# COVID-19 Detection using Deep Learning Model and Chest X-ray images

## A PROJECT REPORT

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This is to certify that the project report entitled **COVID-19 Detection using Deep Learning Model and Chest X-ray images** is the bonafide record of project work done by A.V.AKIL KUMAR(17ECR007), A.DEEPA(17ECR023) in partial fulfilment of the requirements for the award of the Degree of the Bachelor of Engineering in Electronics and Communication Engineering of Anna University, Chennai during the year 2020-2021.

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## DECLARATION

We affirm that the project report titled **COVID-19 Detection using Deep Learning Model and Chest X-ray images** submitted in the partial fulfilment of the requirements for the award of Bachelor of Engineering is the original work carried out by us. It has not formed the part of any other project report for the dissertation based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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# ABSTRACT

The virus SARS-CoV-2 causes COVID-19, a serious respiratory illness. The scientific community has devoted near-unprecedented attention to this disease. Coronavirus is an RNA-type virus that can infect both humans and animals and causes a wide range of respiratory infections. In humans, it sometimes causes pneumonia. It has had disastrous consequences for people's everyday lives, public health, and the global economy. It is important to diagnose positive cases as soon as possible in order to prevent the disease from spreading further and to treat infected patients as quickly as possible. Since there are no reliable automated toolkits available, the demand for auxiliary diagnostic tools has grown. According to recent findings obtained using radiology imaging techniques, such images provide important details about the COVID-19 virus. Advanced artificial intelligence (AI) techniques combined with radiological imaging can help with accurate disease detection and can also help solve the issue of a shortage of specialised physicians in remote villages. A new model for automated COVID-19 detection using raw chest X-ray images is described in this research. The proposed model is designed to provide reliable diagnostics for binary and multiclass classification (COVID vs. No-Findings) (COVID vs. No-Findings vs. Pneumonia). For multi-class scenarios, our model had a classification accuracy of 92.02 percent. In our research, the DarkNet model was used as a classifier for the YOLO (you only look once) real-time object detection scheme. On, 17 convolutional layers were implemented, with different filtering applied to each layer. Our model can be used to help radiologists validate their initial screening and can also be used to test patients immediately through the cloud. With the proposed method, the average classification rate was 99.27 percent.

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| | |
|---|---|
| ARDS | Acute Respiratory Distress Syndrome |
| WHO | World Health Organization |
| PCR | Polymerase Chain Reaction |
| SARS | Severe Acute Respiratory Syndrome |
| RDT | Rapid Antigen Tests |
| SVM | Support Vector Machines |
| RT-PCR | Reverse Transcription Polymerase Chain Reaction |
| CT | Computed Tomography |
| KCV | k–Fold Cross Validation |
| CNN | Convolutional Neural Networks |
| DeTraC | Decompose Transfer Compose |
| GPU | Graphics Processing Units |
| TPU | Tensor Processing Units |
| RGB | Red Green Blue |
| SMO | Social Mimic Optimization |
| COV-2 | Corona Virus |
| DNN | Deep Neural Network |
| AI | Artificial Intelligence |
| YOLO | You Only Look Once |

# CHAPTER 1

# INTRODUCTION

## 1.1 INTRODUCTION

### 1.1.1 COVID-19

COVID-19 is a disease caused by SARS-CoV-2 coronavirus, which is a modern coronavirus. Following a study of a cluster of cases of ‘viral pneumonia in Wuhan, the People's Republic of China, WHO first heard of this new virus on December 31, 2019.

## 1.2 COMMON SYMPTOMS

### 1.2.1 THE MOST POPULAR COVID-19 SYMPTOMS

- Fever
- Cough
- Dryness Exhaustion

### 1.2.2 LESS COMMON SYMPTOMS

- Taste or olfactory loss
- Congestion in the nose
- Conjunctivitis is a condition that affects the eyes (also known as red eyes)
- a scratchy throat
- Migraine
- Pain in the muscles or joints
- Various forms of skin rashes
- Vomiting or nausea is both symptoms of nausea
- Diarrhoea
- Dizziness or chills.

### 1.2.3 SEVERE SYMPTOMS

- Breathing issues
- Appetite loss
- Perplexity
- Chest pain or pressure that persists
- Temperatures above 38 degrees Celsius

### 1.2.4 SOME SIGNS THAT ARE LESS COMMON

- Irritability
- Befuddlement
- A lack of consciousness (sometimes associated with seizures)
- Anxiety, a state of mental depression
- Sleep disturbances
- Strokes
- Brain injury
- Delirium
- Nerve damage is more serious and uncommon neurological complications

People of all ages should seek medical attention right away if they have a fever and/or cough that is accompanied by trouble breathing or shortness of breath, chest pain or pressure, or lack of speech or movement.

## 1.3 EFFECTS OF AFFECTED PEOPLE

The majority of those who experience symptoms (roughly 80%) recover without the need for hospital care. Around 15% become severely ill, needing oxygen, and 5% become critically ill, requiring intensive care. Respiratory failure, acute respiratory distress syndrome (ARDS), sepsis and septic shock, thromboembolism, and/or multiorgan failure, including damage to the heart, liver, or kidn1eys, are all examples of complications that may lead to death. Children may develop a serious inflammatory syndrome a few weeks after infection in rare cases.

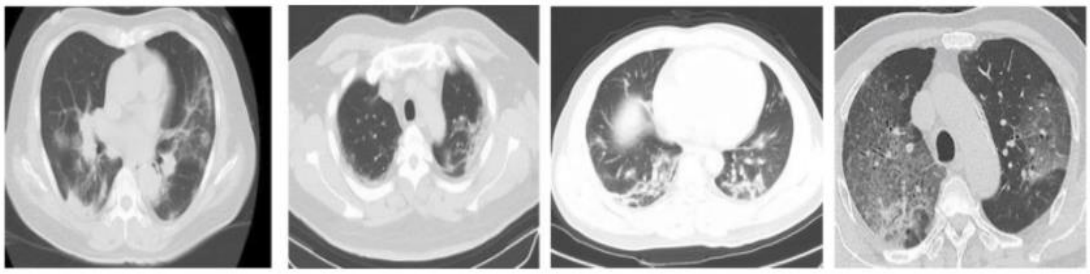


Fig 1.1 Images on Covid-19 positive

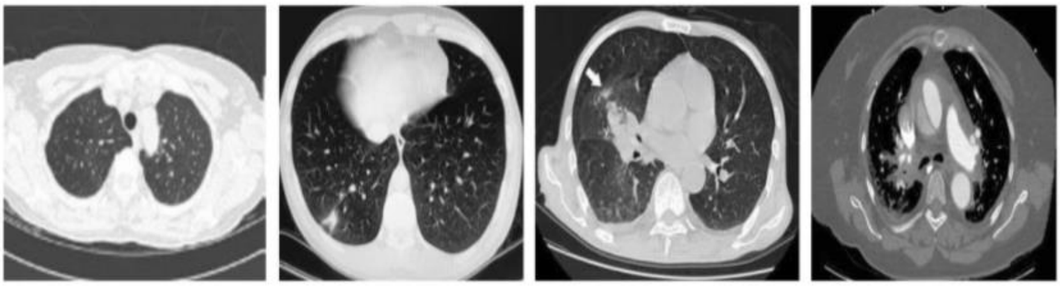


Fig 1.2 Images on Covid-19 Negative

## 1.4 RISK OF PEOPLE WITH SEVERE COVID-19

People over the age of 60, as well as those with underlying medical issues such as high blood pressure, heart and lung disease, diabetes, obesity, or cancer, are more likely to experience severe illness. COVID-19, on the other hand, can make someone sick and cause them to become chronically ill or die at any age.

## 1.5 SIDE EFFECTS AFTER RECOVERY

Whether or not they need hospitalization, some people who have had COVID-19 continue to have symptoms such as exhaustion, respiratory, and neurological symptoms. WHO is collaborating with our Global Technical Network for COVID-19 Clinical Management, academics, and patient organizations around the world to develop and conduct studies of patients beyond the acute course of illness to better understand the proportion of patients who experience long-term effects, how long they last, and why they occur. This research can be used to establish additional patient care advice.

## 1.6 PRECAUTION

Simple measures such as physical separation, wearing a mask when separation is difficult, keeping rooms well ventilated, avoiding crowds and close touch, regularly washing hands, and coughing into a bent elbow or tissue will help stay healthy. Inquire for local advice in the area where all live and work.

## 1.7 STEPS TO TAKE AFTER GETTING AFFECTED

- To find out when and when to get a test, contact health care provider or the COVID-19 hotline.
- To stop the virus from spreading, cooperate with contact-tracing procedures.
- If testing is not available, remain at home for 14 days and avoid contact with anyone.
- Do not go to work, school, or public places when all are in quarantine. Request that someone brings materials.
- Make sure space is well ventilated.
- If sharing a room, make sure the beds are at least 1 metre apart.

Time for fully getting affected

The time between exposure to COVID-19 and the onset of symptoms is usually 5-6 days, but it can be anywhere from 1 to 14 days. This is why people who have been exposed to the virus are advised to stay at home for 14 days and avoid contact with others to prevent the virus from spreading, particularly in areas where testing is difficult to come by.

