Pediatric Pneumonia Classification

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The Problem

PNEUMONIA CASES
DIAGNOSED AS MIMICS:

Upper respiratory infections
Influenza
Cold
Pleurisy
Sinus infection
Seasonal viruses

SERIOUS CONDITIONS
DIAGNOSED AS PNEUMONIA

Acute respiratory failure
COPD, Bronchitis
Lung Cancer
Myocarditis / pericarditis
Pulmonary Embolism, Heart attack
Bronchitis
Legionnaire's, Tuberculosis
Sepsis, Septicimia

PNEUMONIA (ALL AGES)

3.3% Mortality Rate
No formal consensus guideline
1.1 million cases per year
74% Sensitivity (Feldman Et al..)

Increased Mortality
Delay in Treatment
Overuse of antibiotics
Increased Cost
Multiple Visits
Increased Malpractice

https://www.sciencedaily.com/releases/2010/10/101022123749.html.
http://www.rimed.org/rimedicaljournal/2014/08/2014-08-20-cont-maughan.pdf
https://pneumonia.biomedcentral.com/articles/10.1186/s41479-016-0002-1
https://pneumonia.biomedcentral.com/articles/10.15172/pneu.2014.5/464 (feldman)

Our Project

Create a user friendly Machine Learning model that, when provided a frontal chest pediatric x-ray image, can accurately predict whether a child has pneumonia to assist with clinical diagnosis.

Project Goals

1. Build and train a machine learning model which maximizes prediction accuracy.
2. Make the model accessible and easy to use.

Our Data

Our model is trained using a dataset from Kaggle[1] is taken adapted from the original images at Mendeley Data[2].

Dataset features

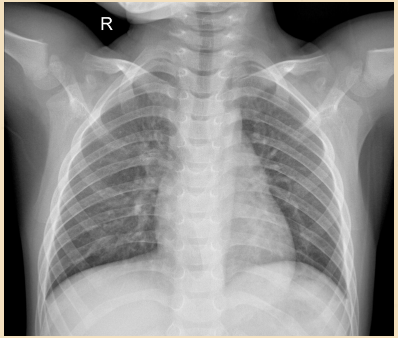
1. 5800 pediatric frontal chest x-rays (black and white medical quality images)
2. Labeled pneumonia 73%, normal images 27%
3. 1200x1200 images or larger with varying aspect ratio
4. Children from infants to adolescents
5. Contains both bacterial and viral pneumonia

1. Kaggle dataset at https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
2. Mendely Dataset at https://data.mendeley.com/datasets/

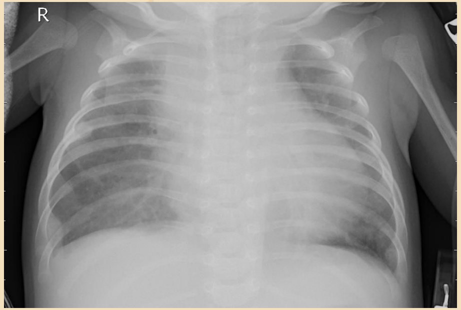
Image Classification

Infant

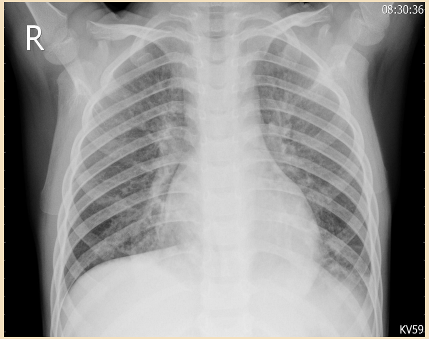
Adolescent



Bacteria



Virus

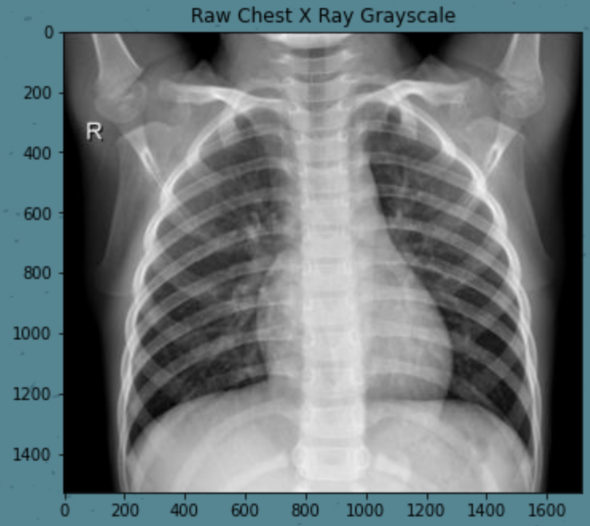


Normal

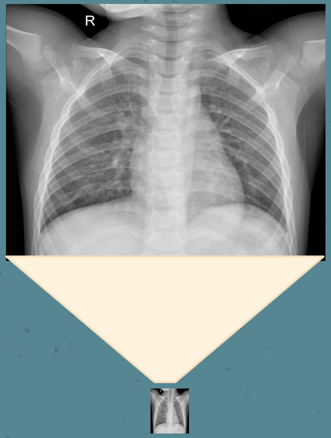
Pneumonia[3]

