DETECTION OF PNEUMONIA

1. ABSTRACT:

Pneumonia, an interstitial lung disease, is the leading cause of death in children under the age of five. It accounted for approximately 16% of the deaths of children under the age of five, killing around 880,000 children in 2016 according to a study conducted by UNICEF. Affected children were mostly less than two years old. Timely detection of pneumonia in children can help to fast-track the process of recovery. This represent presents convolutional neural network models to accurately detect pneumonic lungs from chest X-rays, which can be utilized in the real world by medical practitioners to treat pneumonia. Experimentation was conducted on Chest X-Ray Images (Pneumonia) dataset available on Kaggle. Dropout regularization is employed in the models to minimize overfitting in the fully connected layers. Furthermore, recall and F1 scores are calculated from the confusion matrix of each model for better evaluation.

2. PROBLEM STATEMENT:

The problem statement for detecting pneumonia using AI is to develop an accurate and reliable algorithm that can effectively analyse medical images and accurately identify cases of pneumonia. This algorithm must be able to distinguish between several types of pneumonia, such as bacterial and viral pneumonia, and accurately diagnose the condition in patients with varying degrees of severity. Additionally, the algorithm should be easy to use and integrate into existing medical workflows to enable quick and efficient diagnosis and treatment of pneumonia. Hence, AI-powered pneumonia detection software can help doctors quickly and accurately diagnose the disease, which can improve patient outcomes and reduce the risk of complications.

3. APPROACH:

- **Collect and prepare data:** The first step is to collect a large dataset of chest X-ray images of patients with and without pneumonia. The images should be annotated with labels indicating whether pneumonia is present. The dataset should be cleaned, normalized, and pre-processed to ensure high quality and consistency.
- **Develop a deep learning model:** The next step is to develop a deep learning model using convolutional neural networks (CNNs) that can analyse the chest X-ray images and detect the presence of pneumonia. The model should be trained on the annotated dataset using supervised learning algorithms to learn how to accurately detect pneumonia in chest X-ray images.
- **Test and validate the model:** The model should be tested on a separate validation dataset to evaluate its performance in detecting pneumonia. This involves calculating metrics such as accuracy, precision, recall, and F1-score to measure the model's performance.
- **Integrate the model into software:** Once the model is validated, it can be integrated into pneumonia detection software that can be used by medical professionals to assist in diagnosing the disease. The software should be designed to be user-friendly and easy to use, with clear and concise instructions for interpreting the model's results.
- **Evaluate the software's effectiveness:** The final step is to evaluate the effectiveness of the pneumonia detection software in assisting medical professionals in diagnosing pneumonia. This involves conducting a clinical trial to compare the performance of the software against human experts in diagnosing pneumonia.
- Overall, the approach involves collecting and preparing a large dataset of chest X-ray images, developing a deep learning model to detect pneumonia in the images, integrating the model into pneumonia detection software, and evaluating the software's effectiveness in assisting medical professionals in diagnosing the disease.

4. METHDOLOGY:

CNN models have been created from scratch and trained on Chest X-Ray Images (Pneumonia) dataset on Kaggle. Keras neural network library with TensorFlow backend has been used to implement the models. Dataset consists of 5000+ training images, 1000+ testing images and 100+ validation images. Data augmentation has been applied to achieve better results from the dataset. The models have been trained on the training dataset, each with different number of convolutional layers. Each model was trained for 8 epochs, with training and testing batch sizes of 32. The following sub-headings further explain the above stages in depth.

4.1 *CNN ARCHITECTURE:*

CNN models are feed-forward networks with convolutional layers, pooling layers, flattening layers and fully connected layers employing suitable activation functions.

A.) Convolutional layer: It is the building block of the CNNs. Convolution operation is done in mathematics to merge two functions. In the CNN models, the input image is first converted into matrix form. Convolution filter is applied to the input matrix which slides over it, performing element-wise multiplication and storing the sum. This creates a feature map. 3×3 filter is employed to create 2D feature maps when images are black and white. Convolutions are performed in 3D when the input image is represented as a 3D matrix where the RGB colour represents the third dimension. Several feature detectors are operated with the input matrix to generate a layer of feature maps which thus forms the convolutional layer.

