Duke UNIVERSITY | BIOMEDICAL ENGINEERING

Directional Connectivity-based Segmentation for Medical Images

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JUNE 18-22, 2023
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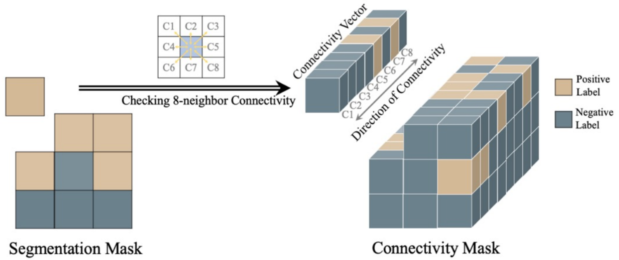
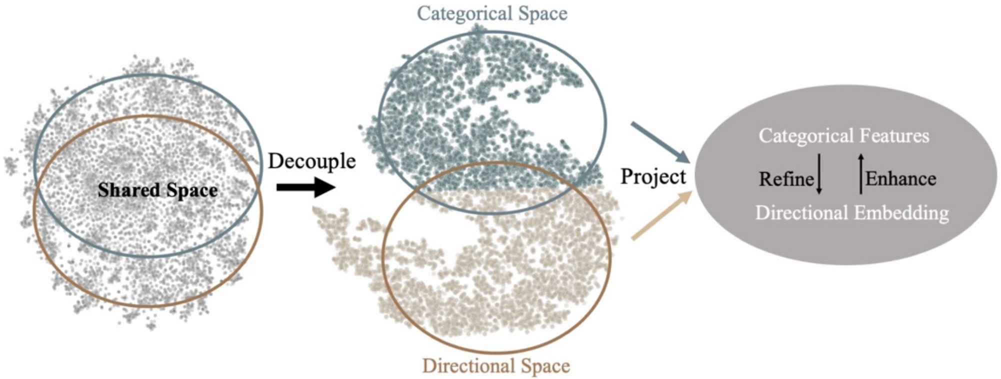
Paper Preview

- Improve a recent method called connectivity modeling on general medical segmentation.



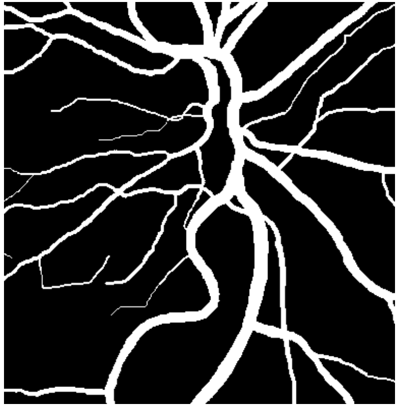
- Propose an efficient pipeline for decoupling the directional sub-latent space from the shared space in a connectivity-based model.



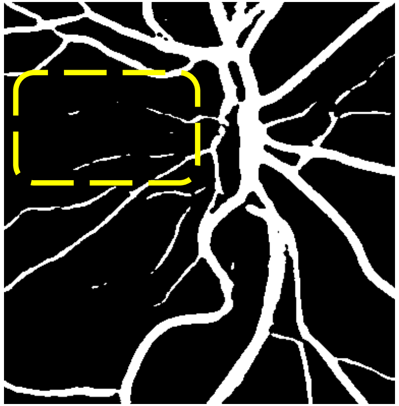
Medical Segmentation

- Maintain anatomical consistency is important in medical segmentation.
- Efforts in deep learning-based methods mainly focus on the internal network structures.
- Pixel-wise classification-based modeling is suboptimal [14-16] and results in low spatial coherence.

