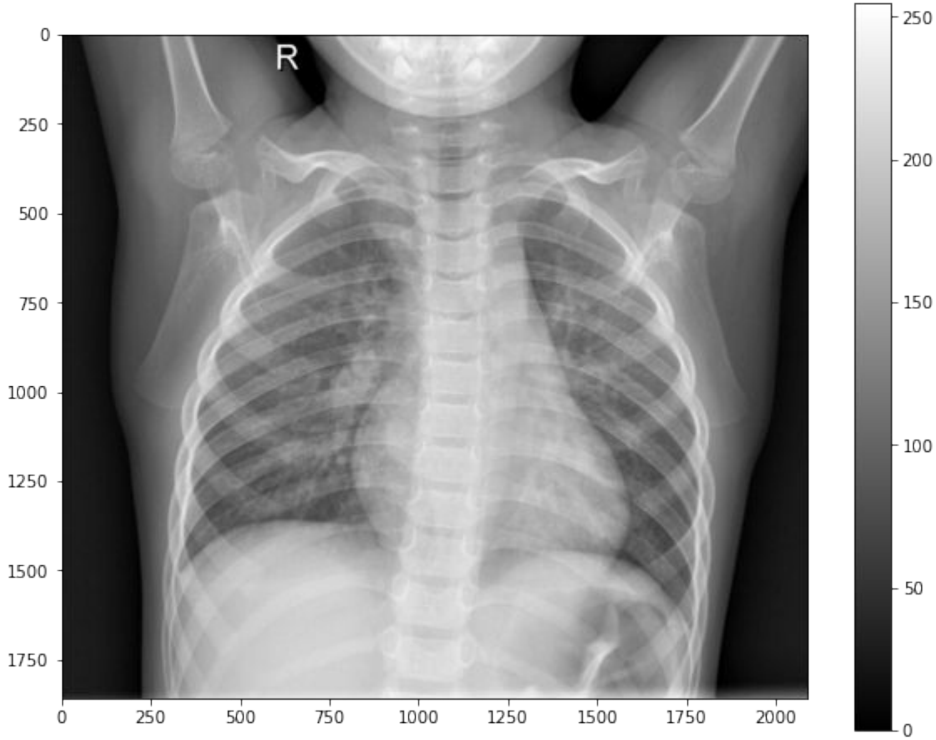
Pneumonia Detection with Computer Vision

Project Objective

Our goal was to train a model to diagnose Pneumonia in medical patients using Computer Vision methods.

This kind of model could be potentially be a tool for hospitals and practitioners.

Deep Neural Networks were used to classify X-Ray images from previous Pneumonia patients.



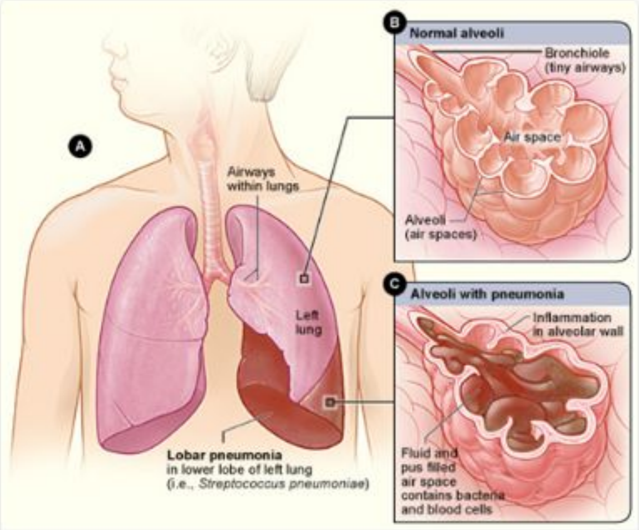
What is Pneumonia?

Pneumonia is an infection that affects one or both lungs. Potential causes include Bacteria, Viruses, or Fungi.

Symptoms include

- Cough and Chest Pain
- Shortness of Breath
- Fever, Nausea, Fatigue

Pneumonia is the deadliest infectious condition in children worldwide (740,180 deaths reported in 2019).



Pneumonia, caused by bacteria. Figure A shows pneumonia affecting part of the left lung. Figure B shows healthy alveoli (air sacs). Figure C shows alveoli filled with mucus.

