UNIVERSITY OF TWENTE. | TECHMED CENTRE

THE TECHMED EVENT | SHAPING A HEALTHY FUTURE

11:00-12:15 | **AI & HEALTH: FROM BENCH TO BEDSIDE** | CHARLOTTE BROUWER

DEEP LEARNING IN RADIOTHERAPY

Dr. ir. Charlotte L. Brouwer **– University Medical Center Groningen**

DISCLOSURE SLIDE

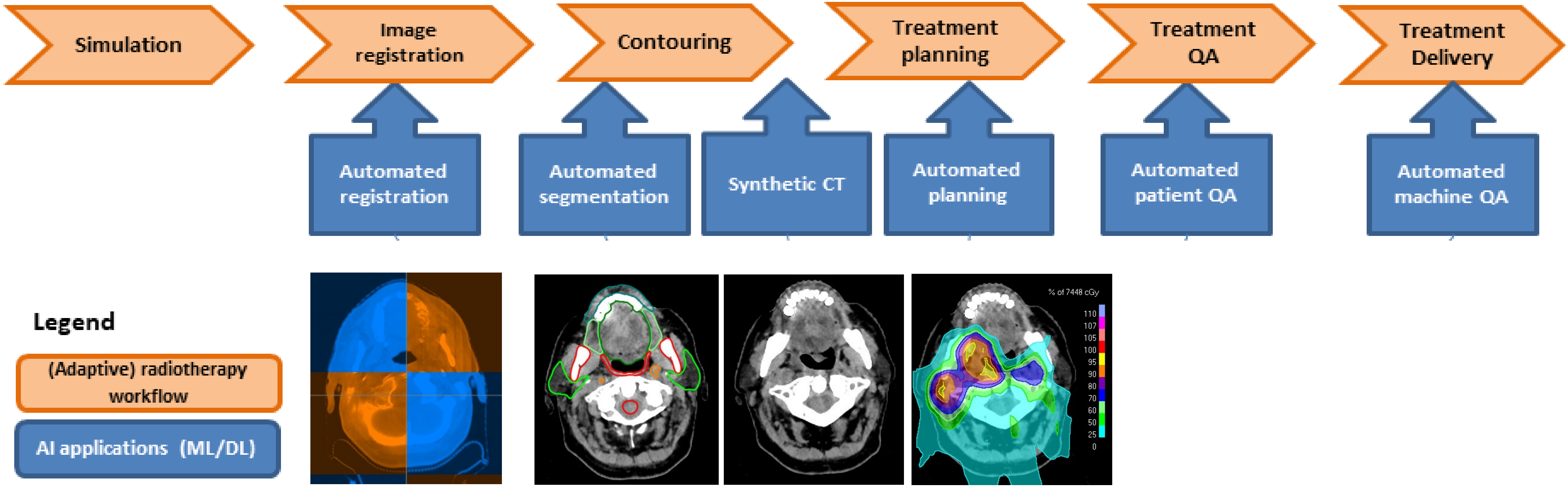
DEPARTMENT OF RADIATION ONCOLOGY

UNIVERSITY MEDICAL CENTER GRONINGEN

- 4500 patients/y
- 2 locations (Groningen + Emmen)
- 8 linear accelerators, orthovolt, brachytherapy
- 2 gantries proton therapy (jan 2018) 600 patients/y
- 40 radiation oncologists
- 19 medical physicists
- >100 technicians

AI IN RADIOTHERAPY

DEEP LEARNING APPLICATIONS



MR and PET-CT

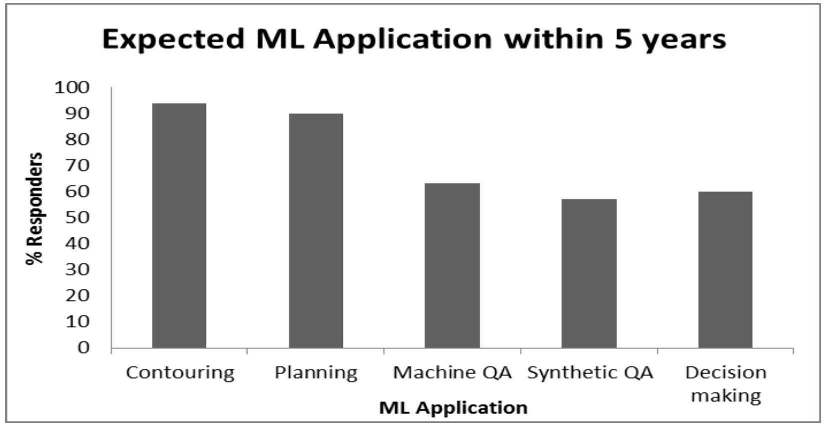
From MR or CBCT

Modified from Claessens et al. Sem Rad Onc 2022

RADIOTHERAPY AI SURVEY RESULTS 2020

EUROPEAN SOCIETY FOR RADIATION ONCOLOGY

- 213 medical physicists from 202 radiotherapy departments and 40 countries
- Clinical application of machine learning based applications: 37%
- Contouring (segmentation) and Treatment planning main applications
- Main motivation for introduction:
    1. Time saving & Quality improvement
    2. Increased consistency
    3. Saving resources



Brouwer et al., Phys Imag Radiat Oncol 2020

RADIOTHERAPY AI SURVEY RESULTS 2020

CHALLENGES

- Resistence/fear against automation/AI
- Guidance needed in clinical implementation

Radiotherapy and Oncology 153 (2020) 55–66

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Radiotherapy and Oncology

journal homepage: www.thegreenjournal.com

Review Article

Overview of artificial intelligence-based applications in radiotherapy: Recommendations for implementation and quality assurance

