



# Unsupervised Detection of Pulmonary Opacities for Computer-Aided Diagnosis of COVID-19 on CT Images

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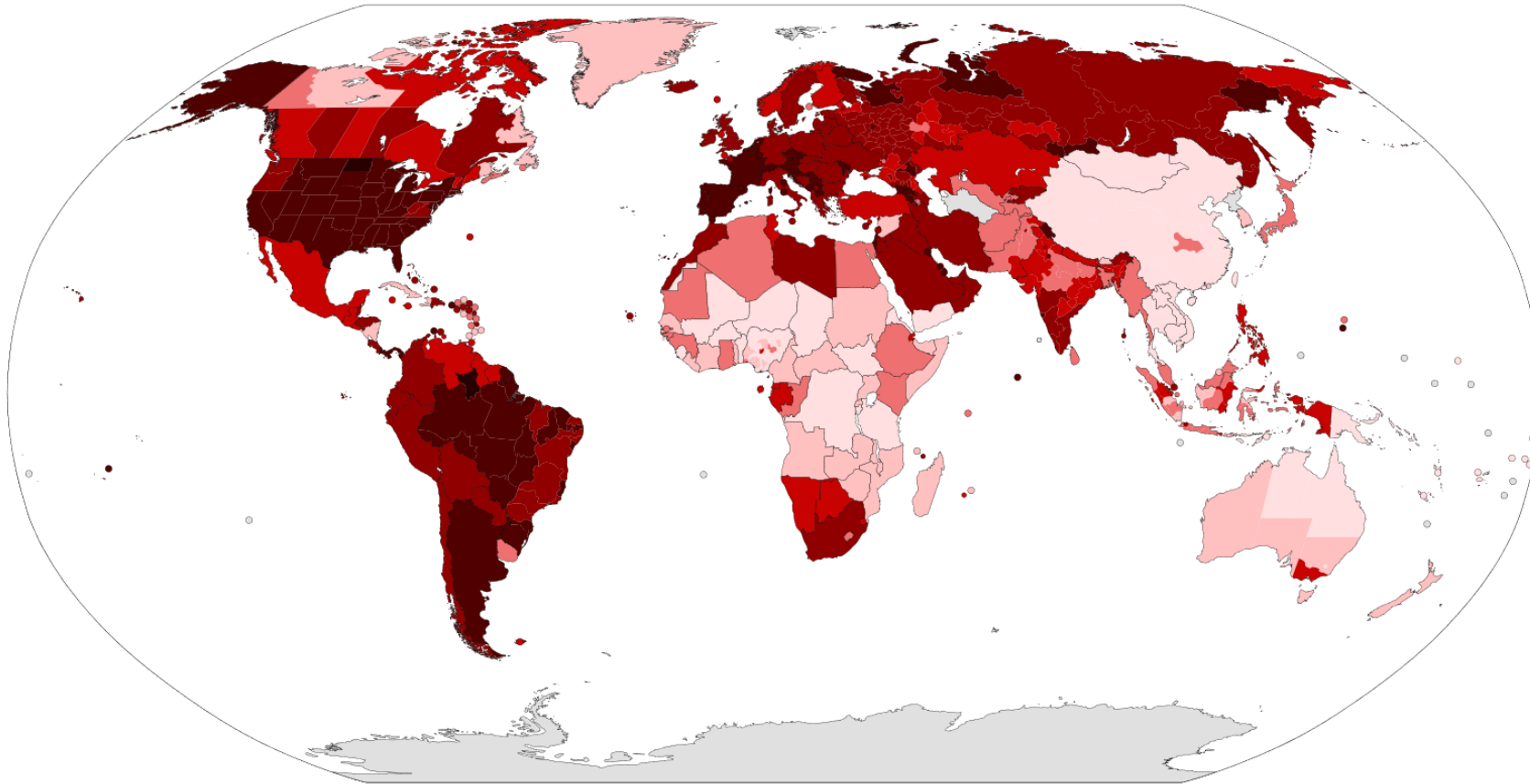
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# Background: Diagnosis of COVID-19 on CT Images

- The world health organization (WHO) has announced that the COVID-19 as a **global healthy emergency** on January 30, 2020.
- The fast growth of COVID-19 patients increases the burden for clinicians and radiologists. **Automatic methods** are highly desired for screening COVID-19 out of CAP.



