
Pneumonia Diagnosis System with Chest X-Ray

APS360: Applied Fundamentals of Deep Learning
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Motivation

Automating pneumonia detection in chest X-rays

What is **Pneumonia**

- An infection that can cause inflammation in lungs
- In severe cases, could lead to respiratory system failure

Our Motivation

1. Pneumonia has a **500,000 global death rate** among children age < 5 years old (WHO)
2. **Imbalanced medical resources** in underdeveloped areas creates difficulty for such detection
3. Insufficient diagnostic time for every patient, leading to **possible incorrect diagnostic decisions**
(avg. 3 min/patient with a radiologist)

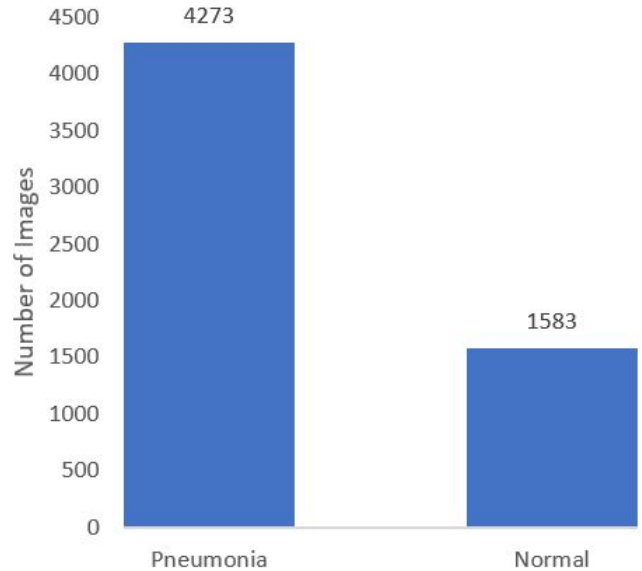


Pneumonia



Normal

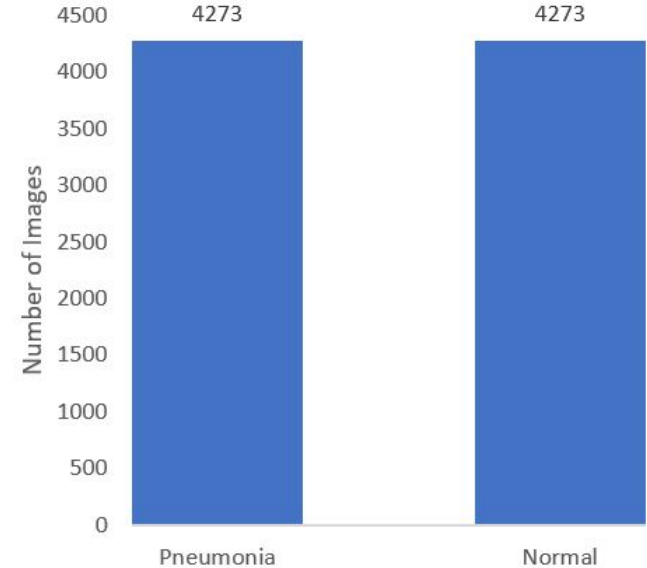
Selecting chest X-ray images for a deep learning neural network for binary classification



Pneumonia Chest X-Ray Images
on **Kaggle** (JPEG)



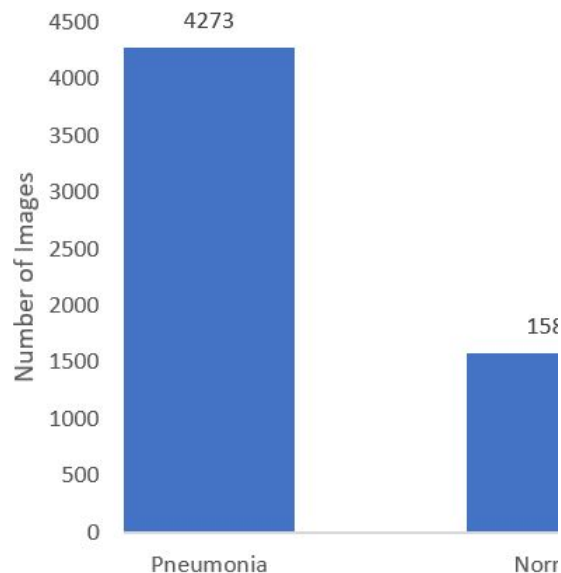
Combine
"Normal" images
from **NIH Chest
X-ray dataset**



