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Improved Convolution Neural Network For Detecting Covid-19 From X-Ray Images

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Abstract: Coronavirus disease 2019 (COVID-19) is a communicable disease caused by coronavirus 2 (SARS-CoV-2), a severe acute respiratory syndrome. It was first identified in Wuhan, Hubei, China in December 2019 and has contributed to a continuing pandemic. As of early July 2020, more than 10.6 million cases throughout 188 countries around the world were identified culminating in much more than 516,000 deaths. To prevent COVID-19 from spreading among people, an automated detection system needs to be introduced as a fast-alternative diagnosis method. Machine learning algorithms based on radiographic images can be used as mechanism to support decision taking and help radiologists speed up the diagnostic process. This work introduces a new paradigm for automatic detection of COVID-19 using raw X-ray images in the chest. The proposed model with 4 Convolutional Layers, 2 Max Pooling Layers and Drop Outs, is designed to provide reliable diagnostics for binary (COVID vs. No-Findings) and multi-class (COVID vs. No-Findings vs. Pneumonia) diagnosis. Our model provided gives 98.9% Binary Classification accuracy and 85% Multi Classification accuracy.

Keywords: Convolutional Neural Networks, COVID – 19, Deep Learning, Binary Classification, Multi Class Classification

1. INTRODUCTION

The COVID-19 pandemic, also known as the coronavirus pandemic, is a continuing global pandemic (COVID‑19), caused by extreme acute respiratory coronavirus syndrome 2 (SARS‑CoV‑2). The outbreak was first detected in December 2019, in Wuhan, China. The epidemic was declared a Public Health Emergency of International Concern by the World Health Organization(WHO) on 30 January 2020 and a pandemic on 11 March. As of early July 2020, more than 10.6 million cases of COVID-19 were registered in more than 188 countries and territories, resulting in more than 516,000 deaths; more than 5.48 million people recovered.

During close contact the virus is primarily transmitted among people, most often through small droplets formed by coughing, sneezing, and talking. The droplets normally fall onto the ground or surfaces instead of moving long distances through air[1]. Research has shown, however, that speech-generated droplets can remain airborne for tens of minutes as from June 2020.More commonly, people may become infected by touching a contaminated surface and then touching their face. It is most infectious within the first three days after the onset of symptoms, but it is possible to spread before symptoms arise and from individuals who do not display symptoms.

Common symptoms include fever, cough, tiredness, shortness of breath, and odour loss. Pneumonia and acute respiratory distress syndrome could also be complications. Usually, the time from exposure to onset of symptoms is about five days but can vary between two and fourteen days. There is no known vaccine or antiviral therapy unique to it. Treatment generally is symptomatic and supportive therapy.

Effective prevention measures include hand washing, covering one's mouth while coughing, keeping distance from other people, wearing a face mask in public settings, and screening and self-isolation for those suspecting that they are sick. Worldwide authorities have responded by enforcing travel bans, lockdowns, danger controls at the workplace and closures of facilities. Some places have also worked to improve the monitoring ability and track contaminated persons connections.

The pandemic has brought about global economic and social turmoil, including the biggest global recession since the Great Depression. This has resulted in the postponement or cancelation of sporting, religious, financial, and cultural activities, severe stock shortages caused by panic purchases, and decreased pollutant and greenhouse gas emissions. In 172 nations, schools, universities and colleges were closed either nationally or locally, affecting approximately 98.5 per cent of the world's student population. Misinformation about the virus has been spreading via mass media and social media. There were cases of xenophobia and prejudice against Chinese citizens and others perceived as being Chinese or from areas with high levels of infection.

Radiologists should be prepared to intensify the incidence of COVID-19. Since the syndrome's etiological and clinical symptoms are near those of SARS and MERS, the experience of these pulmonary syndromes is also useful in handling the emerging COVID-19 outbreak. This modelaims to familiarize radiologists with the imaging spectrum of corona-virus syndromes and discuss the features of COVID-19 reported imagery. As such, it is highly desirable and important to have computer-aided diagnostic systems that can help radiologists perceive X-ray changes which are characteristic of COVID-19 in a more time-efficient and accurate way.

