DeepCOVNet : A Convolutional Neural Network For COVID-19 Detection from Chest X-ray Images with Collective Parallel Binary Pre-training Scheme☆

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Abstract

Since the onset of the COVID-19 pandemic, radiographic image analysis coupled with artificial intelligence (AI) techniques has become popular due to insufficient RT-PCR test kits along with its low sensitivity and long time requirement. In this paper, an automated COVID diagnosis scheme is proposed exploiting the advantages of a proposed deep neural network, named as DeepCOVNet, using chest X-ray images. To overcome the limitations of scarcity of COVID X-rays, a novel pre-training scheme is introduced to exploit the available X-rays of normal and community acquired pneumonia patients to effectively learn the inter-class separability. Due to the similarity of COVID X-rays with traditional community acquired pneumonia, several deep networks are pre-trained on different binary classes relating normal, viral and bacterial pneumonia for extracting effective two-class separable features. Afterwards, features from these pre-trained networks are aggregated in the DeepCOVNet architecture though a joint optimization operation utilizing a balanced COVID and other X-ray database. This scheme increases class separability of extracted features to obtain the optimum performance in final multi-class training stage utilizing the learning of binary pre-training stage. To introduce the advantages of traditional transfer learning scheme, these networks are initialized with ImageNet weights for faster convergence. Extensive experimentations with MobileNet, DenseNet201, Xception and InceptionV3 networks provide very satisfactory performance with a maximum accuracy of 98.04% in 3-class (COVID/Normal/Pneumonia), 88.67% in another 3-class (Normal/Viral/Bacterial Pneumonia) and 90.24% in 4-class (COVID/ Normal/Viral/Bacterial pneumonia) cases that signifies the effectiveness of the proposed scheme.

Keywords: Artificial Intelligence, COVID-19, CNN, Computer-aided diagnosis, Transfer Learning

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1. Introduction

Coronavirus disease 2019 (COVID-19), caused by SARS-COV-2[1], has already brought an unprecedented economic loss and posed a major challenge by creating a dilemma to choose between life and livelihood. It is highly contagious and patients affected by this disease exhibit from mild or no symptoms to severe respiratory problems and multiple organ failure or even death. So, apart from social distancing and hygiene maintenance, numerous testing is recognized to be the best solution till now, since no drug and adequate vaccine is available yet.

As per the test is concerned, reverse transcription-polymerase chain reaction (RT-PCR) is taken to be the gold standard. But in many countries, access to RT-PCR is limited due to high cost and lack of expert technicians. This prompts the requirements of medical-image based diagnosis. In these circumstances, X-ray or computer tomography (CT) scans can be taken into account to deal with the barriers of testing. Though CT is more precise and sensitive, it also has many shortcomings like high cost, less availability, health issue, taking a long time for scanning, leading to alleviate the risk of getting infected of the health professionals. On the contrary, X-ray is cheap, less hazardous, easily available and clearly shows the abnormalities in the lungs. These benefits edge chest X-ray over CT to be used as the suitable modality for COVID-19 detection.

Due to the rapid outbreak and high transmission rate of COVID-19, an automated AI-based deep learning system with chest X-ray images can play a significant role to ensure the early diagnosis of patients that will reduce further transmission and death rate because of coronavirus. As a result, several AI-based publications have been published for COVID-19 diagnosis which are discussed in the related work section. In these studies, it is observed that mainly machine learning and deep learning have been implemented for COVID-19 detection. As COVID-19 is one type of viral pneumonia, it has many similarities with the other bacterial and viral pneumonia. So, COVID-19 should be diagnosed from COVID-19, normal, bacterial pneumonia and viral pneumonia patients' chest X-rays. Hence, COVID-19 detection is a four-class (COVID-19 vs normal vs bacterial pneumonia vs viral pneumonia) problem. But as the four-class classification is often challenging, many researchers opted to perform the binary classification (COVID-19 vs Non-COVID-19) or the three-class classification (COVID-19 vs normal vs pneumonia). Analysing the works it is seen that in some cases COVID-19 is detected by training a deep neural network from the scratch. This may not be an ideal method since the limited chest X-ray data is not sufficient for the optimization of the convolutional neural networks (CNN). To deal with this scarcity of data, two methods such as using deep neural networks as feature extractors and machine learning algorithms as the classifiers and transfer learning are used. Since transfer learning can compensate for the data deficiency problem, the use of machine learning algorithms as classifiers may not be required. In the case of transfer learning, in most studies, the deep neural network is pre-trained on ImageNet dataset. Since there is a significant difference between ImageNet data and the chest X-ray data, pre-training on ImageNet is not also suitable. Again in some cases, similar chest X-ray data are used for pre-training purpose. But in these cases, a similar chest X-ray data are used simply all together. No special combination of the similar X-ray dataset has been investigated in the pre-training stage to enhance the transfer learning further by extracting the efficient inter-class separable features. Moreover, no one in the literature is able to improve the most challenging four-class classification problem as COVID-19 is one type of viral pneumonia too. So, a method capable of dealing with the four-class problem by enhancing the inter-class separable features extraction and efficiently pre-trained using another similar dataset has a great demand.

In this paper, a new model, DeepCOVNet, is proposed to identify COVID-19 utilizing the available chest X-rays of COVID-19 and other common pneumonia patients. To deal with barriers of the scarcity of COVID X-rays and extreme similarities among COVID and other pneumonia X-rays, a novel pre-training scheme is developed to learn the inter class separability effectively by employing the larger dataset of normal and familiar pneumonia X-rays. First, several binary training (normal/pneumonia, normal/bacterial pneumonia, normal/viral pneumonia, bacterial/viral pneumonia) are performed to extract diversified two-class separable features. Then these separable features were combined with the joint features obtained from a balanced COVID, normal and pneumonia (viral and bacterial pneumonia) X-ray dataset by introducing parallel paths in the proposed network. As a result, when optimized, the scheme is able to separate the classes from each other in the final multi-class training stage by applying knowledge of binary pre-training phase more efficiently. Again, to employ the advantage of traditional transfer learning, the binary networks of the pre-training stage and the network apart from binary networks in the multi-stage training were initialized with ImageNet weights. So, the whole architecture is optimized more efficiently and gives a boost in the performance than the traditional process whatever base model is used. Through exclusive experimentation, it is observed that the proposed scheme improves every traditional metrics and outperforms other schemes in the literature for binary, three-class and four-class classifications combined. All the codes and architectures are publicly available at `https://github.com/OishyS11/DEEPCOVNET-architecture`

