Diagnosis of COVID-19 using ADAM Optimization technique in Convolutional Neural Network (CNN)

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Abstract

The new COVID-19 has range promptly among people and is approaching roughly 34,986,502 cases global, as stated in the data of the European Centre for Disease Inhibition and Control. There is an undersupplied quantity of COVID-19 testing equipment offered in hospitals as a consequence of the cumulative cases every day. Consequently, it is essential to carry out a spontaneous disclosure system as a rapid alternate prognosis possibility to avert COVID-19 from spreading among people. In this paper, a novel CNN architecture has been proposed to enhance the accuracy expectation of COVID-19 elicited from chest X-ray input resemblance since vast majority of the positive cases are recognized by taking the chest radiographs. The training process required datasets for machine learning classifiers. The datasets (1576 healthy, 3546 Pneumonia, and 289 confirmed COVID-19) have been taken from the authorized scanning center. The suggested model can attain better accurate results with less training time of data. Inclusively, the proposed model extensively developments the existing roentgenology procedure. For the period of COVID- 19 widespread, it can be a beneficial tool for medical specialists and radiographer to diagnose, quantify, and explore on COVID-19 cases.

Keywords: *COVID-19; CNN; ADAM Optimizer; Max pool*

1. Introduction

In December 2019, the total world faced an infectious termed severe acute respiratory syndrome coronavirus 2 (SARS CoV-2), which is mentioned to as coronavirus infection 2019 (COVID-19). At the time of outbreak COVID-19 worldwide, there is a need for the number of implement accessible to physician challenging the sickness since it is scarce. The high amount of people influenced by Coronavirus is 35,248,330[6]. Nowadays, the world is wrestling with the COVID-19 widespread. However, Artificial intelligence (AI) is considering the best option since AI requires less financial cost and less diagnosing time. Thereby AI is used to brace the doctors who want to serve the COVID victims. The diagnosing period takes 3 to 48 hours for the rapid COVID-19 test, and mostly not all the countries have the permission to access those rapid diagnosing kits. According to a newly issued international agreement declaration by the Fleischner Society, supreme endorsements is to practice chest radiography for patients with

COVID-19 in a supply-controlled atmosphere when admittance to evaluated tomography (CT) is inadequate. Moreover, the price of diagnosing equipment is high, which is a significant issue when struggling with illness. This automated COVID-19 detection using computerized tomography scan has been very useful when the country and hospital will not purchase the test kit. This is noteworthy because, presently, no active cure alternatives have been found, and therefore effectual determination is precarious.

Artificial intelligence provides stable and precise results based on images or other data types [1]. The inspection of COVID-19 considering the chest x-rays by transfer learning is explained in [2-4], which uses different kinds of pre-taught networks such as Inception, Xception, VGG19, and MobileNet V2. Several parameters have been evaluated from two datasets MobileNet V2 and VGG 19. In [3], used the average pixel per node (APPN) pre-training method to determine Alzheimer’s disease. This APPN approach is based on Positron Emission Tomography (PET) images. The researcher in [4] used impermanent memory neural networks to model vehicle interactions and forecasted the vehicles' path. In [5], several machine learning segregation is applied to categorize scholar accomplishment, using a analytical dataset. This classification is done by logistic regression (LR) and decision trees. This literature unveils the Artificial Intelligence (AI) provides high-accuracy results. For those reasons, had used AI in many applications for the past two decades. Artificial intelligence nature is to imitate human behaviors by learning the images and datasets. The benefit of AI-build methodologies in the medical profession has many applications, especially in detecting COVID-19 cases. Lately, several investigators have used X-ray representations for COVID-19 exposure. Wang and Wong initiate a deep learning system for COVID- 19 recognition and gained 83.5% correctness in sorting COVID-19, normal, pneumonia bacteria, and pneumonia-virus modules. Hemdan et al. [6] employed numerous deep learning prototypes to analyze COVID-19 from chest radiographs, and the proposed model contains of seven CNN layers. Narin et al. [7] instruct the ResNet50 model using chest radiographs and accomplished a 98%COVID-19 discovery precision for two modules. In [8], countless convolutional neural network (CNN) prototypes are utilized with a support vector machine (SVM) classifier for COVID-19 taxonomy. Their experiment realized that the ResNet50 model with an SVM classifier delivered the finest enactment. Most freshly, Ozturk et al. [9] recommended a deep network depend on the DarkNet model. This DarkNet model entails of 17 convolution layers with a triggering function. Their model realized the accurateness of 94.04% for binary modules and 83.02% for manifold module.

