COVID-19 Detection from Lung CT-Scan Images using Transfer Learning Approach

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COVID-19 Detection from Lung CT-Scan Images using Transfer Learning Approach

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Abstract

From the onset of 2020, Coronavirus disease (COVID-19) has rapidly accelerated worldwide into a stage of a severe pandemic. COVID-19 has infected more than 29 million people and caused more than 900 thousand deaths. Being highly contagious, it causes community transmission explosively. Thus, health care delivery has been disrupted and compromised by lack of testing kits. The COVID-19 infected patient shows severe acute respiratory syndrome. Meanwhile, the scientific community has been on a roll implementing Deep Learning techniques to diagnose COVID-19 based on lung CT-scans, as computed tomography (CT) is a pertinent screening tool due to its higher sensitivity for recognizing early pneumonic changes. However, large dataset of CT-scan images are not publicly available due to privacy concerns and obtaining very accurate model becomes difficult. Thus to overcome this drawback, transfer learning pre-trained models are used to classify COVID-19 (+ve) and COVID-19 (-ve) patient in the proposed methodology. Including pre-trained models (DenseNet201, VGG16, ResNet50V2, MobileNet) as backbone, a deep learning framework is developed and named as KarNet. For extensive testing analysis of the framework, each model is trained on original (i.e., non-augmented) and manipulated (i.e., augmented) dataset. Among the four pre-trained models of KarNet, the one with DenseNet201 illustrated excellent diagnostic ability with an AUC score of 1.00 and 0.99 for models trained on non-augmented and augmented data set respectively. Even after considerable distortion of images (i.e., augmented dataset) DenseNet201 gained an accuracy of 97% on the testing set, followed by ResNet50V2, MobileNet, VGG16 (96%, 95% and 94% respectively).

Keywords: COVID-19, transfer learning, classification, CT-scan, deep learning

1. Introduction

On December 2019, a novel coronavirus (COVID-19) disease outbreaks in Wuhan, China. A handful of genetic and structural analysis has identified that a protein on its surface makes it highly contagious virus which can spread rapidly. On 30th January COVID-19 was declared as a global health emergency by the World Health Organization (WHO) [1]. On 11th February 2020, a new name for this virus was introduced by the International Committee on Taxonomy of Viruses as "Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)". More than 29 million cases have been confirmed and 929 thousand deaths have occurred worldwide at the time of writing this paper. The fatality rate is 2%, but still, COVID-19 is acute resolved. Also, 19.9 million people have been recovered. Common symptoms of this disease include fever, cough, sore throat, headache, diarrhoea, short breathing. Abnormal situations in CT-chest images of patients has also been noticed. The patient can suffer from acute respiratory distress, multiple organ failure, and ultimately death. This disease is transmitted from a COVID-19 infected person to another person through micron-size droplets from the mouth or/and nose expelled by that person while sneezing, coughing or even speaking. It has been noticed that the old age population is prone to be infected at a much higher rate than young age group. Due to unavailability of vaccine or therapeutic treatment, quarantining and early diagnosis of patients plays the most important role in controlling the spreading of this disease.

Originally, Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) was the only technique to detect this virus from respiratory samples, but due to its time consuming and unreliable results, it faced challenges to prevent COVID-19 from community spreading [2]. Besides this, infected cases cannot be timely identified because of the inadequate

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number of RT-PCR test-kits and unconsciously the virus may continue to spread among the healthy population. To alleviate the inefficiency and lack of testing kits for COVID-19, researchers are continually developing alternative testing methods which include radiological images such as X-rays and chest CT-scans. Radiological characteristics can be effectively determined by these techniques. The first priority of radiologists is X-ray machines as they are widely available in hospitals. However, chest images of X-rays fail to detect soft tissues accurately. Hence, to mitigate this burden from the medical professionals chest CT-scan images is used which can detect soft tissues efficiently and can generate results at a faster rate [3]. To automate the whole process, deep learning (DL) techniques are developed by researchers [4] that can automatically interpret the CT-scan images and predict whether a person is COVID (+ve) or not. Results generated from this work are quite promising, but it has two limitations. First, the lack of publically available lung image CT-scan dataset due to the privacy concerns of patients. This impact immensely in the research and development of more advanced AI methods for more precise results. To meet the clinical standard result, DL technique demands huge datasets during model training. Considering the current situation, where medical professionals are highly involved in taking care of COVID-19 patients, hence it is unlikely to have time to collect and annotate a huge COVID-19 CT-scan dataset for them. Secondly, these works are not sharable, the trained model of one hospital cannot be used in other as well as results cannot be reproduced.

To address this drawback, Transfer Learning approach to build a neural network framework 'KarNet' is used in this paper. In transfer learning, a pre-trained model, with predefined weights and biases is used to train models on a custom dataset. This, in turn, reduces the time consumption for training model, minimizes implementation complexity associated with initializing the weights and biases for layers in deep neural network models [5]. In clinical treatment and teaching task, medical image classification plays an essential role. (Maithra et al., 2019) has briefly described the use of transfer learning in medical image analysis [6]. Despite being trained on ImageNet dataset, transfer learning models have feature independent benefits of the pre-trained weights, such as better scaling and convergence speedups. (Samir et al., 2019) applied convolutional neural network (CNN) and transfer learning-based algorithm on a chest X-ray data set to classify pneumonia and concluded that transfer learning is a more useful classification method on a small dataset compared to CNN [7]. Transfer learning also excelled in lung cancer detection using CT-scan images [8]. The prevailing success of transfer learning models used in medical image classification thus proves to deliver better accuracy than CNN or other machine learning models. Due to the availability of small COVID-19 datasets, the pre-trained neural network was used for the diagnosis of infected patients. Transfer learning technique on lung CT-scan images for COVID-19 detection is very limited. However, KarNet provides satisfactory results even after extreme manipulation of images in the dataset and performed better than current state-of-arts.

