Pneumonia Detection using Deep Learning - CNN

J-Component - Final Review
ECE3009 - Neural Network & Fuzzy Control

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SENSE - ECE - F1+TF1

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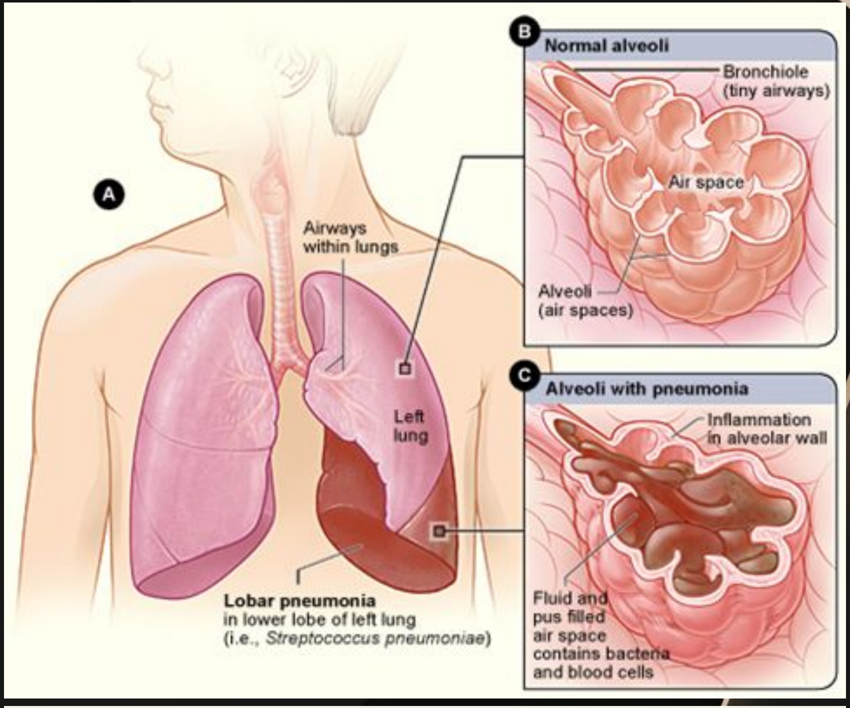
OBJECTIVE

- The objective of the project is to assist the diagnosis of Pneumonia using machine learning and deep learning algorithm.
- A dataset containing images of chest x- rays is taken and an efficient predictive model will be built which predicts whether the patient is diagnosed with pneumonia or not.

WHAT IS PNEUMONIA?

- Pneumonia is an infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus (purulent material), causing cough with phlegm or pus, fever, chills, and difficulty breathing. A variety of organisms, including bacteria, viruses and fungi, can cause pneumonia.

- Pneumonia can range in seriousness from mild to life-threatening. It is most serious for infants and young children, people older than age 65, and people with health problems or weakened immune systems.

