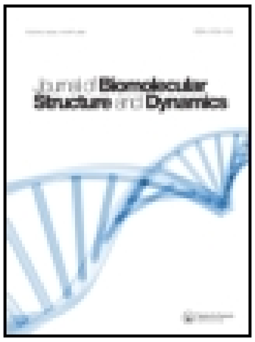

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Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning

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ABSTRACT
Deep learning models are widely used in the automatic analysis of radiological images. These techniques can train the weights of networks on large datasets as well as fine tuning the weights of pre-trained networks on small datasets. Due to the small COVID-19 dataset available, the pre-trained neural networks can be used for diagnosis of coronavirus. However, these techniques applied on chest CT image is very limited till now. Hence, the main aim of this paper to use the pre-trained deep learning architectures as an automated tool to detection and diagnosis of COVID-19 in chest CT. A DenseNet201 based deep transfer learning (DTL) is proposed to classify the patients as COVID infected or not i.e. COVID-19 (+) or COVID (−). The proposed model is utilized to extract features by using its own learned weights on the ImageNet dataset along with a convolutional neural structure. Extensive experiments are performed to evaluate the performance of the propose DTL model on COVID-19 chest CT scan images. Comparative analyses reveal that the proposed DTL based COVID-19 classification model outperforms the competitive approaches.

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COVID-19; classification; deep learning; deep transfer learning

1. Introduction

The first case of novel Coronavirus disease (COVID-19) was reported in Wuhan, China at the end of December, 2019. COVID-19 became an epidemic all over the World (Huang et al., 2020; Wu et al., 2020). This is a respiratory disease, which is caused by a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (World Health Organization, 2020). The common symptoms of COVID-19 are fever, cough, short breathing, sore throat, headache, and diarrhea (Singhal, 2020). Vanishing of taste, tiredness, aches, loss of smell, and nasal blockade can also be observed in patients. There is no definite vaccine available for prevention from COVID-19 and infectious disease. Due to this, the people can be easily infected from the droplet of coronavirus. Isolation of infected person is the only way to stop the spread of virus infection in healthy persons. Initially, Real Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) is the only technique to detect the COVID-19 from respiratory samplings (Wang, Xu et al., 2020). RT-PCR is an effective method for diagnosis of SARS-CoV-2. The main drawbacks of RT-PCR are time consuming and error-prone results (Pathak et al., 2020; Zu et al., 2020). Due to limited availability and drawbacks of RT-PCR, it has posed challenges to prevent the dissemination of coronavirus infection. In contrast with it, radiological imaging techniques are used for diagnosis of SARS-CoV-2 by coalescing with infected person's clinical symptoms, travel history, and laboratory findings (Xie et al., 2020).

The radiological imaging such as chest X-ray and chest CT-scan can be helpful to isolate the infected persons timely and control this epidemic situation (Singh et al., 2020). These techniques can easily detect the radiological characteristics of COVID-19. The first choice of radiologists is chest X-ray as most of the hospitals are equipped with X-ray machines (Basavegowda & Dagnew, 2020). However, chest images obtained from X-ray machines cannot be discriminate soft tissues accurately (Tingting et al., 2019). To remove this problem, chest CT-scan is used to detect the soft tissues efficiently. Radiologists are required to analyze the chest CT images (Kaur et al., 2019). In this pandemic situation, many radiologists is required to diagnosis the COVID-19. However, it is time consuming and error prone task. Therefore, the automatic detection of COVID-19 from chest images is required.

Deep learning (DL) techniques are widely used in the automatic analysis of radiological images (Kaur & Singh, 2019). It has been found that deep learning techniques have been used for screening of Tuberculosis in chest X-ray (Qi et al., 2019). These techniques are able to train the weights of networks on large datasets as well as fine tuning the weights of pre-trained networks on small datasets (Shukla et al., 2020). Due to the small COVID-19 dataset available, the pre-trained neural networks can be used for diagnosis of

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coronavirus. However, these techniques applied on chest CT image is very limited till now (Sarker et al., 2020). Hence, the main aim of this paper to use the pre-trained deep learning architectures as an automated tool to detection and diagnosis of COVID-19 in chest CT.

The main contributions of this paper are:

1. A DenseNet201 based deep transfer learning (DTL) is proposed to classify the patients as COVID infected or not i.e., COVID-19 (+) or COVID (−).
2. The proposed model is utilized to extract features by using its own learned weights on the ImageNet dataset along with a convolutional neural structure.
3. Extensive experiments are performed to evaluate the performance of the propose DTL model on COVID-19 chest CT scan images.
4. Comparisons are also drawn by considering some well-known confusion matrix-based metrics.

