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Implementation of DeepLearning for Automatic Classification of Covid-19 X-Ray Images

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Abstract

*Background:*Reading radiographic images for Covid-19 identification by an expert radiologist requires significant time, therefore the development of an automated analysis system to assisting and saving time in diagnosing Covid-19 is important.

Objective: The purpose of this study is to implement the GoogleNet architecture with various epochs in hope achieving higher level of accuracy in Covid-19 detection.

Methods: We retrospectively used 813 images, i.e. 409 images indicating Covid-19 and 404 normal images. The deep TL model with GoogleNet architecture was implemented.The training was carried out several times to get the best acquisition value with a learning rate of 0.0001 for all levels. The network training was carried out with different epochs, i.e. 12, 18, and 24 epochs, and each epoch with 65 iterations.

Results: It was found that accuracy was determined by changes in the number of epochs. The classification accuracy was 96.9% in epoch 12, 98.2% in epoch 18, and 99.4% in epoch 24.

Conclusion: An increase in the number epochs increases the accuracy in the detection of Covid-19. In this study, the accuracy of the method reached 99.4%. These results are promising for the automation of Covid-19 detection from radiographic images.

Keywords: COVID-19; Transfer Learning; X-ray Images; Deep Learning; Convolution Neural Network; GoogleNet

Introduction

Coronavirus (Covid) is a family of viruses that cause diseases in humans from the common cold to advanced respiratory syndromes such as Middle East Respiratory Syndrome (MERS-COV) and Severe Acute Respiratory Syndrome (SARS-COV) [1, 2]. Covid-19 is a coronavirus that was first discovered in humans in late 2019 in Wuhan, China. Many people are currently infected and are being treated in hospitals throughout the world. On September 29, 2020, the World Health Organization (WHO) published that more than 333 million people were confirmed to be infected by Covid-19 and more than 1 million people had died [3].

Real time polymerase chain reaction (RT-PCR) is the main modality in diagnosing Covid-19, but it has low sensitivity in early cases. Other external factors, such as sampling operations, specimen sources, sampling time, and the performance of detection devices, influence the results of RT-PCR testing so that the tests must be carefully controlled [4-7]. In addition to RT-PCR, a radiological examination such as digital radiographic (DR) modality also has a role in investigating Covid-19. It has been demonstrated that the Covid-19 infection can be diagnosed from chest X-ray images [8]. WHO and the Centers for Disease Control and Prevention guidelines (CDC) established that DR was an additional component in the SARS outbreak diagnostic besides RT-PCR [9].

It is reported that Covid-19 attacks the epithelial cells lining the respiratory tract, so that DR can be used to analyze the patient's lungs [10]. A normal lung image appears dark, while white dots that appear on the image are nodules or small growths on the lung tissue. Meanwhile, in patients with Covid-19 infection, white spots appear on the lungs. However, the spots on the lungs don't really directly identify the Covid-19. This phenomenon can appear in several types of infections such as bacteria or viruses. The only way to identify the difference is to carefully identify its shape and distribution within lungs image. It is reported that Covid-19 infection generally spreads to the corners of the lungs. Hence, reading radiographic images by an expert radiologist requires significant time, hence, the development of an automated analysis system is needed to save time diagnosing Covid -19.

The automated analysis of Covid-19 generally implements a convolutional neural network (CNN) model with a transfer learning (TL) technique for feature extraction from chest X-ray images [11]. Many architectures have been implemented for automated Covid-19 detection, such as Xception [12], COVIDX-Net [13], UNet + 3D Deep [14], VGG-19 [15], InceptionV3 [16], ResNet-50 [17], ResNetV2 [15], MobileNet [15], and GoogleNet [18]. The previous studies reported promising results for automated Covid-19 identification with accuracies from 82.0% up to 99.1%. In the CNN, the accuracy of Covid-19 classification may depend on number of epochs. Hence, the current study aims to implement the GoogleNet architecture with various epochs in hope achieving higher level of accuracy in Covid-19 detection.

Method

1. Dataset

This study used the deep TL model with GoogleNet architecture to retrospectively classify Covid-19 chest X-ray images. The data set included 409 Covid-19 and 404 normal X-ray images. The Covid-19 images were taken from the database provided by Dr. Joseph Cohen, a postdoctoral fellow at the University of Montreal [19] and by Tawsifur Rahman in kaggle.com [20]. The normal images were obtained from Kaggle.com [21].

