Multi-Class Classification of Lung Disease Using X-ray Images

Submitted By

Md. Touhid Hasan Tonu

ID: 191-35-2788

Department of Software Engineering

Daffodil International University

Supervised By

Dr. Md. Fazla Elahe

Assistant Professor

Department of Software Engineering

Daffodil International University

This Thesis report has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering

Fall – 2022

APPROVAL

This thesis titled on "**Multi-class Classification of Lung Disease Using X-ray Images**", submitted by **Md. Touhid Hasan Tonu (ID: 191-35-2788)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

BOARD OF EXAMINERS

____________________________________ **Chairman**

Dr. Imran Mahmud
Head and Associate Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

____________________________________ **Internal Examiner 1**

Afsana Begum
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

Fazla Elahe
____________________________________ **Internal Examiner 2**

Dr. Md. Fazle Elahe
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

____________________________________ **External Examiner**

Mohammad Abu Yousuf, PhD
Professor
Institute of Information Technology
Jahangirnogor University

DECLARATION

I hereby declare that I have done this thesis under the supervision of **Dr. Md. Fazla Elahe,** Assistant Professor, Department of Software Engineering, Daffodil International University. I also declare that this thesis is my original work for the degree of B.Sc. in Software Engineering and that neither the whole work nor any part has been submitted for another degree in this or any other university.

Touhid

Md. Touhid Hasan Tonu
ID: 191-35-2788
Department of Software Engineering,
Daffodil International University.

Certified By:

Fazla Elahe

Dr. Md. Fazla Elahe
Assistant Professor
Department of Software Engineering,
Faculty of Science & Information Technology,
Daffodil International University.

ACKNOWLEDGEMENT

First of all, I’m very grateful to the Almighty Allah for giving us the ability to complete the final thesis. I would like to express our gratitude to my supervisor **Dr. Md. Fazla Elahe** for the consistent help of my thesis and research work, through his understanding, inspiration, energy, and knowledge sharing. His direction helped me to finding the solutions of research work and reach to my final theory. I would like to express my extreme sincere gratitude and appreciation to all of our teachers of **Software Engineering** department for their kind help, generous advice and support during the study.

I also express our gratitude to all of our friend’s, senior, junior, who directly or indirectly, have lent their helping hand in this venture. Last but not least, I'd want to express my gratitude to my family for giving birth to me in the first place and for spiritually supporting me throughout my life.

Touhid

Md. Touhid Hasan Tonu

ID: 191-35-2788

Department of Software Engineering,

Daffodil International University

Abstract

Chest x-ray are commonly used medical imaging technique for medical diagnosis. For lung disease many people died every year. In this crisis, an automated system is needed for detect lung related illness. An automated system helps to reduce reading errors, quick report delivery and decrease work pressure. In this research, seven pre-trained model was applied on a merged dataset and showed these comparisons. In this dataset these are four class which are Covid19, Pneumonia and Normal class. After the pre-processing steps x-ray images were fed for classification in VGG16, VGG19, Xception, InceptionV3, DenseNet121, MobileNet and RseNet101. VGG16 achieved the highest accuracy which was 95%.

Keywords: X-ray images; Computer aided diagnosis; lung disease; vgg16; deep learning

Contents

Table of Figures

List of Table

Chapter 1

Introduction

1.1 Background:

Lung disease is one of the leading causes of death globally. Chest X-rays play an important role for the diagnosis of lung related disease. The risk of lung diseases is extensive, especially in developing and low middle income countries, where millions of people are facing poverty and air pollution. Lung disease is currently increasing every day, there is a lack of accurate detection methods. COVID19 was detected in China and the epidemic has been spreading ever since. About 632 million people were infected and 6.6 million died due to COVID19 (7 November, 2022). The inflammation of pneumonia and tuberculosis is also an alarming rate. Approximately 7% of the world's population is affected by pneumonia every year, and 4 million of the affected patients face fatal risks [1]. So early diagnosis is important for lung disease.

Diagnosis of lung diseases from X-ray images is a challenging task even for a trained radiologist. Many radiology departments the lack of radiologist and work pressure leads to inability to read all the chest X-rays. The appearance of lung disease in X-ray images is not clear and also confusing to other diseases. So, there is an interest in developing a computer aided diagnosis (CAD) system for the radiologist to read X-rays easily. An automated system will help to improve the diagnosis quality and also help to rapid diagnosis. Additionally, this research will help the healthcare industry and it may be operated with less training.

Deep learning is a technique where many layers of information processing stages can be used to detect features. Each layer can extract one or more unique features from the images.

In this research, a deep convolutional neural network applied to improve the performance of the diagnosis. All the dataset is collected from Kaggle, GitHub and National Institute of Health - clinical center [2-5]. In addition, to improve the model performance zoom, flipping and rotation augmentation technique used to increase the dataset. Then we use VGG16, VGG19, InceptionV3, Xception, DenseNet121, MobileNet, ResNet101 pre-trained models. All these methods are transfer learning methods. Then customize these pre-trained models for better performance. By using augmented dataset, we have achieved better classification performance.

1.2 Motivation of the Research

In recent times COVID-19 is spreading all over the world. Besides covid19 other lung related illnesses such as pneumonia, tuberculosis infected people increasing rapidly. The detection of these viruses is a big challenge. Detecting these diseases manually is time consuming. According to the Global Air Pollution Report 2017 Bangladesh claims 1,22,400 lives every year due to lung related diseases. In most of the cases lung disease cannot be traced. Chest X-ray is one of the most useful techniques for detecting lung disease. Chest x-rays are cost efficient and it's also used for the primary stage of diagnosis. This research will help to develop an automated system for the diagnosis of chest x-rays and can be also used for rapid detection of lung disease.

1.3 Problem Statement

Lung disease is at an alarming rate at this moment. Nowadays most of the Bangladeshi people are affected by lung related illness. Covid-19, Pneumonia, Tuberculosis are the common diseases among all other respiratory diseases. According to the World Health Organization (WHO) report in 2020 lung disease deaths in Bangladesh reached 6.38% of total deaths [6]. Many authors worked on this problem. But most of them worked with binary classification. They work with Deep Convolutional Neural Network, Convolutional Neural Network and for classification they applied SVM (Support Vector Machine), Decision Tree, Random Forest and many more.

This literature will show the best model for classification by using chest X-rays among the top 10 Deep Convolutional Neural Network models with highest accuracy.

1.4 Research Question

Which model is better for classifying lung disease?

1.5 Research Objective

In this research, apply seven deep learning model on a merge dataset then model can detect multi class lung disease. Focus on the most common lung disease and compare the best model among seven models.

1.6 Research Scope

To develop a low-cost system that will help the health sector to detect disease from x-ray images. In this research, we applied seven convolutional neural network models which are VGG16, VGG19, InceptionV3, Xception, DenseNet121, MobileNet, ResNet101 for classifying 4 disease classes.

