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Automatic detection of covid-19 based on CT scan images using the convolution neural network

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Abstract — The 2019 coronavirus pandemic (Covid-19) has been declared a health emergency by WHO. With the death rate steadily increasing worldwide, various efforts have been made to deal with this pandemic, from prediction to receiving medical imaging. CT scans and chest X-Ray images have been proven to be accurate to help medical personnel diagnose COVID. This paper proposes a convolutional neural network (CNN) approach and the Dense Net transfer learning model series, which aims to understand and find the best classification for COVID or Non-COVID detection. On CT scan chest images, we made two special models in the Descent series, then compared the CNNs in both models by calculating the Accuracy, Precision, Recall, and F1-Score values and presented the results in the confusion matrix. The testing framework is carried out on CNN. The first model of the DenseNet series uses adam optimization. The input function is 244x244x3. The soft-max function is applied as an activity with losses across entropy categories, epoch 50, and batch size for training and testing 16. In contrast, validation uses batch size 8, the Early Stopping function also determined. From the test results, the CNN model is superior to the DenseNet series of the first model with an accuracy of about 0.76 (76%). When testing the second model, we carried out the shifting, zooming process and changed the input function to 64x64x3, epoch 30 by adding 4 layers. The second model approach produces better accuracy than CNN and the first DenseNet series, but not as good as expected, based on the test results on the second model produces an accuracy of 0.90 (90%) on Densenet169, Densenet121 around 0.88 (88%) and last DenseNet201 is about 0.83 83%), so it is superior to simple CNN models

Keywords – Covid, DenseNEt, CNN, convolutional neural network, CT Scan

I. INTRODUCTION

The 2019 Coronavirus (COVID-19) pandemic has been declared a health emergency with an increasing mortality rate worldwide, including in Indonesia. The need for a fast and accurate diagnosis to assist patient isolation is very helpful in managing and controlling COVID-19. Identification using a real-time polymerase chain reaction (RT-PCR) apparatus can diagnose this pandemic, but its limitations, medical personnel, and sensitivity are limited [1]. The disease COVID-19 is diagnosed as spreading rapidly and at high risk, resulting in insufficient medical resources in many areas, so it is very important to optimize medical resources for early prevention. Although, in this decade, medical imaging has played an important role in the main diagnostic source of COVID-19 using X-rays (chest radiography), and computed tomography (CT) [2] - [5], several studies have proposed a fully automated deep learning system. for diagnostics. COVID-19 and predictive analysis using routine CT [1], as in the study of Rajpal et al. [6], conducted a trial using the Extreme Learning Machine (ELM) classification method to separate COVID-19 cases from normal cases and pneumonia.

Some researchers recommended deep learning for the diagnosis of COVID-19 based on CT Scan and X-Ray. As reported in [7], they developed a deep learning model to improve the accuracy disease prediction from chest X-ray scans. They rely on convolutional neural networks (CNN) to detect structural abnormalities and disease categorization. Which is the key to uncovering hidden patterns and the results they offer have very high accuracy (96.3%) and disadvantages (0.151 binary cross-entropy) using data sets. Ezzat et al. [8] used GSA to diagnose COVID-19 from chest x-rays through four main stages: the data preparation stage, the hyperparameter selection stage, the learning stage, and the performance measurement stage and the results. Demonstrates the effectiveness of the proposed approach in diagnosing the new virus. In their work [9], they took a new approach to the introducting Covid-19 from chest X-ray images. Then used the Convolution Support Estimation Network (CSEN) which is equipped with feature extraction from within advanced neural network solutions for X-ray images. The models proposed achieving a sensitivity of more than 98% and a specificity of more than 95% for the introduction of Covid-19 and [10] proposed CoroNet. Deep Convolutional Neural Network model for automatically detecting COVID-19 infection from chest X-rays. CoroNet achieved an overall accuracy of 89.6%, and more importantly, the precision and recall rates for COVID-19 cases were 93% and 98.2%.

The Covid-19 pandemic is an interesting and important research topic at this time, there are many research works that apply deep learning models to classify lung CT images into positive or negative COVID-19, such as [12] applying LSTM-based CNN networks for COVID-19 detection. , whereas Waheed et al [13] implemented the VGG16 network.

