

Detecting Pneumonia in Chest X-Rays

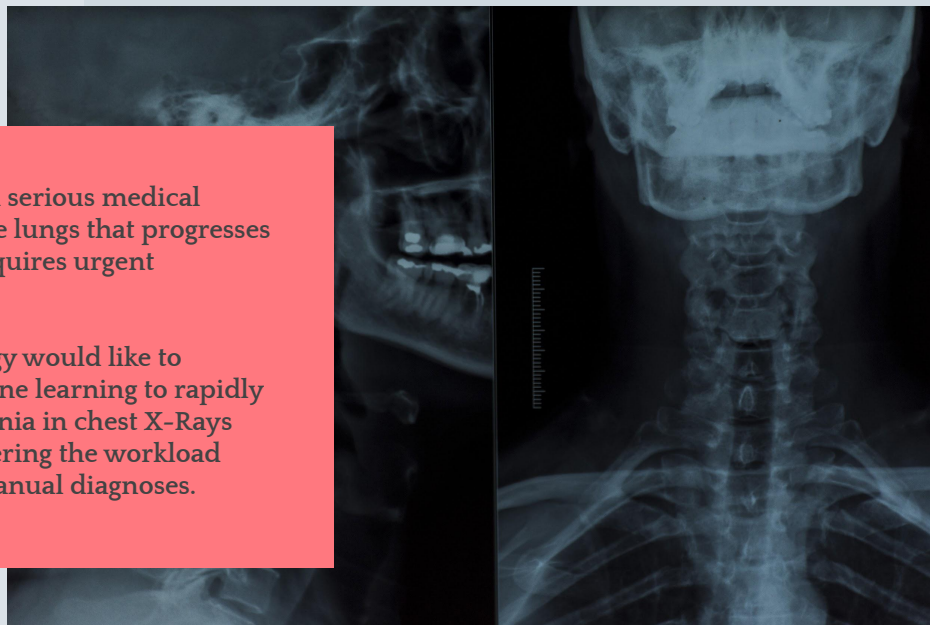
ROBERT HARROW
Flatiron School



INTRODUCTION

Pneumonia is a serious medical condition of the lungs that progresses quickly and requires urgent treatment.¹

ACME Radiology would like to leverage machine learning to rapidly detect Pneumonia in chest X-Rays while also lowering the workload required for manual diagnoses.



1. <https://frontlineer.com/when-to-go-to-urgent-care-for-pneumonia/>

BUSINESS PROBLEMS

1

Save time for ACME Radiology department from having to manually evaluate chest x-rays for Pneumonia

2

Develop machine learning model that achieves at least 90% F1 score

3

Identify model limitations before implementing into the field



SUCCESS METRICS



F1 SCORE

Balance between
precision (no false
positives) and recall
(tolerating some false
positives)

