

# Rapid and Robust COVID-19 Identification from Chest X-rays

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UNIVERSITY OF MINNESOTA

Driven to Discover<sup>SM</sup>

# The core team



**Chris Tignamelli, MD**  
(Surgery & IHI)

**Trauma/Critical Care**



**Ju Sun, PhD**  
(CS&E)

**Computer Vision/AI**



**Erich Kummerfeld, PhD**  
(IHI)

**AI**



**Gene Melton-Meaux**  
PhD, MD  
(Surgery&IHI&Fairview)

**NLP/Informatics**



**Tadashi Allen, MD**  
(Radiology)

**Radiology**

# CV/AI team



Ju Sun (CS&E)



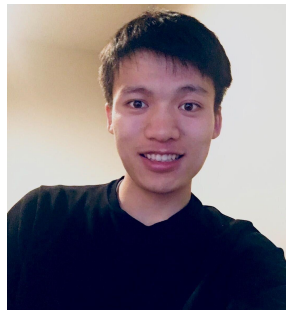
Erich Kummerfeld (IHI)



Daniel Boley (CE&E)



Taihui Li (CS&E)



Le Peng (CS&E)



Dyah Adila (CS&E)

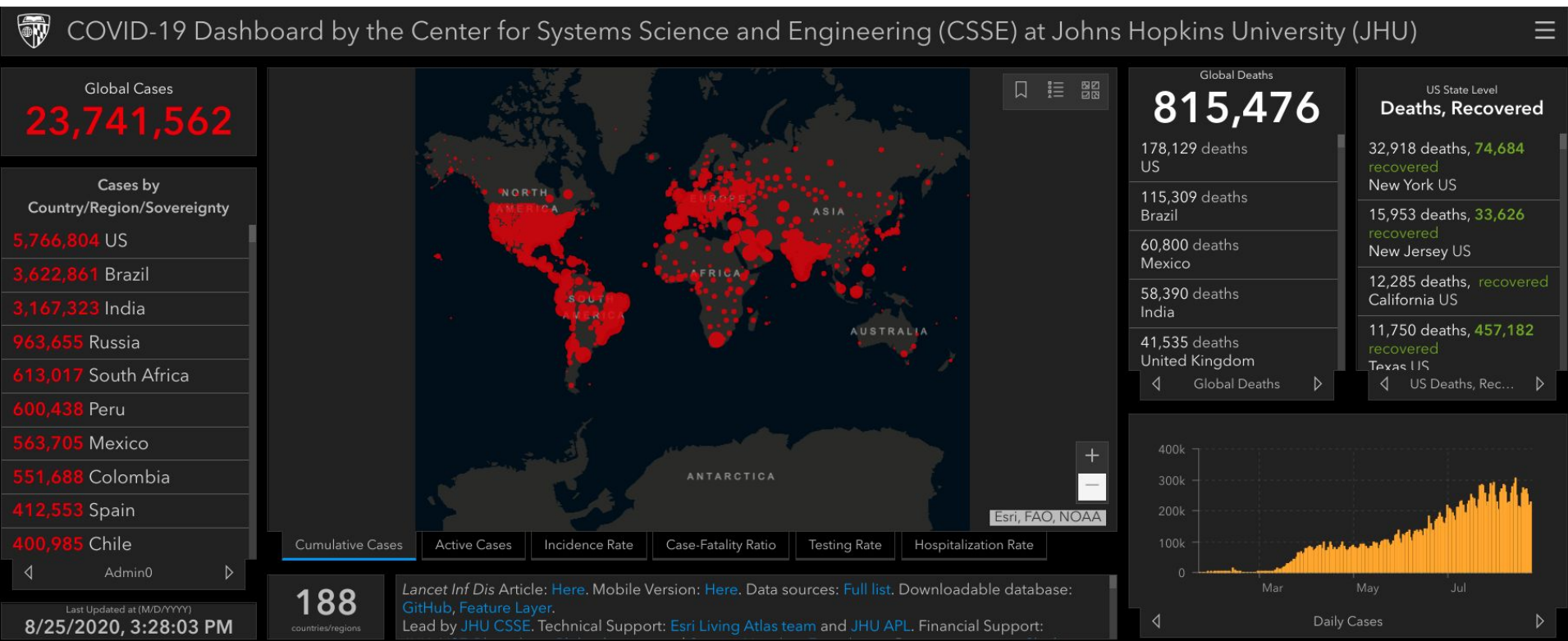
# Deployment



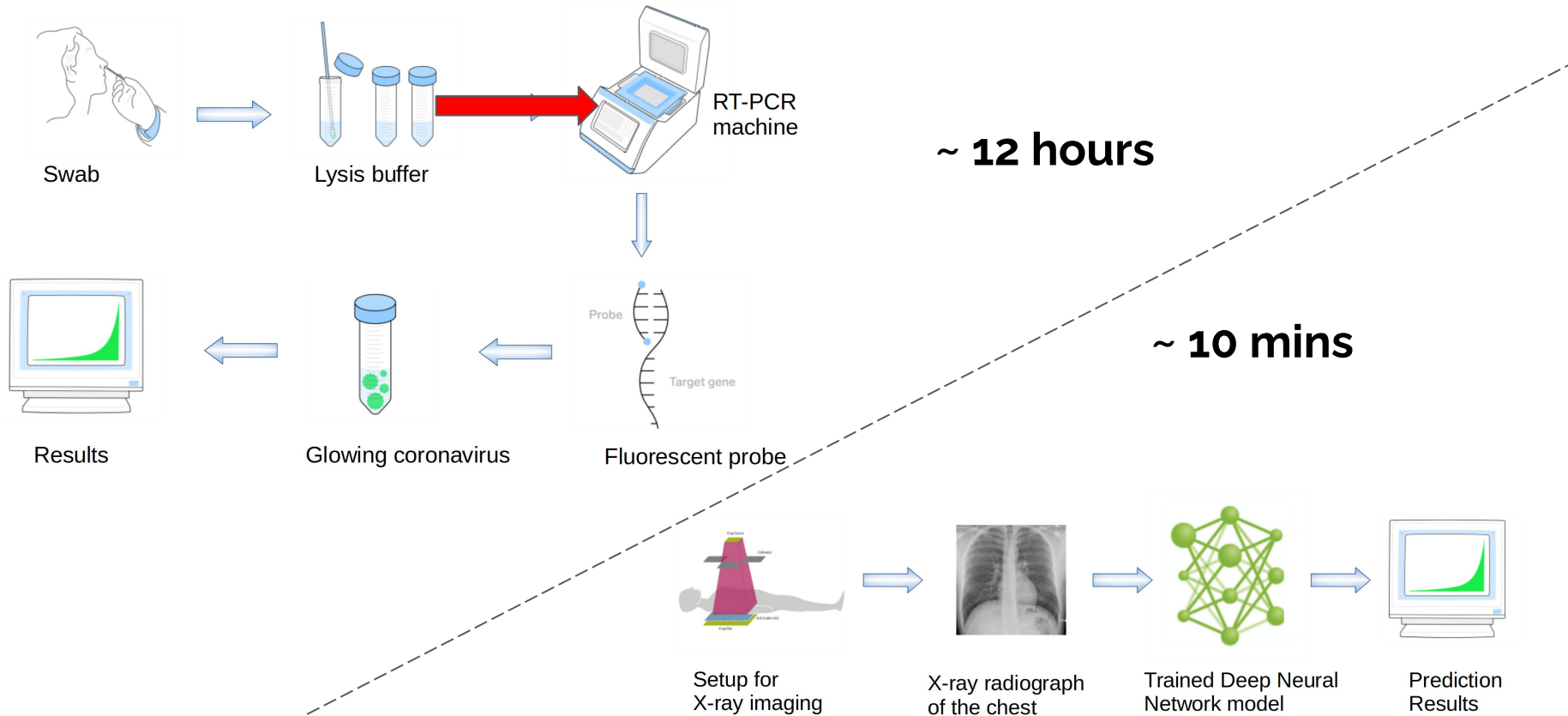
***Epic***

# Overview

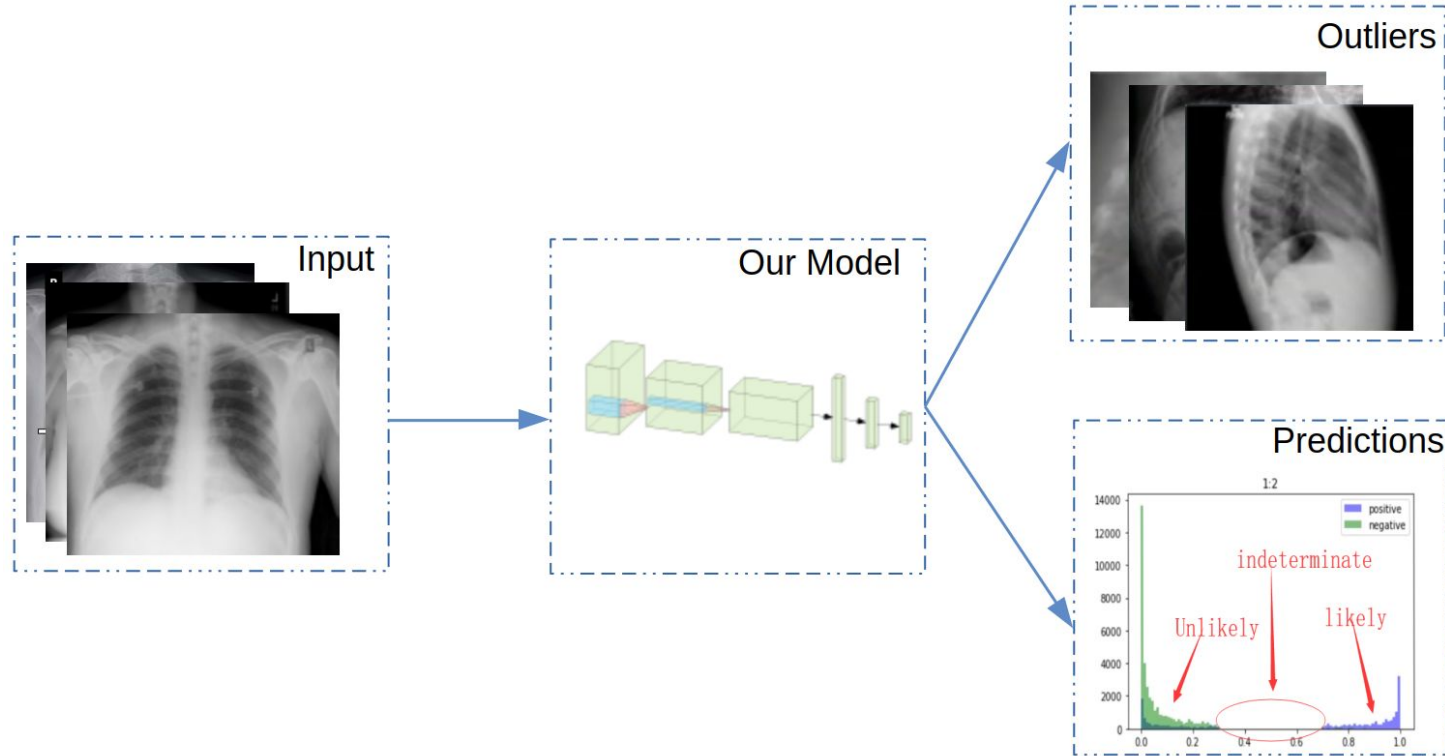
# COVID-19 is killing people



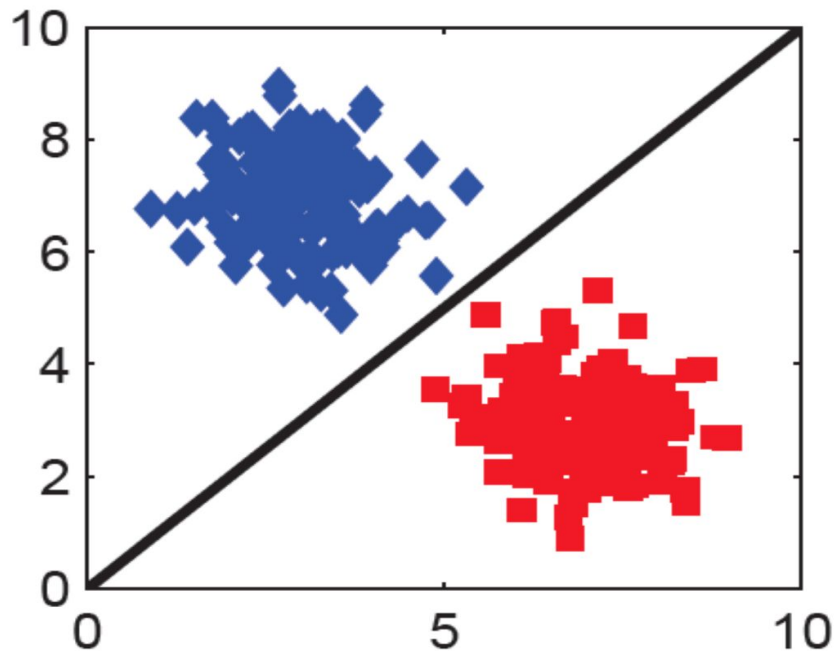
# RT-PCR vs X-rays diagnosis



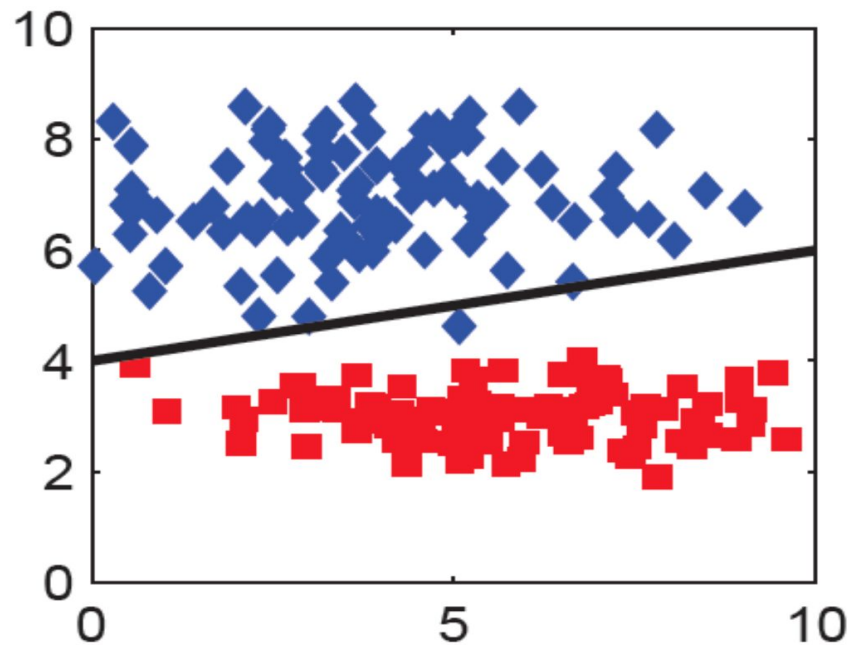
