

# Disease Detection using Chest X-rays

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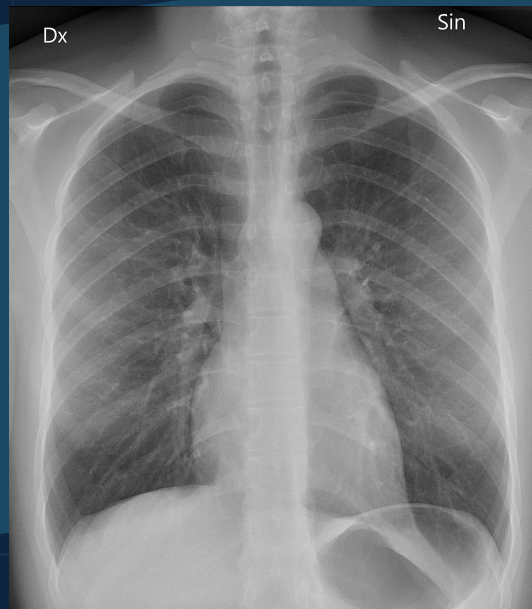


# Introduction

## Motivation behind disease detection using chest X-rays

**Goal:** Use deep learning algorithms to detect diseases using chest x-ray images using CNN architectures.

- Chest X-ray's are the most common used film in medicine to detect lung conditions and were used as a source for detecting Covid-19
- Highly trained radiologists are required to interpret these films
- Image classification techniques can be used to detect anything abnormal and disease progression over time



# Data Sources/EDF

## Mendeley Data

## Kaggle

## NIH

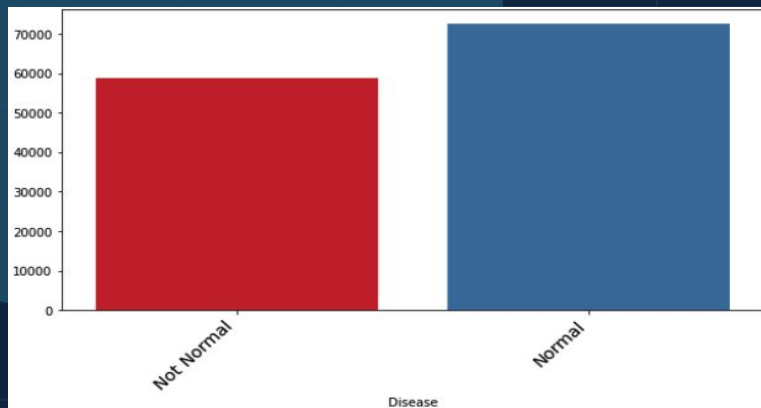


Large Dataset of Labeled  
Optical Coherence  
Tomography (OCT) and  
Chest X-Ray Images