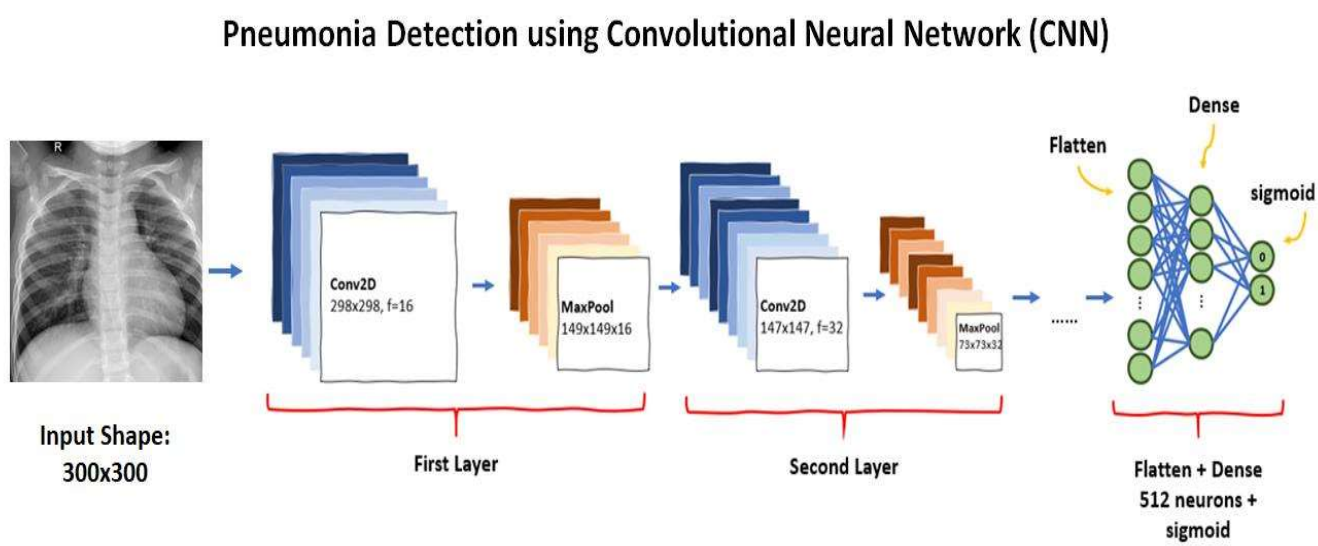
B.) Activation functions: All models presented in this report uses activation function, namely ReLU activation function. The ReLU activation function stands for rectified linear function. It is a nonlinear function that outputs zero when the input is negative and outputs one when the input is positive. The ReLU function is given by the following formula: This type of activation function is used in CNNs as it deals with the problem of vanishing gradients and is useful for increasing the nonlinearity of layers. ReLU activation function has many variants such as Noisy ReLUs, Leaky ReLUs and Parametric ReLUs. Advantages of ReLU over other activation functions are computational simplicity and representational sparsity.

C.) Pooling layer: Convolutional layers are followed by pooling layers. The type of pooling layer used in all models is max-pooling layers. The max-pooling layer having a dimension of 2 × 2 selects the maximum pixel intensity values from the window of the image currently covered by the kernel. Max-pooling is used to down sample images, hence reducing the dimensionality and complexity of the image. Two other types of pooling layers can also be used which are general pooling and overlapping pooling. The models presented in this report use max-pooling technique as it helps recognize salient features in the image.

D.) Flattening layer and fully connected layers: After the input image passes through the convolutional layer and the pooling layer, it is fed into the flattening layer. This layer flattens out the input image into a column, further reducing its computational complexity. This is then fed into the fully connected layer/dense layer. The fully connected layer has multiple layers, and every node in the first layer is connected to every node in the second layer. Each layer in the fully connected layer extracts features, and on this basis, the network makes a prediction. This process is known as forward propagation. After forward propagation, a cost function is calculated. It is a measure of performance of a neural network model.

The cost function used in all models is categorical binary-entropy. After the cost function is calculated, back propagation takes place. This process is repeated until the network achieves optimum performance. Adam optimization algorithm has been used in this model.

E.) Dataset: Chest X-Ray Images (Pneumonia) dataset of 1.16 GB size has been imported from Kaggle, with total of 5856 jpeg images split into Train, Test and Val folders each divided into category Pneumonia and Normal. Chest X-ray images (front and back) were selected from paediatric patients of one- to five-year olds from Guangzhou Women and Children's Medical Centre, Guangzhou.



Above figure shows the pneumonia detection using Convolutional Neural Network (CNN).

4.2 *ResNets*:

Residual Network (ResNet) is a deep learning model used for computer vision applications. It is a Convolutional neural network (CNN) architecture designed to support hundreds or thousands of convolutional layers.

