

# 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

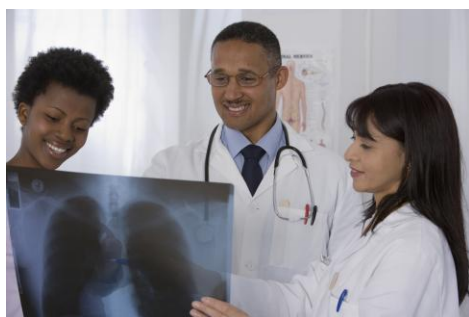


反映肿瘤功能及代谢

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

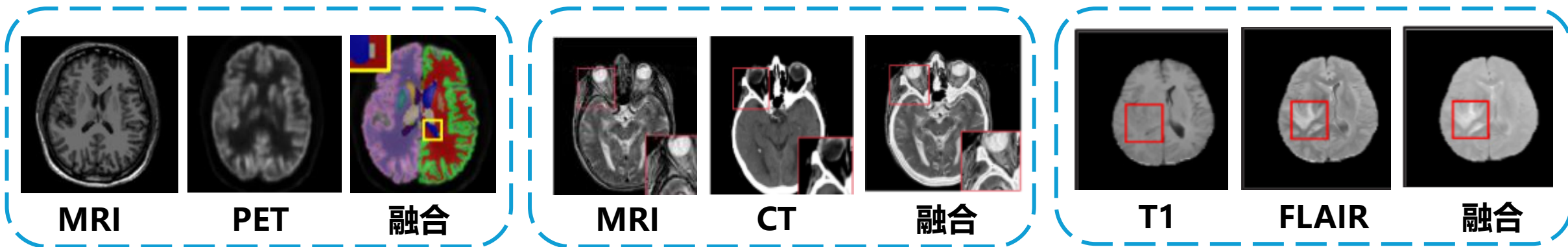


单模态数据提供的信息有限












**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

Hongyan Tang, Zhenxing Huang , Member, IEEE, Wenbo Li , Yaping Wu , Jianmin Yuan, Yang Yang , Yan Zhang, Jing Qin , Senior Member, IEEE, Hairong Zheng , Senior Member, IEEE, Dong Liang , Senior Member, IEEE, Meiyun Wang , and Zhanli Hu , Senior Member, IEEE

**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 quantitative results, with a Dice coefficient of  $85.73\% \pm 0.01\%$ , a Jaccard index of  $76.68\% \pm 0.02\%$ , a sensitivity of  $85.00\% \pm 0.01\%$ , a precision of  $83.26\% \pm 0.03\%$  and a Hausdorff distance (HD) of  $4.4885 \pm 14.85\%$ . 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

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利用**PET和MR图**  
**像的融合**实现对  
**大脑的自动分割**

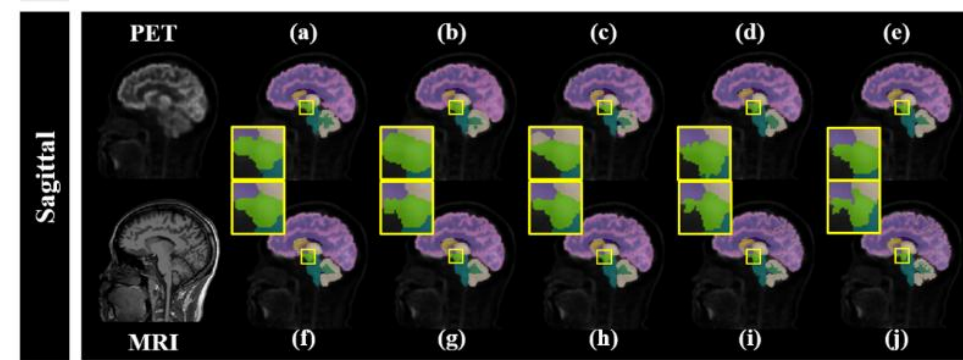
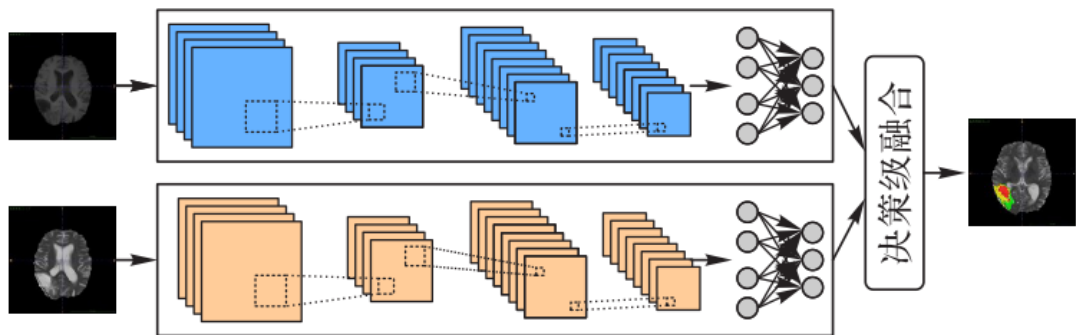
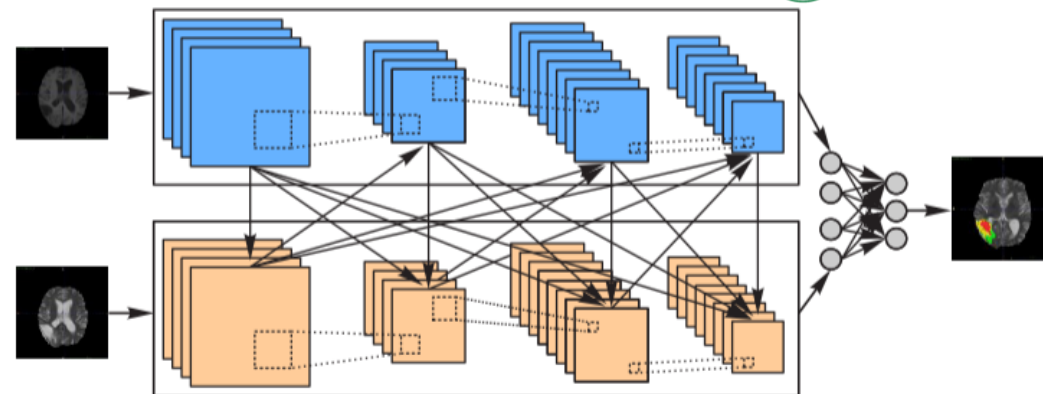


Fig. 2. Visualization of the whole-brain segmentation results shown in axial, coronal, and sagittal views. The method indices are as follows: (a) NestedUNet. (b) ResUNet. (c) VNet. (d) nnFormer. (e) UNETR. (f) SwinUNETR. (g) UNet3D. (h) 3DUXNET. (i) Ours. (j) GT.

