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Radiotherapie
Medische Oncologie
Hematologie




RaySearch
Laboratories

Artificial Intelligence based segmentation and planning of a male pelvis

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Iridium Kankernetwerk is involved in an on-going scientific collaboration with RaySearch Laboratories.

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Evolution of AI technology

The timeline shows three stages of AI technology:

- Artificial Intelligence (1950's - 1970's):** Engineering of making Intelligent Machines and Programs. Represented by a brain icon with a gear.
- Machine Learning (1980's - 2000's):** Ability to learn without being explicitly programmed. Represented by a brain icon with gears.
- Deep Learning (2006's - 2017's):** Learning based on Deep Neural Network. Represented by a neural network icon.

On the right, a Venn diagram shows the relationship between these technologies:

- ARTIFICIAL INTELLIGENCE:** Programs with the ability to learn and reason like humans.
- MACHINE LEARNING:** Algorithms with the ability to learn without being explicitly programmed.
- DEEP LEARNING:** Subset of machine learning in which artificial neural networks adapt and learn from vast amounts of data.

Big Data

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Machine Learning: Principle

Machine Learning

The process flow is: **Input** (car icon) → **Feature extraction** (hand pointing to a screen) → **Classification** (neural network icon) → **Output** (CAR NOT CAR box).

Supervised Learning

- Labeled data
- Direct feedback
- Predict outcome/future

Unsupervised Learning

- No labels
- No feedback
- "Find hidden structure"

Reinforcement Learning

- Decision process
- Reward system
- Learn series of actions

The diagram compares three learning types:


- Supervised learning:** Input (Data with labels) → Supervised learning → Output (Mapping). Includes an Error Critic loop.
- Unsupervised learning:** Input (Data without labels) → Unsupervised learning → Output (Classes).
- Reinforcement learning:** Input (States and actions) → Reinforcement learning → Output (State/action). Includes a Critic loop with a Reinforcement signal.

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Deep Learning: Principle

Deep Learning



Input

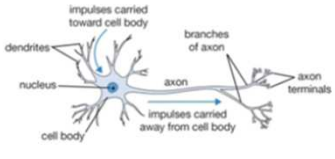


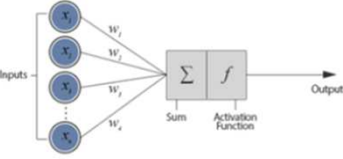
Feature extraction + Classification

CAR
NOT CAR

Output

Biological Neuron versus Artificial Neural Network





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Example: how to recognize a physicist

Machine Learning and Deep Learning

MACHINE LEARNING

How do you engineer the best features?

$N \times N$


(f_1, f_2, \dots, f_K)
 Roundness of face
 Dist between eyes
 Nose width
 Eye socket depth
 Cheek bone structure
 Jaw line length
 ...etc.


CLASSIFIER ALGORITHM
 SVM
 Random Forest
 Naïve Bayes
 Decision Trees
 Logistic Regression
 Ensemble methods

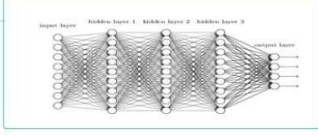
Physicist

DEEP LEARNING

How do you guide the model to find the best features?

NEURAL NETWORK

$N \times N$





Physicist

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AI Hype vs Reality



“AI zal zelfstandig worden en zichzelf steeds sneller opnieuw uitvinden. De mens is beperkt door langzame biologische evolutie en kan niet concurreren. De mens zal worden vervangen.”
-Stephen Hawking

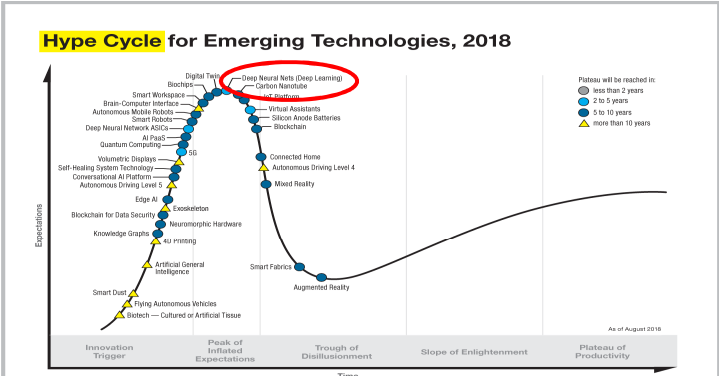


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Hype

Hype Cycle for Emerging Technologies, 2018



gartner.com/SmarterWithGartner

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Gartner.

