Harnessing Large AI Models for Transforming Healthcare

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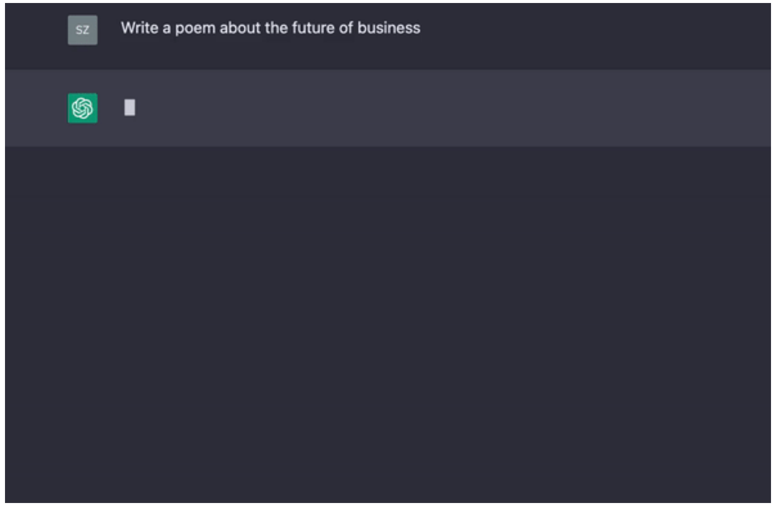
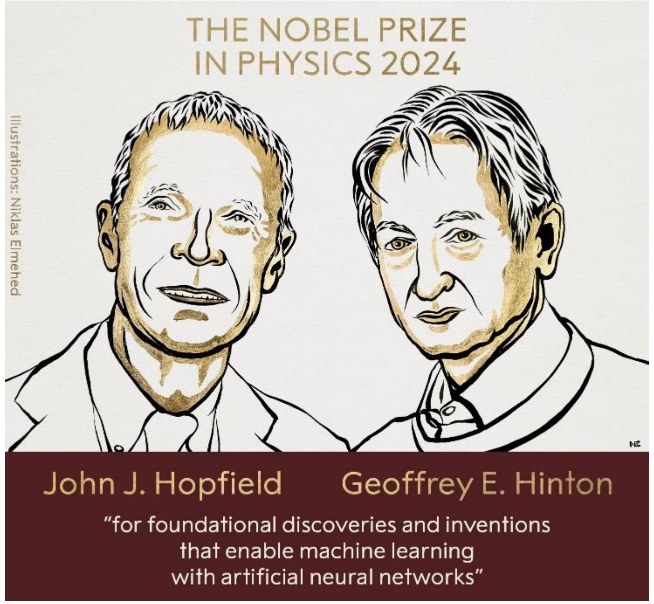
Smart Lab

Background and Impact

Natural Language Processing

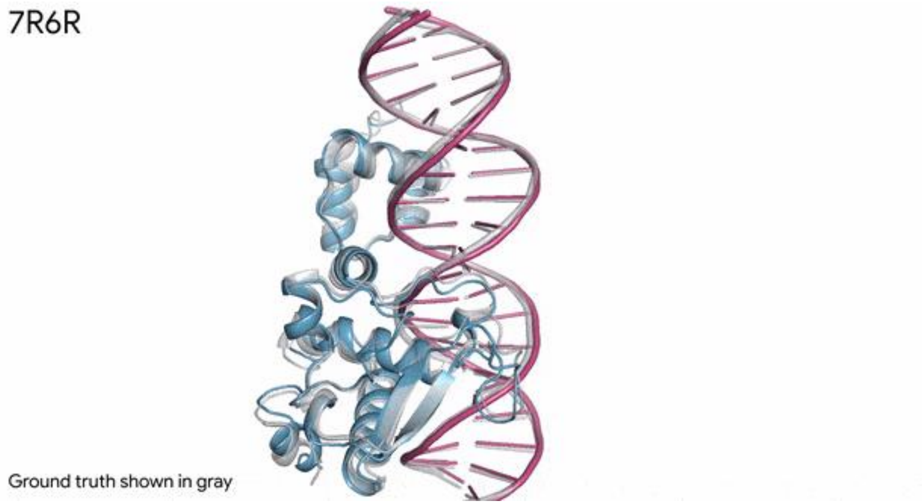


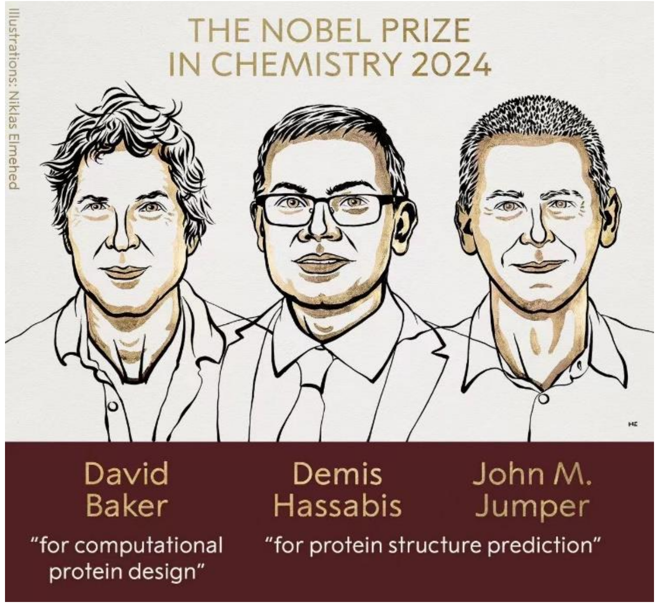
Computer Vision



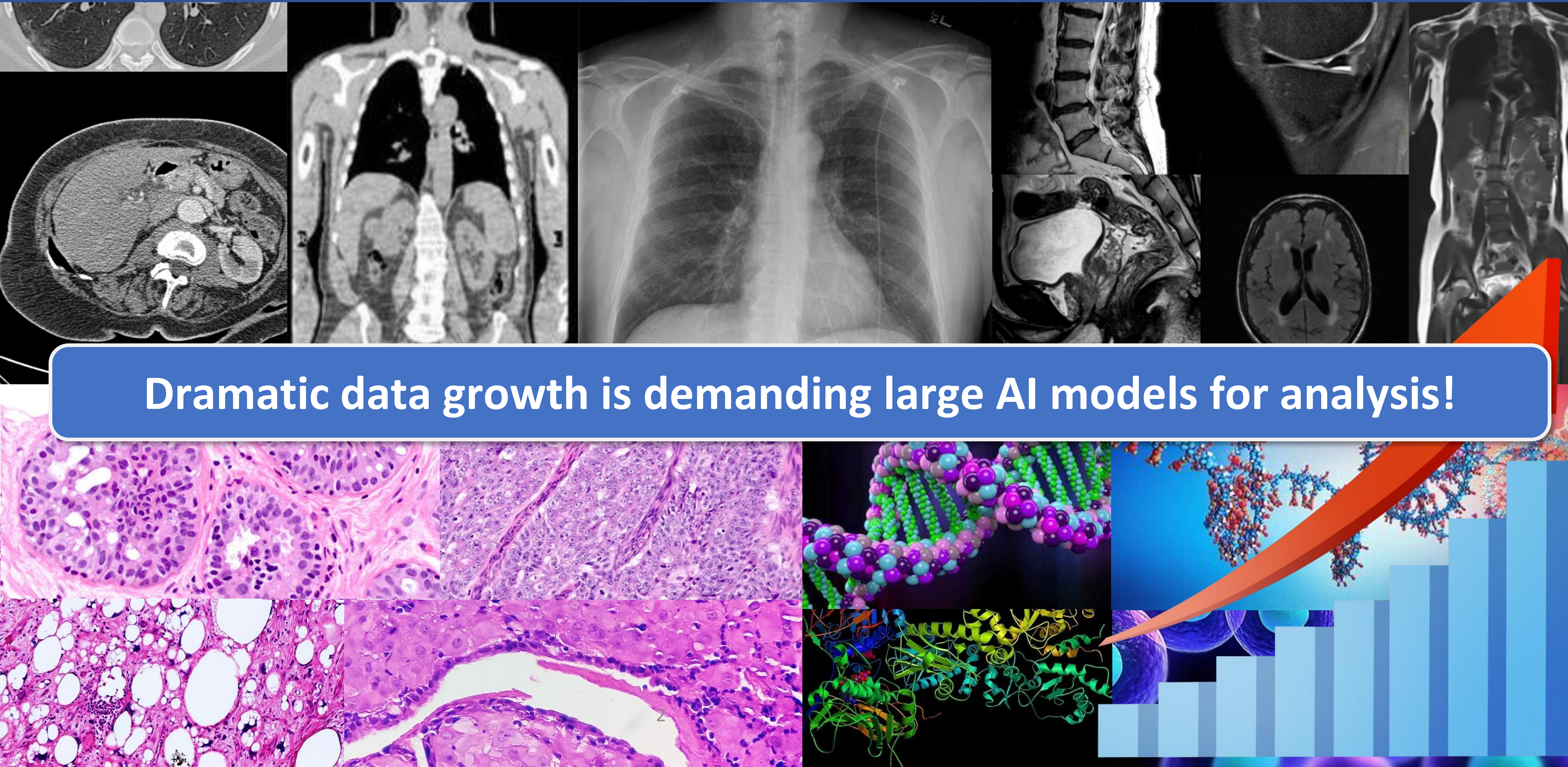
Robotics

Biology and Medicine





Bigger Data, Larger Model



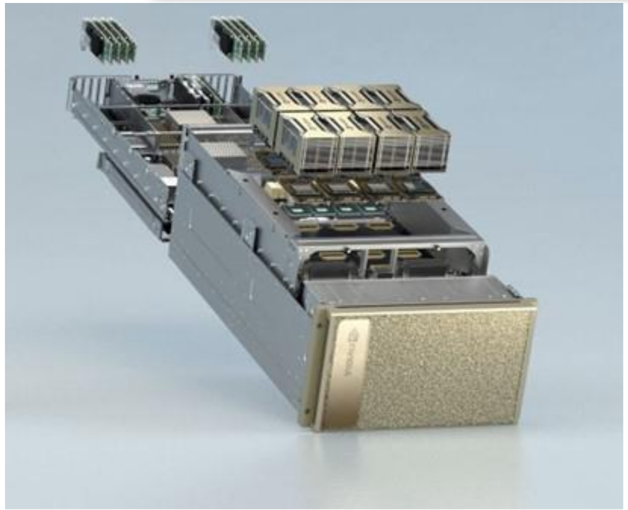
Dramatic data growth is demanding large AI models for analysis!

HKUST SuperPOD

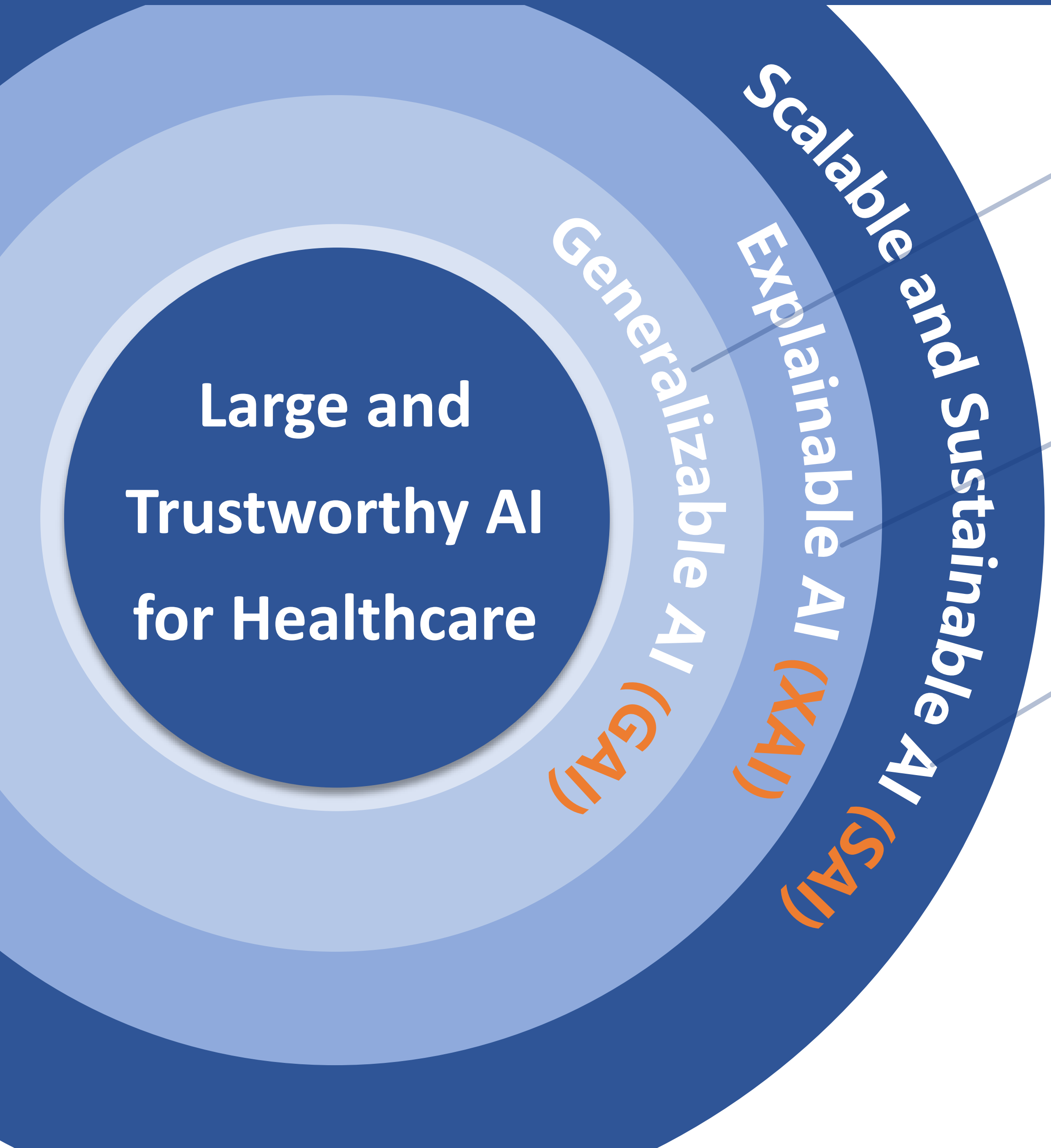
❑ HKUST SuperPOD: State-of-the-art AI Supercomputing Facility

Number of H800 GPUs	**1000+**
Total CPU Cores	**6,160**
Total GPU Accelerator Cores	**8,110,080**
Node Interconnect Bandwidth	**400** Gb/s InfiniBand Connections Per Node
Storage	**500** TB DDN AI400X2 Storage System **2.7** PB Dell Power Scale Storage System
Floating Point Performance	Tensor Float 32 – **448** PFLOPS Floating Point 32 – **30** PFLOPS

Supercomputing speeds up large AI model development!



