Leveraging Patient-Specific Imaging and Contour Data to Improve Deep Learning Autocontouring Models for Adaptive Prostate Radiotherapy

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INTRODUCTION

Online Adaptive Radiotherapy (oART) requires daily imaging and the creation of a new plan while the patient is on the treatment couch.

Longer contouring times increase the risk of patient motion or anatomical changes, which can **negate the benefits of precision oART**.

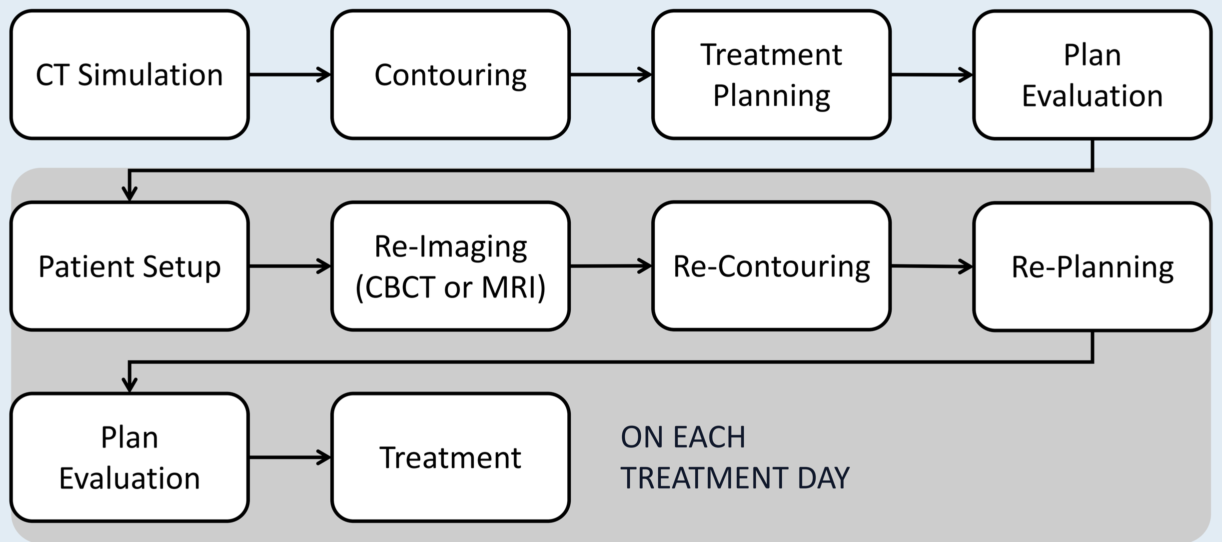

Figure 1. Online Adaptive Radiotherapy workflow.

Figure 2. A picture of Varian Ethos platform.

OBJECTIVE

Develop a deep learning-based autocontouring pipeline that integrates planning and prior fraction images and contours to improve autocontouring of the prostate, bladder, and rectum in adaptive prostate radiotherapy using Ethos with HyperSight imaging.

METHODS

General Model

- The no-new-net (nnU-Net) framework was used to develop deep learning models [1].
- Trained on planning CT (pCT) images and contours from 100 patients with prostate cancer.

Patient-Specific Models

- Created by fine-tuning the general model with each patient's planning CT and subsequent fraction HyperSight CBCT images and contours.
- 25 patients with prostate cancer treated with five-fraction oART on the Varian Ethos platform with HyperSight.
- Fine-tuning was performed cumulatively:
  - Fraction 1 model: fine-tuned on pCT only
  - Fraction 2 model: fine-tuned on pCT + fraction 1 data
  - … and so on.

Autocontouring Evaluation

- Assessed against expert-drawn treatment contours for the prostate, bladder, and rectum.
- Metrics:
  - Dice Similarity Coefficient (DSC).
  - 95^{th} percentile Hausdorff Distance (95HD).

