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# Automatic Detection and Report generation of CORONA disease using chest X- Ray

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**Abstract -** *The sudden spike in the number of patients with COVID-19, has put unprecedented load over healthcare systems across the world. With very limited testing kits and gadgets, it is impossible for every patient with respiratory illness to be getting tested using conventional techniques (RT – PCR Test). The test also has a long turn – around time, with limited sensitivity. Detecting Chest X – Ray of Covid – 19 infections may help quarantine patients with high risk while test results are awaited. X-Ray machines are already available in most healthcare systems, and with modern X-Ray systems already digitalized, there is no transportation time for the samples either. In this we propose the use of chest X-Ray to prioritize the selection of patients for further RT-PCR testing. This may be useful where the present systems are struggling to decide whether to keep the patient isolated in COVID-19 areas or in the ward along with other patients. It would also help in identifying the patients with high risk or likelihood of COVID-19 with a false negative RT – PCR who would need a repeat testing. We have proposed the use of modern Artificial intelligence techniques to detect the COVID-19 patients using X-Ray images in an automated manner, particularly in the settings where radiologists are not present, and help make the proposed testing technology scalable. We present Covid AID, a novel deep neural network-based model to prioritize patients for appropriate testing. On the publicly available covid -chest Xray-dataset [2] dataset, our model gives 90% accuracy for the COVID-19 infection.*

***Key Words*: Covid AID (COVID-19 AI Detector), *RT-PCR* (*Reverse Transcription Polymerase Chain Reaction*)**

## *1.INTRODUCTION*

When it comes to the sudden rise in the number of patients who were targeted by the Novel Corona virus in the year 2019, popularly known as the Covid-19, which is a new Respiratory Virus, there are no precedents found for the same across the world and even around the globe. As we know, in many countries the healthcare systems have been raised drastically to a better level in many countries across the world. The number of resources available is extremely limited, for example there is shortage of kits for diagnosis, limited hospital beds for admission of such patients, limited personal protective equipment (PPE) for healthcare personnel and limited ventilators.

Now there is confusion as to which patients are infected with what type of virus as there are two different types of viruses namely, the SEVERE ACUTE RESPIRATORY ILLNESS (SARI) and the COVID-19. In order to differentiate between both the viruses we need to exactly determine as to which patient has which virus as at this point of time, we cannot the viruses with each other or else the outcome would be the Utilization of the Limited Resources would not take place effectively. The patients who are exhibiting the symptoms of SARI, who are also having Covid-19 infection are supposed to undergo the Chest X-Ray and this is also the proposal made.

With the usage of our tool any covid-19 patient can classify a given X-Ray in one of the four classes namely- Normal, Bacterial Pneumonia, Viral Pneumonia, and Covid Pneumonia.

Mentioned below are the several usages of the aforementioned X-Ray and it also has several advantages over Conventional Diagnostic Tests:

A. When it comes to X-Ray imaging, it is much more widespread and it is an economical method which is cost effective as compared to the conventional diagnostic tests.

B. The Transfer in the digital X-Ray images does not require any transportation from point of acquisition to the point of analysis, thus the diagnostic process becomes extremely quick

C. Unlike CT Scans, portable X-Ray machines also enable testing within an isolation ward, hence reducing the number of requirements of additional Personal Protective Equipment (PPE), an extremely scarce and valuable resource in this scenario. It reduces the risk of hospital acquired infection for the patients.

The main contribution of this work is in proposing a novel deep neural network-based model for high accurate detection of COVID-19 infection from the chest X-Ray images of the patients. Radiographs in the current setting are in most cases are interpreted by non-radiologists who are working on the same project. It is further given that, the novelty of the virus, many of the radiologists themselves may not be aware of all the nuances of the infection, and may be lacking in the sufficient expertise to make highly accurate diagnosis. Therefore, this automated tool can serve as a director for those in the vanguard of this analysis.