1.7 Thesis Organization

In the chapter 1, the background of this work, problem statement, motivation, research questions, research objectives and research scope are discussed. Chapter 2 covers the literature review, methodology, failings and comparison of our work with their work. In chapter 3 chapter we discuss the methodology of our research, architecture of models, data collection and data pre-processing. Chapter 4 presents the experiment result of the methodology. In this ending chapter, we discuss the observation, Suggestion, limitation and future work.

Chapter 2

Literature Review

2.1 Introduction

In this literature review section, we will cover some of previous work on lung disease prediction and also find out their lacking in their works. Find out the limitations and analyze to overcome the limitations to get a better result.

2.2 Previous Work

Combination with pre-trained models and CNN(Convolutional Neural Network) has good capabilities in Image processing. Dina and el at [7] proposed hybrid CNN model to distinguish between covid-19, pneumonia. The Authors use four pre-trained models with convolutional neural networks, Gated Recurrent Unit (GRU) and Bi-Gated Recurrent Unit (Bi-GRU). Among them VGG19 and CNN achieved the highest accuracy 98.05%.

Jin and el at [8] proposed a 3 step base Deep Learning model for Pneumonia and Covid-19 classification. Authors use AlexNet for feature extraction and ReliefF algorithm for feature ranking. Then top features were selected for classification using the SVM classifier. Using only 40 features this algorithm achieved 98.6% accuracy.

The authors in [9] present hybrid VGG with CNN, VDSNet with VGG, Spatial Transformer Network (STN) with CNN. The authors also implemented Vanilla gray, vanilla RGB and custom capsule network. The proposed VDSNet has an accuracy of 73%.

In this research [10], Authors provided a technique for classification of normal, covid and pneumonia classes. They implemented CNN (Convolutional Neural Network) classification method with HOG (Histogram oriented Design) for feature extraction and also used a 10 fold cross validation method on a public dataset. They achieved 80% accuray on their proposed method.

Hashmi and el at [11] presented a weighted classifier including a different deep learning model (Xception, InceptionV3, MobileNetV3 and DenseNet121) for the identification of pneumonia. They have achieved remarkable accuracy, precision and recall values of 98.43%, 98.26%, 99.0% respectively.

The authors in [12] proposed 49 layers of CNN with deep residual architecture for detecting pneumonia. The network was pre-trained on their own dataset rather than ImageNet data set. The results of the experiment were 90.5% accuracy, 89.1% precision and 96.7% recall.

Rahmat and el at [13] employed faster R-CNN for the detection of pneumonia and normal classes. But their dataset was imbalanced and the accuracy of faster R-CNN was 62%.

In this research [14], the authors employed two pre-trained models (VGG16 & Xception) for detecting pneumonia and normal classes from chest X-rays. The accuracy of VGG16 was 87% where the accuracy of Xception was 82%. For detecting normal class VGG16 was better than Xception and also Xception was better for pneumonia class.

Abiyev and el at [15] employed customized CNN, Competitive Neural Network (CpNNs) for detecting pneumonia and normal classes with unsupervised learning techniques and also applied backpropagation neural networks (BpNNs) for detection. The accuracy of customized CNN was 92.4% where CpNN (80.4%) and BpNN (89.57%).

2.3 Conclusion

There are many types of convolutional neural networks applied. In those research articles authors used different types of techniques. Data augmentation, feature extraction, annotation remove technique used for better result. In this work, we also applied different data processing techniques and also applied some pre-trained convolutional neural network model on our balance dataset to overcome lacking's which are mentioned above.

Chapter 3

Methodology

3.1 Research Methodology

We have applied VGG16, VGG19, InceptionV3, Xception, DenseNet121, MobileNet, ResNet101 for this study. **Figure 1** Shows the working procedure.

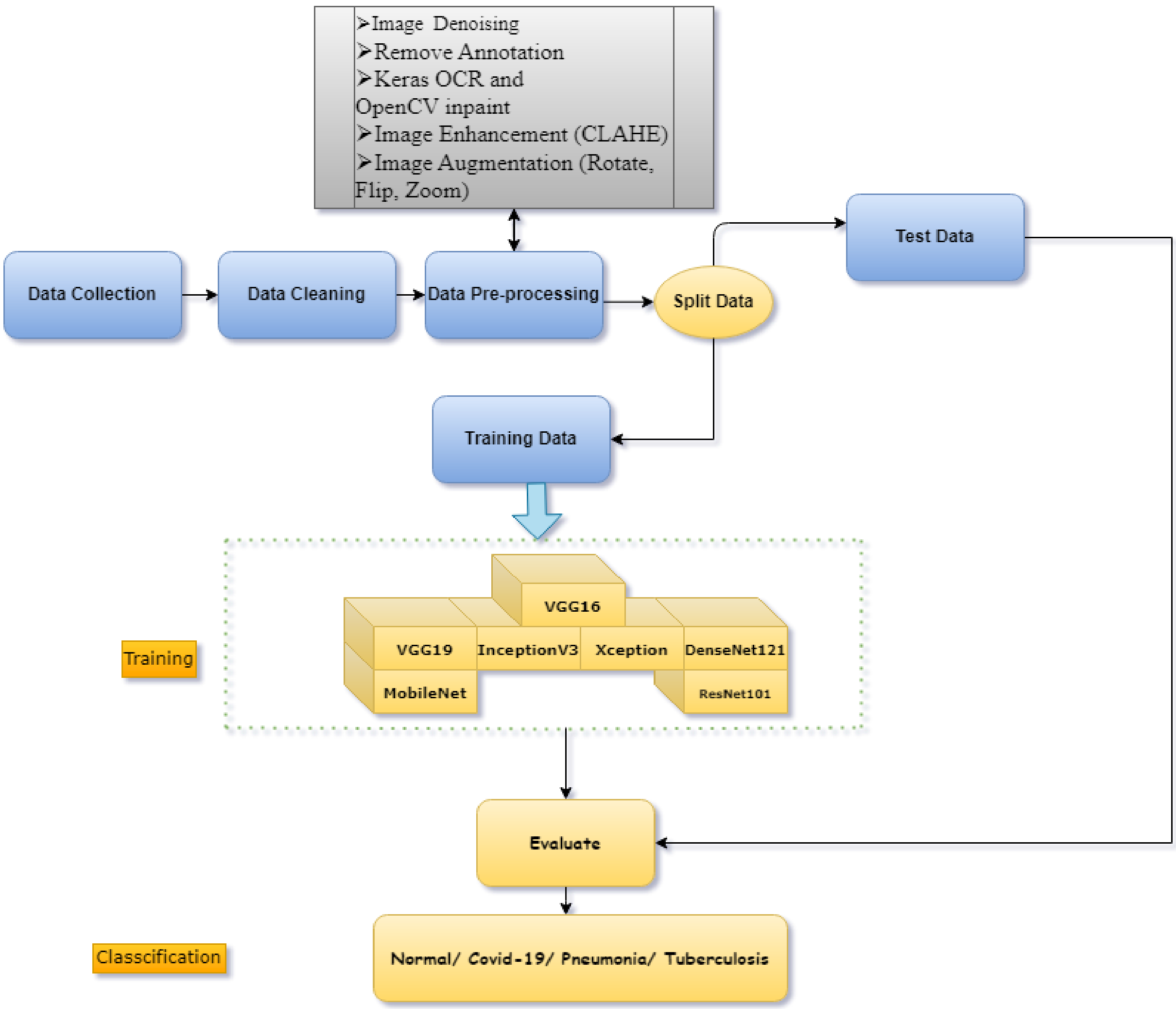

Figure 1: Working Procedure

3.2 Data Collection

In this research, Data were collected from various sources. Kaggle, GitHub, NIH clinical center were the source of our dataset. Collected normal, covid, pneumonia, tuberculosis class data from these sources and then merged them for a collective dataset. Total No of images in the dataset 32,540. **Figure 2** shows 4 class sample images of the merged dataset and Figure 3 shows total dataset images.

