MANIPAL ACADEMY of HIGHER EDUCATION

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MANIPAL SCHOOL OF INFORMATION SCIENCES

(A Constituent unit of MAHE, Manipal)

A MINI PROJECT REPORT

On

CLASSIFICATION OF COVID19 X-RAY IMAGES USING CONVOLUTIONAL NEURAL NETWORK

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DECLARATION

We declare that this mini project, submitted for the evaluation of course work of Mini Project to Manipal School of Information Sciences, is (our original work/ using/implementing idea/concept/code available at (https://towardsdatascience.com/medical-x-ray-%EF%B8%8F-image-classification-using-convolutional-neural-network-9a6d33b1c2a)), conducted under the supervision of my guide Dr Nandish S and panel members, Mr Satyanarayan Shenoy, Mr Sudhakar Upadhya P References, help and material obtained from other sources have been duly acknowledged.

ABSTRACT

Covid-19 virus, which has emerged in the Republic of China in an undetermined cause, has affected the whole world quickly. It is important to detect positive cases early to prevent further spread of the outbreak. In the diagnostic phase, radiological images of the chest are determinative as well as the RT-PCR (Reverse Transcription-Polymerase Chain Reaction) test. which is a convolutional neural network architecture in Covid-19 detection using chest x-ray images. Deep learning algorithms, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. there have been several ways to detect and diagnose COVID-19, one of which is using X-ray images. we examines the use of in-depth features and methods to process two-dimensional data from patients' X-ray images. Convolutional Neural Network (CNN) is a development of Multi-Layer Perceptron (MLP), which is specifically designed to process two-dimensional data or image data. The deep features of the fully connected layer CNN model are extracted and can be immediately classified without the need for any additional techniques. CNN method is used because of its good performance for large datasets that will be used for training and testing. In the classification process, the dataset contains x-ray images and consists of two categories, COVID-19 and normal, that represents a positive or negative classification of Covid-19 infection to a patient. To get the best accuracy of the classification model, the author changed several parameters on CNN, such as the distribution of the dataset and the number of epochs. From the nine models tested, model number 5 and 8 with a dataset ratio of 70:30 and epoch number 30 and 40 respectively, resulted in the best accuracy of 90.91%.

Contents

LIST OF FIGURES

1. Introduction

Coronavirus, commonly known as COVID-19, is a type of virus from the subfamily Orthocronavirinae in the family Coronaviridae and the order Nidovirales first appeared in Wuhan, China, in December 2019. The virus is already a severe problem for the world community as its spread expands. Data on August 24, 2020, people who have contracted COVID-19 in the world have reached 23,424,844 people. Coronavirus can cause diseases in humans and animals. In humans, coronavirus causes respiratory tract infections. According to the World Health Organization (WHO), most people infected with the COVID-19 virus will experience mild to moderate respiratory illness and recover without special treatment. In general, several symptoms will occur when a person is infected with COVID-19, including fever, cough, sore throat, headache, muscle pain, and respiratory problem. However, many sufferers also suffer from severe respiratory distress until death. This is a concern for the people of the world, in addition to demographic conditions such as gender and age, and parameters such as temperature and humidity can also affect the prevalence of the disease in the spread of the virus, One way to do this is to apply rules to limit outdoor activities and require everyone to wear masks. Then another way that can use to detect COVID-19 is through tests. The most common test commonly used to diagnose COVID-19 is using the PCR (Polymerase Chain Reaction) method, commonly referred to as the swab test. However, because the sensitivity of the PCR (Polymerase Chain Reaction) method is low, 60% - 70 % can be done other ways to diagnose the disease early. After knowing how to diagnose the disease, another problem is that the current COVID-19 test process is difficult due to the lack of available tools to diagnose. Due to the limited availability of COVID-19 testing devices, other diagnostic measures other than PCR (Polymerase Chain Reaction) are necessary because the sensitivity of diagnosing is still less optimal for early diagnosis and more accurate. One of them is to use X-ray imagery. Because COVID-19 attacks epithelial cells where these cells line our respiratory tract, another way to do this is to analyze a patient's lung health using X-rays. Also, consider that almost every hospital has an x-ray image machine commonly used to diagnose pneumonia, lymph nodes, and pneumonia – it is possible to use this x-ray media to test COVID-19 without a special test kit. However, in the analysis process to diagnose X-ray images requires a radiologist and takes quite a lot of time, which means cutting out time that is invaluable for medical practitioners if a patient is sick. Therefore, automated systems' development to detect and classify COVID-19 using X-rays is necessary to save medical professional's time

Deep Learning

Deep learning is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Deep learning (DL) is an important machine learning field that has achieved considerable success in many research areas. In the last decade, the-state-of-the-art studies on many research areas such as computer vision, object recognition, speech recognition, and natural language processing were especially led to the awakening of the artificial intelligence from deep sleep. Nowadays, many researchers try to find solutions to many problems in various fields under the light of DL methods. In this study, it is presented important knowledge to guide about DL models and challenging topics that can be used in DL for researchers. This study investigated DL studies which are made in the most popular and challenging fields such as autonomous vehicles, natural language processing, handwritten character recognition, signature verification, voice and video recognition, medical image processing, and big data. Furthermore, this study points out the remaining challenges of these research areas that can be solved by DL, and discusses future topics to help the researchers. In the present day, Deep learning methods have reached better results than humans in object recognition. According to the literature studies on DL, It is foreseen that this success will be achieved in areas such as autonomous vehicles, medical image processing, big data analysis, and character recognition.

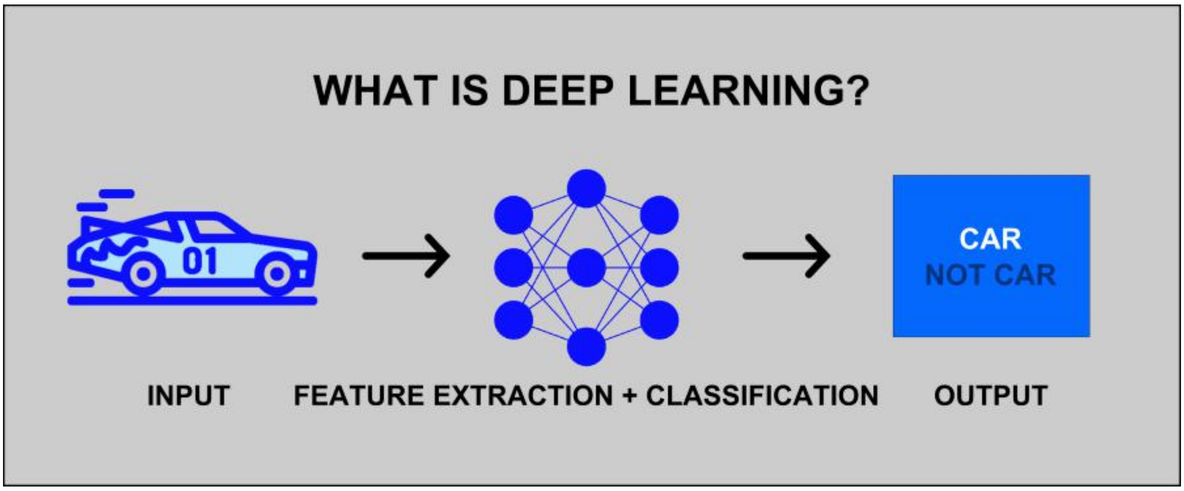

Figure 1.1 : Deep Learning

Neural Network

Neural networks are modeled after our brains. There are individual nodes that form the layers in the network, just like the neurons in our brains connect different areas.

