Prediction of COVID-19 Cases Using CNN with X-rays

Dr D. Haritha
Dept. of Computer Science
SRK Institute of Technology
Vijayawada, India
harithadasari@rediffmail.com

N. Swaroop
Dept. of Computer Science
SRK Institute of Technology
Vijayawada, India
nagothiswaroop25@gmail.com

M. Mounika
Dept. of Computer Science
SRK Institute of Technology
Vijayawada, India
mounikamunagala1999@gmail.com

Abstract— **The Corona Virus Disease popularised as COVID-19 is a highly transmissible viral infection and has severe impact on global health. It impacted the global economy also very badly. Ift positive cases can be detected early, this pandemic disease spread can be curtailed. Prediction of COVID-19 disease is advantageous to identify patients at a risk of health conditions. Applications of Artificial Intelligence (AI) techniques for COVID prediction from X-rays can be very useful, and can help to overcome the shortage of availability of doctors and physicians in remote places. This paper proposes a transfer learning model using Googlenet for COVID-19 prediction from chest X-ray images. For image classification we used GoogleNet which is one of the CNN architecture and is also named as InceptionV1. The positively classified images by our model indicate the presence of COVID-19. The results obtained in COVID prediction using GoogleNet with a training accuracy of 99% and testing accuracy of 98.5% emphasize the use of Transfer Learning models in disease prediction.**

Keywords-- X-ray images of chest, Prediction, COVID-19, GoogleNet.

1 INTRODUCTION

THE[1] CoronaVirus Disease (COVID-19) is caused by Severe Acute Respiratory Syndrome Coronavirus 2(SARS-CoV-2) and is highly transmissible. It came into China government's notice in December, 2019 in Wuhan and more than twenty five million people all over the world were affected by it. Coronavirus is challenging all the people and the technology on the entire planet. As of August 2020, there are more than 27 million COVID-19 cases and 873,000 deaths globally [1]. There's no vaccine or immunizing agent found till date, thus the challenge is how best to fight against the Coronavirus to prevent its transmission. People with low immunity, old age, and medical issues especially associated with lungs are more vulnerable to COVID-19 sickness. The symptoms of COVID-19 are cough, cold, high fever and respiration issues. Preventive measures for COVID-19 square measure to shield oneself by washing hands off, avoid touching mouth, eyes, nose and face, and by maintaining social distance with others.

Since there's no immunizing agent identified till now for COVID-19 and sickness is contagious, the infected people rate is increasing at a faster pace. The tests that square measure the Coronavirus to ascertain the existence of sickness urge to take a look at results, as the variety of symptoms of positive cases has been increasing than the early days of identification of the virus on this planet. As COVID-19 has reached pandemic standing and the number of cases continues to grow at an exponential rate, wide accessibility of diagnostic testing is essential in serving to determine and curtail the spread of this quickly spreading sickness. The most common tests for COVID-19 identification include Chest Tomography imaging like Computed Tomography (CT) scan and X-rays [7]. These can be significantly used in early identification and treating this sickness in addition to RT-PCR (Polymerase chain reaction), isothermal nucleic acid amplification and antigen tests . After a thorough study on CT scan of respiratory organs lungs of patients infected with COVID-19 respiratory disorder, the foremost important respiratory organ is affected and identified after ten to twelve days after getting attacked with the virus. As RT-PCR tests take longer time for prediction, medical practitioners express that quick and early detection from clinical tests of X-rays can help to decide whether the patient is to be kept in observation by isolation until the laboratory test results come. This early prediction from X-rays prevents fast spreading of the disease to others during that gap. The chest X-ray observation is a discriminating factor; if the chest X-ray image is normal, patients can go home and wait for the laboratory test results. That's where the significance of our work carried out in this paper lies. Significant research has been carried out in applying machine Learning for automatic identification of diseases and has recently gained quantity and quality. Deep learning techniques are widely used in medical problems like carcinoma detection, carcinoma classification, and respiratory disorder detection from chest x-ray pictures. It's difficult to facilitate each hospital with clinicians due to the less availability of radiologists. Therefore, the straightforward and properly designed AI models to address the identification of diseases are also useful to beat this downside. Deep learning typically uses convolutional neural networks (CNN) in depth for feature learning automatically, using that knowledge for classification. A deep learning model using transfer learning is proposed in this paper for automatic and fast identification of COVID-19.

