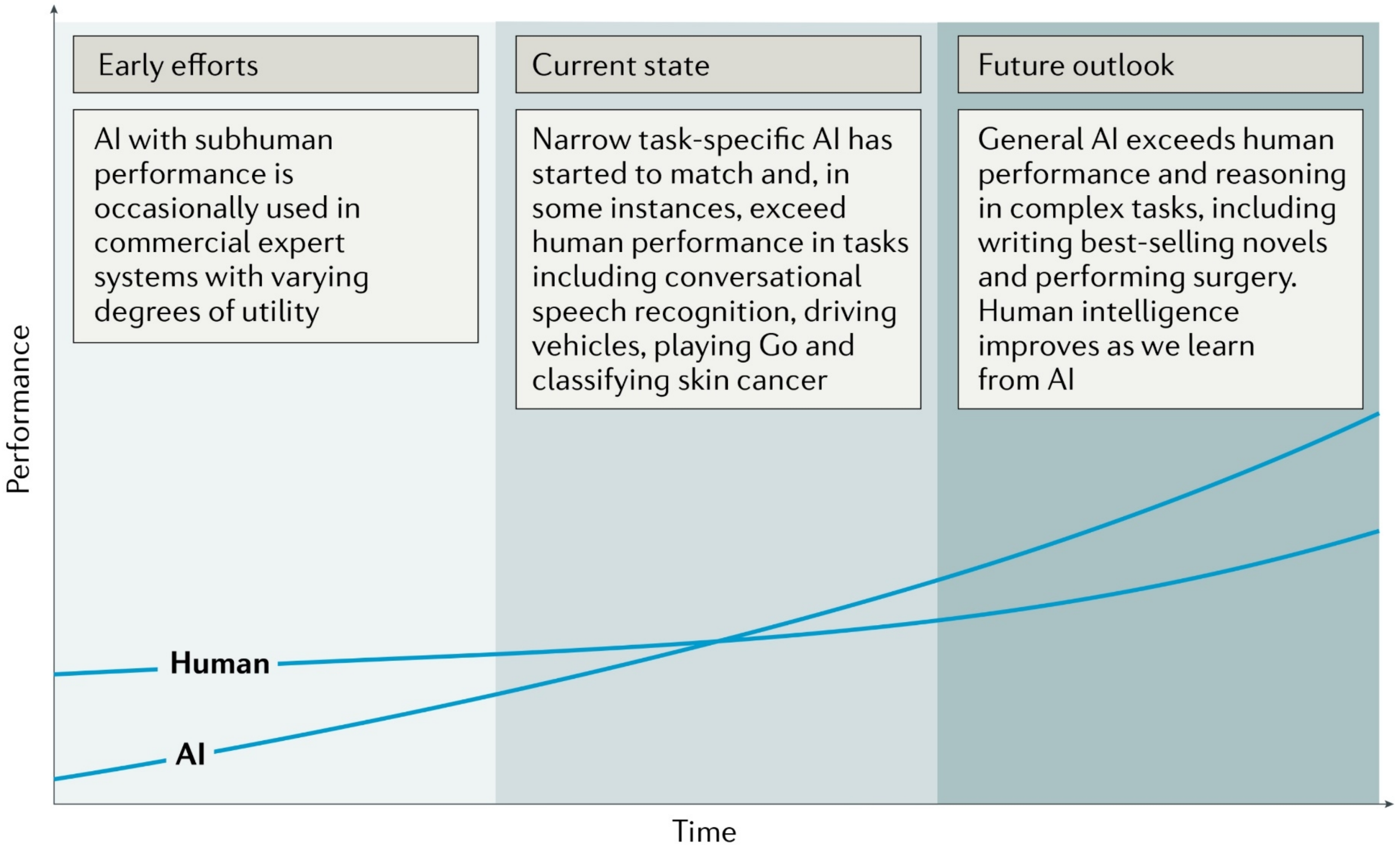
Artificial Intelligence in Radiation Oncology

Ahmed Hosny

Research Lunch - Department of Radiation Oncology

Thursday, June 27th 2019

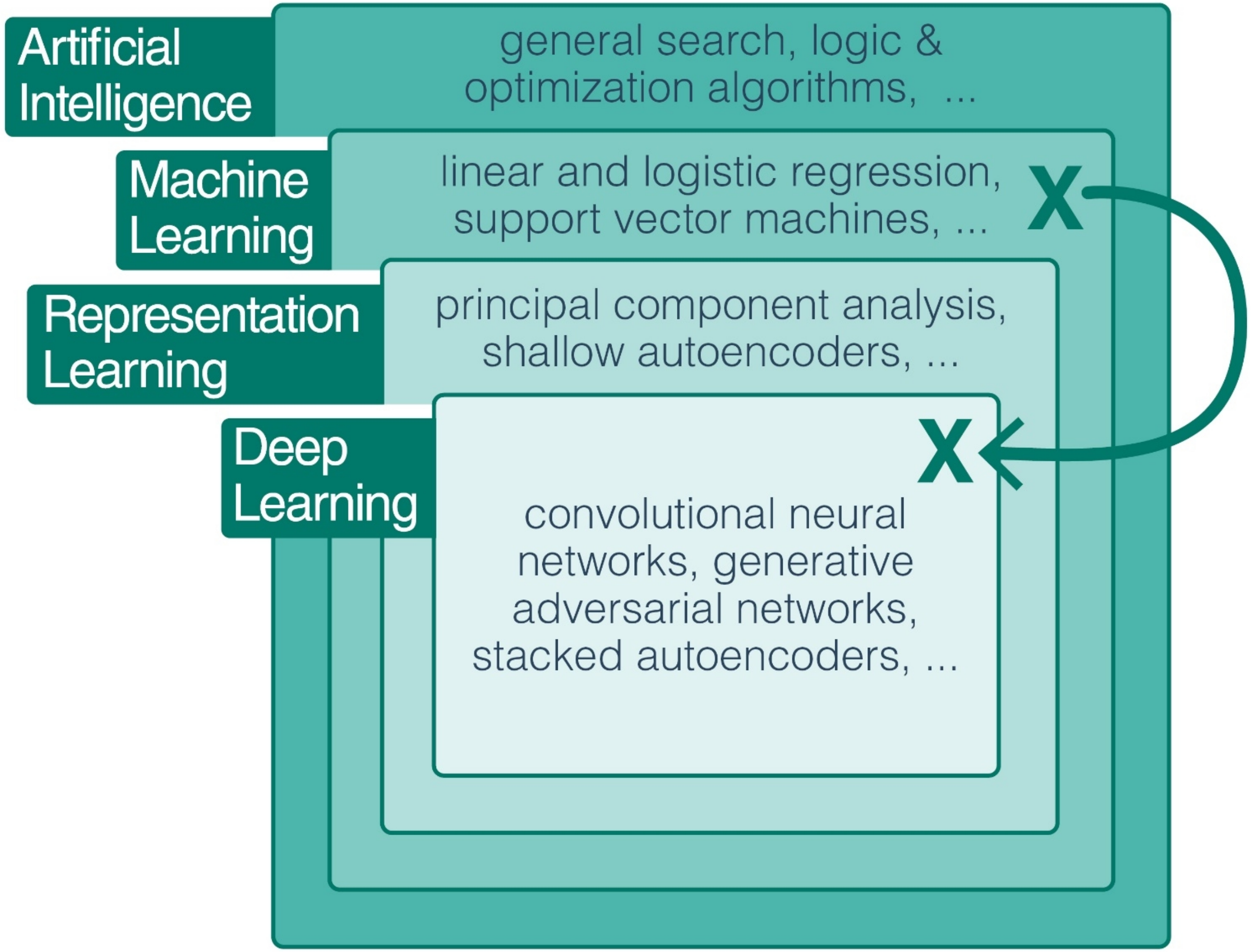
Artificial vs Human Intelligence



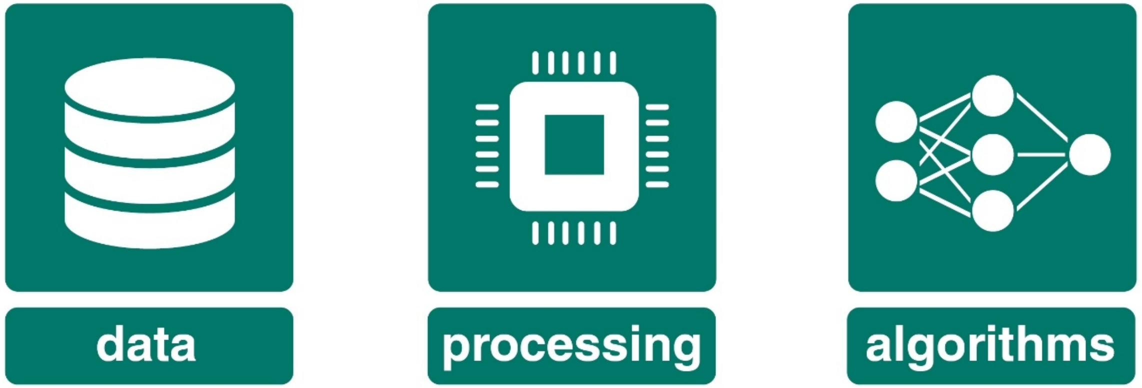
Ahmed Hosny, Chintan Parmar, John Quackenbush, et al.

