Covid-19 Detection Using chest X-ray Images

Prashanth Kumar Daram
Lakehead University
Student ID: 1116540
pdaram@lakeheadu.ca

***Abstract*—The Corona virus which is called as Covid-19 initially started at wuhan city of china, spread all over the world and been treated as pandemic disease by world Health Organization (WHO). The health and wealth of global population has been diversely affected by this Covid-19 pandemic disease. To fight against this pandemic disease, the critical step involved is to detect the Covid-19 positive patients as fast as possible to prevent the disease from further spreading. To diagnose the patients infected by Covid-19, the gold standard method used is Reverse Transcription-Polymers Chain Reaction (RT-PCR). Due to huge demand and less resources, the RT-PCR test kits are under shortage. The supplementary tool is needed to diagnose the infected patients as there are no efficient tool-kits available. The recent studies found that the patients infected by Covid-19 present some characteristic information in the chest radiography images. The rapid advancement in the artificial intelligence techniques combined with radiology imaging helps to detect the disease accurately in the less timely manner. This technique also overcomes the need of radiotherapist in the remote places. In this study, a deep convolution neural network (CNN) is designed to detect the Covid-19 patients from chest X-ray (CXR) images. This paper explains various deep learning models for detecting the Covid-19 patients. The model proposed in this paper performs binary classification such as covid v/s normal. The model resulted an accuracy of 97% for binary classification. The designed deep learning model assist the radiologist in screening the infected patients accurately and helps to accelerate the treatment for high number of patients.**

keywords—Covid-19, CNN, Deep Learning, Artifical Intelligence, CXR, binary classification, radiography images.

I. Introduction

The virus which reported first in the Wuhan city china has grown rapidly and been spread all over the world [1-3]. The virus is names as Covid-19 and founded as family of Severe 10 Acute Respiratory Syndrome (SARS)[4]. The Covid-19 pandemic diversely effecting the health, wealth and economy of global population. The pandemic disease is been spreading from human to human due to zoonotic nature. The symptoms of the Covid-19 are fever, cough, throat pain, headache, and breath shortness [5]. The common technique used to diagnose the covid-19 patients is reverse transcription-polymerase chain reaction (RT-PCR). Due to low sensitivity of RTPCR and insufficient resources resulted increasing need for new technique to screen the infected patients. The RT-PCR results some negative results even patients suffered from covid-19 symptoms. The RT-PCR method take long time to generate the result and it requires manual process which is insufficient.

The recent research found an alternate method to screen the Covid-19 patients. The research states chest radiography imaging such as X-ray (CXR) or computed tomography (CT) presents some characteristics related to covid-19 [8]. The Chinese clinical centers made the diagnosis using clinical and chest X-ray in the beginning of the pandemic due to insufficient RT-PCR test kits [9]. The screening made using X-ray images produced accurate results. Turkey used X-ray or CT scan method to diagnose the infected covid-19 patients due to low number of test kits. Researchers found that radiology images resulted from covid-19 infected patients contain some information helps for diagnosis. Some discoveries have been found by researchers in imaging studies of covid-19. For example, Hang et al. [10] observed most of covid-19 patients presents bilateral airspace opacities in the lung region. Yoon et al. [11] identified that majority of infected covid-19 patients presents single nodular opacity in the lung region. Zhao at al. [12] not only found ground glass opacities (GGO) or mixed GGO in majority of patients, but also observed a vascular dilation in the lesion.

The recent advancements in the artificial intelligence and machine learning made it has one of the adjacent tools for the clinicians [13-15]. Deep Learning which is the sub-field of the artificial intelligence helps to create the model, extract the features automatically without human intervention, train the model, and outputs the results [21-23]. Deep Learning techniques have applied in many medical areas to solve the problems such as heart disease detection [24-25], diabetics prediction [26], breast cancer detection [27], pneumonia detection from chest X-ray [28-30], and lung segmentation[31-33]. Due to overwhelming cases of covid-19, and insufficient testing kits made a demand in this field. It

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results to develop automated deep learning model to detect covid-19 patients. Due to less number of radiologists, it's been challenging task to provide a clinician to every hospital. The deep learning model designed in this project overcomes this problem and provide the results in timely manner [39]. The deep learning model may act as one of the assistance tools to radiologist in determining the disease. In addition, the deep learning model may overcome the disadvantages such as insufficient RT-PCR kits, test result accuracy, cost, and waiting time.

