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Deep Learning in Medical Image Analysis: Techniques for Classification and Segmentation

Tutorial of EE4211

Department of Electrical Engineering
City University of Hong Kong
06/11/2020

Outline

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➢ WCE Image Classification

- Densely Connected Convolutional Networks (CVPR 2017)
- Triple ANet: Adaptive abnormal-aware attention network for WCE image classification (MICCAI 2019)

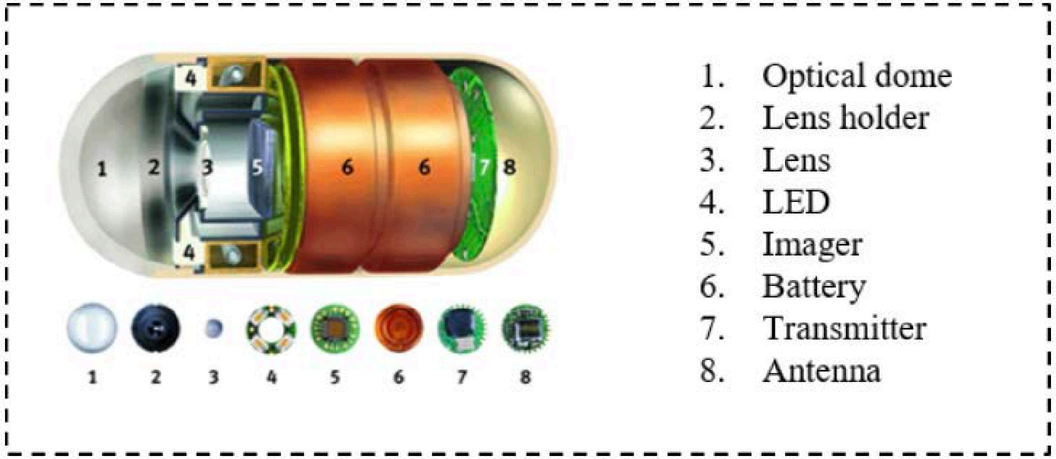
➢ COVID-19 CT Image Segmentation

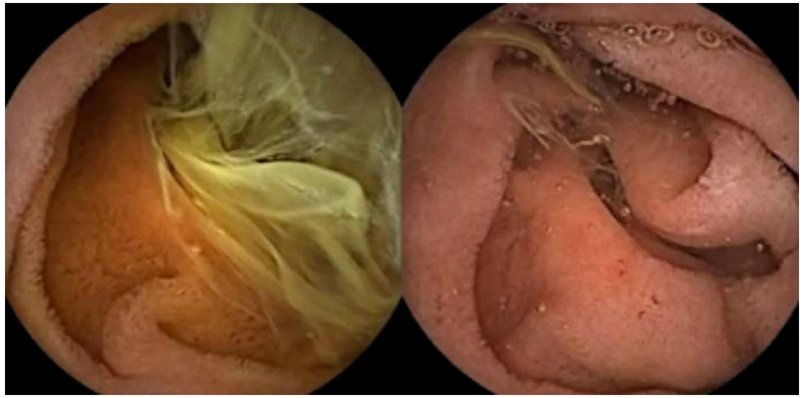
- U-Net: Convolutional Networks for Biomedical Image Segmentation (MICCAI 2015)
- Inf-Net: Automatic COVID-19 Lung Infection Segmentation From CT Images (IEEE TMI 2020)

➢ WCE Image Classification

- Densely Connected Convolutional Networks (CVPR 2017)
- Triple ANet: Adaptive abnormal-aware attention network for WCE image classification (MICCAI 2019)

– WCE denotes `` Wireless Capsule Endoscopy''





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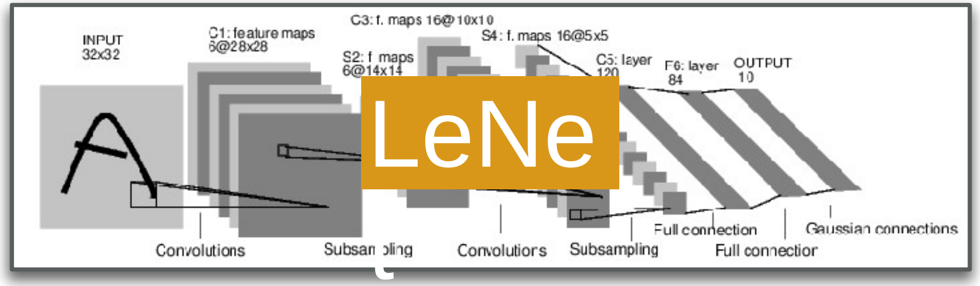
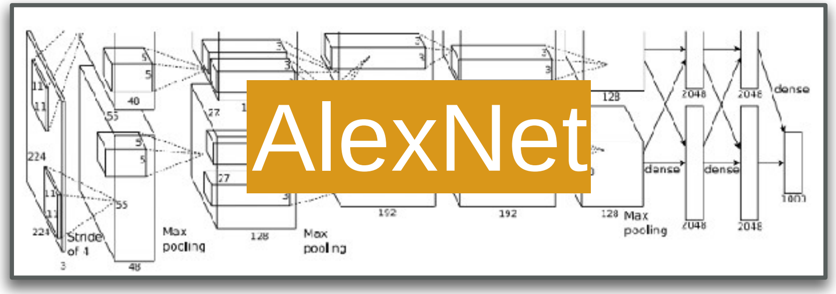
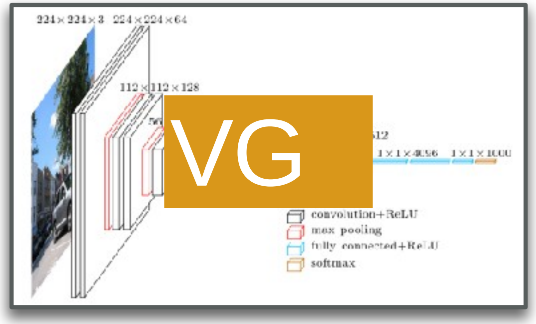
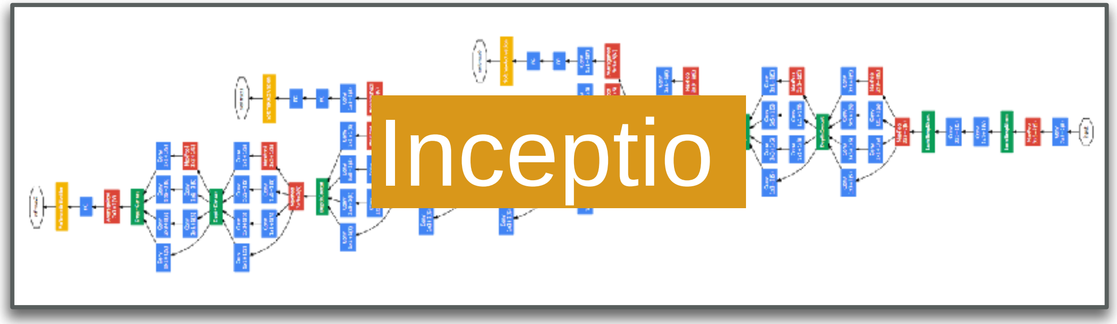
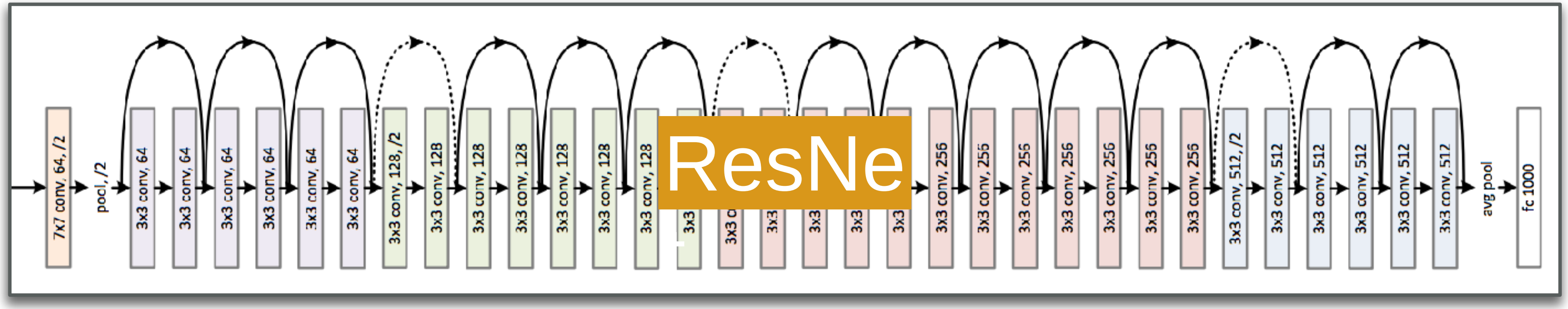
CONVOLUTIONAL NETWORKS



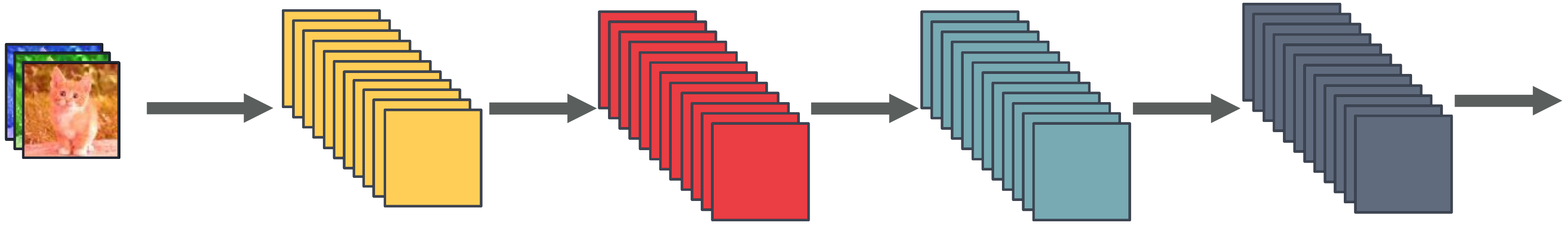






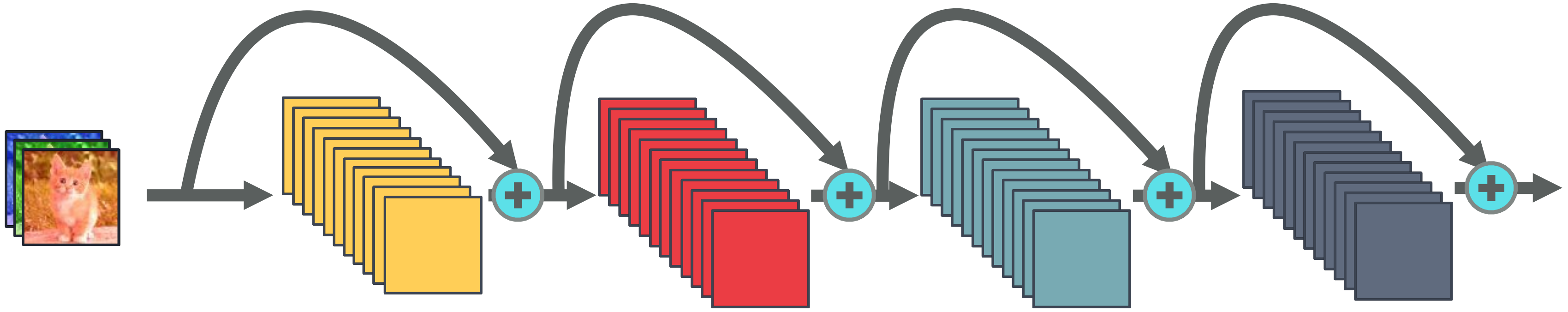


Standard Connectivity



ResNet Connectivity

Identity mappings promote gradient propagation.



: Element-wise addition

He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.