# What our model offers.... In 10 mins



# Transfer learning helps to generalize



(a) Fairview-COVID19



(b) BIMCV-COVID19

# How our model performs

Results on M Health Fairview data

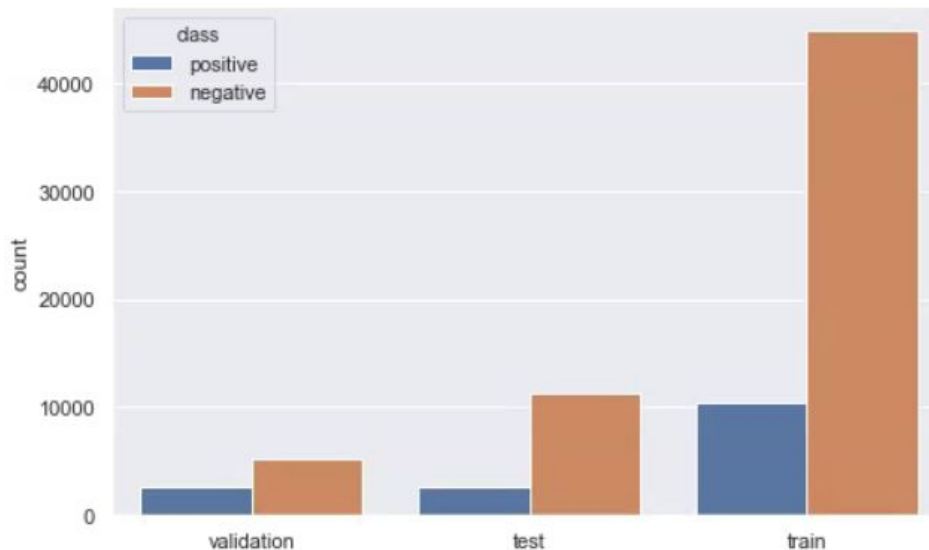


Table 1 test on **before** July 1st

ratio	specificity	sensitivity	ppv	npv
1	0.957	0.82	0.95	0.841
2	0.959	0.82	0.909	0.914
5	0.959	0.818	0.798	0.964

**Uncertain=14.80%**

Table 2 validation on **after** July 1st

