MICCAI2024 Marrakesh MOROCCO

TopCoW: Topology-Aware Anatomical Segmentation of the Circle of Willis for CTA and MRA

Centerline Boundary Dice Loss for Vascular Segmentation

MICCAI 2024

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https://github.com/PengchengShi1220/cbDice

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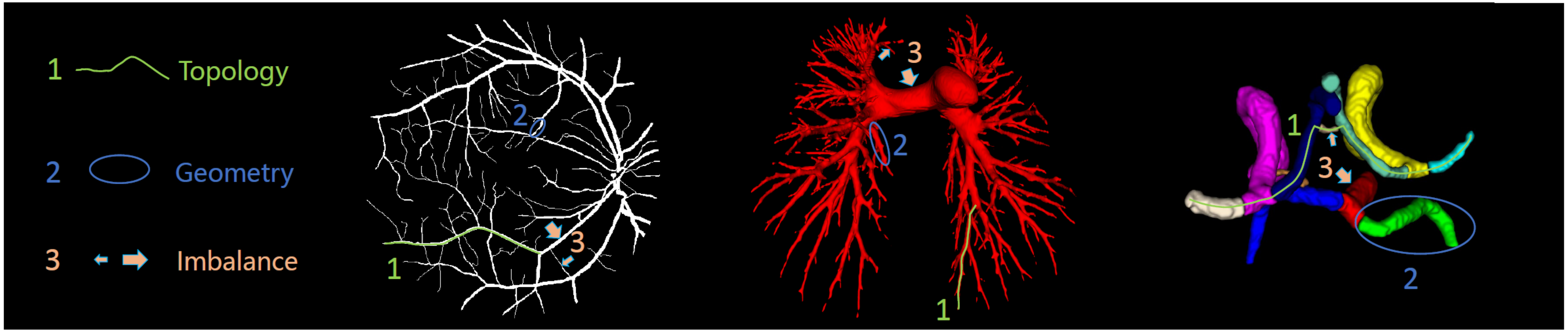
鹏城实验室 PENGCHENG LABORATORY

Code:

Motivation

Challenges in Vascular Segmentation



Legend | DRIVE（2D, binary） | Parse 2022（3D, binary） | TopCoW 2023（3D, multiclass）

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 diagnosing conditions like stenosis.

(3) Ensuring consistent width adjustments within each branch to mitigate **diameter imbalance**.

How to encompass topology, geometry, and vessel diameter consistency in vascular segmentation?

Related Works

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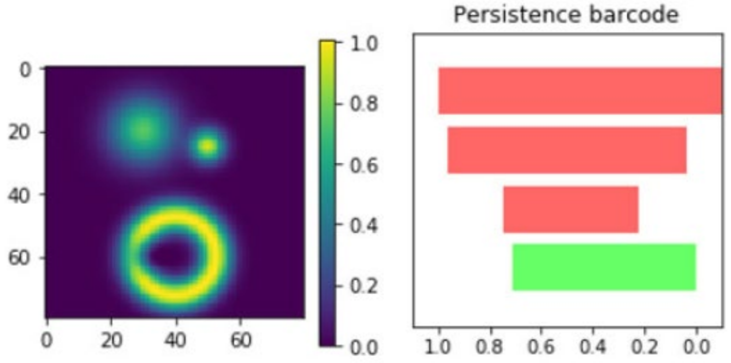
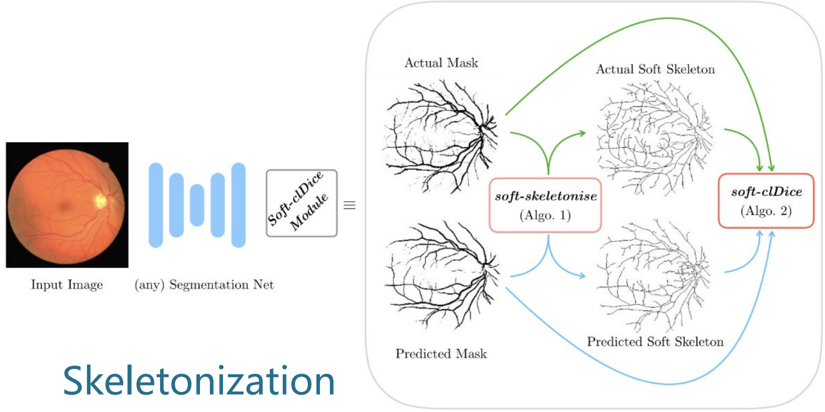
Topology:



Persistent Homology

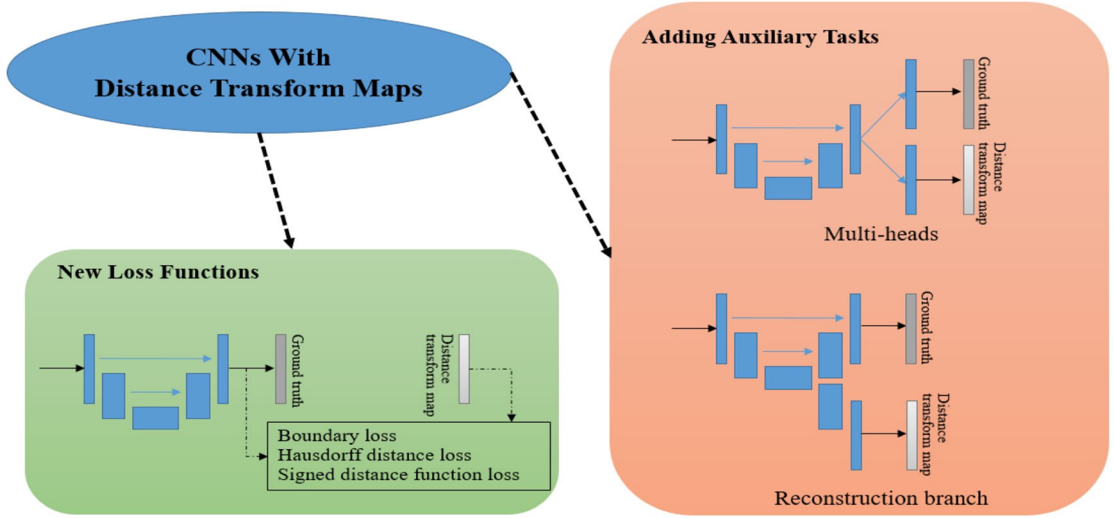
2020, TPAMI, A Topological Loss Function for Deep-Learning Based Image Segmentation Using Persistent Homology



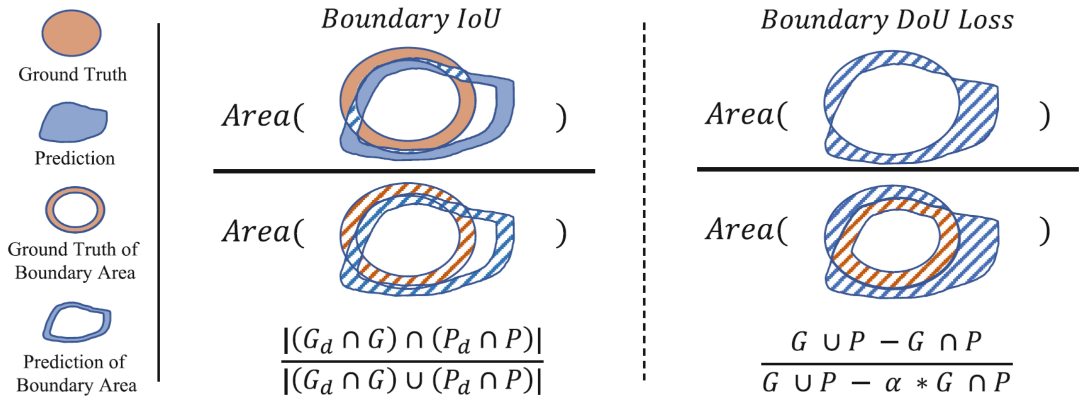
Skeletonization

2021, CVPR, clDice - a Novel Topology-Preserving Loss Function for Tubular Structure Segmentation

Geometry:



2020, MIDL, How Distance Transform Maps Boost Segmentation CNNs: An Empirical Study



2021, CVPR, Boundary IoU

2023, MICCAI, Boundary DoU

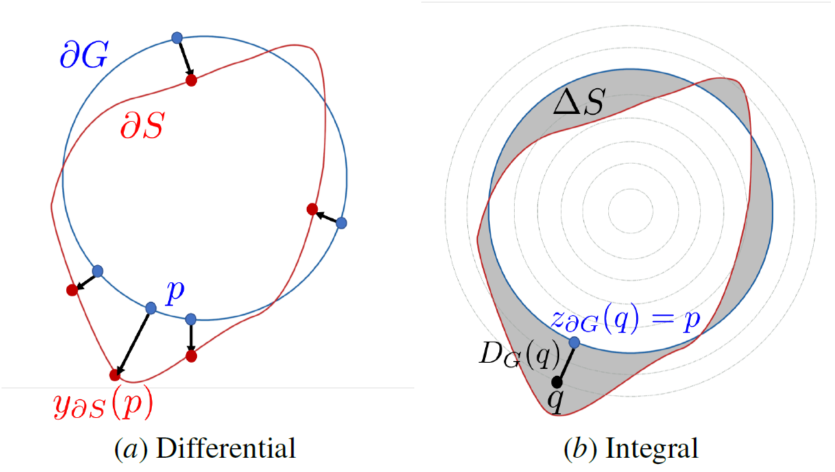
Related Works

Imbalance:

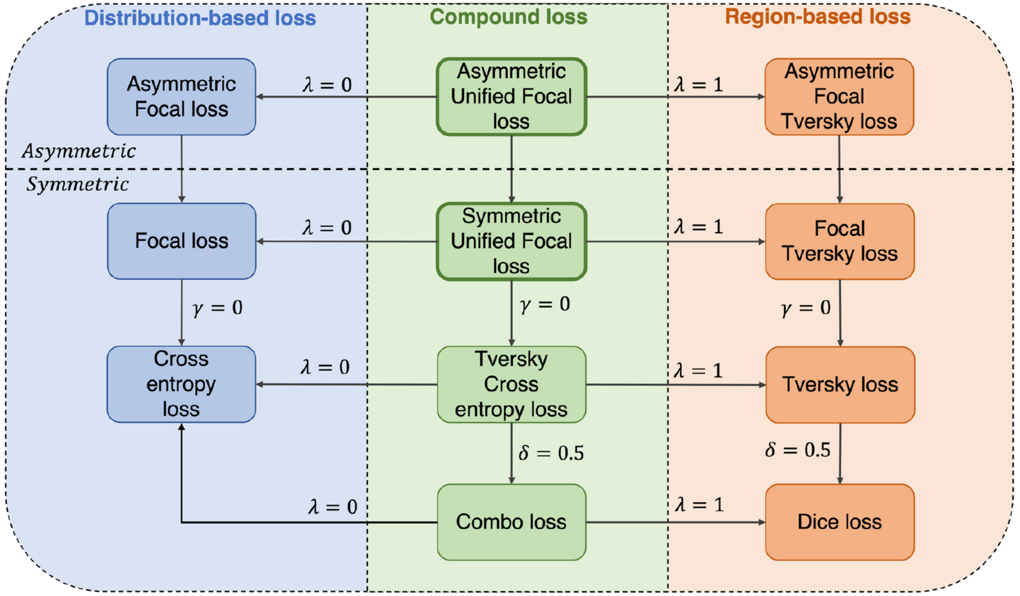
$$\mathrm{GDL} = 1 - 2\frac{\sum_{l=1}^{2} w_l \sum_n r_{ln} p_{ln}}{\sum_{l=1}^{2} w_l \sum_n r_{ln} + p_{ln}}$$

$$w_l = 1/(\sum_{n=1}^{N} r_{ln})^2$$

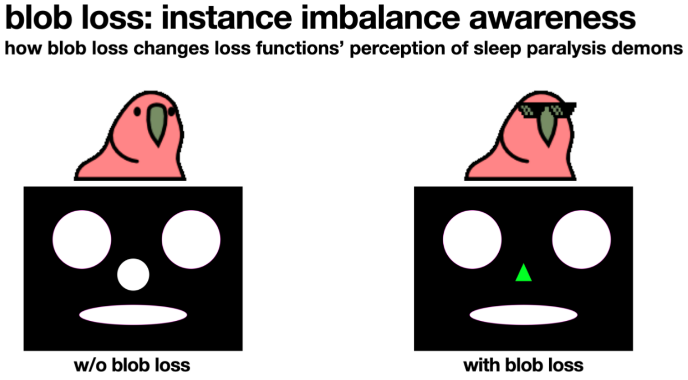
2017, DLMIA, Generalised Dice overlap as a deep learning loss function for highly unbalanced segmentations



2019, MIDL, Boundary loss for highly unbalanced segmentation



2022, CMIG, Unified Focal loss: Generalising Dice and cross entropy-based losses to handle class imbalanced medical image segmentation



2023, IPMI, blob loss: Instance Imbalance Aware Loss Functions for Semantic Segmentation

Method Description

Limitations of centerline Dice (clDice)

$$\mathrm{Tprec}(S_P, V_L) = \frac{|S_P \cap V_L|}{|S_P|}; \quad \mathrm{Tsens}(S_L, V_P) = \frac{|S_L \cap V_P|}{|S_L|}$$

$$\mathrm{clDice}(V_P, V_L) = 2 \times \frac{\mathrm{Tprec}(S_P, V_L) \times \mathrm{Tsens}(S_L, V_P)}{\mathrm{Tprec}(S_P, V_L) + \mathrm{Tsens}(S_L, V_P)}$$

V_P: The predicted segmentation mask.

