# Clinical implementation of deep learning: Automatic contouring via U-Net architecture

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**Thesis:** github.com/matthewdeancooper/masters_thesis

**Video overview:** docs.pymedphys.com/background/autocontouring

THE UNIVERSITY OF SYDNEY

Riverina Cancer Care Centre

PyMedPhys

# Contouring - Current limitations

**Variability**

- Large intra and inter-observer variance (IOV).[1]
- AAPM TG275 risk assessment - multiple human-factor failure modes in RT.[2]

**Time constraints**

- Atlas methods $\Longrightarrow$ significant correction times.[3]

**Deep learning potential**

- Shown to reduce IOV and contouring time.[3]
- Significant improvement cf. atlas methods (time & accuracy).[4]

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[1] Dale Roach et al. "Multi-observer contouring of male pelvic anatomy: Highly variable agreement across conventional and emerging structures of interest". In: *Journal of Medical Imaging and Radiation Oncology* 63.2 (2019), pp. 264–271. DOI: 10.1111/1754-9485.12844

[2] Eric Ford et al. "Strategies for effective physics plan and chart review in radiation therapy: Report of AAPM Task Group 275". In: *Medical Physics* 47.6 (2020), e236–e272. DOI: https://doi.org/10.1002/mp.14030

[3] Shalini K Vinod et al. "A review of interventions to reduce inter-observer variability in volume delineation in radiation oncology". In: *Journal of Medical Imaging and Radiation Oncology* 60.3 (2016), pp. 393–406. DOI: 10.1111/1754-9485.12462

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# Research goals

**Model 1:** QA tool (prostate cancer).

- Compare contours to identify macro contouring errors
- Contoured patient, bladder, rectum volumes.

**Model 2:** Canine vacuum bag.

- Automate time consuming aspect of canine RT.
- Previously, manual vacuum bag contouring $\approx$ 30 min.

**Goal:** Performance similar to human experts.

- Performance metric (sDSC) that takes into account expert IOV.[4]
- Stronger correlation with correction time cf. DSC.[5]

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[5] Femke Vaassen et al. "Evaluation of measures for assessing time-saving of automatic organ-at-risk segmentation in radiotherapy". In: *Physics and Imaging in Radiation Oncology* 13 (2020), 1–6. ISSN: 2405-6316. DOI: 10.1016/j.phro.2019.12.001

# Performance - Surface dice similarity coefficient (sDSC)

$$DSC_{1,2} = \frac{2|M_1 \cap M_2|}{|M_1| + |M_2|}$$

$$sDSC_{1,2}^{(\tau)} = \frac{|S_1 \cap B_2^{(\tau)}| + |S_2 \cap B_1^{(\tau)}|}{|S_1| + |S_2|}$$

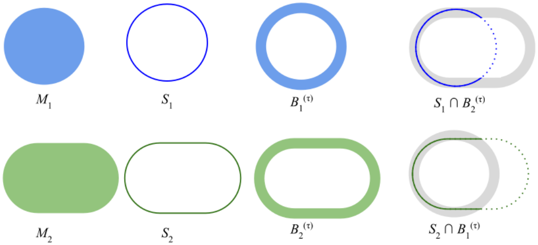


**Figure:** DSC is a volumetric overlap score, sDSC is a surface overlap score - the percentage of surface contoured within an organ specific tolerance representative of expert IOV.[3]

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# All happy models are alike...