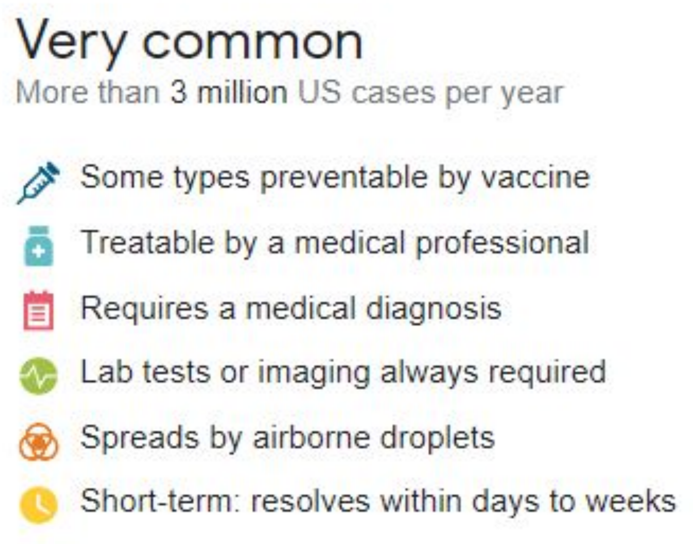
The Importance of Diagnosis

Pneumonia is a very common condition both in the US and worldwide.

However, it is usually treatable if diagnosed!

Treatments include:

- Antibiotics
- Cough Medicine
- Fever/Pain Relievers



Current Diagnostic Methods

Diagnosis

Print

Your doctor will start by asking about your medical history and doing a physical exam, including listening to your lungs with a stethoscope to check for abnormal bubbling or crackling sounds that suggest pneumonia.

Chest X-ray showing pneumonia

If pneumonia is suspected, your doctor may recommend the following tests:

- **Blood tests.** Blood tests are used to confirm an infection and to try to identify the type of organism causing the infection. However, precise identification isn't always possible.
- **Chest X-ray.** This helps your doctor diagnose pneumonia and determine the extent and location of the infection. However, it can't tell your doctor what kind of germ is causing the pneumonia.
- **Pulse oximetry.** This measures the oxygen level in your blood. Pneumonia can prevent your lungs from moving enough oxygen into your bloodstream.
- **Sputum test.** A sample of fluid from your lungs (sputum) is taken after a deep cough and analyzed to help pinpoint the cause of the infection.

Lab Tests

- Blood Tests
- Chest X-Rays
- Pulse Oximetry
- Sputum Testing

Current Diagnostic Methods

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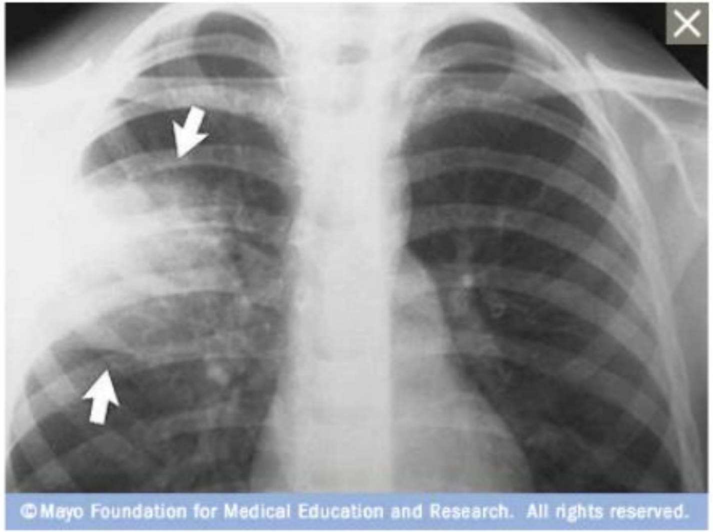
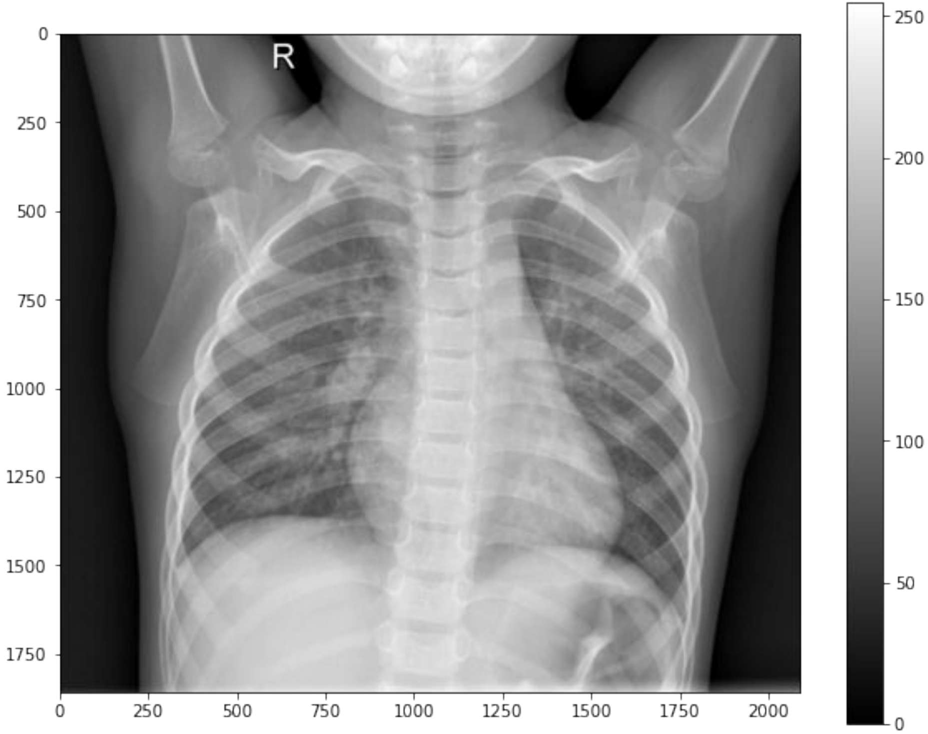
X-Ray Imaging



