LMU KLINIKUM
Munich

Clinical Data Science

Clinical Data Science in Radiology

German Data Science Day| Department of Radiology

July 14, 2022 | Prof. Dr. rer. nat. Michael Ingrisch

Clinical Data Science in Radiology Group












Mission statement

LMU KLINIKUM

Clinical Data Science in Radiology

Clinical questions

Diagnosis

Prognosis

Therapy

Analysis

Statistical modeling

Machine Learning

Image analysis

Computer vision

Image data

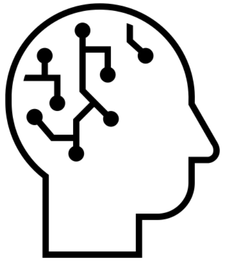
X-ray

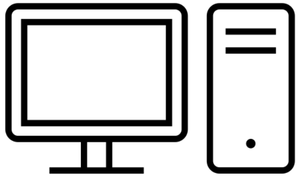
CT

MRI

Clinical information

Artificial Intelligence
Learning machines





Strong AI

Applies intelligence to **any** problem

Might have conciousness and mind

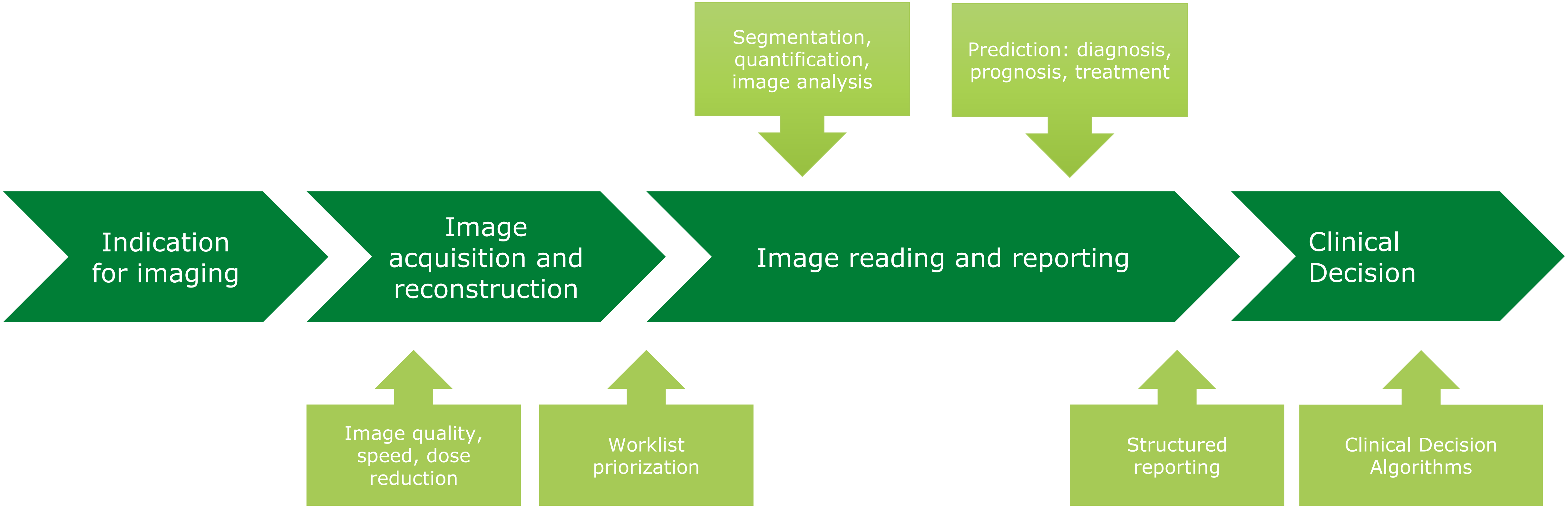
Weak AI

Can solve a single problem

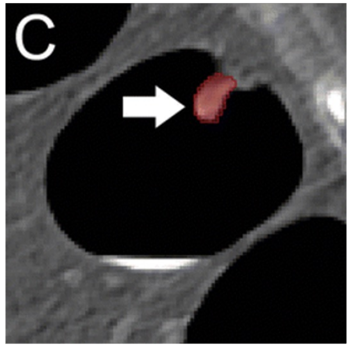
Learns through experience, cannot extrapolate

Learning machines

Tasks for AI in radiology
The radiological value chain



Translation of AI
From scientific proof-of-concept to clinical application



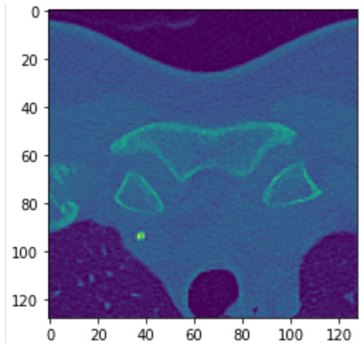
netzwerk universitäts medizin

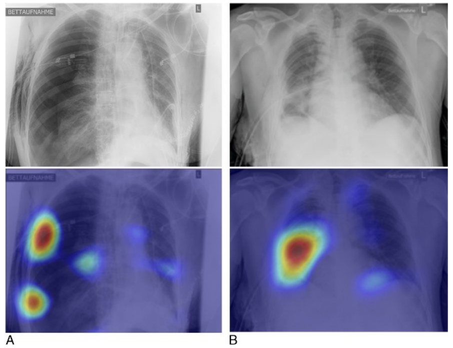
mint medical

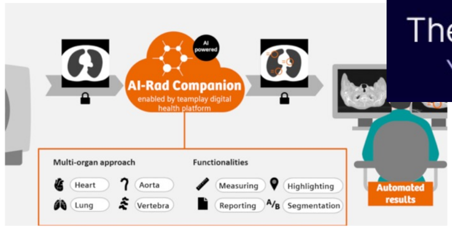
mediaire | DIGITAL INNOVATION IN RADIOLOGY

CORE

Algorithms and proof-of-concept → External validation → Prototypes and platforms → Products

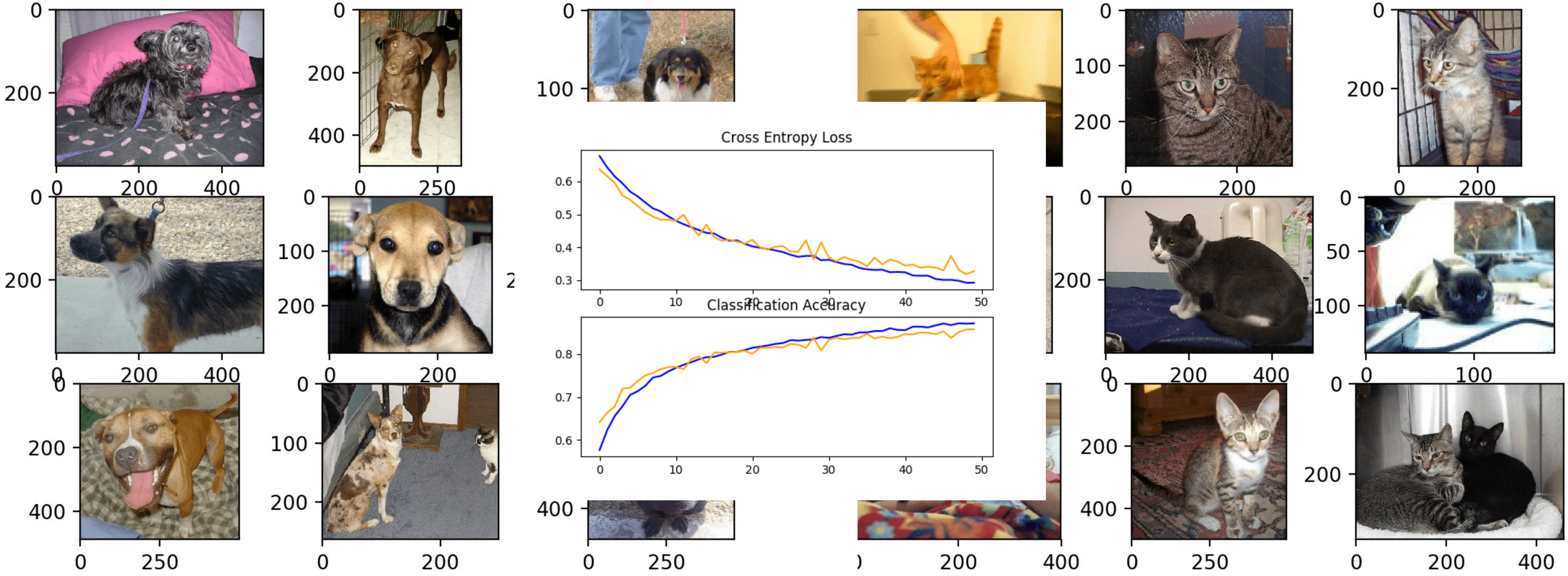






deepcOS
The Radiology AI Platform
Your effortless access to AI

Image classification
Cats vs dogs



https://machinelearningmastery.com/how-to-develop-a-convolutional-neural-network-to-classify-photos-of-dogs-and-cats/

Clinical data science in radiology
Roadmap

Radiology: mapping of image to clinical label – a supervised ML problem

Ask the right questions, and answer them with the right data

Finding the right data: unsupervised and weakly supervised approaches?

