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Predictive Analysis for the Detection of Covid-19 with Chest X-Ray Images using Convolutional Neural Network.

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Abstract

Artificial Intelligence comes up with a lot of ease and advancements in almost all sectors of living. No one of us can deny its contributions in the medical field. Disease detection is one of the greatest achievements of Machine Learning. During the pandemic of COVID-19, medical emergency and less of experts has affected the health sector a lot. Detection of Covid-19 has become much more important than its cure to protect others from the virus. Detection of Covid-19 with our model is much easier through the x-ray images. The model using Convolutional Neural Network has trained on our self-made algorithm which was named to be Lungs X Ray Neural Networks (LxN) providing much more accurate than any other model available. It can process multiple datasets in a batch and our model is generalized very well with an accuracy of 98.8 % on validation and 98.0% on test set. The dataset for solving this problem was obtained from the open-source ieee8023 GitHub Repository, constantly updating with the images around the globe, containing a combo of both corona and non-corona cases. The result obtained from the model is $y \in \{1, 0\}$ indicating Corona presence or absence respectively. Lungs X Ray Neural Networks (LxN) model is not only specialized on corona data but can be fine-tuned on any other lung images like pneumonia. Thus LxN has significant role in the research area of AI in case of medicine.

Keywords

Convolutional Neural Network, Deep Learning, COVID19, AI for Medicine

Introduction

COVID-19, a global pandemic has taken the world into the storm. We can see everyone talking and discussing it, its symptoms, preventive measures, detection and treatment etc. Unfortunately, there is a lot of information and these gossips are incorrect that is creating fear and stigmatization [1].

Pneumonia cases due to newly diagnosed Corona virus entered in Wuhan China in december 2019. First it was named as the 2019-Novel Coronavirus by World Health Organization (WHO). Finally, WHO officially named the disease as COVID-19 [2, 3]. Virus is spreading exponentially throughout the world and the globe is under the COVID-19 pandemic. There is still no proper vaccine; even we don't have any effect and the most trusted way of detection of COVID in patients.

Mostly the symptoms observed in infected persons are high fever, respiration problems, and pulmonary opacities and in severe cases, patients require mechanical ventilation [4]. A minor number of patients are silent carriers, don't have any clinical symptom or radiological issues but are silently transmitting the virus to others [5, 6].

Mostly chest radiography of patients infected by the COVID-19 virus observe the major characteristic of pneumonia-like patterns. The radiologic identifications of COVID-19 have been investigated via chest X-Ray and results were bilateral predominant ground-glass opacities (GGO) with or without consolidation in the peripheral lungs. These chest imaging findings are non-specific and most commonly show a typical pneumonia certainly due to bilateral, peripheral and bi-basal predominant distribution [7, 8].

These X-Ray images pattern can be served as a major source of study and identification of corona affected patients. The current era of artificial intelligence can support a lot in the processing and analysis of these X-Ray images, which can train a model to decide whether the patient is affected with coronavirus or not.

Background

Artificial neural networks are motivated by biological neural networks originated from brain [23]. Artificial intelligence especially deep learning has earned an awardable success in image processing there are different methods available in AI ranging from different types of neural networks e.g. Deep Neural Networks (DNN), Recurrent Neural Network (RNN) and Convolutional Neural Networks (CNN) to variation encoders. In the medical field image analysis such as radiology, X-ray image analysis has been shifted from conventional methods of train physician assessments to Artificial intelligence detection [9].

Growing advancements in AI technologies have presented some non-deterministic deep learning algorithms representing essentially different pattern in machine learning that does not depend on feature definition explicitly [10-13]. Deep learning is known for its evolving advancement in problem-solving and turned out to be extraordinary high dimensional data structure discovery. That's why it is applicable to a various domain of science and technology, beating records in image recognition [14-17], speech recognition [18-20], reconstructing brain circuits [21], natural language processing understanding [22] etc.

Convolutional Neural Network

Convolutional Neural Network is a class of Artificial Neural Network having a supreme method in Computer Vision tasks. It is most established and efficient method among various deep learning models. It processes data having grid patterns, such as images [24, 25]. Hand-crafted feature extraction is most common in radionics studies alongwith conventional machine learning classifiers like forest etc [26, 27]. The specialty of CNN is that it doesn't require extraction that is featured and hand crafted.

Convolutional Neural Networks are typically composed of three layers, also known as building blocks of CNN. These are convolution, pooling, and fully connected layers. Convolution and pooling layers perform extraction of features functionality whereas fully connected layer simply maps the extracted features into the final output such as classification. Convolution layer plays a significant role in CNN consist of mathematical operations stacking such as convolution that involves linear operation [28].

