COVID-19 Severity Detection from Lung CT-Scan Images using CNN

A thesis submitted to the Department of Electrical and Computer Engineering in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering

By

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Spring 2022

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Declaration

This report is prepared as a requirement of the Capstone Design Project of CSE499 A & B which is a two semester long senior design course. We declare that the work presented in report entitled "COVID-19 Severity Detection from Lung CT-scan images using CNN" has not been accepted for any degree and is not concurrently submitted in candidature of any other degree. We would like to request you to accept this report as a partial fulfillment of Bachelor of Science degree in Electrical and Computer Engineering Department of North South University.

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I do hereby declare that the work presented in this thesis entitled, "COVID-19 Severity Detection from Lung CT-scan images using CNN" has been submitted by Fahmida Sultana(ID1812829042), Md. Abdullah Al Sayed(ID1822040642), Sharmin Akter(ID1812349042), Khandakar Mubarshar Uddin(ID1711872042) under my supervision. This report partially fulfills the requirement for the degree of Bachelor of Science in Computer Science and Engineering and has been accepted as satisfactory.

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Acknowledgement

All praises are due to Almighty Allah, Most Gracious, Most Merciful who blessed us to be here at North South University for pursuing the bachelors degree.

We are grateful and wish our profound indebtedness to Dr. Sifat Momen, Associate Professor, Department of Electrical and Computer Engineering (ECE), North South University, Dhaka. Deep Knowledge keen interest of our supervisor in the field of "Machine Learning" and "Deep Learning" to carry out this project. His guidance, constant supervision, enthusiastic encouragement, sagacious advice and an effective surveillance throughout the entire period of the project have made it possible to complete this project.

We would like to express deepest appreciation towards Dr. Mohammad Rezaul Bari, Associate Professor & Chair of Electrical and Computer Engineering Department, North South University, Dhaka, Bangladesh.

We would also like to thank codalab.org for providing us the dataset in COVID-19 Infection Percentage Estimation Challenge.

We would also like to thank our family members, our parents, brothers and sisters who are the very reason of our existence. Without their unconditional love and support it was not possible to complete this project.

Abstract

The severity of COVID-19 was detected in this project from Computed Tomography Scan (CT-scan) images of lungs using CNN. The world is devastated by the COVID-19 epidemic, and the economy is in deep crisis. COVID-19 is one of the most recent high-risk issues worldwide. It is more risky and spreads very quickly through the respiratory tract. Anyone can get sick with COVID-19 and become seriously ill or die at any age. People who suffer from various diseases are more likely to become infected and develop more serious conditions. Most of the seniors are suffering from various lung problems, so they are becoming more infected and most of them have lost their lives. However, medical agencies do not have adequate equipment to detect COVID-19 and its severity. Moreover, sometimes this tool has given wrong results. Therefore, it is very important to identify corona positive patients to prevent the spread of this virus. The best way to prevent this is to detect the severity of COVID-19 from a CT scan because it gives more accurate results and treats accordingly. People will be able to recognize the status of the infected person through this application. The condition may vary from critical, extent, minimal, moderate, normal or severe. The dataset was collected from the COVID-19 Infection Percentage Estimation Challenge arranged by CodaLab. They provided 3053 CT-scan images of lungs. These images have been classified into 6 classes. The classes are balanced by augmentation of the images. After augmentation 8614 images are created in the dataset. Some pre-trained models of CNN architecture like VGG16 and MobileNet have been used. Also, Convolutional Neural Network, densenet121 and Sequential CNN models have been applied for training. The accuracy found after applying these models are 85.92%, 80%, 76%, 69% and 63.87% from VGG16, Densenet121, Convolutional Neural Network, Mobilenet and Sequential models respectively. Among all the models the VGG16 has scored the highest accuracy. In the future, more models will be applied for training and for better accuracy.

Chapter 1

1 Introduction

1.1 Introduce the Problem

COVID-19 is the most recent vulnerable issue in almost all over the world. The disease caused by the World Health Organization (WHO) was named Coronavirus Disease 2019 (COVID-19) on February 11, 2020.[1]. It is an infectious disease caused by Severe Acute Respiratory Syndrome 2 (SARS-CoV-2 virus)[2]. SARS-CoV-2 can spread from person to person so COVID-19 has been declared as an epidemic[3]. SARS-CoV-2 - Coronavirus which is a common RNA virus. It is usually round or oval in shape with a diameter of 60nm to 140nm under an electron microscope. It's outer membrane has unique spikes of about 9nm to 12nm like the solar corona[4]. The most common clinical symptoms in patients with COVID-19 are fever, cough, shortness of breath and tiredness which are similar to the severe acute respiratory syndrome coronavirus (SARS-CoV)[5] and the Middle Eastern respiratory syndrome coronavirus[6]. Usually those who are infected with COVID-19 experience mild to moderate symptoms and recover without special treatment. However, some will become seriously ill and need treatment as soon as possible. Severe cases can lead to acute respiratory distress syndrome or even death. The treatment differs according to the severity of the patient's condition. Anyone can be infected with COVID-19 and become seriously ill or die at any age.[7]. However, senior citizens and those with underlying treatment conditions such as heart disease, diabetes, chronic respiratory disease or cancer are more likely to become seriously ill with COVID-19. Complications may include pneumonia, acute respiratory distress syndrome (ARDS), multiple organ failure, septic shock and death. The lungs are the organs mostly affected by COVID-19[8]. Meanwhile, COVID-19 itself can cause neurological and emotional complications such as delirium, movement and stroke. People with pre-existing mental, neurological or substance abuse disorders are also at higher risk for

SARS-CoV-2 infection and may have serious consequences or even death[9]. Some people have died due to wrong treatment as they were not aware of the risk of COVID-19. Rising mortality rates are affecting a country's economy and ecosystem. Bangladesh is facing a big problem because of this epidemic.

1.2 Problem Statement

Typically, those who are infected with COVID-19 experience mild to moderate symptoms and recover without special treatment. Being isolated at home and by quarantine themselves, without going out anywhere and taking some necessary treatment is able to recover the mild condition of a patient. However, some will become seriously ill and need treatment as soon as possible. In many severe cases it can lead to acute respiratory syndrome or even death. Due to the lack of testing kits in Bangladesh and its time consuming and unreliable results, people have suffered a lot, which has led to the challenge of preventing the spread of COVID-19 in the community. In addition, due to the insufficient number of testing kits, infected cases cannot be detected in time, which means that the virus can spread to healthy populations without being recognized, resulting in many deaths. Thus treatment may vary according to the severity of the patient's condition. If a person does not know the severity of the disease, he/she will be unable to get proper treatment. In order to better understand how a medical condition can affect health if infected with COVID-19 and to reduce the risk of serious COVID-19 illness, the infected person need to have knowledge of the severity of COVID-19 disease. The best way to prevent and slow down the infection is to be well-informed about the disease. So, it is important to know the severity of the disease.

1.3 Project Goal

The main goal of this project is to identify the severity of COVID-19 infected patients. People will be able to recognize the status of the infected person through this application. The condition can vary from different ranges like severe, minimal, moderate, normal etc. Patients with severe conditions are usually hospitalized. On the other hand, patients with minimal conditions can stay at home in quarantine and eventually get better. Thus the purpose of this project is to inform people about their condition by making predictions using CT scan lung images. CT scanning is painless, invasive and more accurate. A major advantage of CT is its ability to depict bones, soft tissues and blood vessels at the same time[10]. Unlike conventional X-rays, CT scanning provides very detailed images of many types of tissues, as well as the lungs, bones and blood vessels. The use of CT-scans is not limited to the detection of COVID-19, it can also be used for other important tasks such as determining the extent of infection and monitoring the evolution of the disease, which can help in treatment and save the patient[11]. Now a days doctors prefer CT scan images. Through this project, it will be easier for doctors to identify the condition of a patient infected with COVID-19.

1.4 Adopted Approach

The project was built using the Deep Learning application. Datasets were collected from the COVID-19 infection Percentage Estimate Challenge sorted by CodaLab. The total dataset consists of 3053 images of Computed Tomography Scan (CT-scan)[11]. The dataset is divided into 6 categories such as Critical, Extent, Minimal, Moderate, Normal and Severe. To maintain the balance of this class, the dataset has been augmented. After augmenting, the number of images is 8614. The project uses the Convolutional Neural Network (CNN). CNN is a type of neural network model that allows for a higher presentation for image content[12]. CNN has been playing a great role in classifying images, in particular medical images. This has opened new windows of opportunities and made the disease detection much more convenient. It also successfully detects recent novel Coro-navirus with higher accuracy[13]. Models like VGG16, MobileNetV2, Densenet121, Convolutional Neural Network and Sequential models of CNN are applied to train the data. With this approach it became possible to predict the severity of COVID-19 with CT scan lung images.

1.5 Novelty of Work

This project contains totally a new dataset which was collected from COVID-19 Infection Percentage Estimation Challenge arranged by CodaLab. They released the Dataset on 16th October 2021 [11]. In this project data has been trained with various models using CT scan images. The CT scan images provides better image detail than X-rays or other source of images. Here CNN has been used. CNN is a Deep Learning (DL) algorithm that is being vastly used for image and document analysis. With very little time and resources, this model successfully detects coronavirus patients with high accuracy. This can help to implement testing of COVID-19 on a much greater scale which would really save both money and time.[13]. Also, the accuracy of the model is quite hereditary. One of the constraints that researchers encounter is a limited dataset for training their model. Being a novel disease, the lung CT scan images dataset of COVID-19 positive patients is also limited. Therefore, to avoid overfitting, a sequential CNN model is proposed for classifying CT scan images and also augmentation is done to increase the image number for getting larger dataset. Accuracy boost a little for dataset augmentation. By this application no one will hurt or no one will get offended, it is totally a new application so there is no copyright issue which have to face.

