Pneumonia Detection Using Convolutional Neural Networks

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Abstract— **Pneumonia is a fatal disease that majorly affects the elderly and may sometimes prove to be life threatening. Early diagnosis of Pneumonia gains a paramount importance for saving many human lives. This paper aims at the detection and classification of patients affected by Pneumonia based on their chest X-rays. A convolutional neural network is employed from scratch to make the above diagnosis and yield highly accurate results. Deep Learning models automate the process and ensure speedy, adroit, and adept results when provided with X-rays of patients. The classification occurs after the image is fed through a series of convolutional and max pooling layers that are activated by using the ReLU activation function that is subsequently fed into the neurons present in the dense layers and finally, the output neuron is activated by the sigmoidal function. The accuracy increases as the model trains and decreases the loss simultaneously. Overfitting is prevented by implementing data augmentation before fitting the model. Thus, efficient, and cogent results are obtained by the proposed deep learning models to classify the chest X-rays for the detection of pneumonia.**

Keywords— Pneumonia, Convolutional Neural Network (CNN), Max Pooling, Sigmoid Function, Rectified Linear Unit (ReLU), Data Augmentation, Deep Learning.

I. INTRODUCTION

Pneumonia is recognized as one of the most threatening disease by the WHO recently estimating over a million premature deaths across the world. According to the World Health Organization, Pneumonia causes nearly 15% of all deaths of children under five years of age. This is nearly 8,08,694 children, as documented in the year 2017. Globally it affects around 450 million people a year. It was the fourth leading cause of death in 2016.

The risk of Pneumonia is increasing day by day and is immense in rapidly growing nations. Pneumonia is a disease caused by various bacteria and viruses and thus, X-rays are the major diagnosis tool to detect Pneumonia. It is often a difficult task to detect pneumonia outright at an early stage by analyzing the various chest X-rays. With the advent of technology there have been an enormous growth in the healthcare sector. However, Chest X-Rays are considered to be effective, examining Chest X-rays can be ambiguous to detect pneumonia as it can be misinterpreted to be a heart failure or various lung cancers. Various Machine Learning models fail to detect such kind of diseases due to their limitations and thus, urging us to employ advanced and more accurate Deep Learning Models, particularly a densely connected Convolutional Neural Networks (CNN) which helps in feature extraction process. The models can be pretrained to improve the efficiency and accuracy. [1]

The main challenge is to build an efficient algorithm that identifies whether a particular patient is suffering from pneumonia or not, by examining his chest X-ray. As the lives of the people are at stake, utmost importance must be given so that the algorithm is extremely accurate. The Convolutional Neural Network (CNN) is one of the most used deep learning neural network and it uses numerous layers along with the max pooling layer. The layers help in automatic image recognition of the X-rays. It also contains the Rectified Linear Unit called ReLU layer which help to improve non-linearity. It is an optimized structure to handle 2D as well as 3D images effectively. It posits a similarity to the fixed network of trial and error system. The paper aims to detect patterns for patients and classifies whether they are affected by pneumonia or not. [2]

The paper is structured as follows: In section 1, the proposed methodology has been explained where in Section 2, a detailed account about the dataset used and the images of chest X-rays with and without Pneumonia, is provided. Further, the dataset was augmented to enhance the performance. In section 3, we have elaborated on the deep learning architectural models like CNN Network, and discussed about the layers used while implementing the models. Section 4 helps in understanding how every image appears after processing through the CNN layers. Section 5 provides a visual understanding of the data using statistical and graphical representation. The results of implementing the classification algorithms have been depicted in the section 6, along with comparison among all the epochs. Finally, the conclusion and future scope have been discussed subsequently in the paper.

II. RELATED WORK

Deniz Yagmur Urey et al. presented a research paper involving the early diagnosis of Pneumonia by using deep learning techniques. The authors posit a novel approach of focusing on the biological aspects of this fatal disease and detecting it by X-ray imaging. The classification methods used are Convolutional Neural Networks (CNN) and Residual Neural Networks. The Comparative study helps detecting Pneumonia at an early stage and thus, appropriate treatment can be provided to cure the disease. This research influenced our paper, to conduct a similar assessment, but on a more generalized data, a plethora of images and on a detailed approach of layers of the neural network to make it more efficient and produce higher accuracy [3].

