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CORONAVIRUS DETECTION USING AI

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ABSTRACT

Covid19is a speedily spreading viral disease that is just not only humans, but animals are also getting infected because of this viral disease . Deep learning is that the most successful technique of machine learning, which provides useful analysis to review an outsized amount of chest xray images which will critically impact on screening of Covid19.In this work, we've taken the PA view of chest xray scans for covid19 affected patients also as healthy patients. After cleaning up the pictures and applying data augmentation, we've used deep learning based CNN models and compared their performance. We have compared Inception V3, VGG16 models and examined their accuracy. To analyze the model performance, 1000 chest xray scans samples have been collected from the github repository, out of which 800 were used for training and 200 for examination . In result analysis, the Inception model gives the highest accuracy (i.e., 96.00%) for detecting Chest Xrays images as compared to other models.

Keywords: Coronavirus (COVID-19), Deep learning, Chest X-ray images, , Machine Learning, Inception V3, VGG-16.

I. INTRODUCTION

Covid-19 may be a severe disease issue where an outsized number of individuals lose their lives a day. This disease affects not only one country, and even the entire world suffered due to this virus disease. In the last few decades, several sorts of viruses (like SARS [1], MERS, Flu, etc.) came into the image, but they represent only in last few months. Many scientists are performing on these sorts of viruses, and few of them are diagnosed thanks to the supply of vaccines prepared by them (i.e., Scientists or researchers). In the times , the entire world is suffering from Covid-19 disease [5], and therefore the most vital thing is not any single country scientists can prepare a vaccine for an equivalent .

Meanwhile, more predictions came into like an image plasma therapy, Xray images, and lots of more, but the precise solution of this deathly disease isn't found. Every day, people lose their life thanks to covid-19 [8], and therefore the diagnostic cost of this disease is extremely high within the context of a rustic , state, and patients. Covid-19 is a plague disease that threatens humans at a worldwide level and turned into a pandemic. To diagnose covid-19 infected patients with healthy patients may be a critical task.

Although rapid point-of-care COVID-19 tests are expected to be utilized in clinical settings at some point, for now, turnaround times for COVID-19 test results range from 3 to quite 48 hours, and doubtless not all countries will have access to those test kit that will produces output fastly. According to a recently published multinational consensus statement by the Fleischer Society, one of the main recommendations is to use chest radiography for patients with COVID-19 in a resource-constrained environment when access to computerized tomography (CT) is restricted .3 The financial costs of the laboratory kits used for diagnosis, especially for developing and underdeveloped countries, are a big issue when fighting the illness.

Using X-ray images for the automated detection of COVID-19 might be helpful in particular for countries and hospitals that are unable to purchase a laboratory kit for tests or that do not have a CT scanner.

Inception V3 and VGG16 achieved 96.40% and 93.75% accuracy.

II. METHODOLOGY

Convolutional Neural Network (CNN)

CNN

In neural networks, the convolutional neural network (convNets or CNNs) is one of the main categories for image recognition, image classification, object recognition, face recognition, etc. are a several places where CNNs are broadly implemented . Enter the photos , process it and classify it into specific classes . Computers see an input image as an array of pixels and depend on the resolution of the image hxwxd (h = height, w = width, d = dimension) For example a 6 x 6 x 3 matrix matrix image of RGB and a 4 x 4 matrix matrix image x 1 grayscale image.

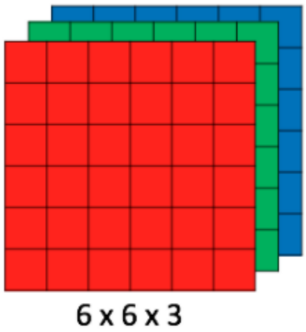

Fig : RGB Matrix

Technically, Deep learning CNN models to coach and examine , each feed image will pass through a series of convoluted layers with filters (Kernals). The below figure is a Finalize flow of CNN to process an feed image and classifies the objects based on values.

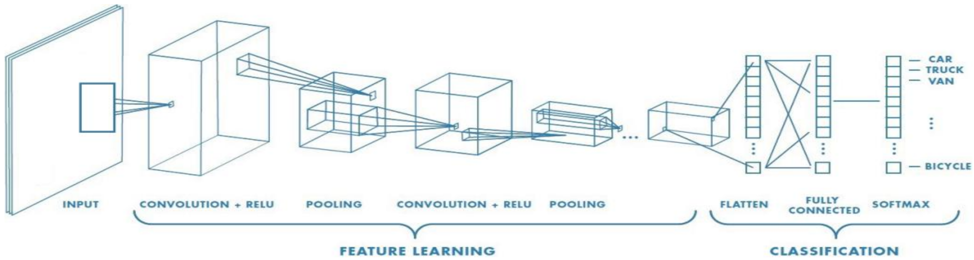

Fig : Neural network with many convolutional layers

It is a mathematical operation that takes two inputs like image matrix and a filter or kernel. Convolution of an image with different filters can perform operations like edge detection, blur and sharpen by applying filters. The below example shows various convolution image after applying differing kinds of filters (Kernels).

CNN Layers

Non Linearity (ReLU Layer)

Rectified long measure for a non-linear operation. The result => Æ'(x) = max(0,x). Why ReLU is critical

: Since, the important global information would wants the ConvNet to seek out out would be non-negative linear values.

The two more non linear functions like tanh or sigmoid which can even be used instead of ReLU.

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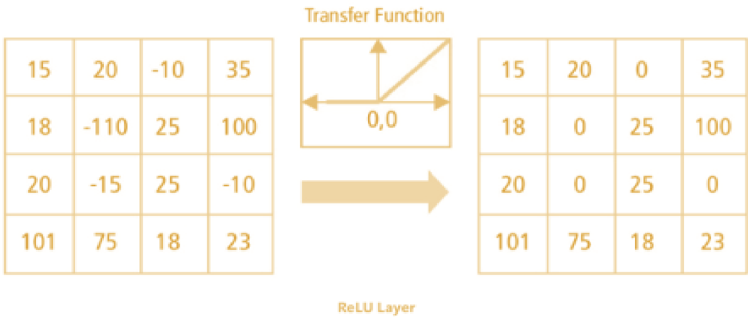

Fig : ReLU Functioning

Pooling Layer

In this actually the convulated image is transform into compress image utilizing the 2 x2 filters.

