COVID-19 PREDICTION USING LUNG X-RAYS

A report submitted under the partial fulfilment of the requirements for the degree of Bachelor of Technology in Computer Science and Engineering.

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CERTIFICATE

This is to certify that the project entitled **"COVID-19 PREDICTION USING LUNG X-RAYS"** carried out by **L. Naga Sai Sri Ravi Teja (121710307017), S. Ritesh Dev (121710307044), K. Bharath (121710307003), T. Yashwanth (121710307049)** in partial fulfilment of for the award of degree Bachelor of Technology in Computer Science and Engineering, GITAM – Deemed to be University, Visakhapatnam during the academic year 2017-2021.

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DECLARATION

I hereby declare that the project entitled **"COVID-19 PREDICTION USING LUNG X-RAYS "** submitted to GITAM, Deemed to be University for the award of the degree of Batchelor of Technology in Computer Science and Engineering is a result of the original research carried out in this thesis. We understand that our report can be made electronically available to the public. It is further declared that the project report or any part there of has not been previously submitted to any University or Institute for the award of degree or diploma.

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ABSTRACT

The Covid-19 (also known as SARS-COV-2) that first occurred in Wuhan, 2019 which spread around the whole world like a wildfire. This contagious disease spreads from person to person through direct contact to another. The effects of Covid-19 can be classified into different scales from mild to severe. At the time of writing this paper a total of 148 million cases and 3.1 million deaths are confirmed. Most of the Covid-19 detection are done with RT-PCR tests which generally take time. Depending the critical scenarios and demands it might even take longer. For a contagious disease like covid-19 the main goal is to restrict it's spread. So, with the help of Machine Learning and Deep Learning Algorithms that are built on Radiology images could help in making the decisions for diagnosis of Covid-19 patients. We proposed in using Transfer-Learning based model for Covid-19 Detection using chest x-ray, because of the scarcity of available data. We performed Transfer Learning approach in order to obtain reliable results which could help us with smaller dataset. Though the x-rays do not provide maximum confirmation we rely the minimal percentage of chance that could help in reducing the spread of Covid-19. The process consists of two phases where in the first we pre-process the images and in the second we train and finetune the model to achieve desirable accuracy of the model.

Publicly available X-ray images (1583 healthy and 712 confirmed COVID-19) AND (712 COVID-19, 4273 Pneumonia and 1583 Normal) were used in the experiments, which involved the training of deep learning and machine learning classifiers. 5 custom CNN (Convolution Neural Network) experiments were, and 5 experiments for both categorical and binary were performed using Transfer Learning Models with ImageNet set as weights.

Keywords: Covid-19, SARS-COV-2, Deep Learning, Pre-Processing, Transfer Learning, Pandemic

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CHAPTER-1

INTRODUCTION

1.1. Motivation :

At the end of 2019, mankind faced a pandemic of Covid-19, since its emergence in Wuhan, China in December of 2019 [2]. The death toll was massive due to the unavailability of data on the cure for the disease. Even with restrictions of travel, the virus spread out throughout the world and the world has gone through a lockdown to reduce the spread of Covid-19. The death toll and spread rate was alarming for which social distancing norms were proposed by WHO(World Health Organization) [3]. Though some screening measures were taken, the spread of the virus did not go down and it reached a huge spike in various countries. The doctors were insufficient of the equipment they had and were affected by the virus losing lives. The treatment was given to the patients in an isolated environment with the necessary precautions [4]. Reverse-transcription polymerase chain reaction (RT-PCR) testing, which can detect SARS-COV-2 RNA is used to detect Covid-19 using respiratory specimens (such as nasopharyngeal and oropharyngeal swabs), is the best screening method for Covid-19 for clear confirmation of Covid-19. Though it provides accurate results the number of test kits available overshadowed the usage. Also with the amount of time taken to obtain the result is from (one day - or two days) [5]. Based on the demand sometimes it also takes a week. This in turn creates uncertainty in people and also increases the spread before the time we get the result. It is found in the earlier study that patients affected by covid-19 show abnormalities in the chest radiographs. So there is an immediate need of using radiology images for testing such as HRCT Scans and Chest X-Ray scans which could provide a visual indication of viral infection. Since Covid-19 affects the lungs, causing pneumonia. Finding out the abnormalities is easier and faster. The HRCT Scans are supposed to provide better image feedback and confirm whether a person has been affected by Covid or not [6]. As the facilities for chest imaging are readily available and also HRCT scans providing high accuracy it could act as an alternative to the RT-PCR tests. Through the X-Rays provide image feedback despite being subtle it is hard to confirm whether or not the person is affected by covid or not. So, the help of computer-aided deep learning or machine learning algorithms will make it more efficient and less time-consuming. And with the spike in the number of cases and cost of HRCT scans are too high to be available easily. So the X-Rays despite being cheaper it's faster to obtain and with help of Deep Learning models, we can use them to predict Covid-19 spread in a person. The goal of this study is to detect the chance of a person to have covid-19 thereby increasing the chance to reduce the spread of the virus and providing accurate treatment to the affected. This further helps in filtering out Covid-19 affected people.

Deep learning techniques have been playing a prominent role in making machines and software. The terminologies like Max Pooling, Convolutional Neural Networks (CNN), Sigmoid Function, and RELU have more prevailed in the part of the Artificial Intelligence, which is used to make machines think like humans by training them concerning different aspects of the field that we are working with. By these, we can depict accurately the disease.

Most fascinating is that CNN will be working similarly to the neurons that a human has. But the difference is that in humans neurons carry messages to the brain, but in CNN neural networks will update the weight of the layers.

The trained neural networks of model will gain knowledge on the particular work that is assigned. The main objective of artificial neural networks is to develop human behavior and intelligence, transfer learning is used to apply the store knowledge of a particular task for another related task. Deep learning for image recognition is capable of learning number of images, and several huge models were trained with different architectures.

The application of advanced AI techniques attaching with radiological imaging can be helpful for the prevention of this disease, and can also be helpful to overcome the problem of a lack of specialized physicians in remote villages.

The proposed model is developed to provide diagnostics for binary classification (COVID vs. No-Findings) and Categorical classification (COVID vs Pneumonia vs Normal).

1.2 Project Objective

The main objective of our project is to prevent the spread of covid-19 using chest X-rays. The use of X-rays is due to its cost-effectiveness and is easily obtained in many remote villages. Though we do not propose the use of X-rays as a complete alternative to HRCT or RT-PCR tests these could help us in filtering out people and providing early treatment. On further thought, with the help of this method, we can perform selective tests of RT-PCR for restricting the spread and provide early treatment.

1.3 Advantages

1.3.1 Early detection and diagnosis of the infection:

ML can quickly analyze irregular symptoms and other ‘red flags’ and thus alarm the patients and the healthcare authorities. It helps to provide faster decision-making, which is cost-effective. It helps to develop a new diagnosis and management system for the COVID 19 cases, through useful algorithms.

1.3.2 Prevention of Spread:

The spread of covid-19 can be restricted and selective tests of RT-PCR can be done as the lesser availability of test kits.

1.4 Drawbacks of the Existing system

Though the existing system using throat and nose swabs for RT-PCR test, Rapid Antigen Test, TrueNat Test provides accurate results, they take considerable amount of time (1day to 1 week) and the labs are not readily available. This takes away the immediate treatment from the effected person and also causes in increasing the virus spread.

1.5 X-Rays and CT Scans

1.5.1 X-Rays

X-rays are a type of radiation that can pass through the body. They can't be seen by the naked eye and you can't feel them.

As they pass through the body, the energy from X-rays is absorbed at different rates by different parts of the body. A detector on the other side of the body picks up the X-rays after they've passed through and turns them into an image.

Dense parts of your body that X-rays find it more difficult to pass through, such as bone, show up as clear white areas on the image. Softer parts that X-rays can pass through more easily, such as your heart and lungs, show up as darker areas.

Figure 1: Shades of Grey

So, as if we see in the image on one end of the spectrum is complete Black ,on other end of the spectrum is complete white and in between there are lesser blacks and lesser whites

In X-rays

1. It creates an 2D images
2. It is primarily used for checking bones and to detect the cancer and pneumonia
3. It uses radiation to produce the images
4. And it is most common & widely available
5. It is cost-effective while compared to other scans

So in any given X-ray, There are four to five densities like:

Black: Air

Less black or greyish: Fat

Less white: They are soft tissues like heart/muscle or blood/fluid

White: It can be metal or calcium in bones

Very Bright: It can be a metallic objects

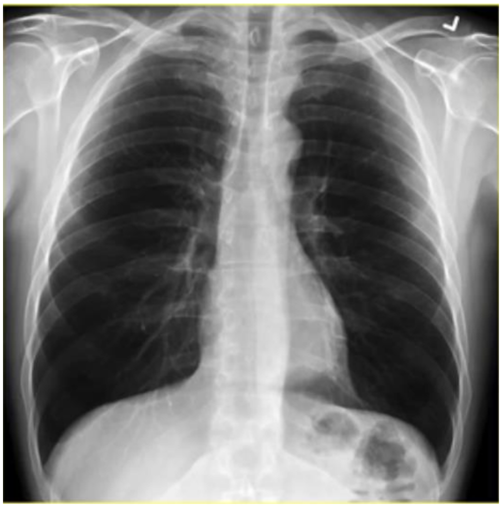

Figure 2 : Lung X-Ray

And this is the sample image to better understanding

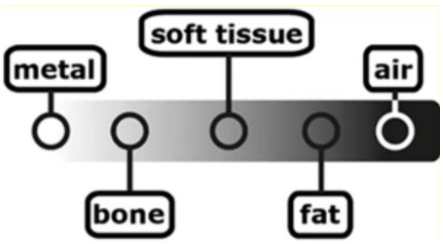

Figure 3 : Shades from X-Ray

1.5.2 CT Scans

A CT Scan it generates high-quality, detailed images of the body. Computer-processed combinations of many X-rays measurements that are taken from different angles .That means it takes a 360-degree images of the spine, vertebrae and internal organs.

So, by using CT scan it can create an detailed, quality images of bones, blood vessels, soft tissue and organs and may be used to help the doctors diagnose medical conditions

In CT scan

1. Create 3D images.
2. It’s primarily used to diagnose conditions in organs and soft tissues.
3. While compared to X-rays it is more powerful.
4. CT scan takes 360-degree image.

Drawbacks of CT Scans:

1. It costs more.
2. CT scans are not available in every hospital.

1.6 Pneumonia in Lungs

Pneumonia is an infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus (purulent material), causing cough with phlegm or pus, fever, chills, and difficulty breathing. A variety of organisms, including bacteria, viruses and fungi, can cause pneumonia [7].

1.6.1 Types of Pneumonia

1. Community-Acquired Pneumonia(CAP).
    - Community Acquired Pneumonia is when a patient gets it outside of the hospital.
2. Hospital-Acquired pneumonia(HAP).

- Hospital Acquired pneumonia as the name suggests is when the patient gets it during their hospital stay.

3. Ventilator-Associated Pneumonia(VAP).

   - Ventilator Associated Pneumonia is when it's acquired while the patient is on the mechanical ventilator.

4. Aspiration Pneumonia.

   - Aspiration Pneumonia is acquired when a patient aspirates bacteria into the lungs , usually from food, saliva, or stomach acid.

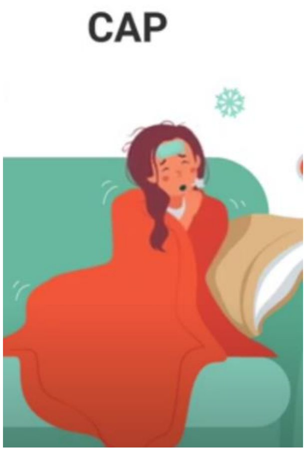

Figure 4: Community Aquired Pneumonia

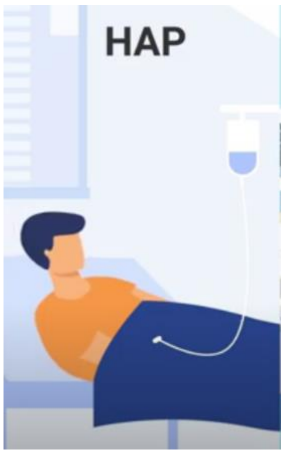

Figure 5: Hospital Aquired Pneumonia

Figure 6: Ventilator Associated Pneumonia

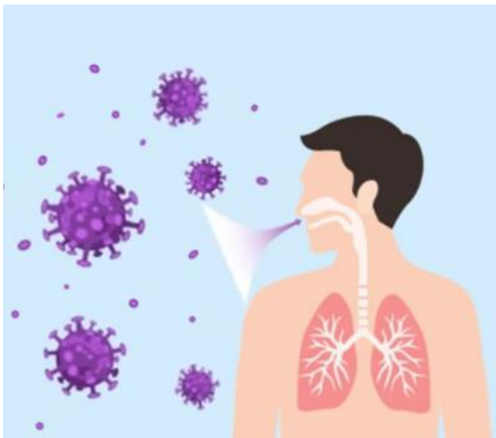

Figure 7: Aspiration Pneumonia

1.7 Covid-19

In December 2019 there was a cluster of pneumonia cases in the city of Wuhan in china. Some of the early cases had reported visiting or working in a sea food and live animal market in Wuhan, investigations found that the disease was caused by a newly discovered corona virus the disease was subsequently named as Covid-19.

Corona virus is a large group of viruses

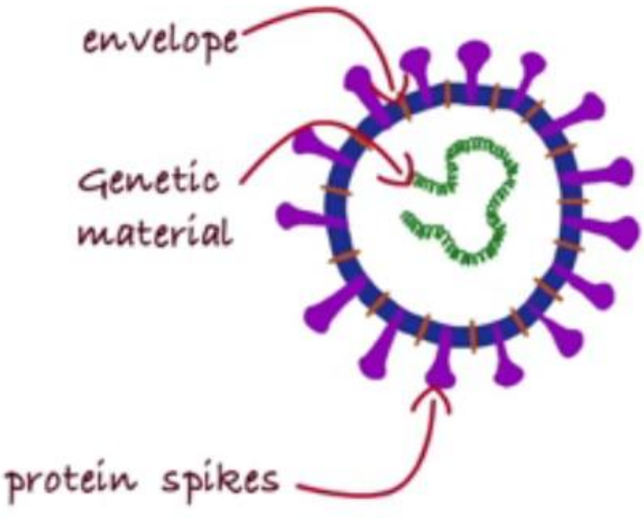

Figure 8: Covid-19 Strain

They consist of a core of genetic material surrounded by lipid envelope with protein spikes. So, this gives it the appearance of a crown as crown in Latin is known or called as Corona and that how these viruses get their name there

Covid-19 pneumonia is different from regular pneumonia:

The symptoms of covid-19 pneumonia may be similar to other types of pneumonia or viral pneumonia. At the initial stages, it was complex to understand for Doctors as well as technicians that to identify which pneumonia this is as there were n number pneumonia. Because of this, it was difficult to estimate or predict for what’s causing for your condition.

