Project Report
on

X- Ray based Lungs Disease Detection

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Abstract

Recently, image processing techniques are widely used in several medical areas for image improvement in earlier detection and treatment stages, where the time factor is very important to discover the abnormality issues in target images, especially in various diseases, cancers, etc. Using a deep learning (artificial intelligence) method, we have developed a model to detect and categorise a range of lung illnesses from chest X-ray images. Lung diseases include COVID-19, viral pneumonia, bacterial pneumonia, and tuberculosis.For this purpose, various deep learning architectures were used so a comparative analysis is made between Inception Resnet V2, DenseNet 201, Resnet 152V2 and Xception and based on the comparisons Resnet 152V2 came out on top. As a source for training data, we used a combined dataset of various Lungs datasets present on Kaggle. During research a problem arose with dataset images as the number of images were insufficient for training. To populate the dataset data augmentation was done with factor 2 which increased the dataset by 2 times per image.

Table Of Contents

Chapter 1: Introduction	1
Chapter 2: Literature Survey	2
Chapter 3: Problem Statement	7
Chapter 4: Project Description	8
Chapter 5: Implementation Details	14
Chapter 6: Result & Analysis	22
Chapter 7: Conclusional Future Scope	28
References	29
Acknowledgement	31

List Of Figures

Figure 1.1 Resnet 152V2 Architecture	11
Figure 1.2 Flowchart	12
Figure 1.3 Dataset Before Augmentation	16
Figure 1.4 Dataset After Augmentation	16
Figure 1.5 Comparative Training Accuracy Graph	19
Figure 1.6 Comparative Training Loss Graph	19
Figure 1.7 Software Architecture Flowchart	20
Figure 1.8 Resnet 152V2 Training Accuracy Graph	23
Figure 1.9 Resnet 152V2 Training Loss Graph	23
Figure 2.0 First Screen	24
Figure 2.1 Second Screen	25
Figure 2.2 After Classification Screen (Bacterial Pneumonia)	25
Figure 2.3 After Classification Screen (Coronavirus Disease)	26
Figure 2.4 After Classification Screen (Tuberculosis)	26
Figure 2.5 After Classification Screen (Viral Pneumonia)	27
Figure 2.6 After Classification Screen (Normal)	27

List Of Tables

Table 1.1 Literature Survey 6
Table 1.2 Project Functions 13
Table 1.3 Dataset Details 15
Table 1.4 Comparative Analysis on Various Architectures 18

Definitions/Glossary

ML: Machine Learning

AI: Artificial Intelligence

DIP: Digital Image Processing

CNN: Convolutional Neural Network

Chapter 1
Introduction

From the beginning to the present, medical researchers have found lung illnesses to be the most fascinating research area. To address this issue, a system like this can only help reduce the chance of human life being jeopardised by the early detection of malignant growth. Eventually, a few structures are presented, although the vast majority of them are still hypothetical plans. The performance of a neural network model is investigated in the following philosophy to handle the issue of identifying malignant cells in image data, which is a common problem in therapeutic imaging applications.

COVID-19 outbreaks and respiratory symptoms are currently claiming the lives of a large number of people around the world. COVID-19, in particular, which is a pandemic that began spreading in the first quarter of 2020, kills a large number of people. Due to the aforementioned rationale, most countries have attempted to solve and mitigate this outbreak, which includes respiratory disorders. In addition, we have a shortage of medical professionals and equipment to address the disorders. It's a difficult task to use technology to analyse photos for disease detection. In this project, we have used the Resnet 152V2 model to detect and categorise a variety of lung disorders from chest X-ray pictures using a deep learning (artificial intelligence) approach. COVID-19, Viral Pneumonia, Bacterial Pneumonia and Tuberculosis are the lung disorders. We rely on publicly available disease datasets that are quite extensive. Our detection and classification algorithms produce excellent results, with accuracy, precision, recall, and F1-measure ranging from 93% to 95%.

Chapter 2
Literature Survey

SR NO.	Title	Work Done/ Algorithm	Remarks
1	Deep learning to distinguish COVID-19 from other lung infections, pleural diseases and lung tumors.	To distinguish COVID-19 from other respiratory diseases, six different deep learning architectures were used namely AlexNet,ResNet-18 ,ResNet-50,VGG,MobileNet-v2 and DenseNet-121 which consist of eight,eighteen,fifty, sixteen,eight,and hundred and twenty one layers, respectively	The paper aims for several deep learning architectures and medical images to clearly distinguish covid-19 from other respiratory diseases that do have similar symptoms.
2	Deep Learning for Screening COVID-19 using Chest X-Ray Images	The study revolves around using the three most popular CNN models, namely AlexNet,	The paper signifies the concept of Gradient Class Activation Map(Grad-CAM)

		VGGNet and ResNet wherein the layers of each model were to be eight,sixteen and fifty respectively.	for detecting the regions where the model needed to be more accurate during the classification.
3	Lung Cancer Disease Diagnosis Using machine Learning Approach	The proposed work captures the CT scan images and formulate an accurate result to predict the possibilities of the disease at different stages,so the phases are-image processing,image filtering,feature extraction,segmentation edge detection and feature recognition.	In this paper, the profound neural system approach is being utilized to achieve more accurate precision in the discovery of lung malignancy and precisely anticipate stages.
4	Hybrid deep learning for detecting lung diseases from X-ray images	A basic CNN with three layers of ConvLayer is selected as the baseline model and the performance of CapsNet is	This paper comprises the use of the different forms of existing deep learning techniques including

		compared with LeNet and the baseline model onto the dataset.	convolutional neural network(CNN),vanilla neural network,visual geometry group based neural network and capsule network for predicting lung disease.
5	An Uncertainty-Aware Transfer Learning-Based Framework for Covid-19 Diagnosis	The proposed paper comprises four pretrained networks onto the dataset so as to import and adapt the task of covid detection.The networks are VGG16,ResNet50, DenseNet121 and InceptionResNetV2	The paper indulges the result in the form of a linear SVM and multilayer perceptron which outperforms the other methods in the term of medical diagnosis accuracy for both X-ray and CT images.
6	Optimize Transfer Learning for Lung Diseases in Bronchoscopy	In this study,a pre-trained DenseNet model is used as their network architecture where	In this paper,the detection of cancers,TB and normal cases were indicated by the CAD system which

