# Early and Prediagnostic Detection of Pancreatic Cancer from Computed Tomography

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JOHNS HOPKINS
UNIVERSITY

# This talk summarizes a lot of research over the last four years

2018 — **FELIX**
Lustgarten

2021 — Joined JHU

2023 — **FELIX-Civitas**
Lustgarten &
McGovern

2025 — **FELIX-Civitas**
Lustgarten &
NIH

**ZONGWEI ZHOU AWARDED $2.8 MILLION NIH GRANT**

HOME / NEWS / ZONGWEI Z

# Early Detection of Cancer (#2 Killer)

- *Almost everyone, whether connected personally or through friends or family members, has been affected by cancer.*
- Early detection of cancer enables surgery and will save many lives.
- The **crisis** is silent: for pancreatic cancer, the five-year survival rate increases substantially if detected at an early stage.

| 7% | 44% |
|---|---|
| 5-year survival rate<br>If late detection | 5-year survival rate<br>If detected early |

# Early Detection of Cancer (#2 Killer)

- Radiologists can detect pancreatic cancer from CT scans, but the sensitivity of early pancreatic cancer is only **33-44%**.
- This motivates the development of AI algorithms for detecting and localizing early cancer from CT scans, less than 2 cm, and even before tumors are visible.

**80** **million**

computed tomography (CT)
performed yearly in the US

**60%**

miss rate for tumor <2 cm
by radiologists

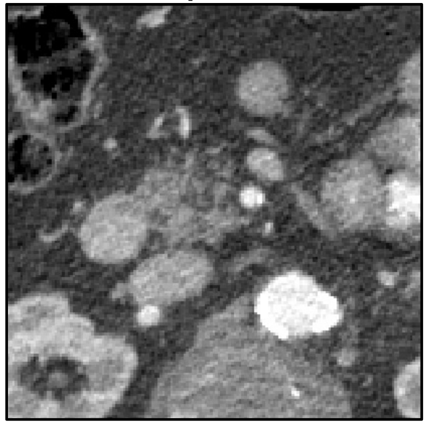
# A Successful Story

- We formulate this problem as *Semantic Segmentation*.
- We developed an AI algorithm and train it to classify voxels as Healthy Pancreas, Tumor, or Background.
- For pancreatic tumors, our AI has achieved very high performance.

| | Sensitivity early tumors ≤2 cm | Sensitivity all-size tumors | Specificity |
|---|---|---|---|
| Radiologists | 33–44% | 76–92% | 82–96% |
| Our AI | 94% | 97% | 99% |

# A Successful Story

Lead time
detection opportunity



Prediagnostic
CT scans

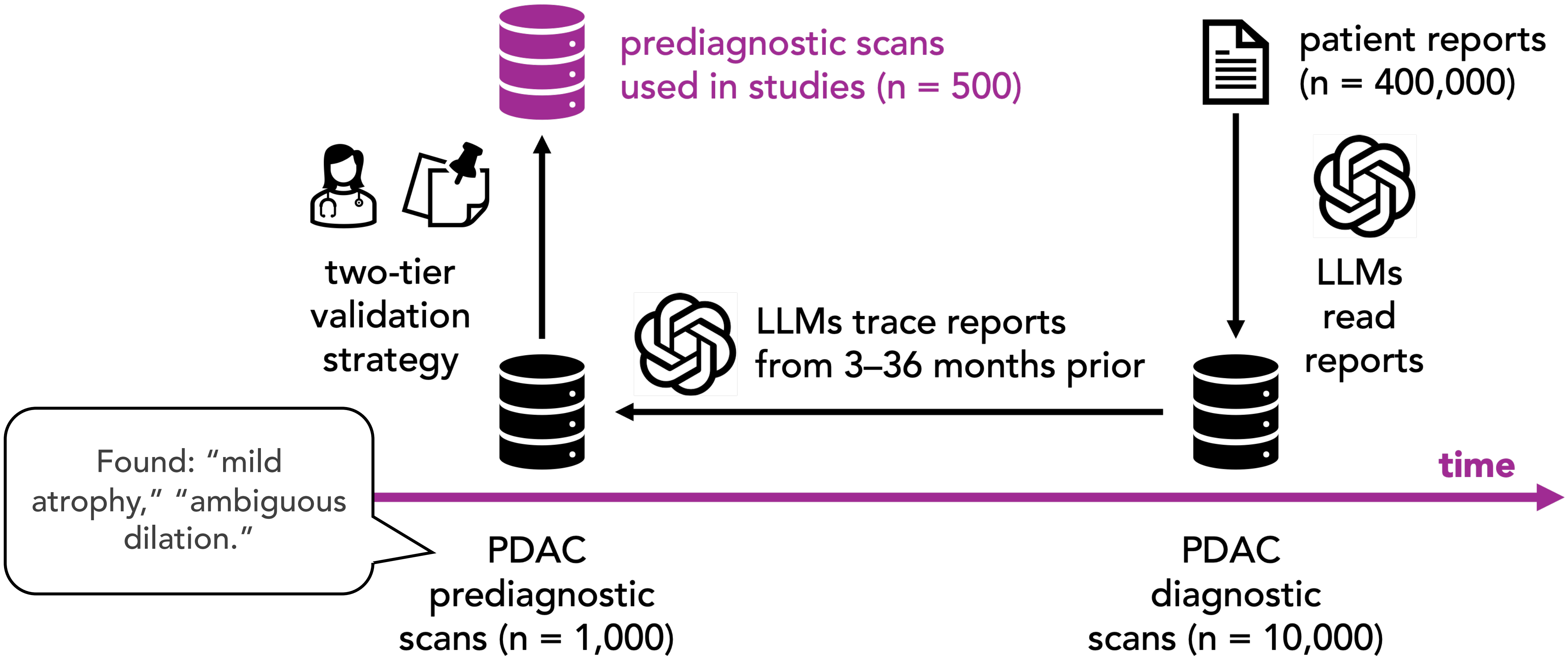
Diagnostic
CT scans

2021

3-36 months
before diagnosis

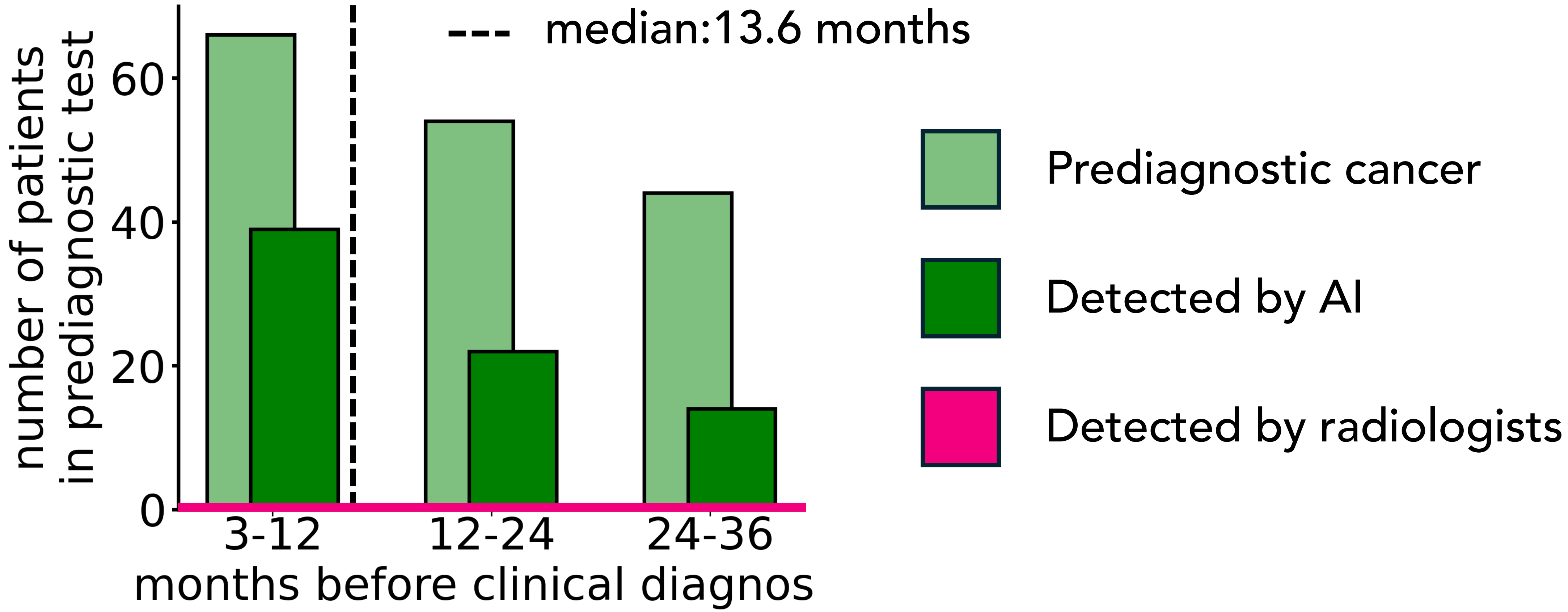
2024

# A Successful Story



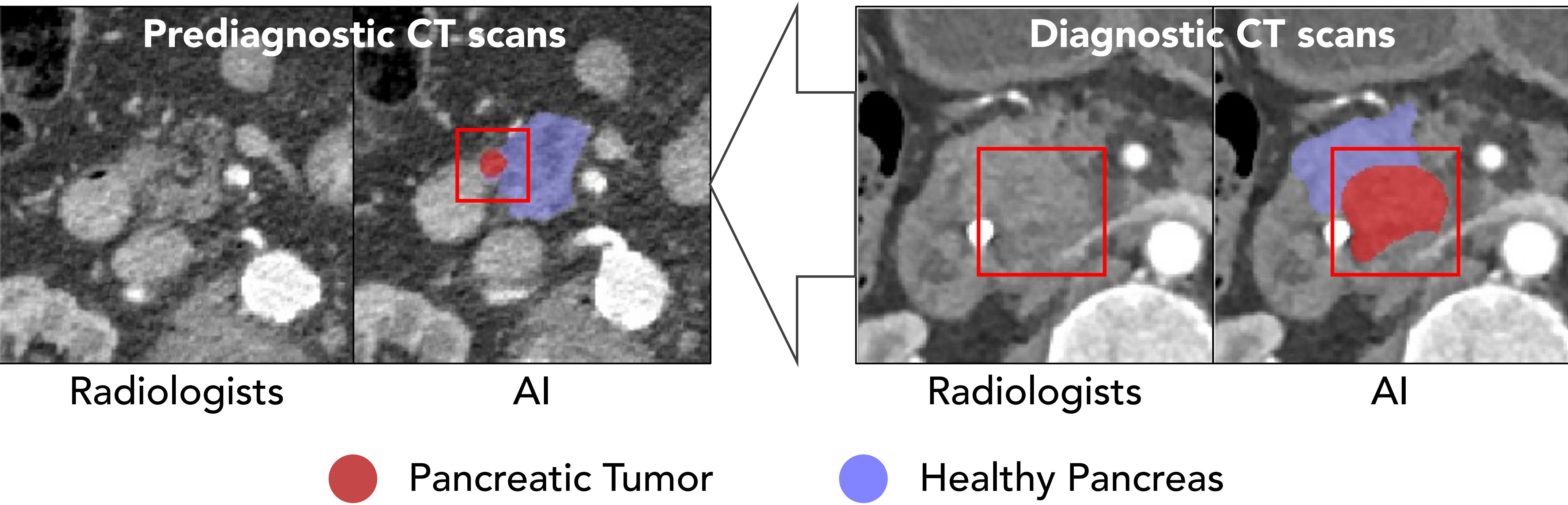
# A Successful Story

- Our AI can detect cancer **13.6 months** earlier than radiologists.

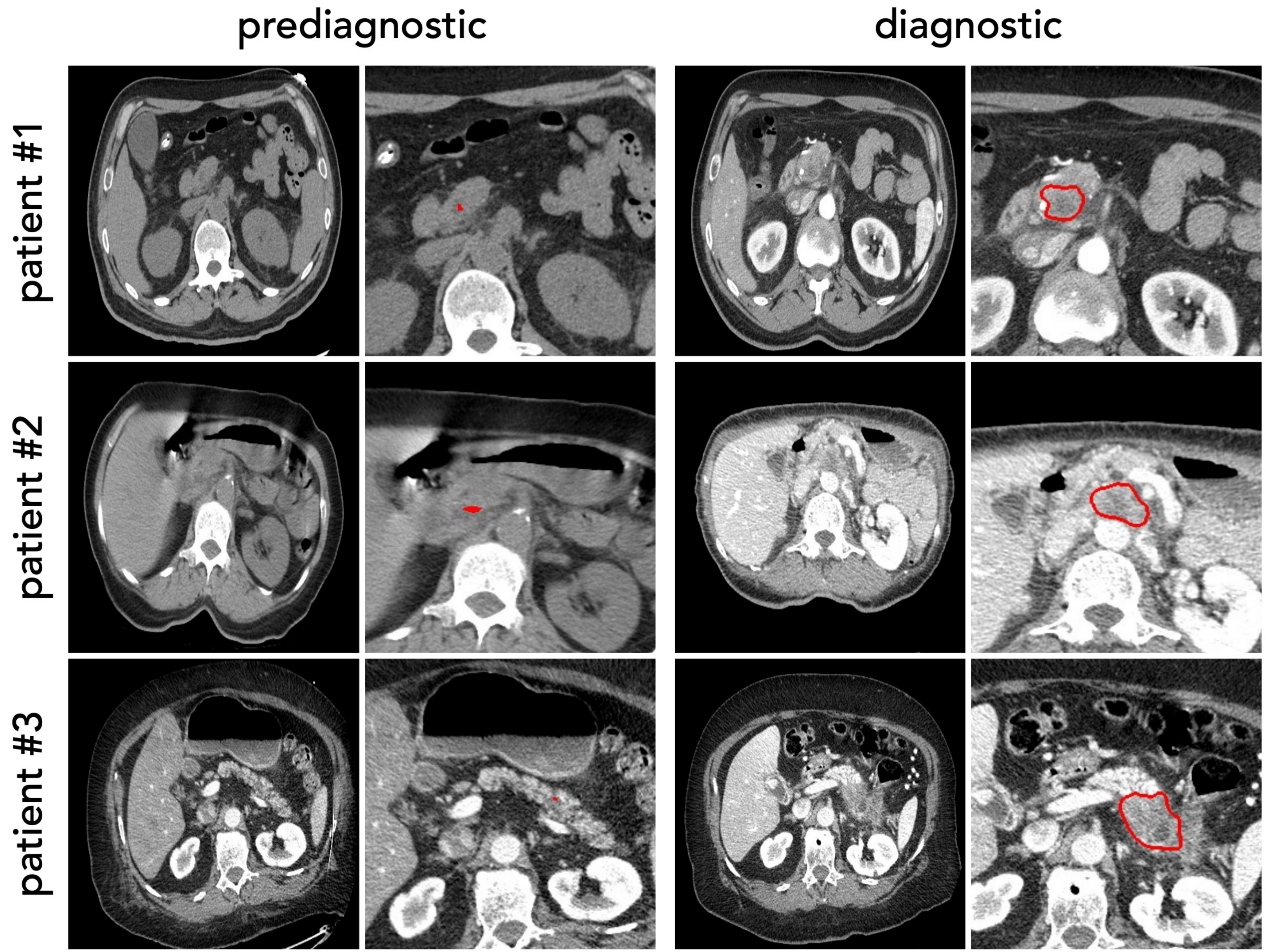


# A Successful Story

- Our AI can also **localize** these cancer in prediagnostic scans.