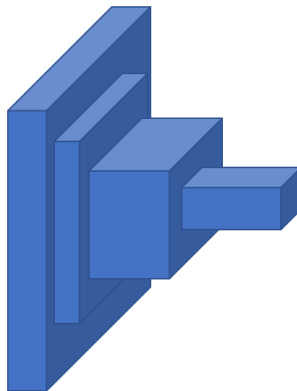
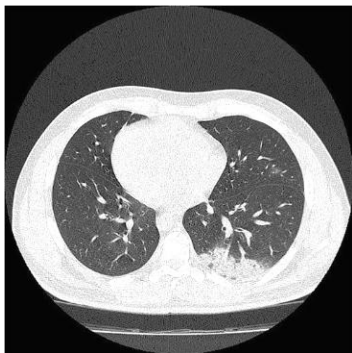
# Background: Diagnosis of COVID-19 on CT Images

- There have been some works that utilize **deep learning based techniques** to automatically analyze CT images for differential diagnosis of COVID-19 against to community-acquired pneumonia (CAP).



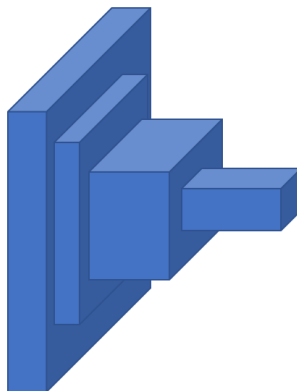
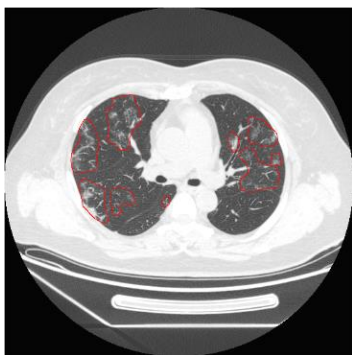
# Background: Diagnosis of COVID-19 on CT Images

- Existing methods learn in an end-to-end manner which limits their performance.



Positive  
or  
Negative

- Opacity-awared methods improve accuracy but need ground-truth.

