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# Transforming Healthcare

## Impact Area of AI

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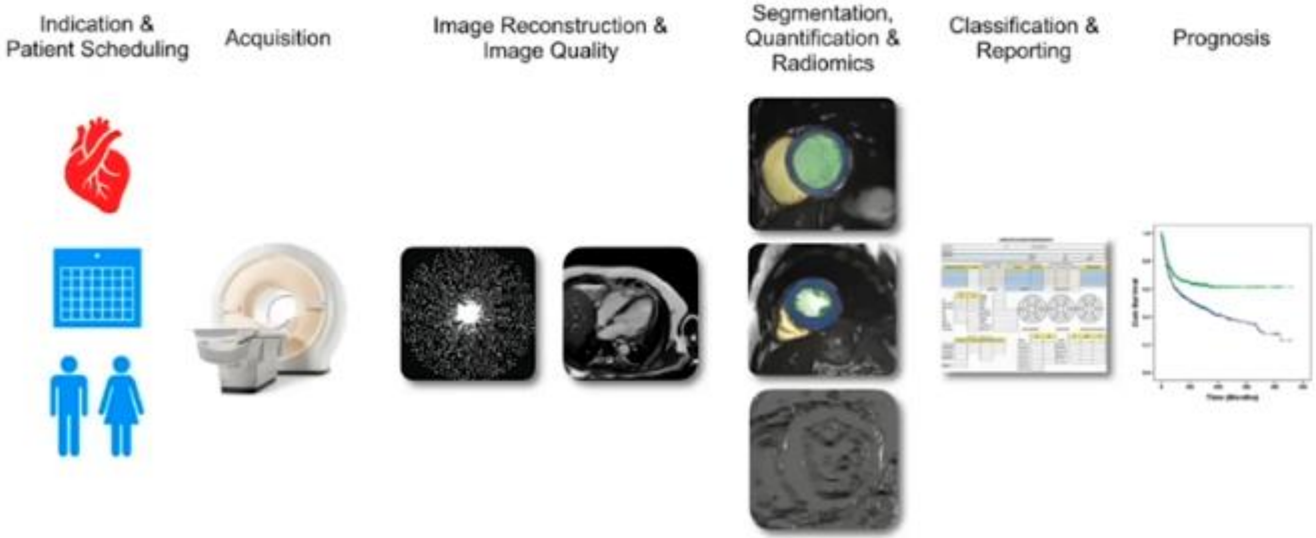
# Impact Areas of AI




Leiner T et al. *Journal of Cardiovascular Magnetic Resonance* 2019;21:61.

# (Limited) Clinical AI Implementation

| Hurdles for AI Implementation | 1,024 Radiologists |
|---|---|
| Costs of software | 363 (35%) |
| Lack of | |
| Knowledge | 584 (56%) |
| High-quality image data | 159 (15%) |
| Generalizability of AI software | 410 (39%) |
| Ethical / legal issues | 630 (61%) |
| Limitation in digital infrastructure | 356 (35%) |

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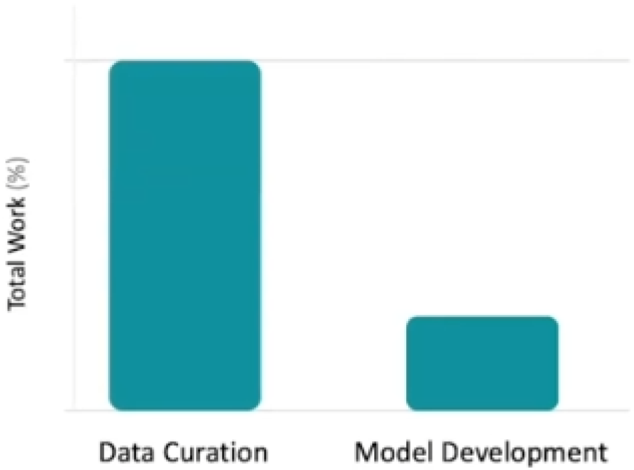