		each layer is directly connected to every other layer in a feed-forward fashion.	had the potential to improve diagnosis and the selective biopsies.
7	Deep learning based diagnosis of Covid-19 using chest CT-scan images.	In this paper,5 fold cross-validation strategy is applied so that the test data is predicted in each fold and after the training the test predictions of each fold are averaged and evaluated against the ground truth.The deep learning architecture used for this study is EfficientNet B4.	This paper focus on the discriminate between the COVID CT-scan images and the normal CT-scan images by defining the different learning rate policies such as reduce plateau,cyclic learning rate and constant learning rate.
8	Fruit Recognition and Grade of Disease Detection using Inception V3 Model.	The proposed work captures the fruit's image and resizes the images into 299x299x3 which is a feed into the inception v3 model as an input. Pre	In this paper, the author has proposed how much percent the fruit is affected and recognize the fruit in the given image. This feature is very useful for

		trained Inception v3 model is mostly used in image recognition and it is a predefined convolutional neural network	the farmers and useful for different purposes. To get better results in the classification and identification of fruit diseases Inception v3 model and Transfer Learning are used.

Table 1.1 Literature Survey

Chapter 3
Problem Statement

In this project we have conducted a study and analysis of our dataset, then applied Deep Learning to predict diseases in Lungs of humans. This software will help detect disease in lungs with ease just by passing the picture(X- Ray) of the lung into the software by uploading the Image. The software will in turn classify the image as either healthy or diseased along with the type of disease. The difficulty is a new dataset, and I will be one of the pioneers to learn it, my analysis is that this is a large dataset but has never been processed full, data has a lot of noise, and X-ray of the lung is not likely to provide enough information to assess whether a patient may be ill also the size of the dataset is not ideal enough to get accurate results so we have to augment it.. We will use Machine Learning as well as Deep Learning to process data as well as create models for diagnosing patients. Our key point here will be: combining the processing of patient information with data from X-rays, using CNN with the well-known pre-trained model, first time using the Resnet 152V2 network for data in this form.

Chapter 4
Project Description

● Project Background

Lung disorders pose a significant threat, particularly in emerging and low-middle-income nations, where millions of people live in poverty and are exposed to pollution. According to WHO estimates, about 4 million people die prematurely each year as a result of diseases caused by household air pollution, such as asthma and pneumonia. As a result, actions must be taken to reduce air pollution and carbon emissions. It's also critical to put in place effective diagnostic technologies that can help diagnose lung problems. A novel coronavirus illness 2019 (COVID-19) has been causing major lung damage and breathing issues since late December 2019. Furthermore, pneumonia, a type of lung disease, can be caused by the COVID-19 causal virus or by another viral or bacterial infection.

As a result, early diagnosis of lung disorders is more critical than ever. For this, machine learning and deep learning can be extremely useful. Digital technology has recently grown in importance around the world. With the use of deep learning methodology, this research report can point doctors and other researchers in the right direction for recognising lung disease. As a dataset, a huge number of X-ray images of the lungs are used. The technique described here can also help to more correctly diagnose diseases, which can safeguard a large number of people and reduce sickness rates. Due to population increase, the health programme has yet to be developed.

● Project Scope

The main aim of this project is to determine the diseased lungs along with their type. To implement this project Deep learning techniques such as Convolutional Neural Network (CNN) and the concept of Transfer learning are implemented for this project. Apart from this a detailed analysis of different architectures of CNN along with their performances have also been investigated in an attempt to determine the optimal architecture for detecting disease in lungs.

● Project Objectives

The objectives of the following project are:

● To have a program that can process images to detect diseases in lungs.

● To have a detailed comparative analysis of different architecture of CNN.

● To understand different concepts of Deep Learning and how to incorporate them to detect diseases in lungs.

● Modules

The primary modules proposed are:

● Upload images.

● Classify images

● Technology

The technologies used are:

● Python (Programming language).

● Google Collab and Pycharm (Code editors).

● Proposed Methodology

Application uses a pre-trained model to predict the possible diseases in lungs. It takes an image as input and uses the dataset used to train the model to classify the type of disease and predict the same. The pre-trained model used is of Resnet 152V2 from the TensorFlow package and Keras sub package. In a Resnet 152V2 model, various techniques for optimizing the network have been used which accounts for easier model adaptation. The techniques consist of factorized convolution, dimension reduction, regularization and parallelized computation. The architecture of the Resnet 152V2 model is built as:

1. Factorized Convolutions: This reduces the number of parameters in the Network and thus helps to reduce computations.

2. Smaller Convolutions: Convolutions of smaller size result in faster training of the model. For example, a 5x5 filter consisting of 25 parameters is replaced to reduce training time by replacing it by 2 3x3 filters thus having only 18 parameters.

3. Asymmetrical Convolutions: A single symmetrical layer is found to be slower than combinations of asymmetrical convolution layers.

4. Auxiliary classifier: An auxiliary classifier is a smaller CNN placed between layers during training, and the loss acquired is included in the main network loss. In Resnet 152V2 an auxiliary classifier acts as a regularizer.

5. Grid Size Reduction: The grid size is reduced towards the end during Pooling operations. Before going through an average pooling layer, the grid size is reduced by adding another filter to increase efficiency of the average pooling layer.

