

**DAYANANDA SAGAR UNIVERSITY**  
KUDLU GATE, BANGALORE - 560068



**Bachelor of Technology  
in  
COMPUTER SCIENCE AND ENGINEERING**

**Major Project Phase-II Report**

**"DETECTION OF COVID-19 FROM CHEST X-RAYS"**

Submitted By:  
**Nikhita A - ENG18CS0192**  
**Pavana M - ENG18CS0207**  
**Pavithra H A - ENG18CS0208**  
**Rutuja Lattimarde - ENG18CS0234**

**Under the supervision of**

**Dr. Girisha G S  
Professor & Chairman,  
Dept. of CSE**

**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING  
SCHOOL OF ENGINEERING  
DAYANANDA SAGAR UNIVERSITY  
BANGALORE**

**(2021-2022)**



**DAYANANDA SAGAR UNIVERSITY**

**School of Engineering  
Department of Computer Science & Engineering**

Kudlu Gate, Bangalore – 560068  
Karnataka, India

**CERTIFICATE**

This is to certify that the Phase-II project work titled “**DETECTION OF COVID-19 FROM CHEST X-RAYS**” is carried out by **Nikhita A (ENG18CS0192)**, **Pavana M (ENG18CS0207)**, **Pavithra H A (ENG18CS0208)**, **Rutuja Lattimarde (ENG18CS0234)**, bonafide students of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2021-2022**.

**Dr. Girisha G S**

Chairman  
Dept. of CSE  
School of Engineering  
Dayananda Sagar University

**Dr Girisha G S**

Chairman  
Dept. of CSE  
School of Engineering  
Dayananda Sagar University

**Dr. A Srinivas**

Dean  
School of Engineering  
Dayananda Sagar University

Date:

Date:

Date:

**Name of the Examiner**

**Signature of Examiner**

1.

2.

## **DECLARATION**

We, **Nikhita A (ENG18CS0192)**, **Pavana M (ENG18CS0207)**, **Pavithra H A (ENG18CS0208)**, **Rutuja Lattimarde (ENG18CS0234)**, are students of the eighth semester B.Tech in **Computer Science and Engineering**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the phase-II project titled "**Detection of Covid-19 from Chest X-rays**" has been carried out by us and submitted in partial fulfillment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2021-2022**.

**Student**

**Name1: Nikhita A**

**USN : ENG18CS0192**

**Name2 : Pavana M**

**USN : ENG18CS0207**

**Name3: Pavithra H A**

**USN : ENG18CS0208**

**Name4:Rutuja Lattimarde**

**USN : ENG18CS0234**

**Signature**

**Place : Bangalore**

**Date :**

## **ACKNOWLEDGEMENT**

*It is a great pleasure for us to acknowledge the assistance and support of many individuals who have been responsible for the successful completion of this project work.*

*First, we take this opportunity to express our sincere gratitude to the School of Engineering & Technology, Dayananda Sagar University for providing us with a great opportunity to pursue our Bachelor's degree in this institution.*

*We would like to thank Dr. A Srinivas. Dean, School of Engineering, Dayananda Sagar University for his constant encouragement and expert advice.*

*It's a matter of immense pleasure to express our sincere thanks to Dr. Girisha G S, Chairman, Dept. of Computer Science and Engineering, Dayananda Sagar University, for providing right academic guidance that made our task possible.*

*We would like to thank our guide Dr. Girisha G S, Chairman, Dept. of Computer Science and Engineering, Dayananda Sagar University, for sparing his/her valuable time to extend help in every step of our project work, which paved the way for smooth progress and fruitful culmination of the project.*

*We would like to thank our Project Coordinators Dr. Meenakshi Malhotra and Dr. Bharanidharan N, and all the staff members of Computer Science and Engineering for their support.*

*We are also grateful to our family and friends who provided us with every requirement throughout the course.*

*We would like to thank one and all who directly or indirectly helped us in the Project work.*

Signature of Students

USN : ENG18CS0192

Name: Nikhita A

USN : ENG18CS0207

Name: Pavana M

USN : ENG18CS0208

Name : Pavithra H A

USN : ENG18CS0234

Name: Rutuja L

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## **LIST OF ABBREVIATIONS**

CNN	Convolution Neural Network
DL	Deep Learning
PCR	Polymerase Chain Reaction
CT	Computed tomography

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## **ABSTRACT**

Corona Virus continues to have an impact on people's lives all across the world. Screening infected people is an important step since it is a quick and low-cost method. Chest X-ray pictures serve a critical role in the assessment and identification of CORONAVIRUS (COVID-19). It will be impossible to assess every patient with a respiratory condition using standard procedures due to a lack of testing kits (RTPCR). Chest X-rays might provide more accurate findings than the current systems. For detection and classification of COVID 19 and other lung diseases such as Pneumonia, Tuberculosis, we are developing an image classification model that employs deep algorithms. A system capable of collecting X-Rays and detecting and classifying COVID and other lung diseases within X-Ray pictures uploaded by users and to present facts that our user can comprehend and apply to get insight.

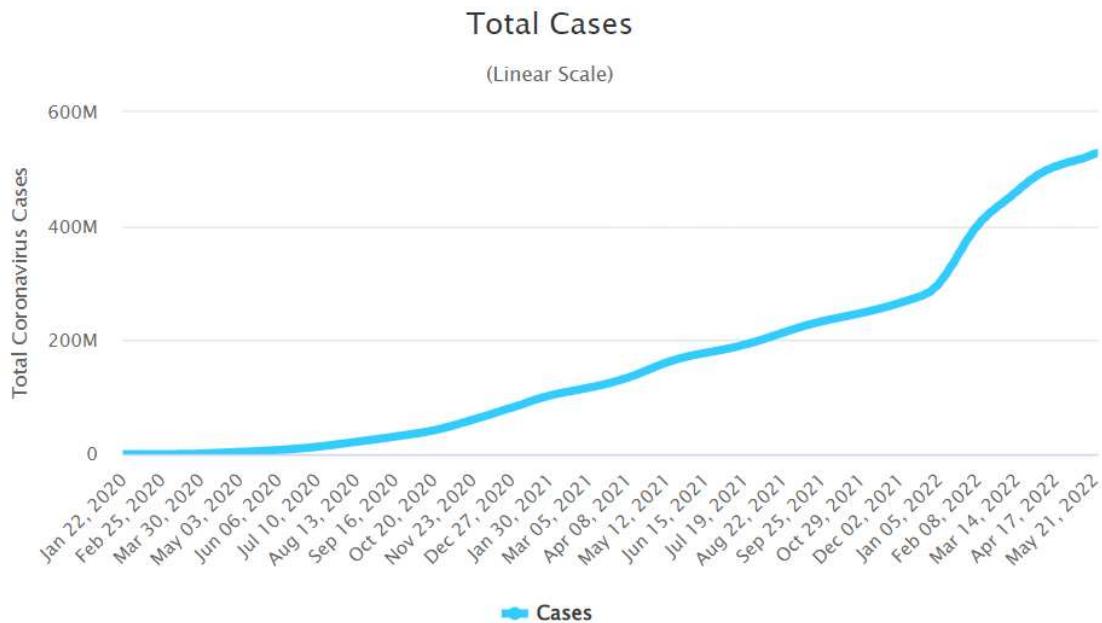
# **CHAPTER 1**

## **INTRODUCTION**

# CHAPTER 1 INTRODUCTION

## 1.1. INTRODUCTION:

Coronavirus disease 2019 (COVID-19) is an infectious illness caused by the coronavirus 2 severe acute respiratory syndrome (SARS-CoV-2). The first known case was discovered in December 2019 in Wuhan, China. The first case in our nation was reported on January 21, 2019. The disease spread around the world, resulting in the COVID-19 pandemic as shown in Fig 1.1. COVID-19 spreads when an infected individual exhales virus-containing droplets and extremely minute particles. Other individuals may breathe in these droplets and particles or they may settle on their eyes, noses, or mouths. They may contaminate surfaces they contact in some cases.



