



BodyMaps

Towards 3D Atlas of Human Body

Zongwei Zhou

Johns Hopkins University

zzhou82@jh.edu



MICCAI 2024

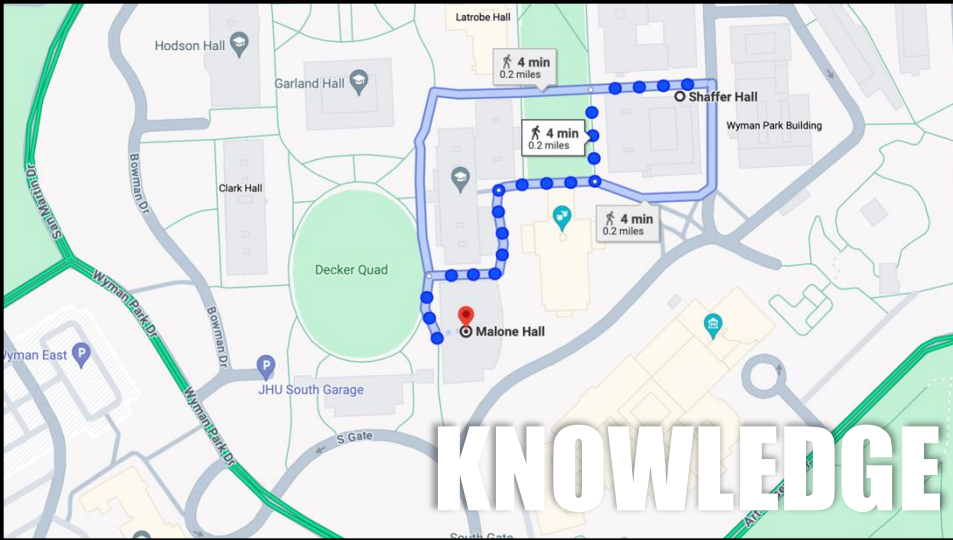
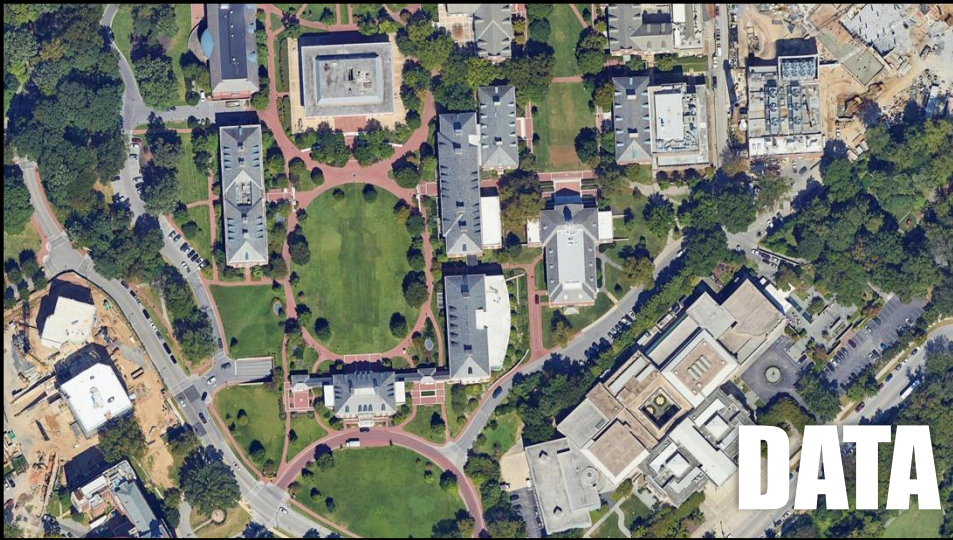


Marrakesh
MOROCCO

BodyMaps

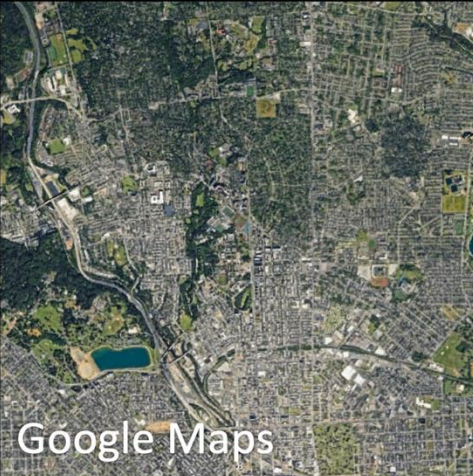
Towards 3D Atlas of Human Body



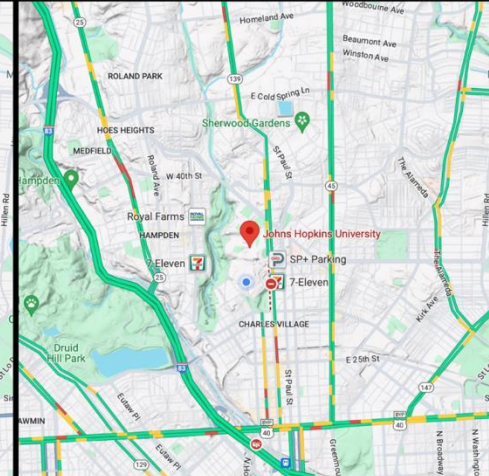
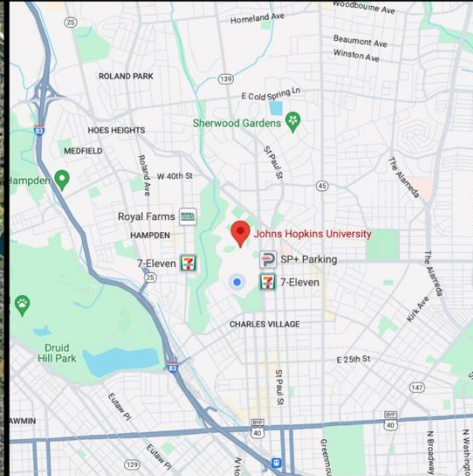


Uber
Lyft

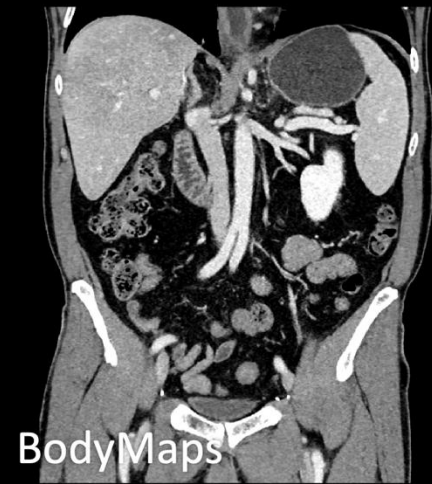
APPLICATION



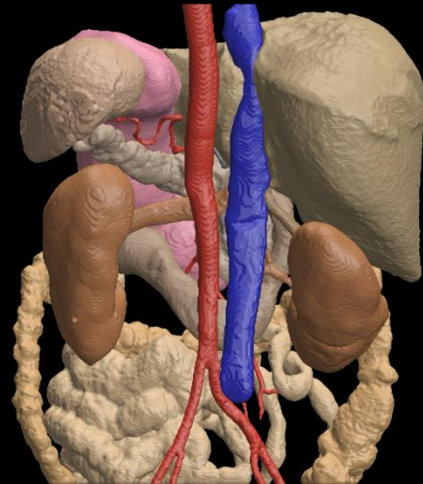
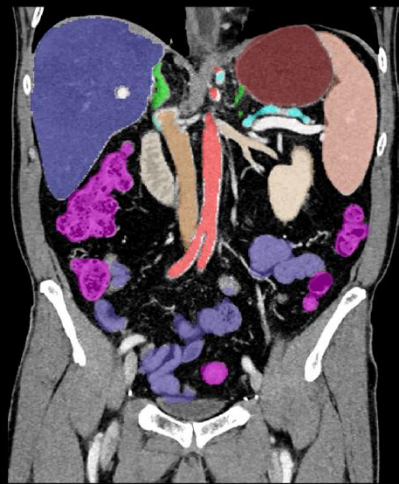
Google Maps

