Alexander Koenig, Li Nguyen

Deep Learning for Medical Imaging, Faculty of Engineering, Tel Aviv University

14th of July 2020

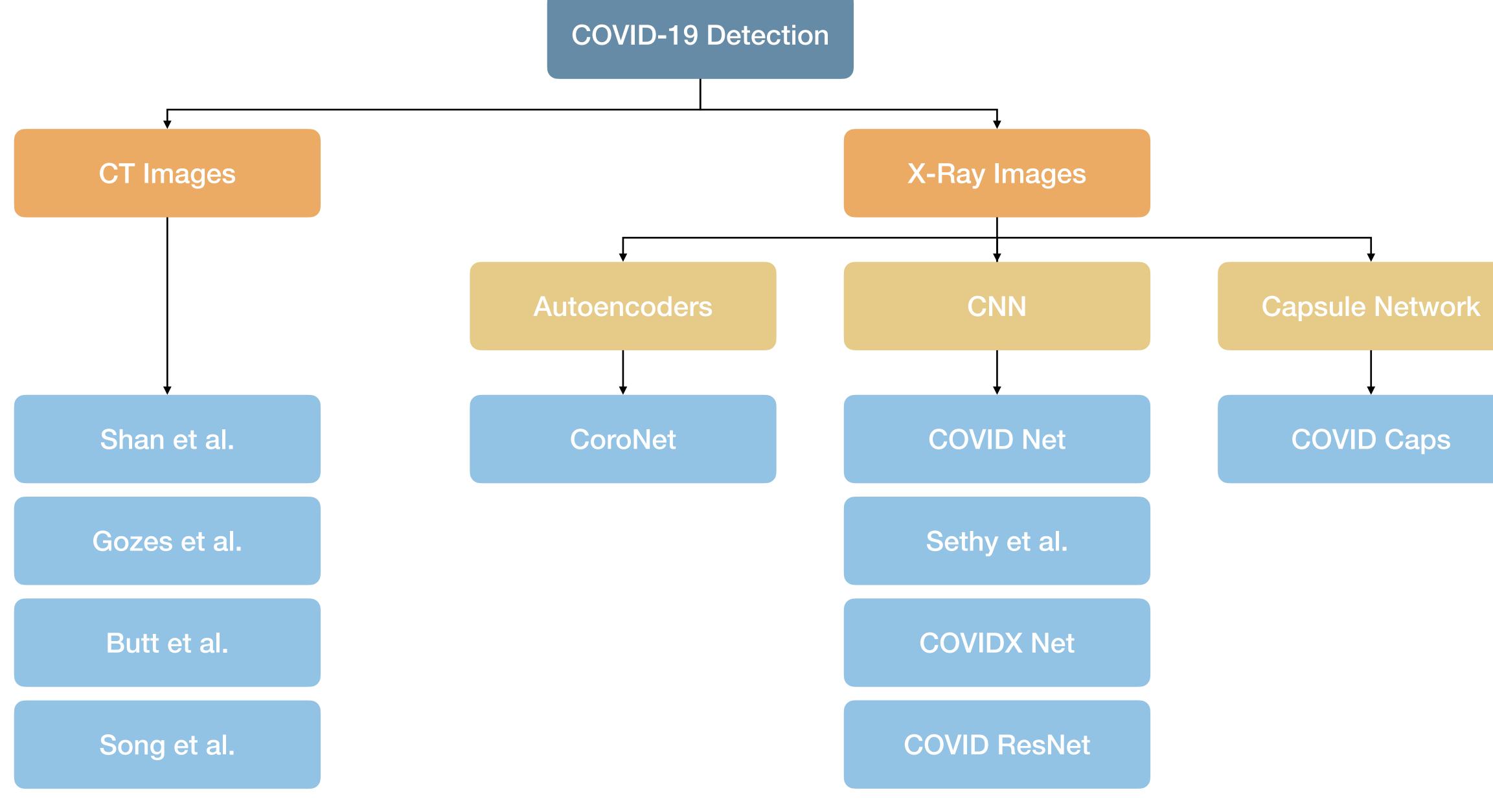
- 1. Introduction
- 2. Related Work
- 3. Datasets
- 4. Methods and Results
- 5. Future Work

