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Centerline Boundary Dice Loss for Vascular Segmentation

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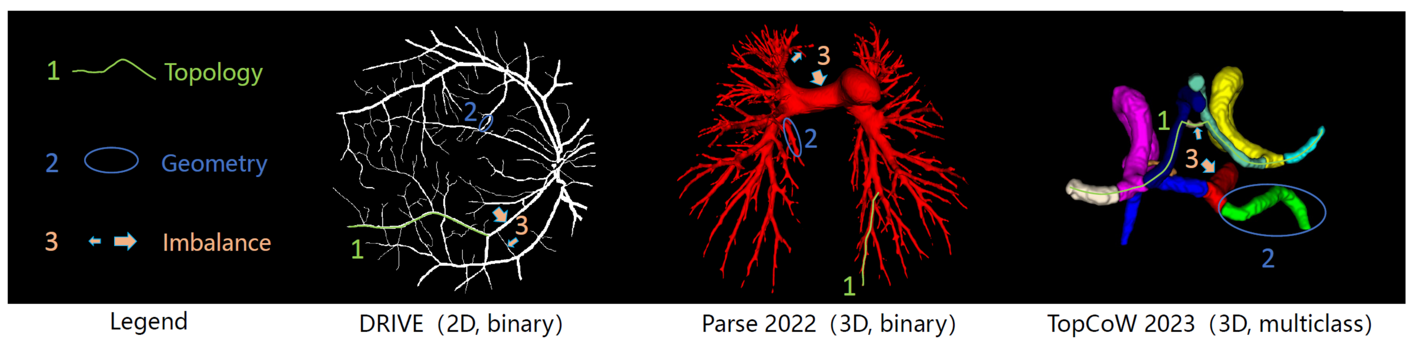
Motivation



Vascular segmentation encounters three significant challenges:

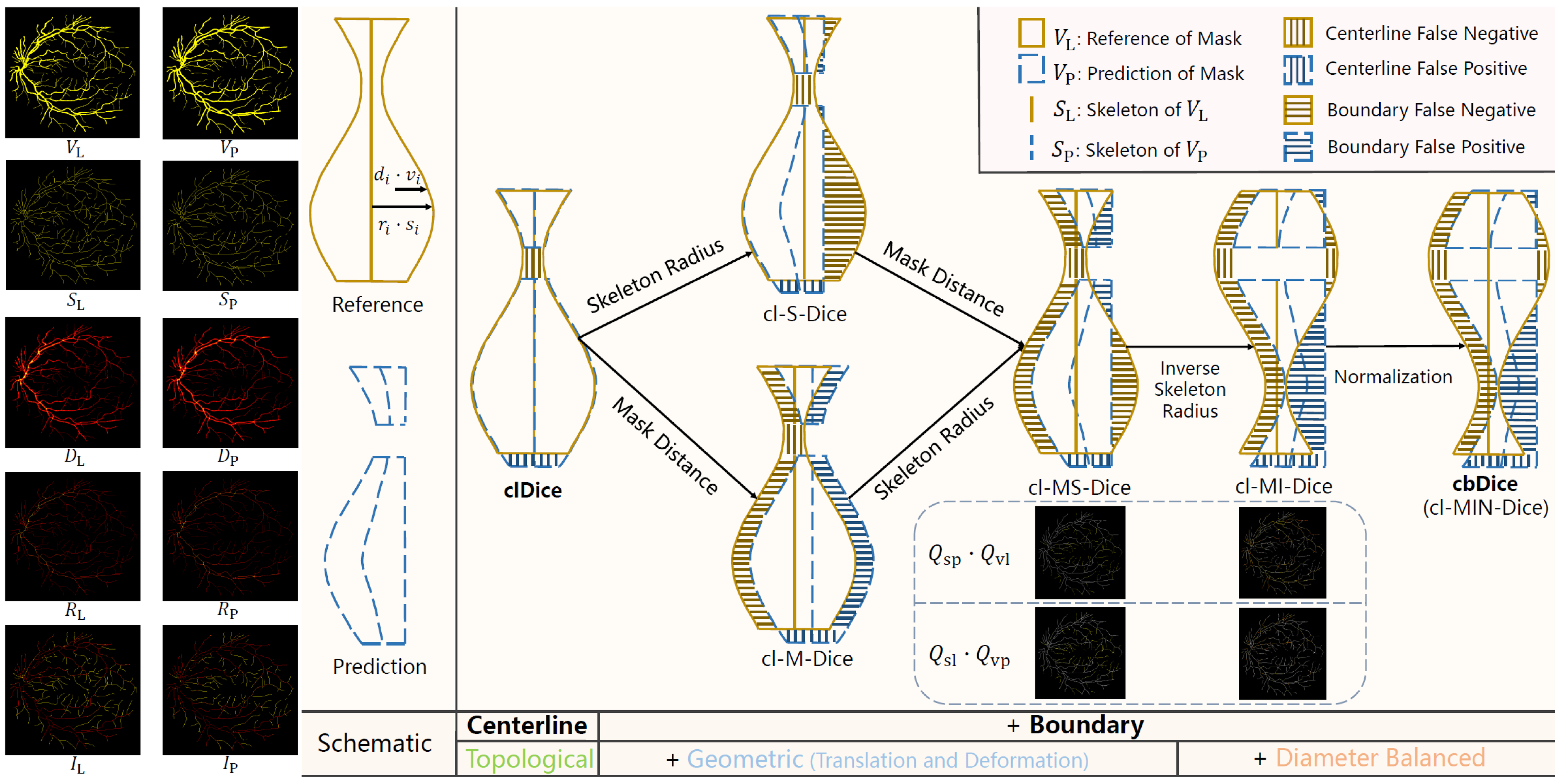
(1) preserving the **topology** of the vascular network to enable accurate hemodynamic analysis.

