EVALUATION OF THE NUMBER OF EPOCHS IN AN AUTOMATED COVID-19 DETECTION SYSTEM FROM X-RAY IMAGES USING DEEP TRANSFER LEARNING

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ABSTRACT

This study aims to evaluate the number of epochs for automated COVID-19 detection from X-ray images using GoogleNet architecture. We used 400 digital X-ray images, with 200 COVID-19 and 200 normal. Each digital image has 1989 × 1482 pixels. To match the pixel size of the GoogleNet architecture (224 × 224 × 3), the pixel size of the original images was resized accordingly. The 3 layers of images were obtained from different kernels. Augmentation techniques of reflection and translation were used to augment the data by maintaining the same labels in the learning process. The training was conducted several times with a learning rate of 0.0001. The training was carried out with different numbers of epochs, i.e. 18, 18, and 24, and the number of iterations was 32. 80% of the data were used for training, and 20% were used for testing. The main output measuring a parameter of the identification was "accuracy". The accuracy is 96.25% at epoch 18, 97.50% at epoch 24, and 100% at epoch 30. It is shown that increasing the epoch numbers will increase the prediction accuracy for COVID-19.

KEYWORD: *Image Processing; Covid-19; Transfer Learning; X-ray Images; Deep Learning; Convolution Neural Network; GoogleNet*

I. INTRODUCTION

Coronavirus (COVID-19) was originally found in Wuhan, China has spread quickly worldwide since late 2019. COVID-19 is a virus that causes diseases in humans and is transmitted by humans. The virus is referred to SARS-CoV-2. It belongs to the same family as that of SARS and MERS, but with a more virulent and aggressive nature (2019-nCoV) and it spreads much faster (through respiratory droplet infection) than normal flu. The typical clinical features of COVID-19 include fever, cough, sore throat, headache, fatigue, muscle pain, and shortness of breath [1-3]. The World Health Organization (WHO) announced in November 2020, that more than 58 million people had been infected with Covid-19 and more than 1 million people had died [4]. The disease has a mortality rate of 2%, due to massive respiratory failure and alveolar damage [5].

Currently, the gold standard diagnosis for COVID-19 is viral nucleic acid detection using a real-time polymerase chain reaction (RT-PCR) [5-11]. In addition to RT-PCR, radiological images of the digital radiographic (DR) modality can contribute to detecting Covid-19. It is reported that an early stage of COVID-19 can be identified from X-ray images [12]. WHO and Centers for Disease Control and Prevention (CDC) guidelines stipulate that DR is an alternative component in SARS outbreak diagnostics [13].

Normal lung X-ray images appear dark, while those infected with COVID-19 have white patches on the lungs. Although it is not certain that the spots on the lungs are due to COVID-19 infection, the indication for COVID-19 can be identified by identifying the type and redistribution of the lung image. In general, COVID-19 stretches to the lungs' corners [13, 14]. Other characteristic findings in the lungs associated with COVID19 can be identified by chest radiographs. It is important to develop an automated analysis system to aid and hasten the diagnosis of COVID-19 by radiologists.

A convolutional neural network (CNN) model is commonly used for the automatic recognition of COVID-19 [16,[17]. Many architectures of automatic COVID-19 detections had been implemented, such as Xception, COVIDX-Net, UNet + 3D Deep, VGG-19, InceptionV3, ResNet-5, ResNetV2, and MobileNet. The results of studies for automatic detection of covid-19 have been reported. A 90% accuracy was reported by Hemdan et al [18], a 98% accuracy by Hussain et al [19] and Narin et al [20], and a 98.2% accuracy by Bukhari et [21]. The accuracy of the detection may depend not only on the architecture used but also on the epoch numbers. Therefore, this research aims to evaluate the epoch numbers using GoogleNet as architecture in the hope of achieving a higher level of accuracy in the detection of COVID-19.

The presentation of the paper is organized as follows. In the introduction, the background of the research is presented. Furthermore, in the second part, it is explained briefly about the deep transfer learning model and the parameters in the identification process. Then in the third part displays and discusses the training process and test results on the developed model. The fourth part is to discuss the results of the model developed and an explanation of previous research. Then, in the last section, are the conclusions and developments in future research.

II. RESEARCH AND METHODS

2.1 Dataset

In this research, X-ray images obtained from two different sources were used for the diagnosis of COVID-19. Dataset was obtained from Dr. Joseph Cohen, a postdoctoral fellow at the University of Montreal [22–24] and by Tawsifur Rahman at kaggle.com [25, 26]. We used 200 images of COVID-19 and 200 normal images. The size of the images was 1989 × 1482 pixels. In order to match the pixel size of the GoogleNet architecture (224 × 224 × 3), the pixel size of the original images was resized accordingly. The 3 layers of images were obtained from different kernels.

