# Lung Disease Classification using Transfer Learning

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# Agenda

Problem Statement

Solution

Data Exploration

Performance of Algorithm

Q & A

# Problem Statement

- The infection of lung that causes inflammation in one or both of the lungs is one of the most serious causes of chronic lung disease, it is imperative to detect that disease to make the recovery successful. When interpreting the x-ray, the radiologist looks for white spots in the lungs (called infiltrates) that identifies an infection. This exam also helps determine if a patient has any complications as abscesses or pleural effusions (fluid surrounding the lungs). Such condition can be detected by medical imaging methods like chest X-ray, CT of the lungs, MRI of the chest, needle biopsy of the lungs.
- By auto-analyzing a patient's medical images through data mining and image processing techniques, the risk of human error in disease detection can be reduced. With machine learning application , the earlier identification of diseases, particularly lung disease, we can be helped to detect earlier and estimate with high accuracy rate.

- Dataset is a large, but has never been processed full, data has a lot of noise, and X-ray of the lung is not likely to provide enough information to assess whether a patient may be ill.

# Solution

- Understand and analyze the x-ray data
- Implement CNN and it’s drawback
- Understand transfer learning method and it’s benefits
- Implement RESNET50 and VGG 16
- Compare the models and finalize on one

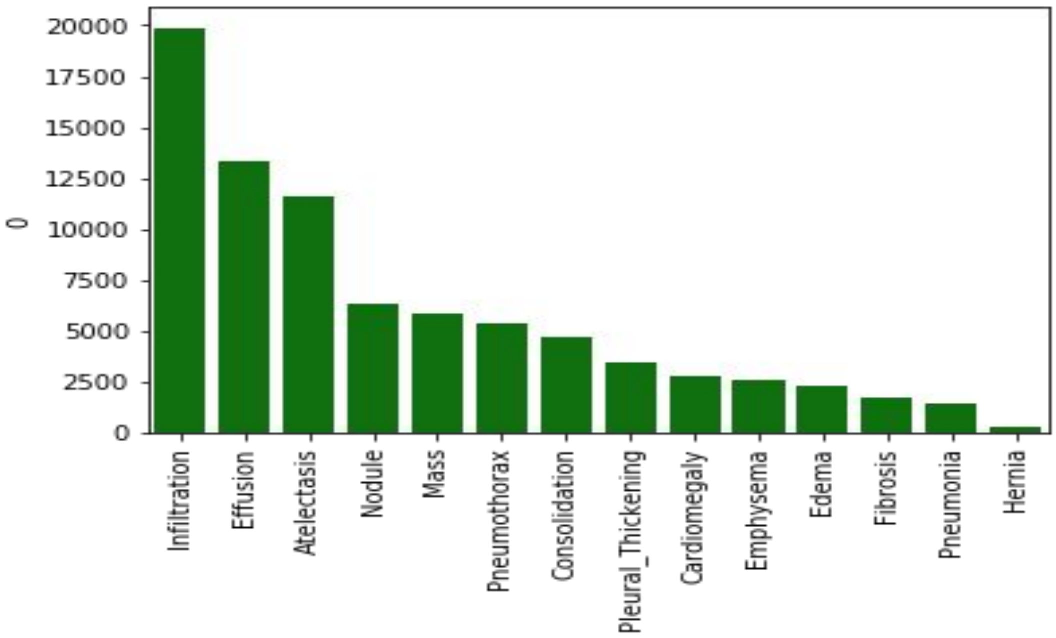
# Methodology

## Data Exploration

- NIH Chest X-ray Dataset (National Institutes of Health Chest X-Ray Dataset) is comprised of 112,120 X-ray images with disease labels from 30,805 unique patients.
- Class labels and patient data for the entire dataset:
  - Image Index: File name
  - Finding Labels: Disease type (Class label)
  - Follow-up #
  - Patient ID
  - Patient Age
  - Patient Gender
  - View Position: X-ray orientation
  - OriginalImageWidth
  - OriginalImageHeight
- Class labels are ['Atelectasis', 'Cardiomegaly', 'Consolidation', 'Edema', 'Effusion', 'Emphysema', 'Fibrosis', 'Hernia', 'Infiltration', 'Mass', 'Nodule', 'Pleural_Thickening', 'Pneumonia', 'Pneumothorax’]

# Methodology

## Data Exploration



# Data Preparation

- Data Generation

  Image - Preporcessing

```
from keras.preprocessing.image import ImageDataGenerator
IMG_SIZE = (128,128)
core_idg = ImageDataGenerator(samplewise_center=True,
                              samplewise_std_normalization=True,
                              horizontal_flip = True,
                              vertical_flip = False,
                              height_shift_range= 0.05,
                              width_shift_range=0.1,
                              rotation_range=5,
                              shear_range = 0.1,
                              fill_mode = 'reflect',
                              zoom_range=0.15)
```