Image



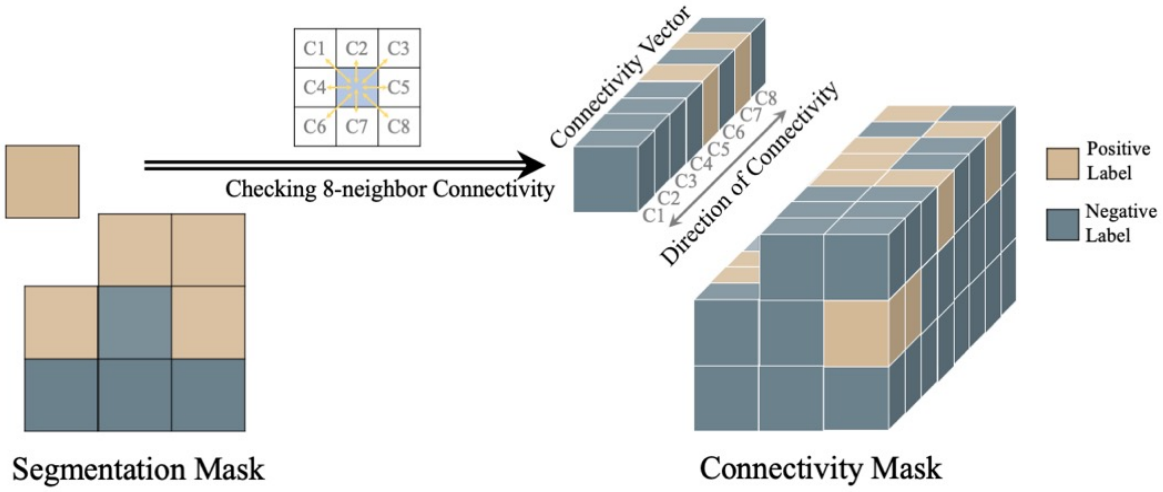
GT



Non-anatomical consistent prediction

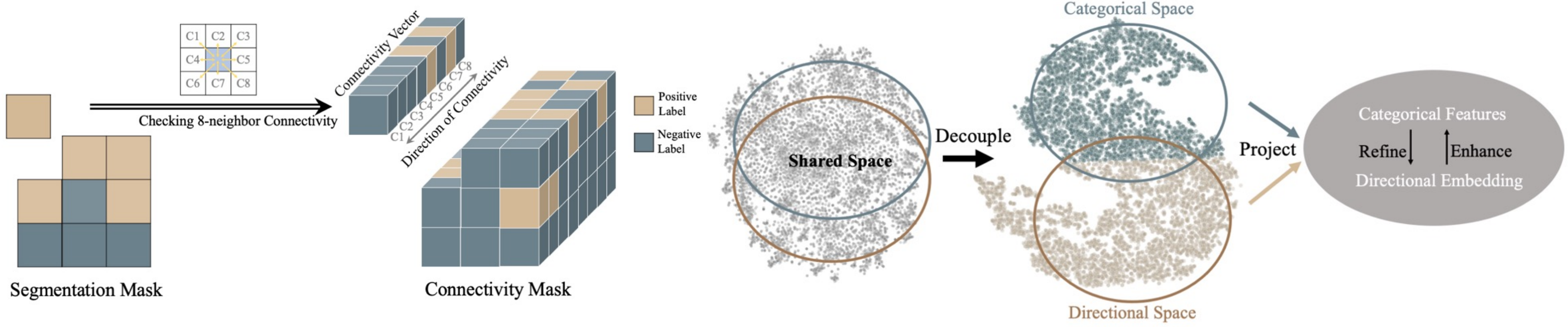
Connectivity Modeling

- Highlights the topological aspects of the segmentation problem with an inter-pixel relation-aware label called connectivity mask.
- Connectivity mask: each channel represents if a pixel on the original image belongs to the same class of interest with one of its neighboring pixels at a specific direction.