The ResNet architecture introduces the simple concept of adding an intermediate input to the output of a series of convolution blocks. This is illustrated below.

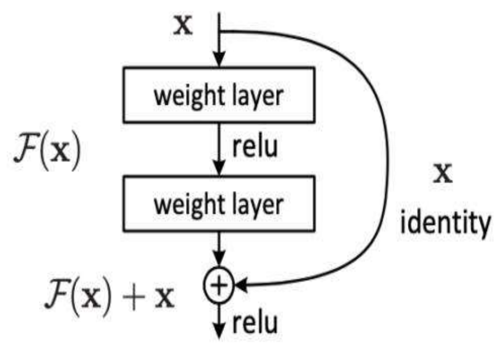
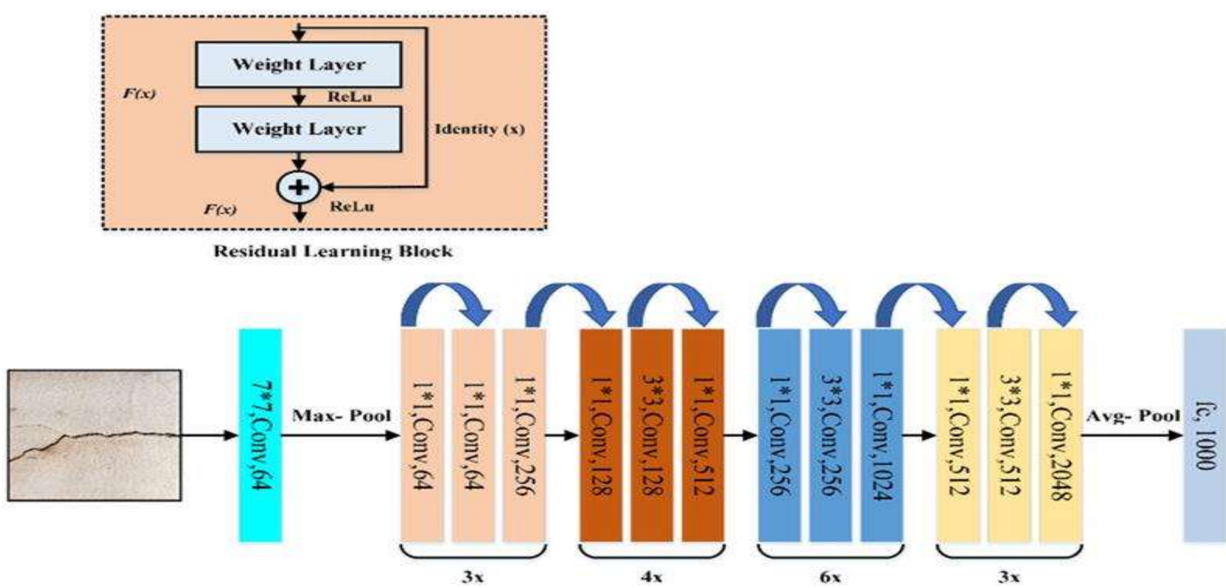


Figure 2. Residual learning: a building block.

The image above shows a typical residual block. This can be expressed in Python code using the expression *output = F(x) + x* where x is an input to the residual block and output from the previous layer, and F(x) is part of a CNN consisting of several convolutional blocks. This technique smooths out the gradient flow during backpropagation, enabling the network to scale to 50, 100, or even 150 layers. Skipping a connection does not add additional computational load to the network.

ResNet 50:

ResNet-50 is a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one average pool layer). Residual neural networks are a type of artificial neural network (ANN) that forms networks by stacking residual blocks.
The original ResNet architecture was ResNet-34, which comprised 34 weighted layers. It provided a novel way to add more convolutional layers to a CNN, without running into the vanishing gradient problem, using the concept of shortcut connections. A shortcut connection "skips over" some layers, converting a regular network to a residual network. The regular network was based on the VGG neural networks (VGG-16 and VGG-19)—each convolutional network had a 3×3 filter. However, a ResNet has fewer filters and is less complex than a VGGNet. A 34-layer ResNet can achieve a performance of 3.6 billion FLOPs, and a smaller 18-layer ResNet can achieve 1.8 billion FLOPs, which is significantly faster than a VGG-19 Network with 19.6 billion FLOPs
The ResNet architecture follows two basic design rules. First, the number of filters in each layer is the same depending on the size of the output feature map. Second, if the feature map's size is halved, it has double the number of filters to maintain the time complexity of each layer.



