Supplemental Material

Streamlining the Annotation Process by Radiologists in Volumetric Medical Images with Few-Shot Learning

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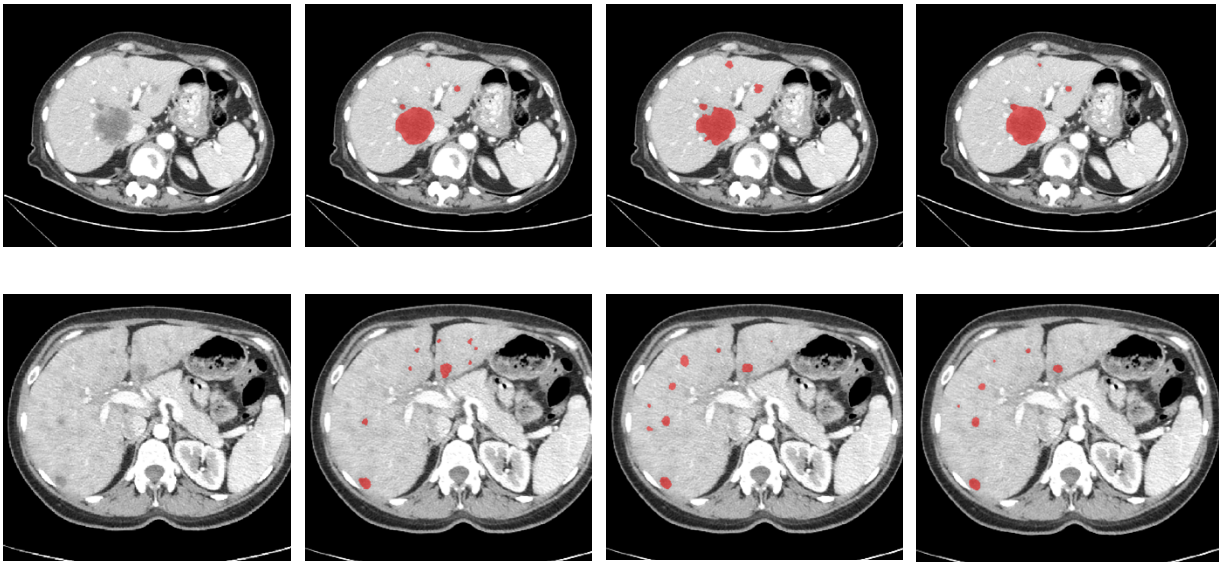
4. Experimental results

Study 3: **Evaluation of the prioritization strategy for manual radiologist correction**.

nnU-Net models trained with support set patch selection		Detection			Segmentation	
		Precision	***Recall***	***F1-Score***	***Dice***	***Dice_with_FN***
Random	**Mean**	**1.00**	**0.80**	**0.83**	**0.79**	**0.62**
	Std	(0.00)	(0.36)	(0.35)	(0.24)	(0.38)
Prioritized	**Mean**	**1.00**	0.78	0.81	**0.79**	**0.61**
	Std	(0.02)	(0.35)	(0.34)	(0.26)	(0.39)

Table S1: Results of Study 3. Performance of two nnU-Net models, one trained on randomly and the other trained on prioritized manually corrected scans on the ***DLIVER_TEST*** dataset. The detection results include precision, recall, F1-score averages, and standard deviations. The segmentation results include the mean and std for the ***Dice*** and ***Dice_with_FN*** scores.



(a) slice

(b) Ground truth segmentation

(c) nnU-Net model trained on random selection

(d) nnU-Net model trained on prioritized selection

Fig. S1: Illustration of the results of Study 3. Two examples of test scan axial images with ground truth annotations and their corresponding liver lesions (red) computed by two nnU-Net models, trained on random and prioritized support set patch selection.