DenseNet Convolutional Neural Networks Application for Predicting COVID-19 Using CT Image

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Research Article

Keywords: COVID-19, CT Image, Deep Learning, DenseNet-121

Posted Date: October 23rd, 2020

DOI: https://doi.org/10.21203/rs.3.rs-96782/v1

Version of Record: A version of this preprint was published at SN Computer Science on October 23rd, 2020. See the published version at https://doi.org/10.1007/s42979-021-00782-7.

Abstract

Public health and human lives recently have been impacted by the devastating effect of Coronavirus 2019. This catastrophic effect has destroyed the human experience by creating a chaotic healthcare situation infinitely more destructive than the Second World War. Strong communicable characteristics of COVID-19 among human communities make the world's situation a severe pandemic. Due to the unavailable vaccine of COVID-19 to control rather than cure, early and accurate detection of the virus can be a promising technique for tracking and preventing the infection spreading (e.g., by isolating the patients). This situation indicates to improve auxiliary COVID-19 detection technique. Computed tomography (CT) imaging is a mostly used technique for pneumonia because of its common availability. The application of artificial intelligence systems integrated with images can be a promising alternative for the identification of COVID-19. This paper presents a promising technique of predicting COVID-19 patients from the CT image using convolutional neural networks (CNN). The novel approach is based on DenseNet is the updated CNN architecture in the present state to detect COVID-19. The results outperformed 92% accuracy, with 95% recall showing good performance for the identification of COVID-19.

Introduction

A dramatic outbreak of the novel Coronavirus disease 2019 (COVID-19) has already been recognized as a global alarming of public healthcare distraction. COVID-19 was first identified in late 2019 at Wuhan, China, and unexpectedly spread more than 200 countries; thus, the World Health Organization (WHO) announced as a pandemic crisis immediately [1]. Due to strong communicable properties among human-to-human in close contacts [2], healthcare professionals and policymakers have failed to control this dramatic pandemic outbreak, rapidly killing people[1]. As secondary infections occurred because of any close human contact in communities, it is crucial to identify and isolate the infected person at the earliest possible conditions and community isolation and social lockdown. Thus early detection of the COVID-19 virus is a paramount option to take proactive steps not only to minimize risks and to spread of infections but also to do the planning of clinical treatment and arrange timely care support. That may play a vital role in better public healthcare management. This may directly impact saving world from the causative virus.

Due to the unavailability of specific drugs and vaccines, there is a crucial need to identify the infected person for taking steps to immediate isolation. Because of the most quickly established laboratory diagnosis method worldwide, the real-time polymerase chain reaction (RT-PCR) analysis (as a vital diagnosis approach clinically) is generally adopted for the detection of COVID-19 virus in clinical practice, following the national recommendation for disease and treatment of pneumonia caused by the 2019-nCoV, started from China.

However, a defective rate of RT-PCR test results [3] might be contributing to any limitations leading to sample collection process and transportation, which involve a time-consuming procedure [4, 5]. This

procedure might not recognize the infected person's (patient) conditions in critical situations, such as patients with intensive care unit (ICU). An infected person may be a carrier to spread the virus to other healthy or ordinary people as this virus (COVID-19) holds transmittable nature. Developing countries, however, suffer from limited scientific resources and a lack of health technologists or professionals [6]. Thus the alternative testing protocol represents a situational demand of the current pandemic environment with limited resources, which will be highly useful to fight against the COVID-19. Computed tomography (CT) imaging is a standard tool for the diagnosis of pneumonia. In this context, the CT image classification using CNN can be a promising alternative methodology for predicting COVID-19, especially for patients with ICU. Literature reveals that the performance of RT-PCR shows a lower sensitivity rate compared to the sensitivity of CT [7].