The rest of this paper is organized as follows. Section 2 presents the work done in the field of deep learning techniques for chest CT images. The proposed technique is described in Section 3. The experimental results and discussions are given in Section 4. The concluding remarks are drawn in Section 5.

2. Related work

A large number of research work has been done to detect the COVID-19 from radiological imaging. It has been observed from literature that chest CT provides low false positive rates than the other imaging techniques such as X-ray (Ai et al., 2020).

Sarker et al. (2020) used DenseNet-121 for classification of COVID-19 patients. They used transfer learning technique to train the deep learning network by removing gradient problem. They developed a website that take radiology images and produced the infected regions. The accuracy obtained from this technique was 87%. Shan et al. (2020) developed a DL-based technique for automatic classification of infected regions in the lung. They evaluated their technique on 300 coronavirus infected persons. The accuracy obtained from this technique was 91%. The developed techniques is unable to detect the severity of other pneumonia. Zhang et al. (2020) used DenseNet to detect the coronavirus infection in the patients. The sensitivities of COVID-19 and non-COVID-19 cases detection are 96% and 70.65%, respectively. Wang, Zha, et al. (2020) implemented pre-trained DL technique to detect COVID-19 infection in lung images. This technique is tested over 1266 patients from six different cities. The accuracy obtained from this technique was 87%.

Barstugan et al. (2020) utilized four different feature extraction techniques to extract features from chest CT images. These extracted images applied on support vector machines (SVM) for classification of COVID-19 patients. They used 10-fold cross validation during the classification process. The classification accuracy obtained from this technique was 99.68%. Gozes, Frid-Adar, Greenspan, et al. (2020) developed DL-based technique to detect and quantify the severity of COVID-19 from chest CT images. They used segmentation, slice classification and grain localization techniques. UNet and ResNet are used for segmentation and slice classification of infected regions in lungs, respectively. The unsupervised clustering technique is used to segment the lung images. They tested over 110 infected persons and classification accuracy obtained from this technique was 94.80%. Asnaoui and Chawki (2020) used convolutional neural network (CNN) models for binary classification of COVID-19 in CT images. They used pre-trained models namely VGG16, Inception_ResNet_V2, VGG19, Xception, Inception_V3, MobileNet_V2, and ResNet50 for classification. 96% classification accuracy was obtained from MobileNet_V2, Inception_ResNet_V2, and ResNet50.

Wang, Kang, et al. (2020) used InceptionNet to detect the abnormalities associated with COVID-19 in lung CT scan images. They tested InspectionNet model on 1065 CT images and identified 325 infected persons with accuracy of 85.20%. Xu et al. (2020) utilized 3D CNN models to distinguish the coronavirus infection from Influenza-A viral pneumonia in CT scan images. ResNet was used to extract the features. The accuracy obtained from CNN model was 86.70%. Chen et al. (2020) utilized UNet++ architecture to detect coronavirus pneumonia. They trained their model on 106 patients and achieved 98.85% classification accuracy. The analysis time was reduced by 65%. Gozes, Frid-Adar, Sagie, et al. (2020) used 2D and 3D DL models to quantify the coronavirus infection in COVID-19 patients. They used CT features for COVID-19 classification and produced corona score. The classification accuracy was 99.60%.

Li et al. (2020) developed COVID-19 detection neural network (COVNet) to extract the features from chest CT images for detection of coronavirus infection in patients. COVNet was trained over 4357 chest CT images of 3322 patients. The accuracy obtained from COVNet was 95%. Due to privacy concerns, CT images used in COVID research works cannot be shared publicly. Zhao et al. (2020) build a COVID-CT dataset that consists of 349 CT images for COVID-19 positive and 397 CT images for COVID-19 negative. This dataset is publicly open for research work. Zheng et al. (2020) proposed a weakly supervised DL technique for diagnosis of COVID-19 patients using 3D CT scans. They used pre-trained UNet technique for segmentation of 3D lung images. The segmented regions are applied on DL technique for prediction of infected regions. The accuracy obtained from their model was 95.9%.

Therefore, to overcome the issues associated with the existing models, a DenseNEt201 (Huang et al., 2017; Zhang et al., 2019) based deep transfer learning model is proposed in this paper to classify COVID-19 infected patients.

