

多模态医学图像融合与分割

研究背景与意义

大量的临床疾病诊断与治疗依赖多模态医学影像



骨骼和高密度组织的信息



提供高分辨率和丰富的软组织信息



反映肿瘤功能及代谢

存在的问题



手动分割医学图像耗时且费力



分割的结果依赖专家的知识

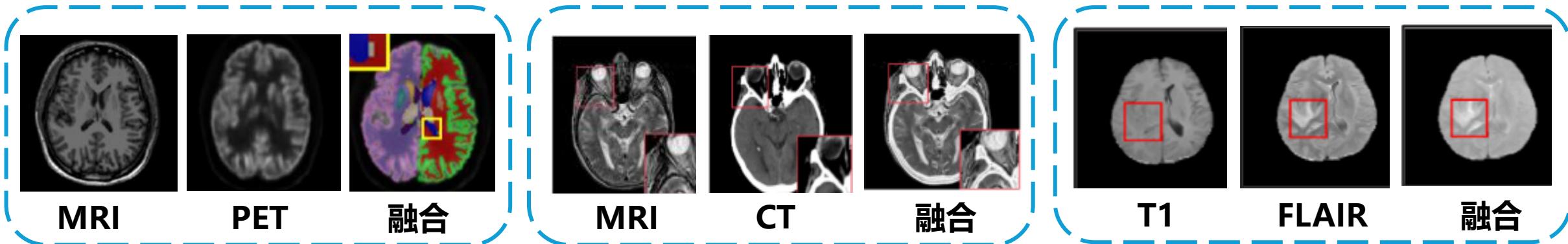


单模态数据提供的信息有限



错诊、误诊，错过最佳的治疗时机和治疗方案，导致病情进一步恶化

多模态医学图像融合



通过融合不同模态中的互补信息，生成一个具有多种模态信息的图像，然后进行分割操作，帮助医生对复杂的病例做出诊断

Automatic Brain Segmentation for PET/MR Dual-Modal Images Through a Cross-Fusion Mechanism

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Abstract—The precise segmentation of different brain regions and tissues is usually a prerequisite for the detection and diagnosis of various neurological disorders in neuroscience. Considering the abundance of functional and

structural dual-modality information for positron emission tomography/magnetic resonance (PET/MR) images, we propose a novel 3D whole-brain segmentation network with a cross-fusion mechanism introduced to obtain 45 brain regions. Specifically, the network processes PET and MR images simultaneously, employing UX-Net and a cross-fusion block for feature extraction and fusion in the encoder. We test our method by comparing it with other deep learning-based methods, including 3DUXNET, SwinUNETR, UNETR, nnFormer, UNet3D, NestedUNet, ResUNet, and VNet. The experimental results demonstrate that the proposed method achieves better segmentation performance in terms of both visual and quantitative evaluation metrics and achieves more precise segmentation in three views while preserving fine details. In particular, the proposed method achieves superior qualitative results, with a Dice coefficient of 85.73% ± 0.01%, a Jaccard Index of 76.69% ± 0.02%, a sensitivity of 85.9% ± 0.01%, a precision of 83.26% ± 0.03%, and a Hausdorff distance (HD) of 4.4895 ± 14.85%. Moreover, the distribution and correlation of the SUV in the volume of interest (VOI) are also evaluated ($PCC > 0.9$), indicating consistency with the ground truth.

利用PET和MR图像的融合实现对大脑的自动分割

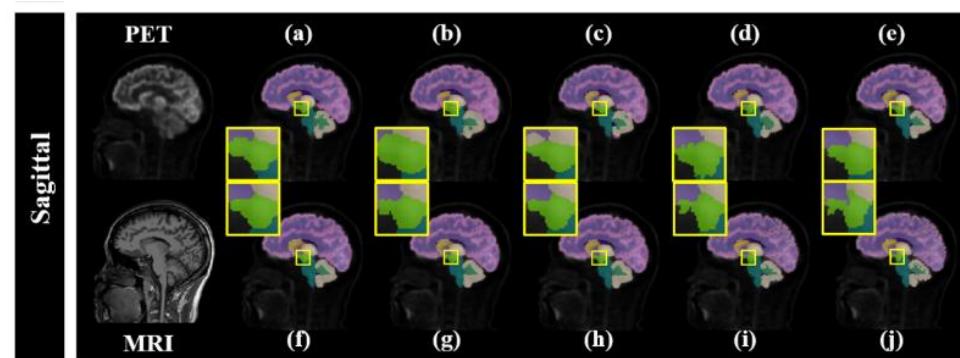
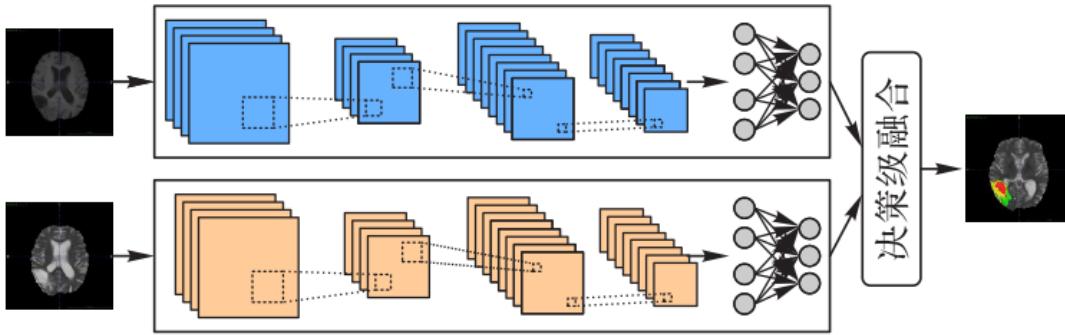
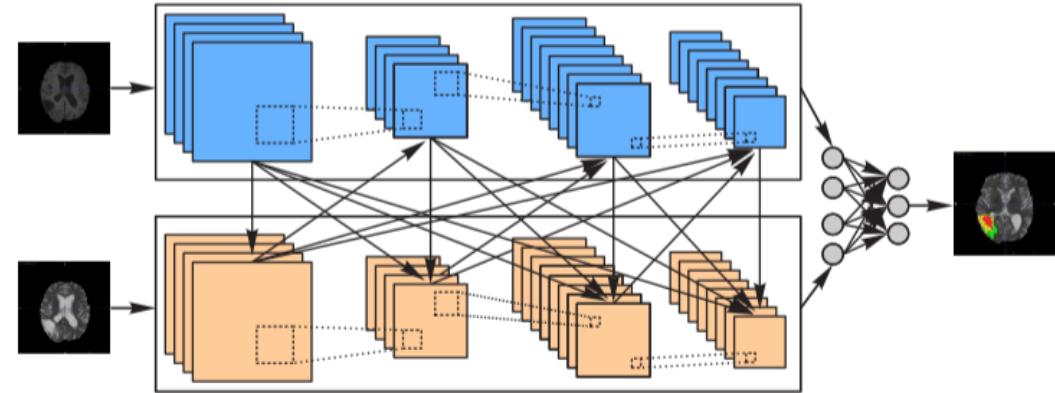


Fig. 2. Visualization of the whole-brain segmentation results shown in axial, coronal, and sagittal views. The method indices are as follows: (a) NestedUNet. (b) ResUNet. (c) VNet. (d) nnFormer. (e) UNETR. (f) SwinUNETR. (g) UNet3D. (h) 3DUXNET. (i) Ours. (j) GT.