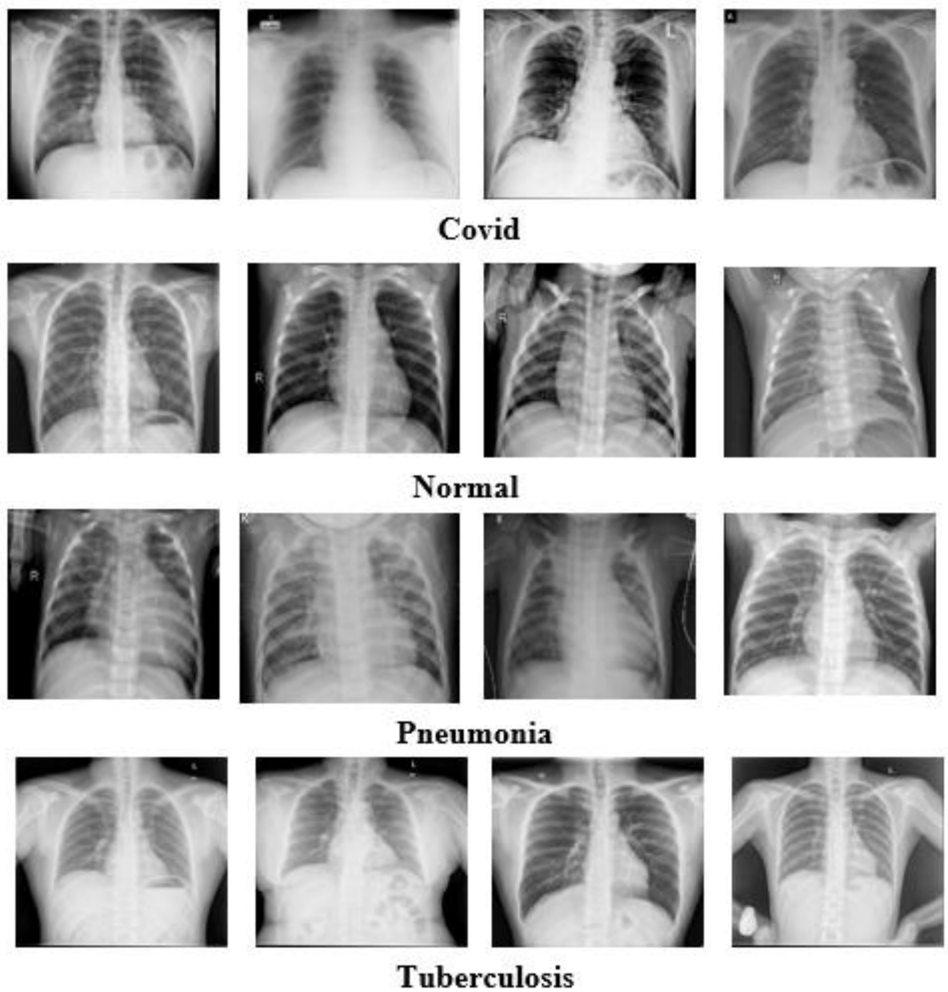

Figure 2: Covid, Normal, Pneumonia, Tuberculosis sample data

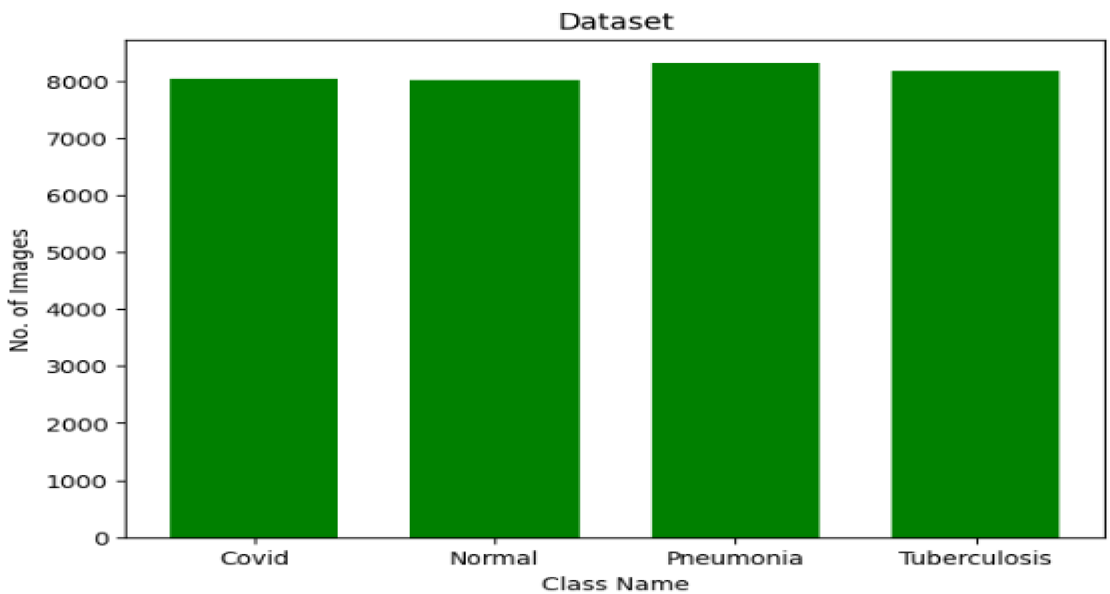

Figure 3: Total Dataset Images

3.3 Data Processing

3.3.1 Image Denoising

Autoencoder is an easy way to remove noise from X-ray images. Denoising with an autoencoder helps to produce more accurate results. This autoencoder is trained on a large dataset [7]. Dataset has been resized for the implementation of autoencoder. Dataset size was 224 x 224 pixels. Figure 4 shows the image denoising architecture.