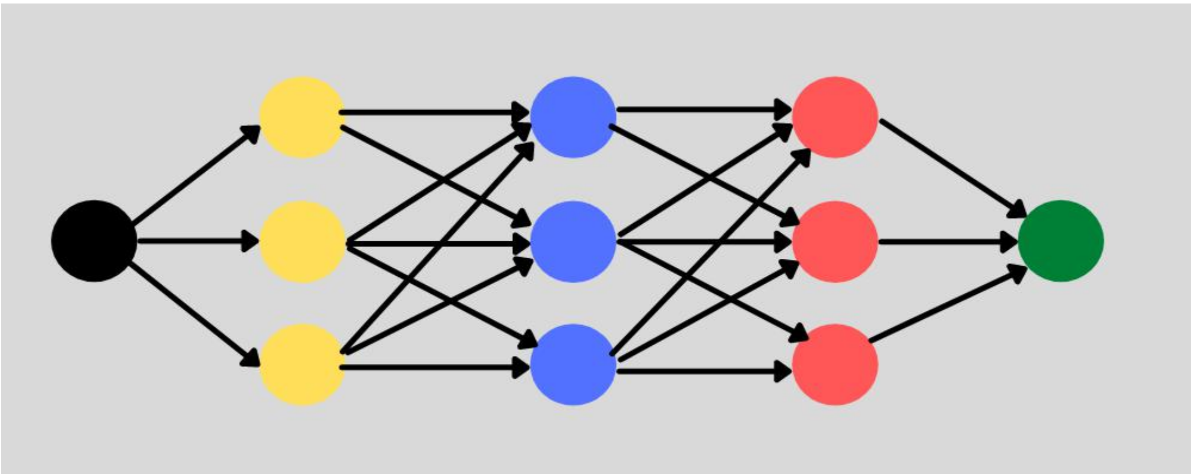

FIGURE 1.2 **:** Neural network with multiple hidden layers. Each layer has multiple nodes.

The inputs to nodes in a single layer will have a weight assigned to them that changes the effect that parameter has on the overall prediction result. Since the weights are assigned on the links between nodes, each node maybe influenced by multiple weights. The neural network takes all of the training data in the input layer. Then it passes the data through the hidden layers, transforming the values based on the weights at each node. Finally it returns a value in the output layer. It can take some time to properly tune a neural network to get consistent, reliable results. Testing and training your neural network is a balancing process between deciding what features are the most important to your model.

2. LITERATURE REVIEW

Several studies in the literature have used X-ray data to demonstrate reasonable performance using various deep learning techniques. DarkCovidNet, a model for early detectionof COVID-19 that used convolutional layers to perform binary and multi-class classification involving normal,COVID, cases, was proposed in. COVID-19 features in data can be de- tected and monitored using existing deep learning models on scan images. Using CNN architectures to distinguish between equipment. The capture equipment and acquisition technique COVID-19 and non-COVID-19 cases.Deep learning was to shown to be a viable technique for identifying COVID-19 from images in their experiments. The trained approach is designed to distinguish COVID-19 cases from normal cases as well as pathological patients with similar symptoms from other respiratory disorders, chest X-ray images from normal patients are grouped along with those from pathological patients with respiratory dis-orders other than COVID-19, and the method predicts Normal and COVID-19 groups. In addition, The current the two types of chest X-ray images used in this study. To infrastructure for detecting COVID-19 positive patients (e.g. do this, we used a series of chest X-ray images from pa- small image data sources with expert la- belled data set) is infected with COVID-19, patients with other patholo- inadequate, and manual detection takes a long time[4]. With gies with similar characteristics to COVID-19, and healthy the increase in global incidences, it is expected that a Deep patients to train a model. Several researchers have been learning-based solution will be developed and combined with working on the virus since it first spread, developing a variety clinical practises to provide cost-effective, dependable, and of methods for detecting and dealing with Covid-19. The use simple automated COVID-19 detection to aid the screening of x-rays in covid-19 prediction was inspired by the initial process. X-ray scans are widely used by radiologists approaches used in detection from chest x-rays to diagnose lung inflammation, swollen lymph nodes, and using deep learning models. It’s also vital to provide a good pneumonia. The COVID-19 virus infects the endothelial cells dataset with confirmed covid19 patients chest x-ray images. that line the lungs once within the body. X-rays may be used. Transfer Learning is a method in which we train a model to determine a patient’s lung health. X-ray analy- sis requires for one proble m and then use it for a few simila r proble m s with an expert and takes a long time. Hybrid approaches to minor changes. In the new model, one or more layers from merging CNN and other ML algorithms are gaining popularity the learned model are used. Instead of results in the literature after outperforming current state of the art associated with various conditions, a deep learning model will in a variety of cases. Created a Hybrid group X-ray images according to the scanning equip- ment Algorithm that combined CNN to achieve a used for the examination. Furthermore, the vast majority percent digit recognition accuracy. of the photographs in these datasets were taken with fixed introduced various hybrid algorithms in his paper and demo n-ray equipment. The capture equipment and acquisition tech-strated that they worked better. By removing a multi affect the quality of chest X-ray images in terms of perceptron layer from CNN, used Faster spatial resolution, contrast, presence of objects, and noise. R-CNN for feature extraction, and features were transferred Furthermore, as RNN and other automated feature extraction to Random Forest, which performed better than CNN. techniques have become more popular, interest in early-stage Various methods were used to analyse the chest X-rays.Machine learning was used to help improve the algorithms, but the systems’ accuracy was poor. Deep learning and the Convolution Neural Network (CNN) began to have an impact in 2007 and things began to change. Deep learning algorithms have an inherent weakness in that they need a large data set to train.One of the most widely used techniques for diagnosing pneumomia is chest radiography (X-ray). A chest X-ray is a simple, low-cost, and widely used clinical procedure. In contrast to computed tomography (CT) and magnetic resonance imaging (MRI), a chest X-ray exposes the patient to less radiation. Making the right diagnosis from X-ray pictures, on the other hand, necessitates expert expertise and experience. A chest X-ray is much more difficult to diagnose than other imaging modalities like CT or MRI. COVID-19 can only be detected using a chest X-ray by a specialized physician. There are fewer experts who can make this diagnosis than there are general practitioners. In many countries around the world, even in normal times, the number of doc- tors per person is inadequate. According to 2017 statistics, Greece has the most doctors per 100,000 people, with 607 doctors. This figure is much smaller in other countries. The health system will collapse in the case of a disaster, including the COVID-19 pandemic, that necessitates simultaneous emergency care due to a lack of hospital beds and medical personnel. COVID-19 is also a highly infectious disease, with physicians, nurses, and caregivers being especially vulnera- ble. Early diagnosis of pneumonia is critical for both slowing the spread of the virus and ensuring the patient's recovery. Computer- aided diagnosis (CAD) helps doctors to diagnose pneumonia from a chest X-ray more rapidly and reliably. Artificial intelligence approaches are becoming more common in the medical field because of their ability to work with large datasets that surpass human capacity. Integrating CAD methods into radiologist diagnostic systems decreases doc- tors' workload while also enhancing accuracy and quantitative analysis. Several deep learning-based methods for classifying diseases have been proposed and evaluated to be effective at the human level. Almost all of these techniques, on the other hand, are designed to diagnose particular diseases like pneumonia, tuberculosis, and lung cancer. Meanwhile, researchers are working on a unified deep learning system for accurately detecting several common thoracic diseases. Reverse transcription polymerase chain reaction confirms the diagnosis of COVID-19. The importance of chest radiography (CXR) is still a hot topic of debate. Present CXR studies on COVID-19 include a range of terms as well as different evaluations of its sensitivity and specificity. This can lead to CXR results be- ing misinterpreted, rendering comparisons between examinations and study studies difficult. We recommend terminology for consistent CXR reporting and severity assessment of individuals under investigation for COVID-19, patients with a verified diagnosis of COVID-19, and patients who may have radiographic symptoms of COVID-19, in or-der to satisfy this need for accuracy. When the diagnosis of COVID-19 is not suspected clinically, results characteristic or indicative of COVID-19 are found. The most common imaging test in the country is chest radiography, which is essential for screening, diagnosing, and treating a variety of life-threatening diseases. From enhanced workflow prioritisation and clinical decision support to large-scale screening and global population health initiatives, automated chest radiograph interpretation at the level of practicing radiologists could provide significant benefit in a number of medical settings. The most popular image analysis requested is chest X-rays (CXRs). Computer Aided Diagnosis (CAD) has gotten a lot of attention in the scientific community, both before and after the success of deep learning. A recent effort has been made to build a new generation of CAD systems for the identification and visualization of common thoracic diseases from CXR images using advances in machine learning, especially deep learning.The area of time series forecasting known as spatial-temporal time series is concerned with variables that shift over time and space. Disease forecasting, such as COVID-19, would benefit from spatial-temporal forecasting because it analyses patterns and provides a reliable predictor for decision makers all over the world, ability to make the right decisions at the right time.