In this paper, a deep learning-based methodology to spot COVID-19 contamination out of chest radiographs is presented. This research proposes a deep convolutional neural network (CNN) prototypical to categorize three varieties of Pneumonia; bacterial Pneumonia, viral Pneumonia, and COVID-19 Pneumonia. The rest of the research paper follows: section 2 defines the Convolutional Neural Network (CNN), and the third section elaborates on the proposed CNN model. Section 4 reflects the simulation outputs and results and section 5 completes the paper along with the future scope and open challenges.

2. Convolutional Neural Network

A convolutional neural network is one kind of Deep learning technique which consists of several layers to experience local connections to form a local receptive field. The performance of the CNN model can be evaluated from accessible arenas and weight allocation between the layers. Deep architecture hinge on layers counts. The deep architecture of this model helps to learn the network's divergent and multiplex attributes efficiently. The Convolutional neural network plays a significant role in computer vision and includes many applications such as autonomous cars, robotics, and visually impaired medications. CNN's core idea is to prevail parochial characteristics from the elevated layer's input images and modifies into multiplex aspects at the nether layers [10-11]. A traditional Convolutional neural network comprises of the ensuing layers:

2.1. Convolutional Layer

The convolutional surface is acting as the leading role in the Convolutional neural network. This convolutional layer is responsible for the convolution operation for the image matrix multiplication [12]. The convolution computation has been carried out by using a set of graspable filters known as kernels. The convolutional layer's prime responsibility is to get the features from local regions of the input images. The obtained local features are used to enrich the throughput of the dataset, and it is harnessed to mapping the appearance to the local feature. The convolution operation of the matrix multiplication is given by,

$$F(i,j) = (I * K) = \sum_m \sum_n I(i+m, j+n) K(m,n) \quad (1)$$

Where I represent the input matrix (image), K is the 2D filter (kernel) of size $m \times n$ and F denotes the output 2D feature map. The convolution functioning includes input image I and filter K and produced output feature map F. This convolutional operation denoted by $I * K$. The output of the convolutional layer is given to the stimulate activity to announce non-linearity. There are many stimulate activities available in the convolutional layer. The primary activation function from the list is called Rectified Linear Unit (ReLU). This particular stimulate activity ReLU enumerate the incitement by benchmark the input at zero. Alternatively stated that the result of ReLU is zero when the output is more significant than zero. Otherwise, it produces raw output. It is analytically given by,

$$f(x) = \max(0, x) \quad (2)$$

2.2. Subsampling (Pooling) Layer

The subsampling layer follows the sequence of the convolutional layer. This subsampling layer is known as the pooling or downsampling layer. Because the pooling operation considerably reduced the input's spatial size and lessened the count of criterions in the network [13-14]. A pooling layer takes each feature map output from the convolutional layer and downsamples it i.e., the pooling layer shortens a sector of neurons in the convolution layer. The supreme aware pooling practice is Max Pooling, which outcomes the input region's maximum value. Additional pooling choices are average pooling and L2-norm pooling.

