EfficientSeg: A Simple but Efficient Solution to MyoPS 2020 Challenge

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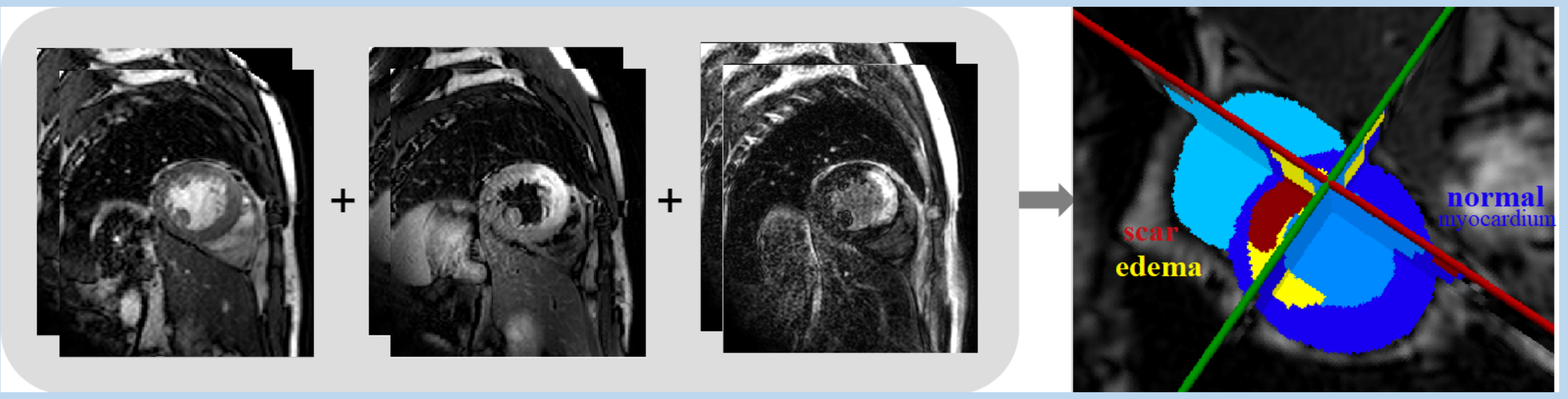
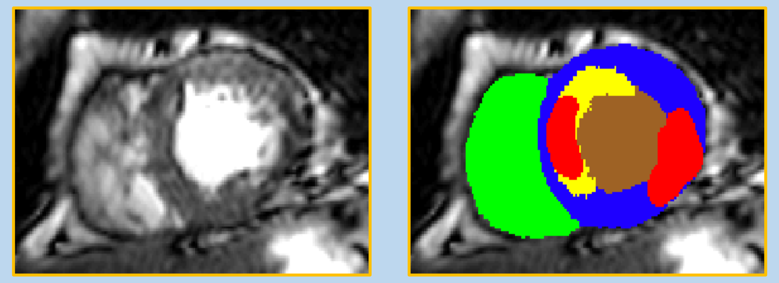
1 INTRODUCTION