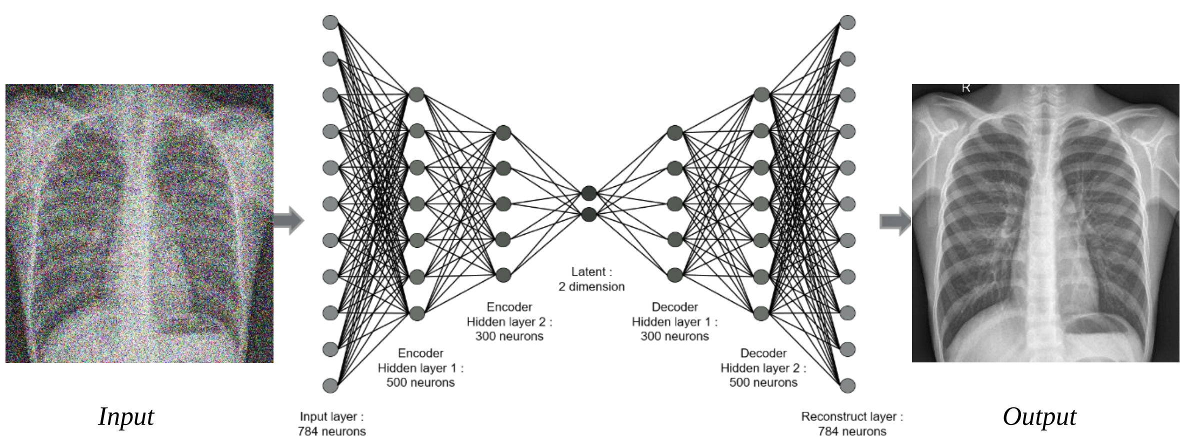

Figure 4: Output and the architecture of Image Denoising

3.3.2 Image Annotation Remove

The objective is to remove annotation from images and fill it with text background color without changing the non-text section. To remove image annotation from x-ray images we used here openCV inpaint and keras OCR. At first keras OCR identifies the text then creates a bounding box of each text. Then apply a mask for each bounding box. Finally apply inpainting to the mark area and we get a text free image without changing the non-text section. Figure 5 show the output after image annotation removal.

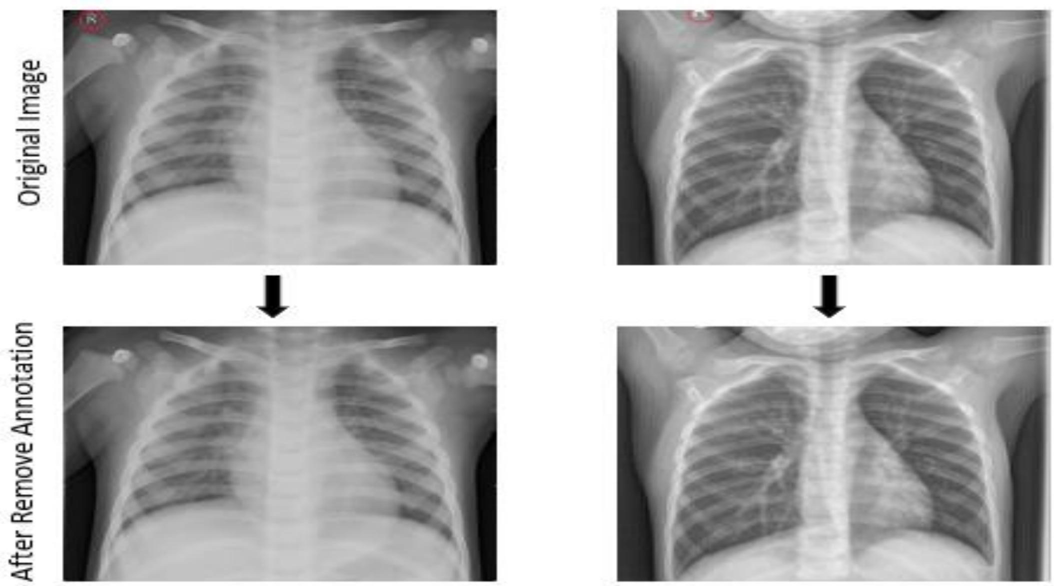

Figure 5: Output after image annotation removal.

3.3.3 Image Enhancement (CLAHE)

To enhance contrast of images we have applied Contrast Limited Adaptive Histogram Equation (CLAHE). CLAHE is a variant of Adaptive Histogram Equation (AHE). It can amplify contrast of image. CLAHE is an effective method for low contrast images. It reduces the false border and to remove artificial boundaries neighboring tiles combined with bi-liner interpolation. The output result shown in the figure 6**.**

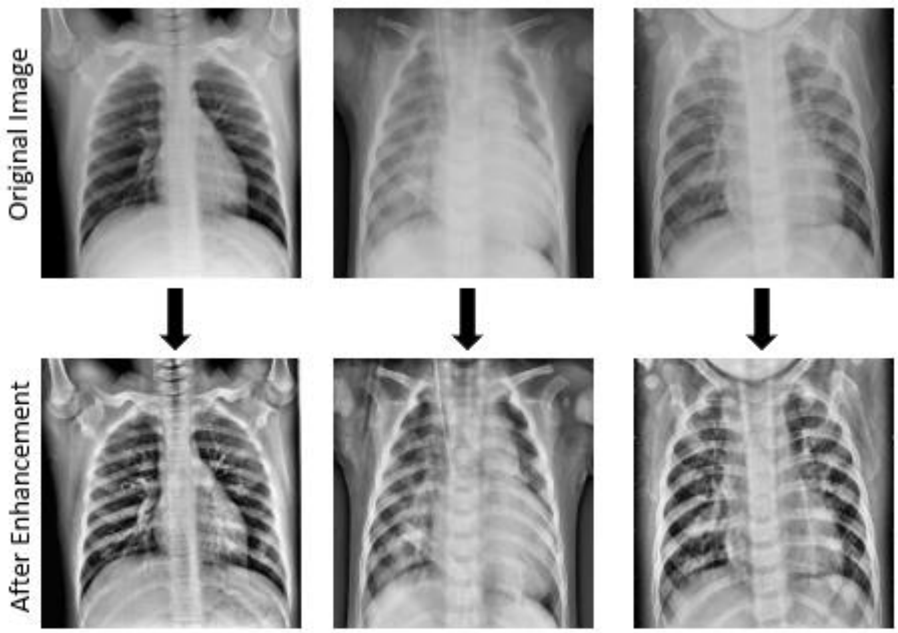

Figure 6: Output after image enhancement.

3.3.4 Image Augmentation

Image augmentation techniques increase the dataset size. It is the process of generating new data from existing data. In this research we use 3 types of augmentation techniques for increasing the dataset size by zooming, flipping and rotating. This increases the performance of deep learning models. In medical Image processing X-ray data labeling and collecting is a time-consuming process. The augmentation result shown in the **figure 7.**