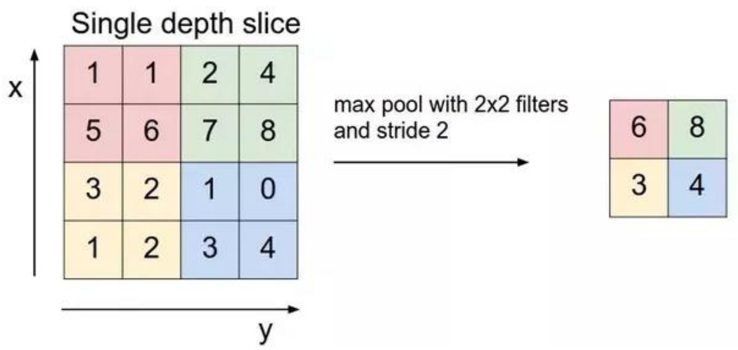

Fig : Max Pooling

Fully Connected Layer

We call this layer a FC layer, we flattered the matrix into vector and gratify it into a totally connected layer quite a neural network.

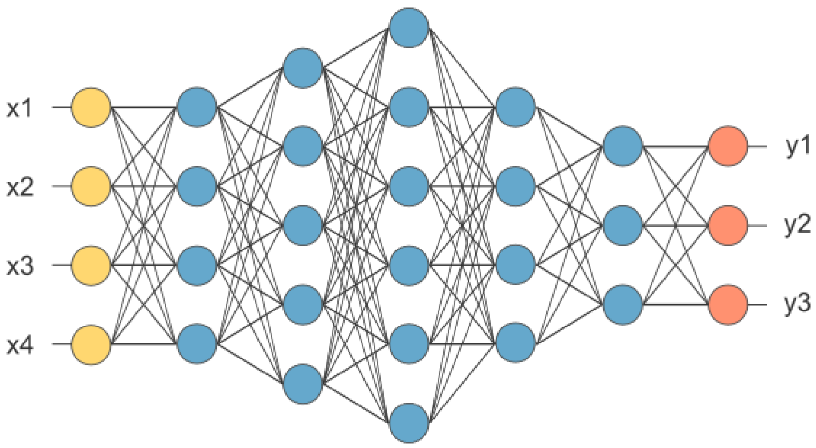

Fig : Final Convulated Layer

In the above diagram, the feature map matrix are getting to be transform as vector (x1, x2, x3, â€¦). With the fully joined layers, we integrate these features together to create a model. Finally, we've an activation function like sigmoid to categorize the results.

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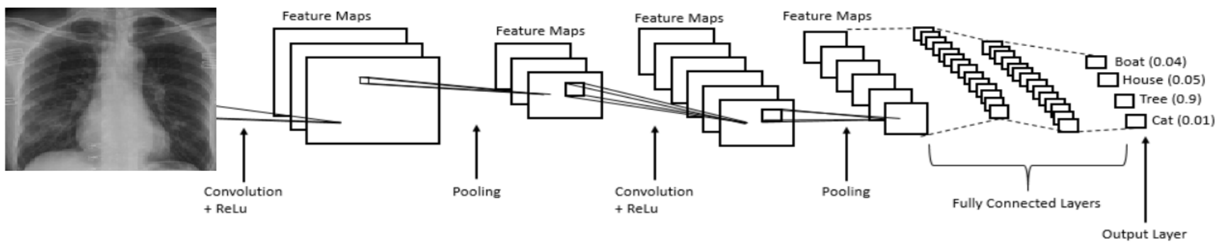


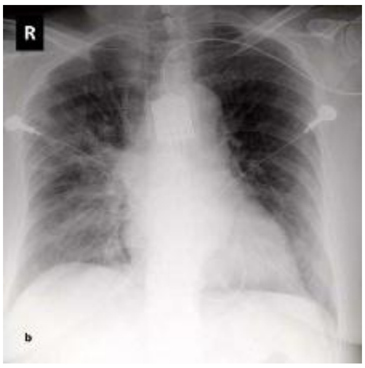
Fig : Final CNN Architecture

Experimental Dataset

The dataset for this work was compiled from the Github repository, which contains chest x-rays of affected, normal, and pneumonia covid-19, also as CT images of the lungs. Diagnostic ability of any deep learning model but exploring alternative ways to efficiently detect coronavirus infections using computer vision techniques. The collected data set consists of a complete of 1000 x-ray images of the chest and 750 computerized tomography images. This data set is split into training (i., 80%) and validation (i., 20%) of normal, Covid and pneumonia. The scans were scaled down by 224 Ã— 224 to permit for a fast training of our model. in line with our covid dataset.The dataset for the project was gathered from two sources:

1. Chest X-ray images (1000 photos) gathered from:
https://github.com/ieee8023/covid-chestxray-dataset

2. CT Scan images (750 images) were obtained from:
https://github.com/UCSD-AI4H/COVID-CT/tree/master/Data-split 80% of the photographs were utilize for teaching the models and thus the remaining 20% for examing.



Normal X-Ray COVID X-Ray

In this we describe how the COVID-CT data set is structured. We first gathered 760 preprints on COVID-19 from bioRxiv3 and medRxiv2 . Many of those preprints report COVID-19 patient cases, and a few of them show CT images within the reports. the pictures are linked with subtitles that expound the clinical locating at CT. We use PyMuPDF4 to extract the low level structural information from preprinted PDF files and locate any embedded figures. The

quality (including resolution, size, etc.) of the figures was well preserved. From the structural information, we also identify the labels related to the figures. Given these extracted numbers and subtitles, we initially selected all of the CT images manually. Then for every CT image. We read the associated label to assist determine if you're positive for COVID-19. If we will not judge by the subtitle We localize the text by analyzing this number in prepress to form a choice for every CT image, we also collect meta information extracted from the article, such as: B. Age, gender, location, medical record , scan time and severity of COVID -19. and radiology report. for every figure that contains multiple CT images as sub-figures, we manually divide them into individual CTs, as shown in Figure

