

OVERVIEW OF ARTIFICIAL INTELLIGENCE IN BIOMEDICINE

Lei Xing, PhD, DABR

Jacob Haimson & Sarah S. Donaldson Professor & Director of Medical Physics Division

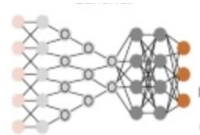
Department of Radiation Oncology & Electrical Engineering (by courtesy)
Institute of Computational and Mathematical Engineering (iCME) & Molecular Imaging Program (MIPS)
Stanford University, Stanford, California

Stanford University

Department of Radiation Oncology
School of Medicine



A DECADE OF AI



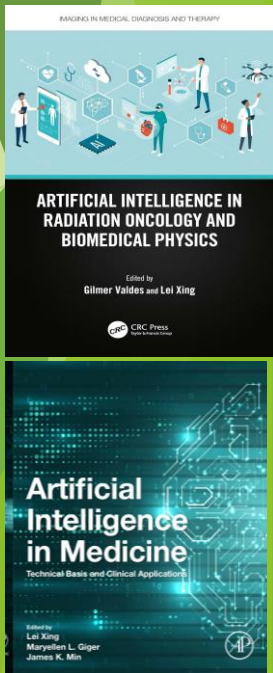
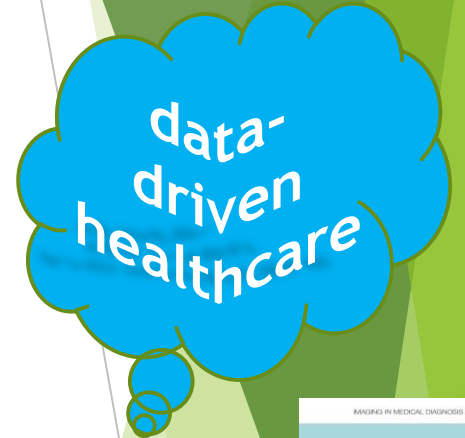
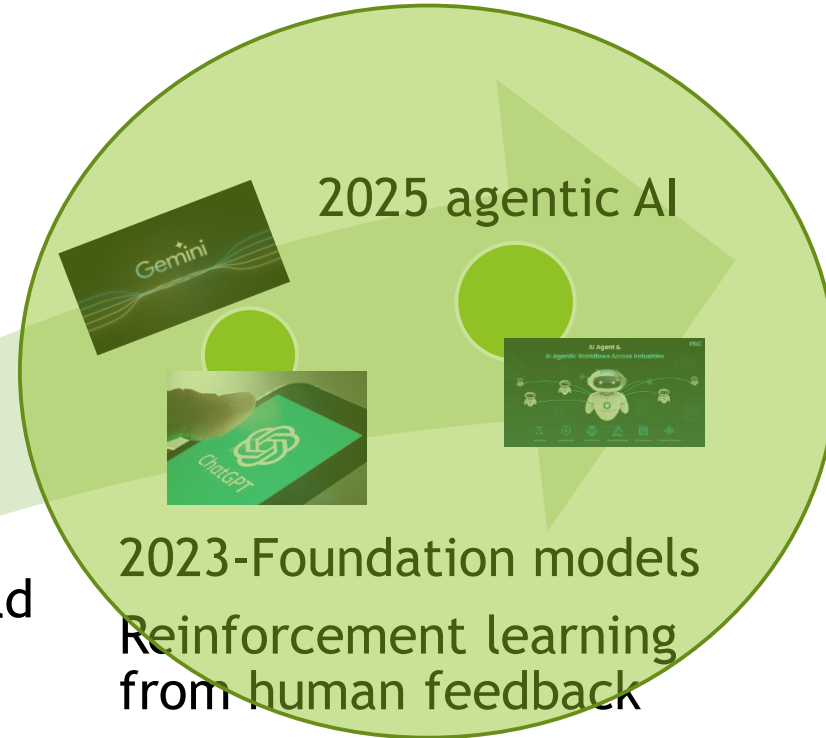
2014 - Deep learning



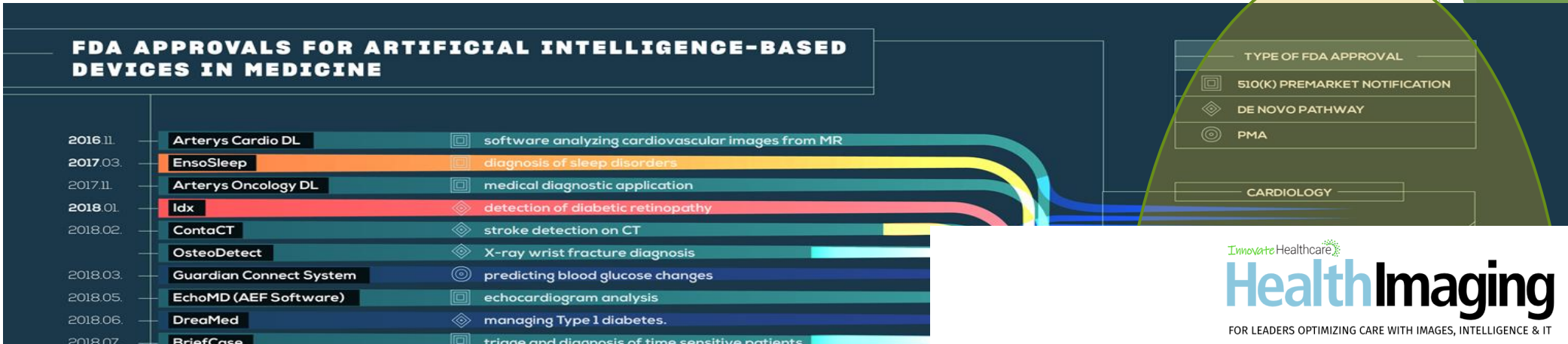
2016-AlphaGo



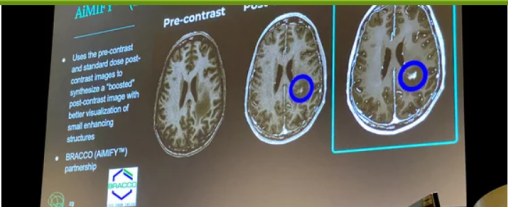
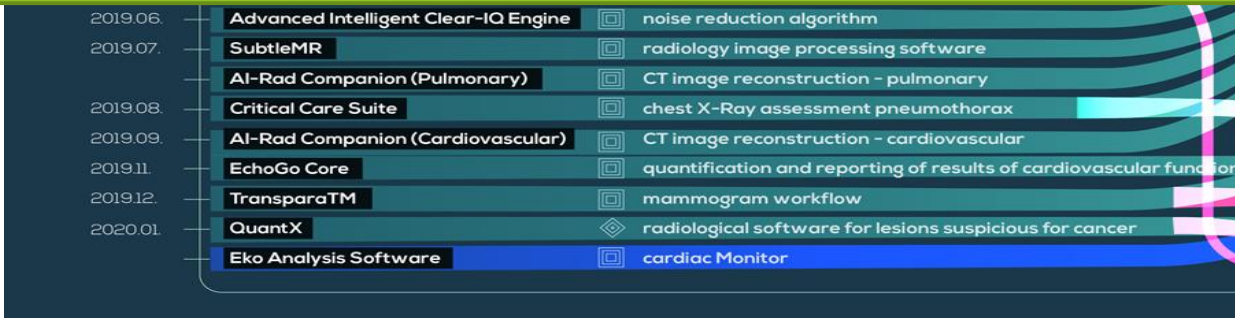
2021-AlphaFold



FDA APPROVED AI PRODUCTS



Projected Market Size is around \$800 billions in 2035 for AI biomedicine!



Dozens of new artificial intelligence-enabled products have made their way onto the United States Food and Drug Administration's list of approvals.

That brings the total number of cleared AI clinical applications to just over 1,000. Radiology leads the way in approvals by a mile, accounting for more than 70% of all clearances.

The latest update brings the total number of radiology-related FDA-approved applications to 758, with 35 new products being added to the list since August. Cardiology is next in line with 101 approvals, plus an additional 60 that also fall under the umbrella of radiology. Neurology sits at a distant third, with 35 listed approvals.

Notable companies in the most recent roundup include United Imaging, Avicenna.AI, Canon Medical Systems, Siemens, Subtle Medical, Nanox, Qure.ai Technologies, GE and more.

Around the web

CARDIOVASCULAR BUSINESS

New data highlight how Heartflow's AI software drives major shifts in heart care

One of the study's most significant findings was that patients managed using the advanced AI software saw LDL cholesterol drops of 18.7 mg/dL, with a 15% reduction in their risk of a cardiac event. Even patients with no calcified plaque saw significant changes in care management.

CARDIOVASCULAR BUSINESS

S. Benjamins, et al, The state of arti devices and algorithms: an online da

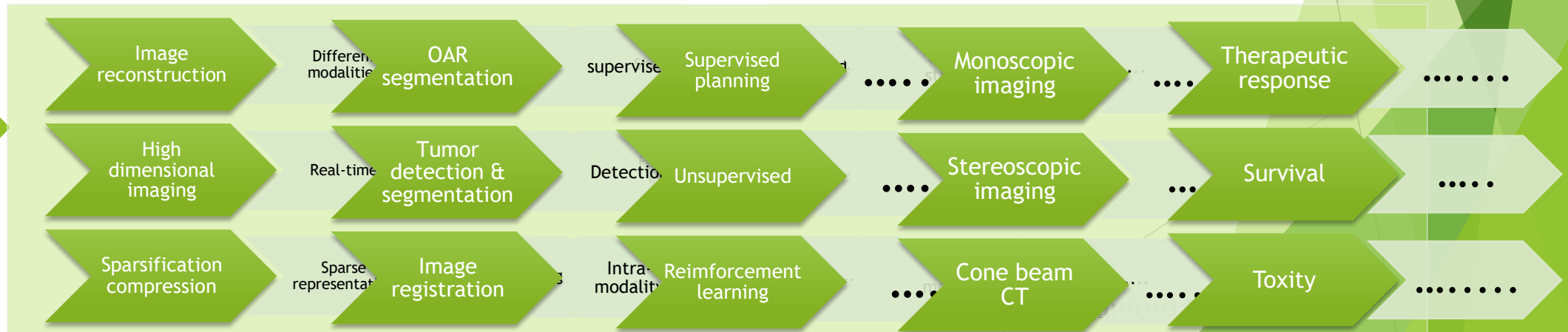
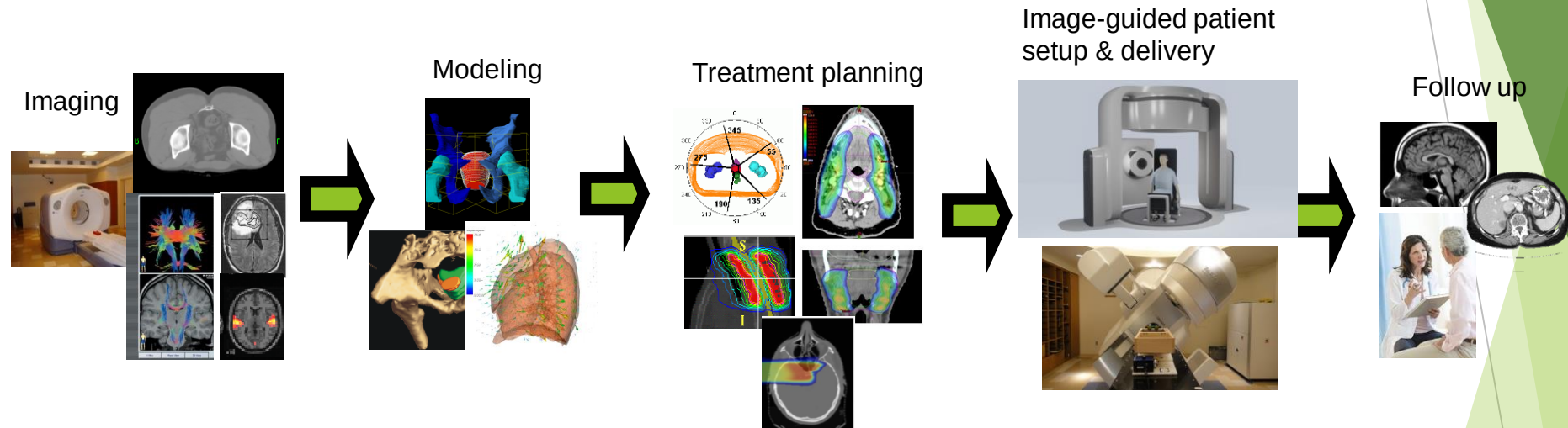
Aidoc Secures Landmark FDA Clearance for First Foundation Model-Powered Clinical AI Solution of Its Kind

Home / About / News / Aidoc Secures Landmark FDA Clearance for First Foundation Model-Powered Clinical AI Solution of Its Kind

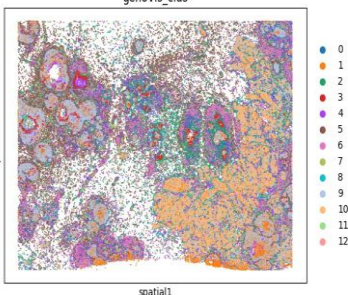
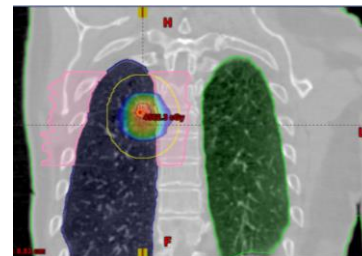
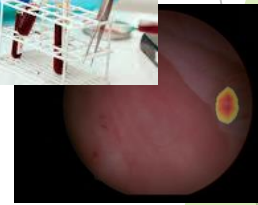
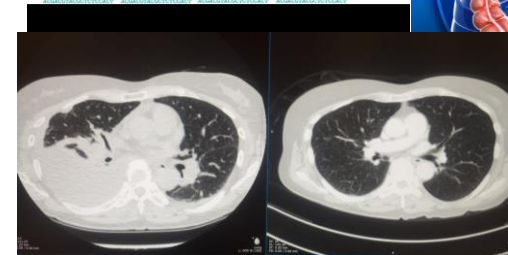
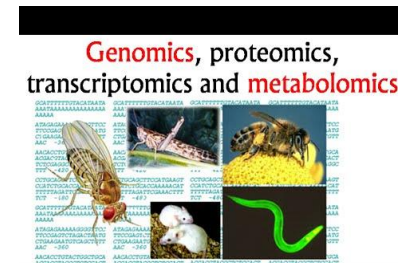
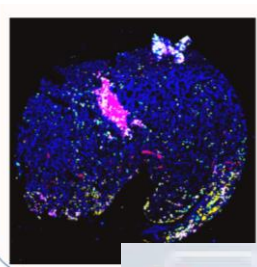
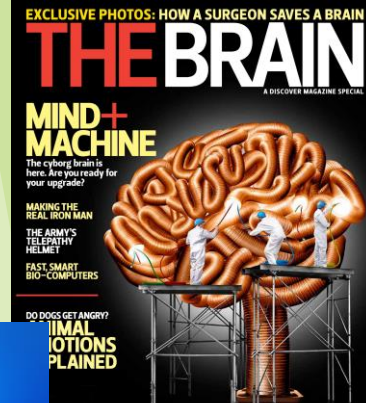
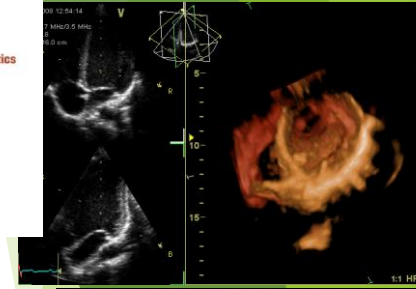
FDA clearance of AI solution powered by groundbreaking technology – the CARE1™ Foundation Model sets a new benchmark in

1. Freeze the core model's weights.
2. Fine-tune it for a specific, low-risk use case.
3. Validate and lock the smaller, task-specific model for regulatory submission.