2. RELATED WORK

Ali Narin, Ceren Kaya, ZiynetPamuk[2] projected some well-liked pre-trained models like ResNet50, InceptionV3, and origin ResNetV2, and these area units trained and tested on chest X-ray pictures[1]. However, it's seen that ResNet50 shows a fast coaching method than different models. Most of the pre-trained models provide high initial values, however these values area unit due to the less knowledge size. There is an area unit different coaching loss value for ResNet50, InceptionV3, and origin ResNetV2. once the loss price is analysed, it's seen that the loss values decrease in 3 pre-trained models throughout the coaching stage. ResNet50 model loss values area unit minimized quicker and approach zero.

Loannis D. Apostolopoulos and Tzani A. Mpesiana[3] have given a study to gauge the performance of varied convolutional neural networks for the medical image classification[2]. Especially, a procedure referred to as Transfer Learning is among the detection of varied abnormalities in little medical image datasets is extraordinarily crucial and to yield nice results. The outcomes conclude that VGG19 and MobileNetv2 design accuracies are the most effective classification accuracy over the remainder of CNN's. Supported the results it's incontestable that deep learning with CNNs could have important effects on the machine-driven detection and automatic extraction of essential options from X-ray pictures related to the identification of the Covid-19.

Tulin Ozturk, Muhammed Talo, Eylul Azra Yildirim, et.al.[4] have shown that the DarkCovidNet model is supposed for the machine-driven detection of COVID-19 mistreatment X-ray pictures, while not requiring any human intervention for feature extraction techniques. The developed model helps doctors in hospitals to help them as a second opinion in detective work the sickness. This may decrease the work on the doctors once creating a call regarding the sickness and assist them to make correct identification in their daily routine work. The projected model will save time and thus specialists will concentrate on a lot of essential cases. to boot, they additionally used the Grad-CAM heat map approach to visually depict selections created by the deep learning model.The areas that are emphasized by the model on the X-ray are highlighted through this heatmap.

Taban Majeed, Rasber Rashid, Dashti Ali, and Aras Asaad[5] have delineated different design CNN's like AlexNet, VGG, GoogleNet, ResNet, DenseNet, SqueezeNet, Inception-ResNetV2 which they additionally projected a simple CNN design which will shell architectures like Xception and Dense web once trained on a small low dataset of image. Hereby, category activation mappings area unit used and classified into positive or negative categories, finally, scores area unit expected. pictures contain multiple examples wherever texts, medical device traces on X-rays are going to be used by CNNs that stop them from learning the actual options of the sickness. pictures area unit classified as a microorganism, COVID-19, and viral, the model is checked with all the delineated architectures equally because of the engineered CNN model.

2.1. About CNN:

Artificial Neural Networks are employed in various classification tasks such as image and video recognition, recommender systems, image classification, medical image analysis, tongue processing, band financial statistic[6-8]. Different forms of Neural Networks are used for different purposes, e.g. to predict the sequence of words we use Recurrent Neural Networks more specifically an LSTM, similarly, we use Convolution Neural Network for the classification of photos. The term "convolutional neural network" indicates the network is using a mathematical method called convolution. Convolution is a linear operation of a specific nature. Convolutional networks are essentially neural networks, which use convolution in at least one of their layers instead of general matrix multiplication.

