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Deep learning algorithms to improve COVID-19 classification based on CT images

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ABSTRACT

In response to the growing threat posed by COVID-19, several initiatives have been launched to develop methods of halting the progression of the disease. In order to diagnose the COVID-19 infection, testing kits were utilized; however, the use of these kits is time-consuming and suffers from a lack of quality control measures. Computed tomography is an essential part of the diagnostic process in the treatment of COVID-19 (CT). The process of disease detection and diagnosis could be sped up with the help of automation, which would cut down on the number of exams that need to be carried out. A number of recently developed deep learning tools make it possible to automate the Covid-19 scanning process in CT scans and provide additional assistance. This paper investigates how to quickly identify COVID-19 using computational tomography (CT) scans, and it does so by using a deep learning technique that is derived from improving ResNet architecture. In order to test the proposed model, COVID-19 CT scans that include a patient-based split are utilized. The accuracy of the model's core components is 98.1%, with specificity at 97% and sensitivity at 98.6%.

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1. INTRODUCTION

An ongoing pandemic that affects nearly all countries with wide-ranging health, economic, and in dividual effects is indeed in contact with the COVID-19 virus. Several procedures to control the COVID-19 pandemic have been implemented globally since the outbreak of the COVID-19 pandemic. Control and containment of the COVID-19 spread require rapid and accurate diagnosis of infected patients, prompt quarantine,and close monitoring. A reverse transcriptase-polymerase chain reaction (RT-PCR) is currently the most signif-icant test for COVID-19 disease identification (RT-PCR). Time-consuming and labour-intensive, the RT-PCR tests [1] require a lot of manual effort. Because of this, the COVID-19 disease is considered to be highly susceptible to the lack and restricted availability of RT-PCR test kits. As a result, for the diagnosis of COVID-19, chest imaging is a reliable alternative. COVID-19 can be diagnosed using computer tomography (CT) because of its high sensitivity, low misdiagnosis rate, and high commercial potential. Nonetheless, the accuracy of a chest scan's COVID-19 diagnosis depends heavily on the expertise of the medical team. COVID-19 is often misdiagnosed by radiologists and doctors for a variety of conditions, including pulmonary infections and pneumonia. A deep learning-based approach to artificial intelligence has been successfully launched, leading to a faster and more accurate diagnosis of COVID-19 and being an effective alternative to the RT-PCR testing tool [2]-[4]. Accurate images of the human body can be obtained using CT scans. The shape, size, texture, and design of internal structures can be seen clearly in CT images, which can be used to classify the structures. While traditional X-rays produce multiple slices of the same area of the body, CT scans produce only one at a time. In this way CT scans pro- vide a more accurate picture of the medical situation than X-Rays. Using this information, you can figure out whether or not a medical condition exists, and if so, what type it is and where exactly it is located.

Conventionally, the majority of the functions used in learning algorithms must be revealed by a subject matter expert in order to reduce the data's ambiguity and make trends more noticeable [5], [6], Deep learning algorithms, on the other hand, try to learn high-level features incrementally from data. There is no longer a need for specialized knowledge in a specific field or for arduous feature extraction techniques. Deep learning and machine learning models were significantly improved by convolutional neural networks. Several models, such as ResNet, Xception, contrastive learning, and VGG, were tested and found to have reliable results [7]-[13]. Convolutional neural networks significantly improved machine and deep learning models. The convolutional layers' emergence of several models such as ResNet, Xception, contrastive learning and VGG were implemented and revealed reliable outcomes [14]-[20]. Numerous studies in the literature have been published that depend on deep learning and convolutional neural network models to identify and recognize COVID-19 with CT images. The researchers in [21] developed a convolutional neural network model for COVID-19 classification based on CT scans of 120 people (2482 CT scans) were acquired, half of whom (60 people) had COVID-19, and several networks identified them, the most accurate of which was close to 97.38%. The researchers in [9] examined 287 patients' CT images, which covered three classes of COVID-19, or viral pneumonia, and healthy. After that, they applied a novel model to detect COVID-19. They classified the data with 91.6% accuracy.