AI IN CLINICAL WORKFLOW OF RADIATION THERAPY



- [illegible]



Revealing hidden patterns in deep neural network feature space continuum via manifold learning

Received: 17 May 2023

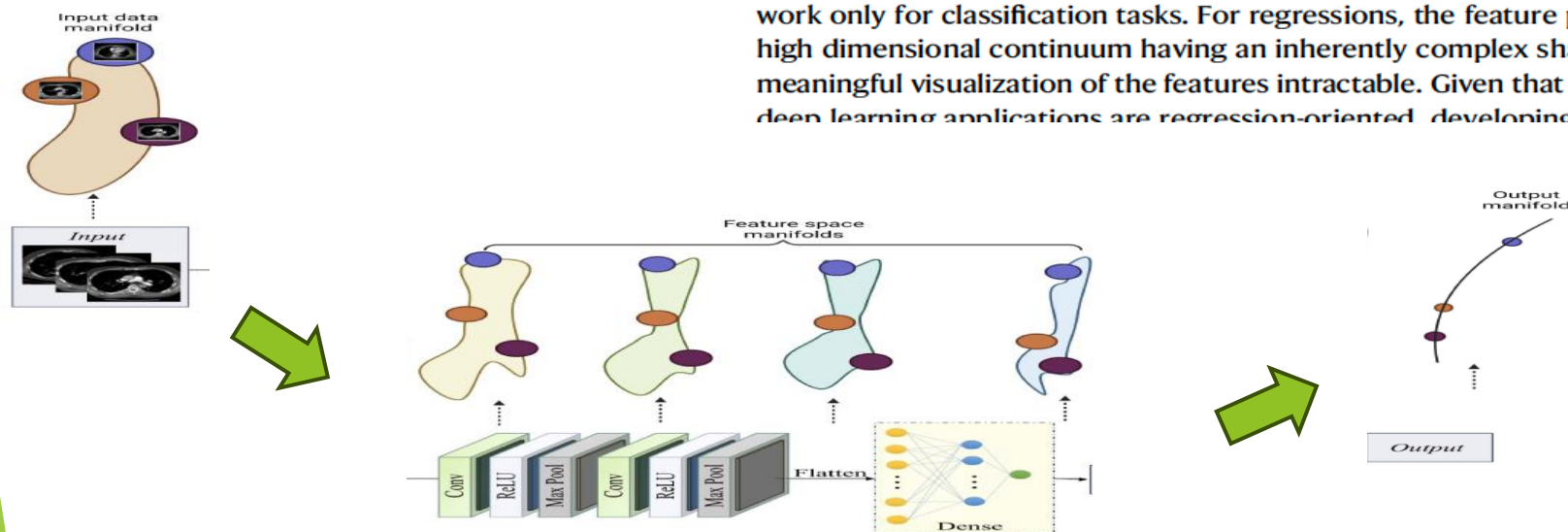
Accepted: 24 November 2023

Published online: 21 December 2023

 Check for updates

Md Tauhidul Islam ^{1,4}, Zixia Zhou ^{1,4}, Hongyi Ren¹, Masoud Badiei Khuzani¹, Daniel Kapp¹, James Zou ², Lu Tian², Joseph C. Liao ³✉ & Lei Xing ¹✉

Deep neural networks (DNNs) extract thousands to millions of task-specific features during model training for inference and decision-making. While visualizing these features is critical for comprehending the learning process and improving the performance of the DNNs, existing visualization techniques work only for classification tasks. For regressions, the feature points lie on a high dimensional continuum having an inherently complex shape, making a meaningful visualization of the features intractable. Given that the majority of deep learning applications are regression-oriented, developing a conceptual



AI for precision healthcare

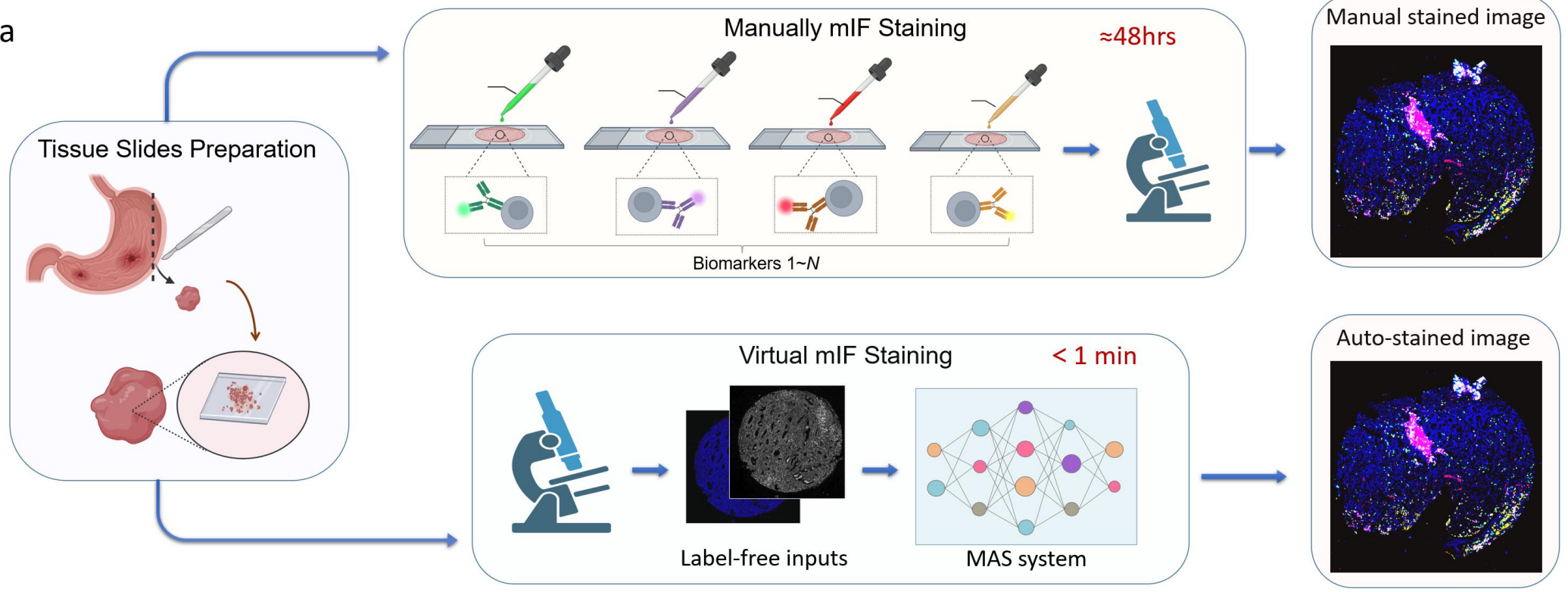


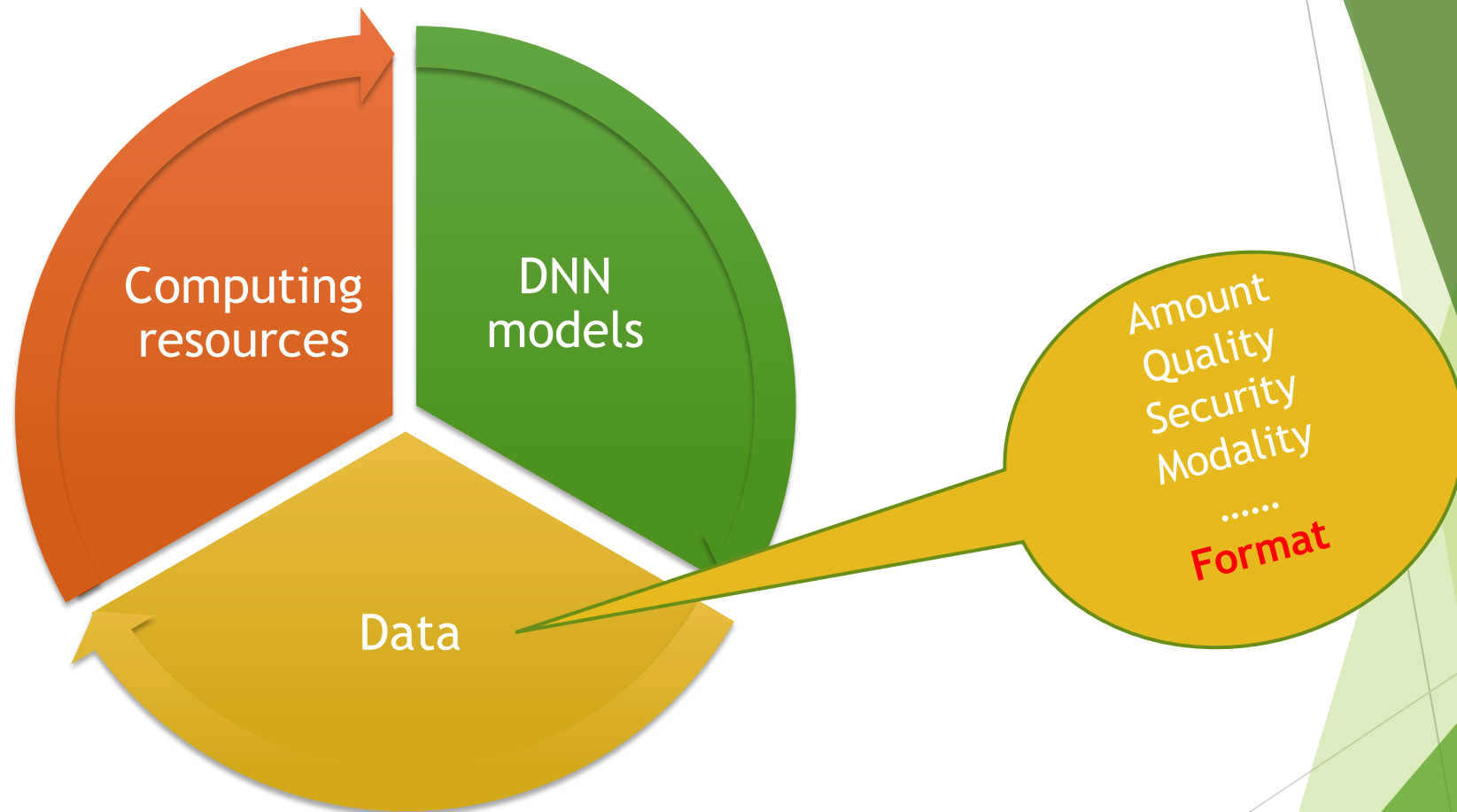
- Denoising image & superresolution imaging
 - Data modality conversion & pattern discovery
 - Clinical decision-making & patient stratification
 - Therapeutic response

AI for virtual staining



a





Data are presented in diverse formats

Image, video, & audio

- Image analysis
- Different modalities

Table

- omics
- Multi-omics
- Sensory data
- Clinical trials

Language

- Different languages
- Specialties

Graph

- Bio-network
- Social network
- Pathology data
- Functional maps
- Spatial transcriptomics

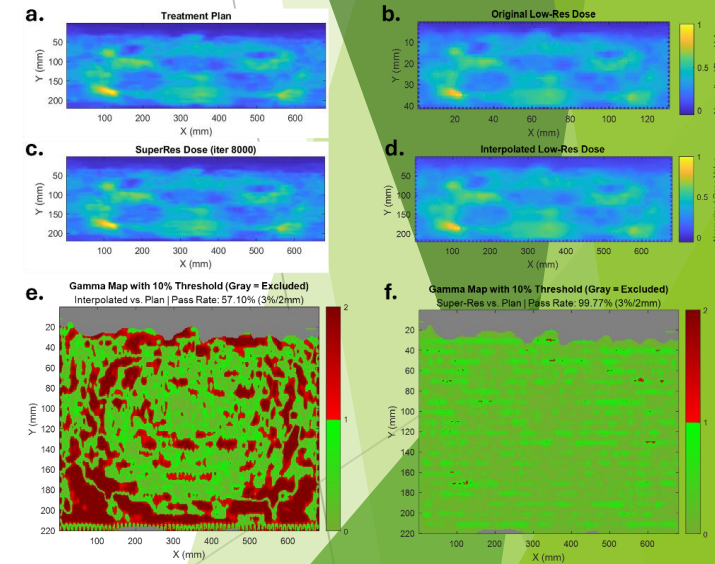
Imaging/video

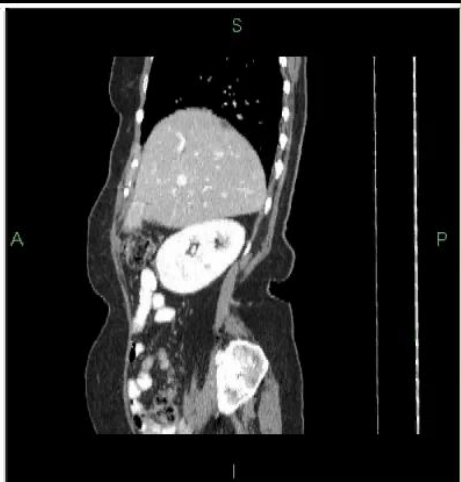
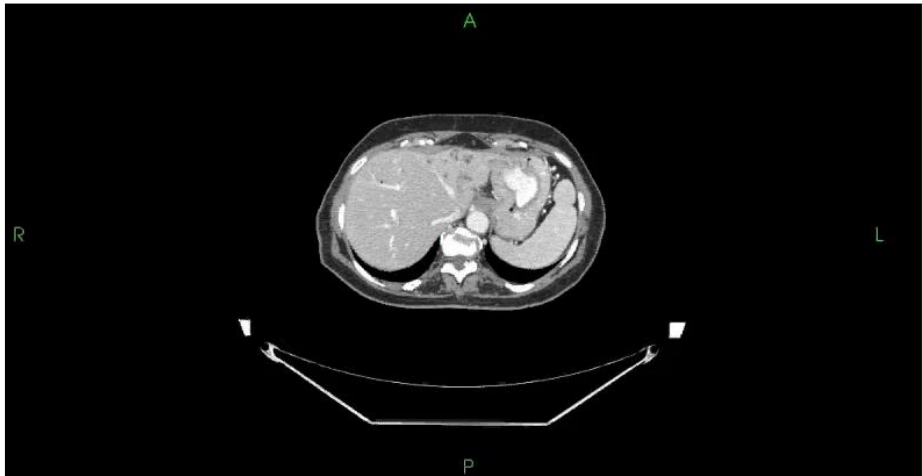
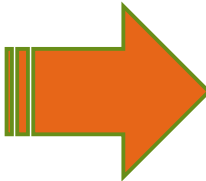
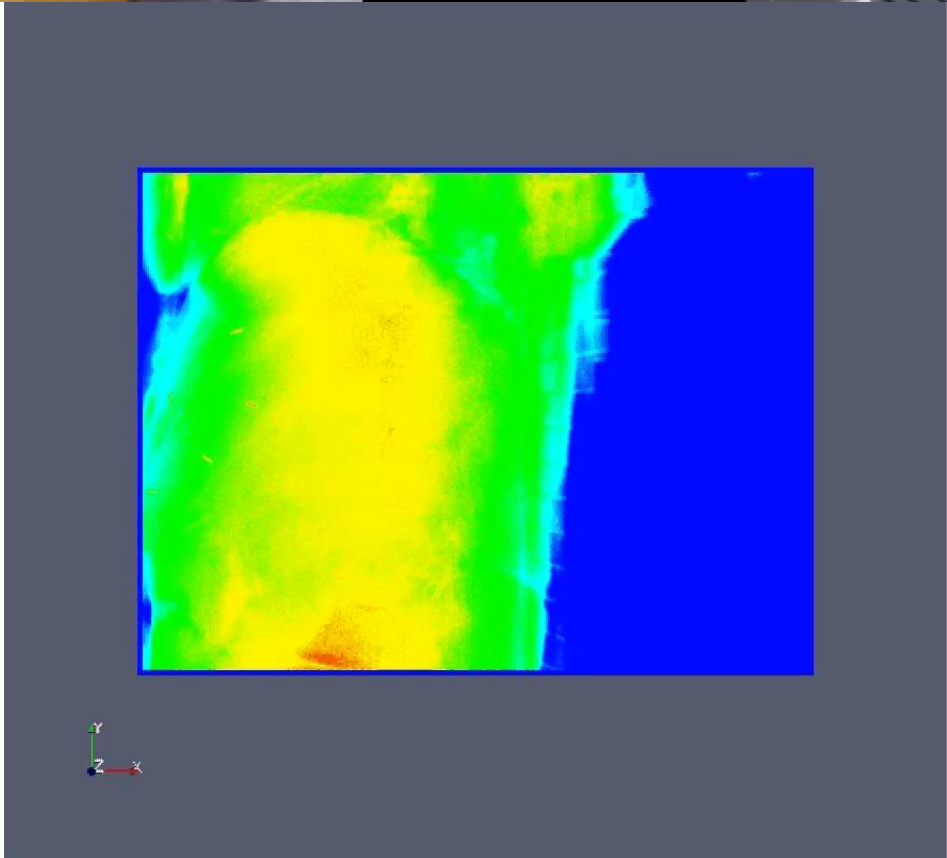
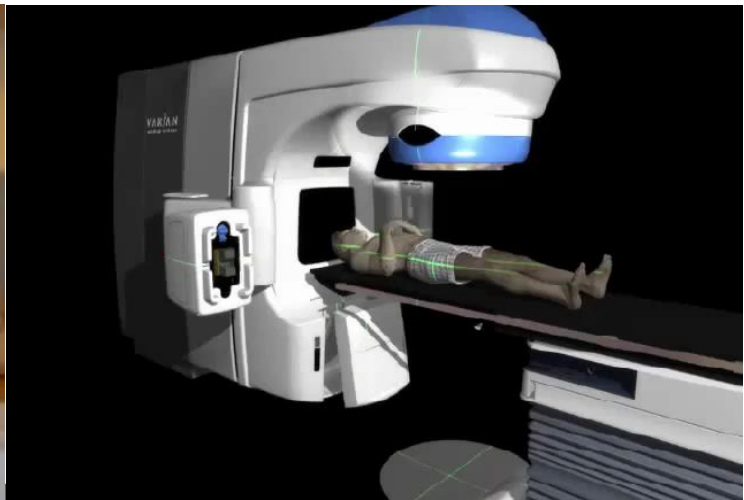
Image, video,
& audio