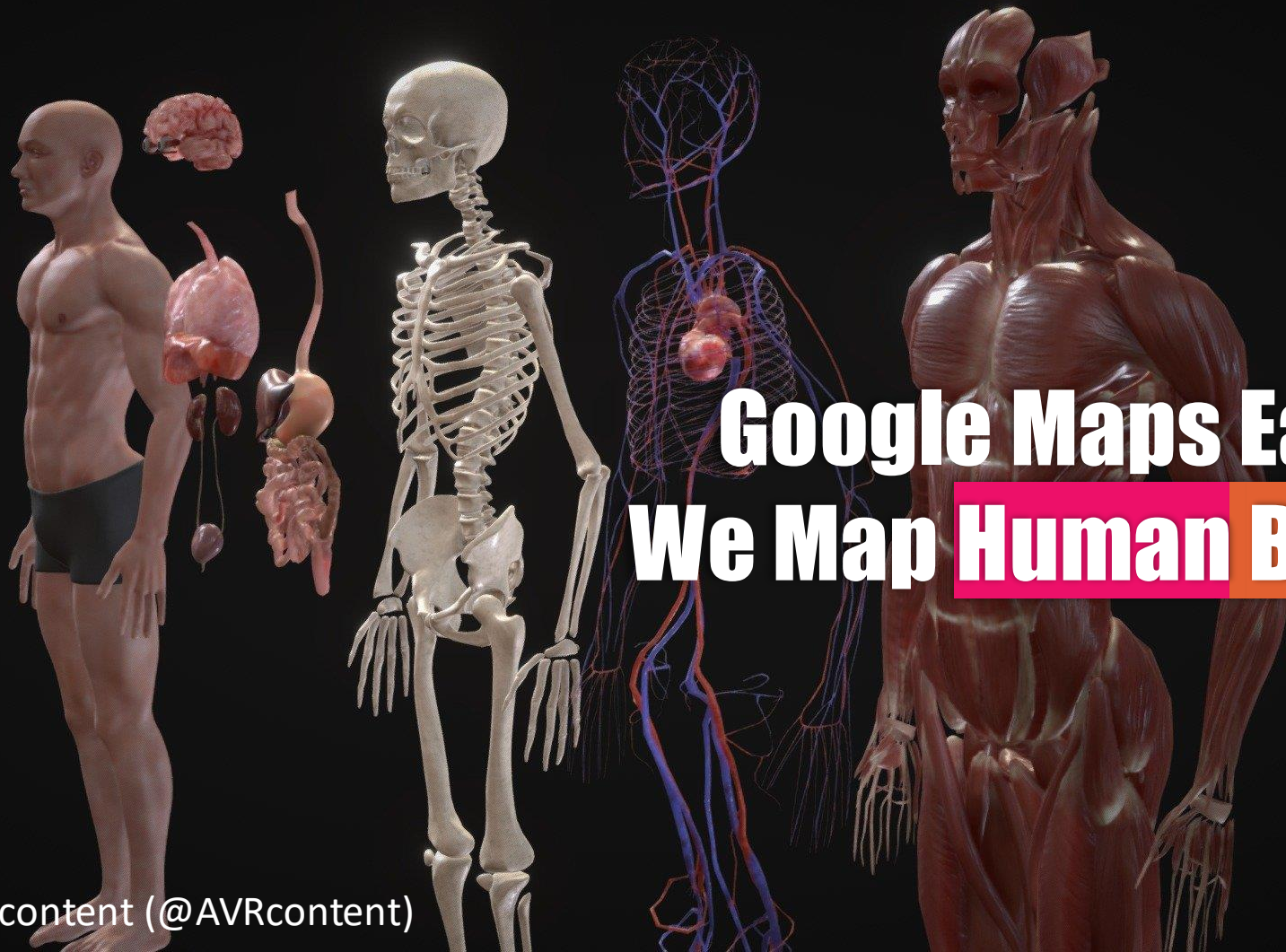


Data → Information → Knowledge → Application



BodyMaps





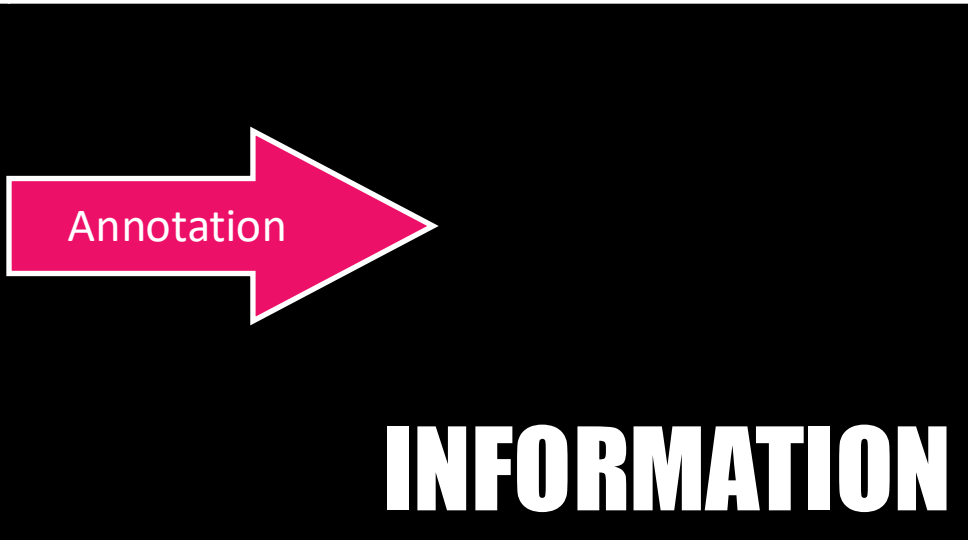
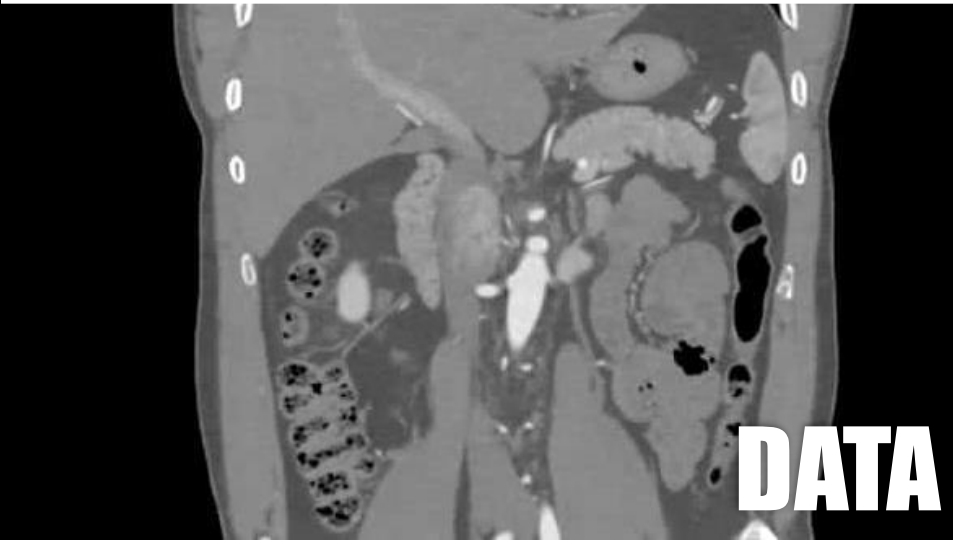
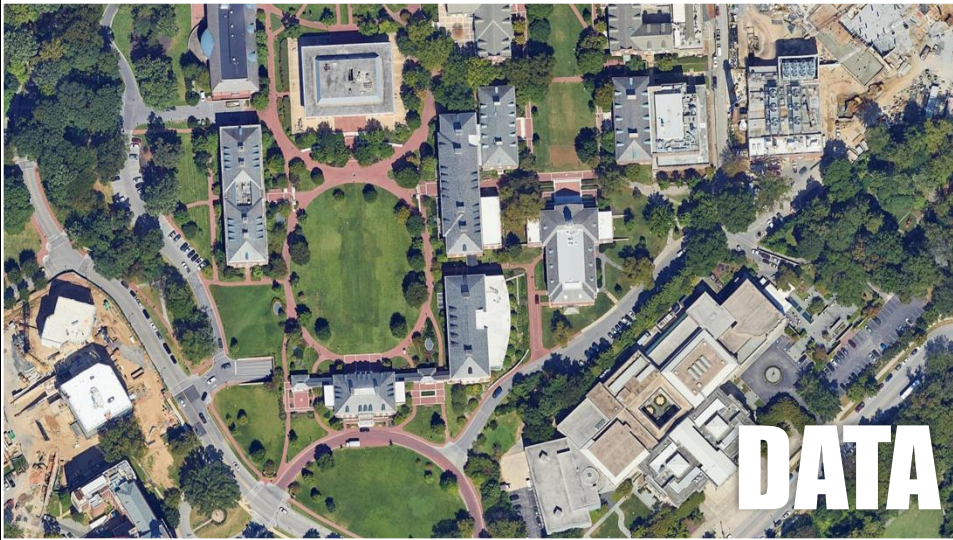
Google Maps Earth We Map Human Body

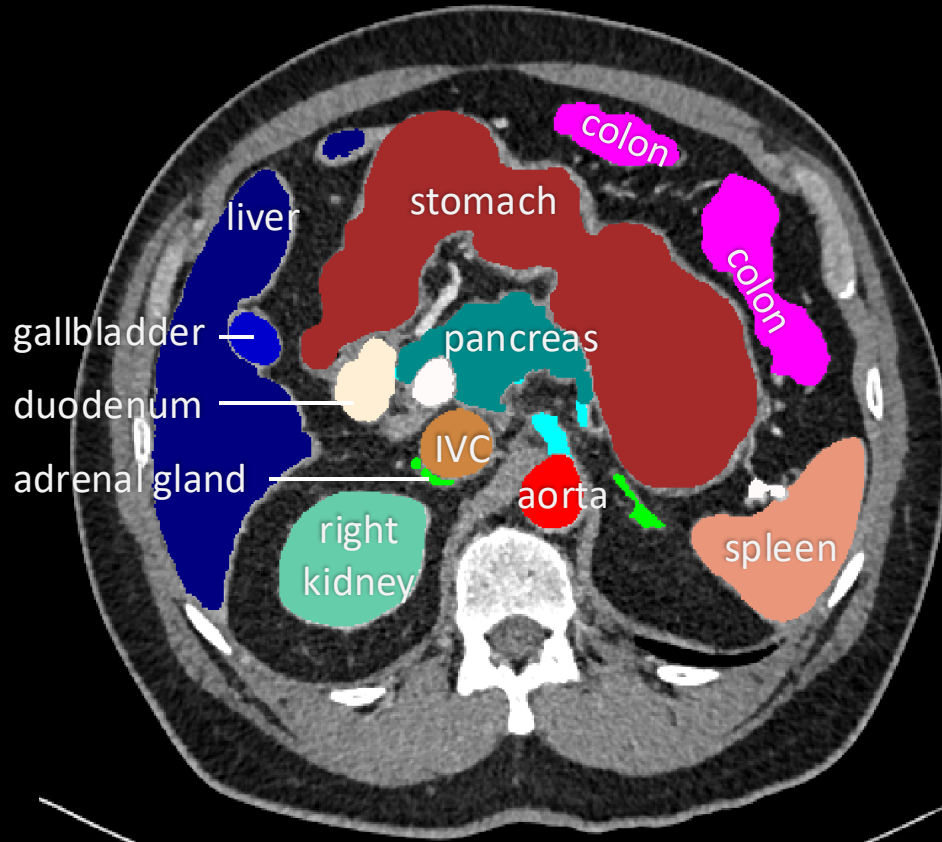
Photo by AVRcontent (@AVRcontent)



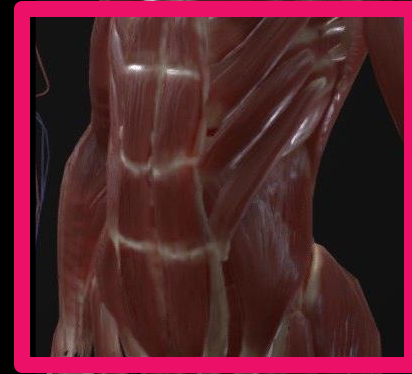
Raw Data

Computed Tomography

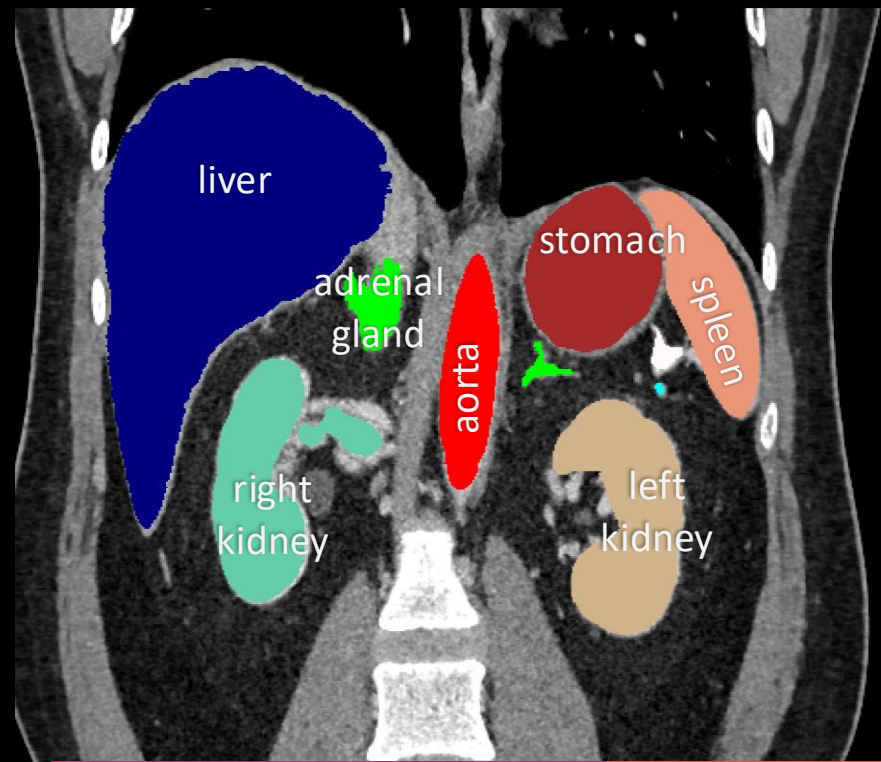
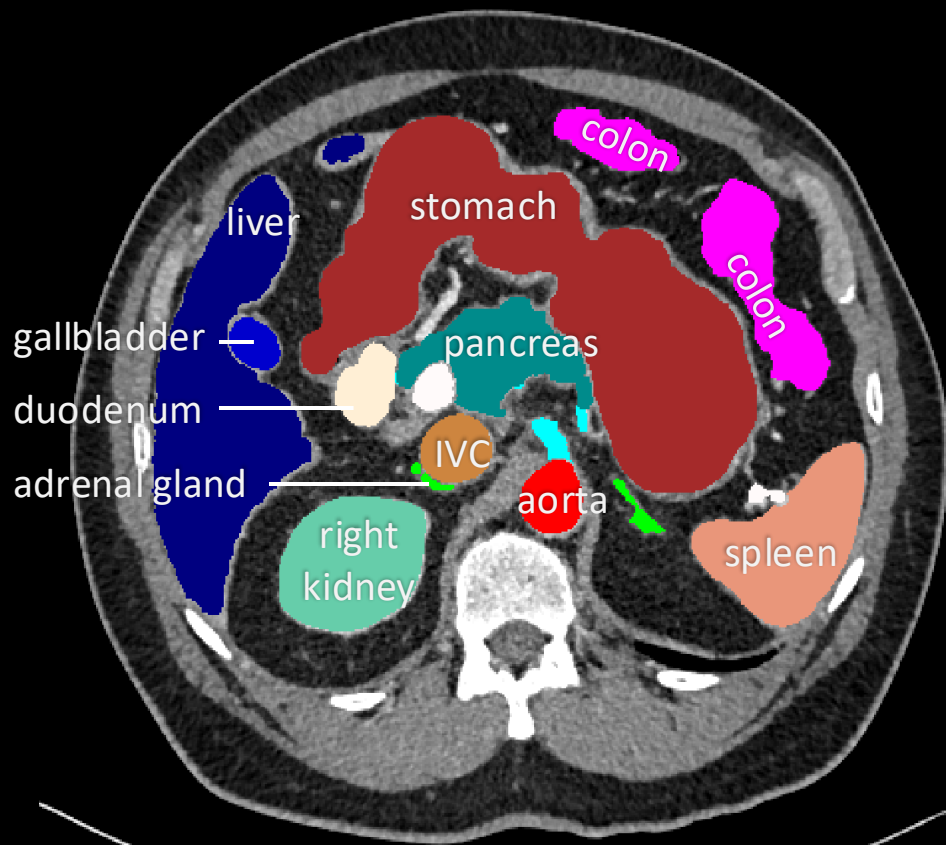