Artificial Intelligence in Radiology
Nature Reviews Cancer - 2018

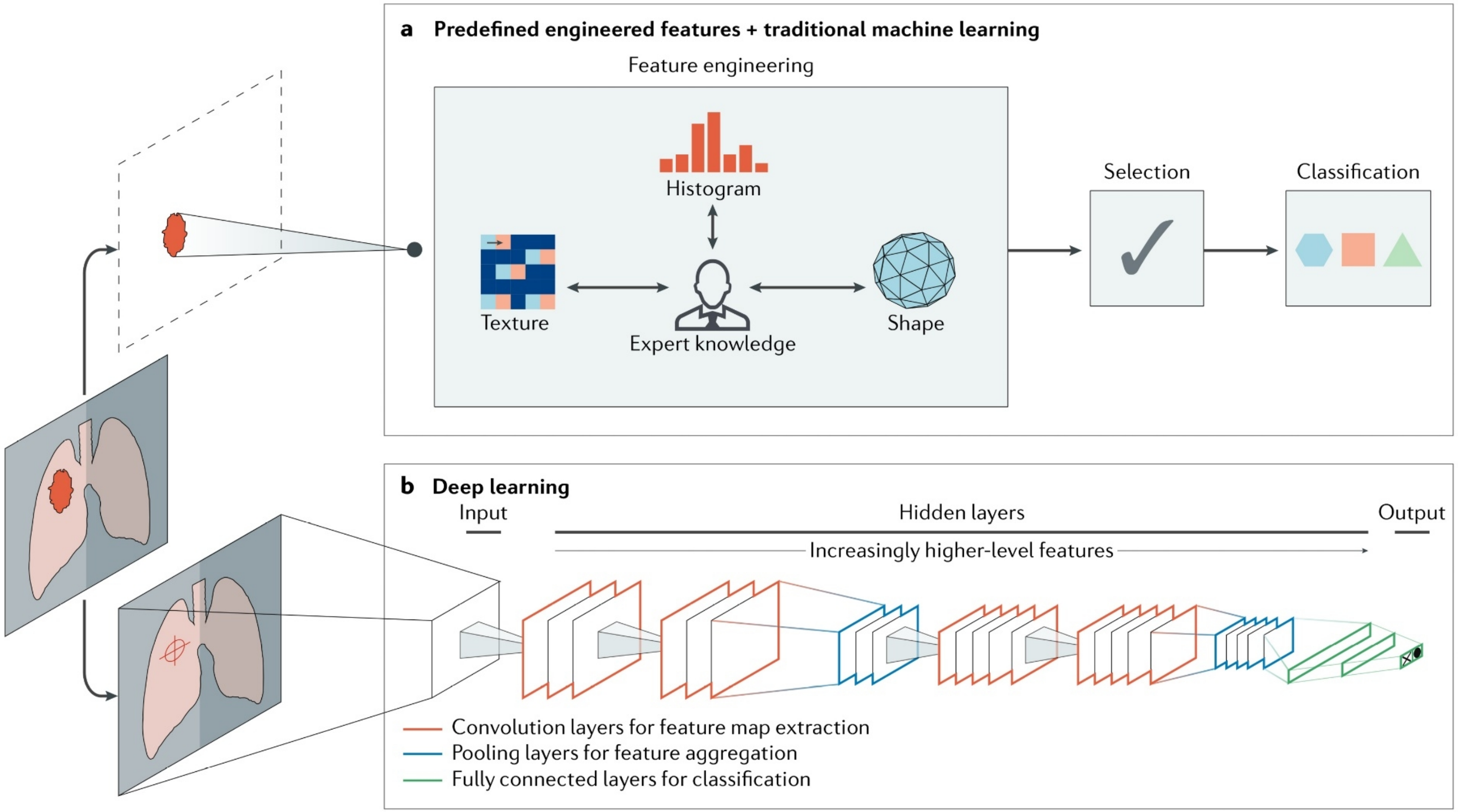
Revival of Research in Neural Networks



Revival of Research in Neural Networks



Deep Learning



Ahmed Hosny, Chintan Parmar, John Quackenbush, et al.

Artificial Intelligence in Radiology
Nature Reviews Cancer - 2018

Deep Learning

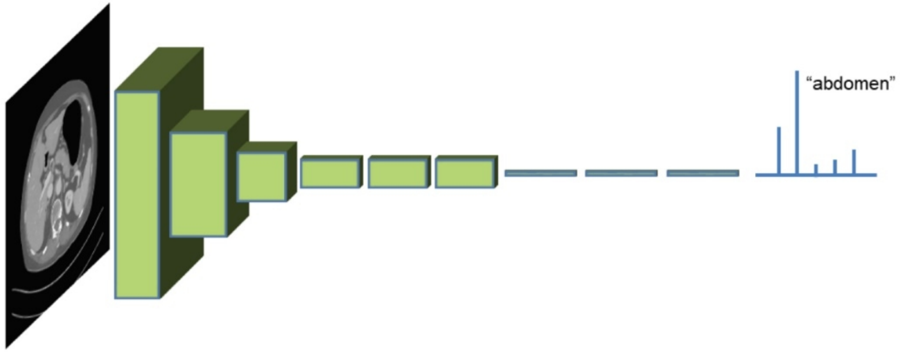


Fig. 1: Convolutional neural network (CNN). A straightforward application of CNNs for anatomy classification in whole body CT scans can be found in [10] (illustration after [2]).

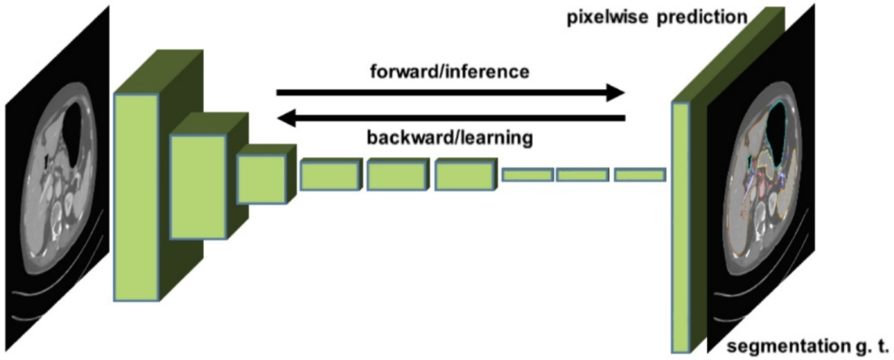


Fig. 2: Fully convolutional network (FCN). Examples of FCNs applied to semantic segmentation tasks in medical imaging can be found in [17]–[19], [25] (illustration after [2]).

Holger R Roth, Chen Shen, Hirohisa Oda, et al.