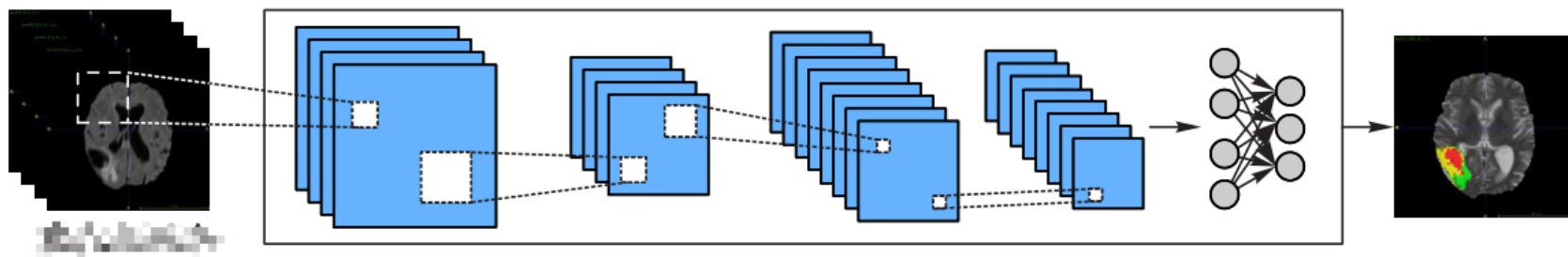
# 研究背景与意义



决策级融合（主流）



特征级融合（主流）

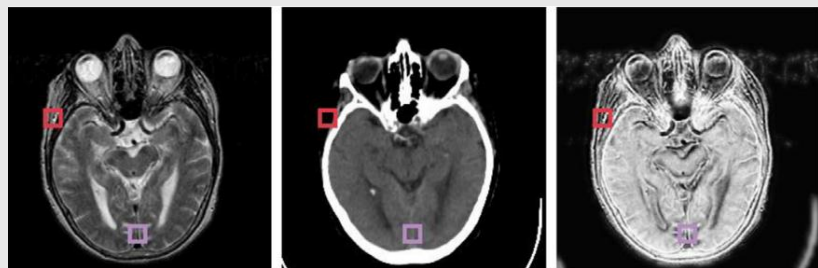


像素级融合

- 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**



模态一

模态二

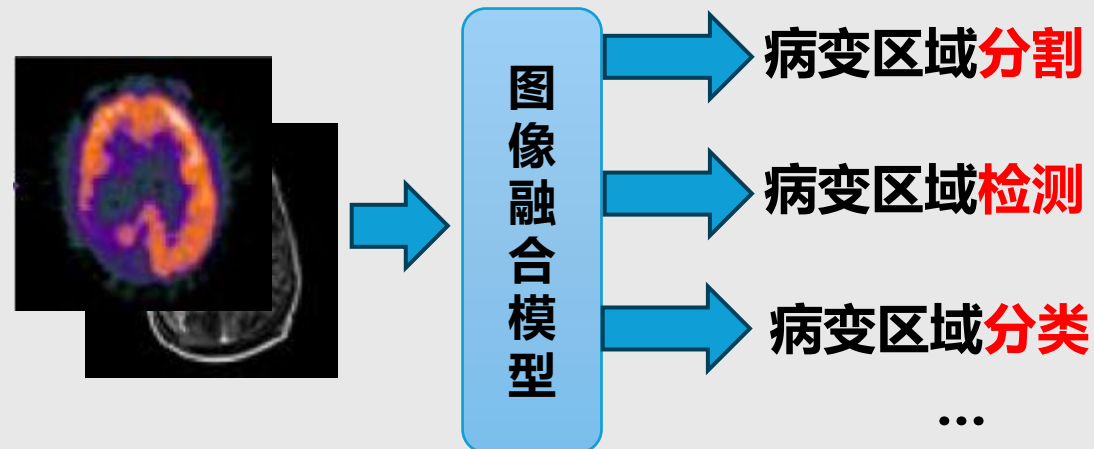
融合

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**



融合图像与下游的**垂直任务**没有关联

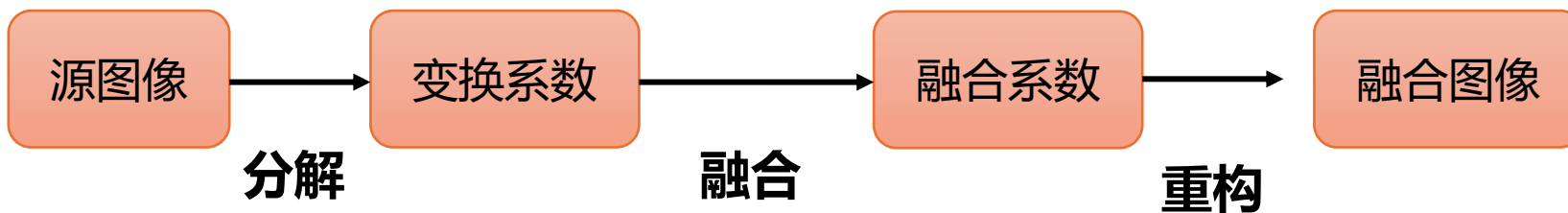


更精准的语义识别方法



# 传统的融合方法

## 经典框架



### ➤ 基于空间域的多模态医学图像融合方法

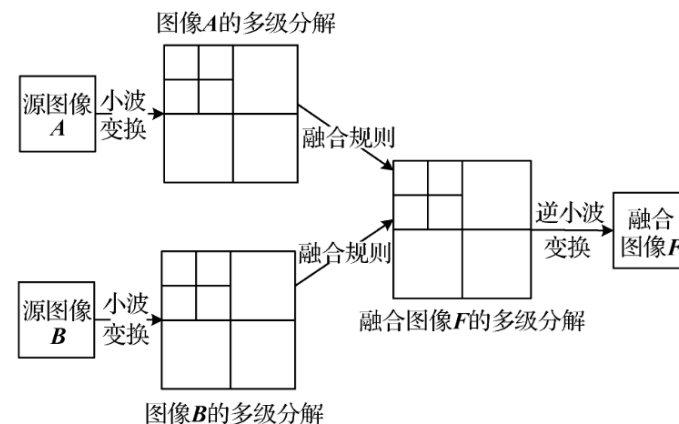
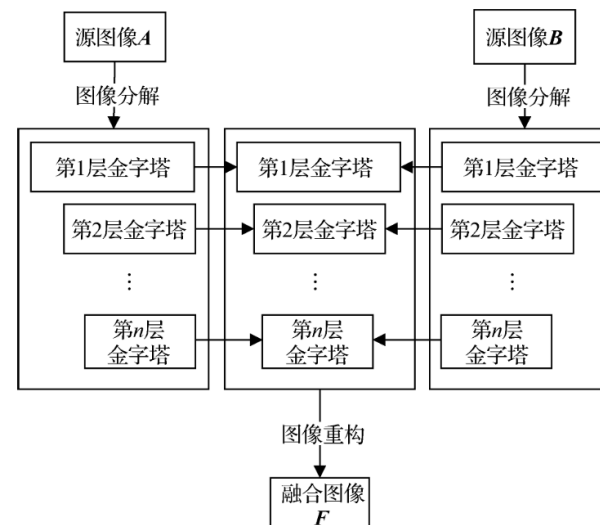
空间域技术利用基础的像素级策略,对图像中的像元值起作用,得到的图像表现出更少的空间失真和较低的信噪比

