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Adaptive Learning of High-Value Regions for Semi-Supervised Medical Image Segmentation

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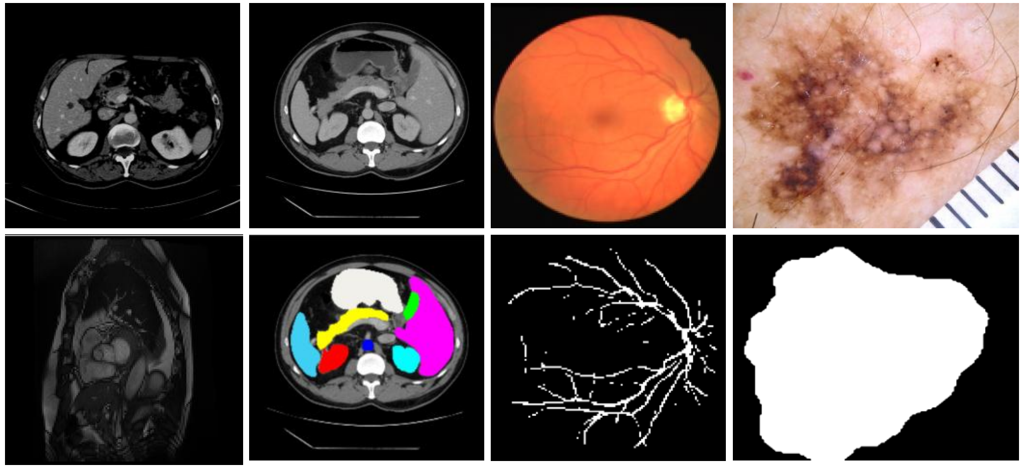
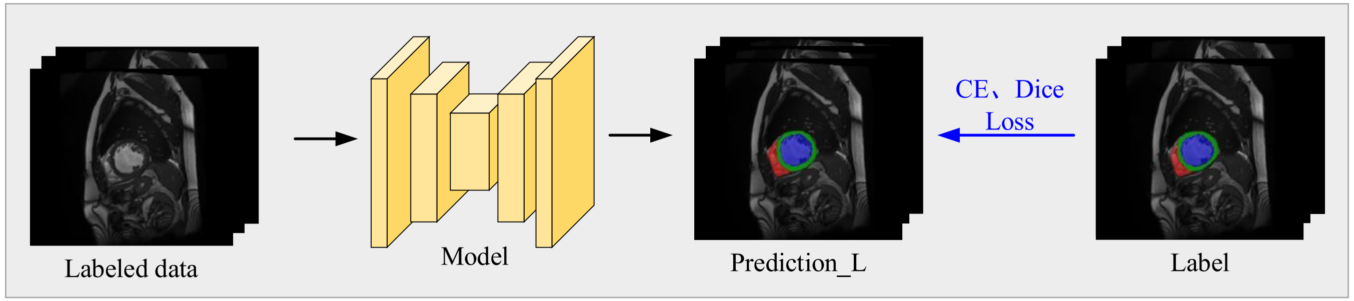
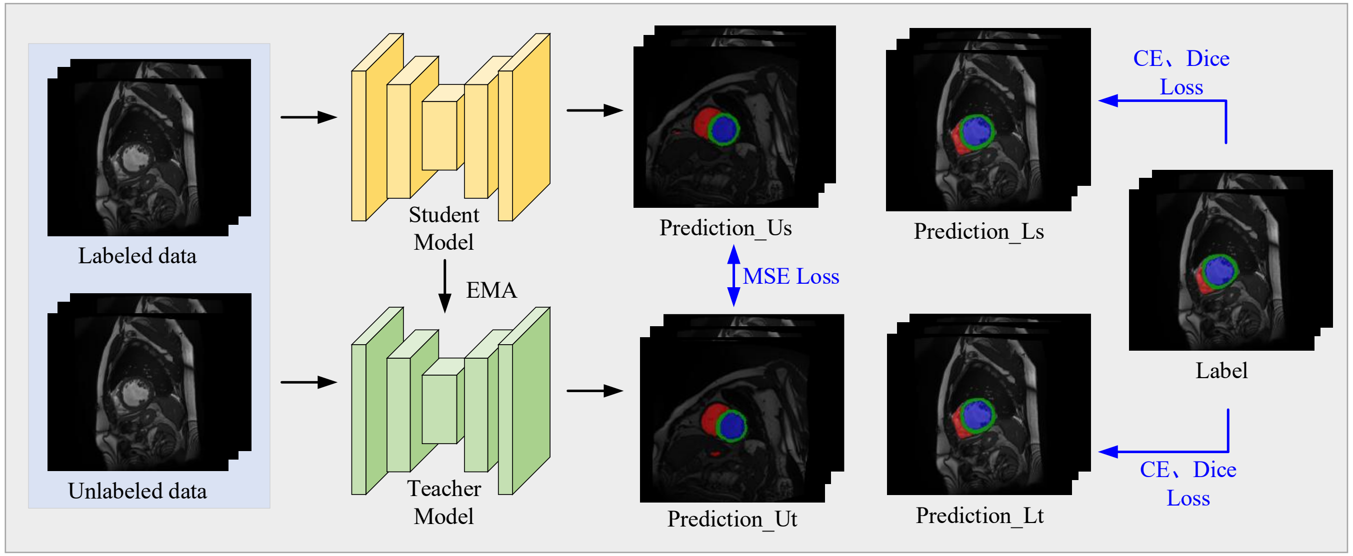
ALHVR: Background

