A Classification Tool for COVID-19 and Bacterial Pneumonia Diagnosis using X-ray Imaging Data

CHL7001

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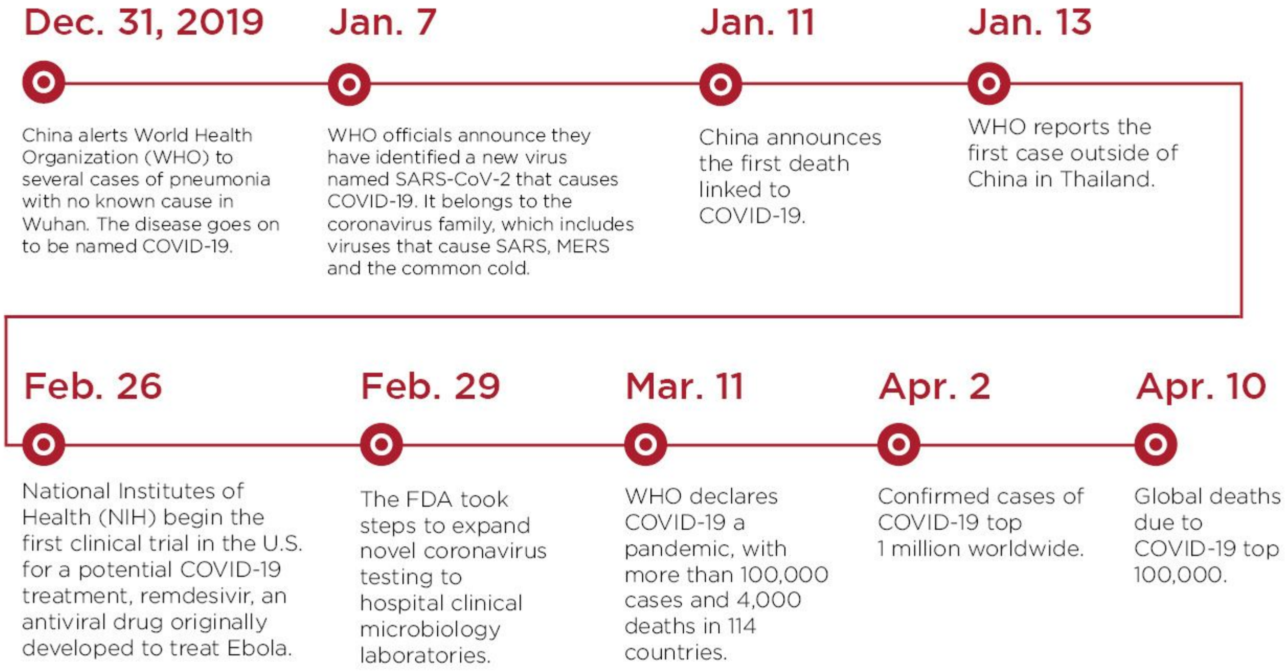
Introduction

Motivation



Source: https://asm.org/Press-Releases/2020/COVID-19-Resources

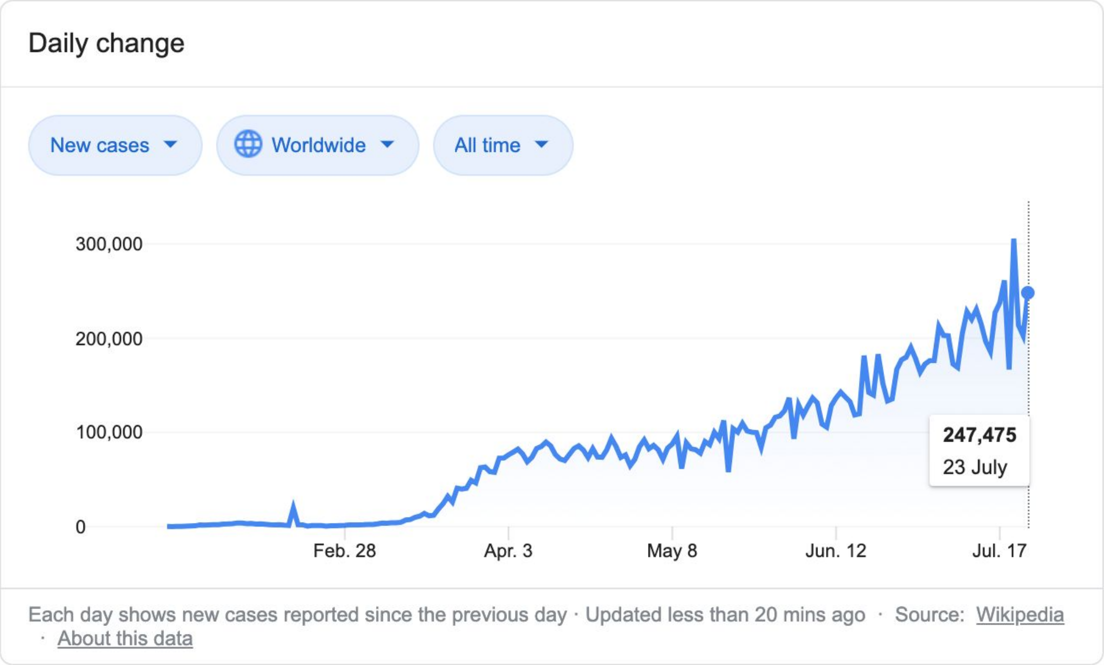
Motivation

Challenges:

- Diagnosis/Testing
- Limited resources
- COVID-19 vs bacterial pneumonia

Ideas:

- Imaging data,
- Computer-based methods



This Project

- **Objective:** Differentiate between healthy individuals, individuals with bacterial pneumonia, and individuals with COVID-19.
- **Idea:** Use deep learning techniques to build a multi-class classifier for these three categories

