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AI for Segmentation in Clinical Practice: How to Get to Fast Implementation?

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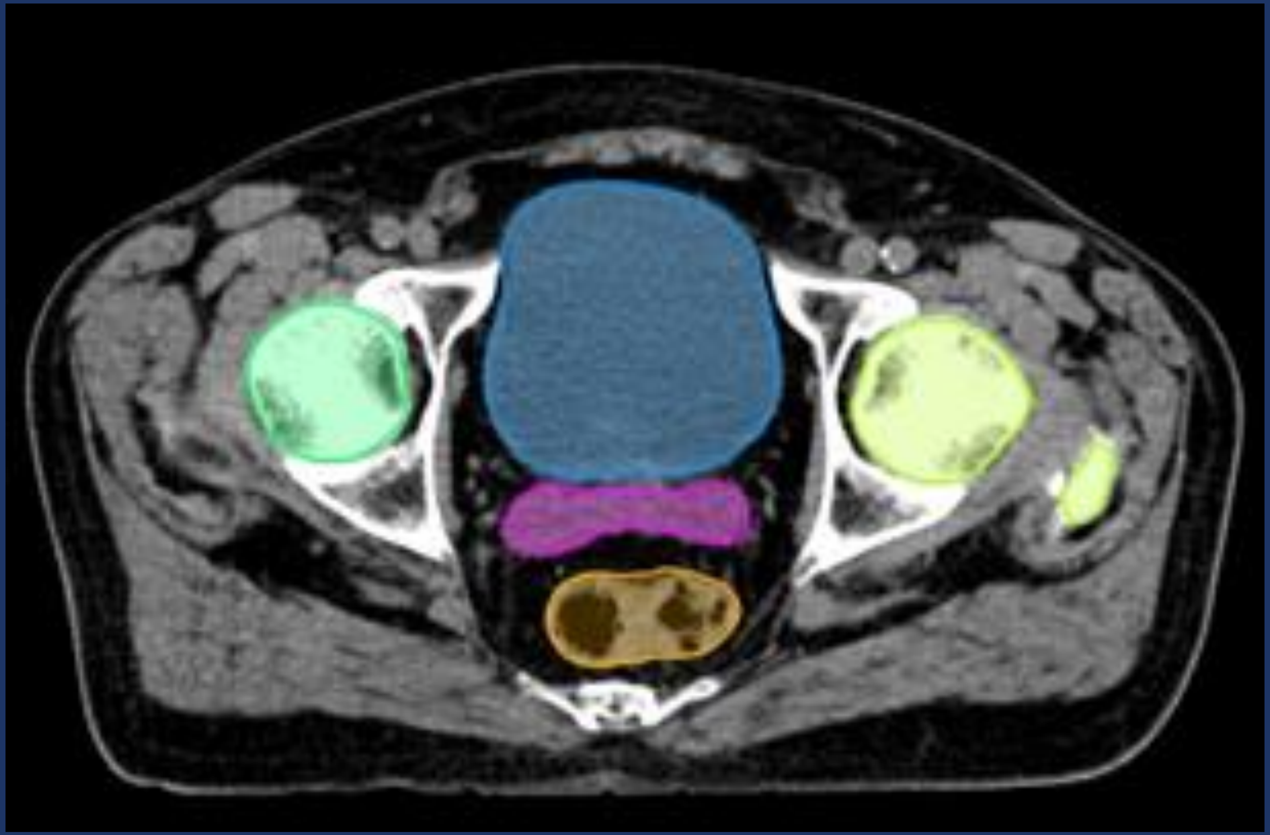
AI for segmentation: Where are we now?



Yeah, we're building AI contouring!

DICE = 0.85

May save time…

Not available for sale in all territories. FDA clearance pending.

FDA CLEARED

AI for segmentation: Where are we now?

C Cardenas et al. Deep learning algorithm for auto-delineation of high-risk oropharyngeal clinical target volumes with built-in dice similarity coefficient parameter optimization function. International Journal of Radiation Oncology* Biology* Physics. 2018;101(2):468-78.

J. Van der Veen J et al. Benefits of deep learning for delineation of organs at risk in head and neck cancer. Radiotherapy and Oncology. 2019;138:68-74.

AI for segmentation: How did we get here?

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- Why deep learning contouring?
- What are the steps to get to fast clinical implementation?

