# Pneumonia Disease detection using the Convolutional Neural Network

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
Brac University
January 2023.

# Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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# Ethics Statement

It is to declare that we have not used any unfair means for conducting the thesis. We are abide by the rules of BRAC University and have not used any unfair means.

# Abstract

A bacterial illness called pneumonia causes inflammation in the air passages with one or even both lungs. The disease can range from mild to life-threatening. Diagnosing the disease at an earlier stage is crucial for the successful recovery of the patient. In this study, we analyze and compare various deep learning algorithms for lung illness identification and propose an updated model for pneumonia detection. The model is implemented to test its efficacy. The convolutional neural network is fed 5856 chest X-ray images split into 3 categories: training, test, and validation. Two chest conditions, namely pneumonia and normal, were detected and classified. The CNN model, trained with these datasets, achieved 94.66% training accuracy and 91.83% validation accuracy. Moreover, we also run some pre-trained models. They are: Resnet50, Inceptionv3, EfficientNet B0, Xception and VGG16,EfficientNet B6. We gained 68.91%, 83.71%, 62.50%, 91.35%, 90.75% and 62.50% accuracy respectively from them. Hence, We can observe that what was suggested. In these experimental results, the CNN model fared better than them.



**Keywords:** Deep Learning,Pneumonia Detection,Image Processing,Convolutional Neural Network(CNN),Neural Network.

# Dedication

This paper is dedicated for the betterment of the modern Science.

# Acknowledgement

We want to thank our supervisor and co-supervisor for guiding us throughout the whole thesis.

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# Chapter 1

# Introduction

## 1.1 Background Information

Pneumonia is a disease which causes inflammation of the lungs and primarily affects the small air sacs known as Alveoli[2]. One or both lungs may become infected with pneumonia, which is typically brought on by bacteria, viruses, or fungi. The infection causes air sacs in the lungs to fill with pus and other liquid. Fever, coughing, and the formation of sputum are some of the usual signs of pneumonia. These signs can resemble those of other non-infectious respiratory disorders. ICDDRB estimates that 12,000 Bangladeshi children under the age of five pass away from pneumonia each year[41]. Another UNICEF study reveals that pneumonia is the most common infectious cause of death in children under the age of five, killing 2000 children per day, or one kid every 43 seconds worldwide[13].Pneumonia diagnosis is usually made based on a patient's severity of the illness and health history. Pneumonia diagnosis at an early stage is essential for the successful recovery of the patient, as the disease can worsen with time and become unrecoverable. Chest X-rays and Blood Tests are the primary and essential steps to diagnose the disease.Chest X-rays produce images of a person's heart, blood arteries, airways, chest, and spine bones, displaying any external fluid or air that may be located in or around patient's lungs. Chest X-ray is done for almost all kinds of chest diseases including Cystic Fibrosis, Asthma, Bronchiectasis, Chest wall Cancer, Shortness of Breath, Severe cough, Pneumonia and so on. High-level professionals do the X-ray radiograph (CXR), and issues are identified by an increased opacity area on the CXR[9]. The diagnosis by this method can be complicated by some other conditions in the lungs such as bleeding, volume loss, lung cancer, fluid overload and surgical changes. Depth of insertion and the positioning of the patient can alter the opacity of the infected areas in the CXR[3]. These factors make it difficult to identify pneumonia. Additionally, the task takes a lot of time, and even a small mistake can change the outcome.
Machine learning's subset deep learning has been essential in advancing image processing technology significantly. Over the years, CNN, a subtype of deep neural networks, has had great success in computer vision, including feature extraction, picture segmentation, and image classification.The sections that make it up the Cnn model include convolution, pooling, and fully connected layers. In recent years, it has become clear that convolutional neural networks have great promise for biomedical image diagnostic systems. The gradients and flow of information make the optimization traceable; Utilizing CNN, extremely effective categorization models

can be created[1]. The performance of the CNN model can be improved further by an engrossing transfer learning approach where models are trained for a particular task and can be used in performing a comparable task using a predetermined set of parameters and weights. It improves model effectiveness and conserves computational resources. The categorization of chest X-ray pictures is used in this research to diagnose pneumonia, and a customized CNN model is suggested along with a number of additional pre-trained models tuned for improved performance.

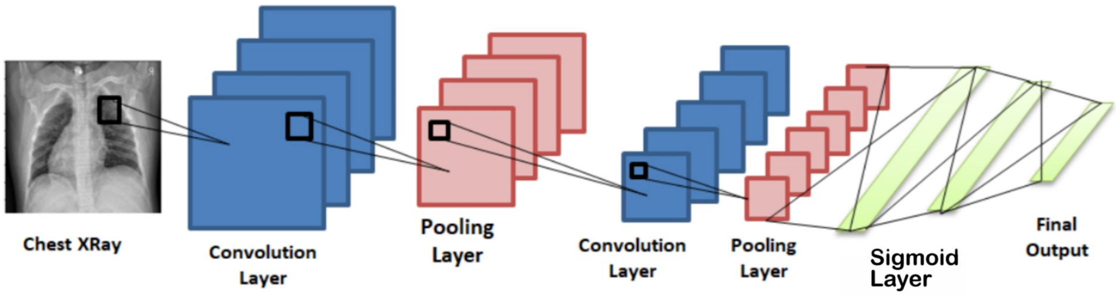


Figure 1.1: An example of a Deep learning task using CNN

## 1.2 Problem Statement

Each year, four million people die from pneumonia, which affects around 7% of the global population and accounts for roughly 450 cases[11]. According to a study published on World Pneumonia Day, the illness would claim the lives of 11 million children under the age of five by 2030[6]. Coronavirus has recently been one of the most significantly damaging diseases in the last few years. Pneumonia is also known to complicate covid-19 disease which has also become a global concern, with confirmed cases in 185 countries across five continents[38]. Streptococcus pneumoniae (also known as pneumococcus) bacteria, which causes lung inflammation and damages the tiny air sacs in the lungs known as alveoli, is a major cause of pneumonia. An X-ray of the patient's chest is typically used to diagnose the illness. Normal and Pneumonia-infected lungs appear differently on an X-ray; the fluid or pus inside the pneumonia-infected lungs causes the X-Ray image to appear brighter than a normal lung's X-Ray image.


Figure 1.2: X-Ray images of normal lungs and Pneumonia-infected lungs

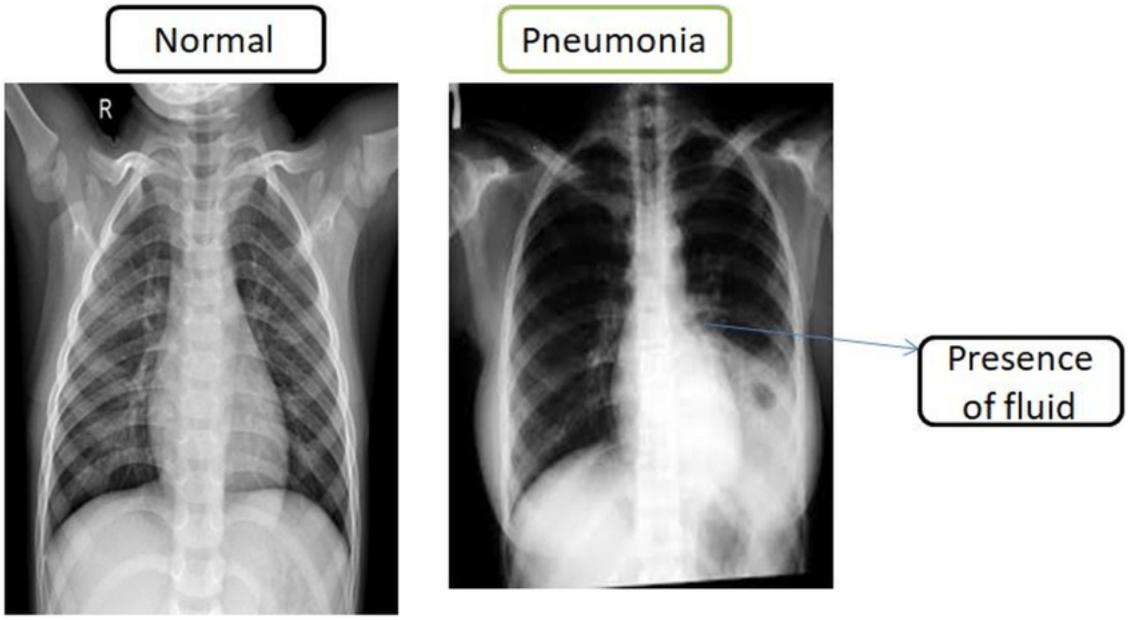


Figure 1.3: Difference in Chest X-Ray Pictures in Normal and Pneumonia

But the X-ray image is not enough to detect pneumonia without knowing the history of the patient. If the patient has symptoms of pneumonia like fever and a cough for a period of time etc only then the doctor can predict the patient might have pneumonia. Sometimes, the X-Ray images can be misleading depending on the patient's condition and some external factors such as the depth of insertion and the positioning of the patient. Also, some other diseases can create a somewhat similar effect on the X-Ray pictures. The below pictures show the X-Ray pictures of pneumonia-infected lungs and covid-19 disease-infected lungs.

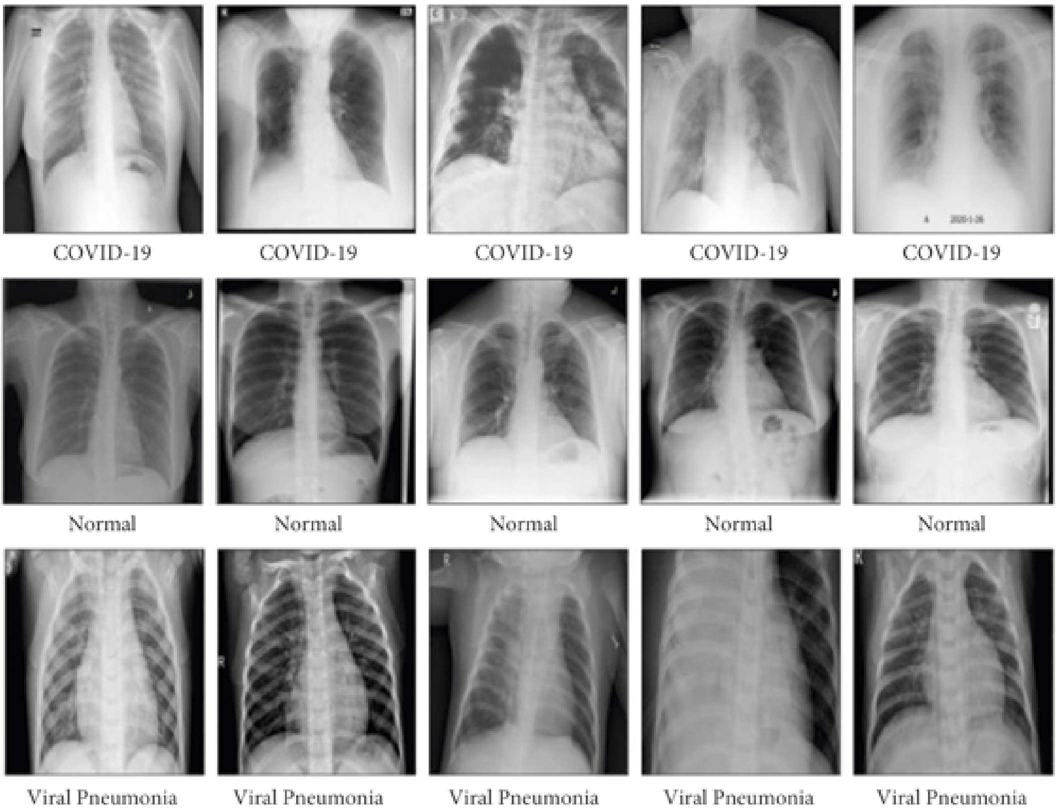


Figure 1.4: Pneumonia infected lungs along with other disease infected lungs and normal lungs

Other diseases or infections like covid-19, Bronchitis, and lung cancer can also create somewhat similar X-Ray images. So the diagnosis of the patient is only based on the X-Ray images and can be misleading to human eyes. An "artificial neural network," which is a sort of machine learning utilized in deep learning, is modeled after the structure of a human brain and is capable of learning from enormous amounts of data. Convolutional Neural networks have been proven to be significantly promising in biomedical image diagnostic systems in recent years. In this paper, Convolutional Neural Network has been used to build a customized model which can successfully detect Pneumonia-infected lungs and distinguish between pneumonia-infected lungs and normal lungs and other disease-infected lungs.