3. Proposed model

An effective way to achieve significant results in classification problems with limited data size is transfer learning. Additionally, hyper-tuning of Deep transfer learning models (DTL) can improve the results further. In this work, a DTL model with DenseNet201 is proposed. The proposed model

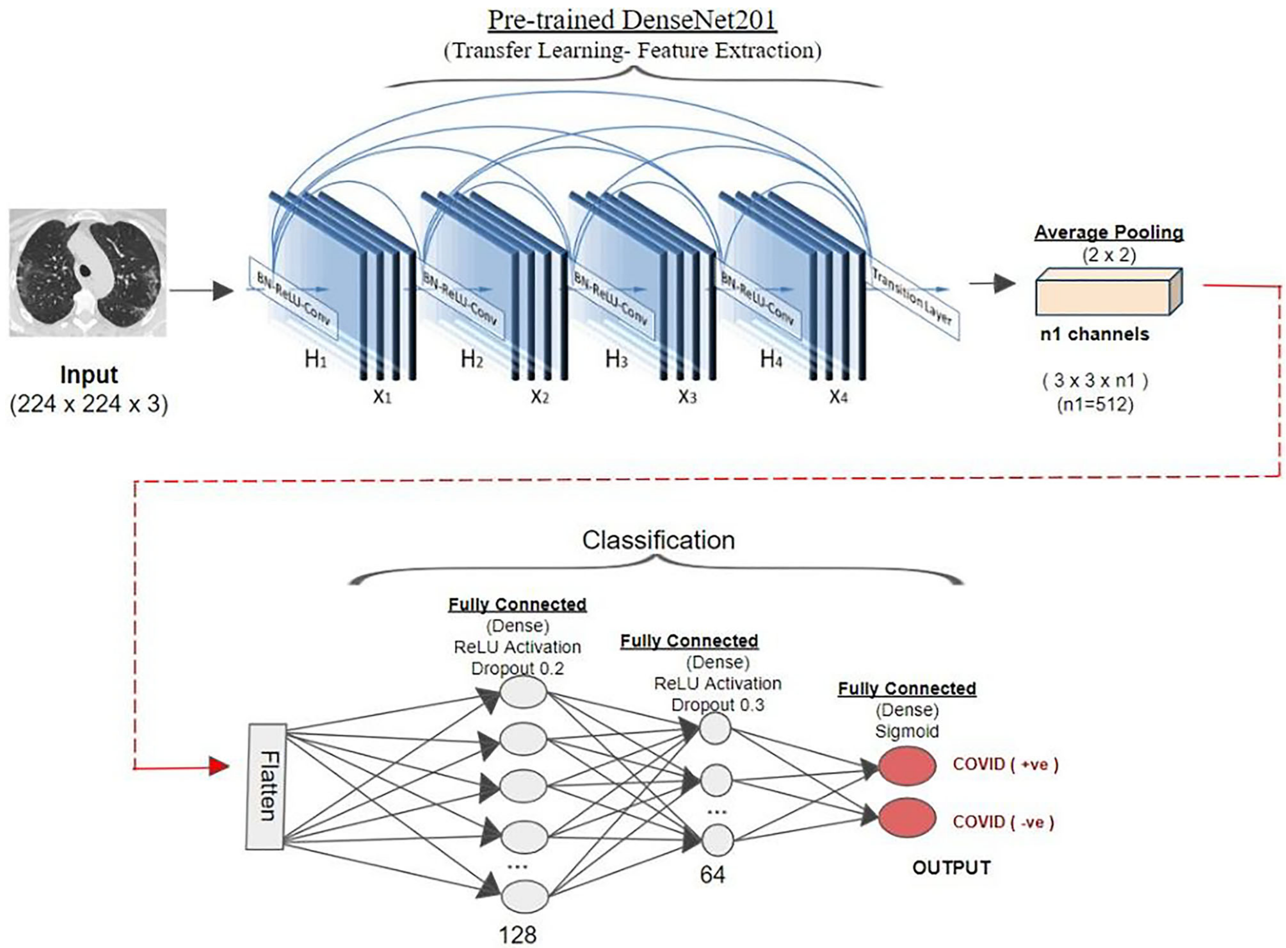

Figure 1. Architecture of proposed transferred DenseNet201 for feature extraction with CNN for classification.

is utilized to extract features by using its own learned weights on the ImageNet dataset along with a convolutional neural structure (for more details please see Huang et al., 2017). The architecture of the proposed DTL model with DenseNet201 for COVID-19 patients classification is presented in Figure 1.

