

Automatic target propagation strategies for MRI-guided cervical brachytherapy



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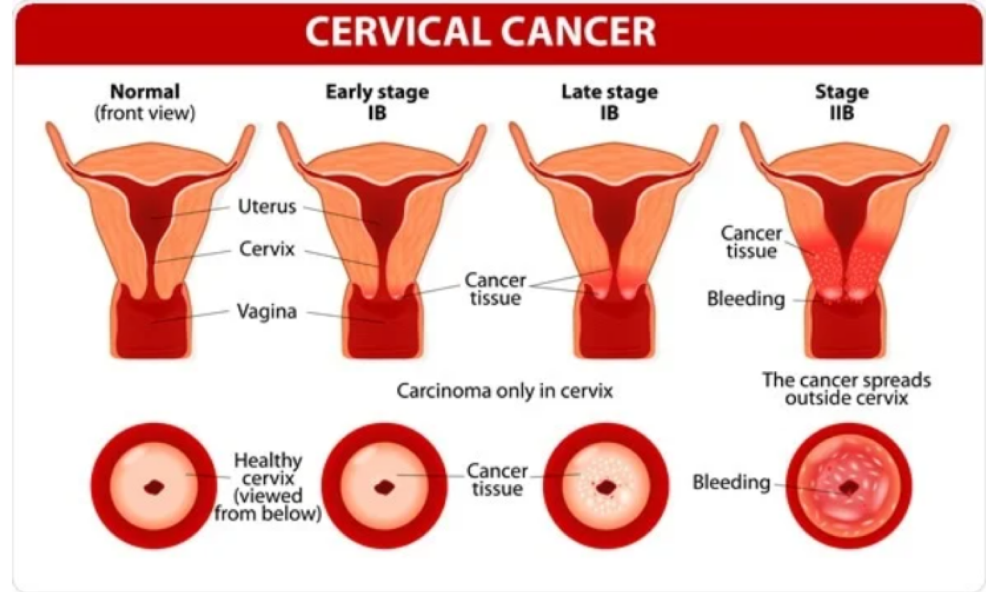
Tomas M. Janssen



Cervical cancer

4th most common cancer
in women

~ 350k deaths in 2022
(WHO)



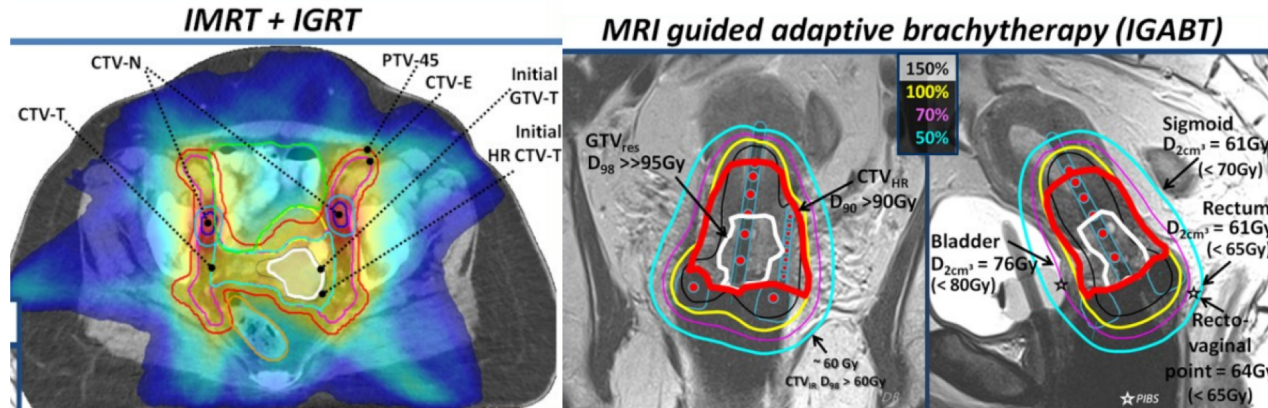
Cervical Cancer. Carcinoma of Cervix. Malignant neoplasm arising from cells in the cervix uteri.
Image Copyright: Designua / Shutterstock

@ Netherlands Cancer Institute: ~50 patients treated per year

Cervical cancer

Standard of care

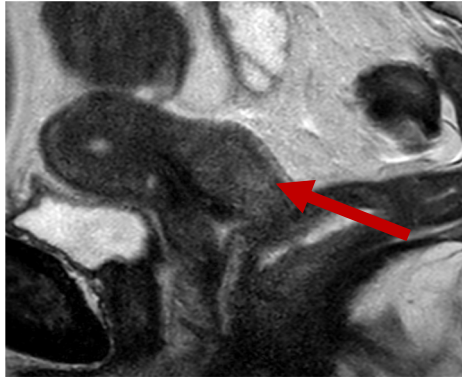
- 25 x 1.8 Gy EBRT + chemo
- 3 x 7 Gy MR-guided adaptive brachytherapy