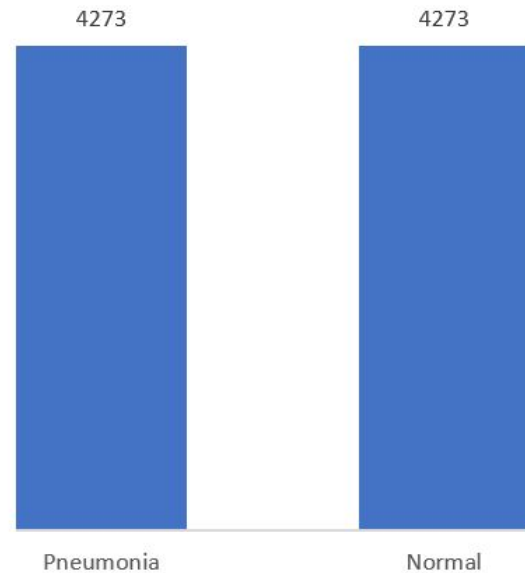
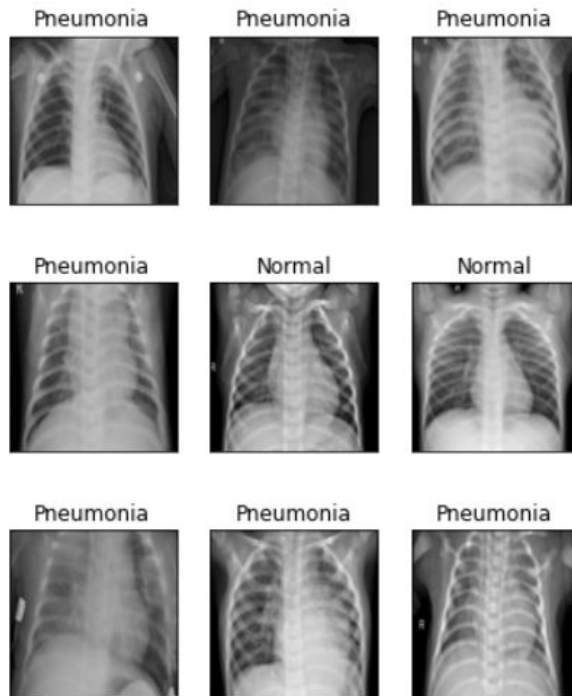
Balanced dataset (JPEG)

- **8,546** images from over 7,000 patients

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Pneumonia Chest X-Ray Images on Kaggle (JPEG)