1. Introduction 2. Related Work **3.** Datasets 4. Methods and Results 5. Future Work

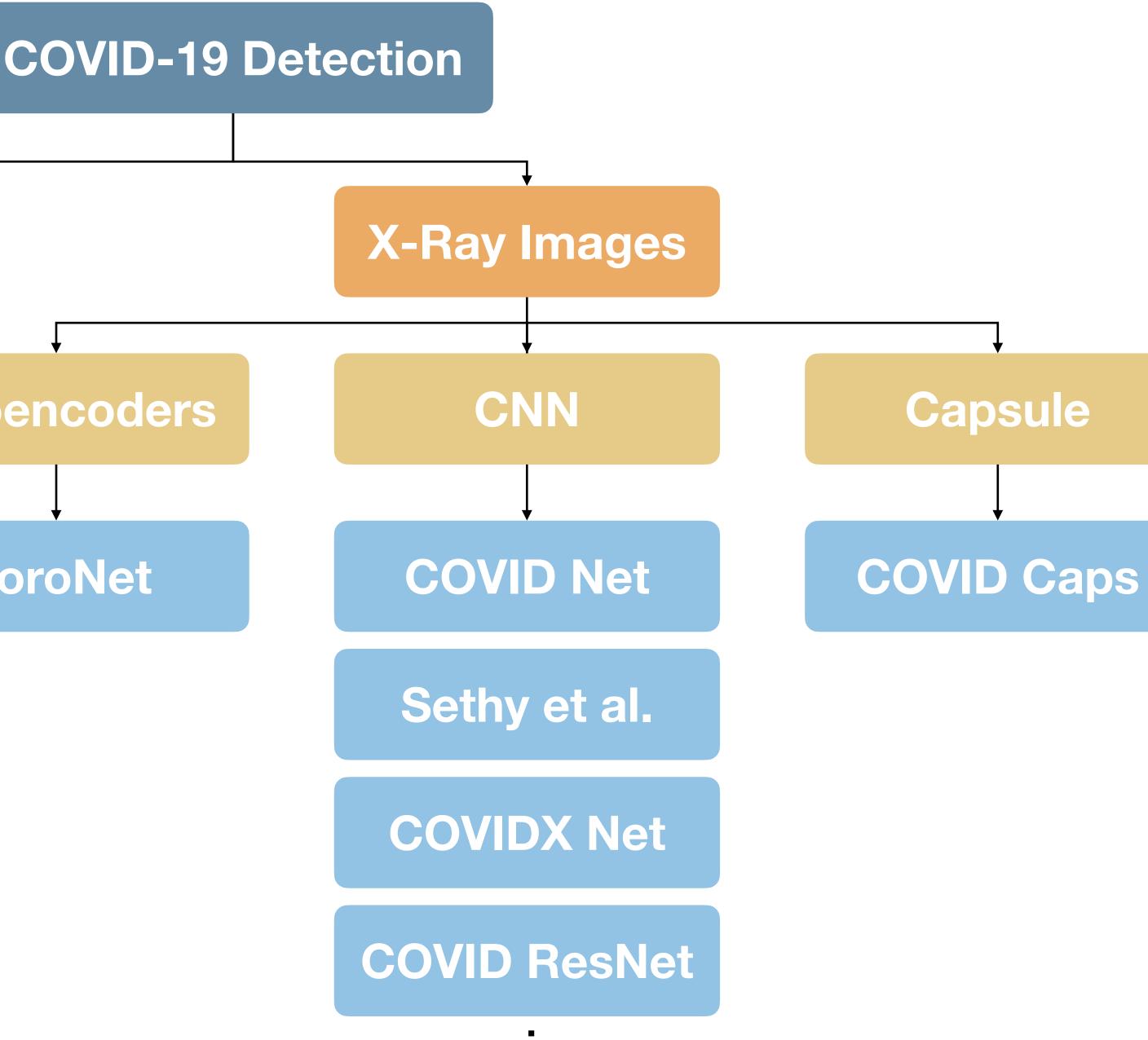
Introduction Motivation

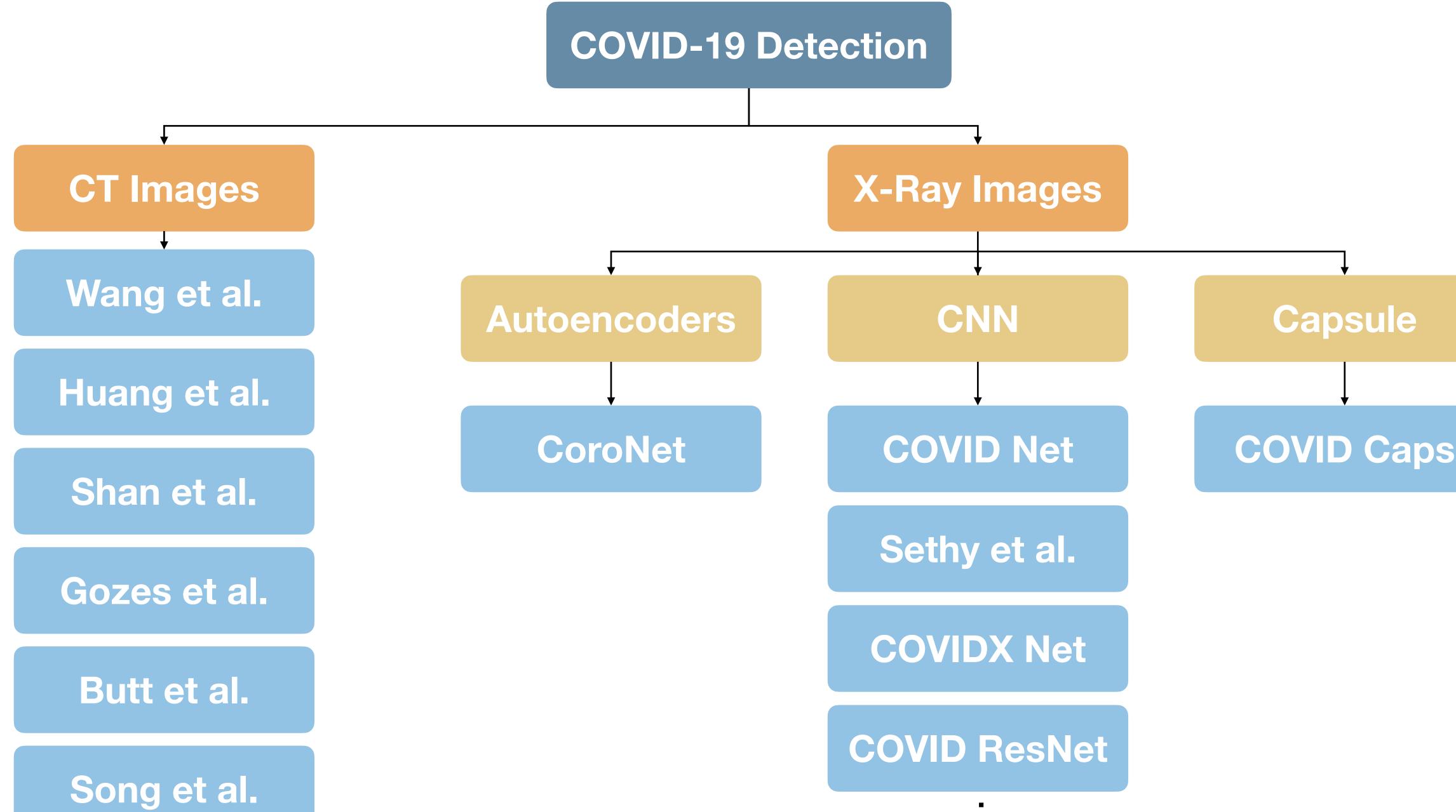
- Cut off virus transmission routes by effective and fast testing
- Visual indicator in Chest X-Ray (CXR) images: Ground glass opacity
- Need for supportive CXR classification systems
- Need for visualisation of COVID anomalies