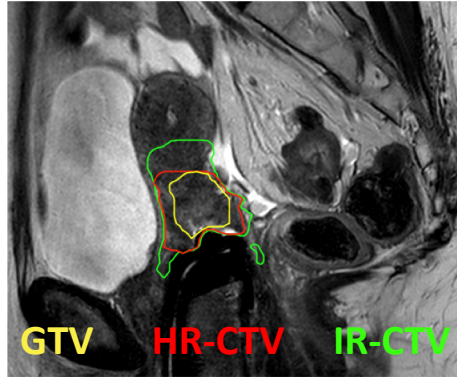
Pötter *et al*
ctRO 2018

→ Time-consuming workflow!

Cervix brachytherapy: target volumes



Pre-treatment



Fraction 1

GTV

visible tumor

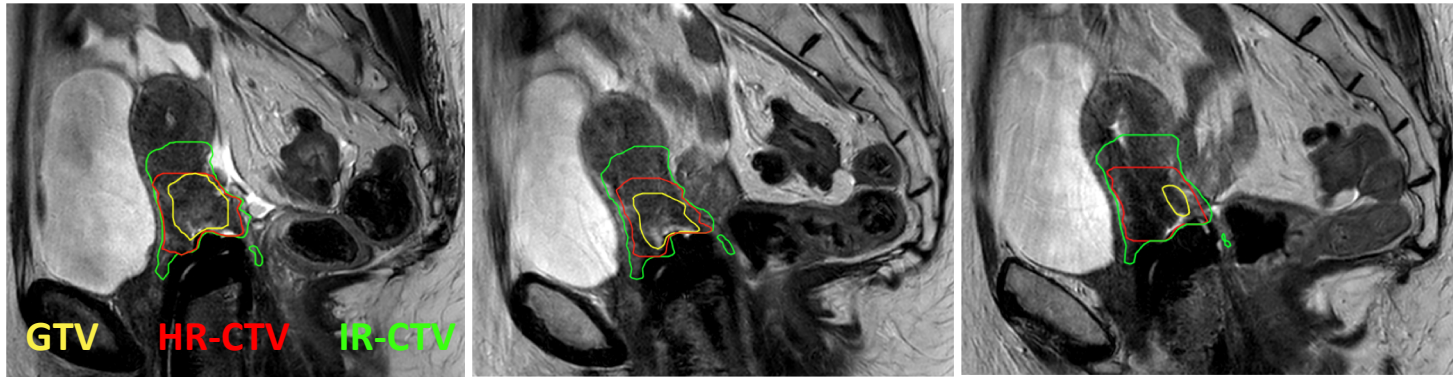
HR-CTV

GTV + microscopic disease
+ cervix

IR-CTV

pre-treatment tumor extent
(+ possible margin on the
HR-CTV)

Cervix brachytherapy: target volumes



Fraction 1

Fraction 2

Fraction 3

How can we best **propagate** structures from **fraction 1** to **fractions 2 and 3**?

Data

1. Training set: **203 patients**, 2011-2021

- tT2 scans
- clinically used structures

	train	validation
patients	168	41
images	455	120

2. Test set: **29 patients** (79 images), February 2022-August 2023

- for all fractions: tT2 scans + clinically used structures
- for fractions 2 and 3: rigidly propagated structures before correction

Methods

- 1) **Rigid registration:** currently used clinically
- 2) **Deformable registration**
- 3) **Image-only auto-segmentation:** MRI as input to auto-segmentation
- 4) **Image+prior auto-segmentation:** MRI + previous segmentations as input
- 5) **Patient-specific fine-tuning:** image-only model is trained on the previous fraction images → one model per patient/fraction