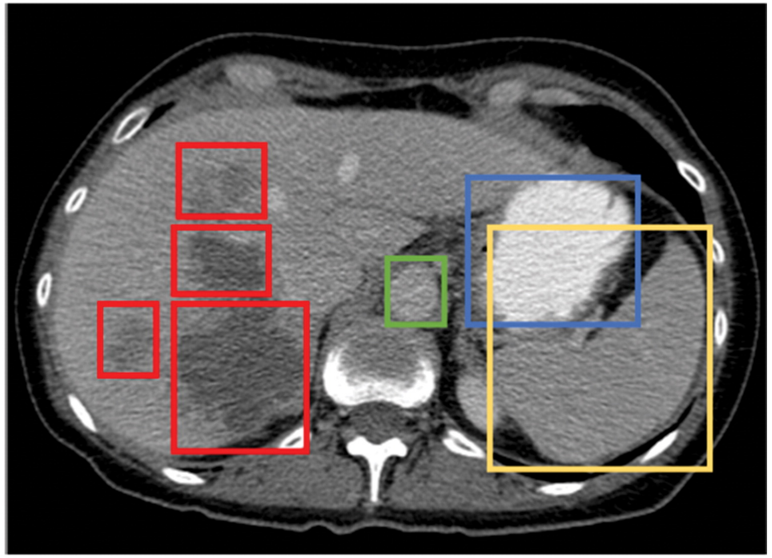
Requirements and adoption barriers for AI in radiology

https://www.kaggle.com/competitions/dogs-vs-cats/overview/description

Supervised machine learning in radiology
Applied computer vision

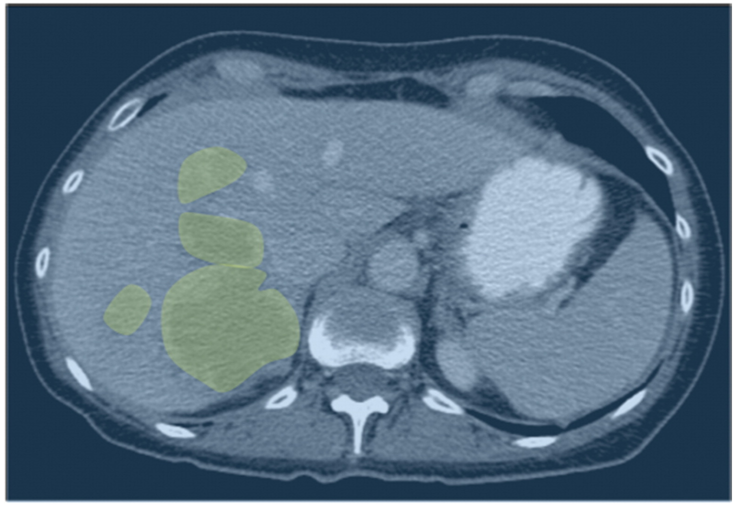
Classification: liver metastases

Object detection



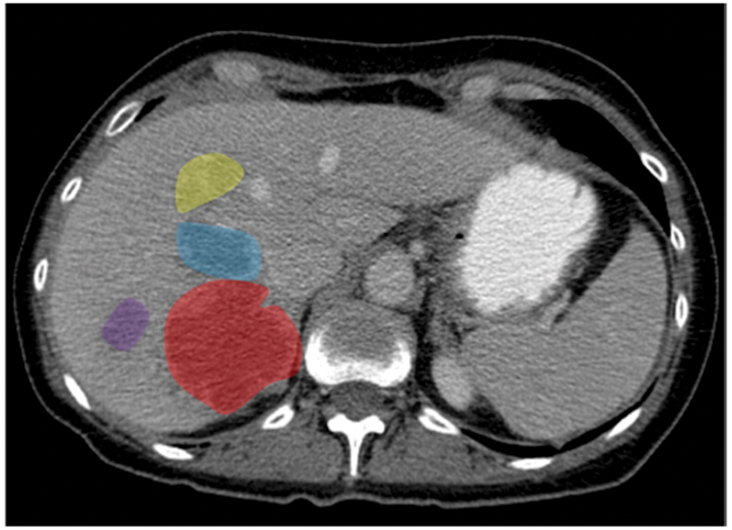
Metastases Aorta Stomach Spleen

Semantic segmentation



Liver metastases No metastasis

Instance segmentation



Metastasis 1 Metastasis 2 Metastasis 3 Metastasis 4

Phillip M. Cheng et al., Deep Learning: An update for radiologists,
RadioGraphics 2021 41:5, 1427-1445

Image classification in oncological imaging

Virtual colonoscopy CT

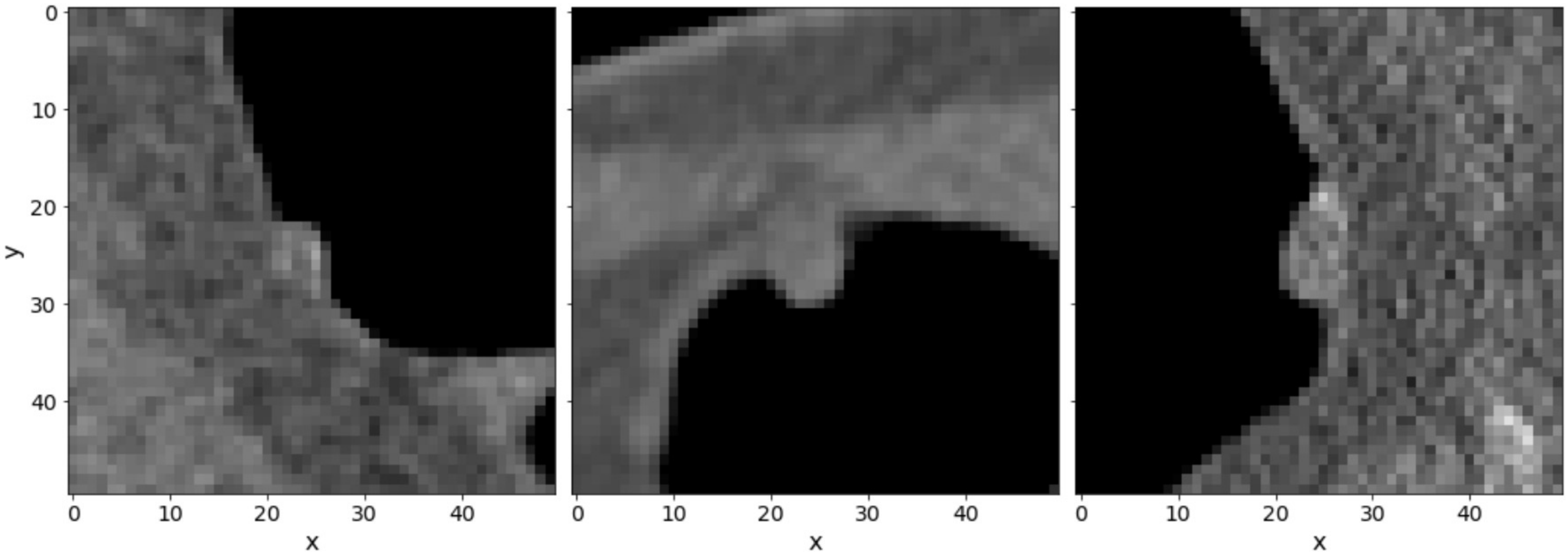
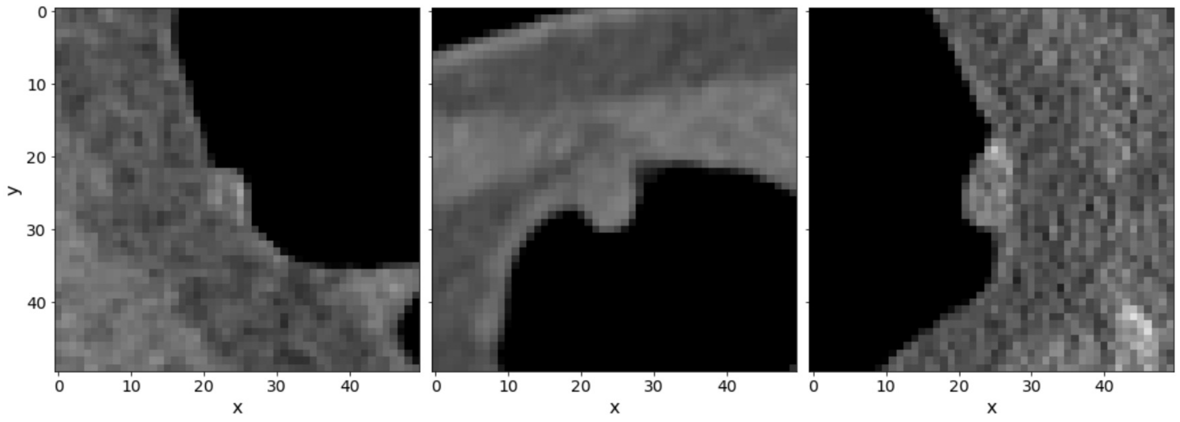
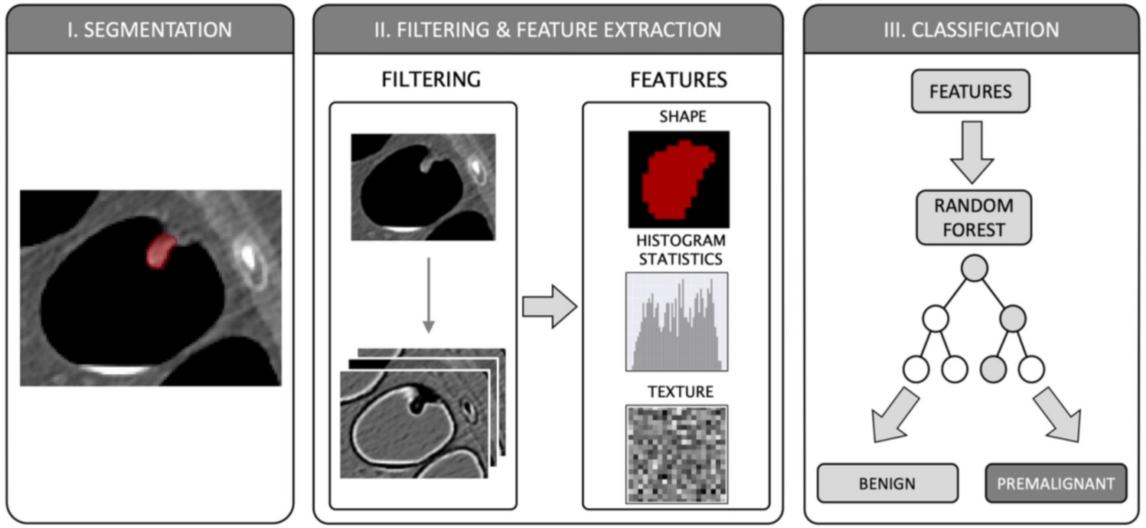