2.2 Deep transfer learning architecture

Transfer learning (TL) is a method for expediting the learning of a system. It can be achieved by using the information obtained from other similar problems and applying it to some unique but related problems [27, 28]. It is possible to do transfer learning in a deep neural network in two ways. The first approach involves the extraction of features using transfer learning, where the original convolutional neural network (CNN) model is treated as an extractor of features, and on top of that a new classifier is trained. To achieve better performance, the second approach requires network adjustment to pre-trained models. Typically, according to the particular task at hand, certain blocks in these models are replaced with new fine-tuned ones. Often fully connected (FC) layers are replaced by a new FC head in the original pre-trained model whose weights are initialized randomly [28, 29].

In this research, we used GoogleNet architecture in the deep transfer learning model. GoogleNet has three convolutional layers, two pooling layers, nine inception modules, and a fully connected layer [30]. The inception module had six convolutional layers and pooling layers. Feature maps with different filters were combined in the output of each module [30]. The second method was used, namely modifying the network to a trained model to get better results. This technique helps FC layers to begin to learn the patterns from convolutional layers that are highly discriminatory and feature-rich. The entire network is enabled to train (unfreeze) with very little learning to achieve adequate accuracy on the new task after FC layers have begun to learn the patterns of a new dataset [28]. Full connectivity (FC) was taken with Softmax layers and a classification layer as an image representation [31]. Initialization was

obtained from the stored original model parameters. The entire system was then split into two parts: the network of pre-training and the network transferred [16].
Augmentation techniques were used to augment data by maintaining the same labels so that they can improve validation and accuracy. In this study, the augmentation techniques were reflection and translation. Augmentation may be a solution for resolving the issue of lack of data from preparation. By design, the classification function layer is used for defining the image output class. The research stages are shown in Figure 1.

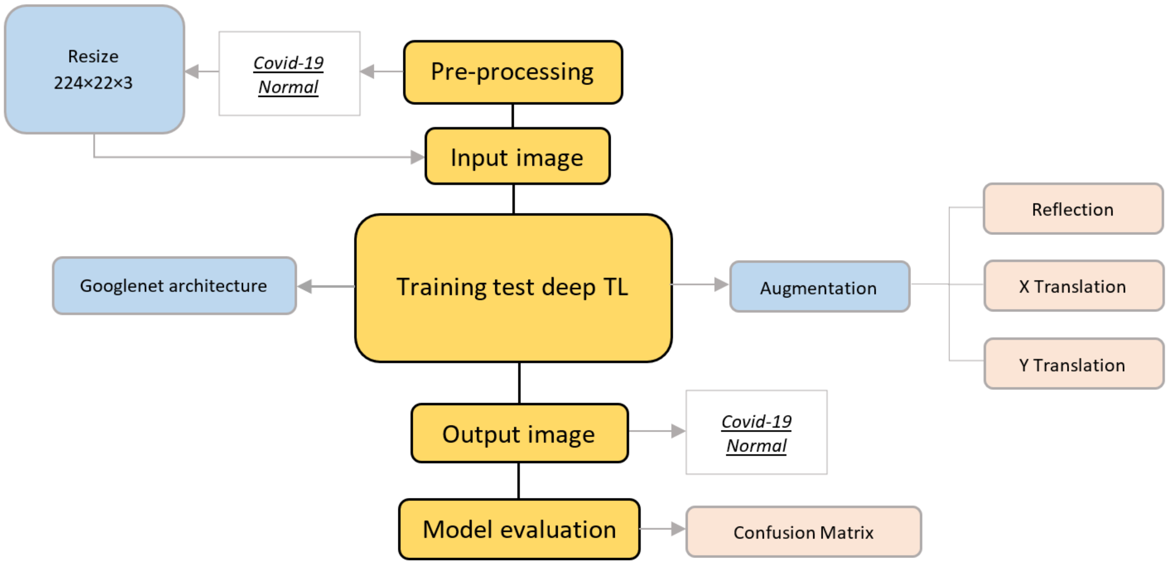

Figure 1. A block diagram representation of the deep model transfer learning (TL) used.

2.3 Identification process

The identification process was carried out by conducting training. The training was conducted several times with a learning rate of 0.0001 at all levels. The training network was carried out with different numbers of epochs, i.e. 18, 24, and 30 using 32 iterations. For calculating the performance of the identification system, a confusion matrix is used. We divided the data into two quarters, 80% for training, and 20% for testing. The results of the confusion matrix were obtained from 20% of the Covid-19 images and normal images of each data test. The output measuring parameters of the identification were true positive (TP), true negative (TN), false positive (FP), false negative (FN), accuracy, error rate, sensitivity, specificity, precision, and recall [32]

III. RESULT

3.1 Training test

We used the deep transfer learning (TL) model with GoogleNet architecture to detect and classify the X-ray images of COVID-19. The deep transfer learning model parameters with GoogleNet architecture are tabulated in Table 1.