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AI in radiation oncology

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RayStation

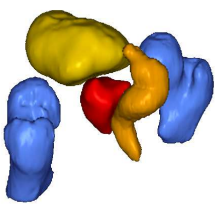
MACHINE LEARNING
FASTER AND SMARTER
TREATMENT PLANNING



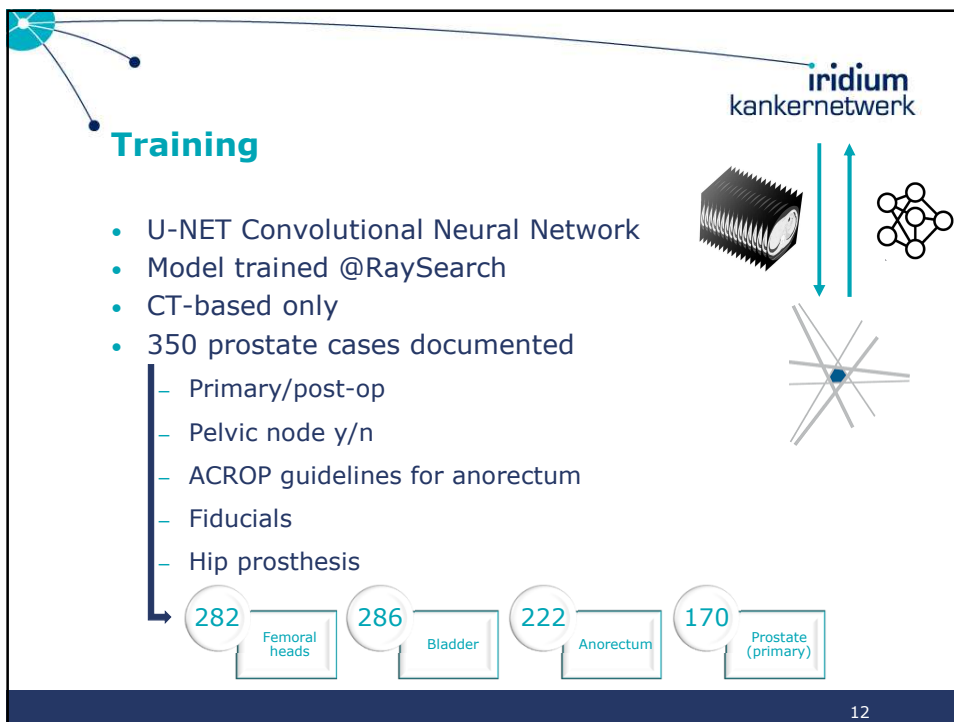
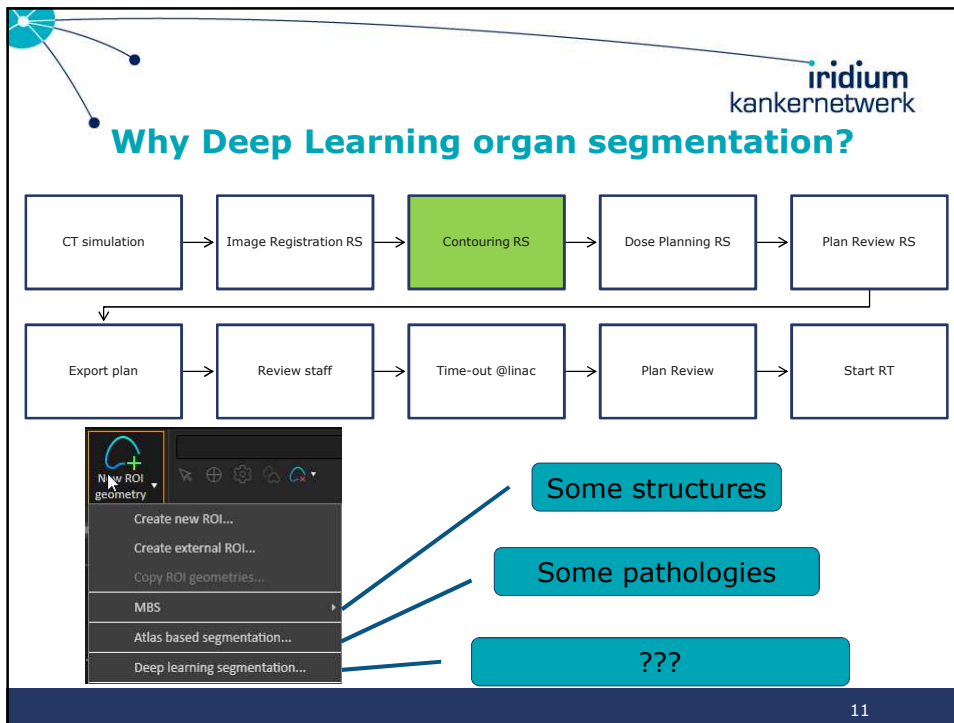
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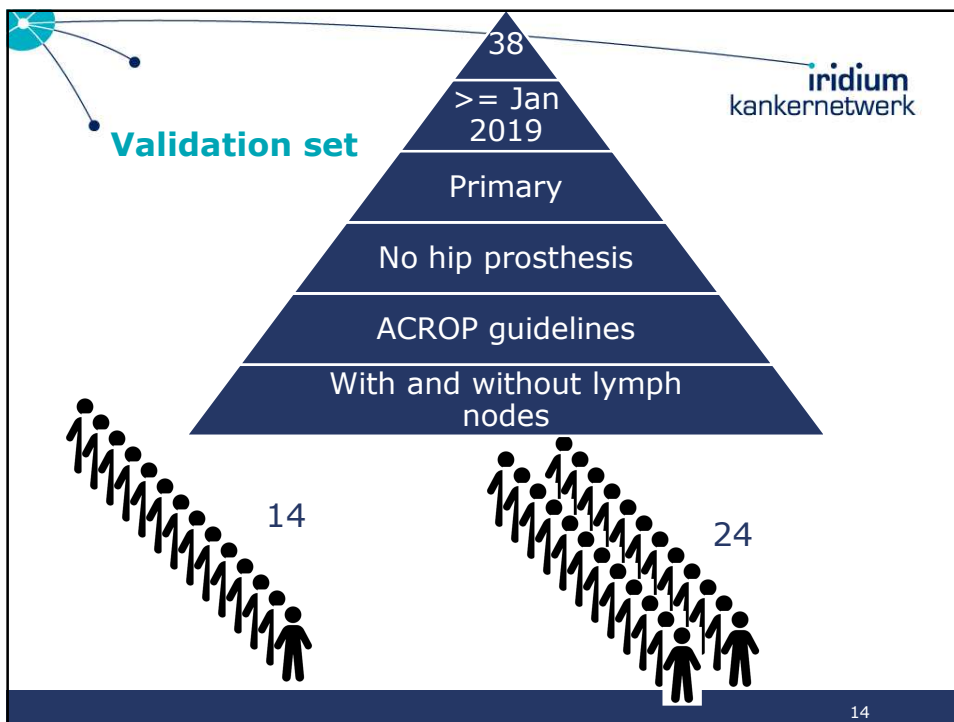
