



半监督医学图像分割

计算机学院（人工智能学院）



DyCON: Dynamic Uncertainty-aware Consistency and Contrastive Learning for Semi-supervised Medical Image Segmentation

Maregu Assefa, Muzammal Naseer, Iyyakutti Iyappan Ganapathi, Syed Sadaf Ali Mohamed L Seghier,
Naoufel Werghi

<https://github.com/CVML-KU/DyCON>

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DyCON: Dynamic Uncertainty-aware Consistency and Contrastive Learning for Semi-supervised Medical Image Segmentation

CCFA

[M Assefa](#), [M Naseer](#), [I Ganapathi](#), [SS Ali](#), [ML Seghier](#), [N Werghi](#)

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Abstract

Semi-supervised learning in medical image segmentation leverages unlabeled data to reduce annotation burdens through consistency learning. However, current methods struggle with class imbalance and high uncertainty from pathology variations, leading to inaccurate segmentation in 3D medical images. To address these challenges, we present DyCON, a Dynamic Uncertainty-aware Consistency and Contrastive Learning framework that enhances the generalization of consistency methods with two complementary losses:

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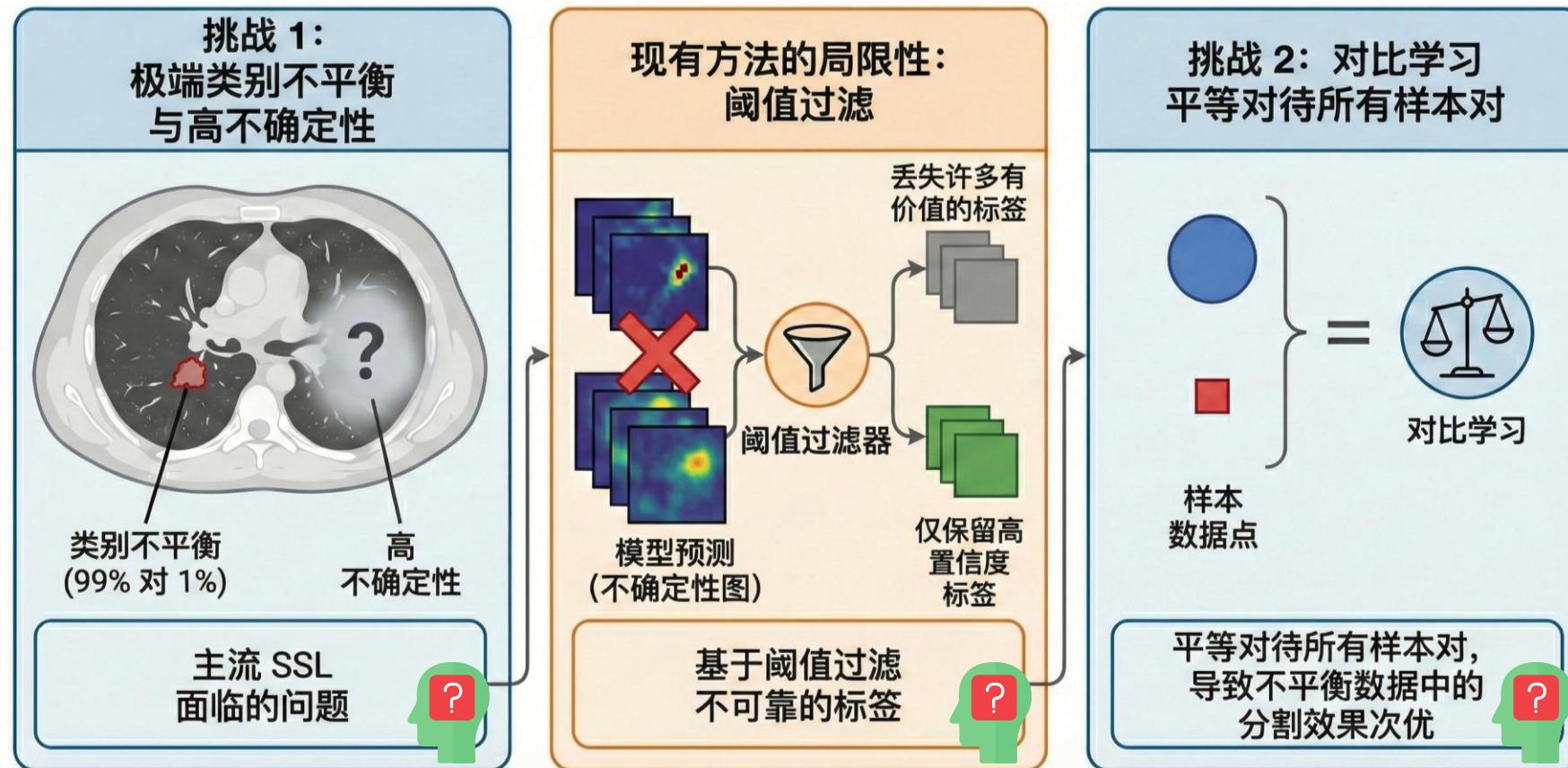
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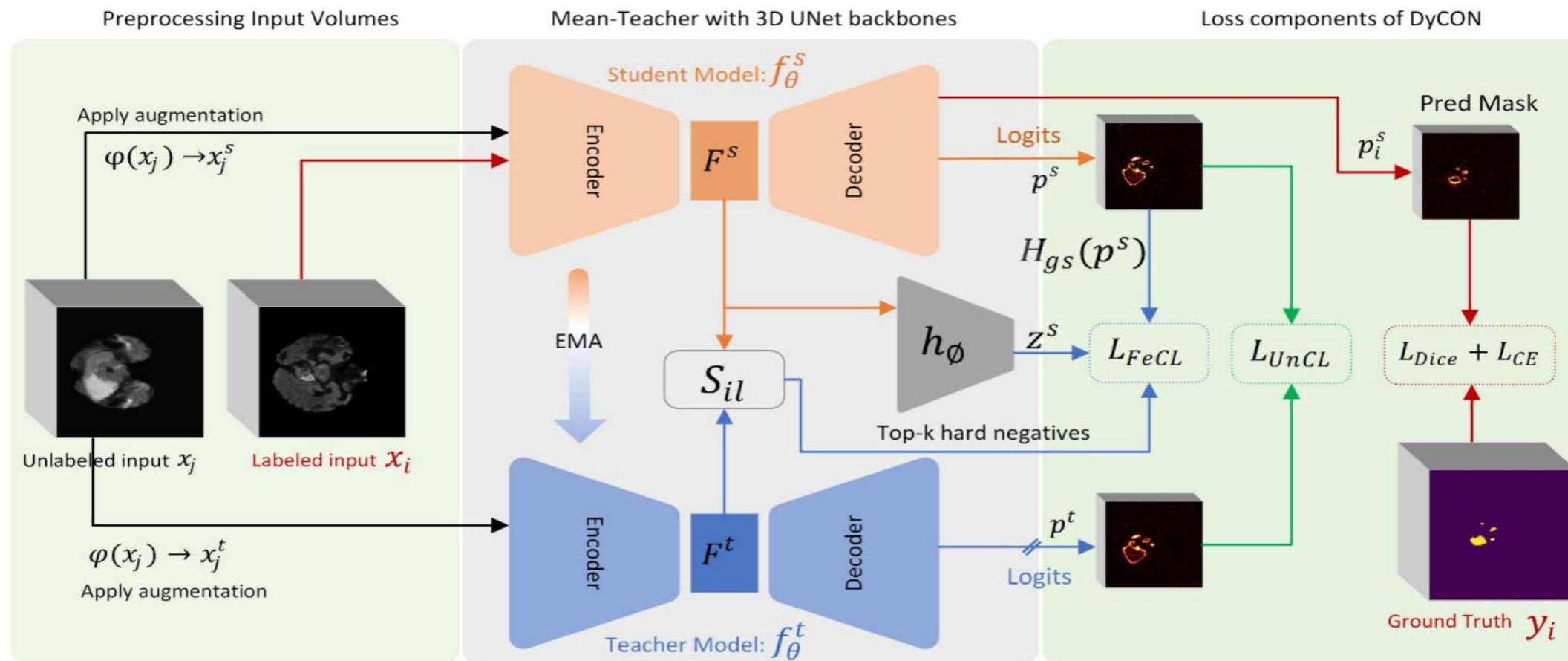
- 主流的SSL在医学图像中面临**极端类别不平衡**和**高不确定性**的挑战
- 现有的**不确定性评估**方法存在局限：基于阈值过滤不可靠预测
- 对比学习方法一致的对待所有样本对，在极度不平衡的数据中导致次优的分割**



DyCON: 提出一种动态不确定性感知一致性与对比学习框架, 解决半监督医学图像分割中的**类别不平衡**和**病灶变化**问题。

UnCL: 设计**不确定性感知一致性损失**, 基于**体素熵**动态调整每个体素对一致性损失的贡献权重。

FeCL: 提出**焦点熵感知对比损失**, 通过双焦点机制 (关注正样本和负样本) 和自适应置信度调整, 增强**局部特征**辨别能力。



教师模型从未标记的输入 x_j^t 生成 p^t ，而学生模型分别从未标记的输入 x_j^s 和标记的输入 x_i 生成 p^s 和标签 p_i^s ，DyCON 最终以端到端半监督的方式使用 **标记损失** 和 **未标记损失** 进行优化。