# Public Data

CANCER IMAGING ARCHIVE

RSNA®

MRNet DATASET

MURA

CheXpert

# Public Data

**Table 2: Large Open-Source Medical Imaging Data Sets**

| Data Set Description | Image Types | No. of Patients | Ground Truth | Single or Multiple Institutions |
|---|---|---|---|---|
| American College of Radiology Imaging Network National CT Colonography Trial (ACRIN 6664) (102) | CT | 825 | Pathology (biopsies) | Multiple |
| Alzheimer's Disease Neuroimaging Initiative (103) | MRI, PET | >1700 | Clinical (follow-up) | Multiple |
| Curated Breast Imaging Subset of the Digital Database for Screening Mammography (36) | Mammography | 6671 | Pathology (biopsies) | Multiple |
| ChestX-ray8, National Institutes of Health chest x-ray database (41) | Radiography | 30 805 | Imaging reports | Single |
| CheXpert, chest radiographs (79) | Radiography | 65 240 | Imaging reports | Single |
| Collaborative Informatics and Neuroimaging Suite (104) | MRI | | Clinical (follow-up) | Multiple |
| DeepLesion, body CT (60) | CT | 4427 | Imaging | Single |
| Head and neck PET/CT (105) | PET/CT, CT | 298 | Pathology (biopsies), clinical (follow-up) | Multiple |
| Lung Image Database Consortium image collection (106) | CT, radiography | 1010 | Imaging, clinical for a subset | Multiple |
| MRNet, knee MRI (80) | MRI | 1370 | Imaging reports | Single |
| Musculoskeletal bone radiographs, or MURA (107) | Radiography | 14 863 | Imaging reports | Single |
| National Lung Screening Trial (108) | CT, pathology | 26 254 | Clinical (follow-up) | Multiple |
| PROSTATEx Challenge, SPIE-AAPM-NCI Prostate MR Classification Challenge (109) | MRI | 346 | Pathology (biopsies), imaging | Multiple |
| Radiological Society of North America Intracranial Hemorrhage Detection (110) | CT | 25 000 | Imaging | Multiple |
| Cancer Genome Atlas Kidney Renal Clear Cell Carcinoma data collection (111) | CT, MRI | 267 | Pathology (biopsies), clinical (follow-up) | Multiple |
| Virtual Imaging Clinical Trial for Regulatory Evaluation (112) | Mammography, digital breast tomosynthesis | 2994 | Imaging | Multiple |

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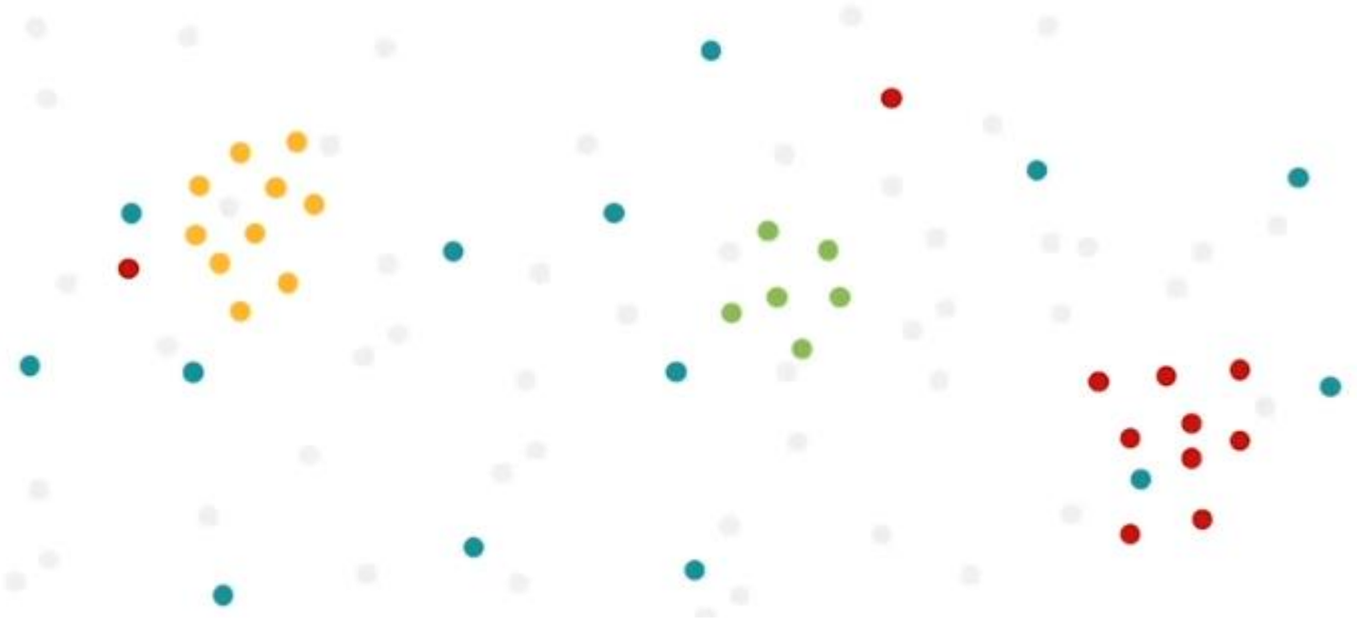
# The Data Issue