## 1.3 Research Motivation

Pneumonia is usually detected by doing a chest X-ray and by analyzing the patient's medical history. Researchers have developed numerous complex algorithms and test equipment to interpret X-ray images due to their laborious nature[37]. These tools have not been proven significantly capable of assisting experts in decision-making[18]. That is why it is quite difficult to determine if a patient has pneumonia or not without analyzing the patient's medical history. In recent years, machine learning and deep learning techniques are being applied in the area of medical imaging for the detection of various diseases like brain tumors[16], breast cancer[14], skin cancer[5], tuberculosis[7] etc and these were quite successful. They occasionally even outperform psychiatrists in terms of prediction accuracy[10].Artificial neural networks with numerous layers are used in deep learning, a field of artificial intelligence and machine learning. and it can be used for better accuracy in detecting diseases based on image classification. Some researchers have already used customized CNN models and pre-trained models to detect pneumonia based on X-Ray images, which is shown in the literature review part. But usage of conventional neural networks for detecting pneumonia is rather new compared to machine learning models and other computer-aided technologies. More customized models need to be developed for detecting the disease at an early stage as it is essential for the successful recovery of a pneumonia patient. Deep learning models proved to be a promising method in detecting many diseases and it can be the tool that the modern medical industry can rely on. This motivates us to propose a customised CNN model detecting pneumonia by extracting features from X-ray images.

## 1.4 Research Objective

The main objective of this research is to create a machine learning model for identifying pneumonia from X-ray images of the patient body. X-ray scans of healthy chests, chests affected with pneumonia, and chests infected with various diseases were used to create a bespoke deep learning model utilizing convolutional neural networks. Also, six pretrained models have been tuned and trained to get a good result from the dataset. A comparative discussion between the custom model and the pre-trained models will also be shown in the study. The pre-trained models that have been used in this study are VGG16, InceptionV3, EfficientNetB0, ResNet50, Xception and EfficientNetB6. After analyzing the accuracy of the custom model with the pre-trained models, a comparative discussion with the other research done on similar topics will be conducted. Furthermore, the model will be continuously trained using other datasets for better accuracy and hopefully, it will be a great tool in detecting the factitious disease. Overall, the key points of the research objectives are

1. Understanding CNN and how it works.
2. Creating a model to recognize pneumonia using X-ray images.
3. Tune and train pre-trained models by using X-Ray pictures, Pneumonia can be identified.
4. To understand the impact of deep learning in our model.
5. To provide guidance and support for ophthalmologists to detect disease faster and accurately.
6. To conduct a comparative discussion between the customized model and pre-trained models.

# Chapter 2

# Related Work

## 2.1 Related Works

A deep learning-based system for disease identification was proposed by Safa Ben Atitallah et al.[31] and is crucial for specialists to use in order to accurately diagnose diseases at various stages.They are especially interested in using the Dempster-Shafer theory to combine five pre-trained CNNs, particularly VGG16, Xception, InceptionV3, ResNet50, and DenseNet201, to diagnose pneumonia from chest X-ray pictures.To justify their method, they used a dataset which has 5800 X-ray images.Their findings demonstrate that, when comparing to other flagship approaches, their methodology has exceptional detection performance, with precision, recall, and accuracy scores of 97.8%, 97.8%, and 97.3% respectively.
A. Beena Godbin et al. 's[36] research of a COVID-19 detection machine learning model based on GLCM extracted features from chest CT images. Moreover, they used SVM, K-nearest neighbours, Random Forest, and XGBoost classifier altogether with LBGM. They used a tuning test to set the hyperparameters of the model. They received the highest accuracy of 99.94% using Random Forest and SVM for GLCM features. Their network's performance was evaluated through sensitivity, accuracy and specificity.
CNNs were trained and confirmed by M.W. Kusk et al.[35] to support the diagnosis of pneumonia on Chest radiograph either simple or pneumonia obtained at various image noise levels.. They used the "Chest X-Ray Pneumonia" dataset which is classified into 1583 normal, 4273 viral and bacterial pneumonia cases. The images had zero mean Gaussian noise added to it. Their level of noise dataset was divided into 80% training data, 10% validation data, and 10% test data for their observations. On the other hand, their five Gaussian noise levels were developed by six classification tasks. Moreover, CNN testing on the other different dataset saw no performance degradation, and the normal dataset were 98.7%, 76.1% and 90.2% for sensitivity, specificity and accuracy. They used a heat map for explaining the CNNs. The CNNs saw no performance drop in their experiment. Their research has the potential for lowering the radiation dose to patients.
In [21] Researchers implemented each image being preprocessed based on the Deep Neural Network .Resizing and normalization were two crucial phases that were involved in their model.Techniques for enhancing data were utilized to analyze the dataset more quickly.They employed ResNet18, DenseNet121, and MobileNetV2 demand images to be 224*224 pixels in size, while InceptionV3 and Xception de-

mand 229 x 229 pixels.The accuracy and AUC scores were computed in order to further assess the stability of the approach.After Comparing between above deep learning models they got the best accuracy of 96.84

Racic L. et al.[26] utilized Numpy, Pandas, Keras, Jupyter Notebook, matplotlib, and seaborn as their primary tools.A machine learning technique built on CNN was used to classify the images.They employed Pooling layers to shrink the size of the input image without missing any crucial details,lower memory consumption and processing costs. Additionally, by lowering the number of factors, this technique lowers the chance of overfitting.The ReLU activation function was applied in their experiments Due of its quick computation.Although they got the model's accuracy is rather high nearly 90% but the magnitude of the dataset raises the danger of overfitting.

In [17] Authors used the ChestX-ray14 dataset, which is freely accessible on the Kaggle platform and contains 112,120 frontal chest X-ray pictures from 30,085 individuals.The suggested method for diagnosing pneumonia included a deep convolutional CNN (DenseNet-169) that divided the model into three discrete stages: preprocessing, feature extraction, and classification.SVM was employed by them as the a classifier for the step of classification.They trained a 169-layer densely connected convolutional neural network beforehand.They performed the aforementioned experimental study to identify the best model for classifying chest X-rays.

Authors in[8] made use of the two-step suggested pneumonia detection system technique.Firstly they took chest X-Ray as input and employed image preprocessing methods to improve design performance in their initial stage.The desired area was obtained in the following stage using lung segmentation.After that They utilize the classification algorithm which is used determine if pneumonia is either present or absent in the picture which was taken as input utilizing VGG16 as the fundamental procedure and is based on CNN.Though there were several approaches but The above algorithm can be further adjusted to enhance the accuracy.The usage of a flexible and moderately sized dataset containing images from multiple hospitals and radiologists has emerged from the numerous datasets , improving the precision and producing a greater result when evaluated on images from diverse datasets.They outperformed those that employed modified VGG16 since the program and had accuracy rates of 96.2% and 93.6% for identifying and classifying pneumonia, respectively.

P. Rajpurkar et al.[20] created an algorithm that outperforms experienced radiologists at spotting pneumonia in chest X-rays.Researchers employed the ChestX-ray14 data, consisting of 30805 distinct patients' 112,120 frontal-view X-ray pictures.They downscale the photos to 224*224 and normalize them in the ImageNet training set before putting those into the system.Then they created 95% bootstrap confidence intervals using the bootstrap method and made a comparison of CheXNet and Radiologist Performance and found out CheXNet outperforms radiologist performance by a statistically significant margin.After that They improved the system to categorize various thoracic diseases.Lastly,By scaling the map Mc to the dimensions of the image and superimposing it over the image, they determined the key elements that the model utilized to predict the disease.

In article[25] authors provided a quick and efficient algorithm for pinpointing the locations of lung opacities. They used Squeeze-and-extinction deep convolutional Neural Networks (CNNs), augmentations, and multi-task learning in their method.

The program performed among the best in the tasks, autonomously identifying lung opacities on chest radiographs.They used the labeled dataset Given the input dataset of the chest X-ray pictures.They put out an answer based on a single model that was combined across a number of checkpoints and four folds. This algorithm uses a pre-trained SE-ResNext101 encoder on ImageNet and an SSD RetinaNet .On contrary They received the Accuracy of 87.5%.
To identify pneumonia from the CS measures of an X-ray image Islam S.R. et al.[32] proposed a DL approach based on a customized CNN and fully connected neural network is developed and operated.Three fully connected layers and three FC levels make up the DL model.Employing the three convolutional layers results in an incremental improvement in accuracy.They utilized the Kaggle dataset34, which consists of 5856 total X-ray pictures including regular and pneumonia which is separated into training, validation, and test sets.To minimize the necessary computing workload during training, X-ray images are downsized into 128*128.The development environment comprises the KERAS libraries and packages, which utilize TensorFlow 2.0 as a backend.After 400 iterations,The training and validation Accuracy reached 96.41% and 95.58% respectively.
Sunil L. Bangare et al.[30] developed a VGG-based CNN model To extract the characteristics from chest X-ray pictures and utilize those characteristics to determine whether a patient has pneumonia.The 5863 X-ray images that make up the suggested database, that will be utilized to evaluate the model's performance, were obtained via Kaggle.The architecture of their organization is made up of two primary parts consisting Conv layers and pool layers.Multiple optimization strategies, including hyper-parameter optimizations, were investigated to increase the model's effectiveness.The Accuracy of the developed model reached 91.98% correct.
Y.Yang et al.[34] gathered arranged datasets of chest X-ray images from both pneumonia patients and healthy individuals.Then Five pneumonia recognition facilities were developed consisting of LeNet5, AlexNet, MobileNet, ResNet18, and Vision Transformer for identifying pneumonia.After comparing between 5 models they found out where the lung structure in the X-ray for pneumonia is hazy and the lung texture in the X-ray for normal breathing is distinct.After analyzing, they got the highest accuracy from AlexNet model which is 83.968% compared to other models.
Nazmus Shakib Shadin et al.[27] presented Convolutional Neural Network(CNN) based Automated Pneumonias with and without COVID-19 Identification from pictures of the X-ray of the chest. Through the use of CNN and CXR images, their research intends to develop a system that can distinguish automatically between pneumonia caused by COVID-19 and pneumonia caused by the other infections. They designed the CNN model, since there were few CXR images with COVID-19 pneumonia that were publicly available. They used Convolutional2D in each convolutional layer of the convolutional network. Specifically, for the first and second thick layers, the "Relu activation function" and the "Sigmoid activation function" were used. They were able to achieve 98.20% inside the training dataset set and 98.22% maximum modeling precision in the validating dataset.
Devansh Srivastav et al.[19] built a computer-aided deep learning approach diagnostics method to identify pneumonia with pictures of chest X-ray. Their article identified pictures of chest X-ray to determine pneumonia using methods of deep learning. To saturate the sample set and improve the system's performance, they created DC-

