Covid-19 Detection from Chest Radiographs using Deep Learning

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Abstract

The Coronavirus is increasing day by day all around the world. Not only the daily life of humans but also the economy of a country is deadly affected by SARS-CoV-2 also known as Covid-19. The medical scientist showed that Covid-19 patients suffer from lung problems. Both CT scans and X-rays are being used to diagnose coronavirus but due to low cost and time, a chest x-ray is more preferable to the other. To stop spreading the virus, quick identification of affected people is one of the top priorities. For identifying a covid patient at an early stage a deep learning-based method is proposed in this paper. A supervised learning-based algorithm with Convolutional Neural Network and ReLU activation function is used to identify Covid-19 virus from chest radiography (X-ray) images. A good amount of augmentation is done upon the dataset as the dataset is not that big which helps to generate a good prediction. The initial experiments show the model performs well on average but in covid cases, it shows exemplary results. I would like to emphasize that this approach is a pre-diagnostic step that would determine if a person needs to do the traditional test or not.

1 Introduction

The novel coronavirus is also known as Covid19 is a pandemic that originated in the Wuhan province of China in November 2019. Since then, it is spreading across the globe and taking its toll on human life. The death rate in many countries is still rising. It is caused by SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) and some of the main symptoms are tiredness, dry cough, fever, headache, loss of taste or smell, difficulty breathing or shortness of breath, chest pain and so on [1]. In some other cases, patients show no symptoms at all which is known as asymptomatic.

The number of affected people is still on the rise even after 1.5 years of its origin. Still, today scientists of many countries are trying to invent different kinds of technology to minimize the spread and effect of this virus. Identification of this disease starts with either a viral test or antibody test [2]. In viral test specimens from the human body namely saliva from the nose are taken via a test kit to detect if the person is currently infected with Covid-19 or not. Moreover, in many developing and underdeveloped countries, the number of test kits is not enough to test all the patients with little to no symptoms. In that case, a rapid diagnosis can be done using a chest X-ray or CT scan [3]. Using X-rays has its advantages over CT scan and some of them are,

1.X-Ray imaging is very popular with mass people and it is easier and cost-efficient than the conventional diagnostic system and CT-scan.

2. In the digital world transportation of digital images such as X-ray images is much more convenient.

3. For CT scan big arrangement is needed as there is no portable CT scan machine available to date but for X-ray, there are lots of mobile X-ray machines. So, the arrangement and manpower are needed much less in this sector.

Many researchers are focusing on deep learning techniques to extract certain features from chest x-ray images of COVID-19 patients for analyzing and determining the virus more accurately. For the last few decades, deep learning has gained popularity in various visual identification tasks and medical image analyzing is one of them. Deep learning has changed the perception of disease diagnosis by automatically accurately identifying, analyzing and classifying hidden patterns in images.

2 Related Work

The Chest X-ray detection method is not just used for covid-19 detection, long ago many researchers did pneumonia and other diseases that affect lung detection using the chest X-ray. Rajpurkar et al. [4] achieved an exceptional result overtaking the radiologist's performance in their ChexNet model which is one of the deep neural network models that detect and classify Pneumonia from a chest X-ray image. Another similar approach was made by Wang et al. [5] called ChestNet, which is also a deep neural network-based model designed to diagnose thorax diseases using chest radiography images.

For Covid-19 detection, Ozturk et al. [6] proposed a deep neural network-based model called DarkNet named "Automated Detection of COVID-19 Cases Using Deep Neural Networks with X-ray Images" for detecting two types of classes, binary class and multi-class. In their model, they used Convolutional Neural Network with 17 hidden layers in between and for activation, Leaky RelU was used. Their model achieved high accuracy at 98.08% for binary classes (first class) and 87.02% for multi-class cases (second class). Though the DarkNet achieves a high score, it uses a relatively small dataset. AM et al. [7] proposed a hybrid system using artificial intelligence in their "Automated Systems for Detection of COVID-19 using Chest X-ray Images and Lightweight Convolutional Neural Networks". They used Convolutional Neural Network (CNN) using SoftMax classifier for detecting covid or non-covid x-rays. Sethy et al. [8] gathered the features from different pre-trained CNN models using chest X-ray images on **"**Detection of Coronavirus Disease (COVID-19) based on Deep Features"**.** They used the ResNet50 along with the Support Vector Machine classifier to build the model and achieved one of the highest accuracies of 95.38% using a very small dataset containing only 50 samples (25 normal and 25 COVID-19 cases).

