Unsupervised Domain Adaptation for Tubular Structure Segmentation Across Different Anatomical Sources

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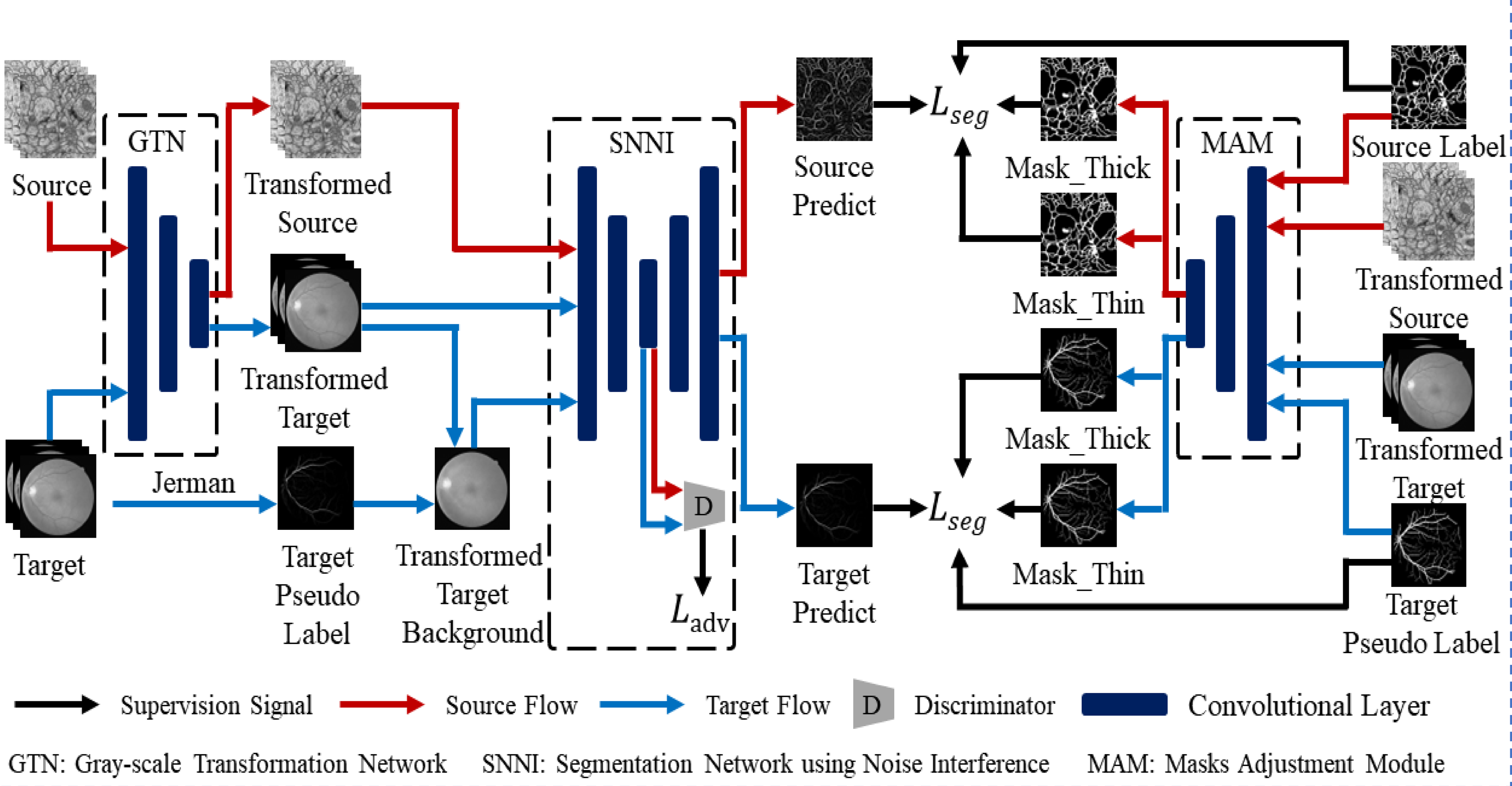
Abstract