2. Related works

Since the outbreak of COVID-19, researchers are continually developing methods to perform screening of this virus. Due to previous success of deep learning techniques in medical image analysis, researchers used CT-scans and X-rays detect COVID-19. Diagnosis models using Chest X-rays include (Chowdhury et al., 2020) who used CNN to build the model [9]. Pre-trained networks are used in many previous works of literature to diagnosis COVID-19 for example [10],[11],[12] used ResNet and gained 96%,99% and 91% accuracy, (Li et al., 2020) used DenseNet121 on a total sample of 429 X-ray images and achieved 88% accuracy with an AUC score of 0.97[13], (Rahaman et al., 2020) examined 15 different pre-trained CNN models and obtained highest classification accuracy of 89.3% using VGG-19[14]. (Asnaoui and Chawki 2020)[15] used InceptionResnetV2, DenseNet201, Resnet50, MobilenetV2, InceptionV3, VGG16 and VGG19. Highest accuracy of 92.18% is obtained by InceptionResnetV2.

It has been noticed in literature that CT-Scans provides low false-positive rates than X-ray. Multiple CNN models to classify COVID (+ve) patients from CT-scan images was implemented by (Wu et al., 2020) [16]. Using CT- slices (Wang et al., 2020) [17] proposed a 3D deep CNN (DeCovNet) to detect COVID-19. (X. He et al., 2020)[18] introduced a dataset comprising a few hundred images of lung CT-scans to detect COVID-19 and proposed an approach named Self-Trans(i.e., self-supervised learning with transfer learning). Also, (Zheng et al., 2020) [19] proposed a weakly-supervised deep learning technique for COVID-19 detection using 3D CT scans. 3D lung samples are segmented using pre-trained U-Net which are then applied on deep learning technique for prediction of infected regions. The model accuracy reported is 95.9%. A novel weakly supervised deep learning framework is proposed by (Hu, Shaoping, et al., 2020)[20] which is capable of detecting and localizing lesions on COVID-19 and CAP CT from image-level label. The performance achieved was around 89% for detection of COVID-19(+ve) patients with an AUC score of 0.923. According to review paper of (Roberts, Michael, et al., 2020)[21] a wide range of models used lung segmentation as a pre-processing step and in most 2D models, the implementation of transfer learning, with network pre-trained on ImageNet can be found. 87% accuracy was obtained by (Sarker et al., 2020) [22] using DenseNet-121 on chest radiographic images. (Li et al., 2020) [23] proposed COVNet and achieved an accuracy of 95% using chest CT-scan images but due to privacy concerns the dataset is not publically available which is over 4357 chest CT images of 3322 patients. (Yang et al., 2020)[24] developed a diagnosis system (DeepPneumonia) using deep learning techniques to identify COVID-19 patients, the model showed an excellent AUC of 0.99. Localization of main lesion features, especially the ground-glass opacity (GGO) is also an added feature of the model. Due to scarcity of publically available dataset (H.S. Maghdid et al., 2020)[25] collected images of chest X-rays and lung CT-

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scan from different sources and trained a CNN and modified AlexNet. To classify COVID-19 against other types of pneumonia (Bai H.X. et al., 2020)[26] carried out lung segmentation of abnormal CT slices and then used a EfficientNet B4 deep neural network architecture, followed by a two-layer fully-connected neural network to pool slices together. U-Net and Res-Net are used for segmentation and grain-localization of infected lungs by (Greenspan, et al., 2020) [27] to detect COVID-19 (+ve) patients. To segment lung images an unsupervised clustering technique is used. More than 110 infected patients are tested and 94.80% accuracy was obtained from this method. (Shah et al., 2020) [28] proposed a method based on CNN having an accuracy of 82.1% and five transfer learning models, out of which VGG-19 outperformed others with an accuracy of 94.52%.

Therefore, to overcome the issues with the existing models a framework based on transfer learning is proposed in this paper to classify COVID-19 infected patients.

