Artificial Intelligence in Radiation Oncology – the dawn of a new era

Dr Indranil Mallick

Tata Medical Center, Kolkata

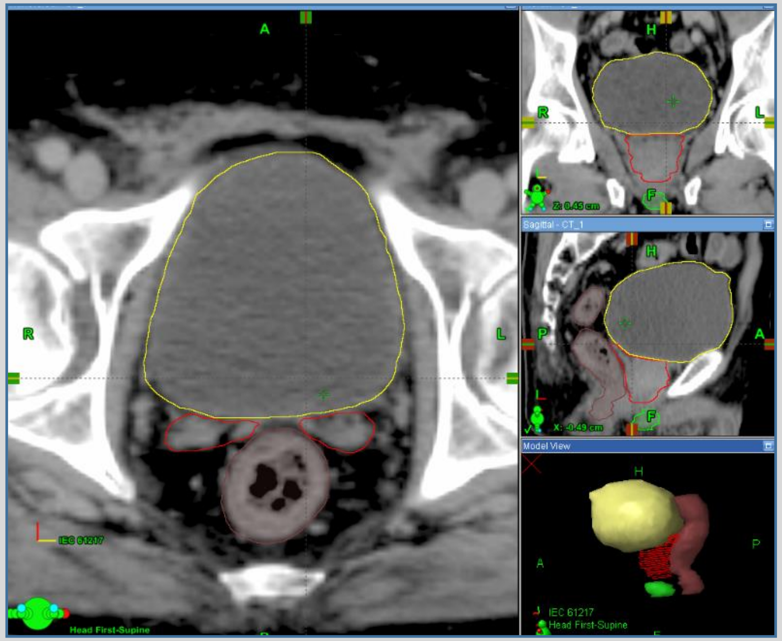
Six steps in radiation oncology

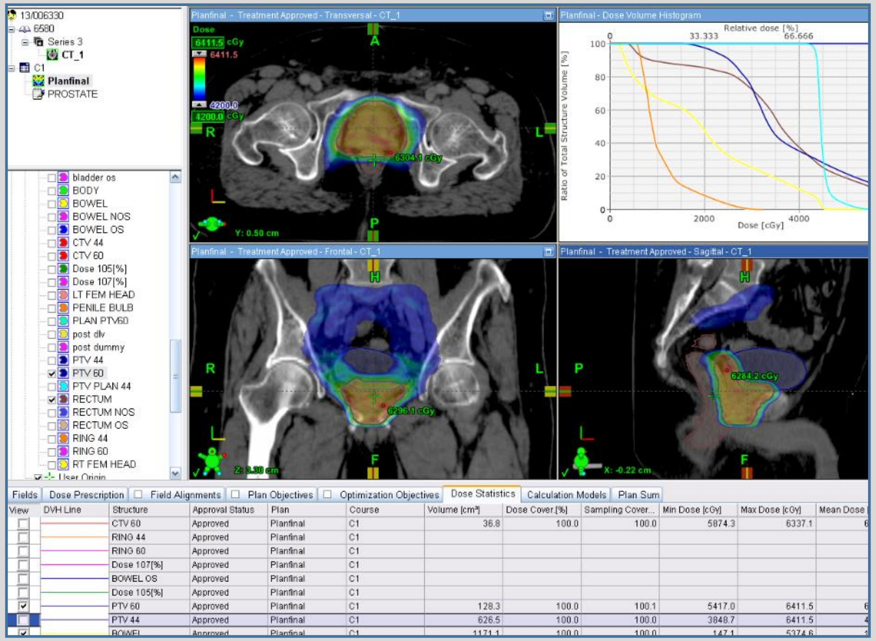
- Treatment decision
- Segmentation
- Planning
- Plan evaluation
- Treatment delivery
- Response evaluation

The human process

Prostate Cancer

- Gleason Score **8**
- Extracapsular extension - **present**
- Seminal Vesicle involvement - **present**
- Nodal involvement **- absent**
- Distant metastases - **absent**





Long term ADT and RT

Segment structures and edges

Evaluate plan based on rules

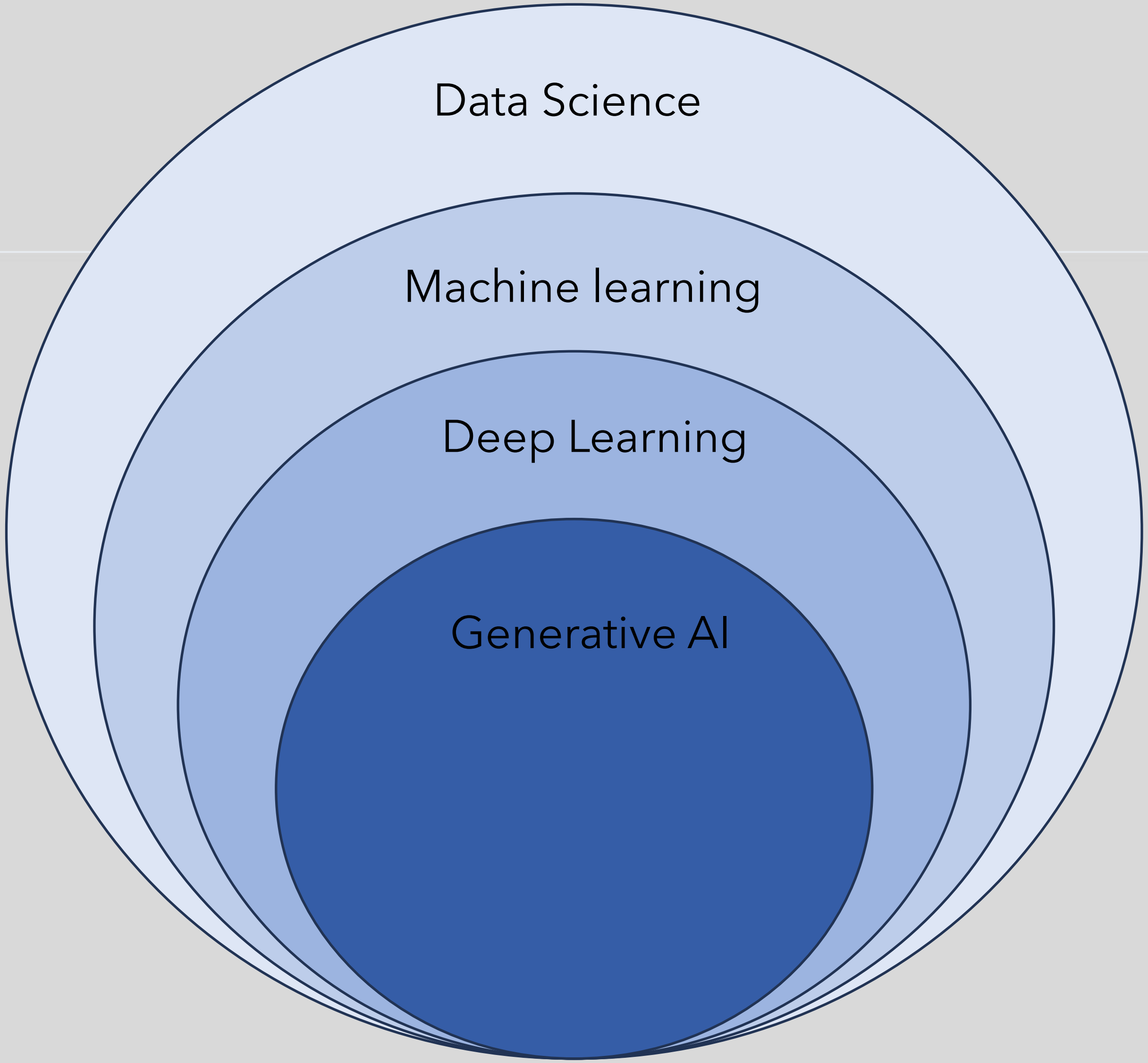
Each step involves complex decisions and calculations based on multiple inputs:
data and images

Problems in the process

- **Manual and repetitive tasks** e.g. segmentation, planning steps, follow up visits
- **Generalized decision-making** – e.g. doses, constraints
- **Inefficiency** – e.g. plan evaluation
- **Difficulty in prediction**

What is AI?

- AI is a broad and rapidly evolving term



Can we put in an image as a ‘parameter’?

Image = Data

512 x 512 = 262,144

10	25	225	213						
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32	220	.	.	.	.	.	.	.	.
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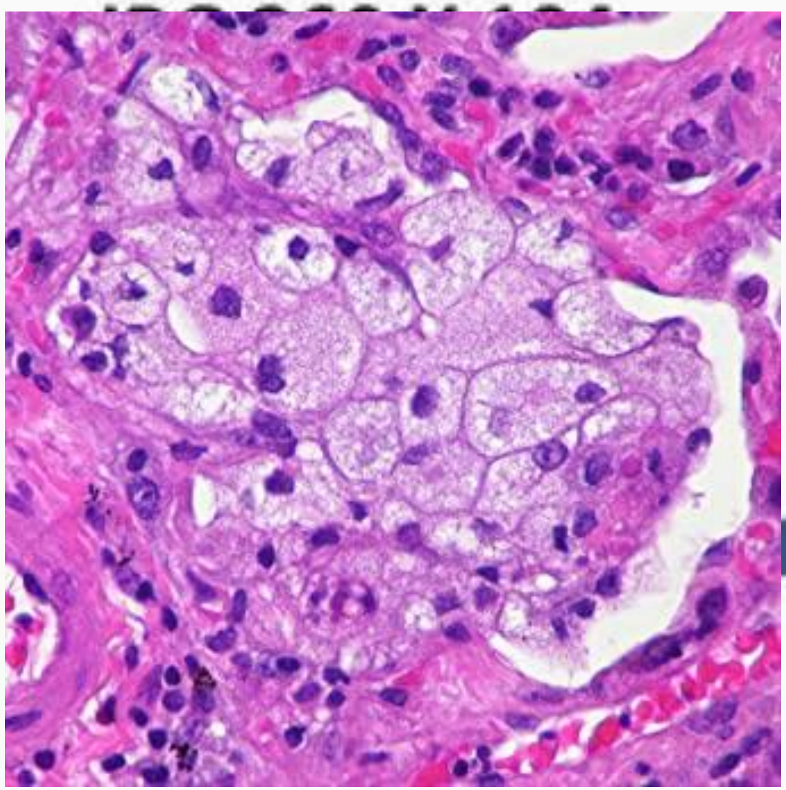
Color images have 3 channels