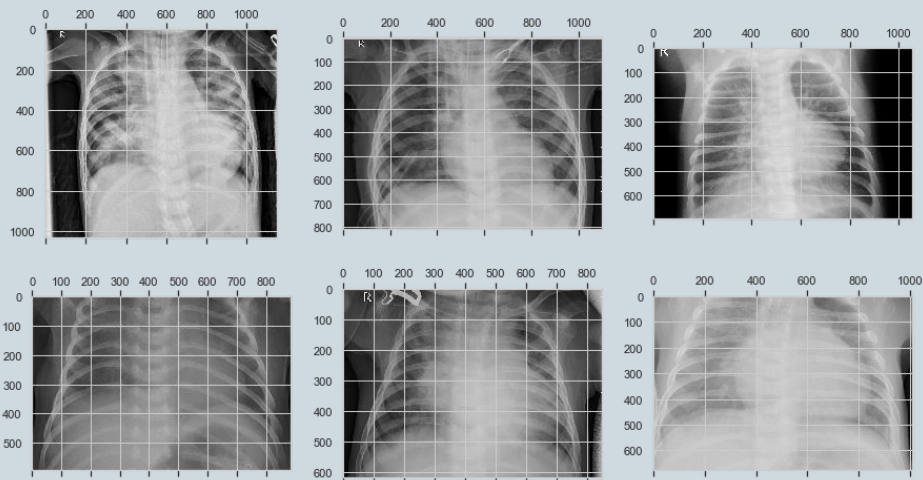
Recall

While F1 is the
primary metric, we
can use Recall as a
tiebreaker

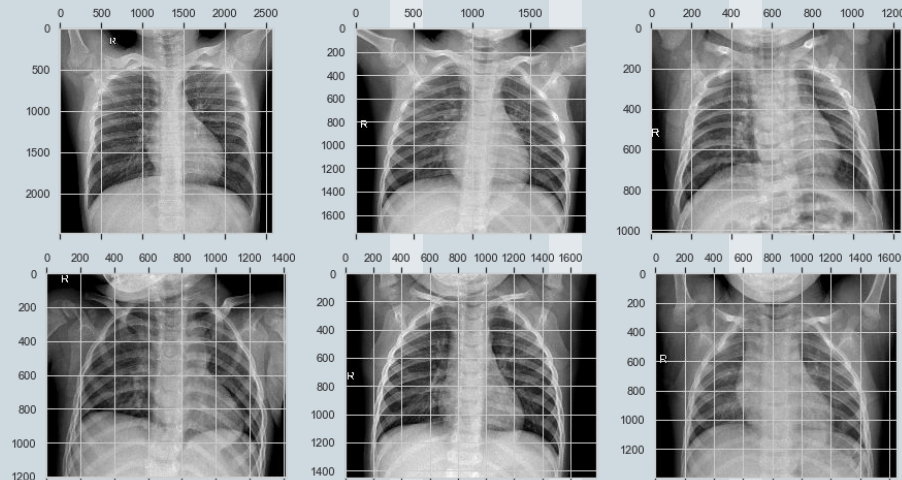


DATA & METHODS

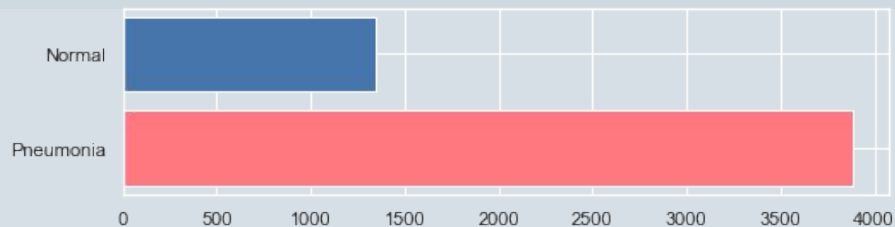
Chest X-Rays with Pneumonia



Chest X-Rays without Pneumonia



of Training Images by Class

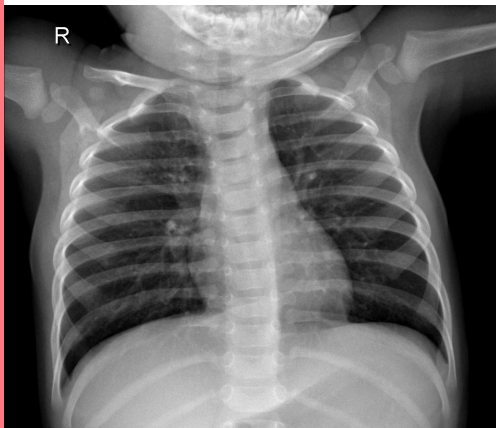


5,232
CHEST X-RAYS

From Kermayn et al. (Mendeley)

WHAT IS THE NEURAL NETWORK LOOKING FOR?