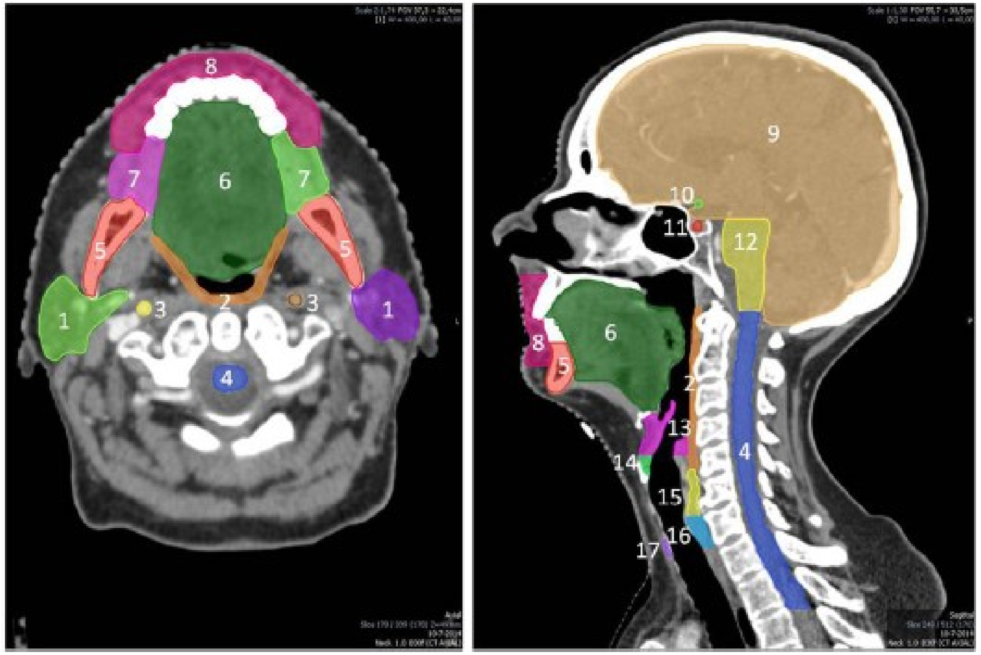
Liesbeth Vandewinckele [a,b,1], Michaël Claessens [c,d,1], Anna Dinkla [e,1,*], Charlotte Brouwer [f], Wouter Crijns [a,b], Dirk Verellen [c,d], Wouter van Elmpt [g]

[a] Department Oncology, Laboratory of Experimental Radiotherapy, KU Leuven; [b] Department of Radiation Oncology, UZ Leuven; [c] Faculty of Medicine and Health Sciences, University of Antwerp; [d] Department of Radiation Oncology, Iridium Cancer Network, Wilrijk (Antwerp); [e] Department of Radiation Oncology, Amsterdam University Medical Center, University of Amsterdam; [f] University of Groningen, University Medical Center Groningen, Department of Radiation Oncology; and [g] Department of Radiation Oncology (Maastro), GROW School for Oncology, Maastricht University Medical Centre+

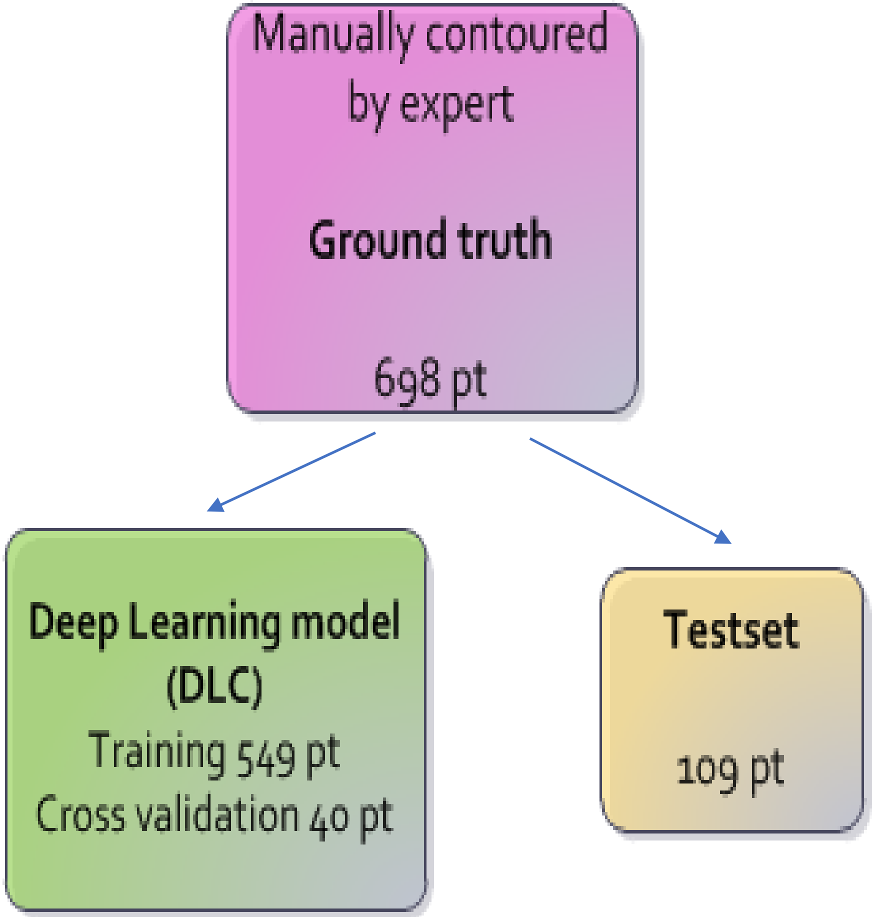
EXAMPLE: DEEP LEARNING AUTO-SEGMENTATION

