MICCAI MICCAI2023 Vancouver CANADA

NORTHWESTERN POLYTECHNICAL UNIVERSITY

SegRap 2023

SEGMENTATION OF ORGANS-AT-RISK AND GROSS TUMOR VOLUME OF NPC FOR RADIOTHERAPY PLANNING

(no-contrast and contrast-enhanced CT, GTVnx & GTVnd & 45 OARs)

ORGANIZED BY

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Automatic Segmentation of OARs of NPC for Radiotherapy Planning via a Fine-tuned UniSeg Model (Task 01)

Yiwen Ye[1], Ziyang Chen[1], and Yong Xia[1,2]

[1]National Engineering Laboratory for Integrated Aero-Space-Ground-Ocean Big Data Application Technology, School of Computer Science and Engineering

[2]Ningbo Institute of Northwestern Polytechnical University, Ningbo 315048, China

1 Introduction

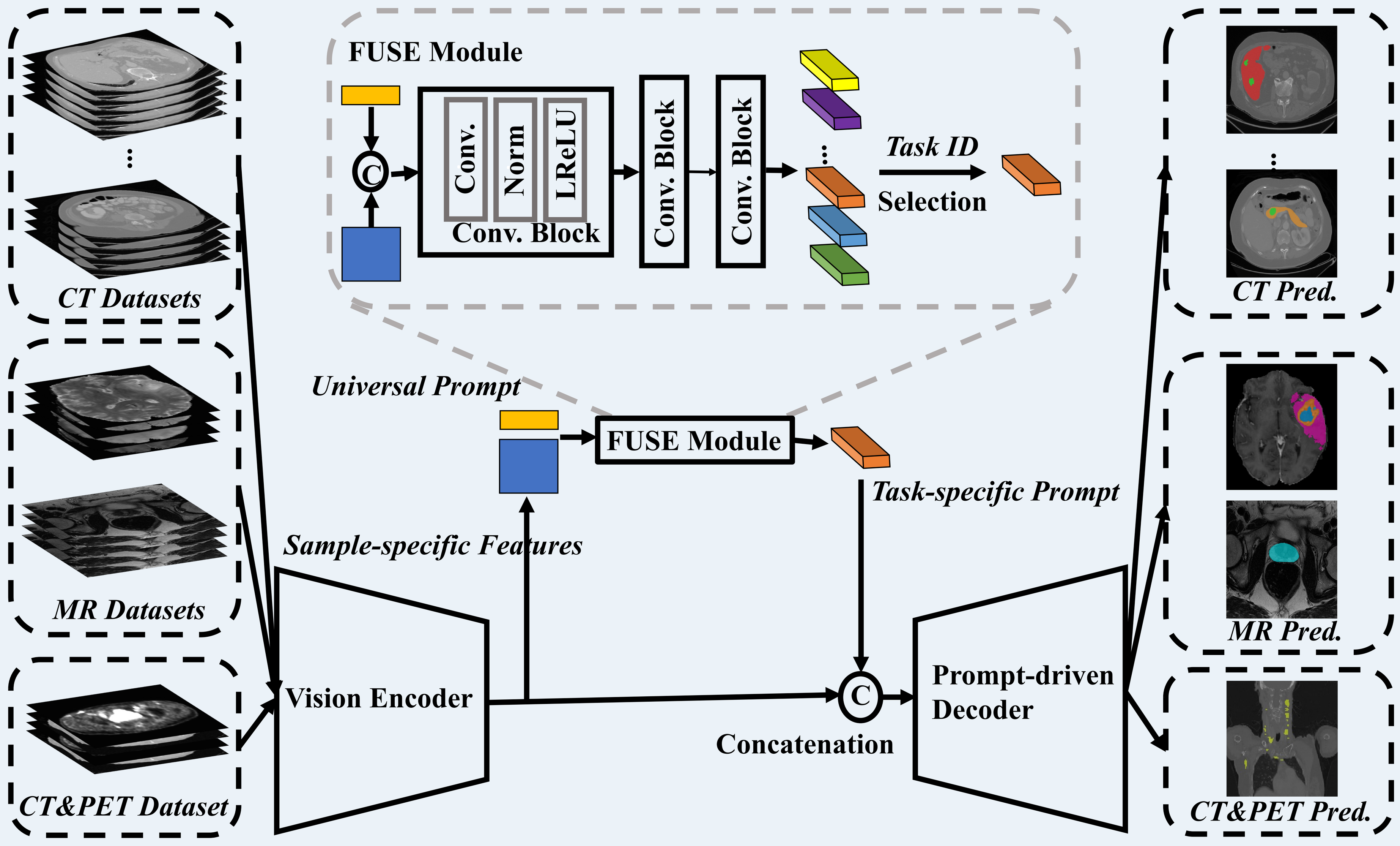
➢Task & Challenges

- Task:
  - a) Segment 45 Organs-at-Risk from CT images with high accuracy and robustness.
- Challenges:
  - a) Class Imbalance: Some organs have far fewer pixels in the image compared to others.
  - b) Ambiguous Organ Boundaries: The boundaries between different organs may not always be clear, complicating the segmentation task.