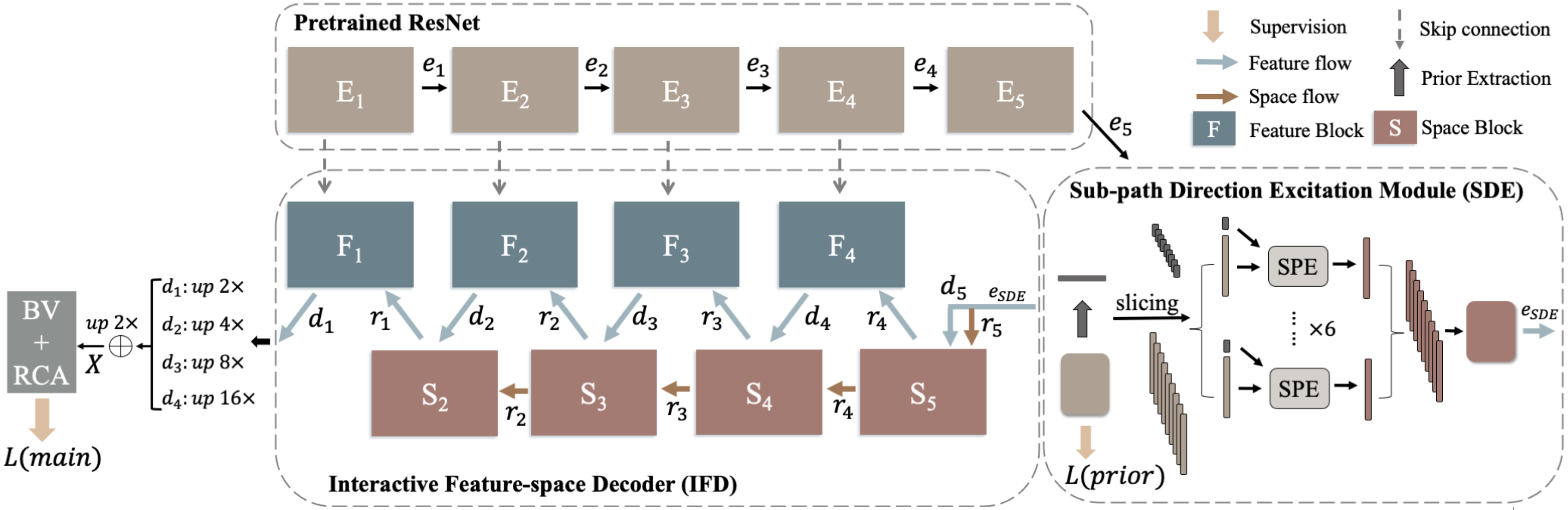
Latent Space of Connectivity Modeling

- Two unique sub-latent spaces: categorical (embedded in pixel connection) and directional (embedded in channels).
- Highly coupled if directly modeling the connectivity.
- Effectively disentangling sub-spaces improves the overall representation.



DconnNet

- Disentangle the sub-spaces with Sub-path Direction Excitation (SDE).
- Enhance directional-based feature with Interactive Feature-space Decoder (IFD).
- Alleviate two-level data imbalance with Size Density Loss (SDL).



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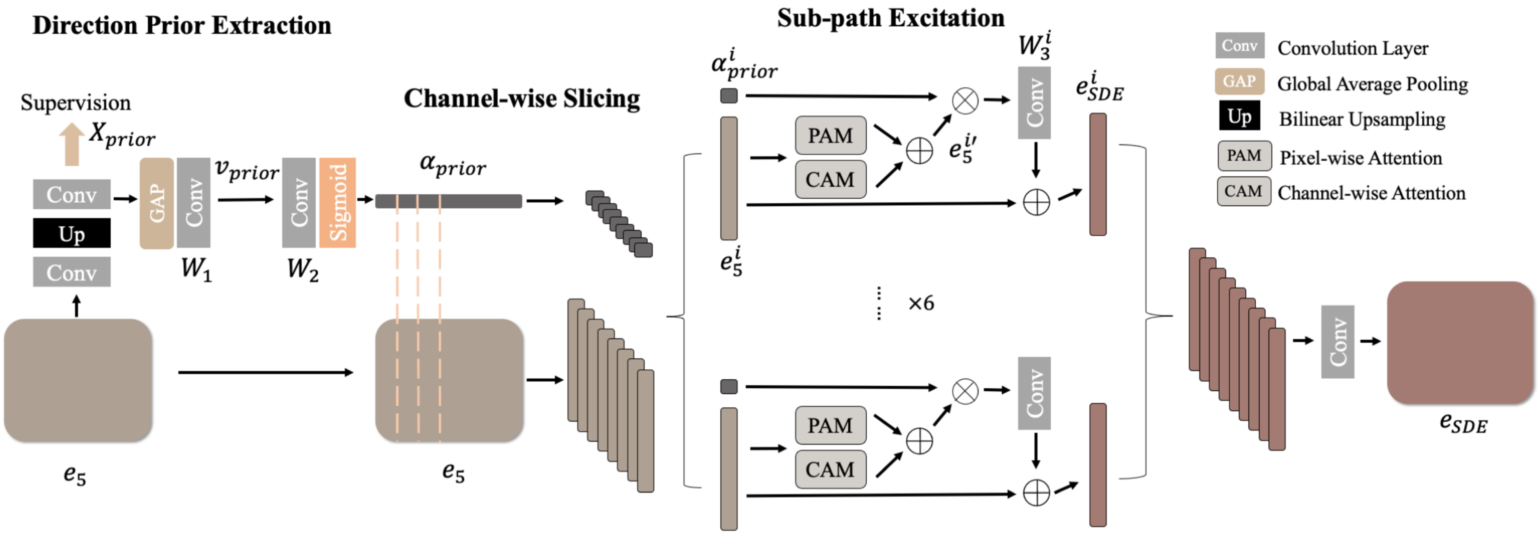
Sub-path Direction Excitation (SDE)

