Incorporating AI Techniques for Medical Imaging

Xavier AI Experts Network October 8, 2021

XAVIER HEALTH

Inspiring collaboration. Leading innovation. Making a difference.

Agenda

XAVIER HEALTH

- Introductions, Mission and Network Co-leaders: 5 minutes
- Presentation: 30 minutes
- Discussion and future topic selection: 25 minutes

AI Experts Network Co-Leaders

Kirthi Devleker
Data Scientist | Global Medical Devices Manager
MathWorks

Szymon Perkowski
Digital Health Technologies – Quality and Systems Lead
Genentech

Arvind Rao
Associate Professor
University of Michigan

Xavier AI Experts Network Mission

XAVIER HEALTH

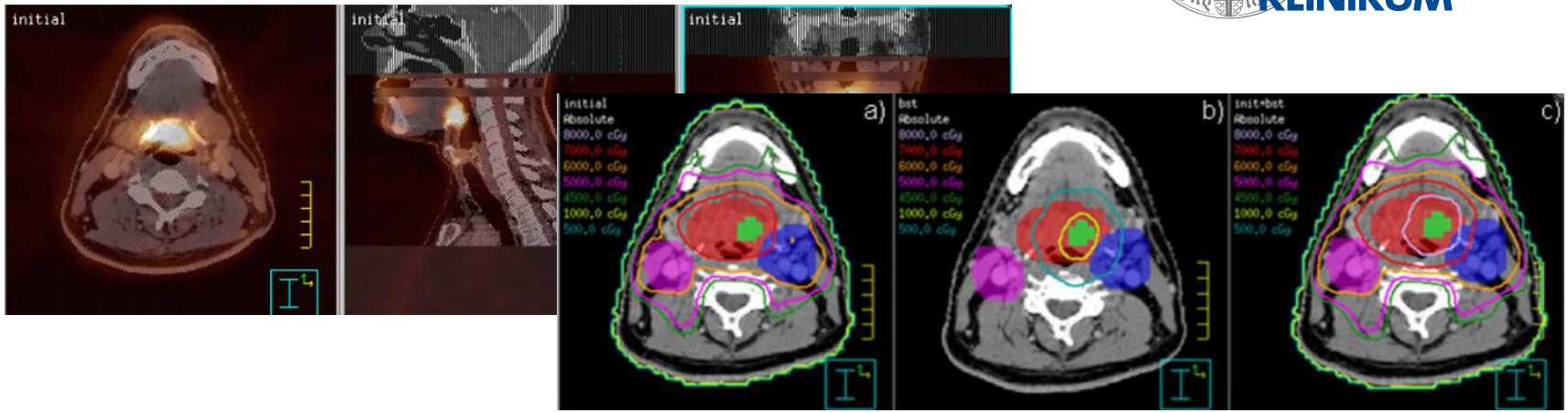
To establish a collaborative forum of AI experts across academia, government, and industry in accelerating the development of artificial intelligence solutions for the benefit of the global healthcare community.

- Discussion and free flow of ideas
- Not aimed at white papers, recommendations, etc.

xavierhealth.org/ai-experts-network

Incorporating AI Techniques for Medical Imaging

Lars Bielak
Researcher
University Medical Center in Freiburg, Germany



3D Tumor Segmentation of Head and Neck Cancer in Multiparametric MRI - Optimization of Input Data

Lars Bielak, University Medical Center Freiburg

2021/10/08

AI Expert

Collecting Experiments, Strasser 2019

Clinical Researcher

AI in Radiology

From Enthusiasm to Skepticism

We should stop training radiologists now. […]

The role of radiologists will evolve from doing perceptual things that could probably be done by a highly trained pigeon to doing far more cognitive things.

Geoffrey E. Hinton (2016)

nature

INNOVATIONS IN · 18 DECEMBER 2019

Rise of Robot Radiologists

Deep-learning algorithms are peering into MRIs and x-rays with unmatched vision, but who is to blame when they make a mistake?

Sara Reardon

https://www.youtube.com/watch?v=2HMPRXstSvQ&feature=youtu.be

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MRI in Freiburg

Research fields in MRI

- Coil development
- Interventional devices
- Sequence development
- Postprocessing
- Imaging techniques (fMRI, …)
- MR safety
- Clinical studies

- AI (segmentation, classification)

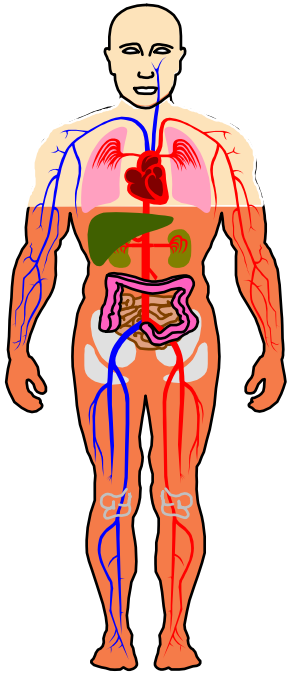
Use AI methods to improve MRI on a basic level