2.3. Fully connected Layer

This film connects individual neuron originating at the antecelayers to the next layers and investigates, which layer value contributes strong prediction to the particular class[15]. The fully connected layer's final output is then feedback to the activation function, which provides the output class scores. The fully connected layer requires two classifiers to predict the features at most care [16]. They are Softmax and Support vector machines (SVM) classifiers are generally utilized in CNN based model. The softmax classifier calculates the probability distribution of the n outcome labels is represented as,

$$Z^k = \frac{e^{x^k}}{\sum_{i=1}^{n} e^{x^k}} \quad (3)$$

Where x and Z is the input and output vector. The total probability value of all outputs Z equals 1. The designed model employs a Softmax classifier, which is accountable for calculating the classes from the x-ray images. Every layers deliberated above are piled up to produce a full-fledged CNN architecture. Furthermore, critical layers stated above, CNN may incorporate discretionary layers like flock standardize layer to enhance the instruction time and dropout layer to perorates the overfitting issue.

3. Proposed Work

3.1. Model Architecture

Figure 1 illustrates the suggested CNN structure for COVID-19 recognition from radiology resemblance. This proposed CNN architecture follows Xception CNN structure [12]. Xception stands for paramount style of Inception which is the previous version. In addition that, this Xception model consists of 71 layers deep CNN architecture. This architecture model pre-trained on ImageNet dataset. The advantage of using Xception mode is to reduce the training time. Because this Xception model uses separable convolution layer instead of traditional convolutional layer. The separable convolution layer provides depthwise learning. So it requires $1 \times 1 \times k$ point-wise convolution operation instead of classic $n \times n \times k$ convolution operation. In this manner the number of operations are reduced by a proportional factor of $1/k$.

The Xception model has a feature called residual connection in those layers. The residual connections are also called skip connections. The reason behind the name is this skip connection directly allows the gradients to enter the network bypassing the non-linear activation functions. Hence the problem of vanishing gradients has been tackled. A weight layer sequences is combined to the true input and then and there delivered over a non-linear activation function in residual connections.

The proposed CNN model uses Xception as a scratch model with a dropout layer and two fully-connected layers added at the end. This model has 10,969,964 parameters in total, out of which 10,915,436 trainable and 54,528 are nontrainable parameters. Architecture details, layerwise parameters, and output shape of the proposed model are shown in Table 1.

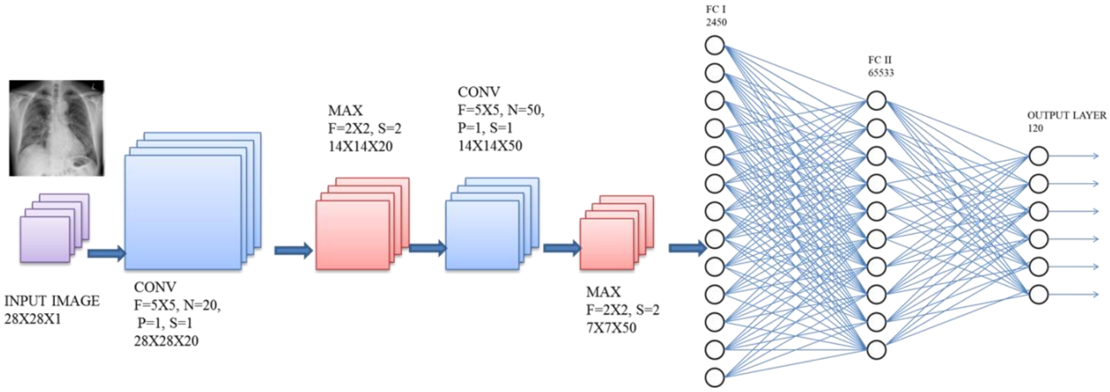

Figure 1. The Xception model for COVID-19 Detection

3.2. Methodology

The detailed design flow of the proposed CNN model has been portrayed in Figure 2. The dataset of 5411 X-ray images (1576 healthy, 3546 Pneumonia, and 289 confirmed COVID-19) collected for the training process from the authenticated scanning centers. From the literature, the Xception model is considered a trustworthy and stable model. Thereby, the proposed CNN model suggested that harnessing the Xception model to improve the recognition rate. Before entry into the architecture model, dataset loading, preparing dataset, and encoding dataset class labels into numeric values are essential. The dataset (x-rays) is loaded with some underlying dependencies such as resizing, binarisation, and noise removal into the model. The data augmentation step is added by the Image Data Generator framework of Keras to reduce the over-fitting problem. The dataset images get altered by this data augmentation step with some image renovation processes such as shearing, rotation, zooming, and translation. Due to these random transformations, the model does not get the same images each time. The dataset is then passed through the dataset split module, where the dataset images are split into training, validation, and testing of the set images. This study's planned technique consisted of three phases, namely, pre-trained model, retraining process with transfer learning technique, and modified recognition portion as exposed in fig 2.