- Extract a directional prior by coarsely supervision and channel squeezing.
- Decouple the directional features from shared latent space by channel-wise slicing.
- Enhance the channel-wise directional representation with sub-path excitation.



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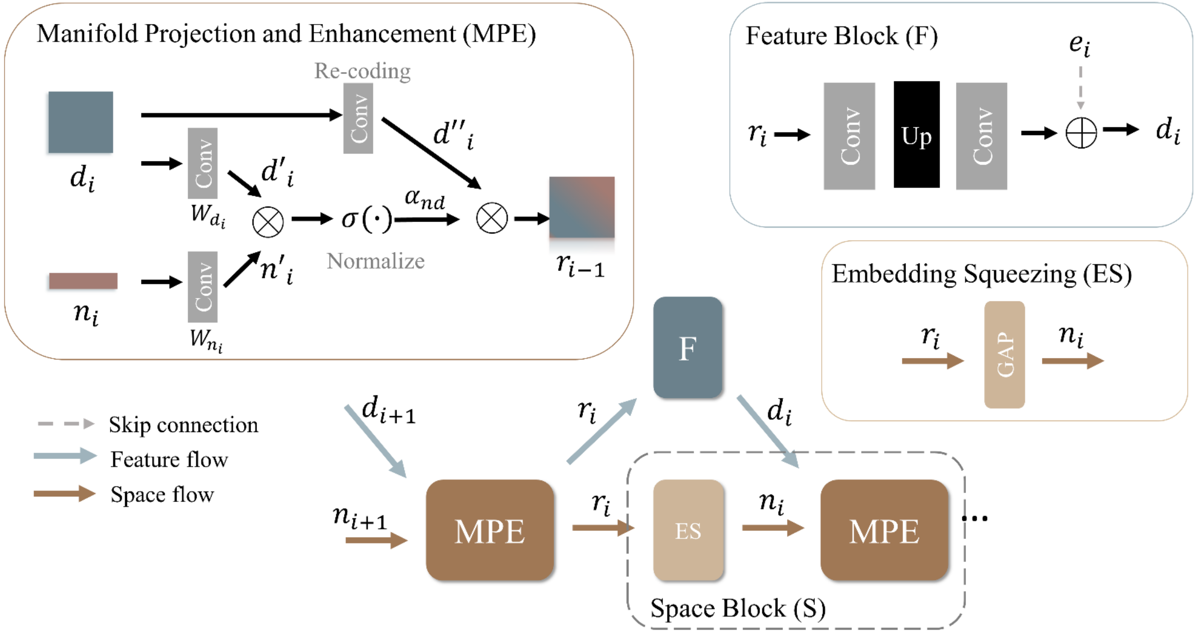
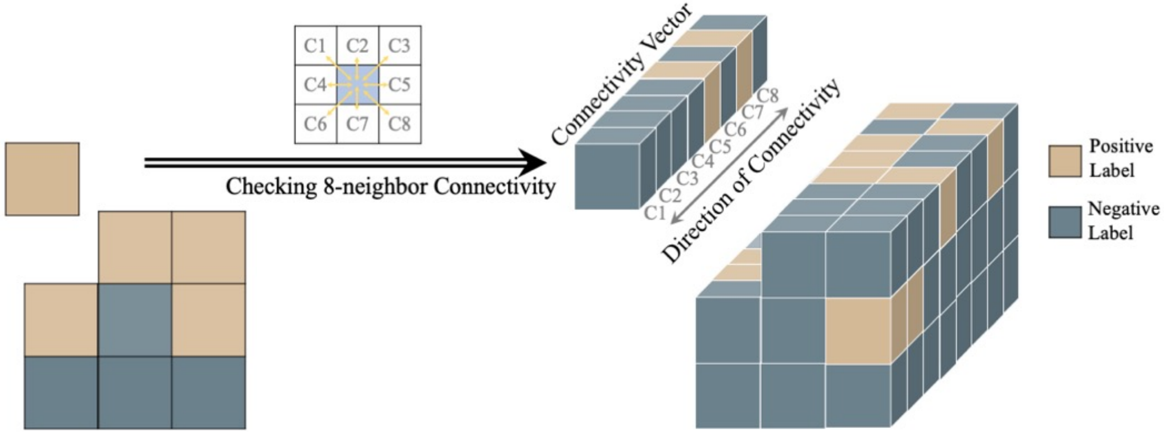
Interactive Feature-Space Decoder (IFD)

