Accurate and Efficient Segmentation for Organs-at-risk in Head and Neck CT

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Background

- Nasopharyngeal Cancer : malignant tumor with rapid increase and high mortality; Screening tool: no-contrast and contrast-enhanced CT;
- Treatment: Radiotherapy with external beam radiation; Radiotherapy planning: Delineating organs-at-risk (OARs) by radiologists

Key Challenge

- Inaccurate segmention caused by ①Complex anatomical structure, ②Low contrast of soft tissue in CT, ③Extremely unbalance in OARs

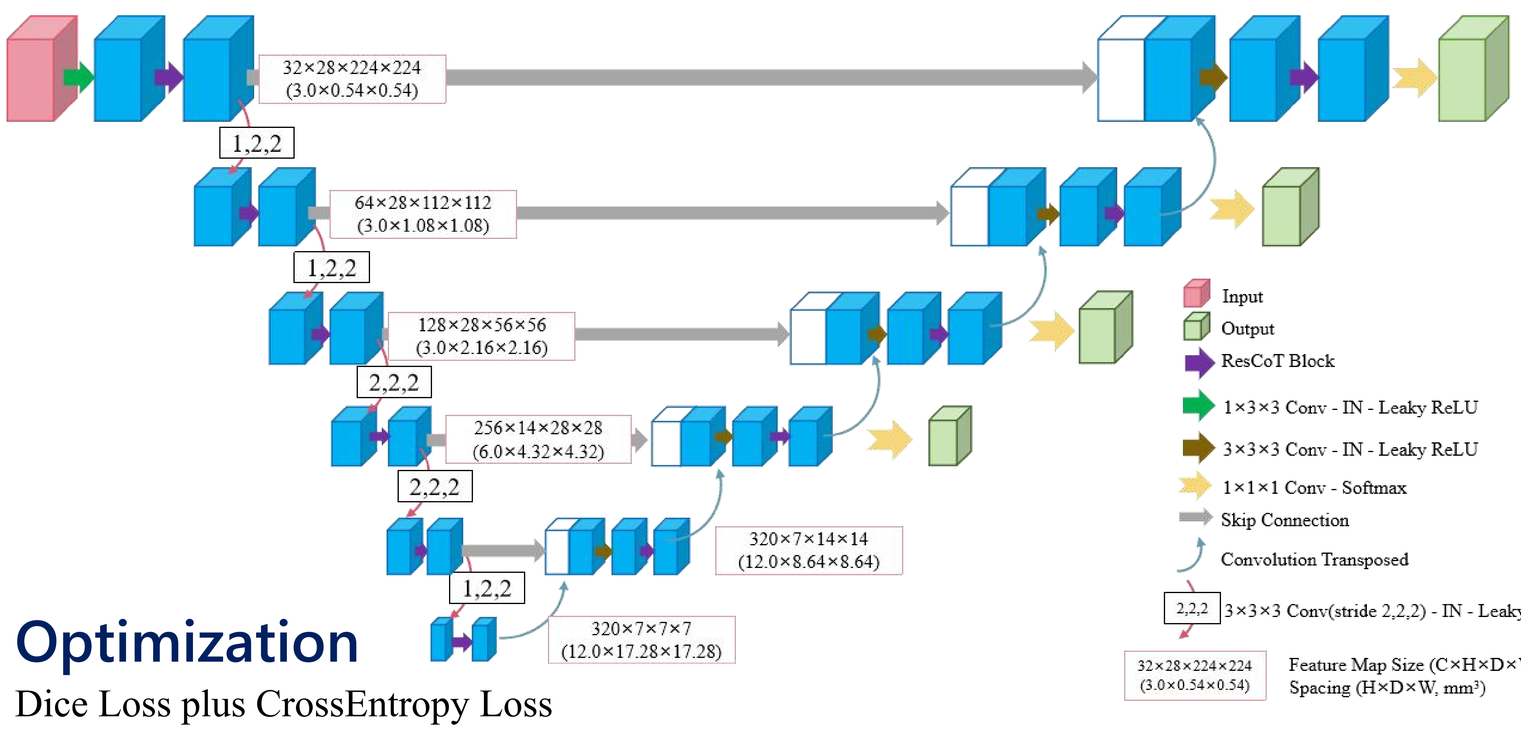
Our Contributions

- Take research on the three training modes to deal with label missing and regions segmentation in SegRap2023 Challenge.
- Consider location of OARs to make a more efficient sliding window setting, significantly reduces inference time consumption.
- Train a single model without pre-training, ensemble or additional data to obtain accurate delineation, has certain clinical significance.

Motivations and Method

A pure 3D U-Net and the deep supervision strategy are utilized to decrease model parameters and enhance learning ablility in different stages, respectively. Two CT scans (no-contrast and contrast-enhanced CT) are concatenated on the channel dimension as network input.

Thus, the framework is as follows:



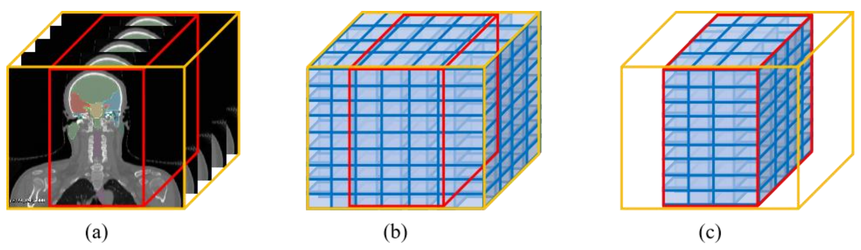
Optimization

Dice Loss plus CrossEntropy Loss

Inference

OARs are concentrated in the center along coronal axis, sliding window setting in coronal axis is changed to pay more attention to central coronal plane:

$$Steps_x = \{i_x \times 0.5 + k \times p_x | k = (-1.0, s-1, 0)\}$$



(a) (b) (c)

(a) Head and neck OARs location. (b) Original sliding window setting. (c) New sliding window setting, focus on the red box.

