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

1. Implementation details

In this section, we supplement the implementation details that are not covered in Section 4.

1.1. DRIVE

The DRIVE dataset contains 40 color images of the fundus retina, where seven images show signs of mild diabetic retinopathy. The resolution of each image is 565×584. The DRIVE dataset contains manually annotated labels from two experts. In our experiments, we use the annotation results of the first expert as the training and validation of all models.

Data pre-processing: The DRIVE dataset provides color images with three channels. The contrast between the thin tubular vessels and the background is low, which is quite difficult for the deep learning model to discriminate. It will affect the accuracy of model segmentation. Therefore, pre-processing the original data is necessary to improve the model's performance. As shown in 1, there is a clear difference in the representation of blood vessels on different channels. The comparison reveals that the blood vessel morphology is most evident on channel G. Therefore, our model selects the images under this channel. To improve the contrast between the blood vessels and the background, we use the CLAHE[1] algorithm to adjust the image's contrast so that the model will focus more clearly on the structure of the blood vessels.

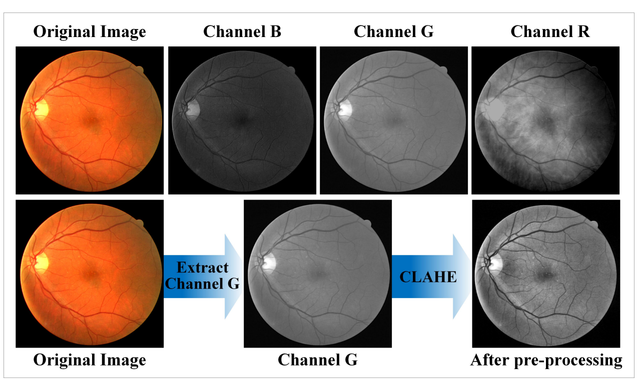

Figure 1. Visual effects before and after pre-processing.

Experimental parameters: Due to the limited amount of data provided by the dataset, it is necessary to further sample and enlarge the input data. In our experiments, the data augmentation consisted of translation, rotation, mirroring, flipping, and random cropping. All data enhancements are performed simultaneously during the training process. The random crop size of 224×224 is used as a fixed size to feed into the model training.

Model training parameter setting: In training, the Adam optimizer is selected with default parameters. The learning rate is set to 0.0001, and the epoch is set to 200. The experimental program is based on Python 3.7 and Pytorch. It uses a Gtx2080ti graphics card to train and test.

1.2. Massachusetts road

The Massachusetts road dataset contains 1108 color images for training, 14 color images for verifying, and 49 color images for testing. The resolution of each image is 1500×1500.

Experimental parameters: The color images provided by the Massachusetts road dataset contain three channels, and we use data information from all three channels simultaneously. Since the morphology of the data varies considerably, we used data enhancement. In our experiments, the data augmentation consisted of translation, rotation, mirroring, flipping, and random cropping. All data enhancements are performed simultaneously during the training process. The random crop size of 256×256 is used as a fixed size to feed into the model training.

Model training parameter setting: In training, the Adam optimizer is selected with default parameters. The learning rate is set to 0.0001, and the epoch is set to 400. The experimental program is based on Python 3.7 and Pytorch. It uses a Gtx2080ti graphics card to train and test.

1.3. Cardiac CCTA

The Cardiac CCTA dataset contains 288 images with contrast agents showing the coronary arteries. 192 images are used in our experiments as the training data and the remaining 96 images are used as the testing data. The original image is 512×512 per slice, with 200 to 500 slices per image. The coronary lumen boundary is delineated by