- Ensure directional information can be effectively fused in each layer.
- Space flow: enhance feature map with directional embedding and generate new embeddings.
- Feature flow: upsample feature with a decoder layer.



Connectivity Modeling Components

- Connectivity masks as label.
- BV and RCA modules as recommended in [16,22].



Size Density Loss

- Designed for the two-level data imbalanced dataset based on the label size distribution.
- Size density weight: inverse proportional to the PDF of label size k of the class j.

$$P_j(k) = \begin{cases} 1, & k = 0, \\ -log\left(PDF_j(k)\right), & k \neq 0. \end{cases}$$

- Final form as a variant of Dice loss.

$$L_{sd} = \sum_{j}^{Class} P_j(k)\left(1 - \frac{2\times\sum(S\times G_s) + \varepsilon}{\sum S + \sum G_s + \varepsilon}\right)$$

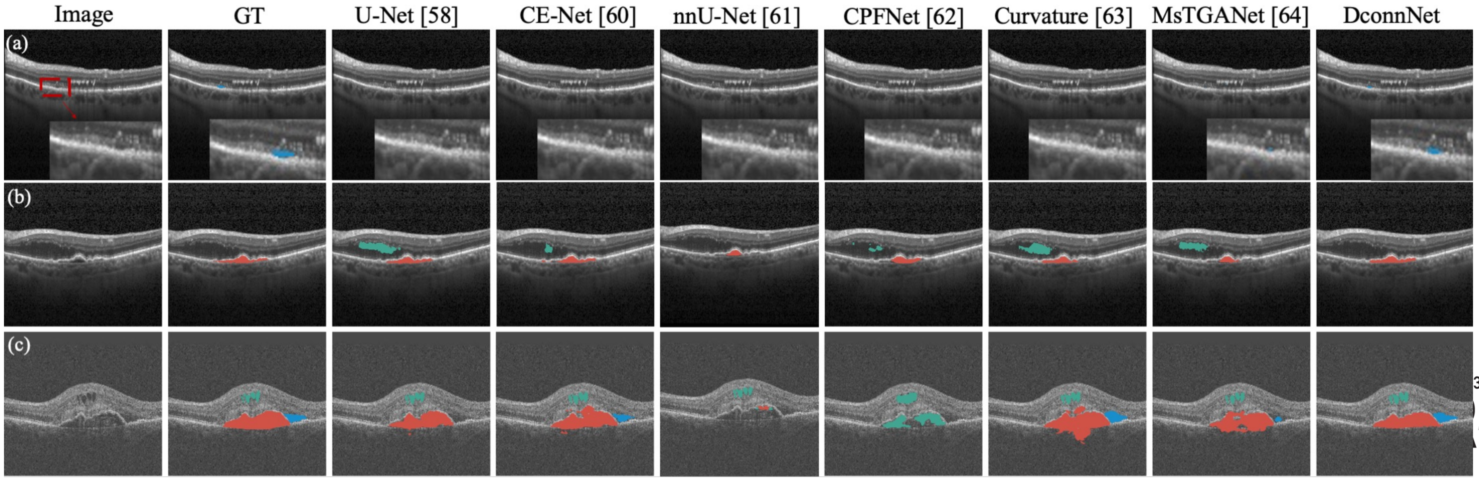
where S is the final segmentation prediction, G is the ground truth, ε is the stabilization term [51] and is usually set as 1.

