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Dynamic Snake Convolution

based on Topological Geometric Constraints for Tubular Structure Segmentation

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I Background —— Tubular Structure

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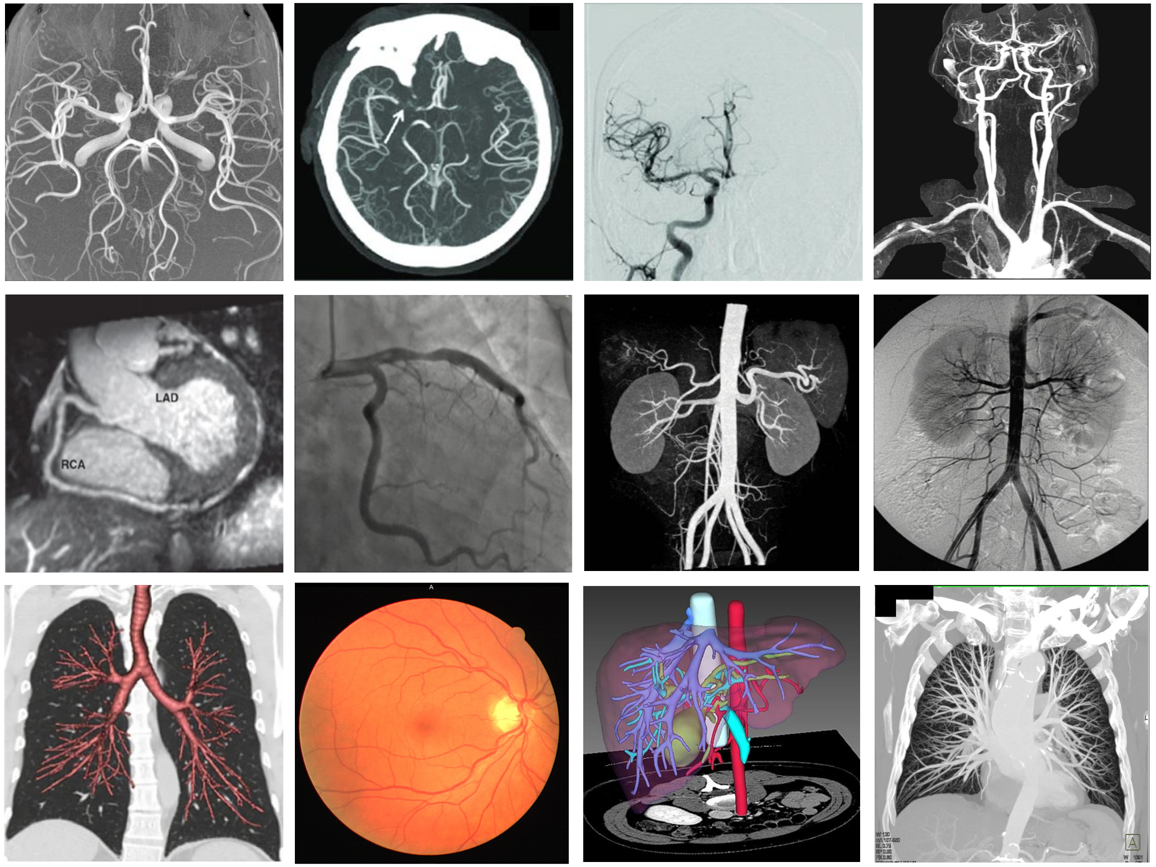
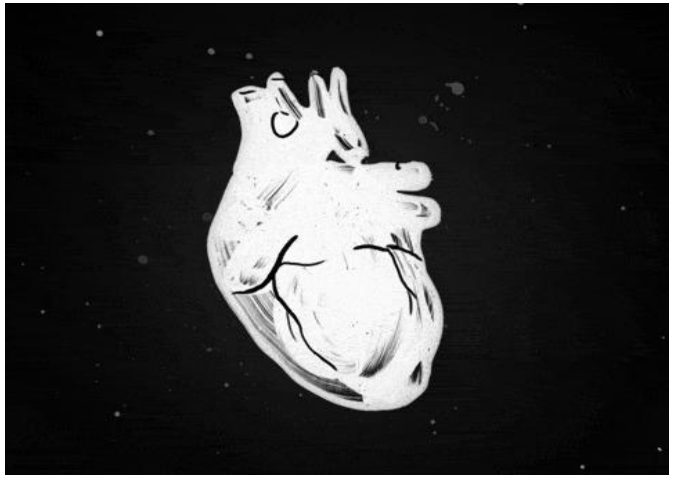
Tubular structures in medical image