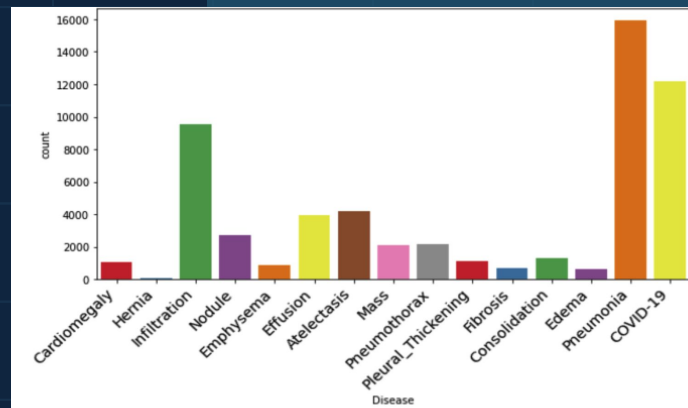
COVID-19 chest X-ray

COVID-QU-Ex Dataset

ChestX-ray8 Database



Distribution of image type



Distribution of not normal images

# Methods - Transfer Learning

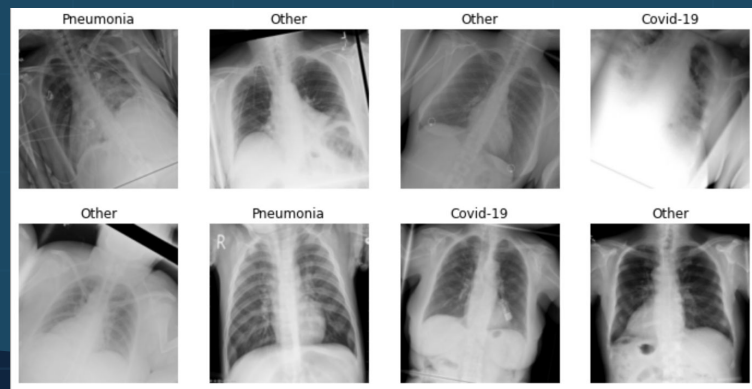
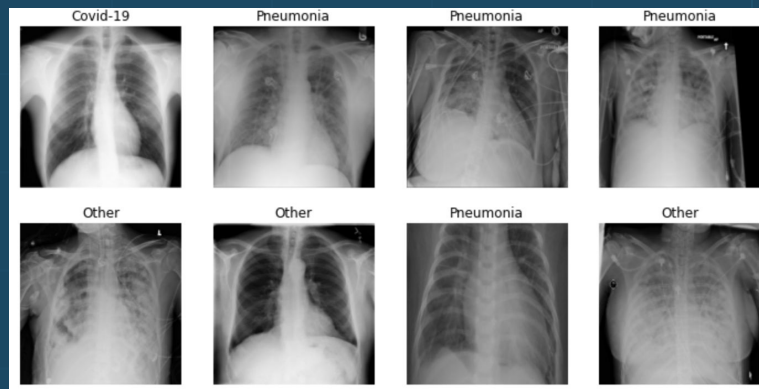
- Explored various transfer learning methods to identify the optimal model binary (normal vs. abnormal) classification multiclass for specific disease (COVID-19, Pneumonia, and Other)
- Adjust hyperparameters further to optimize results

Multiclass Model Hyperparameters								Results
Transfer Learning Model	Data Augmentation	Early Stopping	Optimizer	Learning Rate	Steps per Epoch	Number of Epochs	Etc.	Accuracy
<b>VGG-16</b>								
Model 1	N	N	RMSprop	0.0001	50	5		80%
Model 2	Y	N	RMSprop	0.0001	50	5		87%
<b>VGG-19</b>								
Model 1	Y	Y - Patience: 5	RMSprop	0.0001	50	5		71%
Model 2	Y	Y - Patience: 5	RMSprop	0.0001	50	5		85%
Model 3	N	N	RMSprop	0.0001	50	5		89%
<b>InceptionResNetV2</b>								
Model 1	N	N	RMSprop	0.001			Dropout = 0.7	54%
Model 2	N	N	RMSprop	0.0001			Dropout = 0.5	89%
<b>Inception V3</b>								
Model 1	N	N	RMSprop	0.0001	50	7	Dropout = 0.55	79%
Model 2	N	N	RMSprop	0.0001	50	7	Dropout = 0.7	89%
<b>ResNet-50</b>								
Model 1	N	N	SGD	0.001	50	5		89%
Model 2	Y	N	SGD	0.001	50	5		66%
<b>ResNet-152V2</b>								
Model 1	Y	N	SGD	0.001	50	5		70%
<b>DenseNet-121</b>								
Model 1	N	N	Adam	0.001	50	7	Dropout	31%
Model 2	N	N	Adam	0.001	50	7	Dropout	28%
Model 3	N	N	RMSprop	0.001	50	5	Dropout = 0.5	56%
Model 4	N	N	RMSprop	0.0001	50	5	Dropout = 0.7	95%
Model 5	Y	N	RMSprop	0.0001	50	5	Dropout = 0.7	65%
Model 6	Y	N	RMSprop	0.0001	50	5	Dropout = 0.7	88%
<b>DenseNet-201</b>								
Model 1	Y	N	RMSprop	0.0001	50	5	Dropout = 0.7	68%
Model 2	Y	N	RMSprop	0.0001	50	7	Dropout = 0.8	55%
Model 3	Y	N	RMSprop	0.0001	50	7	Dropout = 0.7	59%
Model 4	Y	N	RMSprop	0.0001	50	5	Dropout = 0.7	81%
Model 5	N	N	RMSprop	0.0001	50	5	Dropout = 0.7	76%
<b>Xception</b>								
Model 1	Y	N	RMSprop	0.0001	50	5		56%
Model 2	Y	N	RMSprop	0.0001	50	5	Dropout = 0.7; Momentum 0.9; Decay 0.01	63%
Model 3	Y	N	RMSprop	0.0001	50	5	Dropout = 0.5; Momentum 0.7; Decay 0.001	65%
Model 4	Y	N	RMSprop	0.001	50	5	Dropout = 0.7; Momentum 0.7; Decay 0.001	53%
Model 5	Y	N	RMSprop	0.0001	50	5	Dropout = 0.5; Momentum 0.7; Decay 0.001	60%