The VGG16 architecture consists of twelve convolutional layers, the work [14] recommends CNN based on the SqueezeNet model on different datasets, they apply the Bayesian method to optimize Hyper-parameters by reporting test results with an accuracy rate of up to 83.00%, sensitivity 85.00%, specificity 81.00%, precision 81.73% and F1Score 0.8333, whereas in work [15] applying 12 CNN networks on three different x-ray datasets, this study investigated chest X-rays of normal viral, bacterial, and viral infections. non-COVID and other viruses and apply to 12 CNN networks, besides that they also build a simple CNN network.

A different approach is presented in the work [16], they trained three different tissues, first, the model was trained for lung segmentation using masks resulting from unsupervised learning methods, trained the model for detection of Covid-19 lesions, and finally localized the COVID-19 lesion that was under scrutiny based on the first model and research [17] proposed a GAN approach on 4 deep learning models for detection of COVID and Pneumonia on the Chest Radiograph Images (CXR) Chest Radiograph CT Scan dataset, the proposed model achieved an accuracy of 89%.

Next, [18] they optimized the transfer learning model by using twofold learning to improve accuracy in classifying chest X-rays on labels: COVID-19, viral pneumonia, and normal. The proposed model reportedly achieves 99.4% accuracy with an F1 score (0.994), in work [19] proposes a new anti-noise framework for the learning of noisy labels for segmentation tasks then proposes a new COVID-19 Pneumonia Lesions segmentation network (COPLE) - Net) to better deal with lesions of various scales and appearances, to make the training process noisy label resilient, they propose a noise-resistant Dice loss function and integrate it into a standalone ensemble framework and the result of this method is the noise function robust loss, and COPLE Net achieved higher performance than the advanced CNN for medical image segmentation, and work [20] reported that chest CT scan images were an effective screening strategy because they could reveal some cases of COVID-19 so it could be applied to shows symptoms in the early stages and pulmonary consolidation in the late stages.

In this study, we propose CNN for the classification of COVID-19 based on CT scan images [11] for the detection of COVID and non-COVID. We build a different CNN network architecture, namely a simple CNN network and CNN based on the DenseNet Transfer Learning Model (Dense121, Dense169, and Dense201). Understanding how the CNN method works and finding the best classification on chest CT images to be COVID or non-COVID. Thus the main contributions in this work are as follows:

1. Build a simple CNN model using 4 layers, each equipped with max pooling, flattening, and output layers using the dense with softmax function.
2. Apply the DenseNet transfer learning model by constructing two experimental models that will be compared with the CNN model.
3. The performance evaluation of CNN and DenseNet series by calculating the Accuracy value, Precision, Recall, and F1-Score and presenting the results in a confusion matrix.

The remainder of this paper is further organized as follows: part 2 of the related research, the data set, and the proposed method are described in section 3, section 4 reports the results and discussion, and section 5 concludes the experimental result.

II. RESEARCH METHODS

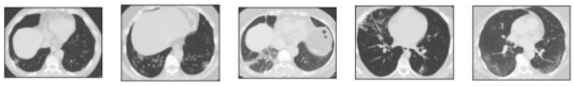
A. Dataset

In this study, we used the open-source SARS-CoV-2 Ct-Scan dataset [11] sourced from Kaggle [21], which contained 1252 CT scans positive for SARS-CoV-2 (COVID-19) infection and 1230 CT scans. For patients not infected with SARS-CoV-2. These data have been collected from real patients in a hospital in Sao Paulo, Brazil. This data set has a png extension with different sizes. The smallest image size has dimensions of 104 × 153, and the largest is 484 × 416. The datasets are grouped by dividing the dataset into training, val, and testing sets with the distribution structure presented in Table 1.

Table 1. Distribution of data sets

Dataset	Covid	Non Covid
Train	918	921
Val	88	63
Test	306	307

The train folder contains 918 COVID images and 921 non-COVID-19 images. The val folder is used to validate the model with 125 COVID-19 images and 122 non-COVID images, while the test is used to test the model with 306 COVID images and 307 non-COVID images. The difference between CT-Scan images infected with COVID-19 and non-COVID images lies in the white patches scattered on the surface of the lungs. An example of CT Scan data for COVID and non-COVID (normal) can be seen in Fig.1.



(a) Covid

(b) Non covid

Fig. 1. An example of a CT image used

B. *The Proposed Model*

The model framework proposed in this study is illustrated in Fig. 1, a set of CT Scan datasets sourced from open datasets as described in the data set section, then the process of sharing the train, Val, and testing data sets, resizing, image processing and augmentation. In the pre-processing stage, the proposed model consists of a simple CNN and DenseNet transfer learning model, which is built using two models. Finally, all models are evaluated for the classification of COVID or Non- COVID with labels 0 and 1 using a confusion matrix.

