

DETECTION AND ANALYSIS OF COVID-19 X-RAY DATA USING TRANSFER LEARNING

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Abstract -For this research X-ray image dataset have been used from the patients with Covid19, bacterial pneumonia diseases, and Normal incidents to detect the Covid-19 disease automatically. The research focuses to out beat the performance of pioneering architectures like (CNN)Convolutional Neural Network which are made in modern years for image classification. Importantly, Transfer Learning architecture was utilized. Various anomaly detection is an achievable goal in small medical image datasets using transfer learning, often leads to exceptional results. The datasets were gathered from open sources medical repositories which are available online. The outcomes specify that combining Transfer Learning with X-ray imaging can excerpt substantial biomarkers related to the Covid-19 disease. As we used three algorithms which are VGG16, Resnet50, Convolutional Layer which provides best accuracy obtained being 96.78%, 98.66%, and 96.46%, respectively. Meanwhile all the previous analytic tests now have such high failure rates that they cause concern, the possibility of incorporating X-rays into the diagnostic process has increased.

Key Words: COVID-19, Pneumonia, X-ray, Transfer Learning, Coronavirus.

1.INTRODUCTION (Size 11, Times New roman)

SARS-CoV-2 caused the most threatening and deadly virus known as COVID-19. On 31st December 2019 in Wuhan covid first case was reported. On 11th March 2020 COVID-19 pandemic was declared by the WHO (World Health Organization). There have been 476,374,234 confirmed COVID-19 cases are reported as of 25th March 2022, counting approx of 6,108,976 deaths, and it has almost spread to every country since its first case was reported. There are several stages in treating COVID19 patients, the first one being screening patients at primary health care facilities with polymerase chain reaction (PCR) tests being used for final diagnosis. In severe cases, hospitals use medical Screening/imaging as it is quick and straightforward, giving doctors enough time to identify the effects of the disease. Patients with COVID-19 must undergo an X-ray session, and if needed, they need to have a CT scan. X-rays and Computer Topography (CT) are used as an alternative measure to detect the virus. To diagnose, X-rays and CT scans of the lungs are used to see the effect of the virus on the patient's lungs. The virus is readily transmissible has burdened the health

infrastructure worldwide, due to which there is a shortage of health workers that can be solved using deep learning methods. These deep learning models have made a lot of progress in recent years because of the increase in computing power and the data available to improve the model's performance and efficiency. Medical Imagery requires a lot of effort and expertise. There is still a lot of room for improvement as we have several algorithms which can improve the accuracy and render the images more quickly. Doctors encounter patients with pneumonia caused by flu, virus, and COVID-19 virus at the same time. So there is an immediate need to have accurate detection and distinguish between different types of pneumonia.

2. LITERATURE REVIEW:

CNN (convolutional neural network) is the most favored method among the other research. Research which are diagnosed with covid-19 using X-ray images of chest have multiple or binary classification. Where some of them use raw data and other use feature extraction process. Jaiswal et al.research uses a model which was based on deep transfer learning his proposed model is DenseNet201 which classifies the whether patients are Covid-19 infected or not.[5]. Apostolopoulos and Bessiana discuss how they used evolutionary neural network, common pneumonia and an covid-19 infected pneumonia for detection of covid-19 automatically. Specifically, they used transfer learning techniques which makes easy to detect the various abnormalities in several minor medical image datasets with extraordinary results.[6]. Zhang et al. research uses chest X-ray images, his model detects the infected covid19 with high sensitivity, providing quick and reliable scanning using his proposed deep learning model [7]. Singh et al.examined the chest CT scan(computed tomography) images which contains both the classes infected and non-infected covid-19 patients using his proposed model MODE(multi – objective differential evolution) which is based in CNN[8]. Alqudah et al discuss how they used two different methods using Chest X-ray images to diagnose COVID-19. The first method was AOCTNET, ShuffleNet, MobileNet CNNs. The second method was to removing features of the images and classifying using SVM(support vector machine),random forest, and finally KNN algorithms[9]. Hemdan et al. discuss about his work where it uses DenseNet and VGG19 models to detect covid- 19 from X-ray images [11] Ghoshal and Tucker. proposed a way to diagnose Covid-19 using their model which was based on drop weights-based Bayesian CNN model [10]. Sahinbas and Catak discuss how they developed and worked on the pre-defined models for the diagnosis of COVID-19.

