

COVID CT NET: A TRANSFER LEARNING APPROACH FOR IDENTIFYING CORONA VIRUS FROM CT SCANS

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ABSTRACT

The pandemic of COVID-19 has been rapidly spreading across the globe since it first surfaced in the Wuhan province of China. Several governments are forced to have nationwide lockdowns due to the progressive increase in a daily number of cases. The hospitals and other medical facilities are facing difficulties to cope with the overwhelming number of patients they can provide support due to the shortage in the number of required medical professionals and resources for meeting this demand. While the vaccine to cure this disease is still on the way, early diagnosis of patients and putting them in quarantine has become a cumbersome task too. In this study, we propose to build an artificial intelligence-based system for classifying patients as COVID-19 positive or negative within a few seconds by using their chest CT Scans. We use a transfer learning approach to build our classifier model using a dataset obtained from openly available sources. This work is meant to assist medical professionals in saving hours of their time for the diagnosis of the Coronavirus using chest radiographs and not intended to be the sole way of diagnosis.

KEYWORDS

COVID-19, Deep Learning, CT Scans, Deep Convolutional Neural Networks, computer tomography scans.

1. INTRODUCTION

The sars-cov2 virus responsible for COVID-19 is rich in a cell surface receptors called angiotensin converting enzyme 2 [3]. The virus after entering to the body attaches to the host cells and creates copies of itself. Our immune system forms antibodies to fight the virus but it is unable to keep up with the myriad copies of the virus, it spreads to the other organs of the bodies. The lung gets affected in this process as it suffers from acute respiratory disease, which is seen in the radiographs as a white space [15]. The primary process for diagnosing the presence for sars-cov2 is by doing a polymerase chain reaction testing. It is a laboratory procedure in which the ribonucleic(RNA) and deoxyribonucleic acid(DNA) are used for finding the exact volume of ribonucleic acids by the help of fluorescence. The samples for this procedure is collected by inserting swab into the nasal area for collecting the secretions. The process is very long and complex and there is shortage of test kits in some countries.

A possible substitute to the PCR testing is the use of chest radiographs like computer tomography scans [2] [6] and x-rays for detecting the presence of the virus. However, doing it manually is cumbersome and requires a specific skill set. In order to automate this process, we propose to make use of deep learn-ing [8]. As deep convolutional neural networks are known to work on images, we use CNN to classify between chest x-rays as healthy or infected with COVID

[7] [10].A Convolutional network [9] is used to extract meaningful features from images and differentiate amongst them by using certain learning parameters. The layers in it are grouped as convolutional layers, pooling layers, fully connected layers and at last an activation function is used in case of a classification task. Due to the small size of the dataset and lower quality of images ,we used transfer Learning. Transfer learning uses a model trained on large datasets like imagenet [5] and MS coco[4]and the pretrained weights collected are taken and layers are added over it to train the model on the new dataset.

2. DATASET DESCRIPTION

The dataset [16] that we used for this study has been collected from a public repository that consists of CT scan images amongst them 349 images are CT scan images collected from 216 COVID patients and 397 images that were CT scan images of healthy patients. The dataset is culmination of different CT scan images collected from websites such as medRxiv, bioRxiv, NEJM, JAMA, Lancet. The dataset also included the age, gender of the patient and the location from where the CT scans were taken.

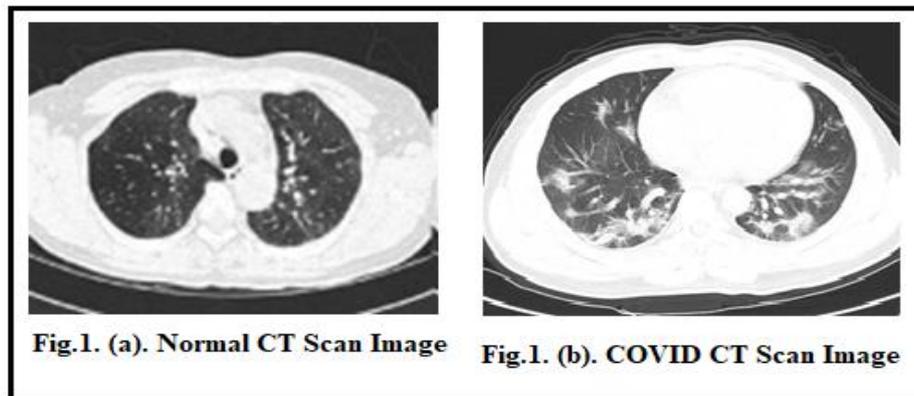


Fig.1. Normal and COVID CT Scan Images

The above figure.1. (b) is an example of a CT-scan belonging to a COVID patient and the figure1. (a) shows an example image of a CT-scan image belonging to a healthy patient taken from the dataset.

