Automatic Detection of COVID-19 Disease in Chest X-Ray Images using Deep Neural Networks

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***Abstract*—The worldwide spread of COVID-19 has marked a devastating impact on the global economy and public health. One of the significant steps of COVID-19 affected patient's treatment is the faster and accurate detection of the symptoms which is the motivational center of this study. In this paper, we have analyzed the performances of six artificial deep neural networks (2-D CNN, ResNet-50, InceptionResNetV2, InceptionV3, DenseNet201, and MobileNetV2) for COVID-19 detection from the chest X-rays. Our dataset consists of 2905 chest X-rays of three categories: COVID-19 affected (219 cases), Viral Pneumonia affected (1345 cases), and Normal Chest X-rays (1341 cases). Among the implemented neural networks, ResNet-50 demonstrated reasonable performance in classifying different cases with an overall accuracy of 96.91%. Most importantly, the model has shown a significantly good performance in detecting the COVID-19 cases in the test dataset (Precision = 1.00, Sensitivity = 1.00, Specificity = 1.00, and F1-score = 1.00). Therefore, among the deep neural networks presented in this paper, ResNet-50 can be adapted as a reliable method for faster and accurate COVID-19 affected case detection.**

Keywords*—COVID-19 Detection, Chest X-ray Image Analysis, Viral Pneumonia, Deep Convolutional Neural Network (DCNN), Transfer Learning, Medical Imaging

I. Introduction

COVID-19, the pandemic that has destabilized the world from every aspect, was first reported in December 2019 in Wuhan, China when patients with cases of unidentified pneumonia emerged and by the end of January 2020, it was declared as a pandemic by the World Health Organization. The virus responsible for the disease, named SARS-CoV-2, belongs to a family of coronaviruses that are zoonotic. Until SARS-CoV-2 surfaced, six types of coronaviruses were known to be able to harm humans by mainly targeting the respiratory system. Four cause mild symptoms while the other two had caused epidemics in the last two decades named SARS-CoV and MERS-CoV. Even though the mortality rates of these epidemics are much higher than that of COVID-19 (10% for SARS and 30-35% for MERS), the cumulative number of deaths for the latter has exceeded that of both the epidemics combined by many times [1]. As of 21 July 2020, the total number of global cases and deaths exceed 14 million and 6.0 lakh respectively [2].

The range of typical onset symptoms of COVID-19 includes fever, dry cough, sore throat, myalgia, fatigue, dyspnea, a loss of taste and smell, and gastrointestinal symptoms. In more severe or progressed cases, pneumonia, development of fluid in the lungs, acute respiratory distress syndrome (ARDS), multi-organ failure, as well as death may occur. Elderly people or people exhibiting comorbid thus having a weak immune system are highly prone to both infection and severity. On the other hand, many carriers of the virus do not show any symptoms i.e., asymptomatic patients. This makes detection and containment of the virus even harder. With no specific treatment at hand, it is imperative that preventive measures such as social distancing, hygiene maintenance, and contact tracing are strictly followed and a system that can diagnose the disease as fast as possible is developed.

The gold standard for COVID-19 diagnosis is the reverse transcription-polymerase chain reaction (RT-PCR) which identifies the nucleotides of the virus from specimens extracted from a nasal swab or oropharyngeal swab. However, this method is tedious and time-consuming as the fastest turn-around time is at least 24 hours. Furthermore, given the rapid spread and hence increased rate of specimen collection required, the laboratories get loaded very easily. It is also laborious, relatively expensive, and has a low sensitivity (60%–70%) [3]. False results may be produced due to specimen handling, stage of disease when the specimen is collected, or quality of specimen [4]. Along with the long period of recovery, limited resources such as testing kits, hospital and ICU beds, ventilators, personal protective equipment (PPE) have overwhelmed the healthcare systems in most countries, thus forcing them to make selective decisions regarding testing, patient admission, ICU beds as well as the provision of ventilators.

Radiography images of the chest (X-ray and CT scan) may assist in various ways such as diagnosing the disease, sorting out the high-risk patients to quarantine and prioritize for selective testing, and identifying false-negative PCR cases. However, since most viral cases of pneumonia's images are similar and overlap, it is very difficult and time consuming for radiologists to distinguish the fine details by vision. In recent years, deep learning (DL) techniques have gained popularity and success in medical image classification applications owing to their powerful accuracy.