2. Deep TL architecture

The classification method implemented deep TL using GoogleNet architecture with 144 layers. GoogleNet had two convolutional layers, two pooling layers, nine inception modules, and a fully connected layer. The inception module had six convolution layers and pooling layers. This module consisted of 1 × 1, 3 × 3 and 5 × 5 filters in it. Feature maps with different filters were combined in the output of each module. In addition, 1 × 1 convolution was carried out before convolution by a larger kernel. This was intended to reduce the dimensions in the calculation [22]. The TL in this study was used to improve the CNN model with GoogleNet architecture and change the classifier to perfect the weight parameters in the target dataset. This technique was expected to speed up training and improve accuracy. The TL method took fully connectivity (FC) as an image representation with two node Softmax layers and classification layers [23]. Other parameters of the original model were preserved and used as initializations. The entire structure was then divided into two parts: the pre-training network and the transferred network [11]. The scheme of the deep TL with GoogleNet architecture is shown in Figure 1.

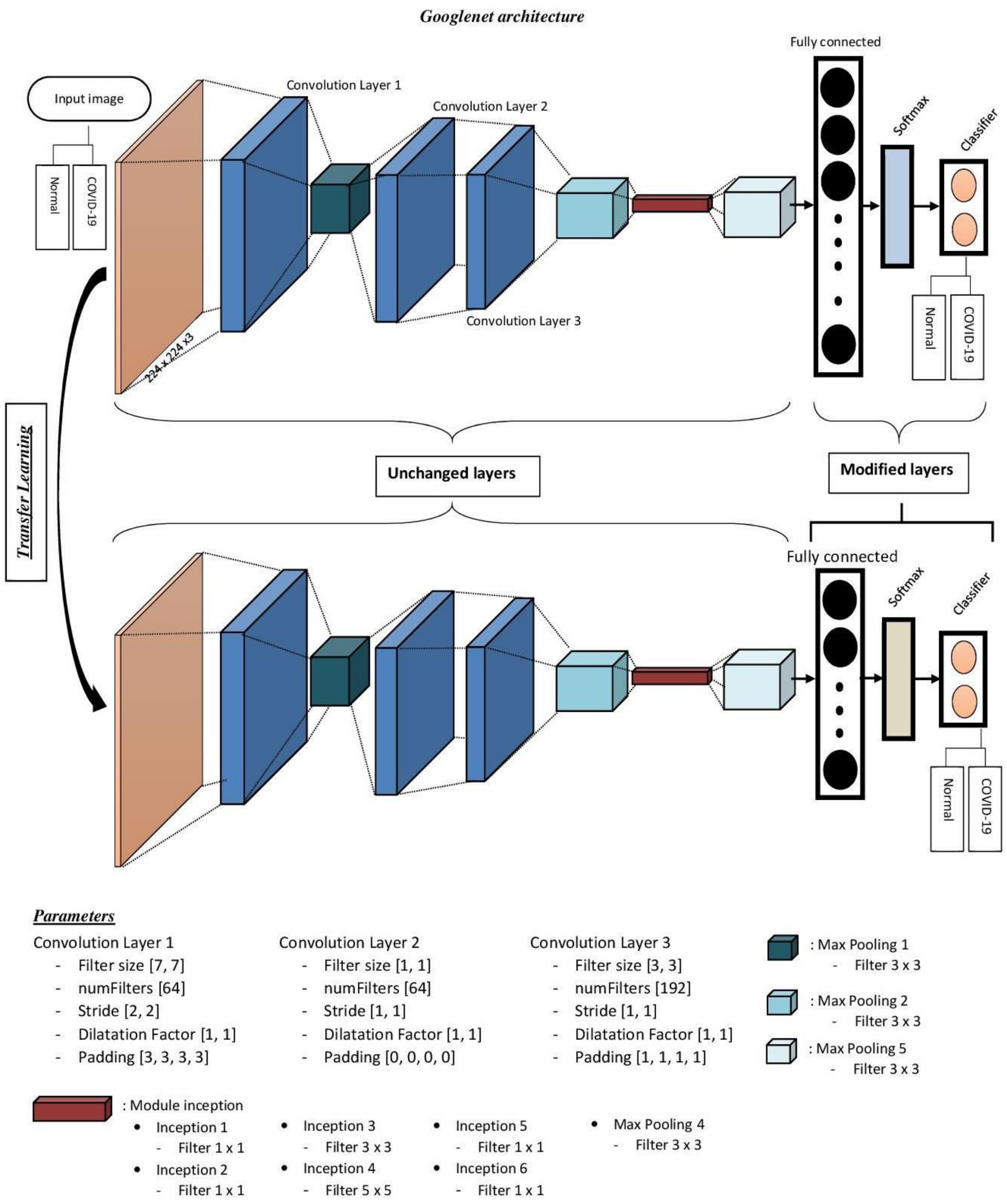

Figure 1. Deep transfer learning with GoogleNet architecture.