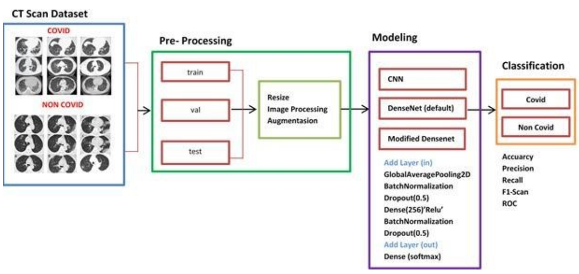


Fig. 2. Outline of the proposed model

Evaluation of the proposed model experiment result uses an evaluation matrix where TP is the number of positive samples labeled accurate (True Positive), TN is the number of negative samples detected correctly (True Negative), At the same time, FP is the number of negative classifications as positive (False Positive). and FN is the number of positive classification estimates (False Negative). Accuracy, Precision, Recall, and F1-Score are the results of the accuracy of COVID detection in the proposed model with the following equation:

$$Accuarcy = \frac{TN+TP}{TN+TP+FN+FP} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

Precision is the number of samples correctly identified among all identified samples. Recall is the number of samples correctly identified from all positive representations, the F1-Score mean precision and corresponding recall, and accuracy is the proportion of samples correctly classified from the sample size.

III. RESULTS

This section we will describe the steps used in testing the COVID-19 classification experiment based on the CT Scan dataset. Application development is carried out on the Google Colab work environment as a platform for creating Python-based applications. All datasets are stored in Google Drive applications with the Runtime hardware accelerator settings is GPU.

A. *First Model Training*

This study proposes a CNN network architecture approach and the Densenet series for COVID or Non-COVID detection. First, we build a simple CNN different CNN network and DenseNet series transfer learning. First for the CNN model defined as sequential, then adding 4 convolutional layers where each the layer is equipped with max-pooling. The Flatten layer is used to flatten all features and functions of the activity using the Dense output layer with the softmax function, At the same time, for the DenseNet series transfer learning model using a network architecture that has been previously trained on the ImageNet dataset, it is clearer the number of parameters used in the first model is clearer as reported in Table 2.

Table 2. Parameter Settings of the First Training Model

Model	Total Parms	Trainable Params	Non-trainable Params
CNN Sequential	4,819,746	4,818,274	1.472
Densenet121	8,062,504	7,978,856	83.648
Densenet169	12,646,210	12,487,810	158.4
Densenet201	18,325,826	18,096,770	229.056

The training of all models uses adam optimization, with input function 244x244x3, the soft-max function is applied as an activation with categorical entropy loss, epoch 50, and batch size for training and testing 16. In contrast, validation uses batch size 8, **EarlyStopping** function is also applied to overcome the overfitting problem. And minimize learning losses in all models. The evaluation results of the accuracy and loss training of all the proposed models are described in Fig.3 for CNN Model and Fig.4 for series DenseNet Model.

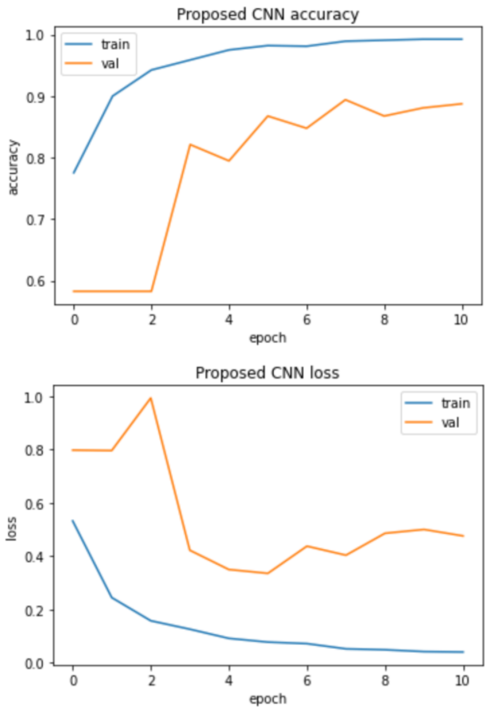
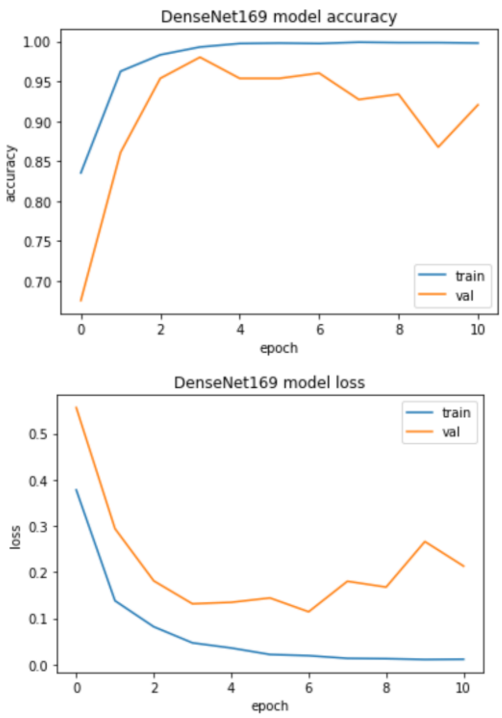