(2) capturing the intricate **geometric morphologies** vital for the diagnosis of conditions like stenosis.

(3) attaining balanced segmentation across vessel diameters and consistent width adjustments within each branch to mitigate **diameter imbalance.**

We seek to address a fundamental question: *How to encompass topology, geometry, and vessel diameter consistency in vascular segmentation?*

Overview



Proposed Method

$$\mathrm{Tprec}(S_{\mathrm{P}}, V_{\mathrm{L}}) = \frac{|S_{\mathrm{P}} \cap V_{\mathrm{L}}|}{|S_{\mathrm{P}}|} \qquad \mathrm{Tsens}(S_{\mathrm{L}}, V_{\mathrm{P}}) = \frac{|S_{\mathrm{L}} \cap V_{\mathrm{P}}|}{|S_{\mathrm{L}}|}$$

$$\mathrm{clDice}(V_{\mathrm{P}}, V_{\mathrm{L}}) = \frac{2 \times \mathrm{Tprec}(S_{\mathrm{P}}, V_{\mathrm{L}}) \times \mathrm{Tsens}(S_{\mathrm{L}}, V_{\mathrm{P}})}{\mathrm{Tprec}(S_{\mathrm{P}}, V_{\mathrm{L}}) + \mathrm{Tsens}(S_{\mathrm{L}}, V_{\mathrm{P}})}$$