V_L : The ground truth mask.

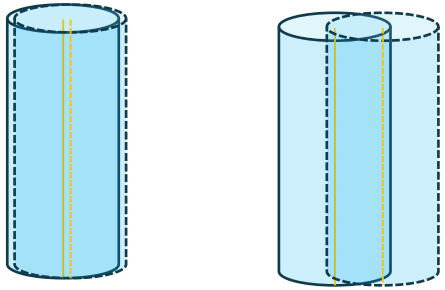
S_P : The skeleton extracted from V_P.

S_L : The skeleton extracted from V_L .

Each of these elements is a **binary** image.

Neglect the boundary FN and FP:

Fully overlap Boundary overlap

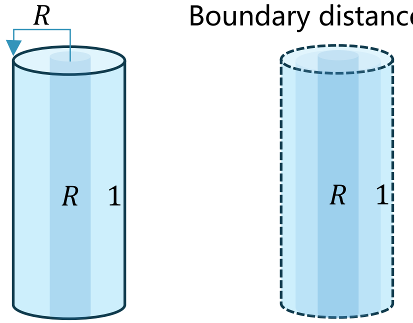


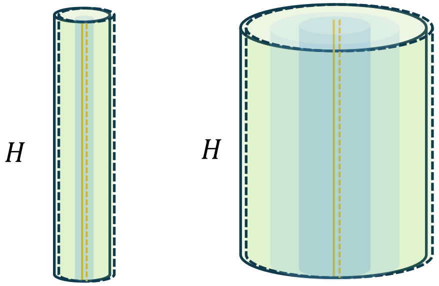
clDice=1 clDice=1

The clDice is insensitive to whether the skeleton line is close to the **boundary or centered** within the vessel.

Add boundary awareness:

Boundary distance map





R_1 $R_1 < R_2$ R_2

$V_1 = \pi {R_1}^2 \cdot H \qquad V_2 = \pi {R_2}^2 \cdot H$

$$\frac{V_2}{V_1} = \frac{{R_2}^2}{{R_1}^2}$$

Mitigate imbalance:

clDice loss needs to **be combined with Dice loss**, and as a result, it cannot avoid the bias towards larger targets.

$$\mathcal{L}_c = (1-\alpha)(1 - \textit{softDice}) + \alpha(1 - \textit{softclDice})$$