Data and Methods

Data

COVID:

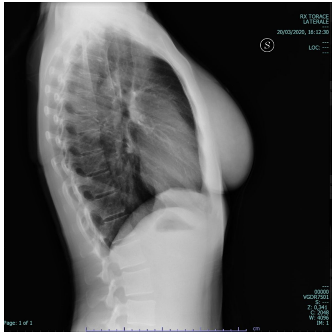
- X-rays and CT scans of patients with COVID-19
- Roughly 200 images
- https://github.com/ieee8023/covid-chestxray-dataset

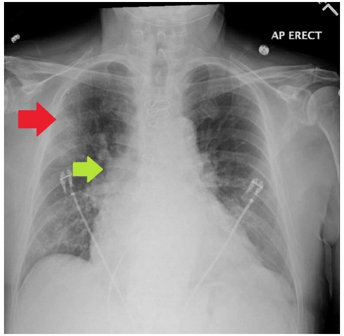
Bacterial Pneumonia + Healthy:

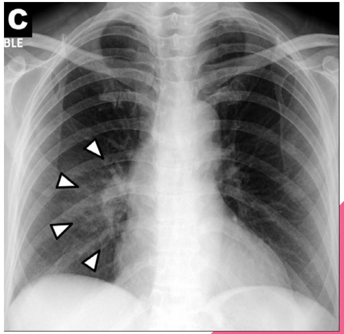
- Chest x-rays for individuals with and without pneumonia
- Over 5,000 images all together
- https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

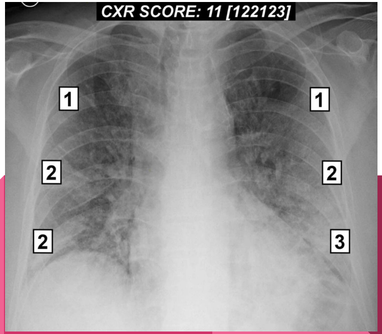
Data Processing

- Filter only x-rays from COVID dataset
- Remove MERS and SARS from COVID dataset
- Remove images that are wrong view or annotated
- Universal crop of all images