Figure 1.1 Resnet 152V2 Architecture

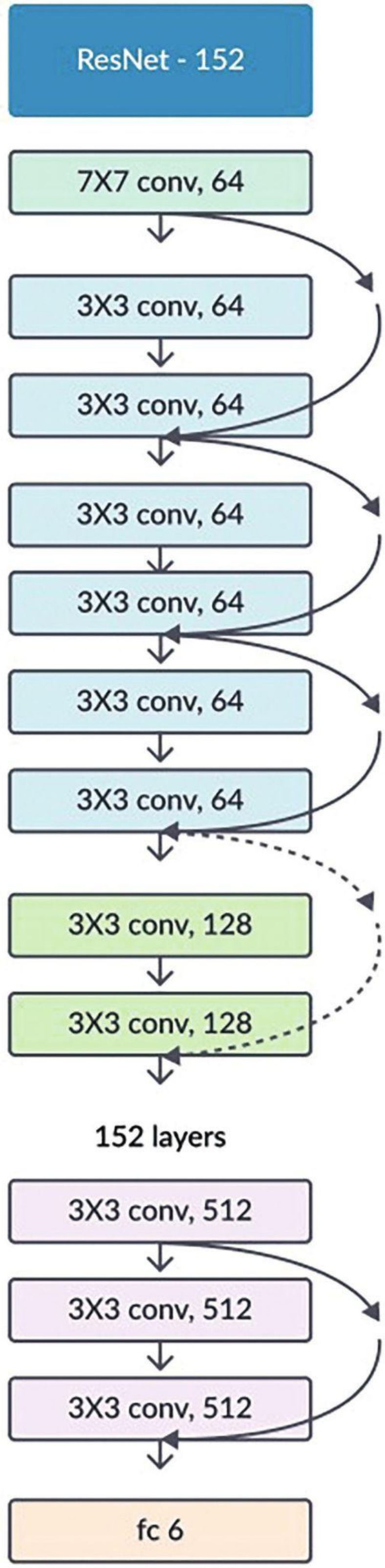

Figure 1.1 Resnet 152V2 Architecture

- **FlowChart**

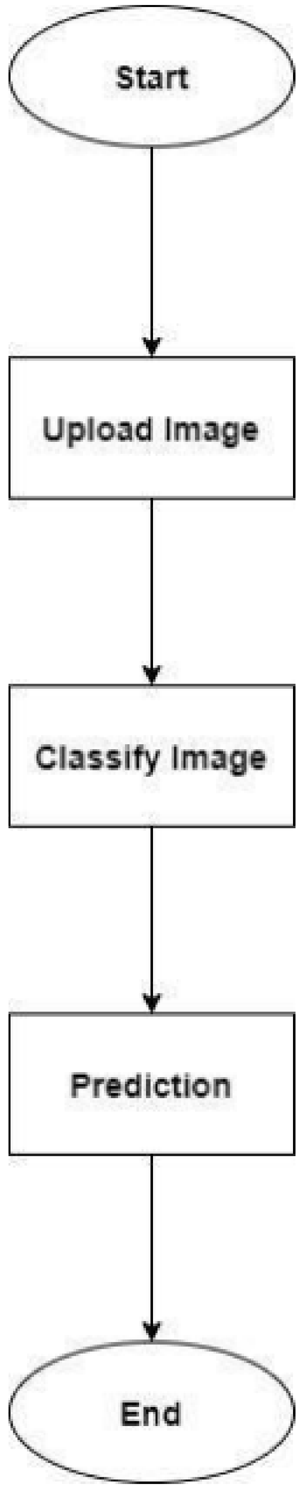

Figure 1.2 Flowchart

- ## Project Functions

FN01	Accepting the Image from the User to the Software.	The Image taken by the user will be passed into the software through the upload button.
FN02	Classifying the Lung Image into its Categories	The lung Image uploaded will be classified by the Trained Model.
FN03	Displaying the result of Classification	The result of classification by the model is passed to the User Interface and displayed.

Table 1.2 Project Functions

- ## General and Design constraints

The major design and implementation constraint has been the platform on which the software would execute. Due to the time constraint the software can only run on any machine having windows. But in the long run an application could be developed by using the trained model.

Chapter 5
Implementation Details

This section defines the implementation details of the entire process i.e., data collection, pre-processing, feature extraction, and the model building. The model will be validated using performance evaluation metrics.

- ## Dataset Collection

The Dataset required for training and testing the models is a combined dataset taken from the following sources:

https://www.kaggle.com/darshan1504/covid19-detection-xray-dataset
https://www.kaggle.com/muhammadrizkyperdana/lungs-dataset
https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
https://www.kaggle.com/jtiptj/chest-xray-pneumoniacovid19tuberculosis?select=train
https://www.kaggle.com/iamsuyogjadhav/chest-x-ray-14-lungs-cropped
https://www.kaggle.com/tawsifurrahman/tuberculosis-tb-chest-xray-dataset

To download our combined dataset, please refer the below link:
https://www.kaggle.com/omkarmanohardalvi/lungs-disease-dataset-4-types

The total images of lungs after combining and removing duplicate images from the above given sources were 7069. Other details related to the images of the dataset are –

- File type: JPEG file
- Dimensions: 300 x 300 pixels
- Horizontal resolution: 96 dpi
- Vertical resolution: 96 dpi

Type	Quantity (Before Augmentation)	Quantity (After Augmentation)
Healthy	1563	2013
Bacterial Pneumonia	1709	2009
Viral Pneumonia	1492	2008
Corona Virus Disease	1625	2031
Tuberculosis	680	2034

Table 1.3 Dataset Details

- ## Dataset Augmentation

Since the dataset is of size 7069, it is not ideal enough to get accurate results. Data Augmentation technique was used to augment images of every category. Images were augmented with a factor of 2 and total images after augmentation were found to be 10095 images. The entire dataset is partitioned into training, testing and validation sets for both healthy and diseases in particular. The sets are partitioned in the ratio of 60% - 20% - 20% (.6.2.2) using the split function Figure 1.3 and Figure 1.4 show illustration of dataset before and after augmentation.

