DEEP LEARNING BASED COVID-19 TRACING USING CHEST X-RAYS

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ABSTRACT:
After being detected, the novel corona virus (COVID-19) has spread rapidly throughout the world and was declared as a pandemic because of the public health emergency. It created adverse effects on the human lives and economies all over the world and even in some leading countries. Infected people experience symptoms after few days. It is important to verify correctly whether the person is infected by COVID-19 or not. RT-PCR testing is a verified testing facility but it takes around 24 hours to get a clear report and therefore is a time consuming process. Artificial Intelligence is applied on the CXR (Chest X-Ray) images to find out COVID-19 positive or negative within a few hours. The proposed model could also be applied in the rural areas and also in an affordable price. Our model gave better accuracies as we trained with more and more images. Many convolutional layers and pooling layers along with specific filtering values were applied on each layer accordingly for obtaining better accuracy. The dataset comprises of 1000 images, all grouped correctly as COVID-19positive and negative images. All the images were correctly split up for training, validation and testing purposes. We got amaximum training accuracy of 100% and testing accuracy of 97%.The proposed model provides a good accuracy in predicting the corona virus amongst people.

1. INTRODUCTION:

The Corona Virus Disease (Covid-19) is a highly contagious viral infection which spreads through saliva or mucus when a person sneezes or coughs. It is easily transmitted to a person by coming close to someone who is infected with the virus already or when someone is in contact with a surface which is already contaminated. Due to underlying health conditions the older people face a high risk and may succumb to severe illness due to ageing. When left untreated the symptoms become adverse and the individual may experience sore throat, head ache, conjunctivitis, tiredness, loss of taste and smell, dry cough, fever, severe shortness of breath, chest pain and pressure, loss of speech and movement and many more side effects. While trying to overcome one of the most difficult times the human era has ever faced, we have a plan to provide a better alternative to the regular COVID-19 testing mechanism. RT-PCR testing is the regular COVID-19 patient screening process which is an arduous and time consuming process [1]. The chest X-rays of the patients are usedas a tool to classify whether they are infected or not. This as a cost effective process and all the needy people could access this easily.

2. RELATED WORK:

In [2], the CXR images were collected from the kaggle repository. To obtain reliable results they needed to clean their data and the medical data wasn't enough for their analysis. So they used augmentation to overcome over-fitting. Over-fitting is a case where testing accuracy is much higher than training accuracy. In [3], for the classification of Chest X-ray images the CNN architecture was based on class decomposition that is DeTraC (Decompose, Transfer and Compose). 93.1% accuracy was obtained. In [4]after applying transfer learning, different architectures of CNN were trained and was adapted to behave as feature extractors for the X-ray images. In [5] the Darknet-19 model is applied. Itis a classifier model that forms the basis of YOLO (You Only Look Once). It is a real time object detection system. In [6] ResNet-101 was selected as the architecture of the classification model. Five types of data augmentations were added including zoom, rotate, shear, flip and shift. For the model development, in[7]it is stated that all the images are resized to 224x224 pixels array before being split to a certain ratio of training and testing data subsets. From [8], the stability of DenseNet121 is much lower and the outcome was worse than ResNet50, VGG16 and VGG19. In [9], the transfer learning with the highest number of image augmentation types could be used to develop a high classification accuracy AI based CXR classification model. In [10], for demonstrating the results qualitatively few saliency maps were generated for model's prediction using RISE. The concept of RISE is that the masks that preserve the semantically vital parts of image leads to higher classification score therefore a higher weight in the final mask for that respective class. From [11], it is evident that masks are applied in the convolutional layer during feature extraction. This is a process of separating images to predefined dimensions of segments and usage of the filters to extract features from images. 3 common ensemble techniques stated in [12] with which their original works were compared includes un-weighted average approach, weighted average approach (by accuracy) and weighted average approach (by ranked accuracy). In [13] a clear approach on how to reduce the over-fitting and under-fitting issues by introducing the dropout factor was provided. In [14] a clear reason for using accuracy as the performance metric was clearly mentioned that is accuracy indicates how well a classification algorithm can discriminate the classes in the test set. The number of channels must never decrease as we progress on to the next level otherwise it may affect our model badly. This was inferred from [15]. In [16], during the training the dataset was divided into 70% for the training set and 30% for the validation set which is an important inference. In [17], the models are evaluated by a 5 fold cross validation using two publicly available repositories containing infected and healthy CXR images. In [18], accuracy was measured as a ration of the sum of True Positive with True Negative to the sum of True Negative with False Positive with True Positive with False Negative. In [19], it was stated that for making successful decisions related with COVID-19 virus diagnosis the object detection models trained with more images of a similar disease and processed with a transfer learning and image normalization algorithm could be done. In [20], a method for synthesizing the results of the components of the model called as fusion rules were well discussed.