**Fig 1.1 Total Covid19 cases trend from Jan 2020 to May 2022 by worldometers**

The tests that are available for COVID-19 detection are viral tests that take samples from your nose or mouth to determine whether you are infected with SARS-CoV-2, the virus that causes COVID-19. These viral tests are of two kinds: Rapid Point-of-care tests, which are conducted or interpreted by someone other than the person being tested, can be completed in minutes and

can include antigen testing; and laboratory tests can take days to complete, including RT-PCR. With limited testing kits, it will be difficult to examine every patient with a respiratory ailment using traditional methods like RT PCR and other viral tests. Chest radiography (CXR) and computed tomography (CT) images are two conventional medical imaging modalities used in lung disease diagnosis. Despite the widespread use of CT scans in the diagnosis of COVID-19, cost and radiation exposure remain major concerns. CXR images are preferred over CT scans because they need less radiation and are more prevalent. As a result, CXR images are used in this study for automatic COVID-19 diagnosis.

Artificial intelligence has demonstrated its effectiveness and superior performance in automated image categorization challenges. The development of strong machine learning techniques over the previous decade, as well as the availability of deep learning models for image recognition trained on massive data sets, will definitely help in the global fight against COVID-19. In this project, we explore how relevant convolutional neural network models may be used to detect and classify the novel coronavirus and other lung diseases like pneumonia and tuberculosis, by utilizing transfer learning and large volumes of image data. We have used four deep learning models, namely: VGG16, ResNet50, InceptionV3 and Xception, on a dataset containing normal, covid, pneumonia and tuberculosis chest X-rays. 80% of the chest X-rays were used for training the models, and the remaining 20% for testing the accuracy of the models.

## **1.2 OBJECTIVES OF THE PROJECT**

1.2.1 Detection and Classification of COVID and other lung diseases – The system should be able to detect and classify the COVID and other lung diseases within the X – Ray images resulting in good accuracy.

1.2.2 Display Results - The system should be able to give information that is appropriately understandable and able to gain insight from it.

### **1.3 SCOPE OF THE PROJECT**

1.3.1 Despite the availability of RT PCR test for the identification of covid-19, medical professionals prefer chest X-rays during surgery.

1.3.2 The early automated diagnosis of the recently discovered coronavirus illness (COVID-19) will aid in limiting its global spread.

1.3.3 COVID-19 instances can be detected quickly. This concept will aid in the fight against the virus while also relieving stress on the healthcare system.

## **CHAPTER 2**

### **PROBLEM DEFINITION**

## CHAPTER 2 PROBLEM DEFINITION

### 2.1 PROBLEM STATEMENT

Covid-19, an infectious disease that initially surfaced in Wuhan, China, in December 2019, has had a tremendous impact on people's mental and physical health all over the world. It has caused extensive damage to the world economy and poses a threat to human health. Given the virus's fast transmission, a reliable and timely means of diagnosing the disease is critical.

### 2.2 SOLUTION OF THE PROBLEM

Chest X-ray radiography is one discipline of medicine that assists in the diagnosis of people who have coronavirus symptoms. With inspiration and information from multiple investigations, this project aims to detect COVID-19 and classify various lung diseases by analyzing multiple deep learning models such as VGG16, ResNet50, InceptionV3 and Xception, on a dataset containing images of COVID, pneumonia, tuberculosis, and normal chest X-rays.

## **CHAPTER 3**

### **LITERATURE REVIEW**

## CHAPTER 3 LITERATURE REVIEW

### 1. Automatic Detection of COVID-19 from Chest X-ray with Convolutional Neural Networks

Deep Learning has advanced significantly in recent years, and it now plays an important role in picture categorization, which includes medical imaging. Convolutional Neural Networks (CNN) have proved successful in diagnosing several ailments. CNN, like other cases, has a good chance of finding COVID-19 individuals using medical pictures such as chest X-rays and CT scans. Until July 11, 2020, the total number of COVID-19 confirmed cases is 12.32 million, with 0.556 million fatalities globally. Detecting Corona positive patients is critical to stopping the spread of this virus. On this conquest, a CNN model is suggested to detect COVID-19 patients from chest X-ray pictures. This model is compared to two different CNN models. The proposed model has an accuracy of 97.56 percent and a precision of 95.34 percent. This model has a Receiver Operating Characteristic (ROC) curve area of 0.976 and an F1-score of 97.61. It may be enhanced further by expanding the dataset used to train the model.

Conclusion: COVID-19 mass testing and early discovery are critical to avoiding the spread of this current worldwide epidemic. The three most important aspects in any disease detection method, particularly COVID-19, are time, cost, and accuracy. To overcome these concerns, this work proposes a CNN-based algorithm for identifying COVID-19 instances from patients' chest X-rays. The model is trained using 330 chest X-ray pictures separated into two classes: 'COVID-19' and 'Normal.' For model validation, an evenly divided picture collection of 82 chest X-rays is employed. This model achieves 97.56 percent accuracy and 95.34 percent precision [1].

### 2. A Lightweight Deep Learning Model for COVID-19 Detection

COVID-19 is a highly contagious disease that has claimed the lives of over 230,000 people worldwide as of the end of April 2020, infecting over 4 million people. The results are usually available in a day or two, which raises the risk of disease spreaders owing to the delay in diagnosis. As a consequence, a rapid screening technique based on current technology, such as X-Rays and computed tomography scans, can help to reduce the burden of mass diagnostic

testing. As a result, a lightweight model is critical since it allows the model to be deployed on a variety of platforms. The proposed model uses a 14-layer convolutional neural network with a modified spatial pyramid pooling module to recognise COVID-19 illness at different severity levels. The suggested SPP-COVID-Net gets the best mean accuracy of 0.946 with the lowest standard deviation among the training folds accuracy, according to the performance findings.

Conclusion: As a necessary consequence, the recommended SPP-COVID-Net has a reasonable mean accuracy when compared to the benchmarked techniques. In terms of training resilience, it is the most stable approach, with lowest accuracy volatility among cross-validation folds that provide accuracy values between [0.938,0.957]. SPP-COVID-strength Net's capacity to manage multiscale features is due to the SPP module integration. The approach described is beneficial for mobile phone apps that can speed up the COVID-19 sickness screening process [2].

### 3. Classification of COVID-19 from Chest X-ray images using Deep Convolutional Neural Networks

The COVID-19 epidemic continues to have a terrible impact on the worldwide population's health and well-being. A successful screening of infected individuals is a critical step in the fight against COVID-19, with radiological imaging employing chest radiography being one of the most important screening methods. The goal of this study was to use deep convolutional neural networks to recognize COVID-19 pneumonia patients using digital chest X-Ray pictures while optimizing detection accuracy (DCNN). There are 864 COVID19 photos, 1345 viral pneumonia images, and 1341 normal chest X-ray images in the collection. In this work, a DCNN-based model called Inception V3 with transfer learning was developed for detecting coronavirus pneumonia infected patients using chest X-ray radiographs, with a classification accuracy of above 98 percent (training accuracy of 97 percent and validation accuracy of 93 percent ). The findings reveal that transfer learning for COVID-19 detection is successful, has a stable performance, and is a simple to use method.

Conclusion: It is critical to anticipate COVID-19 individuals early in order to prevent the disease from spreading to other people. In this article, we suggested a deep transfer learning-based technique for automated diagnosis of COVID-19 pneumonia using chest X-ray

pictures taken from COVID-19 patients, normal and viral pneumonia. COVID-19 was detected with greater than 98 percent accuracy using the suggested classification model. Due to its great overall performance, it is widely assumed that it would assist medical physicians in making scientific practice judgments. COVID-19 was discovered at an early stage utilizing Automated Detection of Covid19 using X-ray pictures. COVID-19 is a virus that has been discovered [3].