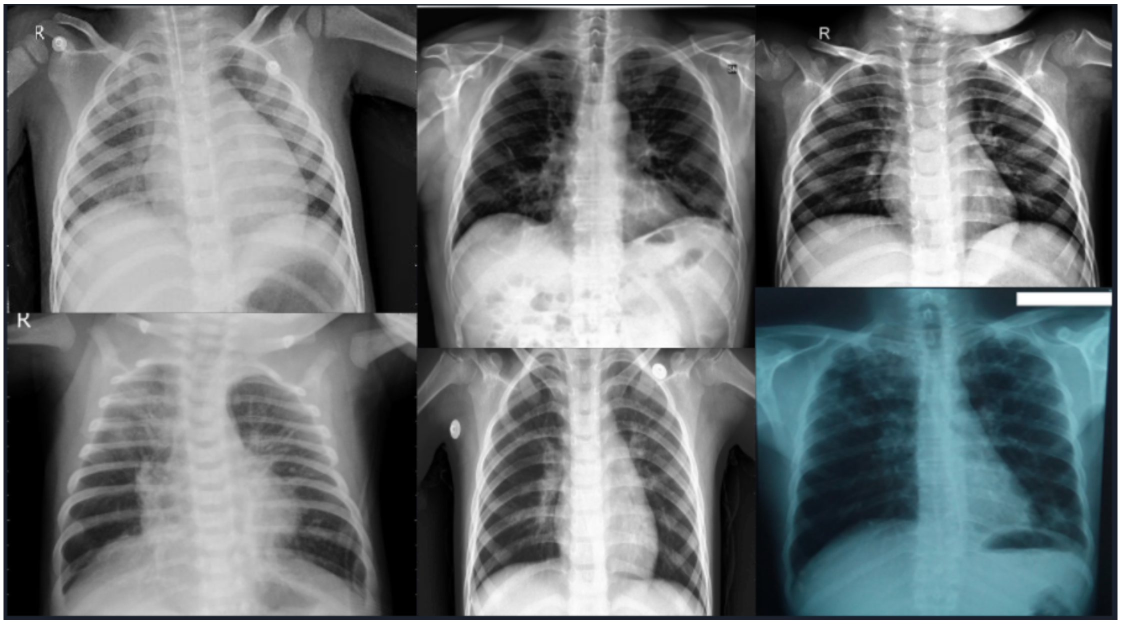

Figure 1.3 Dataset Before Augmentation

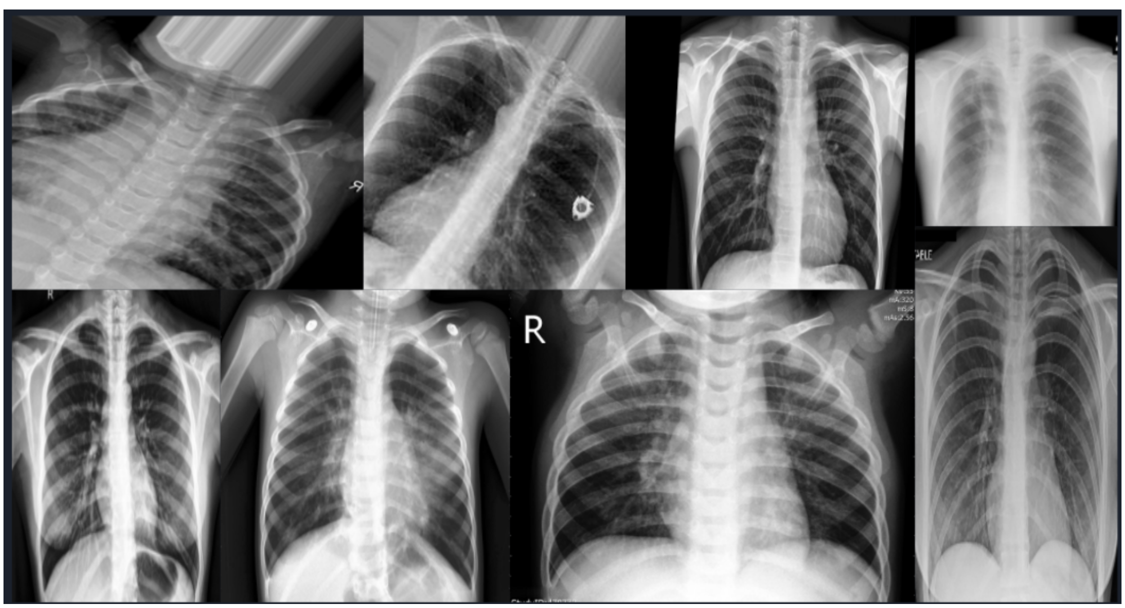

Figure 1.4 Dataset After Augmentation

- **Dataset Pre-processing**

  Dataset Preprocessing is a process of preparing raw data and making it suitable for machine learning. All the training and testing images should be pre-processed before sending them to the network. The PyTorch library is used in this work which is shown in Fig.1. This library includes a transform module that implements the common transformations, including normalization, used in pre-processing. Before going to apply our data to the model, it should be resized to the input size of the network. Next, converting the dataset into tensor data type means, convert a NumPy array in the range of 0 to 255 to a float tensor in the range from 0 to 1. Finally, do all this transformation to each image in the dataset. Data augmentation is also applied to the dataset to increase the size of it and to introduce slight distortion to the images. During the training phase, this data augmentation reduces overfitting.

- **Comparative Analysis**

  The major design and implementation constraint has been the accuracy of the model trained, loss incurred by the model and thus the architecture of the CNN to be used. A detailed study of various architectures of CNN have been undertaken in order to generate the model which would not only serve the purpose but also give accurate results. The architectures trained are namely- Inception-ResNet-V2, denseNet201, Xception and Resnet 152V2. Figure 1.5, Figure 1.6 show comparative graphs and Table 1.4 shows comparative table.

Characteristics	Inception-Resnet V2	DenseNet201	Xception	Resnet 152V2
Layers	164	201	71	152
Input Size	(224,224,3)	(224,224,3)	(224,224,3)	(224,224,3)
Accuracy (Epoch: 15,	80.67	83.77	82.21	84.12

BS: 16)				
Accuracy (Epoch: 25, BS: 32)	87.91	88.26	89.07	88.56
Accuracy (Epoch: 25, BS: 32)	85.91	88.67	92.56	93.10
Accuracy (Epoch: 15, BS: 64)	87.12	90.10	92.81	92.26
Accuracy (Epoch: 25, BS: 64)	86.11	93.12	88.02	95.01
Output Nodes	5	5	5	5

Table 1.4 Comparative Analysis

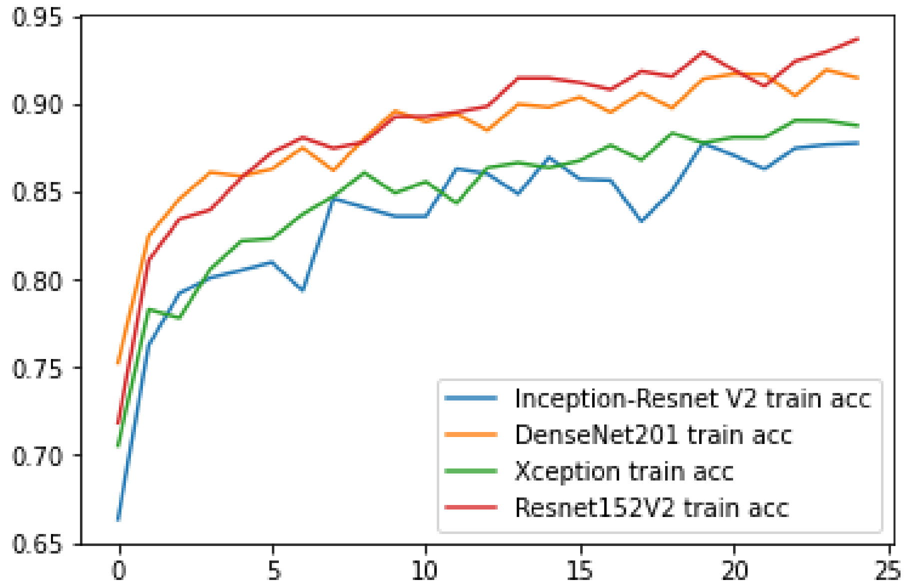

Figure 1.5 Comparative Training Accuracy Graph

Figure 1.6 Comparative Training Loss Graph

- ## Model building

In this work, a Resnet 152V2 network is used for feature extraction as well as classification. Here the Resnet 152V2 is trained by the augmented dataset which contains 10095 images. The structure of Resnet 152V2 is described in section. The software architecture is illustrated in Figure 1.7.