Methods

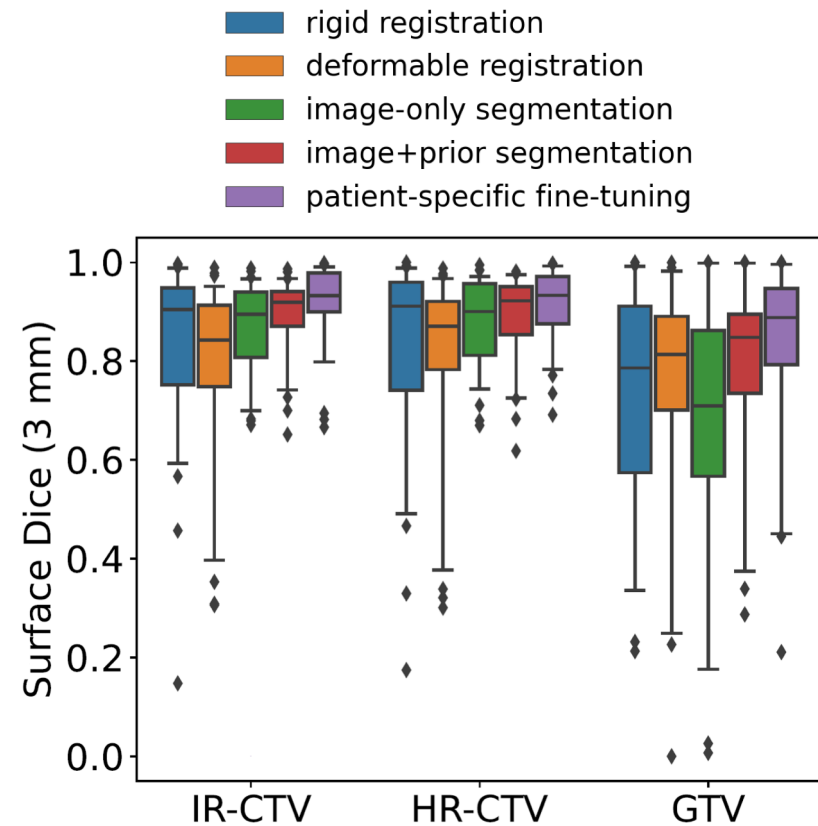
Performance evaluation

- on the 2nd and 3rd fractions of the 29 patients
- clinical structures as ground truth
- surface Dice (3 mm), mean surface distance, added path length
- Wilcoxon signed-rank test

Training details

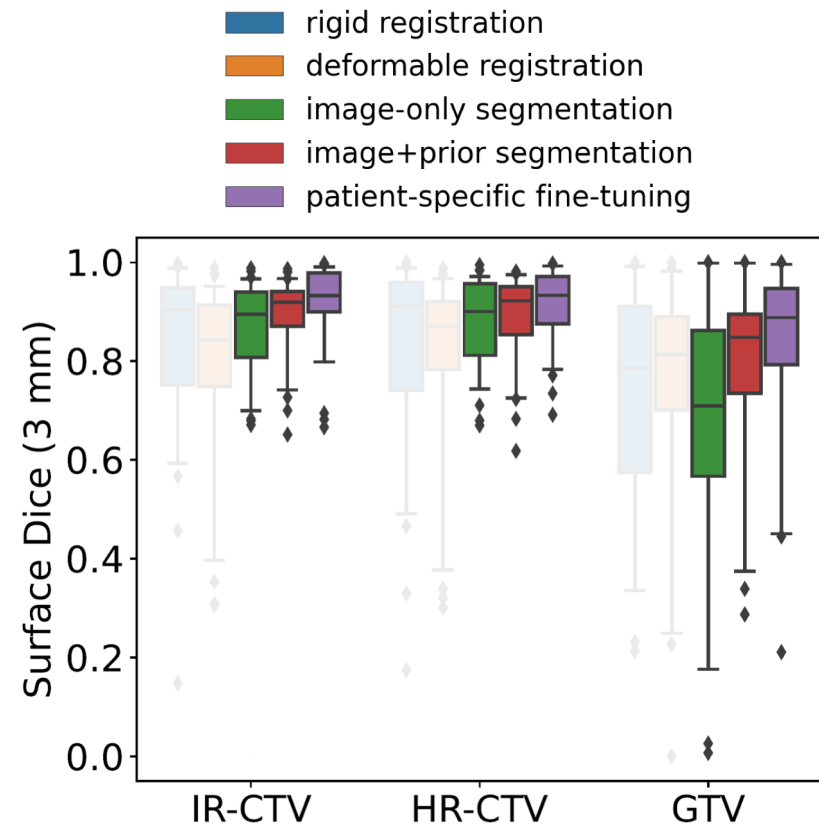
- 1) Training of the **auto-segmentation models** on the training set: 3D nnU-Net
- 2) Patient-specific **fine-tuning** on the test set
 - Continued training the image-only model on **fraction N-1, evaluated on fraction N**
 - Stopped after **5 iterations** (empirically observed that results didn't change much)