## *2. LITERATURE REVIEW*

In the context of the COVID-19 epidemic, extensive research has been conducted with the aim of developing imaging-based diagnostic and diagnostic systems. Following this we review the proposed methods of reliable chest-based imaging programs and CT-scan imaging techniques. These methods follow one of two main frameworks. On the other hand, new deep network structures have been developed and specifically designed to detect and detect COVID-19. Represents one of the first convolutional networks designed to detect COVID-19 cases automatically from X-ray images. Network performance showed an acceptable accuracy of 83.5% and a high 100% sensitivity to COVID-19 cases. Linda Wang and Alexander Wong. Covid-net[5] proposed a CNN-based network called the Coronavirus Recognition Network (CVR-Net) to automatically detect COVID-19 cases in radiography. The network was trained and evaluated on data sets containing X-ray and CT images. The results showed different accuracy scores depending on the number of classes in the X-ray imaging database, as well as an average of 78% accuracy of the CT imaging database.

Ophir Gozes, Maayan Frid-Adar, Hayit Greenspan, Patrick D Browning, Huangqi Zhang, Wenbin Ji, Adam Bernheim, and Eliot Siegel[3] highlighted the importance of in-depth study strategies and chest CT images to differentiate between COVID-19 and influenza pneumonia. The study was conducted on CT images of COVID-19 certified patients from various hospitals in China. Their study confirmed the ability to obtain an accurate diagnosis of COVID-19 from CT imaging and the effectiveness of their proposed system to distinguish between two types of pneumonia. Deep Pneumonia was developed to identify cases of COVID-19 (88 patients), viral pneumonia (100 patients), and healthy cases (86 studies) based on CT images. The model achieved an 86.5% accuracy of the difference between bacterial and viral pneumonia (COVID-19).

Very few studies have used manual extraction methods with standard dividers. In [7], texture features were extracted from X-ray images using popular definition definitions. The features are combined with those released from the pre-assembled inceptionv3 [14] using different fusion techniques. Subsequently, various detectors were used to differentiate between standard X-rays and different types of pneumonia. The best split scheme scored was 83% F1 points.

## *3. PROPOSED SYSTEM*

### *3.1 DATA GENERATION*

Radiology images of COVID-19 infected patients are rare. We used COVID dataset assembled by [5]. They combined open source databases with chest radiology or CT images from online database and the papers which we have referred. We only used X-ray images to train our model and no CT scan images were used. The total number of COVID-19 infected Chest images are 3616.

### *3.2 PRE - PROCESSING*

We used minimal pre-processing of the dataset before it is fed to our model. The only pre-processing was resizing every image to a similar dimension. We used images of height 224 pixels, width 224 pixels, and the number of channels 3 (224*224*3). Minimal pre-processing makes our inference process faster, so when testing, we can generate the model's output (prediction and heatmap) in real-time

### *3.3 MODEL ARCHITECTURE*

Our model is comprised of two parts, feature extractor, and classifier. For the feature extractor, we used VGG16 [6], and for the classifier, we used a fully connected layer with SoftMax activation function. VGG16 is a convolution neural network (CNN) architecture. It is considered to be the excellent vision model architecture till date. The Most distinctive thing about VGG16 is that instead of having a larger number of hyper-parameters they focus on having convolution layers of 3x3 filter with a stride 1 and always used as same padding and maxpool layer of 2x2 filter of stride 2. It basically , follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. At the end it has 2 FC (fully connected layers) followed by a SoftMax for output.