MODEL TRAINING

Head and neck organs at risk



Brouwer et al. Radioth Oncol 2015

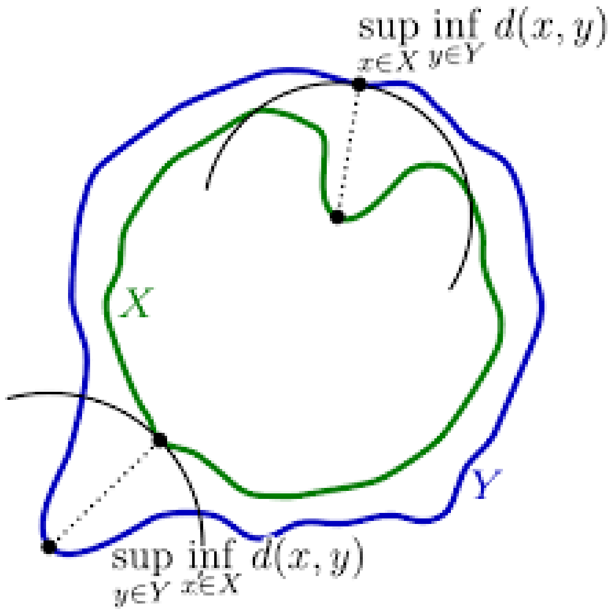


Van Dijk et al. Radioth Oncol 2020

EXAMPLE: DEEP LEARNING AUTO-SEGMENTATION

MODEL EVALUATION METHODS

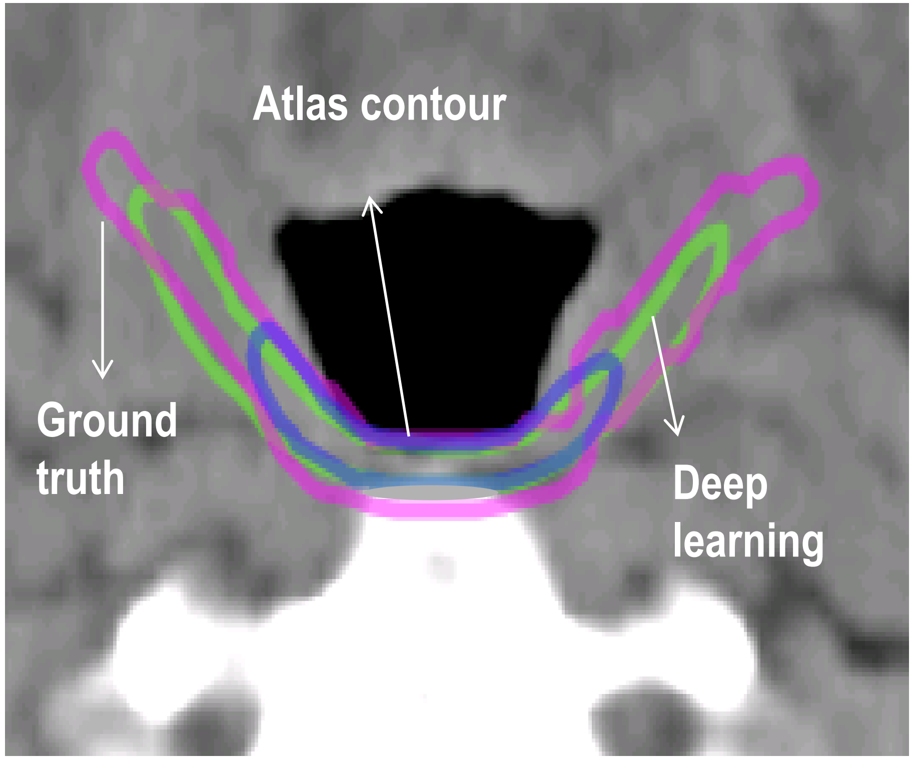
- Test set 109 patients, ground truth, atlas and deep learning
- Quantitative analysis:
  - Overlap
  - Distance
  - Volume
  - Radiotherapy dose
- Qualitative analysis:
  - Time saving
  - Turing Test



Van Dijk et al. Radioth Oncol 2019

EXAMPLE: DEEP LEARNING AUTO-SEGMENTATION

MODEL EVALUATION RESULTS



Van Dijk et al. Radioth Oncol 2020

		DICE	HD	Δdose	Corr. needed
Glandular	Parotid L	DLC better	DLC better	DLC better	DLC better
	Parotid R	DLC better	DLC better	DLC better	DLC better
	Submandibular L	DLC better	DLC better	DLC better	DLC better
	Submandibular R	DLC better	DLC better	DLC better	DLC better
	Thyroid	DLC better	DLC better	DLC better	DLC better
Upper digestive tract	Cricoid	DLC better	DLC better	DLC better	DLC better
	Glottic area	DLC better	DLC better	DLC better	DLC better
	Oral cavity	no significant difference	DLC better	DLC better	ABAS better
	PCM	DLC better	DLC better	DLC better	DLC better
	Buccal Mucosa L	DLC better	DLC better	DLC better	
	Buccal Mucosa R	DLC better	DLC better	no significant difference	
	Esophagus	DLC better	no significant difference	DLC better	
	Supraglottic	DLC better	DLC better	DLC better	
	Arytenoid L	DLC better	no significant difference	DLC better	
	Arytenoid R	DLC better	no significant difference	DLC better	
CNS, mandibular, vessels	Brainstem	ABAS better	ABAS better	no significant difference	
	Cerebellum	no significant difference	no significant difference	no significant difference	
	Cerebrum	ABAS better	no significant difference	no significant difference	
	Spinal cord	ABAS better	ABAS better	ABAS better	
	Mandible	DLC better	DLC better	no significant difference	
	Carotid L	DLC better	DLC better	DLC better	
	Carotid R	DLC better	DLC better	DLC better	

DLC better | ABAS better | no significant difference

EXAMPLE: DEEP LEARNING AUTO-SEGMENTATION

TIME SAVING

- Head and neck organs of 19 patients
- Parotid and submandibular glands, thyroid, cricoid, glottic area, oral cavity and pharyngeal constrictor muscles
- Significant time reduction deep learning vs. atlas-based segmentation for beginner observer