Multiclass Model Hyperparameters

# Methods - Data Augmentation

- Augmented data with horizontal flip and rotation transformations
- Increase the volume and diversity of the data during the training process
- Minimize overfitting



# Results

Type	Multiclass	Binary
DenseNet-121	95%	67%
DenseNet-201	81%	58%
Inception-V3	89%	63%
Inception ResNet-V2	89%	71%
ResNet-50	89%	55%
ResNet-152V2	70%	53%
VGG-16	87%	68%
VGG-19	89%	57%
Xception	65%	56%

# Binary - Additional Metrics

Type	Accuracy	AUC	Precision	Recall
DenseNet-121	67	0.78	0.64	0.84
DenseNet-201	58	0.71	0.56	0.97
Inception V3	63	0.67	0.66	0.75
Inception ResNet V2	71	0.78	0.75	0.67
ResNet-50	55	0.55	0.62	0.91
ResNet-152V2	53	0.5	0.53	0.9975
VGG-16	68	0.76	0.77	0.57
VGG-19	57	0.66	0.55	0.92
Xception	56	0.6	0.8	0.22

- Inception ResNet V2 top performer
- No Data Augmentation
- Adam optimizer with a learning rate = 0.0001

# Conclusions



## Binary vs. Multiclass

As expected from previous research, the multi-classification performed better than binary classification.

Trends are more easily identified for specific diseases rather than generalized for all types of anomalies.



## Data

## Augmentation

Horizontal transformations generated better results than other augmentation strategies.



## Overall

## Performance

DenseNet-121 classified the chest X-rays of COVID-19, Pneumonia, and Other with 95% accuracy.

Inception ResNet-V2 classified chest X-rays as normal and abnormal with 71% accuracy.

