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Detection of Covid-19 on Localized Ct-scan Images Using Deep Learning Convolution Neural Network

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Abstract

Pneumonia Coronavirus Disease 2019 (COVID-19) is an inflammation of the lung parenchyma caused by Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Supporting examinations carried out to establish a diagnosis of Covid-19 is through radiological examinations, one of which is Computed Tomography Scan (CT-Scan). The current method used to diagnose COVID-19 from CT scan images is by studying the 2-D CT Scan image data set using naked eye, then interpreting the data one by one. This procedure is ineffective. Research aim is to develop Covid-19 detection application on localized CT-Scan images using Deep Learning Convolution Neural Network (CNN). Pre-Trained Model used is ResNet-50. Test was carried out 3 times. First test uses original CT image, with an accuracy of 92.5%. Second test used pulmonary CT data that had been separated from surrounding tissue, with an accuracy of 95%. The last test used localized CT data (Covid Candidate), the accuracy obtained was 98%.

Keywords: covid-19, CNN, ct-scan, deep learning, resnet-50

1. Introduction

Severe acure respiratory syndrome coronasvirus 2 (SARS-CoV- 2) is a new virus that was first reported in Wuhan City, Central China, which was reported on December 31, 2019, which finally WHO gave the name Coronavirus disease 2019 (COVID-19) (WHO, 2020). Genome sequence of new Coronavirus (SARS-CoV-2) is known to be almost similar to SARS-CoV and MERS-CoV. In evolutionary terms it is same as SARS-CoV and MERS-CoV but not exactly the same (Wan et al., 2020; WHO, 2020; Li at al., 2020; Kim at al., 2020; Lippi at al., 2020; Taza at al., 2020).

The supporting diagnosis that is carried out to establish a diagnosis of Covid-19 is a radiological examination, which includes: chest X-ray, chest CT scan, and chest ultrasound (Haghanifar, Majdabadi & Ko, 2020; Khana, Shah & Bhat, 2020; Jaiswal at al., 2020; Haque & Abdelgawad, 2020; Desai, Pareek & Lungren, 2020). Radiological results may show: bilateral opacity, subsegmental consolidation, lobar or pulmonary collapse or nodule, groundglass view. In initial stage, a small multiple plaque shadows with obvious intertitial changes appear in the periphery of lung and then develop multiple ground-glass shadows and infiltrate in both lungs. In severe cases, even “white-lung” lung consolidation and (rare) pleural effusion can be found (Huang at al., 2020). During the last few months research on Covid-19 has been widely discussed by

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researchers. Because, this disease was discovered at the end of 2019. From the research that has been done by several researchers, it can be concluded that to detect Covid-19 using an intelligent system, almost all the methods proposed for classification use global-based and region-based. The global-based method used is a color histogram. This method only calculates the pixel frequency of the image so it is very sensitive to light and geometric changes. As a result, two images that have different colors and geometric positions will be recognized as two different images, even though both images are semantically the same. A region based approach, the image is segmented into several regions that represent objects. The weakness of this method is that during the image segmentation process, the segmentation results are often not in accordance with the desired object. Hence the accuracy is low.

This paper describes the classification of Covid-19 and not Covid-19 images on ct-scans which are localized using a deep learning convolution neural network Convolutional Neural Network (CNN) is a deep learning (DL) method that can be used to detect and recognize an object in a digital image. Deep Learning is one of the sub-fields of Mechine Learning. Basically, Deep Learning is an implementation of the basic concept of Mechine Learning which implements the ANN algorithm with more layers. The number of hidden layers used between the input layer and the output layer, this network can be said to be a deep neural net.

The last few years Deep Learning has shown great performance. This is largely influenced by stronger computational factors, large datasets and techniques for training deeper networks (Ozturk at al., 2020). CNN's ability is claimed to be the best model for solving object detection and object recognition problems. In 2012, research on CNN could perform digital image recognition with an accuracy similar to that of humans on this particular dataset (Narin, Kaya & Pamuk, 2020). However, CNN, like other deep learning models, has a weakness, namely, the model training process is quite long. But with the rapid development of hardware, this can be overcome using Graphical Processing Unit (GPU) technology and high specification PC.