AI for segmentation: Where did we come from?

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TABLE II. Commercial software tools for automated medical image segmentation (F = female; H and N = head and neck; M = male TPS = treatment planning system).

Supplier	Product name	Method	Included atlases	Integrated with TPS	Reference
Accuray	MultiPlan 5.0	Atlas-based model-based	Brain, M pelvis	Yes	Reference 101
BrainLab	iPlan	Atlas-based	Brain, H and N,M pelvis, spine, thorax	Yes	Reference 102
Dosisoft	IMAgo	Atlas-based	Brain, H and N	Yes	Reference 103
Elekta	ABAS 2.01	Atlas-based model-based	H And N, M pelvis	No	Reference 14
MIM software	MIM Maestro 6+	Atlas-based	H and N	No	Reference 104
Mirada	RTx 1.4, Workflow box	Atlas-based	Ano-rectal, Breast, H and N, F pelvis, M pelvis, thorax	No	Reference 105
OSL	OnQ RTS	Altas-based	H and N, M pelvis, thorax	No	Reference 106
Philips	SPICE 9.8	Atlas-based model-based	Abdomen, H and N, pelvis, Thorax	Yes	Reference 13
RaySearch	RayStation 4.0	Atlas-based model-based	Abdomen, H and N, F pelvis, M pelvis, thorax	Yes	Reference 107
Varian	Smart Segmentation	Atlas-based	H and N, M Pelvis, thorax	Yes	Reference 108
Velocity	VelocityAI 3.0.1	Atlas-based	Brain, H and N, F pelvis, M pelvis	No	Reference 58

G. Sharp. Vision 20/20: perspectives on automated image segmentation for radiotherapy. Medical physics. 2014;41(5).

Atlas segmentation: Need to improvement?

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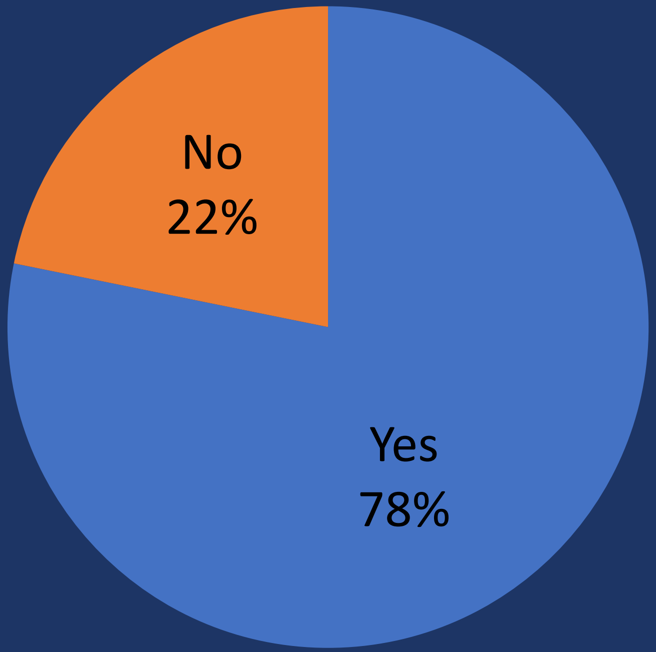
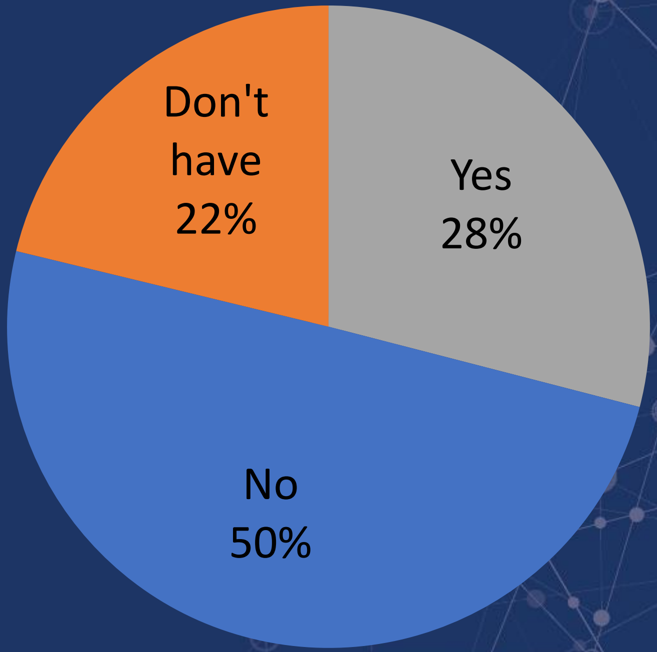
Does your institution **have** an auto-contouring system?