https://www.siemens-healthineers.com/

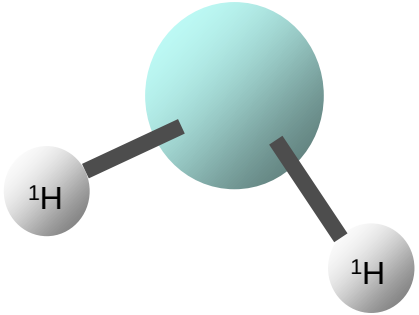
Magnetic Resonance Imaging

Water/Proton Density

H_2O in the Human Body



65 % water



$1g\ (H_2O) = 3.67 \cdot 10^{22}$ molecules

Proton Magnetic Moment

The Source of the MRI Signal

Nuclear Spin

- „Rotation of nuclear charges“
- ^{1}H: $I = 1/2$

Magnetic Moment

- $\mu = \gamma I$
- γ : gyromagnetic ratio
- γ = 42.577 MHz/T for ^{1}H

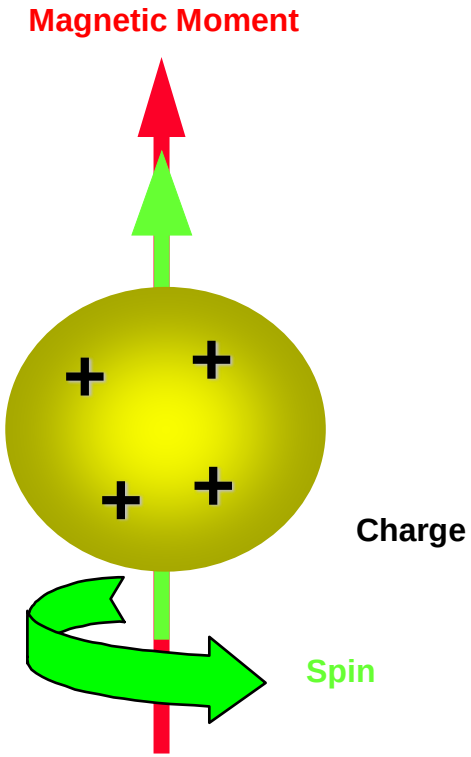


Image Contrast

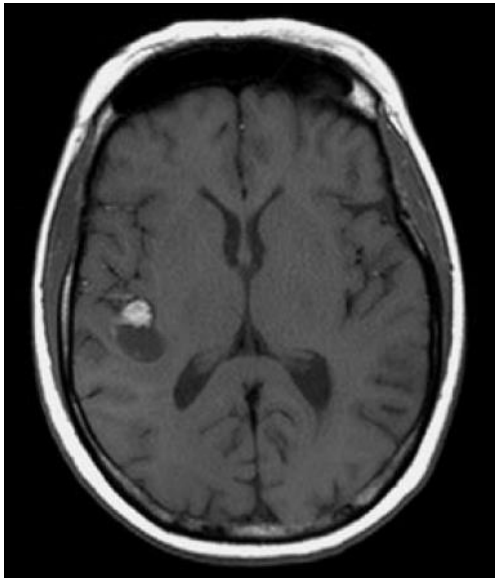
Magnetic Tissue Properties

Longitudinal Relaxation

- Time constant T1
- Return to equlibrium along main magnetic field B_0
- Tissue-dependent
- Changes with B_0
- Can be shortened by contrast agents

Transverse Relaxation

- Time constant T2
- Decay orthogonal to B_0
- Tissue-dependent
- Changes with B_0



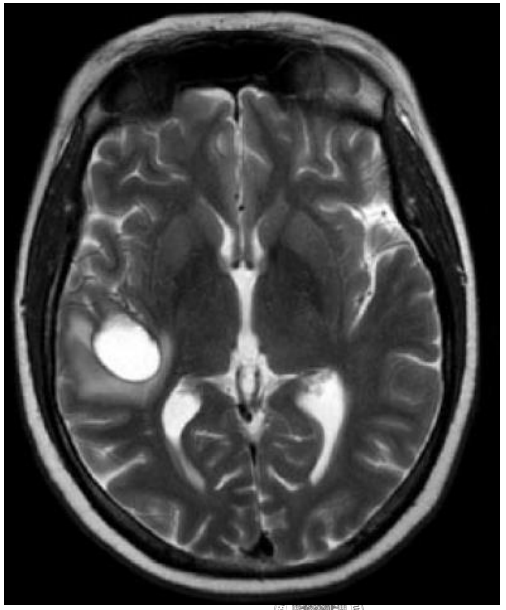
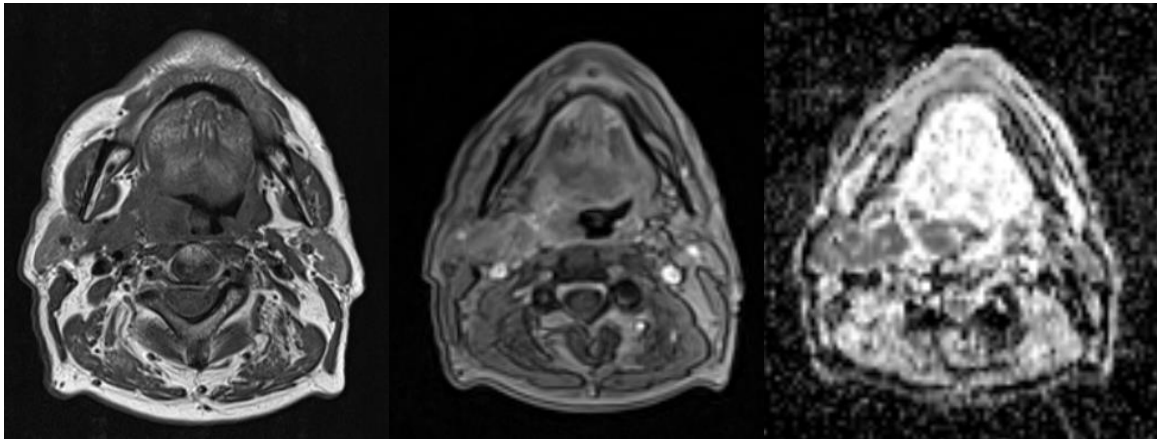


Image Acquisition

Contrasts and differences

- Image contrast is dependent on
  - Sequence & sequence parameters
  - Field strength
  - Patient setup

Images can vastly differ, especially between different sites!



Big Data?

- In research, especially in method development, there is no „Big Data“
- Are small collections of data with lots of content equally valuable?

European Alliance for Personalised Medicine

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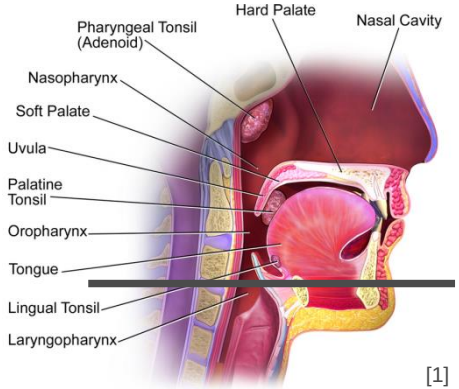
Head & Neck Tumors – The FMISO study

Head & Neck Tumors

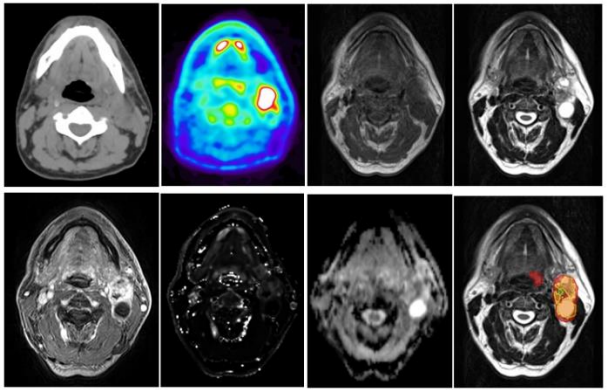
Overview

- Patients affected: > 5 mio. worldwide [2]
- 9th most frequent cause of cancer death (380k pa.) [3]
- Average patient age: 55-65 y
- 5-y survival: 42-64%
- 90% of head & neck cancers have a squamous cell histology (HNSCC)
- Strongly linked to tobacco and alcohol abuse (increased cancer risk of 5-25 fold) [4]

- Key treatment options: Radiation therapy (in combination with chemo therapy) or surgery



[1]