This research is mainly aimed to bring reliable measures to identify patients with COVID-19 from the CT image using CNN. CNN demonstrated excellent results in several computer vision tasks [8, 9]. CNN recently became a dominant in-depth learning approach for medical image classification due to its self-learning ability [10]. We applied a comparatively new approach, CNN, in which the learning technique is designed with an association of densely connected convolutional networks (DenseNet) [11] to identify people with COVID-19. The concept of driving DenseNet would be to link each layer to every other layer behind to improve the flow within the architecture. This helps CNN to settle based on all layers instead of one final layer. CNN's are more sophisticated and can capture image information on a larger scale compared to traditional image processing methods [9].

This study contributes to current literature in some aspects, which are summarized: First, we propose a newly adopted DenseNet technique to classify and identify COVID-19 patients. While RT-PCR test results might be contributing to any limitations for the critical patients, the CT image classification technique might be a promising alternative for the detection of COVID-19. Secondly, this study formulates the emergency patient decision-making issue. Thirdly, by using a real-time COVID-19 CT image data, the applied technique outperforms for identification of COVID-19 infection.

The remainder of the paper is structured accordingly. Section 2 presents a brief background study. Then section 3 undertakes the materials and method followed by the result and discussion part in section 4. Then, the conclusion and implications are presented. Finally, we consider some limitations and provide some further directions for improving the proposed methodology.

[1] According to John Hopkins University, 862,339 deaths out of 25,965,868 total confirmed infection cases with 18,248,738 recovery (Statistical figures are collected on 9 June 2020)

Background Study

With the rapid development of artificial intelligence, different image classification techniques in medical informatics have been proposed for various diversified demands. Recently, the ML technique has been

considered as a prominent tool for the prediction and diagnosis of numerous diseases [12]. However, their accuracy and adequate performance criteria are yet to need improving. AlexNet, VGG, GoogLeNet, and ResNet, for example, are more performing in the classification of medical images. However, these networks are facing the difficulty of convergence, overfitting, and vanishing gradient problems [13]. Therefore, CNN, based on DenseNet, offers options for accurate medical image classification as it enables features [14].

Recently, radiology images have been widely used for the identification of COVID-19 cases using standard ML techniques. For example, Pereira, Bertolini [15] applied the hierarchical image classification using a chest X-ray for COVID-19 identification. Ozturk, Talo [16] proposed a deep neural network for automatic detection of COVID-19 cases. In addition, Khan, Shah [17] performed a multi-level classification using a chest X-ray using an Xception architecture based convolutional neural network in achieving an overall 89.6 % accuracy with 93% percent precision.

Several strategies of deep learning were suggested for better identification of COVID-19. Panwar, Gupta [18] proposed a deep learning-based nCOVnet technique for analyzing X-ray images, which achieved 88.10 % of overall accuracy. Wang, Deng [19] implemented a weekly supervised deep learning framework using a 3D CT image. A noise-robust framework on CT image for automatics segmentation of COVID-19 was applied by Wang, Liu [20]. Soares, Angelov [21] used an eXplainable Deep Learning approach using a CT image. Ucar and Korkmaz [22] used Bayesian optimization additive fine-tuning for SqueezeNet that performs better COVID-19 detection. DenseNet, however, has used in the previous studies for obtaining higher accuracy of other domains like industrial image classification with prominent accuracy which is a more problem-sensitive network architecture and a multi-level innovative fine-tuning process that creates a number of specific networks.

The above discussion reveals that the DenseNet based CNN technique might be an alternative diagnostic tool for significant identification of COVID-19 disease identification using CT image. The CNN model may achieve significant promising results, but results can be improved by further use of new architectures. Therefore the advance application of a CNN model for COVID-19 classification is the main motivation of this study.

2.1 DenseNet

DenseNet is modern architecture of CNN for visual object recognition that has acquired state-of-the-art with fewer parameters. With some principal modifications, DenseNet is very similar to ResNet. DenseNet, along with its concatenates (.) attributes, combines the previous layer output with a future layer while ResNet uses an additive attribute (+) to merges the previous layer with the future layers. Simply, the DenseNet Architecture aims to fix this problem by densely connecting all layers together. Among the different DenseNet (DenseNet-121, DenseNet-160, DenseNet-201), this study employed DenseNet-121 [5+

(6+12+24+16) ×2)=121] architecture. Details of the DenseNet-121 is following: 5- convolution and pooling layers, 3- transition layers (6,12,24), 1- Classification layer (16) and 2- denseblock (1×1 and 3×3 conv).