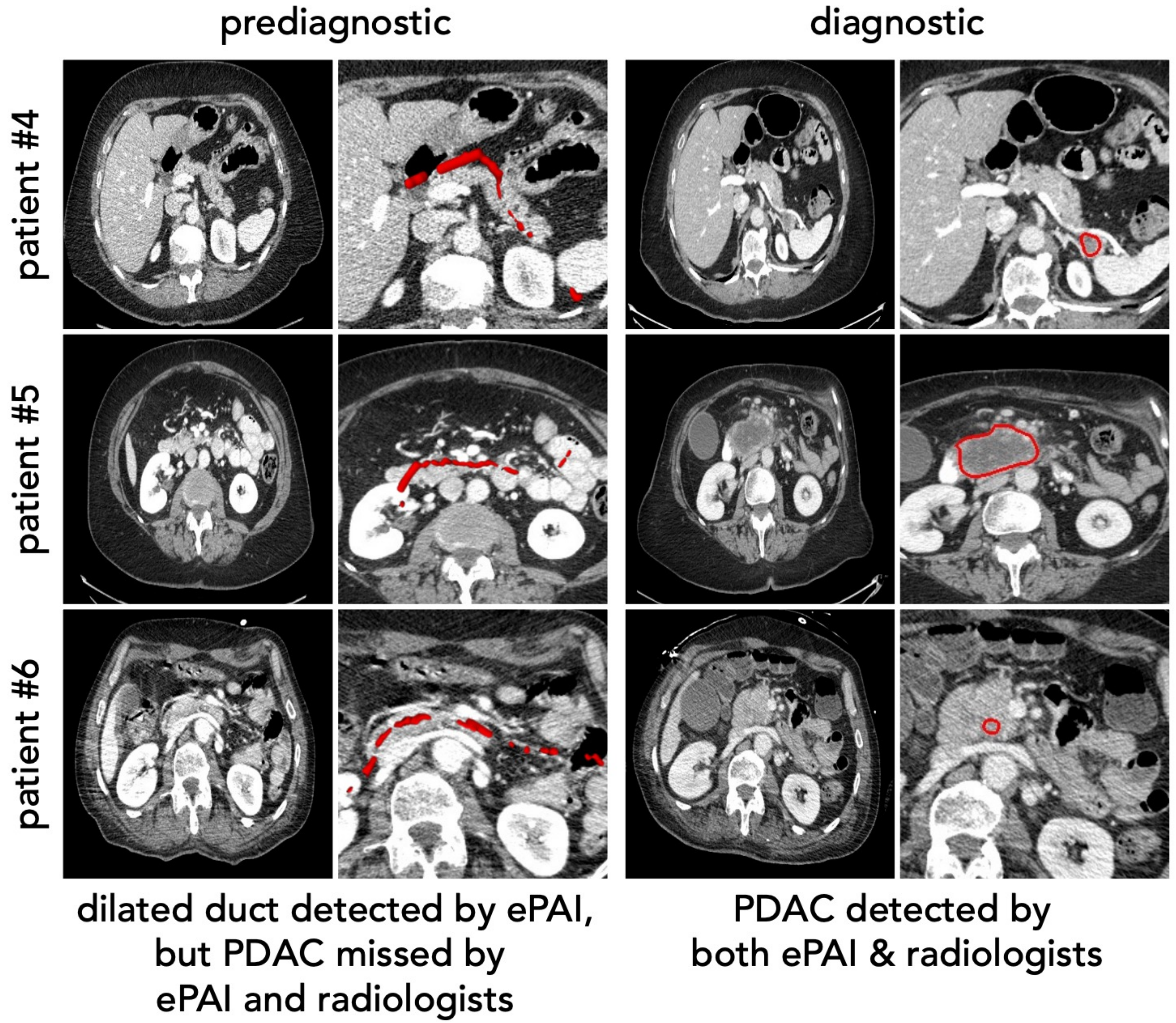
- Many prediagnostic scans were not done to look for cancer.
- Non-contrast CT.




PDAC detected by ePAI, but missed by radiologists

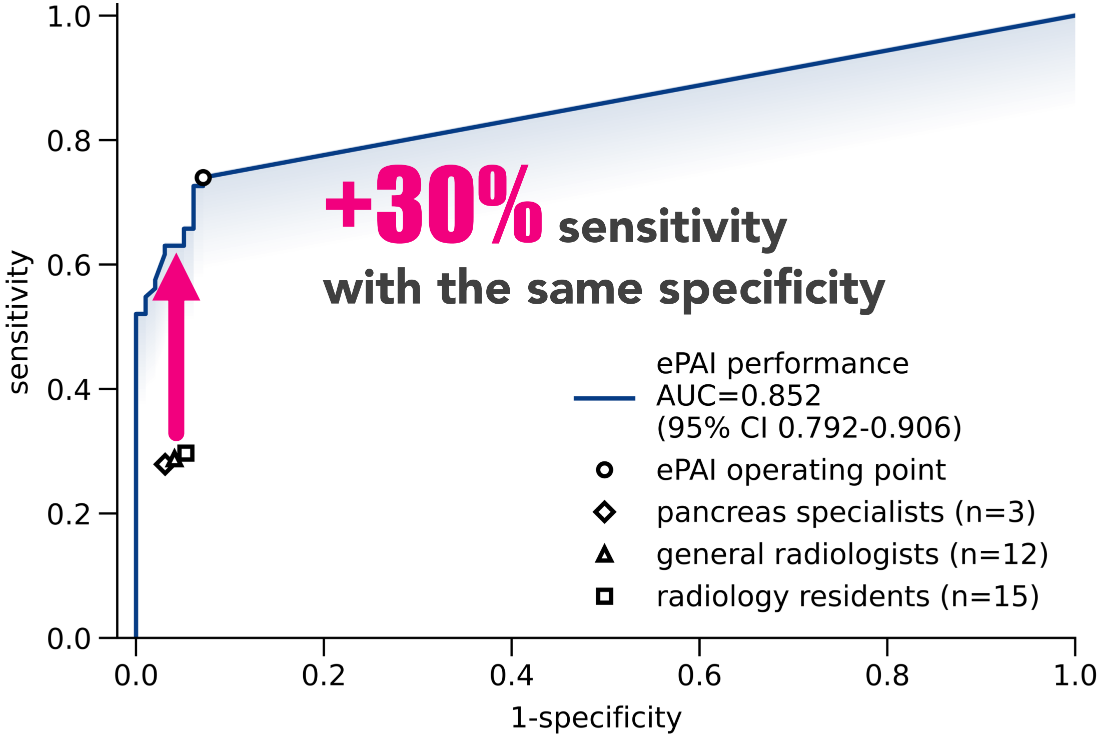
PDAC detected by both ePAI & radiologists

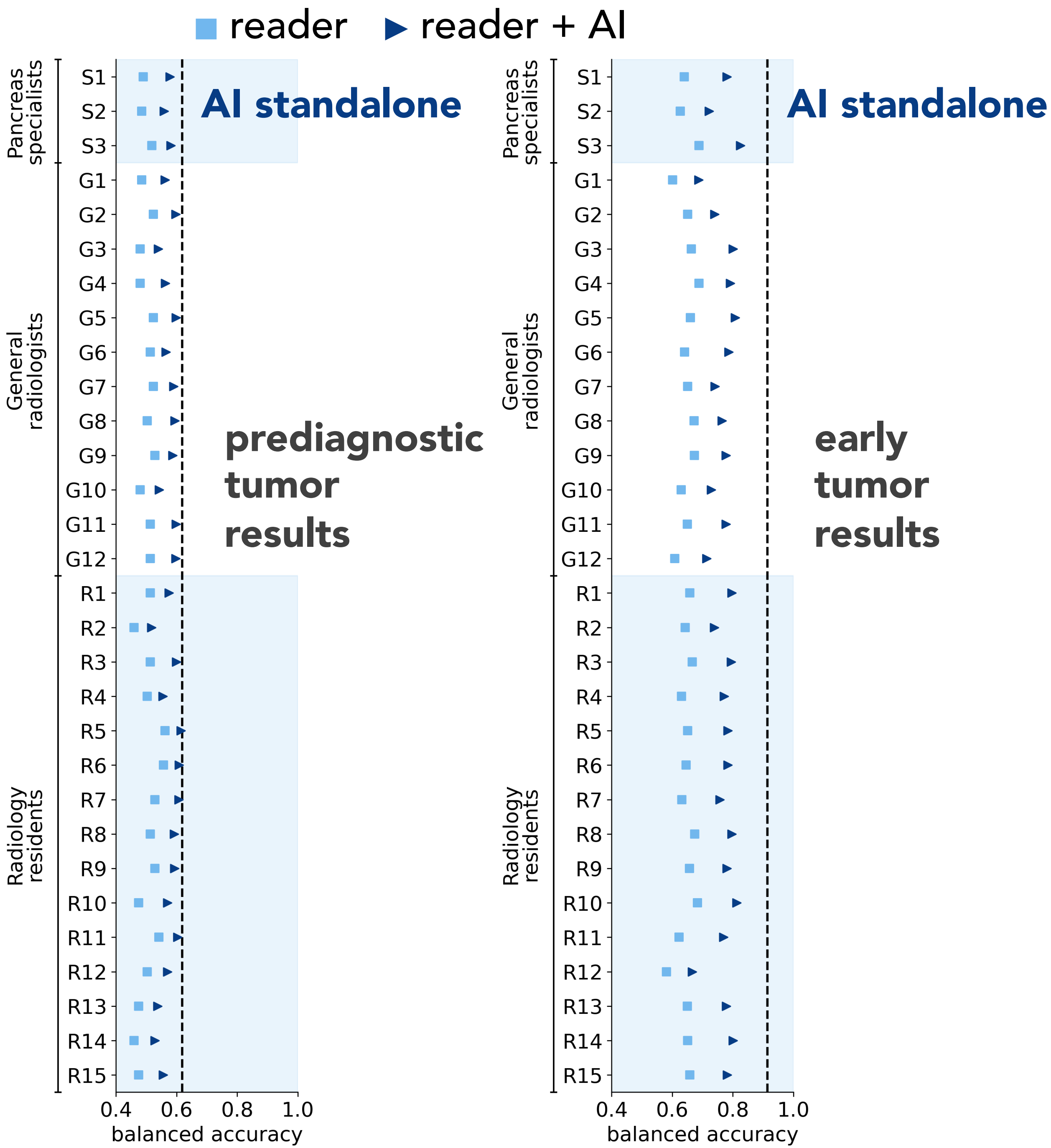
- Many prediagnostic scans do not have visible tumors.
- Other early cues.



# A Successful Story

- Our AI can be an assistive tool for radiologists.



# Why Previous AI Attempts Have Failed?

- **Low prevalence:** Because cancer prevalence is low in screening settings, models can generate many false positives.

- **1 | Data:** Models often overfit to internal datasets and fail to generalize to external institutions.
- **2 | Annotations:** Large-scale tumor annotation is labor-intensive, time-consuming, and costly.
- **3 | Algorithms:** Models fail exactly where early detection is needed, missing small or early-stage tumors.

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# Needle in a Haystack

- Prevalence in general population = 0.01% (100 in 1,000,000)
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**95**/100

True positives

**10,000**

False positives

# Needle in a Haystack

- Prevalence in **high-risk** population = 4% (100 in 2,500)
- JHU-AI obtained Sensitivity = 95%, Specificity = 99% ☺
- But positive predictive value (PPV) = **80%** ☺

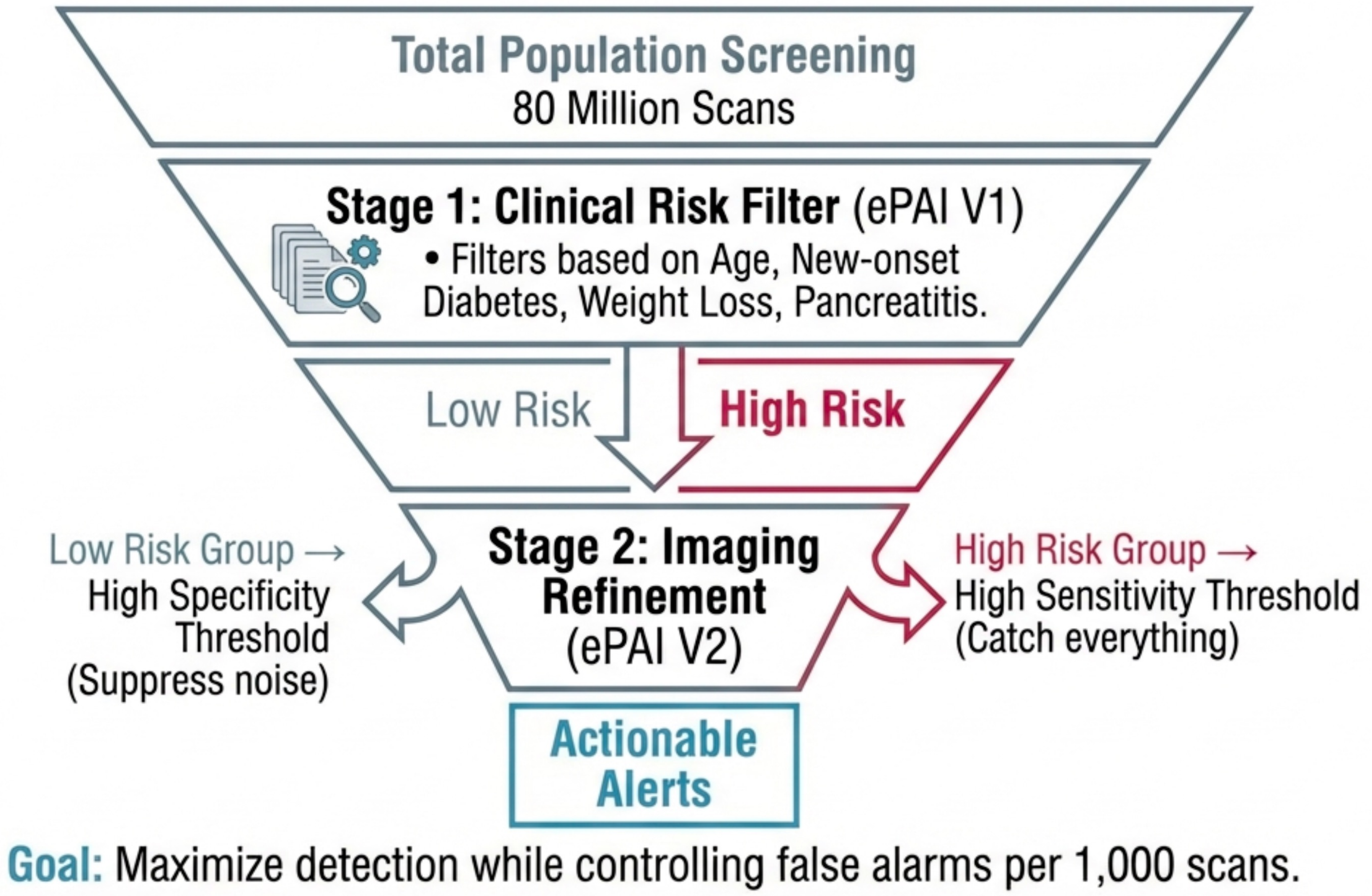
**95**/100

True positives

**25**

False positives

# Two-Stage Risk Stratification Model

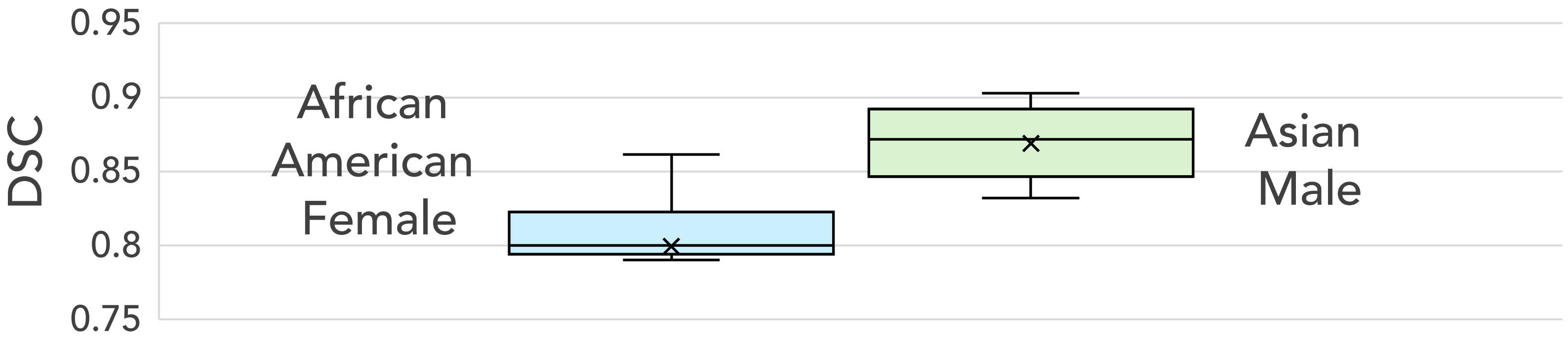


# Challenges (1/3)

- **Data:** Where to get data from different hospitals?
- **Annotations:** How to annotate the data?
- **Algorithms:** How to detect small cancer?