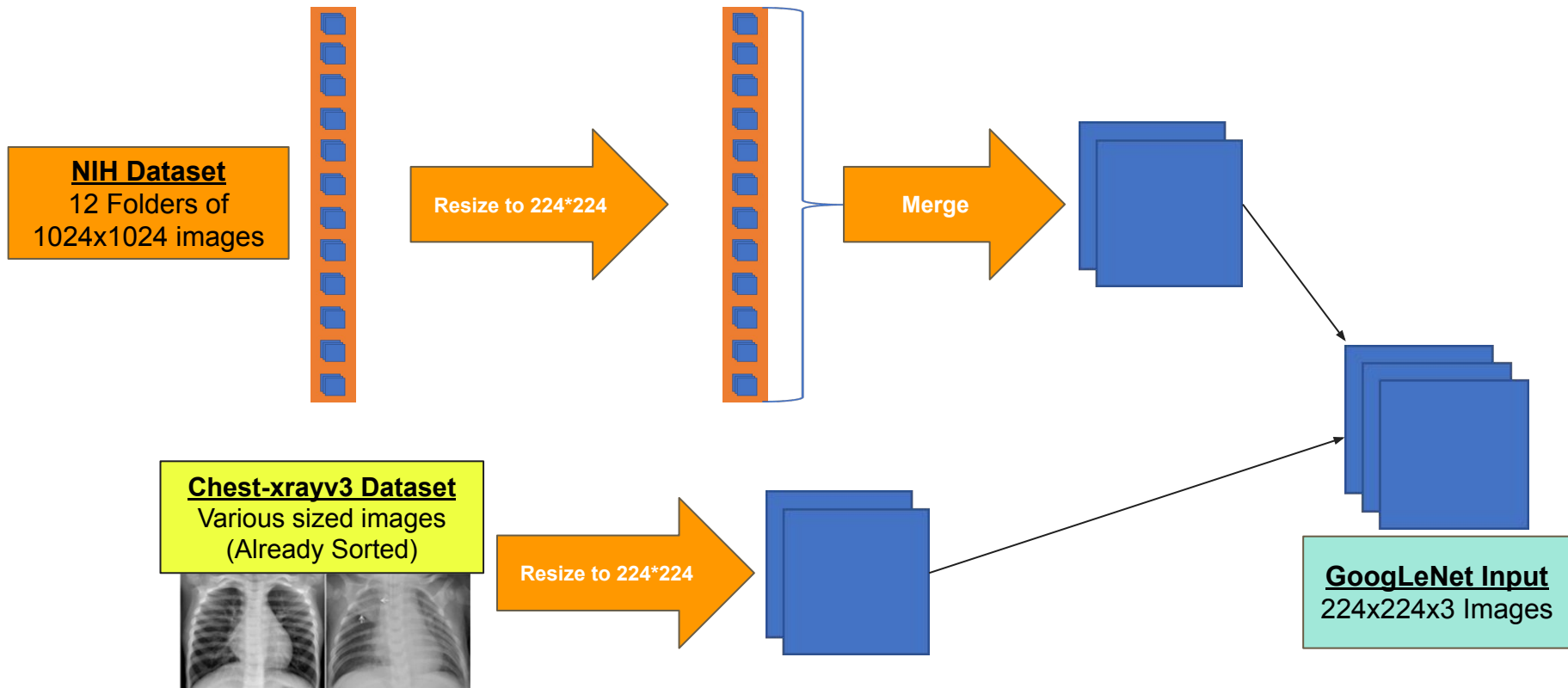
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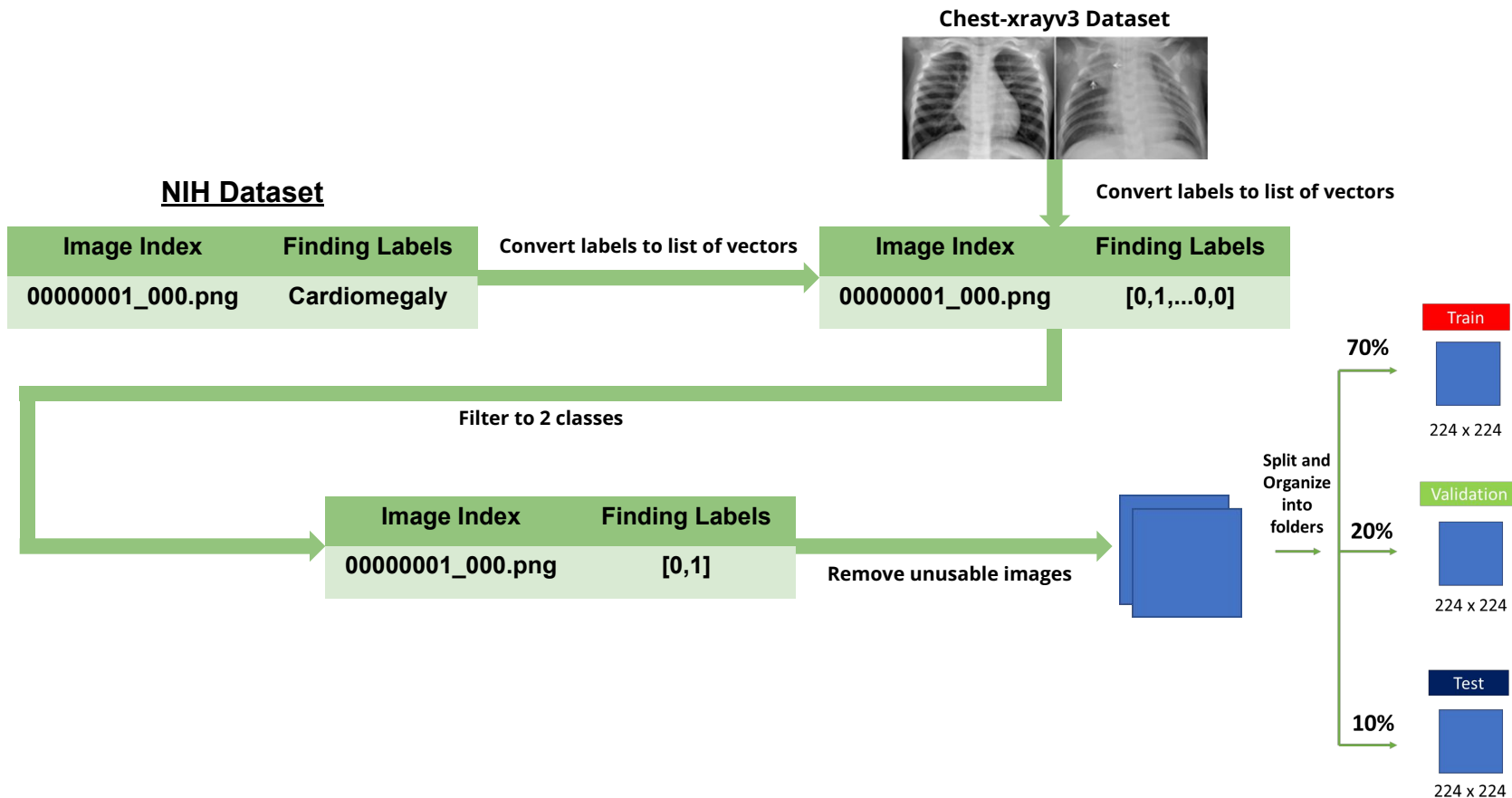
<https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia>
<https://cloud.google.com/healthcare-api/docs/resources/public-datasets/nih-chest>