NO
PNEUMONIA



PNEUMONIA
DETECTED

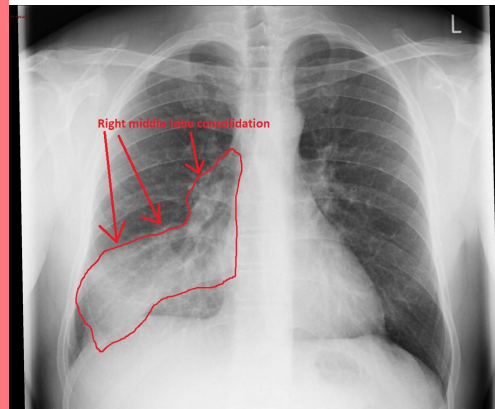


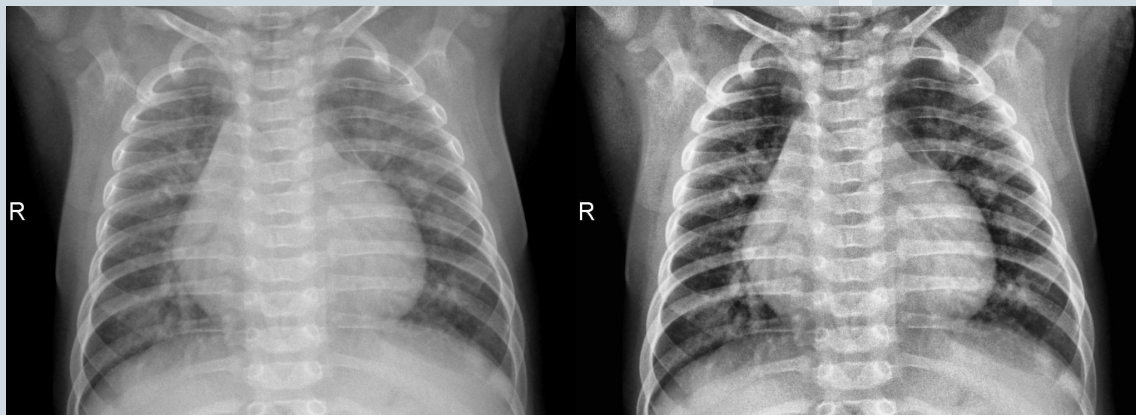
Image Source:
https://www.wikidoc.org/index.php/Pneumonia_chest_x_ray

Histogram Equalization

Research shows this technique **improved model performance** for pneumonia detection and our best performing model incorporated transformed images


ORIGINAL IMAGE

AFTER HISTOGRAM EQUALIZATION



MODEL ITERATIONS

VALIDATION DATA SCORES

	Accuracy	Precision	Recall	F1
Baseline	0.97	0.94	0.96	0.95
'Complex' Dense Model	0.97	0.96	0.95	0.95
'Simple' CNN	0.97	0.97	0.92	0.94
CNN on High-Contrast X-Rays	0.97	0.99	0.87	0.93
 VGG-19	0.98	0.99	0.99	0.99
ResNet-50	0.97	0.99	0.97	0.98