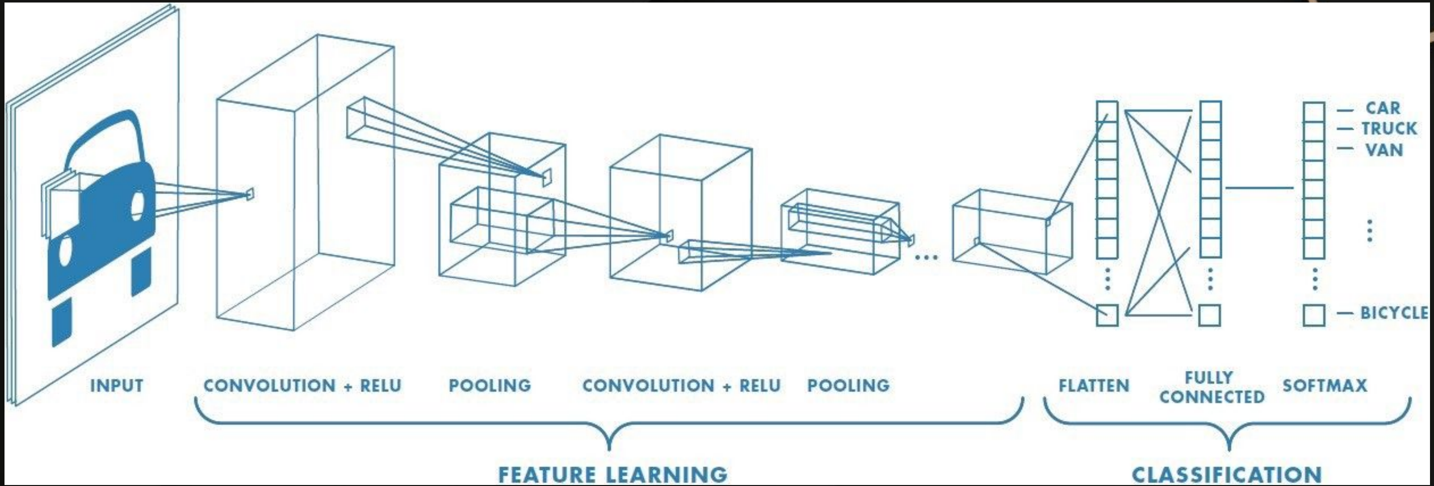


DATASET

- The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal).
- There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).
- Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou.
- All chest X-ray imaging was performed as part of patients' routine clinical care.
- For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans.
- The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert.

ALGORITHM

Convolutional Neural Network - Introduction

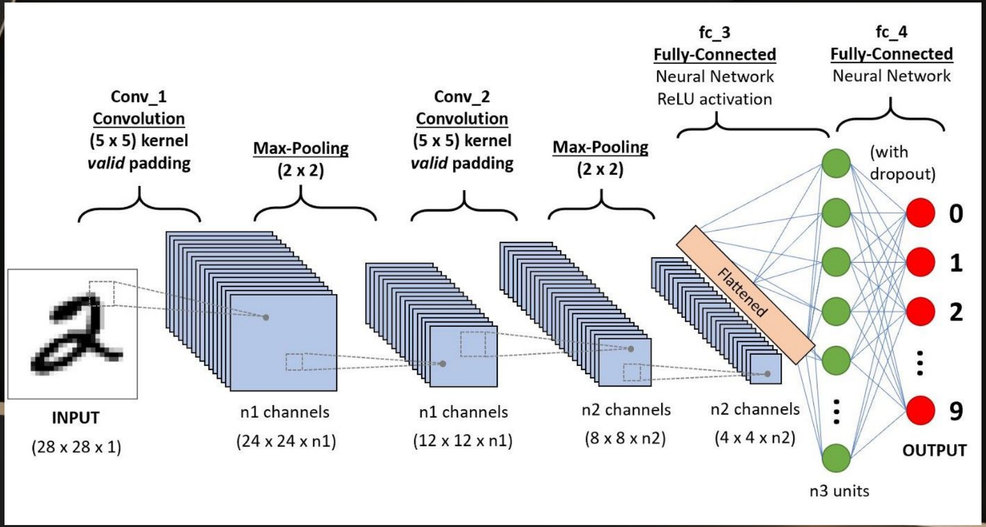


Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision.

The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm — a Convolutional Neural Network.

ALGORITHM

Convolutional Neural Network - Definition



A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

ALGORITHM

Convolutional Neural Network - Architecture

- A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution.

- In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that performs a dot product of the convolution kernel with the layer's input matrix.

- This product is usually the Frobenius inner product, and its activation function is commonly ReLU. As the convolution kernel slides along the input matrix for the layer, the convolution operation generates a feature map, which in turn contributes to the input of the next layer.

- This is followed by other layers such as pooling layers, fully connected layers, and normalization layers.