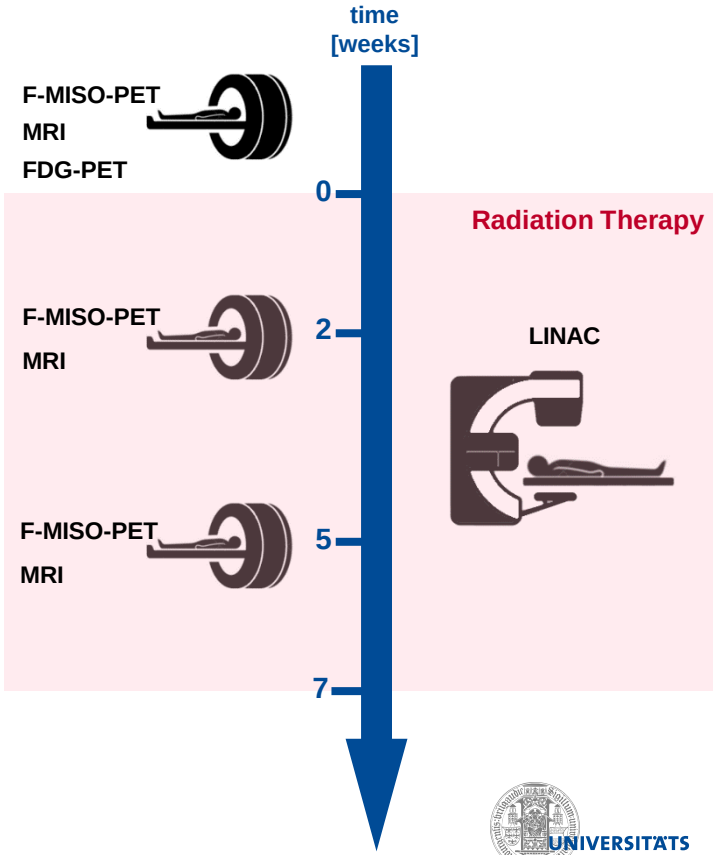


[1] https://de.wikipedia.org/wiki/Tonsille
[2] Stewart BW et al. WHO eds. World Cancer report 2014
[3] Vos T et al., The Lancet 2016;388:1545–1602
[4] Gourin CG, Podolsky RH, The Laryngoscope 2006;116:1093–1106

FMISO Study Protocol

- ^{18}F-FMISO (fluoromisonidazole) = PET tracer molecule for hypoxia imaging

- Duration: 7 weeks
- 3 MRI in total
- 3 PET-CT in total



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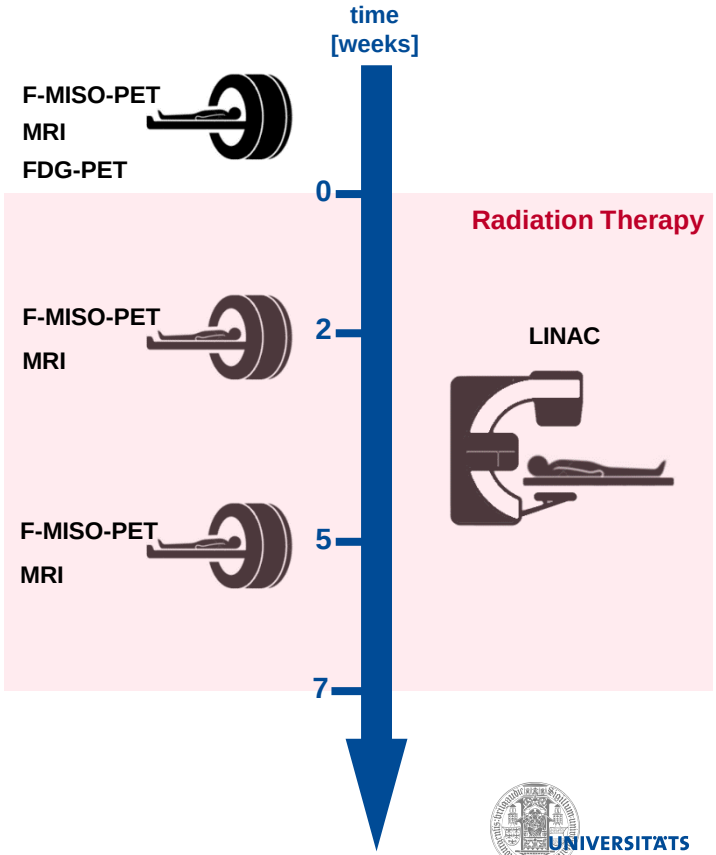


Radiation Therapy Planning

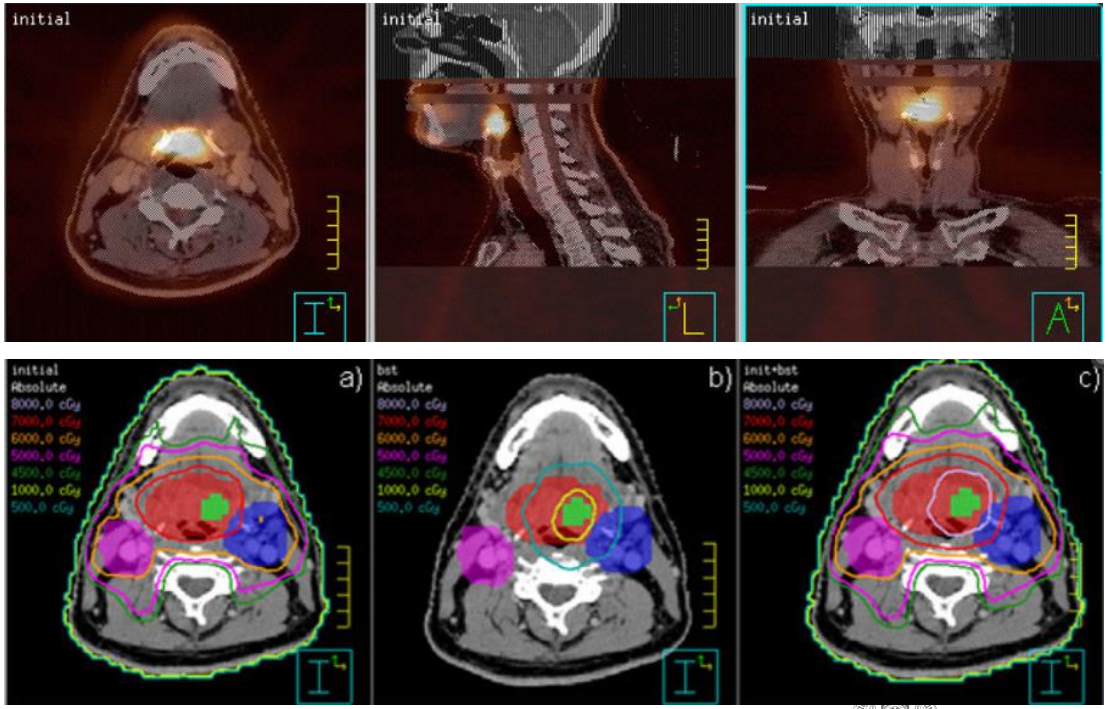
A Tedious Enterprise

Tumor Segmentation

- Definition of Gross Tumor Volume (GTV)
- Manual
- Interactive
- Based on co-registered input data (CT, MRI, PET)