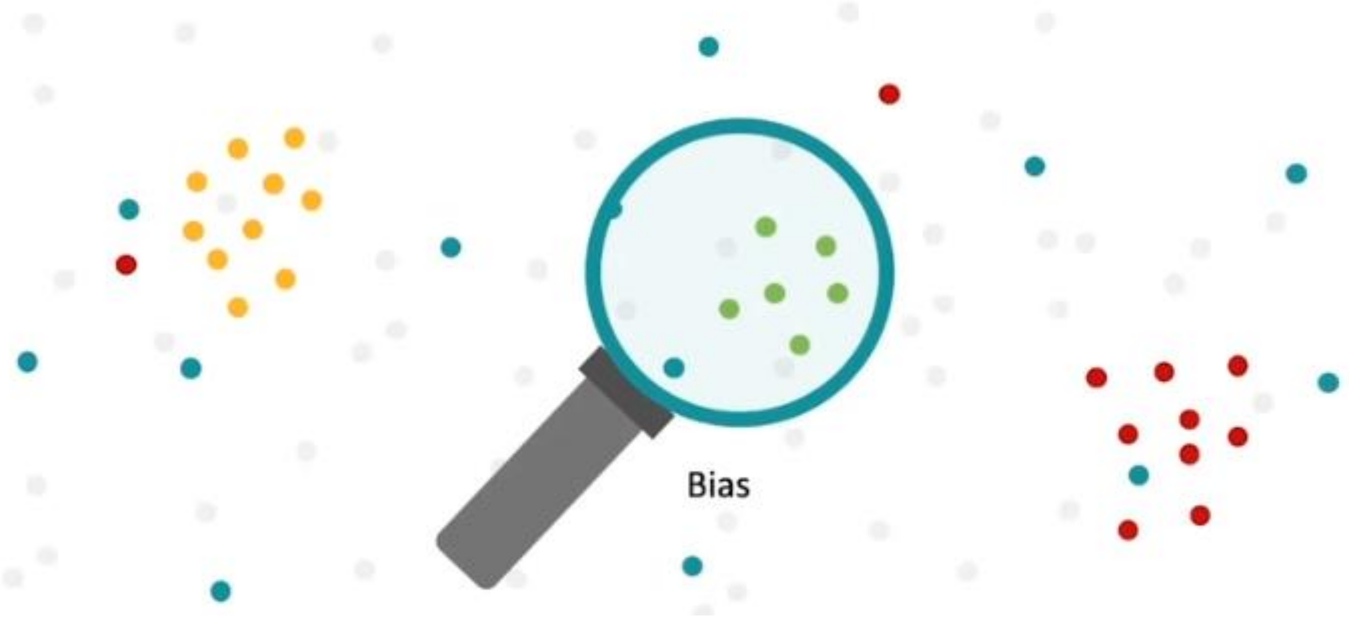
Small sample size

# Diversity Issue



# Diversity Issue

# Diversity Issue



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# The data problem

| True Label | COVID-19 (Training Data) | | COVID-19 (Unseen Data) | |
|---|---|---|---|---|

| Model | Prediction | Confidence | Prediction | Confidence |
|---|---|---|---|---|
| DNN | COVID-19 | 99.7% | Non-COVID | 75.1% |
| BNN | COVID-19 | 95.5% | COVID-19 | 67.1% |

# The data problem

| True Label | COVID-19 (Training Data) | COVID-19 (Unseen Data) | Cat (Unrelated Data) |
|---|---|---|---|


| Model | Prediction | Confidence | Prediction | Confidence | Prediction | Confidence |
|---|---|---|---|---|---|---|
| DNN | COVID-19 | 99.7% | Non-COVID | 75.1% | COVID-19 | 100% |
| BNN | COVID-19 | 95.5% | COVID-19 | 67.1% | COVID-19 | 99.8% |

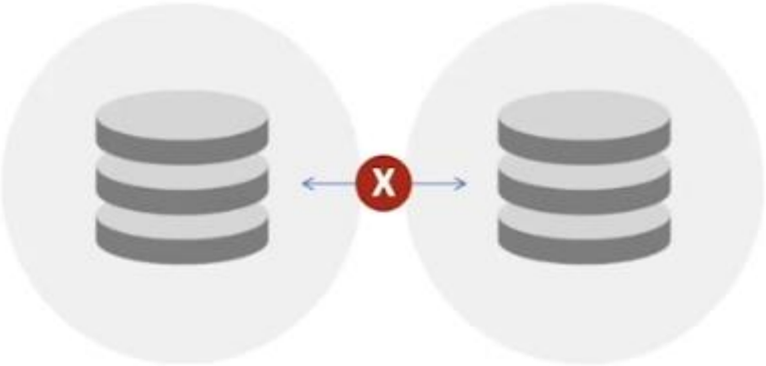
# (More) Data Issues

Anonymized

# (More) Data Issues

# Data preparation overview

# Data Storage and Transfer



Data in siloes

# Data Storage and Transfer

Local storage

- Single center study

External storage

- Multicenter study
- Commercial AI development

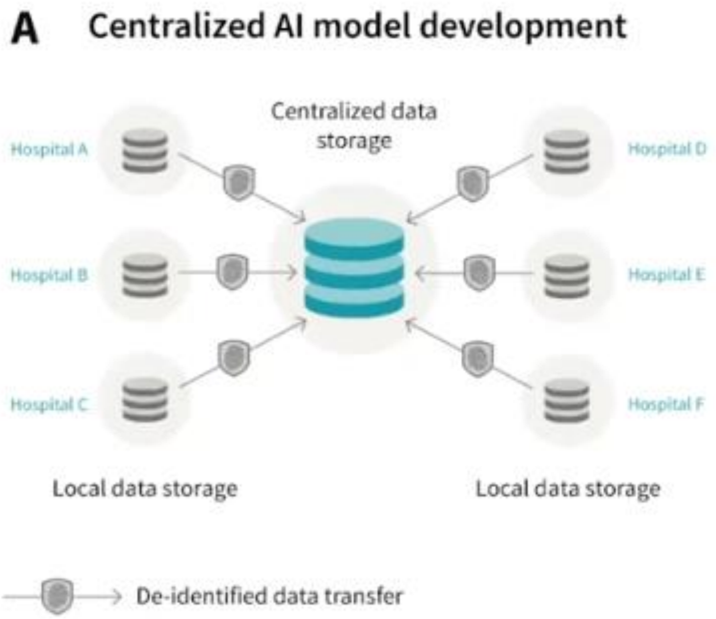
# Data Storage and Transfer

| | Pros |
|---|---|
| **Local storage** | Data safety |
| Single center study | Data availability |
| **External storage** | Data sharing |
| Multicenter study | Data backup |
| Commercial AI development | |