GAN(deep convolutional generative adversarial networks) for the enhancement of artificial pictures. They also employed VGG16 as the foundation model for picture categorization with convolutional neural networks. On the validation set, their model was successful in achieving 94.5% accuracy.
Nada M. Elshennawy et al.[24] aimed for a deep learning system that could automatically spot pneumonia instances in chest X-ray pictures and by classifying the results as pneumonia cases or normal instances, the sickness could be diagnosed promptly and simply. By altering the deep learning technique they utilized, they produced four unique models: a Convolutional Neural Network (CNN), two pre-trained models (ResNet152V2 and MobileNetV2) (LSTM) and a Long Short-Term Memory (LSTM). Their offered models were put into practice, analyzed, and compared with current related studies using Python. Results indicated that their proposed deep learning architecture improves 99.22%, 99.43%, 99.44%, 99.77% and 99.44% of accuracy, precision, F1-score, Area Under the Curve (AUC) and recall.
Harsh Sharma et al.[28] They presented a variety of CNN models to extract features from chest X-ray pictures and categorize the images to determine if a person has pneumonia. Rather than employing transfer learning for this purpose, they created a CNN architecture from scratch. With a drop probability of 0.5 they displayed two CNN designs, one with and one without a dropout layer.

# Chapter 3

# Working Plan

## 3.1 Methodology

Chest x-ray images of pneumonia that we have gathered from the source will be used for our research. Pre-processing is the next step we do after gathering the data. Pre-processing involves lowering image noise and enhancing the quality of the input GRAYSCALING is the first stage of pre-processing. It is employed to gauge the amount of light present in an image. After that, we move on to the scale step, which involves reducing the input image's pixel count. CLAHE is the final stage of pre-processing. In essence, it intensifies contrast in the picture to make it more distinct. Then we go to our subsequent procedure, segmentation. We employ region-based approach strategies in this section. This technique is used to identify pixels in the image that are similar based on a chosen threshold. We turn a color or grayscale image into a binary image using threshold. Furthermore, we are using a convolutional neural network in the methods section (CNN). Using convolution neural network algorithms, we can categorize our image of the chest illness.

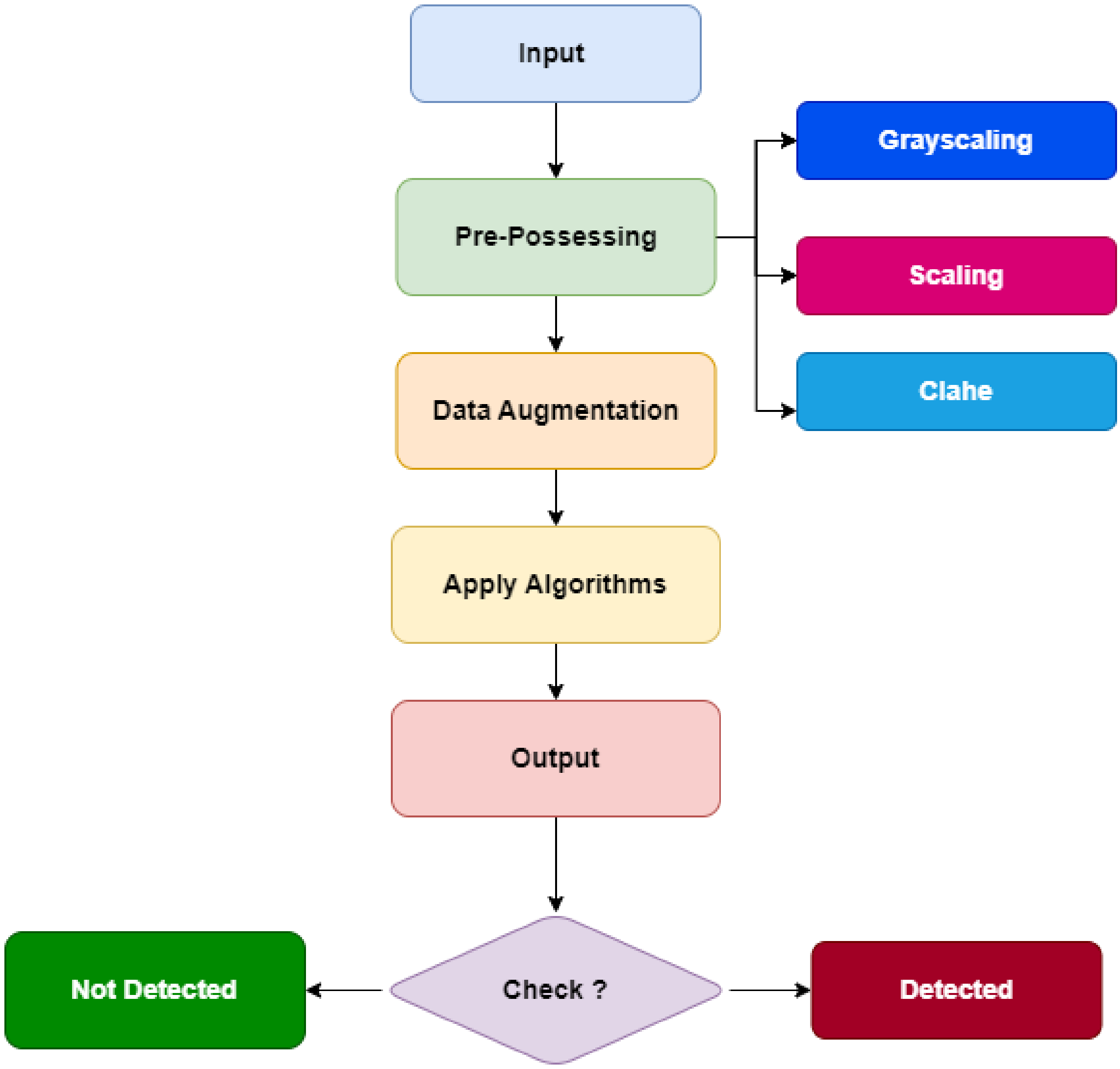


Figure 3.1: Data Flow Diagram

## 3.2 Dataset

Here, we'll go over the strategies we'll employ to accomplish our goal. We will initially make use of the Chest Xray[12], which contains labeled pictures. Deep learning frameworks favor using a lot of high-quality photos for model testing and training. Data thinking can be used to create a solid Xray picture site.This will increase the accuracy and rate of the classification and picture differentiation process. Using a technique known as "data augmentation," practitioners can greatly broaden the range of data readily available for training models without needing to collect any additional data. Applying slight adjustments to the existing dataset enables the creation of artificial images by manipulating factors such as orientation, brightness, scale, position, and more. It is easy to increase the forecast accuracy of the model without making significant changes to the model itself. In our experiment, we'll employ 5856 photographs total, divided into two categories: images with pneumonia and those without it.

## 3.3 Data Sample

Below are images of a normal chest X-ray as well as X-ray images of a damaged chest (Figure no). The pictures display X-rays of the chest. If this is the case, photographs of the chest with a variety of alterations in the region will be impacted, and vice versa.

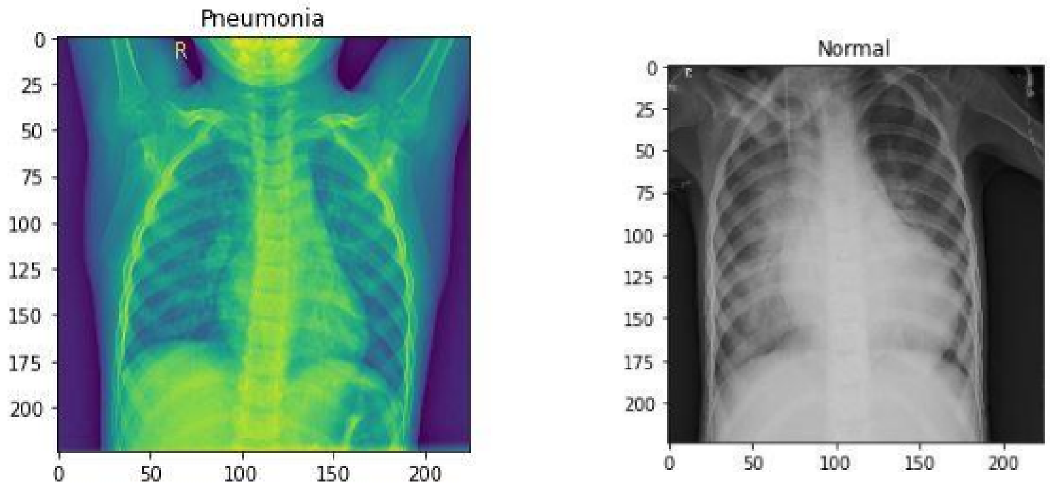


Figure 3.2: Sample Data

## 3.4 Data Processing

Preparing data for use in the Convolutional Neural Network (CNN) method is an essential step. This process is used to get rid of variables that don't improve the accuracy or results of the CNN model[29]. However, at this level, we are able to make all essential modifications on the raw data, which can improve the accuracy and performance of the CNN model.Our picture dataset of the pneumonia disease, which includes Pneumonia and Normal images in separate folders, was initially divided into two halves in order to construct our proposed system for detecting pneumonia disorders. Datasets come in three varieties: training, test, and validation. 85% of the pictures were put in the train folder. Additionally, 5% of the photographs kept in the validation folder are included in the 10% of images stored in the test folder.
Convolutional Neural Network(CNN):- Proposed Mode

- Image size : 224x224
- Batch size : 32
- Rescalling size : 1/255.0
- Zoom range : 0.2
- Horizontal Flip : True

Convolutional Neural Network(CNN):- Vgg16, Inceptionv3, Resnet50,Xception, EfficientNetB0,EfficientNetB6

- Image size : 224x224
- Batch size : 32
- Rescalling size : 1/255.0
- Zoom range : 0.2

• Horizontal Flip : True
We utilized the "binary" class mode since the categorization result in this case falls into either the Pneumonia OR the Normal category. To our test dataset, we also used the same image and batch size. Additionally, we have kept the bianry class mode.

## 3.5 Training Set

A training dataset is used to update the model weights for a successful input-to-output mapping. Neural networks are trained using data and solutions from the actual world, which enables them to transform data into a consistent input-output relationship. A source of input for a system could be output labels or algorithms. An optimization technique is used to handle the training phase of the neural network model, searching through a space of possible weight values for a set of weights that exhibit good performance on the training dataset.

## 3.6 Testing Set

To optimize any potential advantages from leveraging real-world data, the algorithm we deployed will learn from the training set. The algorithm's trust in the real world will increase as a result of the successful outcomes for an unidentified test collection.