Deep Learning and its Application to Medical Image Segmentation

https://arxiv.org/abs/1803.08691

Problems (Features) in Radiation Oncology

Labor- & time- intensive

Requires highly skilled specialists

Large variability

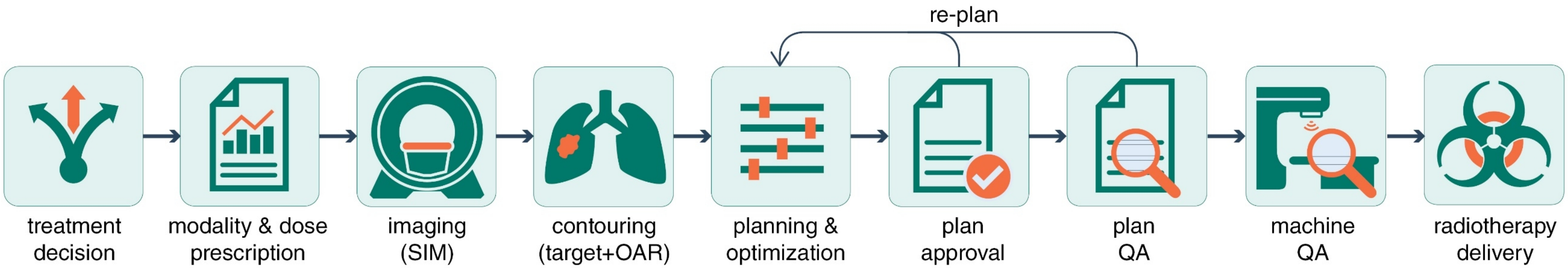
Opportunities in Radiation Oncology

Reliance on human-machine interaction

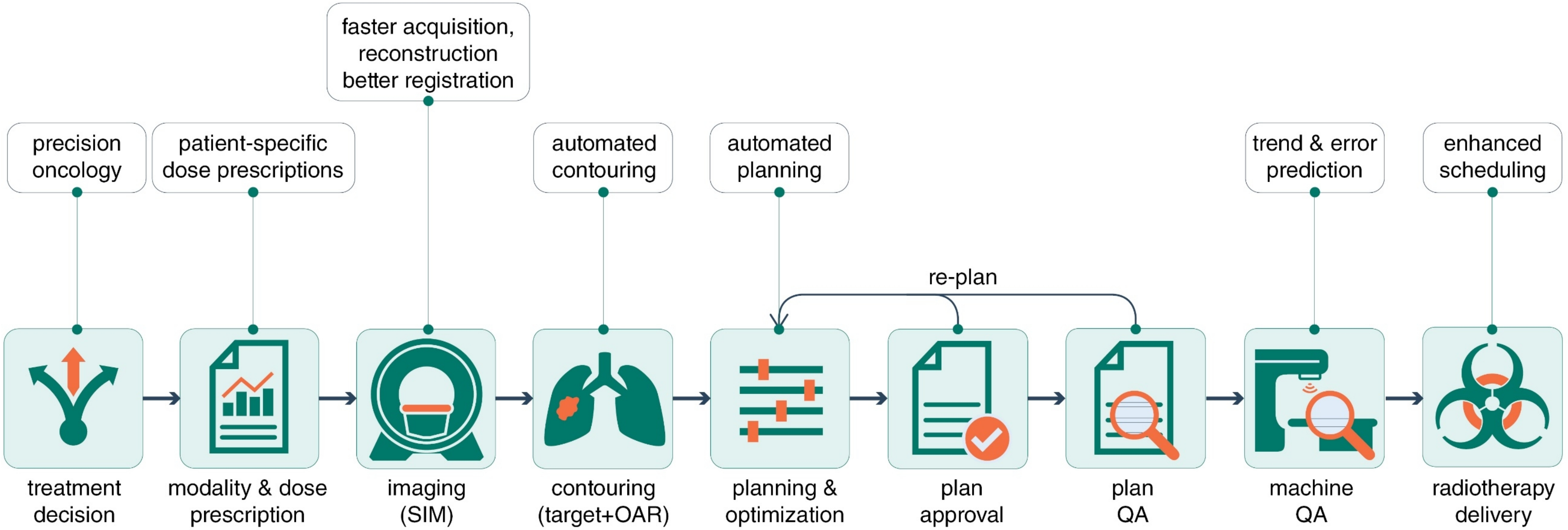
Data-heavy

Knowledge and experience gap

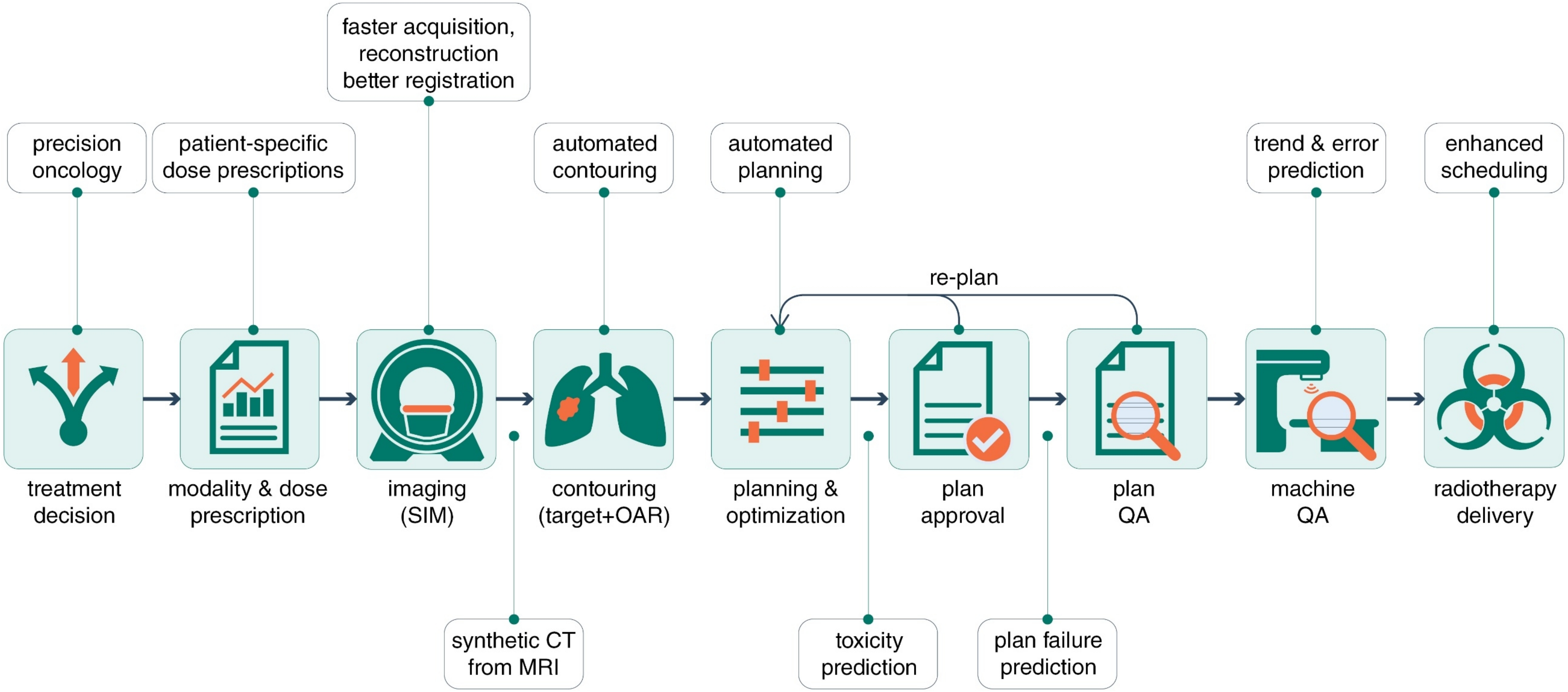
Today's Radiotherapy Workflow



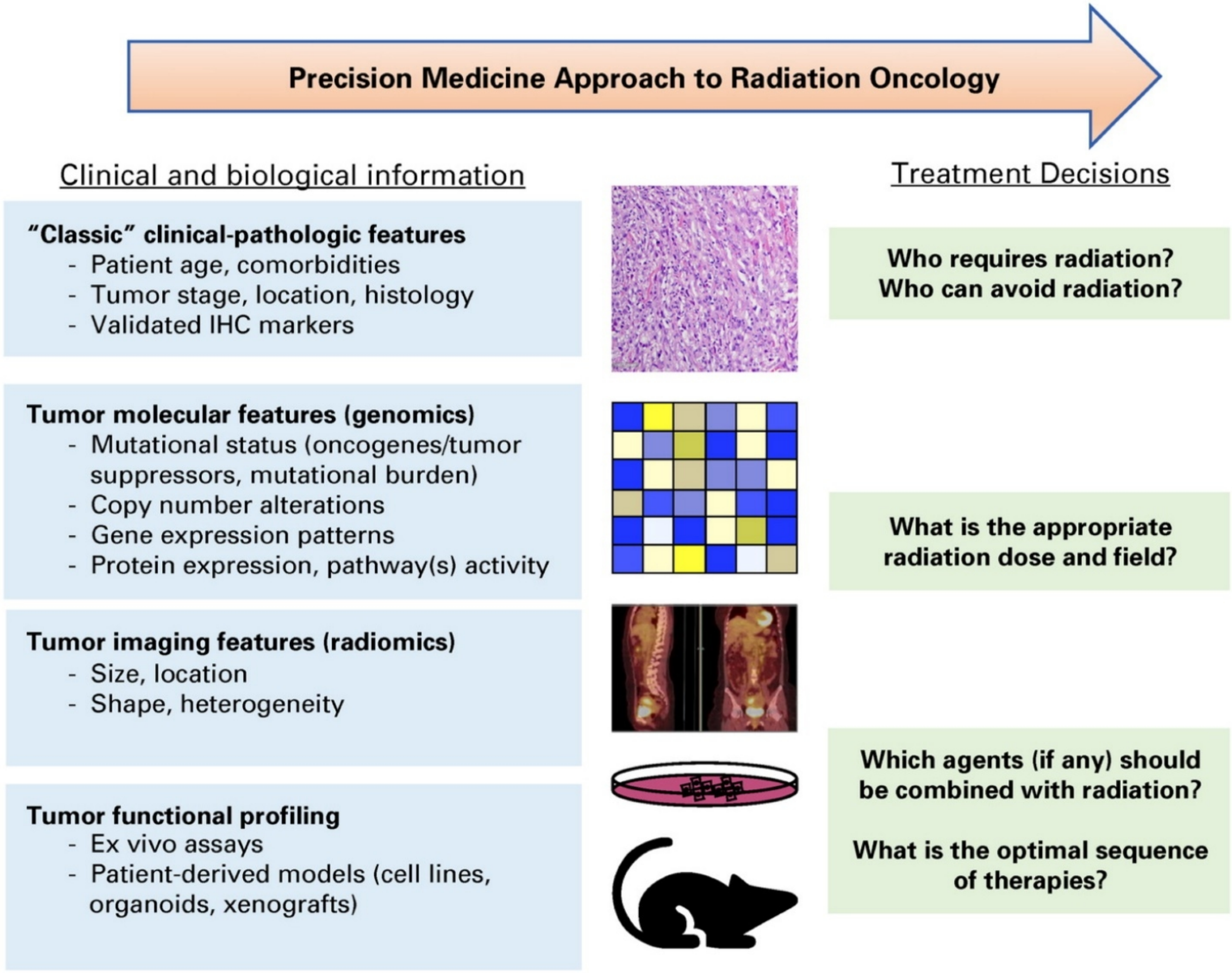
Potential Improvements



New Components



Precision Radiation Oncology

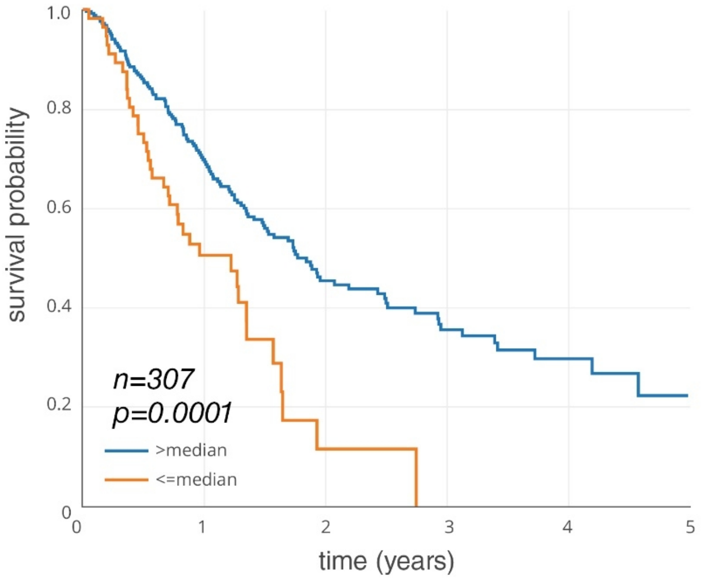