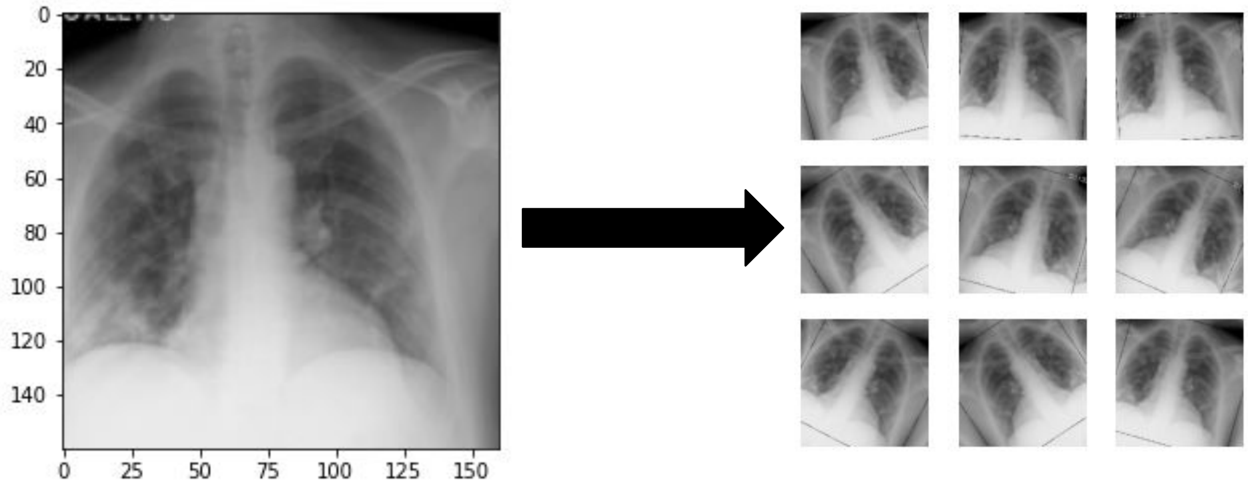


Methods

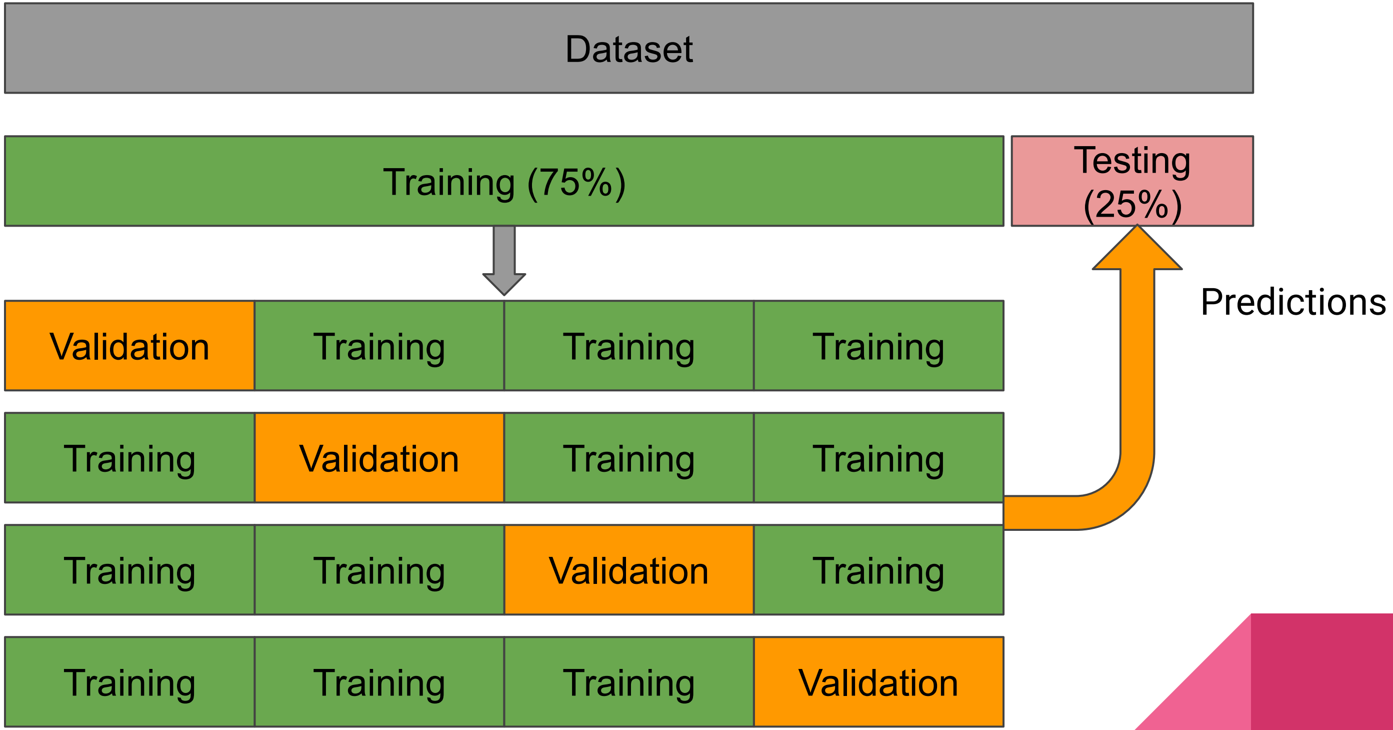
- Multi-class classification with class imbalance
- Limited COVID images:
  - Transfer learning
  - Data augmentation
  - Synthetic Minority Oversampling Technique (SMOTE)
  - Class Weights
- K-fold cross validation (stratified)

Data Augmentation

- Random horizontal flips
- Random rotations up to 36 degrees clockwise or counter-clockwise



Stratified K-fold cross validation



Evaluation

Macro average:

- Recall
- Precision
- F-score

$$Recall_M = \left(\Sigma_{i=1}^{l=3} \frac{TP_i}{TP_i + FN_i}\right)/3 \qquad (1)$$

$$Precision_M = \left(\Sigma_{i=1}^{l=3} \frac{TP_i}{TP_i + FP_i}\right)/3 \qquad (2)$$

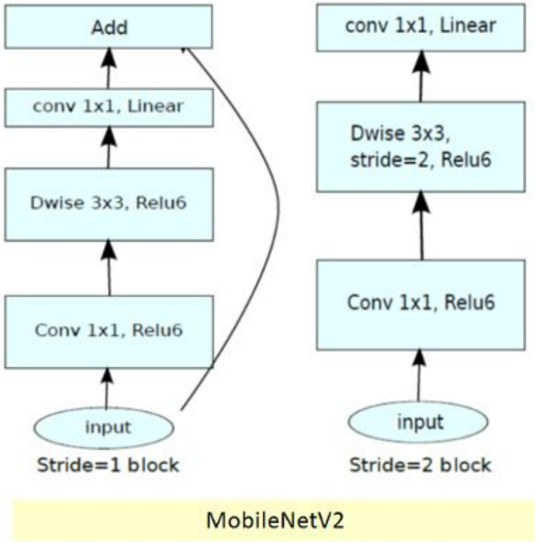
$$Fscore_M = \frac{(\beta^2 + 1) Precision_M Recall_M}{\beta^2 Precision_M + Recall_M} \qquad (3)$$

Transfer Learning Model Architecture

- Two data augmentation layers
- Pre-trained base model initialized with ImageNet weights (MobileNetV2)
- Global average pooling 2D layer
- Prediction layer with softmax activation

```
base_model = tf.keras.applications.MobileNetV2(input_shape=image_shape,
                                               include_top=False,
                                               weights='imagenet')
base_model.trainable = trainable

model = tf.keras.Sequential([layers.experimental.preprocessing.RandomFlip('horizontal'),
                             layers.experimental.preprocessing.RandomRotation(0.1),
                             base_model,
                             tf.keras.layers.GlobalAveragePooling2D(),
                             tf.keras.layers.Dense(3, activation='softmax')])
```



Model Experimentations

Model 1: NP3SMOTE

- Not pretrained
- SMOTE in the training set

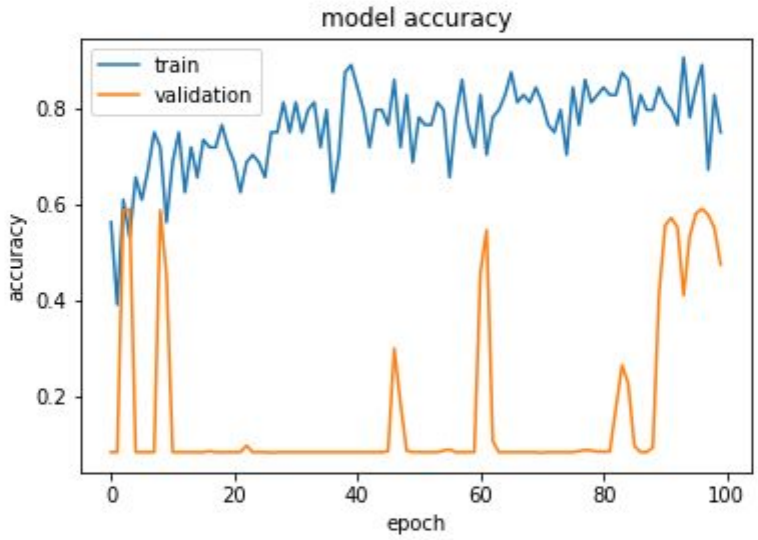
Model Summary:

- Model: not pretrained
- Epochs: 100
- Learning rate: 0.005
- Class weights: No
- SMOTE: Yes

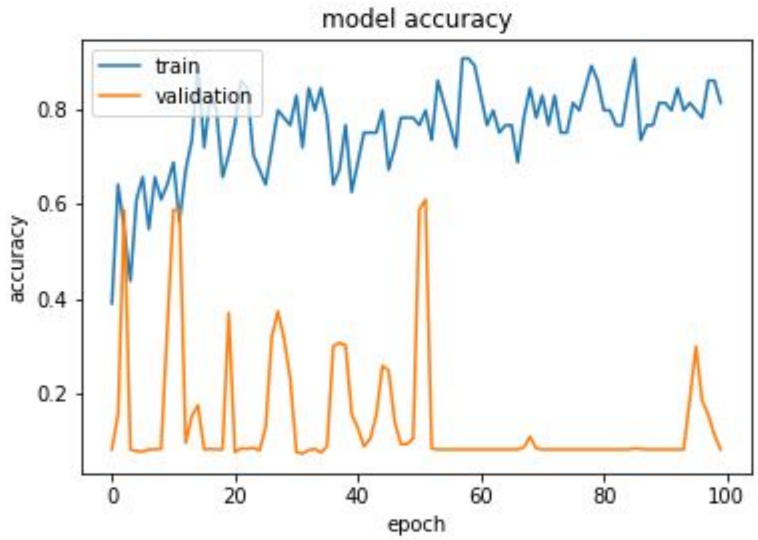
Fold	Accuracy	Loss
1	47.42	2.76
2	8.41	4.75
3	19.75	2.16
4	8.31	4.23
mean	20.97	3.48

Model 1: NP3SMOTE

Best fold



Worst fold



Model 1: NP3SMOTE

Predicted Classes

True Classes

Best fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.58	0.72	0.64	524	377	147	0
class 1	0.19	0.62	0.29	74	28	46	0
class 2	0.00	0.00	0.00	294	244	50	0
accuracy	0.47	0.47	0.47	0.47	-	-	-
macro avg	**0.26**	**0.45**	**0.31**	**892**	**-**	**-**	**-**
weighted avg	**0.36**	**0.47**	**0.40**	**892**	**-**	**-**	**-**

Worst fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.00	0.00	0.00	523	0	523	0
class 1	0.08	1.00	0.15	74	0	74	0
class 2	0.00	0.00	0.00	294	0	294	0
accuracy	0.08	0.08	0.08	0.08	-	-	-
macro avg	**0.03**	**0.33**	**0.05**	**891**	**-**	**-**	**-**
weighted avg	**0.01**	**0.08**	**0.01**	**891**	**-**	**-**	**-**

Model 2: P0SMOTE

- +pretrained
- +SMOTE
- +decreased lr

Model Summary:

- Model: pretrained MobileNet
- Epochs: 100
- Learning rate: 0.0001
- Class weights: No
- SMOTE: Yes

Previous Model:

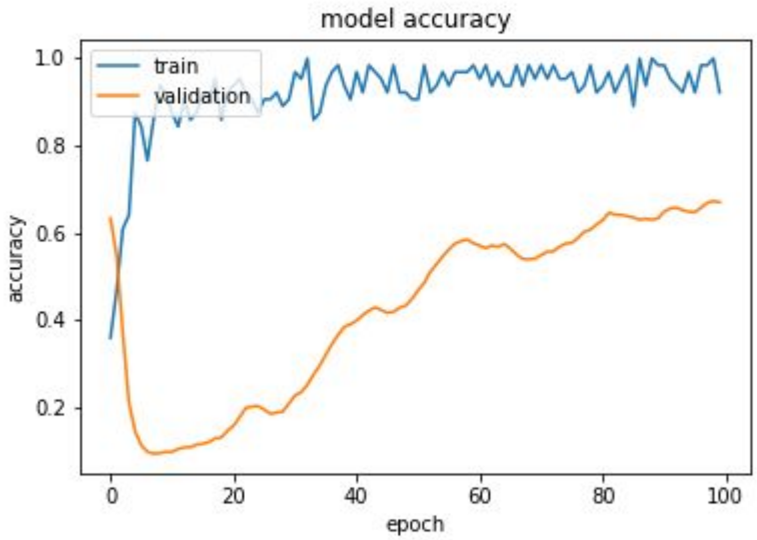
Fold	Accuracy	Loss
1	47.42	2.76
2	8.41	4.75
3	19.75	2.16
4	8.31	4.23
mean	20.97	3.48

Now:

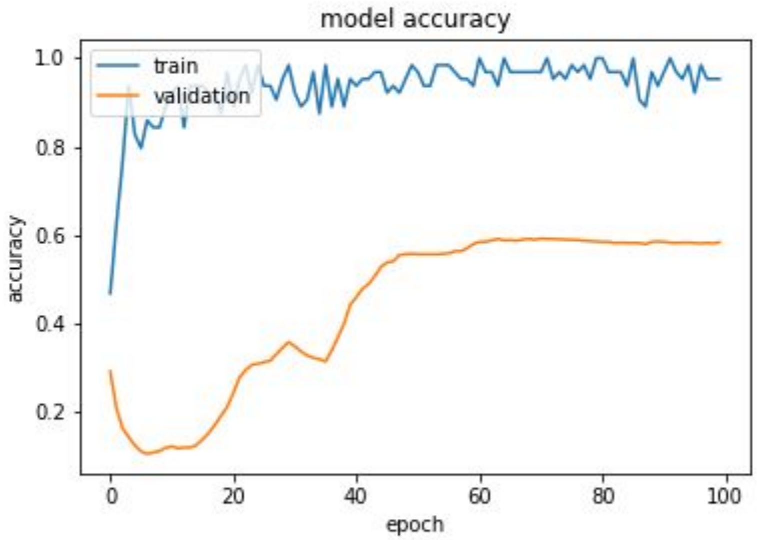
Fold	Accuracy	Loss
1	67.03	0.88
2	60.05	2.86
3	58.42	3.09
mean	61.83	2.28

