MedContext: Learning Contextual Cues for Efficient Volumetric Medical Segmentation

Supplementary Material

1 Comaprison with MedNeXt (Table 1)

Table 1. *Comaprison with MedNeXt (MICCAI'23):* Our proposed MedContext when integrated with MedNeXt architecture improves its performance. Table shows the performance comparison in terms of Average dice score (%) of MedNeXt with and without our approach on synapse dataset.

Method	MedContext	Avg dice score (↑)
MedNeXt-M/K3	✗	85.97
	✓	**87.20**

2 Study on Consistency loss (Table 2)

Table 2. *Consistency loss:* Comparison of our Norm-L2 loss Vs. KL-Divergence for reconstruction. Average DSC (%) on synapse dataset across two architectures verify the effectiveness of our Norm-L2 loss.

Models	Consistency loss	Avg dice score (↑)
UNETR	KL-Divergence	79.67
	Norm-L2 (**ours**)	**81.13**
nnFormer	KL-Divergence	86.20
	Norm-L2 (**ours**)	**87.35**

3 Qualitative Comparisons (Fig. 1 and Fig. 2)

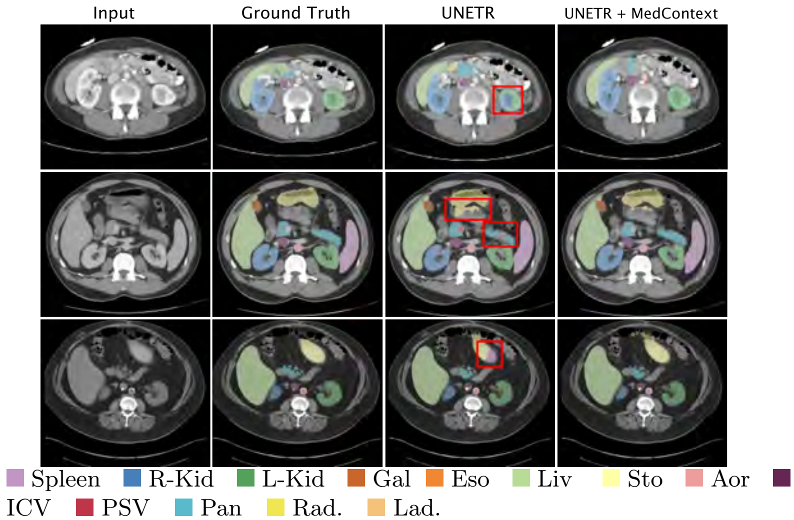

Fig. 1. Qualitative comparison on multi-organ synapse dataset: We showcase the benefit of our MedContext framework implemented on the UNETR architecture. The examples display various abdominal organs, with their corresponding labels in the legend below. The existing baseline method struggles to accurately segment the organs as can be seen from the red boxes. Best viewed in zoom.

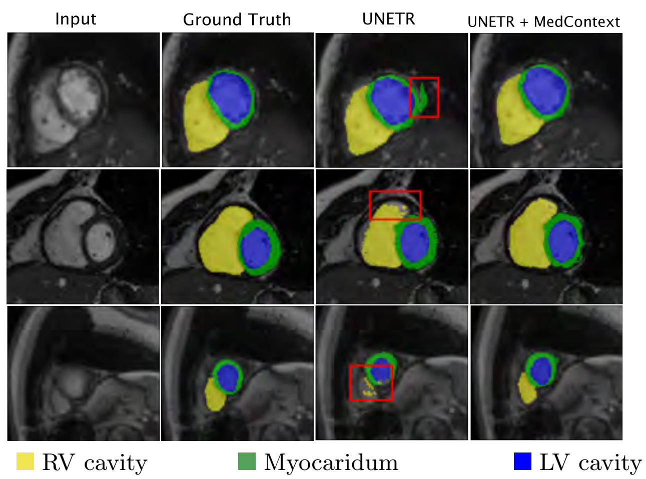

Fig. 2. Qualitative comparison on ACDC dataset using UNETR: We showcase the benefit of our MedContext framework integrated with UNETR architecture on ACDC dataset. The examples display three heart regions with their corresponding labels in the legend below. The baseline UNETR struggles to accurately segment the organs as can be seen from the red boxes. Our approach on the other hand produces correct and sharp segmentation boundaries. Best viewed in zoom.