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# CNN DEEP-LEARNING TECHNIQUE TO DETECT COVID-19 USING CHEST X-RAY

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## Abstract

*Most of the countries around the world are locked down due to the pandemic. Every country has imposed strict travel restrictions and has stopped all types of visas and tourist activities. This created a major impact on the aviation sector and the tourist sector. Even the people not affected by Covid-19 and in real emergence are not able to travel from one place to another. Some countries have laid down quarantine rules, which will be a major hindrance to emergency travellers and tourists. All passengers travelling are tested for COVID-19 using RT-PCR, which can take between 48 to 72 hours to produce the result. But in some cases, people who are tested negative even after 3 or 4 RT-PCR tests show typical pneumonia in the CT Scan or a chest X-ray. If the aviation sector relies only on the RT-PCR test, many patients may be missed. To reduce the risk to some extent and prevent a high-risk patient from travelling, the passenger can be asked to upload his / her chest X-ray before travel. Using an X-ray of the chest, we can predict the possibility of Covid-19 cases before the patients are physically examined. This technique cannot replace the RT-PCR test but can be a stand-by tool to help detect Covid-19 before the RT-PCR test. It would also help to identify patients who are highly prone to the infection. In this paper, we developed a CNN from scratch to identify a patient infected with COVID from a chest X-ray image. The model was trained with the chest X-ray of normal and COVID patients. Later the model was tested on two datasets, one publicly available in GitHub, and the other dataset was compiled from the Italian Society of Medical and Interventional Radiology website using web scrapping. The model produced an accuracy of 96.48 percent with the training dataset. To further improve accuracy, we used the same dataset on a pre-trained network (VGG16) and achieved an accuracy of around 99 percent.*

**Keywords :** Covid-19, Chest X-ray image, CNN, VGG16, Transfer learning

## I. Introduction

The most deadly disease of the year 2019 is the novel coronavirus, officially called Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), in short, called (COVID-19) [X]. Symptoms of COVID-19 include inflammation of the respiratory system, fever, and cough, and in some extreme cases, severe pneumonia [XII]. Pneumonia is an infection that causes inflammation in the airbags of the lungs responsible for oxygen exchange [XII].

Patients who develop symptoms of COVID-19 are tested with RT-PCR. This is the most common method used to detect COVID-19. This test will take about 48 hours to 72 hours to produce the result. At present, international airports are closed because of a pandemic and several countries are discussing standards for reopening air traffic. Some countries require travelers to undergo a PCR test on arrival or to be allowed to travel only if they have a COVID negative certificate. In this case, the traveler may be negative and may become infected during the journey. Sometimes people who are more prone to infection may travel and are at risk of becoming infected. RT-PCR method also produces some false-negative cases where the quality of the samples collected is poor or damaged during collection, transport, and storage.

Anti-body testing is another method used to detect COVID-19. A person infected with the virus is likely to develop immune cell antibodies to fight against the virus. Special test kits are required to perform this test. The drawback of this test, however, is that a person develops antibodies only after 3 days of infection. Therefore, this test cannot be a substitute for the RT-PCR test.

The new coronavirus affects the lungs and it looks different from other pneumonia caused by bacteria. There are certain patterns, which appear in the chest X-ray initially in the outer region, which looks hazy and grey, and when the diseases progress the pattern appears clearer. Therefore, the chest X-ray can be a rapid tool for detecting the novel coronavirus.

In this paper, we propose an image-based detection process. An X-ray of the chest or a CT scan can be used to measure the amount of infection caused by the virus. In the paper, we used the CNN model and trained the network to detect COVID infections. Nonetheless, this approach cannot be used as an alternative to the RT-PCR test. Since the absence of an X-ray abnormality or CT-Scan does not indicate that a person is free from infection. However, this test can be used as an initial screening to enable people with high risk from travel. This method cannot, therefore, be used as a first-line virus detection tool, but can be used as a supporting tool to decide which travelers should be exempted from travel.

This method can be used by the aviation industries for travelers flying from one country to another. Temperature screening alone may not be very successful, as travelers may incubate a disease while traveling, or travelers may have fever due to any infection other than COVID-19. When temperature testing is carried out, an X-ray should also be performed. X-ray scanning can help to identify Covid-19 patients or at least we can identify high-risk patients and take special measures to protect them during the travel.

## II. Literature Review

Rezaul Karim et al [VII], discusses the process of automatic detection of coronavirus from CXR images, usually, an expert radiologists are required to interpret the CXR images. However, the newly developed deep neural network named 'DeepCOVIDExplainer' automatically detect the infection from the CXR images without the intervention of experts. In the paper, the author trained the network with normal, pneumonia, and COVID patients X-rays images. This approach identifies COVID with a positive predictive value of 89.61% and a recall of 83%.