- 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。

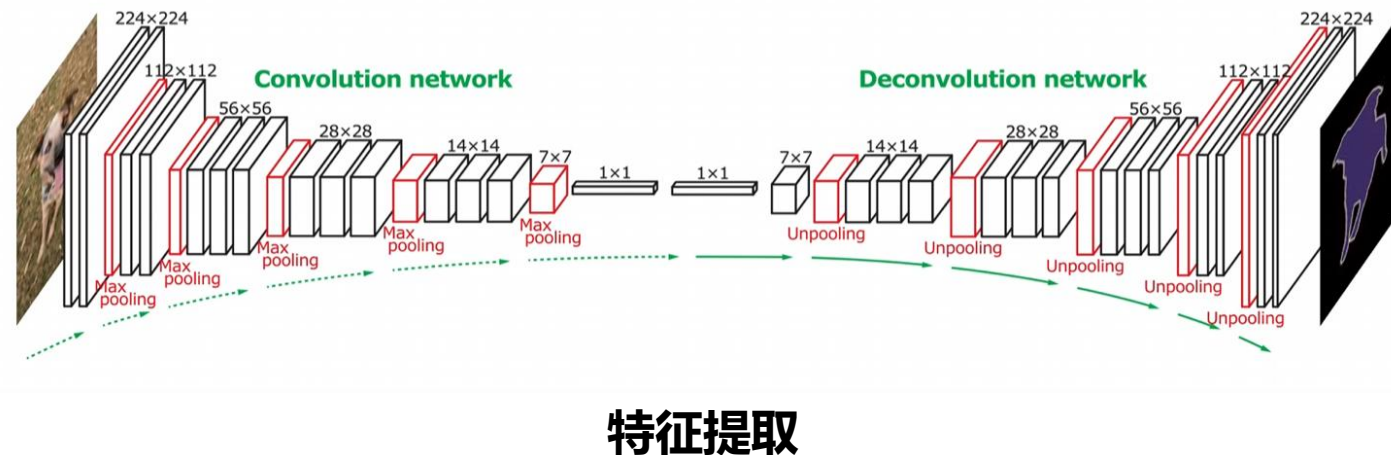
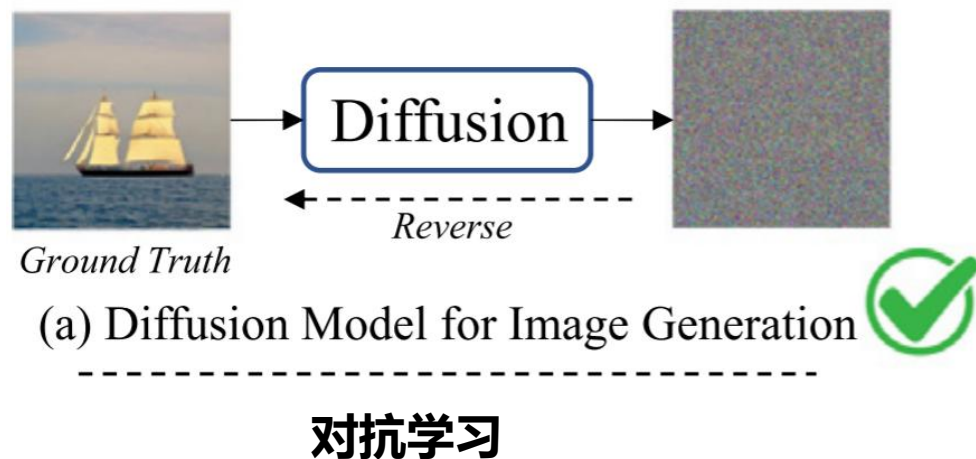
- 基于金字塔的变换: GP、LP、WP
- 基于小波变换: DWT、DTCWT、SWT
- 基于多尺度几何变换: NSCT、NSST



# 基于深度学习的融合方法

## 研究动机

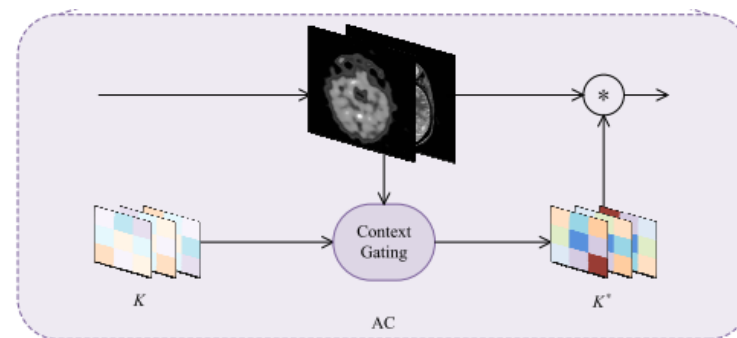
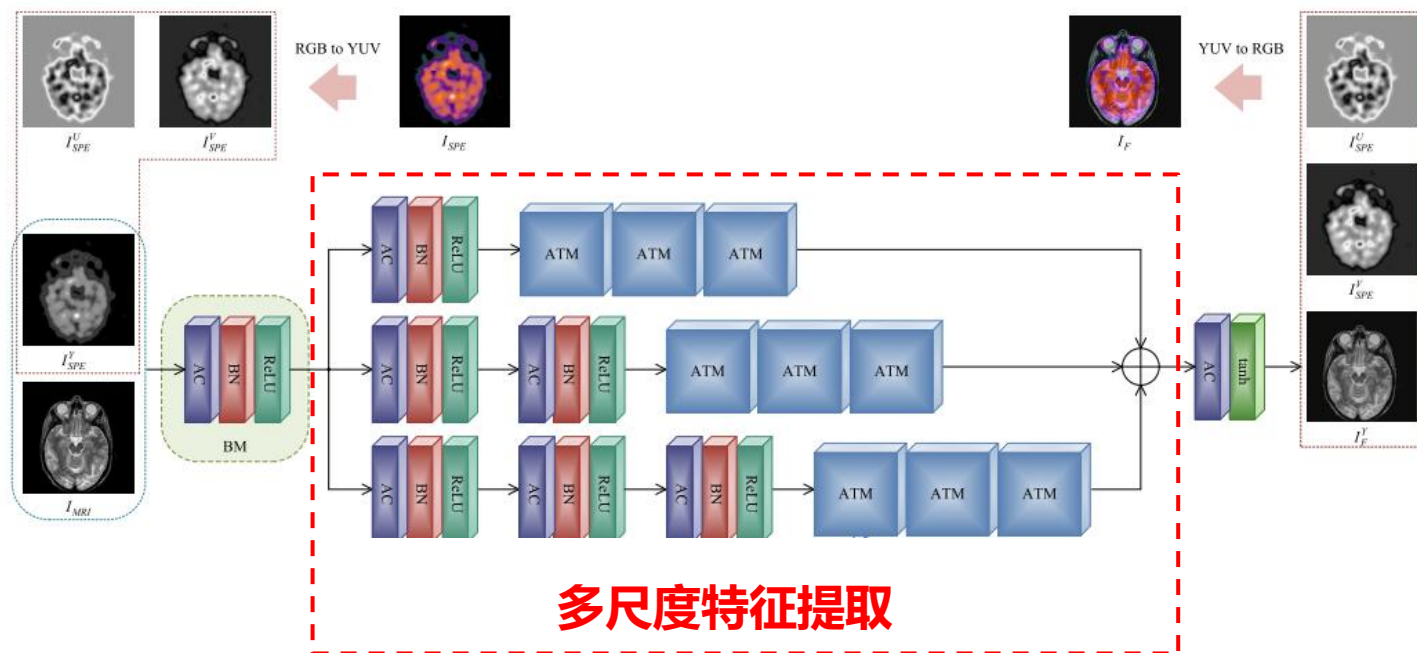
- 改进传统方法中**多尺度和空间变换**存在的局限性
- 传统方法的融合策略设计面临发展的瓶颈期,**深度学习**能够更有效地映射输入与输出之间的相关性
- **CNN**、**GAN**、**CSC**、**AE**、**RNN**、**RBM**