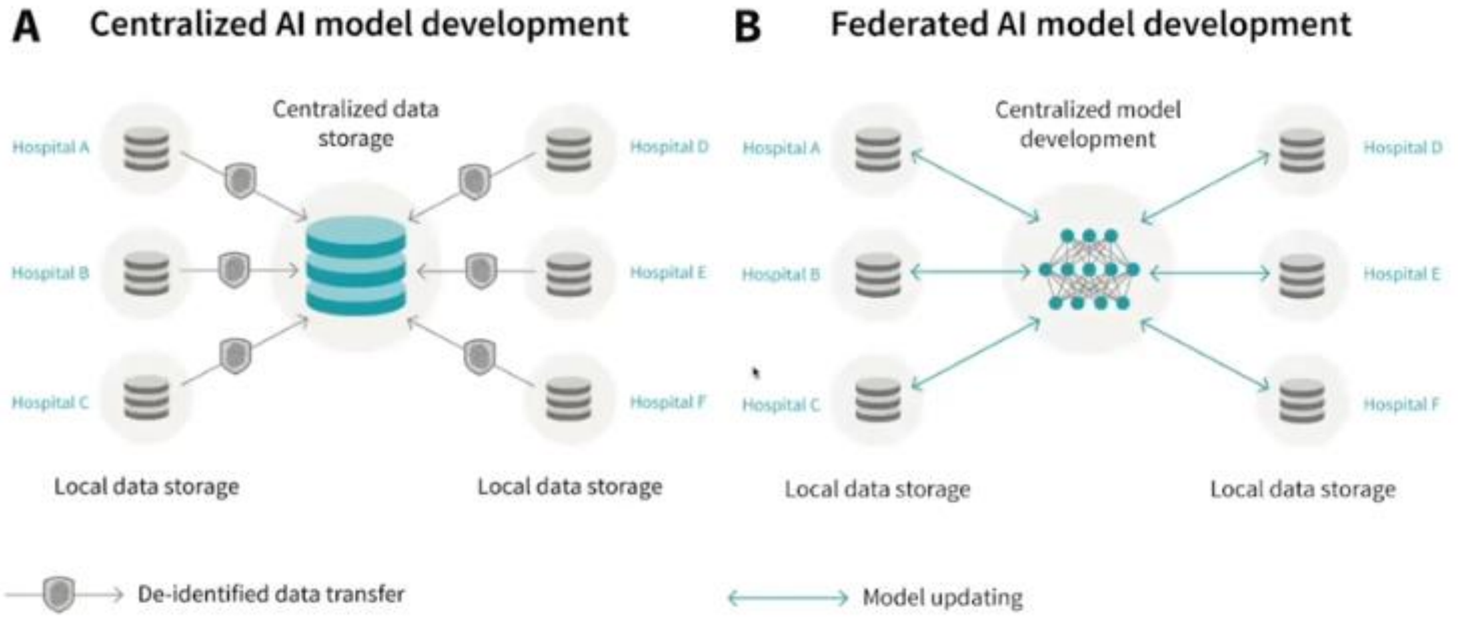
# Data Storage and Transfer

| | Pros | Cons |
|---|---|---|
| **Local storage** | Data safety | Data sharing |
| Single center study | Data availability | |
| **External storage** | Data sharing | Costs |
| Multicenter study | Data backup | Fast connection |
| Commercial AI development | | |

# Federated learning



# Federated learning



# Medical Image File Formats

**Pixel data**

Actual image

**Meta data**

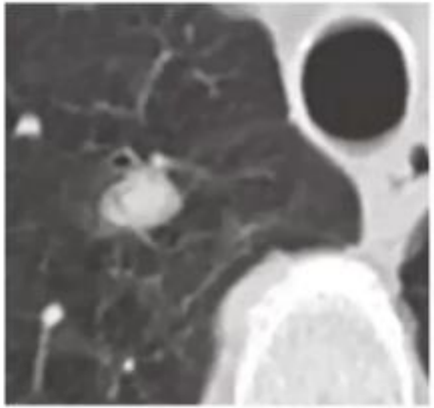
Describes image

- Image matrix dimensions
- Spatial resolution
- Reconstruction settings

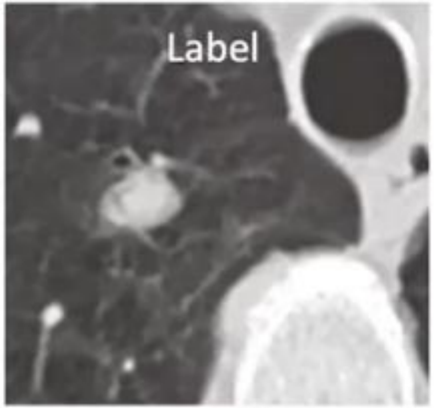
# Medical Image File Formats

| Generated by imaging device | Facilitate post-processing |
| --- | --- |
| DICOM (.dcm) | Analyze (.img and .hdr) |
| | NIfTI (.nii) |
| | Minc (.mnc) |