UnCL: 不确定性感知一致性损失

- 不确定性感知一致性损失用于处理医学图像分割中全局不确定性的核心损失函数，其设计目标是通过动态调整体素对一致性损失的贡献权重，实现模型对不确定区域的探索与对置信区域的精确优化

a) 不确定性量化

采用熵 (Entropy) 作为不确定性度量，通过学生模型和教师模型的预测概率分布计算体素级熵值 $H_s(p^s)$ 和 $H_t(p^t)$ ，熵值越高表示该体素预测的不确定性越大

$$p_j^s = \sigma(f_\theta^s(x_j^s)), p_j^t = \sigma(f_\theta^t(x_j^t))$$

关注 (置信度区域) 低熵 $\mathcal{L}_{\text{UnCL}} = \frac{1}{N} \sum_{i=1}^N \frac{\mathcal{L}(p_i^s, p_i^t)}{\exp(\beta \cdot H_s(p_i^s)) + \exp(\beta \cdot H_t(p_i^t))}$ **均方误差** $+ \frac{\beta}{N} \sum_{i=1}^N (H_s(p_i^s) + H_t(p_i^t))$

正则化：防止模型过早收敛



UnCL: 不确定性感知一致性损失

$$\mathcal{L}_{\text{UnCL}} = \frac{1}{N} \sum_{i=1}^N \frac{\mathcal{L}(p_i^s, p_i^t)}{\exp(\beta \cdot H_s(p_i^s)) + \exp(\beta \cdot H_t(p_i^t))} + \frac{\beta}{N} \sum_{i=1}^N (H_s(p_i^s) + H_t(p_i^t))$$

关注 (置信度区域) 低熵 **均方误差**
正则化: 防止模型过早收敛

b) 自适应参数 β

β 控制不确定性的影响强度, 训练初期 β 值较高 (如 $\beta_{max} = 1.0$) , 优先探索不确定区域; 随训练进行, β 按指数衰减至 β_{min} , 逐步聚焦于置信区域的优化

$$\beta(t) = \max(\beta_{min}, \beta_{max} \cdot \exp(-\lambda \cdot \frac{t}{T}))$$



FeCL: 焦点熵感知对比损失

- **焦点熵感知对比损失**聚焦正负样本对和不确定区域，有效解决**类别不平衡问题**，帮助模型捕捉细微病变边界

$|P(i)|$: 正样本对数量，

$$\mathcal{L}_{\text{FeCL}} = \frac{1}{|P(i)|} \sum_{k \in P(i)} \mathbf{F}_k^+ \cdot \left[-\log \left(\frac{\exp(\mathbf{S}_{ik})}{D(i)} \right) \right] \quad \mathbf{S}_{ik} = \frac{z_i^s \cdot z_k^s}{\tau} \quad \text{i和K的相似性}$$

$$D(i) = \exp(\mathbf{S}_{ik}) + \sum_{q \in N(i)} \mathbf{F}_q^- \cdot \left[\exp(\mathbf{S}_{iq}) + \frac{1}{K} \sum_{l=1}^K \exp(\mathbf{S}_{il}) \right]$$

FeCL使用双焦点加权项 F_k^+ 和 F_q^- 来调整每个Patch对在损失函数中的重要性：

$$\mathbf{F}_k^+ = (1 - S_{ik})^\gamma \cdot \exp(H_{gs}(p_h^s)) \quad \mathbf{F}_q^- = (S_{iq})^\gamma$$

关注正样本对

正样本聚集在一起，负样本远离

负样本对施加惩罚



Total Loss Function

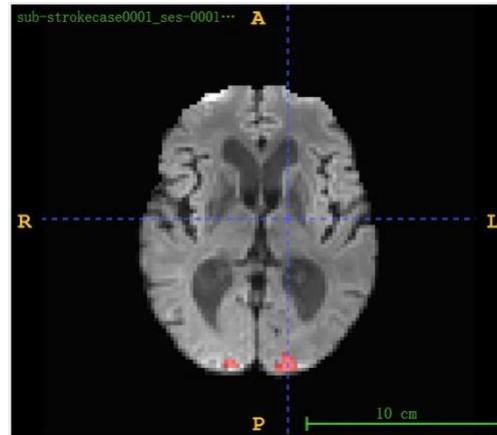
- 总的损失函数=监督损失+DyCON损失

$$\mathcal{L}_{\text{Total}} = \underbrace{\mathcal{L}_{\text{Dice}} + \mathcal{L}_{\text{CE}}}_{\mathcal{L}_{\text{Sup}}} + \eta \cdot \underbrace{(\mathcal{L}_{\text{UnCL}} + \mathcal{L}_{\text{FeCL}})}_{\mathcal{L}_{\text{DyCon}}}$$