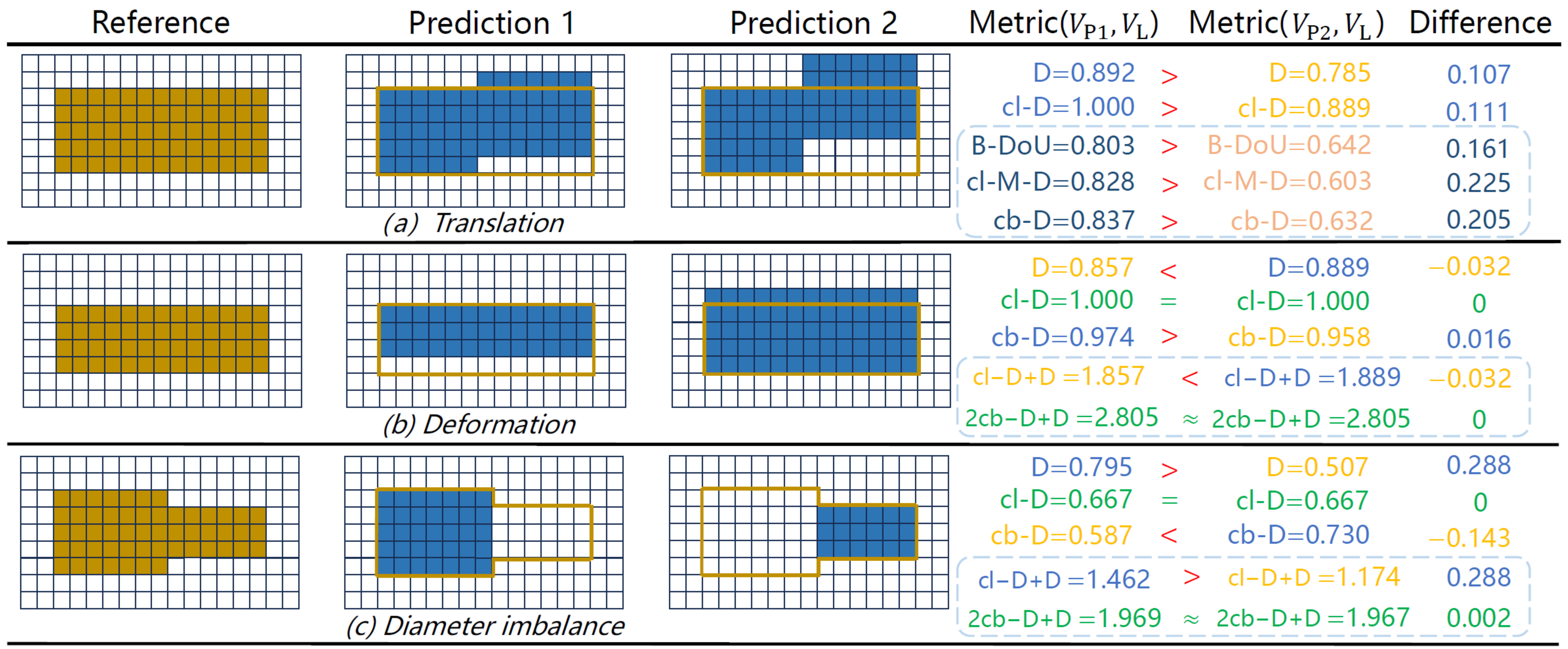
$$\mathrm{Tprec}(S_{\mathrm{P}}, S_{\mathrm{L}}, V_{\mathrm{L}}) = \frac{|Q_{\mathrm{sp}} \cap Q_{\mathrm{vl}}|}{|Q_{\mathrm{sp}} \cap Q_{\mathrm{spvp}} \cap (U - S_{\mathrm{L}})| + |Q_{\mathrm{sp}} \cap Q_{\mathrm{slvl}}|}$$

$$\mathrm{Tsens}(S_{\mathrm{L}}, S_{\mathrm{P}}, V_{\mathrm{P}}) = \frac{|Q_{\mathrm{sl}} \cap Q_{\mathrm{vp}}|}{|Q_{\mathrm{sl}} \cap Q_{\mathrm{slvl}} \cap (U - S_{\mathrm{P}})| + |Q_{\mathrm{sl}} \cap Q_{\mathrm{spvp}}|}$$

$$\text{cl-X-Dice}(V_{\mathrm{P}}, V_{\mathrm{L}}) = \frac{2 \times \mathrm{Tprec}(S_{\mathrm{P}}, S_{\mathrm{L}}, V_{\mathrm{L}}) \times \mathrm{Tsens}(S_{\mathrm{L}}, S_{\mathrm{P}}, V_{\mathrm{P}})}{\mathrm{Tprec}(S_{\mathrm{P}}, S_{\mathrm{L}}, V_{\mathrm{L}}) + \mathrm{Tsens}(S_{\mathrm{L}}, S_{\mathrm{P}}, V_{\mathrm{P}})}$$

Metric	cl-D		cl-S-D		cl-M-D		cl-MS-D		cl-MI-D		cl-MSN-D		**cl-MIN-D**	
Dim	2D	3D	2D	3D	2D	3D	2D	3D	2D	3D	2D	3D	2D	3D
Q_{sl}	S_{L}	S_{L}	R_{L}	R_{L}^2	S_{L}	S_{L}	R_{L}	R_{L}^2	I_{L}	I_{L}^2	$R_{\mathrm{L,N}}$	$R_{\mathrm{L,N}}^2$	$I_{\mathrm{L,N}}$	$I_{\mathrm{L,N}}^2$
Q_{sp}	S_{P}	S_{P}	R_{P}	R_{P}^2	S_{P}	S_{P}	R_{P}	R_{P}^2	I_{P}	I_{P}^2	$R_{\mathrm{P,N}}$	$R_{\mathrm{P,N}}^2$	$I_{\mathrm{P,N}}$	$I_{\mathrm{P,N}}^2$
Q_{vl}	V_{L}				D_{L}						$D_{\mathrm{L,N}}$			
Q_{vp}	V_{P}				D_{P}						$D_{\mathrm{P,N}}$			
Q_{slvl}	S_{L}				R_{L}						$R_{\mathrm{L,N}}$			
Q_{spvp}	S_{P}				R_{P}						$R_{\mathrm{P,N}}$			

