A Minor Project Report
On

Pneumonia Detection Using Image based Deep Learning

SUBMITTED IN PARTIAL FULFILLMENT FOR THE AWARD OF DEGREE OF

Bachelor of Technology

IN

Electronics and Communication Engineering

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CERTIFICATE

This is to certify that the minor project report entitled, "**Pneumonia Detection Using Image based Deep Learning** " submitted by **Apoorv Khare, Vivek Garg** and **Sourabh Kumar** in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in **Electronics and Communication Engineering** of the Jaypee Institute of Information Technology, Noida is an authentic work carried out by them under my supervision and guidance. The matter embodied in this report is original and has not been submitted for the award of any other degree.

Signature of Supervisor:

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DECLARATION

We hereby declare that this written submission represents our own ideas in our own words and where others ideas or words have been included have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission.

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ABSTRACT

Pneumonia can be life-threatening for people with weak immune systems, in which the alveoli filled with fluid that makes it hard to pass oxygen throughout the bloodstream. Detecting pneumonia is from a chest X-ray is not only expansive but also time-consuming for normal people. Throughout this research introduced a machine learning technique to classify pneumonia from Chest X-ray Images. Most of the medical datasets having class imbalance issues in the dataset. The Data augmentation technique used to reduce the class imbalance from the dataset, Ho-rizontal Flip, width shift and height shift techniques used to complete the Aug-mentation technique. Used a five-layer CNN model, to discover new possibilities. After testing proposed model on testing data, we are able to achieve a training accuracy of 90-95 and on testing we achieved an accuracy of 85-90%. As compare with state-of-the-art technique, the proposed method able to achieve high recall but that compromises with Precision.

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CHAPTER 1
INTRODUCTION

Throughout history, epidemics and chronic diseases have claimed the lives of many people and caused major crises that have taken a long time to overcome. To describe a disease within populations that arise over a specific period of time, two words are used epidemic and outbreak. Indeed, we can define epidemic as the occurrence of more cases of illnesses, injury or other health condition than expected in a given area or among a specific group of persons during a particular period. Mostly, the cases are pretending to have a common cause. The outbreak is distinguished from an epidemic as more localized, or the term less likely to evoke public panic.

Past epidemics include pneumonia. The pneumonia is an infection of the lungs most often caused by a virus or bacteria. More specifically, the infection affects the pulmonary alveoli, the tiny balloon-shaped sacs at the end of the bronchioles. It usually affects only one of the 5 lobes of the lung, hence the term lobar pneumonia. Pneumonia is the third leading cause of death in Japan with a higher mortality rate for the elderly, particularly among individuals ≥80 years old. Excluding lung cancer, in Portugal, Pneumonia is the huge cause of respiratory death. As per the national vital statistics report Pneumonia is on 8th rank among 10th leading death cause Heron (2018) [1].

Deep neural network models have conventionally been designed, and experiments were performed upon them by human experts in a continuing trial-and-error method. The process demands enormous time, know-how, and resources. To overcome this problem, a novel but simple model is introduced to automatically perform optimal classification tasks with deep neural network architecture. The neural network architecture was specifically designed for pneumonia image classification tasks. The proposed technique is based on the convolutional neural network algorithm, utilizing a set of neurons to convolve on a given image and extract relevant features from them. Demonstration of the efficacy of the proposed method with the minimization of the computational cost as the focal point was conducted and compared with the exiting state-of-the-art pneumonia classification networks. In recent times, CNN-motivated deep learning algorithms have become the standard choice for medical image classifications although the state-of-the-art CNN-based classification techniques pose similar fixated network architectures of the trial-and-error system which have been their designing principle.

Identifying pneumonia from a chest x-ray is one of the famous techniques developed by doctors, in which fluid is identified in lungs. It is hard for any layman to find fluid in lungs and workload on specially trained practiser increase the risk of pneumonia infected people. To reduce this risk, we need to develop a computer-based system that can identify pneumonia from a chest x-ray. Currently, very few systems can identify the organs and tissue in the medical image analysis, and still makes an issue for implementing AI-based Solution. this research is conducted to develop a system that can identify pneumonia from a chest x-ray, also the primary goal to achieve high recall on classification of disease. In this research custom CNN model developed to carry out this research.

Can the custom CNN model help to improve the recall of pneumonia detection from chest X-ray images as compare state of the art technology?

In this study, we will use the CNN based model which will train for the image classification process.