The DenseNet201 exploits the condensed network providing easy to train and highly parametrically efficient models due to the possibility of feature reuse by different layers which increases variation in the subsequent layer input and improves the performance (Huang et al., 2017). The DenseNet201 has shown remarkable performance on varying datasets such as ImageNet and CIFAR-100. To improve the connectivity in the DenseNet201 model, the direct connections from all preceding layers to all subsequent layers are introduced which is depicted in Figure 2.

The feature concatenation can be mathematically explained as:

$$z^l = H_l\left(\left[z^0, z^1, \ \ldots\ldots.,\ z^{l-1}\right]\right) \tag{1}$$

Here, $H_l\ (.)$ is a non-linear transformation which can be defined as a composite function comprising of batch normalization (BN), followed by a rectified linear unit function (ReLU) (Zu et al., 2020) and a Convolution of (3×3). $[z^0, z^1,\ \ldots\ldots.,\ z^{l-1}]$ refers to the feature map concatenation corresponding to layer 0 to $l-1$ which are integrated in a single tensor for ease of implementation. For down-sampling purposes, dense blocks are created in the network architecture which are separated by layers called transition layers which consist of BN followed by 1×1 convolution layer and finally a 2×2 average pooling layer.

The growth rate in DenseNet201 explains how the dense architecture achieves state-of-the-art results and is denotes by the hyperparameter k. DenseNet201 performs sufficiently well even with a smaller growth rate owing to its architecture where feature maps are considered as a global state of the network. Therefore, each successive layer has access to all feature maps of preceding layers. k feature maps are added to the global state by each layer where the total number of input feature maps at l^{th} layers $(FM)^l$ is defined as:

$$(FM)^l = k^0 + k\ (l-1) \tag{2}$$

Here, the channels in the input layer is given by k^0. To improve computational efficiency, a 1×1 convolution layer is introduced preceding every 3×3 convolution layer (as seen in Figure 3) which decreases the number of input feature maps which are typically more than the output feature maps k. The 1×1 convolution layer is introduced is called as bottleneck layer and produces 4k feature maps.

For classification, 2 dense layers with 128 and 64 neurons, respectively, are added. The feature extraction network i.e. DenseNet201 (top removed) followed by sigmoid activation

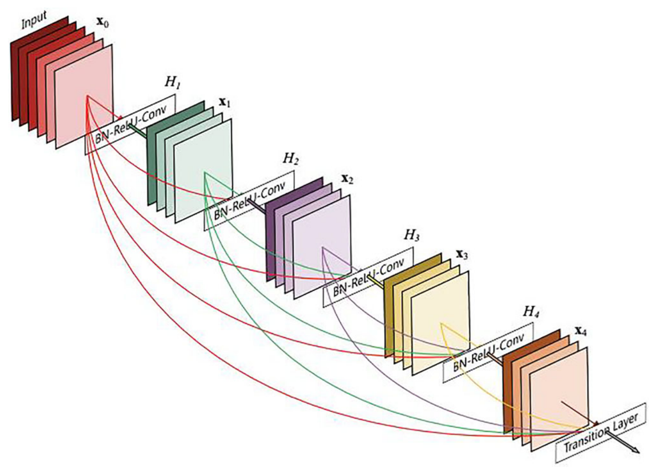

Figure 2. A 5 layered dense block representing direct connections between layers.

function for binary classification replacing the softmax activation function which is used in the classical DenseNet201 architecture (see Figure 1).

Each neuron in the fully connected dense layer is fully connected to each neuron in previous layer. It can be mathematically explained by a fully connected layer l whose input 2D feature map is expanded to a 1D feature vector as (Zhang et al., 2019):

$$t^{l-1} = \mathrm{Bernoulli}(p) \tag{3}$$

$$\ddot{x}^{l-1} = t^{l-1} * c^{l-1} \tag{4}$$

$$\ddot{x}^{l} = f(w^{k}\ddot{x}^{l-1} + o^{l}) \tag{5}$$

Here, Bernoulli function randomly generates a vector t^{l-1} obeying the 0–1 distribution with a specified probability. The vector dimension is c^{l-1}. The first two layers of the full connection layer use the dropout strategy to randomly block certain neurons according to a specified probability, which effectively prevents the over-fitting phenomena in the deep networks. w^l and o^l define the weighting and offset parameters of the fully connected layer respectively. The sigmoid activation function is to convert the non-normalized outputs to binary outputs as 0 or 1. Hence, it assists in the final classification of COVID-19 (+) and COVID-19 (−) patients. The sigmoid function can be defined as:

$$y = \frac{1}{1 + e^{-\left(\sum w_i . x_i\right)}} \tag{6}$$

where y is the output of the neuron. w_i and x_i represent the weights and inputs, respectively.