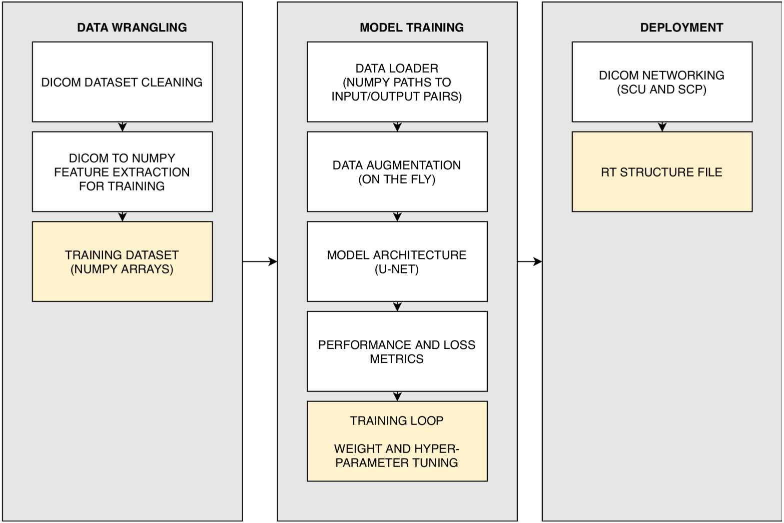


**Figure:** Modules required for end-to-end deep learning model deployment.

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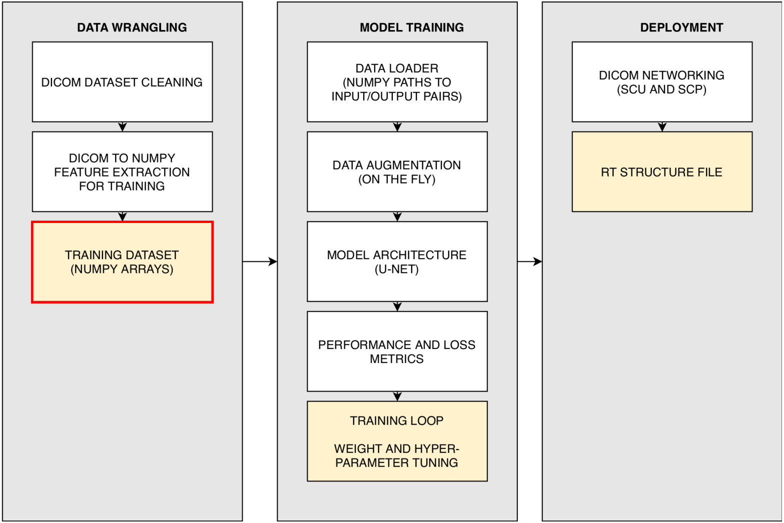


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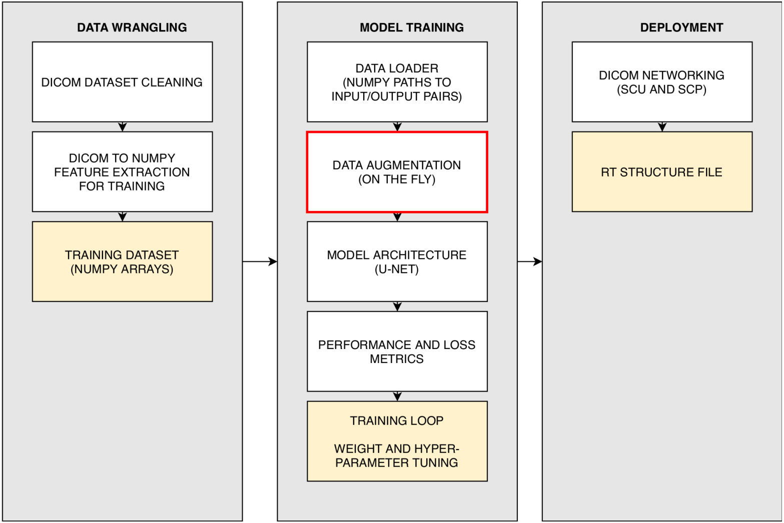