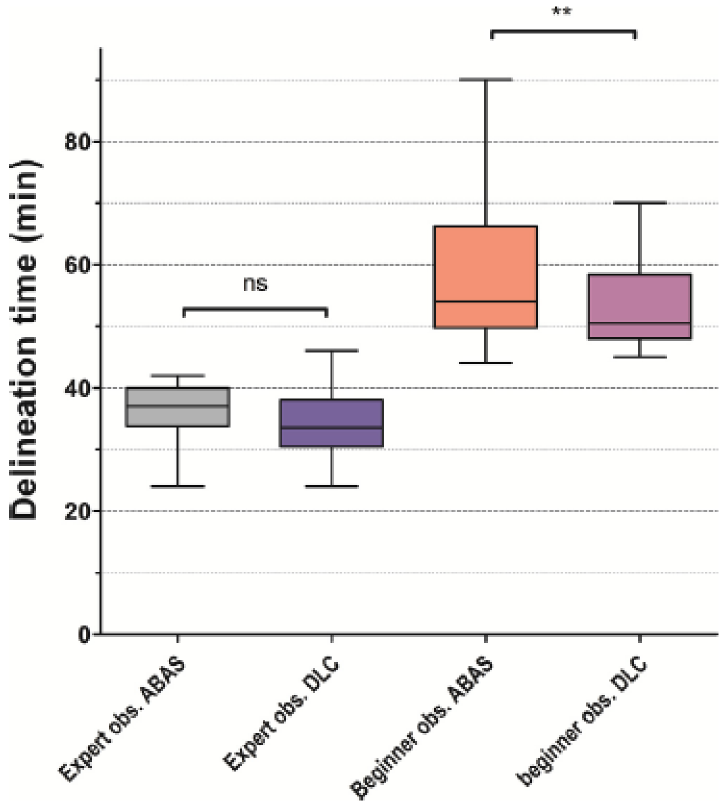
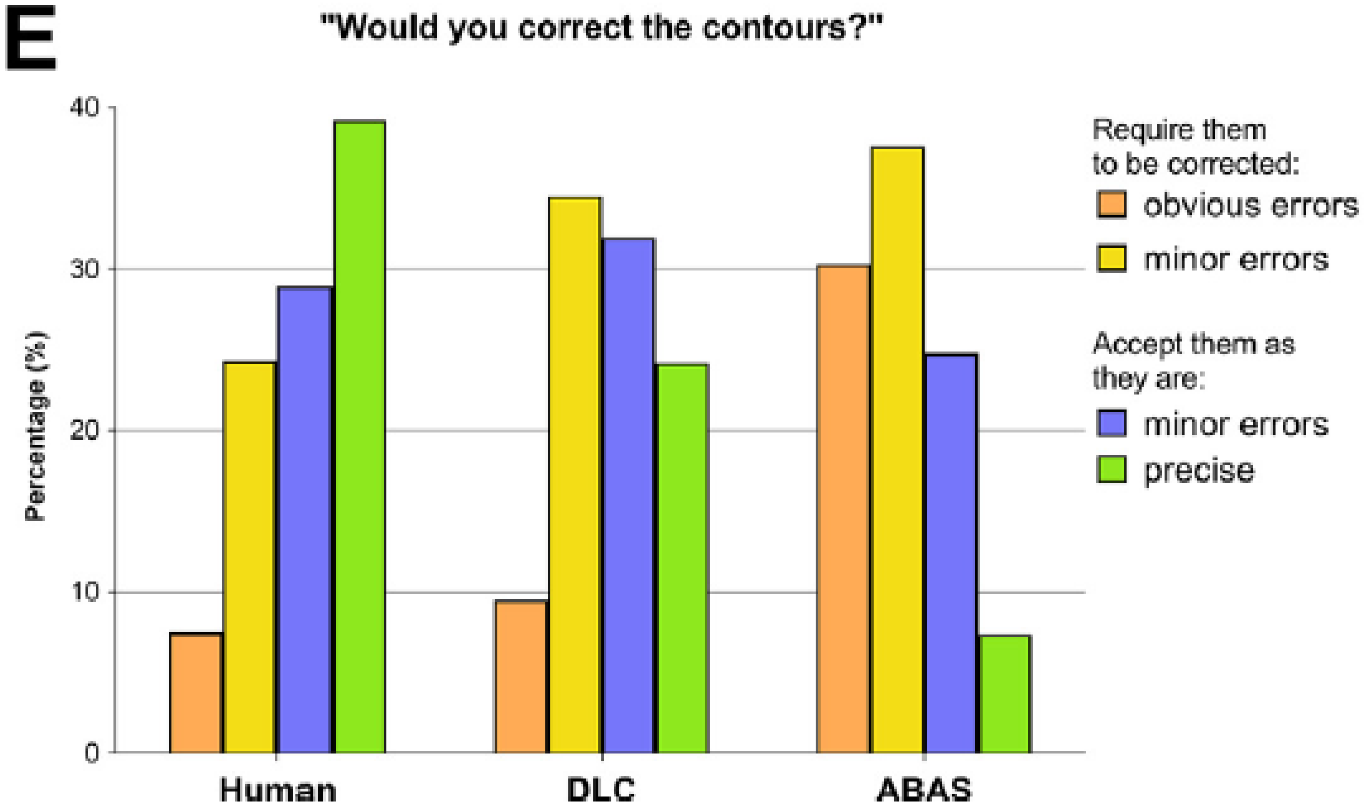


Fig. 5. Time evaluation for adjusting 7 OARs with ABAS vs. DLC for the expert and beginner observer (noted as obs.).