3. PREPROCESSING

We performed the following pre-processing steps for facilitating better feature extraction during our model training.

3.1. Cleaning

The dataset comprised certain images which contained markings or additional labelling as they were taken from journals and books. We choose to remove all the images.

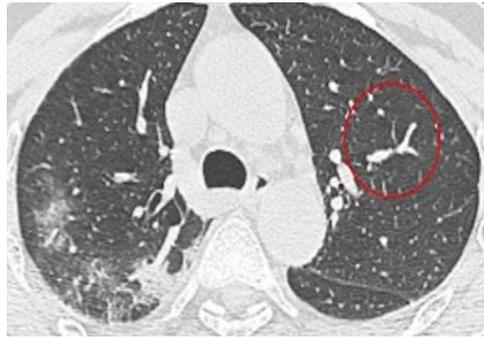


Fig.2. COVID CT Scan Image.

As seen in figure 2 it contains a red circle, these kinds of images were removed and a custom dataset was constructed from the dataset.

3.2. Data Augmentation

Owing to the limited size of the dataset we generated a custom dataset by performing data augmentation, data augmentation is a method used for increasing the size of the dataset by generating different iterations of the samples in the dataset. we subjected the images to different methods which included rotating the image to different perspectives, width and height shifting of the image, flipping the image and also padding the image. This method also helps us to address the class imbalance problem, reduction of over fitting and also improve the convergence rate of the model to yield a better accuracy. **Table.1** shows the increase in number of images after preprocessing.

Table.1. number of images in each class after pre-processing

Classes	No.of images
COVID-Negative	5000
COVID-positive	5000

3.3. Converting the pixel values to Hounsfield Units

In this method we converted all the pixels in a CT scan image to Hounsfield Units, this gives the relative radio density that is used for measuring CT scan images [12].This was done because the dataset the images used were of low quality that lead to the loss of hounsfield units.

3.4. Normalization

The pixel values in the image consists of integers, the lower the value the lower will be the learning time of the neural network, so that is why we normalized images in which the max bound was set to 400.0 and the minimum bound was set to -1000.0.

3.5. Zero Centring

This refers to a pre-processing method in which the mean value is subtracted from each data point, in our case the zero centred value was found to 0.25.

3.6. Model Architecture

In our study we developed a deep convolutional neural network for classifying between two classes of CT-scans. We had to collect the data from various public sources, there was limited number of images available and we had to compromise with the image quality as well hence we used transfer learning [11]. Transfer learning takes advantage of previous knowledge of extraction that was obtained from training the network in datasets like imagenet [5]. The pre-trained model obtained after training a model on a large dataset can be used for a image classification task. The main intuition behind the use of transfer learning is if any model is trained on a large dataset, we can make use of the feature map without requiring to train the model again from scratch on a large dataset.

We make use of Efficient B3 [13] for our experiment, the architecture of Efficient Net B3 optimizes flops by using a multi neural search architecture. The Convolution layers of efficient net are divided into two parts point wise convolution and depth wise convolution, this helps in reducing calculation time while having minimum loss in accuracy. The MBconv block in Efficient Net first extends to the channels of the images and then compresses them which results in lesser number of skipped connections unlike other architectures resnet [14]. Efficient Net also utilises compound scaling, in compound scaling the length breadth and width of the network is increased with respect to the baseline architecture of Efficient Net as seen in table 2.

Table.2. Model Architecture

stage	Operator F_i^{\wedge}	Resolution $H_i * W_i$	# Channels C_i	# Layers L_i
1	Conv 3x3	224x224	32	1
2	MBCConv1, k3x3	112x112	16	1
3	MBCConv, k3x3	112x112	24	2
4	MBCConv, k5x5	56x56	40	2
5	MBCConv, k3x3	28x28	80	3
6	MBCConv, k5x5	14x14	112	3
7	MBCConv, k5x5	14x14	192	4
8	MBCConv, k3x3	7x7	320	1
9	Conc 1x1 & pooling & FC	7x7	1280	1

The layers in Efficient Net have been increased by keeping a fixed constant ratio, this helps in boosting accuracy of the model. In order to make a sequential model we used Efficient Net as the the head model and added layers. The output obtained from the last layer is fed to an average pooling layer where the input is down sampled by a kernel of size 4x4. The output is fed to a flatten layer for converting the matrix of features into vectors which are then fed to a dense layer. Relu activation function is used to introduce non-linearity. In the last layer sigmoid activation is used for classifying the images into 2 classes. The operator column in Table 2 shows the exact orientation of blocks, the resolution represents the input resolution that is gonna be utilised by the blocks and the channels represents the number of output channels of the blocks and the layers represents the number of times the blocks were repeated

3. RESULT

The dataset was split into a ratio of 8:2 that is 80% for train and 20% for test. The Learning rate of our model is set to $5e-5$ with a batch size of 16 on the tensorflow2.0 [1] framework. The model was then trained for a cycle of 100 epochs. The figure 3 shows the accuracy curve obtained after training the model, a validation and test accuracy of 100% was obtained.

