COVID-19 Detection from Chest X-Rays Using CNN

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Abstract:

COVID-19 is a respiratory viral disease caused by SARS-CoV-2 virus which has spread worldwide into a pandemic. In India and other countries with relatively lower levels of healthcare systems, there has been a humongous burden on the system to battle this crisis. The process to test an individual for COVID-19 is through Reverse Transcription Polymerase Chain Reaction (RT-PCR) process which is available as testing kits. These kits are needed to be produced in large quantities to cater to the demands, as the virus has been spreading rapidly there has been a severe lack of these testing kits. These RT-PCR testing kits also have a long turn-around time and also are limited in their sensitivity of the test. A valid alternative to test for COVID-19 can be achieved through Chest X-Rays. Due to the lack of testing kits, Chest X-Rays can be used as preliminary screening of patients before an RT-PCR test to streamline the testing process. With the lack of beds for COVID-19 patients in the faltering healthcare system, time is of the essence and the long waiting time for an RT-PCR test might inhibit the hospitals from admitting some patients to give them care for the disease. By using Chest X-Rays, which are widely available in healthcare systems and also now most of them being digitized, it can be a faster way to prioritize care for the patients who need them. Also, due to the several mutations that has occurred over the course of a year to the SARS-CoV-2 virus, some RT-PCR testing kits are giving false-negative results to the disease which can harm the patient’s health by not being able to find the right kind of treatment. This can also be corrected using the Chest X-Ray testing mechanism as the Chest X-Ray is not looking for the specific virus. We propose a new neural network-based model to detect COVID-19 from the Chest X-Rays of the patient which can give out results faster and with higher sensitivity than the traditional testing mechanisms. We will be using the publicly available covid-chest X-ray-dataset to train our model to better recognize COVID-19 in patients and help them get the best care they need to help in saving lives.

Keywords: COVID-19, Chest X-Ray, CNN.

1. Introduction:

The COVID-19 viral disease originating in Wuhan, China in the late December 2019 has been devastating to the world. The healthcare systems across the world have gone through significant amount of stress in dealing with the number of patients being tested positive for the virus. There has been a shortage of hospital beds to care for the people affected, lack of testing kits to diagnose the disease correctly and also Personal Protective Equipment (PPE) for the healthcare workers to protect them from the infection such that they can keep fighting the war against the virus. The reason for this is the similarity that the COVID-19 disease has with other respiratory illnesses like Severe Acute Respiratory Infection (SARI) and Influenza-like Illness (ILI) which are not as deadly or as communicable as COVID-19 but have similar symptoms during the early stages of the diseases. With the lack of resources, there is a need to differentiate patients with COVID-19 such that they can get the specified care that has been recommended by the medical fraternity and also to quarantine them such that the highly transmissible SARS-CoV-2 virus does not spread to others.

With the lack of testing kits and an increasing spike in the number of people testing positive for COVID-19, we are trying to lower the burden of the healthcare system by introducing a Chest X-Ray based diagnosis for COVID-19. We will use a neural network model to differentiate between the Chest X-Rays of patients with bacterial pneumonia, viral pneumonia and COVID pneumonia.

The reasons for using Chest X-Ray based diagnosis is that:

· X-Rays are readily available in the healthcare system from beforehand and are inexpensive compared to the traditional means of diagnostic test of RT-PCR.

· As X-Rays are now digitized, the transportation of the X-Ray images from the place of the test to a sperate analysis center is not required like for samples taken in RT-PCR tests. This reduces the time to get the results as well.

· CT Scan is also another mode of diagnosis, but CT scans require the patient to be in a separate facility as it is a much complex way of diagnosis with the need of especially skilled personnel to be operated by. Whereas, X-Rays can be taken in the isolation ward where the patient is situated and does not require specialized personnel. As the X-Rays can be taken in the isolation wards, there is lower risk of hospital acquired infection.

The radiographs obtained from the X-Rays sometimes can be misinterpreted by non-radiologists and due to the relatively novel nature of the virus it can be hard for expert radiologists as well to recognize the and diagnose COVID from the radiographs. Thus, through a well-trained neural network taking data from several X-Ray images of COVID-19 patients it is possible to make highly accurate diagnosis with minimal time.