# Image Labeling

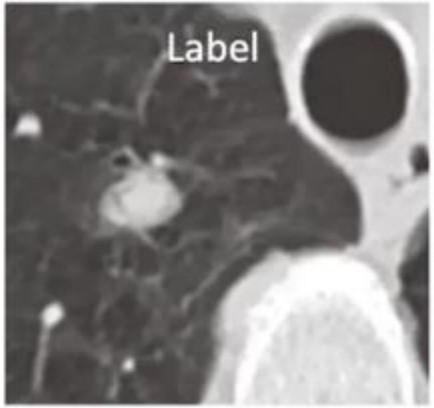


# Image Labeling




Lung nodule: **Present**

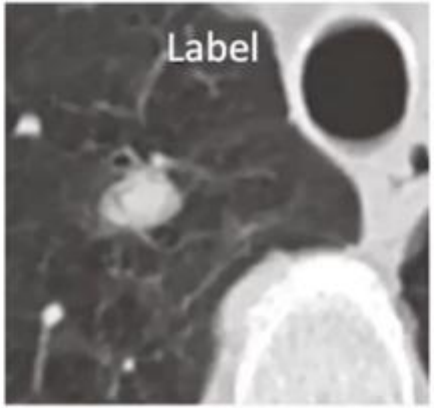
# Image Labeling

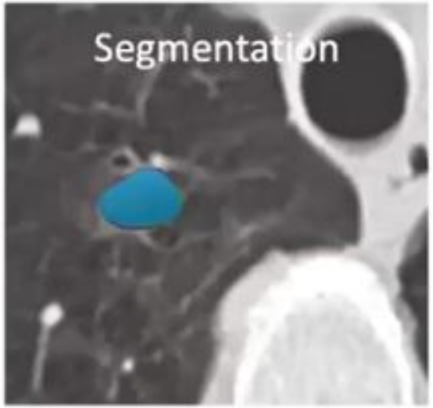



Lung nodule: **Present**

Lung nodule: **4 mm**

# Image Labeling




Lung nodule: **Present**

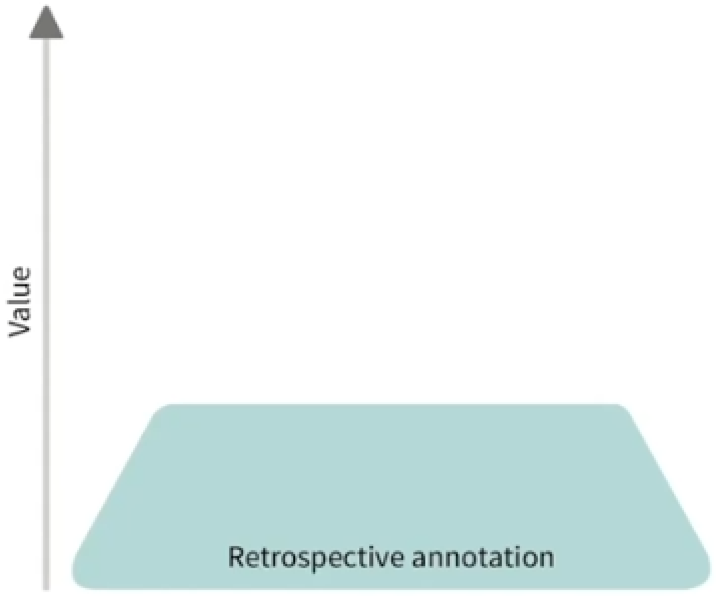
Lung nodule: **4 mm**

Lung nodule: **Benign**

Coordinates

Stanford MEDICINE Segmed

# Image Labeling



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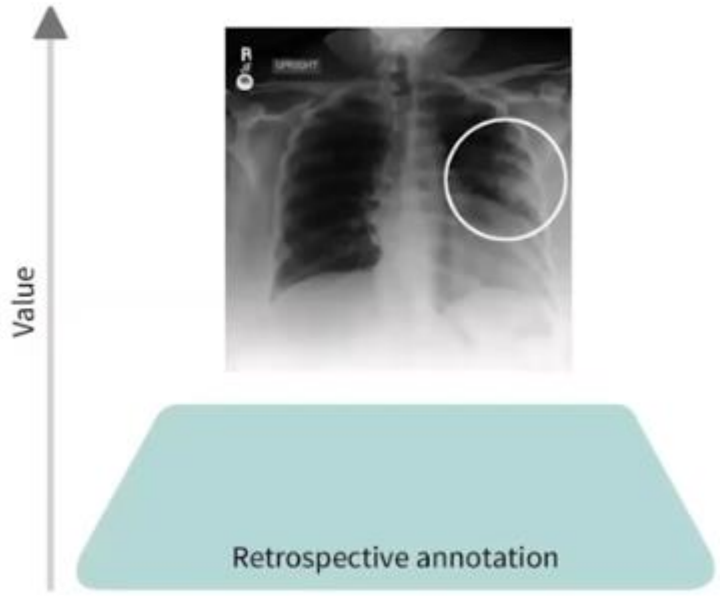

