COVID-19 IMAGE CLASSIFICATION USING VGG-16 & CNN BASED ON CT SCANS

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Abstract

The main purpose of this work is to investigate and compare several deep learning enhanced techniques applied to CT Scan medical images for the detection of COVID-19. In this proposed work we are going to build two Covid-19 Image classification models. Both the model uses Lungs CTScan images to classify the Covid-19. We build the first Classification model using VGG-16 Transfer leaning framework and second model using Deep Learning Technique Convolutional Neural Network (CNN) to classify and diagnose the disease and we able to achieve the best accuracy in both the model.

Keywords: Visual Geometry Group-VGG16, Convolutional Neural Network-CNN, CT Images, X-Ray, rTPCR

1. INTRODUCTION

Coronavirus disease (COVID-19) is an infectious disease and looking at the degree of its spread all through the world, it has been declared as a pandemic by the World Health Organization (WHO) on 11th March 2020. The pandemic pronouncement also stressed the deep worries of the alarming rate of spread and severity of COVID-19. It is the principal recorded pandemic brought about by any coronavirus. It is characterized as a worldwide wellbeing emergency of its time and it has spread everywhere throughout the world. Legislatures of various nations are forcing fringe limitations, flight limitations, social distancing, and expanding consciousness of Organization (WHO) on 11th March 2020. The pandemic pronouncement also stressed the deep worries of the alarming rate of spread and severity of COVID-19. It is the principal recorded pandemic brought about by any coronavirus. It is characterized as a worldwide wellbeing emergency of its time and it has spread everywhere throughout the world. Legislatures of various nations are forcing fringe limitations, flight limitations, social distancing, and expanding consciousness of cleanliness. However, the virus is still spreading at very rapid rate. The majority of the individuals tainted with the COVID- 19 experienced gentle to direct respiratory ailment, while some built up destructive pneumonia. There are assumptions that elderly people with basic clinical issues like cardiovascular ailment, diabetes, ceaseless respiratory infection, renal or hepatic maladies and malignant growth are bound to create genuine disease. Until now, there is no particular immunization or treatment for COVID-19. However, there are numerous continuous clinical preliminaries assessing potential medicines. About 48,030,327 infected cases are confirmed in more than 216 countries until 2nd November 2020, where 1,223,171 deaths, 34,465,814 recovered, 12,252,984 mild and 88,358 critical cases were found.

It has been expressed that so as to battle with the spreading of COVID-19 sickness compelling screening of patients and prompt clinical reaction for the contaminated patients is a crying need. The highest quality level screening strategy utilized for testing the COVID-19 patients is the Reverse Transcription Polymerase Chain Response (RT- PCR) test on respiratory specimens. This procedure is the most generally utilized strategy for testing for COVID-19 identification however is a manual, confused, relentless and time-consuming process with a positivity rate of only 63%. The other diagnosis tools of COVID-19 can be clinical symptoms investigation, epidemiological history and positive radiographic images (computed tomography (CT)/Chest radiograph (CXR)) as well as positive pathogenic testing. The clinical attributes of serious COVID-19 contamination are that of bronchopneumonia causing fever, hack, dyspnea, and respiratory failure with Acute Respiratory Distress Syndrome (ARDS).

Promptly accessible and radiological imaging is another major symptomatic instrument for COVID-19. Most of COVID-19 cases have comparable highlights on radiographic pictures including reciprocal, multi-focal, ground-glass opacities with a fringe or back dissemination, primarily in the lower projections, in the early stage and pulmonary consolidation in the late stage. Although typical CXR images may help early screening of suspected cases, the pictures of different viral cases of pneumonia are comparative and they overlap with other infectious and inflammatory lung diseases. Therefore, it is hard for radiologists to recognize COVID-19 from other viral pneumonia. The side effects of COVID-19 being like viral pneumonia can at times lead to wrong determination in the present circumstance, where medical clinics are over-burden and working nonstop. Therefore, incorrect diagnosis can prompt a non-COVID viral Pneumonia being falsely marked as exceptionally suspicious of having COVID-19 and in this manner deferring in treatment with resulting costs, exertion and danger of presentation to positive COVID-19 patients. Currently many biomedical complications (e.g., brain tumor detection, breast cancer detection, etc.) are using Artificial Intelligence (AI) based solutions. Deep learning techniques can reveal image features, which are not apparent in the original images. In particular, Convolutional Neural Network (CNN) has been demonstrated amazingly helpful in include extraction and learning and therefore widely adopted by the research community. CNN was utilized to improve picture quality in low-light pictures from a high-speed video endoscopy and was additionally applied to distinguish the idea of aspiratory knobs through CT