2. Related Work

Deep learning has been used successfully in medical studies in recent times, especially using chest X-ray images. In [2], deep learning is used to classify X-ray images of potential tuberculosis patients. Here the authors demonstrate the improvement in the result when the model is pre-trained on large-scale chest X-ray images. Again, in [3], authors retrain the ImageNet pre-trained CNN models on large-scale chest X-ray images collected from different sources to evaluate the influence of modality-specific knowledge transfer for tuberculosis detection. This modality-specific transferred knowledge later on fine-tuned helps to improve tuberculosis detection. Ensemble learning is also performed using best-performing CNNs for enhancing the performance. Besides, deep learning is used on X-ray images in pneumonia detection [4–8] and other medical areas [9–13]. So, taking the motivation from these studies and due to the severity of COVID-19, several methods have been proposed by researchers to detect COVID-19 from X-ray images. In some methods, deep learning models have been used by training from the scratch. In [14], a deep model named DarkCovidNet is designed for both binary class (COVID vs No-Findings) and three-class cases(COVID vs No-Findings vs Pneumonia) utilizing the dataset of a researcher named Joseph Paul Cohen from the University of Montreal (127 COVID-19 X-ray images) and Wang et al. [15]. The proposed DarkCovidNet model is formed using the mother architecture DarkNet-19 as a classifier for You Only Look Once (YOLO) real-time object detection system and is trained from scratch. Again, [16], a novel technique called Fast COVID-19 Detector (FCOD) is proposed to have a fast detection of COVID-19 using X-ray images obtained from a GitHub repository [17]. The FCOD is a deep learning model based on the Inception architecture that uses 17 depthwise separable convolution layers. Depthwise separable convolution layers are used here to decrease the computation costs, time and parameters. However, only binary classification is done here and the accuracy is 96% which is low compared to other methods. Since COVID-19 is a recent disease, there is limited data available which may not be sufficient for the optimization of the CNN layers to extract accurate features. For solving this issue, some researchers used different deep learning models pre-trained on ImageNet dataset. In [18], transfer learning method is explored by using five state-of-the-art CNN models, namely VGG19, MobileNet V2, Inception, Xception and Inception ResNetV2 pre-trained on ImageNet data for COVID-19 detection. Three public datasets, one is developed by Cohen JP, one Kaggle repository [19] and the other is formed by Kermany et al. [20], are combined to gather 1427 chest X-ray images (224 COVID-19 images) and MobileNet V2 generates the best result in these datasets for three-class and binary classification claimed by the authors. Again, in [21], four common convolutional neural networks, ResNet18, ResNet50, SqueezeNet, and DenseNet-121, are used to perform binary classification by fine-tuning the pre-trained version of these models on ImageNet. 2000 X-ray images are used for training and 3000 images are used for testing from the combination of the dataset of Cohen JP and ChexPert dataset [22]. Furthermore, in [23], another three pre-trained (ImageNet) convolutional neural networks (DenseNet121, NASNetLarge, and NASNet-Mobile) are fine-tuned on 309 COVID-19 and 2000 pneumonia and 1000 healthy chest X-ray images. However, in [24], a model named CoroNet based on Xception architecture is proposed which was pre-trained on ImageNet data to perform four-class, three-class and binary classification utilizing the dataset of Cohen and a kaggle repository named chest X-ray images (pneumonia). As per accuracy is concerned, CoroNet edges the best performing MobileNet V2 of [18] by a little margin. In [25], modified deep convolutional neural network is proposed by concatenation of Xception and ResNet50V2 for COVID-19 detection. The CNNs are pre-trained on the ImageNet dataset. Despite using large non-COVID-19 X-ray images, the experiment lacks COVID-19 X-ray images(only 149). To deal with the imbalance dataset, the authors perform the training in some phases and the (149 COVID + 34 pneumonia) patients are identical for each training phase and 200 pneumonia and 250 normal cases are different. Only three-class(COVID-19 vs normal vs pneumonia) classification is performed here. Again,in [26], authors propose COVIDiagnosis-Net, a tuned SqueezeNet architecture with Bayesian optimization additive. The proposed model, pre-trained on ImageNet dataset is fine-tuned later. Despite high accuracy, their dataset, gathered by Cohen JP, has only 76 COVID-19 X-ray images and is then augmented and three-class classification is done. In [27], a patch-based convolutional neural network is proposed for the limited dataset. Despite the network being computationally simple, a significantly small number of bacterial and viral pneumonia X-ray images are used for classification. The network is based on ResNet-18 architecture and ImageNet dataset is used for pre-training and transfer learning purposes. Four-class classification is done here. In [28], a deep learning model, modification of VGG19, previously trained on ImageNet dataset is proposed. A trainable multilayer perceptron is introduced on top of the pre-trained VGG-19 model. The dataset is formed by the combination of two publicly available datasets of Cohen JP and Wang et al. Only binary classification is done here. In [29], a model, CovidGAN, is constructed to improve the accuracy of detection of COVID-19 based on data augmentation using auxiliary classifier GAN. The used CNN model is pre-trained VGG16 and is fine-tuned later. But the authors conduct only binary classification (COVID vs Normal) which fails to justify the contribution for multi-class classification and GAN is computationally very expensive. Again in [30], transfer learning technique is used for detecting COVID-19 from other infectious diseases using 352 X-ray images obtained from different public sources. Here, the authors perform 25 different types of augmentation through an open-source augmentation tool CLoDSA. Total 27 datasets (one consists of the original images and other 25 consists of the single augmented images and the last one is the combination of original and the augmented images) are created. The combination of two best-performing models (each trained on 286 images, rotated through 120° or 140° angle) is selected as the proposed technique for the classification of normal, COVID-19, non-COVID-19, pneumonia, and tuberculosis images. Besides using deep learning models pre-trained on ImageNet dataset, some researchers used deep learning models as feature extractors and machine learning algorithms as classifiers. In [31], the X-ray images are re-structured using the Fuzzy Color technique and this restructured images are stacked with the original images of the dataset. Then the stacked dataset is trained with deep learning models (MobileNetV2, SqueezeNet) pre-trained on ImageNet dataset and the feature sets obtained by the models are optimized by Social Mimic optimization method. After that, Support Vector Machine (SVM), a machine learning algorithm, is used for classification by utilizing the combined optimized features obtained from the deep learning models.The authors combine two public datasets for three-class classification. One is developed by Cohen and the other is constructed by a team of researchers from Qatar University and medical doctors from Bangladesh. Despite the inclusion of two datasets, there are only 295 COVID-19 X-ray images, 65 normal X-ray images and 98 pneumonia X-ray images. Again, in [32], an automated detection scheme named EMCNet is proposed to detect COVID-19 patients by chest X-ray images. A CNN is developed to extract deep features and an ensemble of binary machine learning classifiers (random forest, support vector machine, decision tree, and AdaBoost) is used to detect COVID-19 from these features. Here, only binary classification is conducted. In [33], a model based on InceptionV3 architecture and initialized with ImageNet weights is brought forward. In the literature, the model is truncated and three inception modules along with a grid size reduction block are used with SVM classifier. The authors also use the dataset of Cohen JP and Kaggle Chest X-ray images (pneumonia) dataset and two publicly available Tuberculosis datasets but mostly perform binary class (COVID-19 vs combination of other classes) classification. In [34], different texture descriptions (LBP, LPQ, LDN etc) along with Ineception V3 model pre-trained on ImageNet dataset are fused to detect COVID-19 from other pneumonia classes. However, they used a very small number of COVID-19 data, as many as 100 samples obtained from Cohen JP.They perform a seven-class classification. Though in the above three studies machine learning is used due to shortage of COVID-19 dataset, pre-training the deep learning models by similar large pneumonia datasets and then transferring the learned knowledge to detect COVID-19 for smaller dataset may solve the problem of data scarcity. So, in [35], a model named CovXNet is designed which utilizes depthwise convolution with varying dilation rates using transfer learning technique.Four-class and binary classifications are operated. Though a large number of chest X-rays of normal and (viral/bacterial) were used to train the model, no initiatives were taken to extract additional class-wise diversified features to boost the performance of detecting the most challenging bacterial and viral pneumonia class from COVID-19 class.In [36], a transfer learning technique is applied to detect COVID-19 by Xception architecture. The dataset used here is same as of [14] and outperformed the accuracy of CoroNet model of [24].Though they pre-trained their model with large available pneumonia dataset, they did not conduct the four class classification (COVID/Normal/Bacterial/Viral), the most challenging one.As a whole

