

Scaling Datasets, Annotations, and Algorithms for Medical Image Analysis

Zongwei Zhou, PhD

Postdoc, Department of Computer Science
Johns Hopkins University, Baltimore, MD
P: 1-(480)738-2575 | E: zzhou82@jh.edu
www.zongweiz.com

Statistics

7,118 citations

Top 2% of Scientists in 2022

24 first/corresponding authored papers

Significant

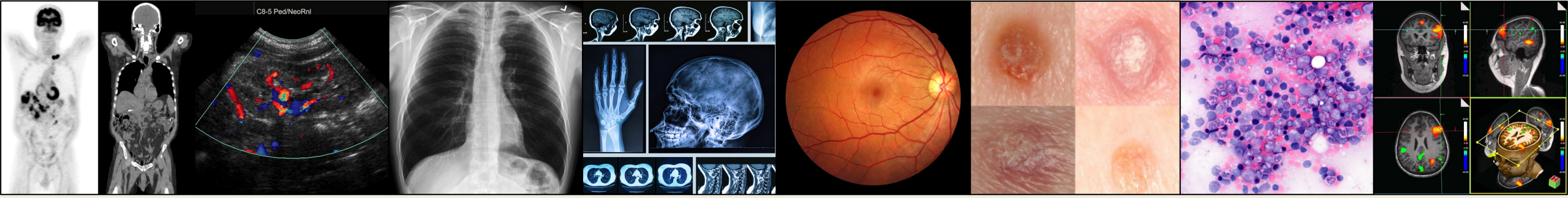
Needful

Applications

Methodologies

Innovative

Impactful

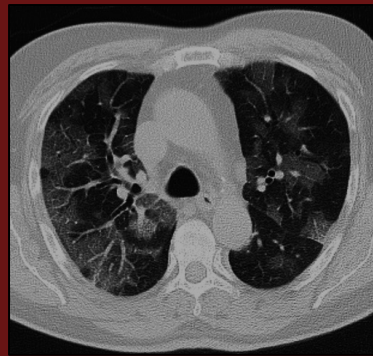


Imaging data account for about **90%** of all healthcare data

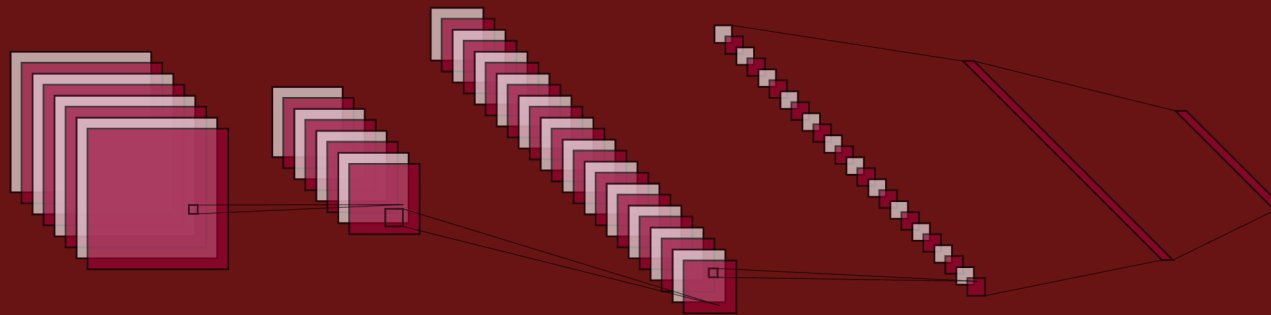
Significant

**Applications
Methodologies**

Impactful



Input image



Hidden layers

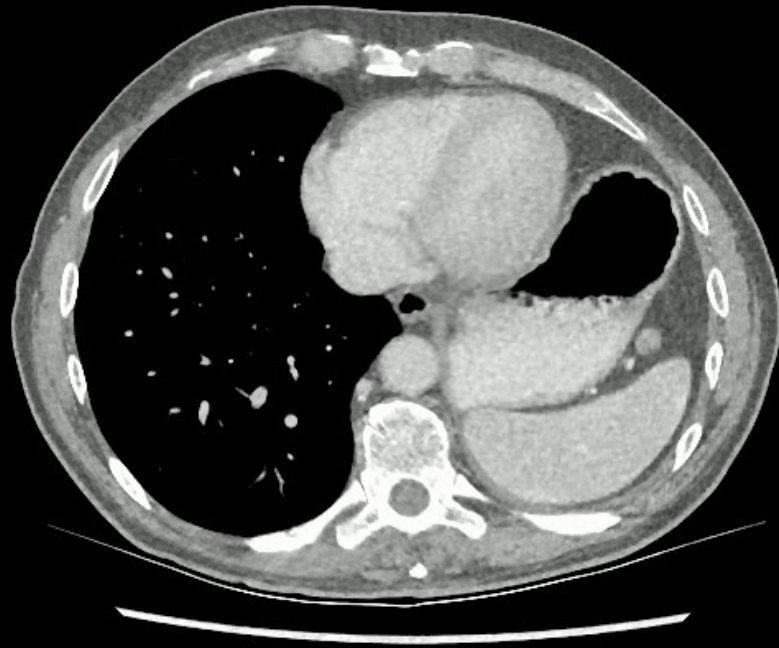
Lung cancer?



Output

Deep Learning has ushered in a revolution in medical imaging

CT



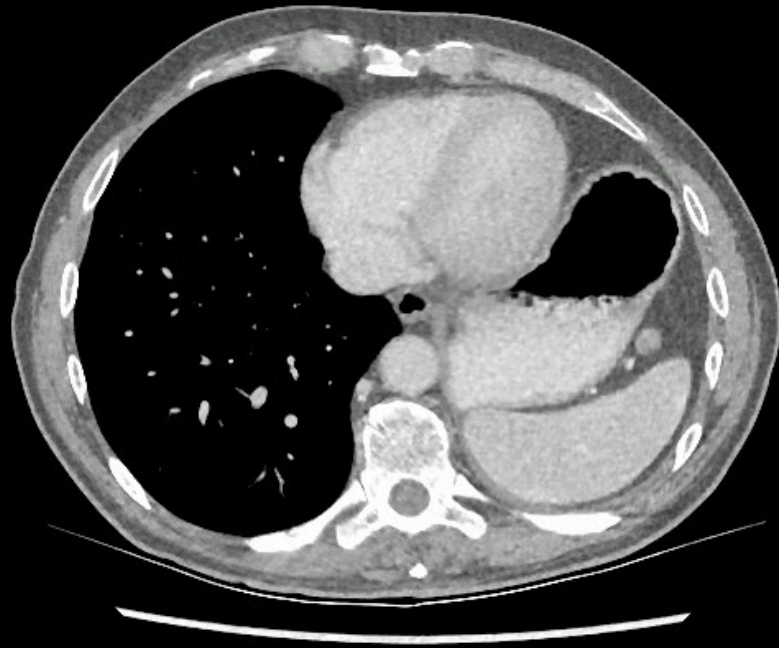
Ground Truth
annotated by human experts

Deep Learning

- Liver
- Liver tumor

Radiologists hate annotation, but computer scientists love annotation.

CT



Ground Truth
annotated by human experts

Deep Learning

- Liver
- Liver tumor

Not enough annotation

Chapter I (2016-2022)

Methodologies: Reducing Annotation Efforts for Radiologists

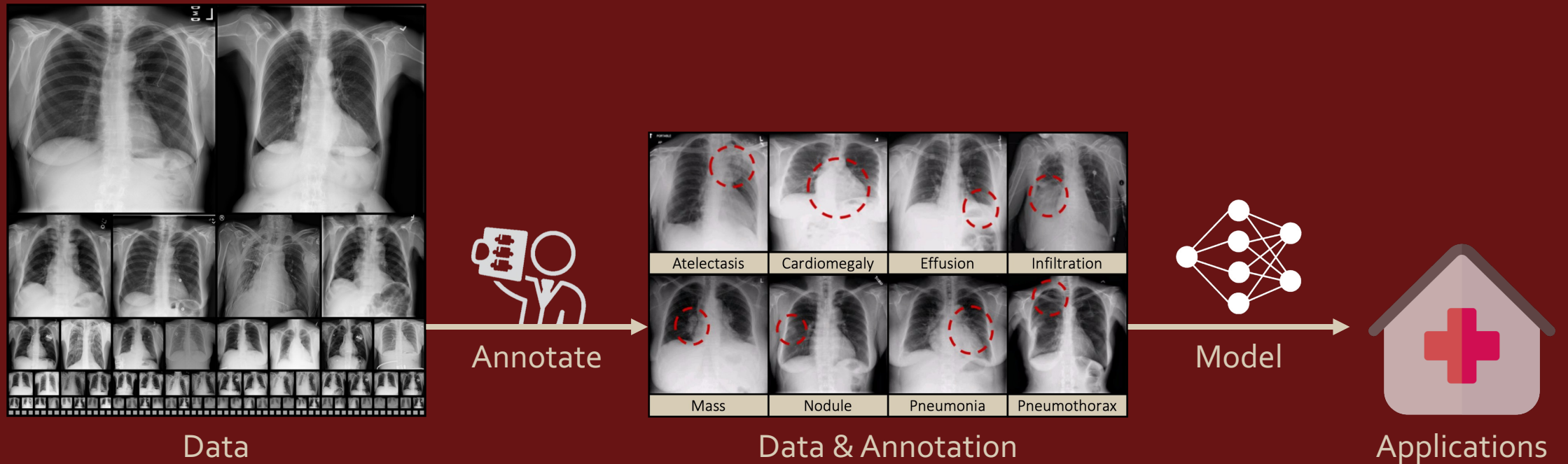
Significant

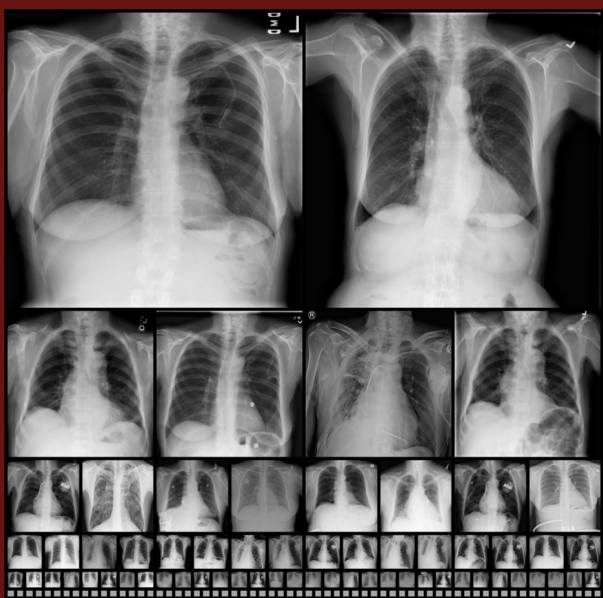
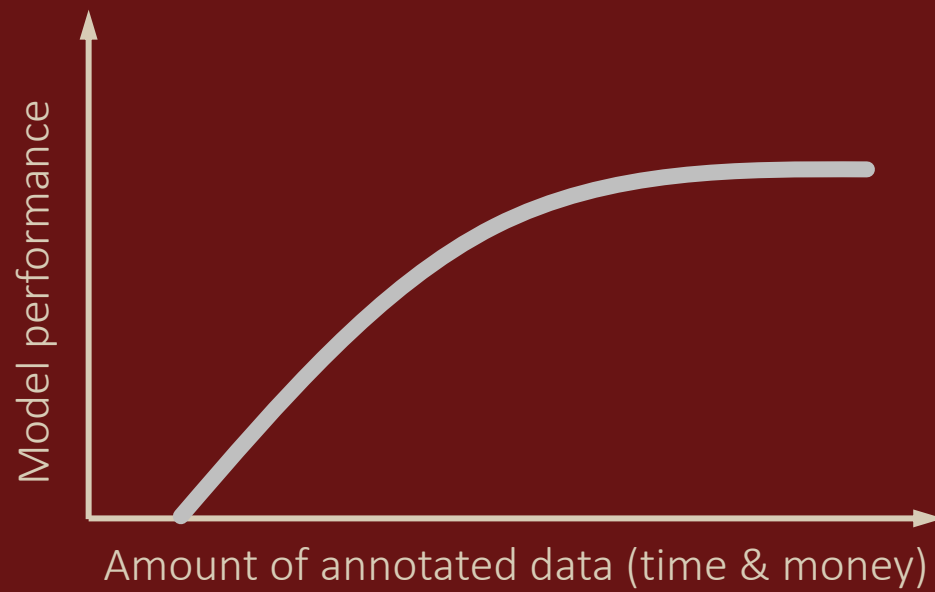
**Applications
Methodologies**

