IterNet: Retinal Image Segmentation Utilizing Structural Redundancy in Vessel Networks

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Background

- Retinal vessel segmentation is important in finding diseases.[1]
- However, it is difficult to make complete yet accurate segmentation.
- Labeled data are very limited. (Training samples ≤ 20 in most datasets)
- Also, for clinical uses, doctors need well-connected vessel maps.[2]
- A new metric is necessary to show the performance of connectivity.

Motivation

- Although much important information is missing in raw images, humans may still be able to infer where the actual vessels are from these resulting vessel maps.
- To give segmentation model the ability to refine its results, the key is how to provide enough labeled defective samples (=> "sharing weights").

IterNet Model

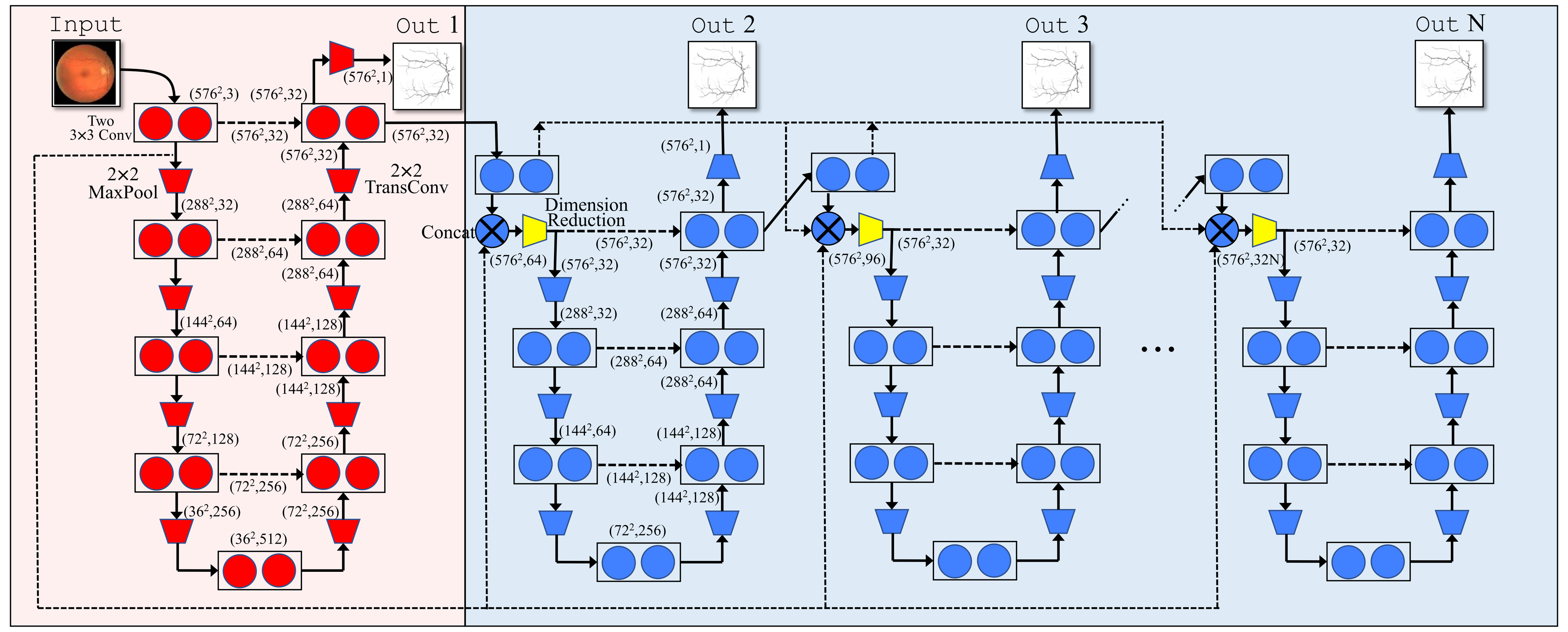


Figure 1. IterNet consists of one UNet and iteration of N–1 mini-Unets (***sharing weights***).