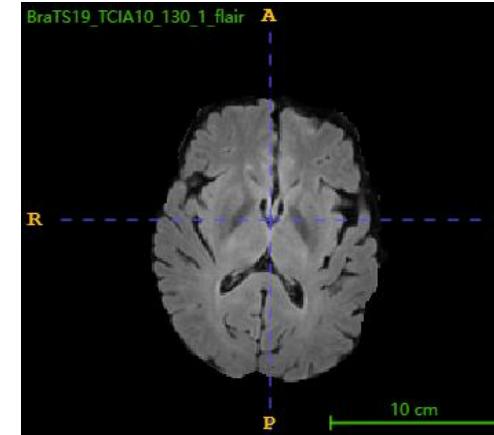
η 是控制UnCL和FeCL对总损失的影响程度



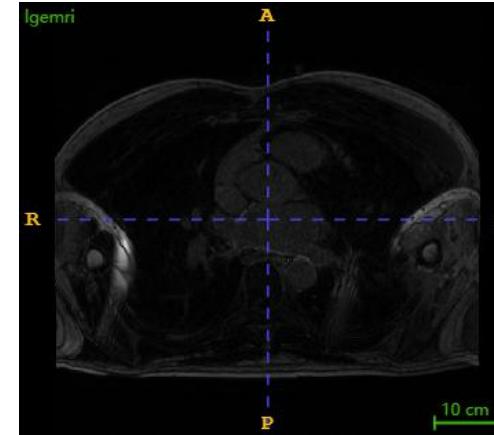
数据集和评估指标



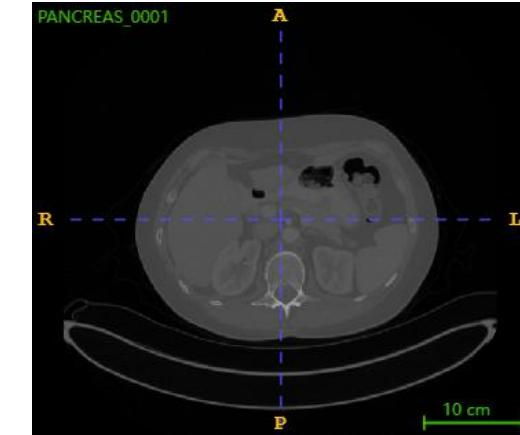
ISLES-2022



BraTS2019



LA



Pancreas-NHI

评估指标

Dice, IoU, HD95和ASD



对比实验结果分析

结果
分析

在ISLES中，DyCON的表现最好

SSL Method	Volumes used in ISLES'22			Metrics		
	Labeled	Unlabeled	Dice (%)↑	IoU (%)↑	HD95↓	ASD↓
W-Net [41]	200 (100%)	0	85.60	—	27.34	—
PAMSNet [11]	200 (100%)	0	87.37	79.14	3.21	—
MT [35]			29.22	20.41	20.18	8.55
UA-MT [49]			49.20	37.21	38.20	9.64
MCF [37]			39.79	29.83	40.67	10.65
CML [39]			46.39	35.16	37.76	4.62
DTC [24]			46.55	34.80	37.33	8.18
AC-MT [46]	10 (5%)	190 (95%)	48.64	36.53	39.71	7.13
MagicNet [7]			51.42	38.18	37.20	5.60
GALoss [28]			53.29	40.17	31.72	4.53
BCP [3]			53.53	41.12	37.06	6.91
DyCON (Ours)			61.48	48.80	17.61	0.75
MT [35]			36.43	24.01	21.80	7.22
MCF [37]			42.96	32.51	42.82	10.86
DTC [24]			45.19	32.80	36.24	5.10
AC-MT [46]			49.47	37.02	39.67	11.10
CML [39]	20 (10%)	180 (90%)	50.88	38.45	36.16	4.94
BCP [3]			57.97	44.32	30.09	4.58
MagicNet [7]			58.84	44.42	29.18	3.64
GALoss [28]			60.13	47.27	24.11	3.17
DyCON (Ours)			65.71	51.09	13.35	0.71
MT [35]			37.70	26.33	19.00	6.45
UA-MT [49]			58.00	44.96	28.99	3.13
DTC [24]			40.23	29.35	41.47	13.13
MCF [37]	40 (20%)	160 (80%)	40.36	31.31	41.10	13.03
AC-MT [46]			54.91	41.55	32.27	2.36
CML [39]			54.31	41.77	30.75	1.35
BCP [3]			60.35	46.41	29.63	3.64
DyCON (Ours)			69.11	54.74	10.58	0.52