- Different imaging modalities

Image analysis & synthesis
(e.g. denoising, superresolution
imaging, & generative models)

Image reconstruction





SPARSE-DATA IMAGING

Dispatch Date: 09.10.2019 · Proof No: 466, p. 1

nature
biomedical engineering

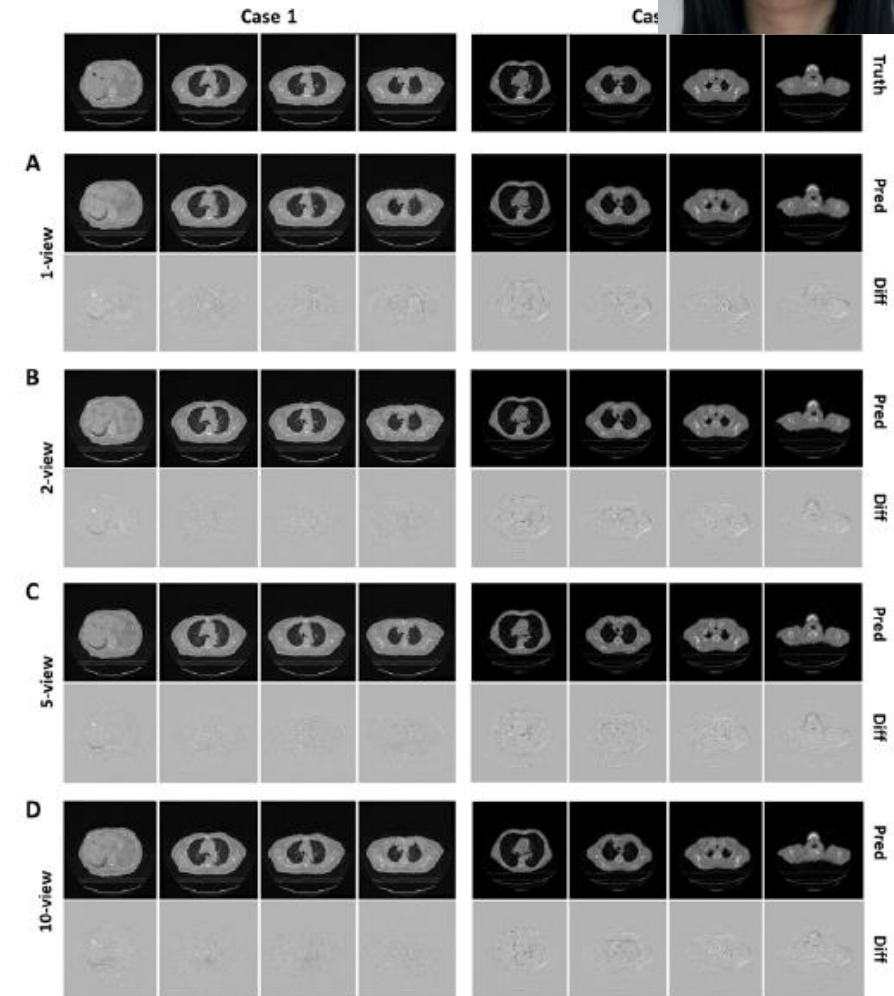
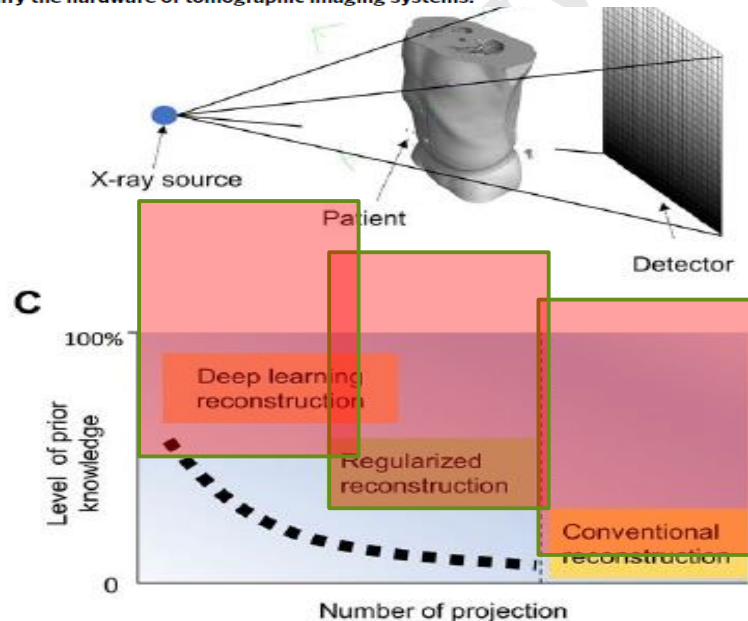
ARTICLES

<https://doi.org/10.1038/s41551-019-0466-4>

Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning

Liyue Shen^{1,2,3}, Wei Zhao^{1,3} and Lei Xing^{1,2*}

Tomographic imaging using penetrating waves generates cross-sectional views of the internal anatomy of a living subject. For artefact-free volumetric imaging, projection views from a large number of angular positions are required. Here we show that a deep-learning model trained to map projection radiographs of a patient to the corresponding 3D anatomy can subsequently generate volumetric tomographic X-ray images of the patient from a single projection view. We demonstrate the feasibility of the approach with upper-abdomen, lung, and head-and-neck computed tomography scans from three patients. Volumetric reconstruction via deep learning could be useful in image-guided interventional procedures such as radiation therapy and needle biopsy, and might help simplify the hardware of tomographic imaging systems.

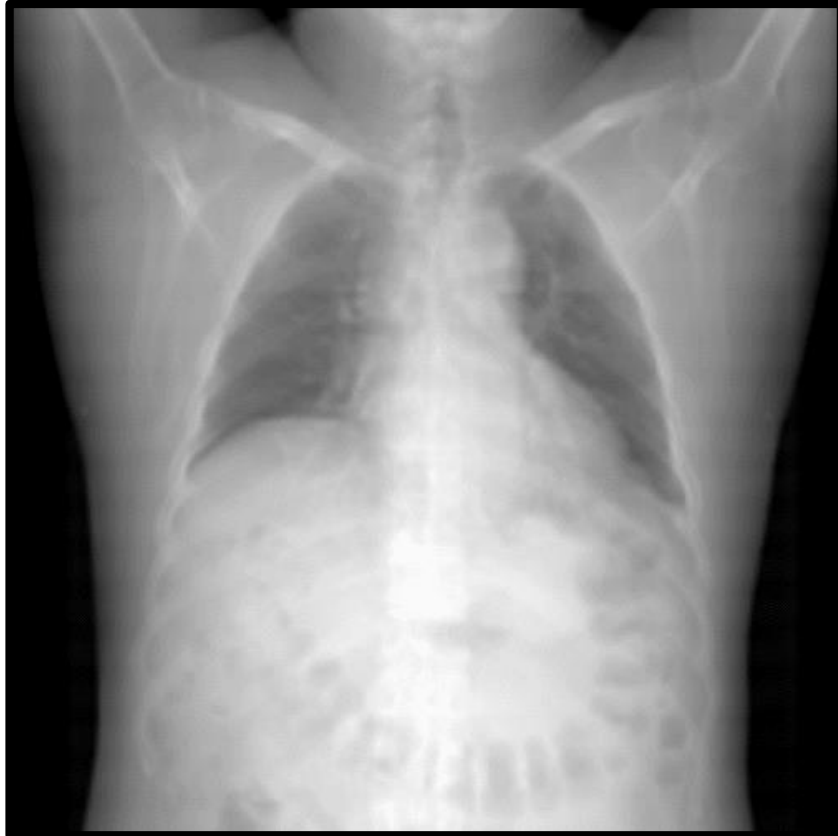


Shen L, Zhao W, Xing L, Nature Biomedical Engineering 3, 880-888, 2019

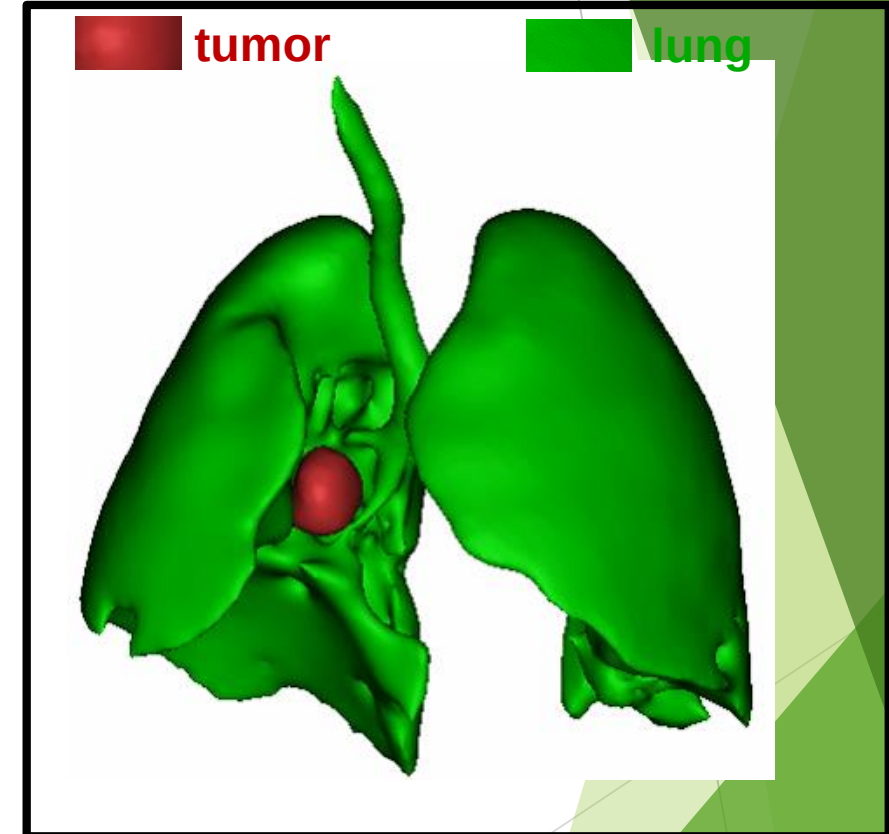


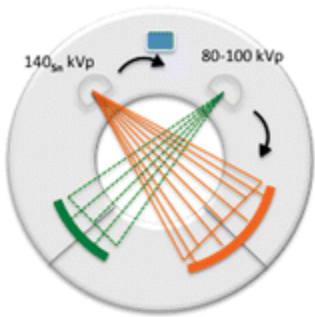
Real-Time Volumetric Image Guidance From A Single Projection View

Input 2D Projection



Output Volume Image + 3D Contours



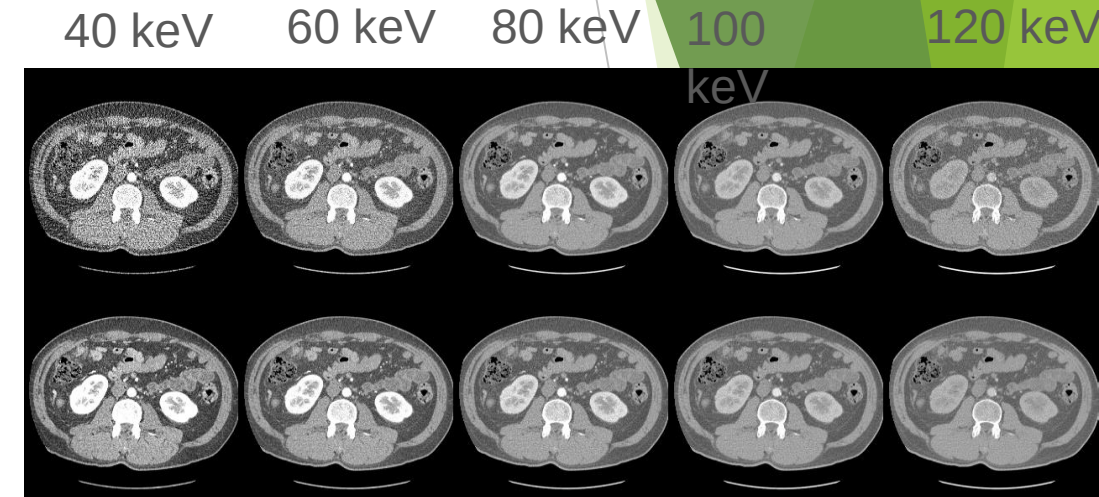
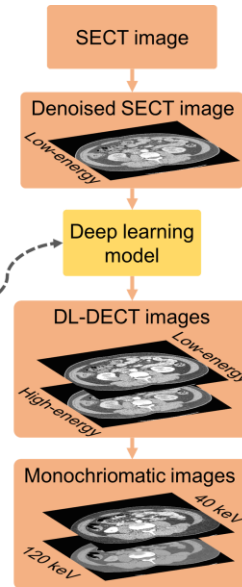
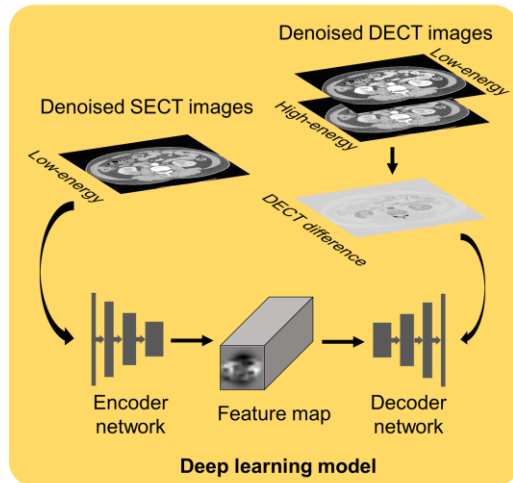
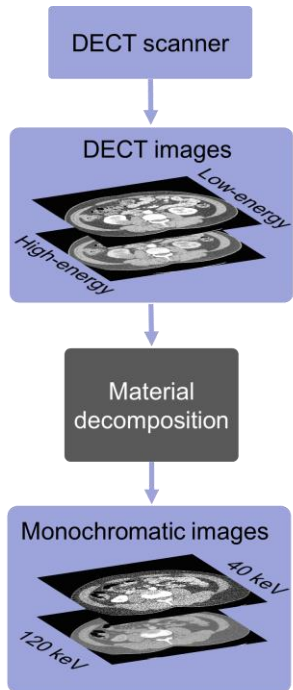