Smart Lab: Large and Trustworthy AI for Healthcare



Multimodal Foundation Model

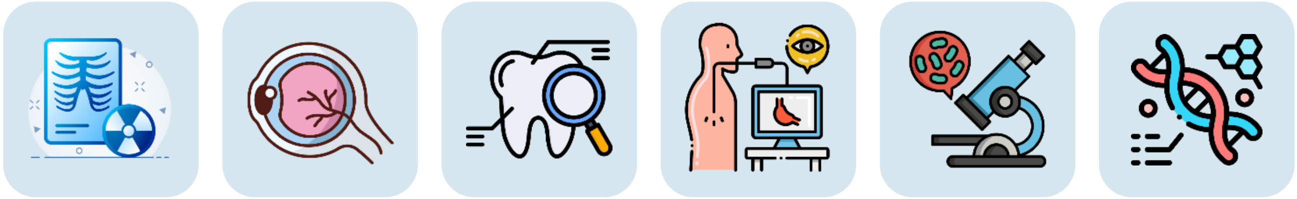
- One multimodal large language model for versatile modalities and tasks.
- Different vertical foundation models.

Explainable AI (XAI)

- Human-understandable explanations for decision-making.
- Enhance the trust and confidence of users.

Scalable and Sustainable Deployment

- Compress large models without compromising performance.
- Hardware-software co-design.
- Sustainably deploy models under low computing resources.

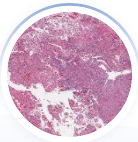


Radiology Ophthalmology Dentistry Endoscopy Pathology Genomics

Large AI Models for Advancing Healthcare

MRI Foundation Model
磁共振基礎模型

CT Foundation Model
CT 基礎模型



Pathology Foundation Model
病理學基礎模型

Multimodal Generalist Foundation Model
多模态通才基礎模型

Disease Diagnosis
疾病診斷

Quantitative Evaluation
量化評估

Disease Prognosis
疾病預後

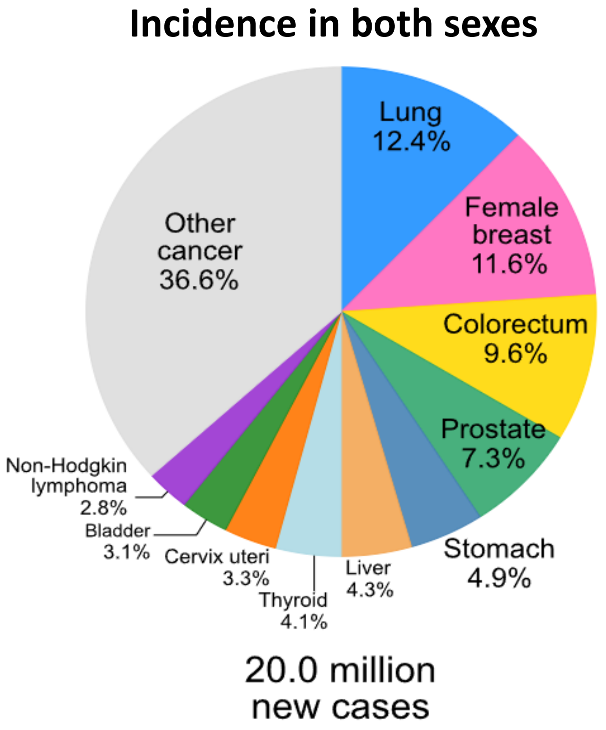
Augmented Procedures
增強手術

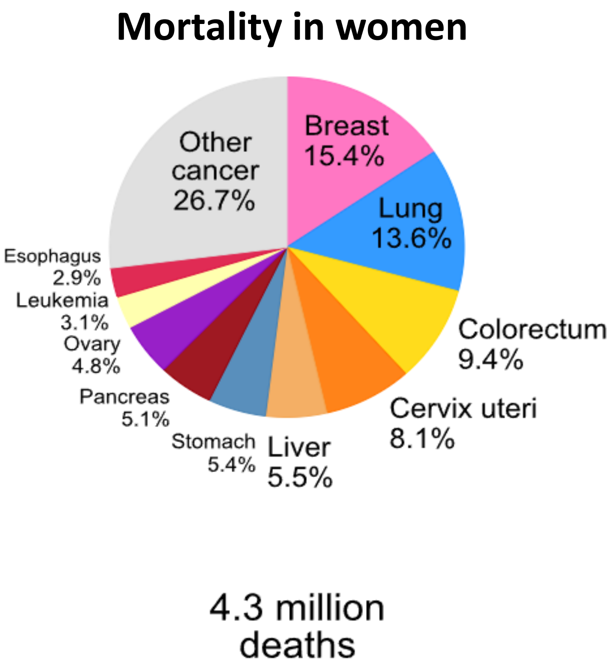
Grounded Radiology Reports
定位報告生成

Bedside Decision Support
床旁決策支持

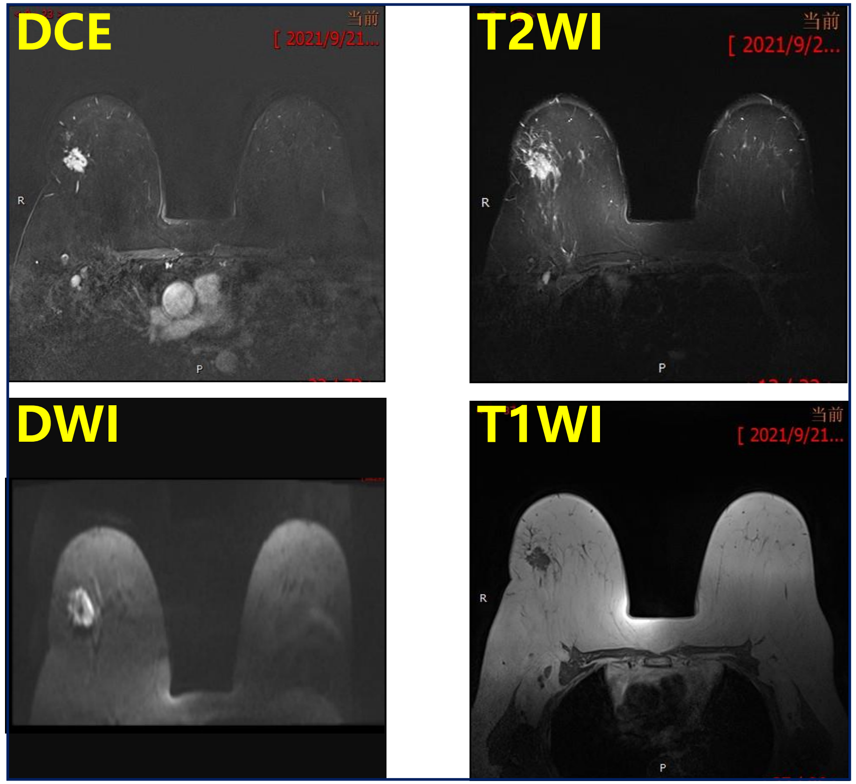
MRI Foundation Model

Breast cancer **ranks No. 1** regarding cancer incidence worldwide and is **leading cause** of cancer-related deaths in women.





Magnetic Resonance Imaging (MRI) is with the **highest sensitivity** for detecting breast cancer.



Goal: Developing an AI model for diagnosing breast multi-parametric MRI (mpMRI) to potentially reduce invasive biopsy and personalize patient's treatment.

Barba, et al. Breast Cancer, Screening and Diagnostic Tools: All You Need To Know. Critical Reviews in Oncology/Hematology, 2021.

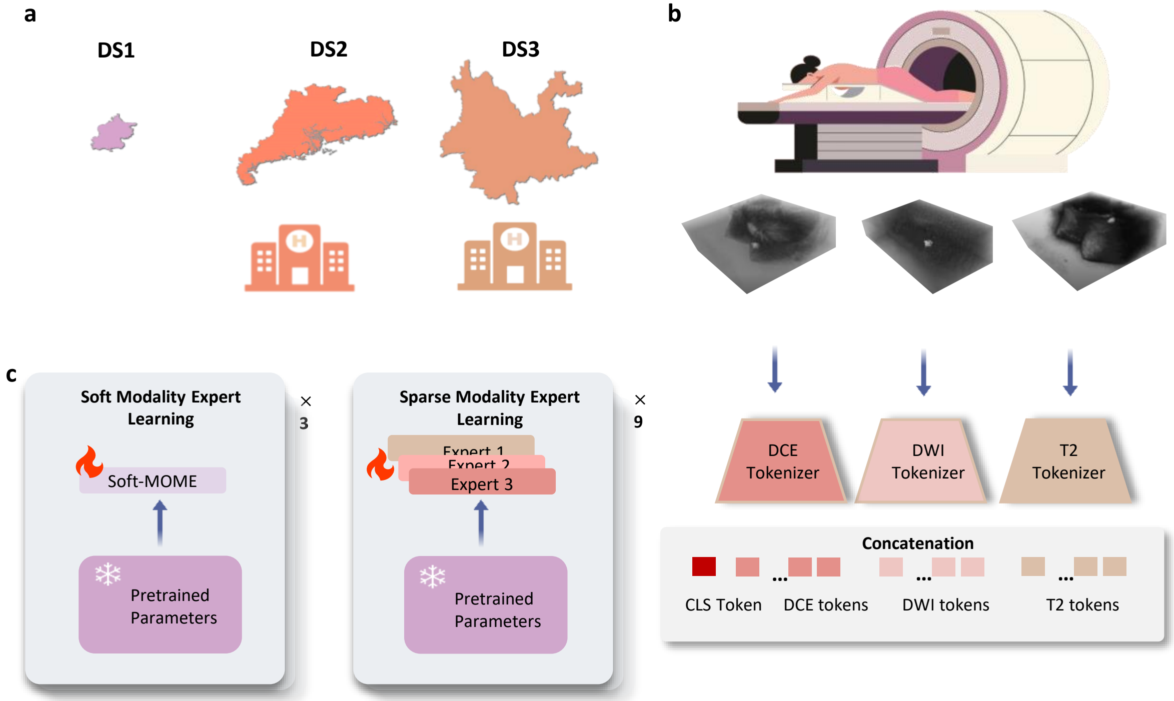
MRI Foundation Model

❑ Large Mixture-of-Modality-Experts (MOME) Model on Multiparametric MRI

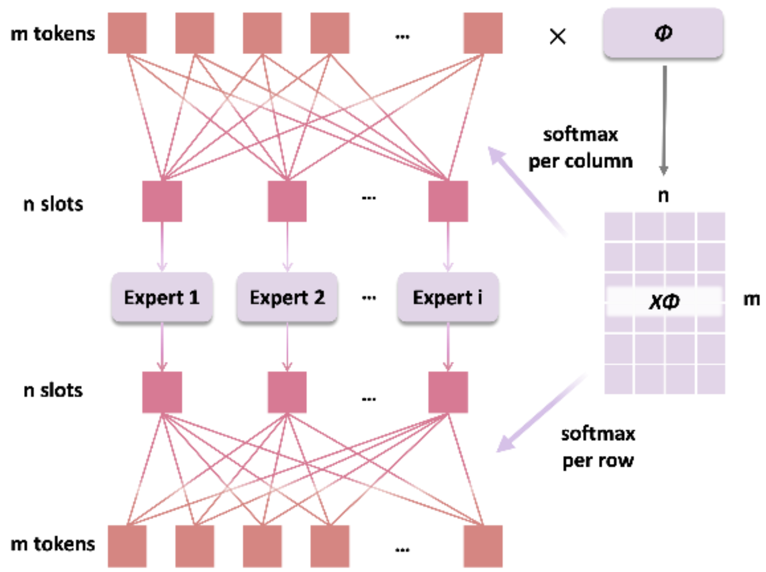
Non-invasive diagnosis and personalized patient management

Luyang Luo

- Largest Chinese breast mpMRI dataset (50K+ patients)



- First adaptation of a large foundation model with a mixture-of-modality-experts