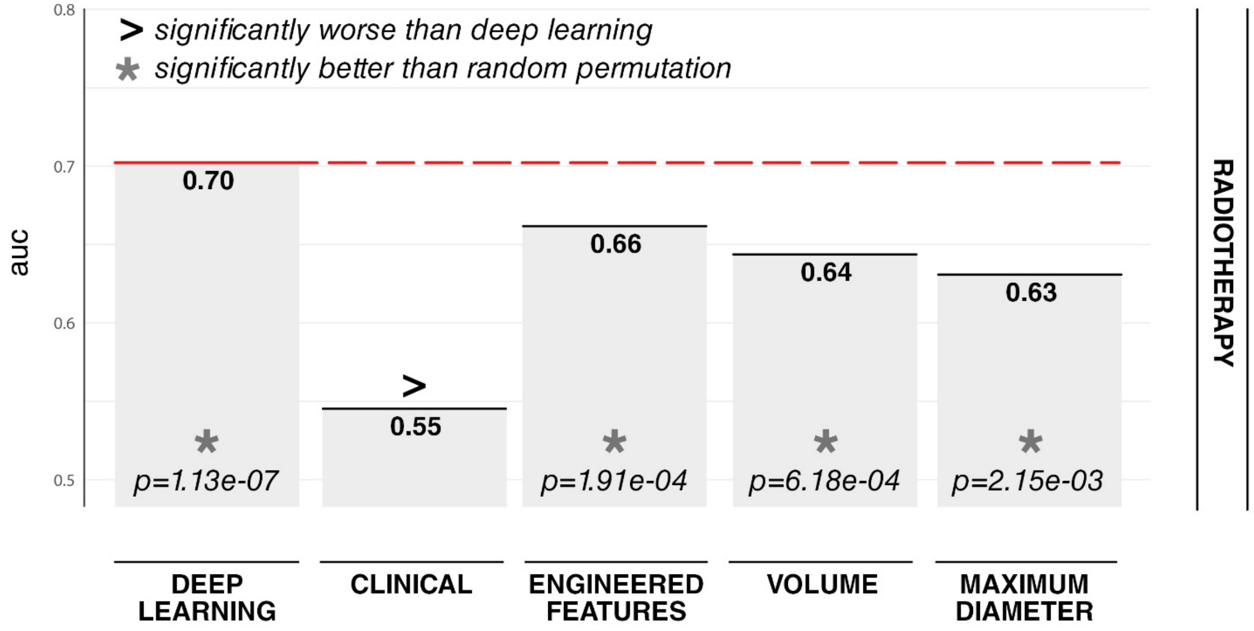
Sophia C Kamran & Kent W Mouw

Applying Precision Oncology Principles in Radiation Oncology

JCO Precision Oncology - 2018

Tumor Characterization



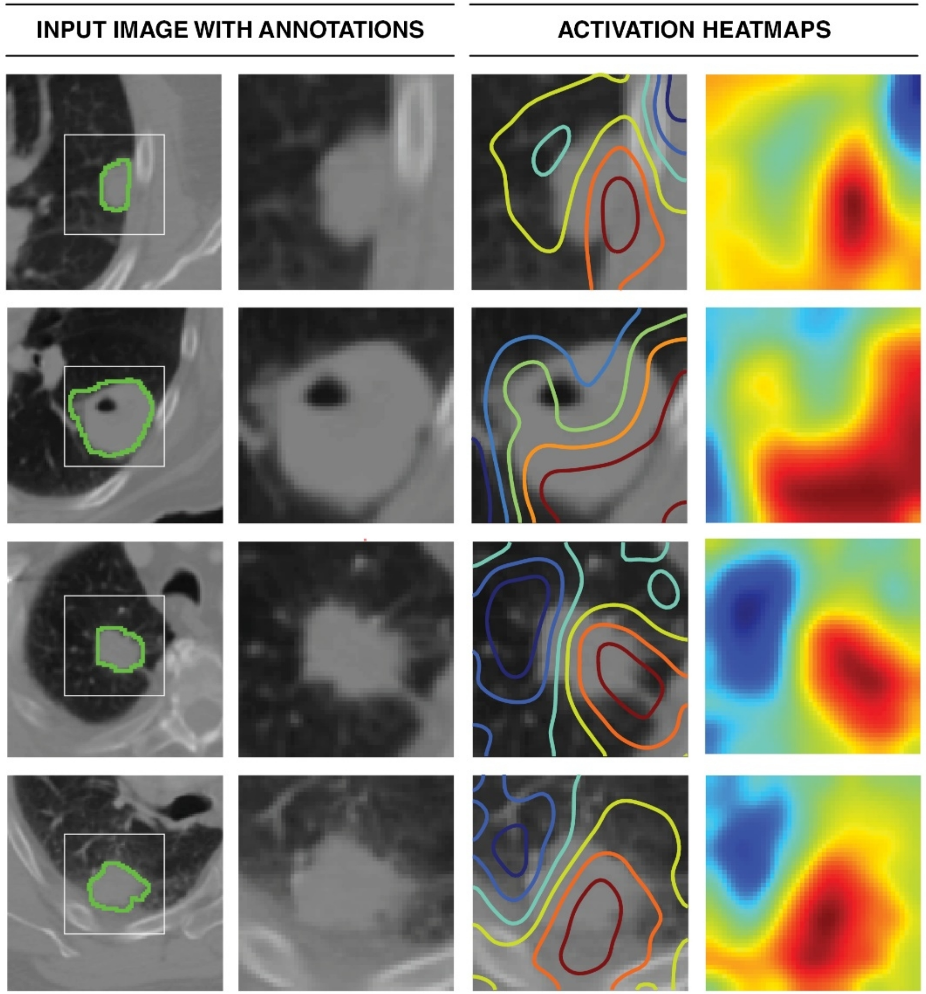


Ahmed Hosny, Chintan Parmar, Thibaud Coroller, et al.

Deep Learning for Lung Cancer Prognostication: A Retrospective Multi-Cohort Radiomics Study

PLOS Medicine - 2018

Tumor Characterization

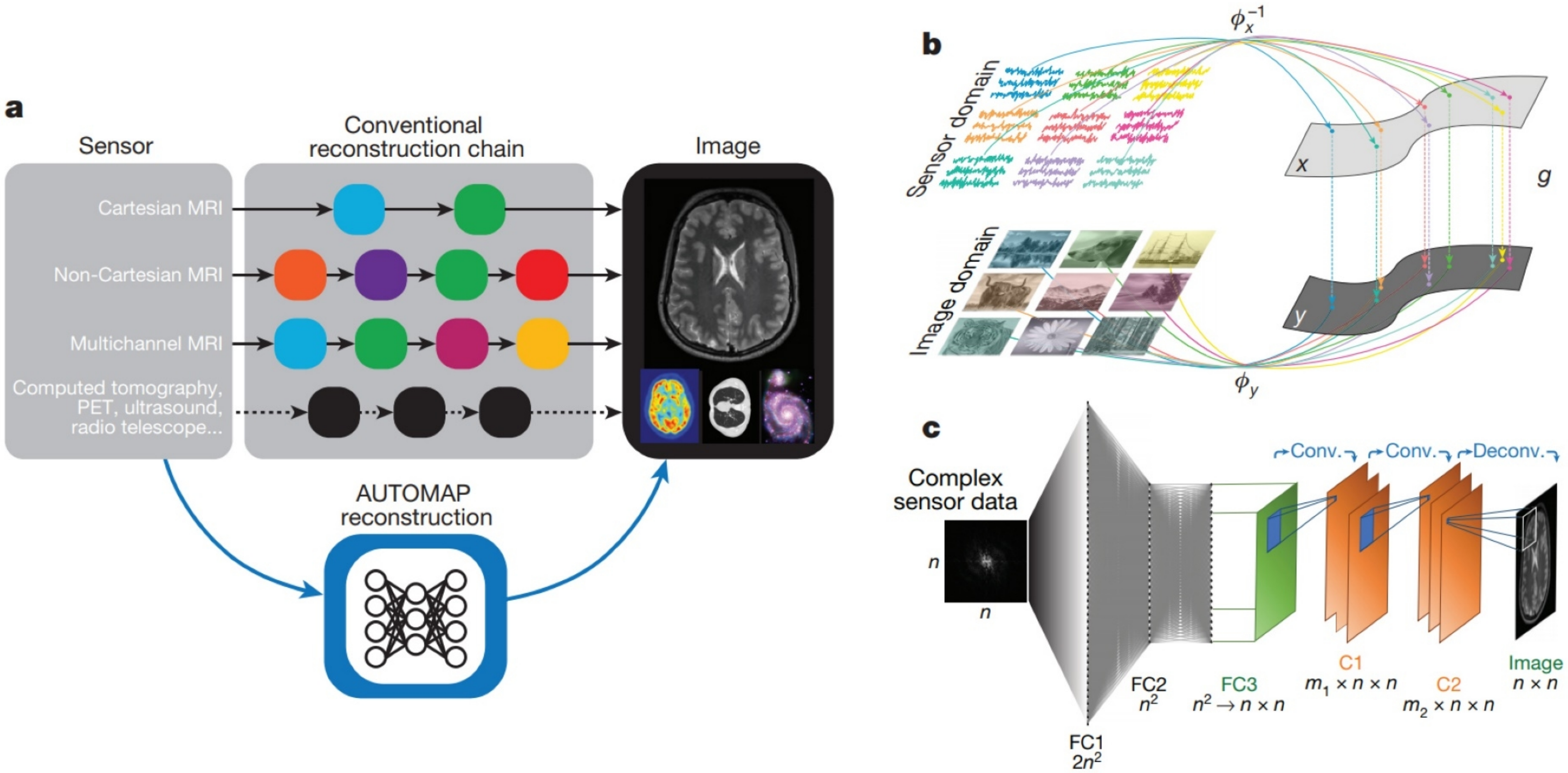


Ahmed Hosny, Chintan Parmar, Thibaud Coroller, et al.

Deep Learning for Lung Cancer Prognostication: A Retrospective Multi-Cohort Radiomics Study