Does your institution **use** an auto-contouring system?



Informal poll during talk at AAMD 2017 (N = ~70)

Atlas segmentation: Need to improvement?

Dependence on registration

Dependence on atlas(es)

Dependence on fusion

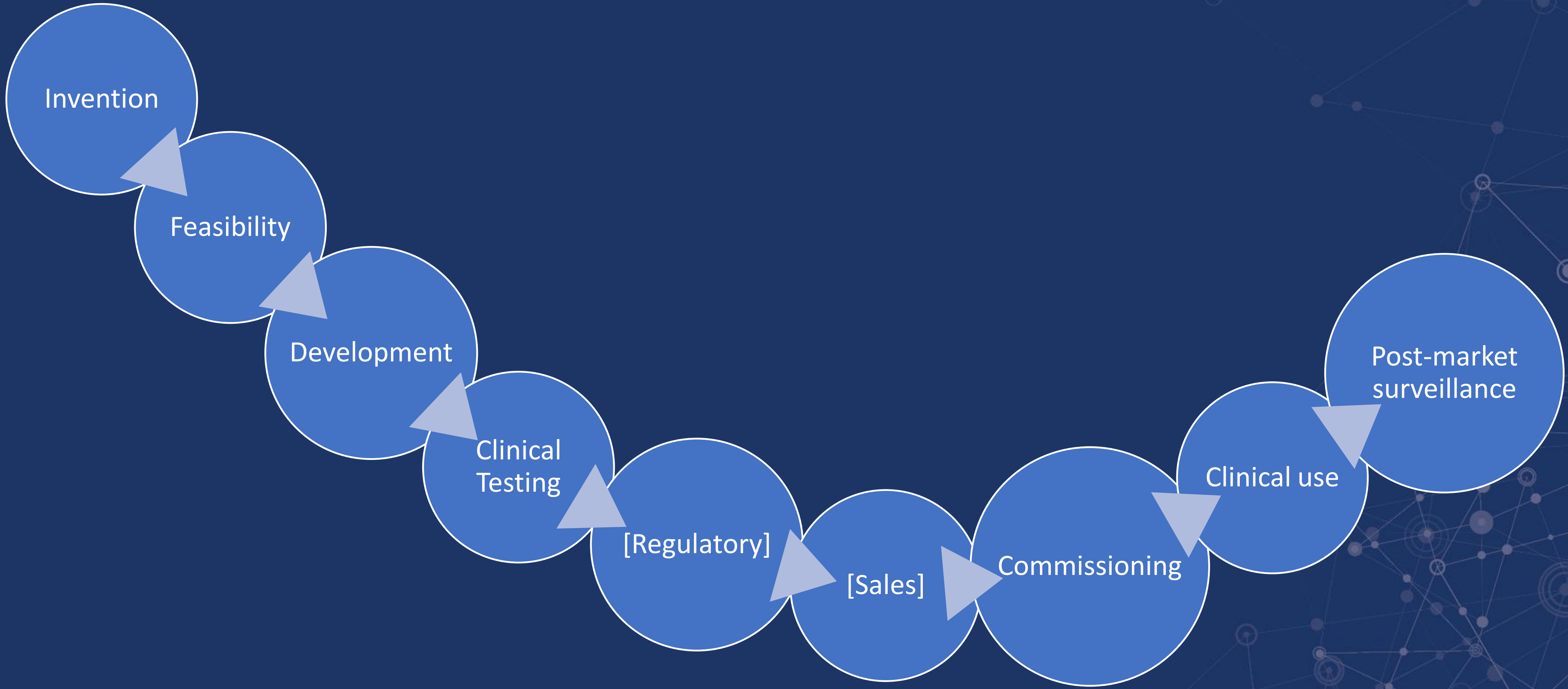
Dependence on selection

L. Ramus & G. Malandain. Assessing selection methods in the context of multi-atlas based segmentation. In 2010 IEEE International Symposium on Biomedical Imaging 2010 (pp. 1321-1324)

B. Schipaanboord *et al.* An evaluation of atlas selection methods for atlas-based automatic segmentation in radiotherapy treatment planning. IEEE transactions on medical imaging. 2019;38(11):2654-64.