3. Dataset

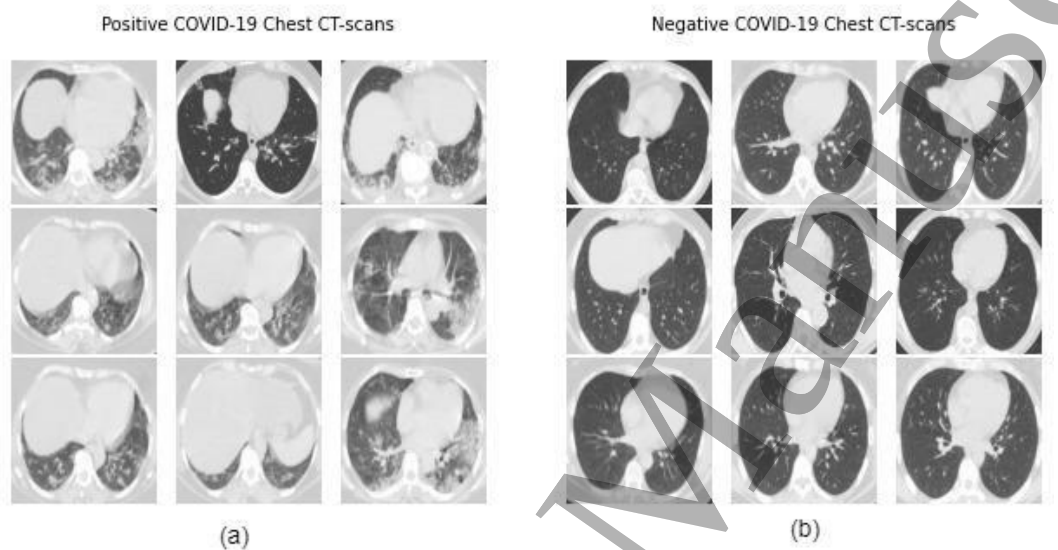

Figure 1. SARS-CoV-2 CT-scan dataset sample images: a) COVID-19 (+ve) patient's chest CT-scans b) COVID (-ve) patient's chest CT-scans.

The proposed work deals with COVID-19 detection from lung CT-scans. (Angelov et al., 2020) prepared lung CT-scan image dataset [29] having two classes COVID and non-COVID by collecting real patients CT-scans from hospitals of Sao Paulo, Brazil. This is publically available at https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset. Total 2481 CT-scan images are used for training and testing purpose. The SAR-CoV-2 CT-scan dataset contains 1252 CT-scans of COVID-19 (+ve) patients and 1229 CT-scans belong to COVID-19 (-ve) patients. Figure 1 represents sample lung CT-scan images of the dataset. This database was split in the ratio of 8:2 for training and testing purpose.

4. Methodology

A simple 2-dimension deep learning framework based on CT-scan images using transfer learning is developed and named as KarNet. Transfer learning is popular for building a model in a short span of time with a minimal dataset. In the proposed work, data augmentation resolved the immense need for a large CT-scan lung dataset. The research is attempted in three phases to get highest possible accuracy: data pre-processing, feature extraction and binary classification. In this current work, four pre-trained models are used as backbone namely: DenseNet201[30], MobileNet [31], ResNet50V2 [32] and VGG16 [33] and integrated them with additional layers to evaluate each one's performance on augmented as well as non-augmented dataset separately. Previously, in literature (A. Jaiswal et al., 2020) [34] achieved an accuracy of 96.25% and 95.45% on testing set of SAR-Cov-2 dataset [29] using DenseNet201 and VGG16 respectively. But KarNet outperforms this score on the same dataset, even with image augmentation KarNet gave promising results. The architecture of the proposed methodology of COVID-19 detection using lung CT-scan images is shown in figure 2.

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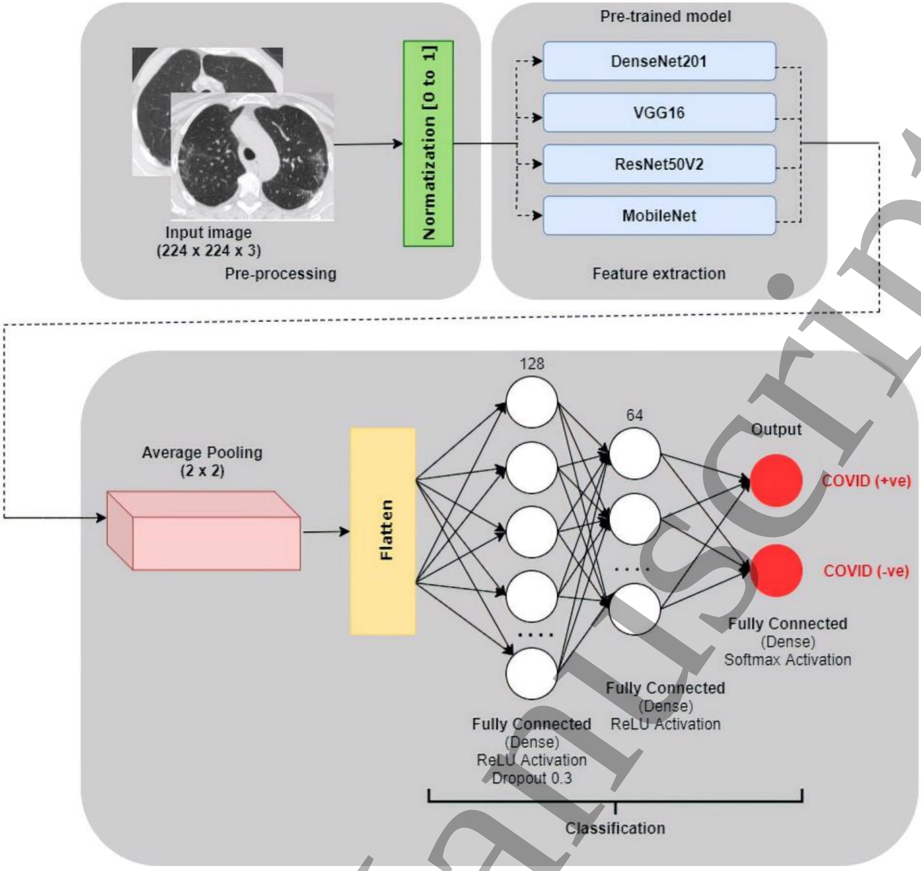

Figure 2. Architecture of the proposed model with transfer learning models for feature extraction and CNN for classification.