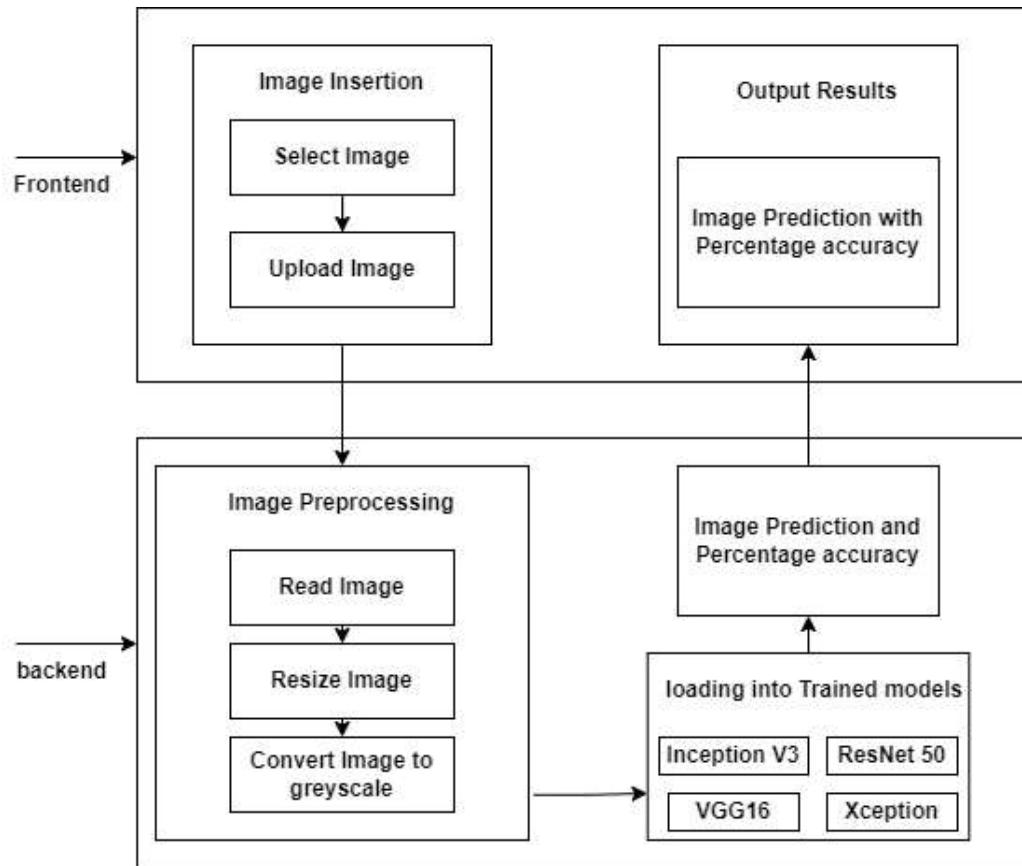
## **CHAPTER 4**

### **PROJECT DESCRIPTION**

# CHAPTER 4 PROJECT DESCRIPTION

## 4.1. PROPOSED DESIGN

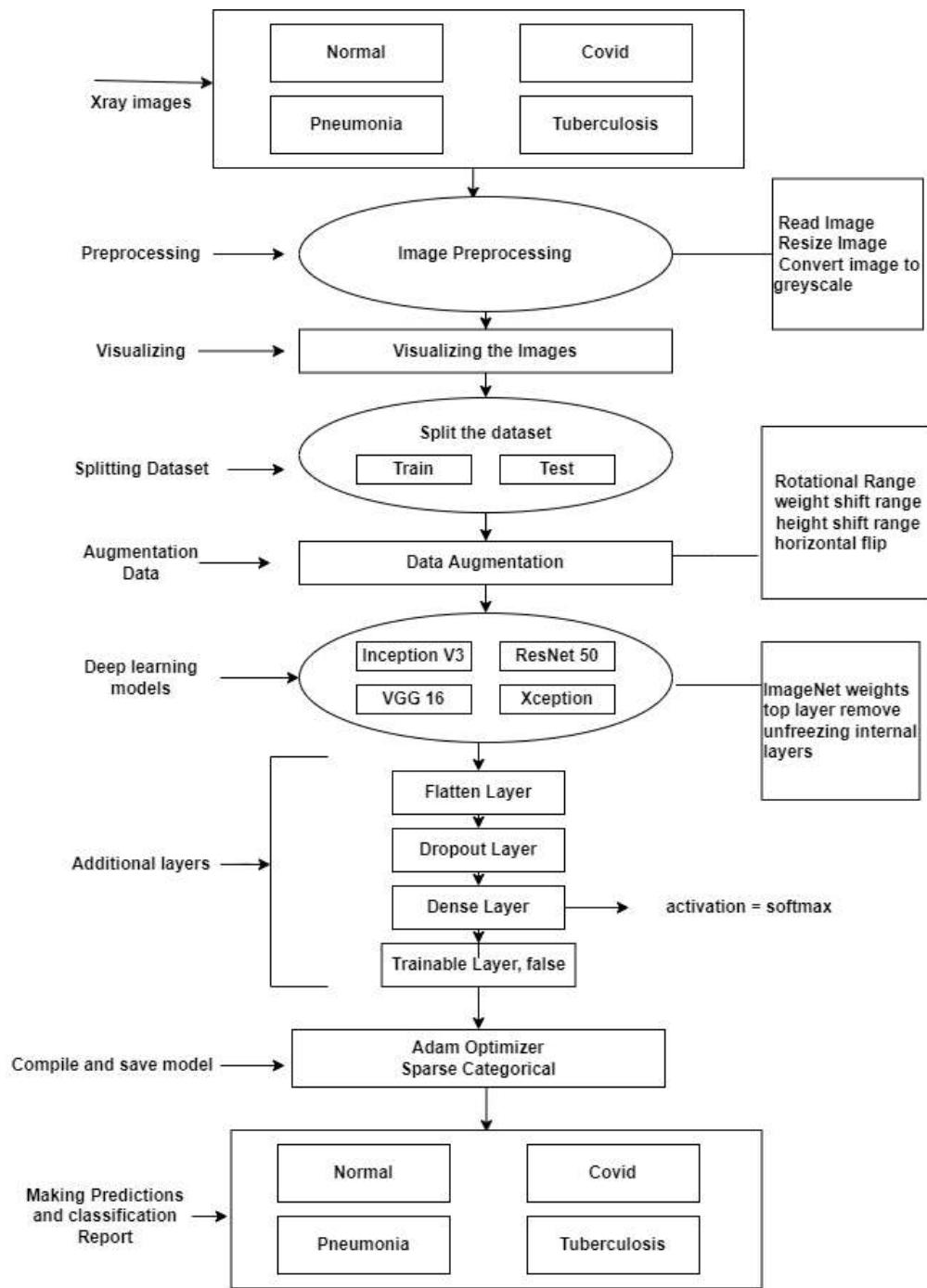
### 4.1.1 Design Architecture



**Fig. 4.1.1 Design Architecture**

As shown in fig. 4.1.1, We can select the image and upload it in the system and then the Image Preprocessing will occur at the backend. Preprocessed images will be loaded into the trained model and image prediction and accuracy percentage will be calculated. Output results with accuracy will be displayed on the frontend.

#### 4.1.2 Model Architecture And Flow Diagram



**Fig. 4.1.2 Model Flow Diagram**

As shown in above fig. 4.1.2, which gives a detailed view of the project . The initial step of the project starts by collecting the chest X-ray dataset of Covid,Pneumonia,Tuberculosis and

normal from the kaggel website. Data preprocessing is applied on the dataset to read and resize the image, then visualization is applied on the preprocessed images . Now, the images are split into a training set and testing set on which data augmentation is performed and the we train images by using various deep learning models like resnet50,vgg19,xception,inception v3 by adding additional layers and with parameters to increase its accuracy.The final step of the model will classify and detect the various diseases .

## **4.2 ASSUMPTIONS AND DEPENDENCIES**

1. Assumed to use Deep learning to train our model.
2. Intended to use the data set that is taken from the kaggel.
3. Presumed to use Jupyter notebook as our platform.

## **CHAPTER 5**

## **REQUIREMENTS**

## CHAPTER 5 REQUIREMENTS

### 5.1 FUNCTIONAL REQUIREMENTS

Useful requirements describe the product's internal activities, that is the technical subtleties, monitoring and handling of data and other specific functionality demonstrating how to satisfy the use cases. They are upheld by non-utilitarian prerequisites that force the plan or execution of imperatives.