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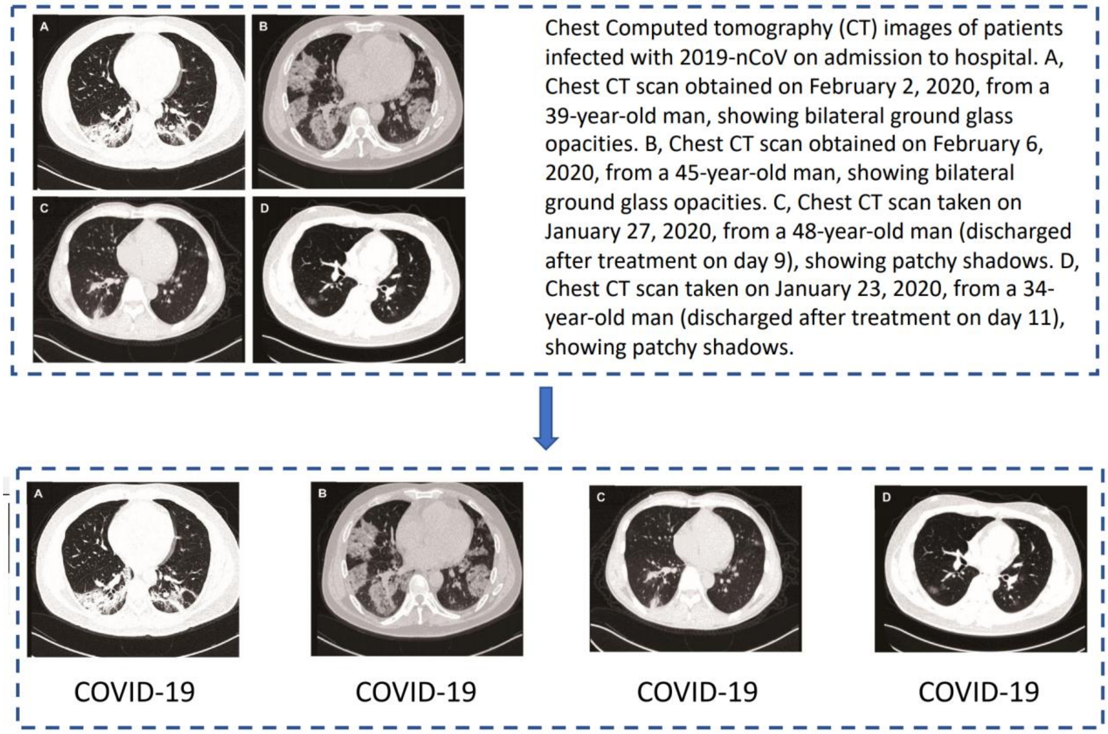

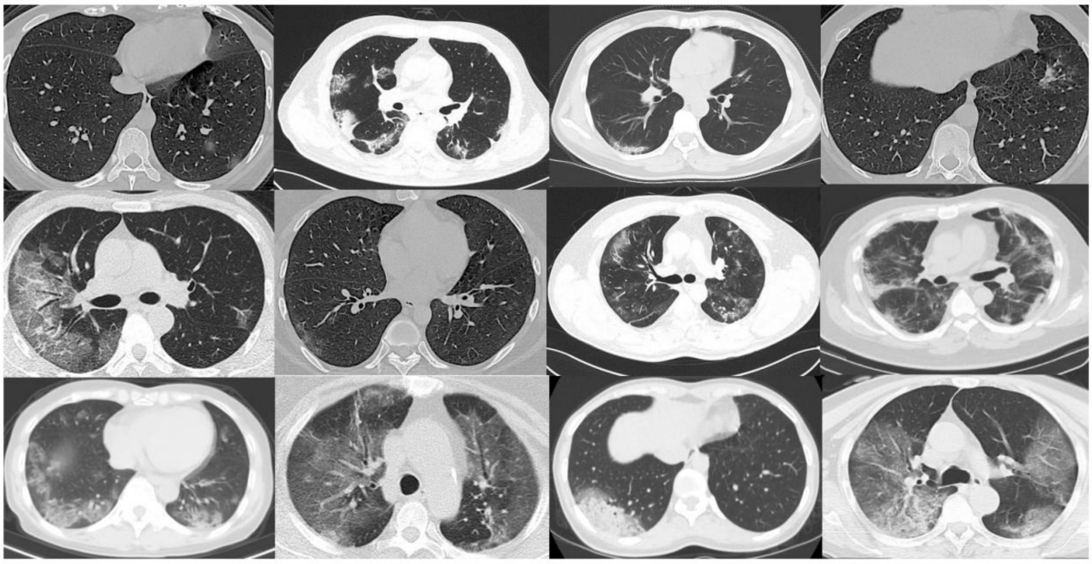

In the end, we received 349 CT images marked positive for COVID-19. These CT images have different sizes. The min, max and average heights are 153, 491 and 1853. The minimum, average, and maximum widths are 124, 383, and 1485. These images show 216 patient cases. The figure shows some samples of the COVID19 CT images. For patients marked positive, 169 of them have age information and137 of them have gender information. The figure shows the age distribution of COVID-19 patients. The figure shows the gender ratio of COVID-19 patients. Male patients are quite female at 86 and 51 respectively. -TC record with others. The COVID-19 CT segmentation dataset contains more COVID19 positive images, but fewer patients. Note that an equivalent patient's CT images are visually very similar. Therefore, the variability of images in our data set is bigger than that within the COVID-19 CT segmentation data set.

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Design Methodology and Framework

In real world , we always like better to reach a diagnosis supported multiple points of view from doctors . The combined opinion of doctors contributes to a more reliable conclusion. Following an equivalent philosophy, several CNN reference models are adopted in our proposal. they need been individually trained to form independent predictions. The models are then combined employing a new weighted average rate technique to predict a category score. This new proposed ensemble method is meant to form the prediction more robust. The work consists of three previously trained CNN: VGG-16 and Inceptionv3. The biggest advantage of the pre-trained CNN model requires comparatively fewer parameters than similar conventional CNN types. Another reason for choosing This Layer inherits the feature maps from all previous layers. as tickets.This helps to strengthen the spread of features and promotes the reuse of features. It is a contemporary convolution network that is easier to train than any other deep convolution network, produces greater precision, and converges faster. In addition, vanishing gradient problems or explosions are fixed by using "residual blocks". in architecture.

