Dual consistency assisted multi-confident learning for the hepatic vessel segmentation using noisy labels

VinBrain

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Introduction

- Automatic hepatic vessel segmentation system is essential to identify the liver segments toward helpful guidance for liver resection and transplantation.
- Noisy hepatic vessel labels from Computer Tomography (CT) are popular due to vessels' low-contrast and complex morphology.
- A good deep learning segmentation model often requires a great number of CT data and their ground-truth, i.e. high-quality (HQ) voxel-wise annotations.
- Low-quality (LQ) annotations lead to undesirable performance degradation in deep learning.
- Semi-supervised learning is the most appropriate approach to explore the auxiliary information from additional datasets and regularize the learner.

Datasets

We used two public datasets:

- 3DIRCADb: high-quality dataset;
- MSD8: low-quality dataset.

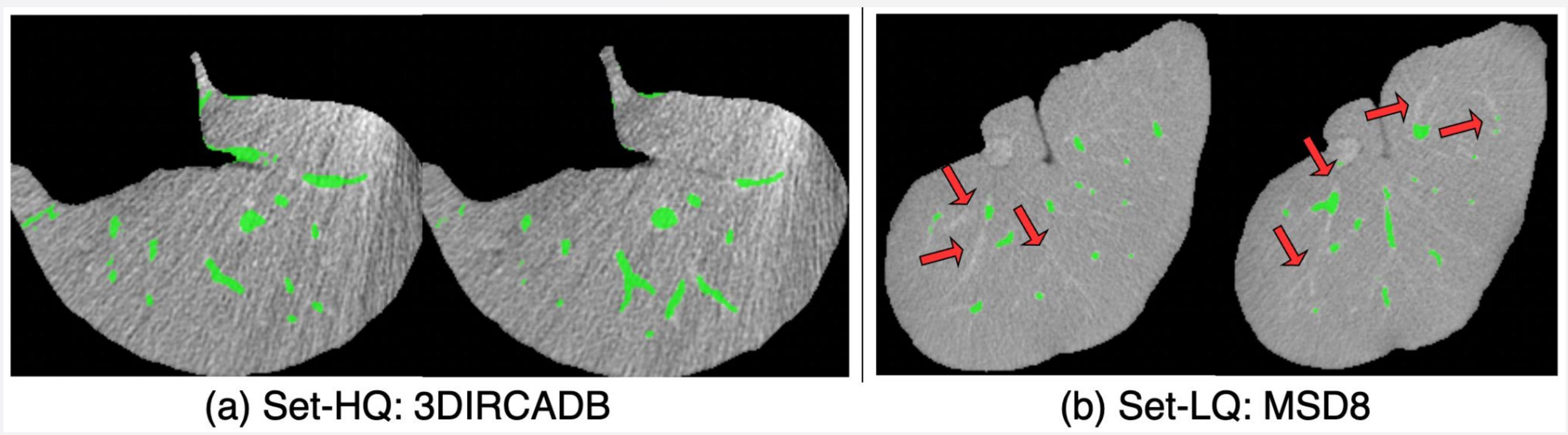

Fig. 1: 2D visualization of two datasets. Green patterns represent the labeled vessels and red arrows point at unlabeled pixels.

*These two authors contributed equally to this work.
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Method

- We proposed a novel semi-supervised framework, called DC-Multi-CL, to exploit the noisy labeled data using dual consistency architecture and multi-confident learning.