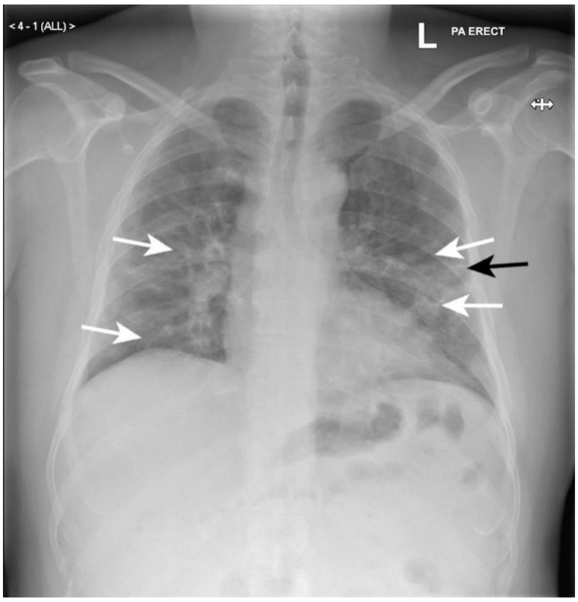

Figure 31: Covid-19 Pneumonia

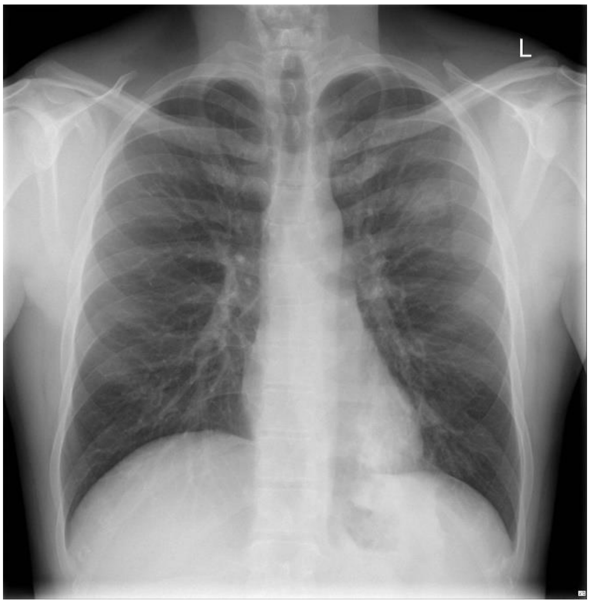

Figure 32: Non-Covid-19 Pneumonia

1.8 Convolutional Neural Network (CNN):

A Convolutional neural network is a neural network that may have one or more convolutional layers and are mainly used for image processing, classification, segmentation and also for other auto correlated data. A convolution is essentially sliding a filter over the input.

1.8.1 Benefits of CNN:

Little reliance on pre-processing, decreasing the needs of human effort developing its functionalities.

It is very easy to understand and super-fast to implement.

It has the best accuracy among all algorithm's that predicts pictures.

There are three types of layers that make up the CNN which are the convolutional layers, pooling layers, and fully-connected layers.

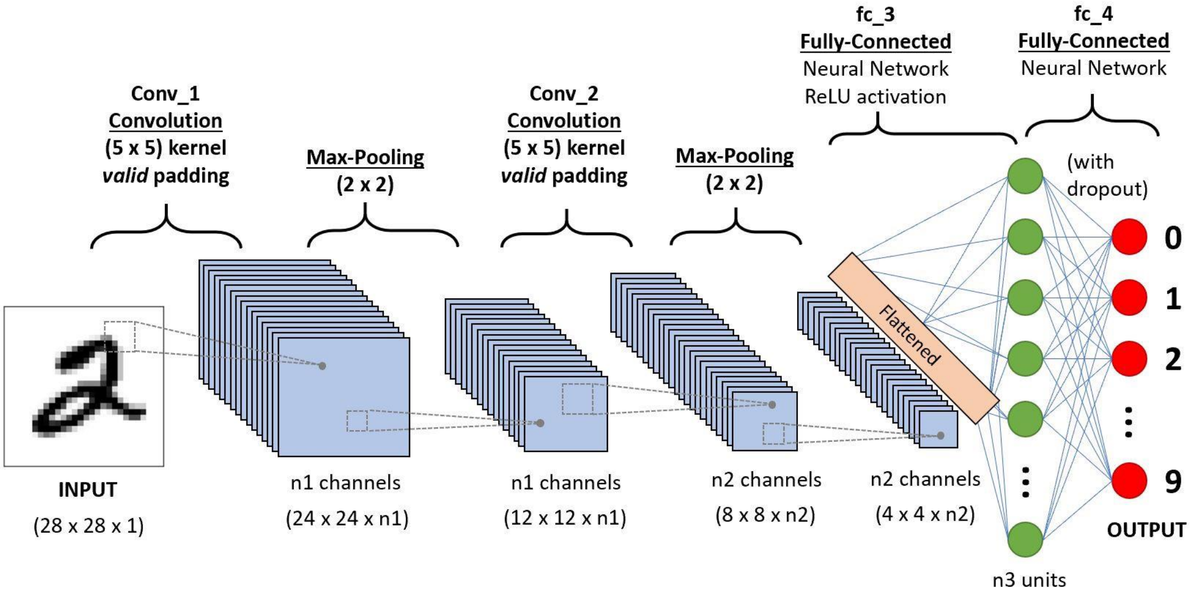

Figure 9: Convolution Neural Network

1.8.2 Input layer:

The input layer of a neural network is made out of artificial input neurons, and carries the starting data into the system for further processing by subsequent layers of artificial neurons. The input layer is the starting of the workflow for the artificial neural network.

1.8.3 Convolutional layers:

Convolutional layers convolve the input and pass its outcome to the following layer. This is like the reaction of a neuron in the visual cortex to a particular boost. Each convolutional neuron measures information just for its responsive field Although fully connected feedforward neural networks can be used to learn features and classify data, this design is for the most part illogical for bigger data sources like high-goal pictures. It would require a high number of neurons, even in a shallow design, because of the enormous info size of pictures, where every pixel is important information included. For example, a completely associated layer for a (little) picture of size 100 x 100 has 10,000 loads for every neuron in the subsequent layer. All things being equal, convolution lessens the number of free boundaries, permitting the organization to be more profound.

For instance, paying little heed to picture size, utilizing a 5 x 5 tiling locale, each with similar shared loads, requires just 25 learnable boundaries. Utilizing regularized loads over fewer boundaries keeps away from the disappearing slopes and detonating inclinations issues seen during backpropagation in conventional neural organizations. Besides, convolutional neural organizations are ideal for information with a grid-like topology (like pictures) as spatial relations between independent highlights are considered during convolution and additionally pooling.

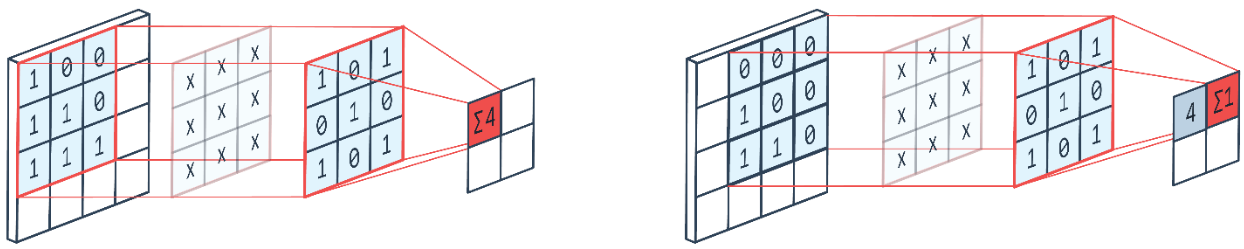

Figure 10 : Process of Convolution

1.8.4 ReLU Activation Function:

ReLU is the truncation of the rectified linear unit, which applies to the non-saturating activation function. It successfully eliminates negative qualities from an activation map by setting them to zero. It introduces nonlinearities with the choice capacity and in the overall network without influencing the open fields of the convolution layers.

Different capacities can likewise be utilized to build nonlinearity, for instance, the saturating hyperbolic tangent, and the sigmoid capacity. ReLU is frequently liked to different capacities since it prepares the neural organization a few times quicker without significant penalty to generalization accuracy.

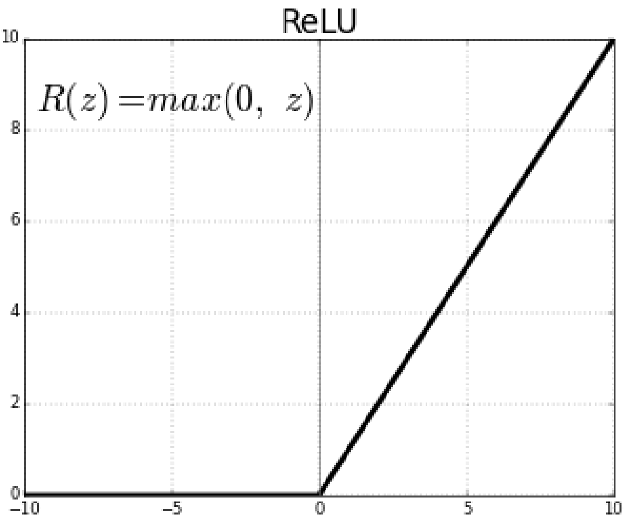

Figure 11: Relu Activation Function

1.8.5 Pooling Layers:

Convolutional networks may incorporate local and/or global pooling layers alongside conventional layers. Pooling layers decrease the components of information by joining the outputs of neuron groups at one layer into a solitary neuron in the following layer. Local pooling joins small clusters, tiling sizes for example, 2 x 2 are regularly used. Global pooling acts on each of the neurons of the component map. There are two common kinds of pooling in well-known use: max and average. Max pooling utilizes the maximum value of each local cluster of neurons in the feature map, while *average pooling* takes the average value.

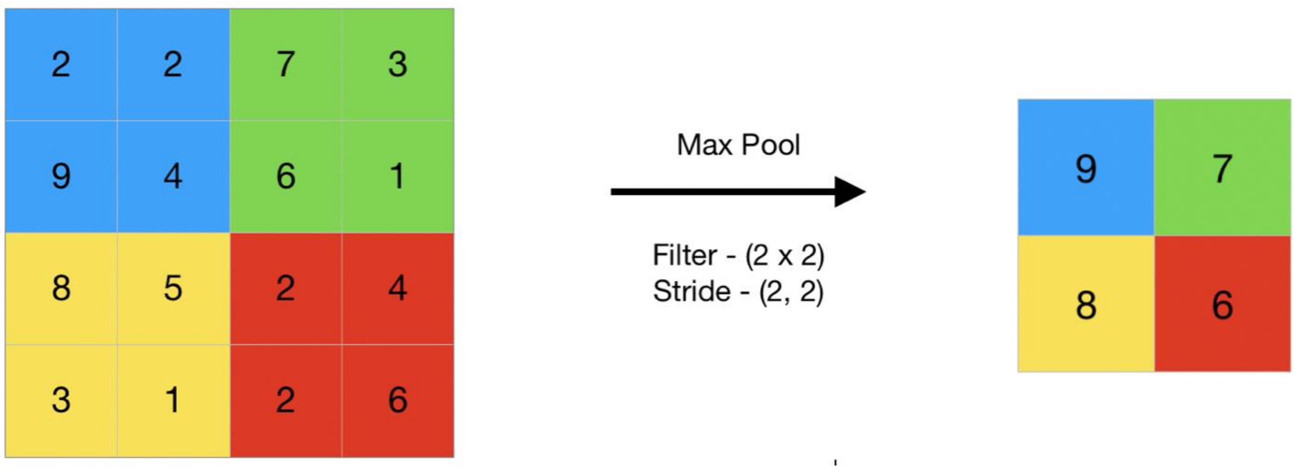

Figure 12: Max Pooling Example

1.8.6 Fully Connected Layers:

Fully connected layers connects every neuron in one layer to every neuron in another layer. It is the same as a traditional multi-layer perceptron neural network. The flattened matrix checks a fully connected layer to classify the images.

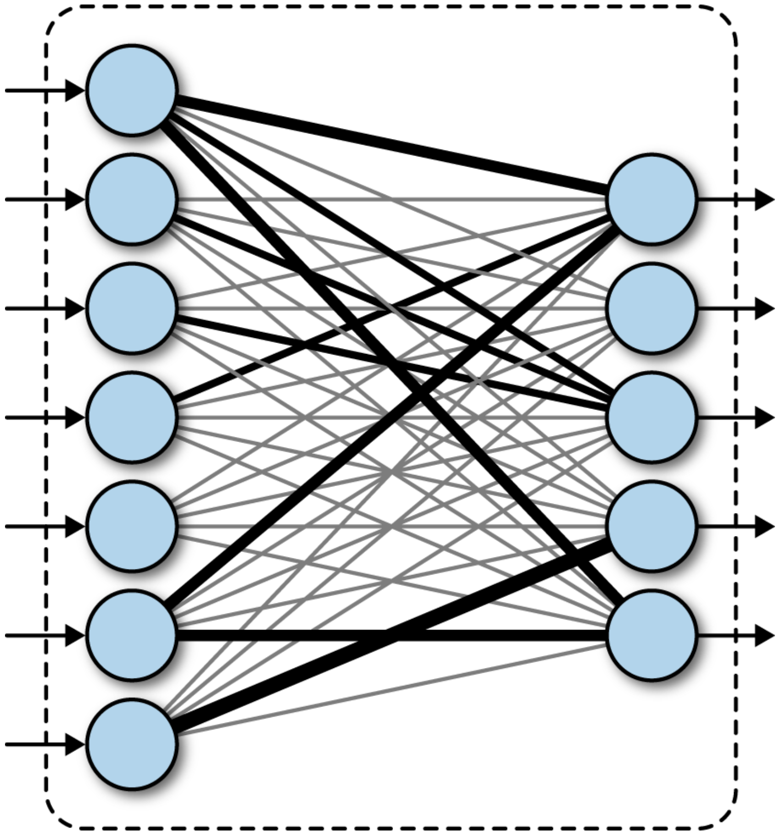

Figure 13: Fully Connected Layer

1.8.7 Weights:

Every neuron in a neural network registers an output value by applying a particular function to the input values got from the receptive field in the past layer. The function that is applied to the input values is dictated by a vector of loads and a bias. Learning comprises of iteratively changing these biases and loads.

The vector of loads and the bias are called filters and address specific features of the input (e.g., a specific shape). A distinguishing feature of CNNs is that many neurons can share the same filter. This decreases the memory impression because a single bias and a single vector of weights are used across all receptive fields that share that filter, instead of each open field having its own bias and vector weighting.

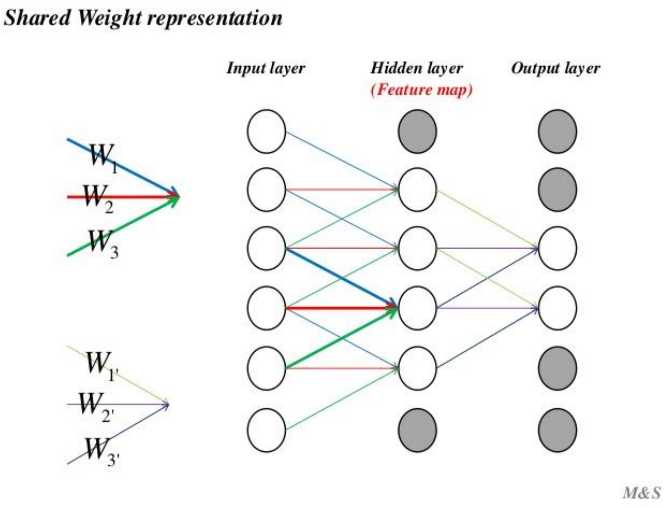

Figure 14: Weight Representation in CNN

1.8.8 Flatten Layer:

Flattening is nothing but it uses in converting the data into a 1-dimensional array for inputting it to the next layer. We flatten the output of the convolutional layers for to create a single long feature vector. And it is to be connected to the final classification model, which is called a fully-connected layer.