Gozes *et al.* [10] introduced the ConvNet deep learning architecture to retrieve features that can be seen from lung CT scans for COVID-19 identification. They have implemented visual features to differentiate between infected and other not infected lung diseases. However, ConvNet is unable to classify the seriousness of this disease. Javaheri *et al*. [8] designed a deep learning model for COVID-19 identifying and quantifying. The method automatically retrieved slices of CT chest scans opacities. The developed system achieved 98.2% sensi tivity and 92.2% specificity. Singh *et al.* [12] introduced a deep learning tool to predict and differentiate COVID-19 from other viral pneumonia. For COVID-19 prediction, the CNN algorithm was implemented. The prediction model's maximum accuracy was 86.7%. Wang *et al.* [22] analyzed CT scans of infected patients with radiographic modifications. They developed a deep learning-based prediction model that utilizes the modified inception transfer learning technique, and the authors achieved a test accuracy of 89.5%. In health care systems, the diagnostic process of a specific disease is essential to early prevent the disease's severity and provide appropriate treatment. Thus, the demand for developing an effective automatic classification model is required, which is also the motivation of this study. There are various reasons for achieving such a goal, including: (1) as a result of the pandemic outbreak, the lack of numerous highly qualified radiologists increases the need for chest x-ray interpretation, (2) increasing number of cases with various progeny and mutations of the disease that require automated tools for recognition, (3) the heavy training of the effective convolution deep learning models makes the task is not scale-able to many images, and (4) on the CT images, the previous studies provide low performance in detecting the symptoms of the disease. Therefore, our contribution is to provide an advance deep learning technique for the early identification of COVID-19 infected patients from their lung CT scans images. The proposed model is based on the effective transfer learning model called ResNet-50. The architecture design of the proposed model is based on alleviating the connections between the blocks of the ResNet-50 model. This reduces the training time for scale-ability and handles the problem of vanishing gradi ent with relevant features on CT images. Furthermore, it provides an effective model of high performance. The proposed model is evaluated using a combination of two publicly available CT image datasets [21], [23].

There are sections of this study arranged in this way. Section 2 provides details on COVID-CT [23] and SARS-CoV-2 CT scan datasets [21]. There are two sections: section 3 explains the methods, and section 4 presents the experiments and promising results. Toward the end of section 5, the work's conclusion is introduced.

2. METHOD

COVID-19 image classification is a challenging task because of the wide range of color, size, and feature differences between covid and non-covid images. This section describes improved approaches for covid image recognition. Covid image classification is enhanced by combining ResNet architecture with FC in this approach. The proposed algorithm demonstrates the model's ability to recognize covid images. A binary cross-entropy loss function can be used to represent the loss function of covid image classification for each image. That's how we get the loss function: by looking at the original image. To achieve high-quality classification of COVID-19 in an image, the proposed method for covid image classification is used in this study. ResNet architecture is improved to extract more high and low features from a covid image, and new FC layers are added to improve the classification of covid images with improved ResNet architecture.

2.1. Pre-processing

One of the most frequent methods used in computer vision is pre-processing. In some cases, preprocessing methods can be used to remove unwanted noise, highlight image features that can aid in the identification, or even aid in deep learning. This study introduces an essential normalization of pixel intensity in the range [0,1]. To ensure model convergence during training, this pre-processing is essential. In addition; images for deep convolutional network models have been reworked so that they are compatible with network architectures. Both datasets had different spatial dimensions, so images had to be resized to match what was wanted as input. Stretching or excessive cropping can be used to merge images with different aspect ratios. In order to avoid violating copyright laws, we used a unique method to insert the image into a predetermined canvas. With padding, the desired shape could be accommodated while maintaining the original image's aspect ratio.