1. Introduction 2. Related Work 3. Datasets 4. Methods and Results 5. Future Work











Introduction
 Related Work

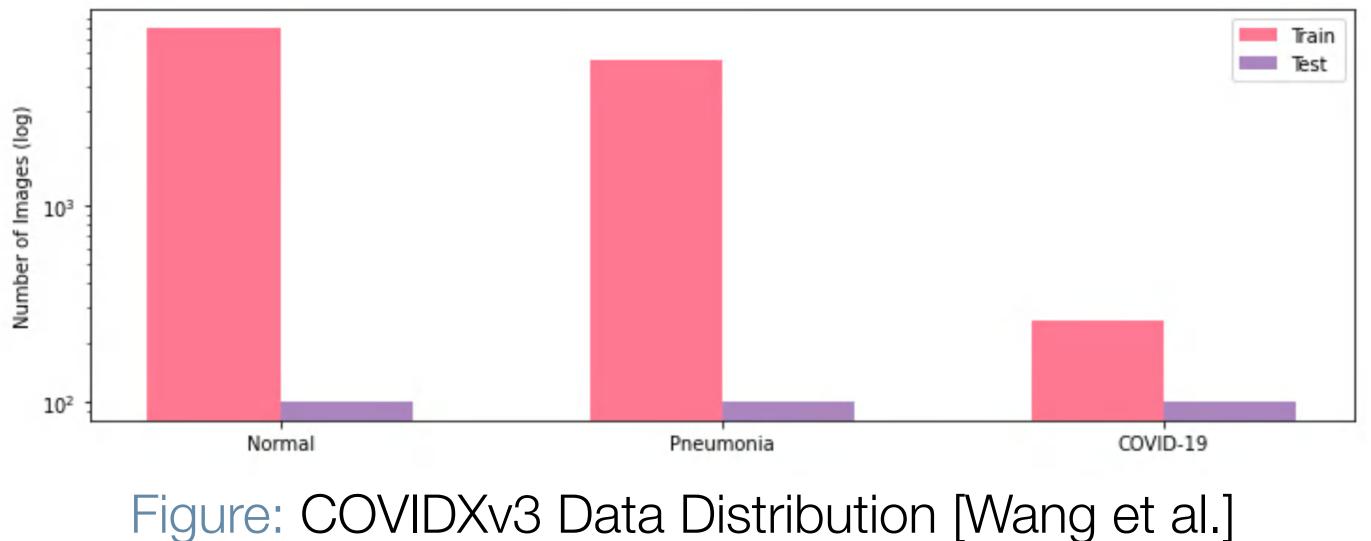
3. Datasets

4. Methods and Results

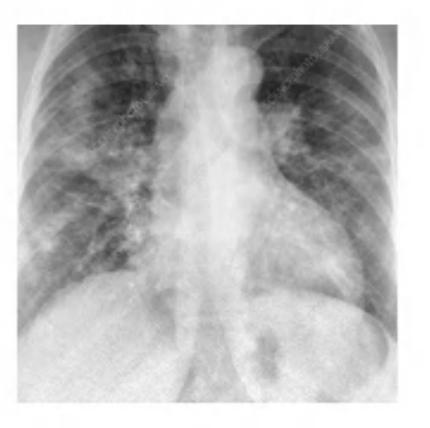
5. Future Work

Dataset

- Weighted Loss Function
- Data Augmentation
- K-Fold Cross Validation









Normal

non-COVID-19 Pneumonia

COVID-19 Pneumonia

Train Test Normal 7966 100 Pneumonia 5451 100 COVID 253 100 300 **Total** 13670

Why no validation data? #66



axkoenig opened this issue on 19 May · 2 comments



axkoenig commented on 19 May • edited +

Hello,

the Generative Synthesis approach produced? It is good practice to do this on a validation set, right? Looking forward to any comments and implementation details on this :) Alex