Chest X-ray showing pneumonia

This chest X-ray shows an area of lung inflammation indicating the presence of pneumonia.

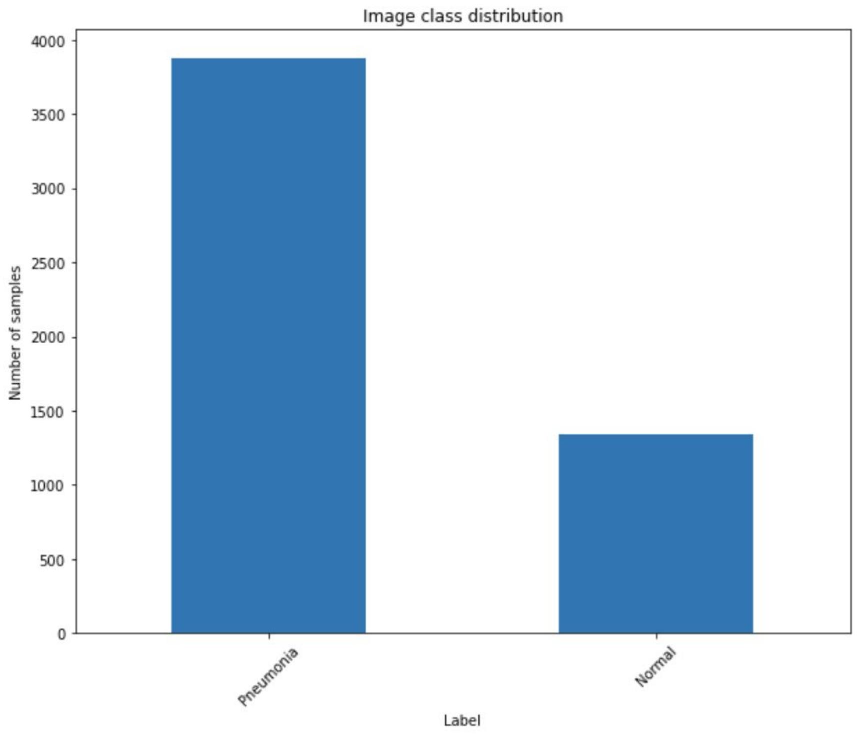


Data Overview

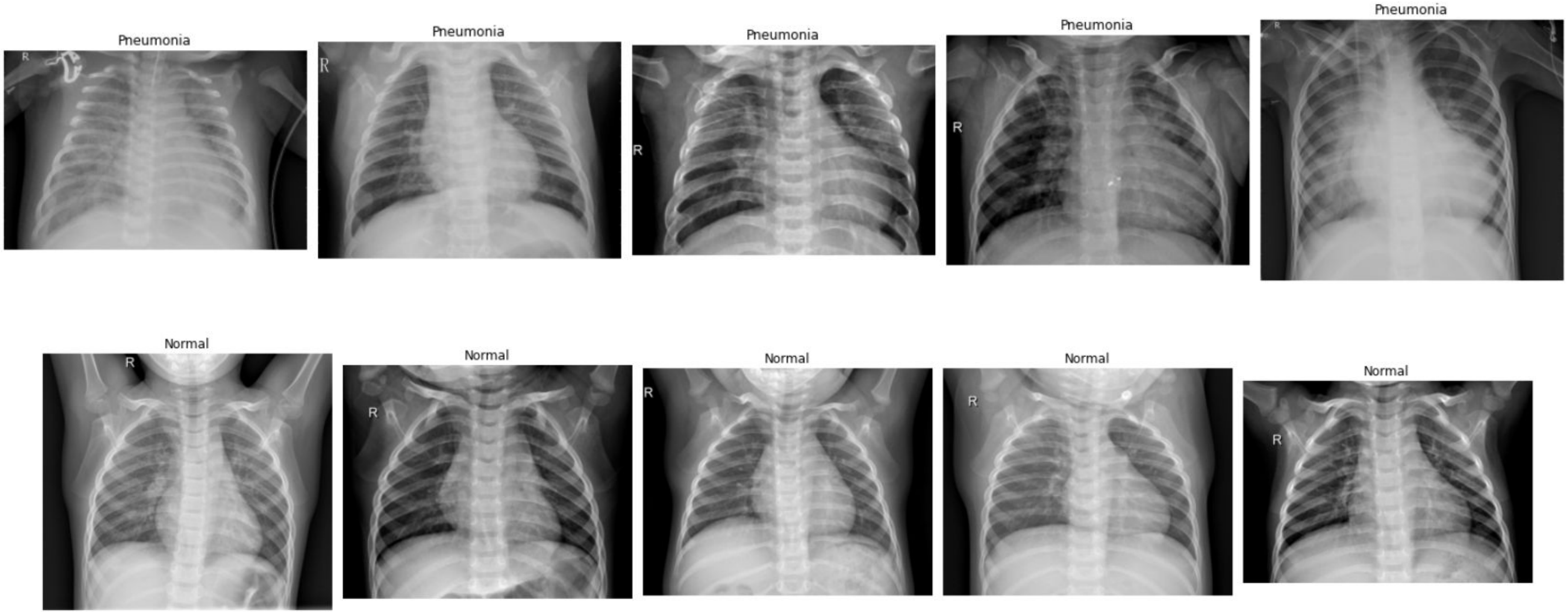
Our training data consisted of 5216 Images:

- 3875 - Pneumonia
- 1341 - Normal