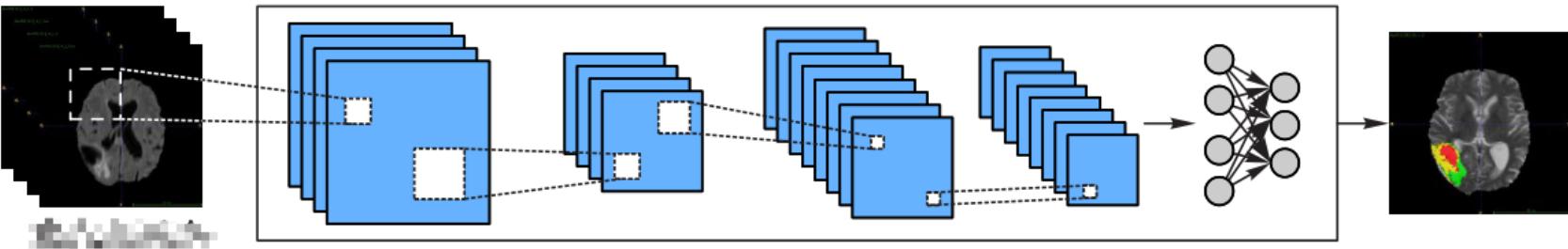
研究背景与意义



决策级融合（主流）



特征级融合（主流）

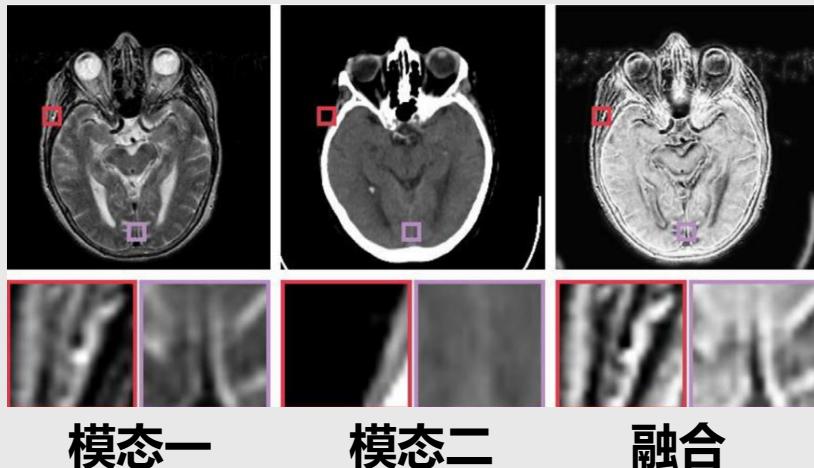


像素级融合

- 充分利用**不同模态**的信息
- 有效的关联**不同模态**的特征
- 快速的确定**病变的区域**

主要挑战

提取的模态信息**有限**

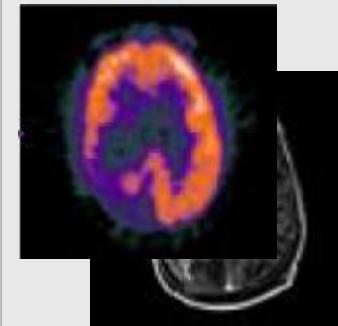


图像丢失**细节纹理**信息，病变区域**边界模糊**



更有效的融合方法

不适用于**下游任务**



图像融合模型

- 病变区域**分割**
- 病变区域**检测**
- 病变区域**分类**

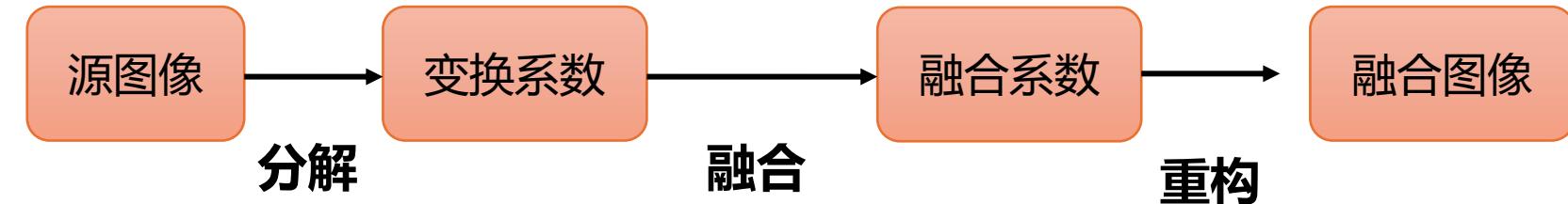
...

融合的图像与下游的**垂直任务**没有关联



更精准的语义识别方法

经典框架



➤ 基于空间域的多模态医学图像融合方法

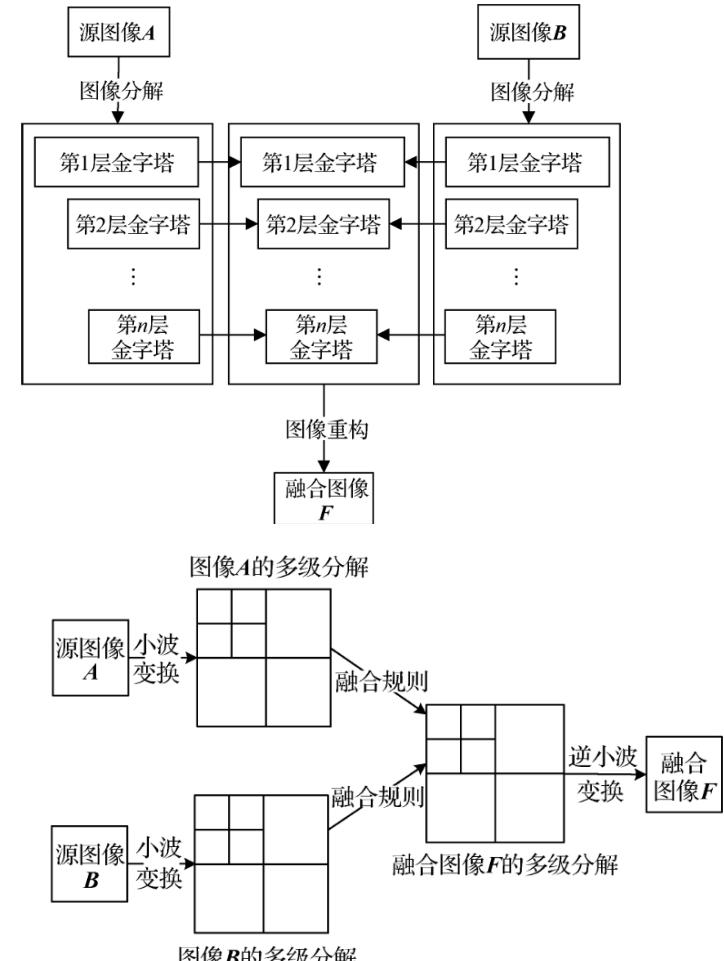
空间域技术利用基础的像素级策略,对图像中的像元值起作用,得到的图像表现出更少的空间失真和较低的信噪比