2.2. The architecture improvement of the proposed ResNet model

This study proposes an adaptive architectural design of ResNet to boost the training process at each layer. As a result, it improves the ResNet backbone's capacity. The following section defines a shortcut or bypass link. There seem to be several issues in ResNet, including a) identifying layers that have not received sufficient training; and b) identifying layers that have received excessive training, as shown in Figure 1(a). The suggested backbone is discussed in the following subsections.

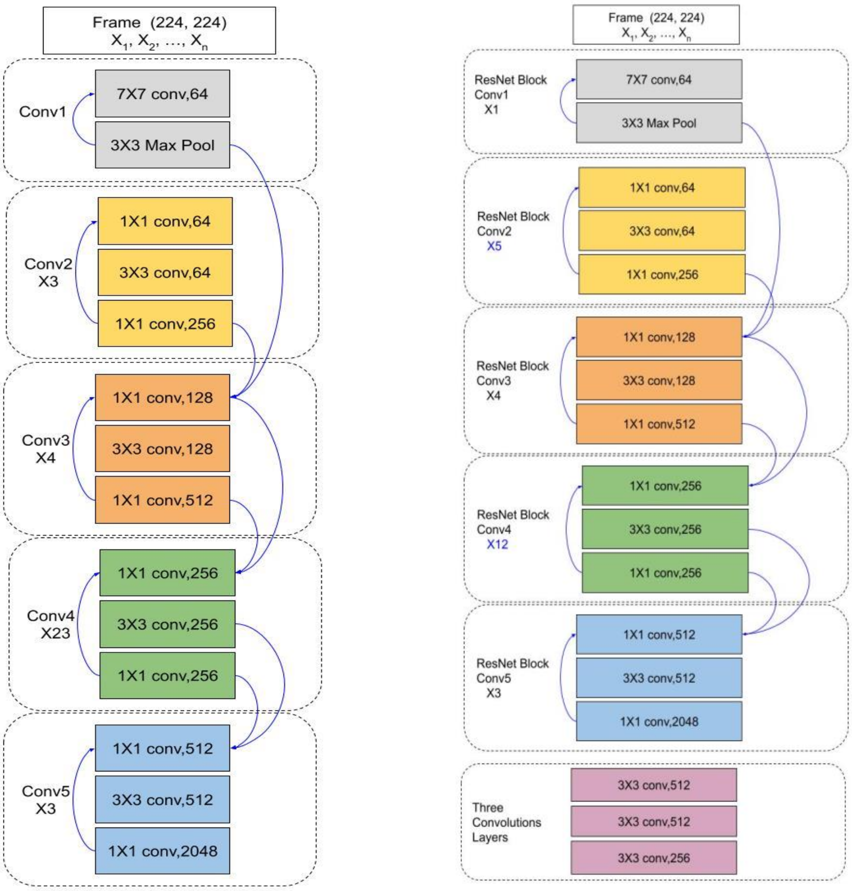
2.2.1. Our proposed adaptive ResNet architecture

In order to improve residual neural network performance and deal with the gradient disappearing issue, ResNet is a deep learning network that includes a series of blocks, as shown in Figure 1(a). Each ResNet block that requires additional training is trained on the output of the previous ResNet block in order to address the gradient diminishing problem. "Skip connection" concatenates the feature maps of a previous ResNet block output with the feature maps of a subsequent ResNet block, a process known as "skip-connection." In our approach, the process of adding ResNet blocks sequentially to the model ensures high-accuracy accuracy at every step. On the basis of how much accuracy can be achieved by attaching ResNet blocks, we generate the model architecture. Until an accuracy value is reached that appears promising, the proposed architecture model relies on iteratively repeating the ResNet blocks. Adopting such a method aids in reducing the network's size, which in turn reduces training time. For the purpose of extracting shallow layer feature maps, the proposed adaptive ResNet model includes three convolution layers in addition to the feature engineering design (see Figure 1(b)). There are a few blocks of ResNet that have high accuracy in the validation set, and then dense layers in the classification part.