1.1 Myocardial pathology segmentation: Segment the regions of scar and edema from the given three MRI sequences.

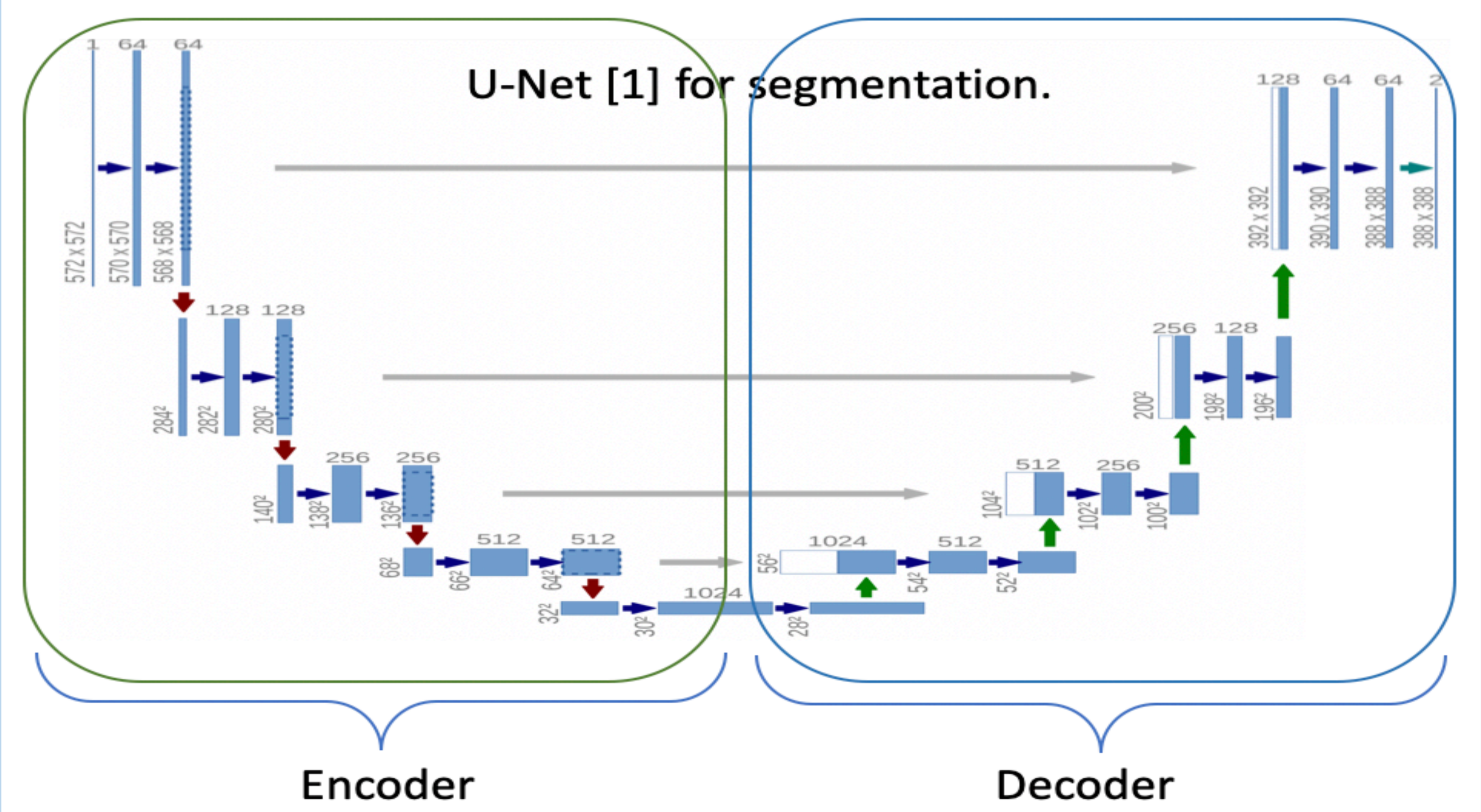


1.2. Challenges:

(1) Big visual difference
(2) Blurry and ambiguous;