Much of our data work explored ways to address this class imbalance.



2 Image Classes: Pneumonia & Normal

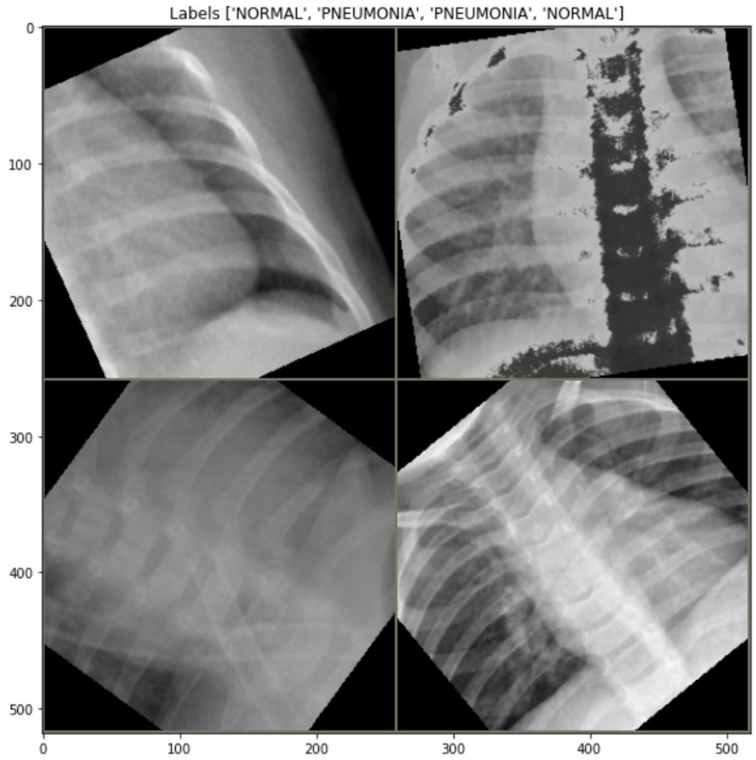


Augmenting Image Data

Because we are in the medical domain, it was a goal to keep the transformations as plausible and “realistic” as possible.