4.3 *TensorFlow*:

TensorFlow is an open-source library developed by Google primarily for deep learning applications. It also supports traditional machine learning. TensorFlow was originally developed for large numerical computations without keeping deep learning in mind. TensorFlow allows you to create dataflow graphs that describe how data moves through a graph. The graph consists of nodes that represent a mathematical operation. A connection or edge between nodes is a multidimensional data array. It takes inputs as a multi-dimensional array where you can construct a flowchart of operations that can be performed on these inputs.

TensorFlow architecture works in three significant steps:

- Data pre-processing - structure the data and brings it under one limiting value.
- Building the model - build the model for the data.
- Training and estimating the model - use the data to train the model and test it with unknown data.

5. EXPERIMENTAL RESULTS:

To study the performance of each CNN classifier model, validation accuracy, recall was evaluated as the performance measures. Accuracy and loss graphs were also studied. The confusion matrix was also computed for each model.

5.1 *Comparison of performance of models*:

The evaluation methods of the related work. To compare the proposed method with the related work, the key evaluation method will be employed for the evaluation of the proposed method. This section will discuss the key evaluation methods, namely accuracy, precision, recall.

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A.) Accuracy:

Accuracy will justify the amount of predicted datapoints with respect to the rest of datapoints. It is used to identify the performance of the model with respect to all classes. Regarding our proposed model, the performance evaluation of accuracy will help to determine the total number of accurate predictions among the total amount of predictions. It is represented as:

Accuracy =number of correct predictions⁄ total number of predictions.

Accuracy will help to determine the efficiency of the proposed model. It will help to analyse the effectiveness of the model with respect to other literatures in terms of correct predictions.

B.) Precision:

Precision will involve the number of positive predictions of the model, which means precision is enhanced when the amount of correct positive predictions is higher, and the total number of incorrect positive predictions are fewer. Precision is abbreviated as:

Precision = true positive// (true positive + false positive) ,

where true positive represents the correct prediction of positive class and false positive represents the correct prediction of negative class. Regarding the proposed model, the evaluation matrix of precision will help to compare the trustiness of model in terms of classifying the positive samples correctly with the other state of art.

C.) Recall:

Recall will compare the correct identification of positive sample with respect to all the available positive samples. It is involved in detecting the positive class and it is apart from the classification of negative samples. Recall is represented as:

Recall = true positive // (true positive + false negative),

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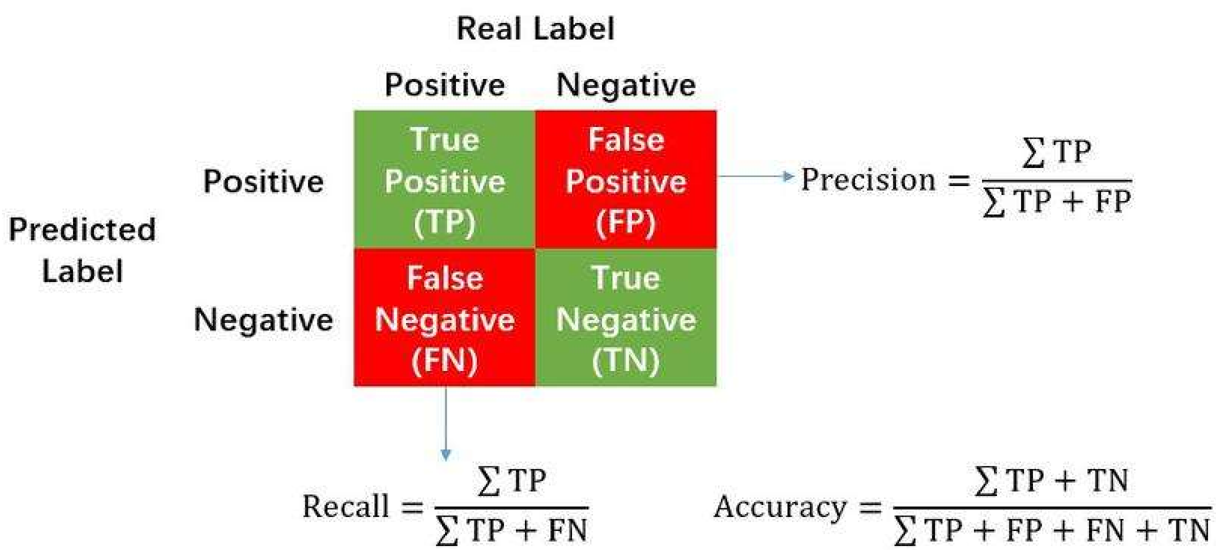
where true positive represents the correct prediction of positive class and false negative represents the incorrect prediction of negative class. The proposed model will compare the number of positive samples being correctly classified.