ratio	specificity	sensitivity	ppv	npv
1	0.906	0.764	0.89	0.794
2	0.906	0.764	0.803	0.885
5	0.906	0.767	0.621	0.951

**Uncertain=16.48%**

# Results on external

## Transfer learning

	ratio	specificity	sensitivity	ppv	npv
1	0.646	0.926	0.724	0.898	
2	0.646	0.928	0.567	0.947	
5	0.646	0.923	0.343	0.977	

Uncertain=14.44%

## Direct learning

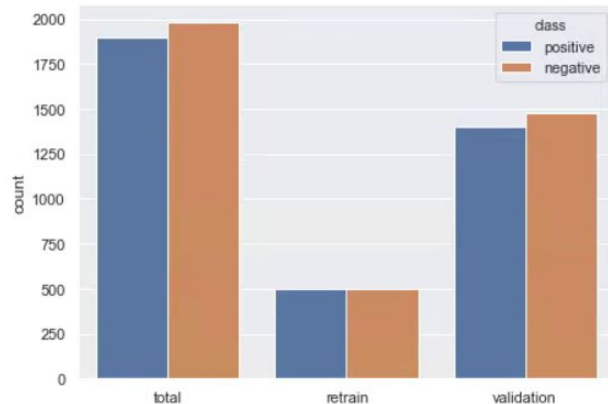
	ratio	specificity	sensitivity	ppv	npv
1	0.544	0.88	0.658	0.819	
2	0.544	0.878	0.49	0.899	
5	0.544	0.878	0.277	0.957	