3. DATA AND METHODOLOGY

The method used in this study is quantitative. Quantitative methods are methods used to find answers to questions or in numbers mathematically. The research process is also experimental, which is to experiment with the Convolutional Neural Network architecture design on x-ray image detection and evaluate the architectural design results to assess the accuracy of the Convolutional Neural Network architecture.

A. Analysis Process

Process analysis is at a stage where the authors will analyze what processes the CNN model will need to classify COVID-19 correctly. The recommended method for classifying COVID-19 with x-ray images using the first CNN model is to collect image datasets to train CNN models to recognize images according to the categories or labels provided in the data evaluation process. Furthermore, CNN process preparation recommends consisting of the preprocessing stage or the stage at which the dataset will reprocess according to the model's needs, such as resizing the image. To run the experimental process, after the preprocessing scene, the author creates an experiment by changing the epoch parameters and dataset ratios within the CNN architecture and inserted into scenarios with different parameters.

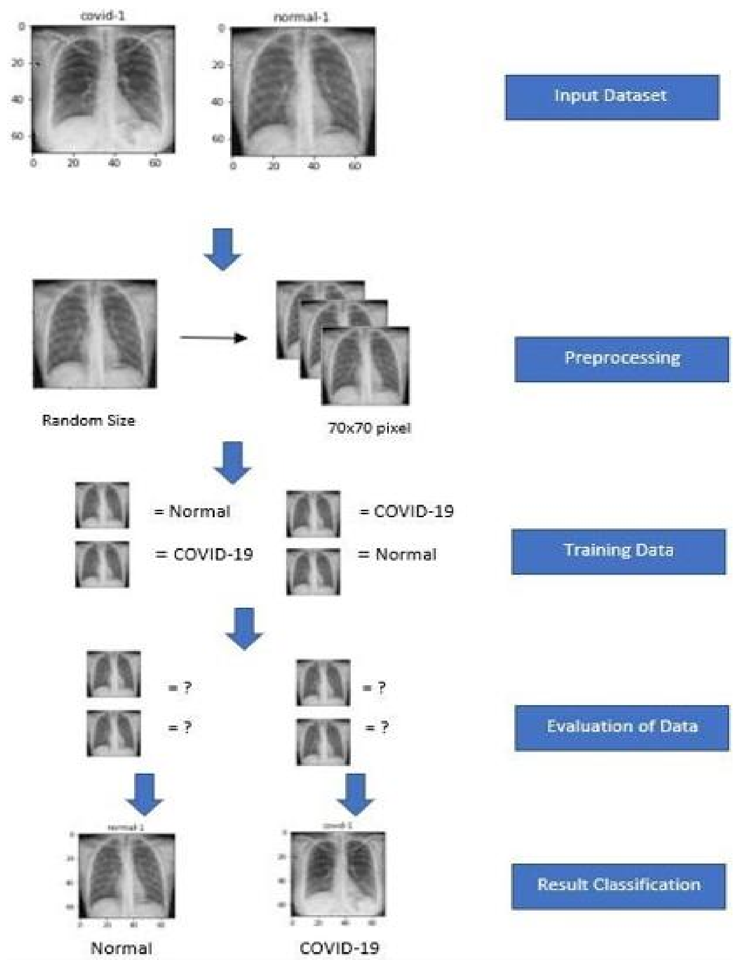

Figure 1.3: Classification Process

the next step is to train the data, this stage aims to allow the CNN model to learn by recognizing x-ray images and distinguishing x-ray images based on the category created and the latter is the evaluation of the data, where the model will test with an x-ray image dataset without being labeled the x-ray image. The more models correctly claim the image, the better it will be. These stages will be explained more fully in the next section, for the complete classification process that we see in the Fig. 1.3:

B. Dataset

The chest x-ray data has been collected from 2 two sources: GitHub and Kaggle. The GitHub Dataset has various kind of x-rays but and a metadata file giving information about the patients' name, age, sex, diagnosis and various distinct features. The Kaggle Dataset consists of chest xray images with the diagnosis of pneumonia or no infection. Both these datasets are downloaded and uploaded into a Jupyter Notebook. For the GitHub dataset, the data is filtered, considering only the patients that have been tested positive for COVID-19 and having Post Anterior (PA) View. The total number of COVID-19 chest x-ray images is 206. the general accuracy would become very high, but not the COVID-19 detection accuracy. This condition is not our goal because the main purpose here is to achieve good results in detecting COVID-19 cases and not to identify wrong COVID-19 cases. The best way to solve this problem is to make the dataset balanced and provide the network almost equal data of each class when training, so that the network will learn to identify all classes. Here because we do not access more open-source datasets of COVID-19 to increase this class data, We combined these two datasets, and the details are listed. As stated, we only had cases infected with COVID-19, which is few data for a class as compared to other classes. If we had combined lots many images from normal classes with few COVID-19 images for training.