1.1 OUR APPROACH

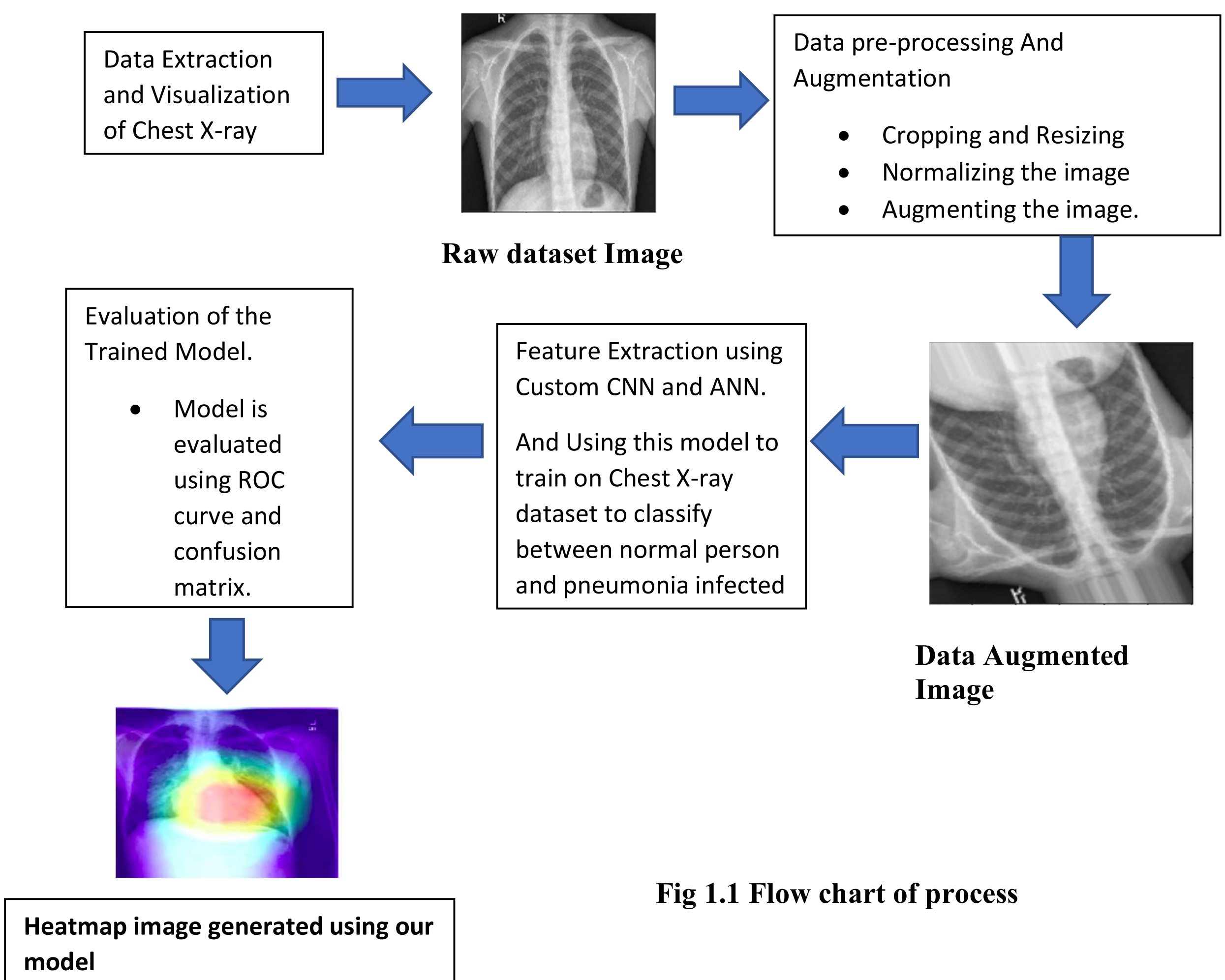


Fig 1.1 Flow chart of process

CHAPTER 2

Literature Survey

In the Field of Pneumonia classification, so many researchers contributed their work to take motivation. Everyone used different techniques, different methodology and different datasets to get state of the art output in same field. most of the Researchers used CNN based Models on different datasets, hence we dividing the literature review into sections with Different available datasets.

Researcher Liang and Zheng (2019) [2] performed pneumonia detection on Chest X-ray dataset which contained a total of 5856 X-ray images of pneumonia and normal as well, also the number of images of normal as compare pneumonia was low, the researcher used image augmentation to reduce the over fitting. The researcher used CNN techniques in which developed their own CNN Architecture with 49 convolutional Layers and 2 dense layers researcher used residual network-based models to differentiate the actual observed values and estimated values this helps the model to learn on small changes. In this research, the researcher used other models like VGG16 Simonyan and Zisserman; 2015[3], Densnet121, Xception and inception V3 used to compare the result with the custom model. The result of this research got the highest recall and precision from custom model, 0.967 and 0.891 respectively as compare with another algorithm.

Using deep convolutional Neural network gives advantages for feature selection and data training process it helps to make task easy but, every network has its own feature selection techniques and different numbers of layers Researcher Islam et al. (2017)[4] used six different neural that is Alexnet, VGG16, VGG 19, ResNet-50, ResNet-101, ResNet- 152 to get the best result. and on the top of that also used ensemble method to compare the result with pre-trained models. This research helps to find out how each network is different from each other, throughout this research ensemble method able to achieve the highest accuracy with 94% but in terms of sensitivity VGG19 network overpowered other networks and in the context of specificity Alexnet got the highest accuracy of 93%. In another research Rahmat et al. (2019)[5] used Faster Regional Convolutional Neural network (Fast R-CNN) for detection in which Reginal proposal Network predicts the object bound and score and also can be used as fully convolutional network, to handle loss three different function used which helps to handle total loss and classification loss, throughout this result researcher able identify pneumonia faster than general practitioner and medical student, with 62% accuracy.

Researcher Liu et al. (2019) [6] used a novel technique called Segmentation Based Fusion Network (SDFN) in this research two CNN based classification models were used as feature extractors and the Lung region generator used to identify the lung regions. For the CNN model Fine-tuned Densnet is used like Pan et al. (2019) [7] and Heo et al. (2019) [8], and in the last FC layer, the sigmoid activation function used to normalization. With this technique approximately 95.84% of lung region detected and 0.719 AUC Score obtain for pneumonia detection.

The most common issue we faced in images-based data is an imbalance, and it will lead to not utilizing a neural network with full potential. In the medical domain, datasets always have data imbalance as compare to another domain. For this study, we collected data from Mendeley like Researcher Ayan and Unver (2019) [9] and Stephen et al. (2019) [10]. These images contain both normal and pneumonia affected, and is freely available for research purposes.