3. PROPOSED METHODOLOGY:

3.1 TRAINING THE MODEL:

The input layer, convolution layer and the pooling layer is a part of feature extraction. The fully connected layer and the output layer is a part of the classification process. All models and layers are imported. A Sequential model is used because in the project the CNN will be processed as a linear stack of layers. While creating the first convolutional 2D layer,32 filters or feature maps are passed. The kernel size is 3x3. Rectified Linear Activation Function (ReLU) is very much preferred in the hidden layer and so we use it here. The dimension is 224x224. All are RGB images (color). Even the images whose size is not 224x224 pixels are converted to 224x224, the standard size. The first pooling layer is created of size 2x2. Max pooling is done. A pooling layer is always created only after a convolutional layer. After processing the obtained final accuracy is low. So, a second convolutional layer is created along with a pooling layer. Number of filters is 64, with same kernel size of 3x3 and ReLU activation function. In the second pooling layer Max pooling is done and the size is 2x2. A third convolutional and pooling layer is created. In the convolutional layer the number of filters is 64, the kernel size is 3x3 and the activation function used is ReLU. In the pooling layer the size of the Max pooling layer is 2x2. The accuracy is better, but not up to the mark. A fourth convolutional layer with 128 filters, kernel size of 3x3 and ReLU activation function is passed. Pool size of 2x2 is chosen for the Max pooling function as shown in fig1.

A flattening layer is created. The pooled feature map is converted to a 1-dimensional array. A sigmoid function is used in the output layer. Since there are only two classes 0 and 1, a sigmoid activation function (Fig2) is preferably used. In the flattening layer again the ReLU activation function is used. Initially when we ran the code there was a huge gap between the training accuracy and the testing accuracy. This over fitting and under fitting was reduced by introducing a dropout value of 25% in all the four layers. In our model we observe that the input from the previous layers of the model affects the sigmoid activation function.

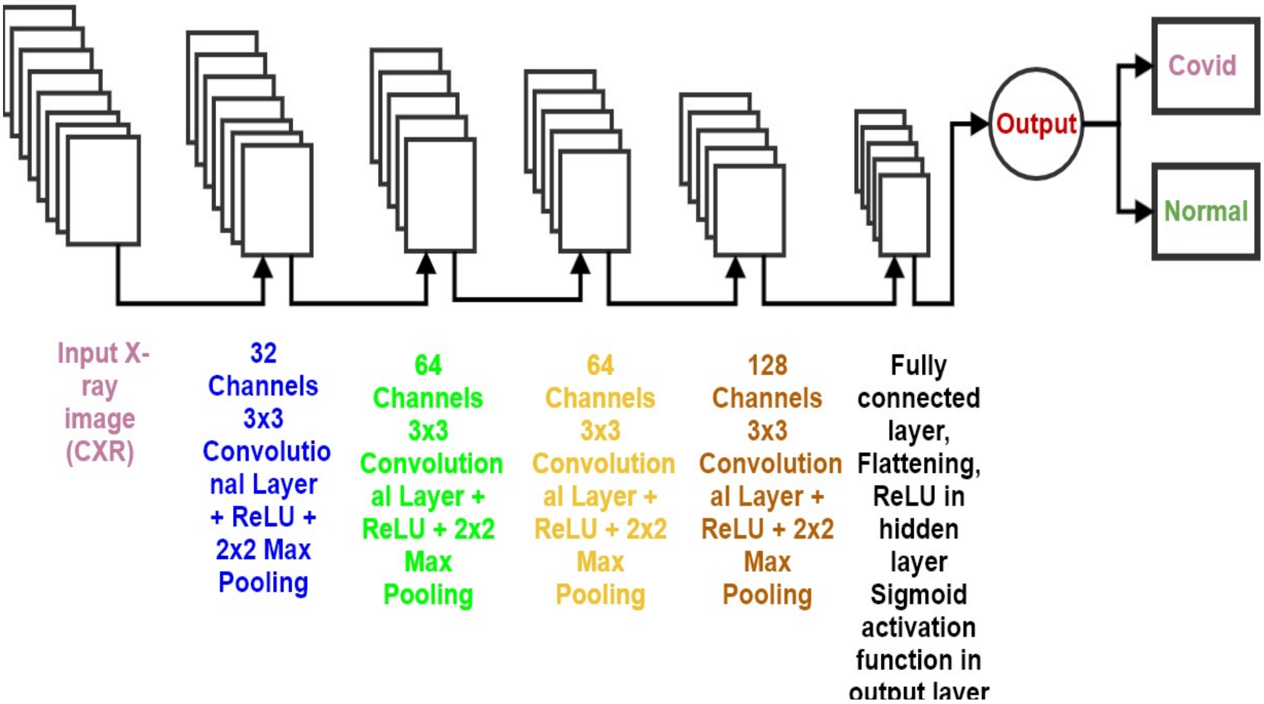
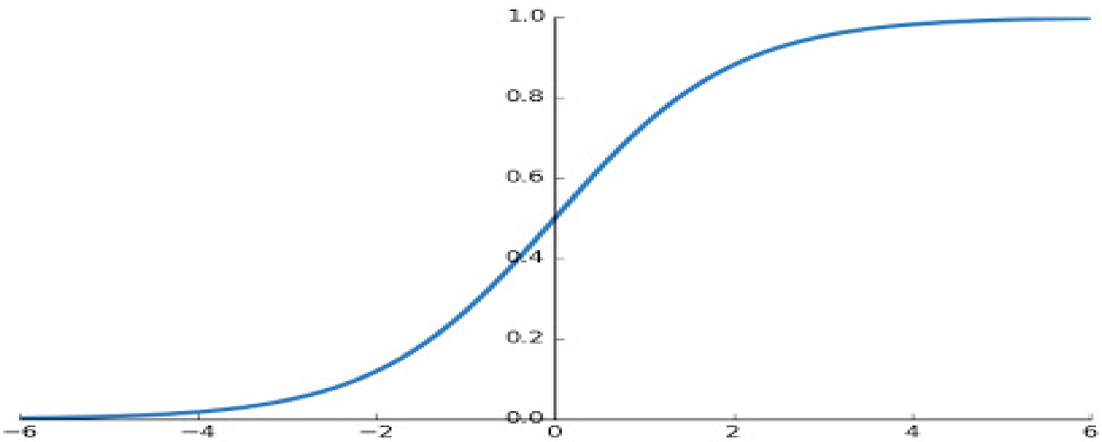


