AI planning approaches

Head and Neck

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Learning objectives

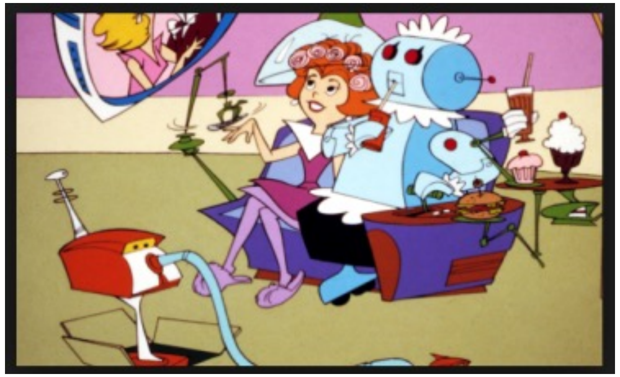
Understand how human intervention and AI can be used in the RT treatment planning process

Discuss what are the specific challenges for head and neck treatment planning

Discuss on the limitations of AI in head and neck planning

Future directions

Artificial Intelligence = The use of a computer to perform tasks that typically require human thought



Scripting (automate repetitive tasks, need instructions)

Machine Learning (yield output from a given input without specific instructions)

- Supervised learning (model generated to give specific output)
- Unsupervised learning (model determines its own output from underlying data)

Deep learning

- Artificial neural network to simulate human reasoning

Challenges in head and neck treatment planning

TAGS

Increasing demand (SIB + IMRT/VMAT standard of care)

- Need to optimize workflow

WORKFLOW OPTIMISATION

Anatomical changes during treatment delivery

- Tumour response
- Weight lose

ADAPTIVE

Dose distribution robustness to patient position (shoulders/chin)

ROBUSTNESS

Quality Assurance (Plan evaluation)

QA

Treatment planning process

Positioning immobilisation → Imaging → Volume delineation → Prescription → Beam setting → Optimisation → Dose calculation → Plan evaluation

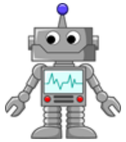
Automation and human intervention in the treatment planning process

WORKFLOW OPTIMISATION

Positioning immobilisation → Imaging → Volume delineation → Prescription → Beam setting → Optimisation → Dose calculation → Plan evaluation

AI based decision support tool

Patient characteristics
Oncologic information



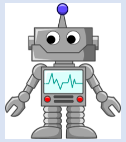
Imaging modality/ies
Imaging protocol (optimization)
Immobilization/position devices

Automation and human intervention in the treatment planning process

ADAPTIVE

Improving image quality (optimization)
Synthetic kV-CT from MR and CBCT
Synthetic MV-CT from MR, kVCT and CBCT

Positioning immobilisation → Imaging → Volume delineation → Prescription → Beam setting → Optimisation → Dose calculation → Plan evaluation



Improving calculation accuracy with a better characterisation of tissues

IOP Publishing Phys. Med. Biol. 67 (2022) 105001 https://doi.org/10.1088/1361-6560/ac6725

Physics in Medicine & Biology

IPEM
Institute of Physics and Engineering in Medicine

CrossMark

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13 December 2021

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4 April 2022

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13 April 2022

PAPER

Improved accuracy of relative electron density and proton stopping power ratio through CycleGAN machine learning

Jessica Scholey[1], Luciano Vinas[2], Vasant Kearney[1], Sue Yom[1], Peder Eric Zufall Larson[3], Martina Descovich[1] and Atchar Sudhyadhom[1,4]

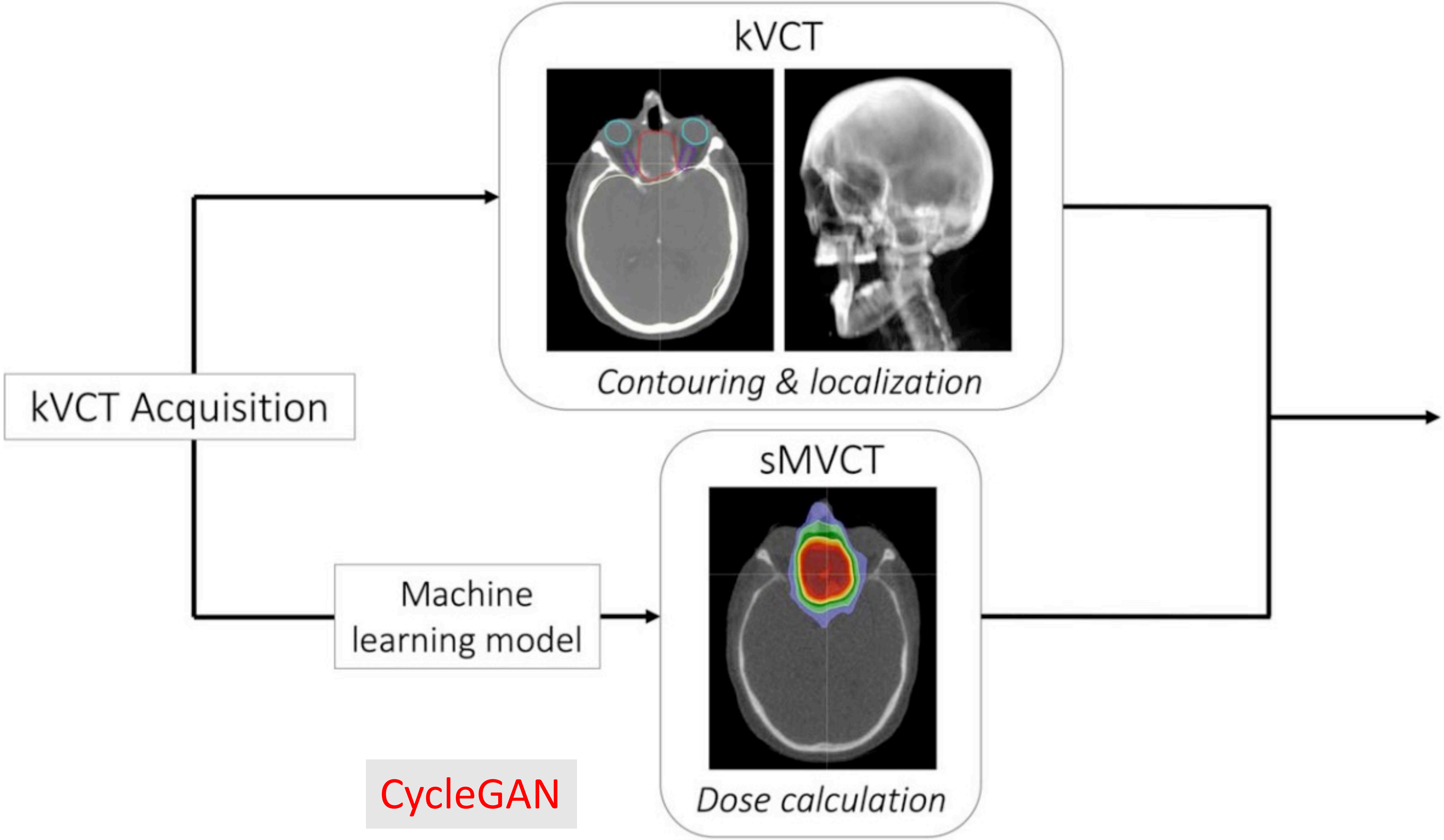

kVCT
Contouring & localization
kVCT Acquisition
sMVCT
Machine learning model
Dose calculation
CycleGAN

Table 2. Results of ρ_e and SPR values calculated using the kV and MVCT calibration curves for skin, muscle, adipose, and spongiosa tissue mimicking phantoms.

