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
Clinical Data Science in Radiology

Mission statement

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 consciousness 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

Indication for imaging

Image acquisition and reconstruction

Image reading and reporting

Clinical Decision

- Prediction: diagnosis, prognosis, treatment
- Structured reporting
- Clinical Decision Algorithms

- Worklist prioritization
- Image quality, speed, dose reduction

- Segmentation, quantification, image analysis

Clinical Algorithms

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

Algorithms and proof-of-concept

External validation

Prototypes and platforms

Products

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Image classification
Cats vs dogs

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/overviewgetDescription
Supervised machine learning in radiology
Applied computer vision

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%

Wesp, Grosu, ..., Ingrisch. European Radiology (2022)
Image classification in oncological imaging
Virtual colonoscopy CT: Radiomics and deep learning

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- Model validation: independent dataset (TCIA)

Wesp, Grosu,…, Ingrisch. European Radiology (2022)
Ask the right questions!

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

- 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 Rajpurkar1, Jeremy Irvin1, Kaylie Zhu1, Brandon Yang1, Hershel Mehta1, Tony Duan1, Daisy Ding1, Aarti Bagul1, Robyn L. Ball2, Curtis Langlotz2, Katie Shpanskaya3, Matthew P. Lungren3, Andrew Y. Ng1

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.”

AI in radiology

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Pneumothorax detection on real-world data

Subgroup analyses

Benchmark cohort
Annotated subgroups
+- pneumothorax
+- thoracic tubes

6434 Chest X-ray images

<table>
<thead>
<tr>
<th></th>
<th>TT</th>
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<tbody>
<tr>
<td></td>
<td>Yes, n (%)</td>
</tr>
<tr>
<td>Unilateral PTX (n = 1476)</td>
<td></td>
</tr>
<tr>
<td>A - Dehiscence &lt;1 cm</td>
<td>446 (72.4)</td>
</tr>
<tr>
<td>B - Dehiscence 1–2 cm</td>
<td>341 (76.1)</td>
</tr>
<tr>
<td>C - Dehiscence &gt;2 cm</td>
<td>295 (71.6)</td>
</tr>
<tr>
<td>Sum, n (%)</td>
<td>1082 (73.3)</td>
</tr>
<tr>
<td>Bilateral PTX (n = 176)</td>
<td></td>
</tr>
<tr>
<td>A - Max. dehiscence &lt;1 cm</td>
<td>36 (78.2)</td>
</tr>
<tr>
<td>B - Max. dehiscence 1–2 cm</td>
<td>62 (96.9)</td>
</tr>
<tr>
<td>C - Max. dehiscence &gt;2 cm</td>
<td>56 (84.8)</td>
</tr>
<tr>
<td>Sum, n (%)</td>
<td>154 (87.5)</td>
</tr>
<tr>
<td>Control cases (n = 4782)</td>
<td></td>
</tr>
<tr>
<td>PTX-negative</td>
<td>627 (13.1)</td>
</tr>
</tbody>
</table>

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

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

AI in radiology

Roadmap

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

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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

Acquire label from oracle (i.e., human in the loop)
Train model on labeled subset
Determine optimal next datum

[Graph]

**MNIST**

*Accuracy*

*Anzahl gelabelter Beobachtungen* (Number of labeled observations)

**UQ-Strategie**
- MCDI
- LA
- SWAG
- DE
- single

**Akquisitionskriterium**
- EU
- AU
- TU
- softmax
- random

*Courtesy Lisa Wimmer, Master's thesis*
AI in radiology

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Requirements and adoption barriers for AI in radiology
Explainability

Does your model do what you think it does?

Feature importance

GradCam Visualization

Generative Approaches

Accumulated Local Effects

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Fabritius, ..., Mittermeier, Ingrisch. J Clin Med 2021
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 resources

AI systems

Explainability

Validation

Increase quality and efficiency

Enable novel, break-through applications
Recognitions and Collaborations

- **CDS Team**
  - B Sabel, J Rückel, S Grosu, J Rudolph

- **Department of Radiology**
  - J Ricke, C Cyran, M Seidensticker, O Dietrich

- **Clinical partners**, LMU Klinikum and beyond

- **Statistical Learning and Data Science**, LMU
  - B Bischl, D Rügamer, A Bender, L Bothmann

- **Informatics** T Lasser (TUM), C Böhm (LMU)

- **Math foundations of AI**, G Kutyniok