PNEUMONIA DETECTION USING CNN MODELS

A Project Report

Submitted by

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Under the guidance of
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in partial fulfillment for the award of the degree

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BACHELOR OF TECHNOLOGY

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BONAFIDE CERTIFICATE

This is to certify that the project report entitled **PNEUMONIA DETECTION USING CNN MODELS** is submitted by Madhav Vempaty (cb.en.u4cse17265), T Jaya Bharath Reddy(cb.en.u4cse17363),C Sai Teja (cb.en.u4cse17617), T Srinivasa Manoj Reddy(cb.en.u4cse17665)in partial fulllment of the requirements for the award of the Degree Bachelor of Technology in Computer Science and Engineering is a bonafide record of the work carried out under our guidance and supervision at Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore.

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DECLARATION

We the undersigned solemnly declare that the project report **PNEUMONIA DETECTION USING CNN MODELS** is based on my own work carried out during the course of our study under the supervision of Mr. A. Baskar, Assistant Professor(SrGr), Computer Science & Engineering, and has not formed the basis for the award of any other degree or diploma, in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgement have been made wherever the findings of others have been cited.

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ABSTRACT

Pneumonia is the deadly disease which causes a death to children and adults of all ages. Every year it is affecting 7 percent of the global population.Chest X-rays are the primary source for the diagnosis of this deadly disease.Despite of all these, even a radiologists find it as a challenging task to examine the chest x-rays.Therefore, analysis and giving the details of the chest x-rays make the radiologists to make their tasks easier and give accurate suggestions.This analysis and giving the details of the chest x-rays can be done with some deep learning image classification algorithms.As the task of examining the chest x-rays is reduced ,they can mainly focus on the solution to the disease.This can not only reduce examining but also time to cure.This computer aided procedure made the potential to improve and increase diagnostic accuracy.So we decided to make computational approach for pneumonia regions detection based on the deep learning algorithms.In this,we develop a computational approach of detecting the regions of the pneumonia using convolutional neural network which is deep learning class used for visual imagery.The series of the convolutional layer with filters, pooling method and using the activation function to classify an image is used to visually interpret the pneumonia regions and analyse the problem involved.The proposed method has the data set that is proved to be a images of a normal,pneumonia.The system was evaluated in the context of the pneumonia and non pneumonia based classification.We have implemented the resnet 50 and vgg 16 models of image classification to classify the images of a pneumonia, and the details of the classification are described using the accuracy and confusion matrix.

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ABBREVIATIONS

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α, β	Damping constants
θ	Angle of twist, rad
ω	Angular velocity, rad/s
b	Width of the beam, m
h	Height of the beam, m
$\{f(t)\}$	force vector
$[K^e]$	Element stiffness matrix
$[M^e]$	Element mass matrix
$\{q(t)\}$	Displacement vector
$\{\dot{q}(t)\}$	Velocity vector
$\{\ddot{q}(t)\}$	Acceleration vector

Chapter 1

INTRODUCTION

Pneumonia is an infection caused due to bacteria,fungus and deadly virus.It mainly causes severe infections to the children but adults and older people show no symptoms as the immunity is a bit higher for a elder people.Despite of the symptoms to the older people it is very difficult for the radiologists to find the disease and at what stage the patient is fighting for with the disease.So they have to be given with the correct information and in a short time to make the treatment earlier.

To make the work easier for a radiologists, by involving the image segmentation of a deep learning models make the work easier and time complexity also reduces.Image segmentation is a task of a computer vision algorithm to label the specific areas of images specifically we are giving pneumonia images.The image segmentation algorithms using here are resnet 50 and vgg 16.These two algorithms are used because, our main goal is to not lose our main images for the training purpose and our models should produce accurate predictions.Why we focus mainly on accurate predictions is our problem should mainly get the true positive result or else it may cause severe infection for patient suffering.

So we are producing the accurate result for the images which makes the easy for the radiologists to get the details of a patient and at which stage is danger.We first use resnet 50 model to train and validate the images and get the accuracy.After the clear training of the models with different images particularly normal and pneumonia,then we test the model with different normal and pneumonia images.

1.1 Problem Definition

Pneumonia detection of the chest X-rays using the convolutional neural networks of deep learning networks.In this mainly we focus on the two algorithms namely resnet 50 Figure 1.1 and vgg 161.2.This typically consists the images as an input and have the system parameters namely, we do conv2D and then the batch normalization later applying the activation function particularly relu.

However, we get the output showing the image that we have uploaded has the this much percentage of the pnemonia.We use two algorithms as to compare which gives the best result and then accept the details of the images.This will tell us which is best suited and can be applied.

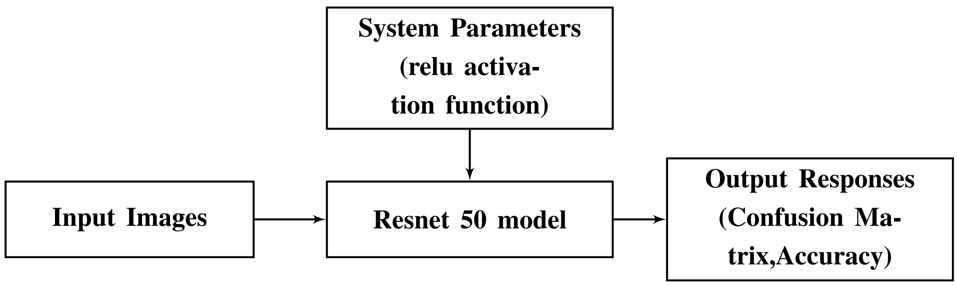

Figure 1.1: Algorithm Resnet 50

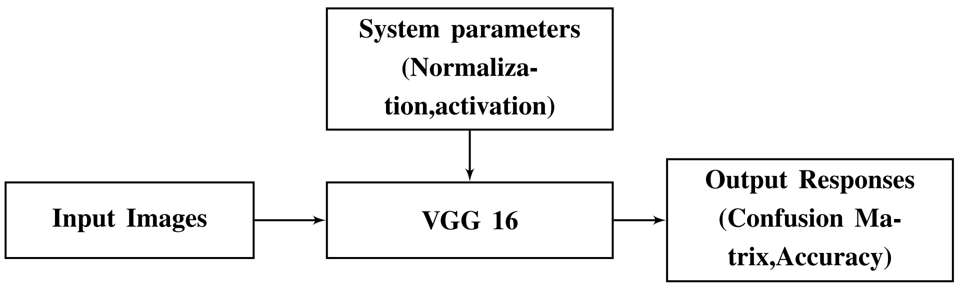

Figure 1.2: Algorithm VGG

For the structural diagram we have shown has the input as the images and get the output the confusion matrix and the accuracy of the algorithm.Then the confusion matrix produce the details of the true positive percentage and true negative percentage of the image which we can conclude whether the patient has the pneumonia or not.

1.1.1 Convolutional Neural Network

This is a class of a deep learning model.It is mainly used in the image segmentation.Dl convolution models are used to train and then test the images that were given as input, each image will be passed into a series of convolution layers.In this cnn we have Pooling advantage,which is the picking the random image such that the model can learn without loosing main information of the image.Then they are passed to a connected layers that are full and a soft max function is applied to classify the object with in the probabilistic values between 0 and 1.This process is simply used to analyse the images using the processing method and grid like topology.