Van Dijk et al. Radioth Oncol 2019

EXAMPLE: DEEP LEARNING AUTO-SEGMENTATION

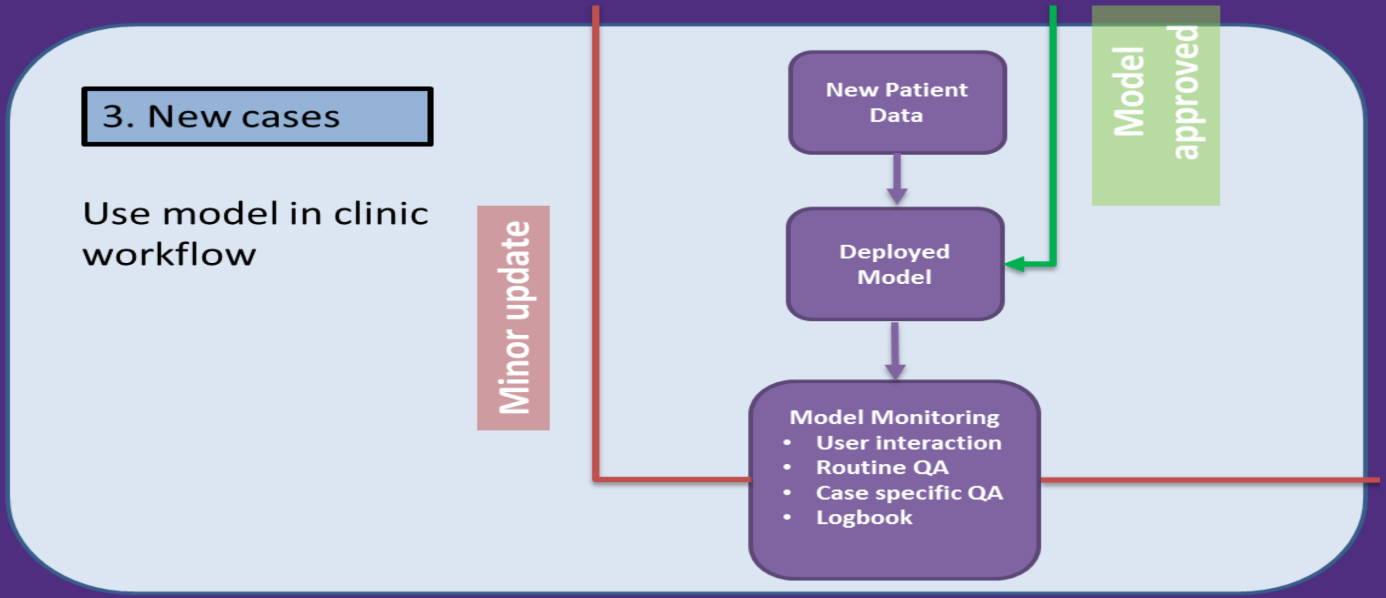
TURING TEST



Van Dijk et al. Radioth Oncol 2020

AI IN CLINICAL PRACTICE
MODEL MONITORING

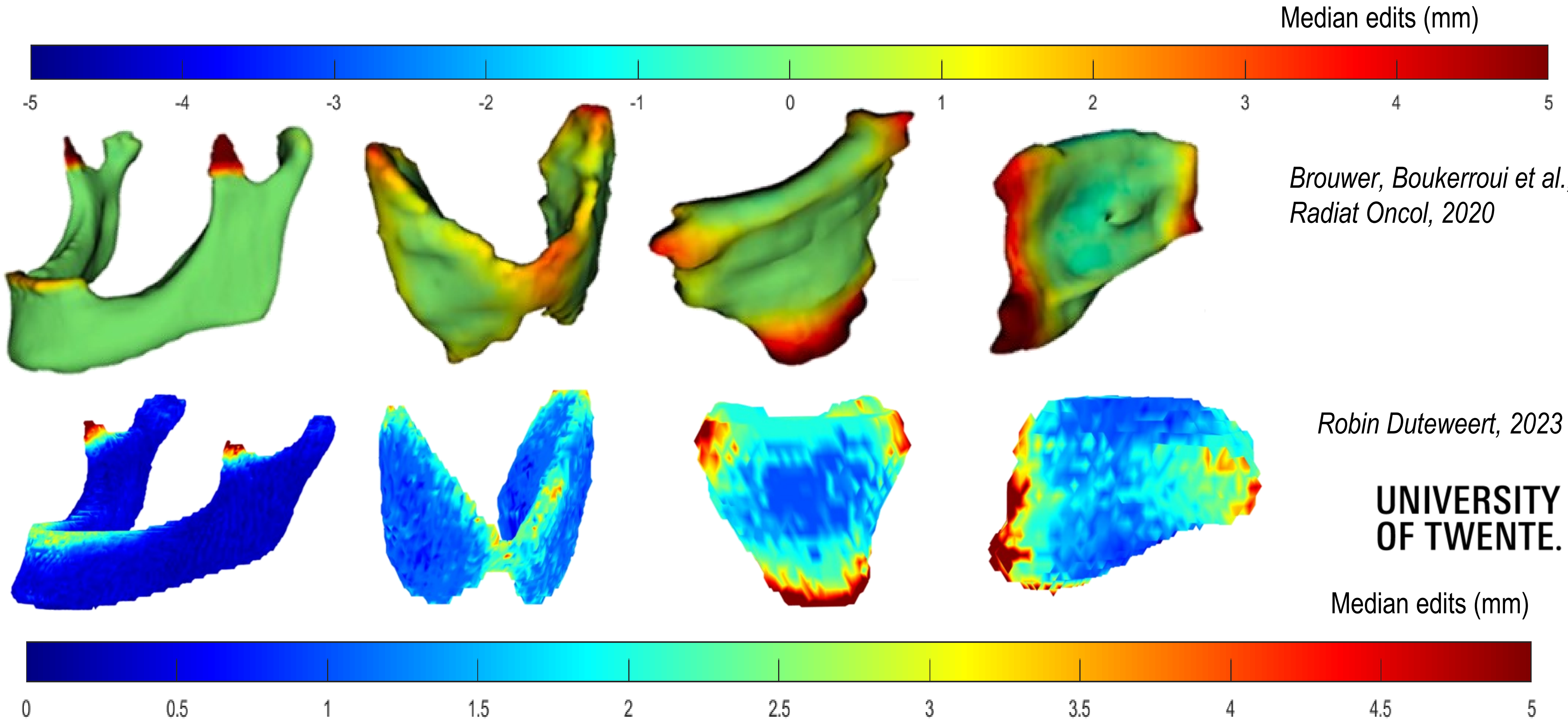
- Patient specific QA
- Routine QA
- Monitoring user interactions