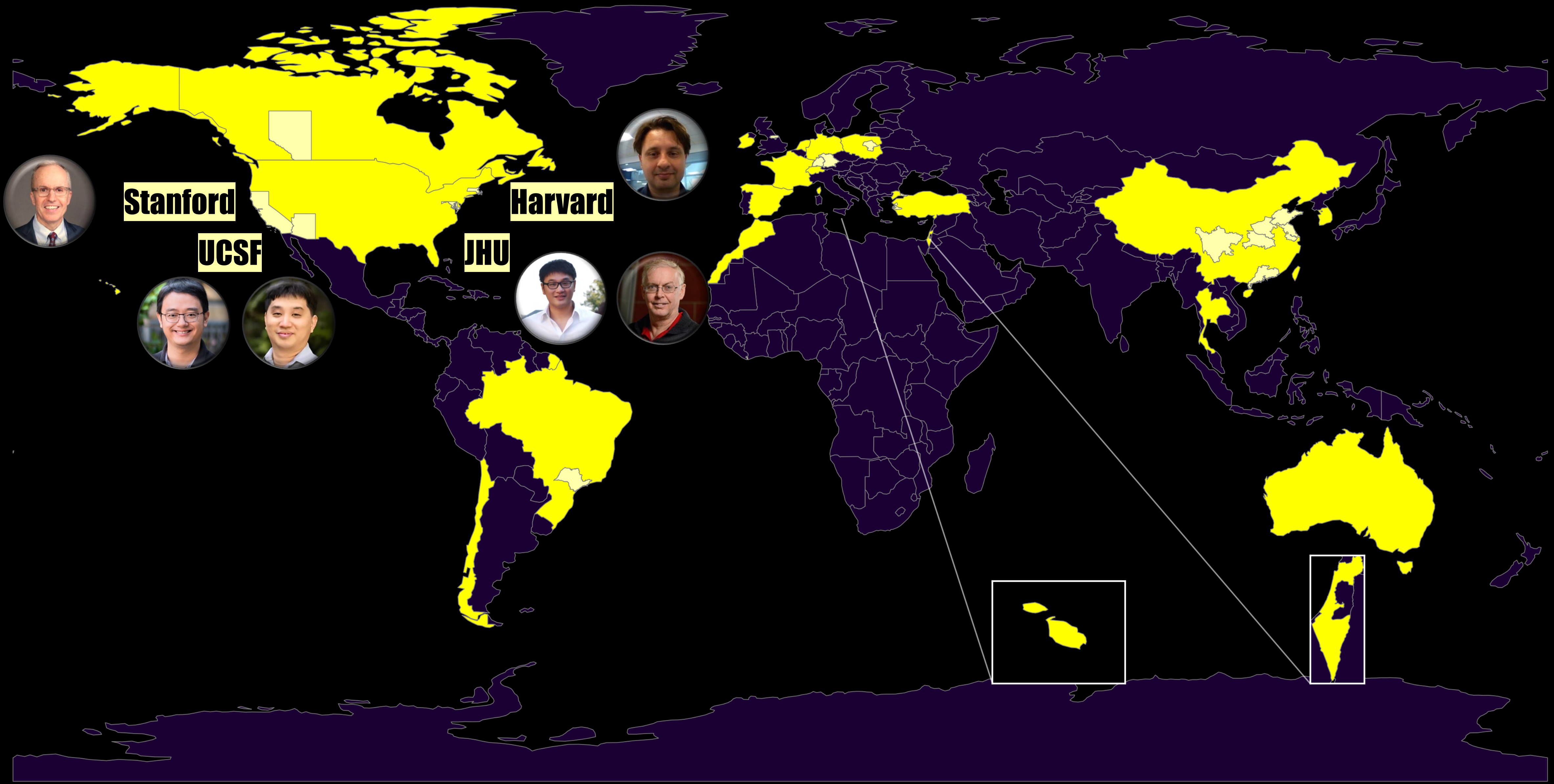
# Rigorously Evaluating Medical AI

- It is critical to test CT scans from other hospitals, as they may use different scanners and imaging protocols, and patient demographics (e.g., race, gender, age) can vary even within the same hospital.
- This is called the *Domain Transfer (DT)* problem (A. Lubonja et al., MICCAIW 2025).




GitHub.com/ariellubonja/RankInsight

# We have access to CT scans from **145 hospitals** worldwide, and our **collaboration** is expanding



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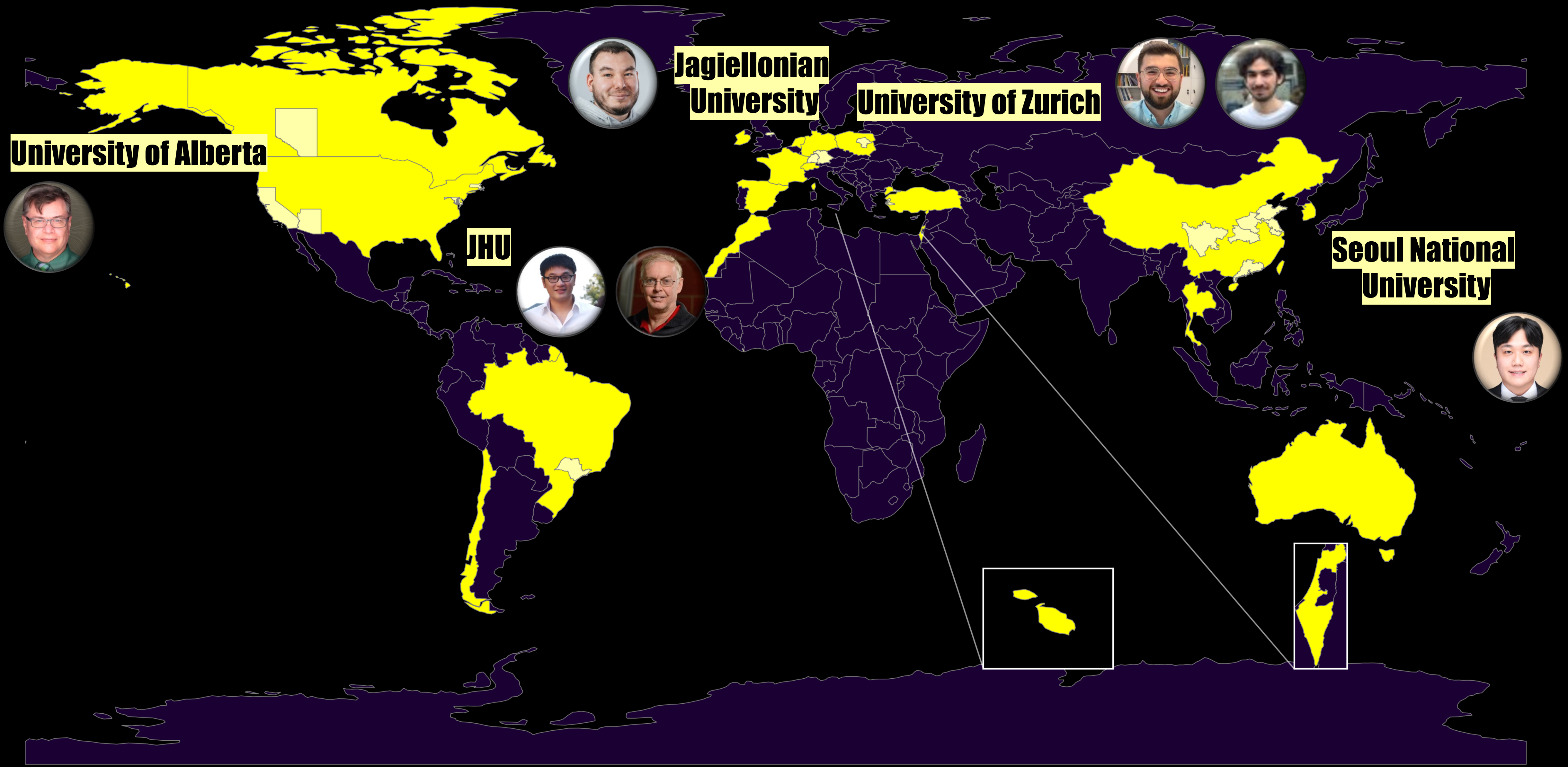
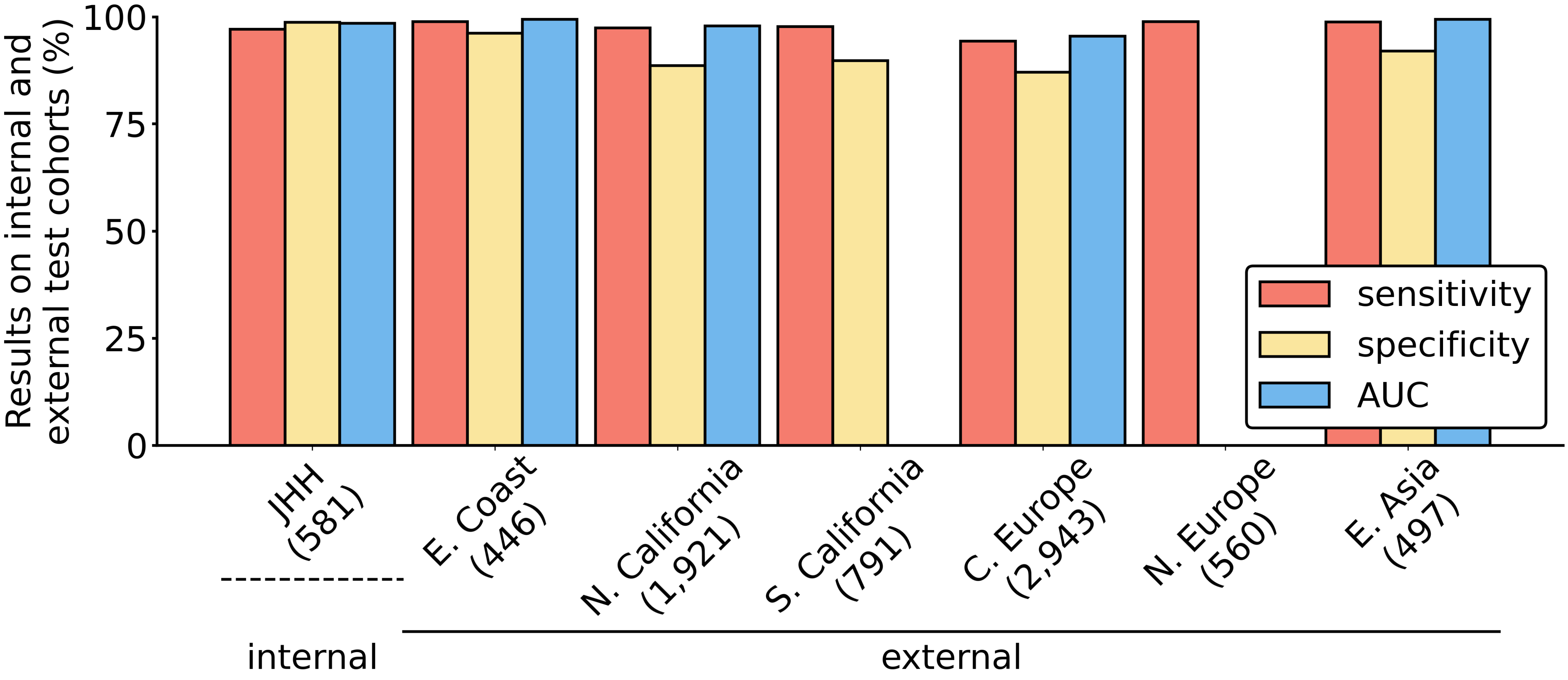
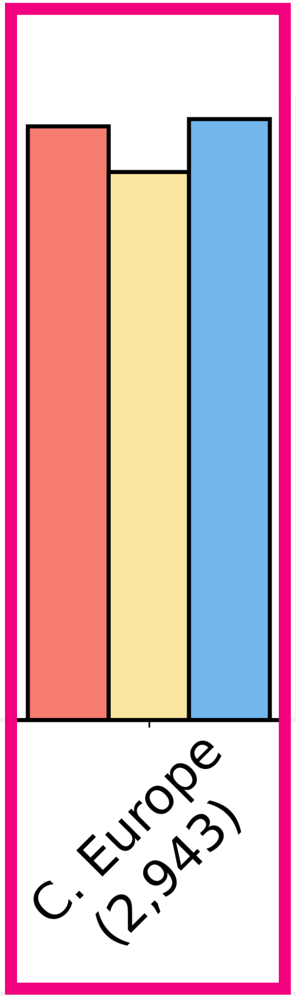


# Rigorously Evaluating Medical AI



# Rigorously Evaluating Medical AI

- This includes a national registry covering all pancreatic cancer diagnoses in Poland.
- *"This AI is very impressive,"* says a radiology specialist in Poland with extensive experience in imaging and treating pancreatic cancer. *"It catches the early precancerous lesions and small pancreatic cancers."*

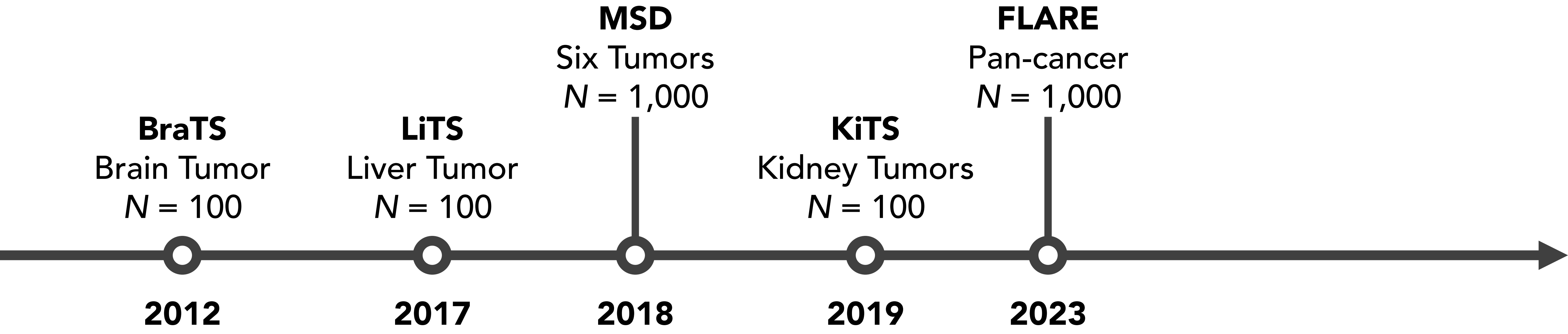


# Challenges (2/3)

- **Data:** Where to get data from different hospitals?
- **Annotations:** How to annotate the data?
- **Algorithms:** How to detect small cancer?