Data Processing

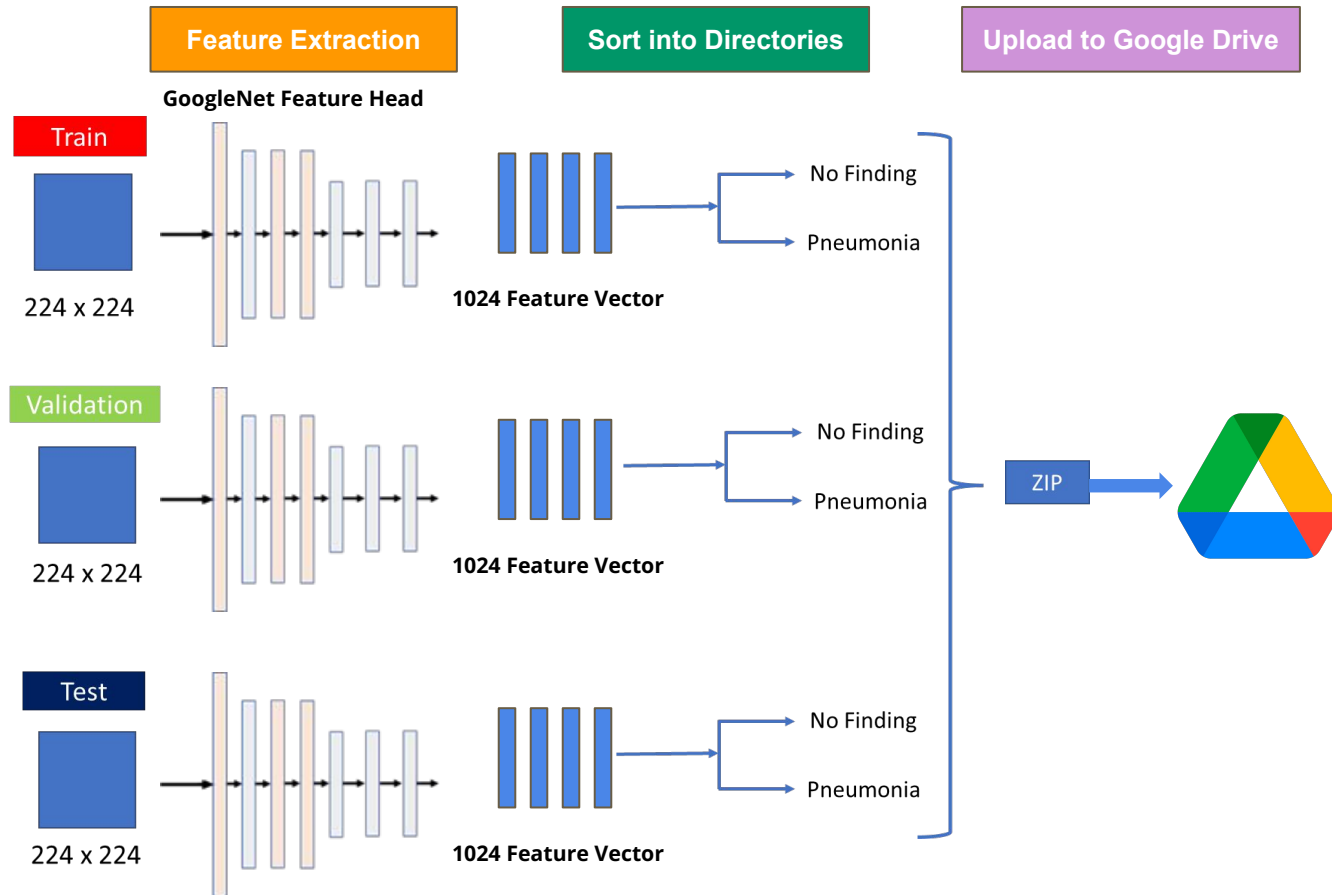
Resizing and merging image dataset



Processing our data distribution for pneumonia detection



Extracting features to speed up training



Advantages

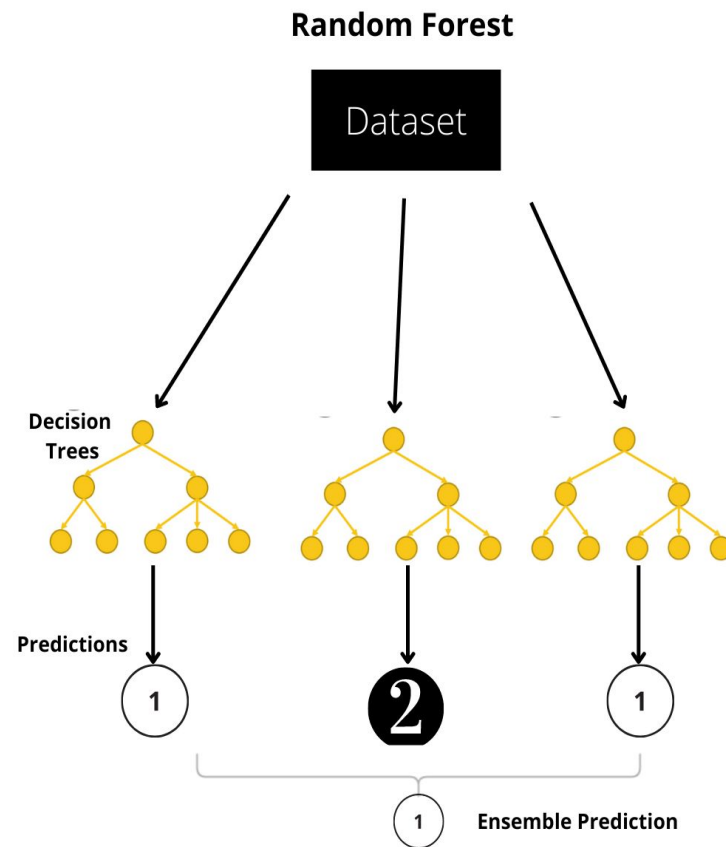
- Performing feature extraction before training has many benefits including:
 - Speeding up training time
 - Reducing the disk space usage on google drive
 - Reducing data loading time