Generally, traditional CNNs calculate the output layers (l^{th}) using a non-linear transformation $H_l(.)$ to the output of the previous layer X_{l-1}

$$X_l = H_l(X_{l-1}) \quad (1)$$

DenseNets don't really sum up the layer output functionality maps with the inputs but concatenate them. DenseNet offers an easy communication model for improving information flow between layers: the lth layer receives inputs from the features of all previous levels: The equation is then again transformed into:

$$X_l = H_l([X_0, X_1, X_2, \ldots\ldots\ldots\ldots\ldots\ldots X_{l-1},]) \quad (2)$$

Where, $[X_0, X_1, X_2, \ldots\ldots\ldots\ldots\ldots\ldots X_{l-1},]$ is a single tensor formed by the concatenation of the output maps of previous layers. This function consists of three major operations, batch normalization (BN), activation (ReLU), and convolution (CONV). DenseNet architecture is presented in figure 1. However, the growth rate k helps to generalize the lth layer in following manner: $k^{[l]} = (k^{[0]} + k(l-1))$. Where $k^{[0]}$ is known as the number of channels.

2.2 Augmentation

Data augmentation is a method that enables practitioners to significantly improve the variety of data for training models without actually collecting new data. Data augmentation techniques such as cropping, horizontal, rotation, etc. are a widely used method for training models. To increase training befinift and decreases the use of network regularization, image augmentation has used in this study. We adopted a widely employed data augmentation technique, which is also used in [13]. Images were in different pixels on each side and then randomly cropped to the 64×64 original image size, where the random rotation range was 360^0. Images were mixed in horizontally and vertically mirrored. Horizontal, vertical, and zoom range were seted into 0.2, which means that the range between height and weight is 0.8 to 1.2 (80% to 120%).

Methods

3.1 Data

To identify the COVID-19 using DenseNet architecture based CNN, a real patient image dataset[2] from a hospital from Sao Paulo, Brazil, was used in this study. Soares, Angelov [21] made this dataset publicly available to encourage further research development for the further stimulation of knowledge. There are

2482 CT images in total, while 1252 CT images were COVID-19 positive, and 1230 CT images were from non-infected by COVID-19 but who presented other pulmonary diseases. The images classes were labeled into two types: COVID and nonCOVID. Figure 2 represents a few instances of CT scans for patients infected and non-infected by COVID-19 that compose the dataset.

3.1.1 Pre-processing

The objective of the image pre-processing stage is to smother unwanted twists present in the picture, resize and normalize the image for further processing. There is numerous image pre-processing technique found in the previous literature based on the requirement of model building. Among them, image resizing, image normalization, and covert level to categorical are generally used techniques. In this study, images were resized to ensuring the same size and the same pixel using the "Pillow 2.7++"[3] python package. This study considers 64×64 pixel values for images. Besides, image normalization is a process in which we adjust the pixel intensity to make the picture increasingly natural. Normally, most of the image pixel integrates the values between 0 to 255. But, due to the use of network architecture, it is better to perform all values between 0 to 1, which will be a good fit for the model building. This reduces the computational complexity during training the model. However, using Eq. (11), images were normalize

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{11}$$

Where X_{min} and X_{max} refers to minimum and maximum pixel values.