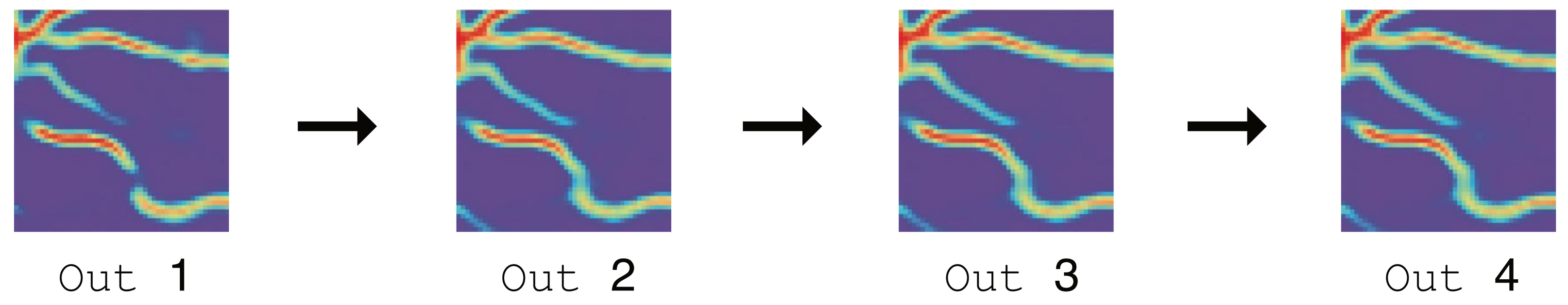


Figure 2. The result of `Out` 1, 2, 3, and 4 from IterNet.