Here is an example of 4 images which used a composition including

- Random Inversions
- Random Resized Cropping
- Rotations of up to 60*



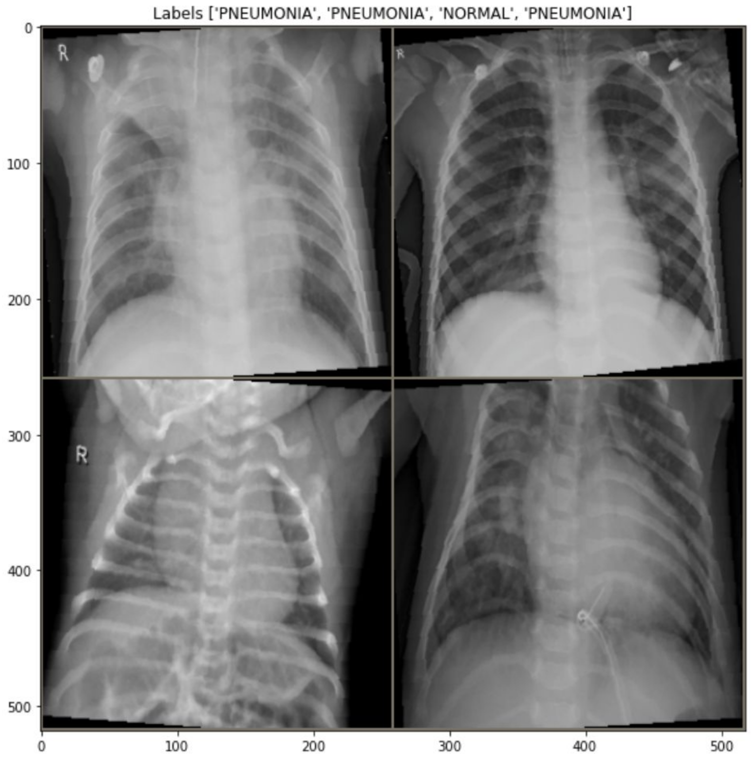
They don’t look very similar to the original data

Augmenting Image Data

Instead, we used compositions of transforms which adjusted or added things like

- Brightness, Contrast, Saturation
- Blur
- Minor Rotations

These much more closely resemble the original data, and could even represent scenarios (patient moving, technician error, etc.).



Modeling

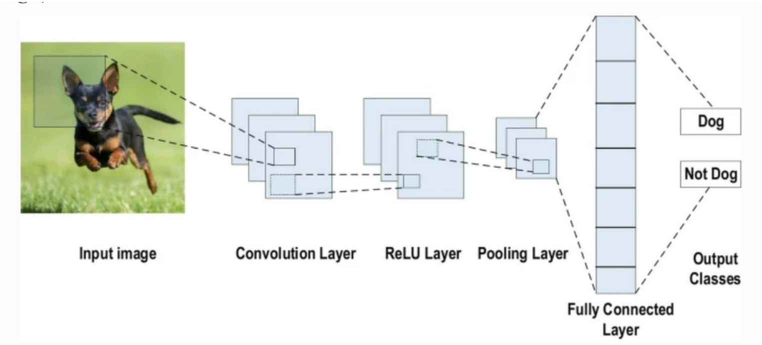
We experimented with 2 fundamental approaches.

1: Building a smaller model from scratch.

2: Altering a larger, existing model to fit our data (Transfer Learning)

Like many Computer Vision models, we employed Convolutional Neural Networks.

These are used in many common technologies, such as facial recognition.



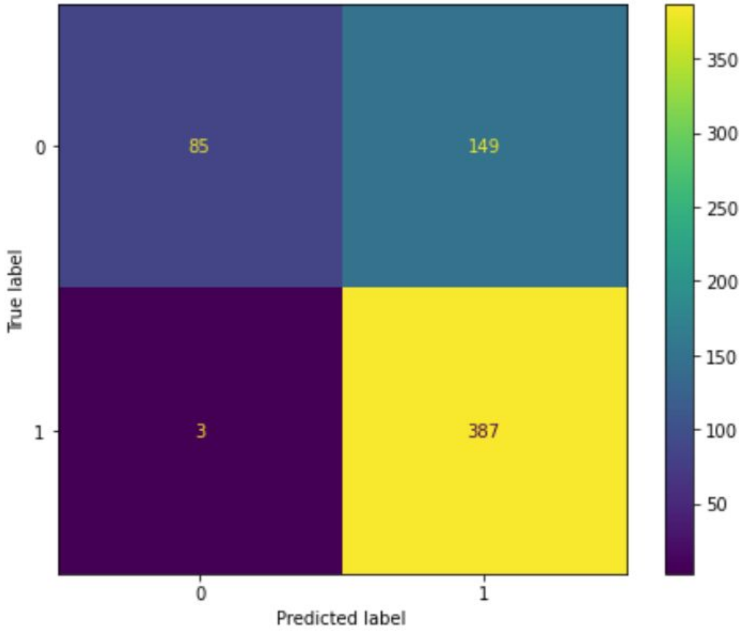
Baseline Model

CNN with 6 layers (2 blocks)