The test samples are preprocessing initially, which is used to prepare the test samples for further processing steps. The next step is segmentation, which involves splitting the whole data into a small data set for easy processing. The decode label is used to transform the pixels into the machines' numeric data to understand the algorithms. And then, the proposed model involves the training process.

The epoch means it is a parameter that denotes the amount of times the learning algorithm work for the entire training dataset. One epoch means the sample of training data had an opportunity to update them to the internal parameter. Then the processed test samples are compared with the available dataset for training loss.

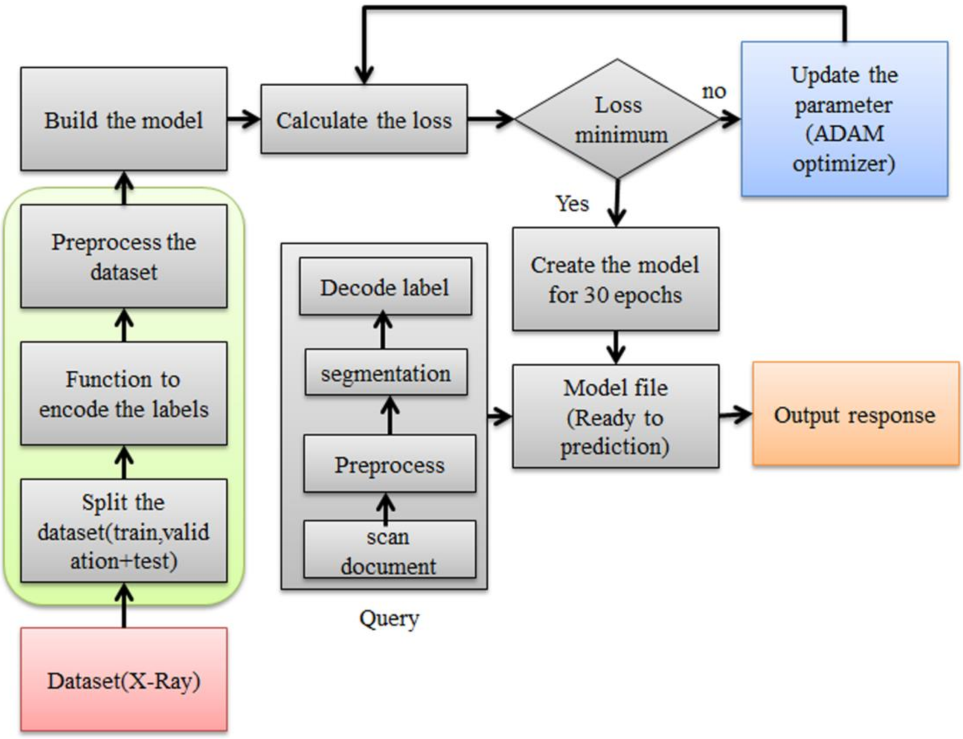

Figure 2. Detail workflow of the Proposed model

Table 1. Details of the Proposed Architecture

Layer (type)	Output Shape	Parameters
Xception (Model)	$5\times 5\times 2048$	
flatten (Flatten)	51,345	0
dropout (Dropout)	51,345	0
dense (Dense)	243	12,103,342
dense_1 (Dense)	5	2023
Total Parameters: 10,969,964		
Trainable Parameters: 10,915,436		
Non-trainable Parameters: 54,528		

The training loss factor is responsible for accuracy. After that, the accurate parameter has been updated in the optimizer. In this work, an ADAM optimizer has been used. Then the correct result has obtained as output response.