- JICA(2021)、GB-VS(2021)、ACM(2019)

➤ 基于频率域的多模态医学图像融合方法

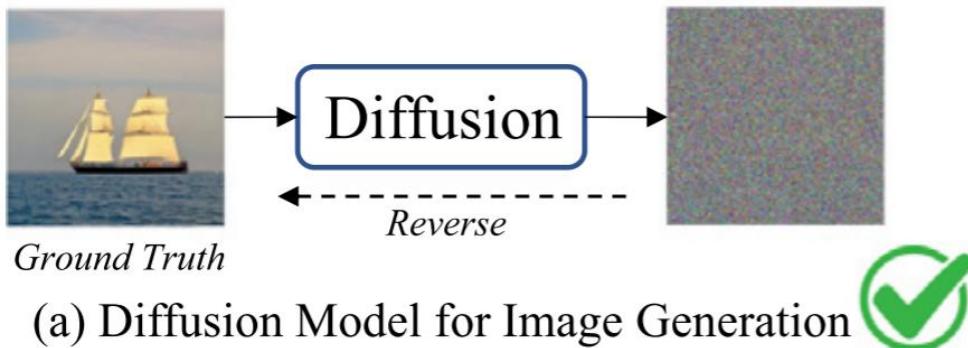
通过计算傅里叶变换将输入的图像从空域转换为频域,然后对转换后的图像应用融合算法,再进行傅里叶逆变换,得到最终的融合图像。

- 基于金字塔的变换: GP、LP、WP
- 基于小波变换: DWT、DTCWT、SWT
- 基于多尺度几何变换: NSCT、NSST

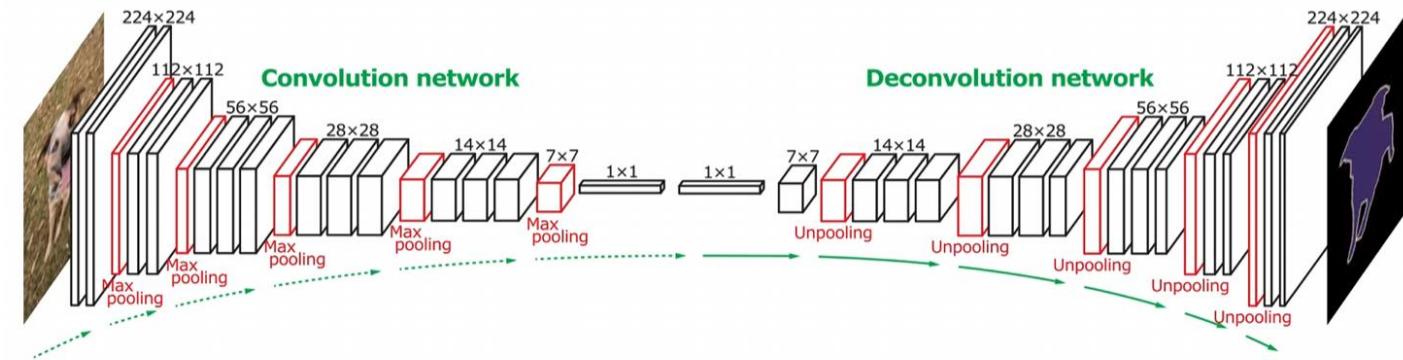


研究动机

- 改进传统方法中**多尺度和空间变换**存在的局限性
 - 传统方法的融合策略设计面临发展的瓶颈期, **深度学习**能够更有效地映射输入与输出之间的相关性
- **CNN、GAN、CSC、AE、RNN、RBM**



对抗学习

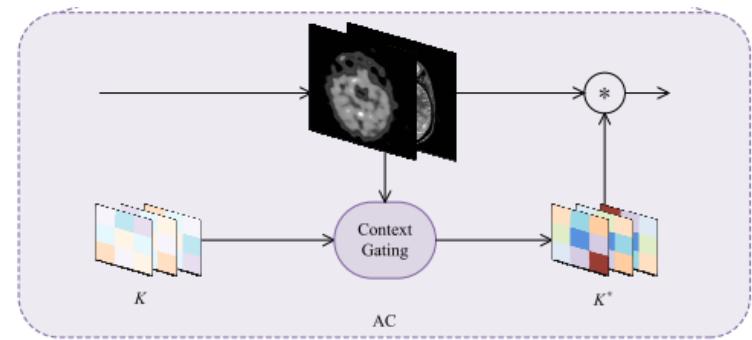
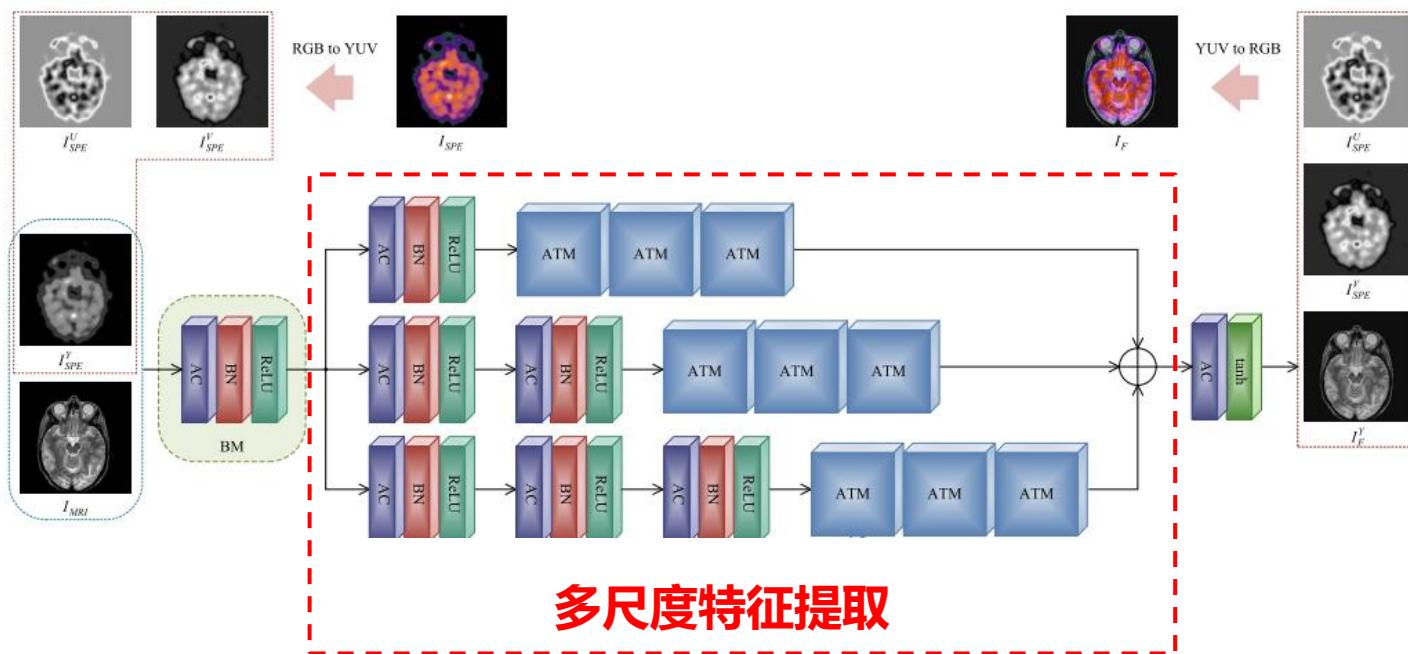