How it works

Convolutional neural networks (CNN) is a main neural deep learing model.It is mainly contains the neurons with learnable weights. Each of the particular neuron takes number of inputs and then sum up giving the weighted average of the sums. So where it passes the weighted sum to an activation function relu and gives the classified image.

Summary

So we are going to show the detailed survey of the some presented papers and then the outcomes we have taken from them for our project are also explained in detail.Then the algorithms implementation is explained and the dataset used and then testing results.

Chapter 2

LITERATURE SURVEY

2.1 Discovery of pneumonia in chest xray using in-depth reading

Hu (2020a)Pneumonia can be a serious condition from mild to life threatening. It is especially dangerous in children and young children, in people over the age of 65, and in people with health problems or weakened immune systems.Infections affecting the lungs. Species of organisms including bacteria, viruses and fungi cause pneumonia.In this work, an effective model of diagnosing pneumonia trained in digital chest X-ray imaging is proposed, which can assist radiologists in making their decisions.A weight-based novel-based approach is introduced, which incorporates weighted predictions from advanced reading models such as ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3 as well.

2.2 Pneumonia Classification of Thorax Images Using Convolutional neural networks

Suyuti and Setyati. (2020) Data processing for the medical data is a big thing in the image processing. As the technology is increasing more rapidly now a days it has been easy to process the medical data using computer.This study is for the thorax image classification using Convolution Neural Network.The dataset taken consists of two types.One of which is normal and the other is pneumonia.In this process the image processing plays a main role.There are 3 stages which are mainly used in image processing.They are scaling,gray scaling and the last one is scratching.In this study the architecture used is Resnet 50.It is used with the Convolution Neural Network method.The main reason for taking Resnet50 architecture into consideration with this study is that during training process the gradient loss is reduced at particular network level depths.

This occurs due to the chest xray image which contains high level visual.To obtain better approximations for the thorax images and to obtain high accuracy Adaptive momentum is used during the traing phase.This makes the doctor essier to identify and examine the thorax image of the patient and the regions in which the disease has occured and will be able to observe the conditions and plan for the better treatment.

2.3 Deep Convolutional Neural Network with Transfer Learning for Detecting Pneumonia on Chest X-Rays

Chhikara and Prateek (2020) This Paper Proposes a convolutional model for diagnosis of pneumonia as chest X-ray as input And Medical Dataset Containing More than 5000 X-rays of Children is taken.Training and Model building is done on the dataset.Performance of the model is calculated from Various Transfer learning Models . Transfer learning is Used in this Model .In transfer learning classification and training data can be a different domain and can have different types of distributions here transfer learning establishes a relationship between pretrained weights and learned weights and output is generated. In this Paper the model proposed is mainly divided into modules such as preprocessing,preparation of dataset,Model Training and Result Generation and Evaluation Using Different Metrics.In the Preprocessing we have to remove or reduce the noise because the taken dataset is medical dataset which contains a lot of imbalance so in order to decrease it Median Filter which decreases the window size and Histogram equalization which improves the contrast of image and gamma correction which is used to display the image accurately.Equalization of this Algorithm is Used For enhancing extent of finding the pneumonia in X-ray images of the dataset.JPEG Compression is used to decrease the image size of xray and gray images without disturbing the contents of the input.

In the preparation preprocessing of images is given a numerical value as pneumonia image gets label as 1 while normal images get label as 0.In Model Training Phase Inceptionv3 contains duplicate blocks known as Inception Block and the parameter Known as hyper-tuning is possible and many filters from 1×1 to 7×7 provide results ng after each repetition. and securely retains all the elements of the image without interfering with the elements of the image.In this Algorithm There is an option to choose between convolutional layers and layers of integration .Algorithm by all four The final layers, the first two layers of the active layers taken directly and the last layers are composite layers that contain a combination of other layers. The final output model contains 94 layers of convolution 2d. All output layers use line functionality. And finally the verification accuracy of the model crossing used is 90.16 percentage. The proposed model on paper reduces the problem of overheating by inserting an exit layer and a composite layer.

2.4 Deep Learning for Medical Image Segmentation: Pneumonia Detection

Ayan and Ünver (2019)This Paper Proposes Pneumonia Detection Using Image segmentation When a X-ray Image is Given as input it gives an output whether it is pneumonia X-ray or a normal X-ray. This paper proposes a model Using Unet and Wnet Models and Algorithms such as Resnet 152, Densenet 121 and Chexnet are Used and Model is Built and Trained and Used.Dataset is the medical dataset containing X-ray Images and Images Over 1lakh across 3000 patients containing 14 diseases including pneumonia and For the Experiment it is consolidated the dataset for only detection of pneumonia signs on chest radiographs and the dataset is further divided into three categories no signs of pneumonia ,patients with illness and patients who does not show the perfect metrics of lung capacity nor they are normal .Unet goal is to find the contracting path to find the exact content of the image inorder to do segmentation. Wnet is combined to Unet and it acts as Encoder and Decoder and it provides Unsupervised Learning and Wnet helps in depthwise separable convolution layers.Pretrained Models of Algorithms Mentioned are Used and Fine tuning is Applied on the algorithms and it changes the last layers and it changes and freezes all the layers and modification is done to the layers. For the models training the dataset is divided into training and validation sets.and for the pretrained models also some dataset images are given.The Main Core of the logic lies here in splitting of the dataset because in the model Various Image Formats are there so that different channels for the neural network and input channels increases and Unet and Wnet is customized Built so input is also customized and one channel on input is built for greyscales.pretrained models are used to train on colour images.In this Model Accuracy Varies by Use of Optimiser and Adam Optimiser shows best results compared to SGD optimiser the best accuracy score is 0.90 and for pretrained accuracy is 0.96 and the proposed model can be Accurate by adding One more layer on the top or Replacing the input layer with Special Designed Custom Layer.

2.5 Xray disease confidence in multi kernel depthwise convolution

Hu (2020b)The endless growth of computer-assisted diagnostic programs created by flexible neural networks. The texture and texture of medical imaging tissues are important features of diagnostic procedures. With the discovery of the Xrays chest, large images are taken along with networks of deep neural convolution.The goal is to achieve and distinguish diseases in X-rays images more quickly and effectively with more accuracy. The proposed system is that in this study, which consists of dynamic characters of various filter sizes in a single deep-layer layer, a multi-kernel depthwise convolution.Suitable for medical data to diagnose activities where the abnormalities have varied in size. In addition, large deep-grained characters are found in MD-Conv a large reception field is well received.

2.6 Summary

From the literature study,we are able to understand the ways in which we can be able to get an optimum solution while detecting of pneumonia by giving chest x-ray dataset taken as input.By using Convolutional neural network method we will be able to apply all the techniques to the Resnet50 architecture to get high accuracy.This makes the doctors easy to diagnose the disease and classify the chest x-ray to normal or pneumonia based on the accuracy.

2.7 Data Set

The dataset which we took for the study is a medical dataset which have chest xray pictures.The dataset contain 5856 files.The format for all the files is in jpeg format.This dataset contains 3 different kinds of folders. 1)test 2)train and 3)val. Each one of the above 3 folders consists of 2 sub folders.The two sub folders are categorised into 2 types namely normal and pneumonia.Since this is the medical data,each one of the chest x-ray image consists of more pixels.So the size of the dataset is nearly 1.15GB.

