AI for Oncology at Varian – Potential Applications and Opportunities

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

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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

<table>
<thead>
<tr>
<th>Global Leader</th>
<th>$2.6B</th>
<th>7,750</th>
<th>&gt;25</th>
</tr>
</thead>
<tbody>
<tr>
<td>in radiation therapy</td>
<td>FY17 revenues</td>
<td>medical linear accelerators</td>
<td>worldwide training centers</td>
</tr>
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</table>

**A focused cancer company**

<table>
<thead>
<tr>
<th>4,600+</th>
<th>65+</th>
<th>6,400+</th>
<th>52%</th>
</tr>
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<tbody>
<tr>
<td>software installs</td>
<td>proton therapy rooms</td>
<td>employees</td>
<td>international order mix</td>
</tr>
</tbody>
</table>
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
RapidPlan™ Knowledge-Based Treatment Planning
Applying Machine Learning to Predict an Achievable Dose Volume Histogram
driving the dose optimization

Less variation.
More consistency.

Before knowledge deployed

After knowledge deployed

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

<table>
<thead>
<tr>
<th>Ground Truth</th>
<th>Standard FDK Recon</th>
<th>adaptation of Varian MKB 4-D CBCT algorithm</th>
<th>With Machine Learning-based artifact reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Ground Truth Image" /></td>
<td><img src="image2" alt="Standard FDK Recon Image" /></td>
<td><img src="image3" alt="adaptation of Varian MKB 4-D CBCT algorithm Image" /></td>
<td><img src="image4" alt="With Machine Learning-based artifact reduction Image" /></td>
</tr>
</tbody>
</table>
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 dependents on user

• Varian offers automated segmentation tools more than a decade

• Need for fully automate 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
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 ≈ 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
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)
# 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
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)

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Mean 3D Surface Distance [mm]</th>
<th>Dice</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.1</td>
<td>0.89</td>
</tr>
<tr>
<td>2</td>
<td>1.7</td>
<td>0.81</td>
</tr>
<tr>
<td>3</td>
<td>1.1</td>
<td>0.89</td>
</tr>
<tr>
<td>4</td>
<td>1.1</td>
<td>0.88</td>
</tr>
<tr>
<td>5</td>
<td>1.4</td>
<td>0.82</td>
</tr>
<tr>
<td>6</td>
<td>1.1</td>
<td>0.86</td>
</tr>
<tr>
<td>7</td>
<td>1.4</td>
<td>0.82</td>
</tr>
<tr>
<td>8</td>
<td>1.2</td>
<td>0.87</td>
</tr>
<tr>
<td>9</td>
<td>1.5</td>
<td>0.84</td>
</tr>
<tr>
<td>10</td>
<td>1.2</td>
<td>0.86</td>
</tr>
<tr>
<td>Overall</td>
<td><strong>1.3 ± 0.2 mm</strong></td>
<td><strong>0.85 ± 0.03</strong></td>
</tr>
</tbody>
</table>

- min: 1.1 mm
- max: 1.7 mm
- min: 0.81
- max: 0.89
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

Today’s Manual Workflow

- Rx Images
- Segment
- Set Beam Geometry
- Predict 3D Dose
- Generate Plan
- Review
- Schedule Patient

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
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 its activities in this field across the development process
- First knowledge based product already on the market
- Deep learning based products are already in development

Thank You