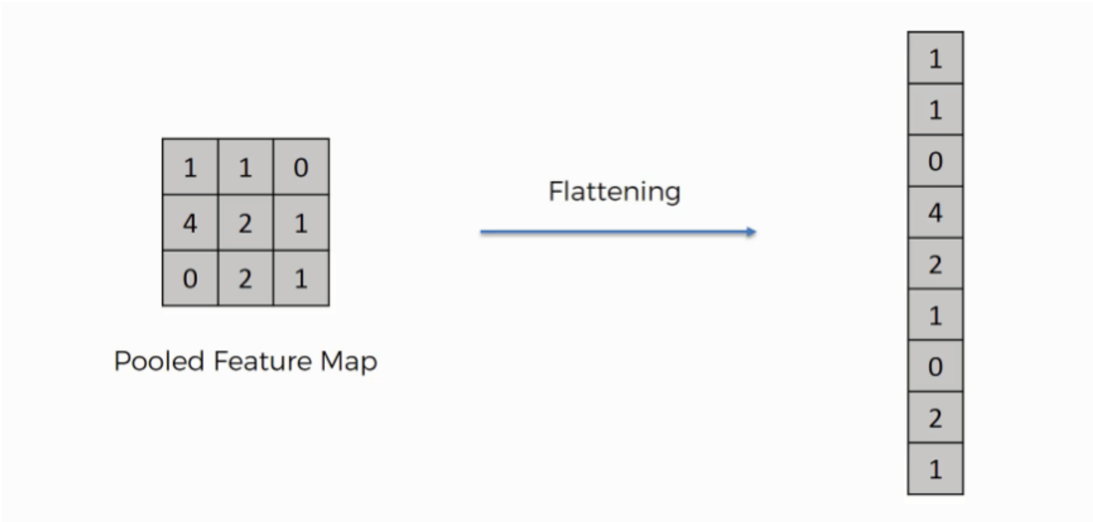

Figure 15: Flattening in CNN

1.8.9 SoftMax Layer:

The SoftMax function is a function that turns a vector of K real values into a vector of K real values that sum to 1. ... For this reason, it is usual to append a SoftMax function as the final layer of the neural network.

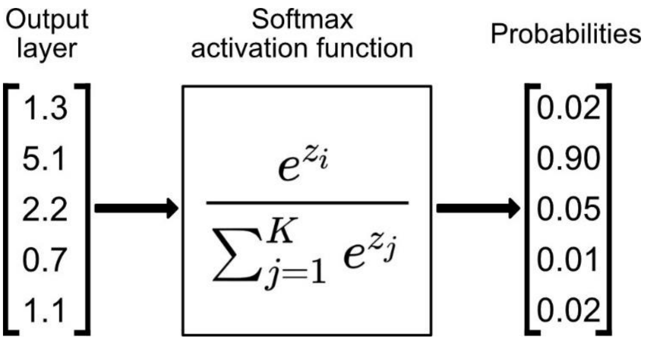

Figure 16: Softmax Function

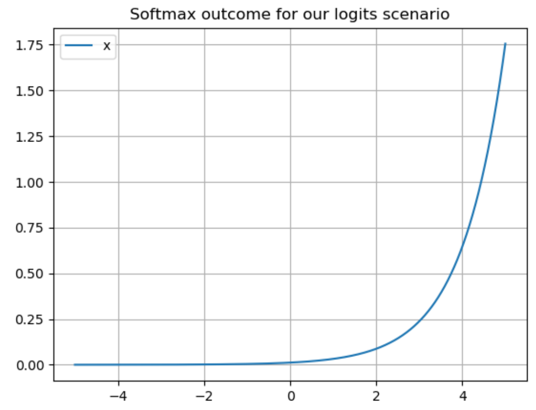

Figure 17: Softmax Graph

1.8.10 Sigmoid Layer:

The main reason why we use sigmoid function is because it exists between (0 to 1). Therefore, it is especially used for models where we have to predict the probability as an output. Since probability of anything exists only between the range of 0 and 1, sigmoid is the right choice.

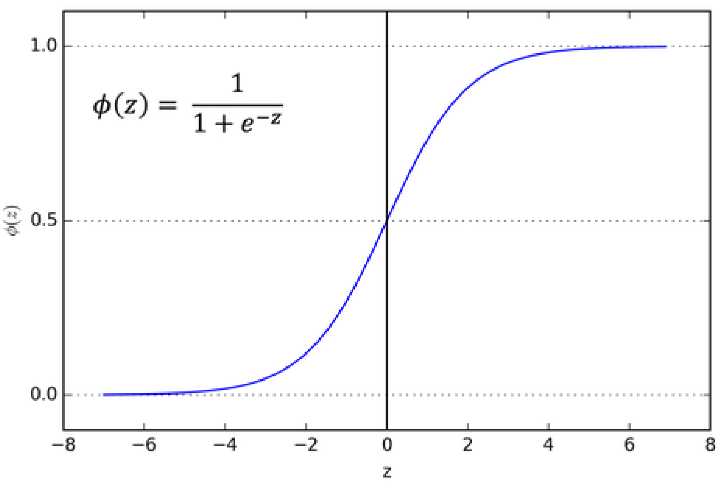

Figure 18: Sigmoid Activation Function

CHAPTER-2

LITERATURE SURVEY

2.1. Novel Feature Selection and Voting Classifier Algorithms for COVID-19 Classification in CT Images by IEEE – Published on IEEE Access

This article proposes two optimization algorithms for feature selection and classification of COVID-19, by taking two datasets (Covid-19 and Non-Covid-19).

The whole paper is divided into three phases. Primarily, the specifications (Fitness and selected size) are considered from the CT scans using a Convolutional Neural Network (CNN) named Alex Net. Secondly, a proposed feature selection algorithm, Guided Whale Optimization Algorithm (Guided WOA) based on Stochastic Fractal Search (SFS), is then applied which improves the classification results. Finally, a proposed voting classifier, Guided WOA based on Particle Swarm Optimization (PSO), takes different classifiers' predictions into account so that it can choose the most voted class. And the result is driven by 3 different terminologies. This provided as one of inspiration in making this project. [8]

2.2. Deep learning-based detection and analysis of COVID-19 on chest X-ray images

This research paper provided us with the information on using X-rays for
Covid-19. The provided paper created models based on the state-of-art CNN architectures modifying them to the requirement of the model. The paper stated out of the three models(Inception V3, Xception, and ResNeXt), the XCeptionNet has the best performance and is suited to be used. But the information we needed was on checking the dependability of X-Rays which we obtained with help of this paper. [9]

2.3. Identifying COVID19 from Chest CT Images - A Deep Convolutional Neural Networks Approach

This article proposes the use of Ensemble learning in providing the best accurate results. Firstly, in this process, individual baseline models are extensively evaluated. These baseline models include VGG16, InceptionV3, ResNet50, DenseNet121, and DenseNet201. In this work, all of these baseline models' convolution parts are kept the same as the standard models, as proposed originally for the ImageNet challenge; however, the fully connected parts of the models are fixed as 3 fully connected layers (4096, 4096, and 1000), each with ReLU activation and finally a single-node prediction layer with Sigmoid activation function. Apart from different from these baseline models, a decision fusion-based approach is also considered in this work. This Research paper provided us with an idea of using ensemble learning to provide more accurate results as to detect Covid-19. [10]

2.4. XCOVNet: Chest X-ray Image Classification for COVID-19 Early Detection Using Convolutional Neural Networks

The developed a convolutional neural network (CNN) categorize the chest X-ray images of patients as positive COVID+ or negative COVID−. Our XCOVNet model uses a CNN with the Adam optimizer and a learning rate 0.001. It does not require any feature selection method and uses a handcrafted seed dataset for CNN local and global features with 196 of COVID+ patient chest X-ray images and 196 of COVID− images.

The proposed XCOVNet model based on computerized automated detection can understand the features more efficiently and detect COVID19 faster than other classical learning methods. The trained CNN comprises three convolutional layers with the kernel size of 3 × 3 followed by a rectified linear unit (ReLU) activation function which takes input images of size 224 × 224 × 3. The proposed XCOVNet system achieved an accuracy of 98.44% in classifying chest X-ray images. [11]

CHAPTER 3
SYSTEM ANALYSIS

3.1 Hardware Requirements

1. It requires a minimum of 4.16 GHz processor.
2. It requires a minimum of 8 GB RAM.
3. It requires 64-bit architecture.
4. It requires a minimum storage of 500GB.
5. It required a minimum of Nvdia 1080Ti GPU

3.2 Software Requirements

1. It requires a Windows Operating System.
2. Latest chrome browser
3. Web Development (HTML, CSS and JS) for designing UI.
4. Using Python for coding and prediction.
5. Using Flask for the BackEnd

3.3 Feasibility Analysis

As the name implies, a feasibility study is used to determine the viability of an idea, such as ensuring a project is legally and technically feasible as well as economically justifiable. It tells us whether a project is worth the investment—in some cases, a project may not be doable. There can be many reasons for this, including requiring too many resources, which not only prevents those resources from performing other tasks but also may cost more than an organization would earn back by taking on a project that isn't profitable.

3.3.1 Economical Feasibility

This assessment typically involves a cost/ benefits analysis of the project, helping organizations determine the viability, cost, and benefits associated with a project before financial resources are allocated. It also serves as an independent project assessment and enhances project credibility— helping decision makers determine the positive economic benefits to the organization that the proposed project will provide. Our project is economically feasible because in this we have used “Python”, “Angular” designer tool which are all available as an open source.

3.3.2 Technical Feasibility

This assessment focuses on the technical resources available to the organization. It helps organizations determine whether the technical resources meet capacity. Technical feasibility also involves evaluation of the hardware, software, and other technology requirements of the proposed system.

CHAPTER-4

SYSTEM DESIGN

4.1 System Architecture:

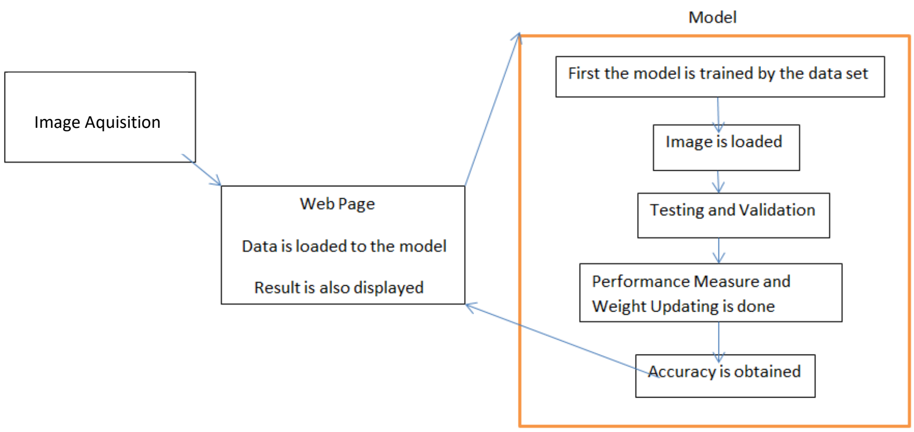

Figure 19: Architecture of the overall project.

4.2 Class Diagram:

Class diagram is a static diagram. Class diagram is used for visualizing, describing, and documenting different aspects of a system. Also for constructing executable code of the software application.

Class diagram describes the attributes and operations of a class. The class diagrams are widely used in the modelling of object oriented systems because they are the only UML diagrams, which can be mapped directly with object-oriented languages.

It is also known as a structural diagram.

- The main reason for the construction of the class diagram is to explain the responsibilities of the system.

- Relationship between the classes are shown by the arrows(Dependency, Association and Generalization).

Here the scan class has the operation depicts where the scan is used to depict the disease, also it has attribute Number of the scan taken and name of the patient. Web page has option as its attribute, and the page can load the data into the model and also can show us the result.

Result class is dependent on what algorithm class will report he get for the further proceedings like treatment or any kind of the operation.

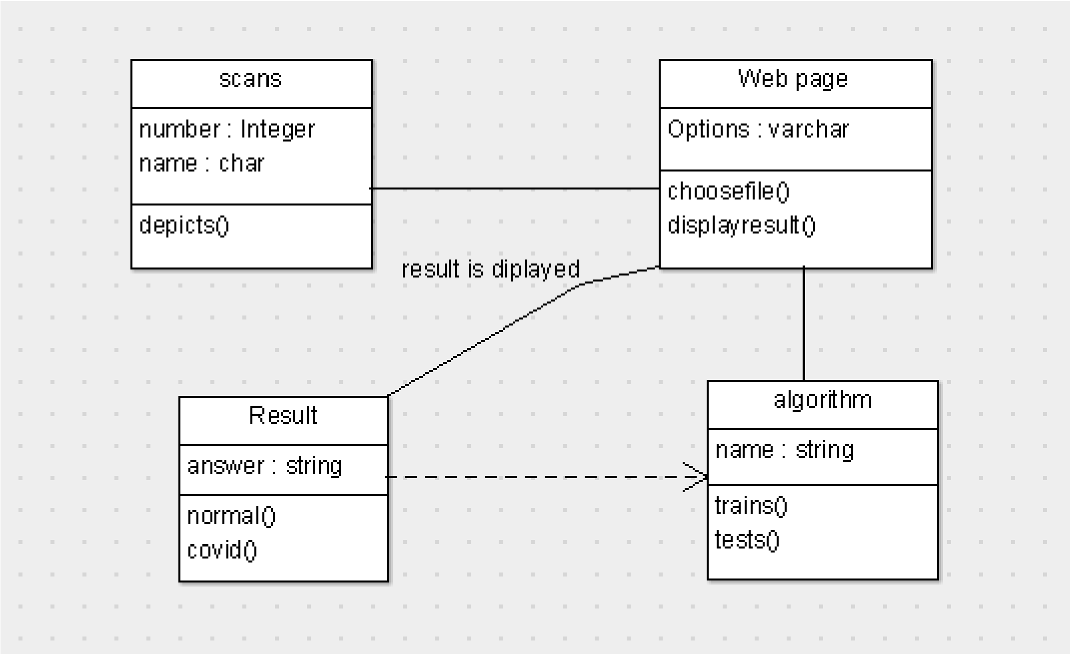

Figure 20: Class Diagram

4.3 Activity Diagram:

Activity diagram is used to describe the changing aspects of the system.
It is basically a flowchart to represent the flow from one activity to another activity. The activity describes operation of the system.

The control flow is from one operation to another. This flow can be sequential, branched, or concurrent.

In the initial stages the system will be in the idle stage because will be having no work.

After that the scans of the patient will be uploaded into the system.

Model does it activity of training through the data and come to a final conclusion, by which it can test the scans and provides its result that the patient has the disease in Yes or No format.

Automatically the results will be displayed showing that the disease is present or not.

The first dot is called the Initial state, where the process will be get started.

Last is the Final state, where the whole process is ended.

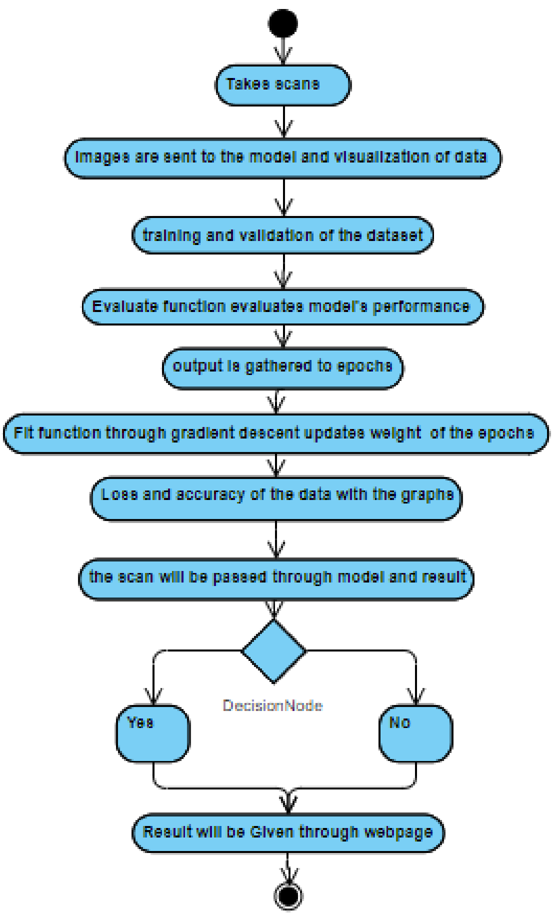

Figure 21: Activity Diagram

4.4 Use Case Diagram:

Use case diagram is one of the dynamic nature of the UML diagrams. These diagrams are used to explain the functionality of the means the functions which are taken by the system.

Here there are actors, use cases, Links and finally the boundary of the system.

Actors are the one who interacts with the use cases I.e the functions. They are the initiators of the use cases, as well as they have expectations from the output.