2.2.2. Enhancing FC using batch normalization layer

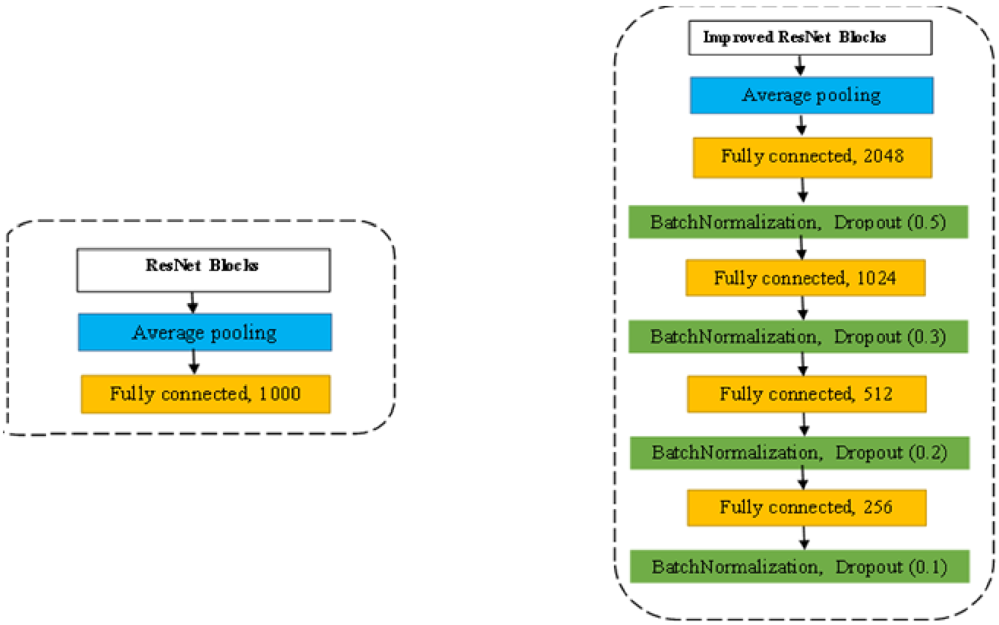
Using dropout and batch normalization to control overfitting and speed up optimization of the existing FC layer in Figure 2(a), the proposed improved FC is achieved as shown in Figure 2(b). For each batch, batch normalization allows our model to avoid internal covariate shifts, making our model more accurate and learning faster. As a result of the dropout, neurons are unable to establish context. For example, if a group of neurons is responsible for distinguishing a specific feature, and they are the only neurons capable of discerning that feature, another neuron will discover patterns that are necessary for obtaining high accuracy. As a result, in order to avoid a collapse of our model, we must use dropout.

The FC is used to determine the presence of the covid image or non-covid in the input image. The enhanced FC is used to manage multi-scale feature maps and produce the feature map for the image, as illustrated in Figure 2(b). Enhancing FC is accomplished by repeating batch normalization and dropout for images to obtain feature maps and achieve better accuracy. Figure 2(a) shows the existing FC layer.



(a) (b)

Figure 1. The derivative of the proposed ResNet model; (a) the baseline architecture model and (b) the proposed architecture model



(a) (b)

Figure 2. The derivative fully-connection layers of the proposed ResNet model (a) the existing FC layer and (b) the proposed enhanced of FC

3. TRAINING PHASE

Training deep learning networks, due to their complexity, require a huge number of images to avoid overfitting. Even so, data is limited for the vast majority of real-world problems. In reality, there are just a few cases when there is a plethora of data, like that of the ImageNet [24] dataset. Two approaches could be employed to overcome this issue: data augmentation and transfer learning.

3.1. Data augmentation

Data augmentation entails increasing the number of training images by transforming the images with out sacrificing semantic information. In this paper, we utilized four transformations to the training images: random rotation, flipping, random zooming, and scaling function as regularizing and helps avoid overfitting.