1.6 Project Organization

This report is further organized into five chapters including Chapter 2: Literature Review, Chapter 3: Methodology, Chapter 4: Result, Chapter 5: Conclusion. The name of the second chapter is literature review where some related papers to our work is described and compared in a table. In the third chapter entitled methodology where data collection, pre-process and all the applied models has been described. Moreover, the detailed results and comparison of the applied model can be found in chapter 4, entitled 'Result'. The final chapter of this report is entitled 'Conclusion' which contains a summary of the whole project. It contains the drawbacks of current promising models.

Chapter 2

2 Literature Review

Paper	Approach	Data Collection Source	Model Applied	Model with Highest Accuracy	Advantage
[14]	To automatically detect and identify the COVID-19 disease this research use X-rays images and computed tomography (CT) images to introduce a deep learning strategy based on the CNN.	The dataset has been downloaded from Kaggle. The dataset provides 11095 CT scan and X-ray images.	Two different classification using CNN such as binary and multiple classification	In binary classification the accuracy is 99.64% and in multiclass classification the accuracy is 98.28%.	Desired results from different available CT scan and X-ray images dataset which assist healthcare workers in quickly detecting COVID-19 positive patients can be produced.
[15]	Applied deep learning techniques to identify COVID-19 infected individuals using CT scan images.	The dataset was collected from Kaggle and the entire dataset contains about 2481 CT-scan images.	Four pre-trained models were used to implement the application, namely DenseNet201, MobileNet, ResNet50V2 and VGG16.	DenseNet201 scored the highest accuracy of 99% for training and 97% for testing with un-augmented data and 98% for training and 97% for testing with augmented data.	This application can improve the COVID-19 testing method because many hospitals are equipped with CT-scanners and serve as an automated alternative testing process.

[16]	This application is a computer-aided diagnosis and severity detection method by using transfer learning and a back propagation neural network.	The dataset was collected from two sources and they are SARS-CoV-2 CT-scan and COVID-CT dataset. The SARS-CoV-2 CT-scan dataset contains 2482 CT-scans and COVID-CT dataset contains 349 positive images and 463 negative images.	Models such as ResNet50, DenseNet201 were used and pre-trained architecture for feature extraction and back-propagation networks were also used to determine the intensity of Covid-19.	The Resnet50 scored highest accuracy of 98.23% in 30 epochs.	This computer-aided application enables medical staff to take care of the arrival of a large number of patients daily and assess the need for ICU facilities and ventilator assistance for those infected and those at high risk.
[17]	The application is able to detect the suspected patient's from (CT) scans which is used to differentiate between a healthy person and a COVID-19 patient using deep learning algorithms.	The dataset was collected from Kaggle which consisted of 3873 lung CT scan images.	For implementing the system CNN architecture such as VGG16, DeseNet121, MobileNet, NASNet, Xception, and EfficientNet was trained.	VGG16 got the highest accuracy with 97.68%.	By this system analyzing CT scan images, the paper identifies widespread and best deep learning architectures to identify COVID-19 in suspected patients and helps to take treatment based on their health condition.

[18]	COVID-19 detection system using CNN based on X-ray images of the chest for determining the condition and severity of COVID-19 patient.	Due to not properly avaiable in online the dataset was created by merging 3 open source datasets available on Kaggle and Github.	Four different pre-trained models applied on the dataset such as InceptionV3, MobileNet, Xception, DenseNet121 and also used transfer learning techniques for transferring the weights.	MobileNet has achieved maximum accuracy with 99%.	Through this application the medical staff and people will be able to recognize the exact condition of the patient and measure the severity thus they will be able to take the treatment considering their condition.
[19]	Prediction of COVID-19 Cases Using CNN with X-rays.	The dataset used for this project is a public dataset available online. It contains 1824 chest X-ray images.	The model uses GoggleNet for image classification, one of the CNN architectures called InceptionV1.	After implementing the model, it has achieved 99% training accuracy in 30 and 50 epochs and 98% validation accuracy for 30 epochs.	The hospital staff cannot treat the patient properly without knowing patient condition. So, through this application people will be able to know the condition of the patient and get treatment based on their health.

[13]	A CNN model is proposed to detect COVID-19 patients from chest X-ray images.	For training the proposed model, 165 chest X-ray images of COVID-19 patients are used which are obtained from open Github repository by Cohen et al.	Sequential CNN model is proposed for classifying X-ray image.	Sequential model performs with accuracy and precision of 97.56% and 95.34% respectively.	Mass tests and early detection of COVID-19 have played a key role in preventing the spread of this recent global epidemic. So this model will make it easier to identify the infected patient and treat them accordingly.
[20]	This study compares the popular deep learning-based feature extraction frameworks for automatic COVID-19 classification.	The performance of the proposed method was validated on a publicly available COVID-19 dataset of chest X-ray and CT images.	MobileNet, DenseNet, Xception, ResNet, InceptionV3, Inception-ResNetV2, VGGNet, NASNet were chosen amongst a pool of deep convolutional neural networks	The DenseNet121 feature extractor with Bagging tree classifier achieved the best performance with 99% classification accuracy.	No clinically approved therapeutic drugs or vaccines were available to prevent COVID-19. Thus, early detection was the best method of that time, it is possible to identify positive patients early through this model.

Table 1: Related Papers

Chapter 3

3 Methodology

3.1 Data Collection

The most important thing in order to create a good AI model is to have a good dataset. Without a good amount of data and well standard data machine learning techniques is unsuitable to train or meaningless work. Deep Learning learns from data and it is critical to feed it with the right data for the problem to solve [21]. So, to implement a deep learning system proper dataset is must to collect.

There are different kinds of CT scan lung image dataset available in different sources. For implementing this system , the dataset was collected from COVID-19 COVID-19 Severity Detection from Lung CT-Scan Images using CNN A thesis submitted to the Department of Electrical and Computer Engineering in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering By Fahmida Sultana ID: 1812829042 Md. Abdullah Al Sayed ID: 1822040642 Sharmin Akter ID: 1812349042 Khandakar Mubarshar Uddin ID: 1711872042 Under the guidance of Dr. Sifat Momen Associate Professor Department of Electrical and Computer Engineering North South University Dhaka, Bangladesh Spring 2022 to classify an object with probabilistic values between 0 and 1.[26] A convolution tool that separates and identifies the various features of the image for analysis in a process called as Feature Extraction. A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages[27].The Convolutional layer is shown in figure 3.4. Figure 3.4: Convolutional Layers 3.3.1 Sequential Model A Sequential model is appropriate for a plain stack of layers where each layer has exactly one input tensor and one output tensor [28]. Since each layer connects only to the previous and following layers, this conventional CNN refer as a “sequential CNN model.[29]. Sequential Model of CNN architecture has been applied to detect the severity of COVID-19 infected patients. To avoid overfitting, a sequential CNN model is proposed for classifying CT scan images. The model has 4 main components : (i) input layers (ii) convolutional layers (iii) fully connected layers and (iv) output layers [11]. The model is implemented in Keras. Necessary libraries like Tensorflow and Numpy 13 has been imported. Here pre-processing was done using Tensor flow. In pre-processing image size has been taken 224. So, the target size of the rescaled image is 224 in length and width. Moreover, images have been sheared 20flipped, rotation 40from training images has been split. For test images, validation images are taken. So, Train:Test is 90:10 in ratio. In sequential model Convolution layer, Max Pool layer and Dense layer has been used. Convolution layer has 64 filter with same padding, kernel size is 3, activation is ReLU function and the input shape is (224, 224, 3) where 3 is used for RGB images. In Max pool layer pool size is 2 and stride is also 2. Now flatten to covert 2D matrix array to 1D matrix. 6 output node is taken as the number of classes is 6. Dense layer activation function is "softmax". Compiled CNN by "adam" optimizers, loss function is "categorical crossentropy" which is used for multiclass and matrix is accuracy. Model is trained in two ways, at first with actual dataset images then with augmented dataset images. The test accuracy of the model without augmentation is 49.8366.44and 63.27into 0.9:0.1 train:test data. So, 2750 images as train data and 303 images as test data is used. The batch size is 128 so there is 24 batch. The test accuracy of the model with augmentation is 63.8767.53into 0.9:0.1 train:test data. So, 7756 images as train data and 858 images as test data is used. Here the batch size is 256 so there is 34 batch. 3.3.2 Convolutional Neural Network Convolutional neural networks are a sort of artificial neural network that uses multiple hidden neurons to analyze picture inputs and have learnable weights and bases for several portions of images that can separate themselves. Neural Networks works kind of like a human brain. The inspiration comes from the animal visual cortex. The visual cortex consists of a small area of visual cells that are sensitive to a specific 14 Infection Percentage Estimation Challenge arranged by CodaLab. The challenge has three sets: Train, Val, and Test. The Train set is obtained from 132 CT-scans, from which 128 CT-scans have been confirmed to have COVID-19 based on positive reverse transcription polymerase chain reaction (RT-PCR) and CT scan manifestations identified by two experienced thoracic radiologists. The rest four CT-scans have not any infection type (Healthy). In total there are 3053 images in the train set. The Val set is obtained from 57 CT-scans, from which 55 CT-scans have been confirmed to have COVID-19 based on positive reverse transcription polymerase chain reaction (RT-PCR) and CT scan manifestations identified by two experienced thoracic radiologists. The rest two CT-scans have not any infection type (Healthy)[11].