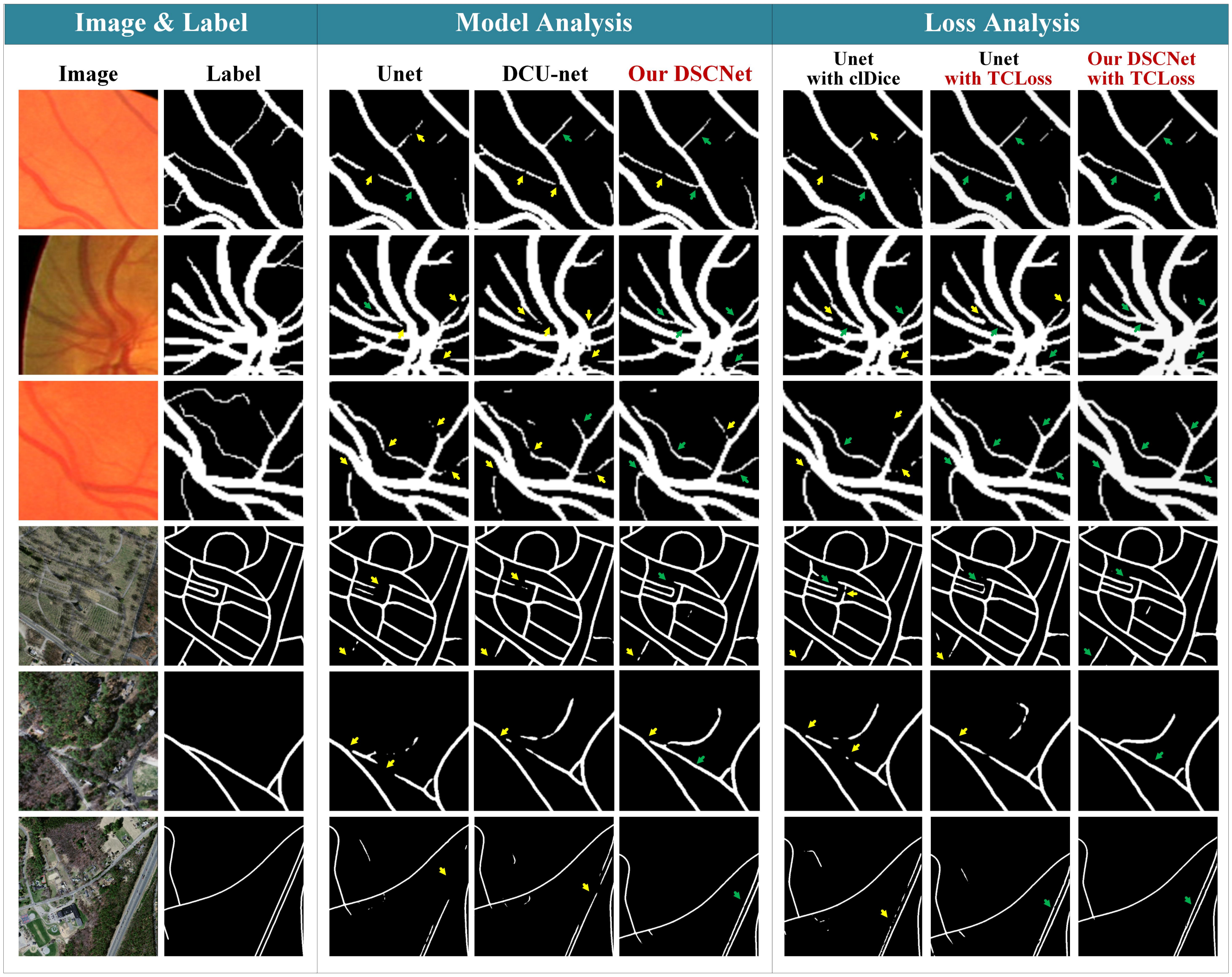

Figure 2. **Qualitative results.** To verify the performance of our method more objectively and efficiently, we selected representative hard-to-segment regions from each dataset. From top to bottom, we show three rows of results for the DRIVE dataset and the Massachusetts road dataset. From left to right, we show the original image, groundtruth, and the results from classical UNet, DCU-net, our DSCNet, UNet with clDice, UNet with our proposed TCLoss, and our DSCNet with TCLoss. The results indicate that our DSCNet and TCLoss outperform the other models regarding segmentation accuracy and topological continuity. The yellow arrows indicate the areas where the segmentation is broken, while the green arrows indicate areas where the segmentation is performing well.

a trained researcher and verified by a clinician. The region of interest (ROI) is extracted and these ROIs are cropped into small 3D patches of $128 \times 128 \times 96$ online due to the limitation of GPU memory.