Baseline Model & Primary Model

Baseline Model

Baseline Model Selection

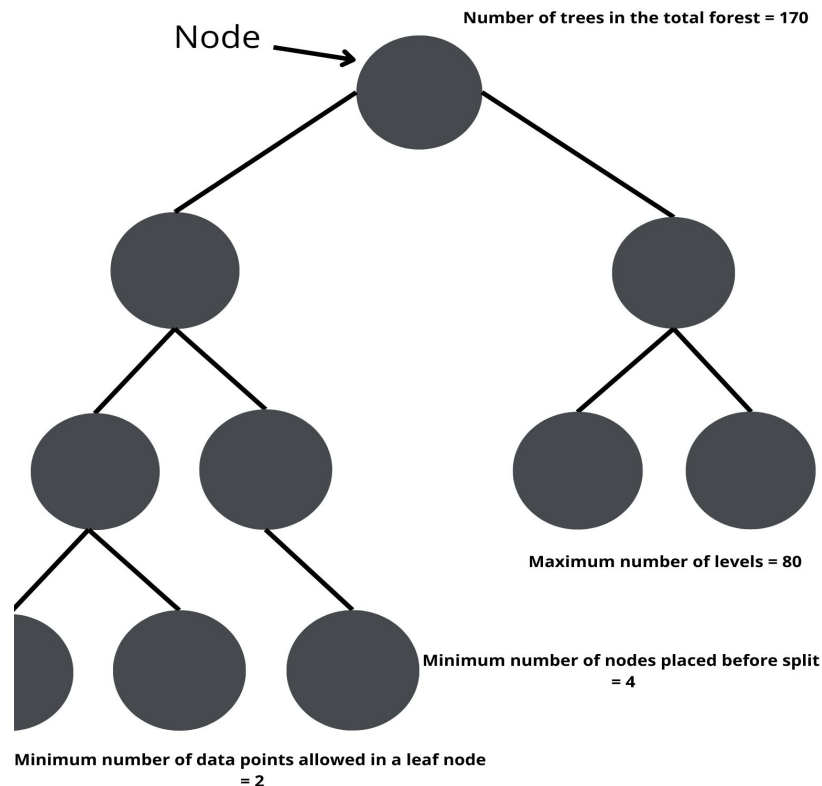
- Chose to use a Random Forest Classifier
 - Provides higher levels of accuracy
- Decision Trees → Nodes → Predictions
= Grouped Prediction
- Limitations of the model
 - Cannot extrapolate data



Baseline Model

Model Complexity & Hyperparameters

1. n estimators
 - number of trees in the forest = 170
2. Maximum Depth
 - maximum number of levels in each decision tree = 80
3. Minimum Samples Split
 - minimum number of data points placed in a node before the node is splitted = 4
4. Minimum Samples Leaf
 - minimum number of data points allowed in a leaf node = 2



Primary model: transfer learning provides deep model complexity on a limited dataset

GoogLeNet¹

Complexity: 22 layers, Inception Blocks

Winning architecture of ILSVRC 2014 competition

1. **6.67%** top-5 error rate

Has only been started to be researched for pneumonia classification since 2020

Was significantly due to the interests of classifying COVID & pneumonia

DenseNet121

Complexity: 58 layers per Dense Block, 4 Dense Blocks

Previous work has been done on similar classification task: **CheXNet²**

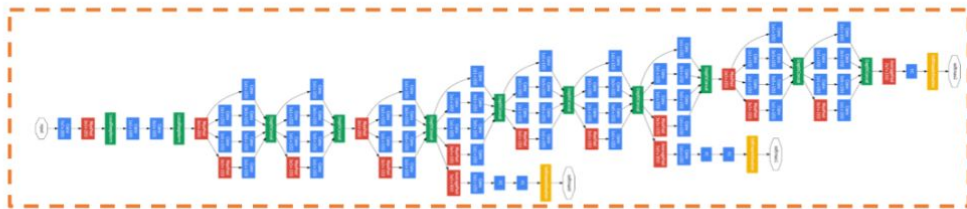
1. Was built on **DenseNet121** to classify lung diseases in chest X-rays
2. Trained on NIH Chest X-ray Dataset (similar to ours)
3. **76.80%** accuracy on pneumonia detection

Used to benchmark the performance with GoogLeNet

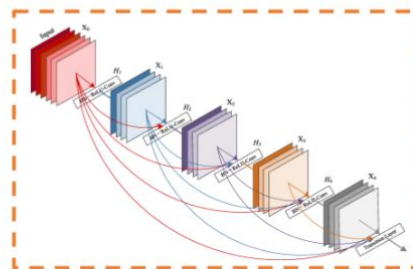
1. Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.
2. Rajpurkar, Pranav, et al. "CheXnet: Radiologist-level pneumonia detection on chest x-rays with deep learning." *arXiv preprint arXiv:1711.05225* (2017).

Pretrained models linked with a 3-layer FC classifier

GoogLeNet (Inception)