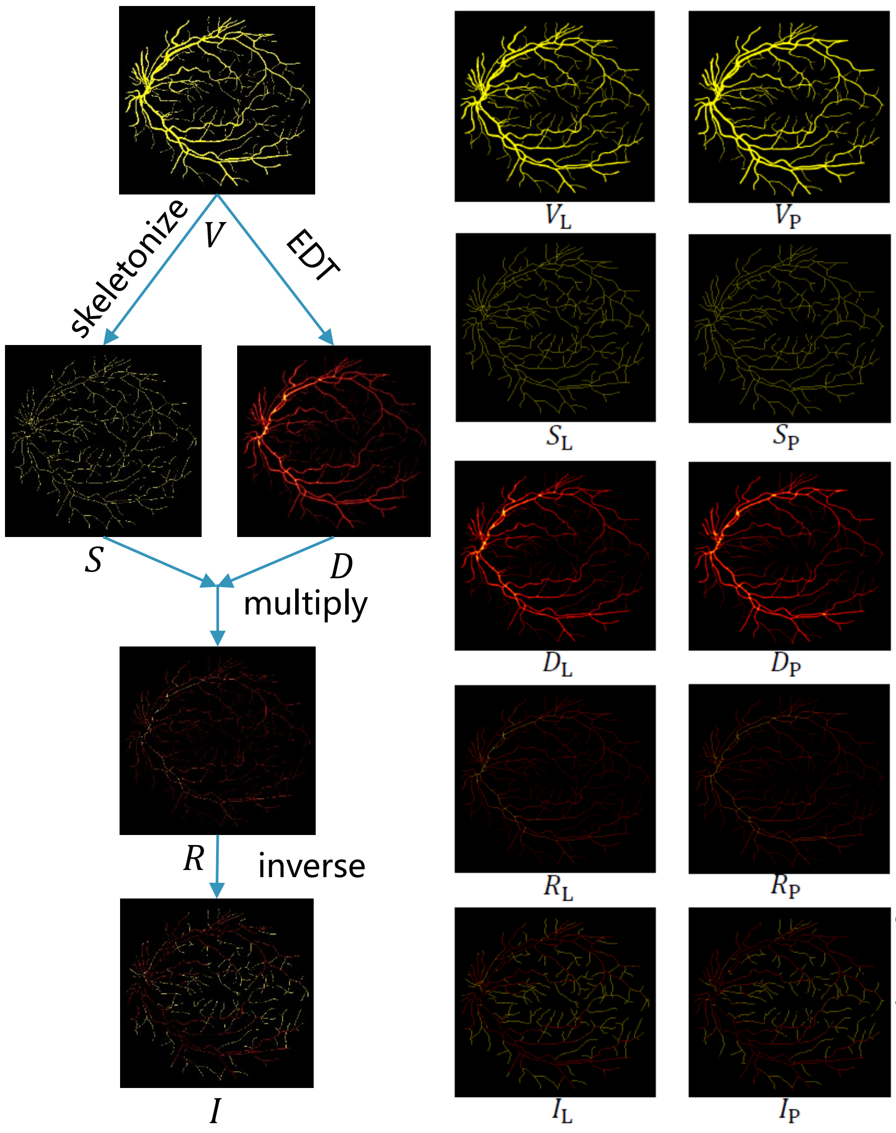
$$\alpha \in [0, 0.5]$$

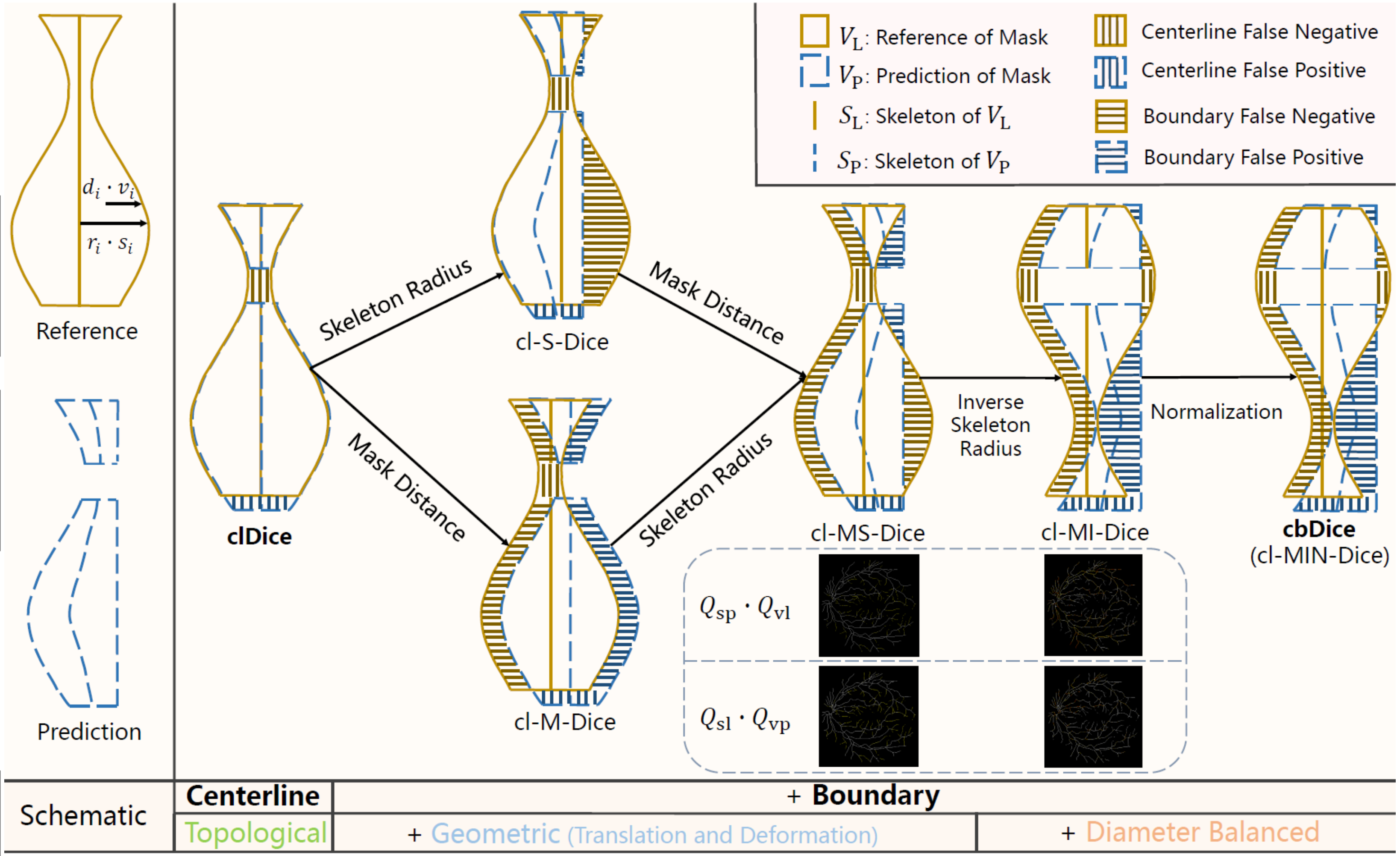
The segmentation towards vessels with **larger diameters** due to the **volume-based** nature of the Dice metric.

