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AI for Oncology at Varian – Potential Applications and Opportunities

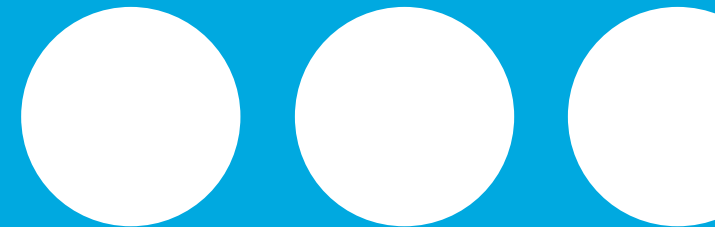
**Applications of Deep Neural Networks in Radiation
Therapy Treatment Planning and Image Guidance**

September 6, 2018

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Sr. Mgr Applied Research
Varian Medical Systems Imaging Laboratory GmbH

Agenda

1. **Varian Medical Systems**
2. **Potential Applications and Expectations**
3. **AI in Medical Image Processing**
4. **AI in Automated 3D Image Segmentation**
5. **AI in Automated Radiation Therapy Planning**
6. **Conclusion and Questions**



Varian today – a snapshot

Global Leader

in radiation
therapy

\$2.6B

FY17
revenues

7,750

medical linear
accelerators

>25

worldwide training
centers

A focused cancer company

4,600+

software
installs

65+

proton therapy
rooms

6,400+

employees

52%

international
order mix



Vision:

A World Without
Fear of Cancer

Mission:

To combine the ingenuity
of people with the power
of data and technology to
achieve new victories
against cancer



Numerous applications for AI in Radiation Oncology

Machine Learning to achieve AI: Augmented Intelligence

- Image processing and reconstruction
- Image segmentation
- Tumor detection & diagnosis
- Patient risk stratification
- 3D dose prediction
- Image registration, matching and registration
- Response assessment
- Patient monitoring, care management
- Biological response prediction
- Clinical decision support (CDS)

Promising early results on external and internal work

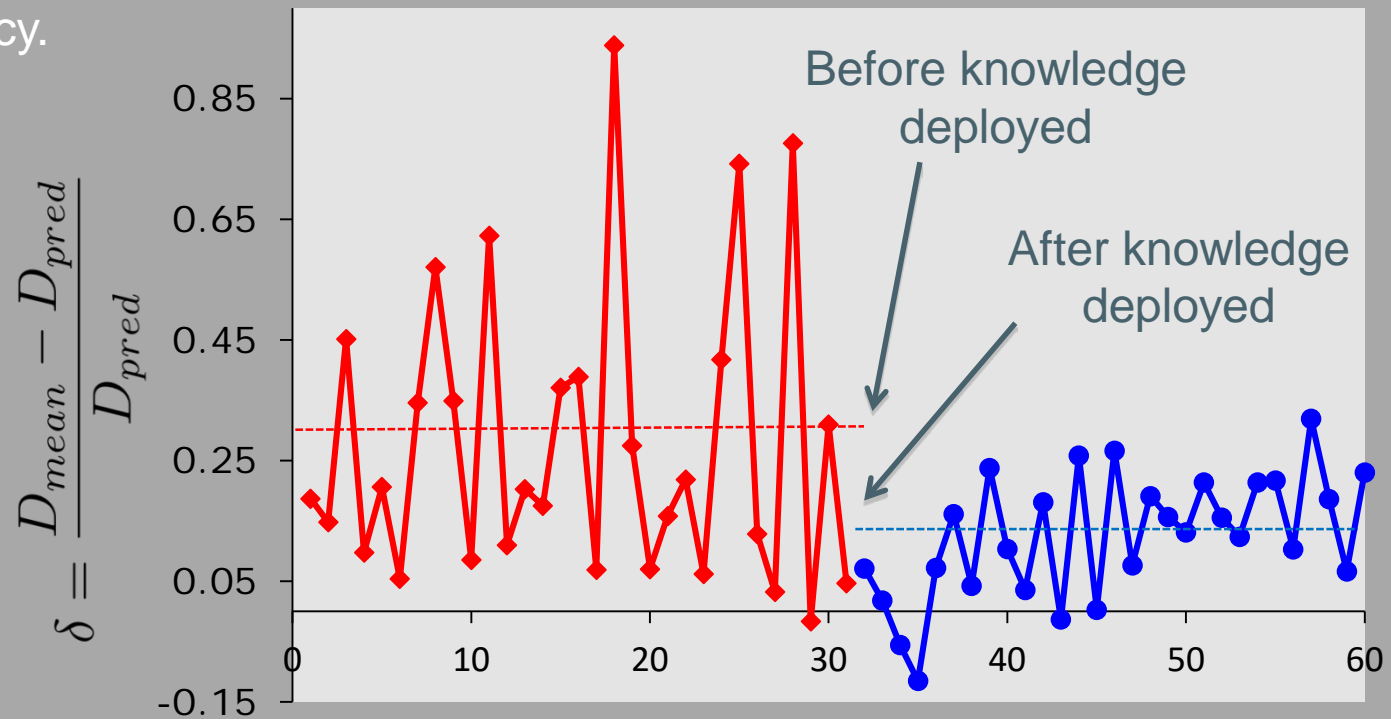
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RapidPlan™ Knowledge-Based Treatment Planning

Applying Machine Learning to Predict an Achievable Dose Volume Histogram driving the dose optimization

Less variation.
More consistency.



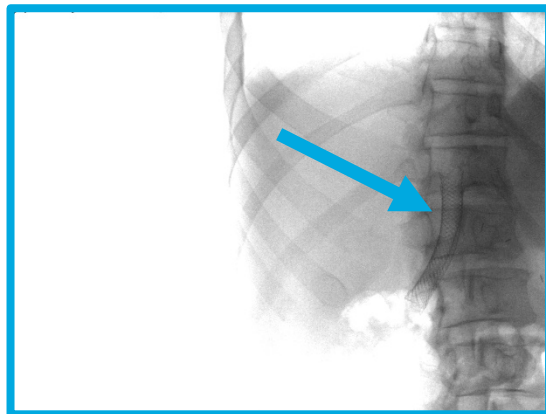
Courtesy Lindsey Olsen, Washington University, St. Louis