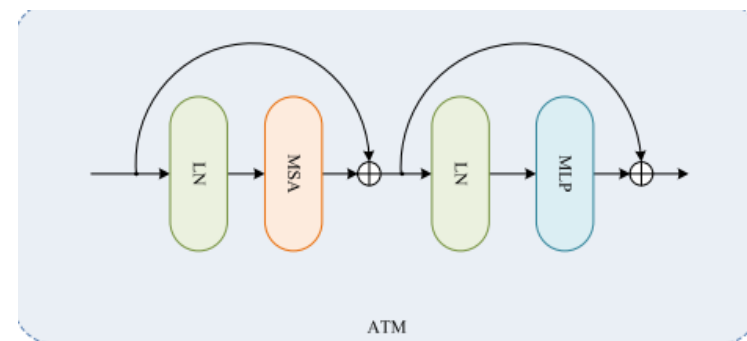
# 基于Transformer的融合方法

## 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

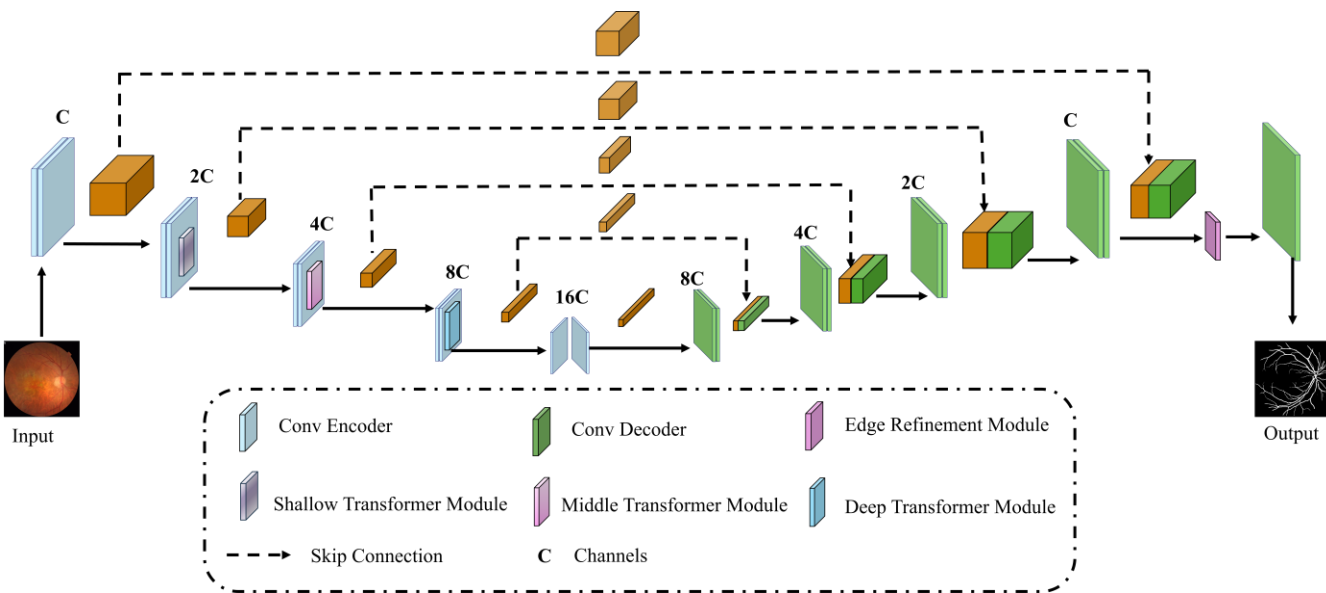


自适应Transformer模块ATM

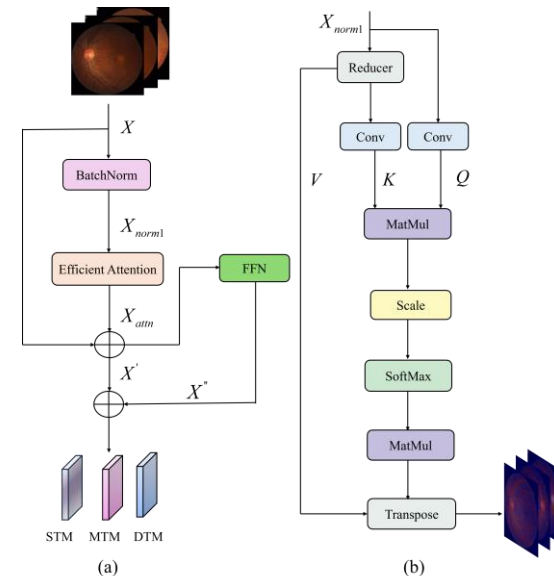


## Hi-ERMNet: Computationally Efficient Retinal Vasculature Segmentation via Lightweight Transformer Encoders and Edge Refinement Module

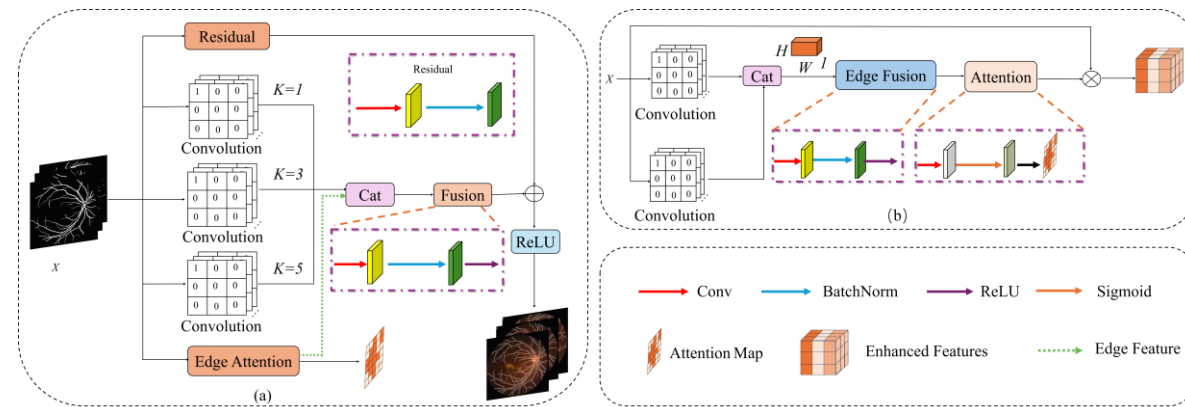
- 当前的**视网膜血管分割**方法主要关注粗血管，忽略了细小血管，本文提出**边缘优化模块**，专门处理细小血管的边缘像素



Hi-ERMNet



轻量化Transformer

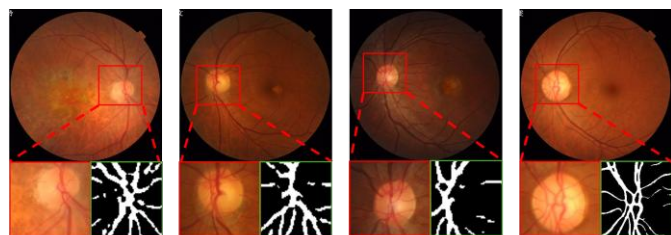


边缘优化模块ERM

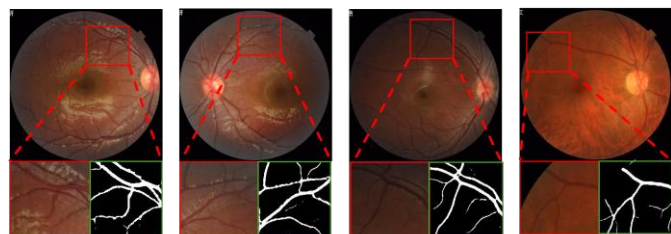
## ➤ 通过对比实验，分析实验结果

Method	CHASE_DB1				DRIVE				HRF				STARE			
	Dice	IoU	Prec.	Acc.	Dice	IoU	Prec.	Acc.	Dice	IoU	Prec.	Acc.	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	<b>77.96</b>	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	<b>92.87</b>	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	<b>99.99</b>	22.04	66.48	50.65	67.26	96.45
Unet	<u>63.46</u>	<u>46.57</u>	<b>78.67</b>	95.68	<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	<b>77.99</b>	<b>64.00</b>	<u>77.72</u>	<b>96.90</b>	<b>73.32</b>	<b>58.02</b>	70.88	<b>97.05</b>	<b>67.01</b>	<b>50.46</b>	93.21	92.25	<b>73.69</b>	<b>58.56</b>	<b>72.69</b>	<b>97.11</b>

