Deep learning for Radiotherapy Autosegmentation Workflow (*DRAW*) : System engineering and preliminary experience with an auto segmentation solution built using open source software.

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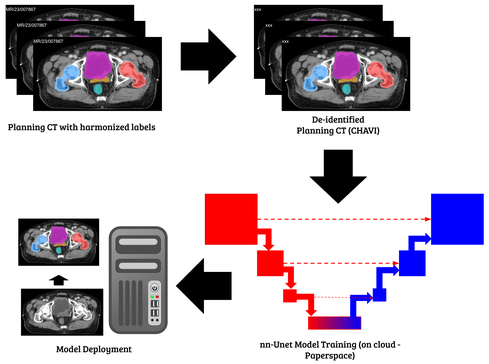
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Introduction

- Segmentation of target volumes and OAR is one of the most error prone steps in Radiotherapy.
- Accurate segmentation is critical for successful radiotherapy.
- An increasing number of commercial systems offer automatic segmentation.
- Open source algorithms for automatic segmentation can provide an alternative.
- We describe our attempt at developing an open source, automatic segmentation workflow for general radiotherapy automatic segmentation using nn-Unet.

Methods



Structure set label harmonized (TG-263)

Overlapping labels separated into separate models

Models for a particular cancer type organized using YAML files

Training using ConvUnet preset

Post Processing for bilateral structures

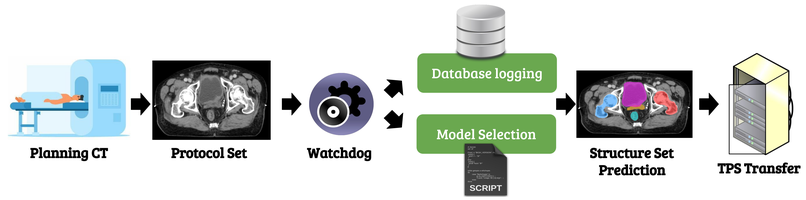
☑️ Deployed a flexible, open source automatic segmentation pipeline

☑️ 701 patients autosegmented since May 2024

☑️ Future plan : Deploy multi-center with client server architecture

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https://github.com/CHAVI-India/draw

Results



Cancer Site	Prostate	Breast	Breast	CNS
Version	1.0	1.0	2.0	1.0
Patients	48	61	125	56
Testing	12	16	32	14
Training Date	01/11/2023	30/05/2024	18/09/2024	13/01/2024
Deployment	Jan 2024	June 2024	Oct 2024	Feb 2024
Models	3	11		4
OAR	Bladder Anorectum Bag_Bowel Femur_Head Penile Bulb	Heart, Lung,Esophagus, Spinal Cord, Brachial Plexus, Breasts, Liver, Left Ant Desc A., Thyroid, Clips		Brain, Cochlea, Eye, Lens, Optic Apparatus, Brainstem, Hippocampi, Temporal lobes
Target	CTVp CTVn	CTVp_TumorBed CTVn_IMN, CTVn_SCF		-NA-
Best DSC	0.97 (Bladder)	0.98 (Lung)	0.99 (Lung)	0.97 (Brain)
Worst DSC	0.66 (Penile Bulb)	0.40 (Cord)	0.41 (Br Pl)	0.37 (Optic Chiasm)

Lessons Learned:

1. Deployment and logging of the prediction tasks in production took longer than model training.
2. Model results may be unreliable for small structures (esp Left Ant Descending A.).
3. Testing in prostate did not suggest a significant benefit from Residual Encoders (testing in small volume structures pending).
4. Default trainer based on smoothened Dice Loss resulted in inability to segment some structures (e.g cohclea / hippocampus)/

References

Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., & Maier-Hein, K. H. (2021). nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 18(2), 203-211.