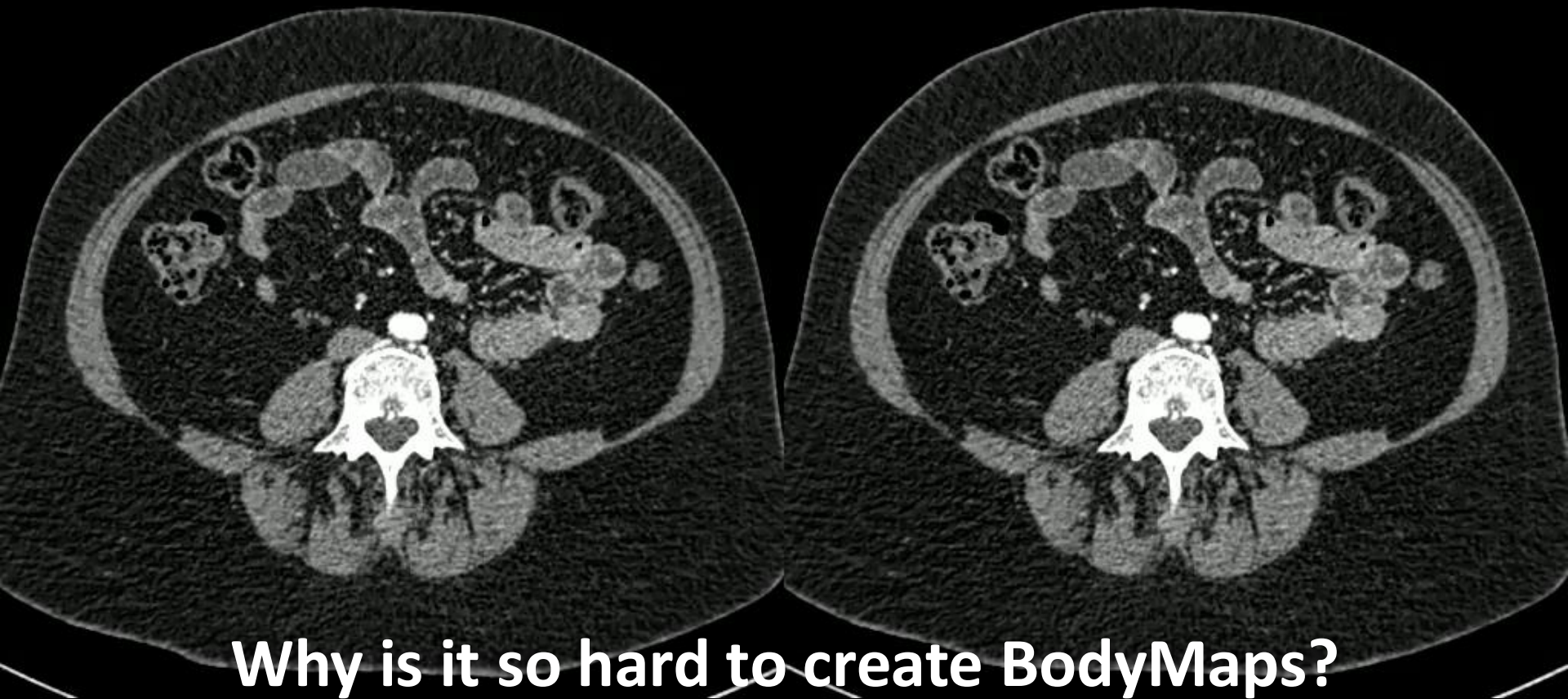
BodyMaps 1.0



AbdomenAtlas



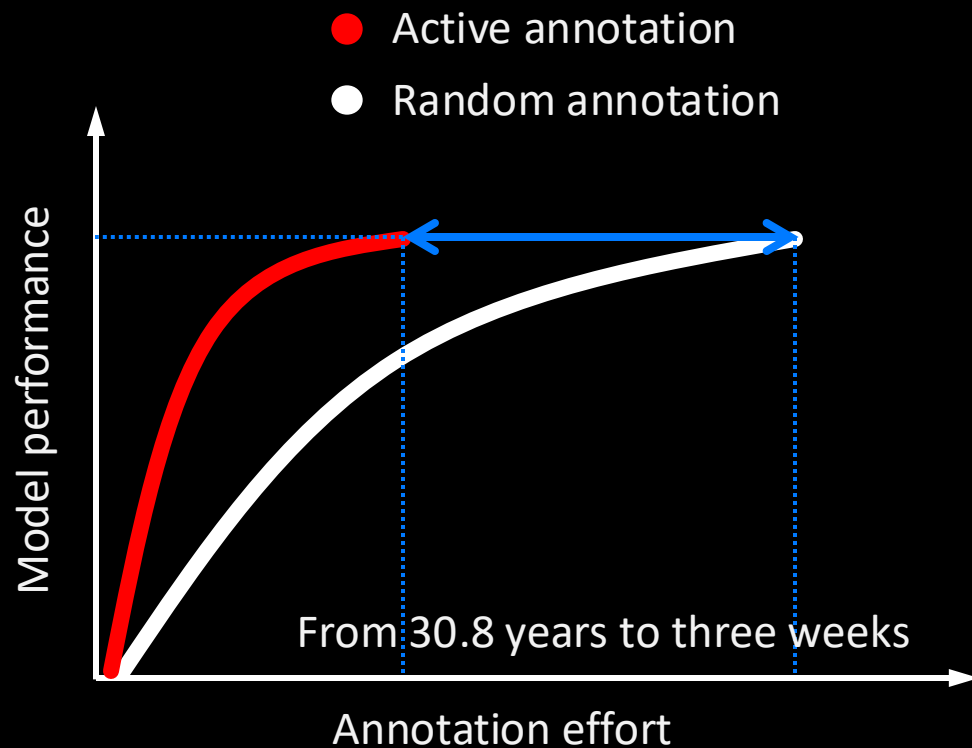
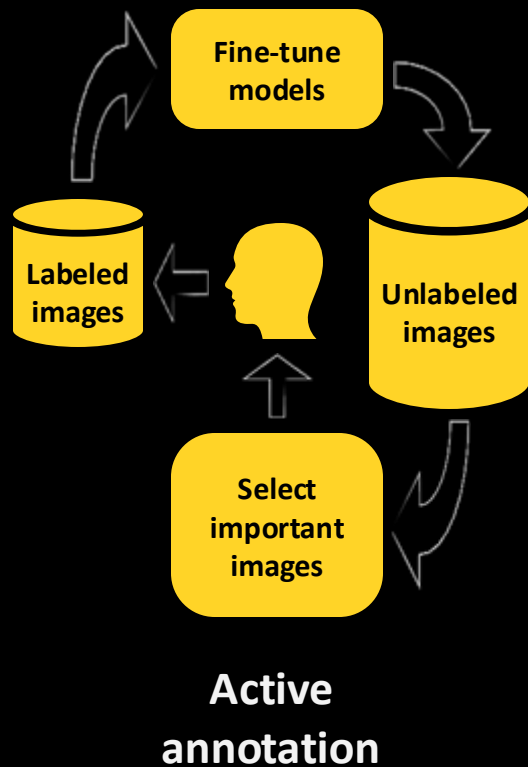
AbdomenAtlas



Why is it so hard to create BodyMaps?

30 minutes /organ /CT

Over 30.8 years to finish annotations for 8,000 CTs





Entropy

CT Scan

Inconsistency

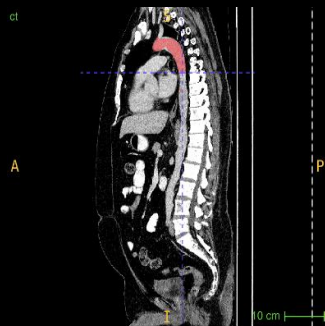
Uncertainty

Overlap

Attention Map

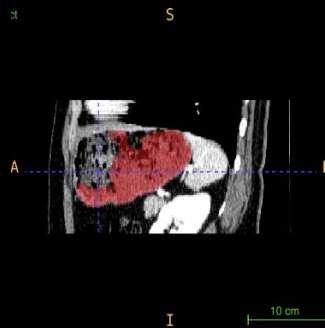
Diversity

We summarized a **taxonomy** of common errors made by AIs and humans [Qiao et al., RSNA 2023]