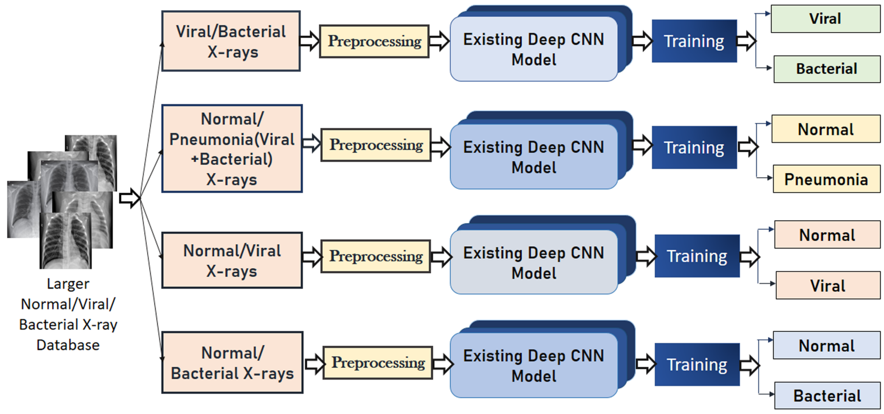

Figure 1: Initial pre-training phase

it is seen that, neither of the authors have dealt with the challenging four-class classification properly. Even most of the author have not done the four-class problem. So, in the case of four class classification, there are still rooms for improvement.

3. Methodology

The proposed scheme consists of mainly two steps:

(1) Initial pre-training for transfer learning

Due to the scarcity of chest X-rays with confirmed COVID-19 cases, it is extremely difficult to train the existing deep convolutional neural network (CNN) models effectively from scratch. Transfer learning can be a viable solution in this regard. In this paper, a two-stage transfer learning approach is adopted to overcome the limitation of conventional single-stage transfer learning that relies on pre-training via the ImageNet dataset. It is well known that the images in the ImageNet dataset are completely different from the chest X-ray images. Hence, direct use of a deep CNN model transfer learning with ImageNet weights cannot be a good choice for diagnosing COVID-19 from chest X-rays. Also, COVID-19 X-rays contain a high degree of similarity with traditional pneumonia chest X-rays caused by a viral or bacterial infection.

In this paper, a scheme is proposed to utilize a large number of available normal and viral/bacterial pneumonia infected chest X-ray images for training the available deep CNN networks so that the trained parameters can be effectively utilized in transfer learning to detect COVID-19 cases even with a small number of COVID-19 X-rays. Also, it allows the network to get more acquainted with chest X-ray images of the available classes like normal, viral or bacterial pneumonia.

As shown in Fig. 1, in the initial pre-training phase, any available deep convolutional neural network was trained individually for four binary classifications namely viral vs. bacterial pneumonia, normal vs. pneumonia, normal vs. viral pneumonia, normal vs. bacterial pneumonia utilizing larger normal/viral/bacterial extracting features in a more precise way and the weight vectors are optimized to obtain maximum separability between the two classes of data. So in this step, the weights of the deep CNN network were updated from Imagenet weights to the weights for binary classifications so that these updated weights can be further utilized for transfer learning in multi-class (COVID-19/normal/viral/bacterial) classification.