4. Performance analysis

This section focusses on the comparative analyses among the proposed and the existing deep transfer learning based COVID-19 classification models. The other pre-trained models which are used in this paper are as: VGG16, ResNet152V2 and Inception-ResNetV2. COVID-19 dataset contains 2492 CT scans, out of which 68% of the total dataset is used for training the model. 17% of the dataset is used for validation purpose. Remaining 15% of the dataset is used for testing purpose. Data Augmentation is also used in all the COVID-19 classification models. The epochs are set to be 300.

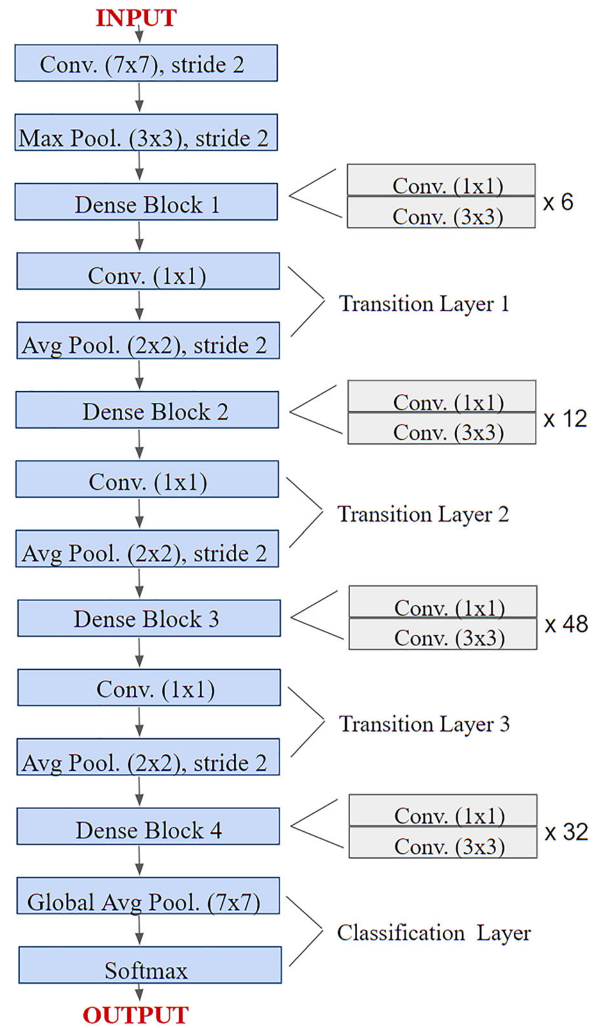

Figure 3. Layered Architecture of DenseNet201.

4.1. Dataset

The SARS-CoV-2 CT scan dataset available on kaggle (www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset) is used for experimental purpose. The dataset consists of a total of 2492 CT-scans out of which 1262 are positive for SARS-CoV-2 infection i.e. COVID-19 (+) and the rest 1230 are negative for SARS-CoV-2 infection i.e. COVID-19 (−). The data augmentation is used with rotation up to 15°, slant-angle of 0.2°, horizontal flipping enabled and the mode for filling new pixels as 'nearest' for better robustness and to have a diverse data. Figure 4 shows a sample of CT scans of COVID-19 (+) patients from the dataset.

4.2. Quantitative analyses

The proposed deep transfer learning (DTL) based COVID-19 classification model is compared with the competitive models by considering the various confusion matrix-based performance metrices. These metrices are as precision, recall, F1-measure, specificity, sensitivity, and accuracy.