Aorta

Inconsistent labeling protocols



Stomach

uncertainty in empty areas

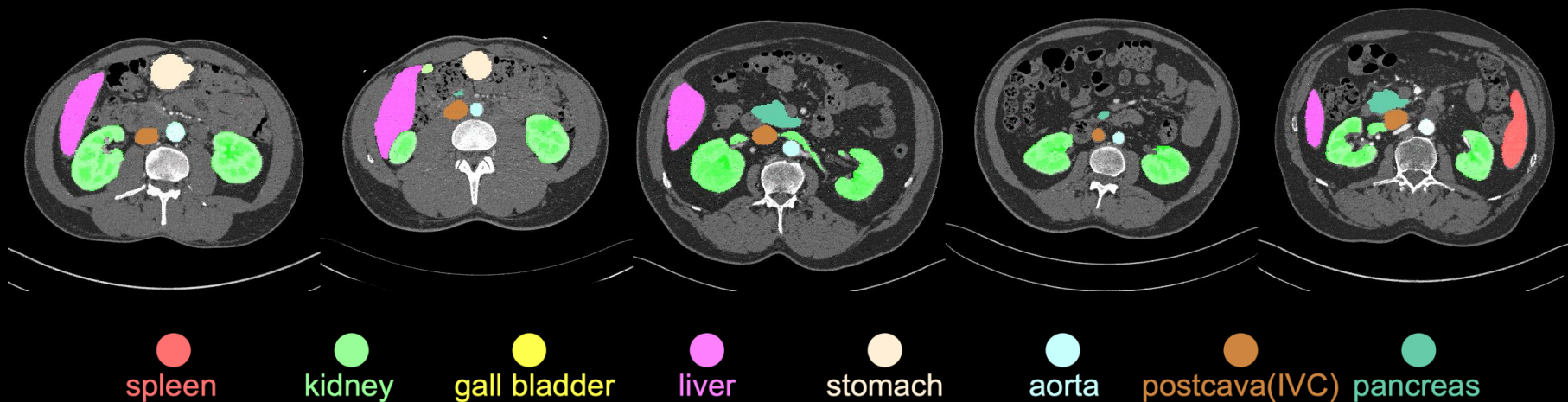


Postcava

ambiguous & blurry boundaries

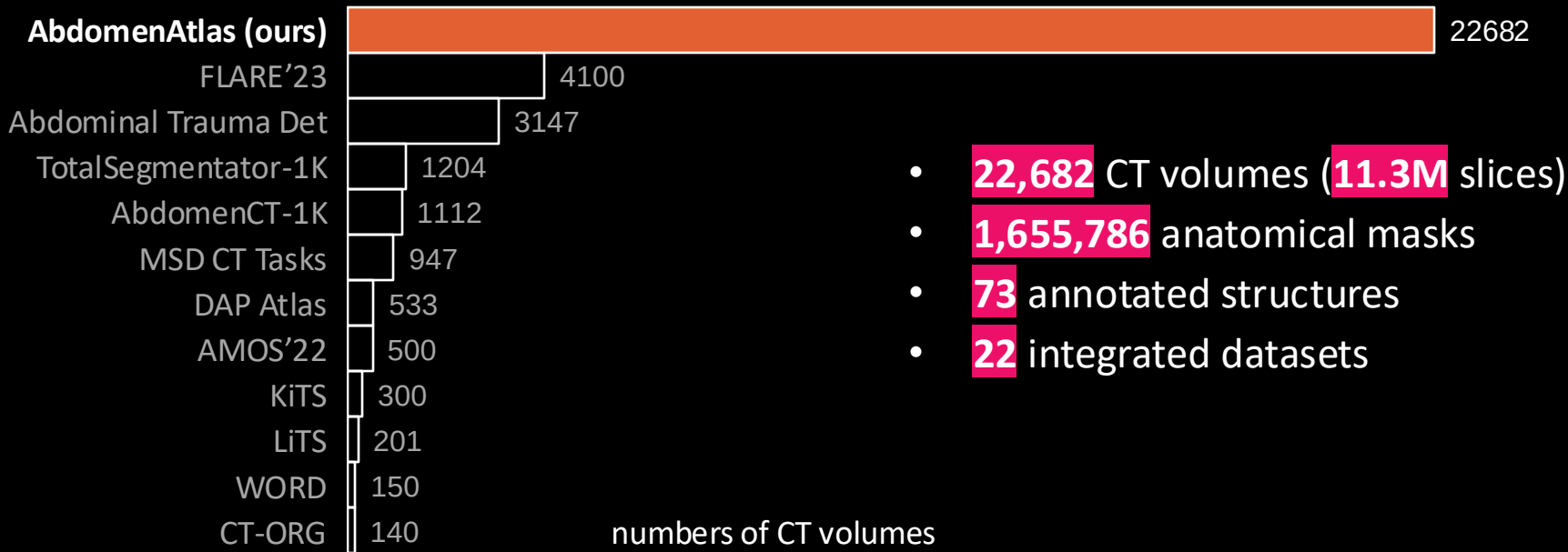
We have released AbdomenAtlas of 9,262 CT volumes and 231K organ masks

[Li et al., ICLR 2024 Oral]

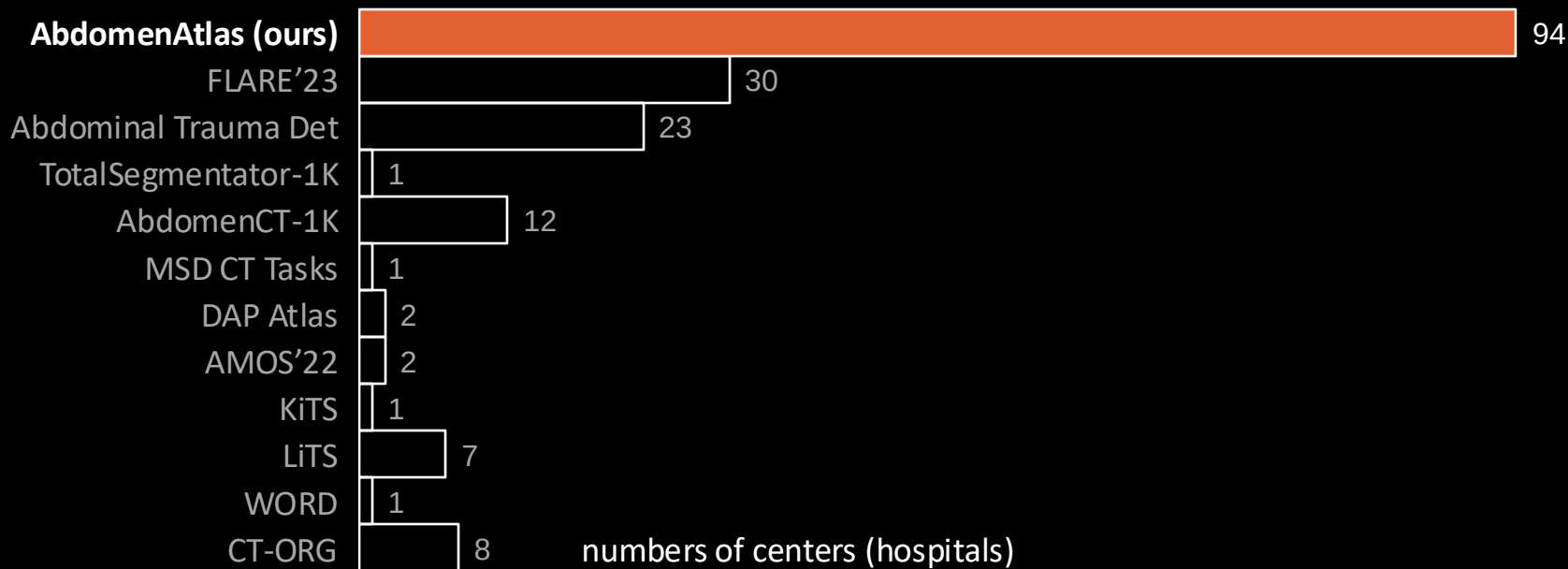


AbdomenAtlas

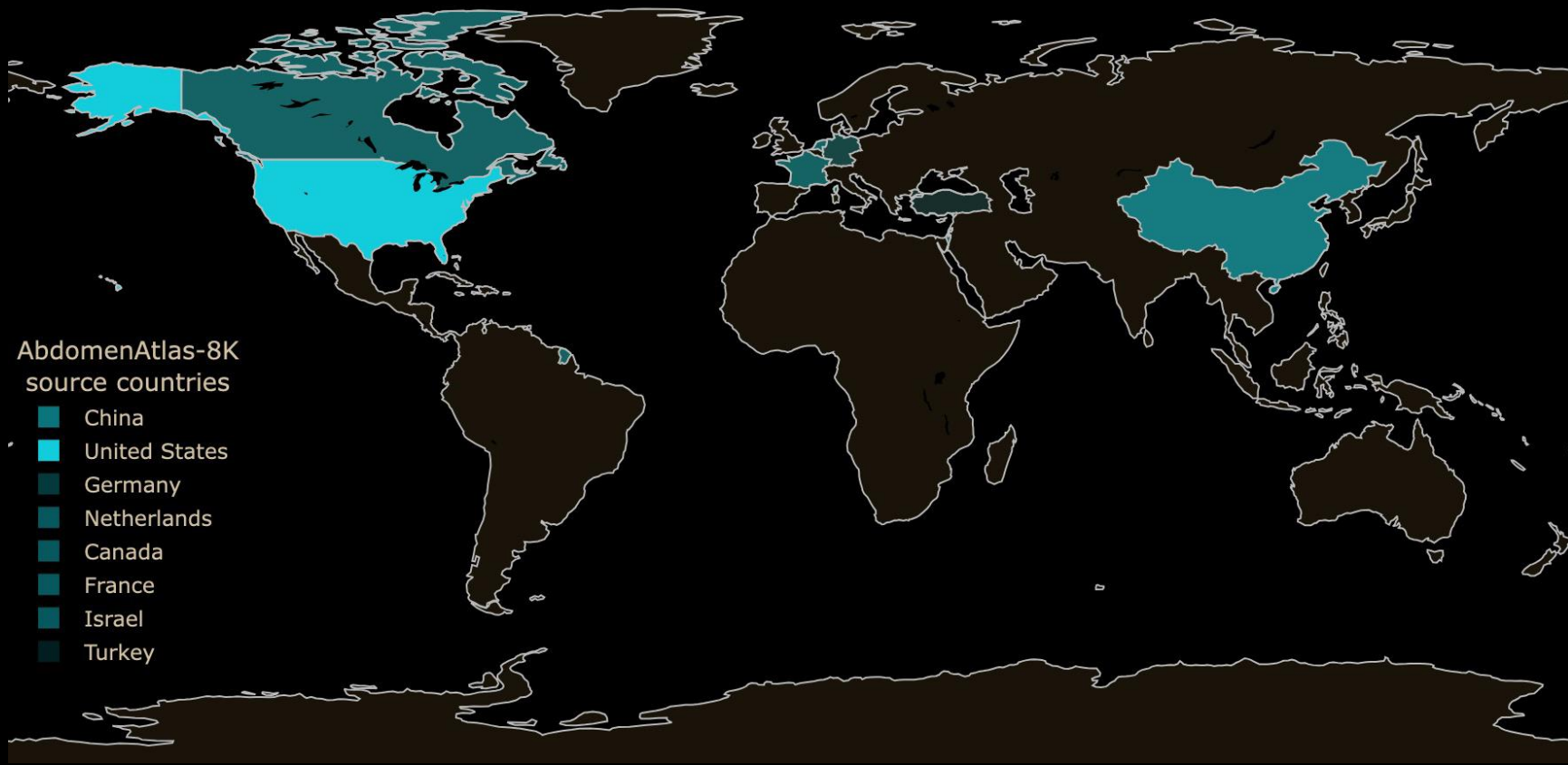
F1. Multicenter CT scans (11.3M)



F1. Multicenter CT scans (94 centers)

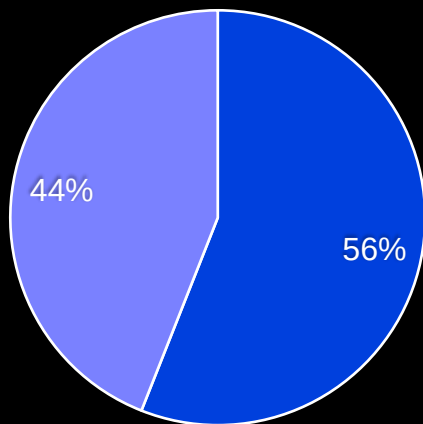


F1. Multicenter CT scans (19 countries)



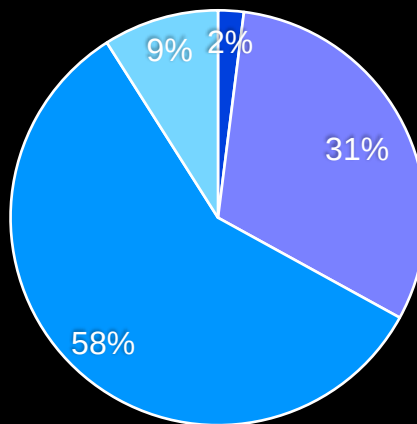
F1. Multicenter CT scans (diversity)

gender



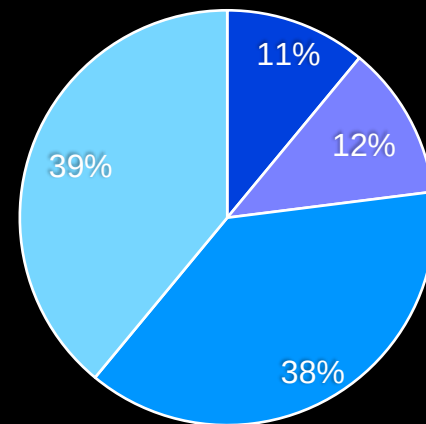
● male ● female

age



● (0,25] ● (25,50]
● (50,75] ● (75,+∞)

scanner



● Toshiba ● Phillips
● Siemens ● GE

F2. Multiple (73) annotated structures

16 Abdominal Organs

gall bladder
kidney left
kidney right
liver
pancreas
spleen
stomach
adrenal gland left
adrenal gland right
bladder
colon
duodenum
esophagus
intestine
prostate
rectum