H. Lee *et al*. Clinical Evaluation of Commercial Atlas-Based Auto-Segmentation in the Head and Neck Region. Frontiers in oncology. 2019;9.

AI for Segmentation: Steps to clinical use (and beyond)



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Steps to clinical: Invention

Technical B. Ibragimov & L. Xing. Segmentation of organs-at-risks in head and neck CT images using convolutional neural networks. Medical physics. 2017 Feb;44(2):547-57.

Clinical: T. Lustberg *et al*. Clinical evaluation of atlas and deep learning based automatic contouring for lung cancer. Radiotherapy and Oncology. 2018 Feb 1;126(2):312-7.

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Steps to clinical: Invention

G. Carneiro & J. Nascimento. Multiple dynamic models for tracking the left ventricle of the heart from ultrasound data using particle filters and deep learning architectures. In2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2010 (pp. 2815-2822)

D. Ciresan *et al*. Deep neural networks segment neuronal membranes in electron microscopy images. InAdvances in neural information processing systems 2012 (pp. 2843-2851).

Steps to clinical: Feasibility

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Study feature	B. Ibragimov *et al.*	X. Feng *et al.*	S. Nikolov *et al.*	Typical study approach
Training Dataset	50 private	36 (AAPM Challenge)	663 private	Whatever is available!
Test set	Same 50 using five-fold cross validation	12 (AAPM Challenge) 30 (private test set)	75 private 24 TCIA 15 PDDCA	Small, single center
Validation method	Dice Similarity	Dice Similarity Editing time reported	Surface Dice Qualitative inspection	Quantitative measures

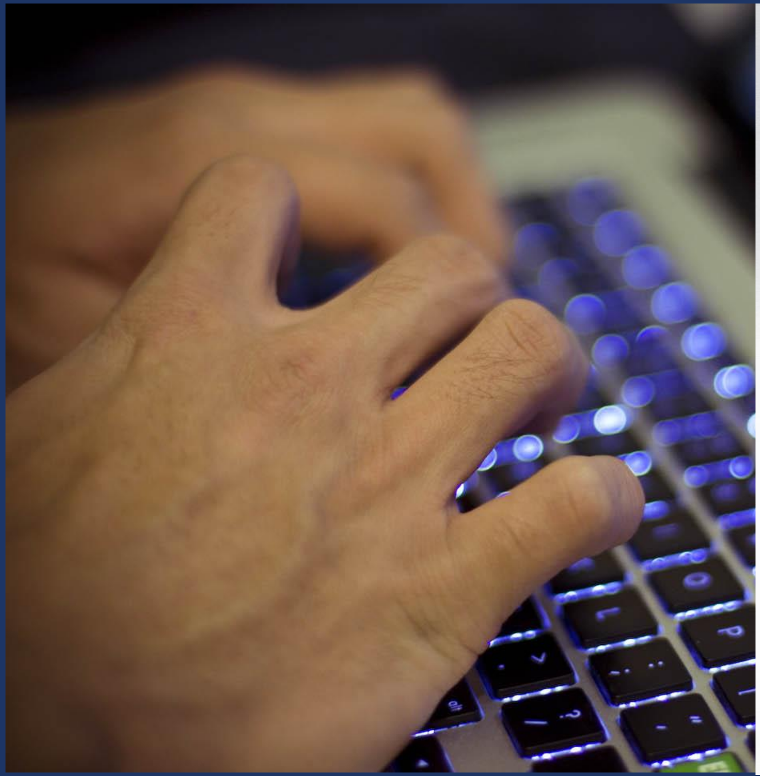
Feasibility studies show future potential for a method!

B. Ibragimov *et al.* Segmentation of organs-at-risks in head and neck CT images using convolutional neural networks. Medical physics. 2017 Feb;44(2):547-57.

X. Feng *et al.* Deep convolutional neural network for segmentation of thoracic organs-at-risk using cropped 3D images. Medical physics. 2018;46(5):2169-80.