Chapter 3

Dataset

3.1 Introduction to Dataset

As we see in previous researches researcher Islam et al. (2017)[4], Liang and Zheng (2019)[2] and Jaipurkar et al. (2018)[11] used the DensNet, VGG16, Inception and ResNet50/101/152 models to classify pneumonia with state of the art techniques using multiple algorithms not only provide broad view about respective networks but also helps to choose the perfect model for solving a problem. Furthermore, Ayan and Unver (2019) [9] used VGG 16against the Xception algorithm, which not used throughout the lit review. While using the Xception model pre-trained ImageNet weights used for initial layers also researcher added 2 fully connected layers with two-way output layers with a SoftMax activation function. This model trained on more than 5000 images which included both normal and pneumonia images while testing on test dataset VGG16 model outperformed in accuracy and specificity against Xception with 0.87 and 0.91 scores but Xception able to achieve the highest sensitivity with 0.85 and recall was 0.94.

- We have selected Mendeley Dataset due to its high credibility.
- Dataset which contains about 5856 images which include both normal x-ray and pneumonia infected x-rays.
- Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of paediatric patients of one to five years old from Guangzhou Women and Children's Medical Centre, Guangzhou. All chest X-ray imaging was performed as part of patients' routine clinical care.
- This dataset is freely available for research purposes. In June 2017 Mendeley awarded by **Data Seal of Approval** which indicates, this data is retrieved from trustworthy sources.

3.2 Dataset Pre-Processing

Data Preprocessing. Data preprocessing/preparation/cleaning is the process of detecting and correcting (or removing) corrupt or inaccurate records from a dataset, or and refers to identifying incorrect, incomplete, irrelevant parts of the data and then modifying, replacing, or deleting the dirty or coarse data.

3.2.1 Cropping and Resizing

- Cropping is cutting off a portion of your image to improve framing, put emphasis on your subject, or change the aspect ratio. This kind of photo manipulation allows you to keep all the elements we want and eliminate the ones we don't need it.

- Image cropping, which aims at removing unexpected regions and non-informative noises from a photo/image, by modifying its aspect ratio or through improving the composition, is one of the basic image manipulation processes for graphic design, photography and image editing.

- Since images can often make up the bulk of the bytes needed to load a web page, everything we can do to make our images smaller and easier to load which increases our training and testing time.

3.2.2 Normalizing the Image

Normalization refers to normalizing the data dimensions so that they are of approximately the same scale. For Image data There are two common ways of achieving this normalization. One is to divide each dimension by its standard deviation, once it has been zero-centered. Another form of this preprocessing normalizes each dimension so that the min and max along the dimension is -1 and 1 respectively. It only makes sense to apply this preprocessing if you have a reason to believe that different input features have different scales (or units), but they should be of approximately equal importance to the learning algorithm. In case of images, the relative scales of pixels are already approximately equal (and in range from 0 to 255), so it is not strictly necessary to perform this additional preprocessing step.

3.2.3 Data Augmentation

- Data, when is highly imbalance can lead research to unwanted output, because the Machine Learning algorithm is developed to maximize the accuracy and reduce the error and in the case of data imbalance, we will not get proper predicted output.
- Data Augmentation technique can used to artificially increase the volume of the dataset.
- Deep Neural network model on a large number of data can help to increase the accuracy of the result and the data augmentation technique can create the modified version of same data.
- As per Farhadi and Foruzan (2019) [12] Data Augmentation technique can used to artificially increase the volume of the dataset. training Deep Neural network model on a large number of data can help to increase the accuracy of the result and the data augmentation technique can create the modified version of same data. To perform the image augmentation keras providing the library that performs augmentation while training model, which reduces the excess space to store new images, In below **Figure 3.2** shows the example of Augmented image generated while training model, although offline augmentation helps you to create a new image and which can store on the system if required. We procced the task using Image Data Generator library which provides good range techniques, for this research specially used image rescaling, horizontal shift, image shift, and image flip techniques. the reason to use these techniques is, this method can use on most type of image Fujita et al. (2019) [13]and other techniques like denoising, segmentation and marker labelling may reduce the number of features from images.

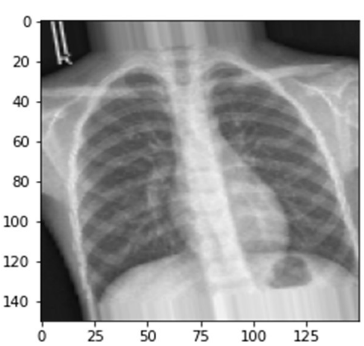


Fig 3.1 Actual Image

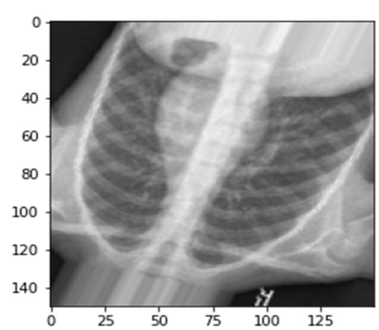


Fig 3.2 Data Augmented image

Chapter 4
Deep Learning

4.1. Introduction to Deep learning

Deep learning is a branch of machine learning which is completely based on artificial neural networks, as neural network is going to mimic the human brain so deep learning is also a kind of mimic of human brain. In deep learning, we don't need to explicitly program everything.

Inspired by biological nodes in the human body, deep learning helps computers to quickly recognize and process images and speech. Computers then **"learn"** what these images or sounds represent and build an enormous database of stored knowledge for future tasks. In essence, deep learning enables computers to do what humans do naturally- learn by immersion and example.