1. System should process the data.
2. System should augment the X-Ray image.
3. System should detect the Lung X-Ray.
4. System should predict and classify the lung X-Ray as COVID or Pneumonia or Tuberculosis or Normal chest X-Ray.

### 5.2 NON FUNCTIONAL REQUIREMENTS

The architecture should be built in such a way that additional modules and features can be added, allowing for application development. The cost should be low because programming packages are freely available.

1. Usability : System should be User Friendly.
2. Reliability : System should be Reliable.
3. Performance : System Should not take excess time in detecting Covid and other lung diseases X-rays .
4. Supportability : System should be easily updatable for future enhancement.

## 5.3 SOFTWARE AND HARDWARE REQUIREMENTS

### 5.3.1 Hardware Requirements

**Table 5.3.1 Hardware Requirements**

System Pentium	IV 2.4 GHz/intel i3/ i4.
Hard Disk	40 GB
RAM	512 Mb Minimum

### 5.3.2 Software Requirements

**Table 5.3.2 Software Requirements**

Operating System	Windows 11
Programming Language	Python,HTML,CSS
Platform	Jupyter Notebook, Visual Studio Code

## **CHAPTER 6**

## **METHODOLOGY**

## CHAPTER 6 METHODOLOGY

### 6.1 COLLECTION OF DATASET

We need multiple chest X-ray photographs for this research because we're trying to forecast covid illness just from chest X-ray images. Our model has been trained on proven covid-19 infected and other normal x-rays for covid prediction, as well as pneumonia and tuberculosis, so it can distinguish between them and forecast them all differently. These datasets are available on the internet as a collection. The gathered chest X-ray dataset comprises 471 covid pictures, 523 normal photos, 437 pneumonia images, and 589 TB images, with 80 percent of the images being used for training and 20 percent being used for testing. The X-rays are obtained from the Kaggle website, and keras libraries are imported into the code.

### 6.2 TRANSFER LEARNING

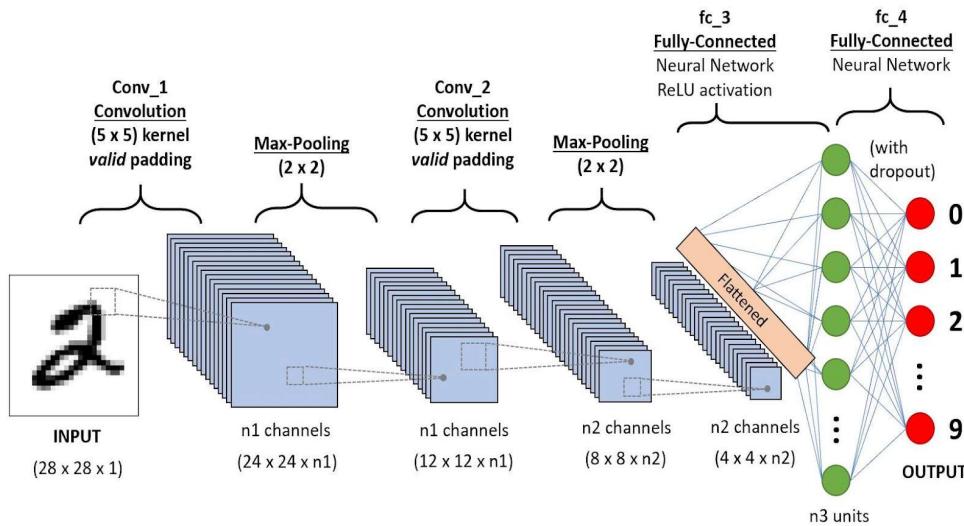
Transfer Learning is a kind of deep learning that allows us to apply previously learned skills and knowledge to new learning or challenge circumstances. Because it allows you to train deep neural networks with relatively little input, it's a popular deep learning method. To train a neural network from the start, a lot of data is usually required, but access to that data isn't always feasible. This is when transfer learning comes in handy. Because the model has been pre-trained, transfer learning can produce an effective deep learning model with less training data. Convolution Neural Networks (CNN) are trained on datasets before being used to analyze fresh sets of pictures and extract features in transfer learning. We employ transfer learning to leverage CNN with these models and assess methods for picture classification and object recognition in medical contexts.

#### 6.2.1 Initialization

- Add first layer (Convolution 2D): We use 64 output filters in the convolution  $3 \times 3$  filter matrix that will multiply to input RGB size image  $64 \times 64$  and use activation relu.
- Apply (MaxPooling2D), Processing, Hidden Layer 1 ( $2 \times 2$  matrix rotates, tilts) to all the images. Step 1 and 2 are repeated twice.
- Adding Flattening: converts the matrix in a single array.

- Adding full connection (128 final layer of outputs, activation=relu & Dense layer, activation=sigmoid).

Below, Fig 6.2.1 gives a detailed view of the Deep Learning architecture



**Fig 6.2.1. The layer of Deep Learning architecture**

## 6.2.2 Performance metrics

To evaluate the performance of the proposed approach, the metrics adopted are classification accuracy, sensitivity and F1-score, measured as follows:

$$\text{Classification accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1 Score} = \frac{2 \times \text{sensitivity} \times \text{precision}}{\text{sensitivity} + \text{precision}}$$

where TP stands for True Positive, FP for False Positive, FN for False Negative and TN for True Negative. In a confusion matrix, the Covid-19 +ve cases that are correctly classified by the model are termed as True Positive and incorrectly classified as Covid -ve are termed as False Positive. Similarly, Covid -ve subjects classified correctly are termed as True Negative and incorrectly classified as Covid +ve are termed as False Negative.

## 6.3 MODULES

### 1 Data Preprocessing

It's one of the most crucial steps in cleaning the data and preparing it for the model. Images of covid-19,normal,pneumonia, and tuberculosis chest X-Rays are taken from the dataset and resized to 224 x 224 pixels before being color transformed from RGB to grayscale.

### 2 Visualization from dataset

The first 40 photos from the dataset of covid-19,normal,pneumonia, and tuberculosis chest x-rays are selected for display and given titles.

### 3 Normalization

Since the model uses a pixel array to take images As a consequence, we'll normalize it and convert it to an array. For improved performance and accuracy, the model is batch normalized, in which the images from the dataset are separated into batches of size 'n' and trained independently.

### 4 Training and Testing

The images of the covid-19,normal,pneumonia, and tuberculosis chest x-rays dataset are split in the ratio of 80:20 for the chosen model in the project. Where 80 percent of the images are utilized for training and 20% are used for testing.

### 5 Building a Model

In our project , we have trained our images on various deep learning models like VGG19, Inception v3, Xception and Resnet50 but out of all the models VGG19 has given good accuracy of 97% for covid-19 , 91% for normal , 83% for pneumonia and 89% for tuberculosis .

### 6 Data Augmentation

Improving model prediction accuracy by reducing data overfitting so we have defined methods like rotation , width shift , height shift and horizontal flip.

## **7 Plotting ROC Curve**

Plotting ROC curve, that is the characteristic curve for the given prediction of covid-19,normal,pneumonia, and tuberculosis chest x-rays. The graph is plotted between True positive rate in Y-axis and False positive rate in X-axis.

## **8 Plotting Confusion Matrix**

The confusion matrix is plotted for two kinds of data where , the first one is the Confusion Matrix without Normalization and the other is the Confusion Matrix with Normalized Values. where , it is plotted between True label in Y-axis and Predicted label in X-axis .

## **9 Model Accuracy and Model Loss**

Model accuracy and model loss are plotted for testing and training data . Here, for model accuracy the Y-axis is given by accuracy and X-axis is given by epoch and in the same way for model loss graph the Y-axis is defined by loss and X-axis is defined by epoch .