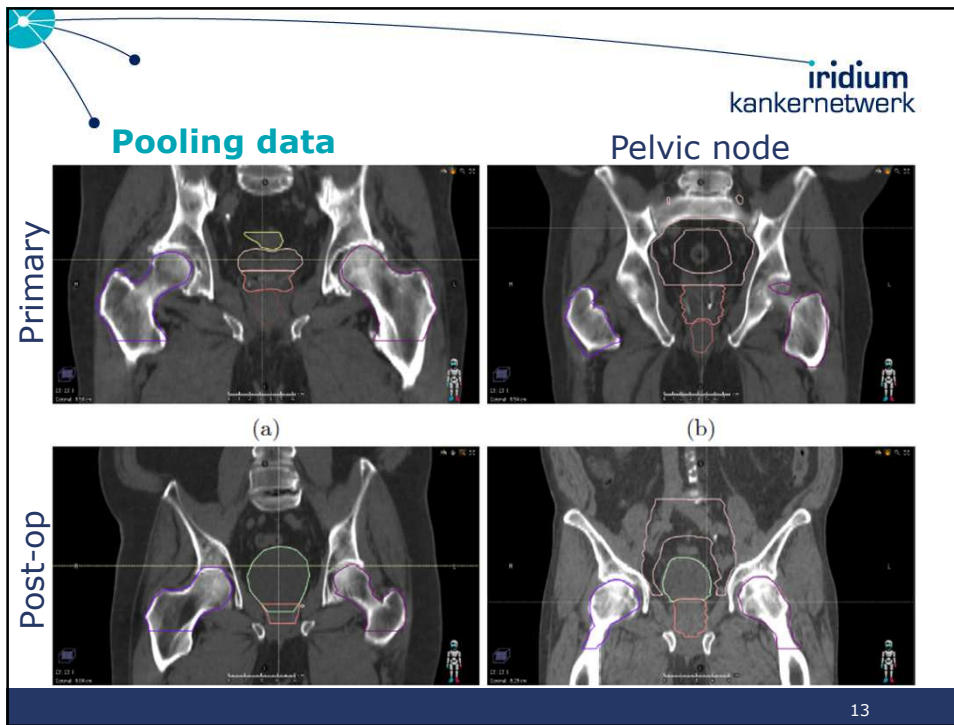
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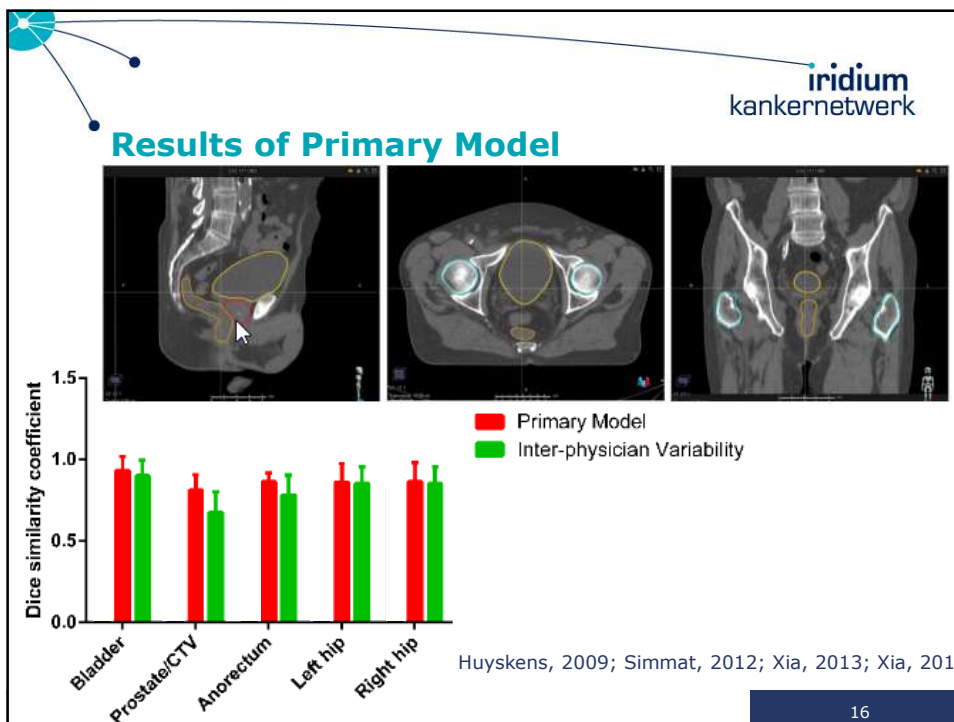
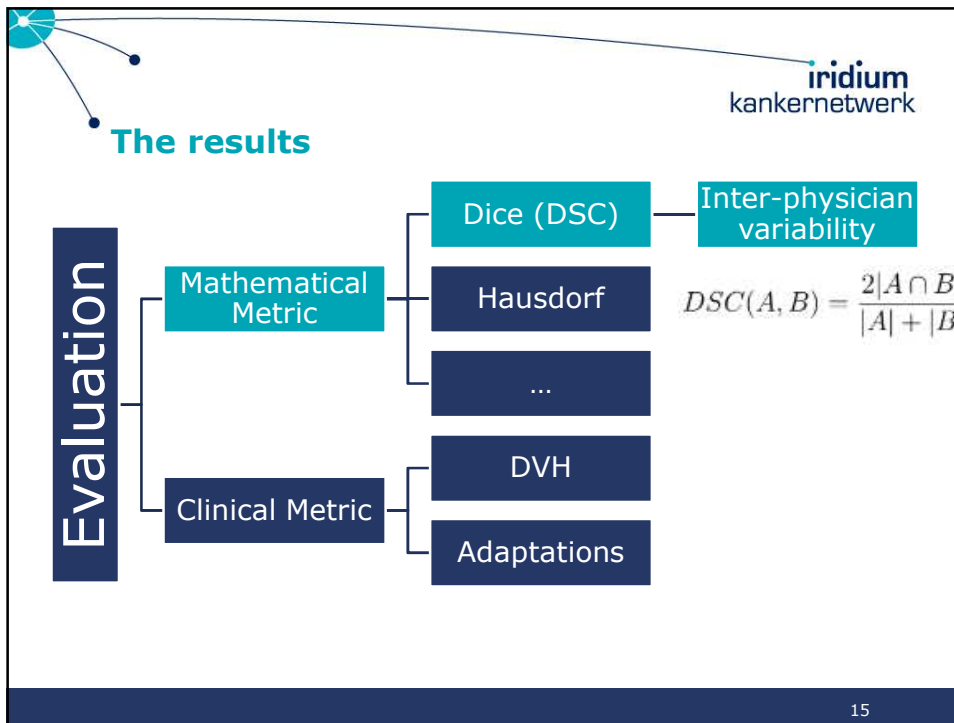
Deep Learning
Segmentation
for prostate cancer



