FDA Submission

Your Name: Dinesh K.

Name of your Device: Pneumonia Reader Assistant

Algorithm Description

1. General Information

Intended Use Statement: Assist radiologist in classifying a given chest x-ray for the presence or absence of pneumonia.

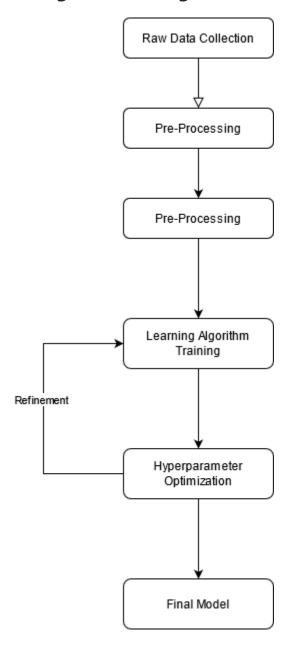
Indications for Use: Indicated for use in screening Pneumonia in males and females of ages 1-95 years having one or more combination of following diseases: atelectasis, heart enlargement, standardization, edema, effusion, emphysema, fibrosis, hernia, infiltration, mass, Creed, pleura thickening and pneumothorax.

Device Limitations:

- GPU processing required for running model. Otherwise, there will be time-lag in prediction.
- Model is trained on available NIH Chest x-ray dataset. The image intensity distribution of pneumonia and other diseases such as Infiltration and effusion are almost similar. This may lead to false results.

Clinical Impact of Performance: The algorithm is designed to have high recall. When a high recall test returns a negative result, we can be confident that the result is truly negative since a high recall test has low false negatives. This is especially useful in worklist prioritization where we want to make sure that people without the disease are being de-prioritized.

2. Algorithm Design and Function



DICOM Checking Steps: The DICOM metadata is checked for following:

- Modality = DX
- Body Part Examined = Chest
- Patient Position in [PA, AP]

Preprocessing Steps: All the images have been normalized in range of [0, 1] using standardization and then the images are resized to (224, 224, 3).

CNN Architecture: Model is created using a pre-trained VGG-16 network with fine tuning done on the last convolution layer. First 17 layers from VGG16 network was used as-is (Frozen /non-trainable). Model architecture is as follows,

Output Shape	Param #
(None, 7, 7,	512) 14714688
(None, 25088)	0
(None, 25088)	0
(None, 1024)	25691136
(None, 1024)	0
(None, 512)	524800
(None, 512)	0
(None, 256)	131328
(None, 256)	0
(None, 64)	16448
(None, 1)	65
	(None, 7, 7, (None, 25088) (None, 25088) (None, 1024) (None, 1024) (None, 512) (None, 512) (None, 552) (None, 256) (None, 256) (None, 64)

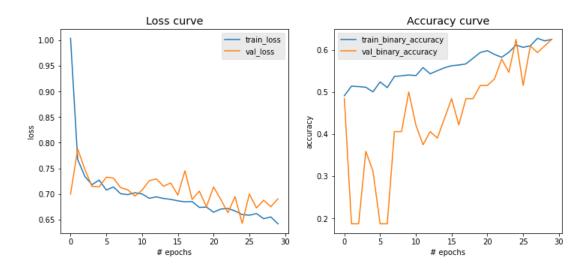
3. Algorithm Training

Parameters:

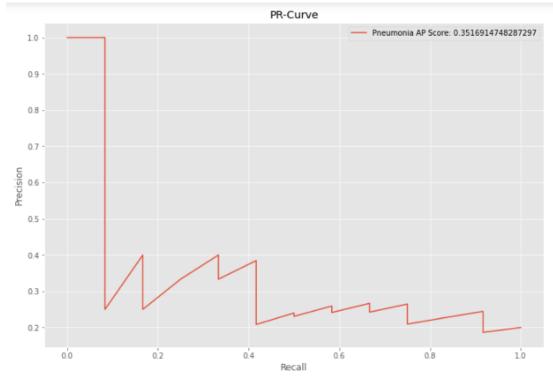
- Types of augmentation used during training:
 - Horizontal Flip
 - o Random Rotation up to 20 degrees
 - o Random shear range of (+/-) 10%
 - o Random width shift of (+/-) 10%
 - $_{\circ}$ Random height shift of (+/-) 10%
 - \circ Random zoom range of (+/-) 12%
- Batch size: 128
- Optimizer learning rate: 1e-4