Model 2: P0SMOTE

Best fold



Worst fold



Model 2: P0SMOTE

Best fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.66	0.92	0.77	698	642	41	15
class 1	0.47	0.36	0.41	99	52	36	11
class 2	0.82	0.30	0.44	392	273	0	119
accuracy	0.67	0.67	0.67	0.67	-	-	-
macro avg	**0.65**	**0.53**	**0.54**	**1189**	**-**	**-**	**-**
weighted avg	**0.70**	**0.67**	**0.63**	**1189**	**-**	**-**	**-**

Worst fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.59	0.99	0.74	697	690	7	0
class 1	0.36	0.04	0.07	98	94	4	0
class 2	0.00	0.00	0.00	393	393	0	0
accuracy	0.58	0.58	0.58	0.58	-	-	-
macro avg	**0.32**	**0.34**	**0.27**	**1188**	-	-	-
weighted avg	**0.37**	**0.58**	**0.44**	**1188**	-	-	-

Model 3: P1SMOTE

- +Class weights
  - {0: 4., 1: 26., 2: 7.}

Model Summary:

- Model: pretrained MobileNet
- Epochs: 100
- Learning rate: 0001
- Class weights: {0: 4., 1: 26., 2: 7.}
- SMOTE: Yes

Previous Model:

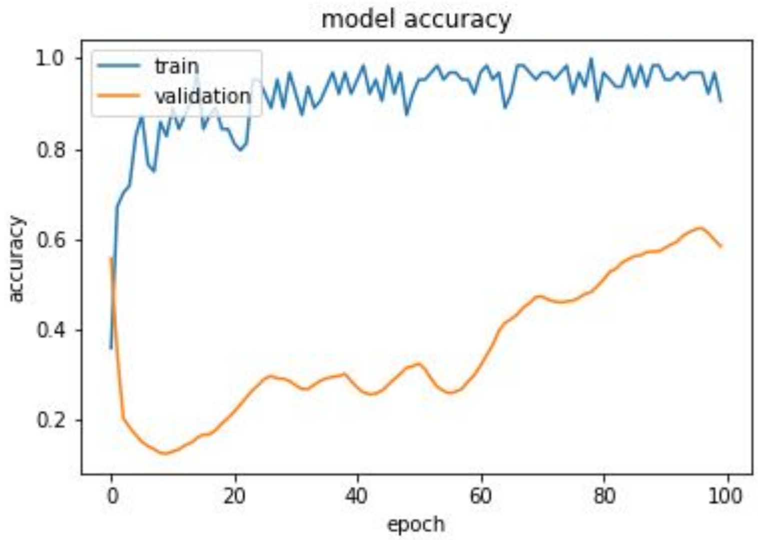
Fold	Accuracy	Loss
1	67.03	0.88
2	60.05	2.86
3	58.42	3.09
mean	61.83	2.28

Now:

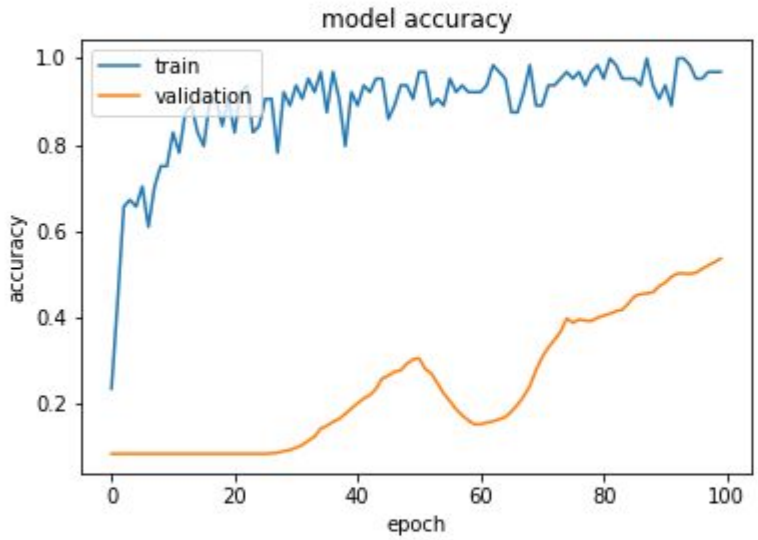
Fold	Accuracy	Loss
1	58.45	1.15
2	53.57	1.31
3	57.58	1.04
mean	56.53	1.17

Model 3: P1SMOTE

Best fold



Worst fold



Model 3: P1SMOTE

Best fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.61	0.81	0.70	698	562	136	0
class 1	0.30	0.60	0.40	99	40	59	0
class 2	1.00	0.19	0.32	392	314	4	74
accuracy	0.58	0.58	0.58	0.58	-	-	-
macro avg	**0.64**	**0.53**	**0.47**	**1189**	**-**	**-**	**-**
weighted avg	**0.71**	**0.58**	**0.55**	**1189**	**-**	**-**	**-**