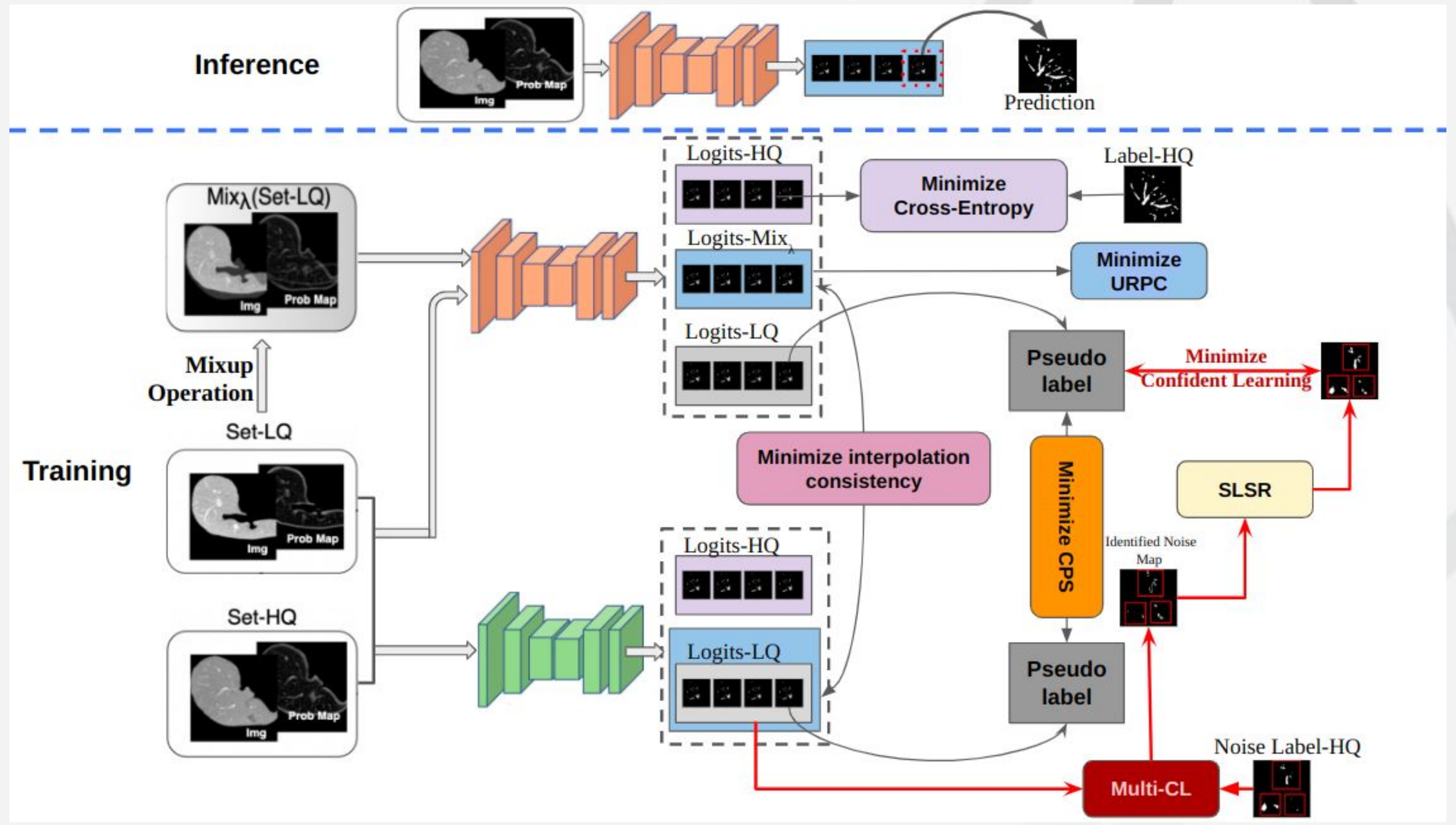

Fig. 2: Overview of the proposed DC-Multi-CL.

- DC-Multi-CL framework learns from both HQ labeled data and LQ labeled data by minimizing the total loss function:

$$\mathcal{L}_{total} = \mathcal{L}_s + \lambda_c \cdot (\mathcal{L}_{cps} + \mathcal{L}_{us} + \mathcal{L}_{urpc}) + \lambda_{cl} \cdot \mathcal{L}_{cl}$$

where:

- L_s: supervised loss , L_{cps}: cross pseudo supervision loss,
- L_{us}: unsupervised interpolation consistency loss,
- L_{urpc}: uncertainty rectified pyramid consistency loss,
- L_{cl}: auxiliary self-denoised Confident Learning loss,
- λ_c, λ_{cl}: hype-params to trade-off b/w losses.

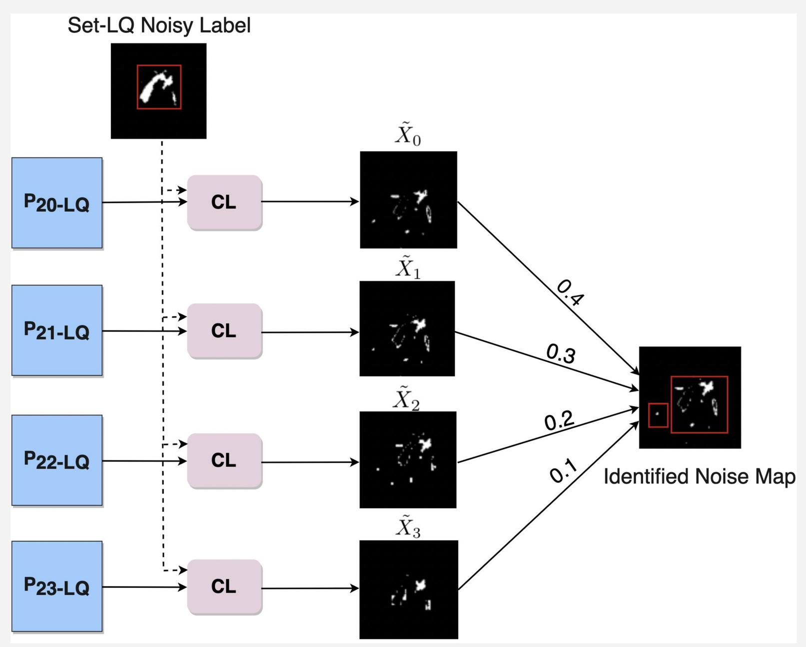

Fig. 3: Illustration of the proposed multi-confident learning.