Image Processing

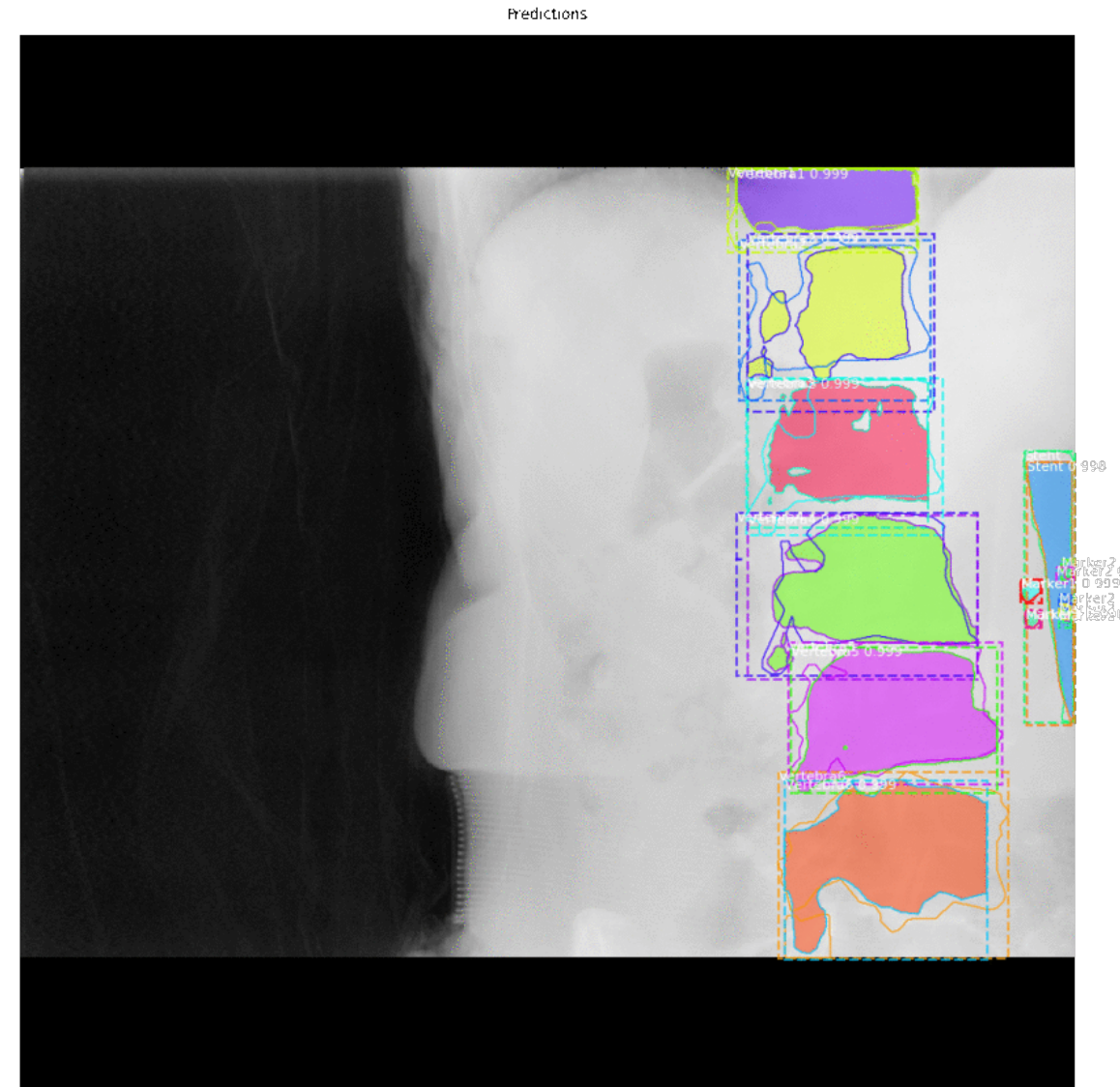
X-ray Projection Images

- Objects:
 - 1 Stent, 3 (different) markers, 6 (different) vertebrae
- Data Set:
 - Training set (750), Validation set (145), Test set (5)
 - Ground Truth semi-automated
- Promising early results
- Clinical refinements required