	Relative electron density			*Stopping power ratio* (115 *MeV*)		
	Measured	kVCT (% diff)	MVCT (% diff)	Measured	kVCT (% diff)	MVCT (% diff)
Skin	1.048 ± 0.002	1.026 ± 0.004 (−2.10)	1.051 ± 0.004 (0.29)	1.049 ± 0.002	1.055 ± 0.004 (0.62)	1.052 ± 0.004 (0.29)
Muscle	1.036 ± 0.002	1.009 ± 0.004 (−2.61)	1.038 ± 0.004 (0.19)	1.036 ± 0.002	1.038 ± 0.004 (0.13)	1.037 ± 0.004 (0.11)
Adipose	0.955 ± 0.002	0.947 ± 0.004 (−0.84)	0.963 ± 0.005 (0.84)	0.953 ± 0.002	0.978 ± 0.004 (2.58)	0.970 ± 0.005 (1.70)
Spongiosa	1.044 ± 0.002	1.067 ± 0.002 (2.20)	1.042 ± 0.003 (−0.19)	1.044 ± 0.002	1.090 ± 0.002 (4.38)	1.042 ± 0.003 (−0.22)

Bone (head phantom)

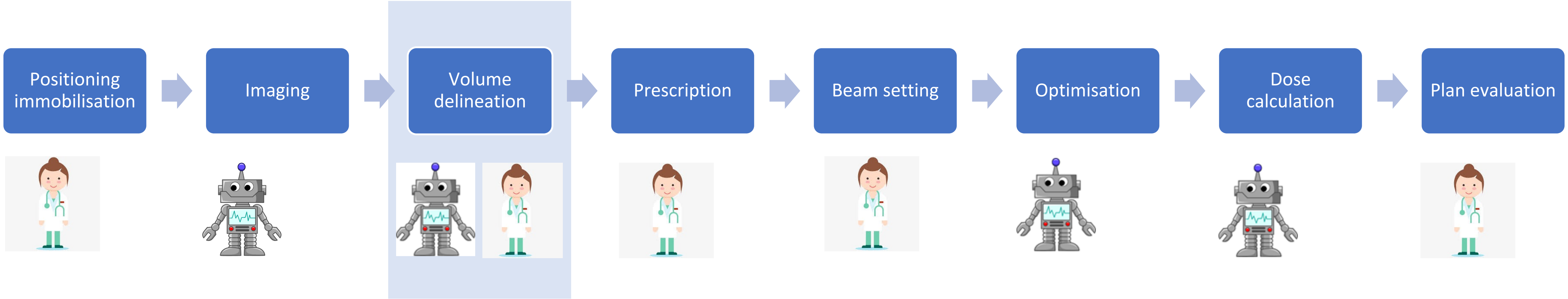
Relative electron density			
Measured	kVCT (% diff)	MVCT (% diff)	sMVCT (% diff)
1.120	1.204 ± 0.10 (7.50%)	1.129 ± 0.13 (0.80%)	1.131 ± 0.20 (0.98%)

Stopping power ratio (115 MeV)			
Measured	kVCT (% diff)	MVCT (% diff)	sMVCT (% diff)
1.125	1.207 ± 0.09 (7.48%)	1.129 ± 0.11 (0.78%)	1.131 ± 0.17 (0.96%)

Automation and human intervention in the treatment planning process

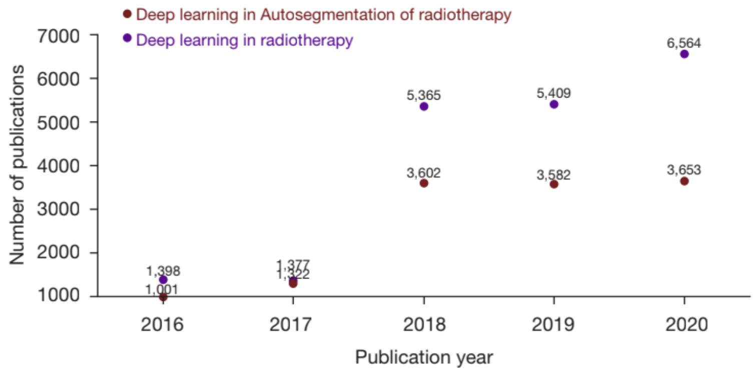
OR segmentation ideal task for automation (repetitive nature and common geometric properties)
Manual segmentation lengthy, tedious and prone to errors

GTV/CTV more difficult due to the abnormal nature of the anatomy

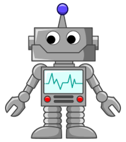


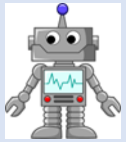
Automation and human intervention in the treatment planning process

Reduces delineation variability and increases efficiency



Positioning immobilisation → Imaging → Volume delineation → Prescription → Beam setting → Optimisation → Dose calculation → Plan evaluation





Category	Name	Developer	Site and method
Research applications Non-machine-learning techniques	SPM	Wellcome Centre for Neuroimaging, University College London, UK	Brain Shape models
	FSL	FMRIB Analysis Group, Oxford University, UK	Brain Shape models
	Freesurfer	Harvard University, USA	Brain Intensity-based
Research Applications Machine-learning techniques	InnerEye Open Source Deep Learning Toolkit	Microsoft Research, USA	Multiple sites CNN
Commercial applications Non-machine-learning techniques	Eclipse	Varian, USA	Multiple sites Atlas-based
	ABAS	Elekta AB, Sweden	Multiple sites Atlas-based
	Prosoma	Medcom GMBH, Germany	Multiple sites Atlas-based & shape models
	OnQ RTS	Oncology Systems Ltd, UK	Multiple sites Atlas-based
	RayStation	Raysearch AB, Sweden	Multiple sites Atlas-based
	SPICE (Pinnacle)	Philips NV, Netherlands	Multiple sites Atlas-based
	MIM Maestro	Mim Software Inc, USA	Multiple sites Atlas-based
	IPlan Elements	BrainLab Ag, Germany	Brain Atlas-based
	Precision	Accuray Inc, USA	Multiple sites Atlas-based
Commercial applications Machine-learning techniques	DLC Expert	Mirada Medical, UK	Multiple sites CNN
	Mvision	Mvision AI, Finland	Multiple sites CNN
	Limbus.ai	Limbus.ai Inc, Canada	Multiples sites CNN
	ART-Plan	Therapanacea, Paris	Multiple sites CNN

Atlas based: Deformable registration to warp contours from a similar atlas patient to the current patient

AI (CNN): Models trained on CT datasets, ground truth expert contours or consensus contours from public datasets

CNN-based OAR contours require less correction than atlas based contours

9% vs 30%

Times needed for Deep Learning-segmentation

DL-segmentation of all OARs:

- 30 s male pelvis
- **120 s head and neck**
- 70 s for abdomen

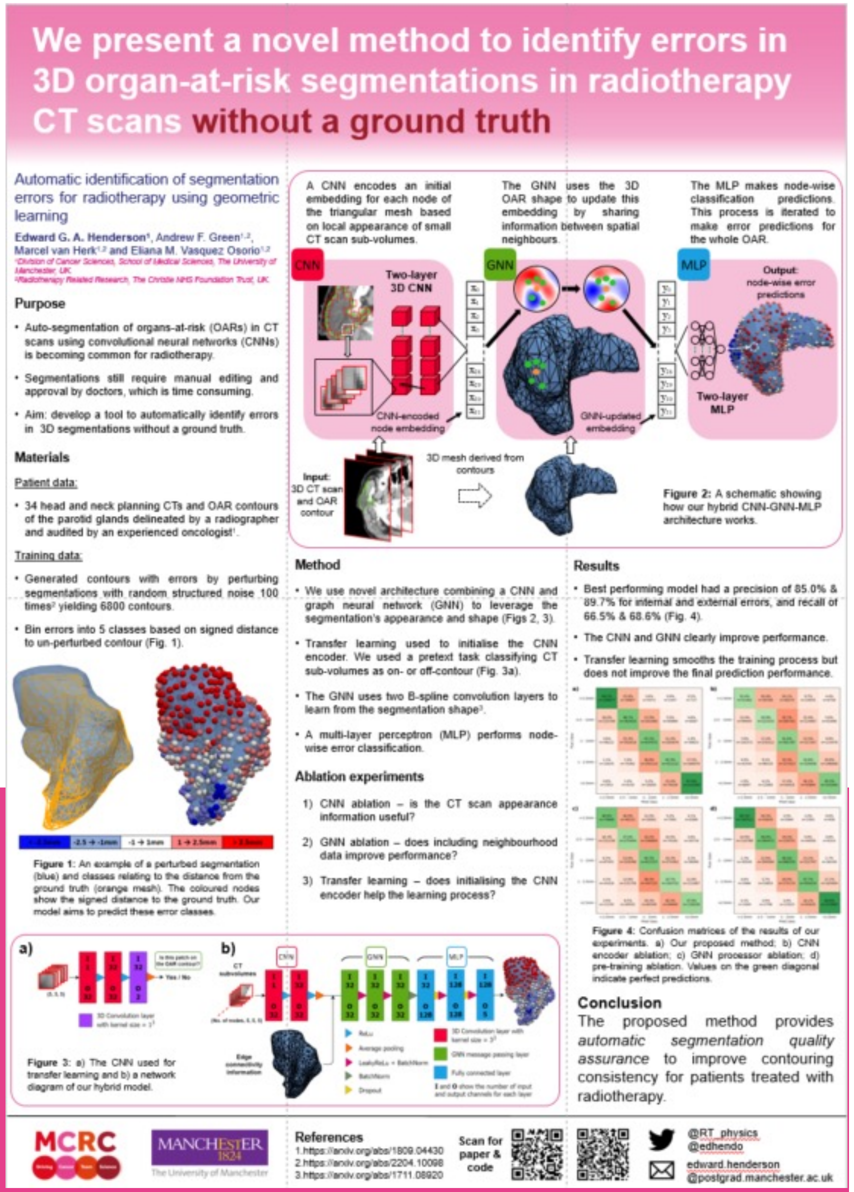
Reductions of DL+manual editing compared to manual contouring from scratch:

- 88% male pelvis
- 80% head and neck
- 65% abdomen

times for visual inspection of DL-contours and manual editing (if needed):

- 5 min male pelvis
- **15 min head and neck**
- 30 min abdomen

Automatic identification of segmentation errors for radiotherapy using geometric learning



Edward G. A. Henderson[1], Andrew F. Green[1,2], Marcel van Herk[1,2] and Eliana M. Vasquez Osorio[1,2]

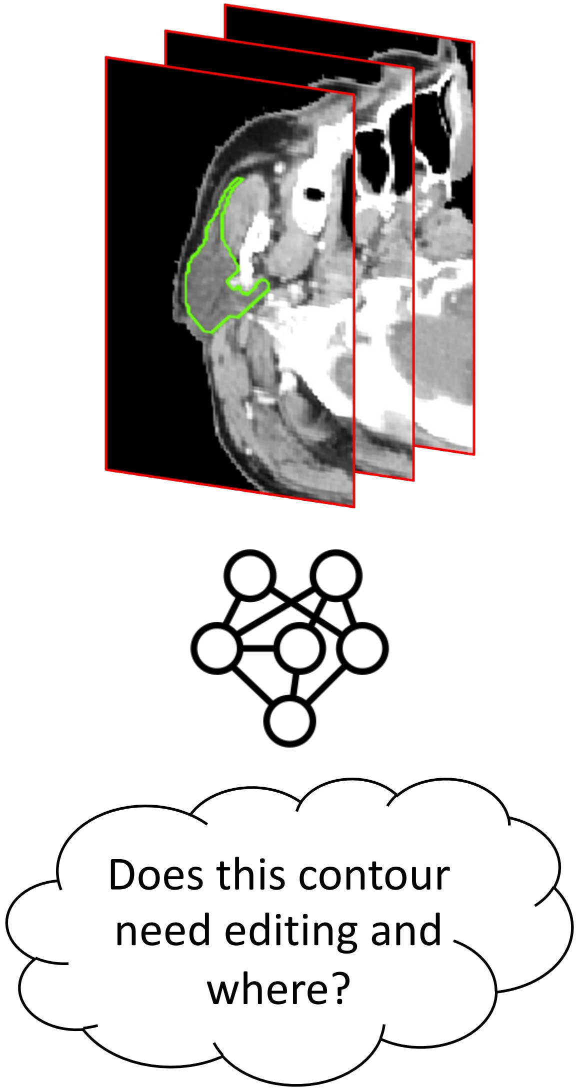
[1]*Division of Cancer Sciences, School of Medical Sciences, The University of Manchester, UK.*

[2]*Radiotherapy Related Research, The Christie NHS Foundation Trust, UK.*

NHS
The Christie
NHS Foundation Trust

What did they do?

- Developed a tool to identify errors in 3D OAR segmentations
- Did so without a known ground truth
- Previous methods predicted global errors (DSC, clinical acceptability, distance metric)
- Identified errors in local areas
- Independent of the contour generation method