This proposed deep learning model needs images of chest x-ray to come out with the identification of COVID. In the training phase, the model is trained with more than a thousand chest x-ray images. As we are having a small size of the COVID-19 samples, transfer learning is better suited to train the deep CNNs and the results presented in this paper demonstrate the same.

2 RELATED WORKS

In this section, we present some of the related works for the prediction of pneumonia, COVID-19 and some other chest related diseases.

Apostolopoulos et al., have taken a dataset comprising X-ray images from patients suffering with respiratory disorders, COVID-19, and other diseases from public repositories for the automated detection of CoronaVirus[2]. They used transfer learning with CNN, for the detection of any abnormalities in medical X-ray image datasets yielding outstanding results approximately 96%. They concluded that Deep Learning from X-ray images can successfully trace significant distinct biomarkers associated with CoronaVirus.

Narin A et al., implemented an automatic detection system as a fast different diagnosing choice to identify COVID-19 spreading among individuals[4]. During their study, they used ResNet50, Inception-ResNetV2 and InceptionV3 models based on the CNN. They used X-rays of infected patients for coronavirus respiratory disorder detection. The pre-trained ResNet50 model provided the best classification accuracy when compared with the other two models InceptionV3 and Inception-ResNetV2.

Parveen Netal., used an unsupervised classification algorithm namely fuzzy c-means for identification of Pneumonia disease in chest X-ray images [5]. Unsupervised fuzzy C-means approach was observed to give better identification results than the rest of the ways like DWT, WFT, and WPT. Abhishek Sharma et al., proposed an approach of using image processing techniques for detection of the presence of respiratory disorder clouds in chest X-rays [6]. They proposed to calculate the ratio of area of healthy respiratory organ region to total respiratory organ region to identify the presence of Pneumonia. Khan Maseeh Shuaib et al., used Convolutional Neural Networks for Pneumonia detection from X-ray images [3] and showed the classification accuracy as 84%.

3 METHODOLOGY/TECHNIQUES

The methodology used is transfer learning which is a deep learning technique. We used the GoogleNet model of transfer learning. The data set used for this is a public dataset available [9]. This data set consists 1824 chest x-ray images of both COVID-19 and normal patients, in which there are 912 x-ray images of each correspondingly.Below figures 3.1(a) and 3.1(b) shows the sample chest x-rays of both COVID-19 and normal patients. The distinct observations from X-ray images of COVID-19 infected from the other X-rays are the lower lobes, and the posterior segments, with a fundamentally peripheral and subpleural distribution. These observations are evident in both the lungs even in the early stages.

Fig. 3.1(a). X-ray image of a normal person

Fig. 3.1(b). X-ray image of covid affected person

Deep learning models use artificial neural networks arranged in multiple layers. The layers are composed of nodes called perceptrons. A node takes inputs from the information with respective coefficients or weights that amplify or dampen the inputs, thereby distributing amplified/dampened inputs to output nodes. The structure of the network and nodes in the network can be varied with reference to the task.

A Convolutional Neural Network (CNN) a type of artificial neural network operates on the principle of convolution. It consists of an input layer, followed by multiple hidden convolution layers. These convolution layers *convolve* the input matrix with a kernel or filter. Convolution operation can be described by overlapping the filter on the input layer and a dot product of two . The result of convolution is fed to the activation function to perform nonlinear transformation. Then it is fed to additional convolution layers or pooling layers to reduce the size, if required fully connected layers and normalization layers. All these layers are referred to as hidden because they reside in between input and output layers and are not visible to the external systems.

3.1 GoogleNet Architecture

GoogLeNet is the one of the CNN architecture used for image classification. It is also named inceptionV1. GoogLeNet was first proposed by google research group in 2014 [8]. They demonstrated the usefulness of Deeper Convolution networks. GoogLeNet model is the winner of the large scale visual recognition challenge by Google in 2014. It attained a top-5 error rate of 6.67%. It's error rate is less compared to AlexNet proposed in 2012, ZF-Net in 2013 and VGG in 2014. This has performance very nearer to human level performance and is the reason why we have chosen GoogLeNet in this work. This model contains 22 layers deep CNN and almost 12x less parameters.