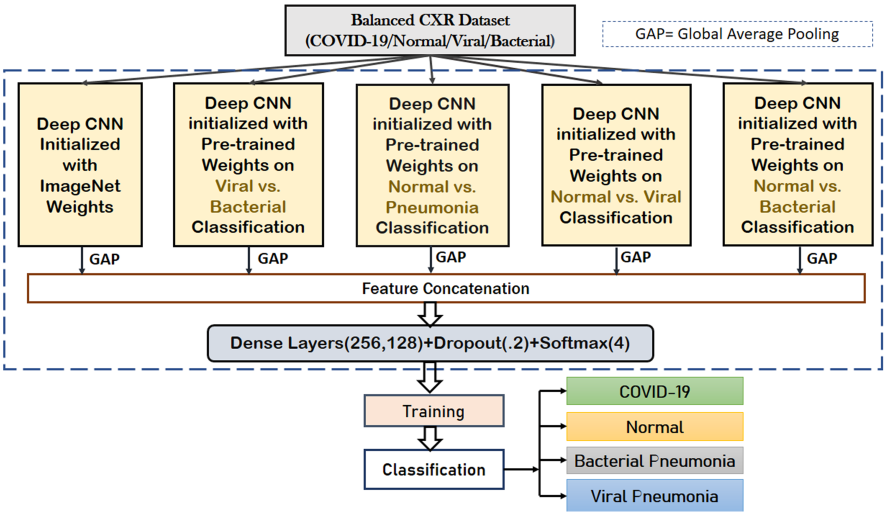

Figure 2: Workflow for proposed DeepCOVNet

pneumonia X-ray database. Here, instead of multi-class training, binary class training has been chosen as it gives the advantage of

(2) Binary pre-training fusion with a multi-class trainer in DeepCOVNet architecture:

The unique idea introduced in the proposed scheme is to add pre-trained binary networks along with the multi-class training network to boost up the overall classification performance. The binary pre-trained networks can be added in parallel to the multi-class training network. Finally, a combined overall optimization is performed considering cascaded features extracted from the parallel networks.

Fig. 2 shows the workflow for the proposed DeepCOVNet architecture. Here, a traditional deep CNN network that was previously trained on four binary classifications individually is added in parallel with the same network initialized with ImageNet weights. Features from all the parallel networks are concatenated through the Global Average Pooling (GAP) layer. Two dense layers, a dropout, and a softmax-activated dense layer are added after concatenation to ensure further training after the concatenation. The whole DeepCOVNet architecture was trained end to end on a smaller balanced CXR dataset containing COVID-19/normal/viral/bacterial pneumonia X-ray images. While training, the weights of parallel binary pre-trained networks were updated for multi-class classification.

It is to be noted that the overall proposed architecture allows all the parallel networks initialized with either ImageNet or binary pre-trained weights to be trained fully with the aid of the desired COVID-19 dataset where all 4-class data are now available in a balanced way.

During the testing phase of the chest X-ray images, the images are passed through the trained DeepCOVNet architecture and predictions are made to classify the images as COVID-19/normal/viral pneumonia/bacterial pneumonia.

3.1. Pre-processing

The datasets used for the initial pre-training phase and final training passed through minimal pre-processing for easier implementation in testing phases. The images were only reshaped to a uniform size before further processing with DeepCOVNet architecture.

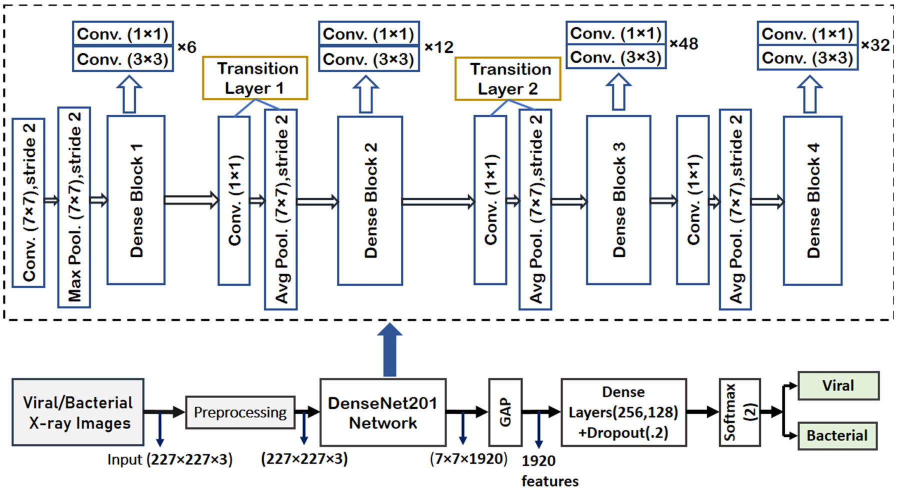

Figure 3: Viral vs bacterial pneumonia classification using DenseNet201 network. The same network has been used for other binary classifications in the pre-training phase.

3.2. Structural units for the pre-training phase

In the initial pre-training phase, the structural unit for each of the four binary classifications (viral vs. bacterial, normal vs. pneumonia, normal vs. viral, normal vs. bacterial) is composed of any available deep CNN and a classification head for extracting distinctive features. MobileNet, DenseNet201, InceptionV3, and Xception were used separately for the pre-training scheme to compare the performance of different existing deep CNN networks in these four binary classifications.

In Fig. 3 detailed network for viral vs. bacterial pneumonia classification in the pre-training phase has been shown. In this network, the DenseNet201 model followed by a Global Average Pooling (GAP) layer has been used. Other binary classifications were performed in the same way using the DenseNet201 CNN model. The classification head contains a dropout(.2) layer followed by two dense layers. The dense layers have 256 and 128 neurons respectively and each is associated with *relu* activation. The DenseNet201 network was initialized with ImageNet weights and end-to-end training was performed. After training for four different binary classifications, DenseNet201 networks extracted two-class separable features. The features are categorized between binary classes with some test data to justify the efficacy of extraction.

This whole pre-training scheme was repeated for some other existing deep learning models namely MobileNet, InceptiionV3, and Xception for comparison purposes.

3.3. Detailed architecture of proposed DeepCOVNet

Four parallel binary pre-trained structural units and an additional path of deep CNN initialized with ImageNet weights constitute the fundamental building blocks of the proposed DeepCOVNet architecture. As mentioned before, any existing deep convolutional neural network model can be used as the base model in the proposed DeepCOVNet architecture.