Table 1. Parameter deep transfer learning with GoogleNet.

Architecture	Epoch	Iteration	Max iteration	Learn rate	Augmentation	Validation accuracy
GoogleNet	18	32	576	0,0001	Reflection X translation Y translation	96.25

	24	32	768	0,0001	Reflection X translation Y translation	97.5%
	30	32	960	0,0001	Reflection X translation Y translation	100%

In table 1 there are 32 iterations for each epoch with the epoch number values 18, 24, and 30. Iterations are repetitions, where the trained data is repeated 32 times for each epoch. The epoch is the average accuracy value resulting from the iteration process. The learning rate is a parameter in algorithmic adjustments for optimization of the step size of each iteration passing to the loss function. The augmentation technique (reflection and translation) is the process of adding data by flipping through the image. The validation accuracy was 96.25, 97.5, and 100%, respectively.

3.2 Test result

We measured the deep transfer learning performance. The confusion matrix results from 20% of the data testing (total of 80 images) are shown in Figure 2. The green column is the result of the classification that the identification correctly (i.e TP for the first row and TN for the second row), and the red column is the result of the incorrect classification (i.e. FP for the first row and FN for the second row).

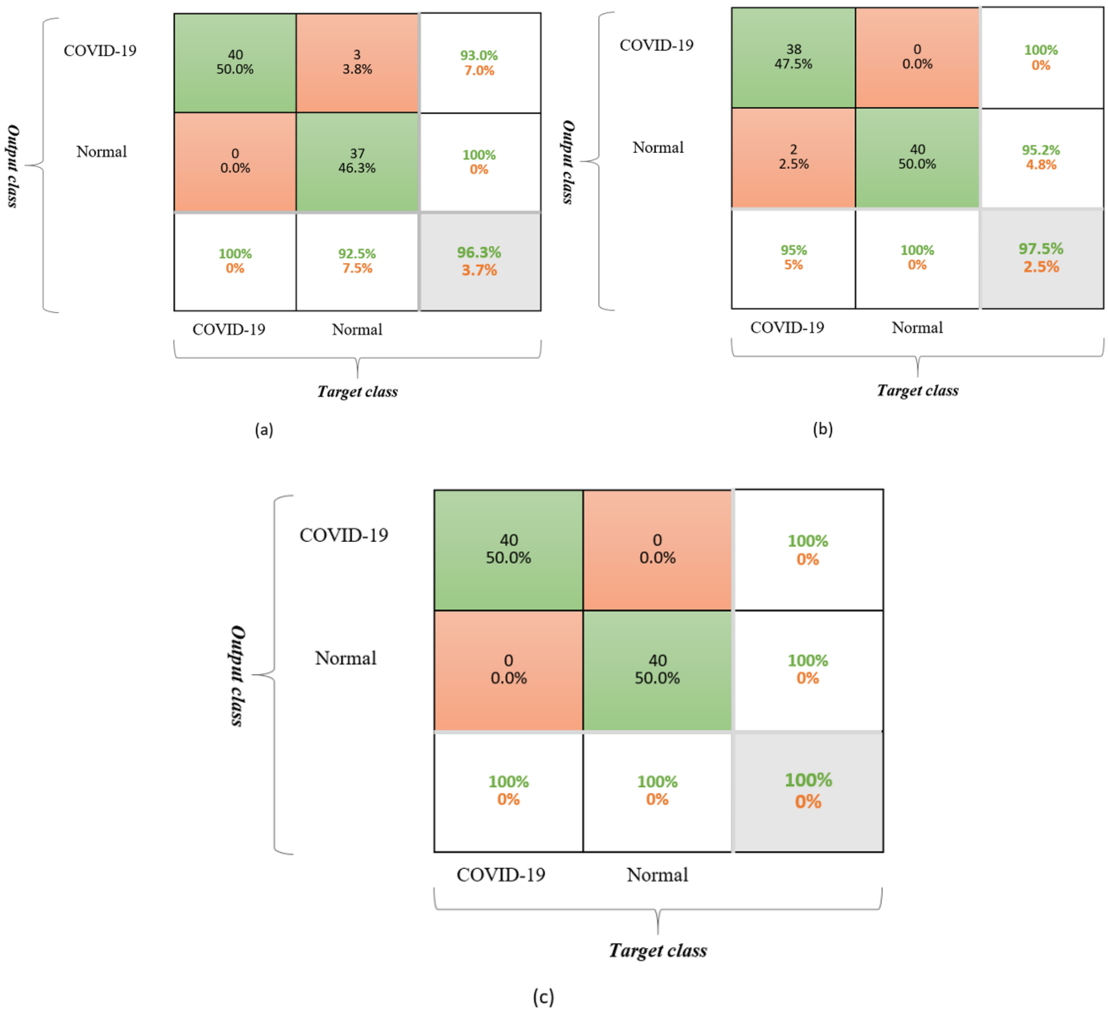

Figure 2. Performance of the confusion matrix identification system. (a) For the epoch-18, (b) for the epoch-24 and (c) for the epoch-30.

The column at the far right of Figure 2 shows the proportions of all COVID-19 classes and normal (the first row is precision, while row two is accuracy and error rate). The bottom row of the plot shows the proportion of all samples from each class classified correctly and incorrectly. (The first column is sensitivity and the second column is specificity). The results of the identification performance of the confusion matrix for the epoch-18, 24, and 30 are tabulated in Table 2. It shows that epoch-30 reached a precision of 100%, higher than the epoch numbers 18 and 24.

Table 2. The performance parameters of the confusion matrix

Parameters	TP	TN	FP	FN	Accuracy	Error rate	Sensitivity	Specificity	Precision	Recall
18 epochs	40	37	3	0	96.3%	3.7%	100%	92.5%	93%	51%
24 epochs	38	40	0	2	97.5%	2.5%	95%	100%	100%	48.7%
30 epochs	40	40	0	0	100%	0%	100%	100%	100%	50%

IV. DISCUSSION

This study aims to design a deep transfer learning model to automatically detect COVID-19 using DR X-ray images without specifically changing the features. DR was widely used in health centers around the world during pandemics. DR chest images can be an accurate and fast method for diagnosing Covid-19. A comparison of our result to several other studies is presented in Table 3.

Table 3 Comparison of the proposed COVID-19 diagnostic method with other methods developed using X-Ray images.