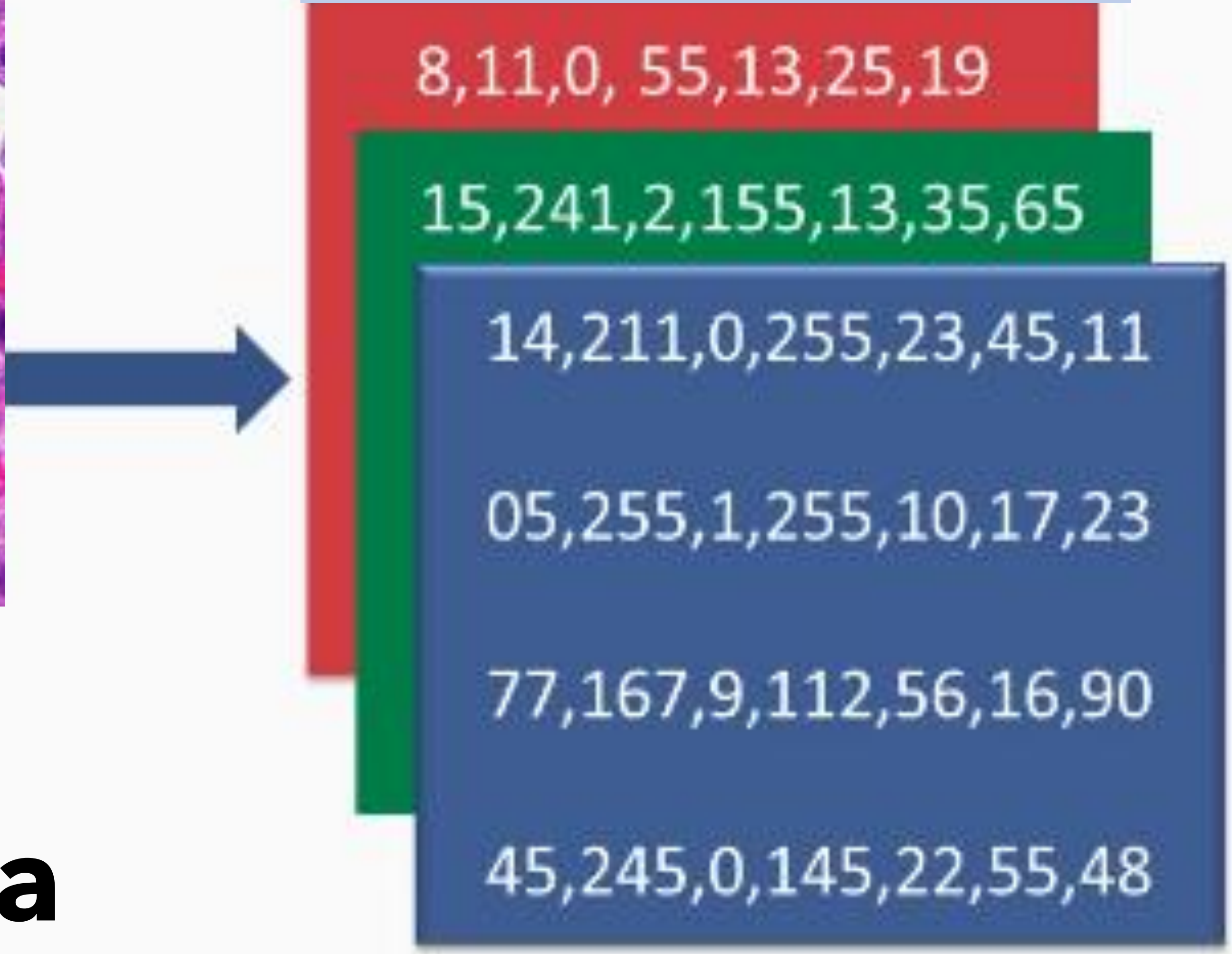
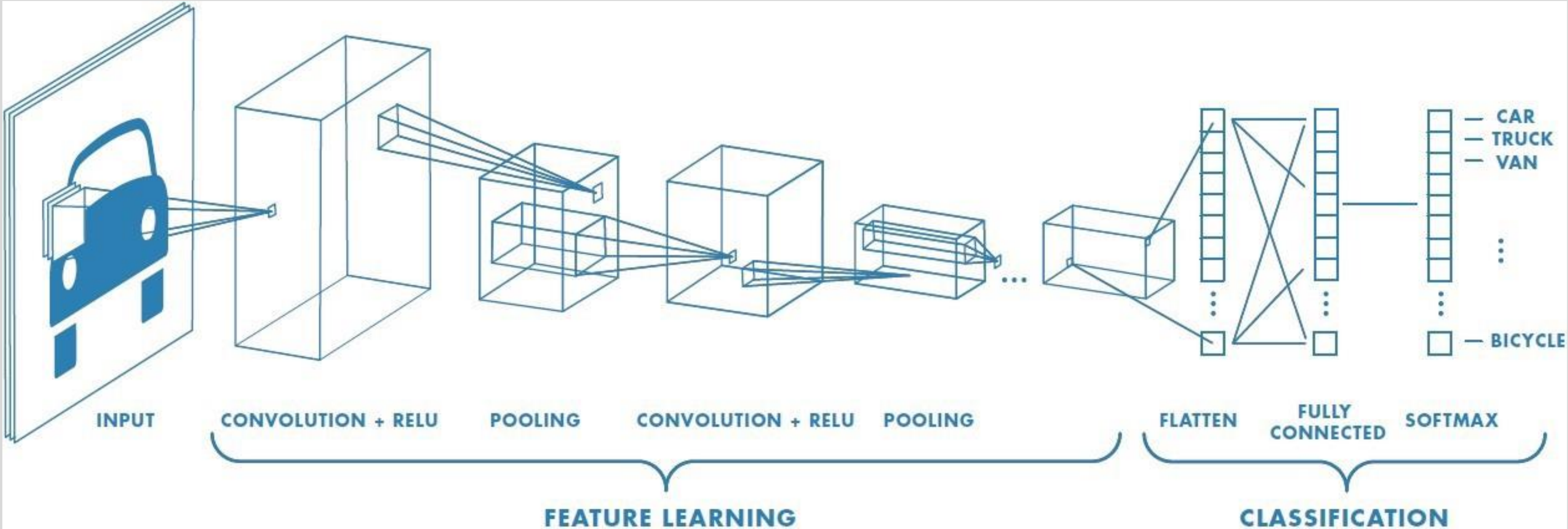


Image = data

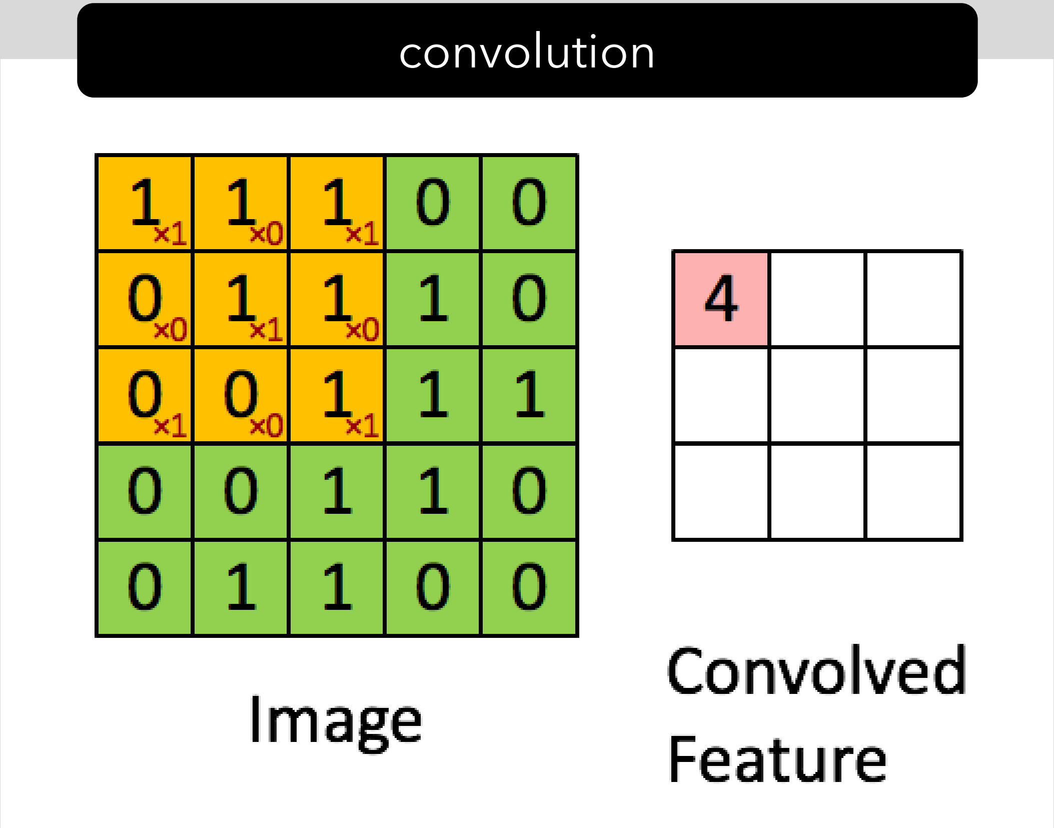
OMG! How will I deal with all these numbers?!!

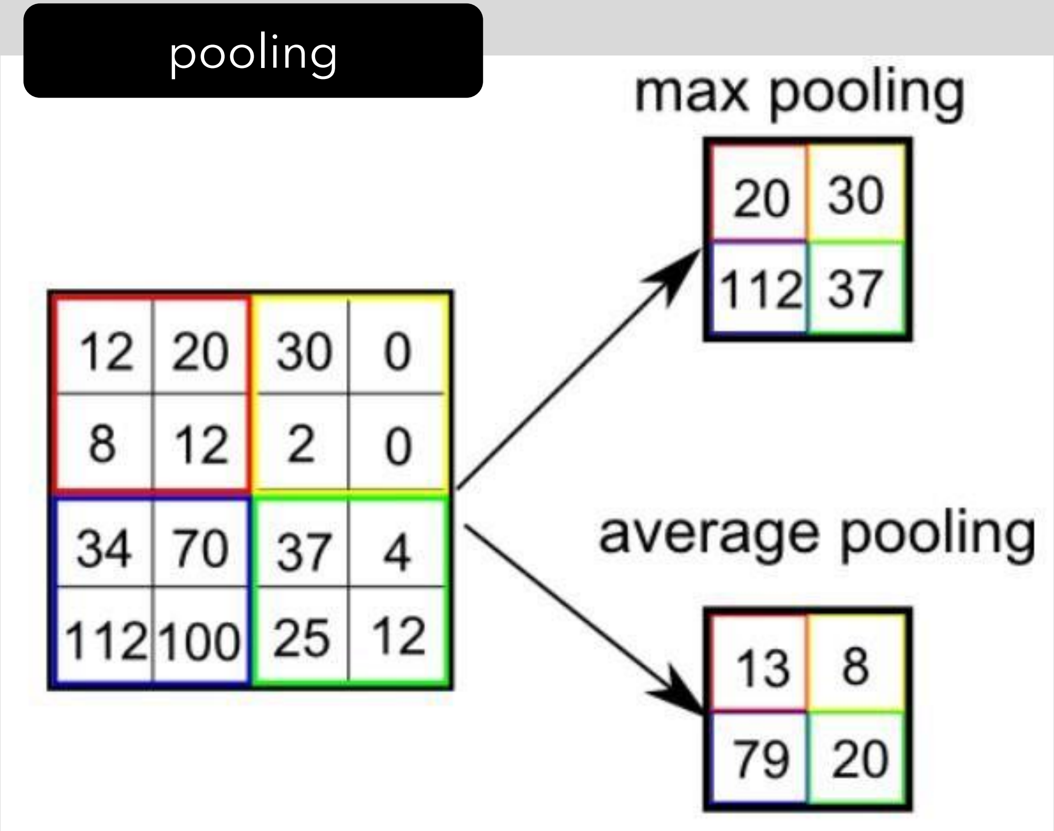
The Convolutional Neural Network (CNN)



- https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Convolution and pooling





- https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

CNN architectures for image segmentation

- The U-Net and its variations are the most common architecture used in the image segmentation domain

