System For Detecting Pneumonia Using Convolutional Neural Network from Chest-Xray Images.

Anupam Jain
Apex Institute of Technology, Chandigarh University,
Kharar, India.
anupamayushij@gmail.com

Lakshit Saini
Apex Institute of Technology, Chandigarh University,
Kharar, India.
lakshitsaini2022@gmail.com

Rajiv Kumar Yadav
Apex Institute of Technology, Chandigarh University,
Kharar, India.
rkcuwork@gmail.com

Mehul Gosavi
Apex Institute of Technology, Chandigarh University,
Kharar, India.
mehul.dev24@gmail.com

Siddharth Kumar
Apex Institute of Technology, Chandigarh University,
Kharar, India.

***Abstract*— Pneumonia is the most common disease in which both lungs' air sacs inflate with fluid. Depending upon the stage it can be lethal and it is extremely important to identify pneumonia in the early stage to cure it. With the help this research, we suggest a machine learning model which uses the concept of a convolutional neural network and deep learning to identify whether a patient is experiencing pneumonia using chest X-ray images(CXI). Our models aim to achieve an improved accuracy than previous work and provide a model that can serve as a tool of use for the general public. We used the public dataset available on Kaggle for carrying out this research and created a model using the convolutional layer, max pooling, and fully connected layers. The model was highly efficient in the testing dataset.**

Keywords— Convolutional Neural Network, Visual Geometry Group, computerized tomography, Vision Transformer, Radiological Society of North America, Chest X-Ray images.

I. Introduction

Pneumonia is a contagious as well as non-contagious disease responsible for the swelling of the lungs. In pneumonia, the tiny sacs of the lungs might fill up with fluids or pus causing coughing, fever, and difficulty in breathing. There can be many different agents that can cause pneumonia like viruses, bacteria, fungi, etc. Untreated pneumonia can lead up to lung abscess where part of the lung disease dies. A person may also suffer from respiratory failure in certain cases. UNICEF data shows that pneumonia killed over 700000 children in the last five years with an average of over 2000 deaths every day[1]. Detecting this hazardous disease becomes a very important scenario. There are several situations where it becomes hard for a patient to consult a doctor or it may be hard for them to get an appointment with a doctor. In several cases, the disease might be left undetected which may lead to severe health issues. Our idea is to create a system that can be used by anyone to analyze the chest X-ray of a patient and determine whether the person is suffering from pneumonia or not. The different images given below show whether a pneumonic or normal chest X-Ray image.

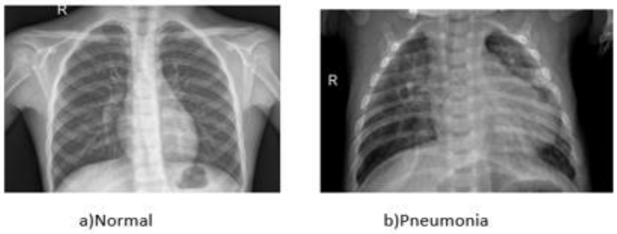

Fig. 1. Visualization of images in the given dataset

We have created an autonomous system with the help of deep learning and the CNN architecture technique. While doing so we have achieved the following objectives:

- We conducted a comparative analysis of all the machine learning problems taken into use by far to solve the problem. We concluded that each and every model has certain advantages and certain drawbacks.
- In some cases, the data available wasn't precise enough and in certain cases, the architecture used wasn't efficient enough or wasn't feasible enough.
- We created a new model that was able to segregate images into pneumonia and normal images.
- The model works on enhancing image pre-processing and segmentation techniques and a lighter and more efficient neural network architecture that reduces the computational cost and provides efficiency.
- With this work, we achieved a system that can be developed into software easily and can be used at the chest X-ray centres to give a briefing about the person's report.
- We implement 9 layers CNN model consisting of convolutional layers and max pooling layers. The ten layers were followed by a flattened layer and two dense layers.

Thus, timely detection of pneumonia can result in saving various lives as we all know each and every life is precious.

The organization of the paper is like this: Section 2 discusses the literature review of the previous works telling us what the previous people have achieved so far. Section 3 talks about the methodology used in order to solve the problem. Section 4 contains the final result we were able to achieve with our model. Section 5 is the final section of the paper that concludes the paper and discusses the scope of future work.