4.1 Input Layer

In the present study, CT-scan images are needed to be compatible with the pre-trained transfer learning models to extract features out of them and classify properly. In the simple pre-processing step: input (224 × 224 × 3 pixels) images are normalized to interval the [0, 1]. The image dataset having two classes is then divided into training and testing categories. Training images are fed into one of the pre-trained model layers to pull out features properly. The pre-trained models can classify lung CT scans based upon class labels assigned to the training dataset, i.e., COVID and non-COVID.

4.2 Pre-trained Model Layers

A Pre-trained model is known to be trained on a large benchmark dataset. DenseNet201, VGG16, ResNet50V2 and MobileNet are investigated using the proposed framework and dataset, to evaluate each once performance according to metric values. Each pre-trained model is divided into two parts, namely a convolutional base and a classifier. For feature generation from the image, a stack of convolution layers is paired up with pooling layers. The classifier is responsible for categorizing the image based on the extracted features. In the pre-trained model layers, the convolutional base is re-trained and the classifier is removed. Additional layers are added and the classifier is replaced with another classifier for COVID-19 (+ve) or COVID-19 (-ve) detection.

4.3 Additional Layers

The activations from, transfer learning pre-trained model layers were fed into the additional layers. The layers acted as classifiers of COVID-19 (+ve) and COVID-19(-ve) patients. In the additional layers, the first average pooling layer is used, which is believed to take out the average values of the features from the feature maps. The 2D average pooling block reduces the size of the data, the number of parameters and amount of computation needed. Pooling also controls overfitting. Then the activations are flattened and two fully connected layers are added: the first layer with 128 nodes and the second with 64 nodes. To avoid overfitting a dropout layer is added in between these dense layers. Subsequently, from the second dense layer, the activations are fed into a Softmax layer with two nodes, which provided the probability for each of COVID-19 (+ve) and COVID-19(-ve). The softmax function is represented by $\sigma(x_j)$ in equation (1)

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$$\sigma(x_j) = \frac{e^{x_j}}{(\Sigma(n)e^{x_j})}(n) \quad (1)$$

The input data is normalized on a scale of [0, 1]. Also, it's output is always 1. So, the neural network model classifies the instance as a class that has an index of the maximum output. As softmax activation function is recommendable with Categorical cross-entropy loss function, hence it is used with Adam optimizer. The categorical cross-entropy calculates the loss by computing sum represented in equation (2) where, $\widehat{y_i}$ is the i^{th} scaler value in the model out, y_i is the corresponding target value and number of scaler values in the model output is the output size.

$$Loss = -\sum_{i=1}^{\substack{output \\ size}} y_i \cdot \log \widehat{y_i} \quad (2)$$

4.4 Data Augmentation

To have a diverse dataset and prevent overfitting data augmentation is performed for each training group of CT-scan images. In the proposed methodology, data augmentation is 3 ways as follows I) for image rotation, angle of rotation between $-20°$ and $20°$ are randomly selected, II) image shift of 0.2 range on width and height is implemented and III) horizontal flipping is enabled. Each pre-trained model comprising additional layers are trained on augmented as well as non-augmented SAR-CoV-2 lung CT-scan dataset [17] and individual performance is evaluated quantitatively.

4.5 Transfer learning model architecture

In comparison with the traditional machine learning methods CNN based transfer learning models has the following upper hand: a) less pre-processing of the dataset is required, b) process of learning is faster, c) declination of numerous parameters can adjust the time complexity and d) works incredibly well for a limited dataset, thus suitable as medical image classifier. In the proposed work, 4 pre-trained transfer learning-based models are used for binary image classification task, namely: DenseNet201, VGG16, ResNet50V2 and MobileNet which were previously trained on ImageNet dataset to classify 1000 object categories. These pre-trained models are re-trained for the binary classification of a lung CT-scan into 2 classes.

All four models require an input size of (224 × 224 × 3). MobileNet has a lightweight architecture comprising only 30 layers which make it an effective convolutional neural network for mobile vision application. Depthwise separable convolution is used by MobileNet which defines that it performs convolution on each colour channel rather than combining all three channels and flattening it. Training MobileNet is thus less time-consuming. Table 1 represents the time taken for the training of each model with and without augmented images. Previously in literature, (Ebru et al., 2020) [35] used MobileNet for detection of COVID-19 using chest X-ray images and gained an accuracy of 87%. However, our framework yields better result on CT-scan images using MobileNet, making use of this particular model mobile application friendly. Nevertheless, ResNet50V2 took the least time while training the model on the non-augmented database and also performed marginally better than MobileNet against the augmented dataset. Residual network (ResNet) was the first neural network that could train thousands of layers without succumbing to the "vanishing gradient" problem. ResNet50V2 uses batch normalization before each weight layer and possesses 50 layers in total. Well-known pre-trained transfer learning model VGG16 was substantially used in medical image classification for COVID-19 detection to a significant extent [34], [18]. (Angelov et al., 2020)[29] scored an accuracy of 94.96% on SAR-CoV-2 CT-scan dataset. Utilizing our framework, VGG16 worked pretty well only for the model trained on non-augmented images.

Models	**Using Non-augmented data**	**Using augmented data**
DenseNet201	56.83 minutes	159.65 minutes
VGG16	40.81 minutes	163.22 minutes
ResNet50V2	34.0 minutes	161.2 minutes
MobileNet	48.57 minutes	174.11 minutes

Table 1. Time taken by models during training process using augmented and non-augmented SAR-CoV-2 dataset to complete 500 epochs.