PLOS Medicine - 2018

Reconstruction of Undersampled MRI

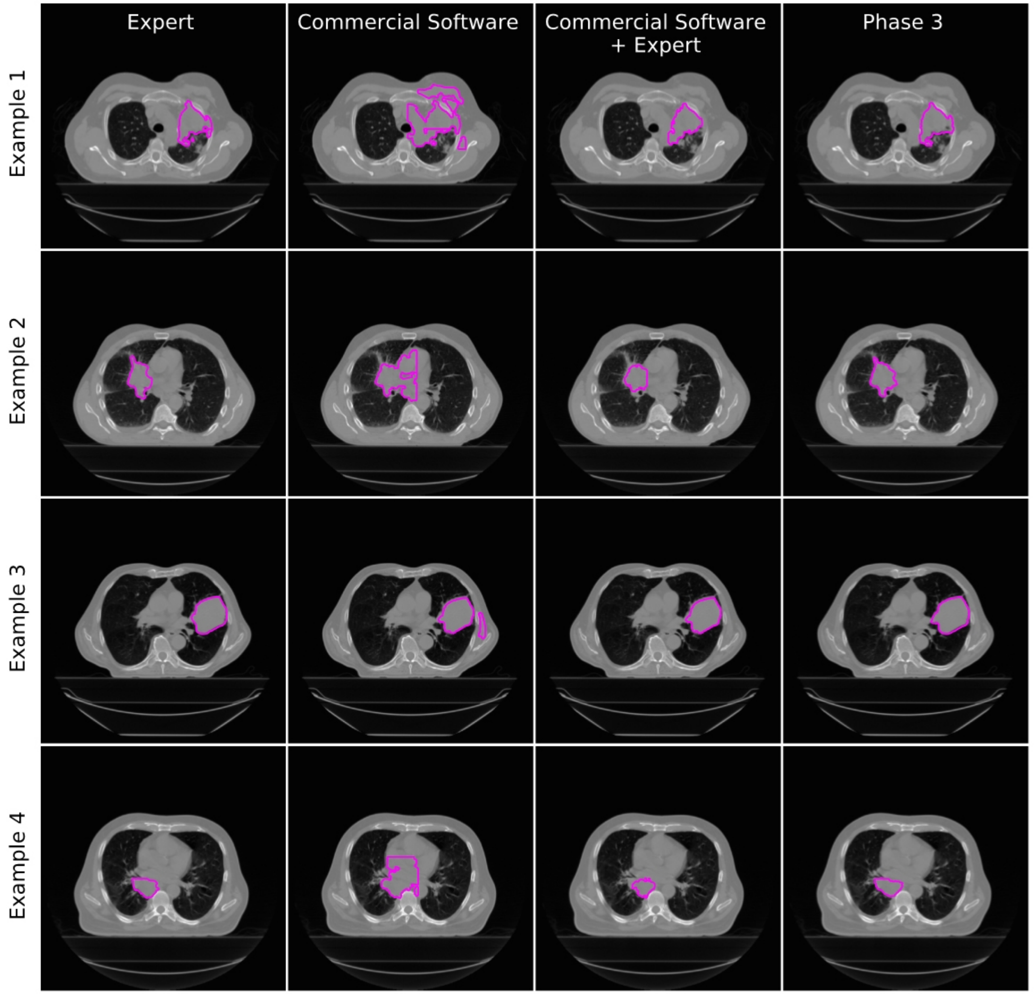


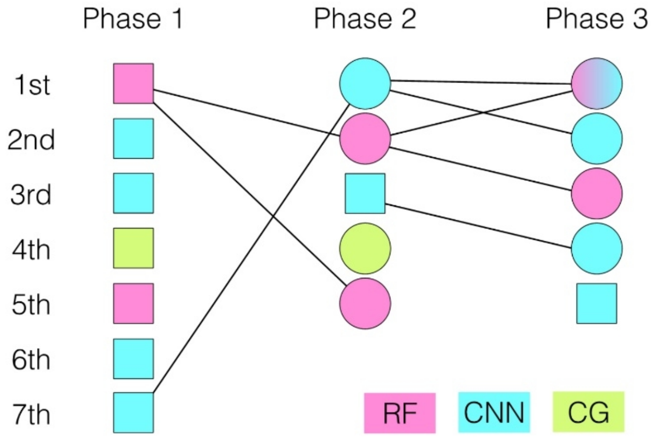
Bo Zhu, Jeremiah Z Liu, Stephen F Cauley, et al.

Image Reconstruction by Domain Transform Manifold Learning

Nature - 2018

Target Segmentation



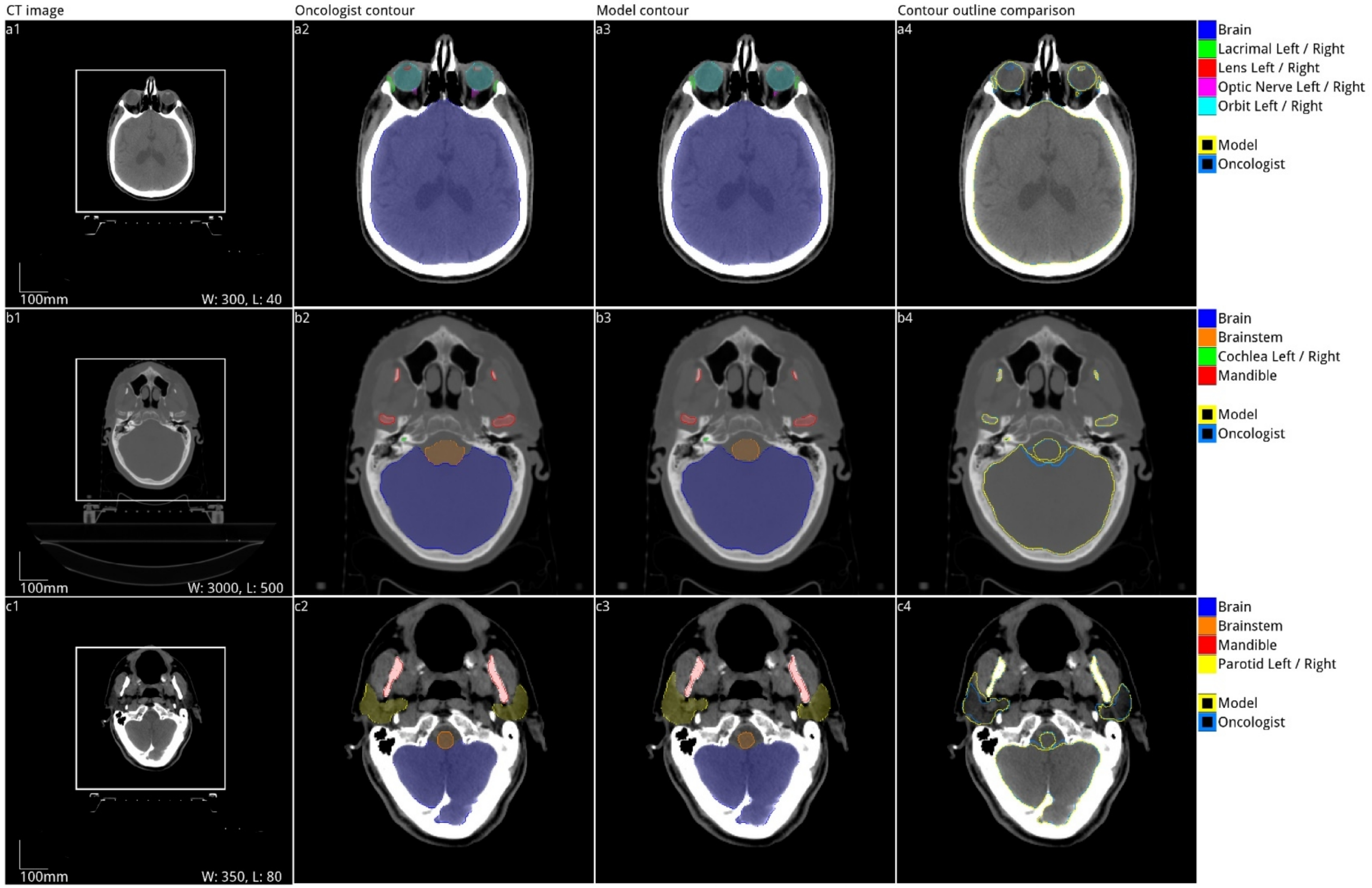


Raymond H Mak, Michael G Endres, Jin H Paik, et al.

Use of Crowd Innovation to Develop an Artificial Intelligence–Based Solution for Radiation Therapy Targeting

JAMA Oncology - 2019

OAR Segmentation



Stanislav Nikolov, Sam Blackwell, Ruheena Mendes, et al.

Deep Learning to Achieve Clinically Applicable Segmentation of Head and Neck Anatomy for Radiotherapy

Medical Image Computing & Computer Assisted Intervention (MICCAI) - 2018

OAR Segmentation

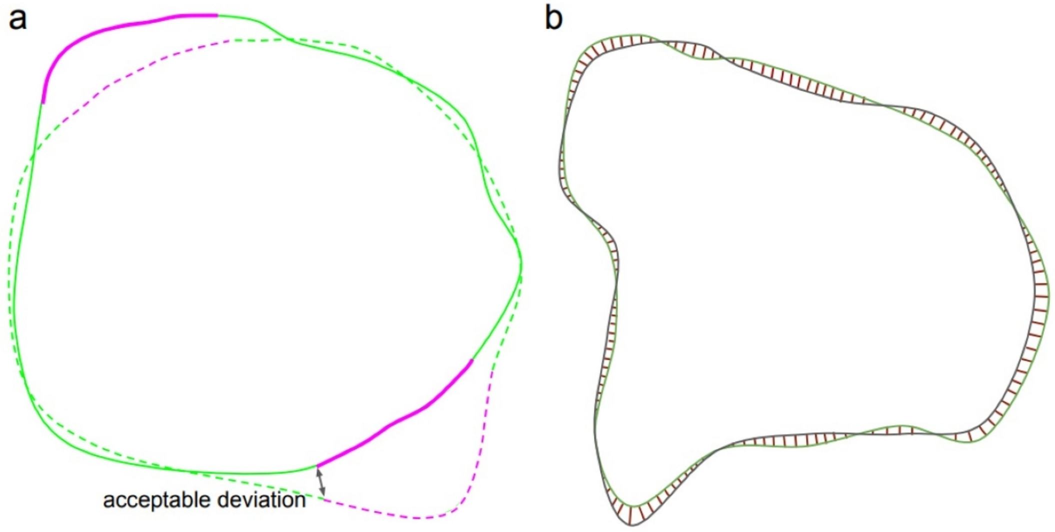


Figure 3 | Surface DSC performance metric. (**a**) Illustration of the computation of the surface DSC. Continuous line: predicted surface. Dashed line: ground truth surface. Black arrow: the maximum margin of deviation which may be tolerated without penalty, hereafter referred to by τ. Note that in our use case each OAR has an independently calculated value for τ. Green: acceptable surface parts (distance between surfaces $\leq \tau$). Pink: unacceptable regions of the surfaces (distance between surfaces $> \tau$). The proposed surface DSC metric reports the good surface parts compared to the total surface (sum of predicted surface area and ground truth surface area). (**b**) Illustration of the determination of the organ-specific tolerance. Green: segmentation of an organ by oncologist A. Black: segmentation by oncologist B. Red: distances between the surfaces. We defined the organ-specific tolerance as the 95th percentile of the distances collected across multiple segmentations from a subset of seven TCIA scans, where each segmentation was performed a radiographer arbitrated by an oncologist, neither of whom had seen the scan previously.