3.3. ADAM Stochastic Gradient Descent Optimization

ADAM optimization algorithm augments the stochastic gradient descent algorithm, which is effectively used for deep learning applications in computer vision and virtual assistants[17-18]. Adam optimization method combines RMSprop (Root Mean Square Propagation) and Stochastic gradient descent with momentum. Adam is an adaptive learning method, which means it estimates the discrete learning rate for various parameters. Its name is obtained from adaptive moment estimation [23]. That is because Adam uses computations of the first and second moments of the gradient to adjust the training rate for each weight of the neural network. N-th moment of a random variable is interpreted as the expected value of that variable to the power of n is given by,

$$m_n = E[X^n] \tag{4}$$

Where, m denotes moment and X is a random variable. The random variable represents the cost function of the neural network. In this equation () the first moment is mean, and the second moment is uncentered variance. Adam uses exponentially moving averages to compute the moments, and the estimated gradient is evaluated on a mini-batch. A current mini-batch is used to split the training data into small sets, model the error, and update the model coefficients.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t \tag{5}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2 \tag{6}$$

Where m and v represent moving averages and g is a gradient on current mini-batch. Also β is the hyper-parameter which is newly introduced parameter. The default value of the β's are 0.9 and 0.999 respectively. At first iteration, the moving average vectors are initialized wit zeros. As we already discussed, the moving averages is used to scale the learning rate separately for each parameter. The weight update has performed the scaling of the learning rate. The following equation used to prepare the weight update,

$$w_t = w_{t-1} - \eta \frac{\widehat{m}_t}{\sqrt{\widehat{v}_t} + \epsilon} \quad (7)$$

Where w is a model weight and η is the step size.

3.4. MAX Pooling Layer

The pooling operation involves inserting a 2D filter at each channel of the feature map and summarizing the features lying within the region covered by the filter. The dimension of the feature map is $n_h \times n_w \times n_c$, but after the pooling layer the dimension will be,

$$(n_h - f + 1)/s \times (n_w - f + 1)/s \times n_c \quad (8)$$

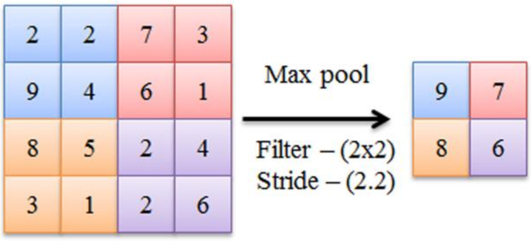

Figure 3. Max pooling Operation

Where, n_h is represents the height of the feature map and n_w is the width of the feature map. The parameter n_c symbolizes the number of networks in the feature map, f is the size of the filter and s represents length of the stride. In general, the CNN model contains of a convolutional layer and pooling layer piled one after the other. Pooling layers are used to bring down the dimensions of the feature maps. Thus, it minimizes the total amount of parameters to learn and hence shrinks the processing time. Moreover the pooling layer comprises the structures of the feature map by the convolution layer. So, further computations are performed on the stint features as a replacement for of exactly positioned features produced by the convolution layer. This creates the model more strong to deviations in the position of the features in the input image[19].

In this paper, Max pooling is used as a pooling layer in the proposed CNN architecture. Max pooling is a pooling operation that selects the supreme component from the province shielded by the filter. Thus, the output after the max-pooling layer would be a feature map containing the earlier feature map's most projecting features. The sample max-pooling operation is presented in figure 3.

4. Result and Discussion

From Figure 4, it can resolve that the proposed CNN model is the most satisfactory model for COVID-19. The variation gap between both the training and authentication correctness can evaluate the enhanced performance. The gap between both factors should be more outstanding. According to figure 4(a), there is a gap between the training and validation accuracy, which denotes the best performance without an over-fitting problem. The over-fitting problem means it learns the model very much, which negatively impacts the CNN model. This over-fitting problem should be avoided. Figure 4(b) is known as the loss graph, which inferences the training loss values. The training loss involves model learning with proper parameters. In this investigational arrangement, the COVID-19 dataset includes the 289 classes. All classes have more algorithm controls over the power of adaptive learning rates methods to find individual learning rates for each parameter. The Loss function performs as monitors to the optimizer if it moves in the right way to range the global minimum.

