X-ray Classification with Chandra

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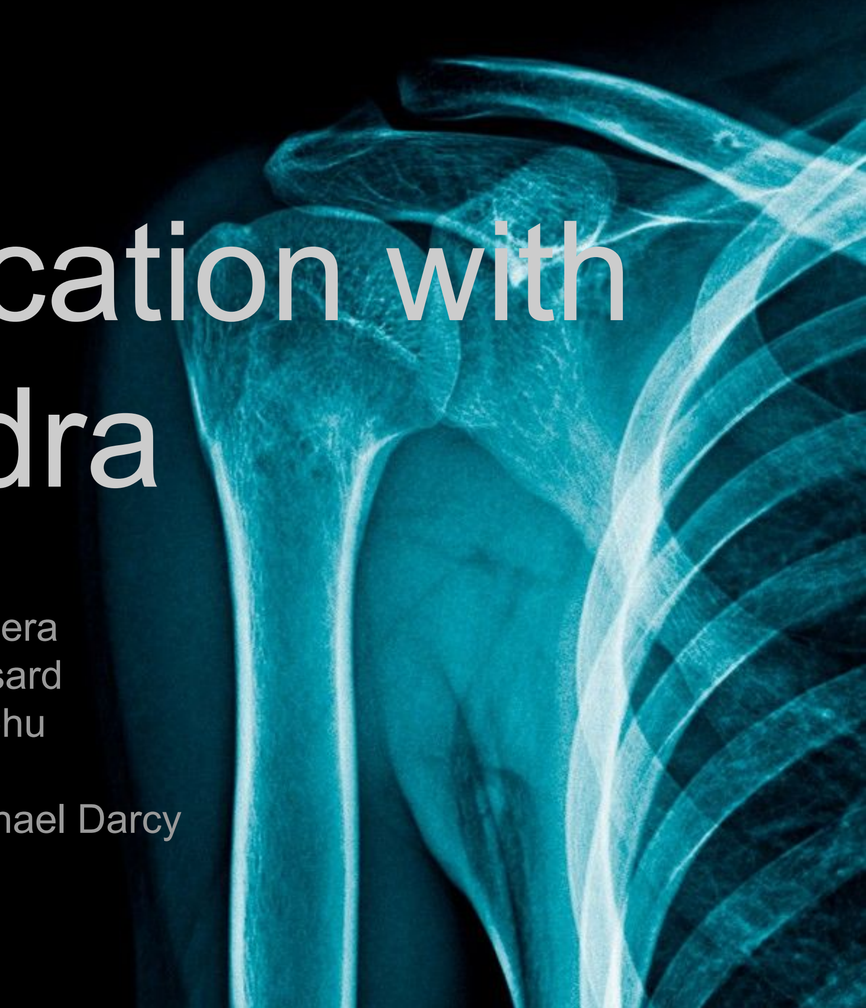
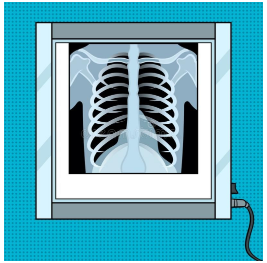


Problem statement



Data source:

We use Chest X-ray images from Guangzhou Women and Children's Medical Center, China. The patients are children of one to five years old.
http://www.cell.com/cell/fulltext/S0092-8674(18)30154-5

5860 X-ray scans (1585 - Normal, 4275 - Pneumonia)

Stakeholders:

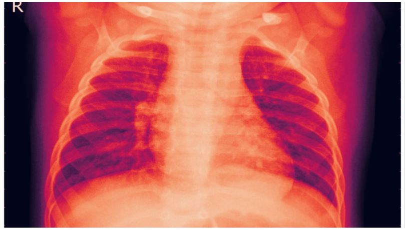
- UNICEF reports that pneumonia kills more children than any other illness.
- It very hard to diagnose X-ray scans, and take decisions deterministically at the right moment.
- Stakeholders are going to be facilities with imaging capabilities who may not have a doctor on hand to interpret X-rays

Chosen Metric

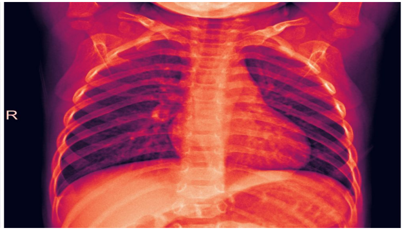
$$F1 = 2\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Metric balances ensuring we catch all of the pneumonia cases (Recall) with not over-classifying cases as pneumonia (Precision)

Exploratory Data Analysis



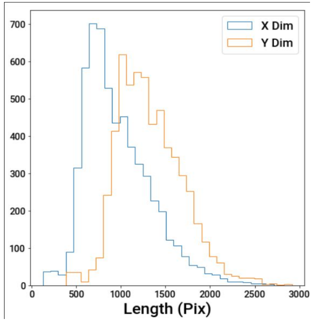
Pneumonia



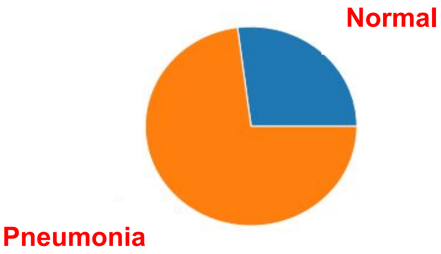
Normal

In cases with Pneumonia, images have higher opacity compared to the normal. Therefore we expect the normal cases to have a higher variance

