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Transfer Learning-Based Benchmarking Study for Diagnosis of COVID-19 from Lung CT Scans

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ABSTRACT

The virus known as Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) or Coronavirus Disease 2019 (COVID-19), which emerged from the city of Wuhan in the People's Republic of China, has affected the whole world. This disease, which is categorized as an epidemic disease, continues to increase despite the various measures taken. It is aimed to reduce death and infected people rates with vaccination studies, inspection and early diagnosis. On the other hand, new types of coronavirus cases are emerging and people are kept under surveillance to prevent the spread of the virus. By keeping the infected people under quarantine, the transmission of the epidemic to more people is prevented. For this reason, early diagnosis kits and tests are vital. Today, various abnormalities are detected by specialists thanks to medical imaging tools. On the other hand, this process is performed on medical images using image processing techniques. Thanks to methods such as image classification, image segmentation, image quantification and various operations such as object detection, localization and quantitative analysis on the object are performed. In this study, it is aimed to detect COVID-19 on lung CT scan images with deep learning methods. CNN-based state-of-art deep learning models, which were pre-trained with millions of images and applied transfer learning method for a similar problem, were used in this study. This process was performed by choosing VGG19, ResNet152 and MobileNetV2 models and the results were compared. According to the performance criteria, validation accuracy of 93.53%, 95% and 87.28% was obtained from VGG19, ResNet152 and MobileNetV2 models, respectively. These results show that these models give good results for the detection of COVID-19 from lung CT scan images.

1. Introduction

On December, 31, 2019, a new viral pneumonia outbreak has emerged in the city of Wuhan, the People's Republic of China. After the report published on the subject, World Health Organization (WHO) learned about the new coronavirus case for the first time. The disease caused by the new coronavirus known as SARS-CoV-2/COVID-19 [1]. According to the WHO report, this disease can be transmitted in many different ways, such as liquid particles coming out of their mouths and noses when talking, sneezing, coughing, yawning among people [2]. Thus, the virus spread rapidly and still does. According to the WHO report dated September 1, 2021, a total of 4.517.240 deaths and 217.558.771 confirmed cases were reported [3]. Therefore, early detection of the corona virus and taking measures such as quarantine against it and thus keeping the virus under control before it spreads to more people play a critical role. In this context, many diagnostic and detection methods are used. Molecular tests such as Polymerase Chain Reaction (PCR), isothermal nucleic acid amplification, antigen tests, antibody tests are just a few of them [4]. PCR is one of the frequently used molecular test methods to diagnose virus since the beginning of COVID-19. It is still used but has some limitations. Some these make this method expensive because the test method is complicated, delays in test reports, specialist laboratory personnel and special equipment are required [5]. This situation has led researchers to diagnostic kits with high detection success and less expensive, and in addition to all these, medical imaging methods have begun to come to the fore. T. Ai, Z. Yang and et al. [6] investigated the correlations between Chest CT and Reverse-Transcription Polymerase Chain Reaction (RT-PCR) tests in their study and reported that Chest CTs have high sensitivity for COVID-19 diagnosis and can be considered as the primary tool for current COVID-19 diagnosis.

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Medical imaging provides many advantages for the diagnosis of COVID-19. The data collected thanks to the medical images make facilitated the diagnosis with image processing techniques, computer vision, deep learning and various artificial intelligence applications such as CT image analysis [7], automatic coronavirus disease detection using X-Ray images [8], lung infection quantification of COVID-19 [9] and multi-class segmentation of COVID-19 chest CT images [10].

Convolutional neural networks (CNNs) are very successful networks in making meaning from image. Computer vision problems with CNN models used in various fields give very accurate results. There are various successful state-of-art CNN models such as ResNet [11], Xception [12], AlexNet [13], VGG [11] and many more [14].

In this study, research was carried out on the detection of COVID-19 disease on dataset which consists of lung CT scan images with the transfer learning method by using some state-of-art models.

2. Materials and Methods

Dataset, pre-processing, data augmentation, transfer learning and fine-tuning phases will be explained in this section.