- Layers of pre-existing architecture that were frozen: First 17 layers of VGG pretrained network
- Layers of pre-existing architecture those were fine-tuned: Last convolutional layer and all fully-connected layers of the architecture. Drop out of 0.5 is used during fully connected layer to fine tune model and avoid overfitting.

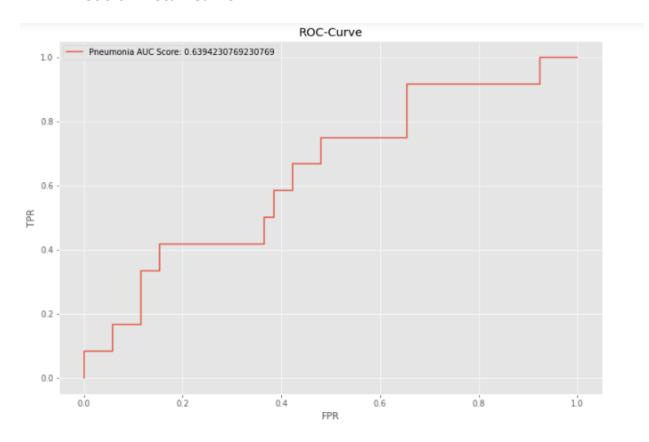
Loss and Accuracy curve



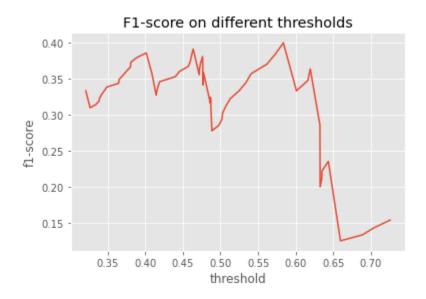
• Precision-Recall Curve



• Precision-Recall Curve



• F1 Scores on different thresholds



Precision at 0.5836243033409119 threshold is 0.38461538461538464. Recall at 0.5836243033409119 threshold is 0.416666666666667. F1 score at 0.5836243033409119 threshold is 0.4.

Final Threshold and Explanation:

- Maximum F1 score of this model at threshold of 0.58 is 0.4.
- This is slightly higher than average Radiologist F1 score which is at 0.38 as per ChexNet paper (https://arxiv.org/pdf/1711.05225.pdf).

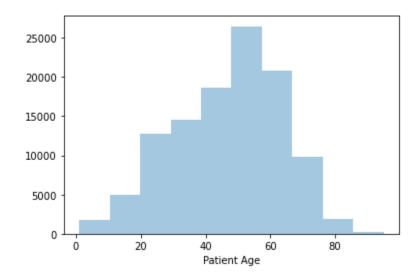
4. Databases

Chest X-ray exams are one of the most frequent and cost-effective medical imaging examinations available. However, clinical diagnosis of a chest X-ray can be challenging and sometimes more difficult than diagnosis via chest CT imaging. The lack of large publicly available datasets with annotations means it is still very difficult, if not impossible, to achieve clinically relevant computer-aided detection and diagnosis (CAD) in real world medical sites with chest X-rays.