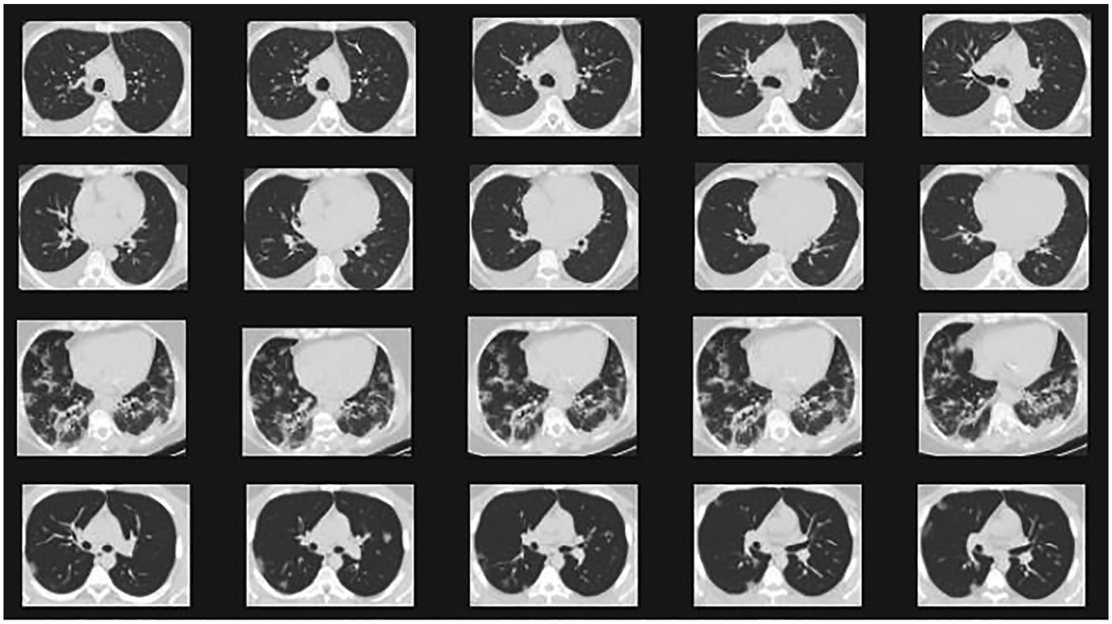

Figure 4. SARS-CoV-2 CT scan dataset sample images.

The main objective of this paper is to determine either the person has been infected from SARS-CoV-2 or not. The test outcome can be positive (recognize the patient has been infected from SARS-CoV-2) or negative (recognize the patient has not been infected from SARS-CoV-2). The test outcomes for every patient may or may not match the patients' actual class. In this setting, it is assumed that true positive (TP) represents COVID-19 (+) patients are correctly recognized as COVID-19 (+). False positive (FP) shows the patients infected from other lung diseases, i.e. COVID-19 (−) that are incorrectly recognized as COVID-19 (+). True negative (TN) represents COVID-19 (−) patients are correctly recognized as COVID-19 (−). Finally, false negative (FN) represents COVID-19 (+) patients are incorrectly recognized as COVID-19 (−). In order to validate the performance of the proposed model, the following performance measures are used.

Accuracy (A_c) is the measure of all the correctly recognized cases. It is commonly used measure especially when both the classes i.e. COVID-19 (+) and COVID-19 (−) are equally important. A_c is defined as the number of all correct classifications divided by the total number of items (Sokolova et al., 2006). A_c can be computed as (Liu et al., 2011):

$$A_c = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

However, A_c does not consider how the data is distributed. Therefore, F-measure (F_m) is used to handle distribution issue with accuracy. It is useful when the dataset contains imbalance classes. It is often introduced as harmonic mean of P_r and $\mathrm{R_c}$. It can be evaluated as (Liu et al., 2011; Sokolova et al., 2006):

$$F_m = \frac{2 \times P_r \times \mathrm{R_c}}{P_r + \mathrm{R_c}} \tag{8}$$

Precision (P_r) is used to evaluate an exactness of the classifiers. Low P_r value indicates that the classifier suffers from a large number of FP. The mathematical formulation of P_r is given below (Liu et al., 2011):

$$P_r = \frac{TP}{TP + FP} \tag{9}$$

Recall ($\mathrm{R_c}$) also called sensitivity defines as a measure of a classifier's completeness. Lower $\mathrm{R_c}$ value indicates that the classifier suffers from the larger FP values issues. The It can be computed as (Liu et al., 2011; Sokolova et al., 2006):

$$R_c = \frac{TP}{TP + FN} \tag{10}$$

Specificity (S_p) defines the proportion of actual negatives that are correctly classified as such (e.g. the percentage of COVID-19 (−) patients who are accurately classified as not having the COVID-19 disease). S_p can be defined as:

$$P_r = \frac{TN}{TN + FP} \tag{11}$$

The value of above-mentioned performance measures should be maximized for better performance. Figure 5 shows the training and validation accuracy and loss analyses of the proposed DTL model with respect to number of epochs. It clearly shows that the proposed model gains significantly more accuracy and loss values even at 100th epoch. It shows the proposed mode convergence at significantly good speed.