Fig. 4 shows the proposed DeepCOVNet with DenseNet201 as the base CNN model. Before feeding to the original network, the images are reshaped to a uniform size. Four DenseNet201 networks that were trained on four binary classifications in the pre-training phase are now added in parallel to a DenseNet201 network with ImageNet weights. After

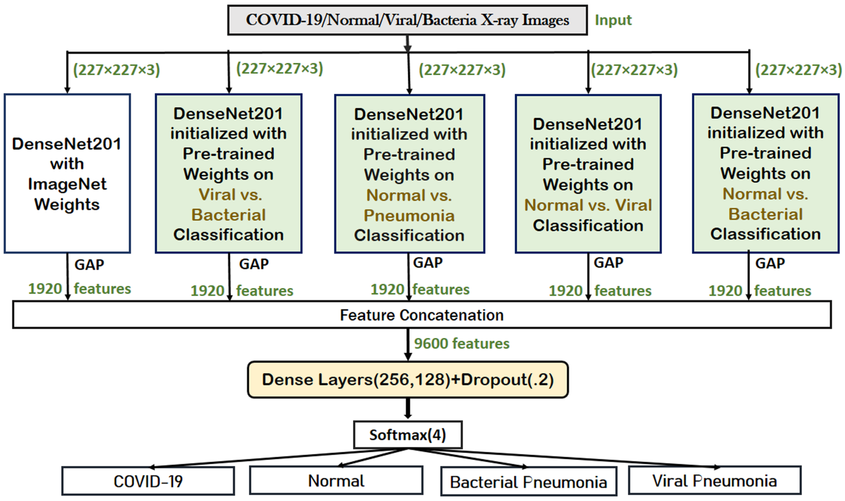

Figure 4: Proposed DeepCOVNet with DenseNet201 as the base CNN model

the global average pooling layer, 1920 feature vectors obtained from each of the parallel paths are concatenated. Finally for a combined overall optimization considering cascaded features extracted from various parallel architectures, two dense layers having 256 and 128 neurons respectively, a dropout(.2) layer is added. This entire deep convolutional network is trained end to end on a smaller balanced dataset containing COVID-19, normal, viral, bacterial pneumonia chest X-ray images for multi-class (4 class/3 class) classification.

For comparison purposes, some other traditional deep CNN models like Mobilenet, Xception, InceptionV3 were also used as the base CNN model in the proposed DeepCOVNet.

Both for binary and multiclass classification, the *Softmax* activation function is used. An ordinary convolutional neural network initialized with ImageNet weights is less likely to extract significant features for pneumonia and COVID-19 classes which results in finding less subtlety in the challenging classification process. Proposed DeepCOVNet outperforms in this regard with its initial pre-training scheme. As the structure is initialized with more reasonable weights, the proposed network converges faster and ensures optimal performance.

4. Results and Discussions

4.1. Datasets

The datasets used in this study comprise COVID-19, normal, viral and bacterial pneumonia chest X-ray images. The images were gathered from two different sources.
COVID-19 images were collected from GitHub [17] repository developed by Joseph Paul Cohen. The repository contains chest X-ray and CT images of detected COVID-19 cases. 408 COVID detected X-ray images were sorted out.
Normal and pneumonia images were collected from Kaggle [37]. The Kaggle dataset is composed of 1583 normal and 4273 pneumonia images of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. 4051 pneumonia and 1583 normal images were singled out from Kaggle. Figure 5 displays the sample images used in the study.

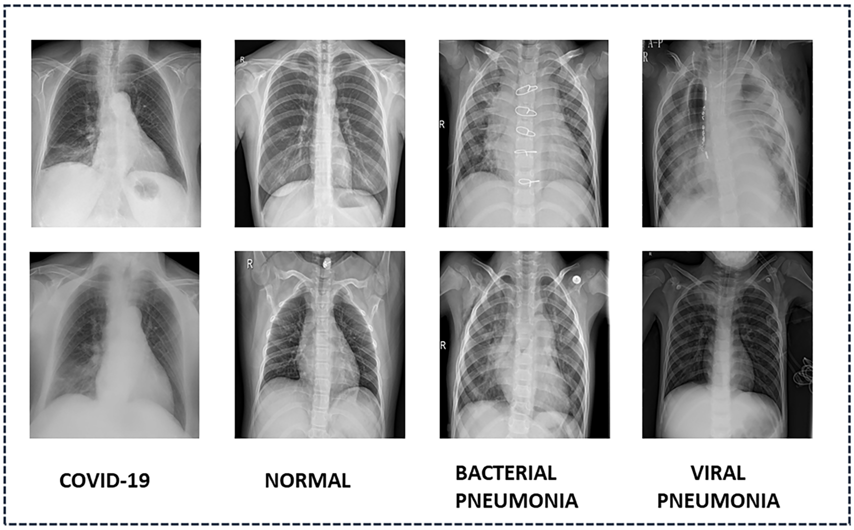

Figure 5: Some samples of COVID-19, normal, viral and bacterial pneumonia images used in the study

According to the scheme, our datasets were set up for two different tasks. A smaller balanced dataset containing 408 images of COVID-19, 408 images of normal, 408 images of bacterial and 408 images of viral pneumonia were first separated for the training of the proposed DeepCOVNet architecture.
Remaining larger number of chest X-ray images of normal, bacterial and viral pneumonia classes were used for pre-training phase. Table 1 depicts the division of images for pre-training. Five fold cross- validation scheme is employed to evaluate the performance of the proposed method in the final stage.
In initial pre-training phase, there arises the class imbalance problem in binary classification tasks. This problem biases the training process and hence the accuracy as well as sensitivity for minority classes reduces significantly. The problem was resolved by weighting the loss function during training.

Table 1: **Dataset for pre-trained transfer models**

Description of classes		Total number of images	
Class 0	Class 1	Class 0	Class 1
Bacterial Pneumonia	Viral Pneumonia	2213	1022
Normal	Pneumonia	1175	3234
Normal	Viral Pneumonia	1175	1022
Bacterial Pneumonia	Normal	2213	1175

4.2. Experimental Setup

For experimentation, Intel(R) Core(TM) i5-7200U CPU @2.50 GHz and two cores along with 8 GB RAM are used. For hardware acceleration, NVIDIA Geforce 940MX GPU having with 384 CUDA cores running 1176 MHz with GDDR5 memory is deployed.
All the experiments were performed in the Google Colaboratory Platform. The resolution of the images were set to 227×227 pixels. The network was trained on for 50 epochs. Adaptive

moment(Adam) was set as the optimizer with learning rate of 0.0001 and minimum learning rate of 0.00001. Loss function was categorical cross-entropy and metrics were accuracy. In the pretraining

4.3. Metrics

Accuracy, precision, recall or sensitivity, specificity, F-1 score are the metrics, based upon which we evaluated the performance of a classification algorithm. These metrics are based on confusion matrix and the numbers inside it.