3.1.2 Experimental Setup and Performance Measurement

The proposed COVID-19 classification model was implemented using Python 3.7 software[4] with related packages. Intel(R) Core(TM) i5-8250U CPU @ 1.60 GHz processor with 16GB primary memory with 4-GB NVIDIA GeForce 940MX Graphics and 64-bit windows operating systems was used. COVID-19 patients' identification aims to determine if a patient is a COVID-19 infected or not. Before model building data was split into three part: training (70%), validation (10%) and testing (20%). The model history is presented in table 3 which was trained with 50 epochs. The DenseNet-121 code of COVID-19 detection is available at https://github.com/shawon100/Covid-19-Disease-Diagnosis. The outcomes of samples of each category correctly and incorrectly classified can be summarized as a confusion matrix, shown in Table 2. We can determine the accuracy based on the confusion matrix (Equation 12). The classification model's performance was calculated using four performance measurements: precision, recall, F1-measure, and G-Mean. Accuracy is the percentage of all instances that are correctly predicted.

Nonetheless, accuracy cannot differentiate between the numbers of correctly classified samples of each class, particularly for the positive class in classification problems. A very reliable classifier may have misclassified the positive classes as negative. Occasionally, accuracy is, therefore, not enough to evaluate model performance in classification problems.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Table 2: Confusion Matrix for COVID-19 Prediction

Actual	Predicted	
	Absence of COVID-19	Presence of COVID-19
Absence of COVID-19	True positive (TP)	False Negative (FN)
Presence of COVID-19	False Position (FS)	True Negative (TN)

Moreover, we implemented two metrics: F-measure, and G-Mean, along with accuracy, which is widely used for classification problems are as follows.

$$F\_Measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (13)$$

$$GMean = \sqrt{\frac{TP}{TP+FP} \times \frac{TP}{TP+FN}} = \sqrt{Precision \times Recall} \quad (14)$$

Where F-measure is the weighted average of the precision and precision is the percentage of correct predictions for the positive class and recall is a measurement of how much a classifier can recognize positive examples. GMean aims to evaluate the two-class recall balance. The GMean value will be lower if the model is highly biased towards one class since this approach has become widely used in the classification problem. Thus, we used F-measure and GMean to assess the model's performance.

Table 3: Model Summary of CNN

Model: "model_1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	(None, 64, 64, 3)	0
conv2d_1 (Conv2D)	(None, 64, 64, 3)	84
densenet121 (Model)	multiple	7037504
global_average_pooling2d_1 (	(None, 1024)	0
batch_normalization_1 (Batch	(None, 1024)	4096
dropout_1 (Dropout)	(None, 1024)	0

```
_________________________________________________________________
dense_1 (Dense)              (None, 256)               262400
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
root (Dense)                 (None, 2)                 514
=================================================================
Total params: 7,305,622
Trainable params: 7,219,414
Non-trainable params: 86,208
```

[2] Source: https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset

[3] Source: https://pillow.readthedocs.io/en/latest/

[4] Source: https://www.python.org/

Results And Discussion

The DenseNet CNN model was trained to classify the CT images for 50 epochs. Each pre-trained model was trained on grayscale images. The model accuracy and loss graph of DenseNet CNN is shown in fig. 3a and in fig. 3b.

The performance of DenseNet-121 was evaluated for grayscale test images. Table 4 shows the overall accuracy of the test data. From figure 4, it is identified that the DenseNet-121 model misclassified only 23 COVID-19 images out of 1252 images, and only 15 nonCOVID-19 images out of 1230 images. The precision, recall, f1-score, and Gmean values of DenseNet-121 using the grayscale test dataset are presented in table 4 for details performance analysis. However, Fig. 5a and Fig. 5b represent the example of image prediction for both COVID-19 and non-COVID-19 perspective.

Table 4: The results obtained using DenseNet-121 on CT images.

	precision	recall	f1-score	Gmean
nonCOVID-19	0.96	0.85	0.90	0.90
COVID-19	0.84	0.95	0.89	0.89
				Overall Accuracy
Macro avg	0.92	0.92	0.92	**0.92**
Weighted avg	0.92	0.92	0.92	

There are a few important studies that used the COVID-19 image classification. Some of the studies used X-ray images, and some used CT images with different accuracy rates.