ALGORITHM

Convolutional Neural Network - Components/Layers

- **INPUT–** As the name implies, this layer holds the raw pixel values. Raw pixel values mean the data of the image as it is. Example, INPUT [64×64×3] is a 3-channeled RGB image of width-64, height-64 and depth-3.
- **CONV–** This layer is one of the building blocks of CNNs as most of the computation is done in this layer. Example - if we use 6 filters on the above mentioned INPUT [64×64×3], this may result in the volume [64×64×6].
- **RELU–** Also called rectified linear unit layer, that applies an activation function to the output of previous layer. In other manner, a non-linearity would be added to the network by RELU.
- **POOL–** This layer, i.e. Pooling layer is one other building block of CNNs. The main task of this layer is down-sampling, which means it operates independently on every slice of the input and resizes it spatially.
- **FC–** It is called Fully Connected layer or more specifically the output layer. It is used to compute output class score and the resulting output is volume of the size 1*1*L where L is the number corresponding to class score

LITERATURE SURVEY

TITLE OF THE PAPER AND AUTHOR	ABSTRACT	SUMMARY
Račić, Luka & Popovic, Tomo & Cakic, Stevan & Šandi, Stevan. (2021). Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network. 10.1109/IT51528.2021.9390137.	This paper describes the use of machine learning algorithms to process chest X-ray images in order to support the decision making process in determining the correct diagnosis whether the patient is affected with pneumonia or not.	The implementation was based on CNN model using Python programming and scientific tools.The activation function used in this experiments was the ReLU activation function. ReLU behaves very good in deep neural networks because it is fast to compute. With the trained model, 334 out of 381 were accurately predicted as images of X-rays with pneumonia, while 187 out of 205 were accurately predicted as X-rays without pneumonia and the model gave an accuracy of 88.90%.
M. A. Islam and M. S. Arefin, "A framework for detecting arsenic disease," 2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), 2016, pp. 1-5, doi: 10.1109/CEEICT.2016.7873149.	Different skin diseases pose different threats.The current method of treatment is very time consuming as well as requires a lot of money. The following paper presents an automated technique of detecting the skin disease using computer algorithms and image processing.	The given paper proposes a model that can gather PSL, perform it's analysis..The system uses image processing methods. It can analyse, create database, find features, process the information and identify the disease. All this is one on features based on the texture of the skin and other morphological features. The input images were fed to see the output. The system was able to almost accurately identify and detect arsenic in the images.
Chithambaram T, Logesh Kannan N, Gowsalya M et al. Heart Disease Detection Using Machine Learning, 27 October 2020, PREPRINT (Version 1) available at Research Square [https://doi.org/10.21203/rs.3.rs-97004/v1]	This paper analyzes the detection of heart disease using machine learning algorithms and python programming.s. The main objective of the paper is to get a better accuracy to detect the heart-disease using algorithms in which the target output counts that a person having heart disease or not.	The paper represented in, is Compared with KNN, SVM, Random classifier, decision tree classifier given accurate result for Heart Disease Prediction System-HDPS. The prediction was made better accuracy of 98.83% by decision tree machine learning method In this, Support Vector Machine algorithm classies the data values by using hyper plane and decision tree is implemented by Gini index method in which highest gain of the attributes gives a better representation of decision tree algorithm with accuracy of 82.6%.