## 1.8 TESTS FOR COVID-19

In the majority of cases, a molecular test is used to detect and validate SARS-CoV-2 infection. The most popular molecular test is polymerase chain reaction (PCR). A swab is used to extract samples from the nose and/or throat. By amplifying viral genetic material to measurable amounts, molecular tests detect the virus in a sample. As a result, a molecular test is used to confirm the presence of an active infection, normally within a few days of exposure and about the time symptoms appear.

## 1.9 RAPID TESTS

Rapid antigen tests (also called RDTs) identify viral proteins (known as antigens). With the aid of a swab, samples are taken from the nose and/or throat. These tests are less expensive than PCR and provide results faster, but they are less reliable in general. While there is more virus circulating in the population and when a sample is taken from a person when they are most infectious, these tests work better.

# CHAPTER 2

# LITERATURE REVIEW

Khair Ahammed et al., proposed a work on 8th of June,2020 that adopts a methodology to find out the Covid-19 cases using the Chest x-ray methodology. Several networks are used to find out the detection of Covid-19. But by adapting the Chest X-ray the detection was as follows, e highest accuracy (94.03%), sensitivity (94.03%) and miss rate (2.98%) respectively. It also evaluated specifically the results of non-Covid patients with higher accuracy than other neural networks. He proposed both Machine Learning and Deep learning approaches by investigating open-source manuals and found Chest X-ray could give better results. His approach may be helpful in clinical practices for the early detection of COVID-19 cases and prevent future community transmission.

Julian D.Arias-Londono et al., proposed a work on 14th December 2020 which describes that the current methods that are used for the detection of COvid-19 includes molecular or antigen tests are generally complemented by plain chest X-Ray. The combined analysis shows a better less false negatives and the presence and severity of the disease. However the method has certain significant complexities. This paper concentrates on the long term goal for the diagnosis of the disease. The prioritize step in this is to automatically diagnose the pneumonia and covid-19 using chest x ray. 79,500 x-rays, more than 500 Covid-19 samples are trained in the CNN in this process and different preprocessing schemes are adopted in this method. The main aim is to preprocess the data affects the results and improves the explainability. It has the accuracy of 91.5% classification of the test cases, with 87.4% average recall for the worst cases.

Mesut Togacar and et al.,proposed a work on June 2020 in which Data classes were restructured using the Fuzzy Color technique as a preprocessing step.In next step, dataset was trained with deep learning models (MobileNetV2, SqueezeNet) Thereafter, efficient features were combined and classified using Support Vector Machines (SVM).The overall accuracy for classification is 90.2%

Pegah Tabarisaadi et al., proposed a work on 14th October 2020 that adopts a methodology by automising the process of analizing of of covid-19 with ct- images saves time and energy. Data Augumentaion is applied for better efficiency and training. A small dataset of 275 ct-images of positive covid results are used. Deep bayesian ensembling appears to be a promising framework for COVID-19 detection based on prediction accuracy and predictive uncertainty estimates for unseen chest CT images. While the proposed system produces good results, having access to a larger dataset would undoubtedly lead to more reliable and confident diagnosis.

Farhan Sadik et al., proposed a work on 19th November 2020 by Automatic Detection of Covid-19 plays a major role in medical field. Fast diagnosis to disease are the best way to prevent from getting affected. Using ResNet152V2 as a backbone network, an effective architecture called ResCovNet is proposed for accurately detecting COVID-19 from chest CT scan images by distinguishing it from three types of pneumonia and normal cases. In the pre-processing stage, Otsu's thresholding is used to improve the features for the classification network. COVID-19 is separated from the other four classes with a very high classification accuracy of 88**m**.1 percent using the proposed architecture. Otsu's thresholding is used in the pre-processing stage to boost the classification network's features. The proposed architecture effectively distinguishes COVID-19 from the other four classes with an accuracy of 88.1 percent. The method can differentiateCOVID-19 from the disease pneumonia, which is essential for clinicians and radiologists to know what steps to take right away.

Amir Khorasani and et al., proposed a work on 28th november 2020 on New Insight into Laboratory Tests and Imaging Modalities for Fast and Accurate Diagnosis of COVID-19: Alternative Suggestions for Routine RT-PCR and CT—A Literature Review. The pretest probability is a clinician’s best estimate of the probability of disease in a group of individuals with similar symptoms. Now, computed tomography (CT) is widely used as the imaging modality for the detection of COVID-19 pneumonia. The fast way in order to imaging that is currently used in hospitals is CT scan. CT for some people such as pregnant women and older adults do not become useable for monitoring and screening goals because the use of ionizing radiation is not recommended. So, should find a CT-alternative imaging modality for patients with COVID-19, which utilized nonionizing radiation in order to screening, monitoring, and follow-up purposes. Magnetic resonance imaging (MRI) and ultrasound imaging are the most useful imaging modalities which employed nonionization radiation for imaging acquisition. This exegesis represents current subject matters for the diagnosis of COVID-19 and also alternative ways for CT scan that must be noticed and understood both by clinicians, clinical microbiology laboratories, and public health specialists

Pranav Rajpurkar and et al., proposed a work on 25th December 2017 on CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. Developing an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Our algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. Four practicing academic radiologists annotate a test set, on comparing the performance of CheXNet to that of radiologists. Finding that CheXNet exceeds average radiologist performance on the F1 metric. Extending CheXNet to detect all 14 diseases in ChestX-ray14 and achieve state of the art results on all 14 diseases.

Asmaa Abbas and et al., proposed a work on 5th September 2020 on Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Chest X-ray is the first imaging technique that plays an important role in the diagnosis of COVID-19 disease. Due to the high availability of large-scale annotated image datasets, great success has been achieved using convolutional neural networks (*CNN* s) for image recognition and classification. However, due to the limited availability of annotated medical imag. Thanks to transfer learning, an effective mechanism that can provide a promising solution by transferring knowledge from generic object recognition tasks to domain-specific tasks. In this paper, on validate and a deep *CNN*, called Decompose, Transfer, and Compose (*DeTraC*), for the classification of COVID-19 chest X-ray images. es, the classification of medical images remains the biggest challenge in medical diagnosis. *DeTraC* can deal with any irregularities in the image dataset by investigating its class boundaries using a class decomposition mechanism. The experimental results showed the capability of *DeTraC* in the detection of COVID-19 cases from a comprehensive image dataset collected from several hospitals around the world. High accuracy of 90.1% was achieved by *DeTraC* in the detection of COVID-19 X-ray images from normal, and severe acute respiratory syndrome cases.

Ioannis D.Apostolopoulos & Tzani A. Mpesiana proposed a work on 3rd April 2020 on Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. In this study, a dataset of X-ray images from patients with common bacterial pneumonia, confirmed Covid-19 disease, and normal incidents, was utilized for the automatic detection of the Coronavirus disease. The aim of the study is to evaluate the performance of state-of-the-art convolutional neural network architectures proposed over the recent years for medical image classification. Specifically, the procedure called Transfer Learning was adopted. With transfer learning, the detection of various abnormalities in small medical image datasets is an achievable target, often yielding remarkable results.. The data was collected from the available X-ray images on public medical repositories. The results suggest that Deep Learning with X-ray imaging may extract significant biomarkers related to the Covid-19 disease, while the best accuracy, sensitivity, and specificity obtained is 89.78%, 87.66%, and 90.46% respectively.

Rodolfo M.Pereira proposed a work on October 2020 on COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios. The COVID-19 can cause severe pneumonia and is estimated to have a high impact on the healthcare system. Early diagnosis is crucial for correct treatment in order to possibly reduce the stress in the healthcare system. The standard image diagnosis tests for pneumonia are chest X-ray (CXR) and computed tomography (CT) scan. COVID-19 identification in chest X-ray using multi-class and hierarchical learners. Using a database that reflects a real world scenario with its natural imbalance.Exploring the textural content from the chest X-ray images with pneumonia.Evaluating handcrafted and learned features to investigate its complementarities.

# CHAPTER 3

# EXISTING SYSTEM

## 3.1 INTRODUCTION

Data is divided into three categories: coronavirus, pneumonia, and standard X-ray images. The data classes were restructured as a preprocessing step in this study using the Fuzzy Color technique, and the images that were structured with the original images were stacked. The stacked dataset was then trained with deep learning models (MobileNetV2, SqueezeNet), and the feature sets obtained were processed using the Social Mimic optimization method. Then, using Support Vector Machines, efficient features were combined and graded (SVM). With the proposed method, the average classification rate was 99.27 percent.

## 3.2 DATASET

The dataset was reconstructed using the Fuzzy and Stacking techniques in this preprocessing. A researcher from the University of Montreal named Joseph Paul Cohen shared the first COVID-19 dataset on the GitHub website. The second dataset is crucial in this study because it allows deep learning models to compare COVID-19 chest images. 70% of the dataset was used for training purposes, while 30% was used for testing purposes.

### 3.2.1 MOBILENET

MobileNet is a deep learning model designed to run on low-cost hardware. The MobileNet model can be used to perform object recognition, segmentation, and classification. The MobileNetV1 model is based on the MobileNetV1 model, and the MobileNetV2 model is derived from it. In comparison to the previous iteration of the MobileNetV2 model, this new model makes the most contribution to the problems of layer linearity. The SVM system was used in the classification process, and the MobileNetV2 model was used as a pre-trained model. Aside from that, there are a few other significant parameters in the MobileNetV2 model. For the MobileNetV2 model, all default parameter values were used without modification.