Uncertain=12.84%

## Direct generalization

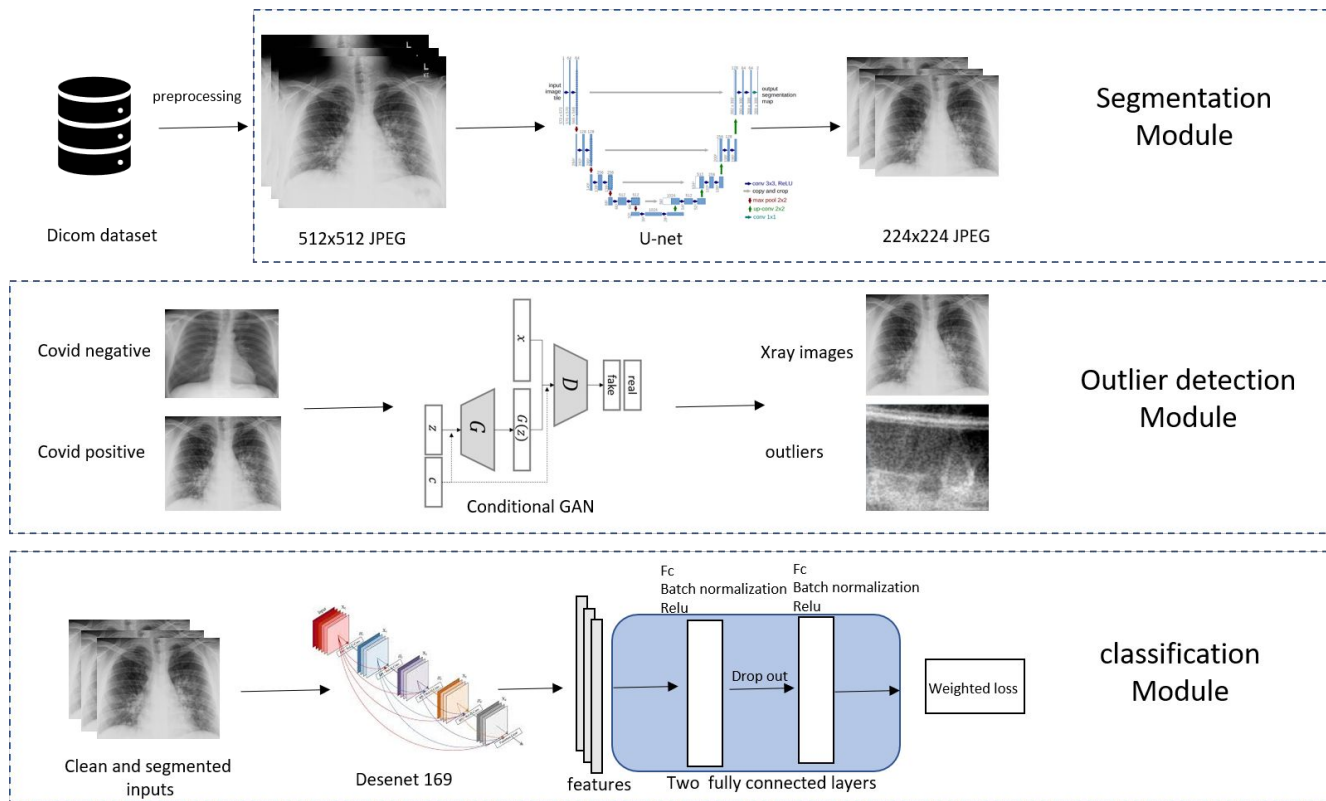
	ratio	specificity	sensitivity	ppv	npv
1	0.885	0.046	0.286	0.481	
2	0.885	0.047	0.171	0.65	
5	0.885	0.046	0.074	0.823	

Uncertain=19.58%

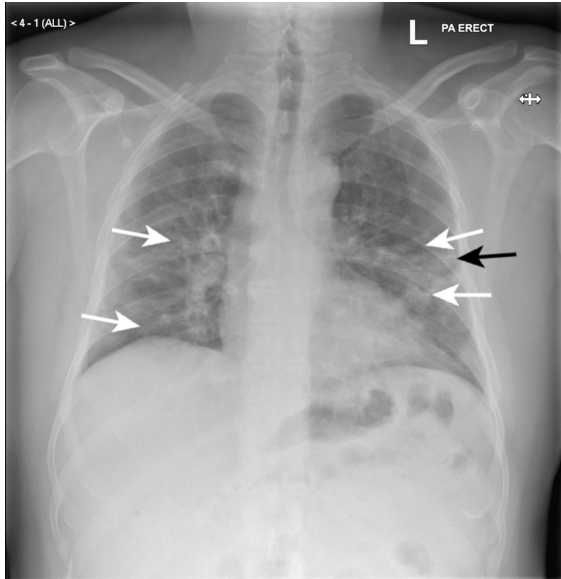


Look into our model

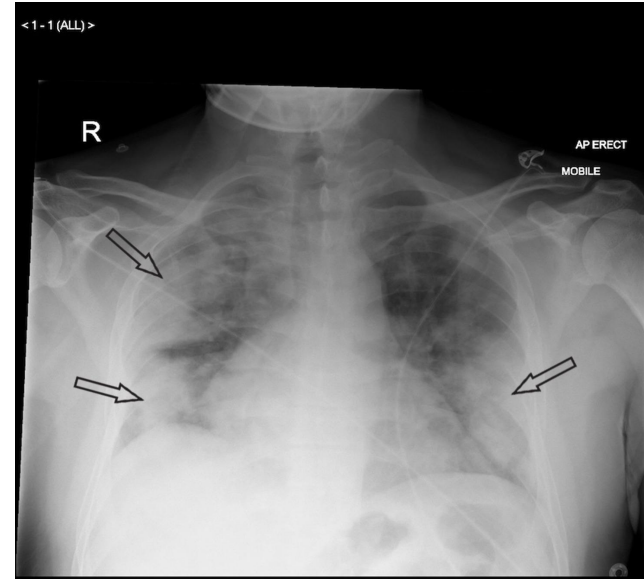
# Look into our model



# Domain (medical) knowledge - I



Ground glass opacity (mid, lower, peripheral)



Consolidation (mid, lower, peripheral)