3.2 Pre-Processing

3.2.1 Dataset Classification

This project presents a new strategy for multi-class classification. It means there are more than two classes needed to be predicted[22].

In the provided dataset, the train split had two files: Images (Slices) Folder and Labeling Folder ('.csv' file) that contains the labels for each Slice (Image). The .csv file contains the Slice Name and the COVID-19 percentage of that image and the patient ID. To classify the severity of COVID-19, the whole train data is divided into six classes based on the percentage of COVID-19 infection. Images with 0 percentage infection are in "Normal" class, 1 to 10 percentage infection in "Minimal" class, 10 to 25 percentage infection in "Moderate" class, 25 to 50 percentage infection in "Extent" class, 50 to 75 percentage infection in "Severe" class and more than 75 percentage infection in "Critical" class. The image classification is shown in the figure 3.1. Also some classified images shown in figure 3.2.

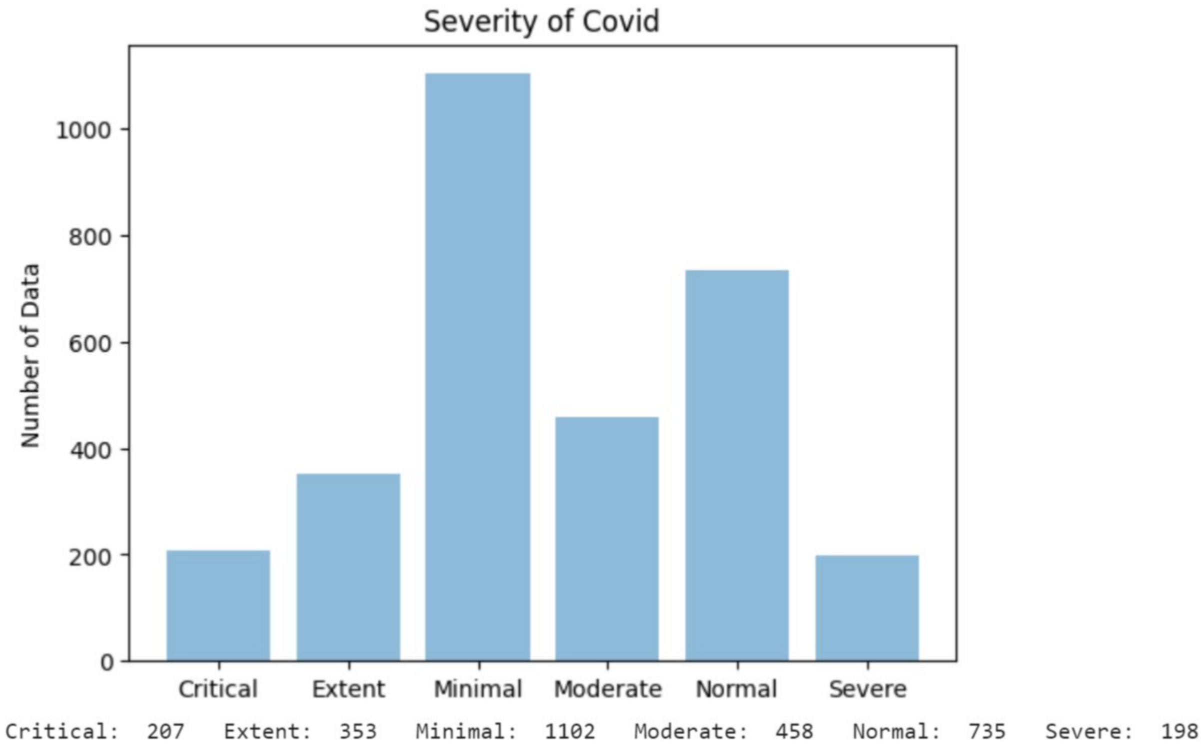

Figure 3.1: Classified Dataset

3.2.2 Dataset Augmentation

Data augmentation in data analysis are the techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularizer and helps reduce overfitting when training a machine learning model. Data augmentation is very useful to augment data or increase the amount of training or validation data[23].

In this project after categorizing the images into six classes, highly imbalanced class based on the number of image per class is founded. So trained models on highly imbalanced class provides low accuracy. To remove the biases data is augmented class by class. In the augmentation part rotation range is 10, width shift, height shift, shear range zoom range is 0.1, horizontal flip is true and fill mode is nearest. The images will be found in the given link[24]. After completing the augmentation 8614 images is created from 3053 images. The differences of 6 classes before and after augmentation is shown in table 2. After augmentation lung images appearance

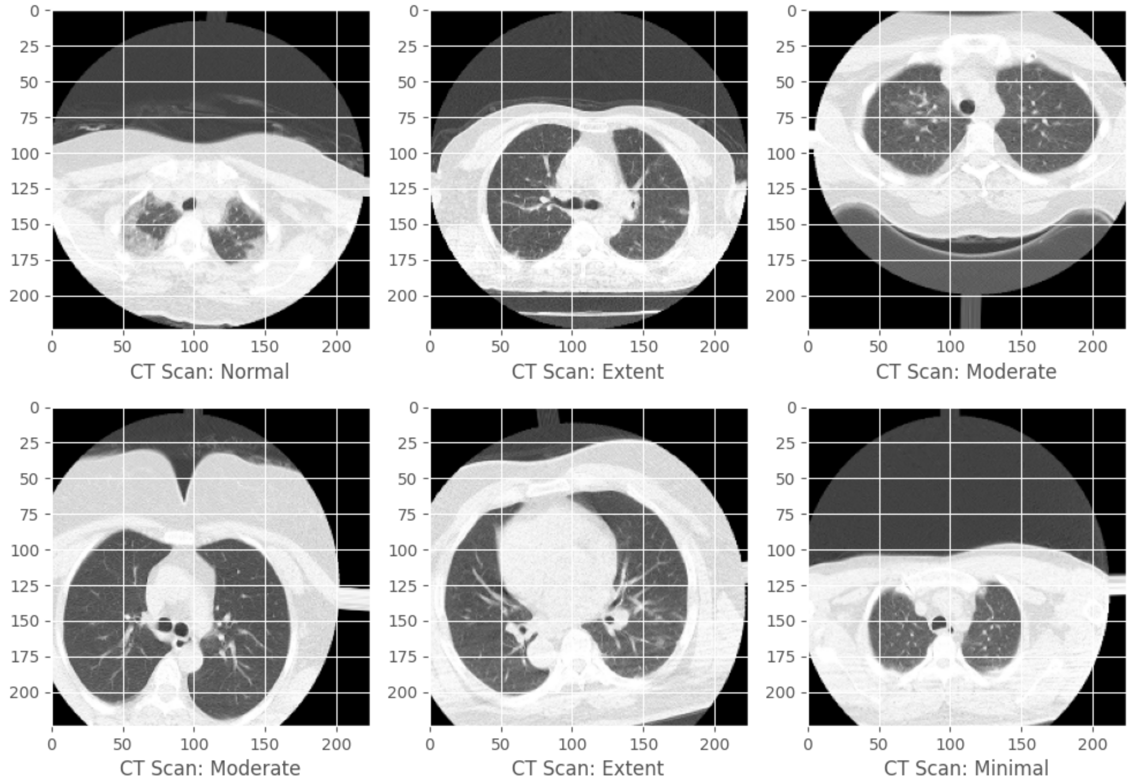

Figure 3.2: Few Classified Images

changes. Some portion cuts and root like structure on the edges is created. This change of appearance is shown in figure 3.3.

Class	Before Augmentation	After Augmentation
Critical	207	1367
Extent	253	1359
Minimal	1102	1504
Moderate	458	1495
Normal	735	1553
Severe	198	1333

Table 2: Number of Images before and after Augmentation in each Class

3.3 Applied Models

In the past few decades, Deep Learning has proved to be a very powerful tool because of its ability to handle large amounts of images data. The interest to use hidden layers has surpassed traditional techniques. One of the most popular deep neural networks

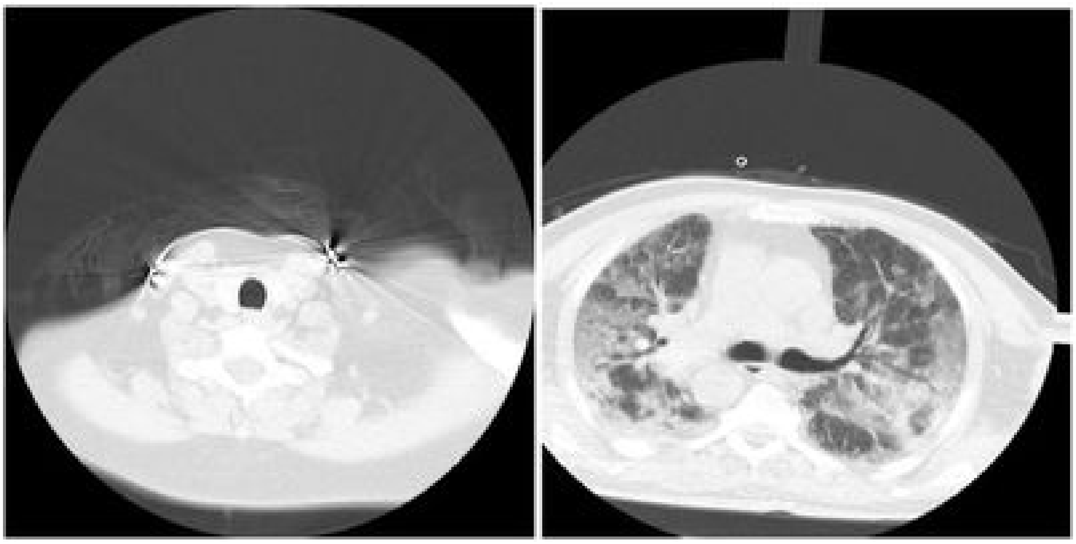

Figure 3.3: Image before and after Augmentation

is Convolutional Neural Networks[25]. Technically, deep learning CNN models train and test each input image will pass it through a series of convolution layers with filters (Kernals), Pooling, fully connected layers (FC) and apply Softmax function to classify an object with probabilistic values between 0 and 1.[26] A convolution tool that separates and identifies the various features of the image for analysis in a process called as Feature Extraction. A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages[27].The Convolutional layer is shown in figure 3.4.

