Interim Report

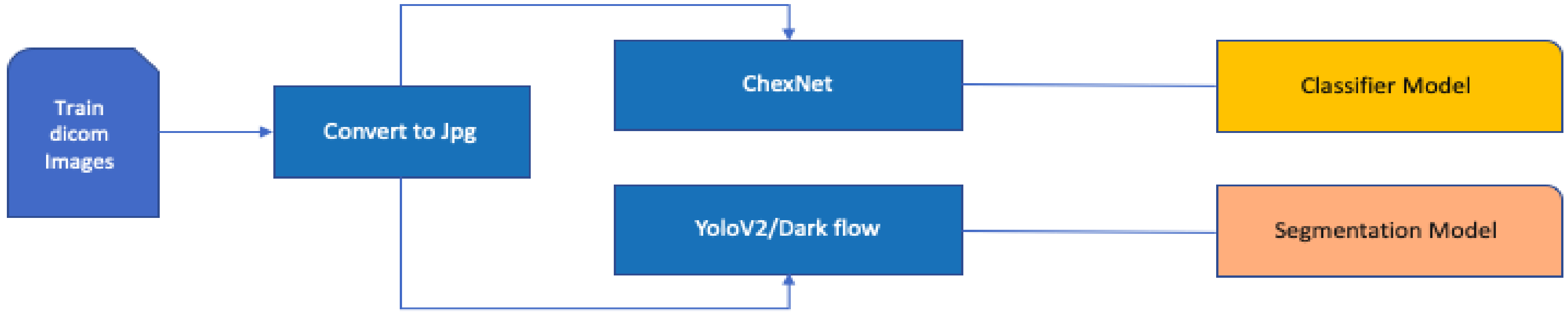
Pneumonia detection challenge

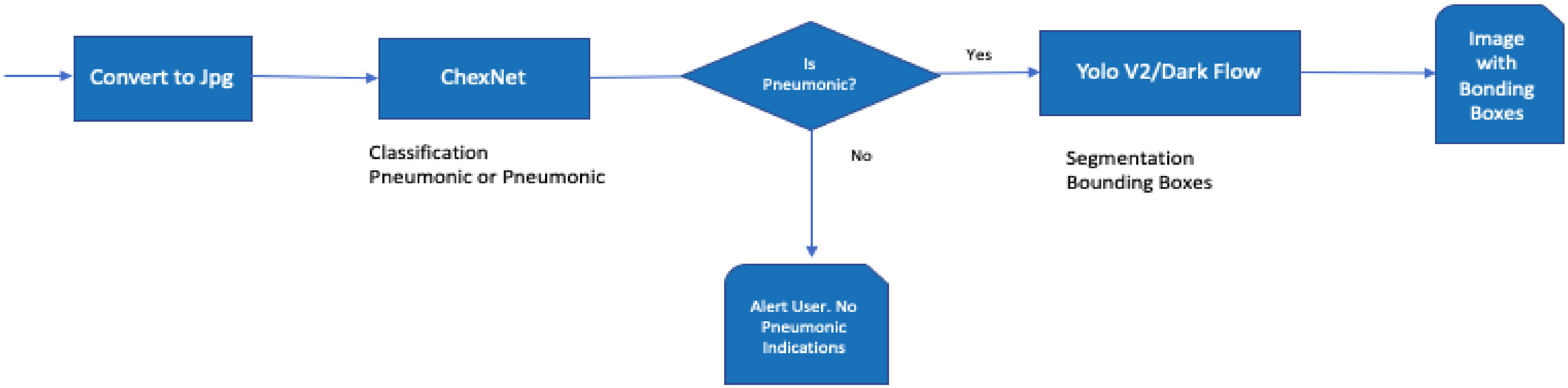
Proposed Solution-

- Build a deep learning model to detect and classify images of potential pneumonia cases so that doctors can prioritize and expedite their review.
- The model should predict whether pneumonia exists in a given image.
- The application should also predict by predicting bounding boxes around areas of the lung.
- Samples without bounding boxes are negative and contain no definitive evidence of pneumonia.
- Samples with bounding boxes indicate evidence of pneumonia.