In medical research especially for critical diseases such as COVID-19, it is significantly important to reduce the false positive and false negative outcomes in the modelling process. False negatives for obvious reasons should be minimum so as to not misclassify any COVID-19 (+) patient as a COVID-19 () may harm our soociety a lot. Also, it is also essential to lower the nuber of false positives as a COVID-19 (−) to classify as COVID-19 (+) may lead to unncessary

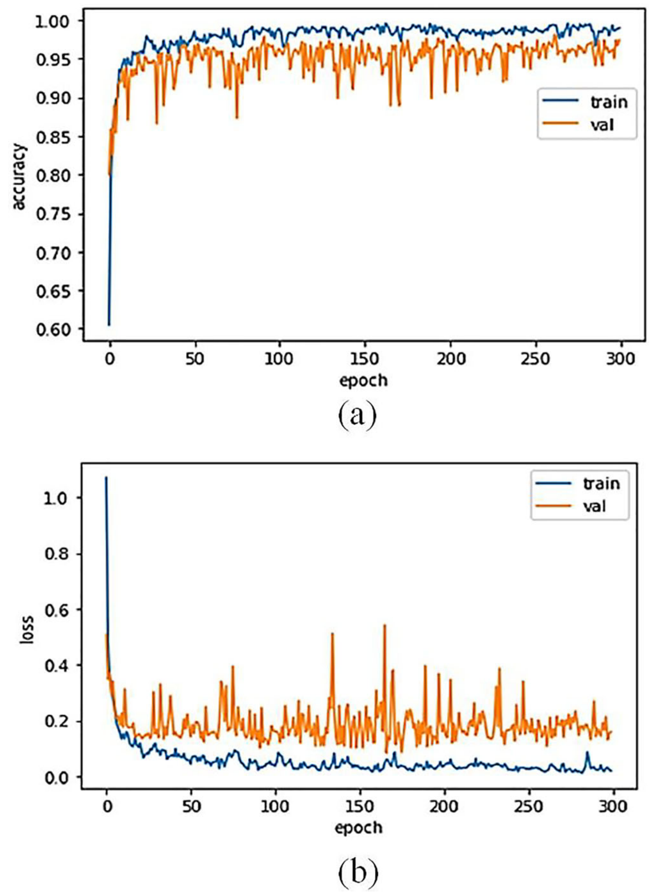

Figure 5. Training and validation analysis over 300 epochs: (a) Training and Testing accuracy analysis and (b) Training and Testing loss analysis.

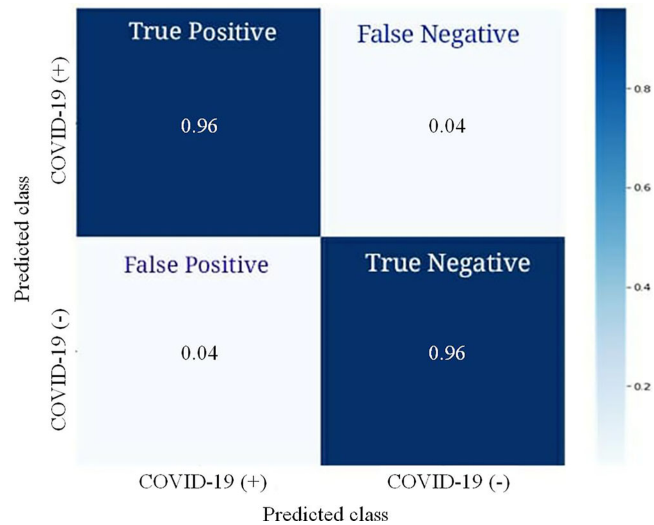

Figure 6. Confusion Matrix analyses of the proposed model represneting TP, TN, FP and FN ratio obtained from the testing dataset.

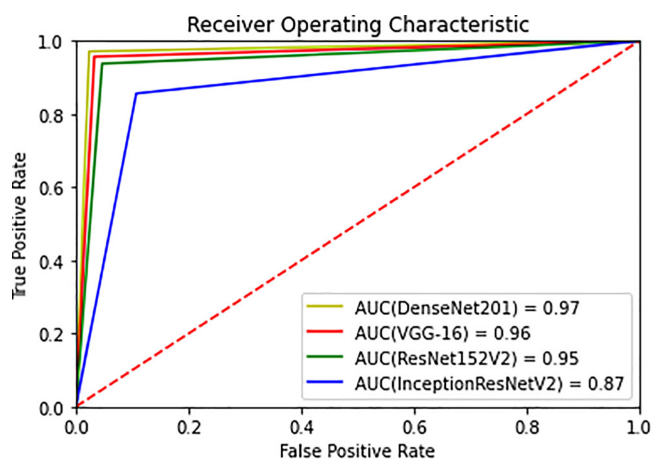

Figure 7. Area Under Curve for proposed model and other transfer learning models.