Overwhelming majority existing approaches used a small dataset while a relatively large dataset was used for the applied DenseNet-121 model. There have been several images and strategies for validation by the different state-of-the-art approaches. The used sample size and validation approach used by the different authors is indicated in Table 5. Because of the variation in data sets, a fair comparison of results for performance assessment and validation methods is indeed not feasible. Nevertheless, it is worth mentioning that in such a relatively large dataset of 2482 COVID-19 and nonCovid-19 images the applied technique proved its effectiveness. There are slightly fewer COVID-19 images used by the other approaches. The method by the Ouchicha, Ammor [23] and Narayan Das, Kumar [24] achieved 97.2% and 97.4% overall testing accuracy in an unbalanced dataset where only 219 and 127 COVID-19 images were used for model building. At the same time, Pathak, Shukla [25] and Shaban, Rabie [26] used CT images and achieved 93% accuracy applying small COVID-19 images. Some other studies [16, 17, 27-31]introduced different approaches for early detection of COVID-19 using X-ray and CT images indicating lower than or around 90% accuracy rate. In this study a DenseNet-121 architecture-based CNN was used for the efficient detection of COVID-19 using a total number of 2482 images (1252 COVID-19 and 1230 nonCOVID-19) to develop our model. The DenseNet-121 has yielded 92% total accuracy with 95% sensitivity (recall), 84% precision, 89% F1-score and 89% Gmean. Compared to other studies in literature, DenseNet-121 based CNN obtained superior results.

For COVID-19 diagnostic test the applied model could be used with CT images. CT images are better suited because for patients in critical conditions due to its readily available and efficient criteria. The model is capable of instantly identifying COVID-19. Therefore, a deep learning model with CT imagery is recommended because it is more powerful.

Finally, a few main advantages of this study are outlined following:

I. CT-image classification provides outperform performance for COVID-19 detection rather than other images like X-ray or Chest images. Additionally, the DenseNet-121 model has better classification accuracy than other studies.
II. There is no hand-made extraction technique needed for the applied architecture.
III. To conclude, our study showed that a deep learning approach could be applied to help doctors and/or healthcare engineers diagnose patients with COVID-19 and recognize lesions from CT images automatically.

Table 5: Result comparison with previous studies

Study	*Method*	*Sample*	*Types of images*	*Accuracy*
Pathak, Shukla [25]	Deep Transfer Learning	413 – covid-19 439 - normal or pneumonia	CT image	93.01%
Abraham and Nair [32]	multi-CNN and Bayesnet	453 – Covid-19 497 – nonCovid-19	X-ray images	91.16%
Panwar, Gupta [27]	deep transfer learning approach	206 – X-ray for covid-19 364 - X-ray for normal 206 – CT image for covid-19	chest X-ray CT-Scan	89.47% 96.55%
Shaban, Rabie [26]	Enhanced KNN	216 – Covid-19 133 – non Covid-19	CT image	93 %
Ouchicha, Ammor [23]	CVDNet (deep CNN)	219 – Covid-19 1341 - Normal 1345 - Viral Pneumonia	chest X-ray images	97.20%
Narayan Das, Kumar [24]	deep transfer learning approach	127- Covid-19 500 – no findings 500 - pneumonia	chest X-ray images	97.40%
Ozturk, Talo [16]	Deep neural network	127- Covid-19 500 – no findings 500 - pneumonia	chest X-ray images	87.02%
Khan, Shah [17]	CoroNet (Deep neural network)	290 – Covid-19 1230 - Normal 931 - Viral Pneumonia 660 – bacterial Pneumonia	chest X-ray images	89.60%
Song, Zheng [29]	DRE-Net	777 – Covid-19 708 – nonCovid-19	CT image	86%
Zheng, Deng [31]	Net+3D Deep Network	313 – Covid-19 229 – nonCovid-19	CT image	90.8%
Wang, Kang [30]		195 – Covid-19 258 – nonCovid-19	CT image	82.9%
Xu, Jiang [28]		219 – Covid-19 175 - Normal 224 - Viral Pneumonia	CT image	86.7%
This Study	**DenseNet-121**	**1252 – covid-19 1230 – nonCovid-19**	**CT image**	**92%**

Conclusion

The automated image classification of CT images by computer-aided systems is of great importance in medical image analysis. Microscopic analysis of CT images is challenging and time-consuming. In this study, identifying COVID-19 patients using CT image classification based on the machine learning technique has demonstrated with outperformed accuracy. The overall accuracy is 92%, and recall is 95%.