YOLO/OpenCV DarkFlow – TensorFlow implementation of YOLO
ChexNet

Training - Architecture





Production - Architecture

Evaluation Metrics-

- The evaluation metrics is based on the mean average precision at different intersection over union (IoU) thresholds. The IoU of a set of predicted bounding boxes and ground truth bounding boxes is calculated as:

$$IoU(A,B)=A\cap BA\cup B.IoU(A,B)=A\cap BA\cup B.$$

- The metric sweeps over a range of IoU thresholds, at each point calculating an average precision value. The threshold values range from 0.4 to 0.75 with a step size of 0.05: (0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.75). In other words, at a threshold of 0.5, a predicted object is considered a "hit" if its intersection over union with a ground truth object is greater than 0.5.

- At each threshold value tt, a precision value is calculated based on the number of true positives (TP), false negatives (FN), and false positives (FP) resulting from comparing the predicted object to all ground truth objects:

$$TP(t)TP(t)+FP(t)+FN(t).TP(t)TP(t)+FP(t)+FN(t).$$

- A true positive is counted when a single predicted object matches a ground truth object with an IoU above the threshold. A false positive indicates a predicted object had no associated ground truth object. A false negative indicates a ground truth object had no associated predicted object.

- **Important note:** if there are no ground truth objects at all for a given image, ANY number of predictions (false positives) will result in the image receiving a score of zero, and being included in the mean average precision.
The average precision of a single image is calculated as the mean of the above precision values at each IoU threshold:

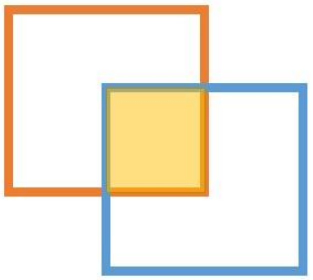
1|thresholds|∑tTP(t)TP(t)+FP(t)+FN(t).1|thresholds|∑tTP(t)TP(t)+FP(t)+FN(t).

- Bounding boxes will be evaluated in order of their confidence levels in the above process. This means that bounding boxes with higher confidence will be checked first for matches against solutions, which determines what boxes are considered true and false positives.

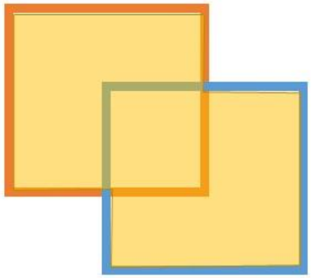
Intersection over Union (IoU)

- Intersection over Union is a measure of the magnitude of overlap between two bounding boxes (or, in the more general case, two objects). It calculates the size of the overlap between two objects, divided by the total area of the two objects combined.

- The two boxes in the visualization overlap, but the area of the overlap is insubstantial compared with the area taken up by both objects together. IoU would be low - and would likely not count as a "hit" at higher IoU thresholds.



$$Intersection\ over\ Union\ (IoU) = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$



Prediction

Ground-truth

Exploratory Data Analysis-

Preliminary EDA insights - class_info dataset

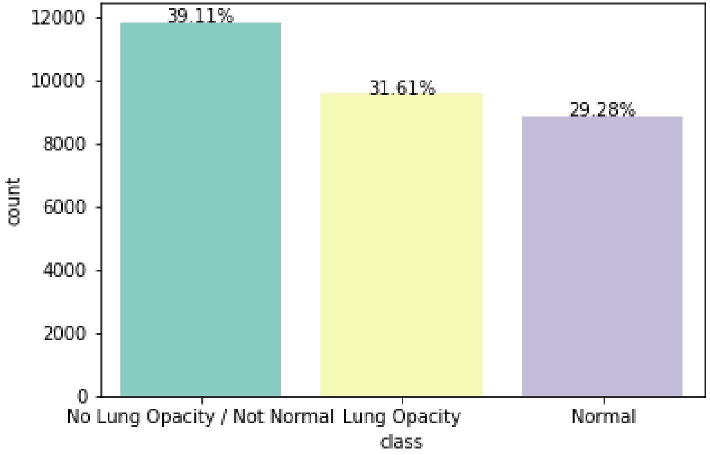
- 30227 rows and 2 columns
    - patientId and class

