An Inception-ResNetV2 Based Deep Learning Model for COVID-19 Detection

Tanees Riaz, Tarim Dar, Hafsa Ilyaas, and Ali Javed

Abstract COVID-19 has become the global epidemic affecting millions of people across the world. The fact that COVID-19 spreads quickly and devastating for elderly person makes this disease lethal as we witnessed a massive mortality rate in first, second, and third wave since 2020. Early diagnosis of COVID-19 is mandatory to prevent the spread and damage control, as only few nations have been able to vaccinate more than 50% of their population. The healthcare professionals commonly use the real-time polymerase chain reaction (RT-PCR) test to identify the COVID-19. Although RT-PCR test is considered more reliable among other COVID-19 detection tests; however, sensitivity of RT-PCR lies in the range of 65%-95% and took hours to diagnose the COVID-19 disease. Therefore, there exists an urgent need to develop more rapid and reliable diagnostics methods for COVID-19. In this regard, Chest X-ray and CT scan images are also being used to determine the abnormalities in the lungs of the COVID-19 patients which are found after the initial symptoms of this disease. We exploit the benefits of convolution neural network (CNN) for reliable detection of various diseases and used it for COVID-19 detection. For this purpose, we proposed a deep learning model to automatically detect the COVID-19 disease by processing the chest X-ray images. More specifically, we presented an Inception-ResNetV2 network-based deep learning model for COVID-19 detection. Performance of our model is evaluated on the publicly available COVID-19 dataset. The accuracy of 96% indicates the effectiveness of the proposed model for COVID-19 detection.

Keywords COVID-19 detection · Chest radiographs · Inception-ResNetV2

1 Introduction

The coronavirus disease, well known as COVID-19, is first identified in the Wuhan city of China during December 2019. The COVID-19 disease is caused by the virus

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named as severe acute respiratory syndrome coronaviruse-2 (SARS-CoV-2) COVID-19 was declared as a global pandemic by the world health organization (WHO) last year due to the rapid spread of this disease around the globe in a short period of time. Till June 13, 2021, COVID-19 has affected 175,306,598 people globally and caused the deaths of 3,792,777 [1]. According to WHO, COVID-19 patients can be either symptomatic or asymptomatic. The symptomatic patients belong to the category where the infected person can have either mild or severe symptoms. In mild, the patient deals with dry cough, fever, tiredness, and in some cases diarrhea, whereas in severe case, patient can feel shortness of breath and pneumonia [2]. The patient may be asymptomatic and such patients can spread COVID-19 to many persons as they are unaware of being infected with the disease and can be more casual when in contact with other persons. Thus, asymptomatic patients become a major reason for a speedy COVID-19 escalation. Automated diagnosis of COVID-19 at earlier stage can prevent the spread and damage control. This becomes more important by considering the fact that COVID-19 vaccination drive will take much time to vaccinate majority of the people across the globe. Primarily, real-time reverse transcription polymerase chain reaction (RT-PCR) method is commonly used to identify the COVID-19 across the world. However, PCR test takes few hours to confirm the presence/absence of COVID and has low sensitivity of 65–95% [3]. Thus, these circumstances increase the urgency of developing a reliable and automated artificial intelligence (AI) tool to effectively diagnose the COVID-19.

Several studies have been presented recently where researchers detect the COVID-19 disease using radiological images (chest X-ray or CT scan). Chest X-ray is also given more importance in this regard. The studies reveal the acute lung abnormalities after the 10 days of initial indications of the disease [4]. Kong [5] found the existence of peripheral ground glass and nodular opacities in lungs. Zhao [6] declared that mostly COVID-19 patients also have vascular expansion and consolidation in the lesion along with mixed ground glass opacities (GGO). Additionally, COVID-19 detection through radiological images has more sensitivity than COVID-19 detection through RT-PCR testing technique. Kim [7] analysis reveals the high diagnostic sensitivity of the CT scan images for patients in critical conditions as compared to RT-PCR. The reason is that the swab or nasopharyngeal sample is required for RT-PCR. If the sample taken from the patient does not contain detectable amount of corona virus, then this can lead toward failure in the COVID-19 detection, thus affecting the testing accuracy of COVID-19 diagnosis. Moreover, RT-PCR technique is costly and needs more time to produce the result. Thus, automated methods to analyze the chest X-ray for diagnosis can be used to overcome the issues associated with RT-PCR test [2].