We applied DenseNet-121 deep learning architecture for image classification. Several classification models were, in example, to validate our claim.

Theoretically, the proposed methodology contributed to the current emerging COVID-19 literature providing an unrevealed best alternative identification technique using a DenseNet-121 CNN. Practically, this method can be applied to the clinical practice for accurate COVID-19 detection. Thus, increasing reliability represented through the proposed computational method for testing could add value to capture a real-picture of infection rate, which has a strong correlation to the number of daily infected cases. The applied methodology offered a powerful machine learning-based approach to minimize errors of human professionals' manual judgment as well as providing a quicker way of offering time and resource-saving.

For further research development, DenseNet can be justified by applying other types of architecture, i.e., DenseNet-161, DenseNet-169, DenseNet-201. However, other deep learning methods or modified deep learning methods could be implemented and tested for further development and assessment for more accurate identification of COVID-19 patients using CT images.

Declarations

Acknowledgment(s)

This study was supported by the National Natural Science Foundation of China under Project No.

71810107003.

Conflict of Interest

There is no potential conflict of interest declared by all authors.

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Figures

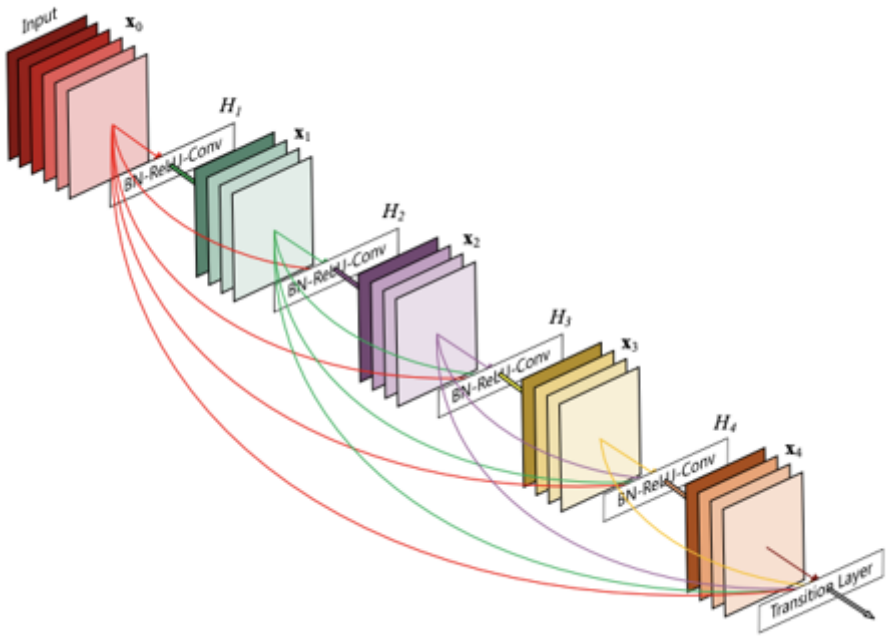

Figure 1

DenseNet Architechture (Source: [11])