$$X_l = H_l([X_0, X_1, ..., X_l - 1]) \tag{1}$$

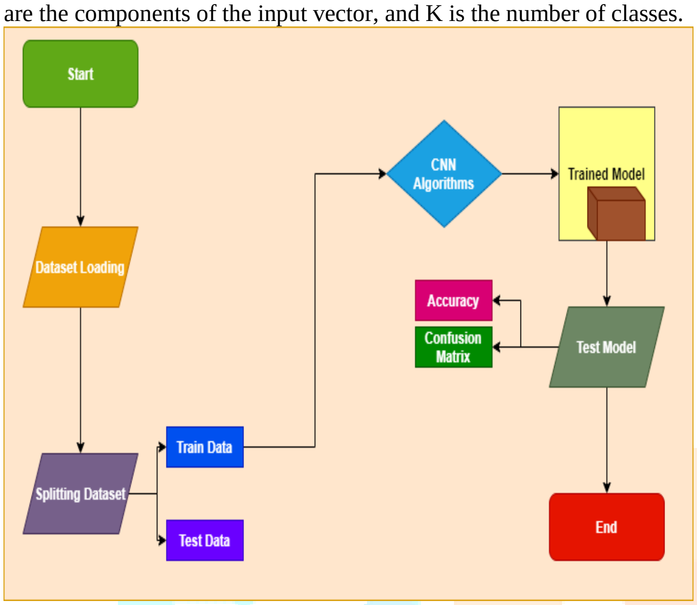
Here, the Hl represents the lth layer, Xl is the output of the lth layer , and [X0, X1, ..., Xl − 1] represents the concatenation operation. This special design improves information flow through the network and alleviates vanishing gradient problem. Another important reason for choosing VGG16 as our architecture is that VGG16 connection has a regularization effect, and it reduces over-fitting on training with smaller data sets , which is our case. Furthermore, VGG16 enhances feature reuse and parameter efficiency and provides each layer the collective knowledge of the network. VGG16 has four 16 blocks and a transition layer between every two VGG16 blocks (Figure 4). Each VGG16 block consists of several convolution layers, and each transition layer consists of a batch normalization, a convolution, and an average pooling layer. To increase nonlinearity ReLU activation function is used in VGG16, which can be described as:

$$ReLu(x) = \begin{cases} x & x > 0 \\ 0 & x \le 0 \end{cases} \tag{2}$$

In our model, the final layer of the VGG16 is a global average pooling layer that generates the features from the input image. The SoftMax activation normalizes the output of the fully connected layer and generates a probability distribution over the predicted output classes. These features are used by the classifier to make the final prediction. For the classifier, we used a fully connected layer, followed by a SoftMax activation function. For 3-class classification, we used a fully connected layer of three units, and for 2-class classification, we used a fully connected layer of two units. The equation of the SoftMax function can be written as follows:

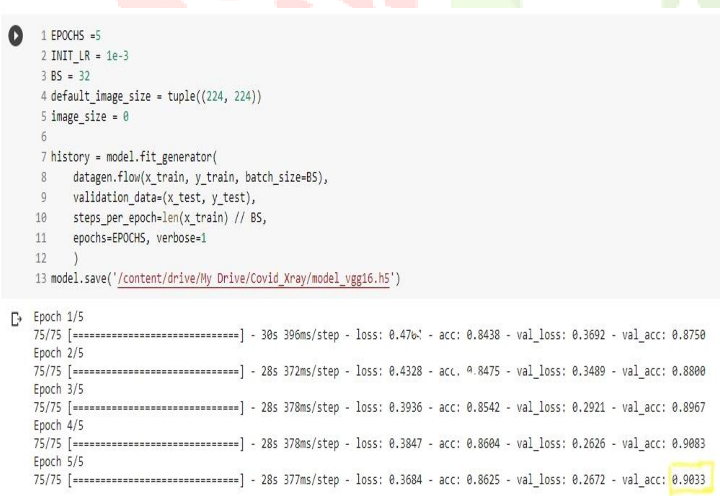
$$\sigma(\vec{z}_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \qquad (3)$$

Here, ~z is the input vector of the SoftMax function, zi values are the components of the input vector, and K is the number of classes.