## **CHAPTER 7**

## **EXPERIMENTATION**

# CHAPTER 7 EXPERIMENTATION

## 7.1 DATA PREPROCESSING

```
● ● ●

covid_labels = []
normal_labels = []
pnuemonia_labels = []
tuberculosis_labels = []

covid_images=[]
normal_images=[]
pnuemonia_images=[]
tuberculosis_images=[]

import cv2

for i in range(len(covid_files)):
    image = cv2.imread(covid_files[i])
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image,(224,224))
    covid_images.append(image)
    covid_labels.append(0)

for i in range(len(normal_files)):
    image = cv2.imread(normal_files[i])
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image,(224,224))
    normal_images.append(image)
    normal_labels.append(1)

for i in range(len(pnuemonia_files)):
    image = cv2.imread(pnuemonia_files[i])
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image,(224,224))
    pnuemonia_images.append(image)
    pnuemonia_labels.append(2)

for i in range(len(tuberculosis_files)):
    image = cv2.imread(tuberculosis_files[i])
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image,(224,224))
    tuberculosis_images.append(image)
    tuberculosis_labels.append(3)
```

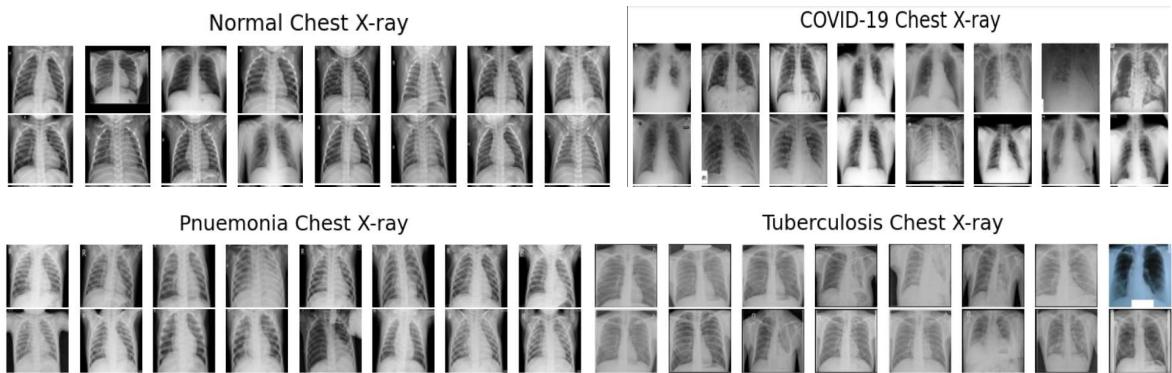
## 7.2 VISUALIZING FIRST 40 IMAGES

```
● ● ●

def plot_images(images, title):
    nrows, ncols = 5, 8
    figsize = [10, 6]
    fig, ax = plt.subplots(nrows=nrows, ncols=ncols, figsize=figsize, facecolor=(1, 1, 1))
    for i, axi in enumerate(ax.flat):
        axi.imshow(images[i])
        axi.set_axis_off()

    plt.suptitle(title, fontsize=24)
    plt.tight_layout(pad=0.2, rect=[0, 0, 1, 0.9])
    plt.show()

plot_images(covid_images, 'COVID-19 Chest X-ray')
plot_images(normal_images, 'Normal Chest X-ray')
plot_images(pnuemonia_images, 'Pneumonia Chest X-ray')
plot_images(tuberculosis_images, 'Tuberculosis Chest X-ray')
```



## 7.3 MODEL BUILDING AND MODEL SUMMARY

```
● ● ●

from tensorflow.keras.applications import VGG19
vggModel = VGG19(weights="imagenet", include_top=False,
    input_tensor=Input(shape=(224, 224, 3)))
outputs = vggModel.output
outputs = Flatten(name="flatten")(outputs)
outputs = Dropout(0.5)(outputs)
outputs = Dense(4, activation="softmax")(outputs)
model = Model(inputs=vggModel.input, outputs=outputs)
for layer in vggModel.layers:
    layer.trainable = False
model.compile(
    loss='sparse_categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy'])
train_aug = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    horizontal_flip=True)
```

## 7.4 TRAINING OF MODEL

```
● ● ●

history = model.fit(train_aug.flow(X_train, y_train, batch_size=32),
    validation_data=(X_test, y_test),
    validation_steps=len(X_test) / 32,
    steps_per_epoch=len(X_train) / 32,
    epochs=10, )
```

## 7.5 MAKE PREDICTIONS

```
● ● ●

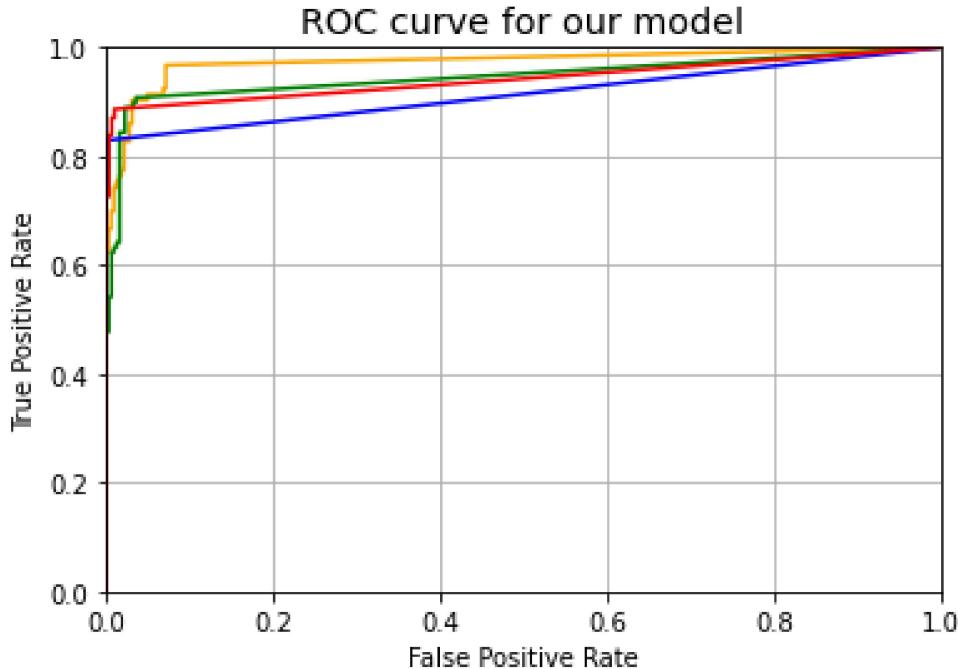
y_pred = model.predict(X_test, batch_size=batch_size)
```

## **CHAPTER 8**

### **TESTING AND RESULTS**

## CHAPTER 8 TESTING AND RESULTS

### 8.1 ROC CURVE

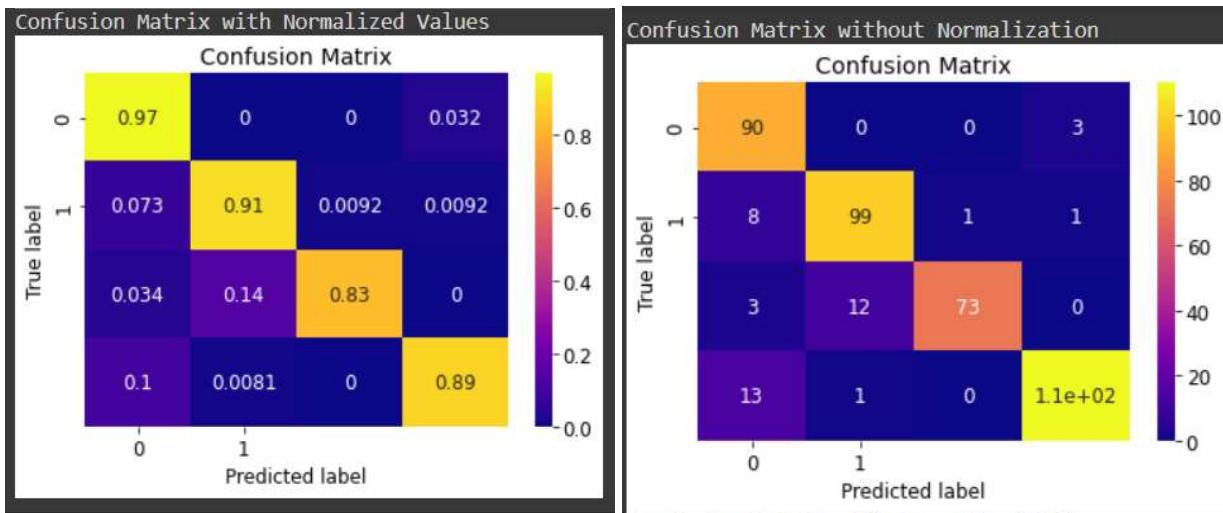


**Fig. 8.1 ROC curve of the model**

Plotting ROC characteristic curve for the given prediction of COVID-19, normal, pneumonia, and tuberculosis chest x-rays. The graph is plotted between TPR in Y-axis and FPR in X-axis.