1.3. Motivation:

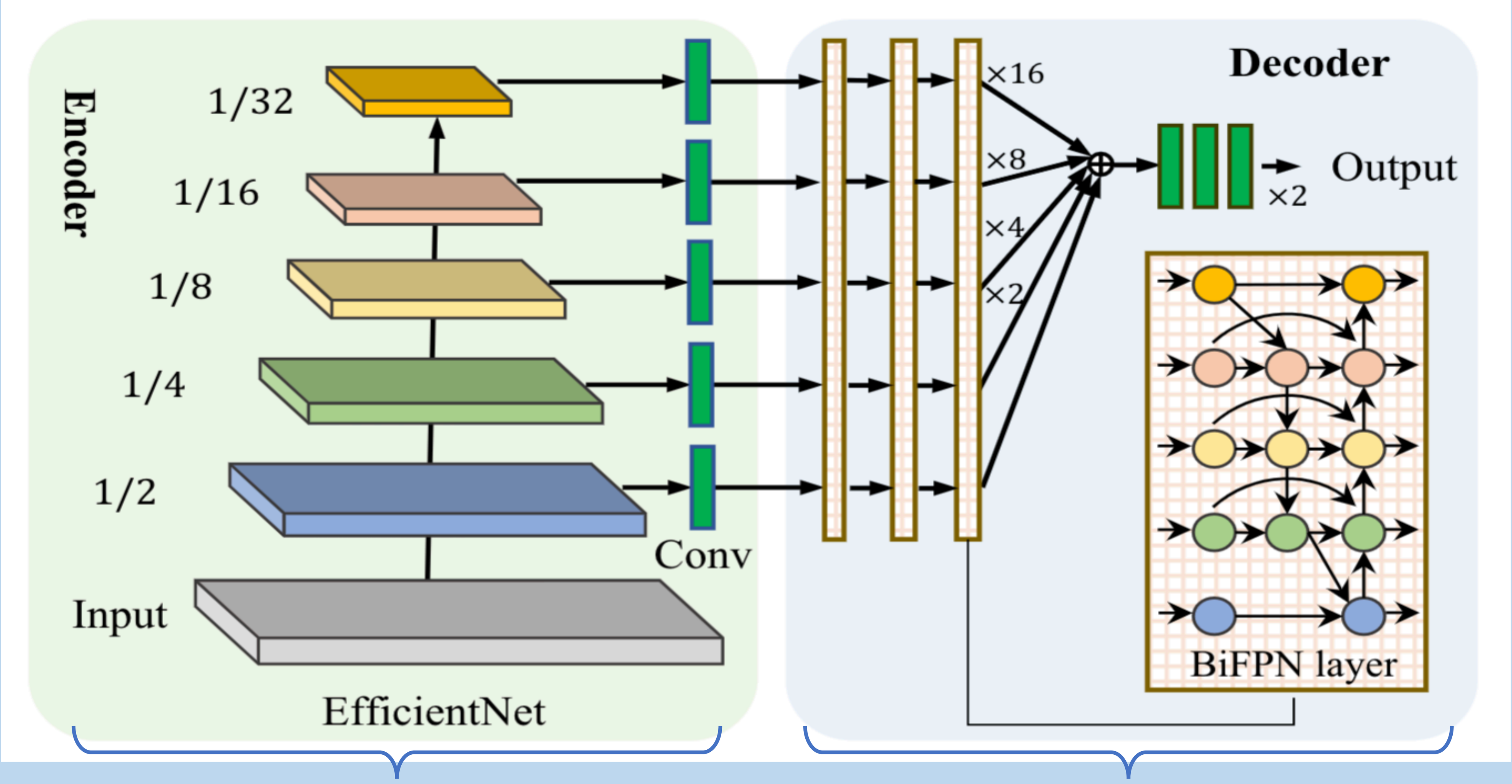


Observation: U-Net achieves the 59.15% and 62.56% Dice score of scar and edema+scar, which is relatively low.

Question: How to improve the encoder and decoder for better segmentation?

2 APPROACH

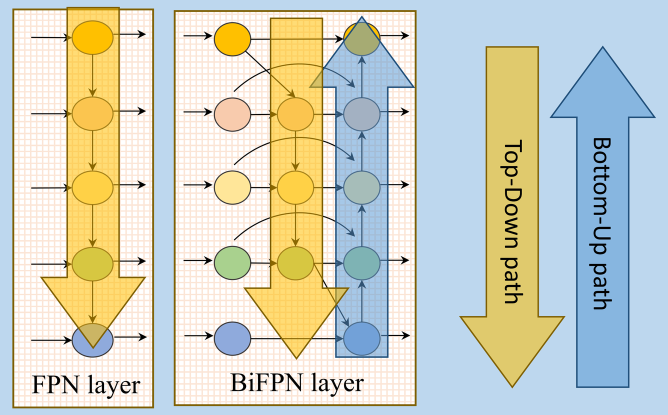
2.1 Framework of EfficientSeg



EfficientNet as Encoder

Example: EfficientNet-B0			
Stage	Operator	Input->Output (*WxHxC*)	L
1	Conv3x3	288x288x3->144x144x32	1
	MBConv 1, k3x3	144x144x32->144x144x16	1
2	MBConv 6, k3x3	144x144x16->72x72x24	2
3	MBConv 6, k3x3	72x72x24->36x36x40	2
4	MBConv 6, k3x3	36x36x40->18x18x80	3
	MBConv 6, k3x3	18x18x80->18x18x112	3
5	MBConv 6, k3x3	18x18x112->9x9x192	4
	MBConv 6, k3x3	9x9x192->9x9x320	1