➢Motivation

Despite nnUNet has laudable performance, even outpacing seasoned experts in some clinical scenarios. nnUNet trained from scratch still leaves room for enhancement, particularly through transfer learning. To address this gap, our previous work developed a supervised pre-trained nnUNet model called UniSeg[1].

2 A Brief on UniSeg



Technical pipeline of our UniSeg, including a vision encoder, FUSE module, and a prompt-driven decoder. The sample-specific features produced by the encoder are concatenated with a learnable universal prompt as the input of the FUSE module. Then the FUSE module produces the task-specific prompt, which enables the model to be `aware' of the ongoing task.

3 Powerful Transfer Performance of UniSeg

Details of eleven upstream datasets and two downstream datasets.

Dataset	Upstream											Downstream	
	CT								MR		CT&PET	CT	MR
	Liver	Kidney	HepaV	Pancreas	Colon	Lung	Spleen	VerSe20	Prostate	BraTS21	AutoPET	BTCV	VS
Organ	✓	✓	✓	✓	×	×	✓	×	✓	×	×	✓	×
Tumor	✓	✓	✓	✓	✓	✓	×	×	×	✓	✓	×	✓
Vertebrae	×	×	×	×	×	×	×	✓	×	×	×	×	×
Train	104	168	242	224	100	50	32	171	91	1000	400	21	193
Test	27	42	61	57	26	13	9	43	25	251	101	9	49

Results of SSL and SL models. Blue numbers are used to indicate the performance gain using per-trained weights. We repeat all experiments three times and report mean values.

Dataset		MG	GVSL	SMIT	UniMiSS	DeSD	DoDNet	UniSeg
BTCV	Sp	86.8	90.6	90.7	95.0	96.1	96.4	96.2
	RKi	85.5	92.3	92.1	92.9	94.6	94.5	94.4
	LKi	83.0	91.2	91.9	91.5	93.2	89.7	91.6
	Gb	63.5	63.7	63.0	67.1	64.4	68.3	68.4
	Es	70.5	72.5	74.8	73.6	75.2	76.9	77.9
	Li	92.4	95.6	95.7	96.4	96.6	96.8	96.7
	St	78.3	80.1	75.9	82.4	88.7	86.5	87.8
	Ao	88.5	87.5	88.6	88.9	90.0	89.8	90.1
	IVC	85.3	84.4	86.4	83.9	87.5	87.7	87.6
	PSV	70.7	71.7	72.8	73.2	75.1	76.1	76.7
	Pa	71.4	72.7	74.3	76.2	79.9	81.9	83.3
	RAG	68.7	68.1	71.3	67.1	70.4	73.2	73.4
	LAG	58.2	63.6	69.5	67.0	70.5	75.2	75.1
	Mean	77.1 (+2.7)	79.5 (+1.9)	80.6 (+1.3)	81.2 (+3.0)	83.3 (+0.8)	84.1 (+0.9)	84.6 (+1.4)
VS	Tumor	79.3 (+7.2)	91.0 (+2.2)	92.2 (+2.3)	91.4 (+2.0)	92.2 (+1.5)	91.8 (+1.1)	92.9 (+2.1)

4 Implementation Details

➢Transfer Learning:

Transfer the pre-trained encoder-decoder to the SegRap Task.

➢Dataset:

Totally 120 no-contrast and contrast-enhanced CT with voxel-level annotations of 45 organs

➢Training and Inference Framework

nnUNet framework

➢Key settings:

Patch size: 32 × 192 × 192; Batch size: 2; Two models: one for 1500 training epochs and the other for 2000 epochs, leveraging all available training data.

5 Results on the Validation Set

Results of our method and the other top 5 methods on the validation leaderboard for Task 1. The best result for each metric is highlighted in blue.

Rank	DSC_Mean	NSD_Mean	DSC_Std	NSD_Std
1 (Ours)	89.25	0.9110	0.0742	0.0862
2	88.76	0.9052	0.0761	0.0872
3	88.81	0.9046	0.0791	0.0892
4	88.45	0.8985	0.0782	0.0911
5	87.95	0.8838	0.0810	0.1026

Performance of several solutions on Task 1. The best result on each metric is highlighted in blue.

Method	DSC_Mean	NSD_Mean	DSC_Std	NSD_Std
UniSeg w/ 1000 epochs (A)	88.82	0.9049	0.0775	0.0889
UniSeg w/ 1500 epochs (B)	89.01	0.9073	0.0745	0.0869
UniSeg w/ 2000 epochs (C)	88.94	0.9060	0.0757	0.0887
UniSeg-Ensemble (A + B)	89.19	0.9104	0.0750	0.0862
UniSeg-Ensemble (B +C) (Ours)	89.25	0.9110	0.0742	0.0862

[1] Ye Y, Xie Y, Zhang J, et al. UniSeg: A Prompt-driven Universal Segmentation Model as well as A Strong Representation Learner[J]. arXiv preprint arXiv:2304.03493, 2023.