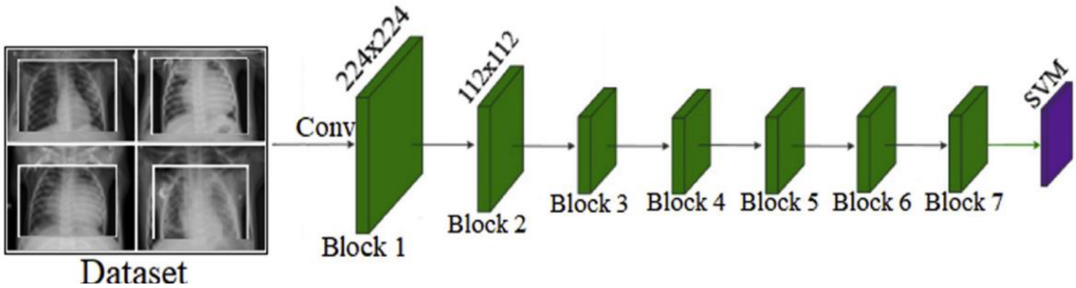



Fig 3.1 The general design of MobileNet model.

### 3.2.2 SQUEEZENET

Convolutional layers, pooling layers, ReLU, and Fire layers make up SqueezeNet, an in-depth learning model with an input size of 224 * 224 pixels. These layers' functions are performed by fire layers. The main advantage of this model is that it can effectively conduct analyses by reducing the number of parameters and therefore the model size power. The SqueezeNet model achieved better results with approximately 50 times fewer parameters than the AlexNet model, lowering the model's cost.

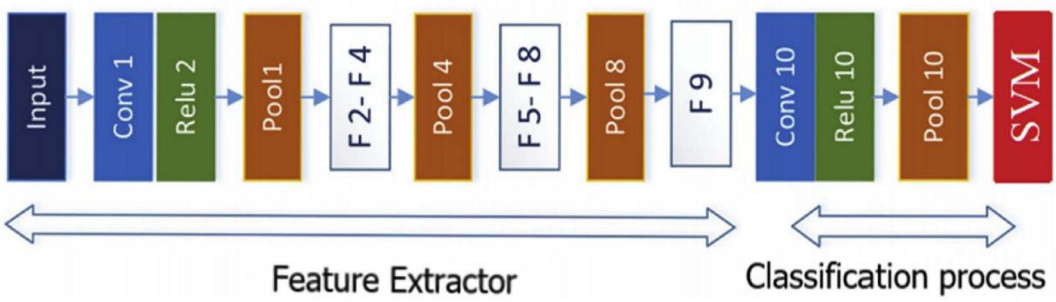



Fig 3.2 The general design of SqueezeNet

### 3.2.3 SVM AND OPTIMIZED METHOD

SVM is a type of machine learning that can be used to perform regression and classification analysis. To separate the features in the data classes, this approach uses a hyper-plane line in the classification process. To evaluate a line, it chooses a position away from the features of the groups. Each class's distances are calculated using the hyper-plane defined by the SVM process. The SVM method was chosen because: I it has a high potential for solving data analysis problems in everyday life; and (ii) it is commonly used for remote pattern recognition and classification problems, allowing several classification processes to be successfully executed. (iii) It outperforms all other machine learning approaches in terms of classification accuracy.

## 3.3 RECONSTRUCTING IMAGES

The Fuzzy definition is recognised based on its level of accuracy, and the next level of accuracy is unknown. Each of the input images in the fuzzy colour technique has three input variables (red,green, and blue - RGB). A single output variable is transferred as a result of this operation. The training data is used to evaluate the input and output values. The Fuzzy Color technique works by dividing the input data into blurred windows. Each pixel in the image has a membership degree to each frame, which is determined using the distance between the pixel and the window. Membership degrees are used to calculate image variance. The finishing output-input is generated using the Fuzzy Color technique. The weights of the images of each blurred window are added together in this process, and the output image is generated using the average. The degree of membership is expressed here as the weight value of each pixel. On recreating the original dataset using Python codes and the Fuzzy Color technique, which reveals the data image's structure.

## 3.4 SOCIO MIMIC OPTIMIZATION

SMO (Social Mimic Optimization) is a technique that encourages people to imitate others. This is a method for distinguishing COVID-19 virus-infected chest images from regular breast images and pneumonia. The original dataset was first recreated using the Fuzzy Color technique, which sought to eliminate noise from the original images. The goal was to create a higher-quality data image. The stacked dataset was trained with MobileNetV2 and SqueezeNet deep learning models, and the two deep learning models were used. The SVM system, which yielded promising results in multiple classifications, was used as the classification process by combining the efficient features.

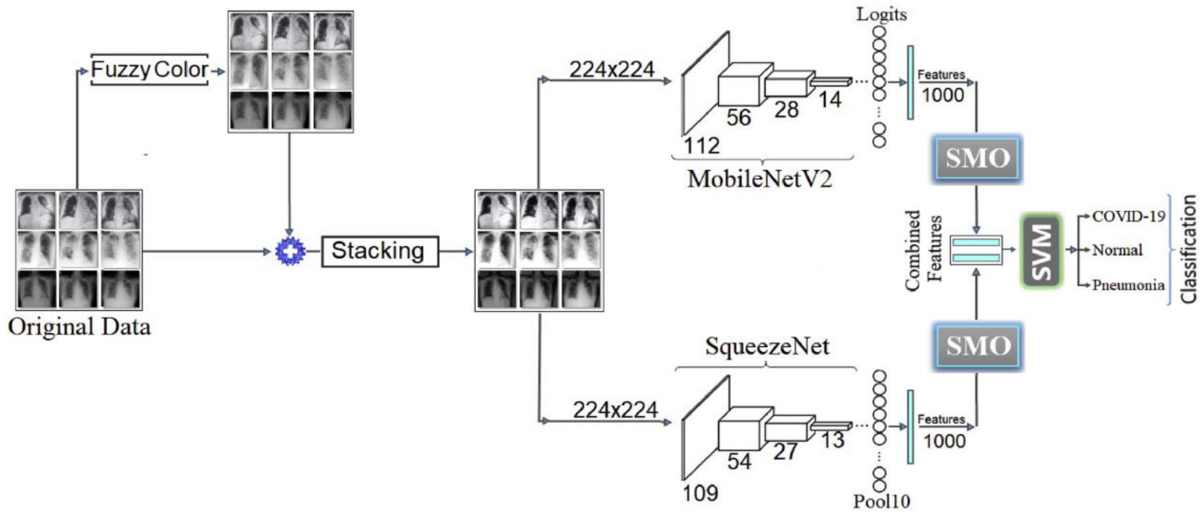



Fig 3.3 The general design of proposed model

## 3.5 EXPERIMENTAL ANALYSIS AND RESULTS

Each CNN model is trained with the original dataset, the dataset organised using the Fuzzy Color technique, and the stacked dataset categorised using the SVM method in the first phase of each model. In the classification of the initial dataset, the SqueezeNet model had an overall accuracy rate of 84.56 percent. The Fuzzy Color technique was graded with an overall accuracy rate of 95.58 percent in the second level. The stacked dataset was trained in the third stage with a classification success rate of 97.06 percent. On performing a new study using a different deep learning model to confirm the validity of these analyses. The overall accuracy rate obtained with the SVM approach was 96.32 percent in the first step. The overall accuracy rate in this classification was 97.05 percent in the second level. The model was trained with the stacked data set in the third stage of the MobileNetV2 model, and the overall accuracy was improved. The MobileNetV2 model was trained with the stacked data set in the third level, and the overall classification accuracy rate was 97.06 percent.

The stacked dataset was categorised using the SVM method in the second phase of this experiment, and the k-fold cross-validation method was used. 30 percent of the dataset was used as test data in the first phase of the experiment. The classification rate with the stacked dataset (with 30% test data) was 97.06 percent in the first phase of this model. The overall accuracy rate achieved with the SqueezeNet model was 95.85% in the second step.

The SMO algorithm was applied to the 1000 feature set in the first step. The SVM approach was used to classify the selected features, with an overall accuracy rate of 97.81 percent. In addition, the SqueezeNet model had a 100% classification success rate in detecting COVID-19 data.

The efficient features were graded in the second stage using the SVM system, which resulted in an overall accuracy rate of 98.54 percent. Furthermore, the MobileNetV2 model had a classification success rate of 99.26% for COVID-19 data detection. Thirty percent of the combined feature set was classified as test data using the SVM process. This classification yielded an overall accuracy rate of 99.27 percent. This result demonstrated that combining specific features with the SMO algorithm improves classification accuracy. The accuracy rate in the classification of COVID-19 data was 100 percent in the third level, and the success rate in the classification of Normal chest images and Pneumonia chest images was 99.27 percent.

## 3.6 DISCUSSION

COVID-19 cases have been reported in millions of people around the world, with thousands of deaths. COVID-19 has been declared a global epidemic by the World Health Organization. Able to detect COVID-19 from X-ray image data using the proposed method. Paid close attention to the structural image's resemblance to the original stack image. The following are some of the benefits of the proposed method: By analysing the X-ray images of COVID-19 patients, it has a 100% success rate in detecting the disease. AI can be used to conduct the research, and the proposed method can be built into portable smart devices (mobile phones, etc.), In comparison to other deep learning models, the proposed approach's deep learning models (MobileNetV2 and SqueezeNet) have fewer parameters. This aids in the improvement of speed and time efficiency. CNN models also save time and speed during the process by using the SMO algorithm. It uses a stacking technique to reduce interference in each image in the dataset and to provide efficient functionality.