# Annotated Tumor Datasets Should Be Open to More Researchers

- There's a huge data gap in medical AI right now, particularly when you have rare diseases, uncommon conditions (e.g., cancer).



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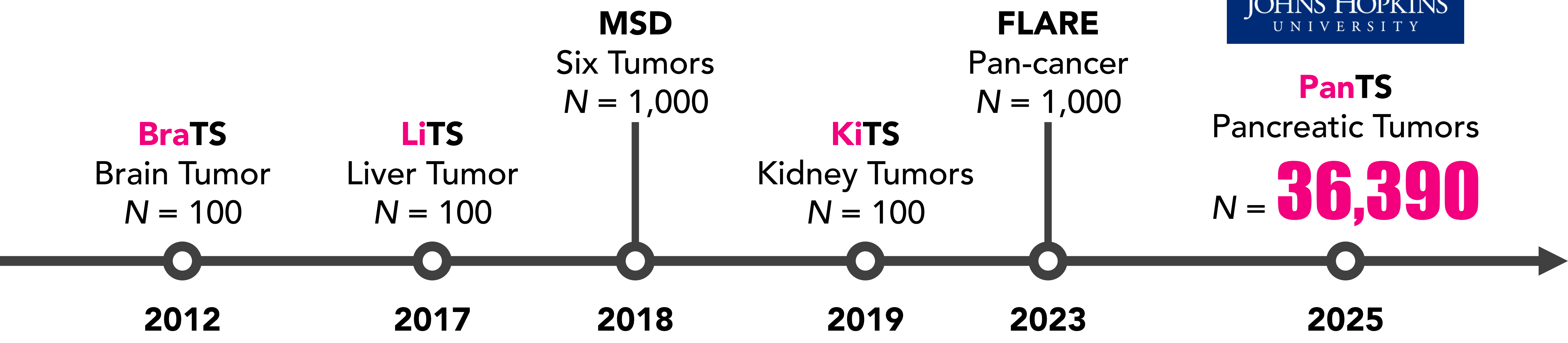
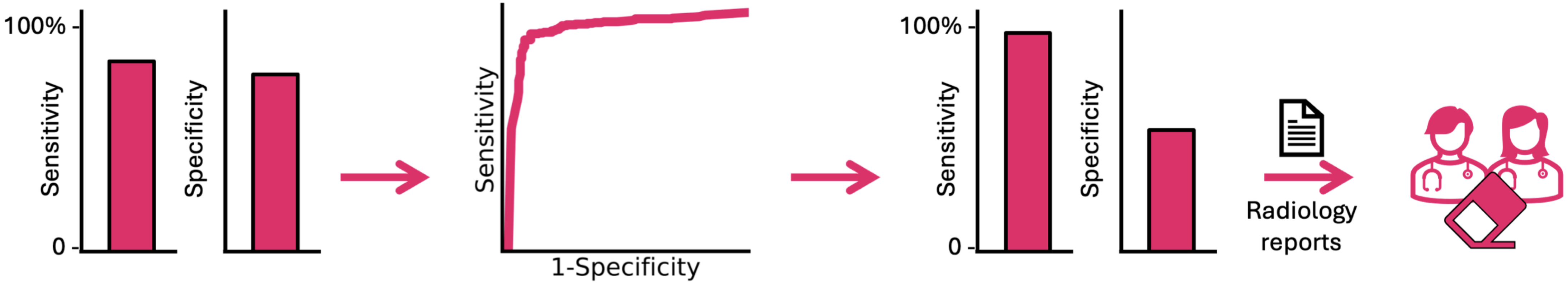


# Efficient Tumor Annotations

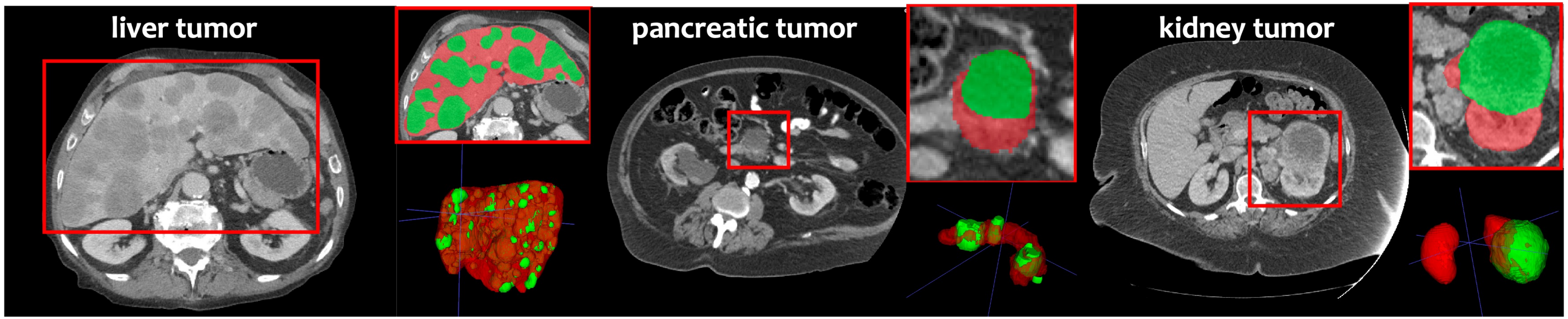
- Make the AI highly sensitive, offering a strong starting point for radiologist review and edit at least **80×** faster (Zhou et al., ISBI 2024).




Adjust AI prediction threshold to make the AI overly sensitive,
*i.e., false negatives -- false positives ++*

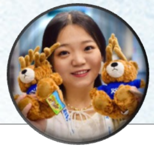
# Efficient Tumor Annotations

- Make the AI highly sensitive, offering a strong starting point for radiologist review and edit at least **80×** faster (Zhou et al., ISBI 2024).
- (I) Editing an AI-generated tumor takes **~1 minute**. (rarely needed)
- (II) Removing a false positive takes **<5 seconds**.
- In contrast, manual annotation from scratch takes **4–5 minutes**.



# PanTS

## Pancreatic Tumor Segmentation

GitHub.com/MrGiovanni/PanTS

```
git clone https://github.com/MrGiovanni/PanTS.git; cd PanTS
bash download_PanTS_data.sh
bash download_PanTS_label.sh
http://www.cs.jhu.edu/~zongwei/dataset/PanTSMini_Label.tar.gz
```

PanTS is a large-scale, multi-institutional dataset, containing **36,390** three-dimensional CT volumes from **145** medical centers, with expert-validated, voxel-wise annotations of over **993,000** anatomical structures, including ***pancreatic tumors, pancreas head, body, and tail, and 24 surrounding anatomical structures such as vascular/skeletal structures and abdominal/thoracic organs.***

(Li et al., NeurIPS 2025)



*GitHub.com/MrGiovanni/PanTS*

**If you had unlimited resources to build a “dream” dataset for AI in cancer research, especially cancer prevention, detection, and treatment, what would it look like?**

What modalities, metadata, and labels would you prioritize?

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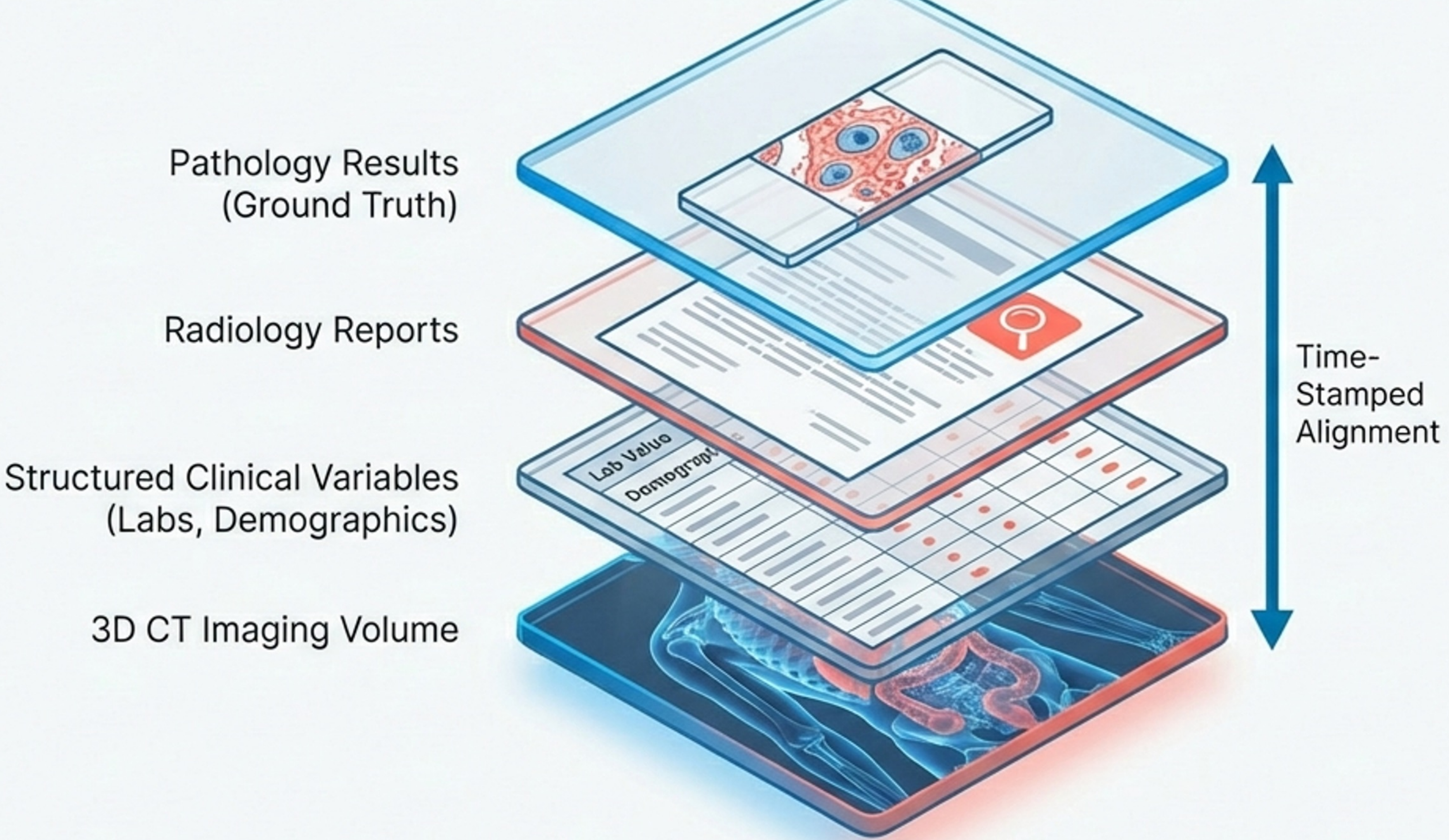
longitudinal & multimodal


Pathology Results
(Ground Truth)
Radiology Reports
Structured Clinical Variables
(Labs, Demographics)
3D CT Imaging Volume
Lab Value
Time-
Stamped
Alignment

# A Huge Annotated Internal Dataset

BodyMaps

*Internal use only; open for collaboration*

Funded by
NIH R01 (PI: Zongwei Zhou, Yang Yang, Kang Wang),
Lustgarten Foundation (PI: Alan Yuille), and
McGovern Foundation (PI: Alan Yuille)

| | | | |
|---|---|---|---|
| **81.7 million** | **241,336** | **377** | **145** |
| 2D CT images | 3D CT volumes | anatomical structures | hospitals |


**A team of 23 board-certified radiologists**

# A Huge Annotated Internal Dataset

**Voxel-wise annotated 16 tumor types:** adrenal · bladder · bone · breast · colon · duodenum · esophagus · gallbladder · kidney · liver · lung · pancreas · prostate · spleen · stomach · uterus