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The augmentation technique was used in an effort to improve validation and obtain better accuracy by performing various manipulations such as reflection and translation to create new images by maintaining the same label. Augmentation has been useful to overcome the problem of lack of sufficient training data. The classification model used in the final stages of the COVID-19 classification system used the Sofmax function to get the output for more than one class. The classification layer function was used by default to define the name of the output class of the validated image. Thus, the accuracy value could be obtained effectively to describe the system performance when using the test dataset. The stages of the research is shown in Figure 2.

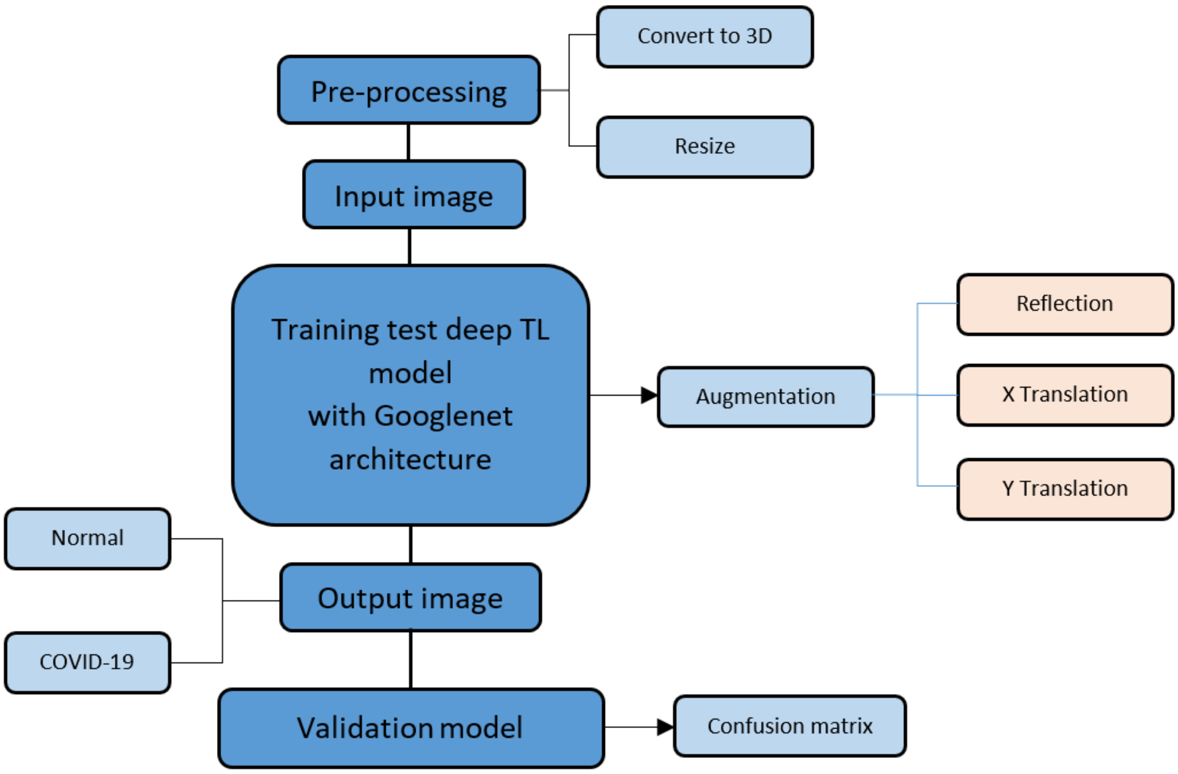

Figure 2.A block diagram representation of the model deep TL used.

3. Identification process

a. Pre-processing

Pre-processing was done by resizing the image from 1989 × 1482 to 224 × 224 and converting it into a three-dimensional (3D) image, so that it became 224 × 224 × 3with a value of 3 is the depth obtained using a different kernel.This stage was necessary to fit the specific design of the GoogleNet architecture (Figure 3).