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Data selection needed?

- 350 prostate cases documented
 - Primary/post-op
 - Pelvic node y/n
 - ACROP guidelines for anorectum
 - Fiducials
 - Hip prosthesis

Primary model

- 185 mixed prostate cases

Mixed model

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GIGO

THIS IS YOUR MACHINE LEARNING SYSTEM?

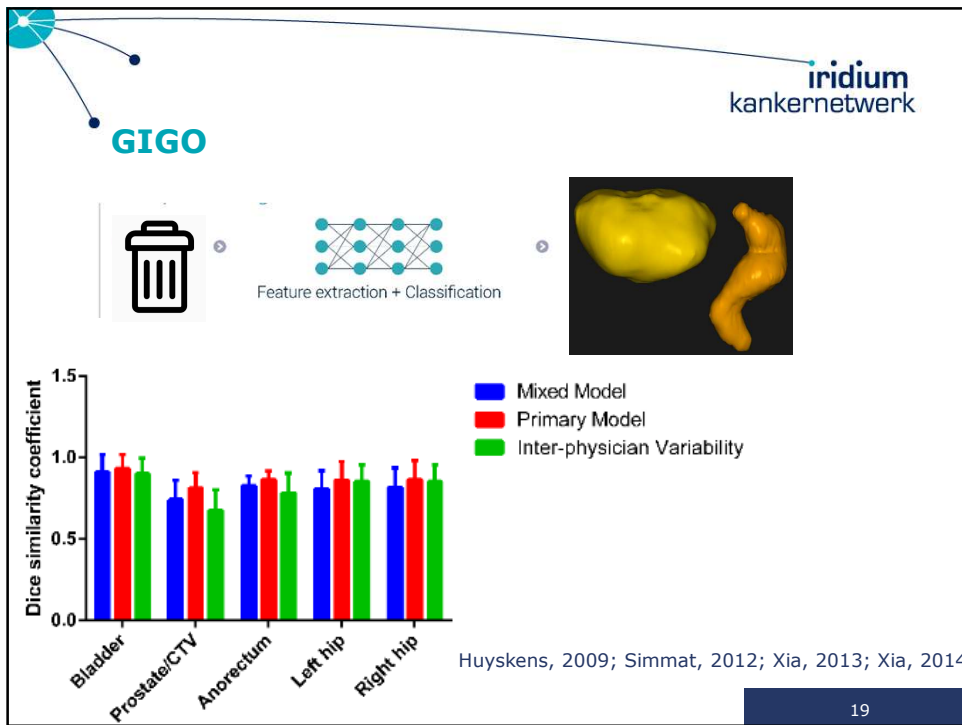
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.

<https://xkcd.com/1838/>

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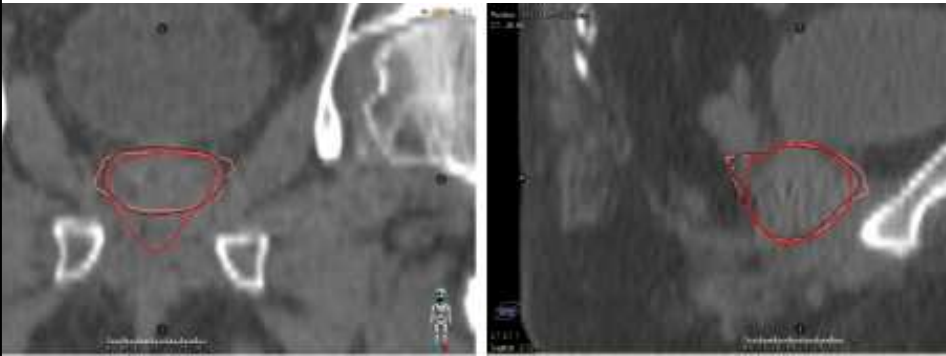
Some more details

