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

C2PS*, Khalifa University

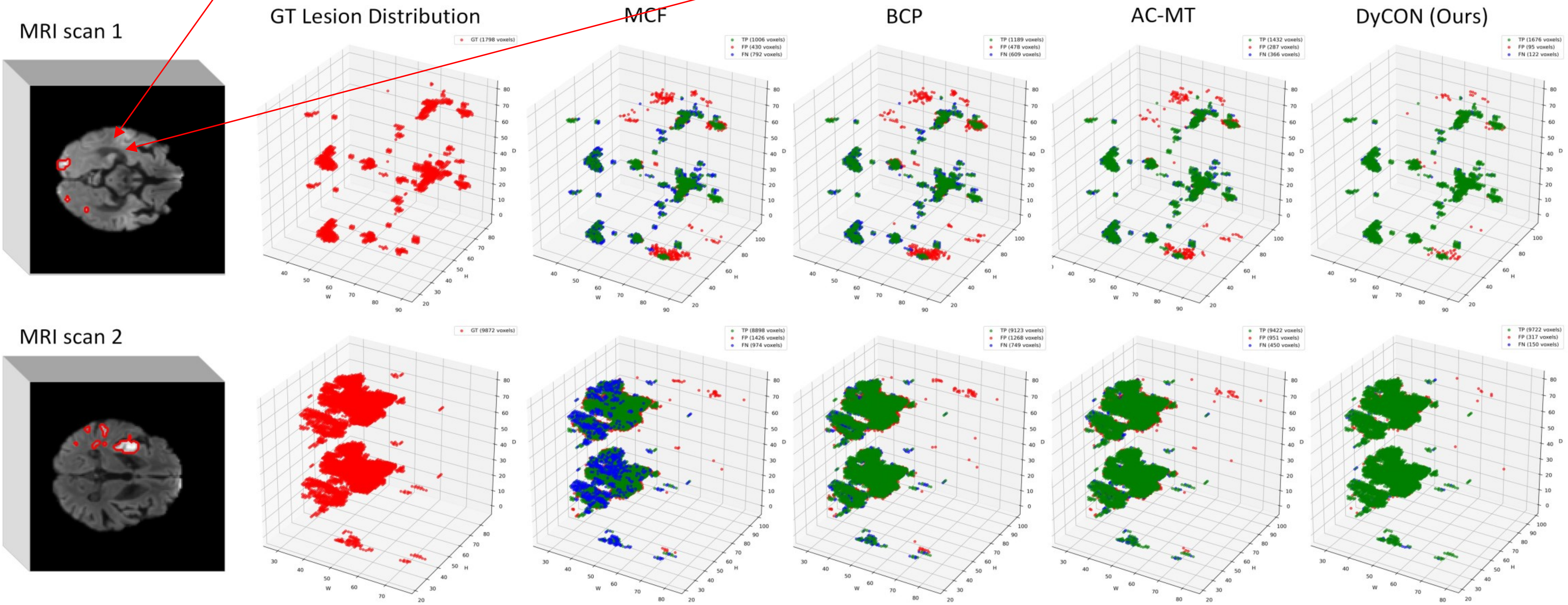
Abu Dhabi, UAE

Poster #450

Motivation

Extreme Class imbalance
e.g., Lesion voxels ≪ background voxels → extreme class imbalance

High uncertainty
e.g., Pathological variations (Lesions vary in size, shape, and appearance → high uncertainty)



Existing SSL Methods

- Popular frameworks, such as ***Mean-Teacher*** and ***Co-training*** often discard high-uncertainty voxels during training, which ignores potentially informative but ambiguous regions -- ultimately missing the global context.