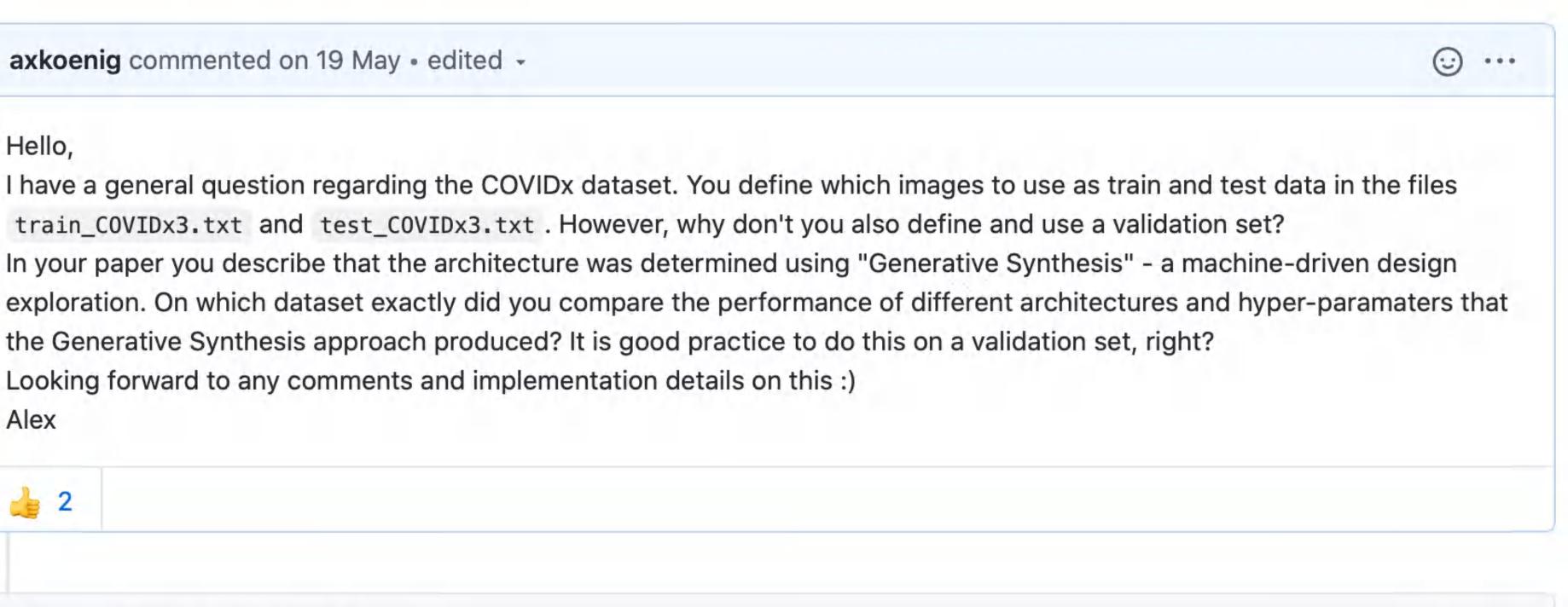


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sergevanhaag commented on 6 Jun

I agree. I am not able to recreate the results if I use a training, validation, and test-set. I am afraid that COVID-NET indirectly overfits on the test-set. I'd suggest using the test-set only once.



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1. Introduction 2. Related Work 3. Datasets 4. Methods and Results 5. Future Work