A. Advantages of CXR Imaging

- The CXR imaging helps to diagnose the patients infected by covid-19 and can determined in parallel with the viral testing to cover high volumes of patients especially in areas where people suffering from insufficient medical resources. Moreover, CXR imaging helps for the patients in certain geographic locations where they are instructed to home quarantine until onset of advance symptoms.

- The CXR imaging is rapidly available and accessible in most of the health care centers and imaging centers because it is considered as mandatory equipment in health care centers. The CXR imaging is readily available in most of the places compare to CT imaging. The CXR imaging is less cost compare to all other testing.

- The CXR imaging is very portable because the scanning is done in a fixed isolation room and there is no risk of spread of covid-19 and it reduces a risk of transmission compare to other testing methods

The radiography screening can be conducted faster and have enough availability of resources for chest radiology imaging systems in modern health system, the radiography CXR imaging making adequate method to RT-PCR testing because CXR imaging is performed as standard part for patients with respiratory problems. The need for alternate method rather than RT-PCR making CXR imaging more necessity.

The bottleneck of this method is less radiology clinicians in most of the places. To solve this problem, a computer aided solution needs to be implemented. The recent advancements in Artificial Intelligence (AI) and Open CV coupled with radiology imaging resulted better solution to screen infected patients. In this paper, a deep learning model is implemented to detect the Covid-19 more accurately.

II. Related Work

We have chosen four different papers in which the authors have worked to build the deep learning model to detect covid-19 using chest X-ray images and we would like to explain about the techniques that are implemented in it. Each has its own ideas in implementation and working. The emerging need for the interpretation of radiology images, many numbers of deep convolution network models have been proposed and the results obtained from this model shown accurate in detecting the infected covid-19 cases through radiography imaging. The most of the deep learning models developed for covid-19 detection results accuracy in between 90% to 96%. Hemdan et al [35]proposed deep learning model recently named COVID-Net to detect the covid-19 infected patients. It used deep learning algorithm's involving end to end connected neural networks. The model resulted an accuracy of 95% on Covidx dataset, which consists of 127 CXR images from 100 covid-19 patients. Ioannis et al [37] designed a deep learning model named Darknet using 224 positive Covid-19 images dataset, it resulted an accuracy of 96%. Narin et al [38] achieved a 96% accuracy for covid-19 detection using ResNet50 ImageNet model. Their research states that the ResNet50 with Support Vector Machine (SVM) classifier provided accuracy better than other models. The proposed deep learning model resulted an accuracy of 97%. The figure(1) shows comparison of all the models.

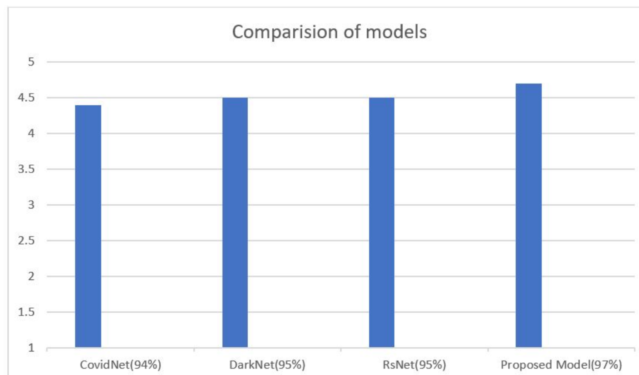

Fig. 1. Comparison of deep CNN models[35,36].

III. Existing Model

In Existing model, RsNet was used in order to develop a neural network [38]. They have used the min-max normalization technique to extract the features. The model consists of one input layer, fiften CNN layers, 4 Maxpooling layers, three dense layers with soft-max activation function. This model generated an accuracy around 95%.