TITLE OF THE PAPER AND AUTHOR	ABSTRACT	SUMMARY
Gabruseva, T., Poplavskiy, D., & Kalinin, A. (2020). Deep Learning for Automatic Pneumonia Detection. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW).	They developed the computational approach for pneumonia regions detection based on single-shot detectors, squeeze-and-extinction deep convolutional neural networks, augmentations and multi-task learning. The proposed approach was evaluated in the context of the Radiological Society of North America Pneumonia Detection Challenge, achieving one of the best results in the challenge.	They propose a simple and effective algorithm for the localization of lung opacities regions. The model was based on single-shot detector RetinaNet with Se-ResNext101 encoders, pre-trained on ImageNet dataset. The results of detection models can change significantly between epochs and depend largely on thresholds. The model was based on RetineNet SSD with Se-ResNext101 encoders pre-trained on ImageNet dataset, heavy augmentations with custom rotation, multi-task learning with global classification, and postprocessing. For the final ensemble, the outputs from the same model for 4 cross-validation folds and several checkpoints were combined before applying NMS algorithms. The postprocessing with re-scaling predictions was applied to compensate for the difference between the train and test sets labelling processes. The training dataset included data for 25684 patients and the test set had data for 1000 patients
Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, & Andrew Y. Ng. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning.	They develop an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Their algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest Xray dataset, containing over 100,000 frontal view X-ray images with 14 diseases. They extend CheXNet to detect all 14 diseases in ChestX-ray14 and achieve state of the art results on all 14 diseases.	Their model, ChexNet is a 121- layer convolutional neural network that inputs a chest X-ray image and outputs the probability of pneumonia along with a heatmap localizing the areas of the image most indicative of pneumonia. Limitations, First, only frontal radiographs were presented to the radiologists and model during diagnosis, but it has been shown that up to 15% of accurate diagnoses require the lateral view. , second neither the model nor the radiologists were not permitted to use patient history, which has been shown to decrease radiologist diagnostic performance in interpreting chest radiographs

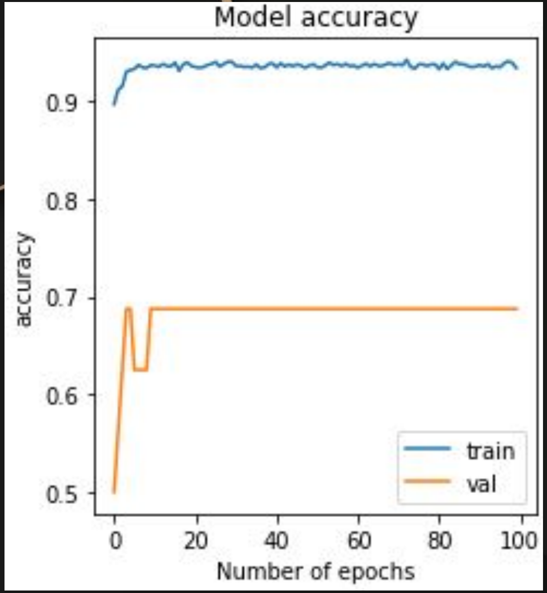
TITLE OF THE PAPER AND AUTHOR	ABSTRACT	SUMMARY
Turbé, V., Herbst, C., Mngomezulu, T. et al. Deep learning of HIV field-based rapid tests. Nat Med 27, 1165–1170 (2021). https://doi.org/10.1038/s41591-021-01384-9	In this paper they have used deep learning to classify images of rapid human immunodeficiency virus (HIV) tests acquired in rural South Africa. Using newly developed image capture protocols with the Samsung SM-P585 tablet, 60 fieldworkers routinely collected images of HIV lateral flow tests. From a library of 11,374 images, deep learning algorithms were trained to classify tests as positive or negative.	In this paper presentation, A pilot field study of the algorithms deployed as a mobile application demonstrated high levels of sensitivity (97.8%) and specificity (100%) compared with traditional visual interpretation by humans— experienced nurses and newly trained community health worker staff—and reduced the number of false positives and false negatives
Gonçalves WGE, Dos Santos MHP, Lobato FMF, Ribeiro-Dos-Santos Â, de Araújo GS. Deep learning in gastric tissue diseases: a systematic review. BMJ Open Gastroenterol. 2020 Mar 26;7(1):e000371. doi: 10.1136/bmjgast-2019-000371. PMID: 32337060; PMCID: PMC7170401.	In this paper, they have performed a systematic review related to applications of deep learning in gastric tissue disease analysis by digital histology, endoscopy and radiology images.	This review highlighted the high potential and shortcomings in deep learning research studies applied to gastric cancer, ulcer, gastritis and non-malignant diseases. Our results demonstrate the effectiveness of gastric tissue analysis by deep learning applications. Moreover, we also identified gaps of evaluation metrics, and image collection availability, therefore, impacting experimental reproducibility.
El Asnaoui K., Chawki Y., Idri A. (2021) Automated Methods for Detection and Classification Pneumonia Based on X-Ray Images Using Deep Learning. In: Maleh Y., Baddi Y., Alazab M., Tawalbeh L., Romdhani I. (eds) Artificial Intelligence and Blockchain for Future Cybersecurity Applications. Studies in Big Data, vol 90. Springer, Cham. https://doi.org/10.1007/978-3-030-74575-2_14	They presented a comparison of recent deep convolutional neural network (CNN) architectures for automatic binary classification of pneumonia images based on fined tuned versions of (VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, MobileNet_V2 and Xception) and a retraining of a baseline CNN.	They conclude that the fine-tuned version of Resnet50 shows highly satisfactory performance with rate of increase in training and testing accuracy (more than 96% of accuracy).