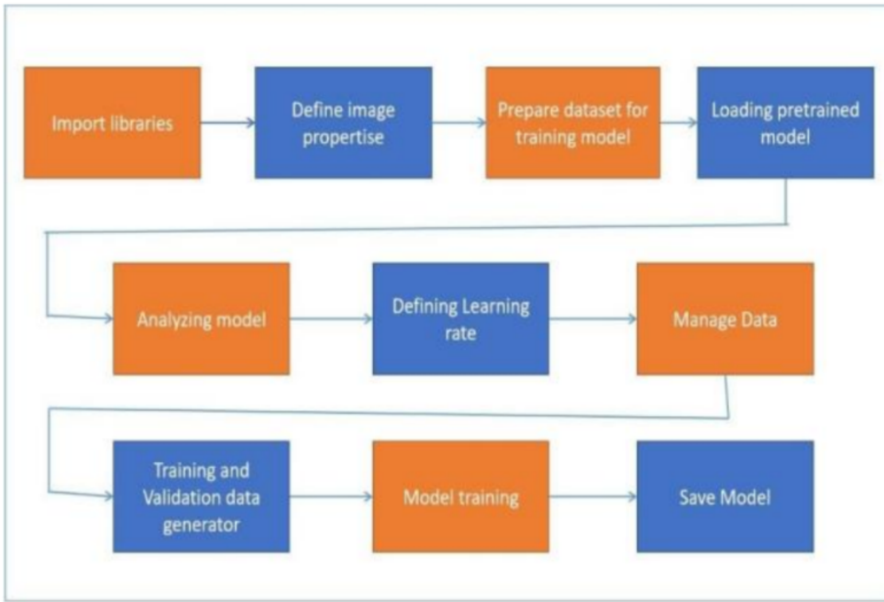

Figure 1.7 Software Architecture Flowchart

- ## Feature Extraction

For extracting the features of lungs from the dataset,transfer learning is used. A pre-trained model is used to classify lungs in various classes. The last layer of the pre-trained model is eliminated and a last layer which classifies the lungs. The model consists of five output nodes.

Transfer learning is basically, retraining the final layer of a deep network. Not only does it help when you don’t have adequate computing resources to train a network from scratch but also for solving problems with limited training examples.

Some models have hundreds of millions of parameters, which might take weeks to train on modest equipment. However, adapting weights via transfer learning is not preferable if you have sufficient data, because the features that were extracted from the original training process are not likely to be suitable for another dataset.

Feature extraction refers to the portion of the training process using which a CNN learns to map input space to a latent space. This is later used for classification via the final layer.

In other words, the hidden layers learn discriminatory features in the form of weight-adjusted (usually by back propagating the error) convolutional filters. Thus, feature extraction is used to define the portion of the training process that occurs before the final layer. By performing deep learning feature extraction, we consider the pre-trained network (i.e.Resnet 152V2) as an arbitrary feature extractor, allowing the input image to propagate forward, stopping at the pre-specified layer, and taking the outputs of that layer as our features.

By doing so, we can still utilize the robust, discriminative features learned by CNN. We have eliminated the last layer of the pre trained Model and added our own layer which does the classification on lungs in different classes.

- **Classification**

After completion of the training process, the model is ready for the classification of any unlabelled X-ray images of lungs. The model takes the image as an input and the comparison is done between the training and testing images and predicts whether the given pair of lungs are diseased or healthy as the output along with the disease type.

Chapter 6
Result and Analysis

Based on a comparison of multiple CNN architectures,Resnet 152V2 had the best accuracy for the Lungs dataset,as it employs a pre-trained model to detect the possible lung disease. It takes an image as input and uses the dataset used to train the model to classify the type of disease and predict the same.

The pre-trained model used is of Resnet 152V2 from the TensorFlow package and Keras sub package. The batch size is set to 64 and 25 was the number of epochs. 60% of images from the augmented lung disease dataset were used to train the accuracy of this model. In every class, 20% of the images were selected for testing and 20% of the images were selected for validation. The testing dataset gives more than 95% accuracy. It means if 100 images are inputted then 95 images were classified correctly. The accuracy and the loss for both training and validation graphs generated by the model are shown below. When the training dataset is increased and epoch the accuracy is also increased. At the 23rd epoch, the model gives the highest accuracy of 95.01%. Figure 1.8 and 1.9 illustrates graphs of training accuracy and validation accuracy, and training losses and validation losses respectively.