Zhou et al. [V] have created a deep learning model to differentiate a pneumonia infection and influenza using a chest computed tomography (CT) images. CT images are much better than CXR images because of their greater ability to display specifics of the pulmonary infection. In this paper, the author used a pre-trained network VGGNet

Li et al.[III] created a deep learning model called COVNet using a pre-trained model ResNet-50 as a backbone. The author trained the network to identify three classes COVID, pneumonia, and normal cases. The author used CT images to train the network. have made use of artificial intelligence technologies to tackle COVID-19 detection on chest CT images. The authors registered an accuracy of 0.96 for COVID-19, and 0.95 for other viral pneumonia, after experimentation.

Narin et al.[I] created a classification model using pre-trained neural network model (i.e. ResNet50, Inception-V3, and InceptionResNetV2). The author trained the network to identify two classes COVID and normal patients. The author generated the training and validation set using cross-validation and got an accuracy of 97% for the Inception-V3 model and 87% accuracy for Inception-ResNetV2.

Gozes et al.[VI] using CT images developed a deep learning model to detect and track COVID-19 patients. The author measured the spread of the disease using the 3D range and the corona ranking system. This is the first work, which is used for detecting, tracking, and characterizing COVID-19. The author used adaptive AI models to integrate the findings with ranking". The authors claim the work is the first that was developed to detect, characterize, and track COVID-19's progression. The authors use comprehensive 2D and 3D deep learning models, as well as modifying and adapting existing AI models, integrating the findings with clinical understanding. The results of the classification, aimed at differentiating images of coronavirus vs. non-coronavirus images from AUROC obtained 0.996. Gozes et al. Also assert that they have effectively quantified and monitored the burden of the disease.

Wang and Wong [IV] have developed the COVID-Net, an open-source deep neural network built specifically to detectCOVID-19 on chest x-ray images. To do this, the authors designed the COVIDx, a dataset that was created specifically to support the COVID-Net experiment. The collection consists of 16,756 chest x-ray photographs taken from 13,645 separate patients from two distinct databases. The authors describe the architecture design of COVID-Net in-depth, and they also illustrate how one can get the dataset.

The initial network design implementation was created based on the principles and best practices of human-driven design, combined with machine-driven design experimentation to generate the network architecture. The authors say that the model developed gained a good tradeoff between the accuracy and complexity of computation. For the COVID test dataset as a whole, they obtained 92.4 percent accuracy in terms of recognition results. For each type of infection / non-infection image, they also reported the following sensitivity rate: 95 percent for "normal" patients, 91 percent for non-COVID-19 infection, and 80 percent for COVID-19.

Khan et al.[II] created the CoroNet, a Convolutional Neural Network (CNN) for COVID-19 detection from CXR videos. The CNN model is Xception based (Extreme Inception) and includes 71 layers trained on the ImageNet dataset. The author also developed a balanced dataset to support and check the configuration of their neural network, which consists of 310 regular, 330 bacterial, 327 viral and 284COVID-19 resized CXR images. According to the authors, the CoroNet proposed for COVID-19 identification obtained an average accuracy of 0.87 and an F1-Score of 0.93.

Ozturk et al.[VIII] suggested a deep model with X-ray images for early detection of COVID-19 cases. The model produced achieved 98.08 percent accuracy for binary classes and 87.02 percent for multi-class instances. The software setup was designed as a YOLO object detection classifier, the DarkNet software. The authors have made the codes available, saying it can be used to create a method to help radiologists verify their initial screening.

## III. Proposed Method

The Convolution Neural Network (CNN) is used for image classification, the architecture of CNN is shown in fig 1. It has two main steps feature extraction and dense layer. Feature extraction consists of convolution and pooling layers. It extracts the features of an image for example texture sharpness, edge detection, etc., to classify images. Features are extracted using a filter of 3X3 2D array, which will be slide across the entire part of the image to extract the different features of the image. CNN receives an input feature map: a three-dimensional matrix where the size of the first two dimensions corresponds to the length and width of the pixel images. The third dimension is of size 3 (corresponding to the three-color picture channels: red, green, and blue). CNN consists of a stack of modules, each of which performs three operations.