Convolution neural networks (CNNs) have been employed to solve various image processing and computer vision tasks. The significance of deep learning models for object detection and classification motivated the research community to adapt the CNNs for various medical imaging applications, i.e., lung diseases classification, brain tumor detection, tumors detection in biological membranes and cells, etc. Recently, researchers have adopted different CNN models including ResNet, AlexNet, GoogleNet, and DenseNet for COVID-19 detection. Wang [8] presented a COVID-Net deep neural network to detect COVID-19 in CXR images. This model was evaluated on COVIDx dataset. Majeed [9] proposed a CNN-x model for four types of cases (normal, COVID, non-COVID viral infected, and bacterial infected) and compared the results of different architectures for each case. This model consists of four layers having 16 filters of three different sizes in each layer. Sethy [10] proposed a method to extract the features from several pretrained CNN models and later used support vector machine (SVM) to classify between the COVID and non-COVID infections. It was concluded that Resnet-50 along with the SVM outperforms all the comparative methods for classification in COVID-19 detection. Rehman [11] classified the features collected from different CNN architectures by applying the binary and multiclass classification. For binary classification, ResNet shows 98.7% accuracy, whereas MobileNet shows 97 and 80% accuracy for three and four classes classification, respectively. Zheng [12] developed a weekly supervised system based on deep learning for automatic detection of COVID-19 by using 3D chest CT volumes. Pretrained Unet was applied to segment each patient lungs region and then fed to 3D deep neural network DeCoVNet for COVID-19 detection. This algorithm achieved an accuracy of 90.8%. Ghoshal [13] reveals that there exists a strong relationship between uncertainty of model and accuracy of prediction. To estimate uncertainty in model, Bayesian convolutional neural network was trained on COVID-19 images using the transfer learning method. Estimating uncertainty in model is necessary to avoid COVID-19 misdiagnosis and allow radiologist in identification of false predictions and unknown cases. Apostolopoulos [14] conducted a comparative analysis to investigate the performance of different CNN architectures (VGG19, MobileNet v2, Inception, Xception, Inception-ResNetv2) with transfer learning for automatic detection, reliable features extraction, and low-cost diagnosis of COVID-19 on dataset which is gathered from Github repository and online Web sites. The results suggest that the MobileNet v2 achieves the best classification accuracy of 96.78% over the rest of the CNN models. Based on the results, it was inferred that CNN models have great significance in diagnosis of COVID-19. Ismael and Şengür (2021) employed a pretrained CNN model to classify between the COVID-19 and healthy chest X-ray images. More specifically, ResNet50 was used to extract the deep features that were then used to train the SVM for classification and achieved an accuracy of 94.7%. Alam et al. [15] employed a fusion of histogram of gradient and CNN for features extraction and used them to train a VGGNet based deep learning model for classification of COVID and non-COVID chest radiographs. This method employed a fivefold cross-validation approach for testing and achieved an accuracy of 99.4%, specificity and sensitivity of 95.7% and 93.6% respectively [15].

In this paper, we proposed a deep learning model to automatically detect the COVID-19 using the chest X-ray images. The proposed model employs the Inception-ResNetV2 architecture [16] containing the hybrid of residual layers and inception blocks. The proposed deep learning model has a flexible architecture having several filters that are changeable in different layers. The major contributions of the paper are as follows:

- We present an effective deep learning model to automatically detect the COVID-19 from chest radiograph images.
- We present a computationally efficient Inception-ResNetV2 deep learning model by using inception blocks in residual-inception.

Rest of the paper is organized as follows. Section 2 presents the methodology for COVID detection. Performance evaluation is provided in Sect. 3. In Sect. 3.4, analysis and discussion is provided, and finally, we conclude our work in Sect. 4.

