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COVID-19 Detection using Artificial Intelligence

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Abstract: Background: X-rays *imaging is one of the possible method for detecting COVID19. Our research aimed to construct a model using deep learning for detecting COVID-19 pneumonia on high resolution X-rays, relieve working pressure of radiologists and contribute to the control of the epidemic.* ***Methods:*** *For the proposed model development, validation, and testing 260 images available from the repository of GitHub and Kaggle were used. The Images consists of 130 COVID-19 (ignoring SARS, MERS and ARDS) and 130 Normal X-ray images.* ***Findings:*** *The proposed model achieved: sensitivity of 100%, specificity of 100%, accuracy of 100%, PPV of 100%, and NPV of 100% in the dataset. For 260 images, the model achieved a comparable performance to that of expert radiologist. With the assistance of the model, the reading time of the radiologists will greatly be decreased.* ***Conclusion:*** *The deep learning model showed a comparable performance with expert radiologist, and greatly will improve the efficiency of radiologists in clinical practice. It holds great potential to relieve the pressure of frontline radiologists, improve early diagnosis, isolation and treatment, and thus contribute to the control of the epidemic.*

Keyword: coronavirus, COVID-19, diagnosis, deep learning, Machine Learning.

1. Introduction

COVID-19 is short for (Coronavirus disease 2019). It is an infectious disease that is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)[1] (See Figure 1). COVID-19 was initially recognized in 2019 in Wuhan, China, and since then spread globally and very fast, resulting in the 2019–2020 coronavirus pandemic [1,4]. The most common symptoms of COVID-19 include cough, fever and shortness of breath. Other symptoms may include diarrhea, muscle pain, sore throat, sputum production, abdominal pain and loss of taste and smell [1,2,5]. Even though the majority of cases end in mild symptoms, some progress to pneumonia and multi-organ failure [1,4]. As of March 26, 2020, the overall rate of deaths per number of diagnosed cases is 4.5 %, but it in fact ranges from 0.2 % to 15 % according to age group and other health problems [3].

Figure 1: Coronavirus

COVID-19 is typically spread during close contact and via respiratory droplets produced when people sneeze or cough [1,2]. Respiratory droplets may be formed during breathing but it is not well-thought-out airborne [1]. It may also spread through fomite transmission. For example, touching a fomite (contaminated surface) and then touching the body's mucous membranes, such as the mouth, nose, or eyes, could potentially introduce the pathogen into the body [1,2]. This is why proper and frequent hand washing is so important. It is most contagious when people are symptomatic, although spread may be possible before symptoms appear [2]. COVID-19 can live on surfaces up to 72 hours [6]. Time from exposure to onset of symptoms is generally between two and fourteen days, with an average of five days [7,8]. The standard method of diagnosis is by reverse transcription polymerase chain reaction (rRT-PCR) from a nasopharyngeal swab [2]. The infection can also be diagnosed from a combination of symptoms, risk factors and a chest CT scan showing features of pneumonia [9,10].

Recommended measures to prevent infection include frequent hand washing, social distancing (maintaining physical distance from others, especially from those with symptoms), covering coughs and sneezes with a tissue or inner elbow, and keeping unwashed hands away from the face [1,11]. The use of masks is recommended by some national health authorities for those who suspect they have the virus and their caregivers, but not for the general public, although simple cloth masks may be used by those who desire

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them [1,2]. There is no vaccine or specific antiviral treatment for COVID-19. Management involves treatment of symptoms, isolation, supportive care and experimental measures [2].

The World Health Organization (WHO) declared the 2019–20 coronavirus outbreak a Public Health Emergency of International Concern (PHEIC) on 30 January 2020[1,12] and a pandemic on 11 March 2020[1]. Local transmission of the disease has been recorded in many countries across all six WHO regions [1]. Table 1 presents the statistics of number of Confirmed cases, received cases and number of died cases worldwide and in the top 30 countries sorted in descending order by the number of confirmed cases as of March 27, 2020[1].