### 8.2 CONFUSION MATRIX

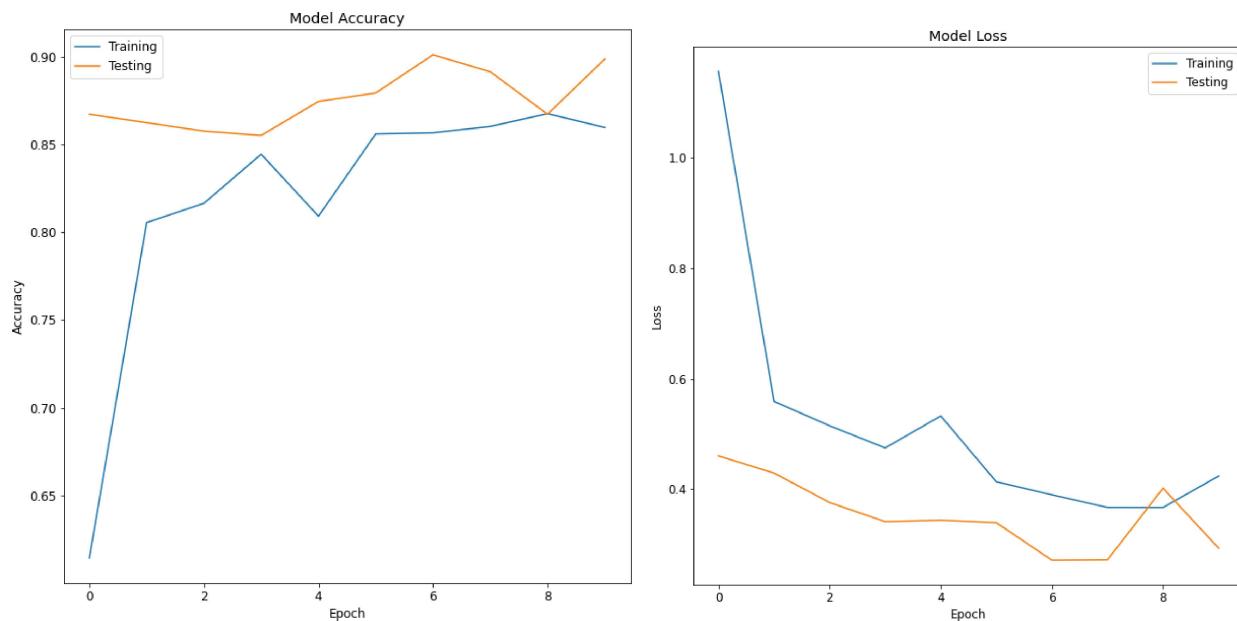
The confusion matrix is plotted for two kinds of data where , the first one is the Confusion Matrix without Normalization and the other is the Confusion Matrix with Normalized Values. where , it is plotted between True label in Y-axis and Predicted label in X-axis .



**Fig. 8.2 (a) Confusion Matrix with Normalized Values (b) Confusion Matrix without Normalized Values**

### 8.3 MODEL ACCURACY AND MODEL LOSS

Model accuracy and model loss are plotted for testing and training data. Here, for model accuracy the Y-axis is given by accuracy and X-axis is given by epoch and in the same way for model loss graph the Y-axis is defined by loss and X-axis is defined by epoch.



**Fig. 8.3 (a) Model Accuracy (b) Model Loss**

## **CHAPTER 9**

### **CONCLUSION AND FUTURE WORK**

## CHAPTER 9 CONCLUSION AND FUTURE WORK

The COVID-19 outbreak has undoubtedly endangered human life. The healthcare system is being strained as a result of measures to contain the disease's spread. The cost of testing for the existence of the virus is high, and it may not be sufficient to reach a broader population. Deep learning algorithms have shown to be an effective technique for sifting enormous volumes of data. This project is successfully able to detect and classify the Lung X-Rays as COVID-19, Pneumonia, Tuberculosis and Normal chest X-Ray. Deep Learning models such as VGG19, ResNet50, InceptionV3 and Xception has been utilized in the healthcare industry to screen for and detect the presence of COVID-19 and other lung diseases from chest X-rays. The VGG19 model correctly identified and classified COVID-19 chest X-rays from other types of chest abnormalities, where it was given 97.0 percent for covid-19, 91 percent for normal, 83 percent for pneumonia and 89 percent for tuberculosis .

Our key objective for the future is to train this model on a huge trustable data set so that we can train it properly and therefore raise the accuracy, as training the deep learning on more data results in the model being much better on invisible data shuts off. This may also be improved to forecast the chance of the affected person surviving. And we would also like to include lung diseases such as bronchitis in our future work so that one model can be used for detection and classification of various lung diseases with better accuracy and performance.

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## APPENDIX A

### VGG MODEL

VGG- Network is a convolutional neural network model proposed by K. Simonyan and A. Zisserman in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition”. It is one of the famous architectures in the deep learning field. Replacing large kernel-sized filters with 11 and 5 in the first and second layer respectively showed improvement over AlexNet architecture, with multiple  $3 \times 3$  kernel-sized filters one after another. It was trained for weeks and was using the NVIDIA Titan Black GPU. The input to the convolution neural network is a fixed-size  $224 \times 224$  RGB image. The only preprocessing it does is subtracting the mean RGB values, which are computed on the training dataset, from each pixel. Then the image is running through a stack of convolutional (Conv.) layers, where there are filters with a very small receptive field that is  $3 \times 3$ , which is the smallest size to capture the notion of left/right, up/down, and center part.

## PUBLISHING PAPER DETAILS

Paper has been published in the **International Research Journal of Engineering and Technology (IRJET)**.

Paper Title : DETECTION OF COVID-19 FROM CHEST X-RAYS

e-ISSN: 2395-0056

p-ISSN: 2395-0072

Date of Publishing : May 2022

## Detection Of Covid-19 From Chest X-Rays

Nikhita A<sup>1</sup>, Pavana M<sup>2</sup>, Pavithra H A<sup>3</sup>, Rutuja Lattimarde<sup>4</sup>, Karishma Chavan<sup>5</sup>

<sup>1,2,3,4</sup>Dept. of Computer Science and Engineering, Dayananda Sagar University, Bangalore, Karnataka, India

<sup>5</sup>Assistant Professor, Dept. of Computer Science and Engineering, Dayananda Sagar University, Karnataka, India

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**Abstract** - The coronavirus (COVID-19) outbreak remains impacting the fitness or wellbeing of the worldwide population, with an excessive price of transmission affecting tens of thousands and thousands of people. In maximum situations, strategies utilized in pathogen laboratories, which include polymerase chain reaction (PCR), take greater time and regularly produce fake poor results, however are the usual strategies for diagnosis. Therefore, there may be a want for quicker and greater correct diagnostic strategies to locate early-level COVID-19 instances to forestall and combat the unfolding of the pandemic. The speedy screening process, primarily based totally on current technology which include X-rays and computed tomography scans, can assist lessen the quantity of labor concerned in big diagnostic tests. A chest X-ray is one of the handiest approaches to diagnose a pneumonia symptom, that's the primary symptom of COVID-19.

This paper aims to propose a model for detecting COVID-19 effectively utilizing digital chest x-ray images with the highest level of accuracy in detection and classifying the images by using Inception V3 method and DNN.