Tubular structures in natural image

I Importance —— Segmentation

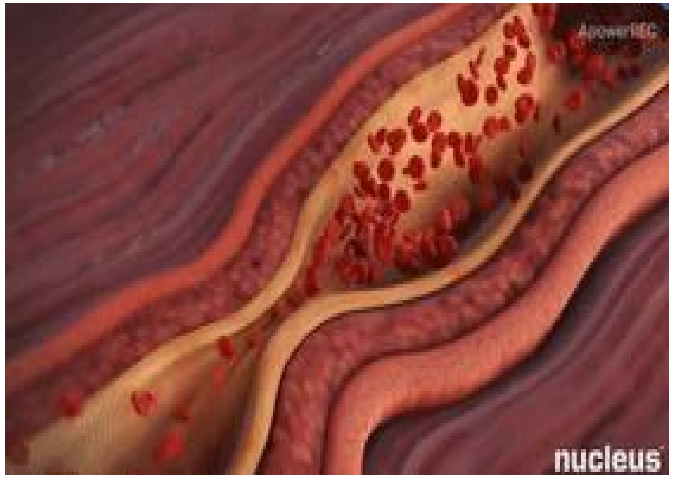


Coronary Artery Disease

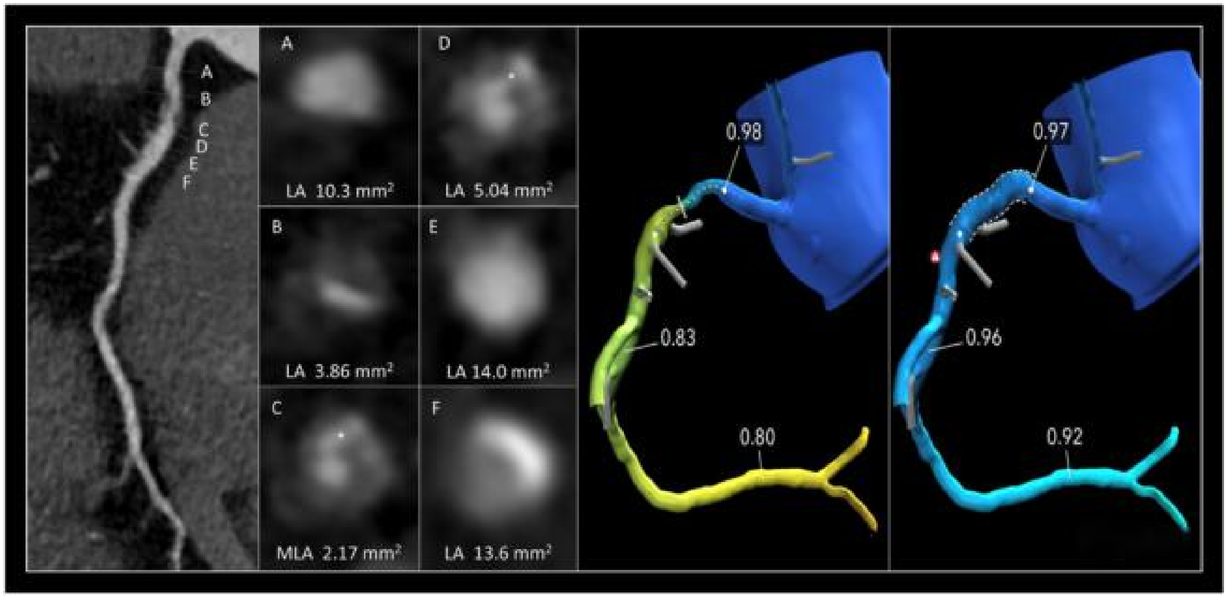
Number one in lethality

Coronary Artery Stenosis

Compress blood vessels

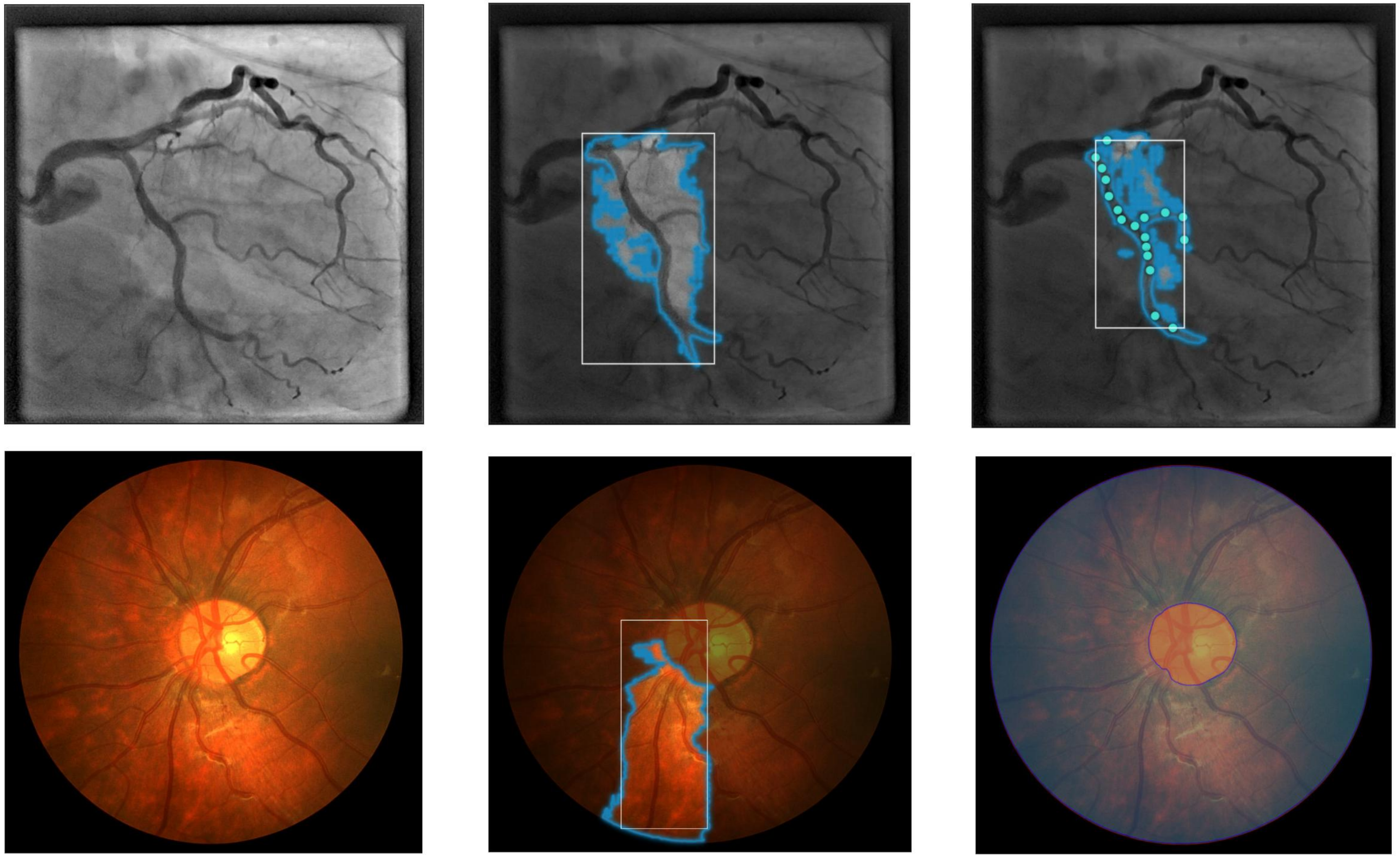


CT-FFR *(Ko JACC 2017)*

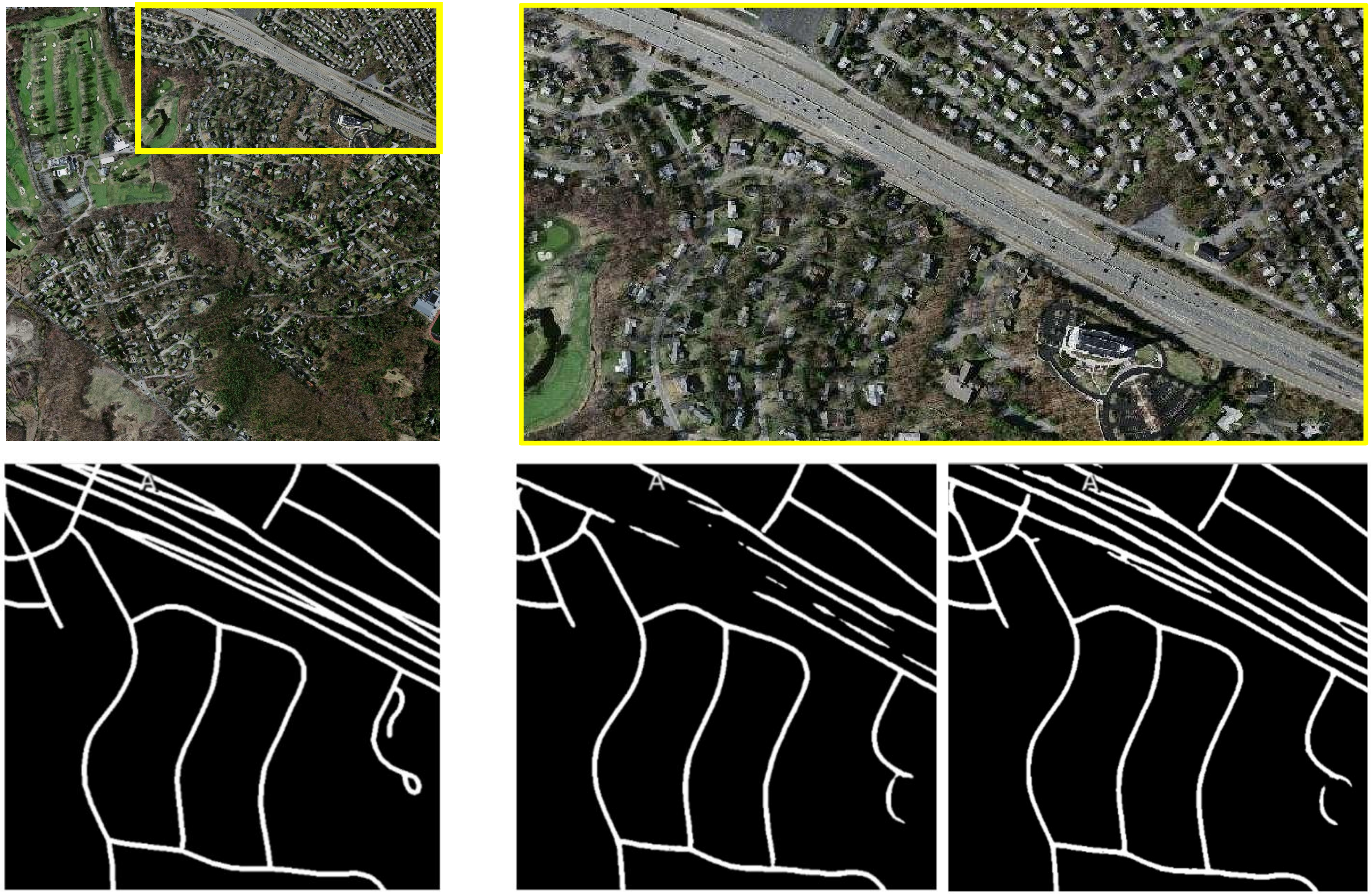


- **CT-FFR** can detect stenosis non-invasively
- **CT-FFR** depends on **C**omputational **F**luid **D**ynamics
- **CFD** relies on well-delineated coronary lumen