Planning

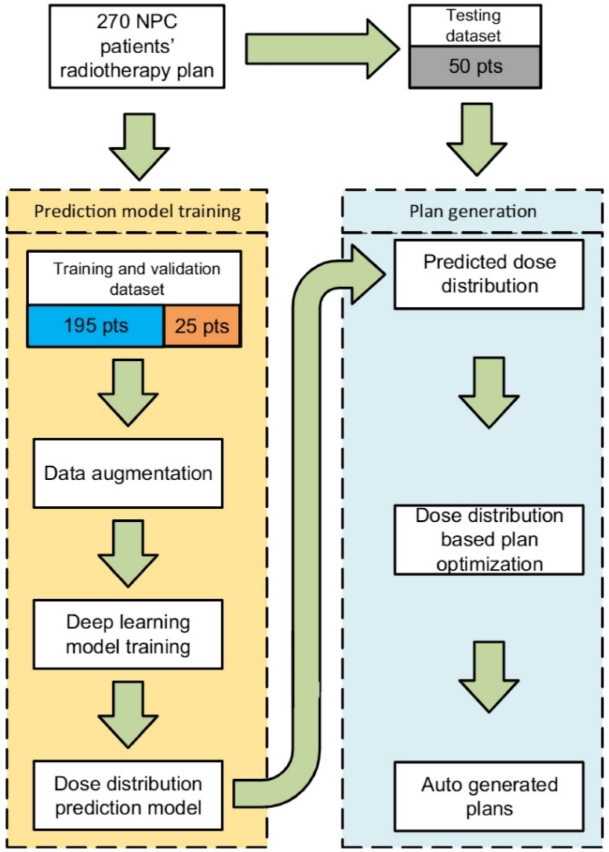


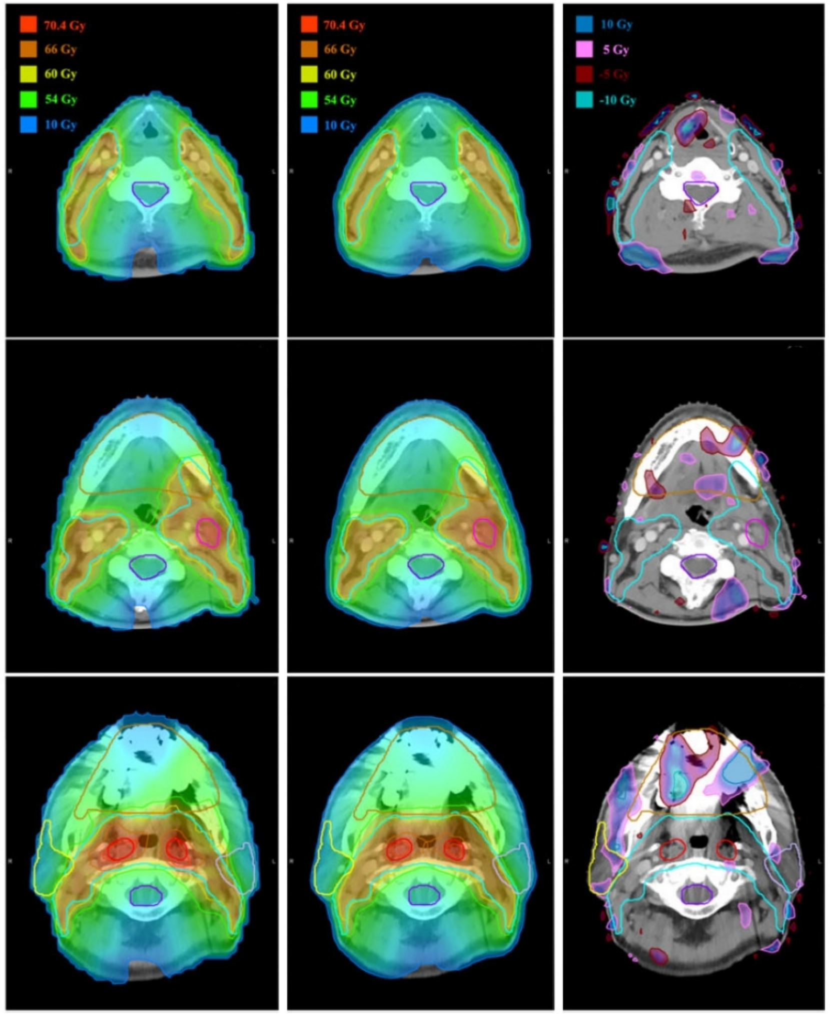
FIG. 1. Flowchart showing the proposed automatic planning process. [Color figure can be viewed at wileyonlinelibrary.com]

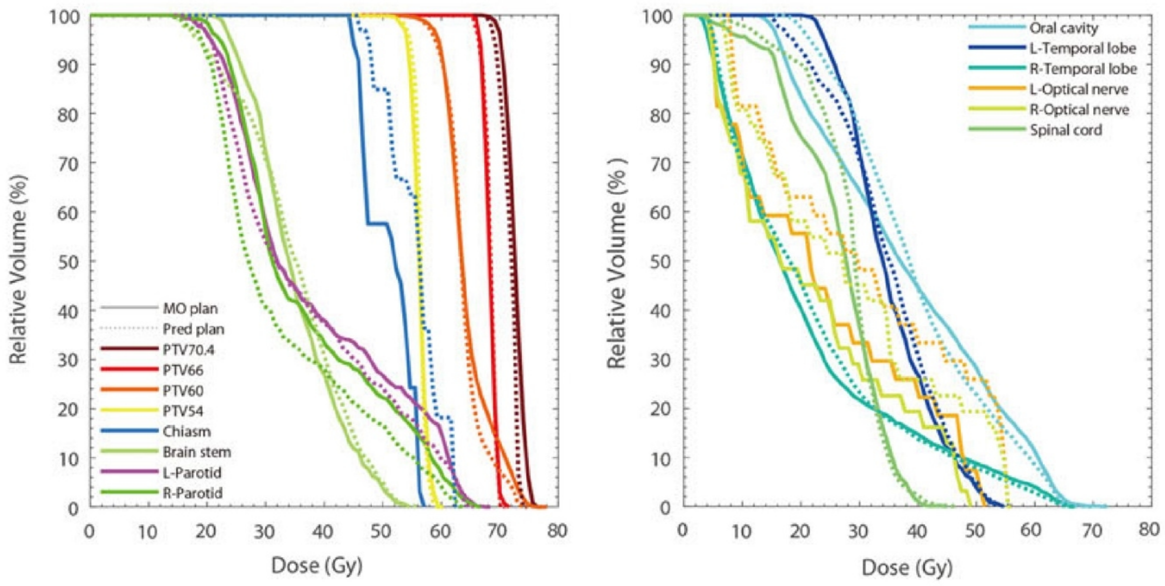
Jiawei Fan, Jiazhou Wang, Zhi Chen, et al.

Automatic Treatment Planning Based on Three-dimensional Dose Distribution Predicted from Deep Learning Technique

Medical Physics - 2019

Planning



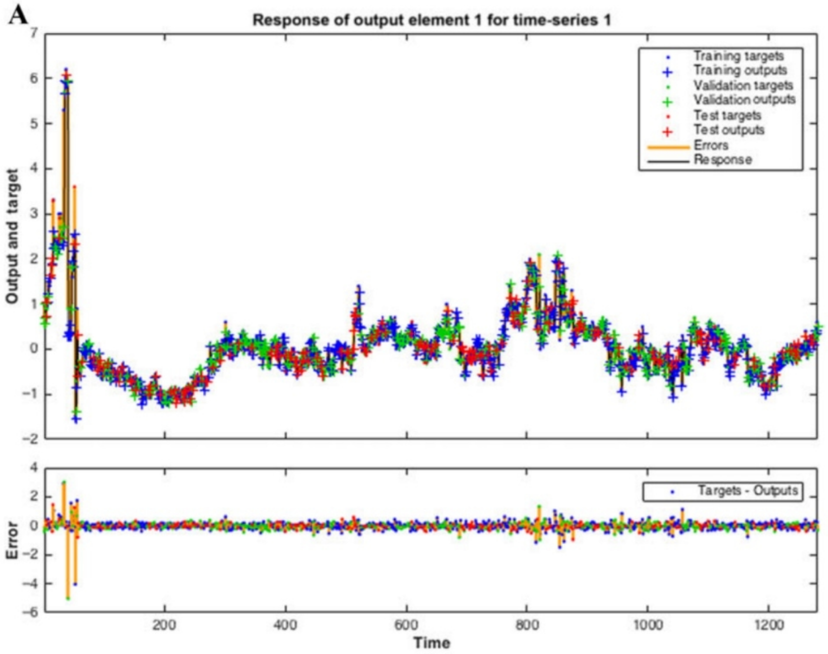


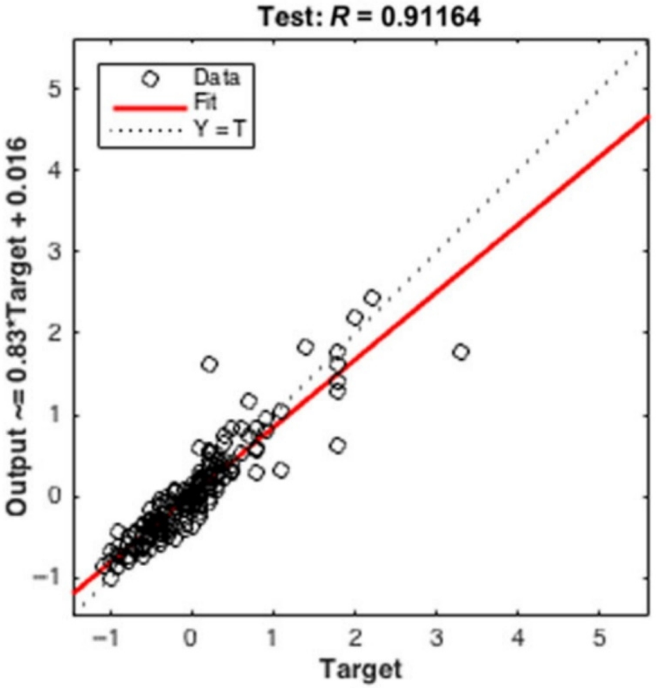
Jiawei Fan, Jiazhou Wang, Zhi Chen, et al.