MCRC
Driving Cancer Team Science

MANCHESTER 1824
The University of Manchester

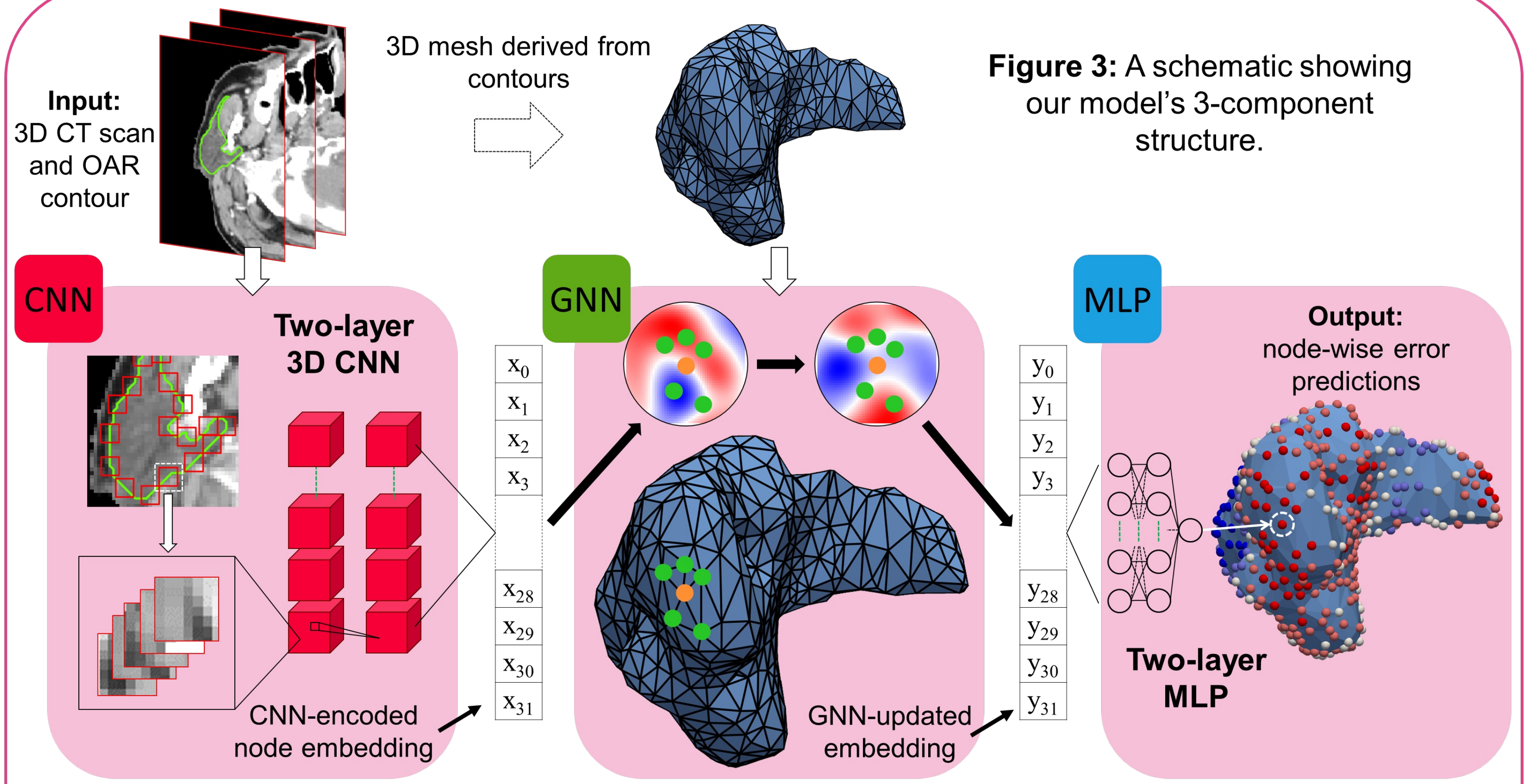


Figure 3: A schematic showing our model's 3-component structure.

A small CNN encodes an initial embedding for each node of the triangular mesh based on local appearance information of small CT scan sub-volumes.

The GNN uses the 3D OAR shape to update this embedding by sharing information between spatial neighbours.

The MLP makes node-wise classification predictions. Error predictions for the whole OAR are found made by iterating

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Conclusion

- The proposed method provides ***automatic segmentation quality assurance*** to improve contouring consistency for patients treated with radiotherapy

- Many applications for such a method:
  - As a second check for auto-segmentation software
  - Improving the efficiency of clinical segmentation auditing
  - Flag important regions for clinicians to check

Factors limiting auto-segmentation

- Lack of standardization of contouring protocols
- Lack of robustness to small changes in data acquisition
- Lack of trust amongst intended users
- Lack of solid ground truth: what are the true borders of (some) OARs and tumors in the images?

  Has impact on training, clinical validation and interpretation of studies
- If there is a difference between expert- and DL contours, who is right?

Future of auto-segmentation

- Make better use of unlabelled datasets in optimising deep-learning models.
- Implement consistent labelling of real-world data by standardising nomenclature for ROIs; for example, following proposed guidelines
- Develop tools that simplify the optimisation of machine-learning algorithms
- Use of heterogeneous datasets (male/female, scanners, acquisition models, etc) reduce overfitting.

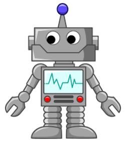
Automation and human intervention in the treatment planning process

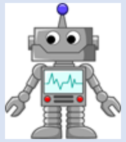
WORKFLOW OPTIMISATION

ADAPTIVE

QA

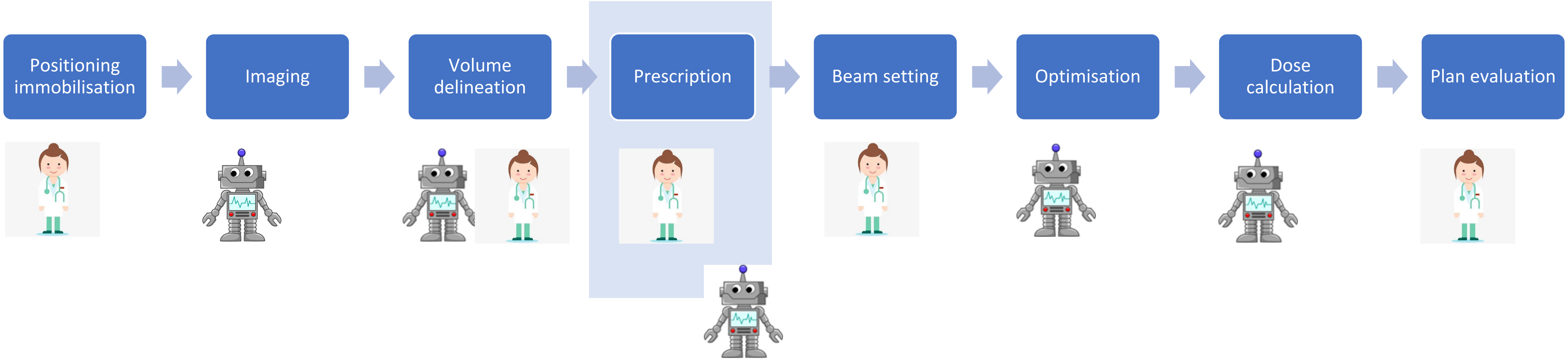
Positioning immobilisation → Imaging → Volume delineation → Prescription → Beam setting → Optimisation → Dose calculation → Plan evaluation





Automation and human intervention in the treatment planning process

WORKFLOW OPTIMISATION



Prescription decision support tools

January 10, 2022 - Case Western Reserve University researchers are using artificial intelligence to identify which patients with certain head and neck cancers would benefit from reducing the intensity of treatments, including radiation therapy and chemotherapy.

Using AI tools like those they developed over the last decade, researchers asked the computer to **analyze digital images** of tissue samples taken from 438 patients with a type of head and neck cancer, known as HPV-associated oropharyngeal squamous cell carcinoma (OPCSCC) from six hospital systems.