Fig1: CNN Layers Description



$$Sigmoid\ \ function\ (a) = \frac{1}{1 +\ exp^{(-z)}}$$

Fig2: Sigmoid Activation Function

3.2 COMPILING THE MODEL:

Since this is a classification problem, we prefer the Cross Entropy (CE) error. Binary cross entropy is used because binary class is used here (0 and 1). The definition is found in Equations (1) and (2) . The gradient descent optimizer used is 'adam'. Here, momentum and adaptive learning rates are used by Adam to converge at a faster rate and we also observe that the results are much consistent. Few benefits of Adam optimizer are, it is a computationally efficient optimization technique, low memory requirements are enough for Adam optimizer and it helps in easy result implementation. Accuracy is the metric used here. Accuracy can be defined as the ratio of number of correct prediction to total number of predictions. Accuracy is very much reliable in the case of balanced data. So accuracy is chosen in our case.

$$CE = -\sum_{i=1}^{C'=2} t_i \log\big(f(s_i)\big)$$

$$= -t_1 \log\big(f(s_1)\big) - (1 - t_1)\log(1 - f(s_1)) \quad \textbf{(1)}$$

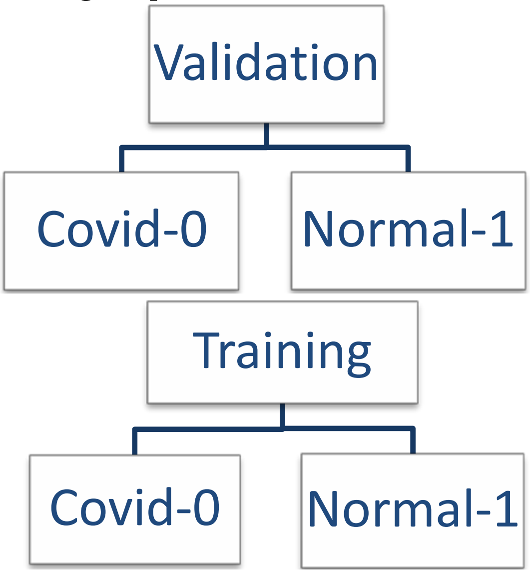
$$CE = -t_1 \log\big(f(s_1)\big) - (1 - t_1)\log(1 - f(s_1)) \quad \textbf{(2)}$$

3.2.1 MOLDING TRAINED IMAGES:

A pre-processing library is been applied. All images are rescaled from 0-255 to 0-1 so that there will be a faster calculation. Shearing of 20% is performed. Zooming of 20% is done. Horizontal flips (lateral inversion) of images are also done. Shearing and zooming improves accuracy. Shearing can be defined as a transformation that can change the shape of an image and image shearing can be done either in X direction (sliding along x-axis), Y direction (sliding along y-axis) or in both directions. Image rotation, lateral inversion and shearing improve the accuracy to a good extent.