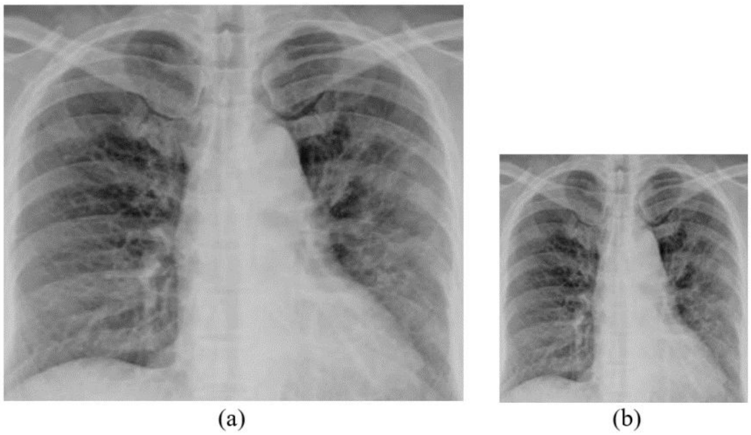

Figure 3.Image of patient infected by COVID-19. (a) original image size 1989 × 1482, (b) image with size 224 × 224.

b. Training test

The training was carried out several times to get the best acquisition value with a learning rate of 0.0001 for all levels. The network training was carried out with different epochs, i.e. 12, 18, and 24 epochs, and each epoch with 65 iterations. The number epochs of 12, 18 and 24 were considered as variation I, variation II, and variation III, respectively.

c. Performance classification

This model used 80% data (of 813 patients) for training and 20% data (of 813 patients) for testing. The results of the TL CNN classification with the GoogleNet architecture were obtained from each of the Covid-19 and normal images. The 20% data for testing consisted of 163 images, i.e. 82 Covid-19 and 81 normal images. The confusion matrix was used to measure performance at the classification stage because it contains information that can be compared to the results of classification. The classification performance measurement parameters are shown in Table 1.

Table 1. Confusion matrix performance measurement parameters.

Metrix	Formula	Evaluation focus
Accuracy	$\frac{TP_i + TN_i}{TP_i + FP_i + TN_i + FN_i}$	Measures the ratio of correct predictions to the total number of instances evaluated.
Error rate	$\frac{FP_i + FN_i}{Tp_i + FP_i + TN_i + FN_i}$	Measures the ratio of incorrect predictions to the total number of instances evaluated.
Sensitivity	$\frac{TP_i}{TP_i + FN_i}$	Measures the fraction of positive patterns that are correctly classified
Specificity	$\frac{TN_i}{TN_i + FP_i}$	Measures the fraction of negative patterns that are correctly classified.
Precision	$\frac{TP_i}{TP_i + FP_i}$	Measures the positive patterns that are correctly predicted from the total

		predicted patterns in a positive class.
Recall	$\frac{TP_i}{TP_i + TN_i}$	Measures the fraction of positive patterns that are correctly classified

Where*TP* is true positive, *FP* is false negative, *TN* is true negative and *FN* is false negative.

Result

1. Training test

The dataset was divided into 80% for training data and 20% for test data. The training test was conducted three times with epoch variations in each iteration andused augmentation techniques with reflection, translation on the X and Y axis.The training performance of CNN TL with GoogleNet architecture is tabulated in Table 2.

Table 2. CNN TL performance GoogleNet architecture with augmentation.

Augmentation	Variation I	Variation II	Variation III
	Reflection X translation Y translation	Reflection X translation Y translation	Reflection X translation Y translation
Epoch	12	18	24
Iteration	65	65	65
Max iteration	780	1.170	1.560
Learning rate	0.0001	0.0001	0.0001
Validation accuracy	96.93%	98.16%	99.39%

There are 65 iterations for each epoch with epoch values of 12, 18, and 24 epochs for variations I, II and III. Learning speed is an adjustment parameter in the optimization algorithm to determine the step size of each iteration that passes to the loss function, and is maintained at 0.0001. The validation accuracies are 96.93, 98.16, and 99.39% for variations I, II, and III, respectively.

The overall results of the training process are shown in Figures 4-6. The blue graph is the accuracy validation and the orange graph is the loss validation.Three training times were used. Figure 4 shows the results of the training for variation I. The accuracy and loss validations reached 96.93% and 3.07%, respectively. Figure 5 shows the results of the training for variation II. The accuracy and loss validations reached 98.16% and 1.84%, respectively. Figure 6 shows the results of the training for variation III. The accuracy and loss validations reached 99.39% and 0.61%, respectively.