特征提取

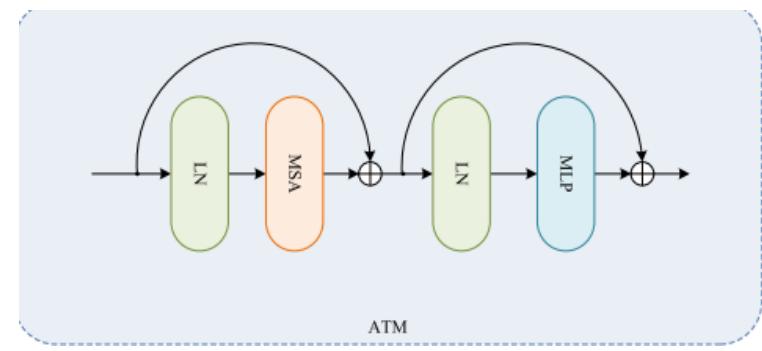
基于Transformer的融合方法

研究动机

- 设计Transformer模块，有效提取全局上下文信息，解决卷积神经网络的限制
- 构建多尺度特征提取结构，丰富特征的尺度多样性



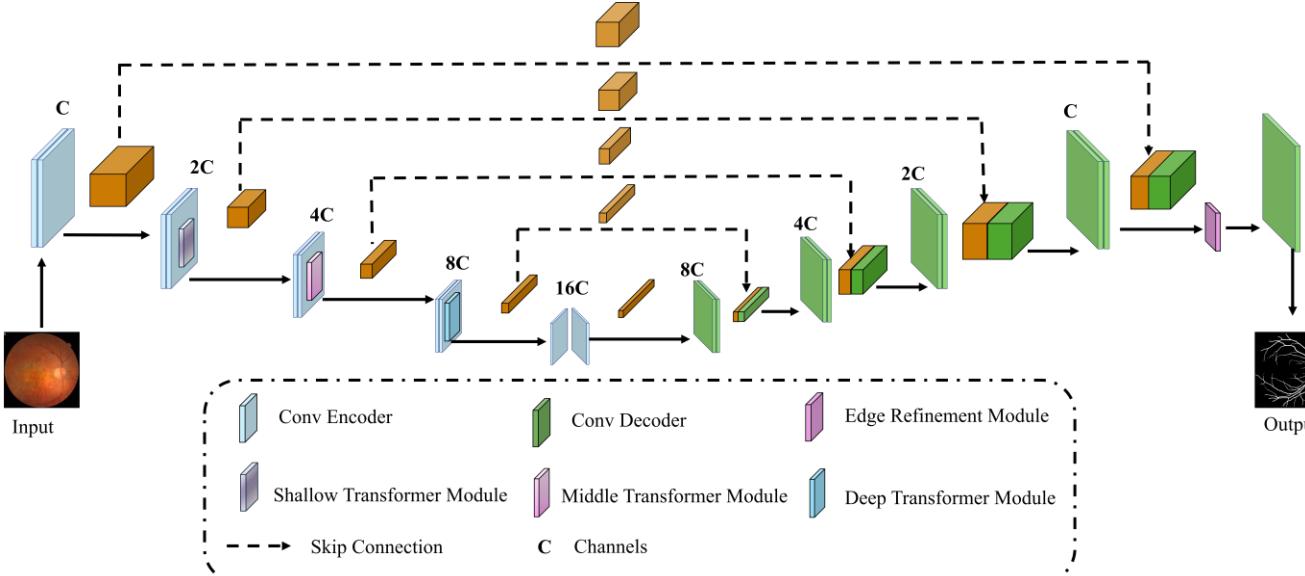
自适应卷积模块AC



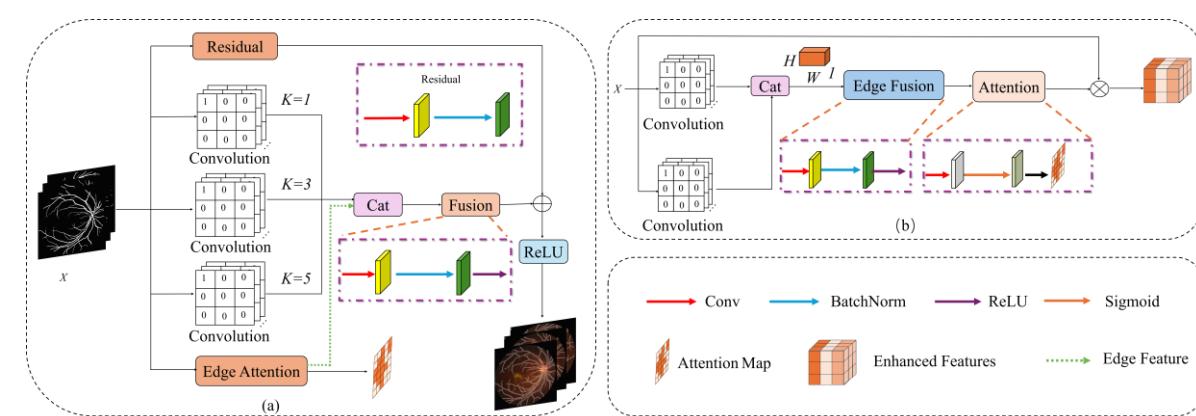
自适应Transformer模块ATM

Hi-ERMNet: Computationally Efficient Retinal Vasculature Segmentation via Lightweight Transformer Encoders and Edge Refinement Module

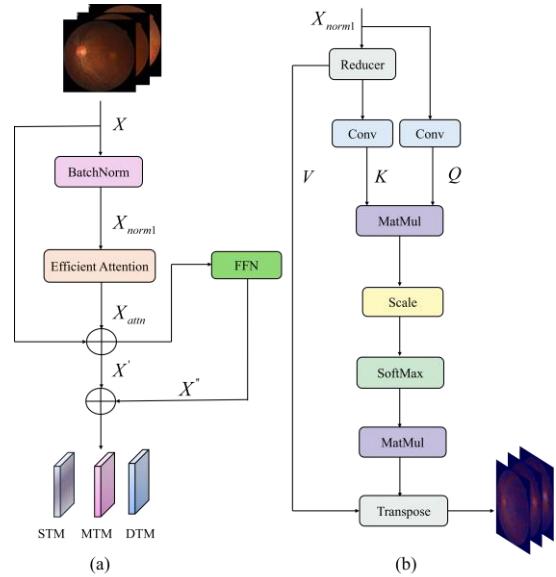
➤ 当前的视网膜血管分割方法主要关注粗血管，忽略了细小血管，本文提出边缘优化模块，专门处理细小血管的边缘像素