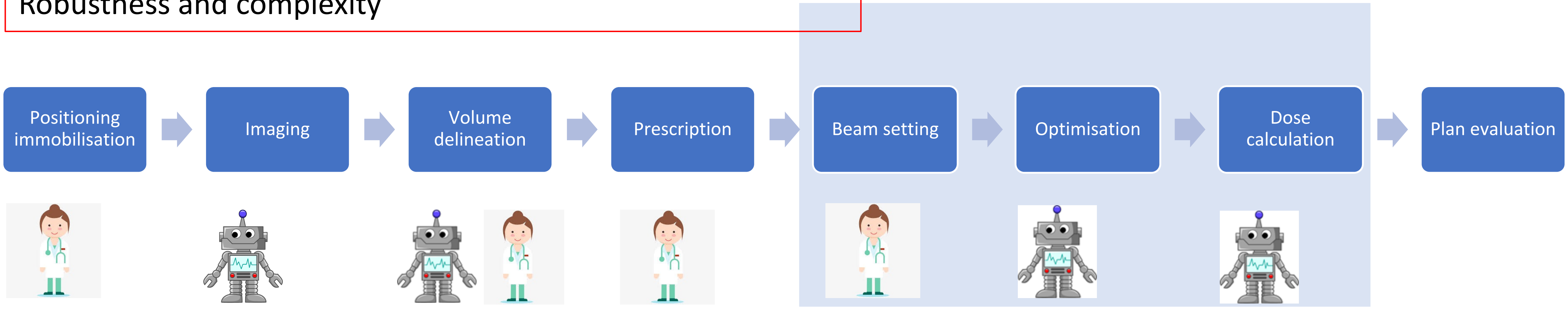
The computer program successfully detected a subset of patients who could benefit from a significantly reduced dose of radiation therapy. According to the research team, their next step is to test the AI method’s accuracy in clinical trials.

This latest research builds on **previous research** by the CCIPD in developing novel imaging biomarkers for risk stratification and outcome prediction of head and neck cancer.

Automation and human intervention in the treatment planning process

Challenges

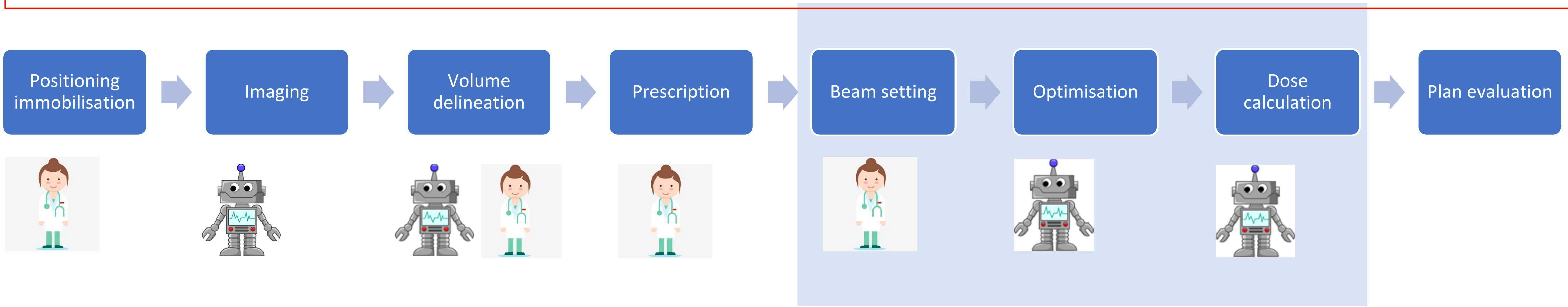
Complex anatomy
Different dose levels (control hot spots outside the PTVs)
Tolerances for OAR (patient specific considerations, priorities)
Robustness and complexity



Automation and human intervention in the treatment planning process

Automated treatment planning

Knowledge based planning systems (Using previous patients to predict the dose distribution in new patient)
Machine learning for dose prediction



WORKFLOW OPTIMISATION

ADAPTIVE

Automation and human intervention in the treatment planning process

IMRT dose prediction: A priory knowledge of the volumetric dose of a prospective patients

Atlas based:

New patient

Extracted Features

Similar patient
+ Dose distribution

Deformation

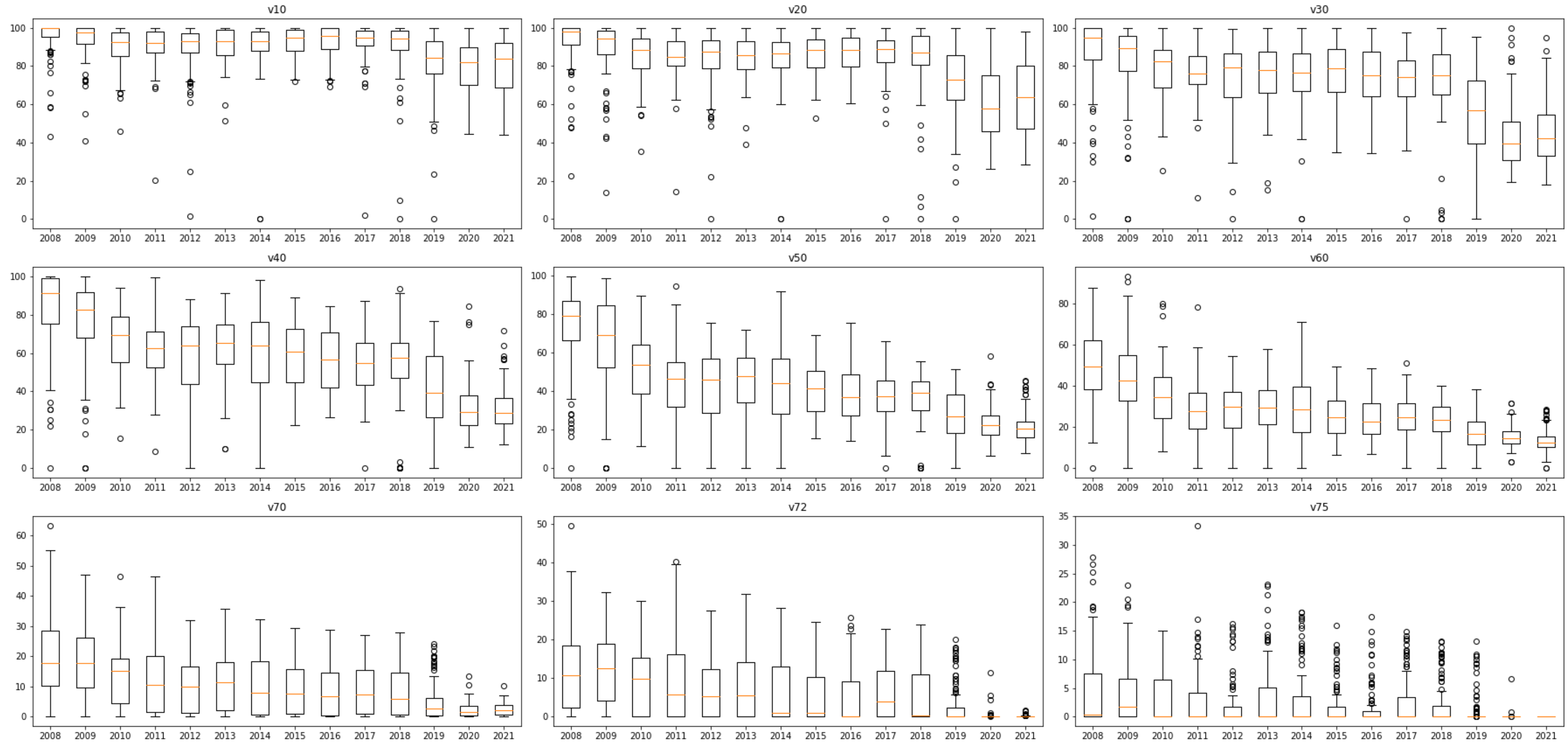
Novel Dose Prediction

IMRT radiotherapy plan

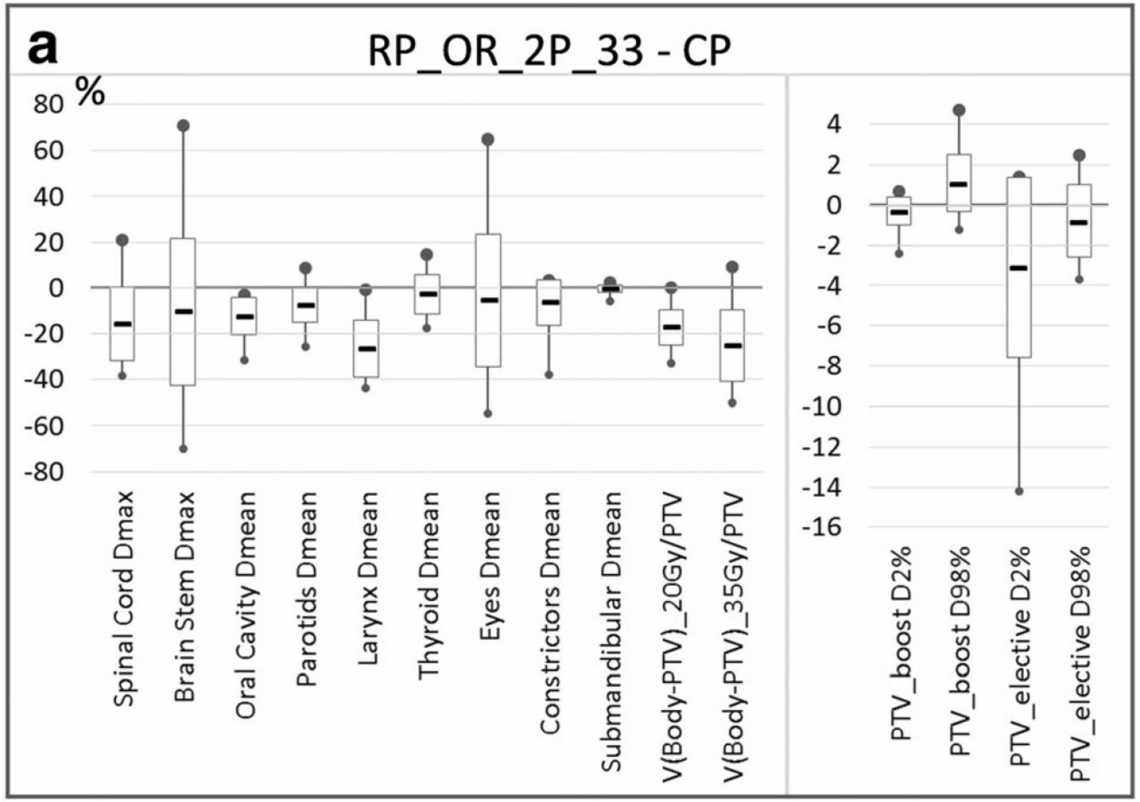
Still needs inverse optimization step to translate the predicted DVH/dose to deliverable fluence maps, which correspond to machine parameters (MLC/gantry speed/ dose rate)

Evolution of rectum DVH from 2008 to 2021

2019 introducción gEUD
2020 introducción RapidPlan
knowledge-based planning



Rapid Plan and head and neck treatments



Fogliata *et al. Radiation Oncology* (2017) 12:73
DOI 10.1186/s13014-017-0808-x
Radiation Oncology
RESEARCH Open Access

RapidPlan head and neck model: the objectives and possible clinical benefit

A. Fogliata[1*], G. Reggiori[1], A. Stravato[1], F. Lobefalo[1], C. Franzese[1], D. Franceschini[1], S. Tomatis[1], P. Mancosu[1], M. Scorsetti[1,2] and L. Cozzi[1,2]

Doses were prescribed for all patients in 33 fractions, to total doses of 69.96 Gy and 54.45 Gy to the boost and the elective PTV, respectively

Model trained with plans with 2-4 arcs
Validated with 2 arcs

Model stability for beam geometry and fractionation.

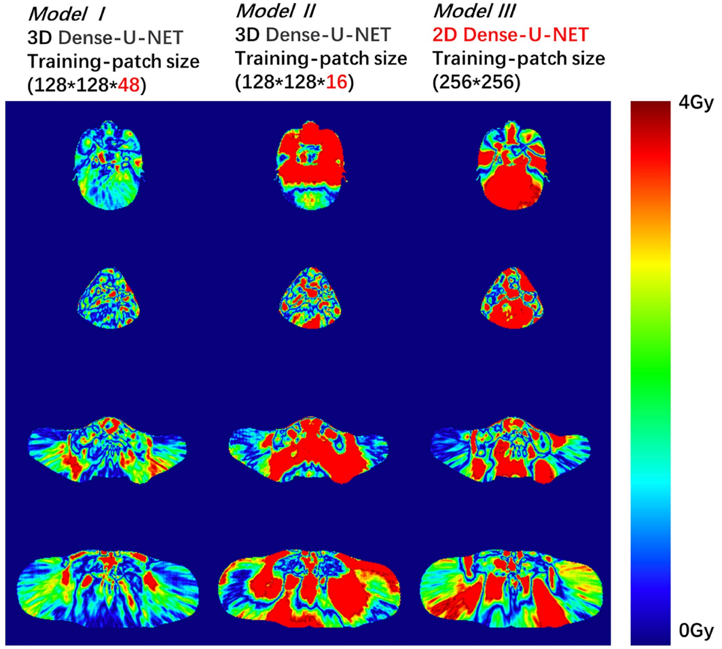
Automation and human intervention in the treatment planning process

Predict the fluence map without inverse planning

Fully connected neural networks

Convolutional neural networks

Prostate: Lee et al. Sci Rep (2019)
Breast: Sheng et al. Front Oncol (2019)
Pancreas: Wang et al. Advances in Radiat Oncol(2021)
Nasopharynx: Liu et al. Front. Oncol. (2021)

