Detecting Pneumonia Lung Infection From X-Ray Images with Deep Learning

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Abstract. Pneumonia is one of the most prominent basis of premature death globally, according to some of the major health institutions like WHO more than 1 billion people around the world get infected and more than 4 million people die prematurely due to pneumonia lung infection. Detection of pneumonia infection requires a lot of medical tests, which can be expensive and time consuming. Deep Learning, the technology which gives computer systems the ability to learn and adapt through unstructured data in order to complex solve real world problems has the potential to make the detection of pneumonia easier, cost effective and less time consuming. The motivation behind this paper is to grasp the criticalness and utilization of deep computational learning and Convolutional Neural Network (CNN) by executing it so as to recognize Pneumonia by examining a patient’s chest x-beam pictures.

Keywords: Pneumonia, Convolutional Neural Network, Deep Learning, Data Preprocessing, Computer Vision.

1. Introduction

As of late, an enormous measure of excitement and enthusiasm for a groundbreaking advancement in Machine Learning, also known as Deep Learning or Profound Learning, governed by the algorithms which are roused by the architecture and functioning of human mind, has emerged among students, researchers and technologist from every different stratum like medical science.

All deep learning models use some form of Convolutional Neural Network [9] as their base algorithm. A Convolutional Neural Network (CNN) takes in information, train themselves to perceive the examples in information and foresee the yield for another arrangement of comparative information. CNN models exhibit a complex set of interconnections between inputs and outputs in order to perform a variety of tasks such as image recognition, natural language processing, music generation, even medical diagnosis and procedures[19][20].

Pneumonia is a severe acute respiratory disease which is caused when the air sacks(alveoli) in lungs are infected by some bacteria, virus or fungi to which the patient’s body has weak resistance. As a result, the alveoli in lungs get filled with pus and are unable to provide oxygen to the patient’s blood. Although, it can be treated by medical care and vaccinations, still it is one of the major causes of death worldwide. Figure 1 shows a radio-graph of a healthy pair of lungs. Now in an x-ray image the area of inflammation in lungs caused by pneumonia infection generally shows more translucency than the rest of the area as shown in Figure 2.

Still for most radiologists determining whether a patient is suffering from pneumonia infection by analyzing an x-ray image alone can be very difficult given that an x-ray can often be affected by noise generated by radiation scattering, source leakage, sensor errors, electronic devices and implantation.
Therefore, building a deep learning model by training a convolution neural network with thousands of x-ray images to determine whether a patient has pneumonia with high accuracy while taking all the noise generated into the account can be an effective solution to this problem.

![Healthy Lungs](image1.png)

**Figure 1. Healthy Lungs.**

![Inflammation in Lungs](image2.png)

**Figure 2. Inflammation in Lungs.**

2. **Related Work**

Contemporary advancements in the stratum of deep learning and computer vision and convenient accessibility of enormous sets of data have empowered digital systems to outclass medical professionals in the field of medical imagery.

By training CNNs with huge set of chest radiographs [5], observation and classification of pulmonary tuberculosis has received plenty of attention, as the combination of AlexNet and GoogleNet CNN has been used to build this model and has achieved an accuracy of greater than 95% in classifying tuberculosis in chest X-rays. CNN is the technique which is used for detecting many diseases like brain cancer, Breast cancer etc. Lisowska et al. [9] has presented a 3D based CNN model for detection of brain stoke.

Ponzio, E. Macii [10] have done the work on deep learning technique based on Convolutional Neural Networks on healthy tissues and benign lesions.

Automated classification and detection of acute pulmonary nodules in lungs in Computed Tomography Images [7] and detection of chest pathology using deep learning [8] have also received plenty of attention as they carry the potential to surpass the current chest radiography techniques in order to accurately classify between healthy and pathological chest radio-graphs.

Wang et al [11] has developed a database related to Chest-Xray with text-mined in which eight disease images have been identified by Natural language processing.
3. Methodology

The goal of this experiment is to build a deep learning model capable enough to classify an input image as ‘Normal’ or ‘Pneumonia’ with maximum testing accuracy possible. In order to achieve that, the methodology adopted is shown in Figure 3.

![Figure 3. Experiment’s Workflow.](image)

3.1 Dataset:

In order to prevent model bias and achieve maximum classification/testing accuracy we need a perfectly balanced dataset. The dataset used to train this model contains 7,750 chest x-ray images as training data and 468 images as validation data, evenly distributed among ‘Normal’ class and ‘Pneumonia’ class as shown in Figure 4:

![Figure 4. Balanced Dataset.](image)
Both ‘Normal’ and ‘Pneumonia’ class consist of 3875 images as training and 234 images as testing data.