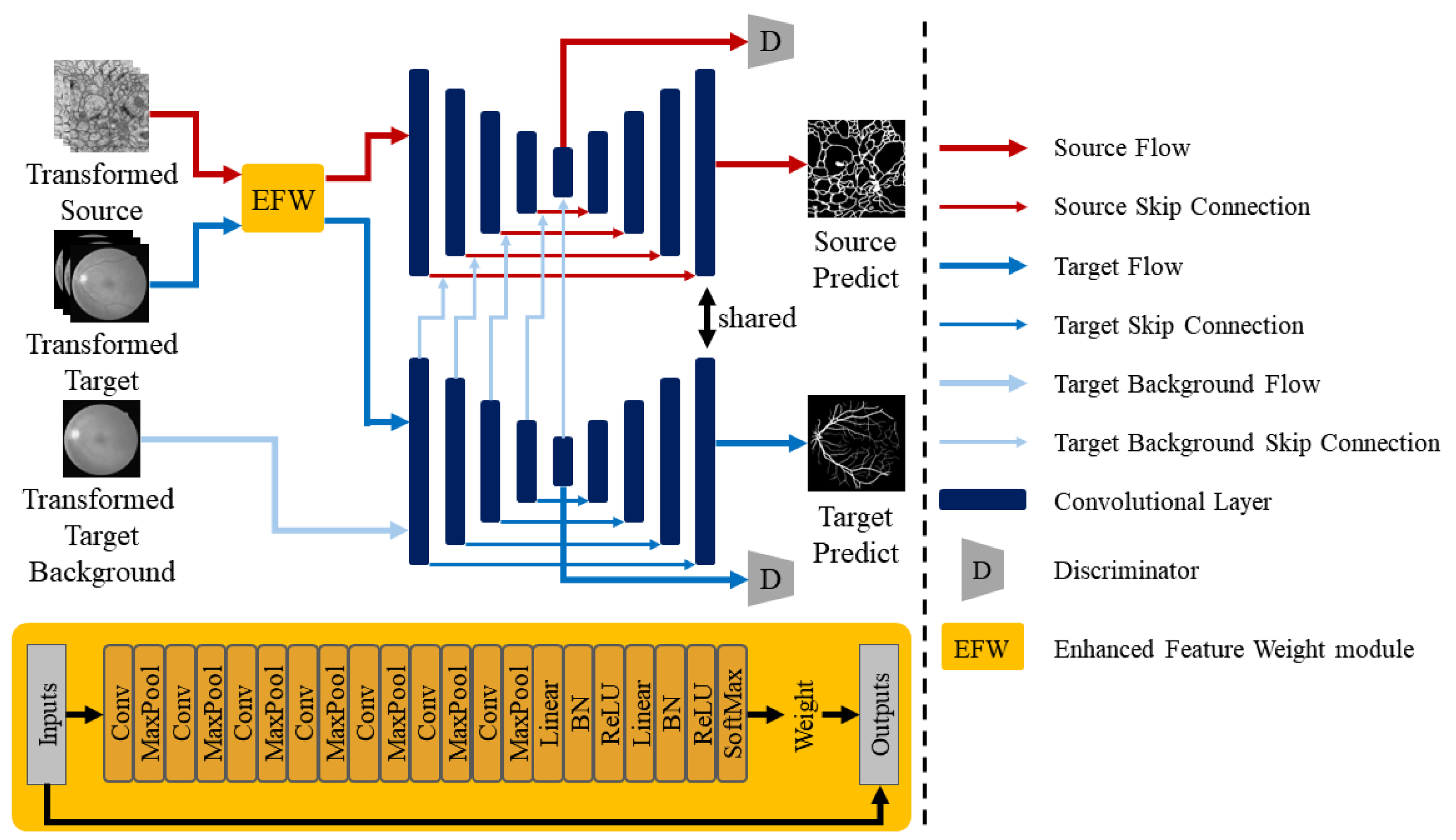
Unsupervised domain adaptation (UDA) aims to boost the generalization ability of deep learning networks by leveraging the unlabeled data, which is a commonly used approach in medical image analysis. However, existing UDA methods only focus on bridging the gap between the same anatomical sites, which leads to the adaptation between different anatomical sites under-explored. UDA under multi-anatomical source settings is more challenging, due to 1) the gray-scale distribution and structural distribution of images of different anatomical sources of tubular structures vary greatly, and 2) The prior knowledge contained in the labels of different anatomical sources is inconsistent. In this paper, we propose an unsupervised domain adaptation method for segmenting tubular structures across different anatomical sources. Specifically, we treat different anatomical sites as different sources. Our method first reduces the domain gap by automatically adjusting the gray-scale distribution of images in different domains using a gray-scale transformation network. Secondly, we introduce target domain noise when training the segmentation network to further improve the segmentation accuracy of the framework in the target domain. In addition, we also design a mask adjustment module for modifying the masks of the raw data in both domains to make the model pay more attention to the common features of the segmentation targets, which further improves the generalization ability of the model. Experimental results on four public datasets at two anatomical sources (eyes and cells) demonstrate the superiority of our proposed method compared with existing state-of-the-art approaches.