Stepwise evolution of **cl-X-Dice** and comparison of 2D and 3D metrics. The abbreviations include reference (**L**), prediction (**P**), centerline (**cl**), Dice (**D**), skeleton (**S**), mask (**M**), inverse skeleton radius (**I**), normalized (**N**), and centerline boundary (**cb**). **cl-MIN-D** is equivalent to **cb-D** in this study.

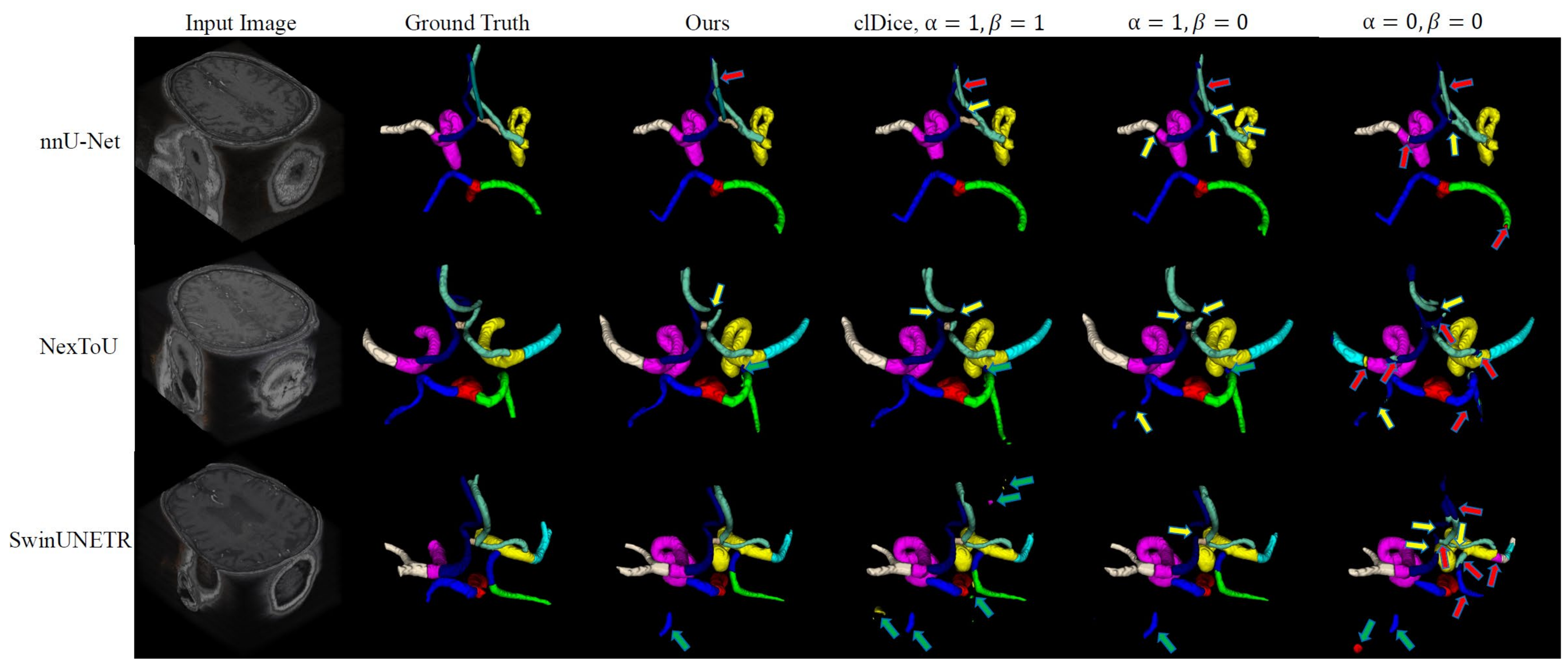


(a) With **translation-only** perturbations, cb-Dice metric sensitivity to cl-M-Dice variations, increasing alongside translation distance, is comparable to B-DoU, while clDice remains near 1.