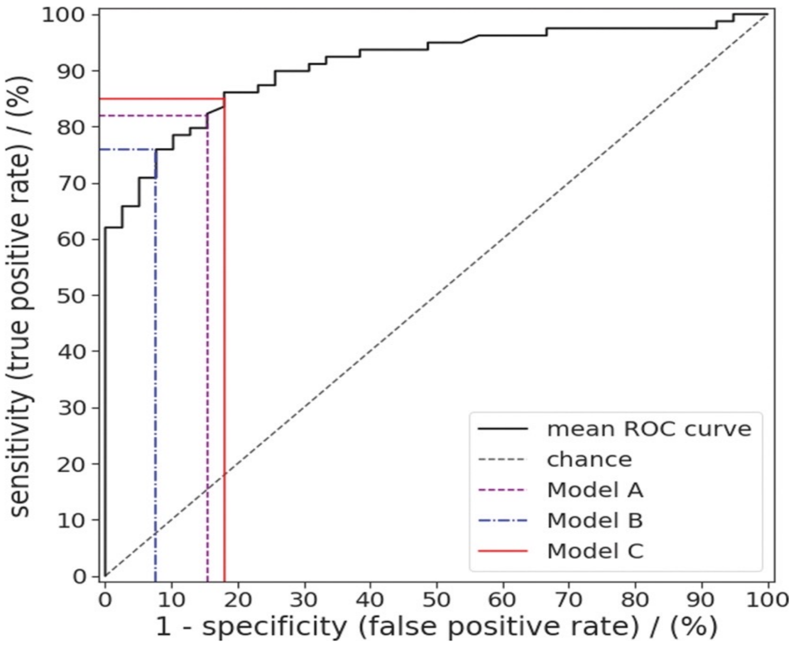
Image classification in oncological imaging

Virtual colonoscopy CT: Radiomics and deep learning





- Differentiation between benign and pre-malignant polyps in virtual colonoscopy CT
- model validation: independent dataset (TCIA)



AUC 0.91,
Sens. 85%
Spec. 82%

Grosu, Wesp, …, Ingrisch, et al. Radiology *299(2), 2021*
Wesp, Grosu,…, Ingrisch. European Radiology (2022)

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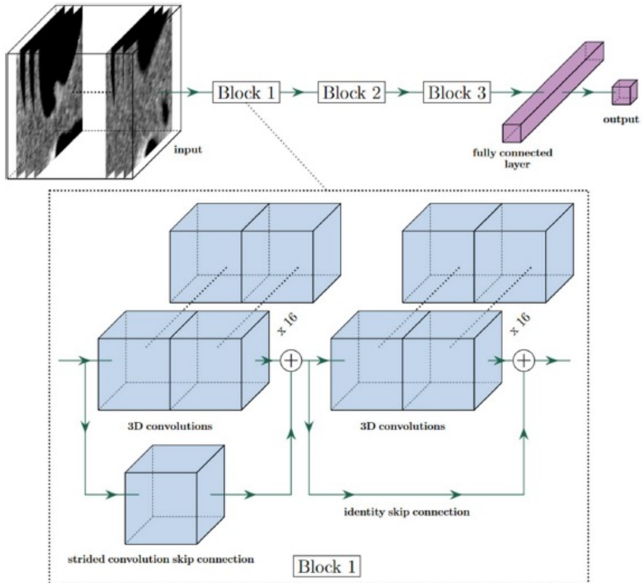
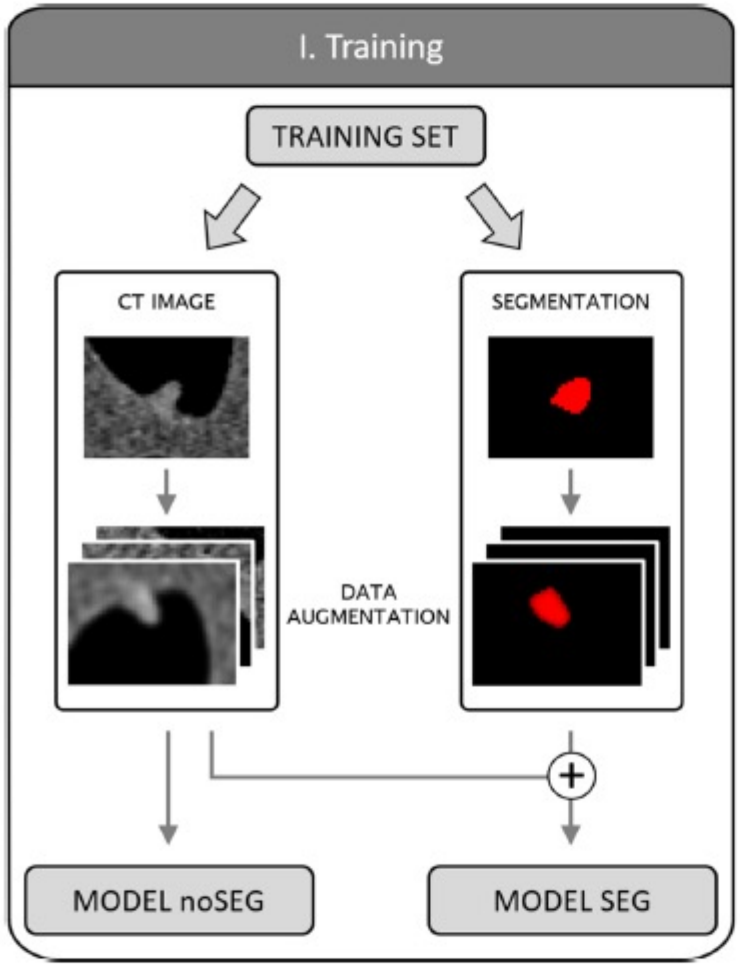
Image classification in oncological imaging
Virtual colonoscopy CT: Radiomics and deep learning