Stent



Mask



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Image Processing

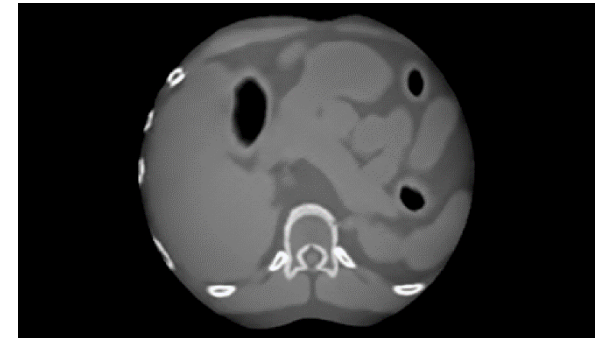
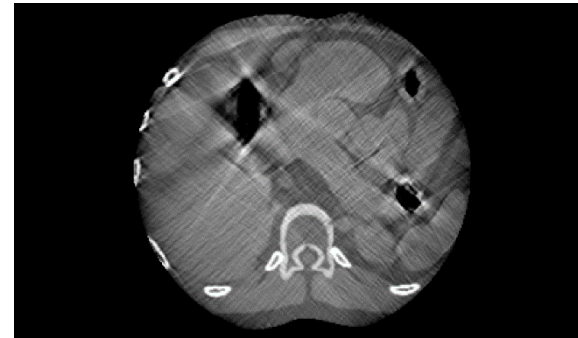
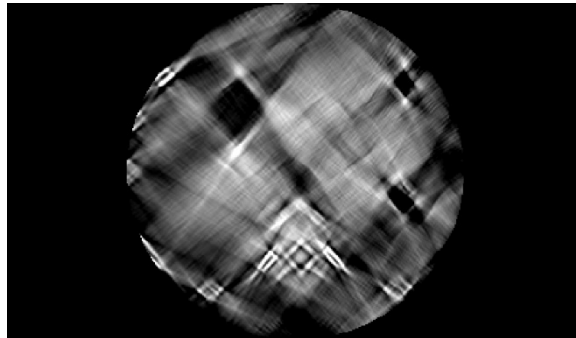
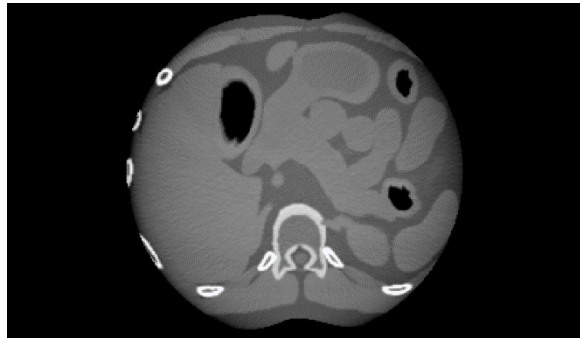
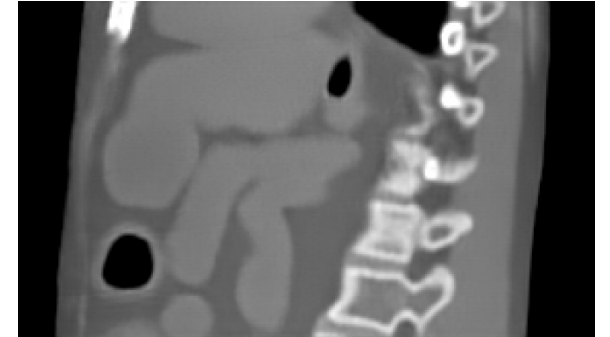
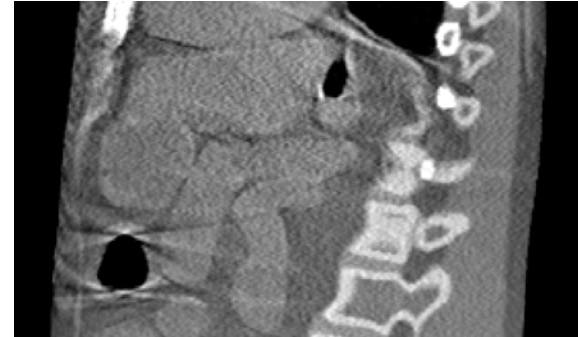
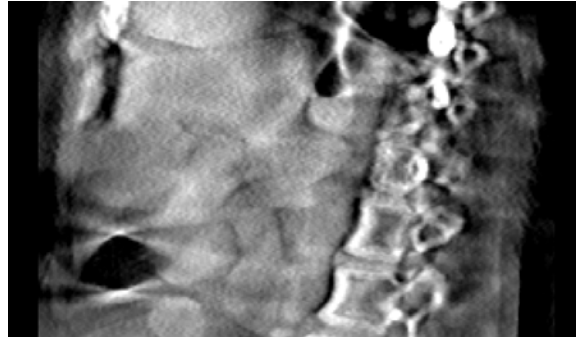
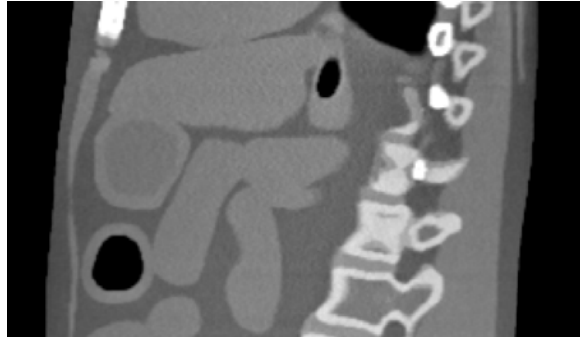
Limited Angle Cone Beam Computer Tomography (CBCT) Image Post-Processing

Ground Truth

Standard FDK Recon

adaptation of Varian
MKB 4-D CBCT algorithm

With Machine Learning-
based artifact reduction

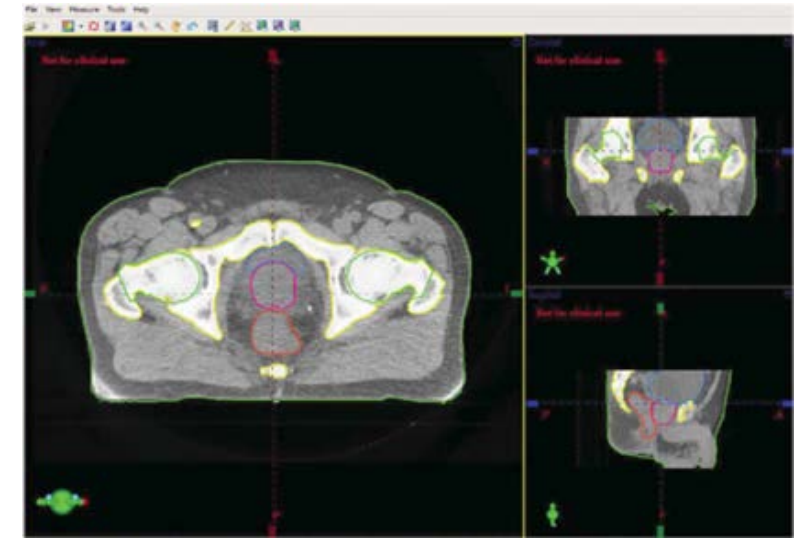


Automated Segmentation

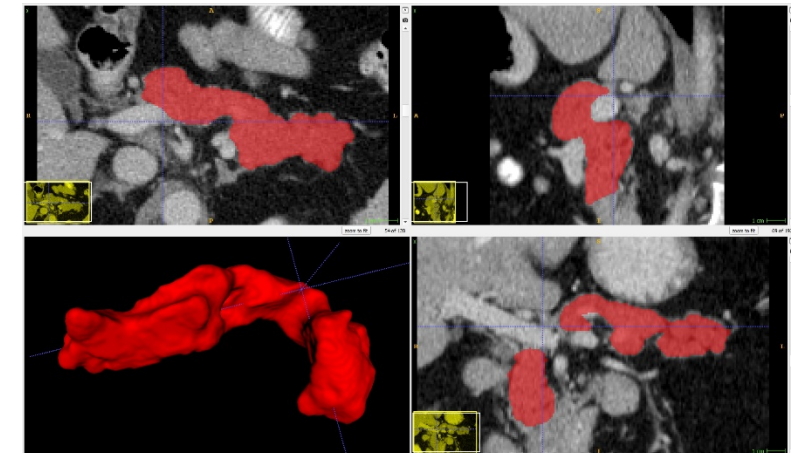
What's the Problem?