Impactful

Computer-Aided Diagnosis

Assisting expert radiologists to see more patients and to deliver more accurate diagnosis (*beyond human eye*)

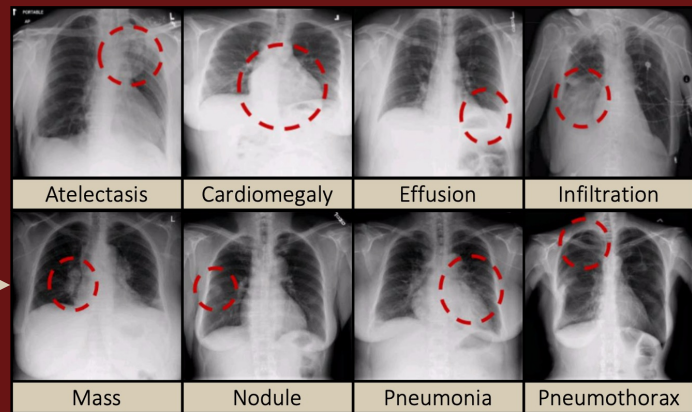




Data



Annotate



Data & Annotation

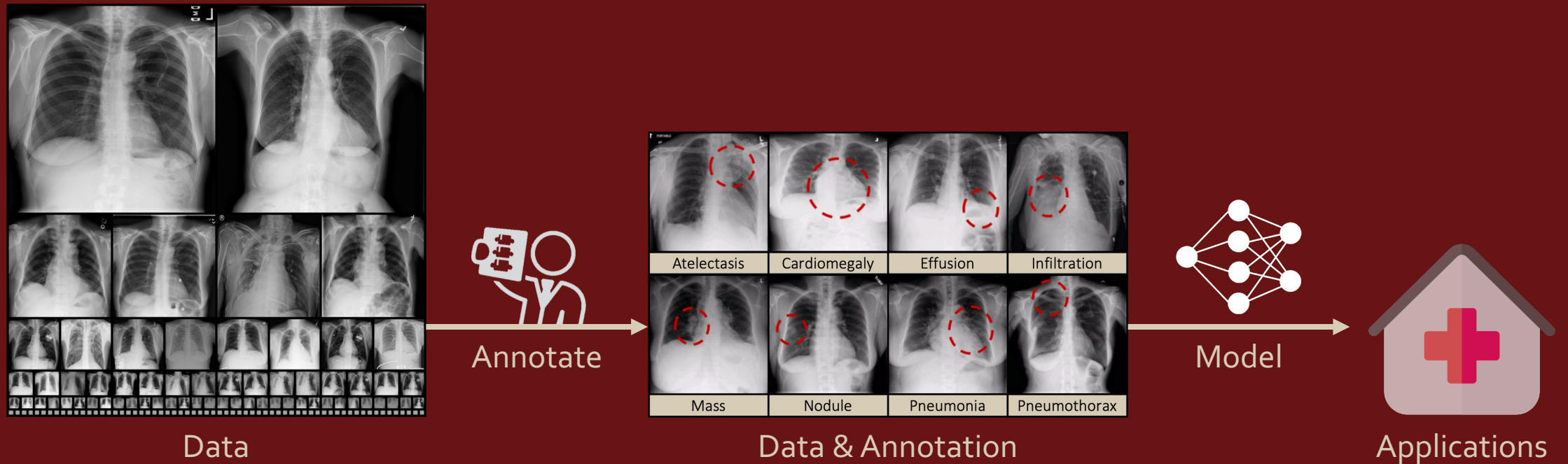
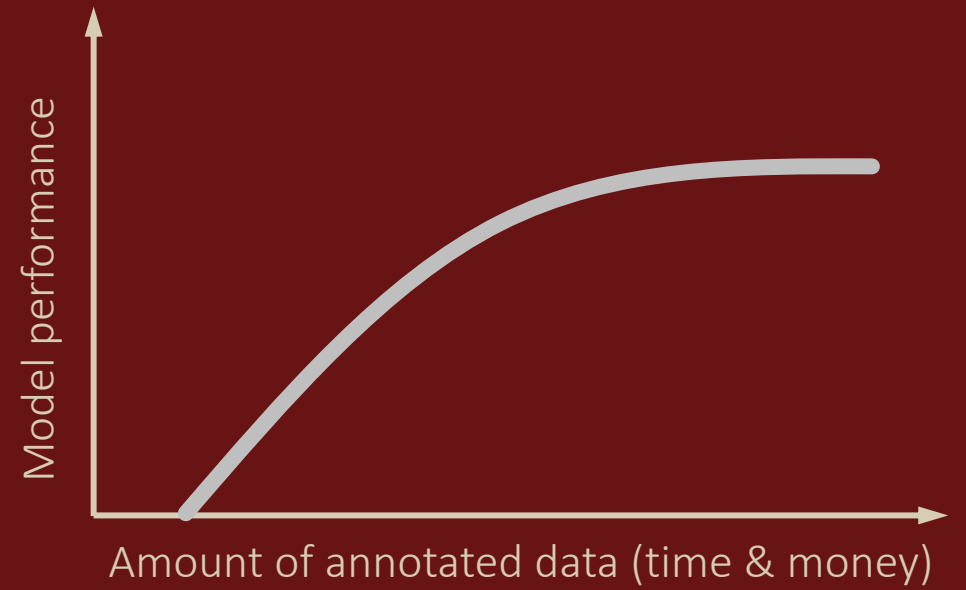


Model



Applications

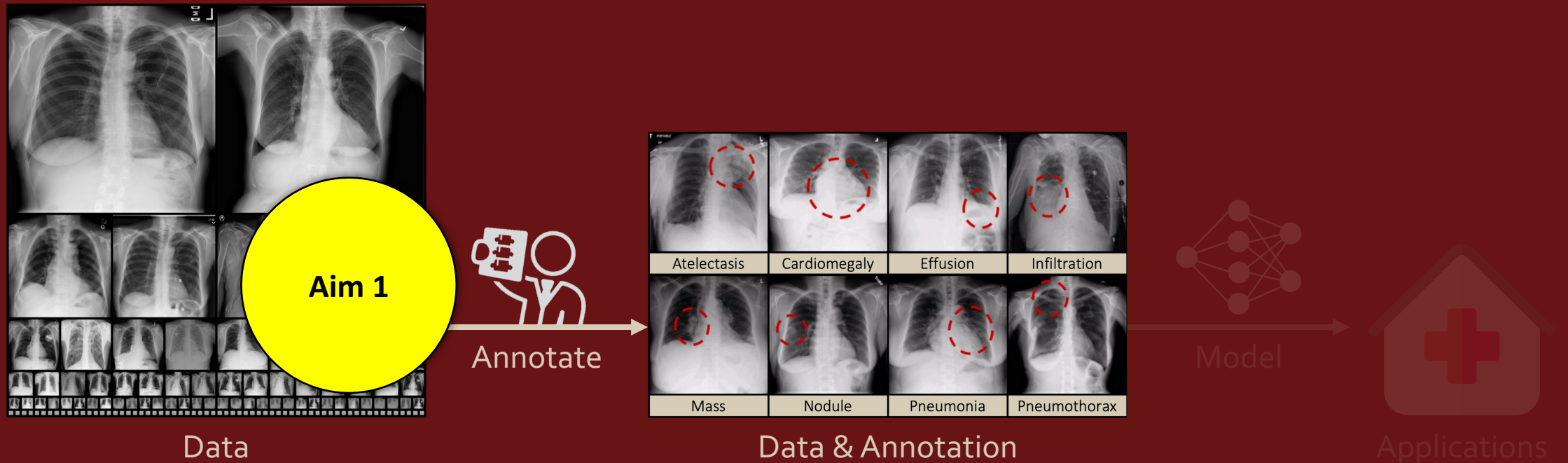
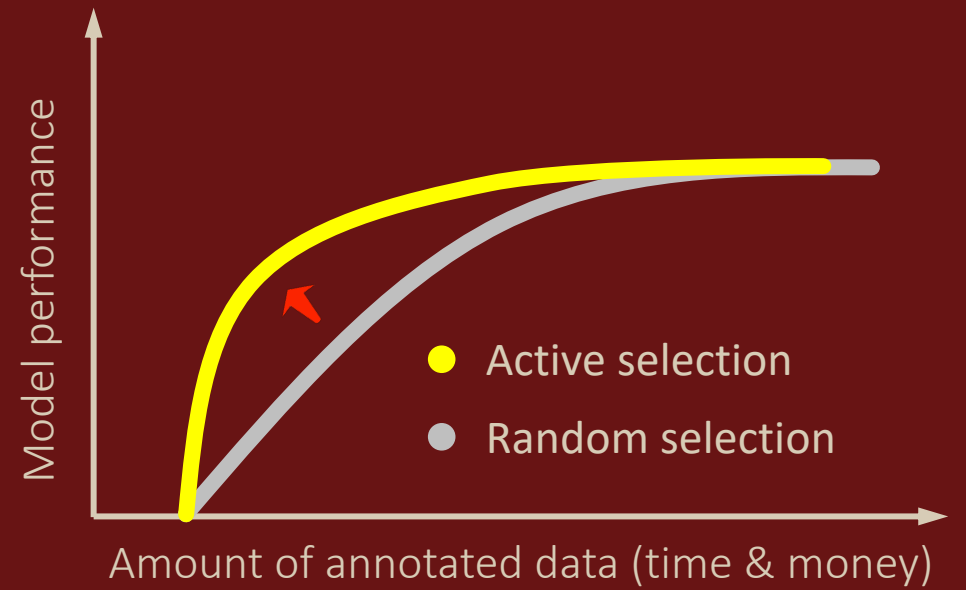
Goal: Reduce annotation efforts for radiologists.



Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.

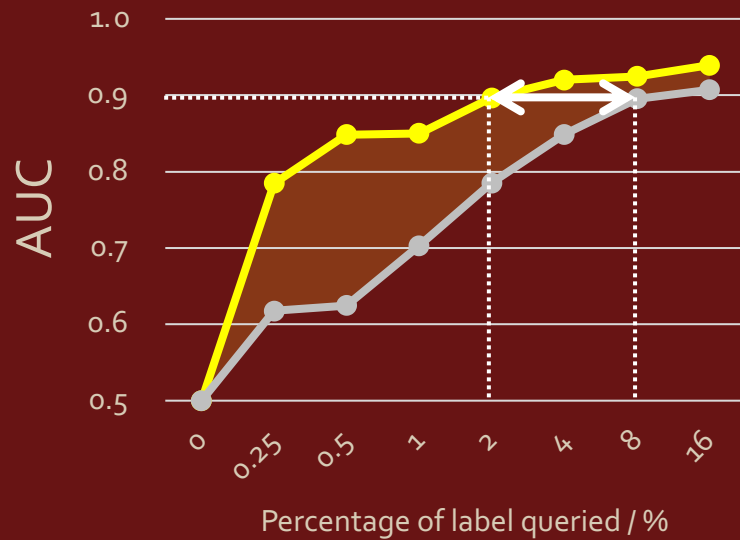
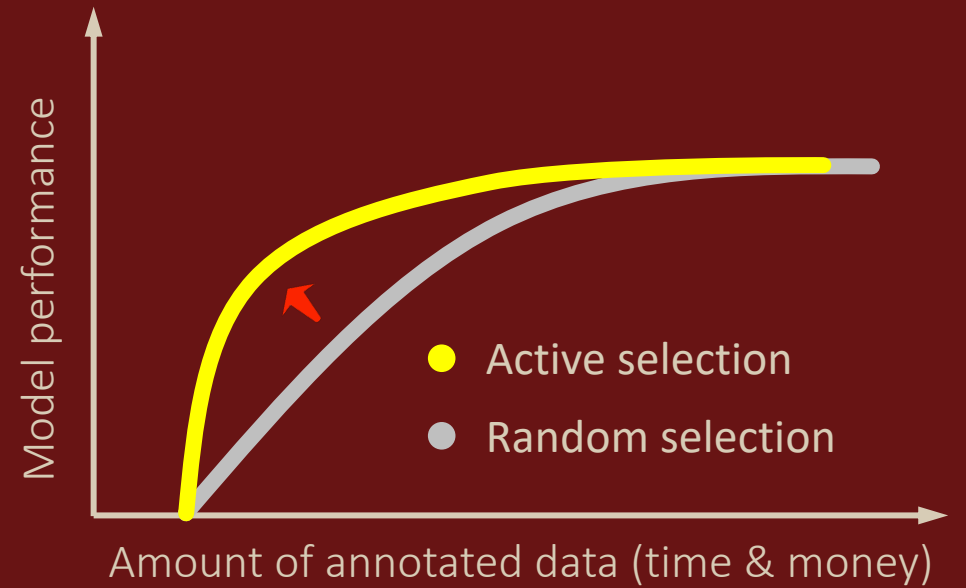
- **Active, Continual Fine-Tuning (ACFT)**
- CVPR'17, MedIA'21, MIDL'23