## 最优实验结果



(a) (b) (c) (d)



(e) (f) (g) (h)

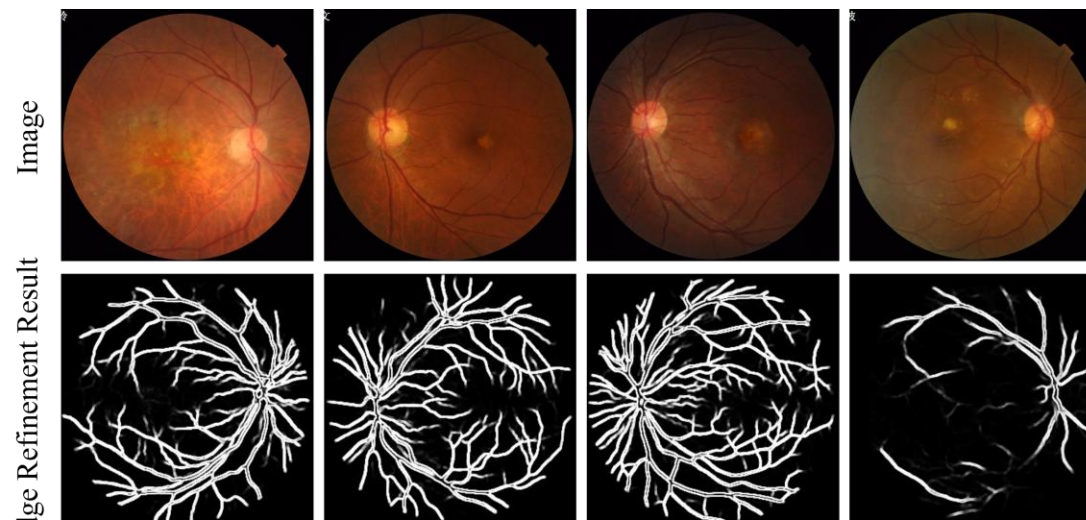
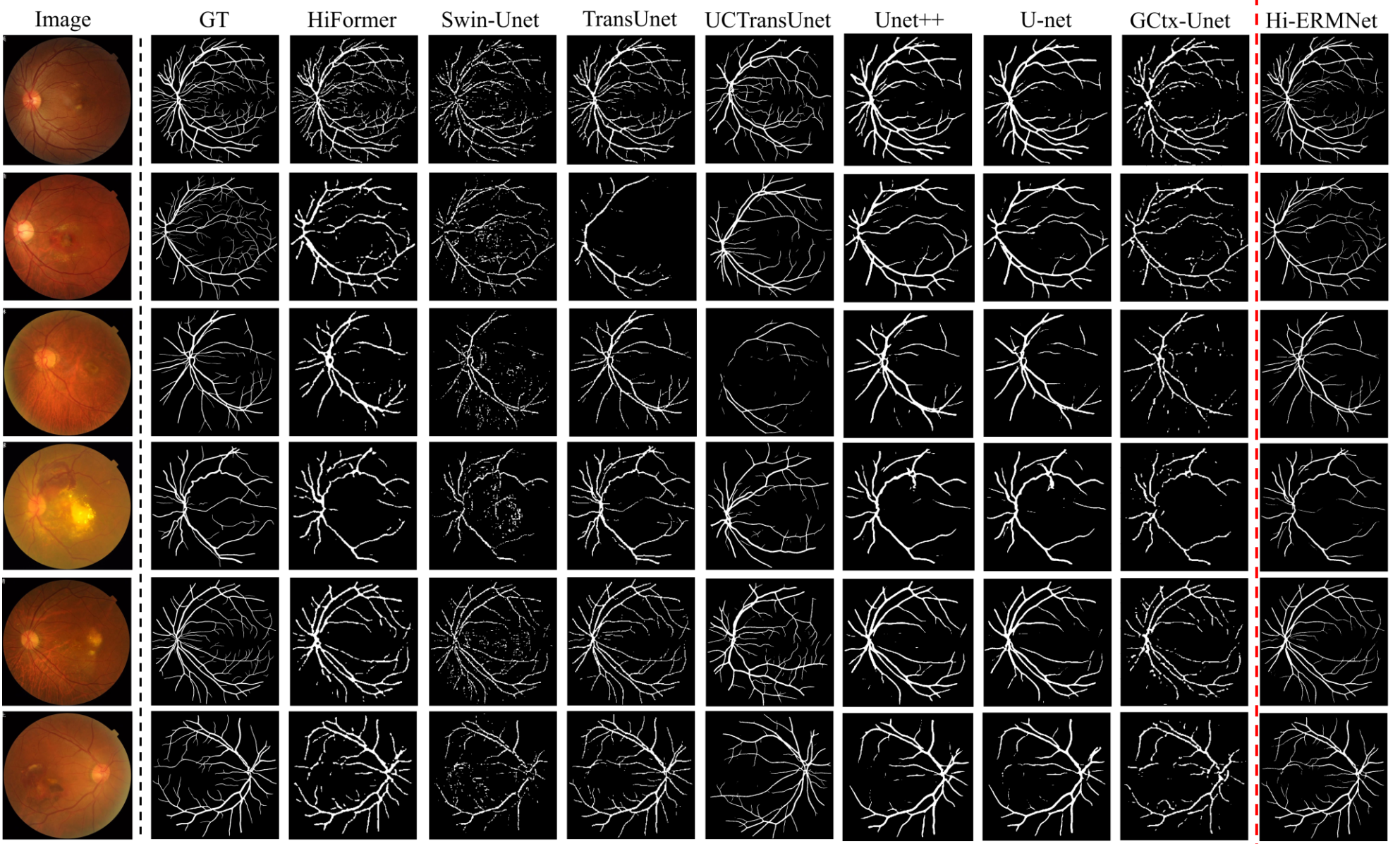