Hi-ERMNet



边缘优化模块ERM



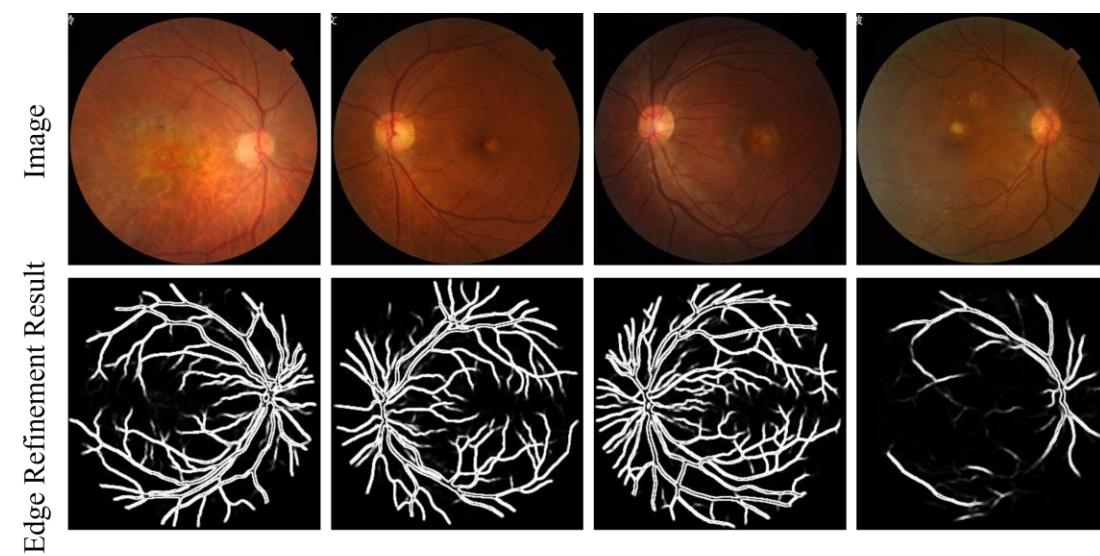
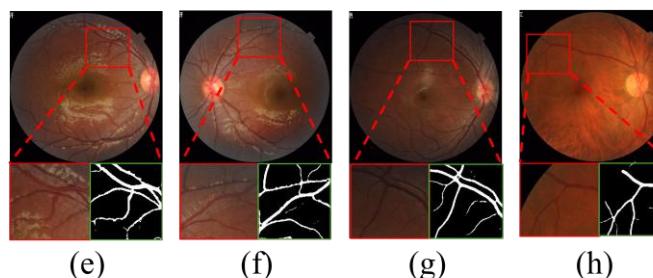
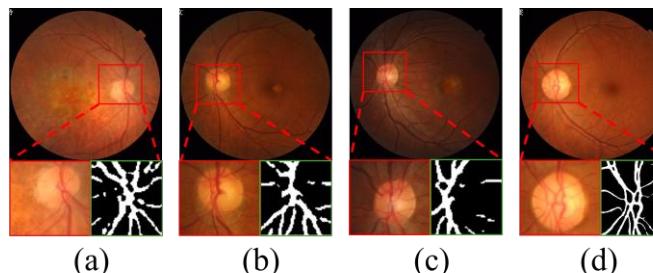
轻量化Transformer

近期学习情况

➤ 通过对比实验，分析实验结果

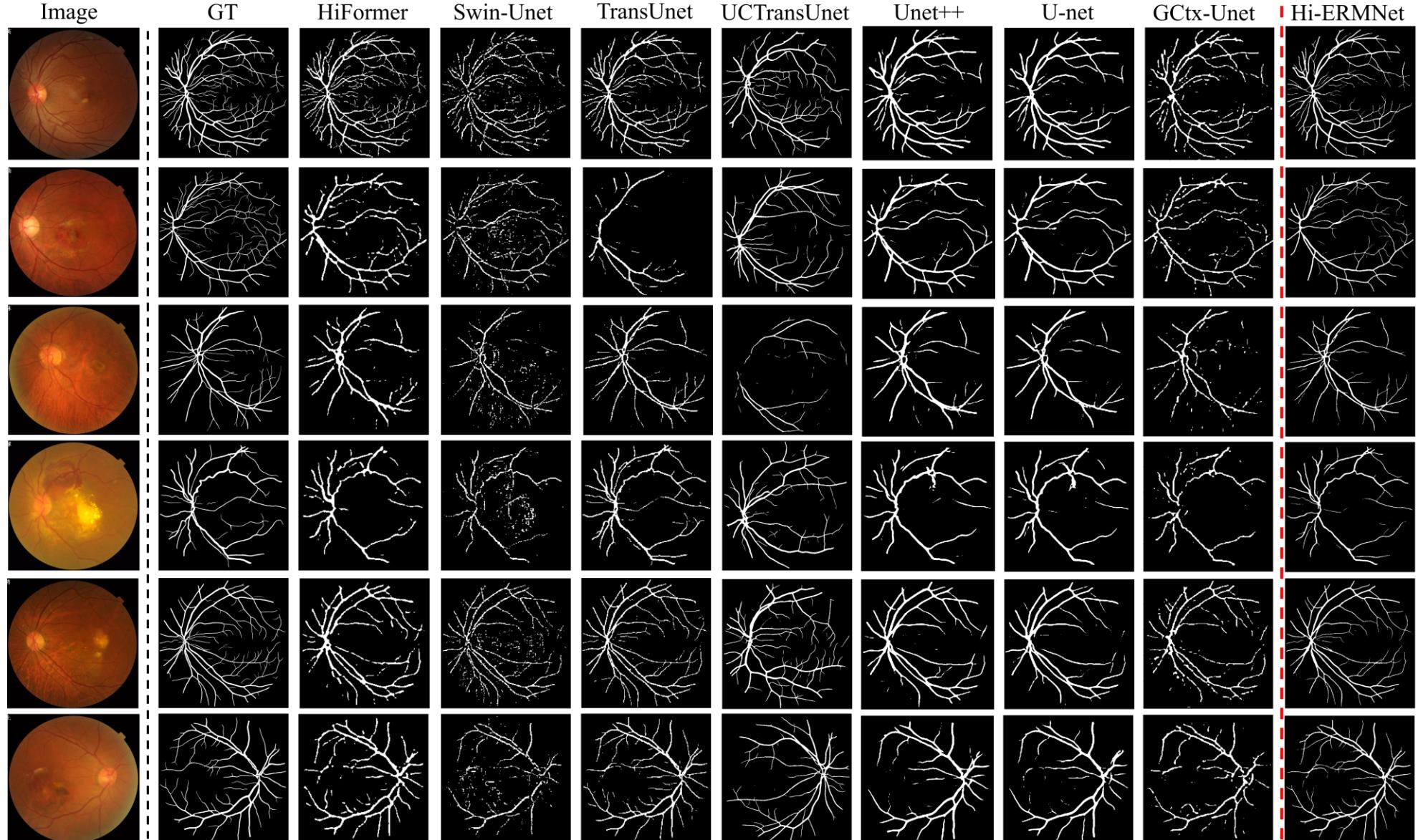
Method	CHASE_DB1				DRIVE				HRF				STARE			
	Dice	IoU	Prec.	Acc.												
HiFormer	20.23	12.25	61.31	93.74	57.58	40.54	59.24	92.92	50.47	33.78	43.67	90.70	59.23	42.21	59.15	93.49
Swin-UNet	27.45	17.79	49.49	94.01	47.91	32.33	77.96	93.59	37.06	24.07	61.67	<u>92.83</u>	33.58	22.42	55.89	92.87
Trans-UNet	62.57	45.60	70.25	95.68	60.04	43.01	64.69	93.60	<u>54.91</u>	<u>37.86</u>	51.32	92.31	64.36	47.51	66.37	94.49
GCtx-Unet	62.16	45.16	64.42	95.37	58.43	41.34	65.02	93.51	53.86	36.93	55.03	92.87	58.66	41.78	60.15	93.65
UCTransNet	43.71	28.08	28.13	81.99	34.77	21.14	21.16	80.27	45.53	29.47	99.66	40.37	35.43	21.65	21.66	80.40
Unet++	62.63	45.70	77.35	95.57	69.94	53.92	<u>71.76</u>	<u>96.87</u>	14.25	7.70	99.99	22.04	66.48	50.65	67.26	96.45
Unet	<u>63.46</u>	<u>46.57</u>	78.67	<u>95.68</u>	<u>71.03</u>	<u>55.23</u>	69.19	96.83	15.96	8.68	<u>99.98</u>	22.87	<u>68.94</u>	<u>53.32</u>	<u>69.57</u>	<u>96.68</u>
Hi-ERMNet	77.99	64.00	<u>77.72</u>	96.90	73.32	58.02	70.88	97.05	67.01	50.46	93.21	92.25	73.69	58.56	72.69	97.11