Many of the DL approaches are being applied for the purpose of detecting COVID-19 from chest X-ray images of patients, which can be observed in the latest works carried out in this field. Since the issue of COVID-19 is new and large datasets are unavailable, therefore, implementation of a

technique known as transfer learning is also being done. For instance, COVID-ResNet model [5] was developed by fine-tuning ResNet-50 architecture for the enhancement of its performance for distinguishing COVID-19 cases from other bacterial as well as viral pneumonia cases. COVIDx dataset was used and the obtained accuracy of the developed model was 96.23%. To detect COVID-19 from X-ray images of chest, the introduction as well as use of a new deep learning framework, COVIDX-Net, was done by Hemdan *et al*. [6]. Furthermore, DarkCovidNet was presented as a new model by Ozturk *et al*. [7] for detecting COVID-19 automatically from raw images of chest X-ray. Both binary (COVID-19 presence) and multi-class classification (between pneumonia and COVID-19) and accuracies of 98.08% and 87.02% were achieved respectively. Chowdhury *et al*. [8] were responsible for the development of a public dataset which comprised of COVID-19, normal case and viral pneumonia chest X-ray images. Moreover, detection of viral pneumonia and COVID-19 pneumonia was done in their work. Four pre-trained CNN architectures (SqueezeNet, AlexNet, ResNet-18 and DenseNet201) were tested on two different schemes. One of the schemes dealt with classifying normal case and COVID-19 pneumonia and another scheme dealt with normal case, COVID-19 pneumonia and viral pneumonia. The highest accuracy was 98.3% for both of the schemes which was obtained by SqueezeNet. For achieving such level of accuracy, an important role was played by image augmentation. Furthermore, Bassi *et al*. [9] used the public dataset and applied a CheXNet based classifier for the classification of chest X-ray images to COVID-19, viral pneumonia and normal case. 97.8% accuracy was obtained according to the results of their model. Therefore, ResNet-50 performed better than the other considered models according to their results. Asif *et al*. [10] used pre-trained Inception V3 model and further trained it on to classify normal, COVID-19 and viral pneumonia from digital X-ray images of the chest and obtained an accuracy of 96.9% as indicated by their results. In a study [11], COVID-19 detection was done by using a total of eleven different pre-trained CNN architectures along with an SVM classifier on digital X-ray images of the chest. Their results indicated that ResNet-50 with SVM displayed superior performance in comparison to the other models.

This research has analyzed the performances of six deep neural networks (DNNs) for the automatic detection of COVID-19 from two other classes (Viral Pneumonia and normal chest X-ray images) in chest X-ray images. An eleven layered 2-D convolutional neural network (CNN) and five pre-trained CNN models with transfer learning (TL) are proposed for the performance evaluation. Chest X-ray images have been analyzed throughout the experiment rather than CT scans for classification as they are relatively cheaper, quicker, and more widely available in contrast to the expensive, higher radiation exposure and time-consuming CT scans. The rest of the paper is structured as follows: Section II and section III comprises of materials and the detailed methodology of the proposed deep neural networks architecture used for the detection of COVID-19 from the other classes of X-ray images. Section IV presents the experimental results and analysis and finally, section V concludes the paper.

II. Materials

A. Chest X-ray Dataset

The database used in this study consists of 2905 posterior-anterior (PA) or anterior-posterior (AP) chest X-ray images and is curated by Chowdhury et al. [8]. Each sample of the database is in Portable Network Graphics (PNG) format and is sized 1024×1024 pixels. They can be easily converted to conventional sizes of 224×224 to be used by popular CNNs. The database consists of 3 categories of images of chest X-rays, of which 219 are COVID-19 positive, 1345 of viral pneumonia, and 1341 of normal chest X-rays. The normal and viral pneumonia images are sourced from the popular Kaggle database by Paul Mooney, 'Chest X-Ray Images (Pneumonia)'. Whereas, the COVID-19 positive images are collected from various open sources including the Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 Database, Novel Corona Virus 2019 (nCOVID-19) Dataset by Joseph Paul Cohen, Paul Morrison, and Lan Dao, and 43 different publications as well. Figure 1 represents the sample X-ray images of the three classes obtained from the chest X-ray database.