The models which are used in their research ResNet, Vgg16, Vgg19, Inception V3 and DenseNet [12]. Medhi et al. uses feature extraction process and segmentation on X-ray images in their research and then detection of COVID-19 was classified using CNN [13].

3. OVERVIEW OF TECHNOLOGIES:

This research is based on implementing various deep transfer learning techniques to test the accuracy of the algorithms, record output, and provide an output based on probability using the SOFTMAX function. We train our dataset before implementing any of these techniques or Algorithms. For COVID-19 X-ray image binary classification, we used two pre-trained CNN models: VGG16, ResNet50, and Two-layered CNN. Applications that require large arrays/objects to be stored in memory will require more RAM, whereas those that require multiple estimates or tasks to be completed quickly will require a powerful processors. Libraries Used in our Project: • Matplotlib • Cv2 • ImageDataGenerator • Tensorflow

Software and hardware Requirements:

DataSets: This experiment uses two datasets—one for Training and another for Testing. First, there is a pool of 1000 x-ray images in the Training dataset, including 300 positive Covid-19 disease, 300 positive pneumonia, and 300 with normal condition. Second, for the testing dataset with 250, including 85 images of positive Covid-19 disease, 80 images of pneumonia, and 80 photos of normal conditions. In dataset all the images in the database are CRX in PNG format of size 256x256.



Fig1: Covid-19 positive



Fig2: Pneumonia positive



Fig3: Normal

The datasets were gathered from open sources medical repositories which are available online. Then these images or datasets are pre-processed which are used for training the models of CNN architecture. • OS : Windows7,8,10 • Processor : intel i3 or above • Ram : 4 gb • HDD : 250gb

Transfer Learning:

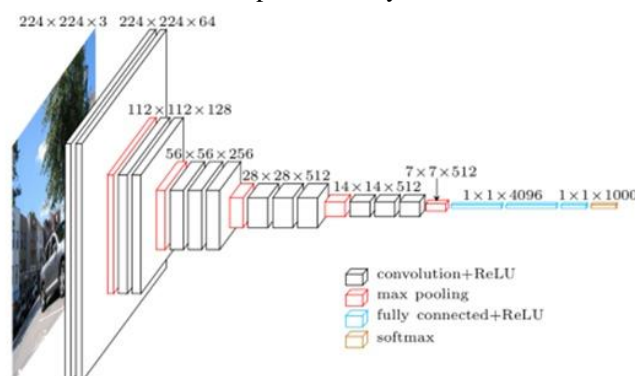
To reduce the time of training period required by deep learning algorithms we apply Transfer Learning technique using ImageNet. Data sets are made modified using model which are trained on ImageNet. Transfer Learning technique fits well to more than one data sets, So, it's make easy to the transfer learning applications to get applied on the labelled data set in the special situation. So in this work VGG16 model is trained during 15epoch of a batch size of 32. Every image is randomly modified in every epoch with help of ImageDataGenerator of keras. Learning rate of 0.001 of adam optimizer from keras. For binary classification of Transfer Learning network we used softmax classifier. For feature extraction pre trained model layers are used which are already fine tuned. Base Neural Network have been kept stationary in

Denser Layer to keep ImageNet weights safe during Training phase. Overfitting in the model can be avoided using Dropout function where its value is kept at 0.5 in the fully connected layers and to get better metrics value further model is trained.