Use cases are the functions of the system where they are linked to the actors,but sometimes some use cases are linked to other use case or they can start their own process too.

Actors and the use cases are linked through communication link, showing message passing between them.

Any use case beyond the system boundary are no considered because they will be not in the process.

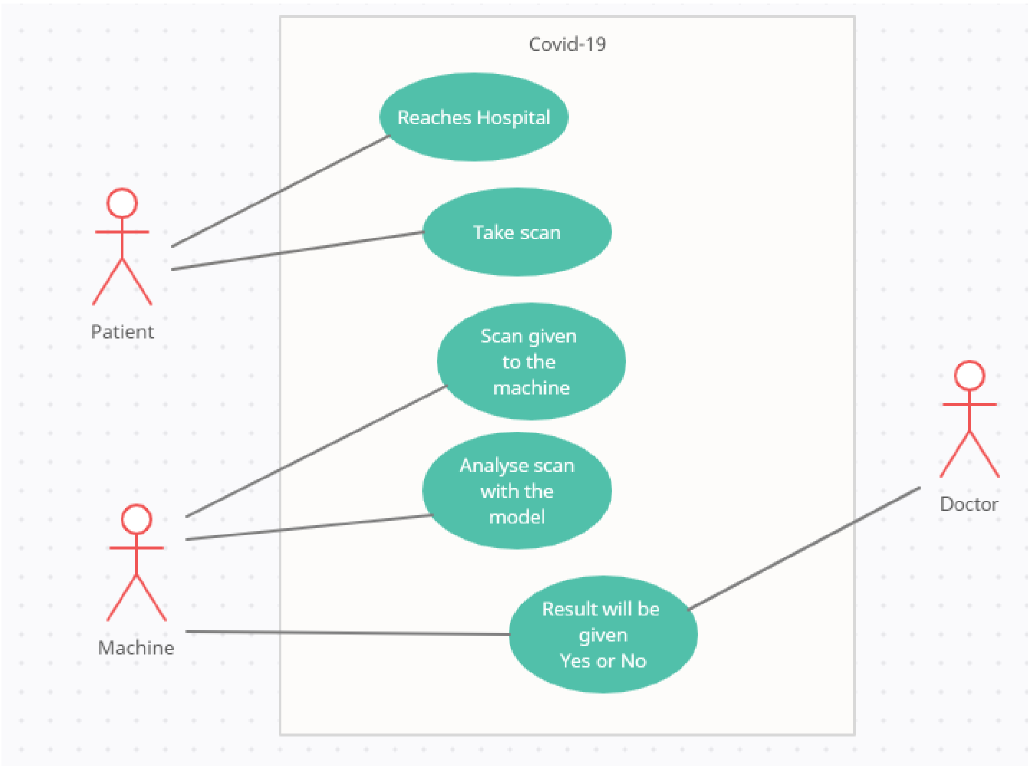

Figure 22: Use Case Diagram

4.5 Sequence Diagram

Sequence Diagrams are the interaction diagrams where the detailed explanation of the process of the work done by the system is explained.

Here the whole process is shown in the form of number in a sequence so that anybody can easily understand the process that is done by the system.

Here the objects are mentioned and the interaction between the objects are mentioned so that we can know about the important objects that are there in the whole system.

The main point in the sequence diagram is that only the objects are involved where the process is going and no other objects are included.

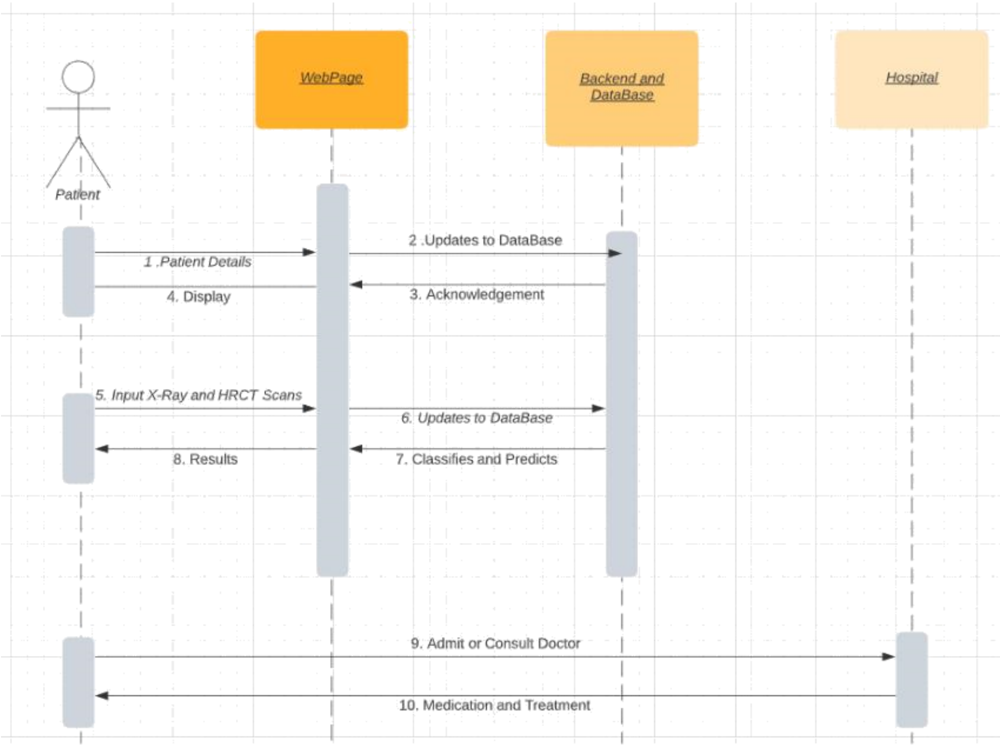

Figure 23: Sequence Diagram

4.6 Component Diagram

Component diagrams are used to model the physical aspects of a system. Physical aspects are the elements like libraries, files, documents, etc. which will be in a node.

The nodes in this diagram will consists of the data that are in the form of files, documents, codes etc.

Here in the diagram scan node has the scans which are associated in the scan as files.

And also the result is displayed through web page is dependent on the Model where the whole process of the prediction is done which are stored in the form of files.

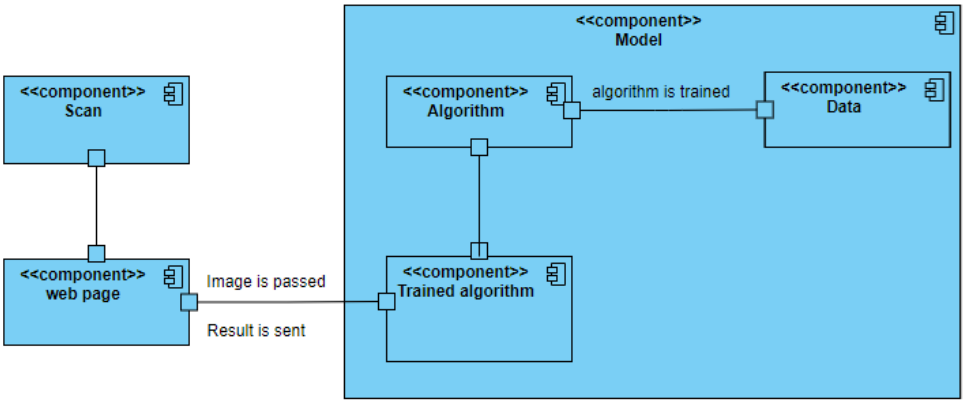

Figure 24: Component Diagram

4.7 Deployment Diagram

Deployment diagrams are used to describe the hardware components where the software
components are deployed. These are used for the static view of the system.
It has node and relationships, where the components are represented as nodes.
Here the Scanner, Computer are nodes(Hardware components) where the
deploy able software component reside.
This diagram is showing how the data the software component will be shared between the hardware components.

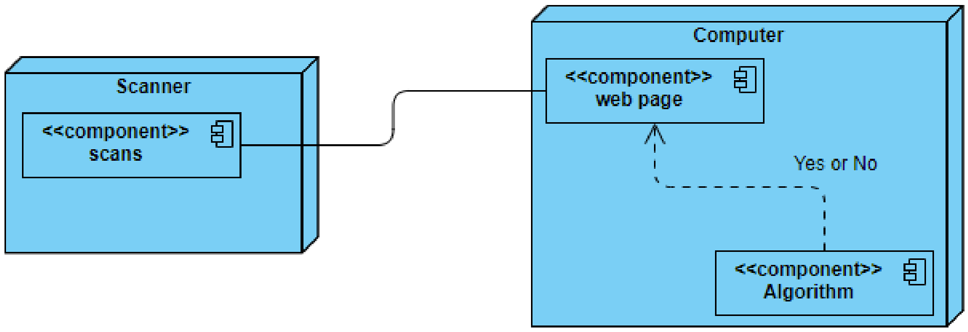

Figure 25: Deployment Diagram

CHAPTER-5

MATERIALS AND METHODOLOGY

5.1 Materials:

5.1.1 Image Data Set Collection:

The dataset for this work has been collected from the Kaggle repository [1.a], which contains Chest X-Ray scans of normal and pneumonia and Github Repository of education454 [1.b], which contains Chest X-ray scans of normal and covid-19.

The collected Dataset is doesn't claim to provide an increase in the diagnosis of the Deep Learning model rather it helps in the research of efficiently detecting Covid-19 infections with the help of Computer Processing Techniques. The collected dataset consists of 6568 total Lung X-Ray images. The directories are listed as ['covid', 'pneumonia', 'normal']. The images seemed to be in-consistent and the below table (Table1) provides the distribution of data. Since the images are equally distributed the classification can be more reliable.

5.2 Data Set Analysis:

Table 1: Dataset Contents

Covid -19	712
Pneumonia	4273
Normal	1583

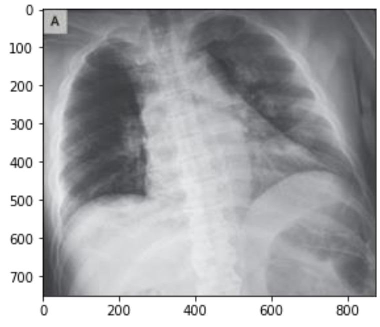

Figure 26: Sample Image

Table 2 & 3: Data Frame of Image File Set

The images in the dataset is classified in a dataframe as below which is split into train and test data to understand the information we have.

	class	o_directory
0	PNEUMONIA	PNEUMONIA/person1493_bacteria_3896.jpeg
1	PNEUMONIA	PNEUMONIA/person54_bacteria_257.jpeg
2	PNEUMONIA	PNEUMONIA/person896_virus_1548.jpeg
3	PNEUMONIA	PNEUMONIA/person441_bacteria_1910.jpeg
4	PNEUMONIA	PNEUMONIA/person72_bacteria_352.jpeg
...	...	...
1630	NORMAL	NORMAL/NORMAL2-IM-1094-0001-0002.jpeg
1631	NORMAL	NORMAL/NORMAL2-IM-0452-0001.jpeg
1632	NORMAL	NORMAL/IM-0189-0001.jpeg
1633	NORMAL	NORMAL/NORMAL2-IM-0684-0001-0001.jpeg
1634	NORMAL	NORMAL/NORMAL2-IM-0583-0001.jpeg

1635 rows × 3 columns

	class	o_directory
0	PNEUMONIA	PNEUMONIA/person1952_bacteria_4883.jpeg
1	PNEUMONIA	PNEUMONIA/person1947_bacteria_4876.jpeg
2	PNEUMONIA	PNEUMONIA/person1949_bacteria_4880.jpeg
3	PNEUMONIA	PNEUMONIA/person1950_bacteria_4881.jpeg
4	PNEUMONIA	PNEUMONIA/person1954_bacteria_4886.jpeg
...	...	...
802	NORMAL	NORMAL/NORMAL2-IM-0354-0001.jpeg
803	NORMAL	NORMAL/NORMAL2-IM-0030-0001.jpeg
804	NORMAL	NORMAL/NORMAL2-IM-0369-0001.jpeg
805	NORMAL	NORMAL/NORMAL2-IM-0373-0001.jpeg
806	NORMAL	NORMAL/NORMAL2-IM-0271-0001.jpeg

807 rows × 3 columns

Table 4 & 5: Data Frame for Binary Classification

The images in the dataset is classified into binary dataset as the dataframe as below for to have easier understanding of the information.

	class	o_directory
0	COVID19	COVID19/COVID19(415).jpg
1	COVID19	COVID19/COVID-19 (313).jpg
2	COVID19	COVID19/COVID19(63).jpg
3	COVID19	COVID19/COVID-19 (371).jpg
4	COVID19	COVID19/COVID19(512).jpg
...	...	...
479	NORMAL	NORMAL/NORMAL(561).jpg
480	NORMAL	NORMAL/NORMAL(1402).jpg
481	NORMAL	NORMAL/NORMAL(301).jpg
482	NORMAL	NORMAL/NORMAL(219).jpg
483	NORMAL	NORMAL/NORMAL(1416).jpg

484 rows × 3 columns

	class	o_directory
0	COVID19	COVID19/COVID19(445).jpg
1	COVID19	COVID19/COVID19(409).jpg
2	COVID19	COVID19/COVID19(373).jpg
3	COVID19	COVID19/COVID19(575).jpg
4	COVID19	COVID19/COVID19(497).jpg
...	...	...
1806	NORMAL	NORMAL/NORMAL(612).jpg
1807	NORMAL	NORMAL/NORMAL(871).jpg
1808	NORMAL	NORMAL/NORMAL(367).jpg
1809	NORMAL	NORMAL/NORMAL(90).jpg
1810	NORMAL	NORMAL/NORMAL(502).jpg

1811 rows × 3 columns

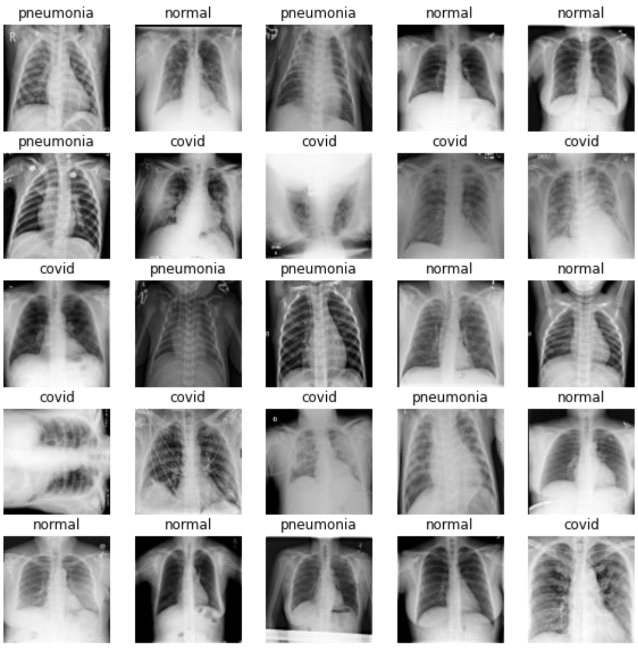

Figure 27: Sample Image Visualization

The data set is divided with testing size of 20%. The split is done with the help of "train_test_split" from the sklearn library.