Table 1: Statistics of Confirmed cases, received cases and number death cases as at March 27, 2020

S.N.	Locations	Confirmed cases	Cases per 1M people	Recovered	Deaths
	Worldwide	**549,474**	**77.98**	**128,701**	**24,883**
1	United States	86,043	263.06	753	1,304
2	China	81,340	59.23	74,588	3,292
3	Italy	80,589	1275.84	10,361	8,215
4	Spain	64,059	1292.81	9,357	4,858
5	Germany	45,251	550.92	6,280	276
6	Iran	32,332	399.20	11,133	2,378
7	France	29,155	431.50	4,955	1,696
8	Switzerland	12,331	1817.39	897	207
9	United Kingdom	11,660	179.68	140	578
10	South Korea	9,332	182.84	4,528	139
11	Netherlands	8,641	530.64	—	547
12	Austria	7,393	943.47	112	58
13	Belgium	7,284	706.69	858	289
14	Portugal	4,268	399.75	43	76
15	Canada	4,030	116.63	228	39
16	Norway	3,677	690.01	—	16
17	Turkey	3,629	43.35	26	75
18	Australia	3,180	138.93	118	13
19	Israel	3,035	266.15	79	10
20	Brazil	2,985	14.48	6	77
21	Sweden	2,893	287.81	16	77
22	Denmark	2,163	389.80	—	52
23	Malaysia	2,161	65.03	259	26
24	Czechia	2,062	193.62	10	9
25	Ireland	1,819	348.26	5	19
26	Chile	1,610	92.11	43	5
27	Luxembourg	1,453	1814.92	6	9
28	Ecuador	1,403	84.75	3	34
29	Japan	1,387	10.94	359	46
30	Romania	1,292	60.19	115	24

Examining of COVID-19 at this time is considered tough task because of shortage of diagnostic system everywhere. Due to the limited availability of COVID-19 examination kits, we look for other diagnostic measures. In the meantime COVID-19 attacks the epithelial cells that line our respiratory tract, X-rays can be used to analyze the lungs of a patient. Doctors often use X-ray images to diagnose pneumonia, lung irritation, swellings, and/or distended lymph nodes. X-ray imaging machines are available in all hospitals, thus X-rays could be used for the examination of COVID-19 without the dedicated examination kits; This requires that a radiology expert must be present to do the task and this consumes much time, which is valuable when people are sick worldwide. Hence, designing and developing a computer based system is necessary to save medical professionals valuable time. The chest X-ray images of COVID-19 are shown in Figure 2 and Figure 3.

