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Multiclass Classification of Covid-19 CT Scan Images With VGG-16 Architecture Using Transfer Learning System

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Abstract

COVID-19 is a respiratory disease caused by the coronavirus. The most common test technique used today for COVID-19 diagnosis is real-time reverse transcription-polymerase chain reaction (RT-PCR). However, compared to RT-PCR, radiological imaging such as X-rays and computer tomography (CT) may be a more precise, useful, and faster technology for COVID-19 classification. X-rays are more accessible because they are widely available in all hospitals in the world and are cheaper than CT scans, but the classification of COVID-19 using CT scan images is more sensitive than X-rays. Therefore, CT scan images can be used for the early detection of COVID-19 patients. One of them is using the deep learning method. In this study, a CNN algorithm with a VGG-16 architecture will be selected to classify COVID-19, intermediate, and non-COVID CT scan images using 2481 image datasets. First, pre-processing is done by resizing the image, converting the image channel into RGB, and dividing the dataset into a training dataset and a testing dataset. Then, the convolution process is continued by utilizing the pre-trained VGG-16 model from ImageNet. The results of testing the data with 97% accuracy were obtained. It is concluded that the model used to classify COVID-19, intermediate, and non-COVID CT scan images is effective and produces good results.

Keywords: Classification, COVID-19, Multiclass, Transfer learning, VGG-16

INTRODUCTION

COVID-19 is a respiratory illness caused by the coronavirus. The most common symptoms include fever, fatigue, dry cough, loss of appetite, body aches, and mucus. The World Health Organization (WHO) declared the 2019 coronavirus disease (COVID-19) outbreak a public health emergency of international concern on January 30, 2020 [1].

The most common test technique used today for COVID-19 diagnosis is *real-time reverse transcription-polymerase chain reaction* (RT-PCR) [2]. However, compared to RT-PCR, radiological imaging such as X-rays and computer tomography (CT) may be more precise, useful, and faster technologies for COVID-19 classification. In this case, X-rays are more accessible because they are widely available in all hospitals in the world and cheaper than CT scans, but the results of COVID-19 classification using CT scan images are more sensitive than X-rays [3]. Therefore, CT scan images can be used for the early detection of COVID-19 patients [1].

Therefore, a technology is needed to identify COVID-19 through CT scan data quickly and precisely. This identification can be done with deep learning method [4]. The application of machine learning methods for automated diagnosis in the medical field has recently been frequently used as an additional tool for doctors. Although radiologists play a very important role because of their experience and knowledge in this field, this deep learning technology in radiology can help to diagnose accurately and quickly so that further action can be taken immediately for the patient. Deep learning can

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also help if hospitals lack medical personnel to read CT scans [2].

Deep learning is one of the functions of artificial intelligence that mimics the way the human brain works in processing data and creating patterns to be used in decision-making. Deep learning is the most efficient technique that can be used in medical science. It is a fast and efficient method for the diagnosis and prognosis of various diseases with a good degree of accuracy. In the medical field, deep learning is used to detect heart problems, tumors using image analysis, diagnose cancer, and many other applications.

Several deep learning algorithms are often used, such as ANN (Artificial Neural Networks), RNN (Recurrent Neural Networks), and CNN (Convolutional Neural Networks). In this research, the CNN algorithm will be chosen because the CNN method is a class of neural networks that specializes in processing data that has a grid-like topology, such as images. The CNN method is often used to solve classification and segmentation problems using medical image data [4]. CNN has several fundamental architectures and aims for image classification, such as AlexNet, VGGNet, ResNet, and DenseNet. In this research, VGG-16 will be used, which is part of VGGNet, using a transfer learning system (pre-trained). VGG-16 is used because it is one of the CNN architectures that has successfully obtained good accuracy and classification results in previous studies. VGG-16 also has a simple and efficient architecture, making it more memory efficient compared to other CNN architectures. Transfer learning is a technique that utilizes pre-trained models to be used to classify new datasets, so there is no need to train data from scratch.

Therefore, the study will conduct a multi-class classification of COVID-19 CT scan images, intermediate, and non-COVID using the VGG-16 architecture with a transfer learning system and look at the accuracy results obtained from the classification.

THEORY/CALCULATION

The Convolutional Neural Network (CNN) architecture consists of several layers, starting with the input layer, convolution layer, batch normalization, activation function, polling layer, flatten layer, fully connected, softmax activation, and drop out.

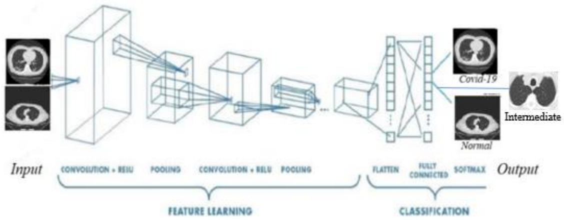


Fig. 1. CNN architecture.