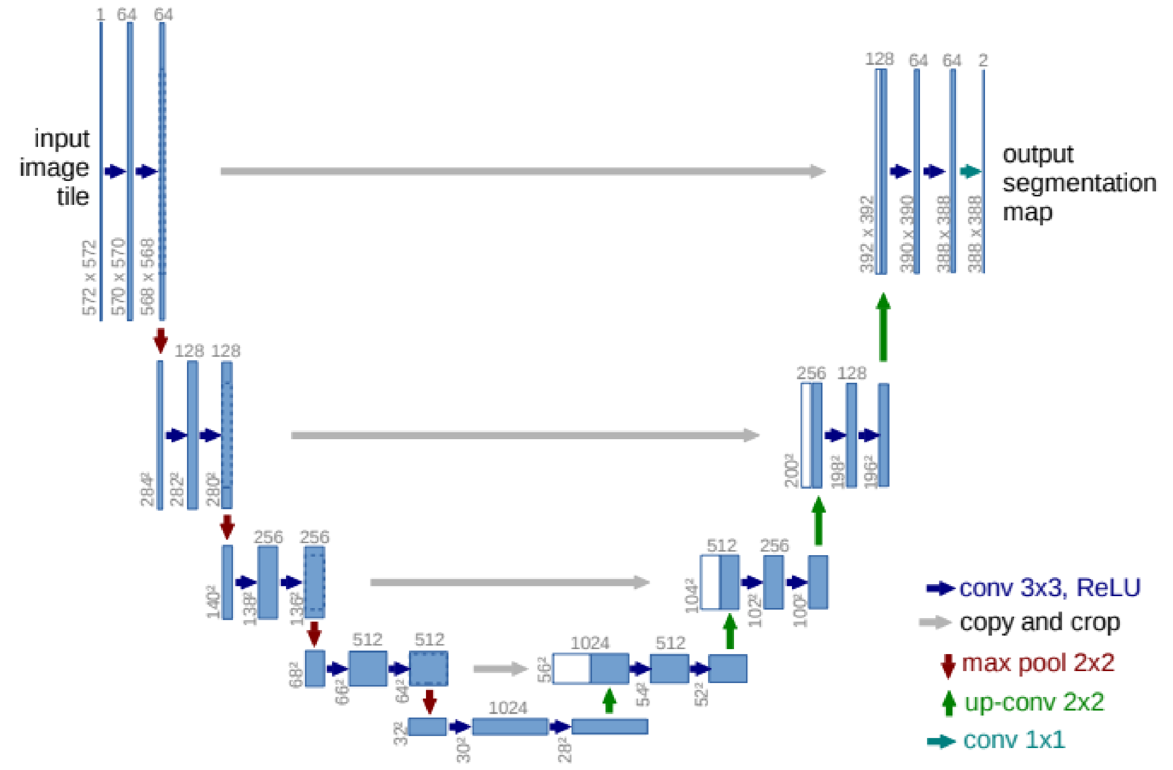
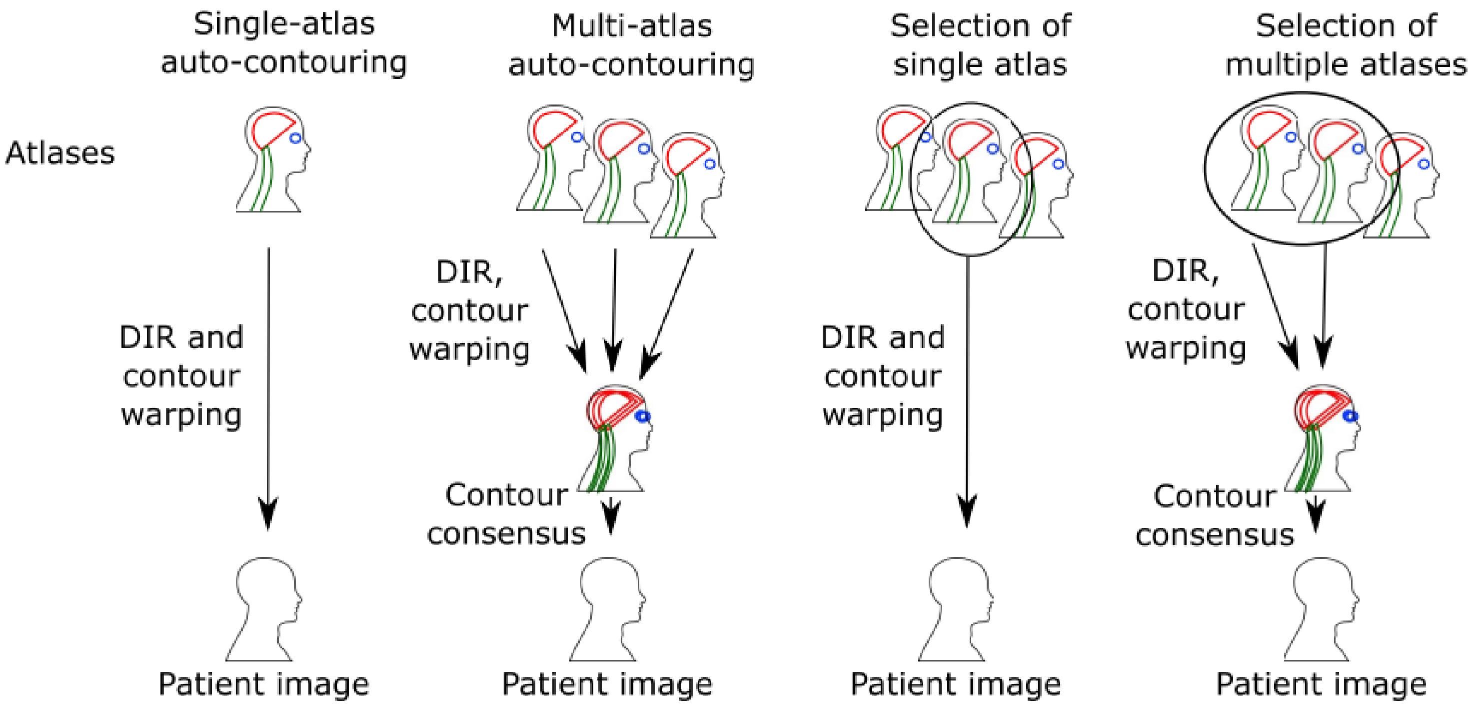


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

Machine learning and AI applications

Atlas based autosegmentation

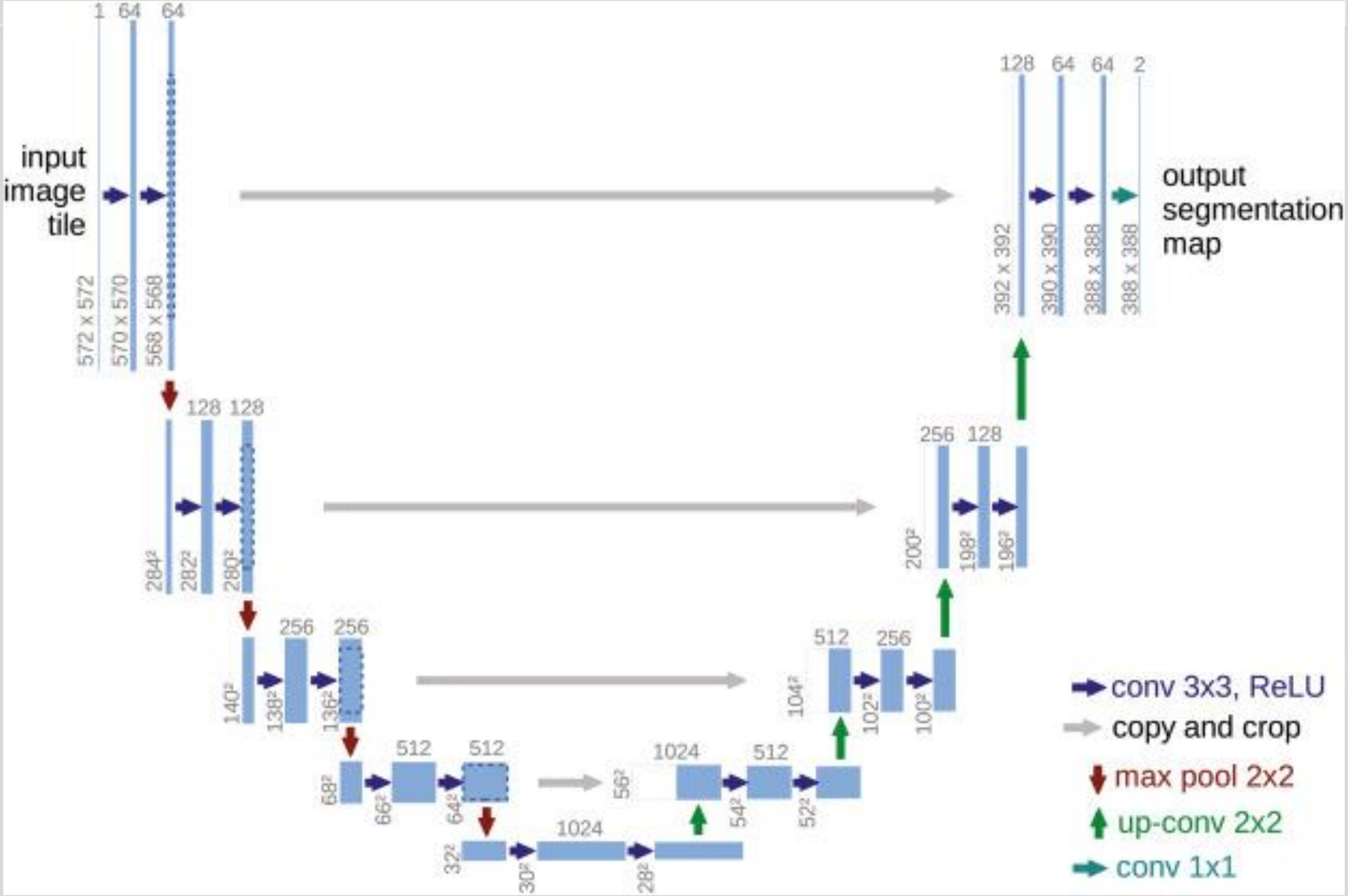
- Uses selection of a similar case (or cases) for a library of patients.
- Then uses deformable registration techniques to warp the segments to fit the contours to a new patient.

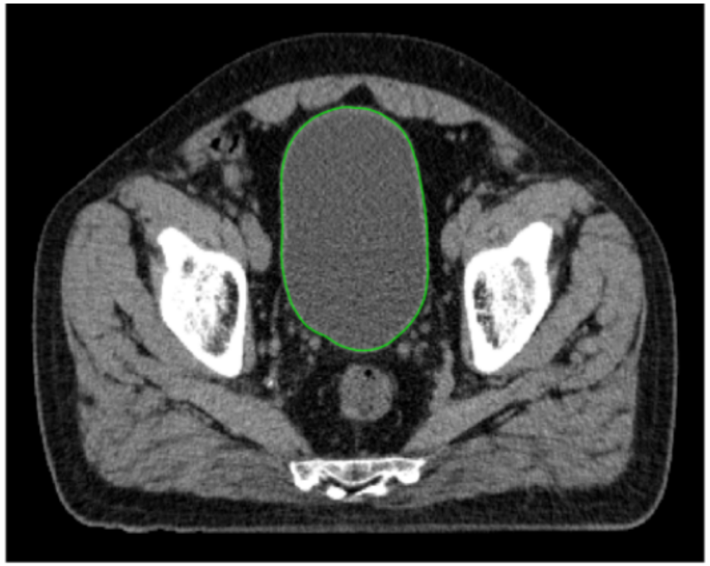


IEEE Transactions on Medical Imaging, 38(1), 99-106.

Deep learning based autosegmentation

- U-Net: A convolutional neural network that is designed for image segmentation
- Allows more accurate results with fewer training image-sets.

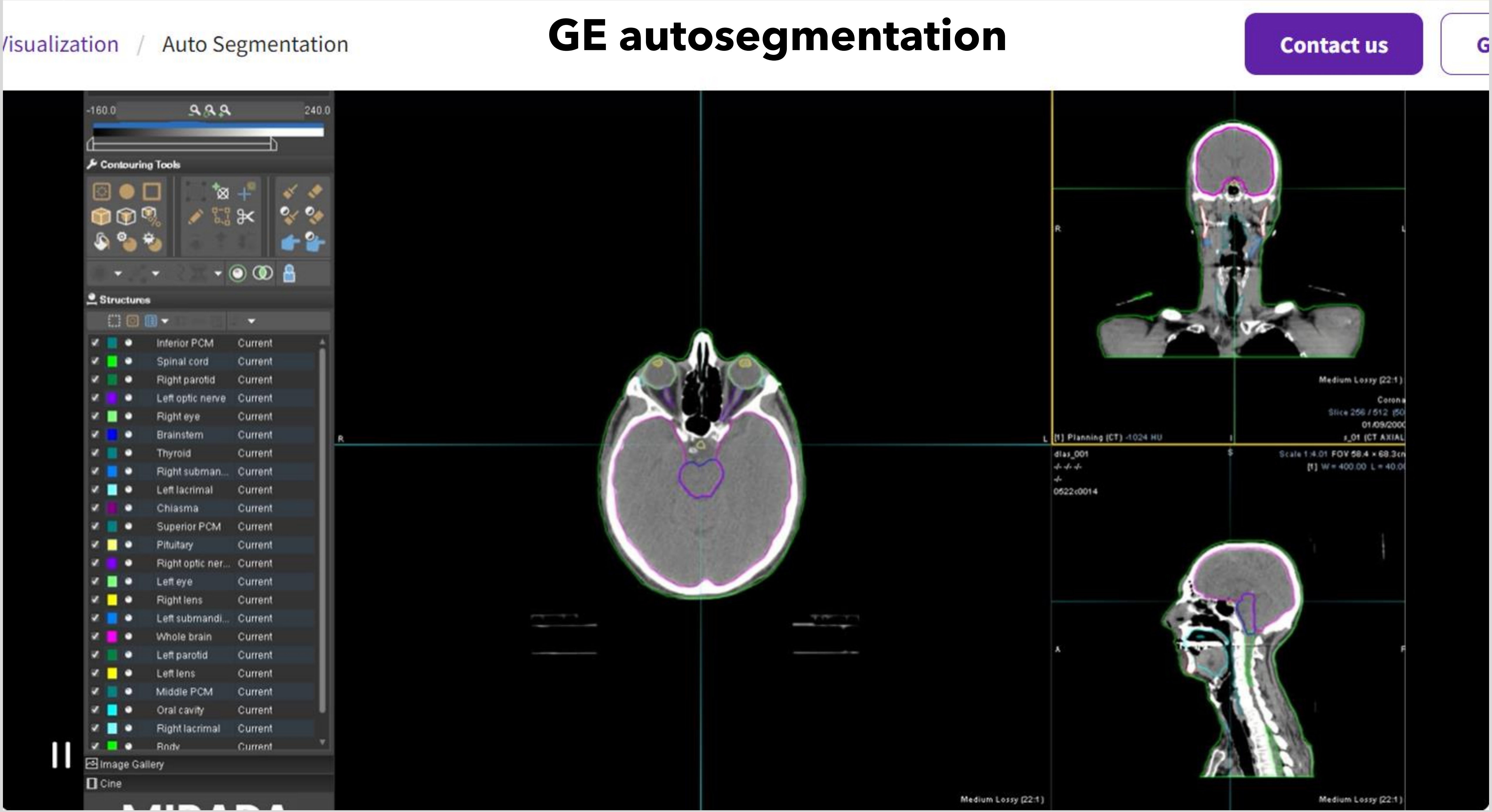




Zero-Click Contouring™

DLC*Expert* uses Mirada's unique Zero-Click Contouring platform to typically deliver contours before you arrive to your planning workstation. The workflow is based on background processing. Contours can be validated using your existing TPS or Mirada's advanced RTx software