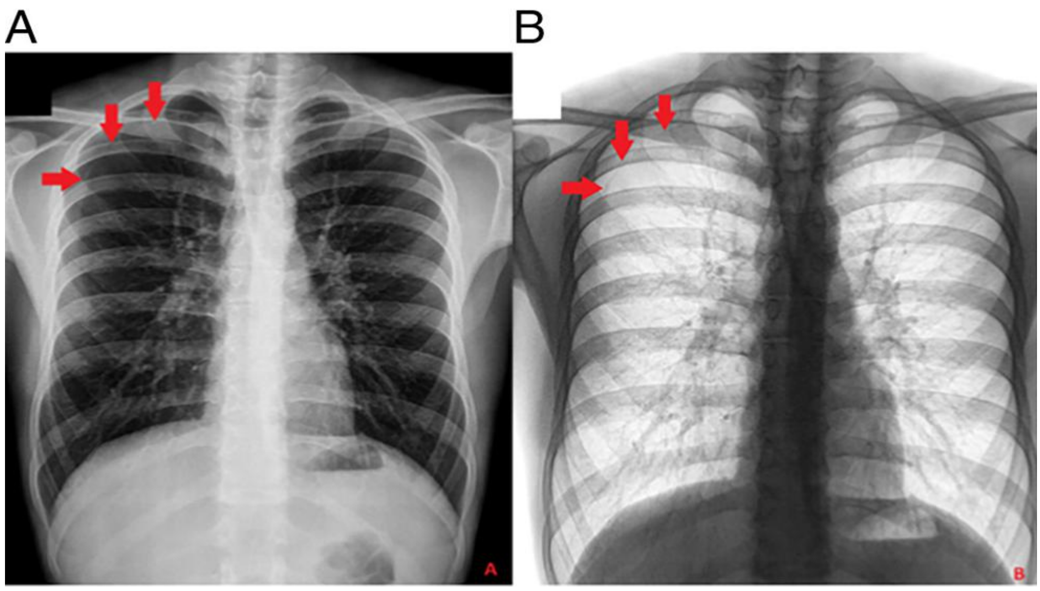

Figure 1.4 : The Covid-19 Positive and Negative

For the Kaggle Dataset, only normal chest x-rays are chosen, which have no infections. In order to keep the dataset balanced, we choose Normal Chest X-rays. The dataset is further divided into train and validation having 80:20 proportion. The dataset contains images of COVID-19 and

Normal Chest X-rays. A CNN model is to be built having two classes in order to distinguish between the Chest X-rays of patients infected with COVID-19 and Normal Chest X-rays. Here are sample Chest X-ray images of COVID-19 and Normal patients respectively.

In order to create the CNN model, Google Collaboratory, or Colab, is used in which Python codes can be written and executed on the browser. The benefits of Colab are no configuration required, free access to GPUs and the file can be easily shared with others. Image datasets can be easily uploaded into Google Colab with a few lines of code which is executed on the power of Google hardware (including GPUs and TPUs), regardless of the power of your machine. Google Colab is widely used for getting started on TensorFlow and making neural network models. The dataset is converted into a zip file to take up less space and is then uploaded onto Dropbox. The Dropbox link is shared on Google Colab, which quickly downloads the zip file. We unzip the file, and the dataset has successfully been uploaded into Google Colab. In order to build the model, Numpy, matplotlib, Keras in-built libraries are used. TensorFlow is running in the backend.

The CNN model consists of two types of layers: Convolutional layers and Fully Connected Layers. A nine layered CNN model is created, consisting of three sets of stacked convolutional and pooling layers followed by two fully connected layers for classifying COVID-19 and normal x-ray images. There are four convolutional layers with filter sizes of 3 x 3 but having increasing filter numbers over the layers.

C. Analysis Process CNN

CNN This section will explain the process that the CNN model will take. The process will start from data preparation or preprocessing, scenario creation to training process from the dataset that has been obtained before. The first process to done to run this CNN model is preprocessing. The purpose of preprocessing is to maximize performance when the training and testing process carry out. After the dataset was created and labeled in this study, the next preprocessing process is done by resizing the image (resize). All images from both label categories change to 70x70 pixels. The second process to done is scenario creation. As explained earlier, this study will propose a model that focuses on the parameters of CNN architecture and does not use pre-trained models. Because this study is experimental, researchers will try to change CNN's architectural model's parameter, searching for the best model accuracy. Researchers will try to create nine different scenario models on the number of epochs and dataset ratios used to find the best architecture for classifying images. Epoch is the number of iterations at the training stage at which models will train to recognize image datasets with pre-defined categories. Then the dataset ratio is how much of a share of the number of datasets will use for training and testing. The parameters to be changed and tested are epochs of 20, 30, and 40 in size, and the dataset ratio will change to 80:20, 70:30, and 60:40. The following detailed scenario that will try to find the best accuracy value.

D. Classification Model

Convolutional neural networks (CNN) are a biologically-inspired trainable architecture that can learn multi-level hierarchies of features. The network extracts implicitly features of visual patterns presented as input and classifies patterns from the extracted features Typical CNN usually consist of convolutional layers, pooling layers, neuron layers and fullyconnected layers. the architecture of a basic CNN. Convolutional layers, have trainable filters that are applied across the entire input, generating feature maps. Each filter detects a particular feature that occurs in any part of the input. Once a feature has been detected, its exact location becomes irrelevant.

