

# A Two-Stage Solution for Organ-at-Risks Segmentation

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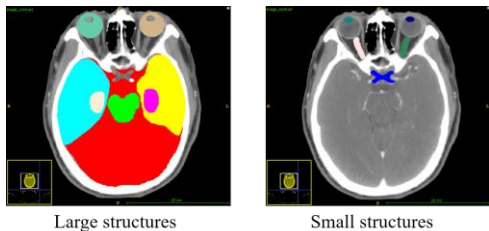
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## Background

- The delineation of organs at risk(OAR) in radiotherapy is crucial for accurate and safe radiation treatment planning.
- Manual OAR delineation is very time consuming, but deep learning models can significantly reduce the physician's workload.

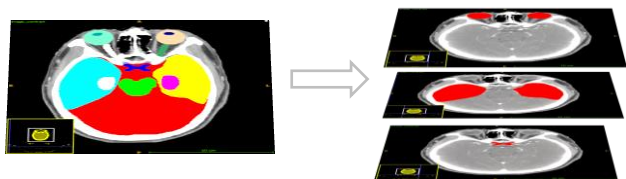
## Introduction

## Challenges

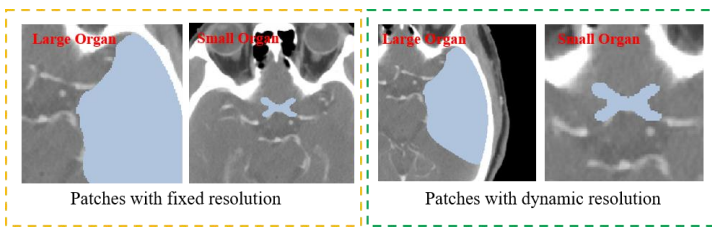


- Complexity of the anatomical structures (eg. overlap between structures)
- Extremely imbalanced size between large and small structures.

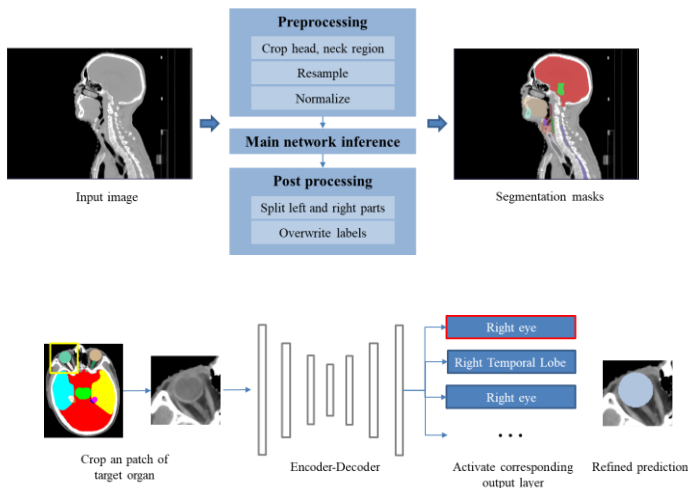
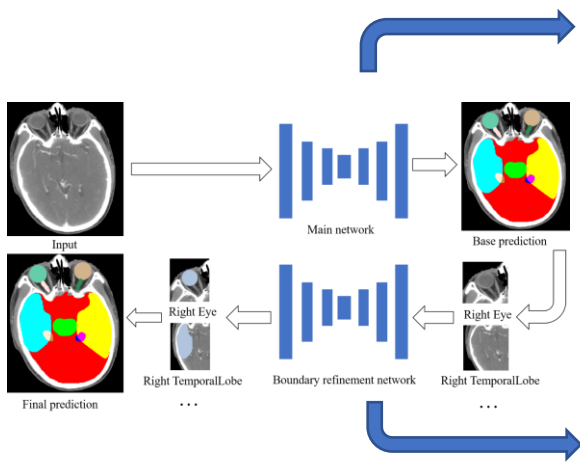
## Methodology



Reduce number of training targets according to anatomical relationships (45 to 29 classes)



Boundary refinement with dynamic resolution



## Result

Table 1. DSC and NSD score of different augmentation methods

Methods	Flip X	Flip Y,Z	DSC	NSD
Augmentation 1	✓	✓	0.8818	0.9013
Augmentation 2			0.8854	0.9121
Augmentation 3		✓	0.8894	0.9134

Table 2. DSC and NSD score of different inference methods. Only the organs that sent to boundary refinement network are evaluated.

OAR	w/o boundary refinement		w boundary refinement	
	DICE	NSD	DSC	NSD
Esophagus	0.8837	0.8819	0.8913	0.8984
Hippocampus <sub>L</sub>	0.8164	0.7522	0.8198	0.7620
Hippocampus <sub>R</sub>	0.8154	0.7591	0.8166	0.7666
TemporalLobe <sub>L</sub>	0.9516	0.8247	0.9539	0.8359
TemporalLobe <sub>R</sub>	0.9537	0.8218	0.9564	0.8352
Eye <sub>L</sub>	0.9507	0.9437	0.9529	0.9458
Eye <sub>R</sub>	0.9418	0.9286	0.9426	0.9280
Mandible <sub>L</sub>	0.9522	0.9459	0.9525	0.9517
Mandible <sub>R</sub>	0.9534	0.9475	0.9549	0.9601
Parotid <sub>L</sub>	0.9316	0.8581	0.9338	0.8689
Parotid <sub>R</sub>	0.9249	0.8439	0.9267	0.8533
Average	0.9159	0.8643	0.9183	0.8733

## Conclusion

- In this study, we propose a robust segmentation method for dealing with multiorgan segmentation. It is expected to provide a powerful tool for radiotherapy planning.
- Our experiments show that the boundary refinement network can improve the accuracy of most organs.

## Reference

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