- Data Augmentation/Normalization

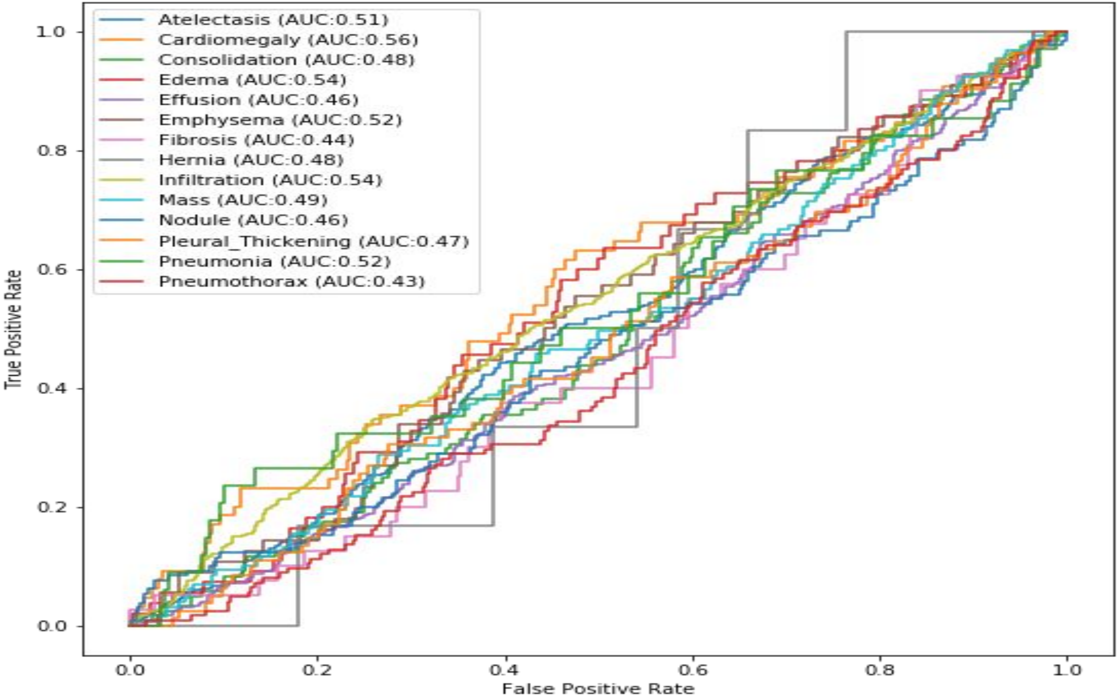
# Model parameters

| | Simple-CNN | Resnet | Vgg16 |
|---|---|---|---|
| **loss** | Binary-Crossentropy | | |
| **optimizer** | adam | | |
| **metrics** | accuracy | | |
| **epochs** | 5 | 2 | 1 |
| **steps-per-epochs** | 15000/160 | | |
| **validation-steps** | 20 | 15000/1280 | 15000/1280 |
| **Activation function** | softmax | | |

# Performance of Algorithms

| Architecture | Epoch | Time elapsed | Loss | Accuracy | val_loss | val_acc | Learning Rate |
|---|---|---|---|---|---|---|---|
| **Simple-CNN** | 5 | 67s | 4.17 | 0.1925 | 4.16 | 0.18 | 0.001 |
| **ResNet50** | 2 | 452s | 4.75 | 0.83 | 0.76 | 0.84 | 0.001 |
| **Vgg16** | 1 | 2769s | 6.55 | 0.84 | 1.68 | 0.84 | 0.001 |

# Benchmark




- For this problem, the benchmark model will be RESNET50
- Atelectasis: 24.80%
- Cardiomegaly: 6.35%
- Consolidation: 11.82%
- Edema: 5.37%
- Effusion: 29.10%
- Emphysema: 5.47%
- Fibrosis: 3.91%
- Hernia: 0.59%
- **Infiltration: 40.72%**
- Mass: 12.60%
- Nodule: 12.79%
- Pleural Thickening: 8.01%
- Pneumonia: 3.32% Pneumothorax: 12.21%

# Conclusion

- In order to evaluate the results obtained from the pre-trained models designed in the study, it is seen that only few epochs are used in, when the training process is examined first. At the end of each epoch, the error rate obtained by writing the lowest error rate shows an accuracy rate of 84 percent after first few epochs. However, this accuracy is the lowest rate of those epochs. When more epochs are considered in this case, it is seen that the average accuracy rate can be maximized. This accuracy is an indication that the model is successful. In the obtained error value, it is possible to say that the first epoch is a very high error ,but it is approaching zero by decreasing to the next epoch.
- Another important factor is the length of the trained process. The training ended after at different time span at the end of these epochs. This value may vary depending on the power of the processor, the size of the image, the number of images in the data set, and the number of convolutional and maxpooling layers used in the models. In fact, the number of filters used in the convolutional layer and the filter size affect both accuracy and training duration.

# Q & A

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