II. Literature Review

In this section of article, we present a brief survey on the existing models related to Pneumonia detection using different techniques of machine or deep learning.

In 2023, **M Ahmed et al**., worked in the field of Neural Networks and Deep Learning to distinguish and find out Pneumonia and COVID 19 with the help of CXI. They proposed an efficient model to find out the patients of the said disease. The model uses ResNet2 Architecture with an additional six layers making the model more robust and error-free. After developing the model, a Gran Cam was used to convert the radiology images into a readable format for the system. Two datasets were gathered to train and test the mode from different sources. The dataset gathered during the research was made publicly available. The dataset contained different labels: normal, COVID, viral, and bacterial pneumonia. It possesses a total of 4593 image with 1143 labelled as COVID 19, 1150 normal, 1150 bacterial and1150 viral. The model then produced an accuracy score of 99.51 for all four labels on the first dataset and an accuracy score of 96.52% for the labels: normal, COVID, and Bacteria. The model also produced an accuracy of 99.13% when it was used to compare the label COVID and Normal. The model aims to help doctors rapidly identify the disease easily and cure the patient timely [3]. In same year**, S Sharma & K Guleria** worked on enhancing the model used for identifying Pneumonia using deep learning. Here, they used VGG16 architecture along with the Neural network to identify pneumonia from CT-Scan images of the chest. They used this approach on two different datasets. On the first data set the model achieved a remarkable accuracy of 92.15%, a recall of 0.9308, a precise of 0.9482, and F1 score of 0.937. The second dataset comprised 6436 images and produced 95.4% of accuracy, 0.954 precise, 0.954 recall, and 0.954 F1-Score. The research shows that the VGG16 along with the Neural network provides remarkably improved performance than the VGG16 architecture used along with methods like K Nearest Neighbouring, Support Vector Machine, Random Forest, and Native Bayes. Finally, they concluded that the model tends to improve with the use of more data feeds, an increased level of data augmentation, and a number of hidden layers used within the model[4].

In 2021, **E Ayan, B Karbulut, and H M Unver** conducted research on Paediatric Pneumonia diagnosis proposing a method to distinguish and recognize the disease using CXI. They provided an ensemble manner after analyzing different deep-learning models. They analyze a total of 7 models that includes VGG 16, MobileNet, etc. All the models were preliminary trained on Image Net Dataset. Appropriate methods were used to finely train the model. After that 3 most yielding models were selected to develop an ensemble model. The end results were attained by combining the observations of the CNN model and the ensemble model. Additionally, the results of the afresh trained model were also compared with the said model. The said model attained an accuracy score of 95.21 and total sensitivity equal to 97.76 while the testing phase with a classification accuracy of 90.71 in CXI as normal, bacterial, and viral categories of the same disease [5]. In 2022, **Mahmoudi R et al.** created a system of Deep learning for diverse pneumonia and COVID-19 infection using Computed Tomography scans. They used Contrast Limited Adaptive Histogram Equalization for pre-processing of image and removing noise and intensity, thus obtaining the area of interest, i.e., the lungs' visuals from the CT scans. A U-net architecture, dependent on the CNN encoder and decoder was used to obtain a velocious and close to accurate model of lung infection segmentation. Fourfold Cross Validation was used for resampling. CNN architecture using 3 layers, with additional layers like fully connected and SoftMax layer, was brought into use. To calculate the volume ratio and determine the infection rate, lung and infection volumes have been reconfigured. With a dataset consisting of 20 ct scans the data was divided into 70% training and 30 % validation dataset. The model produced dice scores of 0.98 and 0.91, respectively, and classification accuracy of 0.98 percent. The system aims at improving the performance of the different systems and also deals with the problem of reduced datasets[6]. In 2023**, Tiamu Wang et al.** delivered a COVID 19 Pneumonia diagnosis system using the VIT.Its hard to differentiate between the minute lung texture from the normal lung image and the sometimes these details might be missed by the model so they come out with the idea of feature extraction from the image of chest X ray. They proposed a VIT based model that lay attention on the channel patches rather than the features. The model is called PneuNet. The model was able to perform 94.96% of accuracy which surpass other deep learning models. However, the model has lots of limitations. It isn't able to classify multiple category easilyIt was also adviced to use better augmentation techniques. It is advised to develop a model that is less complex than the current model because the Punet model is a "black box" model. [7].