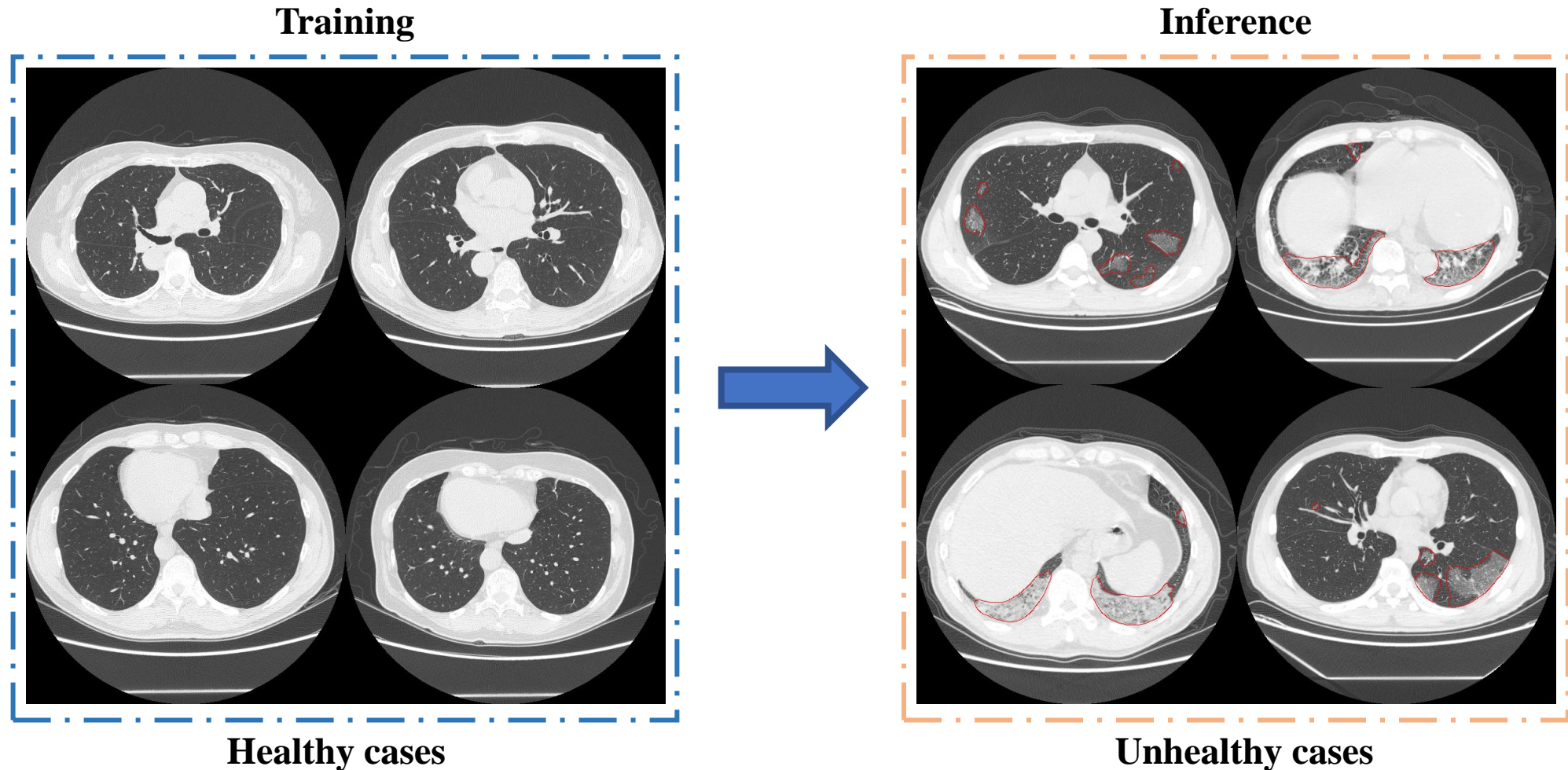


Positive  
or  
Negative



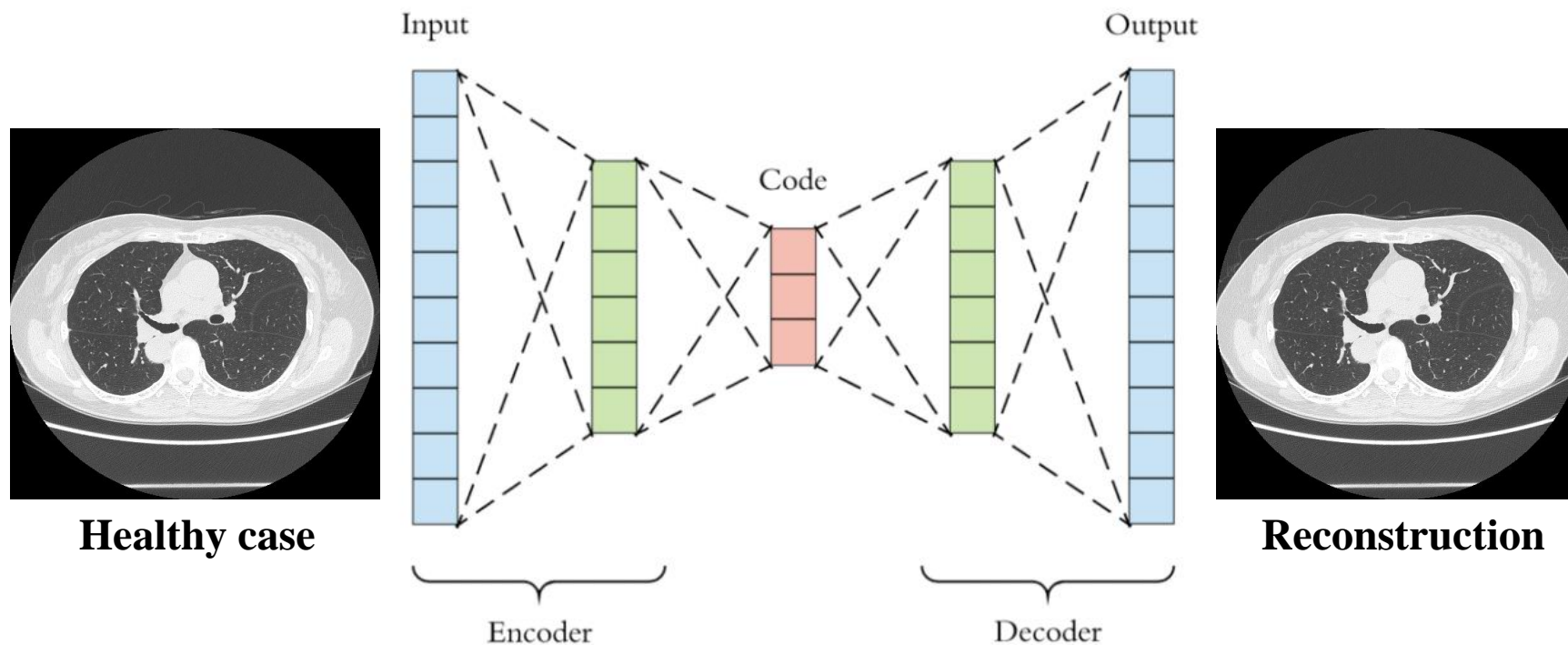
# Unsupervised detection of pulmonary opacities