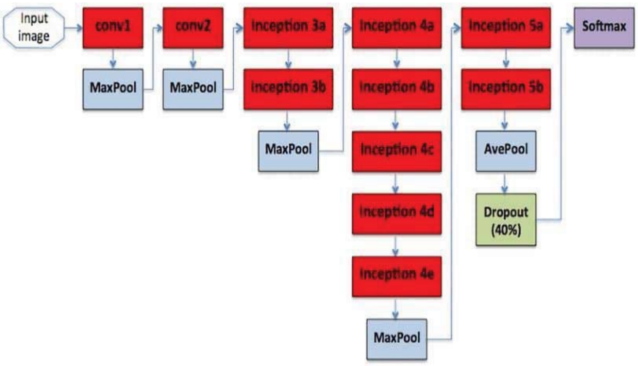

Fig. 3.2: GoogleNet Architecture

3.1.1 GoogleNet

The GoogleNet design principle is different from the AlexNet and ZF-Net networks. It uses variant strategies like 1 D convolution and average pooling layers and hence a deeper network design. Various layers used within the design are:

1×1 Convolution

The first layer uses 1×1 convolution in its design. It reduces the number of parameters like weights and biases.of each layer. The reduction of parameters can lead to an increase in the depth of the network. It exchanges few filters with a smaller perceptron layer with convolutions. In the example shown below to perform 5×5 convolution with forty eight filters, we demonstrate the difference with and without 1x1 convolution in Fig 3.3 (a) and (b)

Without using *1×1* convolution as intermediate:

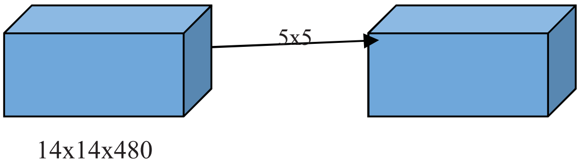

Fig. 3.3(a): Convolution without 1x1

In the case of without 1X1 convolution the total Number of operations: $(14 \times 14 \times 48) \times (5 \times 5 \times 480) = 112.9\ M$

With 1x1 convolution:

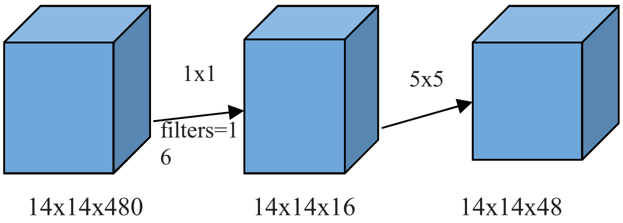

Fig. 3.3(b): Convolution with 1x1

With 1X1 convolution the total number of operations are 14 x 14 x 16 multiplied by 1 x 1 x 480 plus 14 x 14 x 48 multiplied by 5 x 5 x 16 i.e. 5.3M. we can observe that the difference is very large i.e. 107.6M.

Inception Module

The idea of the inception layer is to cover a larger area with a fine resolution for small information on that image. These modules are used for increase in computational efficiency in deep convolutional networks can be achieved through the reduction in dimensionality with stacked 1x1 convolutions as explained above. The naive inception module shown in Figure 3.4 (a), performs a convolution of an input with three different sized filters (1x1, 3x3, 5x5) and a max pooling layers and all the outputs are concatenated. These modules resolve the problem of computational cost and overfitting issues.

To reduce the computational cost in deeper networks, a modified and quite different architecture of the inception layer is shown in Fig 3.4 (b). The number of input channels can be limited by adding an extra 1x1 convolution before the 3x3 and 5x5 convolution layers and max pool layer. Though it seems adding an extra 1x1 convolution operation is counter intuitive, it helps to reduce the number of parameters and is computationally cheaper. Here the result of parallel operations *1×1, 3×3, 5×5* convolution and *3×3* max pooling are concatenated to produce output. The convolution filters of different sizes help to extract object features at multiple scales and hence perform better.