Accuracy: 75.6%

	precision	recall	f1-score	support
0	0.97	0.36	0.53	234
1	0.72	0.99	0.84	390
accuracy			0.76	624
macro avg	0.84	0.68	0.68	624
weighted avg	0.81	0.76	0.72	624

Accuracy Score: 0.7564102564102564
F1 Score: 0.83585313174946

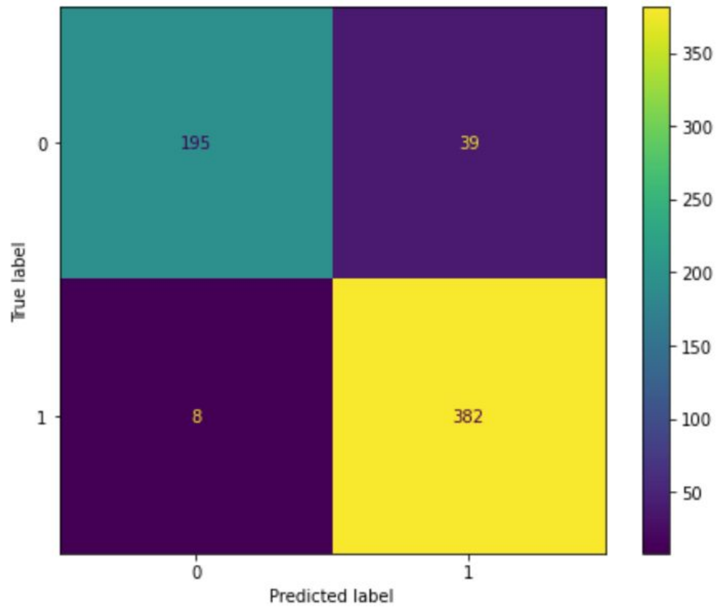


Best Model:

Transfer Learning with Resnet18

Accuracy: 92.4%

	precision	recall	f1-score	support
0	0.96	0.83	0.89	234
1	0.91	0.98	0.94	390
accuracy			0.92	624
macro avg	0.93	0.91	0.92	624
weighted avg	0.93	0.92	0.92	624



Model Architecture Comparison

Baseline Model (left)
Best Model (right)

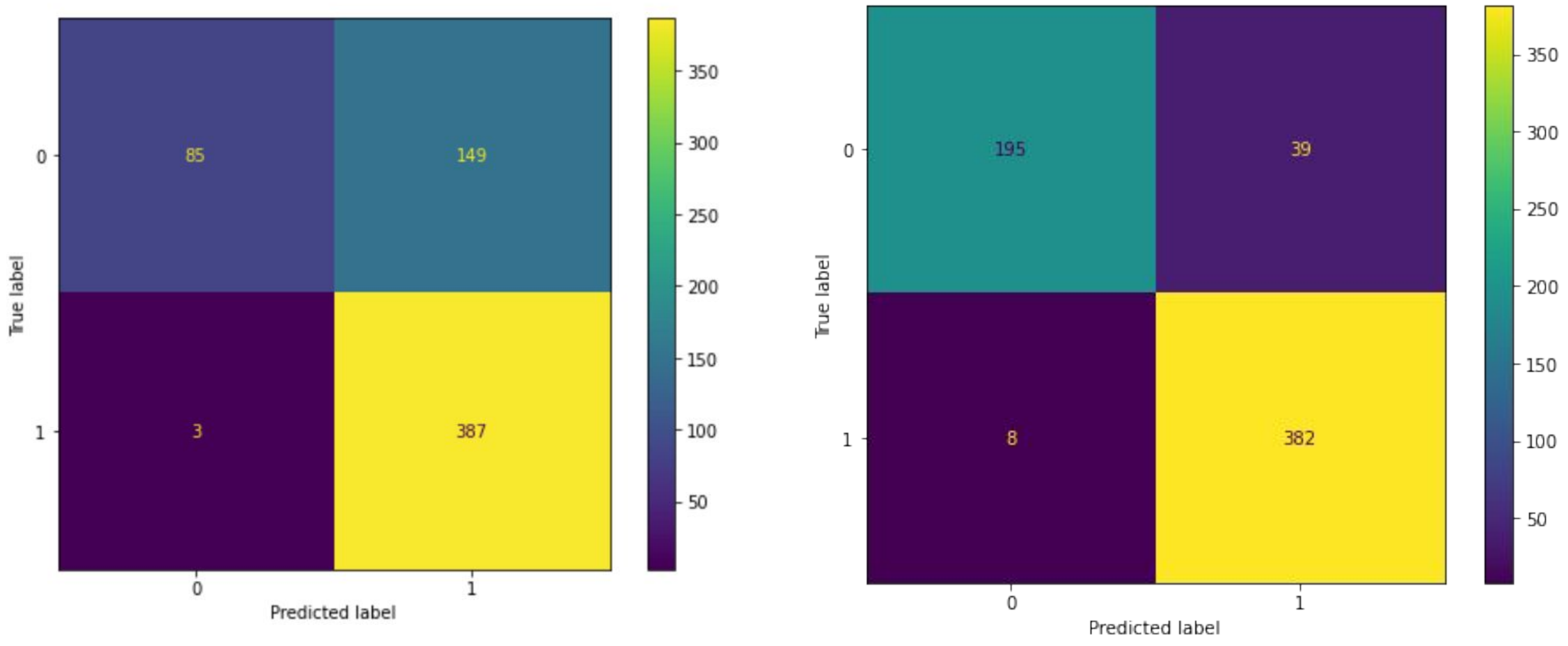
```
summary(model,(images.shape[1], images.shape[2], images.shape[3]))
```

```
torch.Size([2, 16, 61, 61])
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1          [-1, 6, 252, 252]             456
         MaxPool2d-2          [-1, 6, 126, 126]               0
            Conv2d-3         [-1, 16, 122, 122]           2,416
         MaxPool2d-4           [-1, 16, 61, 61]               0
            Linear-5                   [-1, 10]         595,370
            Linear-6                    [-1, 2]              22
================================================================
Total params: 598,264
Trainable params: 598,264
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 5.90
Params size (MB): 2.28
Estimated Total Size (MB): 8.94
----------------------------------------------------------------
```

```
summary(model_ft,(3, 256, 256))
```