3.2 Data Preprocessing and Augmentation:
Data preprocessing and augmentation is an essential step taken to maximize the model’s generalization capabilities during training and to tackle with over fitting problems to get an optimal decision surface to perform classification as accurately as possible by enabling us to increase the variation in the dataset without adding more data points.

Various transformation techniques (with parameters used) employed in this model to perform data augmentation are:

- **Rotation Range (30 degrees)**
  To randomly rotate the image from 0 to 180 degrees.
- **Zoom Range (0.2px)**
  To randomly zoom in or zoom out images.
- **Width Shift (0.1px)**
  Random horizontal translation of images.
- **Height Shift (0.1px)**
  Random vertical translation of images.
- **Horizontal Flip (False)**
  Inverted along vertical axis.
- **Vertical Flip (False)**
  Inverted along horizontal axis.

| Technique             | Setting    |
|-----------------------|------------|
| Rotation              | 30         |
| Vertical Shift        | 0.18       |
| Horizontal Shift      | 0.17       |
| Shear                 | 18         |
| Crop and Pad          | 0.27       |

4. Model
In pursuit to achieve highest class prediction accuracy possible we need a custom built Convolutional Neural Network (CNN). Our model’s CNN mainly consists of four components:

4.1 Convolutional Layer (Cov2d)
This layer performs a blend of linear and non-linear operations essential to perform feature extraction [9]. Our model consists of 5 convolutionally interconnected layers which use two-dimensional kernel [10] of size 3*3 and ‘Relu’ activation function [9]. The first cov2d layer is the input layer which provides input data to the system to be processed further by the consecutive layers of neurons. The input shape of our training data is 150 pixels in height, 150 pixels in width and color Method Settings Rotation range 30 degrees Zoom range 0.2px Width shift range 0.1px Height shift range 0.1px Horizontal flip False Vertical flip False 7 gamut value as 1 for gray scale (for RGB color gamut the value is 3), represented as ‘input shape = (150, 150, 1)’.

4.2 Max-Pooling Layer:
In order to optimize the model so that it fit’s the data properly and avoid any outliers, the max-pooling layer decreases the number dimensions and the number of trainable parameters [10] so the model doesn’t overfit. Our model embodies total 5 max-pooling, each of filter size 2*2 [10].
4.3 Dense Layer:
Then the feature maps [10] are converted or flattened into a 1D array after being extracted from the last convolutional or pooling layer. After the flattening process the output array is used as an input to another thoroughly connected layer known as dense layer [10] which also uses ‘Relu’ as activation function.

4.4 Output Layer:
This layer is the last dense layer of our model. It gives only one output at a time and uses ‘sigmoid function’ as activation function [10] which gives a probability score from 0 to 1 to previous layer’s output. The output that gains the highest score is produced by the output layer. Figure 5 illustrates our model’s architecture.

![Figure 5. Model Architecture.](image)

5. Results
To measure as well as validate the performance of the model. We evaluated its effectiveness on various parameters given as:
Precision: Ratio of truly positive identifications against all identifications for each class

\[ \text{Precision(Class)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \]  \hspace{1cm} (1)

\[ Pr(\text{Pneumonia}) = 0.94 \]
\( Pr(\text{Normal}) = 0.90 \)

Recall: Predicted percentage of relevant identifications for each class.

\[
\text{Recall(Class)} = \frac{\text{True Positive}}{\text{True Positive + False Positive}}
\]

\( (\text{Pneumonia}) = 0.94 \)

\( (\text{Normal}) = 0.89 \)

F1-Score: Test accuracy score derived by precision and recall for each class.

\[
\text{F1 score (Class)} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

\( F1(\text{Pneumonia}) = 0.94 \)

\( F1(\text{Normal}) = 0.90 \)

\[\begin{array}{c}
\text{AlexNet} \\
\text{ResNet18} \\
\text{DenseNet201} \\
\text{SqueezeNet} \\
\text{Our Model}
\end{array}\]

**Figure 6.** Normal and Pneumonia.

\[\begin{array}{c}
\text{AlexNet} \\
\text{ResNet18} \\
\text{DenseNet201} \\
\text{SqueezeNet} \\
\text{Our Model}
\end{array}\]

**Figure 7.** Normal, Bacterial Pneumonia and Viral Pneumonia.
As per above results it is clearly observed that on various parameters our model is giving more accurate results.

6. Conclusion
We have achieved an overall accuracy of 92.14%. Though this experiment was performed with limited computational resources, it is clear that by using deep learning and artificial intelligence some major improvements in medical imagery and diagnosis can be made possible. In future, artificial intelligence may not replace the existing professionals in medical radiography but professionals who make use of AI for fast diagnosis with high accuracy will surely replace the existing ones.

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