Image  
Edge Refinement Result



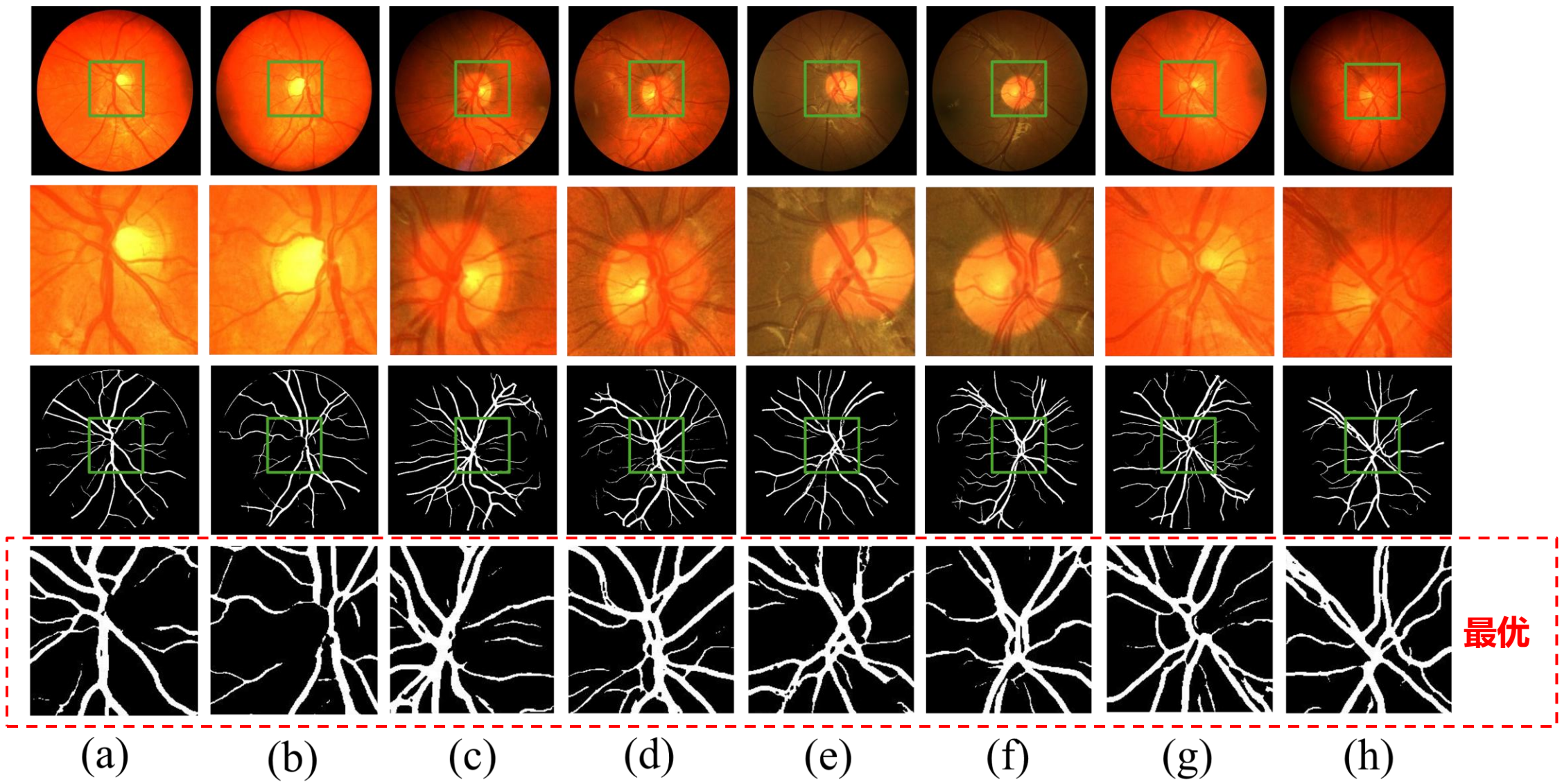
## ➤ 与其他SOTA对比实验的可视化结果



最优

# 近期学习情况

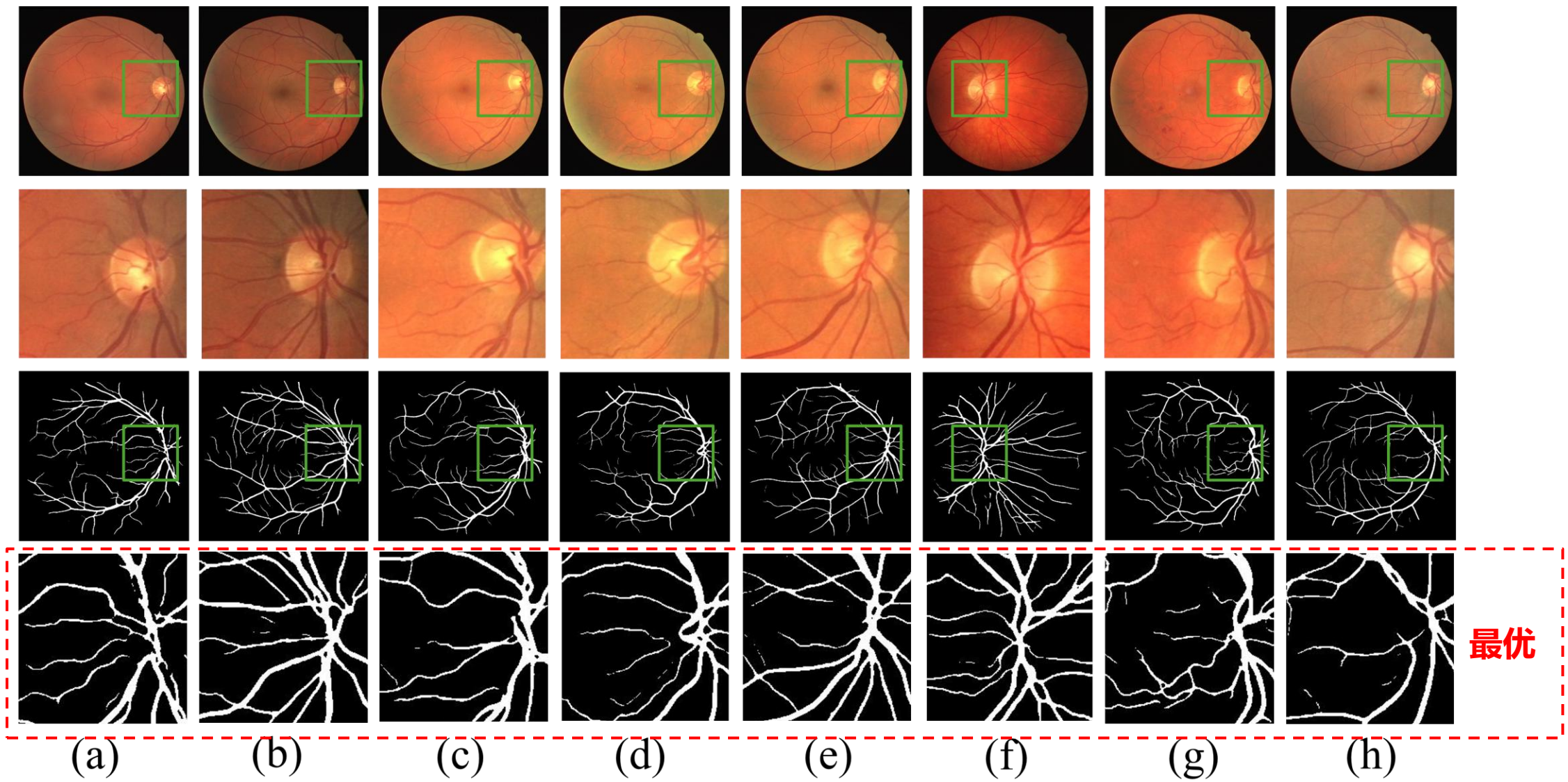
## ➤ 在四种数据集上的可视化结果(CHASE\_DB1)