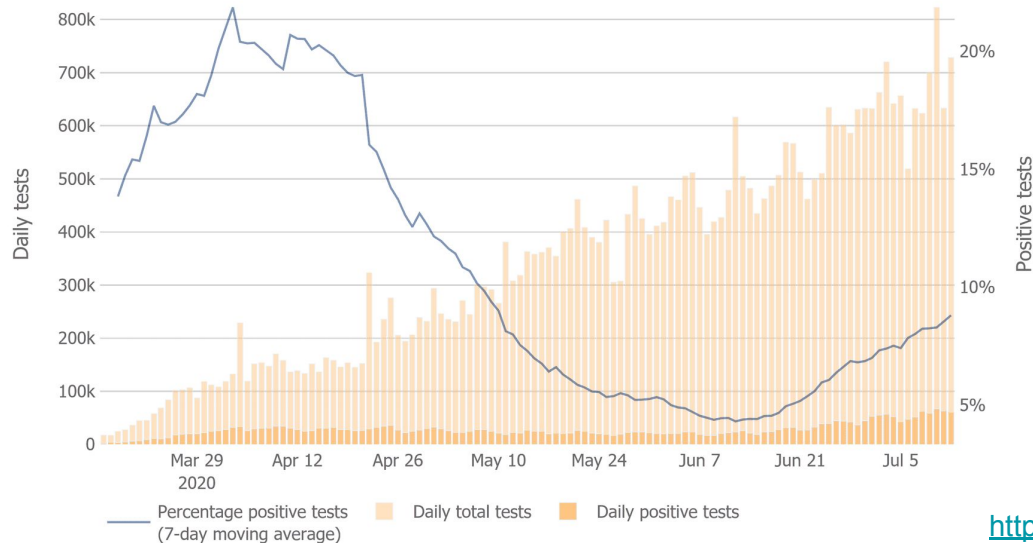
# Domain (medical) knowledge - II

## Case/Control imbalance

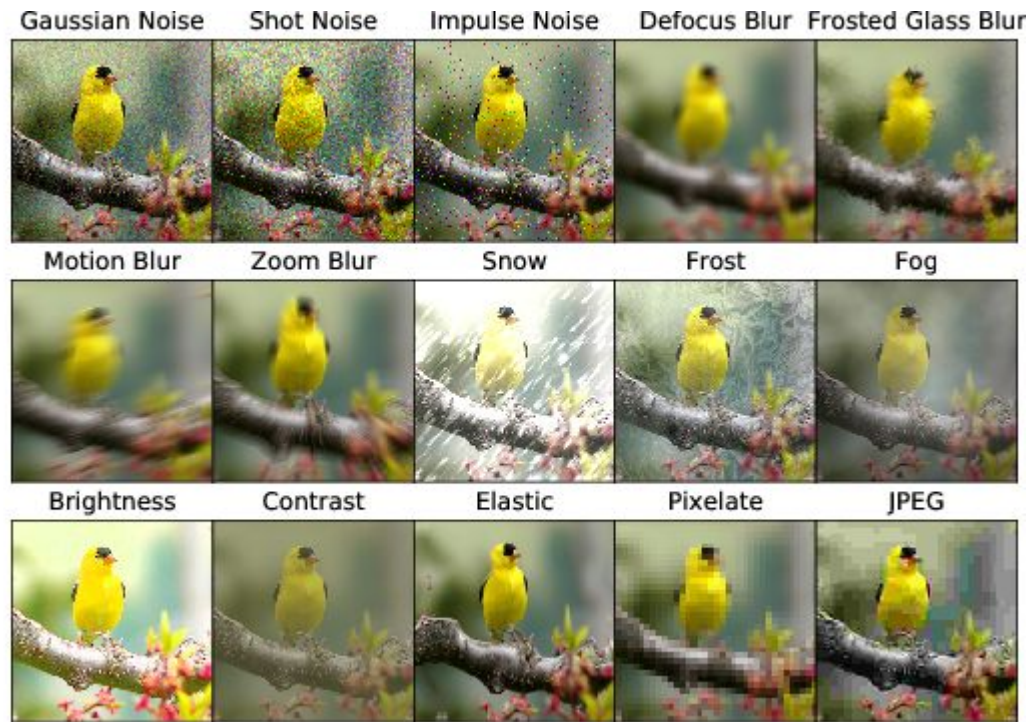
### Rate of Positive Tests in the US Over Time\*

HOW MUCH OF THE DISEASE ARE WE FINDING THROUGH TESTS?

\* This visualization is not a dynamic representation of case data and will not update automatically

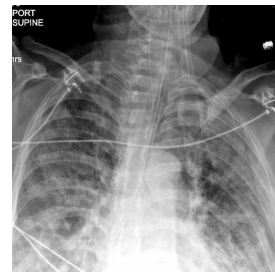
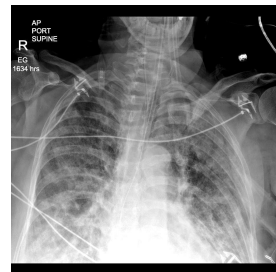
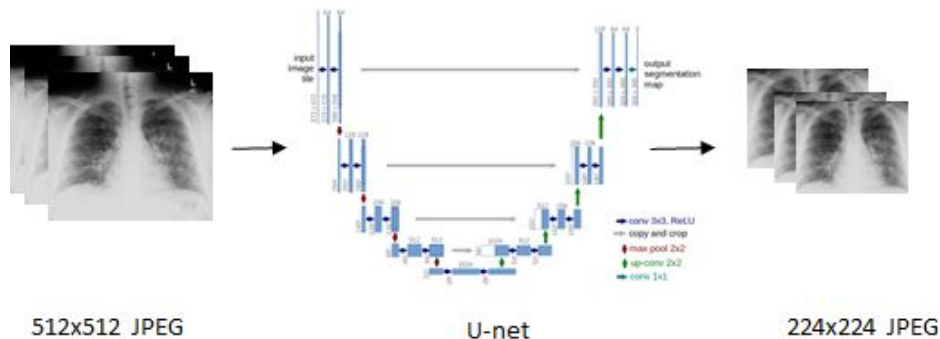