对比实验结果分析

结果分析

在BraTS19中，DyCON的表现超过全监督的3D-UNet

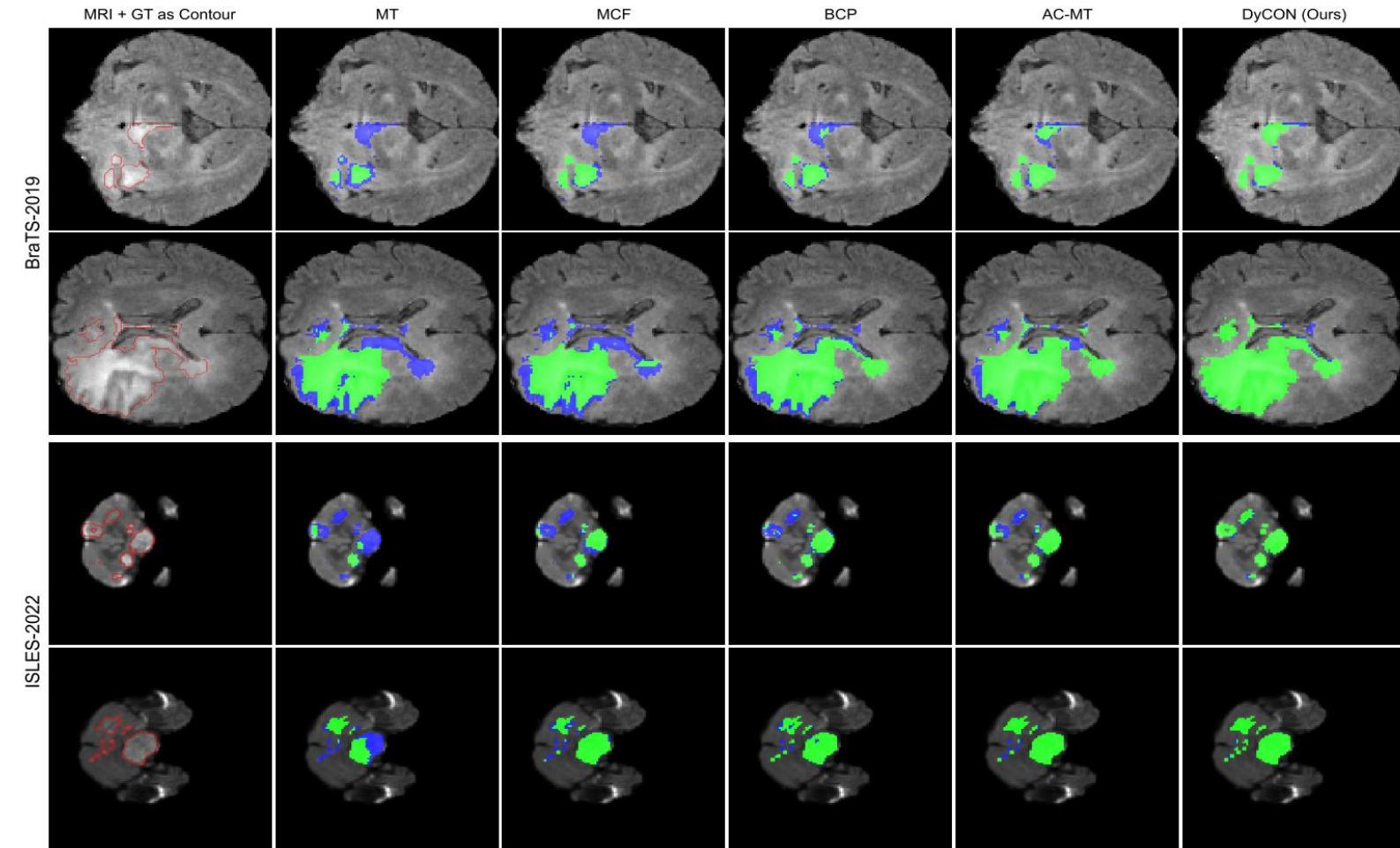
SSL Method	Volumes used in BraTS'19			Metrics		
	Labeled	Unlabeled	Dice (%)↑	IoU (%)↑	HD95↓	ASD↓
3D-UNet [30]	250 (100%)	0	88.23	78.81	7.21	1.53
MT [35]			81.70	70.82	22.29	7.36
URPC [25]			74.59	63.11	13.88	3.72
UA-MT [49]			82.82	72.77	11.29	2.30
DTC [24]			81.57	71.63	15.73	2.56
MCF [37]	25 (10%)	225 (90%)	83.67	72.15	12.58	3.28
BCP [3]			83.42	73.31	10.11	1.89
AC-MT [46]			83.77	73.96	11.35	1.93
CML [39]			85.26	—	9.08	1.83
DyCON (Ours)			87.05	77.73	7.41	1.14
MT [35]			83.04	72.10	9.85	2.32
URPC [25]			82.93	72.57	5.93	3.19
UA-MT [49]			83.61	73.98	11.44	2.26
DTC [24]			83.43	73.56	14.77	2.34
MCF [37]	50 (20%)	200 (80%)	84.85	73.61	11.24	2.29
BCP [3]			82.71	72.72	9.99	1.86
AC-MT [46]			84.63	74.39	9.50	2.11
CML [39]			86.63	—	7.83	1.45
DyCON (Ours)			88.75	80.52	6.33	0.93