2 Proposed Methodology

This section provides the architectural and implementation details of the proposed COVID-19 detection method.

2.1 Architectural Details

The proposed method employs the Inception-ResNetV2 pretrained hybrid convolutional neural network for COVID-19 detection. We exploited the benefits of CNN for generating effective feature maps from the chest radiograph images over other features extraction methods. Additionally, our Inception-ResNetV2 model is computationally efficient over other CNN models. The hybrid Inception-ResNetV2 model is comprised of 164 layers which has combination of residual connections and inception architecture with the ability to classify chest X-rays. The residual model is well known for the training of deep architectures, while inception model is renowned for multi-branch architecture. The network is trained on ImageNet database and takes an input image of size 299×299. Residual connections are pooled with different sized convolutional filters avoiding the degradation caused by deep structures and reducing the computational time [17]. Shown in Fig. 1 is the architecture of Inception-ResNetV2 model.

2.2 Implementation Details

The proposed model contains the pretrained Inception-ResNetV2 model which is fine tuned to identify the COVID-19 disease in X-ray images. All layers of model except last three layers are initialized by using pretrained Inception-ResNetV2, whereas last three layers are replaced to improve the model. The fully connected layer weights are set to 10. The model is trained on dataset by using Adam optimizer. The hyperparameters used for the training are: initial learning rate = le-4, maximum epochs = 20, minimum batch size = 16, and data shuffling in every epoch. Moreover,

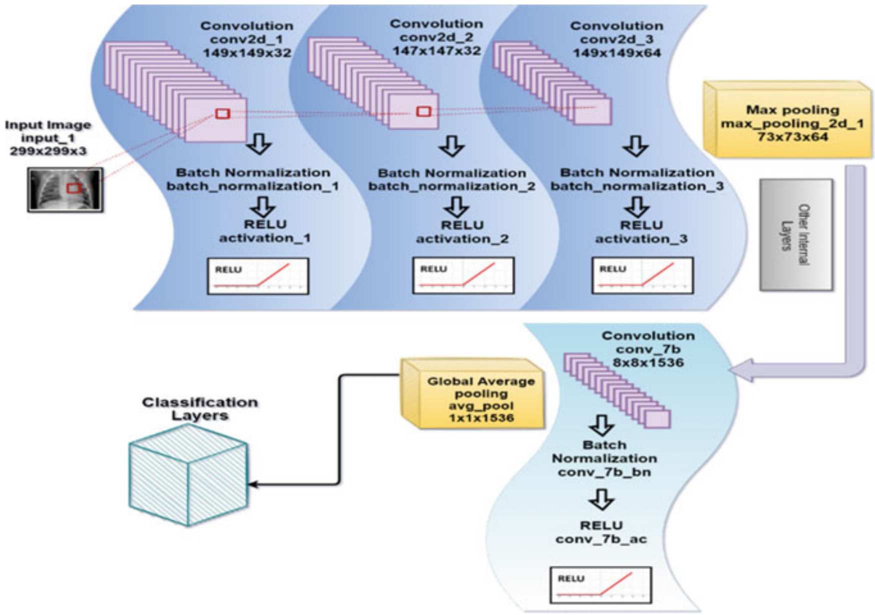

Fig. 1 Proposed Inception-ResNetV2 architecture

we employed the rotation, reflection, and shear methods for data augmentation. The input image is first resized to 299 × 299 dimension before feeding into our Inception-ResNetV2model.

Due to the limited set of X-ray images, K-fold cross-validation is used to randomly split the dataset into *k* partitions. In each fold, data is partitioned into training and testing data. We have divided the dataset into tenfold which enable us to fit the model to ten distinct training set and thus provide better performance estimation. K-fold validation is also used to reduce the biasing effect in the dataset. After dividing the data into testing and training portion, it is fed into Inception-ResNetV2 architecture that extracts the features from the chest X-rays and then fed to the classification layer. The global average pooling calculates the average value of each feature map and delivers the output for predictions to a fully connected layer. Output passes to predictions-softmax layer and then softmax assign decimal probabilities to every class and give output to classification Layer-predictions which is responsible for classification of image between the COVID-19 and non-COVID infections. Figure 2 shows the process of the classification.