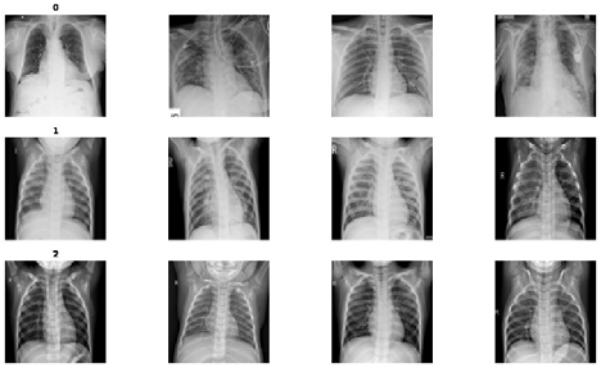

Fig. 1. Sample X-ray images of three classes; 0: COVID, 1: Viral Pneumonia, 2: NORMAL from the chest X-ray database

B. Data Pre-processing and Augmentation

Medical images are very often contaminated by noises due to increasing forms of intrusion. As a consequence, a visual assessment of them could become more challenging. Several pre-processing techniques can be applied to enhance the information the image generates for the unaided eye or to use it as feedback for algorithms.

Firstly, the data samples are resized to 150×150, 224×224 pixels, and are converted to grayscale images. Each image is then merged into 3 channels resulting in an input shape of 150×150×3 and 224×224×3 for different DCNN models. Furthermore, the dataset is normalized using standardization. Standardization, in machine learning algorithms, helps to stabilize the model as well as increases the speed of training. Additionally, the labels of the dataset are one-hot encoded where each class is converted into a binary feature. Doing so helps machine learning algorithms understand the format of input and thus perform better. Data augmentation is a method widely used in DL that helps to generate the number of samples required. Since our dataset is relatively small, we apply some image augmentation techniques to artificially increase the size of our training data. To increase variation within our small database, we have applied image augmentations by gripping Keras ImageDataGenerator during training such as randomly rotating the images by 10˚, randomly zooming images by a

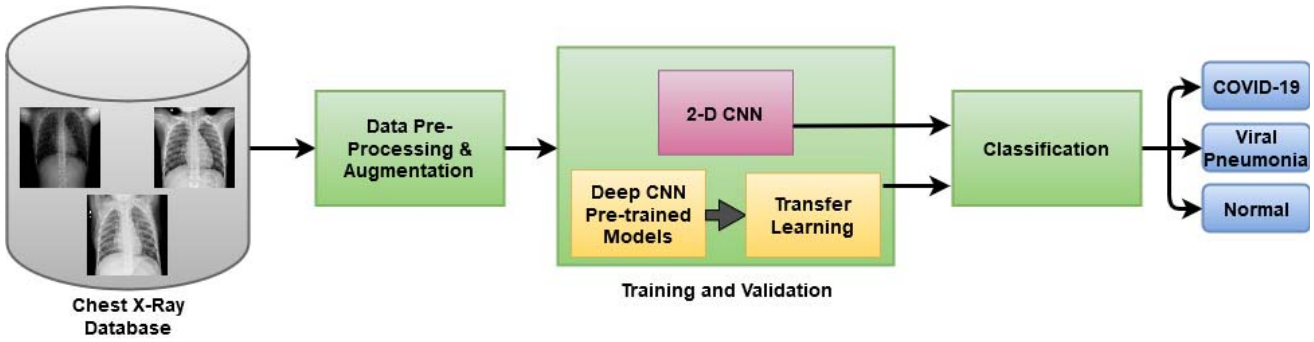

Fig. 2. Workflow of the proposed system for detecting COVID-19 in chest X-ray images using deep neural networks

range of 0.9 to 1.1, as well as translating the images with respect to height and width proportional to a range of -0.1 to 0.1.

C. Dataset Splitting

The dataset of 2905 images is split into training, validation, and test sets with a ratio of 80:10:10. Table I depicts the distribution of images into training, validation, and test sets after splitting.

TABLE I. DISTRIBUTION OF CHEST X-RAY IMAGES AFTER SPLITTING

Classes	Training Set	Validation Set	Testing Set	Total
COVID-19	175	22	22	219
Viral Pneumonia	1075	135	135	1345
Normal	1073	134	134	1341

III. METHODOLOGY

Generally, deep convolutional neural networks (DCNNs) perform better in a greater database than a smaller database. Transfer learning (TL) is useful in those frameworks of CNN with a relatively limited collection of data. In this study, we have undertaken the task of classifying images of chest X-rays into one of three classes: COVID-19 positive, viral pneumonia, or normal.

