ISSN:0975-9646
Karan Singh Garkel / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 13 (6) , 2022, 112-114

CNN Model for COVID-19 Disease Detection

Karan Singh Garkel
Student, Department of Information Technology
Manipal University Jaipur
Jaipur, India

***Abstract* - Detection of COVID-19 is a challenging process since it involves a manual process of testing specimens and is based on the availability of COVID-19 test kits in medical institutions. Hence, it is important to design and deploy an automatic detection system to serve as an alternate diagnosis option for COVID-19 detection that can be employed in a widespread manner. Convolutional Neural Networks (CNNs) have previously proven to be highly useful in the classification of medical images. As a result, we have explored and proposed a CNN model in this study which helps diagnose COVID-19 on the basis of X-ray scans of the patient.This research study shows promising results that can be enhanced to be implemented for scalability and sustainability.**

***Keywords* - Deep Learning, COVID-19, Convolutional Neural Network, Image Classification, Medical Diagnosis.**

I. INTRODUCTION

The COVID-19 pandemic has emerged as one of the most serious public health crises in recent years. The virus spreads quickly: the reproduction number of COVID-19 ranged from 2.24 to 3.58 during the first months of the pandemic, suggesting that each infected person infected two or more people[1]. The coronavirus that causes COVID-19 is thought to be the same one that causes SARS-COV2 and MERS (MERS)[2]. The wide range of symptoms associated with COVID-19 start to manifest after an average incubation time of 5.2 days. Common symptoms include fever, dry cough, and exhaustion. Other symptoms include headache, hemoptysis, diarrhea, dyspnea, and lymphopenia [3,4].

Coronavirus(SARS-COV-2), which first infected a person in December 2019, is mostly spread by droplets created when infected people talk, cough, or sneeze [5,6,7,8,9,10]. Due to the COVID-19's severity and simplicity of transmission, it has spread quickly around the world. Early diagnosis is therefore essential for ensuring that patients receive the right care while lightening the burden on the healthcare system. Although Antigen and RT-PCR diagnostic methods are widely accessible, underdeveloped nations still lack the financial resources to rapidly screen all of their citizens[11].

Millions of people worldwide lost their lives to this illness during the global Covid pandemic in the last few years. Several nations are now working on COVID-19 vaccine development. The WHO has authorized the use of vaccines made by Pfizer, AstraZeneca, Moderna, Serum Institute of India Pvt. Ltd., Janssen, Sinopharm, and Sinovac, among others[12]. The severity of the disease has significantly decreased as a result of these authorized vaccines.

Artificial intelligence is presently being utilized to automate the diagnosis of a number of diseases after demonstrating its effectiveness and good performance in automated image classification problems using various machine learning techniques[13]. Medical image-based diagnostics in particular have benefited greatly from the tremendous upsurge in deep learning applications. When it comes to computer vision issues involving the processing of medical images, deep learning models fare better than conventional machine learning models.[14].

Due to their consistent good results, CNN's are considered as the de facto standard in medical image analysis and categorization. A few of the classification tasks that CNN have been applied to include lung disease, breast cancer detection, wireless endoscopy images, interstitial lung disease, CAD-based diagnosis in chest radiography, classification-based skin cancer diagnosis, and automatic diagnosis of various chest diseases using chest X-ray image classification. [15]
Hence Artificial Intelligence (AI) is leading to rapid progress in the detection of COVID-19 and other kinds of lung inflammation.

In our study, based on the patient's X-ray images, we developed a CNN model to diagnose COVID-19 illness. A variety of image processing techniques were employed to enable the proposed model and to avoid overfitting while also striving to achieve maximum accuracy. Rescaling, shear intensity, zoom range, and horizontal flipping were a few of the image processing methods used.

The following parts will outline the dataset that was utilized and how it was pre-processed; the procedure for creating the model using Python and Keras; the model code and its summary; the final outcome and analysis; the conclusion; and suggestions for the future.

II. DATASET AND PREPROCESSING

A dataset of chest X-rays was used in this study's experiments[16]. It is made up of images from Covid and Normal X-ray scans. While only 20% of the dataset was utilized for testing, 80% of it was used for training. To increase the number and diversity of pictures sent to the classifier for classification, data augmentation and image enhancement techniques were applied.

```
train_datagen = image.ImageDataGenerator(
    rescale = 1./255,
    shear_range = 0.2,
    zoom_range = 0.2,
    horizontal_flip = True,
)

test_dataset = image.ImageDataGenerator(rescale=1./255)
```

Figure 1. Data Pre-processing and Augmentation

For implementing image augmentation, Keras uses the ImageDataGenerator class. It can produce augmented pictures dynamically during model training, making the overall model more robust and precise.

The methods for image augmentation employed include manipulating the picture's pixel values, changing the angle of slant or shear intensity, modifying the zooming in value, and randomly flipping the images horizontally.

III. Methodology

Python and Keras(a high level neural networks library) were the technologies used to build the model. The convolutional neural network was constructed using a sequential model since this model is suited for a simple stack of layers where each layer has precisely one input tensor and one output tensor. The sequential model was developed with multiple stacks of Conv2D, MaxPooling2D, Dropout layers, and filters, which are described below.

Conv2D - Conv2D filters extend through the three channels in an image (Red, Green, and Blue). The filters may be different for each channel too. After the convolutions are performed individually for each channel, they are added up to get the final convoluted image. The output of a filter after a convolution operation is called a feature map.

MaxPooling2D - This stack downsamples the input along its spatial dimensions (height and width) by taking the maximum value over an input window (of size defined by pool_size) for each channel of the input. The window is shifted by strides along each dimension.