3.3.1 Sequential Model

A Sequential model is appropriate for a plain stack of layers where each layer has exactly one input tensor and one output tensor [28]. Since each layer connects only to the previous and following layers, this conventional CNN refer as a “sequential CNN model.[29]. Sequential Model of CNN architecture has been applied to detect the severity of COVID-19 infected patients. To avoid overfitting, a sequential CNN model is proposed for classifying CT scan images. The model has 4 main components : (i) input layers (ii) convolutional layers (iii) fully connected layers and (iv) output

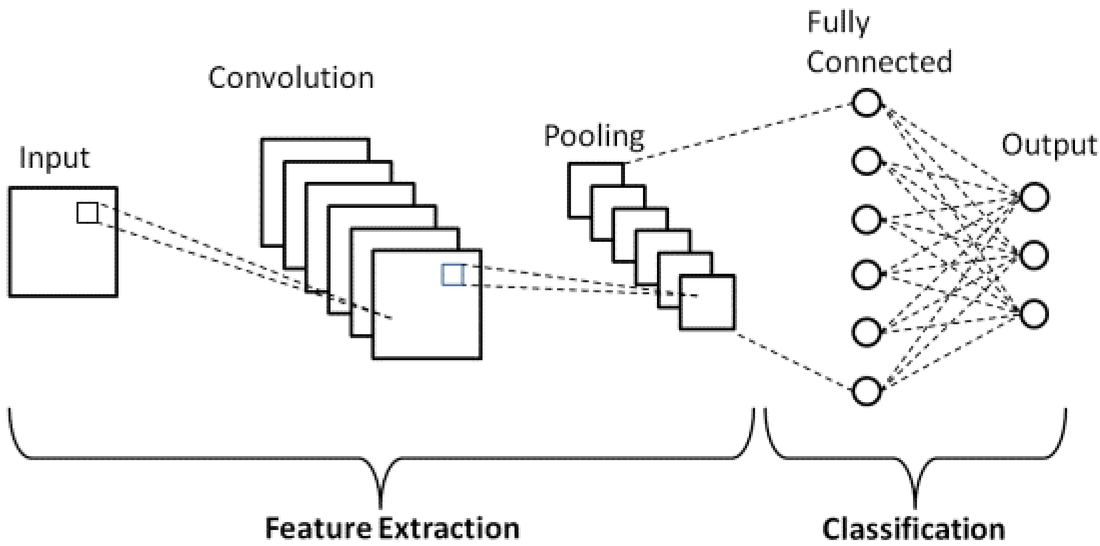

Figure 3.4: Convolutional Layers

layers [11].

The model is implemented in Keras. Necessary libraries like Tensorflow and Numpy has been imported. Here pre-processing was done using Tensor flow. In pre-processing image size has been taken 224. So, the target size of the rescaled image is 224 in length and width. Moreover, images have been sheared 20%, zoom 20%, horizontally flipped, rotation 40%, width shifted 20%, height shifted 20%. For validation 10% from training images has been split. For test images, validation images are taken. So, Train:Test is 90:10 in ratio. In sequential model Convolution layer, Max Pool layer and Dense layer has been used. Convolution layer has 64 filter with same padding, kernel size is 3, activation is ReLU function and the input shape is (224, 224, 3) where 3 is used for RGB images. In Max pool layer pool size is 2 and stride is also 2. Now flatten to covert 2D matrix array to 1D matrix. 6 output node is taken as the number of classes is 6. Dense layer activation function is "softmax". Compiled CNN by "adam" optimizers, loss function is "categorical crossentropy" which is used for multiclass and matrix is accuracy. Model is trained in two ways, at first with actual dataset images then with augmented dataset images.

The test accuracy of the model without augmentation is 49.83% and test accuracy is

66.44% from 100 epoch. When the epoch is 50 accuracy of test and train is 46.86% and 63.27% respectively. Here the number of total images is 3053 which is splitted into 0.9:0.1 train:test data. So, 2750 images as train data and 303 images as test data is used. The batch size is 128 so there is 24 batch.

The test accuracy of the model with augmentation is 63.87% and test accuracy is 67.53% from 100 epoch. Here the number of total images is 8614 which is splitted into 0.9:0.1 train:test data. So, 7756 images as train data and 858 images as test data is used. Here the batch size is 256 so there is 34 batch.

3.3.2 Convolutional Neural Network

Convolutional neural networks are a sort of artificial neural network that uses multiple hidden neurons to analyze picture inputs and have learnable weights and bases for several portions of images that can separate themselves. Neural Networks works kind of like a human brain. The inspiration comes from the animal visual cortex. The visual cortex consists of a small area of visual cells that are sensitive to a specific region of the visual field. CNN uses this concept and utilizes spatial correlations in input data.[30]

Convolutional Neural Networks have the advantage of leveraging the utilization of local spatial coherence in the input images, allowing them to have fewer weights because some parameters are shared.

In traditional CNN there are 4 layers :

- Convolutional
- ReLU Layer
- Pooling
- Fully Connected Layer

For this CNN model the dataset has been divided into 3 folders, train, test, and val(validation). Then applied ImageDataGenerator in each of the folders. ImageDataGenerator augment images while the model is training. In this case, the batch size is 150 and the targeted size for images has been set at 224 pixels for both height and width.

Used relu activation function for the convolutional layers then for the Dense layers both relu and softmax activation functions has been used. Compiled model with adam optimizer at a learning rate of 0.001, with the loss type of categorical_crossentropy. Then ran the model for 40 epochs and got a training accuracy of 94% and a testing accuracy of 76%.

3.3.3 Densenet121

In a Convolutional Neural Network (CNN), each convolutional layer except the first one it produces an output layer receives the output of the previous convolutional layer and produces an output feature map. DenseNets solve this problem by making changes to the normal CNN architecture and making the pattern of connections between layers simpler. The name "Densely Connected Convolutional Network" comes from the fact that each layer in a DenseNet architecture is directly connected to every other layer. Therefore, for 'L' layers, there are 'L' direct connections; one between each layer and the next layer.[31]

At the beginning of the model, imported all the required libraries along with dataset. Dataset has been pre-processed using OpenCV, Numpy, and Tensorflow. The very first step was reading the images from their specific folders and combining them together to build the whole dataset. In this step, while reading the images as arrays using OpenCV and Numpy, took the images as color images and then resized the images to 224 pixels in height and width. Then standardized the labels using LabelEncoder from ScikitLearn, and after that converted the label to a binary class matrix using Tensorflow.

Moving on to the next step, splitted dataset with a ratio of 80:20 for training and testing. The input layer shape of Densenet121 model is (224, 224, 3), and here used imagenet weights and average pooling for the model. The third value in the shape denotes that using RGB images.

The model bears 6 nodes in the output layer as images separated into 6 classes. The activation used for this model is softmax.

Up next compiled the model with adam optimizer, categorical_crossentropy loss type. In the case of multiple output classes, categorical_crossentropy is used. Used the default batch size of 32.

After completing all of the things run model for 30 epochs. While training all the layers of the model the accuracy went up to 98%.

As this is a clear sign of model overfitting, later frozed all the layers keeping only the last 8 layers to detect edges and blobs in the image. And then the testing accuracy has gone up to 75%, and the training accuracy is 98%.

3.3.4 VGG16

VGG16 is a convolutional neural net architechture. ImageNet dataset contains more than 14 million images that belong to 1000 classes. The test accuracy of VGG16 is 97.5 percent in ImageNet. By making a replacement of large kernel-sized filters it improves AlexNet with multiple 3×3 kernel-sized filters. VGG16 is a very useful CNN system for image classification. VGG16 consists of five layers and there is a total of 13 convolutional layers.

Started by importing all the required libraries and the dataset. Dataset has been pre-processed using OpenCV, Numpy, and Tensorflow. Read the images from their specific folders and combined them into a whole dataset. In this step, while reading the images as arrays using OpenCV and Numpy, took the images as color images, and then resized the images to 224 pixels in height and width.