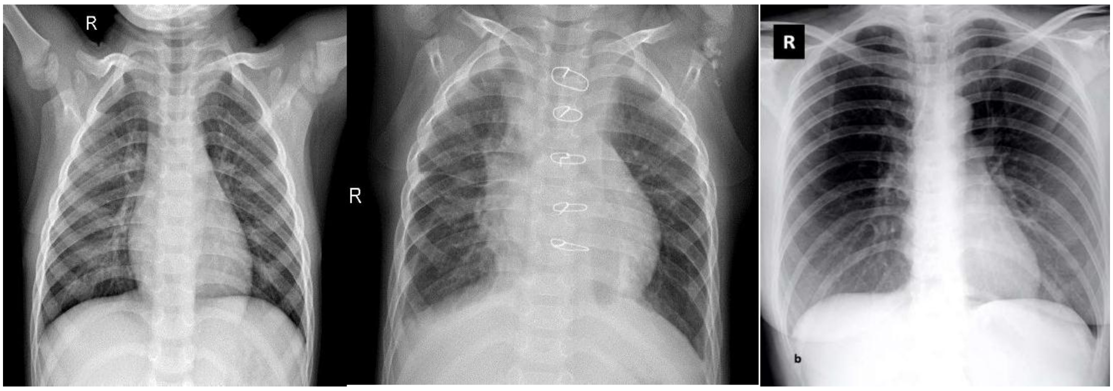
A convolutional neural network is created of an input and output layer, likewise as multiple hidden layers. Usually, the hidden layers of a CNN carry with it a series of convolutional layers which converge with multiplication or other real numbers[9]. The activation function is often a RELU layer, which is subsequently within the middle of additional convolutions like pooling layers, completely linked layers which normalization layers, named as hidden layers because the activation function and final convolution hide their inputs and outputs[10]. A convolutional neural network (CNN, or ConvNet) in deep learning is a subset of deep neural networks, most widely applied to visual image research[11-13]. These also are referred to as shift invariant or space invariant artificial neural networks (SIANN), which supported the characteristics of their shared-weights architecture and invariance translation. Multilayer perceptron are regularized variants of CNNs. Multilayer perceptron usually means networks that are completely connected, that is, each neuron in one layer is linked to all neurons in the next layer. Some networks' "absolute access" makes them vulnerable to data overfitting[14]. Typical types of regularization involve adding some type of weight-measuring magnitude to the loss function. CNN's have a different approach to regularization: using smaller and simpler patterns, they have the advantage of the hierarchical structure in data and create more complex patterns. Therefore, CNNs are at the lower end, on the scale of connectivity and complexity.

The convolutional layer is the cornerstone of a CNN building. The parameters of the layer include a series of learnable filters (or kernels), having a limited receptive field but expanding to the utmost extent of the amount of the input. The filter is translated over the width and height of the input volume during the forward transfer, computing the real between the filter entries and therefore the input, and generating a 2-dimensional activation map for that filter[15]. As a consequence, the network learns filters that enable when some particular form of feature is detected at some spatial location in the input.

3. IMPLEMENTATION

3.1 Dataset

The dataset for this study has been brought from various sources including GitHub, Kaggle, etc. The initial dataset for COVID-19 confirmed chest x rays were taken from Cohen GitHub repository. The data regarding pneumonia and normal chest x-rays were taken from the Internet. The COVID-19 dataset comprises of 359 images of confirmed COVID-19 disease affected people chest x-rays, the pneumonia dataset consists of 3800+ images and the normal chest x-rays dataset consists of 1300 images. These images are grayscale by default. Figure 1 shows some representative images. The distribution of training and testing datasets is discussed in the coming sections.



Normal Pneumonia COVID

Fig.1 Representative Images

Since the images are grayscale every value of the pixel is in between 0-255. Since to take out this large range we have performed min-max normalization on these images before starting the model training.

3.2 Proposed CNN:

In our model, the input layer consists of 784 neurons as the size of every image in the dataset is 28x28. Then we have included 4 convolutional layers, 2 Max pooling layers as the hidden layers.

These convolutional layers consist of filters of size 3x3, 5x5. The first convolutional layer consists of 256 neurons and the output shape is (26, 26, 256). The second convolutional layer consists of 128 neurons but with a kernel size of 5x5 and gives the output of size (22, 22, 128). Then, we have used the max-pooling layer and included a dropout which reduced the output layer to (11,11,128). The third convolutional layer consists of 128 neurons with a kernel size of 3x3 and the next max pooling and drop-out layers reduce the output layer size to (2,2,63). Then the final output is of size 2 denoting whether the given chest x-ray is of the normal or COVID affected person. We have used the same neural network architecture for both binary and Multiclass classification. To avoid overfitting, we have used dropouts in architecture. All the convolutional layers use the ReLu activation function. Here weights are generated using Adam Optimizer with a default learning rate of 0.001. We have implemented this model for 20 epochs with a batch size of 64.