3.2. Transfer learning for CT-based COVID-19 diagnosis

Transfer learning is an efficient representational method where networks trained on many images are applied to initiate networks for tasks with limited data. This study used limited images for training, primarily from the covid dataset [4]. As a result, transfer learning is essential. Transfer learning from pre-trained networks can be applied in two ways in the context of deep learning: feature extraction and fine-tuning. This study recommends fine-tuning as a more successful approach that outperforms feature extraction and produces improved results in this paper, since whole weights are adapted for the current study.

4. RESULTS AND DISCUSSION

This section describes our experimental design as well as detailed tests to demonstrate the efficacy of our fine-tuned networks. First, we'll go over the experimental parameters. Second, we address datasets. Third, we address performance assessment metrics. Finally, we discuss the outcomes of our model on each dataset.

4.1. Experimental settings

The proposed approach utilizes stratified K-fold cross-validation with K = 5 to test the effectiveness of models, keeping the distribution of the two groups constant inside each fold. The final model values were calculated by merging the collected data from the five platforms on their effectiveness varied folds. The experiment was run on an intel (R) core (TM) i7-16 GB OF GPU with 13 GB of RAM, as well as the TensorFlow and Keras systems. The optimization method utilised in this design is Adam optimizer. Over 50 epochs for the SARS-CoV-2 CT Scan dataset [4] and 100 epochs for the COVID19-CT dataset [13], the weight decay was 0.0001, the learning momentum was 0.9, and the learning rate was 0.001.

4.2. Evaluation metrics

In this study, five performance evaluation metrics are used for evaluating models: Accuracy, precision, sensitivity, F1- score (F1) and specificity.

4.3. Datasets

This section proposes two datasets used in this study. To the state of the art, those are the two largest public datasets available to the public.

4.3.1. SARS-CoV-2 CT-scan dataset:

The SARS-CoV-2 CT-scan dataset [4] includes 2482 CT images among 120 patients, with 1252 CT imaging from 60 SARS-CoV-2 infected patients. SARS-CoV-2 infected males (32) and females (28), as well as SARS-CoV-2 infected males (30) and females (30) with pneumonia, are all included in this collection of 1230 CT images. Hospitals in the city of Sao Paulo, Brazil, provided information for this study. Unless otherwise noted, the images in this dataset are scans of paper CT scans (the dimensions of the smallest image in the dataset are 104 153, while the largest images are 484 416). According to [4], a process assessment protocol suggests arbitrarily dividing the dataset into training (80%) and test (20%) partitions.

4.3.2. COVID-CT dataset:

To establish the COVID-CT dataset [13], CT images of COVID-19 infected patients were collected from research papers (pre-prints) published in the medRxiv and biRxiv repositories between January 19 to March 25, and some CT images were provided by hospitals. To achieve high quality, CT images were derived from the manuscripts using the PyMuPDF tool. Patient age, gender, location, medical history, scan time, COVID-19 seriousness, and medical report were systematically derived and attributed among each image. A total of 349 CT images from 216 patients were obtained. The authors gathered CT images of non-covid patients through two additional datasets (MedPix and LUNA), the Radiopaedia website, and other articles and texts accessible at PubMed central (PMC) [25]. A total of 463 CT images from 55 patients were acquired. The COVID- CT dataset, such as the former one, has established standards for aspect ratio and contrast. It's also worth noting that certain images contain text data that may interfere with model prediction. A protocol for creating instruction, validation, and test sets is developed. The validation and test sets were established using COVID-19 images donated by hospitals and derived directly from medical equipment (LUNA and Radiopaedia). The remainder-derived from research articles - is set aside to form the training set.

4.3.3. Convolution layer result

The proposed model was chosen out of the specific number of convolution layers based on the acquired accuracies, as shown in Table 1. A selection of suitable convolution layers was carried out to improve the performance of our model. Based on Table 1, the most suitable number of the convolution layer is three convolution layers to explore more feature maps.