We build the CNN model in Keras. It is a layered architecture. The model used in our method is sequential. The first layer is a convolution layer with 32 numbers of filters, which learns the basic features of the image for example lines, dots, textures, etc., 32 different features will be extracted in the first layer. The kernel size used in this layer is 3X 3, which is the standard size. The activation function used is RELU. The input shape is given as 224 X 224. The second layer is also a convolution layer with 64 filters each of size 3 X 3, with a RELU activation function. By stacking multiple convolution layers we can increase the receptive field of the network. The third layer is the Maxpooling2D layer with pool size 2 X 2. A drop out layer is added to avoid overfitting. Next, a convolution layer with a 64 filter of 3X 3 - kernel size is added.

which is followed by a Maxpooling2D and dropout layer. The same set of convolution, Maxpooling2D, and Dropout is added again to the network with an increased filter size of 128 filters. Totally 4 convolution layer is added. Now a dense layer has to be added. So a flatten layer and dense layer are with relu activation function. In the output layer, one neuron is required and the activation function will be sigmoid since it is a binary classification. After creating the model we need to compile the model with binary cross-entropy loss, optimizer as Adam, and metrics as accuracy. The model summary is shown the Fig 5 there is more than 5 lakhs parameter in this network.

Image Data Generator library is used to make the data ready for the model. Some augmentation like zoom augmentation is used on the original image. The model is trained for epochs 8 or 10. Finally, the model is trained by calling the model. fit function.

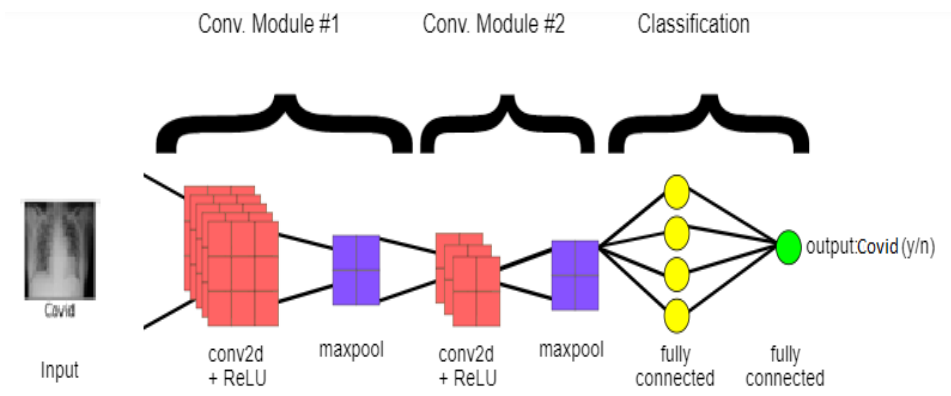


**Fig. 1:** CNN Architecture

### Transfer Learning

Instead of training a network from the scratch, we can make use of some state of art classification models for our problem statement. There are many image classification models available with better accuracy, which can classify 1000 of different classes of images. Models like VGG16, VGG19, ResNet, etc.,. All of these models are available in the Keras library. This state of art algorithm can be used to classify a chest X-ray as normal or COVID. Since these models are providing better accuracy it can be used for our problem statement, this technique is called "Transfer Learning". The model we are going to use is VGG16 and fine-tune some of the layers and alter the output layer so that it will contain only two classes normal and COVID. VGG16 is trained on the ImageNet dataset, we are going to use this on our COVID dataset.

## IV. Experimental Setup

We used python to create the CNN network. All tests are carried out with GPU runtime (25 GB RAM) on Google Colab. Originally, we created CNN from scratch to classify the normal and COVID-19 chest X-ray images. The dataset used was randomly split into two independent datasets with 80% and 20% for training and testing correspondingly.

In experimental analysis, we use the two classes of datasets that are publicly available. The first class is the chest X-ray of normal patients and the second is the chest X-ray of COVID affected patients. Since COVID-19 is a new disease, the number of images associated with this virus is limited. For this analysis, we combined two publicly accessible databases made up of COVID-19 images. The first dataset of COVID-19 (shown in Fig. 2) was shared on the GitHub website by a researcher named Joseph Paul Cohen from the University of Montreal. After the experts had reviewed the photos, they were made available to the public. The picture available in the Joseph Paul Cohen dataset are MERS, SARS, COVID-19, etc. The data for this study were selected from 284 images labeled with COVID-19. The chest X-ray of normal patients is taken from the kaggle (shown in Fig. 4). A training dataset size of 224 images and a testing dataset size of 60 images were used to construct the model from scratch. The model was designed to identify two classes COVID and normal cases.

To validate the network created we used a dataset available in the Italian Society of Medical and Interventional Radiology as shown in Fig. 3 (https:/www.sirm.org/en/category/articles/covid-19-database/). It is society, which encourages research in the field of medicine by publishing datasets for research. It contains 112 X-ray images of different COVID affected patients who had an infection in the chest.