- Manual Segmentation of volumetric (CT) images is a prerequisite for radiation therapy planning
 - Dose optimization
 - Dose reporting
 - Dose accumulation
- Manual segmentation is labor intense and depends on user
- Varian offers automated segmentation tools more than a decade
- Need for fully automated segmentation of Organs at Risk and Clinical Target Volumes
 - Universal Models: Compliant with published consensus guidelines
 - Customizable Models: to center or user preferences
 - Learning Models: Continuously learn from user Corrections

Male Pelvis CT



Pancreas CT



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Segmentation Lessons I

Regarding Deep Learning Methods

- Raw clinical datasets are highly variable
 - Define anatomical boundaries for contours
- Clean, curated training datasets are important
 - 50 curated \approx 250 raw clinical datasets for OARs
 - 350-500 datasets needed to match clinical performance on 99% of cases
- GPU memory is one of the primary technical challenges
- Build the smallest possible model to explain training data
 - Models with 50k and 1.2M parameters are comparable in pancreas
 - Smaller models generalize better to new data (avoids overfitting)
 - Smaller models are easier to train
 - Smaller models infer faster than more complex models

10

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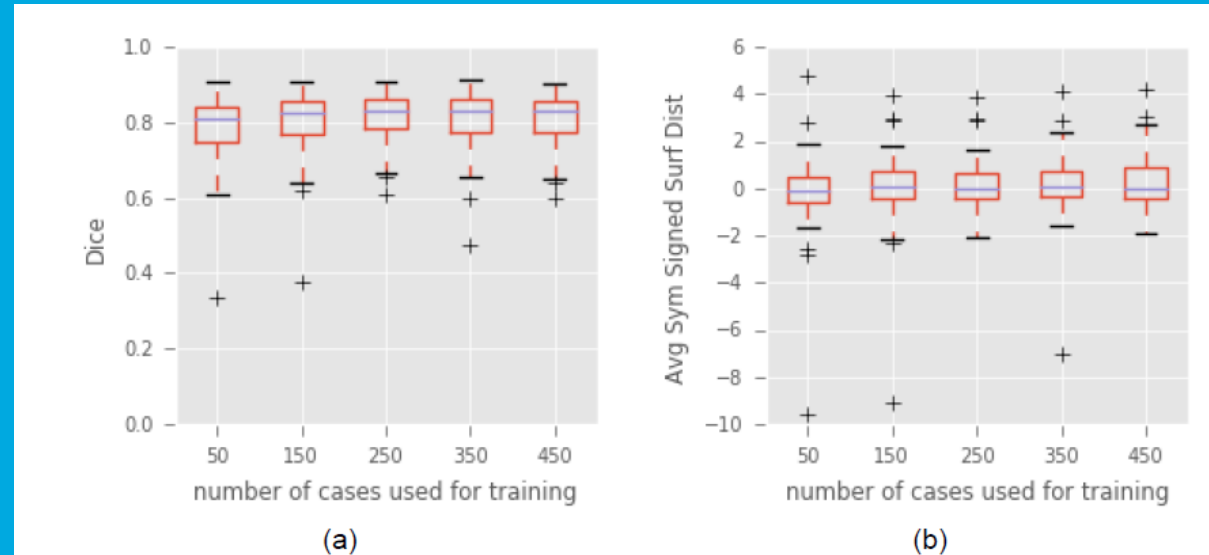


Figure 15: The (a) Dice coefficient and (b) average symmetric signed surface distance were computed on 40 validation cases after training with different numbers of samples.

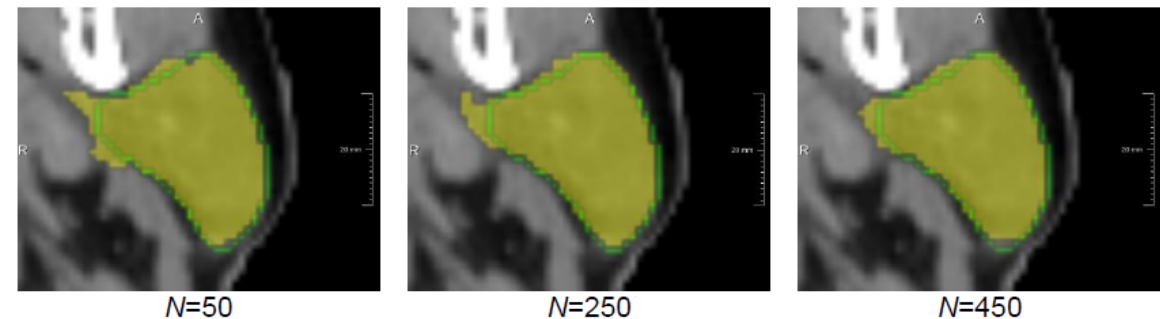


Figure 16: Segmentation result (yellow area) on a validation case and reference (green line) after training on N samples.

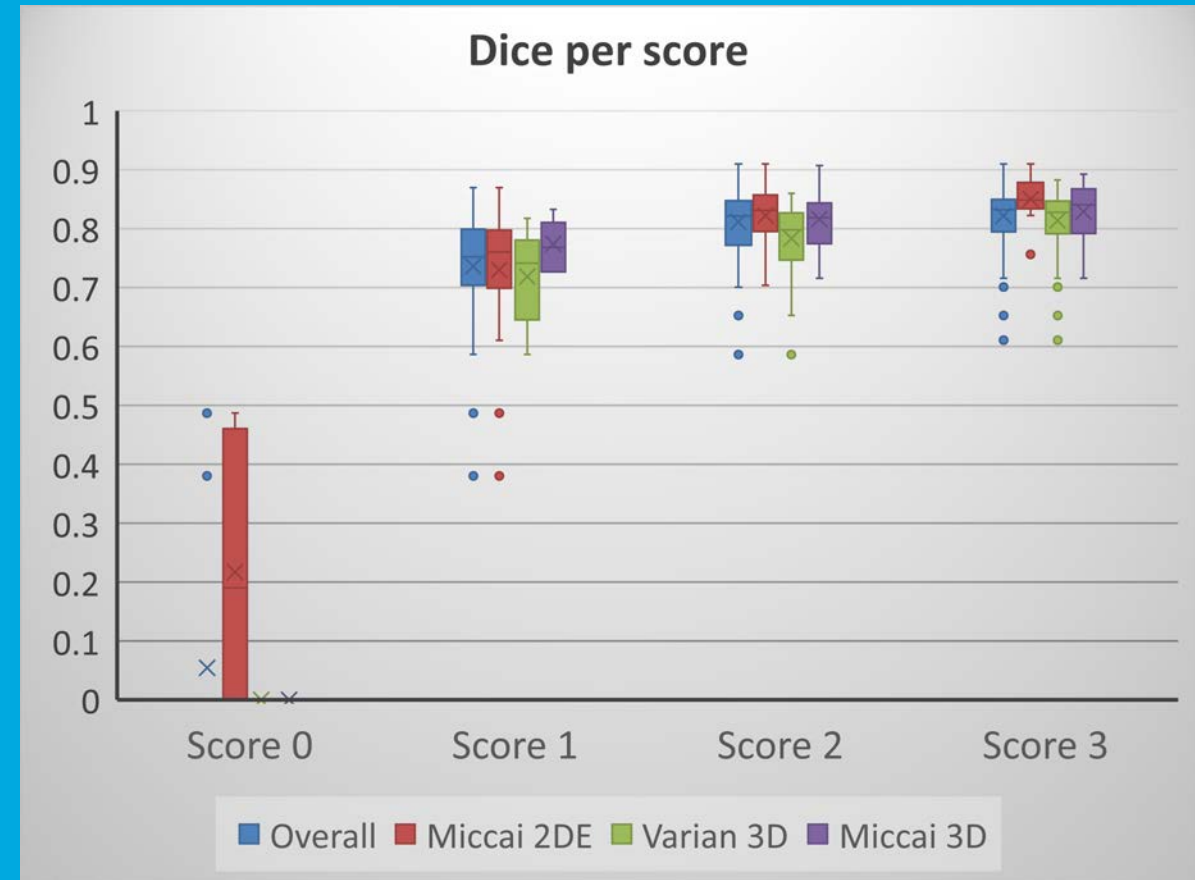
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Segmentation Lessons II