可视化分析

结果分析

DyCON准确分割出接近GT的区域，在所有结果中表现最好



说明 在LA和Pancreas中的结果与上述分析类似，这里不在展示



消融实验结果分析

Scans used		UnCL	β	ISLES-2022			BraTS-2019		
Labeled	Unlabeled			Dice(%)↑	HD95↓	ASD↓	Dice(%)↑	HD95↓	ASD↓
10%	90%	✗	✗	36.43	21.80	7.22	81.70	22.29	7.36
		✓	✗	58.78	19.37	6.16	80.04	14.35	4.23
		✓	0.5	60.97	16.89	5.01	83.11	12.23	3.00
		✓	0.8	62.23	15.18	3.42	84.12	10.1	2.31
		✓	⊤	64.52	14.10	1.05	85.97	8.50	1.78
20%	80%	✗	✗	37.70	19.00	6.45	83.04	9.85	2.32
		✓	✗	60.68	15.76	3.11	81.23	12.14	3.20
		✓	0.5	63.15	14.51	2.13	83.68	10.03	2.74
		✓	0.8	66.05	12.64	1.20	85.77	8.99	1.86
		✓	⊤	68.30	11.12	0.96	87.03	7.18	1.24

分析 使用UnCL到达最好的分割结果



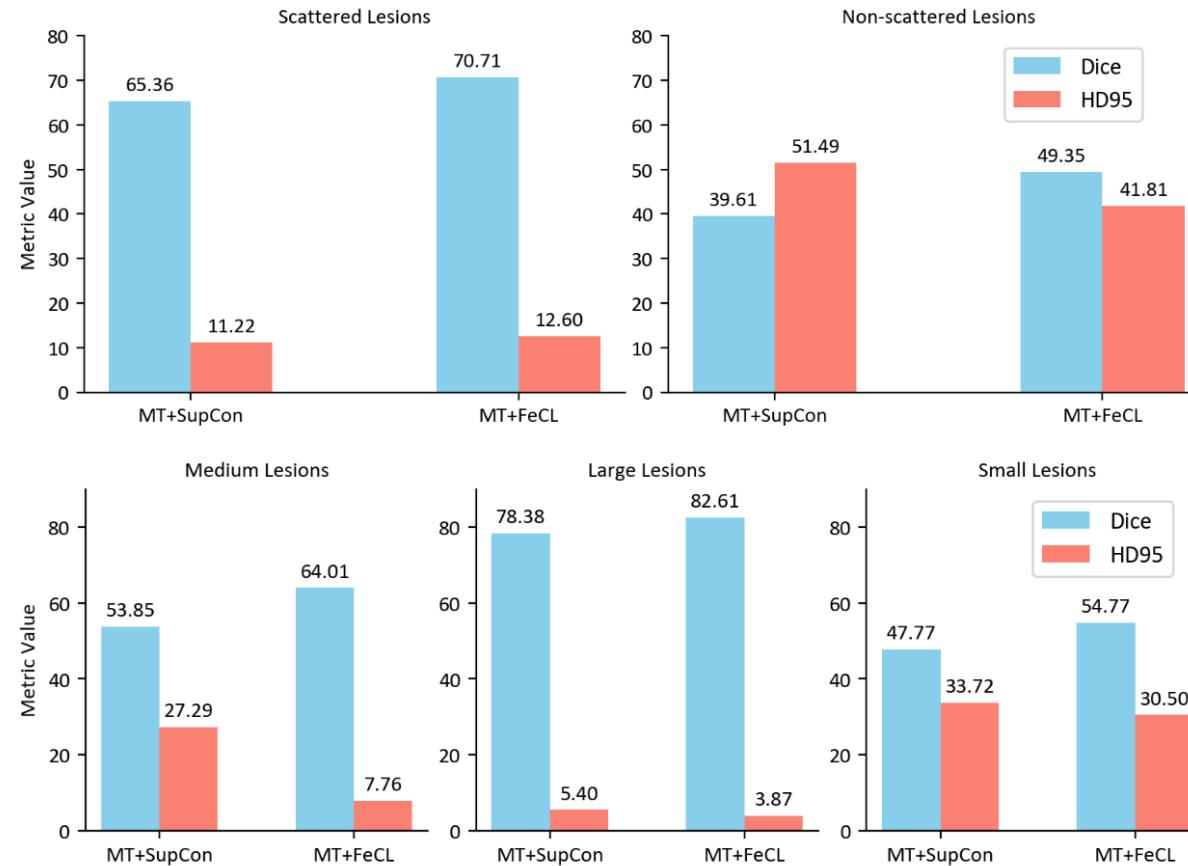
消融实验结果分析

FeCL Elements				ISLES-2022			BraTS-2019		