ALGORITHMS: VGG16 ,RESNET 50 ,Custom Two Layered Convolutional Model

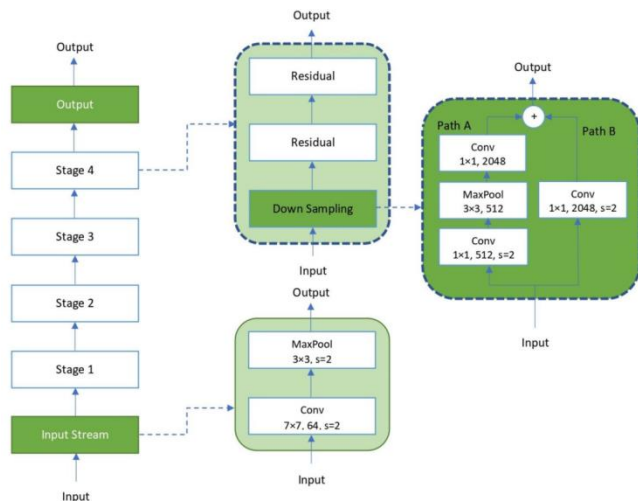
VGG-16 :

In 2014 Karen Simonyan and Andrew Zisserman from University of Oxford developed and introduced the CNN architecture VGG16. For image classification VGG16 is acknowledged as one of the best architectures. The VGG16 architecture is made up of 16 layers, from which 13 are convolutional layers where each layers consist of 3x3 filters and 2x2 max-pooling layers. Between these layer relu activation function is used. Then, there are three fully connected layers in the network which contains utmost parameters. Lastly, the probabilities for each classification of pulmonary symptoms are calculated using a softmax function. For image recognition algorithms VGG16 architecture is a successful model using CNN(Convolutional Neural Networks) as the key network. It has a distinctive network construction which is simple to modify.



RESNET 50:

The ResNet architecture is made up of an input layer, four subsequent stages, and an output layer. Each stage represents a step in the process that we are carrying out sequentially. It takes input from previous stages, runs one step of the CNN, and outputs the results. ResNet is split into five stages, the first of which can be thought of as a pre-processing of INPUT, and the last four of which are made up of a Bottleneck and have a similar form. The input stem performs a 7x7 convolution, a stride of 2, and an output channel of 64. Following that is a 3x3 max pooling layer with a stride of 2.



ResNet was the first to introduce the perception of a skip connection. The diagram below shows a skip connection. Convolution layers are piled one on top of the other in the figure on the left. Then on right the side we are stacking convolutional layers and providing novel input into the output of convolution block's. This concept is known as a skip connection.

Two Reason why Skip connection can work in this conditions: It prevents the gradient from waning by letting the flow to the second shortest path. It helps the model to learn an identity function, which ensure that higher layer performs well or perform better than the lower layer.

Since skip connections have been used in the various model architectures, including the Unet and FCN (Fully Convolutional Network). It moves the data from the model's one layers to the model's another layers. To transfer data from the downsampling layers to upsampling layers they are used in these architecture.

Custom Two Layered Convolutional Model:

Convolutional neural networks (CNNs) belong to a deep neural network category which alleviate image recognition problems. CNN works as the image is given to the computer as input and converted to a format that helps in processing. First images are converted to a matrix format. With the differences in pictures and matrix, the system assigns the image to a label. In the training stage, the images assigned to different labels are used to predict the new images. To have an efficient operation, CNN has three layers: convolution, pooling and fully connected. The first two layers are used to extract the features of the image, and classification is done in the third layer. Convolutional layer: It is the base layer of CNN. In this layer, the pattern characteristics of an image are determined. First the image is filtered, and then a feature map is made using the values obtained while filtering. This layer uses some kernels that help to extract low and high level features in the pattern. The kernel contains a three-dimensional (3D) or five-dimensional (5D) matrix converted by the input pattern matrix.. The stride parameter indicates the series of steps optimised for shifting over the input matrix. The output of a convolutional layer is:

$$x_j^l = f \left(\sum_{a=1}^N w_j^{l-1} * y_a^{l-1} + b_j^l \right)$$

Pooling layer:

The pooling layer is called after the convolutional layer. A pooling layer is typically applied to newly created feature maps to reduce the number of feature maps and network parameters by performing corresponding mathematical computations. We utilized max-pooling and global average pooling in this study. The max-pooling process chooses only the maximum value by utilizing the matrix size specified in each feature map, resulting in fewer output neurons. Before the fully connected layer, a global average pooling layer is also used to reduce data to a single dimension. Following the global average pooling layer, it is linked to the fully connected layer. The dropout layer is another intermediate layer that is used. This layer's primary function is to prevent network overfitting and divergence.