Medical image segmentation is the process of automatically distinguishing and labeling different tissues or lesion regions in medical images.





- Supegrvised models require large labeled datasets
- Medical image labeling is costly and time-consumin

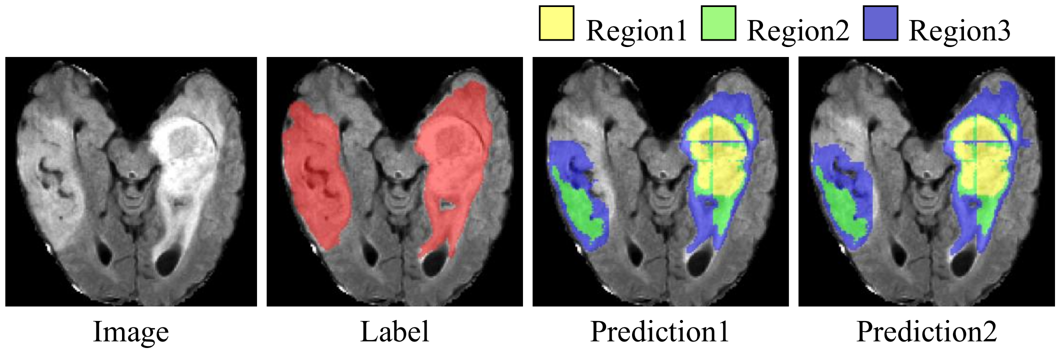


Importance of Medical Imaging:

- Reflects the internal structure of the human body
- Assists in disease diagnosis
- Supports surgical planning
- Enables postoperative evaluation

ALHVR: Motivation

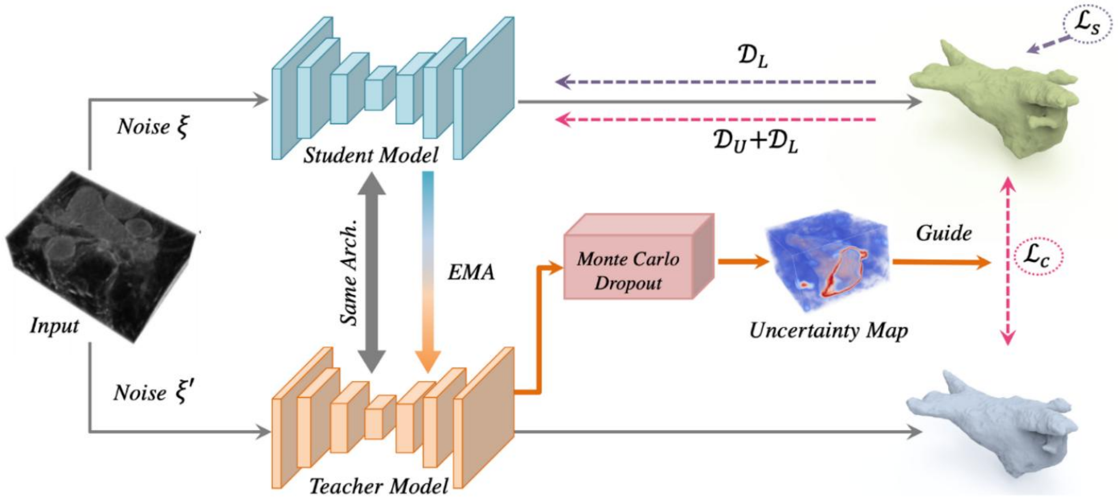
Motivation 1: Which regions have higher learning value for semi-supervised medical image segmentation?