Fig. 3. Accuracy and disadvantages of CNN model



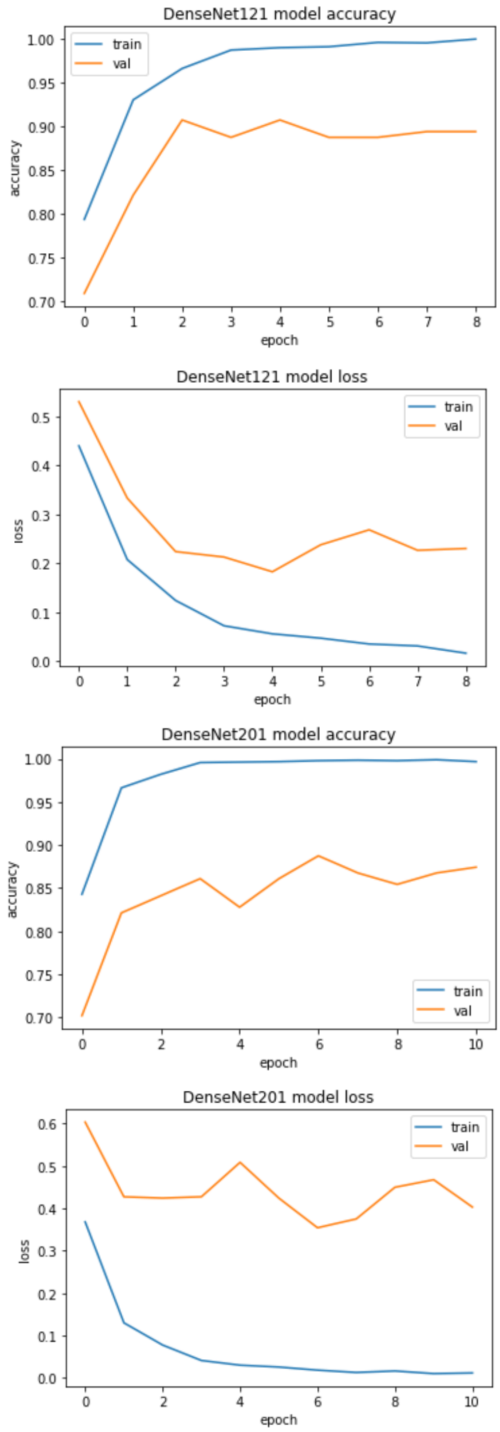


Fig. 4. Accuracy and disadvantages of DenseNet series models

We have shown the training accuracy curves and the disadvantages of all the models used to illustrate model performance against changes in the epoch value. It can be seen that the CNN sequential model accuracy value continues to increase from epoch 0 to epoch 4 and begins to stabilize at epoch 8, while the Densenet169 and Densenet201 series are the most stable compared to Densenet121 and CNN, but Densenet121 has the fastest time compared to other models, the clearer results of the accuracy, shortcomings and training time of all our models are reported in Table 3.