2.8 Software/Tools Requirements

1.Visual Studio code

2. Bulma css framework

3.PyCharm for python

4.Python libraries and dependencies

5.Stream lit library

6.Tensor Flow

7.Keras python library

Chapter 3

PROPOSED SYSTEM

3.1 System Analysis

Here you can provide the deatis of modules; explanation with diagram. The modules we are using are

1.Data Collection

2.Image Processing and Data Augmentation

3.Implement Architecture and Create data generators

4.Train the model using the loss function

5.Test the model on the unseen data

3.1.1 System requirement analysis

Functional Requirements Algorithm Implementation is Done in Python Environment of version 3.6.5 basic requirements So Minimum as 8GB RAM with storage more than 2 GB can efficiently run the project without any disturbances. Because the dataset is so huge that is nearly 2GB so a minimum of 8 gb ram is required for smooth processing.

The Requirements are:

Python - version (3.6.5)

Keras- version (2.4.3)

TensorFlow Version (2.2.0)

Streamlit Version (0.81.1)

Non Functional Requirements:

1.Pycharm

2.Visual Studio Code

3.2 System Design

3.2.1 Architectural Diagram

Radiologist Gives the X-ray image as a input in the streamlit interface and accuracy score and performance matrix is displayed whether it is pneumonia or normal x-ray But First when input is given image preprocessing and image augmentation is done using several methods and techniques in the backend before a model is tested and model is trained and that model is built here using the algorithms Vgg16 and resnet50 and that model which has been built is used and output is generated and classification is done and gives the output to streamlit to display and classify

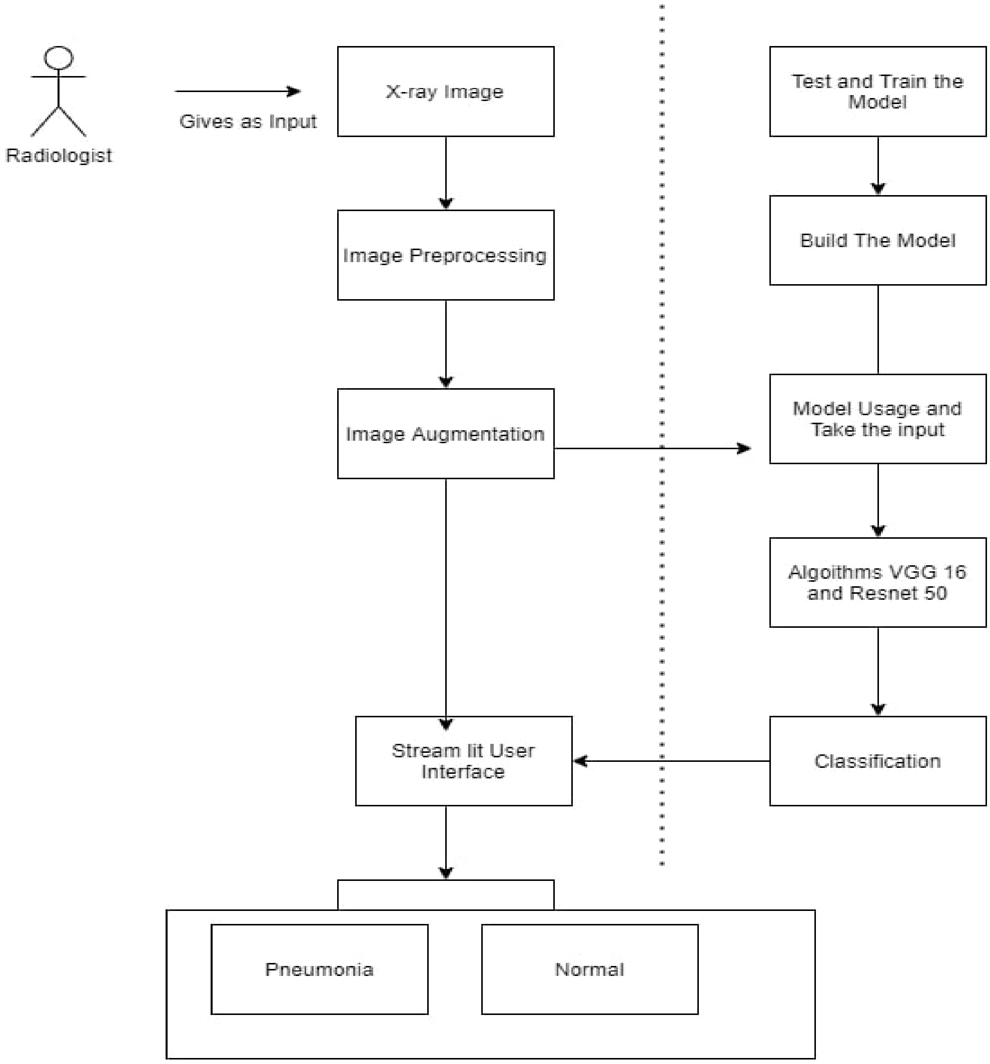

Figure 3.1: architectural Diagram of system

3.2.2 Flow Chart

X-ray image is provided as Input and Processing is done on various various techniques such as sharpening, blocking, Cannyedge, Sobelxy processing input image and Rescaling and Horizontal Flip is done in it and Now Algorithms Resnet 50 and VGG 16 are and Model is Built .Model training is done on the dataset and now validation is done on images and predictions are made on unseen images and differentiate them whether it is a normal x-ray or pneumonia chest x-ray and accuracy is predicted with different metrics such as confusion matrix, accuracy score is also used