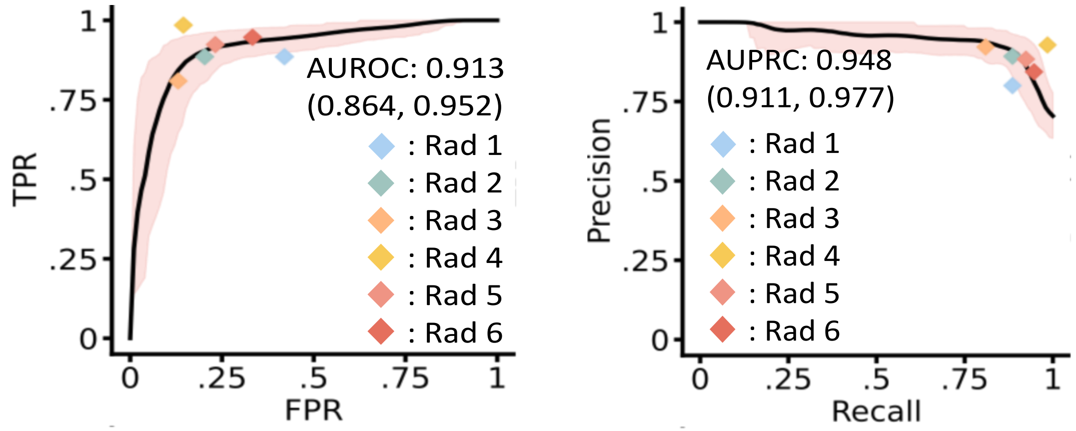


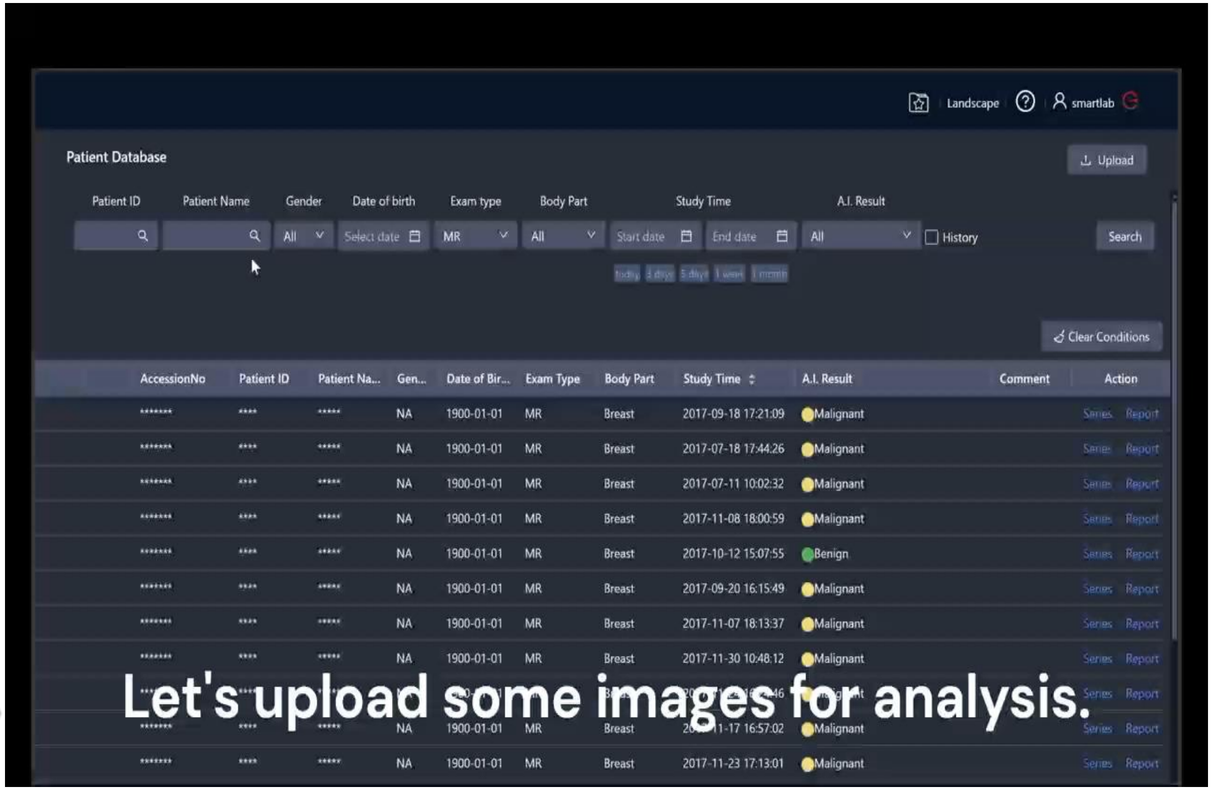
Luo, et al. A Large Model for Non-invasive and Personalized Management of Breast Cancer from Multiparametric MRI. Nature Communications 2025.

MRI Foundation Model

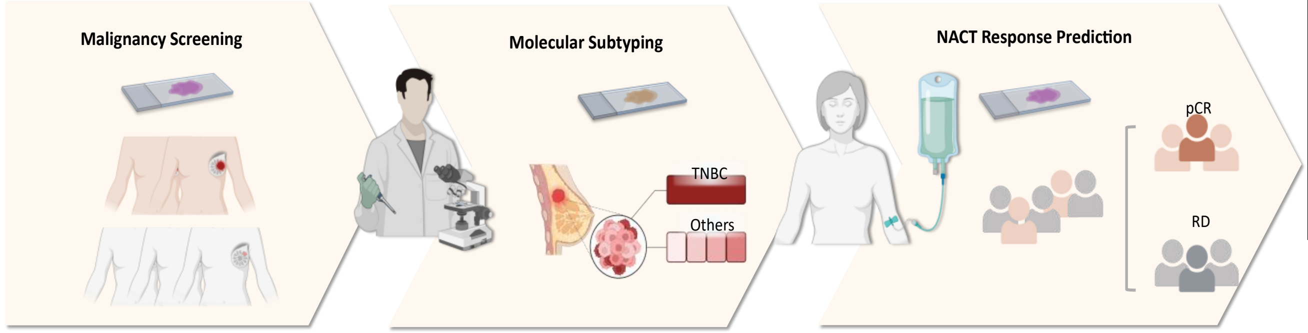
❑ Comparison to radiologists

Achieve radiologist-level accuracy in malignancy detection





Personalized management for breast cancer patients



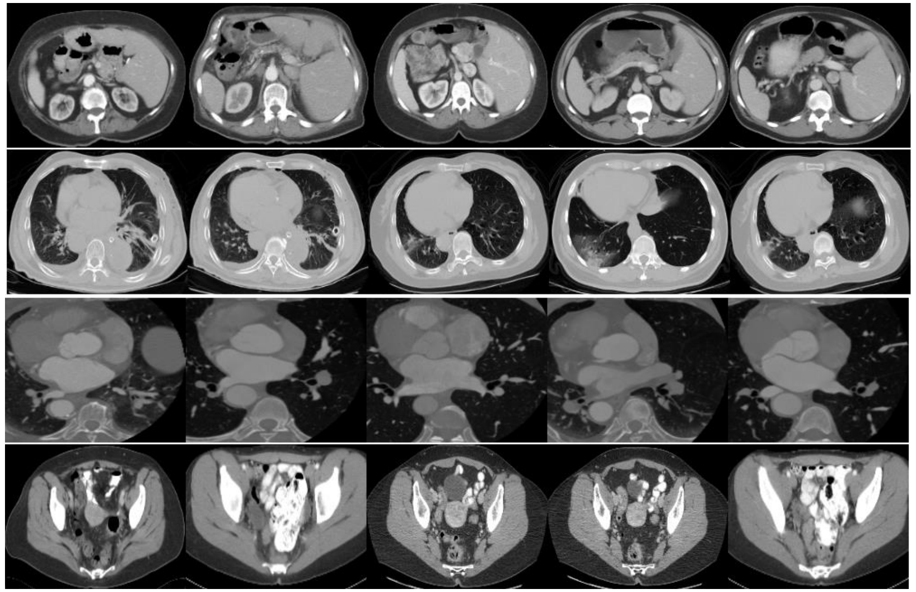
Luo, et al. A Large Model for Non-invasive and Personalized Management of Breast Cancer from Multiparametric MRI. Nature Communications 2025.

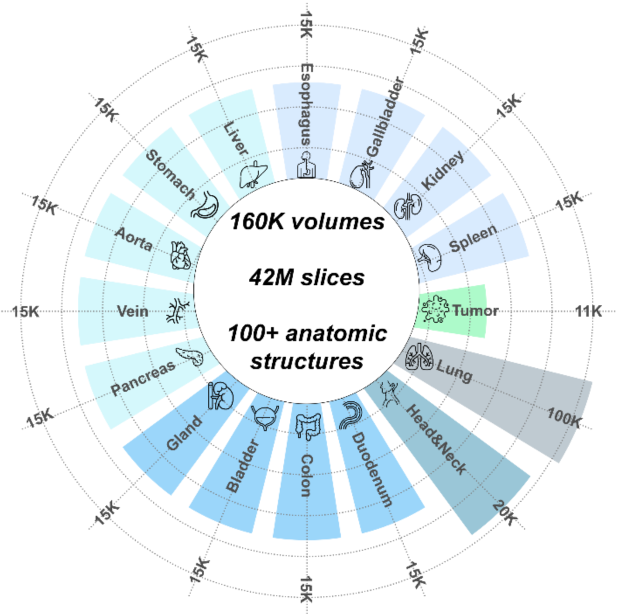
CT Foundation Model

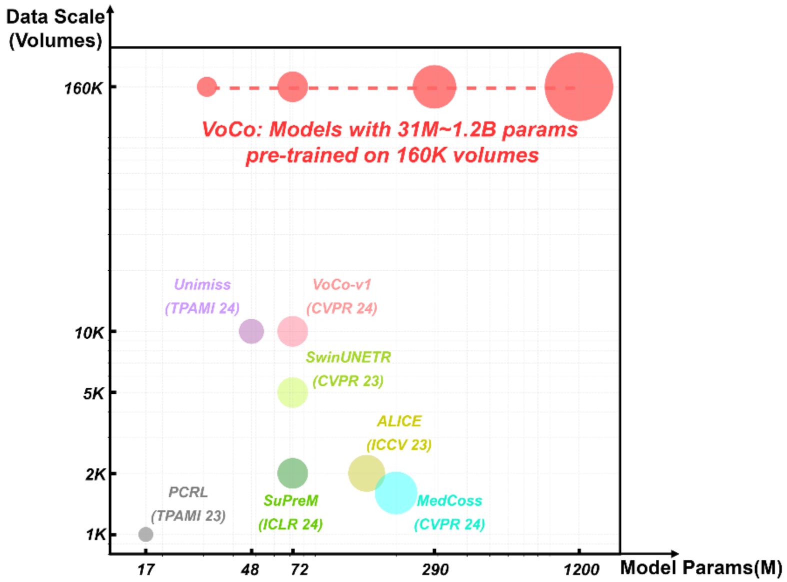
- The scarcity of annotations poses a significant challenge in 3D medical image analysis

- We collect **160K** Computed Tomography (CT) volumes for large-scale 3D medical image pre-training, alleviating the scarcity of annotations and significantly improving the performances across **51** downstream tasks.

Linshan Wu







Goal: Developing a foundation model for 3D medical image analysis.

Wu, et al. Large-Scale 3D Medical Image Pre-training with Geometric Context Priors. arXiv preprint, 2024
Wu, et al. VoCo: A Simple-yet-Effective Volume Contrastive Learning Framework for 3D Medical Image Analysis. CVPR 2024

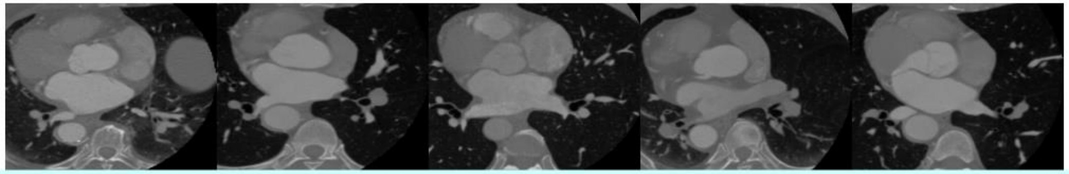
CT Foundation Model

Leveraging Geometric Context Priors for Contrastive Learning

- **Motivation:** We observe that in 3D medical images, geometric relations between different organs are relatively consistent.

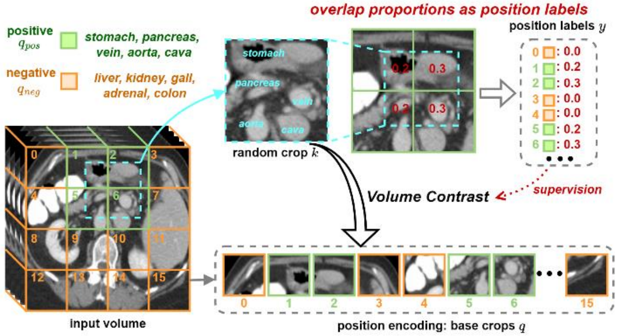
Abdomen: The stomach is in the upper and the liver is in the right. Beneath the liver is the gallbladder. The spleen is on the left side near the stomach and the pancreas is behind the stomach. The kidneys are located on each side.

Chest: The heart is in the center, slightly tilted to the left. The lungs are near the heart on either side. The abnormalities (e.g., COVID-19) are often seen in the outer regions rather than the central areas.