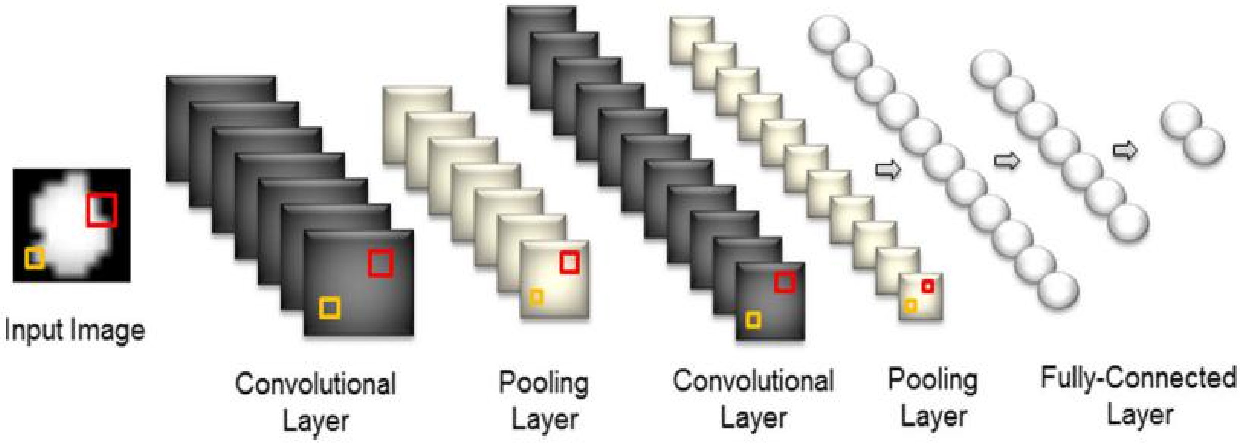

Figure 1.5: Convolutional neural networks

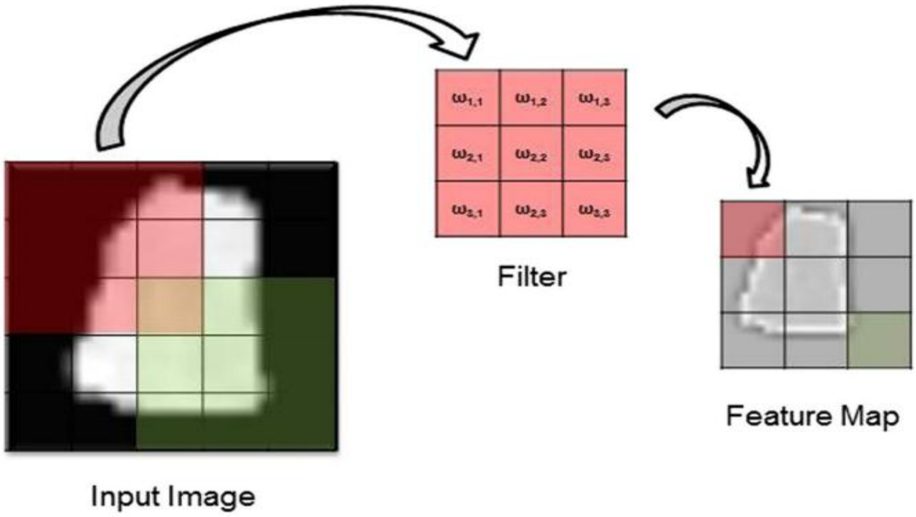

Figure 1.6 : Convolutional Layer

Pooling layers are non-linear down-sampling layers that yield maximum or average values in each sub-region of input image or feature maps. Pooling layers increase the robustness of translation and reduce the number of network parameters. the max-pooling layer. Neuron layers apply non-linear activations on input neurons. Common activations are softmax function, sigmoid function, rectified linear unit, etc. Fully-connected layers are responsible for classifying patterns presented to CNN, generally a multilayer perceptron (MLP). Supervised training is performed using a form of stochastic gradient descent (SGD) to minimize the discrepancy between the desired output and the current output of the network, based on some loss function. All the weights of all the filters in all the layers are updated simultaneously with the backpropagation algorithm. Such neural networks trained with backpropagation admit a large variety of specific architectures applicable to a wide range of applications.

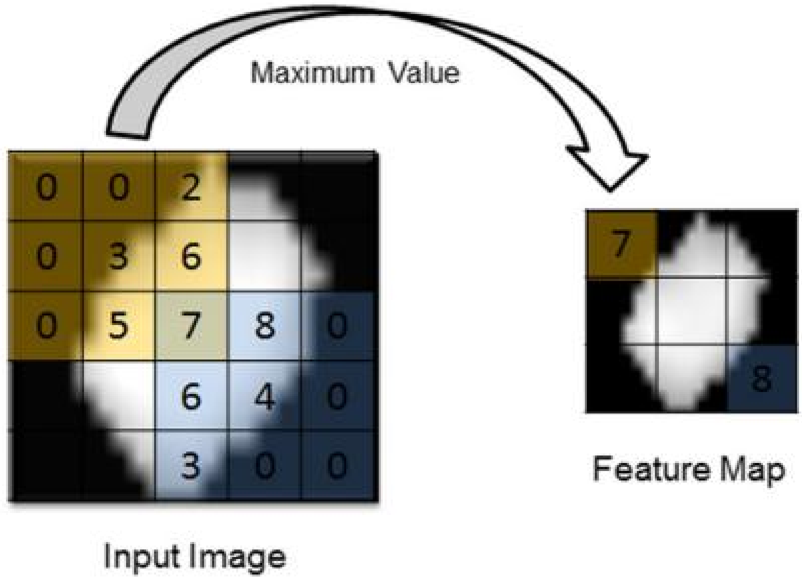

Figure 1.7 : Pooling Layer

However, not all network architectures can be expected to learn a given task successfully. Therefore, we propose an evolutionary approach to this problem.Its was used to optimize the CNN parameters such as number of filters in the convolutional layers and number of neurons in the MLP.

4. CNN ARCHITECHTURE

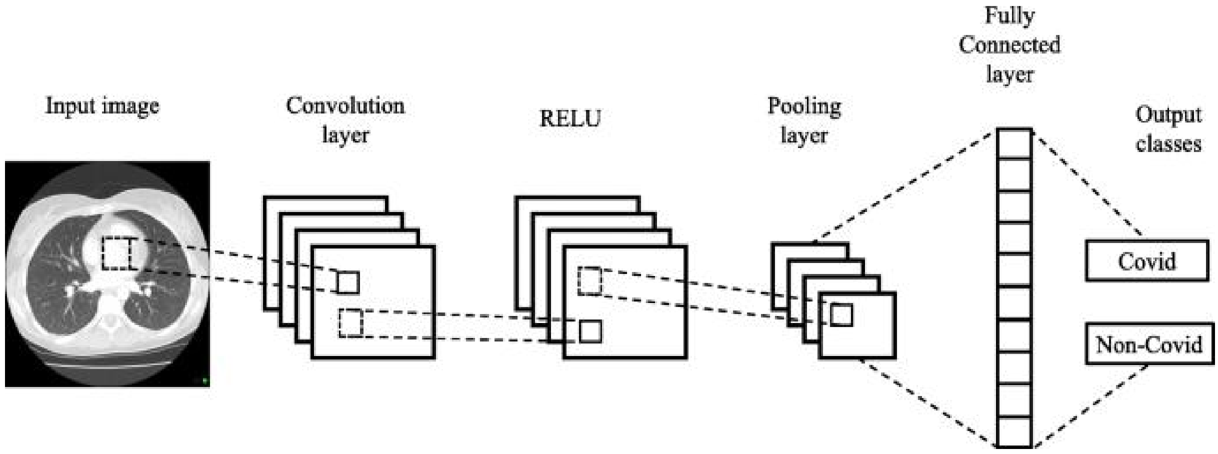

Figure 1.8: CNN Architecture

The initial layers are small in the beginning because the lower layers detect features in small parts of the images and can find small patterns in the image as we go deeper into the layers, the receptive field of the CNN layer increases. The kernel size is 3 x 3, which is a standard choice. Activation of Relu layer is used in the convolutional layers for non-linearity. Since this is the first layer, we specify the input size as 224 x 224 x 3. There are three pooling layers with filter size 2 x 2 each which is the default size, by using Max Pooling, the receptive field of the layer increases.