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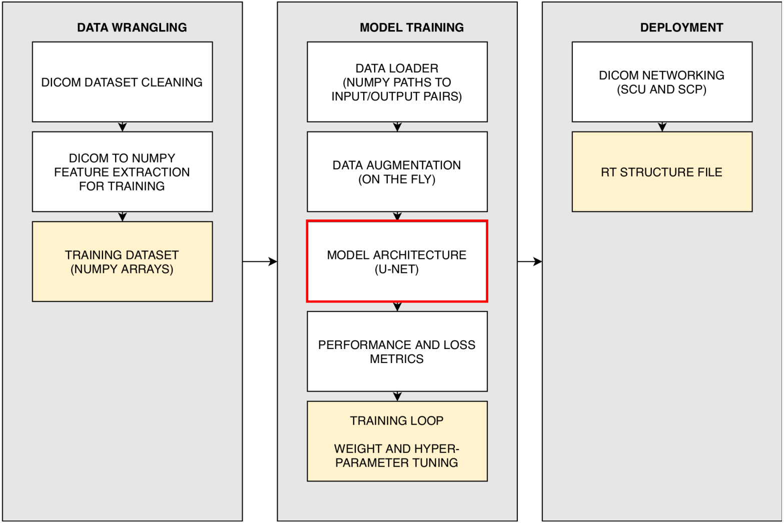


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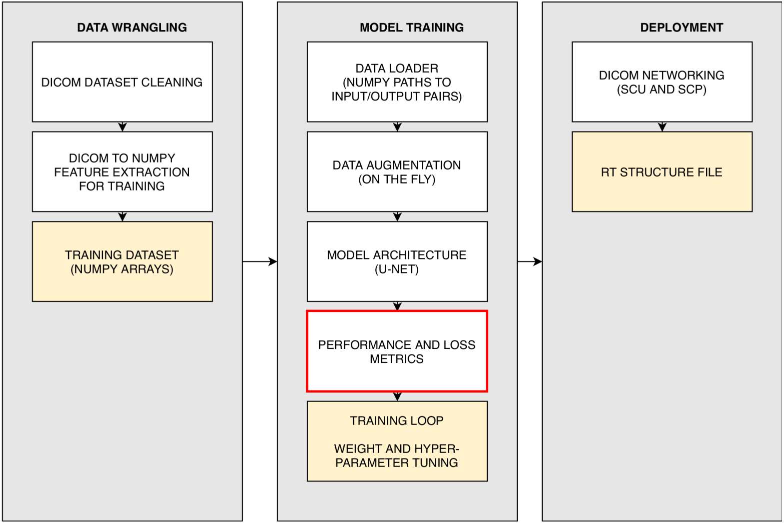


**Figure:** Modules required for end-to-end deep learning model deployment.

# Deployment - DICOM networking

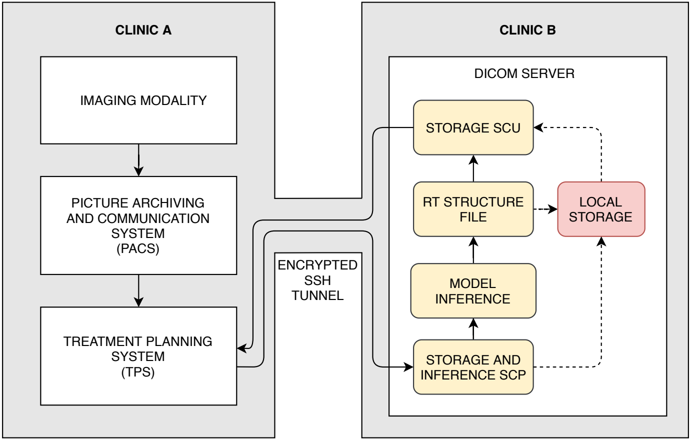


**Figure:** TPS exports to remote server via DICOM networking protocol.

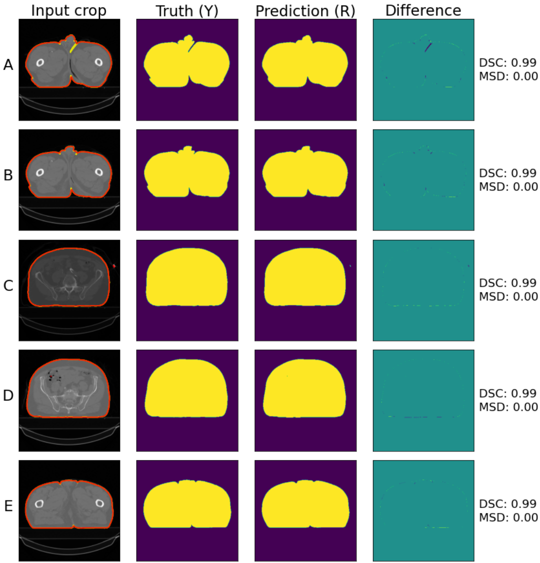


**Figure:** Representative output for **patient**. Truth contour (yellow), prediction contour (red). Metrics: Dice similarity coefficient (DSC), and mean surface distance (MSD) in mm.