Related Works

a) Pneumonia using Chest X-Rays

A lot of deep learning and neural network-based algorithms have been introduced to diagnose thoracic diseases like pneumonia. One of those is CheXNet which can detect pneumonia from X-Rays that even practicing radiologists can miss and we chose to build on top of this network. ChestX-ray14 is a public dataset of chest x-rays that is the largest publicly available of its kind and the CheXNet is also trained on this data set. This approach has better performance and also a simpler architecture. CheXNet is a DenseNet based model trained on the ChestXray-14 dataset that is 121 layers deep and contains over 1 lakh frontal-view images of Chest X-Rays. The model is trained such that it can classify these images into 14 different classes of thoracic diseases. As there is visual similarity between the input samples, this is the closes pre-trained backbone to develop a model for detection of COVID pneumonia.

b) COVID using Chest X-Rays

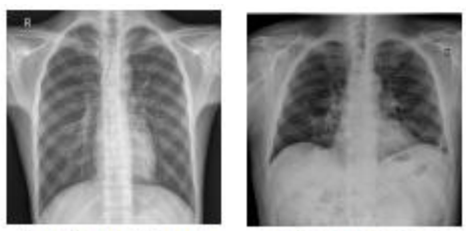
Because of the latest surge in the number of cases of COVID-19 there were several approaches to diagnose COVID19 due to lack of testing kits. But there were only a few open-source applications available that used Chest X-Rays. COVID-Net is a well-maintained tool which is open source and has the capabilities to identify COVID-19 and as well as other pneumonia while showing good sensitivities to COVID-19 detection.

2. Proposed Method

Given the limited number of X-Ray samples available, it is difficult to train a deep neural network from scratch. Therefore, we use a pre-trained model trained in a big dataset. Our methods use a pre-trained Sequential model, developed by Weng et al. .

2.1 Problem Formulation and Loss Function

We aim to separate the image provided by the X-Ray chest attached to the following classes: General and COVID-19. We train our model in two settings, which separates the above two classes.



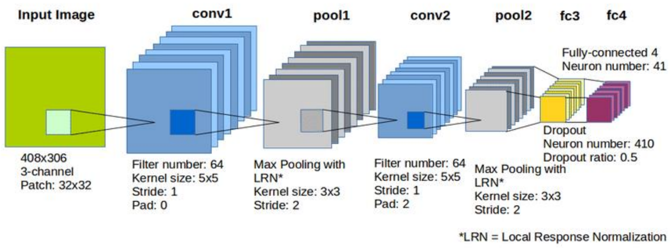
(a) Normal Lung (d) COVID-19

Similar to Sequential, we treat each class as a binary classification problem, with input as a frontal-view chest X-Ray image X and output being a binary labels yc ∈ {0, 1}, indicating absence or presence of class c symptoms in the image respectively. We use the weighted binary cross-entropy loss as suggested by Sequential:

$$\mathcal{L}(X, y; \theta) = \sum_{c=1}^{C} \big(-w_c^{+} \mathbb{1}\{y = c\} \log p_c(\hat{y} = 1 \mid X; \theta) \\ - w_c^{-} \mathbb{1}\{y \neq c\} \log p_c(\hat{y} = 0 \mid X; \theta) \big) .$$

2.2 Model Architecture

Our model consists of a pre-trained Sequential, with a Convolution nets Architecture, followed by a fully connected layer. It consists of 3 hidden layers. Layer 1 consists of 32 filters; Layer 2 consists of 64 filters and Layer 3 consists of 128 filters. The activation function used is Relu.



2.3 Training

For training we initialize our model with pre-trained weights from Sequential implementation by Weng et al., and then following the two-stage training process described below:

1. In the first step, Convolution nets' backbone weights are frozen and only the final fully connected layer is trained. Training is performed using Adam optimizer with following parameters: β1 = 0.9, β2 = 0.999, and learning rate 10−4. We use mini-batches of size 16, and train for about 30 epochs. The model with the lowest validation loss is selected for the next stage.
2. In the second stage, the network weights are initialized from above, but the whole network is trained end-to-end (all layers), using the same hyperparameters. We use a mini-batch size of 8 in this stage due to memory constraints, and train for 10 epochs. Again, the model with lowest validation loss is selected for testing.