Methods

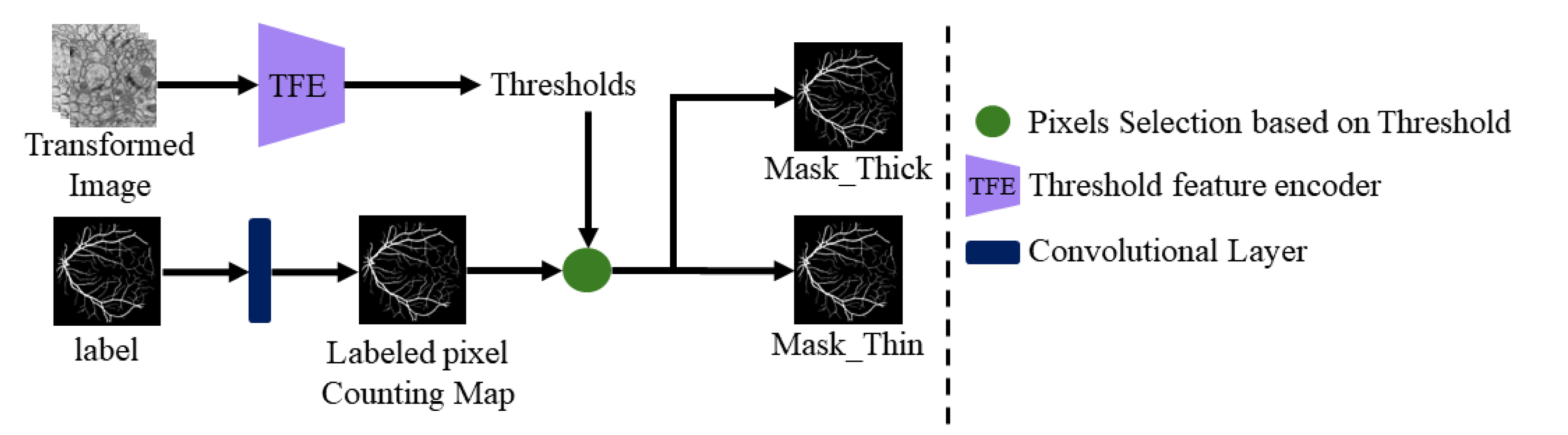
UDA Tubular Structure Segmentation Framework