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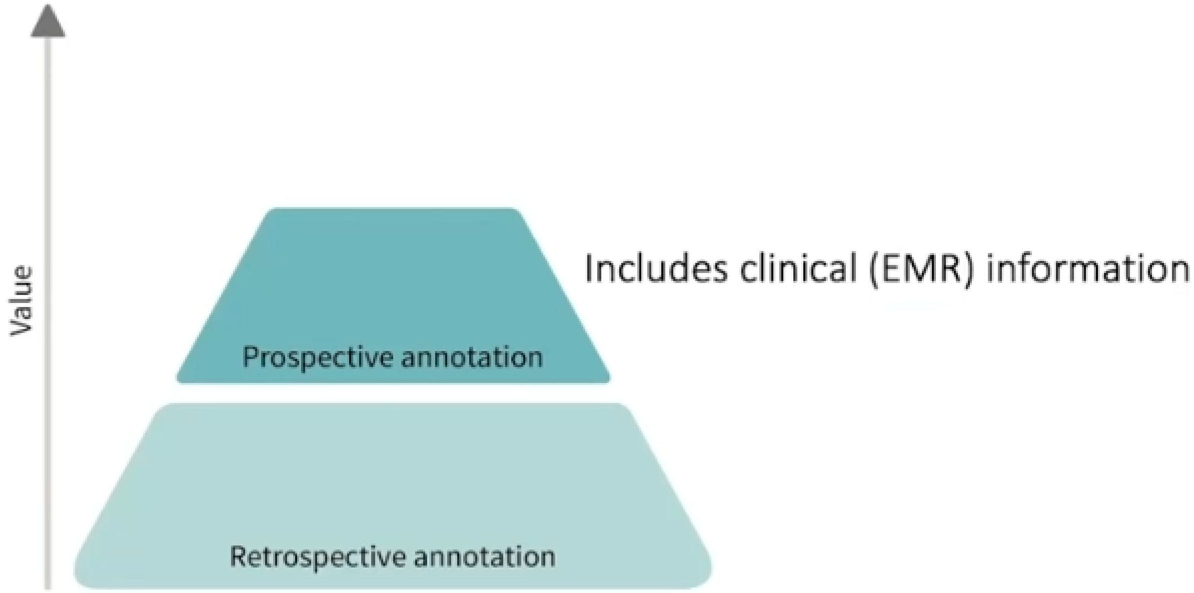

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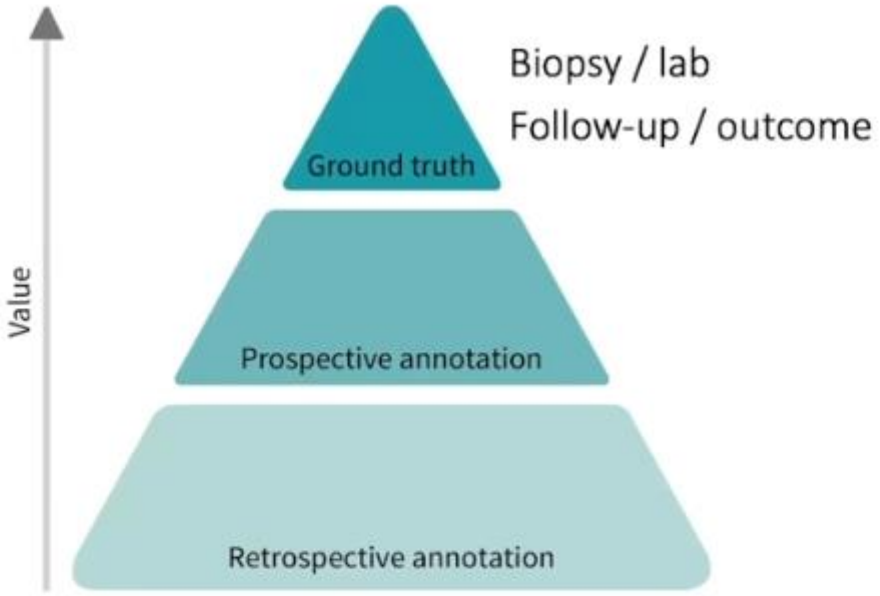
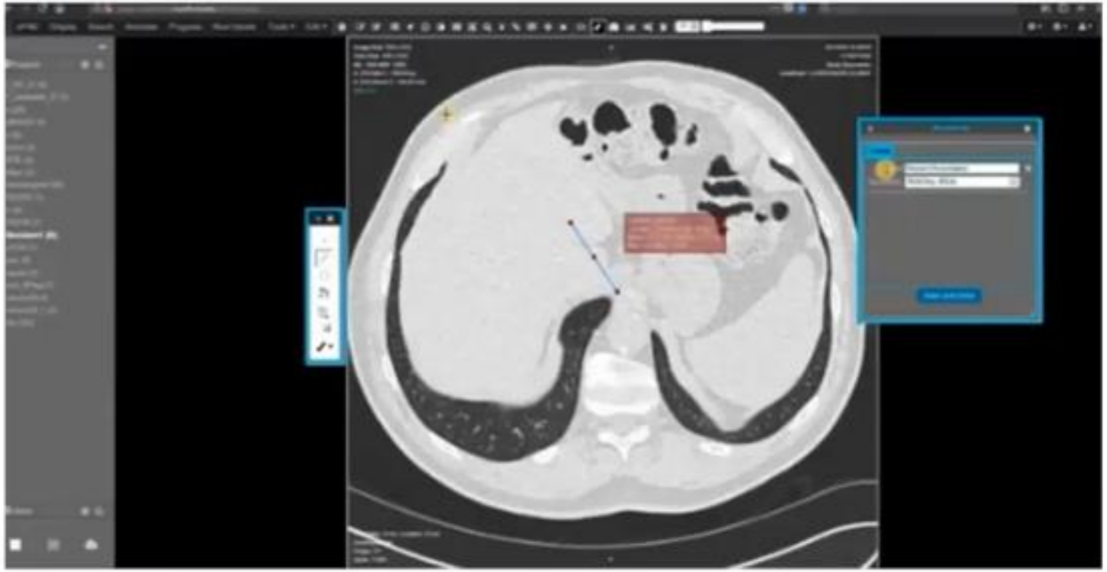