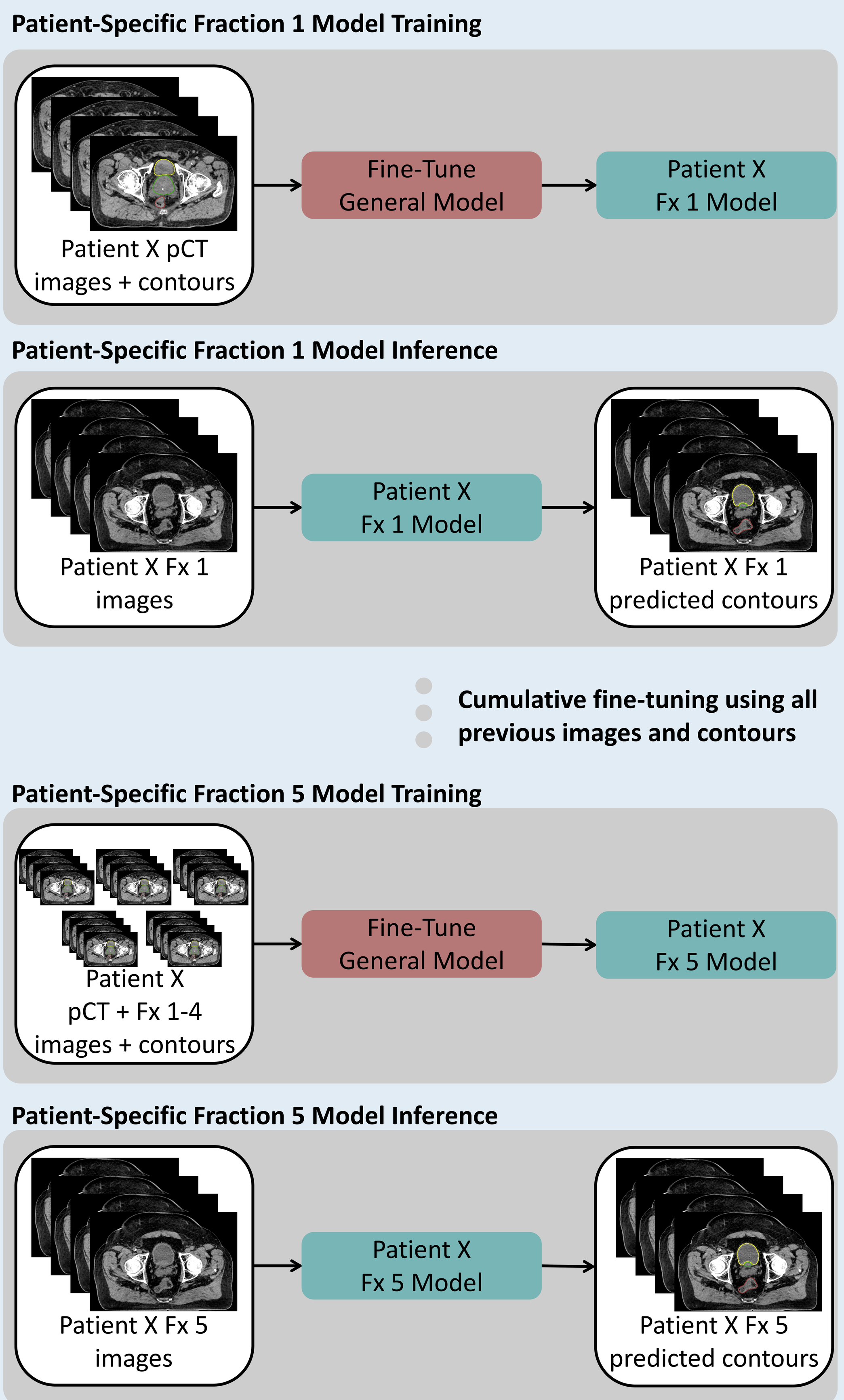

Figure 3. Patient-specific model training and inference.