最优实验结果



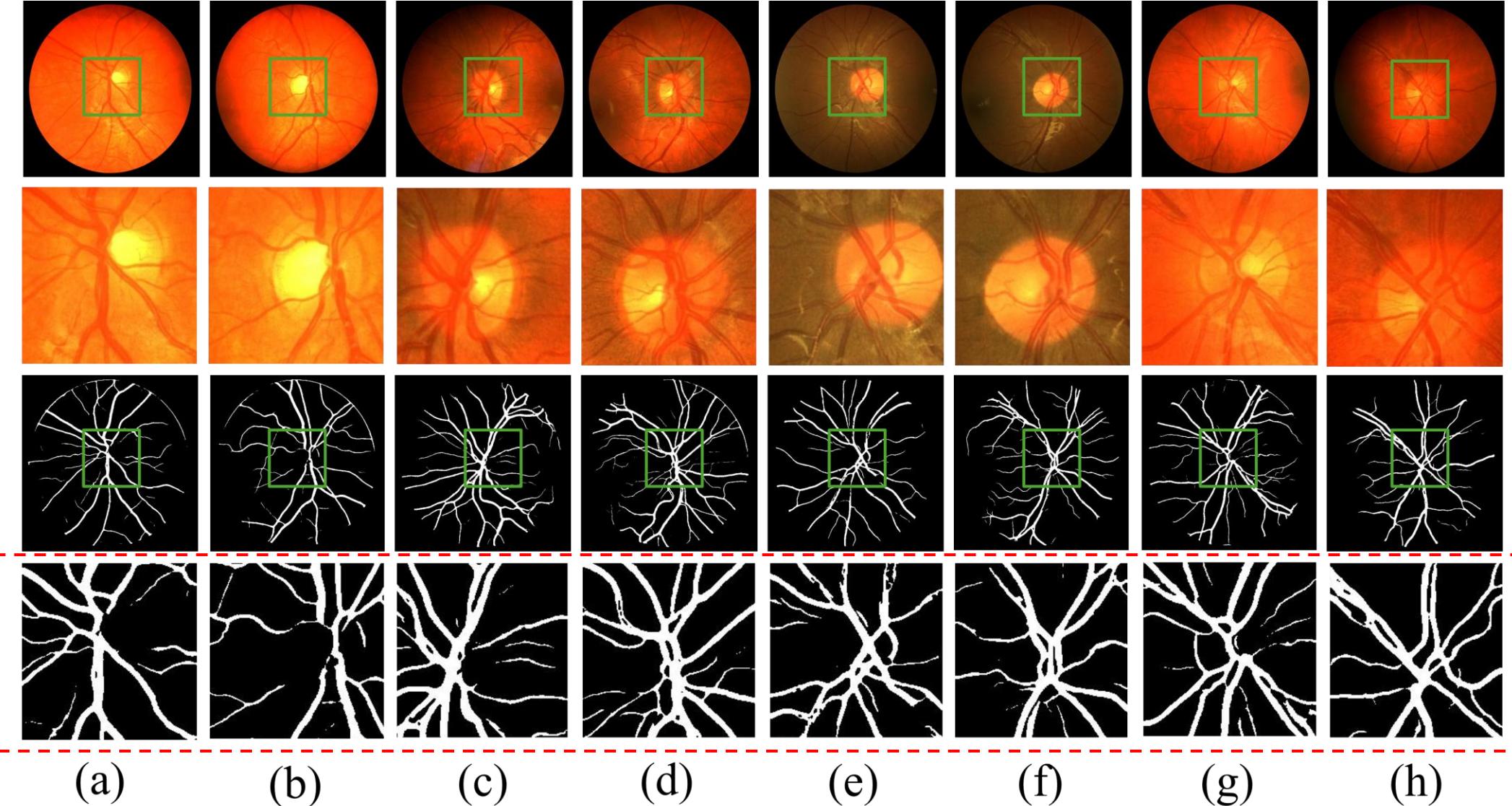
近期学习情况

➤ 与其他SOTA对比实验的可视化结果



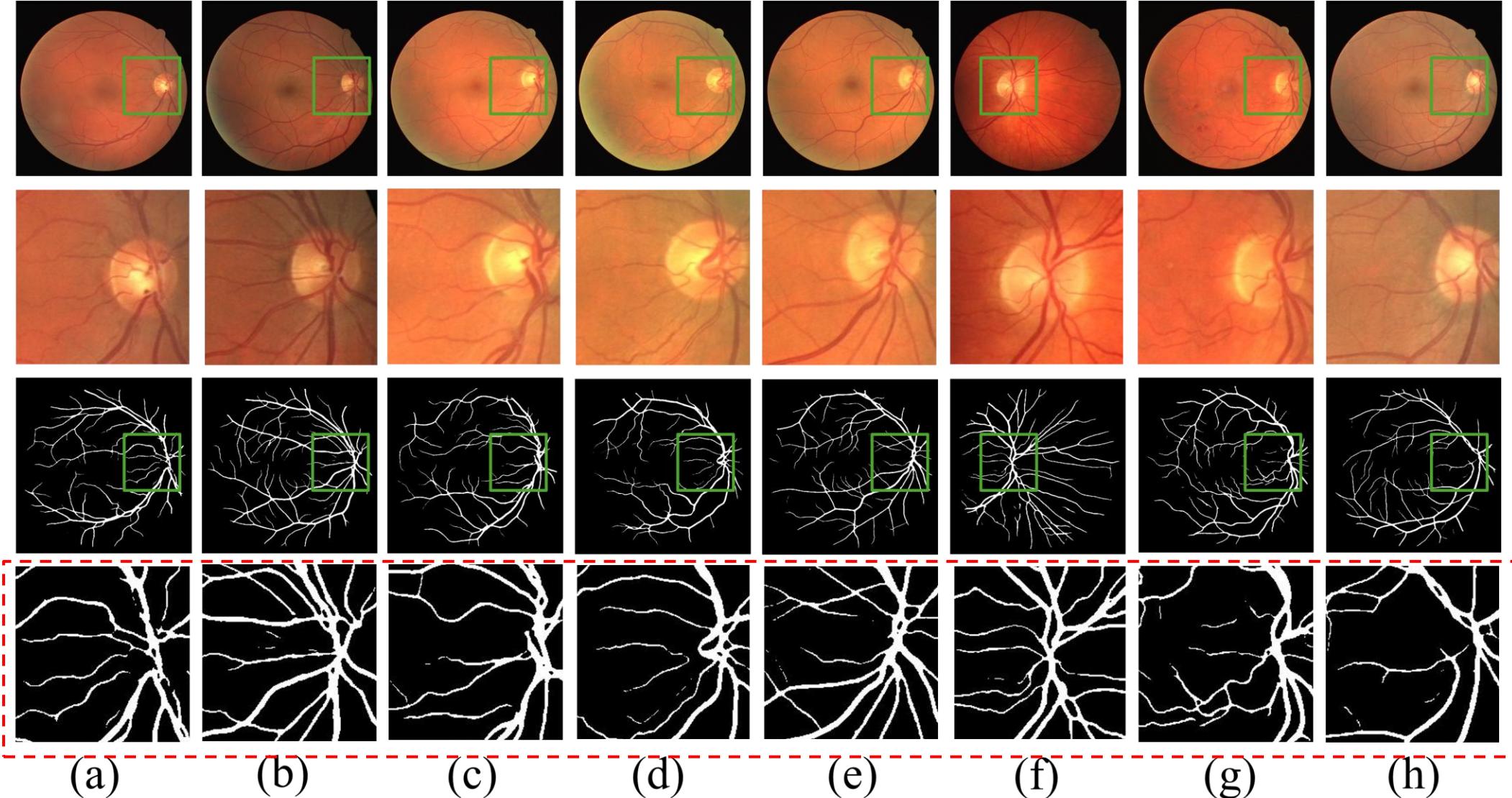
