
AI COLLABORATION TOOLKIT FOR HEALTH DATA

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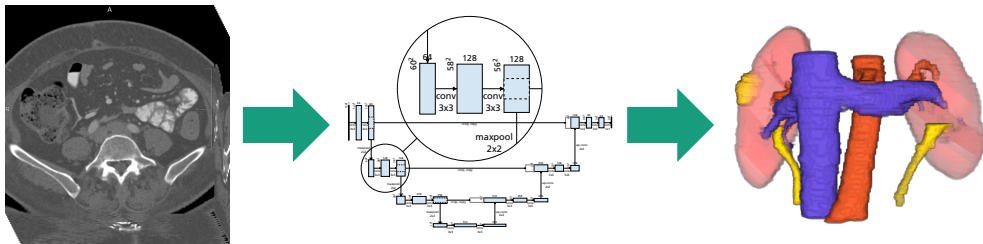
Zukunft Teleradiologie
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Research & Development of Data-Driven Algorithms

Example: Extraction of Kidney Anatomy

AI algorithm for assessment of renal cancer:

- Input: CA-CT (computer tomography) images of renal region
- Output: geometry of important anatomy (kidneys, tumors, vessels)

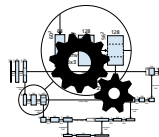
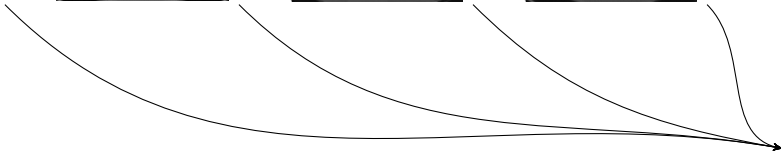
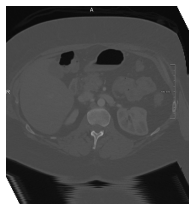
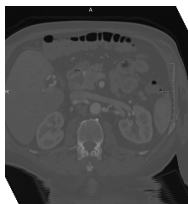
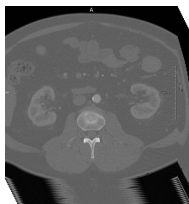


Goal: automatic measurements, quantitative assessment

Data used in the following: 2021 Kidney and Kidney Tumor Segmentation Challenge (KiTS 21)

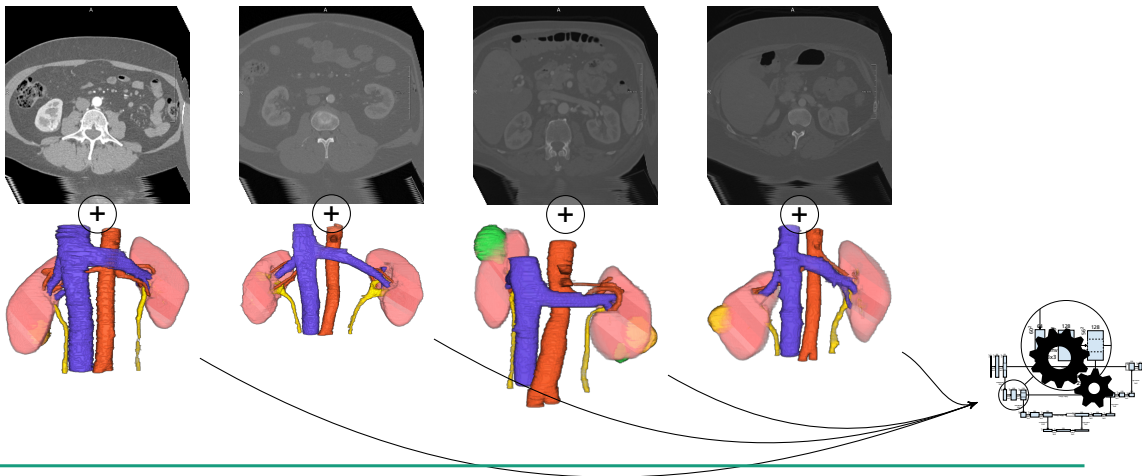
Pipeline for Training an AI (Supervised Learning)

Now how does the AI learn how to extract anatomy?