2.1. CT Scan Dataset

In this study, the SARS-CoV-2 CT scan dataset [15] was used. The dataset consists of 2482 CT scan images collected from 1252 positive cases (COVID-19) and 1230 negative cases (non-COVID-19). This dataset consists of data from real patients collected from hospitals in Sao Paulo, Brazil. Some of the samples from dataset are shown in Fig. 1.

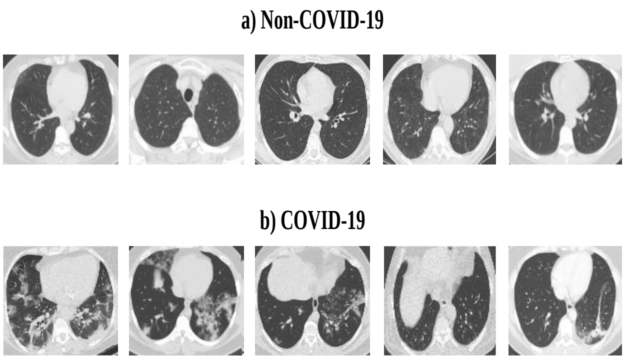

Figure 1. Samples from dataset [15].

2.2. Preprocessing

At this stage, the images in the CT Scan dataset serve to clean up the parts of the model that are not needed for better results. Here, thresholding has been applied on the images using Otsu's method [16] and both unnecessary values have been eliminated and background and foreground have been separated from each other.

In addition, all the images in the dataset were converted to a single format (.png) and the input size determined during the model training phase was adjusted to a fixed size (e.g., 224 x 224 x 3) (see Figure 2)

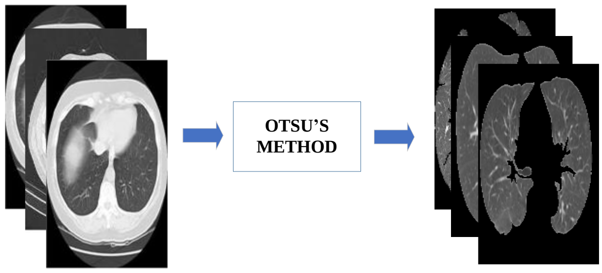

Figure 2. Otsu's method (thresholding)

2.3. Data Augmentation

Data augmentation is a method of increasing the amount of data by applying various changes (such as rotation, flipping, zooming, etc.) to the data in the existing dataset [17]. In this way, it helps to reduce the overfitting encountered during model training and the number of data has been increased. In this study, flipping and rotation processes were applied on images, both horizontally and vertically, as shown in Figure 3.

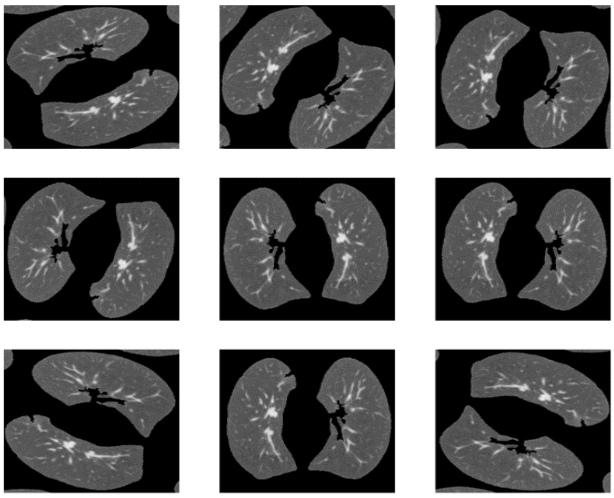

Figure 3. Data augmentation method shown on an image in the dataset (both rotated and flipped).

2.4. Transfer Learning

Transfer learning is a research problem in which the knowledge gained for one problem is used for another related problem. This allows us to achieve higher success rates with fewer datasets and faster learning for the model.