BiFPN as Decoder



2.2 Model optimization

\# Dice loss

$$\mathfrak{L}_{Dice} = 1 - \frac{1}{C}\sum_{c}^{C}\frac{2\sum_i^N Y_i^c P_i^c}{\sum_i^N Y_i^c + \sum_i^N P_i^c}$$

\# Cross-Entropy loss

$$\mathfrak{L}_{CE} = -\frac{1}{N}\sum_{i}^{N}\sum_{c}^{C} Y_i^c \log P_i^c$$

\# Boundary loss

$$\phi_Y(x) = \begin{cases} -||x - z_{\partial Y}(x)||, & if\ x \in Y \\ ||x - z_{\partial Y}(x)||, & otherwise \end{cases}$$

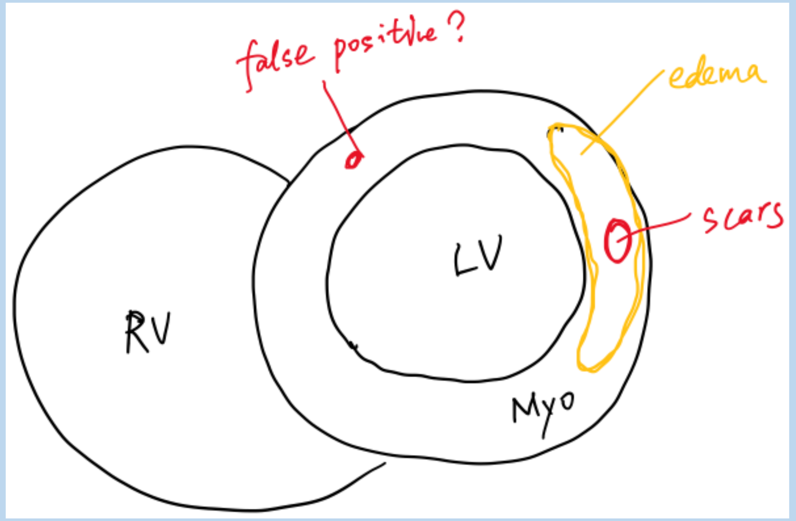
$$\mathfrak{L}_{Bound} = \int_{\Omega} \phi_Y(x) P(x) dx$$

\# Compound loss

$$\mathfrak{L} = \alpha(\mathfrak{L}_{CE} + \mathfrak{L}_{Dice}) + (1-\alpha)\mathfrak{L}_{Bound}$$

$$\alpha = 1 - \frac{1-0.01}{K} \cdot k$$

2.3 Post-Processing



Reducing false positive predictions

3 EXPERIMENT AND RESULTS

3.1 Dataset

25 cases for training and validation and 20 cases for testing.

3.2 Comparing to SOTA

Table 1. Comparison of different segmentation methods on the test set. †: Fine-tuning the model using the pretrained ImageNet weights [3]; ⋆: Final submission to the MyoPS 2020 Challenge; Ensembles: Ensemble B1, B2 and B3; pp: post-processing.