## 4. RESULT AND DISCUSSION:

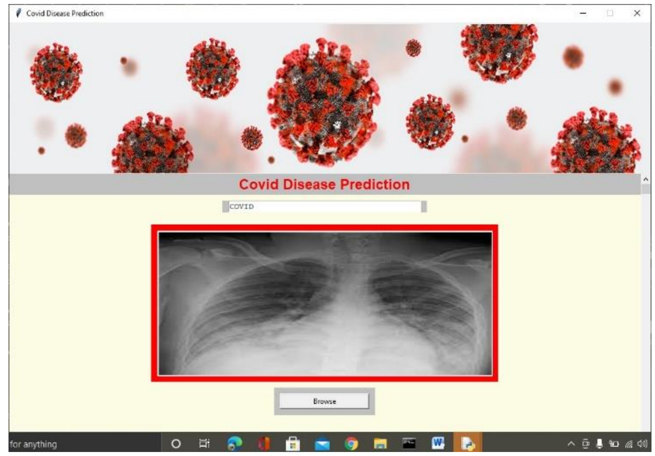
We have compared many model such as Dense-net 12, Resnet 50 and VGG16 after training every model we have proposed the model which has given us the highest accuracy. VGG16 using CNN is our proposed model we have pretrained it and we have got an optimum accuracy of 90%.



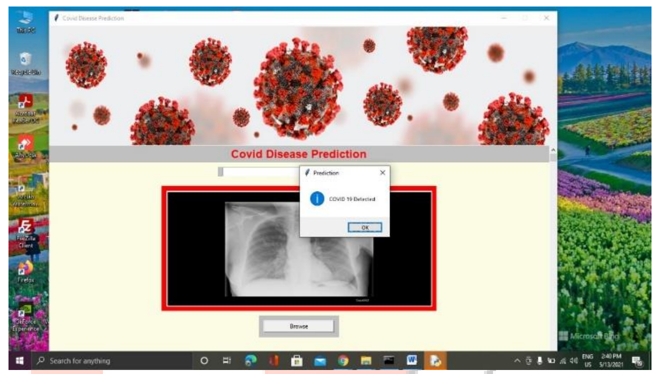
```
EPOCHS =5
INIT_LR = 1e-3
BS = 32
default_image_size = tuple((224, 224))
image_size = 0

history = model.fit_generator(
    datagen.flow(x_train, y_train, batch_size=BS),
    validation_data=(x_test, y_test),
    steps_per_epoch=len(x_train) // BS,
    epochs=EPOCHS, verbose=1
    )
model.save('/content/drive/My Drive/Covid_Xray/model_vgg16.h5')
```

```
Epoch 1/5
75/75 [==============================] - 30s 396ms/step - loss: 0.476 - acc: 0.8438 - val_loss: 0.3692 - val_acc: 0.8750
Epoch 2/5
75/75 [==============================] - 28s 372ms/step - loss: 0.4328 - acc: 0.8475 - val_loss: 0.3489 - val_acc: 0.8800
Epoch 3/5
75/75 [==============================] - 28s 378ms/step - loss: 0.3936 - acc: 0.8542 - val_loss: 0.2921 - val_acc: 0.8967
Epoch 4/5
75/75 [==============================] - 28s 378ms/step - loss: 0.3847 - acc: 0.8604 - val_loss: 0.2626 - val_acc: 0.9083
Epoch 5/5
75/75 [==============================] - 28s 377ms/step - loss: 0.3684 - acc: 0.8625 - val_loss: 0.2672 - val_acc: 0.9033
```

After the using the pre – trained model we need to put out the X-Ray images in our GUI. There is text field where we can browse and select the X-Ray images which we have from the dataset.




As we have our GUI built and pre-trained as per the VGG16 model we have used. Will get the following result as the X-ray which we have selected is into following category COVID, Viral Pneumonia, or Normal.




## 5. CONCLUSION

In this work, we showed a novel transfer learning-based approach to detect COVID-19. To assure that our model can differentiate COVID-19 radiology images from both healthy persons and pneumonia patients, we performed both 2-class and 3-class classifications. Our extensive experiments suggest that COVID - VGG16 can be used effectively for detecting COVID-19 from chest radiology images. To guarantee the robustness and consistency of our model, we implemented patient-wise 10- fold cross-validation. Moreover, we performed an explain ability analysis to interpret and visualize how our model works.

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