# How to Label Images

ePAD



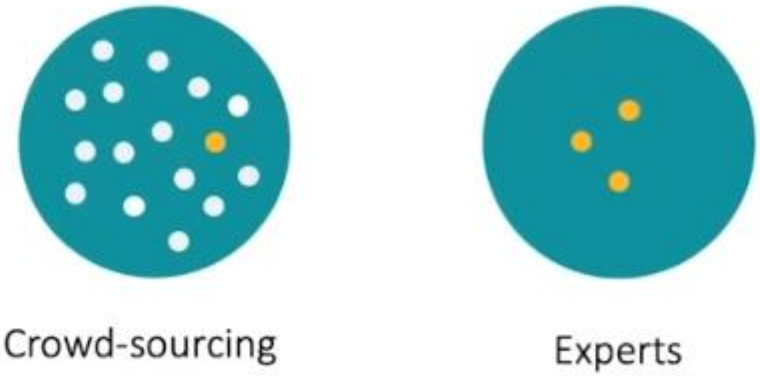
# How to Label Images

3DSlicer

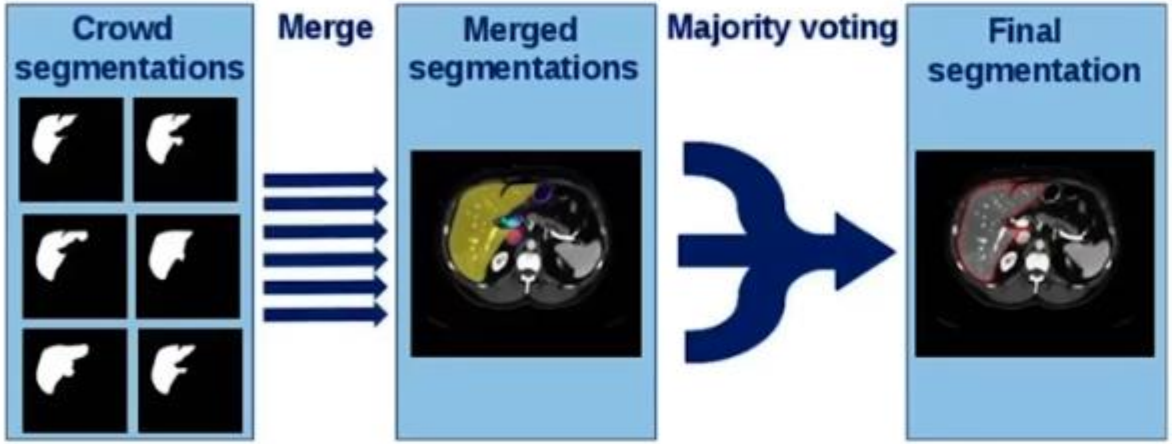
OSIRIX

ImageJ
Image Processing and Analysis in Java

# Challenges in Data Labeling



# Challenges in Data Labeling



# Label data

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xAIM

2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

# Deep Learning-Based 3D Segmentation of True Lumen, False Lumen, and False Lumen Thrombosis in Type-B Aortic Dissection

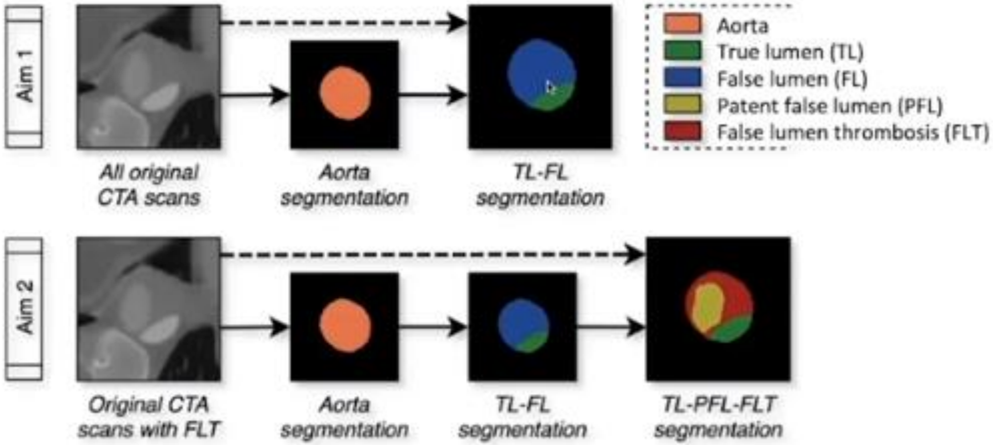
Liana D. Wobben[1,2], Marina Codari[1], Gabriel Mistelbauer[3], Antonio Pepe[4], Kai Higashigaito[1], Lewis D. Hahn[5], Domenico Mastrodicasa[1], Valery L. Turner[1], Virginia Hinostroza[1], Kathrin Bäumler[1], Michael P. Fischbein[6], Dominik Fleischmann[1], and Martin J. Willemink[1]