IV. Proposed Model

The Main Steps that are involved in the Model:

- **Pre-setup**
- **Dataset Processing**
- **Network Creation**
- **Training the model**
- **Testing the model**

The proposed model is based on implementation of Convolution Neural Network for generating the output. Firstly, Load the Chest X-ray images dataset into working environment (such as Google Colab or Jupyter Notebook). Once dataset is loaded, perform the data normalization operations such as data pre-processing and data augmentation, then we will be using a predefined CNN model such as VGG16 for building the model. Further, we will be dividing the dataset into training and testing. In this model we are dividing dataset into 80% for training and 20% for testing. we will be creating a customized method to train our new model in batches and let it run for few epochs. At last, we need to evaluate the model based on the testing dataset to see its performance.

The semantic representation of flow of input data from convolution layers, maxpooling layer, and fully connected layers are shown in fig(2)

A. Pre-Setup

In this project, the chest X-ray images are loaded from two different sources. First, Covid-19 X-ray images was loaded from Covid-Chest-X-ray image database. This database is opensource and constantly updated by researchers from various regions. At present there are 200 Chest X-ray images of Covid-19 positive patients. The normal chest images are loaded from Chest-Xray database developed by the Wang et al. The database contains total of 5586 images of normal and pneumonia patients. In this project, we are loading only normal images from Chest-Xray database. In this project, we loading Covid-19 chest X-ray images and Normal X-ray images from different databases and concatenating them into one dataset.

B. Data Pre-processing

Feature Scaling: Data Preprocessing consists of certain tasks such as extracting the labels from the images, converting the image into RGB format, resizing the image, and performing the feature scaling. The feature scaling is a normalization technique, it is performed on the independent variables of the input data to standardize it into certain fixed range. It helps to bound the values between two numbers mainly between [0,1]. The X-ray images in the dataset are first converted into RGB and resized to 224*224 pixel using Open CV functions. The standard image size ranges in between [0,255], where 255 is the maximum size of the image. Firstly, images and labels are loaded into two separate datasets, then these datasets are converted into NumPy array for feature scaling. Here max normalization is performed on the images such as dividing every image by the maximum size (255) and transforming the data in range between [0,1]. The one hot encoding is performed on the labels data to covert it from categorial to binary values.

Data splitting: The dataset needs to split into training and testing portions. In this model, the dataset is split into 80% for the training and 20% for the testing.

Data Augmentation: Data Augmentation is a technique that is used to increase the size of the data by performing random transformations on the original data. The keras deep learning provide ImageDataGenerator class to fit the model through image data augmentation. In this model, data augmentation is performed on the training data through ImageDataGenerator. It contains parameters such as rotation range and fill mode. The rotation range states the degree range for rotating the images randomly. The fill mode states about the points that were outside boundary are filled according to the specified mode. The rotation range is assigned to 15 and fill mode is specified as nearest in this model.

C. Network Creation

The recent advancements in deep learning mechanisms revolutionized artificial intelligence. The word deep states increase in the size of the network layers in the model. The CNN structure contains a convolution layer, maxpooling layer, and a dense layer. The convolution layer extracts a features from the input data through the filters, a max-pooling layer is used to reduce the size which helps in computational performance, a dense layer helps in connecting the layer which is stated as fully connected layer. By combining all these layers, a completed CNN model is created. The hyperparameters of CNN model are adjusted to perform particular task such as classification or object detection.

In this project, the pretrained deep learning model is used instead of developing it from the scratch. The deep learning model used in this project is VGG16. The VGG16 is a deep convolution neural network proposed by the Oxford University members. It is very deep convolution neural network helps for image classification and image recognition. The model achieved 93% accuracy in ImageNet, which is collection of 14 million images that belongs to more than 1000 classes. It overcomes the problems of AlexNet by replacing the size of kernel filters with multiples of 3*3 size. In this project we have added some more layers to the existing VGG16 model to increase the accuracy. For better understanding of this model, first, we need to understand the basics of VGG16, which consists of 13 convolution layers, 5 maxpooling layers, and 3 dense layers. These layers are CNN model layers with different number of filters, sizes, and stride values. The architecture of VGG16 model is shown in figure(3). The VGG16 model is indicated as

C11-C12-M1-C21-C22-M2-C31-C32-M3-C41-C42-M4-C51-C56-M6-D1-D2-D3

In the above statement, C represents convolution layer, M represents maxpooling layer, and D represents Dense layer.