3. British Medical Journal “Differentiation of bacterial and viral pneumonia in children”: https://thorax.bmj.com/content/57/5/438

Preprocessing our data



Original Image
1600x1400



Reduced Image
150x150
(Loss of 98% of image)

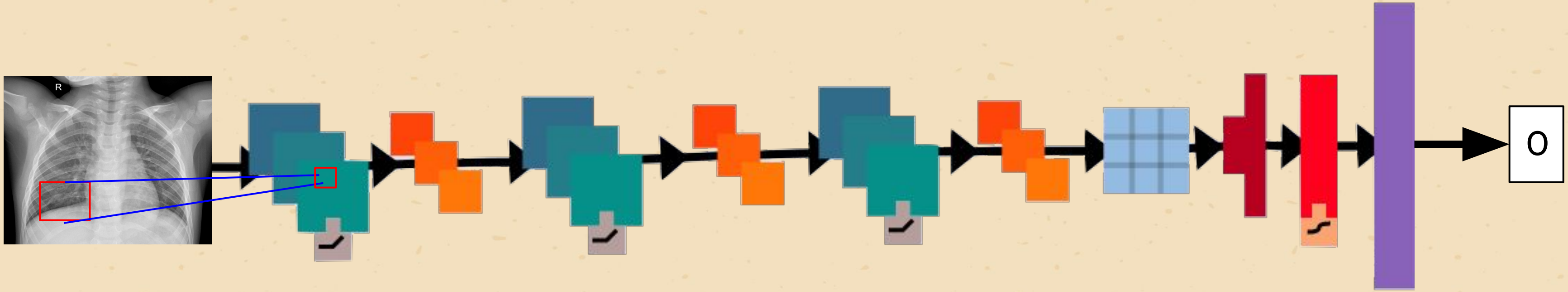
To prepare our images for training:

- Images are sorted by classification
- Images are randomized
- Split dataset: 80% images used for training, 20% for validation and testing
- Images are resized (loses >90% of original)

Convolutional Neural Network (CNN)

Model was trained using CNN

- Layers extract features of the image
- Model improves from training image feedback
- Trains over many iterations to improve the prediction accuracy