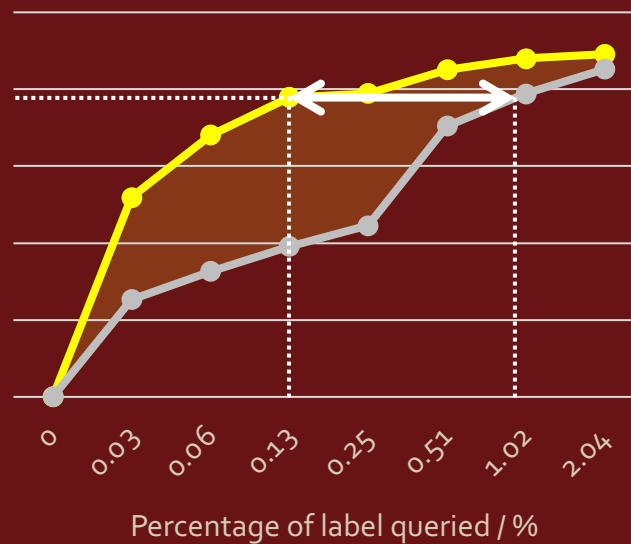
Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.

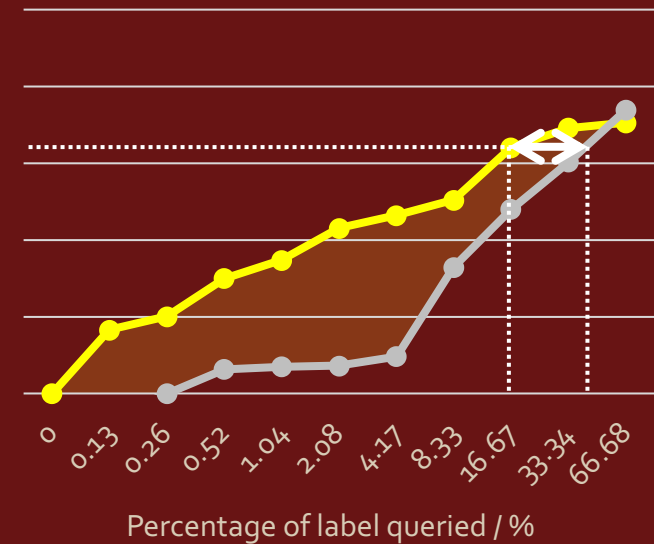
- **Active, Continual Fine-Tuning (ACFT)**
- CVPR'17, MedIA'21, MIDL'23
- Integrating uncertainty and diversity criteria
- Reducing over **80%** annotation cost



Colonoscopy Frame Classification (-81.5%)



Polyp Detection (-86.3%)

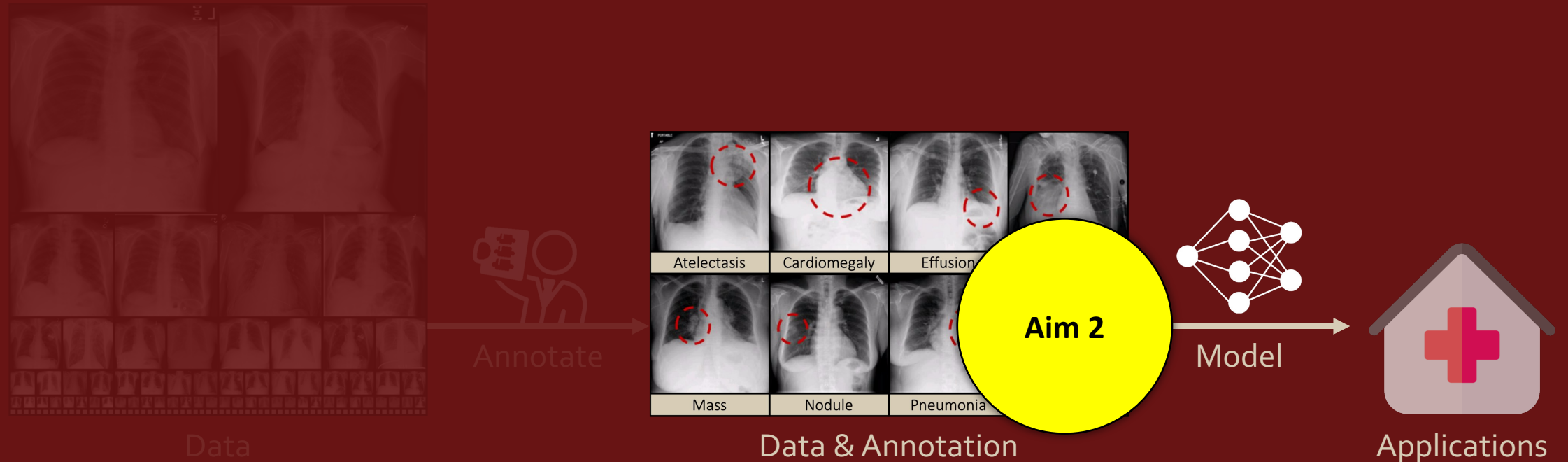
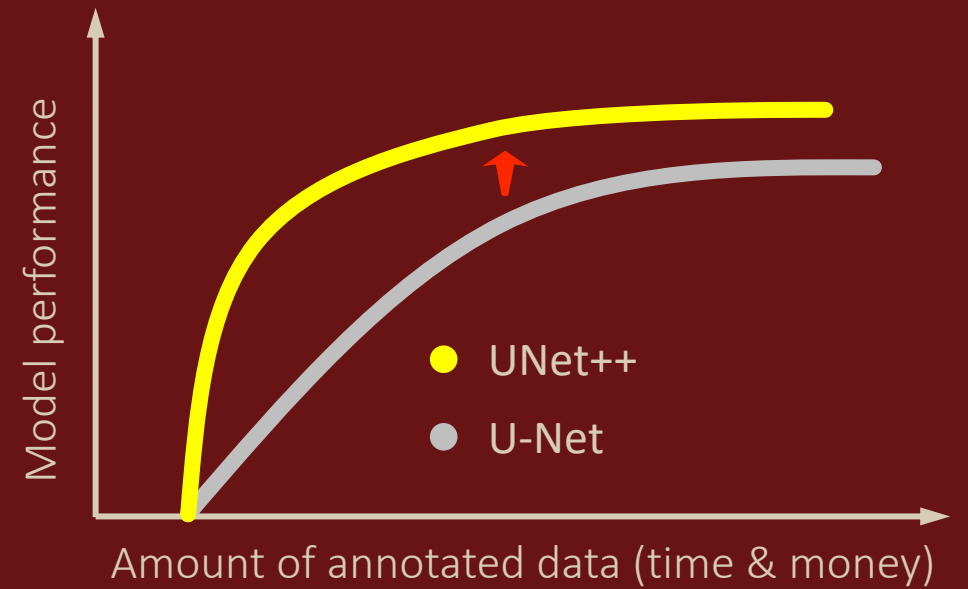


Pulmonary Embolism Detection (-80.3%)

Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.

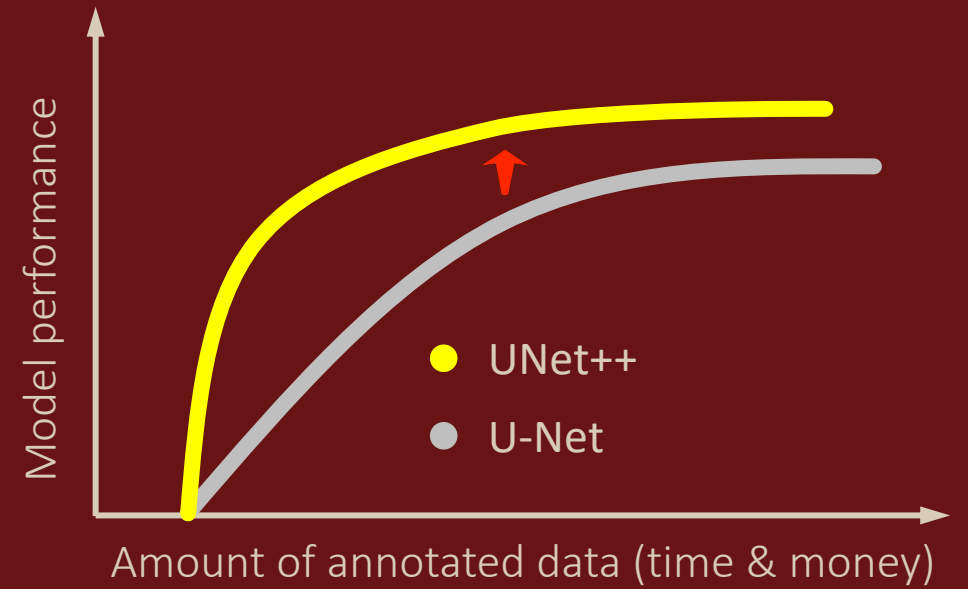
- **UNet++**
- MICCAIW'18, IEEE TMI'19 (*Most Popular Articles*)



Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.

- **UNet++**
- MICCAIW'18, IEEE TMI'19 (*Most Popular Articles*)
- Aggregating multi-scale, multi-resolution features
- Detecting **very small tumors** without too many FPs



CT



Ground Truth



UNet++ Prediction

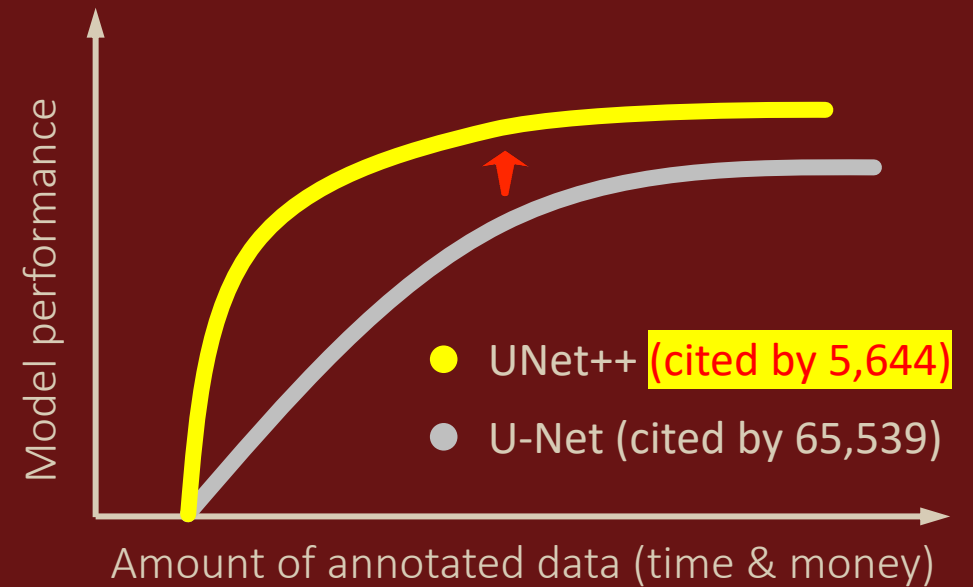


- Liver
- Liver tumor

Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.