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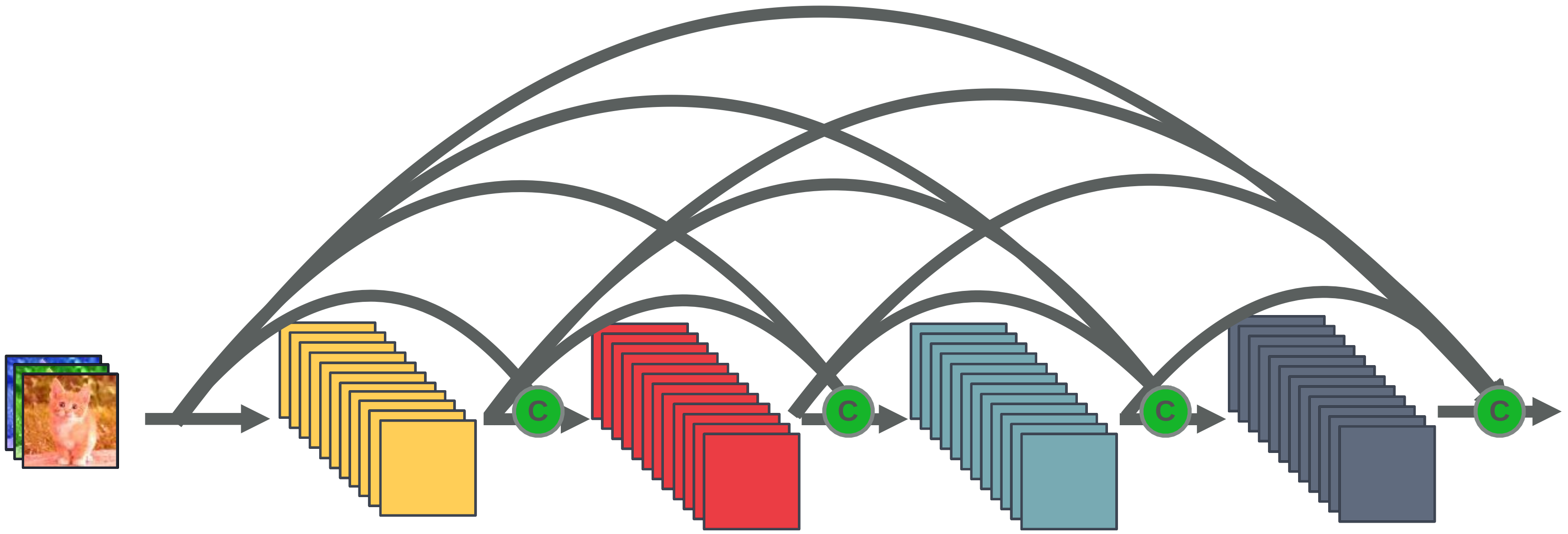
Dense Connectivity



C : Channel-wise concatenation

Huang, Gao, et al. "Densely connected convolutional networks." CVPR, 2017.

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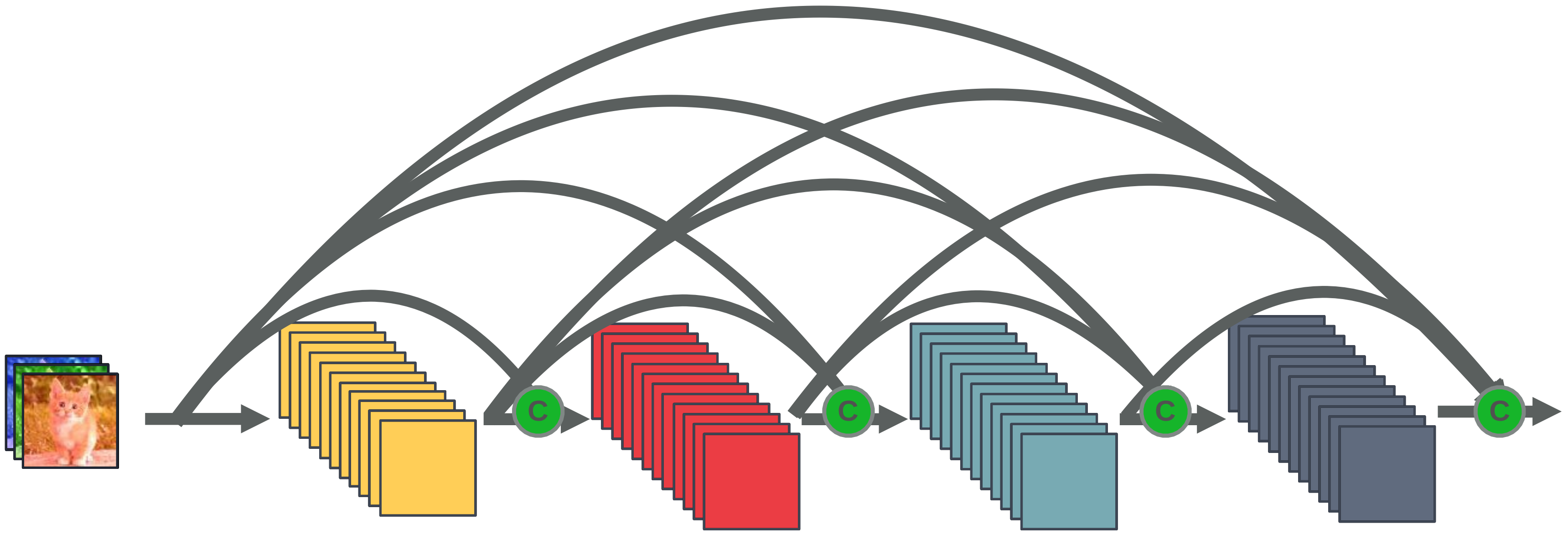
Dense and Slim



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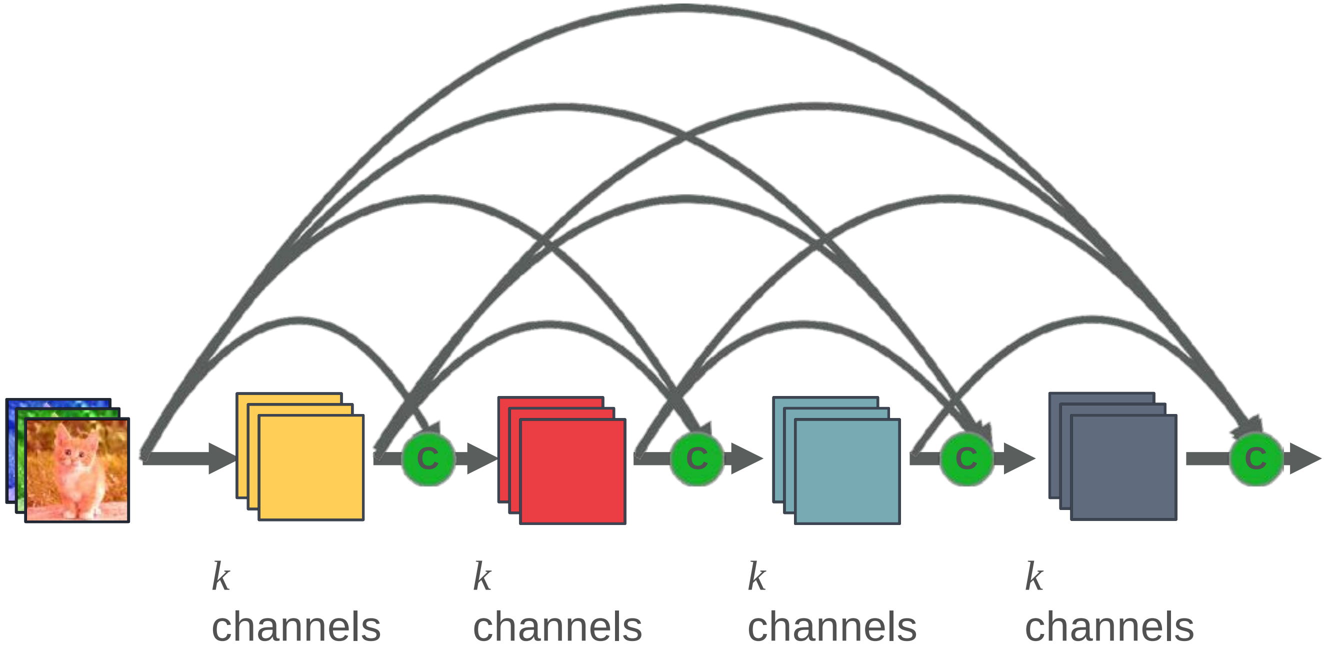
Dense and Slim



k : Growth Rate

Huang, Gao, et al. "Densely connected convolutional networks." CVPR, 2017.

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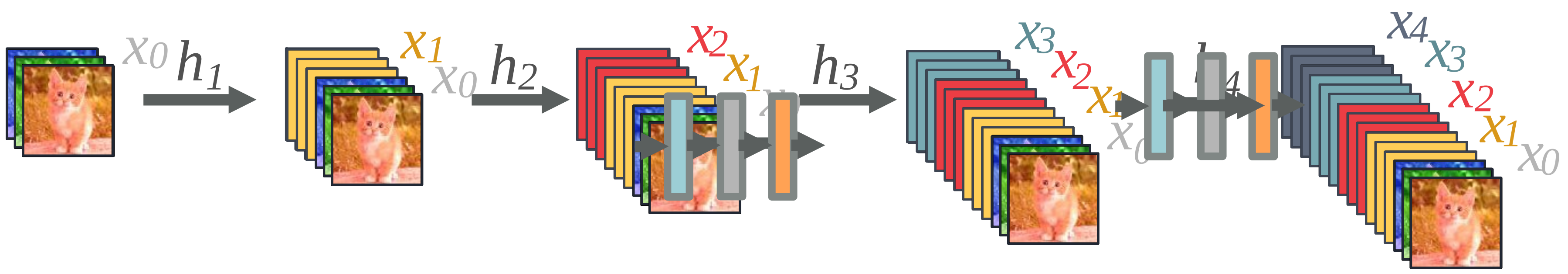
Forward Propagation of Dense Block



Huang, Gao, et al. "Densely connected convolutional networks." CVPR, 2017.

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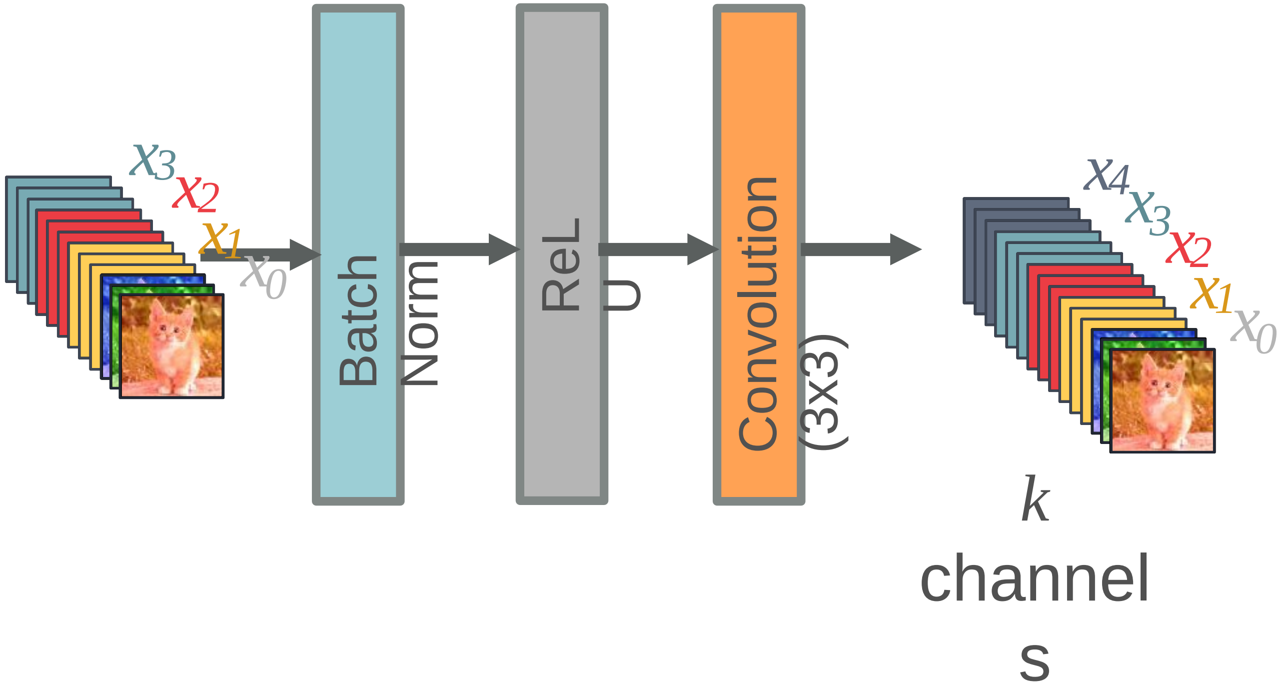
Composite Layer in DenseNet



$$x_5 = h_5([x_0, \ldots, x_4])$$

Huang, Gao, et al. "Densely connected convolutional networks." CVPR, 2017.