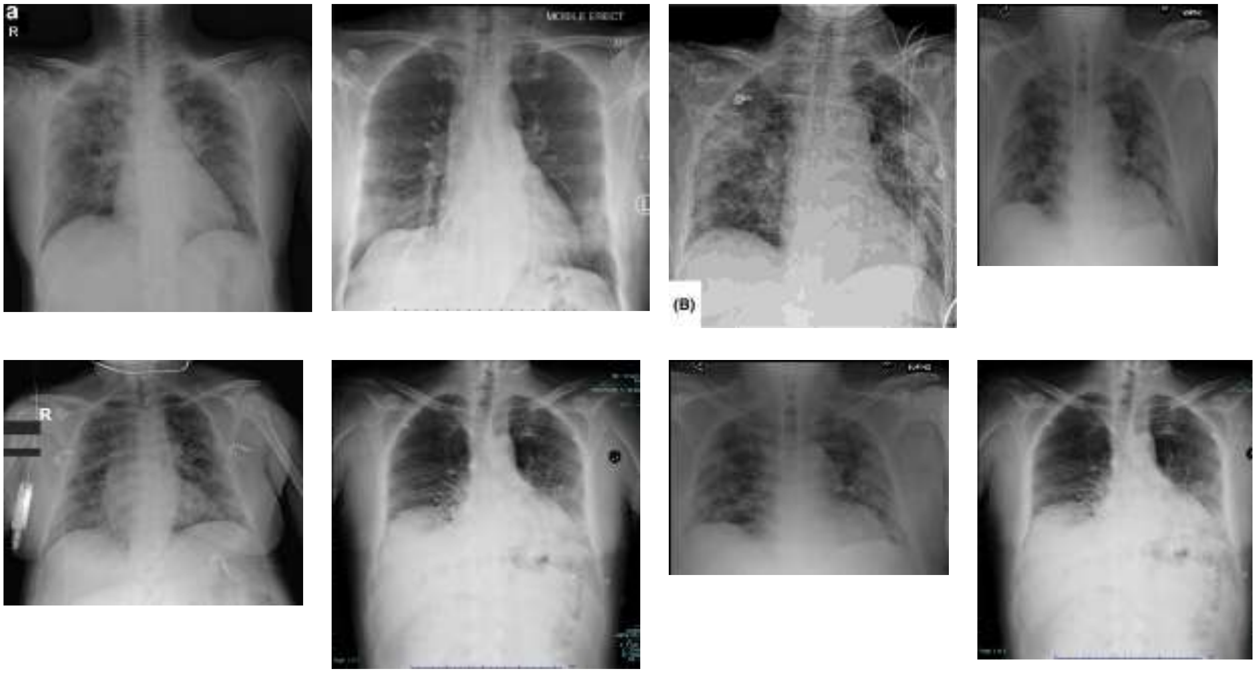

Figure 2: COVID-19 Images

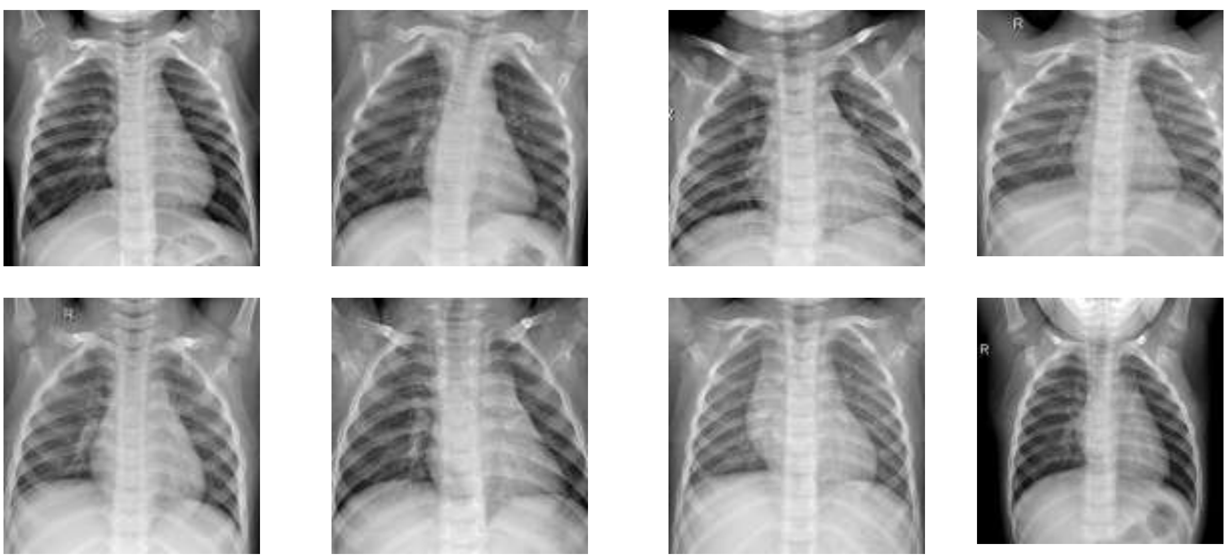

Figure 3: X-ray Normal Images

2. Deep Learning

Deep learning is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence (AI) that has networks capable of learning unsupervised from data that is unstructured or unlabeled. It is known as deep neural learning or deep neural network. Deep learning has evolved hand-in-hand with the digital era, which has brought about an explosion of data in all forms

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and from every region of the world. This data, known simply as big data, is drawn from sources like social media, internet search engines, e-commerce platforms, and online cinemas, among others. This enormous amount of data is readily accessible and can be shared through fin tech applications like cloud computing. However, the data, which normally is unstructured, is so vast that it could take decades for humans to comprehend it and extract relevant information. Companies realize the incredible potential that can result from unraveling this wealth of information and are increasingly adapting to AI systems for automated support.