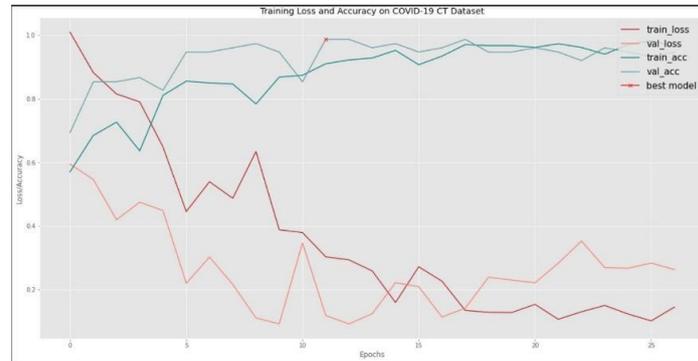


Fig.3. Training Accuracy.

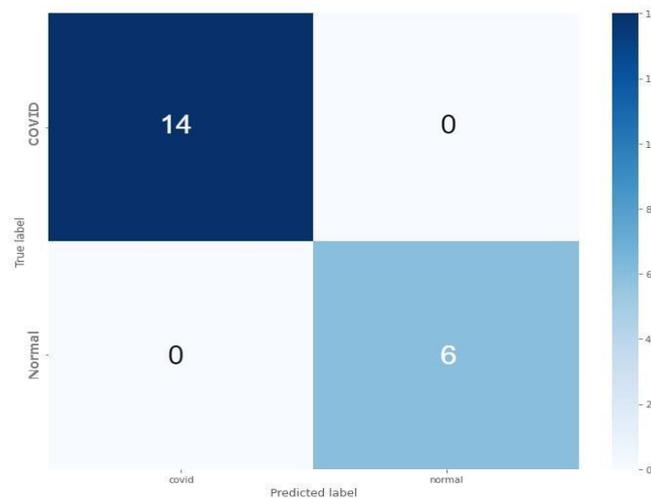


Fig.4. Confusion Matrix.

Figure.4. shows the confusion matrix that was obtained from our model. The confusion matrix defines the performance of the model on a set of data in which the score of certain parameters are known.

Precision: This score refers to the number of predictions about patients having COVID-19 was true, the score obtained was 1.00.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (1)$$

Recall: It gives a measure of the number of classifications of patients having COVID-19 the model can predict correctly and the score obtained was 1.00.

$$\text{Recall} = \text{Tp}/(\text{TP} + \text{FN}) \quad (2)$$

F1 score: The F1 score being a function of precision and recall determines the number of instances our model accurately classifies without missing a significant number of instances. The F1 score obtained was 1.00.

$$\text{F1 score} = 2 \times [(\text{Precision} \times \text{Recall}) / (\text{precision} + \text{Recall})] \quad (3)$$

Specificity: It is a percentage of COVID Negative patients that were actually classified as COVID Negative, For our proposed model the score was 100%.

Sensitivity: It is the percentage of COVID Positive patients that were actually classified as COVID Positive. For our proposed model the score was 100%.

Table.3. shows the different scores obtained from our architecture

Classes	Precision	Recall	F1-score
COVID-Negative	1.00	1.00	1.00
COVID-Positive	1.00	1.00	1.00

4. CONCLUSION

In this study we propose to automate the process of detection of COVID-19 using chest CT scans of patients with deep Convolutional Neural Networks. Under the hood, we used a transfer learning technique to leverage the benefits of Efficient Net for training our image classifier to categorize the CT Scans as COVID-19 positive or negative. We made use of a transfer learning approach in which we used Efficient Net and customized it by adding layers to accurately classify chest images. We obtained a test and validation accuracy of 100% and equally high scores in other parameters. The data was obtained from a public dataset that was curated from different sources. It was subjected to preprocessing methods like data augmentation, conversion of pixels to Hounsfield units, zero centering and normalization to improve feature extraction of our architecture. Our experiment is intended to be a starter work for automatic diagnosis of COVID-19 to assist the medical professional amidst this pandemic to serve the people in a more efficient way. It requires further clinical validations to be used as a fully fledged detection tool.

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