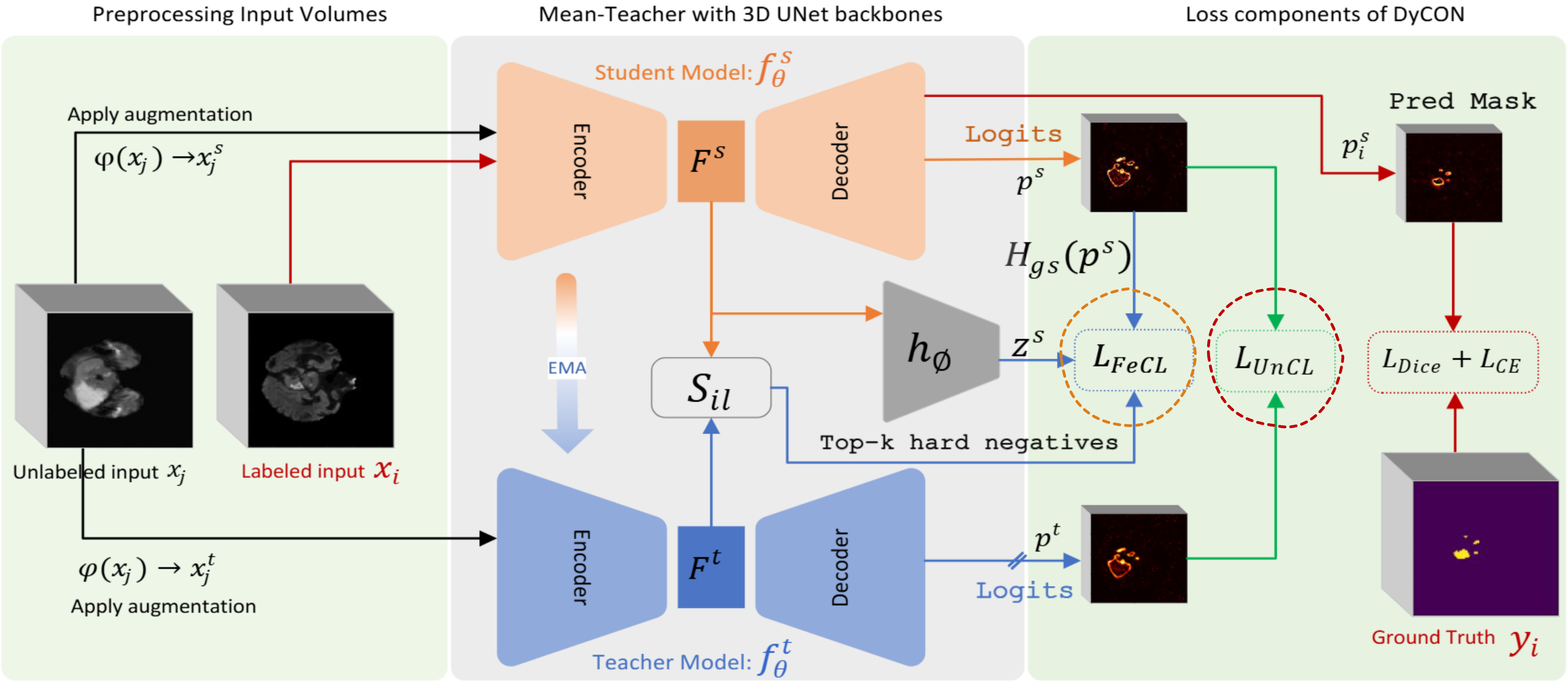
Monte Carlo Dropout (MC-dropout) and Ensembles.

Dual network/decoder disagreements

- Traditional contrastive learning treats all *contrastive pairs equally*, limiting fine-grained discrimination under class imbalance.

🔥 Can we leverage **uncertainty**, rather than discard it, to significantly enhance semi-supervised segmentation**?**

DyCON: Overview of Core Components



- **Uncertainty-aware Consistency Loss (UnCL)** – dynamically weights the importance of each voxel based on its predicted uncertainty.
- **Focal Entropy-aware Contrastive Loss (FeCL)** – adapts the contrastive loss to focus on the most informative and challenging pairs.

DyCON: Overview of Core Components

Uncertainty-aware Consistency Loss (UnCL):

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

- Where $\mathcal{L}(p^s, p^t)$ is any distance-based loss function (e.g., MSE in our case).
- The consistency alignment is *inversely* weighted by the sum of exponentiated entropies.