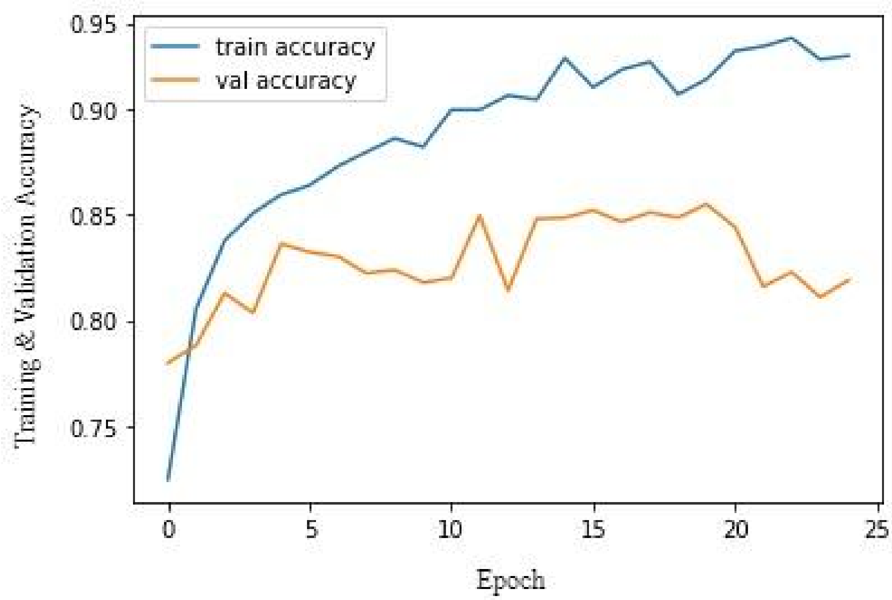

Figure 1.8 Resnet 152V2 Training Accuracy Graph

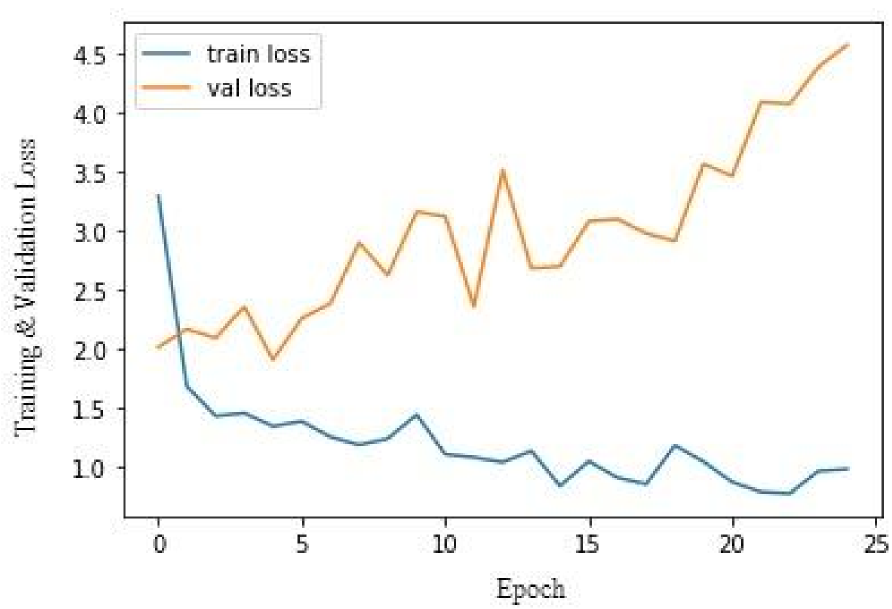

Figure 1.9 Resnet 152V2 Training Loss Graph

The tkinter gui application framework provides different tools to create a gui application in python. The created gui application by using tkinter shown below.

This application contains two buttons such as upload and classify buttons. The images can be downloaded from the web or the images can be captured by phone camera or normal camera and uploaded on the gui. The color images are considered and the images should be in the .jpg format. After uploading the images, it will display the predictions for the uploaded image on the same window. It shows the image along with whether the given pair of lungs are diseased or healthy, if diseased it will display the disease name. Figure 2.0 onwards shows the application screenshots.