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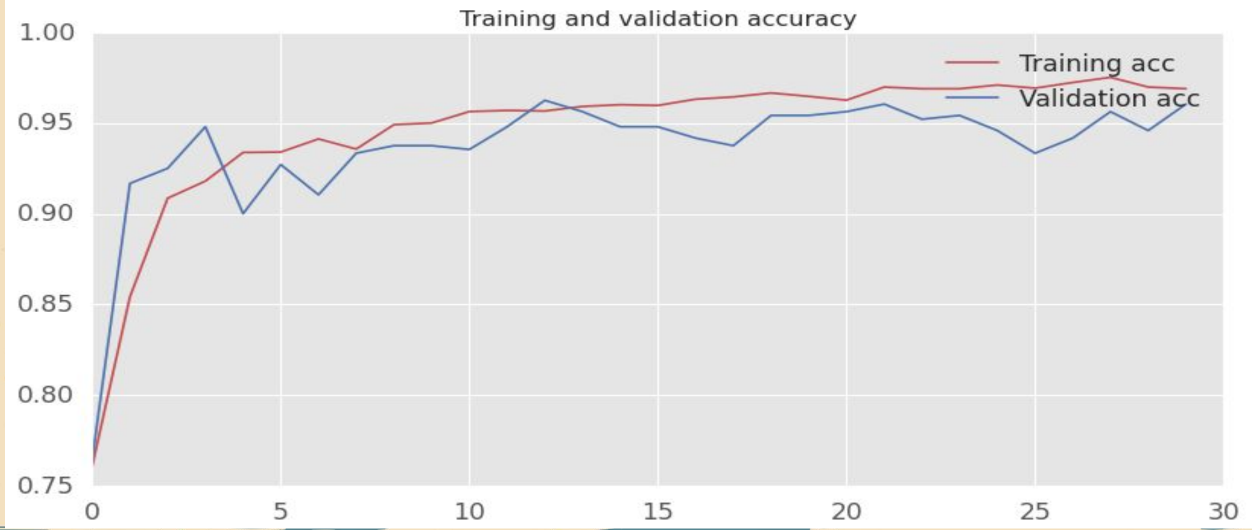
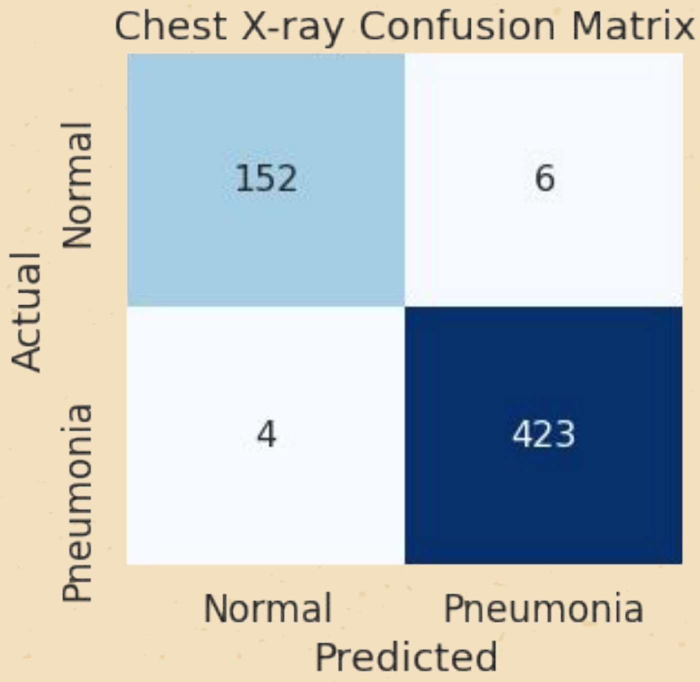


Our Model Results

Test accuracy **98.3%**

Recall* **99.1%**

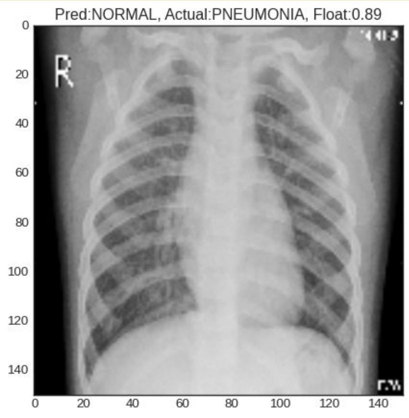
* Missed only 0.9% of positive cases
N test images = 585 (missed 10)

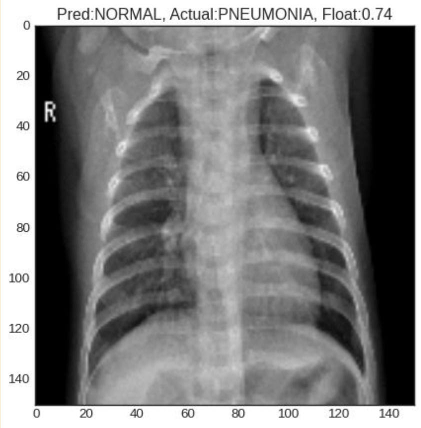


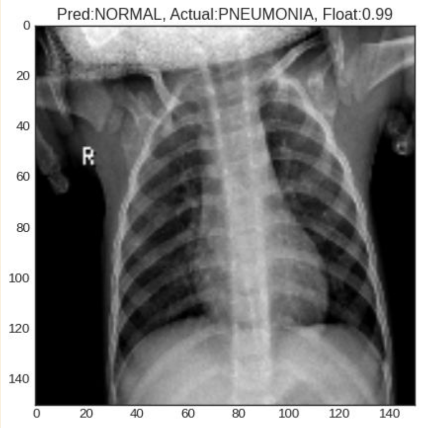
Missed images

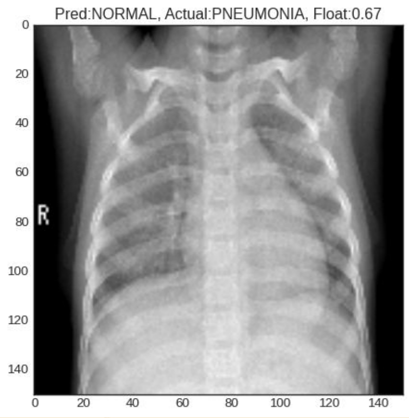
Characteristics of miscategorized images