For the input image (X) and kernel k, the 2D convolutional operator is defined as

$$(X * K)(i,j) = \sum_m \sum_n K(m,n)X(i-m, j-n)$$

Where * represents mathematical representation of

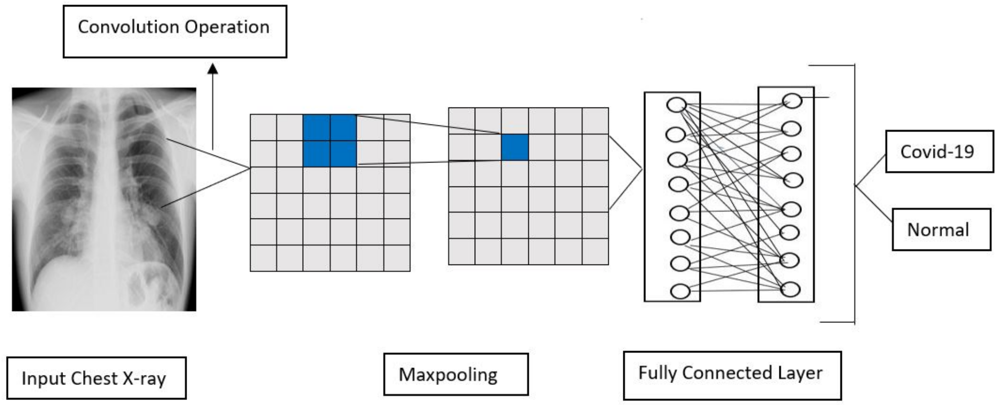

Fig. 2. Semantic Representation of CNN Layers[38].

convolution operation, the k matrix moves over the input data matrix with stride parameter. The rectified linear unit (relu) is used as activation function in VGG16 model for maintaining nonlinearity. The equation of the RELU function is represented as

$$f(x) = \begin{cases} max(0, x) & \text{for } x > 0 \\ 1 & \text{for } x <= 0 \end{cases}$$

In the figure(3), VG-CN states VGG16 model convolution layer. VG-CN contains two convolution layers and one max-pooling layer.

The bottleneck of this project is classifying the images accurately with in depth details. To perform such classification, the model should have a structure which can capture and learn in depth pixels.

In the proposed model, some more layers are added to the VGG16 model to yield the accurate results. The proposed model has 13 convolutional layers, 6 maxpooling layers, 3 dense layers, and one flatten layer. In this model, after each convolution layer, a batch normalization and relu operations are performed. The batch normalization operation helps to standardize the inputs along with other benefits such as reducing training time and to increase the model stability. In the proposed model maxpooling layer is used in all the pooling operations. Maxpool reduces the size of the input by selecting the maximum region determined by its filter. The layers parameters are given in table 1. The model performs binary classification such as covid 19 positive or normal. The model layer details and parameters are given in table 1. The developed deep learning model consists of 14,747,650 parameters. The proposed model architecture is shown in fig(4)

D. Training and Testing the model

To train the model, we are using the adam optimizer and binary_crossentrophy loss. The performance of the model is measured using the accuracy metric. Finally the model is tested.