Dual source DECT
(Somatom Definition Flash and Force;
Siemens Medical Solutions, Forchheim,
Germany)

Dual energy & spectral CT imaging



Using a single energy scanner to obtain DE CT



T Lyu, W Zhao, et al, Estimating dual-energy CT imaging from single-energy CT data with material decomposition convolutional neural network, *Medical Image Analysis* 70, 2021

- Metal artifacts corrections
- Scatter removal
-

MEDICAL PHYSICS

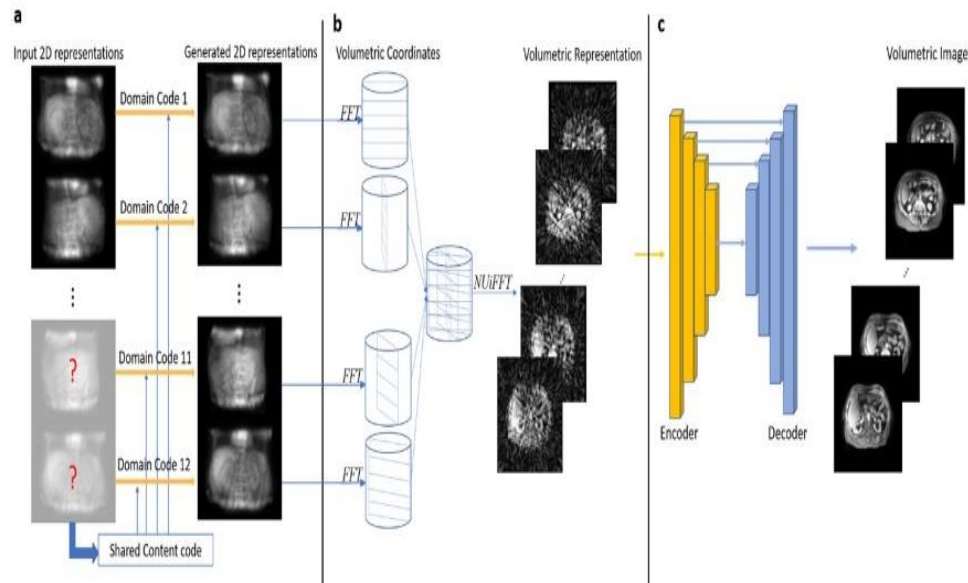
The International Journal of Medical Physics Research and Practice

RESEARCH ARTICLE

Real time volumetric MRI for 3D motion tracking via geometry-informed deep learning

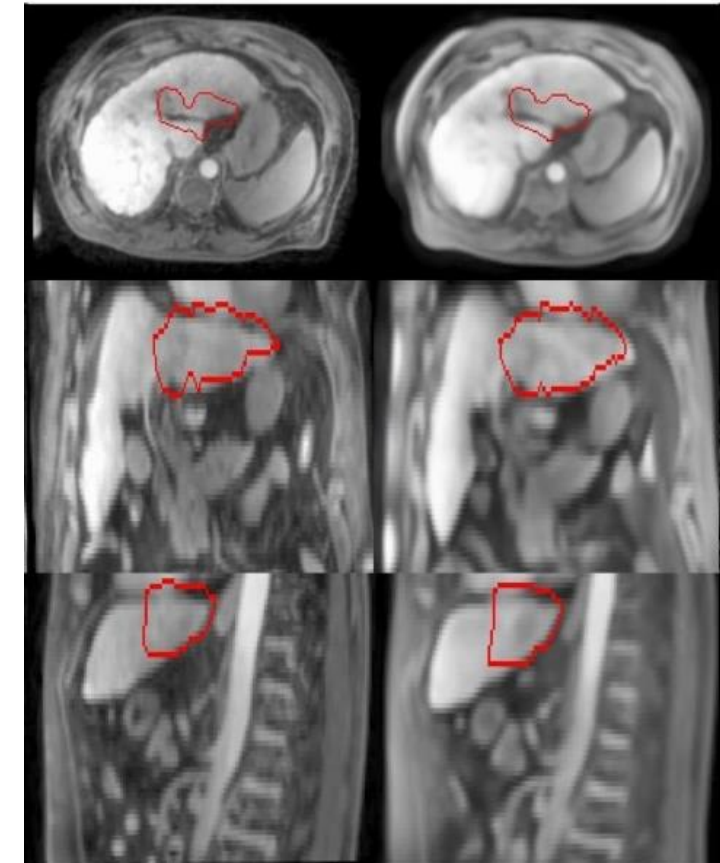
Lianli Liu ✉, Liyue Shen, Adam Johansson, James M. Balter, Yue Cao, Daniel Chang, Lei Xing

First published: 29 June 2022 | <https://doi.org/10.1002/mp.15822>



Testing 1

Prediction 1



3D DOSIMETRY WITH 2D MEASUREMENT

MEDICAL PHYSICS

The International Journal of Medical Physics Research and Practice



Volume 48, Issue 11

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Pages 6810-6819



RESEARCH ARTICLE

Deep learning-enabled EPID-based 3D dosimetry for dose verification of step-and-shoot radiotherapy

Mengyu Jia, Yan Wu, Yong Yang, Lei Wang, Cynthia Chuang, Bin Han, Lei Xing

First published: 14 September 2021 | <https://doi.org/10.1002/mp.15218>



Related

Recommen

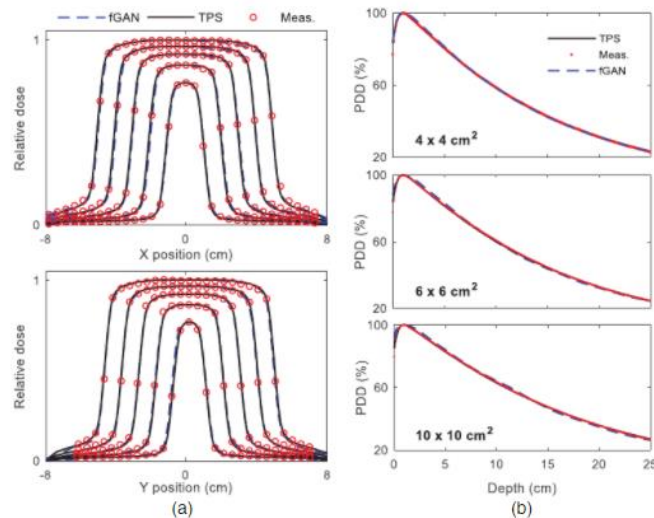


FIGURE 5 (a) Dose profiles along X and Y directions at 10 cm depth produced by reconstruction, treatment planning system (TPS), and measurement for field sizes of $2 \times 2 \text{ cm}^2$, $4 \times 4 \text{ cm}^2$, $6 \times 6 \text{ cm}^2$, $8 \times 8 \text{ cm}^2$ and $10 \times 10 \text{ cm}^2$. Normalization of the dose to $10 \times 10 \text{ cm}^2$ field was used. (b) Percentage depth dose (PDD) comparisons for field sizes of $4 \times 4 \text{ cm}^2$, $6 \times 6 \text{ cm}^2$, and $10 \times 10 \text{ cm}^2$

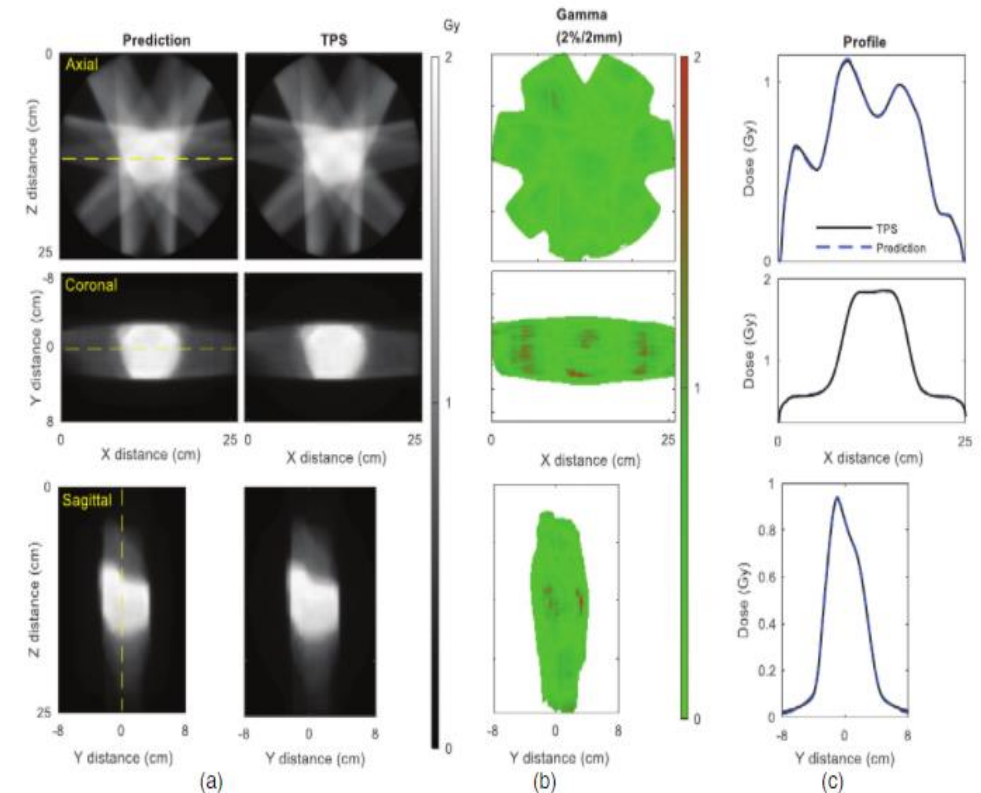


FIGURE 6 (a) Axial, coronal and sagittal views of 3D cumulative dose distributions of prostate intensity-modulated radiation therapy (IMRT) calculated by the treatment planning system (TPS), and reconstructed from electronic portal imaging device (EPID). (b) Different views of 3D gamma values between the two dose distributions. (c) Dose profiles along the yellow dashed lines in (a)

Modeling linear accelerator (Linac) beam data by implicit neural representation learning for commissioning and quality assurance applications

Lianli Liu¹ | Liyue Shen² | Yong Yang¹ | Emil Schüller¹ | Wei Zhao¹ | Gordon Watson² | Lei Xiao^{1,2}

LINAC BEAM MODELING USING NERF

MEDICAL PHYSICS

3142

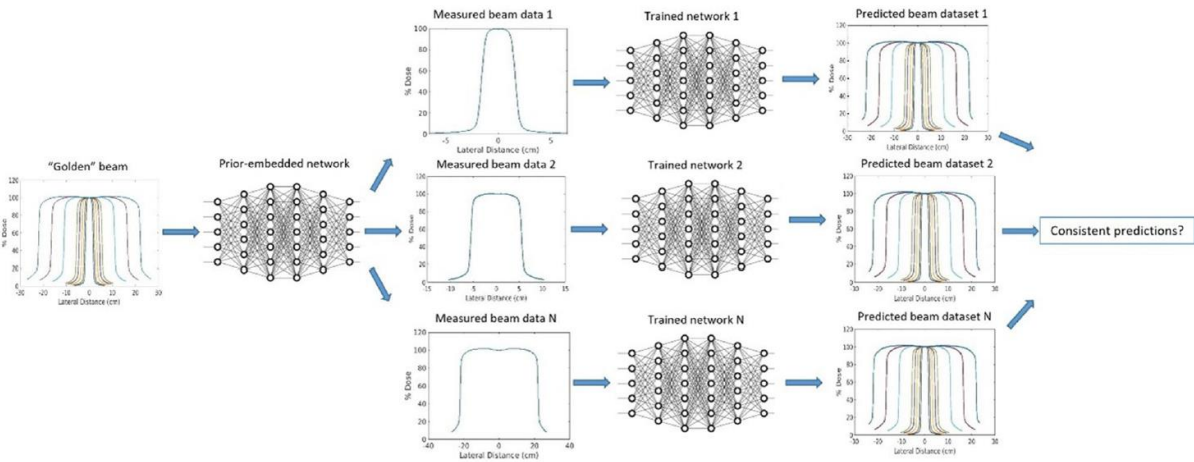


FIGURE 2 Workflow of our model-based “self-consistency” check of beam datasets. The prior-embedded network trained using the “golden” beam was further trained to fit each of the measured beam data samples. Consistency across beam datasets predicted by different networks is used as an indicator of the consistency across the measured beam data samples

Identifying the source of discrepancy may be challenging and require clinical experience. Instead of evaluating the consistency between the acquired beam data and the “golden” beam data, we evaluated whether the beam data samples were acquired consistently (e.g., consistent collimator settings and measurement depth) with each other using the proposed beam model. By evaluating such “self-consistency” of a beam dataset, data samples that were collected with mistakes can be

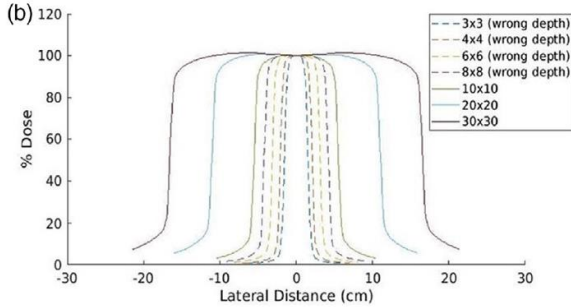
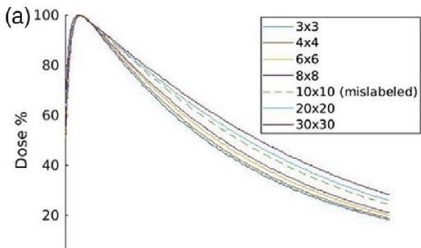


FIGURE 3 Beam datasets that contain erroneous data samples. (a) 6 MV PDD dataset where PDD at 10 × 10 cm² was collected with a collimator setting of 15 × 15 cm². (b) 6 MV beam profile dataset

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LINAC BEAM MODELING

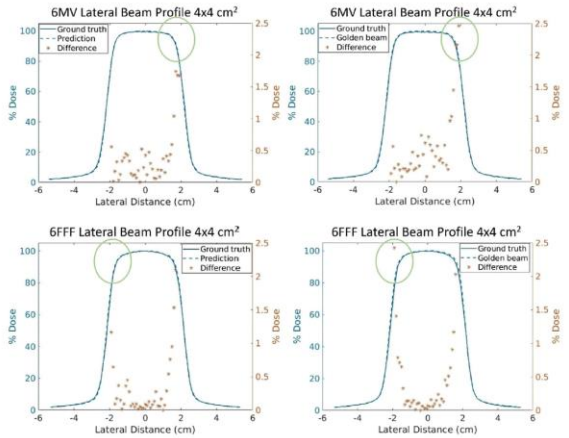


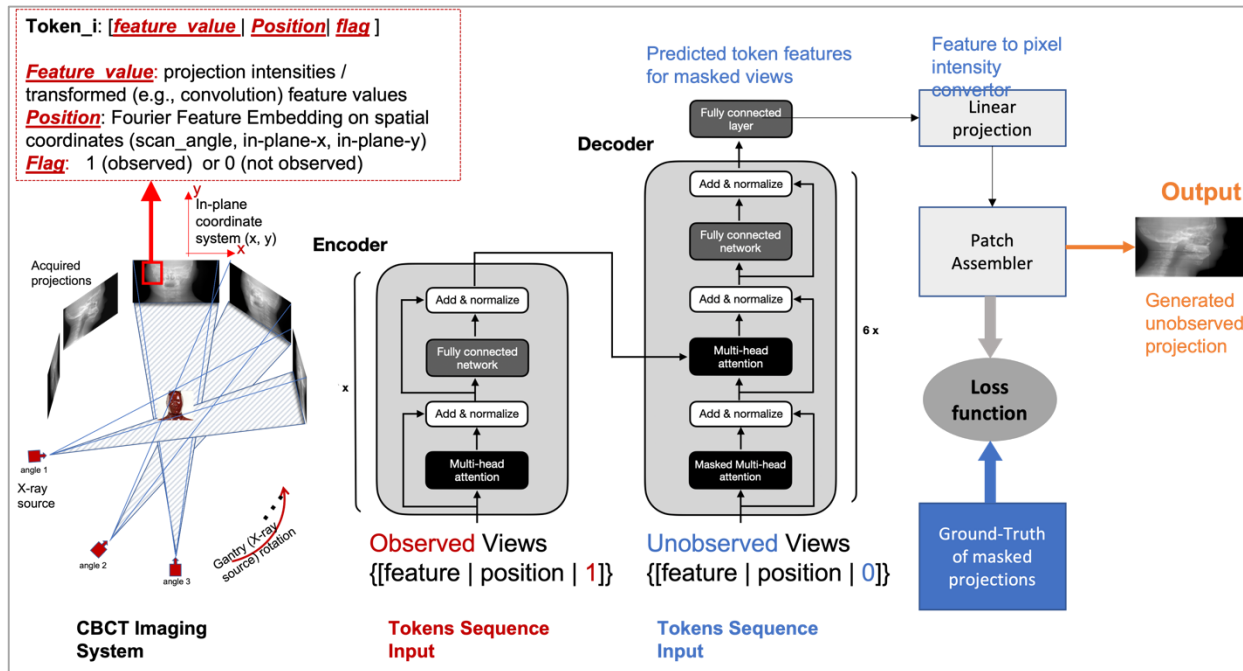
FIGURE 4 Example beam profile predictions for 6 MV and 6 FFF beam at 4 × 4 cm² field size. Improved consistency with the ground truth water tank measurements was observed by fitting the prior-embedded network to sparse beam measurement instead of using the “golden” beam data directly, as indicated by the green circles

measuring beam profiles with inconsistent setups, we generated a beam profile dataset that consists of small field (less than 10 × 10 cm²) beam profiles collected

