Accurate and Efficient Segmentation for Gross Tumor Volume 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 gross tumor volume (GTVs) by radiologists

Key Challenge

- Inaccurate segmention caused by ①Individual differences, ②Low contrast of soft tissue in CT, ③Unbalance of bg and fg, ④Multi-regions

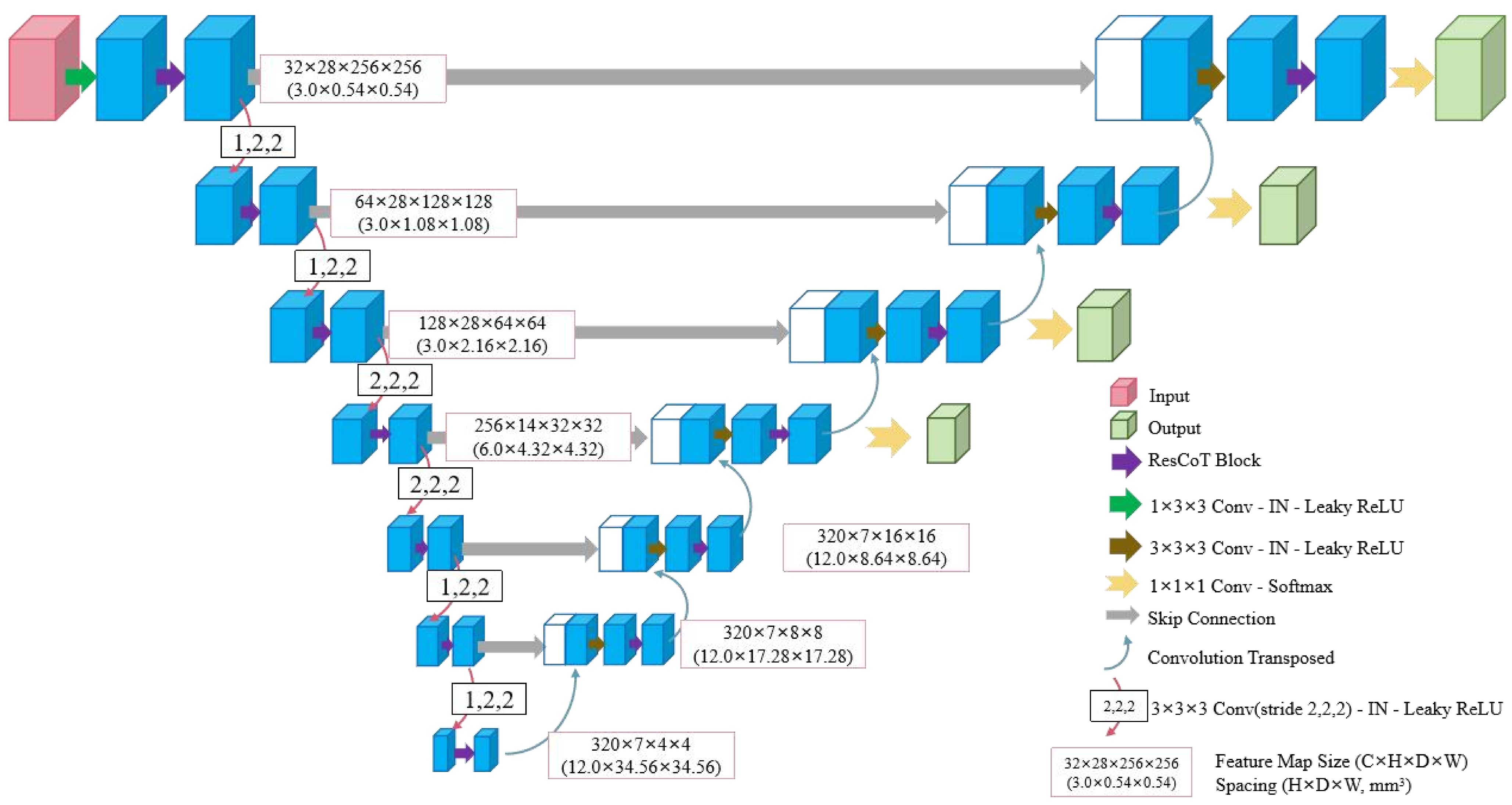
Our Contributions

- We combine the Focal loss to make the model focus on the GTVs which are not prone to distinguish.
- 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:



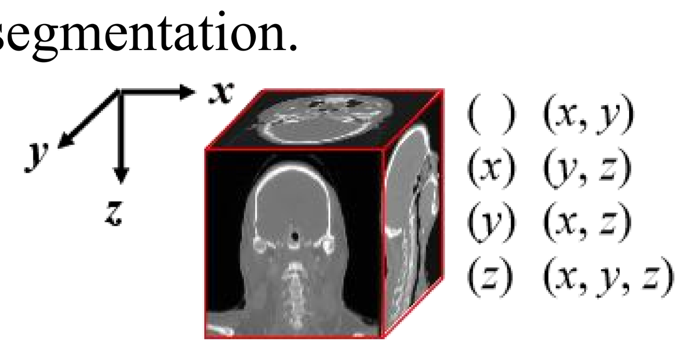
Optimization

Dice Loss plus Focal Loss

$$
\begin{aligned}
L &= L_{Dice} + L_{Focal} \\
&= \sum_{c=0}^{C-1}\left(1-\frac{TP_p(c)}{TP_p(c)+\alpha FP_p(c)+\beta FN_p(c)}\right)/C \\
&\quad -\sum_{n=1}^{N}\sum_{c=0}^{C-1}\left[g_n(c)(1-p_n(c))^2\log(p_n(c))\right]/N
\end{aligned}
$$

Inference

Flipping Testing Time Augmentation (TTA) is used in inference to performance more accurately GTVs segmentation.