Here $\boldsymbol{\beta}$ serves as a *scaling factor* that amplifies or diminishes the impact of uncertainty.

$$\beta(t) = \max(\beta_{\min}, \beta_{\max} \cdot \exp\left(-\lambda \cdot \frac{t}{T}\right)) \quad (2)$$

- **Early training**: emphasizes uncertain voxels for exploration.
- **Later training**: emphasizes confident predictions for refinement.

DyCON: Overview of Core Components

Focal Entropy-aware Contrastive Loss (FeCL):

$$\mathcal{L}_{\text{FeCL}} = \frac{1}{|P(i)|} \sum_{k \in P(i)} \mathbf{F}_k^{+} \cdot \left[-\log \left(\frac{\exp(\mathbf{S}_{ik})}{D(i)} \right) \right] \quad (3)$$

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

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

Focal weights for hard positive/negative pairs, reducing the effect of trivial pairs.

$$\mathbf{S}_{il} = \text{Top-}k \left((F_i^s \cdot (F_l^t)^T) \odot \mathbf{M}_i \right) \quad (4)$$

Top-K teacher hard negatives, introducing diversity

$$\mathcal{L}_{\text{Total}} = \underbrace{\mathcal{L}_{\text{Dice}} + \mathcal{L}_{\text{CE}}}_{\mathcal{L}_{\text{sup}}} + \eta \cdot \underbrace{(\mathcal{L}_{\text{UnCL}} + \mathcal{L}_{\text{FeCL}})}_{\mathcal{L}_{\text{DyCon}}} \quad (5)$$

Experiments

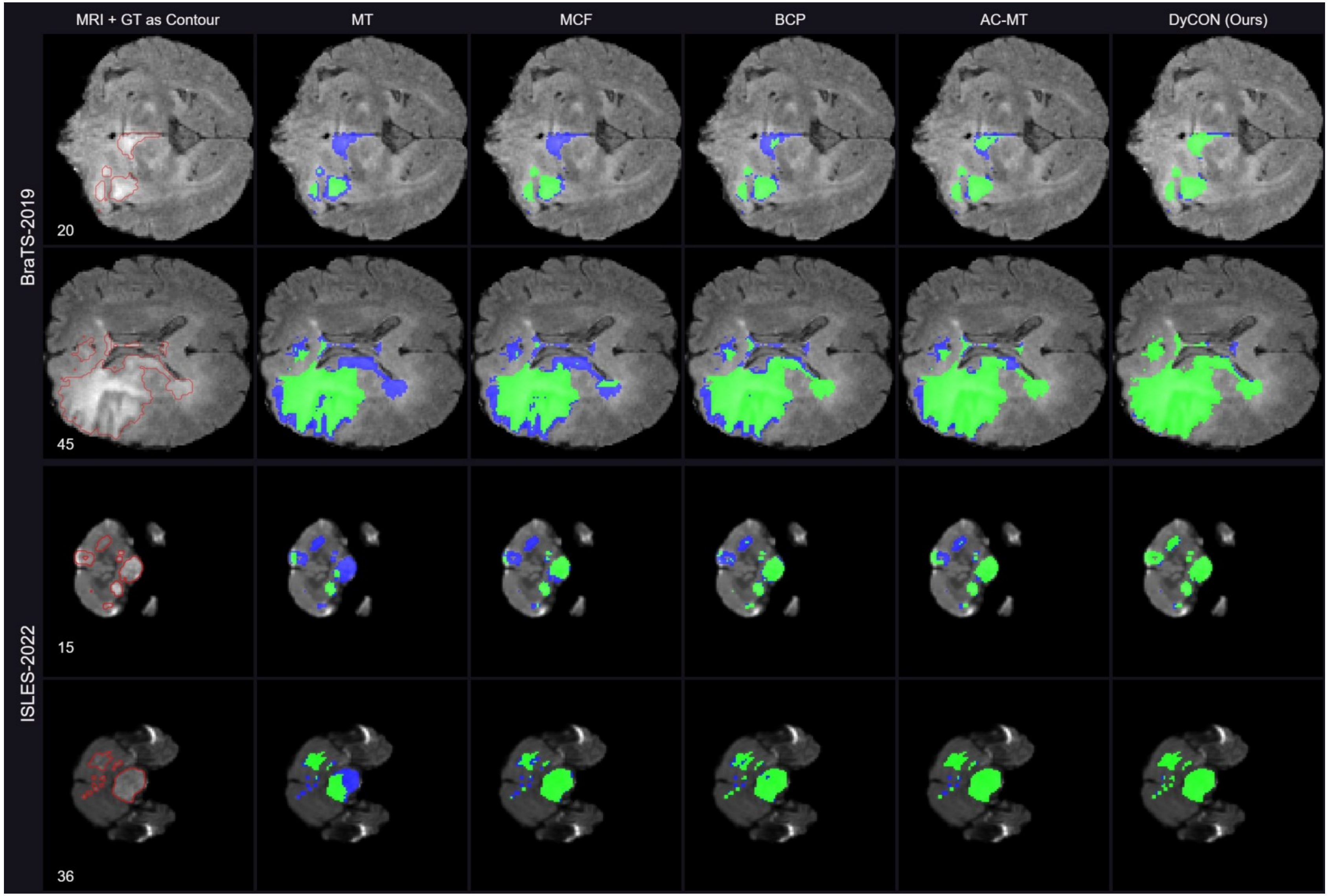
SSL Method	Volumes used in ISLES'22		Metrics			
	Labeled	Unlabeled	Dice (%)↑	IoU (%)↑	HD95↓	ASD↓
W-Net [41]	200 (100%)	0	85.60	—	27.34	—
PAMSNet [11]	200 (100%)	0	87.37	79.14	3.21	—
MT [35]	10 (5%)	190 (95%)	29.22	20.41	20.18	8.55
UA-MT [49]			49.20	37.21	38.20	9.64
MCF [37]			39.79	29.83	40.67	10.65
CML [39]			46.39	35.16	37.76	4.62
DTC [24]			46.55	34.80	37.33	8.18
AC-MT [46]			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]	20 (10%)	180 (90%)	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]			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]	40 (20%)	160 (80%)	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]			40.36	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**