pictures, the conclusion of pediatric pneumonia by means of chest X-ray pictures, robotized marking of polyps during colonoscopy recordings, cryptoscopic picture acknowledgment extraction from recordings.
Machine learning techniques on chest X-Rays are getting popularity as they can be easily utilized with low-cost imaging techniques and there is an abundance of data available for training different machine- learning models. Concept of transfer learning in deep learning framework was utilized by Vikash et al, for the recognition of pneumonia utilizing pre-trained ImageNet models and their ensembles. A customized VGG16 model was used by Xianghong et al. for lung regions identification and various sorts of pneumonia characterization. Wang et al, used a large dataset and Ronneburger et al. used image augmentation along with CNN to show signs of improvement results via preparing on little arrangement of pictures. Rajpurkar et al. announced a 121-layer CNN on chest X-rays to identify 14 distinct pathologies, including pneumonia utilizing an ensemble of different networks. A pre-trained DenseNet-121 and feature extraction techniques were used in the accurate identification of 14 thoracic diseases in. Sundaram et al. used AlexNet and GoogLeNet with image augmentation to obtain an Area Under the Curve (AUC) of 0.95 in pneumonia discovery.
The test of COVID-19 is currently a difficult task because of inaccessibility of diagnosis system everywhere, which is causing panic. Because of the limited availability of COVID-19 testing kits, we have to depend on different determination measures. Since COVID-19 assaults the epithelial cells that line our respiratory tract, we can utilize X-rays to investigate the strength of a patient's lungs. The medical practitioner frequently uses X-ray images to analyze pneumonia, lung inflammation, abscesses, and enlarged lymph nodes. And almost in all hospitals have X-ray imaging machines, it could be possible to use X-ray’s to test for COVID-19 without the dedicated test kits. Again, a drawback is that X-ray examination requires a radiology master and takes huge time, which is valuable when people are sick around the world. Therefore, developing an automated analysis system is essential to save medical professionals valuable time.
Recently, several groups have described deep-learning based COVID-19 pneumonia detection techniques. Shuai et al. [35] used deep learning techniques on CT images to screen COVID-19 patients with an accuracy, specificity and sensitivity of 89.5%, 88% and 87% respectively. Linda et al. [34] presented a DCNN, called COVID-Net for the detection of COVID-19 cases from the chest X-ray images with an accuracy of 83.5%. Ayrton used a small dataset of 339 images for training and testing using ResNet50 based deep transfer learning technique and reported the validation accuracy of 96.2%. In this study, we have developed an automatic detection of COVID-19 using a DCNN based Inception V3 model and Chest X-ray images. This paper proposes advanced deep learning approach to predict the COVID-19. The

proposed work is implemented with TensorFlow and Inception V3 pre-trained models that was trained to classify normal, viral and COVID-19 pneumonia images and tested on Chest X-ray images and obtained more than 98% of classification accuracy.

A. Problem Definition

In order to control the spread of COVID-19, a large number of suspected cases need to be screened for proper isolation and treatment. Pathogenic research facility testing is the indicative best quality level however it is tedious with noteworthy bogus negative outcomes. Quick and precise analytic strategies are desperately expected to battle the sickness. In light of COVID-19 radiographical changes in X-ray pictures, we meant to build a deep learning method that could extract COVID-19's graphical features so as to give a clinical analysis in front of the pathogenic test, thus saving critical time for disease control. In this paper, (DCNN), a machine learning classification technique is used to classify the Chest X-ray images. As accuracy is the most significant factor in this issue, by taking a more prominent number of pictures for training the network and by increasing the number of iterations, the DCNN accuracy can be improved. Tensor Flow is a large-scale machine learning system developed by Google and Inception V3 is Google's CNN architecture]. Here, the DCNN algorithm is executed with Tensor Flow and Inception V3.

2. MATERIALS AND METHODS

DCNN typically perform better with a larger dataset than a smaller one. Transfer learning can be beneficial in those applications of CNN where the dataset is not large. The idea of transfer learning uses the trained model from large datasets such as ImageNet is used for application with comparatively smaller dataset. This eliminates the requirement of having large dataset and also reduces the long training period as is required by the deep learning algorithm when developed from scratch.