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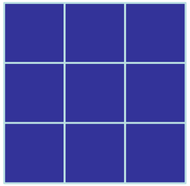
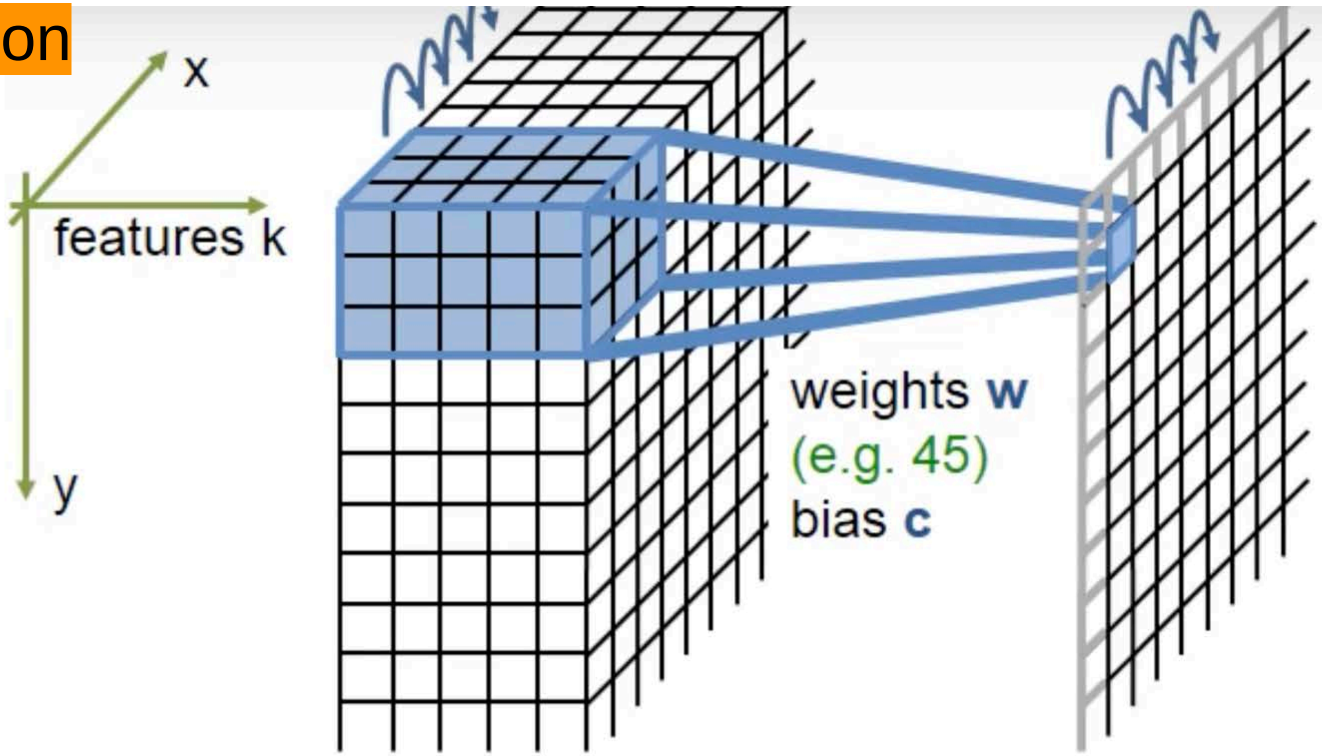
Convolution



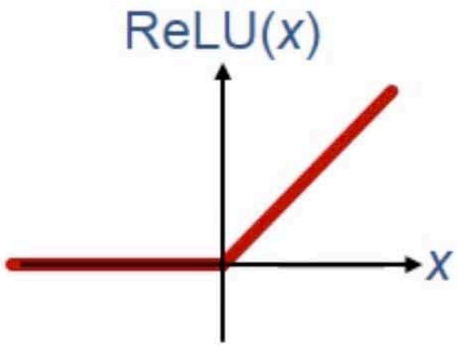
3x3 kernel



input feature map a
(e.g. 5 channels)

output feature map b
(only 1 channel shown)

- Only valid part of convolution is used.
- For 3x3 convolutions a 1-pixel border is lost



$$b_{x,y,l} = \mathrm{ReLU}\left(\sum_{\substack{i\in\{-1,0,1\} \\ j\in\{-1,0,1\} \\ k\in\{1,\ldots,K\}}} w_{i,j,k,l} \cdot a_{x+i,y+j,k} + c_l \right)$$

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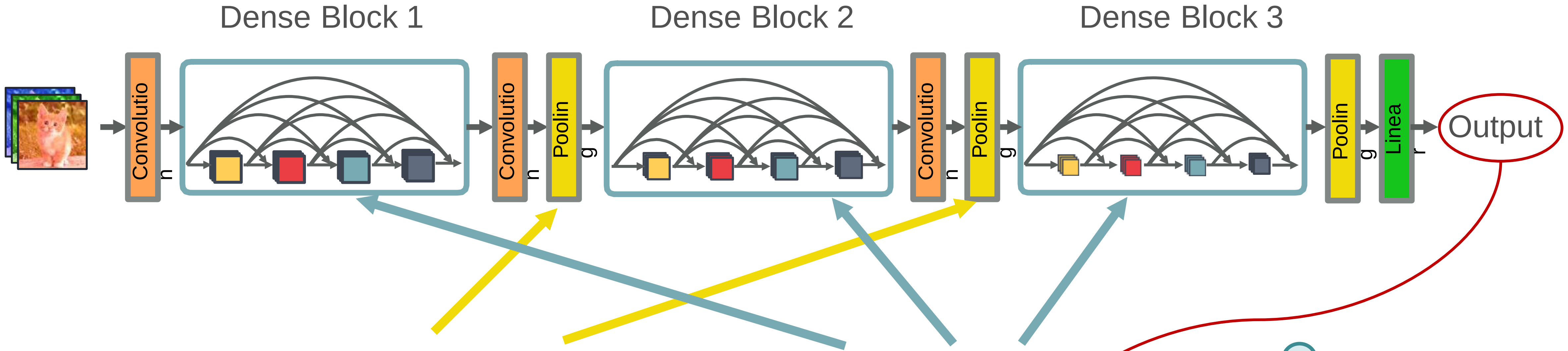
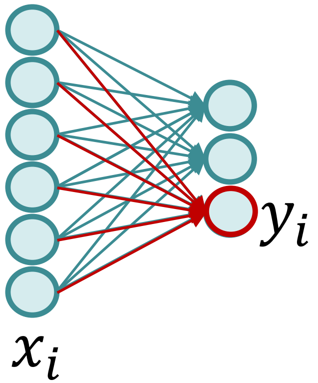
DenseNet



Pooling reduces feature map sizes

Feature map sizes match within each block

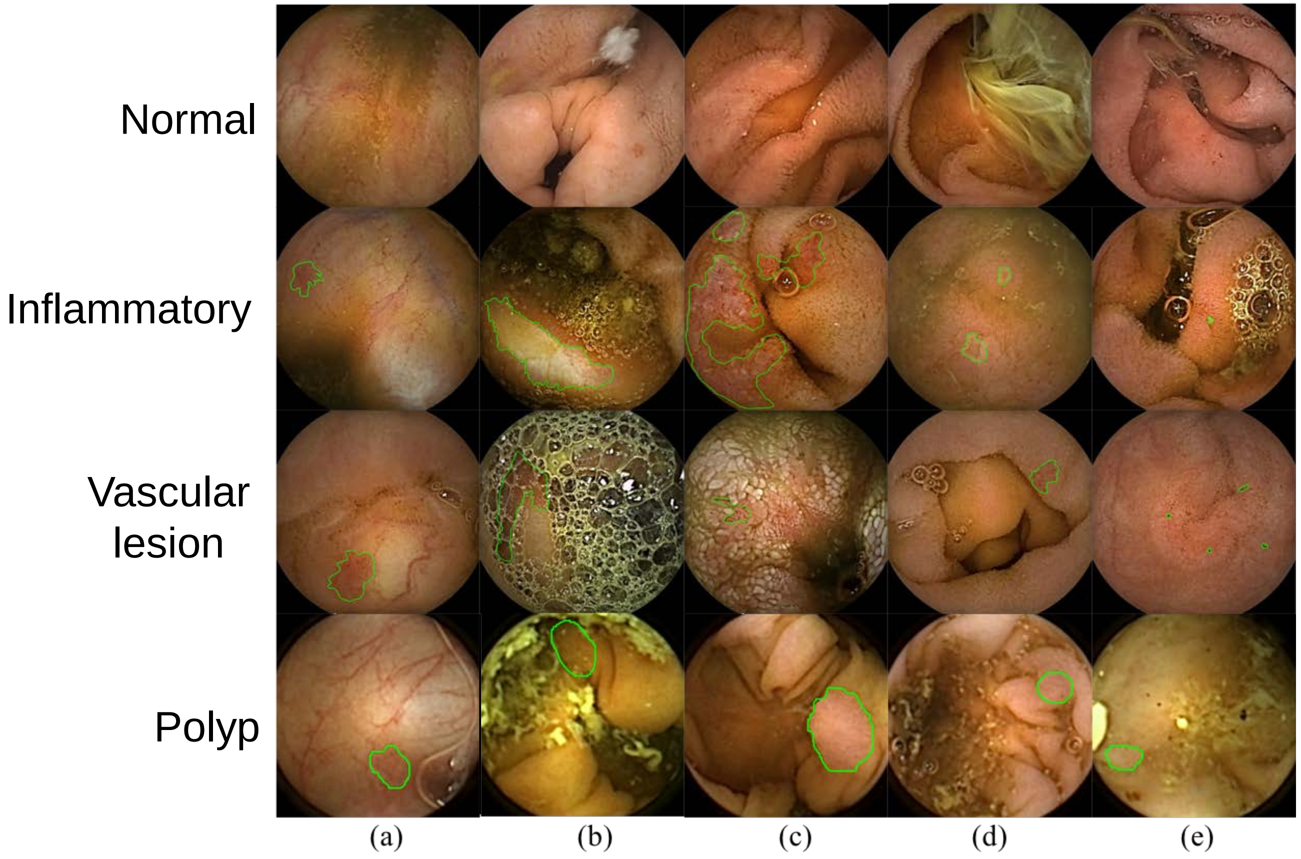
Cross Entropy Loss $L_{softmax} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{e^{W_{y_i}^{\top}x_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_j^{\top}x_i + b_j}}$



Huang, Gao, et al. "Densely connected convolutional networks." CVPR, 2017.