Dimpy Varshni et al. explained the development of an automatic system for detection of pneumonia through various deep learning models. The authors analyzed medical images and developed a Convolutional Neural network for disease classification and scaling of data. The architecture consists of a DenseNet-169 layer architecture for feature extraction. The architecture was combined with a SVM Model for binary classification. The results of the model are analyzed with visualization curves and a summary is provided for the same. [4]

Garima Verma et. al. presented a research paper which analyses and identifies pneumonia, based on X-ray images, using convolutional neural network. The implementation was done using 6 convolutional layers followed by max-pooling layers after each. This provided us with an insight to incorporate lesser number of convolutional layers, for faster computing and classification of the deep learning model. The research helps detect pneumonia, based on Chest X-rays. [5]

Okeke Stephen et. al. provides a similar insight on classifying numerous x-rays to detect pneumonia based on convolutional neural networks. The accuracy obtained through their research helps us evaluate our model in comparison, depending on the loss and accuracy of the neural network. Their network is provided with a (200x200x3) dimension input shape, while the images are focused and it uses (64x64x3) dimensions, to decrease the computations. [6]

III. PROPOSED METHODOLOGY

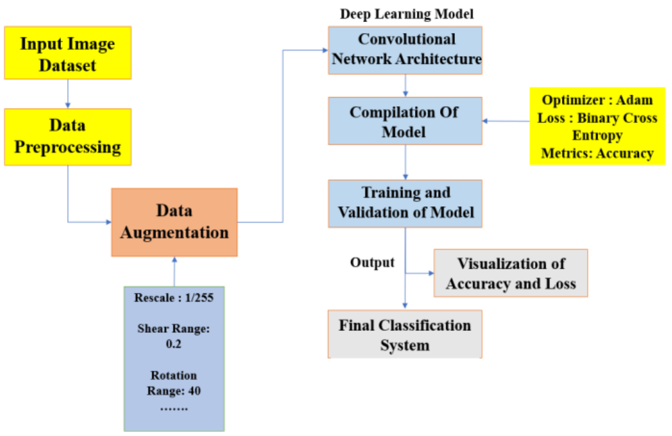

Fig. 1 System Architecture

In the above system, the image dataset i.e. chest X-ray images used is pre-processed and transformed using various NumPy and Pandas Libraries of Python Programming Language. Further, the data is augmented in this phase to provide enhance and adequately efficient results in the various deep learning models. The data augmentation part considers the attributes like Rescale factor, Sheer Range, Rotation Range and other numerous attributes. This data is then fed to the Deep learning Model that is the Convolutional Network where it undergoes a series of steps. An optimizer named Adam is used to measure accuracy and the loss in the form of binary cross entropy in order to optimize the results during the compilation phase. Further, the model is trained and validated according to the convolutional network architecture. The output of this stage helps us to visualize and compute various curves and graphs displaying the dependency of loss, validation, and other myriad features. The output after all the steps obtained is the Final Classification System which diagnoses whether the patient has pneumonia or not.

IV. DATASET

The dataset used for all the diagnosis is based on a Chest X-ray dataset which is released by the radiological department/society on the Kaggle website. All the images are X-rays consisting of the RGB format. The Keras open-source deep learning framework along with the TensorFlow backend is employed to build and train the Convolutional Neural Network. The dataset obtained consisted of the training, testing and validation images each divided by the Pneumonia and Normal chest X-rays. A total of approximately 6000 images of anterior posterior are present. The data is modified into the training and validation set to enhance the system and increase efficiency. A total of around 5216 images are included in the training set and similarly, a total of 624 images are allocated to the validation set in order to improve the overall accuracy.