A. Collection of Dataset

In this study, 315 chest X-ray images of COVID-19 patients have been obtained from the open source GitHub repository shared by Dr. Joseph Cohen. This repository is containing chest X-ray/CT images of mainly patients with acute respiratory distress syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia, severe acute respiratory syndrome (SARS). In addition, 330 COVID-19 positive radiographic images (CXR and CT) were carefully chosen from Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 DATABASE. Out of 330 radiographic images, 70 images are chest x- ray images and 250 images are lung CT images. This database is updated in a random manner and until 29 March 2020, there were 63 confirmed COVID-19 cases were reported in this database. In addition, 2905 chest X-ray images were selected from COVID-19 Radiography Database. Out of 2905 radiographic images, there are 219 COVID-19 positive images, 1341 normal images and 1345 viral pneumonia images. Fig. 1 shows a sample of chest x-ray scans of COVID-19, Normal and Viral Pneumonia.

Figure 1. Example chest radiography images of: (a) COVID-19 Viral Infection (b) Non COVID-19 infection (c) Viral Pneumonia

B. Image Pre-processing

One of the significant phases in the data preprocessing was to resize the X-Ray images as the image input for algorithm were different. We implemented some image pre-processing technique to increase the performance to our system by speeding up training time. First, we resized all our images to 299x299x3 to increase processing time and also to suitable in Inception V3. In the image preprocessing step, we need to label the data since the learning technique of convolution neural network fits into administered learning in machine learning.

C. Image Augmentation

CNN needs a sufficient amount of data to achieve excellent performance. We apply data augmentation techniques to increase the insufficient data in training, and the techniques used include vertical flip, horizontal flip, noise, translation, blur and then rotate the image 60 °, 90 °, 180 °, 270 °. Fig. 2 presents an example of the applied data augmentation. Therefore, the initial dataset consisting of 864 COVID-19 images, 1341 normal images, and 1345 viral pneumonia images was expanded to a total of 8,640 COVID-19 images, 13,410 normal chest X-ray images, and 13,450 viral pneumonia images as presented in Table I.

Table I. Details of Training, Validation and Test Set.

Class	Images	Augmented Total	With Augmentation		
			Training	Validation	Test
COVID-19	864	8640	7340	500	800
Normal	1341	13410	12000	910	500
Viral Pneumonia	1345	13450	12000	950	500