Based on the above background, this research applies the implementation of deep learning method using CNN with modification of ResNet-50 architecture to detect Covid-19 on a localized Ct-Scan. This study focuses on how to classify Covid-19 CT-Scan and Normal CT-Scan Images

This research is divided into four stages.The first is taking CT-Scan images from the internet. The second is Ct-Scan image preprocessing. The third is the determination of Region of Interest (ROI) from CT-Scan Images containing Covid-19 and normal CT-Scan. The fourth is to detect COVID-19 automatically by classifying the image suspected of being COVID-19 on a localized CT-Scan using the Deep Learning Convolution Neural Network method.

2. Method

2.1 Detection of Covid-19 Using a Deep Learning Convolution Neural Network

Convolutional Neural Network (CNN) is a development of a multilayer perceptron (MLP) which is designed to process two-dimensional data in the form of images (Trnovsky, 2017; Visalini,

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2017). CNN is included in the type of Deep Neural Network because of its high network depth and is widely applied to image data. Deep Learning is one of the areas of Machine Learning that utilizes artificial neural networks to implement problems with large datasets. Deep Learning techniques provide a very strong architecture for Supervised Learning. In this study, a model for the classification of Covid-19 and Noncovid-19 images was created using Convolutional Neural Network (CNN) method with modification of ResNet-50 architecture and used as transfer learning. ResNet-50 is a convolutional neural network trained on more than one million images. This network has a depth of 50 layers and can classify images into 1000 object categories. The network has an input image size of 224x224. CNN ResNet-50 block diagram is shown in figure 1.

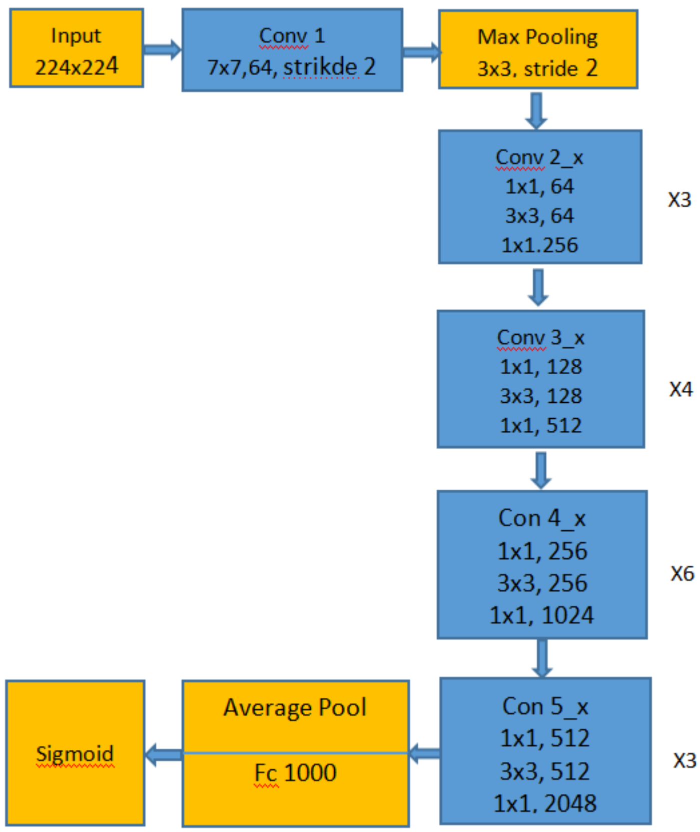

Figure 1. CNN ResNet-50 Block Diagram

The first step before detecting Covid-19 is preprocessing. This stage is an image processing stage that aims to produce a better image for further processing. This preprocessing stage consists of resize and grayscale processes. The resizing process is needed to adjust pixel size of image to be processed at testing stage. Image input used in this study has different pixel sizes. Because it is necessary to resize so that each training data and testing data has the same dimension size and value range. The greater number of pixels, more time it takes in the image processing process. Grayscale process is to convert images that have RGB mode into grayscale mode, because color characteristics are not topic of this research. For classification using the Convolution Neural Network consists of two stages, namely Feature Learning and classification. For a clearer classification using a Convolution Neural Network, it will be explained step by step as shown in Figure 2 below.