The input layer takes images and sends them to the kernel layers. In the first layer, there are two 224x224 kernels with a depth of 64 and one 112x112 max-pooling layer. In the second layer, there are two 112x112 kernels with a depth of 128 and one 56x56 max-pooling layer. In the third layer, there are three 56x56 kernels with a depth of 256 and one 28x28 max-pooling layer. In the fourth layer, there are three 28x28 kernels with a depth of 512 and one 14x14 max-pooling layer. In the fifth layer, there are three 14x14 kernels with a depth of 512 and one 7x7 max-pooling layer.

"Softmax" has been considered as the activation function. Softmax classifier activation is used to load the pre-trained weights. With every epoch, the model is trained with optimized parameters. The convolution layer in the VGG16 model applies a filter in every layer for feature extraction. Multiple layered convolutions can help the system determine features that would be lost otherwise during flattening. Feature maps generated from the convolution layer are calculated in the max-pooling layer. Run the model for 30 epochs and got 94% for training accuracy and 79% for testing accuracy.

3.3.5 MobileNetV2

MobileNetV2 is a convolutional neural network architecture that was designed to do a good performance on mobile devices. It is built on an inverted residual structure, with residual connections between bottleneck levels. As a source of non-linearity, the intermediate expansion layer filters features with lightweight depthwise convolutions. MobileNetV2's overall design includes a fully convolutional layer with 32 filters, followed by 19 residual bottleneck layers and 53 convolution layers and 1 AvgPool with nearly 350 GFLOP. MobileNet V2 model has two main components: i) Inverted Residual Block and ii) Bottleneck Residual Block.[1] This CNN pre-trained model has been applied to detect the severity of COVID-19 infected patients in this project. All experiments were performed on Google Colaboratory (Colab) Linux server with the Ubuntu 16.04 operating system using the online cloud service with Central Processing Unit (CPU), Tesla K80 Graphics Processing Unit (GPU) or Tensor Processing Unit (TPU) hardware for free. Keras framework is used. Data has been splitted into train and validation set into 80% and 20% ratio respectively. 2445 images fall into train classes and 608 images fall into validation classes. Also images have been sheared 20%, zoom 20%, horizontally flipped, rotation 40%, width shifted 20%, height shifted 20%. To use the pre-train MobileNetV2 model, selected the image input shape (224, 224, 3). Here Batch size was 64. Softmax activation function has been used for multiple classification. Compiled the architecture by "adam" optimizers. Ran 10 epochs and got 57.07% accuracy before augmentation. The model already fell into overfitting at that time. To solve the problem, applied augmentation on the data set. After augmentation the train and validation dataset images increase to 6895 and 1719 respectively.

Also images have been sheared 10%, zoom 10%, horizontally flipped, rotation 10%, width shifted 10%, height shifted 10%.To use the pre-train MobileNetV2 model we select the image input shape (224, 224, 3). Batch size was 64. Softmax activation function has been used for multiple classification. Compiled the architecture by "adam" optimizers. Ran 30 epochs and got 77.25% accuracy after augmentation. Also tried to increase the batch size to 224 and image input shape (512,512,3) but because of colab resource limitation we were only able to run 16 epochs and got 74% test accuracy .

Chapter 4

4 Result and Analysis

4.1 Models without Augmentation

At first the models have been trained with unaugmented data. There are 3053 images before augmentation. These images has been trained by different CNN and pretrained model. Here batch size is smaller than the batch size taken in model training with augmentated dataset.

4.1.1 Comparison Among Models with Unaugmented Dataset

Highest accuracy is obtained by the pretrained model of CNN named VGG16. Model ran with 30 epoch in VGG16. Train loss is also lowest in VGG16. Traing accuracy is almost 100%. In mobileNetV2 train and test accuracy difference is less than other model's accuracy.With only 10 epoch it provides testing accuracy 57.07%. Sequential model ran with 100 epoch but didn't get expected test accuracy. But the test loss is very low. Convolutional Neural Network and Densenet121 also gave comparatively better result. Detailed information of all models accuracy with epoch number is shown in table 3.

Model	Train Accuracy	Test Accuracy	Train Loss	Test Loss	Epoch
VGG16	99.84	85.92	0.1565	0.5016	30
Densenet121	77.89	69.23	0.5864	0.7313	30
Sequential CNN	65.89	50.83	0.7855	1.1999	100
MobileNetV2	56.85	57.07	0.9883	0.9888	10
Convolutional Neural Network	98.63	80.59	0.1405	0.6354	40

Table 3: Comparison Among Models with Unaugmented Dataset

4.1.2 Accuracy and Loss Function Graph

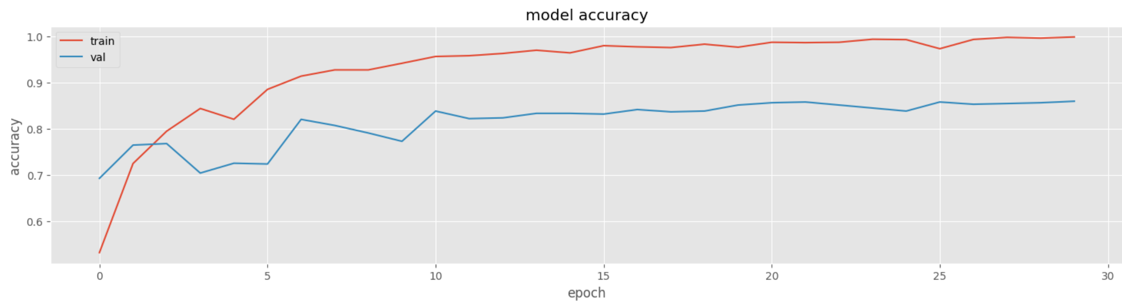

Figure 4.5: Accuracy Graph of VGG16

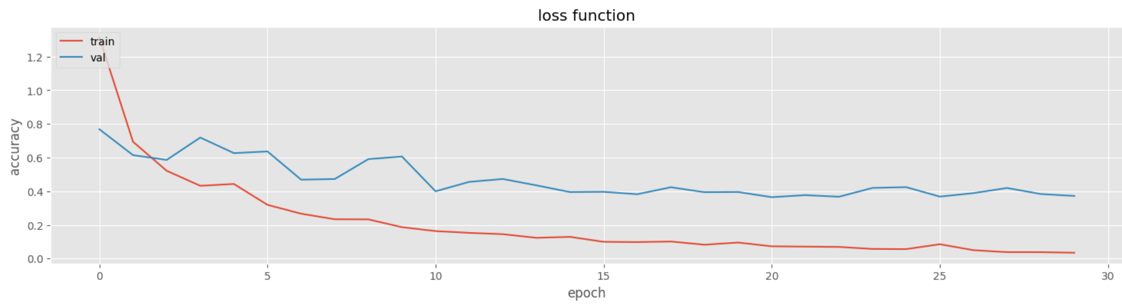

Figure 4.6: Loss Function Graph of VGG16

Figure 4.5 and 4.6 shows the learning curve accuracy and loss between training and test obtained by VGG16. The red and blue curve shows the training and validation accuracy respectively.

Accoriding to Figure 4.5, the VGG16 model performed better in case of training data compare to testing data. It is seen that, the traning curve of accuracy is rising up and loss curve is going down with the increased number of epochs. On the other hand, model is not performing as well as training for validation data. With the increasing number of epochs, a steady minimization phase is not observed. Even after 13 epochs, accuracy didn't get increased significantly.

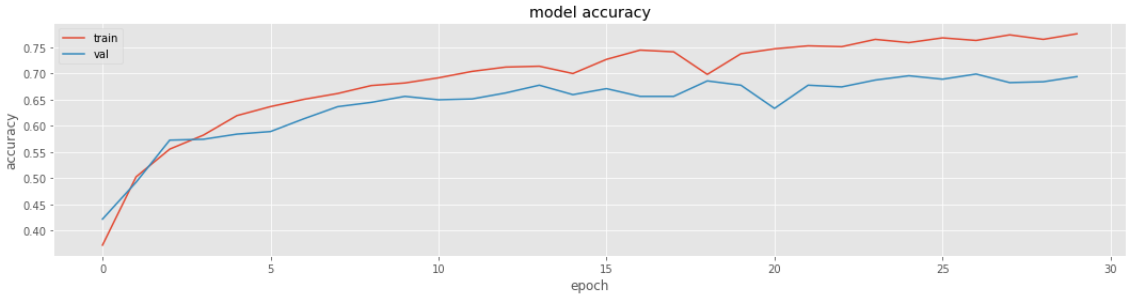

Figure 4.7: Accuracy Graph of Densenet121

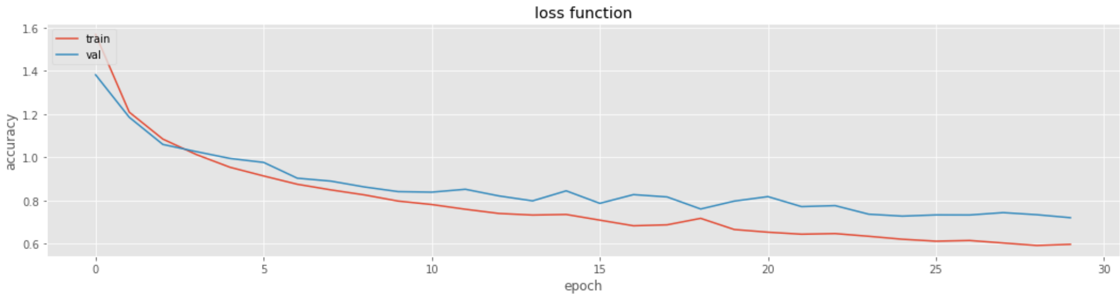

Figure 4.8: Loss Function Graph of Densenet121

Figure 4.7 and 4.8 shows the learning curve accuracy and loss between training and test obtained by Densenet121.The red and blue curve shows the training and validation accuracy respectively.