Segmentation Performance

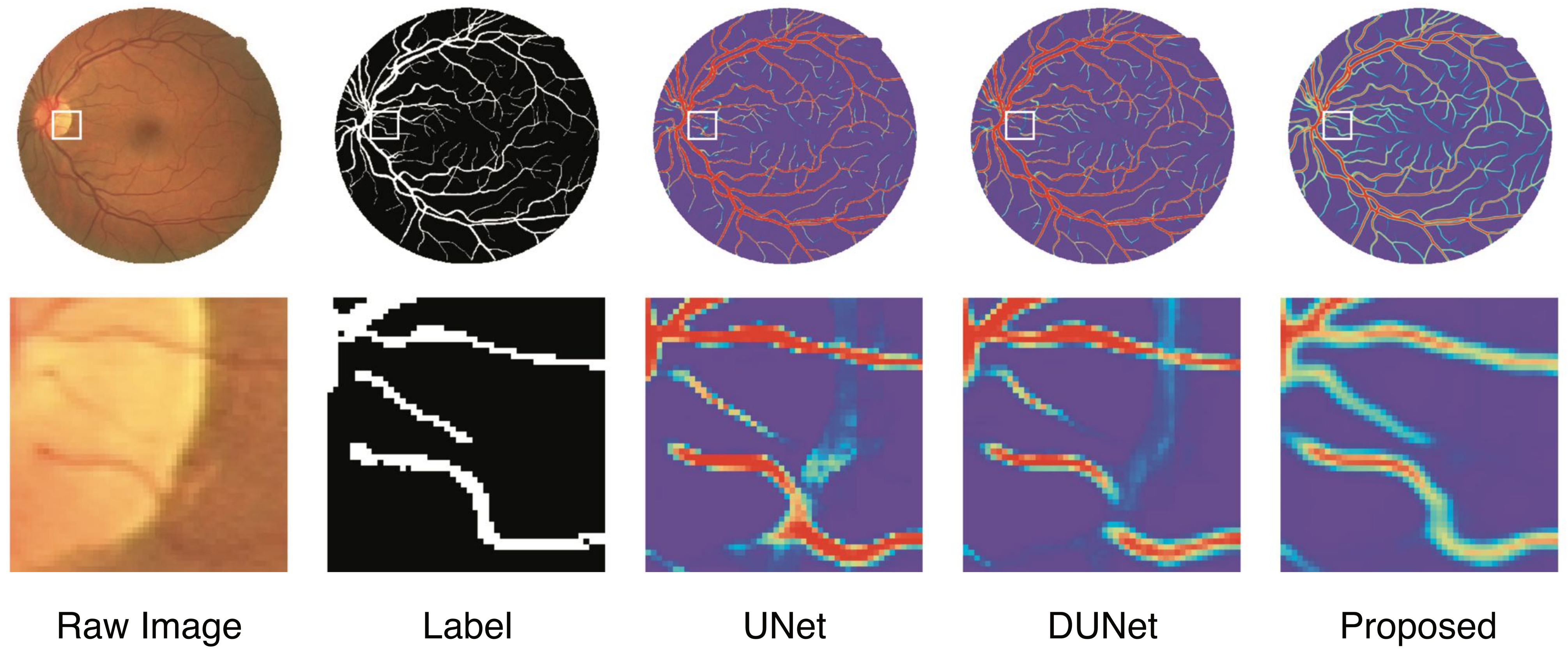


Figure 3. Vessel segmentation results of several different methods.

Vessel Connectivity

- AUC is in pixel level and can not reflect the performance on the vessel network level.
- Therefore, we adopt a new metric called connectivity[3,4]:

$$C(\theta) = \begin{cases} 1 - \dfrac{|S_P(\theta) - S_G|}{S_{Max}} & \text{for } |S_P(\theta) - S_G| \le S_{Max} \\ 0 & \text{otherwise} \end{cases}$$

- $S_p(\theta)$ is the number of segments when threshold is θ; S_G is ground-truth number; S_{Max} is a pre-defined maximum number.
- With this definition, we can draw the curve of θ versus $C(\theta)$. (=> Figure 4)
- The area under this curve is adopted as the connectivity metric.
- An example from CHASE-DB1 dataset is shown in Figure 5.

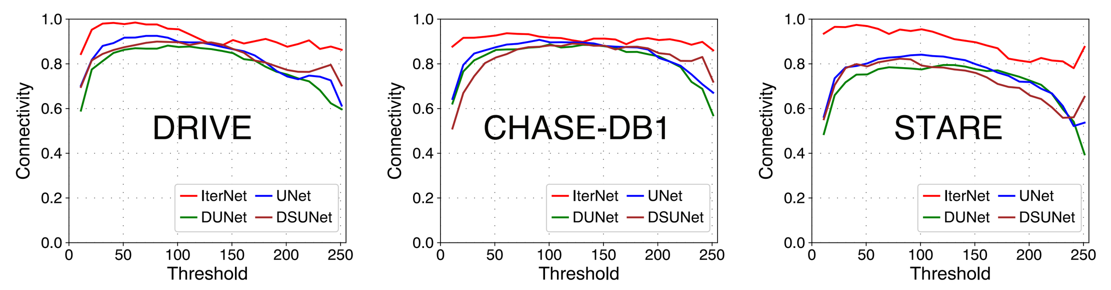


Figure 4. Connectivity versus threshold on three datasets.