Results

- DC-Mutil-CL vs. other SOTA methods

Table 1: Comparison of DC-Mutil-CL to other SOTA methods in terms of Dice score (DSC) and Hausdorff distance (HD).

Learning approaches	Methods	DSC↑	HD↓
Supervised learning	U-net [5]	64.01±5.11	9.50±2.03
	Swin-Unet [20]	63.95±3.61	9.99±1.46
Semi-supervised learning	MT [18]	65.78±4.17	8.55±1.36
	URPC [10]	66.47±4.94	8.49±1.23
	CCT [12]	66.10±4.47	8.85±1.25
	CPS [2]	66.55±4.19	8.85±1.63
Semi-supervised learning with LQ and HQ data	MTCL [21]	66.29±4.87	8.75±1.38
	Proposed DC-Multi-CL	**67.41**±4.68	**8.38**±1.56

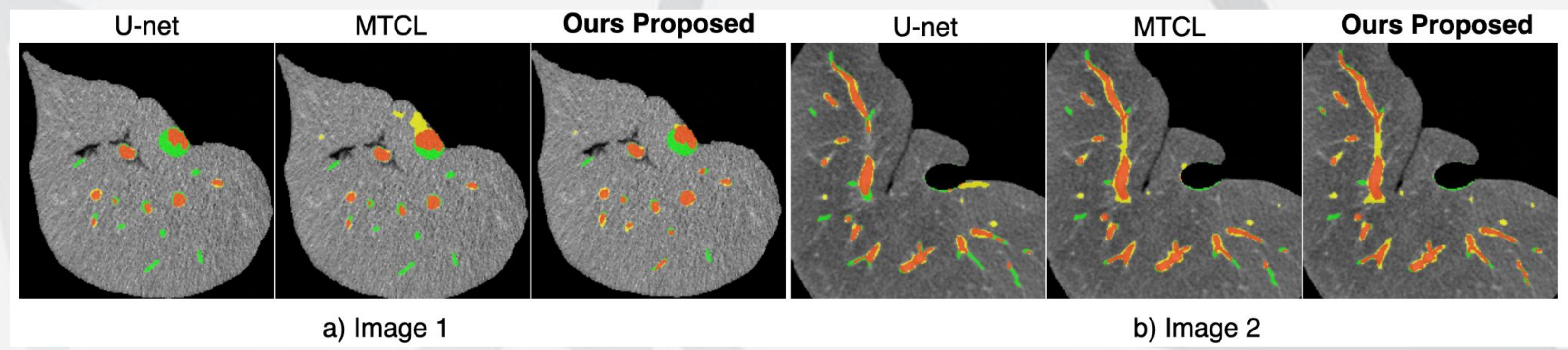

Fig. 4: Visual results on 3DIRCADb dataset. Orange indicates the correct segmented area, green the false negative and yellow the false positive.

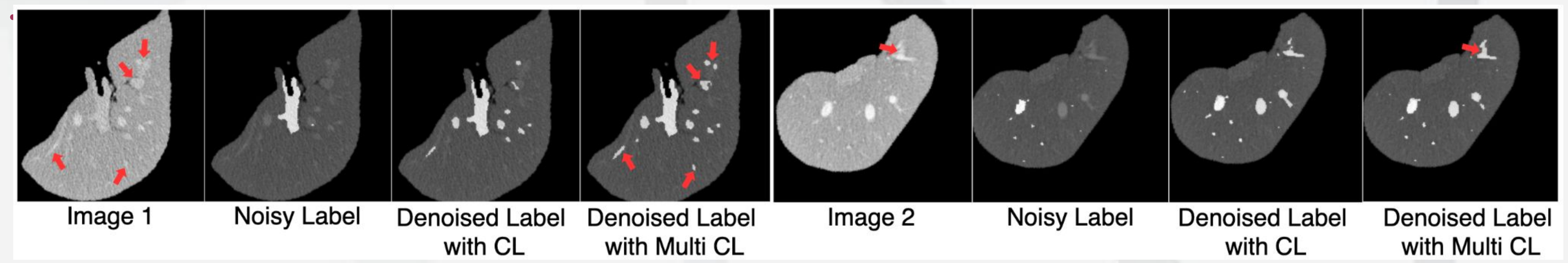

Fig. 5: Illustration of the mutil-confident learning performance for the MSD8 dataset.

- Ablation study

Table 2: Effectiveness to each component.

Method	DSC↑	HD↓
CPS [2]	66.55±4.19	8.85±1.63
CPS+ICT	66.53±4.54	8.51±1.51
CPS+Multi-CL	66.62±4.60	8.62±1.33
CPS+ICT+Multi-CL	66.71±4.62	8.73±1.43
CPS+URPC	66.53±4.15	8.53±1.25
CPS+ICT+URPC	66.87±3.90	8.58±0.94
CPS+Multi-CL+URPC	66.60±3.69	8.76±1.12
Proposed DC-Multi-CL	**67.41**±4.68	**8.38**±1.56

- Source code available at: https://github.com/VinBrainJSC/DualConsistency_Mutil-CL.