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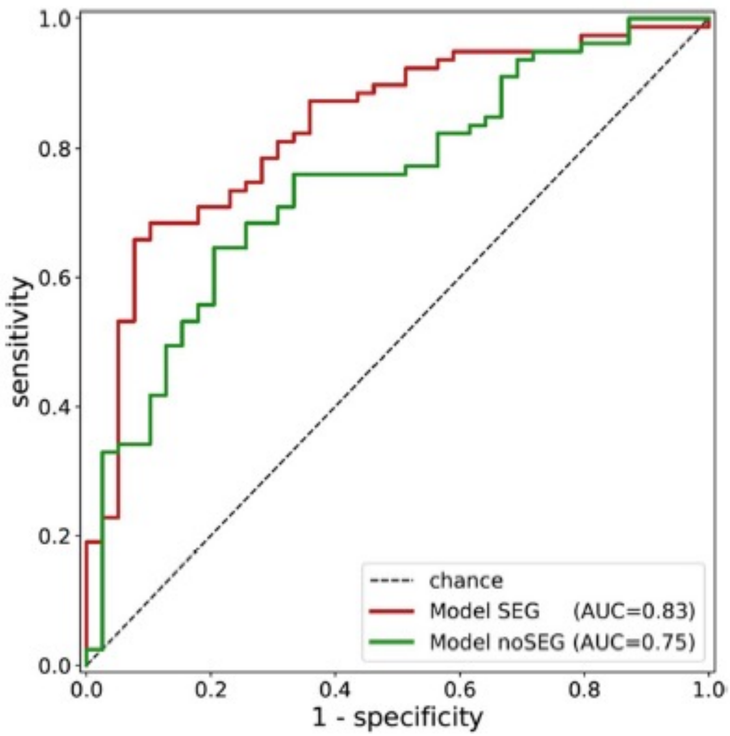
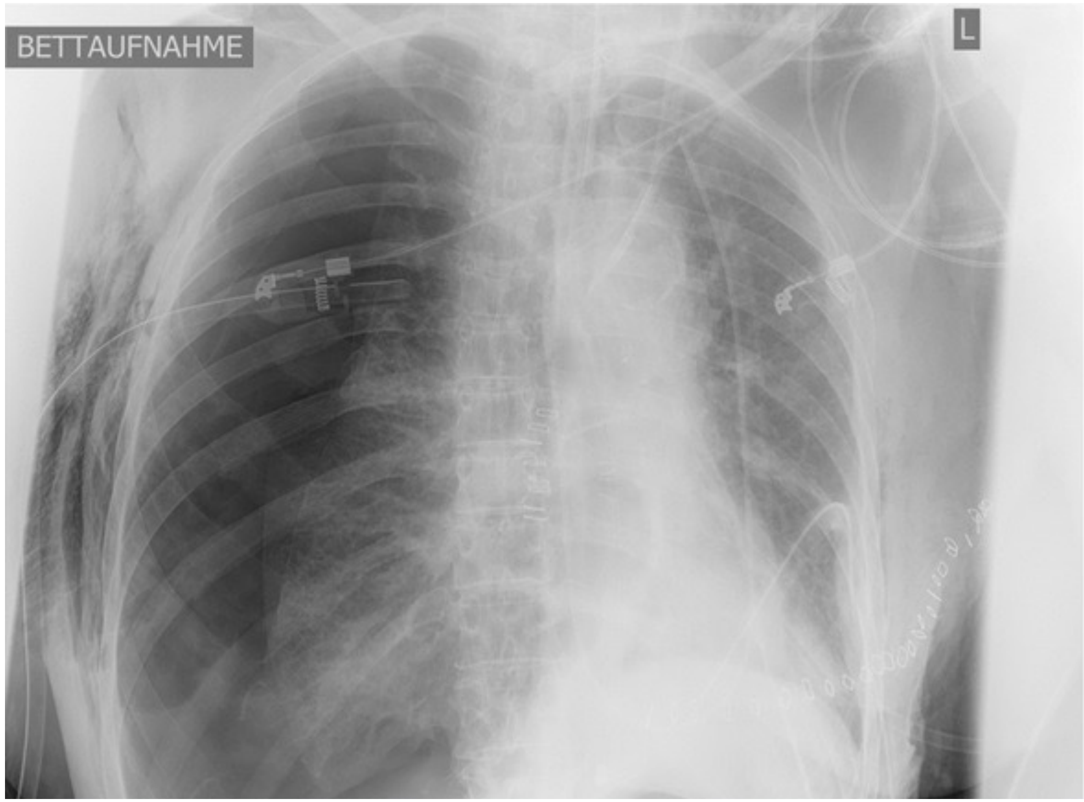
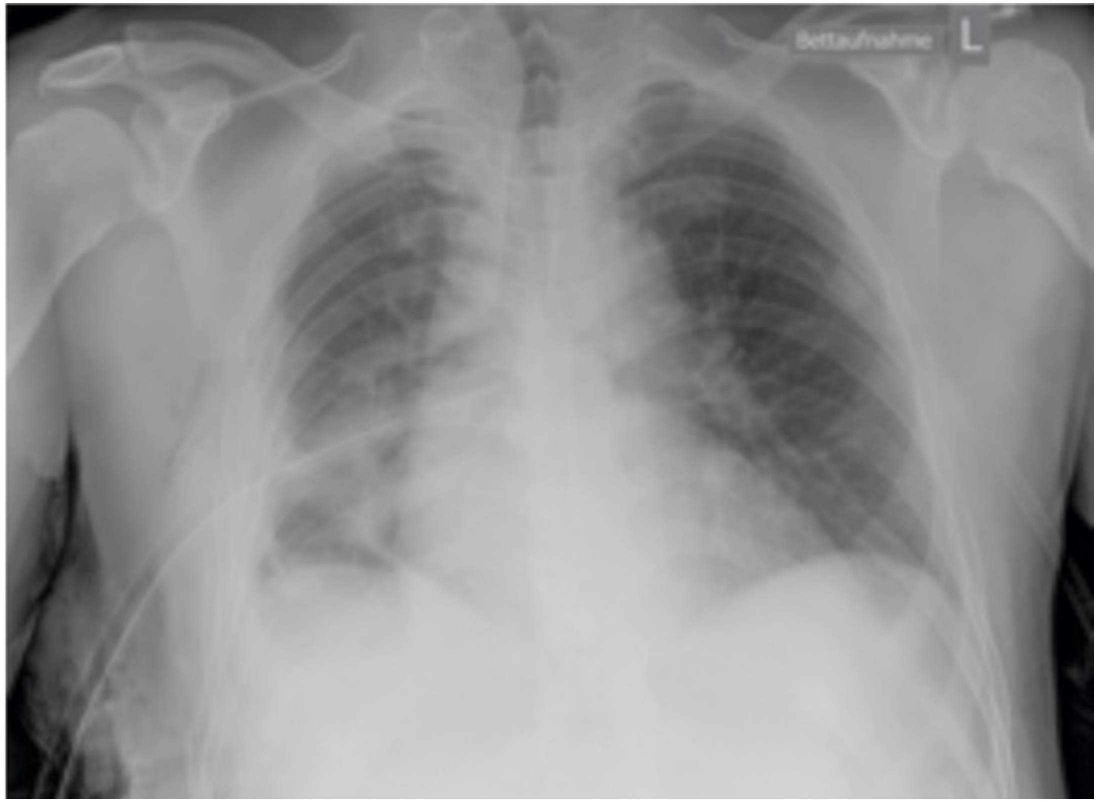


Grosu, Wesp, …, Ingrisch, et al. Radiology *299(2), 2021*
Wesp, Grosu,…, Ingrisch. European Radiology (2022)

Ask the right questions!
Detection of pneumothorax on chest X-rays





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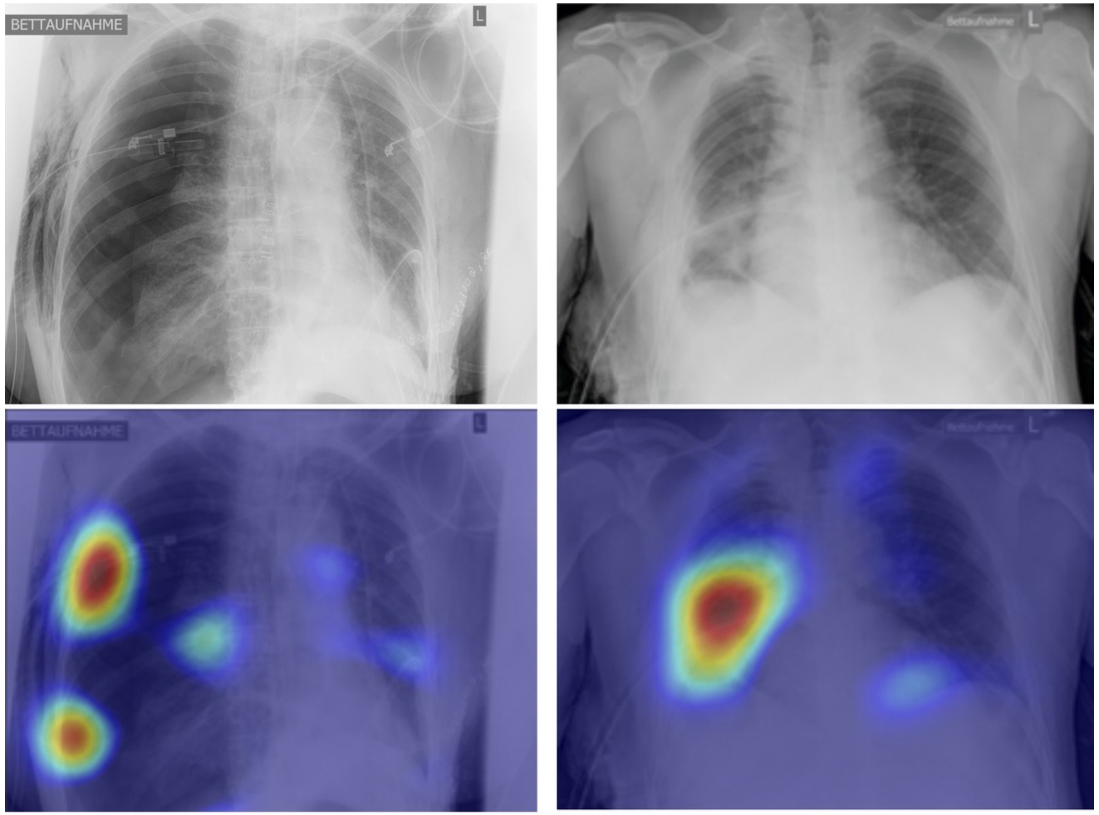


A B

- Large datasets are publicly available
- ChestX-ray 14: 14 pathology labels, ~100k images
- Presence of pneumothorax can be predicted with reasonable performance
- CheXnet: AUC 0.89

CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Pranav Rajpurkar *[1] Jeremy Irvin *[1] Kaylie Zhu[1] Brandon Yang[1] Hershel Mehta[1] Tony Duan[1] Daisy Ding[1] Aarti Bagul[1] Robyn L. Ball[2] Curtis Langlotz[3] Katie Shpanskaya[3] Matthew P. Lungren[3] Andrew Y. Ng[1]

arXiv:1711.05225v3

Image classification in radiology: A solved problem?