The proposed model makes use of the end-to-end learning scheme, which is one of CNN models' major advantages. Activation maps that retained the discriminative features of the input data were used to detect and identify pathologic patterns. The time-consuming and labor-intensive feature extraction method was isolated in this way, resulting in a highly sensitive decision tool.

## 3.7 CONCLUSION

The aim of this study was to differentiate people with COVID-19-related lung damage from healthy people or people who had pneumonia (not infected by COVID-19). COVID-19 was detected with the aid of deep learning models.

The application of pre-processing measures to the images is one of the innovative aspects of the proposed method. More effective features are derived from the image data when pre-processing steps are used. Each pixel of equivalent images is superimposed using the stacking technique, and the pixels with low efficiency are increased. The SMO algorithm was used to extract efficient features with the proposed method. The aim of the model was to generate results that were both faster and more reliable.

The MobileNetV2 model, which can be evaluated on mobile devices without the use of any hospital devices, also demonstrates the applicability of our approach to smart mobile devices. The classification of COVID-19 data was 100 percent successful, and the classification of Normal and Pneumonia images was 99.27 percent successful. To improve the datasets, planing to establish a future methodology that employs various structuring techniques. On using AI to create a solution-oriented study once have data on the factors that influence the virus in human chemistry (e.g. blood group, RNA sequence, age, gender, etc.).

# CHAPTER 4

# PROPOSED METHOD

## 4.1 PNEUMONIA, NORMAL AND COVID-19 DATASET

Pneumonia is an infection that causes the air sacs in one or both lungs to become inflamed and filled with fluid. The letters CO, VI, and D stand for corona, virus, and disease, respectively. X-ray images of patients with pnemonia and covid-19 disease, as well as standard X-ray images, are included in the dataset.

## 4.2 MACHINE LEARNING

The study of computer algorithms that improve themselves over time is known as machine learning. Artificial intelligence is regarded as a subset of it. Machine learning algorithms create a mathematical model based on training data to make predictions or decisions without having to be specifically programmed. Algorithms for machine learning are used in a wide range of applications, including email filtering and computer vision.

### 4.2.1 DEEP LEARNING

Deep Learning is a type of machine learning algorithm that employs multiple layers to extract higher-level features from raw data. If it's a linear or non-linear relationship, the DNN finds the right mathematical manipulation to transform the input into the outputEach level of deep learning learns to translate its input data into abstract and composite representations. The network traverses the layers, measuring the likelihood of each output. Data flows from the input layer to the output layer without looping back in DNNs. DNN built a map of virtual neurons and assigned random numerical values, or weights, to their connections. The inputs and weights are multiplied, and the result is a value between 0 and 1. Photos, text, and sound can all be used to express observations. Deep Learning enables machines to solve complex problems even when they are given a large, unstructured, and interconnected data set..

### 4.2.2 CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) are data processing systems that use several layers of arrays to process data. This form of neural network is used in image recognition and face recognition applications. The main difference between CNN and other neural networks is that CNN uses a two-dimensional array as input and operates directly on the images rather than relying on feature extraction.CNN utilizes spatial correlation that exist within the input data. A neural network's concurrent layers bind some input neurons. This area is known as the local receptive zone. The secret neurons are the target of the local receptive field. The input data is processed by the hidden neurons within the mentioned area, with no awareness of changes beyond the defined boundary.

### 4.2.3 DARKNET MODEL

Artificial intelligence has been transformed with the introduction of deep learning technologies. The term "deep" refers to the network's size expanding as the number of layers increases. The structure is named after the mathematical operator convolution. A convolution layer extracts features from the input with the filters it applies, a pooling layer reduces the size for computational efficiency, and a completely connected layer, which is a neural network, are all part of a standard CNN structure. A CNN model is developed by integrating one or more of these layers, and its internal parameters are modified to accomplish a specific mission, such as classification or object recognition. Rather than starting from scratch with a deep model construction, a more realistic approach is to build a model using previously proven models. As a result, the Darknet-19 model was chosen as the starting point for the deep model used in this analysis. The classifier model Darknet-19 is the foundation of the YOLO real-time object detection scheme (You only look once). This device is equipped with cutting-edge object detection technology. On the basis of this successful design, the DarkNet classifier is used. Instead of creating a model from scratch, the DarkCovidNet architecture is inspired by the DarkNet architecture that has proved itself in deep learningCompared to the original DarkNet architectures, there are fewer layers and filters used. The incremental addition of more filters, such as 8, 16, and 32. To better understand this new architecture, first learn the fundamentals of the

Darknet-19, which uses Maxpool to build 19 convolutional layers and five pooling layers. These are standard CNN layers with various filter numbers, sizes, and stride values. A convolutional layer is denoted by the letter C, and a Maxpool layer is denoted by the letter M. Darknet-19 has the following layer structure since C1 is used as the input layer..

C1-M1-C2-M2-C3-C4-C5-M3-C6-C7-C8-M4-C9-C10-C11-C12-C13-M5-C14-C15-C16-C17-C18-C19

### 4.2.4 LEAKY RELU

The ReLU activation function has been enhanced with the Leaky ReLU function. In the case of the ReLU activation function, the gradient is 0 for all input values less than zero, deactivating the neurons in that region and possibly causing the dying ReLU problem. The two-dimensional convolution operation can be defined as follows for input signal X (image) and kernel K.

(X*K)(i,j)=summation*k(m,n) X( i-m, j-n)

The discrete convolution operation is described by *. With the stride parameter, the K matrix slides over the input matrix. In the DarkNet architecture, the Leaky rectified linear unit (Leaky ReLu) is used as an activation function. Equation gives the formula for calculating the leaky ReLu function (2).

F(x)= 0.01x for x<0

0 for x>0

The flow of input data from the convolution layer (C) and the Max-pooling layer (M) is depicted schematically.

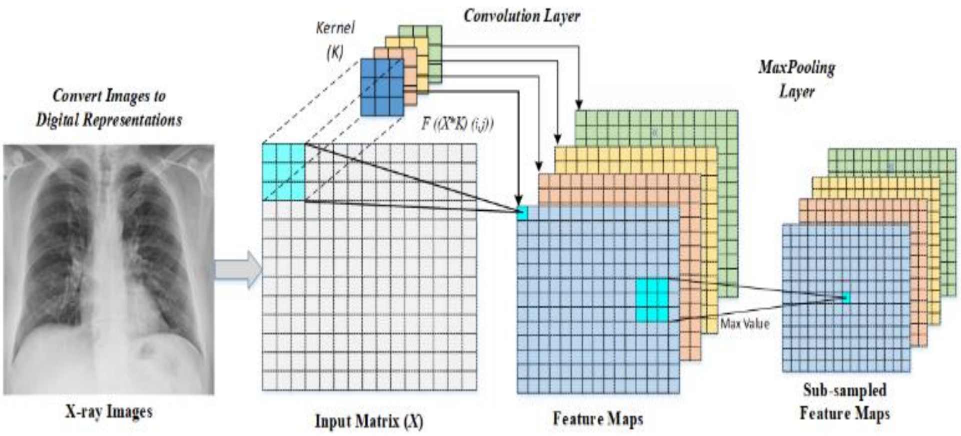



Fig.4.1 A schematic presentation of convolution and Max-pooling layer operations.

The outputs of this model are generated by the Avgpool and Softmax layers. Finally, for the feature extraction of a real-time object detection system, a deep model with a large number of layers is neededThe classification model, such as ResNets or ResNext, should have a framework that can catch and learn small differences rather than being very deep. LeakyReLU is a variant of the ReLU operation that is used to keep neurons from dying. LeakyReLU has a small epsilon value to solve the dying neuron problem, unlike ReLU or sigmoid activation functions, which have zero value in the negative part of their derivatives..

## 4.2.5 17 CONVOLUTION LAYER

There are 17 convolution layers in the proposed model. Each DN (DarkNet) layer has one convolutional layer, BatchNorm, and LeakyReLU operations, and each 3Conv layer has the same configuration three times in succession. The batch normalisation operation is used to standardise the inputs, and it has other advantages such as minimising training time and improving model stability. LeakyReLU is a variant of the ReLU operation that is used to keep neurons from dying. Unlike ReLU and sigmoid activation functions, which have zero value in the negative part of their derivatives, LeakyReLU has a small epsilon value to avoid the issue of dying neurons.

## 4.2.6 MAXPOOLING METHOD

The Maxpool system is used in all pooling operations, similar to the Darknet-19 model. Maxpool reduces the size of an input by taking the maximum of a filter-defined field. The proposed model performs the COVID-19 detection task while operating with two groupsThe same model performs the classification task to assess the labels of the input chest X-ray images as COVID-19, Pneumonia, or No Findings if three different classes of images are included in the input. Finally, Table 1 lists the model's layer information and layer parameters. A total of 1,164,434 parameters make up the deep learning model created.