- The process of learning to locate pulmonary opacities in CT images for radiologist is similar with anomaly detection.



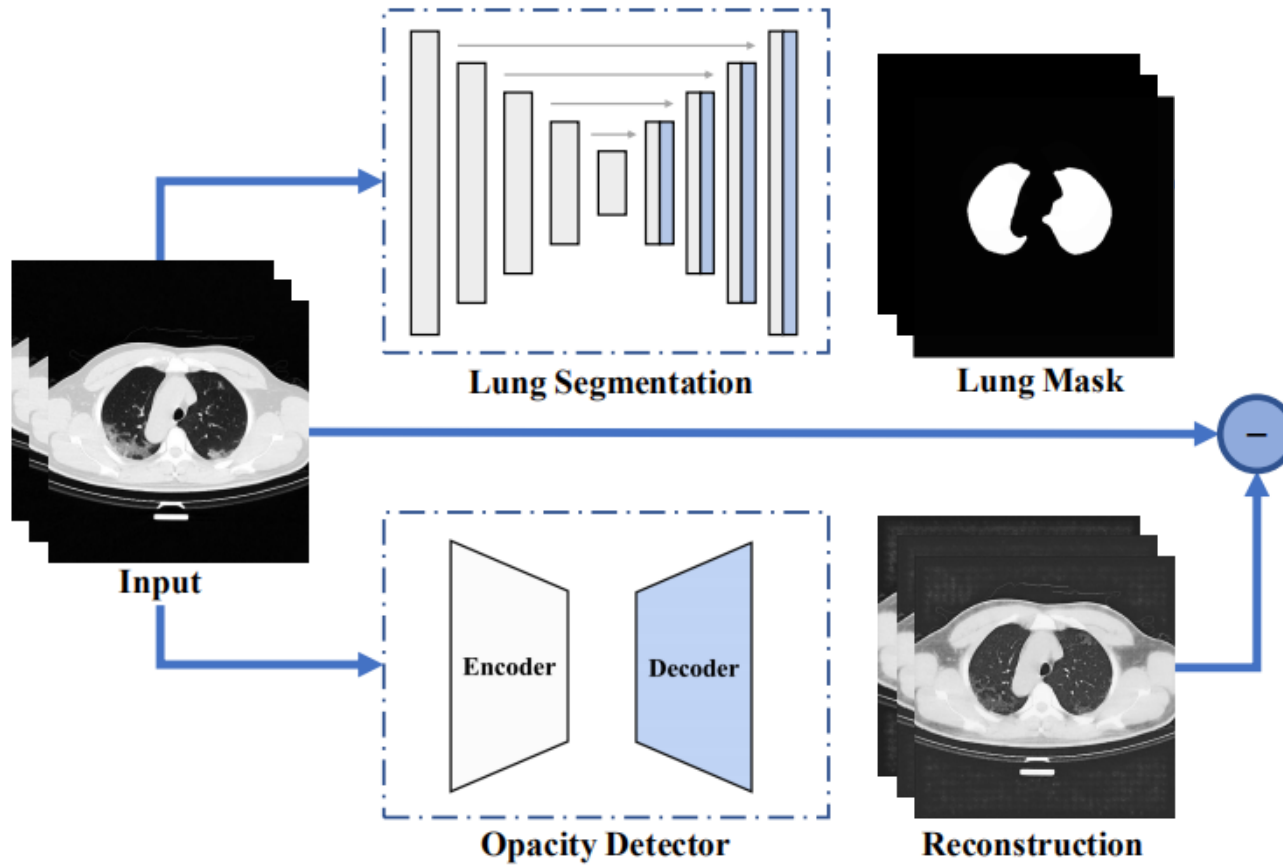
# Unsupervised detection of pulmonary opacities

- Exploit anomaly detection to train an opacity detector. An auto-encoder that can **only** reconstructs healthy CT images well but failed on unhealthy CT images.
- The **difference** between the abnormal image and its reconstruction can be considered as pulmonary opacity.