Ⅰ Challenge —— Segment Anything

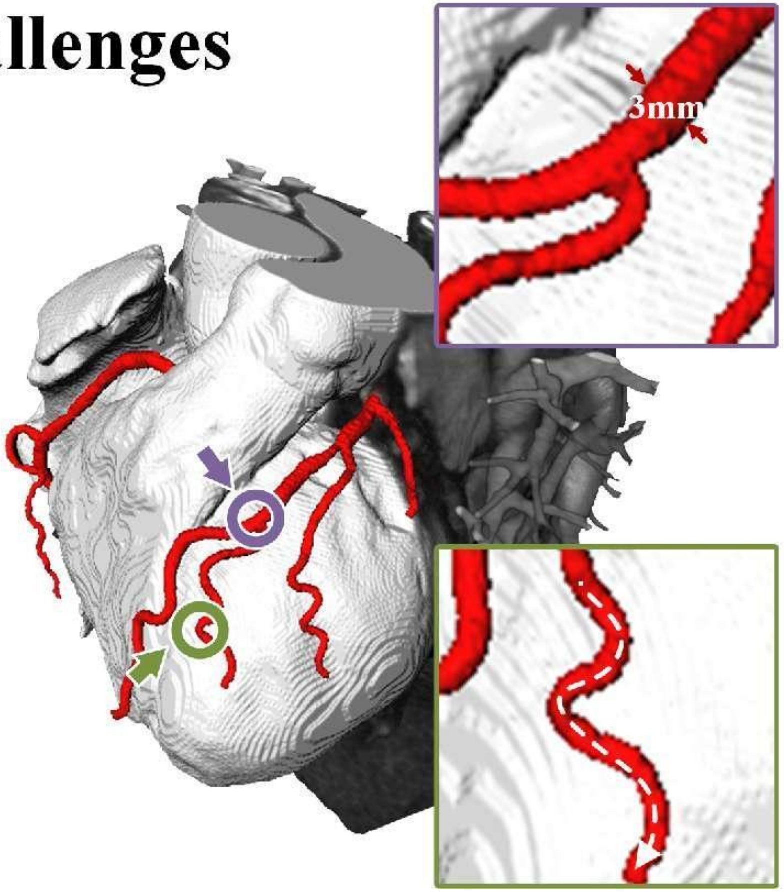


Ⅰ Challenge —— The inaccurate results



Groundtruth DCU-Net **our** DSCNet

Challenges

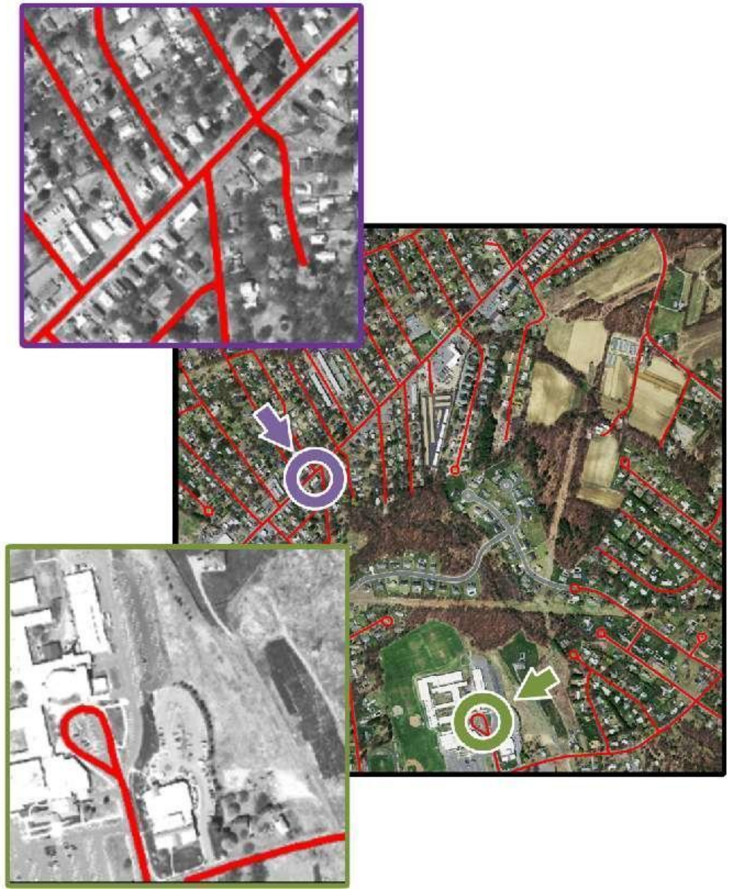


Challenge 1

Thin and fragile local structure

Challenge 2

Complex and variable global morphology



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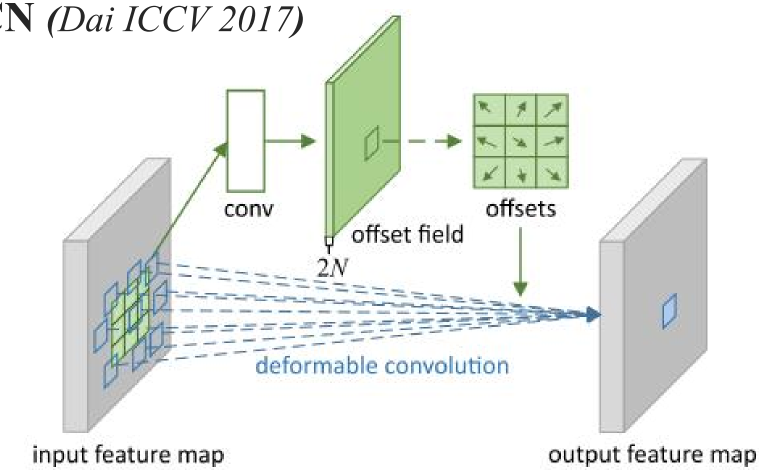
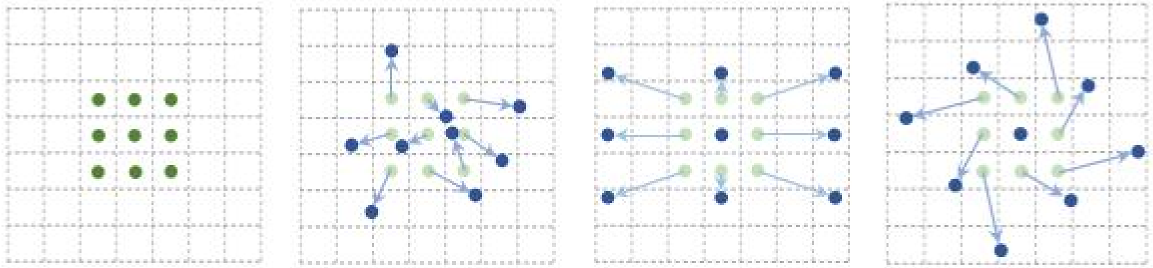
DCN *(Dai ICCV 2017)*