The first convolutional layer is reshaped into 224 x 224 with three channels because the x-rays are RGB images. On carefully noticing the images, it is observed that the chest x-rays are not greyscaled images but RGB in nature because some pictures have a tone of blue or yellow. In the first set of a stacked convolutional layer, two convolutional layers of 3 x 3 kernel size have been used instead of one convolutional layer of 5 x 5 kernel size. Using two layers is advantageous to the model as it increases non-linearity in the model, and there are fewer parameters which in-turn reduce overfitting. The model can detect a higher level of features in images with the model layers deepening. After every pooling layer, a dropout layer is added to reduce the risk of overfitting with the dropout rate of 25%.

After inputting the convolutional and pooling layers, the output shape has to be changed in order to go forward with the fully connected layers. Hence, the model is converted from a two dimensional layer to one dimension by using a flattening layer and then connected to a fully connected layer. The fully connected layer uses the ReLU function for activation. For the output layer, there is only one filter applied since we have to classify the images between COVID-19 and Normal chest x-ray images. Due to this reason, the activation function of Sigmoid is used.

The model is compiled with binary entropy loss and adam optimizer, which is the default optimizer function using accuracy metrics. This model uses 56 lakh parameters in total, which is trained from scratch. The input shape at the beginning is 224 x 224, which converts into 222 x 222 after the first convolutional layer. The shape is changed to 26 x 26 or 26 x 128 before the flattening layer.

The in-built Keras Image Generator library is used to train the dataset. In order to aid data convergence, the dataset is rescaled for normalization of RGB images by 1/255. Moreover, usage of sheer and zoom augmentation is inculcated, allowing the model to take random crops from images and zooming into the images with 20% magnitude of the image. Vertical flipping of the image has been restricted in order to get accurate results. For the validation dataset, the Image Generator library is used to rescale the images for normalization by 1/255.

For the training dataset, the flow from directory function is applied to reshape the image with a target size of 224 x 224, having a batch size of 32 and using binary classification to distinguish between COVID-19 and Normal Chest x-rays. The same has been done for the validation dataset. The input size of 224 x 224 is a standard choice used by data scientists. Most of the ImageNet problems are solved using this input size.

The model would be difficult to train if the input size would be big, and it would be challenging to capture fine-grained features if the input size would be small. In the training process, ten epochs are used with eight steps per epoch. This model is simpler than other models like VGG16, ImageNet and TransferNet as it uses few parameters.

The other models will not give good results since they contain over a million parameters. Since the dataset contains chest x-rays, the models would have to be carefully finetuned with several modifications which Moreover, the dataset is too small and would hence lead to overfitting. The other models require at least 3000 images for training in order to give a good accuracy score.

5. IMPLEMENTATION

A. Importing the dataset

```
import os
import pandas as pd
import numpy as np
import cv2
data_path='dataset'
categories=os.listdir(data_path)
labels=[i for i in range(len(categories))]
label_dict=dict(zip(categories,labels)) #empty dictionary
print(label_dict)
print(categories)
print(labels)
```

B. Data Preprocessing

```
img_size=100
data=[]
target=[]
for category in categories:
folder_path=os.path.join(data_path,category)
img_names=os.listdir(folder_path)
for img_name in img_names:
img_path=os.path.join(folder_path,img_name)
img=cv2.imread(img_path)

try:
gray=cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
  #Coverting the image into gray scale

resized=cv2.resize(gray,(img_size,img_size))
 #resizing the gray scale into 100x100, since we need a fixed common size for all the images in the
dataset

data.append(resized)
target.append(label_dict[category])
#appending the image and the label(categorized) into the list (dataset)

except Exception as e:
print('Exception:',e)
#if any exception rasied, the exception will be printed here. And pass to the next image
```

C. Modelling

```
import numpy as np
data=np.array(data)/255.0
data=np.reshape(data,(data.shape[0],img_size,img_size,1))
target=np.array(target)

from keras.utils import np_utils  #from tensorflow.python.keras import utils

new_target=np_utils.to_categorical(target)
np.save('data',data)
np.save('target',new_target)
data=np.load('data.npy')
target=np.load('target.npy')

from tensorflow.keras.models import Sequential,Model
from tensorflow.keras.layers import Dense, Dropout, Flatten,Conv2D,Activation,MaxPooling2D
#from tensorflow.keras.layers import
from tensorflow.keras.utils import normalize
from keras.layers import Concatenate
from tensorflow.keras import Input
from keras.callbacks import ModelCheckpoint

input_shape=data.shape[1:] #50,50,1
inp=Input(shape=input_shape)
convs=[]
parrallel_kernels=[3,5,7]
for k in range(len(parrallel_kernels)):
   conv = Conv2D(128, parrallel_kernels[k],padding='same',activation='relu',input_shape=(100,
100,3),strides=1)(inp)
   convs.append(conv)
out = Concatenate()(convs)
conv_model = Model(inputs=inp, outputs=out)
model = Sequential()
model.add(conv_model)
model.add(Conv2D(64,(3,3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(32,(3,3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten())
model.add(Dropout(0.5))
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(2,input_dim=128,activation='softmax'))
model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
model (Functional)	(None, 100, 100, 384)	11008
conv2d_3 (Conv2D)	(None, 98, 98, 64)	221248
activation (Activation)	(None, 98, 98, 64)	0
max_pooling2d	(None, 49, 49, 64)	0
conv2d_4 (Conv2D)	(None, 47, 47, 32)	18464
activation_1 (Activation)	(None, 47, 47, 32)	0
max_pooling2d_1	(None, 23, 23, 32)	0
flatten (Flatten)	(None, 16928)	0
dropout (Dropout)	(None, 16928)	0
dense (Dense)	(None, 128)	2166912
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8256
dropout_2 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 2)	130

Total params: 2,426,018
Trainable params: 2,426,018
Non-trainable params: 0

D. Training and Testing