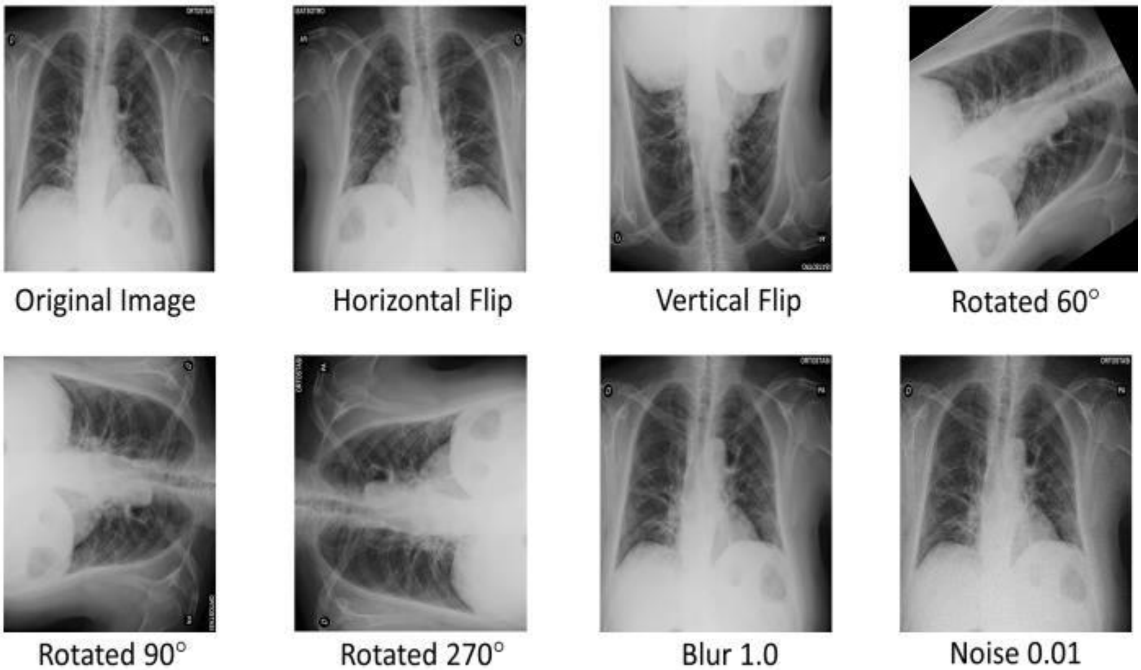

Figure 2. Example of augmented images by rotating, flipping, blur and noise

D. Transfer Learning

Transfer learning is a machine learning technique [40] which is based on the concept of reusability Transfer learning is often used with CNN in the way that all layers are kept except the last one, which is trained for the specific problem. This technique can be particularly useful for medical applications since it does not require as much training data, which can be hard to get in medical situations. In the analysis of medical data, one of the biggest difficulties faced by researchers is the limited number of available datasets. Deep learning models often need a lot of data. Labeling this data by experts is both costly and time consuming. The biggest advantage of using transfer learning method is that it allows the training of data with fewer datasets and requires less calculation costs. With the transfer learning method, which is widely used in the field of deep learning, the information gained by the pre-trained model on a large dataset is transferred to the model to be trained.

E. Proposed Architecture

Fig. 3 provides a step-by-step procedure for the proposed work model. The steps for the projected classification architecture are as follows:

- Recursively perform convolution and pooling on images.
- Apply drop out and fully connected. Now the image must be classified according to the labelled training class.

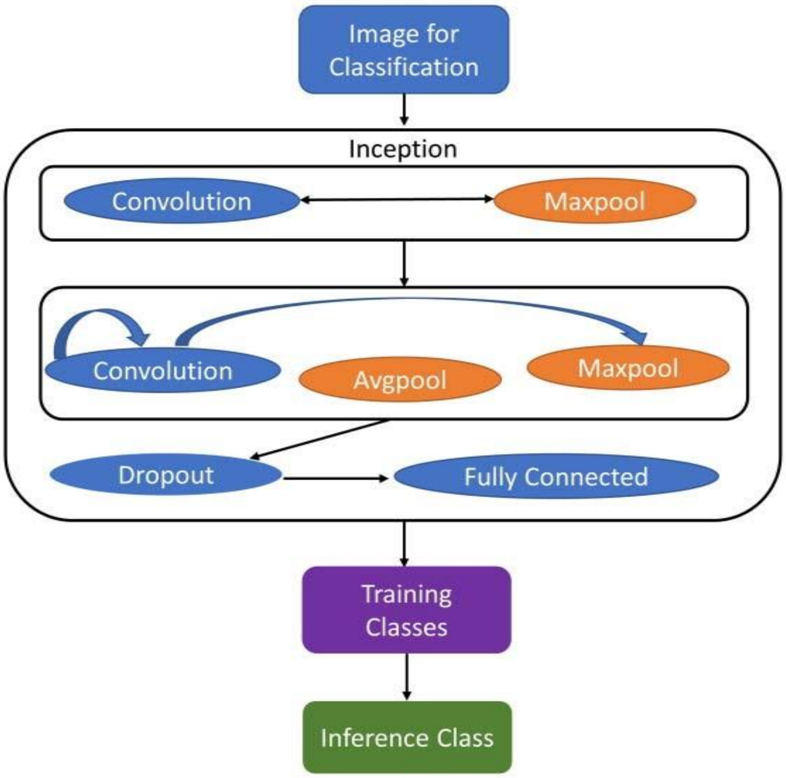

Figure 3. Proposed work architecture

Convolution is a gradual process. Extracts various features of input. Each kernel is responsible for producing output function. Low-level features of the image, such as edges, lines and corners are determined by the lower layer, and the higher-level features are extracted by the higher layer. Pooling is applied to make the features obtained from convolution robust against noise. Pooling layers are usually of two types namely, average pooling and max pooling. It is basically a dimensionality reduction or feature extraction step.

A simple example of max and average pooling is shown in Fig. 4.