Table 3. Accuracy, losses, and time spent training models

Model	Accuracy	Loss	Time
CNN Sequential	0.7488	0.8114	3s 87ms/step
Densenet121	0.7325	0.8305	4s 91ms/step
Densenet169	0.7471	0.9698	4s 92ms/step
Densenet201	0.7292	10,379	4s 93ms/step

Table 3 represents all models, where we report accuracy, losses, and time spent training the model for each change in epoch value. For example, densenet121 model takes less time, around 4s 91ms per epoch change than the Densenet model169 4s 92ms, Densenet201 around 4s 93ms, and the last one is CNN Sequential around 3s 87ms. But, the highest accuracy is on the CNN Sequential model at 0.7488 (77%) and Densenet169 at 0.7471 (74%).

B. *First Model Testing*

In this section, we show the results of experimental tests carried out on the first model, the Accuracy, Precision, Recall, and F1-Score results are reported in Table 4 and the configuration matrix is presented in Fig. 5.

Table 4 shows the results of the performance analysis representing all models in the first model test. Where the Densenet201 and Densenet169 models produce the best precision values for the COVID classification of 1.00 (100%), Densenet121 0.99, and CNN Sequential 0.82, while the Value The highest for the Non-COVID classification is CNN Sequential 0.72, then the Densenet169 0.66, Densenet121 and Densenet201 models produce a precision value of 0.65.

Table 4. Analysis of the performance of the second model test classification

Model	Label	Precision	Recall	f1-score	Support	Accuracy	ROC UAC
CNN Sequential	**Covid**	0.82	0.66	0.73	306	0.76	0.76
	Non Covid	0.72	0.86	0.78	307		
Densenet169	**Covid**	1.00	0.49	0.66	306	0.75	0.74
	Non Covid	0.66	1.00	0.80	307		
Densenet121	**Covid**	0.99	0.47	0.64	306	0.73	0.73
	Non Covid	0.65	1.00	0.79	307		
Densenet201	**Covid**	1.00	0.46	0.63	306	0.73	0.72
	Non Covid	0.65	1.00	0.79	307		

For the best accuracy results, the CNN Sequential model is 0.76 (76%), then Densenet169 is 0.75 (75%), finally Densenet121 and Densenet201 are 0.73 (73%). The evaluation using a confusion matrix for all models is presented in Fig.5.

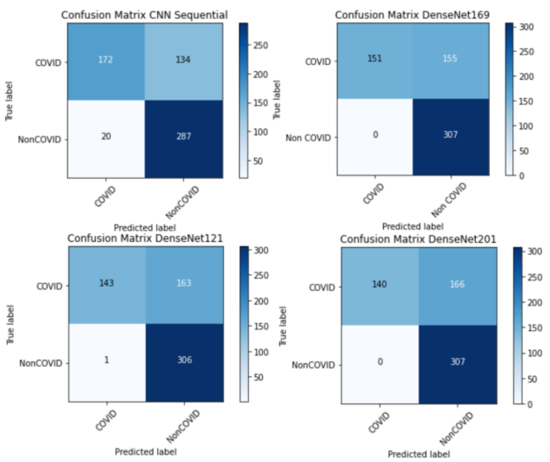


Fig 5. CNN confusion matrix and DenseNet first model series

C. *Second Model Training*

The experiment in the second model was specifically built to optimize the Densenet series transfer learning model by making several changes. 80% of the dataset for training and 20% of the tests were taken randomly using seed 42. The image size dataset to be 64x64 pixels (see Fig.6), so that the function input becomes 64x64x3, batch size 64, augmentation function by doing 360° rotation, horizontal and vertical sliding range 0.2, zoom range 0.2, horizontal flip, and vertical flip 0.2.