# Unsupervised detection of pulmonary opacities

- An overview of the proposed method.



# Lung Segmentation

- We collect data from different datasets to build a **generalized dataset** that covers most of the abnormalities in lungs.

Name	Description	Volumes	Split
LCTSC	Chest CT scans from cancer patients of three different institutions	60	Train
VESSEL12	Chest CT scans contain abnormalities such as emphysema and nodules	20	Train
StructSeg	Chest CT scans from cancer patients	50	Train
DLDsOsaka	Scans contain seven categories of pulmonary textures	217	Train&Test
COVID-19-CT-Seg	Chest CT scans diagnosed as COVID-19	20	Test
COVID-19-ZJU	COVID-19 CT scans collected by ZheJiang University	16	Test

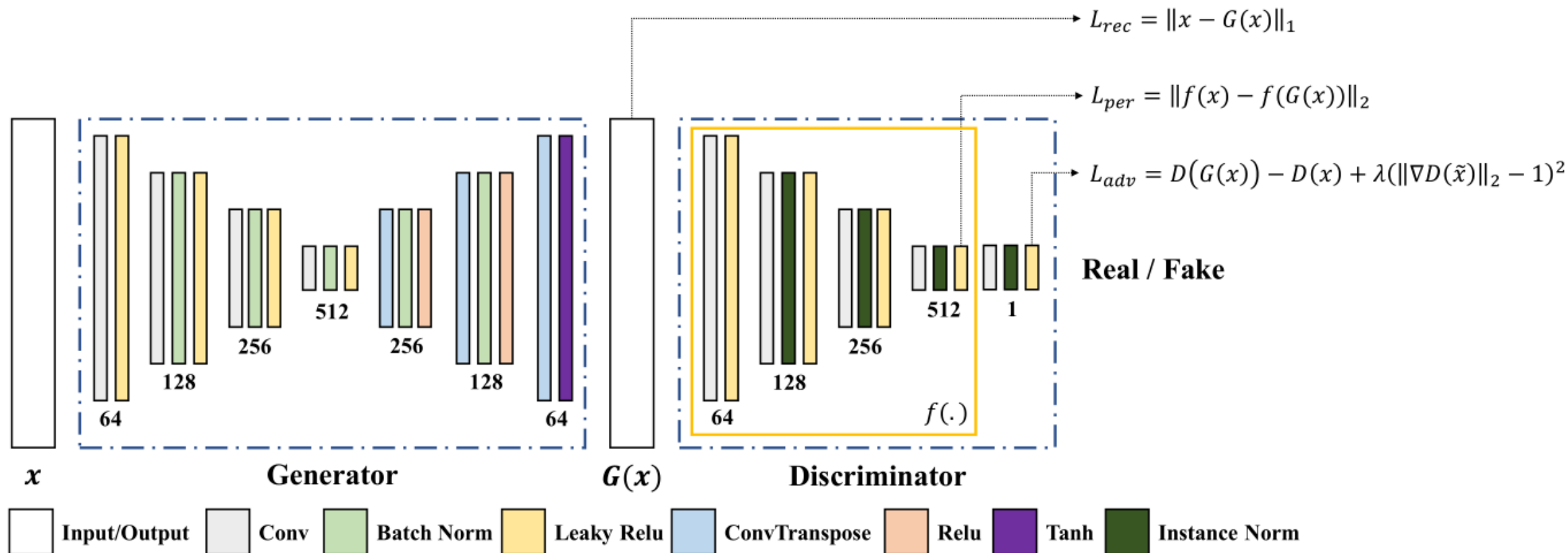
- We utilize the U-Net architecture with different pre-trained encoders as backbone to evaluate the performance on test set. (Metrics: dice similarity coefficient)