**Key Words:** COVID-19, Convolutional Neural Network, Deep Learning, Inception V3, Deep Neural Network

### 1. INTRODUCTION

Coronavirus (COVID-19) disease is a virus-borne infectious disease. The World Health Organization (WHO) labeled it a pandemic on March 11, 2020, due to its global expansion and its frightening velocity at which the disease spreads and the intensity with which it is manifested. Authorities in a lot of countries have established peripheral limitations, flight restrictions, home quarantine, social isolation, and increased cleanliness awareness. The virus, on the other hand, continues to spread at a quick speed. The majority of the patients infected with COVID-19 developed mild to moderate respiratory illness, but a few people suffered from life-threatening pneumonia.

The following are some of the major issues with current methods for identifying COVID-19 patients.

1. Healthcare providers must obtain respiratory tract samples. Nasopharyngeal swab collection is a typical procedure that requires the nurse to be in close proximity

to the patient [6]. Cross infection may become more likely as a result of this.

2. The WHO-recommended RT-PCR kits for testing COVID cases are expensive, and the number of kits available in underdeveloped countries is insufficient to test the huge population. As a result, establishing cost-effective testing methods is required [7].

3. The sensitivity of fast antigen testing is not high enough to be utilized alone for first screening [8].

4. A delay in receiving the test result will cause a delay in tracking the afflicted individual's connections with another healthy person.

It has already been stated that obligatory patient screening and rapid clinical response for contaminated patients are crucial in preventing the spread of COVID-19 disease. The Reverse Transcription Polymerase Chain Response (RT-PCR) test is the highest quality level testing approach used for assessing COVID-19 patients. Although it is the most commonly used technique for COVID-19 identification, it is a difficult, time-consuming process and sometimes it gives false negative test results. Additional COVID-19 diagnostic approaches include clinical symptom evaluation, epidemiologic record, affirmative radiographic screening (CT)/(CXR), and positive pathogenic testing [4]. Due to a paucity of testing kits, it will be hard to examine every patient with a respiratory illness using routine techniques (RT PCR), X-rays were the first technology to play a significant role in COVID-19 illness diagnosis. Chest X-rays and computerized tomography (CT) imaging are considered viable screening methods because of their sensitivity and speed [2]. Chest X-rays might yield more accurate results than existing techniques.

Many biological problems (for example, detection of breast cancer, identification of brain tumor, and so on) are now being addressed with Solutions that are based on artificial intelligence (AI). Image features that were not included in the original photos can be revealed using a variety of Deep learning methods [4]. Convolutional Neural Networks (CNN) in particular have been shown to be extremely effective in the extraction and learning of data, and as a result, they have earned universal support among scientists. In low-light images from a high-speed video endoscopy, CNN was used to improve image quality and to distinguish the idea of aspiratory knobs using CT

images. The goal of this study is to use chest X-ray pictures to identify and classify Covid-19 disease, healthy people, and pneumonia patients.

## 2. LITERATURE REVIEW

In the paper "COVID19 detection using transfer learning and convolutional neural networks". To detect COVID19, the concept of deep learning of transfer learning is provided. Chest x-ray analysis to assess lung disease, compared to the total number of affected people, has become an essential technique for both diagnosis and prognosis of COVID 19 patients in the current situation. This study describes a metastatic learning (CNN) technique for detecting COVID 19 infections in X-ray images. A multivariate Neural network model (CNN) with Transfer learning approach Inception V3 has been created in the proposed model. It uses convolution and pooling to extract features in the same manner as CNN does, except this transfer learning model contains weights from the ImageNet dataset. As a result, it can recognize characteristics rather successfully, providing it an advantage in terms of accuracy. This model highlights how computer vision has the potential to change radiological image analysis. The recommended model performs well with a small dataset, with a validation accuracy of eighty four percent compared to seventy one percent for the InceptionV3 model. This model also surpasses all prior CT scan-based models.

COVID-19 victims must be discovered as soon as avert the infection from spreading. Inception V3 with transfer learning, a DCNN-based model for the diagnosis of coronavirus pneumonia patients using chest X-ray radiographs, was created in 2020, with a classification accuracy of more than ninety eight percent. Transfer learning was found to be an effective, robust, and easily deployable technique for COVID-19 identification. By quickly training itself from a smaller number of photos, the Inception V3 model works brilliantly in identifying COVID-19 pneumonia. Researchers believe that using this computer-aided diagnosis approach will increase the speed and accuracy of diagnosing COVID-19 patients significantly. [4].

According to the study detection of Covid chest Xray based on Multi-Level Thresholding and Support Vector Machine, published in 2020, the early detection of SARS-CoV-2, is currently a serious problem for clinical practitioners. The proposed method is widely recommended for using X-ray images to detect COVID-19 infected people. The assist vector device identifies corona-affected X-ray images from others by utilizing deep characteristics. The proposed multi-level thresholding using SVM technique shown high precision in characterizing the affected lung with Covid-19. The pictures were all the same size and format, JPEG with a

resolution of 512 \* 512 pixels. The average sensitivity, specificity, and accuracy were ninety-five, ninety-nine, and ninety seven percent, respectively [9].

A lung X-ray is one of the most effective methods for detecting pneumonia, the most significant symptom of COVID-19. As a result, a minimalist model is essential since it enables the model to function on a number of services, including cell devices and conventional PCs, independent of flash volumes. To diagnose COVID-19 illness at various levels of severity, the proposed model employs fourteen layers of convolutional layers and a redesigned spatial pyramid pooling module. The proposed SPP-COVID-Net seems to have the highest accuracy correctness of 0.946 and the smallest mean error among the training layers accuracy, according to the performance data. It's perfect for quick results.[9].

## 3. METHODOLOGY

### 3.1 Chest X-Ray Image Datasets

In most cases, the ranges of symptoms of pneumonia and the Covid-19 virus are the same. Both are infections of the lungs. Hence, the dataset consists of three separate datasets of X-rays of the chest (COVID-19 patients, normal people, and pneumonia patients). There are 300 photos in all (100 COVID-19 images, 100 pneumonia images and 100 healthy images). After that, the datasets are divided into two sections: training and testing the classifiers. Fig 1,2,3 shows an example of chest X-ray image collections.



Fig. 1. COVID chest X-Ray images



Fig. 2. PNEUMONIA chest X-Ray images



Fig. 3. NORMAL chest X-Ray images

### 3.2 Transfer Learning Approach

Transfer Learning is a kind of deep learning that allows us to apply previously learned skills and knowledge to new learning or challenge circumstances. Because it allows you to train deep neural networks with relatively

little input, it's a popular deep learning method. To train a neural network from the start, a lot of data is usually required, but access to that data isn't always feasible. This is when transfer learning comes in handy.

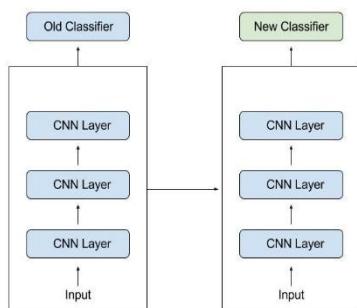


Fig. 4. Transfer Learning

Because the model has been pre-trained, transfer learning can produce an effective deep learning model with less training data. Fig 4 shows the working of transfer learning approach.

Shorter training timeframes, improved neural network performance in most circumstances, and the elimination of a large amount of data are few of the advantages of transfer learning. This is particularly valuable in the field of medicine because most medical cases do not have most of the labeled data in the initial days. For example, COVID-19, for example, is an illness that has only recently been found. As a result, the covid chest image sample is insufficient. To detect this ailment, a transfer learning model was applied. In this situation, Inception V3 can be used to provide results with a smaller training dataset. It is always preferable to develop a deep learning model on top of a foundation of an established and tested model rather than starting from scratch [14].