- **UNet++**
- MICCAIW'18, IEEE TMI'19 (*Most Popular Articles*)
- Aggregating multi-scale, multi-resolution features
- Detecting **very small tumors** without too many FPs

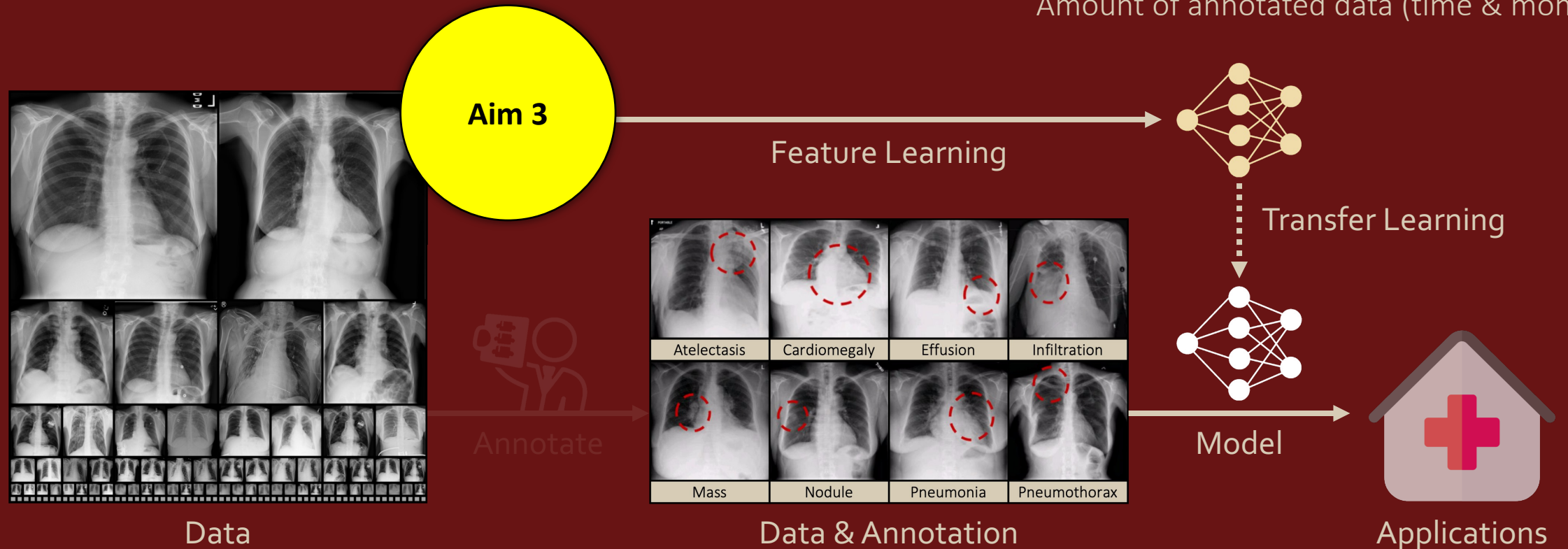
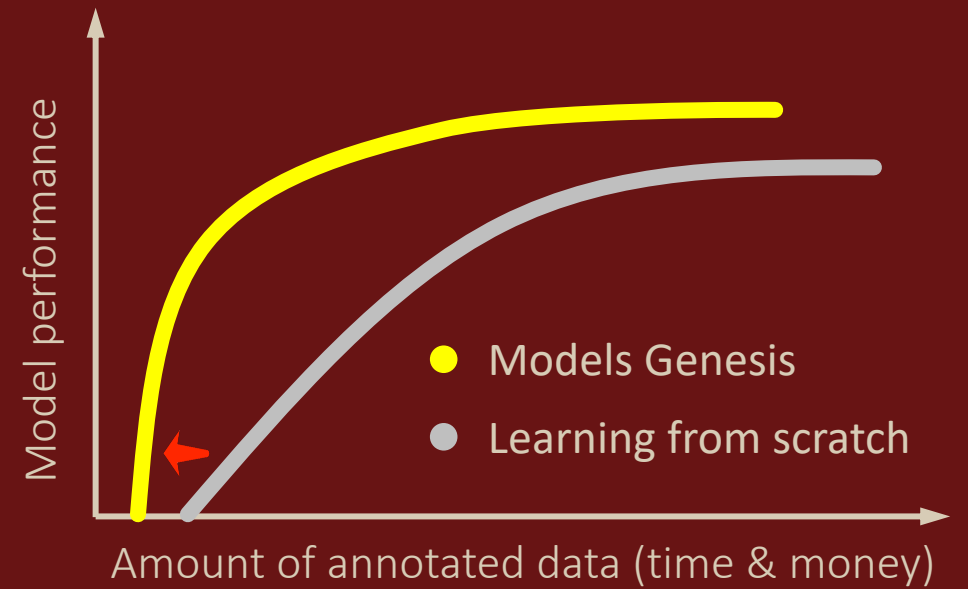


43.9% → 58.1% (U-Net → UNet++) Covid-19 segmentation (CT) [Fan et al., IEEE TMI]	78.6% → 82.9% (U-Net → UNet++) Fiber tracing (corneal confocal microscopy) [Mou et al., MICCAI]	86.5% → 89.5% (U-Net → UNet++) Spleen segmentation (MRI) [Li et al., Computers & Graphics]
86.6% → 87.2% (U-Net → UNet++) SegTHOR 2019 Challenge (CT) [Zhang et al., IEEE TMI]	90.2% → 92.0% (U-Net → UNet++) Optic Disc & Cup Segmentation (fundus image) [Meng et al., MICCAI]	60.3% → 71.6% (U-Net → UNet++) Ground-glass opacity segmentation (CT) [Zheng et al., IEEE Access]
51.2% → 58.6% (U-Net → UNet++) Esophagus segmentation (CT) [Huang et al., IEEE Access]	63.7% → 66.3% (U-Net → UNet++) Liver tumor segmentation (CT) [Bajpai et al., Master Thesis]	90.7% → 91.6% (U-Net → UNet++) Heart segmentation (MRI) [Ji et al., MICCAI]

Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.
3. Extracting generic knowledge directly from unannotated images.

- **Models Genesis**
- MICCAI'19 (*Young Scientist Award*), MIA (*Best Paper Award*)

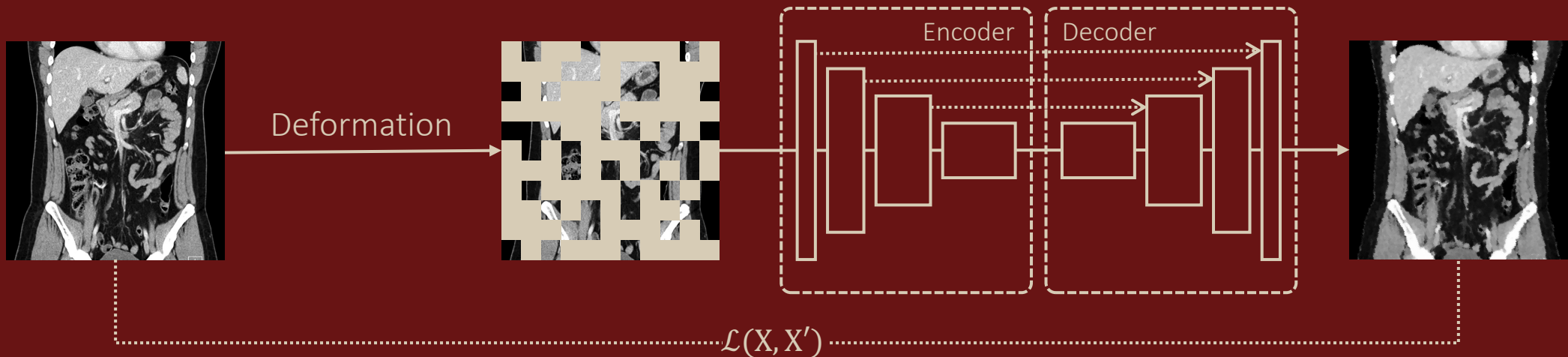
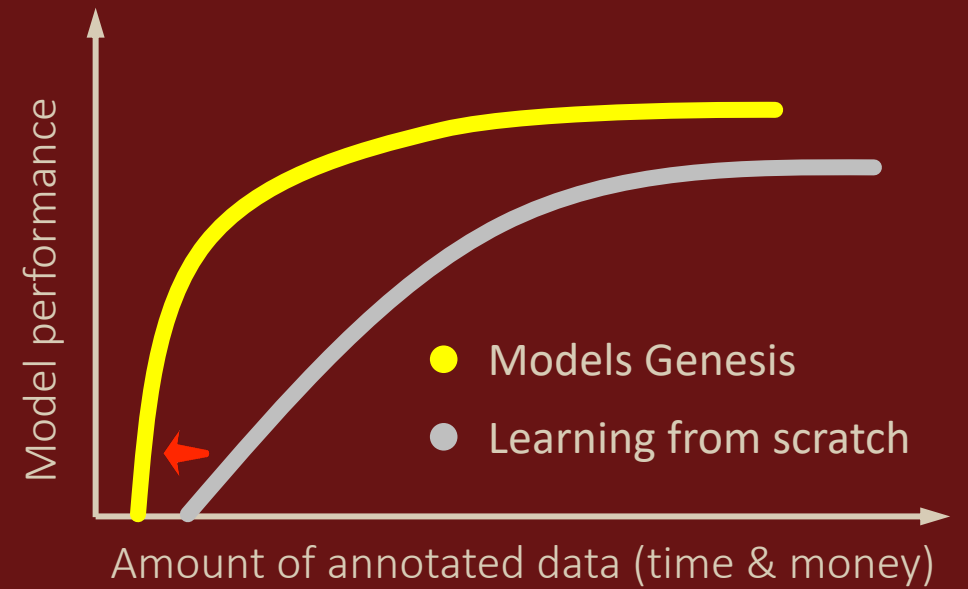


Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.
3. Extracting generic knowledge directly from unannotated images.

- **Models Genesis**

- MICCAI'19 (*Young Scientist Award*), MIA (*Best Paper Award*)
- The **First** publicly available 3D pre-trained model
- A demonstration of **masked image modeling** in medicine