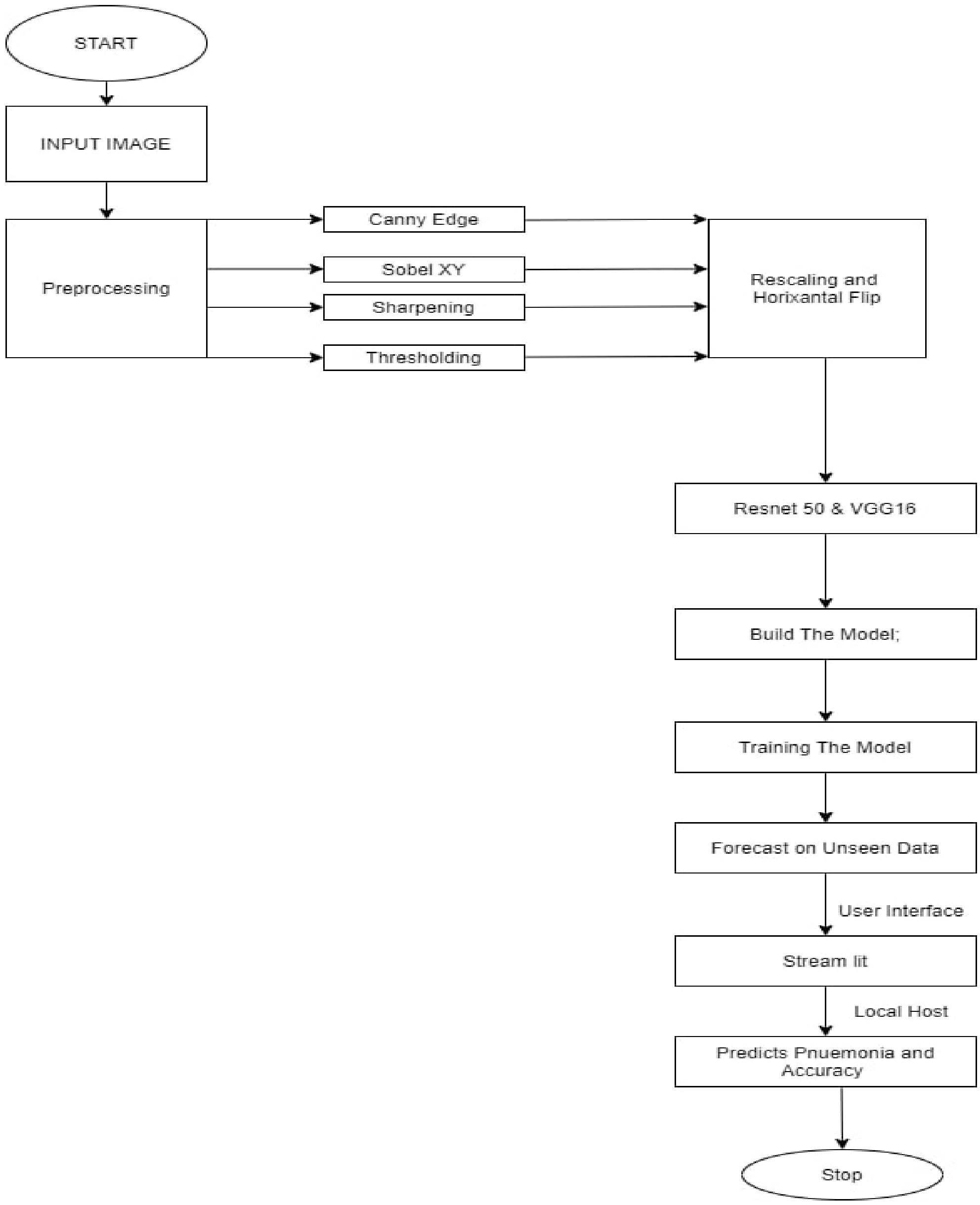

Figure 3.2: Flow Diagram

3.2.3 Module details of the system

1.Data Collection:

DataSet is Taken from Kaggle medical data set.File Format is Images (.JPEG). Data set contain 5,863 X-Ray images and 2 categories such as pneumonia and Normal.Most of medical datasets are imbalanced and noisy.So we have Used right metrics to reduce imbalance and Noise in the data set.

2.Image Processing and Data Augmentation:

Tatiana Gabruseva (2020) The dataset is a medical data set which consists of chest x-ray images.All the important libraries are included such as randrange,cv2 ,constants,os ,numpy.So we have used most consistent open cv functions like canny edge detection , Sobel XY.Image Re-scaling is done and Horizontal flip also should de done.Too Much of Preprocessing disturbs the image and resolution of the image decreases.Matplot is used to plot the images after Processing

Sobel Edge Detector Technique:

At first ,the image is refined in the X ad Y directions respectively.The new image is formed while obtaining the result, which actually is the addition of the X and Y edges of the image.This approach works through calculation of the image intensity at every pixel within the image.It has two kernels(3*3 matrix).One of them correspond the X(horizontal) and the other shall be used for the Y(vertical) direction.These two kernels shall be convoluted with the original image under process and through which the edge points are calculated with ease.The kernel values are fixed for sobel filter and cannot be altered. The Gaussian filter play a vital role in the entire process.

Canny edge detection technique:

Canny edge detection technique,not just a plain edge detection technique.It has an additional feature.It also suppressess the noise while detecting the edges flawlessly. it mainly converts the rgb image to grey scale.Gaussian Blur is an operator,which helps in removing the noise in the input image.This noise removed image shall enable further processing to be smooth and flawless. The sigma value has to be set appropriately for better results.Intensity Gradient Calculation is sobel filter is to be used in the process.Sudden intensity change is the edge and in fact,the intensity change of the pixel is the edge.Now the sobel operator has to applied over the input image and the steps and sequences remain the same as the process explained in the Sobel Edge Detection process. The resultant Sobel operator image is generated and is referred as Gradient Magnitude of the image.

3.Implement Architecture and Create data generators:

First Resnet 50 and Vgg16 algorithms are implemented Separately.Implementation of Resnet50 is Done by Keras models,preprocessing,backend and imagenet is also used and convolution and identity block are Defined.For Keras Preprocessing Imagedata Generators are Imported.Weights are Generated through Imagenet,channels and tensorflow and Model is built This Models are Stored in Hdf5 files and Weights are stored in h5 files.Implementation of vgg16 is done by keras backend and Imagenet and layers and models are imported and used in the algorithm implementation Weights are loaded through imagenet and Model is built and model is stored in hdf5 files and weights are stored in h5 files.

4.Train the Model by defining loss function callbacks:

We have two algorithms like resnet 50 and vgg algorithm that are used to train and test.After Building of the model.that model is trained and validated and then it is tested.Model is trained by loss function and validated after validation optimisers are used and accuracy is used as metric for checking whether model is correct or not .First we have trained our data on both the algorithms and compared the two algorithms on their accuracy.So we have found the resnet 50 classifier is more accurate and fits to our data set and deployed on the resnet 50 than vgg16.

Resnet 50:

This model is available for both Theano and tensorflow backend.Tensorflow is used to train and test the dataset .Tensorflow is the one only which by default takes the length and height model building is done by tensorflow.The importance of tensor flow is dataset is completely a image dataset as in which length and height are given at most important.

VGG 16:

VGG16 is a cnn and it has only has conv and pooling layers in it and Number 16 refers that it has a total of 16 layers that has some weights.The Need of Using Vgg16 is It has an accuracy of 92.7 percentage.and it is trained on ImageNet data.

5.Test the Model on Unseen Data:

By Using Streamlit a Html User interface is created and hosted in localhost .A image input is given and Accuracy is found out and Prediction will be done whether it is normal or pneumonia affected.To check the performance of the model, we evaluate the model on unseen data.We use some performance metrics like confusion matrix to predict the output.

Chapter 4

IMPLEMENTATION AND TESTING

Recently, in-depth CNN-based learning models have been used to address computer vision problems. Using CNN's in-depth design based on ResNet-50, Vgg-16 models combined with transfer learning techniques to separate Pneumonia Chest X-ray image data between a normal patient and a Pneumonia patient. Transfer learning also helps to deal with insufficient information and modeling time to practice. The image below shows how the image is categorized:

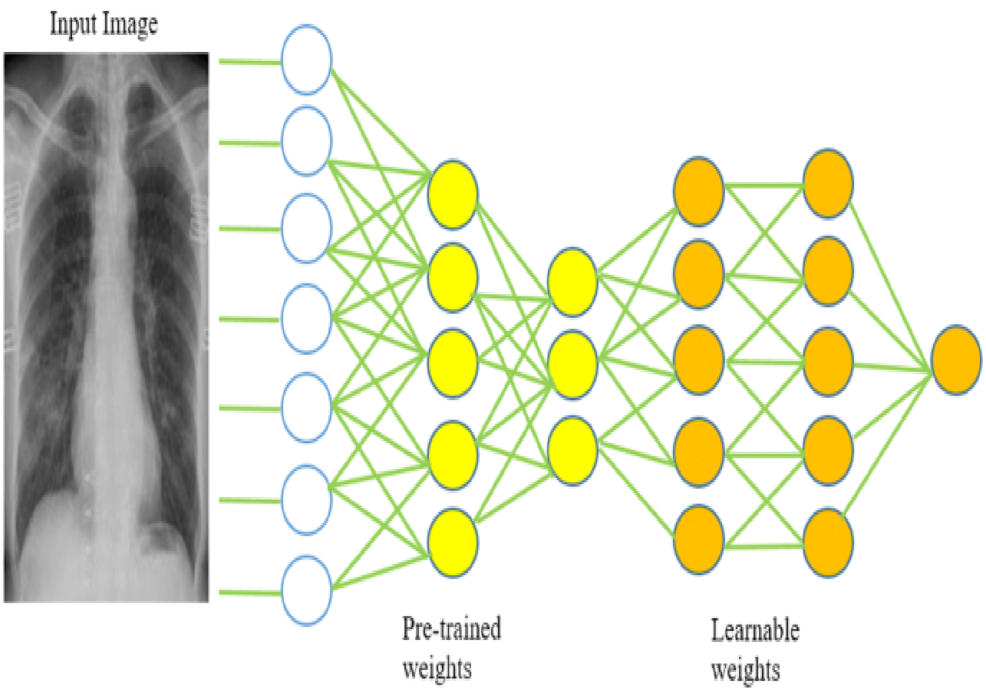

Figure 4.1: resnet architectural flow

Imagenet: Image Net is a research project to create a very large database of images with annotations, for example images and their displays.
The images and their descriptions have been the subject of the ImageNet Large Scale Visual Recognition Challenge or ILSVRC since 2010. The result is that research organizations fight them on predefined data sets to see who has the best model for visualizing

objects in images.

For segmentation work, images should be divided into 1,000 unique categories. Over the past few years the most advanced models of convolutional neural network have been used to overcome these challenges and the results of activities exceed human performance.

Resnet Implementation:

Working to train deep networks new construction comes with a residual learning framework known as ResNet. In this design the layers of the network are redesigned by learning using residual functions in relation to the installation of the layers. ResNet is also referred to as a residual network that adapts to the idea of skipping connections to deal with the problem of extinct gradient. This prevents visible distortion as the network becomes deeper and more complex. ResNet alternative ResNet-50 is used as one of the models. This used a 50-layer network and was trained using the ImageNet database. The ResNet-50 building consists of a convolutional layer, 4 convolutional blocks, a large pool, and a standard dam to deal with the deterioration of accuracy. This helps generate deeper CNNs by maintaining accuracy. The development of ResNet-50 provided developers with a way to build deeper CNNs without compromising accuracy. ResNet-50 was among the first CNNs to use the batch normalization feature.

ResNet-50 represents the Residual Network where 50 looks at the number of layers. ResNet used to solve the problem of gradient explosion and destruction it encountered while training a deep neural network model. First trained on more than a million images set in the ImageNet data set. This pre-trained model is used for training in chest X-ray image databases. ResNet 50 has 48 layers of convolution, 1 average pool layer and 1 max pool layer and has 3.8×109 point functions. X-ray images are fed by model and various parameters are set as size of batch equals 32, epoch value is equal to 50 and literacy rate is 3e-2. Networks with a large number (even thousands) of layers can be easily trained without increasing the percentage of training error.

ResNet uses below blocks to construct the entire network:

RachnaJaina Preeti (2019) **Convolution Block:**

Convolution is utilized for many things like calculating derivatives, identify edges, apply blurs and so on and all this is done utilizing a "convolution kernel".

The conv block helps to modify and rebuild the incoming data so that the output of the first layer matches dimensions of the third layer so they can be added.

Pooling:

Pool insertion layers are used to reduce the size of the feature maps. In this way, reduce the number of parameters to be read and the number of computers generated in the network. The integration layer summarizes the features present in the feature map region formed by the convolution layer.

Identity block:

ResNet build block is called residual block or ID . The residual block is actually when layer performance is immediately deployed in a deep layer on the neural network.

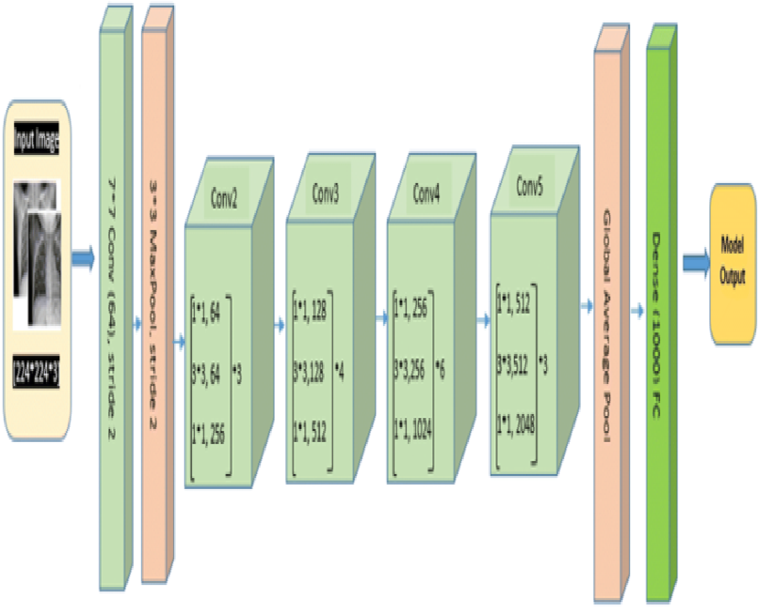

Figure 4.2: Reconstruction of the ResNet-50 Pneumonia Chest X-ray image section

Flow:

First we took a chest xray of data, we saw that it is the highest rating of pneumonia class images, so we measured the data first by keeping the same number of images in both classes in the train folders and verification.

Next, we have selected resnet50 algorithm first, we have trained the resnet50 model on these images, we have used pre-trained weights for initial layers of resnet50, That pre-trained model is actually trained on Imagenet dataset. Now, we have trained the final layers of the resnet50.

We have taken proper care while training the algorithm, we have ran the training for

50 epochs. Now, we have saved the best weights during this training process. We are selecting the best weights by testing the model on validation data after every epoch.

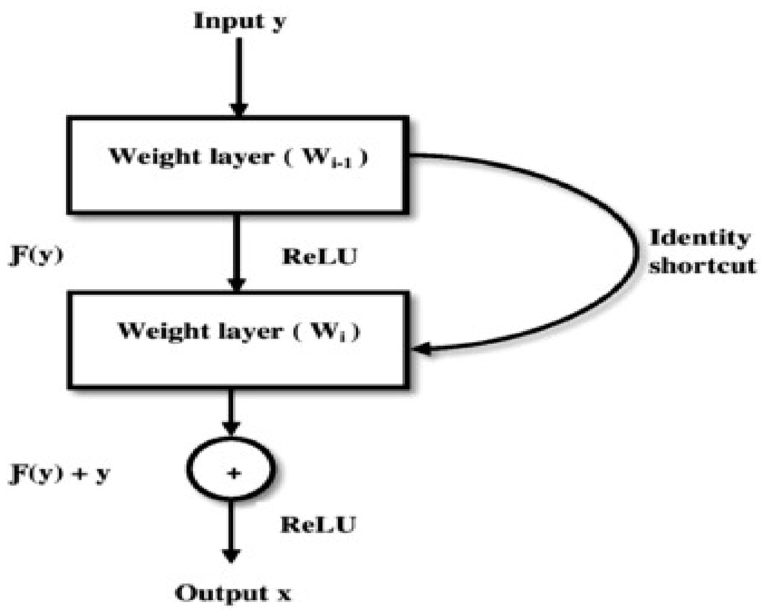

Figure 4.3: Work-flow

VGG 16:

Kim (2018) The Vgg16-trained learning model is generated by a benchmark benchmark dataset similar to the ImageNet image recognition task. Trained for millions of images using ImageNet in a multi-classroom environment. The main motivation for using weight loss learning, bias and features of a pre-trained model can be transferred to our scheme instead of the original. This is achieved by applying these parameters while training in the X-ray image database. Training a CNN model from scratch is time-consuming compared to training a pre-trained model and cheaper mathematically if the database contains a small number of images. The Vgg-16 model has 16 network layers built into the ImageNet database whose main purpose is the recognition and classification of images. Chest X-ray images provided for the model are compiled and made to a size of 224×224. . The Vgg-16 model consists of a 13-layer convolution using 3×3 convolution filters, 5 multi-layer composites for sample reduction, 2 fully integrated layers and a dense and flat layer.