Clinical Usability – Time Savings

- Clinical rating score
 - 0: Not acceptable, manual (re)drawing of the entire structure required
 - 1: Acceptable, major corrections necessary but with acceptable effort
 - 2: Accepted, only minor corrections required
 - 3: Accepted, no corrections required
- Clinical meaning of DICE
 - DICE can distinguish between acceptable / unacceptable at level approx. 0.75
 - DICE cannot distinguish between discarded and kept
 - DICE cannot distinguish between need for minor or no corrections (ratings 2 and 3)

$$Dice = \frac{2 \cdot |mask \cap prediction|}{|mask| + |prediction|}$$



Segmentation Problem Classes

Class 1



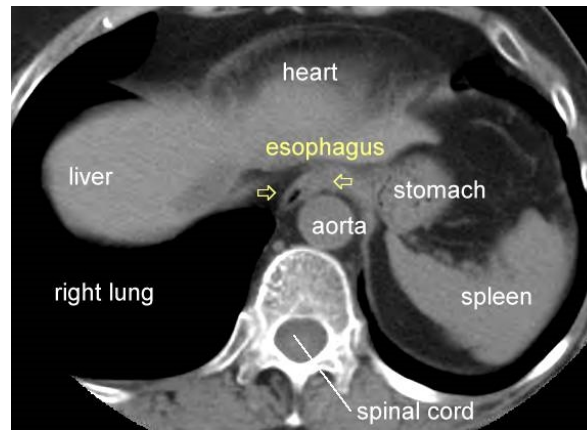
- Visible on CT, common agreement on shape
- Parotids, Bladder



Class 2



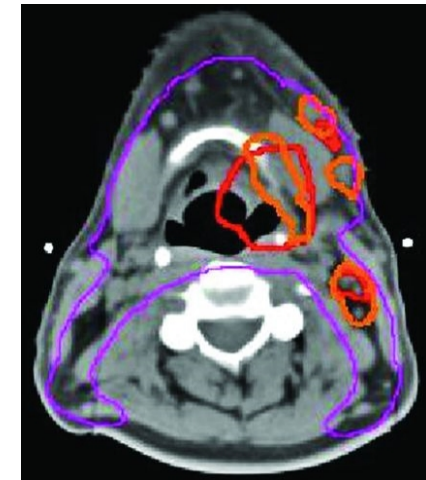
- Ground truth needs multiple clinicians and/or modalities
- Rectum, Esophagus, Uterus, Prostate



Class 3

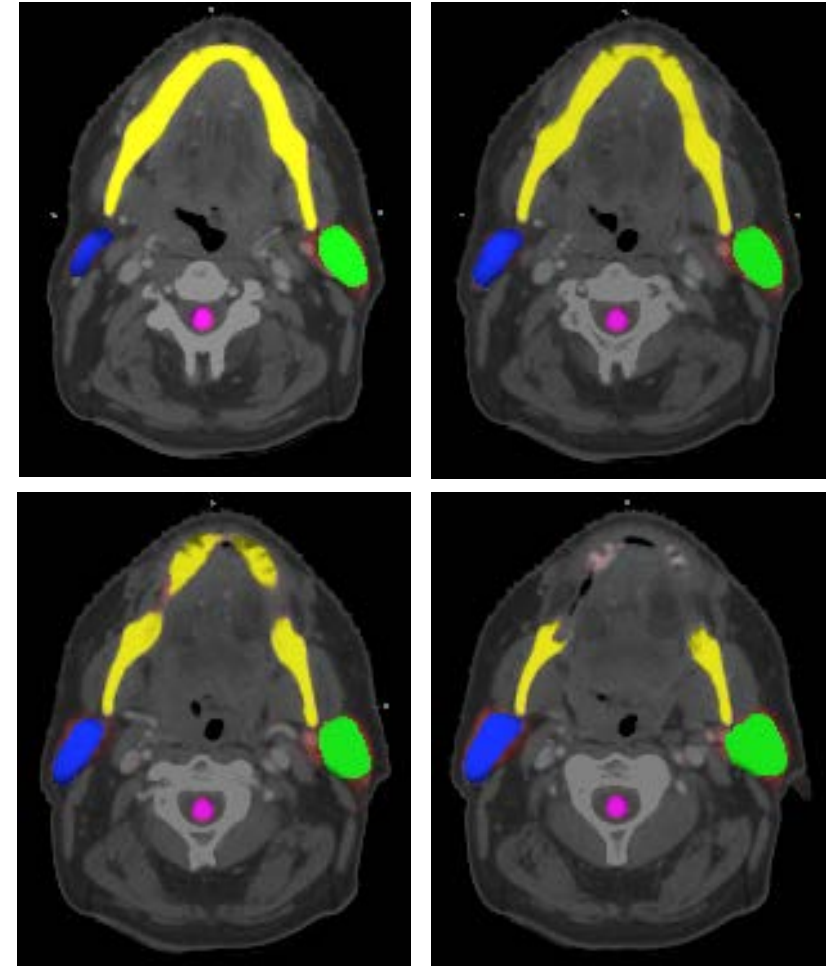


- Ground truth depends on guideline, disease, physician
- nodal targets, oral cavity



Multi-Aspect Head-and-Neck Results

- Multi-aspect model that contours at once:
 - parotids (left and right)
 - 0.83 median Dice
 - mandible
 - 0.90 median Dice
 - spinal cord
 - 0.82 median Dice
- 90/10/35 training/validation/test patients
 - RapidPlan data
- No postprocessing



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Bladder Results

- Bladder model
 - 0.94 / 0.96 mean / median Dice
- 140/20/38 training/validation/test patients
- No postprocessing