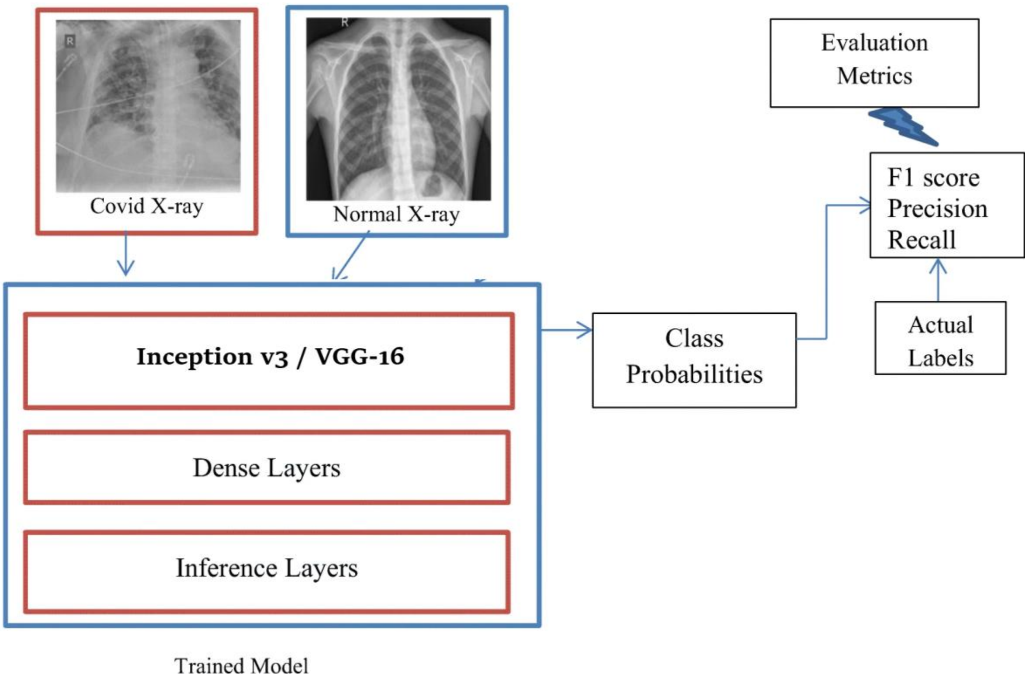

Fig : Purposed model

Feature extraction and feature selection

Patients infected with nCOVID-19 have dissimilar radiographic appearance design , as: B. spotty opacities of the ground glass (Figure 2 a), lung consolidations (Figure 2c), reticulonodular opacities (Figure 2b) etc. in CXR images (Hosseiny et al., 2020). These subtle visual features can be efficiently represented using radiomic texture descriptors. The study used eight first order statistical features (FOSF). Grayscale Coexistence (GLCM) (in four different orientations) and 8100 oriented gradient histogram (HOG) properties. The FOSF describes the whole picture at a glance using mean, variance, roughness, smoothness, kurtosis, energy and entropy, etc. You can easily quantify global texture patterns. However, no local neighborhood information is dealt with.To overcome this deficiency, the GLCM and HOG feature descriptors are used to perform an in-depth texture analysis. The Grayscale Coexistence feature describes the spatial correlation in the middle of pixel intensities in radiographic texture design along 4 unlik directions (i.e. 0∘, 45∘, 90∘, 135∘), while the HOG function encodes the local shape / texture information.

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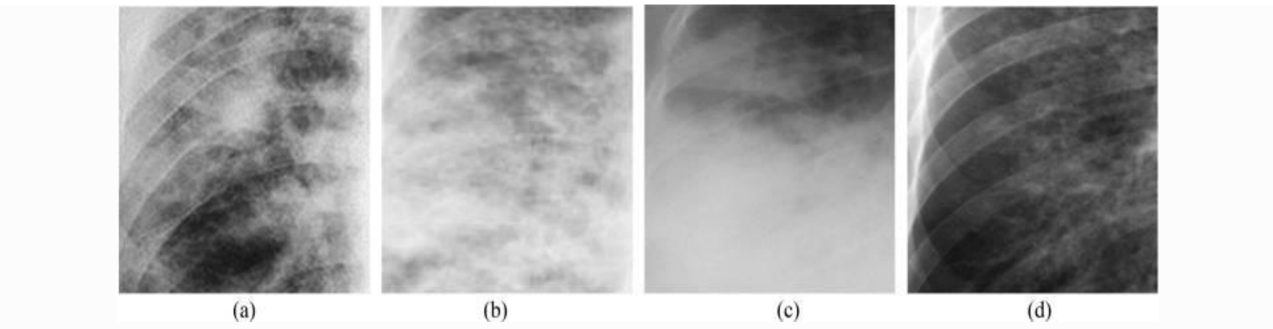

Fig : nCOVID-19 infected Chest X-ray images showing: (a) Ground-glass opacities, (b) Reticular opacities, (c) Pulmonary consolidation, (d) Mild opacities.

In these research , a total of 8196 features (8 FOSF, 88 GLCM, 8100 HOG) are extracted from each CXR image (see Appendix A). However, not all extracted features are relevant for the exact characterization of the associated visual indicators with nCOVID-19. Therefore, in order to select the most meaningful features, we used a recently developed metaheuristic approach called binary gray wolf optimization (BGWO). The method mimics the management, encirclement and hunting strategies of gray wolves. Mathematically, gray wolves are divided into four categories labeled Delta (δ), Omega(The Wolf α), Alpha (α) and Beta (β), is the one who makes the decisions and manages the hunting process with the help of Beta. β-wolves are the most suitable candidate to replace the alpha when the alpha is very old or dead. Next in the hierarchy, they obey the instructions of α and β wolves, but they dominate the omega wolves. The wolves are the lowest in the hierarchy and report to these leading wolves. The wolves' rounding up strategy is described in equation (1).

$$X(t+1)=Xp(t)-A.D \quad (1)$$

$$\text{Where } D=|C.Xp(t)-X(t)| \quad (2)$$

III. MODELING AND ANALYSIS

3.1 Proposed CNN Trained Models

3.1.1 Inception Net V3

A typical CNN consists of stacked convolutional layers combined with maximum

clustering and failure. With larger amounts of data like Imagenet, deeper architectures are used for better results and waiver is used to avoid overfitting. GoogLeNet was created by stacking Inception layers to create Deep CNN. In a typical CNN layer, we choose a 3x3 filter stack or a 5x5 filter stack or a maximum grouping layer. In general, all of these factors are beneficial to the modeling performance of the network. The starter module suggests using all of them. This means that instead of adding a specific filter size level, we'll add all 1x1, 3x3, 5x5 filters and fold the output of the previous levels. Since pooling is critical to the success of today's CNNs, the starter module also includes an addition to the pooling path. The output of all filters is concatenated and passed as input to next layer.