The convolutional layer is the foundation of CNN, which is a filter or kernel that initially has a random weight, and this weight will be updated during training. The output of this process is usually called a feature map [5]. Batch normalization works by equalizing the distribution on each input value that is constantly changing due to the parameter change on the previous layer during the training process. The goal is to optimize network training so that the learning process is faster, allows higher learning levels, makes weights easy to initialize, and makes more activation functions work well [6].

The activation function is a mathematical function added after a convolution process. ReLU (Rectified Linear Unit) is an activation layer with a function $f(x) = \max(0,x)$ that makes the entire pixel value minus zero on an image will be zero [5]. The pooling layer is a filter of a certain size that shifts across the feature map area. Max pooling is an operation that takes the maximum value of each patch (sub-region) on a feature map. Average pooling takes the average value of the entire patch on the features map. The purpose of a pooling layer is to reduce the down-sampling feature map, so it can speed up computing because the weight that needs to be updated is less and less without ignoring the important information in it to perform overfitting control.

Flatten layer is a process of reshaping features by me-reshaping feature maps into one-dimensional array vectors. The fully connected layer consists of the input layer, the hidden layer, and the output layer. The primary purpose of a fully connected layer is to process data so that image classification can be done. The output of this stage is the probability of the category when using the softmax activity for the output layer [5].

The softmax activation function is a generalization of the sigmoid activation function. The purpose of using this softmax activation is to calculate the probability of each target class among all existing target classes. The advantage of using these activations is that the output probability range is 0 to 1. Dropout regularization is a regulatory technique to prevent the model from overfitting, where a neuron is randomly selected and not used for training. These neurons are randomly removed. This results in the removed neuron contribution being temporarily discontinued and new weights not being applied to the neuron at the time of the backpropagation process.

VGG-16 model is a pre-training CNN model released by the Oxford Group. The VGG-16 model has 13 convolution layers, 5 max-pooling layers, and 3 fully connected layers within 6 blocks. There are 138 million trainable parameters. VGG-16 emphasizes the importance of depth in feature extraction and provides excellent results in a variety of image recognition tasks.

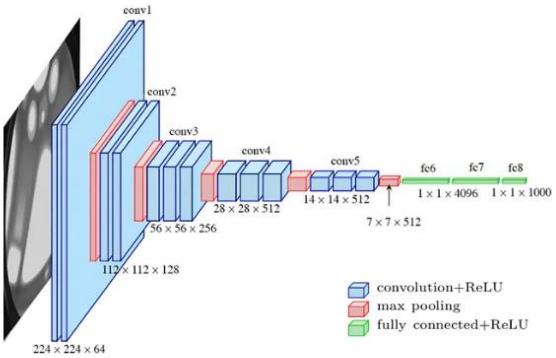


Fig. 2. VGG-16 architecture.

Transfer learning is a technique that utilizes pre-trained models to be used to classify new datasets, so there is no need to train data from scratch [7]. Transfer learning has two types, namely feature extraction and fine-tuning. A feature extractor is a transfer learning method used by freezing the layers of the pre-trained model. Fine-tuning is a transfer learning method used by utilizing the pre-trained model without freezing the neural network layer in the pre-trained model.

The result of the classification will be mapped into the confusion matrix. A confusion matrix is a matrix used to measure the performance of a classification model by comparing the information of a class to the result of the classification. There are four elements in the confusion matrix. The first is true positive (TP), which is when the actual class is true and the output also shows the true result. The next is true negative (TN), that is, the real-class condition is wrong and the prediction result is also wrong. Next, in the false positive (FP), the actual state of the class is wrong, but the predicted result is true. Last, the state of false negative (FN) is the state when the class is actually true but its prediction results are wrong [8].

	Predicted		
Actual	COVID-19 (0)	Intermediate (2)	non-COVID (1)
COVID-19 (0)	**TP**	(0,2)	(0,1)
Intermediate (2)	(2,0)	**TP**	(2,1)
non-COVID (1)	(1,0)	(1,2)	**TP**

Fig. 3. Confusion matrix 3x3.

Measuring the performance of a classification model is an important thing to do to explain how good a proposed system is in a data classification. Some of the parameters that can be used to measure the performance of a classification model are accuracy, precision, and recall or sensitivity, and F1-score [9].

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

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

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

$$f1\ score = \frac{2\times Recall\times Precision}{Recall+Precision} \tag{4}$$

EXPERIMENTAL METHOD

The data processing of this study is divided into image processing and image data analysis. The CT dataset of COVID-19 lung scans and non-COVID images used each amounted to 1252 COVID-19 images and 1229 non-COVID images, totalling 2481 images. The image data was obtained from the CC BY-NC-SA 4.0 licensed machine learning data platform of Kaggle. The image processing stage is performed with several processes that can be seen in the following diagram.