In the proposed work, DenseNet201 is the best performing model trained on non-augmented as well as the augmented dataset, thus its architecture is explained in details in figure 3. The fundamental building block of ResNet architecture is, the

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previous layer is merged with the future layer. Additive merges force the network to learn residuals wherein, DenseNet, proposes concatenation of outputs from the preceding layer instead of using the summation. DenseNet (Dense Convolution Network), connects each layer to every other layer in a feed-forward fashion. DenseNet201 is a CNN(convolutional neural network) that is 201 layers deep. It has compelling advantages such as I) mitigate the vanishing-gradient problem, II) reinforce feature propagation, III) stimulate feature re-usability and IV) parameter reduction. DenseNets are easily trainable due to enriched flow of information and gradient throughout the network. From the original input signal and the loss function, each layer has direct access to the gradients which helps in training of deeper network architectures. Further, to alleviate over-fitting on tasks with smaller training set sizes, dense connections use a regularizing effect.

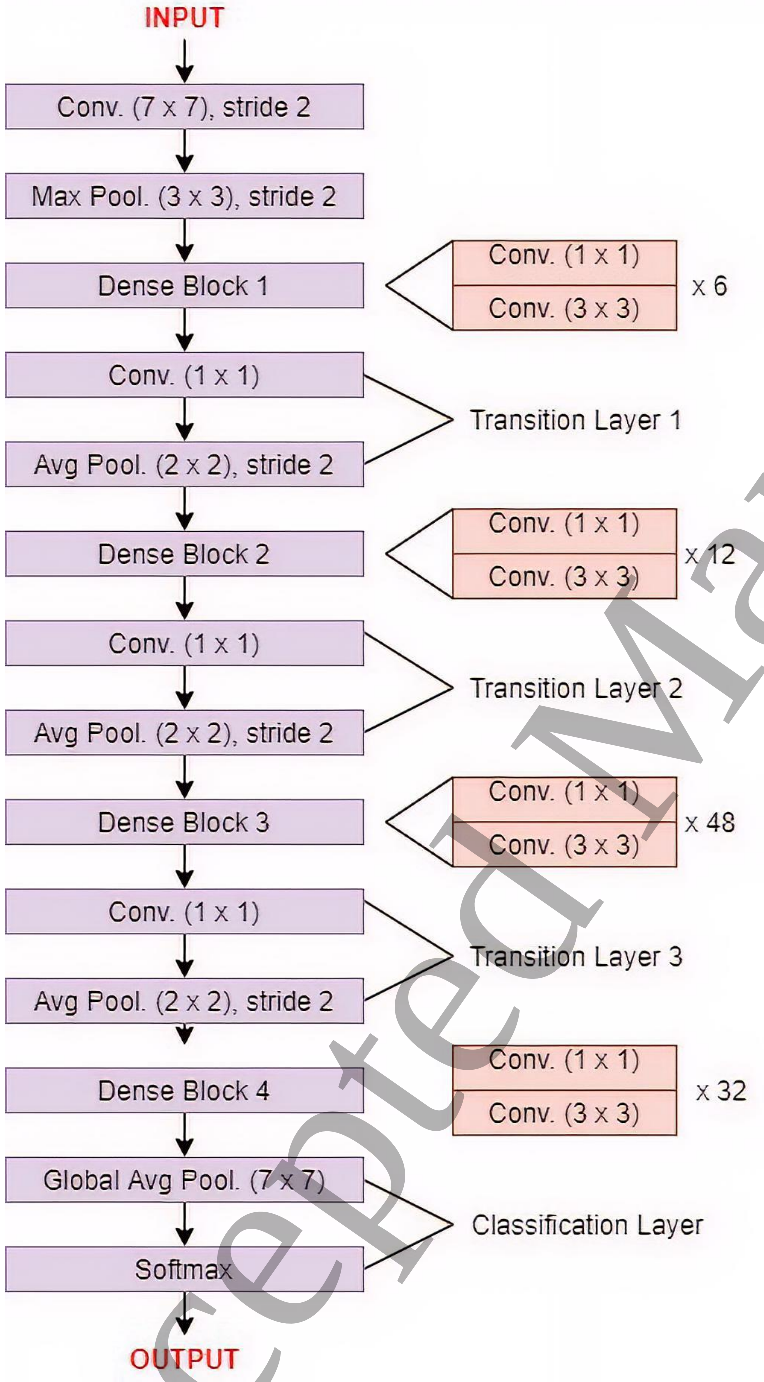


Figure 3. Architecture of DenseNet201

4.5 Implementation Details

As transfer learning approach allows transferring of pre-trained models to re-train, it saves computational time as well as system requirements to meet training of the models. For developing countries, it plays a vital role in experimentation as a model training from scratch demands for high-end hardware systems. Current work implementation is on Tensorflow and 12GB RAM is utilized. 500 epochs and a batch size of 32 is maintained throughout the experiment.