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Pollution - Prostate

- Primary and post-op

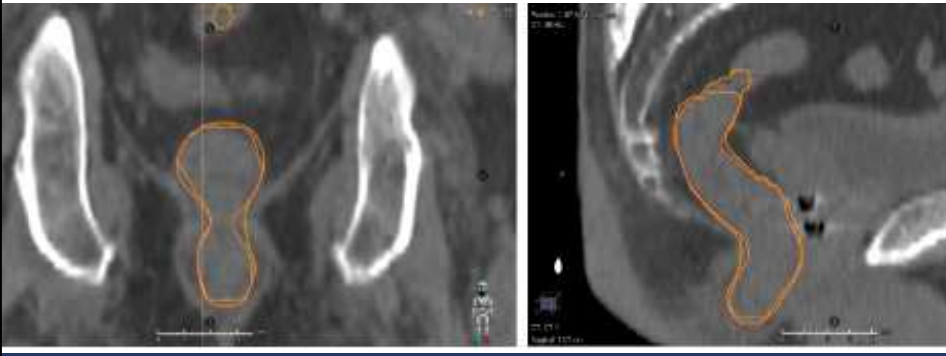


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Pollution - Rectum

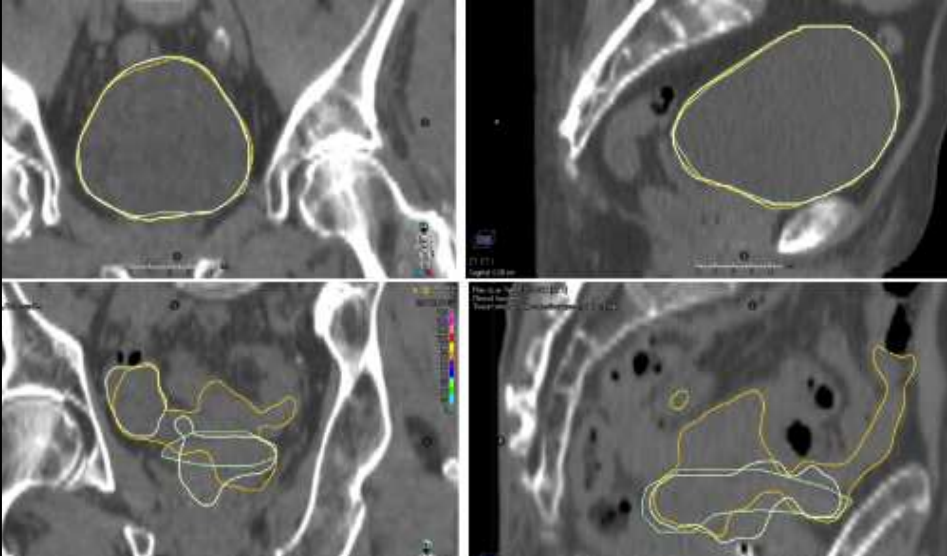
- ACROP guidelines



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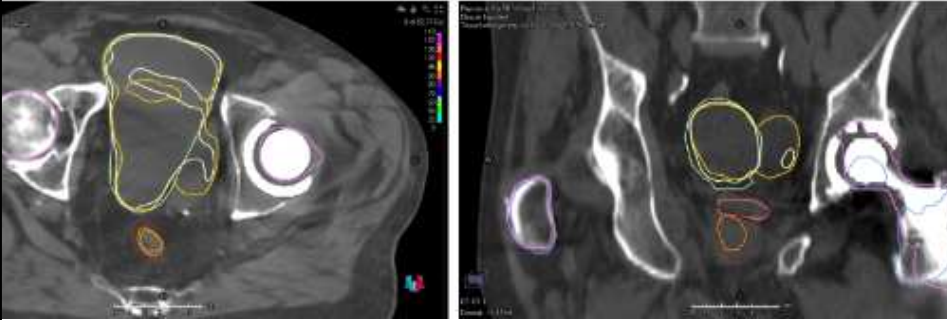
The perfect bladder