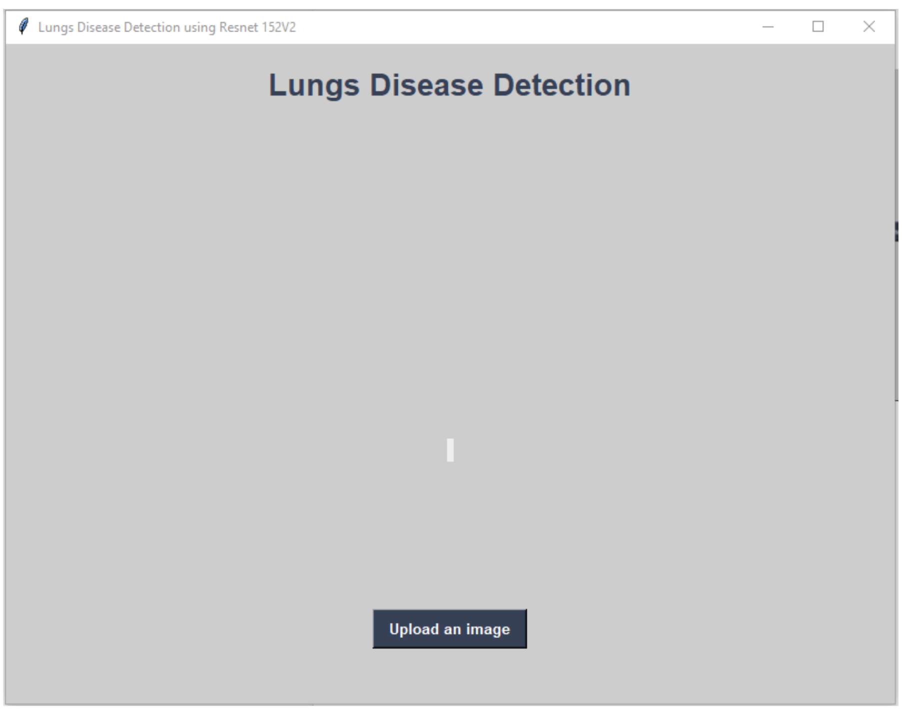

Figure 2.0 First Screen

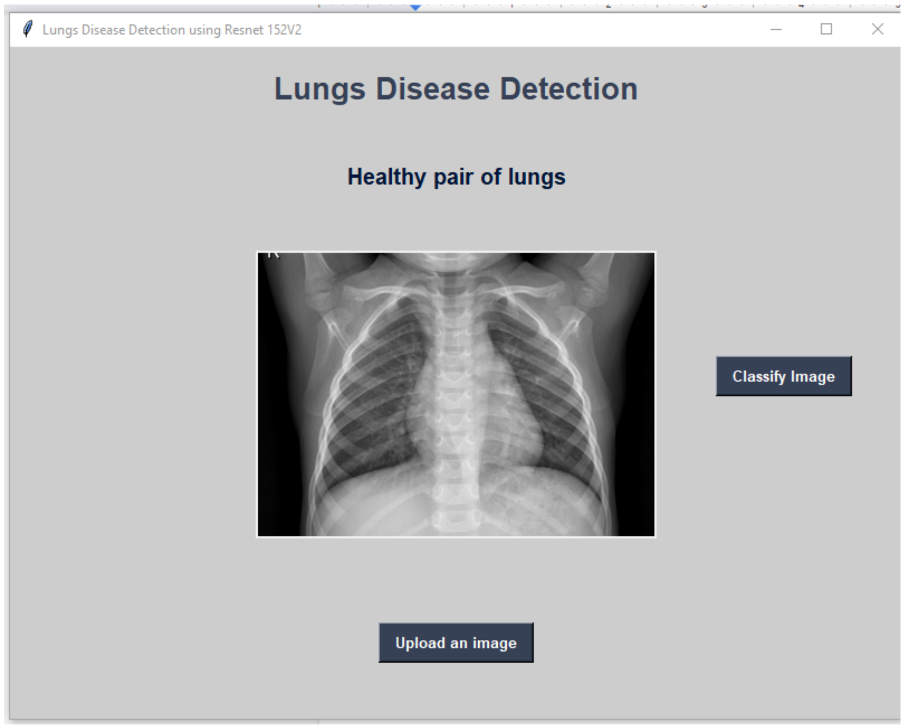

Figure 2.1 Second Screen

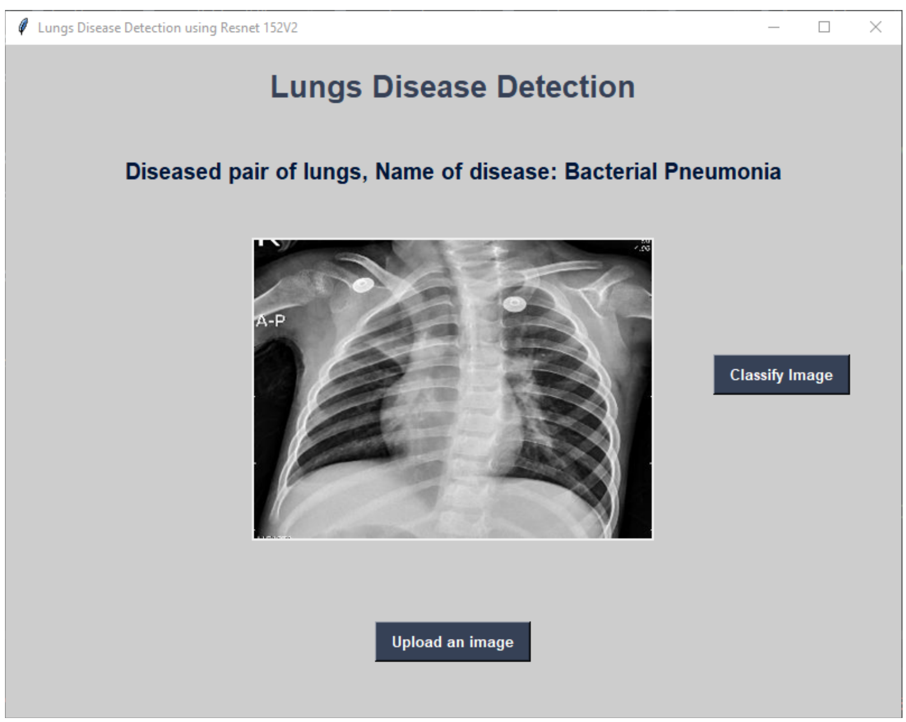

Figure 2.2 After Classification Screen (Bacterial Pneumonia)

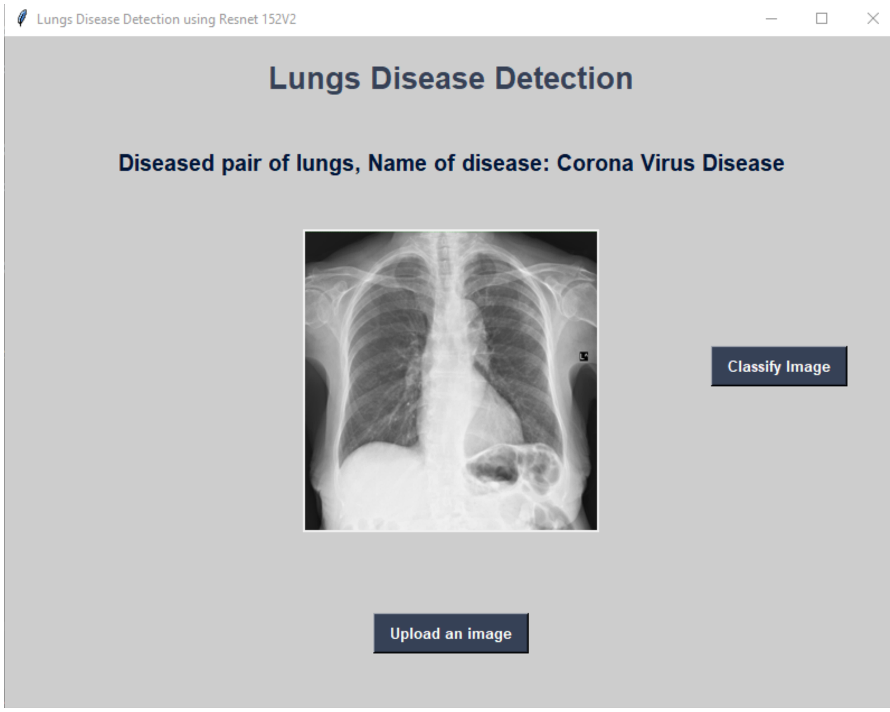

Figure 2.3 After Classification Screen (Corona Virus Disease)