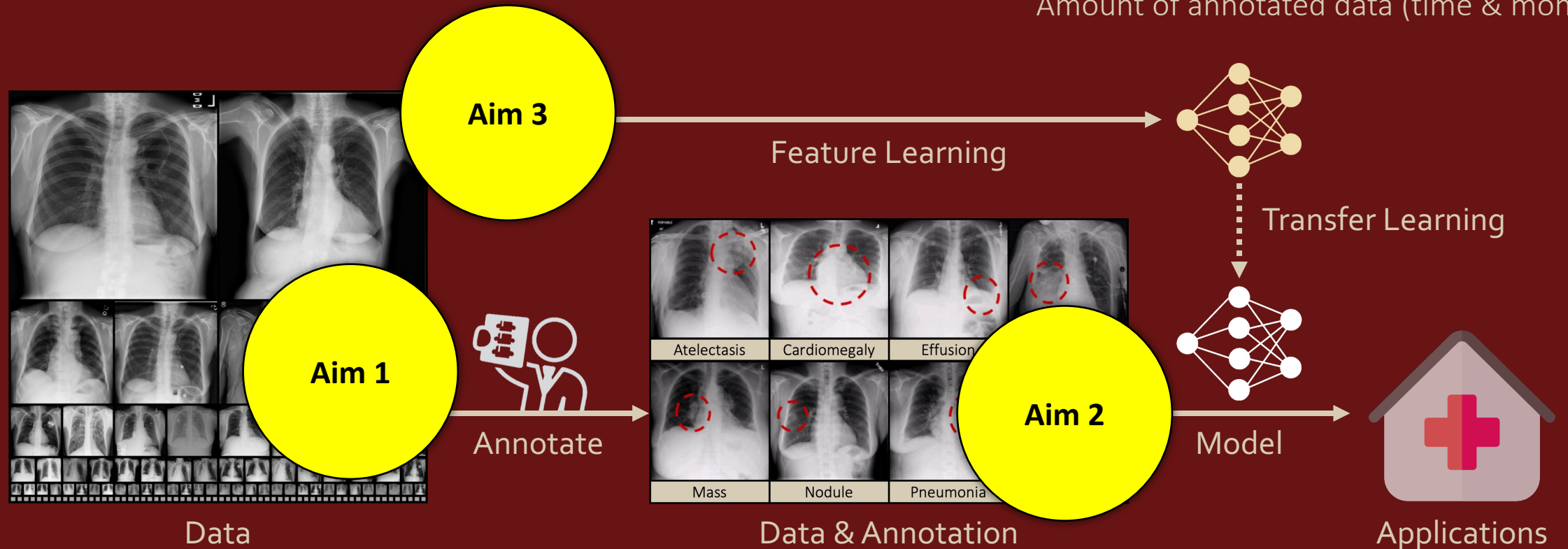
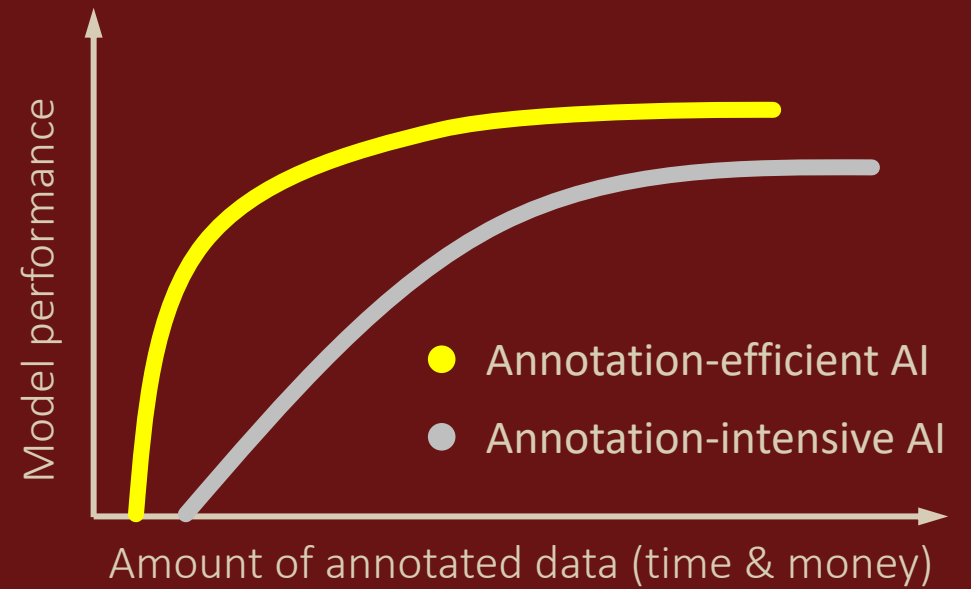
Goal: Reduce annotation efforts for radiologists.

1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.
3. Extracting generic knowledge directly from unannotated images.

—PhD dissertation—



Doctoral Dissertation Award Winner

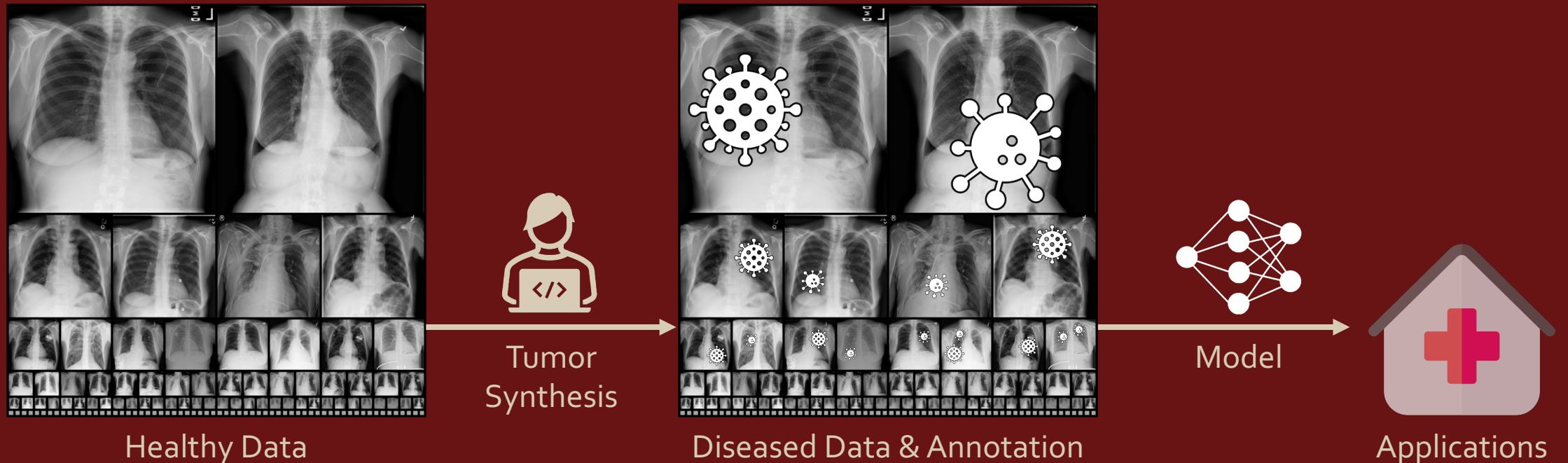
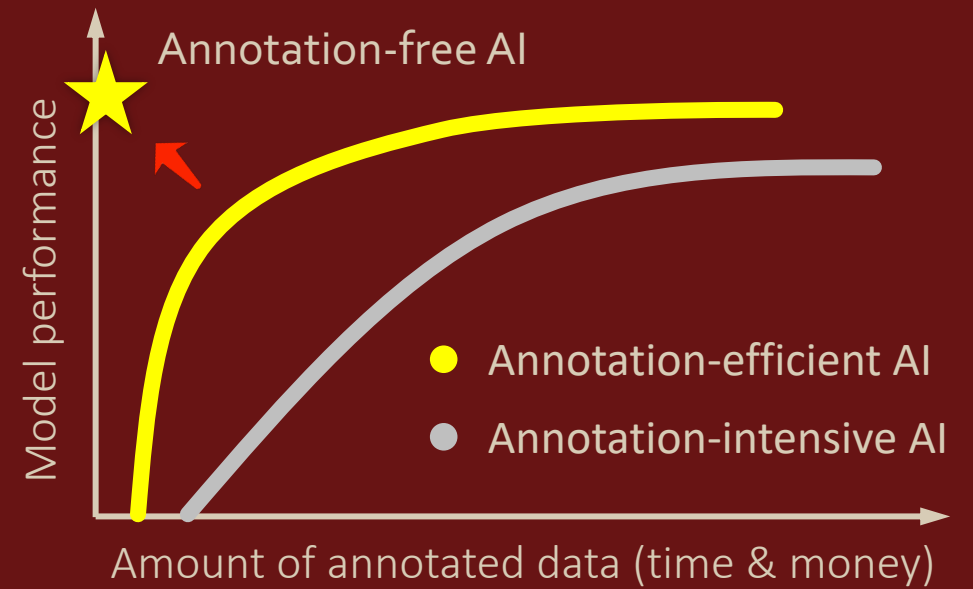


Goal: Reduce annotation efforts for radiologists.

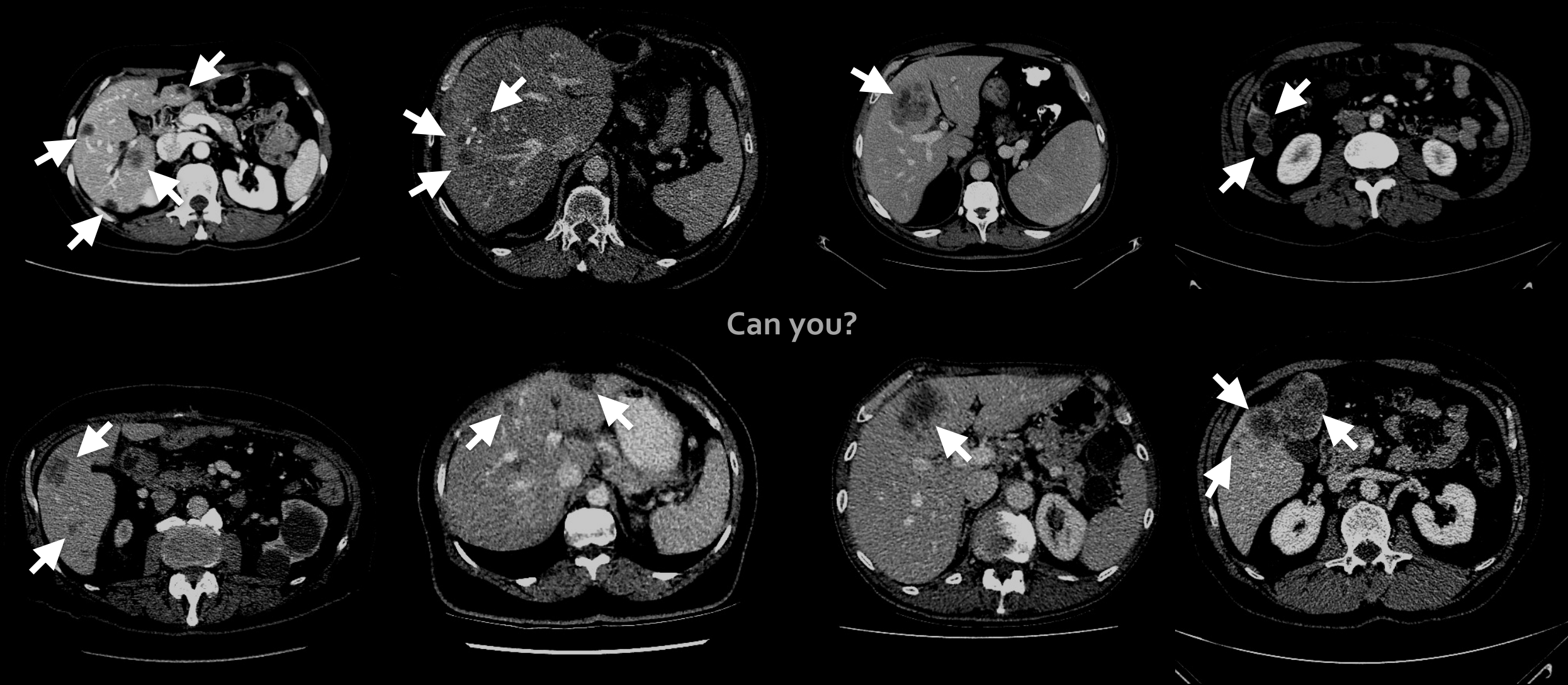
1. Acquiring necessary annotation efficiently from human experts.
2. Utilizing existing annotation effectively from advanced models.
3. Extracting generic knowledge directly from unannotated images.

—PhD dissertation—

4. Generating annotation automatically from **tumor synthesis**.



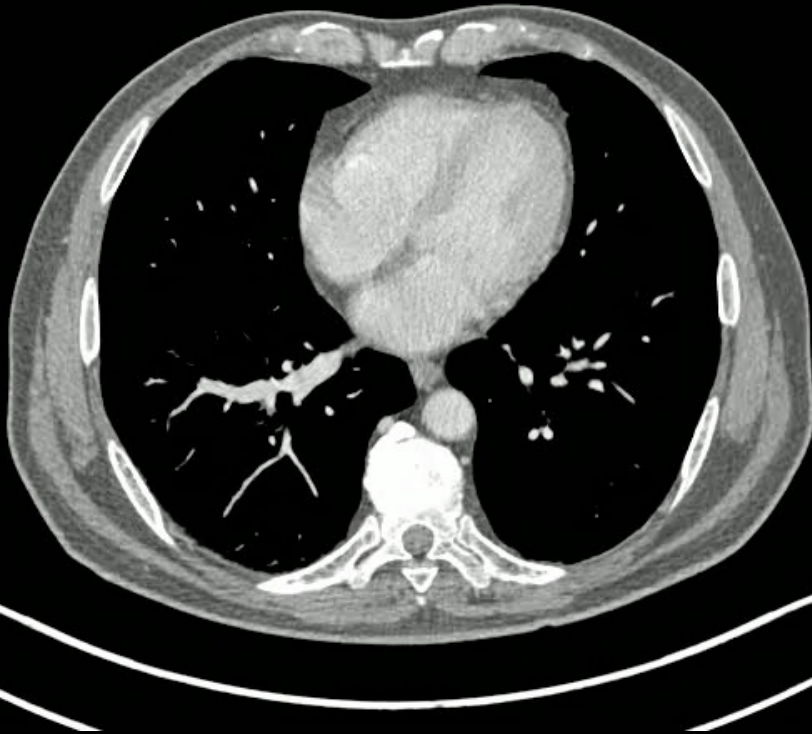
Medical professionals cannot tell which are real and which are synthetic tumors



1. Hu, Qixin, Yixiong Chen, Junfei Xiao, Shuwen Sun, Jieneng Chen, Alan Yuille, and Zongwei Zhou*. "Label-Free Liver Tumor Segmentation." CVPR-2023.