## 3.7 Validation Set

An objective evaluation of model fit is used to adjust the model's hyperparameters on our training dataset. When the effectiveness of the validation dataset on the chosen model is indicated in the design model, an unfair measurement results.

# Chapter 4

# CNN model Implementation

## 4.1 CNN

A convolutional neural network, sometimes known as a CNN, is a specific kind of neural network that is optimized for the processing of input that has an architecture similar to a grid, such as an image[22]. Neural networks are made up of many different parts, one of which is the convolutional neural network (CNN). In order to identify objects, recognize faces, and so on, CNNs employ visual recognition and classification. They are composed of neurons that may be trained to change their weights and biases. The most common usage of CNNs is to categorize pictures, group them into clusters based on similarity, and then identify specific objects. Faces, street signs, animals, and other recognizable objects may all be recognized by algorithms that use CNNs[15]. The convolutional, pooling, and fully linked layers of a CNN are the most common.The first layer of a CNN network, the Convolutional Layer, does the majority of the computing effort. Utilizing filters or kernels to generate convolutional data or images. By adjusting the slider, we may add filters to the data. If the RGB value of the image's depth is 4, a filter with the same depth would also be applied. For each sliding movement, a particular value is taken from each filter in the picture and added together. A 2D matrix is the result of applying a 3D color filter on a convolution with a 2D output. Down sampling features are the third step in the Pooling Layer. Every layer of the 3D volume is coated with it. Flattening is the last step in the process of creating a fully connected layer. The neural network is given a single column of the pooled feature map matrix, which is subsequently processed. We were able to develop a model by connecting all of the layers together. We can then use an activation function like SoftMax or Sigmoid to further categorize the data generated by the algorithm. Softplus units increase DNN performance and reduce convergence time compared to sigmoid and ReLU units[4].

$$\text{Wout} = (\mathbf{W} - \mathbf{F} + 2P)/S + 1$$

Here, $W$ = the spatial size of the output
volume $F$ = field size of the Conv Layer neurons
$P$ = the amount of zero padding used on the border.
S = the stride

### 4.1.1 Optimizer Adam

An optimizer is a technique or method that modifies the parameters and learning rate of a CNN architecture. Some examples of these characteristics are: As a result, it helps to reduce damage overall and actually improves efficiency[40] Adam is a development of stochastic gradient descent, a deep learning technique that has been prominent in computer vision and natural language processing. These include methods for voice recognition and image processing[39].Reiterating the optimizer is a deep-learning strategy. Equation(1) explains the "Adam" optimizer function.

$$\omega t + 1 = \omega t - \alpha mt \tag{4.1}$$

mt = aggregate of gradients at time t, = learning rate at time t, t = weights at time t, t+1 = weights at time t + 1.

### 4.1.2 Sigmoid

A sigmoid function is a mathematical function that has a recognizable "S"-shaped slope, also referred as a sigmoid curve. A classic example of a sigmoid is the regression model, which is shown in the first image and is indicated by the formula.

$$\begin{aligned} &\mathbf{S}(\mathbf{x}) = 1/1 + e - \mathbf{x} \\ &= \mathbf{ex} + 1\mathbf{ex} \\ &= 1 - S(-\mathbf{x}) \end{aligned} \tag{4.2}$$

A sigmoid is a limited, variational, real function that is specified for all actual input values and has precisely one inflection point. Every point also has a pro derivative. The concepts of "sigmoid" and "sigmoid curve" are interchangeable.

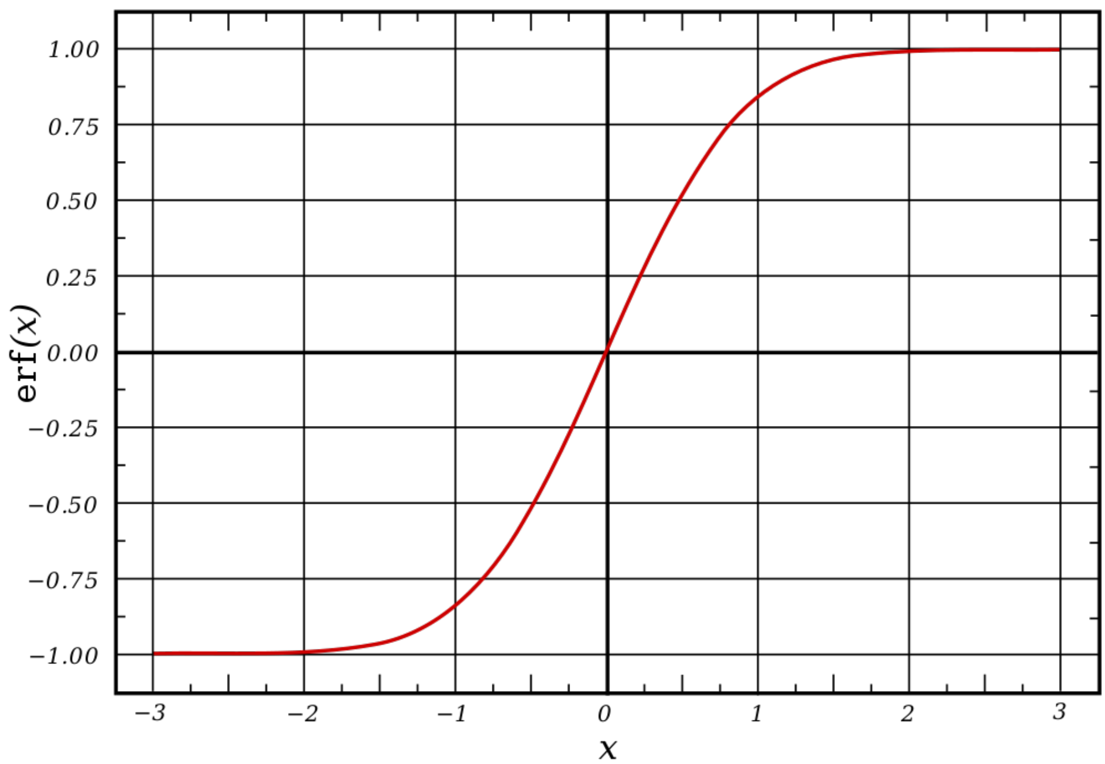

Figure 4.1: Sigmoid Function

### 4.1.3 Model Architecture Using CNN

Machine learning techniques like deep learning train computers to mimic human behavior. It is a machine learning subset that uses a three-layer neural network. A computer model learns to categorize using images, text, or voice. Multi-layer neural network typologies and a lot of labeled data are utilized to train models. Prior to producing a statistical model as an output, each algorithm in the hierarchy nonlinearly modifies its input. One of the most popular deep learning methods for evaluating visual input is convolutional neural networks. It is the center of a CNN and the location of the majority of calculation.As the visual input progresses through various levels, the CNN detects larger components or shapes of the item until it recognizes the desired entity.When inputs contain visual, aural, or auditory data, convolutional neural networks perform better than traditional neural networks. They have three distinct layers: Convolutional, Pooling, and Fully Connected (FC). All of these layers come together to form a CNN architecture. The dropout layer and the activation function are two more crucial parameters in addition to these three layers.

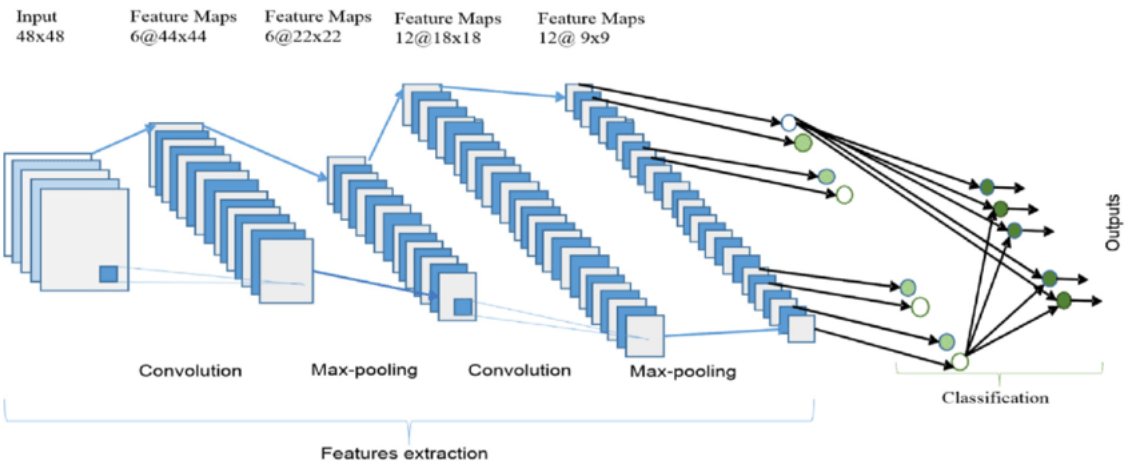


Figure 4.2: CNN Architecture

### 4.1.4 Pooling Layer

A new layer known as a pooling layer is placed after the convolutional layer. Specifically following the addition of a nonlinearity to the extracted features a convolutional layer generates. The pooling layer reduces the size of the images between convolution layers, enabling the next layer's total parameters to be as small as possible.The L2 norm of the surrounding rectangle, the average of the rectangular neighborhood, and based upon the distance from either the central pixel, a weighted average are three pooling techniques that are accessible. The most commonly utilized method is max pooling, which captures the highest localized output .

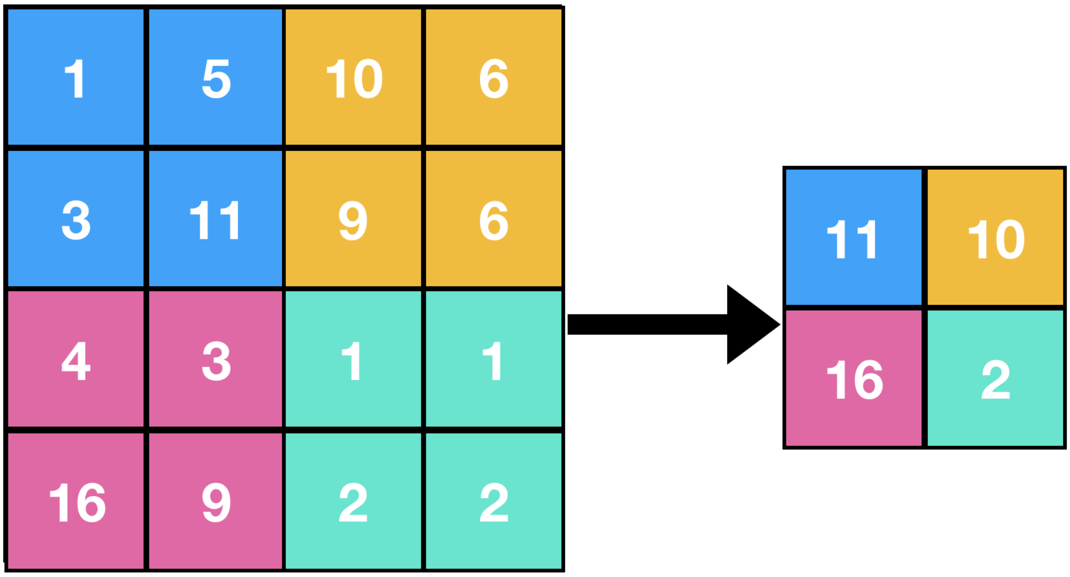


Figure 4.3: Pooling Layer

### 4.1.5 Fully Connected Layer

The layer that has been flattened and comprises connection, This requires turning the complete convolutional feature map sequence into a single column in order to process the neural network. We used the fully linked layers to combine these features into a model.To categorize the output, we use an activation function similar to softmax (or matrix multiplication). In the Fully Connected layer, Each neuron in a layer is linked to every other neuron. in every other layer. The connections between each neuron act as feature classifiers that are transmitted to the final output layer.