Table 1. Training analysis of the proposed and the existing deep learning based COVID-19 classification models.

Model	Precision	Recall	F-measure	Specificity	Accuracy
VGG16	0.9932	0.9965	0.9982	0.9982	99.82%
Inception ResNet	0.9436	0.9755	0.9593	0.9401	95.80%
Resnet 152V2	0.9953	0.9822	0.9976	0.9952	99.76%
DenseNet	0.9999	0.9965	0.9982	0.9923	99.82%

Table 2. Testing analysis of the proposed and the existing deep learning based COVID-19 classification models.

Model	Precision	Recall	F-measure	Specificity	Accuracy
VGG16	0.9574	0.9523	0.9549	0.9567	95.45%
Inception ResNet	0.9015	0.9206	0.9109	0.8972	90.90%
Resnet 152V2	0.9292	0.9735	0.9509	0.9243	94.91%
DenseNet	0.9629	0.9629	0.9629	0.9621	96.25%

emotional disruption for an individual. The proposed model achieves 96% accurate classification results and the impact of false postive and false negative rate is shown in Figure 6 with the help of confusion matrix. It clearly shows that the proposed approach provides lesser false negative and false positive rate. Thus, the proposed model can be best alternative of rapid COVID-19testing kits.

Receiver operating characteristic (ROC) curve is a graph which shows the classification performance of a model on two parameters i.e. true positives and false positives. Figure 7 shows the area under ROC curve (so called area under curve (AUC)) analyses of the proposed model along with VGG-16, ResNet152V2, and InceptionResnetV2 based COVID-19 classification models. It is observed that the proposed DTL with DenseNet201 based COVID-19 classification model (with AUC = 0.97) performs significantly better as compared to the existing COVID-19 classification models.

The analyses are carried out on the training and testing data in Tables 1 and 2, respectively. The training and validation analysis with respect to number of epochs are given in Figure 2. The training accuracy of the proposed model is found to be 99.8232%, whereas validation accuracy is 97.48291%. Therefore, it is observed that the proposed model trains efficiently keeping the minimum losses and owing to the minimal variation between validation and training accuracies. Thus, proposed model is least effected by over-fitting issue. Also, the proposed model can be efficiently utilized to classify the patients under examination as COVID (+) or COVID (−) from the chest CT-scans.

5. Conclusion

In this paper, a novel deep transfer learning model is designed for COVID-19 disease with the help of convolutional neural network and the pre-trained DenseNet201 model. The proposed model classifies the chest CT-scans with the training, testing, and validation accuracy as 99.82%, 96.25%, and 97.4%, respectively. Comparative analyses revealed that the DenseNet201 based CNN performs significantly better as compared to some well-known deep transfer learning models.

The accuracy achieved from the proposed model is 97%. However, the accuracies obtained from VGG-16 and Resnet152V2 are 96% and 95%, respectively. 1% improvement has been achieved from the proposed model, when it was compared with the competitive models. However, when we apply the proposed model to a larger size population, then the performance gain of 1% can be saved a lot of lives.

As CT scans facility are available in most of the medical institutions, thus, the proposed model can improve the COVID-19 testing process. Therefore, the proposed model can act as an alternative to various COVID-19 testing kits.

The future work intends to develop a full system for COVID-19 by combining deep learning and feature extraction using different techniques such as color (El Asnaoui et al., 2015), texture (El Asnaoui et al., 2016), shape (Chawki et al., 2018; Ouhda et al., 2017), meta-heuristic techniques (Gupta et al., 2020; Kaur, Singh, Kumar, et al., 2020; Kaur, Singh, Sun, et al., 2020; Kaur & Kumar, 2018; Kaur & Kumar, 2020), image filters (Yu et al., 2019; Singh et al., 2019a, 2019b), etc. In addition, the performance may be improved using more datasets and more sophisticated feature extraction techniques.

Disclosure statement

The authors declare no conflict of interest regarding the publication of this paper.

Ethical approval

This research work does not involve chemicals, procedures or equipment that have any unusual hazards inherent in their use.

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