work out scenarios that have rehearsed. The model considers having recognized the chest x-ray image according to the existing label until the training stage. The next step is the evaluation or classification stage. The proposed model will test again using a dataset of chest x-ray images without being labeled first. Models will be required to classify themselves with knowledge during the previous training phase. This stage aims to measure or assess a model of whether the classification model is good or less good. The proposed classification model is sequential, with a rate of 0.01, and uses stochastic gradient descent (SGD) as an optimizer. In the classification process, researchers deliberately change some parameters, such as the epoch and dataset ratio. But there are also fixed parameters. For this classification, other settings are defined with the same value, i.e., architecture using two convolutional layers, two-layer pooling, two fully connected layers, 32 filters, 3x3 kernel that collects 2x2 size and uses softmax as a classification function. For the classification process, we can look at Fig. 4

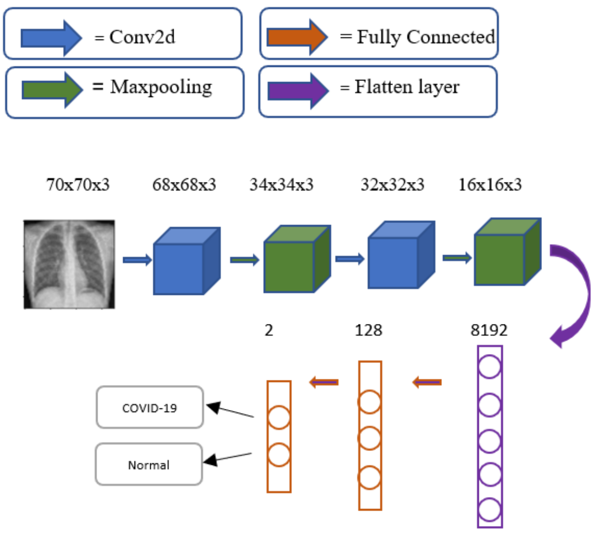

Fig. 4. Classification Process

E. *Model Performance*

Creating a model proves that a model is good or not when a model's success can be measured. The study proposes to use a technique called the confusion matrix to scur the success of a model. Confusion matrix has a rigorous evaluation process with validity or no opportunity to hide errors and provide additional information about the type and source of errors [30]. The confusion matrix usually uses to calculate accuracy in the concept of data mining or decision support systems to test results, whether it is good or not good from the resulting accuracy results. This method provides information that compares the results of the model classification with the actual category. Here is the concept matrix confusion can be seen in table 3.

TABLE III. DETAIL CONFUSION MATRIX

Prediction Result	**Prediction Class**	
	Positive	***Negative***
Positive	TP (True Negative)	FP (False Positive
Negative	FN (False Negative)	FP (False Positive)

True Positive (TP) is data that accurately predicts as a positive or correct output. True Negative (TN) is data that is predicted exactly as a negative or incorrect output. False-positive (FP) is incorrect prediction data if the output is positive or correct. The latter is False Negative (FN) is data that predicts less precisely. To measure matrix models' performance from the confusion matrix, several performance models are typically used, namely, Accuracy, Precision, and Recall.

A. *Accuracy*

Accuracy will calculate how accurately and accurately a model or architecture classifies correctly. The formula can see in equation (1)

$$\frac{\sum_{i}^{n} \frac{TPi + TNi}{TPi + FPi + TNi + FNi}}{n} \quad (1)$$

Equation (1) is the true (positive and negative) prediction ratio of the aggregate data. It can say that accuracy is the level of proximity of the predicted value to the true value.

B. *Precission*

Precision is a description of the accuracy of the demand data with the model's prediction results. The formula can see in (2)

$$\frac{\sum_{i}^{n} \frac{TPi}{TPi + FPi}}{n} \quad (2)$$

Equation (2) is a positive true Precision ratio compared to the overall positive predicted result.