In our experiment, the collected database of chest X-ray images are initially pre-processed and augmented to increment its variation and make it more suitable for classification. We proposed 6 DCNN classification models consists of a 2-D 11 layered CNN model and 5 pre-trained models of DCNN with TL, ResNet-50 [12], InceptionResNetV2 [13], InceptionV3 [14], DenseNet201 [15], and MobileNetV2 [16]. Figure 2 represents the schematic of the overall workflow of the proposed method.

A. Proposed 2-D CNN COVID-19 Classifier

Convolutional Neural Network (CNN) is a class of machine learning neural network which specializes in image segmentation and inspection. It consists of two parts which are the most distinctive features of CNN. Starting with the first part, it comprises of the main learning method. The input images fed to the learner consist of the smallest units which bring out the accuracy. CNN consists of several layers and the first part uses the convolutional layer which acts on a specific region and not all over. It extracts the distinctions from raw input and transforms that layer to the preceding layer. Next, the pooling layer learns from the previous layer and proceeds to reduce the process complexity. In the second part, the fully connected layer executes the features learned from all the previous layers giving the desired categorized outputs.

In our research, we opted for 2-D CNN architecture which delivers a better faster approach towards feature extraction. It contains a total of 11 layers where the training is executed, with 4 convolutional which work at 4 different filter sizes each incrementing by a product of 2, followed with 4 pooling layers or otherwise called the max-pooling layer which halves the parameters used, followed by a flattening layer, a fully connected or dense layer and finally a softmax. All models are built over a stride of 1 with a kernel size of 3×3, all of which are running under the Rectified Linear Unit (ReLU) activation function. Figure 3 demonstrates our overall architecture of the proposed DCNN models used for the classification of COVID-19 in chest X-ray images.

The first 2-D convolutional layer comprises of 32 filters, keeping all the other parameters the same as mentioned above. This also goes for the next 3 convolutional layers which contain 64, 128, and 256 filters respectively. After ReLU execution of the first convolutional layer comes the max-pooling layer with a pool-size of 3×3 and the same stride number of 1. Here, within the pool size, the layer selects the neurons containing the maximum activation number, splitting the parameters in return, all the while keeping the padding unchanged to have the inputs and outputs in the same dimensions. To solve the overfitting problem of the network, a 0.5 dropout is included after the max pool layer in order to randomly shut down 50% of the neurons. This dropout comes after the third convolutional layer is executed. The second, third, and fourth convolutional layers with different filters are then executed simultaneously. The output has a multi-dimensional feature vector and for it to be fed to the fully connected layer, it must be transformed into a 2-D feature vector which is done by the following flattening layer. Now, with the converted output fed to the dense or fully-connected layer of 512 units, it conjoins each neuron of the preceding with the succeeding layer. This is further followed by another dropout layer to reevaluate the overfitting issue and finally passed on to the last layer where the softmax activation function is utilized in the classification of input data giving an output in the size of 3.