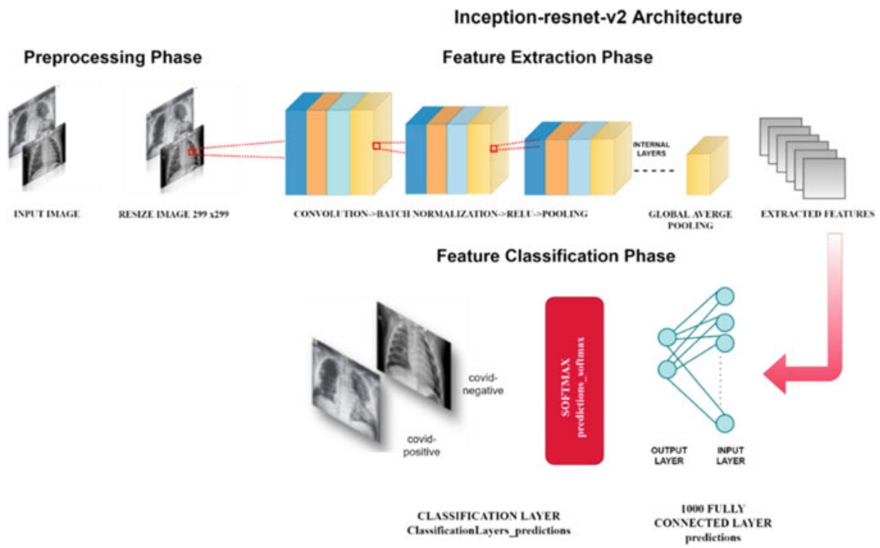

Fig. 2 Classification process

3 Experiments and Results

This section presents the results of the experiments used for performance evaluation. The details of the dataset are provided in this section. We visualize the training progress of each fold to analyze the entire process of training. We employed the accuracy, precision, recall, and F1-score as metrics for performance evaluation. The proposed model is implemented using MATLAB 2020a. We performed the experimentation on the system with the following specifications: 8 GB RAM, 1.61 GHz processor, Windows 10 operating system.

3.1 Dataset

Performance of the proposed method is evaluated on publicly available dataset of chest radiograph images [18] containing 468 COVID-19 cases. This dataset provides 468 X-ray images for COVID-19 patients. We used the 468 normal chest X-ray images from the Kaggle's chest X-ray images dataset [19] to create the final repository for experimentation. So, our dataset comprises of 936 images in total, and all images are of different dimensions. Therefore, we have resized all images to 299 $\times$ 299 dimension before feeding them into our model. Figure 3 shows the chest X-ray images of normal and COVID-19 infected patients.