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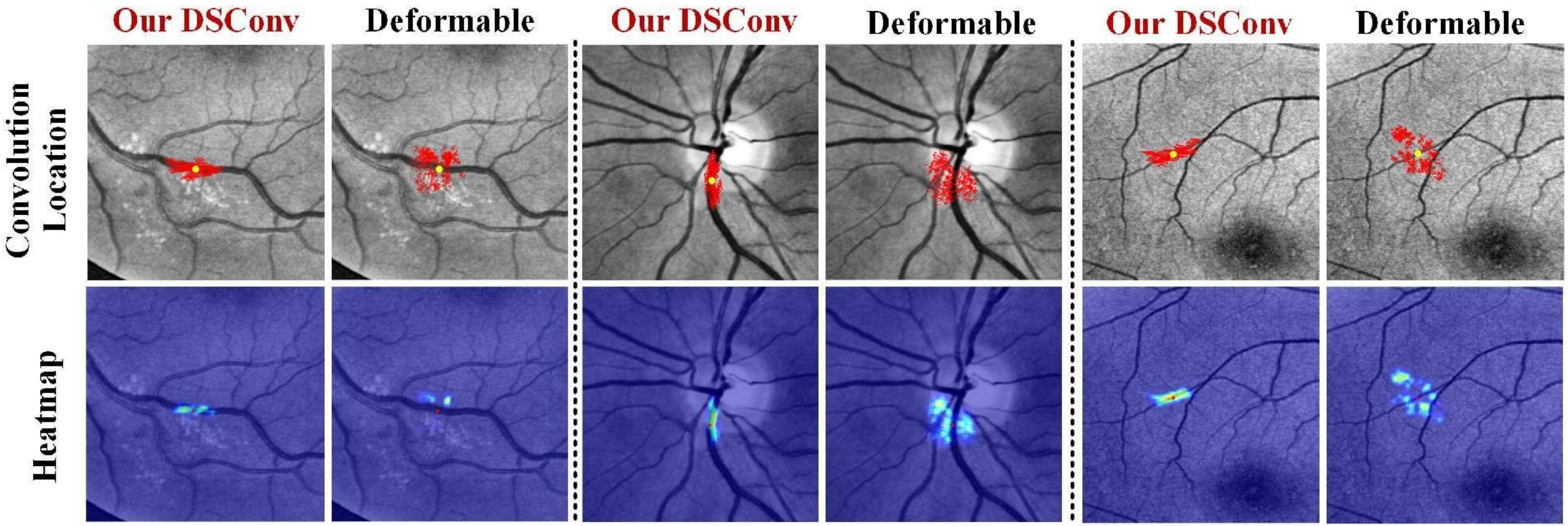
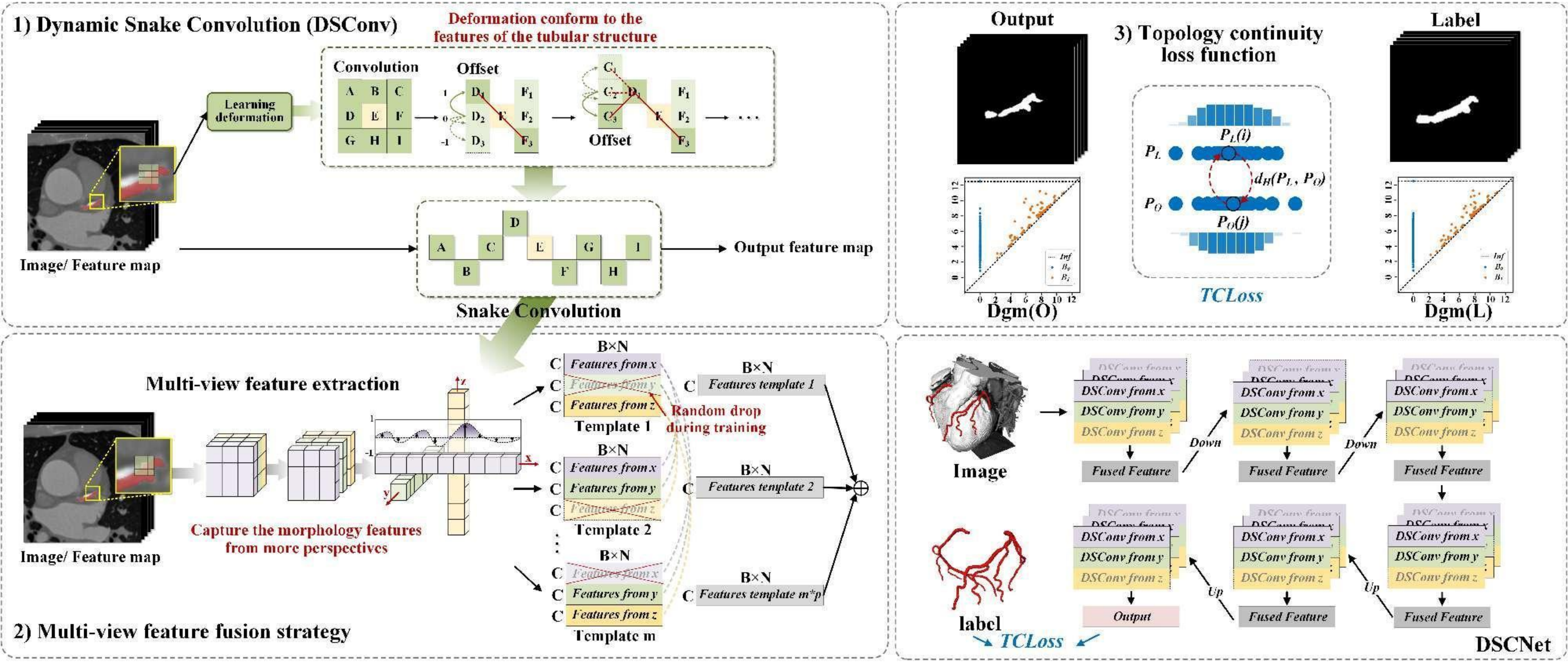


Wandering outside the target

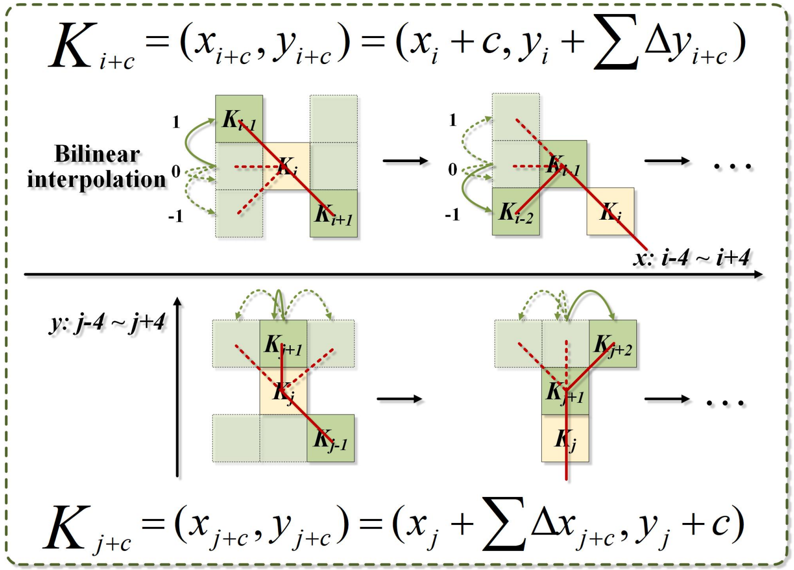
1. Since the <**offset**> is not constrained, which is learned completely freely
2. Due to the special features of the tubular structure, such as: **‘thin’**, **‘wide distribution’...**

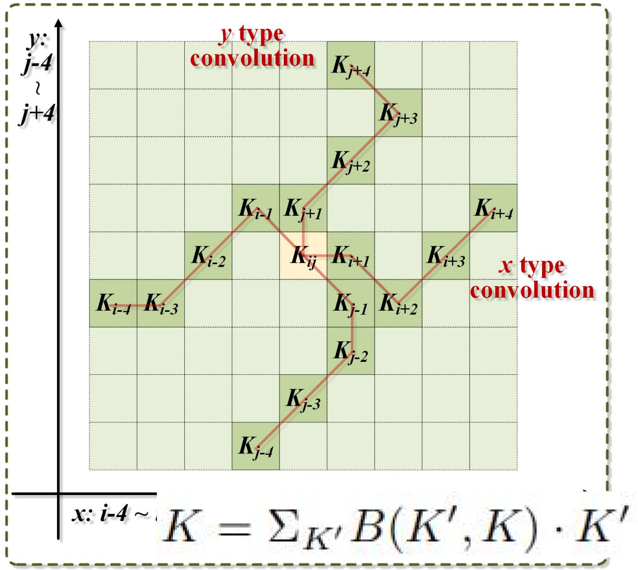
Ⅱ DSCNet



原文链接 https://arxiv.org/abs/2307.08388
知乎解析 https://zhuanlan.zhihu.com/p/644206121