Methods

Approach 1

ResNet-50 Baseline Classifier

Approach 2

Anomaly **Detection with U-Net**

Approach 3

Multitask Learning

Methods

Approach 1

ResNet-50 Baseline Classifier

Approach 2

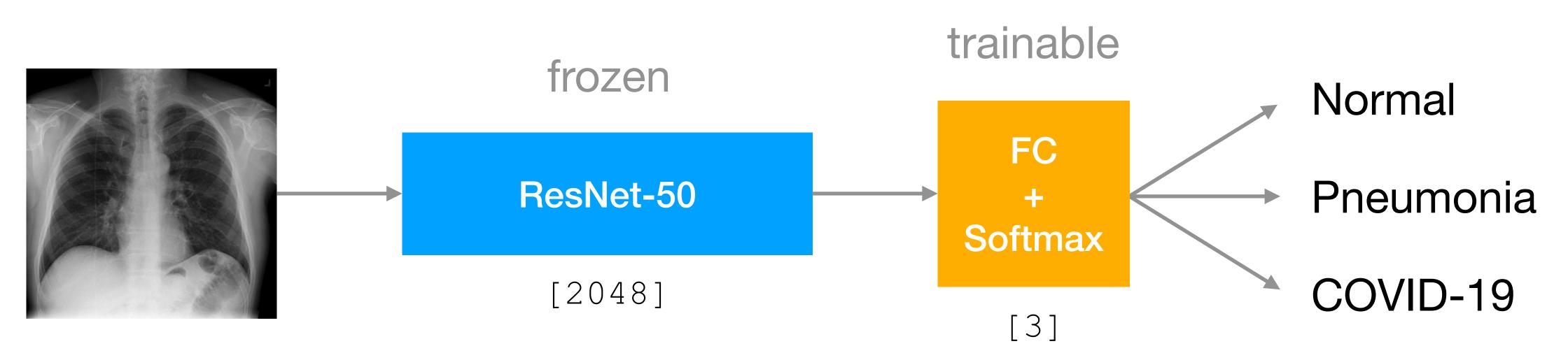
Approach 3

Anomaly **Detection with U-Net**

Multitask Learning

ResNet-50 Baseline Classifier

- Transfer Learning on pre-trained model
- Replace last FC layer of ResNet-50

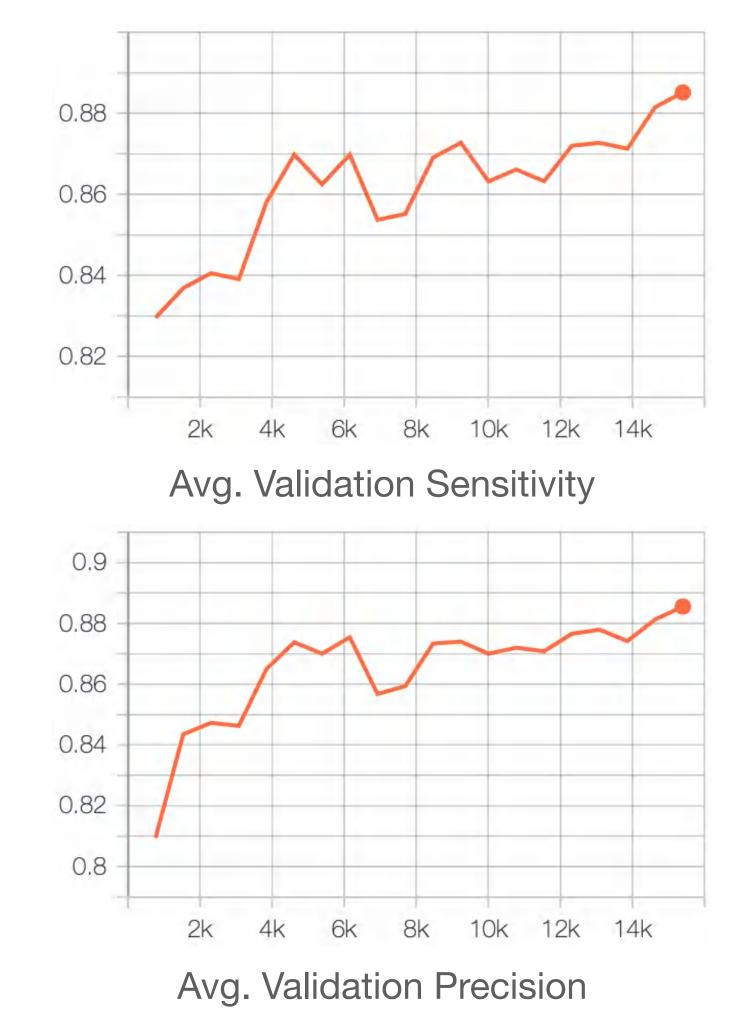


[3,224,224]

ResNet-50 Baseline – Test Results

Pred. True	Normal	Pneumonia	COVID
Normal	88	12	0
Pneumonia	11	88	1
COVID	18	40	42

In %	Normal	Pneumonia	COVID	Average
Sensitivity	88.0	88.0	42.0	72.7
Precision	75.2	62.9	97.7	78.6