Geoffrey Hinton, 2016:

"People should stop training radiologists now. It's just completely obvious that within five years, deep learning is going to do better than radiologists."

Machine Learning and Market for Intelligence Conference. Toronto, Canada. 2016. https://www.youtube.com/watch?v=2HMPRXstSvQ.

AI in radiology
Roadmap

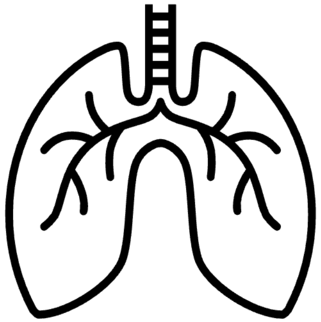
Radiology: mapping of image to clinical decision – supervised ML problem

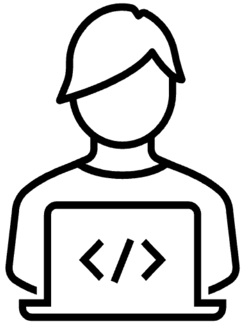
Ask the right questions, and answer them with the right data

Finding the right data: unsupervised and weakly supervised approaches?

Requirements and adoption barriers for AI in radiology

Pneumothorax detection on real-world data
Subgroup analyses





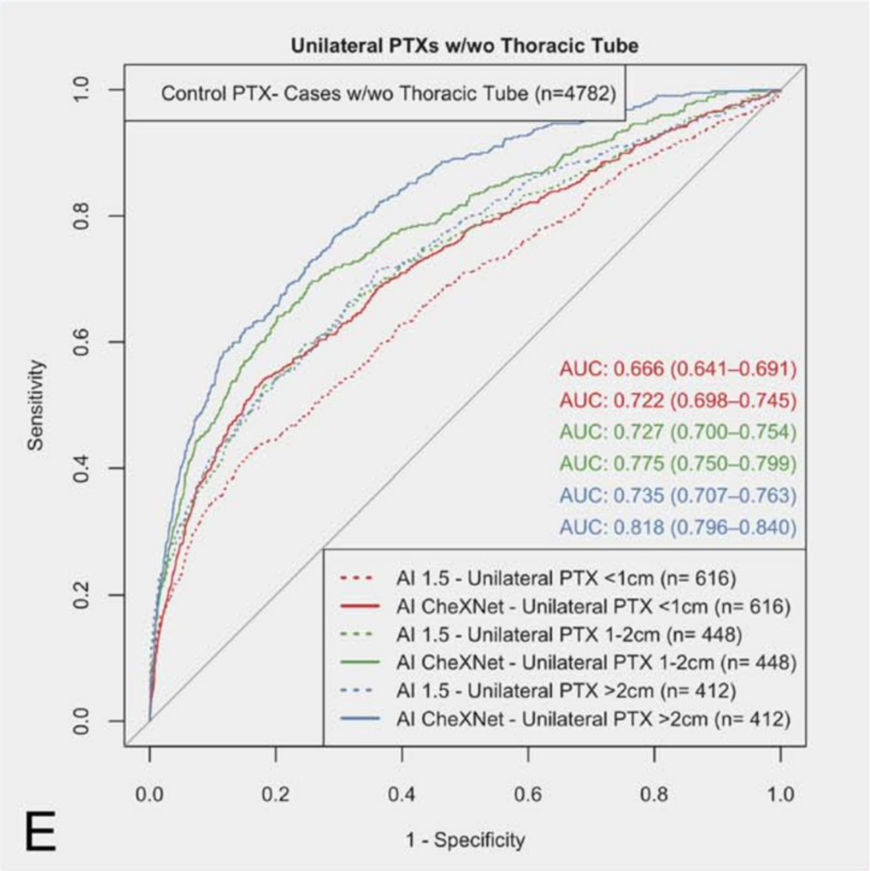
6434
Chest X-ray images

Benchmark cohort
Annotated subgroups
+- pneumothorax
+- thoracic tubes

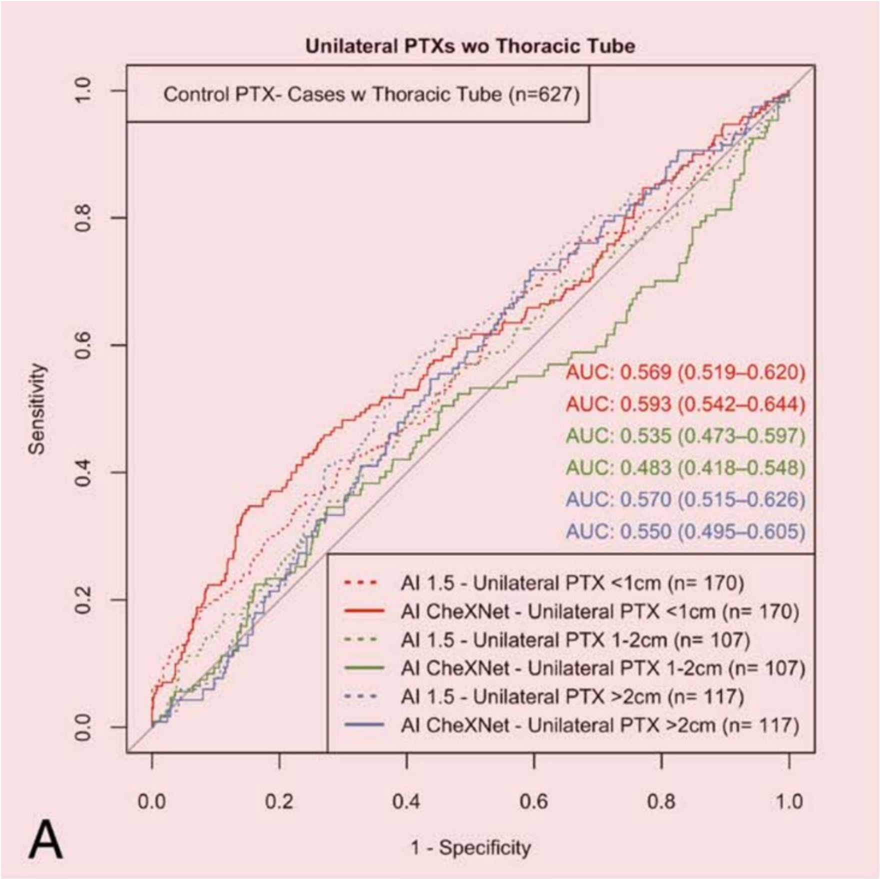
		TT		
		Yes, n (%)	**No, n (%)**	**Sum, n (%)**
Unilateral PTX (n = 1476)				
A	Dehiscence <1 cm	446 (72.4)	170 (27.6)	616 (41.7)
B	Dehiscence 1–2 cm	341 (76.1)	107 (23.9)	448 (30.5)
C	Dehiscence >2 cm	295 (71.6)	117 (28.4)	412 (27.8)
Sum, n (%)		1082 (73.3)	394 (26.7)	
Bilateral PTX (n = 176)				
A	Max. dehiscence <1 cm	36 (78.2)	10 (21.8)	46 (26.1)
B	Max. dehiscence 1–2 cm	62 (96.9)	2 (3.1)	64 (36.4)
C	Max. dehiscence >2 cm	56 (84.8)	10 (15.2)	66 (37.5)
Sum, n (%)		154 (87.5)	22 (12.5)	
Control cases (n = 4782)				
PTX-negative		627 (13.1)	4155 (86.9)	4782

PTX-positive cases are radiologically annotated for PTX size, PTX location (unilateral vs bilateral), and inserted TTs. PTX-negative control cases are radiologically annotated for inserted TTs.