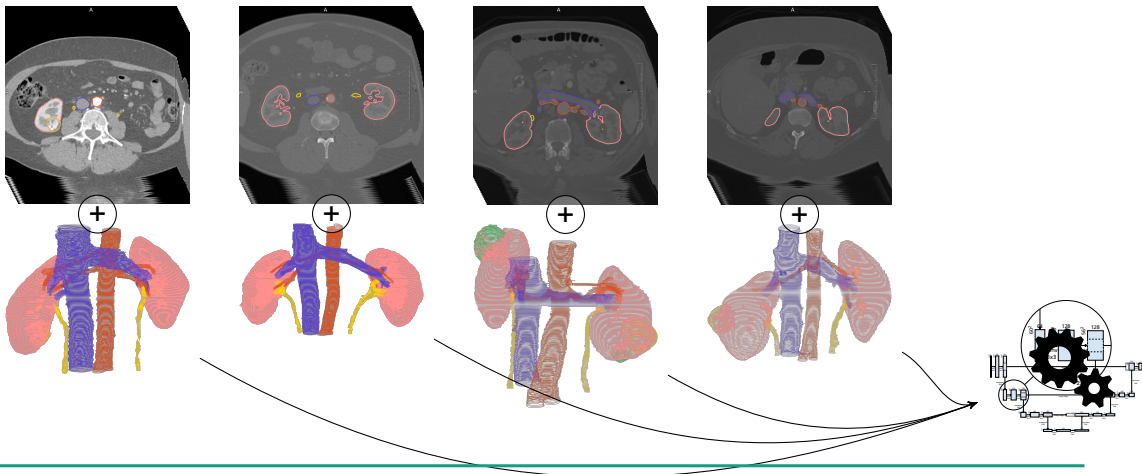
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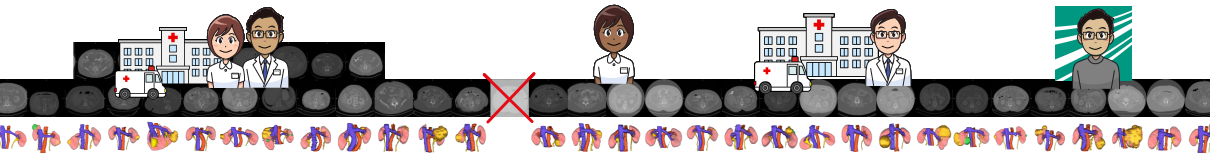
Complexities of Collaborative R&D

In practice, there are many complicating factors

case_00000

	Kidneys	Ureters	Arteries	Veins	Cysts	Tumors	
Localization	⊗	⊙	⊗	⊙		⊗	⊗
Guidance	⊗	⊙	⊗	⊙		⊗	⊗
Delineation	○	○	○	○		○	○

- data collected by doctors, needs to be accessible to technical scientists
 - anonymization has to be applied to data leaving the hospital
 - data needs to be reviewed by both physicians and AI specialists
 - annotations take a lot of time and need to be reviewed by experts
 - data comes in batches, numbers increase over time, more than one site, ...
 - problematic cases excluded at any time, annotations may need corrections, ...
 - algorithm results or application prototypes have to be shared
- ⇒ *lots* of communication, many *different versions* of curated data



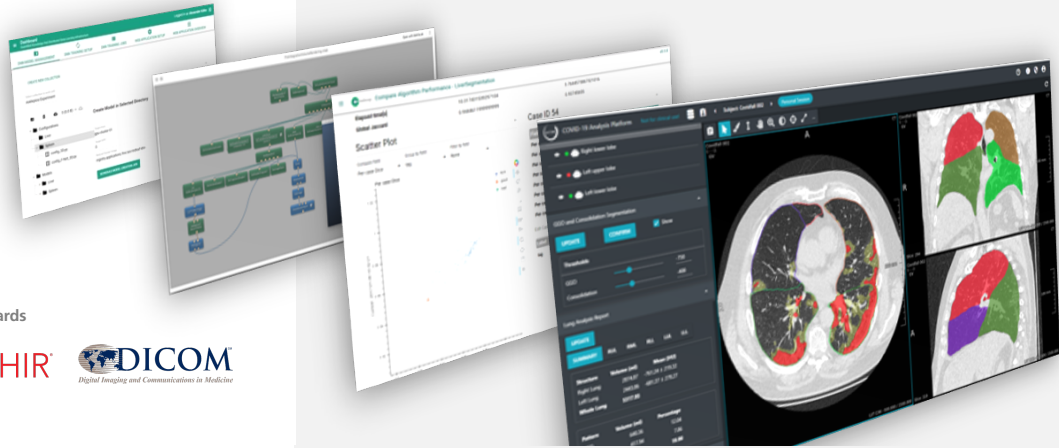
PURPOSE / SCOPE

Our toolkit speeds up collaborative R&D of data-driven algorithms

Professional tooling for large, multi-site data collection & curation

Data curation  AI dev   Application prototypes  

- Viewing
- Filtering
- Annotation
- Model training
- Model evaluation
- Clinical evaluation
- Workflow and UX assessment