5. Quantitative analysis

For each of the different four pre-trained models (DenseNet201, VGG16, ResNet50V2, MobileNet) in KarNet, classification performance is evaluated based on various confusion matrix based performance metrics on models trained with augmented and non-augmented image dataset. These performance metrics are as F1 score, accuracy, precision, recall and specificity on a testing set of CT-scan images. The main objective of this paper is to determine either the person has been infected from COVID-19 or not. The outcome can be positive (indicating the patient has been infected with this virus) or negative (indicating the patient has not been infected with the virus). The test results of every patient may or may not fall in the same category of the patient's actual class. In this adjustment, it is assumed that true positive (TP) demonstrate COVID-19(+ve) patients are accurately recognized as COVID-19(+ve) patients and the true negative (TN) shows COVID-19(-ve) patients are recognized as COVID-19(-ve). False-positive (FP) represents the COVID-19(-ve) patients are incorrectly recognized as COVID-19(+ve) patients. Finally, false negative (FN) shows COVID-19(+ve) patients are incorrectly recognized as COVID-19(-ve). In order to justify the performance of the model, the following performance measures are used.

$$A_{covid19} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

Accuracy ($A_{covid19}$) is the measure of all the classes which are correctly recognized. In this paper, COVID-19(+ve) and COVID-19(-ve) classes are equally important, hence $A_{covid19}$ in equation (3) is used which can be calculated as the number of all correct classifications divided by the total number of items.

$$F_{covid19} = \frac{2 \times P_{covid19} \times R_{covid19}}{P_{covid19} + R_{covid19}} \quad (4)$$

Although, division of data is not determined by $A_{covid19}$. Thus F-measure in equation (4) is used to handledistribution problems with accuracy. Precision evaluates the exactness of the classifiers. Large number of FP corresponds to low $P_{covid19}$ value. Recall($R_{covid19}$) also known as sensitivity defines the completeness of the classifier. Large FN corresponds to low $R_{covid19}$. The mathematical formulation is given below in equation (5) and equation (6) respectively.

$$P_{covid19} = \frac{TP}{TP + FP} \quad (5)$$

$$R_{covid19} = \frac{TP}{TP + FN} \quad (6)$$

Specificity($S_{covid19}$) defines the proportion of actual negatives that are accurately classified as such (eg., the percentage of people not affected by the COVID-19 disease are correctly classified as COVID-19(-ve) patients. $S_{covid19}$ is formulated in equation (7).

$$S_{covid19} = \frac{TN}{TN + FP} \quad (7)$$

The receiver operating characteristic curve (ROC) curve is also plotted and the area under the curve (AUC) for each of the four different models are calculated. ROC curve is a commonly used in binary classification problem and this graphical plot illustrates the diagnostic ability of classifier using TP and FP rates at various decision threshold. In medical image analysis, especially in COVID detection, it is significantly important to have minimum FP and FN value, it demonstrates a better classification performance of the model. Misclassification of COVID-19 patients may lead to a wrong diagnosis of patients.

6. Results and discussion

For exhaustive testing, each pre-trained model with CNN layers is trained on original images (i.e., non-augmented dataset) and distorted images (i.e., augmented dataset). This helps to investigate the capability of KarNet architecture in dual scenarios. Training performance on the non-augmented and augmented dataset is shown in table 2. Testing analysis of KarNet models are based on four transfer learning pre-trained models in the classification of COVID-19 positive and COVID-19 negative patients using lung CT-scans before augmentation and after augmentation of images while training them is summarized in table 3. The four models namely DenseNet201, VGG16, ResNet50V2 and MobileNet have been analyzed based on metric values of accuracy, sensitivity, specificity and F1 score. From the table, it is noticeable that all four models showed very good classification performance on the testing set. ResNet50V2 achieved 96% accuracy in both the models trained using augmented and non-augmented images respectively. During testing data analysis VGG16 managed to get 97% accuracy in case of original (i.e., non-augmented) dataset trained model but scored 94% for augmented one. However, the performance of MobileNet differs marginally for both the dataset trained models. The model trained with non-augmented images achieved an accuracy of 96% and the other model gave 95% accuracy.

Models	**Using Non-augmentation data**		**Using augmented data**	
	Training	**Validation**	**Training**	**Validation**
DenseNet201	99%	97%	98%	97%
VGG16	99%	96%	94%	94%
ResNet50V2	99%	96%	96%	95%
MobileNet	99%	97%	97%	95%

Table 2. Training and validation accuracy of the models using non-augmented and augmented dataset.

Model trained on non-Augmented Lung CT-scan image dataset					
Models	**Accuracy**	**Precision**	**Recall**	**Specificity**	**F1-Score**
DenseNet201	97%	0.95	0.98	0.95	0.97
VGG16	97%	0.96	0.98	0.96	0.97
ResNet50V2	96%	0.97	0.94	0.97	0.96
MobileNet	96%	0.95	0.97	0.94	0.96
Model trained on augmented Lung CT-scan image dataset					
DenseNet201	97%	0.95	0.98	0.95	0.97
VGG16	94%	0.95	0.94	0.95	0.94
ResNet50V2	96%	0.95	0.97	0.95	0.96
MobileNet	95%	0.94	0.96	0.93	0.95

Table 3. Testing analysis using model trained on non-augmented and augmented SAR-Cov-2 lung CT-scan images.

DenseNet201 performed exceptionally well in both the scenarios, scoring 97% accuracy, even after extreme manipulation of the images in augmented lung CT-scan images while training. Figure 4 represents accuracy and loss analysis of training and validation dataset of DenseNet201 with the respective number of epochs. 98% of COVID-19 patients are correctly recognized as COVID-19 patients in both the trained models of DenseNet201. Impact of TP and TN is demonstrated with the help of confusion matrix in figure 5. A graphical illustration of ROC curve with AUC value for models trained with the original and the augmented dataset is represented in figure 6. AUC score of DenseNet201 is 1.00 and the rest of the models scored 0.99 for models trained on non-augmented CT-scans. For models trained with distorted images (i.e., augmented dataset) DenseNet201and MobileNet gained an AUC score of 0.98 and others scored 0.97. Hence, DenseNet201 surpass other transfer learning models used in this work. Thus, with a relatively small dataset, KarNet overcame many drawbacks and gave an excellent diagnostic ability as a binary classifier. Table 4 illustrates the comparison of other literature's transfer learning model performance and ours. In future, a sustainable artificial intelligence system will be established that can continue to train the proposed framework using widely collected lung CT images.