Radiation Planning

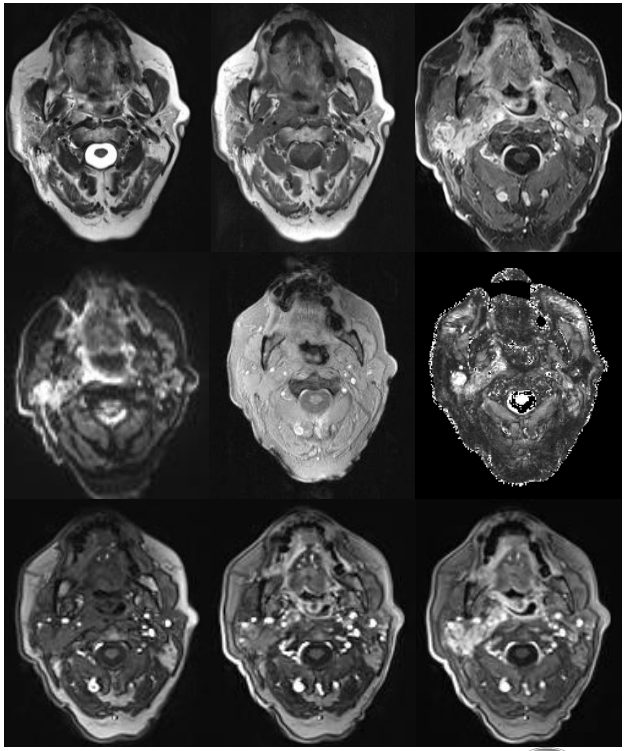
- Definition of Planning Target Volume (PTV)
- Definition of dose application scheme
- Dose calculation and verification



Hendrickson K, et al.
Radiother Oncol. 2011;101(3):369-75.

FMISO Study Protocol

MRI Method	# images
Pre contrast T2w:	45
Pre contrast T1w:	45
Diffusion weighted :	3*25 + 25
Multiecho T2w:	12*25 + 25
Dynamic contrast enhanced (DCE):	36*20 + 3*20
Post contrast T1w:	4*160
Total amount of images:	1935



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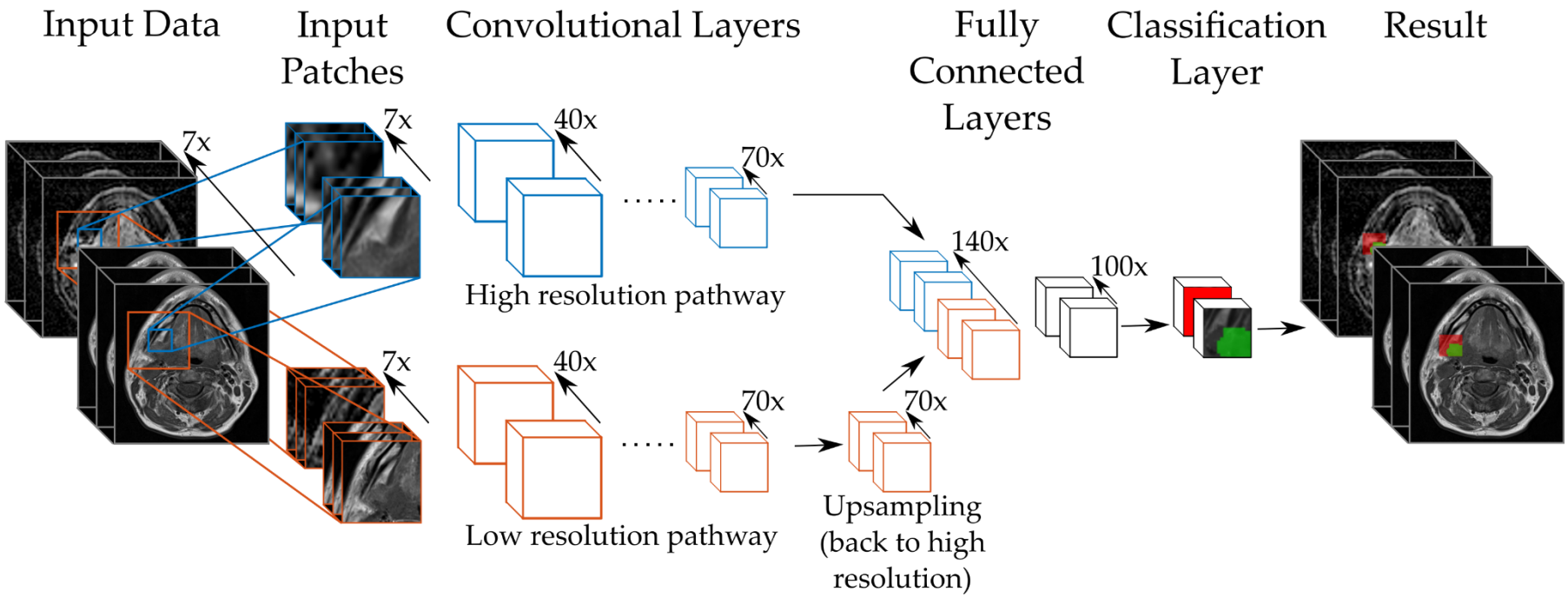
FMISO Study Protocol

- Patient setup with fixation mask
- Protocol duration: 35-60 min
  - Extremely uncomfortable
  - Low patient compliance

Tumor Segmentation using CNNs

Network Architecture

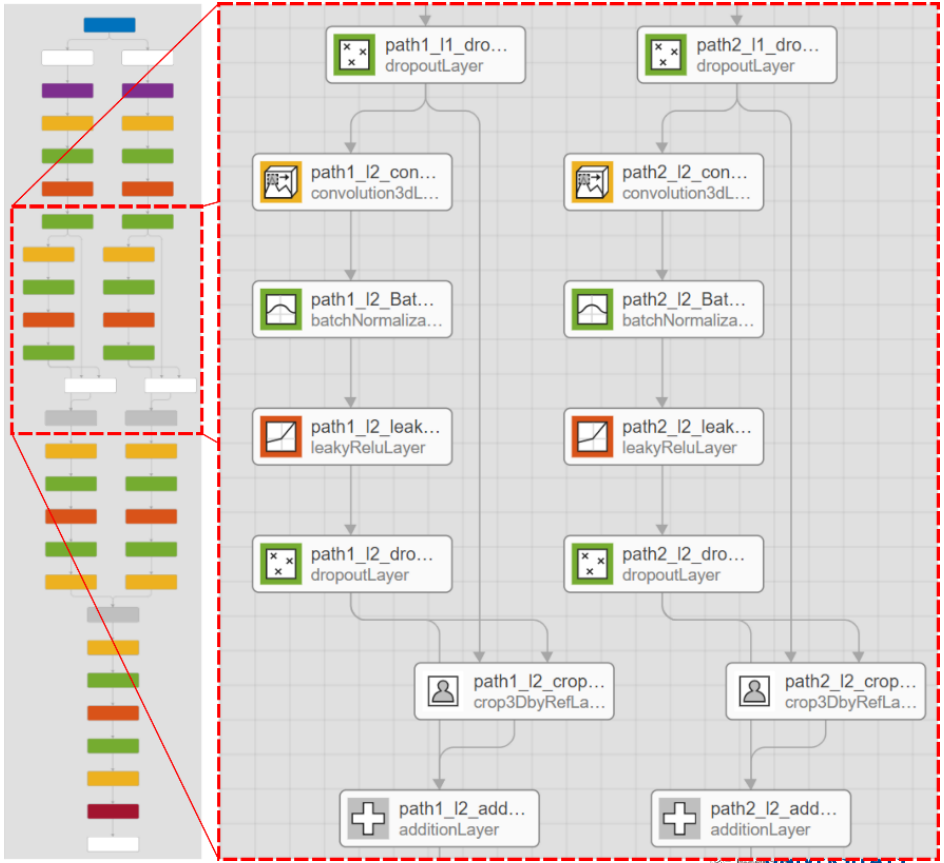
DeepMedic [1]