DenseNet121



or



224 x 224 RGB
Normalized Input

Freeze weights
& biases

Pre-trained
Model

1000
Channels

Classifier
Input

200
Channels
(40% dropout rate)

3-Layer FC Classifier

50
Channels

Binary Classification

Classifier
Output

Label
Pneumonia
Confidence
95%

Demonstration

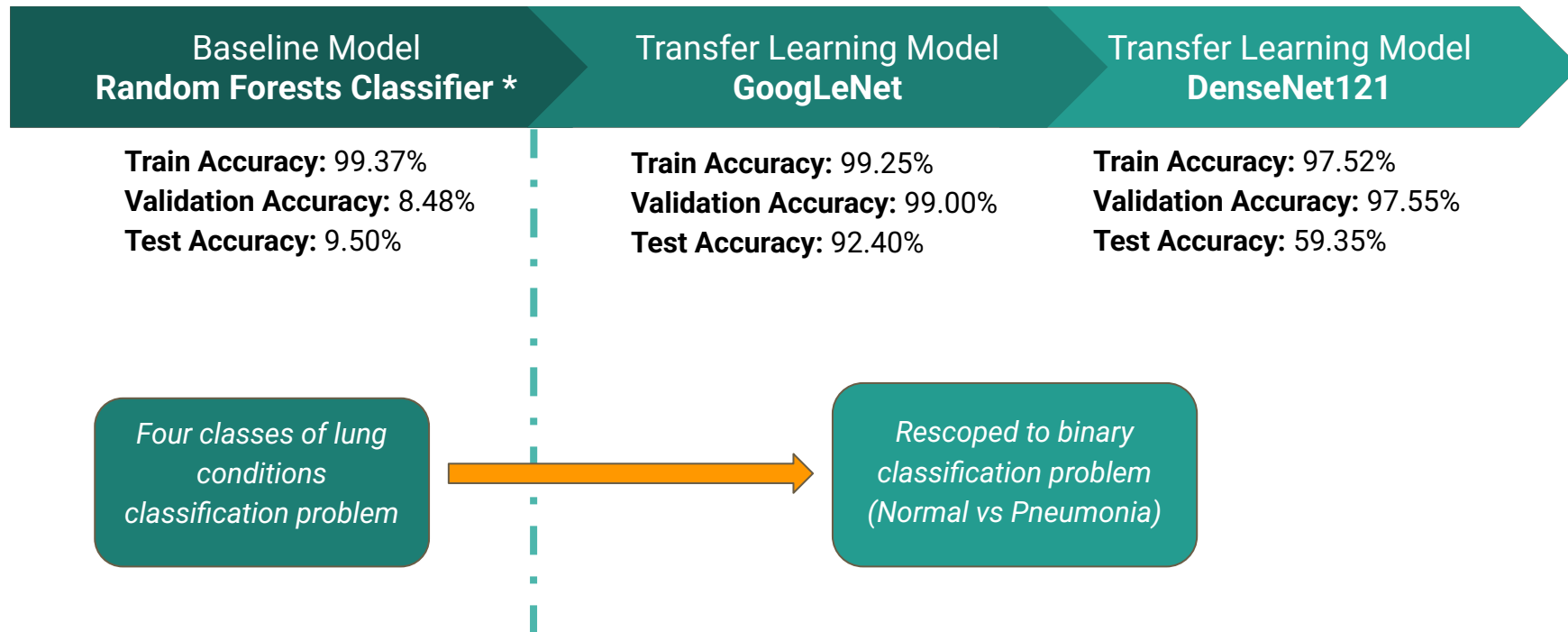
~30 seconds



Results



Baseline model serves to compare the results with the transfer learning models



DenseNet VS. GoogLeNet

(batch_size = 64, epoch = 5)

| | |
|----------------------------------|---------------------|
| Final Training Accuracy | 0.9752348420153715 |
| Final Validation Accuracy | 0.9755194990037005 |
| Testing Accuracy | 0.5935374149659863 |
| Recall | 0.15584415584415584 |

| | |
|----------------------------------|--------------------|
| Final Training Accuracy | 0.9925989183034444 |
| Final Validation Accuracy | 0.9900370054084828 |
| Testing Accuracy | 0.9236161616161616 |
| Recall | 0.9351851851851851 |

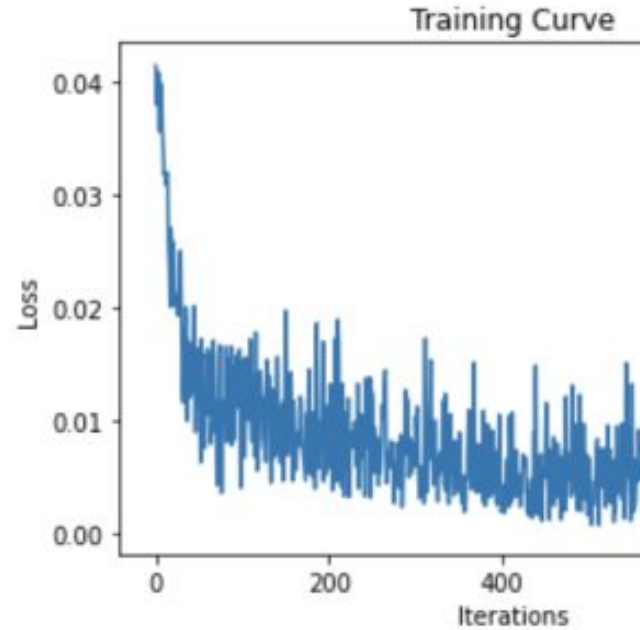
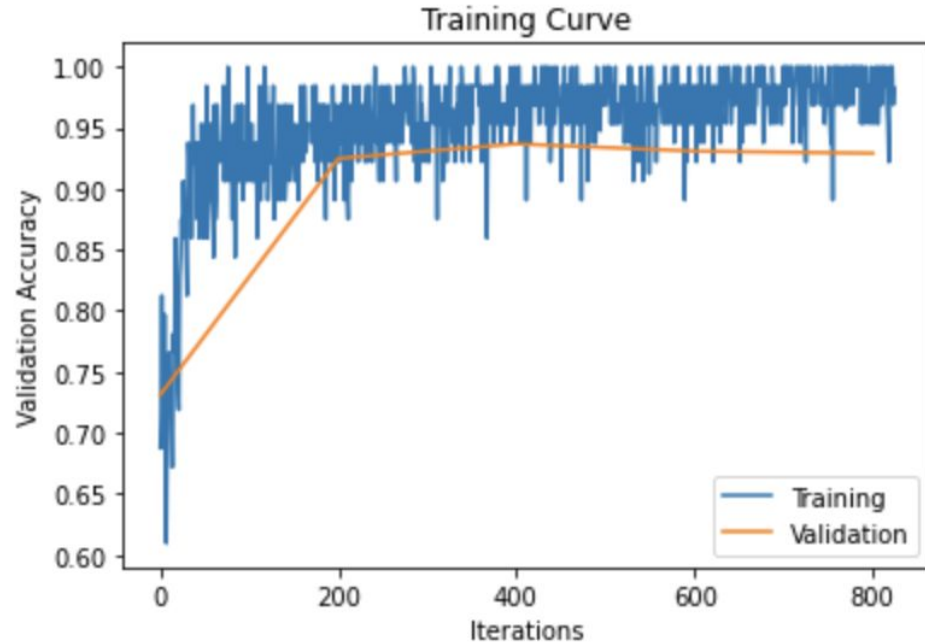
| | |
|----------------------------|---------------------------|
| True Positives (TPs): 32 | False Positives (FPs): 36 |
| False Negatives (FNs): 184 | True Negatives (TNs): 180 |