Table 1. Acute Stroke lesion **MRI** segmentation comparison with SOTA methods on ISLES-2022 dataset.

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]	25 (10%)	225 (90%)	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]			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]	50 (20%)	200 (80%)	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]			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**

Table 2. Brain tumor segmentation comparison with SOTA methods on BraTS-2019 dataset.

Experiments



Lesion and **Tumor** segmentation visualization

Red: ground truth contour

Green: True predictions

Blue: False Negative (FN) predictions

Experiments

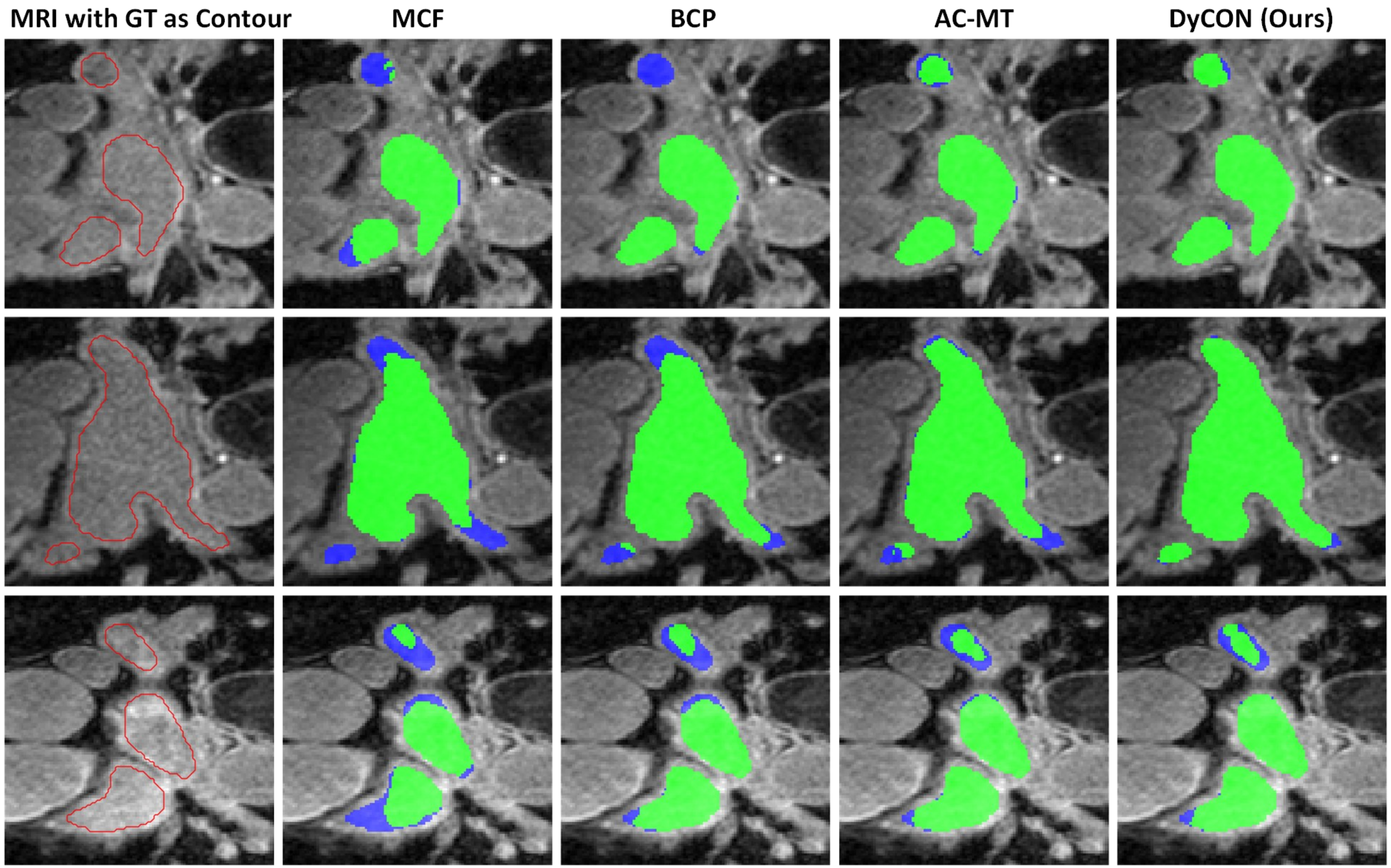
Table 3. Pancreas organ segmentation comparison with SOTA methods on Pancreas-CT dataset.

SSL Method	Volumes used in **Pancreas CT**		Metrics			
	Labeled	Unlabeled	Dice (%)↑	IoU (%)↑	HD95↓	ASD↓
V-Net [30]	62 (100%)	0	69.95	55.56	14.23	1.64
MT [35]	12 (20%)	50 (80%)	71.43	60.21	15.44	4.11
UA-MT [49]			77.26	63.82	11.90	3.06
DTC [24]			78.27	64.75	8.36	2.25