**Flatten Layer :** A single flatten layer will be used after the fourth MaxPooling layer has been implemented. In the long term, this is favorable for the network as a whole.
**Dense Layer :** This model has two dense layers in addition to the flattening layer.All of the neurons in this layer receive the outputs from the aforementioned levels.
**Dropout Layer :** In order to prevent the model from becoming excessively precise during training, this layer will periodically reset all of the inputs to zero.

# Chapter 5

# Proposed CNN Model

## 5.1 Implement to Proposed Model

We have created a Convolutional Neural Network (CNN) model that can identify different chest conditions using image data. In order to identify which chest photographs are damaged and which are not, this classification problem will use features from a given image to identify distinct patterns and be able to distinguish between different shots depending on those features. Graphic processing power is required to process the input data for this classification task using photographs. Consequently, a dedicated GPU (Graphics Processing Unit) is required. Because the GPU is capable of performing intensive graphic processing activities, we needed a specialized GPU. Python is being used as the basic programming language for this assignment because it is the most popular.

## 5.2 Proposed Model Architecture

### 5.2.1 13-Layered CNN Model

Convolutional Neural Networks, also known as CNN or ConvNet for short, are a kind of neural networks that specialise in processing data that has a power structure, such as images[3]. We refer to a digital picture as a binary number of visual data.It is made up of a series of pixels. To distinguish between authentic and false photos, the proposed system makes use of a cross deep CNN model. A CNN model's core components are its connected (FC), recurrent neural network, and max pooling. We shall discuss each layer's details in more detail below.

### 5.2.2 Convolutional Layer

A convolutional layer is a crucial part of a CNN.All the settings for these filters (or kernels) must be learned during the training process. It's common for filters to be smaller in size than the image they are in-tended to enhance. This layer uses kernel filters to extract essential information from the input images that are convolutionally processed. The kernel filters are similar to the input images, but they have lower constant parameters. Edge detection, blurring, and sharpening can be accomplished through the convolution of an image with several filters. In the convolutional layer, we used the Conv2D layer to construct this CNN model. The model was built with a total of four Conv 2D layers[23].

### 5.2.3 Pooling Layer

Following the convolutional layer in convolutional neural networks are layers known as pooling layers. In order to improve the efficiency of the compu-tations being performed, pooling is used to reduce the amount of the features that are extracted, and therefore, the number of trainable parameters. The quantity of the area that is collected by the pooling technique is determined by the pooling filter. The outline is 2x2 in size if the filter's parameters are 2x2. With more layers present, we can see a total of four layers here[33].

### 5.2.4 The FC (Fully Connected Layer)

All feed-forward neural networks make up this layer. Fully Connected Layers(FNN) are the layers that come after the final few in the network's architecture. After that, the output of the last pooling or convolutional layer is flattened before it is sent on to the fully connected layer as the input. This model carries the following layers

### 5.2.5 Flatten Layer

Once the fourth MaxPooling layer has been used, a single flatten layer will be applied. In the end, this is beneficial for the network as a whole in general.

### 5.2.6 Dense Layer

In addition to the flattening layer, this model has three dense layers.The outputs of previous levels are sent to all neurons in this layer.

## 5.3 Proposed model Summary:

It's common to refer to the overall number of parameters as the amount of parameters in a specific layer of "learnable" (if such a concept exists) components for a filter. We used the keras neural network toolbox to develop a sequential CNN model for the proposed system after separating the dataset into train, test, and validation data. This was carried out to assess the model's precision. Our model has a total of 13 layers. In addition to a total of four 2D convolutional layers, we also included four max pooling layers.Next, we applied three layers of thick paint followed by one layer of flattening. In the end, we were able to precisely gather 1,84,86,641 trainable parameters that the model used to train the images.

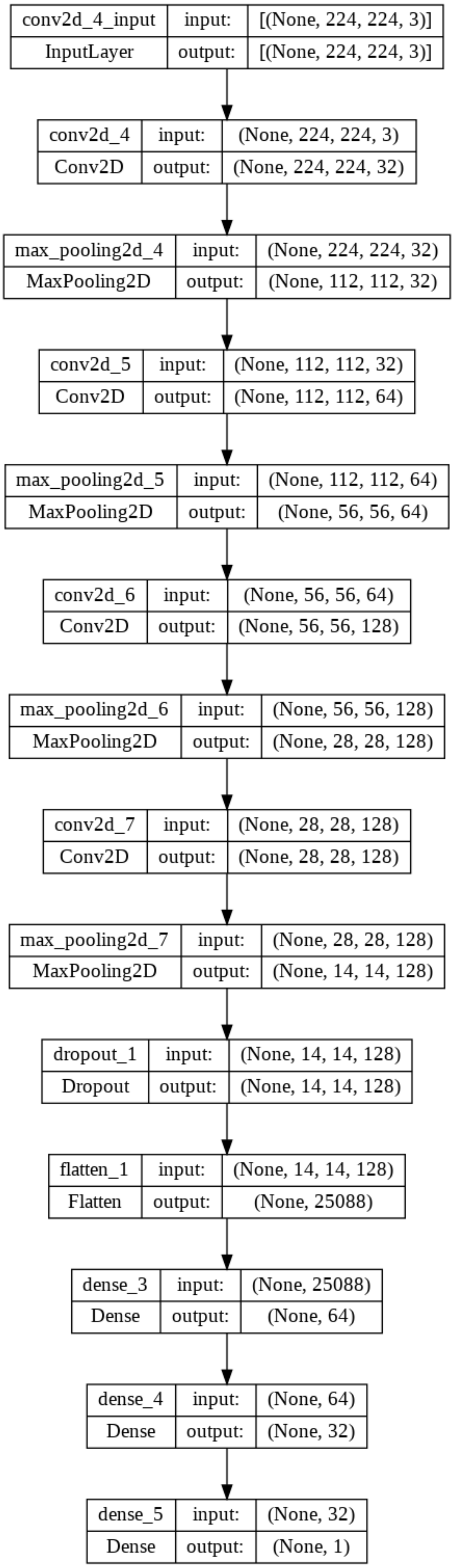
conv2d_4_input
InputLayer
input:
output:
[(None, 224, 224, 3)]
[(None, 224, 224, 3)]
conv2d_4
Conv2D
input:
output:
(None, 224, 224, 3)
(None, 224, 224, 32)
max_pooling2d_4
MaxPooling2D
input:
output:
(None, 224, 224, 32)
(None, 112, 112, 32)
conv2d_5
Conv2D
input:
output:
(None, 112, 112, 32)
(None, 112, 112, 64)
max_pooling2d_5
MaxPooling2D
input:
output:
(None, 112, 112, 64)
(None, 56, 56, 64)
conv2d_6
Conv2D
input:
output:
(None, 56, 56, 64)
(None, 56, 56, 128)
max_pooling2d_6
MaxPooling2D
input:
output:
(None, 56, 56, 128)
(None, 28, 28, 128)
conv2d_7
Conv2D
input:
output:
(None, 28, 28, 128)
(None, 28, 28, 128)
max_pooling2d_7
MaxPooling2D
input:
output:
(None, 28, 28, 128)
(None, 14, 14, 128)
dropout_1
Dropout
input:
output:
(None, 14, 14, 128)
(None, 14, 14, 128)
flatten_1
Flatten
input:
output:
(None, 14, 14, 128)
(None, 25088)
dense_3
Dense
input:
output:
(None, 25088)
(None, 64)
dense_4
Dense
input:
output:
(None, 64)
(None, 32)
dense_5
Dense
input:
output:
(None, 32)
(None, 1)

Figure 5.1: Table of proposed CNN model

## 5.4 Pre-Trained Model of CNN VGG16 :

VGG16 is widely regarded as one of the greatest vision model architectures ever made. Andrew Zisserman and Karen Simonyan initially introduced this CNN architecture at Oxford. The approach was initially made public during the 2014 ILSVRC Imagenet Large Scale Visual Recognition, despite having been proposed in 2013. They named it VGG after the Oxford Visual Geometry Group, where they worked.Authors provided various network setups based on depth. A stack of many convolutional layers (3 x 3, stride 1, padding 1) is used in each ImageNet Challenge configuration, which is then followed by a 2 x 2 maxpooling layer. Several stack combinations were cycled to achieve different depths. Each configuration's number indicates how many weight-parameter layers are present. Consistently utilized are convolution and max pool layers. finishing with 2 FC and a SoftMax. Using VGG16, layer 16 has weights. This network contains 138 million parameters.


Figure 5.2: VGG16 Architecture

### 5.4.1 InceptionV3 :

In 2015, The Revised Inception for Computer Vision was published. VGGNets (memory and other resources) are outperformed by Inception Networks (GoogleNet/ InceptionV1) both in terms of the overall quantity of characteristics offered by the system and the corresponding monetary cost. With the help of this tool, photos can be arranged into more than a thousand different object groupings. One of the most prominent options for transfer learning is the Inception-v3 model.This enables us to train the last layers of the current products more quickly by going back. The Inception-v3 model from the ImageNet database was trained on more over a million images, demonstrating that it can be used with excellent accuracy on a
smaller dataset. The model can be used to a smaller dataset with acceptable classification accuracy without retraining. The parameter sets are 5 million (V1) and 23 million (V2) (V3). classes that need retraining. a collection of convolutional layers known as the Inception Layers (11, 33, and 55, respectively), which combine the output filters into a single output vector to produce the stage's subsequent set of parameters. To avoid any operational advantages, changes to a Creation Care must be applied when handling the network. It is challenging to update an Inception network for various usage situations because the new network's performance is so foggy.As of right now, Inception v3 has offered a number of methods to enhance

the connection in order to get rid of restrictions and speed up model acceptance. parallel processing, batch normalization, and downsampling One technique used in parametric modeling is calculation.