Study	Image Covid-19	Normal	CNN architecture	Classification	Accuracy
Hussain et al. [20]	150	150	ReNet + Custom VGG	SVM	98%
Hemdan et al. [18]	25	25	COVIDX-Net	SVM	90%
Sethy et al. [33]	25	25	ResNet50	SVM	95.4%
Narin et al. [19]	50	50	ResNet50 Inception V3 ReNet V2	SVM	98% 97% 87%
Current research	200	200	GoogleNet	Softmax	100%

In Table 3, several previous studies using automatic classification of COVID-19 using X-Ray images To improve the training data, augmentation techniques such as rotation, shearing, reflection [20], horizontal flip, random rotation, random zoom, random lighting, random warp [21] were used. The final stage for classification layers was machine support vector (SVM) [18–20, [33].

GoogleNet architecture was used in this current study, with a transfer learning-based model. Softmax was used as an image identification system. Softmax's main benefit is that it has a probability range of output from 0 to 1 and the sum of all probabilities will be equal to 1. Also, the exponential (e-power) of the given input value is used by Softmax. From the ratio of input values and the sum of exponential values, the output of the Softmax function is then generated. For epoch-18, 24, and 30, the accuracy achieves 96.25, 97.5, and 100%.Consequently, the accuracy obtained in this study (number of epochs 30) is higher than in previous studies.

Although, we achieved 100% accuracy in this study, further studies with more images are needed to confirm this finding, since relatively little data (i.e. 400 images) were analyzed in this study. The efficiency of the CNN model which relies on large-scale datasets to obtain more parameters and obtain images that are identical to the texture of the COVID-19 image. This can be overcome by using several pre-processing techniques, such as filtering, denoising techniques, image enhancement, etc., Thus, even if the data set is relatively minimal, it can actually improve the accuracy. Given the seriousness of the Covid-19 pandemic worldwide, increased automation will significantly help health professionals in the process of diagnosing Covid-19.

V. CONCLUSION

The deep learning model to automatically detect COVID-19 using DR chest X-ray images has been implemented. We evaluated the model with the epoch number for the identification of Covid-19 using GoogleNet architecture. We found that the accuracy was determined by the epoch numbers. The detection accuracy is 96.25% for the epoch-18, 97.5% for the epoch-24, and 100% for the epoch-30. We believe that such a model can be used as an initial diagnosis for helping medical professionals to identify COVID-19.
As consideration for future research, this model can be developed to identify the redistribution of white patches in the corners of the lungs on X-ray images obtained from patients with COVID-19 on the first day, second day, and so on, to identify the initial symptoms of COVID-19.

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