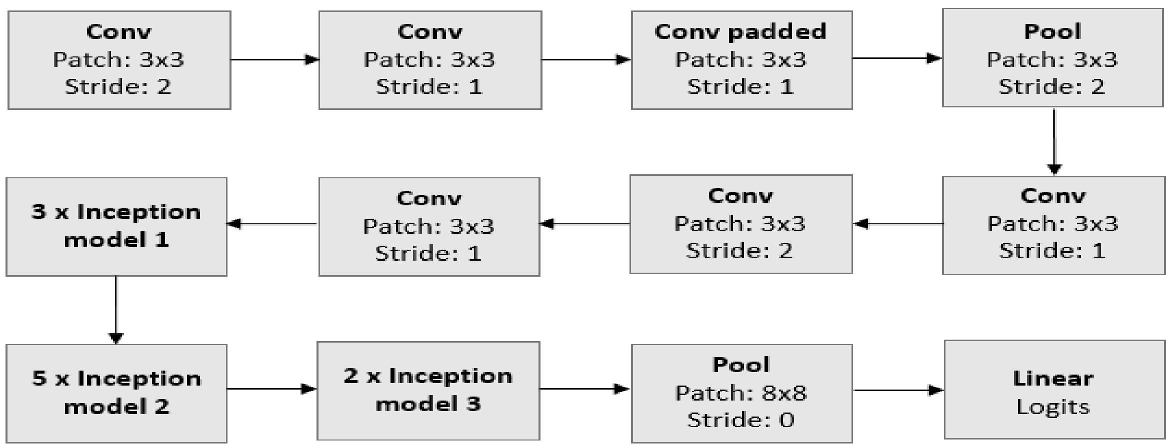

Fig : Inception Architecture

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3.1.2 VGG 16

The model achieved an accuracy of 92.7% in the top 5 tests by ImageNet, a data set with more than 14 million images from 1000 classes. The input into the VGG-based convNet is a 224 * 224 RGB image. The preprocessing level records the RGB image with pixel values in the range from 0 to 255 and subtracts the image mean values that are calculated over the entire training set. from ImageNet. The preprocessing is directed through these weight layers. The training photos are skilled a stack of convolution layers. Their were a complete of 13 folding layers and three fully joined layers within the VGG16 architecture. VGG has smaller filters (3 * 3) with more depth rather than large filters. it's an equivalent effective receiving field as if it had just 1 7 x 7 convolutional layer.

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 X Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 X Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 128	3x3	2	relu
5	2 X Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 256	3x3	2	relu
7	3 X Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 X Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu
13	FC	-	25088	-	-	relu
14	FC	-	4096	-	-	relu
15	FC	-	4096	-	-	relu
Output	FC	-	1000	-	-	Softmax

Fig : VGG16 Architecture

The two initial layers are convolution layers with 3 * 3 filters and the two initial layers ustilize 64 filters, resulting in a volume of 224 * 224 * 64 because the same turns are used.The filters are always 3 * 3 with a step of 1. After that, the grouping layer with a maximum group of 2 * 2 size and tride 2 was used, which reduces dimension from 224 * 224 * 64 to 112 *. 112 * 64.

This shadowed by 2 more convoluted layers with 128 filters. This leads to the new dimension 112 * 112 * 128. After using the grouping layer, the dimension is compress to 56 * 56 * 128. Two more layers of convolution with 256 filters are added each shadowed by a down sampling layer that compress the dimesions to 28 * 28 * 256.

Two further stack, each of 3 folding layers, are separated by a maximum group layer. After the last grouping layer, the 7 * 7 * 512 vol. flattered into the Fully Connected Layer (FC) with 4096 channels and a Softmax output of the 1000 class.

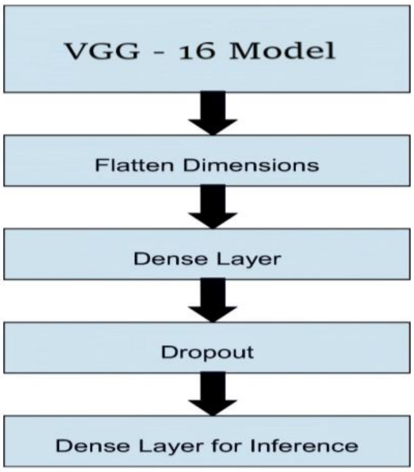

Fig : VGG Model

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Hardware & Software Requirement