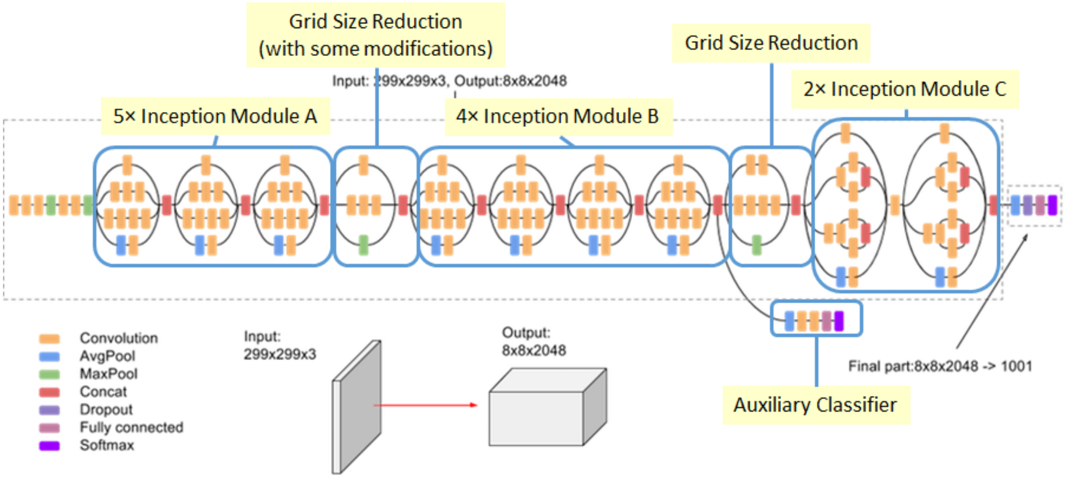


Figure 5.3: InceptionV3 Architecture

### 5.4.2 EfficientNetB0:

A convolutional neural network scaling method is called EfficientNet. It employs a composite coefficient to scale all depth, breadth, and resolution parameters uniformly. The EfficientNet model was developed with the idea that, despite there being numerous different models that are either focused on performance or computational efficiency, equivalent architectures may address both of these issues. They provided a common CNN skeleton design and three parameters—the width, depth, and resolution. The depth, resolution, and breadth of a model are determined by the dimensions of the input image, the quantity of layers, and the number of channels that are present in each layer, respectively.They claimed that by keeping all these parameters small, one might create a competitive yet computationally efficient CNN model. On the other side, by simply increasing the value of these parameters, one may construct a heavier model that is more accuracy-focused. Despite the fact that it has previously been proposed, Squeeze and Excitation Layers were the first to incorporate this idea into traditional CNN.
Cross-channel interactions are offered by SE layers without the need for spatial information. The impact of less important channels can be reduced by doing this. Additionally, they replaced ReLU with Swish activation, which significantly improved performance. EfficientNets now perform the best across a range of compute resource availability categories.

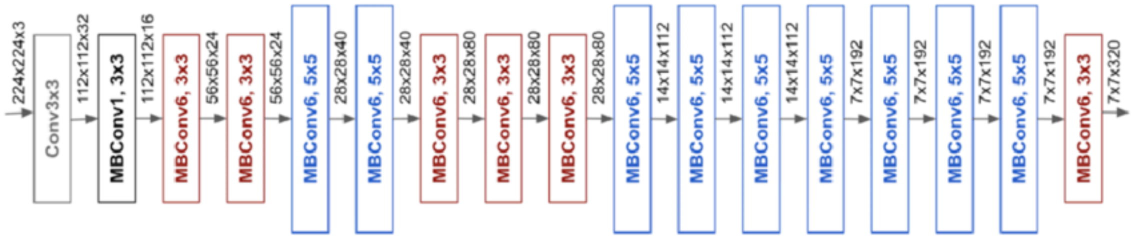

Figure 5.4: EfficientNetB0 Architecture

### 5.4.3 ResNet50:

A convolutional neural network with 50 layers is known by the name ResNet50. ResNet, often referred to as RNs or Remnant Networks, is a well-liked class of neural network that serves as the basis for numerous computer vision applications. The fundamental goal behind ResNet was to enable us to train extremely intricate neural networks with more than 150 layers. This cutting-edge neural network was first brought to the world by Kaiming He, Shaoqing Ren, Xiangyu Zhang, and Jian Sun in their 2015 paper "Deep Residual Learning for Image Recognition." One of the main issues with convolutional neural networks is the "Vanishing Gradient Problem". Gradient strength is significantly reduced by backpropagation, while Weights hardly ever vary. ResNet is used to overcome this restriction. "SKIP CONNECTION" is used.

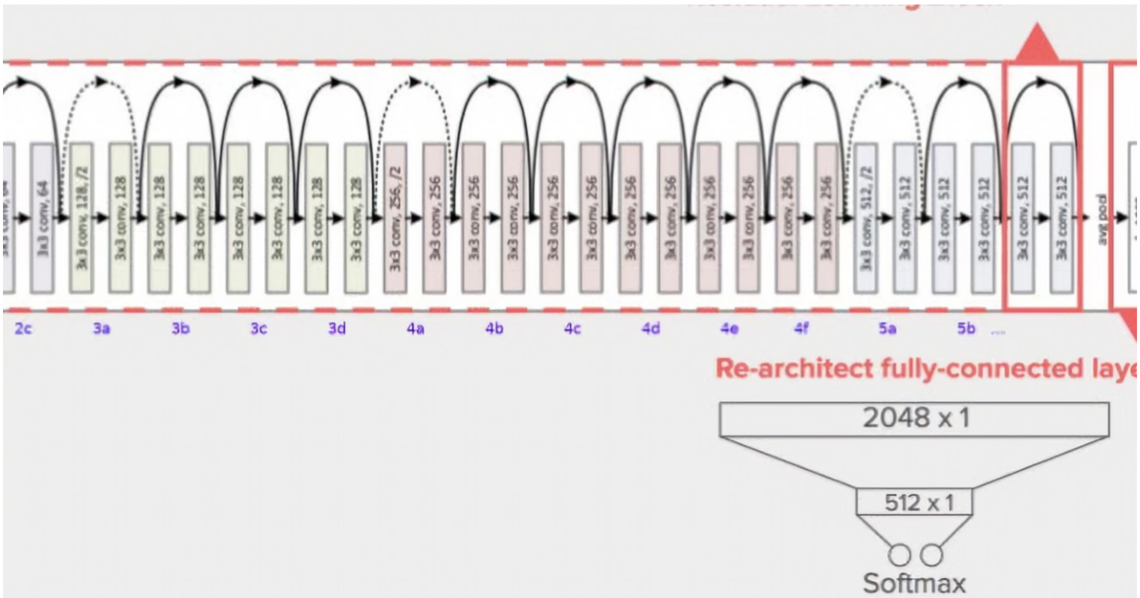


Figure 5.5: Resnet50 Architecture

### 5.4.4 Xception:

The Xception 71-layer convolutional neural network. A version of the network that has previously been pre trained on a large number of photographs is present in the ImageNet database. A picture can be categorized by the pretrained network into one of a thousand different groups, including diverse animals, a keyboard, a mouse, and a pencil.Size 244x244 is the largest image that can be entered into the network. Extreme Inception makes perfect sense as an abbreviation for "Architecture Xception". In Xception, the feature extraction framework is built on a total of 36 convolutional layers.The exit flow, the intermediate flow, which is iterated through eight times make up the initial data progression.Be aware in mind that each Conv and Separable Cnn model is followed by batch normalization (not included in the diagram). There is no depth expansion and the depth multiplier of each layer of the separable convolution is set to 1. model = xception('Weights','imagenet') returns an Xception network trained on the ImageNet data set.

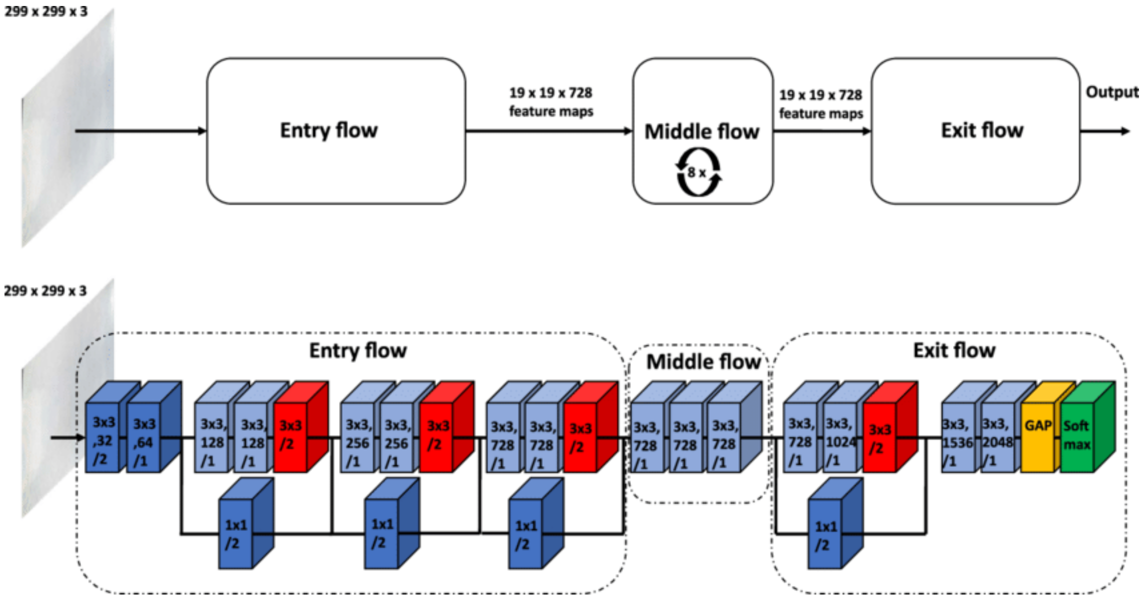


Figure 5.6: Xception Architecture

### 5.4.5 EfficientNetB6:

A neural network convolution scaling method is called EfficientNet . All depth, width, and resolution parameters should be scaled. consistently, it uses a composite coefficient. Although there are several models that are either centered on performance or computational efficiency, the EfficientNet model was created with the notion that similar topologies may address both of these problems. They gave three parameters—the
breadth, depth, and resolution—along with a standard CNN skeleton architecture. The quantity of layers, the provided image's size, and the number of channels contained in each layer, in that order, determine the depth, resolution, and breadth of a model.

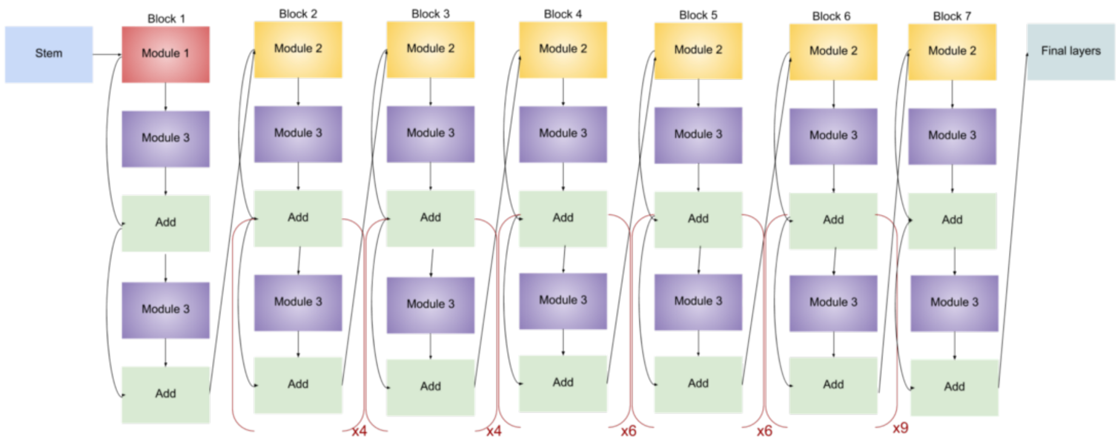


Figure 5.7: EfficientNetB6 Architecture

# Chapter 6

# Performance Analysis:

The goal of doing a performance analysis is to confirm the creative technological solutions that have been used to boost performance. This gives us a summary of the entire work and draws attention to the successes and shortcomings of a particular work, which helps us improve current methods and discover new ones. It can also be used to assess the virtues and shortcomings of others. The three most critical components of performance analysis are movement analysis, tactical and technical evaluation, and statistics collection. [34].