Vandewinckele et al. Radioth Oncol 2020

QA: MONITORING USER INTERACTION

- Consistency in acceptance of deep learning contour?
- Guideline compliance?
- Trends over time

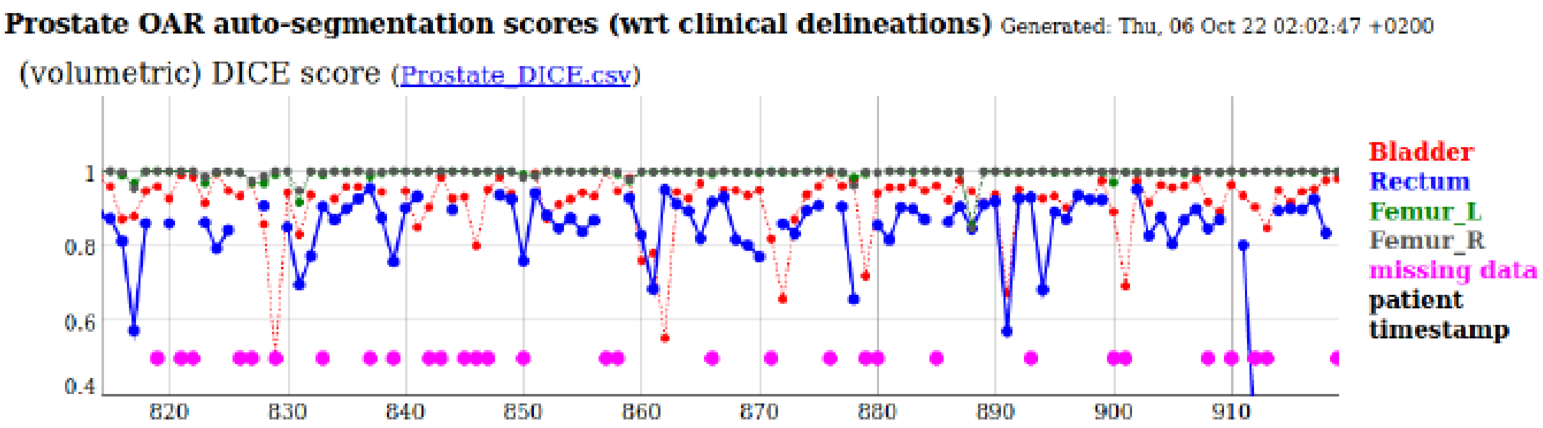


Brouwer, Boukerroui et al., Phys Imag Radiat Oncol, 2020

Robin Duteweert, 2023

UNIVERSITY OF TWENTE.

QA: MONITORING USER INTERACTION



DLinRT Symposium October 2022, Alexis Kotte, UMCU

FUTURE PERSPECTIVES

CAN AI QA ITSELF?

- Full automation needed to benefit from AI
    - Online adaptive radiotherapy
    - Trust?
    - Human machine interface

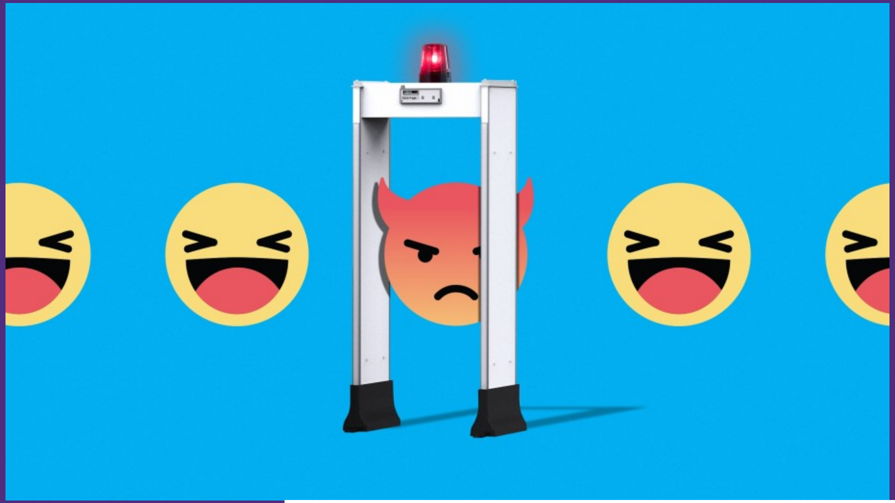


ILLUSTRATION: SAM WHITNEY; GETTY IMAGES

AUTOMATED PATIENT SPECIFIC QA?

SECONDARY ALGORITHM

Physics in Medicine & Biology

IPEM
Institute of Physics and Engineering in Medicine

PAPER

Machine learning-based detection of aberrant deep learning segmentations of target and organs at risk for prostate radiotherapy using a secondary segmentation algorithm

Michaël Claessens[1,2], Verdi Vanreusel[1], Geert De Kerf[1], Isabelle Mollaert[1], Fredrik Löfman[3], Mark J Gooding[4], Charlotte Brouwer[5], Piet Dirix[1,2] and Dirk Verellen[1,2]

1 Department of Radiation Oncology, Iridium Network, Wilrijk (Antwerp), Belgium
2 Centre for Oncological Research (CORE), Integrated Personalized and Precision Oncology Network (IPPON), University of Antwerp, Belgium
3 Department of Machine Learning, RaySearch Laboratories AB, Stockholm, Sweden
4 Mirada Medical Ltd, Oxford, United Kingdom
5 University of Groningen, University Medical Center Groningen, Department of Radiation Oncology, The Netherlands

E-mail: michael.claessens@uantwerpen.be

Keywords: quality assurance, auto-segmentation, artificial intelligence, machine learning, deep learning, time-saving

AUTOMATED PATIENT SPECIFIC QA?