Ⅱ Dynamic Snake Convolution

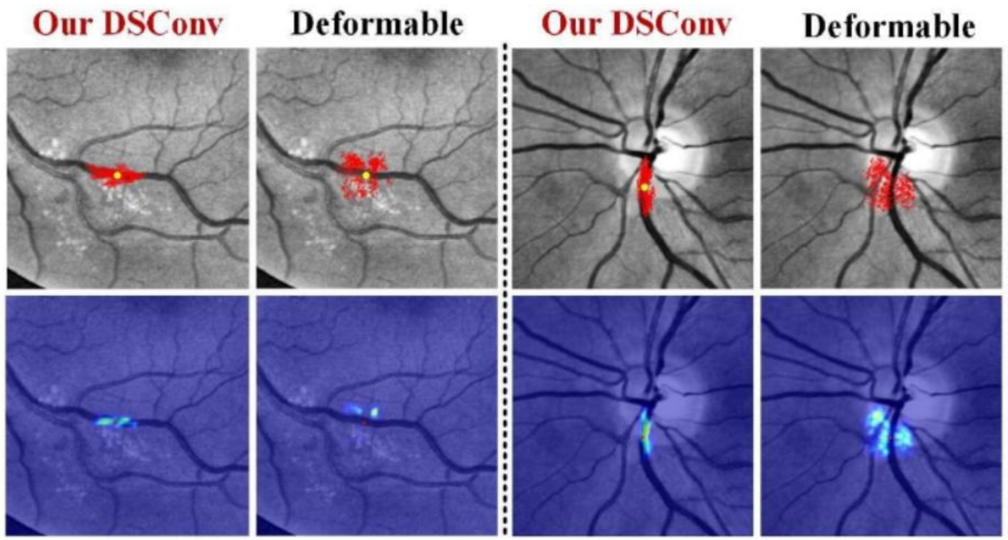




1. **D**ynamic **S**nake **C**onvolution:
- Dynamically adapt to the tubular structure

2. **M**ulti-view **F**eature **F**usion **S**trategy:
- Fuse Feature from multi perspective

3. **T**opological **C**ontinuity **C**onstraint **Loss**:
- Use Persistent Homology to constrain continuity



$$K = \{(x-1, y-1), (x-1, y), \cdots, (x+1, y+1)\} \quad (1)$$

$$K_{i\pm c} = \begin{cases} (x_{i+c}, y_{i+c}) = (x_i + c, y_i + \Sigma_i^{i+c} \Delta y), \\ (x_{i-c}, y_{i-c}) = (x_i - c, y_i + \Sigma_{i-c}^{i} \Delta y), \end{cases} \quad (2)$$

$$K_{j\pm c} = \begin{cases} (x_{j+c}, y_{j+c}) = (x_j + \Sigma_j^{j+c} \Delta x, y_j + c), \\ (x_{j-c}, y_{j-c}) = (x_j + \Sigma_{j-c}^{j} \Delta x, y_j - c), \end{cases} \quad (3)$$

Ⅱ Multi-view Feature Fusion

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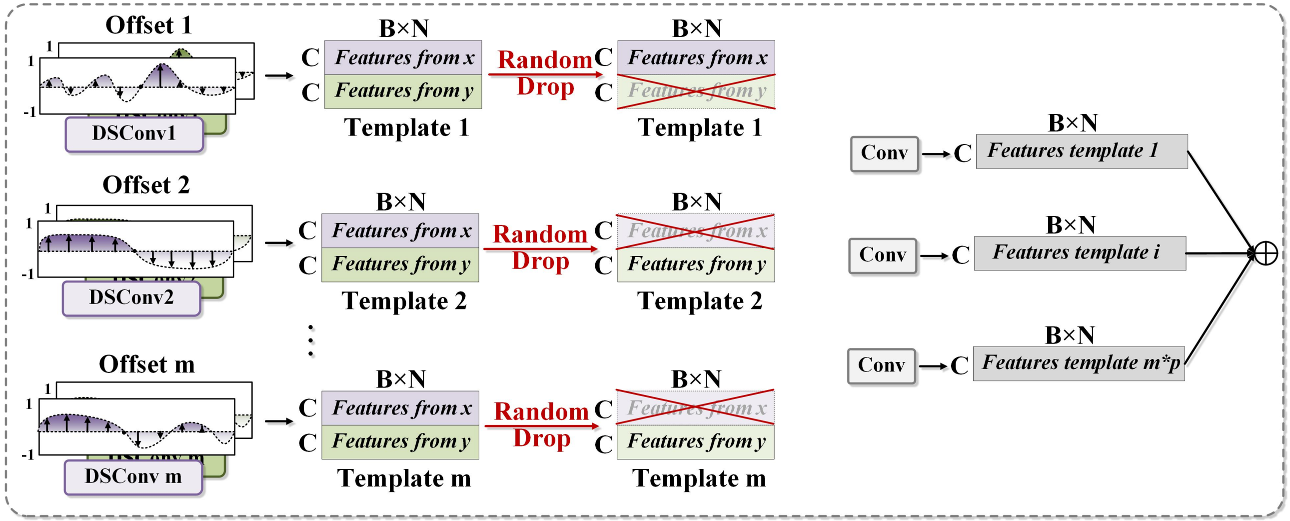


1. Dynamic Snake Convolution:
- Dynamically adapt to the tubular structure

2. Multi-view Feature Fusion Strategy:
- Fuse Feature from multi perspective

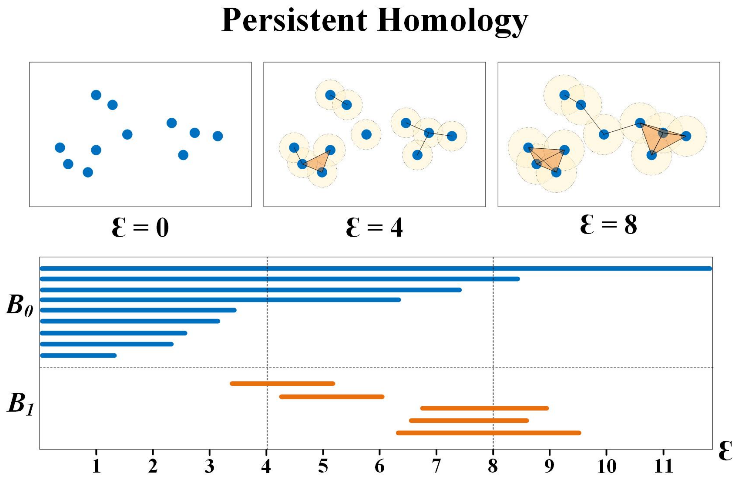
3. Topological Continuity Constraint Loss:
- Use Persistent Homology to constrain continuity

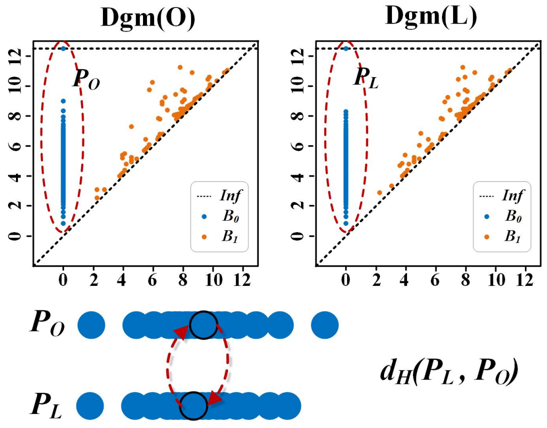
$$f^l(K) = \{\underbrace{\Sigma_i w(K_i)\cdot f^l(K_i)}_{f^l(K_x)}, \underbrace{\Sigma_j w(K_j)\cdot f^l(K_j)}_{f^l(K_y)}\} \quad (6)$$

$$T^l = (\underbrace{f^l(K_x), f^l(K_y)}_{T_1^l}, \underbrace{f^l(K_x), f^l(K_y)}_{T_2^l}, \cdots \underbrace{f^l(K_x), f^l(K_y)}_{T_m^l})$$

$$\begin{cases} r^l \sim \text{Bernoulli}(p) \\ \hat{T}^l = r^l \cdot T^l \\ f^{l+1}(K) = \Sigma^{\lfloor m\times p \rfloor} \hat{T}_t^l \end{cases}$$

Ⅱ Persistent Homology





1. **D**ynamic **S**nake **C**onvolution:
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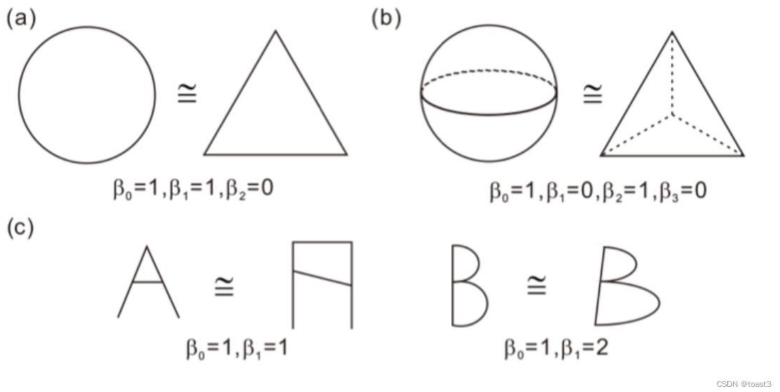
   - Use Persistent Homology to constrain continuity