Reference	**Total CT-Scan Samples**	**Pre-trained Model**	**Accuracy**
Shah et al. [28]	738	VGG-19	94.52%
		DenseNet169	93.15%
		VGG-16	89%
		ResNet50	60%
		InceptionV3	53.4%
Bai HX et al.[26]	118401	EfficientNet B4	96%
H.S Maghdid et al.[25]	339	AlexNet	82%
Angelov et al [29]	2481	VGG-16	94.96%
A.Jaiswal et al.[34]	2481	DenseNet201	96%
		VGG-16	95%
		Resnet 152V2	94.91%
		Inception ResNet	90.90%
Ours	2481	**DenseNet201**	**97%**
		VGG-16	94%
		ResNet50V2	96%
		MobileNet	95%

Table 4. Comparison with other methods. All the above references used transfer learning based methodology to classify the CT-scan images as COVID-19 positive or negative with different accuracies according to the specific models. The highest accuracy and model is bolded in the above table.

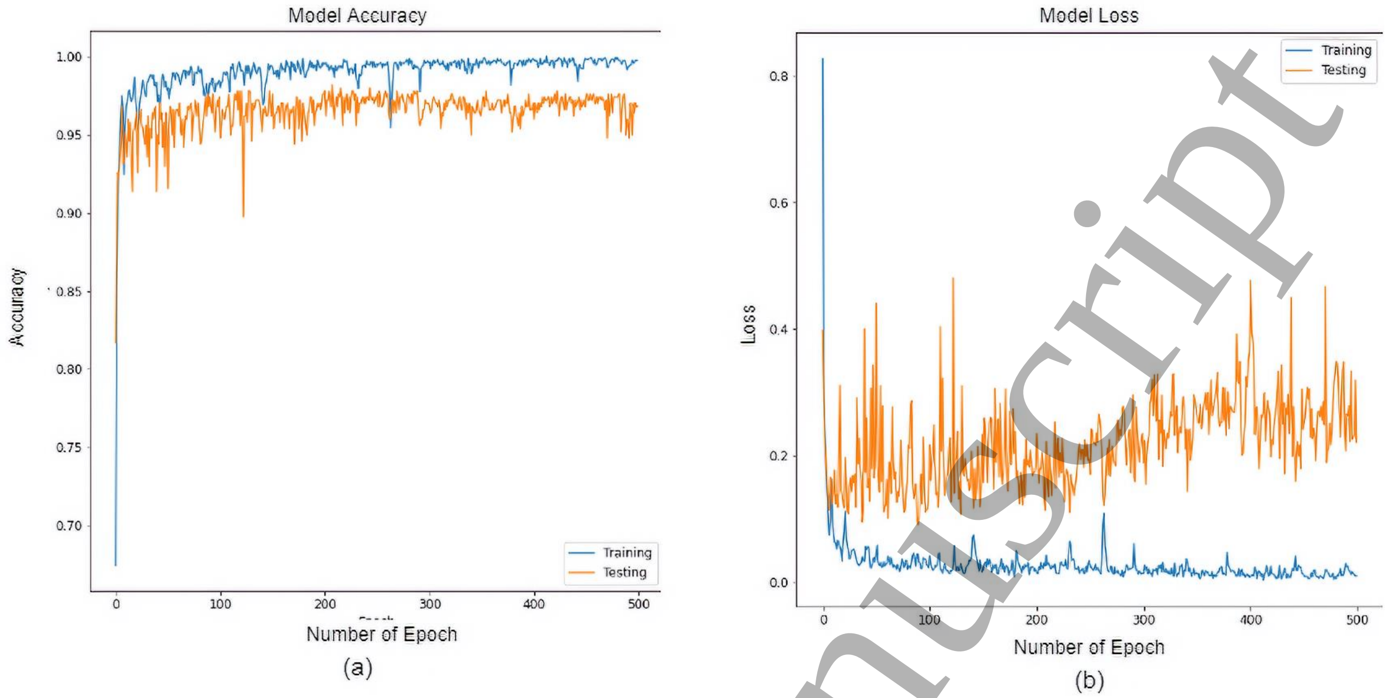


Figure 4. Training and validation analysis over 500 epochs of re-trained DenseNet201model on the non-augmented dataset. a) training and testing model accuracy analysis b) training and testing model loss analysis.