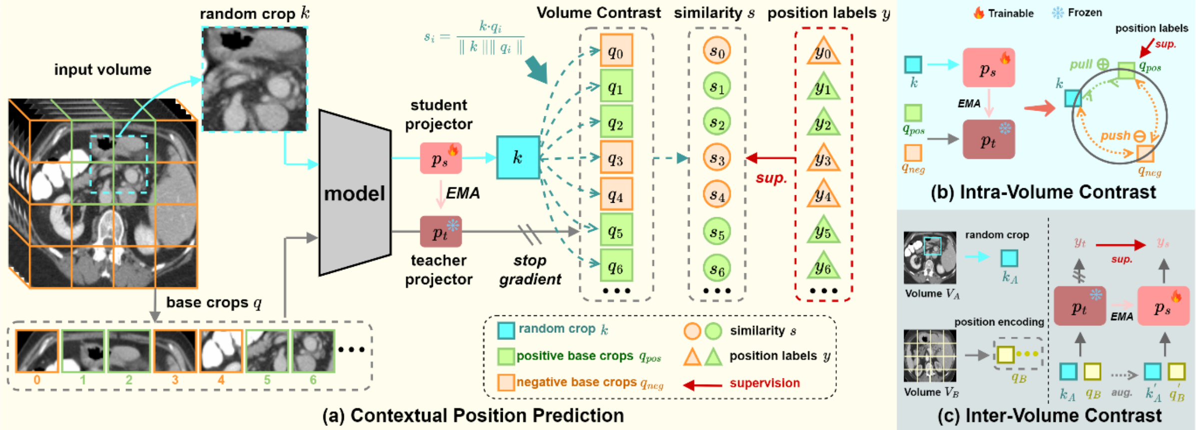


Cardiac: The ascending aorta (AA) is located at the top. The left atrium blood cavity (LAC) is below the AA. Adjacent to the LAC is the left ventricle blood cavity (LVC). The myocardium of the left ventricle surrounds the LVC.

- **Method:** Leveraging the consistent geometric context, we generate positive and negative pairs of organs for contrastive learning



Generate positive and negative pairs



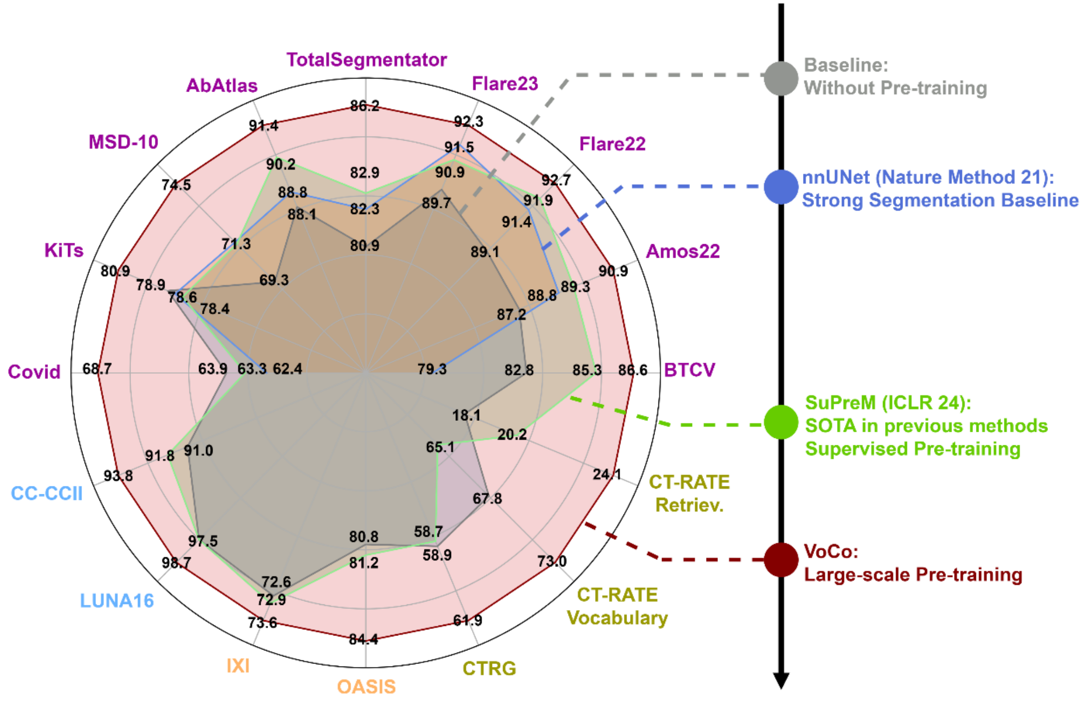
Contrastive Learning

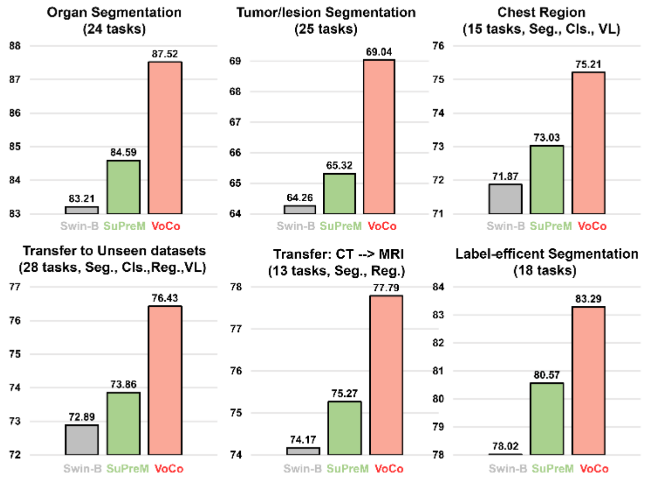
Wu, et al. Large-Scale 3D Medical Image Pre-training with Geometric Context Priors. arXiv preprint, 2024
Wu, et al. VoCo: A Simple-yet-Effective Volume Contrastive Learning Framework for 3D Medical Image Analysis. CVPR 2024

CT Foundation Model

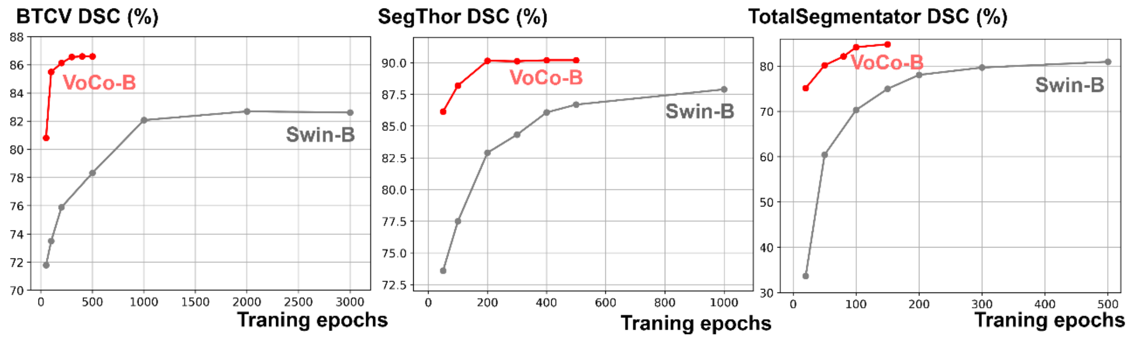
Significant improvements on 50+ downstream tasks

- Extensive experiments on 50+ downstream tasks across segmentation, classification, registration, and vision-language demonstrated the effectiveness of large-scale pre-training.





Significant improvements across different tasks



Faster Finetuning Convergence

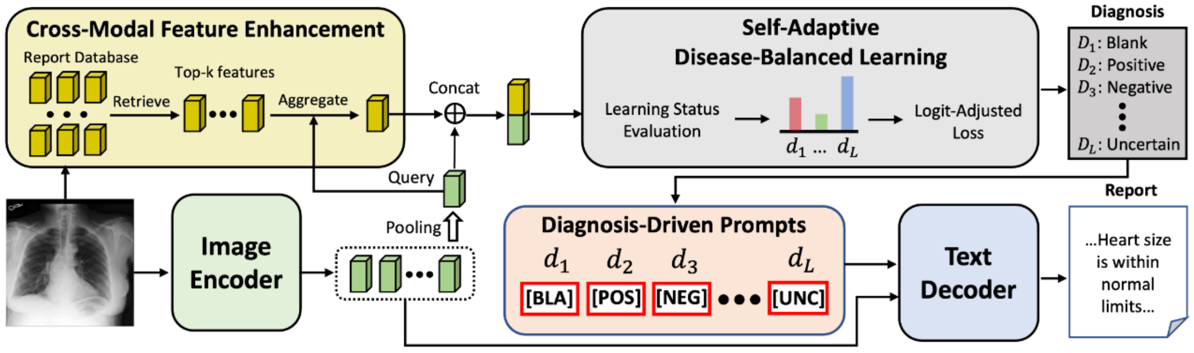
Wu, et al. Large-Scale 3D Medical Image Pre-training with Geometric Context Priors. arXiv preprint, 2024

Wu, et al. VoCo: A Simple-yet-Effective Volume Contrastive Learning Framework for 3D Medical Image Analysis. CVPR 2024

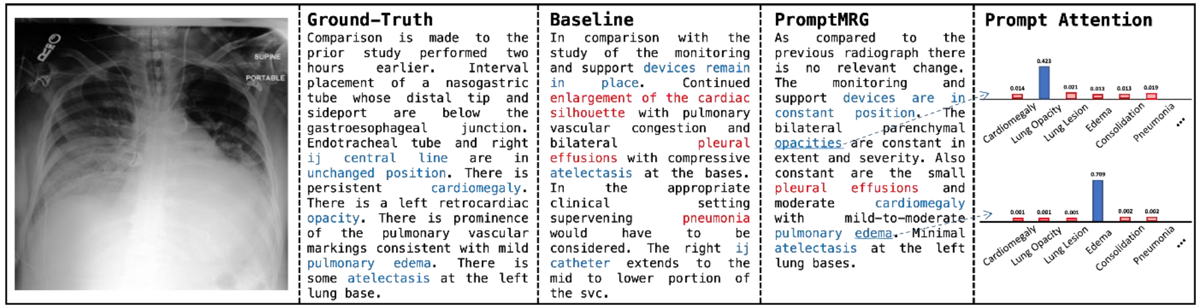
Vision-Language Model for Report Generation

❑ Diagnosis-driven Prompts for Report Generation

- Diagnosis-driven prompts for medical report generation with cross-modal feature enhancement and self-adaptive disease-balanced learning.