Accoriding to Figure 4.7, the densenet121 model performed better in both training and testing cases. According to both of the figure 4.7 and 4.8, both training and testing curve of accuracy is rising up and loss curve is going down with the increased number of epochs. In addition, there is a minimal difference between training and testing accuracy. Therefore, it shows the effectiveness of this model in detecting COVID-19 cases.

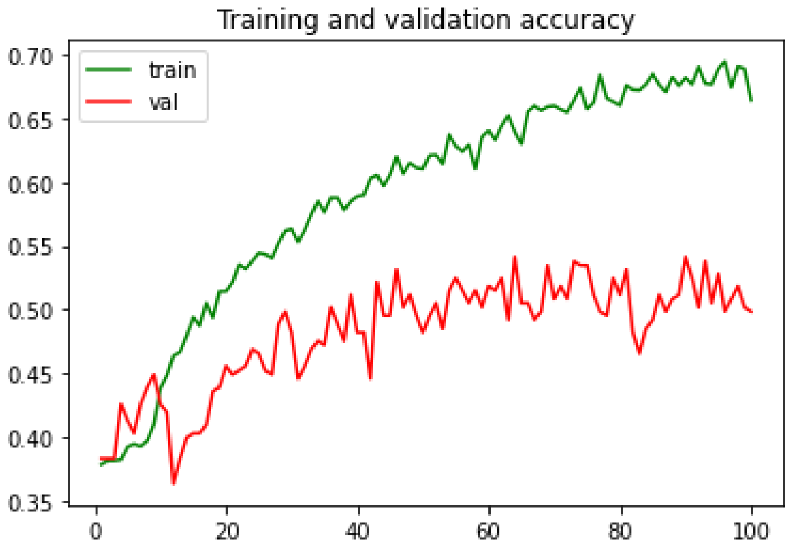

Figure 4.9: Accuracy Graph of Sequential CNN

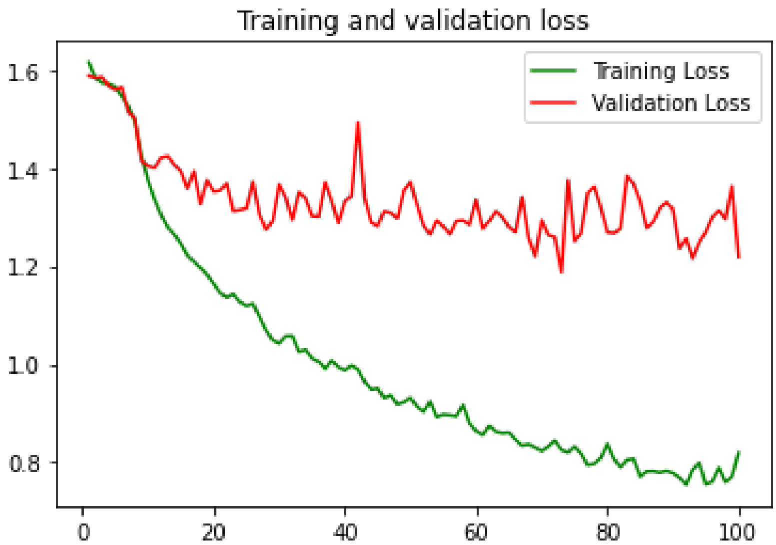

Figure 4.10: Loss Function Graph of Sequential CNN

Figure 4.9 and 4.10 shows the learning curve accuracy and loss between training and test obtained by Sequential Model of CNN architecture. The green and red curve shows the training and validation accuracy respectively.

According to Figure 4.9, the Sequential model performed better in case of training data compare to testing data. It is seen that, the training curve of accuracy is rising up and loss curve is going down with the increased number of epochs. On the contrary, model is giving lower accuracy with higher fraction of error. Even in 100 epochs, the loss for validation is more than 1.2 rate and accuracy is 50% where training accuracy is close to 70%. It is clearly seen that there is significant difference between training and testing accuracy which depicts that this model could not identified COVID-19 cases efficiently.

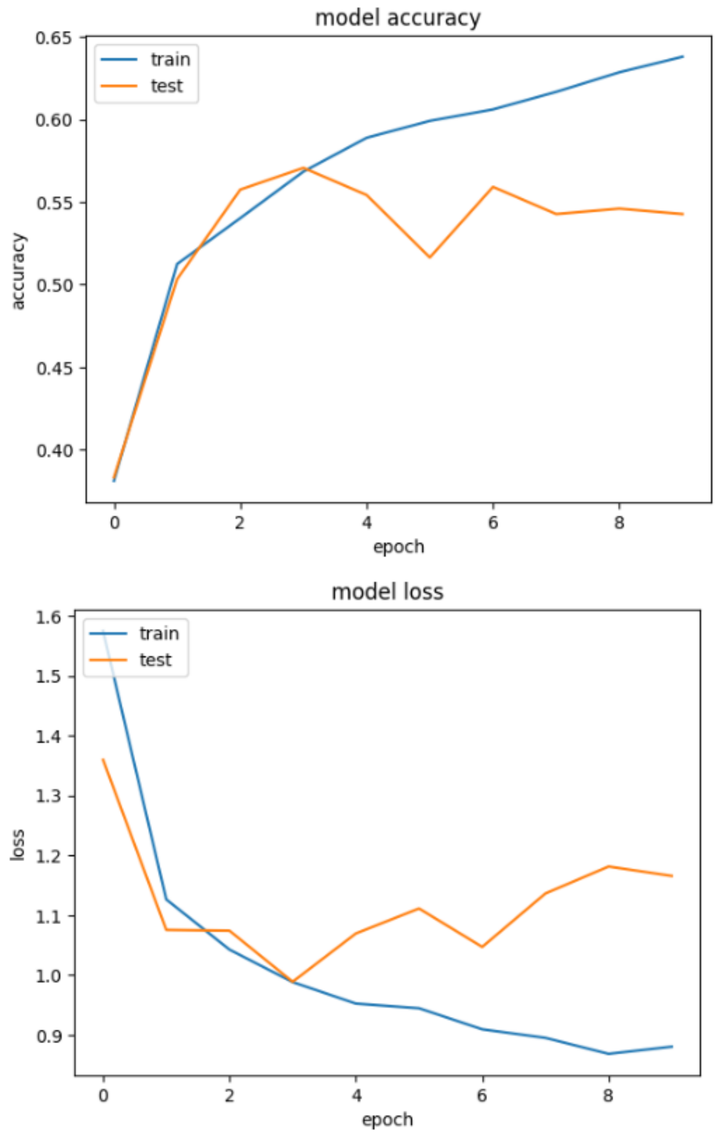

Figure 4.11: Accuracy and Loss Function Graph of MobileNetV2

In figure 4.11 before augmentation 10 epochs was applied and got 57.07% accuracy and the model already fell into overfitting at that time. To solve the problem, applied augmentation on the data set. After augmentation the model has been trained again and after 30 epochs accuracy 77.25%. Also tried to increase the batch size to 224 and image input shape (512,512,3) but because of colab resource limitation it was not possible to run 16 epochs and got 74% test accuracy.

