Unified Medical Lesion Segmentation via Self-referring Indicator

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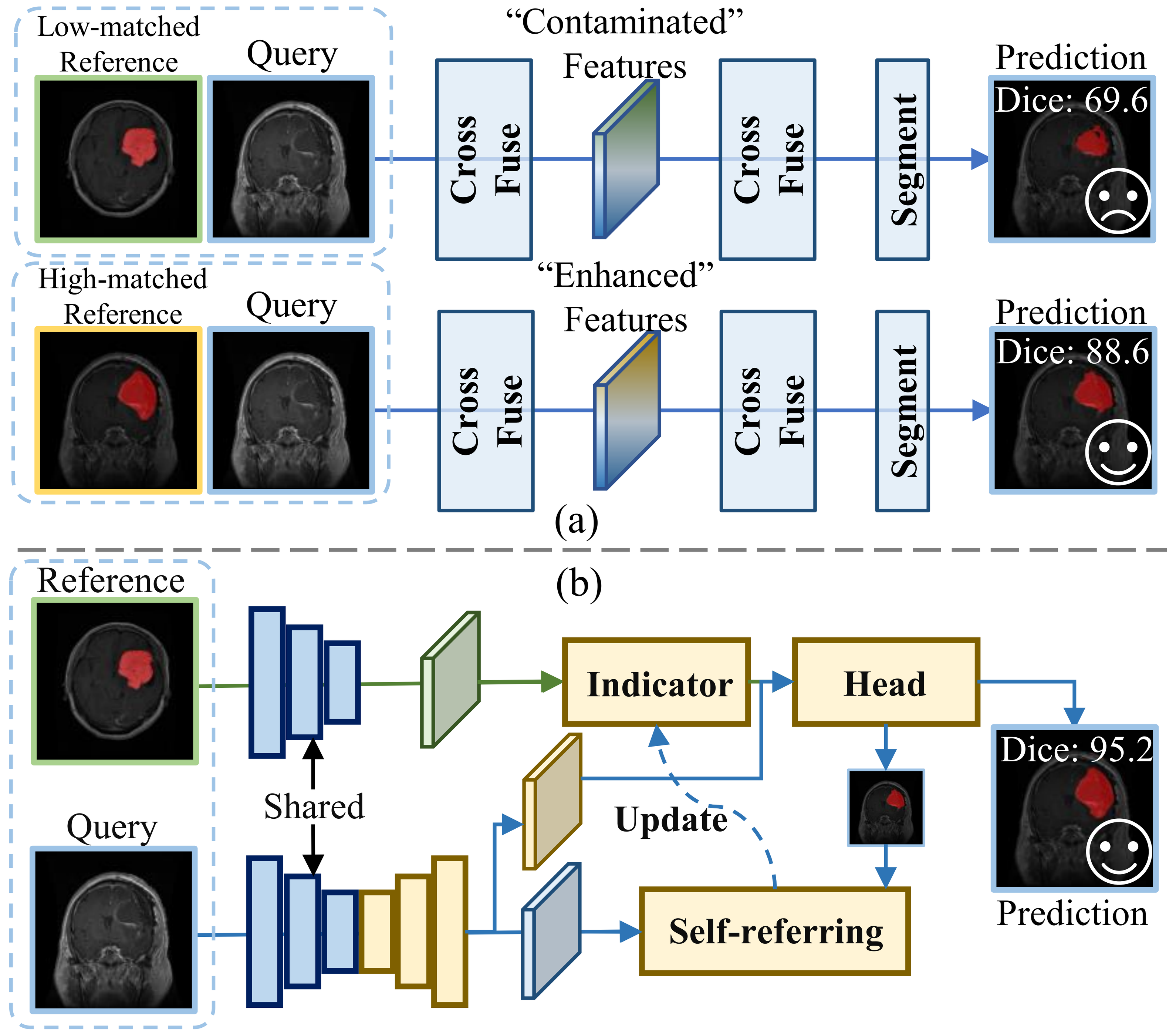
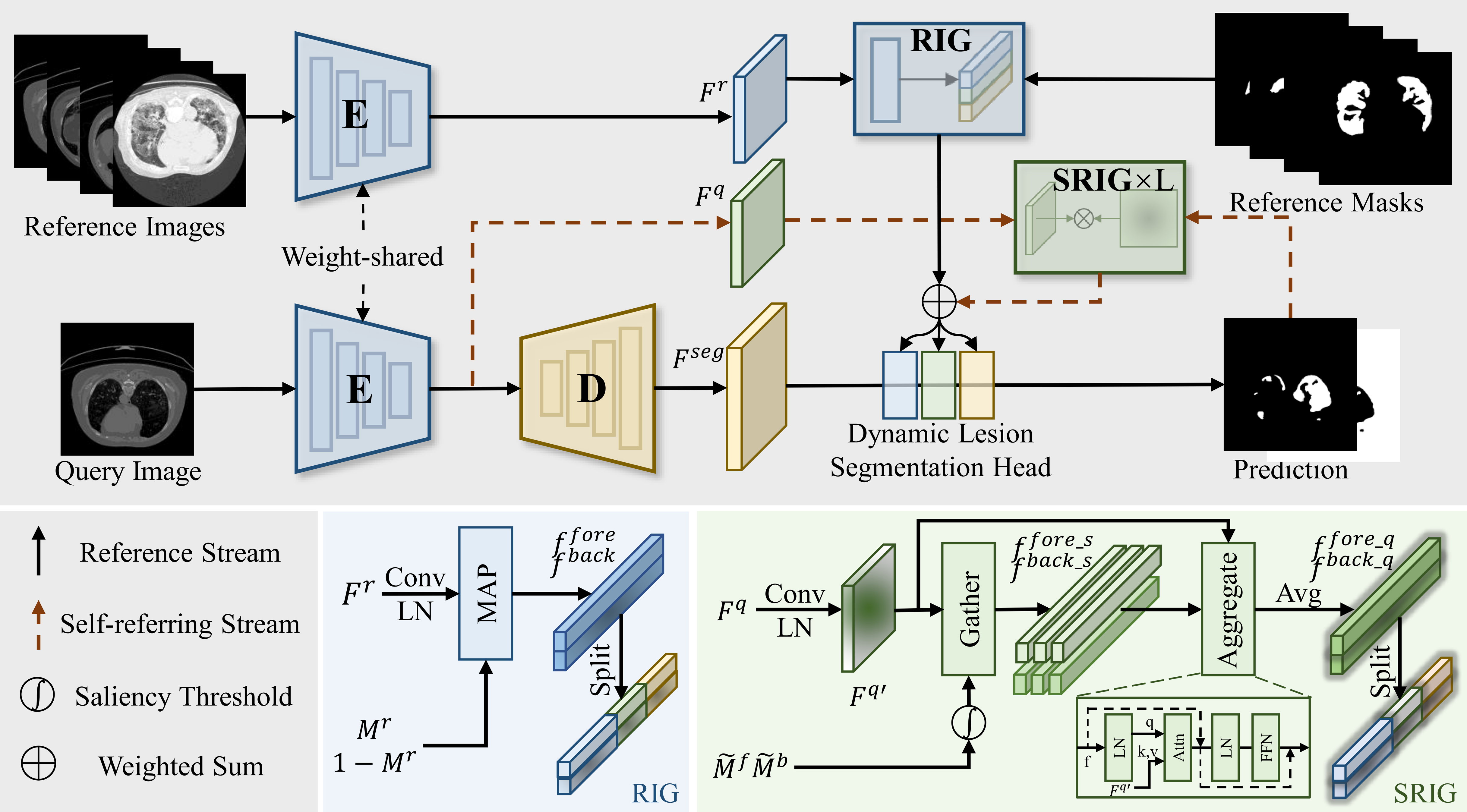
Motivation/Contributions