| **81.7 million** | **241,336** | **377** | **145** |
|---|---|---|---|
| 2D CT images | 3D CT volumes | anatomical structures | hospitals |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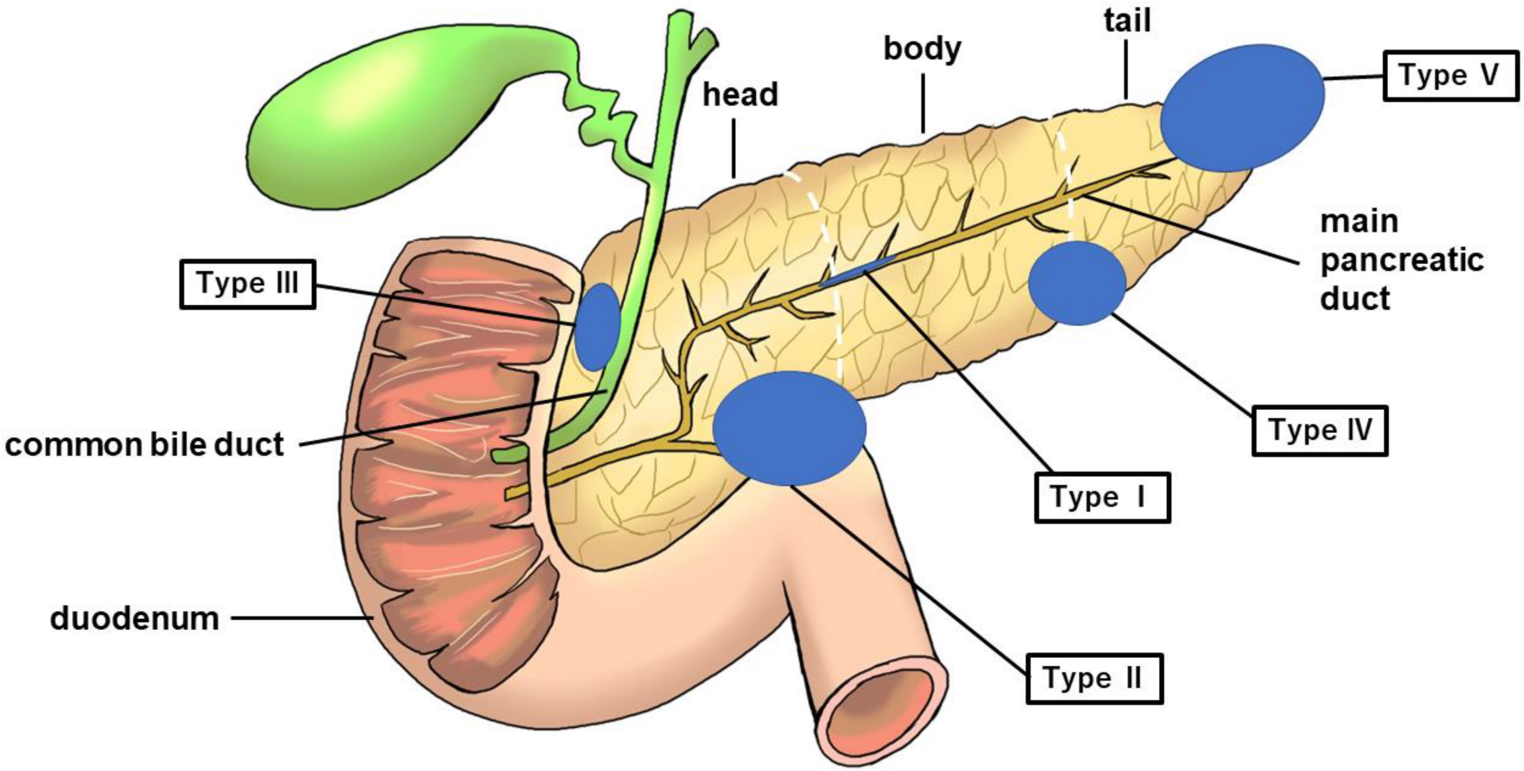
**Voxel-wise annotated 377 anatomical structures:** abdominal cavity · adrenal gland left · adrenal gland right · airway · anterior eyeball segment left · anterior eyeball segment right · anterior scalene left · anterior scalene right · aorta · arm left · arm right · arms · artery brachiocephalic · artery common carotid left · artery common carotid right · artery internal carotid left · artery internal carotid right · artery subclavian left · artery subclavian right · atrial appendage left · arytenoid cartilage · auditory canal left · auditory canal right · autochthon left · autochthon right · bladder · blood · body · body extremities · body trunc · bones · both lips · brachiocephalic trunk · brachiocephalic vein left · brachiocephalic vein right · brain · brain ventricle · brainstem · breast left · breast right · bronchus · buccal mucosa · carotid artery left · carotid artery right · carpal · carpal left · carpal right · caudate nucleus · cbd stent · celiac artery · celiac trunk · central sulcus · cerebellum · cerebrospinal fluid · cervical esophagus · cheek left · cheek right · clavicula left · clavicula right · cochlear left · cochlear right · colon · colostomy bag · common bile duct · common carotid artery left · common carotid artery right · common iliac artery left · common iliac artery right · common iliac vein left · common iliac vein right · compact bone · coronary artery · costal cartilages · cricoid cartilage · cricopharyngeus · digastric left · digastric right · duodenum · esophagus · eye lens left · eye lens right · eyeball · eyeball left · eyeball right · face · fat · femur left · femur right · fibula · fibula left · fibula right · fingers left · fingers right · frontal lobe · gall bladder · gland structure · glottis · gluteus maximus left · gluteus maximus right · gluteus medius left · gluteus medius right · gluteus minimus left · gluteus minimus right · gonads · gray matter · hard palate · head · heart · heart atrium left · heart atrium right · heart myocardium · heart tissue · heart ventricle left · heart ventricle right · hepatic vein · hepatic vessel · hip left · hip right · humerus left · humerus right · hyoid · hypopharynx · iliac artery left · iliac artery right · iliac vena left · iliac vena right · iliopsoas left · iliopsoas right · inferior oblique muscle left · inferior oblique muscle right · inferior pharyngeal constrictor · inferior rectus muscle left · inferior rectus muscle right · inferior vena cava · insular cortex · intermuscular adipose tissue · internal capsule · internal carotid artery left · internal carotid artery right · internal jugular vein left · internal jugular vein right · intestine · kidney · kidney left · kidney right · lacrimal gland left · lacrimal gland right · larynx · lateral pterygoid left · lateral pterygoid right · lateral rectus muscle left · lateral rectus muscle right · lentiform nucleus · leg left · leg right · legs · levator palpebrae superioris left · levator palpebrae superioris right · levator scapulae left · levator scapulae right · liver · liver segment 1 · liver segment 2 · liver segment 3 · liver segment 4 · liver segment 5 · liver segment 6 · liver segment 7 · liver segment 8 · lung · lung left · lung lower left lobe · lung lower right lobe · lung middle right lobe · lung right · lung trachea bronchia · lung upper left lobe · lung upper right lobe · lung vessels · mammary gland left · mammary gland right · mandible · masseter left · masseter right · medial pterygoid left · medial pterygoid right · medial rectus muscle left · medial rectus muscle right · mediastinal tissue · mediastinum · metacarpal · metacarpal left · metacarpal right · metatarsal · metatarsal left · metatarsal right · middle pharyngeal constrictor · middle scalene left · middle scalene right · muscle · muscle fat · muscle of head · nasal cavity left · nasal cavity right · nasopharynx · occipital lobe · optic chiasm · optic nerve left · optic nerve right · oral cavity · oropharynx · pancreas · pancreas body · pancreas head · pancreas tail · pancreatic duct · parietal lobe · parotid gland left · parotid gland right · parotid glands · patella · patella left · patella right · pericardium · phalanges feet · phalanges hand · pituitary gland · platysma left · platysma right · portal vein · portal vein and splenic vein · postcava · posterior eyeball segment left · posterior eyeball segment right · posterior scalene left · posterior scalene right · prevertebral left · prevertebral right · prostate · prosthetic breast implant · psoas major muscle left · psoas major muscle right · pulmonary artery · pulmonary vein · radius · radius left · radius right · rectum · rectus abdominis muscle left · rectus abdominis muscle right · renal vein left · renal vein right · rib cartilage · rib left 1 · rib left 2 · rib left 3 · rib left 4 · rib left 5 · rib left 6 · rib left 7 · rib left 8 · rib left 9 · rib left 10 · rib left 11 · rib left 12 · rib right 1 · rib right 2 · rib right 3 · rib right 4 · rib right 5 · rib right 6 · rib right 7 · rib right 8 · rib right 9 · rib right 10 · rib right 11 · rib right 12 · sacrum · scalp · scapula left · scapula right · seminal vesicle · septum pellucidum · sigmoid colon · skeletal muscle · skin · skull · small bowel · soft palate · spinal canal · spinal cord · spleen · spongy bone · sterno thyroid left · sterno thyroid right · sternocleidomastoid left · sternocleidomastoid right · sternum · sternum corpus · sternum manubrium · stomach · styloid process left · styloid process right · subarachnoid space · subclavian artery left · subclavian artery right · subcutaneous adipose tissue · submandibular gland left · submandibular gland right · submandibular glands · superior mesenteric artery · superior oblique muscle left · superior oblique muscle right · superior rectus muscle left · superior rectus muscle right · superior vena cava · supraglottis · tarsal · tarsal left · tarsal right · temporal lobe · temporalis left · temporalis right · thalamus · thoracic cavity · thymus · thyrohyoid left · thyrohyoid right · thyroid cartilage · thyroid gland · thyroid left · thyroid right · tibia · tibia left · tibia right · toes left · toes right · tongue · trachea · trapezius left · trapezius right · ulna · ulna left · ulna right · uterocervix · uterus · veins · venous sinuses · vertebrae C1 · vertebrae C2 · vertebrae C3 · vertebrae C4 · vertebrae C5 · vertebrae C6 · vertebrae C7 · vertebrae L1 · vertebrae L2 · vertebrae L3 · vertebrae L4 · vertebrae L5 · vertebrae S1 · vertebrae T1 · vertebrae T2 · vertebrae T3 · vertebrae T4 · vertebrae T5 · vertebrae T6 · vertebrae T7 · vertebrae T8 · vertebrae T9 · vertebrae T10 · vertebrae T11 · vertebrae T12 · visceral adipose tissue · white matter · zygomatic arch left ·

**Voxel-wise annotated 377 anatomical structures:** abdominal cav
segment right · anterior scalene left · anterior scalene right · aorta · a
right · artery internal carotid left · artery internal carotid right · artery
auditory canal right · autochthon left · autochthon right · bladder · bl
vein left · brachiocephalic vein right · brain · brain ventricle · brainstem
carpal left · carpal right · caudate nucleus · cbd stent · celiac artery · ce
· clavicula left · clavicula right · cochlear left · cochlear right · colon · c
iliac artery left · common iliac artery right · common iliac vein le
cricopharyngeus · digastric left · digastric right · duodenum · esophag
· fibula · fibula left · fibula right · fingers left · fingers right · frontal lobe
left · gluteus medius right · gluteus minimus left · gluteus minimus
myocardium · heart tissue · heart ventricle left · heart ventricle right
iliac artery left · iliac artery right · iliac vena left · iliac vena right · iliops
constrictor · inferior rectus muscle left · inferior rectus muscle right · in
left · internal carotid artery right · internal jugular vein left · internal ju
larynx · lateral pterygoid left · lateral pterygoid right · lateral rectus
superioris left · levator palpebrae superioris right · levator scapulae l
liver segment 5 · liver segment 6 · liver segment 7 · liver segment 8
trachea bronchia · lung upper left lobe · lung upper right lobe · lung
pterygoid left · medial pterygoid right · medial rectus muscle left · m




right · metatarsal · metatarsal left · metatarsal right · middle pharyngeal constrictor · middle scalene left · middle scalene right · muscle · muscle fat · muscle of head · nasal cavity left · nasal cavity right · nasopharynx · occipital lobe · optic chiasm · optic nerve left · optic nerve right · oral cavity · oropharynx · pancreas · pancreas body · pancreas head · pancreas tail · pancreatic duct · parietal lobe · parotid gland left · parotid gland right · parotid glands · patella · patella left · patella right · pericardium · phalanges feet · phalanges hand · pituitary gland · platysma left · platysma right · portal vein · portal vein and splenic vein · postcava · posterior eyeball segment left · posterior eyeball segment right · posterior scalene left · posterior scalene right · prevertebral left · prevertebral right · prostate · prosthetic breast implant · psoas major muscle left · psoas major muscle right · pulmonary artery · pulmonary vein · radius · radius left · radius right · rectum · rectus abdominis muscle left · rectus abdominis muscle right · renal vein

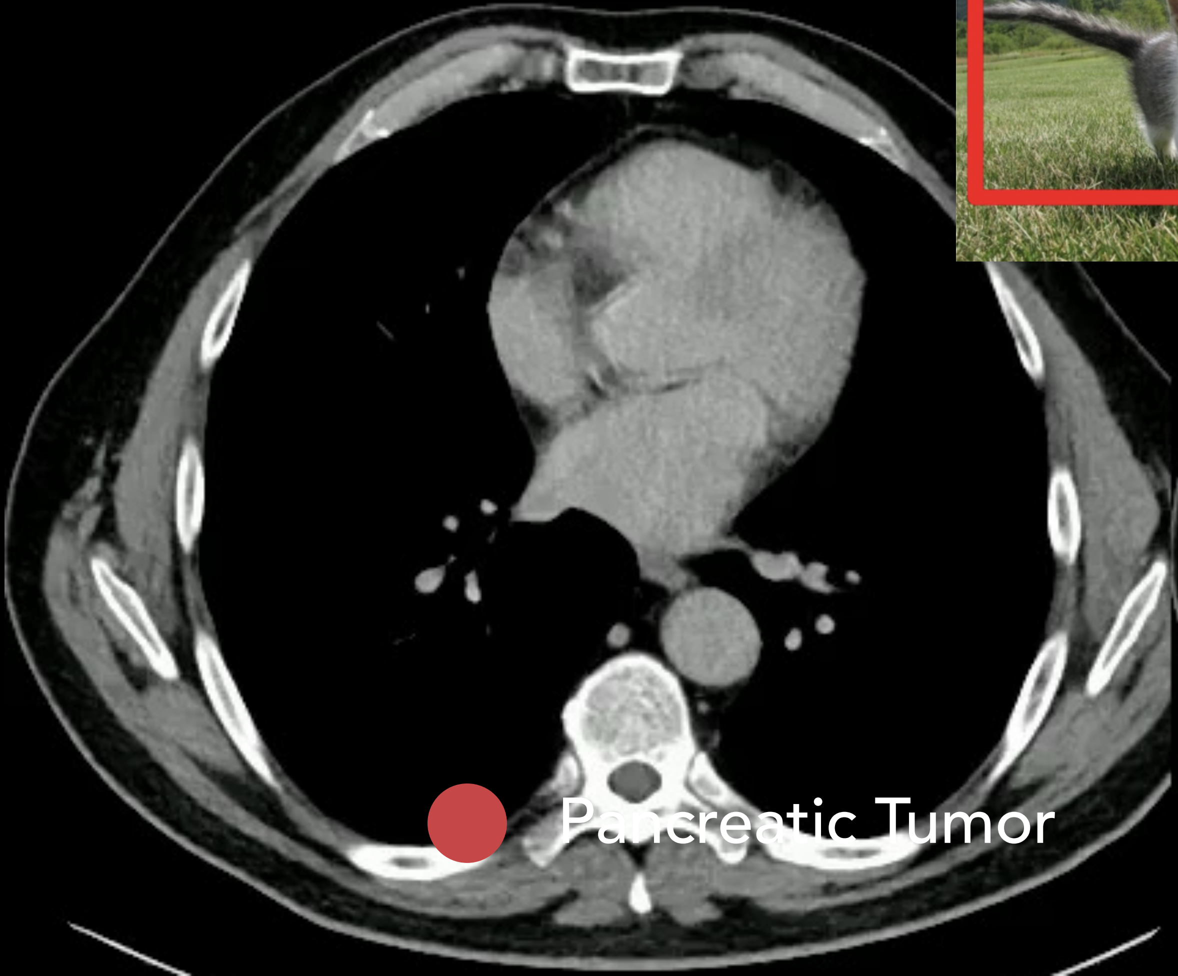
# Focusing on specific type of cancer will require finer annotations.

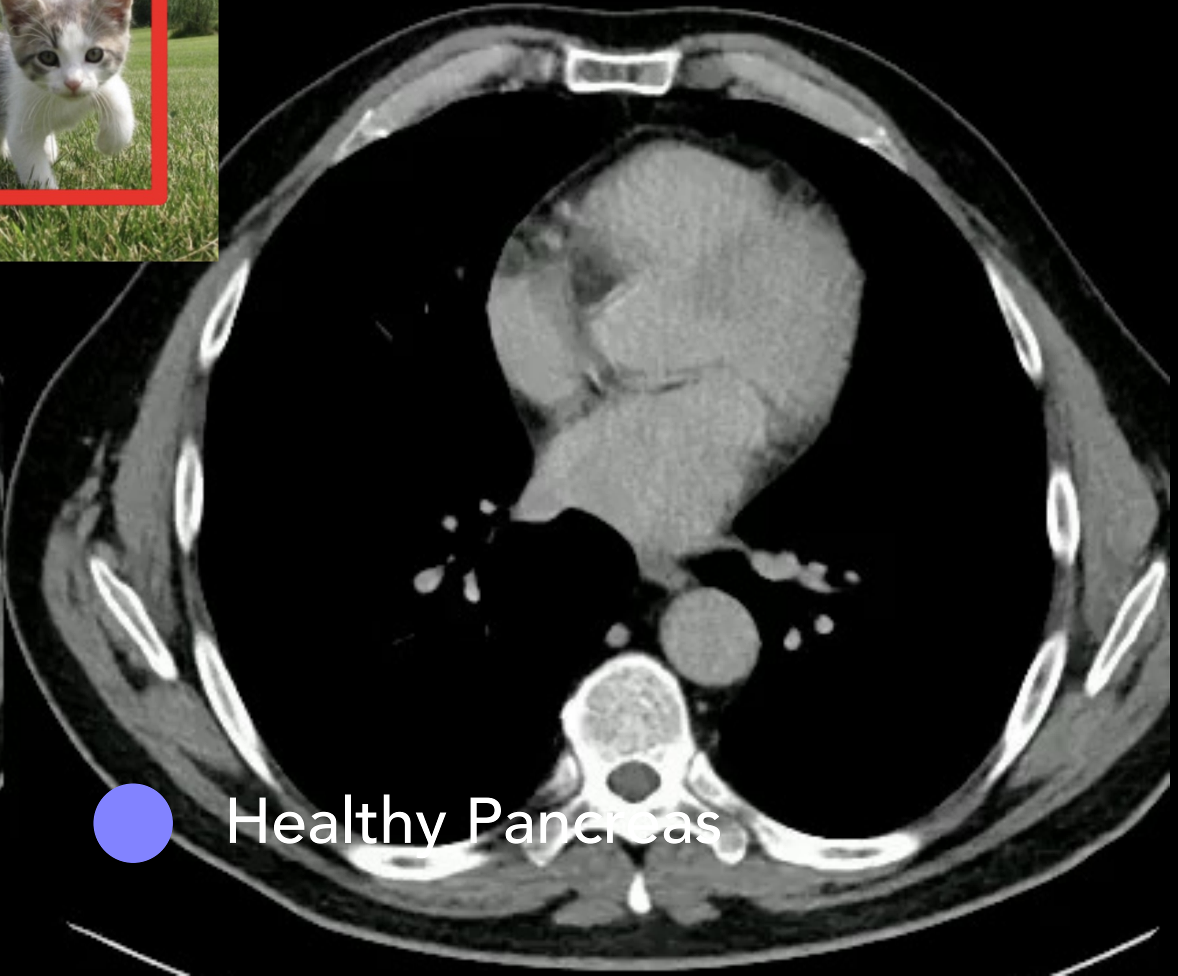
right · seminal vesicle · septum pellucidum · sigmoid colon · skeletal muscle · skin · skull · small bowel · soft palate · spinal canal · spinal cord · spleen · spongy bone · sterno thyroid left · sterno thyroid right · sternocleidomastoid left · sternocleidomastoid right · sternum · sternum corpus · sternum manubrium · stomach · styloid process left · styloid process right · subarachnoid space · subclavian artery left · subclavian artery right · subcutaneous adipose tissue · submandibular gland left · submandibular gland right · submandibular glands · superior mesenteric artery · superior oblique muscle left · superior oblique muscle right · superior rectus muscle left · superior rectus muscle right · superior vena cava · supraglottis · tarsal · tarsal left · tarsal right · temporal lobe · temporalis left · temporalis right · thalamus · thoracic cavity · thymus · thyrohyoid left · thyrohyoid right · thyroid cartilage · thyroid gland · thyroid left · thyroid right · tibia · tibia left · tibia right · toes left · toes right · tongue · trachea · trapezius left · trapezius right · ulna · ulna left · ulna right · uterocervix · uterus · veins · venous sinuses · vertebrae C1 · vertebrae C2 · vertebrae C3 · vertebrae C4 · vertebrae C5 · vertebrae C6 · vertebrae C7 · vertebrae L1 · vertebrae L2 · vertebrae L3 · vertebrae L4 · vertebrae L5 · vertebrae S1 · vertebrae T1 · vertebrae T2 · vertebrae T3 · vertebrae T4 · vertebrae T5 · vertebrae T6 · vertebrae T7 · vertebrae T8 · vertebrae T9 · vertebrae T10 · vertebrae T11 · vertebrae T12 · visceral adipose tissue · white matter · zygomatic arch left ·