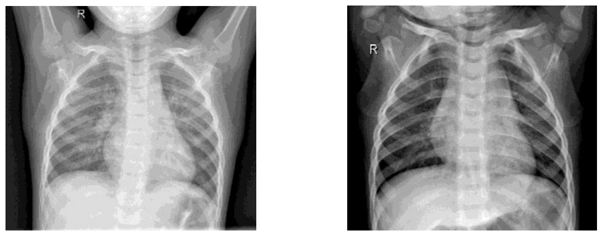

Fig. 2 X-ray Sample without Pneumonia

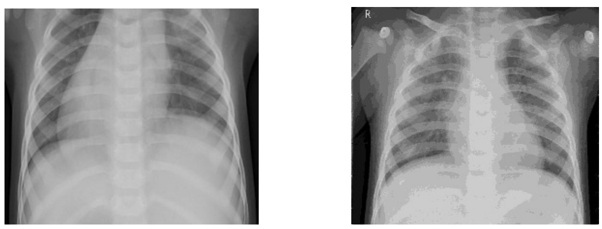

Fig. 3 X-ray Samples with Pneumonia

V. DATA AUGMENTATION

Data Augmentation techniques are extensively used to enhance the performance of deep learning algorithms. Data augmentation is primarily used to improve the performance of the convolutional neural network model, used to classify the chest x-rays. Data Augmentation is implemented on the training data, which are the images in this case, to enhance and augment the quality, adeptness, and size of the data.

Numerous operations are carried out to increase the size of the data and help the Deep Learning model capture multiple nuances in the training images. Convolutional Neural Networks are fed the augmented data to prevent overfitting of the data, to optimize the performance of the model. Overfitting is an undesirable condition where a machine learning or deep learning model performs well on the training set but yields undesirable results on the testing and validation sets. Thus, overfitting of the model is not advisable and should not occur during the implementation. [7]
Increasing the training dataset enables the Deep Learning and Computer Vision algorithms to fit the models more efficiently and adroitly. There are various data augmentation techniques, which have been used to train the model. This practically does not change the original dataset and is only implemented during the run time, without any unnecessary disk space being utilized to store the modified and augmented images. [8]
The data augmentation techniques implemented to improve the accuracy of our Deep Learning model are-

i. Rescale Normalization – This is used to decrease the amount of computation and processing involved, while dealing with image datatype. The value of pixels can be between 0 to 255 for any image. To normalize this wide range, each value is multiplied by a rescaling factor of 1.0/255.0, in order to obtain the values between 0 and 1. Thus, the required computational and processing power is significantly reduced. This is called while loading and processing the images into training and validation sets using ImageDataGenerator function of the TensorFlow library in Python.

ii. Geometric Transformations – These are used to modify the geometric properties of images and enabling the model to capture the training images modified with respect to these properties. It enables the model to recognize and process images similar to the original training set, but with slight modifications in their physical traits. To explicate this, a zoomed in image may not be clearly understood by a model given zoomed out training images. Thus, changing the geometric properties of height, width and zoom, new training images are developed, which may help the model correctly identify the test image. This includes various attributes and parameters, mentioned in the ImageDataGenerator function, like the 'width_shift_range', 'height_shift_range' and the 'zoom_range'.

iii. Flipping – A mirror image of a training image might not be correctly recognized and evaluated by the model, in the testing phase. Thus to ensure adequate and optimal performance of the model on these mirrored images, flipping is used to augment the data and provide flipped images of the training data, without actually having to store mirrored images of each training sample, onto the disk storage. Thus, a dynamically efficient flipping augmentation process helps improve the performance of the Deep Learning model on the chest x-ray dataset.

iv. Shearing – Introducing shearing to the training images, helps obtain sheared images, to have the Deep Learning model accustomed to images in a sheared orientation. It is likely that some test images may be similar to some training images, with a sheared orientation. Thus, to accurately deal with these test images, the sheared orientation of certain training set images provides us a better insight.

v. Rotation – Training images may be rotated by certain degrees, to obtain modified images, in order to augment and increase the contents of the training dataset. This is done by setting the 'rotation_range' to an appropriate value, while initializing the ImageDataGenerator function. Thus, various angles of the rotated images are used in data augmentation.