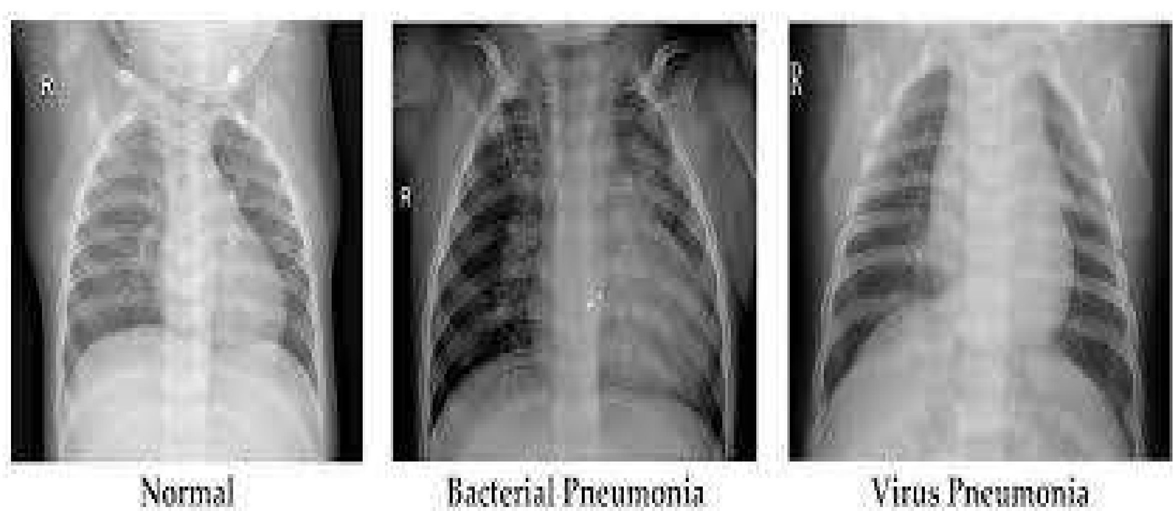


Figure shows different images of lungs with Pneumonia and Normal lungs

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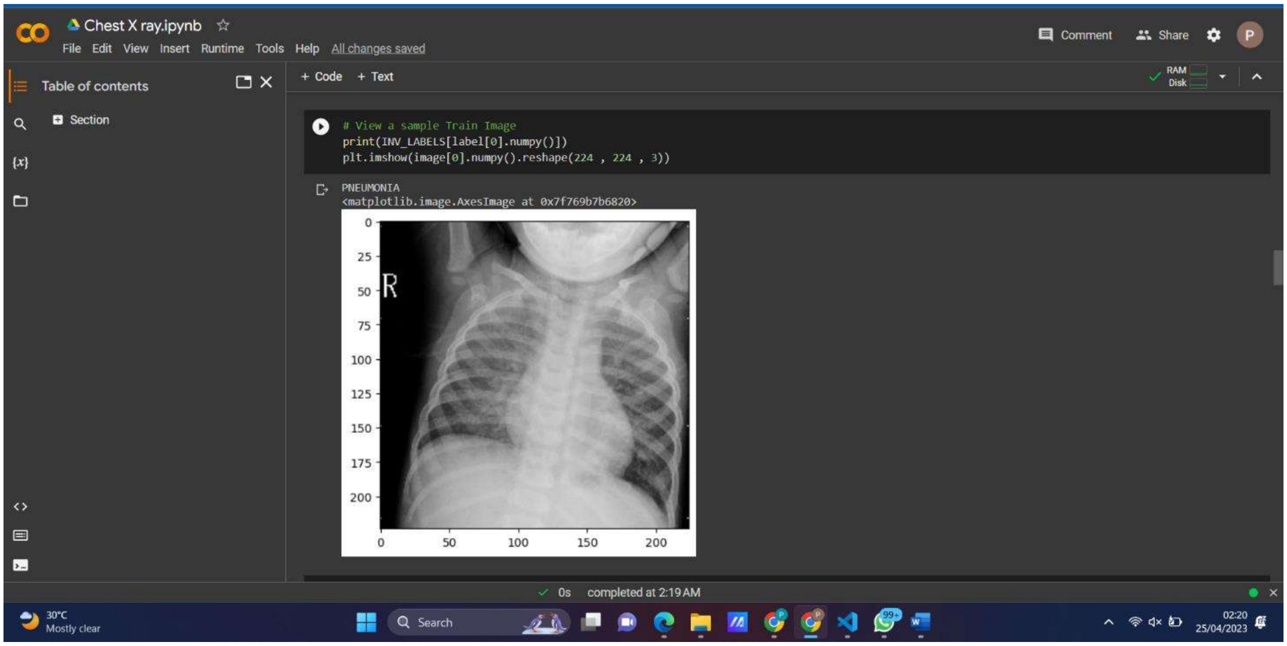

Figure shows lungs having Pneumonia.