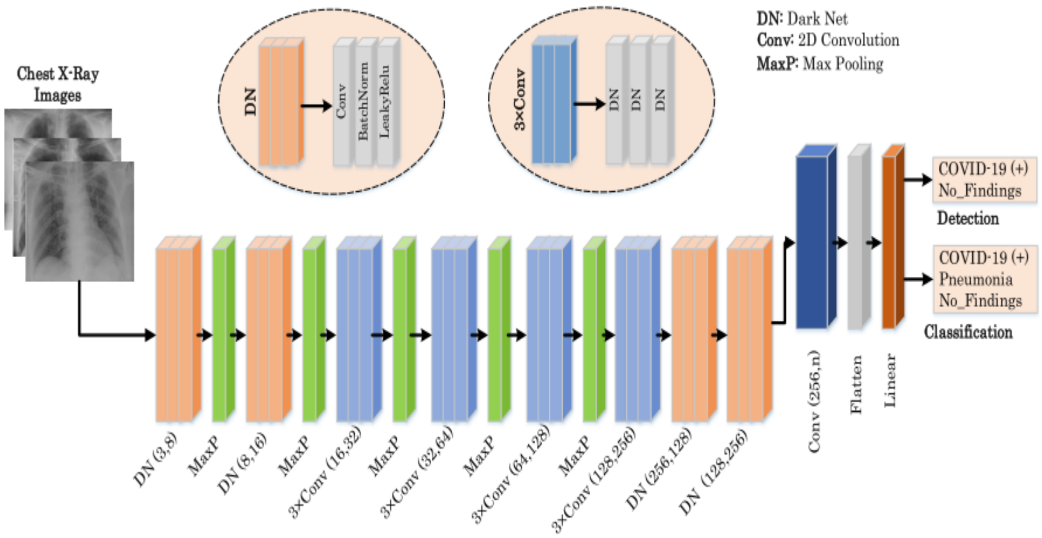



Fig 4.2 Architecture of Dark CovidNet

## 4.2.7 5 FOLD CROSS-VALIDATION

In two separate cases, X-ray images were used to detect and classify COVID-19. First, the DarkCovidNet deep learning model was trained to categorise X-ray images into three groups: COVID-1, No-Findings, and Pneumonia. Second, the DarkCovidNet model is trained to recognise two types of data: COVID-19 and No-Findings are two types of COVID. For both the binary and triple classification problems, the proposed model's output is evaluated using the 5-fold cross-validation process. X-ray images are used for training 80% of the time and validation 20% of the time. Five times the tests are carried out. To use in the validation step, all of the split k parts are wrapped in folds. DarkCovidNet has been conditioned for 100 epochs. The multi-class classification training and validation failure graphs, as well as the validation accuracy graphs, are shown for the Fold-1.

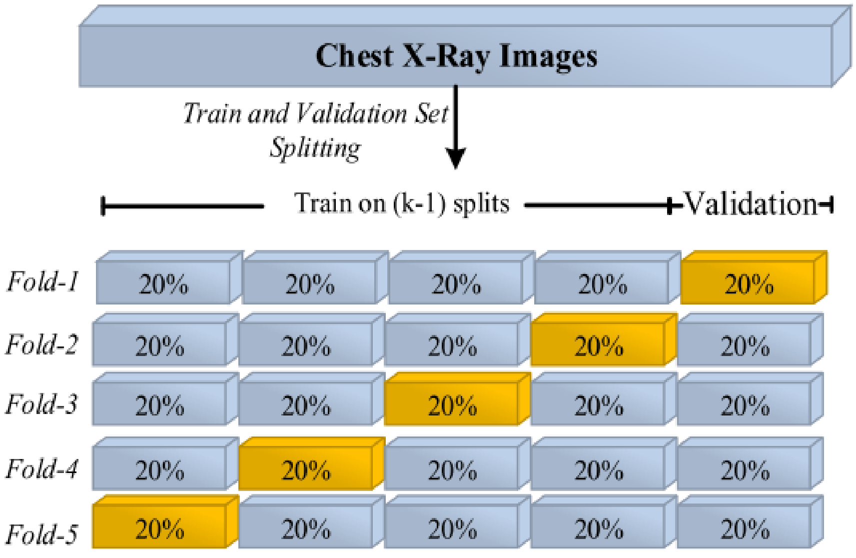



Fig 4.3 Schematic representation of training and validation scheme employed in the 5-fold crossvalidation procedure.

It can be noted from that there is a significant increase in loss values in the beginning of the training, which decrease substantially in the later stage of the training. The number of data in the COVID-19 class, which is much less than the other two (Pneumonia and No-Findings) classes, is the primary cause of this sharp increase and decrease. These rapid ups and downs are gradually decreased in the later part of the training as the deep model analyses all X-ray images for each epoch over and over again.

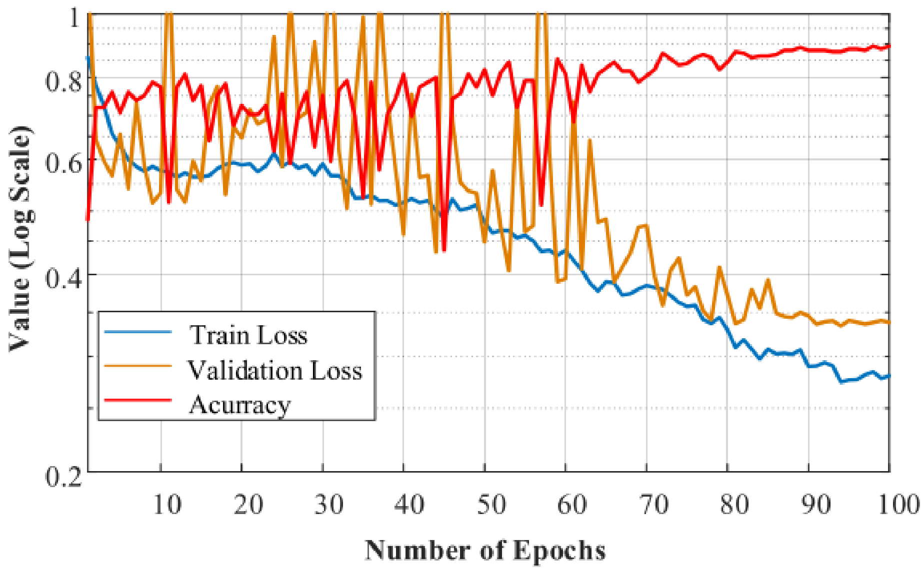



Fig 4.4 Validation, training loss and validation accuracy curves obtained for DarkCovidNet model in fold-1.

### 4.2.8 CONFUSION MATRIX

A confusion matrix is a method of summarising a classification algorithm's results. When there are an unequal number of observations in each class or when there are more than two classes in a dataset, classification accuracy alone can be misleading. An N x N matrix is used to evaluate the efficiency of a classification model, where N is the number of target groups. The matrix compares the real goal values to the machine learning model's predictions. This provides us with a comprehensive picture of how well our classification model is doing and the types of errors it makes. For a binary classification query, a 2 x 2 matrix with four values, as shown below, will be used.:

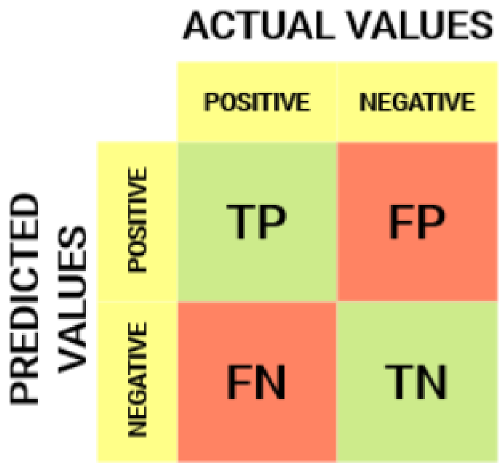



Fig 4.5 example of confusion matrix

The number of the CMs obtained in all folds is used to establish the overlapped CM. As a result, the goal is to get a sense of the model's general perforations. The DarkCovidNet model classified no results, COVID-19, and Pneumonia with an average classification accuracy of 87.02 percent. The deep learning model categorised COVID-19 better than the pneumonia and no findings classes, as shown by the overlapped uncertainty matrix of the multi-class classification mission. The sensitivity, precision, and F1-score values obtained are 85.35, 92.18, and 87.37 percent, respectively. Second, Fig. 8 shows the results of uncertainty matrixes for the binary classification problem in detecting COVID-19 positive. Table 3 also includes results for the binary classification task in terms of sensitivity, specificity, precision, F1-score, and accuracy.