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Sample}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives}$$

$$F - 1\ score = \frac{2 * Precision * Recall}{Precision + Recall}$$

4.4. Performance Evaluation

Initially, different traditional CNN models like MobileNet, DenseNet201, Xception, InceptionV3 were trained on the smaller balanced dataset (408 X-ray images of each class) using traditional transfer learning approach. For all the models, a classification head containing two dense layers (256 and 128 neurons with *relu* activation), a dropout(.2) layer and a final dense layer with *Softmax* activation is added after the global average pooling layer. The networks were initialized with ImageNet weights and end to end training was performed using the balanced datasets containing images of 4 classes. Table 3 shows the average performance of the state-of-the-art transfer learning approach for five folds for different models. The results for this scheme were less satisfactory as the features extracted by this transfer learning approach could not effectively separate challenging classes like viral and bacterial pneumonia properly. Also some of the viral and bacterial class images were mis-classified as normal images. As a result, the accuracy varied from 84% to 88% for different models in this approach.

In order to improve performance, pre-training scheme has been addressed on different binary classification like viral/bacterial, normal/bacterial, normal/viral, normal/pneumonia. The CNN models used for transfer learning approach were trained to extract separable features for the binary classifications. Remaining larger dataset, as mentioned in Table 1 was used for pre-training. Accuracy for the binary classifications for different CNN models are given in Table 2. For the viral/bacterial classification accuracy varies from 89% to 92% and for other classifications, it varies from 96% to 98%. As per the metrics, diversified two-class separable features have been achieved by approaching the initial pre-training scheme.

As shown in the proposed DeepCOVNet architecture, the four pre-trained networks with the respective CNN models were then concatenated through GAP layers. The balanced datasets containing 408 images of each class were used to train the proposed architecture.

Table 2: **Results for Pre-training Phase**

Classification Task	Accuracy(%)			
	MobileNet	DenseNet201	Xception	InceptionV3
Viral/bacterial	90.85	92.07	90.24	89.63
Normal/bacterial	97.56	96.95	97.56	97.56
Normal/viral	96.34	95.73	92.07	95.73
Normal/pneumonia	96.95	95.73	98.17	97.56

Table 3: **Performance comparison of the proposed DeepCOVNet architecture and traditional transfer learning scheme for 4 Class(COVID-19/normal/viral/bacterial pneumonia) problem**

CNN Model Used	Scheme	Precision(%)	Sensitivity(%)	Specificity(%)	F-1 score(%)	Accuracy(%)
MobileNet	**Proposed**	**89.67**	**89.26**	**96.41**	**89.16**	**89.26**
	Simple Transfer Learning	85.72	84.24	94.74	83.04	84.24
DenseNet201	**Proposed**	**90.51**	**90.24**	**96.77**	**90.04**	**90.24**
	Simple Transfer Learning	89.08	88.46	96.14	88.31	88.46
Xception	**Proposed**	**90.23**	**89.76**	**96.48**	**89.65**	**89.77**
	Simple Transfer Learning	87.68	87.17	95.74	87.03	87.13
InceptionV3	**Proposed**	**90**	**89.64**	**96.76**	**89.61**	**89.64**
	Simple Transfer Learning	87.14	89.26	95.42	85.45	86.26

While training, the left most path with any of the CNN models was initialized with ImageNet weights and kept trainable. The rest four pre-trained networks were initialized with the weights of binary classification and fine-tuned to converge quickly for unknown datasets.

Table 3 shows the performance of the proposed DeepCOVNet architecture for different models. From the table, it is evident that concatenation with the pre-trained networks has brought a great deal of improvement in all the performance metrics compared to usual transfer learning approach which was performed initially.

Fig. 6 displays the comparison of combined confusion matrix for five folds between proposed DeepCOVNet architecture and usual transfer learning approach using MobileNet model. As mentioned earlier, for ordinary transfer learning, 32% viral were identified as bacterial pneumonia and 15% were mis-classified as normal. After introducing pre-trained networks, the sensitivity of viral class increased to 80% from 52%.

Our network was further trained on 3-class dataset to justify the efficacy of the novel pre-training approach. The 3-class datasets were of two types.

- Normal/viral/bacterial pneumonia
- COVID-19/normal/pneumonia

In the first phase of 3-class classification, the proposed architecture was trained on a large number of available normal/viral/bacterial pneumonia dataset. As pneumonia caused by

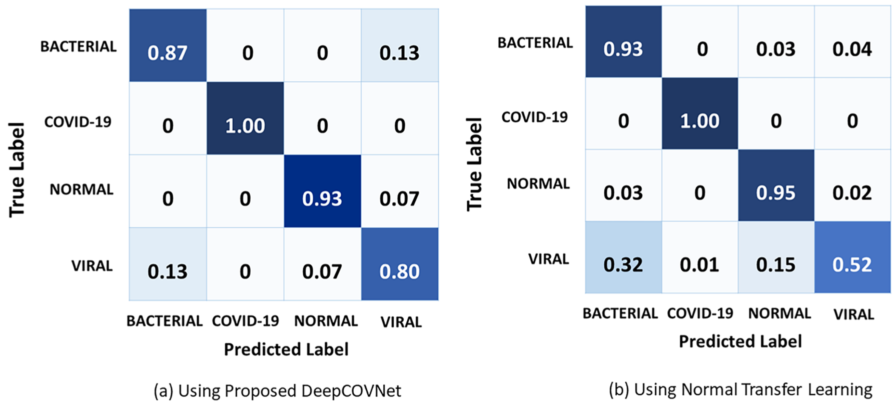

Figure 6: Combined confusion matrix for five folds for 4 class problem using MobileNet model

Table 4: **Performance comparison of the proposed DeepCOVNet architecture and simple transfer learning scheme for 3 Class (Normal/viral/bacterial)problem**