SOFTWARE REQUIREMENT

Language : Python

Framework :Flask

Front End : HTML,CSS

Domain : Deep Learning , Machine Learning

Algorithm : CNN

CNN Model : VGG-16 , Inception V3

Dataset : Covid Xray and CT Scan Images

HARDWARE REQUIREMENT

Processor : i3 or greater

RAM : 4GB or greater

Hard Disk : 50 GB or greater

Connectivity : LAN or WIFI

Implementation

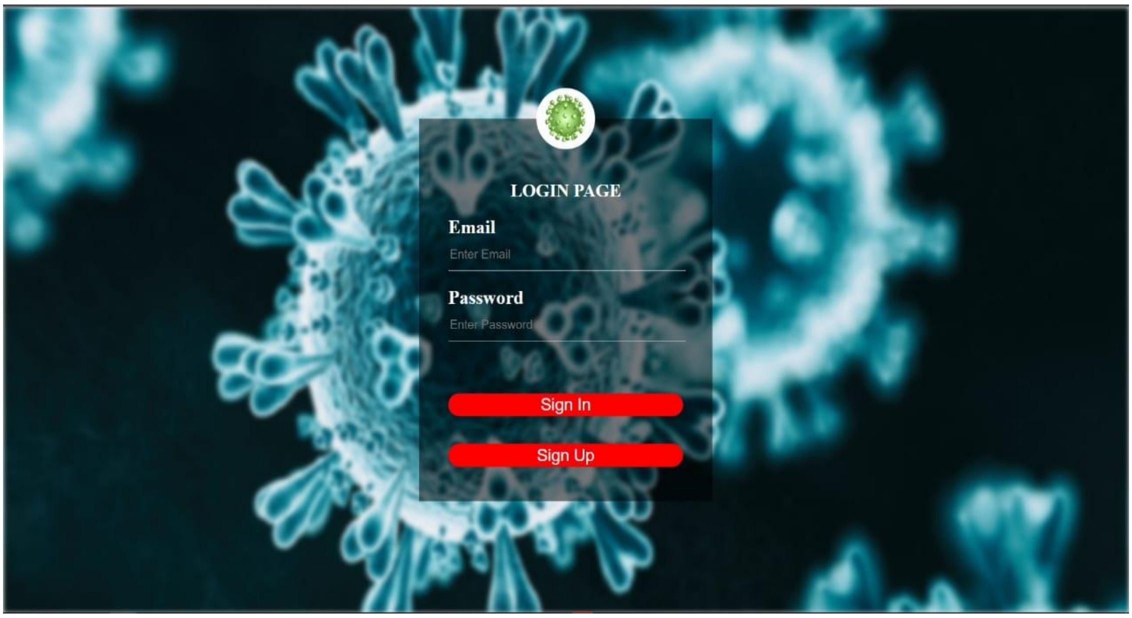
3.1 In our purposed system it has six different modules and each separate module has their our use discussed as below.

1. Login Module

a) In this module the doctor will login into system and then they will use the model for patient.

b) The login module contains email a and password for accessing the system.

c) This module will allow doctor to enter in the system to use the system for checking that the patient is corona positive or not.



2. Algorithm Training Module (for Chest X-Rays)

a) In this module we train the cnn algorithm with the covid - 19 X ray dataset

b) In this module we had train cnn algorithm with two different model layer such as

i. InceptionV3 with 96 % accuracy

ii. VGG layer with 93 % accuracy

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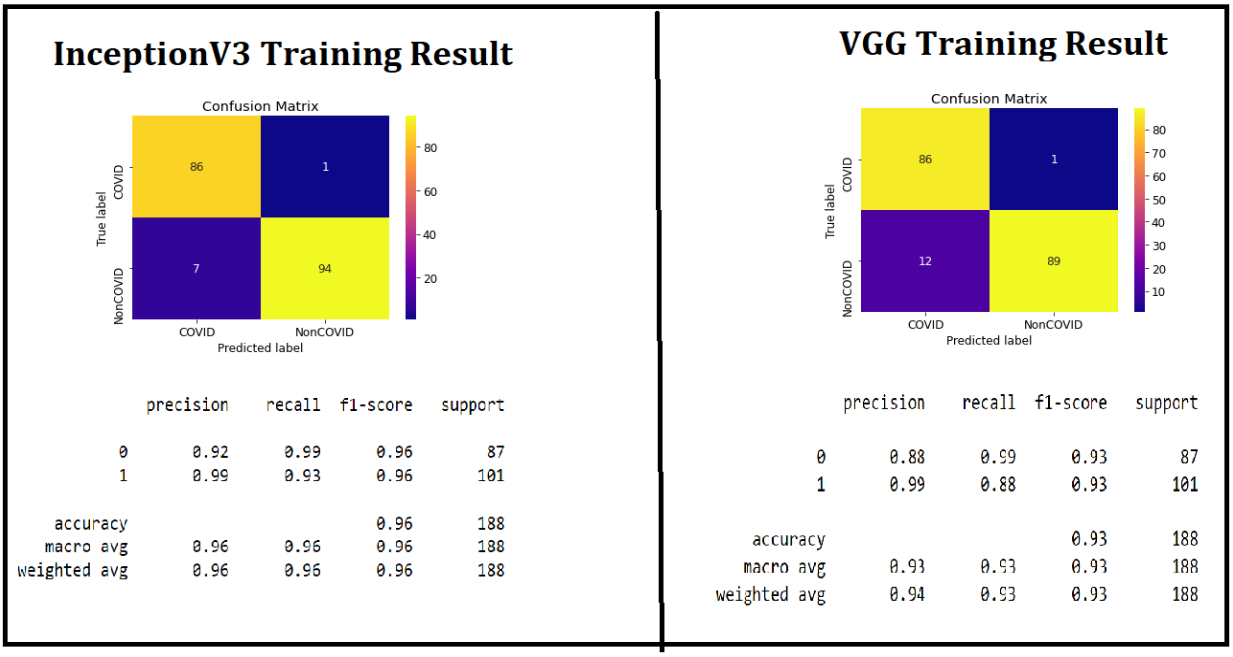
C)we have used 500 ephocs for training we have used google colab for execution.

d)This module will basically about training algorithm on X-ray images



3) Image Selection Module

a) In this module we have to select the input x ray image.

b) From this module selected image will directly pass to our trained and saved model

c) It allows image to select in jpeg and png format both.