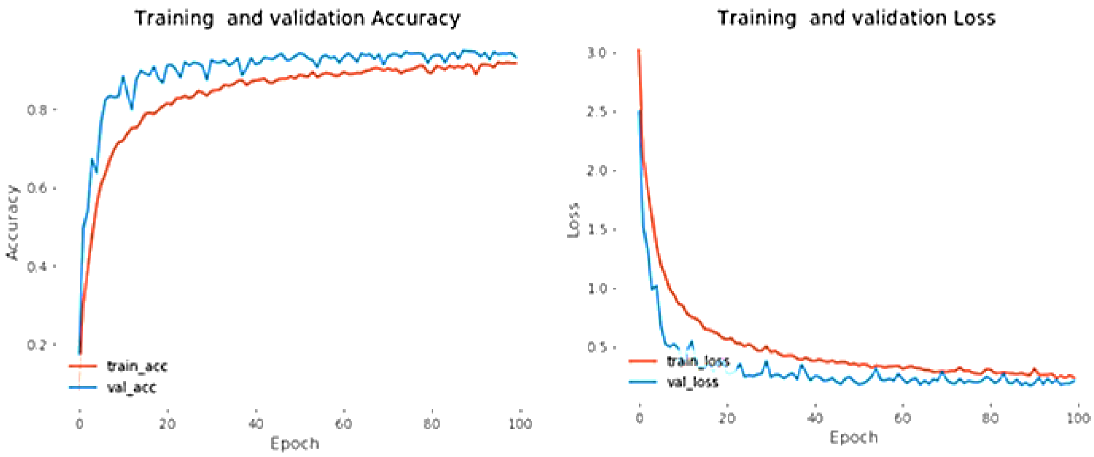

Figure 4. Performance analysis of the COVID-19 using Xception with transfer learning : (a) Accuracy and (b) Loss

In the proposed work, categorical cross-entropy is used as a loss function to optimize the projected model's parameter values. The loss value suggests how a model performs at every end of the iteration of the training process. For comparison analysis, the proposed CNN model compared with the present works in the literature in Table 2.

The Xception model trains the COVID-19 dataset with modified fully-connected layers by selected hybrid parameters. The prepared model file is saved. The real-time input image is considered a query image passed through the pre-processing process such as resizing, noise removal, slant correction, and slope removal. Then the pre-processed query image is given into the saved proposed model file. Based on that saved model file, labels are assigned to the output in the class of the given query image. Some of the real-time output of input queries is shown in Figure 5. The results have been simulated and taken from MATLAB software.

The proposed COVID-19 model is trained with different deep learning architectures based on heuristic-based and meta-heuristic based optimizer. Based on the experiments, the comparison table for other optimization techniques is illustrated in Table 2. The best model is determined based on accuracy and learning speed. When considering the Xception model without a transfer learning approach, the model takes a long time to train since the Xception is an intense model. Because the simple CNN model without transfer learning techniques takes nearly 2132s per epoch.

Table 2. Comparative Analysis of various optimization techniques

Model	Optimizer	Accuracy	Training time per Epoch
4-Class CoroNet [20]	**Stochastic Gradient Descent**	**83.1**	**2276s**
3-Class CoroNet [21]	**non-convex optimization**	**84.2**	**2224s**
Binary CoroNet [22]	**Nesterov Accelerated Gradient Descent**	**87.4**	**3254s**
Proposed Model	**Adam**	**95.3**	**774us**