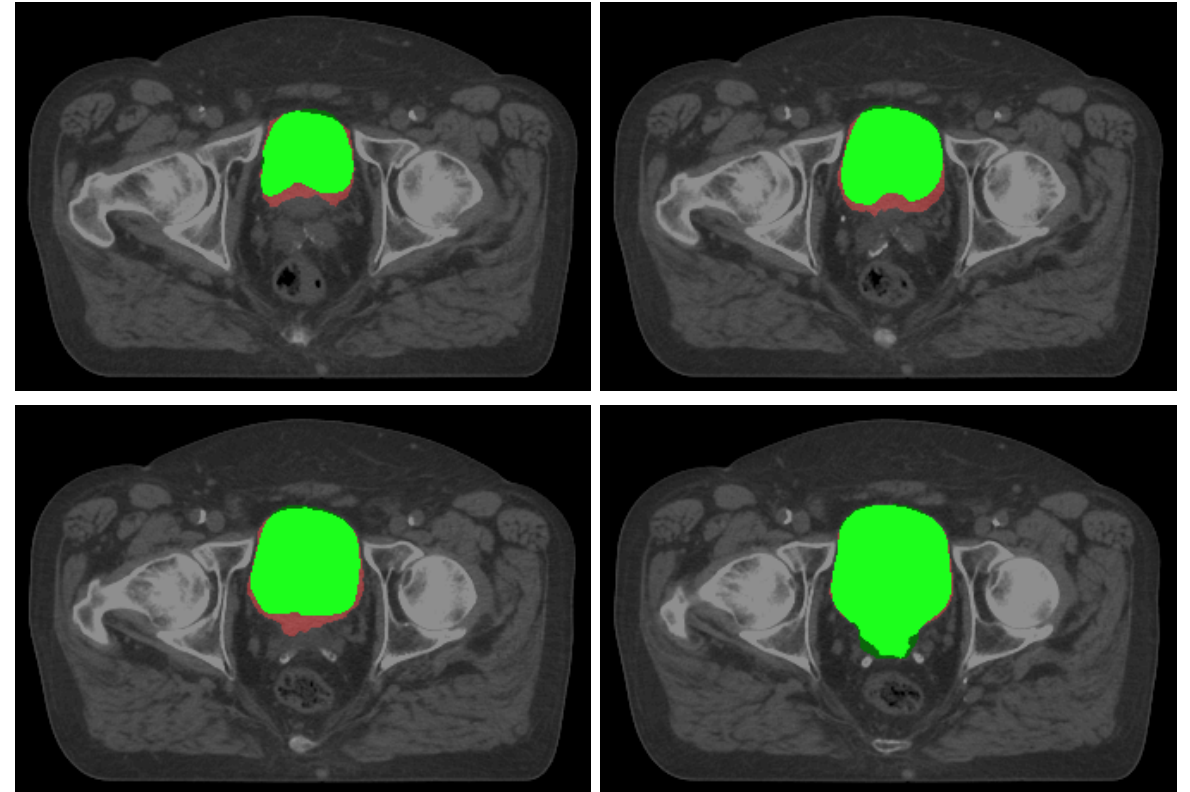
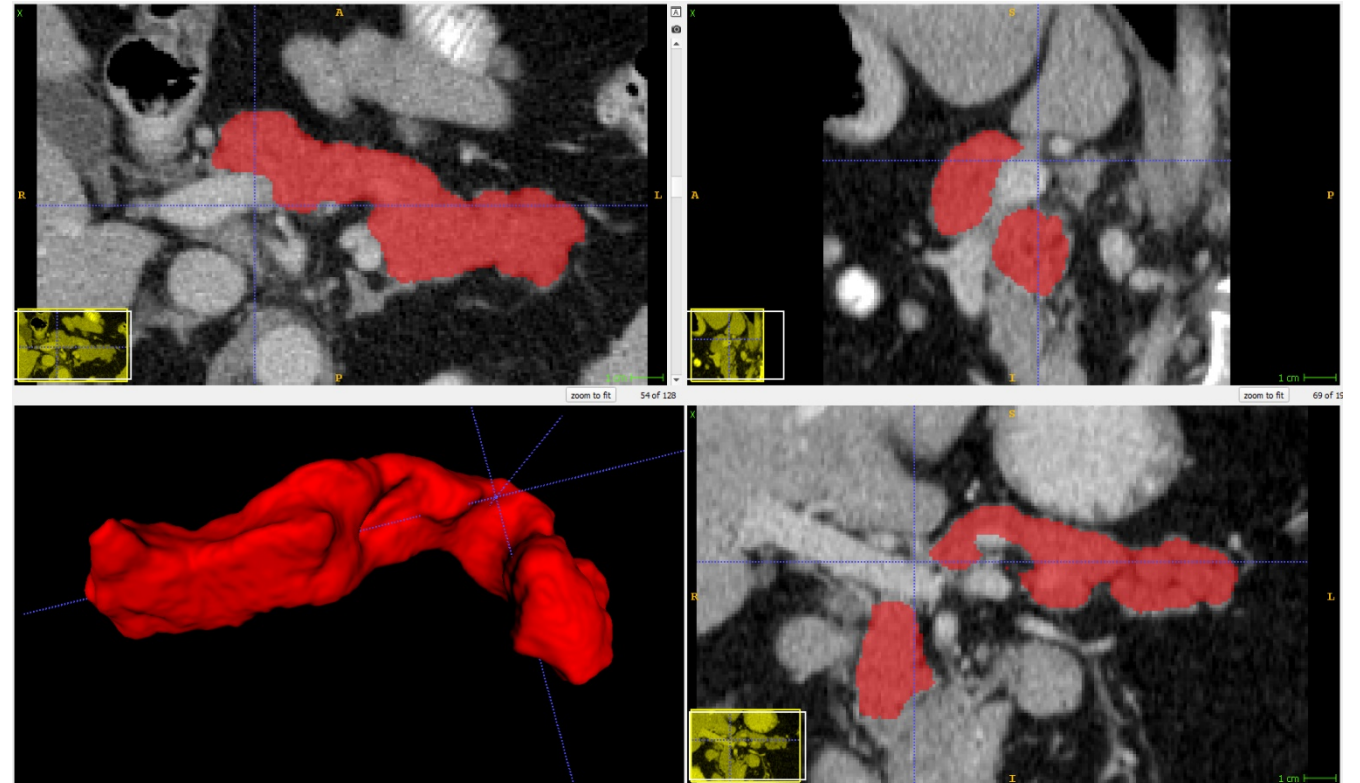


Image Segmentation: Pancreas Simulation-CT

Validation Study (N=10)