# Robustness of AI



<https://github.com/hendrycks/robustness>

# Step 1: Lung segmentation



<https://www.kaggle.com/nikhilpandey360/lung-segmentation-from-chest-x-ray-dataset>

## Step 2: Outlier detection - I

Lung area



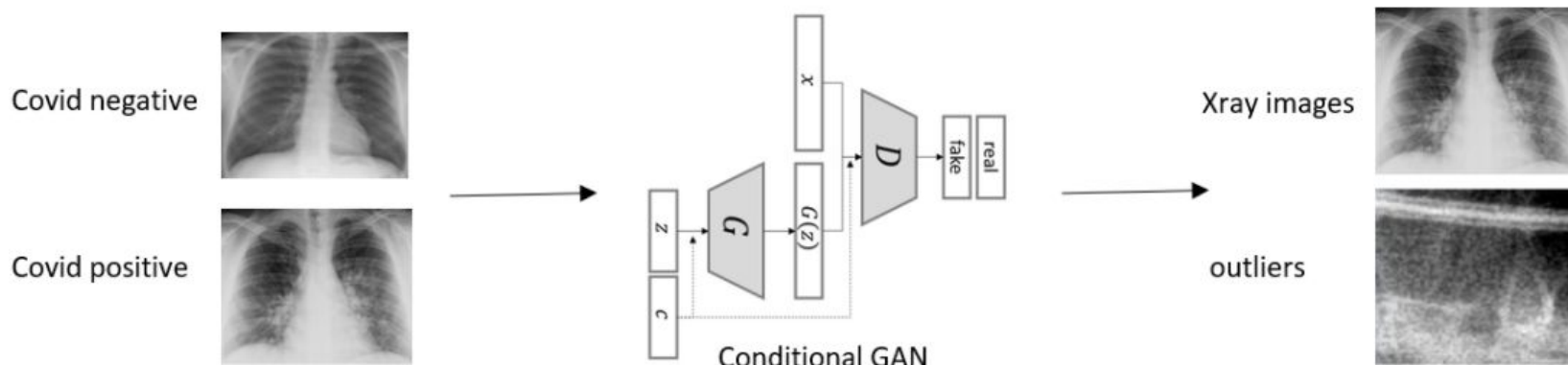
Outliers(True Positive)



Outliers(False Negative)

# Step 2: Outlier detection II

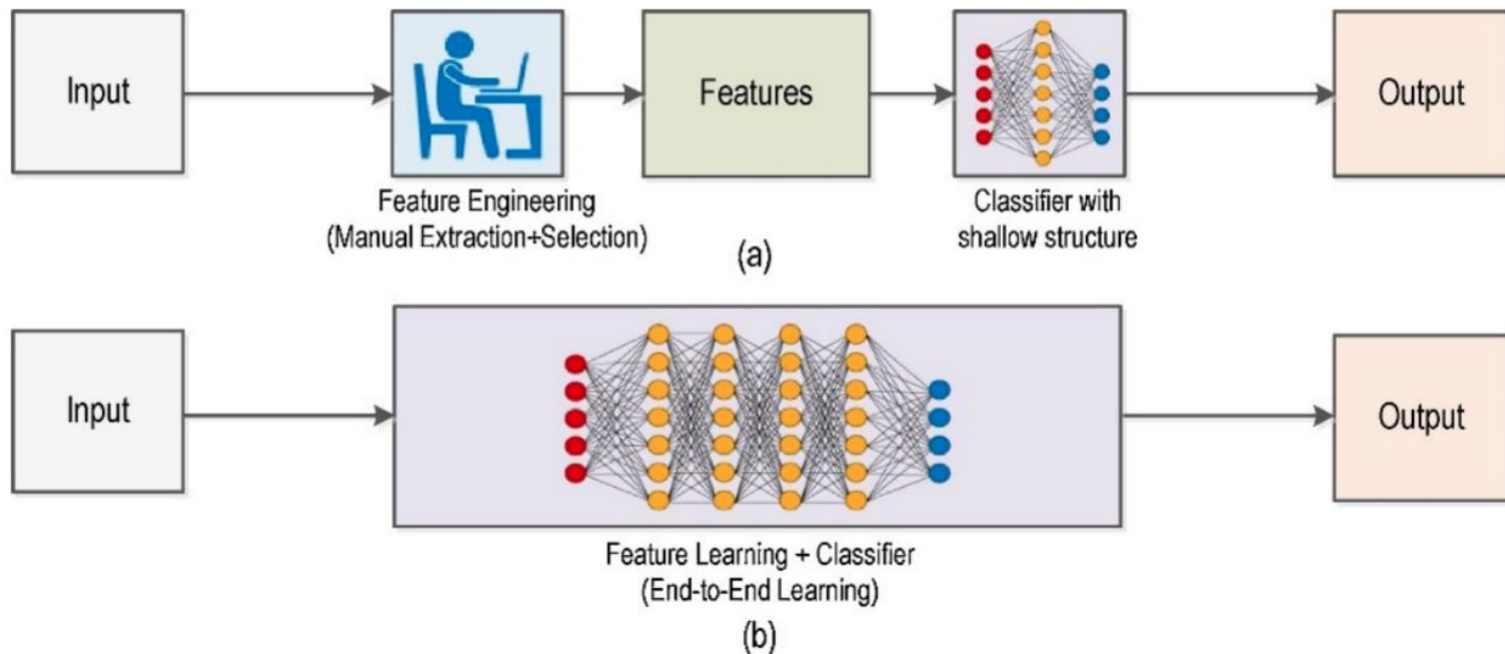
## Conditional GAN



examples



## Step 3: Feature extraction



Choose **pretrained DNN models** to counter **data imbalance** and maximize **generalization**