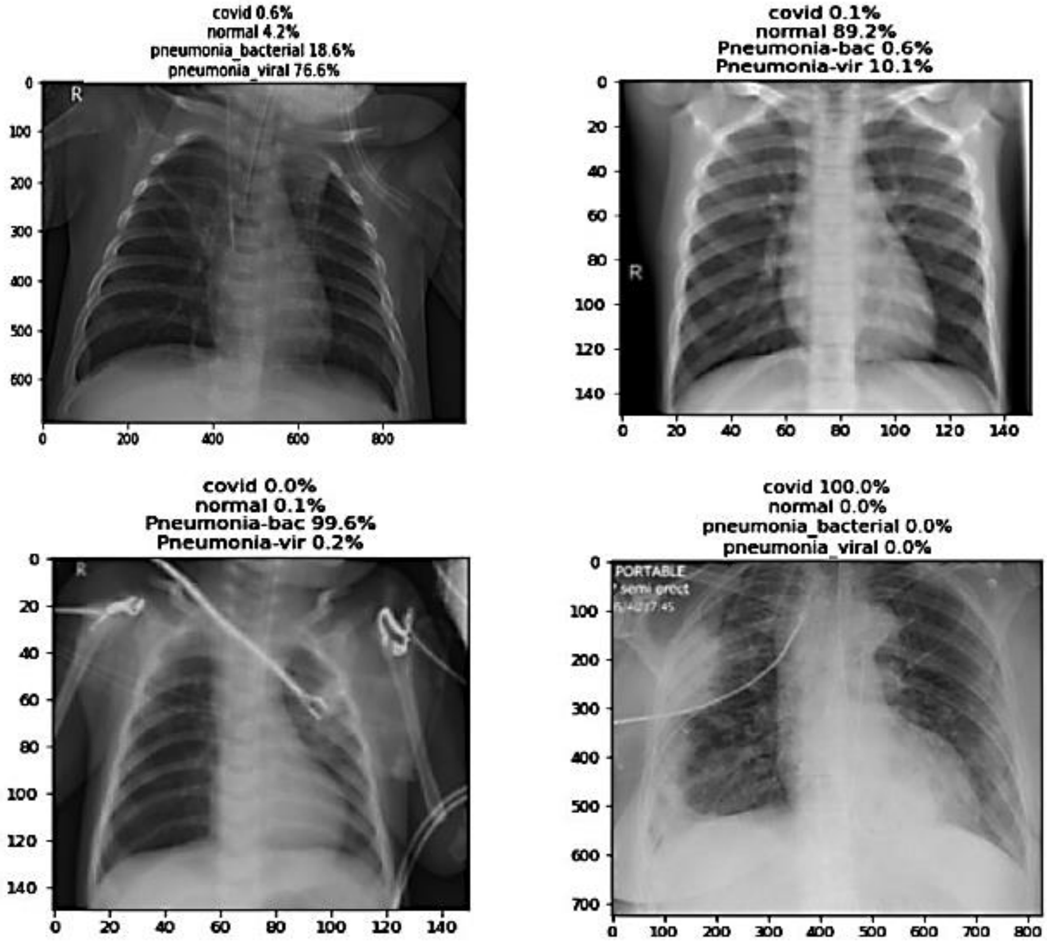

Figure 5. Some real-time output queries

When considering 30 epochs, it is a long time process. Simultaneously, the Xception model with transfer learning technique takes only 774us per epoch, even though it is a profound model. Based on the speed and accuracy rate, the recommended model is the best. The comparison work based on the COVID-19 system with different existing work is exposed in Table 2. Figure 4 and Table 2 demonstrate that the proposed Adam optimizer-based CNN model with the Xception system is the best in terms of accuracy and less learning.

5. Conclusion

The proposed work is used to detect the COVID-19 with chest radiographs using the Convolutional neural network (CNN). The benefits of this research are to accomplish high-accuracy detection with less training time. This scheme is beneficial for not having insufficient test kits and doctors. The performance results illustrate that the proposed deep learning model provides high-accurate detection with less training period than the existing models. The proposed model developed its accuracy of 95% than the other deep learning models. The accuracy and learning time is based on optimization techniques. The proposed model used Adam optimizer for better performance. Thereby, it is alleged that it will help radiologists make clinical practice decisions due to advanced performance.

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