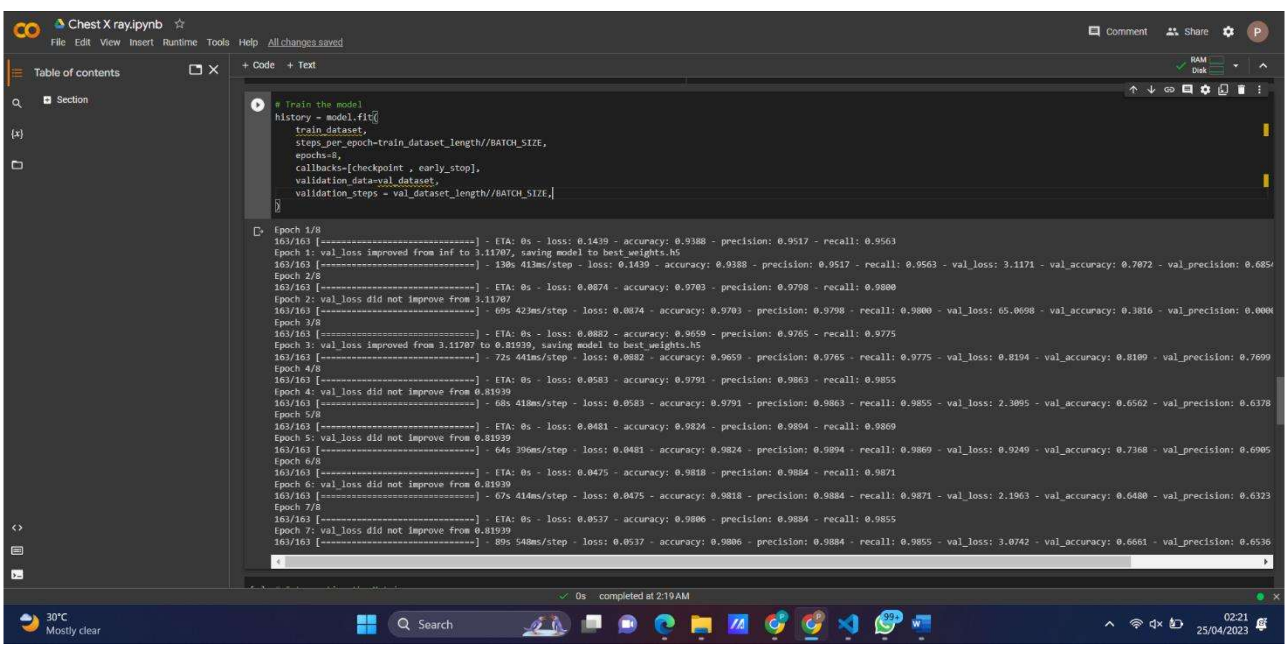

Figure: Training the dataset

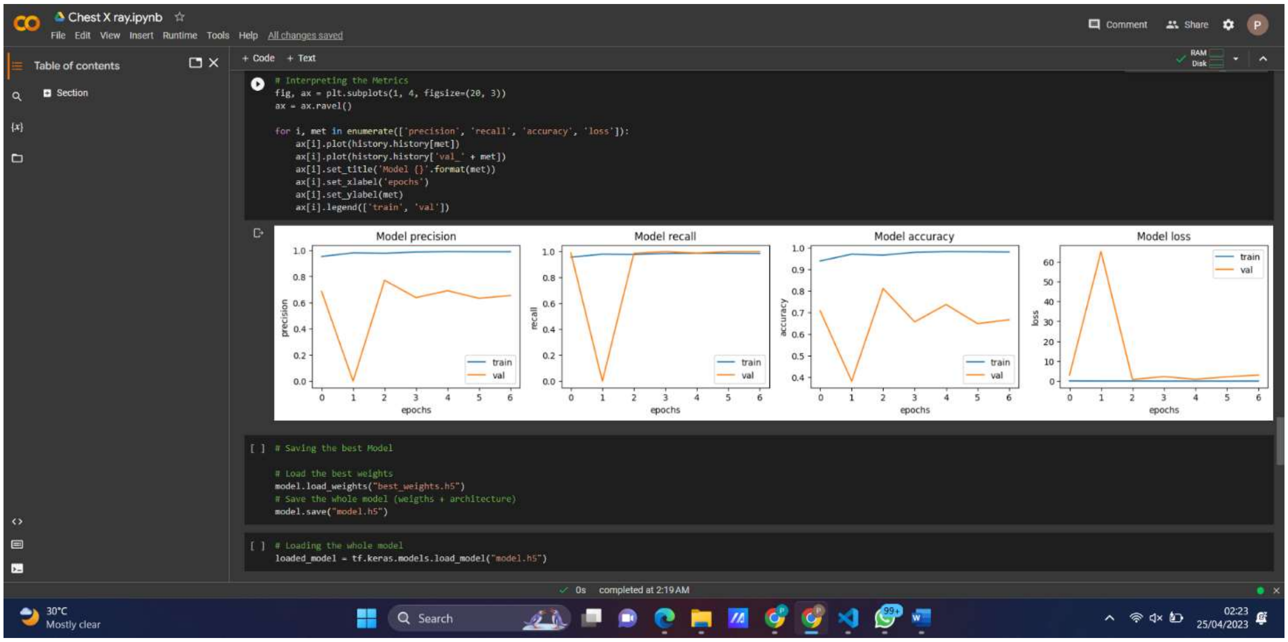

Figure: It shows the accuracy, loss, recall, and precision after training, testing and validating the dataset

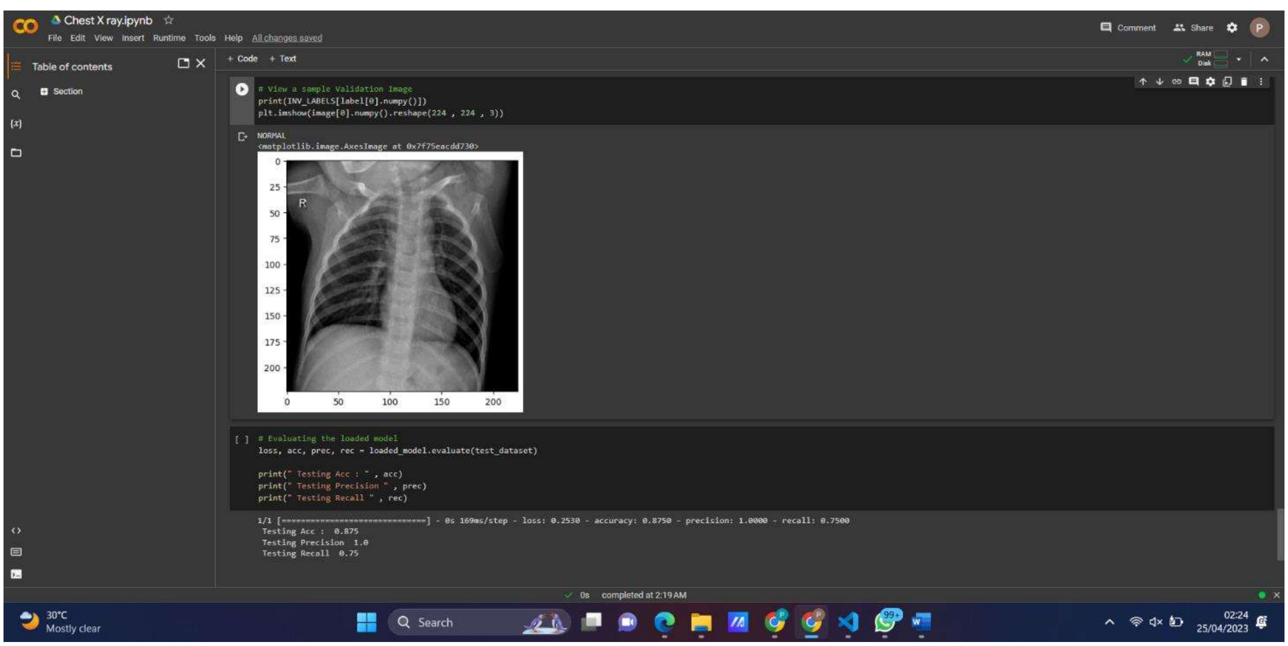

Figure: Normal lungs and the evaluation of the loaded model

6. RELATED WORK:

In recent time, exploration of Machine learning (ML) algorithms in detecting thoracic diseases has gained attention in research area of medical image classification. Lakhani and Sundaram (2017) proposed a method of detecting pulmonary tuberculosis following the architecture of two different DCNNs AlexNet and GoogleNet.