Literature Studies

Relatively few studies on COVID-19 virus disease advent. Prabira et al. [29] proposed COVID-19 detection using X-ray images based on Support Vector Machine (SVM). From GitHub, Kaggle and Open-I repository, X-ray images collection is made. By removing CNN models deep features and feeding them individually into SVM classifier, analysis is made. Accuracy about 95.38% attained for ResNet50 and SVM.

Prediction about COVID-19 patients by another group [30] using "VB-Net" neural network by segmenting COVID19 infection regions in CT scans. Statistically, the results are handled as 91.6% dice similarity coefficient achievement exists. An early prediction model proposed by Xiaowei et al. [31] to classify COVID-19 pneumonia from Influenza. The best average accuracy of their CNN model was 86.7%. Shuai et al. [32] used CT images to identify COVID-19 cases. Inception transfer-learning model is used to build up an algorithm. They obtained an accuracy of 89.5% with a specificity of 88.0% and sensitivity of 87.0%. Cohen et al. [33] incorporated transfer learning from DensNet Model for the detection of COVID-19 Pneumonia Severity on Chest X-ray. DenseNet models have been shown to predict Pneumonia well [34]. Using Transfer learning, DarkNet YOLO model has also been implemented for the COVID detection with an accuracy of 98.08% and 87.02% for binary and multi-classes respectively [35]. All of the mentioned researches have used pre-trained deep learning model for high accuracy. However, this paper presents a self-trained model which is used to predict corona severity with an accuracy of 98.8%. The proposed model has been given the name "LxN" so that this model can contribute more researches or advancements in the world of Artificial Intelligence.

Problem Determination

A binary classification problem is Corona identification where chest X-Ray Image is considered as an input X and y ∈ {1, 0}is the output for Corona absence or presence identification. As a training set example optimization of the weighted binary cross entropy loss given as

$$L(X, y) = -w^{+} \cdot y \, \log p(Y = 1|X)$$

$$L(X, y) = -w^{-} \cdot (1 - y) \log p(Y = 1|X) \qquad (1)$$

Where $(Y = i|X)$ is probability that the network assigns to the label i, $w^{+} = |N|/(|P| + |N|)$, and $w^{-} = |N|/(|P| + |N|)$with $|P| \; and \; |N|$ are positive cases and negative cases corona numbers respectively.

X-Ray Image Dataset

The dataset for solving this problem was obtained from the open-source ieee8023 GitHub Repository [36]. Results are continuously modified with images provided by researchers from various countries. Currently, 738 images were present in this repository including both categories i.e corona and non-corona. Among all these images some of them are duplicates which we remove from the algorithm made by Dr Adrian Rosebrock [37]. Thus after further cleaning only 264 images were retained for this paper. Among them 224 images were separated for training data that were classified into two directories namely, corona and normal and the rest of the images were put in validation and test directories. Out of 738 images, 253 female and 429 male images are present. Average age considered is approximately 55 years in which 50 years old people are the most repeated. Experts findings are shown in figure (i).