Fully connected layer:

CNN's single most important layer is the fully connected layer. This layer works the same way as a multilayer perceptron. Rectified linear unit (ReLU) activation function is usually used on the fully connected layer. In contrast, the softmax activation function is being used to predict output images in the fully connected layer's last layer. The following is the mathematical evaluation of these two activation functions:

$$\text{ReLU}(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{if } x \geq 0 \end{cases}$$

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{y=1}^m e^{x_y}}$$

x_i and m refer to the number of classes and input data, respectively. Neurons in a fully connected layer have complete access to all activation functions in the preceding layer.

Table -1: Evaluation Metrics:

The performance of these various approaches discussed in this paper are evaluated using various performance measures based on a confusion matrix comprising TP (True Positives), FP (False Positives), FN (False Negatives), TN (True Negatives) as shown in the below table.

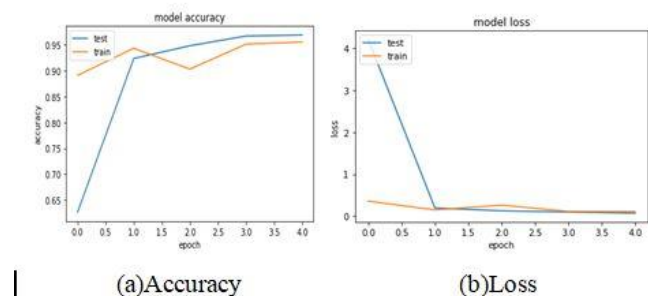
		Actual Class	
		Positive	Negative
	Positive	TP	FP
	Negative	FN	TN

Accuracy: It is defined as total number of correct predictions predicted by the model.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

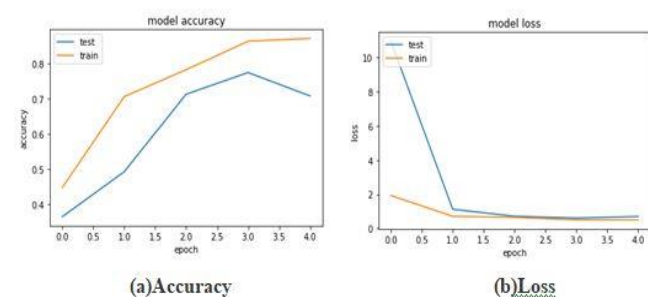
Experimental Results:

We used three binary classification on 3 classes (Covid-19, Bacterial pneumonia, normal). Below figures depicts the accuracy values of all the three binary classification (VGG16, Resnet50, Custom two layered convolutional)



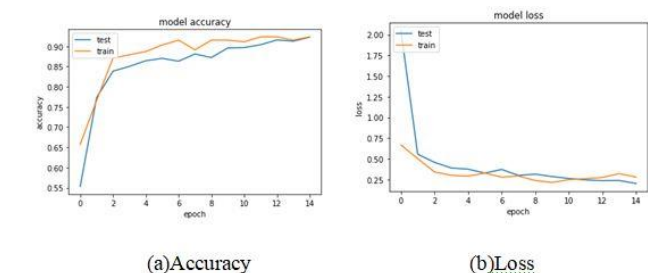
(a)Accuracy (b)Loss
Model VGG16 For COVID-19

Above diagram shows the results of VGG16 Model for the classification of COVID-19, We see that the result accuracy of VGG16 model is very high and accurate with the score of 96%.

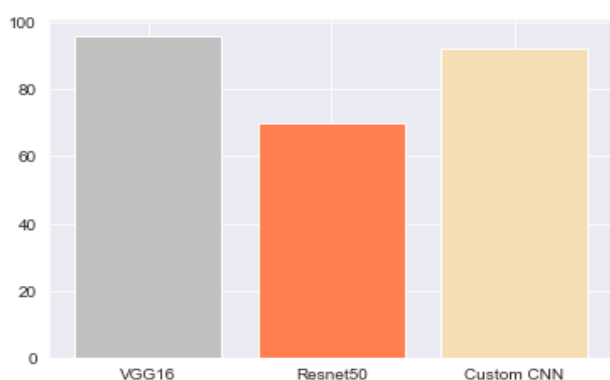


(a)Accuracy (b)Loss
Model RESENET50 For COVID19

Above diagram shows the results of RESNET50 Model for the classification of COVID-19, We see that the result accuracy of RESNET50 model is low and accurate with the score of 70%.