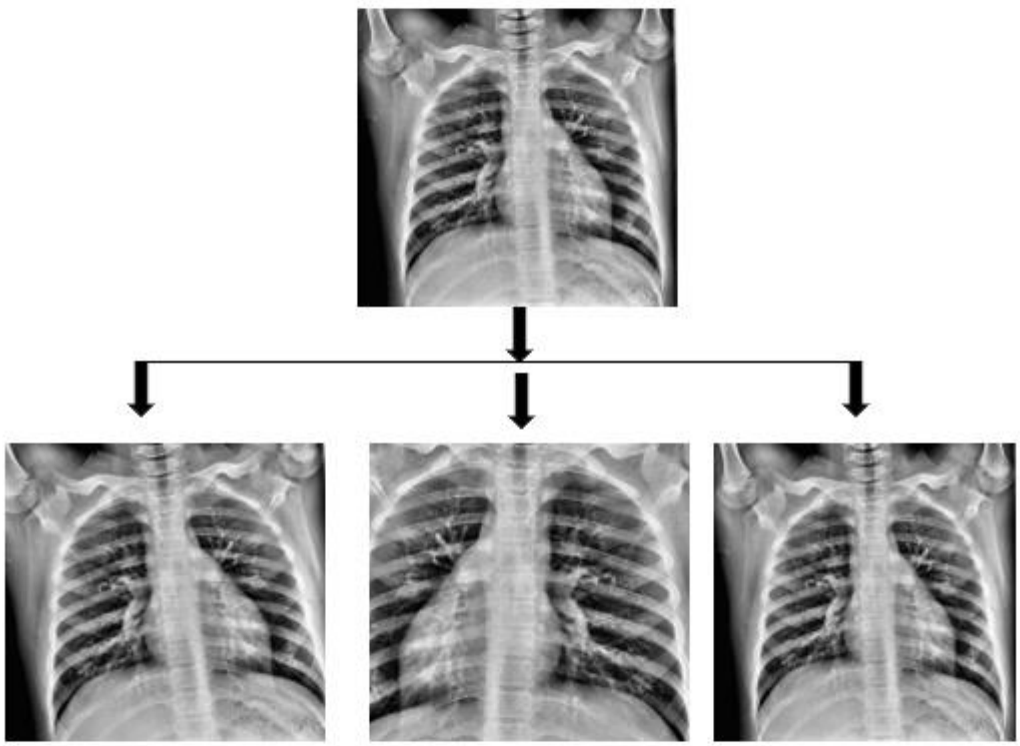

Figure 7: Output of Image Augmentation

3.3.5 Data Normalization

In image processing, normalization of images changes the values of the pixel intensity. Normalization ensures the input parameter has a similar distribution. This will help train the network faster. The pixel value from 0 to 255.

3.3.6 Data Resizing

Resizing images is essential to feed deep learning models. Dataset contains various types of images. In this work, we resize it to (224 x 224) pixels.

3.4 Transfer Learning Models

Transfer learning is the process of transferring previous acquired knowledge to new problem-solving situations. In this research, we used 7 pre-trained models for detecting lung related illness from chest X-ray images. All of these pre-trained models were trained on a large dataset. Extract features from X-ray images by using pre-trained models is a transfer learning technique.

3.4.1 Proposed Model

The objective of this research is to produce adequate classification result utilizing transfer learning models. By hyper tuning VGG16 customized transfer learning model was developed to achieved the highest accuracy among all other pre-trained model. The name of this proposed model is MediNet22.

3.4.2 VGG 16

VGG 16 is a pre-trained model and it was developed by Zisserman and Simonyan in 2014. VGG16 is the improved version of AlexNet. It was trained on a large ImageNet dataset and the collection of images over a million. VGG16 refers to 16 layers of widget. VGG16 contains 13 convolutional layers, 5 max pooling layers and 3 dense layers. The input layer dimensions are (224, 224, 3).

3.4.3 VGG 19

VGG19 is a convolutional neural network which was developed by Simonyan and Zisserman. It has 19 layers with 16 convolutional layers and 3 fully connected layers. The input sizes of VGG19 are (224, 224, 3). It used (3*3) size of kernel and 1 pixel size of stride. Spatial padding and max pooling were performed in this network. Max pooling was (2*2) pixel with stride 2. ReLU (Rectified Linear Unit) implemented in VGG19 which reduces the computational time and helps to classify better.

3.4.4 InceptionV3

Inception V3 was trained on ImageNet dataset and it reduces computation power. The input size of inceptionV3 is 299x299x3 and the output size is 8x8x2048. Convolution layer, average pooling, max pooling, concat, dropout and fully connected layer are used to develop this model. SoftMax was used for loss calculation.

3.4.5 Xception

Xception is 71 layers of convolutional neural network. The dimension of input images shape is (299,299). Xception is the improve version of Inception. This model is divided into 3 flows. Entry flow, Middle flow and exit flow. Start from the entry flow then middle flow and this repeated 8 times finally show output with the exit flow. Xception architecture shows depth wise separate convolution and max pooling.

3.4.6 DenseNet121

DenseNet121 resolve convolutional neural network feed forward problem and simplify the connectivity pattern between layers. DenseNet121 has 1 (7x7) convolution, 58 (3x3) convolution, 61 (1x1) convolution, 4 average pooling and 1 fully connected layer. DenseNet121 allows feature reuse and also require fewer parameters.

3.4.7 MobileNet

MobileNet has 13 (3x3) Depth wise convolution layer, 1 (3x3) convolution and 13 (1x1) convolutions. This pre-trained model was trained using ImageNet dataset. The parameter of MobileNet is 4.2 million.

3.4.8 ResNet101

ResNet101 is 101 layers deep and it was trained on ImageNet dataset. ResNet101 represents the deep residual network framework. The concept of ResNet101 residual learning and skip connection. This helps Resnet101 to train much deeper. ResNet101 has zero padding, average pooling, flatten layer and fully connected layer.

3.5 Evaluation Method

In this research, confusion matrices were used for evaluating the result. For model performance evaluation, the confusion matrix is commonly used. In a confusion matrix each column represents the predicted category and each row represents the true attribution of data. For evaluation, a confusion matrix needs true positive, true negative, false positive and false negative.

True positive (TP) is an outcome when the model correctly predicts positive class. When a model correctly predicts a negative class, it is True Negative (TN). False positive incorrectly predicts positive class and false negative incorrectly predicts negative class.

3.5.1 Accuracy

Accuracy is the ratio between the correctly predicted observation and the total observation. Accuracy is calculated by using **equation 1**.

$$Accuracy = \frac{True\ positive + True\ Negative}{True\ positive + True\ Negative + False\ Positive + False\ Negative} \quad \text{----------} \ (1)$$

3.5.2 Precision

Precision is the ratio between correctly predicted positive observations and total predicted positive observation. Precision is calculated by using **equation 2.**

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$= \frac{True\ Positive}{Total\ Predicted\ Positive} \quad \text{-------------------------} \quad (2)$$

3.5.3 Recall

Recall is the ratio of correctly predicted positive observations to all observations in actual classes. Recall is calculated by using **equation 3.**

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$= \frac{True\ Positive}{Total\ Actual\ Positive} \quad \text{------------------------------} \quad (3)$$

3.5.4 F1 Score

F1 score is the weighted average of Precision and Recall. F1 is more useful than accuracy because it takes both false positives and false negatives values to calculate F1 Score. The F1 formula is given is **equation 4**.

$$\text{F1} = 2 \times \frac{Precision * Recall}{Precision + Recall} \quad \text{-----------------------------} \quad (4)$$

Chapter 4

Result & Discussion

4.1 Introduction

The lung disease classification report is described in this part. After data collection and pre-processing I have applied some pre trained model which is described previously for classification technique. All these used model performances are described in this section.