MCF [37]			75.00	61.27	11.59	3.27
CML [39]			77.26	56.21	25.82	1.52
BCP [3]			82.91	70.97	6.43	2.25
DyCON (Ours)			**84.81**	**73.86**	**5.41**	**1.44**

Table 4. LA organ segmentation comparison with SOTA methods on LA dataset.

SSL Method	Volumes used in **LA**		Metrics			
	Labeled	Unlabeled	Dice (%)↑	IoU (%)↑	HD95↓	ASD↓
3D-UNet [10]	80 (100%)	0	91.51	84.04	1.53	5.61
UPC [23]	4 (5%)	76 (95%)	86.36	76.24	13.83	3.64
UA-MT [49]			88.34	76.11	10.01	4.43
DTC [24]			81.25	74.26	14.90	3.99
MCF [37]			86.52	77.43	9.12	2.40
BCP [3]			88.02	78.72	7.90	2.15
CML [39]			87.63	—	8.92	2.23
AC-MT [46]			89.12	80.46	11.05	2.19
DyCON (3D-UNet)			90.96	83.54	5.39	1.91
DyCON (VNet)			**91.18**	**84.16**	**5.16**	**1.39**
UPC [23]	8 (10%)	72 (90%)	89.65	81.36	6.71	2.15
UA-MT [49]			90.16	82.18	6.50	1.98
DTC [24]			87.51	78.17	8.23	2.36
MCF [37]			88.71	80.41	6.32	1.90
BCP [3]			89.62	81.31	6.81	1.76
AC-MT [46]			90.31	82.43	6.21	1.76
CML [39]			90.36	—	6.06	1.68
DyCON (VNet)			91.58	84.40	5.02	1.52
DyCON (3D-UNet)			**92.77**	**86.21**	**4.20**	**1.23**