Based on standards



SATORI – A Highly Customizable Annotation Tool

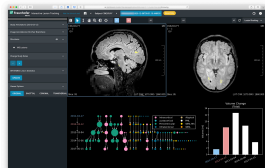
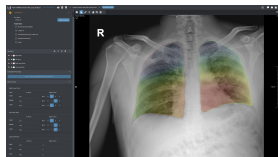
Main frontend visible to clinical users

Basic Features

- Import / Export in many formats (DICOM, SEG, NifTI, ...)
- Automatic categorization, tagging and preprocessing
- User and group management, private / shared sessions, audit mode
- Customizable hangings and layouts
- Structured annotations (subject / study / image / structure)
- Efficient segmentation and correction of structures

Advanced Features through **extensibility**

- Smooth transition towards application prototypes
- Deployment options (MEVIS, on site, cluster, cloud, ...)
- Direct connection to Deep Learning



Study Annotations (2012-03-12)

Image Annotations (3D_Flair BrainView)

Structures

MS Lesions

Change Study Dates

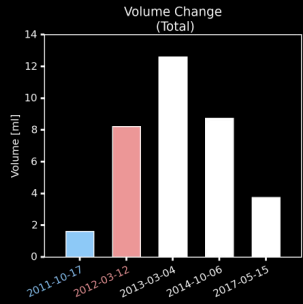
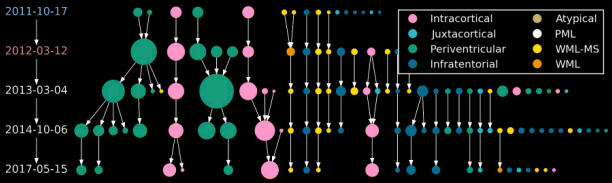
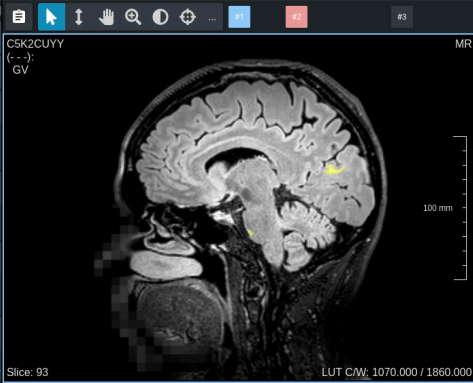
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INFORMED Lesion Statistics

UPDATE

Viewer Options

ORIGINAL SAGITTAL CORONAL TRANSVERSAL



Structures

- Show Fiber Tracts
- CST L
 - CST R
 - CTT L
 - CTT R
 - PTT L
 - PTT R
 - Medial Lemniscus L
 - Medial Lemniscus R

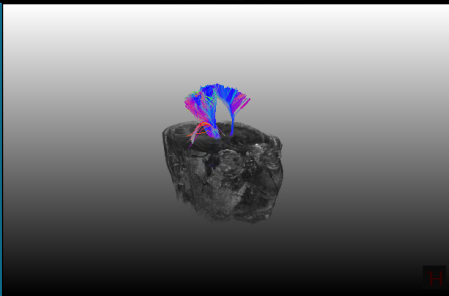
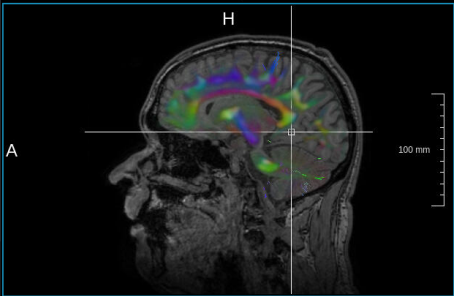
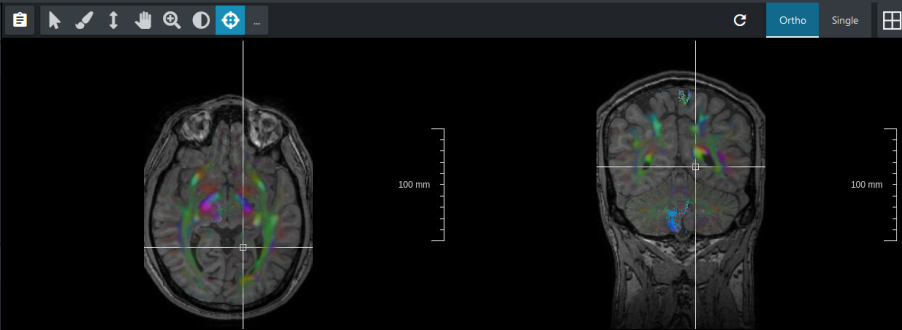
Viewer Settings

Ortho View

- DTI Color Overlay
- Hint: Hold shift during windowing for application to overlay.