C. *Recall*

Recall illustrates the success of the model in rediscovering information. Then, recall is a true positive prediction ratio compared to overall true positive data. The formula can see in (3)

$$\frac{\sum_{i}^{n} \frac{TP}{TPi + FNi}}{n} \quad (3)$$

IV. RESULT AND EVALUATIONS

In this study, we tested classification models' performance to diagnose COVID-19 based on nine scenarios with different epoch parameters and dataset ratios. Experimental research conduct using pythons with the help of several packages such as Tensorflow and Keras. All applications run on laptops, namely Lenovo Ideapad 310 core i5 7th Gen (4 Gb / 1 TB HDD / Windows 10 Pro). Performance measurement of each classification assesses in terms of accuracy, precision, and recall. After evaluation, the results using the confusion matrix shows that the proposed model for diagnosing and classifying COVID-19 x-ray images works very well. Of the nine scenarios that have to perform, it shows that scenarios on CNN 5 with an epoch number of 30 and a dataset ratio of 70: 30 and scenarios on CNN 8 with an epoch number of 40 and a dataset ratio of 70: 30 produce the same score and produce the highest test compared to other scenarios. From the scenario results showing that the ratio of datasets or dataset sharing for the process of training and beaked test to the model's accuracy, the dataset divide to be more balanced for optimal results. Furthermore, epochs 30 and 40 produce the highest accuracy as more training processes, and accuracy test results will be better as models learn more to recognize chest x-ray images. For the full results can be seen in Fig. 5

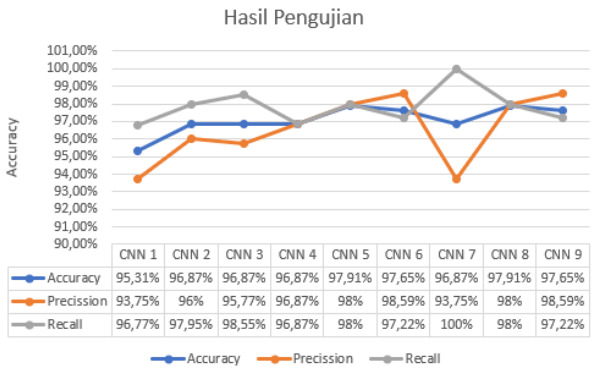

Fig. 5. All Scenario Results

The results reported in Fig. 5 base on evaluation values performed five times each in each scenario and will take the highest amount of each scenario. It appears that scenarios on CNN 5 and CNN 8 get the highest classification results for classifying COVID-19 chest x-ray images. This proposed model delivers 97.91% accuracy, 98% precision, and 98% recall. This CNN model performs well in terms of accuracy. However, because the metric relies heavily on the number of samples representing each label, its unilateral evaluation leads to incorrect conclusions. To that be the point, the combination of accuracy, precision, and recall should be the best model selection criteria.

V. Conclusion

Based on research, implementation, and testing, the following conclusions can be interesting:

In the research that has done, it can conclude that the Convolutional Neural Network algorithm model using two convolutional layers, two layers of pooling, fully connected layer with epoch 40 and dataset ratio of 70: 30 can classify COVID-19 x-ray images with 97.91% accuracy, 98% precision and 98% recall. The model also runs the system automatically without the need for manual extraction and can be redeveloped when it will retest with another image dataset of a larger size. Changing epoch and dataset ratios also play an important role in helping this classification model, from previous research focused on trying pre-trained to get accuracy and research that adds another method as the classification is felt that this model is more effective because it only focuses on the parameters of the architecture model alone without having to try many pre-trained models and add other algorithms.

Some of the limitations that expect to be able to be completed; further research are to add dataset limitations to this research so that the analysis can be done more in-depth. Use different methods or algorithms to determine the accuracy value generated in the COVID-19 x-ray image classification. Also, developing a model that can distinguish COVID-19 from similar viruses becomes interesting for future researchers.

Nevertheless, this study contributes to the possibility of diagnosing COVID-19 by saving medical practitioners little time on the application of scoring that can be used as a filtering tool on COVID-19 subjects and confirmed. Also, even though the right treatment is not always answered only with x-ray images because this model also aims not at the type of treatment that should give but in the application of timely quarantine measures.

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