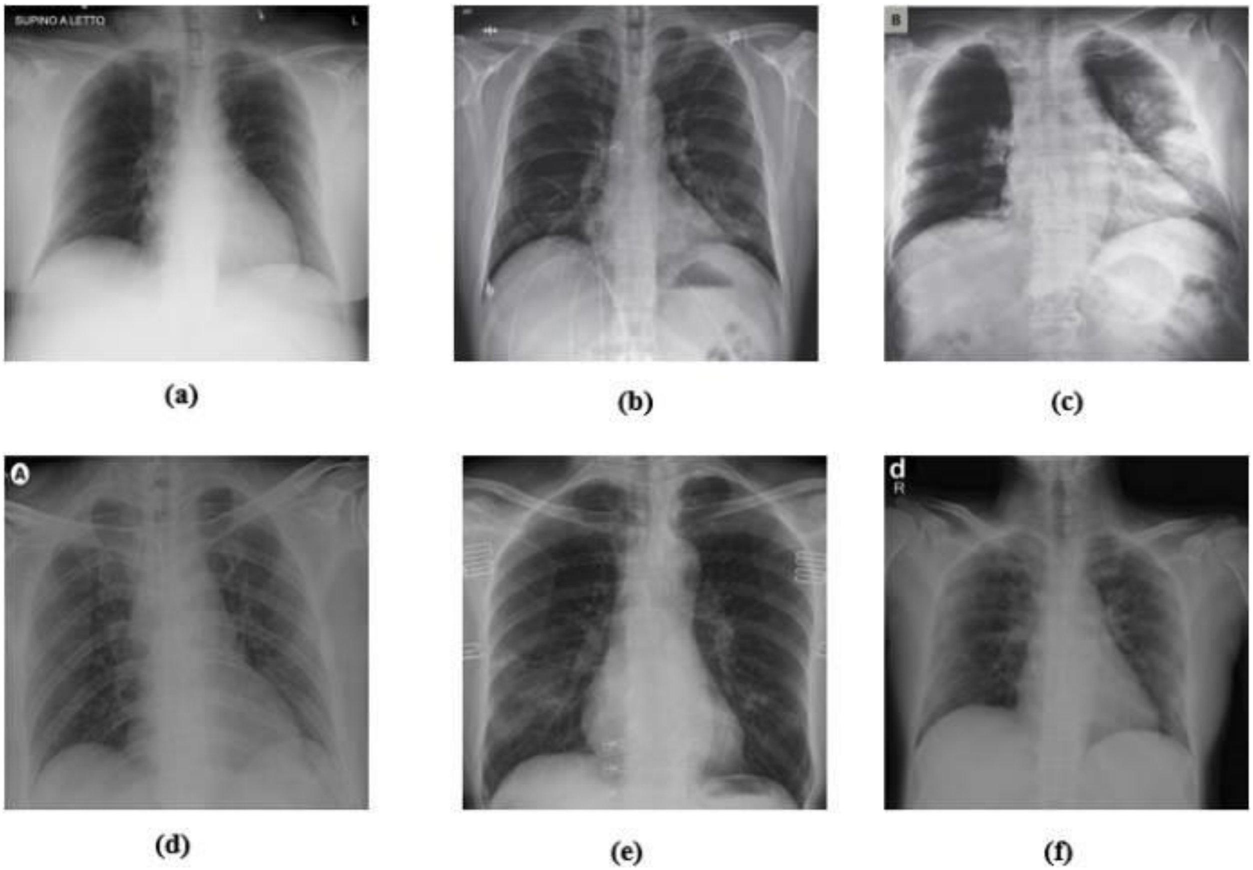

Figure (i) : Pictorial representation of few COVID-19 cases (a) Cardio-vasal shadow within the limits [38] (b) Increased left basilar opacity indication of pneumonia [39] (c) Progressive infiltrate and consolidation [40] (d) Small consolidation in right upper lobe and ground-glass opacities in both lower lobes [41] (e) Infection demonstrates right infrahilar airspace opacities [42] (f) Progression of prominent bilateral perihilar infiltration and ill-defined patchy opacities at bilateral lungs [43].

Proposed LxN Model

A standard CNN layout has three layers:

- A convolution layer that removes features from the input by using filters
- A pooling layer that decreases numerical efficiency size
- A completely connected layer that involves neural network.

By integrating one or more layers, creation of a CNN model takes place with modification of internal parameters perform specific task such as classification or object recognition. Despite using pre-trained model that all the previous researches have incorporated for solving similar problems, we are proposing our own self-trained LxN model. Figure (ii) shows the complete architecture of LxN that will be described completely in the later sections of this paper. The complete LxN Architecture written in python language using tensorflow is given in the following link:

https://github.com/Lungs-X-Ray-Neural-Network/LxN__Lungs-X-Ray-Neural-Network-Model/blob/master/LxN_Model_Architecture.ipynb