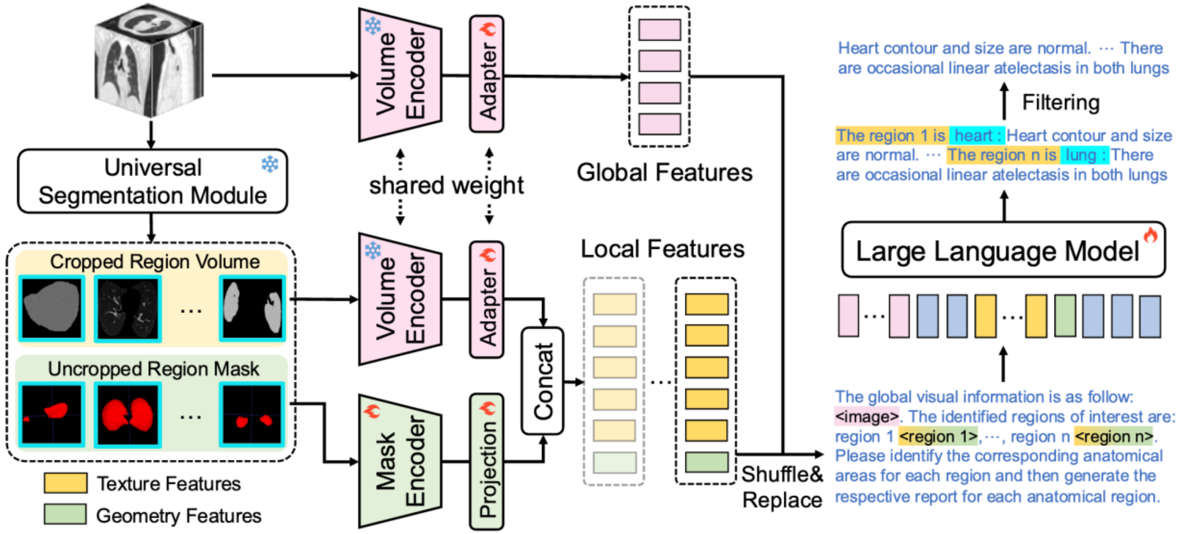


The proposed PromptMRG covers most key descriptions



❑ Large Language Model-driven CT Report Generation

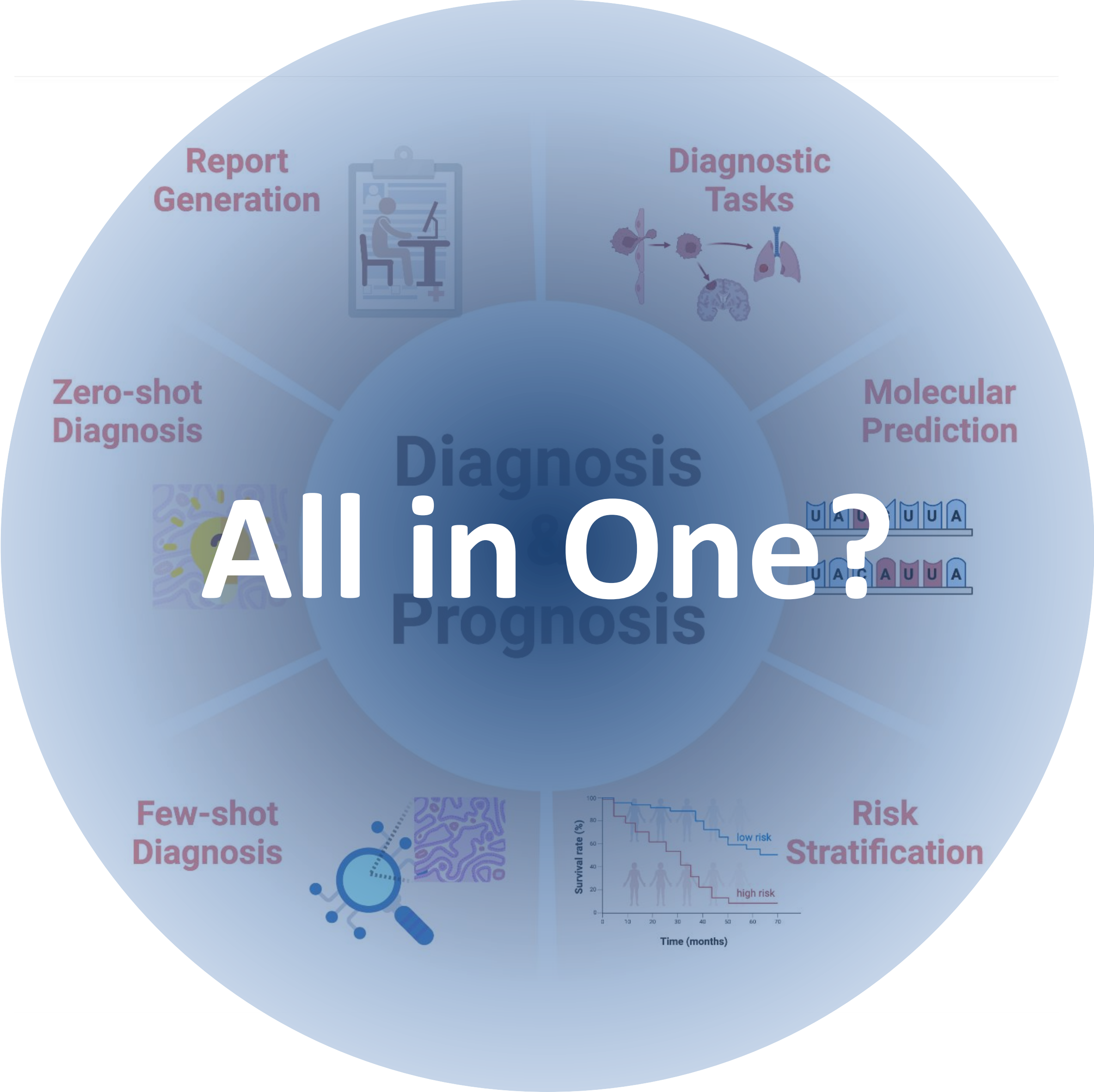
- Adapt LLaMA2-7B for Fine-grained CT report generation via the region-guided referring and grounding.



Dataset	Method	Year	BL-1	BL-2	BL-3	BL-4	MTR	RG-L
RadGenome-ChestCT	R2GenGPT [43]	2023	43.28	34.11	28.16	24.16	39.85	32.26
	MedVInT [22]	2023	44.28	34.91	28.75	24.60	40.39	32.58
	RadFM [4]	2023	44.20	34.49	28.06	23.65	39.94	31.53
	CT2Rep [3]	2024	44.42	34.43	27.94	23.56	40.16	30.99
	M3D [5]	2024	43.57	34.48	28.54	24.49	39.95	32.61
	Reg2RG	-	**47.25**	**36.49**	**29.57**	**24.87**	**44.07**	**36.65**

Jin et al. PromptMRG: Diagnosis-Driven Prompts for Medical Report Generation. AAAI 2023.
Chen et al. Large Language Model with Region-guided Referring and Grounding for CT Report Generation. IEEE TMI 2025.

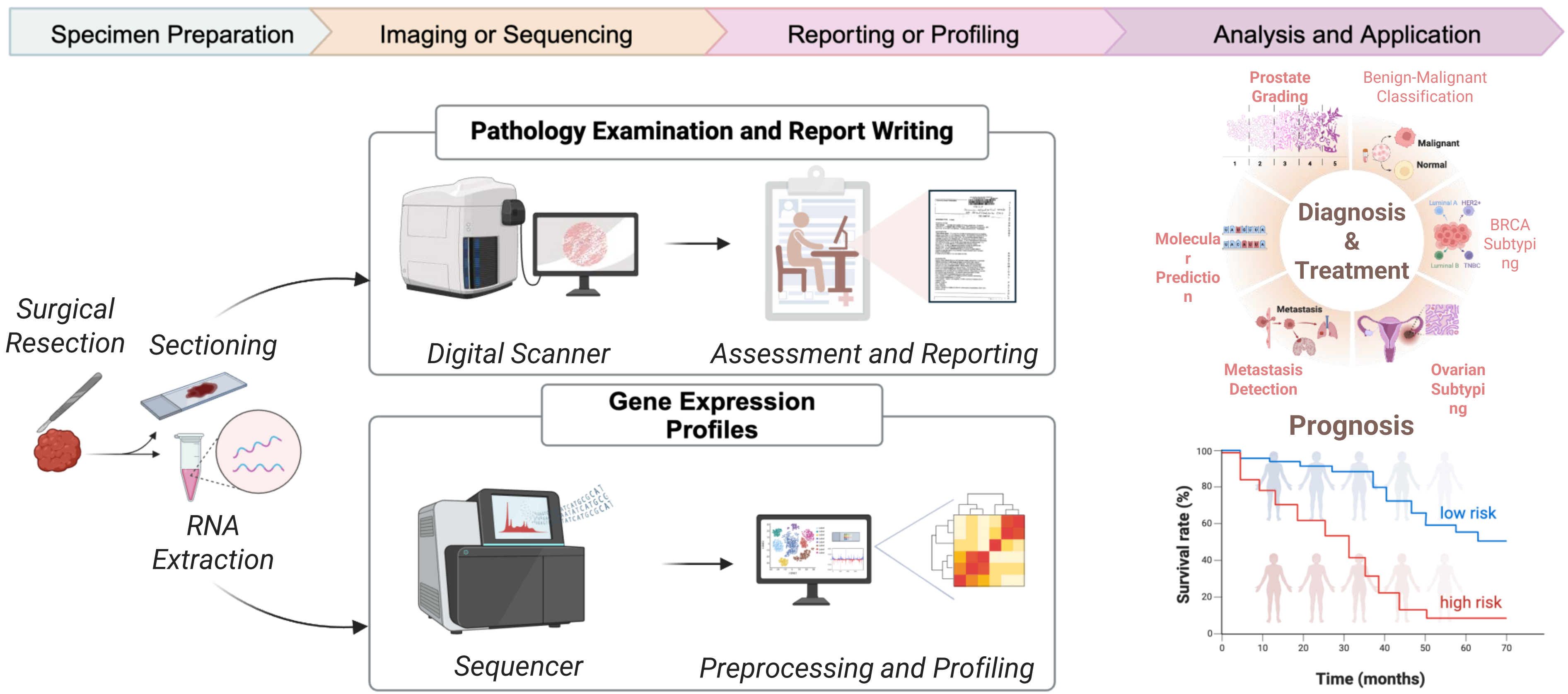
Pathology Foundation Model



All in One?

Pathology Foundation Model

❑ mSTAR: The First Multimodal Knowledge-enhanced Whole-slide Pathology Foundation Model



Yingxue Xu

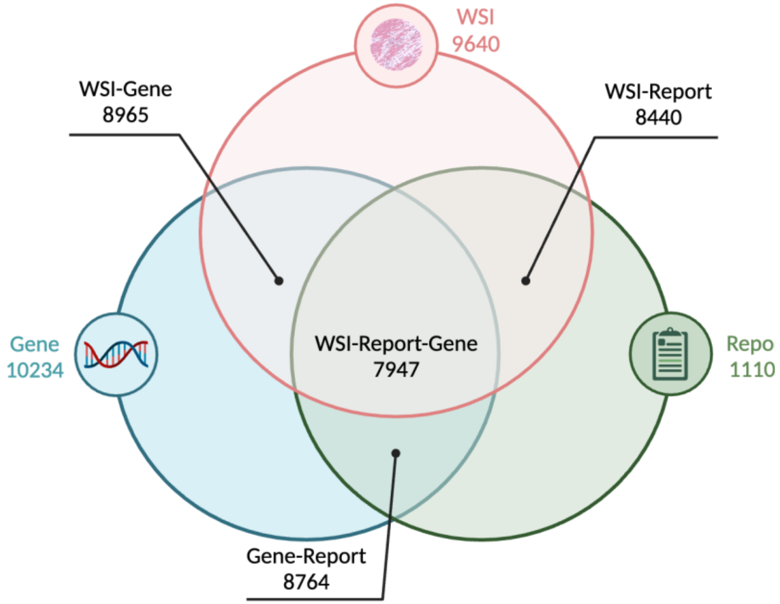
Yihui Wang

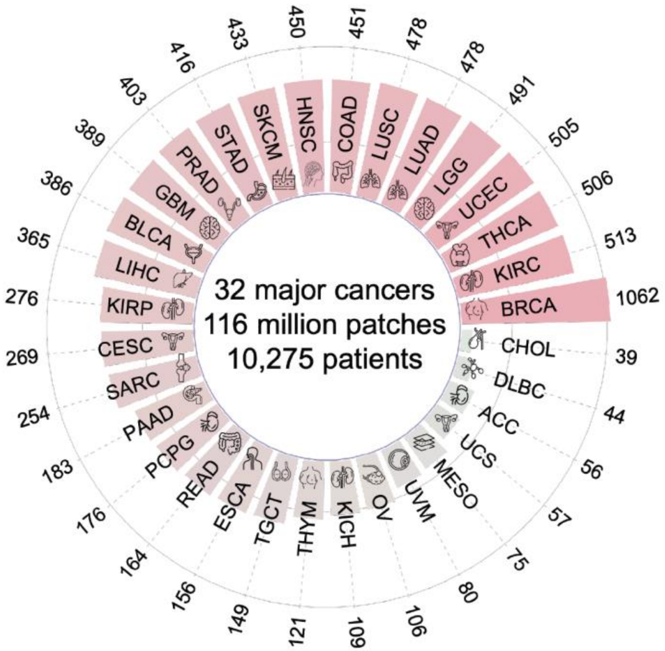
Fengtao Zhou

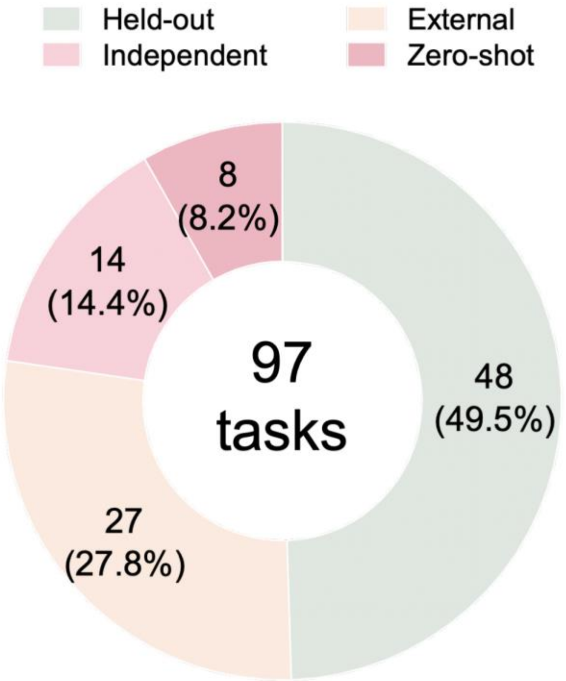
Xu, et al. A Multimodal Knowledge-enhanced Whole-slide Pathology Foundation Model. arXiv, 2024.

Pathology Foundation Model

❑ Dataset Construction







The largest multimodal pretraining dataset

10,275 patients, **32** major cancer types

over **116 million** pathology images

The largest spectrum of downstream tasks

97 diverse diagnostic and prognostic tasks

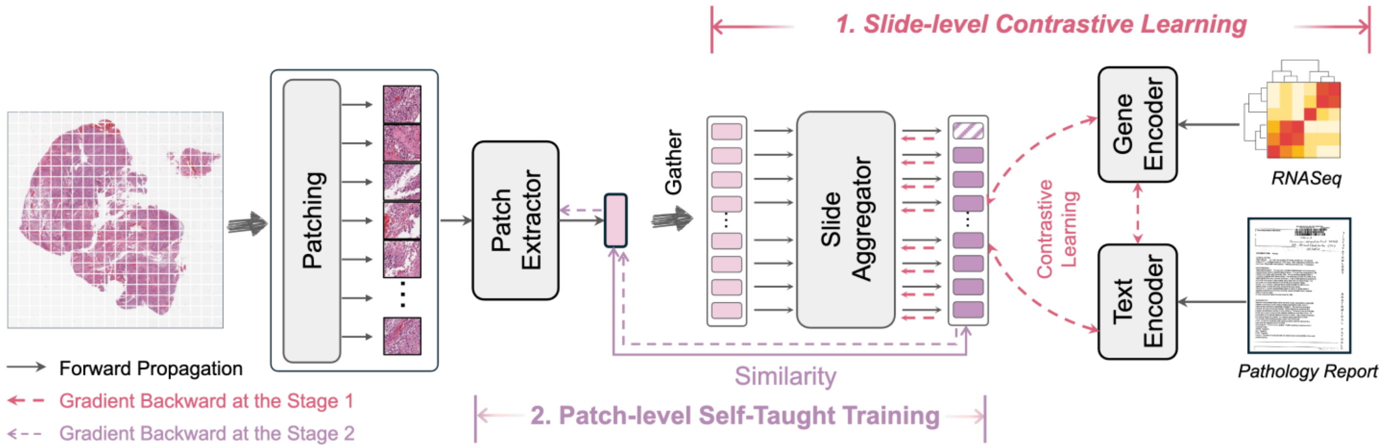
4 evaluation strategies

Xu, et al. A Multimodal Knowledge-enhanced Whole-slide Pathology Foundation Model. arXiv, 2024.