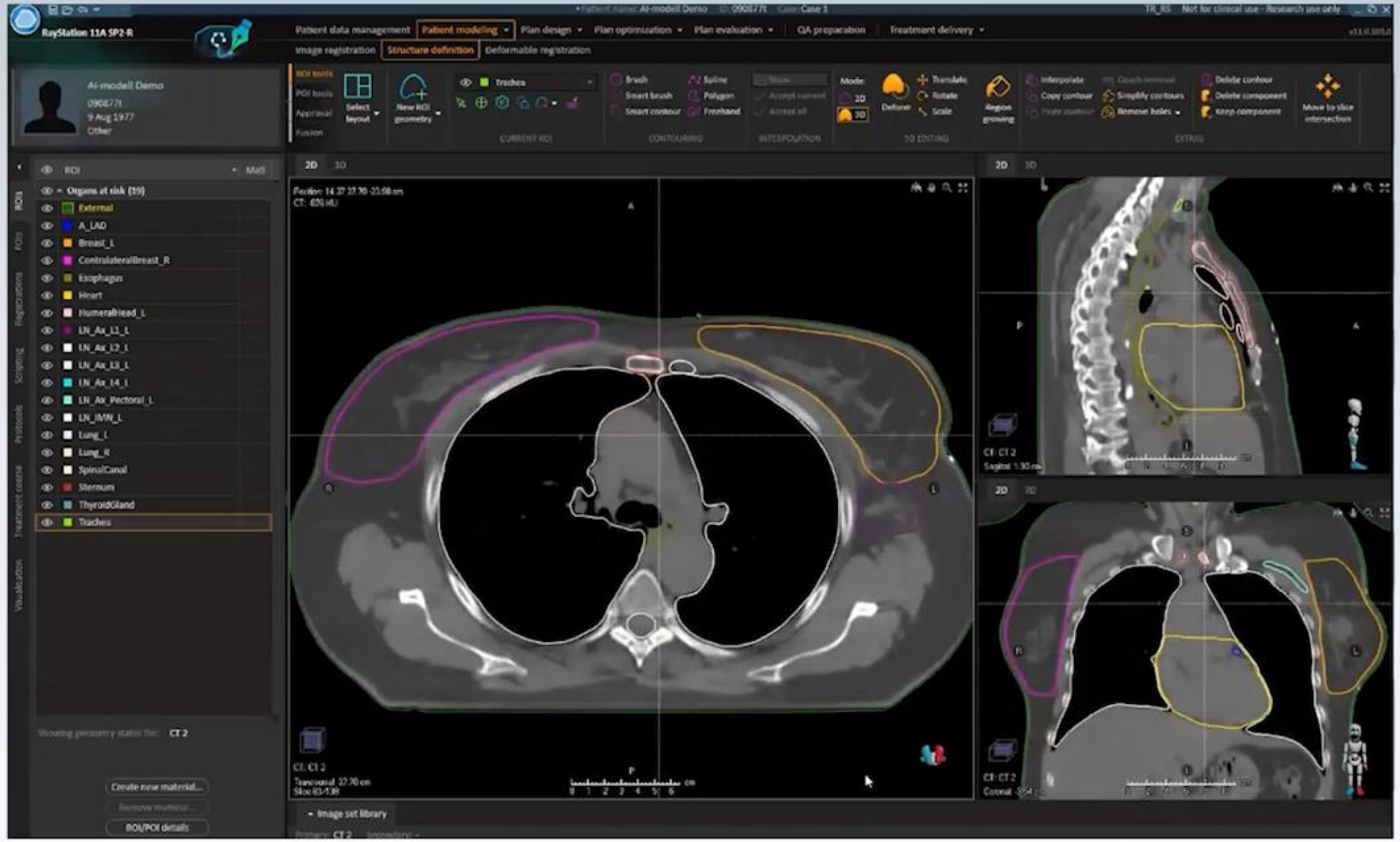
GE autosegmentation



RaySearch autosegmentation

Demo

- Structures generated in 1.5 minutes
- Review/corrections ~ 10-15 minutes
- Manual delineation approx. 1 hour (?)



DL based autosegmentation consistently outperforms atlas-based techniques.

Radiotherapy and Oncology 126 (2018) 312–317

Contents lists available at ScienceDirect

Radiotherapy and Oncology

journal homepage: www.thegreenjournal.com

Atlas contouring in lung cancer

Clinical evaluation of atlas and deep learning based automatic contouring for lung cancer

Tim Lustberg[a,*], Johan van Soest[a], Mark Gooding[b], Devis Peressutti[b], Paul Aljabar[b], Judith van der Stoep[a], Wouter van Elmpt[a], Andre Dekker[a]

[a] Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Centre+, The Netherlands; [b] Mirada Medical Ltd., Oxford, United Kingdom

Journal of Medical Radiation Sciences

Open Access

ORIGINAL ARTICLE

Clinical evaluation of deep learning and atlas-based auto-segmentation for critical organs at risk in radiation therapy

Eddie Gibbons, BSc (RT)[1], Matthew Hoffmann, BIT[1], Justin Westhuyzen, MSc, PhD[2], Andrew Hodgson, BSc (RT)[1], Brendan Chick, PhD[1], & Andrew Last, DPhil, FRCR[1]

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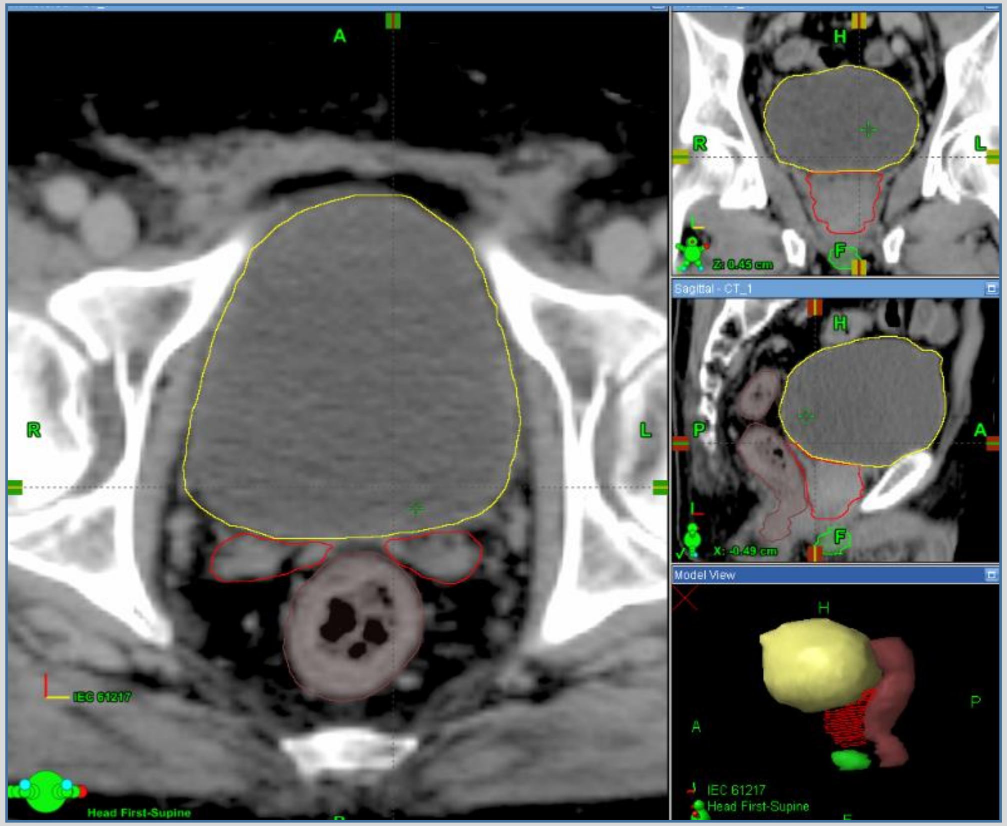
DL autosegmentation in real life

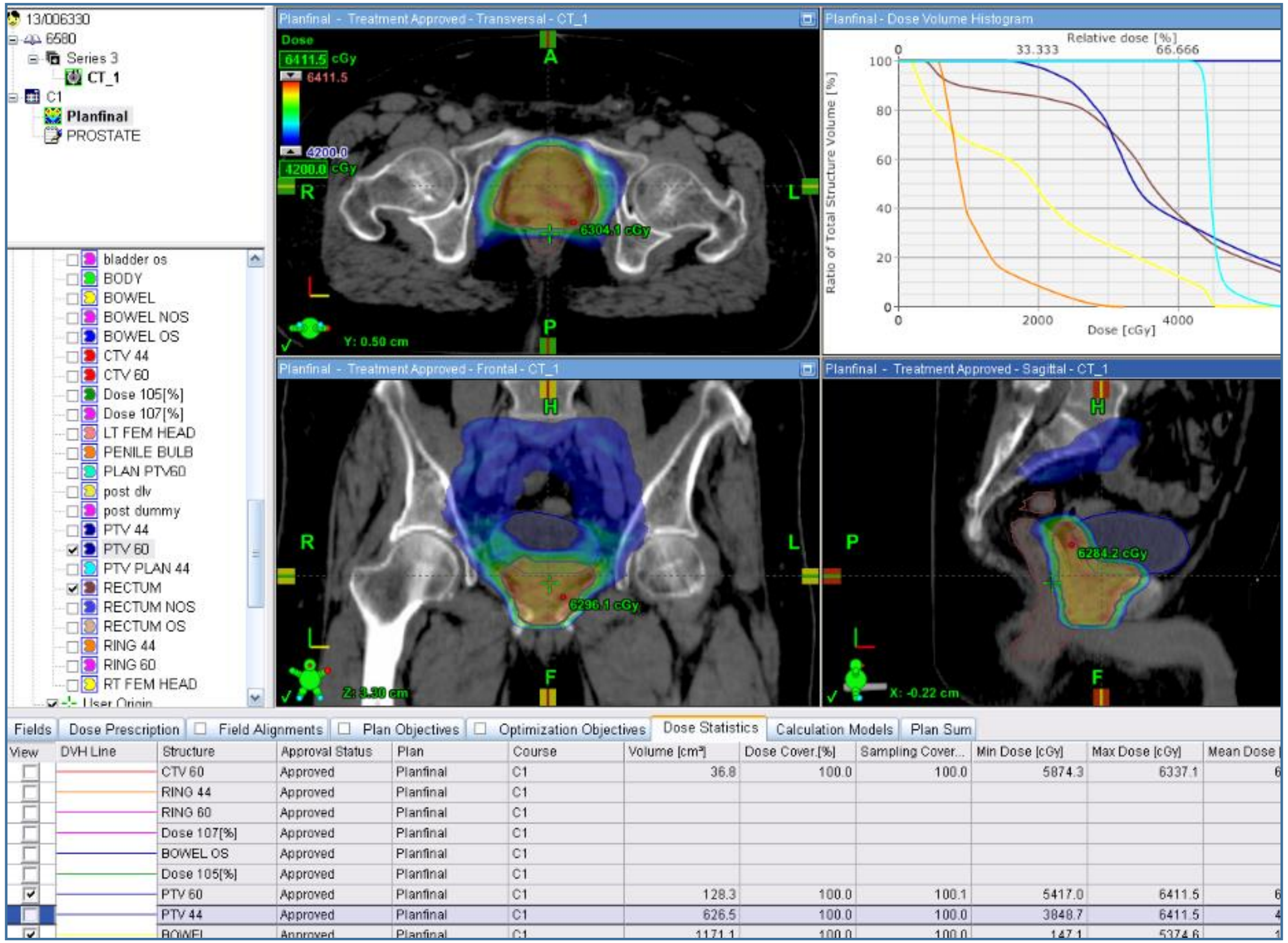
- At Tata Medical Center, our in house research feeds into clinical practice.
- DL based autosegmentation models are used daily currently in 3 anatomical sites, but eventually in most anatomical sites



Auto-segmentation progress

- Autosegmentation is now more or less a solved technical problem
- What needs to be done:
  - Validation on CT scans in our own patients
  - Cost and availability
  - Continuous improvement in accuracy
  - Accommodating changes in practice guidelines.