CNN Model Used	Scheme	Precision(%)	Sensitivity(%)	Specificity(%)	F-1 score(%)	Accuracy(%)
MobileNet	**Proposed**	**87.56**	**86.32**	**95.73**	**86.45**	**86.82**
	Simple Transfer Learning	84.23	83.81	94.54	83.71	83.56
DenseNet201	**Proposed**	**88.32**	**87.81**	**95.62**	**87.37**	**87.24**
	Simple Transfer Learning	86.29	86.76	95.74	85.38	85.62
Xception	**Proposed**	**89.54**	**88.28**	**96.75**	**88.45**	**88.67**
	Simple Transfer Learning	86.58	85.71	96.24	85.63	85.36
InceptionV3	**Proposed**	**88.05**	**86.88**	**95.35**	**86.90**	**86.93**
	Simple Transfer Learning	86.82	85.77	95.28	85.67	85.77

virus and bacteria exhibits a high degree of similarity, the pre-training scheme has eased the classification process. Table 4 shows the significant improvement in all metrics with the proposed DeepCOVNet architecture. Using ordinary transfer learning, MobileNet, DenseNet201, Xception and InceptionV3 networks yield accuracy of 83.56%, 85.62%, 85.36%, 85.72% respectively. The proposed DeepCOVNet arhitecture outperforms the state-of-the-art transfer learning in terms of all performance metrics. Mobilenet, DenseNet201, Xception, InceptionV3, as the base models of DeepCOVNet architecture, yield 86.82%, 87.82%, 88.67%, 86.13% accuracy respectively. Fig. 7 displays the comparison of combined confusion matrix between proposed DeepCOVNet architecture and usual transfer learning approach using Xception model. The sensitivity of bacterial, normal and viral class have been improved by 2%, 3% and 2% after introducing pre-training approach.

In the second phase of 3-class classification, the DeepCOVNet architecture is again trained on COVID-19/ normal/ pneumonia dataset. Table 5 shows the comparison of performance metrics between proposed and transfer learning method. As per perfomance met-

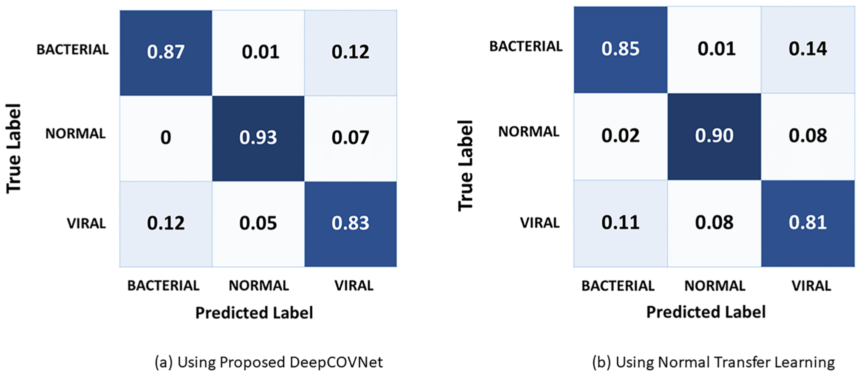

Figure 7: Combined confusion matrix for five folds for 3 class (Bacterial/normal/viral pneumonia problem using Xception model

Table 5: **Performance comparison of the proposed DeepCOVNet scheme and simple transfer learning scheme for 3-Class(COVID-19/normal/pneumonia)problem**

CNN Model Used	Scheme	Precision(%)	Sensitivity(%)	Specificity(%)	F-1 score(%)	Accuracy(%)
Xception	**Proposed**	**98.06**	**98.04**	**99.02**	**98.04**	**98.04**
	Simple Transfer Learning	94.98	94.85	97.46	94.83	94.45
DenseNet201	**Proposed**	**97.36**	**97.30**	**98.65**	**97.29**	**97.30**
	Simple Transfer Learning	94.19	93.70	96.84	93.67	93.70
MobileNet	**Proposed**	**97.84**	**97.79**	**99.09**	**97.78**	**97.79**
	Simple Transfer Learning	95.52	95.50	97.76	95.48	95.51
Inception	**Proposed**	**97.46**	**97.39**	**98.69**	**97.38**	**97.39**
	Simple Transfer Learning	95.55	95.34	97.66	95.33	95.34

rics, DeepCOVNet architecture outperforms as usual with 98.04%, 97.30%, 97.79%, 97.39% accuracy using MobileNet, DenseNet201, Xception and InceptionV3 as base models respectively. The simple transfer learning scheme yields 94.45%, 93.70%, 95.51%, 95.34% accuracy using MobileNet, DenseNet201, Xception, InceptionV3 respectively.

Fig. 8 exhibits the comparison of combined confusion matrix between proposed DeepCOVNet architecture and usual transfer learning approach using Xception model. The Xception network excels among all networks in both 3-class classification while the MobileNet model outperforms in 4-class.

As the previous 3-class classification categorized the pneumonia class between viral and bacterial, it posed a challenge in the task and so the classification accuracy along with other performance metrics is significantly lower than the second 3-class classification. The proposed DeepCOVNet architecture almost overcomes the challenging task with its initial pretraining approach. Performance comparison of the proposed scheme and transfer learning scheme is shown in Table 4. Like previous classification, significant improvements can be observed in all the performance metrics for COVID-19/normal/pneumonia classification. Of all the models, Xception model provides the best accuracy of 98.04% for our proposed Deep-

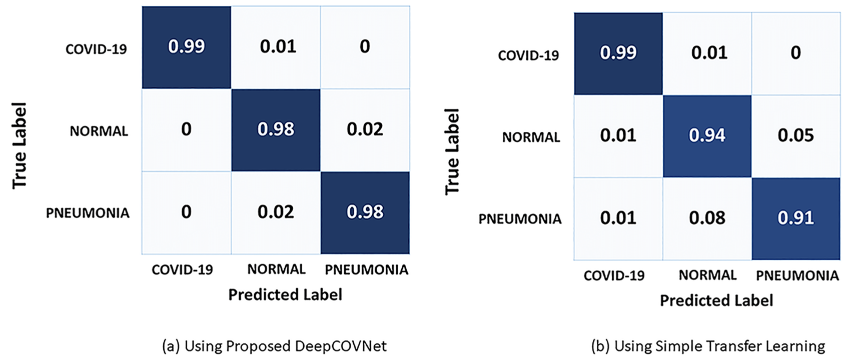

Figure 8: Combined Confusion Matrix for five folds for 3-class classification (COVID-19/normal/pneumonia) using Xception Model