Backbone	DLDsOsaka	COVID-19-CT-Seg	COVID-19-ZJU
MobileNetV2	0.98411	0.98168	<b>0.99229</b>
VGG19	<b>0.98504</b>	<b>0.98174</b>	0.99136
ResNet50	0.98473	0.98159	0.99116



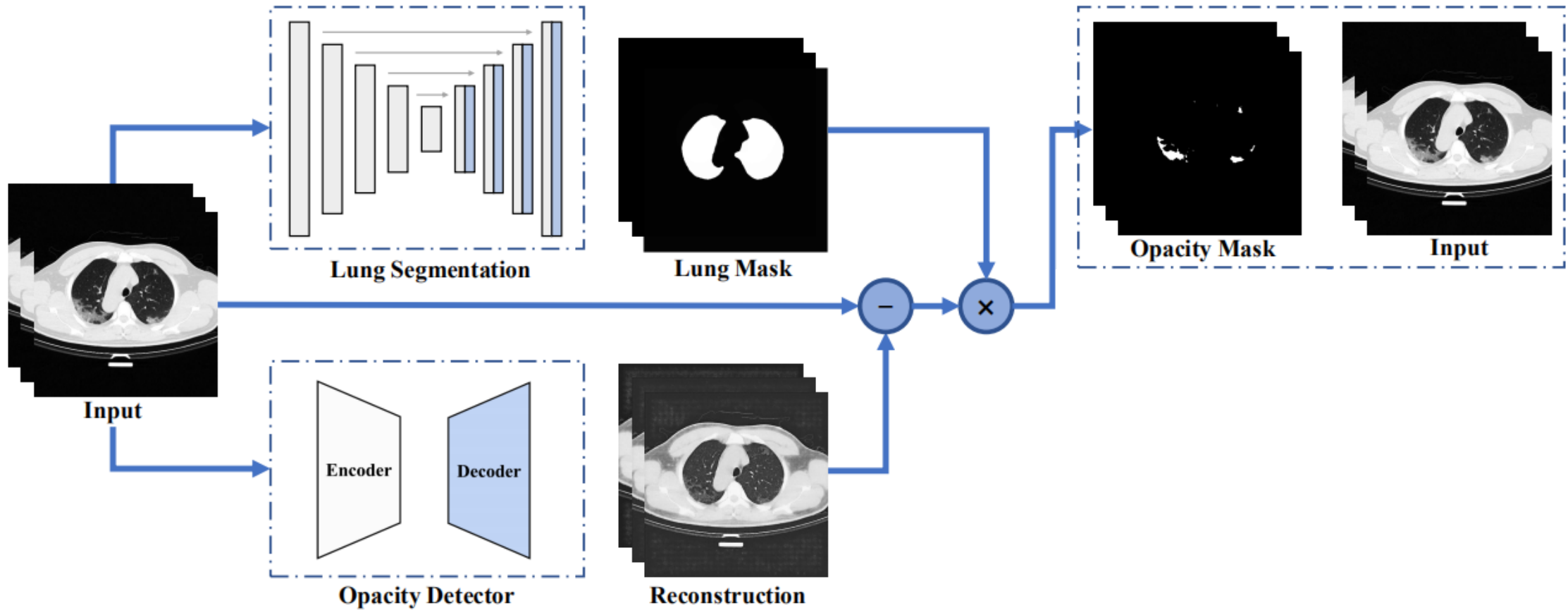
# Opacity Detector

- We build a GAN-based auto-encoder to identify anomalies. The network consists of two sub-networks, a generator G and discriminator D.
- Three loss functions are used for training.
- We collect 30 healthy CT scans from DLDsOsaka dataset for training.



