

Automated Detection and Classification of Pneumonia and Tuberculosis using Chest X-Ray Images

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Abstract— *Pneumonia and tuberculosis are leading causes of death in children and the elderly. Furthermore, the fact that despite being curable with proper treatment the numbers of deaths by these diseases are high. In a country with such a large population, the smaller number of doctors is a problem due to which the diagnosis of these diseases is not that accurate and often flawed. Our research proposes a deep learning based model to classify and detect pneumonia and tuberculosis using Convolutional Neural Networks. The dataset used for Pneumonia consists of chest x-rays of 1 - 5 years of age from Guangzhou women and children's medical center, Guangzhou, consisting of 5,863 images and for tuberculosis contains 662 chest x-rays. Our model detected pneumonia with an accuracy and recall percentage of 91% while the accuracy achieved in detecting tuberculosis is 87% with a recall percentage of 88%..*

Index Terms— Machine Learning, Deep Learning, Convolutional Neural Network, Max Pooling, Kernel

I. INTRODUCTION

The objective of this research is to provide an automated diagnosis of pneumonia and tuberculosis using Chest Radiography and classify its types using Deep Learning Methodologies. Pneumonia has been one of the most common and deadliest diseases throughout the history of mankind. Globally around 450+ million people are affected by pneumonia resulting in about four million deaths per year.[1,2, 3] Pneumonia results in inflamed lungs, which is caused by microorganisms, such as viruses, bacteria and fungi[4], which may become life-threatening for infants and children, people having low immune system, elderly people and people who have adverse lifestyle like smoking cigarettes.[5,6] Based on its because there are primarily three variants of pneumonia: Viral pneumonia, Bacterial pneumonia and Fungi pneumonia.

Pneumonia caused by viruses is less harmful as compared to pneumonia caused by bacteria. [7] However, it becomes difficult to differentiate between the two. India being a developing nation is about five times more frequent in these cases than the other developing nations. [1] UNICEF in its recent survey and assessment ranked India second in terms of number of people passing because of pneumonia. Most of these deaths took place among children under the age of two and the fact that it is a curable and preventable disease makes it even more alarming.[8] Another such disease is Tuberculosis. As of 2018 around 25% of the world's population is affected by Tuberculosis.[9] Globally, In 2017 there have been more than 10 million diagnosed TB cases out of which 1.6 million resulted in death which made it the infectious disease resulting into most number of death.[10]

Tuberculosis is generally affects the lungs of the person and spreads through air.[11,12] In India, nearly 200,000+ deaths from Tuberculosis are reported annually.[12] According to World Health Organization, India faces the largest burden of TB worldwide with statistics of 2011 to offer an approximate incidence of 2.2 million TB cases in India out of 9.6 million cases reported globally.[14,15]

Therefore, an accurate prognosis of such diseases is very crucial and fundamental in order to provide a timely treatment to those needed. But in a country with ever increasing population and limited doctors it is difficult to achieve this.

With the recent advancements in Deep Learning, Convolutional Neural Networks could be used to determine the presence of disease using the dataset of X-ray images of patients suffering from pneumonia and tuberculosis and also classify its type. [16] For instance, in cases of pneumonia like a doctor analyzes the X-Ray images by identifying the white patches in the lungs, similarly CNN uses feature extraction layer by layer to detect pneumonia.

The paper is broken down into 7 sections. The first section gives the introduction. The second section tells about the related works by different researchers on this topic. The third section describes the methodology which includes the description of dataset, input structure, convolutional layer and pooling layer. The fourth section talks about the various metrics of evaluation used in deep learning like confusion matrix and ROC curve. The fifth section consists of the results and brief discussion of the same. The sixth section is a comparison of the paper. The last section is the conclusion which provides the summary for our research. In the end references and citations used for this paper are listed.

II. RELATED WORK

Chest radiographs generally present for a variety of manifestations, including arteries, focal lesions, opacity joint and ears that add to the problems of diagnosing TB alone. [17] extracted and studied the local texture of CXRs to get a contrasting touch, which was one of the first proposed approaches for automatic TB diagnosis. The winged areas are split into multi-point zones. The nearest K neighbor was then used at the district level to conduct classic operations. For example, Wang et al. [18] proposed a new dataset named Chest X-ray 8 which consisted of images of 32,717 unique patients, whose 108,948 frontal X-ray images were obtained. With this dataset they were able to attain favorable results using CNN with deep network. Furthermore, they declared that the dataset is expandable by increasing the disease labels. [19], using data augmentation techniques in addition to CNN, the authors achieved significant accuracy, even upon training small batches of images.