3DView

- Clip Plane Orientation
- axial
 - sagittal
 - coronal
- Flip Clip Plane



Knee SATORI Not for clinical use! Subject: DFG_Patient 02 Shared Session

Femur **COORDINATES** **DOWNLOAD RESULTS**

Show Patella

View Settings

Smooth

ANTERIOR **LEFT** **POSTERIOR** **RIGHT**

Femur Parameters

Cartilage Area
10358.2

Cartilage Co.
43.7863

Show Medial Condyle Radius
21.9960

Show Lateral Condyle Radius
23.5268

Angle Between TEA and TCA
0.16016

Angle Between TEA and PCA
0.14709

Angle Between TCA and PCA
0.06265

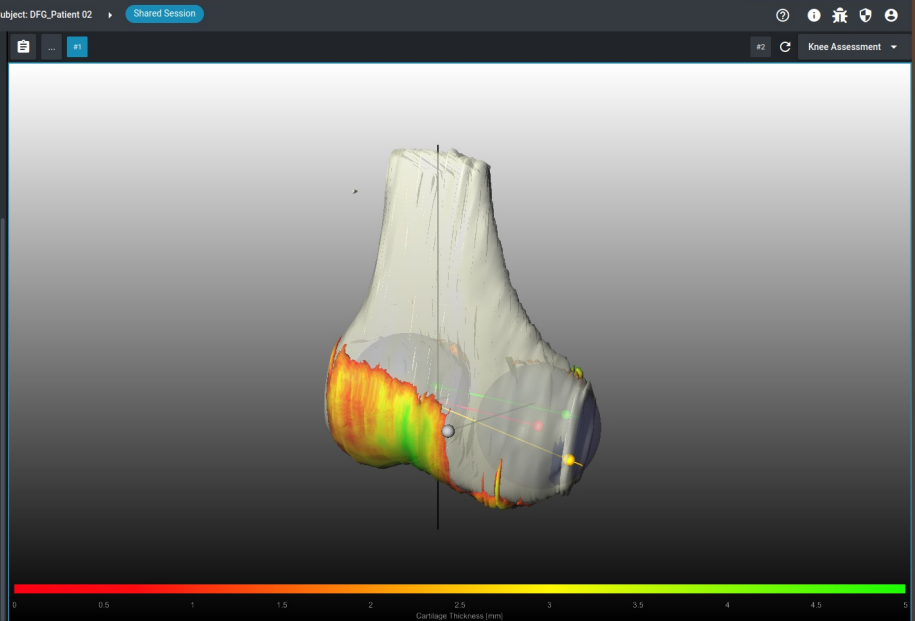
Length of TEA
88.6437

Length of PCA
54.1993

Length of TCA
54.1993

Lateral Trochlea Height (%)
80.6318

Medial Trochlea Height (%)
77.9467





Technology Goal 1: In-Situ Correction

Only dynamically learning AI appears really "intelligent"

Long history of application prototypes with manual correction facilities

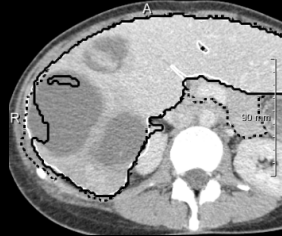
- Doctors become frustrated when software repeats the same mistake again and again

Our highly integrated web-based AI collaboration toolkit makes these corrections more sustainable

- Corrections enter data pool...
- ...undergo review / curation...
- ...and can be used for training / evaluation.

Thought on Deep Learning

We expect corrections to be *particularly valuable!*



Technology Goal 2: Federated Learning

Because multi-centric data is key to robust AI & real-world applicability

Toolkit supports on-site deployment

⇒ **data does not have to leave the hospital**

Trained models may travel, though

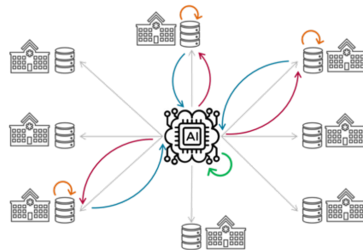
- for evaluation / application
- for learning on data from multiple sites

Our toolkit provides interfaces also for models

- goal: supporting real-time communication betw. hospitals

Problem dimensions

- hurdles for data sharing
- firewalled IT (as a consequence)
- training strategies



Conclusions

We are building an AI Collaboration Toolkit with integrated platform components for

- data curation
- AI research & development
- custom application prototypes

Integration enables

- dynamically learning AI and
- federated learning

The toolkit is used in ongoing projects, internally and with various partners

- RACOON-SATORI currently deployed to all German UMC (NUM)