Betti Data



$$\begin{cases} d_H(P_O, P_L) = \max\limits_{u \in P_O} \min\limits_{v \in P_L} \| u - v \| \\ d_H(P_L, P_O) = \max\limits_{v \in P_L} \min\limits_{u \in P_O} \| v - u \| \\ d_H^* = \max\{d_H(P_O, P_L), d_H(P_L, P_O)\} \end{cases}$$

$$\mathcal{L}_{TC} = \mathcal{L}_{CE} + \mathcal{L}_{PH} = \mathcal{L}_{CE} + \sum_{n=0}^{N} d_H^*$$

[1] Xiaoling Hu, Fuxin Li, Dimitris Samaras, et al. Topology preserving deep image segmentation. Advances in neural information processing systems, 32, 2019.
[2] Chi-Chong Wong and Chi-Man Vong. Persistent homology based graph convolution network for fine-grained 3d shape segmentation. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pages 7098–7107, Oct 2021.

Ⅲ Results

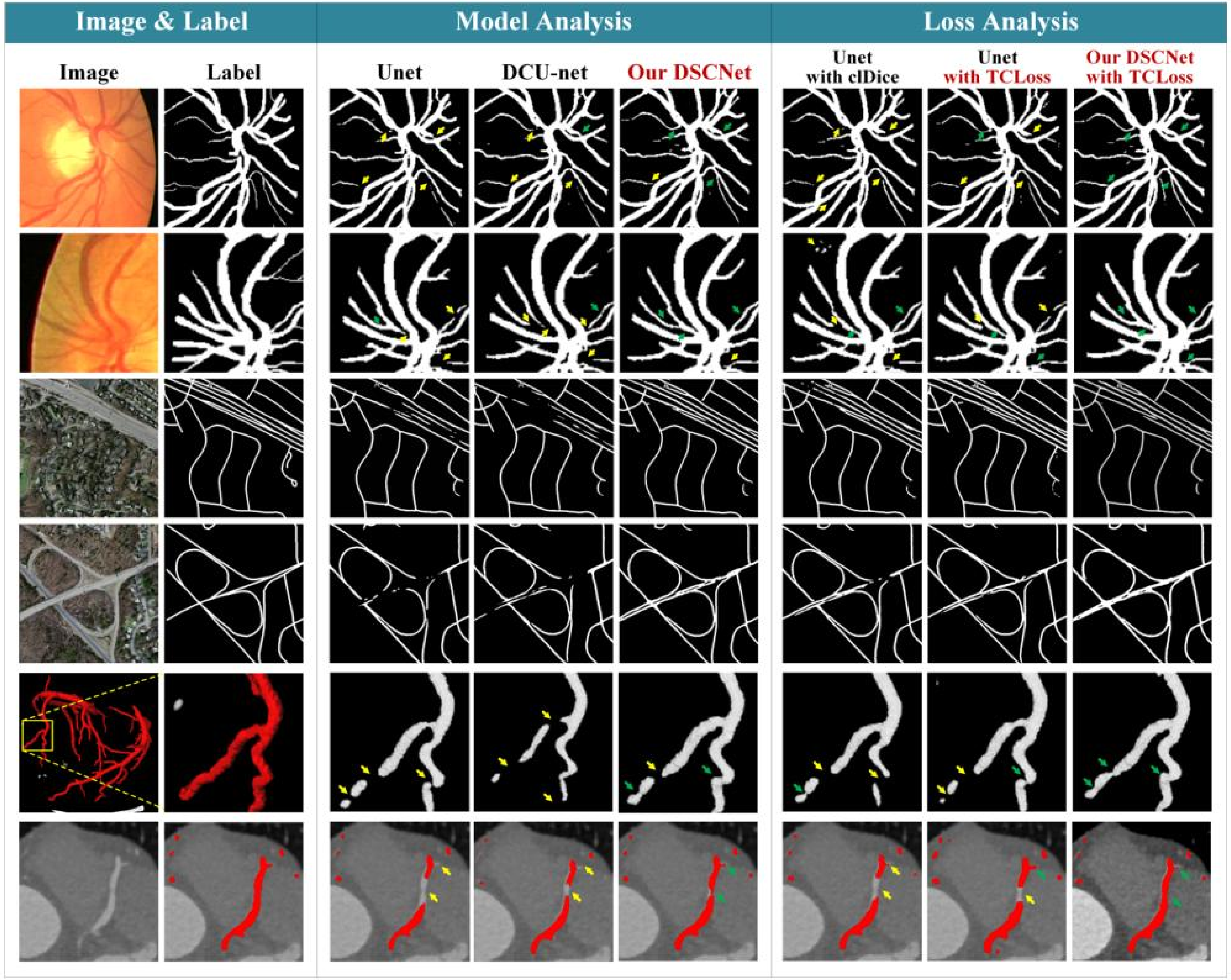
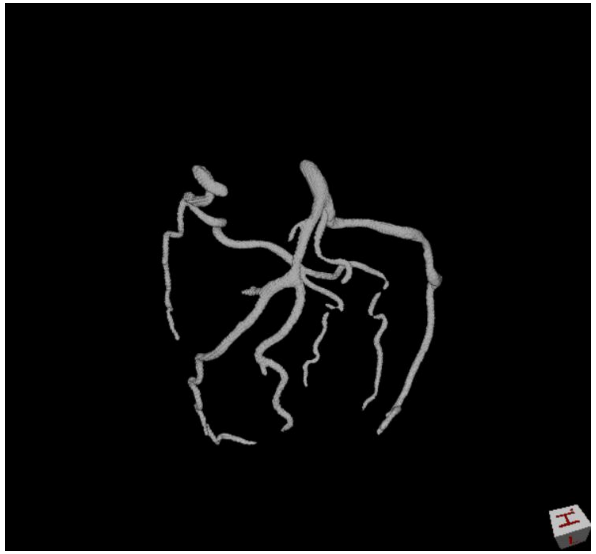
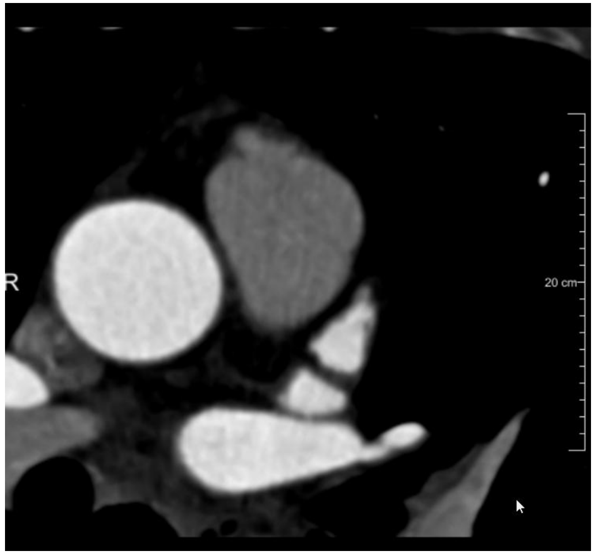


Image & Label
Model Analysis
Loss Analysis
Image
Label
Unet
DCU-net
Our DSCNet
Unet
with clDice
Unet
with TCLoss
Our DSCNet
with TCLoss