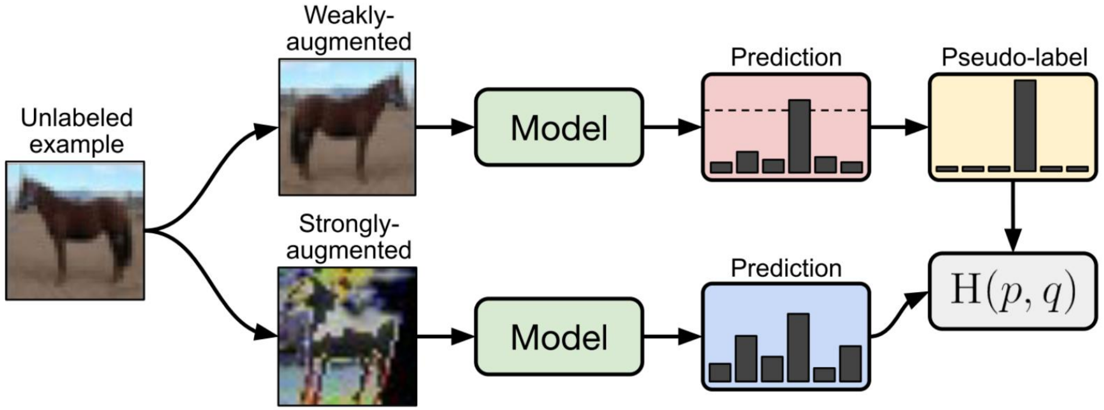


Region1: reliable and stable regions (**Easy regions**)

Region2: reliable and unstable regions (Harder regions)

Region3: unreliable and stable regions (Harder regions)





FixMatch focuses on Region 1 with high confidence

UA-MT focuses on Region 1 with low value of entropy

$$\mathcal{L}_c(f', f) = \frac{\sum_v \mathbb{I}(u_v < H) \, \|f'_v - f_v\|^2}{\sum_v \mathbb{I}(u_v < H)}$$

$$\ell_u = \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}(\max(q_b) \geq \tau) \, \mathrm{H}(\hat{q}_b, p_{\mathrm{m}}(y \mid \mathcal{A}(u_b)))$$

ALHVR: Motivation

Motivation 2: How to design different learning strategies for these various high-value regions?

Dataset	Region 1	Region 2	Region 3	Dice
ACDC	✓	✓	✓	85.34
	✓			$\boxed{87.13}$
		✓		$\boxed{88.46}$
			✓	$\boxed{88.20}$
	✓	✓		87.41
	✓		✓	82.51
		✓	✓	**88.58**

Table 1. Experimental results of training on the ACDC dataset with 10% labeled data using the CPS framework under different masked region settings.

Region1: reliable and stable regions (it is better than R1+R2+R3, Easy regions)
Region2: reliable and unstable regions (it is better than R1, Harder regions)
Region3: unreliable and stable regions (it is close to R2, Harder regions)

Discovery 1: harder regions have higher learning value

An example of image filtering:

- **High-frequency** information uses a **small filtering window**
- **Low-frequency** information uses a **large filtering window**

Discovery 2: different regions should use different strategies

Region2:

- One prediction is good while the other is poor, maybe we should use **the good one to supervise the poor one**. Besides, prototype provides global information

Region3:

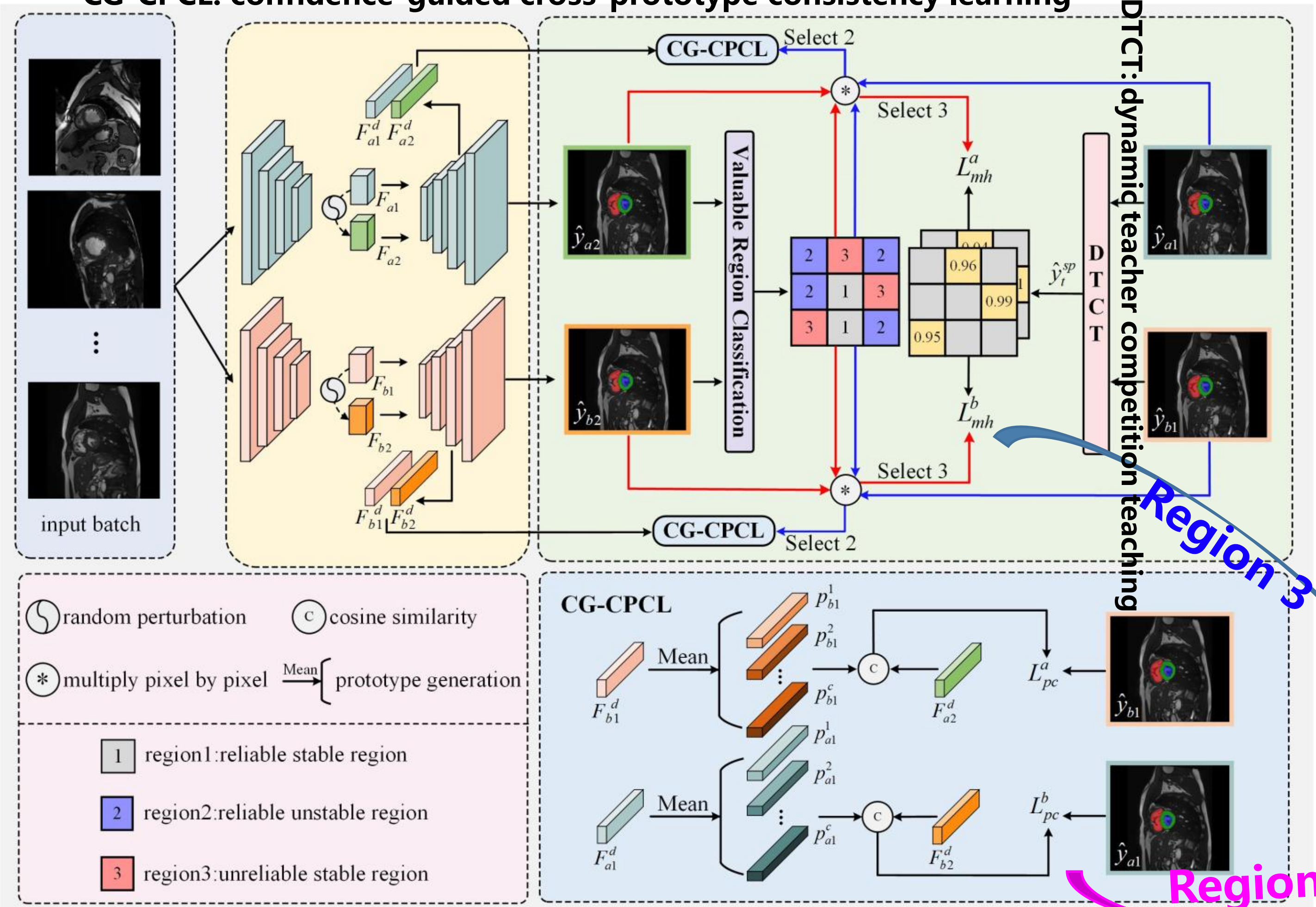
- The two predictions are both poor with low confidence, maybe we should use **ensemble strategies to obtain a better supervised signal**.

ALHVR: Method

Contributions:

Con is confidence map

CG-CPCL: confidence-guided cross-prototype consistency learning



The red line denotes CG-CPCL(prototype, R2 unstable) and blue line denotes DTCT (competition, R3 unreliable)

Contribution 1: The high-value regions are grouped into Region 2 and Region 3

$$con_{a2} = max(\hat{y}_{a2}), con_{b2} = max(\hat{y}_{b2})$$

$$\Omega_1 = \{con_{a2} \geq \gamma \ \& \ con_{b2} \geq \gamma\}$$

$$\Omega_2 = \{(con_{a2} > \gamma \ \& \ con_{b2} < \gamma) \mid (con_{a2} < \gamma \ \& \ con_{b2} > \gamma)\}$$

$$\Omega_3 = \{con_{a2} < \gamma \ \& \ con_{b2} < \gamma\}$$

$$\gamma = \frac{1}{K}\sum_{i=1}^{K} con(i)$$

Contribution 2: CG-CPCL is used for training Region 2 and DTCT is used for training Region 3

We use MSE loss and entropy regularization

$$L^b_{mh} = L^b_{mse}(\hat{y}_{b2}, (\hat{y}_{a1}, \hat{y}_{b1})) + H_{b1}(\hat{y}_{b1}) + H_{b2}(\hat{y}_{b2})$$

$$L^b_{pc} = L^b_{ce}((F^d_{b2}, p^c_{a1}), \hat{y}^p_{a1}) + L^b_{cos}(F^d_{b2}, p^c_{a1})$$

We use CE loss and prototype consistency

ALHVR: Experiments

Overall experiments:

Table 2. Comparisons with state-of-the-art semi-supervised segmentation methods on the ACDC dataset.