- Missing values – nil
- 26684 unique patients
- Class distribution

	patientId	class
0	0004cfab-14fd-4e49-80ba-63a80b6bddd6	No Lung Opacity / Not Normal
1	00313ee0-9eaa-42f4-b0ab-c148ed3241cd	No Lung Opacity / Not Normal
2	00322d4d-1c29-4943-afc9-b6754be640eb	No Lung Opacity / Not Normal
3	003d8fa0-6bf1-40ed-b54c-ac657f8495c5	Normal
4	00436515-870c-4b36-a041-de91049b9ab4	Lung Opacity

```
[ ]  classes

No Lung Opacity / Not Normal    11821
Lung Opacity                     9555
Normal                           8851
Name: class, dtype: int64
```



Preliminary EDA insights - train labels dataset

- 30227 rows and 6 columns
  - patientId and x, y coordinates, width, height of the bounding boxes and target indicating Pneumonic case or not
- Missing values – nil
- 26684 unique patients

	patientId	x	y	width	height	Target
0	0004cfab-14fd-4e49-80ba-63a80b6bddd6	NaN	NaN	NaN	NaN	0
1	00313ee0-9eaa-42f4-b0ab-c148ed3241cd	NaN	NaN	NaN	NaN	0
2	00322d4d-1c29-4943-afc9-b6754be640eb	NaN	NaN	NaN	NaN	0
3	003d8fa0-6bf1-40ed-b54c-ac657f8495c5	NaN	NaN	NaN	NaN	0
4	00436515-870c-4b36-a041-de91049b9ab4	264.0	152.0	213.0	379.0	1

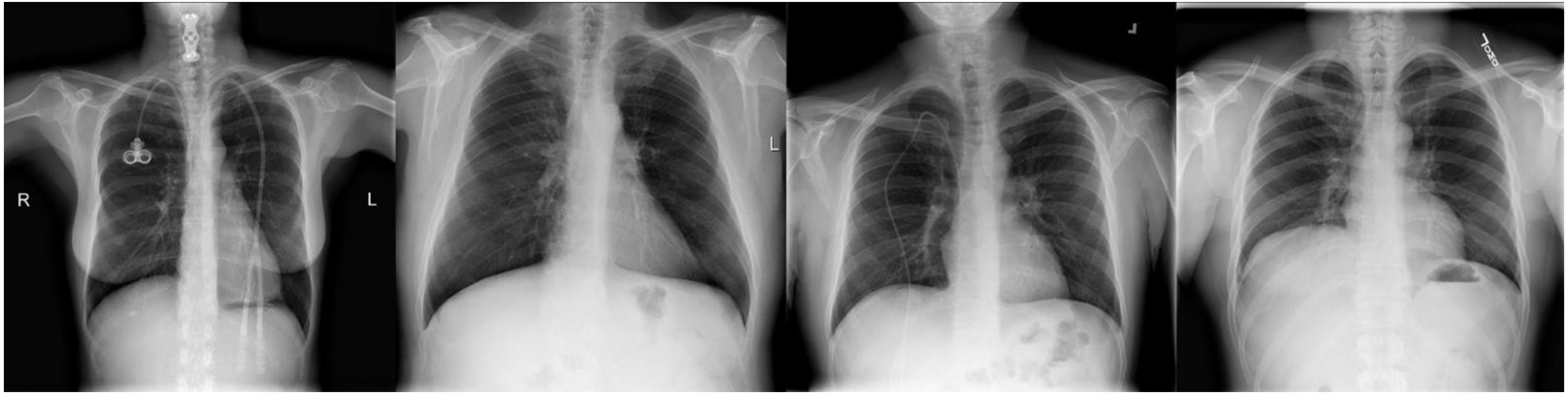
Preliminary EDA insights – training images

- Training has 26684 images
- Images are dcm format
- Every image has the following details
    - Patient sex;
    - Patient age;
    - Modality;
    - Body part examined;
    - View position;
    - Rows & Columns;
    - Pixel Spacing.