In 2023**,R. Chiwariro and Julius B. Wosowei** computed a comparative analysis on various CNN network and models used to identify and detect pneumonia. The paper basically reviews the performance of five different models i.e. ResNet50, InceptionNet v3, VGG19, VGG16, and YOLO v5.t. All of the aforementioned models underwent training. using the RSNA pneumonia detection dataset. Results were further evaluated and compared. Benchmarks used to compare the results were Validation Accuracy and Area under the Curve. After implementing the models on the testing dataset VGG16 produce the highest validation accuracy of 88 percent and the AUCROC of 91.8% whereas the YOLO v5 is administered to compute the regions of inflammation with a level of confidence of 99%. After comparing the models it was concluded that a viable combination of the VGG16 and YOLO 19 models is possible. To improve the performance of the models collecting huge amounts of data with precise information is required. Also, the current model is not almost accurate, they might still be bound by certain issues. Resnet produces a deviation from the target position and elongates training time. One more common problem models face was to identifying the person not having pneumonia as having pneumonia. This can be resolved with better training data and feature extraction[8]. In 2019, **O Stephen et al.** a Deep Learning and Machine Learning professional and proposed an ML-grounded model for distinguishing the cases suffering from Pneumonia by feeding the Chest X-Rays of cases to the model as an input. The dataset used in this work holds three directories: Training, testing and validation flyers and a gross of 5,856 X-ray images. Various data augmentation methods like rotating, rescaling, etc. were applied to the images performing in a better-quality dataset. CNN armature is used to train the model in a three-Stratum format: Convolution, max-pooling, and bracket subcaste. Levelling the affair of the CNN part is passed on to the bracket subcaste and in the last step, sigmoid function eventually executes the bracket tasks successfully performing in training veracity of 95.31% and training loss of 12.88% along with validation veracity and loss of 93.73% and 18.35% respectively [9].

In 2020, **A Kalinin et al.** Made a model employing Machine Learning for the diagnosis of Pneumonia sufferers by studying the CXR based on Single-shot detectors, squeeze-and-excitation module, etc. Dataset used contains CXRs of 26,684 distinct sufferers out of which 1000 is for testing data and remaining for training and each CXR can be catalogued into one of the Divisions: Lung Opacity, No Lung Opacity, and Normal. For Training the model, an SSD RetinaNet and SE-ResNext-101 encoder are used. During Preprocessing stage original images were rescaled to resolution of 512x512 px and image augmentation was implemented in 5 stages with each stage having different settings resulting in awesome results. Heavy augmentations but no rotation results in best validation mAP score of 0.260971[10]. In 2023, **MN Nasef et al.** Conducted exploration in the field of medicine for betterment of pneumonia victims by proposing three models for the diagnosis of Pneumonia. Dataset used in this model contains 4,684 images for assessment and 1,172 training photos. Model consists of two phases: feature extraction and logistic regression algorithm to classify X-Ray images. Images of resolution 64x64 px are fed into all the models by using pure inception in the first Baseline model performing in test delicacy of 95.05% and inception-residual in next Baseline giving test accuracy of 94.96% but both the models are overfitting the data as they were giving 100% training delicacy. Out of three proposed models, model using Inner residual inception gave training fidelity of 99.3% and balanced veracity of 95.08%. This model succeeded in perfecting veracity and reduce overfitting which took place in both Base models. This model was not tested for real time data and cannot replace doctors completely [11].