3.2.2 RESHAPING THE IMAGES:

Images are converted to a size of 224x224 pixels in a batch of size 32 and the class mode is binary. This reshaping is very much important because it directly alters the accuracy of the model. All images need to be in the same size for a better output. While showing the output, this is how the folder names are renamed during the process.



3.2.3 TRAINING THE MODEL:

Initially the training generator data is passed. The number of iteration (epoch value) is taken as 20. The step value for epoch is taken as 7 (since 224/32=7). 7 will be the number of batches. When the complete data-set is passed forward and backward through the neural network once completely it is called as one epoch. More number of epochs could lead to an over-fitted model. Therefore epoch value of 20 is taken in our model. This process could take some time. Say 100 samples of images are taken. If passed through 32 filters there will be 32*100=3200 feature maps. After passing through the pooling layer, 3200 feature maps will be there (No of Convolutional map=No of Pooling map). Now if we pass these 3200 to 64 filters there will be 3200*64=2,04,800 samples. If passed through the third layer there will be 2,04,800*64=1,31,07,200 samples. If passed through the fourth layer there will be 1,31,07,200*128=1,67,77,21,600 samples. This means that, if there are 100 samples there will be 1,67,77,21,600 neurons in the input layer.

4. RESULTS AND DISCUSSIONS:

A random chest x-ray image was downloaded from the internet. For testing an images library and numpy library was imported. Then the image was loaded to the model. The image was converted to the target size of 224x224. The image was converted to array. The image was flattened (converted to 1 dimension) and the model was run. The result we obtained was that the image was Covid positive. Another random image was downloaded and passed through the model which was also found to be a Covid negative image. The dropout function significantly reduced the gap between the training and testing results. We also infer that that there is a significant rise in the accuracy level of the model. Maximum accuracy level reached is testing is 100%. Detailed values of can be found infig3.

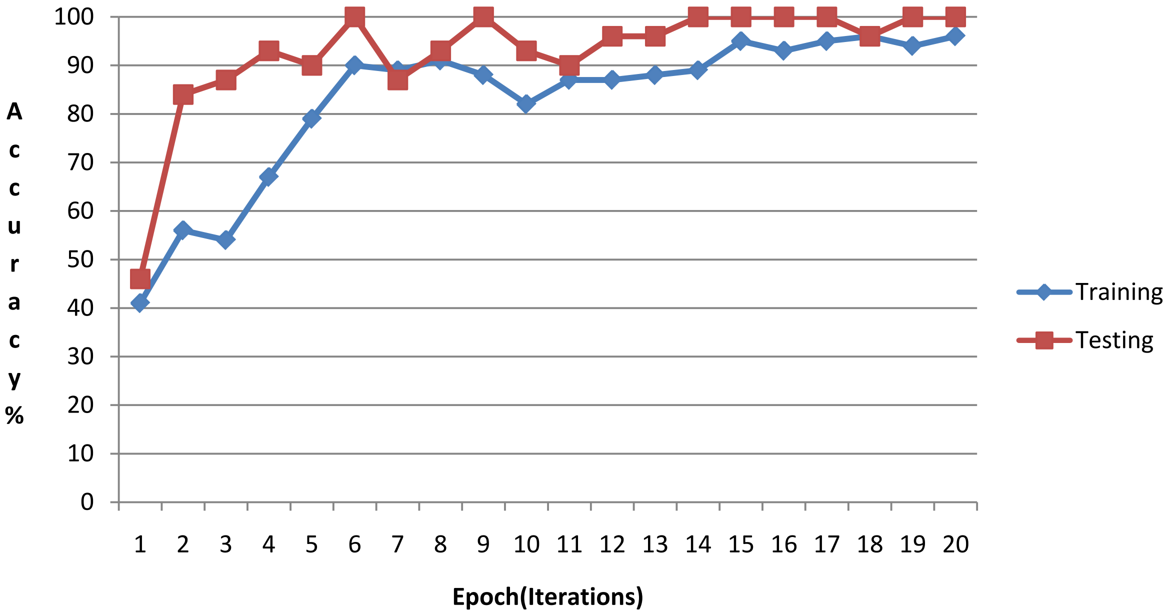


Fig3: Testing and Training Accuracy

CONCLUSION AND FUTURE WORK:

This project could be used in all the Covid-19 testing centers. The simplicity and easy execution of this model makes it an easily and compatible tool for testing. People in rural background could also easily access this testing facility. Other lung ailments such as general inflammation and lung tumors could be easily identified by this process. Reasons for interrupted breathing could also be found by this methodology. Lung Cancer which is nowadays predominantly found in many people which is treated by chemotherapy and radiation therapy is initially identified by this method. This may warn the individuals with thisailment before the tumor reaches a malignant stage.

In future we will try to deploy the model in a real time hospital environment to get live testing on covid-19 patients. The next work is to compare out base model against benchmark models and provide a comparative analysis report on the best fit model.

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