In a separate study, [20] the authors explained how deep CNNs can be leveraged for detecting lymph nodes. They achieved assuring results despite poor image quality. [21] Worked in CNN's architecture and solved the problem of lung disease diagnosis. The study of [22] aims to visualize the high-performance network in a model based on CNN, which is used for the chest X-ray examination. Using machine learning algorithms, computer-aided softwares were created to study CXRs with anomalies so as to reduce delays and limited resources.

[23] researched using a method based on the CNN technique, which was concatenated with lung field segmentation and rib suppression. For the pixel spots fetched from the lung region, 3 different CNN models were trained using images with varying resolution. Feature fusion method was used to concatenate the entire info obtained. [24] Curated a network which was created using 49 different convolutional layers. In addition to the CNN layers, 1 average pooling layer and 2 fully connected dense layers were used to detect pneumonia. [25] Used a 25-layer, deep CNN with eight residual connections. [26] Used two architectures of the 3D specialized mixed connection network (CMixNet). Recognition of the lung nodule was carried out with faster RCNN. [27] Proposed a custom neural network which was made using 5 different CNN blocks (each with 2 (3,3) convolutions with Rectified Linear Units (ReLU), which was succeeded by an average pooling layer and a dense layer with 2 outputs activated with softmax function.

[28] Used a CNN model which was based on AlexNet for lung patch detection tasks. Further, a 2nd CNN model using ResNet18 as a backbone, was created to remodel the lacking blocks in the lung area. The output was fetched by the ensemble model created using the initial segmentation and reconstruction. [29] utilized the state-of-the-art network architectures such as ResNet, VGG16/19, and Inception etc. and modified and experimented with the pooling and flattening functions. Final results were fetched by dense layers activated using the sigmoid function. Along with this, CNNs tend to perform optimally on fairly large datasets but most of the time, they produce incorrect outputs on small datasets.

III. METHODOLOGY

3.1 Description of the Dataset

3.1.1. Pneumonia

The dataset includes anteroposterior chest radiographs obtained from pediatrics in the age band of 1 to 5 years from Guangzhou women and children's medical center, Guangzhou. [30] The chest radiographs are obtained during the clinical medical tests of the patients suffering from pneumonia or having symptoms of pneumonia.



Figure 1 : Chest X ray images indicating the following (a) Normal (b) Bacterial Pneumonia (c) Viral Pneumonia

The data is organized into three folders: training, testing, and validation, with references to each of the four image categories (Pneumonia / General). There are over 5,800 JPEG X-Ray images and two phases (Pneumonia / Normal). [31]

For the study of x-ray images, originally, all x-rays were checked for quality control. Before being cleared to be used as a dataset for our deep learning model, the diagnoses for the images were graded by two expert physicians. In case of grading errors, the test set was also double-checked by a third expert. In case of pneumonia, the alveoli gets filled with a secreted liquid and is visible as a white patch on the x-ray image. This condition is known as pulmonary consolidation where pulmonary alveoli is filled with inflammatory liquid. In radiography, the whitish area or the opacity corresponds to the pulmonary consolidation which is one of main features in detection of pneumonia. [32]

3.1.2 Tuberculosis

The dataset used for training the model of tuberculosis included over 500 X-Rays images with 336 cases of tuberculosis in addition to 326 normal cases, which were collected from the "National Library of Medicine, National Institutes of Health, Bethesda, MD, USA and Shenzhen No.3 People's Hospital, Guangdong Medical College, Shenzhen, China". [33] The data set also contains radiology data, which is provided in the form of a text file.

3.2 Input Structure

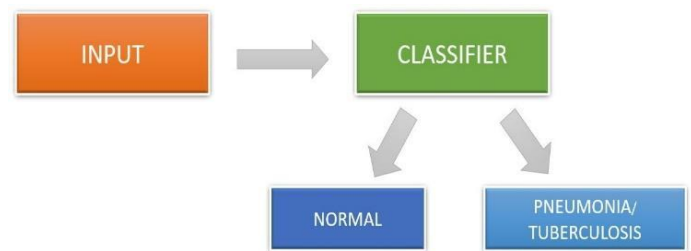


Figure 2 : Classification Structure

The input image is fed to the proposed model which classifies the input image into two classes - Normal or Pneumonia. Images are converted to grayscale and normalized between 0 and 1.