WCE Image Classification

Main Difficulties



Diverse characteristics

1, huge intra-class variances

2, high degree of inter-class visual similarities

WCE Image Classification

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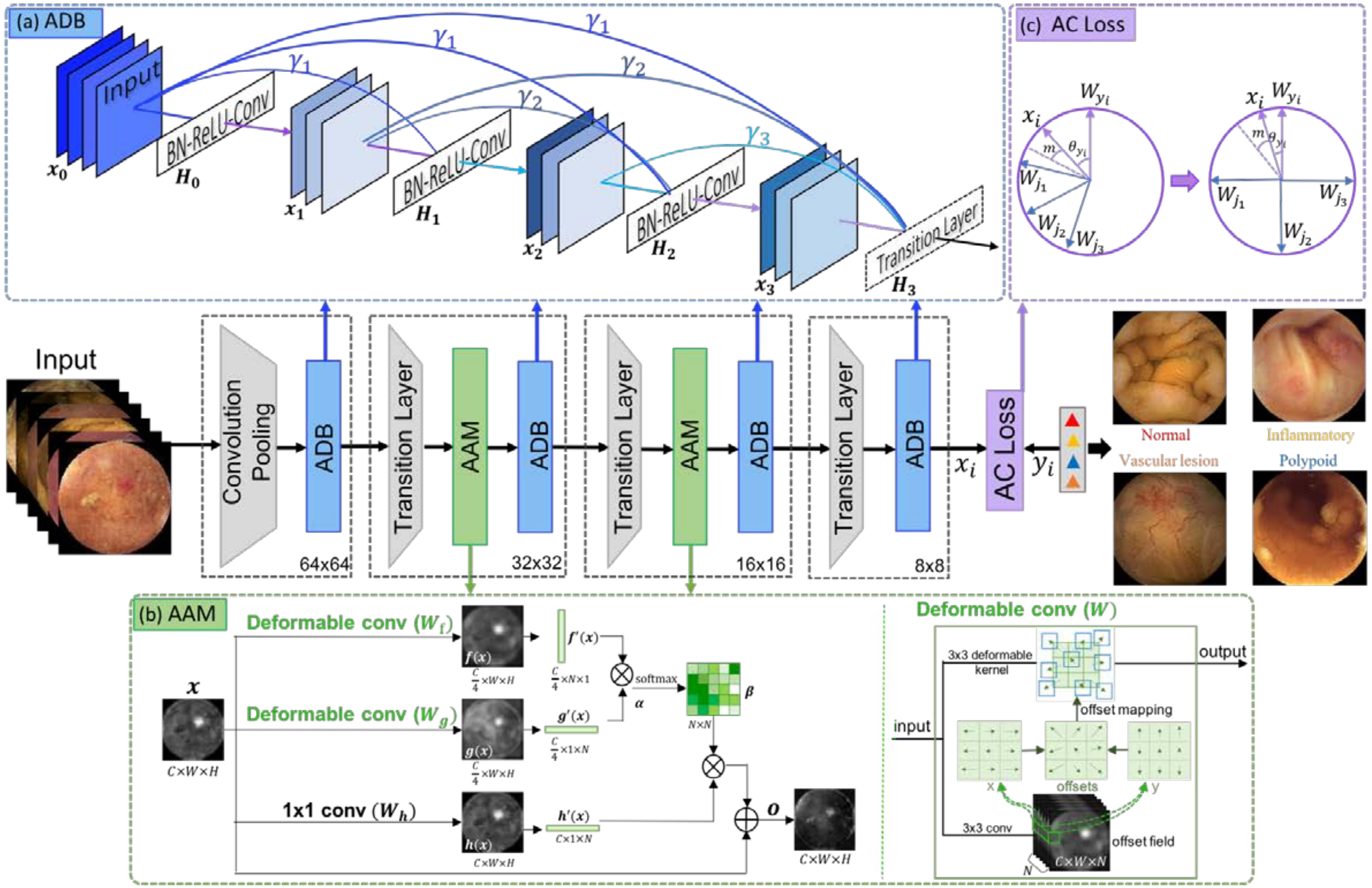
Framework

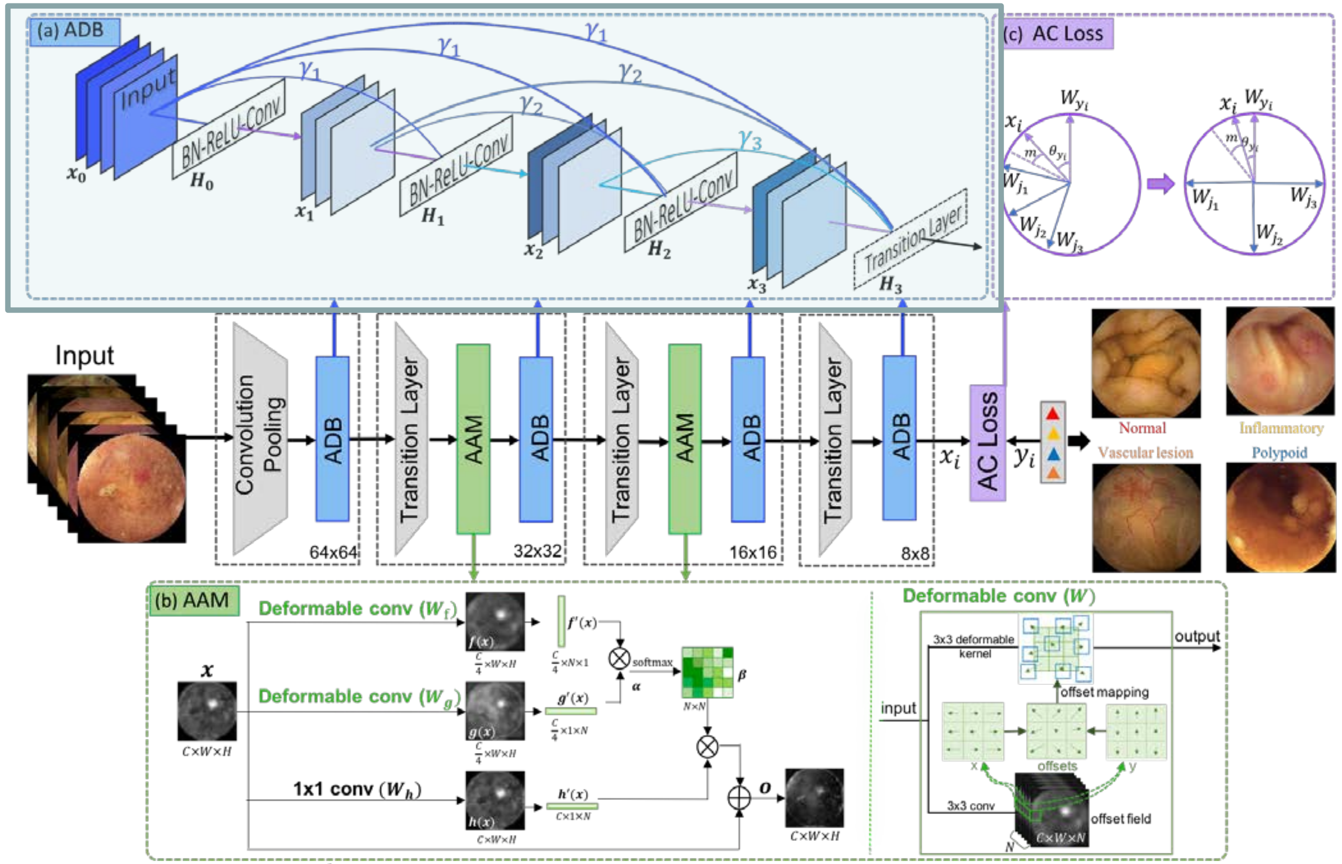


- ADB:
Adaptive Dense Block
- AAM:
Abnormal-aware Attention Module
- AC Loss:
Angular Contrastive Loss

Guo, Xiaoqing, and Yixuan Yuan. "Triple ANet: Adaptive abnormal-aware attention network for WCE image classification." MICCAI, 2019.

WCE Image Classification

ADB: Adaptive Dense Block



Let x_l denote output of l^{th} layer and γ_l is its corresponding weight scalar, adaptive dense connectivity is formulated as $x_l = H_l([\gamma_0 x_0, \gamma_1 x_1, \cdots, \gamma_{l-1} x_{l-1}])$. $H_l(\cdot)$ is a composite function with BN, ReLU and Conv, and each $H_l(\cdot)$ produces k = 12 feature maps.

Guo, Xiaoqing, and Yixuan Yuan. "Triple ANet: Adaptive abnormal-aware attention network for WCE image classification." MICCAI, 2019.

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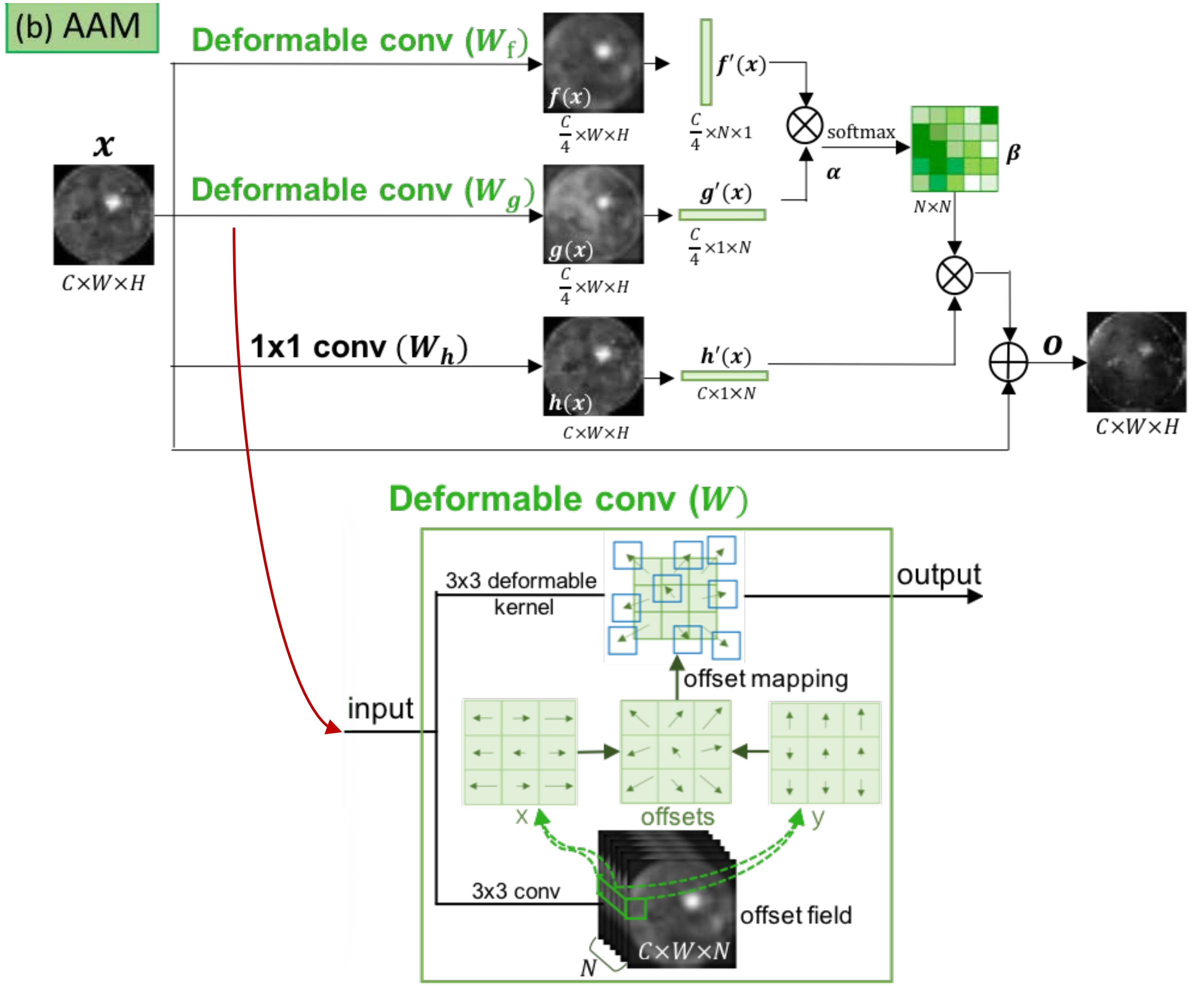
AAM: Abnormal-aware Attention Module



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AC Loss: Angular Contrastive Loss

$$L_{softmax} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{e^{W_{y_i}^{\top}x_i+b_{y_i}}}{\sum_{j=1}^{n}e^{W_j^{\top}x_i+b_j}}$$

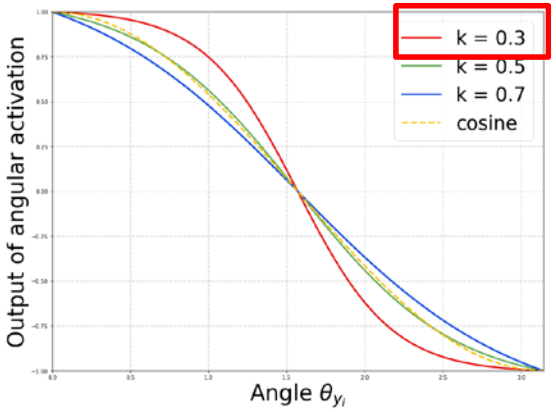
$$F(W_j, x_i) = ||W_j|| \cdot ||x_i|| \cos\theta_j \qquad ||x_i|| = 1 \;\; ||W_j|| = 1$$