2 Thoracic Organs

lung left
lung right

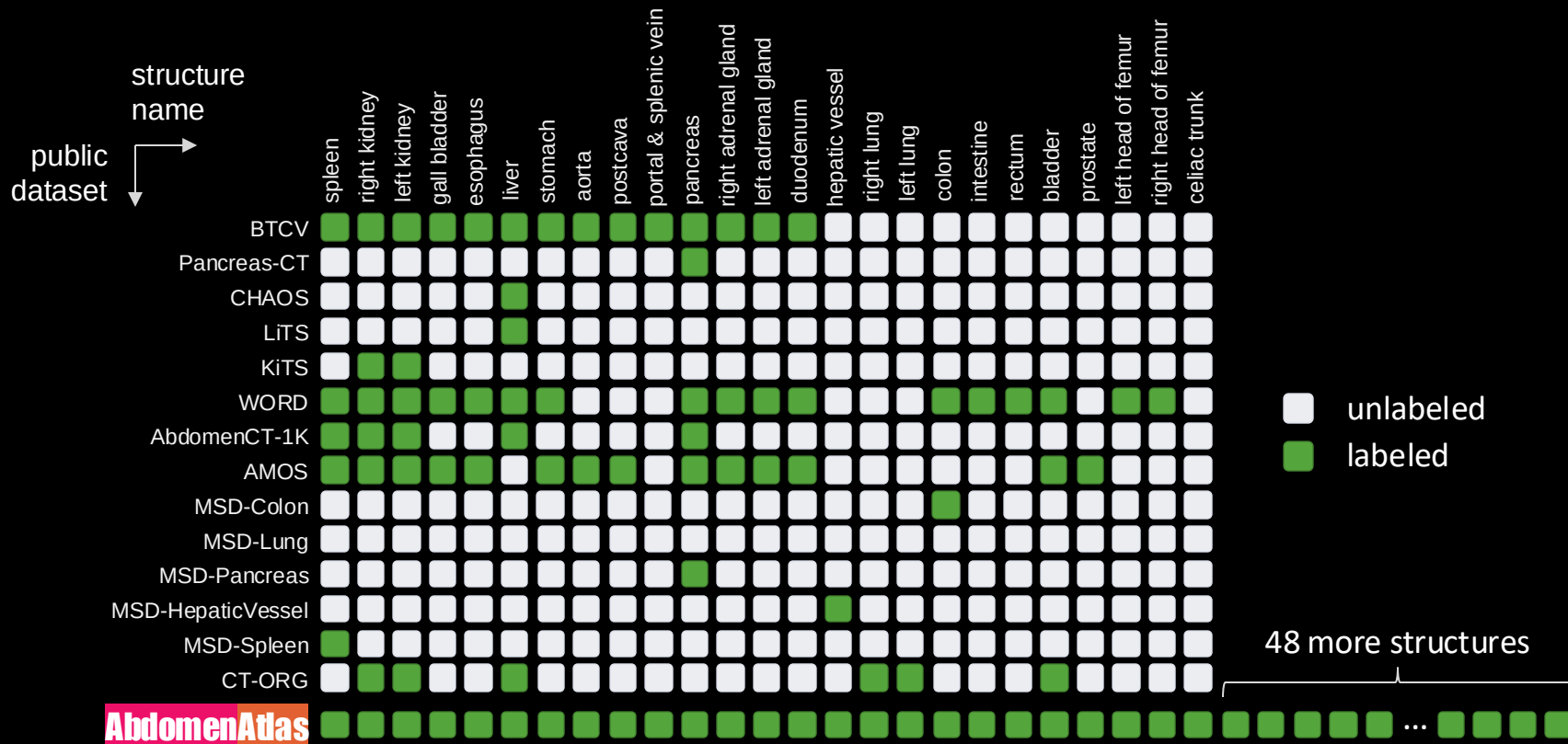
5 Vascular Structures

aorta
celiac trunk
postcava
hepatic vessel
portal & splenic vein

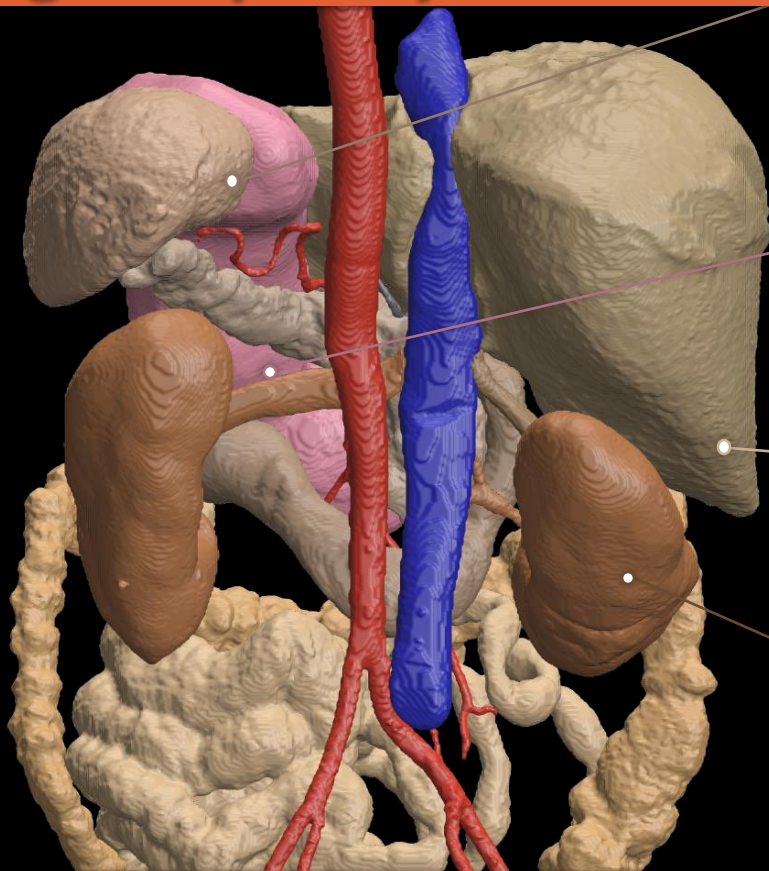
50 Skeletal Structures

vertebrae L1-L5
vertebrae T1-T12
vertebrae C1-C7
ribs left 1-12
ribs right 1-12
femur left
femur right

F2. Multiple (73) annotated structures



F3. Higher quality annotations



AbdomenAtlas



BTCV



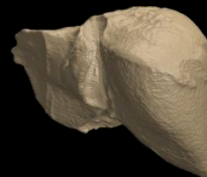
AbdomenAtlas



FLARE'23



AbdomenAtlas



LiTS

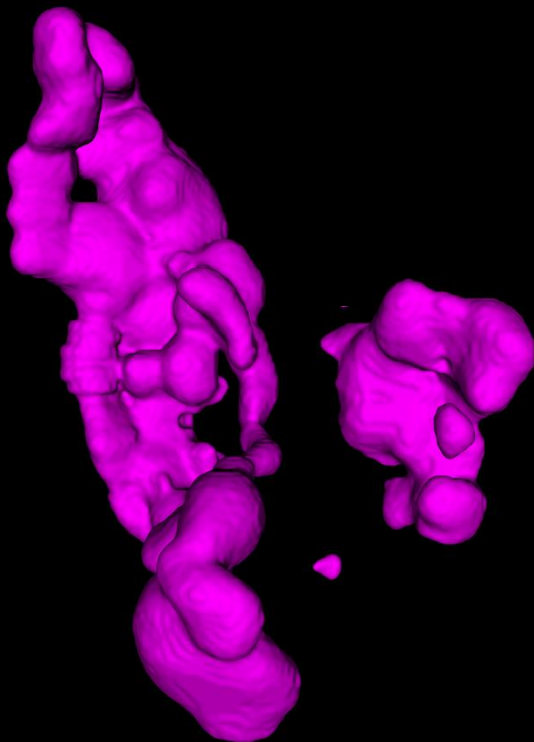


AbdomenAtlas



KiTS





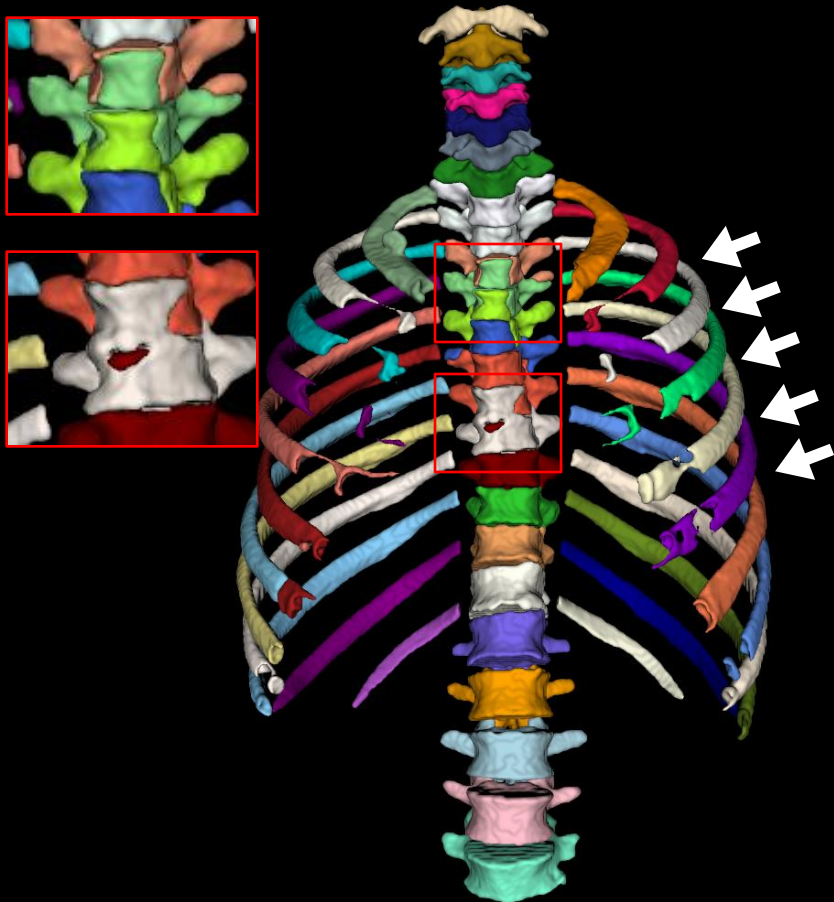
annotated colon in
TotalSegmentator

“The colon contour should include entire wall and lumen of cecum, appendix, ascending colon, transverse colon, descending colon and sigmoid colon **continuously**, as well as any colon lesions. **Adjacent structures** such as small intestine, surrounding fat, mesentery, and omentum should be excluded. The boundary between the ileum and colon is defined by the ileocecal valve. The boundary between the rectum and sigmoid colon is defined by the sigmoid take-off.”