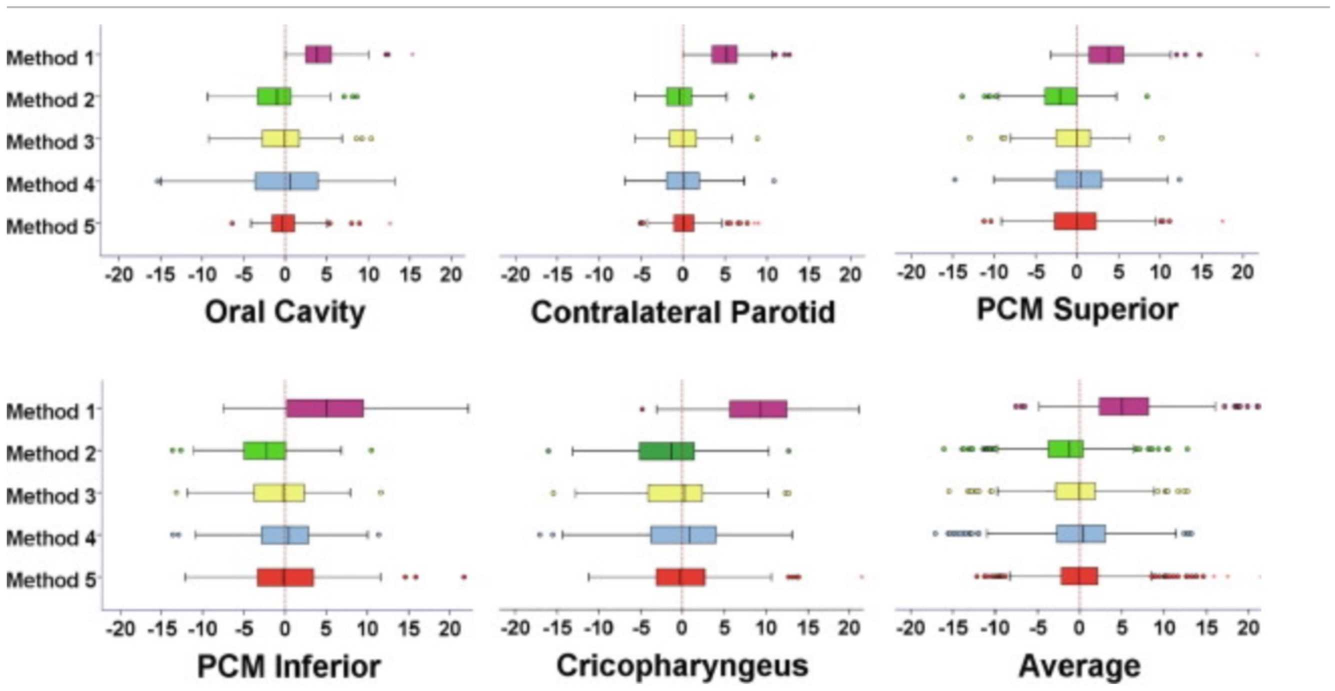


Limited precision in predicting accurate doses in no-contoured areas
The deep-learning model needs to know the spatial relationship between OARs and PTV.
Accuracy highly dependent on the technique, equipment…

Automation and human intervention in the treatment planning process

Treatment decision supporting tool: Protons vs X-ray

WORKFLOW OPTIMISATION



Linear regression models for individual OARs were created to predict the D_{mean} to the OARs for VMAT and IMPT plans.

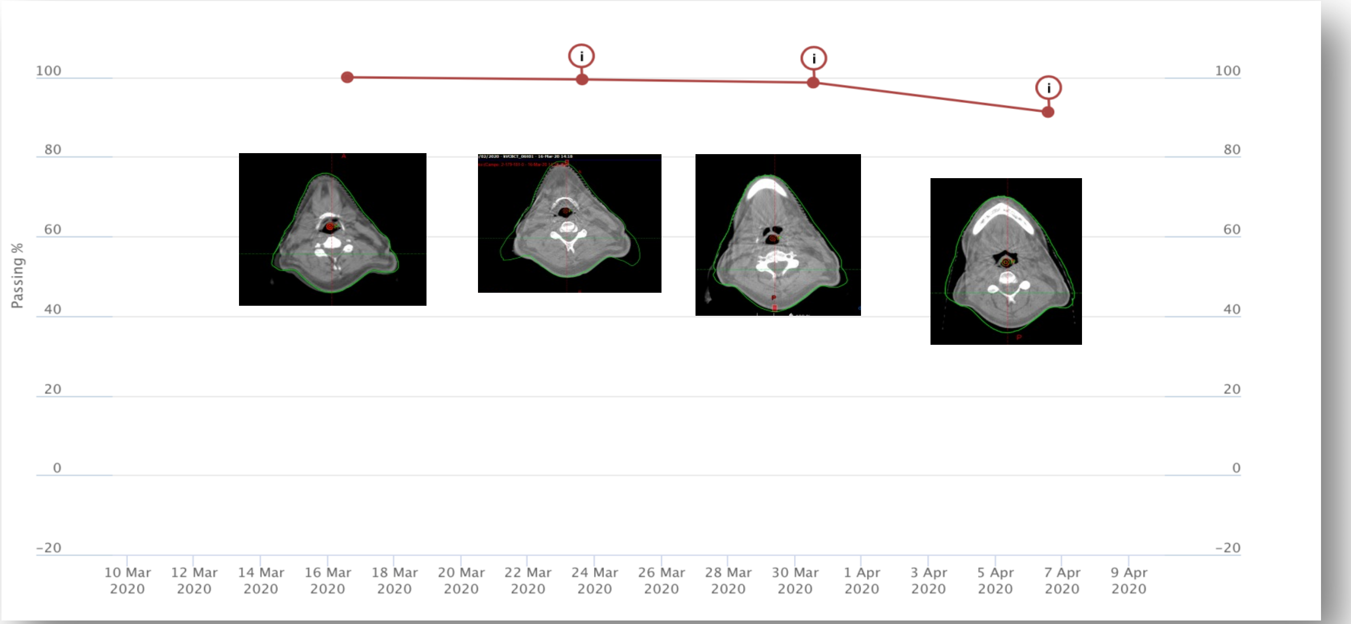
Positive = IMPT potential overestimated.
Smaller width box: smaller difference between predicted and actual IMPT dose

Tambas et al. Cancers 2022

ART: Replanning

Geometrical and anatomical variations occur during the course of curative intent treatments for HNC

77% of patients the 4th week undergo significant morphological and dosimetric changes (Guidi et al,2015)



2D in vivo transmission gamma passing rates

3D dosimetric impact will depend on the robustness of the dose distribution

ART Replanning: Prediction models (WHEN)

CHALLENGE CHALLENGE CHALLENGE

1. Not all dose distributions are equal regarding robustness to anatomical variations.

2. Confounding factor: Suboptimal immobilisation, shoulders' position differed significantly to that seen on their planning CT.

cancers https://www.mdpi.com/journal/cancers 2022 MDPI

Article

Early Prediction of Planning Adaptation Requirement Indication Due to Volumetric Alterations in Head and Neck Cancer Radiotherapy: A Machine Learning Approach

Vasiliki Iliadou [1,*], Ioannis Kakkos [1,2], Pantelis Karaiskos [3], Vassilis Kouloulias [4], Kalliopi Platoni [4], Anna Zygogianni [5] and George K. Matsopoulos [1]

Radiomics on CBCT to predict which patients will have **significant** anatomical variations

Dose distribution

WORKFLOW OPTIMISATION

ADAPTIVE

ART Replanning: Prediction models (WHEN)

1. Not all dose distributions are equal regarding robustness to anatomical variations.

2. Confounding factor: Suboptimal immobilisation, shoulders’ position differed significantly to that seen on their planning CT.