近期学习情况

➤ 在四种数据集上的可视化结果(CHASE_DB1)



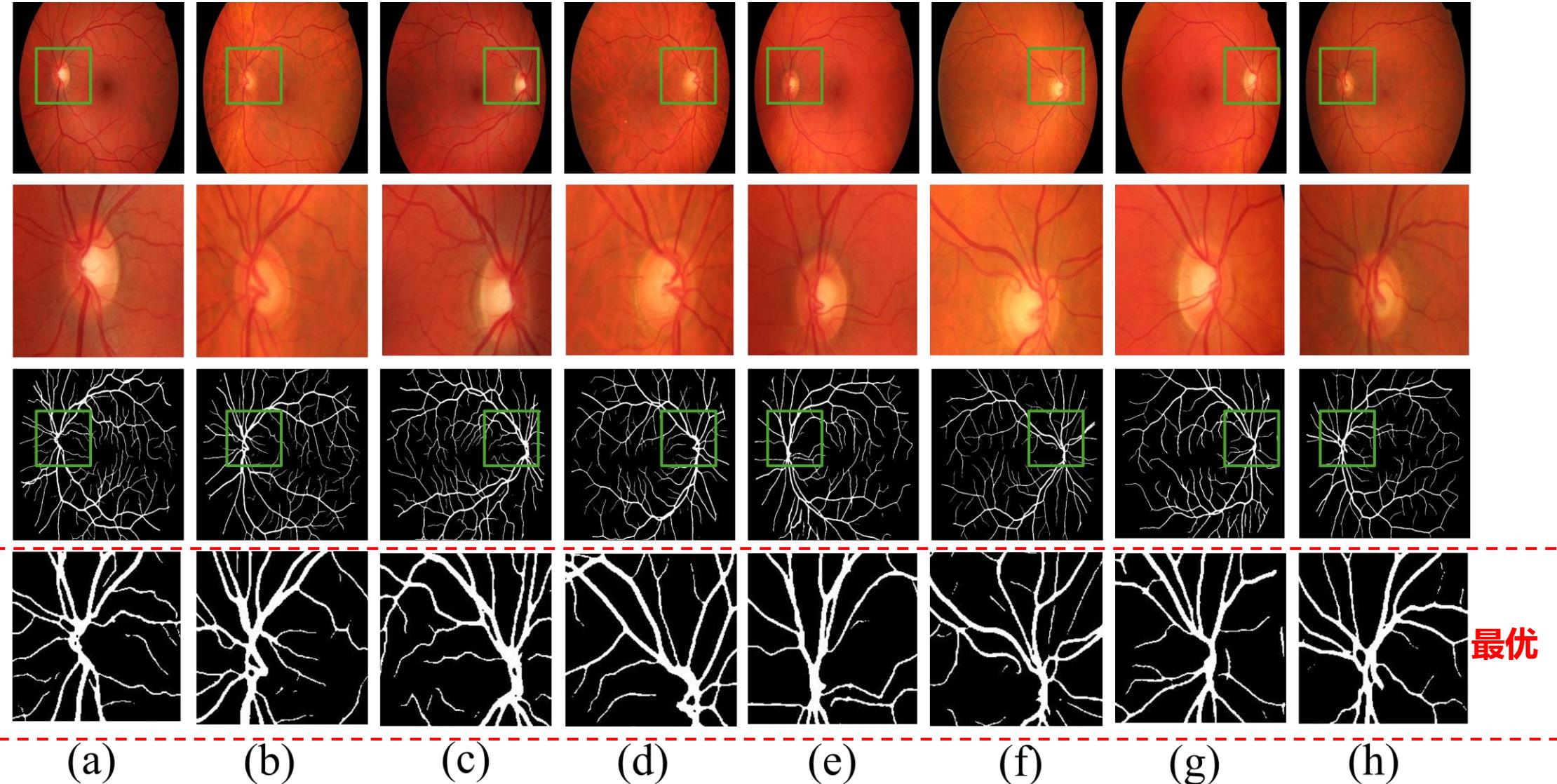
近期学习情况

➤ 在四种数据集上的可视化结果(DRIVE)