Hemdan et al. [9] proposed a model named COVIDX-Net based on seven different architectures of Deep Convolutional Neural Network; namely VGG19, DenseNet201 [10], InceptionV3, ResNetV2, InceptionResNetV2, Xception, and MobileNetV2 [11] in "COVIDXNet: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images" All these combinations of models were trained and tested on COVID-19 dataset provided by Cohen et al. [12] on 'COVID-19 Image Data Collection'. They found the best model which is the combination of VGG19 and DenseNet201 resulted in an F1-score of 0.91 for COVID-19 cases.

Wu et al. [13] used the largest dataset that contains 144,167 images from 750 patients including 400 COVID patients. As deep-learning models are data-hungry and work better with large datasets, this surely provides a more realistic and clinically relevant performance. With this huge dataset, the classifier achieves a sensitivity of 95% and a specificity of 93%.

3 Preliminaries

3.1 Network Structure

The whole method's structure can be dived into three parts: Dataset, Model and Evaluation Metrics. These three are the backbone of the whole project.

3.1.1 Dataset

The dataset used in this model is collected from Kaggle [14], which contains a total of 6432 x-ray images that are subdivided into test and train datasets. This comparative big dataset provides various research paths about detecting the Covid-19 virus in various computer vision ways. The whole dataset contains x-rays of three classes, Normal, Pneumonia and Covid-19 and the distribution can be seen in table 1.

Class	Train	Test
Normal	1266	317
Pneumonia	3416	855
Covid-19	460	116

Table 1: Classes and Number of Training and Testing Dataset

From the table, we can see that there are very few covid images than the other two classes. This distribution can work in our favour as it can differentiate covid-19 images better.

3.1.2 Model

The deep neural-based model contains different kinds of layers and functions such as a convolutional layer, fully connected layers, max-pooling and so on. A brief overview of these functions are given below,

- Convolutional Layer works as a filter that strides through the whole input image and generates a feature map. The height and weight of the filters are smaller than the input image.
- Dense Layer or Fully connected layers are those neural layers where each neuron or node gets the input from all the neurons of the previous layer (flatten). Here, all the nodes are fully connected.
- Max pooling is the way of taking the maximum value from the patch of the feature map where the max-pooling kernel is set.
- Adam optimizer is an adaptive learning method. It computes individual learning rates for different parameters.
- Early Stop Function: Early stop function is usually used to set a limit on the training of the model to prevent overfitting. It checks the validation loss in every epoch and compares the value with the previous validation loss. If the value is lower than the previous value the models continue to iterate but if the loss value is higher than the previous loss function in six consecutive terms it stops the model from further epoch.
- Activation function:

  1.Rectified Linear Unit (ReLU) is used as the activation function for all the convolutional layers and the first two Dense layers in this model.

  The purpose of the ReLU is to give non-linearity to the model. It set all the negative values to zero and preserves only positive values. This function helps to reduce unnecessary noises from the data.

  2. Soft Max activation function is used for the last dense layer in this model. The function is used when the output value is needed to be normalized. It converts the inputs from weighted sum values into probabilities that range from zero to one.

The flow diagram of the model is shown in Figure 1.

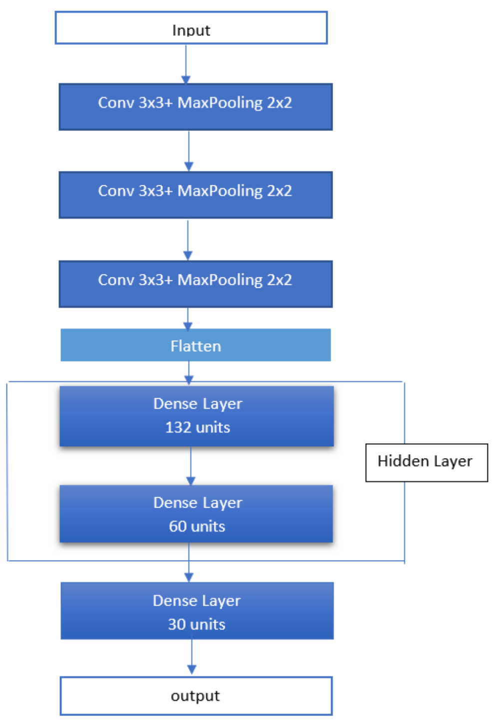

Figure 1: Flow chart of the model

There are three convolutional layers based on 3x3 filters with 2x2 maximum pooling. They are followed by 2 hidden and dense layers of 130 and 60 neurons, and finally the same 30 neuron SoftMax layer to compute the probabilities.