Retrospective Clinical Evaluation of a Decision-Support Software for Adaptive Radiotherapy of Head and Neck Cancer Patients

Sebastien A. A. Gros[1], Anand P. Santhanam[2], Alec M. Block[1], Bahman Emami[1], Brian H. Lee[1] and Cara Joyce[3]*

Front. Oncol. 12:7 77793.
doi: 10.3389/fonc.2022.777793

Deformation of planned dose distribution on the daily CBCT

Prediction algorithm that analysed dosimetric parameter (DP) trends against user-specified thresholds to proactively trigger adaptive re-planning up to four fractions ahead

WORKFLOW OPTIMISATION

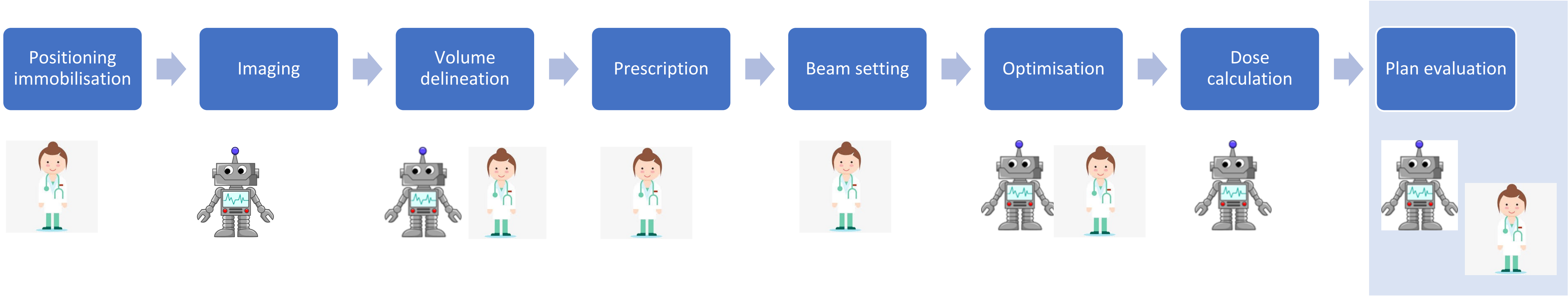
ADAPTIVE

ROBUSTNESS

Automation and human intervention in the treatment planning process

Including:

Evaluation of the treatment plan quality (dose distribution, robustness, complexity)
Are dose calculations accurate (redundant dose calculation)
Can the plan be delivered as planned (pre-treatment verification and in vivo dosimetry)



Automation in pre-treatment verifications

Reduce the number of plans that need to be verified.

Methods		Advantages	Drawbacks	References
Machine Learning	• Multivariate regression models • Tree-based algorithms	• Interpretability • Identifies the critical parameters	• Portability • Selection training data • It is very difficult for a single institution to collect adequate amounts of low GPR plans for model training. Overfitting risk • Selection training data	Valdes G et al. Med Phys. (2016) Valdes et al. J Appl Clin Med Phys.(2017) Lam D. et al. Med Phys (2019) Wang Li J et al Int. J. Radiat. Oncol. Biol. Phys. (2019) Granville DA. et al. Phys. Med. Biol. (2019)

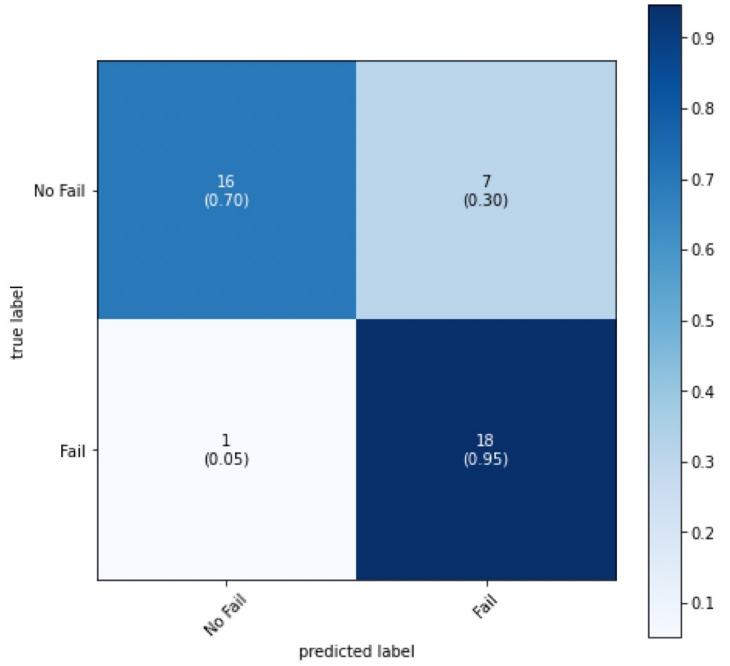
Automation in pre-treatment verifications

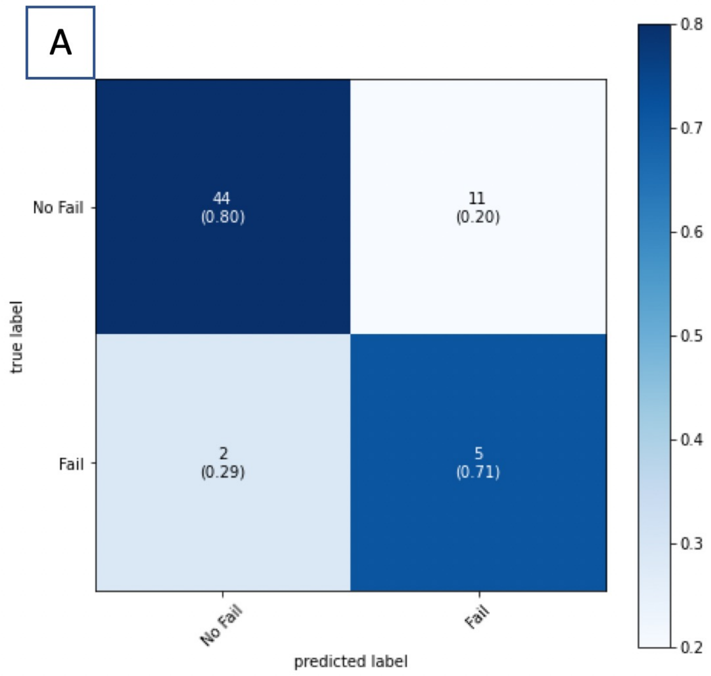
Analysis of results

Methods		Advantages	Drawbacks	References
Deep Learning	• CNN • ANN	• It does not require additional domain knowledge • Overcome Gamma analysis	• Selection training data • It is very difficult for a single institution to collect adequate amounts of low GPR plans for model training. Overfitting risk • Interpretability • Selection training data	Interian Y et al. Med Phys. (2018) Tomori S. et al Med Phys (2018) Mahdavi S. et al Br. J. Radiol. (2019) Kimura Y. et al. Phys. Medica (2020) Nyflot M.J. et al Med. Phys (2019)

Portability

Random forest model (VMAT complexity metrics used to predict results of pre-treatment plan verification)





5% false negatives

29% false negatives

Model applied to another institution data set,
same equipment,
same QA criteria (gamma)

Claessens et al. submitted for publication

To keep in mind

"The models presented in this **study may not be valid for use in other centres**, as both regression coefficients of the parameters in the models as well as the level of rescaling is expected to differ from center to center

Also **within institutions**, or specific subgroups of patients, **inter-patient variance** could be larger and the performance and applicability of any model could be reduced. Therefore, it is essential to assess the model parameters and rescaling factors, by validating, and if necessary **revising or updating our models** with own institute-specific patient data.

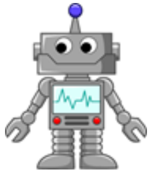
Moreover, as radiation technologies and center performance evolve over time, **regular updating of the model** and rescaling factors is paramount within each centre"

QA: Regular assessment of models

Final thoughts

1. AI is a tool

2. AI is not the solution to all head and neck planning challenges

3.   AI as a decision support tool

Automation vs. Human intervention: What is the best fit for the best performance?

Thanks

Eliana Vazquez-Osorio
Ben Heijmen
Pedro Gallego