Results



Results

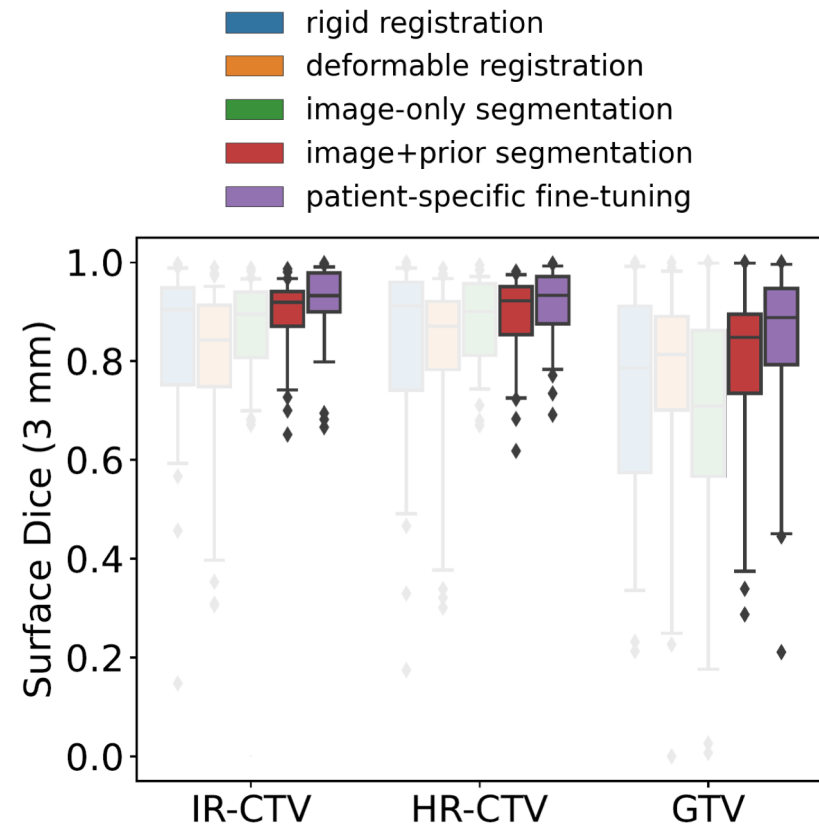
Deep learning-based auto-segmentation outperformed the registration methods