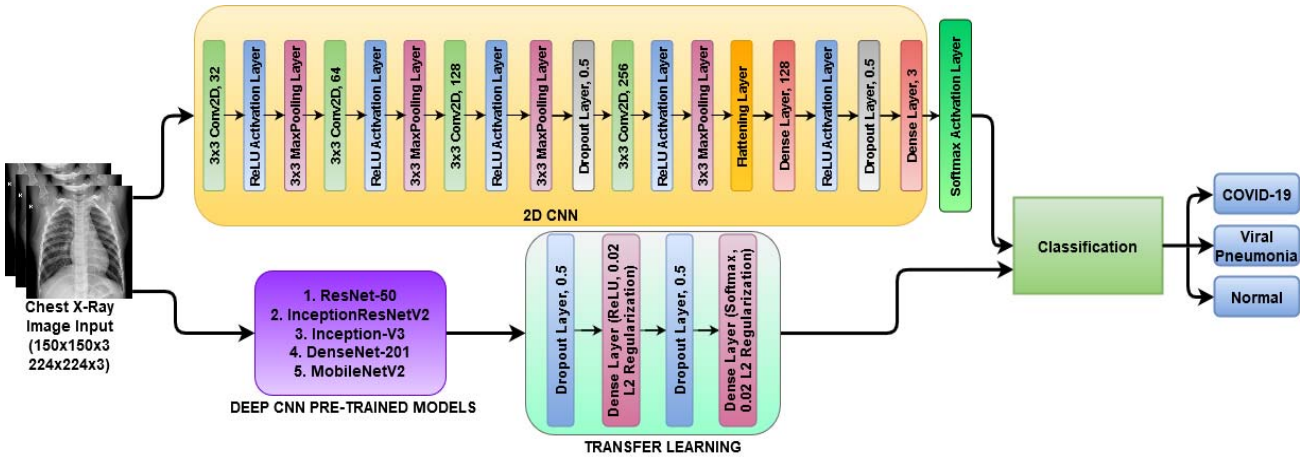

Fig. 3. Proposed architecture of deep neural network models for the classification of COVID-19 in chest X-ray images

B. DCNN models with the proposed transfer learning

Training a new model for a specific task can be challenging and building one from scratch can be near impossible with the given time. To eliminate such, the concept of transfer learning (TL) was introduced. It dictates the use of a pre-trained neural network that has already learned the features from a similar existing large dataset domain and training it further using our dataset. It is advantageous as we only have to feed new knowledge to the network saving us from the tedious work of building one. In our research, we adopted five pre-trained DCNN models, ResNet-50, InceptionResNetV2, InceptionV3, DenseNet201 and MobileNetV2 where all the weights are trained on ImageNet.

InceptionResNetV2, consisting of 164 layers is an excellent model for medical applications for its distinctive classification features from the million images it was trained with. InceptionV3, on the other hand, contains 48 layers and has high accuracy in classifying images. ResNet-50, by far is the most popular DCNN for its accuracy using 50 layers. DenseNet201 and MobileNetV2 both comprises of 201 and 53 layers respectively. DenseNet201 specializes in connecting each layer to another in a feed-forward structure while MobileNetV2 uses an inverted residual structure.

In our experiment, we chose all 5 of the DCNNs models along with 4 task-specific layers for each using TL. All of the proposed DCNNs come pre-trained with ImageNet weights followed with average pooling which are running consequently, the only difference is the input sizes for different models. In ResNet50, InceptionV3 and MobileNetV2, the input size taken was 224×224×3 as for InceptionResNetV2 and DenseNet201, the size was 150×150×3. We implemented transfer learning onto the DCNNs to further train the models with our chest X-Ray image dataset for better classification of COVID-19. The dense layer is replaced by the 4 extra layers we added to each of the models. These 4 layers collectively perform the TL process. The first is the 50% dropout layer which eliminates half of the parameters to resolve the overfitting issue. Next, comes the ReLU activation layer with an L2 regularization value of 0.02 which is also required to reduce overfitting. The second last layer is another 50% dropout and the final layer comprises a softmax activation layer with the same L2 regularization value. Lastly, the output size depends on our categorization which is set to 3 for 3 different states.

IV. Results Analysis and Discussion

A. Experimental Setup

To train our DCNN models, we utilized the stochastic gradient descent (SDG) as the optimizer with a learning rate of 0.0001 for a total epoch of 60 and categorical cross-entropy as the loss function for our multi-class classification problem. Moreover, we have used the Snapshot Ensemble approach during the training of our model. This approach allows us to control the learning rate in a way that helps us travel through all the local minima during the SDG algorithm and thus forming multiple models in one neural network. The learning rate starts at a fixed maximum value (of 0.001 in our case), and drops quickly near local minima, and subsequently jumps to the fixed maximum value again. We have selected to have an ensemble of 3 models in this task where each model is comprised of 20 epochs, i.e. we assist the model to converge to a local minimum within 20 epochs. Throughout our experiment, we used a workstation with the LINUX 4.0.0 LTS server (Ubuntu 16.04.6), NVIDIA GeForce RTX 2080Ti GPU. The DCNN model was executed using python in Keras package, running on TensorFlow backend on Intel Xeon E5-2620, Core i5-2.4GHz processor, 16GB RAM.

B. Models Performance Analysis

The chest X-ray dataset consists of X-rays of three types: COVID-19, Viral Pneumonia, and Normal. In our implementation of the deep neural networks, 80% of the total data was used for testing, 10% data for validation, and the remaining 10% for testing. Table 1 presents the performance comparison among the deep neural network models in the case of the X-ray dataset classification. As the dataset is imbalanced, rather than solely relying on the classification accuracy as a model performance evaluating metric, for analyzing and comparing the overall performance of a model we considered metrics like precision, sensitivity, specificity, F1-score, and AUC (Area under the ROC curve).