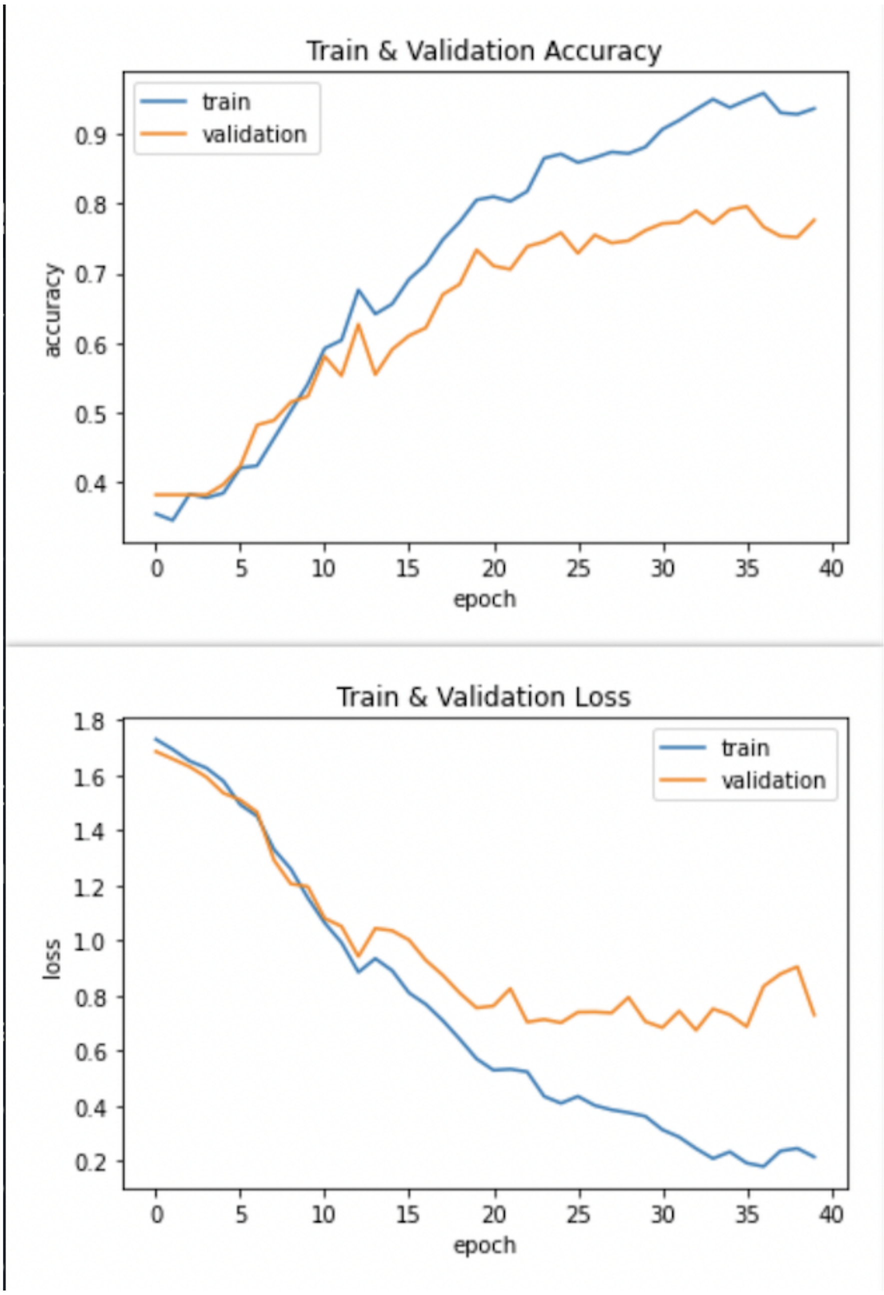

Figure 4.12: Accuracy and Loss Function Graph of CNN Model

Figure 4.12 shows the learning curve accuracy and loss between training and test obtained by the CNN model. The blue and orange curve shows the training and validation accuracy respectively. It is seen that the training curve of accuracy is rising up and the loss curve is going down with the increased number of epochs. On the other hand, the model is not performing as well as training for validation data. With the increasing number of epochs, a steady minimization phase is not observed. After the 20th epoch, accuracy didn't get increased significantly in the case of validation. So, finally the achieved testing accuracy was 80.59%, and training accuracy was 98.63%.

4.2 Models with Augmentation

Model has been trained with augmented dataset after training with unaugmented dataset. There are 8614 images after augmentation. VGG16, DenseNet121 and Convolutional Neural Network was not able to train data with augmented images. But accuracy was obtained using mobileNetV2 and Sequential Model. Accuracy of the model increased by training and testing with augmented data.

4.2.1 Comparison Among Models with Augmented Dataset

Sequential CNN model give better accuracy with augmented data. Before augmnentation training accuracy was 65.85% and testing accuracy was 50.83% respectively. After augmentation training and testing accuracy increases to 69.49% and 53.80% with same number of epoch. Simillarly before augmentation train and test accuracy of MobileNetV2 is 56.85% and 57.07% respectively. After augmentation train and test accuracy increases to 88.85% and 77.25% respectively. So in case of MobileNetV2, due to augmentation accuracy increases a lot. Almost 32% and and 20% train and test accuracy increased in MobileNetV2 due to augmentation. Detailed information of all models accuracy with epoch number is shown in table 4.

Model	Train Accuracy	Test Accuracy	Train Loss	Test Loss	Epoch
Sequential CNN	69.49	53.80	0.7826	0.8870	100
MobileNetV2	88.85	77.25	0.2861	0.6361	10

Table 4: Comparison Among Models with Augmented Dataset

4.2.2 Accuracy and Loss Function Graph

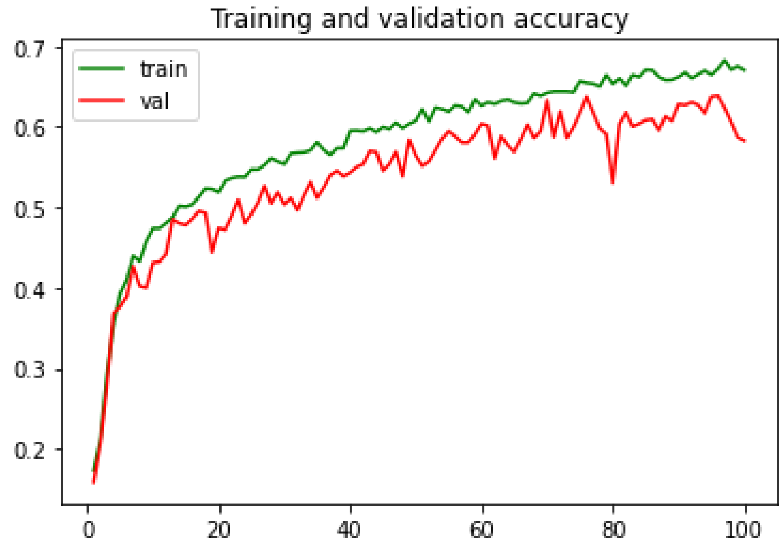

Figure 4.13: Accuracy Graph of Sequential Model

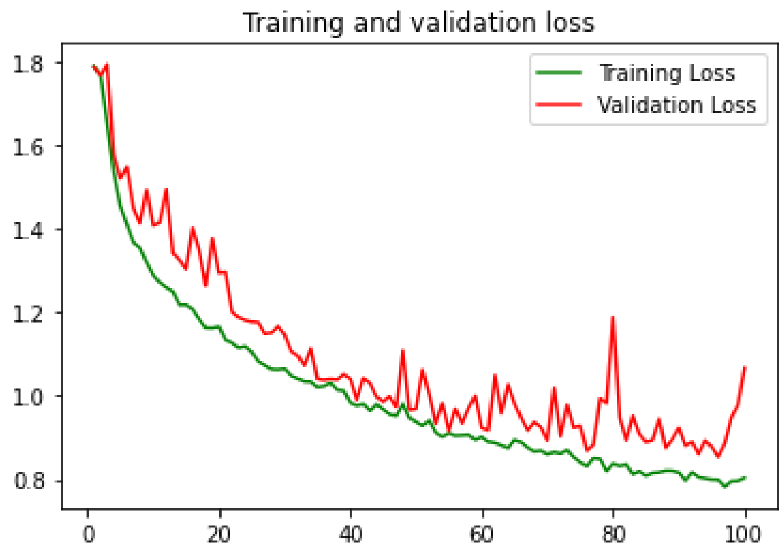

Figure 4.14: Loss Function Graph of Sequential Model

Figure 4.13 and 4.14 shows the learning curve accuracy and loss between training and test obtained by Sequential Model of CNN.The green and red curve shows the training and validation accuracy respectively.

According to Figure 4.13, the sequential model performed better in both training and testing cases. Both training and testing curve of accuracy is rising up and loss curve is going down with the increased number of epochs. In addition, there is a negligible difference between training and testing both accuracy and loss.Therefore, it also shows the effectiveness of this model in detecting COVID-19 cases.

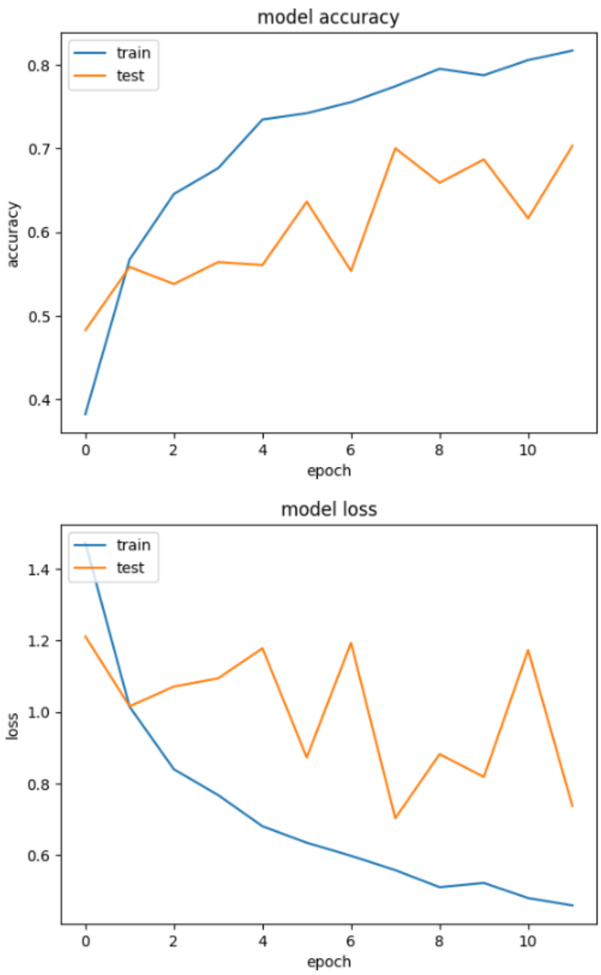

Figure 4.15: Accuracy and Loss Function Graph of MobileNetV2

The graph 4.15 shows the accuracy and loss between training and test obtained by MobileNetV2 Model. During training the model with a large amount of augmentated data the process got halted after 16 epochs due to the limitation of google colab. That is why to get the graph we set the epoch number at 12. After augmentation we were able to run 16 epochs and got 74% test accuracy by this model which is better compared to unaugmented data.