RESULTS

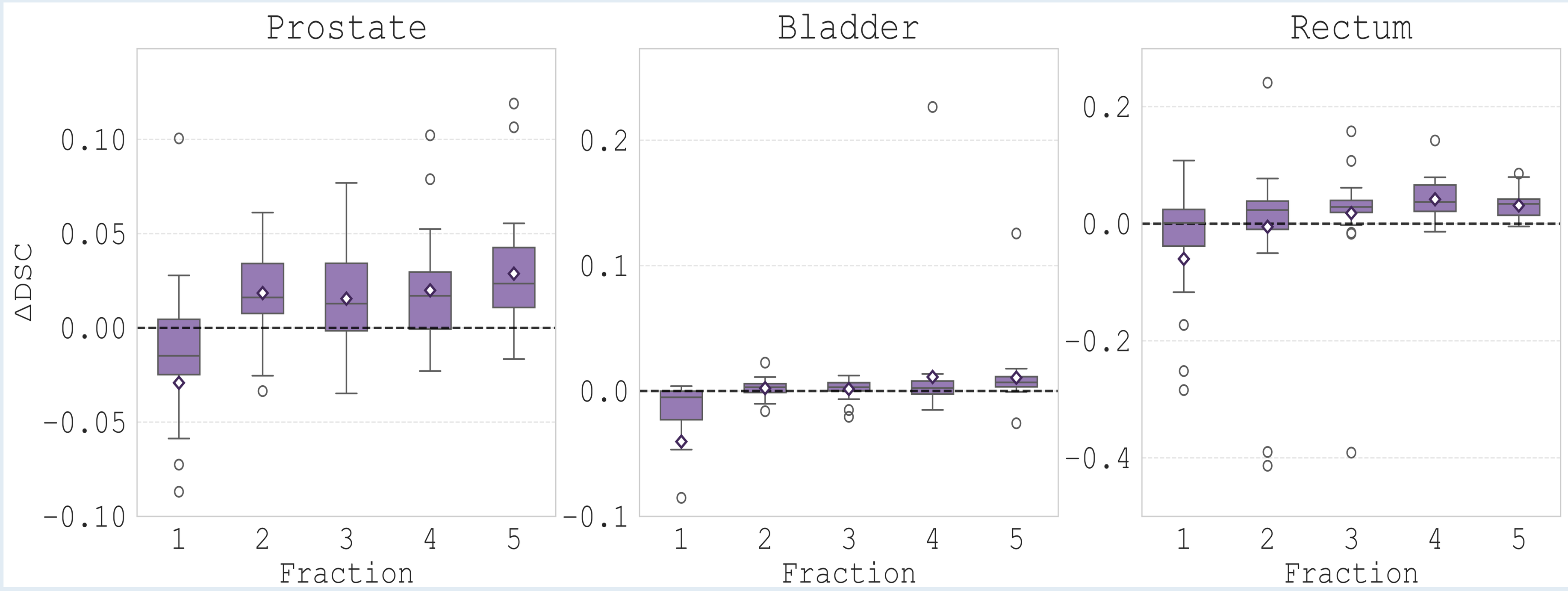

Figure 4. Distributions of ΔDSC (patient-specific minus general model) across five fractions for the prostate, bladder, and rectum on the independent test set (N = 25). Mean values are represented by diamonds. Positive values indicate improvements. For clarity, one outlier was excluded per structure (prostate: -0.464; bladder: -0.704; rectum: -0.922).