Table 1. Number of the convolution layer based on SARS-CoV-2 CT scan dataset

Model	Accuracy
Our model without convolution layer	94.2
Our model with one convolution layer	96.2
Our model with two convolution layer	97.6
Our model with three convolution layer	98.1

4.3.4. Result of the evaluation of the proposed enhanced FC layer on our backbone

Table 2 presents the results of the existing FC layer and proposed FC layer. Regarding that, multiple methods are presented in this study to solve the issues identified with over- fitting and inner logarithm shift issues by incorporating dropout and batch normalization. The FC was enhanced for each classification method's efficiency by capturing several local and accu-rate features on the shallow layers. It is expected that the improved FC layer will be able to boost the degree ofregression. The expected enhancement in the FC intends to minimize disparities in the training stage and enable proper training distribution to reduce overfitting and effects concerning the classification of the proposedbackbone. Hence, the current technique significantly improves formula covid and non-covid classification accuracy.

Table 2. Performance of proposed enhanced FC layer on our backbone based on SARS-CoV-2 CT scandataset

FC layer	Backbone	Accuracy
Existing FC Layer	Improved backbone	95.1
Enhanced FC layer	Improved backbone	98.1

4.3.5. Result of the evaluation of the proposed ResNet backbone

Table 3 presents the performance of various backbone networks and our proposed backbone on SARS-CoV-2 CT Scan dataset. Our proposed backbone outperformed other backbones in the evaluation. As shown in Table 3, the implemented backbone model employs a particular number of convolution layers. The performance was improved by choosing an appropriate number of convolution layers and optimizing FC to handle multi-scale feature maps and extracting the features of an input image. Moreover, by collecting many local andextracting function maps from shallow layers, the convolution layer boosts the performance of the selection process. In comparison to other backbones, the features are given into other layers, resulting in high performance in accuracy and parameters. This indicates that the performance complexity of the proposed backbone is approximately as much as Resnet50 and better than Resnet-101 models. To reduce the complexity during deployment, transfer learning approaches train the model offline on a large number of images. The testing process, on the other hand, is conducted when the model is deployed online [26]. As a result, the time complexity during the training phase may take a few hours on average depending on the datasets utilized, howeverthe time complexity during the testing phase online may take a few seconds up to two seconds [27]. Therefore,the performance complexity of a transfer learning model is evaluated on testing perceived images not on offlinetraining. In this study, our proposed model takes a few seconds in testing phase on 10% of the dataset, which provide an evidence of the efficiency of the model to be a promising model for future use.

4.3.6. Comparison with state-of-the-art classification algorithms

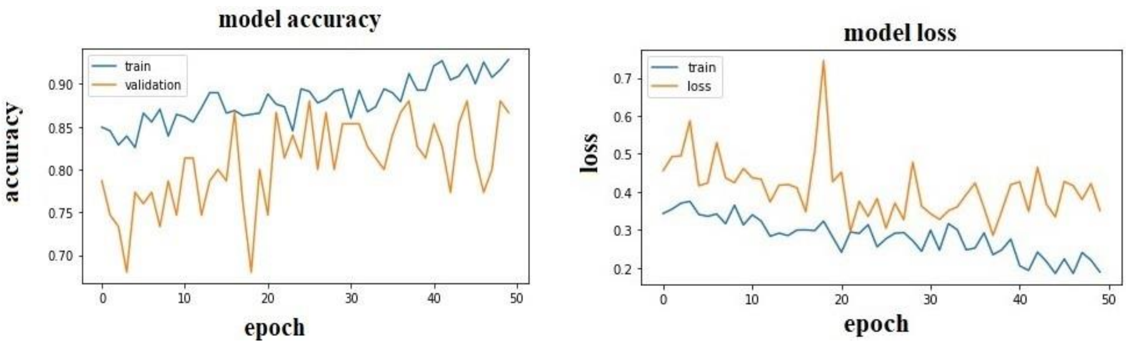
Herein, the COVID-19 CT image classifications are analysed and discussed by using proposed fine-tuned deep networks. The quantitative results are recorded. Table 4 shows the mean measurement value for each CT image dataset through various methods. All values are in percentages and the best results are boldly written. In general, there have been some output variations between the SARS-CoV-2 CT findings and the COVID19-CT datasets. In comparison with similar techniques in the recent work, we noticed the effectiveness of our method. The proposed model delivers superior results across almost all assessment parameters on the SARS-CoV-2 CT and COVID19-CT due to the improved backbone and enhanced FC layer. The model accuracy and model loss training for the proposed model using COVID19-CT dataset can be seen in Figures 3(a) and 3(b). The proposed model using SARS-CoV-2 CT-scan dataset can be seen in Figures 4(a) and 4(b).