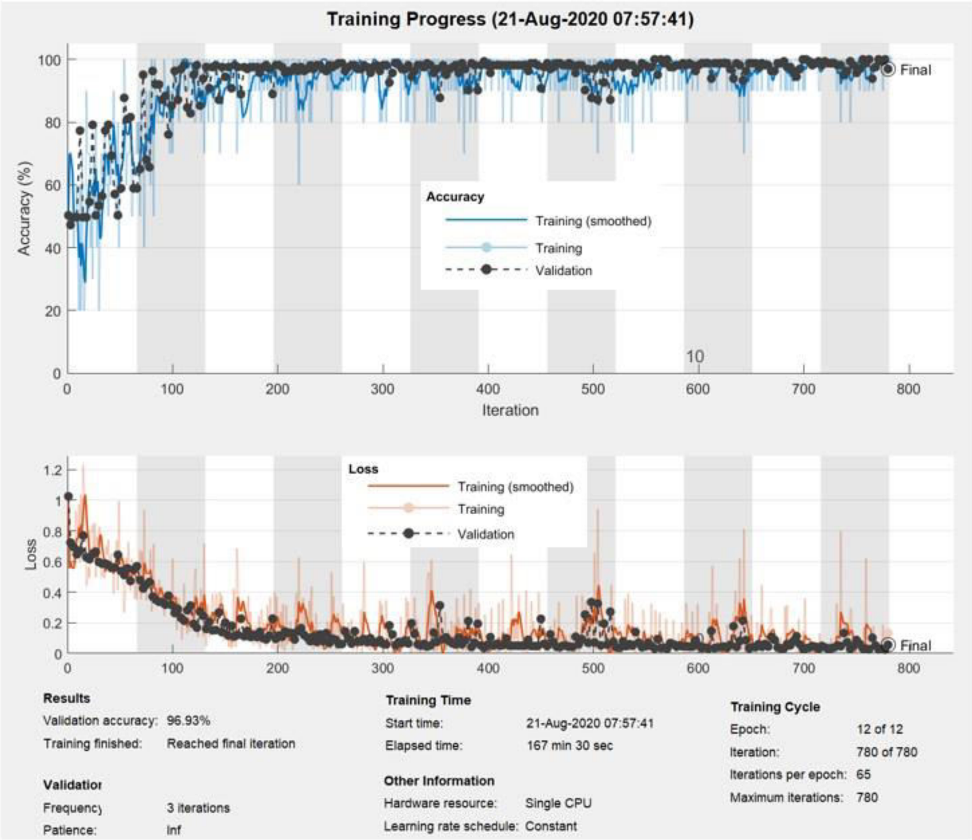

Figure 4. The results of the training progress for variation I.