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 198, 198, 32)      896
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 196, 196, 32)      9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 98, 98, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 96, 96, 64)        18496
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 94, 94, 64)        36928
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 47, 47, 64)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 45, 45, 128)       73856
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 43, 43, 128)       147584
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 21, 21, 128)       0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 19, 19, 256)       295168
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 17, 17, 256)       590080
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 16384)             0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               8389120
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 513
=================================================================
Total params: 9,561,889
Trainable params: 9,561,889
Non-trainable params: 0
_________________________________________________________________
```

Figure(ii)– Architecture of proposed LxN model

In the diagnosis of COVID-19-infectious patients, the characteristics of chest X-Ray images are used to identify patients whether or not they belong to the infectious community. The process also involves repeated classification, calculations and computations. The following procedures are used to identify COVID-19-infected patients using the CNN model.

Feature Extraction

LxN model consists of typical CNN layers with different filter numbers, sizes, and stride values. A convolution layer extracts features from the input with application of filters. Two-dimensional (2D) convolution operation defined as follows for the input signal X (image) and kernel K.

$$(X + K)(i, j) = \sum_m \sum_n K(m.n)X(i - m, j - n) \qquad (2)$$

Where * represents the discrete convolution operation. The K matrix slides with the stride parameter over the input matrix. Figure (iii) shows how kernel/filter can extract potential features by using the stride.

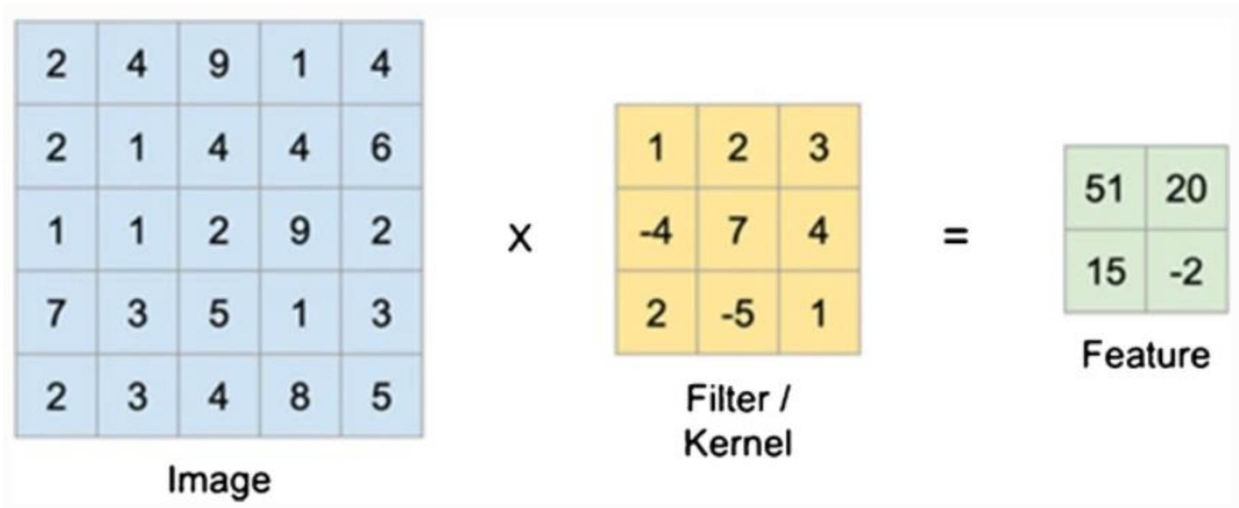

Figure (iii) – Convolution operator with kernel size 3 and stride 2.

Max pooling layer used to reduce the dimensions of convolved features. The overfitting issue has been resolved by it. From convolution operator, it covers maximum region from the featured map [44]. If we talk about specifically our proposed LxN model, let C denotes a convolutional layer and M denotes the max pool layer then LxN has a layered layout which can also be seen in figure (ii).