Table 6: Data Set Split into Training and Testing for Categorical

	Training	**Testing**
Covid-19	545	167
Pneumonia	3875	398
Normal	1341	242

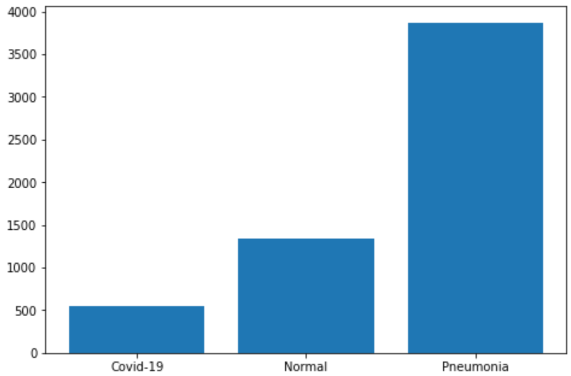

Figure 40: Training Split (Categorical)

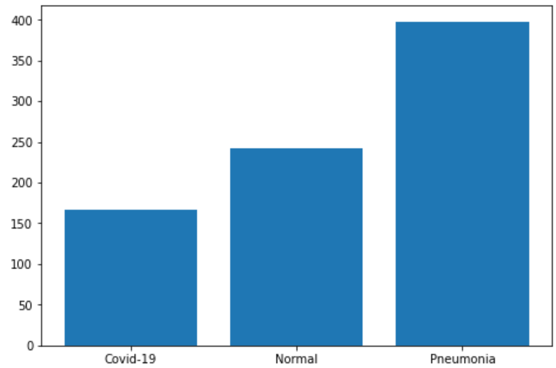

Figure 41: Testing Split (Categorical)

Table 7: Data Set Split into Training and Validation for Binary

	Training	**Testing**
Covid-19	545	167
Normal	1341	242

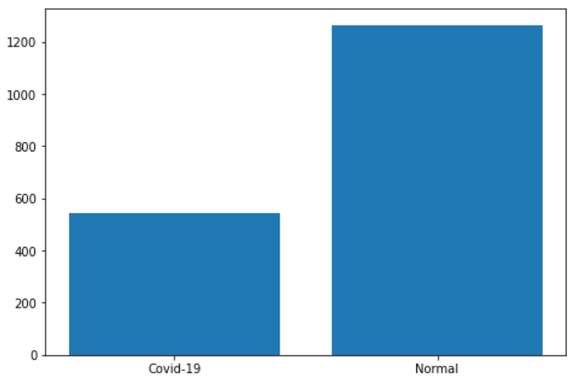

Figure 42: Training Split (Binary)

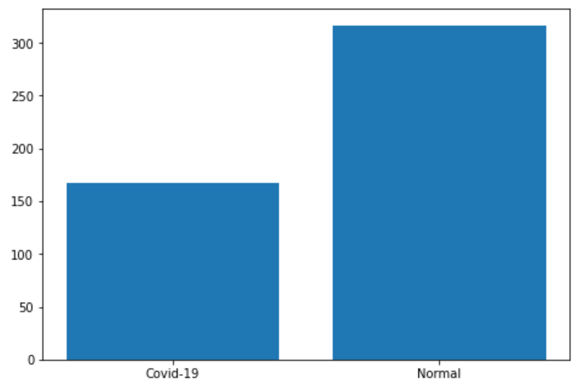

Figure 43: Testing Split (Binary)

The Data is then further saved into a output folder where the dataset is split into the following order.

Table 8: Directory Specification

Categorical Classification Data	**Binary Classification Data**
• Categorical Dataset ○ train ▪ Normal ▪ Covid ▪ Pneumonia ○ test ▪ Normal ▪ Covid ▪ Pneumonia	• Binary Dataset ○ train ▪ Normal ▪ Covid ○ test ▪ Normal ▪ Covid

These images considered for analysis. Since this is a prediction-based study large sizes in the dataset are required. As this is a medical problem the images are hard to be obtained.

5.3 Image Pre Processing:

With the help of keras.preprocessing method "ImageDataGenerator" validation split of 0.1 is performed with data generator on the training data to create validation and training datasets for model fitting. Along with the testing data where the augmentation is unnecessary. The augmentation is performed to reduce the overfitting of the data.
While drafting the paper the images we had were scaled down to 256 × 256 for faster training of the model, consistent image size, and by considering the computational capability of the system as in [6].

The training and validation datasets are created from the training data created in the dataset folder. The datasets are created with a batch size of 16 and shuffle is performed. The seed value is set to a random value of 1932.

Table 9: Training and Validation Split (Categorical)

	Training	**Validation**	**Testing**
[Covid/Normal/Pneumonia]	5186	575	807

Table 10: Training and Validation Split (Binary)

	Training	**Validation**	**Testing**
[Covid/Normal]	1449	362	484

Rescaling of 1./255 is done as referred to [5] and is explained in the below figure.

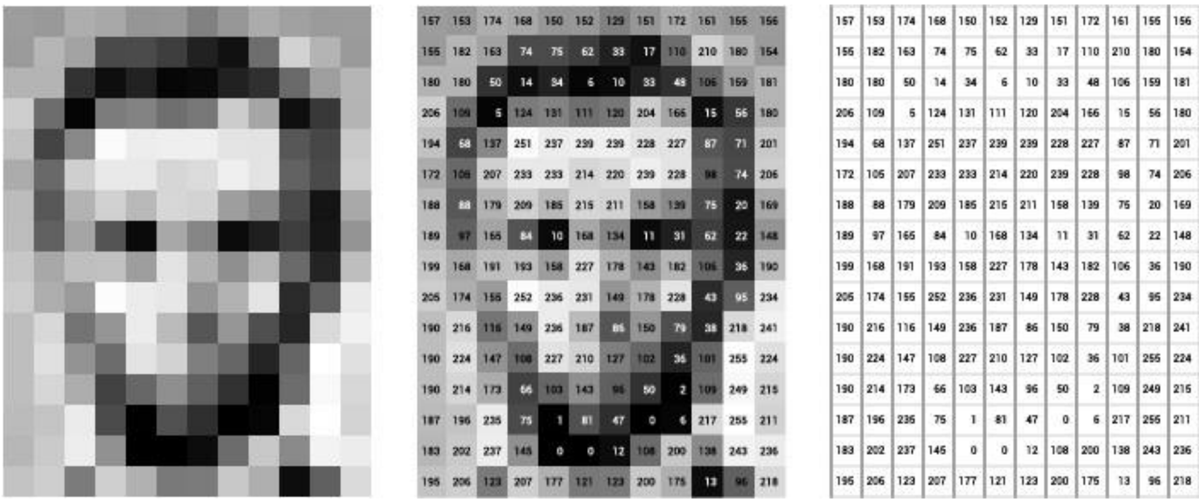

Figure 28: Rescaling Example

With rescaling the values of the pixel which ranges from [0, 255] gets converted into [0,1] allowing us to treat all images in same way. Since X-Rays are based on Grayscale Mechanism the augmentation is made as grayscale color format reducing the channels of the image.

Now the preprocessed data can be used to fit in a model.

5.3 Image Classification Process:

Image classification process is performed as below in our analysis.

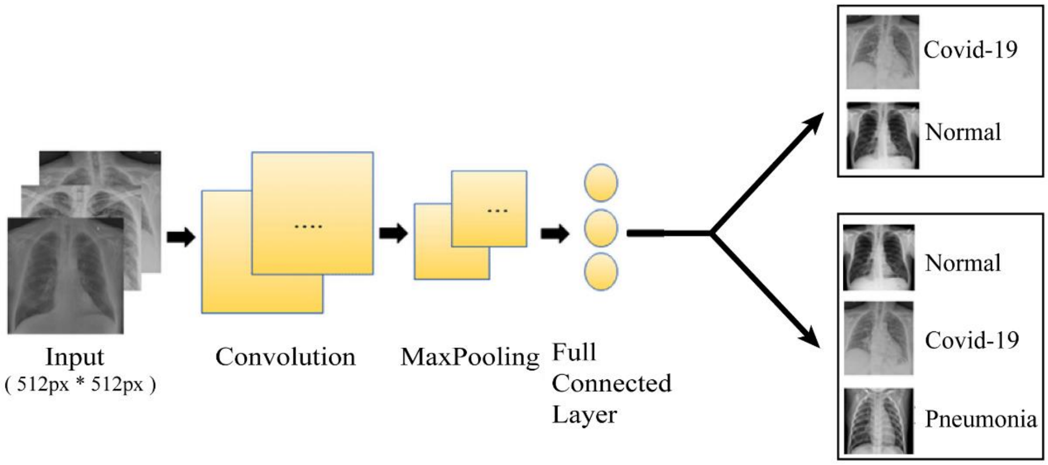

Figure 47: Image Classification

5.5 Experiments:

5.5.1 Preliminary Testing

Several experiments are conducted on to evaluate the best efficiency of the CNN considering the image database. Experiments are conducted on Covid-19/Normal. The network architectures with varying numbers of convolutional and fully connected layers, and basic image pre-processing techniques to test the results using various structures and pre-processing methods.

CNN Experiments, the first structure (CNN#1) consisted of two convolutional layers with 64 and 16 filters, respectively, with two fully connected (dense) layers with 256 and 1 neurons. It was the lightest architecture considered in this study. The second CNN structure CNN#2 included three convolutional layers with 256, 128, 64 and 128, 64, 32 filters, respectively, and two fully connected layers were implemented with 128 and 1 neurons. CNN#3, which was the deepest architecture in this study, consisted of four convolutional layers (256, 128, 128, and 64 filters) and three fully connected layers (128, 64, and 1 neurons). The filter sizes were considered as 4×5 for all structures, and

0.5 dropout was used for each layer. Pooling was applied as maximum pooling, and 2×2 pooling was

considered for each layer except the last convolutional layer of each structure. The pooling was applied as 1×1 in the last convolutional layer of each structure, to not minimize the features extracted by convolutional layers.

Table 9 show the architectural properties of four considered CNNs.
A total of 5 experiments were performed in this category of COVID-19/Normal, to evaluate and analyze the performance of CNNs under different conditions to achieve an optimal classification of COVID-19 images.

Table 11. Architectural Properties of Four Considered CNNs.

Architecture	**CNN Layer**	**Filters**	**Filter Size**	**Pooling and Size**	**Dropout**	**Activation**
CNN#1	1	128	5*5	Max-Pooling 2*2	0.5	ReLU
	2	32		Max-Pooling 1*1		
CNN#2	1	128	5*5	Max-Pooling 2*2	0.5	ReLU
	2	64				
	3	32				
CNN#3	1	256	5*5	Max-Pooling 2*2	0.5	ReLU
	2	128				
	3	64				
	4	32				
CNN#4	1	32	5*5	Max-Pooling 2*2	0.5	ReLU
	2	64				
CNN#5	1	256	5*5	Max-Pooling 2*2	0.5	ReLU
	2	128				

Based on the results above CNN#4 is selected for the preliminary testing for the dataset in order to finetune the parameters.

The simple CNN#4 structure is selected for the preliminary tests where a sequential model is selected with 2 layers depth with filters of (64, 32) and filter size of (5,5) and dropout of (0.5) to avoid overfitting of data. Adam Optimizer with a learning rate of 0.001 is used as it is providing better accuracy. Activation function "Relu" is used for hidden layers and 'SoftMax' as the final layer for prediction of data into 3 classes for Categorical classification, and 'Sigmoid' as the final layer for prediction of data into binary classes for Binary classification.
A basic comparison hyper parameter tuning has been done on various learning rates for Adam Optimizer which provided 0.001 as a better learning rate. So, 0.001 is selected as learning rate.

5.5.2 Test 1: Augmentation vs No-Augmentation:

In this category most of the studies preferred to do augmentation to avoid overfitting of the data. Where as in scenarios like x-rays where the detection is dependent on position it could cause inconsistent results resulting in False Positives and False negatives. A simpler test on the categorical dataset is performed to confirm that scenario.

5.5.3 Test 2: Image Sizes (256,256) vs (512, 512):

Two different image sizes listed above are considered for this study. Max size of (512, 512) is taken as it is the limit of the computational ability where as the minimum is taken as (256, 256) as going below will cost a lot of details from the image as the image classification relies majorly on black and white details.
With the above preliminary test further tests are made the results are noted for further observations. Since we have lesser data, creating a model from scratch is not dependable hence we relied on Transfer Learning Algorithms to obtain better prediction results.

So, 5 Transfer Learning models are selected based on our study to train which are further used for weighted classifier.

- DenseNet201
- ResNet50
- VGG16
- InceptionV3
- InceptionResNetV2

5.5. Transfer Learning Experiments:

Since the dataset is small Transfer Learning is used to find the model that provided accurate results for the dataset. In-order to increase the reliability each model is assigned by weight since each model has different structure combinations.
ImageNet weights are used for the model for this experiment. Being state-of-art models, these provide the baseline accuracy for further study of the classification.

DenseNet121[13] connects each layer to every other layer in a feedforward fashion. The initial convolutional layer is followed by a fully connected layer, and the rest of the convolutional layers are followed by the pooling and a fully connected layer. It has 121 layers and more than 8 million trainable parameters.

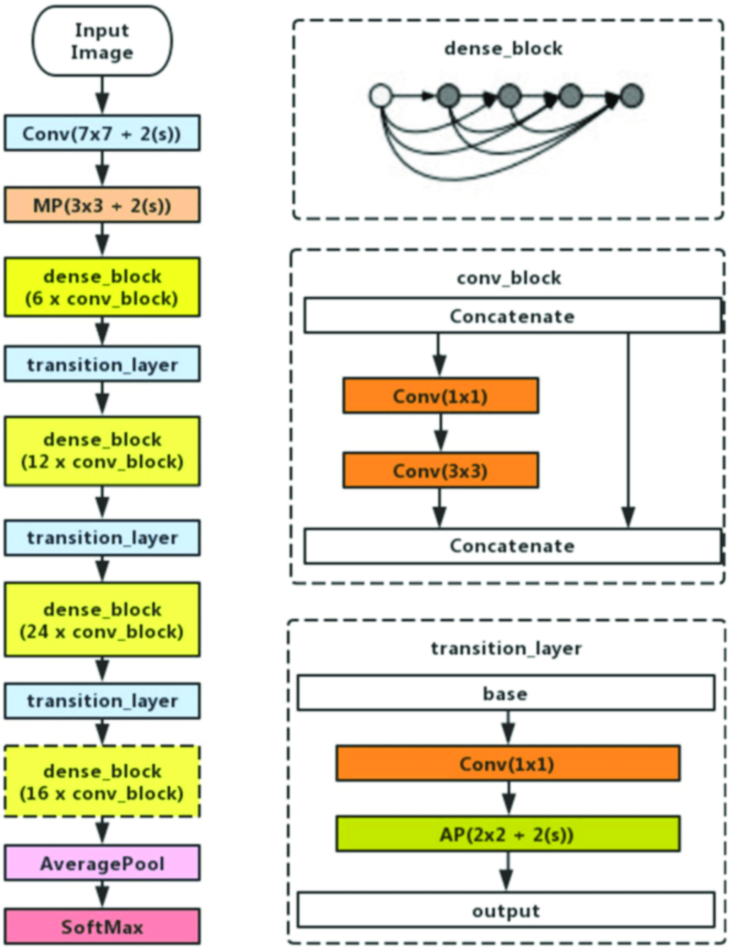

Figure 33: DenseNet121 Structure

ResNet50[14] has 50 residual layers, which aim to solve problems such as time consumption when the network becomes deeper. Its principle is based on skip connections between layers called identity function, and this increases the accuracy of the model and decreases the training time. It has more than 23 million trainable parameters.

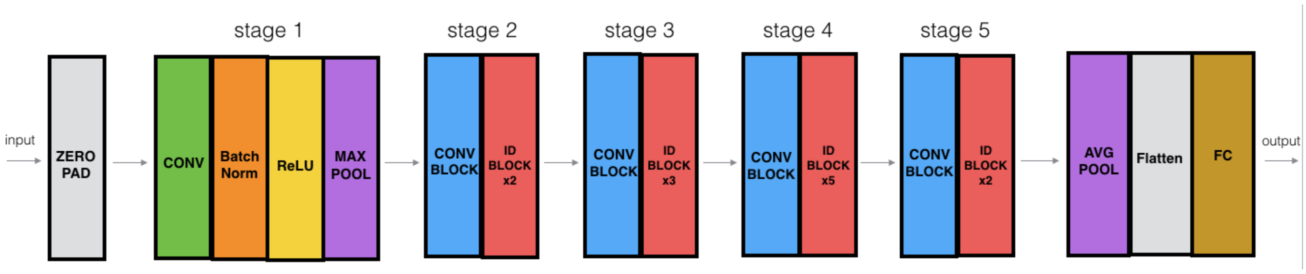

Figure 34: ResNet50 Structure

VGG16[15] is a CNN architecture that has 16 layers with weights and uses 3×3 filters. After convolutional layers, it has two fully connected layers, followed by a SoftMax for output. It has approximately 138 million parameters for the network. VGG19[13] is similar to VGG16, but it has 19 layers with weights, and this provides approximately 143 million parameters for the network.