S. Nikolov *et al.* Deep learning to achieve clinically applicable segmentation of head and neck anatomy for radiotherapy. arXiv:1809.04430. 2018.

Development: In-house vs Commercial



Programming

Requirements & Testing Documentation

Risk Analysis

Steps to clinical: Clinical Testing

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Study feature	***Lustberg et al.***	***van der Veen et al.***	**van Dijk *et al.***	**Typical study approach**
Training Dataset	450 cases	70 cases	589 cases	Larger, curated, datasets
Test set	20 patients same institution	15 patients same institution	14 patients (time / subjective) 104 patients (quant./dose) same institution	Small, single center
Validation method	Time saving vs manual Quantitative measures	Time saving vs manual Quantitative measures	Time saving vs manual Dosimetric difference Subjective Quantitative measures	Clinical impact Quantitative measures

Demonstrates clinical potential to end users
Evidence of effectiveness to support regulatory clearance

T. Lustberg *et al*. Clinical evaluation of atlas and deep learning based automatic contouring for lung cancer. Radiotherapy and Oncology. 2018;126(2):312-7.

J. van der Veen *et al*. Benefits of deep learning for delineation of organs at risk in head and neck cancer. Radiotherapy and Oncology. 2019;138:68-74.

L. van Dijk *et al*. Improving automatic delineation for head and neck organs at risk by Deep Learning Contouring. Radiotherapy and Oncology. 2020;142:115-23.

Steps to clinical: Regulatory

Safe & Effective

Photo: David Knight https://www.flickr.com/photos/david_knight/7785203594/

Steps to clinical: Sales

Understand the stakeholders

Ask for evidence

"While the impact a data-centric approach can have on improving the quality of treatment for cancer patients is clear, utilizing such a method will require a cultural shift at both the professional and institutional levels."

Feng M et al. Machine learning in radiation oncology: opportunities, requirements, and needs. Frontiers in oncology. 2018;8:110

Steps to clinical: Commissioning

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Confirm performance on local data ✓

~~**Demonstrate the segmentations are correct**~~

Evaluate the safety of the system ✓

⚠ "All segmentations should be carefully reviewed and approved by the local clinical staff (eg radiation oncologists) before use in a treatment plan."

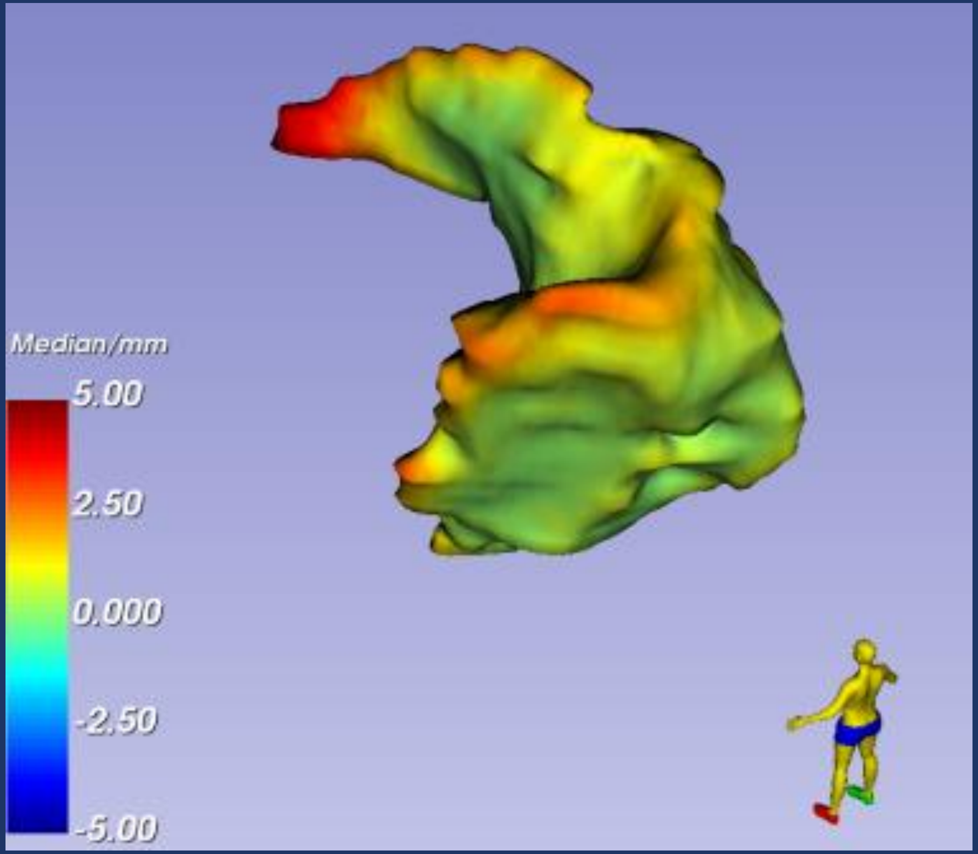
Cardenas et al. Advances in auto-segmentation. Seminars in Radiation Oncology 2019;29(3):185-197