Table 1 Image Augmentation Settings

Hyperparameters for Data Augmentation	**Values**
Shear Range	0.2
Zoom Range	0.2
Rotation Range	40 (In Degrees)
Horizontal Flip	True
Width Shift Range	0.2
Horizontal Shift Range	0.2
Fill Mode	Nearest

VI. CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNN) is a class of deep neural networks which is used to analyze visual imagery. It consists of an input as well as output layer along with its many hidden layers. The input is a tensor with shape of the form (number of images) * (image height) * (image width) * (image depth). The image becomes abstracted to a feature map after passing through the convolutional layer, with shape (number of images) * (feature map height) * (feature map weights) * (feature map channels). Technically, the CNN models are used to train and validate each input image of the dataset which pass through a series of layers with filters consisting of kernels, pooling, fully connected layers and even apply Softmax function to classify an object between probabilistic values between 0 and 1. [9]

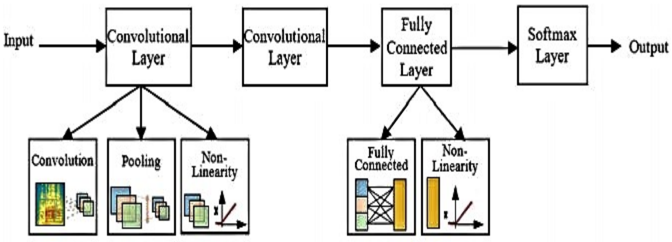

Fig. 4 CNN Block Diagram

The dimensions of the output matrix - considering padding and stride - can be calculated using the following formula.[10]

$$n_{out} = \frac{n_{in} + 2*p - k}{s} + 1 \text{ ----------------- } \quad (1)$$

nout: number of output features ; nin : number of input features ;k : convolutional kernel size ;p : convolutional padding size ; s : convolutional stride size.

The main advantage of CNN over the other neural networks is that it automatically detects the important features without any human supervision efficiently and effectively. The key feature is that CNN works almost perfectly on image datasets. Convolutional neural networks can extract informative features from images, eliminating the need of processing manual image processing methods every time. CNN's are extremely successful in areas where large, unstructured data is involved. CNN's are more powerful than machine learning algorithms and are also computationally efficient. There are various activation functions used in CNN's like the sigmoid function, tanh function and the ReLU function which is used extensively.[11]

CNN's deals with the optimization of various hyperparameters like batch size, optimizer to be used, target size, number of hidden layers, number of epochs which in return play a huge role in the accuracy of the network. Thus, Convolutional Neural Networks are specialized networks that optimize two dimensional structure efficaciously.

VII. Deep Learning Model Architecture

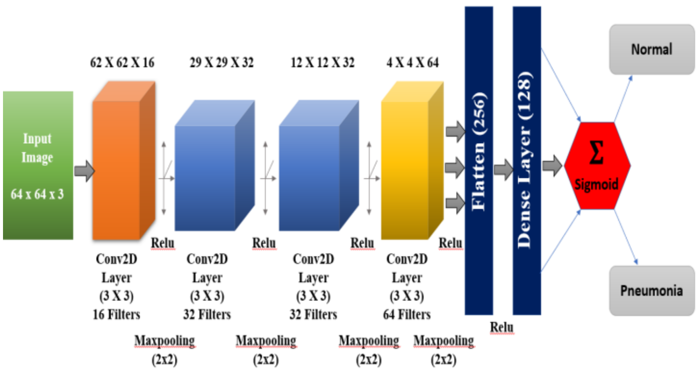

Fig. 5 CNN Architecture

A. Layer Description

A Deep Learning approach has been used to detect whether a given chest X-ray image has pneumonia or not. For this, the Convolutional Neural Network have been implemented, which consists of numerous two dimensional convolutional layers, followed by two dimensional Maxpooling layers and subsequently, the output of last convolutional and Maxpooling layer is flattened and fed into a dense layer with 128 neurons. This is then finally fed into a layer activated using the Sigmoid Function. Since, our classification is binary, where the output is in terms of Normal or Pneumonia infected, having used the sigmoid activation function at the last layer of the Deep Learning Network.[12]