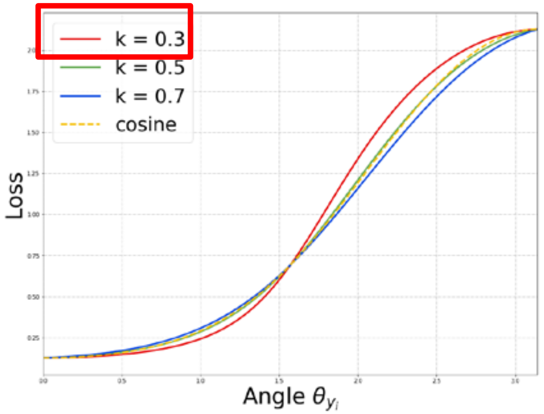
$$L_{cosine} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{e^{s\cos\theta_{y_i}}}{\sum_{j=1}^{n}e^{s\cos\theta_j}}$$

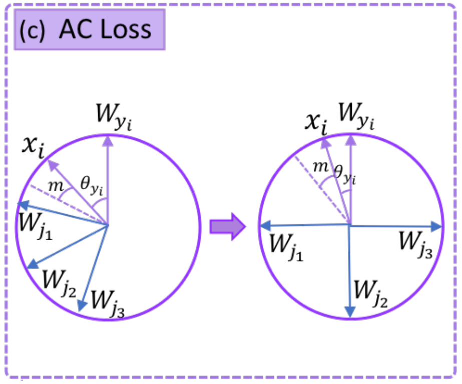
$$F(W_j, x_i) = s||W_j|| \cdot ||x_i|| \cdot A(\theta_j)$$

$$L_{AC} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{e^{sA(\theta_{y_i}+m)}}{e^{sA(\theta_{y_i}+m)}+\sum_{j\neq y_i}^{n}e^{sA(\theta_j)}} + \frac{1}{n}\cdot\frac{1}{n-1}\sum_{y_i=1}^{n}\sum_{j\neq y_i}^{n}W_{y_i}^{\top}W_j$$

$$A(\theta_j) = \frac{1+e^{(-\frac{\pi}{2k})}}{1-e^{(-\frac{\pi}{2k})}}\cdot\frac{1-e^{(\frac{\theta_j}{k}-\frac{\pi}{2k})}}{1+e^{(\frac{\theta_j}{k}-\frac{\pi}{2k})}}$$







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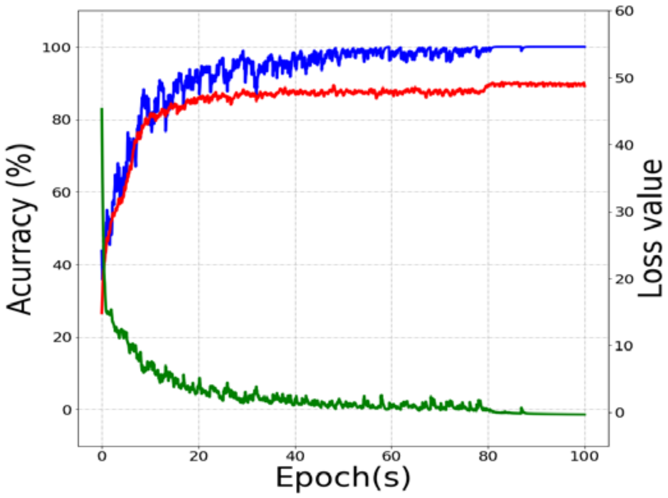
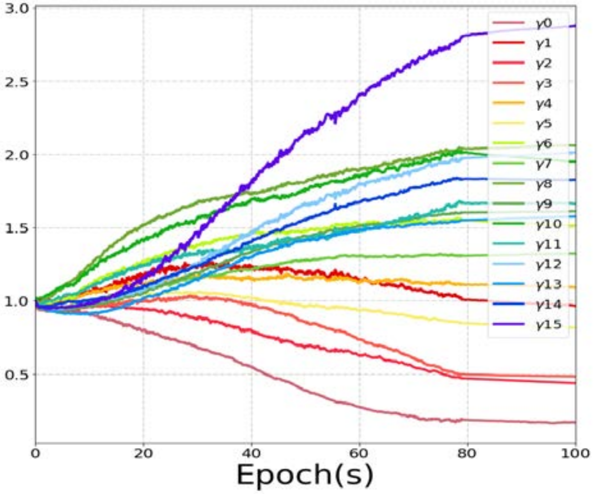
Results





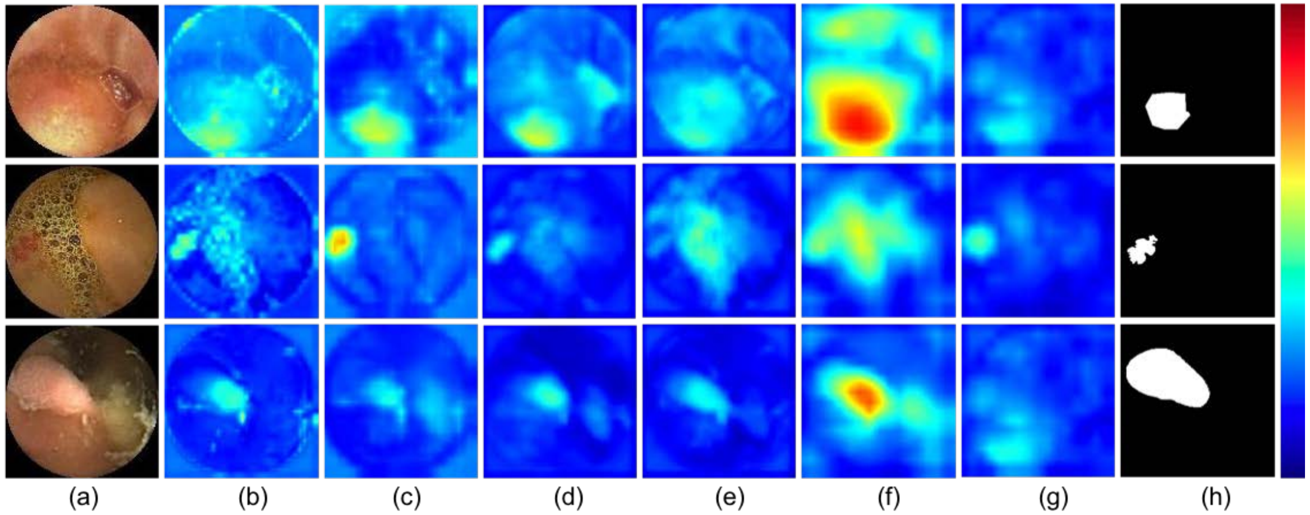


Table 1: Comparison results for WCE image classification. w/ ADB, w/ AAM and w/ AC Loss denote DenseNet with ADB (instead of original dense block), DenseNet with AAM and DenseNet minimized by AC Loss (instead of original softmax cross entropy loss), respectively.

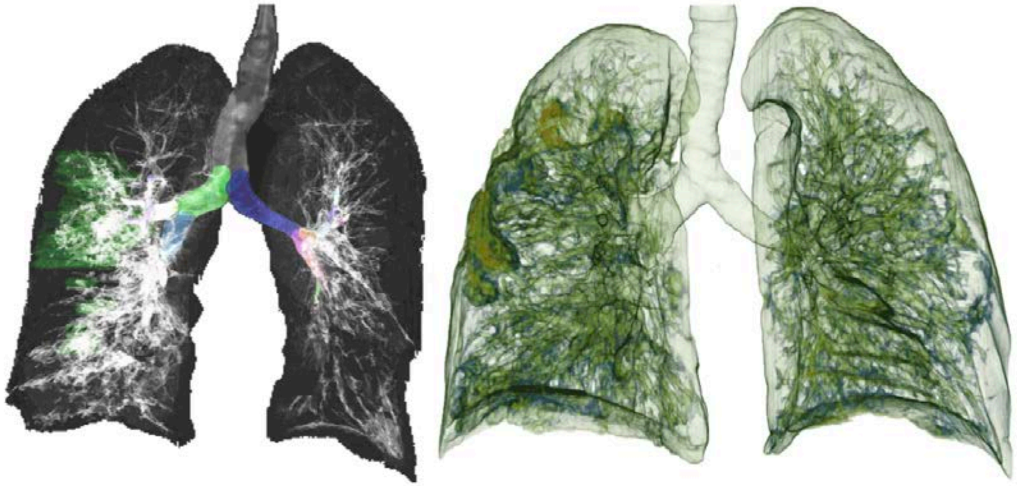
Methods	Normal ACC(%)	Inflammatory ACC(%)	Vascular lesion ACC(%)	Polyp ACC(%)	OA	Cohen's Kappa
DenseNet [4]	92.69±0.49	90.12±0.54	93.71±0.52	97.59±0.39	87.05±0.45	82.66±0.60
w/ ADB	93.03±0.40	89.94±0.18	93.61±0.15	97.71±0.27	87.14±0.21	82.78±0.28
w/ AAM	**94.06±0.17**	91.49±0.81	94.47±0.77	97.78±0.42	88.89±0.52	85.13±0.69
w/ AC Loss	93.59±0.30	91.20±0.33	94.94±0.34	97.69±0.46	88.70±0.20	84.87±0.27
Triple ANet	94.03±0.09	**91.73±0.29**	**95.26±0.33**	**97.81±0.20**	**89.41±0.23**	**85.82±0.31**
Fan et al. [3]	85.44±1.43	83.09±0.79	90.19±0.96	95.47±0.89	77.10±1.14	69.30±1.58
Jia et al. [5]	86.16±1.07	83.37±0.71	90.32±0.88	95.81±0.59	77.83±1.28	70.31±1.74
Seguí et al. [7]	92.11±0.60	89.71±0.48	94.21±0.57	97.31±0.12	86.67±0.84	82.15±1.12
Yuan et al. [9]	93.44±0.30	90.79±0.26	93.91±0.17	97.73±0.35	87.93±0.07	83.84±0.08

Guo, Xiaoqing, and Yixuan Yuan. "Triple ANet: Adaptive abnormal-aware attention network for WCE image classification." MICCAI, 2019.

➢ COVID-19 CT Image Segmentation

- U-Net: Convolutional Networks for Biomedical Image Segmentation (MICCAI 2015)
- Inf-Net: Automatic COVID-19 Lung Infection Segmentation From CT Images (IEEE TMI 2020)

– Automated detection of lung infections from computed tomography (CT) images offers a great potential for the diagnosis of COVID-19



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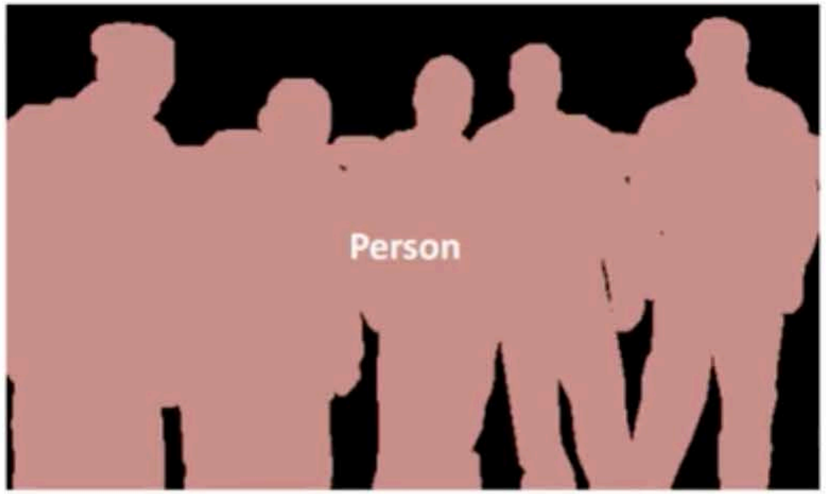
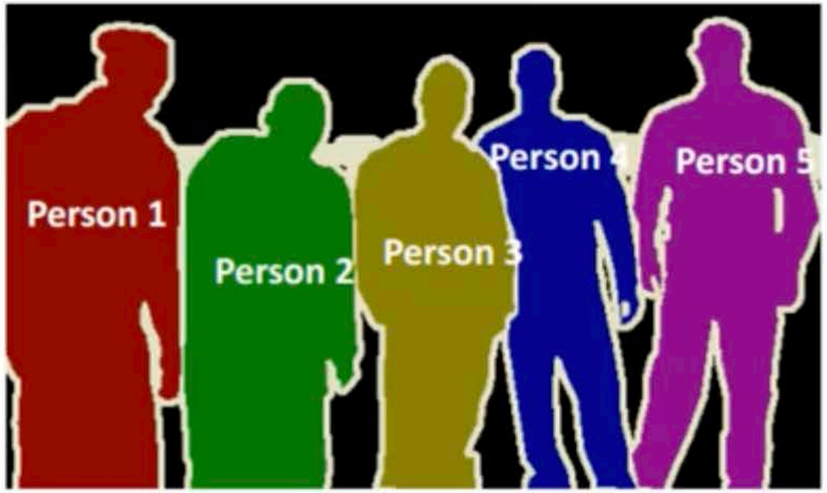
Object Detection