4. RESULTS AND ANALYSIS:

4.1 Binary Classification:

With the above architecture described, we have implemented our CNN model on the COVID-19 dataset which has 300+ images of COVID classification and 1200+ images of Normal images. When we tried COVID detection in this binary classification, we have achieved an accuracy of 98.91%. We have taken a batch size of 64 and used adam optimizer by taking 6s for an epoch for 20 epochs. With the end of 20 epochs, the validation loss is less than 0.08 which means that the model is not too much overfitted. But when we tried to increase the number of epochs the model started overfitting and the validation loss began increasing. Fig.2 and Fig.3 show the results of the same.

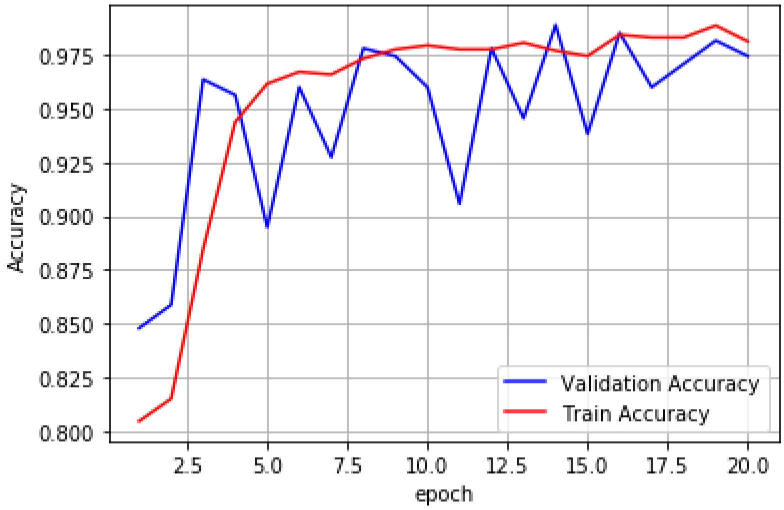


Fig.2.Validation Accuracy vs Train Accuracy for Binary Classification

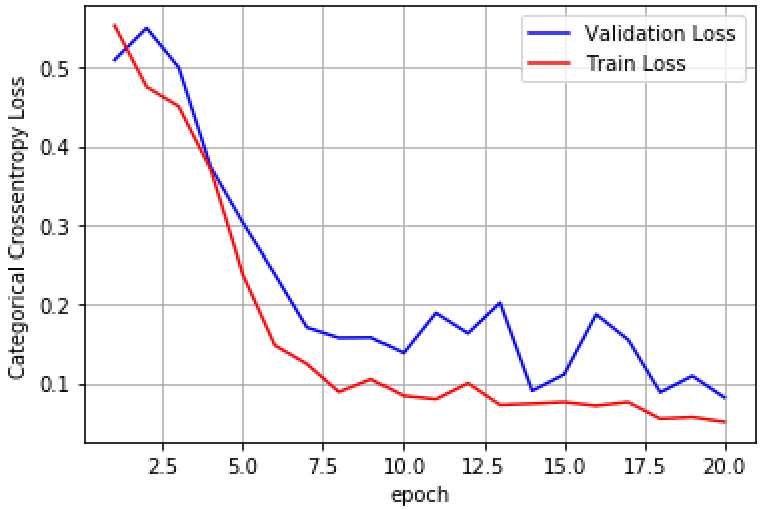


Fig.3.Validation Loss vs Train Loss for MultiClass Classification

With 20 examples of Normal chest x rays and 15 examples of COVID chest x-rays we have performed validation tests and brought the confusion matrix and the classification report. Fig.4 depicts the Confusion matrix obtained.