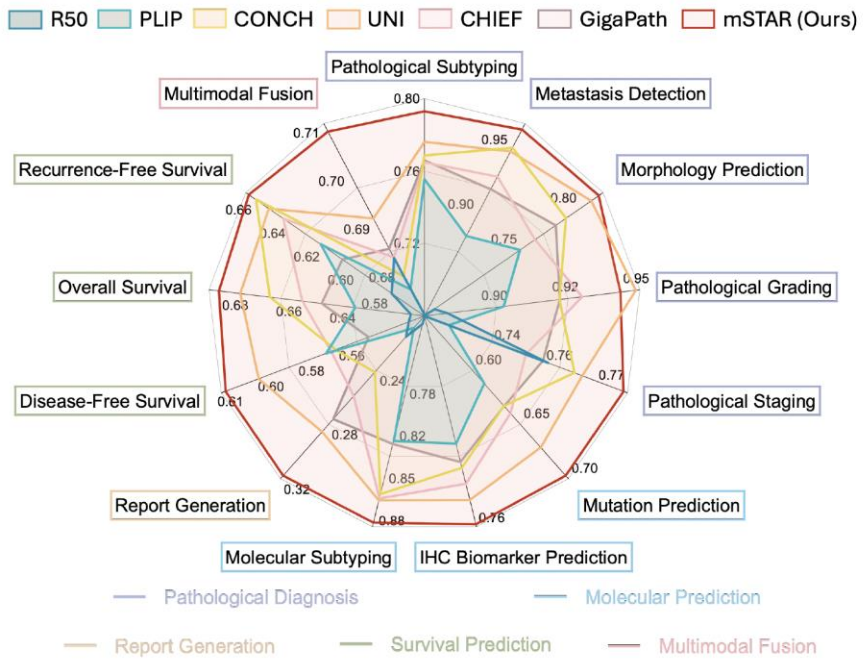
Pathology Foundation Model

Method and Experiments

- A new slide-level pathology pretraining paradigm.
- The first endeavour to inject multimodal knowledge at the whole-slide context into pathology foundation models.
- Establish the largest spectrum of oncological downstream benchmark.



- Overall superiority across 7 categories of oncological applications in 15 types of 97 practical tasks, compared to previous state-of-the-art FMs.



Xu, et al. A Multimodal Knowledge-enhanced Whole-slide Pathology Foundation Model. arXiv, 2024.

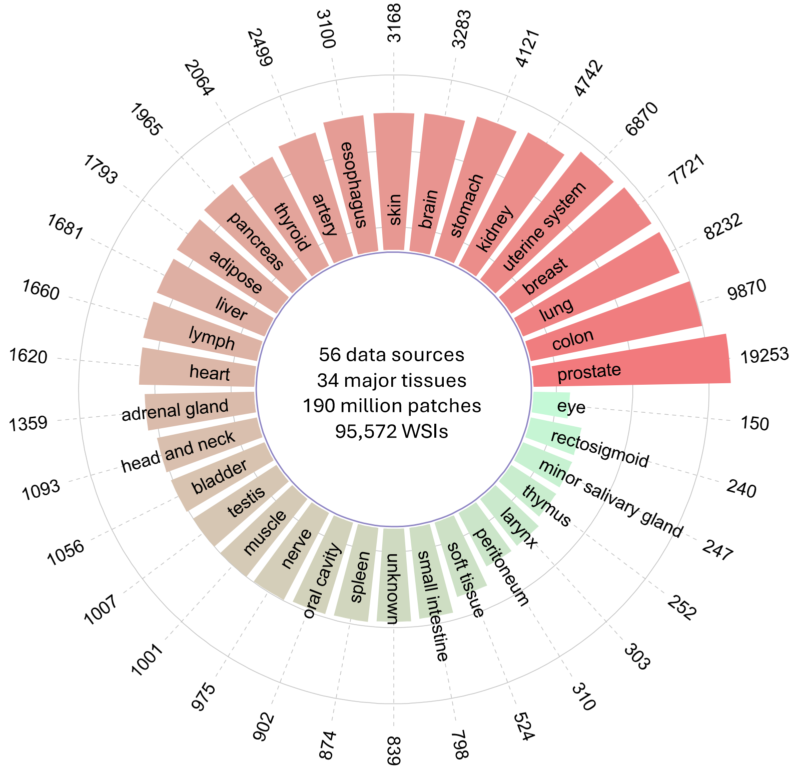
Pathology Foundation Model

❑ Towards A Generalizable Pathology Foundation Model via Unified Knowledge Distillation

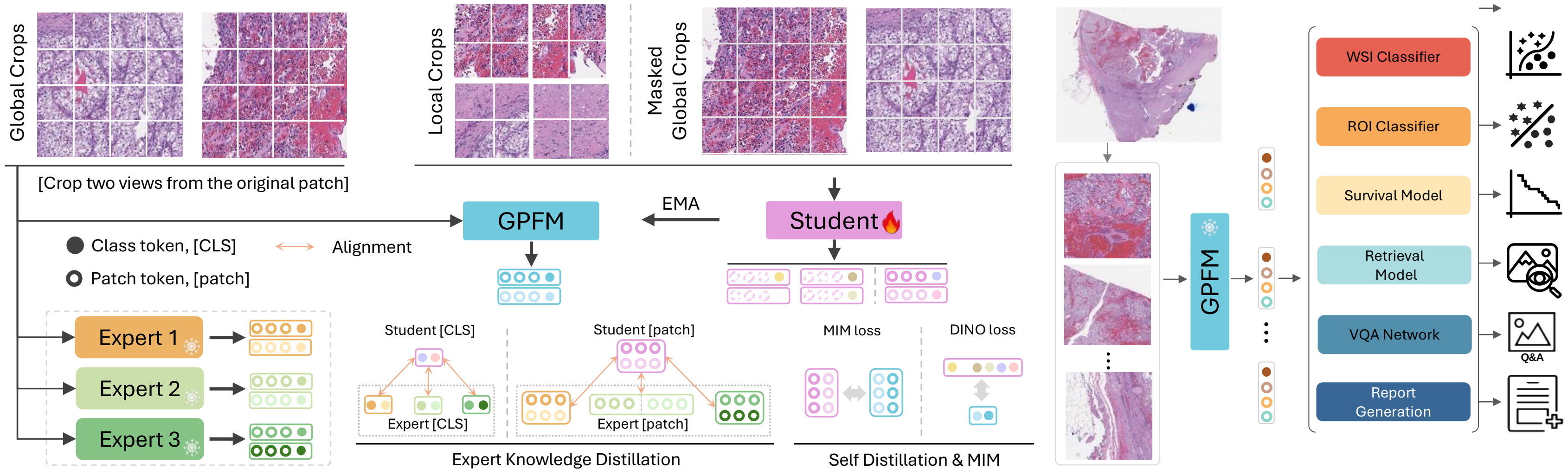

Jiabo Ma


Zhengrui Guo

Data



Methods



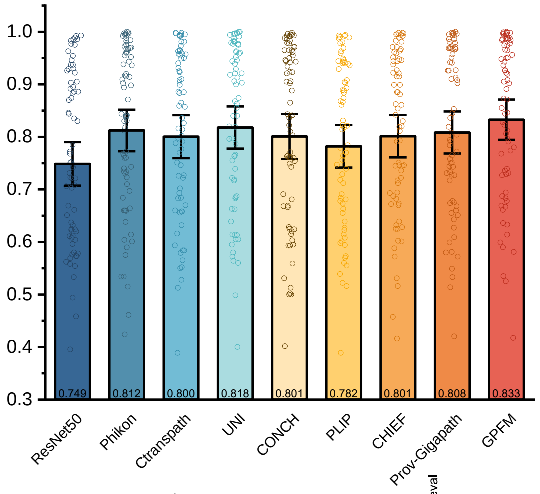
上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

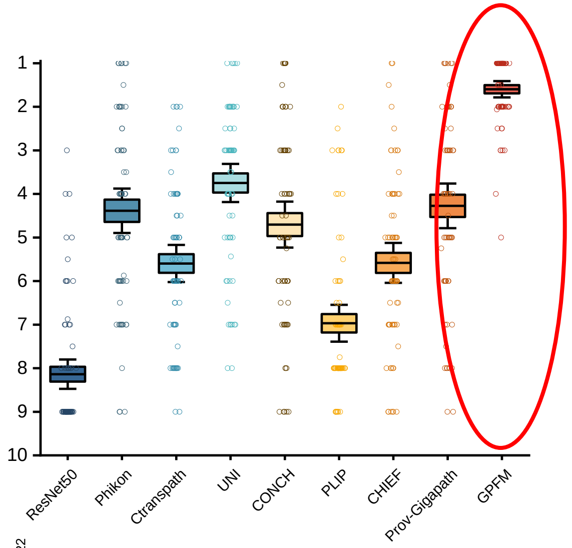
Ma et al. Towards A Generalizable Pathology Foundation Model via Unified Knowledge Distillation. Nature Biomedical Engineering, 2025.

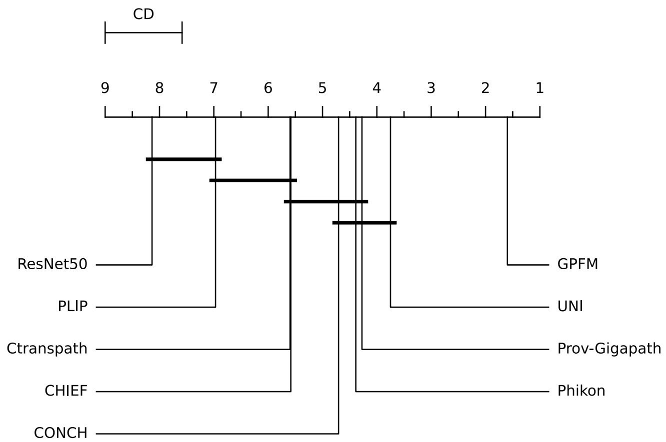
Pathology Foundation Model

❑ Results

	WSI Classification	Survival Analysis	ROI Classification	Image Retrieval	VQA	Report Generation
PLIP	×	×	√	√	×	×
CONCH	√	×	√	√	√	×
Ctranspath	√	×	√	√	×	×
UNI	√	×	√	√	×	×
Phikon	√	√	√	×	×	×
CHIEF	√	√	×	×	×	×
Prov-Gigapath	√	×	×	×	×	×
GPFM	√	√	√	√	√	√







	TCGA-BRCA	TCGA-BLCA	TCGA-KIRC	TCGA-KIRP	TCGA-STAD	TCGA-CESC	TCGA-LUAD	CPTAC-LUAD	TCGA-LUSC	TCGA-COADREAD	TCGA-GBM	TCGA-LGG	TCGA-HNSC	TCGA-SKCM	CRC100K	CCRCC-TCGA-HEL	BACH	BreakHis	UniToPatho	CRC-MSI	PanCancer-TCGA	PanCancer-TIL	ESCA	PCAM	WSSS4LUAD	Chaoyang	GasHisDB	CRC Tissue Retrieval	Path VQA	WSI-VQA	TCGA-Report	PatchGastricADC22	Mean
GPFM	1	2	1	2	1	5	4	2	2	2	1	2	2	2	2	2	3	2	3	2	1.5	1	3	1	1	2	2.5	2	2	2.1	2	2	2
Prov-Gigapath	5	3	6	7	9	2	9	8	1	3	2	3	3	5	4	2	6	2	2	1	3	5	3	3	6	1	2.5	1	4	5.2	4	4	3.9
UNI	7	7	4	1	6	5	2	6	6.5	5	3	8	1	6	7	4	1	2	4	5	4	2	1	2	3.5	3.5	2.5	3	3	5.4	3	7	4.1
Phikon	2	1	2	9	5	1	1	9	4	6	7	5	5	9	6	2	7	4	5	7	1.5	3	7	4	3.5	3.5	2.5	5	8	5.9	1	1	4.5
CONCH	3	4	3	8	4	7	3	5	9	9	5	1	6	1	5	6	5	7	1	3	6	4	3	5	7	7	6	4	1	5.2	5	5	4.8
CHIEF	6	5	9	3	3	8	5	1	6.5	1	9	6	4	7	2	6	3	5.5	7.5	6	7	7	5.5	6	3.5	6	6	9	5	1.5	6	9	5.5
Ctranspath	4	9	8	4	2	5	8	3	3	7	4	7	8	8	2	6	3	5.5	6	4	5	6	5.5	8	3.5	5	6	7	7	5	8	6	5.6
PLIP	8	8	5	5.5	8	9	7	4	8	4	6	9	7	3	8	9	9	8	9	9	8	8	8	7	8	8	8	8	6	7.8	7	3	7.2
ResNet50	9	6	7	5.5	7	3	6	7	5	8	8	4	9	4	9	8	8	9	7.5	8	9	9	9	9	9	9	9	6	9	6.9	9	8	7.5

Internal

	Center-1-NSCLC	Center-2-LMD2	Center-2-LMD6	Center-3-RCC	Center-3-LD	Center-3-BRCA	EBRAINS-IDH1	Center-3-Ovary	EBRAINS-Subtyping	Center-3-Colon-WSI	Center-4-Lauren	Center-5-Lauren	Center-4-Vascular	Center-5-Vascular	Center-4-Perineural	Center-5-Perineural	HANCOCK	Center-3-TIL	Center-3-Colon	Center-3-GC	Mean
GPFM	1	2	1	1	2	1	1	1	1	1	2.5	1	1	2.5	1	1	2	1	2	1	1.4
UNI	2	3	3	2.5	3	8	3	2	2	3	6	7	3	4	2	4.5	1	3	3	3	3.4
Phikon	7	4	6	5	1	6	6	3	3	7	4	6	2	1	7	2	7	5	4	2	4.4
Prov-Gigapath	5	8	8	8	6	3	2	5	4	4	7	5	5	8	4	6	3	4	1	4	5
CONCH	9	1	2	6	9	9	4	8	5	2	1	2	6	6	3	4.5	8	2	7	6	5
CHIEF	4	6	5	2.5	5	4.5	7	4	6	6	5	4	8	5	5.5	3	4	6	6	7	5.2
Ctranspath	6	5	4	4	4	4.5	5	9	8	8	8	8	4	2.5	5.5	7	5	7	5	5	5.7
PLIP	3	7	7	7	7	2	8	7	7	5	2.5	3	7	7	8	8	6	8	8	9	6.3
ResNet50	8	9	9	9	8	7	9	6	9	9	9	9	9	9	9	9	9	9	9	8	8.6

External

Ma et al. Towards A Generalizable Pathology Foundation Model via Unified Knowledge Distillation. Nature Biomedical Engineering, 2025.

