

# ADS599 Capstone Project

Team 7

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GitHub link: [https://github.com/dingyiduan7/ADS599\\_Capstone\\_Image\\_Recognition](https://github.com/dingyiduan7/ADS599_Capstone_Image_Recognition)

## Abstract:

Our goal is to aim to create an assisting tool to provide a simple yet efficient tool to reduce cost and diagnosis waiting time for Pneumonia classification using X-ray images. Our working dataset consisted of 5,216 prelabeled chest x-ray images, from which we tested a wide variety of image augmentation techniques, as well as a variety of both machine learning and deep learning models. We then developed a pipeline that would take an image from upload to classification within seconds. This was done by standardizing all x-ray image inputs into a consistent, gray-scaled color space and resizing all images into a standard size. After baselining several of the most common general machine learning models compared to convolutional neural networks, an optimized convolutional neural network model was deployed via a simple interface using Flask.

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## Business Background

It is becoming increasingly important to develop models that can help these pocket-sized computers recognize what they “see” within the ever-growing landscape of videos and photos. In just the United States, 1.5 million people were diagnosed with pneumonia in 2018 alone, resulting in more than 40,000 deaths (Centers for Disease Control and Prevention, 2021). On a global scale, children under 5 are more likely to die from pneumonia than other infectious diseases. Chest x-rays remain the main diagnostic method of detecting pneumonia, and if detected early on, they can lead to prevention and targeted treatment (Amatya et al., 2018).

## Problem Statement

Chest X-rays remain the most popular diagnostic test performed for pneumonia detection for various reasons, the most important of which remains its lower cost and lower dosage of radiation compared to alternatives such as computed tomography (CT) scans (Amatya et al., 2018). Thus, we are motivated to proceed in creating an easy-to-use and efficient tool to provide a quicker diagnosis of pneumonia. This application could then be implemented alongside medical professional guidance, and it will function by uploading a chest X-ray image through an accessible application, which will then provide a preliminary diagnosis based on image classification techniques.

## Summary of The Findings

Among all models being contested, all four general machine learning models (SVM, KNN, Decision Tree and Random Forest) have achieved similar results on model accuracy, recall, precision, F1 score and ROC curves while CNN scored 20.5% higher in accuracy, 8.1% higher in F1 score and 71.2% higher in ROC curves as a clear winner. However, despite of the superior performance, the CNN model still suffers from overfitting issue as the test accuracy is about 20% lower than the training and validate set. This can be verified by running our application and the probabilities of classifying for positive cases are much higher (false positives) than the NORMAL cases (negative).

## Business Questions

The main business questions can be described as below:

How would this application help/improve traditional Pneumonia diagnosis process?

How accuracy and adequate is the model driven application?

How easy/hard is it to be used by non-technical users?

How do users gain access to this application

## Scope Of Analysis

We will mainly focus on a few aspects regarding our analysis. This includes: Enough image data to provide adequate training process – we have over 5000 images for training which is adequate despite of the class imbalance issue; The image augmentation/ processing steps for effective image transformation for training – which consists of resizing, gray scaling, reflection/flip, blurring, histogram equalization, rotation, channel and color conversion; The different image dimensions/ features in the training data – this depends on whether we want to utilize the images in its gray scale form or colorful form; And the baseline models for model selection – this is used for initial model selection to minimize the unnecessary cost and labor that goes into the other models.

## Approach

We started with 4 general machine learning models, 1 genuine CNN model and 1 pre-trained CNN variant: VGG16 with the same data preprocessing pipeline. As far as the flask deployment goes, it does not make much difference for saving and loading the model. Therefore, we want to focus on the performance among the candidates. Since the data is unstructured, intuitively we think that the genuine CNN and VGG16 would outperform the rest right off the bat. After running the baseline models, the genuine CNN has achieved an at least 10% higher in all evaluation matrices. Therefore, we choose the genuine CNN for our optimal model to be used for deployment for its unique ability to extract unique features from image data.

## Limitations

Our main limitations include:

- Class imbalance due to the lack of “NORMAL” X-ray images
- Limited trials on selecting the most optimal image processing / augmentation techniques for training
- Hyperparameter tuning for CNN
- A complete monitoring / closed feedback loop system to ensure the model performance can be re-evaluated and the model to be re-trained.

## Solution Details

When compared to other projects, ours provides a transparent walk-through on every step we took with clear explanations and convincing results with a successful deployment of the final model. It may not be the most accurate model in the market; However, the model accuracy alone does not fully justify the full capacity of a well-developed product. Our project provides the unique logical and critical thinking and demonstrates how the images are processed and manipulated before the training happens, which would elaborate into more possible alternatives. We kept the model to be simple yet effective enough within limited time scope to present an acceptable result that fulfils our initial motivation and open for more modifications in the future. The interface is clean and simple, without extra decorations and distractions, users can simply learn how to use it and see the results in literally split of a second. It's fast, and intuitive.

## Concluding Summary

Pneumonia is a disease that can be easily diagnosed, but due to the lack of availability of trained radiologists, has resulted in unnecessary deaths globally. Although the results of our

deployment did not produce metrics of accuracy as impressive as other similar projects, we believe that we were able to deliver and deploy a model that was more efficient, less computationally intensive, and easier to use in comparison to similar studies. In our study, we developed an image augmentation pipeline of the most sensible and applicable techniques to aid all experimented machine learning and deep learning models in classifying chest x-ray images. By comparing the baseline models, we determined that the CNN model was optimal for the chest x-ray images due to the built-in convolutional layers, which reduced the complex shape of the images while maintaining all the useful features. Our final model was measured on metrics of accuracy, recall, precision, F1 scores, and AUC scores. This model was then saved for use via Flask, resulting in an easy-to-use application to aid in diagnosis. Successful deployment of our model in the healthcare industry would lead to a measurable increase in efficiency that can be measured in the turnaround time it takes for a patient to be recommended for x-ray tests to their final diagnosis. This would provide value to doctors and healthcare professionals as a tool that can expedite the pipeline between patient diagnosis and treatment.

## Call To Action (CTA)

If you would like to reach out to express further interests, please contact the authors through their LinkedIn profiles:

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## References

- Amatya, Y., Rupp, J., Russell, F. M., Saunders, J., Bales, B., & House, D. R. (2018). Diagnostic use of lung ultrasound compared to chest radiograph for suspected pneumonia in a resource-limited setting. *International Journal of Emergency Medicine*. 11(1).  
<https://doi.org/10.1186/s12245-018-0170-2>
- Centers for Disease Control and Prevention. (2021). *Pneumonia*. Centers for Disease Control and Prevention. <https://www.cdc.gov/dotw/pneumonia/index.html>