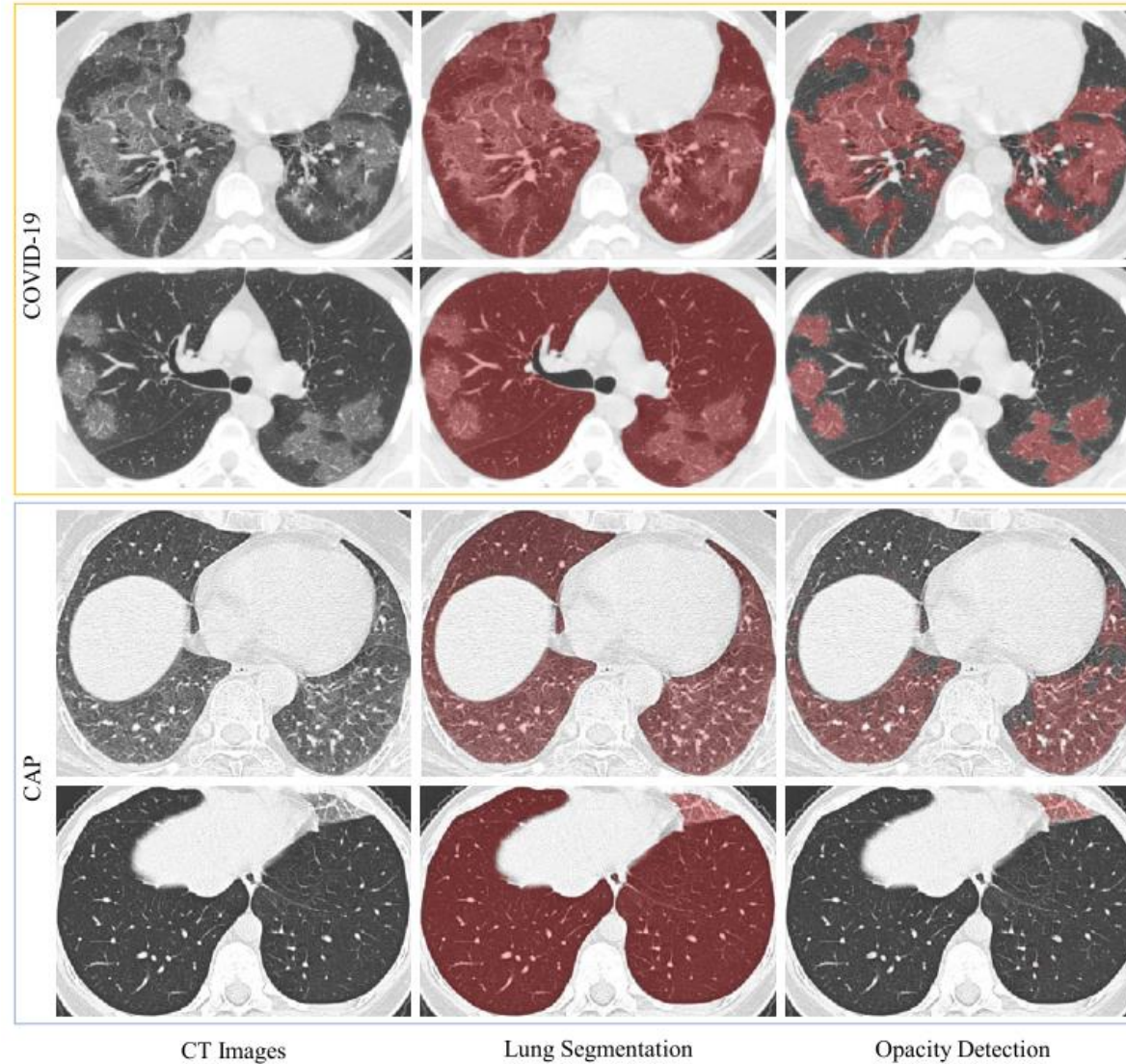
# Unsupervised detection of pulmonary opacities

- An overview of the proposed method.