# 近期学习情况

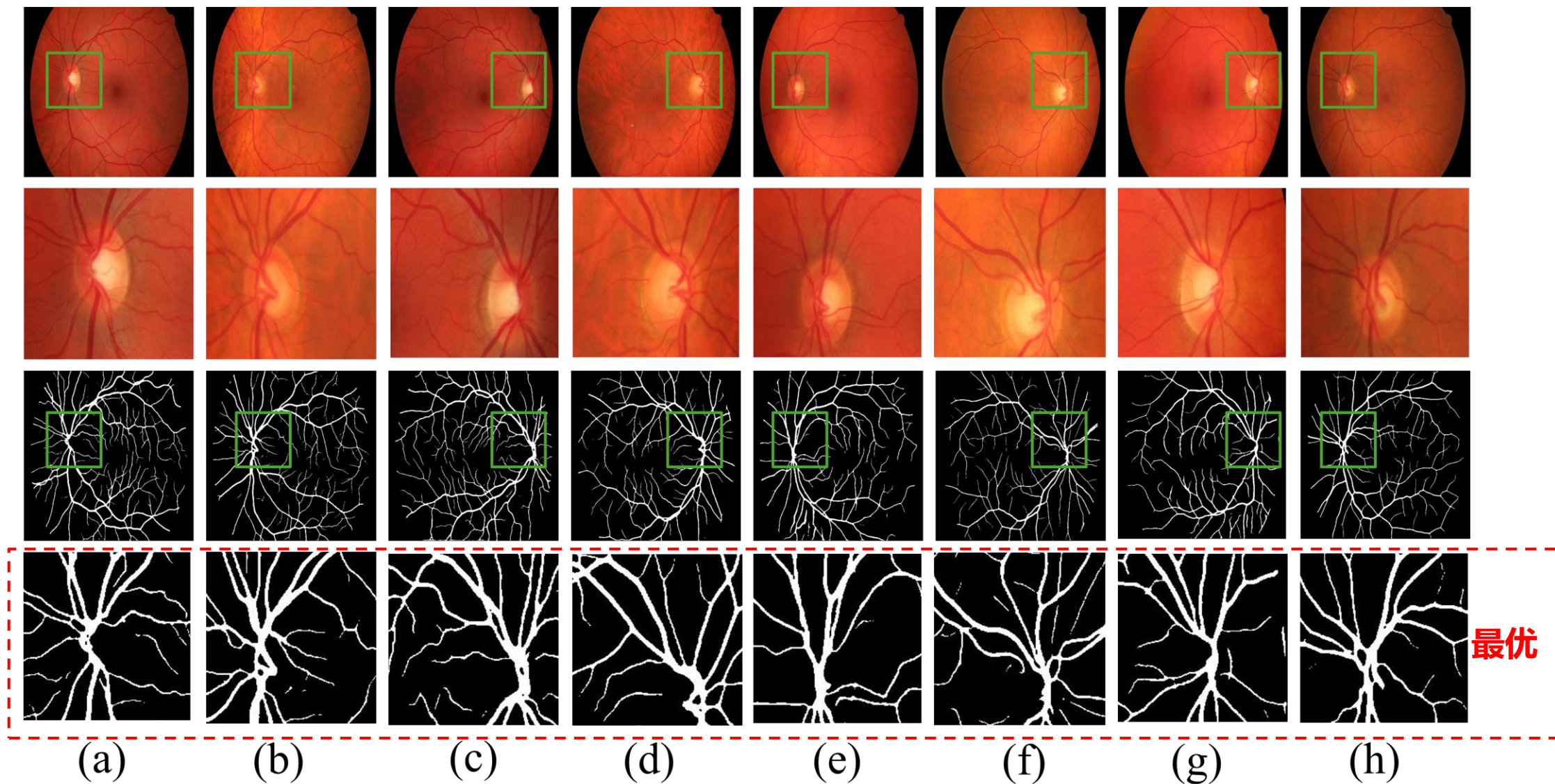
## ➤ 在四种数据集上的可视化结果(DRIVE)