Experiments

1. Training and Validation:

Target	Dice and CE loss		Dice and Focal loss	
	DSC(%)	NSD(%)	DSC(%)	NSD(%)
GTV_p	79.86±6.80	72.28±12.26	80.44±5.92	72.61±11.71
GTV_{nd}	77.37±8.04	73.12±7.80	77.26±9.44	73.09±9.09
Average	78.61±7.55	72.70±10.28	78.85±8.04	72.85±10.49
AVG Score	75.66±8.38		**75.85±8.70**	

✦Dice-Focal Loss performs higher than Dice-CE Loss, making model focus on those hard-to-segment.

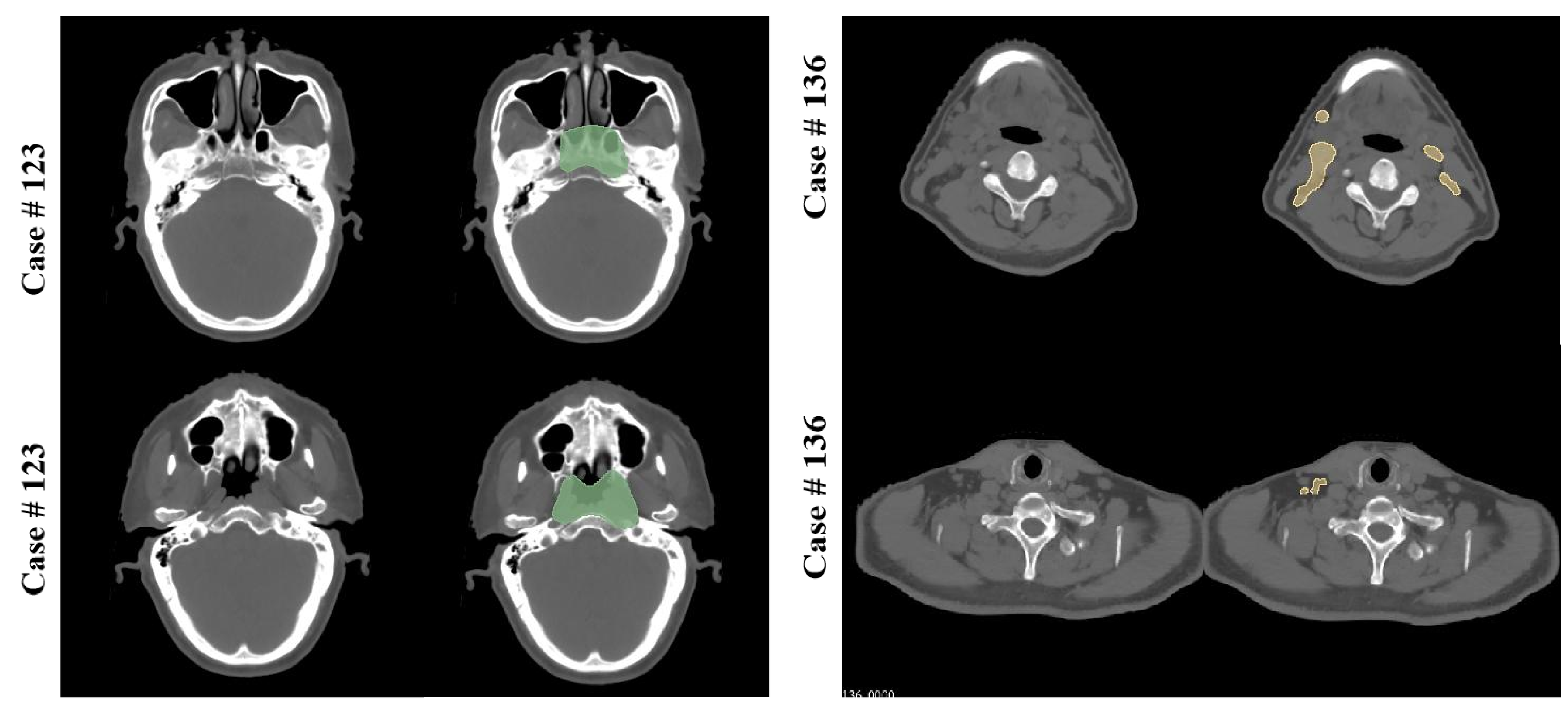
✦ Validation: ***75.85***±***8.70*** ranking ***4th*** on leaderboard

2. Test:

Target	Dice and Focal loss	
	DSC(%)	NSD(%)
GTV_p	78.76±6.60	35.92±11.05
GTV_{nd}	67.41±13.78	63.08±15.37
Average	73.09±12.21	49.50±19.07
AVG Score	61.29±12.18	

✦ Final Result: ***61.29***±***12.18*** on 60 testing cases

3. Visulization:



References

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

[3] Lin, Tsung-Yi, et al. "Focal loss for dense object detection." ICCV. 2017.