Worst fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.60	0.78	0.68	698	547	151	0
class 1	0.30	0.80	0.43	99	20	79	0
class 2	1.00	0.03	0.05	392	345	36	11
accuracy	0.54	0.54	0.54	0.54	-	-	-
macro avg	**0.63**	**0.54**	**0.39**	**1189**	-	-	-
weighted avg	**0.71**	**0.54**	**0.45**	**1189**	-	-	-

Model 4: P2SMOTE

- +adjusted class weights
    - {0: 4., 1: 26., 2: 12.}

Model Summary:

- Model: pretrained MobileNet
- Epochs: 100
- Learning rate: 0.0001
- Class weights: {0: 4., 1: 26., 2: 12.}
- SMOTE: Yes

Previous Model:

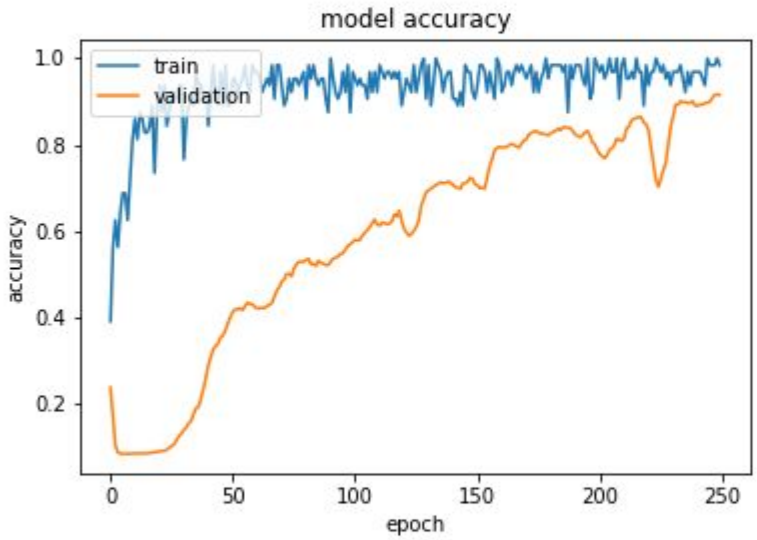
Fold	Accuracy	Loss
1	58.45	1.15
2	53.57	1.31
3	57.58	1.04
mean	56.53	1.17

Now:

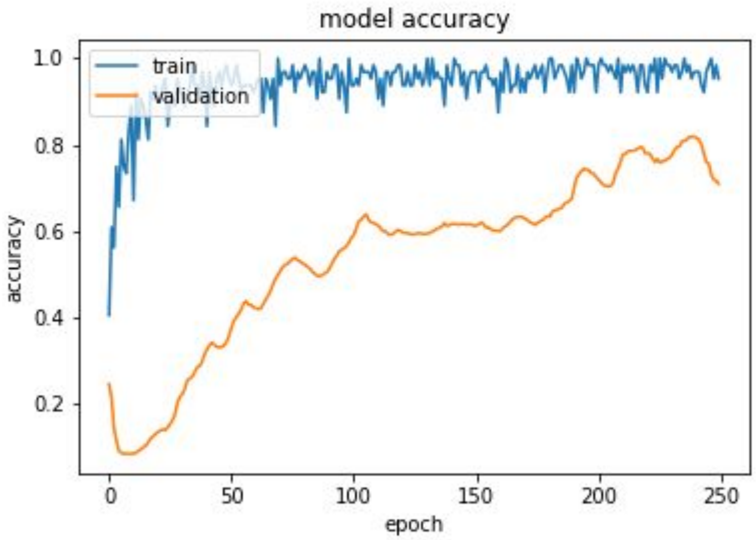
Fold	Accuracy	Loss
1	91.50	0.23
2	75.69	0.68
3	71.04	0.64
mean	79.41	0.52

Model 4: P2SMOTE

Best fold



Worst fold



Model 4: P2SMOTE

Best fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.95	0.92	0.93	698	643	14	41
class 1	0.84	0.82	0.83	99	8	81	10
class 2	0.88	0.93	0.9	392	27	1	364
accuracy	0.92	0.92	0.92	0.92	-	-	-
macro avg	**0.89**	**0.89**	**0.89**	**1189**	-	-	-
weighted avg	**0.92**	**0.92**	**0.92**	**1189**	-	-	-

Worst fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.69	0.96	0.8	697	669	6	22
class 1	0.89	0.52	0.66	98	31	51	16
class 2	0.77	0.32	0.45	393	269	0	124
accuracy	0.71	0.71	0.71	0.71	-	-	-
macro avg	**0.78**	**0.6**	**0.64**	**1188**	-	-	-
weighted avg	**0.73**	**0.71**	**0.67**	**1188**	-	-	-

Model 5: P3SMOTE

- +increased steps per epoch

Model Summary:

- Model: pretrained MobileNet
- Epochs: 100
- Learning rate: 0.0001
- Class weights: No
- SMOTE: Yes

Previous Model:

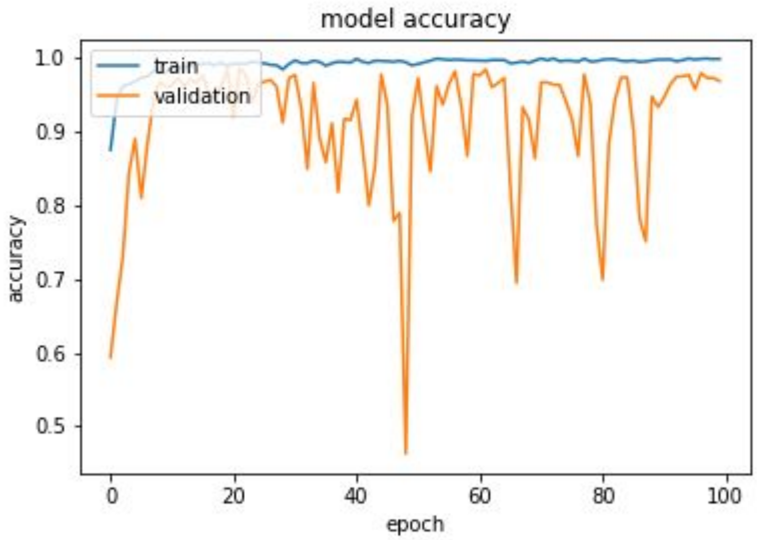
Fold	Accuracy	Loss
1	91.50	0.23
2	75.69	0.68
3	71.04	0.64
mean	79.41	0.52