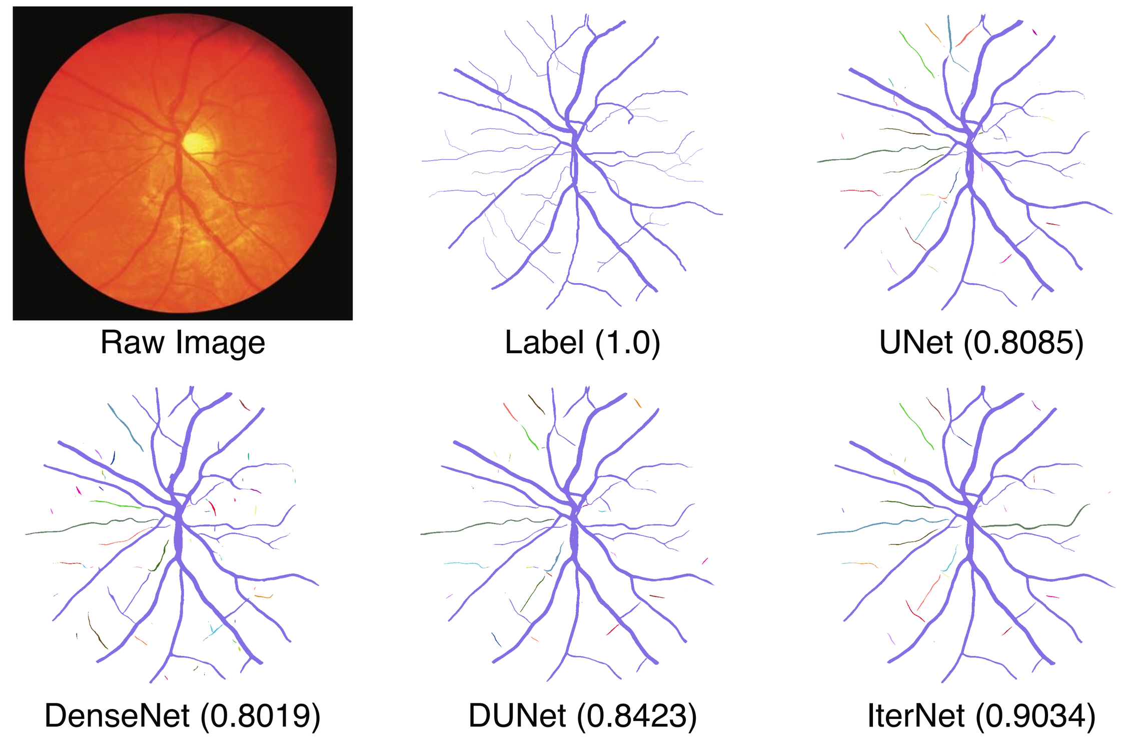


Figure 5. Vessel segments and C value. (threshold=110)