3.1.3 Evaluation Metrics

The proposed model is evaluated using Precession, Recall and F1 score.

- Precision: Precision can be defined as the percentage of the detection of true positive among all the predictions (false positive+ true positive). The equation [15] can be given as,

$$\frac{True\ Positive}{True\ Positive + False\ Positive}$$

- Recall: Also known as sensitivity. A model can find all the relevant cases. The equation [15],

$$\frac{True\ Positive}{True\ Positive + False\ Negative}$$

- F1 Score: The F1 score is the harmonic mean of the previous two (precision and recall) and can be shown as [16],

$$2 * \frac{Precesion * Recall}{Precesion + Recall}$$

3.2 Training Process

The training process can be divided into two major steps, data pre-processing and training the model. The whole process takes approximately 4.15 hours of which the maximum time is taken for the training process.

3.2.1. Data Pre-processing

As the images in the dataset are not consistent in the dimension size, this data pre-processing step reshaped them to be a consistent size.

Pneumonia class is the biggest class in the dataset both in training and testing, so pneumonia for the training set is used for determining the average dimension. It can be seen from the Figure 2 that different image has different dimension, starting roughly from 250 and end in 2000+ for x dimension. Thus, the average dimension for both x and y-axis- is quite high and it would take a long time to train the model perfectly. Reshaping images into a dimension of (128,128,3) will reduce the training time a lot but efficiency will decrease a lot. A middle ground of (400,400,3) is used to reshaped the image to generate good efficiency.

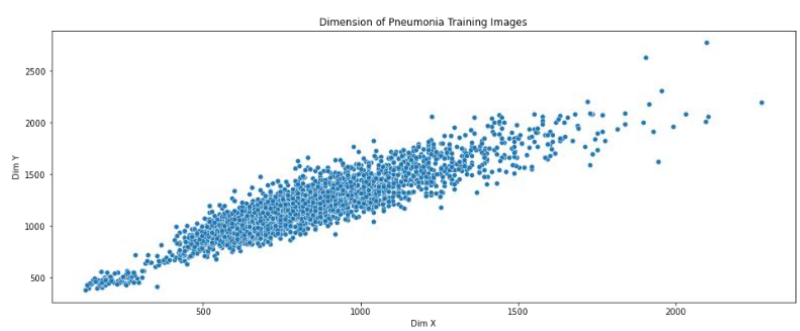

Figure 2: Dimension of testing image for Pneumonia Class

After determining the reshaped image dimensions, using Keras library [17] image generator is declared. For the image generator,

i. The rotation angle is kept 0, as no rotation in the image is needed.
ii. Fill mode = Nearest (default)
iii. Horizontal and Vertical flip = False; as there will be no patient who will do X-ray upside down.
iv. Zoom range=0.2

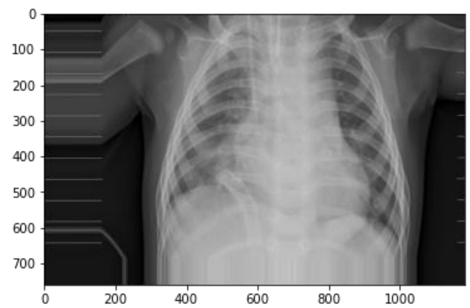

Figure 3: Output of image generator

Figure 3 demonstrates a random image using an image generator. By analyzing the image, it is clear that no information is lost by feeding the image to the image generator.
Using this image generator function, train image and test image generators were generated. This train image generator and test image generator will be fed to the model. The average image size is used as the target size for both these generators. One notable fact, for the training generator my model shuffles the label but for the testing, generator shuffle is not used as it would shuffle the label and would produce inaccurate results.

3.2.2. Training Model

The next step is to feed the model with the generated train image generator for training purposes. The test image generator works as validation data for our model. For this model, the iteration value is set to 100, which means this training dataset will train the model in up to 100 epochs. The model never needs to go to up to 100 epochs as an early stopping function with patient 6 is used to stop the iteration when the minimum validation loss function is generated. For this specific setting, it goes up to 37 epochs. It takes around 4 hours to train the model.

4 Experiment

For the experimenting purpose, the model is altered to see which specification gives the best accuracy for predicting covid-19 cases.

Case1: For case 1 experiment are done with a model which is exactly as same as the described 3.1.2 section.