Experiments

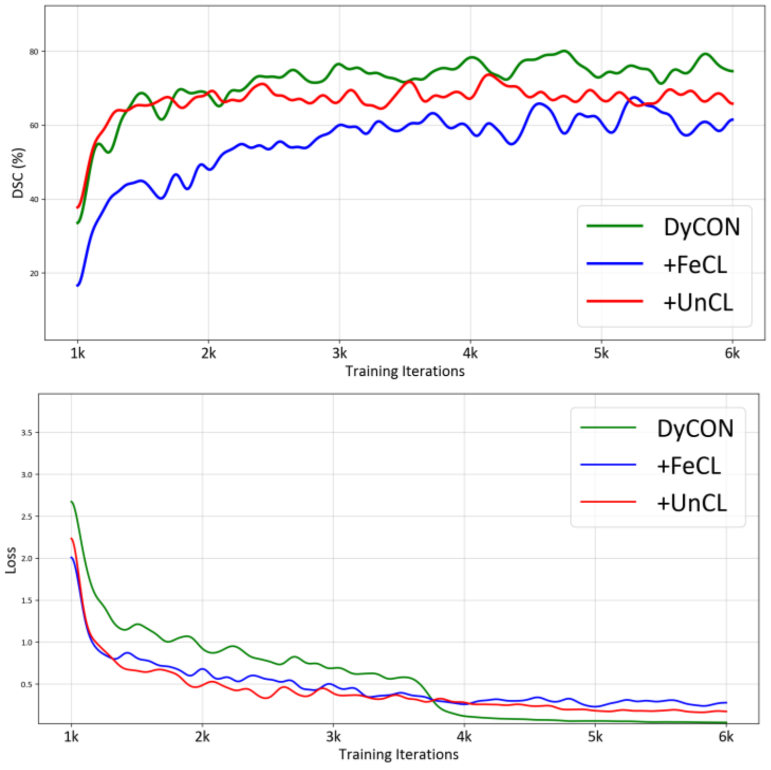


Left Atrial organ segmentation visualization.

Ablation Experiments

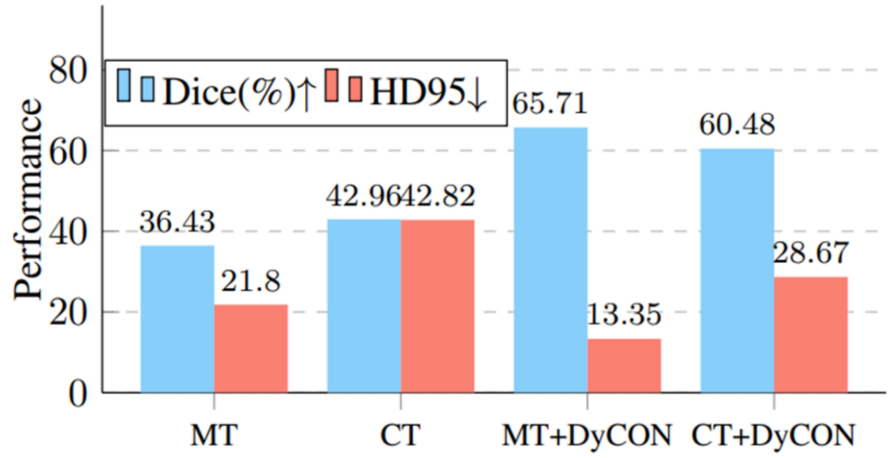
Table 5. Validation of various components in DyCON