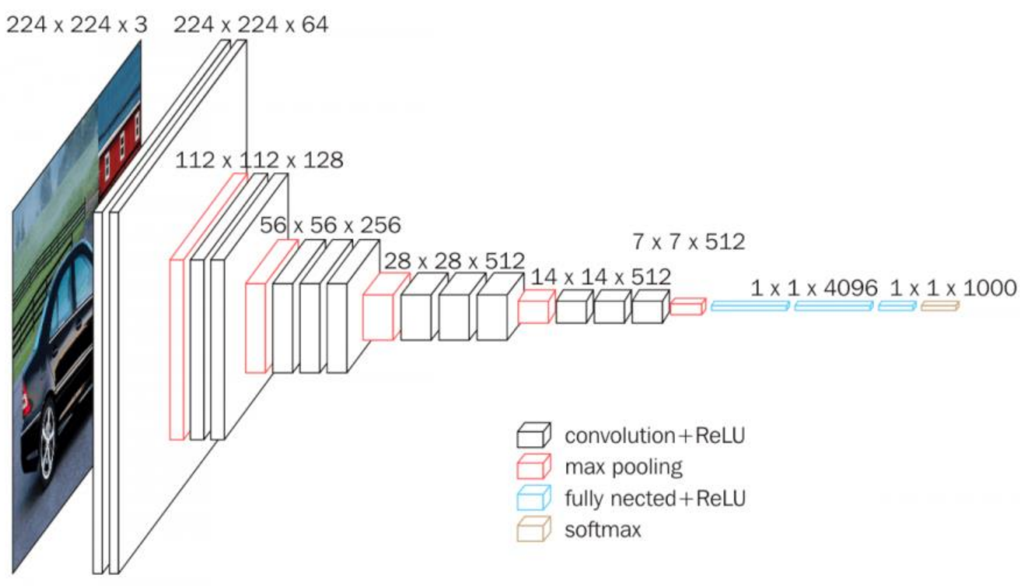

Figure 35: VGG16 Structure

InceptionV3[16] has 42 layers and 24 million parameters. It factorizes convolutions to reduce the number of parameters without decreasing the network efficiency. In addition, novel downsizing was proposed in Inception V3 to reduce the number of features.

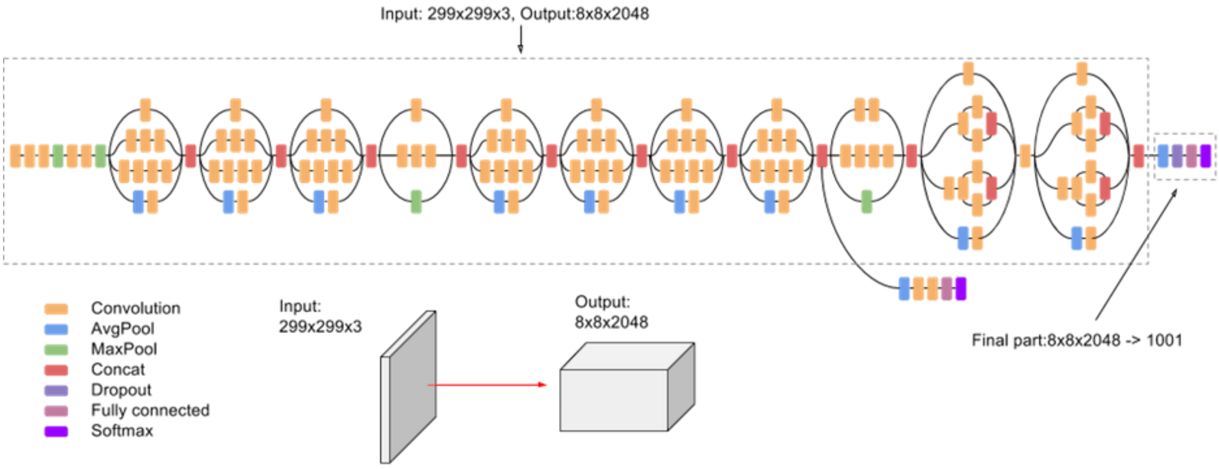

Figure 36: InceptionV3

Inception-ResNet-v2[17] is a convolutional neural network that is trained on more than a million images from the ImageNet database [1]. The network is 164 layers deep and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299.

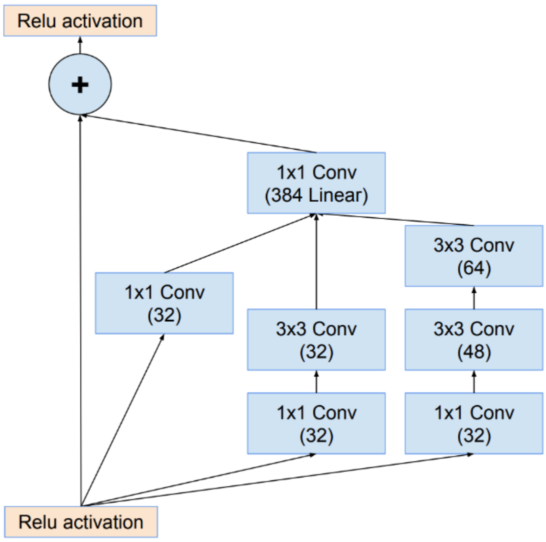

Figure 37: Inception-ResNet-v2 Structure

Each X-ray image was sent to the considered networks with the minimum dimensions required. The performed pre-processing on the considered models to provide consequent images to the models. After training of each model with pre-trained weights, maximum pooling was applied, and features were sent to the fully connected layer (128). The test is performed on each model based the below mentioned scenarios.

5.6 Image Classification:

5.6.1 Scenario-1: Covid19 vs Non-Covid:

In this binary classification the classification is made on Covid vs Non-Covid images on the above transfer learning algorithms.

5.6.2 Scenario-2: Covid19 vs Pneumonia vs Non-Covid

In this categorical classification is made on Covid vs Pneumonia vs Normal are made. Though the bias is present towards the Pneumonia because of the larger dataset of images proper evaluation is done to reduce the false positives and negatives.

5.7 Larger Dataset Experiment:

A simpler test using DenseNet201 is made on a handcrafted larger dataset was used in this experiment.

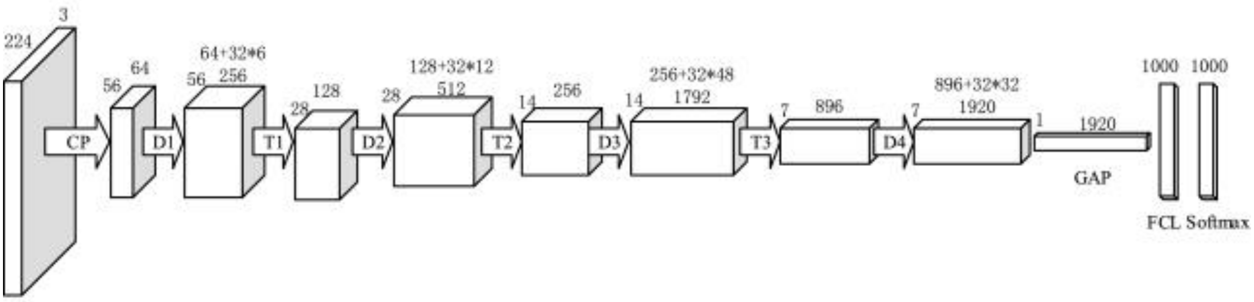

Figure 44: DenseNet201 Architecture

DenseNet-201[18] is a convolutional neural network that is 201 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

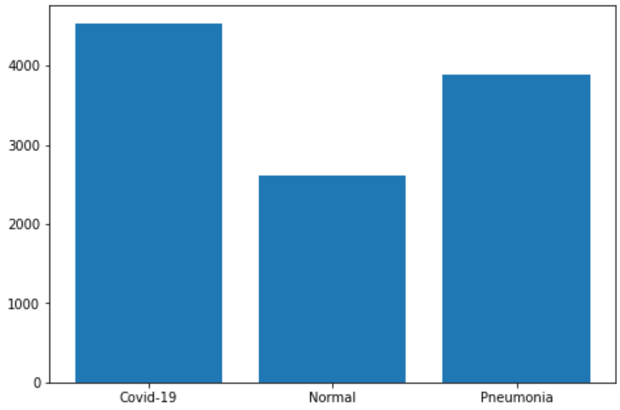

Figure 45: Training Dataset 2

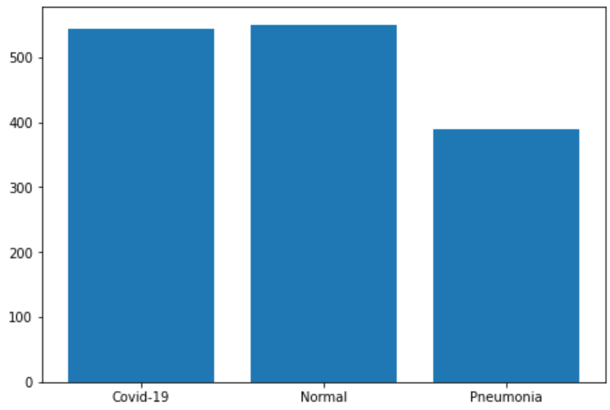

Figure 46: Testing Dataset 2

Testing:	**Testing:**
TOTAL: 11037	TOTAL: 1486
PNEUMONIA: 3883	PNEUMONIA: 390
COVID19: 4539	COVID19: 545
NORMAL: 2615	NORMAL: 551

This dataset is collective combination of education454 GitHub repository[1.b] and from Kaggle by paultimothymooney which provided pneumonia and normal lung x-rays [1.a] and by Quatar university which provided covid x-rays [1.c]. These 3 datasets are combined manually to create this large dataset and used for prediction analysis.

5.8 Model Evaluation Criteria:

Models can be evaluated using different criteria, such as classification accuracy, Precision, Recall etc. (true positive rate. Accuracy and sensitivity/specificity criterion is not enough, however, especially for imbalanced data; while higher scores can be obtained in one metric, lower scores can be produced by other metrics. By considering all the above-mentioned criteria, AUC was used to evaluate the model performance for the statistical measurement, COVID-19/Normal which had two output classes (labels) and COVID-19/Pneumonia/Normal had 3 output classes(labels). AUC is used to measure the performance of a model. In medical applications, the model with the higher ROC AUC score is more capable of distinguishing between patients with COVID-19 and without COVID-19. "Positive" and "negative" results are the responses of the outputs (classification predictions) obtained from the model. "True" and "false" are the actual data. The accuracy, precision, and recall are calculated as given in

Equation (1), Equation (2), and Equation (3), respectively:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$\text{Precision} = (TP) / (TP+FP) \quad (2)$$

$$\text{Recall} = (TP) / (TP + FN) \quad (3)$$

where TP and TN denote the true-positive and true-negative values, respectively; and FP and FN represent false-positive and false-negative values, respectively. 20% and 80% of the data were used for testing and training, respectively. 10% of images are randomly selected for both healthy and coronavirus-infected patients were selected as the validation set.

CHAPTER-6

RESULTS

6.1 CNN Results:

Results of COVID-19/Normal Experiments. In this group, a total of 2295 images (712 COVID-19 and 1583 Normal) were trained in each experiment with the data augmentation procedure, which artificially increases the training samples. The highest accuracy of Experiments 1– 4 was obtained in Exp.4 (98.44%). The highest sensitivity, highest specificity, which is the primary indicator for an imbalanced dataset. Exp.2 and Exp. 3 could not achieve higher rates than Exp.1 and Exp.4 in the evaluation metrics.

Table 12: CNN Experiment Results

Experiment	Sensitivity [Threshold of 0.75]	Accuracy	Loss
CNN#1	100%	97.11%	7.8%
CNN#2	100%	97%	7%
CNN#3	99.07%	95.54%	6.83%
CNN#4	99.39%	99.01%	6.4%
CNN#5	99.79%	97.90	6.13%

The above table shows the obtained results of loss and accuracy along with Sensitivity of the Prediction. Based on the comparison if results Experiment 4 i.e., Convolution Neural Network Model 4 provide a better accuracy and results with minimal loss value.

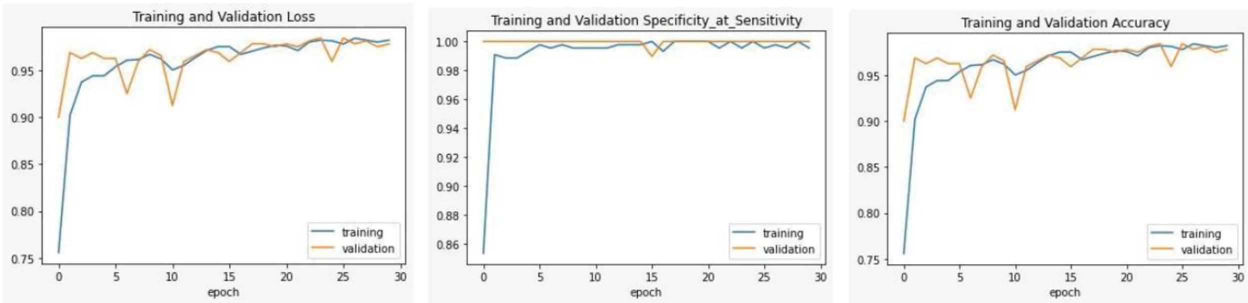

Figure 38: CNN#4 Result Graphs

6.2 Results of Test 1:

Table 13: Augmentation Prediction

	Accuracy	Precision	Recall	Epochs
	Training/ Testing	Training/ Testing	Training/ Testing	
Augmented	0.88/0.76	0.90/0.77	0.89/0.75	11
Not Augmented	0.96/0.80	0.96/0.80	0.95/0.78	11

The Non-Augmented providing better results compared to Augmented results in terms of accuracy, precision and recall values.

6.3 Results of Test 2:

Table 14: Image Size Prediction

Since the Non-Augmented data provided better results, we chose Non-Augmented data and variable image sized to choose which provides us the better results.

Image Size	Accuracy	Precision	Recall	Epochs
	Training/ Testing	Training/ Testing	Training/ Testing	
(256, 256)	0.95/0.79	0.96/0.77	0.95/0.75	5
(512, 512)	0.87/0.78	0.89/0.81	0.84/0.88	5

Despite getting better accuracy for smaller image, it has better precision and recall value compared to smaller image size.

6.4 Results of Transfer Learning Experiments:

Accuracy, Precision, Recall and AUC (Area under curve) are considered as metrics for the evaluation of each model. Finally, F1-Score is calculated to find a better model for prediction.

6.4.1 Scenario 1: Covid-19 vs Normal

Results of COVID-19/Normal Experiments. In this group, a total of 2295 images (712 COVID-19 and 1583 Normal) were trained in each experiment without the data augmentation procedure. The images were then split into training and testing data.

Table 15: Transfer Learning Results – Scenario 1

Table 15.1 Training:

Model Name	Accuracy	Loss	Precision	Recall	F1-Score	AUC
DenseNet121	99.11	0.07	0.9908	99.68	0.995	98.85
ResNet50	69.89	0.68	0.69	1	0.79	50
VGG16	99.9	0.003	1	0.99	0.99	99
InceptionV3	99.9	0.05	0.99	0.99	0.992	99
Inception-ResNet-V2	99.7	0.11	0.99	0.99	0.996	99

Table 15.2 Testing:

Model Name	Accuracy	Loss	Precision	Recall	F1-Score	AUC
DenseNet121	98.3	0.67	0.975	1	98.75	97.9
ResNet50	68.26	0.68	0.654	1	0.79	50
VGG16	98.76	0.02	98.44	0.99	0.996	99.9
InceptionV3	98.97	1.72	0.99	0.99	99.2	98.9
Inception-ResNet-V2	99.59	0.10	0.993	1	0.996	99.2

Though we were able to obtain high accuracy results there is a significant amount of loss present in the testing data evaluation and also there is a significant amount of validation loss obtained through the model training. This is due to the overfitting of data in the process of training the model. Out of the obtained results VGG16 seems to provide better predictions with lower amount of loss for the binary classification.