Deep learning then can be defined as neural networks with a large number of parameters and layers in one of four fundamental network architectures:

- Convolutional Neural Networks
- Recurrent Neural Networks (RNN)
- Recursive Neural Networks

4.2 Convolution Neural networks:

Convolutional Neural Networks are very similar to ordinary Neural Network. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. Each hidden layer is made up of a set of neurons, where each neuron is fully connected to all neurons in the previous layer, and where neurons in a single layer function completely independently and do not share any connections. The last fully-connected layer is called the "output layer" and in classification settings it represents the class scores. **We are using this type of network for our classification.**

4.3 Recurrent Neural Networks (RNN)

RNNs are called *recurrent* because they perform the same task for every element of a sequence, with the output being depended on the previous computations. Another way to think about RNNs is that they have a “memory” which captures information about what has been calculated so far. In theory RNNs can make use of information in arbitrarily long sequences, but in practice they are limited to looking back only a few steps

Recurrent neural networks, also known as RNNs, are a class of neural networks that allow previous outputs to be used as inputs while having hidden states. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition.

4.4 Recursive Neural Networks

Recursive neural network is a kind of deep neural network created by applying the same set of weights recursively over a structured input, to produce a structured prediction over variable-size input structures, or a scalar prediction on it, by traversing a given structure in topological order. RNNs have been successful, for instance, in learning sequence and tree structures in natural language processing, mainly phrase and sentence continuous representations based on word embedding. RNNs have first been introduced to learn distributed representations of structure, such as logical terms. Models and general frameworks have been developed in further works since the 1990s

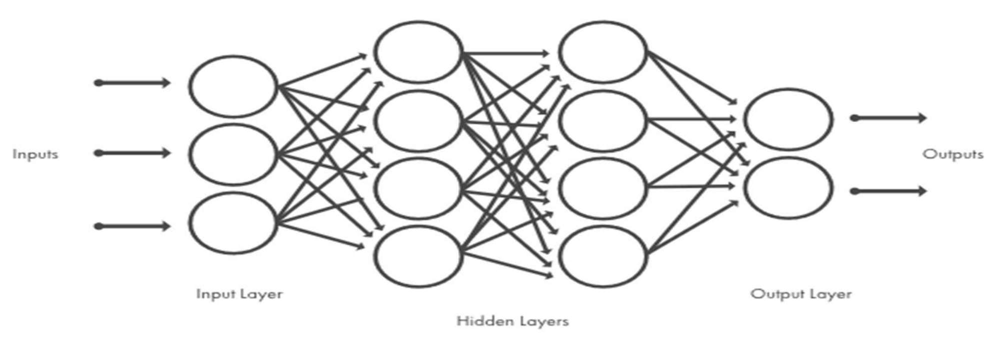


Fig 4.1 Representation of Neural Network

Chapter 5

Convolutional Neural Networks

5.1 Introduction to Convolutional Neural Networks

A convolutional neural network (CNN) is a specific type of artificial neural network that uses perceptron, a machine learning unit algorithm, for supervised learning, to analyse data. CNNs apply to image processing, natural language processing and other kinds of cognitive tasks.

CNN is also computationally efficient. It uses special convolution and pooling operations and performs parameter sharing. This enables CNN models to run on any device, making them universally attractive.

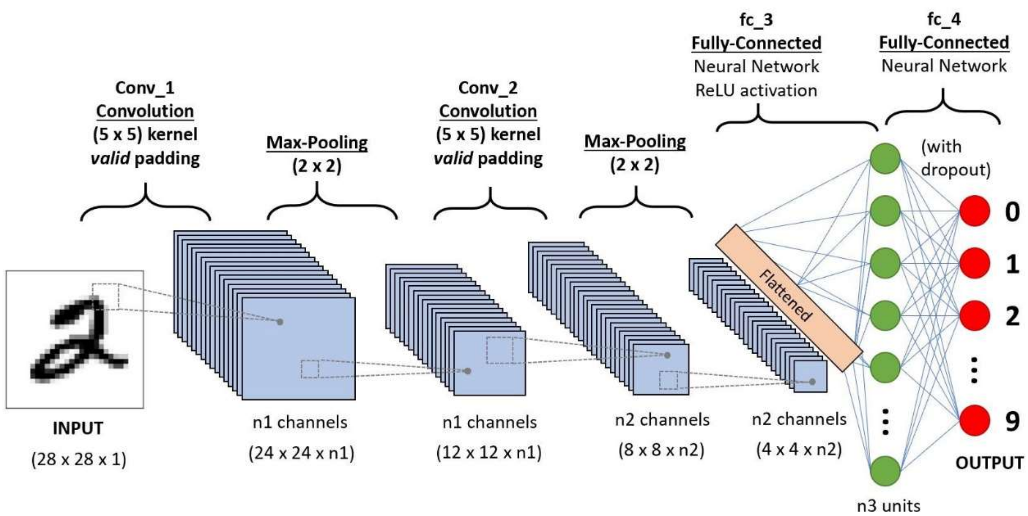


Fig 5.1 Basic CNN architecture

A CNN is composed of several kinds of layers:

- **Convolutional layer:** Creates a feature map to predict the class probabilities for each feature by applying a filter that scans the whole image, few pixels at a time.
- **Pooling layer (down sampling)**: Scales down the amount of information the convolutional layer generated for each feature and maintains the most essential information (the process of the convolutional and pooling layers usually repeats several times).

- **Fully connected input layer:** It **"**flattens" the outputs generated by previous layers to turn them into a single vector that can be used as an input for the next layer.
- **Fully connected layer**: Applies weights over the input generated by the feature analysis to predict an accurate label.
- **Fully connected output layer: Generates** the final probabilities to determine a class for the image.