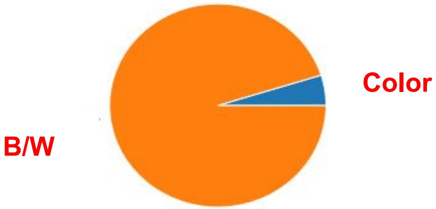
Challenges with the dataset



Wide variety of image dimensions and aspect ratios



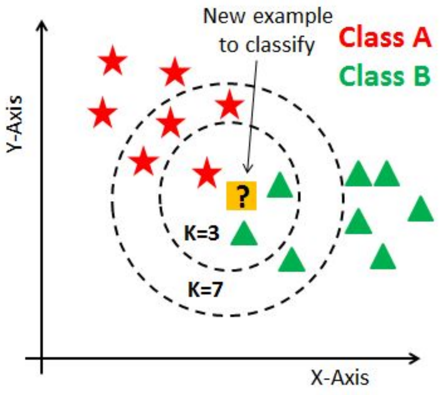
Dataset skewed towards Pneumonia cases



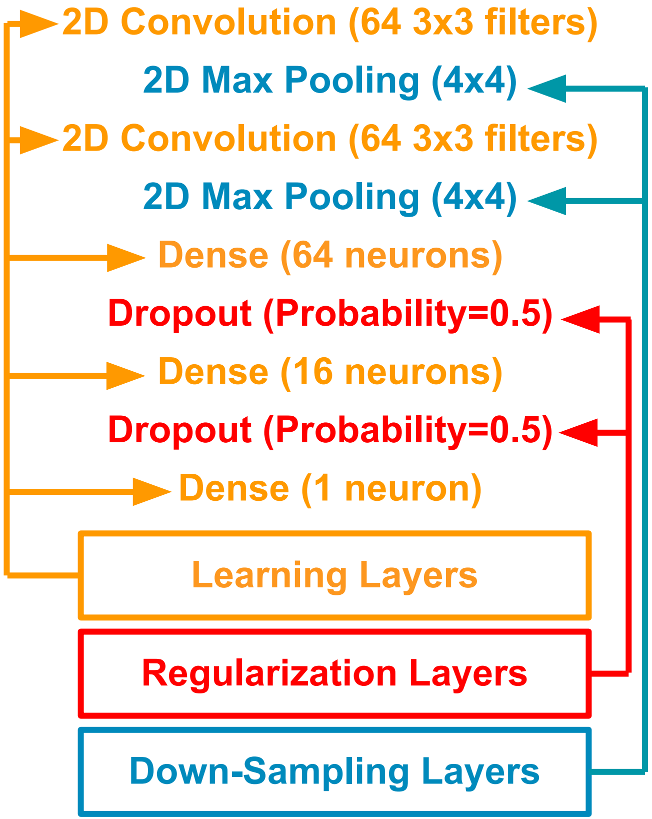
Some images were in color

Model Selection

Model 1: K- nearest neighbors (KNN Model)



Model 2: Convolutional Neural Network (CNN Model)



2D Convolution (64 3x3 filters)

2D Max Pooling (4x4)

2D Convolution (64 3x3 filters)

2D Max Pooling (4x4)

Dense (64 neurons)

Dropout (Probability=0.5)

Dense (16 neurons)

Dropout (Probability=0.5)

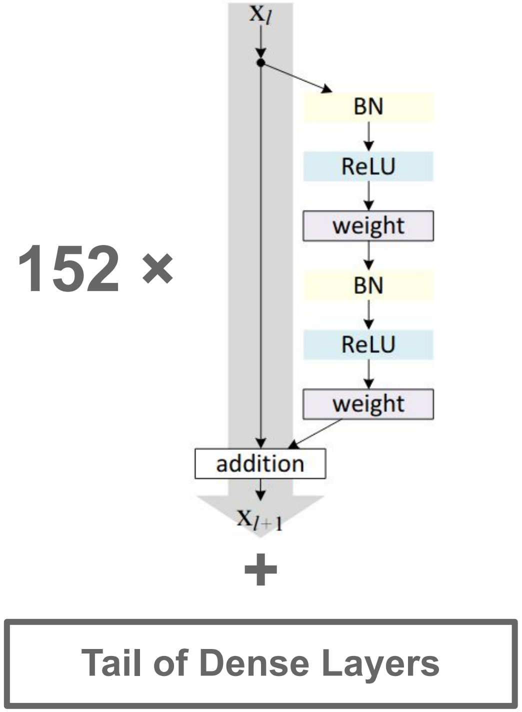
Dense (1 neuron)

Learning Layers

Regularization Layers

Down-Sampling Layers

Model 3: Transfer Learning (TL Model)