In 2021, **MK Gourisaria et al.** Developed Machine Learning based model by employing various CNN architectures containing 2 to 5 convolution layers and comparing their veracities for detection of Pneumonia using CXR. The dataset used comprises 4,264 Pneumonia and 1,583 Normal patient CXRs. A variety of Image Augmentation techniques like flipping, shearing, etc. were used to expand the dataset size and 64x64 px or 128x128 px images were fed to CNN. Based on all the performances of architectures, architecture 5 is used as it gives remarkable results for Sensitivity and Specificity of 90.07% and 92.16% respectively [12]. In 2022, **Barhoom, A. M., & Abu-Naser, S. S.** conducted an exploration when it comes to Deep Learning to develop a model based on the CXI of patients for early identification of pneumonia. Dataset used consists of 9,048 images of Chest x-ray which can be further classified into two directories of Training and Testing images and three sub-directories of Normal, Viral Pneumonia and Bacteria Pneumonia. To prevent overfitting, Adam optimization and Five data augmentation operations like Width Shift, horizontal flip, etc. were performed and images were resized to 128x128 px for efficient model training. The proposed model employs VGG16 deep neural network with 16 convolutional layers for training the model. The Model also contains hidden layer and dropout layer with ReLU activations in all the layers. Model results in approximately 100% balanced accuracy for 10 epochs[13]. In 2022, **A Mabrouk et al.** Conducted research in the field of Deep Learning by employing Deep Learning framework which utilizes Ensemble Learning methodology for the categorization of cases of Pneumonia based on their CXI. 5,856 photos are included in the dataset utilised in this study. and images of 224x224 px resolution are fed into a model with a batch size of 32 and 20 epochs. The classification of images is completed by applying the Sigmoid activation function in the top layer.. Nine CNN models are trained their comparison is done based on their accuracy, Precision, Recall, and F1- Score. MobileNetV2, DenseNet169 and VIT gave excellent results as compared to other CNN models resulting in 90.87%, 91.35%, and 92.47% veracity, respectively. After Using the Ensemble Learning technique, we were able to achieve 93.91% delicacy[14]..

III. Methodology

In the following section, we will discuss the procedure we use to detect pneumonia using CXI. We are encoprating a CNN technique in machine learning in order to create this model.

3.1. Data pre-processing

The dataset that we acquired has around 6000 images divided into three categories. These categories include training, validation, and testing. All these images were further classified into two categories that were Pneumonia and Normal. After cleaning the data and visualizing the data we added labels to the dataset. These labels can be used as the target variable to train our model. We further enhance the quality of our dataset by resizing the images in our dataset and converting the images to grayscale using open cv. The data was further standardized with the aim of reducing the complexity. We achieved the said objective by converting the data available into a numpy array.

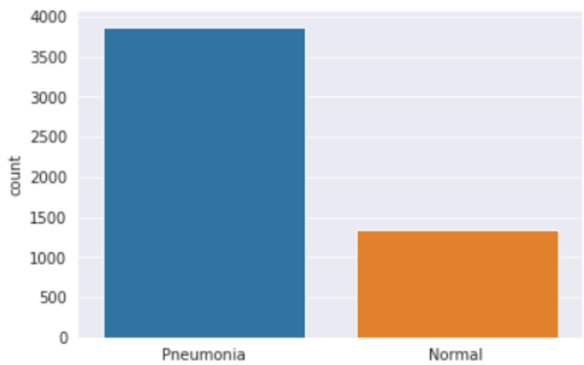

Fig. 2. Unbalanced dataset with less number of normal images and more no of Pneumonia images

3.2. Creating a CNN.

CNN is a subbranch of artificial intelligence or machine learning. It is an effective way of finding different types of similarities or patterns in objects such as text, images, noises, etc. It can be used to solve various kinds of problems such as classifying object, recognizing object etc. It can be divided in various sublayers and we can use these sublayers to create a model.

3.2.1. Convolutional Layers

It is the most important part of the CNN and is responsible for maximum computation inside a CNN. There are certain requirements as input to create a convolutional layer. We need to provide a filter and a feature map along with the data to create a convolutional layer. A kernel or simply putting feature finder moves across the parts of input to determine the presence of a feature. The process of finding the features in the input with the help of Kernal is known as Convolution. The feature finder is a 2-d array of weights which is just a small part of the image. The filter generally a 3X3 matrix, is applied to the different parts of the image, and a dot product is obtained between this area and the filter. Later on, the kernel moves a stride to calculate the next product until the entire image is covered. All the dot product obtained works as an output layer. We can use single as we all s multiple convolutional layers to form a hierarchal model.

3.2.2. Pooling Layers

These layers work in a similar manner as the convolutional layer but instead of applying weight, we use an aggregate function in the pooling layer. This is why this layer is often referred to as the down-sampling layer as they capitalize the size of the input image. There are different kind of pooling layers.

One of the dominant ones is the max pooling layer in which we select the part of data or simply pixel with maximum weight to send to the output. It is used quiet often compared to other kind of pooling layers.