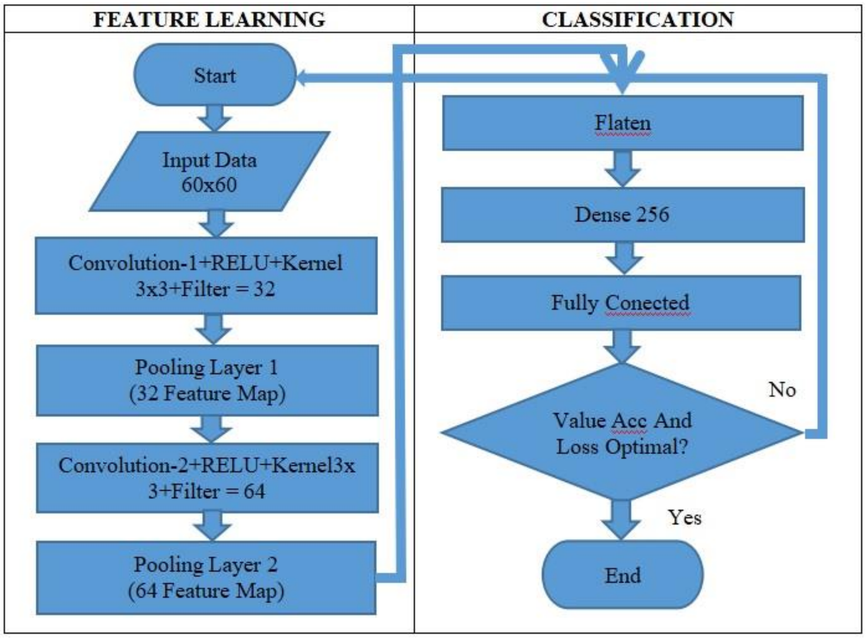

Figure 2. Flowchart Classification Using Convolution Neural Network

Based on the figure above, it is explained that there are two stages in CNN's architecture, namely Feature Learning and classification (Wicaksono at al., 2017; Zhang, 2016). Feature learning is a technique that allows a system to run automatically to determine the representation of an image into features in the form of numbers that represent the image. The classification stage is a stage where the results of feature learning will be used for the classification process based on predetermined subclasses. If the flowchart above is converted into an image, it can be seen as shown in Figure 3 below:

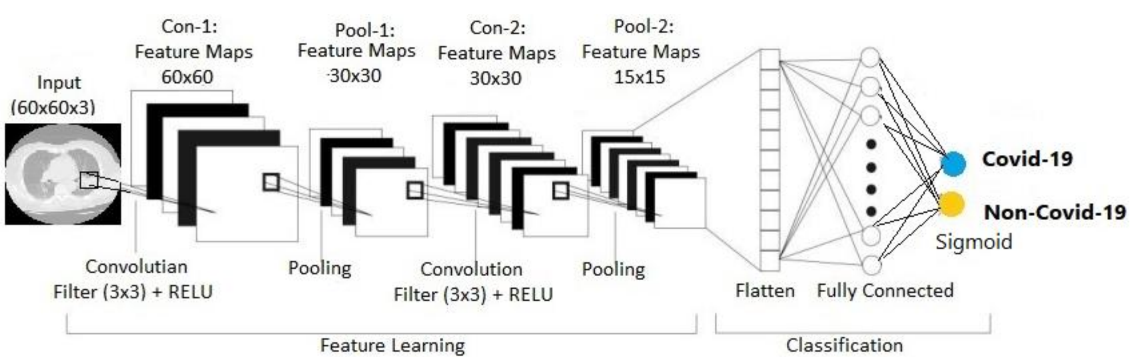

Figure 3. CNN Architecture

Feature learning is a technique that allows a system to run automatically to determine the representation of an image into features in the form of numbers that represent the image. The image used is a CT-Scan image that contains Covid and those that do not contain Covid which is obtained from the segmentation process. The first segmentation is lung field segmentation using Active Shape Model (ASM) (Widodo & Wijiyanto, 2014), second segmentation is segmentation of Covid-19 candidates using morphological mathematics (Widodo, Rohmah & Handaga, 2019; Widodo, 2017; Widodo, Rosyid & Faizuddin 2020; Widodo, Rosyid & Faizuddin, 2020). The results of morphological process are described in Figure 4.