$C1 - C2 - M1 - C3 - C4 - M2 - C5 - C6 - M3 - C7 - C8 - M4$

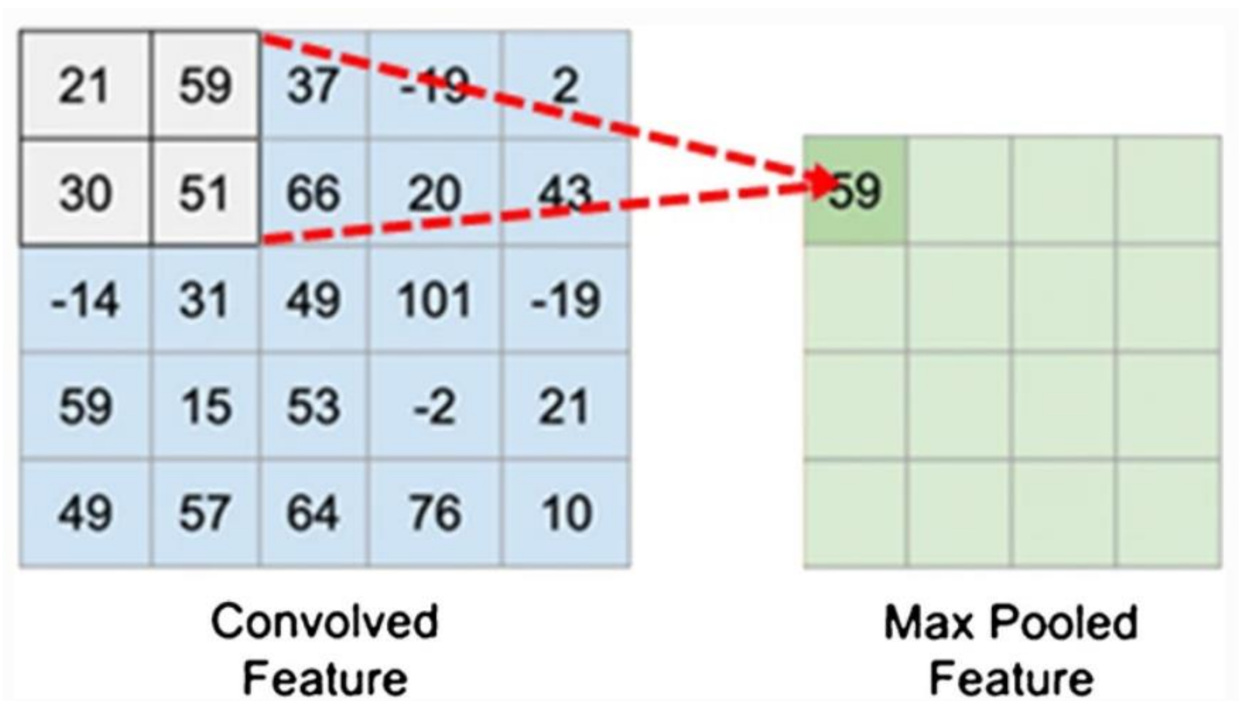

Figure (iv) – Tabular representation of Max pooling alongwith single pooled feature.

Rectified linear unit labelled as ReLU in the LxN architecture is considered as an activation parameter functionalit. ReLu Uactivation function measurements are given in equation (3):

$$f\ (x)\ =\ x^{+}\ =\ max\ (0\ , x) \qquad (3)$$

Complex functionality based mapping between the input and response variables is performed using ReLU activation function [45,46]. A linear function used to emits the input directly if positive; else zero output will be attained.

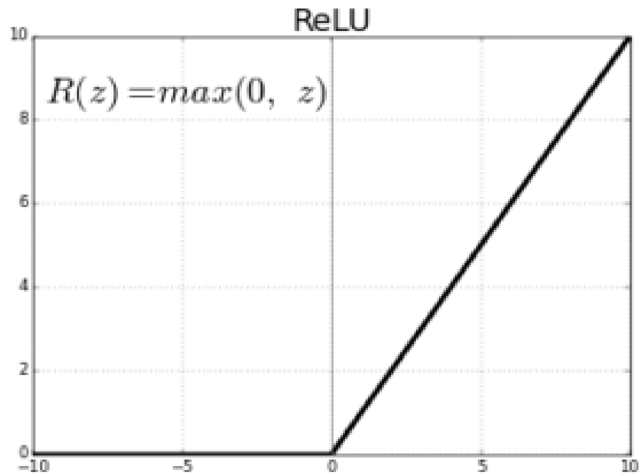

Figure (v) – Schematic representation of activation function of rectified linear unit.

Pictorial representation of input data flow for both convolution layer (C) and Max-pooling (M) layer respectively is given in figure (vi).

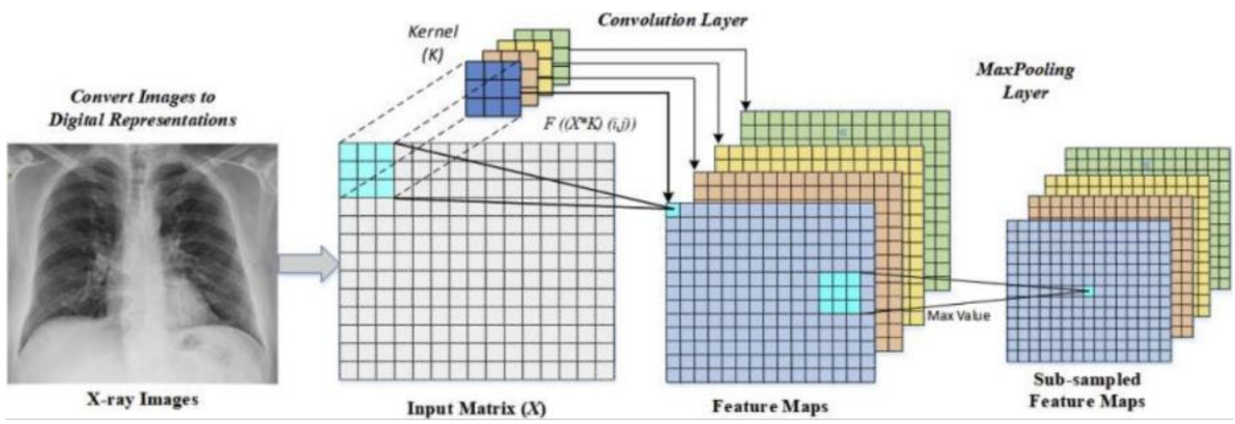

Figure (vi) - A schematic re presentation of convolution and Max-pooling layer operations.

Model has 8 convolution layers with padding = valid and a default stride set by Keras. Since the input image is of size (200 x 200 x 3) so it can be seen in fig (ii) that after first convolution layer the size remains (198 x 198 x 32) where 32 represents the number of filters used in convolution operation However 4 max pool layers are used with default stride. Finally, all the details of layers and model are given in fig (ii) where it can be seen that last convolutional layer generates 5900800 parameters which consist of all the extracted features of an input x-ray image which then fed to a dense classifier for predicting whether the features results in COVID (+) or COVID (-).

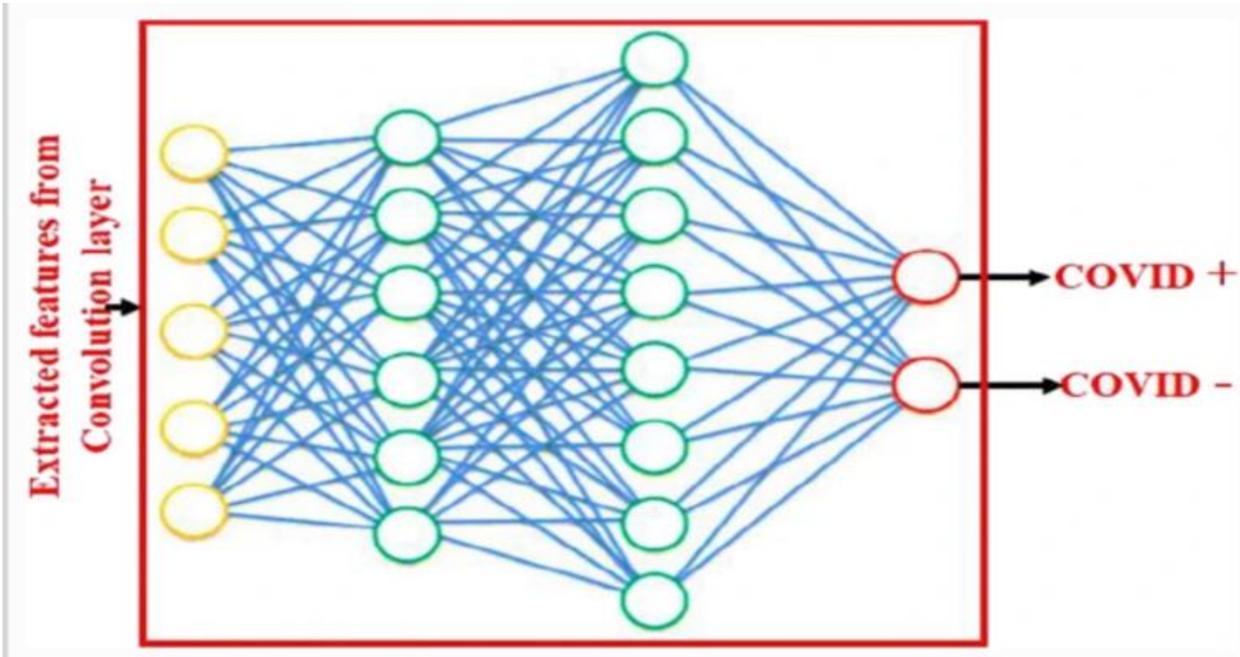

Figure (vii) – Fully connected classifier for detecting Corona.

Classification

Fully connected layers' act as a classifier in this step. The features obtained from the convolutional neural network is fed into fully connected classifiers and it analyze object probability in the images [47]. Figure (ii) indicates flattened features firstly through flatten layer and then fed into the dense classifier. The first dense layer has 512 neurons and then the second layer is the output layer which incorporated a sigmoid activation function in order to classify corona and non-corona x-rays. The sigmoid function can be defined as:

$$g(z) = \frac{1}{1+e^{-z}} \quad (4)$$