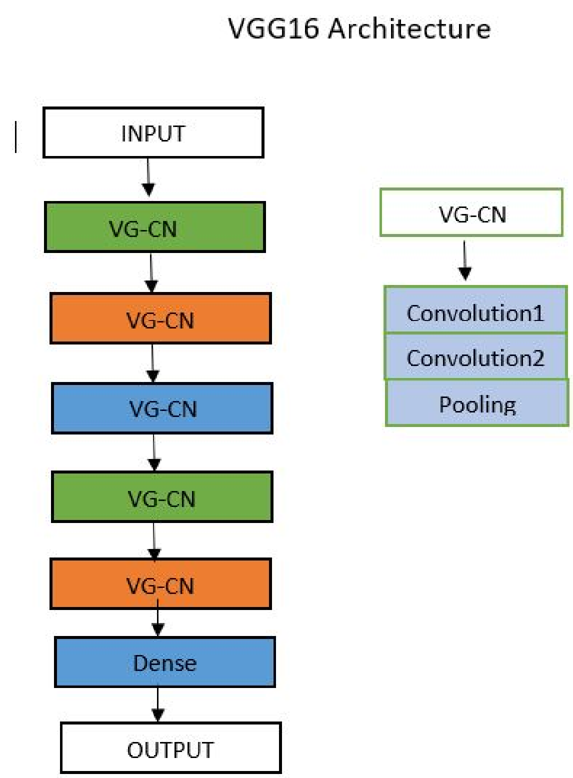

Fig. 3. VGG16 Architecture[38].

E. Hyperparameters tuning

Hyperparameters are tuned in optimizing the model. They also help in finding the closest value of hyperparameter that gives the highest performance. We tuned three hyperparameters that include 1) Learning rate, 2) epochs, and 3) batch_size. We perform random searches using different

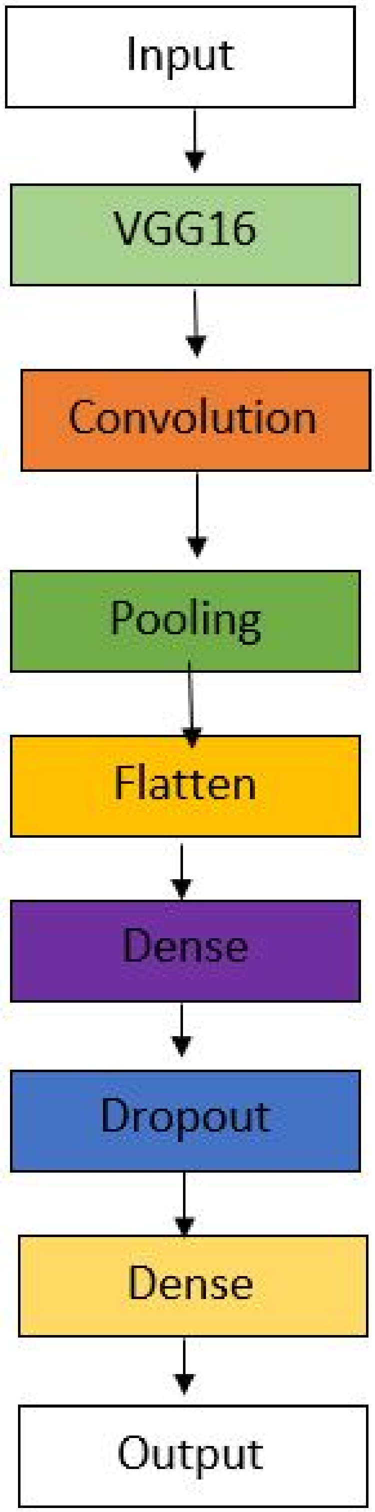

Fig. 4. Proposed Model Architecture[37].

TABLE I
PROPOSED MODEL LAYERS AND LAYER PARAMETERS.

Proposed Model			
Number of Layers	Layer Type	Output shape	Number of trainable parameters
1	Input	[224,224,3]	0
2	Conv2D	[224,224,64]	1792
3	Conv2D	[224,224,64]	36298
4	Maxpooling2D	[112,112,64]	0
5	Conv2D	[112,112,128]	73856
6	Conv2D	[112,112,128]	147584
7	Maxpooling2D	[56,56,128]	0
8	Conv2D	[56,56,256]	295168
9	Conv2D	[56,56,256]	590080
10	Conv2D	[56,56,256]	590080
11	Maxpooling2D	[28,28,512]	0
12	Conv2D	[28, 28,512]	1180160
13	Conv2D	[28, 28,512]	2359808
14	Conv2D	[28, 28,512]	2359808
15	Maxpooling2D	[14, 14,512]	0
16	Conv2D	[14, 14, 512]	2359808
17	Conv2D	[14, 14,512]	2359808
18	Conv2D	[14, 14,512]	2359808
19	Maxpooling2D	[7,7,512]	0
20	Averagepooling2D	[1,1,512]	0
21	flatten	[512]	0
22	dense	[64]	32832
23	dropout	[64]	0
24	dense	[2]	130

values of hyper-parameters until the performance of the model improves.