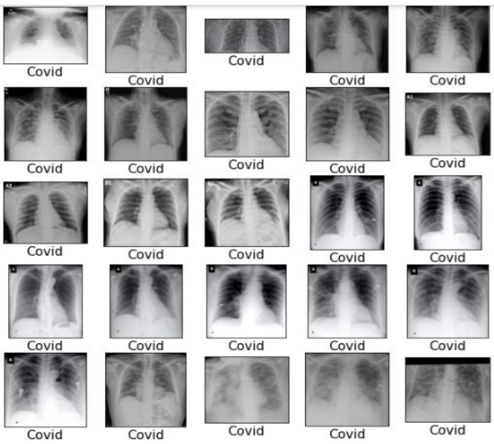


**Fig. 2:** Chest X-rays of Covid-19 patients obtained from GitHub

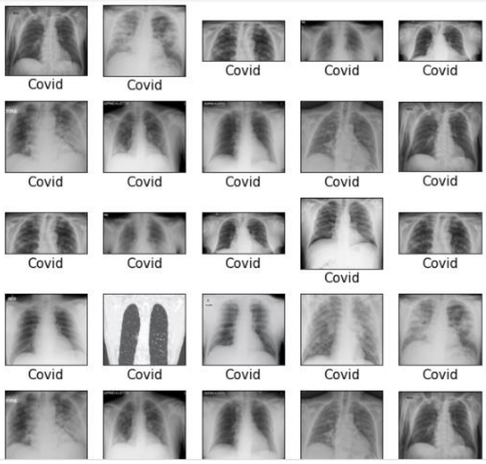


**Fig. 3:** Chest X-ray of Covid-19 patients from the Italian Society of Medical and Interventional Radiology

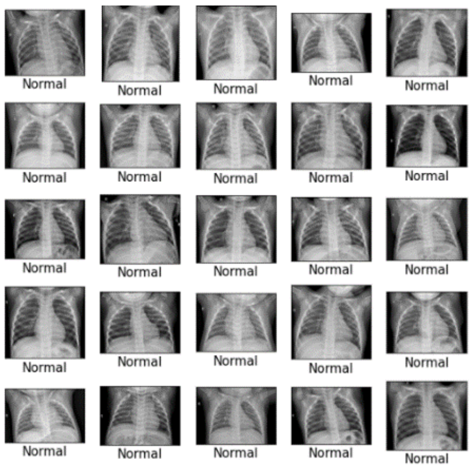


**Fig. 4:** Chest X-rays of normal patients from the Kaggle website

Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d_5 (Conv2D) | (None, 222, 222, 32) | 896 |
| conv2d_6 (Conv2D) | (None, 220, 220, 64) | 18496 |
| max_pooling2d_4 (MaxPooling2 | (None, 110, 110, 64) | 0 |
| dropout_5 (Dropout) | (None, 110, 110, 64) | 0 |
| conv2d_7 (Conv2D) | (None, 108, 108, 64) | 36928 |
| max_pooling2d_5 (MaxPooling2 | (None, 54, 54, 64) | 0 |
| dropout_6 (Dropout) | (None, 54, 54, 64) | 0 |
| conv2d_8 (Conv2D) | (None, 52, 52, 128) | 73856 |
| max_pooling2d_6 (MaxPooling2 | (None, 26, 26, 128) | 0 |
| dropout_7 (Dropout) | (None, 26, 26, 128) | 0 |
| flatten_2 (Flatten) | (None, 86528) | 0 |
| dense_3 (Dense) | (None, 64) | 5537856 |
| dropout_8 (Dropout) | (None, 64) | 0 |
| dense_4 (Dense) | (None, 1) | 65 |

Total params: 5,668,097
Trainable params: 5,668,097
Non-trainable params: 0

**Fig. 5:** Model Summary

During the training, we have reached an accuracy of 96% in 8 epochs. We also tested the accuracy for 10 and 15 epochs, respectively. We have used a transfer technique to improve precision and used a pre-trained CNN model called VGG16 with random initializing weights using the Adam optimizer. The number of epochs was experimentally set at 8, 10, and 15 for all experiments.

## V. Result and Discussion

We tested the network for echoes 8, 10, and 15 and found the losses and accuracy as shown in figures 6 and 7. As the available dataset is of limited size, we found the model to be over-fitting.