Now:

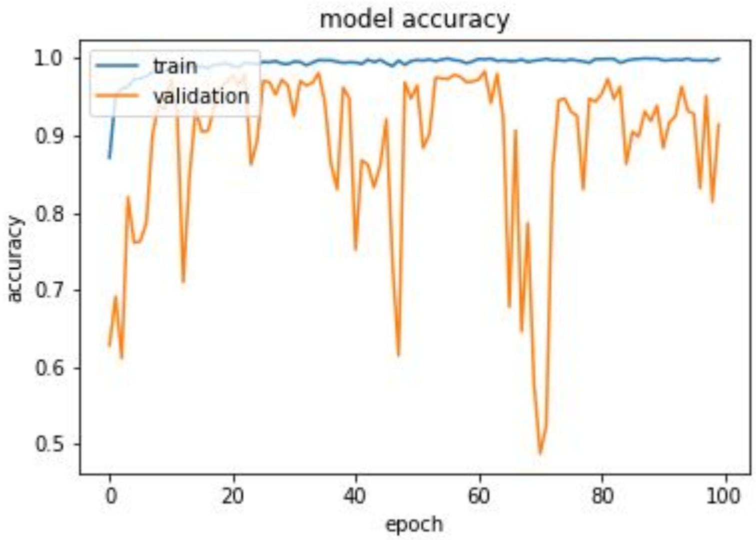
Fold	Accuracy	Loss
1	92.60	0.65
2	96.89	0.21
3	91.41	0.52
mean	93.63	0.46

Model 5: P3SMOTE

Best fold



Worst fold



Model 5: P3SMOTE

Best fold

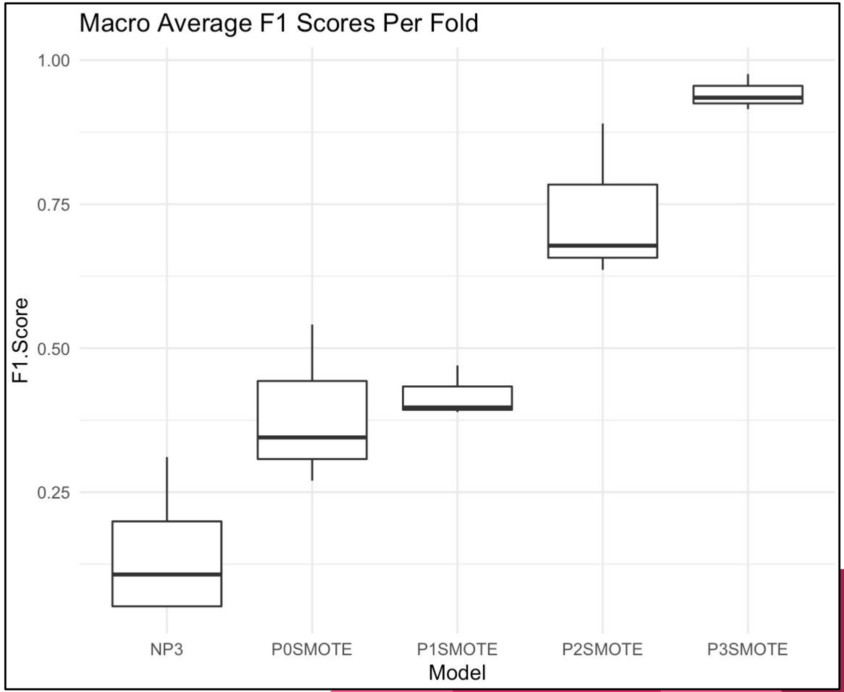
	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.99	0.95	0.97	698	665	0	33
class 1	1	1	1	99	0	99	0
class 2	0.92	0.99	0.95	392	4	0	388
accuracy	0.97	0.97	0.97	0.97	-	-	-
macro avg	**0.97**	**0.98**	**0.98**	**1189**	-	-	-
weighted avg	**0.97**	**0.97**	**0.97**	**1189**	-	-	-

Worst fold

	precision	recall	f1-score	support	pred_0	pred_1	pred_2
class 0	0.99	0.88	0.93	697	611	0	86
class 1	1.00	0.87	0.93	98	1	85	12
class 2	0.80	0.99	0.89	393	3	0	390
accuracy	0.91	0.91	0.91	0.91	-	-	-
macro avg	**0.93**	**0.91**	**0.92**	**1188**	-	-	-
weighted avg	**0.93**	**0.91**	**0.92**	**1188**	-	-	-

Model experimentation

Model	Change	Macro Average F1-Score for Fold				Average F1-Score
		1	2	3	4	
NP3		0.311	0.052	0.162	0.051	0.144
P0SMOTE	+pretrained +SMOTE +decreased lr	0.541	0.345	0.27	-	0.385
P1SMOTE	+class weights	0.47	0.389	0.397	-	0.419
P2SMOTE	+adjusted class weights	0.89	0.678	0.636	-	0.735
P3SMOTE	+increased steps per epoch	0.935	0.976	0.915	-	0.942
P6SMOTE	-decreased steps per epoch -decreased epochs	**0.924**	**0.893**	**0.974**	**-**	**0.930**



Challenges

- All images getting classified into the same category
- Balancing class weight
- Real world interpretation of the results

Next Steps

- Tune parameters
    - Class weights
    - Learning rates
    - Epochs
- Evaluate model performance on test set
- Clean up our code

Q & A

Thanks for listening! Any questions?