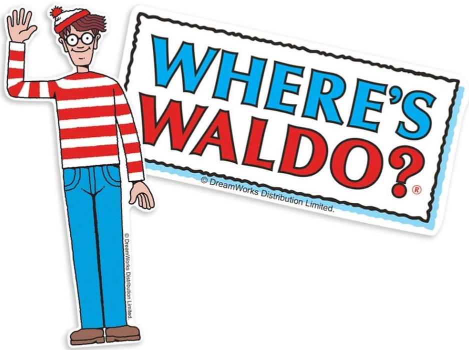
# Challenges (3/3)

- **Data:** Where to get data from different hospitals?
- **Annotations:** How to annotate the data?
- **Algorithms:** How to detect small cancer?

# Tumors (0.0001%) in 3D medical images vs. objects (5-50%) in 2D natural images




WHERE'S WALDO?
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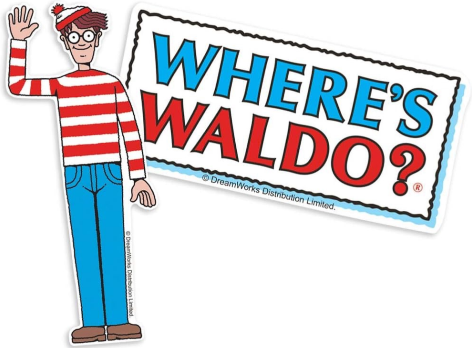
WHERE'S WALDO?
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# New Segmentation Architectures

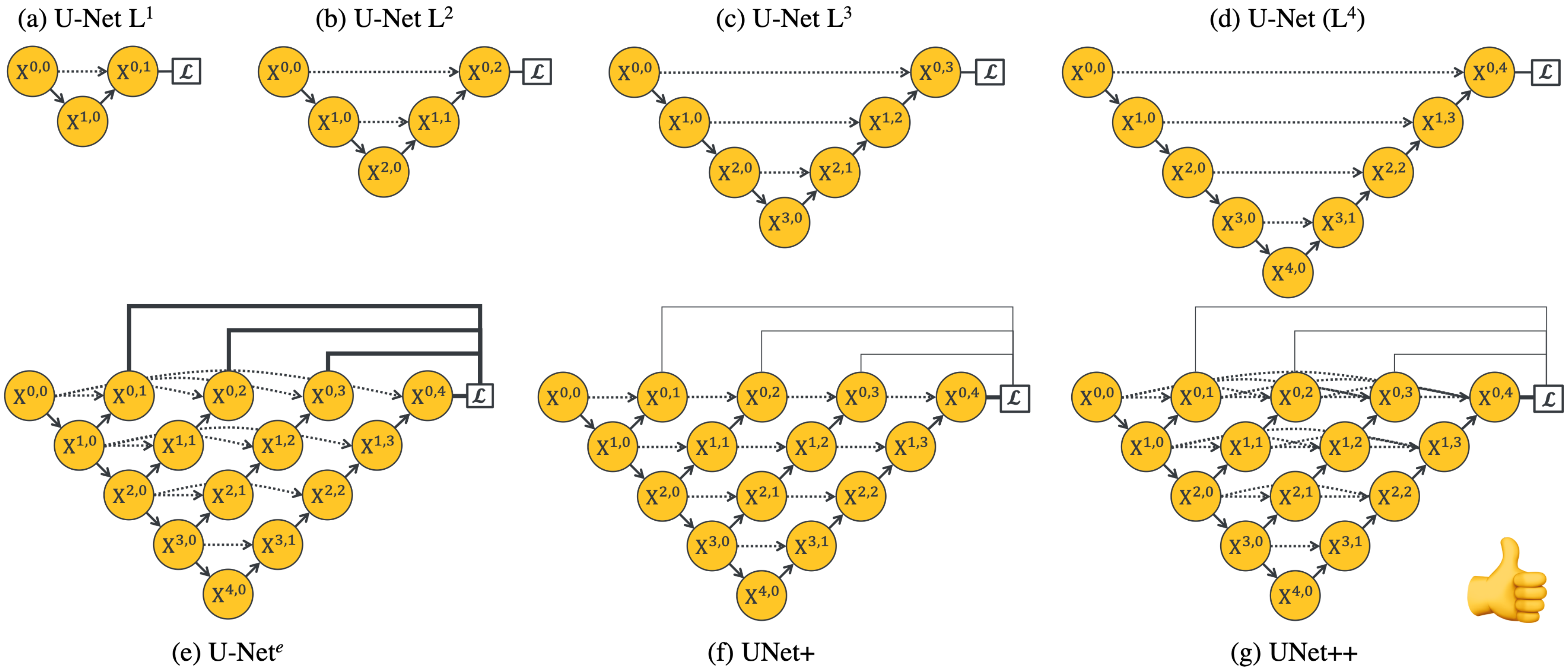
- AI is an extremely dynamic research field. Novel AI algorithms are continually being created and improved.

*Medical Image Segmentation*

| | | | |
|---|---|---|---|
| 1. | U-Net | (O. Ronneberger et al., 2015) | 134,200 cites |
| 2. | UNet++ | (Z. Zhou et al., 2019) | 17,400 cites |
| 3. | TransU-Net | (J. Chen et al., 2021) | 9,900 cites |
| 4. | nnU-Net | (F. Isensee et al., 2020) | 9,300 cites |
| 5. | … | | |

# New Segmentation Architectures

- UNet++ is suitable for segmenting tumors of a wide range of sizes (Z. Zhou et al., TMI 2019; AMIA Edward H. Shortliffe Doctoral Dissertation Award).



# Developing Novel AI Algorithms

- UNet++ is suitable for segmenting tumors of a wide range of sizes (Z. Zhou et al., TMI 2019; AMIA Edward H. Shortliffe Doctoral Dissertation Award).
- Models Gensis is the first medical foundation model that transfers knowledge from anatomical structures to multiple diseases (Z. Zhou et al., MedIA 2021; Elsevier-MedIA Best Paper Award; MICCAI 2019 Young Scientist Award).

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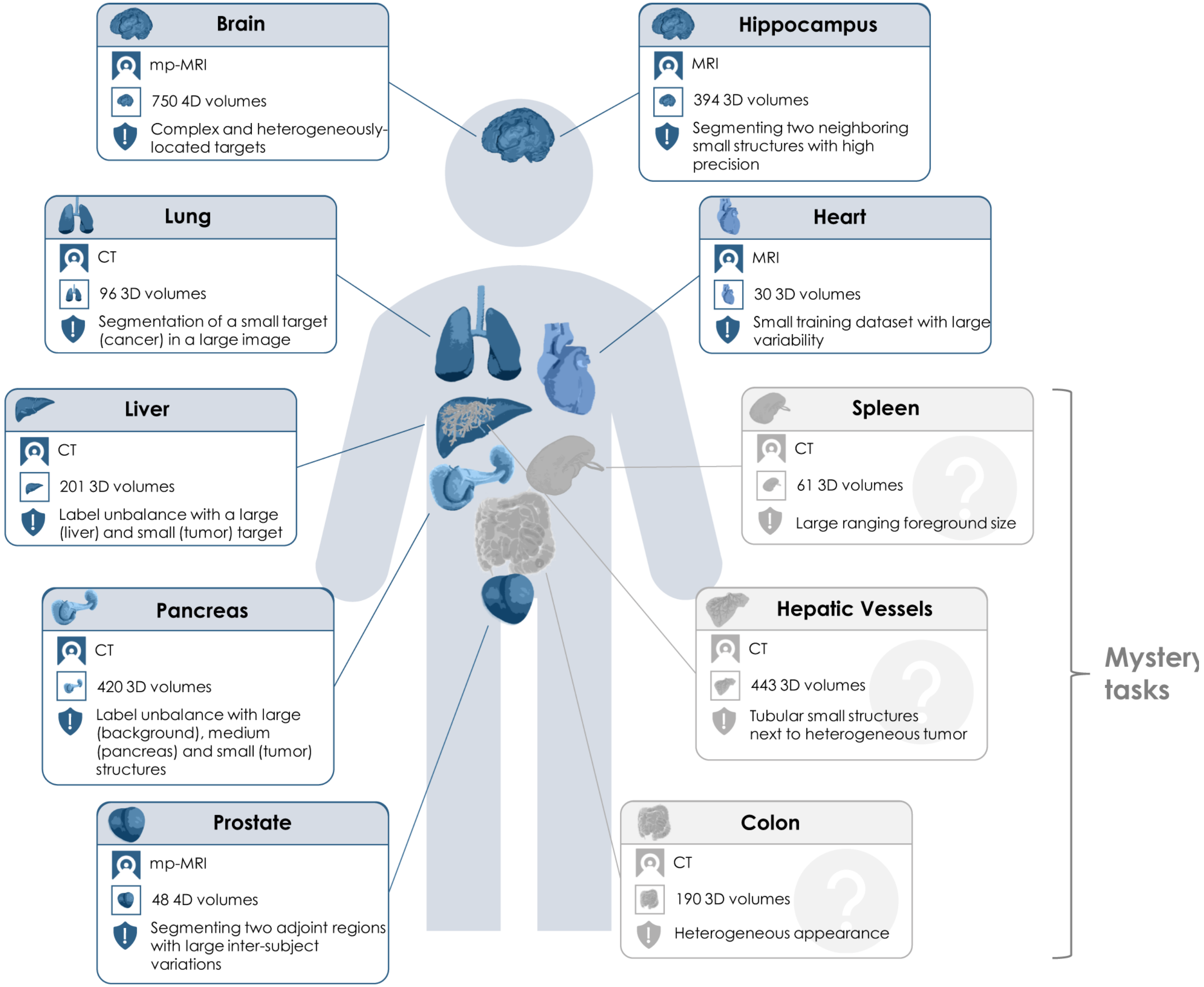
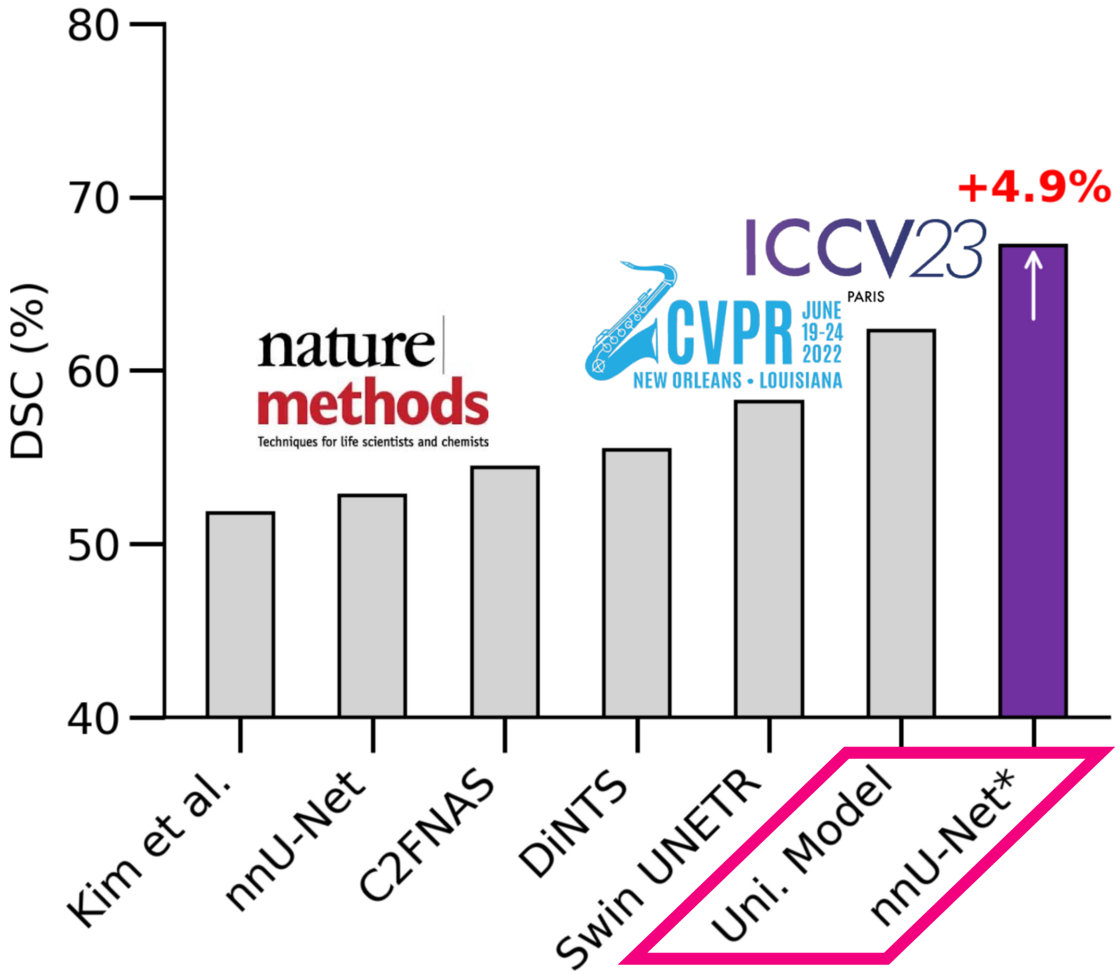
- Universal Model improves tumor segmentation by language prompts (J. Liu et al., ICCV 2023; Rank First in Medical Segmentation Decathlon).