3.3 Convolution Layers

The model's first layer is made up of the first two convolutional layers which does the main feature extraction and identification by using a filter. [34] Its

filters are made up of an array with distinct values for the purpose of detecting the features. These filters move on all parts of the images and generate a high value if the feature is found. If the feature is not detected, then they generate a low value. To elaborate, the filters can be considered as a kernel of matrix consisting of distinct values. [35] The image is also a matrix of integer values which represent the intensity of the pixel present at that point, with values in the range: 0 – 255.[36,37] These kernels move from left to right as well as top to bottom. While doing so, they multiply the kernel values with the pixels in the image matrix and the total of all the values is recorded in the output matrix. Doing so aids to extract features from the given image. For the model used in this paper, a (3,3) size kernel was considered to be used experimentally, as it provided higher accuracy in the time required to traverse the whole image.

$$G[m, n] = (f * h)[m, n] = \sum_j \sum_k h[j, k] f[m - j, n - k] \dots (1)$$

Subsequent map values are determined using the formula given above, where the input image is denoted by f and our kernel is denoted by h . The result matrix rows and column indexes are labelled with m and n , respectively.

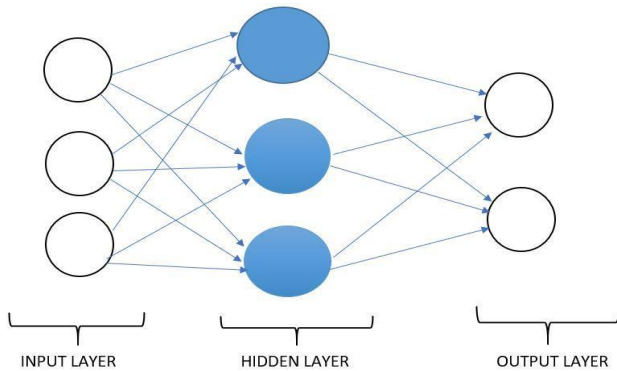


Figure 3 : Neural Network Structure

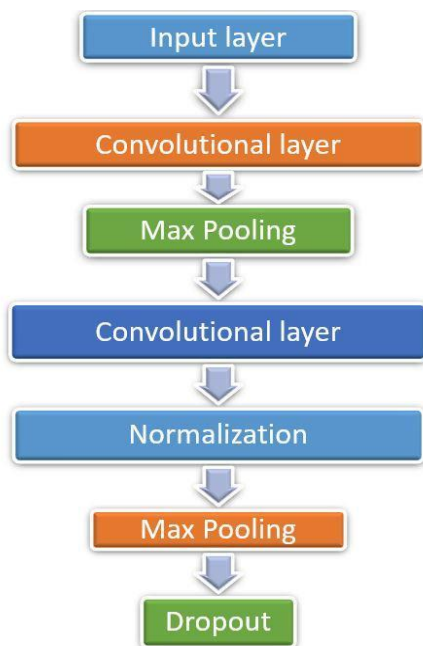


Figure 4 : Model Architecture consisting of different layers of operation

3.4 Max Pooling

After convolutional layers, we used a Max-pool layer. The Pooling layer is the same as the Convolutional layer. It is used to reduce the spatial scale of the expressed feature. It also helps to reduce the training time as well as avoids overfitting. [38] It reduces the computational power for data processing by reducing the dimensionality.[39] In addition, it prevents overfitting by extracting dominant positional and rotational invariant features. Pooling is of two types. First Average Pooling where an average of all values from the kernel covered portion of the image is returned. Second Max Pooling as the name suggests returns the maximum value of all the values covered by the kernel image portion. Max pooling is better than average pooling as it also acts as Noise Suppressant along with dimensionality reduction. [40] The model used in this research has used max pooling.