Dropout - The Dropout layer randomly sets input units to 0 with a frequency of rate at each step during training time, which helps prevent overfitting. Inputs not set to 0 are scaled up by 1/(1 - rate) such that the sum over all inputs is unchanged.

Flatten and Dense - A flatten layer is used to convert the 2 dimensional output of the pooling layer into a one dimensional vector which can be passed onto the fully connected or dense layer to finally classify the image.[17]

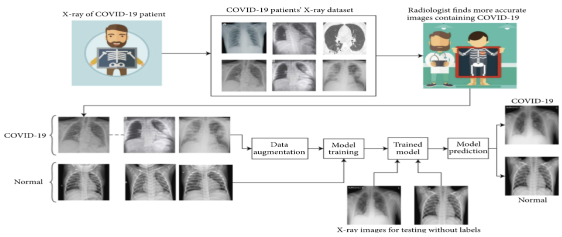

Figure 2. Working of the proposed CNN model [18]

IV. CNN Based Model in Keras

The sequential model employs the following algorithm -

- The convolutional layer that conducts the convolution process receives the image's pixels as input.
- It results in a convolved map
- A rectified feature map is created by applying the convolved map to a ReLU function.
- For finding the features, the image is processed using several convolutions and ReLU layers.
- To detect particular sections of the image, numerous pooling layers with different filters are used.
- The pooled feature map is flattened and fed to a fully connected layer to get the final output.

A. Code

```
model = Sequential()
model.add(Conv2D(32,kernel_size=(3,3),activation='relu',input_shape=(224,224,3)))
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(64,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(128,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1,activation='sigmoid'))

model.compile(loss=keras.losses.binary_crossentropy,optimizer='adam',metrics=['accuracy'])
```

Figure 3. Model Code

B. Model Summary

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 32)      896

 conv2d_1 (Conv2D)           (None, 220, 220, 64)      18496

 max_pooling2d (MaxPooling2D  (None, 110, 110, 64)     0
 )

 dropout (Dropout)           (None, 110, 110, 64)      0

 conv2d_2 (Conv2D)           (None, 108, 108, 64)      36928

 max_pooling2d_1 (MaxPooling  (None, 54, 54, 64)       0
 2D)

 dropout_1 (Dropout)         (None, 54, 54, 64)        0

 conv2d_3 (Conv2D)           (None, 52, 52, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 26, 26, 128)      0
 2D)

 dropout_2 (Dropout)         (None, 26, 26, 128)       0

 flatten (Flatten)           (None, 86528)             0

 dense (Dense)               (None, 64)                5537856

 dropout_3 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

=================================================================
Total params: 5,668,097
Trainable params: 5,668,097
Non-trainable params: 0
_________________________________________________________________
```

Figure 4. Model Summary

V. Results and Analysis

As was previously noted, 80% of the dataset after pre-processing was utilized for training, whereas 20% was used for testing. The suggested CNN architecture was then fed the input data.

During the experiment, the accuracy and loss of both the training and validation set were recorded for 10 consecutive epochs.

Finally, it was found that the model's accuracy on the training set and validation set were 97.32% and 98.33%, respectively, and that the loss created during the training and validation sets was 0.1043 and 0.0854, respectively. This can also be confirmed by observing the figure below.

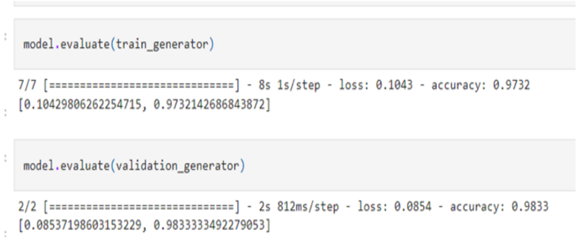

Figure 5. Model testing and validation accuracy along with their loss values

Confusion Matrix:

The confusion matrix below shows how the CNN model test employs 60 X-ray pictures from the dataset, of which 30 are from the COVID-19 class and 30 are from the normal class. The CNN model performs well in testing and accurately predicts 59 images with an error rate of 1.66%.

{'Covid': 0, 'Normal': 1}

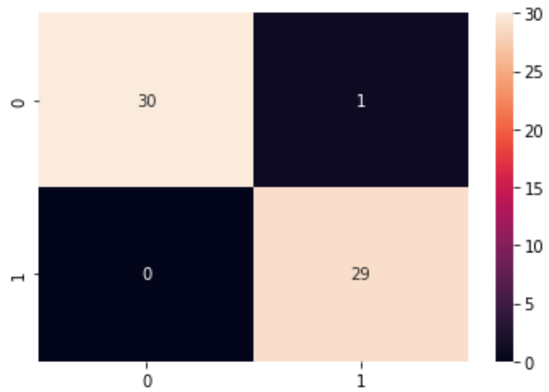

Figure 6. Confusion Matrix

VI. Conclusion and Future Plan

The purpose of this research was to show how COVID-19 may be effectively and precisely diagnosed using CNN that was trained on datasets of chest X-ray images. When trained on the abovementioned dataset, the CNN architecture described in this work produced encouraging results.

In a pandemic situation like the current one, our findings will help physicians use an appropriate model for a variety of image analysis techniques, which is crucial when time and resources are constrained. The suggested strategy may be used in further research on a dataset that contains more pulmonary disease classifications, such as COVID-19, pulmonary fibrosis, chronic obstructive pulmonary disease, pneumonia, and asthma. It may also be utilized to provide the groundwork for the commercial development of an AI application to diagnose Covid-19.

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