AI in treatment planning



Traditional automated treatment planning

Automated Rule Implementation	Knowledge Based Planning	Multi-criteria Optimization
Automate the sequence of planning steps	Library of cases	Deals with changing DVH criteria by creating anchor plans for each criterion – 'Pareto surface'
	Derive beam arrangement and DVH constraints	
	Input into TPS	
Varian ESAPI Pinnacle AutoPlanning	Varian RapidPlan Voxel based planning	RaySearch Raystation Varian ECLIPSE

Technical Innovations & Patient Support in Radiation Oncology 26 (2023) 100206

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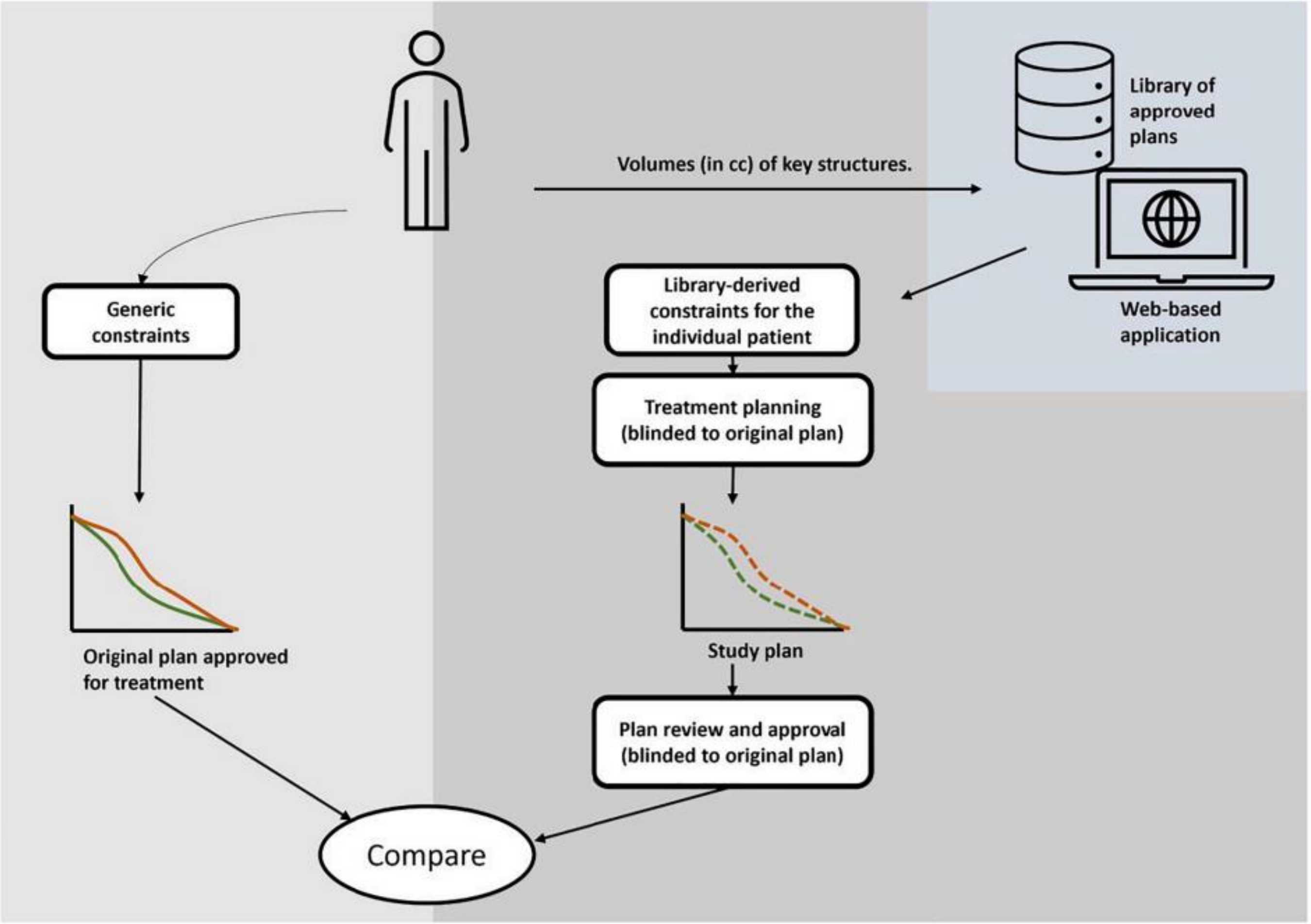
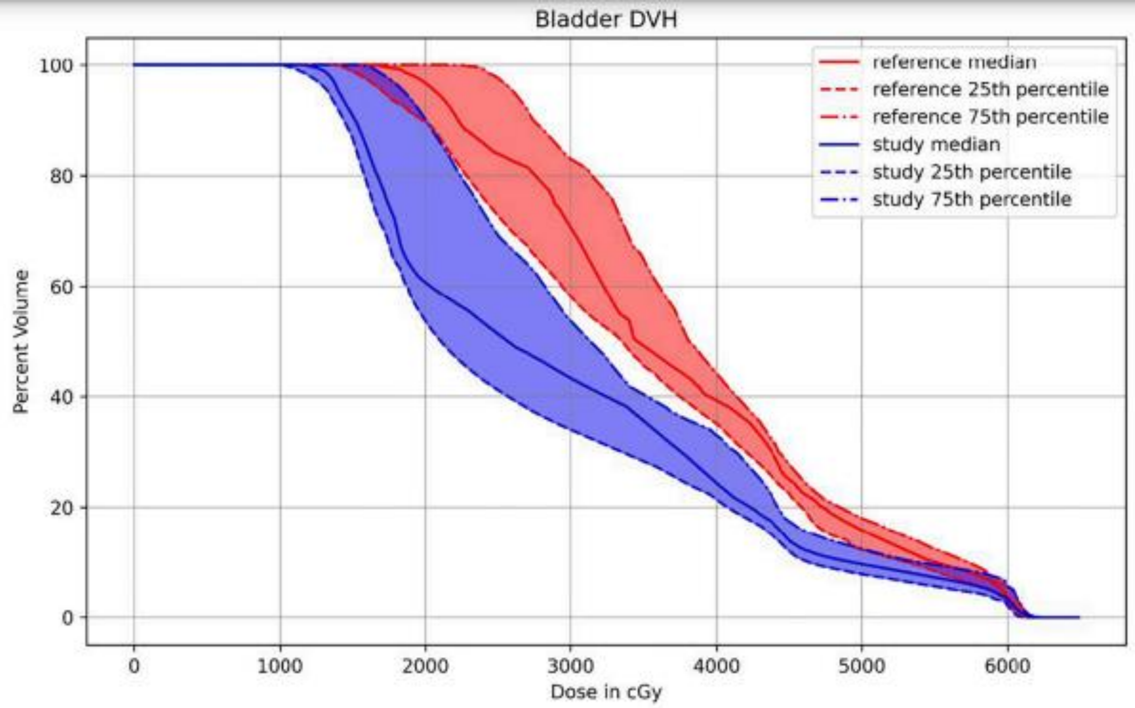
Contents lists available at ScienceDirect

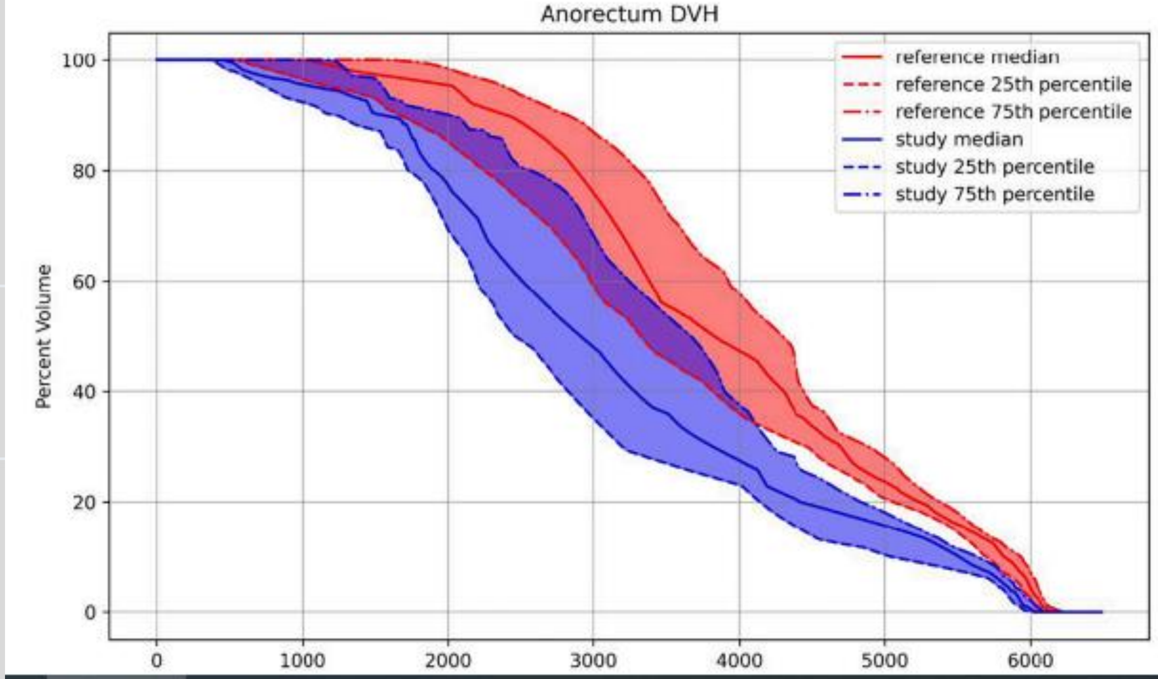
Technical Innovations & Patient Support in Radiation Oncology

journal homepage: www.sciencedirect.com/journal/technical-innovations-and-patient-support-in-radiation-oncology

ICON-P – A double-blind evaluation of quality improvements with







Current automated treatment planning

Automated Rule Implementation	Knowledge Based Planning	Multi-criteria Optimization
Automate the sequence of planning steps	Library of cases	Deals with changing DVH criteria by creating anchor plans for each criterion – 'Pareto surface'
	Derive beam arrangement and DVH constraints	
	Input into TPS	
Varian ESAPI Pinnacle AutoPlanning	Varian RapidPlan Voxel based planning	RaySearch Raystation Varian ECLIPSE