Model training parameter setting: In training, the Adam optimizer is selected with default parameters. The learning rate is set to 0.0001, and the epoch is set to 200. The experimental program is based on Python 3.7 and Pytorch. It uses a Gtx3090 graphics card to train and test.

2. Additional Qualitative Results

In this section, we provide more qualitative analysis of our methods.

References

[1] K. Zuiderveld. Contrast limited adaptive histogram equalization. *Graphics Gems*, pages 474–485, 1994.

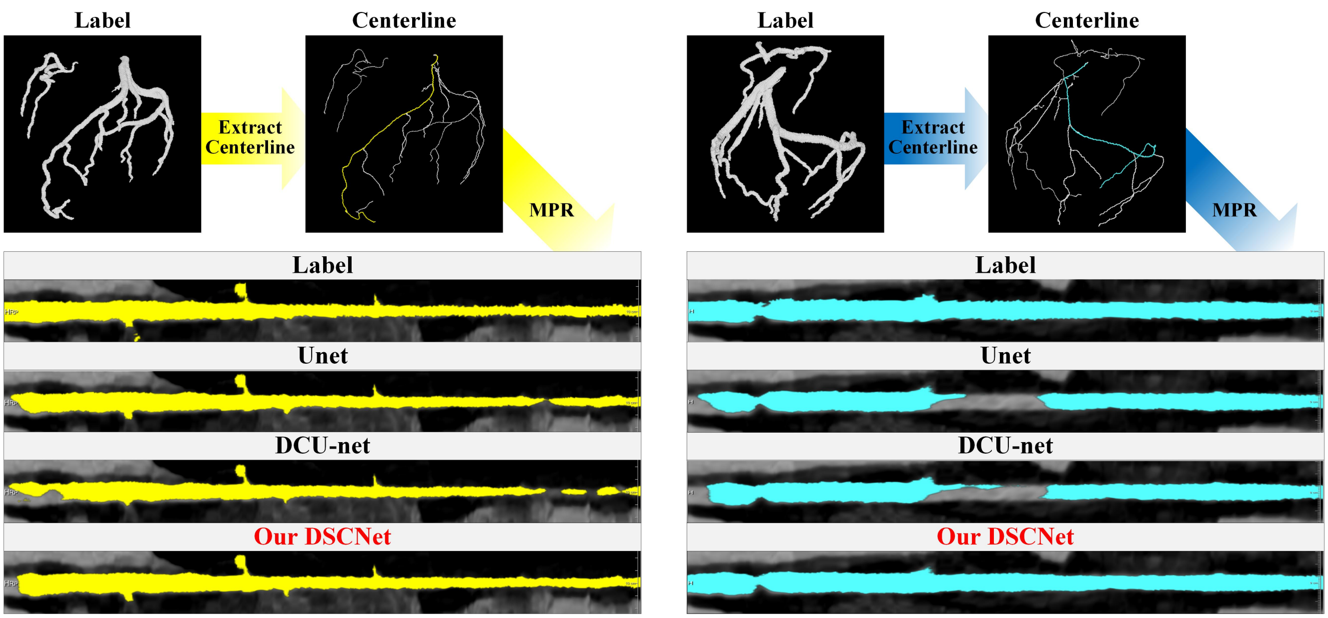

Figure 3. MPR view of segmentation results for the entire coronary artery. Compared with the ground truth, our proposed DSCNet has a good continuous segmentation effect in topological continuity, while other methods have different degrees of fracture problems.