| | |
|---------------------------|---------------------------|
| True Positives (TPs): 203 | False Positives (FPs): 20 |
| False Negatives (FNs): 13 | True Negatives (TNs): 196 |

Obtaining best results after hyperparameter tuning

| | |
|------------------------|-----------------------------|
| Optimizer | Stochastic Gradient Descent |
| Loss Function | Binary Cross Entropy |
| Batch Size | 64 |
| Learning Rate | 0.01 (SGD default) |
| Momentum | 0.9 (SGD default) |
| Training Epochs | 10 |

Best classification results from GoogLeNet - Qualitative



GoogLenet Learning Curves - Quantitative Results

| | |
|----------------------------------|--------------------|
| Final Training Accuracy | 0.9758041559920296 |
| Final Validation Accuracy | 0.9817819527469399 |
| Testing Accuracy | 0.9259259259259259 |
| Recall | 0.9490740740740740 |
| Precision | 0.9070796460974932 |
| F1 Score | 0.9276018099966283 |

True Positives (TPs):
205

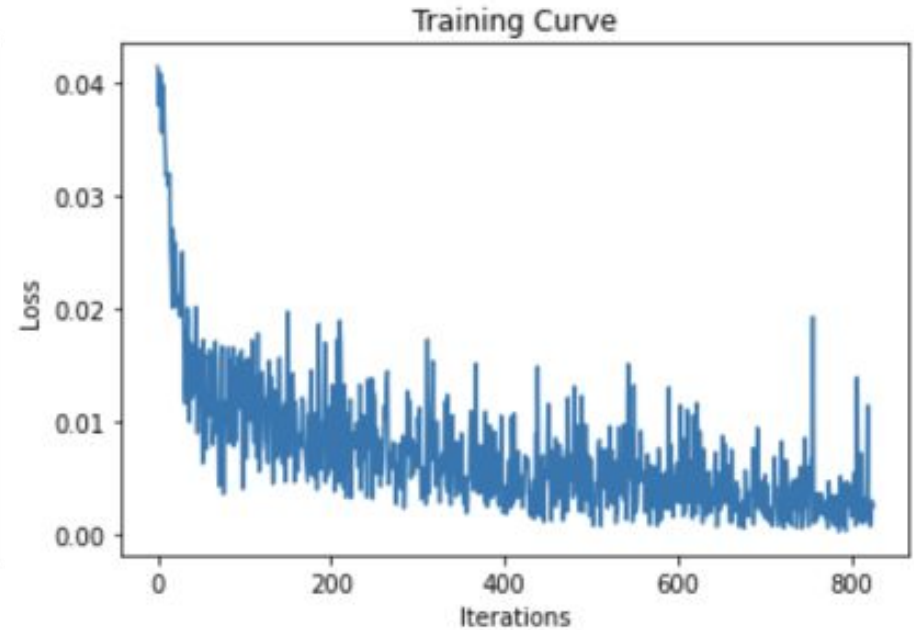
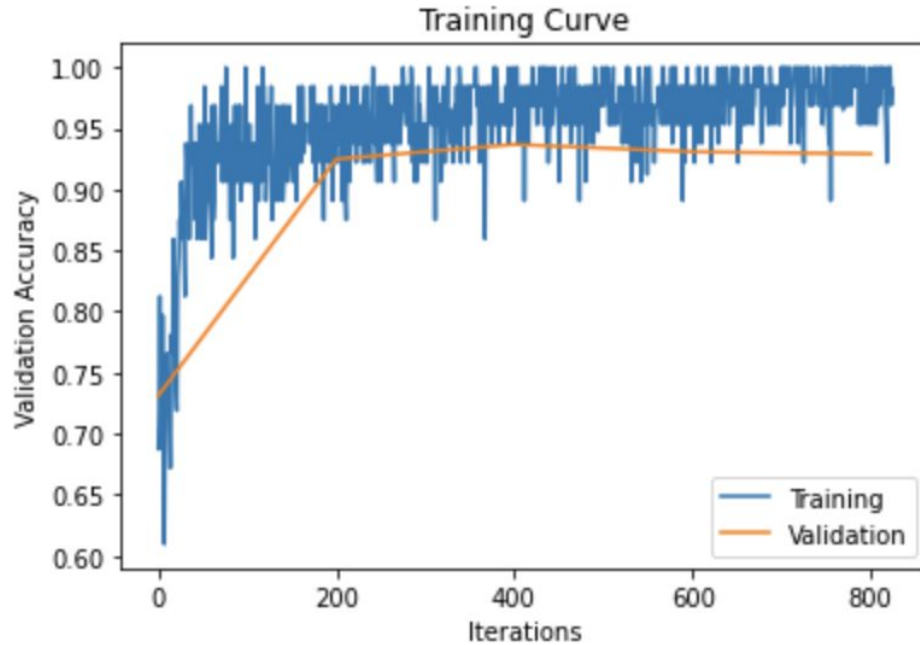
False Positives (FPs):
21