Case2: Here, the kernel size of the convolutional layer is changed to 2x2. The stride value for the convolutional layer is also changed to 2x2. Other specification remains same as Case1.

Case 3: An extra convolutional and pooling layer is added to Case 2 model. All other elements remain the same as case 2.

Classes	Case 1			Case 2			Case 3		
	precision	recall	F1 score	precision	recall	F1 score	precision	recall	F1 score
Covid-19 (class 0)	0.99	0.97	0.98	0.97	0.94	0.96	0.88	0.93	0.90
Normal (class 1)	0.91	0.92	0.92	0.87	0.92	0.89	0.89	0.80	0.84
Pneumonia (class 2)	0.97	0.97	0.97	0.97	0.95	0.96	0.93	0.95	0.94
Accuracy	-------	------	0.96	------	------	0.94	-------	------	0.91

Table 2: Comparison of different Cases

Table 2 is the summary of all the experiments that are conducted by altering the model. It is clear from the table that Case 1 works the best with the highest accuracy and Case 3 works the worst among the three.
In the case of Covid-19, case 1 produced the best result in all the sections (precision, recall and F1 score), which are above .95 and for precision matric it is almost 1. For case 2 all three matrices produce quite high scores but for case 3 it is below 90 for precision.
For Normal chest x-rays, all the evaluation metrics scores are higher than that of case 2 and case 3.
For the last case which is Pneumonia, similar results are seen in the Covid-19 class. But here, all three cases give good results which are all above .90.
Finally, when accuracy is generated from F1-score Case 1 gives more accuracy than cases 2 and 3. And it achieves an accuracy of 96%.

5. Results

From section 4, it is clear that Case 1 works the best for the given dataset. In figure 4, the loss for training and validation data is shown. It is clear from figure 4 that loss for both training and validation data drops as the number of epochs increases. Although the loss of the training set is less than the loss of validation still it is pretty low for the test set. The exact opposite result can be seen for the accuracy curve, the accuracy increased linearly with the number of epochs. Figure 5 represents the accuracy for training and validation data. For both figures 4 and 5, the blue line represents the scores for training data and the orange line represents the scores for validation data. The final score is given in table 2.

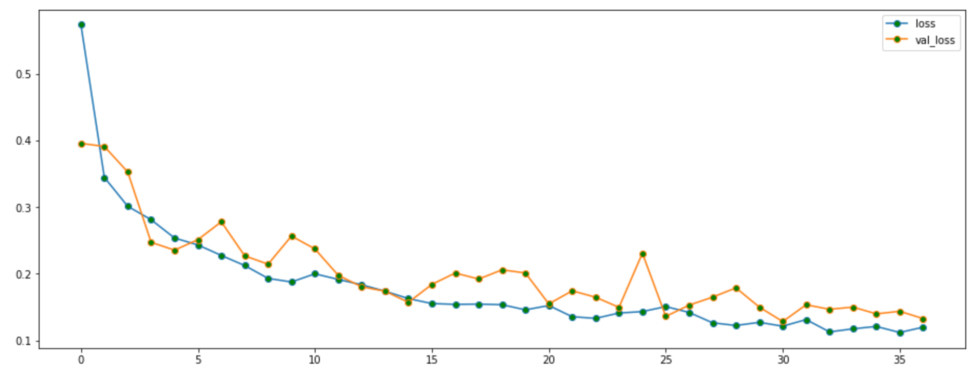

Figure 4: Loss score for train and test dataset

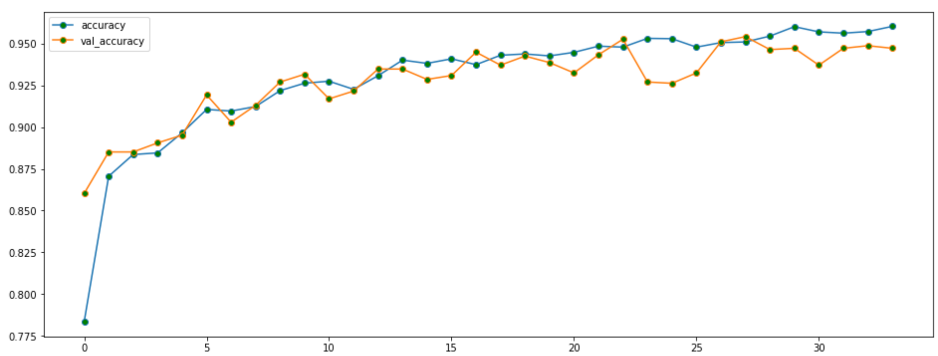

Figure 5: Accuracy score for both test and train dataset

The precision for covid-19 and normal classes are good especially for covid-19 which is 99%. That means it detects covid-19 without any difficulty for given covid-19 x-ray images. But for the pneumonia class, it predicts the wrong prediction in many cases. All the three evaluation metrics scores are presented in figure 5. Here, Covid 19, Normal and Pneumonia classes are denoted as class 0, class 1 and class 2.