[1] Kamnitsas et. al., Med. Image Anal. (2017)

Implementation

- Matlab backend
- Cooperation with Mathworks developers
- Networks run on cloud server



Pre-Processing

Interpolation

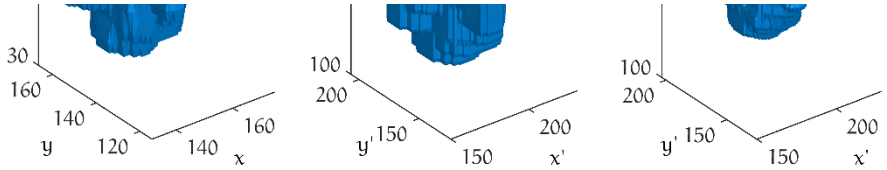
Different image resolutions

- In plane and trough plane

Ground truth segmentations defined as 2D structures

- Conversion to 3D
- Interpolation to new Matrix

SEQUENCE	TE [ms]	TR [ms]	RESOLUTION [mm^3]	COMMENTS / OTHER
T_1 FSE	11	504	0.7×0.7×4	
T_2 FSE	100	5000	0.7×0.7×4	
Multiecho GRE	5–33	600	1.1×1.1×3	n_{Echoes}=12, reconstructed map: T_2^*
ss DW-EPI	71	3500	2×2×3	b={50, 400, 800} s/mm^2 reconstructed map: ADC
rs DW-EPI	51	2510	2×2×3	b={50, 400, 800} s/mm^2 reconstructed map: ADC
DCE	1.56	4.65	1.4×1.4×3	$n_{Timepoints}$=36, reconstructed maps: K^{trans}, k_{ep}, v_e
T_1 VIBE Dixon	2.45	8.67	0.45×0.45×2	Post contrast. Water image used.



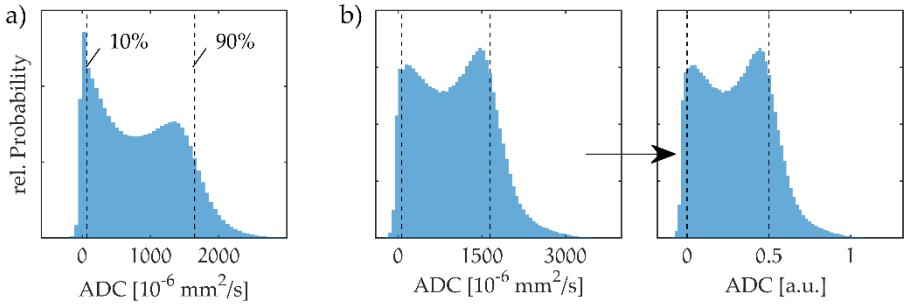
Pre-Processing Normalization

Contrast weighted:

- Based on all available data
- Data masking
- Modified z-score normalization (mean and std = 0.25)

Quantitative:

- Based on all available data
- Data masking
- Histogram approach to preserve physical meaning



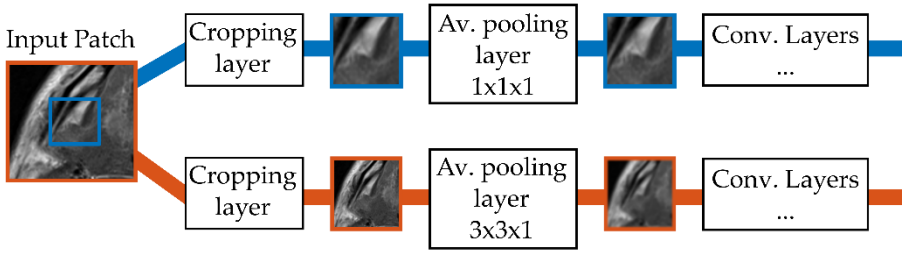
Parameter Optimization

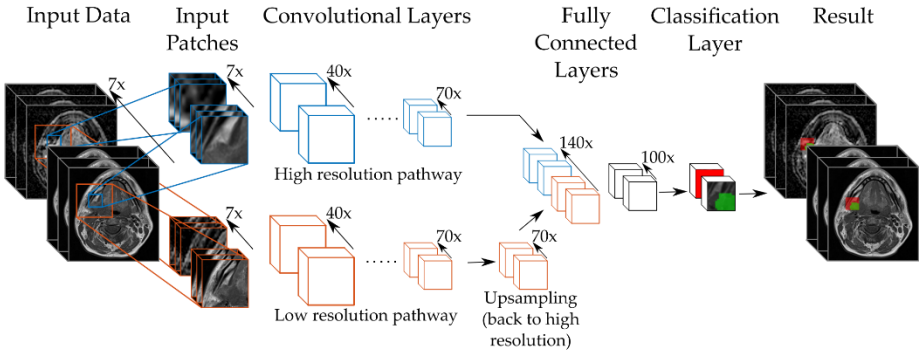
How do you optimize a large network with a huge space of hyperparameters?

- Bayesian optimization?
- Educated guessing?

Result:

- 10+3 conv. layers
- 104 + 150 FM per layer
- Batch-Norm, leaky ReLu activation, dropout (20%)
- Dice Loss
- Input size: 78x78x8 (38x38x8) px
  0.45x0.45x2 mm