# Benchmark on Cancer Imaging Leaderboard



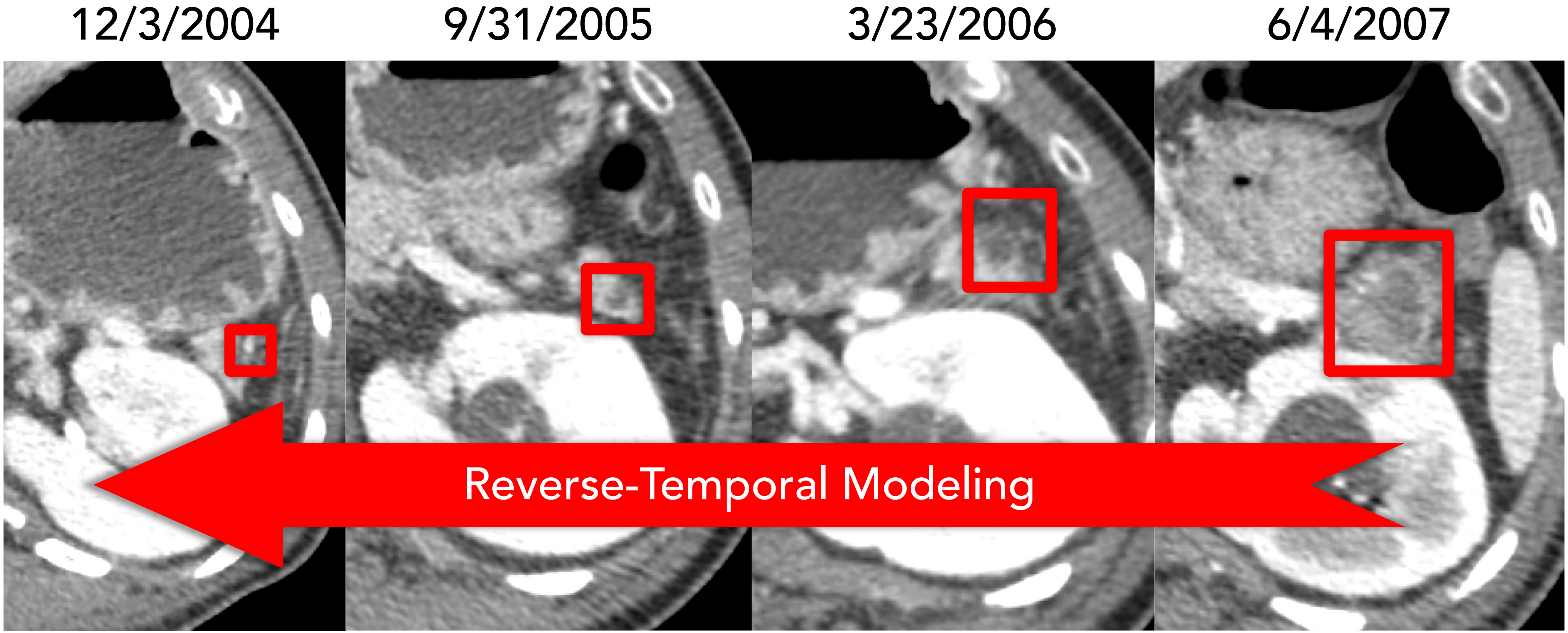
# Synthetic Data Improves Sensitivity

- There's a huge data gap in medical AI right now, particularly when you have rare diseases, uncommon conditions (e.g., cancer).
- Early-stage tumor scans are 10–20 times less common than late-stage scans in clinical datasets.
- We don't have enough early-stage tumor scans to train these models; unfortunate these are the tumors we must detect to improve survival.

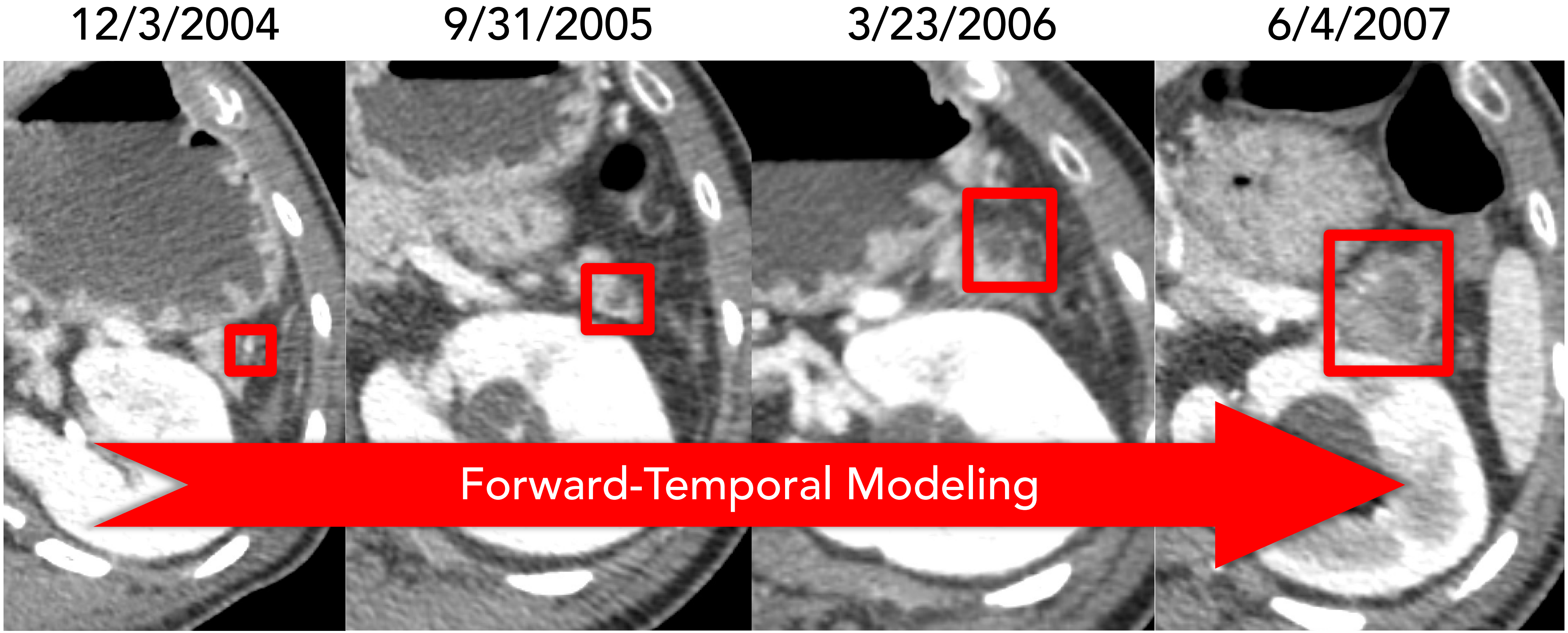
- Synthetic data can be a big piece of that puzzle (Lai et al., MICCA 2024).

GitHub.com/MrGiovanni/Pixel2Cancer

# Synthetic Tumors as Time Machine

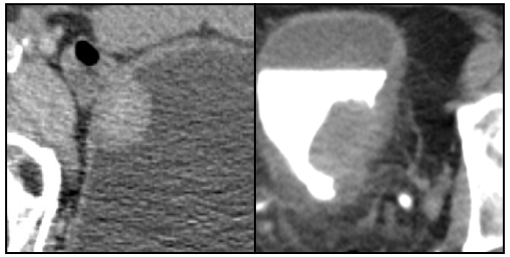


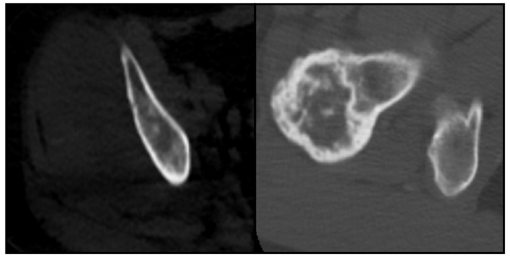
# Synthetic Tumors as Time Machine

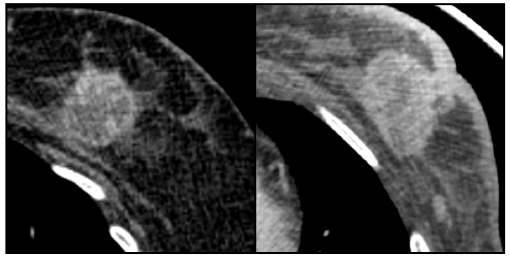


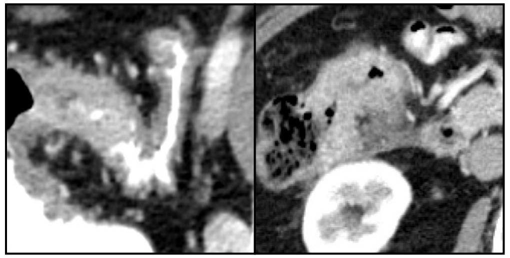
# Visual Turing Test for Radiologists

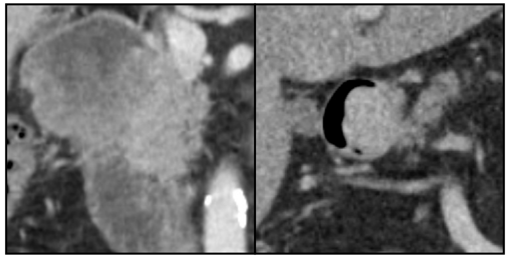
(a) real or fake test

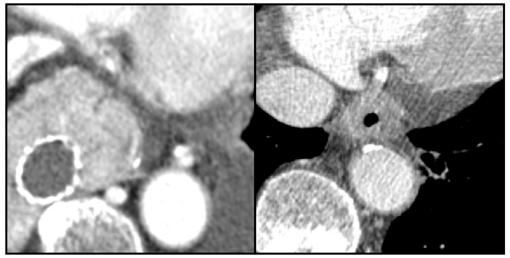

(b) bladder tumor

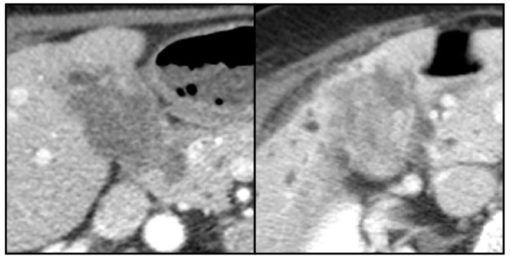

(c) bone tumor

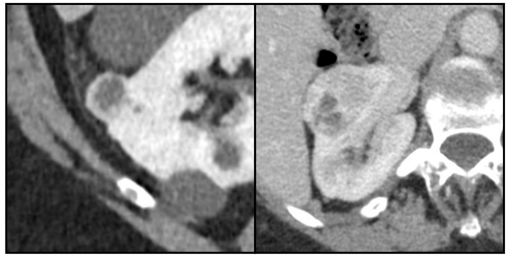

(d) breast tumor

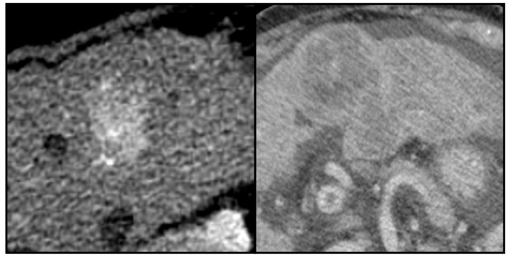

(e) colon tumor

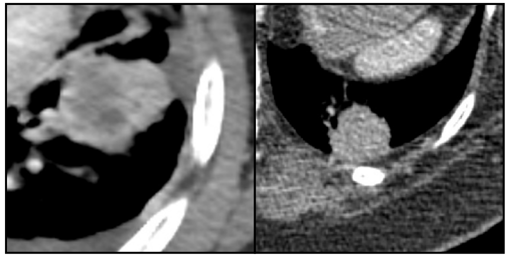

(f) duodenum tumor

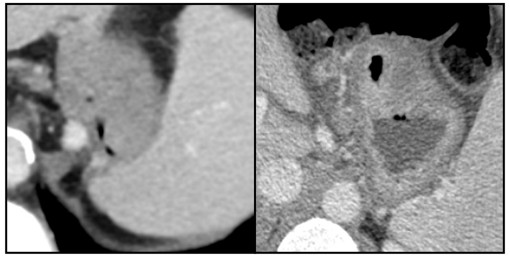

(g) esophagus tumor


(h) gallbladder tumor


(i) kidney tumor

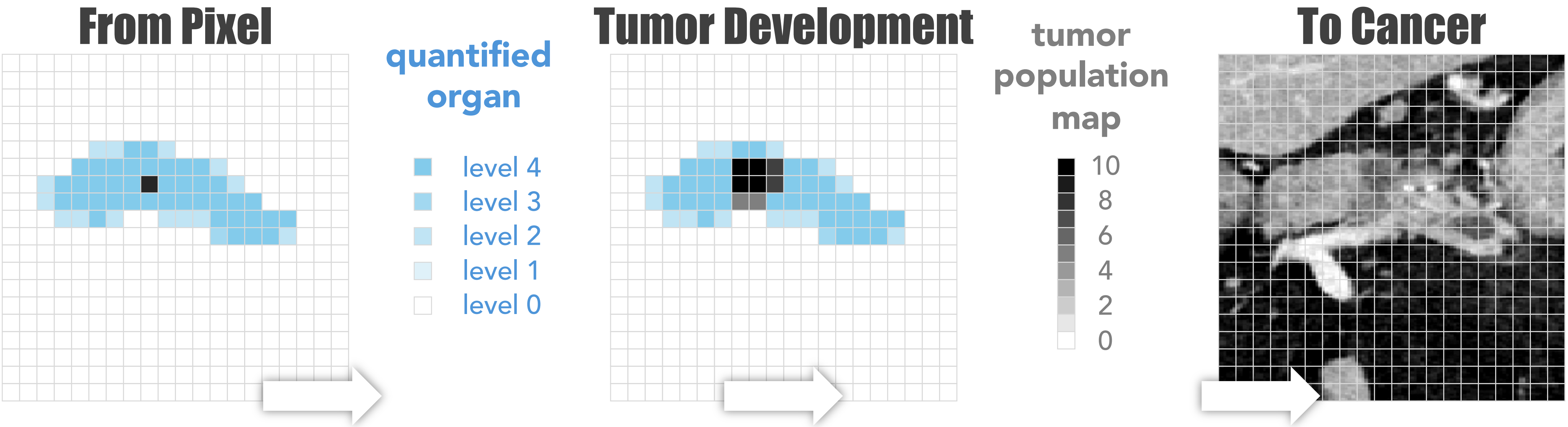

(j) liver tumor


(k) lung tumor


(l) stomach tumor

# Tumor/Vessel/Duct/Organ Synthesis

- We developed "game of life" to simulate tumor development (Lai et al., MICCAI 2024) and applied diffusion models to create synthetic tumors.