DATA METHODS

VGG-19 NEURAL NETWORK

MODEL STRUCTURE

- 1 Input Layer (224 x 224 x 3)
- 5 MaxPooling2D Layers
- 16 Conv2D Layers

20,024,384 Non-Trainable Parameters

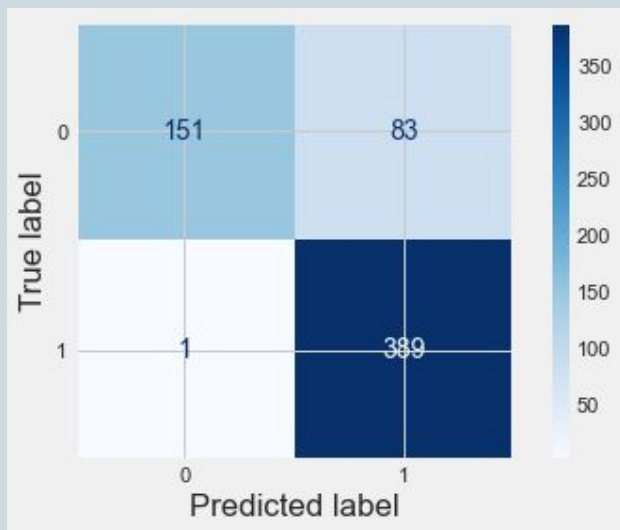


- 1 MaxPooling2D Layer
- 1 Flatten, 1 Dropout Layer
- 1 Output Layer

50,178 Trainable Parameters

FINAL MODEL EVALUATION

VGG-19 NEURAL NETWORK



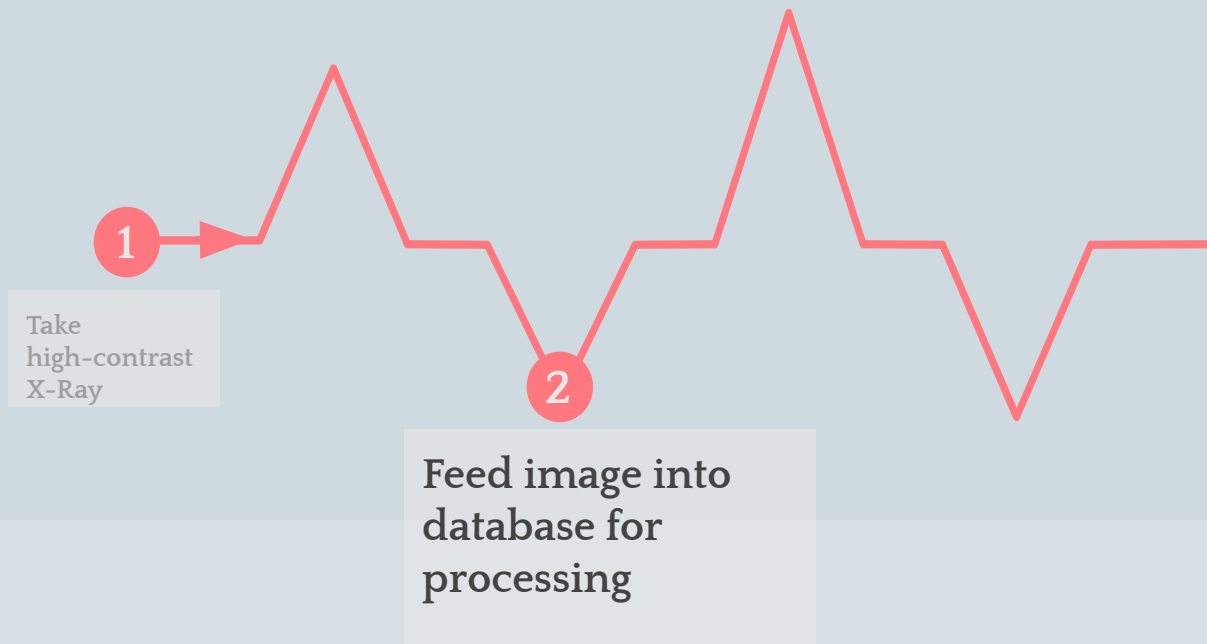
- Accuracy: 0.87
- Precision: 0.82
- Recall: 0.99
- F1 score: 0.90