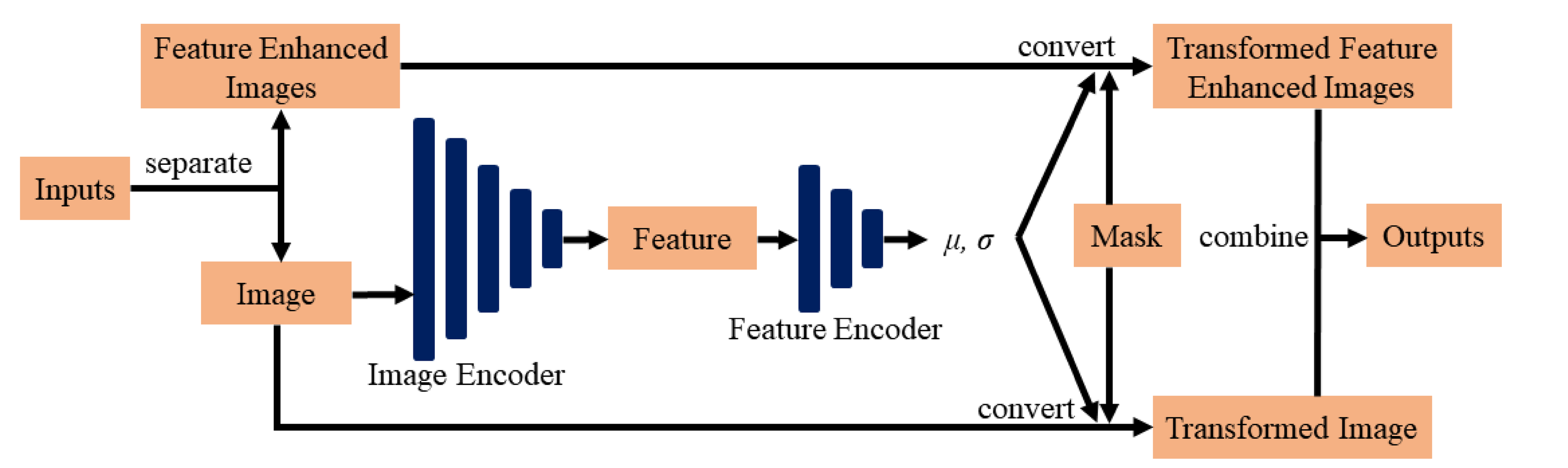
SNNI: Segmentation Network using Noise Interference