The architecture of the Convolutional Network is depicted in Fig.4. A sequential model is implemented using the layers provided by the Keras API of the TensorFlow library in Python. The input image is brought to a standard size of (64x64), with three filters for the colour (RGB). The input image is then fed into the first layer whose dimensions are (3x3) with 16 filters. This can also be denoted as (3x3x16). The image is then broken down by the convolutional layer into new dimensions of (62x62x16). This image is then fed into the Maxpooling layer, after the first convolutional layer. The Maxpooling layer has a window dimension of (2x2). Thus, the size of the image is again altered.[13]

Next, the image is passed through the second convolutional layer, defined by the sequential model in Keras. This convolutional layer is of shape (3x3) with 32 filters, denoted as (3x3x32). The image attains new dimensions at this stage. Now, the resultant image is of (29x29x32) shape. Further, another Maxpooling layer is introduced of shape (2x2). This again modifies the image shape.

Moreover, the altered image is passed through another convolutional layer of the same dimension as denoted by the second blue box in fig. 4. The shape of this convolutional layer is the same as that of the previous one (3x3x32). Thus, the image is processed again by the convolutional layer, to capture finer details of the X-ray image. The image attains a new shape of (12x12x32). Now, the image is fed through a Maxpooling layer of (2x2) dimension.[14]

The last layer of the convolutional network is the two-dimensional convolutional layer with 64 filters. This convolutional layer of shape (3x3x64) captures finer details of the previously modified image, thus yielding a resulting image of shape (4x4x64). The maxpooling layer once again changes and generates finer instances of the image for better processing and classification.

All the above convolutional layers were activated by the ReLU function. ReLU stands for Rectified Linear Unit and is conventionally used when there is classification involved [15].

After the final convolutional layer, the resultant is fed into the neural network layer (DNN), where the input is flattened. This is subsequently fed into the next layer, with 128 neurons to process the key aspects of the image and to enable the neural network to classify, based on the observation and calculation of the neurons. This layer also uses the ReLU activation function to process the input and calculate output for that specific layer. The information from this dense layer of the DNN is passed through the last dense layer with a single

output neuron to determine whether Pneumonia is detected in the given Chest X-ray or not.
The sigmoid activation function is generally used to deal with binary type output, where the output has to be classified primarily into two categories. Thus, the above is the summary of the Deep Learning Model, which includes Convolutional Neural Networks as well as Deep Neural Networks.[16]

B. Model Summary

The Model Summary depicted below delineates the Output Shape along with the number of Parameters included at every layer of the Deep Neural Network. The layers used in our CNN model are in order as they appear in the network along with each layers output shape dimensions and the number of parameters. There are four Convolutional layers along with the same number of Maxpooling layers followed by the flatten layer of zero parameters and the dense layers of around 32000 parameters. Thus, the total trainable parameters in the network amount to 65,857 parameters. This model summary gives a quick brief information of the Deep Neural Network employed. [17]