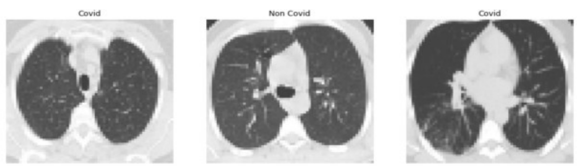
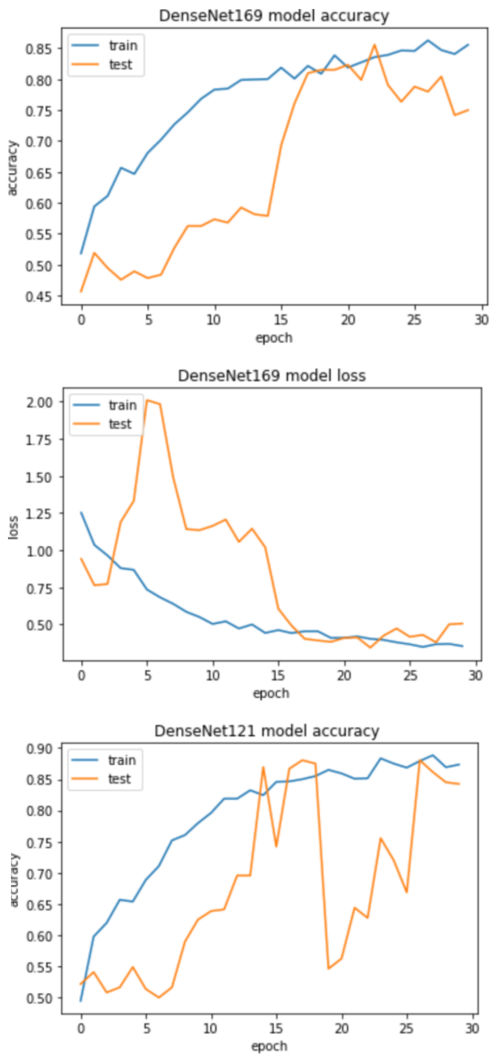


Fig 6. is an example of changing the size of a 64x64 training image

We also specially added a special layer for the image to vector conversion. Batch Normalization contains 2 untrained weights updated during training, two Dropout layers with added Batch Normalization layer, and 1 Relu Density layer respectively added a Dense output layer with an activation function. Softmax and all models are trained with a learning speed of 0.002, epoch 30, and Adam optimization. Finally, the ReduceLROnPlatea function as a callback to reduce the learning speed when the results stop increasing and for overfitting problems. The gradual change in learning speed by a factor of 0.5. All parameter changes are reported in table 5. We also present the accuracy and training loss curves in Fig.7.

Table 5. Second model parameter settings

Model	Total Parms	Trainable params	Non-trainable params
Densenet121	7,305,622	7,219,414	86.208
Densenet169	13,077,398	12,915,158	162.24
Densenet201	18,823,062	18,589,654	233.408



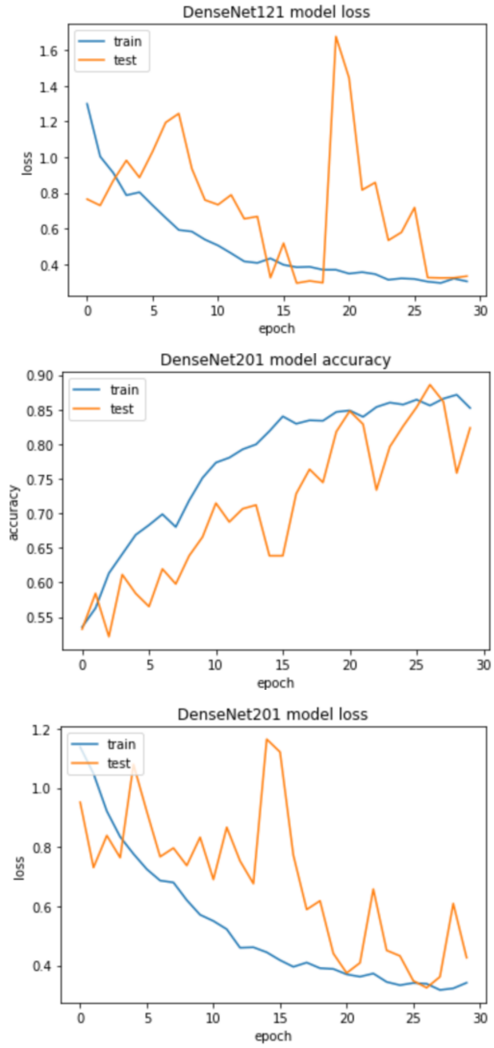


Fig.7. Accuracy curve, DenseNet second model series disadvantages

As shown in Fig.7 the accuracy curve, the drawback of the DenseNet series of the second proposed model, the Densenet121 model, produces the most stable accuracy values with the best training and testing accuracy (table 6), this model produces an accuracy value of 0.84 (84%) and a loss of 0, 3 (30%) after reaching the epoch value of 30, then Densenet201 is 0.8234 and finally, Densenet169 is 0.7500, for the Densenet121 model training time requires 0s 13ms / step which indicates the second model training time is faster than the first model.