Training AI on synthetic tumors performs almost as well as training it on real tumors

CT

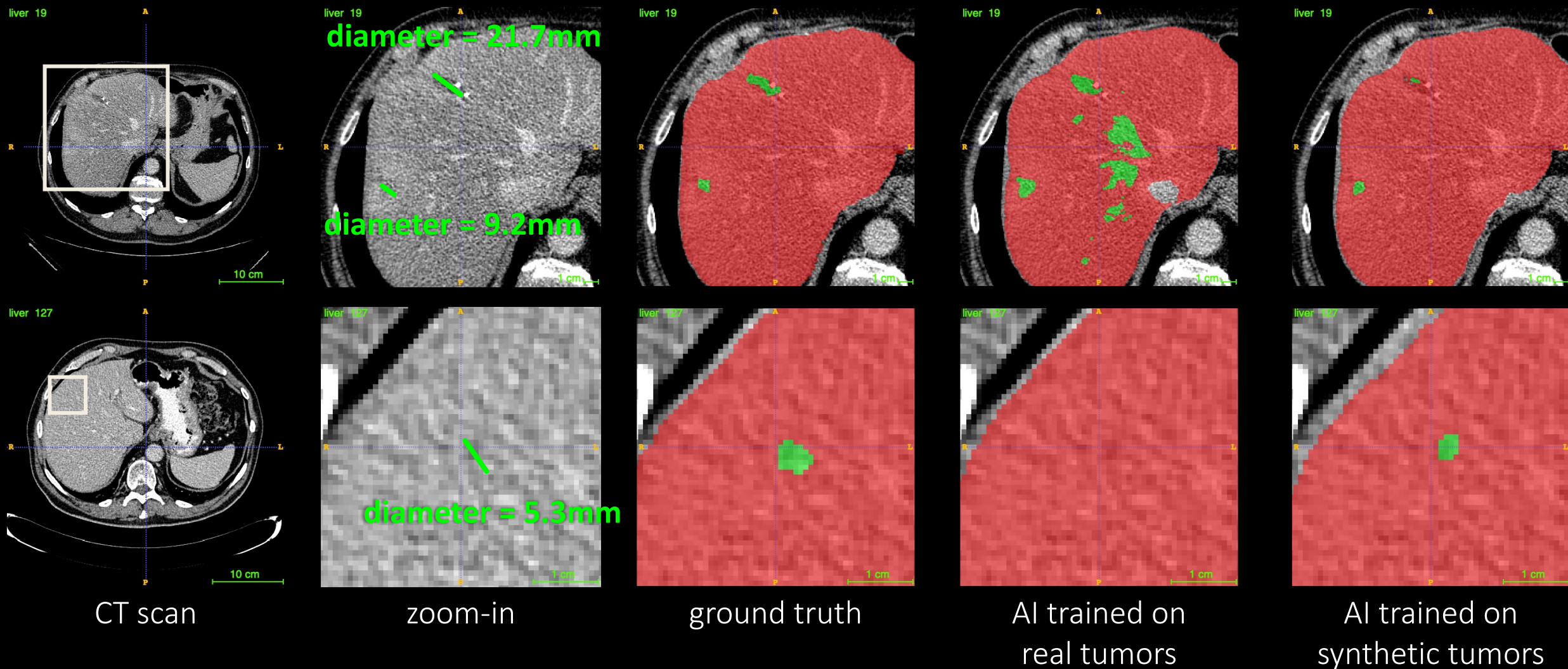


AI prediction
trained on real tumors
with per-voxel annotation
DSC = 58% [52% - 63%]

AI prediction
trained on synthetic tumors
with no annotation
DSC = 60% [55% - 65%]

- Liver
- Liver tumor

[Qualitative] Generating enormous small tumors for training AI models

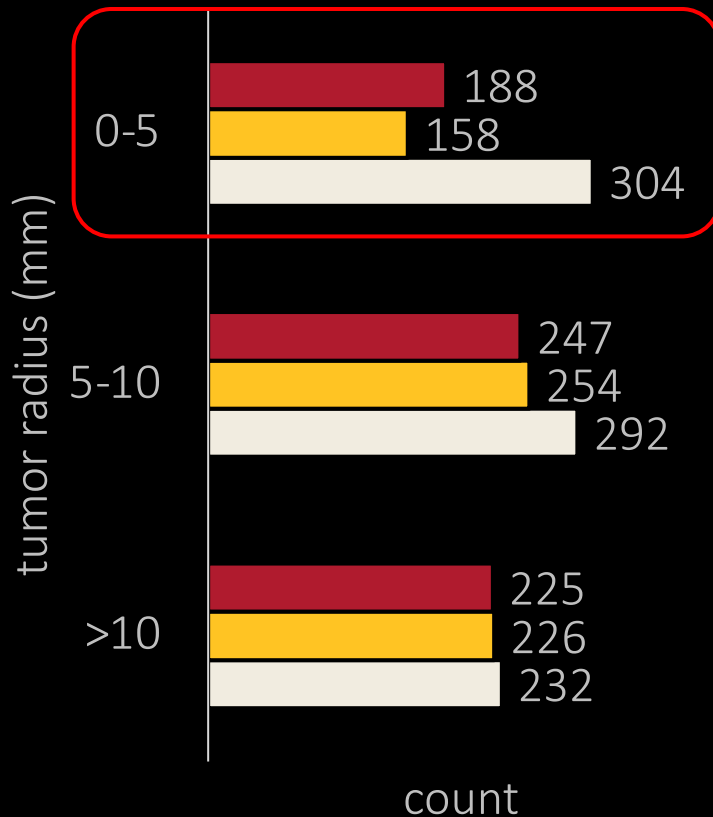


1. Hu, Qixin, Yixiong Chen, Junfei Xiao, Shuwen Sun, Jieneng Chen, Alan Yuille, and Zongwei Zhou*. "Label-Free Liver Tumor Segmentation." CVPR-2023.

[Quantitative] Generating enormous small tumors for training AI models

- AI trained on synthetic tumors
- AI trained on real tumors
- ground truth

Observation: Compared with real tumors, AI trained on synthetic tumors improves Sensitivity from 52% to 62% for detecting small tumors (0-5mm).



- Needed for early detection
 - Early signs of cancer can be subtle
 - 1/2 of liver cancer are missed by radiologists
- Needed for AI development
 - CT scans with early cancer are limited
 - Annotations for early cancer are hard
- Needed for medical education
 - Junior radiologists have an Accuracy of 20%
 - Senior radiologists have an Accuracy of 78%

1. Hu, Qixin, Yixiong Chen, Junfei Xiao, Shuwen Sun, Jieneng Chen, Alan Yuille, and Zongwei Zhou*. "Label-Free Liver Tumor Segmentation." CVPR-2023.

Significant

**Applications
Methodologies**

Impactful

**Annotation-intensive
deep learning**



**Annotation-efficient
deep learning**



**Annotation-free
deep learning**

Chapter II (2020-present)

Applications: Developing 3D Maps of Whole Body

Significant

Applications
Methodologies

Impactful

Image-guided surgery

Quantitative analysis of disease progression

Earlier detection of cancer

Radiomics and predictive analytics

Neuroimaging

Edward H. Shortliffe, MD, PhD



[Shortliffe Home](#)

[Professional Interests](#)

[Personal Statement](#)

[Personal Interests](#)

[C.V. & Biosketch](#)

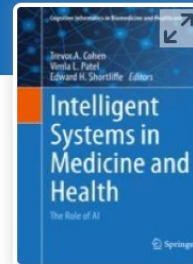
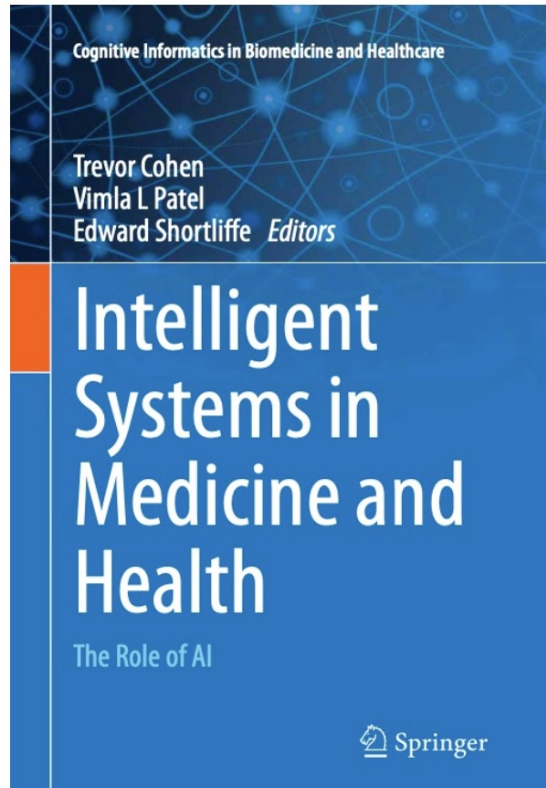
[Textbook: Intelligent Systems in Medicine and Health \(2022\)](#)

[Textbook: Biomedical Informatics \(5th edition, 2021\)](#)

[Rule-Based Expert Systems: MYCIN \(1984\)](#)

[Readings in Medical Artificial Intelligence \(1984\)](#)

[Computer-Based Medical Consultations:](#)



[Intelligent Systems in Medicine and Health](#) pp 343–371 | [Cite as](#)

[Home](#) > [Intelligent Systems in Medicine and Health](#) > [Chapter](#)

Interpreting Medical Images

[Zongwei Zhou](#), [Michael B. Gotway](#) & [Jianming Liang](#)

Chapter | [First Online: 10 November 2022](#)

663 Accesses | **1** Citations

Part of the [Cognitive Informatics in Biomedicine and Healthcare](#) book series (CIBH)

Image-guided surgery	Quantitative analysis of disease progression	Earlier detection of cancer	Radiomics and predictive analytics	Neuroimaging
----------------------	--	------------------------------------	------------------------------------	--------------