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**

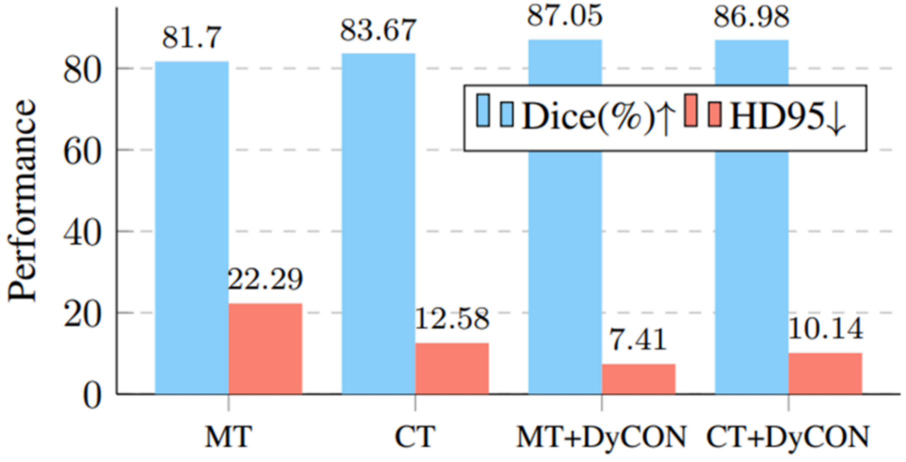


Loss and dice accuracy on ISLES22 with 10% labels

Comparative performance when integrating DyCON into **MT** and **CT** frameworks with 10% labeled data.



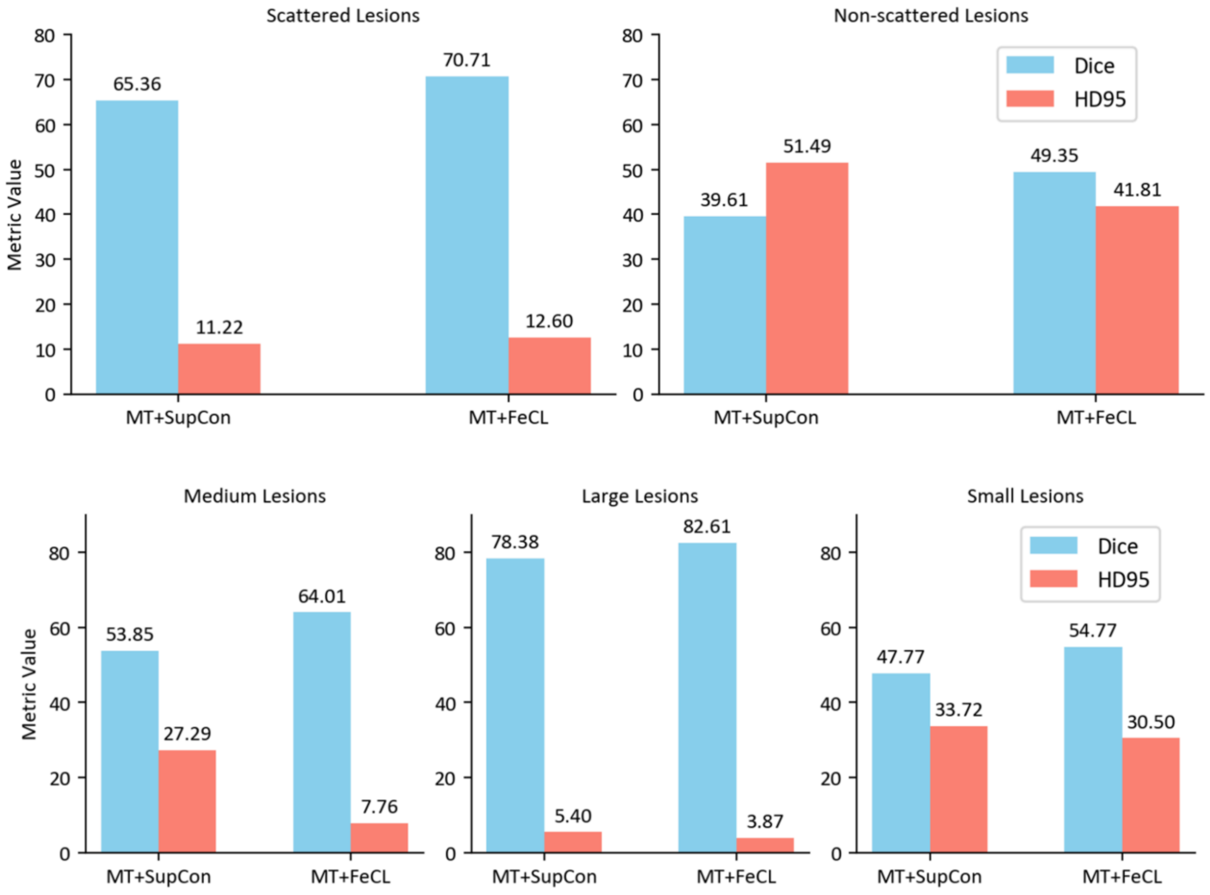
(a) ISLES'22 Results.