Pneumothorax detection on real-world data



All data

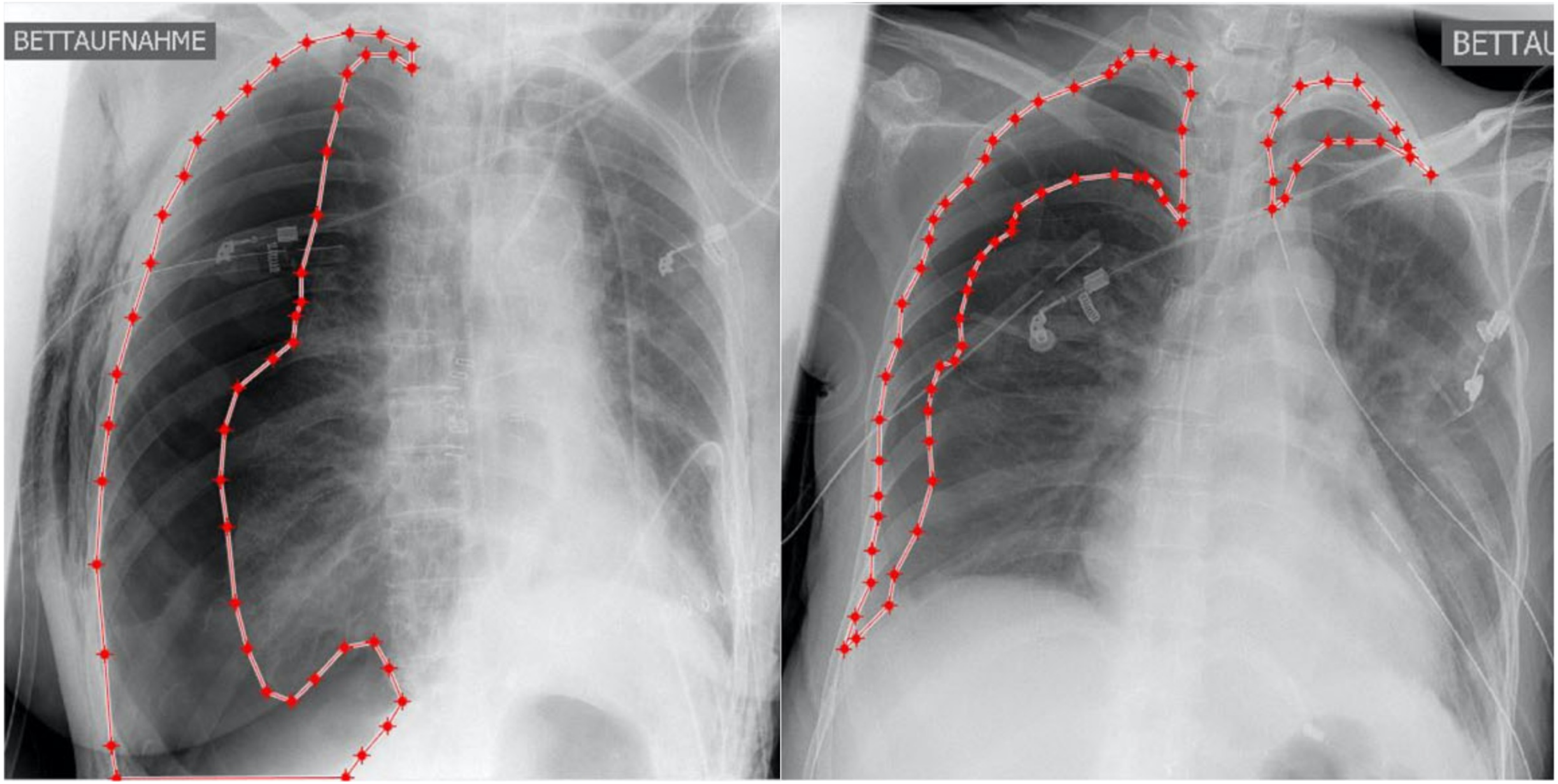


Critical subgroup: untreated PTX

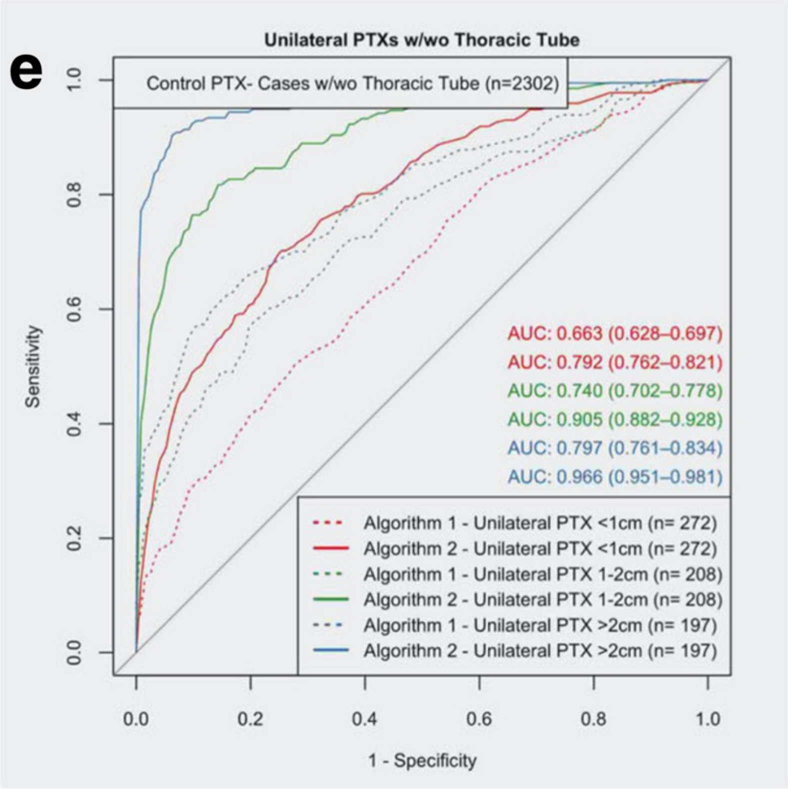
Rückel, … Ingrisch, Sabel. Investigative Radiology 55,12 (2020)