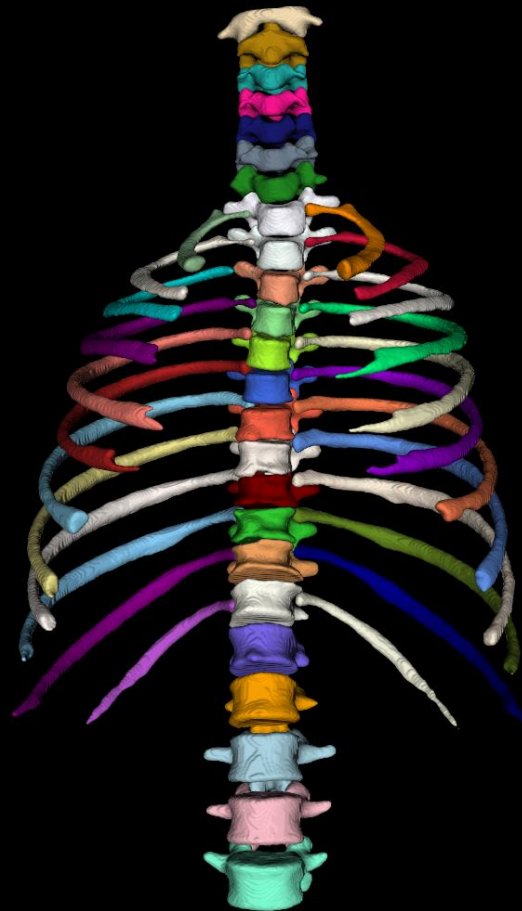
— **Annotation standard** for the colon



annotated colon in
AbdomenAtlas



annotated ribs and vertebrae in
TotalSegmentator



annotated ribs and vertebrae in
AbdomenAtlas



F4. Touchstone

@MICCAI 2024 Challenge



Backbone	Author	Institute	Publication	Backbone	Author	Institute	Publication
U-Net	O. Ronneberger	Uni Freiburg	MICCAI	nnU-Net	Fabian Isensee	DKFZ	Nat. Methods
nnFormer	Hong-Yu Zhou	HKU	TIP	SAT	Ziheng Zhao	SJTU	arXiv
CoTr	Yutong Xie	NPU	MICCAI	Swin UNETR	Ali Hatamizadeh	NVIDIA	MICCAIW
UniverSeg	Victor Ion Butoi	MIT	ICCV	UniSeg	Yiwen Ye	NPU	MICCAI
UNet++	Zongwei Zhou	ASU	TMI	MagicNet	Duowen Chen	ECNU	CVPR
TransUNet	Jieneng Chen	JHU	ICMLW	MedSegDiff	Junde Wu	NUS	AAAI
Swin-Unet	Hu Cao	Huawei	ECCVW	3D UNeXt	Jeya Maria Jose	JHU	MICCAI
DINTS	Yufan He	JHU	CVPR				

So far, **53 groups** have confirmed the contribution—we will invite more authors of **famous backbones** for medical segmentation.



Touchstone Benchmark: Are We on the Right Way for Evaluating AI Algorithms for Medical Segmentation?



Pedro R. A. S. Bassi^{1,2,3*} Wenxuan Li^{1*} Yucheng Tang⁴ Fabian Isensee^{5,6}
Zifu Wang²⁹ Jieneng Chen¹ Yu-Cheng Chou¹ Tassilo Wald^{5,6}
Constantin Ulrich⁵ Michael Baumgartner^{5,6} Saikat Roy^{5,18}
Klaus H. Maier-Hein^{5,30} Paul Jaeger^{6,7} Yiwen Ye⁸ Yutong Xie⁹ Jianpeng Zhang¹⁰
Ziyang Chen⁸ Yong Xia⁸ Yannick Kirchhoff^{5,18,19} Maximilian Rokuss^{5,18}
Pengcheng Shi¹¹ Ting Ma¹¹ Yuxin Du¹² Fan Bai^{12,13} Tiejun Huang^{12,14}
Bo Zhao^{20,12} Zhaohu Xing¹⁵ Lei Zhu^{15,16} Saumya Gupta¹⁷ Haonan Wang¹⁶
Xiaomeng Li¹⁶ Ziyang Huang²⁰ Jin Ye²¹ Junjun He²¹ Yousef Sadegheih²²
Afshin Bozorgpour²² Pratibha Kumari²² Reza Azad²³ Dorit Merhof^{22,24}
Hanxue Gu²⁵ Haoyu Dong²⁵ Jichen Yang²⁵ Maciej A. Mazurowski²⁵
Linshan Wu¹⁶ Jiaxin Zhuang¹⁶ Hao Chen²⁶ Holger Roth⁴ Daguang Xu⁴
Matthew B. Blaschko²⁹ Sergio Decherchi²⁷ Andrea Cavalli^{2,27,28}
Alan L. Yuille¹ Zongwei Zhou^{1†}

¹Department of Computer Science, Johns Hopkins University

²Department of Pharmacy and Biotechnology, University of Bologna

³Center for Biomolecular Nanotechnologies, Istituto Italiano di Tecnologia

⁴NVIDIA

⁵Division of Medical Image Computing, German Cancer Research Center (DKFZ)

⁶Helmholtz Imaging, German Cancer Research Center (DKFZ)

Full affiliations are given in Appendix F.

Code, Models & Data: <https://github.com/MrGiovanni/Touchstone>

rank	model	organization	average DSC	paper	github
🏆	MedNeXt	DKFZ	89.2	arXiv 2303.09975	Stars 327
🏆	STU-Net-B	Shanghai AI Lab	89.0	arXiv 2304.06716	Stars 269
🏆	MedFormer	Rutgers	89.0	arXiv 2203.00131	Stars 262
🏆	nnU-Net ResEncL	DKFZ	88.8	arXiv 1809.10486	Stars 5.7k
🏆	UniSeg	NPU	88.8	arXiv 2304.03493	Stars 163
🏆	Diff-UNet	HKUST	88.5	arXiv 2303.10326	Stars 149
🏆	LHU-Net	UR	88.0	arXiv 2404.05102	Stars 23
🏆	NexToU	HIT	87.8	arXiv 2305.15911	Stars 55
9	SegVol	BAAI	87.1	arXiv 2311.13385	Stars 212
10	U-Net & CLIP	CityU	87.1	arXiv 2301.00785	Stars 565
11	Swin UNETR & CLIP	CityU	86.7	arXiv 2301.00785	Stars 565
12	Swin UNETR	NVIDIA	80.1	arXiv 2211.11537	Stars 1.8k
13	UNesT	NVIDIA	79.1	arXiv 2303.10745	Stars 1.8k
14	SAM-Adapter	Duke	73.4	arXiv 2404.09957	Stars 120
15	UNETR	NVIDIA	64.4	arXiv 2111.04004	Stars 1.8k



Univ



University of California
San Francisco



National University
of Singapore



JOHNS HOPKINS
UNIVERSITY



Abdo



HEIDELBERG
UNIVERSITY
HOSPITAL



ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA



上海人工智能实验室
Shanghai Artificial Intelligence Laboratory



北京大学
PEKING UNIVERSITY



THE HONG KONG
UNIVERSITY OF SCIENCE
AND TECHNOLOGY



上海交通大学
SHANGHAI JIAO TONG UNIVERSITY



Duke
UNIVERSITY



香港中文大學
The Chinese University of Hong Kong



Stony Brook
University



HELMHOLTZ
INFORMATION & DATA SCIENCE
SCHOOL FOR HEALTH



哈尔滨工业大学(深圳)
HARBIN INSTITUTE OF TECHNOLOGY, SHENZHEN



西北工业大学
NORTHWESTERN POLYTECHNICAL UNIVERSITY



UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386



ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Zongwei Zhou
zzhou82@jh.edu

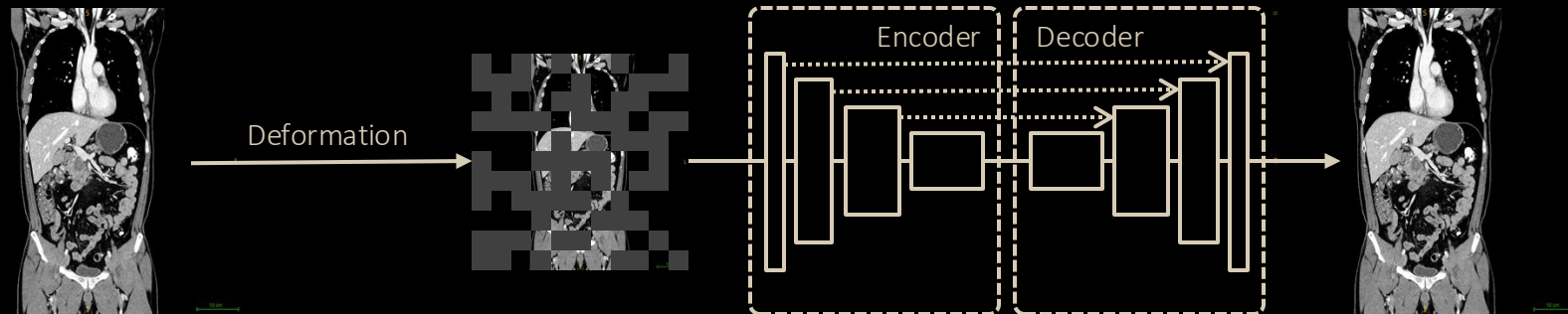
Code, Dataset, & Model:
<https://github.com/MrGiovanni/AbdomenAtlas>

F5. Foundation Models

AI models pre-trained on broad data and can be applied across tasks

SuPreM

Supervised
Pre-trained Models



Option 1. Self-supervised pre-training

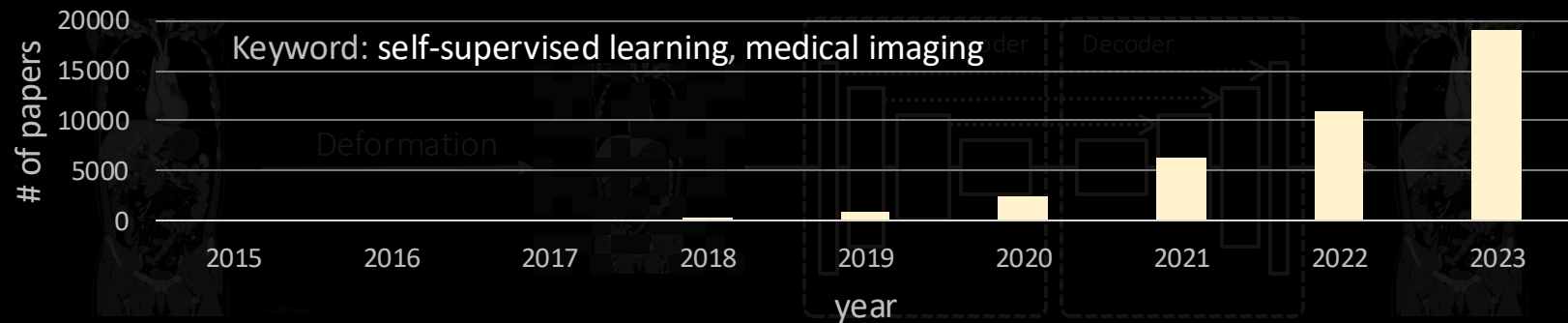
De-noising [Vincent et al., 2010]
Positioning [Doersch et al., 2015]
In-painting [Pathak et al., 2016]
Jigsaw [Noroozi and Favaro, 2016]
DeepCluster [Caron et al., 2018]
Restoration [Chen et al., 2019]

Models Genesis
[Zhou et al., MICCAI 2019]
MICCAI Young Scientist Award
Media Best Paper Award