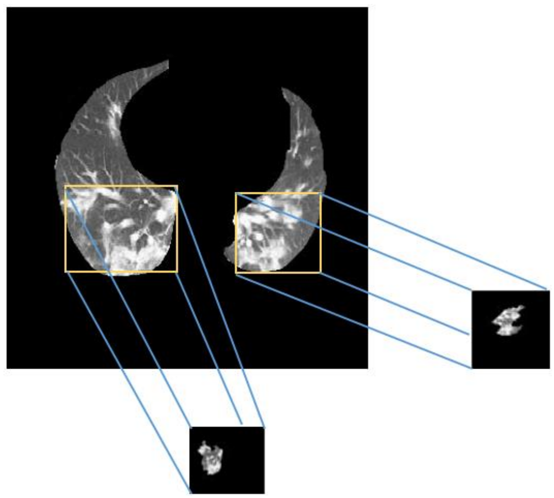

Figure 4.Covid-19 Candidates

The first stage in feature learning is convolution. Convolution is the process of combining two number series to produce a third number series. Convolution is in the form of a matrix array. In Figure 3, input is in the form of an image that has a pixel size of 60x60x3, this shows that the pixel height and width of the image is 60 and image has 3 channels, namely red, green, and blue or what is commonly referred to as RGB. Each channel pixel has a different matrix value. The input will be convoluted with the specified filter value. A filter is another block or cube with a smaller height and width but the same depth that is swept over the base image or original image. Filters are used to determine what patterns will be detected which are then convoluted or multiplied by the value in the input matrix, the value in each column and row in matrix is highly dependent on the type of pattern to be detected. Number of filters in this convolution is 60 pixels with kernel size (3x3), this means that the resulting image of convolution will be 60 map features. Convolution process is shown in figure 5.

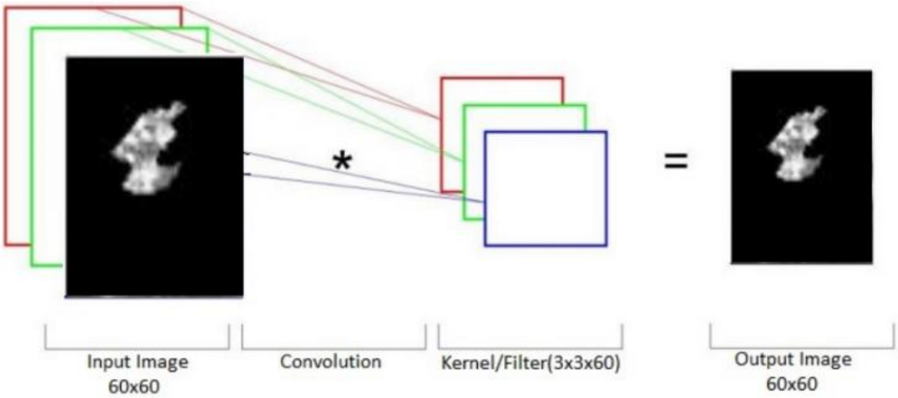

Figure 5. Convolution Process

The first convolution process used a 3x3 kernel and 32 filters. This convolution process is a combination process between two different matrices to produce a new matrix value. After the convolution process, an activation function is added, namely RELU (Retrified Linear Unit). This activation function aims to convert negative values to zero (eliminating negative values in a convoluted matrix).The result of this convolution has the same size, namely 60x60, because during the convolution process the padding value of 0 is use. The second covolution process is to continue the results of the first pooling process with an image matrix input of 32 x 32 with a total of 64 filters and a kernel size of 3x3.This second convolution process both uses the RELU activation function.