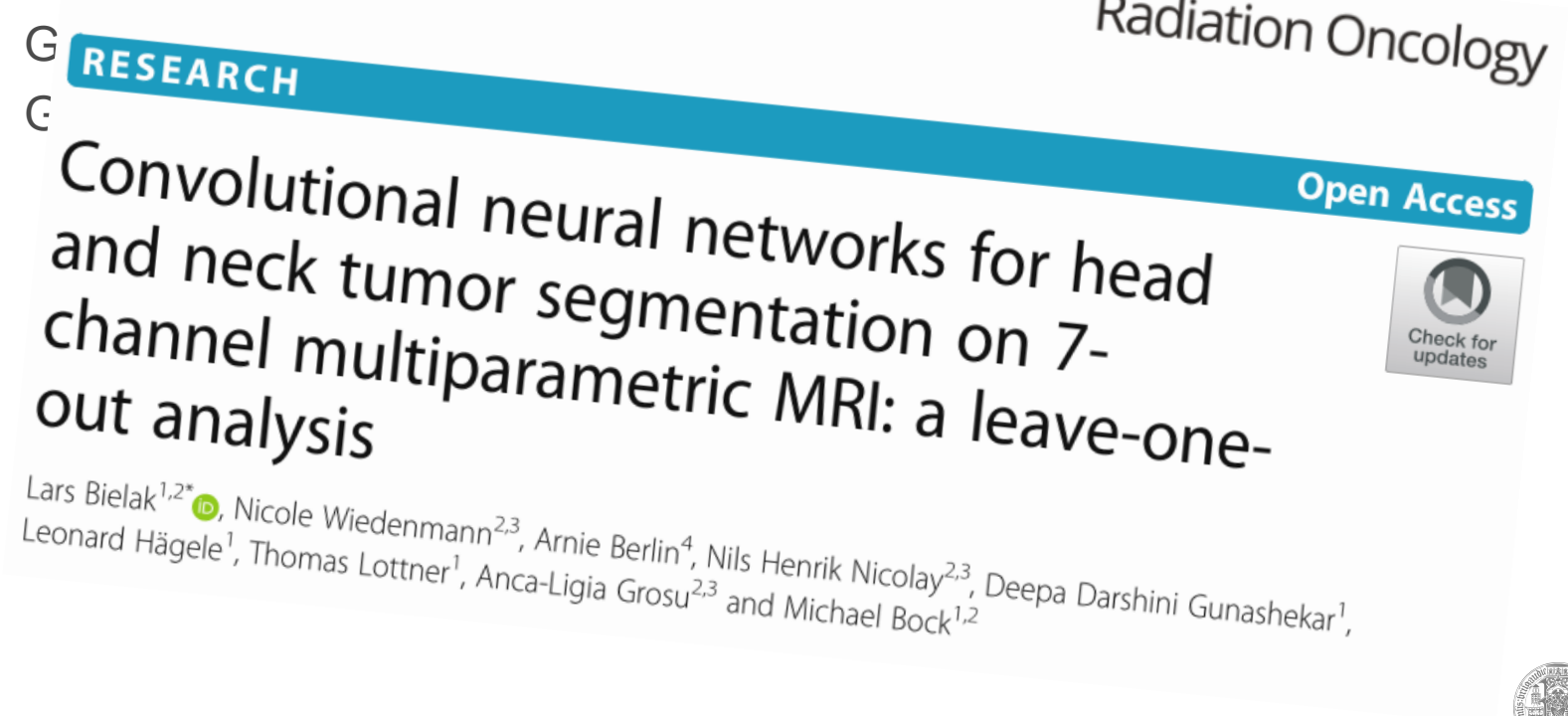




The Scientific Question

Which sequence (contrast) is the most important?

- G
- G



Bielak et al. Radiation Oncology

RESEARCH

Open Access

Convolutional neural networks for head and neck tumor segmentation on 7-channel multiparametric MRI: a leave-one-out analysis

Lars Bielak[1,2*], Nicole Wiedenmann[2,3], Arnie Berlin[4], Nils Henrik Nicolay[2,3], Deepa Darshini Gunashekar[1], Leonard Hägele[1], Thomas Lottner[1], Anca-Ligia Grosu[2,3] and Michael Bock[1,2]

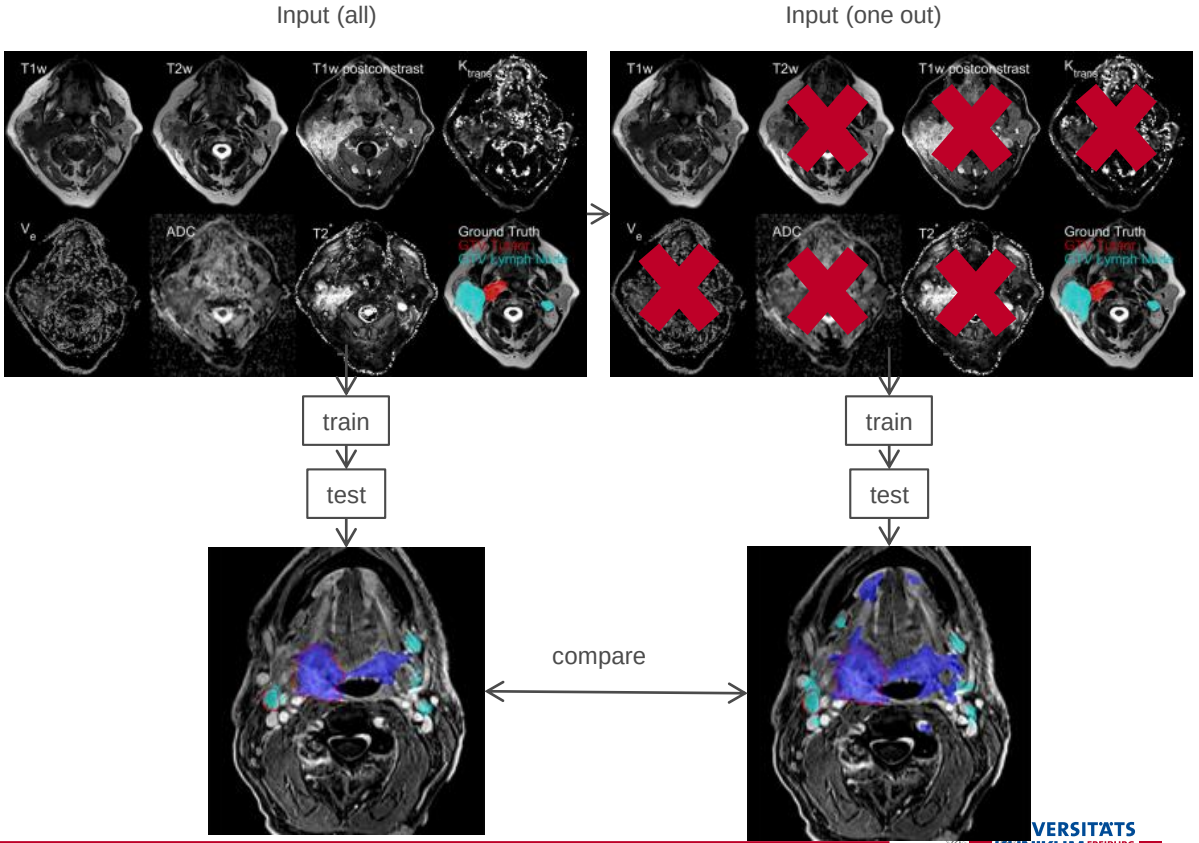
Check for updates

Methods

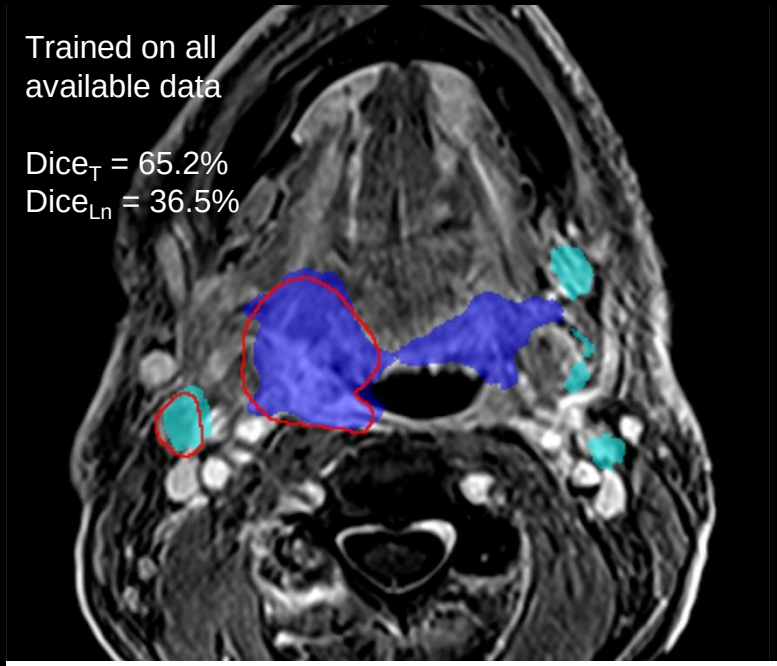
Leave one out Analysis

1. Split data into training and testing sets
2. Train a network on a training set with all available channels
3. Leave one of the channels out
4. Compare results with respect to segmentation performance on the test set
5. Repeat steps 3-4 with a different channel