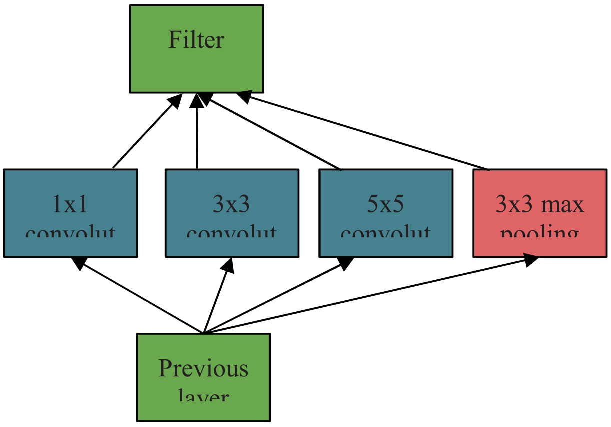

Fig. 3.4(a): Inception module, naive version

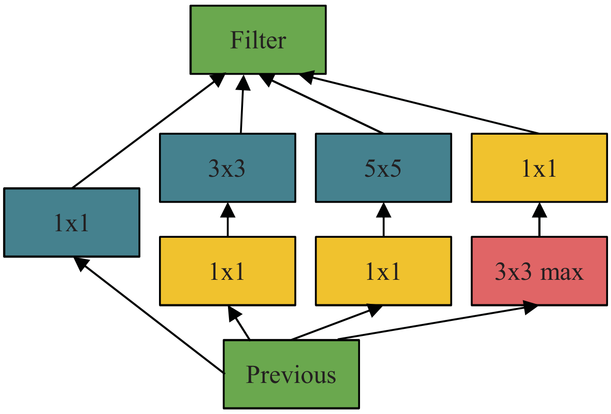

Fig3.4(b): Inception module with dimension reductions

The Googlenet architecture is 22 layers deep as shown in Fig 3.2. This architecture was designed keeping computational efficiency into account and can be run on devices with less computational resources.The above googlenet architecture is used for the prediction of COVID-19 that is whether the person was infected with coronavirus or not. It takes a chest X-Ray image as input and the image is passed to several convolution layers with different filters, pooling layers and fully connected layers(FC). In the output layer softmax function is applied as it is binary classification and binary cross entropy for the performance evaluation.

4 ALGORITHM

Inception net attained a milestone in CNN classifiers when earlier models were just going deeper to improve the performance and accuracy but negotiating the computational cost. The Inception network, on the other hand, is highly engineered. It uses more tricks to impulse performance, both in terms of speed and accuracy. It has shown significant performance improvement over AlexNet, ZFNet , and VGGNet. The Googlenet is implemented for binary classification i.e. classification of two classes COVID-19 chest X-ray images and non COVID-19 images.

- The dataset consists of chest X-ray images of both COVID-19 patients and non COVID-19 patients and all these images are preprocessed into an array of some default shape.
- We classify the dataset set in the ratio 7:3 for training and testing dataset. We need to give more prior to the training than the testing.
- Our Googlenet model consists of inception modules embedded into convolutional neural networks to reduce computational cost and perform convolution on an input with different sized filters and hence extracts different features.
- And pooling is performed to accumulate features from maps generated by convolving a filter over an image. This pooling is used to reduce the parameters and computation in the network.
- Our model contains several inception layers and the resulting output of every inception layer is concatenated and passed to the next layer.
- After the completion of successive inception modules, the global average pooling is performed which minimizes the overfitting as it reduces the number of parameters in the model.
- The next layer is the Dropout layer. The dropout technique used for over-fit reduction in neural networks.
- The final layer is the dense layer or fully connected layer that connects all outputs from the previous layer to all neurons in the output layer and each neuron provides an output. Our COVID-19 prediction model consists of a dense layer with 2 neurons.

5 EXPERIMENTAL RESULTS

We trained our model for COVID detection using Googlenet with the dataset divided as 70% training data and 30% testing data. The images of the dataset are resized to (224,224). Our model consists of overall 5975602 trainable parameters. After training the model we got training accuracy of 99% and validation accuracy of 98%. We have noted some hyperparameter values during the training process which are useful for the better performance of the model.

Epochs	Test size	Batch size	Initial learnin g rate	Training Accuracy	Validation Accuracy
10	0.3	32	0.01	51	49
20	0.3	32	0.01	96	93
25	0.3	32	0.01	97	96.5
30	0.3	32	0.01	98	98
40	0.3	32	0.01	98	97.5
50	0.3	32	0.01	98	96

Table.5.1: Hyperparameter values

The hyperparameters such as learning rate, loss weights. All these values are tuned in order to improve the performance of our model. By tuning these values at last we have attained 98% accuracy of training accuracy with good performance measures Precision 1.00 and Recall 0.97.Figure 5.1 shows the confusion matrix obtained for the test set, which describes the performance of our classification model.From this confusion matrix the performance measures like Precision, Recall and Accuracy are evaluated as shown below.