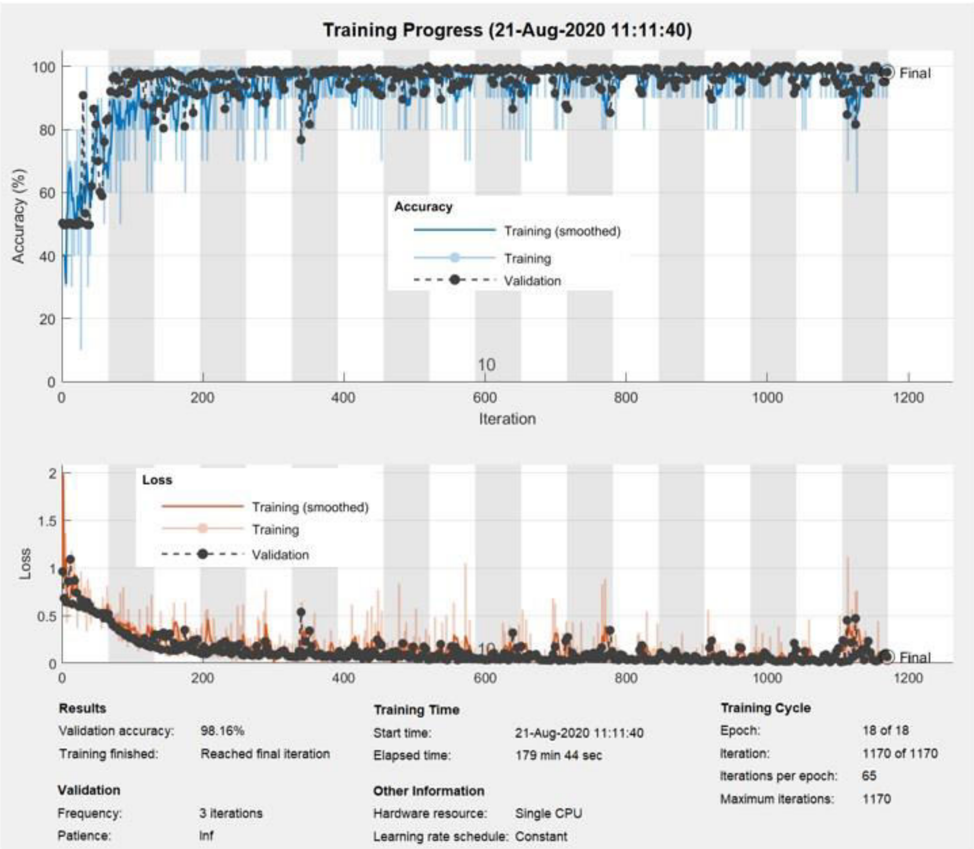

Figure 5. The results of the training progress for variation II.

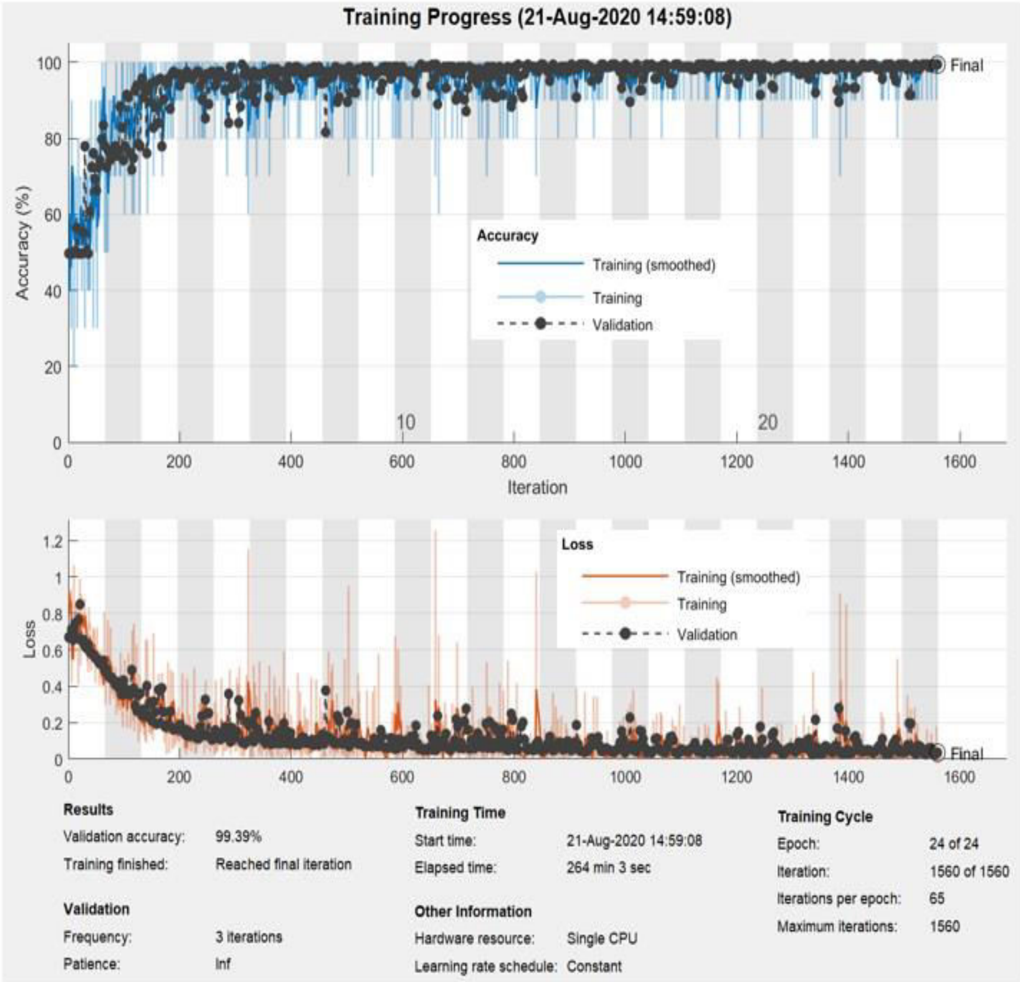

Figure 6. The results of the training progress for variation III.