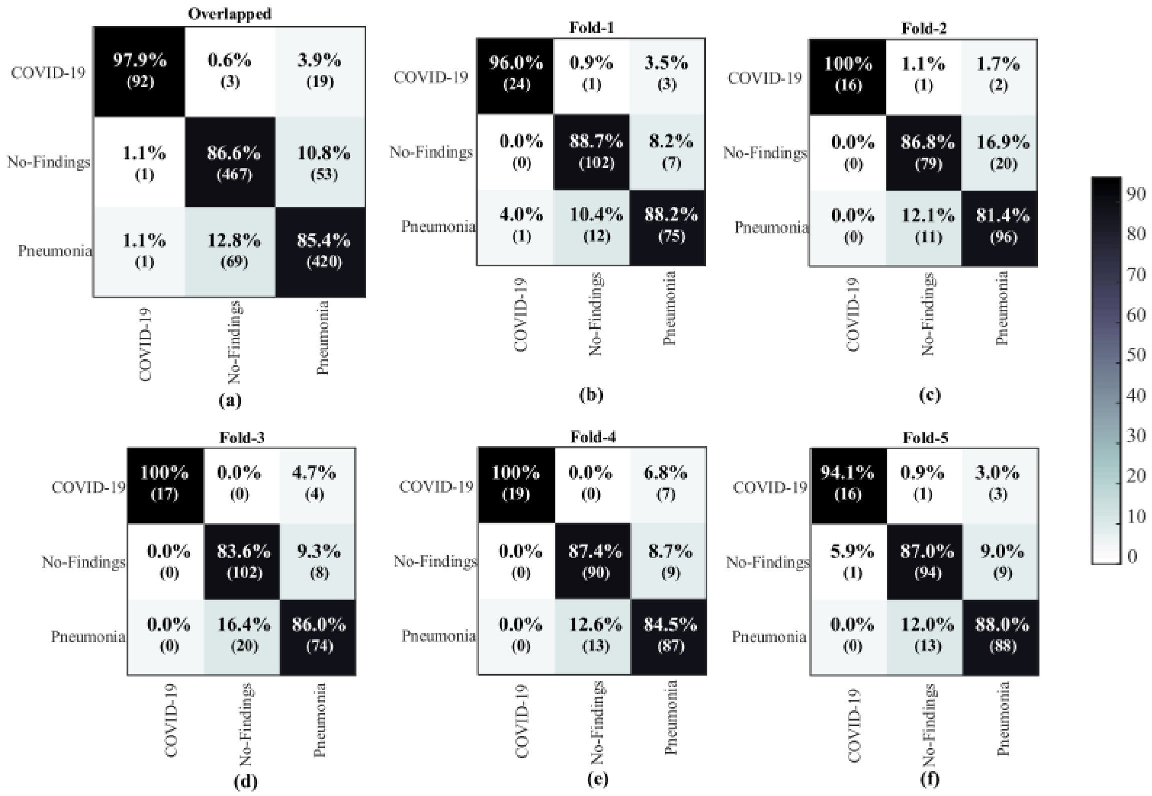



Fig 4.6 The overlapped and 5-fold confusion matrix results of the multi-class classification task

# CHAPTER 5

# RESULTS

```
#######TRAINED COVID19 PNEUMONIA VS NORMAL LUNG TEST REPORT [LOADED MODEL/WEIGHTS]
Set: train, normal images: 1341, illness-positive images: 3875
Set: test, normal images: 234, illness-positive images: 390
Found 5216 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
WARNING: AutoGraph could not transform <function Model.make_predict_function.<locals>.predict_function at 0x00000208DD6186A8> a
nd will run it as-is.
Please report this to the TensorFlow team. When filing the bug, set the verbosity to 10 (on Linux, `export AUTOGRAPH_VERBOSITY=
10`) and attach the full output.
Cause: 'arguments' object has no attribute 'posonlyargs'
To silence this warning, decorate the function with @tf.autograph.experimental.do_not_convert

<matplotlib.figure.Figure at 0x208dd6322e8>


CONFUSION MATRIX FORMAT ------------------

[true positives    false positives]
[false negatives    true negatives]


CONFUSION MATRIX ------------------
[[201  33]
 [ 54 336]]

TEST METRICS ----------------------
Accuracy: 86.0576923076923%
Precision: 91.05691056910568%
Recall/Sensitivity: 86.15384615384616%
Specificity 85.8974358974359%
```

Fig 5.1 Output of Covid-19 pneumonia vs normal lung test with predicted accuracy and confusion matrix.

Images that are used for training are 1341 normal X-ray images (85% are used for training) and 3875 covid pneumonia X-ray images (90% are used for training). Images that are used for testing are 234 normal X-ray images (15% are used for training) and 390 positive X-ray images (10% are used for training).

## 5.1 TEST RESULT

201 X-ray images are correctly detected as normal images and 33 covid pneumonia images are wrongly detected as normal. 336 X-ray images are correctly detected as covid pneumonia images and 54 normal images wrongly detected as covid pneumonia images. The accuracy for the detection of the covid images is 86% with precision 91% and sensitivity of about 86% and specificity of 85%.

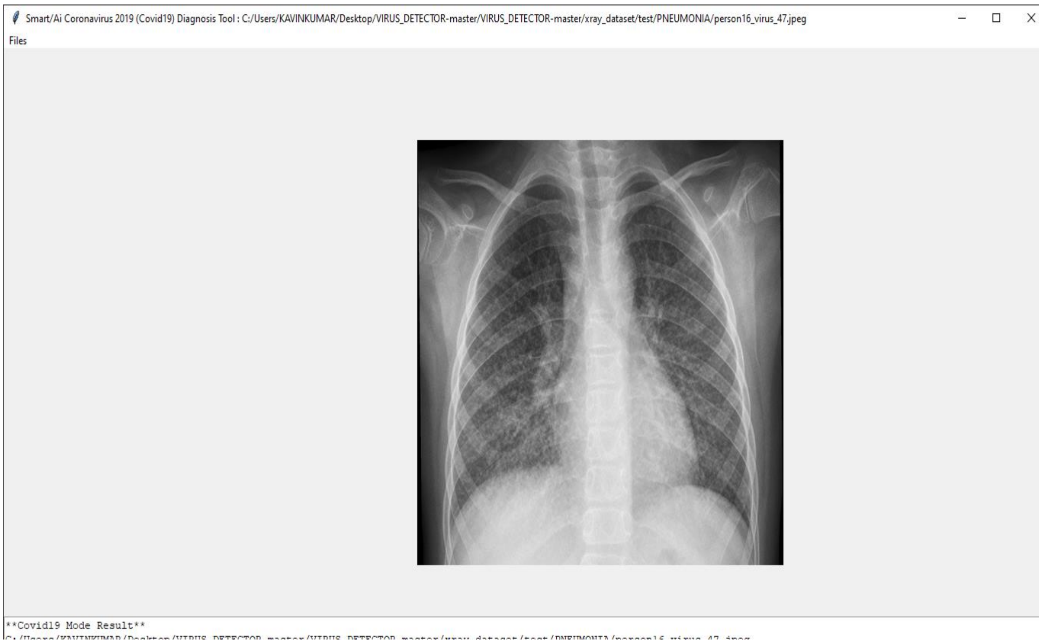



Fig 5.2 Covid X-ray images used for testing.

```
#######TRAINED NON-COVID19 PNEUMONIA VS NORMAL LUNG TEST REPORT [LOADED MODEL/WEIGHTS]
Set: train, normal images: 1341, illness-positive images: 3875
Set: val, normal images: 8, illness-positive images: 8
Set: test, normal images: 234, illness-positive images: 390
Found 5216 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
WARNING: AutoGraph could not transform <function Model.make_predict_function.<locals>.predict_function at 0x00000208C6E7AA60> a
nd will run it as-is.
Please report this to the TensorFlow team. When filing the bug, set the verbosity to 10 (on Linux, `export AUTOGRAPH_VERBOSITY=
10`) and attach the full output.
Cause: 'arguments' object has no attribute 'posonlyargs'
To silence this warning, decorate the function with @tf.autograph.experimental.do_not_convert

<matplotlib.figure.Figure at 0x208c6f5ae48>


CONFUSION MATRIX FORMAT ------------------

[true positives    false positives]
[false negatives    true negatives]


CONFUSION MATRIX ------------------
[[207  27]
 [ 41 349]]

TEST METRICS ----------------------
Accuracy: 89.1025641025641%
```

Fig 5.3 Output of non Covid-19 pneumonia vs normal lung test with predicted accuracy and confusion matrix.

## 5.2 TEST RESULT

207 X-ray images are correctly detected as normal and 27 covid pneumonia images are wrongly detected as normal. 349 X-ray images are correctly detected as covid pneumonia images and 41 normal images wrongly detected as covid pneumonia image. The accuracy for the detection of the covid images is 89%.

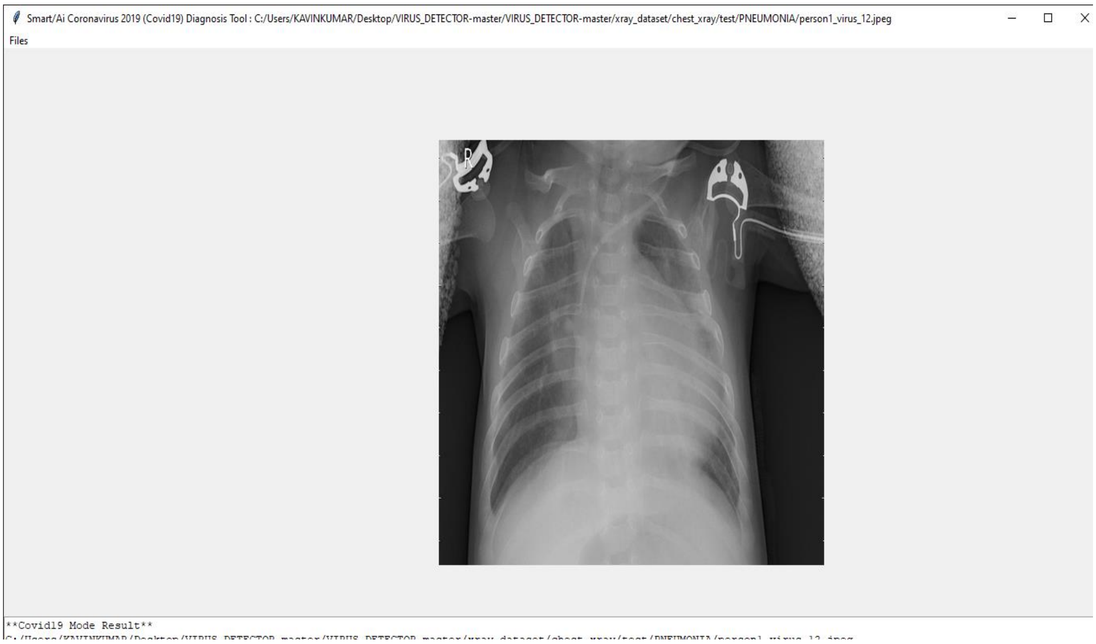



Fig 5.4 pneumonia images used for testing.

```
Pneumonia detected
Raw Neural Network Output : 0.99594504. A value closer to 1 signifies illness, while a value closer to 0 signifies normalness.


**Covid19 Mode Result**
C:/Users/KAVINKUMAR/Desktop/VIRUS_DETECTOR-master/VIRUS_DETECTOR-master/xray_dataset/chest_xray/test/PNEUMONIA/person1_virus_1
2.jpeg

Covid19 detected
Raw Neural Network Output : 0.99946153. A value closer to 1 signifies illness, while a value closer to 0 signifies normalness.


**Covid19 Mode Result**
C:/Users/KAVINKUMAR/Desktop/VIRUS_DETECTOR-master/VIRUS_DETECTOR-master/xray_dataset/test/NORMAL/IM-0001-0001.jpeg

Normal lungs detected
Raw Neural Network Output : 0.018167168. A value closer to 1 signifies illness, while a value closer to 0 signifies normalness.
```