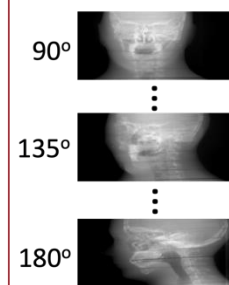
ties, the network-predicted beam data showed improved consistency with the water tank measurements, as comparing to the “golden” beam dataset. Table 1 sum-



PHYSICS-INFORMED FOUNDATION MODEL FOR IMAGE RECONSTRUCTION

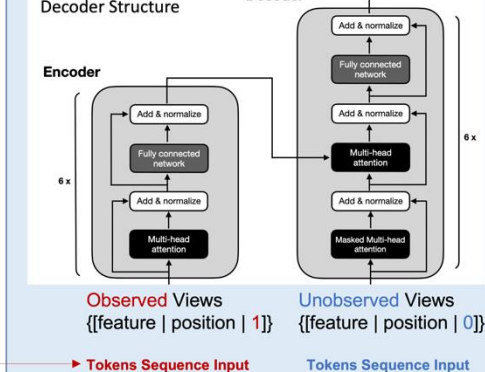


Input: acquired limited-angle scan projections

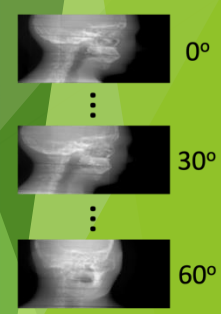


Transformer-based View Generation Core

Transformer Encoder-Decoder Structure



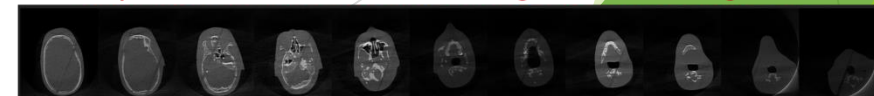
Generated missing projections



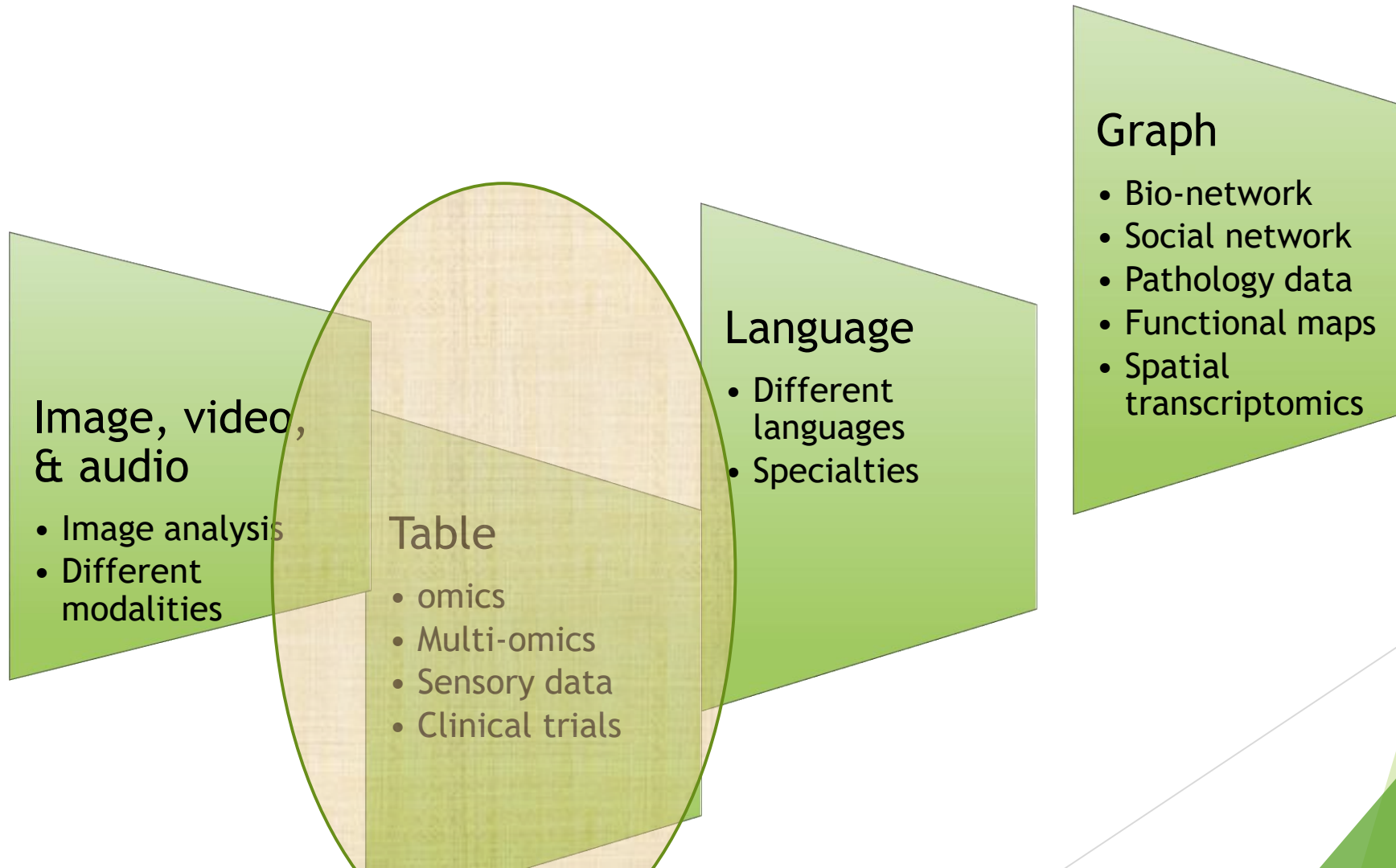
Projection Assembler

Full-view-based Reconstruction Engine (e.g., FBP)

Output: Reconstructed volumetric CT image under limited-angle scan

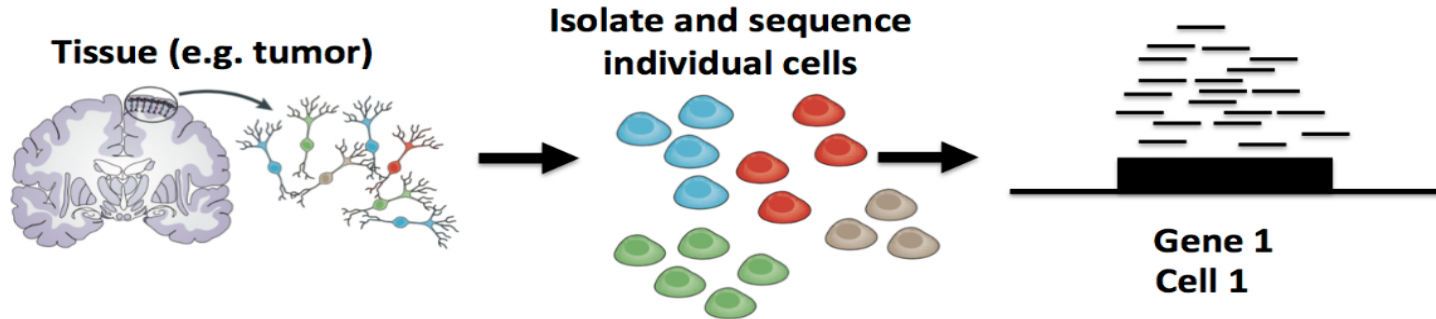


Data are presented in diverse formats



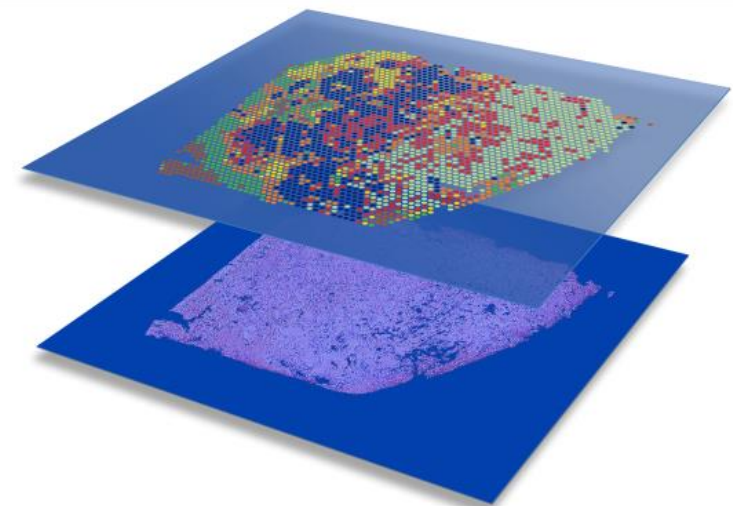
AI FOR OMICS DATA PROCESSING

Single-cell RNA-Seq (scRNA-Seq)



Genes	Cell A	Cell B	Cell C	Cell D
Gene1	50	200	150	80
Gene2	10	5	80	120
Gene3	300	100	50	400
Gene4	200	180	150	250
Gene5	500	520	510	495

<https://speakerdeck.com/stephaniehicks/welcome-to-the-world-of-single-cell-rna-sequencing?slide=3>



<https://www.scdiscoveries.com/blog/knowledge/spatial>

Interpretable discovery of patterns in tabular data via spatially semantic topographic maps

Received: 15 March 2023

Accepted: 23 September 2024

Published online: 15 October 2024

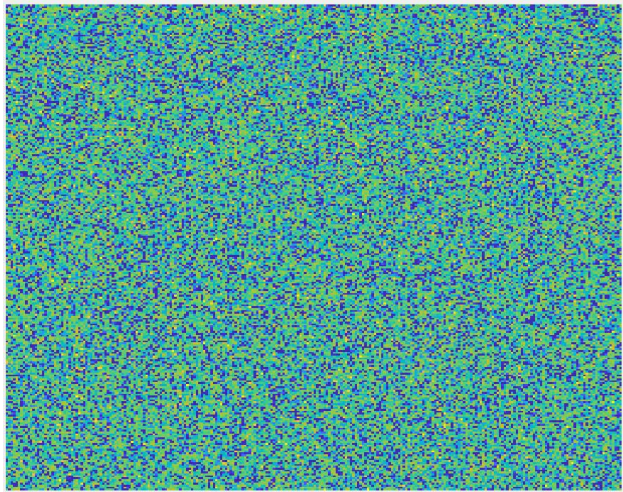
 Check for updates

Rui Yan^{1,4}, Md Tauhidul Islam^{2,4} & Lei Xing^{1,2,3}✉

	Gene 1	Gene 2	Gene 3		Gene N
Cell 1					
Cell 2					
Cell 3					
...					
...					
Cell M					

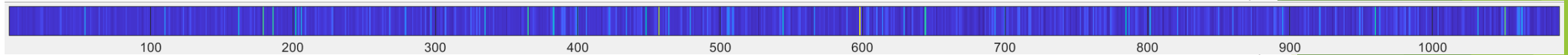


BIOLOGY- AND PHYSICS-INFORMED AI



We must better understand the data, the structure and interactions within the data, and their interactions with models to truly harness the AI foundation models

BIOLOGY-INFORMED AI FOR OMICS DATA PROCESSING



nature communications



Article

<https://doi.org/10.1038/s41467-023-36383-6>

Cartography of Genomic Interactions Enables Deep Analysis of Single-Cell Expression Data

Received: 19 August 2022

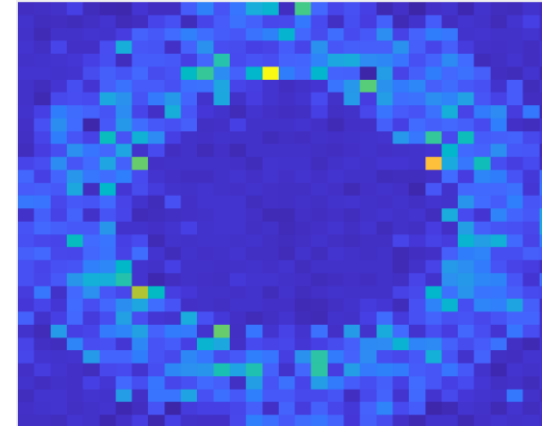
Accepted: 30 January 2023

Published online: 08 February 2023

Check for updates

Md Tauhidul Islam¹ & Lei Xing¹✉

Remarkable advances in single cell genomics have presented unique challenges and opportunities for interrogating a wealth of biomedical inquiries. High dimensional genomic data are inherently complex because of intertwined relationships among the genes. Existing methods, including emerging deep learning-based approaches, do not consider the underlying biological characteristics during data processing, which greatly compromises the performance of data analysis and hinders the maximal utilization of state-of-the-art genomic techniques. In this work, we develop an entropy-based cartography strategy to contrive the high dimensional gene expression data into a



<https://www.nature.com/articles/s41467-023-36383-6>



BIOLOGY-INFORMED AI FOR OMICS DATA PROCESSING

nature communications



Article

<https://doi.org/10.1038/s41467-023-36383-6>

Cartography of Genomic Interactions Enables Deep Analysis of Single-Cell Expression Data