F ⁺ +F ⁻	HN	Entropy	UnCL	Dice(%)↑	HD95↓	ASD↓	Dice (%)↑	HD95↓	ASD↓
✗	✗	✗	✗	38.24	20.16	6.35	82.68	21.53	5.89
✓	✗	✗	✓	63.78	13.94	1.10	84.57	8.53	1.75
✓	✓	✗	✓	64.39	13.76	1.00	85.23	8.11	1.59
✓	✗	✓	✓	65.46	13.52	0.85	86.32	7.86	1.32
✓	✓	✓	✓	66.07	13.34	0.75	86.97	7.46	1.16

分析 使用FeCL到达最好的分割结果



消融实验结果分析

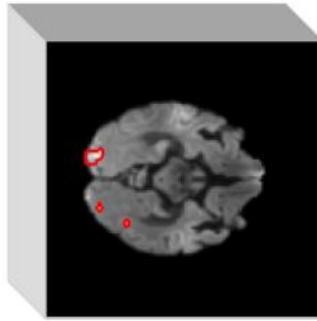


分析 使用MT+FeCL的分割结果总是优于MT+SupCon

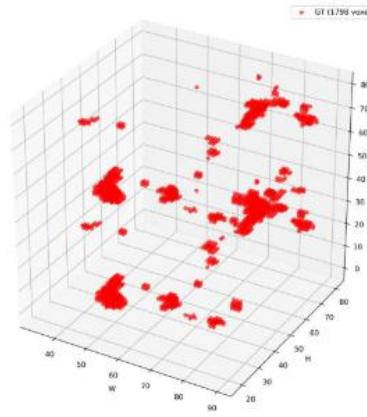


消融实验结果分析

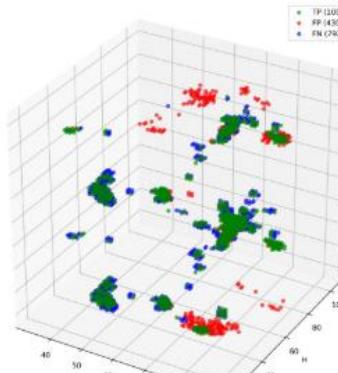
MRI scan 1



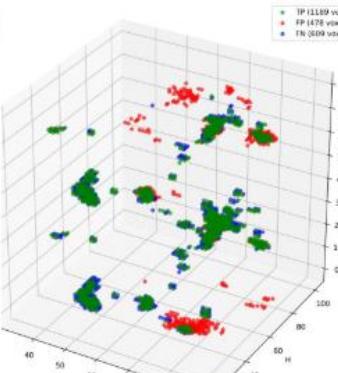
GT Lesion Distribution



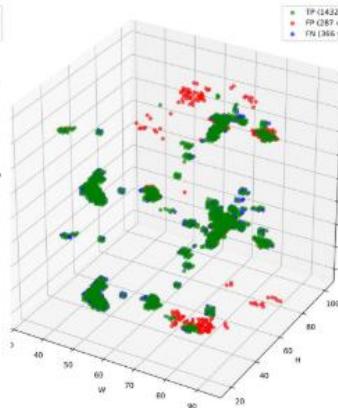
MCF



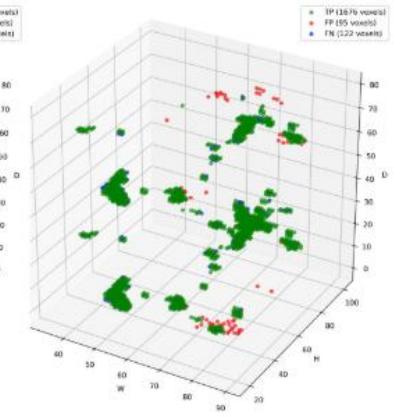
BCP



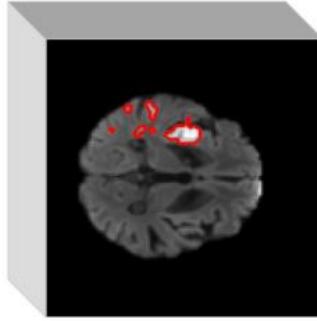
AC-MT



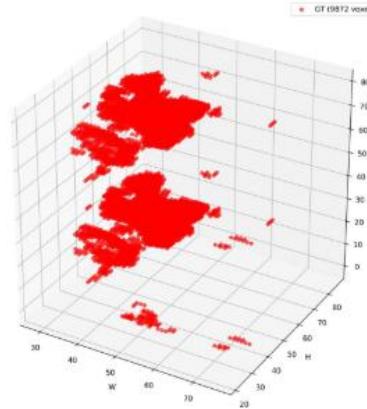
DyCON (Ours)