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 62, 62, 16)        448

max_pooling2d (MaxPooling2D) (None, 31, 31, 16)        0

conv2d_1 (Conv2D)            (None, 29, 29, 32)        4640

max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0

conv2d_2 (Conv2D)            (None, 12, 12, 32)        9248

max_pooling2d_2 (MaxPooling2 (None, 6, 6, 32)          0

conv2d_3 (Conv2D)            (None, 4, 4, 64)          18496

max_pooling2d_3 (MaxPooling2 (None, 2, 2, 64)          0

flatten (Flatten)            (None, 256)               0

dense (Dense)                (None, 128)               32896

dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 65,857
Trainable params: 65,857
Non-trainable params: 0
```

Fig. 6 Model Summary

VIII. Results And Discussions

A. Pictorial Representation after Each Layer

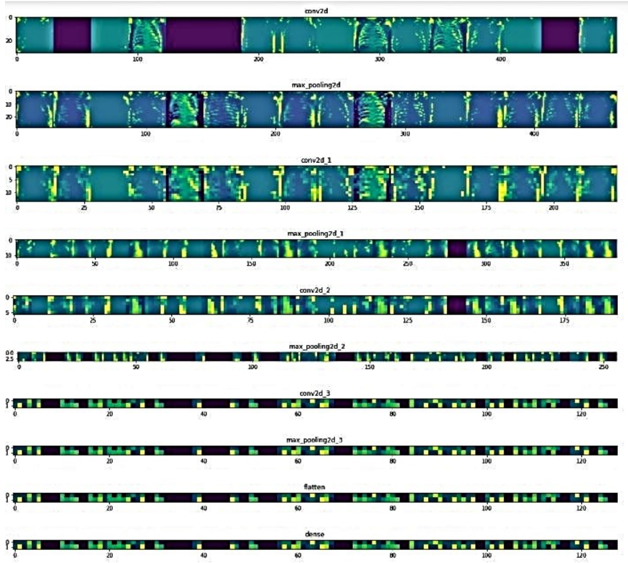

Fig. 7 Resultant Image After Each Layer

The figure above depicts how the input image is processed at each step and layer of the Convolutional Neural Network implemented above. It shows how at each layer the image is analyzed for finer details in order to detect and diagnose Pneumonia based on the chest X-ray image fed into the deep learning model. This representation provides an insight how each Maxpooling and each convolutional layer process the input image in a pictorial format. [18]

B. Training and Validation Results

The model is trained for 25 epochs, with a batch size of 32 for the training phase which amounts to 163 steps per epoch for training and a batch size of 16 was employed for the testing phase which contributes towards 39 steps per epoch for testing. Thus, training for 25 such epochs yielded optimized results, with high accuracy of 96.36% and a minimal loss of 0.1020 for training and a corresponding 91.51 % accuracy and 0.2705 loss for validation. [19]

Table 2 Performance of the Deep Learning Model

Epoch Stage	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.7893	0.4567	0.8526	0.3088
5	0.9385	0.1649	0.8125	0.4679
10	0.9515	0.1246	0.9022	0.2762
15	0.9519	0.1265	0.9231	0.2079
20	0.9561	0.1139	0.9103	0.2806
25	0.9651	0.0962	0.9247	0.2290

The above table documents the performance yielded by the Convolutional neural network architecture. The table shows the training accuracy, training loss, validation accuracy and validation loss obtained at various epochs. A description of the training and validation characteristics for every five epochs has been provided. The above table shows that the validation accuracy is almost similar to the training accuracy. Hence, suggesting the absence of overfitting in our deep learning model.

C. Performance Matrix For Validation Phase

Table 3 Performance Metrics for CNN

Epoch	True Positive	True Negative	False Positive	False Negatives
1	351	181	53	39
5	387	120	114	3
10	385	178	56	5
15	383	193	41	7
20	385	183	51	5
25	384	193	41	6

The above table indicates the performance metrics to calculate accuracy based on the classification results. The true positive metrics denotes that the model correctly predicts a case of Pneumonia. True Negative signifies a case where it correctly predicts when a person is not affected by Pneumonia. False Negative means that the model misinterprets a person having pneumonia as being benign. False Positive signifies that a person not affected by pneumonia is classified to have it.
Thus, based on such classification, we see from the table above how many validation cases have been categorized into each metrics.
This helps to calculate the accuracy of the model. For instance, at the 25^{th} epoch, the validation accuracy can be derived as follows – [20]

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \qquad \text{-------------------------} \qquad (2)$$

Where TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative.