References

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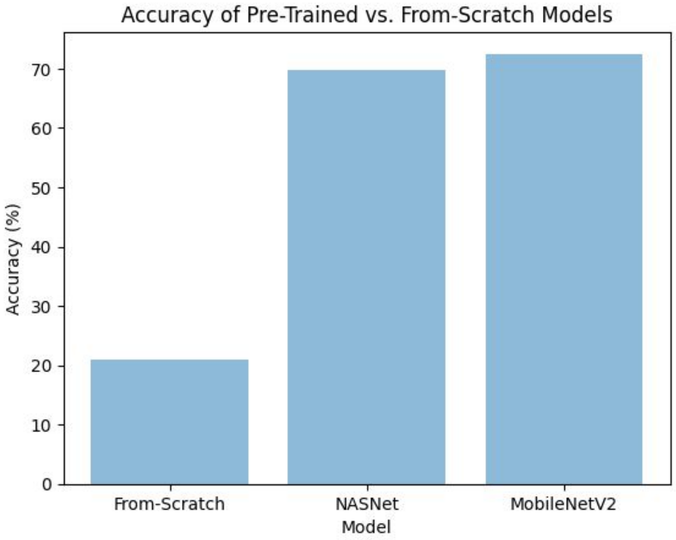
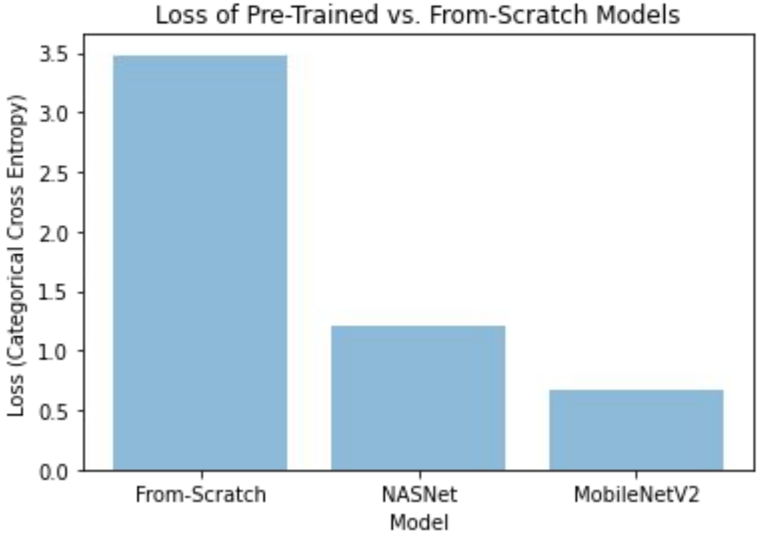
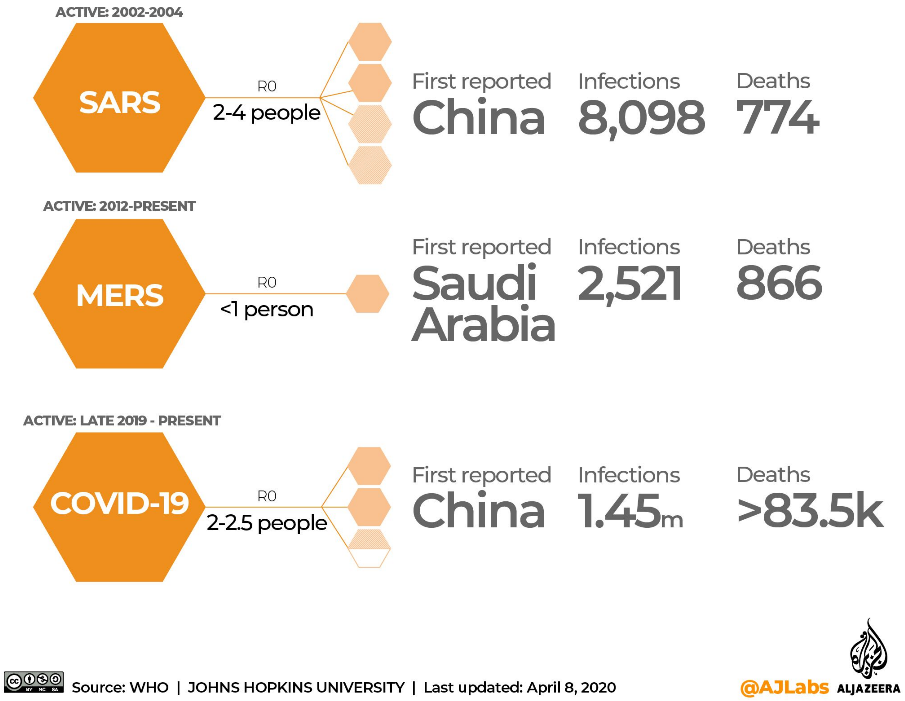
Appendix

Pre-trained models comparison





Motivation


ACTIVE: 2002-2004
SARS
R0
2-4 people
First reported
China
Infections
8,098
Deaths
774
ACTIVE: 2012-PRESENT
MERS
R0
<1 person
First reported
Saudi Arabia
Infections
2,521
Deaths
866
ACTIVE: LATE 2019 - PRESENT
COVID-19
R0
2-2.5 people
First reported
China
Infections
1.45m
Deaths
>83.5k
Source: WHO | JOHNS HOPKINS UNIVERSITY | Last updated: April 8, 2020
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