The FELIX Project

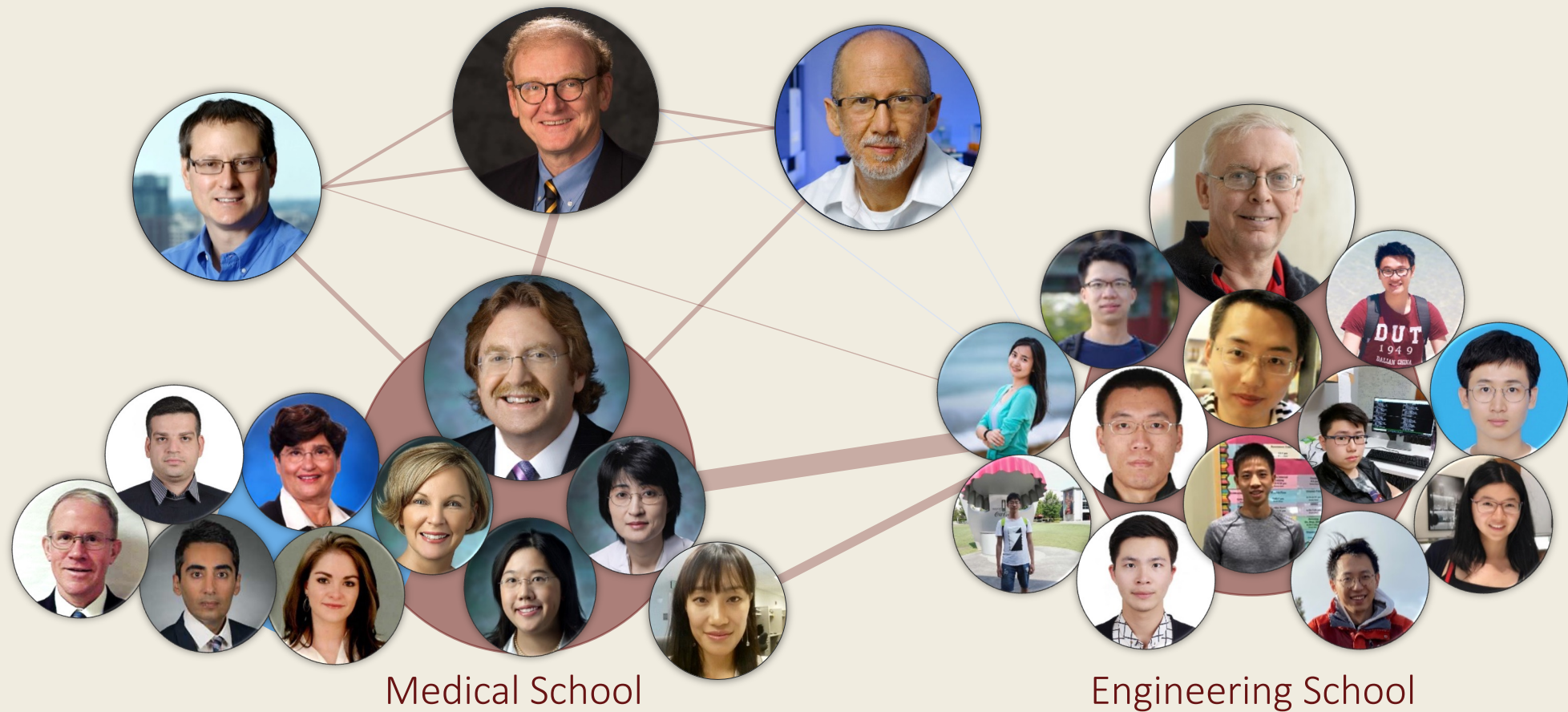


Image-guided surgery	Quantitative analysis of disease progression	Earlier detection of cancer	Radiomics and predictive analytics	Neuroimaging
----------------------	--	------------------------------------	------------------------------------	--------------

The FELIX Project

Goal: Earlier detection of pancreatic cancer

- 40,000,000 abdominal CT scans are performed each year in U.S.
- 1/3 of pancreatic cancer in these scans are missed by Radiologists.
- Pancreatic cancer is treatable if detected early.
- Deep Learning can see things in images that most humans miss.
 - 5,038 annotated CT scans at Johns Hopkins 📄 Sensitivity=97%, Specificity=99%
 - *This dataset took **15 years** to annotate for a human.*

1. Xia, Yingda, Qihang Yu, Linda Chu, Satomi Kawamoto, Seyoun Park, Fengze Liu, Jieneng Chen et al. "The felix project: Deep networks to detect pancreatic neoplasms." medRxiv (2022): 2022-09.

Image-guided surgery	Quantitative analysis of disease progression	Earlier detection of cancer	Radiomics and predictive analytics	Neuroimaging
----------------------	--	------------------------------------	------------------------------------	--------------

The FELIX-Civitas Project

Goal: Earlier detection of pancreatic cancer

New Goal: Earlier detection of a variety of cancers

- Body Maps: 3D Maps of Whole Body
 - Conceptually similar to Google Maps, but it focuses on human anatomy rather than the Earth's geography.
 - (1) Accurate segmentation of 104 anatomical structures.
 - (2) Cancer screening and localization across various structures.
 - (3) Language interaction between users and systems.

Image-guided surgery	Quantitative analysis of disease progression	Earlier detection of cancer	Radiomics and predictive analytics	Neuroimaging
----------------------	--	------------------------------------	------------------------------------	--------------

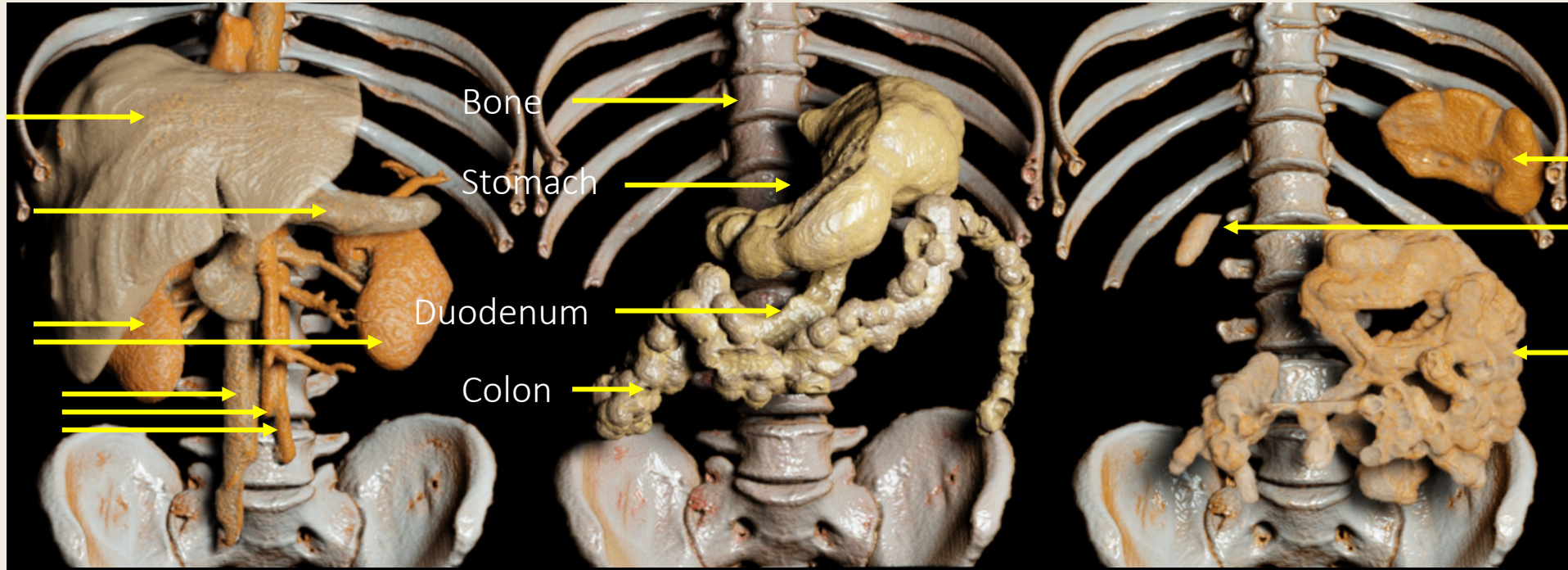
The FELIX-Civitas Project

Goal: Earlier detection of pancreatic cancer

New Goal: Earlier detection of a variety of cancers

- Body Maps: 3D Maps of Whole Body
 - Conceptually similar to Google Maps, but it focuses on human anatomy rather than the Earth's geography.
 - (1) Accurate segmentation of 104 anatomical structures.
 - (2) Cancer screening and localization across various structures.
 - (3) Language interaction between users and systems.
 - McGovern and Lustgarten (role: Team Investigator; status: **awarded**)
 - NIH K99/R00 (role: PI; status: under review)
 - NIH R01 and ACS Grant (role: Team Investigator; status: under review)