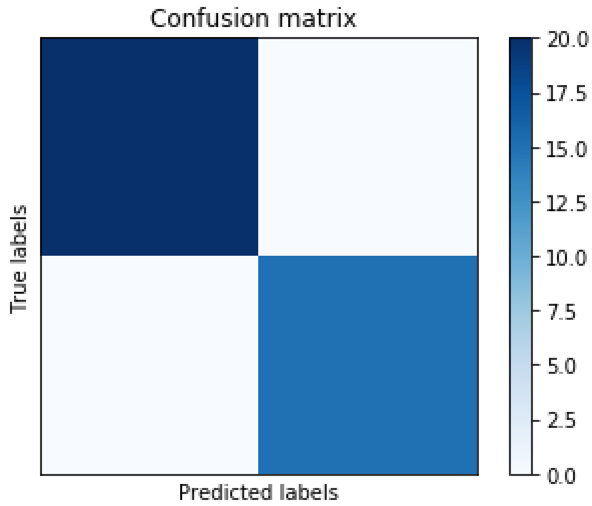


Fig.5.Confusion Matrix of Binary Classification

Table 1. Classification Report of Binary Classification

	Precision	**Recall**	**F1-score**	**support**
Normal	1.00	1.00	1.00	20
COVID	1.00	1.00	1.00	15
Accuracy			1.00	35
Macro avg	1.00	1.00	1.00	35
Weighted avg	1.00	1.00	1.00	35

4.2 MultiClass Classification (Normal vs Pneumonia vs Covid):

We have used a similar kind of our own CNN implementation which we used on Binary classification. With 3000+ examples of a new class Pneumonia adding with the previous model we have achieved 85% accuracy on this model. Here, we have tested the model for 20, 50, 100, 150 epochs and observed that the validation accuracy reaches a maximum of 85% and when we run the model for more than 50 epochs the validation loss started increasing which means the model is getting overfitted. Fig.5 and Fig.6 show the plotted graphs for the same.

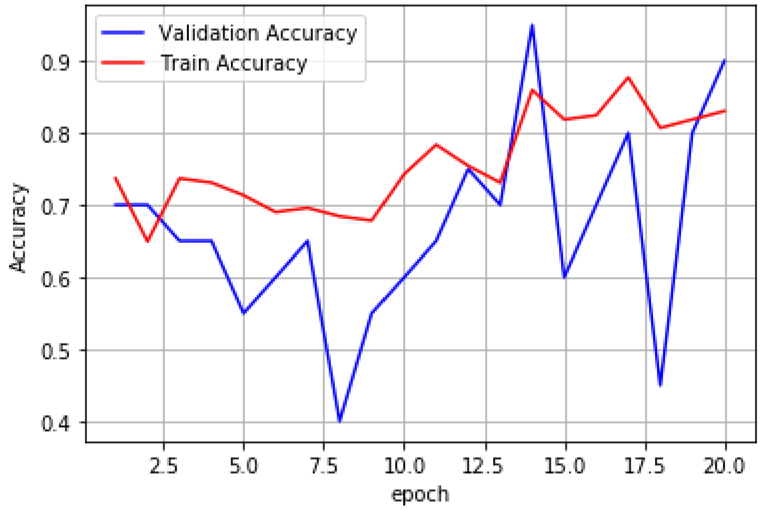


Fig.5.Validation Accuracy vs Train Accuracy for MultiClass Classification

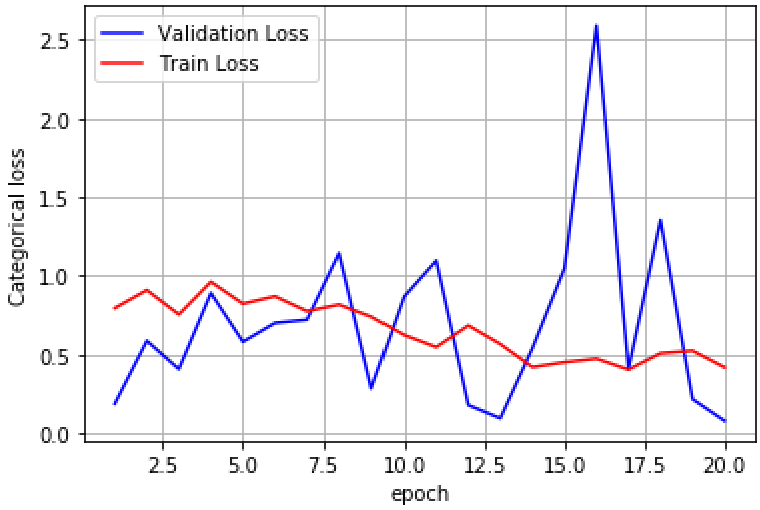


Fig.6.Validation Loss vs Train Loss for MultiClass Classification

With 20+ examples of Pneumonia, 20+ examples of Normal and 15+ examples of COVID, we have performed the validation tests and obtained accuracy, precision, score of each class through classification report. Table 2 depicts the results obtained.