PATHBench: Pathology Foundation Benchmark

The Most Comprehensive Benchmark for Pathology Foundation Models

PATHBench

Join the World's First Open, Multi-Task, and Multi-Organ Benchmark for Pathology Foundation Models

SMART LAB

THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Overview | Leaderboard | Performance | Models

Overall Performance

Task Name	Source	ResNet50	PLIP	UNI	CONCH	CHIEF	Prov-GigaPath	mSTAR
HER2 Level Prediction for Breast Cancer	ZJ1	0.733	0.737	0.776	0.763	0.743	0.761	0.795
Molecular Subtyping for Breast Cancer	ZJ1	0.589	0.711	0.784	0.724	0.792	0.701	0.795
HER2 Status Prediction for Breast Cancer	ZJ1	0.386	0.628	0.615	0.652	0.643	0.621	0.643
Pathological Subtyping for Gastric Cancer	YN3	0.552	0.566	0.592	0.501	0.541	0.505	0.605
ER Level Prediction for Breast Cancer	ZJ1	0.701	0.762	0.789	0.783	0.786	0.785	0.802
Vascular Invasion Detection for Gastric Cancer	NFH	0.625	0.757	0.789	0.765	0.713	0.766	0.797
Metastasis Detection and Primary Site Prediction for Lung Cancer	NFH	0.894	0.938	0.955	0.970	0.960	0.950	0.974
Metastasis Detection for Lung Cancer	QFS	0.657	0.728	0.925	0.927	0.878	0.844	0.950
Metastasis Detection and Primary Site Prediction for Lung Cancer	QFS	0.722	0.856	0.913	0.907	0.882	0.853	0.921
Perineural Invasion Detection for Gastric Cancer	NFH	0.867	0.892	0.975	0.976	0.953	0.945	0.978
PR Status Prediction for Breast Cancer	ZJ1	0.424	0.524	0.549	0.545	0.545	0.490	0.567
Lauren Subtyping for Gastric Cancer	YN3	0.637	0.735	0.717	0.734	0.727	0.718	0.748
Pathological Subtyping for Gastric Cancer	NFH	0.519	0.592	0.585	0.582	0.637	0.574	0.620
Metastasis Detection for Lung Cancer	NFH	0.904	0.965	0.966	0.970	0.981	0.977	0.988
ER Status Prediction for Breast Cancer	ZJ1	0.668	0.735	0.834	0.835	0.831	0.846	0.853
Pathological Subtyping for Gastric Cancer	YN1	0.550	0.516	0.553	0.538	0.531	0.519	0.567

Welcome to Join us!

10+ Organs

19 Foundation Models

20+ Hospitals

200+ Oncological Tasks

500k+ Whole Slide Images

PathBench

https://smartlab.cse.ust.hk/showcase/pathbench

SmartPath Demo

Multimodal Medical Foundation Model

Multimodal training corpus

- Text
- Video
- EHRs
- Omics
- Images
- Audio
- Signals
- Graphs

Medical domain knowledge

- Literature
- Publications
- Clinical notes
- Knowledge graphs

Applications

- Disease diagnosis
- Quantitative evaluation
- Disease prognosis
- Augmented procedures
- Grounded radiology reports
- Bedside decision support

- **Modality-specific foundation models excel in precision.**
- **Multimodal generalist foundation model exhibit superior generalizability.**
- **Generalist-specialist collaboration to explore the synergy between two models.**

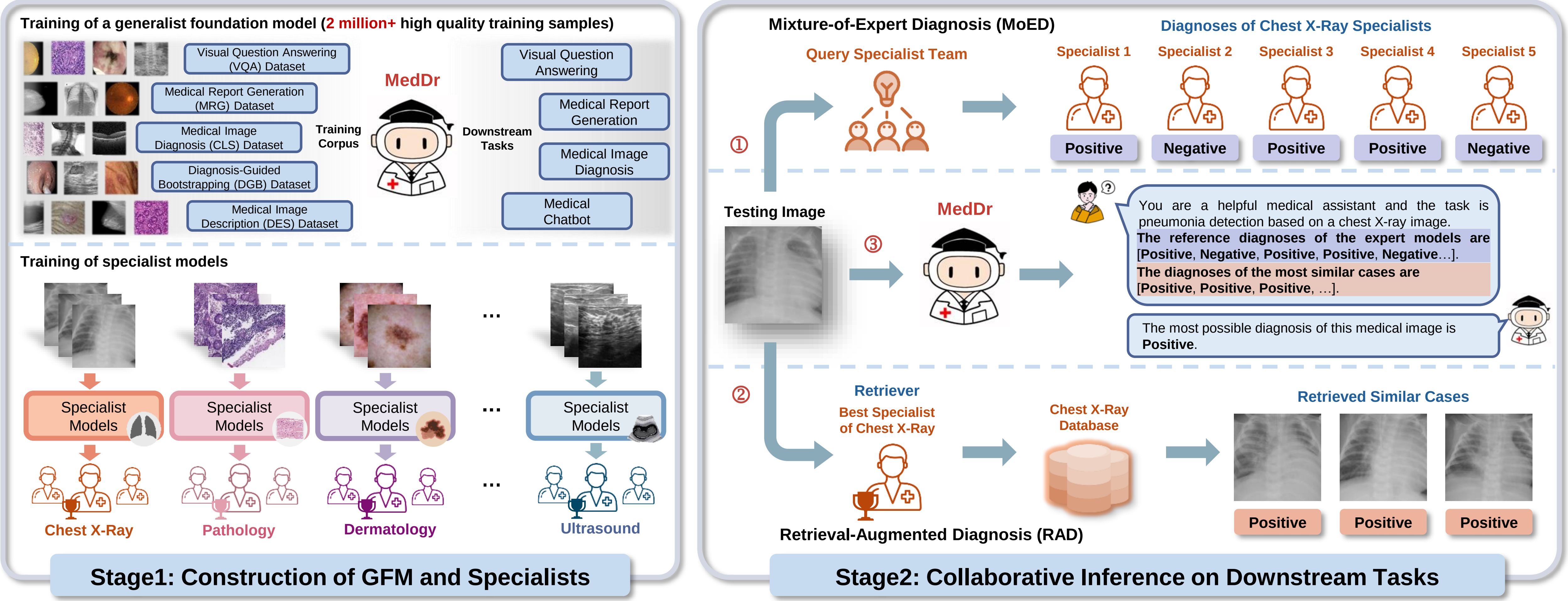
Moor et al. Foundation Models for Generalist Medical Artificial Intelligence. Nature 2023.
Tu et al. Towards Generalist Biomedical AI. NEJM AI 2024.

Generalist Foundation Model

❑ Towards Generalizable AI in Medicine via Generalist-Specialist Collaboration

- MedDr: one of the largest open-source generalist foundation models for medicine.
- Generalist-Specialist Collaboration (GSCo): explore the synergy between the GFM and specialists.


Sunan He Yuxiang Nie

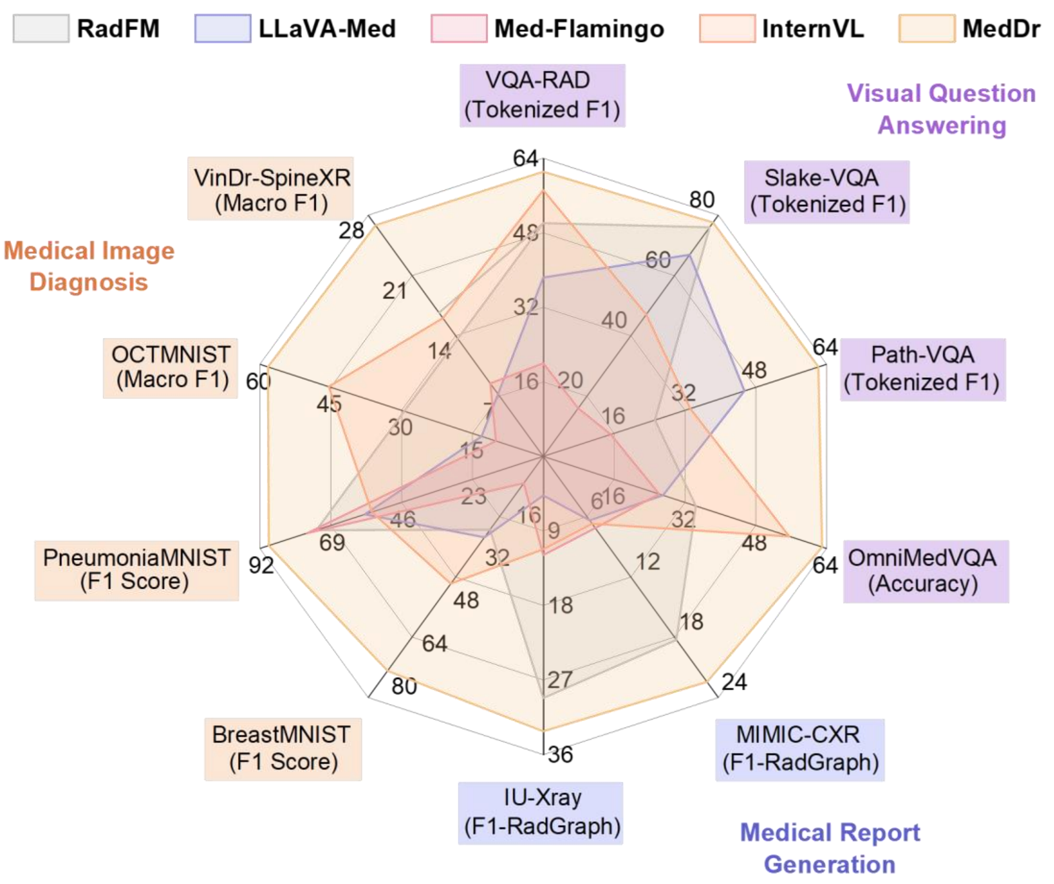


He, et al. MedDr: Diagnosis-Guided Bootstrapping for Large-Scale Medical Vision-Language Learning. arXiv 2024.
He, et al. GSCo: Towards Generalizable AI in Medicine via Generalist-Specialist Collaboration. arXiv 2024.

Generalist Foundation Model

❑ Experiments on Downstream Datasets

- MedDr **consistently outperforms** state-of-the-art GFMs on downstream datasets.



He, et al. MedDr: Diagnosis-Guided Bootstrapping for Large-Scale Medical Vision-Language Learning. arXiv 2024.
He, et al. GSCo: Towards Generalizable AI in Medicine via Generalist-Specialist Collaboration. arXiv 2024.

腾讯优图

SmartCare for Patient-centered Care

Dr. Justin Cheng

Pre-Consultation Module

SmartChat Voice Input Medical Chatbot

Intelligent voice interaction system collects preliminary symptoms and medical history, enhancing pre-consultation experience.

SmartTriage Customizable Triage System

Intelligently allocates medical resources based on clinical environment, optimizing patient flow and waiting times.

Consultation Module

SmartConsult Intelligent Transcription

Real-time transcription of doctor-patient conversations, allowing physicians to focus on patient interaction rather than documentation.