Schematically the classification process can be shown in figure (vii).

Analysis of LxN model on Chest X-Ray Images

Programming language named as python was used to design model using Keras and Tensorflow Libraries. All experiments were tested on a Linux server collaborated with google with operating system Ubuntu version 16.04 using Tesla K80 GPU. First of all, the dataset was extracted into the Colab environment and then the images of the training set were augmented by using image data generator of Keras. Data augmentation is a technique which is used when we have limited amount of data and we increase our dataset by adjusting the pixels of image randomly so that accuracy will be improved, and overfitting will be minimum [48]. But validation and test set was not incorporated by data augmentation so that model will be generalized on real-world images. The images were then resized to 200 x 200 pixels with a class equal to binary class (corona and non-corona) which will feed into the model with a batch of 20 images. The images were labelled as negative images for Corona as annotated pathologies by considering other as positive images. The model is then compiled by using an RMSprop optimizer. RMSprop is a gradient-based optimization method used in the training of neural networks. This normalization balances the step size (momentum), reducing the step for large gradients so that it doesn't explode and increasing the step for small gradients to avoid vanishing. Finally, the model was able to fit all training dataset images with steps per epoch equal to 70, epochs equal to 10 and validation steps equal to 30. In each epoch, all the images in a training set will go into the LxN model where it extracts the features of images and then fed these features to fully connected classifier which predict the output of the given image. By using output image probabilities, the cost function computed indicated as follows:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}\log(h_\theta(x^{(i)})) + \left(1 - y^{(i)}\right)\log(1 - h_\theta(x^{(i)}))] \qquad (5)$$

Where m indicates training examples numbers in data. This algorithm called as the forward propagation in which cost is computed on the basis input images. After computing the cost, the model is then optimized by using optimization function (RMSprop in our case). This algorithm is called back propagation where the model is optimized in order to reduce the cost for another epoch. The same process is repeated in all epochs and finally, in the end, our model is generalized with a validation accuracy of 98.8 % shown in figure (viii).