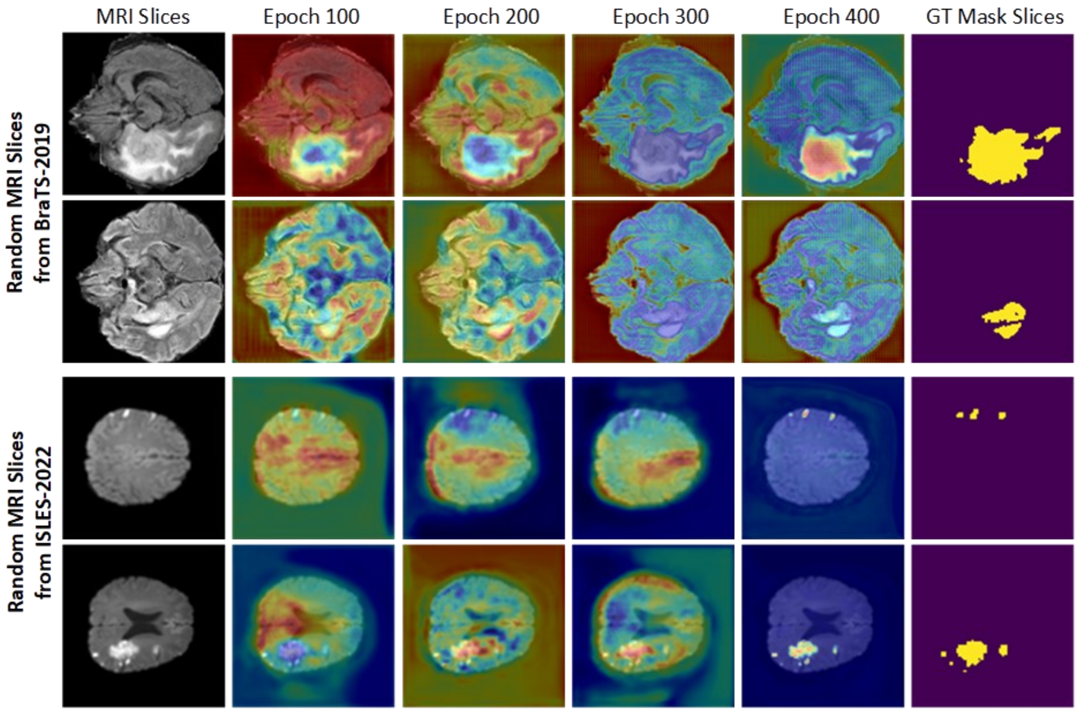
(b) BraTS'19 Results.

Ablation Experiments

Sensitivity analysis of FeCL loss across different lesion sizes and distributions.



Evolving **Grad-CAM** visualization



✔ Refer to the **supplementary** material for more ablation analysis.

Conclusion

- **DyCON** significantly improves performance by explicitly addressing class imbalance and voxel-level uncertainty.
  - **UnCL**: Dynamically balances exploration and refinement via dual-entropy weighting, effectively preserving uncertain yet informative voxels.
  - **FeCL**: Strategically emphasizes hard-to-distinguish pairs using adaptive focal weighting and entropy-based sampling, thus improving discrimination power.

Thank you!

Scan for GitHub Code