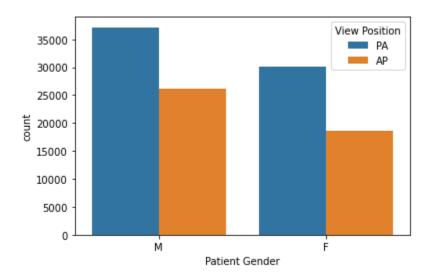
This NIH Chest X-ray Dataset is comprised of 112,120 X-ray images with disease labels from 30,805 unique patients. The CSV file has following columns:

- 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
- OriginalImagePixelSpacing_x
- OriginalImagePixelSpacing_y

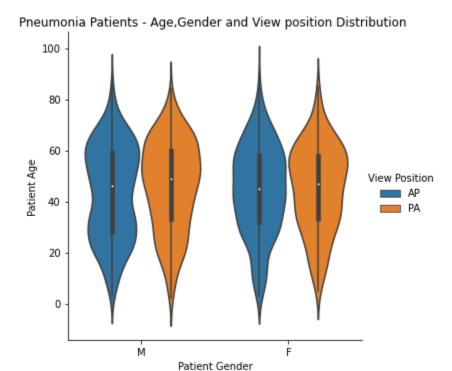
Patient Age Distribution



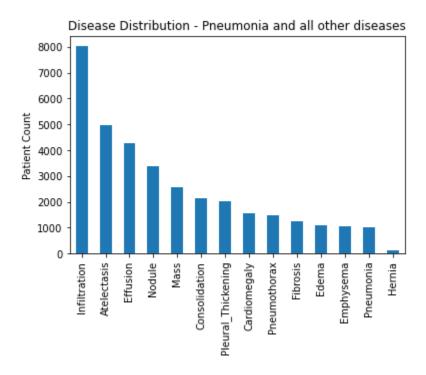
• Patient Gender Distribution along with X-ray view position (PA vs AP)



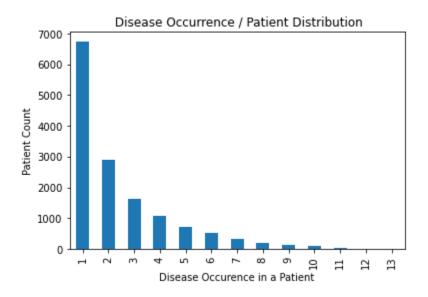
Pneumonia patients – Age, Gender and X-ray view position (PA vs AP)
 Distribution



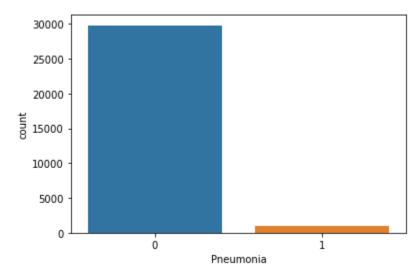
Disease Distribution - Pneumonia and all other diseases



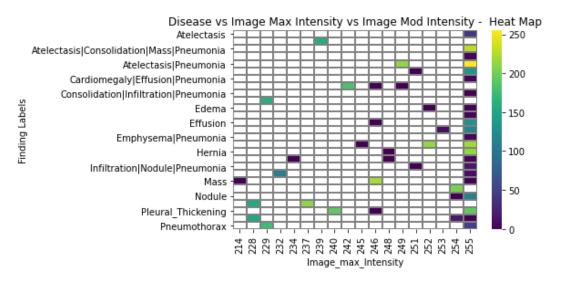
• Disease Occurrence/Patient Distribution - Pneumonia and all other diseases