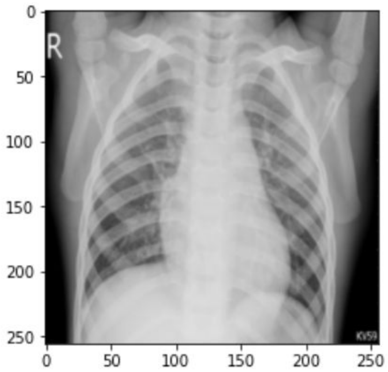
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 64, 128, 128]           9,408
       BatchNorm2d-2         [-1, 64, 128, 128]             128
              ReLU-3         [-1, 64, 128, 128]               0
         MaxPool2d-4           [-1, 64, 64, 64]               0
            Conv2d-5           [-1, 64, 64, 64]          36,864
       BatchNorm2d-6           [-1, 64, 64, 64]             128
              ReLU-7           [-1, 64, 64, 64]               0
            Conv2d-8           [-1, 64, 64, 64]          36,864
       BatchNorm2d-9           [-1, 64, 64, 64]             128
             ReLU-10           [-1, 64, 64, 64]               0
       BasicBlock-11           [-1, 64, 64, 64]               0
           Conv2d-12           [-1, 64, 64, 64]          36,864
      BatchNorm2d-13           [-1, 64, 64, 64]             128
             ReLU-14           [-1, 64, 64, 64]               0
           Conv2d-15           [-1, 64, 64, 64]          36,864
      BatchNorm2d-16           [-1, 64, 64, 64]             128
             ReLU-17           [-1, 64, 64, 64]               0
       BasicBlock-18           [-1, 64, 64, 64]               0
           Conv2d-19          [-1, 128, 32, 32]          73,728
      BatchNorm2d-20          [-1, 128, 32, 32]             256
             ReLU-21          [-1, 128, 32, 32]               0
           Conv2d-22          [-1, 128, 32, 32]         147,456
      BatchNorm2d-23          [-1, 128, 32, 32]             256
           Conv2d-24          [-1, 128, 32, 32]           8,192
      BatchNorm2d-25          [-1, 128, 32, 32]             256
             ReLU-26          [-1, 128, 32, 32]               0
       BasicBlock-27          [-1, 128, 32, 32]               0
           Conv2d-28          [-1, 128, 32, 32]         147,456
      BatchNorm2d-29          [-1, 128, 32, 32]             256
             ReLU-30          [-1, 128, 32, 32]               0
           Conv2d-31          [-1, 128, 32, 32]         147,456
      BatchNorm2d-32          [-1, 128, 32, 32]             256
             ReLU-33          [-1, 128, 32, 32]               0
       BasicBlock-34          [-1, 128, 32, 32]               0
           Conv2d-35          [-1, 256, 16, 16]         294,912
      BatchNorm2d-36          [-1, 256, 16, 16]             512
             ReLU-37          [-1, 256, 16, 16]               0
           Conv2d-38          [-1, 256, 16, 16]         589,824
      BatchNorm2d-39          [-1, 256, 16, 16]             512
           Conv2d-40          [-1, 256, 16, 16]          32,768
      BatchNorm2d-41          [-1, 256, 16, 16]             512
             ReLU-42          [-1, 256, 16, 16]               0
       BasicBlock-43          [-1, 256, 16, 16]               0
           Conv2d-44          [-1, 256, 16, 16]         589,824
      BatchNorm2d-45          [-1, 256, 16, 16]             512
             ReLU-46          [-1, 256, 16, 16]               0
           Conv2d-47          [-1, 256, 16, 16]         589,824
      BatchNorm2d-48          [-1, 256, 16, 16]             512