Novel AI approaches

Anatomy

Constraints

Prescription

Machine Learning Models

Planning weights and priorities for DVH

Auxiliary structures

Deep Learning Models

U-net

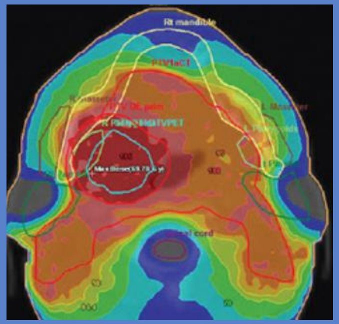
Resnet

Dosenet

RL

GAN

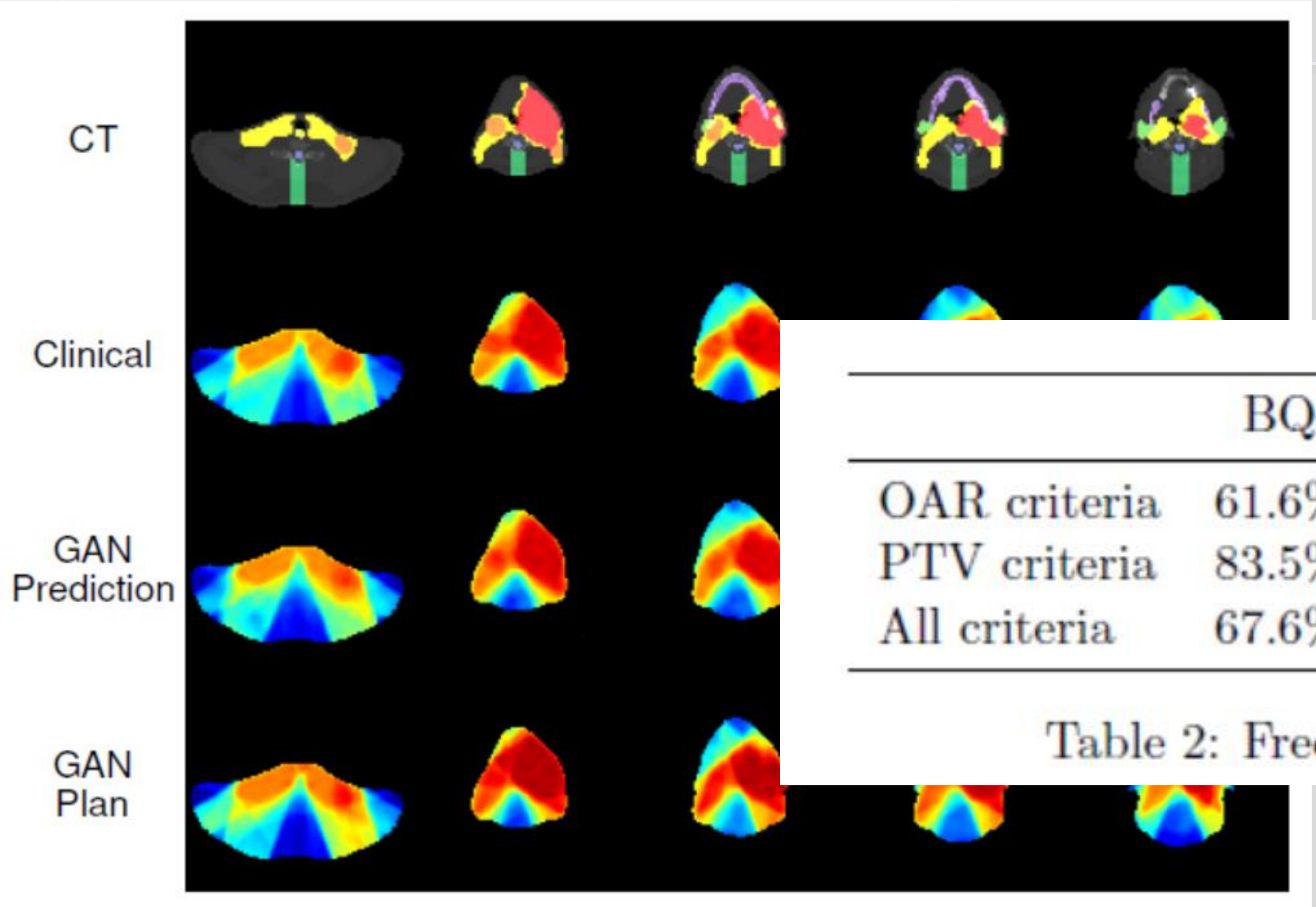
Spatial voxel based dose distribution



GAN in Automated Treatment Planning

Automated Treatment Planning in Radiation Therapy using Generative Adversarial Networks

Rafid Mahmood RMAHMOOD@MIE.UTORONTO.CA
Department of Mechanical and Industrial Engineering
University of Toronto, Toronto, ON, Canada



	BQ	gPCA	RF	CNN	GAN	Clinical
OAR criteria	61.6%	65.8%	71.5%	72.5%	72.8%	72.0%
PTV criteria	83.5%	85.7%	68.0%	76.3%	81.3%	76.8%
All criteria	67.6%	71.2%	70.7%	73.6%	75.2%	73.3%

Table 2: Frequency of clinical criteria satisfaction.

WEBINAR: Deep learning planning in RayStation

In this webinar we presented our latest release of deep learning planning models, machine learning news in RayStation 11B and how deep learning planning can be implemented at your clinic. Demonstrating how your clinic can configure and commission a released and validated model for your protocol, planning trade-offs and treatment machines.

rpa.mdanderson.org

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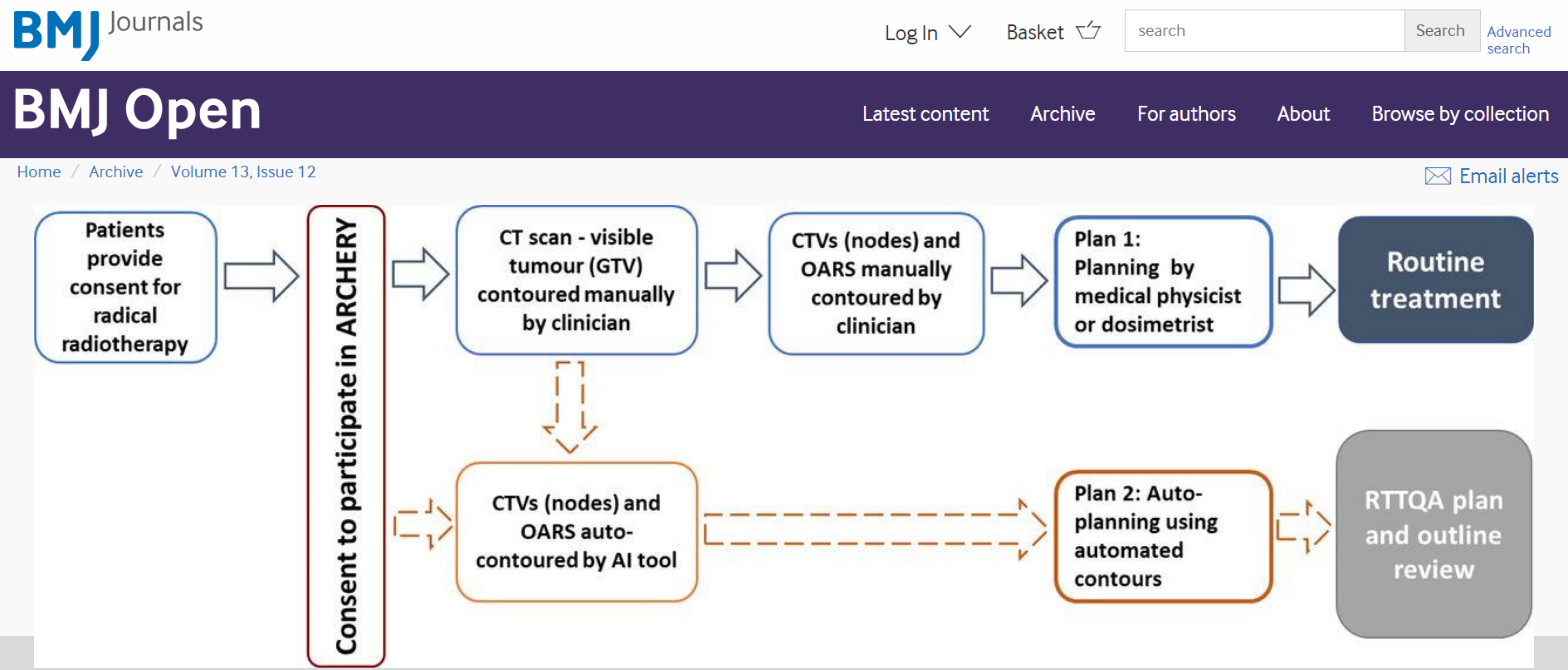
THE UNIVERSITY OF TEXAS
MD Anderson Cancer Center

Available Services

Treatment Units	Auto-Contouring	Treatment Planning	Planning Quality Assurance
Varian (2100, TrueBeam, etc.)	✓	✓	*
Varian Halcyon	✓	*	*
Elekta Versa / Synergy (Agility Head)	✓	✓	*
Other	✓	*	*

* These services are under development. More details can be found under the 'Our Services' page

Does automation work in real life?

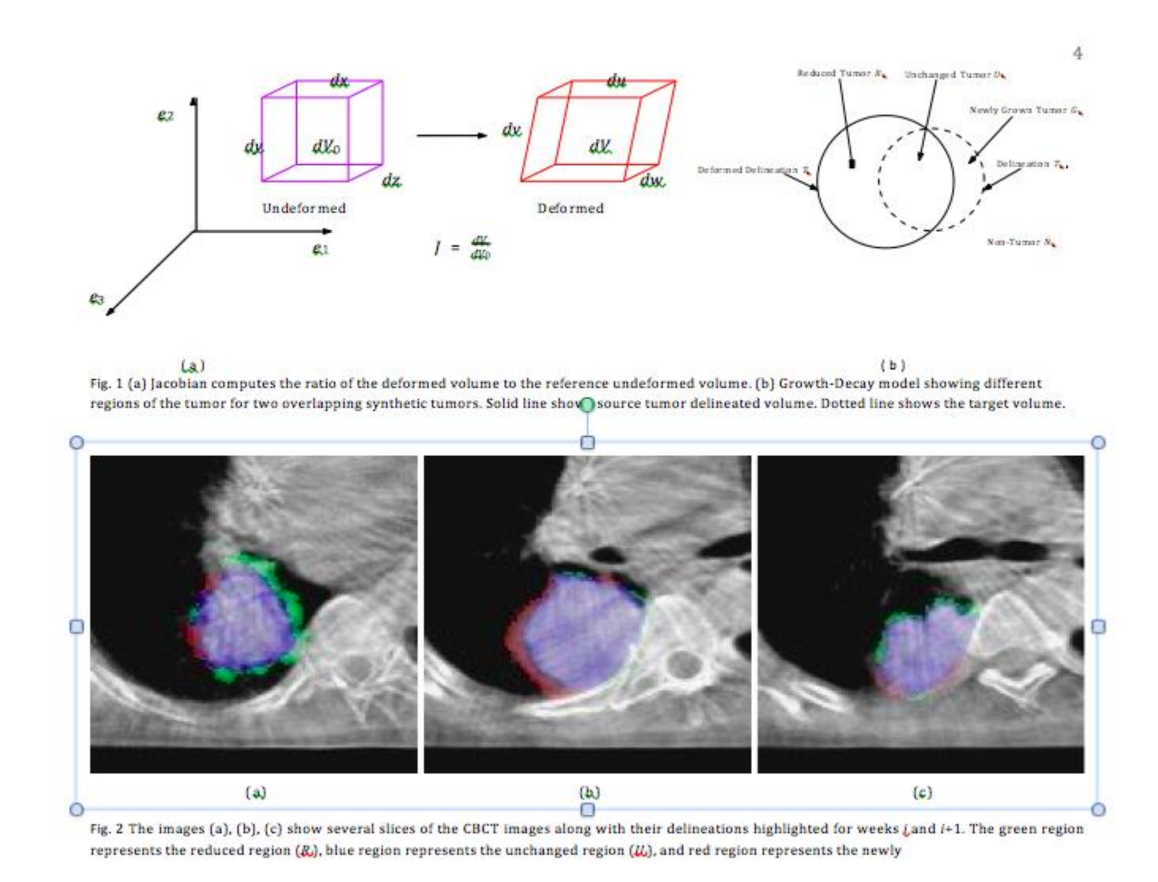


AI in Clinical Decision Support

Published Clinical Decision Support Systems

Cancers	Input data	No of patients	Endpoint	Author
Lung and HN Cancer	Radiomics	1,019	Prognosis	Aerts
Prostate Cancer	Imaging (mpMRI, PIRADS)	223	Active surveillance	De Corbelli
Colon	Clinical Data	5,301	Benefit of adjuvant therapy	Steele
Breast/ Liver	Clinical Data	2,458	General feasibility	Gorunescu
Brain metastases		495	Survival after SRS in lung cancer brain mets	Zindler
Skin	Photos from mobile phones	129,450	Diagnosis and classification of skin cancer	Esteva
Cervical Cancer	Cytology images	2,267	Diagnosis of cancer	Kyrgiou
Bladder	Clinical/Path	1,964	Pathological upstaging	Mitra

Clinical prediction models - TMCK



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Computer Methods and Programs in Biomedicine

Volume 195, October 2020, 105669

Prediction of survival outcome based on clinical features and pretreatment ^{18}FDG-PET/CT for HNSCC patients

Sayantani Ghosh [a], Shaurav Maulik [c], Sanjoy Chatterjee [c], Indranil Mallick [c], Nishant Chakravorty [b], Jayanta Mukherjee [a]

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https://doi.org/10.1016/j.cmpb.2020.105669