Received: 19 August 2022

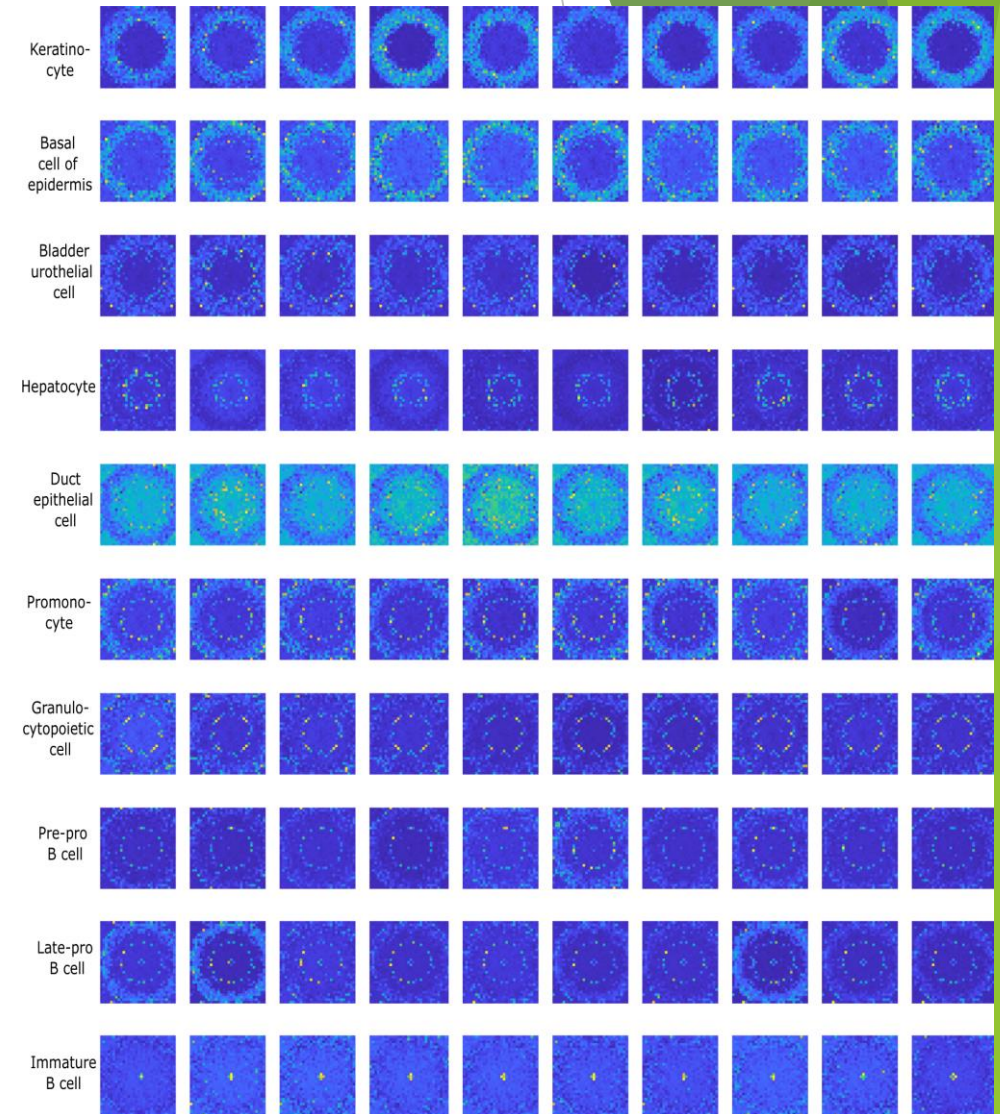
Accepted: 30 January 2023

Published online: 08 February 2023

Check for updates

Md Tauhidul Islam¹ & Lei Xing¹ ✉

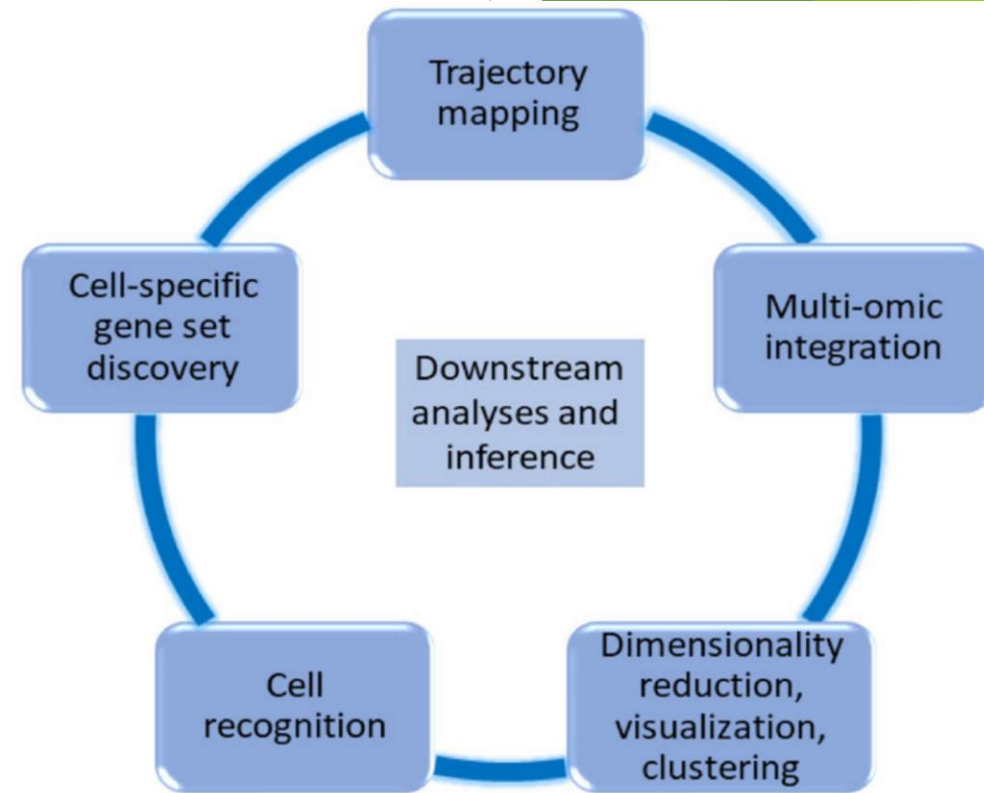
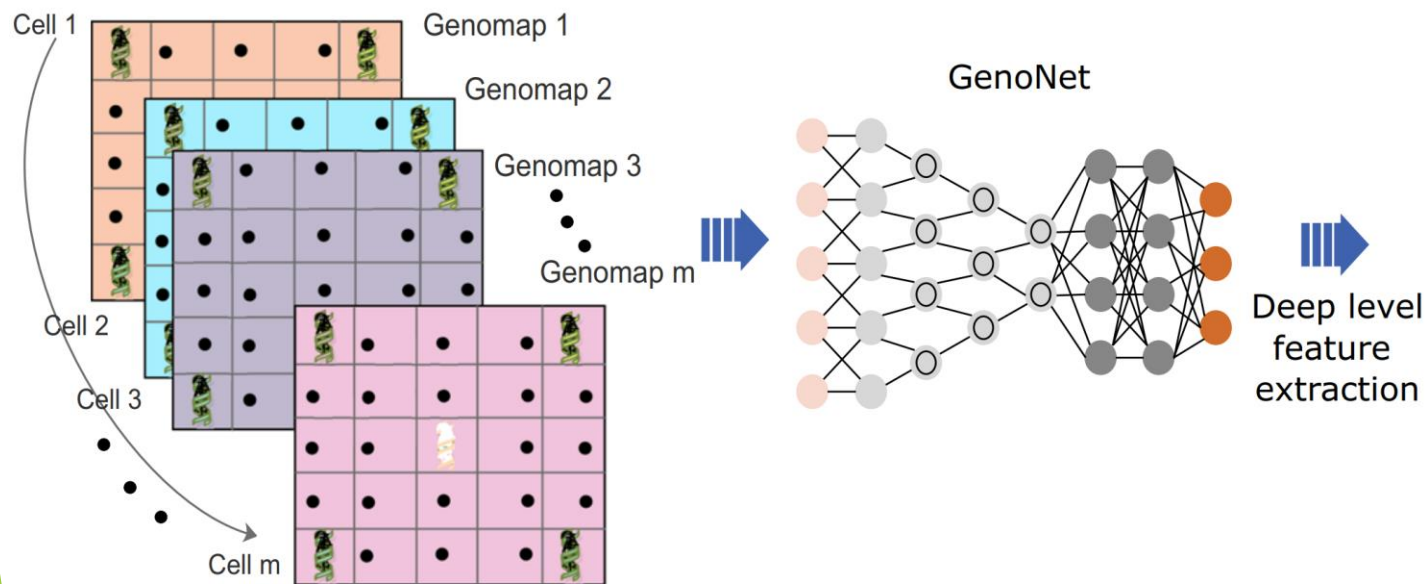
Remarkable advances in single cell genomics have presented unique challenges and opportunities for interrogating a wealth of biomedical inquiries. High dimensional genomic data are inherently complex because of intertwined relationships among the genes. Existing methods, including emerging deep learning-based approaches, do not consider the underlying biological characteristics during data processing, which greatly compromises the performance of data analysis and hinders the maximal utilization of state-of-the-art genomic techniques. In this work, we develop an entropy-based cartography strategy to contrive the high dimensional gene expression data into a



www.analyXus.com

Islam, M.T. and Xing, L., 2023. Nature Communications, 14, 679.

Applications of omics-to-image conversion in single-cell biology



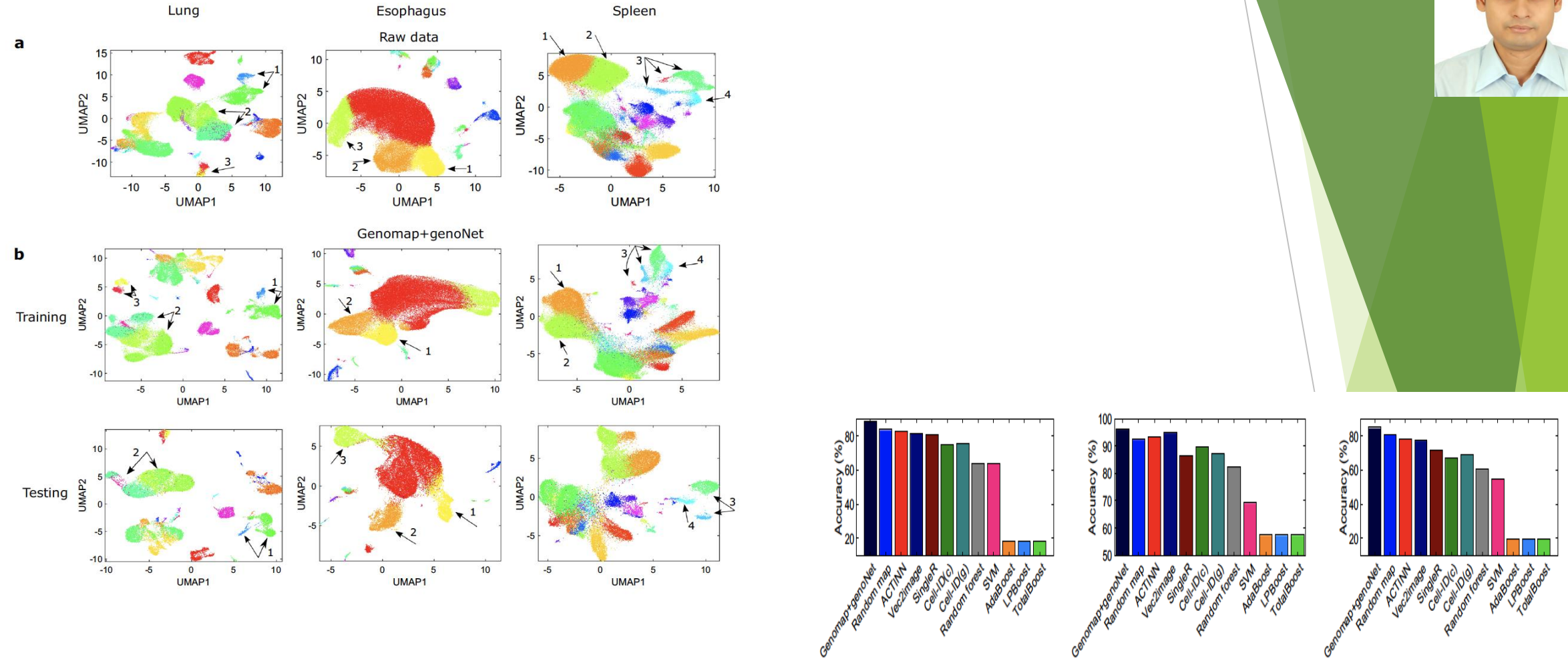


Fig. 4 | Visualization of ischaemic sensitivity dataset (left-lung, middle-esophagus, right-spleen). a UMAP visualizations of raw data. **b** UMAP visualizations of the genomap features at the fully connected layer of the genoNet. Major improvements in cluster separation are indicated by arrows. Color legends of the data classes are added in Supplementary Fig. S22. **c** Classification accuracy of different techniques including genomap+genoNet. Here, Cell-ID(c) and Cell-ID(g) denote Cell-ID technique with cell-to-cell and cell-to-group matching formulation. Source data are provided as a Source Data file.

<https://www.nature.com/articles/s41467-023-36383-6>

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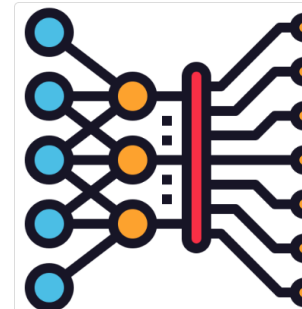
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Single Cell

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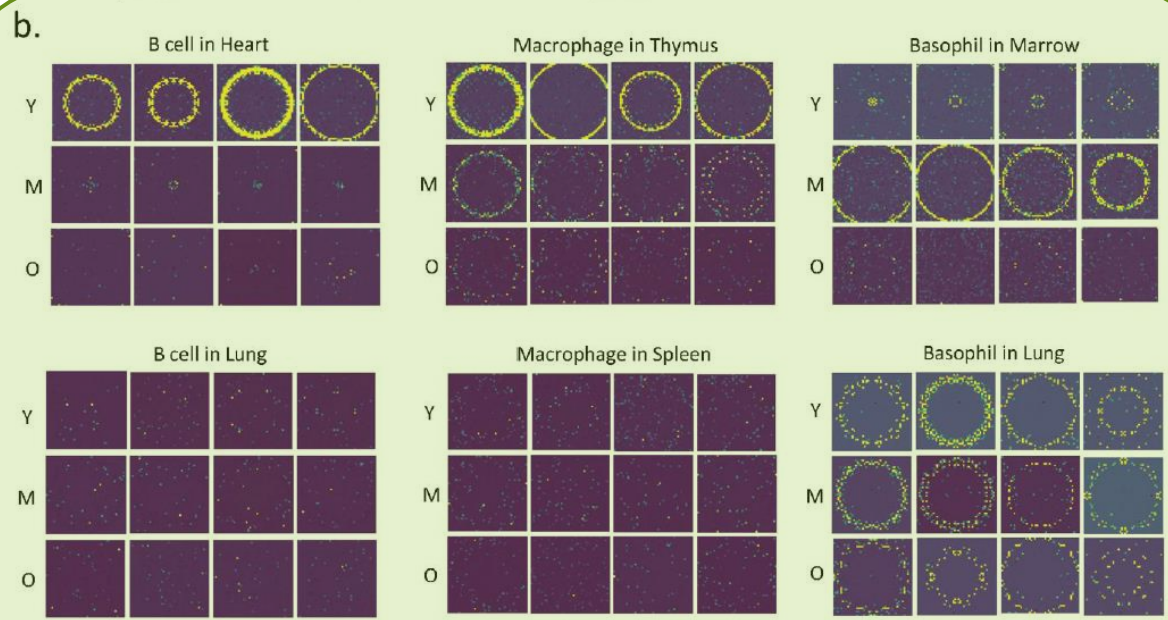
Deep Neural Network Features