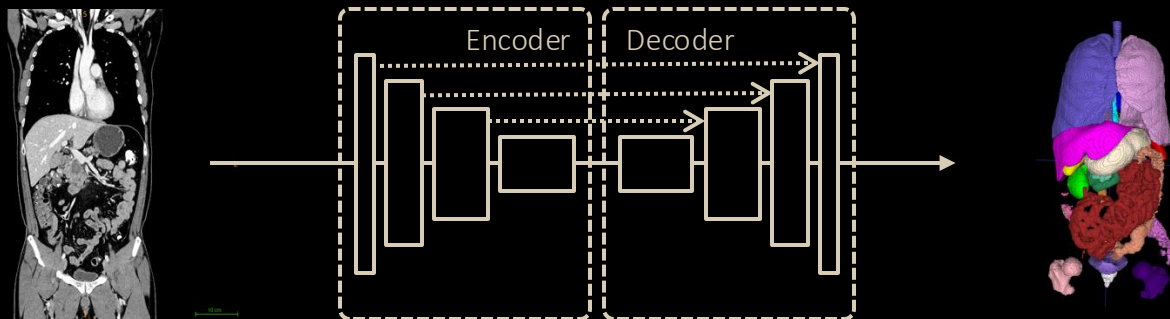
Rubiks Cube
[Zhuang et al., MICCAI 2019]

Swin UNETR
[Tang et al., CVPR 2022]

UniMiSS
[Xie et al., ECCV 2022]

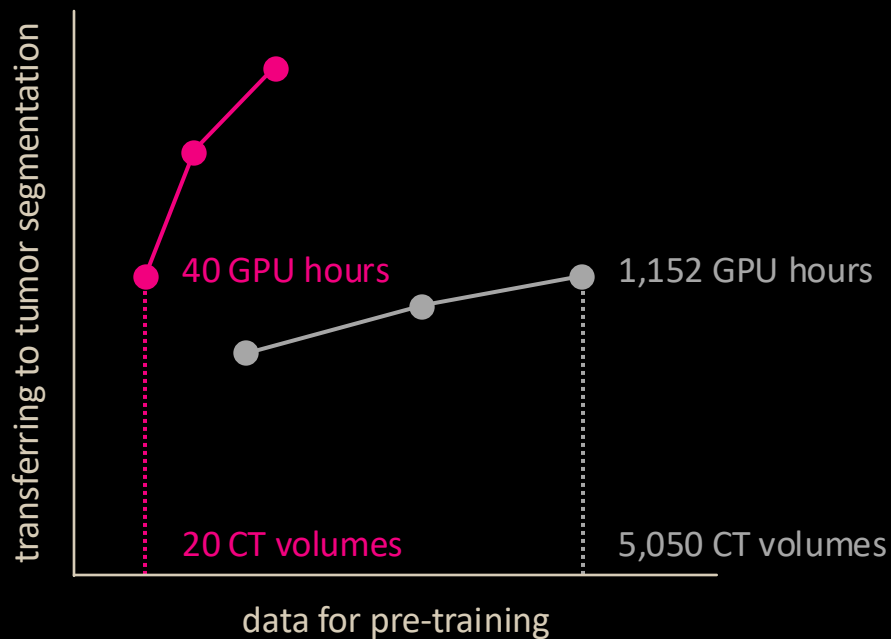


Option 1. Self-supervised pre-training



Option 2. Supervised pre-training

Supervised > Self-supervised
data & computation efficiency



F5. Foundation Models

AI models pre-trained on **broad** data
and can be applied across tasks

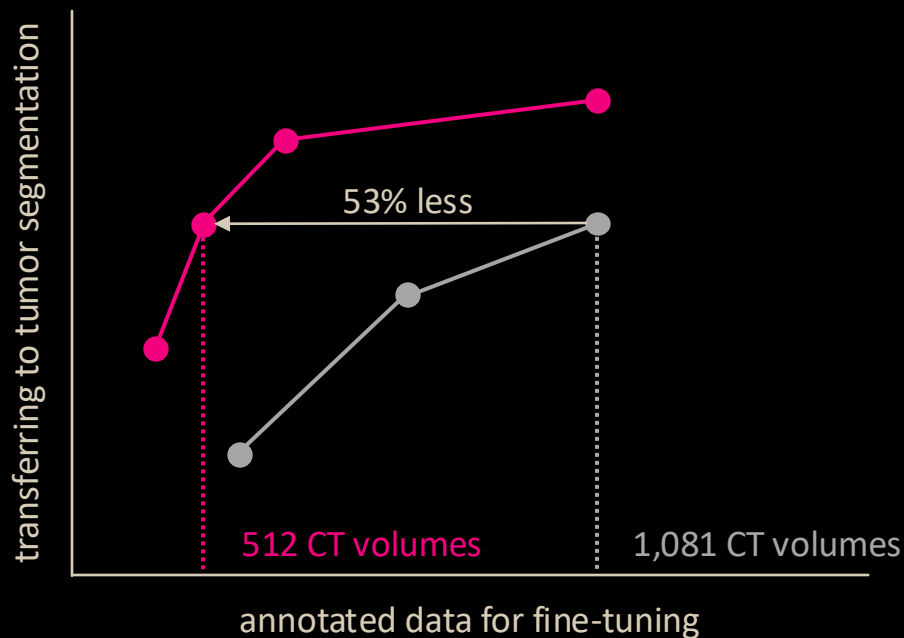
Expensive?

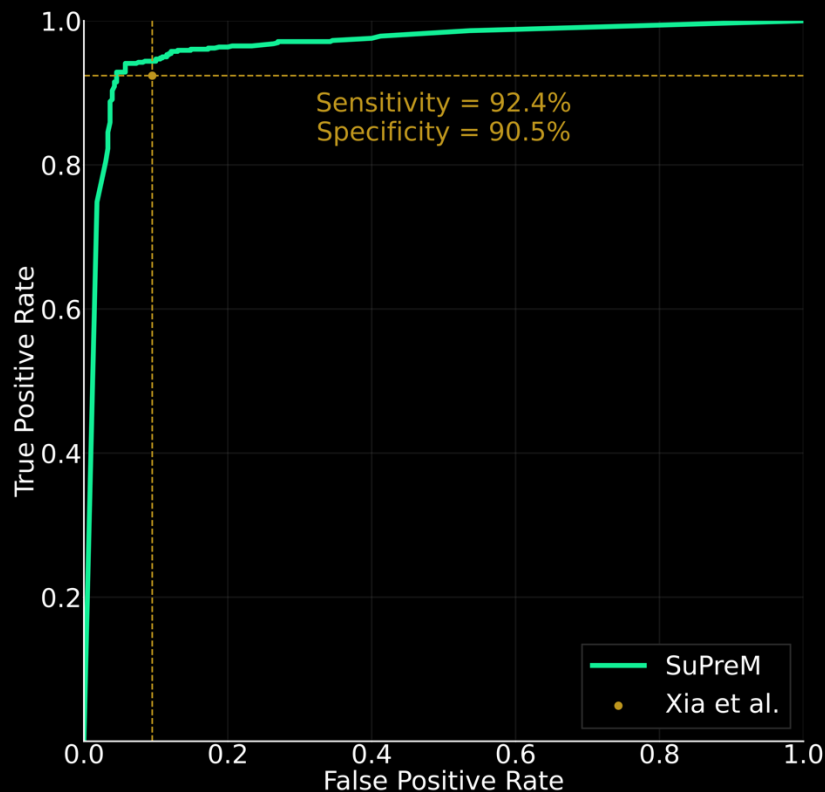
F5. Foundation Models

AI models pre-trained on broad data
and can be applied **across** tasks

Annotation-efficient?

Supervised > Self-supervised
annotation & learning efficiency



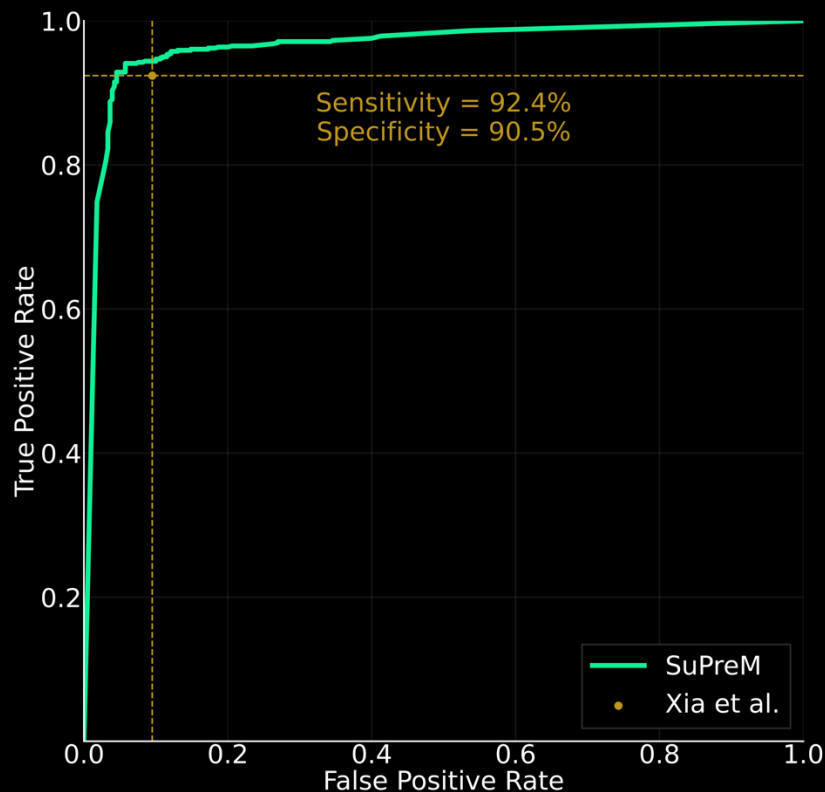


The FELIX Project: Deep Networks To Detect Pancreatic Neoplasms

Yingda Xia^{1,†}, Qihang Yu^{1,†}, Linda Chu^{2,†}, Satomi Kawamoto^{2,†}, Seyoun Park², Fengze Liu¹, Jieneng Chen¹, Zhuotun Zhu¹, Bowen Li¹, Zongwei Zhou¹, Yongyi Lu¹, Yan Wang¹, Wei Shen¹, Lingxi Xie¹, Yuyin Zhou¹, Christopher Wolfgang³, Ammar Javed³, Daniel Fadaei Fouladi², Shahab Shayesteh², Jefferson Graves², Alejandra Blanco², Eva S. Zinreich², Benedict Kinny-Köster³, Kenneth Kinzler^{4,6,7,8}, Ralph H. Hruban⁵, Bert Vogelstein^{4,6,7,8,9}, Alan L. Yuille^{1,*}, Elliot K. Fishman^{2,*}

¹Department of Computer Science, Johns Hopkins University; ²Department of Radiology and Radiological Science, Johns Hopkins Medicine; ³Department of Surgery, New York University; ⁴Department of Oncology, Johns Hopkins Medicine; ⁵Department of Pathology, Johns Hopkins Medicine; ⁶Ludwig Center, Johns Hopkins University School of Medicine; ⁷Sidney Kimmel Comprehensive Cancer Center, Johns Hopkins University School of Medicine; ⁸Sol Goldman Pancreatic Cancer Research Center, Johns Hopkins University School of Medicine; ⁹Howard Hughes Medical Institute, Johns Hopkins Medical Institutions

Abstract Tens of millions of abdominal images are performed with computed tomography (CT) in the U.S. each year but pancreatic cancers are sometimes not initially detected in these images. We here describe a suite of algorithms (named FELIX) that can recognize pancreatic lesions from CT images without human input. Using FELIX, >90% of patients with pancreatic ductal adenocarcinomas were detected at a specificity of >90% in patients without pancreatic disease. FELIX may be able to assist radiologists in identifying pancreatic cancers earlier, when surgery and other treatments offer more hope for long-term survival.