*Abstract*— **Patients with initially uncomplicated type-B aortic dissection (uTBAD) remain at high risk for developing late complications. Identification of morphologic features for improving risk stratification of these patients requires automated segmentation of computed tomography angiography (CTA) images. We developed three segmentation models utilizing a 3D residual U-Net for segmentation of the true lumen (TL), false lumen (FL), and false lumen thrombosis (FLT). Model 1 segments all labels at once, whereas model 2 segments them sequentially. Best results for TL and FL segmentation were achieved by model 2, with median (interquartiles) Dice similarity coefficients (DSC) of 0.85 (0.77-0.88) and 0.84 (0.82-0.87), respectively. For FLT segmentation, model 1 was superior to model 2, with median (interquartiles) DSCs of 0.63 (0.40-0.78). To purely test the**

## I. INTRODUCTION

Medical management of initially uncomplicated type-B aortic dissection (uTBAD) is associated with a poor long-term survival of only 60% at five years, due to a high rate of late adverse events (LAEs) [1]. Early identification of patients who may potentially benefit from preventative thoracic endovascular aortic repair (TEVAR) is thus highly desirable. Several studies suggest that morphological features extracted from computed tomography angiography (CTA) might predict LAEs in patients with uTBAD [2], [3]. False

# DL-based 3D segmentation of TL, FL, and FLT in TBAD



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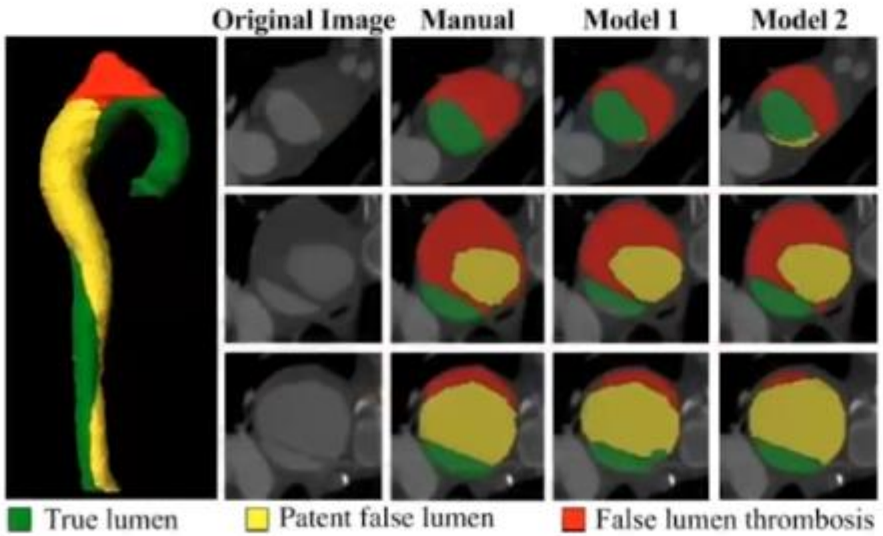

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# DL-based 3D segmentation of TL, FL, and FLT in TBAD

Dice similarity coefficients

| Model | Phase | Aorta | TL | FL | PFL | FLT |
|---|---|---|---|---|---|---|
| 1 | Training | 0.94 (0.92 - 0.94) | 0.84 (0.77 - 0.87) | 0.85 (0.78 - 0.90) | 0.84 (0.73 - 0.90) | 0.75 (0.66 - 0.79) |
| | Validation | 0.93 (0.90 - 0.94) | 0.81 (0.69 - 0.85) | 0.82 (0.69 - 0.87) | 0.80 (0.68 - 0.87) | 0.72 (0.66 - 0.77) |
| | Testing | 0.93 (0.91 - 0.94) | 0.74 (0.71 - 0.77) | 0.83 (0.79 - 0.84) | 0.82 (0.79 - 0.86) | 0.63 (0.40 - 0.78) |
| 2 | Training | 0.96 (0.96 - 0.97) | 0.93 (0.93 - 0.94) | 0.94 (0.91 - 0.95) | 0.93 (0.88 - 0.94) | 0.77 (0.66 - 0.83) |
| | Validation | 0.95 (0.94 - 0.96) | 0.92 (0.86 - 0.93) | 0.91 (0.85 - 0.92) | 0.90 (0.85 - 0.93) | 0.76 (0.68 - 0.79) |
| | Testing | 0.96 (0.95 - 0.96) | 0.86 (0.77 - 0.88) | 0.86 (0.84 - 0.88) | 0.85 (0.83 - 0.86) | 0.50 (0.19 - 0.65) |