2.1 CNN

A convolutional neural network (CNN) is one of the most popular algorithms for deep learning, a type of machine learning in which a model learns to perform classification tasks directly from images, video, text, or sound. CNNs are particularly useful for finding patterns in images to recognize objects, faces, and scenes. They learn directly from image data, using patterns to classify images and eliminating the need for manual feature extraction. A convolutional neural network can have tens or hundreds of layers that each learn to detect different features of an image. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer. The filters can start as very simple features, such as brightness and edges, and increase in complexity to features that uniquely define the object as seen in Figure 4.

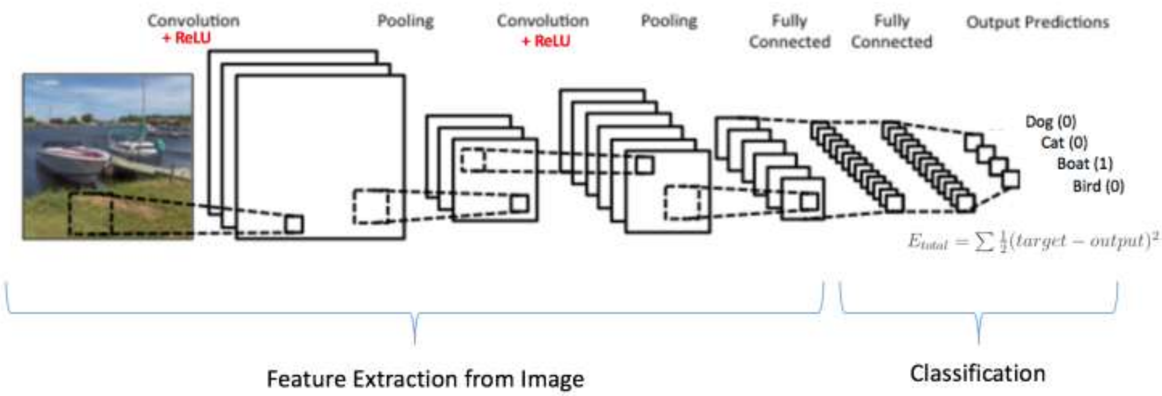

Figure 4: Convolutional Neural Network

3. Literature Review

Due to the rapid spread of COVID-19 a great number of researchers have been working on finding solution to help mankind [5-10]. Deep learning is a branch of Machine learning is recent techniques applicable in the field of medicine for diagnostic purposes [16-25].

In this study, a model based on deep Convolution Neural Networks was designed and developed for the identification of the X-ray image has COVID-19 or it does not (Healthy).

4. Methodology

In this section we describe the proposed solution as selected convolutional network architecture and discuss associated design choices, evaluation methods and implementation aspects.

4.1 Dataset

In this study, we used a dataset which contains 130 of COVID-19 and 130 Normal X-ray images. The COVID-19 X-ray images are collected from the GitHub repository shared by Dr. Joseph Cohen, a postdoctoral fellow at the University of Montreal [13]. The Normal X-ray images of pneumonia collected from Kaggle repository [14] and Open-i repository [15]. The COVID-19 excludes the MERS, SARS, and ARDS Images. The dataset was examined in the proposed model. We use this dataset for deep feature extraction based on deep learning architectures such as VGG16, ResNet50 and InceptionV3. We used InceptionV3 as a transfer learning approach for the identification of COVID-19. Finally, we trained, validated and evaluated the performance of the proposed model.

4.2 Convolutional layer

A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons. In other words, the filter is slid across the width and height of the input and the dot products between the input and filter are computed at every spatial position. The output volume of the convolutional layer is obtained by stacking the activation maps of all filters along the depth dimension. Since the width and height of each filter is designed to be smaller than the input, each neuron in the activation map is only connected to a small local region of the input volume, and the activation map is obtained by performing convolution between the filter and the input, the filter parameters are shared for all local positions. The weight sharing reduces the number of parameters for efficiency of expression, efficiency of learning, and good generalization[26-27].

4.3 Pooling

Pooling layers compute the maximum or average over a region of a feature map, there are several non-linear functions to implement pooling among which max pooling is the most common. It partitions the input image into a set of non-overlapping rectangles and, for each such sub-region, outputs the maximum, the exact location of a feature is less important than its rough location relative to other features. This is the idea behind the use of pooling in convolutional neural networks. The pooling layer serves to progressively reduce the spatial size of the representation, to reduce the number of parameters, memory footprint and amount of computation in the network, and hence to also control over fitting. It is common to periodically insert a pooling layer between successive convolutional layers in a CNN architecture. The pooling operation provides another form of translation invariance. The pooling layer operates independently on every depth slice of the input and resizes it spatially[28-30].