4.2 Result Discussion

After the implementation of these model, training and validation accuracy, loss and validation loss graph are shown. In this research, VGG16 was employed with flatten layer, dropout 0.5, dense layer and used activation function as SoftMax for 50 epochs. Training and validation accuracy graph, loss and validation loss graph are shown in **Figure 8**.

VGG19 was applied with flatten layer and dropout 0.3, dense layer and used activation function as SoftMax for 50 epochs. Model accuracy and model loss graph are shown in **Figure 9**.

InceptionV3 pre-trained model was trained with merged dataset with 50 epochs and also shown model accuracy and model loss graph in **Figure 10**.

Xception was trained on same dataset but loss was greater than all other pre-trained models. Model loss and accuracy graph are show in **Figure 11**.

DenseNet121 was trained with flatten layer, dropout 0.5, activation function sigmoid, loss function categorical entropy and Adam optimizer. Model loss and model accuracy graph shown in **Figure 12.**

MobileNet was employed for training with hyper tuning. Used categorical entropy as loss function, optimizer as rmsprop. Validation loss was high. Accuracy graph and loss graph shown **Figure 13.**

ResNet101 model was trained on same dataset without dropout and used SoftMax for activation function. Accuracy and validation graph shown **Figure 14.**

4.2.1 VGG16