## 6.1 Performance Parameter :

For each of these models, the F1 score, precision, accuracy, and recall have been calculated in order to assess and compare the results. This was accomplished in order to evaluate, examine, and emphasize a comparative analysis of the results based on a comparison of the performances of conventional and pretrained CNN models. This section will start off by going over the equations used for the performance metrics used throughout the inquiry.

$$\text{Accuracy} = \mathbf{T}P + (\text{TN}/\text{CP}) + \mathbf{CP} + \text{CN}$$
$$\text{Precision} = \text{T P} *( \text{ T P R/T P } ) + \mathbf{FP}$$
$$\text{Recall} = \mathbf{TP} * (\mathbf{TPR}/\mathbf{TP}) + \mathbf{FN}$$
$$\text{fl score} = \mathbf{TP}/(\mathbf{TP} + 12 * (FP + FN))$$

Here, TP=True Positive, TN= True Negative, CP= Condition Positive, CN= Condition Negative, TPR= True Positive Rate, FP= False Positive, FN= False Negative.

Based on a number of factors, the proposed network is compared to the training dataset for this model. Batch size, epoch, learning rate, optimizer, and callbacks are some of these parameters. The pre-processing of the dataset must be finished before training may start. Prior to the start of training, the Transfer Learning methodology allows for the adjustment of its parameters. The user can select between pre-trained models and customized CNN models before starting the machine learning process. Depending on the size of the first layer of data, the directory holding both sets of newly generated categories is then imported.The optimizer used is called "Adam" [35], and it is a gradient-based technique that concentrates on new forecasts of cases that are of relatively low importance. Using this method, randomized goal functions may be enhanced.Because it is simple to construct, effective, uses little memory, and resists gradient diagonal resizing, the "Adam" optimizer is used. This is so that the approach can be used in situations when there are vast amounts of data and/or parameter values [36].We used a total of 32 batches and 80 epochs. In the section relating to the loss, we have used "Binary CrossEntropy."

| Parameter | 13-layer proposed model | Pre-trained model |
|---|---|---|
| Training Data | 85% | 85% |
| Testing Data | 10% | 10% |
| Batch Size | 32 | 32 |
| Target Size | 224 | 224 |
| Epoch | 80 | 80 |
| Execution Environment | GPU | GPU |
| Optimizer | Adam | Adam |
| Loss Function | Categorical | Categorical |
| Class Mode | Binary | Binary |

Table 6.1: Proposed And Pre-trained Model Analysis

## 6.2 Performance of proposed model:

We made the decision to assess 5856 X-ray images in total, which were split into two categories: images of pneumonia and photos of normal anatomy. The model we had suggested was found to be accurate 94.66 percent of the time in the end. The accuracy and loss results from training and testing are shown in the table below.

| Testing Accuracy | Testing Loss | Training Accuracy | Training Loss |
|---|---|---|---|
| 91.83% | 50.29% | 94.66% | 14.32% |

Table 6.2: Accuracy and Loss of the Proposed CNN Model in Training and Testing

The table shows the testing and training accuracy of the proposed 13 layers model which is 94.66% and 91.83% respectively. The model has a loss of 50.29% in testing data and 14.32% while training data.

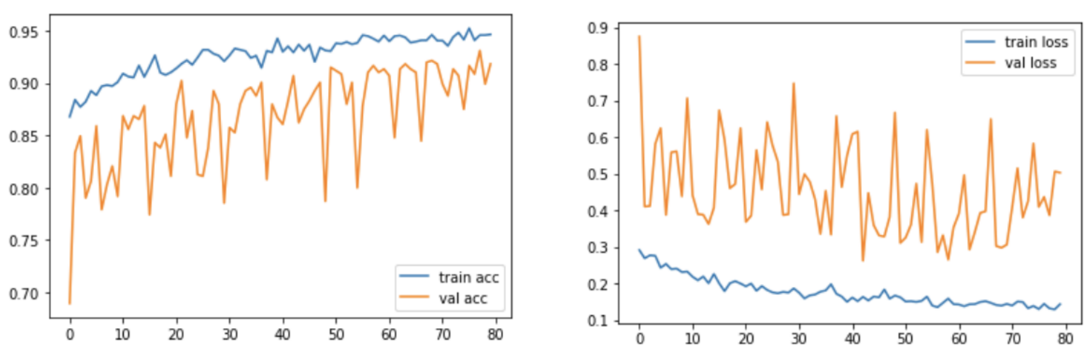


Figure 6.1: Training and validation graph of Proposed Model

The accuracy and loss of the discovery in terms of the training and validation datasets can be estimated from the aforementioned graphs. The training dataset's scattered random lines and acceleration margin are displayed on the accuracy graph. The same study, however, is depicted on the loss graph in a declining manner.
We generate the confusion matrix for our CNN model. The CNN model successfully predict 375 pneumonia,15 pneumonia-normal,,41 normal-pneumonia and 193 normal.

| | 0 | 1 |
|---|---|---|
| 0 | 375 | 15 |
| 1 | 41 | 193 |

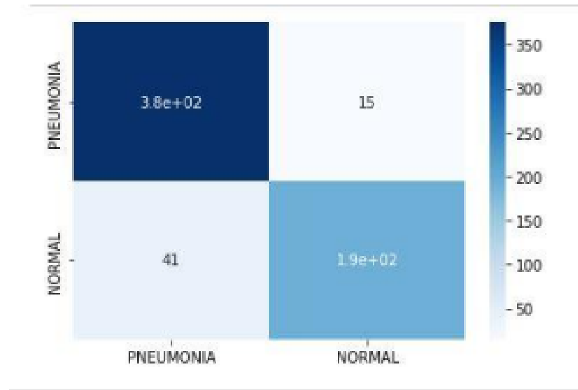


Figure 6.2: Confusion Matrix

## 6.3 Performance of pre-trained models:

### 6.3.1 VGG16:

Using the VGG16 model, 99.31% training accuracy and 90.71% testing accuracy were attained. demonstrates the VGG16 training and validation graph. We can observe from the graph that training loss has decreased over time. As a result, regression cannot be said to be taking place. We may also conclude from figure 8.4 that training accuracy improved over time.

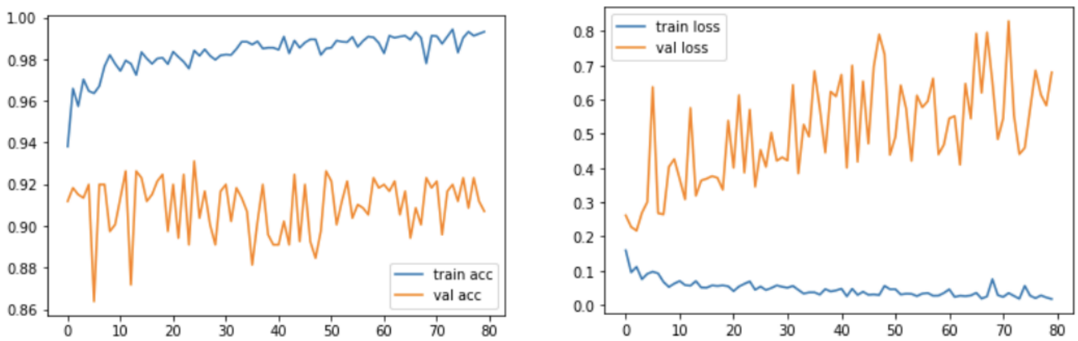


Figure 6.3: Training and validation graph of VGG16 Model

### 6.3.2 Resnet50:

Using the Resnet50 model, training accuracy of 92.31% and testing accuracy of 68.91% were both attained.A training graph and a validation graph are shown in this picture, respectively.We can infer from the graph that training accuracy and validation accuracy both rise over time.

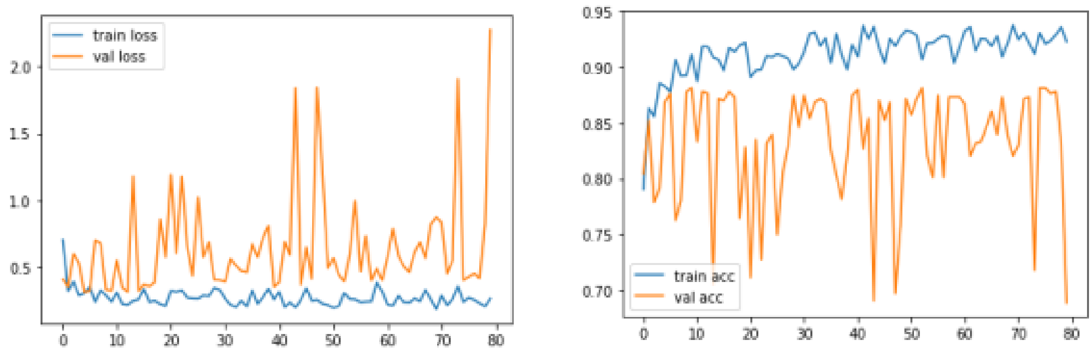


Figure 6.4: Training and validation graph of Resnet50 Model

### 6.3.3 Inceptionv3:

Using the Inceptionv3 model, training accuracy of 98.03% and testing accuracy of 83.17% were both attained. This figure displays the inceptionv3 training graph, and figure 21 displays the inceptionv3 validation graph. We can infer from figure that training accuracy improves over time.

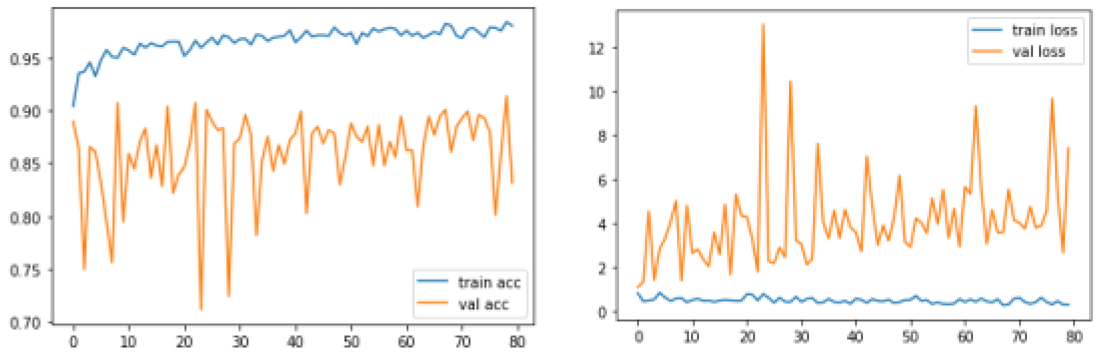


Figure 6.5: Training and validation graph of InceptionV3 Model

### 6.3.4 EfficientNet B0:

Using the EfficientNetB0 model, 65.47% training accuracy and 62.50% testing accuracy were attained. EfficientNet B0's training graph is shown in this figure, and its validation graph is shown in this figure. The figure shows that training accuracy gradually improves over time. The training accuracy of all the pre-trained models is the second lowest.