The volume's sensitivity to r^2 suggests that a weighting scheme **inversely proportional to r^2** can mitigate the bias.

Method Description

Centerline boundary Dice loss





2024, MICCAI, Centerline Boundary Dice Loss for Vascular Segmentation

Method Description

Centerline boundary Dice loss

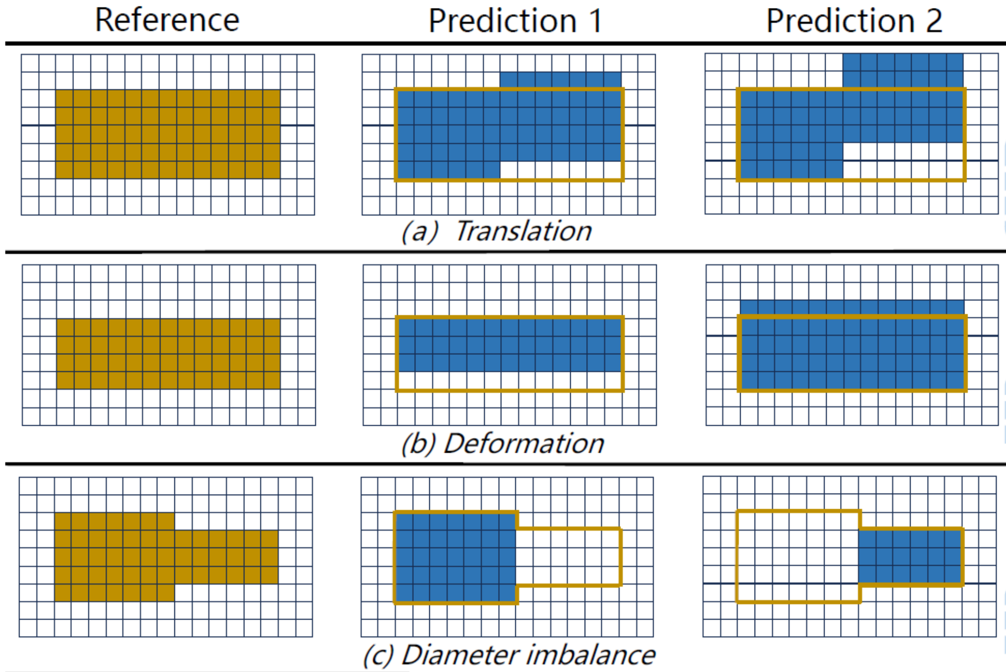
$$\mathrm{Tprec}(S_\mathrm{P}, S_\mathrm{L}, V_\mathrm{L}) = \frac{|Q_\mathrm{sp} \cap Q_\mathrm{vl}|}{|Q_\mathrm{sp} \cap Q_\mathrm{spvp} \cap (U - S_\mathrm{L})| + |Q_\mathrm{sp} \cap Q_\mathrm{slvl}|}$$

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

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

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^2_L	S_L	S_L	R_L	R^2_L	I_L	I^2_L	$R_\mathrm{L,N}$	$R^2_\mathrm{L,N}$	$I_\mathrm{L,N}$	$I^2_\mathrm{L,N}$
Q_sp	S_P	S_P	R_P	R^2_P	S_P	S_P	R_P	R^2_P	I_P	I^2_P	$R_\mathrm{P,N}$	$R^2_\mathrm{P,N}$	$I_\mathrm{P,N}$	$I^2_\mathrm{P,N}$
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						$R_\mathrm{P,N}$			

Examples:



Case	Metric($V_\mathrm{P1}, V_\mathrm{L}$)		Metric($V_\mathrm{P2}, V_\mathrm{L}$)	Difference
(a) Translation	D=0.892	>	D=0.785	0.107
	cl-D=1.000	>	cl-D=0.889	0.111
	B-DoU=0.803	>	B-DoU=0.642	0.161
	cl-M-D=0.828	>	cl-M-D=0.603	0.225
	cb-D=0.837	>	cb-D=0.632	0.205
(b) Deformation	D=0.857	<	D=0.889	−0.032
	cl-D=1.000	=	cl-D=1.000	0
	cb-D=0.974	>	cb-D=0.958	0.016
	cl−D+D =1.857	<	cl−D+D =1.889	−0.032
	2cb−D+D =2.805	≈	2cb−D+D =2.805	0
(c) Diameter imbalance	D=0.795	>	D=0.507	0.288
	cl-D=0.667	=	cl-D=0.667	0
	cb-D=0.587	<	cb-D=0.730	−0.143
	cl−D+D =1.462	>	cl−D+D =1.174	0.288
	2cb−D+D =1.969	≈	2cb−D+D =1.967	0.002