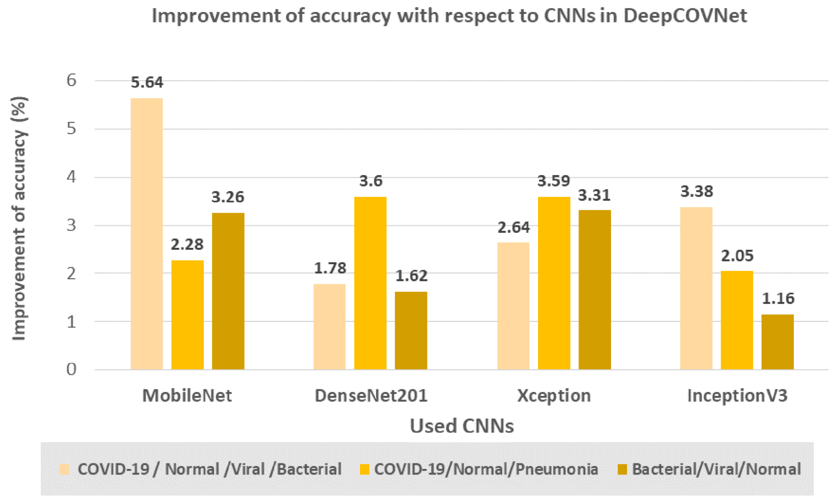

Figure 9: Improvement of accuracy with the proposed DeepCOVNet compared to simple transfer learning approach for different CNN models

COVNet architecture. Fig. 8 shows the comparison of combined confusion matrices for proposed and transfer learning scheme using Xception Model. For proposed scheme, the sensitivity of pneumonia class has increased 7% and for normal class the improvement is 4%.

A comparison among the used CNNs (MobileNet, DenseNet201, Xception, InceptionV3) in improvement of accuracy(%) is shown with a in Fig. 9. For 4-class classification MobileNet and for 3 class classification DenseNet201 and Xception exhibits highest improvement in accuracy.

The proposed method is compared with other existing state-of-the-art approaches for COVID-19 detection from X-rays in Table 6. Ioannis et al [18] compared five CNN models namely VGG19, MobileNetV2, Inception, Xception and Inception ResNet V2 with conventional transfer learning scheme from ImageNet database. MobileNetV2 and VGG19 generated the best result claimed by the authros. Dipayan et al. [33] also came up with a model based on InceptionV3 architecture. But they initialized the weights from ImageNet datasets. Ozturk et al. [14] proposed a deep neural network DarkCovidNet and didn't apply any trans-

Table 6: **Comparison of proposed model with other existing deep learning models**.

Study	**Image type**	**Total Number of images used**	**Architecture**	**Accuracy(%)**
Ioannis et al. [18]	X-ray	224 COVID-19+500 Normal+500 Pneumonia	MobileNetV2 VGG-19	92.85 93.48
		224 COVID-19+1204 Non-COVID-19	MobilenetV2 VGG-19	97.40 98.75
Dipayan et al. [33]	X-ray	162 COVID-19 vs. Non Covid(500 Normal+500 Pneumonia)	Truncated Inception Net	99.96
		162 COVID-19 vs. Non Covid(500 Normal+500 Pneumonia+400 TB)		99.92
Tanvir et al. [35]	X-ray	305 COVID-19 vs. 305 Normal	CovXNet	97.4
		305 COVID-19 vs. 305 Viral Pneumonia		87.3
		305 COVID-19 vs. 305 Bacterial Pneumonia		94.7
		305 COVID-19 vs. 305 Viral Pneu. vs.305 Bacterial Pneu.		89.6
		305 COVID-19 vs. Normal vs. 305 Viral Pneu. vs.305 Bacterial Pneu.		90.3
Ozturk et al. [14]	X-ray	125 COVID-19 vs. 500 No-findings	DarkCovidNet	98.08
		125 COVID-19 vs. 500 No-findings vs 500 Pneumonia		87.02
Wang and Wong [38]	X-ray	53 COVID-19 vs. 5526 Non-Covid-19	CovidNet	92.4
Khan et al. [24]	X-ray	284 COVID-19 vs.310 Normal vs. 330 Bacterial Pneu. vs. 327 viral Pneu.)	CoroNet	89.6
		284 COVID-19 vs.310 Normal vs. combined(330 Bacterial+327 viral Pneumonia)		94.59
		284 COVID-19 vs.310 Normal		99
Proposed Model	X-ray	408 COVID-19 vs.408 Normal vs. 408 Bacterial Pneu. vs 408 Viral Pneu.	**DeepCOVNet (DenseNet201)**	90.24
		408 COVID-19 vs. 408 Normal vs 408 Pneumonia)	**DeepCOVNet (Xception)**	98.04
		408 Normal vs. 408 Viral vs 408 Bacterial Pneumonia)	**DeepCOVNet (Xception)**	88.67

fer learning strategies. Khan et al. [24] came up with the model CoroNet which is based on Xception architecture and initailized the model with the weights of imagenet to do multiclass and binary classification. In all these state-of-the-art approaches, imbalanced dataset containing a small number of COVID-19 X-rays is used. As a result, the results are biased. Also, they have used traditional transfer learning approach from Imagenet database which is not ideal for operating challenging classifications like viral vs bacterial pneumonia.
We have shown previously by different comparison metrics that how our proposed DeepCOVNet architecture performs better than these simple transfer learning approaches. From pre-training phase, the proposed method is able to learn diversified two class separable features utilizing a large number of NON-COVID X-rays. As a result, our 4 class and 3 class classification accuracies are also higher than state-of-the-art approaches.

5. Conclusion

The DeepCOVNet architecture proposed a novel pre-training method that yielded improvement in every traditional metrics, especially about 6% and 4% improvement in the accuracy for the four-class and three-class classification respectively. Since it is a medical-based research, the improvement in metrics like sensitivity and specificity is also immensely significant. In this regard, it is again worth mentioning that the proposed scheme manages to elevate the sensitivity of the challenging viral pneumonia class from 52% to 80% for the four-class problem. So, it can be said that the proposed DeepCOVNet has performed exceptionally well as compared to other state-of-the-art methods thanks to its pre-trained inter-class separable features. Hence, it is expected that the proposed scheme might play an exclusive role for rapid detection and isolation for positive patients to accelerate the process of removing lockdown partially or fully and mobilize the economy. For validating the scheme fully, large COVID X-ray data is required which we will continue to seek and pursue other possible pre-trained binary class configurations to improve further with the proposed scheme.

Conflict of interest

The authors declare that they have no conflict of interest.

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