3.2.3. Fully Connected Layers

As the name suggests the main operation is to connect one point of the output layer that contains the layer before. Only a small portion of the pooling layer's output is related to the input images' pixel values.. The fully connected layer's main job here is to connect these output layers to the input layer. Unlike the convolutional layer which relies on an activation function like real, the fully connected layers might use the sigmoid function to produce an output.

3.3 Our Model.

Five Convolutional layers and four max-pooling layers in total were used in our model. Initial convolutional layer takes an input shape of (100,100,3) where (100, 100) is an image size and 3 is the color channel. The activation function used is real and the number of filters is 16 with the kernel 3. The size of the features was increased to 32 in the second layer, 64 in the following layer, and 128 in the final layer. A max-pooling layer is implemented following each convolutional layer. After completing these layers, we placed two thick layers on top of a flat layer..

TABLE I. MODEL SUMMARY

Layer(type)	Output Shape	Parameters
conv2d (Conv2D)	(None, 98, 98, 16)	448
max_pooling2d (MaxPooling 2D)	(None, 49, 49, 16)	0
conv2d (Conv2D)	(None, 47, 47, 32)	4640
max_pooling2d (MaxPooling 2D)	(None, 23, 23, 32)	0
conv2d (Conv2D)	(None, 21, 21, 64)	18496
conv2d (Conv2D)	(None, 19, 19, 64)	36928
max_pooling2d (MaxPooling 2D)	(None, 9, 9, 64)	0
conv2d (Conv2D)	(None, 7, 7, 128)	73856
max_pooling2d (MaxPooling 2D)	(None, 3, 3, 128)	0
flatten (Flatten)	(None, 1152)	0
dense (Dense)	(None, 256)	295168
dense (Dense)	(None, 1)	257

IV. PERFORMANCE EVALUATION

As we have performed the classification of CXI to identify whether a person is experiencing pneumonia or not. There are various ways to assess how well our model is working. During the training phase, our model was able to obtain an accuracy rate of 99.2% over the validation data with a loss of 0.0237 after repeating 10 epochs which is an extremely good result. Talking about the accuracy of the testing data, our model achieved an accuracy of 97%. Let us evaluate our model using various machine learning parameters.

4.1. Confusion Matrix

It is the best way to understand how our model is working so far. The confusion matrix tells us how many times it is predicting true positive values or true negative values out of the total number of the prediction it makes. The confusion matrix can be represented as:

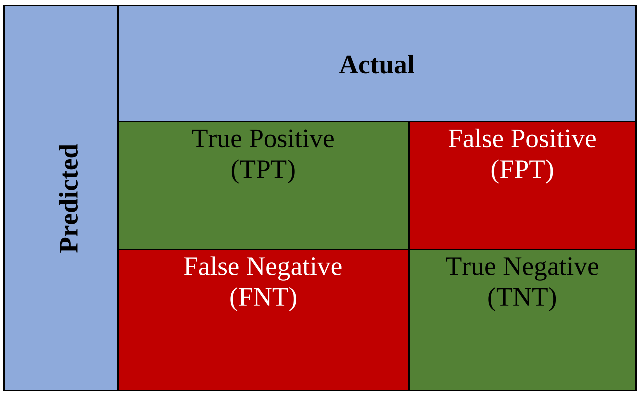

Fig. 3. Representation of matrix of confusion

This is the confusion matrix of our model.

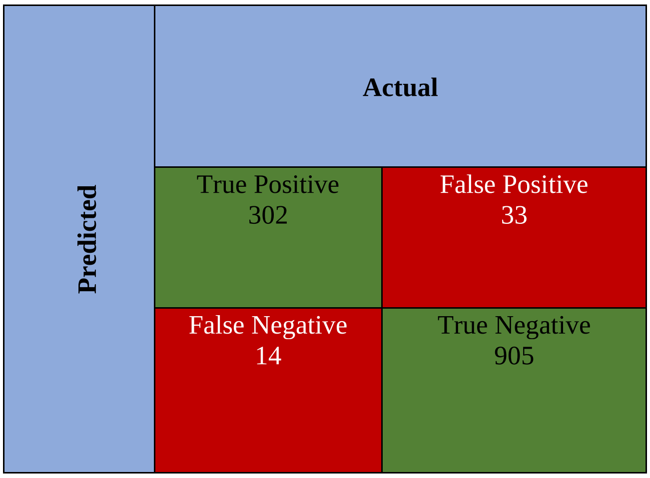

Fig. 4. Representation of confusion matrix of the model.