3. Database and performance metrics

We use the Covid Dataset of COVID-19 and common lung in the chest X-Ray view imaging. We use a pre-trained Sequential model, thus utilizing powerful features found in the background training on the ChestX-ray14 database.

	Train (80%)	**Test (20%)**
COVID	156 images	40 images
Normal	276 images	70 mages

3.1 Evaluation

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 222, 222, 32)      896       
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 220, 220, 64)      18496     
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 110, 110, 64)      0         
_________________________________________________________________
dropout (Dropout)            (None, 110, 110, 64)      0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 108, 108, 64)      36928     
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 64)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 54, 54, 64)        0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 52, 52, 128)       73856     
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 26, 26, 128)       0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 26, 26, 128)       0         
_________________________________________________________________
flatten (Flatten)            (None, 86528)             0         
_________________________________________________________________
dense (Dense)                (None, 64)                5537856   
_________________________________________________________________
dropout_3 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 65        
=================================================================
Total params: 5,668,097
Trainable params: 5,668,097
Non-trainable params: 0
```

4. Results

The convolutional neural network is built using Keras. Three hidden convolution layers are used in this network. The first layer contains 32 filters, and the subsequent layers contain 64 and 128 filters. The number of convolutional filters increases as the network goes deeper. The patterns are more complex as the layers increase. Thus, to capture a large number of combinations, the filter size is increased. The function **'flatten'** converts the pooled feature map to a single column and is passed to the fully connected layer. The function **'dense'** adds the fully connected layer to the neural network. The output is a single neuron. Binary classification is performed, and a sigmoid activation function is used.

Image augmentation is a method to artificially inflate the size of the training set by creating modified versions of existing images. This adds variety to the training set, thus enhancing the performance and ability of the model.

Various image augmentation used are:

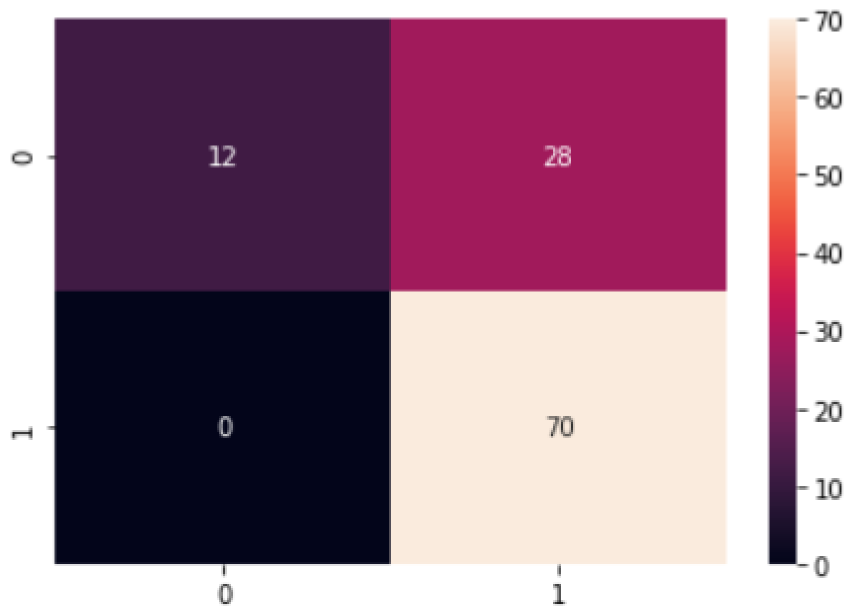
- Shearing
- Zooming
- Flipping

Images are augmented before training the dataset. About *80*% of the dataset goes *into* the training set, and *20*% of the dataset goes *into* the validation set.

The model is trained for ten epochs, and there are eight steps per epoch. After ten epochs, the training accuracy is 92.92%, and the validation accuracy is 96.88%.