4.4 Fully-connected layer

To finally classify the image into a category, we will set up a multilayer perceptron (Multi-Layer Perceptron) on top of the last convolution layer. The previous convolution and pooling operations have greatly reduced the size of the input image to keep uniquely the meaningful characteristics for the classification. Since feeding a MLP requires input vectors (one-dimension arrays or 1d arrays), we need to "flatten" the output feature map. The MLP therefore receives small-sized feature map as 1d array and chooses the corresponding category with regard to those feature maps[31-35].

4.5 Performance measure for the developed model

To evaluate the performance of the model on X-Ray images, five metrics including the accuracy, sensitivity, specificity, PPV and NPV were calculated as follows[36-38]:

- Accuracy = true predictions/total number of cases,
- Sensitivity (Recall) = true positive/positive,
- Specificity = true negative/negative,
- Positive Prediction Value (PPV)(Precision) = True Positive/(True Positive + False Positive,
- Negative Prediction Value (NPV) =True Negative/(True Negative + False Negative).
- F1-score uses a combination of precision and recall to calculate a balanced average result

Where:
The True Positive (TP) is the number of correctly predicted COVID-19 pneumonia cases/images,
The False Positive (FP) is the number of mistakenly predicted COVID-19 pneumonia cases/images,
The Positive is the number of cases/images of COVID-19 pneumonia patients,
The True Negative (TN) is the number of correctly predicted non-COVID-19 pneumonia cases/images,
The False Negative (TN) is the number of mistakenly predicted non-COVID-19 pneumonia cases/images and
The Negative is the number of non-COVID-19 pneumonia cases/images enrolled.

For image-based metrics, 130 images containing infection lesions identified by radiologists among patients of COVID-19 pneumonia were used as the positive sample, and 130 X-rays images from patients of non-COVID-19 pneumonia were used as the negative sample.

The following equations show how to calculate these values, where TP, TN, FP and FN are True Positive, True Negative, False Positive, and False Negative respectively.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(1)$$

$$\text{PPV}(Precision) = \frac{TP}{TP + FP} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(2)$$

$$\text{Sensitivity (Recall)} = \frac{TP}{TP + FN} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(3)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(4)$$

$$\text{NPV} = \frac{TN}{TN + FN} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots...(5)$$

$$f1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(6)$$

4.6 Training and Validation of the model

After creating the CNN model which based on the algorithm of IncepyionV3, we trained the model for 20 epochs and using data augmentation [36-43] for preventing the model from overfitting. We have used the metric measures which we have discussed in the previous section which include the accuracy, sensitivity, specificity, PPV and NPV. The result came as seen in the figure to be 100% in all measures as shown in Figure 5. The training loss and validation Loss were nearly 0 as shown in Figure 6.