	precision	recall	f1-score	support
0	0.99	0.97	0.98	116
1	0.91	0.92	0.92	317
2	0.97	0.97	0.97	855
accuracy			0.96	1288
macro avg	0.96	0.95	0.96	1288
weighted avg	0.96	0.96	0.96	1288

Figure 6: Evaluation Matric Score for Final Model

Many random images from 3 classes are fed to the model to see what is the predicted results. Below Figure 7 shows the rightly predicted values and figure 8 wrongly predicted values. The model predicts most of the covid cases from the validation data rightly.

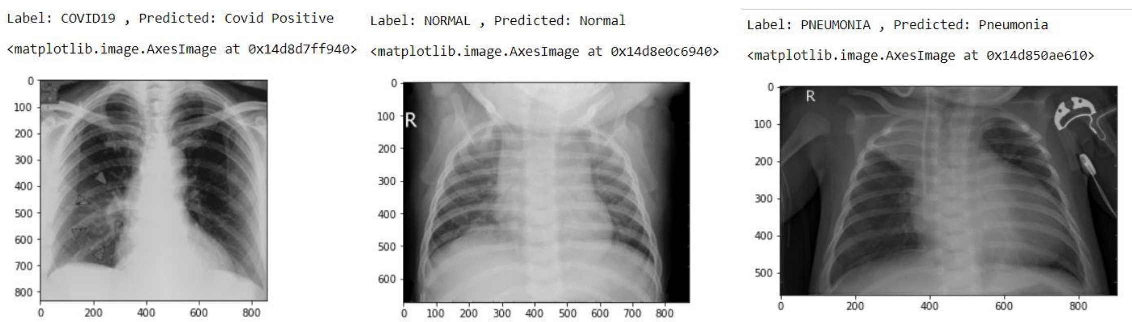

Figure 7: Right Prediction made by the model

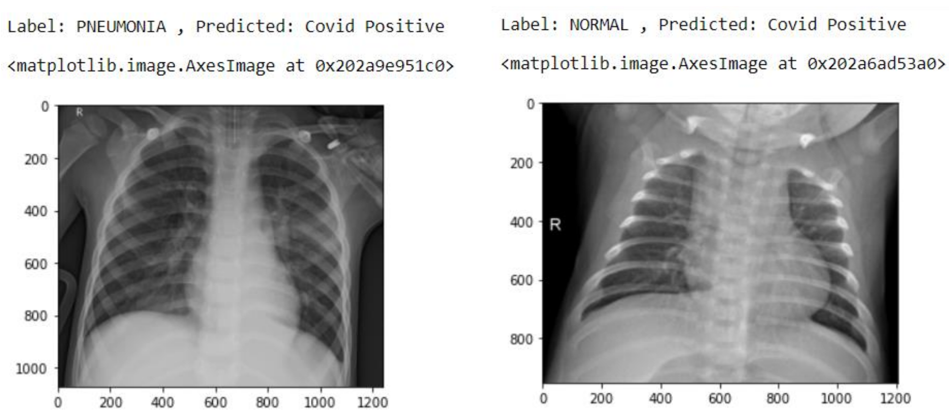

Figure 8: Wrong Prediction made by the model

6. Conclusion and Future Work

As the cases of COVID-19 are increasing daily, to date many countries are facing a shortage of resources to identify all the correct cases. To deliver the medical help properly, every single positive case must get identified. For that reason, this paper proposed a deep learning approach to detect COVID-19 cases from chest X-ray images. Though it shows a promising result for detecting covid-19 from the covid-19 class, it is not 100% accurate for detecting all three classes, especially for pneumonia class. In future, the overall accuracy can be increased by increases the accuracy of detection for the other two classes. Different specifications of the neural model can be applied to determine for which specification the precision of pneumonia increases. Moreover, this model can be trained into a bigger dataset for making a more accurate prediction.

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