(b) In **uniform scaling** (enlargement or reduction), cbDice-Dice pairing ensures more consistent evaluations than clDice-Dice, effectively adapting to scale changes.

(c) For **diameter imbalances**, cbDice-Dice consistently assesses varied diameter branches, outperforming clDice-Dice.

Results



Comparative visualization of results on the TopCoW 2023 dataset. Yellow arrows mark areas of segmentation false negatives, green arrows point to false positives, and red arrows identify areas of misclassification.

$$\mathcal{L} = 0.5 \times \mathrm{CE} + \frac{\alpha}{2\times(\alpha+\beta)} \cdot \mathrm{Dice} + \frac{\beta}{2\times(\alpha+\beta)} \cdot \mathrm{X}$$

where X denotes cl-X-Dice. Parameters α and β are non-negative numbers; with both set to 0, it reverts to CE loss.

Network	Loss			Parse 2022 (50 epochs)				TopCoW 2023 (100 epochs, classes average)					
	X	α	β	Dice	clDice	β^{err}	NSD	Dice(L)	Dice(S)	clDice	β^{err}	NSD(L)	NSD(S)
nnU-Net	–	0	0	82.55	68.91	331.5	78.51	81.51	7.012	90.10	–	89.78	14.08
	–	1	0	85.05	80.11	277.7	86.04	84.03	0	88.22	–	91.90	0
	clDice	1	1	85.30	80.23	**263.4**	86.20	**84.21**	38.46	90.72	–	92.45	47.85
	cbDice	1	1	**85.46**	**80.76**	266.1	**86.57**	84.11	41.55	91.34	0.96	92.21	50.42
	cbDice	1	2	84.91	80.02	275.8	85.98	84.01	**43.38**	**91.95**	0.98	91.99	**54.11**
	cbDice	1	3	84.97	78.98	285.6	85.26	84.18	42.68	90.63	**0.95**	**92.67**	51.76
SwinUNETR	–	0	0	78.91	58.53	508.7	70.80	61.22	0	88.64	–	70.64	0
	–	1	0	81.94	69.87	496.9	78.33	**83.19**	37.32	90.18	1.40	89.55	46.36
	clDice	1	1	82.06	70.12	499.4	78.80	83.16	34.72	90.03	1.31	**90.73**	43.65
	cbDice	1	1	**82.19**	**71.04**	476.5	**79.36**	82.29	37.34	90.21	1.43	89.51	46.49
	cbDice	1	2	81.88	69.96	**469.0**	78.89	82.86	38.38	**90.56**	1.29	90.70	**48.37**
	cbDice	1	3	81.59	68.62	477.5	77.54	83.09	**38.85**	90.24	**1.27**	90.67	47.52
NexToU	–	0	0	81.33	64.80	387.7	75.35	56.33	0	89.93	–	67.79	0
	–	1	0	85.08	79.39	288.5	85.49	**84.52**	42.37	90.44	0.99	92.30	51.82
	clDice	1	1	84.88	79.27	274.3	85.23	84.30	43.90	90.19	0.66	92.02	53.31
	cbDice	1	1	85.19	**80.07**	248.95	**85.88**	84.32	44.51	90.72	0.68	92.18	55.62
	cbDice	1	2	**85.22**	79.72	**216.2**	85.56	84.37	47.39	90.45	**0.65**	**92.37**	57.71
	cbDice	1	3	85.05	79.18	289.6	85.31	84.21	**48.43**	**90.89**	0.66	92.30	**58.91**

Comprehensive comparison of results on the Parse 2022 and TopCoW 2023 datasets. Here, L denotes large (non-communicating) arteries, and S represents small (communicating) arteries.

Conclusion

In this paper, we introduce the centerline boundary Dice (cbDice) loss function, which harmonizes topological integrity and geometric nuances, ensuring consistent segmentation across various vessel sizes. Furthermore, we conducted a theoretical analysis of clDice variants (cl-X-Dice). We validated cbDice's efficacy on three diverse vascular segmentation datasets, encompassing both 2D and 3D, and binary and multi-class segmentation.

Acknowledgments

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