Quality Assurance for AI-Based Applications in Radiation Therapy

Michaël Claessens, Msc,[†,1] Carmen Seller Oria, Msc,[‡,1] Charlotte L. Brouwer, PhD,[‡] Benjamin P. Ziemer, PhD,[§] Jessica E. Scholey, PhD,[§] Hui Lin, PhD,[§] Alon Witztum, PhD,[§] Olivier Morin, PhD,[§] Issam El Naqa, PhD,[‖] Wouter Van Elmpt, PhD,[#] and Dirk Verellen, PhD[†]

Table 1 QA Tools for AI-Based Applications in RT

Application	Routine QA	Case-Specific QA
1. QA for AI-based auto-segmentation	Inter-institutional datasets[27] Software for auto segmented ROIs comparison[28] Turing test[29]	Statistical models[17,18] ML-based with features[19-21] ML-based secondary algorithm[15,22,23] DL-based probability/uncertainty maps[24]

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Uncertainty Assessment for Deep Learning Radiotherapy Applications

Cornelis A.T. van den Berg,* and Ettore F. Meliadò†

Epistemic (model) uncertainties:

- Model limitations, approximation uncertainty
- Can be reduced by adding more data

Aleatoric (data) uncertainties:

- Related to random probability (stochastic process)
- Cannot be reduced by adding more data

Modeling uncertainty by e.g.

- Monte Carlo dropout
- Ensemble learning

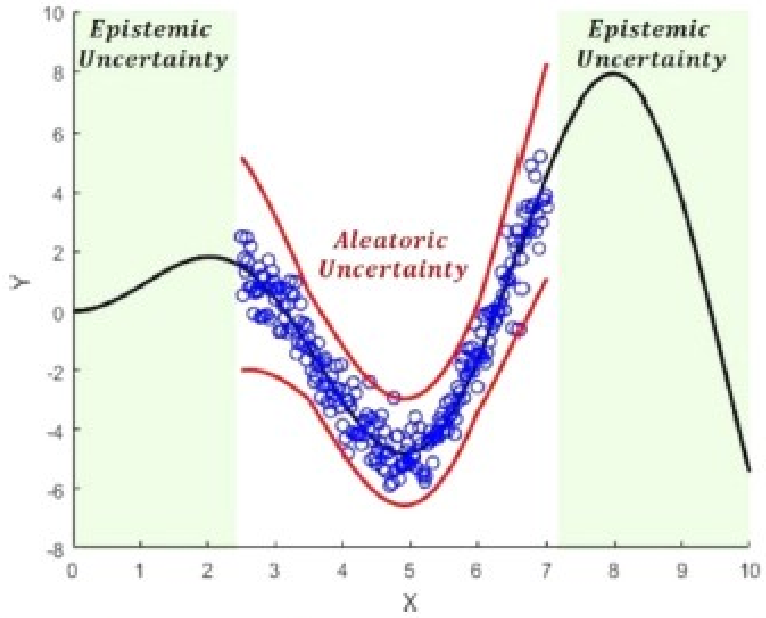
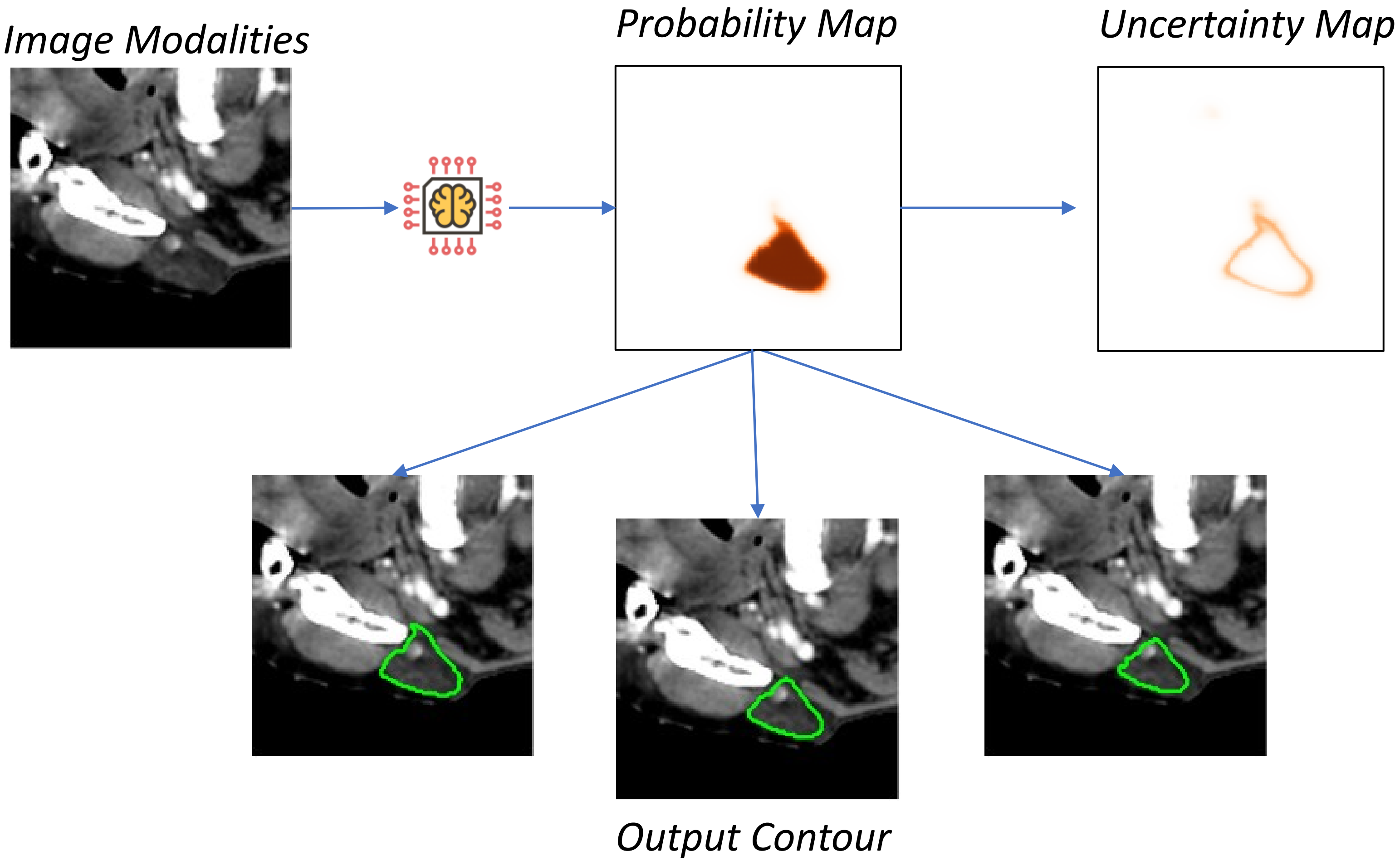