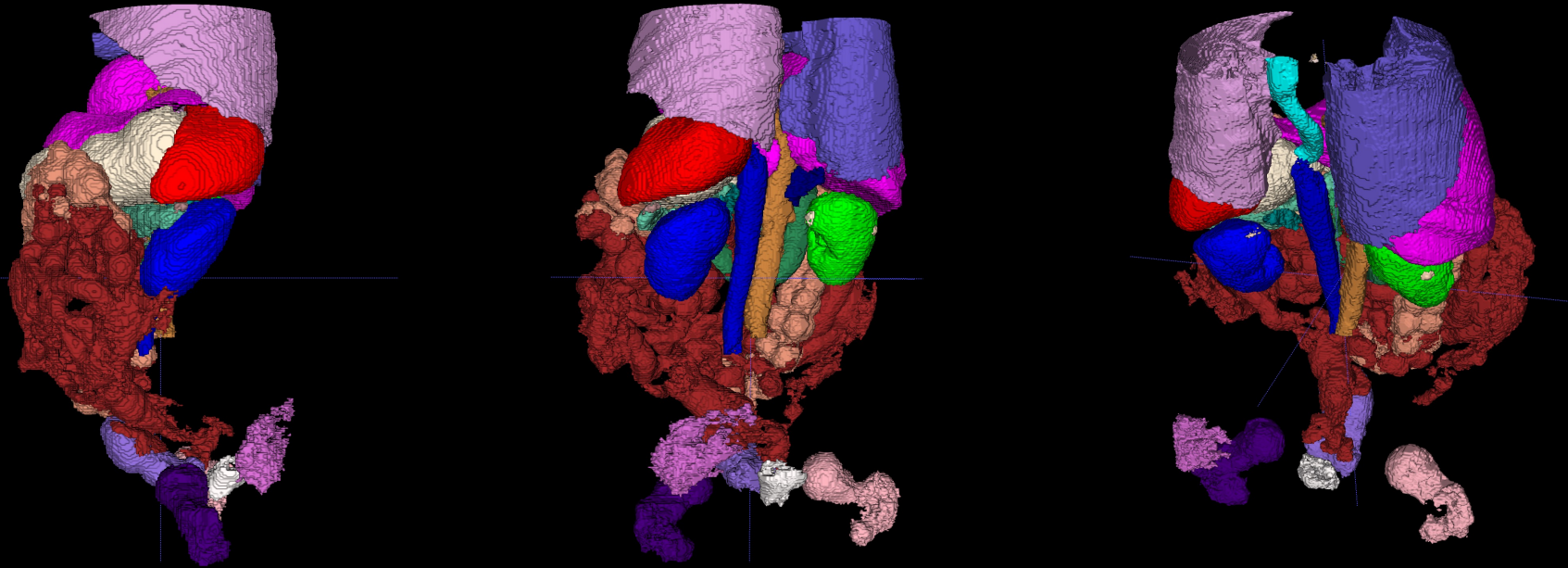
Body Maps: 3D Maps of Whole Body

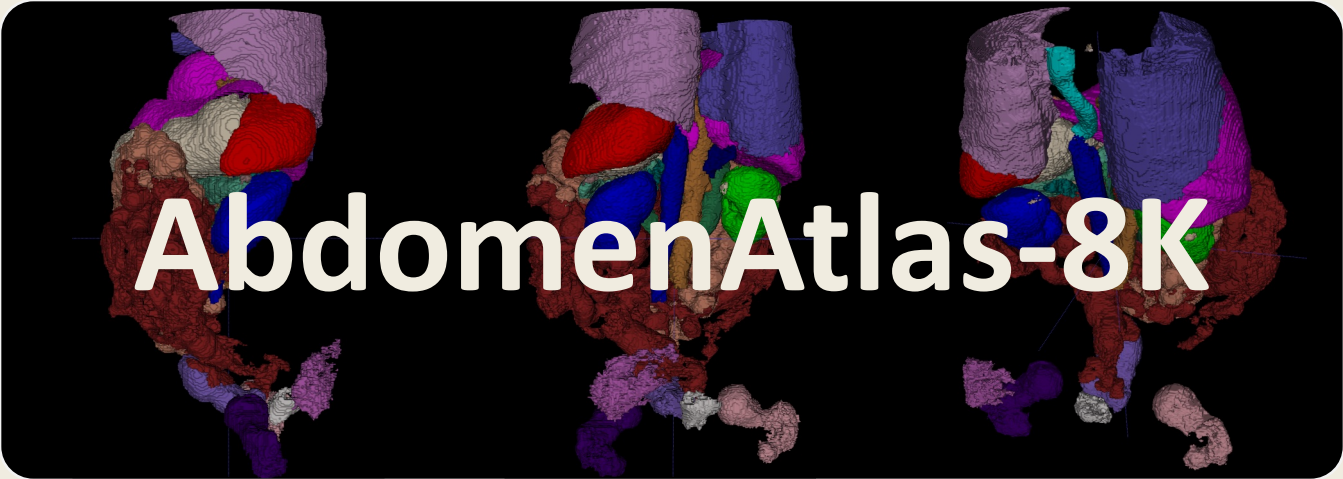


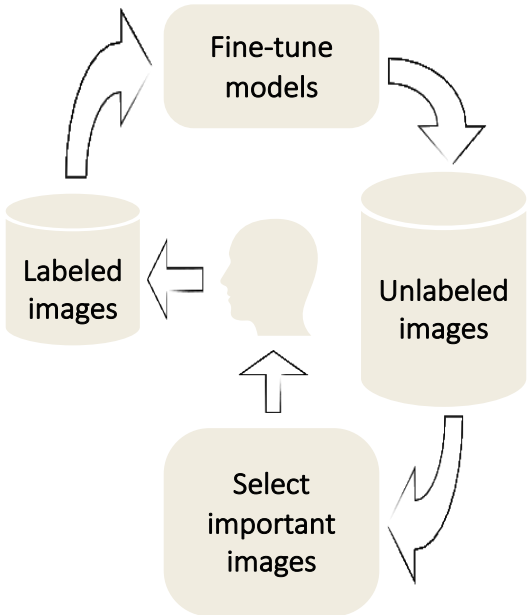
Liver
Pancreas
Kidney
Blood vessels

Bone
Stomach
Duodenum
Colon

Spleen
Gallbladder
Small bowel







Interactive segmentation

Annotated

25

organs

Annotated

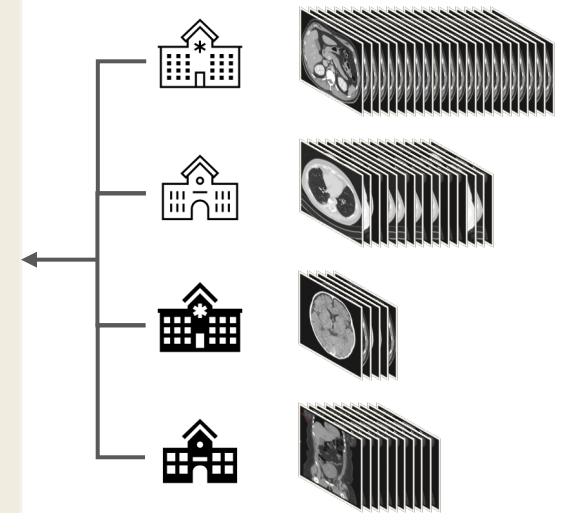
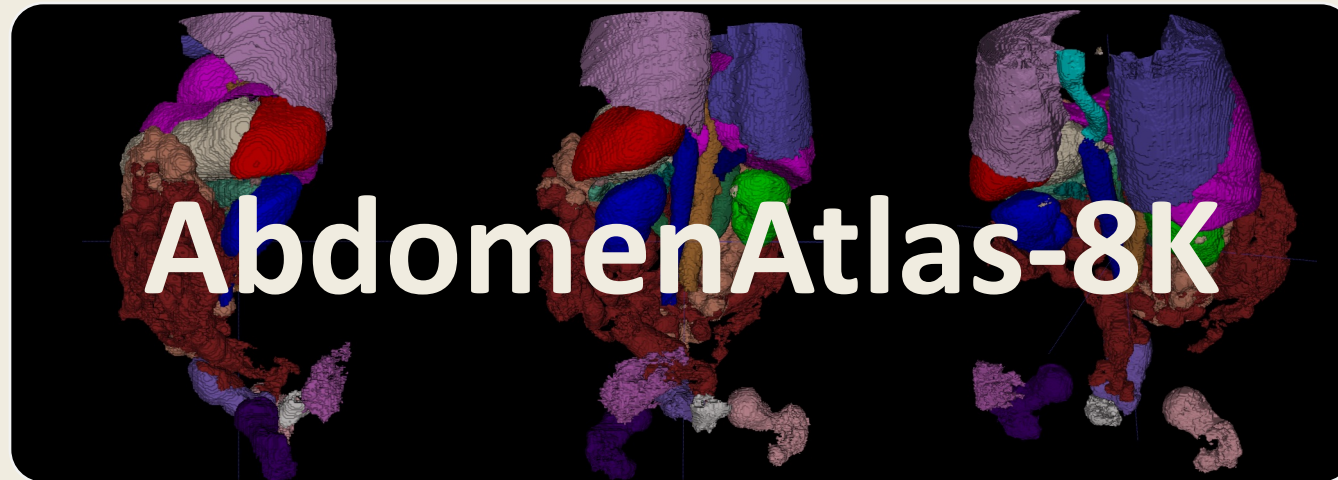
7

cancers

Integrated

15

public datasets



Collected from

27 hospitals

worldwide

Up to
533x faster
than previous strategies

Annotated

3.2M

images

Annotated

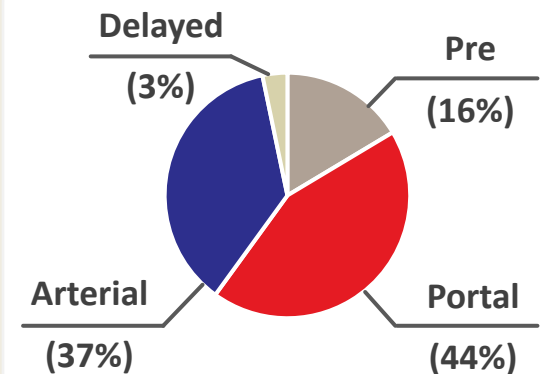
8,448

CT volumes

Created in

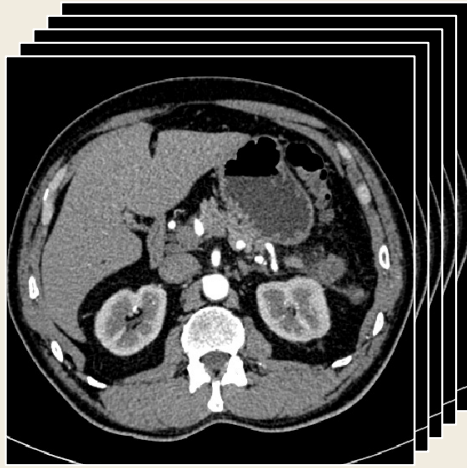
3 Weeks

by 1 annotator



MONAI⁺

featured in
ChimeraX
at UCSF



Vision Encoder
& Decoder

featured in
MONAI
at NVIDIA

Universal Model

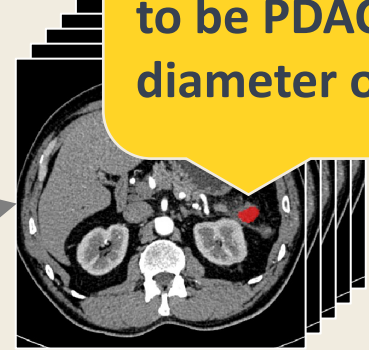
Please segment the tumor in the tail of the pancreas and then measure its size.

Take a look at these CT scans and mark the suspected tumor region.

.....

Text Encoder

This tumor is likely to be PDAC with a diameter of 25mm.

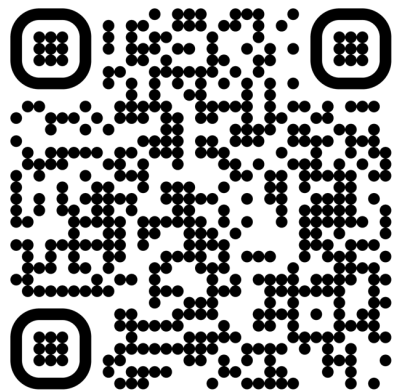


Two potential tumors are framed in bounding boxes.



AbdomenAtlas-8K

8,848 annotated CT volumes



Medical Segmentation Decathlon



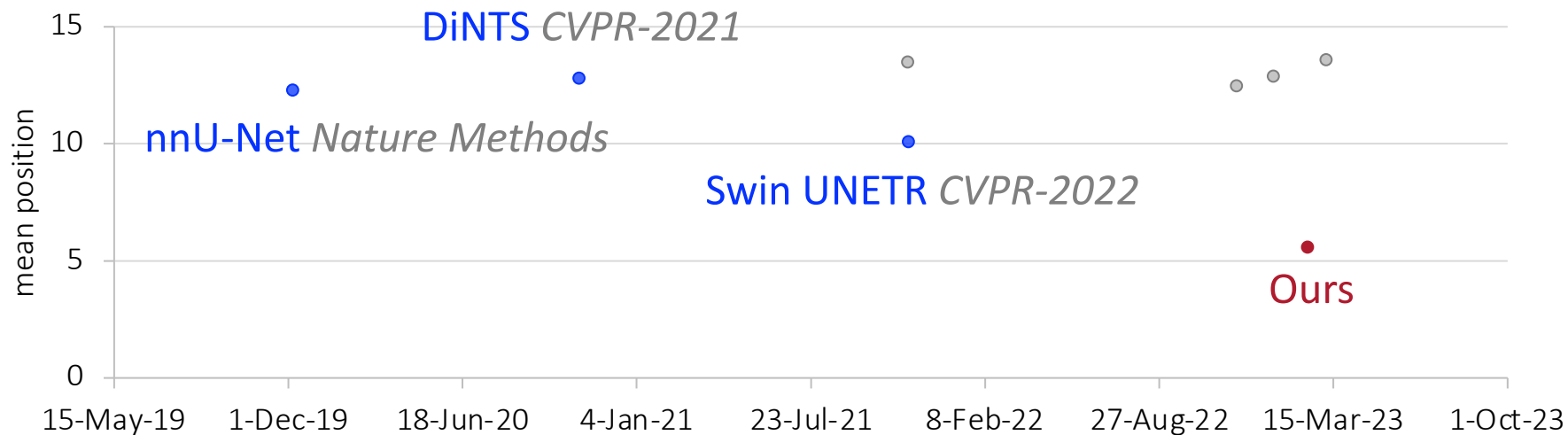
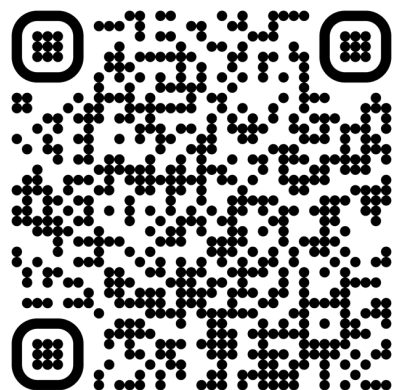
Info Leaderboard Statistics

Join

#	User (Team)	Created	Mean Position
1st	zongwei.zhou (universal_model)	13 Feb. 2023	5.6
2nd	Swin_UNETR	13 Nov. 2021	10.1
3rd	ahatamiz2	12 Nov. 2021	10.1
4th	lsensee	6 Dec. 2019	12.3
5th	AndyL	24 Nov. 2022	12.5
6th	heyufan1995	30 Oct. 2020	12.8
7th	qsyung	5 Jan. 2023	12.9

Universal Model

25 organs and 7 cancers



**Earlier detection
of cancers**

**Earlier detection
of cancer**



Developing 3D Maps of Whole Body

Significant

Applications



Impactful

Methodologies

Reducing Annotation Efforts for Radiologists

**Annotation-intensive
deep learning**



**Annotation-efficient
deep learning**



**Annotation-free
deep learning**

New Chapter (2020s)

Challenges and Questions

Significant

Applications
Methodologies

Impactful

Scaling datasets

Multiple modalities
Diverse institutes
IRB approval

Tumor **Synthesis**

Annotation-free deep learning

Scaling annotations

Efficient annotation
Human in the loop
Novel disease

AbdomenAtlas-**8K**

8,848 annotated CT volumes

Scaling algorithms

Vision-language
Lifelong learning
Reader study

Universal Model

25 organs and 7 cancers

Thank You!

Zongwei Zhou, PhD

Postdoc, Department of Computer Science
Johns Hopkins University, Baltimore, MD
P: 1-(480)738-2575 | E: zzhou82@jh.edu
www.zongweiz.com

Statistics

7,118 citations

Top 2% of Scientists in 2022

24 first/corresponding authored papers