Methods

Approach 1

ResNet-50 Baseline Classifier

Approach 2

Approach 3

Anomaly **Detection with U-Net**

Multitask Learning

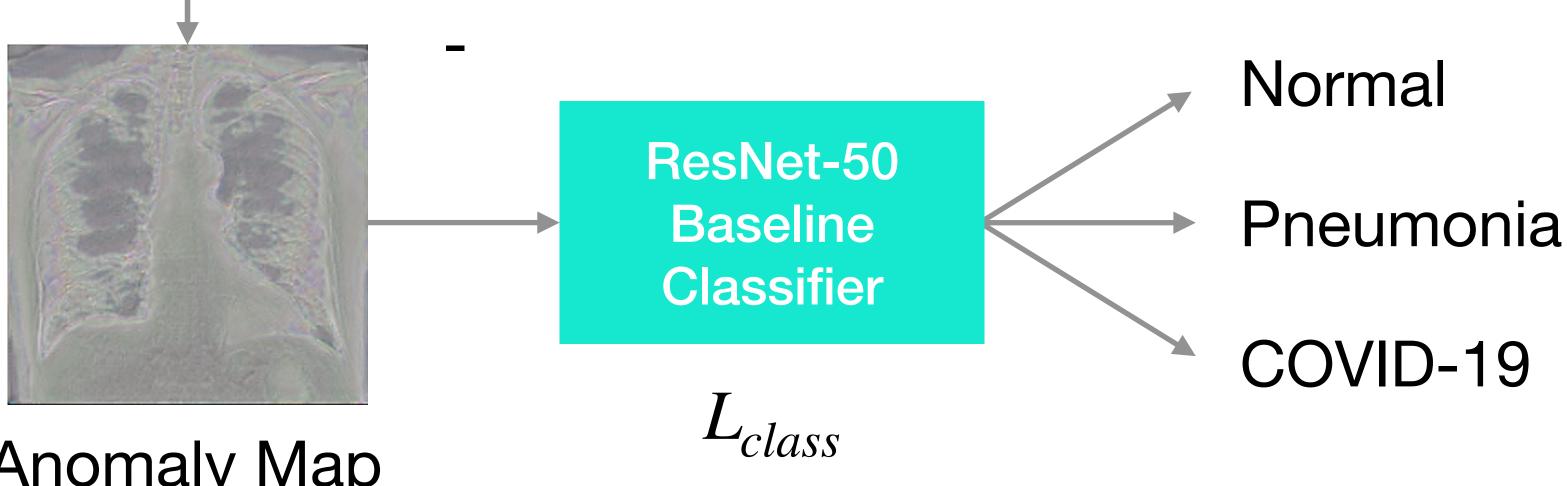
Anomaly Detection with U-Net

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Original



Cloby/10)-a19



Anomaly Map

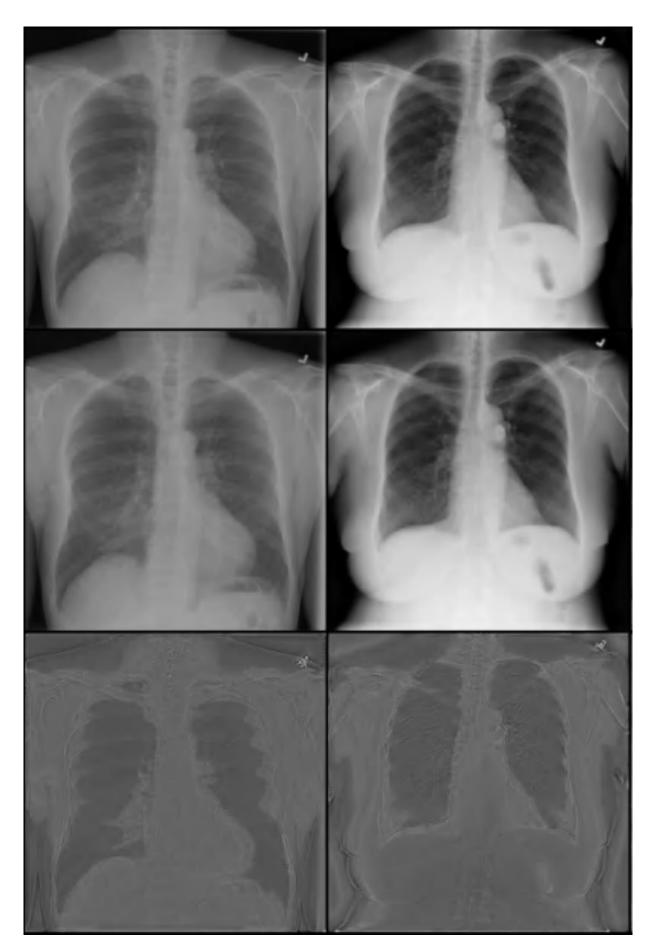
Reconstruction

Anomaly Maps

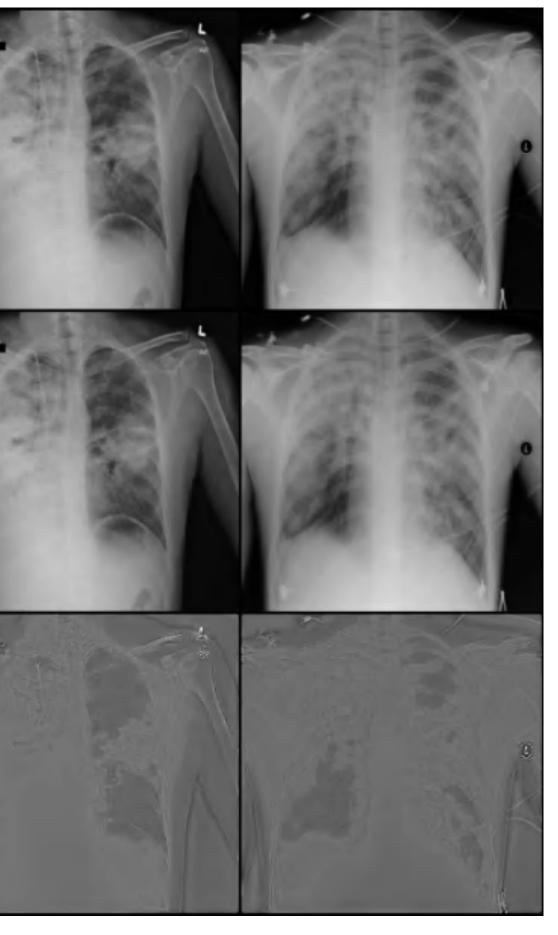