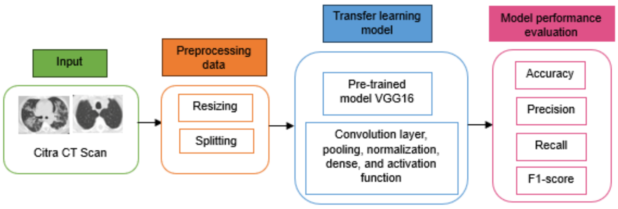


Fig. 4. Image processing diagram.

This section uses the supervised learning approach, which is a machine learning method where the model is trained using data that has been labelled before. Starting with the COVID-19 and non-COVID CT Scan image data input, the input data will be grouped into folders according to the disease label, then enter the pre-processing phase that consists of changing the image pixel size for the entire data to 224x224 so that it is uniform, followed by scanning the contents of the image-containing folder that will be used as data training to make it even better in the learning process. The next step is to divide the dataset into two, consisting of 80% of the images that have been collected as training datasets and 20% of the images that are used as testing data sets. The separation of datasets can be seen in Table 1 below.

Table 1. Separation of training and testing data

Dataset	Training Dataset	Testing Dataset	Total Data
COVID-19	1001	251	1252
non-COVID	983	246	1229
Total	1984	497	2481

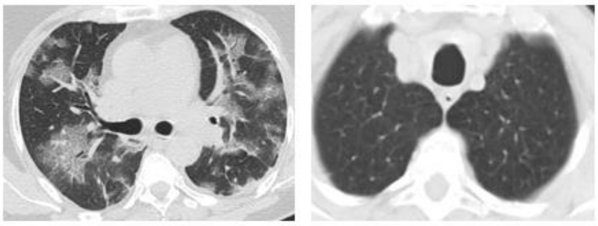
This research was conducted using Google Colab with a GPU runtime type of NVIDIA Tesla T4 and using Keras framework and TensorFlow version 2.15. Create a CNN model for the VGG-16 pre-trained architecture using the Keras library. The weights in the VGG-16 pre-trained layer will be retained and will be trained with new data. The model optimization used is the Adaptive Moment Estimation (ADAM) method which functions to update the weights in order to obtain weights that can minimize the loss function. And the loss function chosen is categorical entropy. To determine the best result, find the highest accuracy value and the least overfitting and underfitting in each parameter in the model. The parameters are batch size, learning rate, and number of epochs.

The model will be trained using CT scan image datasets that have been divided into training datasets. At this stage, the model is run with different epochs and learning rate parameters. Epochs are tested starting from epoch 5, and the best is 55, getting balanced accuracy between the training process and the testing process. The learning rate tested starts at 0.001, and the best is 0.003. While the batch size used is 32.

Image data analysis is carried out to evaluate the accuracy of the classification results. The determination can be seen from the plot of the training and testing curves of the model training results and can be obtained through the calculation of accuracy, recall, and precision measurement indices for measuring model performance from the confusion matrix classification results for three classes (multiclass) of COVID-19, intermediate, and non-COVID output, with each class given a value range of 0.0-0.40 (non-COVID), 0.41-0.50 (Intermediate), and 0.51-1.0 (COVID-19).

RESULTS AND DISCUSSION

Image pre-processing is done to improve the quality of the image used before the learning process. The following is the input image of this research.



(a) (b)

Fig. 5. CT scan image of lung (a) COVID-19 and (b) non-COVID.

The output of this architecture model is 3 neurons (classes). Details of the layer parameters used in the model can be seen in Table 2. The total parameters of the developed VGG-16 architecture are 14,733,463.

Table 2. The parameter layer used to model the VGG-16 architecture

Layer type	Output Shape	Number Trainable Parameter
Input	224,224,3	0
Conv2D	224,224,3	84
VGG-16	7,7,512	14,714,688
Global Average Pool2D	512	0
Batch Normalization	512	2,048
Dense	32	16,416
Batch Normalization	32	128
Dense	3	99
Total Parameter: 14,733,463		

The results of this test are shown in Figures 6 and 7, where both show the journey of epoch results from 1 to 55 on the VGG-16 model. Figure 6 shows the accuracy results of training and validation are increasing, and the smaller the difference between the two, which means the more trained repeatedly, the more the model learns well. While in Figure 7, the epoch journey for the loss function is also seen in training and validation. The longer the difference between the two means, the higher the epoch value or trained continuously, the less underfitting.