R
20 cm

Ⅲ Results

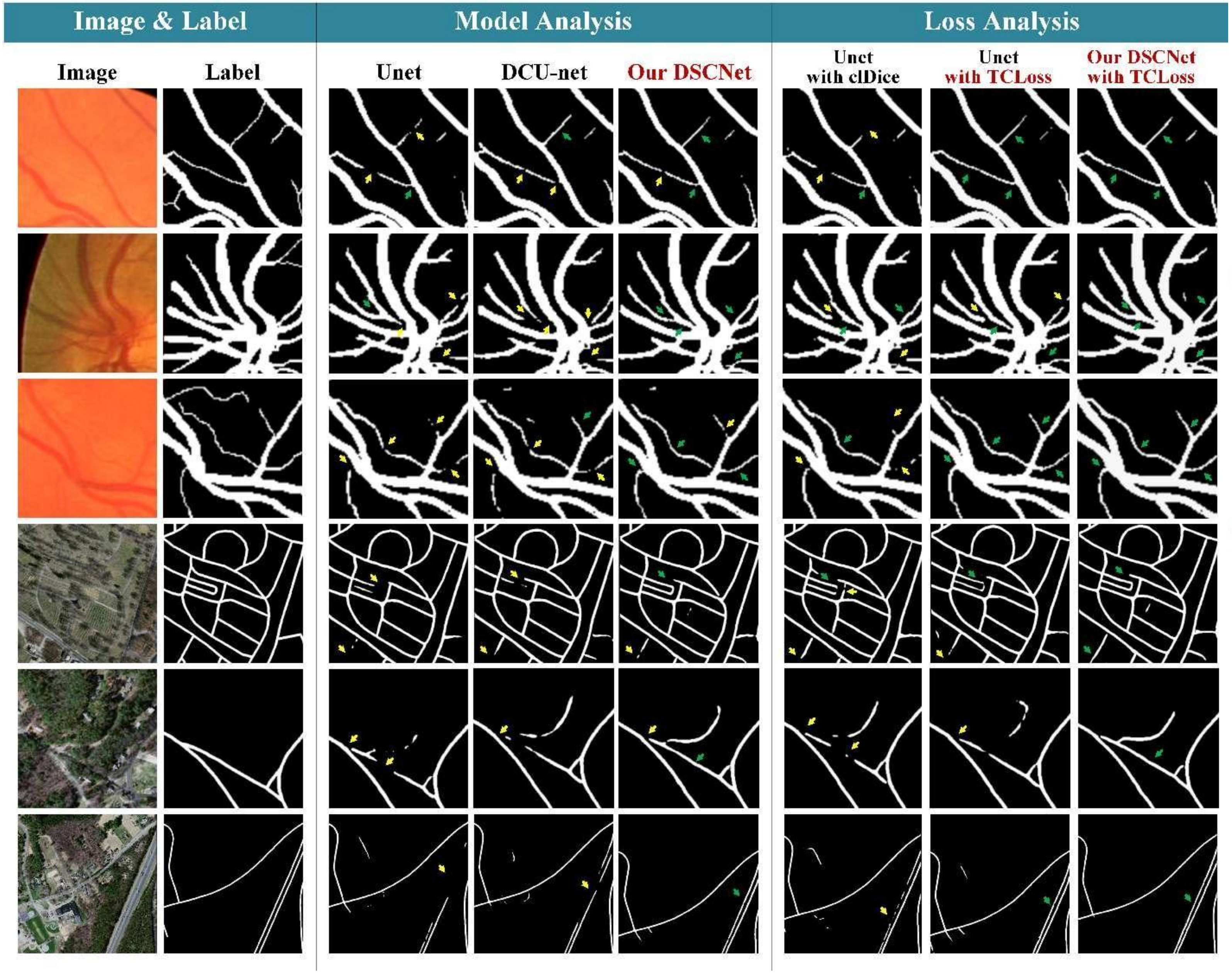
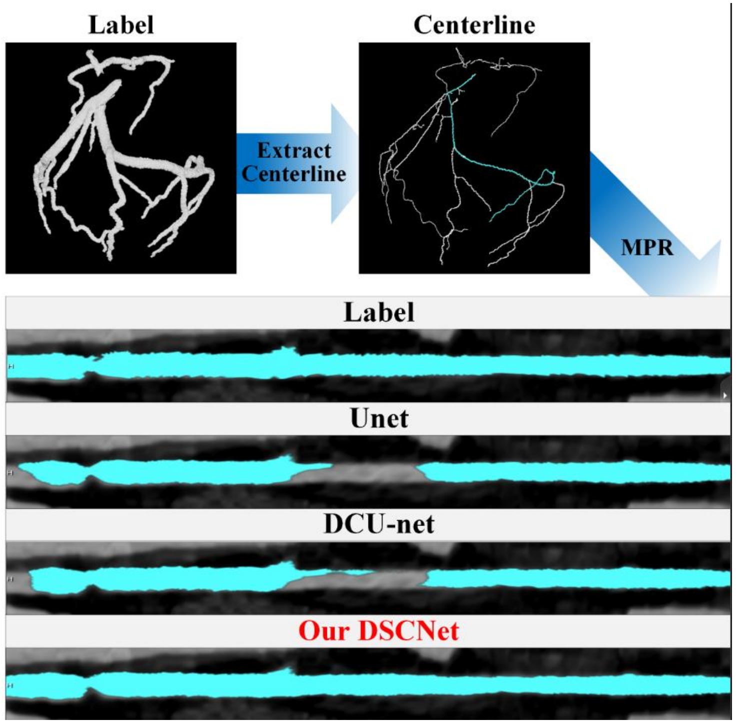


Image & Label
Model Analysis
Loss Analysis
Image
Label
Unet
DCU-net
Our DSCNet
Unet with clDice
Unet with TCLoss
Our DSCNet with TCLoss