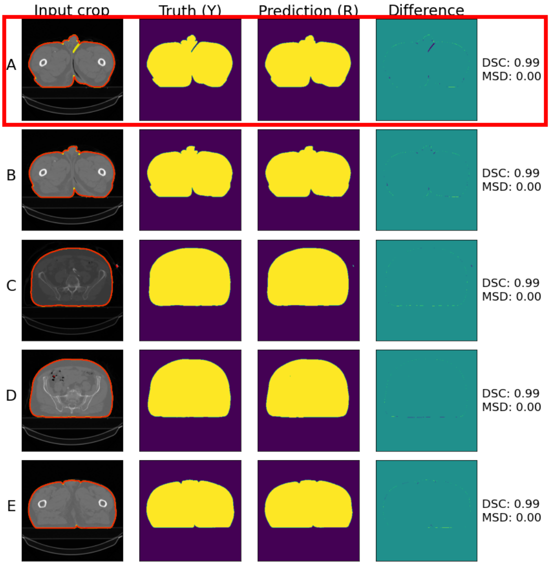


**Figure:** Representative output for **patient**. Truth contour (yellow), prediction contour (red). Metrics: Dice similarity coefficient (DSC), and mean surface distance (MSD) in mm.

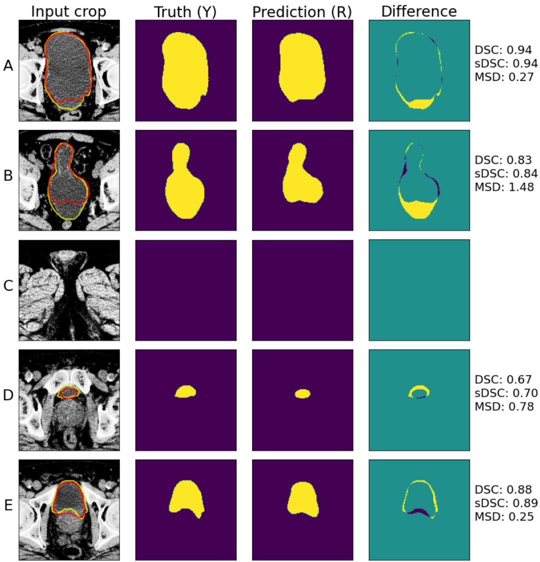


**Figure:** Representative output for **bladder**. Truth contour (yellow), prediction contour (red). Metrics: Dice coefficient (DSC), surface dice coefficient (sDSC), and mean surface distance (MSD) in mm.

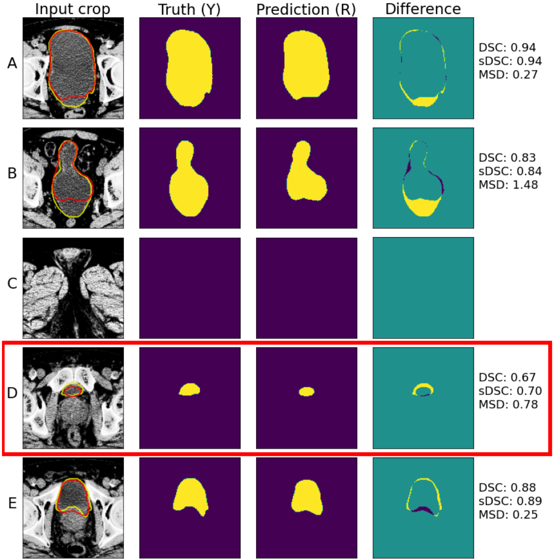


**Figure:** Representative output for **bladder**. Truth contour (yellow), prediction contour (red). Metrics: Dice coefficient (DSC), surface dice coefficient (sDSC), and mean surface distance (MSD) in mm.