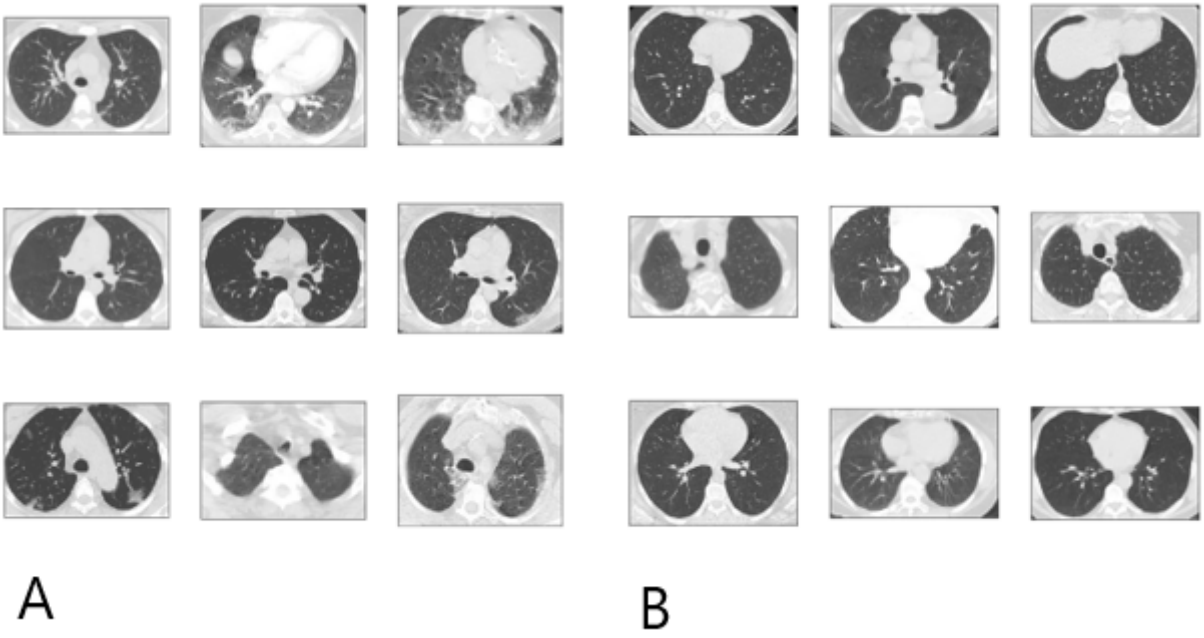

Figure 2

a: COVID-19 infected. b: COVID-19 non-infected

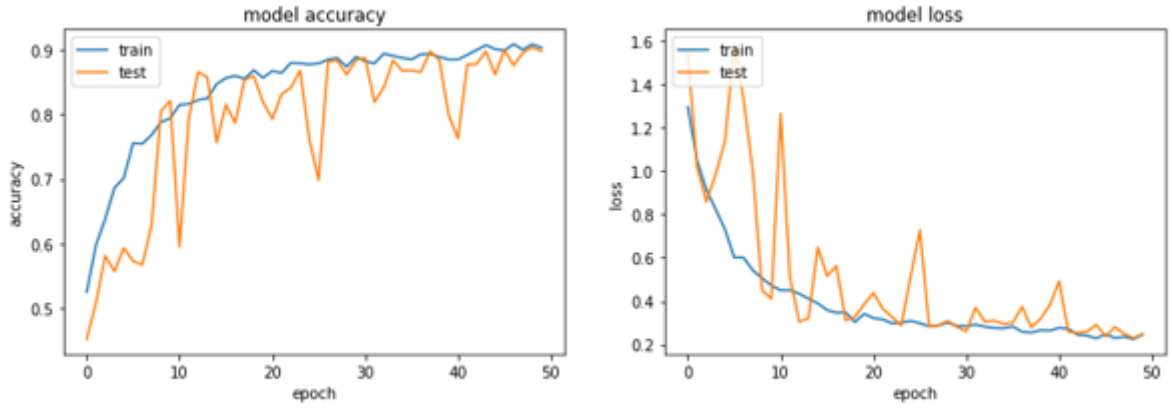

Figure 3

a: Model Accuracy. b: Model Loss