RECOMMENDATIONS

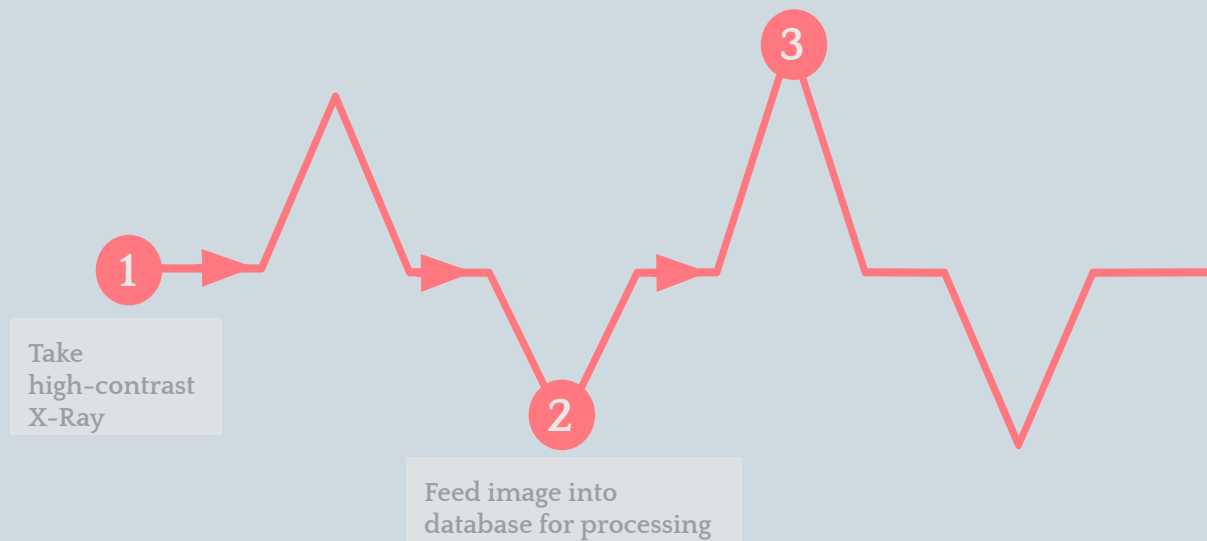
1

Take
high-contrast
X-Ray

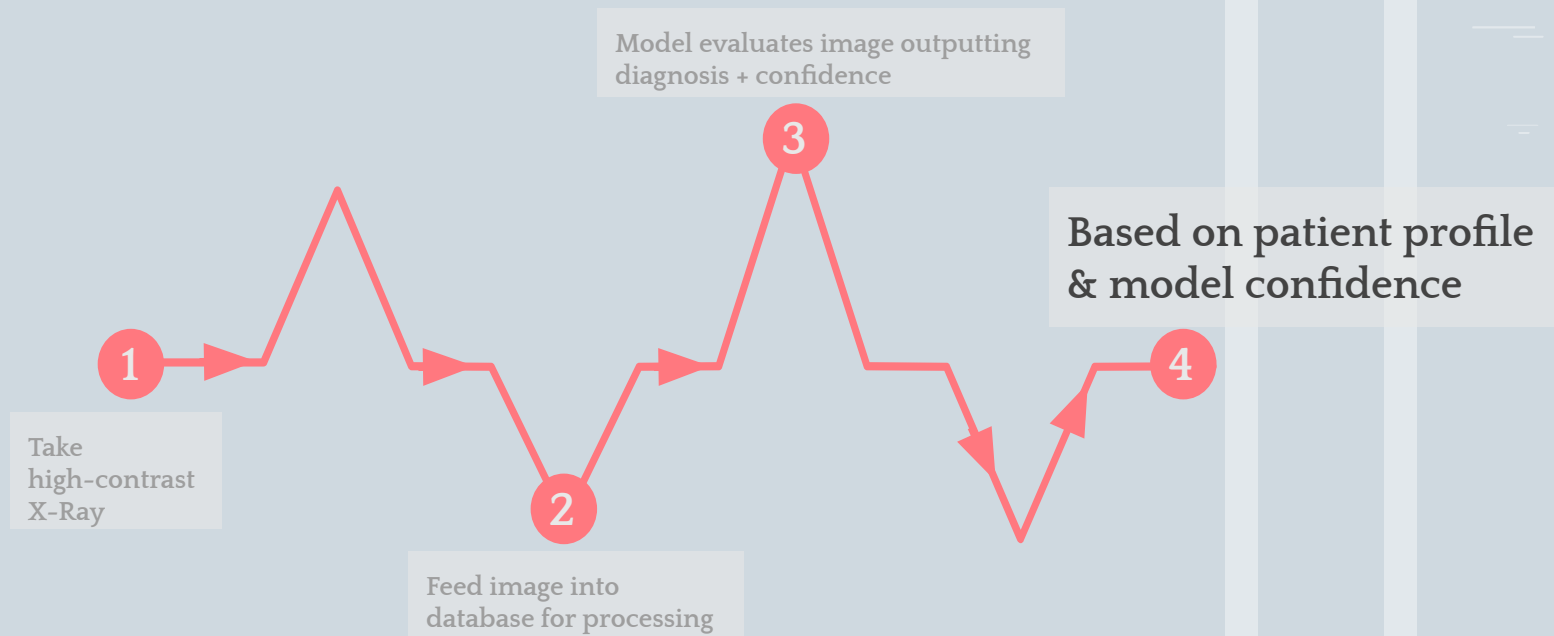
RECOMMENDATIONS



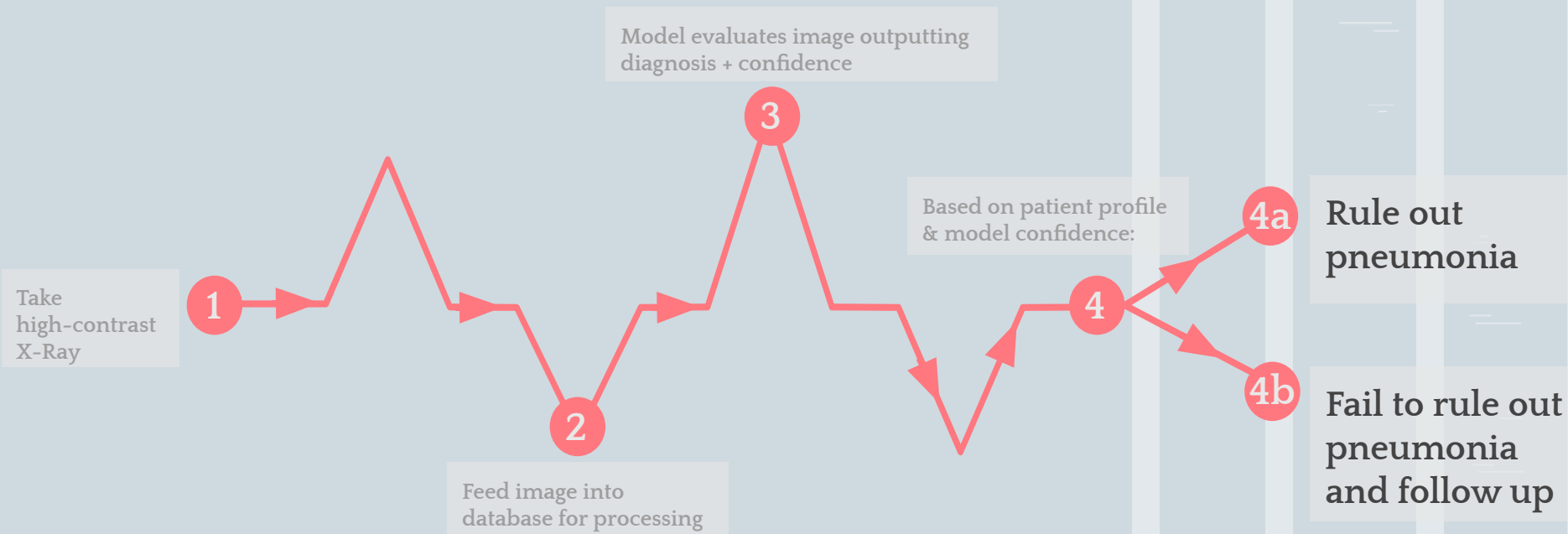
RECOMMENDATIONS



RECOMMENDATIONS



RECOMMENDATIONS



MODEL LIMITATIONS



Limited healthy
samples in
training set



Confidence
threshold is
currently arbitrarily
set at 50%



Potential for
misdiagnosis when
diseases present
symptoms similar to
Pneumonia



- **Productionize and deploy** model into ACME workflow
 - **Develop web interface** for medical staff
- **Collect more healthy samples** to train model
- **Educate staff** on how to interpret model results
- Future work should **explore transfer learning with other promising models**, including MobileNet and DenseNet-201

THANK YOU

Does anyone have any questions?

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<https://www.linkedin.com/in/robert-harrow/>

<https://github.com/robertharrow>



APPENDIX

TRANSFER LEARNING

*“Transfer learning is a machine learning method where a **model developed for a task is reused as the starting point for a model on a second task**.” – Jason Brownlee, Machine Learning Mastery*

- Naronglerdrit P, Mporas I, Sheikh-Akbari A. COVID-19 detection from chest X-rays using transfer learning with deep convolutional neural networks – [Epub \(2021\)](#)
- Chakraborty S, Paul S, Hasan KMA. A transfer learning-based approach with deep CNN for COVID-19- and pneumonia-affected chest X-ray image classification. – [PubMed \(2022\)](#)
- B. Pardamean, T.W. Cenggoro, R. Rahutomo, A. Budiarto, E.K. Karuppiah. Transfer Learning from Chest X-Ray Pre-trained Convolutional Neural Network for Learning Mammogram Data – [Procedia Comput. Sci., 135 \(2018\)](#)

FULL MODEL STRUCTURE

VGG-19 NEURAL NETWORK

MODEL STRUCTURE

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv4 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv4 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv4 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dropout (Dropout)	(None, 25088)	0
dense_13 (Dense)	(None, 2)	50178
=====		
Total params: 20,074,562		
Trainable params: 50,178		
Non-trainable params: 20,024,384		

These layers are pre-trained
on over **1 MILLION** images

We transfer the model's
learnings from those million
images to our image
classification problem

We then add additional
output layers to train model
on our X-Ray Images