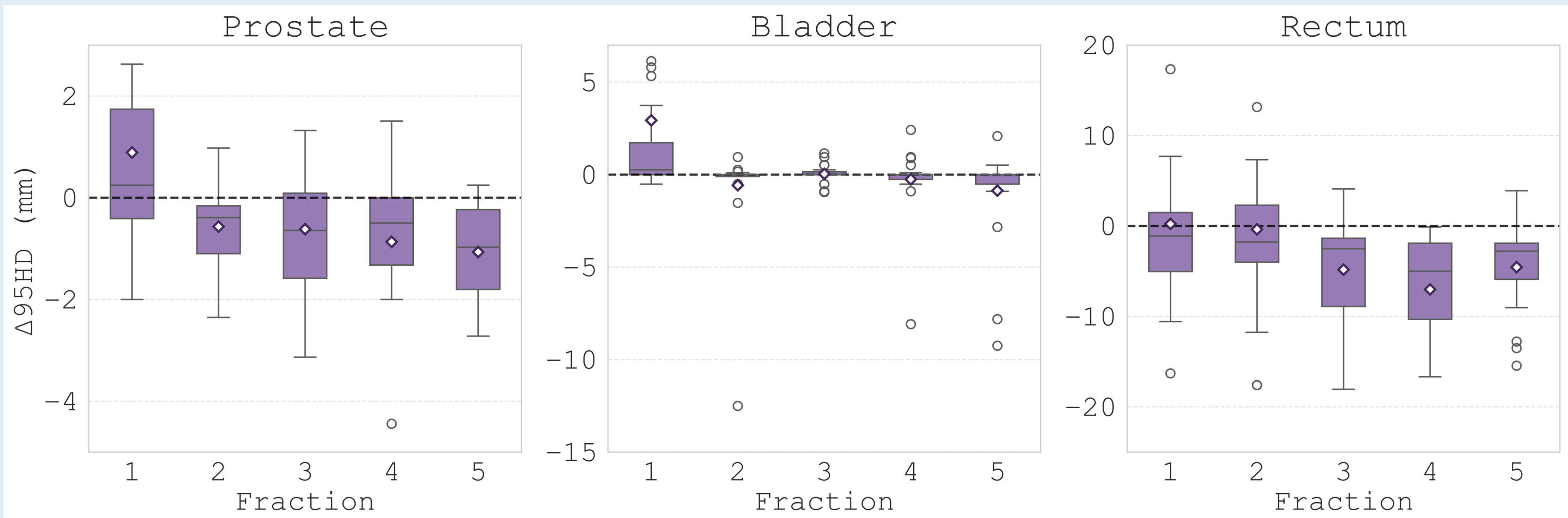

Figure 5. Distributions of Δ95HD (patient-specific minus general model) across five fractions for the prostate, bladder, and rectum on the independent test set (N = 25). Mean values are represented by diamonds. Negative values indicate improvements. For clarity, outliers were excluded for the prostate (12.3 mm), bladder (30.3 and 17.7 mm), and rectum (59.1, 45.5, 36.6, and 34.0 mm).

DISCUSSION

Patient-specific models **surpassed the general model from Fraction 2 onward.**

Patient-specific models performed **worse at Fraction 1**. Possibly due to:

- The general model was trained only on pCT, not HyperSight.
- Fine-tuning on one dataset is not enough.

A patient-specific model is particularly **valuable in an outlier patient**.

- The general model consistently did not perform well on a patient with atypical anatomy, but **the patient-specific model learned how to contour** that patient after Fraction 1.

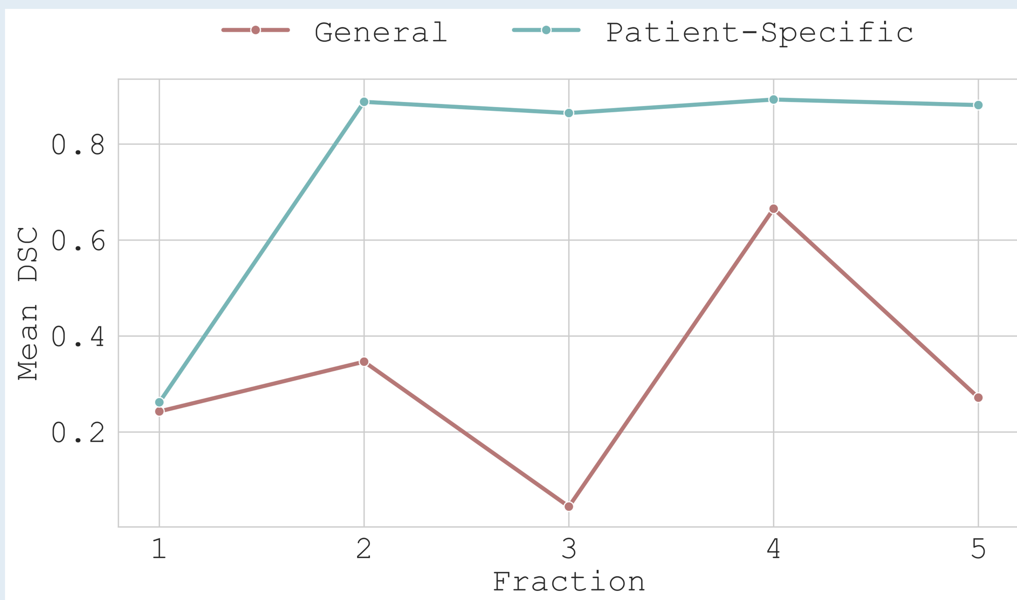

Figure 6. Mean DSC across fractions for the general and patient-specific models in an outlier patient with atypical anatomy.

REFERENCES

[1] 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.

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