152 ×

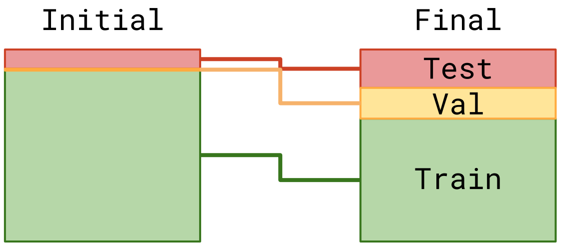
+

Tail of Dense Layers

Data Preprocessing

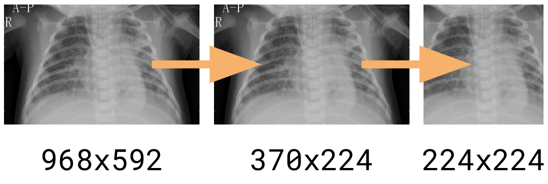
Redistributing Train, Test, and Validation Datasets

- Dataset is pre-sorted into train, test, validation sets
- Combine all of these into a single dataset and re-distributing them, giving full control over data splitting and stratification



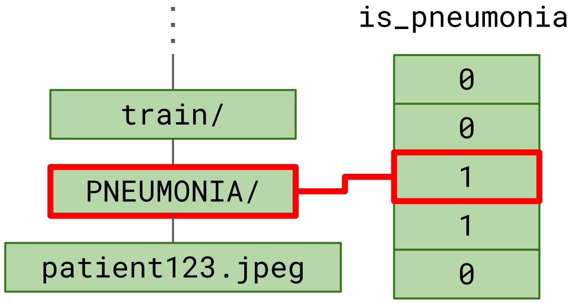
Homogenizing Image Dimensions

- Resize the images, maintaining axis ratio to prevent distortion and loss of information
- Crop the long axis of the image from the center to protect the region with the most information



Transforming Categorical Variable into Binary

- Read the folder structure to generate a binary indicator of pneumonia
- Save resized images along with references to their original files



Model Selection and Validation

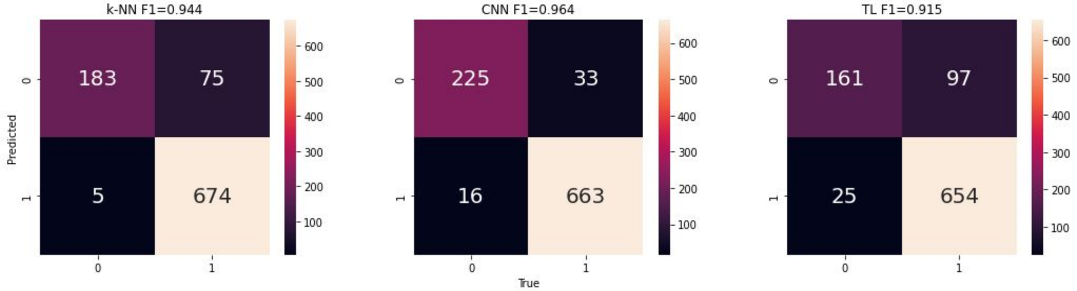
***k*-NN Model:** Struggles to correctly identify a sizeable portion of the pneumonia cases

CNN Model: Greatly improves false negatives with only a small increase in false positives

TL Model: More false negatives and false positives than the other two models

F1-Score of the three models on validation sample

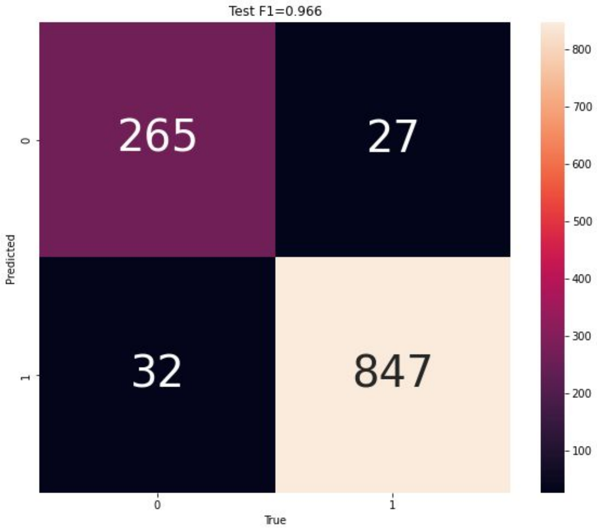
***k*-NN**	**CNN**	**TL**
0.944	0.964	0.915



We choose the custom-trained CNN as our final model as this achieves the highest **F1 score** of **0.964**.

Final Conclusions

- F1 Score balances finding all pneumonia cases against correctly classifying pneumonia
- Trained three models of varying complexity: a *k*-Nearest Neighbors model, a convolutional neural network (CNN) model, and a CNN with transfer learning
- Recommend CNN model to healthcare providers
    - Low incidence of false negatives means patients get the care they need
    - Low incidence of false positives means radiologists don't waste time treating healthy patients



CNN with a test-sample F1 score of 0.966