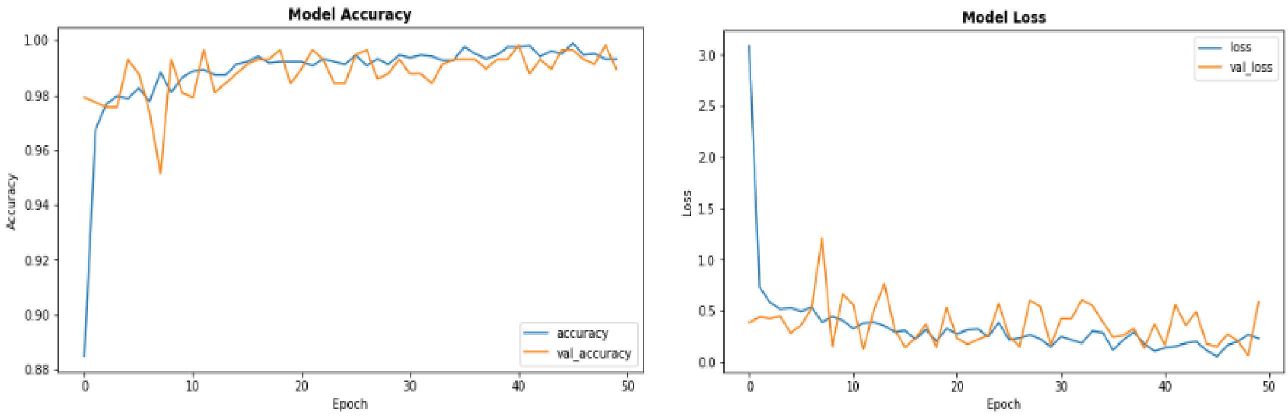

Figure 8: Model Accuracy and Model Loss of VGG16

4.2.2 VGG19

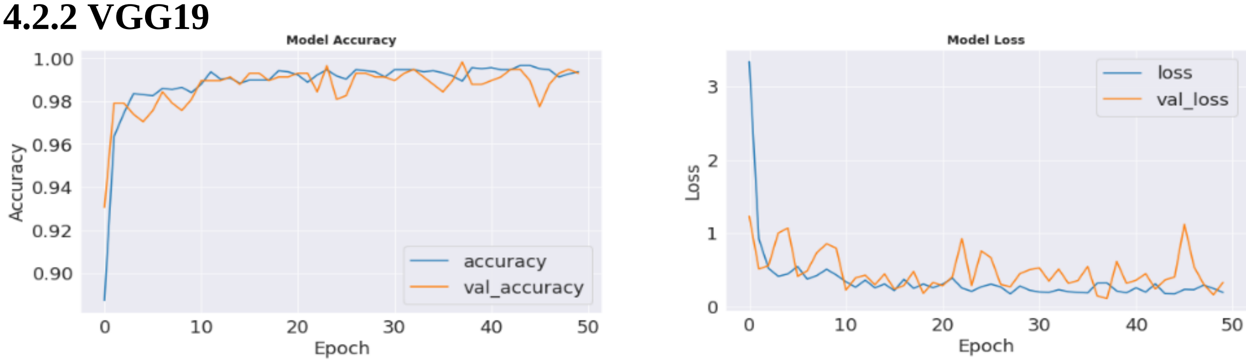

Figure 9: Model Accuracy and Model Loss of VGG19

4.2.3 InceptionV3

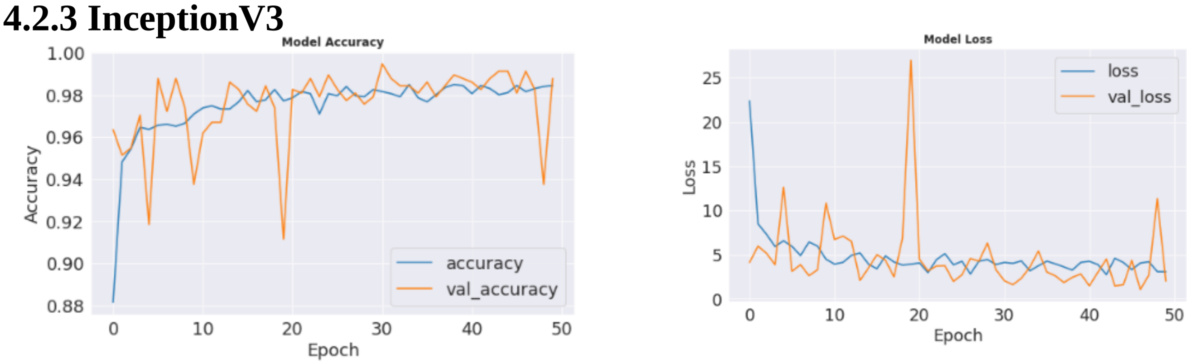

Figure 10: Model Accuracy and Model Loss of InceptionV3

4.2.4 Xception

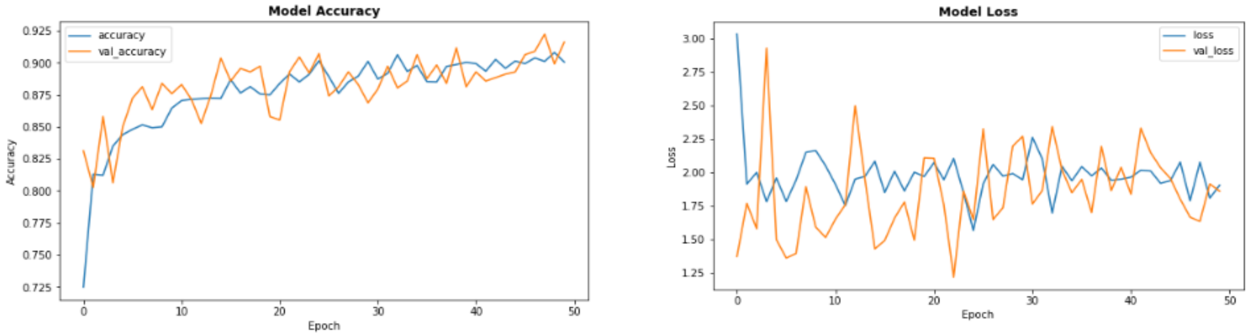

Figure 11: Model Accuracy and Model Loss of Xception

4.2.5 DenseNet121

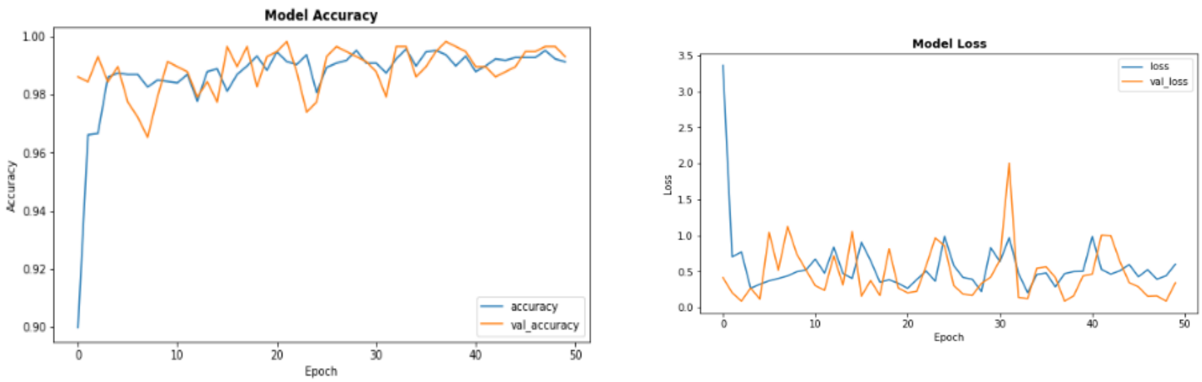

Figure 12: Model Accuracy and Model Loss of DenseNet121

4.2.5 MobileNet

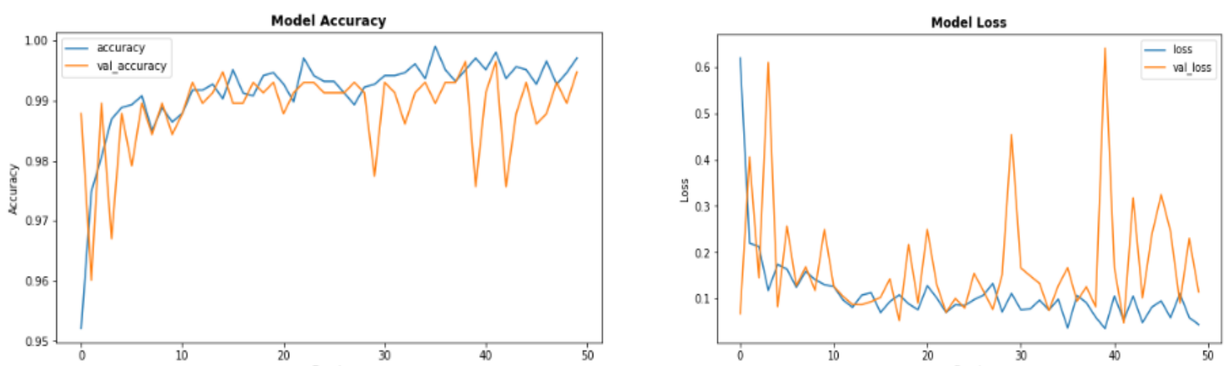

Figure 13: Model Accuracy and Model Loss of MobileNet

4.2.6 ResNet101

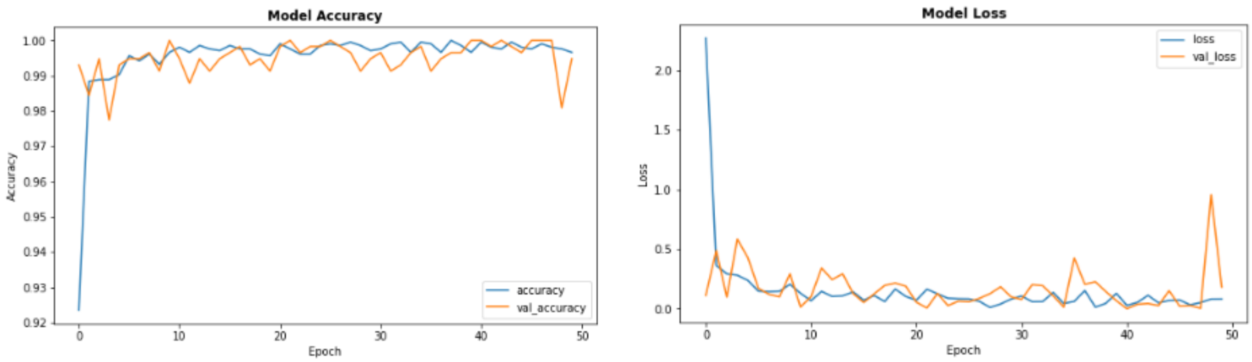

Figure 14: Model Accuracy and Model Loss of ResNet101

In table [1] classification reports of seven pre trained model has been shown. By analyzing this table, Xception, MobileNet, DenseNet121, ResNet101, InceptionV3, VGG19 and VGG16 accuracy is 75%, 80%, 82%, 84%, 85%, 89% and 95% respectively.

Model Name	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
MediNet22	91	96	95	95
VGG16	90	89	91	91
VGG19	90	89	89	89
Xception	81	75	76	75
InceptionV3	87	86	86	85
DenseNet121	85	83	82	82
MobileNet	80	81	80	80
ResNet101	83	84	84	84

Table 1: Classification reports of pre-trained models and proposed model

In **Figure 15** an accuracy bar graph which is the comparison of accuracy and Confusion matrix result shown in **Figure 16.**