Original

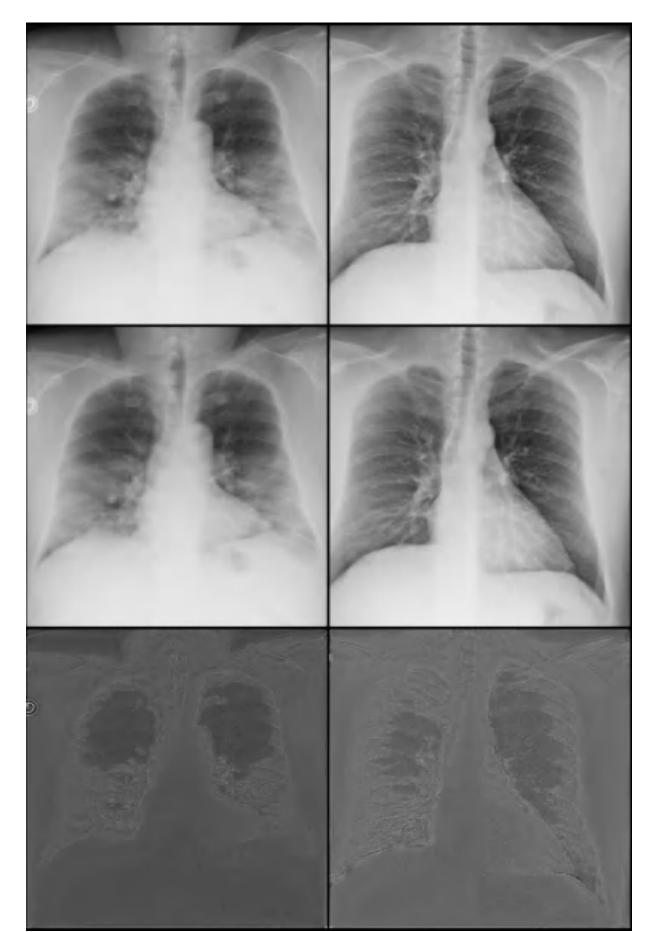
Reconstruction

Anomaly Map



Normal





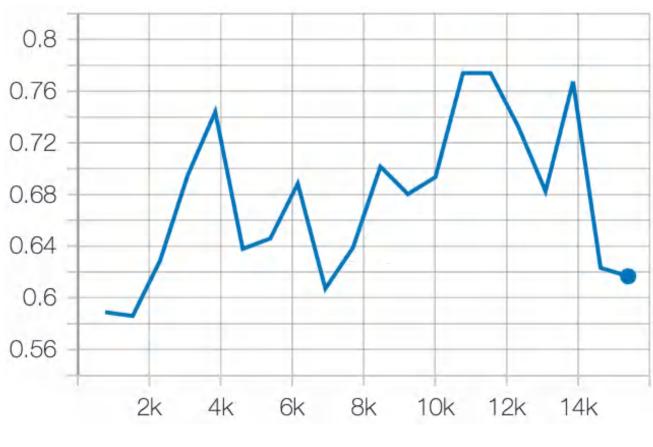
Pneumonia

COVID

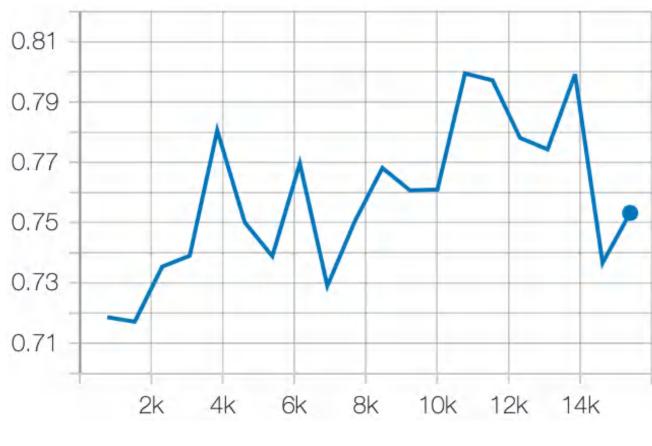
Anomaly Detection – Test Results

Pred. True	Normal	Pneumonia	COVID
Normal	46	47	7
Pneumonia	3	89	8
COVID	7	35	58

In %	Normal	Pneumonia	COVID	Average
Sensitivity	46.0	89.0	58.0	64.3
Precision	82.1	52.0	79.5	71.2