V. EXPERIMENT AND EVALUATION

Model 1:
In model 1, I added two convolution layers, one flatten layer, and three dense layers to VGG16 model. Firstly, the model was trained with batch_size equal to 32 and epochs equal to 5. Secondly, the same model was trained with batch_size equal to 64 and epochs equal to 10.

TABLE II
MODEL 1 RESULTS.

Model 1			
Epochs	Batch Size	Loss	Accuracy
5	32	0.302	0.934
10	64	0.354	0.925

Model 2:
In model 2, I added one convolution layer, one flatten layer, and two dense layers. Firstly, the model was trained with batch_size equal to 64 and epochs equal to 20. Secondly, the same model was trained with batch_size equal to 128 and epochs equal to 20.

Comparison of All 2 Models: The table 3 shows all the two models scores. In all two models, model 2 is better than other model 1. It have accuracy and other metrics more than other model. So, model 2 was the final model.

TABLE III
MODEL 2 RESULTS.

Model 2			
Epochs	Batch Size	Loss	Accuracy
20	64	0.052	0.975
20	128	0.105	0.953

TABLE IV
COMPARISON OF MODELS.

Comparison of Models			
Epochs	Batch Size	Loss	Accuracy
5	32	0.302	0.934
20	64	0.052	0.975

Graphs:
The proposed model accuracy and loss graphs are shown in figure 5 and figure 6.

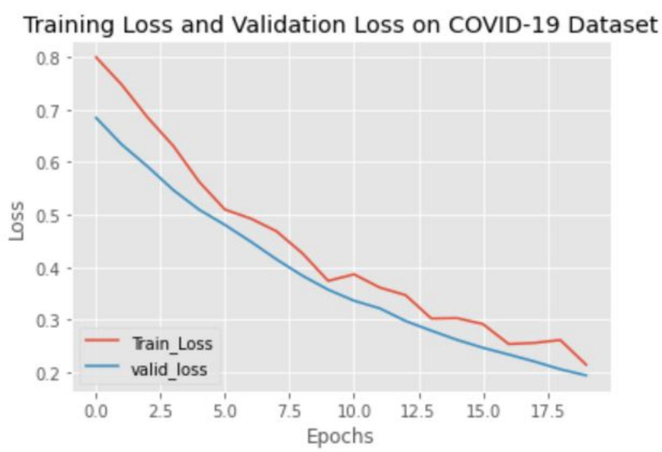

Fig. 5. Model 2 Loss v/s Epoch graph.

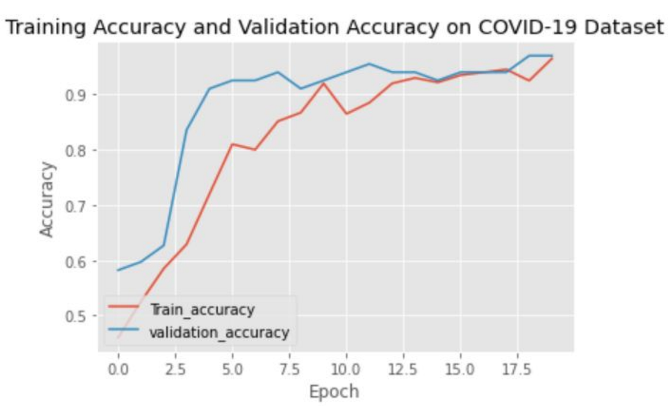

Fig. 6. Model 2 Accuracy v/s Epoch graph.

VI. CONCLUSION

The model is developed by adding some layers to VGG16 architecture. The model detects the Covid-19 patients accurately using chest X-ray images. The existing model used RsNet architectures and resulted an accuracy of 95%. In the proposed model, VGG16 have been used and resulted an accuracy around 97%. The results are shown in table 5.

TABLE V
FINAL RESULTS.

Epochs	Batch Size	Loss	Accuracy
20	64	0.052	0.975

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