Steps to clinical: Clinical use

”While the impact a data-centric approach can have on improving the quality of treatment for cancer patients is clear, utilizing such a method will require a cultural shift at both the professional and institutional levels.”

Feng M et al. Machine learning in radiation oncology: opportunities, requirements, and needs. Frontiers in oncology. 2018;8:110

Steps to clinical: Post-market surveillance



How is it performing in practice?

What improvements to workflow / systems can be made?

Are there unanticipated risks?

C. Bouwer *et al*. Assessment of editing performed in clinical practice following deep learning contouring for head and neck. *Under review*

Fast implementation: What are the barriers?

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Fast implementation: Where do we go now?

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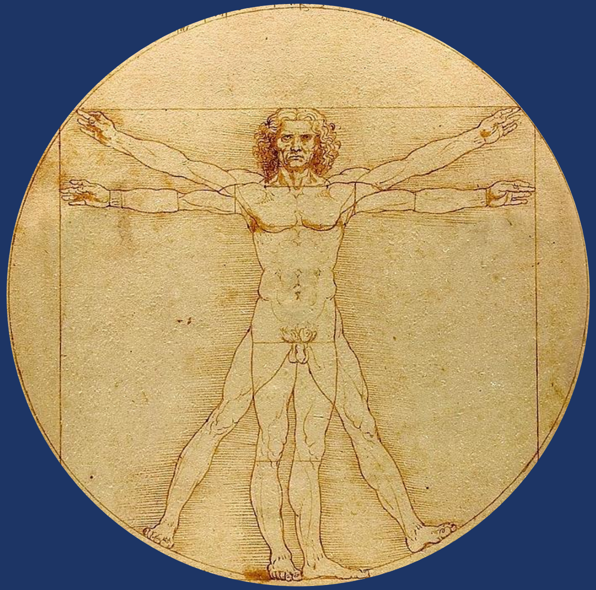

Dosimetry research

Post-market research

Reading List: Summary of Papers

Review articles

- G. Sharp. Vision 20/20: perspectives on automated image segmentation for radiotherapy. Medical physics. 2014;41(5).
- Feng M et al. Machine learning in radiation oncology: opportunities, requirements, and needs. Frontiers in oncology. 2018;8:110
- Cardenas et al. Advances in auto-segmentation. Seminars in Radiation Oncology 2019;29(3):185-197

Challenges of atlas selection

- L. Ramus & G. Malandain. Assessing selection methods in the context of multi-atlas based segmentation. In 2010 IEEE International Symposium on Biomedical Imaging 2010 (pp. 1321-1324)
- H. Lee *et al*. Clinical Evaluation of Commercial Atlas-Based Auto-Segmentation in the Head and Neck Region. Frontiers in oncology. 2019;9.
- B. Schipaanboord *et al.* An evaluation of atlas selection methods for atlas-based automatic segmentation in radiotherapy treatment planning. IEEE transactions on medical imaging. 2019;38(11):2654-64.

AI technical and validation articles

- G. Sharp. Vision 20/20: perspectives on automated image segmentation for radiotherapy. Medical physics. 2014;41(5).
- T. Lustberg et al. Clinical evaluation of atlas and deep learning based automatic contouring for lung cancer. Radiotherapy and Oncology. 2018;126(2):312-7.
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- C Cardenas et al. Deep learning algorithm for auto-delineation of high-risk oropharyngeal clinical target volumes with built-in dice similarity coefficient parameter optimization function. International Journal of Radiation Oncology* Biology* Physics. 2018;101(2):468-78
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