That implies it correctly predicted 302 cases of a patient having cancer and 905 cases of a patient not having cancer.

4.2. Accuracy Score

It is given as the proportion of the truly positive and negative values to the complete number of predictions made. Mathematically it can be written as given below:

Accuracy score= (TNT+TPT)/(TNT+FPT+TNT+FNT)

The steeper the accuracy of a model, the better it performs. Our model succeeded to obtain an overall accuracy of 97% on the final data and an accuracy of 99.2% using the validation data.

4.3. ROC Curve

Receiver Operating Characteristic is calculated using two values i.e., True Positive Rate or TPR and False Positive Rate or FPR. The said process is used for the evaluation of a classification model on various threshold limits. TPR is given as,

$$TPR=TPT/(FNT+TPT)$$

FPR is given as,

$$FPR=FPT/(FPT+TNT)$$

The ROC graph is plotted as TPR vs FPR and the ROC graph for the given model is shown below:

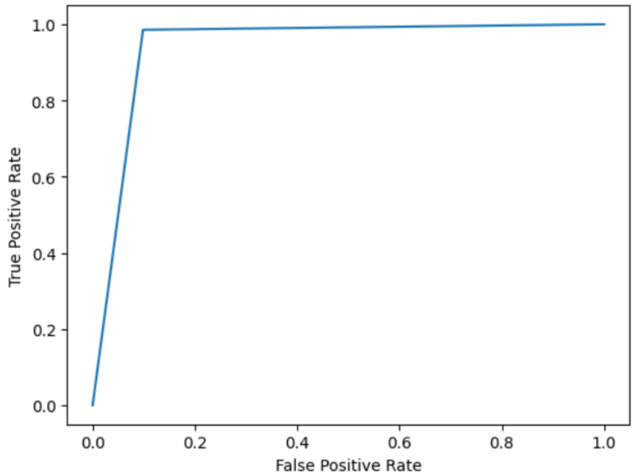

Fig. 5. ROC curve of the predicted model.

In general, the higher the final data's area under the ROC curve, the better it may perform. We were successful in obtaining a high AUC_ROC value, demonstrating the effectiveness of our model.

4.4 Accuracy and Loss Analysis.

As the overall number of epochs utilised to train the model increased, we also looked at general trends in the training and testing accuracy of our model. As the number of epochs used increases the result pretty match become stagnant without a lot of change in the data.

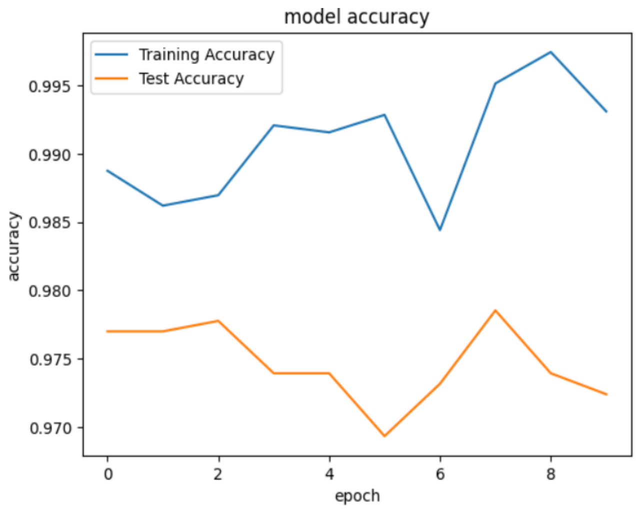

Fig. 6. Accuravy v/s epochs graph

Similarly, it can be said the training and testing loss and testing loss. The value of the loss stabilizes after a certain period of time. We also created a graph for the said against the values in 10 epochs.