Then before proceeding to the pooling layer process, to eliminate negative values in the results, the network architecture uses ReLU (Rectified Linear Unit) activation after the convolution process. The function of this activation is to "threshold" from 0 to infinity. The values that are in the resulting negative convolution will be changed by this activation to zero and the others until infinity. After the convolution process is the pooling process. Pooling is a reduction in the size of the matrix by using a pooling operation. The method used in the pooling process uses max-pooling. Max-pooling is a common method commonly used by researchers related to deep learning research. In a study conducted by Dominik Scherer et al (Scherer, 2010), it was shown that the use of the max pooling method was superior to the sub-sampling method. The use of this method is one of the best methods in the pooling process. An overview of the pooling process is shown in the following figure 6.

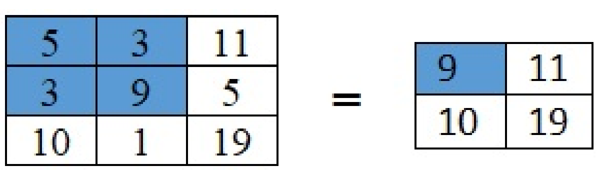

Figure 6. Pooling Process

This pooling process uses a size of 2x2 with a stride of 1, where the number of shifts in the kernel to the input matrix is one. In this pooling process, the max-pooling method is used, where the window will be shifted according to its size and strident to get the maximum value. It can be seen in Figure 7 that the output of this process has the maximum value that is taken from the convolutional map feature matrix. The max-pooling results are 2x2 in size. Basically, the pooling layer consists of a filter of a certain size which will alternately shift the entire feature map area. This study uses max-pooling to obtain new matrix values as a result of the pooling process. Based on the results of pooling, it produces a new matrix measuring 30x30 using a 2x2 pooling kernel. The way max-pooling works is to take the maximum value based on the shift in the kernel as the value of the stride is 2. The next process enters the second pooling process, this process is almost the same as the first hang pooling process, but there is a difference in the final output value of the matrix. The resulting output has an image size of 15x15. The next step is the classification of Covid-19 and Noncovid-19. At the classification stage, it is divided into 2, namely Flaten and Fully Conected. At this stage only one hidden layer is used in the Multi Layer Perceptron (MLP) network. Flatten converts the output pooling layer into a vector. Before doing the classification process or predicting an image, this process uses the Dropout value. Dropout is a neural network regulation technique with the aim of selecting several neurons randomly and not to be used during the training process, in other words, these neurons are randomly discarded. The purpose of this process is to reduce overfitting during the training process. The last process is to use Sigmoid function activation. This function is specifically used in the classification methods of multinomial logistic regression and multiclass linear discriminant analysis. The last process is the Fully Connected Process. The second stage in the classification process is the Fully Connected Layer. This process aims to transform the dimensions of the data so that the data can be classified linearly. Process Of Fully Connected Layer shown in Figure 7.

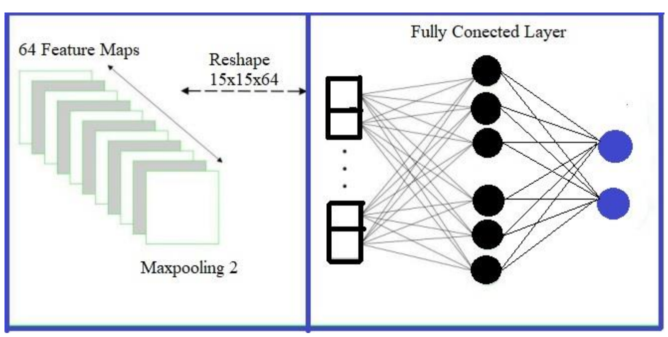

Figure 7. Process Of Fully Connected Layer

2.2. Dataset

Dataset used in this study came from Wuhan China. Image data used is a CT-Scan image with a thickness of 0.5 mm. Total number of images collected for a sample of 800, with 400 CT-Scan images for each type category. Covid and Non-Covid CT-Scan images are shown in Figure 8.