2	3	4	5	7	3	1	8	7
6	5	2	3	4	5	3	9	5
8	5	9	7	3	5	8	5	8
4	1	3	1	7	3	6	1	3
3	2	7	8	5	1	4	2	5
1	5	3	5	4	6	1	3	6
6	4	5	3	2	9	4	1	2
2	3	6	7	2	5	7	2	5
3	1	5	7	5	3	8	4	1

9	7	9
7	8	6
6	7	8

Maximum value of portion of the image matrix is stored

Figure 5 : Example of Max pooling with 9x9 image

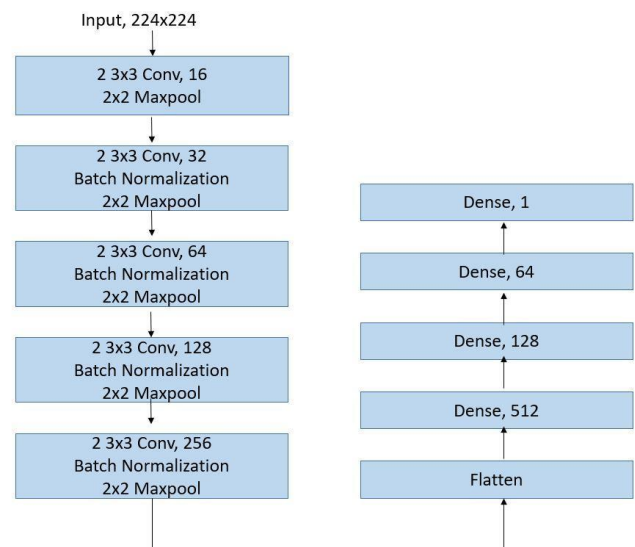


Figure 6 : CNN Architecture for (a) Pneumonia

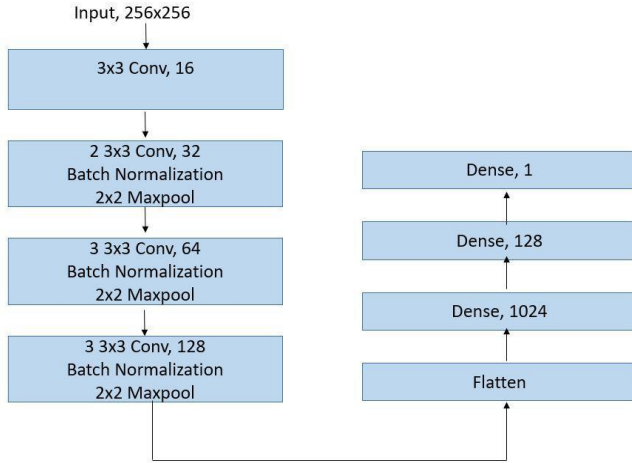


Figure 7 : CNN Architecture for (b) Tuberculosis

IV. EVALUATION METRICS

4.1 Confusion Matrix

A matrix consisting of accurate and erroneous predictions of the model and the original labels is known as the Confusion Matrix. [41]

- True Positive: Number of people who suffer from pneumonia as predicted by the model.
- False Negative: Number of people who are infected with pneumonia but are predicted healthy by the model.
- False Positive: Number of people not actually infected but predicted as pneumonia-affected, by the model.
- True Negative: Number of people whose x-ray is normal and the model predicted them as normal.

4.2 ROC Curve

The Receiver Operating Characteristic Curve or ROC curve is a graphical image that is used to represent the relationship between the true positive value and the false positive value under the limit of different decisions. The true positive rate is the recall or probability of classification. The ROC curve is an important metric of evaluation in determining the reliability of diagnostic tests.[42] The analysis by ROC curve helps in optimization of the model by providing tools to select the most fitting model. It can be described as a straight way to benefit the decision making process of the model. It is the most used metric in the machine learning community. [43]

4.3 Precision, Recall and f1-score

In classification, precision is part of the optimal conditions between the obtained conditions, and the recall is part of the total number of correct conditions actually obtained. Thus, both precision and recall are based on measurement and perceptual processing. F1 score is the measure of a test's accuracy. [44]

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$f1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where, TP = True Positive, FN = False negative, and FP = False Positive.

V. RESULTS

This section contains the results of both proposed models to classify pneumonia and tuberculosis.