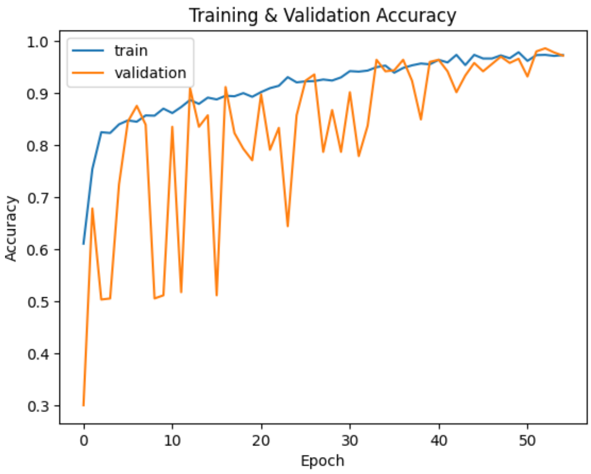


Fig. 6. Graphic plot of VGG-16 model train results for accuracy.

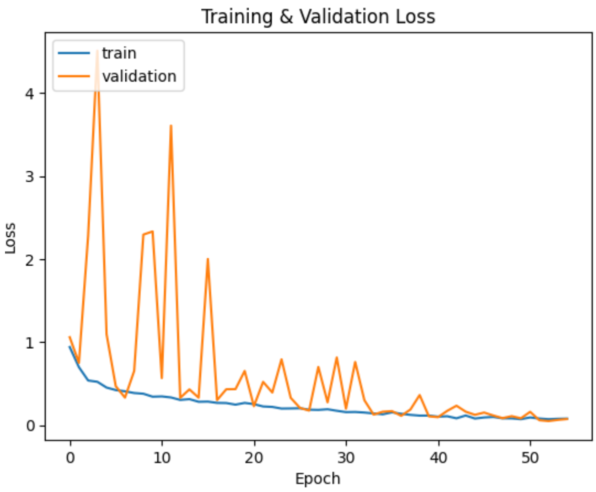


Fig. 7. Graphic plot of VGG-16 model train results for loss.

After the process is completed from epoch 1 to 55, a fairly high accuracy is obtained, namely 0.97 or 97%. When viewed from the results of the graph, it is concluded that the higher the epoch value, the accuracy value obtained tends to increase, while the loss will tend to decrease along with the increase in epoch value. The results of accuracy and loss values can be caused by the number of epoch values, learning rates, and other hyperparameters used. The curve results are also used to see the architecture model with parameters that produce curves with the least overfitting and underfitting, to determine which one is best for the data used in this study.

The following figure shows the confusion matrix for multiclass classification, which is the output of the evaluation method in this study.

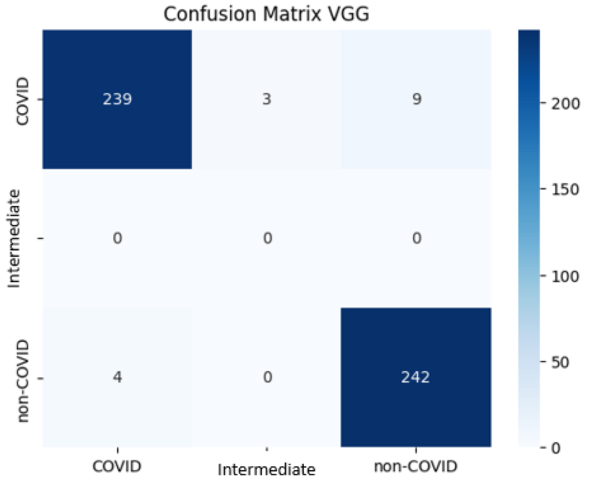


Fig. 8. VGG-16 model confusion matrix results in heatmap.

Predictions from the CNN model on testing data totalling 497 data points displayed in Figure 8 show good results. Class predictions are divided into three; for the COVID class, the correct number is 239. For the intermediate class, the actual value is 0 because the initial input of CT scan images has been labelled into two classes, namely COVID and non-COVID only, and the model used in this study uses the supervised learning method. Then there are classes that should be COVID, but the model classifies them into the intermediate class. There are 3 images due to the range of probability values given. As for the non-COVID class, there are 242 images. It should be COVID, but the model classifies it as non-COVID with as many as 9 images. And there are 4 images that should be non-COVID but are classified as COVID.

Calculation of system performance accuracy, recall, and f1-score for the classification of CT Scan images with pre-trained VGG-16 gets an accuracy value of 97% with a precision for COVID of 98% and a non-COVID image of 96%, for COVID recall of 96% and a non-COVID image of 98%, while the f1-score for both COVID predictions and non-COVID images is 97%. As for the intermediate class, everything is 0 because there is no TP value in this class because the model uses a supervised learning method.

CONCLUSION

Classification of CT Scan images with 3 output classes (COVID-19, Intermediate, and non-COVID) with pre-trained VGG-16 trained with ImageNet and using a supervised learning approach in the model obtained good results in testing with the dataset used in this study. The accuracy obtained is 97% with the parameters of epoch 55, learning rate 0.003, and batch size 32.

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