Figure 4, 5, 6, 7, 8, and 9 depicts the confusion matrices [17] of the DCNN models implemented in this paper on test data. On the basis of performance, the ResNet-50 outperforms other neural network models with a classification accuracy of 96.91%.

TABLE II. PERFORMANCE OF THE DEEP NEURAL NETWORK MODELS IN CLASSIFYING COVID-19

Classification Model	Class	Precision	Sensitivity	Specificity	F1-score	AUC	Accuracy
11 layered 2-D CNN	COVID-19	1.00	0.89	1.00	0.94	1.00	94.85%
	Viral Pneumonia	0.97	0.92	0.98	0.94	0.99	
	NORMAL	0.93	0.99	0.93	0.96	1.00	
ResNet-50	COVID-19	1.00	1.00	1.00	1.00	1.00	96.91%
	Viral Pneumonia	0.98	0.95	0.98	0.96	1.00	
	NORMAL	0.96	0.98	0.96	0.97	1.00	
InceptionResNetV2	COVID-19	1.00	0.89	1.00	0.94	0.89	95.19%
	Viral Pneumonia	0.97	0.93	0.98	0.95	1.00	
	NORMAL	0.93	0.97	0.93	0.95	0.98	
InceptionV3	COVID-19	1.00	1.00	1.00	1.00	1.00	94.16%
	Viral Pneumonia	0.98	0.88	0.99	0.93	0.99	
	NORMAL	0.90	0.99	0.90	0.94	0.99	
DenseNet201	COVID-19	1.00	1.00	1.00	1.00	1.00	96.22%
	Viral Pneumonia	1.00	0.92	1.00	0.96	1.00	
	NORMAL	0.93	1.00	0.93	0.96	1.00	
MobileNetV2	COVID-19	1.00	1.00	1.00	1.00	1.00	95.88%
	Viral Pneumonia	0.95	0.95	0.96	0.95	1.00	
	NORMAL	0.96	0.96	0.96	0.96	1.00	

In the case of detecting the COVID-19 X-ray images, the ResNet-50 demonstrated nearly perfect precision, sensitivity, specificity, F1-score, and AUC. The nearest competitors of the ResNet-50 model are DenseNet201 and MobileNetV2 with classification accuracies of 96.22% and 95.88%, respectively. On the other hand, the InceptionV3 model showed the least performance with a classification accuracy of 94.16%. For the COVID-19, viral pneumonia, and normal healthy cases the ResNet-50 model demonstrated sensitivity values of 1.00, 0.95, and 0.98, respectively, which substantiates the superior performance of the ResNet-50 compared to the other classification model. Moreover, the AUC values suggest that the ResNet-50 model can also identify all 3 classes (COVID-19, Viral Pneumonia, and Normal cases) from the chest X-rays with reasonable accuracy (AUC = 100%). Therefore, the ResNet-50 model can be considered as a reliable method for faster and accurate COVID-19 case detection.