Optimized AI model

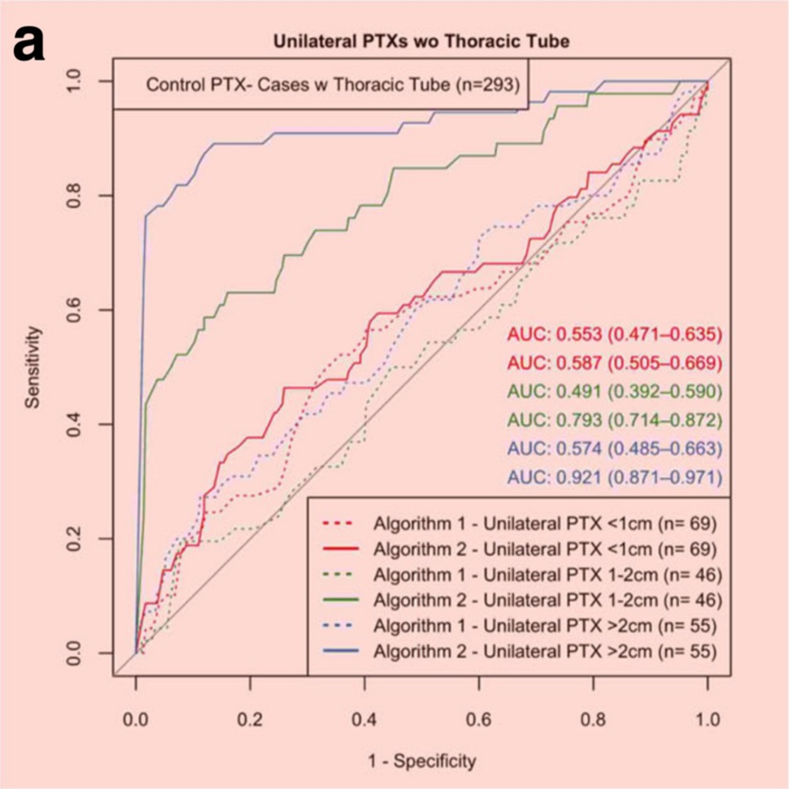
In-image annotations of pneumothorax



Pneumothorax detection on real-world data
Optimized algorithm



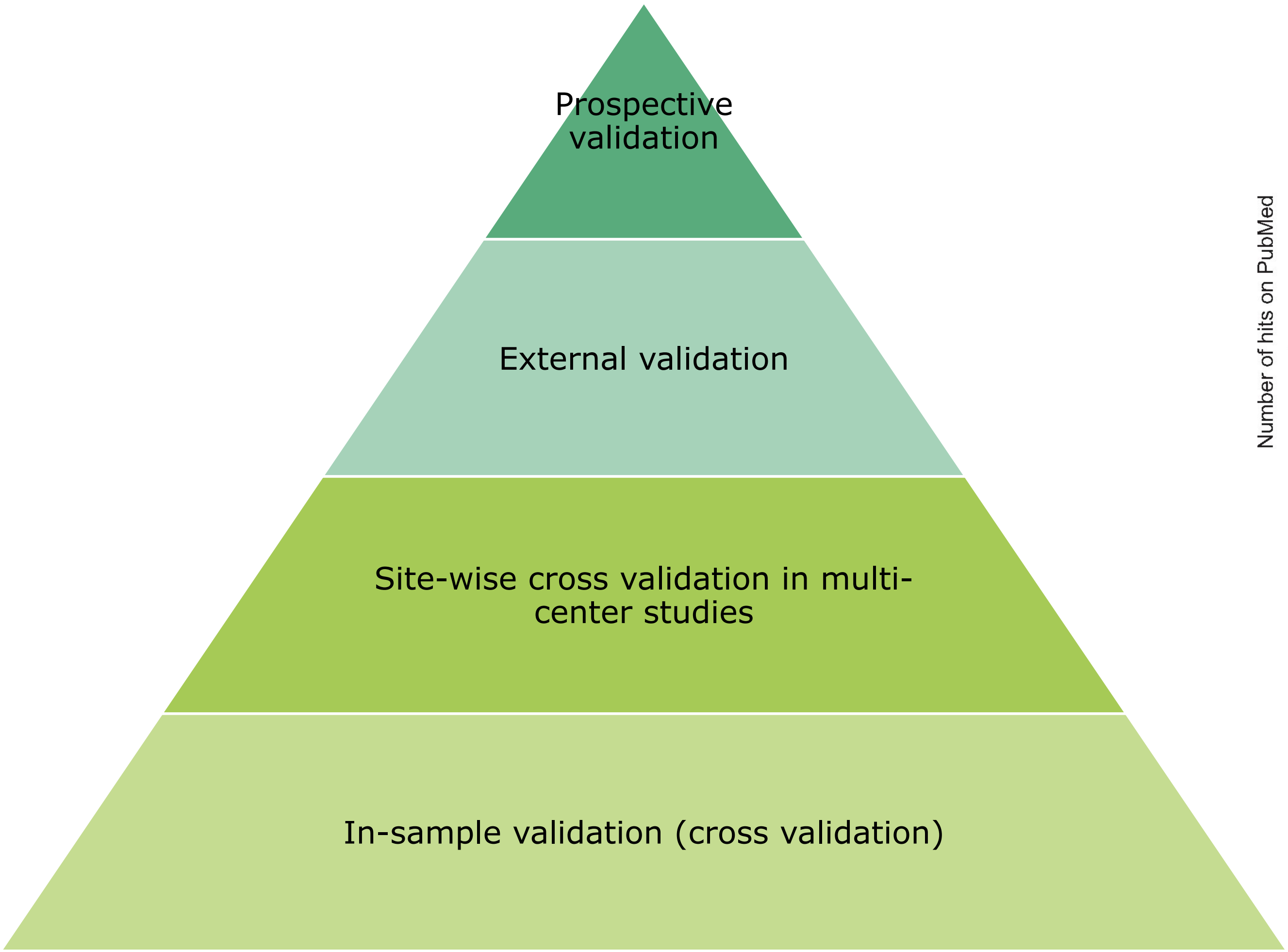
All data

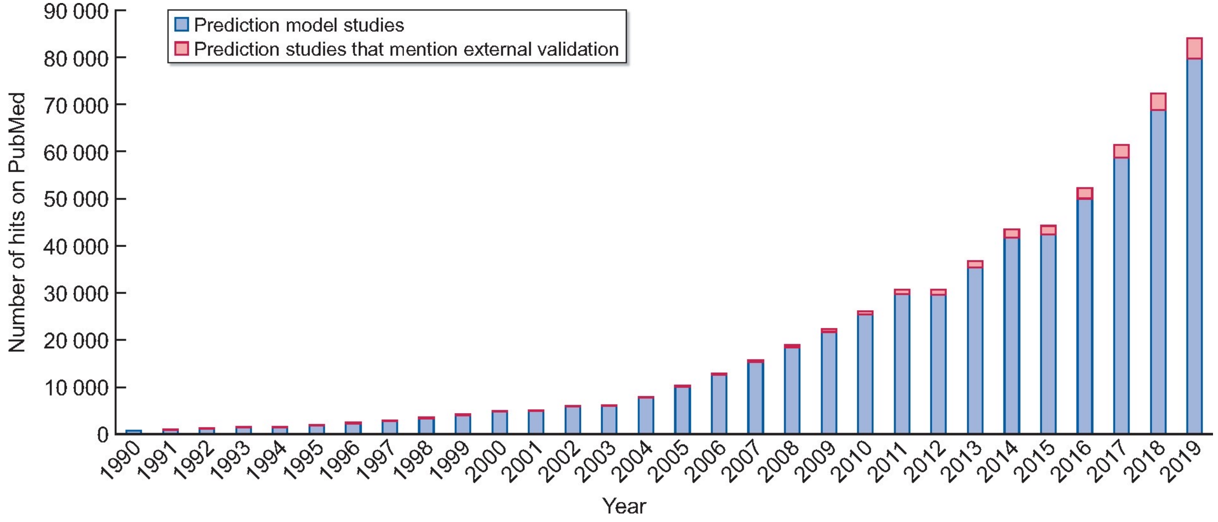


Critical subgroup: untreated PTX

Rückel, … Ingrisch , Sabel. European Radiology 2021

Model validation in clinical trials
Essential for clinical application





External and prospective validation of AI are required for clinical acceptance

Ramspek et al., External validation of prognostic models: what, why, how, when and where? *Clinical Kidney Journal*, Volume 14, Issue 1, January 2021, Pages 49–58

AI in radiology
Roadmap

Radiology: mapping of image to clinical decision – supervised ML problem

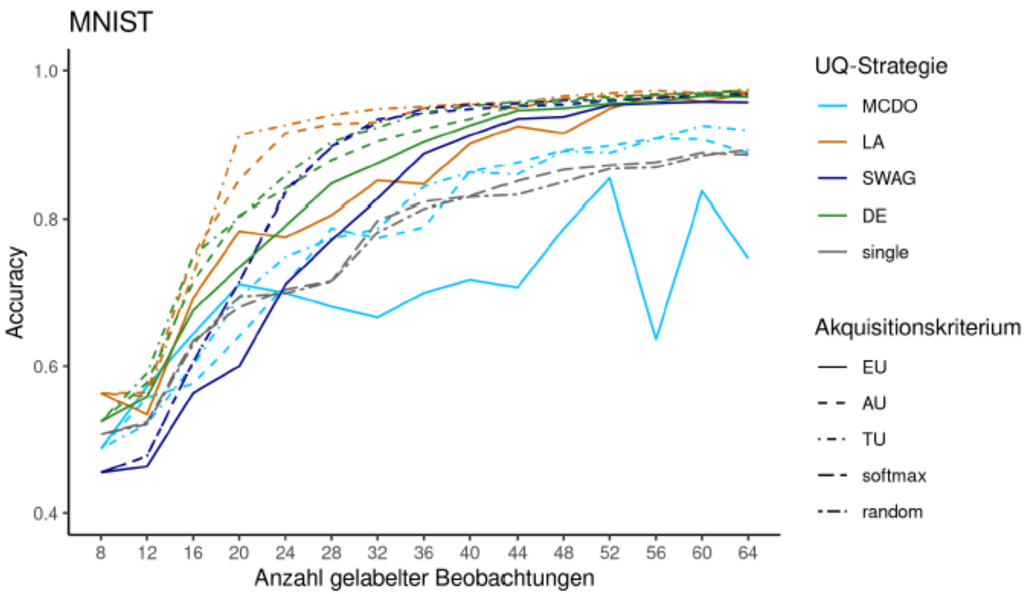
Ask the right questions, and answer them with the right data

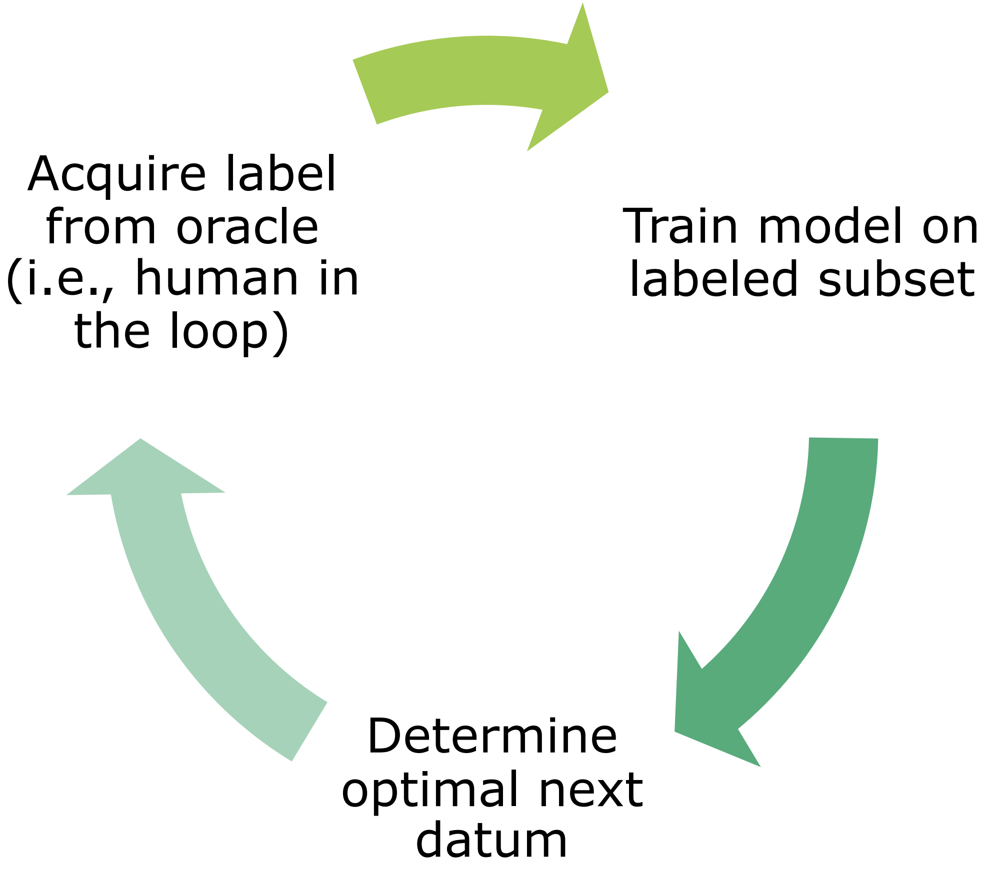
Finding the right data: unsupervised and weakly supervised approaches?