Fig 5.5 Percentage of severity

In pneumonia detection the output detected as 0.99594504 from the scale of 0-1 the output matches to 1 so it is detected as pneumonia. After covid-19 is tested and output is 0.99946153 from the scale of 0-1 the output matches to 1 so it is detected as covid-19. While testing for normal images the output given as 0.018167168 so the output matches to 0 so it is detected as normal images.

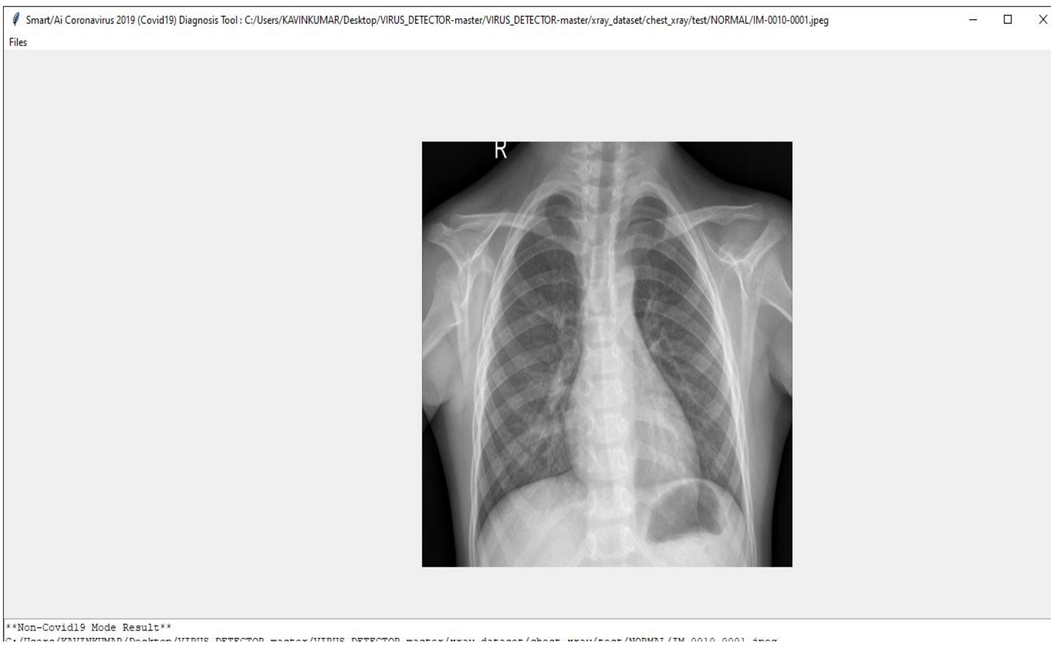



Fig 5.6 normal X-ray images used for testing

In [17]:
```
learn.fit_one_cycle(100, max_lr=3e-3)
```

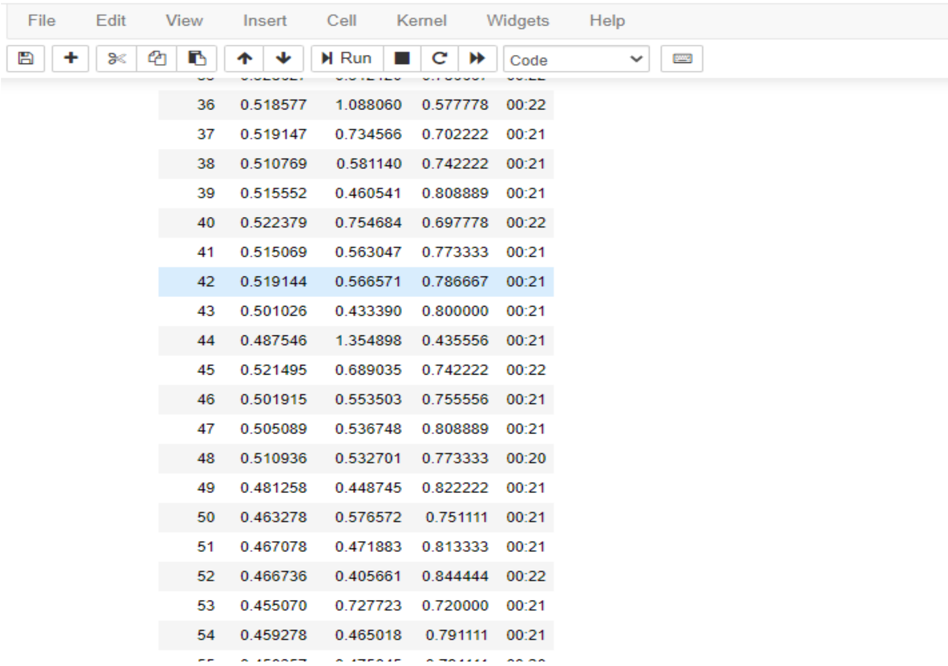
| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 0.858251 | 1.179491 | 0.484444 | 00:24 |
| 1 | 0.777954 | 0.643197 | 0.720000 | 00:24 |
| 2 | 0.723462 | 0.595972 | 0.720000 | 00:23 |
| 3 | 0.655952 | 0.565903 | 0.760000 | 00:24 |
| 4 | 0.628582 | 0.655289 | 0.706667 | 00:23 |
| 5 | 0.599323 | 0.541184 | 0.760000 | 00:23 |
| 6 | 0.584792 | 0.733112 | 0.737778 | 00:21 |
| 7 | 0.574960 | 0.585806 | 0.751111 | 00:21 |
| 8 | 0.585414 | 0.514000 | 0.786667 | 00:21 |
| 9 | 0.576228 | 0.533401 | 0.773333 | 00:21 |
| 10 | 0.573735 | 1.250966 | 0.515556 | 00:21 |
| 11 | 0.563315 | 0.539523 | 0.773333 | 00:20 |
| 12 | 0.572081 | 0.515643 | 0.808889 | 00:21 |
| 13 | 0.563877 | 0.596464 | 0.737778 | 00:21 |
| 14 | 0.564036 | 0.555707 | 0.777778 | 00:21 |
| 15 | 0.566451 | 0.727351 | 0.640000 | 00:21 |
| 16 | 0.580530 | 0.775214 | 0.751111 | 00:21 |

Fig 5.7 Epoch (0-16) with training loss and validation loss with accuracy and computation time

Run Code

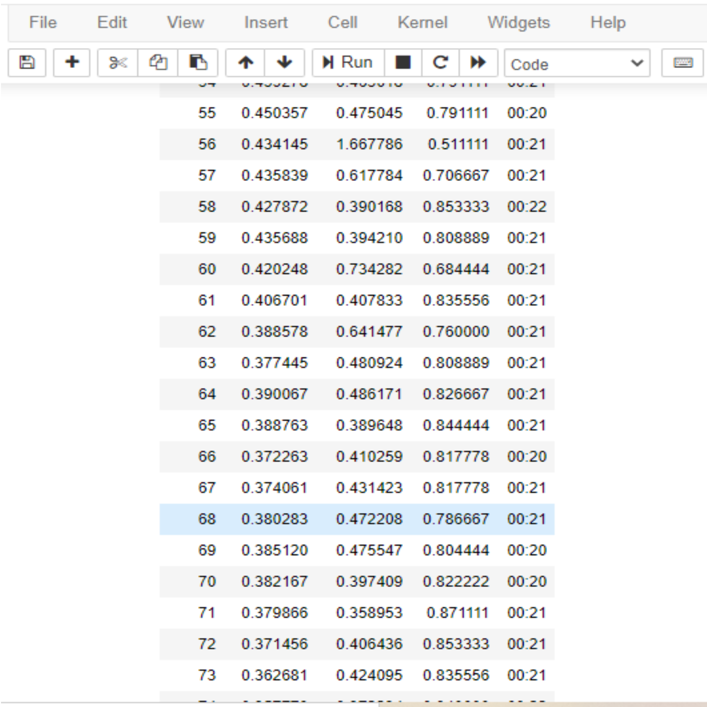
| | | | | |
|---|---|---|---|---|
| 16 | 0.580530 | 0.775214 | 0.751111 | 00:21 |
| 17 | 0.589160 | 0.529869 | 0.782222 | 00:20 |
| 18 | 0.592872 | 0.672026 | 0.675556 | 00:21 |
| 19 | 0.588015 | 0.647101 | 0.724444 | 00:21 |
| 20 | 0.590411 | 0.714638 | 0.702222 | 00:21 |
| 21 | 0.574496 | 0.679330 | 0.702222 | 00:23 |
| 22 | 0.586382 | 0.689531 | 0.724444 | 00:21 |
| 23 | 0.612731 | 0.922392 | 0.617778 | 00:20 |
| 24 | 0.585181 | 0.585091 | 0.755556 | 00:20 |
| 25 | 0.595105 | 1.066644 | 0.591111 | 00:20 |
| 26 | 0.581255 | 0.692776 | 0.706667 | 00:21 |
| 27 | 0.587679 | 0.708042 | 0.760000 | 00:22 |
| 28 | 0.567914 | 0.906922 | 0.626667 | 00:21 |
| 29 | 0.590494 | 0.693620 | 0.751111 | 00:21 |
| 30 | 0.566304 | 1.415233 | 0.595556 | 00:20 |
| 31 | 0.565950 | 0.619892 | 0.764444 | 00:21 |
| 32 | 0.553827 | 0.504516 | 0.791111 | 00:21 |
| 33 | 0.523444 | 0.734000 | 0.697778 | 00:21 |
| 34 | 0.524042 | 0.989776 | 0.524444 | 00:21 |
| 35 | 0.528627 | 0.512120 | 0.786667 | 00:22 |