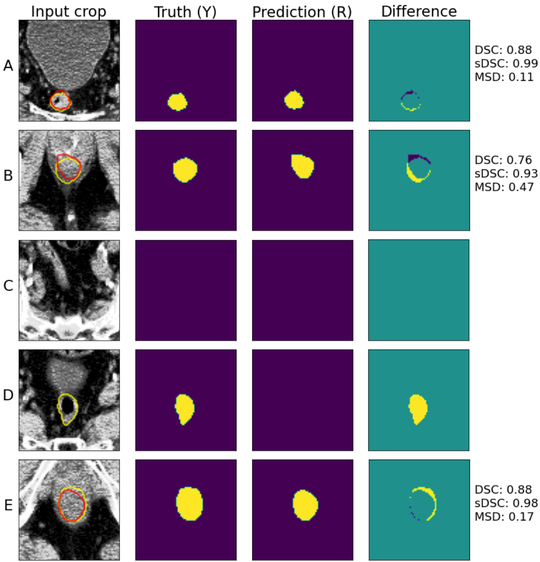


**Figure:** Representative output for **rectum**. Truth contour (yellow), prediction contour (red). Metrics: Dice coefficient (DSC), surface dice coefficient (sDSC), and mean surface distance (MSD) in mm.

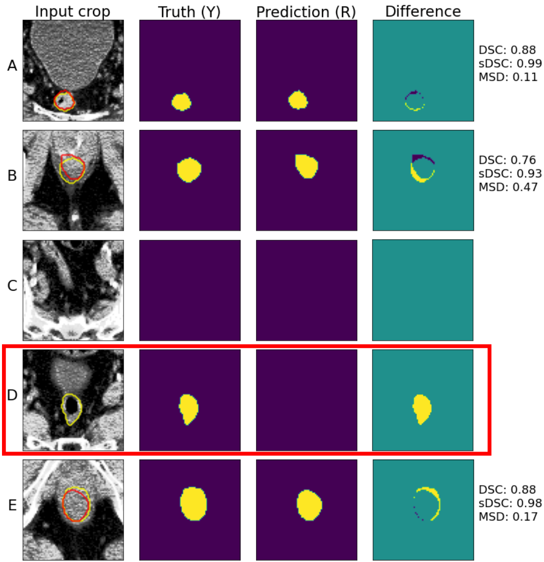


**Figure:** Representative output for **rectum**. Truth contour (yellow), prediction contour (red). Metrics: Dice coefficient (DSC), surface dice coefficient (sDSC), and mean surface distance (MSD) in mm.

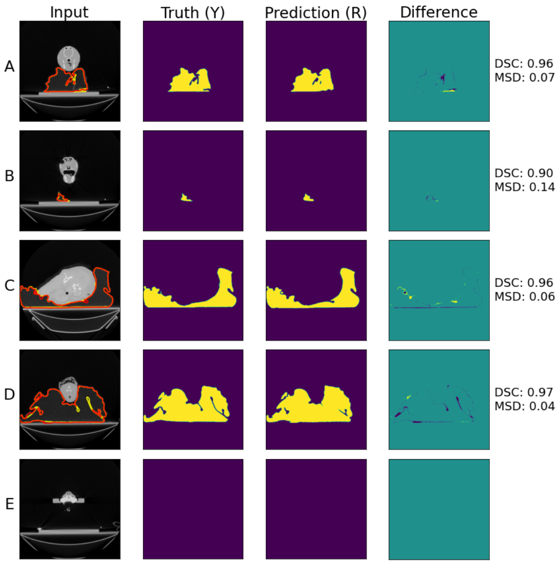


**Figure:** Representative output for **vacuum bag**. Truth contour (yellow), prediction contour (red). Metrics: Dice similarity coefficient (DSC), and mean surface distance (MSD) in mm.