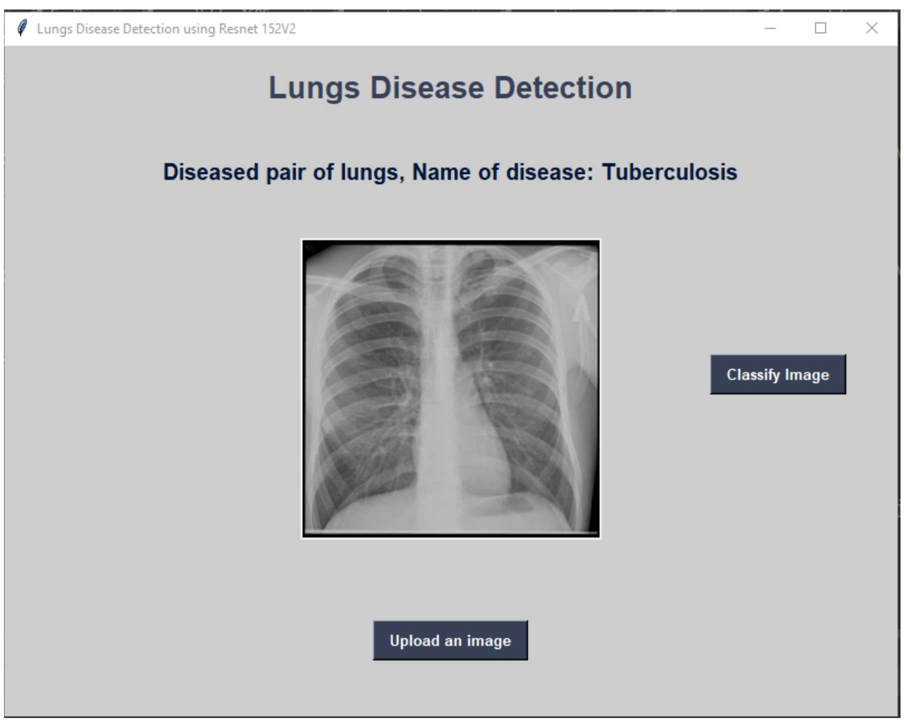

Figure 2.4 After Classification Screen (Tuberculosis)

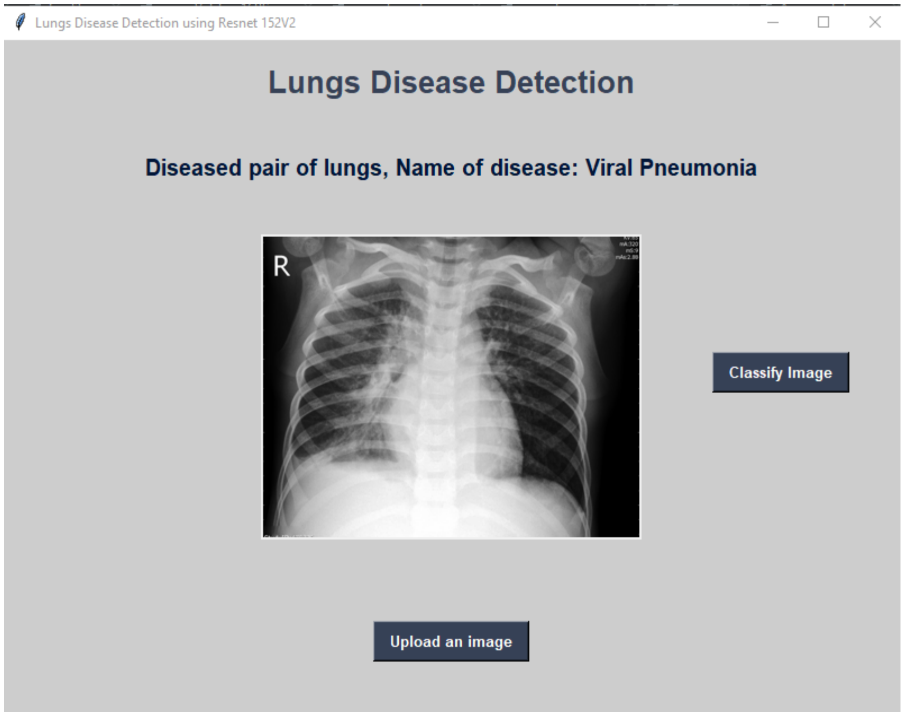

Figure 2.5 After Classification Screen (Viral Pneumonia)

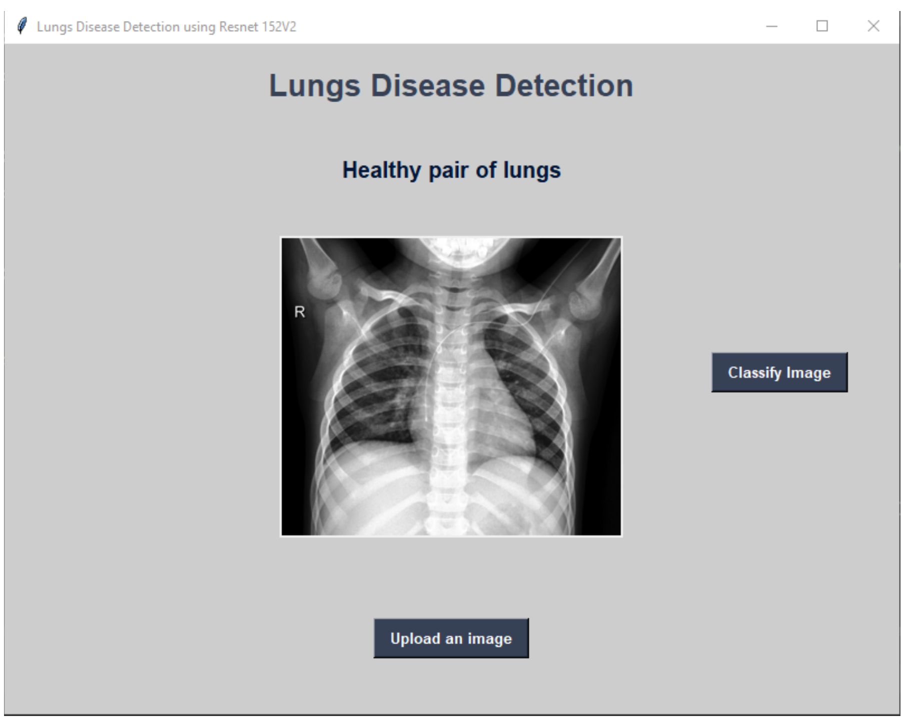

Figure 2.6 After Classification Screen (Normal)

Chapter 7
Conclusional Future Scope

The purpose of this study was to investigate the suitability of deep transfer learning for lung disease diagnosis using medical imaging. Further,leveraging the transfer learning framework we applied a comparative analysis of four pretained architecture models namely Inception-Resnet V2, DenseNet201, Xception, Resnet 152 V2 to hierarchically extract informative and discriminative features from X-ray images.Then as per the formulated results we suppressed our dataset with the Resnet 152 V2 model to form the network.It was also observed that better prediction results and medical diagnosis could be achieved by using the CT images as they are much richer in information compared to X-ray images.

The performance of transfer learning algorithms could be majorly improved by fine-tuning them to extract more informative and discriminative features.Features obtained from different transfer learning models could be combined to develop hybrid models.Also,predictions from individual models could be combined to form ensembles.Last but not the least,a method could be applied for more comprehensive estimation of the uncertainty measures.

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