4) Covid X ray Prediction

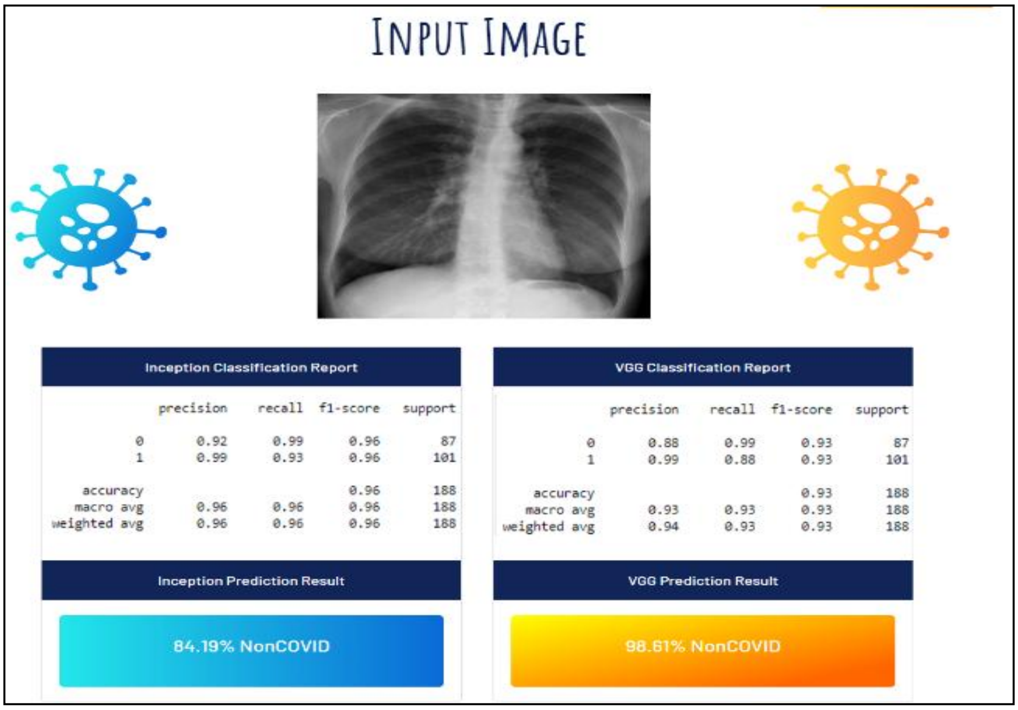
a) In this module we can able to predict whether the patient is suffering from covid or not

b) In this module we have to choose the X-Ray image of patient

c) In this module we have used our trained cnn algorithm with two different model layer such as

1. InceptionV3 with 96 % accuracy
2. VGG layer with 93 % accuracy

d) In this module we just have to pass the x-ray image and system will apply the algorithm and make prediction whether patient has covid infection or not



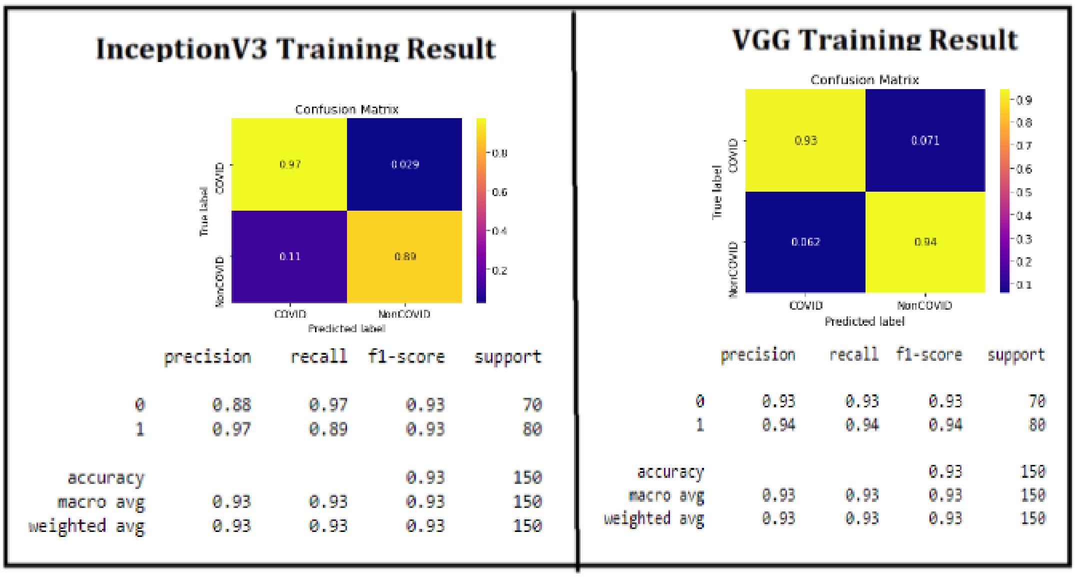
5. Algorithm Training Module (for Chest CT - Scan)

a) In this module we can able to predict is the patient is suffering from covid or not

b) In this module we have to choose the CT-Scan image of patient.

c) In this module we have used our trained cnn algorithm with two different model layer such as 1. InceptionV3 with 93 % accuracy 2. VGG layer with 93 % accuracy

d) In this module we just have to pass the CT-Scan image and system will apply the algorithm and make prediction whether patient has Covid infection or not