```
Epoch 1/10
8/8 [==============================] - 24s 3s/step - loss: 0.7463 - accuracy: 0.6167 - val_loss: 0.6623 - val_accuracy: 0.7188
Epoch 2/10
8/8 [==============================] - 23s 3s/step - loss: 0.5718 - accuracy: 0.6875 - val_loss: 0.5361 - val_accuracy: 0.9531
Epoch 3/10
8/8 [==============================] - 22s 3s/step - loss: 0.3793 - accuracy: 0.8583 - val_loss: 0.1623 - val_accuracy: 0.9531
Epoch 4/10
8/8 [==============================] - 23s 3s/step - loss: 0.2088 - accuracy: 0.9297 - val_loss: 0.1292 - val_accuracy: 0.9688
Epoch 5/10
8/8 [==============================] - 23s 3s/step - loss: 0.2016 - accuracy: 0.9375 - val_loss: 0.0837 - val_accuracy: 0.9844
Epoch 6/10
8/8 [==============================] - 24s 3s/step - loss: 0.1528 - accuracy: 0.9688 - val_loss: 0.0673 - val_accuracy: 0.9844
Epoch 7/10
8/8 [==============================] - 25s 3s/step - loss: 0.1902 - accuracy: 0.9453 - val_loss: 0.0196 - val_accuracy: 1.0000
Epoch 8/10
8/8 [==============================] - 22s 3s/step - loss: 0.2040 - accuracy: 0.9333 - val_loss: 0.1028 - val_accuracy: 0.9844
Epoch 9/10
8/8 [==============================] - 21s 3s/step - loss: 0.1705 - accuracy: 0.9417 - val_loss: 0.0807 - val_accuracy: 0.9844
Epoch 10/10
8/8 [==============================] - 23s 3s/step - loss: 0.2257 - accuracy: 0.9292 - val_loss: 0.0754 - val_accuracy: 0.9688
```

Confusion Matrix Obtained:



5. Conclusion

The model to detect COVID-19 from chest X-Rays is designed using the Convolutional Neural Network. This primitive model contains three hidden layers, each containing 32,64 and 128 filters. The model looks promising, with an accuracy of 93%. The accuracy of this model can be improved by increasing the number of hidden layers to detect minute features.

REFERENCES

Das, A.K., Ghosh, S., Thunder, S. *et al.* Automatic COVID-19 detection from X-ray images using ensemble learning with convolutional neural network. *Pattern Anal Applic* (2021).

Neural Networks & Fuzzy Control

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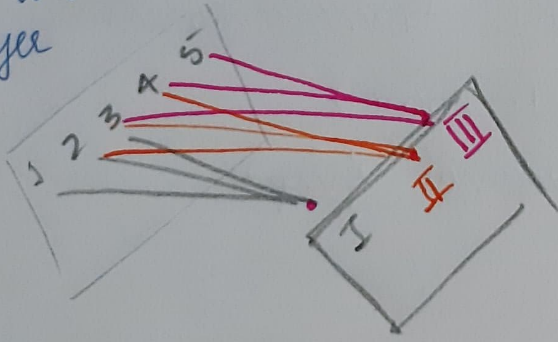
Project - Writeup

Group: 14 - Epoch

- The CNN is built using Keras. Layer 1 extracts 32 different features and the kernel size is 3x3. The input is resized to 224x224 and is of the type RGB. Layer 2 & 3 consists of 64 and 128 filters respectively. The final layer is a single neuron with SIGMOID ACTIVATION

★★★

When 2 convolved layers of 3x3 are stacked against each other, it uses 5x5 matrix of first layer



We prefer 2 layers of 3x3 each instead of using 5x5 from the first layer because:

- 2 CONVOLVED LAYERS INCREASES THE NON LINEARITY
- HENCE, INCREASES THE HYPOTHESIS SPACE &
- NUMBER OF COMPLEX FUNCTIONS CAN FIT IN THE MODEL

- IMAGE AUGMENTATION

- Image augmentation is a method to artificially inflate the size of the training set by creating modified versions of existing images

- This adds variety to the training set, thus enhances the performance & ability of the model.

AUGMENTATIONS USED IN OUR PROJECT

- Shear (20% transformation)
- Zoom (20% zoom)
- Flip. (Horizonal flip)