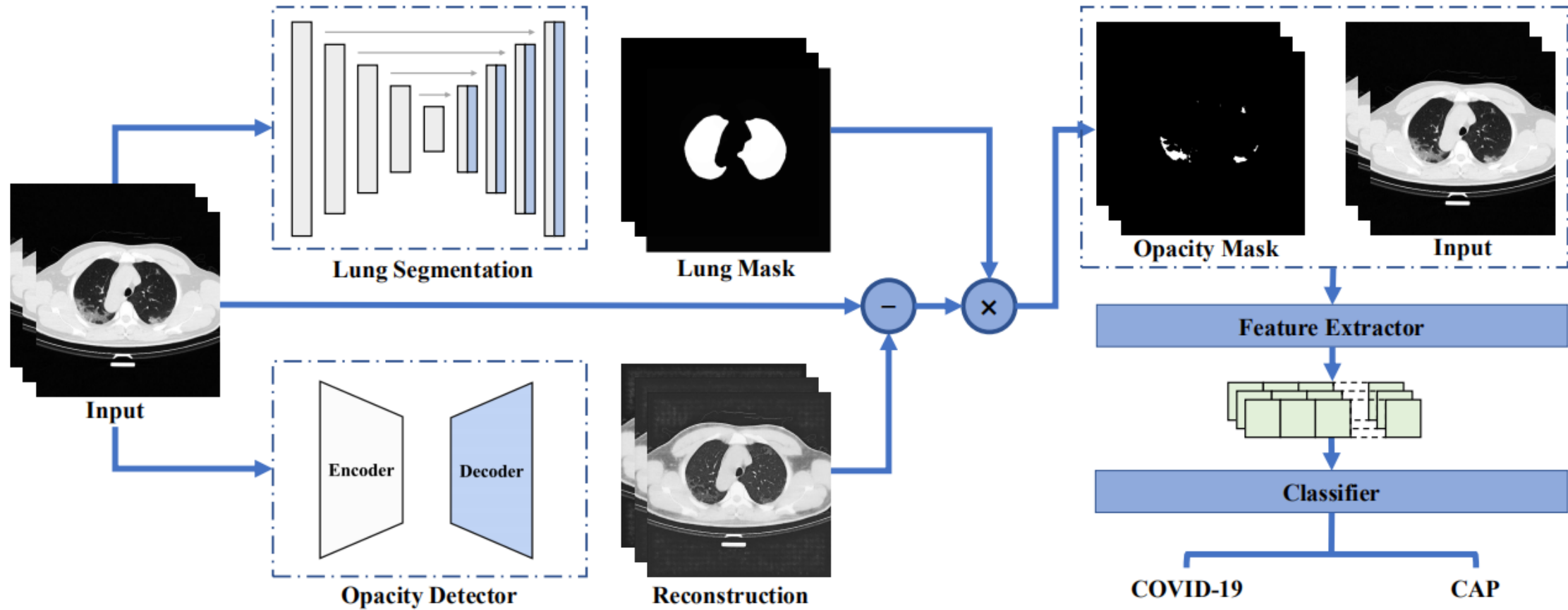
# Unsupervised detection of pulmonary opacities

- Visualization of segmentation and opacity detection results on COVID-19 and CAP cases



# Unsupervised detection of pulmonary opacities

- An overview of the proposed method.



# Feature extraction and classification

- We apply radiomics for feature extraction.
- We compare the features extracted from opacity regions and lung regions with different machine learning methods.
- 100 confirmed COVID-19 cases and other 100 CAP cases are used for testing.

Methods	Feature Extraction		Evaluation				
	Lung	Opacity	Accuracy	Precision	Recall	F1-score	AUC
Linear SVM	✓		0.9350	0.9674	<b>0.9000</b>	0.9302	0.9565
		✓	<b>0.9400</b>	<b>0.9905</b>	0.8900	<b>0.9338</b>	<b>0.9585</b>
RBF SVM	✓		0.9350	0.9674	0.9000	0.9302	0.9565
		✓	<b>0.9550</b>	<b>1.0000</b>	<b>0.9100</b>	<b>0.9510</b>	<b>0.9590</b>
Random Forest	✓		0.9400	0.9889	0.8900	0.9342	0.9640
		✓	<b>0.9450</b>	<b>0.9895</b>	<b>0.9000</b>	<b>0.9402</b>	<b>0.9720</b>
AdaBoost	✓		0.9200	0.9285	<b>0.9100</b>	0.9178	0.9620
		✓	<b>0.9400</b>	<b>0.9714</b>	<b>0.9100</b>	<b>0.9372</b>	<b>0.9640</b>
XGBoost	✓		0.9200	0.9443	0.8900	0.9155	0.9560
		✓	<b>0.9450</b>	<b>0.9800</b>	<b>0.9100</b>	<b>0.9416</b>	<b>0.9600</b>

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

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

- Extracting features from opacity regions obtained from our opacity detector perform better.



# Conclusion

We propose an opacity detection model for diagnosis of COVID-19

- save huge labors of manual annotation of opacity regions
- apply the unsupervised detection of pulmonary opacity to develop a CAD system to distinguish COVID-19 and CAP on CT images



Thanks For Your Attention