Accuracy	Pneumonia	Tuberculosis
Training Data	94.5%	91.8%
Validation Data	93.12%	83.0%
Test Data	91.0%	84.0%

Table 1 : Performance on Training, Validation and Test Data

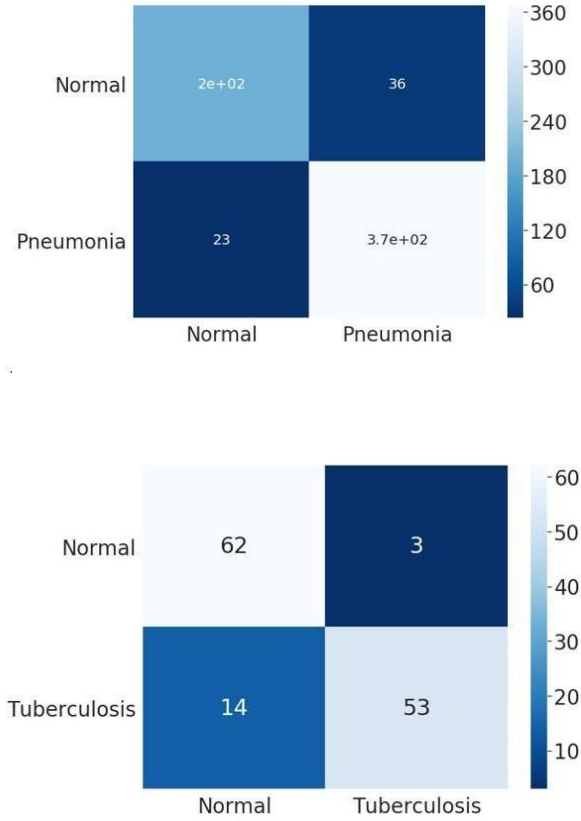


Figure 8 : Confusion Matrix for (a) Pneumonia (b) Tuberculosis

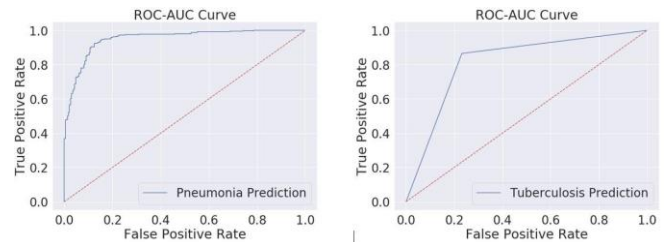


Figure 9 : ROC Curve for (a) Pneumonia (b) Tuberculosis

	precision	recall	f1-score	support
0	0.90	0.85	0.87	234
1	0.91	0.94	0.93	390
accuracy			0.91	624
macro avg	0.90	0.89	0.90	624
weighted avg	0.91	0.91	0.90	624

	precision	recall	f1-score	support
0	0.82	0.97	0.89	65
1	0.96	0.79	0.87	67
accuracy			0.88	132
macro avg	0.89	0.88	0.88	132
weighted avg	0.89	0.88	0.88	132

Figure 10 : Precision, Recall and f1-scores on Test Set of (a) Pneumonia (b) Tuberculosis

VI. COMPARISON

This paper utilizes the pre-trained models given below to classify X-rays.[45] First, The residual neural network (ResNet). It is a neural input network of the type that builds on counterfying cells. The residual neural networks do this by skipping connections, or shortcuts to get more into other layers. Standard ResNet models are used with double or triple skip with nonlinearities (ReLU) and batch normalization.[46] It's a convolutional neural network that is trained in over a million images from ImageNet data.[47] And Lastly DenseNet which is also a convolutional neural network but with 201 layers whereas in Inception Resnet it had 164 layers. The Table below displays the results of these three pre-trained models on different datasets.

Pre-trained model	Internal Chest X-ray 14	Montgomery	Shenzhen
ResNet 152	0.8675	0.7005	0.7496
Inception-ResNet	0.9606	0.8552	0.9179
DenseNet121	0.9872	0.9139	0.9384

VII. CONCLUSION

The research study presents two deep learning models to detect and classify pneumonia and tuberculosis using CNN. The proposed models for both pneumonia and tuberculosis gave noteworthy results with the accuracy for pneumonia being 91% and for the latter being 87%. The main aim of this research was the application of deep learning and machine learning in the healthcare sector. With more advancements in future the models can be trained to classify many more diseases and help in various diagnoses with improved accuracy and precision.

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