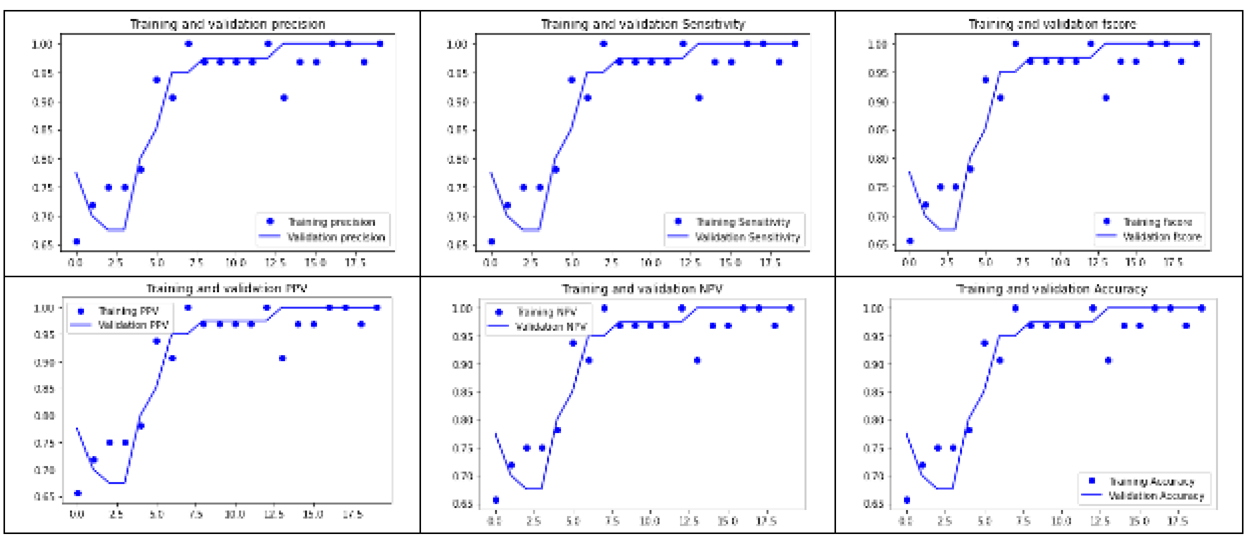

Figure 5: shows the Training Validating Performance Measures

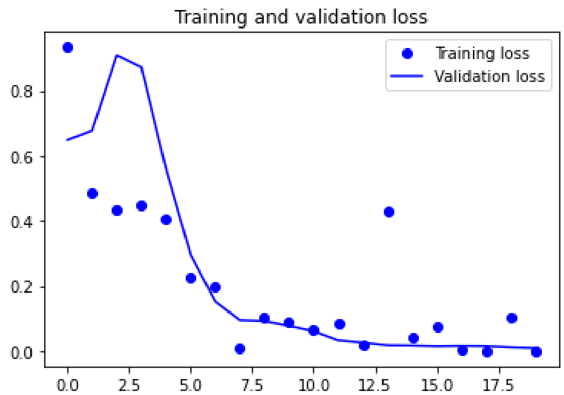

Figure 6: shows the Training Validating Loss

4.7 Testing of the model

A total of 30 X-rays samples were selected randomly from each group (COVID-19 and healthy) for the test set, following the rule that this person (owner of this X-Ray) had not been included in the previous training or validation stages. The accuracy of the testing came out 100%.

5. Results and Discussion

In this study, we examined the performance of the model for detecting weather an image has COVID-19 or Healthy. The experimental study was implemented using the Google **Colaboratory** environment and python. The measurement of performance of model was measured in terms of accuracy, sensitivity, specificity, PPV and NPV, F1 Score. The results reported in Table 4 and Table 5 was based on the average value of 50 epochs. The training, validation and testing ratio was 70 images for traing, 30 images for validation and 30 images for testing from each category (COVID-19 and Healthy). Images were selected randomly for the training, validation and testing. The results reported in Table 4 and Table 5 are the cases of coronavirus excluding SARS, MERS and ARDS i.e. only for COVID-19.

Note: The result is based on the data available in the repository of GitHub, Kaggle and Open-i as per their validated X-ray images.

Table 4: analysis of different performance measure for the training of our model using deep learning

CNN Model	Number of Epochs	Accuracy	Sensitivity	Specificity	(PPV) (Precision)	NPV	F1-score
Inceptionv3	50	100%	100%	100%	100%	100%	100%

Table 5: analysis of different performance measure for the Validating of our model using deep learning

CNN Model	Number of Epochs	Accuracy	Sensitivity	Specificity	(PPV) (Precision)	NPV	F1-score
Inceptionv3	50	100%	100%	100%	100%	100%	100%

6. Conclusion

The content of the study about the COVID-19 based on the data available in WHO, European Centre for Disease Prevention and Control An agency of the European Union and other official websites worldwide. The chest X-ray images are used for simulation purposes are collected from GitHub, Kaggle and Open-i repository. For detection of COVID-19 using X-ray images based on deep learning features. We extracted the deep learning feature of the pre-trained CNN model. We analyzed the performance of this model using 6 measures. The Inceptionv3 reached an accuracy of 100% in all performance measures. The proposed model for detecting COVID-19 achieved 100% accuracy.

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