Fig 5.8 Epoch (17-35) with training loss and validation loss with accuracy and computation time




| | | | | |
|---|---|---|---|---|
| 36 | 0.518577 | 1.088060 | 0.577778 | 00:22 |
| 37 | 0.519147 | 0.734566 | 0.702222 | 00:21 |
| 38 | 0.510769 | 0.581140 | 0.742222 | 00:21 |
| 39 | 0.515552 | 0.460541 | 0.808889 | 00:21 |
| 40 | 0.522379 | 0.754684 | 0.697778 | 00:22 |
| 41 | 0.515069 | 0.563047 | 0.773333 | 00:21 |
| 42 | 0.519144 | 0.566571 | 0.786667 | 00:21 |
| 43 | 0.501026 | 0.433390 | 0.800000 | 00:21 |
| 44 | 0.487546 | 1.354898 | 0.435556 | 00:21 |
| 45 | 0.521495 | 0.689035 | 0.742222 | 00:22 |
| 46 | 0.501915 | 0.553503 | 0.755556 | 00:21 |
| 47 | 0.505089 | 0.536748 | 0.808889 | 00:21 |
| 48 | 0.510936 | 0.532701 | 0.773333 | 00:20 |
| 49 | 0.481258 | 0.448745 | 0.822222 | 00:21 |
| 50 | 0.463278 | 0.576572 | 0.751111 | 00:21 |
| 51 | 0.467078 | 0.471883 | 0.813333 | 00:21 |
| 52 | 0.466736 | 0.405661 | 0.844444 | 00:22 |
| 53 | 0.455070 | 0.727723 | 0.720000 | 00:21 |
| 54 | 0.459278 | 0.465018 | 0.791111 | 00:21 |

Fig 5.9 Epoch (35-54 ) with training loss and validation loss with accuracy and computation time




| | | | | |
|---|---|---|---|---|
| 55 | 0.450357 | 0.475045 | 0.791111 | 00:20 |
| 56 | 0.434145 | 1.667786 | 0.511111 | 00:21 |
| 57 | 0.435839 | 0.617784 | 0.706667 | 00:21 |
| 58 | 0.427872 | 0.390168 | 0.853333 | 00:22 |
| 59 | 0.435688 | 0.394210 | 0.808889 | 00:21 |
| 60 | 0.420248 | 0.734282 | 0.684444 | 00:21 |
| 61 | 0.406701 | 0.407833 | 0.835556 | 00:21 |
| 62 | 0.388578 | 0.641477 | 0.760000 | 00:21 |
| 63 | 0.377445 | 0.480924 | 0.808889 | 00:21 |
| 64 | 0.390067 | 0.486171 | 0.826667 | 00:21 |
| 65 | 0.388763 | 0.389648 | 0.844444 | 00:21 |
| 66 | 0.372263 | 0.410259 | 0.817778 | 00:20 |
| 67 | 0.374061 | 0.431423 | 0.817778 | 00:21 |
| 68 | 0.380283 | 0.472208 | 0.786667 | 00:21 |
| 69 | 0.385120 | 0.475547 | 0.804444 | 00:20 |
| 70 | 0.382167 | 0.397409 | 0.822222 | 00:20 |
| 71 | 0.379866 | 0.358953 | 0.871111 | 00:21 |
| 72 | 0.371456 | 0.406436 | 0.853333 | 00:21 |
| 73 | 0.362681 | 0.424095 | 0.835556 | 00:21 |

Fig 5.10 Epoch (55-74) with training loss and validation loss with accuracy and computation time

File Edit View Insert Cell Kernel Widgets Help

Run Code

| | | | | |
|---|---|---|---|---|
| 75 | 0.359056 | 0.383452 | 0.857778 | 00:22 |
| 76 | 0.341428 | 0.351937 | 0.866667 | 00:21 |
| 77 | 0.337034 | 0.341431 | 0.857778 | 00:21 |
| 78 | 0.343955 | 0.410234 | 0.822222 | 00:20 |
| 79 | 0.329430 | 0.372199 | 0.844444 | 00:21 |
| 80 | 0.309703 | 0.336752 | 0.875556 | 00:21 |
| 81 | 0.318068 | 0.341242 | 0.871111 | 00:21 |
| 82 | 0.307724 | 0.379614 | 0.857778 | 00:21 |
| 83 | 0.297219 | 0.355399 | 0.862222 | 00:22 |
| 84 | 0.307929 | 0.392915 | 0.862222 | 00:21 |
| 85 | 0.302612 | 0.349374 | 0.866667 | 00:21 |
| 86 | 0.303524 | 0.345227 | 0.880000 | 00:21 |
| 87 | 0.302229 | 0.343968 | 0.880000 | 00:21 |
| 88 | 0.307099 | 0.350245 | 0.888889 | 00:21 |
| 89 | 0.289549 | 0.345907 | 0.880000 | 00:21 |
| 90 | 0.290048 | 0.335931 | 0.880000 | 00:22 |
| 91 | 0.293699 | 0.338813 | 0.880000 | 00:21 |
| 92 | 0.290154 | 0.339982 | 0.875556 | 00:20 |
| 93 | 0.274261 | 0.333936 | 0.875556 | 00:21 |
| 94 | 0.276202 | 0.340441 | 0.884444 | 00:21 |

Fig 5.11 Epoch (75-94) with training loss and validation loss with accuracy and computation time

File Edit View Insert Cell Kernel Widgets Help

Run Code

| | | | | |
|---|---|---|---|---|
| 80 | 0.309703 | 0.336792 | 0.875556 | 00:21 |
| 81 | 0.318068 | 0.341242 | 0.871111 | 00:21 |
| 82 | 0.307724 | 0.379614 | 0.857778 | 00:21 |
| 83 | 0.297219 | 0.355399 | 0.862222 | 00:22 |
| 84 | 0.307929 | 0.392915 | 0.862222 | 00:21 |
| 85 | 0.302612 | 0.349374 | 0.866667 | 00:21 |
| 86 | 0.303524 | 0.345227 | 0.880000 | 00:21 |
| 87 | 0.302229 | 0.343968 | 0.880000 | 00:21 |
| 88 | 0.307099 | 0.350245 | 0.888889 | 00:21 |
| 89 | 0.289549 | 0.345907 | 0.880000 | 00:21 |
| 90 | 0.290048 | 0.335931 | 0.880000 | 00:22 |
| 91 | 0.293699 | 0.338813 | 0.880000 | 00:21 |
| 92 | 0.290154 | 0.339982 | 0.875556 | 00:20 |
| 93 | 0.274261 | 0.333936 | 0.875556 | 00:21 |
| 94 | 0.276202 | 0.340441 | 0.884444 | 00:21 |
| 95 | 0.276630 | 0.338368 | 0.884444 | 00:22 |
| 96 | 0.281360 | 0.336015 | 0.880000 | 00:21 |
| 97 | 0.284294 | 0.338093 | 0.893333 | 00:21 |
| 98 | 0.277733 | 0.340329 | 0.884444 | 00:21 |
| 99 | 0.280343 | 0.338089 | 0.893333 | 00:22 |

Fig 5.12 Epoch (81-99) with training loss and validation loss with accuracy and computation time

# CHAPTER 6

# CONCLUSION

## 6.1 CONCLUSION

To detect and classify , have proposed a deep learning based model COVID-19 cases from X-ray images. Our model has an end-to-end layout that eliminates the need for manual function extraction. Our developed system is able to perform binary and multiclass tasks with an accuracy of 92.02% .

## 6.2 FUTURE SCOPE

In future the DarkNet model and structured data may be used to improve the accuracy.

# CHAPTER 7

# REFERENCE


1. Khair Ahammed and et al.," Early Detection of Coronavirus Cases Using Chest X-ray Images Employing Machine Learning and Deep Learning Approaches"proposed in medRxiv on June 8,2020.

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