Table 2. Classification Report of MultiClass Classification

	Precision	**Recall**	**F1-score**	**support**
Normal	0.90	0.95	0.92	19
Pneumonia	0.95	0.90	0.93	21
COVID	1.00	1.00	1.00	15
accuracy			0.95	55
Macro avg	0.95	0.95	0.95	55
Weighted avg	0.95	0.95	0.95	55

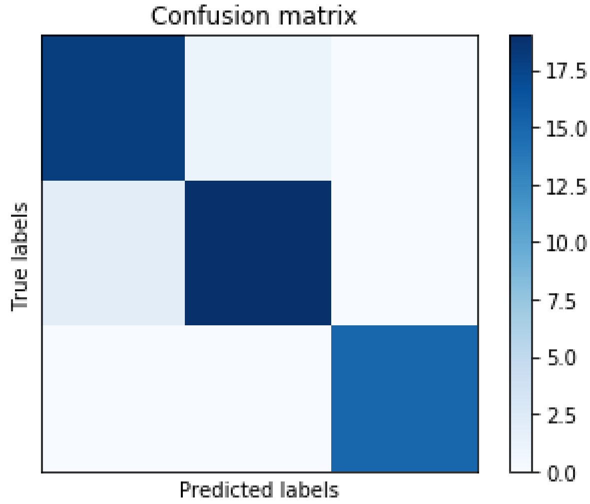


Fig.7.Confusion Matrix of MultiClass Classification

In the case of binary classification, the model predicted all the 35 samples of validation dataset in to correct classes. But in the case of MultiClass Classification, we can see that the model predicted 3-4 mistakes in between Normal and Pneumonia classes due to which we can see that a light shade of colors in regions at “Normal but classified as Pneumonia” and “ Pneumonia but classified as Normal” in the confusion matrix shown in Fig.7.

5. CONCLUSION AND FUTURE WORK

Though the medical field is not depending completing with the Deep Learning models, there is little lookup for these models, when humans are making errs or diagnosis, takes much time if done manually. But then Deep Learning models are making much impact in the research areas. There are many real-world scenarios in which Deep Learning is applicable. One such scenario is the diagnosis of diseases. In this COVID-19 diagnosis model, when a binary-class image classifier is used, that is whether the image is positive or negative for COVID-19, accuracy is 98.9%. But in some cases, the dataset with COVID-19 images have a similar resemblance to the Pneumonia images. So, some of the Pneumonia images are also combined with the previous dataset, and then the multi-class classifier came into the picture and classifies image into one of the categories of COVID-19, not COVID-19 and Pneumonia. The performance of this classifier is 81.3%. Though the accuracy is high, these models cannot directly pace up on the real cases. Sometimes this model may go wrong when a new diagnosis is done and can cost a life. For Example, in COVID-19 diagnosis when an image with similar viral cases like SARS, or with different variety of Pneumonia are given, there are chances to get a wrong prediction. Besides, Deep Learning can make an automatic prediction and can be used as a timely application. This may not be an appropriate step for direct treatment of the patients but can be useful for the initial screening of the cases. Hence the model built on CNN architecture with multi-class classification can help an easy diagnosis of the COVID-19 with an automation detection even from an image with low exposure.
This Deep Learning model with the CNN architecture can be further trained with more images. Images of different varieties of Pneumonia and viral diseases related to lungs resemble the same with COVID-19 images. There are more chances that the model gives a wrong prediction. So, a large dataset of the above variety of X-ray images is required, and then training the model with that dataset can make the model predict better. Another word can be added to this, the predicted image is labelled into one of the categories say COVID-19,

not COVID-19, Pneumonia. If the label predicted is COVID-19, then the infected area in the X-ray can be segmented. This segmented area from the X-ray helps to find out to what level the infection is spread across the lungs. According to the area of the infection, the severity of the disease can be predicted. When this is done, it is very much helpful for an immediate and proper medication corresponding to the severity of the infection. In this way, an initial diagnosis can be done using the Deep learning model easily and treat patients accordingly.

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