4.3 Comparison of Applied Models with Related Works

Comparison of accuracy of the models applied in this project with the related works provided in table 1 in shown in table 5. Applied models of this project VGG16 and Convolutional Neural Network has more accuracy than the founded related works [17] and [14] respectively. In [14] number of images in dataset is 11095 and in this project number of images is 3053. So with less images Convolutional Neural Network shows better accuracy in this project than related work. [14]. In case of VGG16 the related work [17] has 3873 images and their accuracy is also than this project's application. In [16] and [19] they used Resnet50 and InceptionV3 with 98.23% and 98% accuracy in 30 and 50 epoch respectively. In this project VGG16 and Densenet121 is done with 30 epoch, Convolutional Neural Network is done with 40 epoch, MobileNetV2 with 10 epoch and Sequential CNN with 100 epoch respectively. In [13] there is only 165 images but in this project sequential has more number of images. So ultimately sequential CNN did not perform so well. Also Densenet121 and MobileNetV2 give less accuracy than related work [20] and [18] respectively.

Model Name	Applied Model Accuracy	Related works model accuracy
VGG16	99.84	97.68 [17]
Densenet121	77.89	99.0[20]
Sequential CNN	69.49	97.56[13]
MobileNetV2	58.85	99.00[18]
Convolutional Neural Netwrok	98.63	98.28[14]

Table 5: Comparison of Applied Models with Related Works

Chapter 5

4.4 Conclusion

The pandemic of coronavirus disease 2019 (COVID-19) poses several challenges to clinicians. This project can be beneficial for those challenges. For recommending proper treatment it is necessary to know patient's condition. In our project CT-scan images are used to measure or detect the severity for a patient. As CT-scan images have been used so the detection will be fast and detailed. The concept of DL has been broadly utilized with CNN based systems. Mass testing, early detection and acknowledge the severity of COVID-19 play an important role in preventing the spread of this global pandemic. Time, cost, and accuracy are the few major factors in any disease detection process specially COVID-19. To address these issues, some CNN based model like VGG16, Densenet121, MobileNetV2, Sequencial CNN and basic Convolutional Neural Network is proposed in this paper for detecting the severity of COVID-19 cases from patients lung CT scan images. Dataset containing 3053 images collected from COVID-19 Infection Percentage Estamation Challange arranged by CodaLab[11] are divided into 6 classes named Critical, Extent, Minimal, Moderate, Normal and Severe. Classes has been balanced by dataset augmentation. After augmentation dataset contain 8614 images. Among all the applied models VGG16 provides the highest training and testing accuracy of 99.84% and 85.92% respectively. This model can be improved further with the availability of the larger dataset. Moreover other CNN models like Imagenet, ResNet50 or InceptionV3 can be applied to the sysytem. So, CNN has great prospects in detecting the severity of COVID-19 with very limited time, resources, and costs. Though the proposed model shows promising results, it is in no way clinically tested. This model needs deployment, further improvements and clinical testing for it to work in clinical diagnosis.

References

[1] [Online]. Available: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200211-sitrep-22-ncov.pdf?sfvrsn=fb6d49b1_2.

[2] *Naming the coronavirus disease (covid-19) and the virus that causes it.* [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it?fbclid=IwAR2YIah5xgLnsFqvNZIn9tBJrJM3gRJlx1C8kmEq7wkKbfi4h26cZKjoHPA.

[3] J. F.-W. Chan, S. Yuan, K.-H. Kok, *et al.*, "A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: A study of a family cluster," *The lancet*, vol. 395, no. 10223, pp. 514–523, 2020.

[4] N. Zhu, D. Zhang, W. Wang, *et al.*, "A novel coronavirus from patients with pneumonia in china, 2019," *New England journal of medicine*, 2020.

[5] A. Assiri, J. A. Al-Tawfiq, A. A. Al-Rabeeah, *et al.*, "Epidemiological, demographic, and clinical characteristics of 47 cases of middle east respiratory syndrome coronavirus disease from saudi arabia: A descriptive study," *The Lancet infectious diseases*, vol. 13, no. 9, pp. 752–761, 2013.

[6] N. Lee, D. Hui, A. Wu, *et al.*, "A major outbreak of severe acute respiratory syndrome in hong kong," *New England Journal of Medicine*, vol. 348, no. 20, pp. 1986–1994, 2003.

[7] *Coronavirus.* [Online]. Available: https://www.who.int/health-topics/coronavirus?fbclid=IwAR26dqLQw4pCOFxGzZJlSecv8sa3IKI_6DqCmLOVM25_7MvsxkDMKGVGaEw#tab=tab_1.

[8] *Covid-19*, May 2022. [Online]. Available: https://en.m.wikipedia.org/wiki/COVID-19?fbclid=IwAR2taha7VkB3QSjoFvtGXtGSMZ1J6LtSUvojBD_21Dk7bowxmD2A0A6cGBk.

[9] [Online]. Available: https://www.who.int/news/item/05-10-2020-covid-19-disrupting-mental-health-services-in-most-countries-who-survey?fbclid=IwAR3_AQSWiqbP4vtfoBRko-6HI8tuaKZP1PZgtbHlFCG2-xSJgE5ecFdhal8#:~:text=Meanwhile%2C%20COVID%2D19,outcomes%20and%20even%20death.

[10] R. a. ACR, *Chest ct*, Jun. 2020. [Online]. Available: https://www.radiologyinfo.org/en/info/chestct.

[11] *Competition.* [Online]. Available: https://competitions.codalab.org/competitions/35575.

[12] V. Tatan, *Understanding cnn (convolutional neural network)*, Dec. 2019. [Online]. Available: https://towardsdatascience.com/understanding-cnn-convolutional-neural-network-69fd626ee7d4.

[13] K. F. Haque, F. F. Haque, L. Gandy, and A. Abdelgawad, "Automatic detection of covid-19 from chest x-ray images with convolutional neural networks," in *2020 International Conference on Computing, Electronics & Communications Engineering (iCCECE)*, IEEE, 2020, pp. 125–130.

[14] S. Thakur and A. Kumar, "X-ray and ct-scan-based automated detection and classification of covid-19 using convolutional neural networks (cnn)," *Biomedical Signal Processing and Control*, vol. 69, p. 102 920, 2021.

[15] A. Halder and B. Datta, "Covid-19 detection from lung ct-scan images using transfer learning approach," *Machine Learning: Science and Technology*, vol. 2, no. 4, p. 045 013, 2021.

[16] A. Aswathy, A. Hareendran, and V. C. SS, "Covid-19 diagnosis and severity detection from ct-images using transfer learning and back propagation neural network," *Journal of Infection and Public Health*, vol. 14, no. 10, pp. 1435–1445, 2021.

[17] S. Kogilavani, J. Prabhu, R. Sandhiya, *et al.*, "Covid-19 detection based on lung ct scan using deep learning techniques," *Computational and Mathematical Methods in Medicine*, vol. 2022, 2022.

[18] R. M. Rawat, S. Garg, N. Jain, and G. Gupta, "Covid-19 detection using convolutional neural network architectures based upon chest x-rays images," in *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*, IEEE, 2021, pp. 1070–1074.

[19] D. Haritha, N. Swaroop, and M. Mounika, "Prediction of covid-19 cases using cnn with x-rays," in *2020 5th International Conference on Computing, Communication and Security (ICCCS)*, IEEE, 2020, pp. 1–6.

[20] S. H. Kassania, P. H. Kassanib, M. J. Wesolowskic, K. A. Schneidera, and R. Detersa, "Automatic detection of coronavirus disease (covid-19) in x-ray and ct images: A machine learning based approach," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 3, pp. 867–879, 2021.

[21] *Importance+of+dataset+in+deep+learning*. [Online]. Available: https://search.yahoo.com/search?fr=mcafee&type=E210US714G0&p=importance%2Bof%2Bdataset%2Bin%2Bdeep%2Blearning.

[22] J. Brownlee, *Multi-class classification tutorial with the keras deep learning library*, Dec. 2020. [Online]. Available: https://machinelearningmastery.com/multi-class-classification-tutorial-keras-deep-learning-library/.

[23] *Data augmentation*, Apr. 2022. [Online]. Available: https://en.wikipedia.org/wiki/Data_augmentation.

[24] *Augmented data*. [Online]. Available: https://drive.google.com/drive/u/1/folders/1petz7S4lznT2RVFCmIiCLFAeDZhAqj4X.

[25] *Cnn for deep learning: Convolutional neural networks*, Jul. 2021. [Online]. Available: https://www.analyticsvidhya.com/blog/2021/05/convolutional-neural-networks-cnn/.

[26] Prabhu, *Understanding of convolutional neural network (cnn) - deep learning*, Nov. 2019. [Online]. Available: https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148.

[27] *Basic cnn architecture: Explaining 5 layers of convolutional neural network*, Dec. 2021. [Online]. Available: https://www.upgrad.com/blog/basic-cnn-architecture/.

[28] K. Team, *Keras documentation: The sequential model*. [Online]. Available: https://keras.io/guides/sequential_model/.

[29] Z. Xue, S. Rajaraman, R. Long, S. Antani, and G. Thoma, "Gender detection from spine x-ray images using deep learning," in *2018 IEEE 31st International Symposium on Computer-Based Medical Systems (CBMS)*, IEEE, 2018, pp. 54–58.

[30] *Working of convolutional neural network - javatpoint*. [Online]. Available: https://www.javatpoint.com/working-of-convolutional-neural-network-tensorflow.

[31] *Opengenus iq: Computing expertise legacy. 2022. architecture of densenet-121*. [Online]. Available: https://iq.opengenus.org/architecture-of-densenet121/.