Visual Geometry Group (Vgg) created the 41-layer Vgg16 network. Vgg simplifies the process by making 3×3 filters in each layer. Use of equal and moderate filter limitations at Vgg can produce more complex features and lower processing compared to AlexNet.

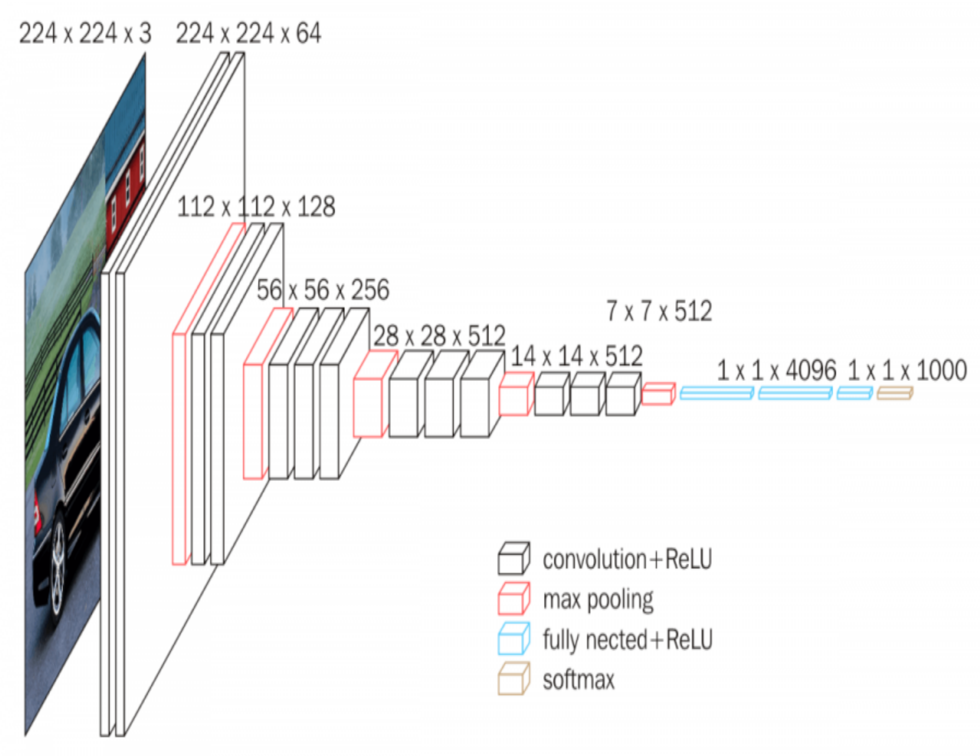

Figure 4.4: Layers construction of VGG-16 model

VGG16 Implementation:

1.Collect the database. By creating any model, the basic requirement is a data capture.

2.Then train the model using VGG16.

3.Download the VGG16 weights and freeze them.

4.Install new layers of fine tuning.

5.Check and use the model.

6.Upload the model for testing purposes.

7.Launch the model.

8.Evaluating the Model.

9.Learning from curves.

Why Max pooling is used in VGG16:

Max pooling chooses the brighter pixels from the image. When classifying the dataset utilizing CNN, max pooling is utilized because the background in these images is made black to Lessen the computation cost. Max pooling is finished by applying a max filter to (usually) non-overlapping subregions of the underlying representation.

Flow:

First we have taken the chest xray dataset, we have seen that it's highly class imbalance towards pneumonia class images, so we have balanced the data first by keeping same number of images in both the classes in train validation folders.

Next, we have selected vgg16 algorithm first, we have trained the vgg16model on these images, we have used pre-trained weights for initial layers of vgg16, That pre-trained model is actually trained on Imagenet dataset. Now, we have trained the final layers of the vgg16.

We have taken proper care while training the algorithm, we have ran the training for 50 epochs. Now, we have saved the best weights during this training process. We are selecting the best weights by testing the model on validation data after every epoch.

Testing:

aiswal (2019)Once we got the best model, we tested it's performance on unseen test data. We have calculated confusion metrics and accuracy. Once we got the model, we used streamlit for creating web application and ran it in localhost. We uploaded the image in UI, then the model classifies the uploaded image and returns the output. Based on the output we got, we can see which got the more percentage. Based on that, we classify the image as Normal or Pneumonia image.

Chapter 5

RESULTS AND DISCUSSION

To measure the performance of pre-trained CNN architectures to classify the Chest X-ray images we use accuracy which uses the below terms: **Performance metrics:**.

1.True Positiveness (TP): shows a common case with pneumonia is correctly predicted as normal with pneumonia respectively.

2.True Negativeness (TN): shows that the normal case is predicted as well as the normal.

3.False Positiveness (FP): shows this case is common and predicted as a case of pneumonia.

4.False Negativeness (FN): shows the case is pneumonia and is predicted as a common case.

Accuracy usage:

Accuracy is defined as the total no. of records separated by the total number of records in the database.

This accuracy measure will work best shown in the equation when we have the same number of images for both categories. Therefore, to predict the accuracy of the models we use other metrics.

Pre-processed images can not be classified correctly because necessary data present in the image gets lost because of pre-processing . so, they can not produce good results.

Vgg and Resnet comparision versus validation:

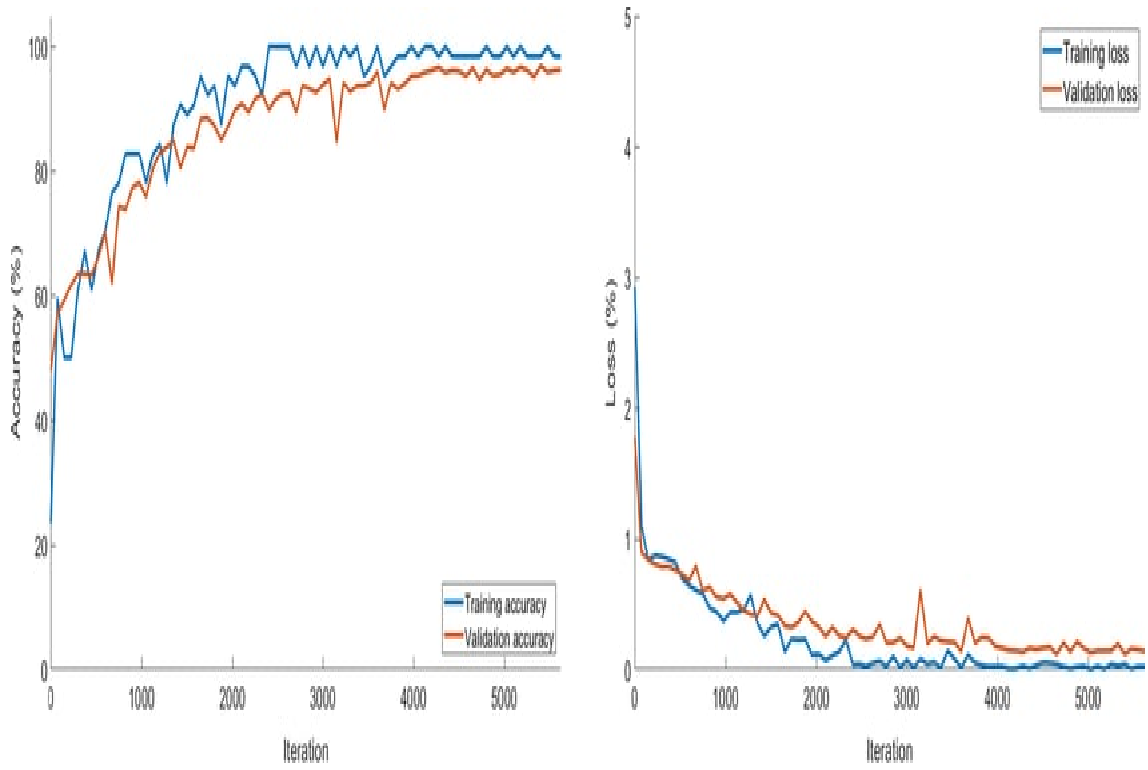

Figure 5.1: vgg accuracy and loss function vs Validation

The below pre-processed images got classified using vgg16 and resnet50:

From test scores, we can say that the proposed method accurately presents non-preprocessed images in all classrooms as normal with pneumonia. We can therefore say that the fine-tuning of CNN's pre-trained facilities can be used as one of the most useful methods in the medical field for the separation of Chest X-ray images.