In this study, transfer learning was applied on the dataset we have in order to achieve faster learning and better results. Pre-trained CNN models were used to perform this operation. Some of these models used in this study are as follows; ResNet152 [18], VGG19 [11] and MobileNetV2 [19]. With these models, the binary class problem (COVID-19 and non-COVID-19) has been solved on the dataset consisting of lung CT scan images. The hyperparameter values selected for the created models are shown in Table 1.

Table 1. Some of Hyperparameters of Resnet152, Vgg19 and Mobilenetv2 Models

Hyperparameters	Values
Learning Rate	0.0001
Optimizer	Adam
Batch-Size	16
Epochs	30

During the model training, the binary cross entropy value for the loss function and the 0.3 dropout value for the regularization were selected. In addition, the model is set to interrupt the epoch automatically when the validation loss value falls below a certain value.

After the model training are completed, the graphs showing the accuracy and loss values of the CNN models are shown in Fig. 4, Fig. 5 and Fig. 6.

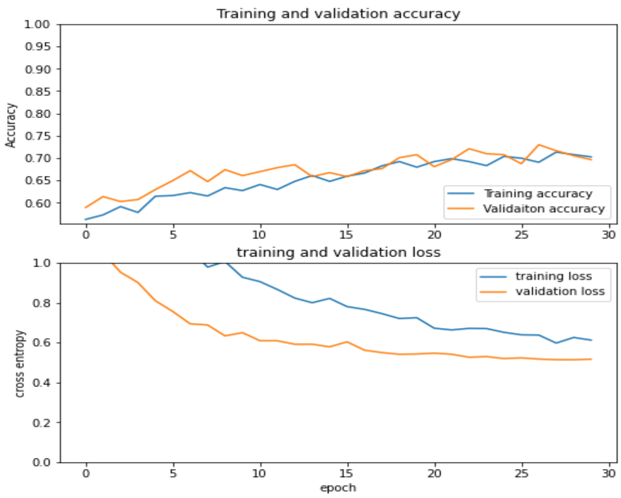

Figure 4. Accuracy and loss graph of VGG19 model for training and validation.

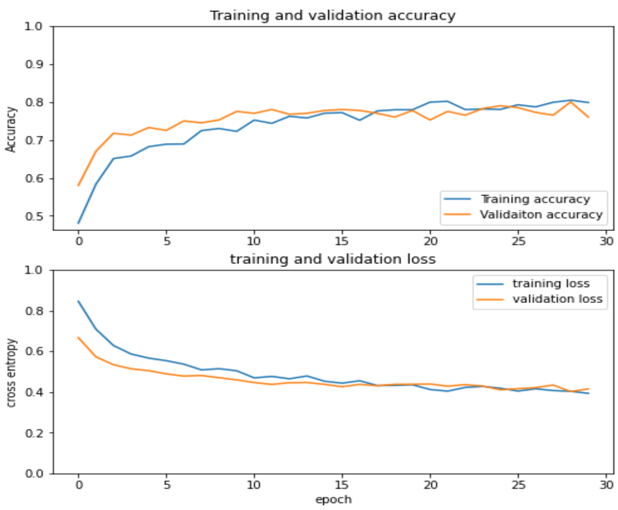

Figure 5. Accuracy and loss graph of ResNet152 model for training and validation.

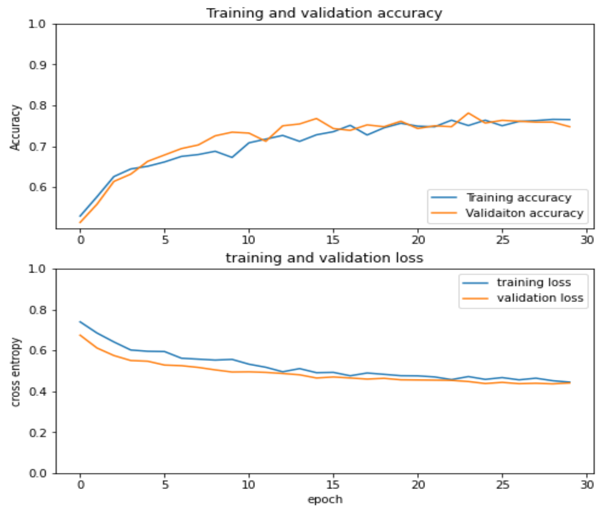

Figure 6. Accuracy and loss graph of MobileNetV2 model for training and validation