Figure 8. CT-Scan images
(a) Covid, (b) Non Covid

3. Results

The purpose of this study was to classify two image classes, namely Covid and Non-Covid on Ct-Scan using the Convolutional Neural Network (CNN) algorithm. The classification process begins with the training data process. Data training process aims to create a model that will be used for testing data testing. Parameter to measure success rate of the model is accuracy value. Accuracy value can be determined by testing using testing data. This process uses a total of 20 epochs, the value of learning rate is 0.001. The test was carried out 3 times. The first test uses original CT image with a size of 1024x1024. Second test uses CT image of lung that has been separated from surrounding tissue, with an image size of 340x340. Third test uses a CT Candidate Covid image with a size of 60x60. Three tests are described as follows.

3.1. Testing with Original CT-Scan Image Dataset

This test uses the original CT-Scan image dataset, with a size of 1024 x 1024 pixels. Total number of training data used was 640, each class was 320. Test data used were 160 (80 Covid-19 data, 80 Noncovid-19 data). The results of test are shown by Confusion Matrix as shown in Table 1.

Table 1. Confusion Matrix Testing Using CT-Original Image Training Data

<table>
<tr><th colspan="2" rowspan="2">Matrix</th><th colspan="2">Predict Class</th></tr>
<tr><td>Covid-19</td><td>Not Covid-19</td></tr>
<tr><td rowspan="2">Actual Class</td><td>Covid-19</td><td>70</td><td>10</td></tr>
<tr><td>Not Covid-19</td><td>2</td><td>78</td></tr>
</table>

Based on table 1 above, the predictive results of the model against testing data using training data show good results. Predictions for Covid-19 are classified as Covid-19, the total is 70, Covid-19 is classified as non-Covid-19 by 10, predictions in non-Covid-19 images are classified as Covid-19 totaling 2, and non-Covid-19 images are classified as non-Covid-19 images by 78. The calculation of the accuracy of the entire matrix above is as follows:

$$\text{Overall Accuracy} = \frac{TP\ all}{\text{Tota Number of Testing Entries}}$$

$$= \frac{148}{160}$$

$$= 0.925\ (92.5\%)$$

So the accuracy of testing with the original CT-Scan image input, the learning rate value of 0.001 and the number of testing samples 160 data, obtained an accuracy value of 92.5%.

3.2. Second Test Uses Ct-Scan Data for Lung Area

Second test uses training data and testing data from CT-Scan images of the lungs that have been separated from the surrounding tissue. Method used for lung segmentation is Active Shape Model (ASM). Training data used were 160 CT-Scan images (80 Covid-19 lungs, 80 Non-Covid-19 lungs). Test data used were 40, for each class 20 data. Confusion matrix results are as follows:

Table 2. Confusion Matrix Testing Using CT-Lung Image Data

Matrix		**Predict Class**	
		Covid-19	Not Covid-19
Actual Class	Covid-19	**20**	**0**
	Not Covid-19	**2**	**18**

Based on table 2 above, the prediction results from testing data using CT data for the lung area show good results. Prediction against Covid-19 is classified as Covid-19, as many as 20, predictions on the Covid-19 image and classified as non-covid-19 as much as 0, Non-Covid-19 images are classified as non-Covid-19 totaling 18, and non-covid-19 images are classified as Covid-19 images totaling 2. Calculation of the accuracy of entire matrix above is as follows:

$$\text{Overall Accuracy} = \frac{TP\ all}{\text{Tota Number of Testing Entries}}$$

$$= \frac{38}{40}$$

$$= 0.95\ (95\%)$$

So the accuracy generated by the model with an image input of 340x340 pixels, a learning rate of 0.001 and the number of testing samples of 40 data obtained an accuracy value of 95%.

3.3. Third Test Used Covid-19 Candidate Ct-Scan Data

Third test is testing using training data and testing data from image of Covid-19 candidate that comes from results of lung segmentation using morphological mathematical methods. Image of Covid-19 candidate is shown in Figure 4. Training data used totaled 400 images of Covid-19 candidates (200 Covid-19 candidates, 200 Non-Covid-19 candidates). Test data used is 100, for each class as many as 50 data. Confusion matrix results are shown in Figure 9.