2. Test results

The results of identification on 20% of the test data (a total of 163 images) are presented in a confusion matrix in Figure 7. The green column indicates the correct classification results (i.e. *true positive* for first row and *true negative* for second row). The red column indicates an incorrect classification result (i.e. *false positive* for first row and *false negative* for second row). (*True positive* is the COVID-19 image identified as COVID-19. *False positive*is the normal image but identified as COVID-19.*True negative* is the normal image identified as normal. False negative is the COVID-19 image but identified as normal).

The column at the right end of the plot shows the percentage of all classes of COVID-19 and normal. The bottom row of the plot shows the percentage of all examples of each class that are classified correctly and incorrectly.

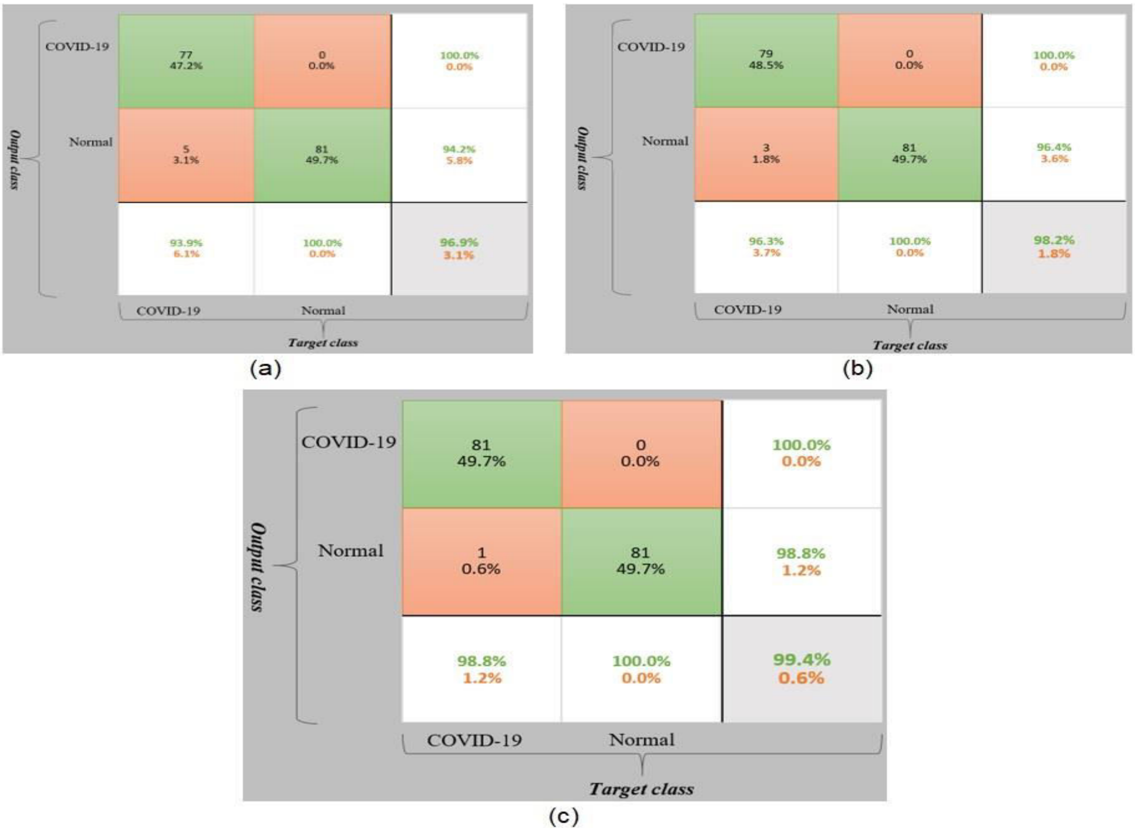

Figure 7. The results of the COVID-19 classification as a confusion matrix. (a) For variation I, (b) For variation II and (c) For variation III.

TP, *TN*, *FP*, *FN*,*accuracy*, *error rate*, *sensitivity*, *specificity*, *precision*, and *recall* for variations of I, II, and III are tabulated in Table 3. It is clear that variation III produces the highest performance compared to variations I and II. The accuracy in the variation III is almost perfect at 99.4%.

Table 3. The percentage values of performance of measurement parameters in terms of*accuracy*, *error rate*, *sensitivity*, *specificity*, *precision*, and *recall* for variationsof I, II, and III. *TP, TN, FP,* and*FN*.