Get rights and content

Generative AI

AI models that create text, art, music or any other creative output

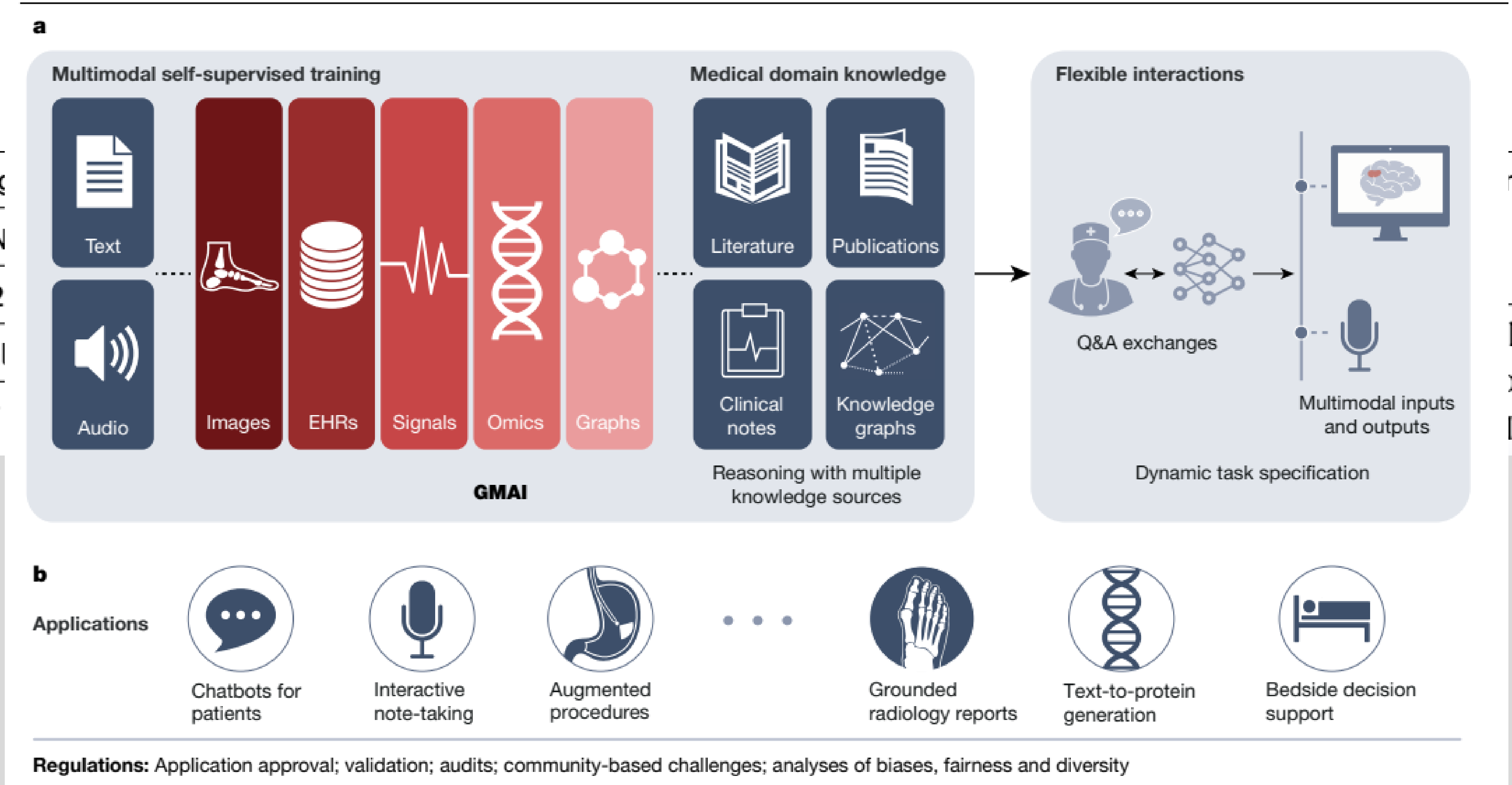
ChatGPT and many others

Logarithmic scale of development

Rapid advances into healthcare

Perspective

Foundation models for generalist medical artificial intelligence



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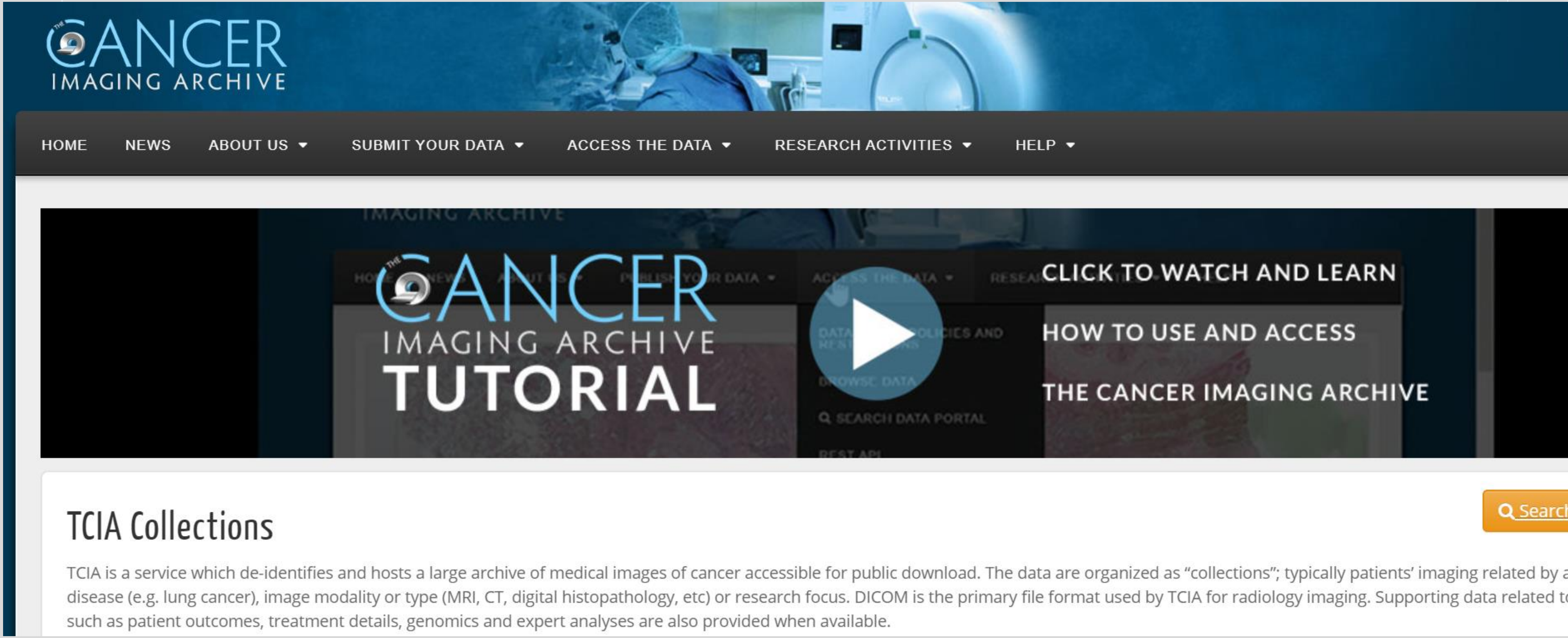
Many challenges in clinical applications

Algorithms need 'lots of data'	Data needs 'consistent annotation'	Images need 'uniform acquisition'
Medical Data needs 'Privacy controls'	Medical data needs 'interoperability'	Models need 'external validation'

Need for data and image repositories



Tata Medical Center - **CHAVI-RO**

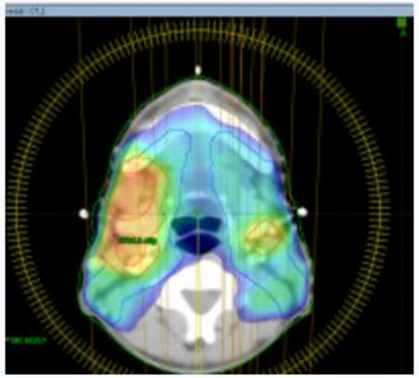
- The First Appropriately annotated image bank in India
- Pilot using primarily Radiation Oncology Images (CHAVI-RO) as the first in the world
- Set deliverables within 18 months:

Informed consent and infrastructure set up

Set up software (medical and clinically customised)

Collaborative effort- Integrate departments

Projects in CHAVI

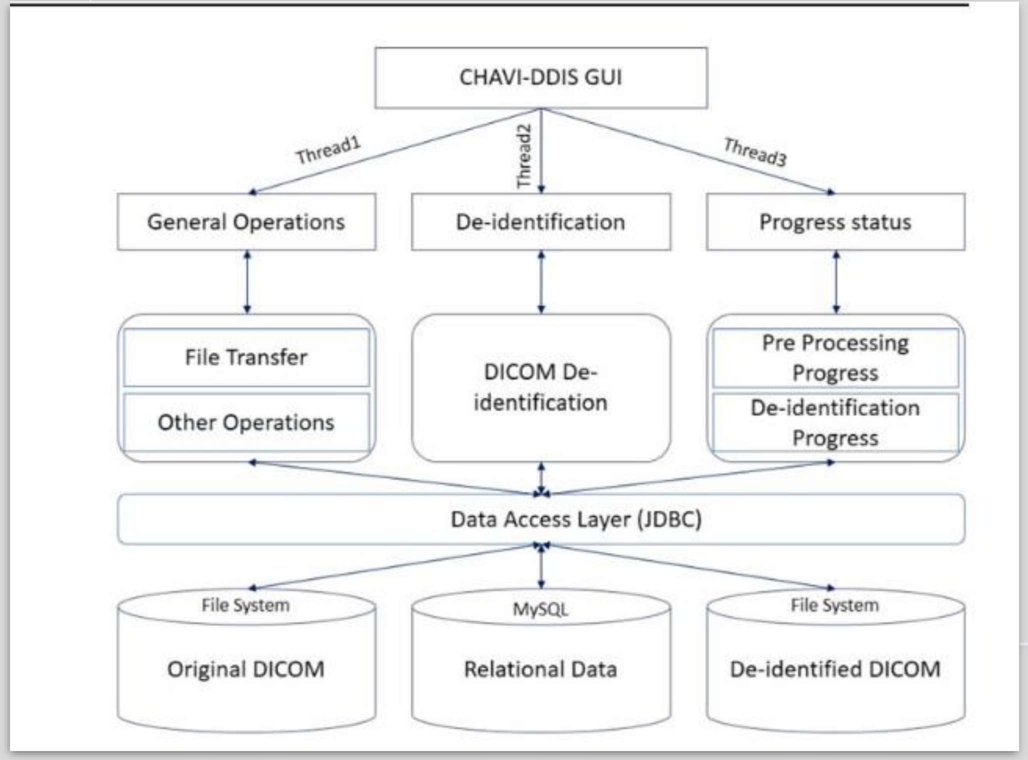


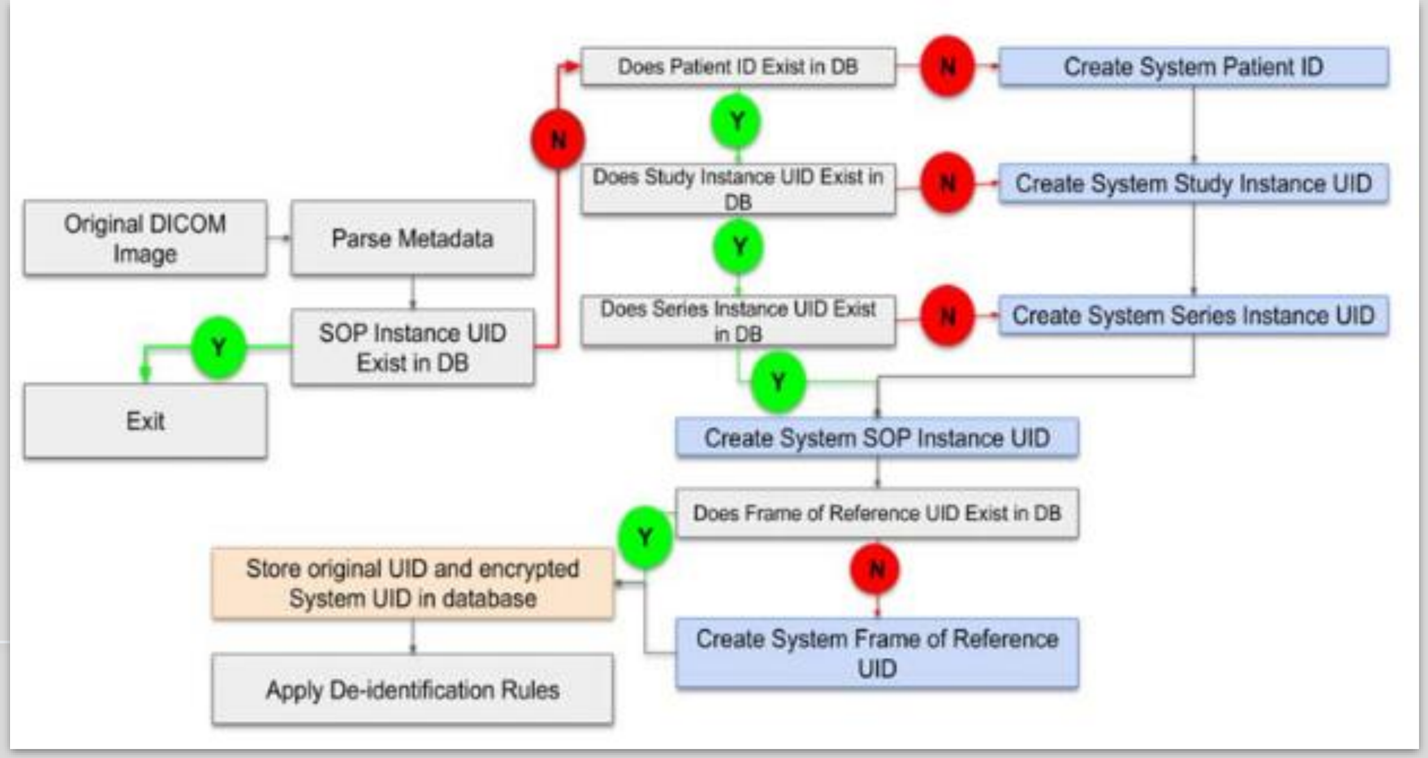
INTELHOPE

INTELHOPE is a prospective randomized trial which is investigating the impact of radiation dose escalati to the PET defined gross disease in patients with locally advanced oropharyngeal, laryngeal...