Requirements and adoption barriers for AI in radiology

Finding and labeling the right radiological data
Unsupervised and weakly supervised?

- Radiological data is typically insufficiently labelled (noisy, different context, free text reports, choose your nightmare)
- Labeling is expensive
  - Diagnosis, but even more so segmentation
- Minimize data to be labeled: **Active learning** to the rescue





Courtesy Lisa Wimmer, Master's thesis

AI in radiology
Roadmap

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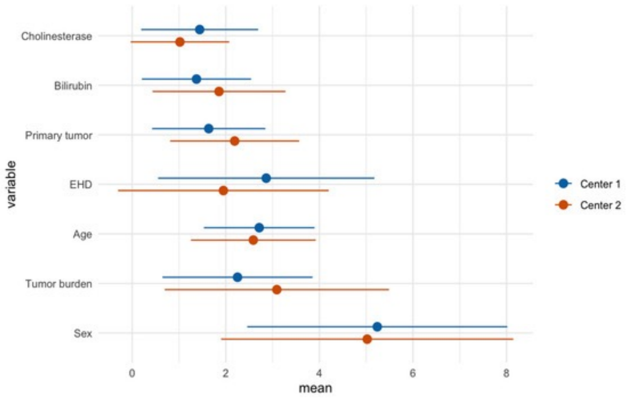
Finding the right data: unsupervised and weakly supervised approaches?

Requirements and adoption barriers for AI in radiology

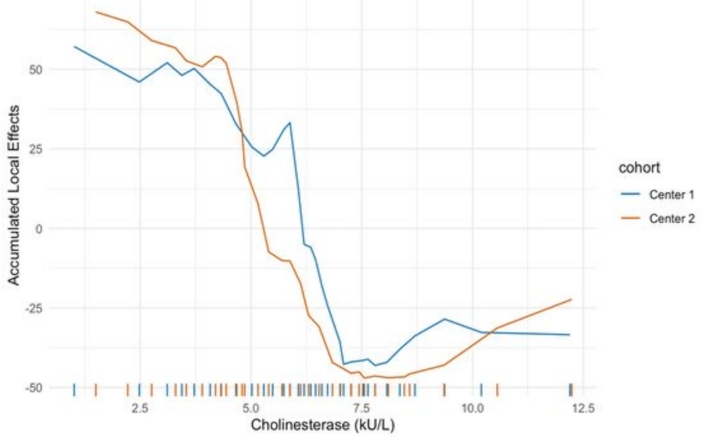
Explainability

Does your model do what you think it does?

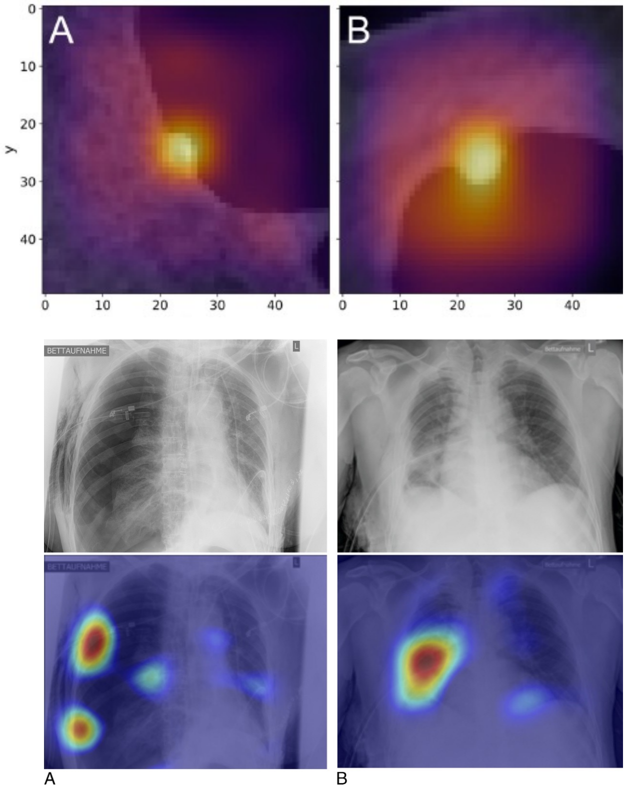
Feature importance



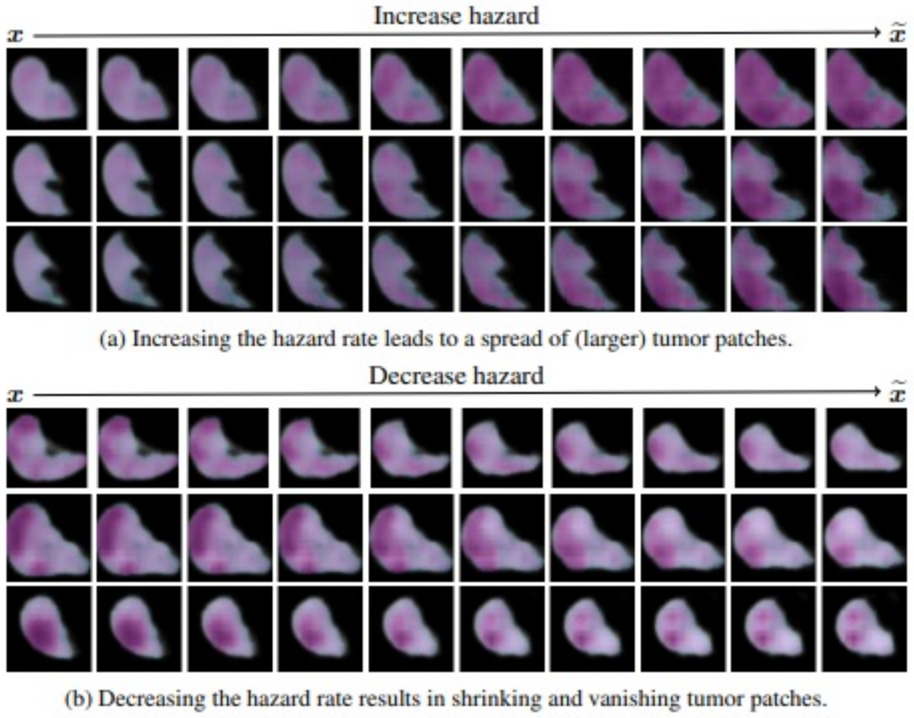
Accumulated Local Effects



GradCam Visualization



Generative Approaches



Fabritius, …, Mittermeier, Ingrisch. J Clin Med 2021
Weber T, Ingrisch M, Bischl B, Rügamer D. NeurIPS 2021, Bridging the Gap: From Machine Learning Research to Clinical Practice.
Wesp, Grosu,…, Ingrisch. European Radiology 2022

Adoption barriers for AI

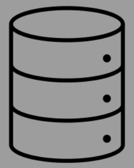
What hinders translation of AI into clinical routine

Development and deployment

Data access

IT landscape

Regulations



Quality assurance

Transparency

Sources of bias

Validation

Liability and responsibility

Who is responsible when something goes wrong?

Clinical acceptance of AI in medicine
What is required?

Clinically relevant questions

Effective use of ressources

AI systems

Explainability

Validation

Increase quality and efficiency

Enable novel, break-through applications

Acknowledgements and collaborations

- **CDS Team**
  - B Schachtner, K Jeblick, A Mittermeier, P Wesp, T Stüber, T Weber, C Stampfl, J Topalis, J Dexl
  - B Sabel, J Rückel, S Grosu, J Rudolph
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- **Informatics** T Lasser (TUM) , C Böhm (LMU)
- **Math foundations of AI**, G Kutyniok

MCML

SIEMENS Healthineers

CAS Research Focus NEXT GENERATION AI

Bundesministerium für Gesundheit

netzwerk universitäts medizin

DZL Deutsches Zentrum für Lungenforschung

OSC LMU Open Science Center

OSIM Open Science in Medicine

GRK 2274

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