Post-Consultation Module

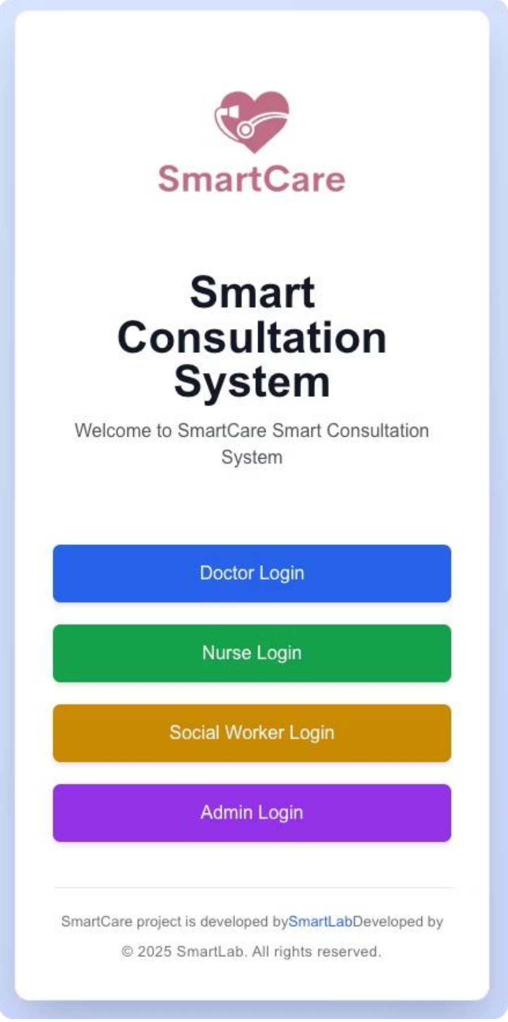
SmartDoc Automated Documentation

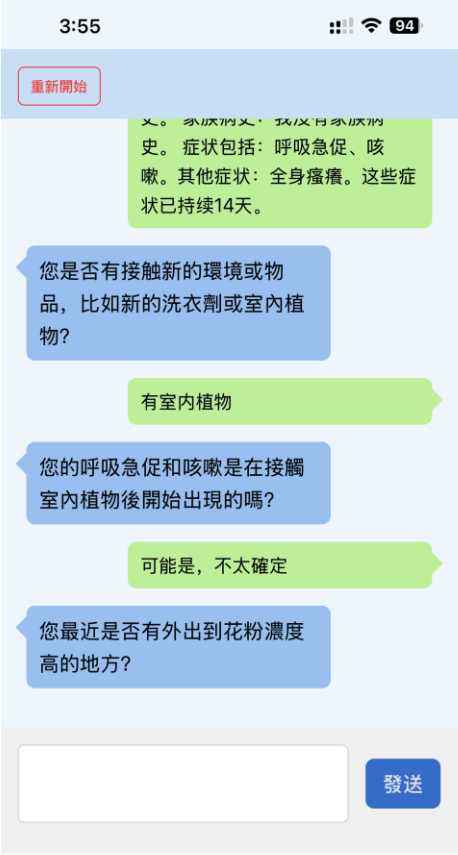
Automatically generates 30+ types of medical documents, significantly reducing administrative burden and accelerating overall service process.

SmartCare for Patient-centered Care

❑ Pre-consultation (online booking at home, or at the Waiting Room)

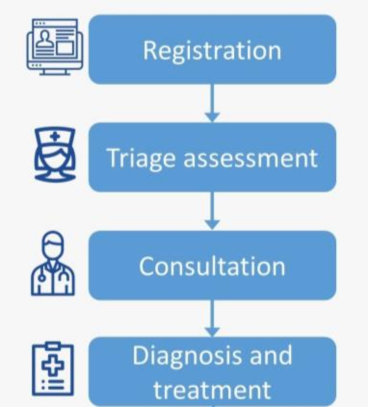
Health Care Professionals (HCPs): Drs, Nrs, Allied Health





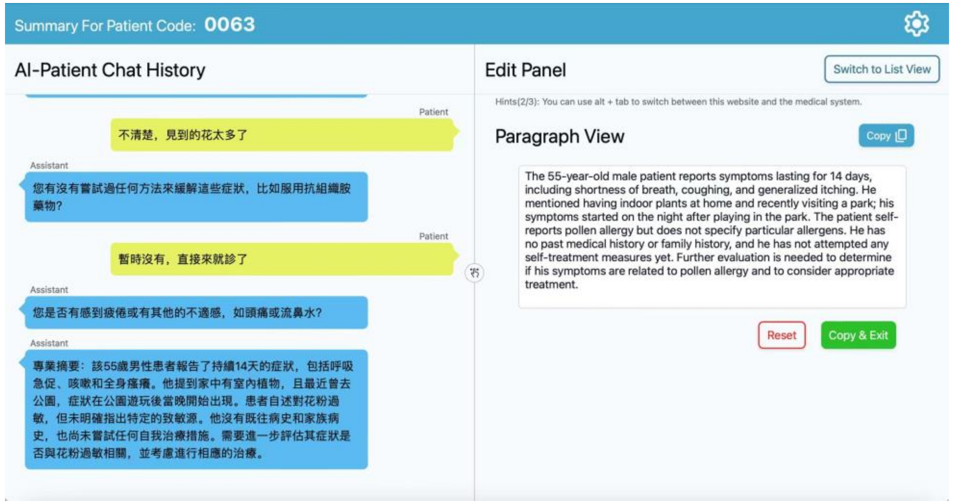
1: Online Link / Waiting Rm QR to Pt

2: Pt's Speech / Text Answer -> Summary



Patients are classified into three categories according to their medical conditions:

Category 1 – Critical	Category 2 – Urgent	Category 3 – Non-urgent
• For example: • Cardiac or respiratory arrest • upper airway obstruction • Respiratory failure or distress • Unstable vital signs	• For example: • Patient with severe pain • Higher fever with a body temperature >40°C • Dehydration • Low blood pressure • Active blood loss • Chest pain suspected of cardiac in origin	• For example: • Common cold • Gastroenteritis • Urinary tract infection • Minor injuries



4: Triage then Initial Summary for HCPs to Starts Consultation

SmartCare for Patient-centered Care

❑ Large Language Model (LLM) in the “Research Consultation Room”

Dr： 您好，陳女士 。
Pt： 唉，醫生，最近又**頭暈**又**無力**，仲有少少**胸口痛**，成日都覺得唔舒服
Dr： 頭暈、無力同胸口痛呢啲情況持續咗幾耐？
Pt： 差唔多有**一個月**啦，每日都覺得好辛苦，**行路**唔方便
Dr： 之前有冇睇過其他醫生？佢哋有冇比過咩意見您？
Pt： 之前睇過**兩個醫生**，但**食嗰啲藥**冇乜效，我都唔知點好
Dr： 除咗頭暈、無力同胸口痛，仲有冇其他症狀或病呀？
Pt： 有呀，我仲有**高血壓**、**糖尿病**同**關節炎**，成日都**腰痛**、**膝頭痛**，晚晚**瞓唔好**。
Dr： 咁多種問題，真係辛苦您喇，有冇人幫您照顧下？
Pt： 我個**女**會偶爾嚟**幫手**，但佢自己都有啲忙，成日都唔喺度。
Dr： 我明白，我會幫您檢查下身體嘅情況，再安排做一啲檢查，睇下有冇咩問題。
Pt： 唔該晒醫生，真係麻煩您喇，我**好擔心**自己嘅健康。
Dr： 唔使擔心，陳女士，我哋會全力幫您搵出問題所在，再制定一個適合您嘅治療計劃。
Pt： 多謝您，醫生，我希望盡快可以好返啲。

Questions Reminder

1: Transcription (Pt - HCPs Convers.)

"BP Pulse stable, no fever" "Pupils equal reactive, no jaundice no pallor, thyroid normal." "Regular heart sounds, slight irregular rhythm irregular." "Clear clear" "Abdomen non-tender, normal bowel sounds, no masses, liver and spleen not enlarged." "Moderate ankle swelling" Both knees tender, limited motion, other joints NAD" "Reflexes intact, no focal deficits, sensation normal, mild lower limb weakness."

2: Transcription (Physical Exam)

Name: CHAN Ming Yu. Age: 67 years old. Gender: Female
Medical Record Number: 9384987937. Date of Visit: 5 March 2025
•Chief Complaint: Headache, fatigue, chest pain

Subjective:
•Patient reports dizziness, fatigue, and mild chest pain for the past month.
•Difficulty walking and performing daily activities.
•Reduced appetite and overall weakness.
•Multiple chronic conditions including hypertension, diabetes, and arthritis.
•Difficulty sleeping due to joint pain.

Objective:
- Appears tired and in mild discomfort.
- Regular heart sounds, slight rhythm irregularity
- Moderate swelling in both ankles
- Significant pain and limited range of motion in both knees
- No focal neurological deficits

Suggested Assessment:
•Hypertension (poorly controlled)
•Type 2 Diabetes Mellitus
•Osteoarthritis of the knees
•Mild Heart Arrhythmia

SOAP Editor

3: LLM Generated Medical Record (MR)

Suggested Plan:
1.Order blood work to evaluate glucose levels, kidney function, and electrolytes.
2.Perform an ECG to investigate the rhythm irregularity.
3.Prescribe medication adjustments for hypertension and diabetes management.
4.Refer to a specialist for arthritis management.
5.Schedule a follow-up appointment in 2 weeks to review test results and adjust treatment plan as needed.

Suggested Instructions to Patient:
•Monitor blood pressure and blood sugar levels at home.
•Take prescribed medications as directed.

4: LLM Recommendations added to MR

Downstream Forms & Letters Generated by LLM

- Referral Letter
- Reply Letter
- Prescription Letter
- Medical Cert
- Pre-Approval Form
- Fitness to Work
- Patient Instructions
- Claim Forms
- Follow-up Appt Letter
- Medical Report
- Labs Forms
- Imaging Forms

Challenges

Data

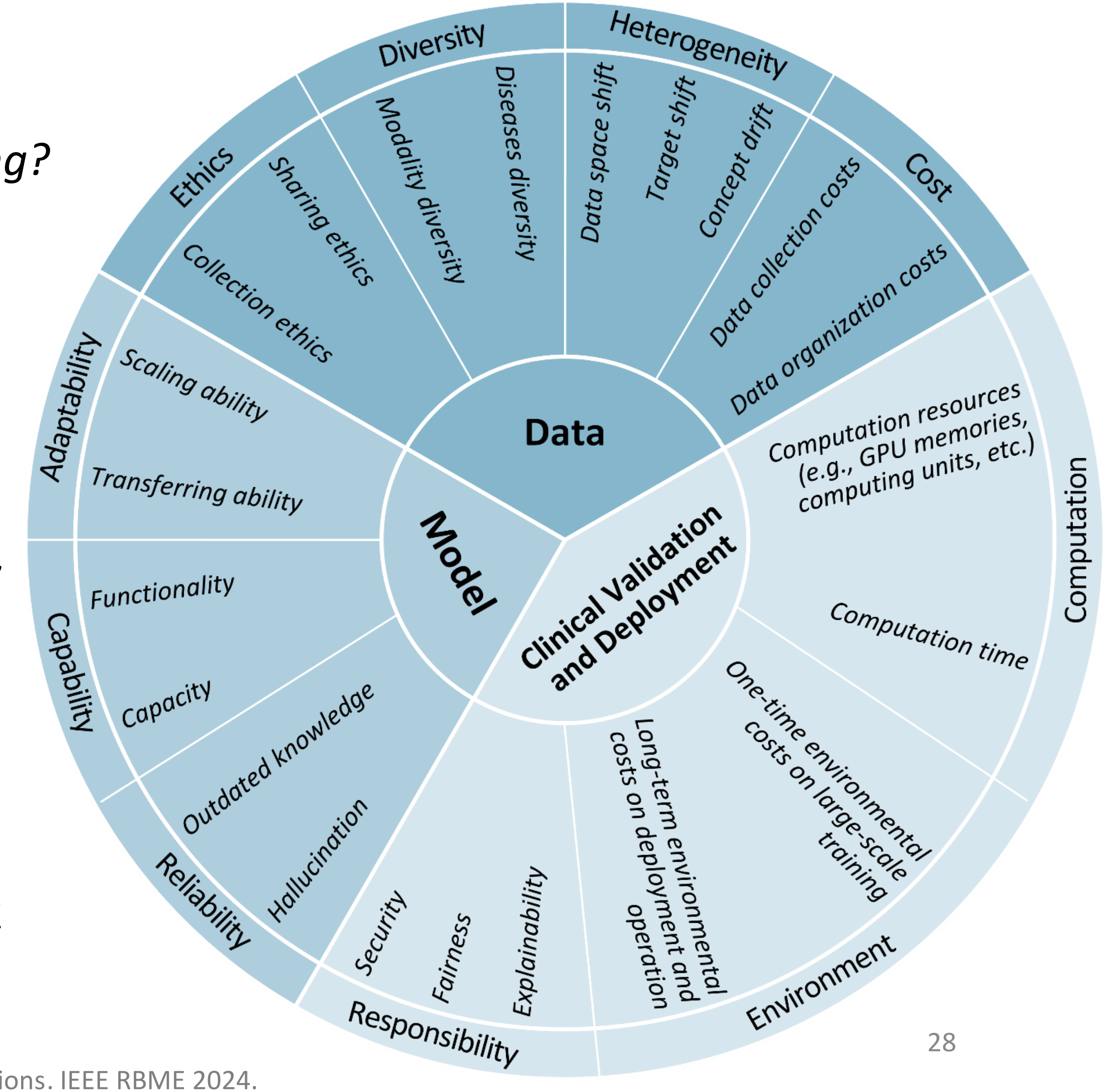
- *How to get **large-scale high-quality medical data** for foundation model training?*
- *Challenges include ethical issue, heterogeneity, cost, etc.*

Model

- *How to construct **powerful AI models** for medical knowledge learning?*
- *Challenges include adaptability, capability, reliability, etc.*

Clinical Validation and Deployment

- *How to **widely deploy** AI models in clinical settings?*
- *It is essential to establish **human-machine collaboration** and ensure responsibility.*



He et al. Foundation Model for Advancing Healthcare: Challenges, Opportunities and Future Directions. IEEE RBME 2024.

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腾讯优图

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Innovation and Technology Commission

中华人民共和国科学技术部
Ministry of Science and Technology of the People's Republic of China

AYS ASIAN YOUNG SCIENTIST Fellowship

Thank You!

Smart Lab: Large and Trustworthy AI for Healthcare

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About Me

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Smart Lab

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