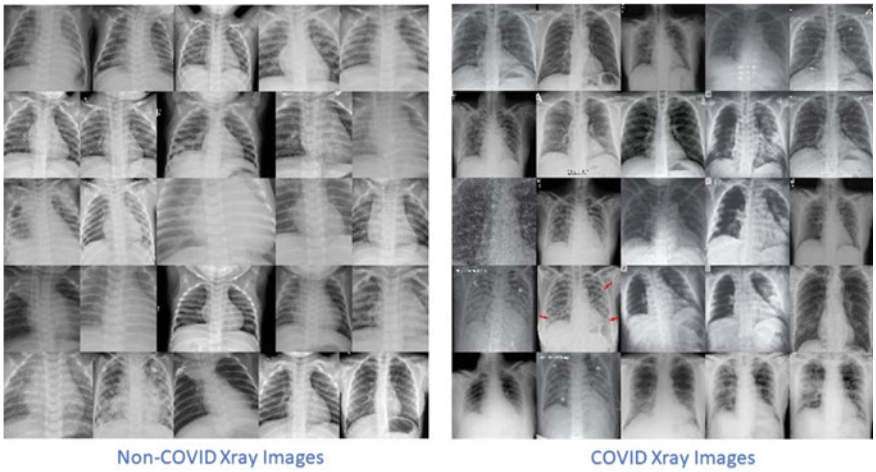

Fig. 3 X-ray images of non-COVID and COVID-19 infected patients

3.2 Performance Evaluation

We designed an experiment to measure the performance of our model for COVID detection. We measured the accuracy, precision, recall, and F1-score using the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). In our case, TP represents the frames of COVID-19 infected images that are also detected as COVID-19 images, whereas FP represents the frames of non-COVID images that are falsely detected as COVID-19 images by our model. Similarly, TN represents the frames of non-COVID images that are also detected as non-COVID, whereas FN represents the frames of COVID-19 images that are falsely detected as non-COVID images by our model. We computed the accuracy, precision, recall, and F1-score as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{FP}}{\text{Total Positives} + \text{Total Negatives}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F1\_ score} = \frac{2 * (\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}} \tag{4}$$

We obtained the precision of 92.6%, recall of 100%, specificity of 92%, F1-score of 96.15%, and accuracy of 96% for our method. From this experiment, we can

Table 1 Comparison with existing deep learning models

Architecture	Accuracy (%)
VGG19	90
DenseNet201	90
InceptionV3	70
ResNetV2	50
Proposed model	96

observe that our model correctly predicts all the COVID-19 cases, whereas only 4% of normal X-rays are classified as COVID-19 by our model. These results signify that the proposed method can reliably be used to detect the COVID-19 infections in the chest radiograph images.

3.3 Comparison with Existing Models

To evaluate the significance of the proposed model over existing DL models, we compared the performance of our model against the VGG19, DenseNet201, InceptionV3, and ResnetV2 DL models on the same dataset. The results in terms of accuracy are reported in Table 1. This experiment reveals that the ResNetV2 DL model performed the worst by achieving only 50% accuracy, whereas the proposed model performed the best and achieved an accuracy of 96%. It is important to mention that VGG19 and InceptionV3 also achieved better results and were joint second-best performers among all the DL models used in this experiment.

3.4 Discussion and Analysis

The results of different experiments performed in this paper revealed the significance of our Inception-ResNetV2 based model for reliable COVID-19 detection using radiological images. Moreover, it is important to mention that the inception blocks in residual-inception are computationally efficient than pure inception blocks. A filter-expansion layer is used for increasing the dimensionality reduced by each inception block. Expansion-layer is a convolutional layer without activation which expands the dimensions of the filter bank to equalize it with the depth of input.

Experimental results show that the proposed architecture has 0% false negative rate, which contributes to achieve 100% sensitivity. This level of sensitivity assures that the architecture will detect all COVID-19 patients correctly. RT-PCR testing technique is the most common technique used for the detection of COVID-19. As RT-PCR testing has a high false negative rate, thus our proposed architecture better addresses this issue.

Further analysis of results show that proposed architecture is able to successfully classify 92% of the normal X-ray images correctly while leaving only 8% of incorrect detection of normal cases. The proposed model along with current COVID testing techniques is able to help the physicians in better detection of COVID-19. Further evaluation of the proposed deep learning model for COVID-19 detection on a large-scale and more diverse dataset including cross-dataset evaluation can help to better generalize the proposed model for reliable COVID detection.

4 Conclusion

This paper has presented an effective and efficient deep learning-based Inception-ResNetV2 model for COVID-19 detection from chest radiograph images. We have presented a reliable COVID-19 detection system capable of accurately diagnosing the COVID-19 quickly. We evaluated the performance of our model on the publicly available COVID-19 X-ray images dataset. The accuracy of 96%, precision of 92.6%, and recall of 100% illustrate the effectiveness of the proposed model for COVID-19 detection. Our model will facilitate the doctors/physicians for automatic screening of COVID-19 cases using radiological images in quick time. In future, we plan to test the effectiveness of the proposed deep learning model for COVID-19 detection on a large-scale and more diverse dataset including cross-dataset evaluation.

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