Semantic Segmentation



Instance Segmentation

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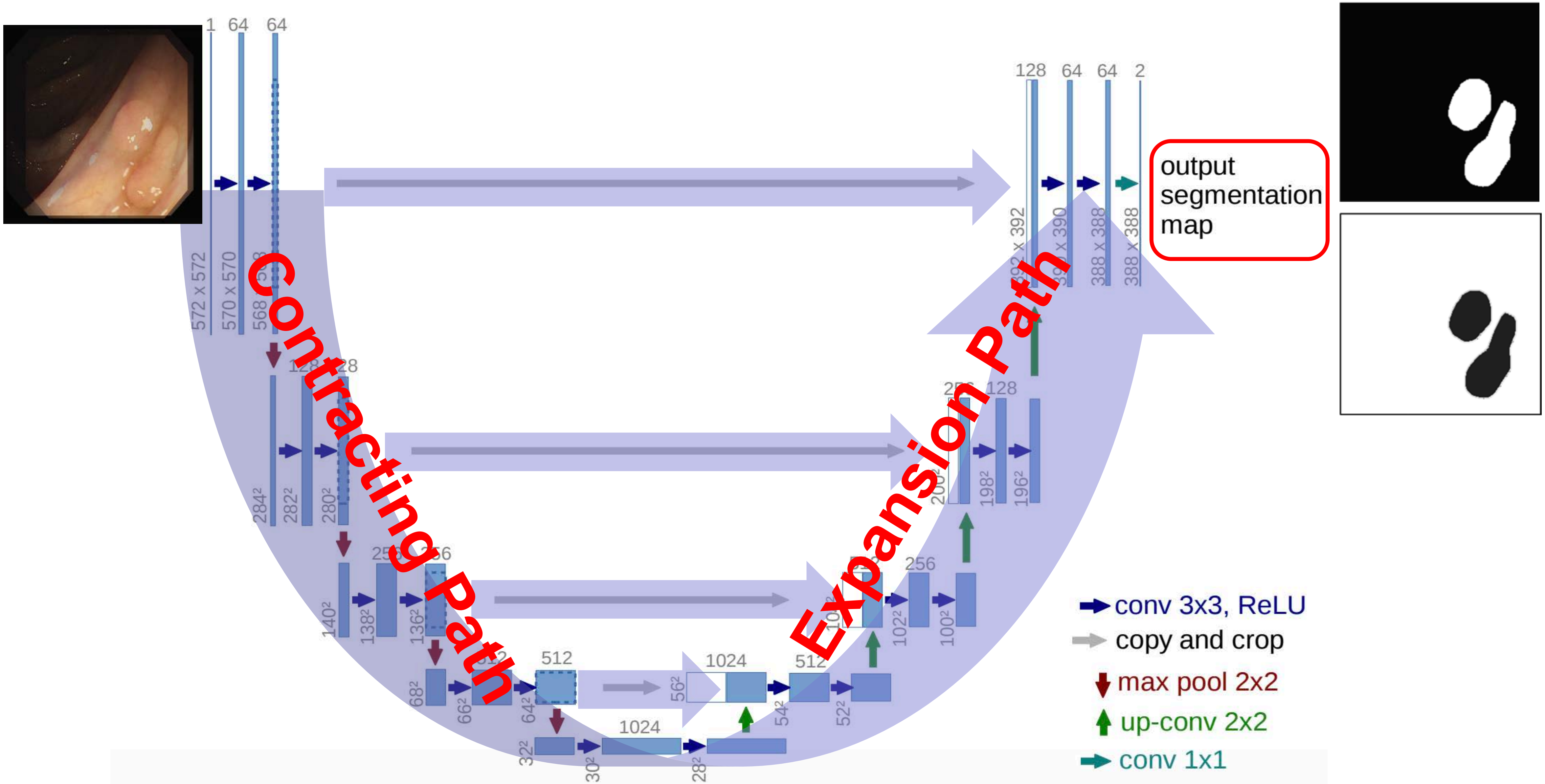

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." MICCAI, 2015.

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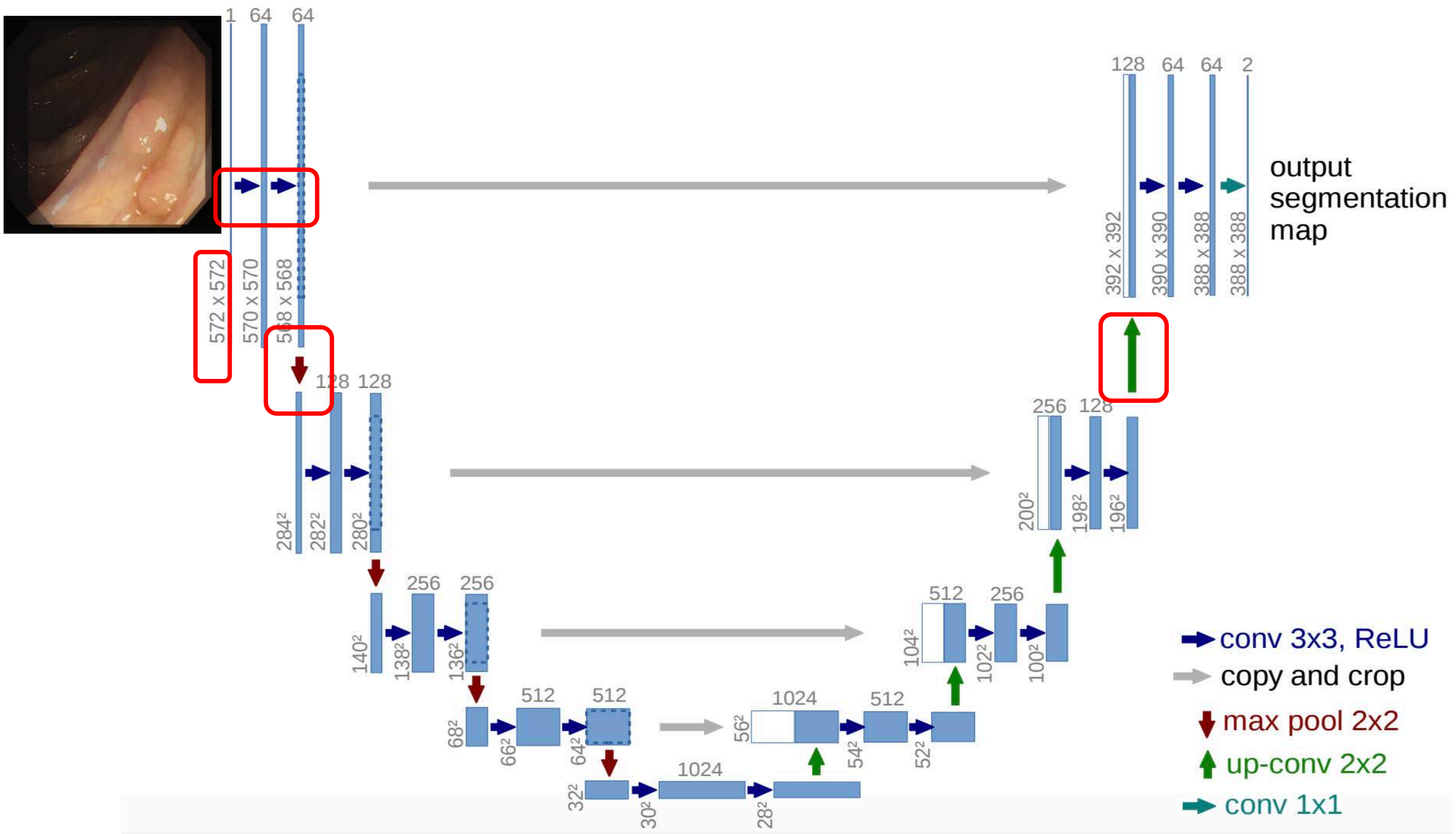
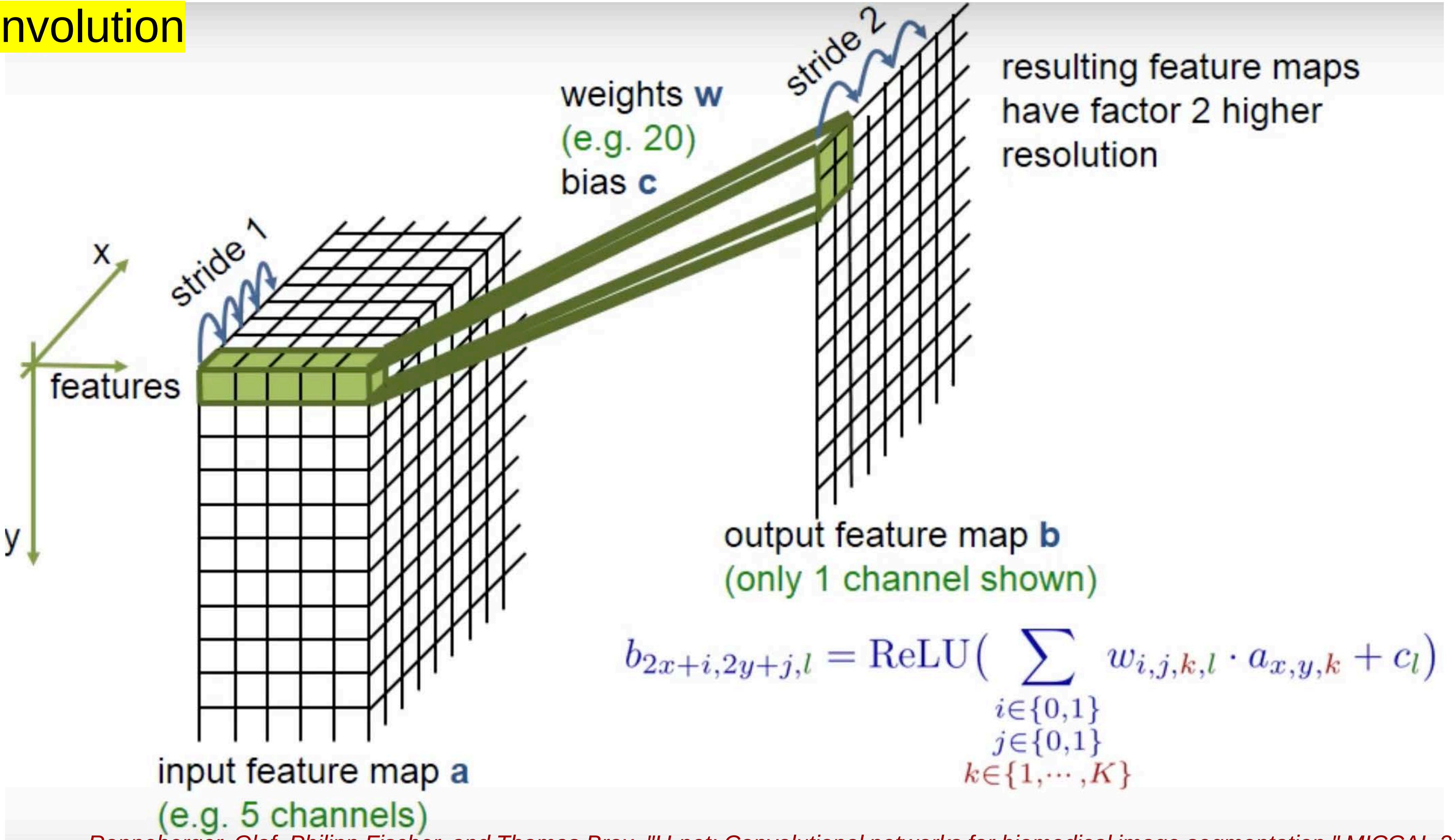


Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." MICCAI, 2015.