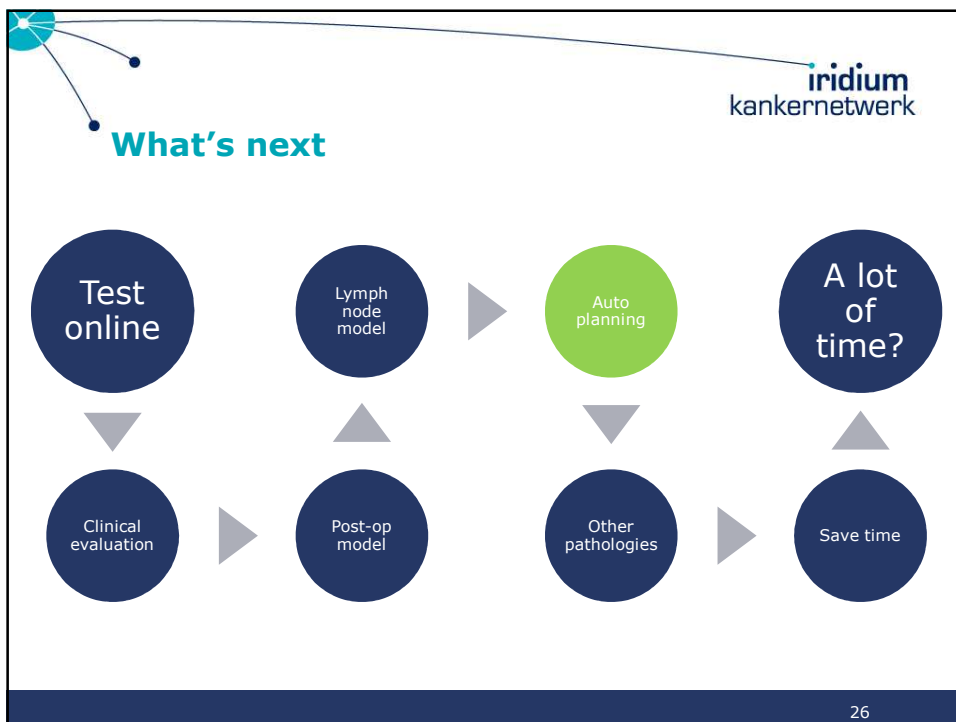
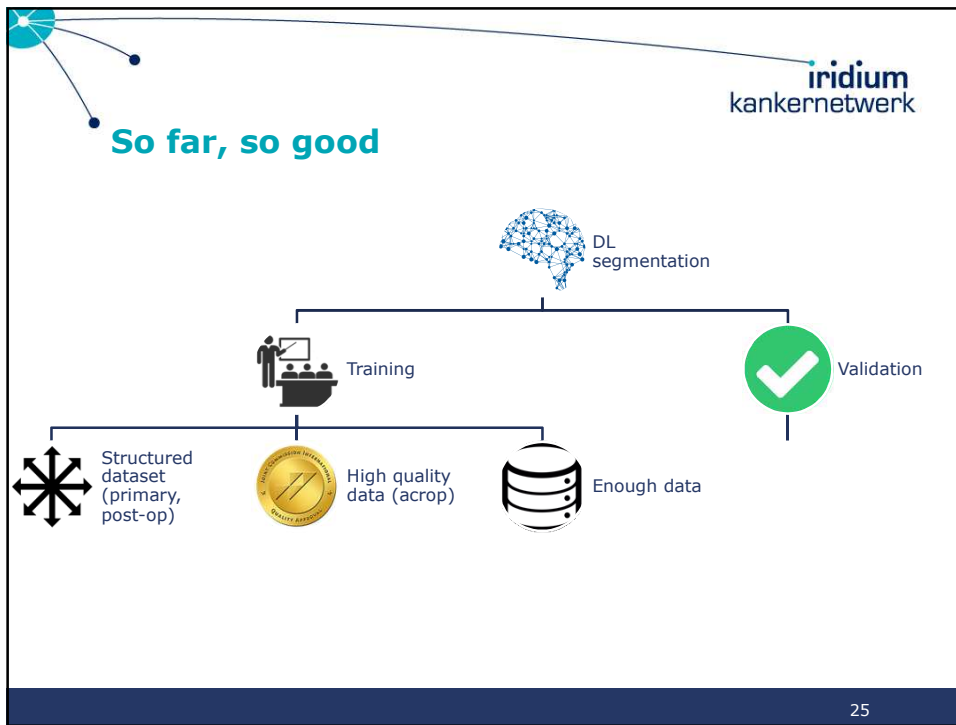



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Hip prostheses

- Model trained with or without prostheses








Machine Learning treatment plan generation

'Automation is the future of
planning'

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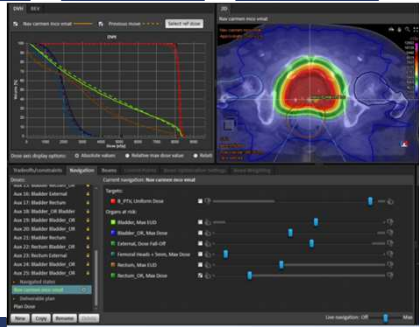
Planning

```

    graph LR
      A[CT simulation] --> B[Image Registration RS]
      B --> C[Contouring RS]
      C --> D[Dose Planning RS]
      D --> E[Plan Review RS]
      E --> F[Export plan]
      F --> G[Review staff]
      G --> H[Time-out @linac]
      H --> I[Plan Review]
      I --> J[Start RT]
  
```

Purpose:

- Machine parameters:
 - Gantry and collimator angle
 - Leaf position, beam weights
- Algorithm-based 3D dose distribution
- High PTV coverage ⇔ low OARs radiation