2024, MICCAI, Centerline Boundary Dice Loss for Vascular Segmentation

Theorem proof of cl-X-Dice

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

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

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

Theorem 1. *For vertical translations along skeleton lines without deformation, cl-M-Dice coefficient is sensitive to translations of mask V within radius R, whereas clDice remains invariant.*

Proof. In 2D, cl-M-Dice is defined thus (extendable analogously to 3D):

$$\mathrm{Tprec}(S_{\mathrm{P}}, S_{\mathrm{L}}, V_{\mathrm{L}}) = \frac{|S_{\mathrm{P}} \cap D_{\mathrm{L}}|}{|R_{\mathrm{P}} \cap (U - S_{\mathrm{L}})| + |S_{\mathrm{P}} \cap R_{\mathrm{L}}|} \tag{1}$$

$$\mathrm{Tsens}(S_{\mathrm{L}}, S_{\mathrm{P}}, V_{\mathrm{P}}) = \frac{|S_{\mathrm{L}} \cap D_{\mathrm{P}}|}{|R_{\mathrm{L}} \cap (U - S_{\mathrm{P}})| + |S_{\mathrm{L}} \cap R_{\mathrm{P}}|} \tag{2}$$

Under vertical translations maintaining constant radius, $|S_{\mathrm{P}} \cap R_{\mathrm{L}}|$ equals $|S_{\mathrm{L}} \cap R_{\mathrm{P}}|$. This reduces cl-M-Dice's denominator to $|R_{\mathrm{P}}|$ (and analogously for R_{L}), making its sensitivity dependent solely on the numerator. Hence, cl-M-Dice reacts to spatial displacements of V within R. Conversely, clDice, assessing overlap between S and V, is not influenced by these variations.

Theorem 2. *cl-S-Dice, unlike clDice, is sensitive to radius variations at the skeleton under deformation without perpendicular translation. In cases of complete overlap, cl-S-Dice equals clDice with a value of 1.*

Proof. In 2D, cl-S-Dice is defined thus (extendable analogously to 3D):

$$\mathrm{Tprec}(S_{\mathrm{P}}, S_{\mathrm{L}}, V_{\mathrm{L}}) = \frac{|R_{\mathrm{P}} \cap V_{\mathrm{L}}|}{|R_{\mathrm{P}}|}, \quad \mathrm{Tsens}(S_{\mathrm{L}}, S_{\mathrm{P}}, V_{\mathrm{P}}) = \frac{|R_{\mathrm{L}} \cap V_{\mathrm{P}}|}{|R_{\mathrm{L}}|} \tag{3}$$

For clDice $\neq 1$ (partial overlap), changes in radius (R_{P}, R_{L}) affect both $|R_{\mathrm{P}} \cap V_{\mathrm{L}}|$ and $|R_{\mathrm{L}} \cap V_{\mathrm{P}}|$. Specifically, with $S = \{s_i, b_j^{\mathrm{s}} \mid i \in [1,n], j \in [1,m]\}$ and $R = \{r_i \cdot s_i, b_j^{\mathrm{s}} \mid, i \in [1,n], j \in [1,m]\}$, variances in r_i at any s_i modify cl-S-Dice. When clDice $= 1$ (complete overlap), $|R_{\mathrm{P}} \cap V_{\mathrm{L}}| = |R_{\mathrm{P}}|$ and $|R_{\mathrm{L}} \cap V_{\mathrm{P}}| = |R_{\mathrm{L}}|$, aligning cl-S-Dice with clDice, highlighting cl-S-Dice's sensitivity to radius changes in other scenarios.

Method Description

Implementation details

Differentiable Binarization:

To obtain a differentiable binarized predicted probability map of the foreground, follow these steps:

```
y_pred_fore = y_pred[:, 1:]
y_pred_fore = torch.max(y_pred_fore, dim=1, keepdim=True)[0]  # C foreground channels -> 1 channel
y_pred_binary = torch.cat([y_pred[:, :1], y_pred_fore], dim=1)
y_prob_binary = torch.softmax(y_pred_binary, 1)
y_pred_prob = y_prob_binary[:, 1]  # predicted probability map of foreground
```

Distance map:

We implement the Euclidean distance transform (EDT) using a **GPU-accelerated** approach with the **cupy** and **cuCIM** library.

```
pip install monai

# For CUDA 12.x
pip install cucim-cu12
pip install cupy==12.3
```

Skeletonization:

Topology-preserving skeletonization: "A Skeletonization Algorithm for Gradient-based Optimization" (ICCV, 2023). This method ensures high topological accuracy but operates at a slower speed.