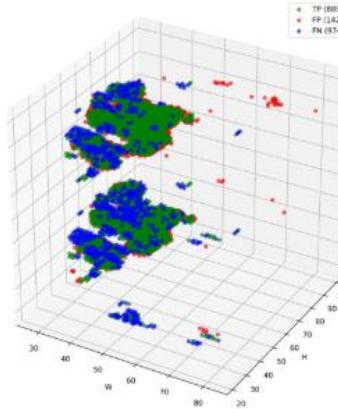
MRI scan 2



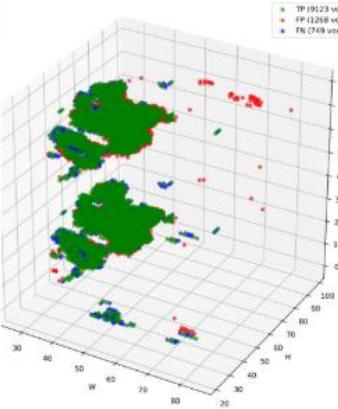
GT Lesion Distribution



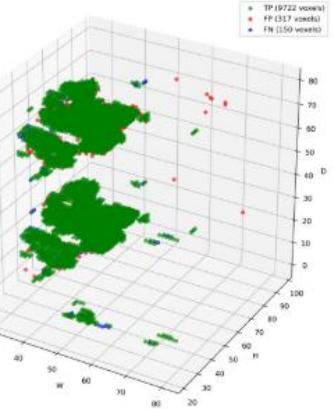
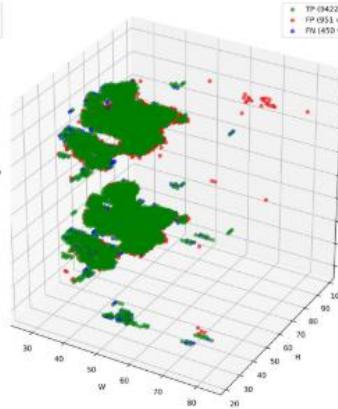
MCF



BCP



AC-MT



分析 DyCON能够检测小区域和离散区域病变



提出不确定性感知一致性损失 (UnCL)

利用熵作为不确定性的代理指标，动态调整整体素对损失的贡献权重。



提出焦点熵感知对比损失 (FeCL)

通过双焦点机制和自适应置信度调整增强局部特征辨别能力，优先处理正样本和负样本，有效解决类别不平衡问题。

```
import numpy as np
import matplotlib.pyplot as plt
import torch
from torch.autograd import Variable
import torch.nn as nn
from torch import optim
import time
from torch.optim import lr_scheduler
import pandas as pd
import argparse
from datasets.retinal_dataset import BinaryLoader
from utils.loss import *
from tqdm import tqdm
import json
from models.waverNet import SAMB
import albumentations as A
from albumentations.pytorch.transforms import ToTensor
from monai.metrics import MeanIoU
```

+ 目录结构:

- + WaveRNet_GitHub/
 - + models/
 - | | waerNet.py # 主模型
 - | | sdm.py # Spectral-guided Domain Modulator
 - | | fadf.py # Frequency-Adaptive Domain Fusion
 - | | hmpr.py # Hierarchical Mask-Prompt Refiner
 - + datasets/
 - | | retinal_dataset.py # 完成
 - + utils/
 - | | loss.py # 完成
 - | | transforms.py # 完成

 Chanchan-Wang	Update README.md	92099
 configs	Initial commit: WaveRNet implementation	
 models	Initial commit: WaveRNet implementation	
 pretrained	Initial commit: WaveRNet implementation	
 utils	Initial commit: WaveRNet implementation	
 .gitignore	Initial commit: WaveRNet implementation	
 LICENSE	Initial commit: WaveRNet implementation	
 README.md	Update README.md	
 eval.py	Initial commit: WaveRNet implementation	
 requirements.txt	Initial commit: WaveRNet implementation	
 train.py	Initial commit: WaveRNet implementation	



谢谢大家!

计算机学院（人工智能学院）