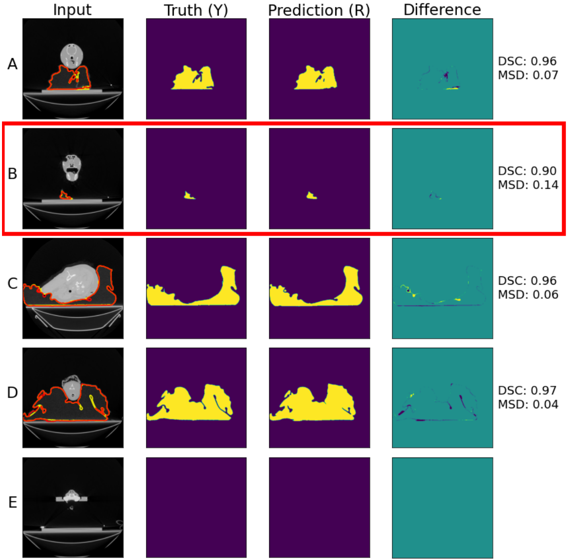


**Figure:** Representative output for **vacuum bag**. Truth contour (yellow), prediction contour (red). Metrics: Dice similarity coefficient (DSC), and mean surface distance (MSD) in mm.

# Structure averaged metrics

**Table:** Organ specific evaluation on independent dataset.

| | sDSC | DSC | MSD (mm) |
|---|---|---|---|
| **Pelvic imaging**[a] | | | |
| Patient | | 0.99(1) | 0.00(5) |
| Bladder ($\tau$ 1.46 mm) | 0.9(2) | 0.9(2) | 1(3) |
| Rectum ($\tau$ 6.99 mm) | 0.9(1) | 0.7(1) | 1(2) |
| Average | | 0.9(2) | 0.6(2) |
| **Canine imaging** | | | |
| Vacbag | | 0.952(1) | 0.2(3) |

[a] Organ specific tolerance $\tau = \mathrm{MSD}_{95}$ (Top 95% expert performance).

## Cf. expert IOV.[1]

- Clinically 'acceptable' bladder and rectum DSC $\geq 0.7$
- Bladder: DSC 0.93(3), MSD 0.9(3) mm.
- Rectum: DSC 0.81(7), MSD 3(2) mm.

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# Conclusion and future work

**Pelvic imaging model:**

- Patient contouring within tolerances.
- Suspect more data will improve bladder and rectum segmentation.
- 3D architecture may improve detection of gaseous rectal volumes.

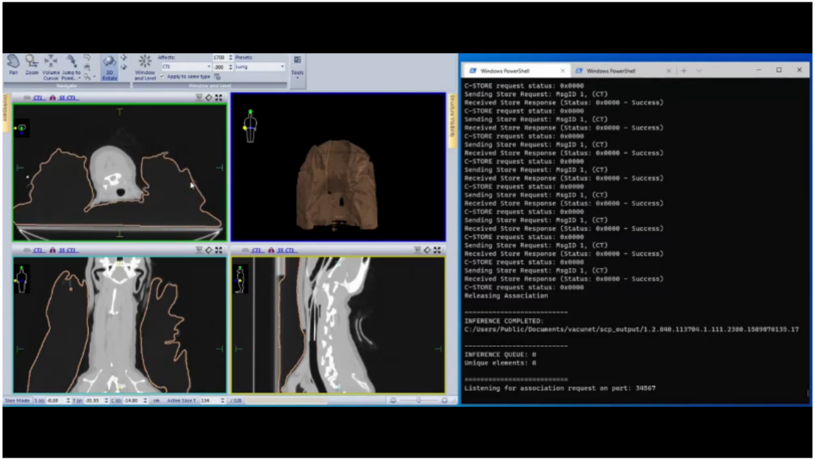
**Canine imaging model:**

- Successfully deployed to clinic under a prototype warning.
- Performance improvement of approximately 30 minutes per patient.

**Future**

- Develop a continuous valued surrogate for sDSC to optimise directly.

# Questions




**Video overview:** docs.pymedphys.com/background/autocontouring

# References I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