Morphological skeletonization: "clDice - a Novel Topology-Preserving Loss Function for Tubular Structure Segmentation" (CVPR, 2021). This method runs faster but offers lower topological accuracy.

Loss function:

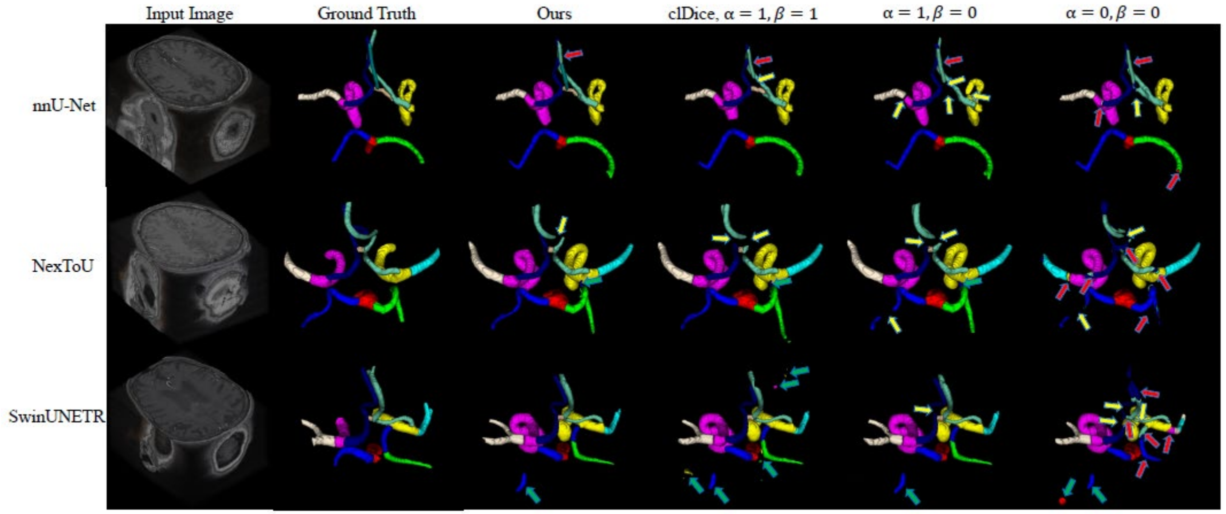
$$\mathcal{L} = 0.5 \times \mathrm{CE} + \frac{\alpha}{2\times(\alpha+\beta)} \cdot \mathrm{Dice} + \frac{\beta}{2\times(\alpha+\beta)} \cdot \mathrm{X}$$

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

Code:

Results

Qualitative and quantitative results



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

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

nnU-Net framework, No Deep Supervision, No Mirroring for TopCoW2023

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**

TopCoW2024 (CTA and MRA, Deep Supervision, No Mirroring, 100epochs):

Network	Loss			Dice	Dice(Large)	Dice(Small)
	X	α	β			
nnU-Net	--	1	0	72.88	**85.82**	43.77
	clDice	1	1	72.62	83.89	47.26
	cbDice	1	1	**73.57**	84.95	**47.98**

Time Comparisons:

Configuration	Trainer	Skeletonization Type	Epoch Time (s)
Default (CE_DC)	nnUNetTrainerNoMirroring_3d_fullres	N/A	70.3
CE_DC_CLDC	nnUNetTrainer_CE_DC_CLDC_NoMirroring_3d_fullres	Morphological (iter_=10)	86.9
CE_DC_CBDC	nnUNetTrainer_CE_DC_CBDC_NoMirroring_3d_fullres	Morphological (iter_=10)	92.6
CE_DC_CLDC	nnUNetTrainer_CE_DC_CLDC_NoMirroring_3d_fullres	Topology-Preserving	318.2
CE_DC_CBDC	nnUNetTrainer_CE_DC_CBDC_NoMirroring_3d_fullres	Topology-Preserving	324.0

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TopCoW: **Top**ology-Aware Anatomical Segmentation of the **C**ircle **o**f **W**illis for CTA and MRA

Thanks for your attention!

https://github.com/PengchengShi1220/cbDice

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Code:

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