Method	Labeled	Unlabeled	Dice↑	Jaccard↑	95HD↓	ASD↓
U-Net	7(10%)	0	81.59	70.74	8.07	2.35
U-Net	14(20%)	0	84.83	75.33	7.61	2.09
U-Net	70(All)	0	91.10	84.04	4.90	1.14
MT[25][NIPS'2017]	7(10%)	63(90%)	83.65	73.15	13.45	3.61
CPS[6][CVPR'2021]			85.34	75.50	8.78	2.37
MC-Net[28][MICCAI'2021]			86.07	76.58	11.48	3.37
MCF[27][CVPR'2023]			85.18	75.22	10.73	2.78
AC-MT[31][MIA'2023]			86.36	76.86	9.64	2.59
UG-MCL[36][AIIM'2023]			86.84	77.60	7.77	1.94
EVIL[7][CBM'2024]			87.25	78.18	5.31	1.35
AAU[1][MIA'2024]			86.46	76.99	8.00	2.06
MLRP[24][MIA'2024]			87.10	78.16	4.91	1.30
ours			**90.56**↑3.31	**83.21**	**2.57**	**0.78**
MT[25][NIPS'2017]	14(20%)	56(80%)	86.55	77.49	6.86	2.15
CPS[6][CVPR'2021]			87.03	78.13	6.66	2.12
MC-Net[28][MICCAI'2021]			86.58	77.68	15.99	4.93
MCF[27][CVPR'2023]			87.32	78.43	6.53	2.00
AC-MT[31][MIA'2023]			87.99	79.34	7.85	2.14
UG-MCL[36][AIIM'2023]			88.40	79.86	9.12	2.44
EVIL[7][CBM'2024]			88.34	79.90	6.46	1.68
AAU[1][MIA'2024]			87.71	78.92	8.51	2.14
MLRP[24][MIA'2024]			88.00	79.54	5.41	1.58
ours			**91.09**↑2.69	**84.05**	**2.71**	**0.73**

Table 3. Comparisons with state-of-the-art semi-supervised segmentation methods on the AbdomenCT-1K dataset.

Method	Labeled	Unlabeled	Dice↑	Jaccard↑	95HD↓	ASD↓
U-Net	1(5%)	0	67.39	57.14	46.87	11.37
U-Net	3(10%)	0	75.66	66.33	22.44	6.89
U-Net	30(All)	0	86.93	79.27	11.55	2.45
MT[25][NIPS'2017]	1(5%)	29(95%)	71.82	61.19	42.03	9.23
CPS[6][CVPR'2021]			78.14	68.32	26.25	6.68
MC-Net[28][MICCAI'2021]			80.97	71.43	32.98	7.48
MCF[27][CVPR'2023]			80.79	71.30	26.13	7.81
AC-MT[31][MIA'2023]			76.18	65.99	36.12	8.89
UG-MCL[36][AIIM'2023]			74.06	63.58	26.93	7.06
EVIL[7][CBM'2024]			80.68	71.47	23.72	6.33
AAU[1][MIA'2024]			80.65	71.03	32.68	9.04
MLRP[24][MIA'2024]			80.30	70.67	20.94	5.43
ours			**84.75**↑3.78	**76.35**	21.15	5.59
MT[25][NIPS'2017]	3(10%)	27(90%)	78.75	69.10	25.35	6.88
CPS[6][CVPR'2021]			82.71	74.11	17.30	4.90
MC-Net[28][MICCAI'2021]			82.94	74.13	19.35	4.59
MCF[27][CVPR'2023]			83.34	74.63	16.97	4.72
AC-MT[31][MIA'2023]			82.32	72.97	26.52	7.54
UG-MCL[36][AIIM'2023]			81.43	72.56	20.29	5.67
EVIL[7][CBM'2024]			84.24	75.75	18.14	5.25
AAU[1][MIA'2024]			81.42	71.82	29.69	8.25
MLRP[24][MIA'2024]			84.55	75.99	13.82	4.05
ours			**85.68**↑1.13	**77.35**	21.96	6.22

Thank you for watching

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Paper Link : https://sust-reynole.github.io/download/ALHVR.pdf
Code Link: https://github.com/ziziyao/ALHVR.