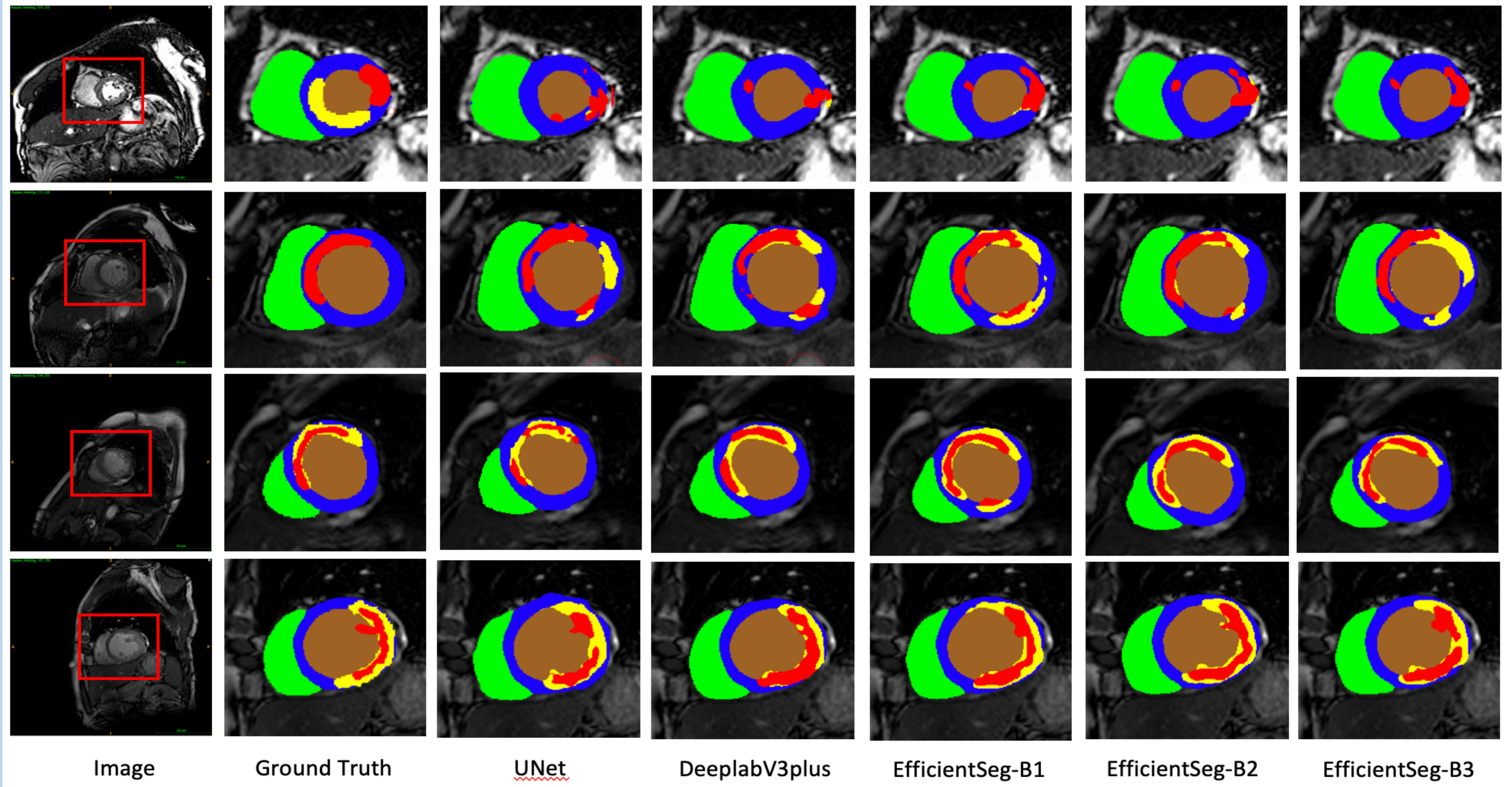
Method	# Parameters ($\times 10^6$)	Dice score %	
		Scar	Edema+Scar
U-Net	17.3	59.15	62.56
DeeplabV3plus	54.7	60.60	64.71
DeeplabV3plus †	54.7	63.01	69.05
EfficientSeg-B1 †	6.5	62.94	68.98
EfficientSeg-B2 †	7.9	63.08	68.78
EfficientSeg-B3 †	11.7	62.56	69.47
EfficientSeg-Ensembles †	/	64.35	70.10
EfficientSeg-Ensembles + pp † ⋆	/	**64.71**	**70.87**

3.3 Ablation study of loss functions

Table 2. Comparison of different loss functions on the test set.

Method	Dice score %	
	Scar	Edema+Scar
EfficientSeg-B1 + $\mathfrak{L}_{CE}$	61.59	67.61
EfficientSeg-B1 + $\mathfrak{L}_{Dice}$	62.13	68.21
EfficientSeg-B1 + $\mathfrak{L}_{CE}$ + $\mathfrak{L}_{Dice}$	62.41	68.11
EfficientSeg-B1 + $\mathfrak{L}_{CE}$ + $\mathfrak{L}_{Dice}$ + $\mathfrak{L}_{Bound}$ (Ours)	**62.94**	**68.98**

3.4 Qualitative comparison



4 References

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[2] Tan M, Chen B, Pang R, et al. Mnasnet: Platform-aware neural architecture search for mobile. CVPR 2019.
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[4] Kervadec H, et al. Boundary loss for highly unbalanced segmentation. MIDL 2019.