MAM: Masks Adjustment Module



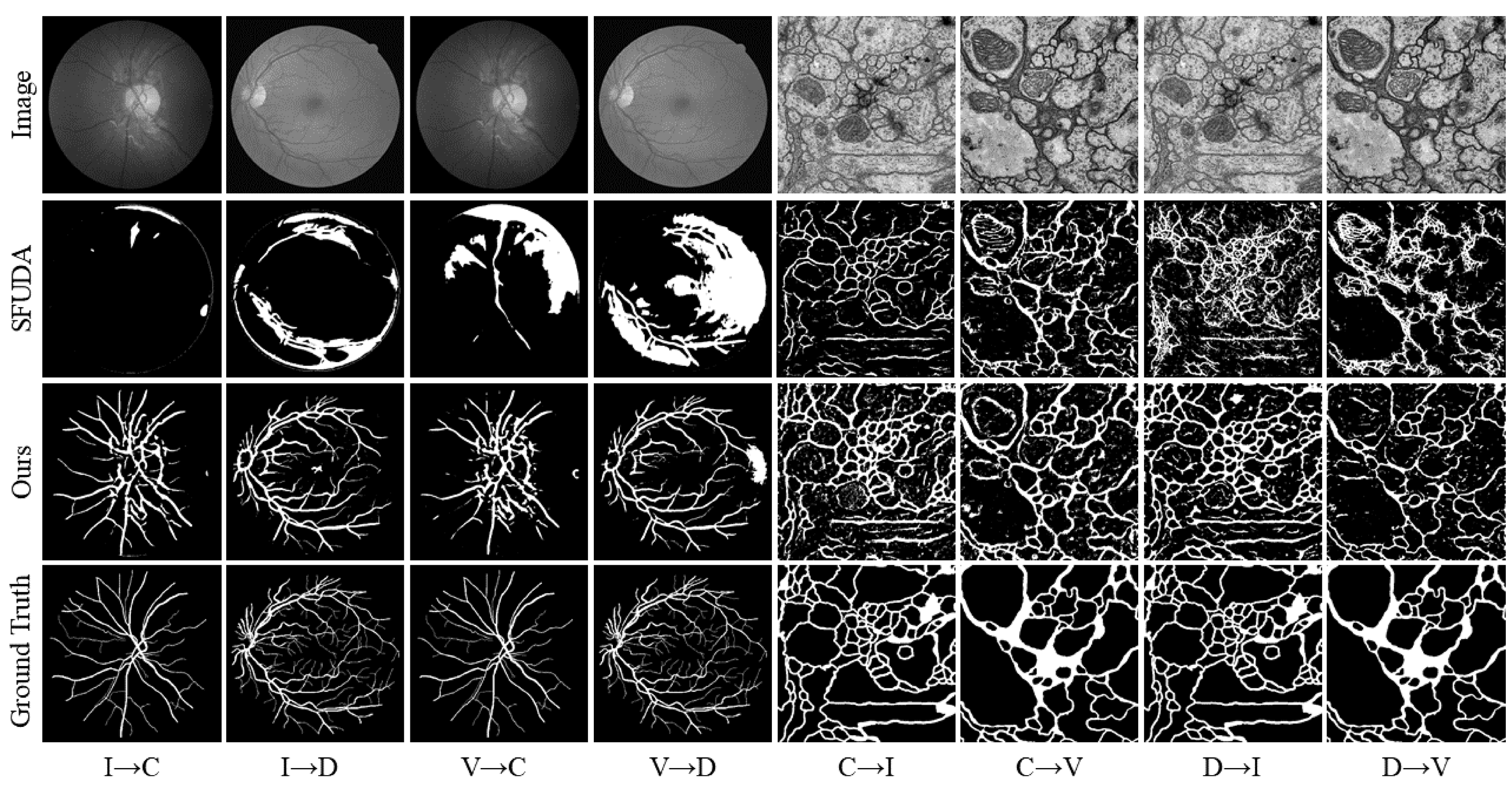
GTN: Gray-scale Transformation Network



Datasets

The experiment aims to segment tubular structures across anatomical sources. The experiment includes four publicly available datasets from two anatomical sources. These consist of two cell datasets: ISBI 2012 EM Segmentation Challenge (ISBI) and Neural Tissue Segmented Anisotropy ssTEM dataset (VNC), and two eye datasets: Digital Retinal Images for Vessel Extraction (DRIVE) and a subset of retinal images of multiethnic children from the Child Heart and Health Study in England (CHASE). **I: ISBI, V: VNC, C: CHASE, D:DRIVE.**

Visualization



Experiments

Comparison experiments. I: ISBI, V: VNC, C: CHASE, D: DRIVE.

Method	I→C	I→D	V→C	V→D	C→I	C→V	D→I	D→V
DANN [1]	12.34%	13.75%	13.43%	19.27%	57.88%	62.81%	47.88%	44.84%
UMDA-SNA [2]	15.87%	10.85%	13.75%	21.35%	42.36%	32.24%	37.70%	19.57%
DCDA [3]	15.92%	14.17%	16.33%	20.16%	61.23%	63.06%	46.59%	45.28%
SAM-UDA [4]	14.10%	10.78%	13.92%	16.89%	43.43%	39.95%	40.35%	22.83%
ADANet [5]	11.43%	9.69%	14.31%	12.49%	65.40%	36.48%	41.69%	23.56%
FFO [6]	19.73%	18.13%	14.80%	20.04%	48.57%	36.67%	46.90%	35.33%
SFUDA [7]	13.79%	26.40%	14.80%	26.43%	54.44%	64.75%	54.15%	59.51%
MIC [8]	15.42%	10.86%	14.85%	15.13%	61.85%	68.74%	59.14%	64.57%
LA-UDA [9]	36.76%	39.70%	24.67%	26.34%	56.19%	44.15%	45.29%	47.80%
Ours	**60.46%**	**67.11%**	**53.93%**	**61.68%**	**67.52%**	**70.84%**	**68.05%**	**69.94%**

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