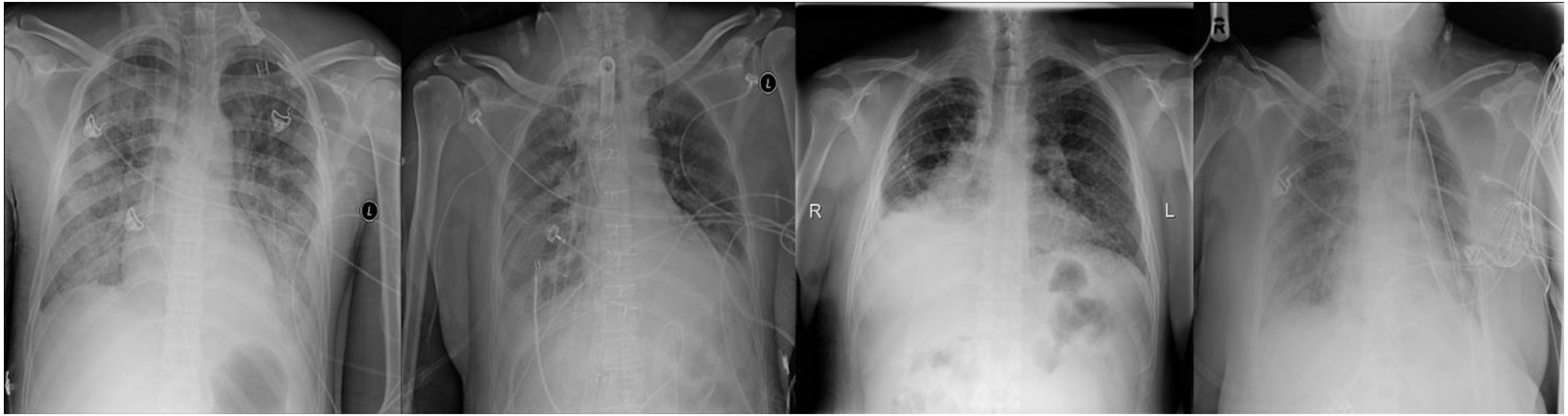
```
(0008, 0005) Specific Character Set              CS: 'ISO_IR 100'
(0008, 0016) SOP Class UID                       UI: Secondary Capture Image
(0008, 0018) SOP Instance UID                    UI: 1.2.276.0.7230010.3.1.4
(0008, 0020) Study Date                          DA: '19010101'
(0008, 0030) Study Time                          TM: '000000.00'
(0008, 0050) Accession Number                    SH: ''
(0008, 0060) Modality                            CS: 'CR'
(0008, 0064) Conversion Type                     CS: 'WSD'
(0008, 0090) Referring Physician's Name          PN: ''
(0008, 103e) Series Description                  LO: 'view: PA'
(0010, 0010) Patient's Name                      PN: '0a2c130c-c536-4651-836
(0010, 0020) Patient ID                          LO: '0a2c130c-c536-4651-836
(0010, 0030) Patient's Birth Date                DA: ''
(0010, 0040) Patient's Sex                       CS: 'M'
(0010, 1010) Patient's Age                       AS: '30'
(0018, 0015) Body Part Examined                  CS: 'CHEST'
(0018, 5101) View Position                       CS: 'PA'
(0020, 000d) Study Instance UID                  UI: 1.2.276.0.7230010.3.1.2
(0020, 000e) Series Instance UID                 UI: 1.2.276.0.7230010.3.1.3
(0020, 0010) Study ID                            SH: ''
(0020, 0011) Series Number                       IS: "1"
(0020, 0013) Instance Number                     IS: "1"
(0020, 0020) Patient Orientation                 CS: ''
(0028, 0002) Samples per Pixel                   US: 1
(0028, 0004) Photometric Interpretation          CS: 'MONOCHROME2'
(0028, 0010) Rows                                US: 1024
(0028, 0011) Columns                             US: 1024
(0028, 0030) Pixel Spacing                       DS: ['0.14300000000000002',
(0028, 0100) Bits Allocated                      US: 8
(0028, 0101) Bits Stored                         US: 8
(0028, 0102) High Bit                            US: 7
(0028, 0103) Pixel Representation                US: 0
(0028, 2110) Lossy Image Compression             CS: '01'
(0028, 2114) Lossy Image Compression Method      CS: 'ISO_10918_1'
(7fe0, 0010) Pixel Data                          OB: Array of 146200 bytes
```