Discover Tools

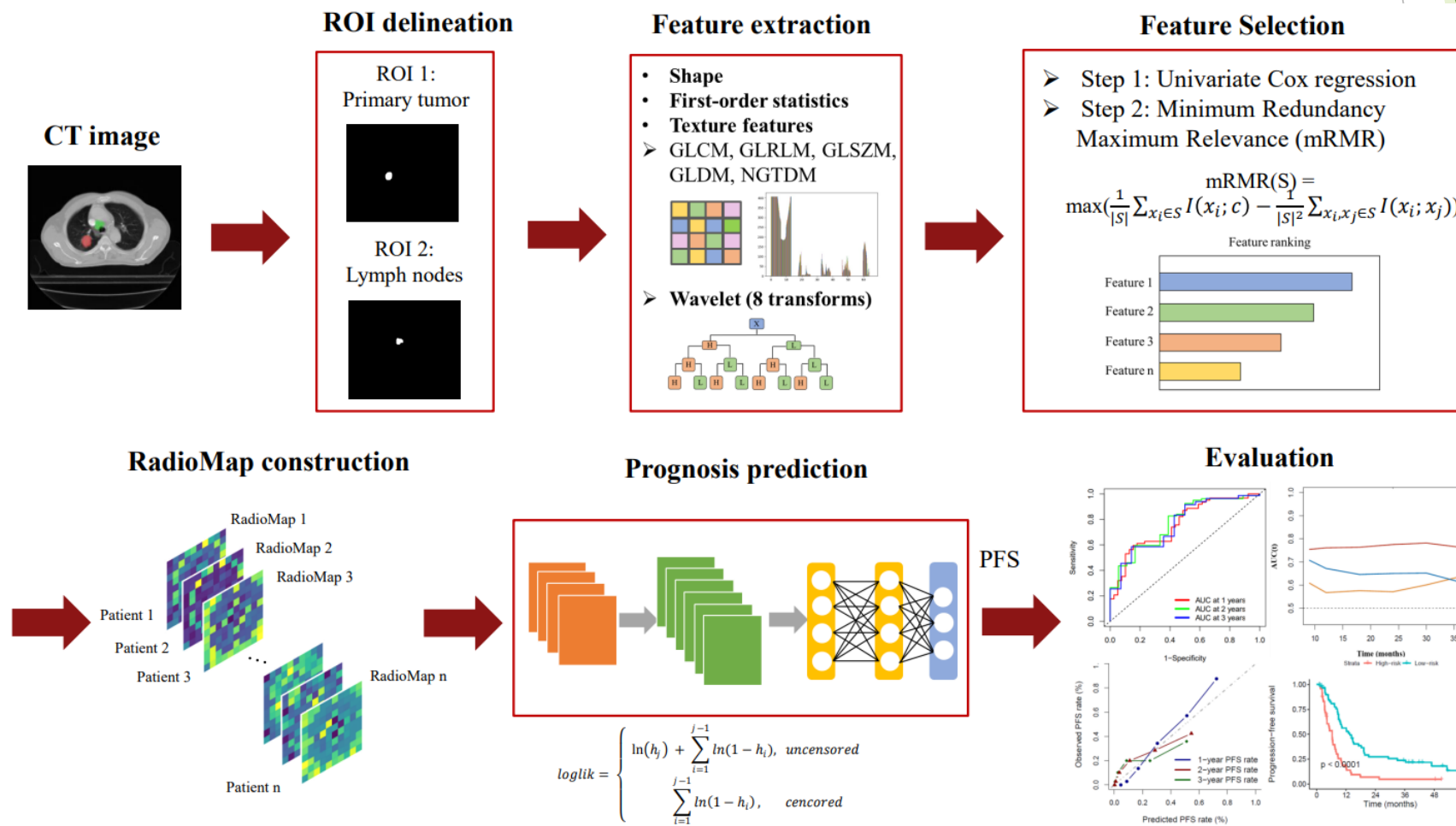


Tabular Data

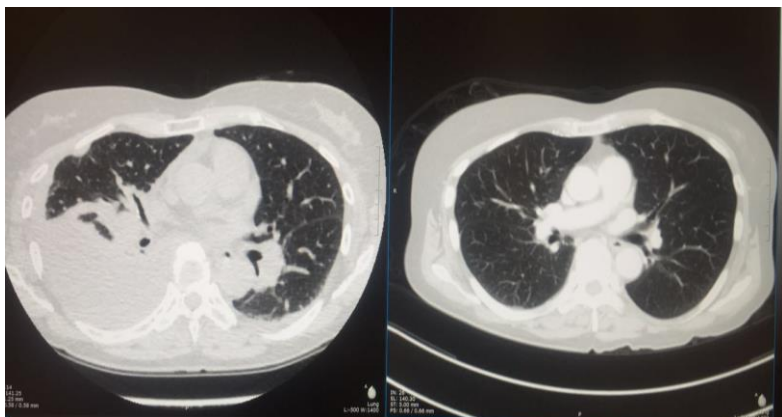
Discover Tools



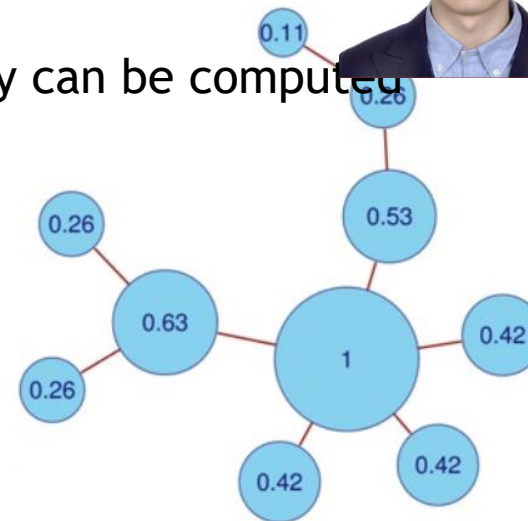
DATA PREPROCESSING FOR DEEP RADIOMICS



AI FOR INDIVIDUALIZED IMMUNOTHERAPY

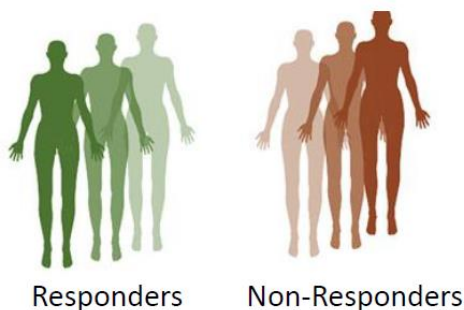
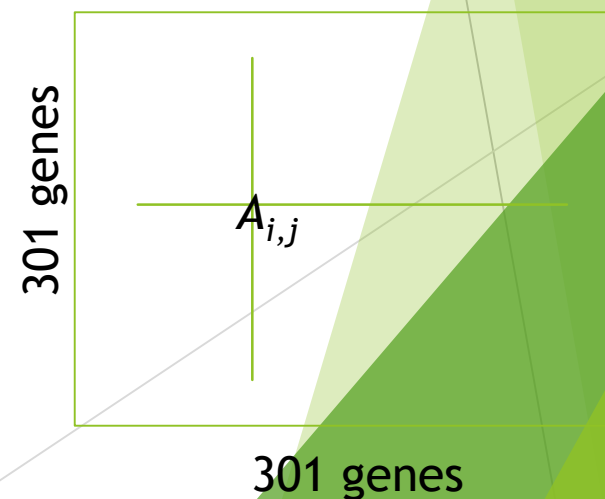


Node centrality can be computed from graph

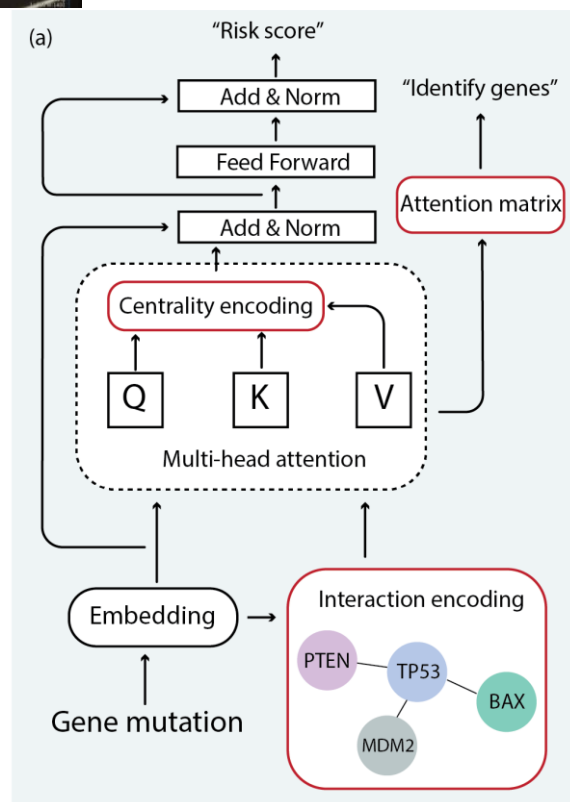


The attention matrix is then encoded as

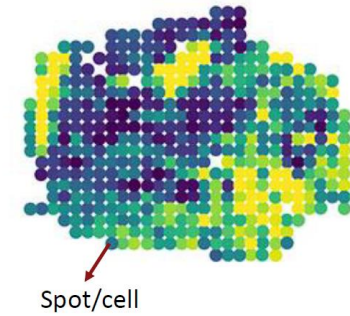
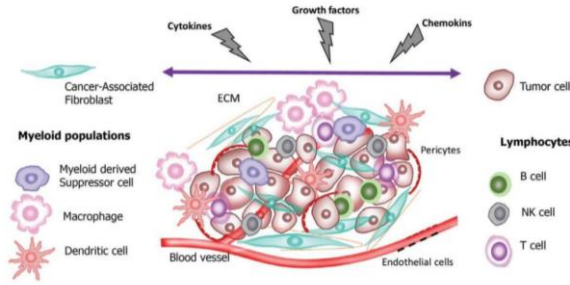
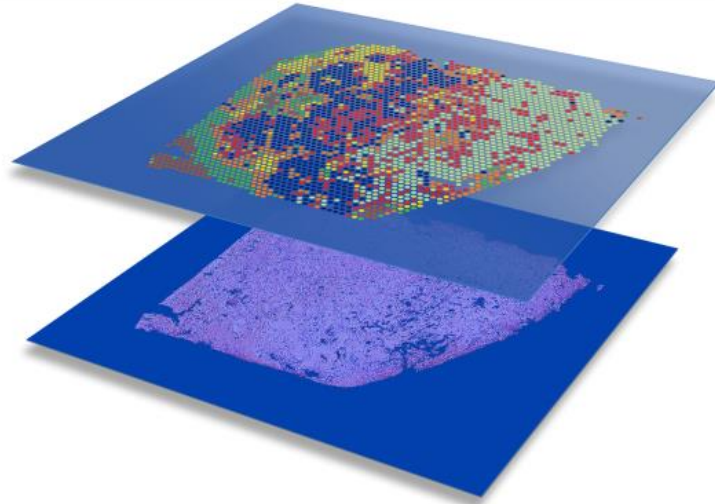
$$A_{i,j}^* = (\text{Centrality}(i) + \text{Centrality}(j)) / 2$$



njp: digital medicine 7, 117, 2023

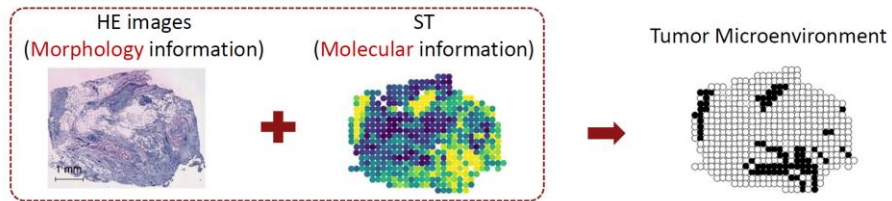


Spatial transcriptomics



<https://www.scdiscoveries.com/blog/knowledge/spatial-transcriptomics-5-key-applications/>

HE + ST integration

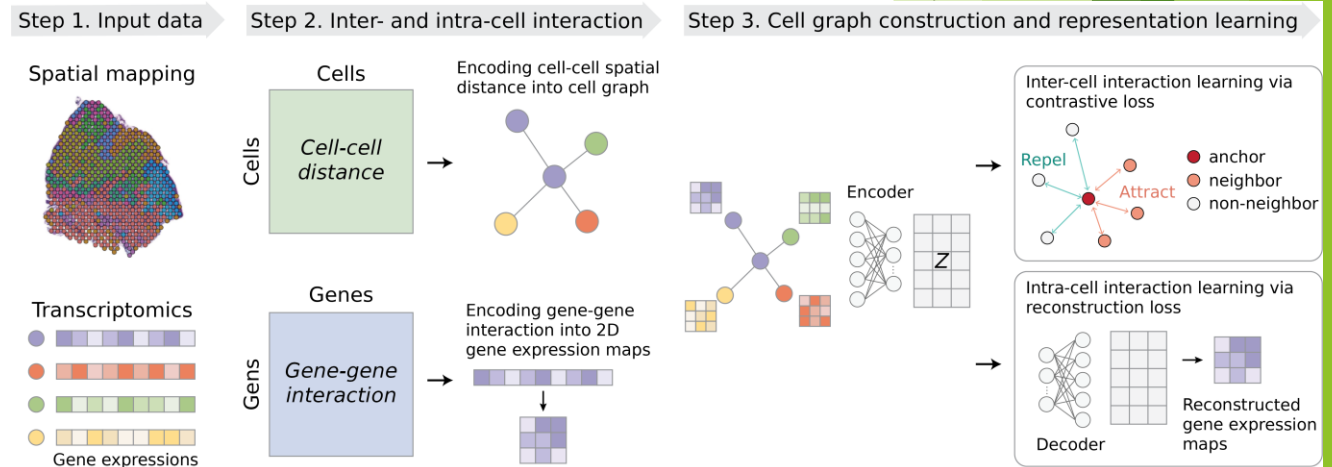


Spot-level Tasks (Biology):

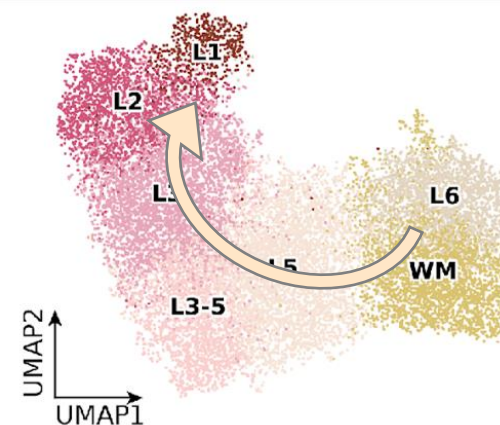
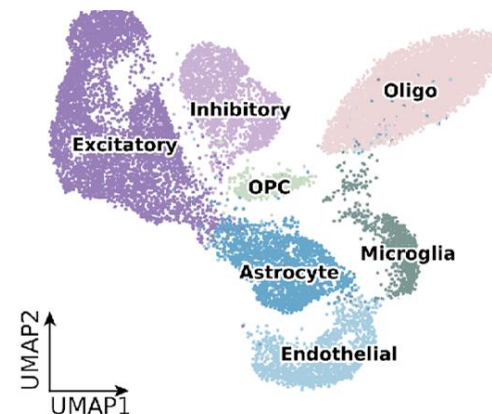
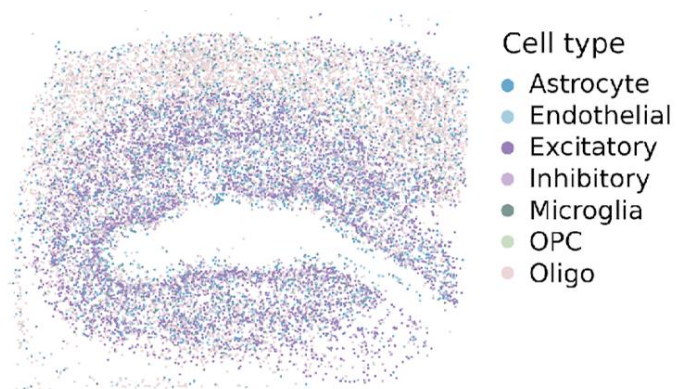
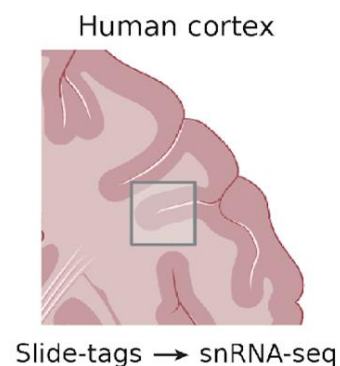
- Spatial domain detection.
- ST super-resolution.
- Cell type decomposition/deconvolution.
-

Patient-level Tasks (Clinical):