(a)Accuracy (b)Loss
Custom 2 Layer ConV For Covid-19



Above diagram shows the results of Custom 2 Layer ConV Model for the classification of COVID-19, We see that the result accuracy of Convolutional layer model is very high and accurate with the score of 92%.

Below bar graph depicts the overall comparison accuracy values of three binary

3. CONCLUSIONS

During the beginning of pandemic it was very hard to predict and detect COVID-19 patients. In this study, we used a deep transfer learning technique using Chest X-ray images which are obtained from patient who are infected with COVID-19, bacterial pneumonia and those who are normal. Vgg16 model yielded the highest accuracy amongst the three models. We believe that it will help the radiologist in clinical practice because of higher performance. To detect the COVID-19 during an early stage, this work gives perception to know how deep transfer learning can be used. In the future, we can use some better and more efficient binary classification models such as VGG19, Inception V3, Etc. These models can help us improve the network performance compared to the present performance. Our future work would include implementing covid-19 detection using X-ray/CT-scan in a live site.

REFERENCES

- [1]. Ali Narin, Ceren Kaya, Ziyne Pamuk, Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional networks (2021).
- [2]. Roosa K, Lee Y, Luo R, Kirpich A, Rothenberg R, Hyman JM et al (2020) Realtime forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. Infect Dis Model 5:256–263
- [3]. Yan L, Zhang H-T, Xiao Y, Wang M, Sun C, Liang J et al (2020) Prediction of criticality in patients with severe COVID-19 infection using three clinical features: a machine learning-based prognostic model with clinical data in Wuhan. medRxiv 2020.02.27.20028027
- [4]. Stoecklin SB, Rolland P, Silue Y, Mailles A, Campese C, Simondon A et al (2020) First cases of coronavirus disease 2019 (COVID-19) in France: surveillance, investigations and control measures, January 2020. Eurosurveillance 25(6):2000094
- [5]. Jaiswal A, Gianchandani N, Singh D, Kumar V, Kaur M (2020) Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning. J Biomol Struct Dyn. <https://doi.org/10.1080/07391102.2020.1788642>
- [6]. Apostolopoulos ID, Mpesiana TA (2020) Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Phys Eng Sci Med 43:635–640
- [7]. Zhang J, Xie Y, Li Y, Shen C, Xia Y (2020) COVID-19 screening on chest X-ray images using deep learning based anomaly detection. arXiv:2003.12338v1
- [8]. Singh D, Kumar V, Kaur M (2020) Classification of COVID-19 patients from chest CT images using multi-objective differential evolution-based convolutional 37 neural networks. Eur J Clin Microbiol Infect Dis 39:1379–1389. <https://doi.org/10.1007/s10096-020-03901-z>
- [9]. Alqudah AM, Qazan S, Alqudah A (2020) Automated systems for detection of COVID-19 using chest X-ray images

and lightweight convolutional neural networks.
<https://doi.org/10.21203/rs.3.rs-24305/v1>

[10]. Ghoshal B, Tucker A (2020) Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection. arXiv:2003.10769v

[11]. Hemdan EED, Shouman MA, Karar ME (2020) COVIDX-Net: a framework of deep learning classifiers to diagnose COVID-19 in X-ray images. arXiv:2003.11055 [12].

Sahinbas K, Catak FO (2020) Transfer learning based convolutional neural network for COVID-19 detection with X-ray images.

<https://www.ozgurcatak.org/files/papers/covid19-deep-learning.pdf>

[13]. Jamil M, Hussain I (2020) Automatic detection of COVID-19 infection from chest X-ray using deep learning. medRxiv. <https://doi.org/10.1101/2020.05.10.20097063>.