Test Case	Mean 3D Surface Distance [mm]	Dice
1	1.1	0.89
2	1.7	0.81
3	1.1	0.89
4	1.1	0.88
5	1.4	0.82
6	1.1	0.86
7	1.4	0.82
8	1.2	0.87
9	1.5	0.84
10	1.2	0.86
Overall	1.3 ± 0.2 mm min: 1.1 mm max: 1.7 mm	0.85 ± 0.03 min: 0.81 max: 0.89



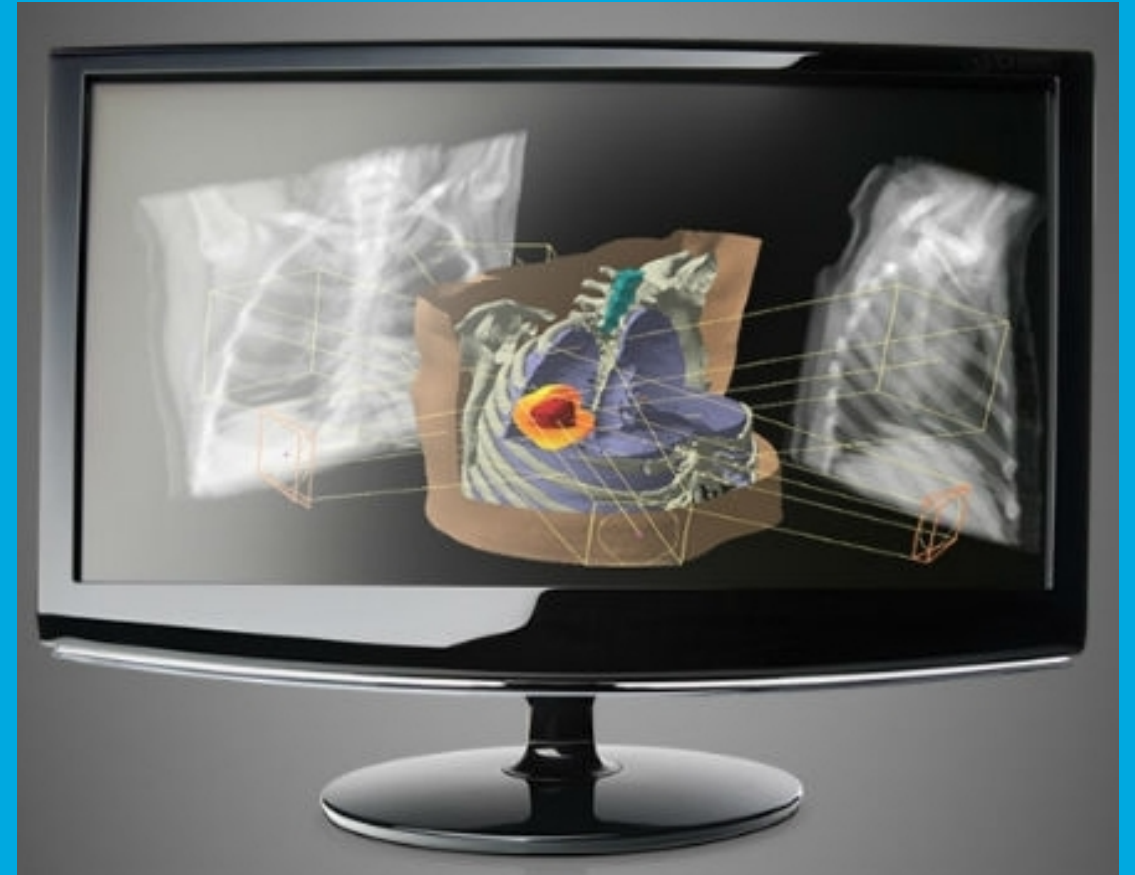
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Automated Treatment Planning

Needs and Opportunities

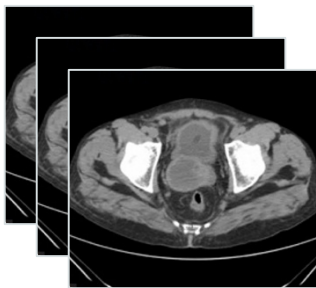
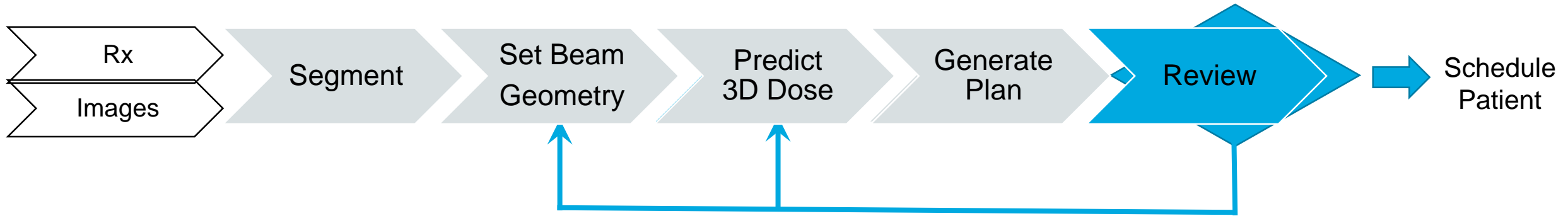
- Market: LMIC have limited access to skilled treatment planners and limiting their access to radiation therapy equipment
- Customer: Developed markets want standardization, high quality and efficiency (time and resource intense)
- Varian: Radiation therapy industry will move quickly on AI for automation
- Opportunities
 - AI can automate many of these processes
 - Training data can be made available
 - Computing power is available and affordable



Automating Treatment Planning

■ Manual Process
■ Automated Process

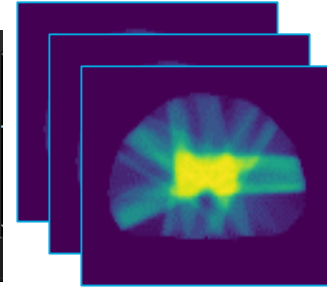
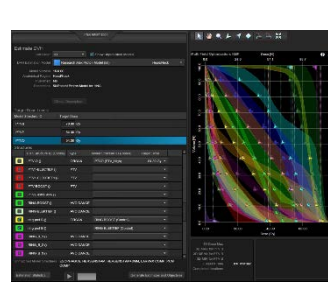
Today's Manual Workflow