Table 6. Accuracy, disadvantages, and training time of the second model

Model	Accuracy	Loss	Time
Densenet121	0.8424	0.3334	0s 13ms/step
Densenet169	0.7500	0.5063	0s 17ms/step
Densenet201	0.8234	0.4263	0s 23ms/step

D. *Second Model Testing*

Based on the results of the second model DenseNet training series, in this section, we present the test results by calculating the Accuracy, Precision, Recall, and F1-Score values reported in Table 7. In contrast, the confusion matrix is presented in Fig.8. As we report in Table 7, Densenet121 produces the highest precision value for the COVID label around 0.81 or 81%, then Densenet201 0.77 and Densenet169 0.69 while for the Non-Covid label Densenet169 produces 0.93, Densenet121 0.89, and Densenet201 0.77, for the best accuracy of the DenseNet series. A value of about 0.84 with a UAC ROC value of 0.83 on the Densenet121 model, then Densenet201 at 0.81, and finally Densenet169 at 0.74.

Table 7. Analysis of the performance of the second model test classification

Model	Label	Precision	Recall	f1-score	Support	Accuracy	ROC UAC
Densenet121	**Covid**	0.81	0.92	0.86	192	0.84	0.83
	Non Covid	0.89	0.76	0.82	176		
Densenet169	**Covid**	0.69	0.96	0.8	192	0.75	0.74
	Non Covid	0.93	0.52	0.66	176		
Densenet201	**Covid**	0.77	0.93	0.85	192	0.82	0.81
	Non Covid	0.91	0.7	0.79	176		

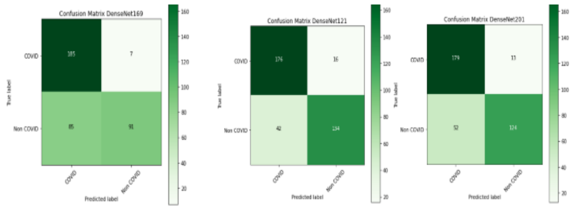


Fig.8. DenseNet second model series confusion matrix.

IV. DISCUSSION

Based on the test results, the CNN model produces better accuracy than all the Densenet series of the first model, with an accuracy rate of 0.76 (76%). On the other hand, the second approach, Densenet, with the addition of a special network, produces an accuracy of about 0.90 (90%) for the Densenet169 model, then Densenet121 is 0.88 (88%), and Densenet201 is 0.83 (83%) which shows better than CNN.

Using a CNN with fewer layers has the advantage of lower hardware and less training time compared to the DenseNet series of both the first and second approaches. Shorter training times make it possible to test more hyperparameters and facilitate the overall training process. The approach of DenseNet's second model with a change in the image resolution size can improve accuracy compared to the first model. Besides that, a shorter training time can simplify the required resources. This result is also evidenced by the findings of B. Liu et al. [5] proposed a new data-saving LA-DNN model focusing on the main task of binary classification for COVID diagnosis. -19. This model produces an accuracy rate of 94.0% on the source CT SCAN dataset. M. Polsinelli et al. [14] built a lightweight CNN architecture based on the SqueezeNet model for efficiently discriminating of CT COVID-19 images with other CT images (community-acquired pneumonia and/or healthy images). This model achieves 83.00% accuracy, 85.00% sensitivity, 81.00% specificity, 81.73% precision, and F1Score 0.8333, which proves to be better than the proposed CNN model.

We have presented a report of experimental results on CNN and DenseNet models with domestic network architecture for COVID-19 detection, we realize that the proposed model is not satisfactory, but the second model approach produces better accuracy but is not as good as expected. Hence, it still needs evaluation and improvement. Other model improvements that can later be done in future work.

V. CONCLUSSION

This study aims to build a COVID-19 automatic detection model based on ct scan images. The experiment was carried out by testing the CNN model and the DenseNet series. The Densenet series model experimented by building two models then evaluating to compare the most accurate models. Based on the test results, CNN models outperform all Densenet series with an accuracy rate of about 0.76 (76%). In comparison, the second model Densenet series has a good increase in accuracy of about 0.90 (90%) on the Densenet169. Both Densenet121 models are around 0.88 (88 %). Finally, the Densenet201 model is around 0.83 (83%), so it is superior to the CNN model. We have presented experimental reports of CNN and DenseNet models with trained network architectures for COVID-19 detection. We realize that the first model of the proposed DenseNet series classification results is not satisfactory. However, but the second model approach yields better accuracy but not as good as expected, so it still needs evaluation and improvement on other models, which can be done later.

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