Avg. Validation Sensitivity



Avg. Validation Precision

Methods

Approach 1

ResNet-50 Baseline Classifier

Approach 2

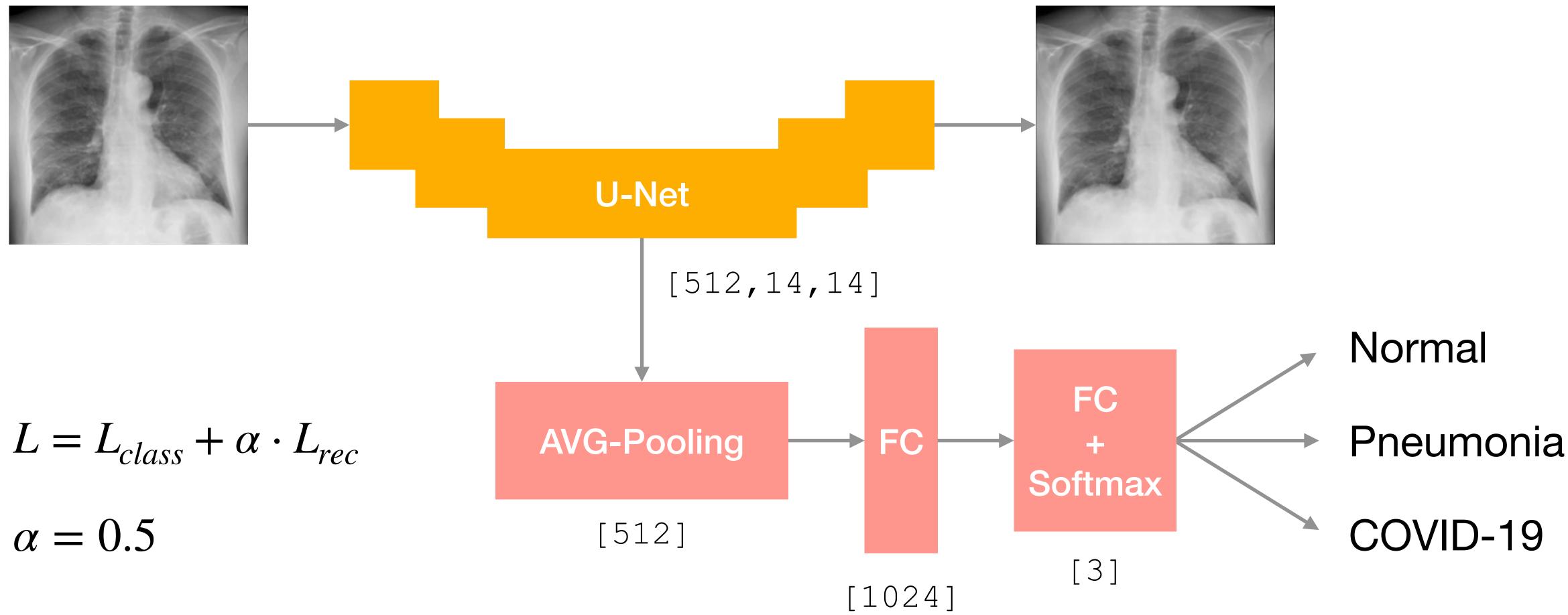
Anomaly **Detection with U-Net**

Approach 3

Multitask Learning

Multitask Learning

Original

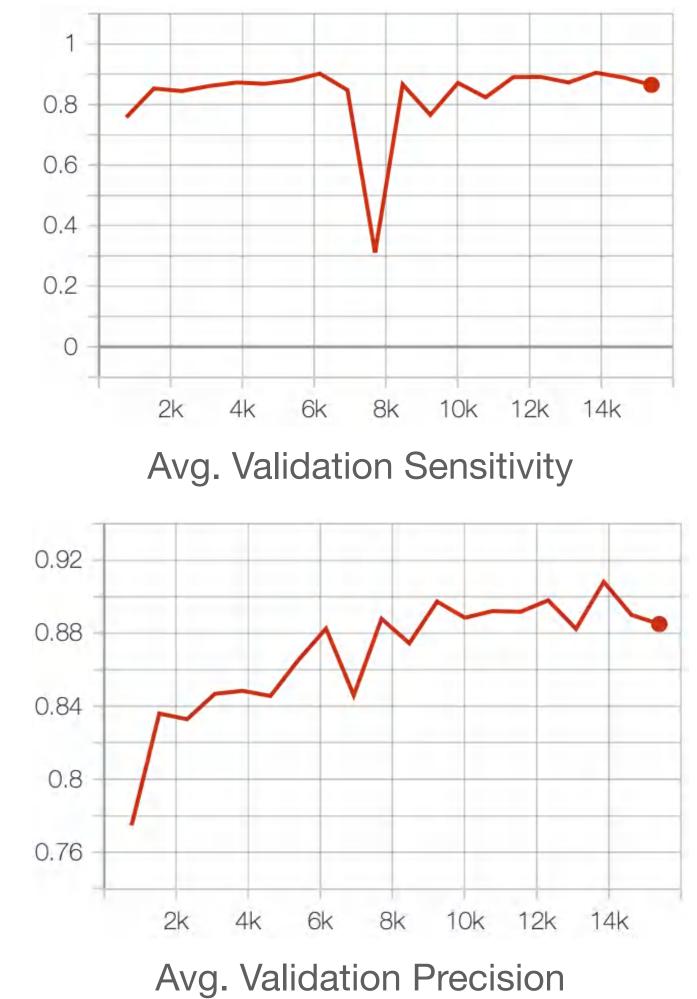


Reconstruction

Multitask Learning – Test Results

Pred. True	Normal	Pneumonia	COVID
Normal	87	11	2
Pneumonia	4	88	8
COVID	7	28	65

In %	Normal	Pneumonia	COVID	Average
Sensitivity	87.0	88.0	65.0	80.0
Precision	88.8	69.3	86.7	81.6



Comparison – Test Results

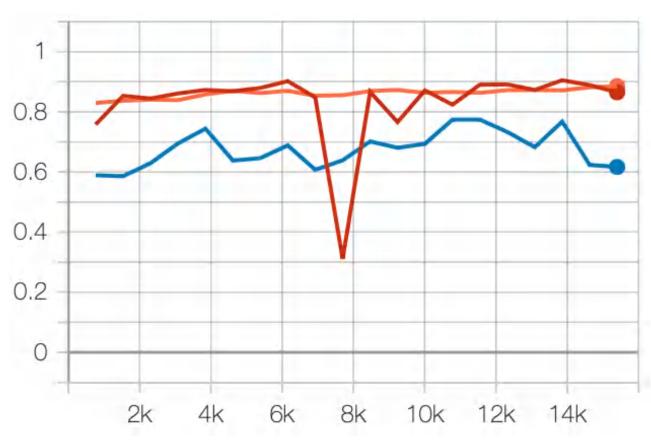
In %	Normal	Pneumonia	COVID	Average
ResNet-50	88.0	88.0	42.0	72.7
Anomaly	46.0	89.0	58.0	64.3
Multitask	87.0	88.0	65.0	80.0

Sensitivity

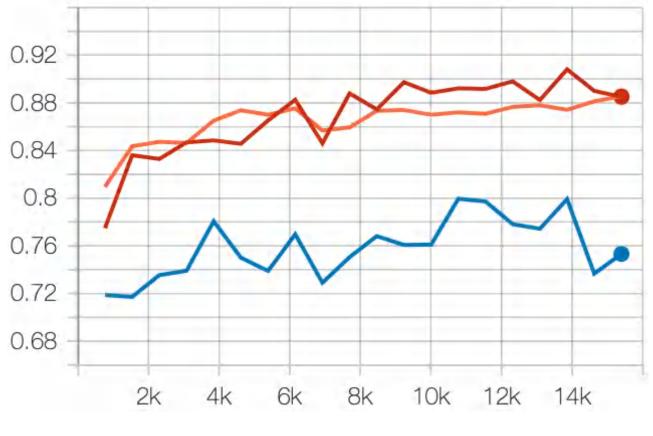
In %	Normal	Pneumonia	COVID	Average
ResNet-50	75.2	62.9	97.7	78.6
Anomaly	82.1	52.0	79.5	71.2
Multitask	88.8	69.3	86.7	81.6

Precision

ResNet-50 Anomaly Multitask



Avg. Validation Sensitivity



Avg. Validation Precision





Future Work

- Improvements
 - Train classifiers for more than 20 epochs
 - Different loss function, e.g. cosine loss by Barz et al.
 - Combine loss function weighting with oversampling
- Extensions
 - Use bigger COVIDXv4 Dataset
 - Which approach is worth refining?



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