5.2 Convolution Layers [14]

Convolutional neuron layers are the key component of CNN. In image classification tasks, one or more 2D matrices (or channels) are treated as the input to the convolutional layer and multiple 2D matrices are generated as the output. The number of input and output matrices may be different. The process to compute a single output matrix is defined as:

$$\boldsymbol{A_j = f(\sum_{i=1}^{N} I_i * K_{i,j} + B_j)}$$

Firstly each input matrix Ii is convoluted with a corresponding kernel matrix **K i,j.** Then the sum of all convoluted matrices is computed and a bias value **Bj** is added to each element of the resulting matrix. Finally, a non-linear activation functions is applied to each element of the previous matrix to produce one output matrix **Aj**. Each set of kernel matrices represents a local feature extractor that extracts regional features from the input matrices. The aim of the learning procedure is to find sets of kernel matrices **K** that extract good discriminative features to be used for image classification. The **back-propagation** algorithm that optimizes neural network connection weights can be applied here to train the kernel matrices and biases as shared neuron connection weights.

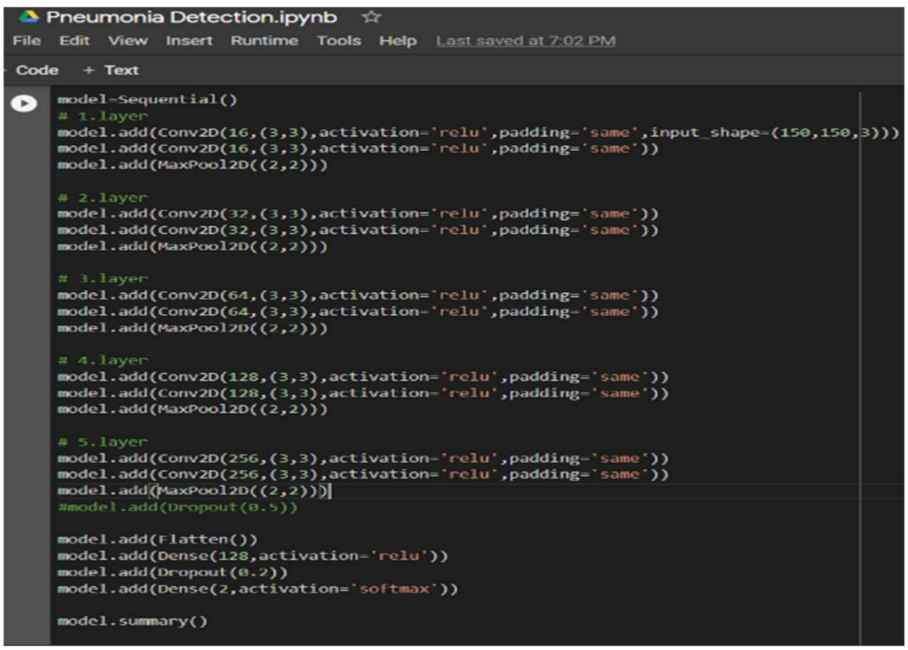
5.2.1 Pooling Layer

Pooling layer plays an important role in CNN for feature dimension reduction. In order to reduce the number of output neurons in the convolutional layer, pooling algorithms should be applied to combine the neighbouring elements in the convolution output matrices. Commonly used pooling algorithms include max-pooling and average-pooling. In this work, max-pooling layer with 2×2 kernel size selects the highest value from the 4 neighbouring elements of the input matrix to generate one element in the output matrix.

During error backpropagation process, the gradient signal must be only routed back to the neurons that contribute to the pooling output.

5.3. Custom Convolution Neural Networks

- A Custom Convolution Neural Networks is a type of artificial neural network that does not use pre-trained models like Inception, VGG 16 etc to recognize a variety of features.
- Custom Convolution Neural Networks can help in reducing complexity as well as improve accuracy.
- It is also used to reduce overfitting of data.
- We have used a five-layer custom convolution network.
- Each layer is composed of multiple convolution layer and a pooling layer.



Pneumonia Detection.ipynb

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Code + Text

```
model=Sequential()
# 1.layer
model.add(Conv2D(16,(3,3),activation='relu',padding='same',input_shape=(150,150,3)))
model.add(Conv2D(16,(3,3),activation='relu',padding='same'))
model.add(MaxPool2D((2,2)))

# 2.layer
model.add(Conv2D(32,(3,3),activation='relu',padding='same'))
model.add(Conv2D(32,(3,3),activation='relu',padding='same'))
model.add(MaxPool2D((2,2)))

# 3.layer
model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
model.add(MaxPool2D((2,2)))

# 4.layer
model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
model.add(MaxPool2D((2,2)))

# 5.layer
model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
model.add(Conv2D(256,(3,3),activation='relu',padding='same'))
model.add(MaxPool2D((2,2)))
#model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(2,activation='softmax'))

model.summary()
```

Fig 5.2 Used Custom CNN model.

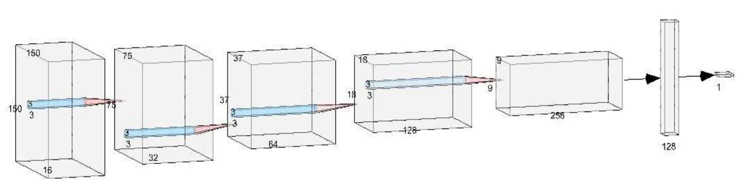

Fig 5.3 Our Diagram of CNN Model

Chapter 6
Implementation and Results

6.1 Implementation

- Importing libraries like keras, TensorFlow, matplotlib, scikit.
- Importing concerned Dataset into Google Colaboratory.
- Splitting the dataset into train, test, validation.
- Data Augmentation of training Dataset.
- Creating Custom CNN model and importing Pretrained CNN models for classification purposes.
- Training the model on the training dataset and simultaneously evaluating with the validation dataset and saving the best performing model.
- Importing the saved model and testing the imported model on testing dataset.
- Plotting the confusion matrix for analysing correct/incorrect results.
- Plotting ROC for analysing the confusion matrix.
- Obtaining the Grad-Cam output for each model to see actual performance of model.