- We propose a self-referring mechanism that adaptively extracts information from the query itself to overcome the negative impact caused by low-matched reference sets.
- We design reference indicator generation to efficiently utilize reference information instead of cross-fusion mechanisms which heavily rely on reference sets, facilitating the self-referring mechanism.
- Our designs successfully apply ICL to unified MLS. SR-ICL has impressive performance even with weak reference annotations such as boxes and points. Furthermore, it has relatively low memory requirements during training.

Method: SR-ICL

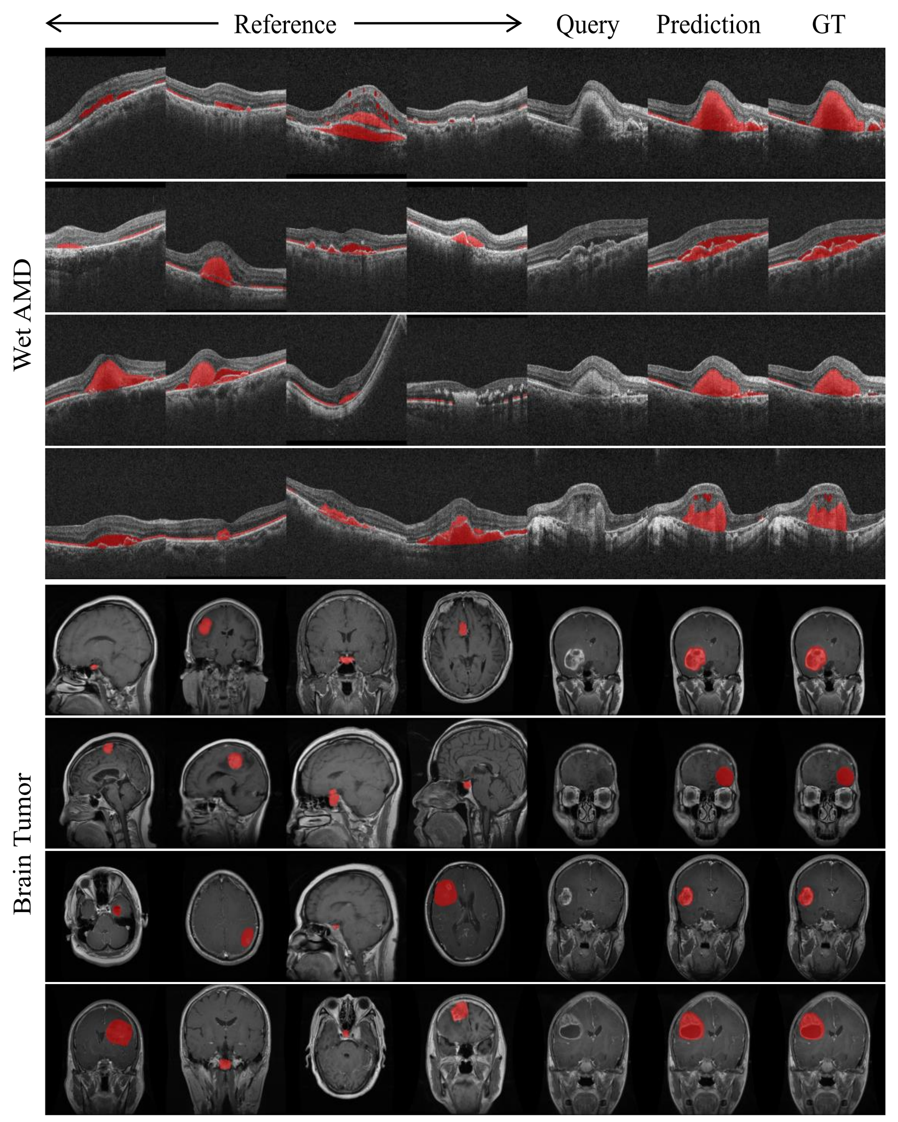


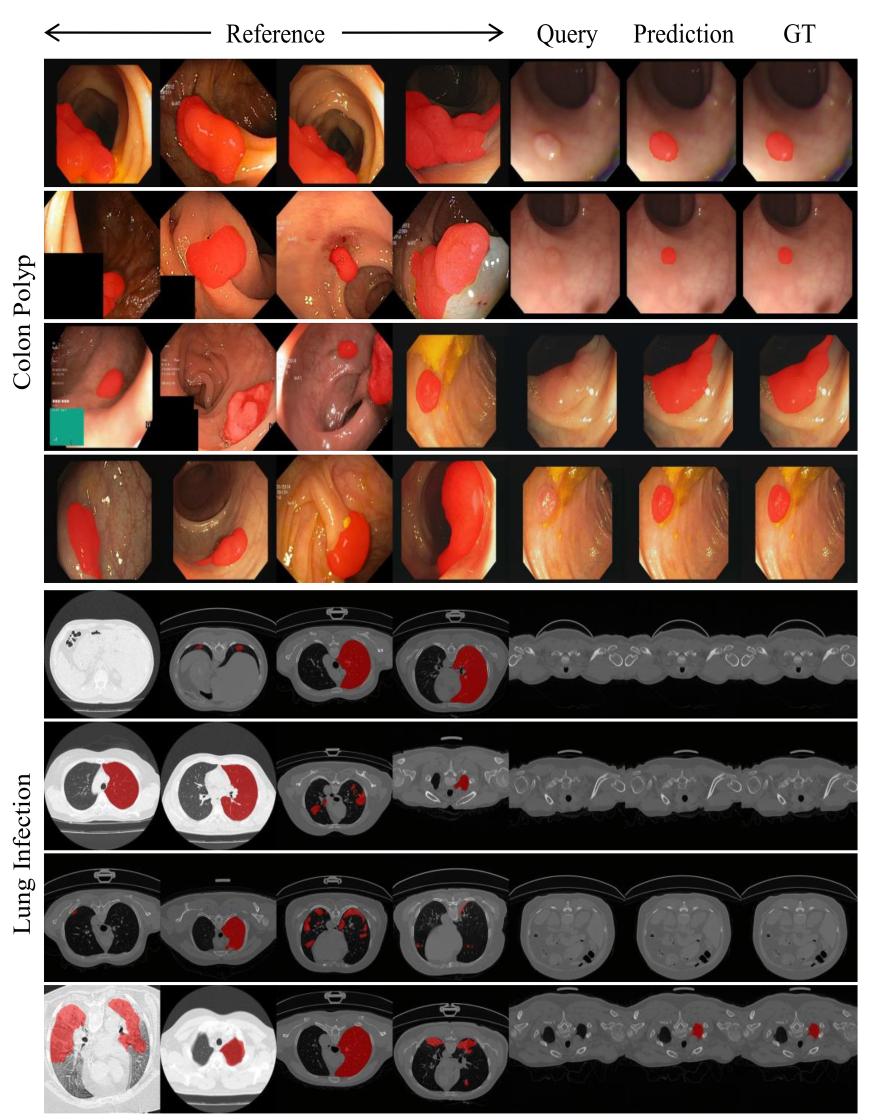
Algorithm 1 "Separate BP - Average Update"

Training iteration with $N = 12$ and $B = 1$.

Require: A batch $D = \{D_t\}_{t=1}^{8}$ and $Q = \{Q_t\}_{t=1}^{8}$. D_t and Q_t are N and B image-mask pairs randomly selected from training set of task t.

```
create reference image tensor I_r ∈ R^{8×N×3×H×W} from D
create reference mask tensor M_r ∈ R^{8×N×1×H×W} from D
create query image tensor I_q ∈ R^{8×B×3×H×W} from Q
create query mask tensor M_q ∈ R^{8×B×1×H×W} from Q
avg_grads ← []                                   // empty list
for each param in SR-ICL.parameters() do
    zero_tensor ← torch.zeros_like(param)
    avg_grads.append(zero_tensor)
end for
L ← 0
for t ← 1, 8 do
    R_t^I ← I_r[t, ...]                          // reference images
    R_t^M ← M_r[t, ...]                          // reference masks
    P_t^I ← I_q[t, ...]                          // query images
    P_t^M ← M_q[t, ...]                          // query masks
    P_t ← SR-ICL(R_t^I, R_t^M, P_t^I)            // get prediction
    L ← Loss(P_t, P_t^M)
    zero_grad(Optimizer)
    backward(L)                                  // get gradients
    for each (avg_grad, param) in (avg_grads, SR-ICL.parameters()) do
        avg_grad ← avg_grad + param.grad
    end for
end for
for each (param, avg_grad) in (SR-ICL.parameters(), avg_grads) do
    param.grad ← (avg_grad / 8)                  // average gradients
end for
step(Optimizer)                                  // update parameters
```





Results:

Methods	Methods	Wet AMD Dice	Wet AMD mIoU	Brain Tumor Dice	Brain Tumor mIoU	Adenocarcinoma Dice	Adenocarcinoma mIoU	Thyroid Nodule Dice	Thyroid Nodule mIoU	Polyp Dice	Polyp mIoU	Lung Infection Dice	Lung Infection mIoU	Breast Lesion Dice	Breast Lesion mIoU	Skin Lesion Dice	Skin Lesion mIoU
Specialized Models (One model for one task)																	
TRSRD-Net [2]	ICISN24	-	-	-	-	-	-	85.40	84.65	-	-	-	-	-	-	-	-
LDNet [57]	MICCAI22	-	-	-	-	-	-	-	-	64.25	74.41	-	-	-	-	-	-
WeakPolyp [52]	MICCAI23	-	-	-	-	-	-	-	-	74.90	80.66	-	-	-	-	-	-
Inf-Net [16]	TMI20	-	-	-	-	-	-	-	-	-	-	43.24	52.85	-	-	-	-
DECOR-Net [19]	ISBI23	-	-	-	-	-	-	-	-	-	-	40.25	69.49	-	-	-	-
AAU-Net [8]	TMI22	-	-	-	-	-	-	-	-	-	-	-	-	47.45	65.15	-	-
CMU-Net [44]	ISBI23	-	-	-	-	-	-	-	-	-	-	-	-	54.52	83.02	-	-
MALUNet [36]	BIBM22	-	-	-	-	-	-	-	-	-	-	-	-	-	-	86.32	85.37
EGE-UNet [37]	MICCAI23	-	-	-	-	-	-	-	-	-	-	-	-	-	-	85.88	84.98
UNet [35]	MICCAI15	76.01	80.88	60.44	73.79	91.94	75.33	80.16	83.94	66.29	75.20	54.59	71.10	70.04	75.71	85.93	81.69
TransUNet [9]	MIA24	76.72	81.29	57.92	72.46	91.85	74.23	78.24	82.90	66.41	75.52	43.89	65.33	75.67	80.62	86.40	82.53
RollingUNet [27]	AAAI24	77.13	81.54	61.38	74.71	92.26	75.05	78.96	83.17	69.20	78.33	62.75	76.36	73.84	79.59	87.68	85.04
Generalist Models (One model performs new tasks without fine-tuning)																	
SegGPT [50]	ICCV23	39.42	62.68	24.43	58.61	73.60	61.71	21.33	57.64	60.62	74.05	26.08	58.78	37.79	62.87	29.28	53.62
UniverSeg [5]	CVPR23	45.90	63.66	32.83	61.29	80.85	45.66	60.95	73.63	29.31	53.46	39.98	65.21	65.51	74.16	77.16	76.01
DSC-ICL [18]	TMI24	-	-	-	-	-	-	76.03	-	-	-	-	-	71.88	-	81.51	-
Unified Models (One model for all tasks)																	
UNet [35]	MICCAI15	75.29	80.46	54.95	70.35	91.21	72.66	78.41	82.88	60.31	70.24	47.87	66.66	74.83	79.30	86.88	82.89
TransUNet [9]	MIA24	75.46	80.43	56.59	71.77	90.34	69.16	78.57	83.21	55.81	66.21	36.68	61.62	74.66	79.53	86.14	80.67
RollingUNet [27]	AAAI24	76.46	81.11	60.48	74.43	92.17	71.62	82.26	85.24	62.48	74.53	68.63	79.05	77.58	82.16	87.30	83.92
SegGPT [50]†	ICCV23	71.66	78.64	44.17	67.30	94.24	80.14	79.69	85.18	78.29	84.66	50.10	65.91	78.87	83.87	87.90	85.42
Spider [61]†	ICML24	78.51	82.66	71.59	79.86	93.65	80.30	86.52	88.40	80.66	85.30	73.85	82.07	81.16	84.80	88.79	87.18
Ours	-	**80.54**	**83.84**	**74.29**	**81.50**	**94.96**	**81.98**	**87.91**	**89.18**	**83.26**	**86.53**	**82.36**	**87.21**	**84.92**	**87.08**	**90.85**	**87.29**

Segmentation Task	Dataset	Modality	#Train	#Val
Wet AMD	AMD-SD [20]	OCT	2346	703
Brain Tumor	BTD [10, 11]	MR-T1	2298	766
Adenocarcinoma	EBHI-Seg [39]	Pathology image	636	159
Thyroid Nodule	TNUI 2021 [63]	Ultrasound	966	276
Colon Polyp	Five datasets [4, 23, 40, 43, 47]	Endoscopy image	1450	798
Lung Infection	COVID-19 data [16]	CT	894	383
Breast Lesion	BUSI [1]	Ultrasound	486	161
Skin Lesion	ISIC 2018 [13]	Dermoscopy image	1886	808

Method	Task Number	Batchsize	Memory
Balance FP - Unify BP	8	6/2	16.8G
Balance FP - Unify BP	8	12/4	OOM
Ours	8	6/2	5.7G
Ours	8	12/4	8.3G
Ours	16	12/4	8.3G

Conclusion

- The self-referring mechanism improves the robustness to the reference information.
- SR-ICL achieves good performance with weak annotations.
- The training strategy enables SR-ICL to balance any number of datasets even with one single RTX 3090 GPU.

Future Work

- Dynamic selection of the reference images.
- Large-scale pre-training on medical data.
- Extend to 3D medical segmentation dataset.