Figure 5.2: Canny Edge Detection pre-processing

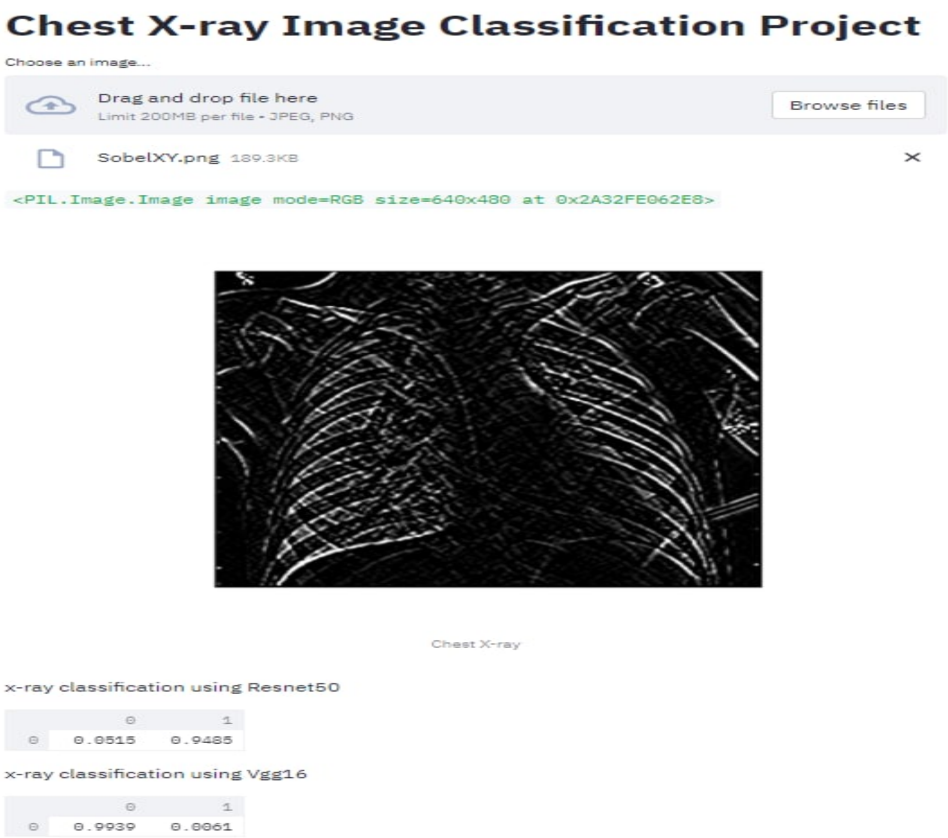

Figure 5.3: Sobel XY pre-processing

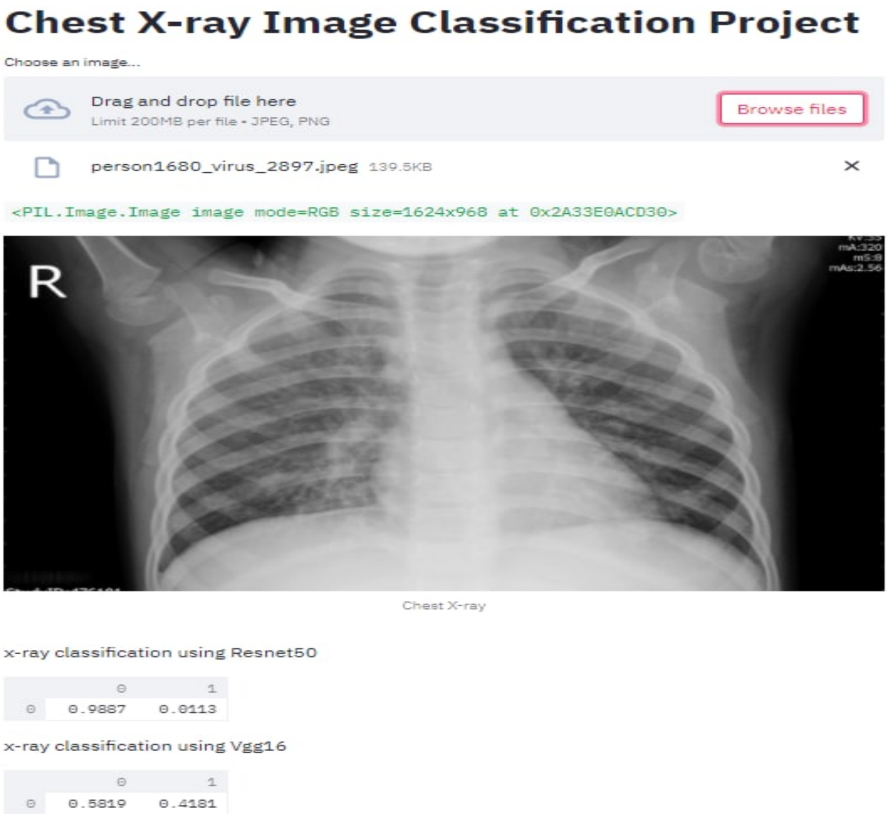

Figure 5.4: algorithm1 resnet

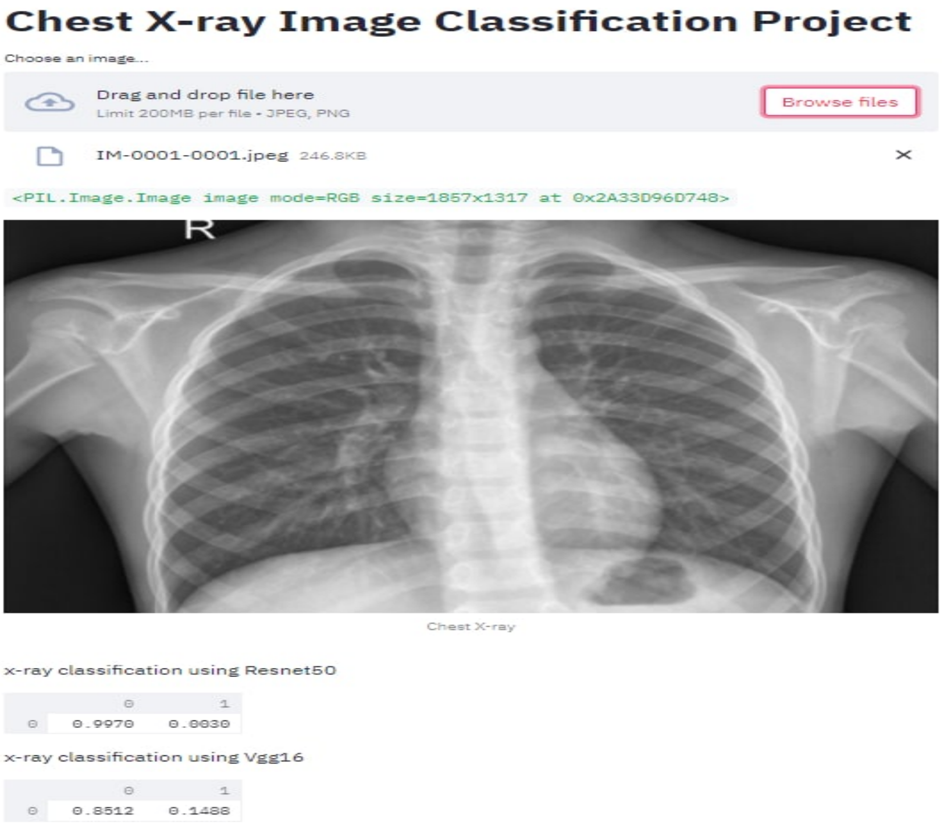

Figure 5.5: algorithm2 vgg

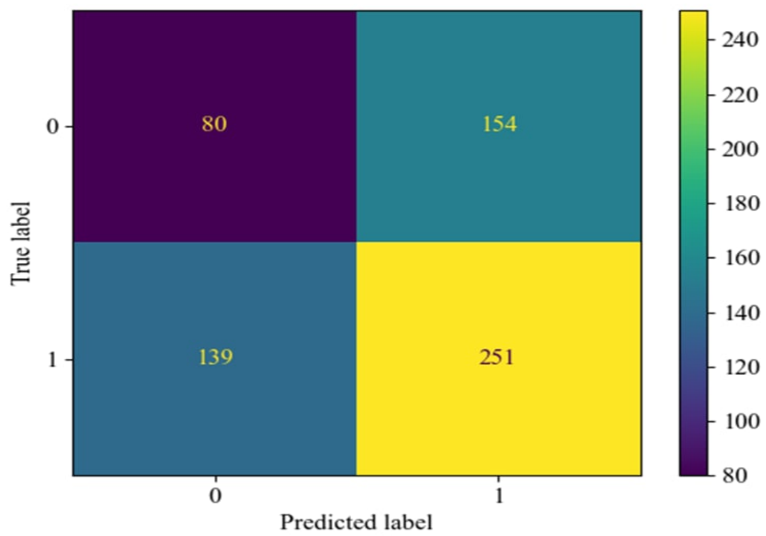

Figure 5.6: Confusion Matrix for Vgg

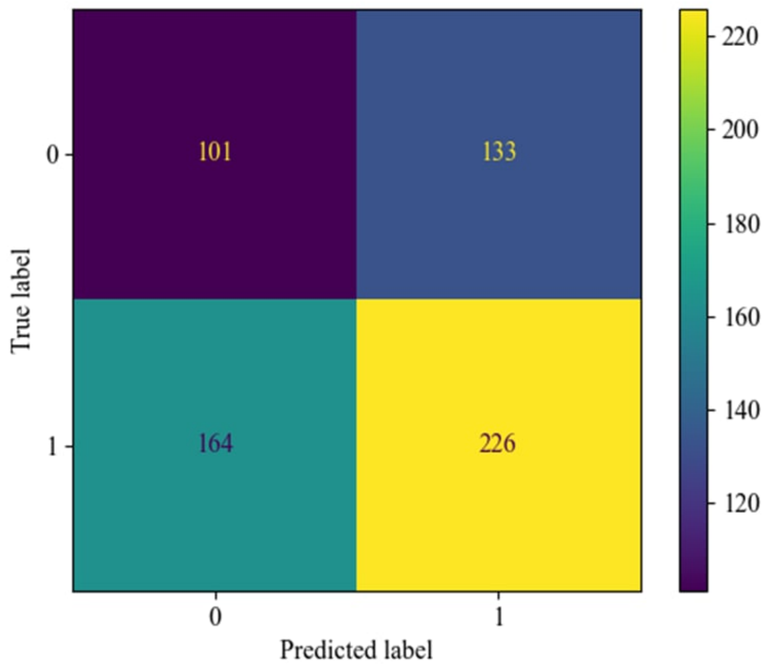

Figure 5.7: Confusion Matrix for Resnet

Chapter 6

CONCLUSION

Intensive studies using X-ray in the chest of patients showed promising results in the diagnosis of Pneumonia. We have worked on a simple network design used with two spinal cords (VGG-16, and ResNet50 pre-trained in ImageNet database) to detect Pneumonia in chest X-ray images. Indeed, with fewer no. of images in the Pneumonia category, good results obtained because of network in the test database having valid value of more than 80percentage in two models. We have used previously trained technologies to improve the effectiveness of the diagnosis of Pneumonia. Our finding with high accuracy can help doctors and researchers make decisions on clinical practice. We would like to emphasize that it will be able to improve the quality of training and acquisition with more images and new data collected in the Pneumonia category. Our results also demonstrate the use of network extension techniques that can benefit from improved precision development and can produce a more common and robust model.

Chapter 7

FUTURE ENHANCEMENT

V. Sirish Kaushik (2020)we will try to apply our approach to larger databases, address other medical issues such as cancer, tissue and so on and move on to other computerized fields such as energy, agriculture, and transportation in the coming days. Future research indicators will include exploring ways to add image data to improve even greater accuracy while avoiding overuse. We have realized that performance can be continuously improved, by increasing the size of the database, using the data add-on method, and using hand-made features.

In the future, if clinical notes and other metadata, for example, provide the need for intubation and additional oxygen, it is possible to train mixed image models with metadata. These types of hybrids can provide predictions and assumptions and are very important in risk identification, patient management, and customized care planning in this resource-intensive problem. All models designed for this task have a memory capacity of less than 100 megabytes. Next, another future guide from this study will extend the model implementation of the standard smartphone processor to make a faster and more balanced trend on the device. To provide evidence of the concept of power transfer of deep learning models on mobile devices, we would like to build on our previous knowledge by transferring such models using the TensorFlow lite (TFlite) library.

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