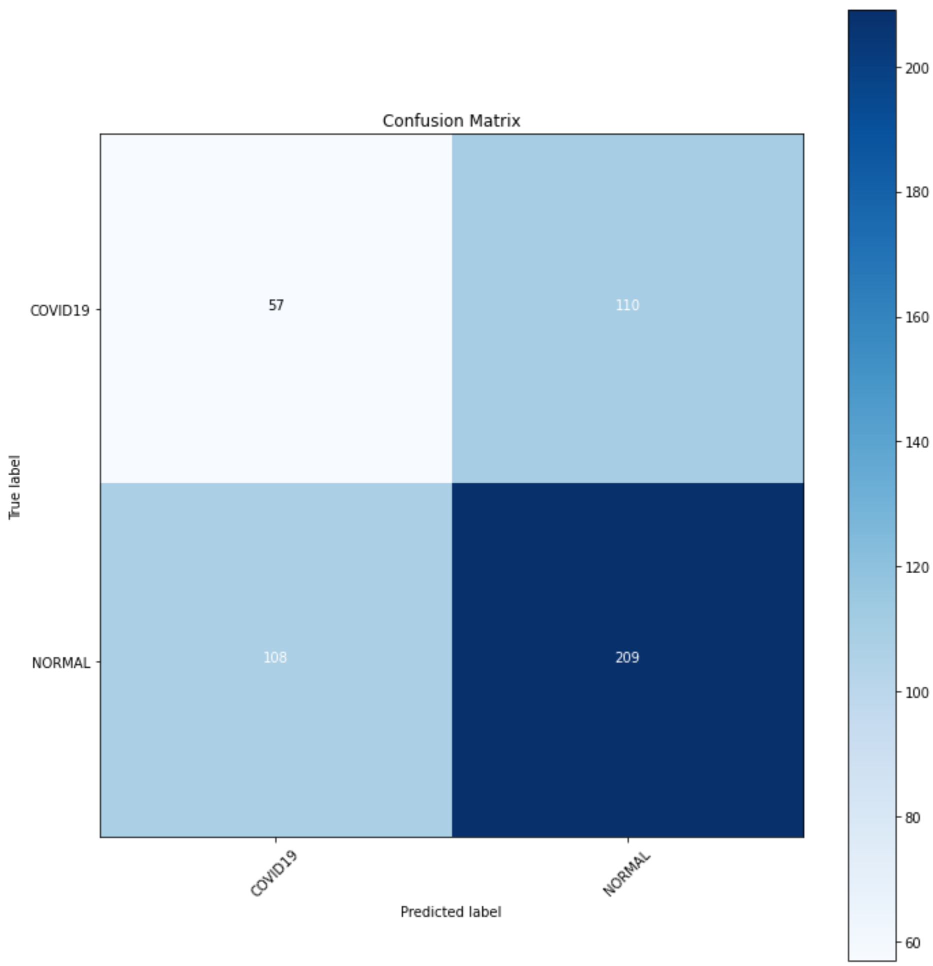

Figure 38: Confusion Matrix – VGG16

6.4.2 Scenario 2: Covid-19 vs Pneumonia vs Normal

Results of COVID-19/Pneumonia/Normal Experiments. In this group, a total of 5568 images (712 COVID-19, 4273 Pneumonia and 1583 Normal) were trained in each experiment without the data augmentation procedure. The images are further split into training and testing data.

Table 16: Transfer Learning Results – Scenario 2

Table 16.1 Training:

Model Name	Accuracy	Loss	Precision	Recall	F1-Score	AUC
DenseNet121	98.9	0.24	0.99	0.98	0.985	98.94
ResNet50	77	0.9	0.776	0.769	0.71	90
VGG16	98.8	0.24	0.98	0.988	0.98	99.3
InceptionV3	96.59	0.19	0.965	0.965	0.789	98
Inception-ResNet-V2	99.51	0.02	0.995	0.995	0.995	99.9

Table 16.2 Testing:

Model Name	Accuracy	Loss	Precision	Recall	F1-Score	AUC
DenseNet121	79	0.62	0.81	0.78	0.82	92
ResNet50	71.62	1.12	0.718	0.712	0.71	87.93
VGG16	86.25	8.9	0.86	0.863	0.862	90.06
InceptionV3	78.9	4.04	0.79	0.789	0.789	85.75
Inception-ResNet-V2	82.28	3.2	0.823	0.82	0.823	88.98

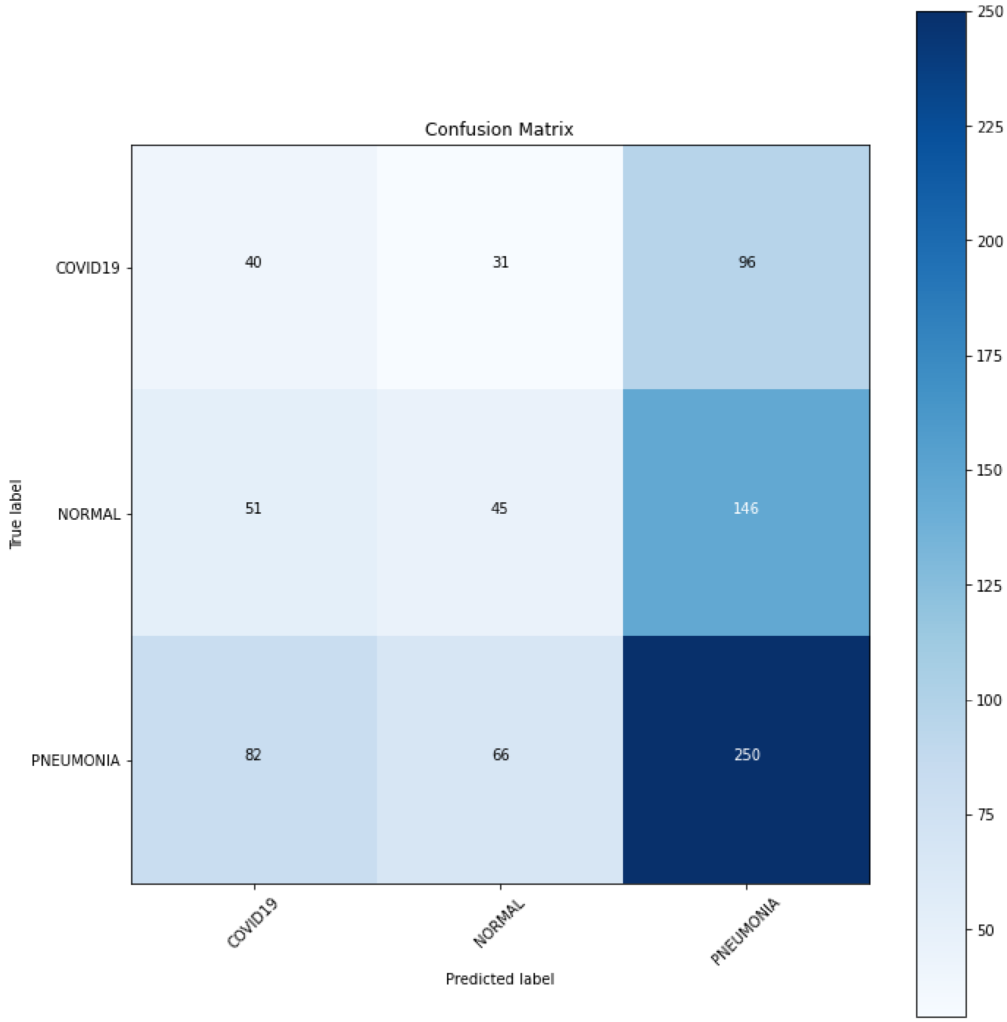

Figure 39: Confusion Matrix – DenseNet121

Despite obtaining high accuracy results there is a significant amount of loss present in the training and testing data and there is a significant amount of validation loss obtained through the model training. This is due to the overfitting of data in the process of training the model. Out of the obtained results DenseNet121 seems to provide better predictions with lower amount of loss for the categorical classification.

There are issues like overfitting of data increasing the loss of the model. Further tests should be made on the model by freezing and unfreezing required layers in Transfer Learning methods. The lower image quality and inconsistent images resulted in increase of False positives and Negatives. Manual of checking of proper images and collection of such data will help in increasing the quality analysis of the research. Since the study depends on the minimal chances of detecting covid by variating from the pneumonia the bias was obvious causing the categorial and binary classification biased towards pneumonia or normal classes. To reduce the bias in the model we need to increase the Covid-19 data, augmenting the data could reduce the data quality and reduce the minimal chance of detecting covid-19.

Implementing methods like Weighted Classifier and Ensemble Learning could be used to obtain better classification of the model. Larger dataset with classified images and of better quality will be needed to reduce false positives and negatives for the results.

6.5 Results of Larger Dataset Experiment

With the handcrafted dataset we tested a Transfer Learning Algorithm such as DenseNet201 for the following test where we have done about 5 epochs and obtained the following results.

Table 17: Training and Testing larger dataset

DenseNet201	Accuracy	Loss	Precision	Recall	F1-Score	AUC
Training	87.6	0.3	0.889	0.86	0.874	99.05
Testing	83.6	0.38	0.84	0.83	0.81	95.6

Thought the accuracy is low, the prediction showed better results than that of the previous tests made.

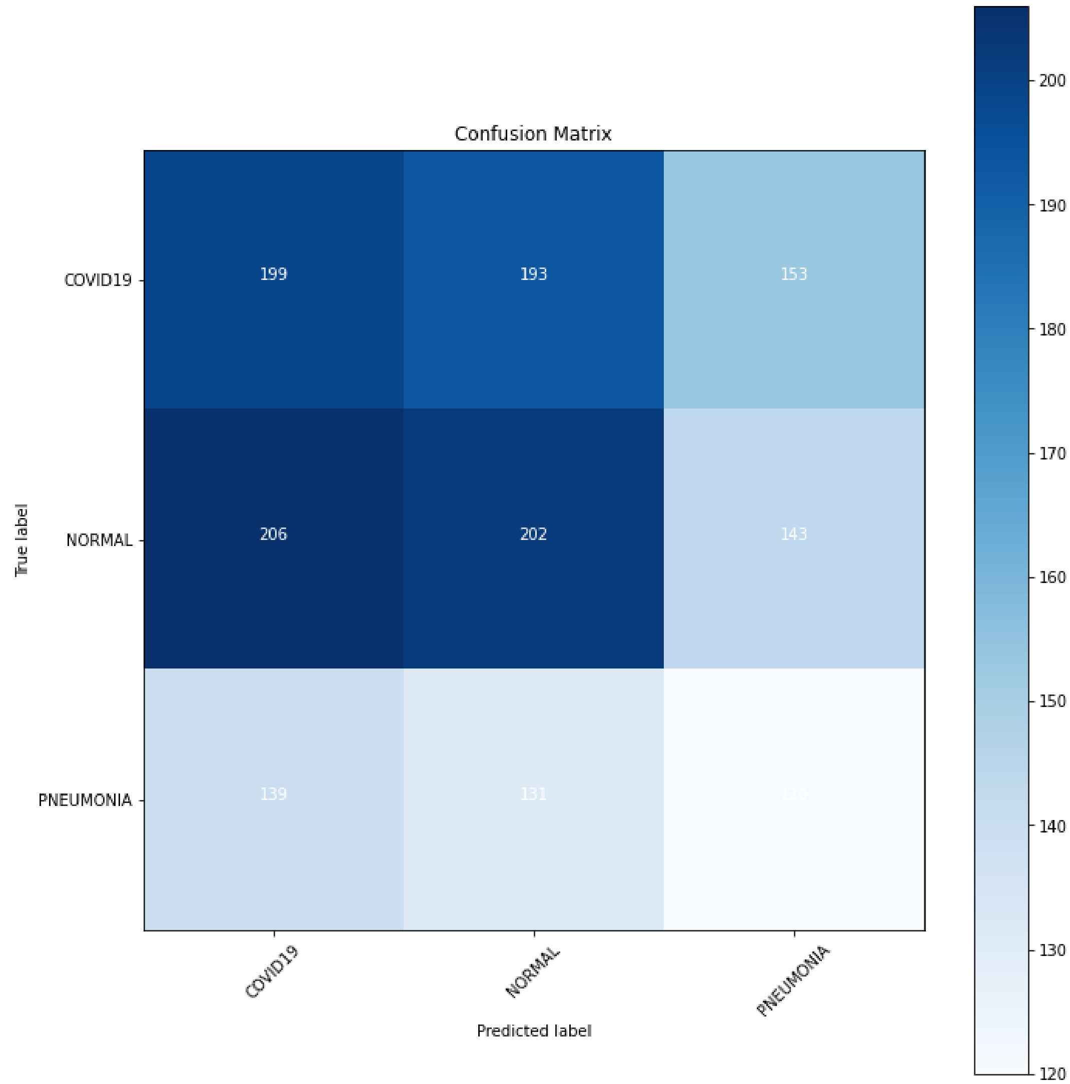

Figure 47: Confusion Matrix – Categorical – Larger DS

Though there are fair share of false positives and false negatives, it also can be noticed that the true positives and negatives increased in this scenario where larger datasets is used. This further proves the point of having inconsistent data is not reliable. The above result can be improved further by fine-tuning the model and improving the quality of the database. As the images in the dataset have both Posterior-Anterior (PA) and Anterior-Posterior (AP) where we only need Posterior-Anterior for our classification.

CHAPTER-7

THE USER INTERFACE MODEL

7.1 Header

The user interface design is related to visual design which is actually you are displaying or conveying information visually. So, to make model useful, more interactive there should be a UI. So, a UI with flask framework and Flask backend makes it much interactive with the user and the model we design.

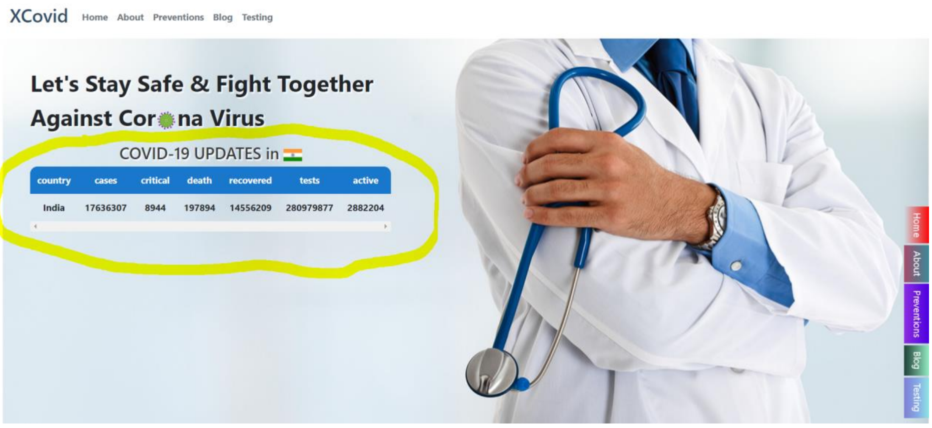

Figure x: Header

This is the home page, and the data presented in the table changes with the update with the change in confirmation of data.

7.2 Fetch Code:

```
fetch(`https://corona.lmao.ninja/v2/countries/india`)
.then((response)=>{
    return response.json();
})
.then((data)=>{
    document.getElementById("flag").src = data.countryInfo.flag;
    document.getElementById("country").innerHTML = data.country;
    document.getElementById("cases").innerHTML = data.cases;
    document.getElementById("critical").innerHTML = data.critical;
    document.getElementById("death").innerHTML = data.deaths;
    document.getElementById("recoverd").innerHTML = data.recovered;
    document.getElementById("tests").innerHTML = data.tests;
    document.getElementById("active").innerHTML = data.active;
})
```

Figure x: Fetching Cases

The data comes from an API , from which we fetch the country flag, country name, cases in that country, critical patients count, number of deaths, number of recovered, number of active cases etc.