Experiment: Retouch

- Retouch Dataset: an OCT retinal fluids segmentation benchmark.

Method	DSC_v	DSC	AVD	$BACC$	Size / Speed
DeepLabv3+ [57]	60.2	82.7	0.023	86.5	59.3 / 38
U-Net [58]	66.1	84.2	0.021	87.4	13.4 / 38
Att-UNet [59]	65.3	83.4	0.022	86.6	34.9 / 36
CE-Net [60]	67.3	84.2	0.026	84.6	29.0 / 37
nnU-Net [61]	67.2	84.3	0.023	86.4	30.0 / 20
CPFNet [62]	69.0	85.7	0.022	88.0	43.3 / 37
Curvature [63]	68.2	84.7	0.024	87.1	43.3 / 37
MsTGANet [64]	68.9	85.0	0.023	87.1	11.6 / 37
DconnNet	**78.2**	**87.7**	**0.020**	**90.5**	36.4 / 40

DSC_v: volume-level Dice
DSC: image-level Dice
AVD : absolute volume difference
$BACC$: volume-wise balanced accuracy



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Experiment: ISIC 2018

- ISIC2018 Dataset: a skin lesion segmentation benchmark.

Method	*DSC*	*IOU*	*ACC*	*PREC*
U-Net [58]	88.41	81.23	95.53	90.7
BCDU-Net [77]	88.33	80.84	95.48	89.68
CE-Net [60]	89.23	82.34	95.76	91.51
nnU-Net [61]	89.24	82.35	95.79	91.45
HiFormer [78]	88.54	81.45	95.59	91.09
CPFNet [62]	89.34	82.64	95.89	91.38
FATNet [79]	88.84	81.79	95.62	91.18
Ms RED [71]	89.48	82.71	95.89	**91.83**
DconnNet	**90.43**	**83.91**	**96.39**	91.54

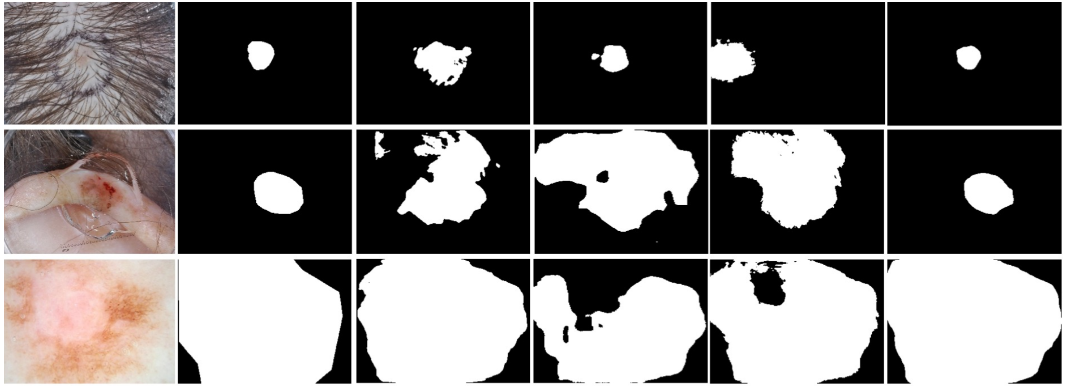
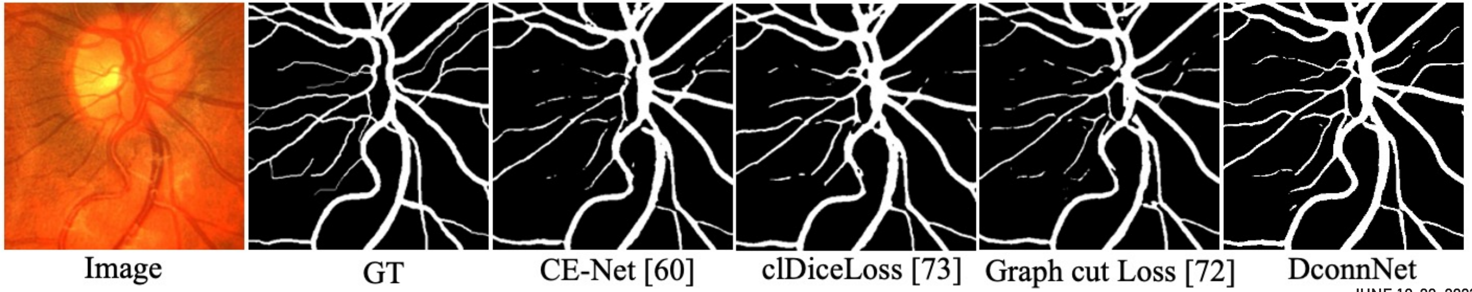


Image GT CPFNet [62] FATNet [79] Ms RED [71] DconnNet

Experiment: CHASEDB1

- CHASEDB1 Dataset: a retinal vessel segmentation benchmark.