Lung nodule classification mainly for diagnosing lung cancer proposed by Huang et al also adopted deep learning techniques. Performance of different variants of Convolutional Neural Networks (CNNs) for abnormality detection in chest X-Rays was proposed by Islam et al using the publicly available OpenAI dataset. For the better exploration of machine learning in chest screening, Wang et al (2017) released a larger dataset of frontal chest X-Rays.

Recently, Pranav Rajpurkar, Jeremy Irvin (2017) explored this dataset for detecting pneumonia at a level better than radiologists, they referred their model as ChexNet which uses DenseNet-121-layer architecture for detecting all the 14 diseases from a lot of 112,200 images available in the dataset.

After the CheXNet [17] model, Benjamin Antin et al. (2017) worked on the same dataset and proposed a logistic regression model for detecting pneumonia. Pulkit Kumar, Monika Grewal (2017) using the cascading convolutional networks contributed their research for multilabel classification of thoracic diseases. Zhi Li (2018) recently proposed a convolutional network model for disease identification and localization.

7. SUMMARY:

This survey demonstrates the number of procedures been used in the past for the detection of lungs disease, especially pneumonia. Various tools and techniques have followed effective detection.

However, it can be observed from the literature that the methods based on the ML are quite effective in the medical image detection from the image datasets. To make the ML model more productive, it is required to have a larger volume and variety of datasets to train the model.

The lab-based datasets are limited to be used for effective training of ML model in a real-time scenario like in hospitals or medical institutions. Therefore, we need to have a solution of using real-time data to fulfil the requirements of having a more significant and variety of data. Our proposed model of using a CNN with deep learning can significantly enhance the capability of the ML model.

While deep understanding (neural networks) can be used to learn the image patterns effectively that will enhance the detection process. Our proposed work will give the new dimensions in the field of medical image detection.

8. REFERNECES:

1. Jaiswal, A.K., Tiwari, P., Kumar, S., Gupta, D., Khanna, A., Rodrigues, J.J.: Identifying pneumonia in chest x-rays: a deep learning approach. Measurement 145, 511–518 (2019)
2. Kim, D.H., MacKinnon, T.: Artificial intelligence in fracture detection: transfer learning from deep convolutional neural networks. Clin. Radiol. 73(5), 439–445 (2018)
3. Bernal, J., Kushibar, K., Asfaw, D.S., Valverde, S., Oliver, A., Martí, R., Lladó, X.: Deep convolutional neural networks for brain image analysis on magnetic resonance imaging: a review. Artif. Intell. Med. 95, 64–81 (2019).

4. Arthur, F., Hossein, K.R.: Deep learning in medical image analysis: a third eye for doctors. J. Stomatology Oral Maxillofacial. Surg.
5. Rubin, J., Sanghavi, D., Zhao, C., Lee, K., Qadir, A., Xu-Wilson, M.: Large Scale Automated Reading of Frontal and Lateral Chest X-Rays Using Dual Convolutional Neural Networks (2018).
6. Lakhani, P., Sundaram, B.: Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology 284(2), 574–582 (2017)
7. Guan, Q., Huang, Y., Zhong, Z., Zheng, Z., Zheng, L., Yang, Y.: Diagnose Like a Radiologist: Attention Guided Convolutional Neural Network for Thorax Disease Classification (2018).
8. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., Lungren, M.P.: Chexnet: Radiologist-Level Pneumonia Detection on Chest X-rays with Deep Learning (2017).
9. Krizhevsky, A., Sutskever, I., Hinton, G.E. ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097–1105 (2012)
10. Simonyan, K., Zisserman, A.: Very Deep Convolutional Networks for Large-Scale Image Recognition (2014)
11. Xu, Y., Jia, Z., Ai, Y., Zhang, F., Lai, M., Eric, I., Chang, C.: Deep convolutional activation features for large scale brain tumour histopathology image classification and segmentation. In: 2015 international conference on acoustics, speech and signal processing (ICASSP), pp. 947– 951 (2015)
12. Anthimopoulos, M., Christodoulides, S., Ebner, L., Christi, A., Mougiakakou, S.: Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. IEEE Trans. Med. Imaging 35(5), 1207–1216 (2016).