Up Convolution



$$b_{2x+i,2y+j,l} = \mathrm{ReLU}\Big(\sum_{\substack{i\in\{0,1\}\\ j\in\{0,1\}\\ k\in\{1,\cdots,K\}}} w_{i,j,k,l} \cdot a_{x,y,k} + c_l \Big)$$

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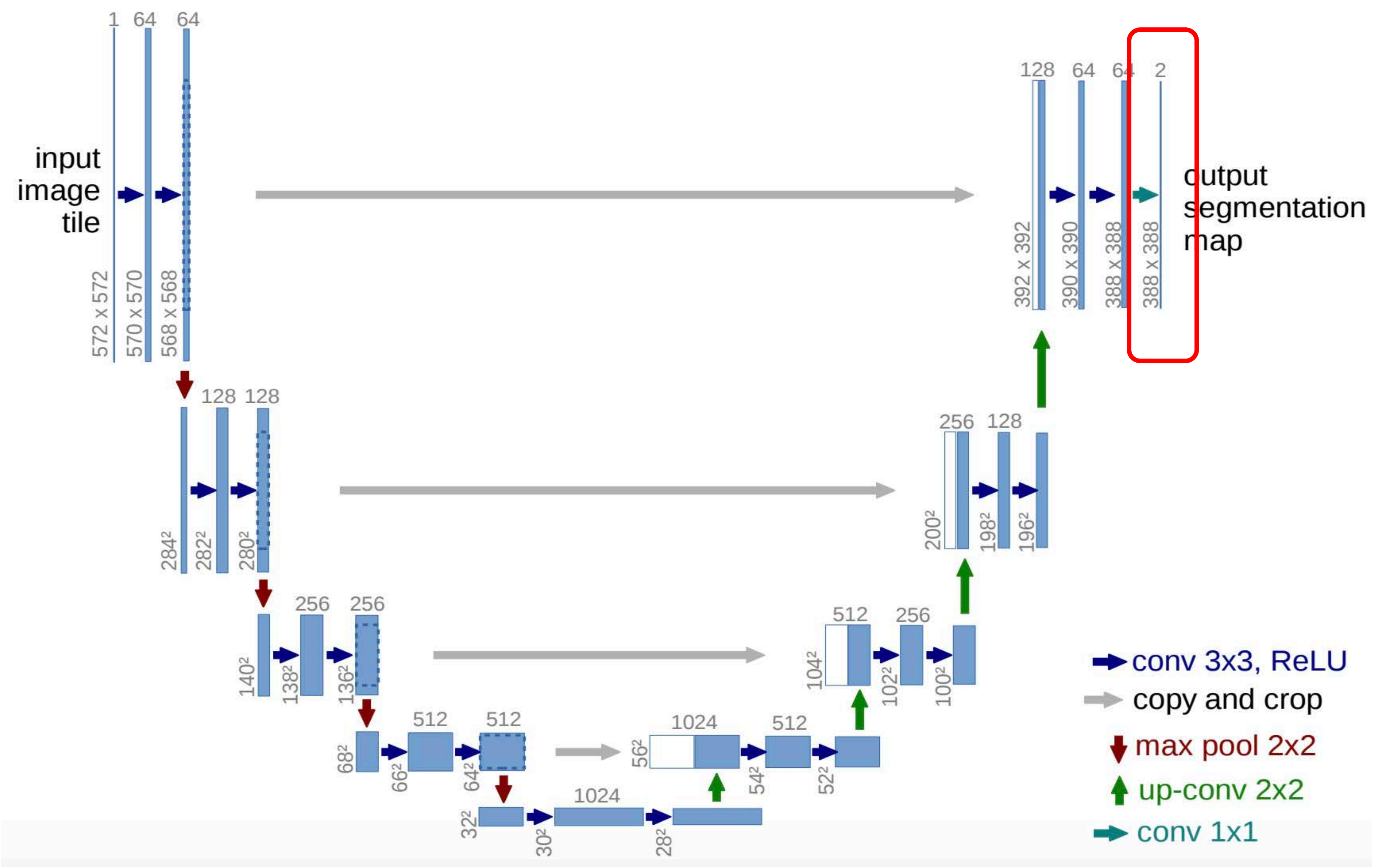
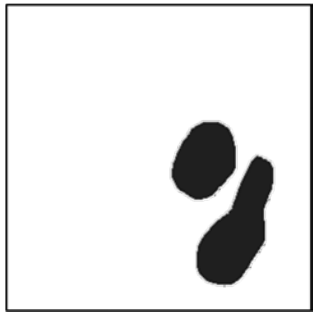
COVID-19 CT Image Segmentation





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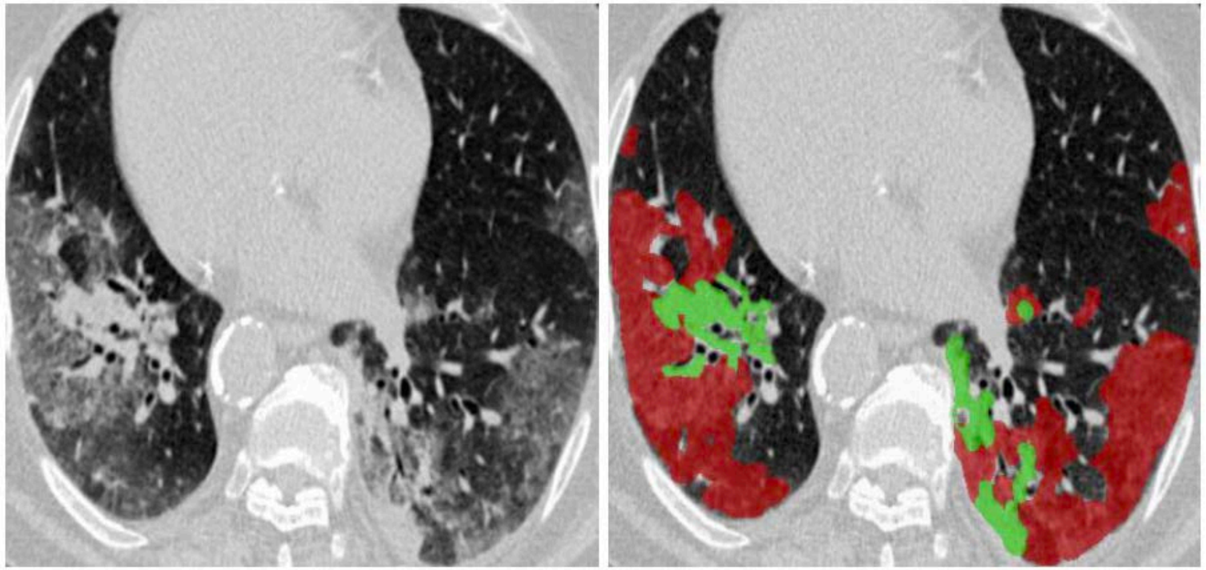

Fig. 1. Example of COVID-19 infected regions (B) in CT axial slice (A), where the red and green masks denote the GGO and consolidation, respectively. The images are collected from [9].

Segmenting infected regions from CT slices faces several challenges:

- High variation in infection characteristics
- Low intensity contrast between infections and normal tissues

Fan, Deng-Ping, et al. "Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images." IEEE Transactions on Medical Imaging (2020).

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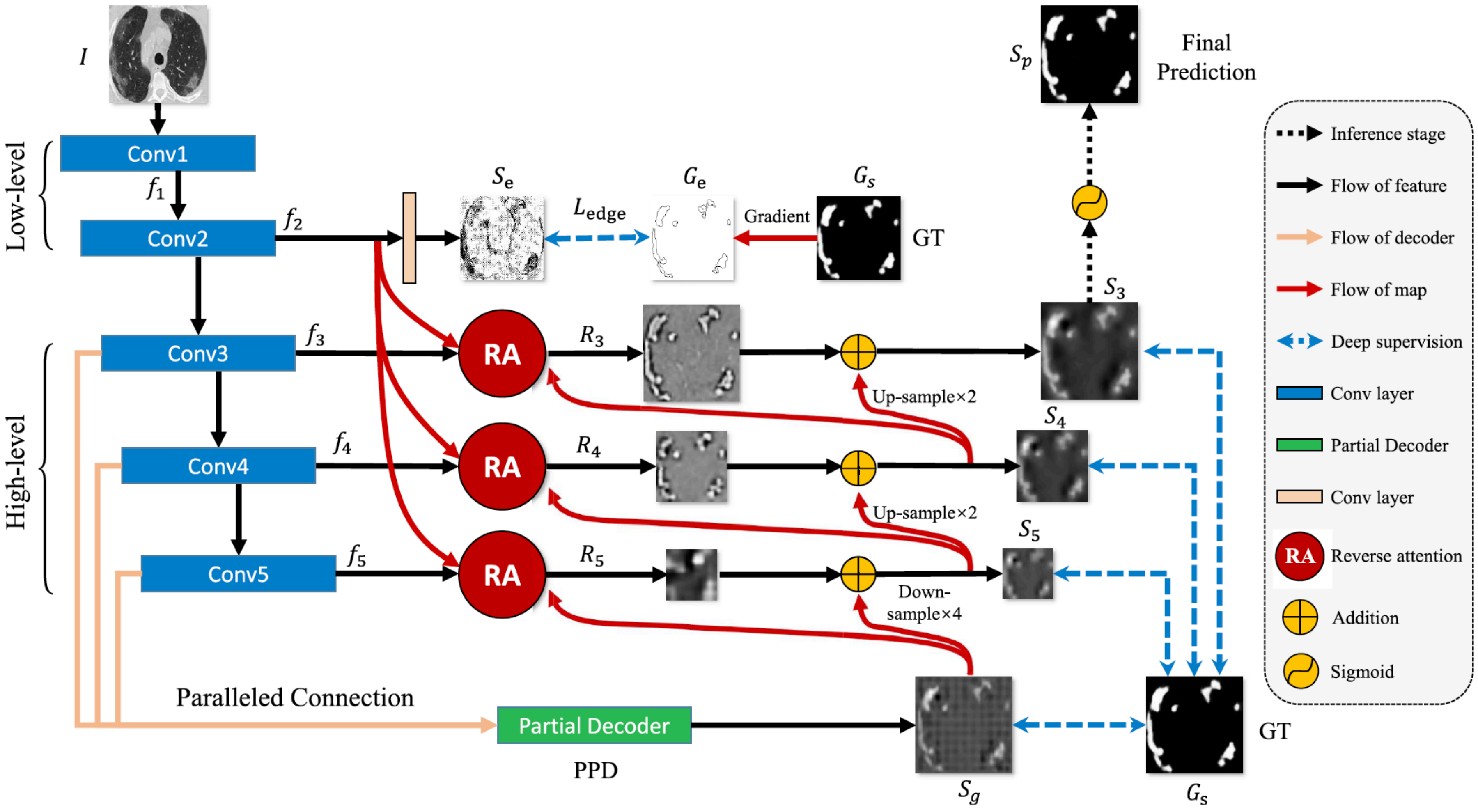

Fig. 2. The architecture of our proposed *Inf-Net* model, which consists of three reverse attention (RA) modules connected to the paralleled partial decoder (PPD). See § III-A for details.

Fan, Deng-Ping, et al. "Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images." IEEE Transactions on Medical Imaging (2020).