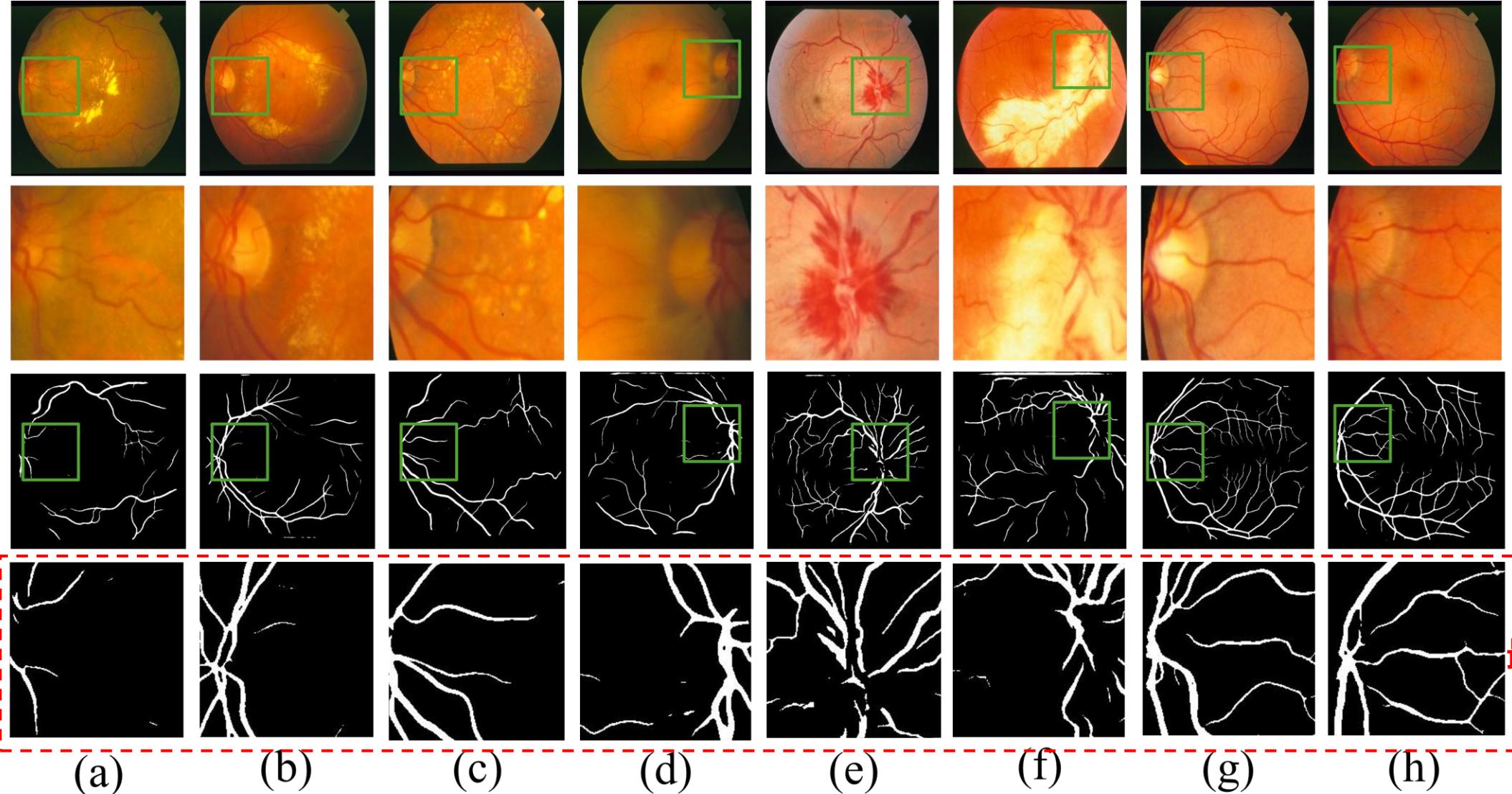
近期学习情况

➤ 在四种数据集上的可视化结果(HRF)



近期学习情况

➤ 在四种数据集上的可视化结果(STARE)



- 实现多模态视网膜血管分割
- 将模型应用到其他的医学领域中，比如胶质瘤，心脏分割等
- 优化模型的参数量，引入的轻量化Transformer导致模型的参数量暴涨

Artificial Intelligence
Multi-modal Object Detection
Pattern Recognition

Medical Imaging

Brain Convolutional Networks
Feature Extraction
Image Analysis

MRI

Fusion PET Segmentation

Computer Vision

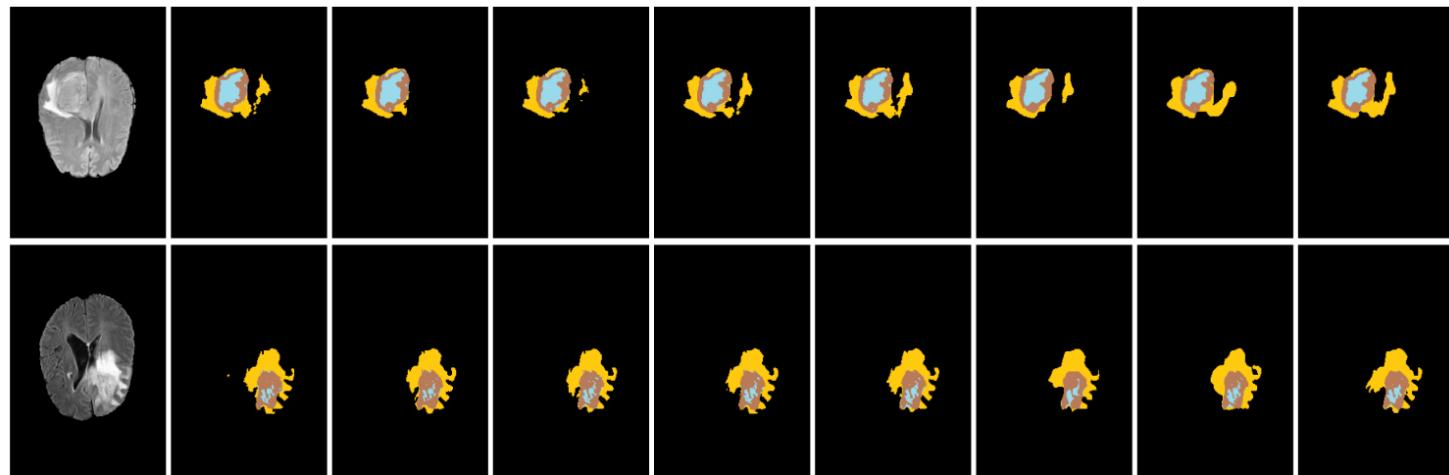
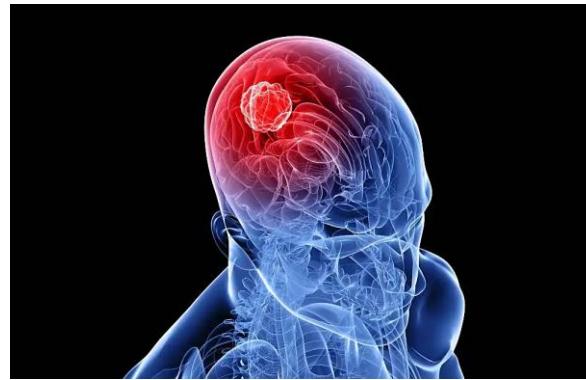
Deep Learning Transfer Learning

Diagnosis

总结

接下来的研究将关注**多模态脑肿瘤分割**

- 脑肿瘤：发病率高，致死率高，治愈率低
- MRI能够给医生提供脑组织的解剖结构信息，常用于检测脑肿瘤
- 脑肿瘤分割本质上是**3D多模态医学图像分割问题**



Thank you