- 33 Patients total, imaged at weeks 0, 2 and 5 = 99 datasets
- 44 datasets with complete imaging information
- 36 datasets with acceptable image quality
  - → **Very small dataset for deep learning!**
  - → Decrease size of test set to 1
  - → Repeat steps 1-5 with a new test set



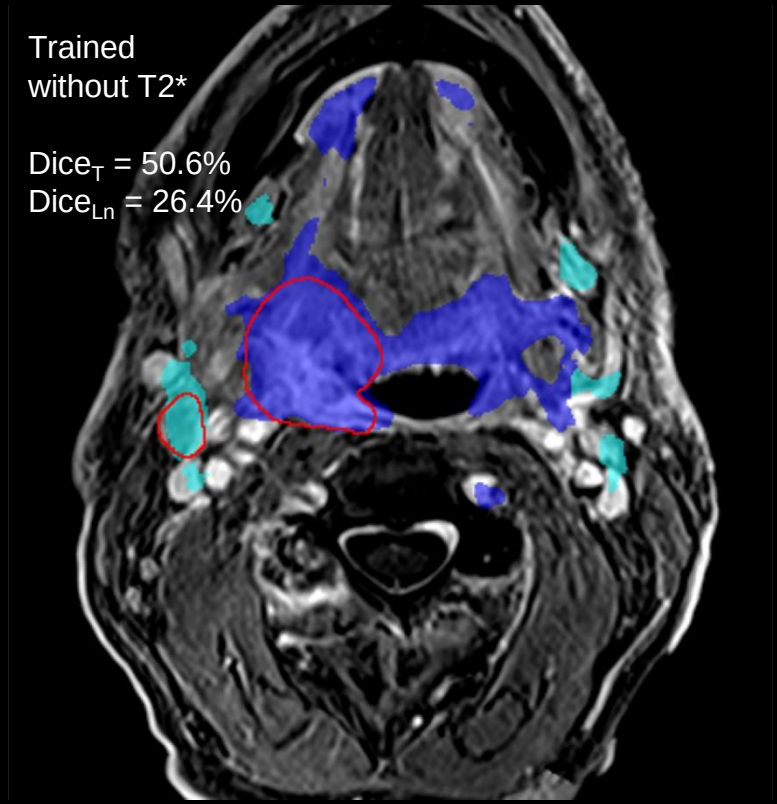
Segmentation Results



Trained on all available data

$Dice_T$ = 65.2%
$Dice_{Ln}$ = 36.5%

$$\text{Dice} = \frac{2|X \cap Y|}{|X| + |Y|} = \frac{2TP}{2TP + FP + FN}$$

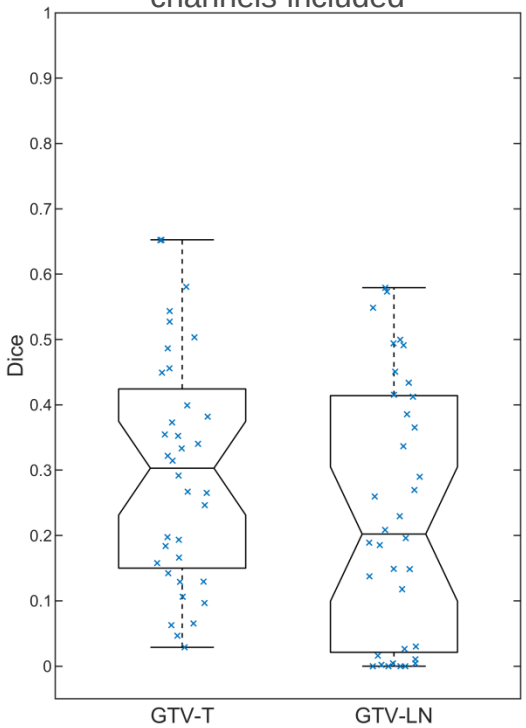


Trained without T2*

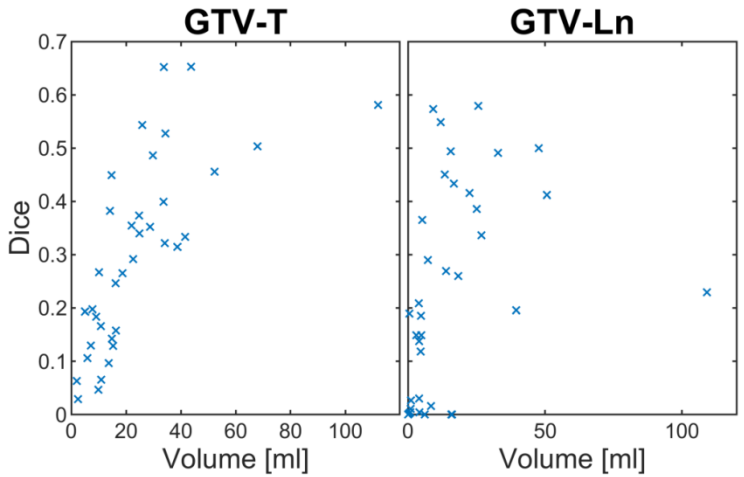
$Dice_T$ = 50.6%
$Dice_{Ln}$ = 26.4%

Results

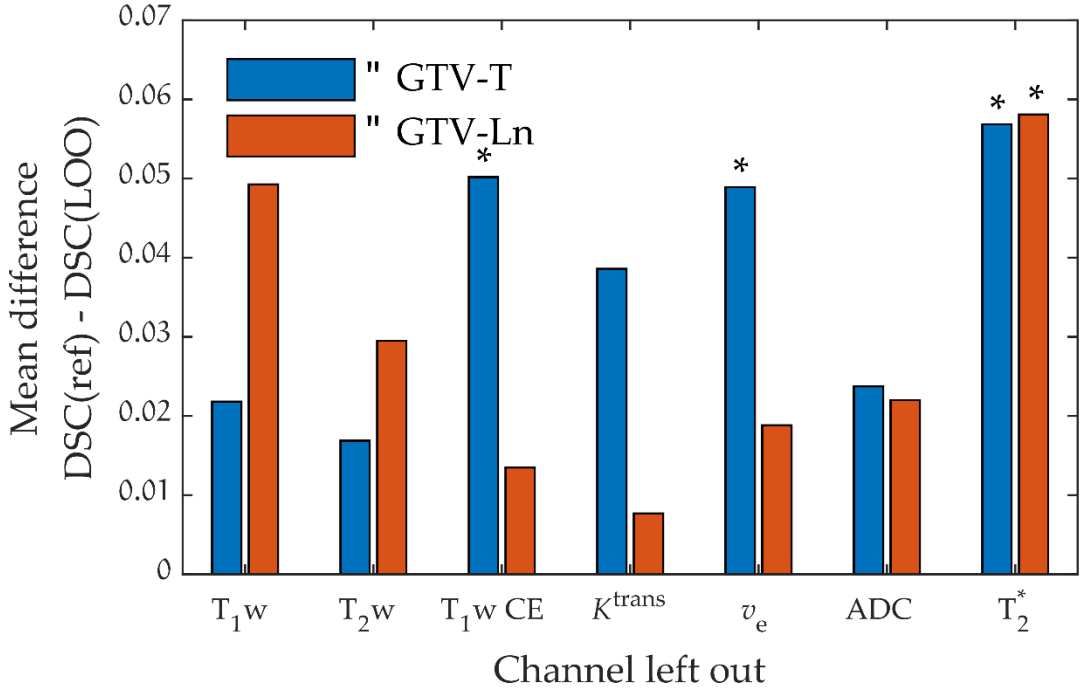
Overall segmentation performance with all channels included



Segmentation performance vs volume to segment



Input Channels Results



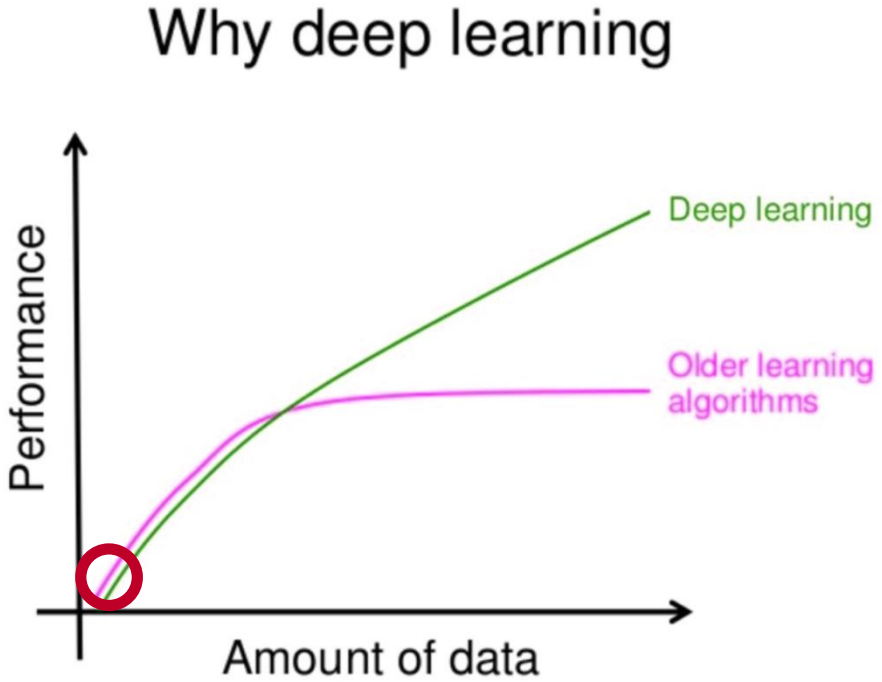
Summary

Summary

- Based on a “small” database, we identified important input channels for HNSCC tumor segmentation
- T2* contrast has most influence on both, GTV-T and GTV-Ln

- Excellent data quality
- Excellent ground truth

- Few data, questionable generalization
- Histology as ground truth?



https://machinelearningmastery.com/improve-deep-learning-performance/

AI Expert

Clinical Researcher

European Alliance for Personalised Medicine

Big data methods on small data collections?