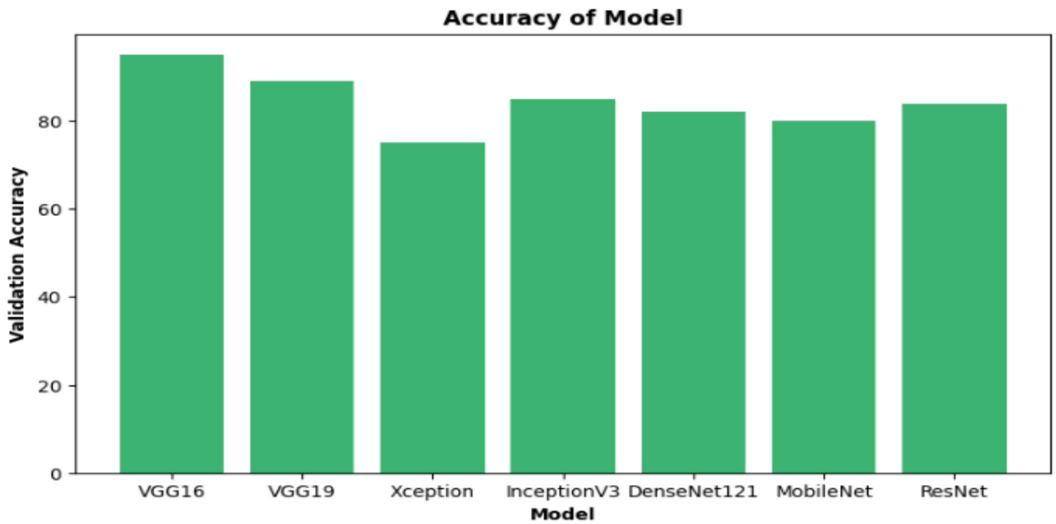

Figure 15: Accuracy of pre-trained model

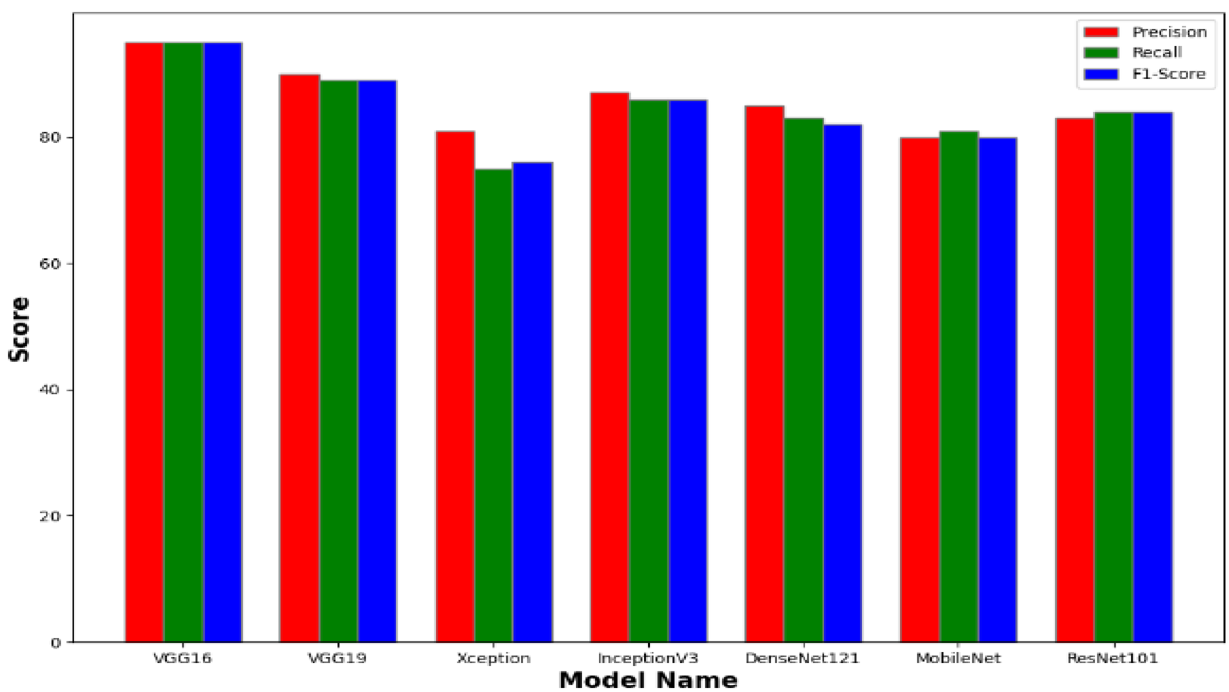

Figure 15: Precision, Recall, F1-Score Comparison of pre-trained model.

Chapter 5

CONCLUSION & FUTURE WORK

Conclusion & Future Work

The goal of this research is to develop a rapid lung detection system which helps radiologists and doctors analyze x-ray images quickly. Manually check X-ray images is time consuming and its difficult even for a trained radiologist. It will also help patients to get report timely and ensue proper treatment. In this research several data processing technique has been applied. The method of image annotation removal was applied. Also used image enhancement and image augmentation for better classification result. Augmentation technique increases the dataset size and 3 types of augmentation technique was applied. To train this dataset 7 pre-trained model was used. This work shows the comparison of these models. Among these models VGG16 shows highest accuracy and minimum validation loss. The accuracy of this model was 95%.

In the future, I will apply these models in different dataset with fine tuning. Manual label dataset is needed for better performance and also need to increase the dataset.

References

[1]. Shen, Yuechun, et al. "Impact of pneumonia and lung cancer on mortality of women with hypertension." *Scientific reports* 6.1 (2016): 1-9.

[2]. Kaggle. Available online: https://www.kaggle.com/prashant268/chest-xray-covid19-pneumonia

[3]. Kaggle. Available online: https://www.kaggle.com/jtiptj/chest-xray-pneumoniacovid19tuberculosis

[4.] Github. Available online: https://github.com/ieee8023/covid-chestxray-dataset

[5]. NIH Dataset. Available online: https://nihcc.app.box.com/v/ChestXray-NIHCC/folder/36938765345

[6]. https://www.worldlifeexpectancy.com/bangladesh-lung-disease

[7]. https://openi.nlm.nih.gov/detailedresult?img=CXR111_IM-0076-1001&req=4

[8]. Ibrahim, Dina M., Nada M. Elshennawy, and Amany M. Sarhan. "Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases." *Computers in biology and medicine* 132 (2021): 104348.

[9]. Jin, Weiqiu, et al. "Hybrid ensemble model for differential diagnosis between COVID-19 and common viral pneumonia by chest X-ray radiograph." *Computers in biology and medicine* 131 (2021): 104252.

[10]. Chen, Joy Iong-Zong. "Design of accurate classification of COVID-19 disease in X-ray images using deep learning approach." *Journal of ISMAC* 3.02 (2021): 132-148.

[11]. Hashmi, Mohammad Farukh, et al. "Efficient pneumonia detection in chest xray images using deep transfer learning." *Diagnostics* 10.6 (2020): 417.

[12]. Liang, Gaobo, and Lixin Zheng. "A transfer learning method with deep residual network for pediatric pneumonia diagnosis." *Computer methods and programs in biomedicine* 187 (2020): 104964.

[13]. Liang, Gaobo, and Lixin Zheng. "A transfer learning method with deep residual network for pediatric pneumonia diagnosis." *Computer methods and programs in biomedicine* 187 (2020): 104964.

[14]. Rahmat, Taufik, Azlan Ismail, and Sharifah Aliman. "Chest X-ray image classification using faster R-CNN." *Malaysian Journal of Computing (MJoC)* 4.1 (2019): 225-236.

[15]. Ayan, Enes, and Halil Murat Ünver. "Diagnosis of pneumonia from chest X-ray images using deep learning." *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*. Ieee, 2019.

[16]. Abiyev, Rahib H., and Mohammad Khaleel Sallam Ma'aitaH. "Deep convolutional neural networks for chest diseases detection." *Journal of healthcare engineering* 2018 (2018).