Extending Supervised Pretraining on Large Organ Dataset to Universal Lesion Segmentation

Yannick Kirchhoff, Maximilian R. Rokuss, Saikat Roy, Klaus H. Maier-Hein
German Cancer Research Center (DKFZ), Heidelberg, Germany

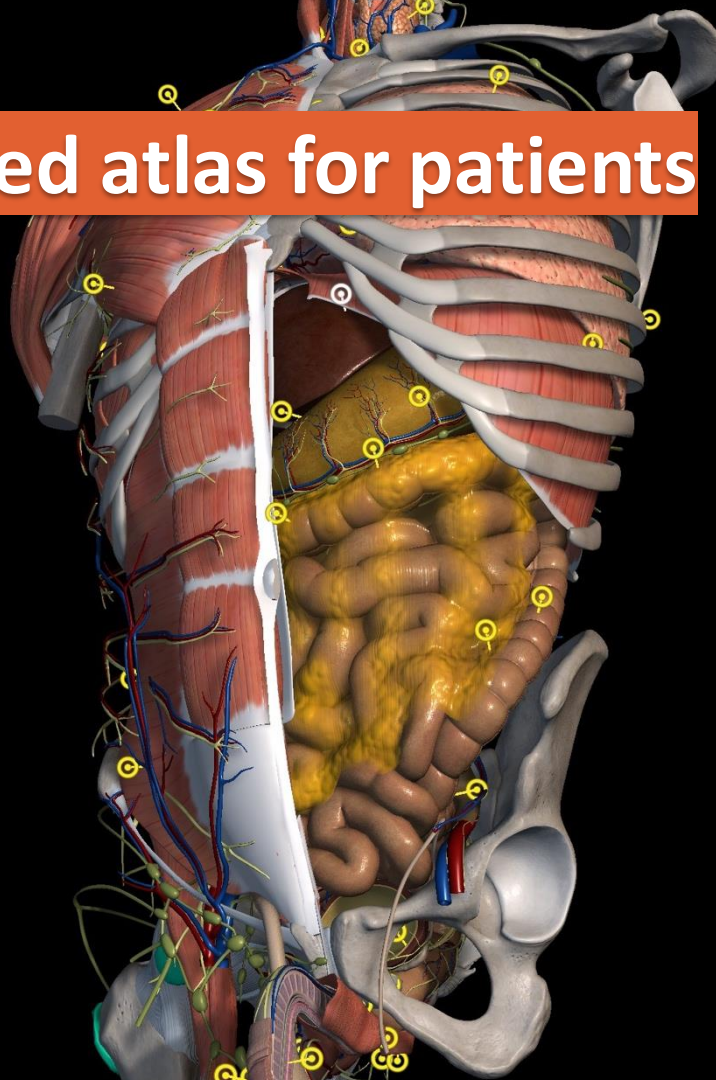
Method Description:

Our method uses a lightweight nnUNet [1] pretrained on a large organ segmentation dataset. We used supervised pretraining on the Abdomen Atlas 1.0 [2,3] dataset with 8 annotated organs over 5000 CT samples. Our work demonstrates that we can efficiently train the smallest possible models to learn robust representations of CT images from a large organ database which does not have any label overlaps with the ULS23 labelset. Our priority is not solely about reaching the very best Dice score. Instead, we aim for a very lightweight design while maintaining comparable accuracy.

References:

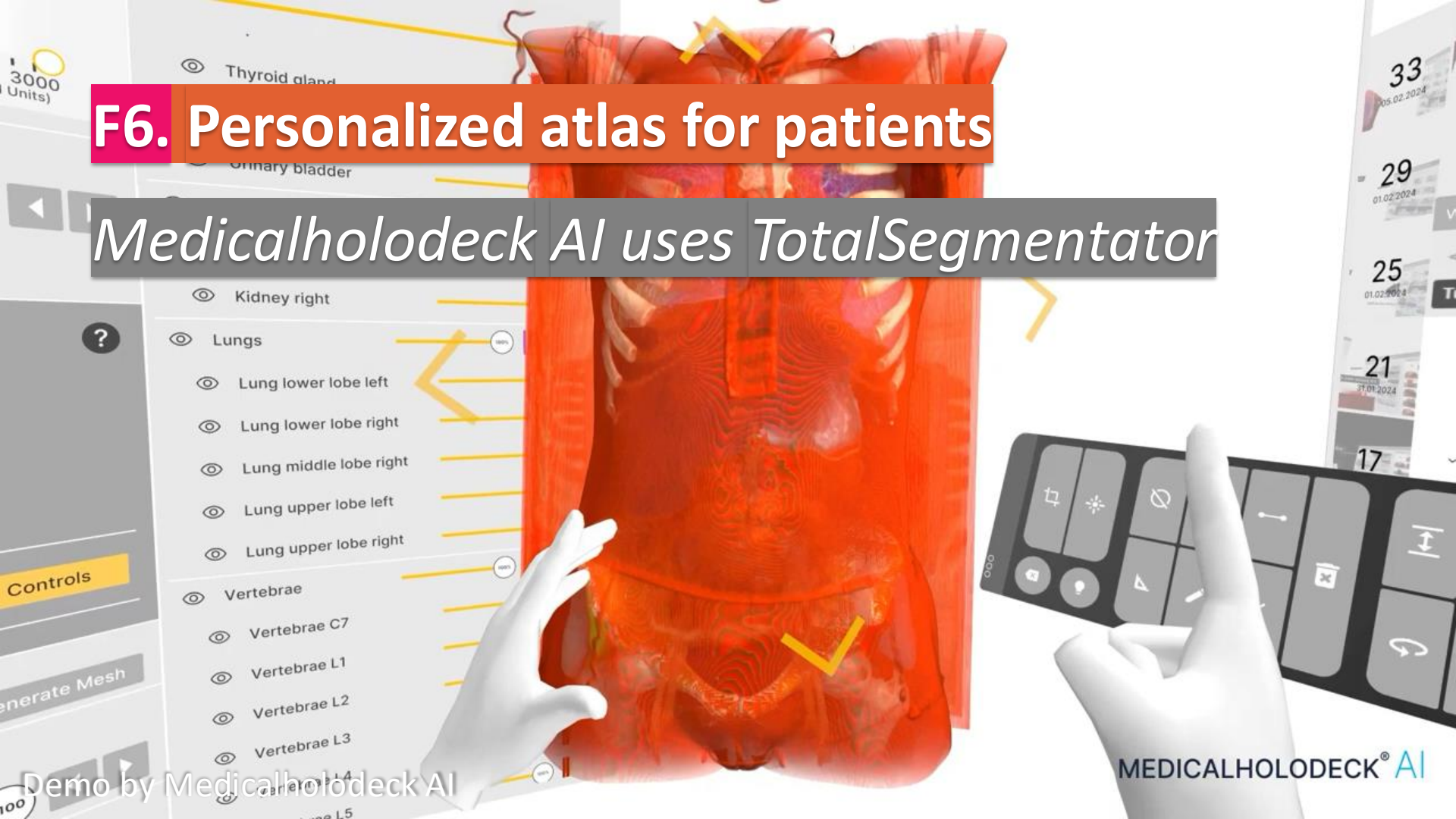
- [1] Isensee, Fabian, et al. "nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation." *Nature methods* 18.2 (2021): 203-211.
- [2] Qu, Chongyu, et al. "Abdomenatlas-8k: Annotating 8,000 CT volumes for multi-organ segmentation in three weeks." *Advances in Neural Information Processing Systems* 36 (2024).
- [3] Li, Wenxuan, Alan Yuille, and Zongwei Zhou. "How well do supervised models transfer to 3d image segmentation?." *The Twelfth International Conference on Learning Representations*. 2023.

F6. Personalized atlas for patients



F6. Personalized atlas for patients

Medicalholodeck AI uses TotalSegmentator



F6. Personalized atlas for patients



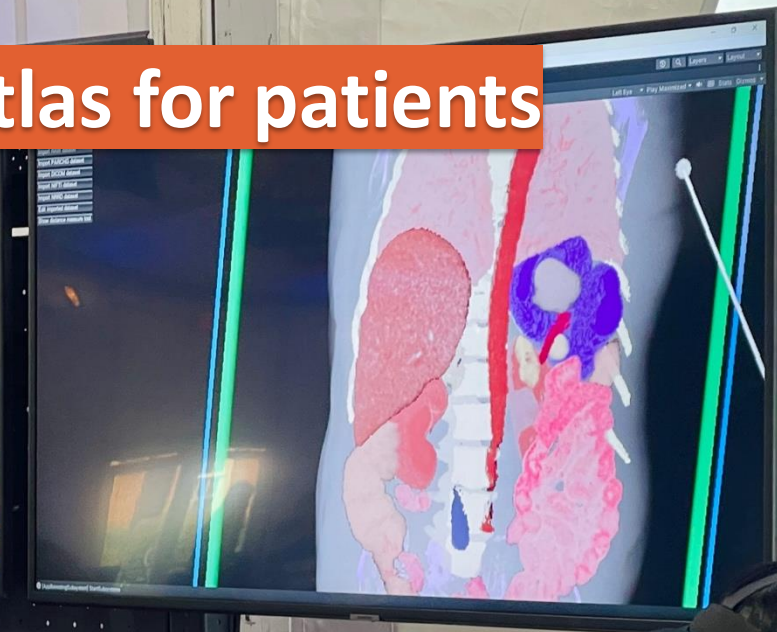
F6. Personalized atlas for patients



F6. Personalized atlas for patients



F6. Personalized atlas for patients



External Collaborators

Yucheng Tang, PhD (NVIDIA)

Yang Yang, PhD (University of California, San Francisco)

Kang Wang, MD, PhD (University of California, San Francisco)

Mehmet Can Yavuz, PhD (University of California, San Francisco)

Jianning Li, PhD (University Hospital Essen)

Alberto Santamaria-Pang, PhD (Microsoft)

Ho Hin Lee, PhD (Microsoft)

Challenges: Towards 3D Atlas of Human Body

IEEE International Symposium on Biomedical Imaging ([ISBI'24](#))

International Conference on Medical Image Computing and
Computer Assisted Intervention ([MICCAI'24](#))

Become Part of the BodyMaps Project?

Contact: Zongwei Zhou <zzhou82@jh.edu>



Post



JHU Computer Science

@JHUCompSci

Stop by and say hi to JHU CS at the Department
Showcase tent on Decker Quad! 💙



ALT

APPLY

REQUEST INFORMATION

GIVE

Vision

Education

Research

Translation

Admissions

**Student
Life**

Alumni

Diversity

 Search

 Info For ▾

 [HOME](#) > [NEWS](#)

AI and Radiologists Unite to Map the Abdomen

Hopkins researchers have leveraged the synergy between medical professionals and artificial intelligence algorithms to create the largest annotated multi-organ dataset to date.

“While a dataset of this size would have taken an experienced human annotator almost 31 years to fully annotate, the team completed this task in only three weeks.”



PUBLISHED
February 9, 2024

AUTHOR
Jaimie Patterson

SHARE THIS STORY

Thank you!

Acknowledgement: Chongyu Qu · Xiaoxi Chen · Pedro R. A. S. Bassi · Tiezheng Zhang · Hualin Qiao · Jessica Han · Jie Liu · Yucheng Tang · Pedro Ricardo Ariel Salvador Bassi · Yijia Shi · Lihua Gao · Wenlan Zhou · Guiqin Zhang · Damin Li · Yixiao Zhang · Jieneng Chen · Linda Chu · Satomi · Kawamoto · Seyoun Park · Christopher Wolfgang · Ammar Javed · Daniel Fadaei · Shahab Shayesteh · Jefferson Graves · Alejandra Blanco · Eva S. Zinreich · Benedict Kinny-Köster · Kenneth Kinzler · Ralph H. Hruban · Bert Vogelstein · Elliot K. Fishman · Jaimie Patterson · Junfei Xiao · Yongyi Lu · Xinyi Li · Huimiao Chen · Yaoyao Liu · Qi Chen · Jianning Li · Yu-Cheng Chou · Angtian Wang · Yixiong Chen · Yuxiang Lai · Jincheng Wang · Huimin Xue · Yining Cao · Haoqi Han · Xiaorui Lin · Yutong Tang · Meihua Li · Yujiu Ma · Jinghui Xu · Jiawei Liu · Zheyuan Zhang