```
Epoch 1/10
70/70 [==============================] - 82s 1s/step - loss: 0.6153 - acc: 0.6621 - val_loss: 0.7388 - val_acc: 0.6017
Epoch 2/10
70/70 [==============================] - 72s 1s/step - loss: 0.4169 - acc: 0.8328 - val_loss: 0.1646 - val_acc: 0.9367
Epoch 3/10
70/70 [==============================] - 78s 1s/step - loss: 0.3707 - acc: 0.8566 - val_loss: 0.1239 - val_acc: 0.9233
Epoch 4/10
70/70 [==============================] - 70s 1s/step - loss: 0.2974 - acc: 0.8817 - val_loss: 0.2385 - val_acc: 0.9650
Epoch 5/10
70/70 [==============================] - 72s 1s/step - loss: 0.2452 - acc: 0.9072 - val_loss: 0.0792 - val_acc: 0.9833
Epoch 6/10
70/70 [==============================] - 79s 1s/step - loss: 0.2120 - acc: 0.9189 - val_loss: 0.1200 - val_acc: 0.9700
Epoch 7/10
70/70 [==============================] - 72s 1s/step - loss: 0.1457 - acc: 0.9486 - val_loss: 0.0501 - val_acc: 0.9800
Epoch 8/10
70/70 [==============================] - 78s 1s/step - loss: 0.1673 - acc: 0.9409 - val_loss: 0.1075 - val_acc: 0.9717
Epoch 9/10
70/70 [==============================] - 71s 1s/step - loss: 0.1438 - acc: 0.9486 - val_loss: 0.3549 - val_acc: 0.9117
Epoch 10/10
70/70 [==============================] - 71s 1s/step - loss: 0.1391 - acc: 0.9485 - val_loss: 0.0488 - val_acc: 0.9883
```

Figure (viii) – Successive epochs accuracy during training.

Experimental Results

From figure (viii) it can be clearly seen that at training procedure ending, our model is generalized very well with 98.8 % accuracy on validation set. The graphical interpretation of accuracy and loss is shown below in figure (ix) and figure (x).

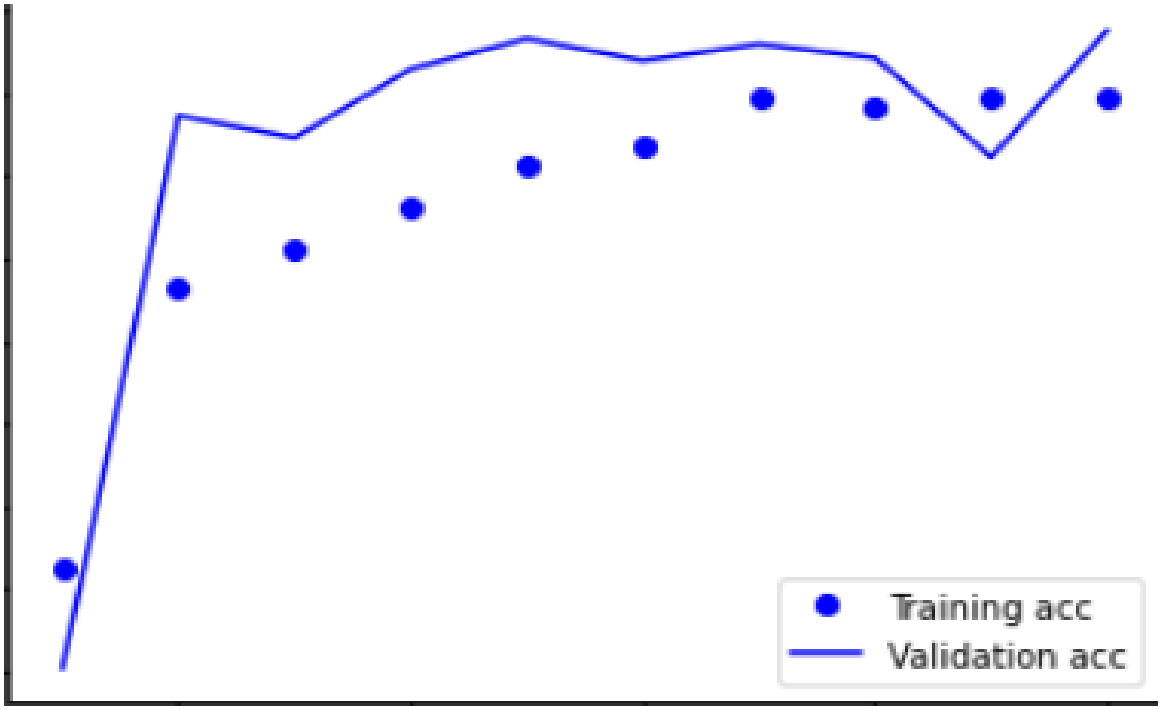

Figure (ix) – Training accuracy vs validation accuracy

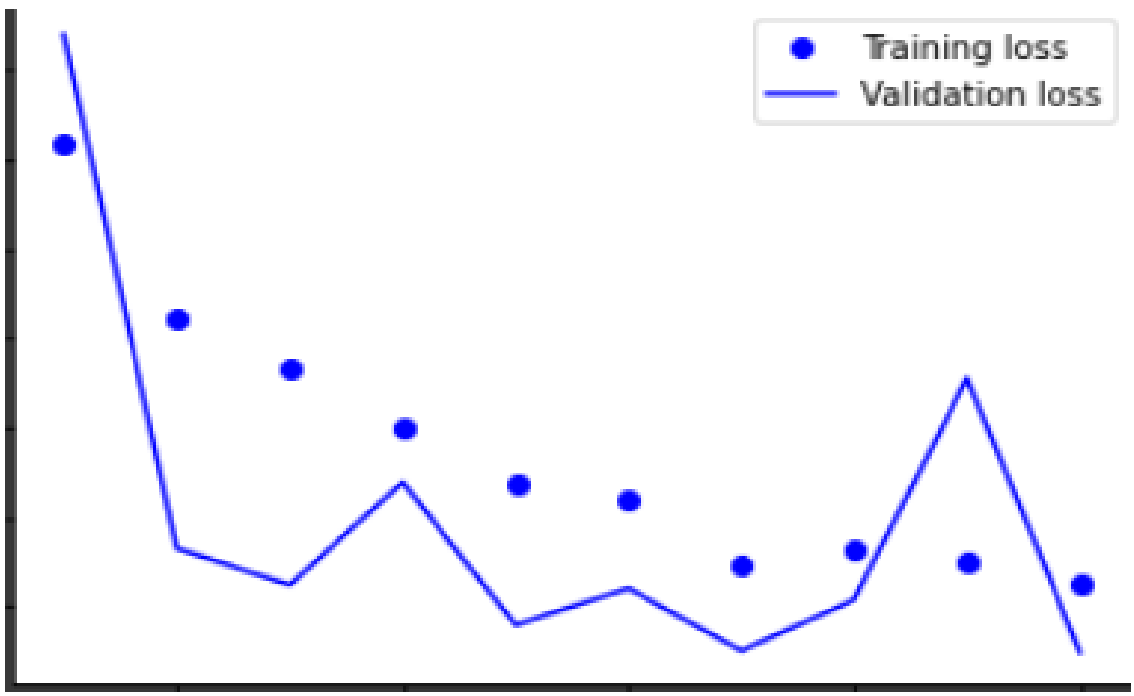

Figure (x) - Graph plotted between training loss versus validation loss.