Automatic Treatment Planning Based on Three-dimensional Dose Distribution Predicted from Deep Learning Technique

Medical Physics - 2019

Machine Trend & Error Prediction



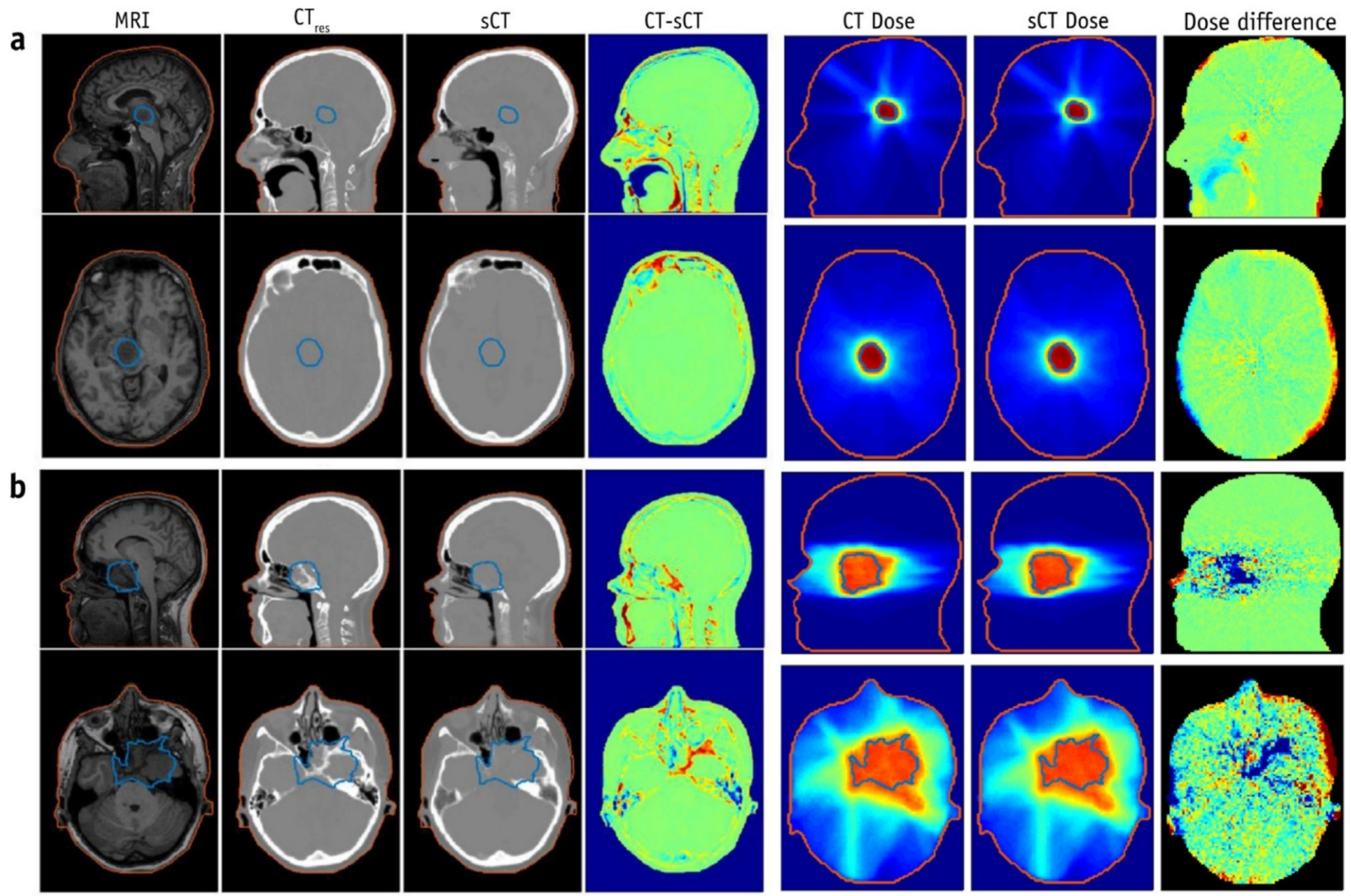


Qiongge Li & Maria F Chan

Predictive Time-series Modeling using Artificial Neural Networks for Linac Beam Symmetry: An Empirical Study

Annals of the New York Academy of Sciences - 2016

MRI to Synthetic CT

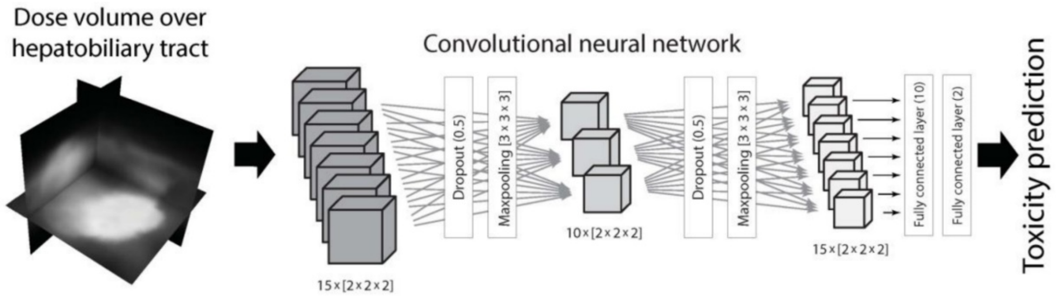


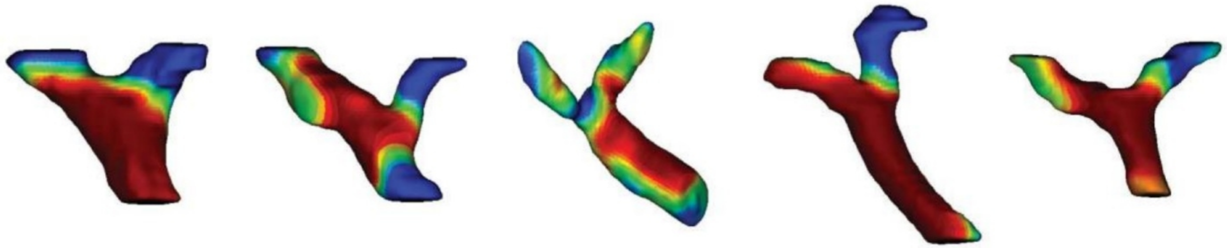
Anna M Dinkla, Jelmer M Wolterink, Matteo Maspero, et al.

MR-Only Brain Radiation Therapy: Dosimetric Evaluation of Synthetic CTs Generated by a Dilated Convolutional Neural Network

International Journal of Radiation Oncology - 2018

Toxicity Prediction





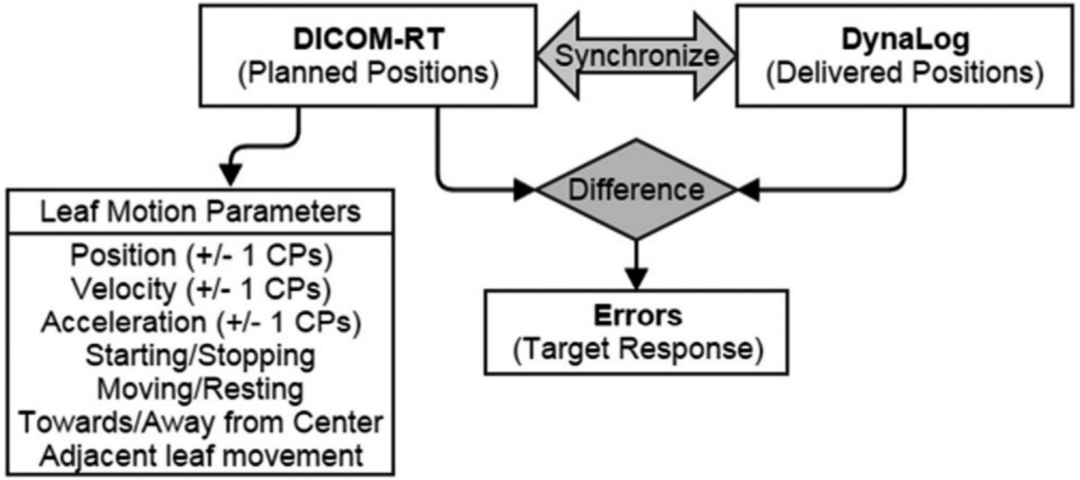
Proximal PV	0.972	0.620	0.778	0.909	0.904
Left PV	0.208	0.246	0.428	0.137	0.471
Right PV	0.591	0.819	0.535	0.797	0.872
Bifurcation	0.965	0.973	0.601	0.936	0.979

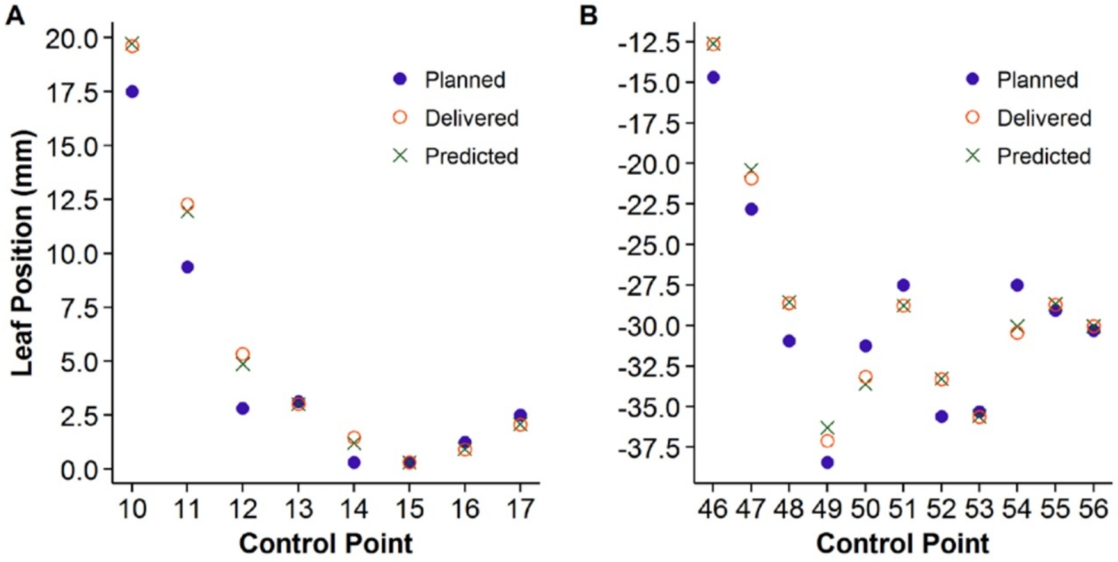
Bulat Ibragimov, Diego Toesca, Daniel Chang, et al.

Development of Deep Neural Network for Individualized Hepatobiliary Toxicity Prediction after Liver SBRT

Medical Physics - 2018

Plan Error Prediction





Joel N K Carlson, Jong M Park, So-Yeon Park, et al.

A Machine Learning Approach to the Accurate Prediction of Multi-leaf Collimator Positional Errors

Physics in Medicine & Biology - 2016

Lack of External Validation

Table 1. Subject Fields of Articles Analyzed

Subject Fields*	Number of Articles (%)
Radiology (including nuclear medicine)	366 (70.9)
Ophthalmology	54 (10.5)
Pathology	41 (7.9)
Dermatology	19 (3.7)
Gastroenterology	19 (3.7)
Other fields	15 (2.9)
Combined fields	
Radiology and cardiology	1 (0.2)
Pathology and nuclear medicine	1 (0.2)
Total	516 (100)

*Listed in descending order of article number.