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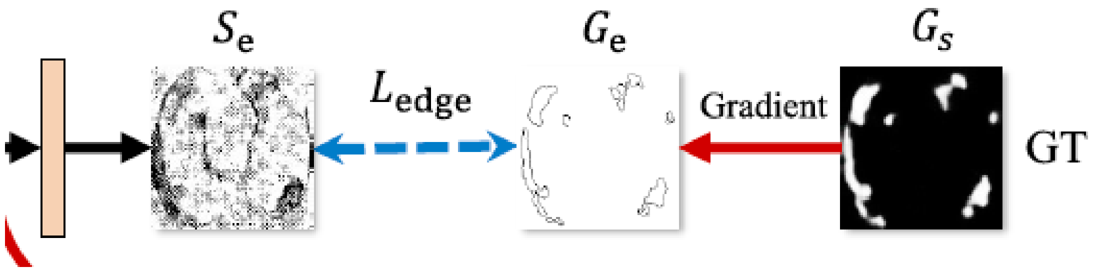
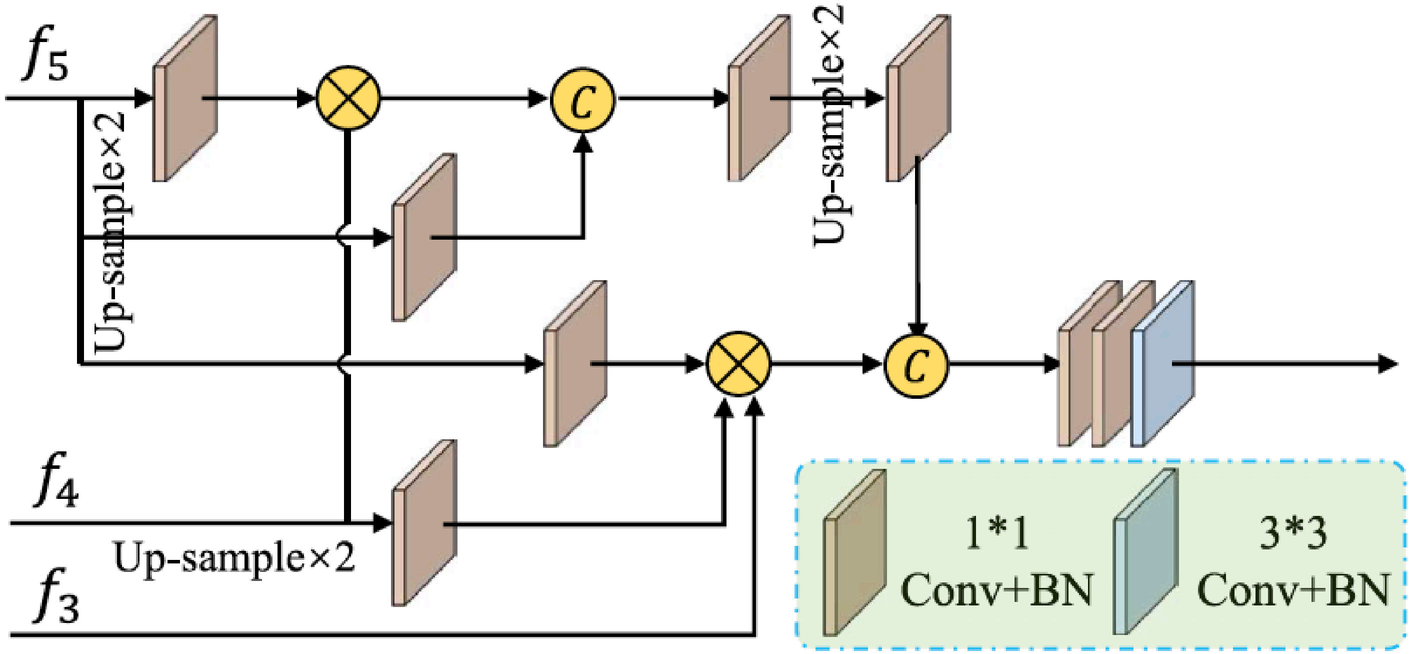
Edge Attention Module（EAM）



$$\mathcal{L}_{edge} = -\sum_{x=1}^{w}\sum_{y=1}^{h}[G_e log(S_e) + (1 - G_e)log(1 - S_e)],$$

Fan, Deng-Ping, et al. "Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images." IEEE Transactions on Medical Imaging (2020).

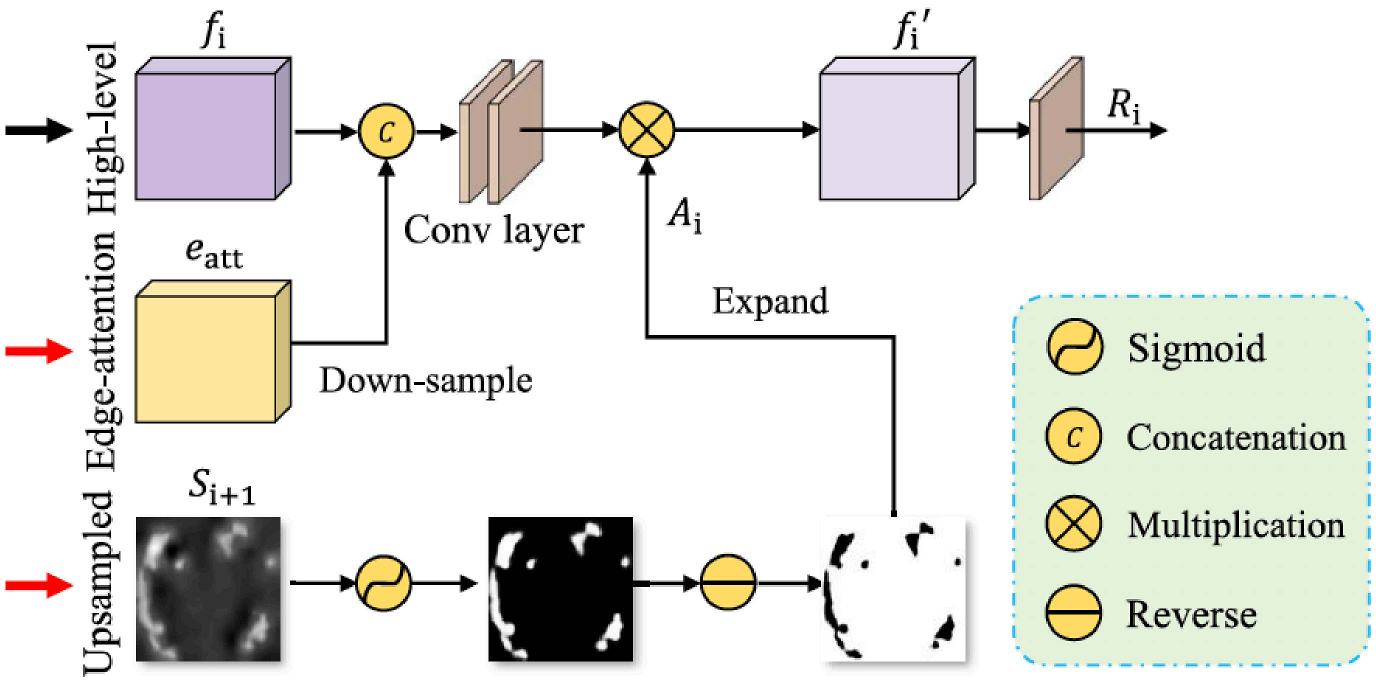
Paralleled partial decoder（PPD）



Fan, Deng-Ping, et al. "Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images." IEEE Transactions on Medical Imaging (2020).

COVID-19 CT Image Segmentation

Reverse attention module (RAM)



Fan, Deng-Ping, et al. "Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images." IEEE Transactions on Medical Imaging (2020).

COVID-19 CT Image Segmentation

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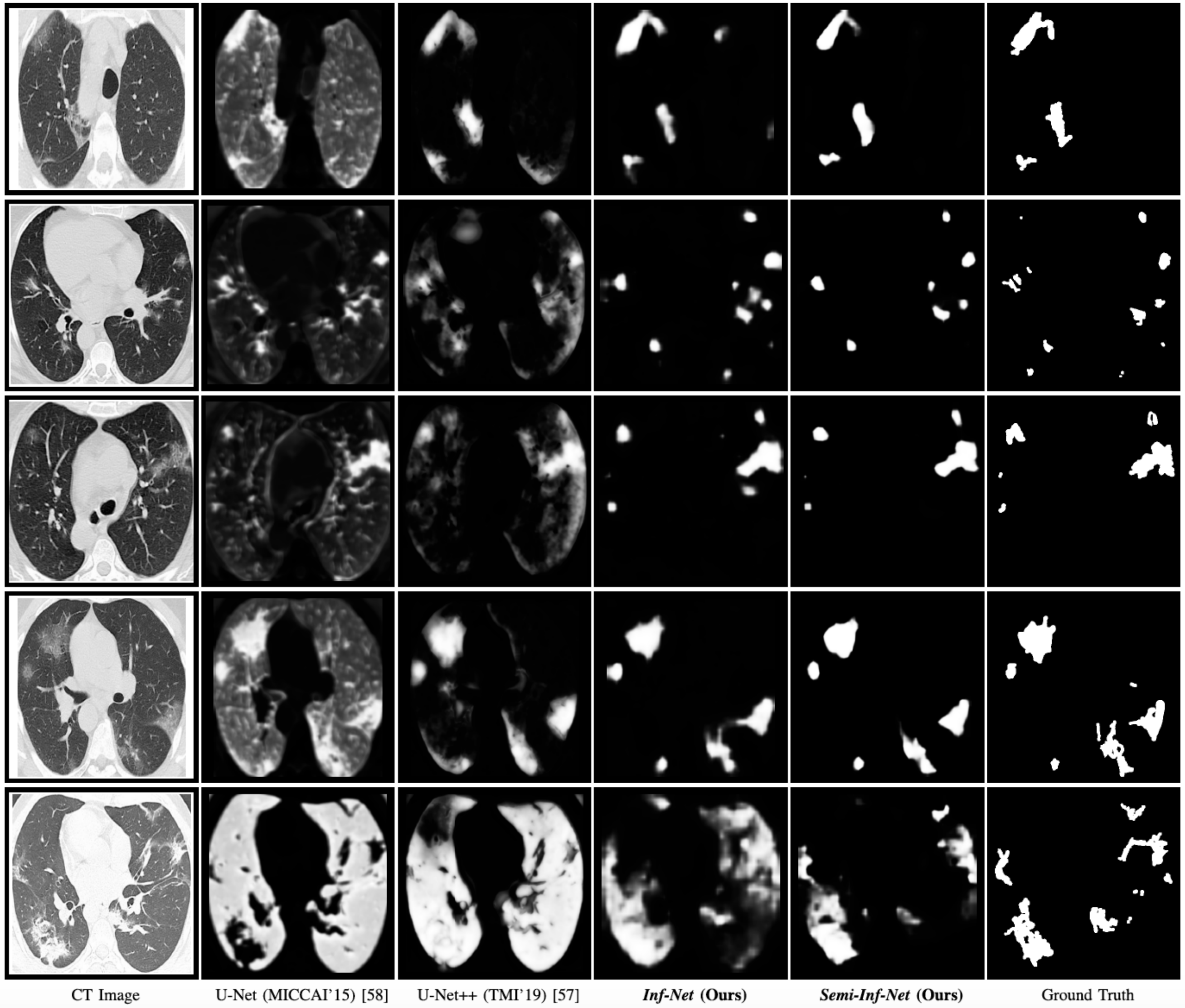
Results

TABLE IV
ABLATION STUDIES OF OUR *Semi-Inf-Net*. THE BEST TWO RESULTS ARE SHOWN IN RED AND BLUE FONTS

Methods	Dice	Sen.	Spec.	S_α	E_ϕ^{mean}	MAE
(No.1) Backbone	0.442	0.570	0.825	0.651	0.569	0.207
(No.2) Backbone+EA	0.541	0.665	0.807	0.673	0.659	0.205
(No.3) Backbone+PPD	0.669	0.744	0.880	0.720	0.810	0.125
(No.4) Backbone+RA	0.625	0.826	0.809	0.668	0.736	0.177
(No.5) Backbone+RA+EA	0.672	0.754	0.882	0.738	0.804	0.122
(No.6) Backbone+PPD+RA	0.655	0.690	0.927	0.761	0.812	0.098
(No.7) Backbone+PPD+RA+EA	0.739	0.725	0.960	0.800	0.894	0.064



Fan, Deng-Ping, et al. "Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT Images." IEEE Transactions on Medical Imaging (2020).

ANACONDA https://www.anaconda.com/

PyTorch https://pytorch.org/