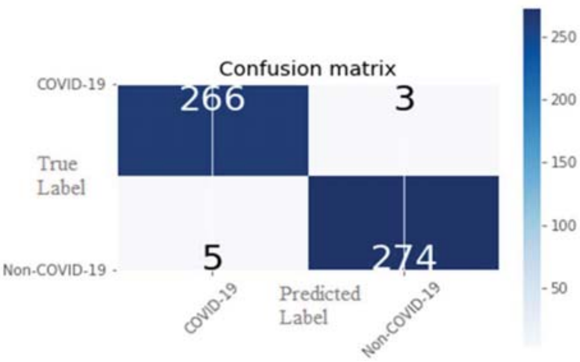

Fig. 5.1: Confusion Matrix for the test set

- Recall = (TN)/(TN+FN)

  = (266)/(266+5)

  = 0.9815

- Precision = (TP)/(FP+TP)

  = (274)/(3+274)

  = 0.9891

- Accuracy=2*(Precision*Recall)/(Precision+Recall)

  = 2*(0.9815*0.9891)/(0.9815+0.9891)

  = 0.9852

Figures 5.2 shows the plots of training and validation(test) accuracy and loss as the number of epochs varies. From the graph we can observe that the difference between training and validation(test) accuracy is very minimal after 30 epochs. The loss difference is more after the 30th epoch .We can simply observe from the Fig:5.2 that there is increment in loss after the 30th epoch. So in order to avoid overfitting and in order to avoid the increment in loss ,the number of epochs for this model can be optimally selected as 30.

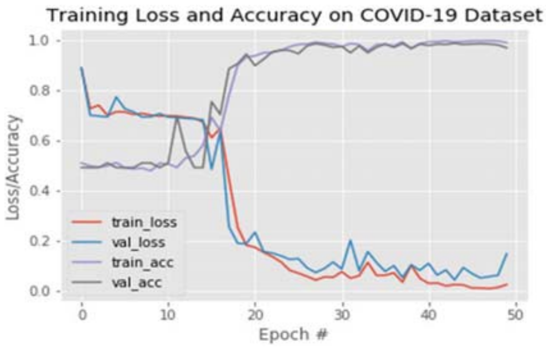

Fig. 5.2: Graph of Training and Validation Accuracy & Training and Validation Loss

6 Conclusion

In this paper, a methodology for using Googlenet to predict COVID-19 infected cases from patient chest X-ray images is presented. We demonstrated how transfer learning can be effectively used for novel COVID-19 prediction. This model can be used for rapid and reliable diagnosis of COVID-19 from patients' chest X-rays. Our trained model was able to obtain a training accuracy of 99% and testing accuracy of 98.5%. This automatic COVID-19 prediction system can be used by primary health workers in remote places where the experienced practitioners are not available. This work can further be extended for building a large dataset of X-rays of COVID and non COVID patients suffering with other Pneumonia diseases to further improve specificity and sensitivity further. The system can be integrated with the Internet of Things (IOT) to further assist the medical practitioners as it has been spreading at a faster rate and till now its vaccine has not been discovered.

7 REFERENCES

[1]https://www.who.int/emergencies/diseases/novel-coronavi rus-2019/question-and-answers-hub/q-a-detail/q-a-coronaviruses

[2] Apostolopoulos ID, Mpesiana TA., "*COVID-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks*". Physical and Engineering Sciences in Medicine. 2020 Apr 6:1.

[3] Khan Maseeh Shuaib , Solkar Ahmed Shahid , Ansari Almas Javed , Mohammed Zaid., "*Pneumonia Detection through X-Ray Using Deep Learning* ", IOSR Journal of Computer Engineering (IOSR-JCE) e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 22, Issue 1, PP 08-11.

[4]Narin A, Kaya C, Pamuk Z. *"Automatic detection of coronavirus disease (COVID-19) using x-ray images and deep convolutional neural networks*", arXiv preprint arXiv:2003.10849. 2020 Mar 24.

[5]Parveen N, Sathik MM. "*Detection of pneumonia in chest X-ray images".* Journal of X-ray Science and Technology. 2011 Jan 1;19(4):423-8.

[6] Abhishek Sharma, Daniel Raju, Sutapa Ranjan, "*Detection of pneumonia clouds in chest X-ray using image processing approach*", Nirma University International Conference on Engineering , 2017.

[7]Ranjan, Rajesh. (2020). "*Predictions for COVID-19 outbreak in India using Epidemiological models",*10.1101/2020.04.02.20051466.

[8]. Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich*," Going Deeper with Convolutions",2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, 2015, pp. 1-9.*

[9].https://md-datasets-public-files-prod.s3.eu-west-1.amazonaws.com/bc9f750d-b663-48a7-844e-4e8246751706