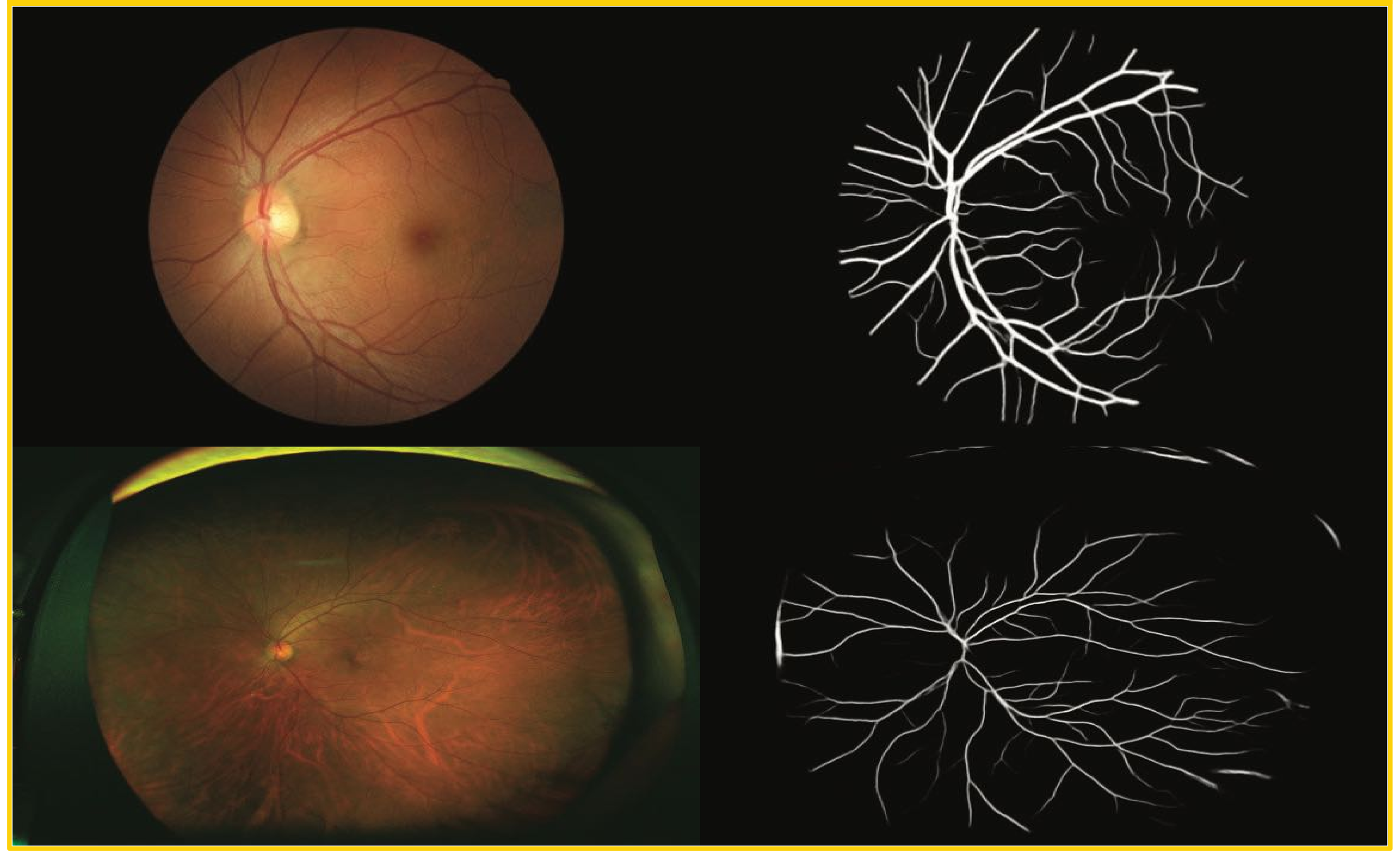
Experimental Results

Table 1. Performance comparison on the DRIVE dataset (with mask).

Methods	C	AUC	F1	Sens.	Spec.	Acc.
U-Net	0.7948	0.9752	0.8174	0.7822	0.9808	0.9555
Residual UNet	-	0.9779	0.8149	0.7726	0.9820	0.9553
Recurrent UNet	-	0.9782	0.8155	0.7751	0.9816	0.9556
R2UNet	-	0.9784	0.8171	0.7792	0.9813	0.9556
DenseNet	0.8332	0.9756	0.8146	***0.7928***	0.9776	0.9541
DUNet	0.8314	0.9778	0.8190	0.7863	0.9805	0.9558
IterNet	***0.9193***	***0.9816***	***0.8205***	0.7735	***0.9838***	***0.9573***

* Results on other datasets are availble in the paper.

Other Datasets (without Fine-tuning)



Future Works

A/V Classification

- A model utilizes IterNet to perform vessel classification.
- A post-processing algorithm to refine the results.
- Submitted to MIDL2020.

Arteriolosclerosis

- A method uses IterNet to extract arteriovenous patches.
- A validation and grading model for diagnosing artery hardening.
- Submitted to MICCAI2020.

References

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[2] F. Caliva, M. Aletti, B. Al-Diri, and A. Hunter, "A new tool to connect blood vessels in fundus retinal images," in *EMBC*, 2015, pp. 4343–4346.

[3] S. Moccia, E. D. Momi, S. E. Hadji, and L. S. Mattos, "Blood vessel segmentation algorithms: review of methods, datasets and evaluation metrics," *Computer Methods and Programs in Biomedicine*, vol. 158, pp. 71–91, 2018.

[4] M. E. Gegundez-Arias, A. Aquino, J. M. Bravo, and D. Marin, "A function for quality evaluation of retinal vessel segmentations," *IEEE TMI*, vol. 31, no. 2, pp. 231–239, 2012.

Paper & Code