```
from sklearn.model_selection import train_test_split
train_data,test_data,train_target,test_target=train_test_split(data,target,test_size=0.2)

checkpoint = ModelCheckpoint('model-
{epoch:03d}.h5',monitor='val_loss',verbose=0,save_best_only=True,mode='auto')
#save_weights_only=TRUE
history=model.fit(train_data,train_target,epochs=20,callbacks=[checkpoint],validation_split=0.1)
```

E. Computer Vision

```
import cv2
from tensorflow.keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_array,
load_img

img = cv2.imread('F:/data_science/deep learning/DL All Content/Covid-19 prediction using X-
Ray images -20201119T072858Z-001/Covid-19 prediction using X-Ray images/dataset1/Covid19
Negative/16691_1_1.jpg')  # this is a PIL image
#img=cv2.imread(img_path)
gray=cv2.cvtColor(im,cv2.COLOR_BGR2GRAY)
resized=cv2.resize(gray,(100,100))
x1 = img_to_array(resized)
x2 = x1.reshape((1,) + x1.shape)# a Numpy array with shape (1, 3, 150, 150)
```

6. RESULT ANALYSIS

In order to get a summary of the results on a classification problem, a confusion matrix is computed to visually understand the results of the model. It summarizes the correct and incorrect predictions broken down by each class. It shows how the classification model gets confused when it makes predictions and gives an insight not only into the magnitude of errors being made but also regarding the type of errors being made While using deep learning, a model uses more than one epoch since the training since the model accuracy and loss may vary over epochs.

The model is unable to make any meaningful predictions in the beginning. After a few epochs, it fits perfectly fine to the dataset as the training and validation accuracy stagnates and rarely increased at some epochs. Initially, the validation accuracy linearly increased but then becomes constant since gap between the training and validation accuracy reduces over time, it implies that that the model has very less indication of over-fitting and has given good accuracy results over epochs.

A. Accuracy Model

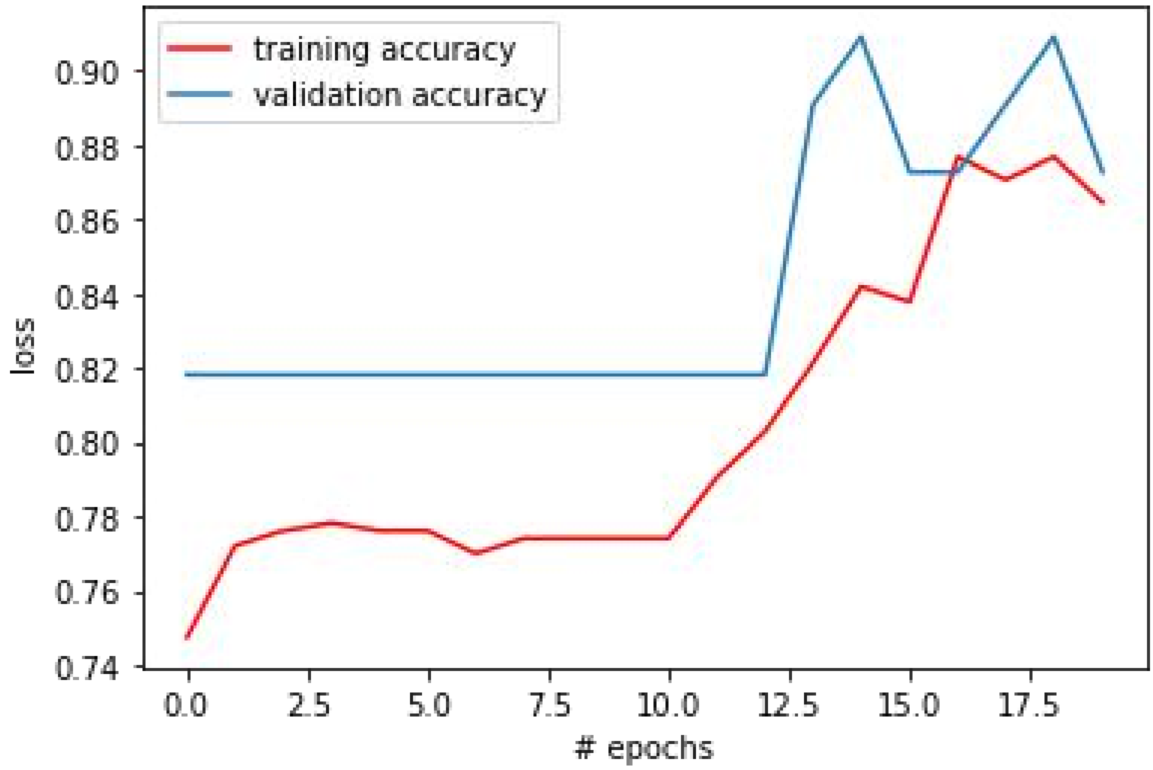

Figure 1.9: Model Accuracy on Covid-19 Image Dataset

B. Loss Model

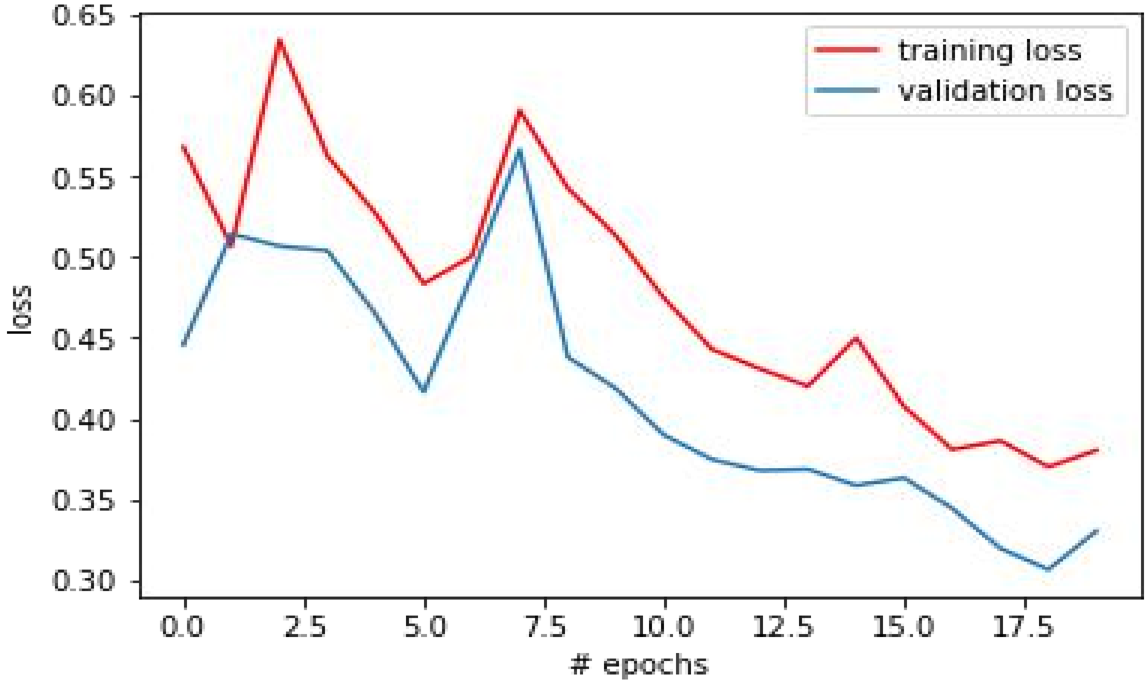

Figure 1.10: Model Loss on Covid-19 Image Dataset

Model loss, on the other hand, indicates how well a model performs after an iteration of optimization. It is the summation of errors a model has on the training and validation dataset. Looking at Figure 6.3, it is observed that the model achieves a stable learning rate. Similar to the validation accuracy, the validation loss falls linearly initially, but after some epochs, it stabilizes. This indicates that the model has succeeded in memorizing the data. The model loss will always be positive.