6.2 Result Analysis

6.2.1 Performance Measure

Custom CNN model:	Testing Accuracy – 89.743%
Pretrained CNN Model: **VGG16**	Testing Accuracy – 90.70%

Table 6.2.1 Performance Analysis.

6.3 Identification Result

6.3.1 Confusion Matrix

A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. **The confusion matrix shows the ways in which your classification model is confused when it makes predictions**.

It gives us insight not only into the errors being made by a classifier but more importantly the types of errors that are being made.

The predicted classes are represented in the columns of the matrix, whereas the actual classes are in the rows of the matrix. We then have four cases:

- **True positives (TP)**: the cases for which the classifier predicted 'correct class' and the persons were actually spam.
- **True negatives (TN)**: the cases for which the classifier predicted 'not correct class' and the persons class were actually real.
- **False positives (FP)**: the cases for which the classifier predicted 'spam' but the emails were actually real.
- **False negatives (FN)**: the cases for which the classifier predicted 'not spam' but the emails were actually spam.

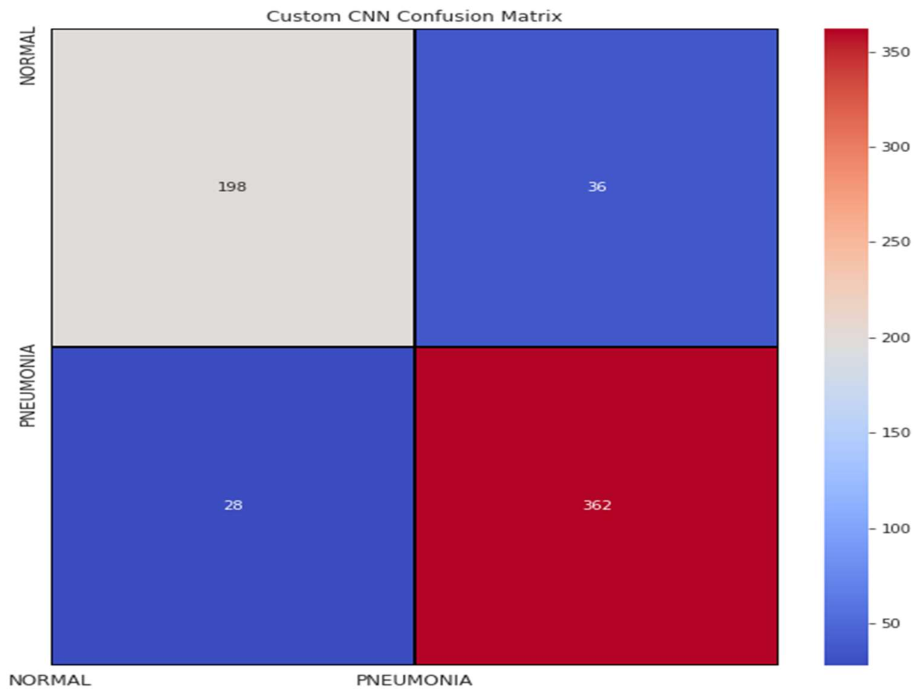

Fig. 6.1 Showing Confusion Matrix of Custom CNN

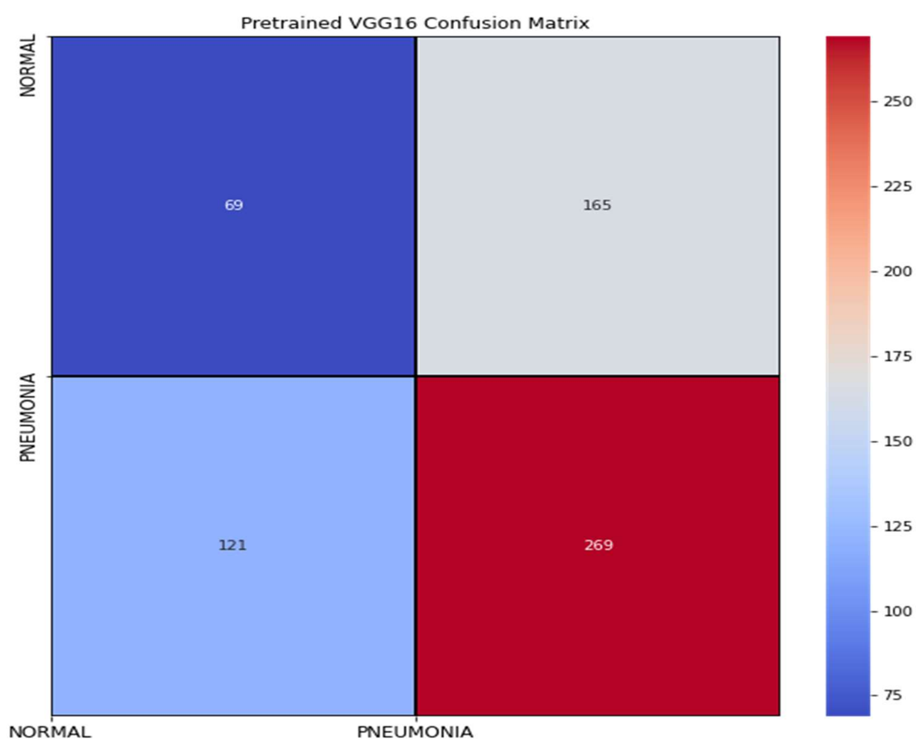

Fig. 6.2 Showing Confusion Matrix of VGG16 CNN

6.3.2 Discussion:

By seeing the above Matrix, we came to know how much confuse the model is while classifying between Normal and Pneumonia.