7.3 Information

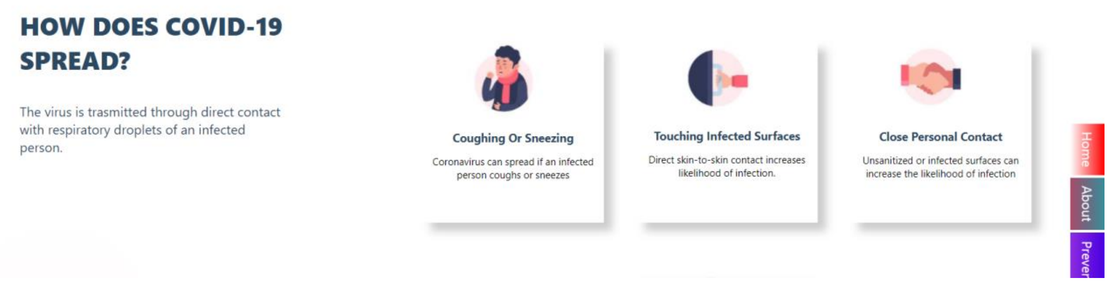

Figure x: Helpers

This page is about how does that covid-19 spread as the virus is transmitted through direct contact with respiratory droplets of an infected person.

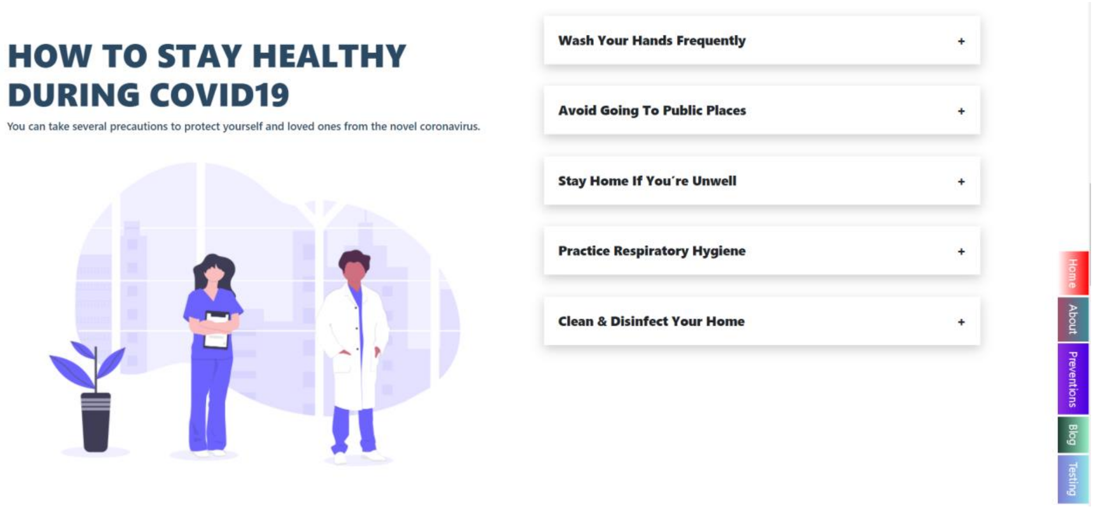

Figure x: Suggestions

This component is about prevention or measurements to be taken to avoid spread of corona. The prevention tips are given through the box, each box has a message inside it which will be displayed once we press the plus button.

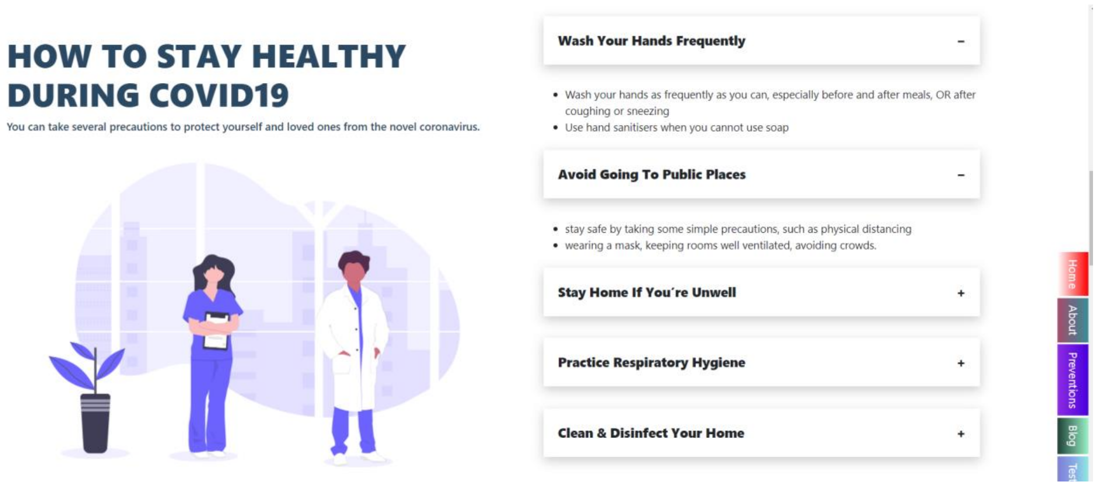

Figure x: Working Suggestions Sample

An accordion is used to show (and hide) HTML content.

7.4 Social Media Updates

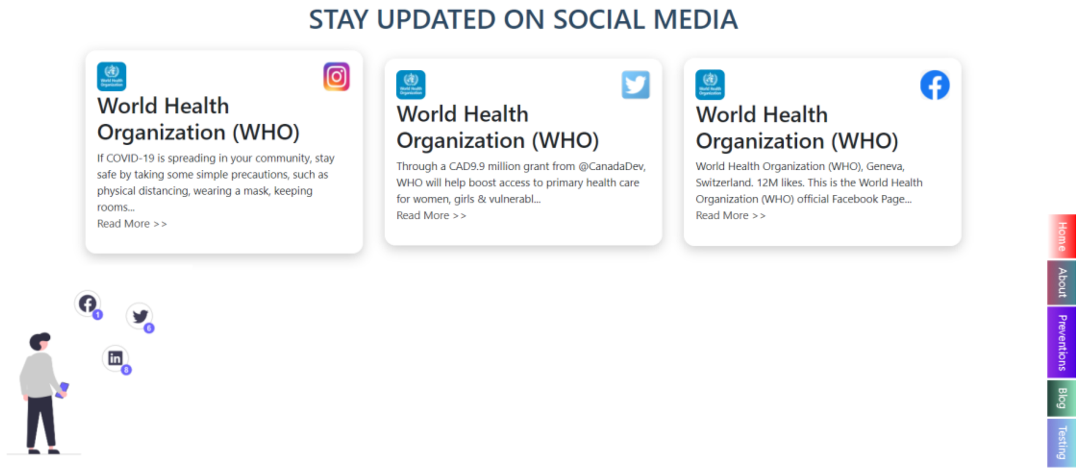

Figure x: Social Media Helpers

Social media is everywhere, we can figure out the news from social media updates during this pandemic time. This component keeps us updated about the prevention and measurements that are to be taken in this pandemic time

7.5 Prediction Analysis

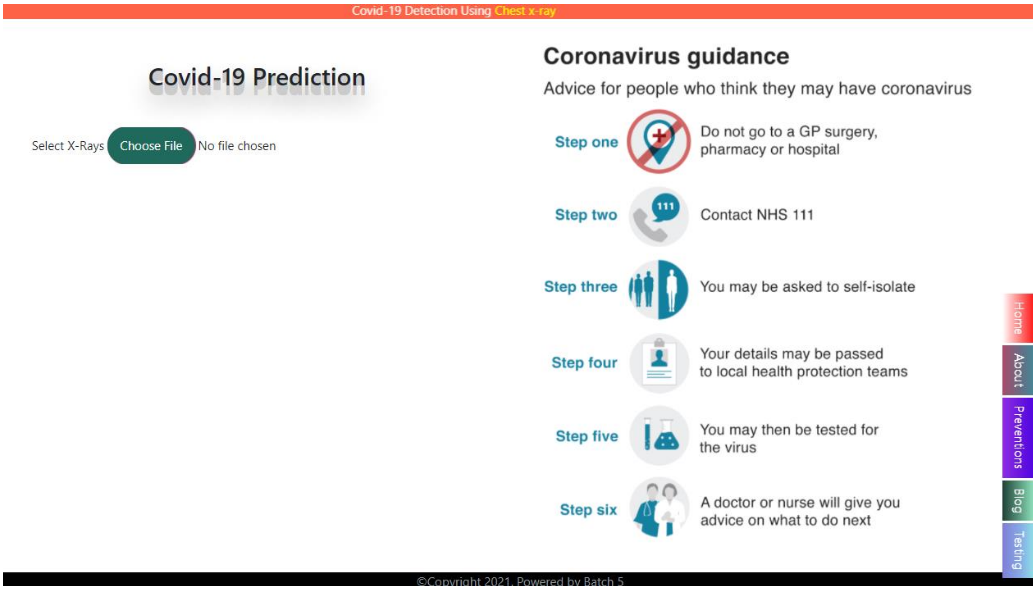

Figure x: Upload X-Rays

Finally, the prediction part is done here and we will be choosing an x-ray image

The main goal in our User interface is that to make the website Responsive so that our website can be more interactive with the users.

So, the view is made responsive to be made open in different formats.

7.6 View in tablet

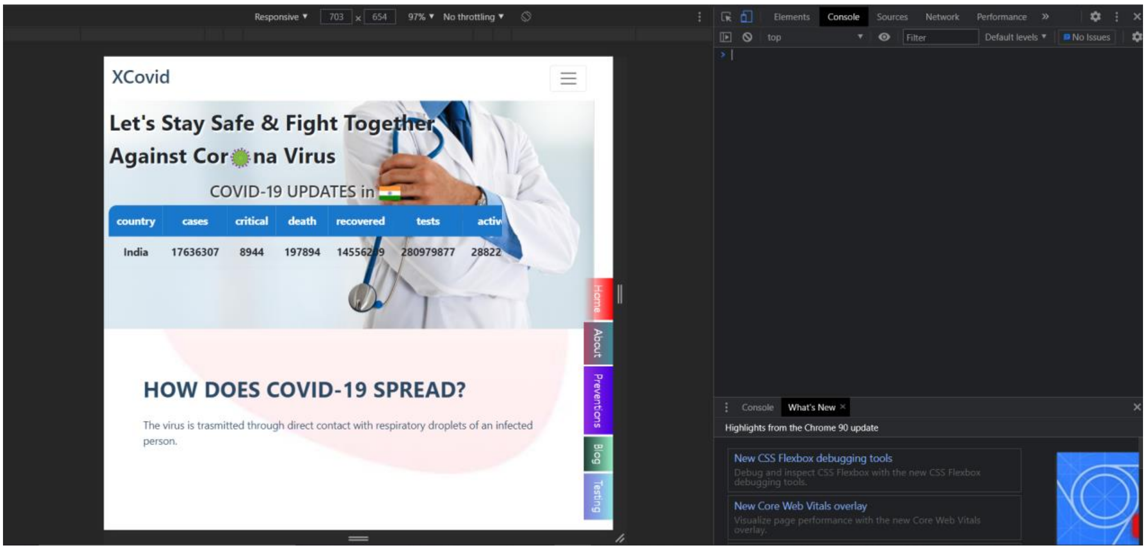

Figure x: Tablet View

7.7 View in Mobile

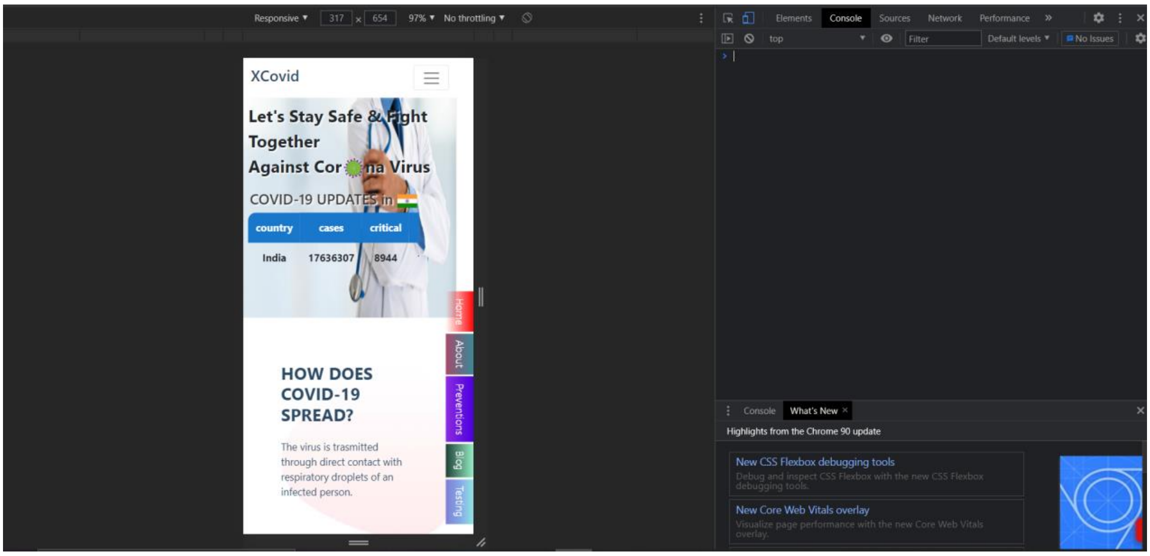

Figure x: Mobile View

CHAPTER-8

CONCLUSION

COVID-19 pandemic continues devastating effect on the health of the global population. The major step for the prevention or eradication is to predict it and after which curing should be done. Prediction is a major task in this case because the lung scans that we are using here can have fibrosis which can be solved through image classification

Here we have implemented some of the deep learning algorithms by which we can predict the covid-19. Detection of COVID-19 from chest X-ray images plays a vital role for both doctors and patients to decrease the diagnostic time and reduce financial costs. Artificial intelligence and deep learning are capable of recognizing images for the tasks taught. In this study, several experiments were performed for the high-accuracy detection of COVID-19 in chest X-ray images using CNNs. COVID-19/Normal and COVID-19/Pneumonia/Normal were considered for the classification. Different image dimensions, different network architectures, state-of-the-art pre-trained networks, and machine learning models were implemented and evaluated using images.

With the less amount of data at hand the prediction could be made of good accuracy but are not reliable enough to be used in clinical trial. Further data and higher computational ability are needed to provided better results that are reliable and useful. Though our current project could not be reliable enough, further study can prove it to be more useful and reliable. More time and study are needed to make this research complete. Issue like overfitting and lower precision values are observed in the study over which quality analysis should be made to create more accurate results. The inconsistent databases resulted in false predictions as well as smaller working time resulted in hurried results.

With more availability of data even better study can be possible for the image classification Covid-19 prediction. Which also helps us in providing early treatment for pneumonia patients.

The results obtained in this study can be the base for further study.

CHAPTER-9
FUTURE SCOPE

The scarce availability of data created bias results in the model. Further research can be made with a larger amount of data with the use of other methods like oversampling or SMOTE methods instead of compromising over the lesser data. Also with the increased computational ability, a generalized model could be made to obtain better results. On further research, a better model can be made from scratch with a larger dataset and can be made clinically available. Larger dataset with better quality images needs to be searched for designing a better model. On further improvements of the dataset, it is possible to increase the precision of the model. Fine Tuning the transfer learning models will also create better prediction models. With smaller computational ability we had to compromise over the smaller image size and data.

Also, with the Larger Dataset it seemed to provide better results which can be improved further by fine-tuning the models and improving the quality of dataset and pre-processing of algorithms.

Ensemble learning can be used to get even more accurate results and reduce the number of false positives and negatives.

CHAPTER-10

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