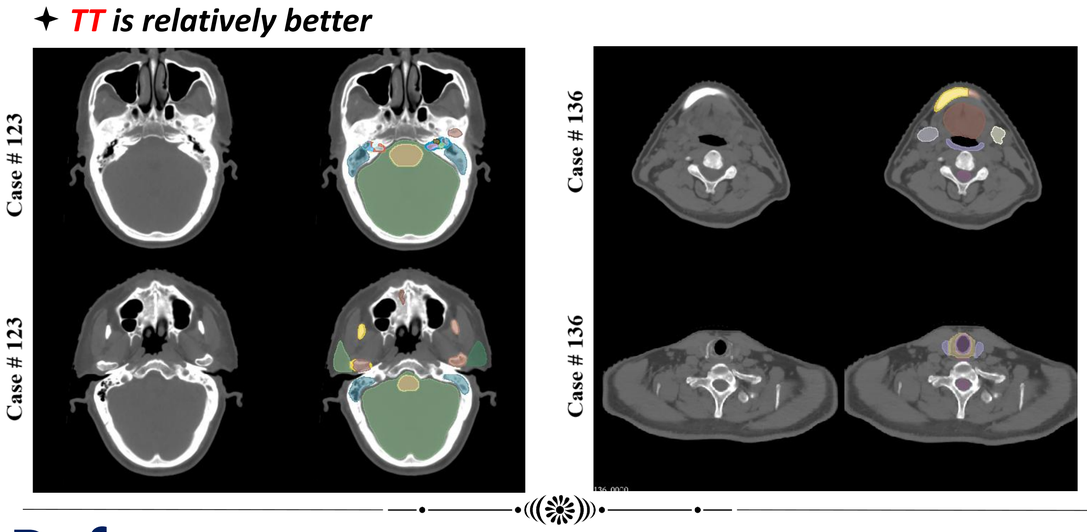
Experiments

1. Training Modes:

Modes	DSC(%)	NSD(%)	AVG(%)
TT	**88.47**	**89.82**	**89.15**
MT	86.43	87.51	86.97
RT	87.90	88.36	88.13

- Traditional training (**TT**): CE+Dice
- Masked training (**MT**): masked loss
- Region-based training (**RT**): BCE+Dice

✦ ***TT is relatively better***



2. Validation and Test:

✦ Validation: ***88.16±7.92*** ranking ***5th*** in leaderboard

Target	DSC(%)	NSD(%)	Target	DSC(%)	NSD(%)
Brain	98.62±0.31	89.64±5.29	BrainStem	91.88±2.62	80.27±9.95
Chiasm	69.67±13.72	76.18±14.36	Esophagus	76.69±8.15	68.06±11.69
Cochlea Left	94.54±2.13	78.90±7.67	Cochlea Right	94.63±2.52	78.21±9.29
ETbone Left	76.82±12.69	68.81±15.40	ETbone Right	93.53±4.74	90.73±9.33
Eye Left	91.60±11.29	87.15±11.96	Eye Right	77.72±8.99	89.90±9.64
HPC Left	74.88±12.74	85.63±15.20	HPC Right	78.60±9.48	86.41±10.69
IAC Left	79.26±13.27	86.74±14.40	IAC Right	86.78±5.93	89.68±7.50
Larynx	86.62±7.24	96.54±5.56	OralCavity	92.60±3.74	96.88±3.37
LG	82.80±9.32	94.19±8.04	LS	82.28±13.03	93.90±13.54
Lens Left	80.64±7.51	91.17±6.82	Lens Right	82.33±7.76	91.10±8.19
Mandible Left	82.75±9.03	94.83±7.22	Mandible Right	82.25±9.04	94.23±7.32
Mastoid Left	83.49±8.23	95.11±7.39	Mastoid Right	81.50±13.63	93.99±11.00
ME Left	80.92±6.77	94.19±5.78	ME Right	74.61±12.70	89.55±11.08
ON Left	76.58±16.14	84.78±16.08	ON Right	94.94±1.60	75.09±10.34
Parotid Left	91.73±6.08	88.57±10.41	Parotid Right	89.00±7.61	82.42±13.51
PhConst	86.46±12.04	78.32±18.06	Pituitary	90.25±4.48	74.12±16.19
SM Left	92.55±2.70	89.25±7.04	SM Right	92.35±3.60	88.69±9.14
TMJ Left	81.86±8.01	79.67±12.52	TMJ Right	89.14±4.19	87.33±7.75
TL Left	88.88±7.36	87.27±12.41	TL Right	89.43±5.55	88.38±9.64
Thyroid	89.27±4.05	86.09±10.95	Trachea	84.08±2.20	75.30±5.88
TC Left	89.23±2.38	73.72±9.52	TC Right	84.04±4.92	84.77±9.92
VS Left	90.59±3.12	87.78±9.05	VS Right	85.48±7.87	74.97±14.70
SpinalCord	88.99±5.73	71.53±17.16			
Average	85.62±10.48	85.33±13.42	Avg Score	85.48±10.53	

✦ Final Result: ***85.48±10.53*** on 60 testing cases

References

[1] Isensee, Fabian, et al. "nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation." Nature methods. 2021.

[2] Ronneberger, et al. "U-net: Convolutional networks for biomedical image segmentation." Int. Conf. on MICCAI. 2015.

[3] Huang, Ziyan, et al. "Revisiting nnU-net for iterative pseudo labeling and efficient sliding window inference." Int. Conf. on MICCAI Challenge. 2022.