The Custom CNN model is showing much less confusion than the VGG16 model. And this confusion in VGG16 is due to low precision and recall values.

Also, this VGG16 model used is trained on ImageNet dataset and the dataset used here in this model is out of its scope. Since we know our Deep Learning model are very sensitive to data.

6.4 Verification Analysis

6.4.1 ROC (Receiver operating characteristics)

AUC – ROC curve is a performance measurement for classification problem at various thresholds settings. ROC is a probability curve and AUC represent degree or measure of separability. **It tells how much model is capable of distinguishing between classes.** Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1s. By analogy, Higher the AUC, better the model is at distinguishing between patients with disease and no disease.

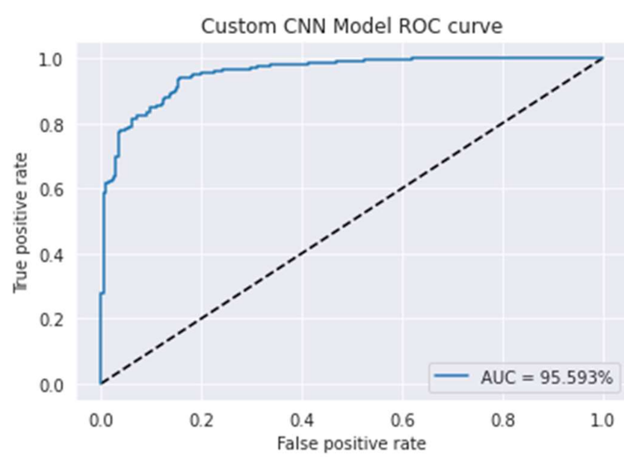

Fig. 6.3 Showing ROC curve for Custom CNN

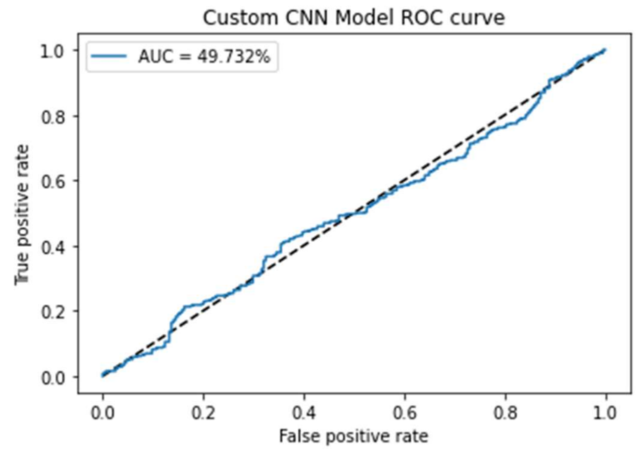

Fig. 6.4 Showing ROC curve for VGG16 CNN

6.4.2 Discussion:

In the above results we conclude that the ROC-AUC of the VGG16 is not up to mark as expected. **Though test accuracy of VGG16 is 90.70% but the actual accuracy obtained is 50-60%. Whereas in Custom CNN our model testing accuracy and actually obtained are approximately 90%.**

6.4.3 Grad-Cam (Gradient-weighted Class Activation Mapping)

Gradient-weighted Class Activation Mapping (Grad-CAM), uses the class-specific gradient information flowing into the final convolutional layer of a CNN to produce a coarse localization map of the important regions in the image. Grad-CAM requires no re-training and is broadly applicable to any CNN-based architectures.