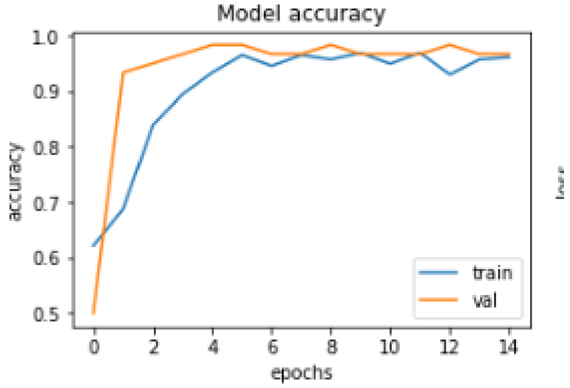


**Fig. 6:** Model Accuracy

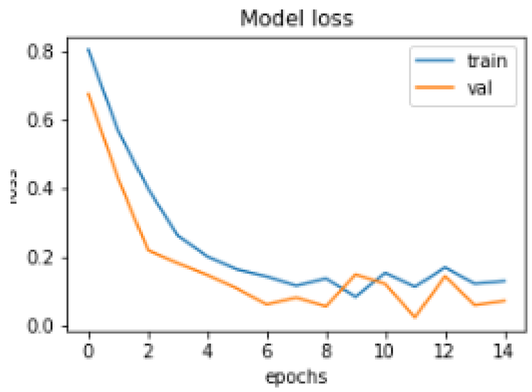


**Fig. 7:** Model Loss

## VI. Improving the Accuracy of the Result

To improve the accuracy of the model, we used a transfer learning technique in which we used a pre-trained VGG16 Kera model. The size of the filter used in this model increases as we move down the layer from 64->128->256->512. The hidden layers have all been activated by the Relu activation function. The 2-D convolution network used the size of the kernel [3, 3]. The summary of the model is shown in Figure 8. This determines the width and height of the convolution window. VGG16 is a model trained in the ImageNet dataset. ImageNet is an image database of more than 14 million images belonging to more than 20 thousand categories created for competitions for image recognition. In our problem statement, we only have two categories, "COVID, Regular," so the last layer is substituted to detect two categories. Pre-trained models have been shown to produce very high results in a small dataset. The accuracy and loss are shown in fig 9 and 10 respectively.

```
=================================================================
input_1 (InputLayer)         (None, 224, 224, 3)       0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 50178
=================================================================
Total params: 14,764,866
Trainable params: 50,178
Non-trainable params: 14,714,688
```

**Fig. 8:** Summary of VGG16 Model

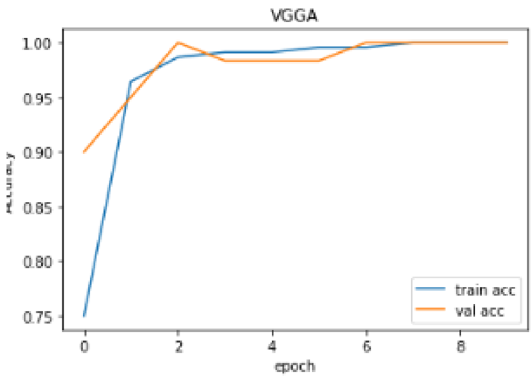


**Fig. 9:** Accuracy with VGG16 Model

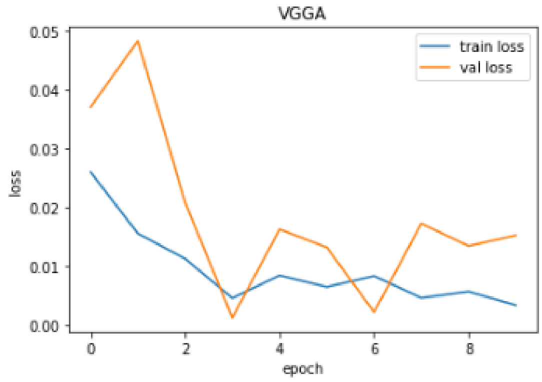


**Fig. 10:** Loss with VGG16 Model

### VII. Conclusion

This method of detecting Covid-19 using a chest X-ray can be used in the aviation sector to authorize a travel schedule for specific passengers. With this method, we can classify patients with other lung diseases and take precautions as they fly. Since only a small amount of dataset is available, the model appears to be over-fitting. More unseen data from similar distributions are needed for further evaluation to avoid possible out-of-distribution issues. There may be several instances where only the radiologist's forecast can be correct. However, reliable predictions are not only based on single imaging techniques but may also draw on additional modalities such as CT and other main variables such as the demographic and symptomatic assessment report for patients. Given the drawbacks, this approach can be used as a pandemic support device.

### Conflict of Interest :

Authors decleared : There is No conflict of interest regarding this article.

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