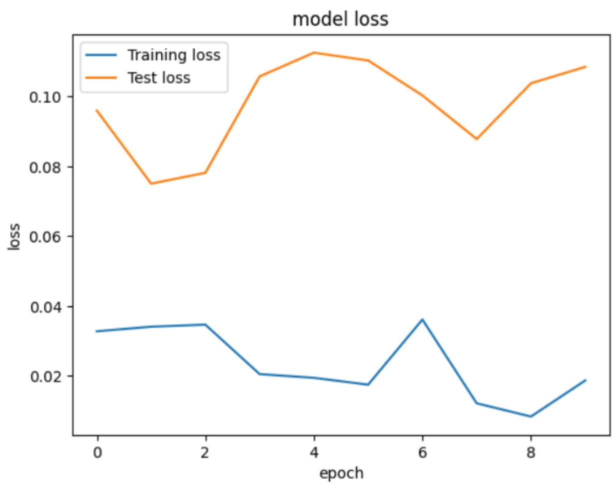

Fig. 7. Loss v/s epochs graph

We achieved a good-performing model with an accuracy of 99.2 percent that can be used to classify whether the patient has pneumonia or not using CNN and machine learning. We were able to enhance the performance of our model and achieve high accuracy in the model.

V. CONCLUSION AND FUTURE SCOPE

We were successful in developing a deep-learning CNN model that could be applied to the patient's CXI and identify whether the person has pneumonia or not. We worked on a dataset of nearly 600o images and our model was successfully distinguished between the normal and the pneumatic patient chest X-ray images. In the validation stage, we were able to reach an accuracy of 99.2%, and during testing, we were able to achieve an accuracy of 97%. The model produced better results than previously build CNN models and could be used in real-life scenarios.

In the future, we will try to implement the testing of our model in a real-time environment like a hospital, clinic, etc. and after the feedback from the doctors, on how our model is performing we can create an application for the general users so that they can use it to check their CXI themselves. The model can be further enhanced with the availability of more data and enhanced data augmentation.

REFERENCES

[1] https://data.unicef.org/topic/child-health/pneumonia.

[2] https://www.medindia.net/health_statistics/diseases/pneumonia-india-healthstatistics.asp

[3] Ahamed, M., Uddin, K., Islam, M. M., Uddin, M., Akhter, A., Acharjee, U. K., ... & Moni, M. A. (2023). DTLCx: An Improved ResNet Architecture to Classify Normal and Conventional Pneumonia Cases from COVID-19 Instances with Grad-CAM-Based Superimposed Visualization Utilizing Chest X-ray Images. Diagnostics, 13(3), 551.

[4] Sharma, S., & Guleria, K. (2023). A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks. Procedia Computer Science, 218, 357-366.

[5] Ayan, E., Karabulut, B., & Ünver, H. M. (2022). Diagnosis of pediatric pneumonia with an ensemble of deep convolutional neural networks in chest x-ray images. Arabian Journal for Science and Engineering, 1-17.

[6] Mahmoudi, R., Benameur, N., Mabrouk, R., Mohammed, M. A., Garcia-Zapirain, B., & Bedoui, M. H. (2022). A deep learning-based diagnosis system for COVID-19 detection and pneumonia screening using CT imaging. Applied Sciences, 12(10), 4825.

[7] Wang, T., Nie, Z., Wang, R., Xu, Q., Huang, H., Xu, H., ... & Liu, X. J. (2023). PneuNet: deep learning for COVID-19 pneumonia diagnosis on chest X-ray image analysis using Vision Transformer. Medical & Biological Engineering & Computing, 1-14.

[8] Chiwariro, R., & Wosowei, J. B. Comparative Analysis of Deep Learning Convolutional Neural Networks based on Transfer Learning for Pneumonia Detection.

[9] Stephen, O., Sain, M., Maduh, U. J., & Jeong, D. U. (2019). An efficient deep learning approach to pneumonia classification in healthcare. *Journal of healthcare engineering*, *2019*.

[10] Gabruseva, T., Poplavskiy, D., & Kalinin, A. (2020). Deep learning for automatic pneumonia detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops* (pp. 350-351).

[11] Nasef, M. M., Shehata, A. E. S., & Sauber, A. M. (2023). An effective model for the detection of pneumonia from chest X-ray images using inner residual inception.

[12] GM, H., Gourisaria, M. K., Rautaray, S. S., & Pandey, M. A. N. J. U. S. H. A. (2021). Pneumonia detection using CNN through chest X-ray. *Journal of Engineering Science and Technology (JESTEC)*, *16*(1), 861-876.

[13] Barhoom, A. M., & Abu-Naser, S. S. (2022). Diagnosis of pneumonia using deep learning.

[14] Mabrouk, A., Díaz Redondo, R. P., Dahou, A., Abd Elaziz, M., & Kayed, M. (2022). Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks. *Applied Sciences*, *12*(13), 6448.