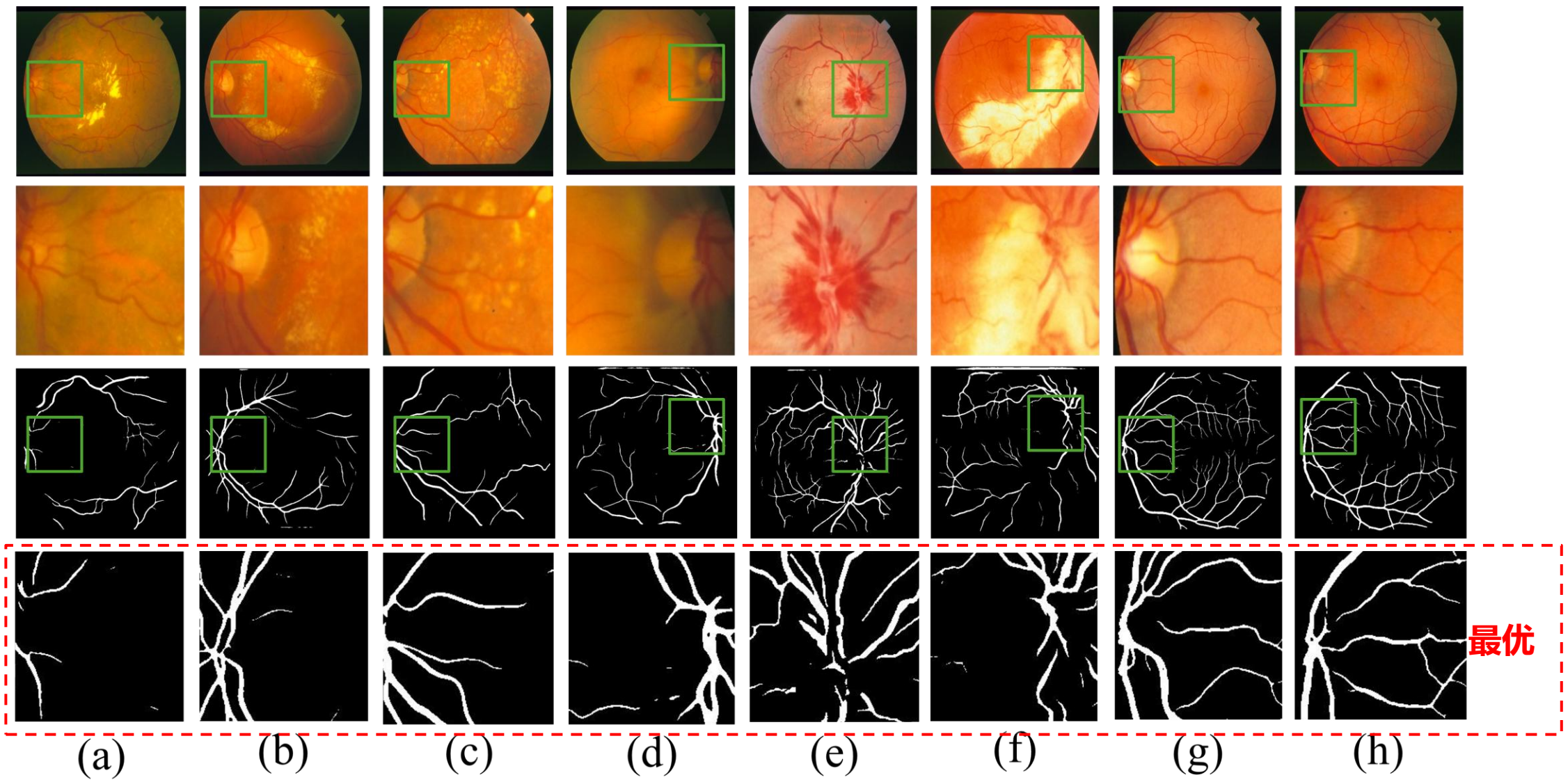
# 近期学习情况

## ➤ 在四种数据集上的可视化结果(HRF)



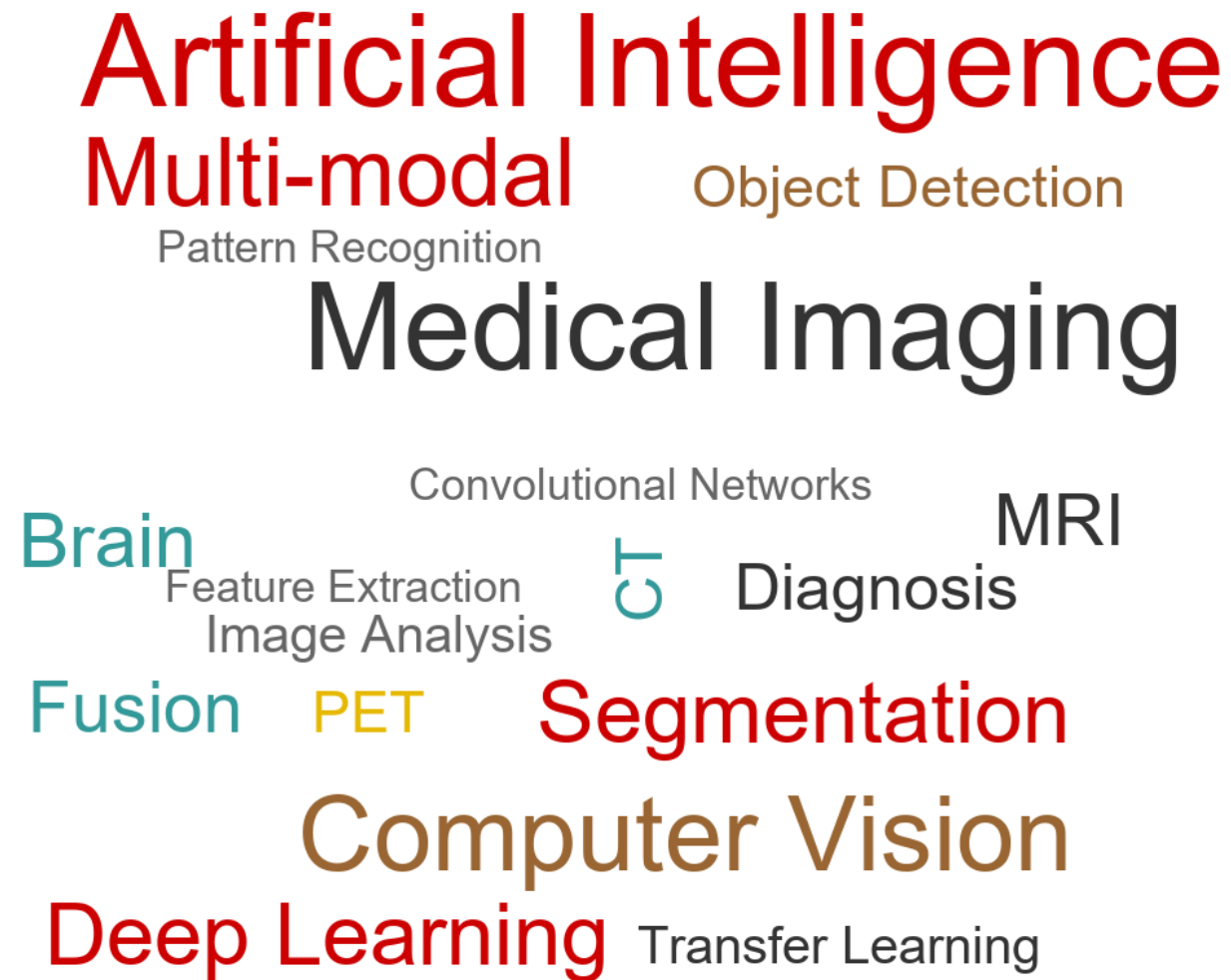
# 近期学习情况

## ➤ 在四种数据集上的可视化结果(STARE)



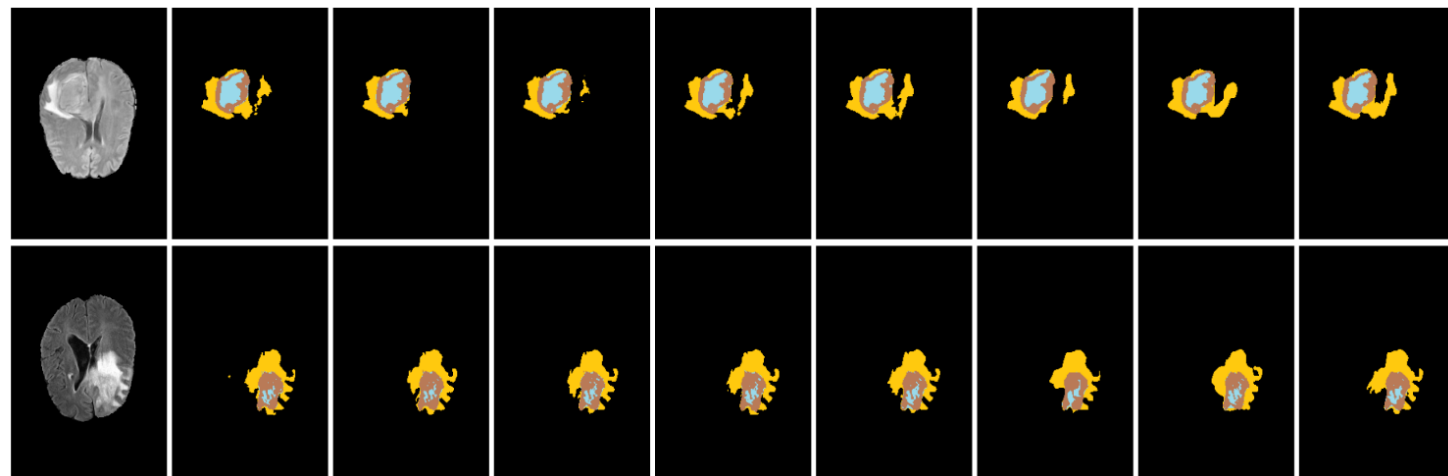
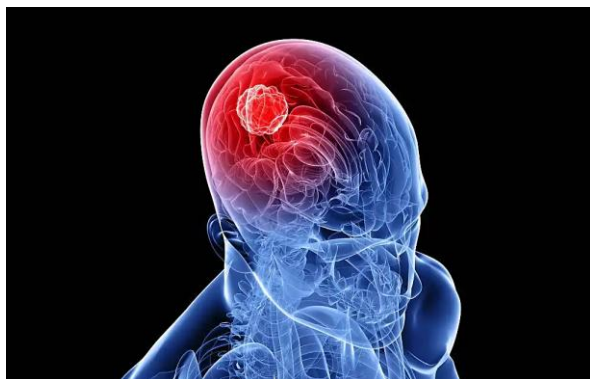


- 实现**多模态**视网膜血管分割
- 将模型应用到其他的医学领域中，比如**胶质瘤，心脏分割**等
- 优化模型的**参数量**，引入的轻量化  
Transformer导致模型的参数量暴涨



## 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**