Pneumonia Detection using Convolutional Neural Networks

Abhay Donthi¹, Abhijith Tammanagari¹, Andrew Huang¹

¹Department of Computer Science, University of North Carolina at Chapel Hill, NC 27599, USA

Summary: Pneumonia is a common problem in the US, as well as internationally, and is a leading cause of death in many parts of the world. Diagnosing pneumonia involves reviewing a chest radiograph (CXR), but other medical conditions can look similar to pneumonia on the radiograph. To speed up diagnosis, we explored the binary classification problem of detecting pneumonia in chest radiographs using a convolutional neural network model. We utilized our convolutional model to predict the presence of pneumonia in new chest radiographs. We created multiple models where one could accurately predict the presence of pneumonia and the other could accurately predict the lack of pneumonia.

Introduction

• Pneumonia affects millions of people and is one of the top 10 causes of death in the United States.¹
• It can be seen in a chest radiograph (CXR) as one or more areas of increased opacity.
• Medical professionals use the patient’s medical history and symptoms to diagnose pneumonia, but the CXR is one of the most important parts in the diagnosis.²
• We utilized a convolutional neural network model (CNN) to analyze CXRs to detect potential cases of pneumonia.
• This project was part of the RSNA Pneumonia Detection Challenge.³

Motivation

Quick diagnosis is key to effective treatment of pneumonia, but this can be difficult. Different medical conditions like excess fluid, internal bleeding, lung cancer, and many others can also show similar opacities in a CXR.² It requires time for a careful review of the CXR, and some clinicians need to process a large amount of CXRs in a short amount of time. The goal of our model is to predict whether a patient has pneumonia with a high sensitivity and specificity.

Method

• We trained a convolutional neural network model on the raw CXR image data to address the binary classification problem of identifying pneumonia.
○ We utilized the Keras neural network library and Microsoft Cognitive Toolkit (CNTK) as our backend to work with Python 2.7.
• For comparison, we ran 3 models:
  1. CNN classifying pneumonia vs. no pneumonia
  2. Combination CNN model
     a. First, we ran a CNN classifying normal vs. abnormal CXRs (healthy patients vs. patients with some lung opacity).
     b. Then, we ran another CNN on the abnormal CXRs to classify pneumonia vs. other disease.
     a→b. Then we ran a CNN where the first model would first classify normal vs. abnormal CXRs. If an image was classified as abnormal, it was then run through 2b to determine if it had pneumonia.

Both CNN models were run using a batch size of 32, 668 steps per epoch, and 3 epochs. We found that more epochs resulted in overfitting, and the low batch size improved generalizability. The loss function for the CNN models was binary cross entropy.

Data

• Images were provided in DICOM format, which is a standard for medical scans.
• These were converted to 1024x1024 PNG files which were then downsampled to 128x128 to improve the runtime of the model learning process.

Experimental Results

• We achieved the following specificity, sensitivity, and accuracy for our models 1, 2a, 2b, and 2a → 2b.

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
<th>Sensitivity (TPR)</th>
<th>Specificity (TNR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>78.5%</td>
<td>90.7%</td>
<td>36.7%</td>
</tr>
<tr>
<td>2a</td>
<td>68.8%</td>
<td>63.0%</td>
<td>80.5%</td>
</tr>
<tr>
<td>2b</td>
<td>69.9%</td>
<td>40.5%</td>
<td>85.9%</td>
</tr>
<tr>
<td>2a → 2b</td>
<td>78.9%</td>
<td>38.2%</td>
<td>90.5%</td>
</tr>
</tbody>
</table>

Conclusions

• Model 1 had a high sensitivity and low specificity, meaning that it was able to accurately predict the existence of pneumonia in abnormal CXRs, but was not able to accurately detect the lack of pneumonia in healthy CXRs.
• Model 2a was able to classify abnormal CXRs as abnormal, and was even better at correctly classifying normal CXRs as normal. 2b was not able to accurately classify CXRs with pneumonia, but was able to tell when abnormal CXRs with no pneumonia did not have pneumonia. Feeding abnormal outputs from 2a to 2b allowed for accurate detection of no pneumonia in abnormal CXRs without pneumonia but was the least accurate model in detecting pneumonia in abnormal CXRs with pneumonia.
• Thus our models were successful in certain aspects, but the accuracies can definitely be improved on.
• Due to the shrunken image size the speed of our classification is faster, but the accuracy is worse.

References:


Sample Chest Radiographs

Normal lungs  Lungs with cancer  Lungs with pneumonia