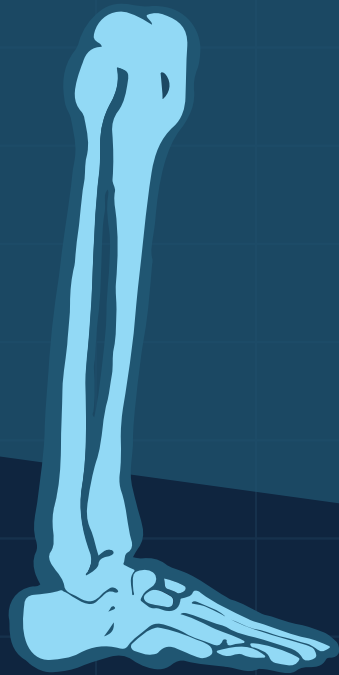


# Questions



# Appendix

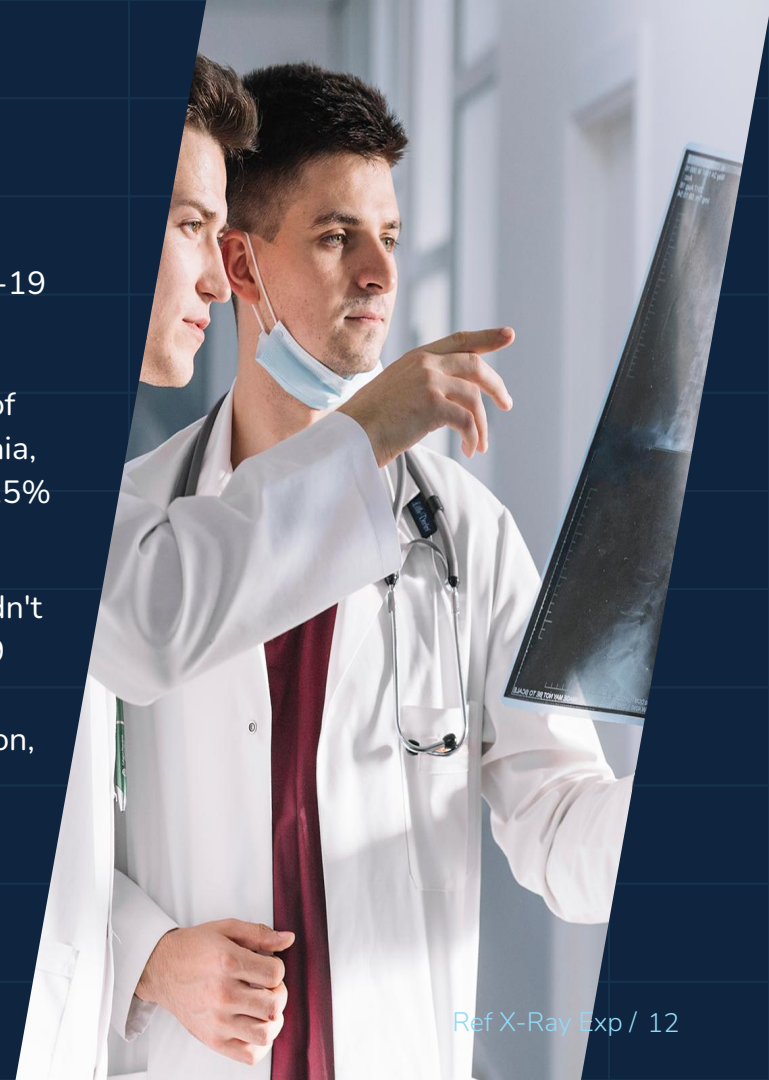
# Literature Review



- X-ray detection via deep learning can provide high accuracy over multiple illness
  - Many existing algorithms that leverage deep learning methods on chest X-ray images were for specific clinical conditions such as cancer, pneumonia, tuberculosis, etc.
- In one study, multiple CNN architectures were evaluated that included GoogleNet, SqueezeNet, DenseNet, SuffleNet and MobileNetV2 to classify lung tumors into malignant and benign categories.
- Generally, radiologists can improve their performance by reviewing results from a deep-learning model

# Literature Review

- There have been many research papers published related to Covid-19 that utilize deep learning techniques using chest x-rays
- In one study, chest x-ray images were classified into a similar set of three classes as compared to previous articles: Covid-19 pneumonia, no-Covid-19 pneumonia, and non-pneumonia and resulted in a 94.5% overall accuracy
  - This improves upon a previously mentioned study that couldn't as accurately classify Covid-19 pneumonia and no-Covid-19 pneumonia because this experiment uses two image pre-processing steps to remove most of the diaphragm region, remove image noise and improve image contrast as well as creates a pseudo color image to feed into an existing deep learning model that is already a strong performer for color images in a transfer learning strategy



# Contributions

## Manpreet Dhindsa

- Multi-Class Classification
- Supported Binary Classification
- Wrote Report/Slides

## Gretchen Larrick

- Data Preparation and Handling
- Binary Classification
- Wrote Report/Slides

## Sarah Rodgers

- Data Augmentation
- Supported classifications
- Wrote Report/Slides