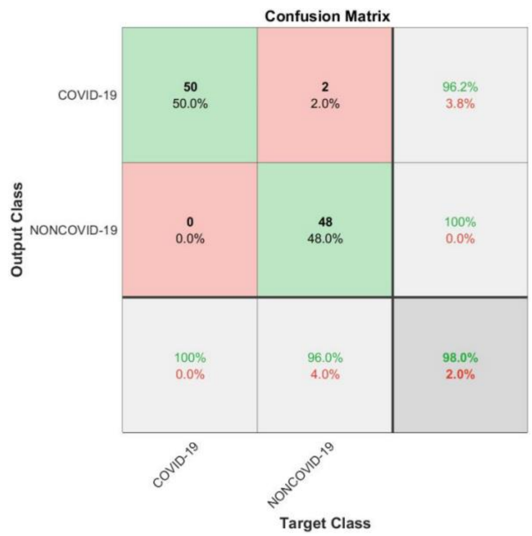

Figure 9. Confusion Matrix for Testing Using Covid-19 Candidate Data

Based on Figure 9 above, prediction results from model against testing data using CT data for the Covid-19 Candidates show good results. Predictions for Covid-19 are classified as Covid-19, as many as 50, predictions on image of Covid-19 and are classified as non-Covid-19 as many as 0, Images for non-Covid-19 are classified as non-Covid-19 totaling 48, and images for non-covid-19 classified as a Covid-19 image numbering 2.

$$\text{Overall Accuracy} = \frac{TP\ all}{\text{Tota Number of Testing Entries}}$$

$$= \frac{98}{100}$$

$$= 0.98\ (98\%)$$

Accuracy obtained by inputting an image with a size of 60x60 pixels, a learning rate of 0.001 and number of sample testing 100 data obtained an accuracy value of 98%.

Three tests were carried out with aim of finding out the most appropriate training data for Covid-19 detection. First test using original CT image with size of 1024x1024 has an accuracy of 92.5%. Second test uses lung training data that has been separated from surrounding tissue, with size of 340x340. Accuracy obtained is 95%. While third test is testing using localized CT-Scan training data, namely by taking an image that is suspected of being Covid-19 (Candidate Covid-19). Image size 60x60. Accuracy obtained is 98%.

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4. Discussion

Three tests were carried out with aim of finding out the most appropriate training data for Covid-19 detection. First test using original CT image with size of 1024x1024 has an accuracy of 92.5%. Second test uses lung training data that has been separated from surrounding tissue, with size of 340x340. Accuracy obtained is 95%. While third test is testing using localized CT-Scan training data, namely by taking an image that is suspected of being Covid-19 (Candidate Covid-19). Image size 60x60. Accuracy obtained is 98%.

Comparison of accuracy with other papers is shown in Table 3.

Table 3. Comparison of Accuracy with Other Papers

No	Work	Material	Database(Sample)	Accuracy
1	T. Ozturk	X-Ray	Cohen JP (127)	87,02%
2	Ali Narin,	X-Ray	Dr. Joseph Cohen (100)	87%
3	Asmaa Abbas	X-Ray	Japanese Society of Radiological Technology (*JSRT*) (1764)	93,36%
4	Md Zahangir Alom	X-Ray	different sources around the world and a publicly a (5216)	84,67%
5	Chuangsheng Zheng	CT 3D	Union Hospital, Tongji Medical College, Huazhong University of Science and Technology (540)	95%.
6	Chunqin Long	CT	204	83,3%.
7	Widodo, S.	CT	Wuhan (400)	98%

5. Conclusion

From the experiments conducted, it can be seen that detection of Covid-19 uses Deep Learning Convolution Network with ResNet-50 architecture with localized training data measuring 60x60, learning rate of 0.001, a filter size of 3x3, number of Epochs 20, 400 training data, and 100 testing data, the highest accuracy obtained and the least time required.

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