Figure 5 Illustration of aleatoric and epistemic uncertainties. While the epistemic uncertainty can be reduced by including more training data, the aleatoric uncertainty cannot be reduced because the stochastic component of the data always remains present.

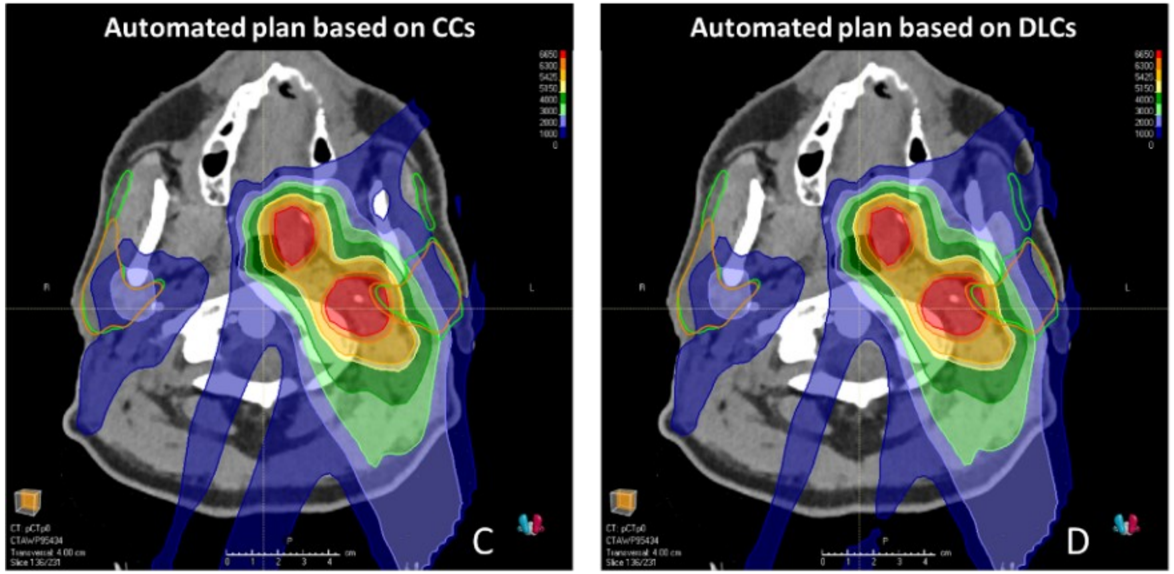
VISUALIZATION OF UNCERTAINTY



From: Alessia de Biase

AUTOMATED PATIENT SPECIFIC QA?
FUTURE

- Technical medicine research line
- Deep learning to detect clinically relevant errors



Joelle van Aalst, 2023

CONCLUSION

DEEP LEARNING IN RADIOTHERAPY

- AI segmentation of healthy tissue adopted on large scale in clinical practice
- Other applications (treatment planning, synthetic imaging) upcoming
- To improve models and facilitate clinical adoption
  - Optimize and harmonize ground truth definition
  - Develop & integrate automated QA aspects within clinical workflow
- Multi-disciplinary collaboration of all parties involved is and remains crucial

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October 2022

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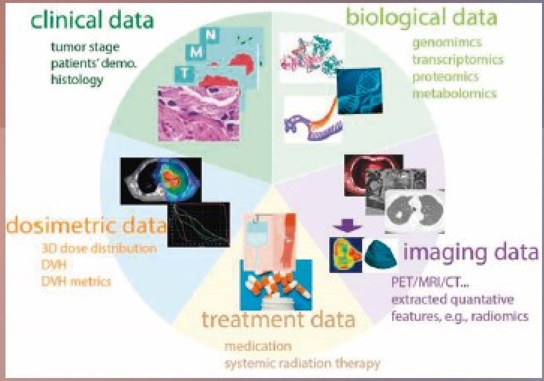
Akila Viswanathan, MD, MPH
Editor



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Guest Editors
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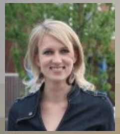

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Artificial Intelligence: Methods and Applications in Radiotherapy
***Charlotte L. Brouwer and Ke Sheng**, Guest Editor*

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THE TECHMED EVENT | SHAPING A HEALTHY FUTURE

11:00-12:15 | **AI & HEALTH: FROM BENCH TO BEDSIDE** | CHARLOTTE BROUWER