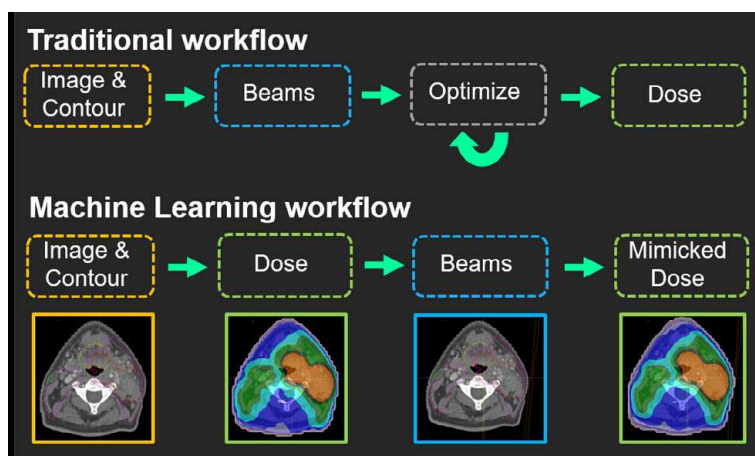
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Why automation?

- Goal is to create high quality plans to meet clinical objectives
- Efficient Process
 - Automate standard procedures
- Clinic time constraints
 - Spend more valuable time on complex cases
 - Evaluate different treatment techniques
- Help department workflow

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ML workflow



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Atlas-based regression forest

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Impact of speed on planning quality

- Automated tools affect the planner's speed
- Given a high performing system, a dosimetrist will produce higher quality plan compared to one equipped with a slow system
- Relationship between speed and plan quality
- Planning on the faster computer had significant increase in fulfilment of clinical goals

RayStation

THE EFFECT OF PLANNING SPEED ON VMAT PLAN QUALITY

Plan optimization and dose calculation for complex VMAT plans are computationally challenging tasks. Depending on the efficiency of the TPS implementation, and the hardware on which it runs, calculation times can range from a few minutes to up to more than a half hour. In order to research that a dosimetrist equipped with a high performing system should be able to produce plans of higher quality compared to one equipped with a slow system, independent of his/her experience level. This planning study of complex prostate and head and neck cases, in two different RayStation setups (PS), aims to measure the effect of planning speed on plan quality.

SETUP
22 people with 100+ years VMAT planning experience from clinics that use RayStation participated in the study. Two RayStation configurations were used: the one equipped with the high RayStation 4.7 and the other one equipped with the slow RayStation 4.6. The order was determined in the optimization and dose calculation step. 10 beams target their usual. Two patient cases were used, one very complex prostate case and one complex head and neck case. For both cases, 100 VMAT plans were created for each case, a scoring system based on the fulfillment of clinical goals.

had been created and was communicated to the participants. In the first four sessions, all participants planned for the slow case, half of the participants used their fast system and half used the slow system. For the second four sessions, all participants planned for the fast case and half of the participants used their fast system and half used their slow system. The new, 40 participants planned both cases and used both systems. The participants were not informed about the speed of the difference between the systems, only that there were two different types.

EXAMPLE RESULTS CASE ONE

In the graph above, the plan P1B5 was planned on a fast system and P1F4 and P1F5 on slow systems. P1B5 and P1F5 scored 100% for all 8 goals, while P1F4 scored 100% for 7 goals. P1B5, being planned on a fast system, had a significantly better plan quality than P1F4. In general, P1B5 achieved a much better balance between target coverage and normal tissue sparing.

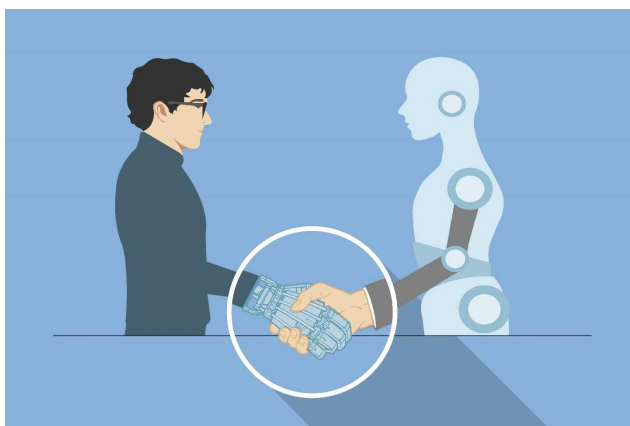
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Future of planning

- Future is knowledge-based planning
 - Use previous experience to drive the solution
- Plan optimization driven by big data
- Computer speed
 - Need advanced hardware, algorithms, and techniques
- More patients needing adaptive therapy will increase workload
 - Day to day dose tracking
 - Implementing multiple changes over the course of treatment
- Automation will help bring efficiency to the workflow and higher quality care to the clinic

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THANK YOU!



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