TITLE OF THE PAPER AND AUTHOR	ABSTRACT	SUMMARY
Sharma, Abhishek; Raju, Daniel; Ranjan, Sutapa (2017). [IEEE 2017 Nirma University International Conference on Engineering (NUiCONE) - Ahmedabad, India (2017.11.23-2017.11.25)] 2017 Nirma University International Conference on Engineering (NUiCONE) - Detection of pneumonia clouds in chest X-ray using image processing approach. , (), 1–4. doi:10.1109/NUICONE.2017.8325607	This article presents a novel approach for detecting the presence of pneumonia clouds in chest X-rays (CXR) by using only Image processing techniques. For this, we have worked on 40 analog chest CXRs pertaining to Normal and Pneumonia infected patients.	To detect pneumonia clouds we have used Otsu thresholding which will segregate the healthy part of lung from the pneumonia infected cloudy regions. We are proposing to compute the ratio of area of healthy lung region to total lung region to establish a result.
Li, Feng; Engelmann, Roger; Pesce, Lorenzo; Armato, Samuel G.; MacMahon, Heber (2012). Improved detection of focal pneumonia by chest radiography with bone suppression imaging. European Radiology, 22(12), 2729–2735. doi:10.1007/s00330-012-2550-y	Standard chest radiographs in 36 patients with 46 focal airspace opacities due to pneumonia (10 patients had bilateral opacities) and 20 patients without focal opacities were included in an observer study. A bone suppression image processing system was applied to the 56 radiographs to create corresponding bone suppression images. In the observer study, eight observers, including six attending radiologists and two radiology residents, indicated their confidence level regarding the presence of a focal opacity compatible with pneumonia for each lung, first by use of standard images, then with the addition of bone suppression images. Receiver operating characteristic (ROC) analysis was used to evaluate the observers' performance.	The mean value of the area under the ROC curve (AUC) for eight observers was significantly improved from 0.844 with use of standard images alone to 0.880 with standard plus bone suppression images ($P<0.001$) based on 46 positive lungs and 66 negative lungs.
A. Tilve, S. Nayak, S. Vernekar, D. Turi, P. R. Shetgaonkar and S. Aswale, "Pneumonia Detection Using Deep Learning Approaches," 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), 2020, pp. 1-8, doi: 10.1109/ic-ETITE47903.2020.152.	This paper focuses on surveying and comparing the detection of lung disease using different computer-aided techniques and suggests a revised model for detecting pneumonia, which will then be implemented as part of their future research. They used image pre- processing techniques to convert raw X-ray images into standard formats for analysis and detection, machine learning techniques such as CNN, RESNET, CheXNet, DENSENET, ANN and KNN, which is an important phase in accurate pneumonia detection.	There are several approaches used to detect lung diseases using computer-aided diagnoses but techniques using machine learning algorithms have proved to be more reliable.