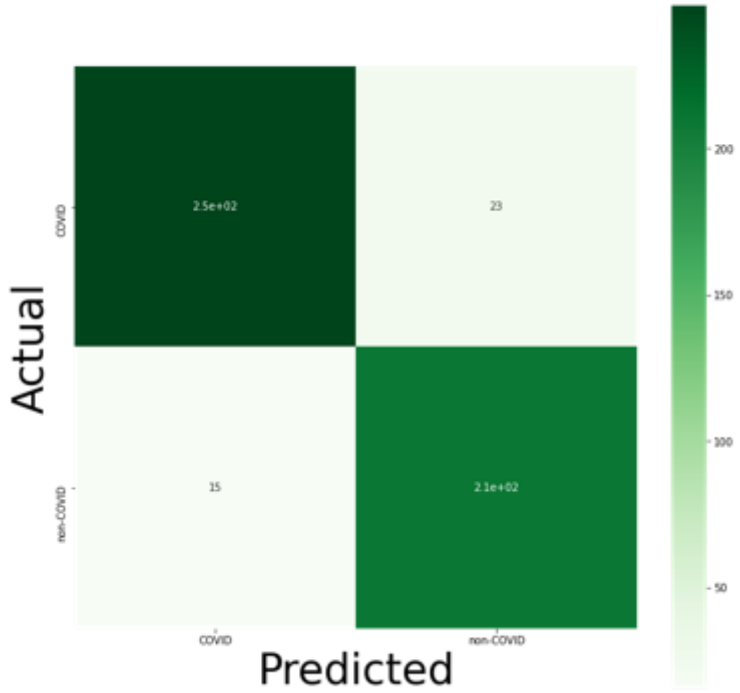

Figure 4

Confusion Matrix

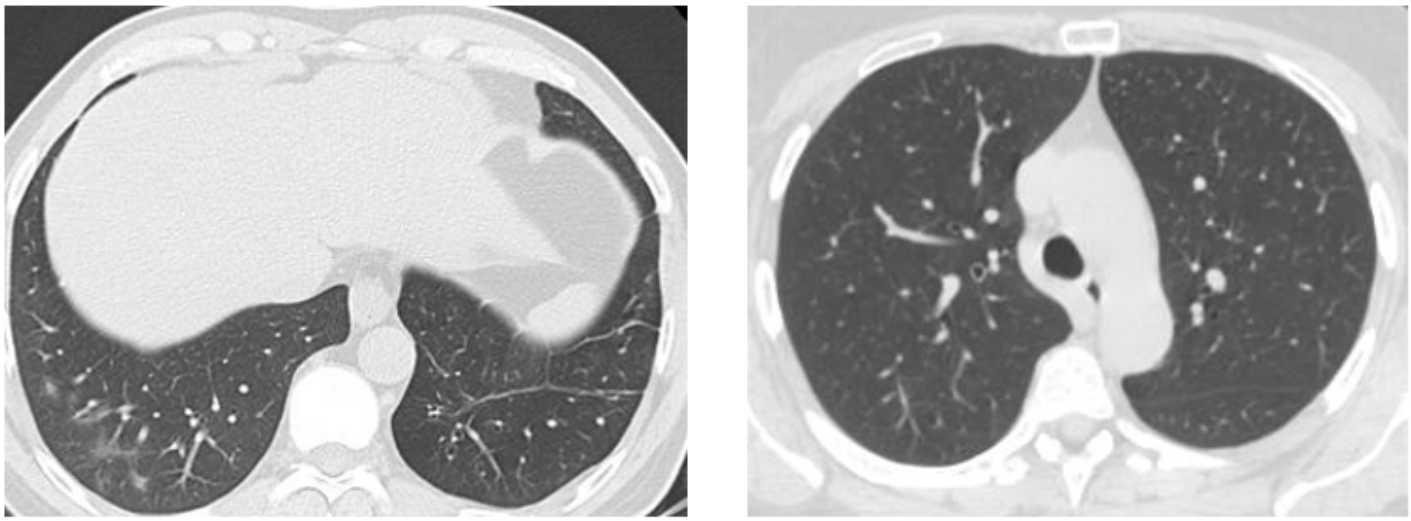

Figure 5

a: Predictive Image: Covid-19 Infected. b: Predictive Image: Covid-19 nonInfected