Read More >>

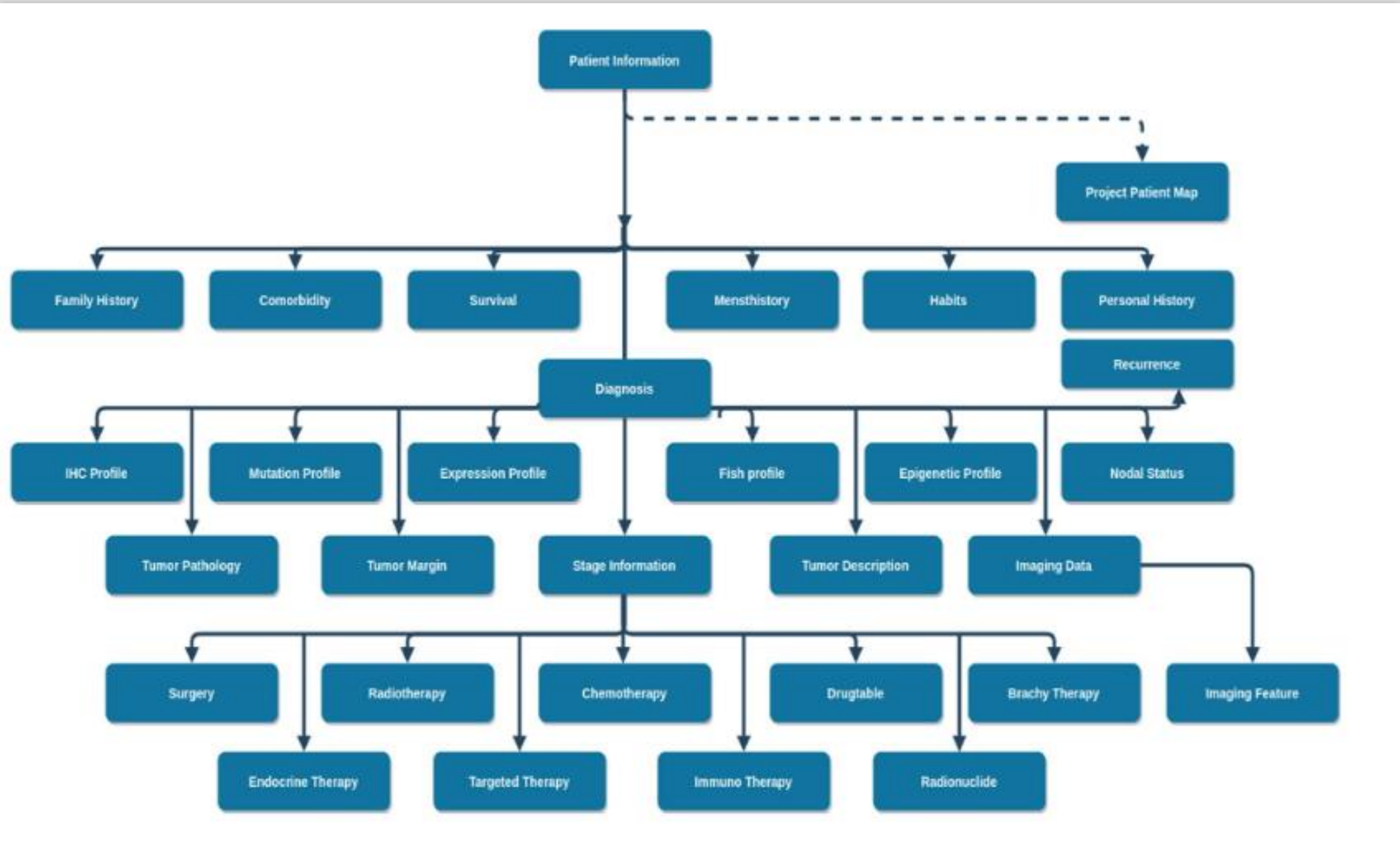
CHAVI – Image De-identification System





Kundu S, Chakraborty S, Chatterjee S, Das S, Achari RB, Mukhopadhyay J, et al. De-Identification of Radiomics Data Retaining Longitudinal Temporal Information. J Med Syst 2020;44:99. https://doi.org/10.1007/s10916-020-01563-0.

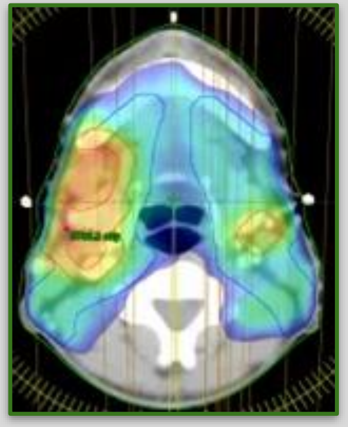
CHAVI – Relational (MySQL) Database

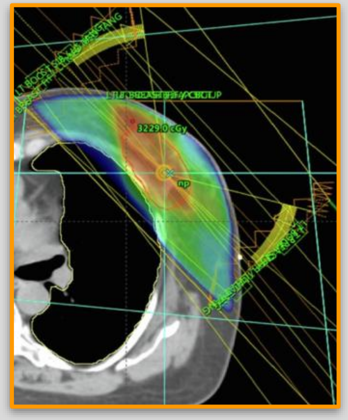


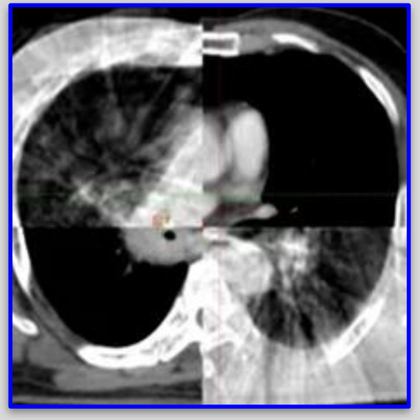
Kundu S, Chakraborty S, Mukhopadhyay J, Das S, Chatterjee S, Basu Achari R, et al. Research Goal-Driven Data Model and Harmonization for De-Identifying Patient Data in Radiomics. J Digit Imaging 2021. https://doi.org/10.1007/s10278-021-00476-9.

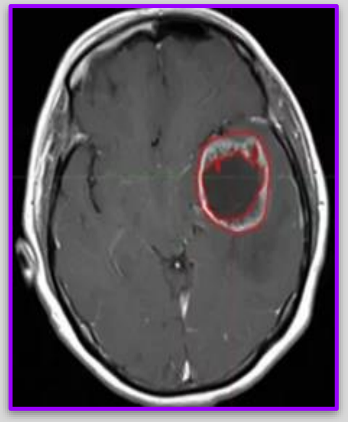
Projects

Intelhope PET-Radiomics	Hyport-adjuvant Doseomics	IMPRINT Prediction	RadGlio High MRI-Radiomics
Clinical, molecular, QA, treatment & outcomes banked in CHAVI			



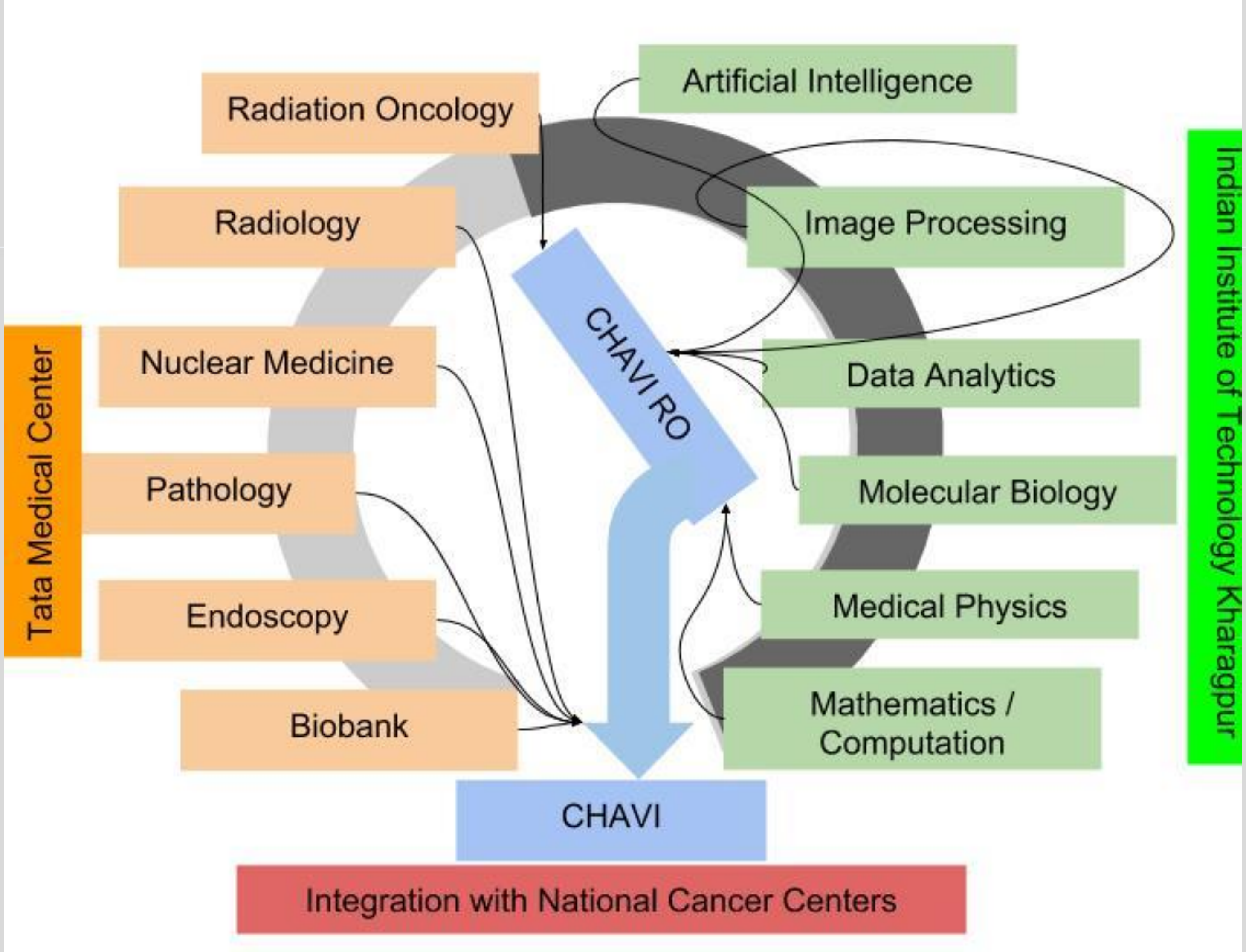






Integration is the key

- We believe that the future lies in integrating images and data from a myriad sources.



AI will transform radiation oncology

- Approximately 70% of our work will get automated within 5-10 years
- Roles and responsibilities will change.
- Job market will change, even in India, over the next decade.
- Generative models will further impact our work in ways which we cannot fathom right now.

When the winds of change blow, some people build walls, while others build windmills.

Chinese Proverb