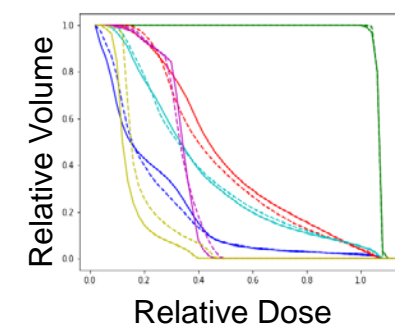
DICOM
CT Image



DICOM
RT Structure Set



DICOM
RT Dose



DVH

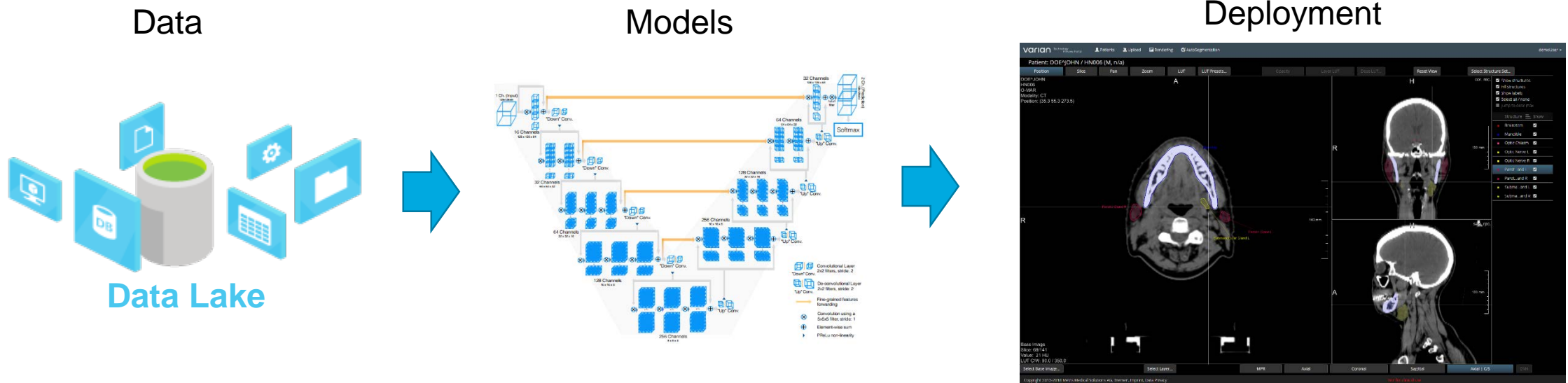


DICOM
RT Plan

Varian's machine learning (ML) environment

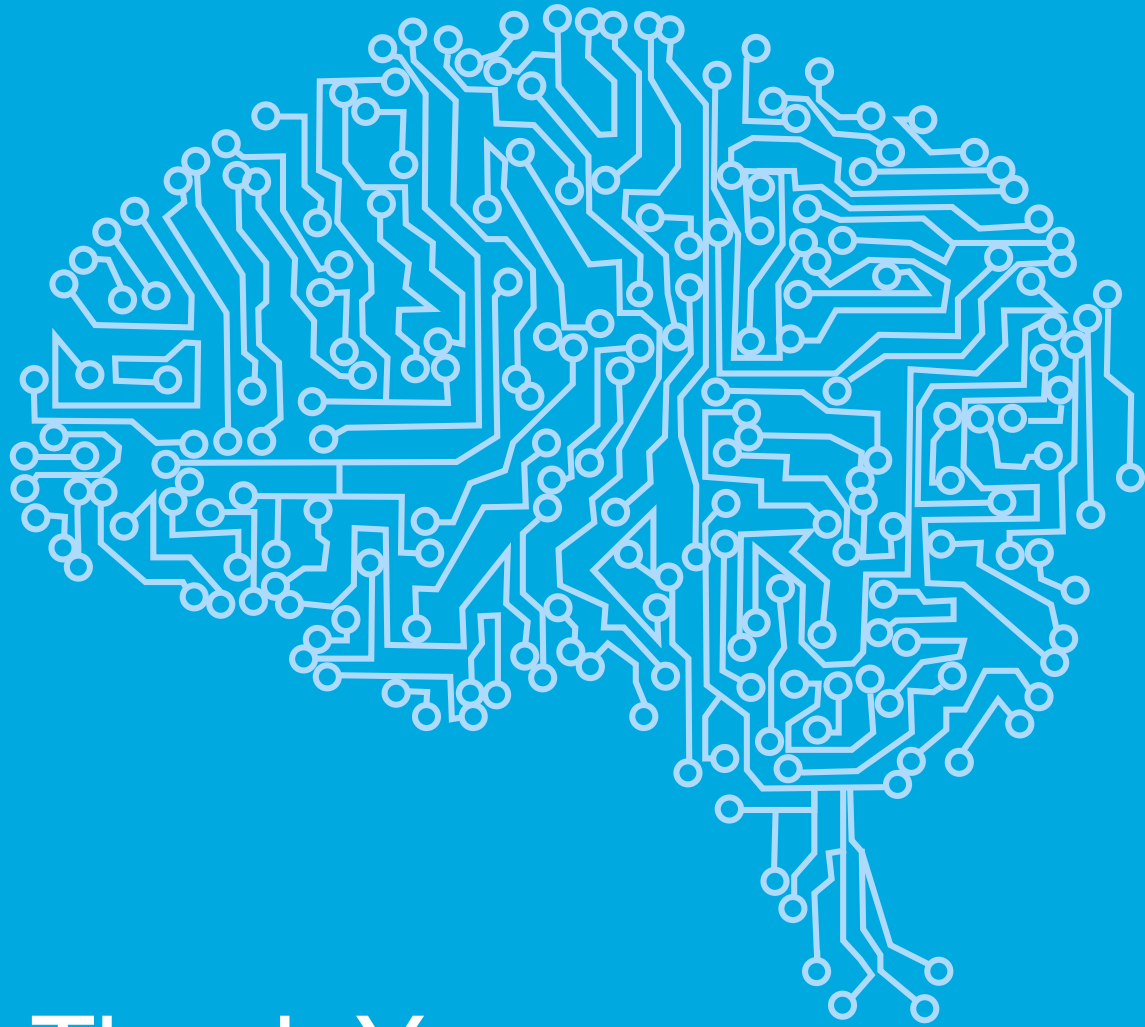
Work in Progress

- Develop a terabyte-scale storage solution for semi-structured clinical data – data consortium
- Establish a ML environment for use by Varian and consortium partners – federated data, distributed learning
- Develop expertise in AI model deployment to guide technical and business decisions



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Thank You

Conclusions

There is a bright future ahead

- Very positive but early evidence that deep learning based segmentation algorithms are outperforming existing ones
- Model responses are fast
- We see various areas in our domain where AI and deep learning can significantly help solving existing shortcomings and increase efficiency
- Varian Medical Systems is increasing it's activities in this field across the development process
- First knowledge based product already on the market
- Deep learning based products are already in development

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