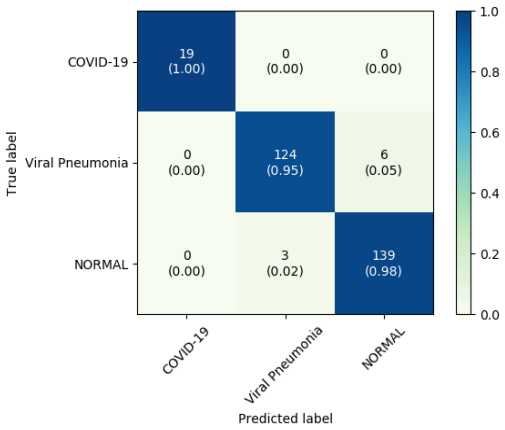

Fig. 5. Confusion matrix of ResNet-50 model

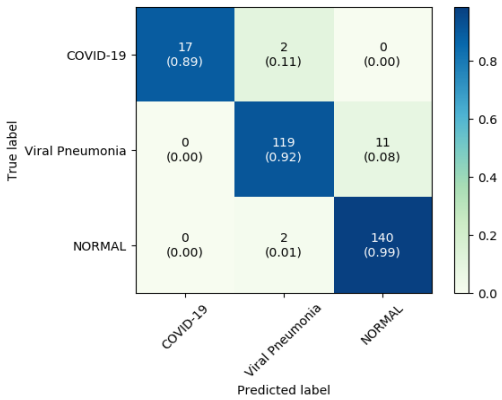

Fig. 4. Confusion matrix of 2-D CNN model

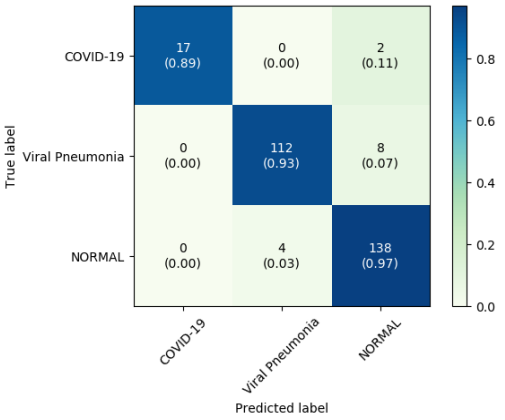

Fig. 6. Confusion matrix of InceptionResNetV2 model

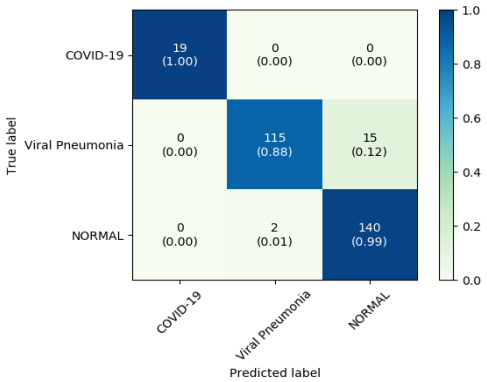

Fig. 7. Confusion matrix of InceptionV3 model

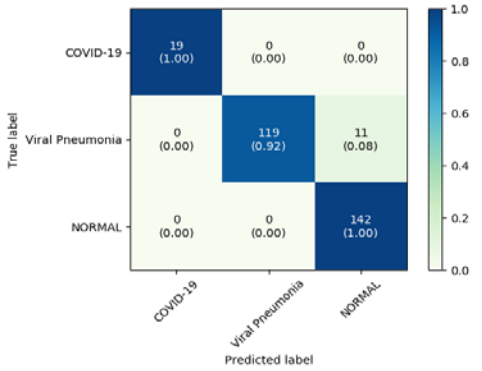

Fig. 8. Confusion matrix of DenseNet201 model

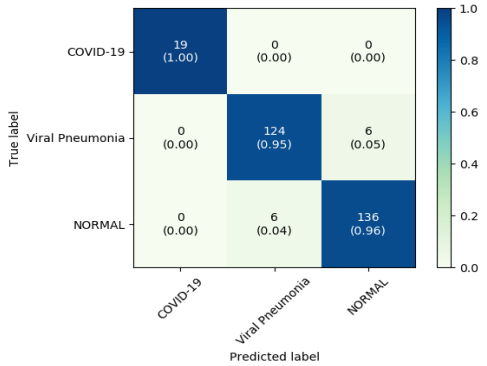

Fig. 9. Confusion matrix of MobileNetV2 model

V. Conclusion

Seven months have passed since the advent of COVID-19 and worldwide researchers are still striving to grasp a full picture of it ranging from health to social to economical aspect. One of the crucial steps of containing the virus better is prompt detection which requires effective testing. The PCR test is the gold standard for diagnosis at present but suffers from drawbacks including a turnaround time of at least 24 hours. Thus, this research explores an alternate quicker option of detecting COVID-19 using deep learning techniques in chest X-ray images. The performances of six deep neural networks (2D CNN, ResNet-50, Inception ResNetV2, Inception V3, DenseNet201, and MobileNetV2) in classifying the chest X-ray dataset have been evaluated. ResNet-50 yielded the best performance with a classification accuracy of 96.91%, closely followed by DenseNet201 and MobileNetV2 with classification accuracies of 96.22% and 95.88%. All three of these pre-trained neural networks scored (AUC = 100%) for detecting the COVID-19 X-ray images. The 11-layered 2-D CNN performed better than the pre-trained InceptionV3 model which has the least classification accuracy of 94.16%. It also scored a higher AUC value than that of InceptionResNetV2 for detecting the COVID-19 X-ray images. Moving forward, further, development can be carried out on the networks to achieve higher accuracies and efficiency in diagnosis of COVID-19 as well as other chest-related diseases.

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