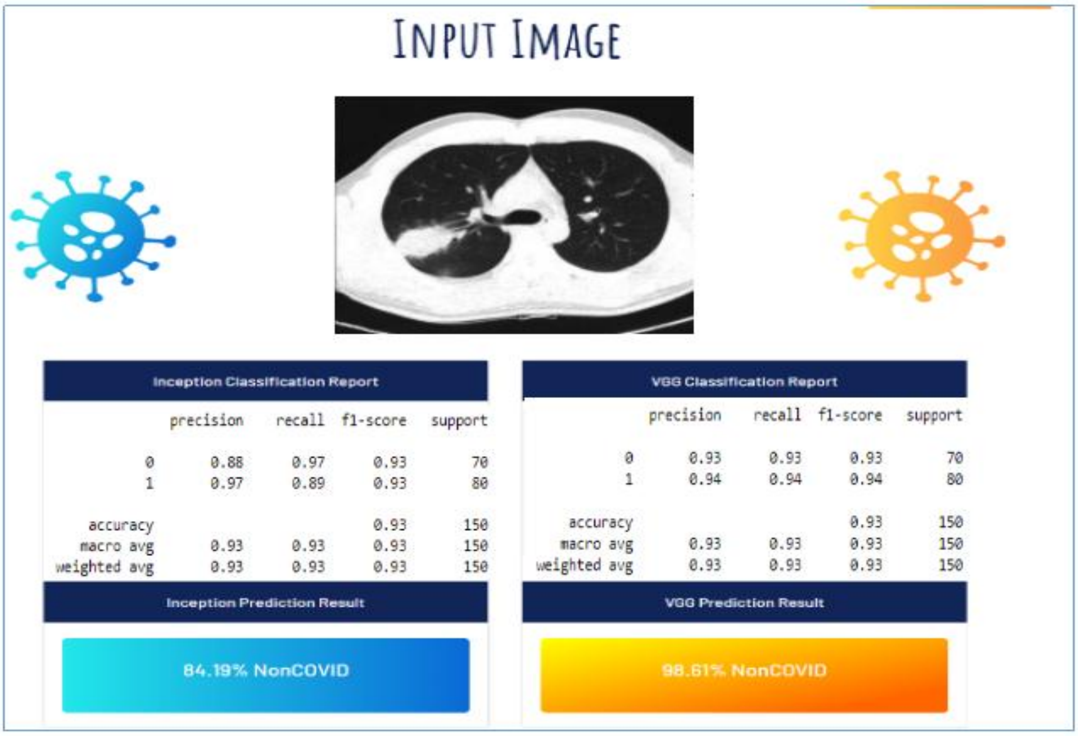
6. Covid Prediction from CT Scan Image

a. In this module we can able to predict is the patient suffering from covid or not

b. In this module we have to choose the CT image of patient.

c. In this module we have used our trained cnn algorithm with two different model layer such as 1. InceptionV3 with 93 % accuracy 2. VGG layer with 93 % accuracy

d. In this module we just have to pass the CT_image and system will apply the algorithm and make prediction whether patient has covid infection or not.



Medical imaging is additionally a way of analyzing and predicting the consequences of covid-19 on the physical body . In this, fit persons and Covid-19 contaminated patients are often analyzed in parallel with the assistance of CT (Computerised Tomography) photos and chest X-ray photos. For helping in analyzing the Coronavirus, we gathered uploaded information of X-ray images of physically fit and covid-19 contaminated patients from different sources and applied three different models (InceptionV3, VGG-16). The analysis of this gathered data is completed with the assistance of CNN, a machine learning tool. This work mainly focuses on the utilization of CNN models for classifying chest X-ray photos for coronavirus contaminated patients. we've attempted to draw a parallel to the previous add the sector and appearance for potential models of the task, which may be help further to justify their usefulness in practical scenarios.

IV. RESULTS AND DISCUSSION

The COVID-19, which began with the reporting of unknown causes of pneumonia in Wuhan, on 31 st December, 2019, has rapidly converted into a pandemic. called COVID-19 and the virus is called SARS-CoV-2.Most coronaviruses affect animals, but due to their zoonotic nature they can also be transmitted to humans. Many small period respiratory disorder (SARS-CoV) and Middle Eastern respiratory coronavirus (MERS-CoV) have caused severe respiratory diseases and deaths in human. Typical clinical features of COVID-19 are fever, cough, sore throat, headache, fatigue, muscle pain . The most common test technique currently used to diagnose COVID-19 is a real- time reverse transcription po-limerase chain reaction (RT-PCR). Chest x-rays, such as computed tomography (CT) and x-rays, play an crucial role in the early detection and treatment of this disease. Because of its lower tactful of RT-PCR of 60% - 70%, even with negative results, symptoms can be determined by examining x-rays of patients.

CT is said to be a sensitive method in detecting the COVID-19 pneumonia and can be viewed as a screening instrument with RT-PRC. CT findings are observed for a long time after symptoms appear, and patients normally have a normal CT scan in the intial 0 to 2 days. In a study of lung CT scans of patients who survived COVID19 pneumonia, the most significant lung disease was observed 10 days after symptoms appeared. After the pandemic, the Chinese clinical centers had insufficient test kits, which also leads to a high rate of false negative results. Therefore, doctors are advised to make a diagnosis based solely on clinical and CT results is utilize to identify COVID19 in countries like Turkey where a small number of test kits were available at the beginning of the pandemic. Researchers claim that the combination of clinical imaging features with laboratory results can contribute to the early detection of COVID19. Radiological images from COVID19 cases provide useful information for diagnosis. Some studies have found changes in chest xrays and CT images prior to the onset of COVID19 symptoms.

Researchers have made significant discoveries in imaging studies of COVID19. et al observed opacities of the right infrahilar air space in a patient with COVID19.. Zhao et al. found not only mat opacities (GGO) or mixed GGO in most patients, but also observed vascular consolidation and expansion in the lesion. Li and Xia reported GGO and consolidation, thickening of the interlobular septum, and bronchogram signs in the air with or without vasodilation as common features of the CT scan of COVID19 patients.

Another observation is the focal or multifocal peripheral GGO, which affects both lungs in 50 to 75% of patients. Similarly, Zu et al. and Chung et al found that 33% of chest CT scans can show rounded lung opacities. and explanations of these images are also given.

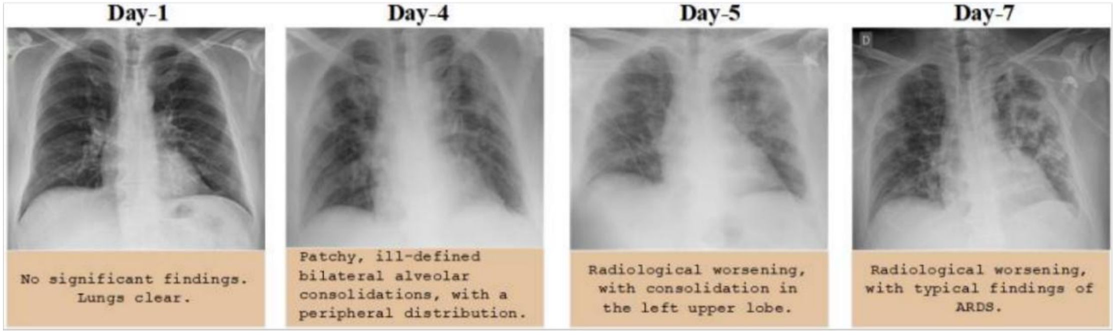


Fig : Images of Chest X-ray of a 50-year-old COVID-19 patient with pneumonia over a week

V. CONCLUSION

Hence we have successfully created the Coronavirus Detection System using Artificial Intelligence. The system has been designed taking the chest X-rays images and scan CT images of the patients. We also collected meta information such as Age, Gender ,Location, Medical History, Scan time and Severity of COVID-19 and Radiology report.

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