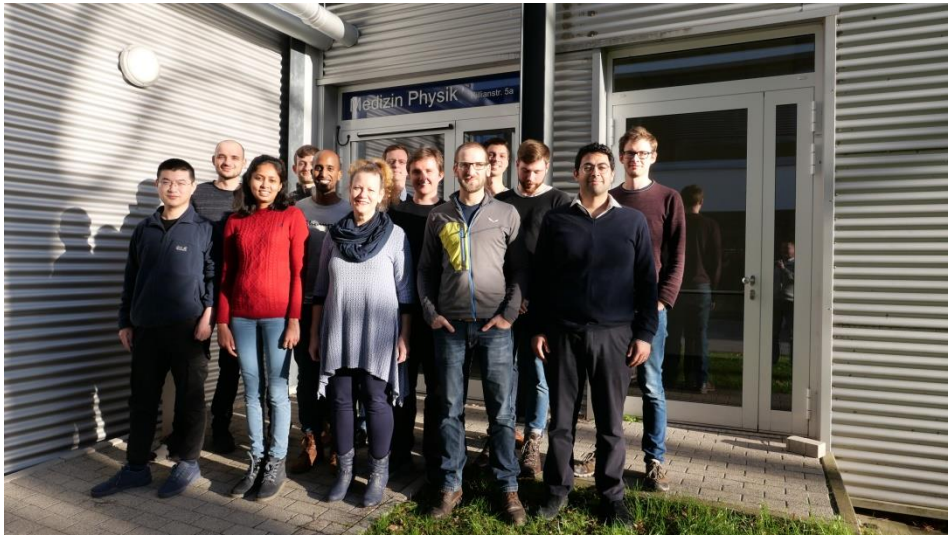
Yes, we can; and we should!

Bridging the gap between basic science an AI users

Credit: B. MELLOR, https://doi.org/10.1038/453840a

Thank you!

Experimental Radiology



Department of Radiation Oncology
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Raluca Stoian

MathWorks®
Arnie Berlin
Alex Taylor

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XAVIER HEALTH

Discussion
and
future topic Selection

Upcoming Xavier AI Experts Network Meetings

XAVIER HEALTH

Join your peers for the next Xavier AI Experts Network meetings:

December 3, 2021, 12pm to 1pm ET

Alexej Grossman (FDA)

Issues in reference standard determination for performance evaluation studies of AI/ML-based medical devices

2022 meetings – First Friday of even months

February 4	**August 5**
April 1	**October 7**
June 3	**December 2**

Thank you for participating today!

XAVIER HEALTH

Join us for more from the AI community!

- **Xavier AI Summit**
  - Workshop - Virtual Sprints: Nov. 4 & 5, 2021
  - Main Sessions - Virtual Sprints: Nov. 9, 10 & 12, 2021
- **Xavier AI Working Teams**
  - AI in Operations (AIO)
  - Good Machine Learning Practices (GMLP)
  - AI at the Point of Care (AI@POC)
- **Xavier AI Blog**
  - xavierhealth.org/artificial-intelligence-blog

And join us on slack

xavierhealth.org/ai-experts-network