2.5. Fine Tuning

Fine-tuning is a process that takes a pre-trained model for a particular task and then adjusts or modifies the model to perform a similar task. In this way, the performance values of the model can be increased even more. Computer vision, face recognition, object detection, action and activity detection are being developed thanks to CNNs [20]. Therefore, CNN models are frequently used in transfer learning. Simply a CNN model consists of two main parts. These consist of the convolutional base part that is responsible for extracting features and the classifier part that provides the classification [21, 22]. It is possible to train models in three different ways, as seen in Fig. 7, in the convolutional base and classifier sections. The first is to train the entire model. The second is to freeze some layers in the model and train the remaining layers. The third is to freeze only the convolutional base part of the model and train the classification part.

3. Results

In this study, only the classifier part is trained during the model training before fine-tuning phase. Afterwards, some layers in the convolutional base part of the model were unfreeze and the model were retrained to perform fine-tuning.

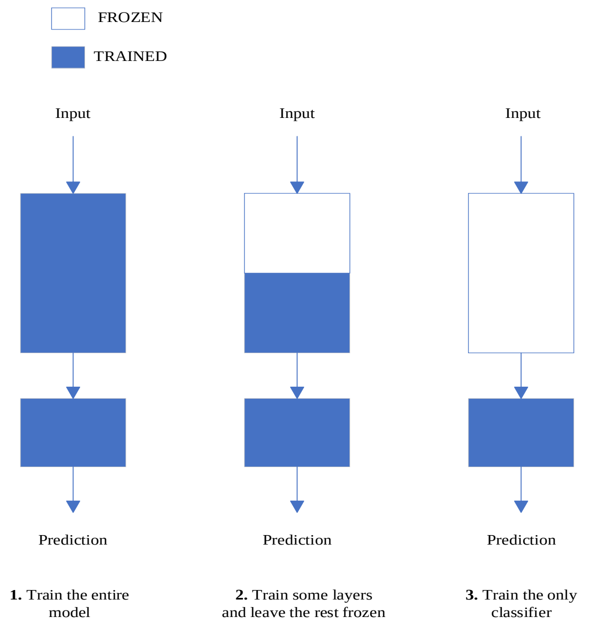

Figure 7. Fine-tuning strategies. 1. Train the entire model. 2. Train some layers and leave the rest frozen. 3. Train the only classifier.

In the fine-tuning phase, the epoch value is selected as 30 for retraining the networks, but for early stop operation, the training will automatically interrupt the iteration when the validation loss (val_loss) value falls below a certain value. In addition, at this stage, the learning rate (learning_rate) value will automatically and gradually decrease itself to obtain a more robust validation accuracy (val_accuracy). The frozen layers were selected as the first 8 layers for VGG19 model, the first 250 layers for ResNet152 model, and finally the first 90 layers for MobileNetV2 model.

After fine-tuning, the model results are shown respectively in the graph in Fig. 8, Fig. 9, Fig. 10 depending on the accuracy and loss values and compared with the values before fine-tuning phase.

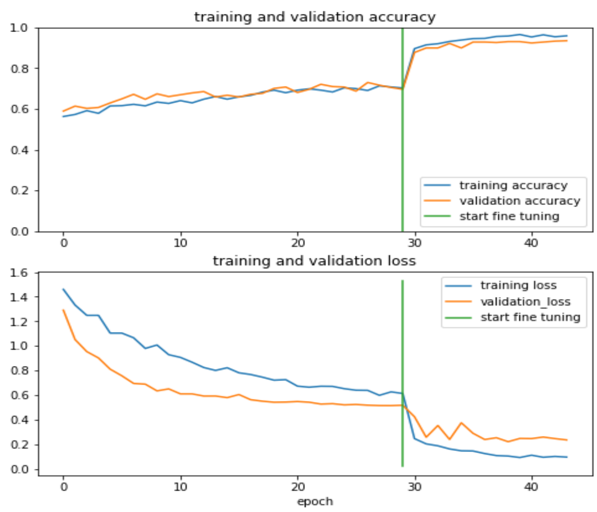

Figure 1. Accuracy and loss graphs of VGG19 model for training and validation after fine-tuning.