             ReLU-49          [-1, 256, 16, 16]               0
       BasicBlock-50          [-1, 256, 16, 16]               0
           Conv2d-51            [-1, 512, 8, 8]       1,179,648
      BatchNorm2d-52            [-1, 512, 8, 8]           1,024
             ReLU-53            [-1, 512, 8, 8]               0
           Conv2d-54            [-1, 512, 8, 8]       2,359,296
      BatchNorm2d-55            [-1, 512, 8, 8]           1,024
           Conv2d-56            [-1, 512, 8, 8]         131,072
      BatchNorm2d-57            [-1, 512, 8, 8]           1,024
             ReLU-58            [-1, 512, 8, 8]               0
       BasicBlock-59            [-1, 512, 8, 8]               0
           Conv2d-60            [-1, 512, 8, 8]       2,359,296
      BatchNorm2d-61            [-1, 512, 8, 8]           1,024
             ReLU-62            [-1, 512, 8, 8]               0
           Conv2d-63            [-1, 512, 8, 8]       2,359,296
      BatchNorm2d-64            [-1, 512, 8, 8]           1,024
             ReLU-65            [-1, 512, 8, 8]               0
       BasicBlock-66            [-1, 512, 8, 8]               0
AdaptiveAvgPool2d-67            [-1, 512, 1, 1]               0
           Linear-68                    [-1, 2]           1,026
================================================================
Total params: 11,177,538
Trainable params: 11,177,538
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 82.00
Params size (MB): 42.64
Estimated Total Size (MB): 125.39
----------------------------------------------------------------
```

Error Tradeoff

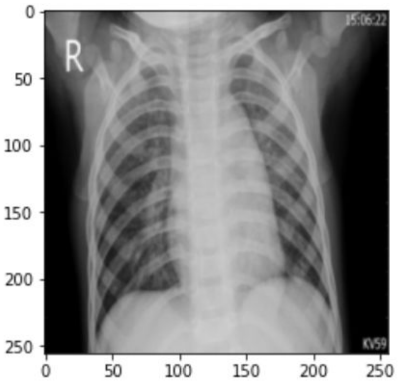


Misclassification Examples

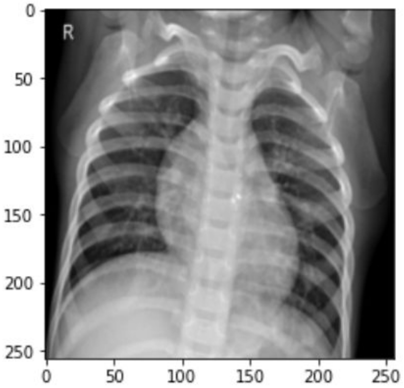
Actual: NORMAL predicted: PNEUMONIA



Actual: NORMAL predicted: PNEUMONIA



Actual: PNEUMONIA predicted: NORMAL



Upside Potential

- Small practical changes on the client side could potentially improve the performance even more.
  - Our model had to account for data with a wide range of image sizing. This resulted in some images being downscaled.
  - We also dealt with inconsistent sizes for testing classifications.

- If new images had consistent size and quality, more predictive information could be preserved, likely resulting in higher case by case accuracy.

Key Takeaways

- Using neural networks as a diagnostic tool shows remarkable promise
    - We were able to create a model with over 92% accuracy, having relatively little training data.
        - According to the WHO, there are ~1.4 billion chest x-rays taken each year. We only had access to ~6 thousand.

- As the recent pandemic has shown, medical personnel shortages can occur, leaving hospitals overwhelmed.
- Technology such as the model created in this project could have tremendous value.

Thank you!

References:

Mayo Clinic:

https://www.mayoclinic.org/diseases-conditions/pneumonia/symptoms-causes

National Institute of Health (NIH):

https://www.nhlbi.nih.gov/health/pneumonia

World Health Organization (WHO):

https://www.who.int/news-room/fact-sheets/detail/pneumonia
https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2019-chapter8.pdf