Table 3. Performance of various backbone networks and our proposed backbone on SARS-CoV-2 CT scan dataset

Backbone	Accuracy	Parameters
Resnet-50	90.2	25,680.984
Resnet-101	96	145,972,225
Our backbone	98.1	34,471,553

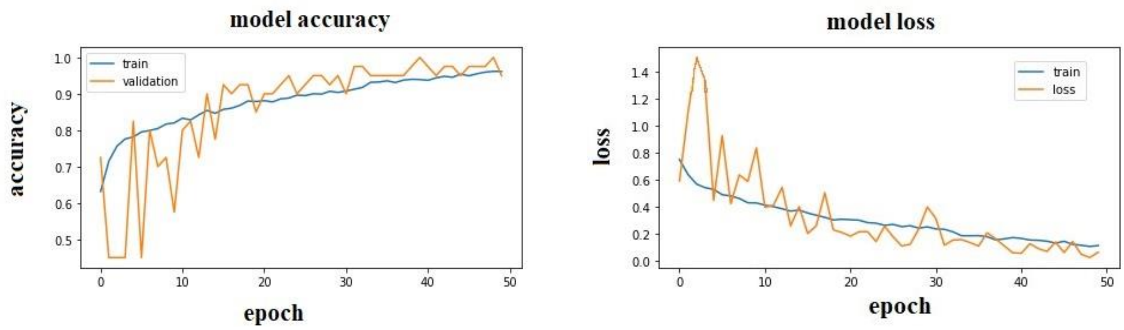
Table 4. Performance of various backbone networks and our proposed backbone on SARS-CoV-2 CT scan dataset

Dataset	Approach	Accuracy	Precision	Specificity	Sensitivity	F1-Score
	[4]	97.38	99.16	-	95.53	97.31
CoV-2 CT Scan	[8]	91.66	-	94	87.5	-
	[12]	90.8	95.7	-	85.8	90.8
	Proposed Model	98.1	96.7	97	98.3	97.48
	[28]	86	-	79	94	-
COVID19-CT	[29]	87.6	84.3	85.2	91.5	87.1
	[30]	83	81.73	81	85	-
	[31]	87.6	-	-	-	86.19
	Proposed Model	90.6	88	86.6	94	91.4



(a) (b)

Figure 3. The results of training pahse using COVID19-CT dataset of the proposed model; (a) model accuracy and (b) model loss



(a) (b)

Figure 4. The results of training pahse using SARS-CoV-2 CT-scan dataset of the proposed model; (a) model accuracy and (b) model loss

5. CONCLUSION

COVID-19 rapid classification was proposed in this study from CT images. In this paper, we propose a new design for ResNet improvement that can recognize COVID-19 from CT images. The two largest datasets from the COVID-19 CT examination were used with a split patient-based in this case study. The accuracy and specificity scores were 98% and 97%, respectively, and the sensitivity was 98%, according to the results of the testing. It is clear from these findings that the proposed COVID-19 classification model performs better than previous studies using CT scans to detect COVID-19. In addition to smartphones and tablets, this model could also be used to promote the integration of radiology systems with the rest of the IT infrastructure. CT scan systemic features will be correlated to other factors, such as epidemiological, genomic, and medical data, in the future to improve diagnostics for multi-modelling testing. To improve the proposed method, we plan to use preprocessing techniques like noise filtering and contrast enhancement.

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