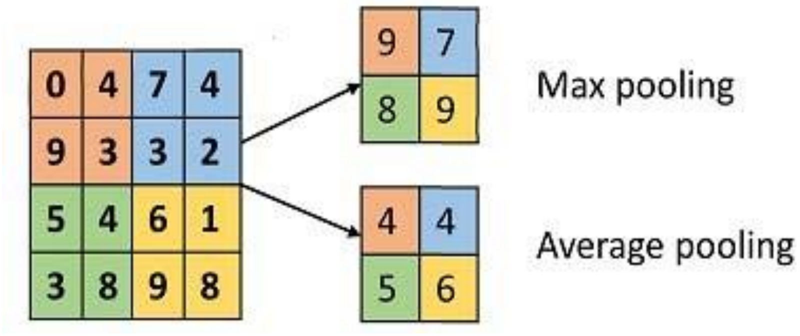

Figure 4. Example of max and average pooling.

In this study, we built DCNN based InceptionV3 model for the classification of COVID-19 Chest X-ray images to normal, viral pneumonia and COVID-19 classes. In addition, we applied transfer learning technique that was realized by using ImageNet data to overcome the insufficient data and training time. The schematic representation of conventional CNN including InceptionV3 model for the prediction of COVID-19 patients, viral pneumonia and normal were depicted in Fig. 7. Chest X-ray images are taken as input, Inception V3 is applied, convolution, pooling, SoftMax, and fully connected processes are performed. Upon completing these tasks, they are classified according to different training modules and eventually classified as normal, viral pneumonia and COVID-19 classes.

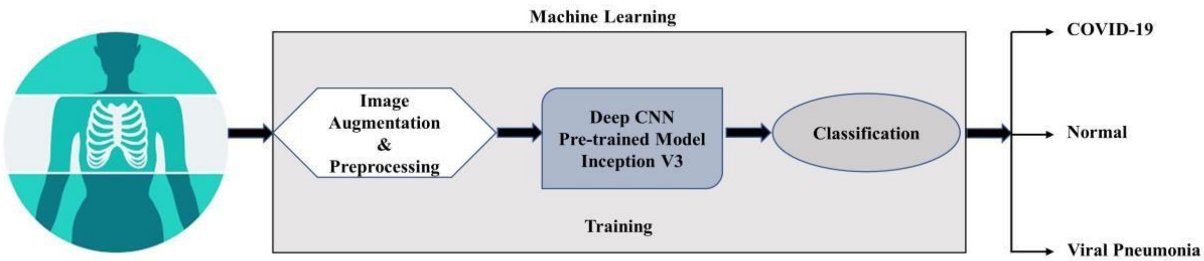

Figure 5. Schematic representation of pre-trained model for the prediction of COVID-19 patients, normal and viral pneumonia.

Inception V3 is one of the states of art architectures in image classification challenge. The best network for medical image analysis seems to be the Inception V3 architecture and it preforms better than even the more recent architectures. So, we selected Inception V3 model that is implemented using TensorFlow and hence the retraining is done with TensorFlow.

The steps for classification using the proposed work are follows:

Algorithm TensorFlow Classification

Step 1: Start

Step 2: Create list of images // start training the model

Step 3: Provide a directory for storing the bottleneck value of each image

Step 4: Provide inference to the images // to create bottleneck values

Step 5: Create a folder for all images of bottleneck values Step 6: Generate bottleneck values for each individual image

Step 7: Create new softmax layers and fully connected layers // end of training

Step 8: Test new image // input chest x-ray image to get the result

Step 9: Finish

3. CONCLUSION

Early prediction of COVID-19 patients is important to avoid spreading the disease to different people. In this study,we proposed a deep transfer learning-based approach the useof chest X-ray images obtained from COVID-19 patients, normal and viral pneumonia for automatic detection of COVID-19 pneumonia. The proposed classification model for the detection of COVID-19 achieved more than 98% accuracy. In the light of our findings, it's far believed that it's going to help medical doctors to make decisions in scientific practice due to the high overall performance. In order to comeacross COVID-19 at an early stage, this study gives insight onhow deep transfer learning methods can be used. COVID-19 has already become a danger to the world's healthcare systemand thousands of people have already died. Deaths wereinitiated by way of respiration failure, which ends up in the failure of other organs. Since a big range of sufferers attending out-door or emergency, doctor's time is limited and computer-aided-analysis can save lives via early screening and proper-care. Inception V3 model exhibits an excellent performance in classifying COVID-19 pneumonia by effectively training itself from a comparatively lower collection of images. We believe that this computer-aided diagnostic tool can significantly improve the speed and accuracy of diagnosing cases with COVID-19. This could behighly useful in a pandemic, where the burden of disease andthe need for preventive measures do not match the availabilityof resources.

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