RESULTS

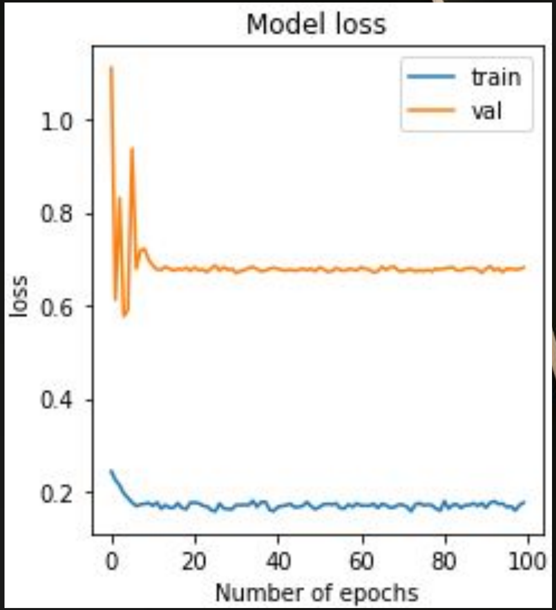
Accuracy: It is the ratio of the number of correct predictions to the total number of input samples. A higher accuracy implies a better performance in a model. It is calculated by:

Loss: Sparse Categorical Cross Entropy calculates the compares each of the predicted probabilities to actual class output. A lower loss implies a better model.



$$\frac{TP+TN}{TP+FP+TN+FN}$$

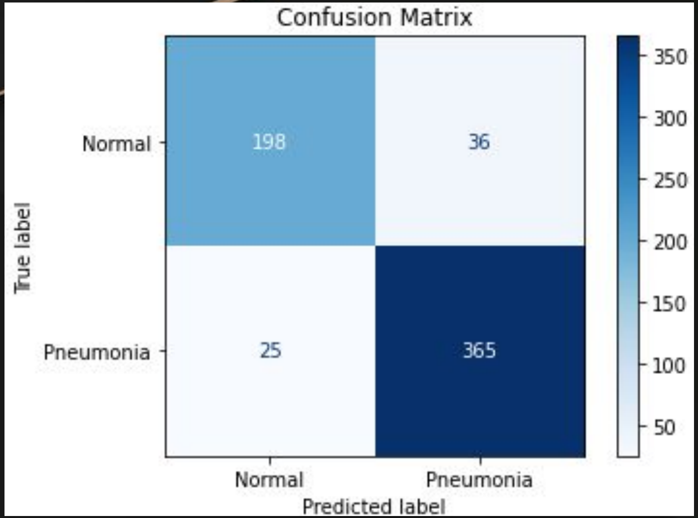
$$J(\mathbf{w}) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]$$



RESULTS

Confusion Matrix: In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one.

Classification Report: A Classification report is used to measure the quality of predictions from a classification algorithm. The report shows the main classification metrics precision, recall and f1-score on a per-class basis. The metrics are calculated by using true and false positives, true and false negatives.



	Precision	Recall	F1 - score	Support
Normal	0.89	0.85	0.87	234
Pneumonia	0.91	0.94	0.92	390

Training Accuracy: 93.4% **Validation Accuracy**: 68.75%

CONCLUSION

- The goal of this challenge was to assess whether a person has pneumonia or not. A model was created to find the same and we were able to achieve an accuracy of 93 percent.
- When a patient has pneumonia and is misdiagnosed as healthy, the model is incorrect, however, in the model we constructed, the chance of a patient being misdiagnosed with pneumonia is less than 10%.
- We can generalize the data and improve the accuracy of diagnosis by gathering additional data from various patients in different hospitals in different regions of the world.
- Furthermore, this model may be used as a patient screening test since, as seen in the graph, the model virtually always detects a person with pneumonia.

FUTURE SCOPE

- Pneumonia Detection can also help in the detection of COVID since both of them actively work on the same bases, akin the lungs get affected. So this model can be extended in order to help ease COVID detection as well.

THANK YOU :)