Method	*clDice*	*DSC*	*IOU*	β_0	β_1
U-Net [58]	74.0	74.7	59.3	1.390	2.633
Att-UNet [59]	75.3	75.7	61.0	1.330	2.531
GT-DLA [80]	81.0	80.6	67.4	0.790	1.969
CE-Net [60]	82.0	81.0	68.1	0.383	1.670
clDiceLoss [73]	82.9	81.0	68.1	0.345	1.656
GraphCutLoss [72]	82.6	81.4	68.8	0.437	1.692
DconnNet	**83.3**	**81.8**	**69.4**	**0.341**	**1.630**



Ablation Study: Overall

- Ablation study were conducted on Retouch Dataset.

Table 4. Ablation study of the Retouch Dataset. Conn stands for connectivity modeling with L_{bicon}. DS stands for dice loss.

	Conn	Module		Loss		DSC	DSC_v	AVD	$BACC$
		SDE	IFD	DS	SDL				
1				√		83.2	65.0	0.025	87.0
2	√			√		85.8	70.3	0.024	87.7
3	√	√		√		86.2	73.7	0.023	87.9
4	√	√	√	√		86.7	75.2	0.023	88.3
5	√	√	√		√	87.7	78.2	0.020	90.5

Ablation Study: Prior and Sub-path

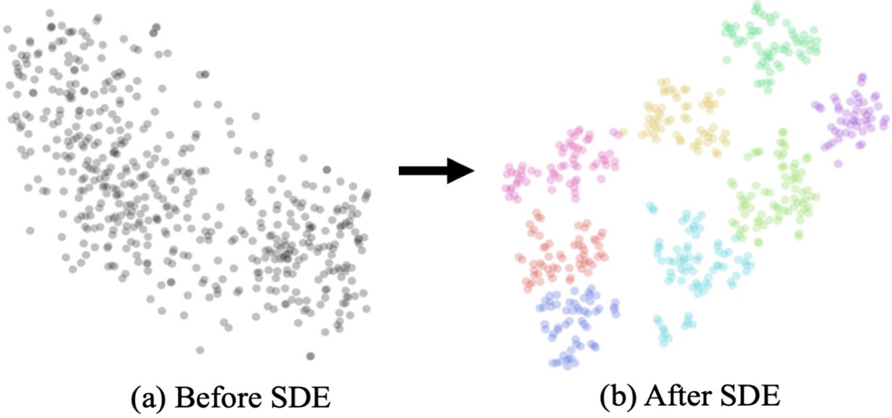
- Ablation study on directional prior and the sub-path attention mechanism.

Table 5. Ablation study on directional prior.

DconnNet	DSC	DSC_v	AVD	$BACC$
w/o. prior	86.3	72.3	0.023	89.1
w/. prior	**87.7**	**76.6**	**0.020**	**90.5**

Table 6. Ablation study on Sub-path attention. Backbone_Conn is the connectivity-based modeling on backbone [16], DA is the dual attention, and NL is the non-local module.

Backbone_Conn	DSC	DSC_v	AVD	$BACC$
+ DA [10]	84.7	69.5	0.027	86.2
+ NL [42]	85.1	70.0	0.028	87.2
+ SDE	**87.7**	**76.6**	**0.020**	**90.5**



Visualization of latent channel embeddings of DconnNet before and after SDE module using T-SNE.

Conclusion

- Proposed a directional connectivity modeling scheme for segmentation that decouples, tracks, and utilizes the directional information across the network.
- Experiments on various public medical image segmentation benchmarks showed the effectiveness of our model.
- A future direction is 3D segmentation, due to the relatively small parameter increase in 3D connectivity modeling.

arXiv

GitHub