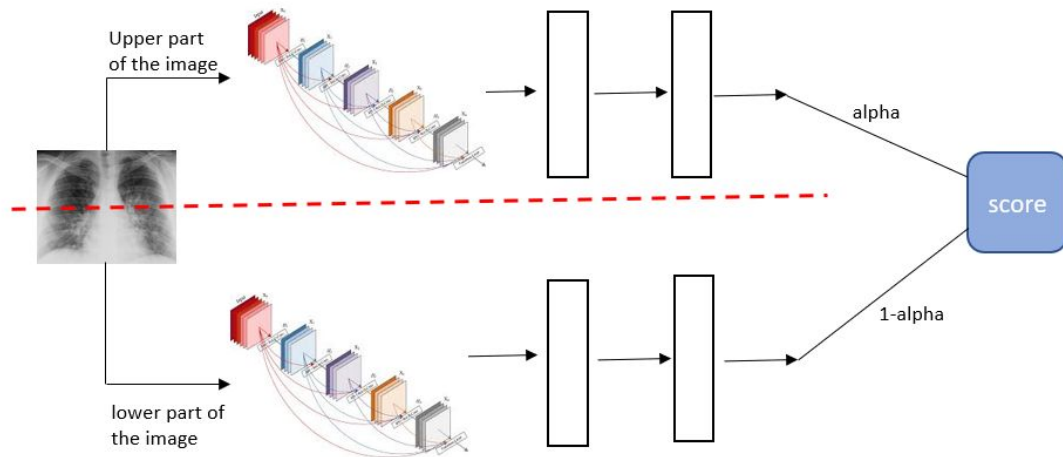
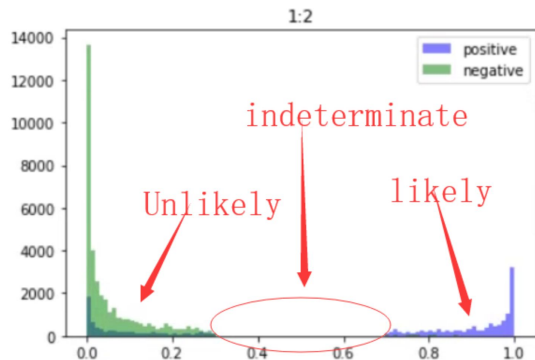
# Step 4: Classification

- Imbalance problems

$$L = \max(L_{\text{positive}}, L_{\text{negative}})$$

where L is BCE loss function.

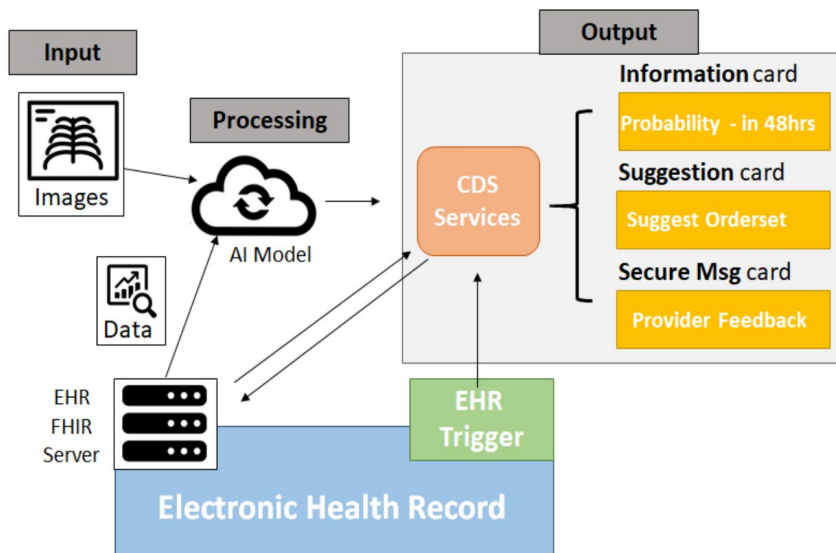
- Three decision values



# Deployment & Future Work

# Deployment and public release

## M Health Fairview CDS: 12 hospitals



## Epic App Orchard: 450+ customers



Explore Apps

Healthcare is better together.

The App Orchard is where developers can learn about Epic's APIs and list their apps for Epic community members to explore and access.



### Marketplace for apps

Access a marketplace of apps for reporting, visualizations, content, and more.



### Access to hundreds of APIs

Get documentation for Epic's APIs, including examples and a testing sandbox.



### Opportunities to collaborate

Attend conferences with others working on the Epic platform.



### Support from Epic developers

Our team will be there to lend a hand if you get stuck.

# Next

- Prognosis: adverse outcomes prediction