Table 2. Study Design Characteristics of Articles Analyzed

Design Characteristic	All Articles (n = 516)	Articles Published in Medical Journals (n = 437)	Articles Published in Non-Medical Journals (n = 79)	P*
External validation				1.000
Used	31 (6.0)	27 (6.2)	4 (5.1)	
Not used	485 (94.0)	410 (93.8)	75 (94.9)	
In studies that used external validation				
Diagnostic cohort design	5 (1.0)	5 (1.1)	0 (0)	1.000
Data from multiple institutions	15 (2.9)	12 (2.7)	3 (3.8)	0.713
Prospective data collection	4 (0.8)	4 (0.9)	0 (0)	1.000
Fulfillment of all of above three criteria	0 (0)	0 (0)	0 (0)	1.000
Fulfillment of at least two criteria	3 (0.6)	3 (0.7)	0 (0)	1.000
Fulfillment of at least one criterion	21 (4.1)	18 (4.1)	3 (3.8)	1.000

Data are expressed as number of articles with corresponding percentage enclosed in parentheses. *Comparison between medical and non-medical journals.

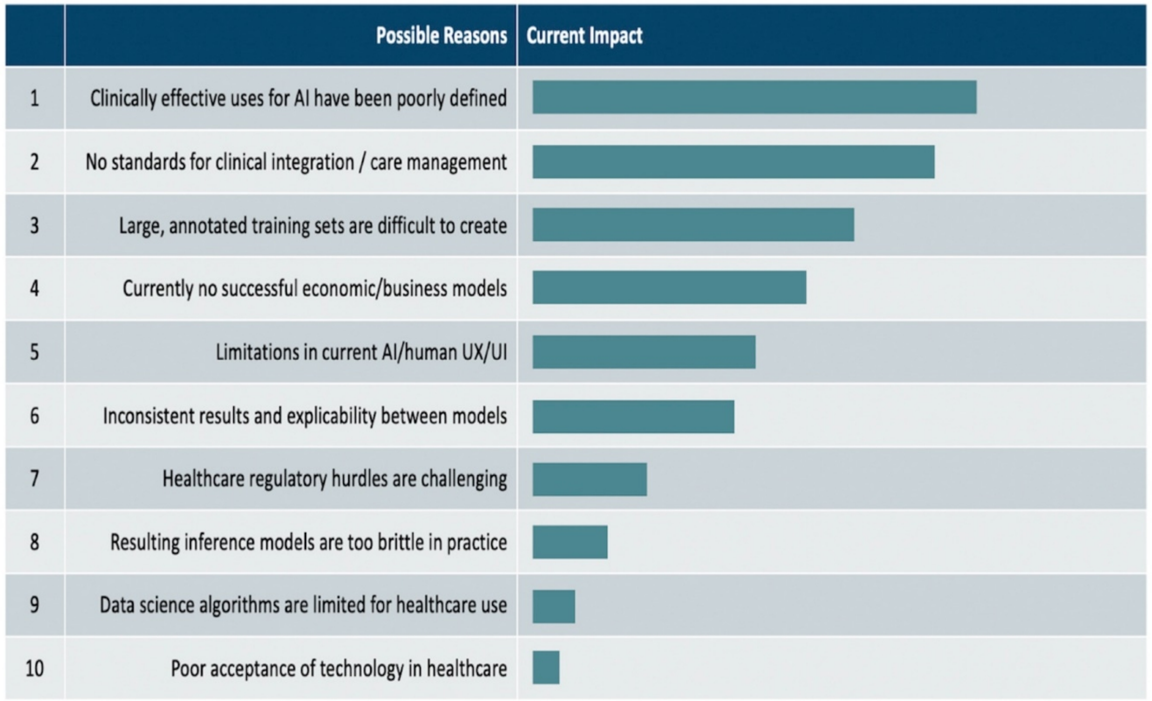
Dong W Kim, Hye Y Jang, Kyung W Kim, et al.

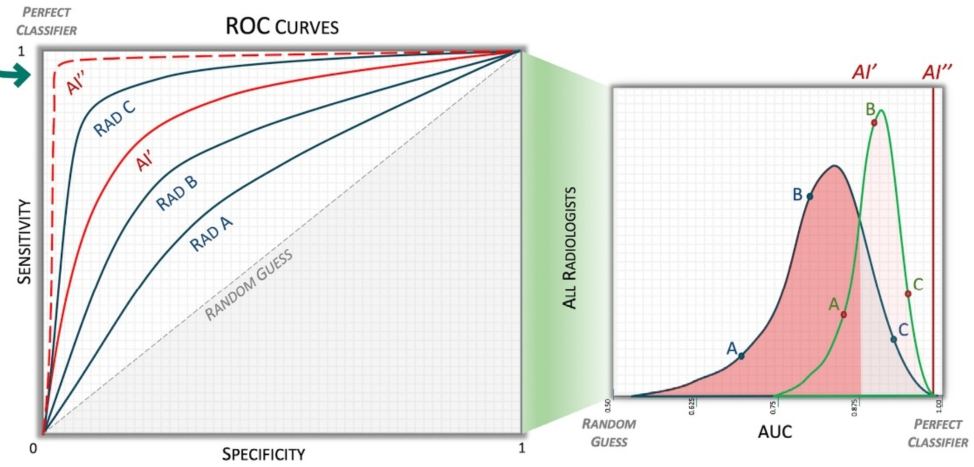
Design Characteristics of Studies Reporting the Performance of Artificial Intelligence Algorithms for Diagnostic Analysis of Medical Images

Korean Journal of Radiology - 2019

Clinical Translation

HEALTHCARE AI CHALLENGES



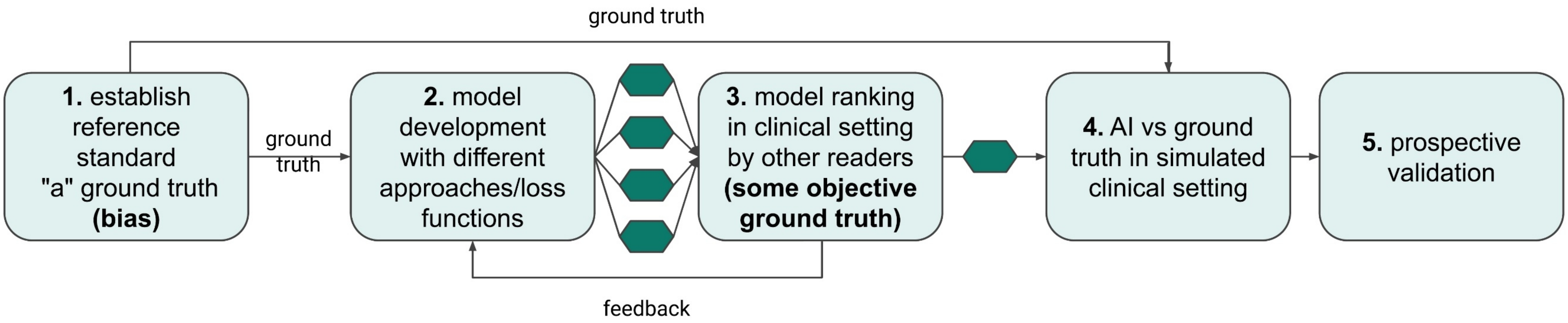


Bibb Allen, Steven E Seltzer, Curtis P Langlotz, et al.

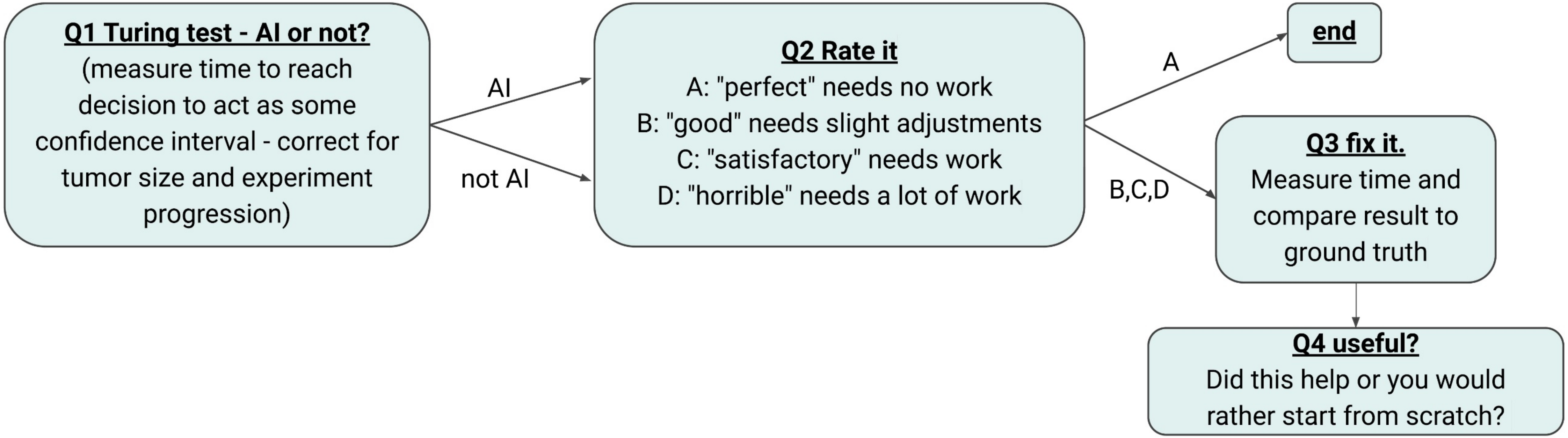
A Road Map for Translational Research on Artificial Intelligence in Medical Imaging: 2018 NIH/RSNA/ACR/The Academy Workshop

Journal of the American College of Radiology - 2019

Validation Framework



Validation Framework



Validation Framework

Recruiting non-research staff to conduct experiments

Assessing time and effort assessment in carrying out clinical tasks

Develop plugins for clinical systems

Clinical Adoption

Clinical Adoption

RaySearch Laboratories VARIAN medical systems PHILIPS

Poor performance?

Poor implementation?

Lack of time?

Thank you!