7. SNAPSHOT

Figure 1.11: Covid Positive

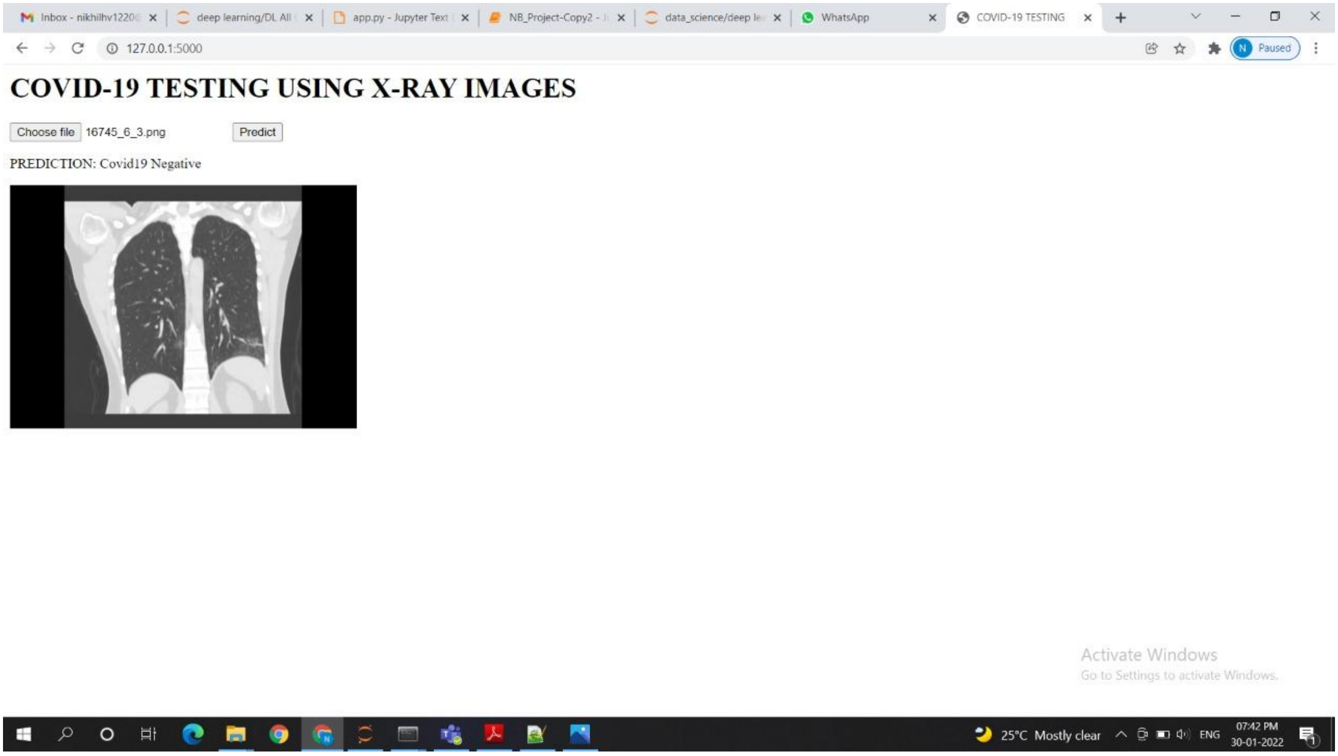

Figure 1.12: Covid Negative

8. CONCLUSION

Chest X-ray images play a vital role in the detection of COVID-19. In this study, a CNN Model was used to detect COVID-19 using Chest X-ray images obtained from COVID-19 patients and Normal patients. CNN enables learning highly representative and hierarchical local image features directly from data. The model performance is 97% which is a high accuracy score with the recent origins of the virus. Although this paper is only for educational and research purposes, not for medical purposes, it will aid doctors to make better decisions in clinical practice due to the higher performance of the model. However, the irregularities in annotated data remain the biggest challenge in coping with COVID- 19 cases from Chest X-ray images.

The limitations of this paper are:

a) Lack of COVID-19 Chest X-rays due to the recent emergence of the virus.

b) No medical guidance was used for the analysis of the project.

Scope for further work

As for future work, Based on the file correlation analysis, small files are classified as multiple types and customized approaches will be supplied to different types to further improvement of efficiency. In the future work, the cut- off point between large and small files will be further studied.

References

1. Yan et al., "Prediction of criticality in patients with severe Covid19 infection using three clinical features: a machine learning-based prognostic model with clinical data in Wuhan," medRxiv,p.2020.02.27.20028027,2020,doi:10.1101/2020.02.27.2002 8027.
2. K. Roosa et al., "Real-time forecasts of the COVID-19 epidemic in China from February 5 to February 24, 2020," Infect. Dis. Model.,vol.5,pp. 256–263, 2020, doi: 10.1016/j.idm.2020.02.002.
3. M. Rahimzadeh and A. Attar, "A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2," Informatics Med. Unlocked, vol. 19, p. 100360, 2020, doi: 10.1016/j.imu.2020.100360.
4. G. Litjens et al., "A survey on deep learning in medical image analysis," Med. Image Anal., vol. 42, no. December 2012, pp. 60–88, 2017, doi: 10.1016/j.media.2017.07.005.
5. Y. Zhong, "Using Deep Convolutional Neural Networks to Diagnose COVID-19 From Chest X-Ray Images," 2020, [Online]. Available: http://arxiv.org/abs/2007.09695.
6. S. Ruuska, W. Hämäläinen, S. Kajava, M. Mughal, P. Matilainen, and J. Mononen, "Evaluation of the confusion matrix method in the validation of an automated system for measuring feeding behaviour of cattle," Behav. Processes, vol. 148, pp. 56–62, 2018,
7. Rick Rogers, John Combardo, Zigard Mednieks and Blake Meiko. Android Application Development, programming with Google SDK, May 2000.