applying three generic rules

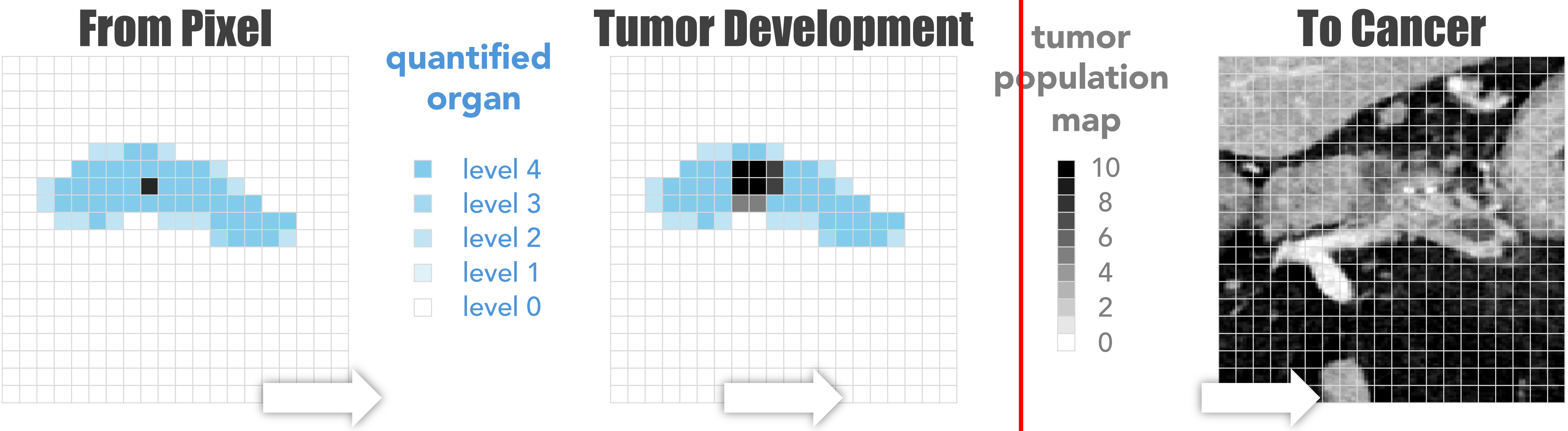
simulating tumor & organ interaction

mapping tumors to CT images

# Tumor/Vessel/Duct/Organ Synthesis

## Cellular Automata

*a mathematical model that uses simple rules to simulate complex systems*

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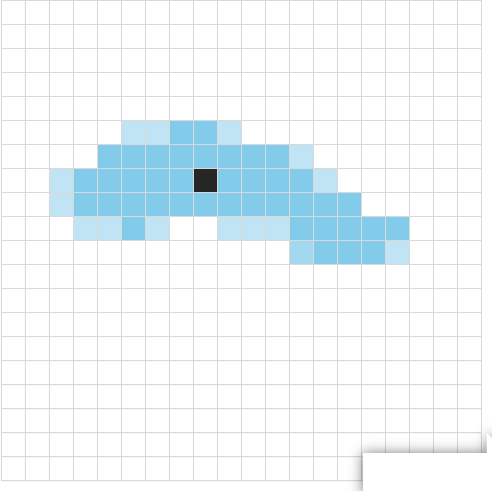
# Tumor/Vessel/Duct/Organ Synthesis

## Diffusion Models

*conditioned on tumor/vessel/duct/organ shapes simulated by cellular automata*

### From Pixel

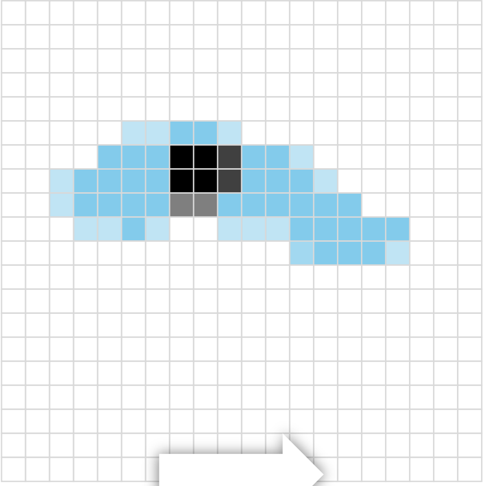


**quantified organ**

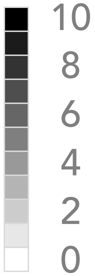
- level 4
- level 3
- level 2
- level 1
- level 0

applying three generic rules

### Tumor Development

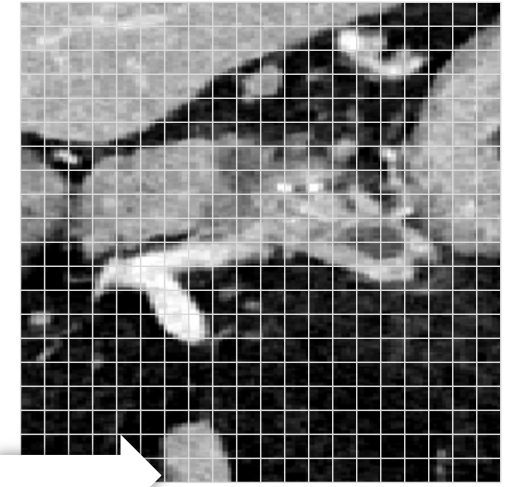


**tumor population map**




simulating tumor & organ interaction

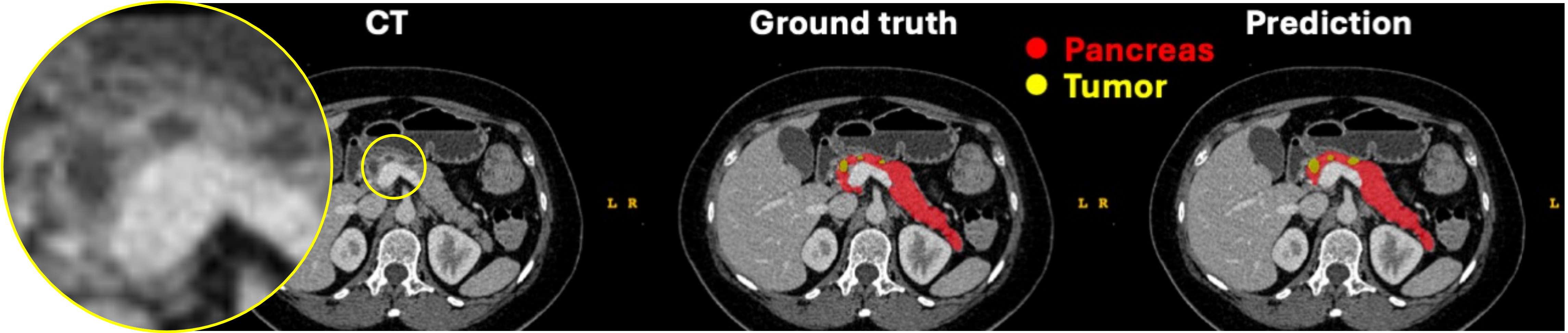
### To Cancer



mapping tumors to CT images

# Synthetic Data for Small/Tiny Tumors

- Synthetic data improves sensitivity of detecting small tumors (≤2 cm) by **5% (89% → 94%)** (Q. Chen et al., CVPR 2024; Q. Hu et al., CVPR 2023)
- The smallest lesion we detected was 2 mm.




GitHub.com/MrGiovanni/SyntheticTumors

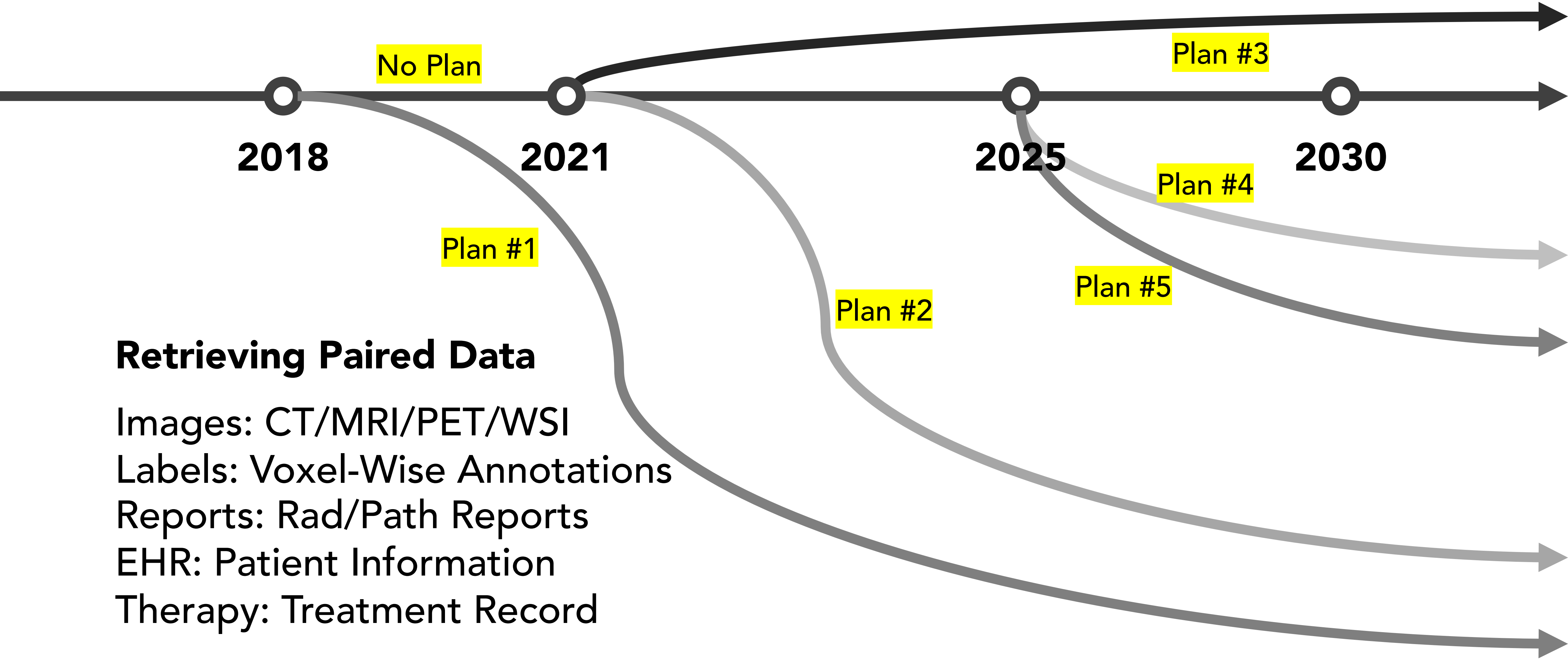
# Synthetic Data for Small/Tiny Tumors

- Real-world tumor datasets are often biased.
  - E.g., Tumor location: about 65% of pancreatic tumors arise in the head of the pancreas with the remaining roughly one-third in the body or tail.

- Targeted data augmentation enabled by error analysis and synthetic data (X. Li et al., TMI 2025)
  - The AI often misses small tumors in the body or tail of the pancreas.
  - We can add more synthetic small tumors in these regions during training.

*GitHub.com/MrGiovanni/TextoMorph*

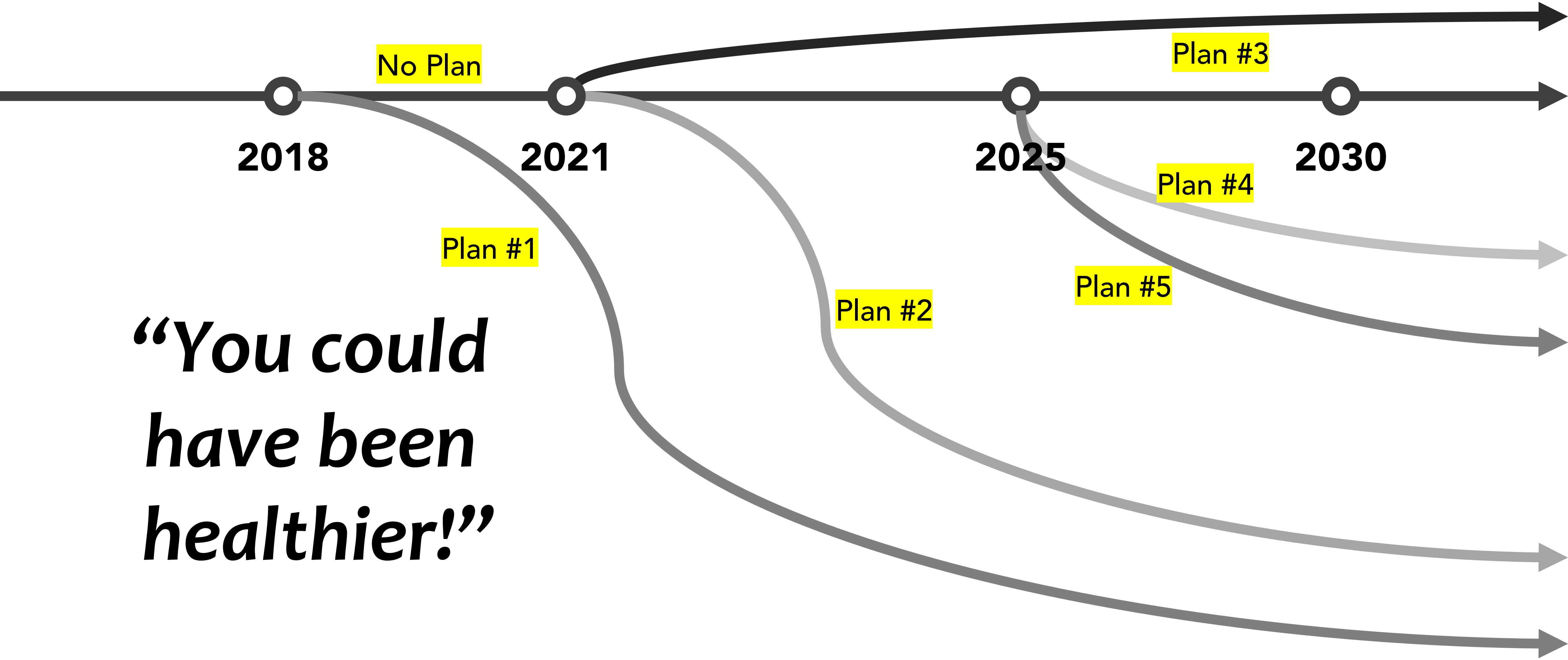
# NIH R01: Multimodal+Longitudinal Analysis




**Retrieving Paired Data**

Images: CT/MRI/PET/WSI
Labels: Voxel-Wise Annotations
Reports: Rad/Path Reports
EHR: Patient Information
Therapy: Treatment Record

# NIH R01: Multimodal+Longitudinal Analysis




***"You could have been healthier!"***


# The One Possibility

## Over 14 Million Futures

Report Generation

Early Cancer Detection

Organ Segmentation

Patient Retrieval

## Applications

## Algorithms

| Research Topics | Featured Achievements | Peer-Reviewed Publications |
|---|---|---|
| I. Segmentation Architectures | UNet++, 17,000 Citations | TMI, MIA, ICCV, NeurIPS, RSNA |
| II. Annotations with Active Learning | AbdomenAtlas, $N$ = 240,000 | MIAx2, CVPRx2, MICCAI, NeurIPS, RSNAx12 |
| III.A. Medical Foundation Models | Models Genesis, MICCAI Best Paper Award & MIA Best Paper Award | TPAMI, TMI, MIA, CVPRx2, ICLRx2, ICCV, MICCAIx4, RSNAx12 |
| III.B. Vision & Language | Finalist, MICCAI Best Paper Award | ICCV, MICCAI, ISBI, RSNAx2 |
| III.C. Tumor Synthesis & Generation | Segmentation of 16 Cancer Types | CVPRx2, ICCVx3, MICCAI, RSNAx10 |

# About the BodyMaps Program

BodyMaps is a rigorously mentored research program at the convergence of Artificial Intelligence (AI) and Medicine, hosted at the Computational Cognition, Vision, and Learning (CCVL) lab. It welcomes students, researchers, clinicians, and developers around the world. Over 9 to 12 months, candidates will lead high-impact research, receive training and working in small interdisciplinary teams.

# BodyMaps AI Bootcamp

We can host visiting students from outside Hopkins. There are training positions open for undergraduates, graduate students, and post-doctoral scholars:

- Research Assistant
- Developer

https://www.zongweiz.com/apply

Rolling applications, reviewed at the end of every month.

# BodyMaps Demonstration Award

The BodyMaps Demonstration Award provides multiple one-year awards of up to **$100,000** to support projects with strong potential to develop AI algorithms for early cancer detection from CT scans of the abdomen, pelvis, and chest. The program emphasizes multi-cancer early detection and prioritizes innovative approaches that demonstrate the potential to significantly outperform expert radiologist performance in both sensitivity and specificity.

All letter of intents should be submitted as PDFs here.