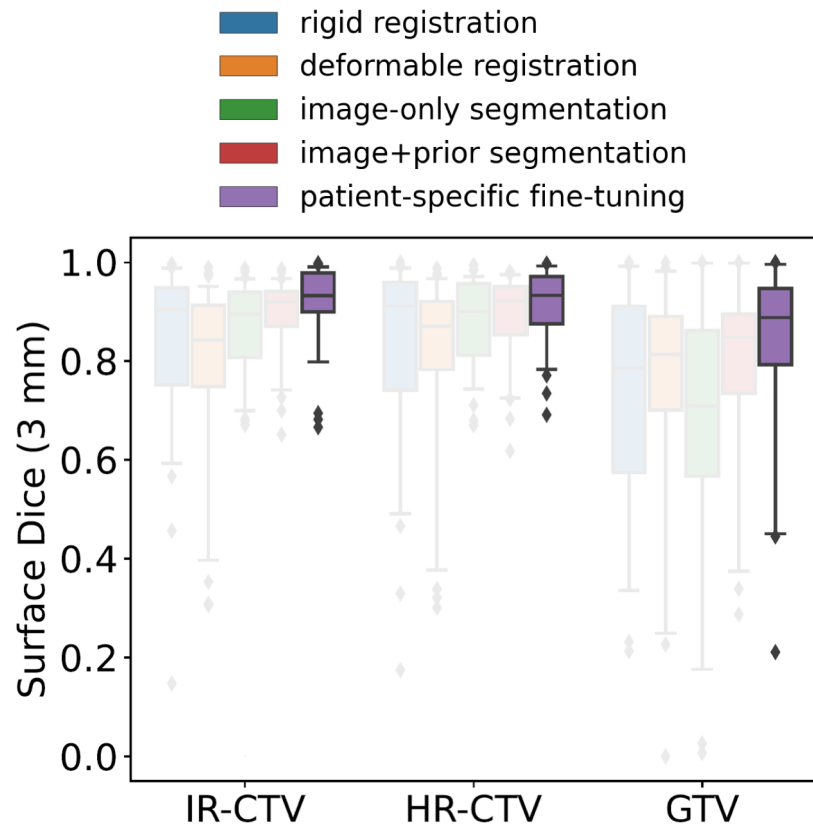
Results

Deep learning-based auto-segmentation
outperformed the registration methods

Adding patient-specific information
improved upon the image-only model



Results



Deep learning-based auto-segmentation outperformed the registration methods

Adding patient-specific information improved upon the image-only model

Patient-specific fine-tuning outperformed the image + prior model

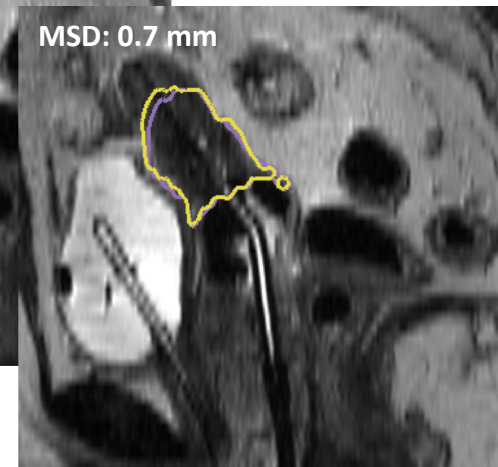
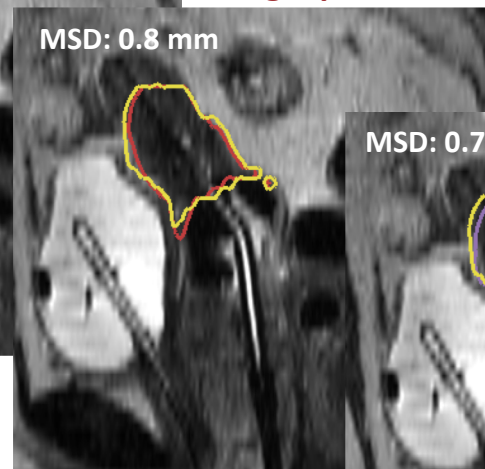
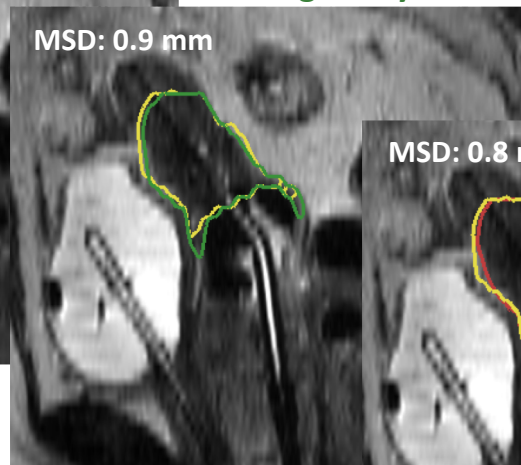
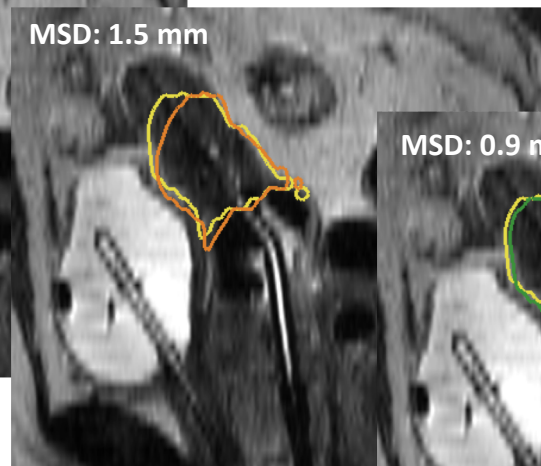
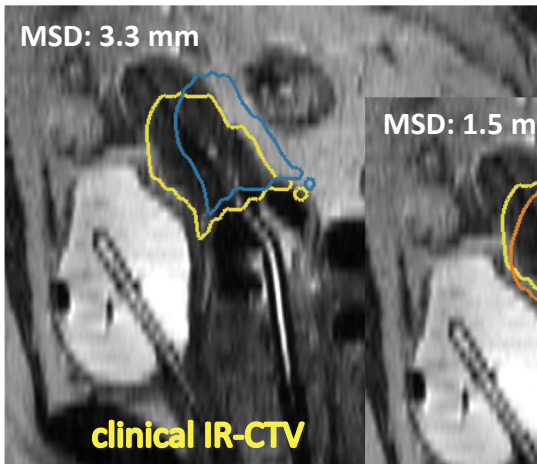
Rigid

Deformable

Image-only

Image+prior

Fine-tuning



Current steps

Evaluation of the potential clinical impact of using the **image-only** and the **patient-specific** models

- Automation bias
- Dosimetric impact
- Inter-observer variability
- Time gains

Clinical implementation!

Thank you!



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