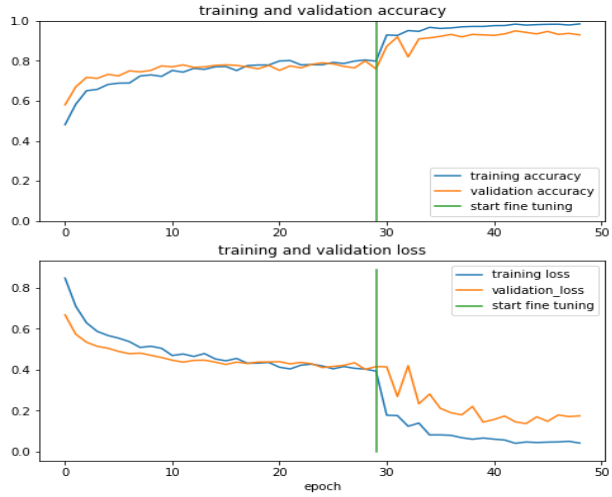

Figure 2. Accuracy and loss graphs of ResNet152 model for training and validation after fine-tuning.

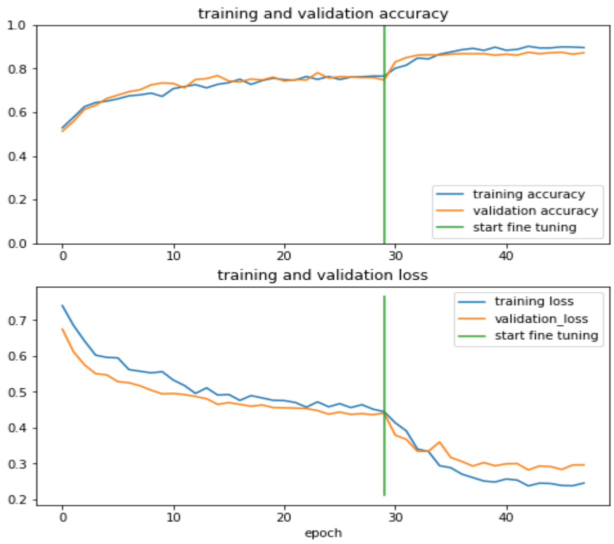

Figure 3. Accuracy and loss graphs of MobileNetV2 model for training and validation after fine-tuning.

Pre-trained CNN-based neural network models such as VGG19, ResNet152 and MobileNetV2, which were tried in this study, and then fine-tuning stage successfully classified the binary class problem (COVID-19 and non-COVID-19 classes). Obtained performance metrics from the CNN models are shown in Table 2. According to the results, ResNet152 obtained the best validation accuracy. Thus, the images reserved for the validation in the dataset were detected with 95% validation accuracy.

Table 2 Performance Metrics of CNN Models

Models	Accuracy	Loss	Validation Accuracy	Validation Loss
VGG19	0.9792	0.1815	0.9353	0.2343
ResNet152	0.9583	0.0397	0.95	0.1753
MobileNetV2	0.8838	0.2960	0.8728	0.2967

4. Discussions

The results obtained in the study show that COVID-19 can be detected quickly and without overfitting. CNN models in different architectures can provide different accuracy in COVID-19 detection. Different pre-processing methods can be tried to improve the dataset to be trained for the model. In this way, model success can be increased.

5. Conclusion

The results obtained from the trained VGG19, ResNet152 and MobileNetV2 models are 93.53%, 95% and 87.28%, respectively. Among these models, the ResNet152 model achieved higher validation accuracy than the other two models. In order to obtain higher results, different CNN models can be used, more data can be collected and the model can achieve higher results, and different pre-processing, data augmentation and hyperparameter selection can be made. Thus, the performance criteria obtained from the models can be compared with other models.

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