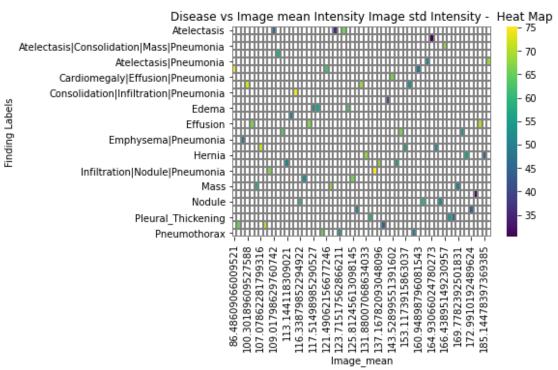


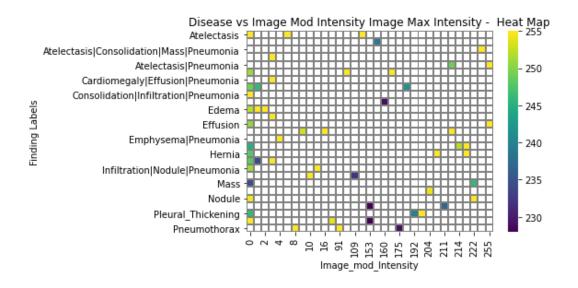
• Patient count with Pneumonia(1) and Non-Pneumonia disease(0)

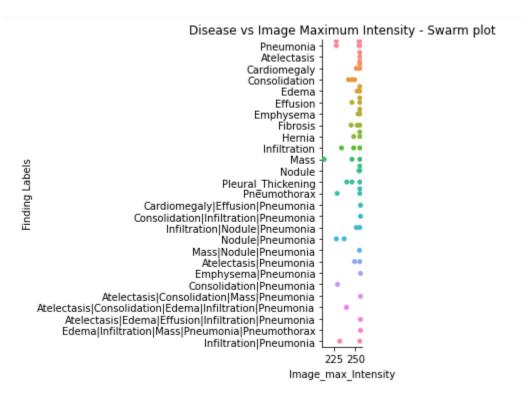


• Diseases pixel intensity plots(Sample data)

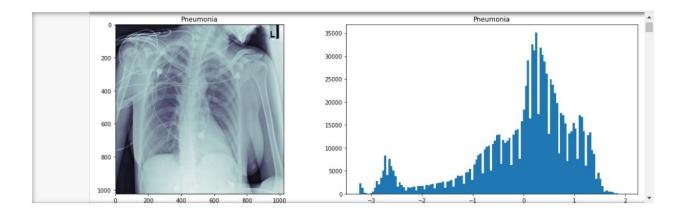








Sample Pneumonia image and standardized intensity distribution



Description of Training Dataset: The training data has 2290 chest-xray images. These are evenly distributed to have 50% pneumonia cases and 50% non-pneumonia cases.

```
Total number of records in this dataset is: 112120 ###Training Dataset Information###:

Total number of records in the training dataset is: 2290

Total number of Pneumonia records in the training dataset is: 1145

Total number of Non-Pneumonia records in the training dataset is: 1145
% of Pneumonia cases in the training dataset is: 50.0
% of Non-Pneumonia cases in the training dataset is: 50.0
```

Description of Validation Dataset: The training data has 1430 chest-x-ray images. These are distributed to have 20% pneumonia cases and 80% non-pneumonia cases to be a representation of real-world scenario.

```
Total number of records in this dataset is: 112120 ### Validation Dataset Information###:
Total number of records in the validation dataset is: 1430
Total number of Pneumonia records in the validation dataset is: 286
Total number of Non-Pneumonia records in the validation dataset is: 1144% of Pneumonia cases in the validation dataset is: 20.0% of Non-Pneumonia cases in the validation dataset is: 80.0
```

5. Ground Truth

To create these ground truth, the authors used Natural Language Processing to textmine disease classifications from the associated radiological reports. The labels are expected to be >90% accurate and suitable for weakly-supervised learning.

6. FDA Validation Plan

Patient Population Description for FDA Validation Dataset: The FDA Validation dataset contains patients (both male and female) in age-range of 1-95 years. It includes 20% pneumonia cases and 80% non-pneumonia cases. Dataset includes multiple follow-up records for a given patient. Total number of records in the validation set is 1430.

Ground Truth Acquisition Methodology: The image labels are NLP extracted with estimated accuracy > 90 %. There could be chance that some labels are incorrect.

Algorithm Performance Standard: The algorithm performance has been validated using F1-score. The F1 score combines both precision and recall. F1 score allows us to better measure a test's accuracy when there are class imbalances. Model F1-score is 0.4 which is better than radiologist average F1-score of 0.387.