Exploratory visualization

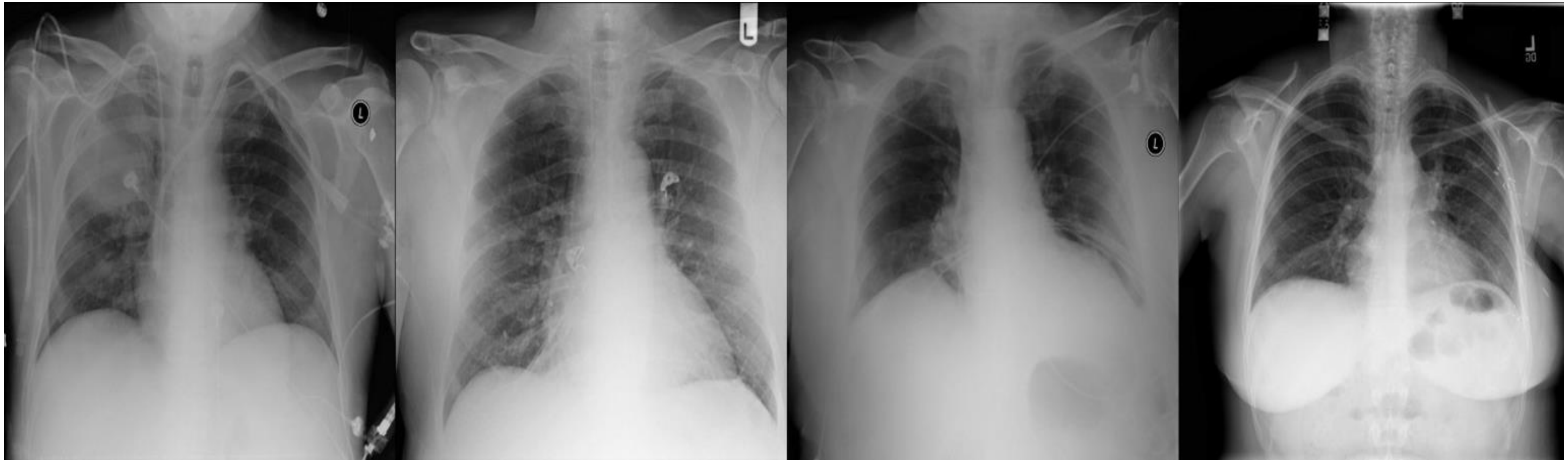
- Normal lungs are filled with air. In the x-rays below, you can see normal lungs. We can note that we mostly see white skeletal matter and black matter, which is primarily air.



- When a person has pneumonia, however, air is replaced by fluid, bacteria, immune system cells, and other objects. In an x-ray, the opacities tend to have a greyish color, and a cloudy appearance, rather than being black or white. You can see some images with pneumonia-related opacities below.



- While we are theoretically detecting “lung opacities”, there are lung opacities that are not pneumonia related.
- In the data, some of these are confusingly labeled “Not Normal / No Lung Opacity”. These non-pneumonia “Not Normal” detections end up being a primary source of frustration in building models.
- The images below show a few of the examples in the “Not Normal” class.



Summary of Initial Findings

Intial Findings shows it automatically locate lung opacities on chest radiographs, but only the opacities that look like pneumonia, and discard other types of opacities like the ones caused by fluid overload (pulmonary edema), bleeding, volume loss (atelectasis or collapse), lung cancer, post-radiation or surgical changes. Outside of the lungs, fluid in the pleural space (pleural effusion) also appears as increased opacity on CXR. A pneumonia opacity is a part of the lungs that looks darker on a radiograph and has a shape that indicates that pneumonia is (or may be) present.

Challenges

- Specifically, the algorithm needs to automatically locate lung opacities on chest radiographs, but only the opacities that look like pneumonia, and discard other types of opacities like the ones caused by fluid overload (pulmonary edema), bleeding, volume loss (atelectasis or collapse), lung cancer, post-radiation or surgical changes. Outside of the lungs, fluid in the pleural space (pleural effusion) also appears as increased opacity on CXR

- A pneumonia opacity is a part of the lungs that looks darker on a radiograph and has a shape that indicates that pneumonia is (or may be) present

Next Steps

We are working on improving the accuracy and building the end to end pipeline.