Parameters	Variation I	Variation II	Variation III
TP	77	79	81
TN	81	81	81
FP	0	0	0
FN	5	3	1
Accuracy	96.9%	98.2%	99.4%
Error rate	3.1%	1.8%	0.6%
Sensitivity	93.9%	96.3%	98.8%

Specificity	100%	100%	100%
Precision	100%	100%	100%
Recall	48.7%	49.3%	50%

Discussion

This study presented the deep TL model for the identification of Covid-19 within chest X-ray images. This study focused on chest x-ray images because DR is more commonly used than CT in hospitals, especially in Indonesia. Additionally, because Covid -19 attacks the epithelial cells lining the respiratory tract, the DR chest image might be an accurate and fast tool for diagnosing Covid -19. WHO and CDC have established DR modality as additional component in the diagnosis of SARS disease aside from PCR [9]. Several studies related to the model to automatically diagnose Covid -19 from chest X-ray images are presented in Table 5.

Table 5. shows various studies using extraction and classification algorithms with different features to classify Covid -19 data. These studies used the same X-ray modality. It can be noted that various classification methods and systems used in previous research are ReNet + Custom VGG [24], DeTrac and ResNet18 [25], ResNet50 [26], ResNet50, Incenception V3 and ReNet V2 [27] as the architecture used in the classification system training. The augmentation technique used: rotate, shear, reflection [24], horizontal flip, random rotate, random zoom, random lighting, random warp [26] in order to increase training data. The final stage for classification is the support vector machine (SVM) [24, 25, 27] and fast artificial intelligent (fastAI) [26].

Table 5. A comparison of classification studies for Covid-19 from X-ray images.

Studies	Image		CNN architecture	Augmented		Classification	Accuracy
	Covid -19	Normal		Method	Parameter		
Hussain and Khan [24]	150	150	ReNet + Custom VGG	Rotate	[-5, 5]	SVM	98%
				Shear	[-0.05,0.05]		
				Reflection	X: [-1, 1], Y: [-1, 1]		
Abbas et al [25]	105	80	DeTrac - ResNet18	-	-	SVM	95.1%
Bukhari et al [26]	89	93	ResNet50	Horizontal flip	0.5	AI API	98.2%
				Random rotate	[-10, 10]		
				Random	[0, 10]		

				zoom			
				Random lighting	-		
				Random warp	[-0.2, 0.2]		
Narin et al [16]	50	50	ResNet50	-	-	SVM	98%
			Inception V3				97%
			ReNet V2				87%
Current study	102	104	GoogleNet	Reflection	[-30, 30]	Softmax	**Variation I** 96.9%
				X Translation	[-30, 30]		**Variation II** 98.2%
				Y Translation	[-30, 30]		**Variation III** 99.4%

In this study, the popular GoogleNet model was used. In addition, this study used a transfer learning-based approach to classify Covid-19 and normal X-ray data. The image classification system used Softmax. The main advantage of Softmax that the output probability ranges from 0 to 1 and the sum of all probabilities will equal 1. In addition, Softmax used the exponential (e-power) of the given input value and the sum of the exponential values of all the values in the input. Then the exponential ratio of the input value and the sum of the exponential values is the output of the Softmax function. The accuracy reaches 96.9% in epoch 12, 98.2% in epoch 18, and 99.4% in epoch 24. Thus, the accuracy obtained in this study (epoch 24) is higher than previous studies.
The efficiency of the CNN model depends on large scale datasets, so we can get more parameters and get identical images according to the texture of the Covid-19 image. Therefore, a deep TL model can be improved by adding as many data sets as possible. In addition, some pre-processing techniques, such as filtering, denoising techniques, improving image quality, etc., will help to increase the percentage of predictions even though the dataset is relatively small. We hope to explore pre-image processing to achieve improved accuracy. Given the scale of the Covid-19 pandemic world-wide, improved automation would greatly assist medical experts in the process of diagnosing Covid-19.

Conclusions

In this study, we implemented a CNN model with the TL approach and evaluated the number of epochs for Covid-19 classification of chest X-ray images. The architecture used GoogleNet as a model design, and augmentation techniques were used to increase the size of the dataset and increase accuracy.It was found that accuracy was determined by changes in the number of epochs. The classification accuracy was 96.9% in epoch 12, 98.2% in epoch 18, and 99.4% in epoch 24.

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