Thus, for the last epoch, we get –

$$\text{Validation Accuracy} = \frac{384 + 193}{384 + 193 + 41 + 6} = 0.9247$$

$$\text{Validation Accuracy} = 0.9247 * 100 = 92.47 \%$$

D. Graphical Representation

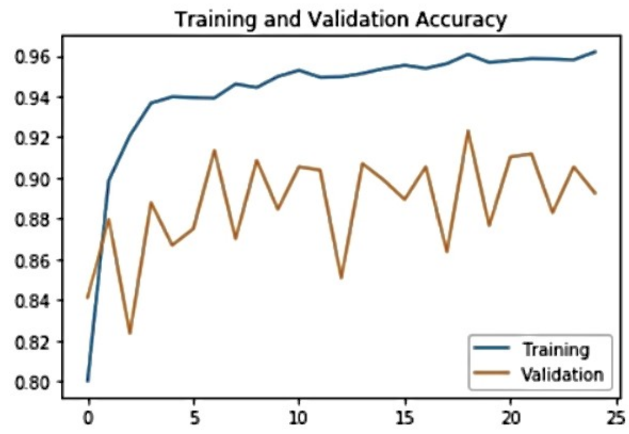

Fig. 8 Training And Validation Accuracy

The figure given above describes the trending graph as to how the training and validation accuracy varies with the epoch count. On close evidence, the graph posits that as soon as the number of epochs increase there is a considerable increase in the training accuracy whereas there is a gradual rise and dip in the validation accuracy. At the end of the 25^{th} epoch the training accuracy obtained is about as high as 96 % in compared to the 92 % accuracy yielded by the validation curve. There is an incessant increase in the training accuracy curve after every epoch as we have set around 163 steps per epoch in contrast to the 39 steps per epoch in the validation accuracy curve in order to yield as optimal and efficient results.

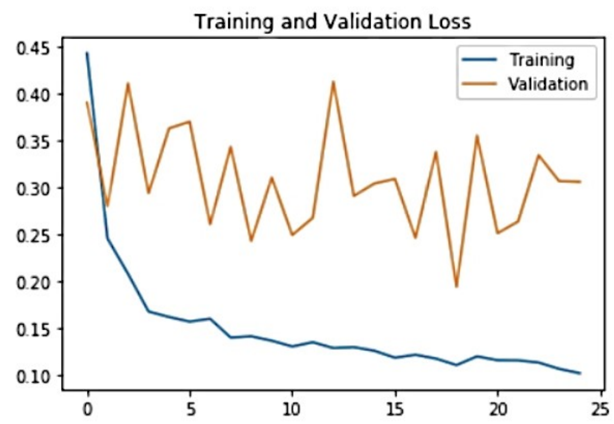

Fig. 9 Training And Validation Loss

The figure 9 given above delineates the rise and fall of loss in the network as the number of epochs increase. On scrutiny, we conclude that there is a great dip in the training loss as the number of epoch reach 25. The loss greatly decreases making the network more accurate and efficient. The training loss at the end of all the epochs results to 0.0962. The validation loss on the hand has a gradual increase and decrease as the epochs increases due to fewer steps per epoch as compared to the training curve. The validation loss at the end of all epochs results to 0.2290. Thus, these visualizations support the results obtained and renders our network efficient and accurate for diagnosis of Pneumonia.

IX. CONCLUSION

Therefore, it is concluded that the deep learning model proposed above classifies the Chest X-rays for Pneumonia diagnosis in a very accurate manner. The loss of the model is minimized while training and the accuracy simultaneously increases through each epoch stages in order to yield distinct results for classifying the Pneumonia affected and non-affected individuals. The data augmentation and preprocessing stages help to ensure that the performance of convolutional neural networks and deep neural networks is not subjected towards overfitting, thus the results obtained will always remain coherent. With a smaller number of convolutional layers, the proposed model predicts adroitly whether a given sample of Chest X-ray has pneumonia, or is normal. This is immensely helpful in the medical field for early and accurate diagnosis for Pneumonia in patients. Early diagnosis is of paramount importance in saving a person's life, by ensuring effective and timely treatment of the patient.

Future Scope: The model presented can be enhanced further to provide stage wise diagnosis for Pneumonia. This study can also be extended to diagnose the Corona Virus (Covid-19) in patients, which is a pandemic of the year 2020 and has affected myriad people across the globe. An X-ray based detection of Corona virus would help reduce the danger of exposure to the medical staff in charge of testing and will ensure a faster and accurate testing process as well. The Deep Learning model can be extrapolated for the diagnosis of Covid-19, using transfer learning as well, given sufficient amount of data. Moreover, the Deep Learning model can also be employed for other medical purposes and diagnosis, like for bone suppression in chest cavity, to diagnose lung cancer or other such respiratory diseases. Thus, this project has immense scope in the field of medicine and health care, and can be continued for other such insightful innovations.

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