Label
Centerline
Extract Centerline
MPR
Label
Unet
DCU-net
Our DSCNet

Dataset	Network	Loss	Volumetric (%) ↑					Topology ↓		Distance ↓
			Dice	RDice	clDice	ACC	AUC	β_0	β_1	HD
DRIVE	UNet	$\mathcal{L}_{CE}$	$80.73_{\pm 1.77}$	$87.94_{\pm 3.32}$	$79.66_{\pm 4.00}$	$96.74_{\pm 0.28}$	$88.57_{\pm 2.44}$	$1.209_{\pm 0.342}$	$0.883_{\pm 0.135}$	$6.86_{\pm 0.56}$
	Transunet	$\mathcal{L}_{CE}$	$80.56_{\pm 2.14}$	$87.14_{\pm 3.82}$	$79.02_{\pm 5.05}$	$96.75_{\pm 0.32}$	$88.02_{\pm 2.79}$	$1.210_{\pm 0.309}$	$0.844_{\pm 0.157}$	$6.83_{\pm 0.52}$
	CS^2-Net	$\mathcal{L}_{CE}$	$77.53_{\pm 2.94}$	$82.55_{\pm 4.10}$	$74.88_{\pm 5.27}$	$96.46_{\pm 0.36}$	$84.73_{\pm 2.82}$	$1.391_{\pm 0.331}$	$0.906_{\pm 0.177}$	$6.90_{\pm 0.48}$
	DCU-net	$\mathcal{L}_{CE}$	$80.83_{\pm 1.99}$	$87.73_{\pm 3.60}$	$80.19_{\pm 4.80}$	$96.77_{\pm 0.31}$	$88.45_{\pm 2.67}$	$1.104_{\pm 0.327}$	$0.817_{\pm 0.166}$	$6.84_{\pm 0.58}$
	DSCNet(ours)	$\mathcal{L}_{CE}$	$\mathbf{81.85}_{\pm 1.74}$	$\mathbf{88.93}_{\pm 3.36}$	$\mathbf{81.16}_{\pm 4.54}$	$\mathbf{96.91}_{\pm 0.28}$	$\mathbf{89.38}_{\pm 2.54}$	$\mathbf{1.094}_{\pm 0.301}$	$\mathbf{0.780}_{\pm 0.162}$	$\mathbf{6.68}_{\pm 0.49}$
	UNet	$\mathcal{L}_{TC}$(ours)	$80.93_{\pm 1.97}$	$88.00_{\pm 3.41}$	$80.28_{\pm 4.41}$	$96.78_{\pm 0.30}$	$88.63_{\pm 2.56}$	$1.117_{\pm 0.286}$	$\mathbf{0.797}_{\pm 0.151}$	$6.88_{\pm 0.53}$
	Transunet	$\mathcal{L}_{TC}$(ours)	$80.79_{\pm 2.11}$	$87.78_{\pm 3.80}$	$79.86_{\pm 4.90}$	$96.76_{\pm 0.32}$	$88.48_{\pm 2.82}$	$1.176_{\pm 0.295}$	$0.818_{\pm 0.176}$	$6.83_{\pm 0.51}$
	CS^2-Net	$\mathcal{L}_{TC}$(ours)	$79.69_{\pm 2.31}$	$86.14_{\pm 3.82}$	$77.72_{\pm 5.09}$	$96.64_{\pm 0.32}$	$87.25_{\pm 2.76}$	$1.308_{\pm 0.334}$	$0.848_{\pm 0.160}$	$6.93_{\pm 0.45}$
	DCU-net	$\mathcal{L}_{TC}$(ours)	$81.18_{\pm 1.90}$	$87.89_{\pm 3.43}$	$80.60_{\pm 4.54}$	$96.83_{\pm 0.31}$	$88.59_{\pm 2.57}$	$1.076_{\pm 0.313}$	$0.817_{\pm 0.167}$	$6.80_{\pm 0.56}$
	UNet	clDice	$80.77_{\pm 1.92}$	$87.53_{\pm 3.42}$	$79.93_{\pm 4.48}$	$96.77_{\pm 0.31}$	$88.29_{\pm 2.52}$	$1.199_{\pm 0.303}$	$0.833_{\pm 0.157}$	$6.93_{\pm 0.54}$
	UNet	$\mathcal{L}_{WTC}$	$80.89_{\pm 1.95}$	$87.85_{\pm 3.55}$	$80.03_{\pm 4.75}$	$96.78_{\pm 0.29}$	$88.53_{\pm 2.64}$	$1.144_{\pm 0.339}$	$0.814_{\pm 0.176}$	$6.79_{\pm 0.47}$
	DSCNet(ours)	$\mathcal{L}_{TC}$(ours)	$\mathbf{82.06}_{\pm 1.44}$	$\mathbf{90.17}_{\pm 3.04}$	$\mathbf{82.07}_{\pm 4.35}$	$\mathbf{96.87}_{\pm 0.24}$	$\mathbf{90.27}_{\pm 2.32}$	$\mathbf{0.998}_{\pm 0.312}$	$0.803_{\pm 0.179}$	$\mathbf{6.78}_{\pm 0.51}$
ROADS	UNet	$\mathcal{L}_{CE}$	$76.90_{\pm 6.30}$	$84.07_{\pm 6.46}$	$86.87_{\pm 6.59}$	$97.97_{\pm 1.27}$	$98.29_{\pm 1.24}$	$1.107_{\pm 0.551}$	$1.505_{\pm 0.467}$	$8.11_{\pm 2.42}$
	Transunet	$\mathcal{L}_{CE}$	$75.82_{\pm 6.83}$	$81.50_{\pm 6.65}$	$86.04_{\pm 7.40}$	$97.97_{\pm 1.28}$	$98.23_{\pm 1.15}$	$1.105_{\pm 0.615}$	$1.570_{\pm 0.663}$	$8.11_{\pm 2.53}$
	DCU-net	$\mathcal{L}_{CE}$	$77.24_{\pm 6.30}$	$84.26_{\pm 6.37}$	$86.98_{\pm 6.53}$	$98.03_{\pm 1.14}$	$98.34_{\pm 1.19}$	$1.085_{\pm 0.653}$	$1.474_{\pm 0.497}$	$8.04_{\pm 2.53}$
	UNet	$\mathcal{L}_{TC}$(ours)	$77.70_{\pm 6.07}$	$84.80_{\pm 5.96}$	$87.47_{\pm 6.31}$	$98.03_{\pm 1.23}$	$98.41_{\pm 1.13}$	$1.072_{\pm 0.631}$	$1.401_{\pm 0.496}$	$8.04_{\pm 2.72}$
	UNet	clDice	$77.37_{\pm 5.57}$	$84.18_{\pm 5.99}$	$87.05_{\pm 6.34}$	$98.03_{\pm 1.22}$	$98.40_{\pm 1.12}$	$1.079_{\pm 0.613}$	$1.407_{\pm 0.603}$	$8.08_{\pm 2.46}$
	DSCNet(ours)	$\mathcal{L}_{CE}$	$78.04_{\pm 5.77}$	$85.35_{\pm 5.42}$	$\mathbf{87.74}_{\pm 6.02}$	$98.05_{\pm 1.21}$	$98.39_{\pm 1.19}$	$1.118_{\pm 0.641}$	$1.441_{\pm 0.523}$	$7.96_{\pm 2.43}$
	DSCNet(ours)	$\mathcal{L}_{TC}$(ours)	$\mathbf{78.21}_{\pm 5.77}$	$\mathbf{85.85}_{\pm 5.56}$	$87.64_{\pm 5.99}$	$\mathbf{98.05}_{\pm 1.21}$	$\mathbf{98.46}_{\pm 1.08}$	$\mathbf{1.053}_{\pm 0.523}$	$\mathbf{1.396}_{\pm 0.456}$	$\mathbf{7.34}_{\pm 2.48}$

Dataset	Network	Loss	Volumetric (%) ↑			Topology OF ↑			Distance ↓
			Dice	RDice	clDice	LAD	LCX	RCA	HD
CORONARY	UNet	$\mathcal{L}_{CE}$	$76.87_{\pm 5.38}$	$84.48_{\pm 4.55}$	$81.43_{\pm 6.02}$	$0.806_{\pm 0.252}$	$0.847_{\pm 0.239}$	$0.849_{\pm 0.267}$	$7.727_{\pm 3.30}$
	Transunet	$\mathcal{L}_{CE}$	$76.70_{\pm 6.65}$	$83.23_{\pm 6.72}$	$78.71_{\pm 6.93}$	$0.810_{\pm 0.274}$	$0.694_{\pm 0.307}$	$0.816_{\pm 0.303}$	$8.580_{\pm 4.11}$
	DCU-net	$\mathcal{L}_{CE}$	$78.33_{\pm 5.00}$	$85.67_{\pm 4.29}$	$82.29_{\pm 5.31}$	$0.833_{\pm 0.219}$	$0.746_{\pm 0.296}$	$0.835_{\pm 0.300}$	$7.331_{\pm 3.06}$
	UNet	clDice	$77.86_{\pm 5.25}$	$84.42_{\pm 4.65}$	$82.37_{\pm 5.54}$	$0.817_{\pm 0.256}$	$0.845_{\pm 0.234}$	$0.859_{\pm 0.265}$	$7.412_{\pm 3.68}$
	DSCNet(ours)	$\mathcal{L}_{CE}$	$79.92_{\pm 5.26}$	$85.98_{\pm 4.60}$	$84.95_{\pm 5.76}$	$0.858_{\pm 0.198}$	$0.853_{\pm 0.241}$	$0.862_{\pm 0.267}$	$6.326_{\pm 2.85}$
	DSCNet(ours)	$\mathcal{L}_{TC}$**(ours)**	$\mathbf{80.27}_{\pm 4.67}$	$\mathbf{86.37}_{\pm 4.16}$	$\mathbf{85.26}_{\pm 4.98}$	$\mathbf{0.866}_{\pm 0.195}$	$\mathbf{0.885}_{\pm 0.210}$	$\mathbf{0.882}_{\pm 0.250}$	$\mathbf{5.787}_{\pm 2.99}$

https://github.com/YaoleiQi/DSCNet

Dynamic Snake Convolution based on Topological Geometric Constraints for Tubular Structure Segmentation

[NEWS!]This paper has been accepted by ICCV 2023!

[NOTE!!]The code will be gradually and continuously opened!

YaoleiQi DSCNet for 2D segmentation

Name	Last commit message
..	
S0_Main.py	DSCNet for 2D segmentation
S1_Pre_Getmeanstd.py	DSCNet for 2D segmentation
S2_Pre_Generate_Txt.py	DSCNet for 2D segmentation
S3_DSCNet.py	DSCNet for 2D segmentation
S3_DSConv.py	DSCNet for 2D segmentation
S3_Data_Augumentation.py	DSCNet for 2D segmentation
S3_Dataloader.py	DSCNet for 2D segmentation
S3_Loss.py	DSCNet for 2D segmentation
S3_Train_Process.py	DSCNet for 2D segmentation

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- Github: https://github.com/YaoleiQi