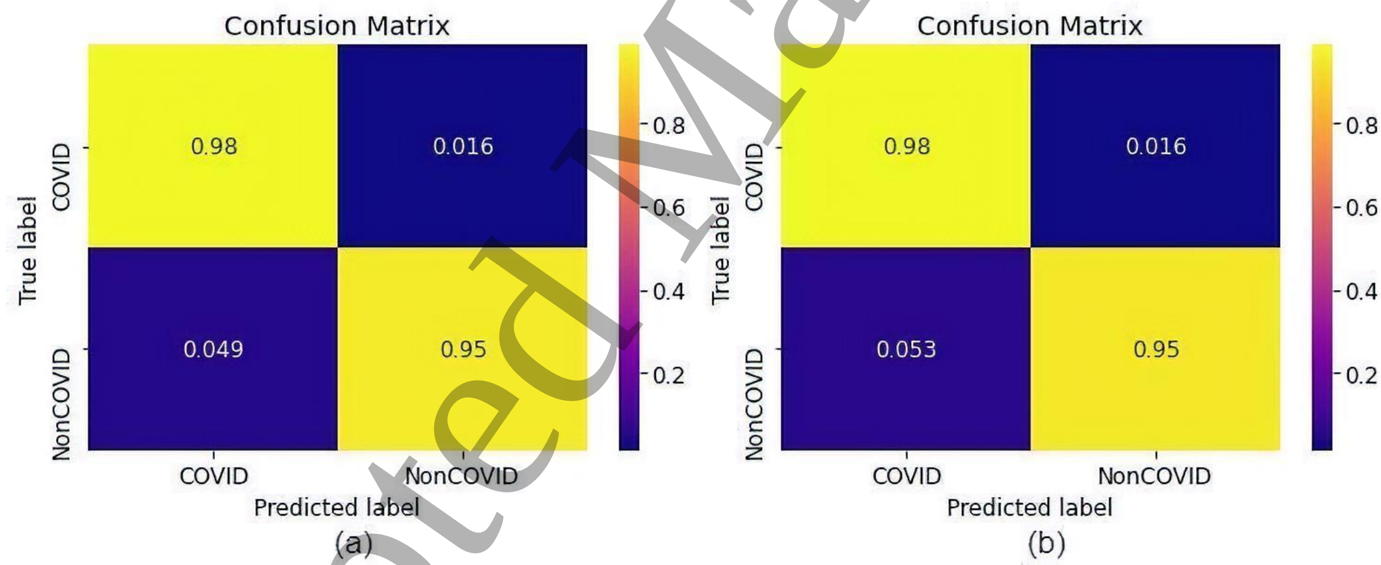
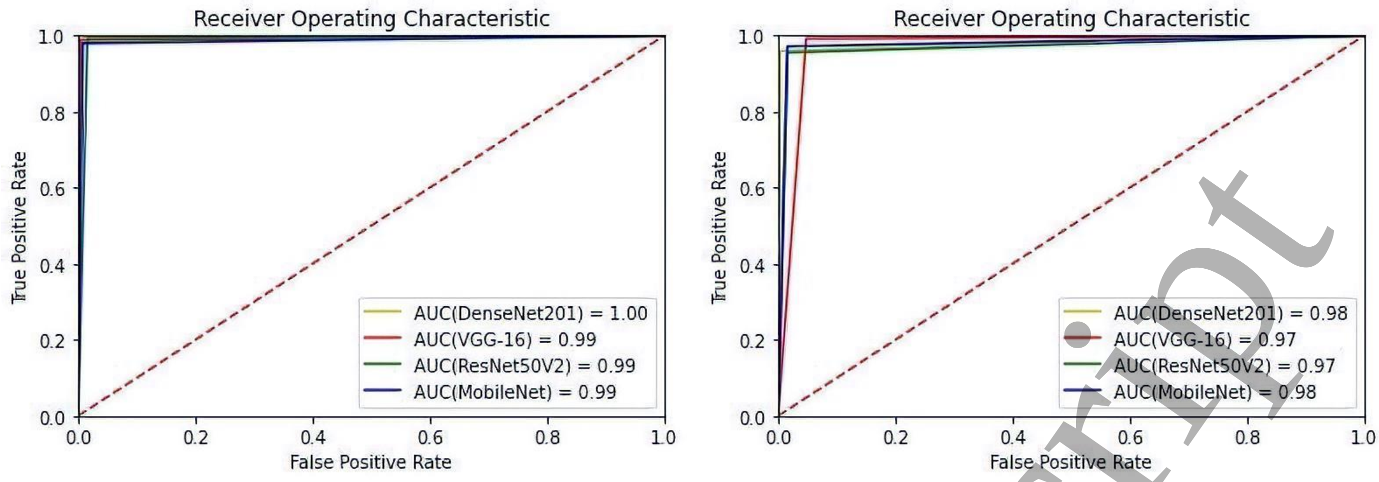


Figure 5. Confusion matrix analysis of the proposed re-trained DenseNet201model trained on: a) non-augmented dataset b) augmented dataset.



(a) (b)

Figure 6. Area Under Curve (AUC) of all transfer learning models trained on: a) non-augmented dataset b) augmented dataset.

7. Conclusion

KarNet, a simple 2-dimensional deep learning framework provided an excellent diagnostic performance in the detection of COVID-19 patients from lung CT-scan images. The KarNet model is based on transfer learning pre-trained models. For this experiment, each model is trained on non-augmented (i.e., original) and augmented (i.e., manipulated) dataset to investigate the framework's capability to a greater extent and it has been found that DenseNet201 appears to perform the best by scoring 97% accuracy on testing and validation dataset for both models trained using augmented dataset and non-augmented CT-scan dataset. VGG16, ResNet50V2 and MobileNet also achieved promising accuracy on testing images. The proposed architecture significantly improved the diagnostic ability of the model with an excellent AUC score. Therefore, KarNet proved to outperform present state-of-arts and classify COVID-19 patients precisely.

As most of the hospitals are equipped with CT-scans, the proposed model can be implemented to improve COVID-19 testing method. Hence, this model can serve as an automatic alternative testing process, saving time and lives of an infected patient before it's too late.

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