False Negative (FNs):
11

True Negatives (TNs):
195

Discussion

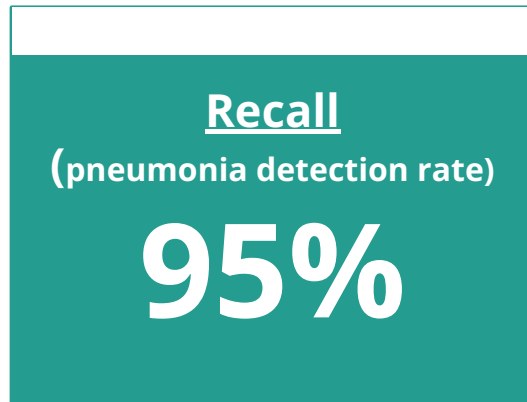
GoogLeNet Model Performance Evaluations



| | |
|---------------------------|--------------------|
| Final Training Accuracy | 0.9758041559920296 |
| Final Validation Accuracy | 0.9817819527469399 |
| Testing Accuracy | 0.9206484641638225 |

GoogLeNet Model Performance Evaluations

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True Positives (TPs): 205

False Positives (FPs): 21

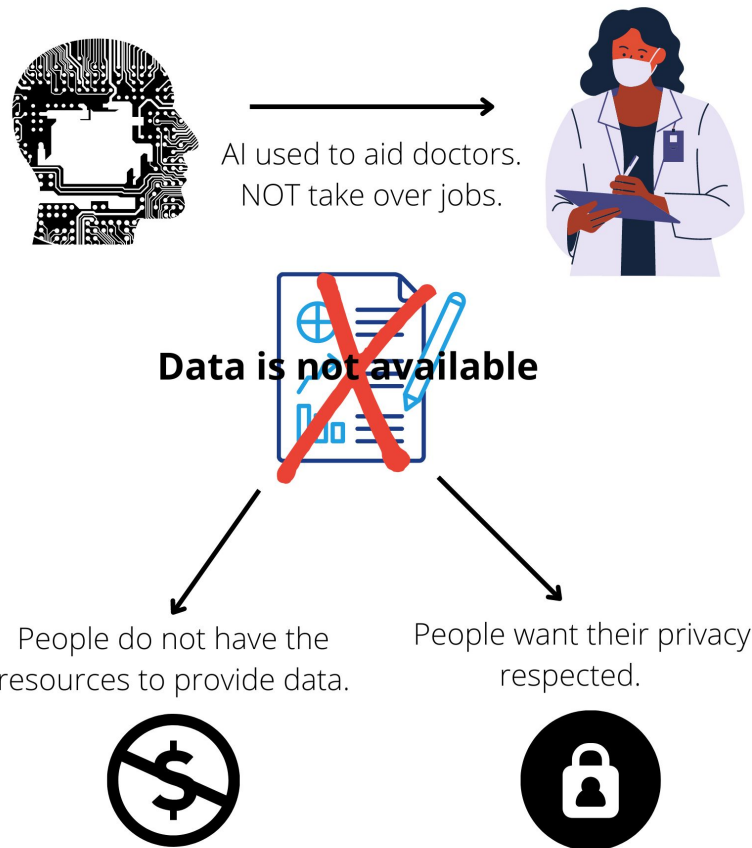
False Negative (FNs): 11

True Negatives (TNs): 195

Final Thoughts

Applications & Ethical Considerations

- People do not want technology overtake the healthcare system
 - Although this may be beneficial in some cases.
- Patient privacy & inconsistent data
 - Marginalized groups who do not wish to share their data or who do not have the resources to obtain scans.



Baseline model

| | | Actuals | |
|-------------|------------|--------------------------------------|--------------------------------------|
| | | Pneumonia | No Finding |
| Predictions | Pneumonia | True Positives (TPs): 310 | False Positives (FPs): 56 |
| | No Finding | False Negative (FNs): 122 | True Negatives (TNs): 376 |

Primary model

| | | Actuals | |
|-------------|------------|--------------------------------------|--------------------------------------|
| | | Pneumonia | No Finding |
| Predictions | Pneumonia | True Positives (TPs): 410 | False Positives (FPs): 42 |
| | No Finding | False Negative (FNs): 22 | True Negatives (TNs): 390 |

Key Takeaways

1. AI-ML field is growing due to diverse people from different academic backgrounds



2. There will always be questions to be answered, facts that we know and exploration to be done