Decreasing trend in the training loss as well as validation loss on successive epochs is shown. However accuracy is increasing as shown in figure (ix) and figure (x).

After evaluating a model in training and validation set, we evaluated it using the test set and achieved accuracy of about 98.0 % as shown in figure (xi).

```
load_model.evaluate(test_gen)

3/3 [==============================] - 1s 399ms/step
[0.4946973919868469, 0.9800000190734863]
```

Fig ix – Accuracy on test set

Conclusion

COVID global pandemic has taken the world into an emergency where everyone wants quick results to cope up with its effects. We lack medical experts and this medical surge has burdened our medical field. The detection of disease at a faster rate will help us to cope up with its rapid spread to healthy peoples. X-ray is serving as a source of detection of a lot of diseases and it is very common and familiar to all of us. COVID effects on lungs, so COVID detection through X-ray is a very economical and rapid process for the identification of the presence of this virus. COVID detection by a machine will be a great positive add in the medical situation around the globe. Our model which is self-designed with great compatibility and higher accuracy rates. We evaluated it on the test set and achieve a satisfactory accuracy of 98.0 % on the test set. The training and validation loss is decreasing on successive epochs however accuracy is increasing. The result obtains from our model includes $y \in \{1, 0\}$ pointing towards Corona presence or the absence. This model can be applied to applications that take the relative information along with the current chest x-ray of the patient and can generate results that either he/she is affected or not. We can also apply this model to some automated gates having cameras which can pass x-rays and gets images of the chest to ensure the person is well and can alert about the infected person.

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