- Mostly “Landscape” oriented (skinny lungs after resize)
- Significant black edges compared to most images
- Infants over represented
- Numerical uncertainty by model
- Blurry or low contrast images
- Many can be corrected by image preprocessing (crop and contrast)









Conclusion and Next Steps

This model is a valid way to assist in identification of pneumonia

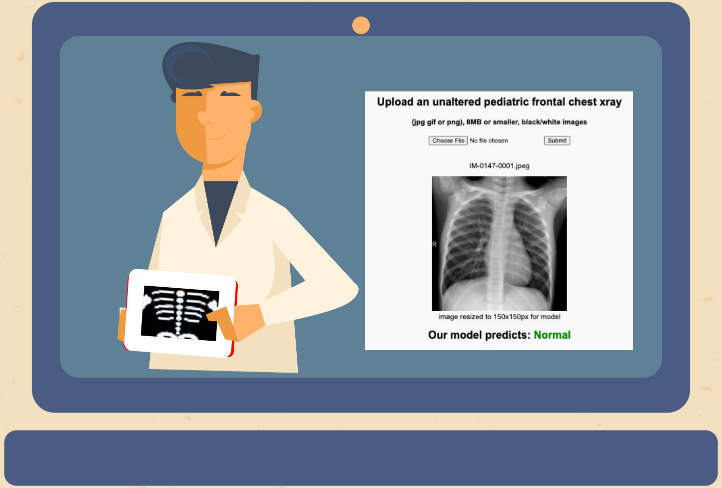
Ways to improve the model accuracy

- More training images
- More layers to neural network
- Tuning our model
- Higher image quality used in model (currently 150x150)
- More computer resources and time required
- More advanced techniques (early model)

Make different models for age groups (infants are different)
Classify viral and bacterial pneumonia (perhaps COVID-19)

Web App of Model

The model is live
https://xray-pred.herokuapp.com/



Questions?

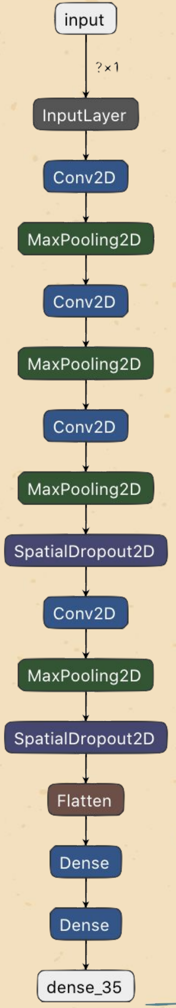
Appendix (models)

Final Model

- CNN with Dropouts
- 3x3 kernel
- 3 Layers (Conv + MaxPooling + Dropout(20%)), relu
- Flatten > Dense 512 > Dense (sigmoid) (binary output)

Other Models considered

- Baseline model
  - Sequential 1D
  - 3 Dense Layers, relu
  - 92% acc
- CNN model (no dropout
  - 3x3 kernel
  - 3 Layers (Conv + MaxPooling)
  - Flatten > Dense 512> Dense 1 (sigmoid)



Appendix (final model metrics)

Accuracy: 98.29%

Precision: 99.06%

Recall: 98.60%

F1-score: 98.83

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_12 (Conv2D)           (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 72, 72, 64)        18496
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 36, 36, 64)        0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 34, 34, 128)       73856
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 17, 17, 128)       0
_________________________________________________________________
spatial_dropout2d (SpatialDr (None, 17, 17, 128)       0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 15, 15, 128)       147584
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 7, 7, 128)         0
_________________________________________________________________
spatial_dropout2d_1 (Spatial (None, 7, 7, 128)         0
_________________________________________________________________
flatten_3 (Flatten)          (None, 6272)              0
_________________________________________________________________
dense_14 (Dense)             (None, 512)               3211776
_________________________________________________________________
dense_15 (Dense)             (None, 1)                 513
=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

Appendix (resources)

Computing resources:

- 4 hours on Google Colab servers to run all models created.
- Final model 1.5 hours by itself on Google with GPU. (No GPU ~5hr)
- Larger image size would require Colab Pro services for extra RAM

Appendix (web app)

Hosted on Heroku (limits of free account)
Made with Python (Flask)
Uses Gunicorn WSGI
Uploaded files are held in session cookies, but never saved to file or database

Image histogram

Some images (like this one) have lots of black pixels and few at the high end. This anecdotally is more common among pneumonia images. (looked at about 50)

Normal images have twce the number of black pixels and similar in other respects.

Investigate whether doctors use higher contrast on potential pneumonia images