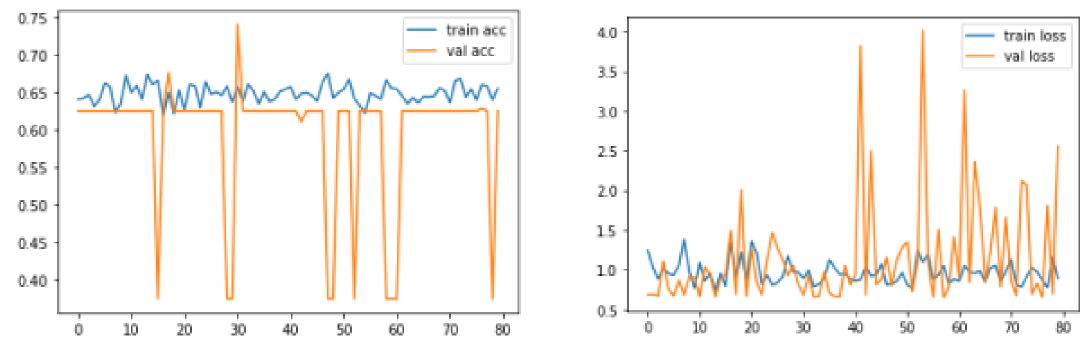


Figure 6.6: Training and validation graph of EfficientNet B0 Model

### 6.3.5 Xception :

Training accuracy of 97.85% and testing accuracy of 91.35% were both reached using the Xception model. The inceptionv3 training graph is shown in this picture, and the xception validation graph is shown in figure. Figure suggests that training accuracy increases over time.

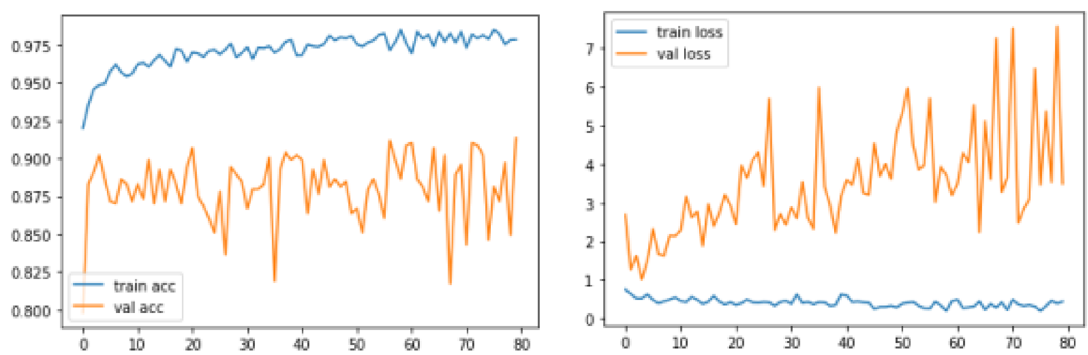


Figure 6.7: Training and validation graph of Xception Model

### 6.3.6 EfficientNet B6:

The EfficientNetB6 model produced accuracy ratings of 62.12% during training and 62.50% during testing. Here is the EfficientNet B0 training graph, and here is the EfficientNet B0 validation graph. According to the figure, training accuracy gradually improves over time. In comparison to other pre-trained models, training accuracy is the lowest.

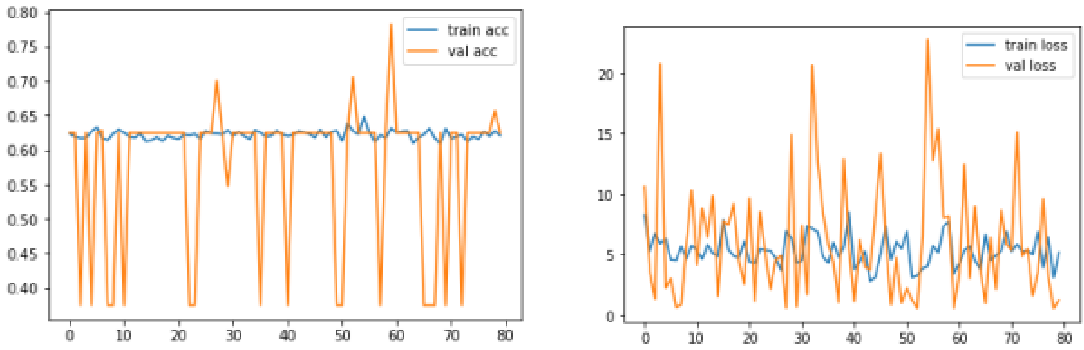


Figure 6.8: Training and validation graph of EfficientNetB6 Model

## 6.4 Compare and Analysis:

This study uses the following six pre-trained models: VGG16, Inception V3, ResNet50, EfficientnetB0, Xception, and EfficientnetB6. Additionally, a performance comparison between the suggested 13-layer CNN model and sic pre-trained models is provided. The statistics in the tables demonstrate that the suggested models outperform the current models by a large margin. A bar graph illustrating the CNN models' accuracy is shown in Figure alongside the custom model and previously trained models.The proposed model produced a 94.66 percent training accuracy, which is the highest result that could have been obtained. Resnet50 had a 92.31 percent accuracy compared to VGG16's 99.31 percent accuracy. Each of the following exhibits an accuracy that is proportionately 65.47 percent, 97.85 percent, 98.03 percent, and 62.12 percent, respectively: EfficentnetB0, Xception, InceptionV3, and EfficentnetB6. We can see that different models' abilities to detect the disease vary when using the same dataset. However, the proposed model, with a 91.83 percent accuracy rate, produced the most accurate testing result possible. VGG16 achieved a testing accuracy of 90.71 percent, while Resnet50 achieved a testing accuracy of 68.91 percent. EfficentnetB0, Xception, InceptionV3, and EfficentnetB6 each exhibit a testing accuracy that is proportionately 62.50 percent, 91.35 percent, 83.71 percent and 62.12 percent respectively.

| Architecture | Training Accuracy | Testing Accuracy |
|---|---|---|
| Proposed Model | 94.66% | 91.83% |
| ResNet50 92. | 31% | 68.91% |
| EfficientnetB0 65. | 74% | 62.50% |
| Xception | 97.85% | 91.35% |
| Inception V3 | 98.03% | 83.71% |
| VGG16 99. | 31% | 90.71% |
| EfficientnetB6. | 62.12% | 62.50% |

Table 6.3: Comparison between architectures

Based on the experimental results displayed in the bar chart, we may draw the conclusion that the customized CNN models perform better than other previously trained CNN models. An example of a bar graph showing CNN model accuracy is presented in figure.

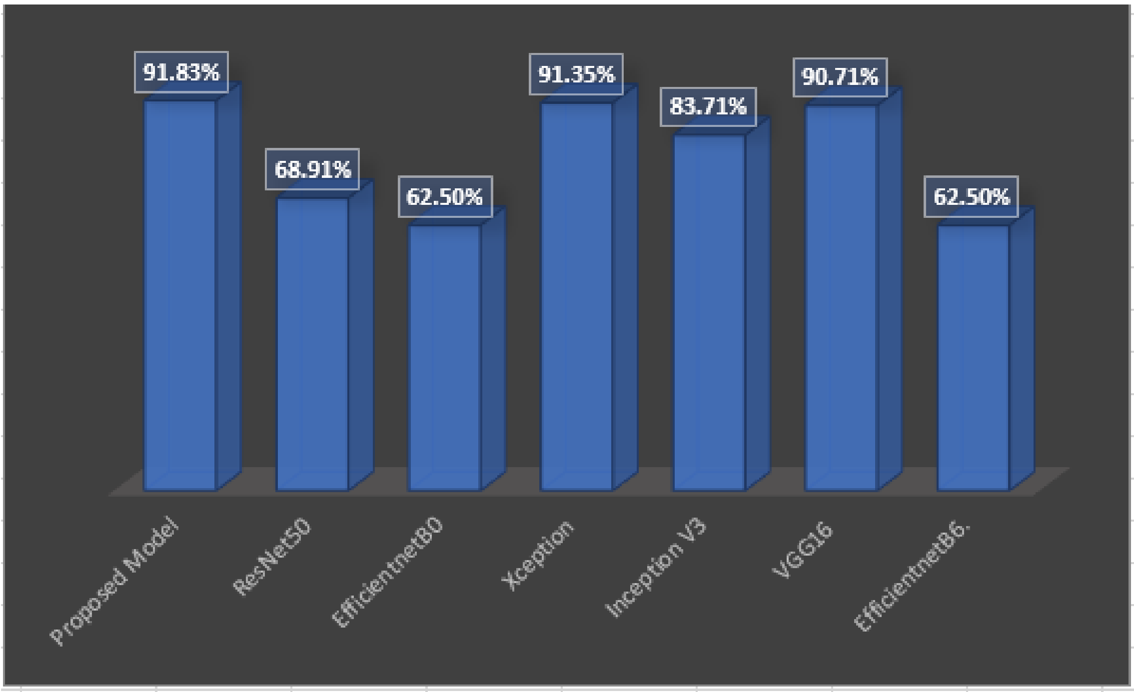


Figure 6.9: Accuracy Comparison

# Chapter 7

# Future work:

In the future, we want to employ various optimizers and other data augmentation methods in an effort to further raise the suggested CNN architecture with data augmentation's classification accuracy. By building a bigger dataset, we'll also try to demonstrate how different machine learning, deep learning, and transfer learning models apply to this problem. To estimate the probability of pneumonia, the patient's medical history will be taken into account.

# Chapter 8

# Conclusion:

Each year, more than 150 million people throughout the world suffer from pneumonia, the majority of them are young children under the age of 5. Pneumonia is a leading cause of mortality in young children under the age of five in poor nations. This disease needs to be treated more efficiently to decrease this death rate. There has been numerous research about pneumonia published and in current days this disease is less dangerous than before. But to cure this sickness, more future work is needed. Infections like COVID-19, the flu, or even a common cold can cause pneumonia. There, fungi, bacteria, and other organisms may also be responsible for it.This necessitates a prompt pneumonia diagnosis so that the patient can receive the right treatment. The method that is most frequently used to diagnose pneumonia is a chest X-ray scan. Finding pneumonia requires thorough examination of chest X-ray images, requiring radiologists/experts who are knowledgeable, talented, and experienced. Chest X-rays create pictures of a person's heart, blood vessels, lungs, airways, and the bones of their spine and chest, identifying if there is any external fluid present in or around the patient's lungs or air around a lung. Nearly all types of chest illnesses, such as Cystic Fibrosis, Asthma, Bronchiectasis, Chest Wall Cancer, Shortness of Breath, Severe Cough, Pneumonia, and others, can be diagnosed using a chest X-ray. High-level professionals do the X-ray radiograph (CXR), and issues are identified by an enlarged opacity region on the CXR[4]. Other lung disorders, such as haemorrhage, volume loss, lung cancer, fluid overload, and surgical alterations, might confuse the diagnosis made using this approach. The opacity of the diseased regions in the CXR might change depending on the patient's location and the depth of insertion. These factors make it difficult to detect pneumonia. Additionally, the work takes a lot of time, and even a small mistake might change the outcome.

The goal of this research was to increase the pneumonia classification's precision. For that a modified CNN model is suggested together with many other pre-trained models customized for superior performance to detect pneumonia by categorization of chest X-ray pictures. Along with other studies employing related technologies, comparisons between the customized model and pre-trained models were also carried out. 5856 chest X-ray pictures are supplied to the convolutional neural network in three categories: training, test, and validation. We identified and categorized two types of chest conditions: pneumonia and normal. These datasets were used to train the CNN model, which had validation accuracy of 91.83% and training accuracy of 94.66%.

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