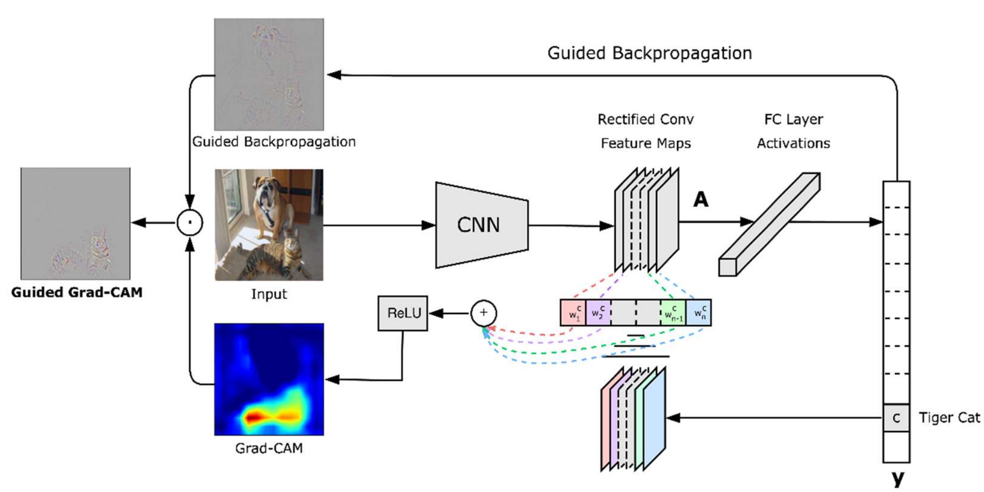

Fig 6.5 Flow-chart of Grad-Cam

Result obtained using Grad-Cam

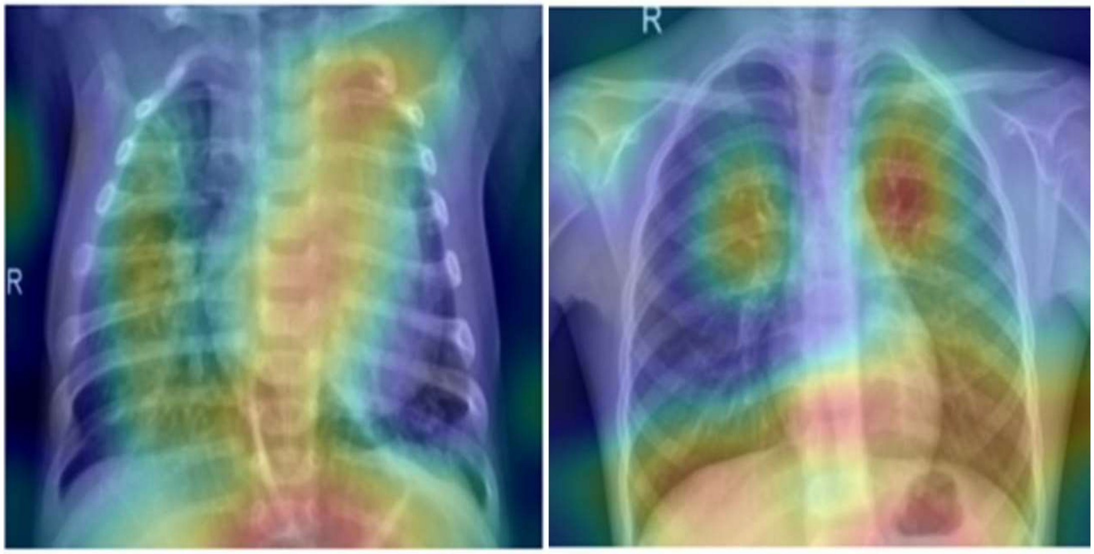

Fig 6.6 Showing Grad-Cam output on Custom CNN model. Left predicting Pneumonia And right predicting Normal

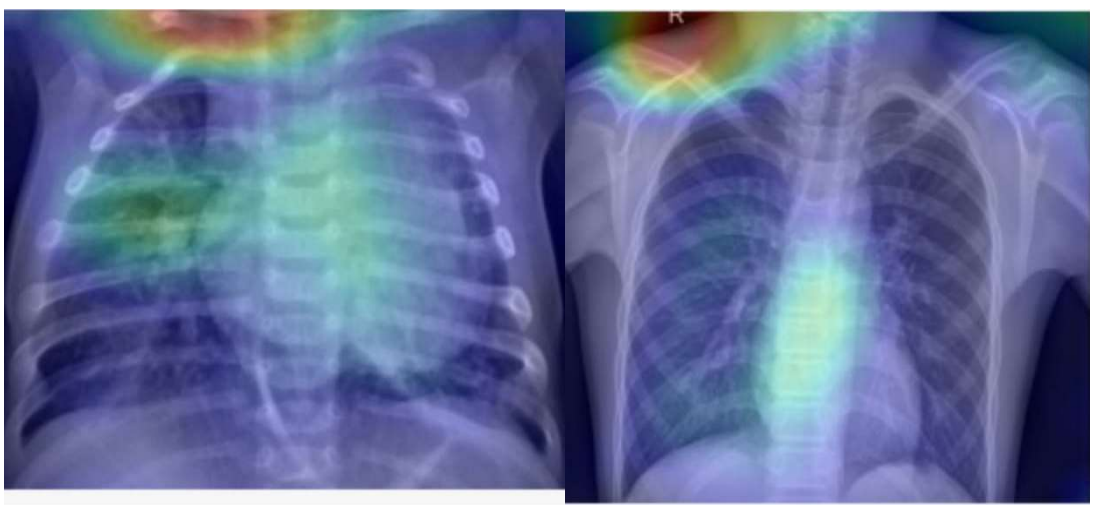

Fig. 6.7 Showing Grad-Cam output on VGG16 CNN model. Left predicting Pneumonia And right predicting Normal

Discussion:

From above figures we can exactly see what features our model is seeing while predicting Normal or Pneumonia. **Grad-CAM of Custom CNN is up to the mark it is trying to see inflammation in lungs. But in VGG16 our model is lying more importance to shoulder area than lungs. Thus, from this we can see why VGG16 is randomly predicting.**

Chapter 7
Conclusion and Future Scope

7.1 Conclusion

From above results, we conclude that though Custom CNN shows very good actual performance as compared to Pretrained model. Also, we came to know faults in our model that caused low accuracy in Pretrained model also we came across the term Class imbalance which affected our model accuracy but in case of Custom CNN model its effect was negligible. Also, Grad-Cam helped us to verify the model and its performance.

7.2 Future Scope

In future, we can expand our model to detect multiple disease like Covid-19, Pneumothorax, Atelectasis, Cardiomegaly, Infiltration, etc. from Chest X-ray analysis. Also, we can use some pretrained models like **ResNet50, Inception V3, VGG19**, etc. to save time and can have better accuracy. Also, we can research to reduce the false positive and false negative of the model in order to make the model marketable.

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Appendices

1. **Back-Propagation**: Back Propagation Neural is a multilayer neural network consisting of the input layer, at least one hidden layer and output layer. As its name suggests, back propagating will take place in this network. The error which is calculated at the output layer, by comparing the target output and the actual output, will be propagated back towards the input layer.

2. **VGG 16:** VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition". The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's.

3. **VGG 19:** VGG-19 is a convolutional neural network that is 19 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

4. **Inception V3:** Inception-v3 is a convolutional neural network that is 48 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299.

5. **ResNet 50:** ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

6. **AlexNet:** AlexNet was much larger than previous CNNs used for computer vision tasks. It has 60 million parameters and 650,000 neurons and took five to six days to train on two GTX 580 3GB GPUs. Today there are much more complex CNNs that can run on faster GPUs very efficiently even on very large datasets. AlexNet consists of **5 Convolutional Layers** and **3 Fully Connected Layers**

7. **Xception:** Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database.