In this paper, a two-section deep learning-based neural network model is proposed. The initial component of this is a transfer learning model called Inception V3. second part of this network is a customized deep neural network (DNN) layer, while the

### 3.2.1) Inception V3:

The Inception family's Inception-V3 is a convolutional neural network. that includes factorized  $7 \times 7$  convolutions. You can simply import a pre-trained version of the network from the ImageNet database, which has been trained on over a million photographs. Inception Net was the first CNN classifier to apply precise approaches to assure improved performance while balancing speed and accuracy. The Convolution Layer can be factorized in the Inception-v3 model, lowering the number of parameters while preserving accuracy. It can combine the max-pooling

and convolutional layers, allowing for more effective feature reduction [13].

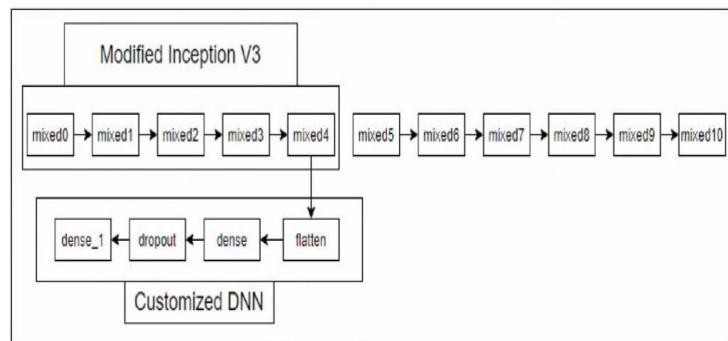


Fig. 5. Neural Network Model Structure [13]

The model has the advantage of allowing output to be extracted from any concatenated node. There are 11 of them, and they're called mixed layers. Total number of layers in order to enhance the model's effectiveness, the model's general structure was changed as a result of the experiment. Fig.5 shows how to use only four of them. Otherwise, it's possible due to our limited dataset causing overfitting.

### 3.2.2) DNN Model:

The model's final layers were replaced with a DNN that extracted the output using four customized layers, flatten to convert the mixed layer output to a one-dimensional array, and a dense layer of 1024 layers. The following layer was utilized to drop out 20% of the neurons. Finally, a dense 1 layer with sigmoid activation function of 1 neuron was employed [13].

## 3.3 Performance metrics

Class accuracy, sensitivity, and F1-score are the measures used to evaluate the overall efficiency of the suggested technique, and they are determined as follows.:

$$\text{Classification accuracy} = \frac{\text{TP} + \text{T N}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1 Score} = \frac{2 \times \text{S} \times \text{P}}{\text{S} + \text{P}}$$

Where, TP denotes True Positive, FP denotes False Positive, FN is False Negative, and Volunteer State denotes True Negative, with S denoting sensitivity and P denoting accuracy. We will draw a confusion matrix for the model, if the model gives a correct classification for Covid positive cases then it is correct positive and misclassified Covid negative cases then it is correct negative. Similarly, true negative participants are accurately identified as Covid

negative, while false negative subjects are wrongly labeled as Covid positive.

### 3.4 Experimentation

Our Inception V3 model performs admirably and accurately predicts Covid-19. To that goal, we conducted a number of trials. These experiments and their outcomes are described in the following sections:

#### 3.4.1) Dataset

We had given chest x-rays as input for our model, where we split the dataset into an 8:2 ratio, with 80% of the images reserved for training purposes and 20% of the images for testing purposes. By default, all set of data photos are downsized to the (224,224) image size.

#### 3.4.2) Feature Extraction

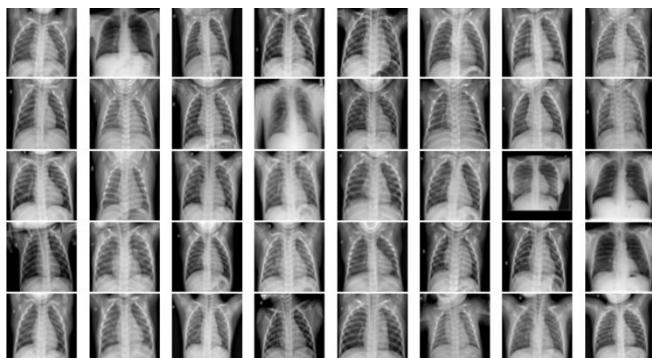


Fig. 6. Feature extraction in inception v3 from chest x-ray

For the feature extraction component of Inception v3, the layers from the input layer to the last max pooling layer are taken into account [10]. Figure 6 depicts the process of inception v3 extracting features from photos.

#### 3.4.3) Hyperparameter Tuning

To encourage a stable model, the parameter settings have been fine-tuned. The learning rate, optimizer selection, loss functions, dynamic epoch variation, stack size, inspect dimensions, rotations span, and other parameters are all changed. We tried a variety of other optimizers and loss functions, but none had a substantial influence on the model's performance, so we stuck with Adam as the optimizer and the binary cross entropy as the loss function throughout the model. The number of epochs is defined by the number of times the model is applied to coaching data, and the batch size is determined by the number of samples in the network. Dropout could be a regularization strategy that requires training while ignoring certain random neurons. In most cases, increased dropout will improve accuracy [10].

## 4. RESULTS

Initial Random callbacks were used to train all of the models for 50 epochs. The Adam optimizer, which is a mix of SGD with momentum and RMSProp, is used for quicker parameter determination.

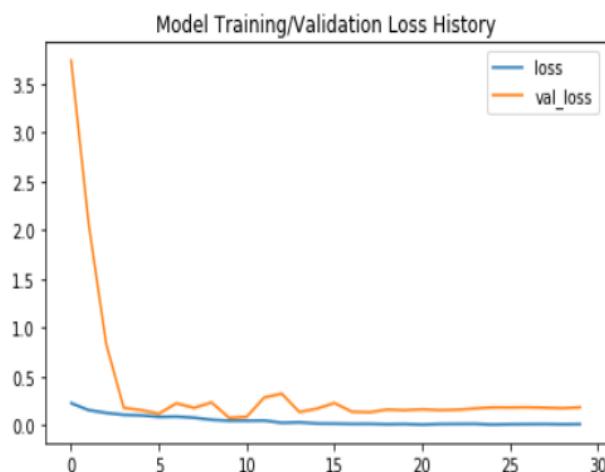


Fig. 7. Training and validation loss of Inceptionv3

C	<b>0.906</b>	0.03	0.064
N	0.07	<b>0.82</b>	0.11
P	0.024	0.15	<b>0.826</b>
	C	N	P

Fig. 8. Confusion Matrix

For the inception v3 model, model training takes 19 seconds each epoch. For the inception v3 model, the gradual change in loss (both training and validation/testing) during epoch was depicted in Fig.7. This shows that during training the models, Inceptionv3 has the lowest loss.

Figure 8 depicts the confusion matrix for the behavior of several trained models over various layers where C is Covid, P is Pneumonia, and N is normal chest Xrays. The suggested inception v3 model produces the most accurate results even while being one of the best, with significant

true positive and true negative counts for all COVID +ve and COVID -ve pictures.

## 5. CONCLUSIONS

The COVID-19 outbreak has undoubtedly endangered human life. The healthcare system is being strained as a result of measures to contain the disease's spread. The cost of testing for the existence of the virus is high, and it may not be sufficient to reach a broader population. Deep learning algorithms have shown to be an effective technique for sifting enormous volumes of data. The purpose of this study was to demonstrate that deep learning techniques might be utilised to identify COVID-19 infection. Deep neural network (DNN) models, according to the study's findings, can be utilised in the healthcare industry to screen for and detect the presence of COVID-19 in chest X-rays. Transfer learning has been demonstrated to improve the model's learning ability. The model Inception V3 with DNN correctly identified and classified COVID-19 chest X-rays with 90.64 percent, whereas from other types of chest abnormalities it was 85.06 percent. This study illustrates that by properly using AI technology, the burden on medical institutions may be reduced. Because no physical exams are required of doctors or patients at the screening level, the use of this technology minimizes the danger of disease dissemination while increasing the number of cases.

## 6. FUTURE WORK

Our key objective for the future is to train this model on a huge trustable data set so that we can train it properly and therefore raise the accuracy, as training the machine learning on more data results in the model being much better on invisible data shuts off. This may also be improved to forecast the chance of the affected person surviving.

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