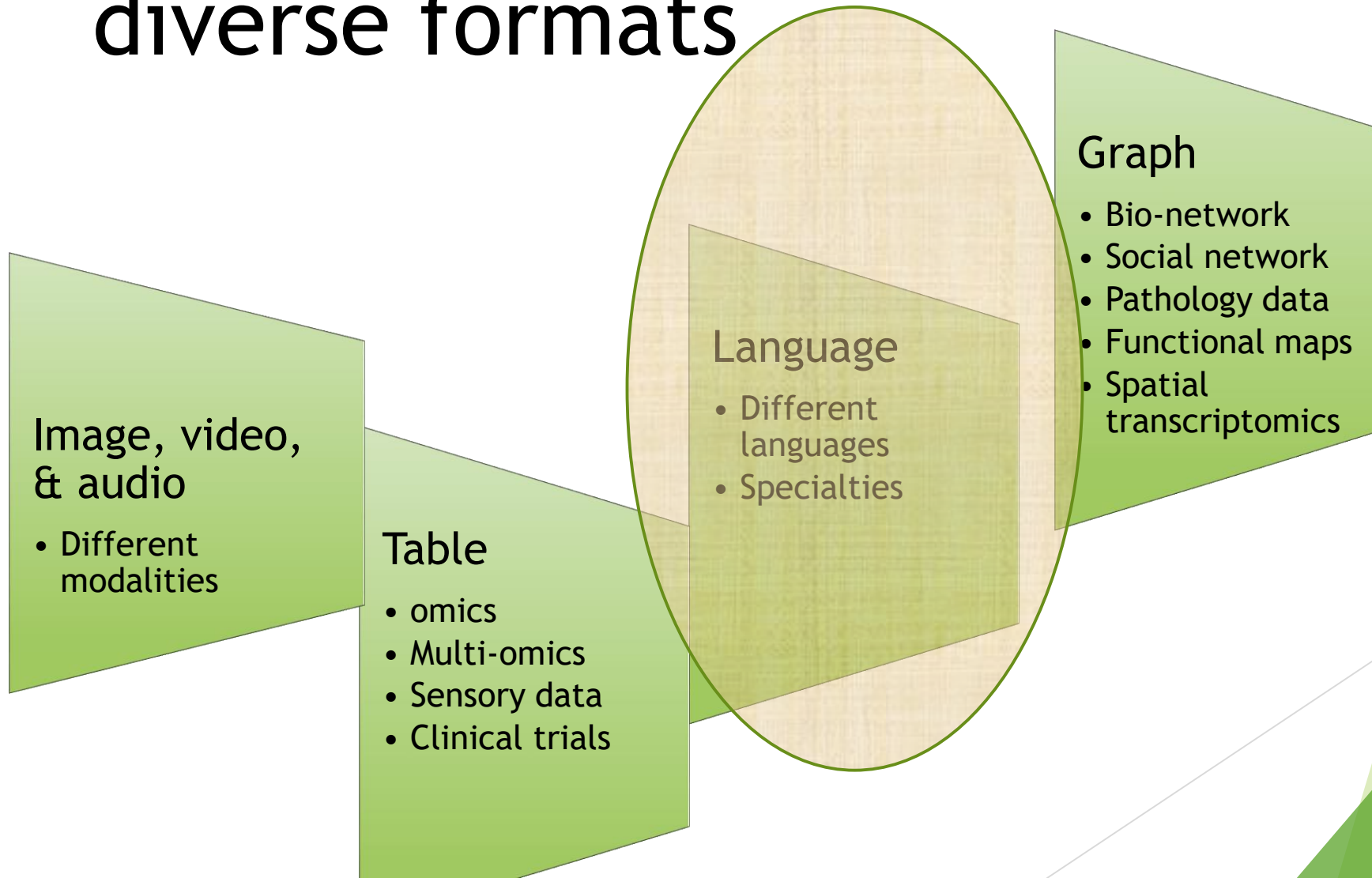
- Cancer subtyping.
- Gene mutation prediction.
- Response to immunotherapy.
-



Cell type and spatial domain identification



Data are presented in diverse formats



Automated radiotherapy treatment planning guided by GPT-4Vision

Sheng Liu^{1,2*}, Oscar Pastor-Serrano^{1*}, Yizheng Chen¹, Matthew Gopaulchan¹, Weixing Liang³, Mark Buyyounouski¹, Erqi Pollom¹, Quynh-Thu Le¹, Michael Gensheimer¹, Peng Dong¹, Yong Yang¹, James Zou^{2,3†}, and Lei Xing^{1†}

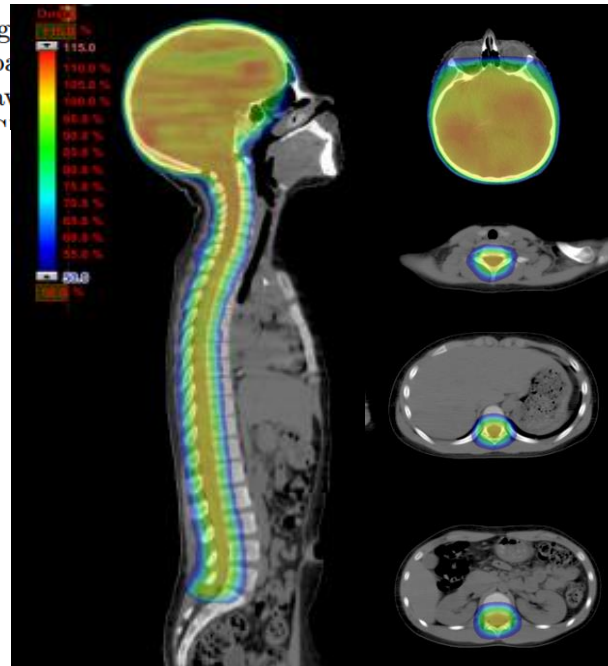
¹Department of Radiation Oncology, Stanford University, Stanford, CA, USA

²Department of Biomedical Data Science, Stanford University, Stanford, CA, USA

³Department of Computer Science, Stanford University, Stanford, CA, USA

Abstract

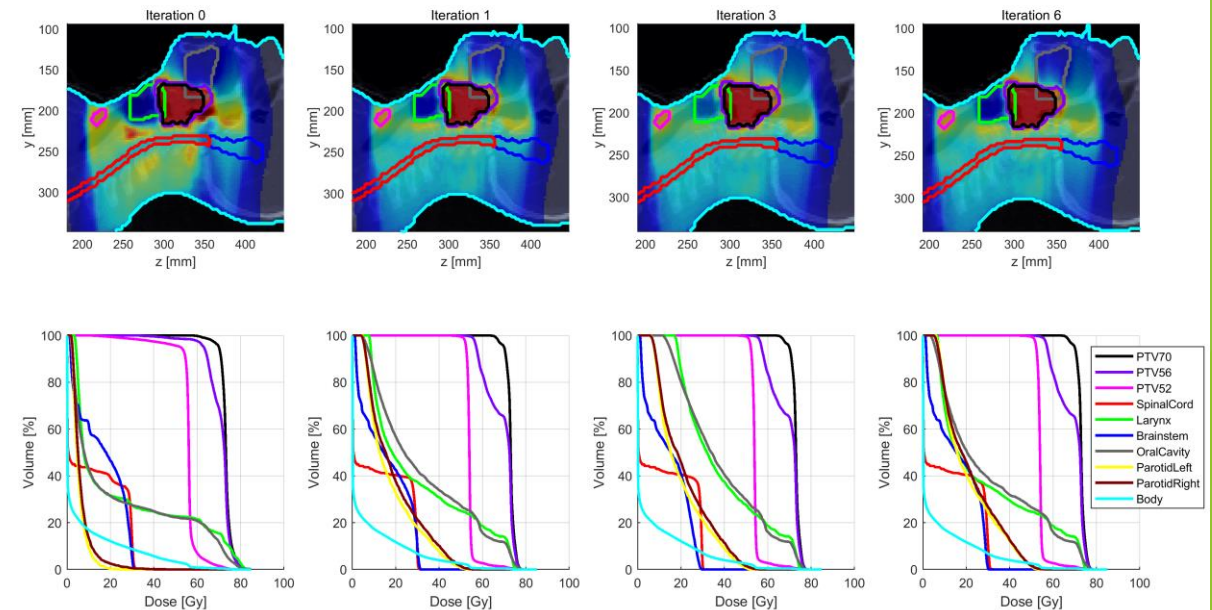
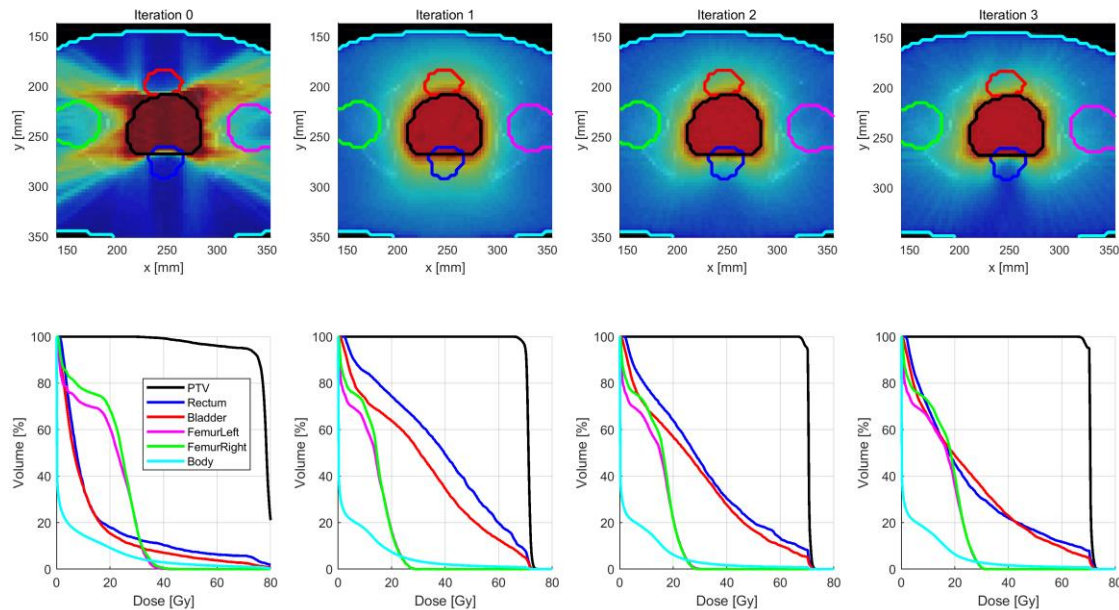
Radiotherapy treatment planning is a time-consuming process that involves the iterative adjustment of model parameters to balance tumor control and normal tissue toxicity. Recent advancements in frontier AI models offer promising avenues for automating and optimizing clinical decision-making. This study introduces GPT-4Vision, a large language model (LLM) with vision capabilities, for automated radiotherapy treatment planning. We demonstrate that GPT-4Vision can generate treatment plans that are comparable to those created by human experts, significantly reducing the time and cost of the planning process. Our results suggest that GPT-4Vision has the potential to revolutionize radiotherapy treatment planning by enabling faster, more accurate, and more personalized care for cancer patients.



Liu S, Pastor-Serrano O, ..., Physics in Medicine & Biology 70, 2025
doi: 10.1088/1361-6560/adf02c.

Planning trajectories

1. Initialize plan based on average parameters
2. Ensure PTV homogeneity and conformity
3. Spare OARs while maintaining PTV coverage



Data are presented in diverse formats

Image, video, & audio

- Different modalities

Table

- omics
- Multi-omics
- Sensory data
- Clinical trials

Language

- Different languages
- Specialties

Graph

- Bio-network
- Social network
- Pathology data
- Functional maps
- Spatial transcriptomics

Bio-networks

Deep representation learning of biological graphs for enhanced pattern discovery

ABSTRACT

Biological networks encompass interactions among diverse biological entities and are fundamental for understanding the dynamics within biological systems. Despite their pivotal role in modern biology, reliably discerning patterns from these intertwined networks remains a significant challenge. The essence of the challenge lies in how to holistically characterize the relationships of each node with others in the network and effectively utilize the information for accurate pattern discovery. In this work, we introduce a self-supervised network embedding approach termed discriminative network embedding (DNE). Unlike conventional methods that primarily focus on direct or limited-order node proximity, DNE characterizes a node in the network both locally and globally by harnessing the contrast between contributions from neighboring and distant nodes. This process ensures that the nodal embedding captures both local patterns and interactions with the broader network structure, maximizing structural preservation. Our experimental results demonstrate the superior performance of DNE over existing techniques across various critical biological network analyses, including the inference of biological interactions and the identification of functional modules. DNE emerges as a robust strategy for node representation in biological networks, offering promising avenues for diverse biomedical applications.

R. Yan, T. Islam, L. Xing, Science Advances 10, 1-12, 2024.

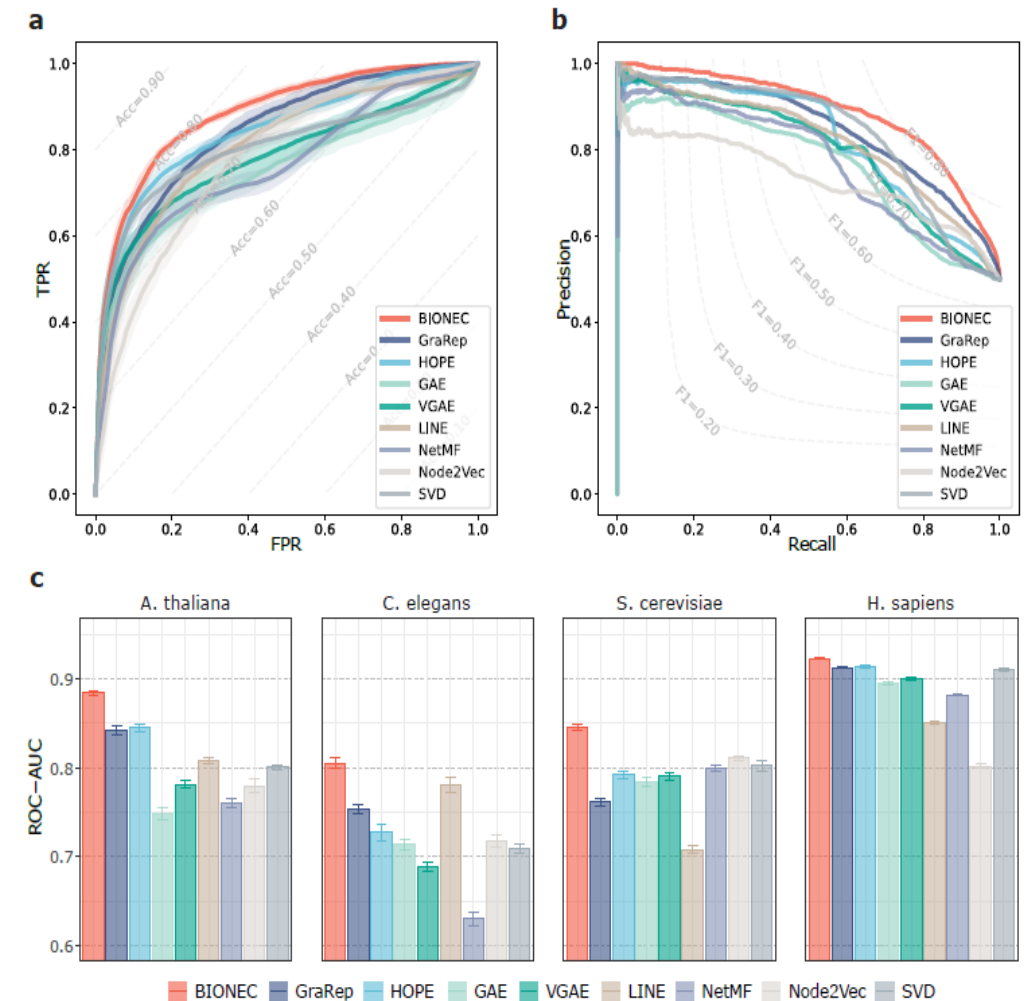


Figure 2. Performance of different network embedding methods for link prediction in four PPI benchmarks. a) ROC and b) precision-recall curves of DNE compared with eight other network embedding methods for PPI prediction on the *A. thaliana* dataset. Dashed lines represent level curves for accuracy and F1-score in a) and b), respectively. c) ROC-AUC scores computed from 10 independent runs across four PPI datasets. Mean values are reported, with error bars representing the standard deviations of the scores.

SUMMARY

Biomedical AI Foundation Models

1



AI is changing the landscape of biomedicine

2



Prior physics/biology knowledge

3



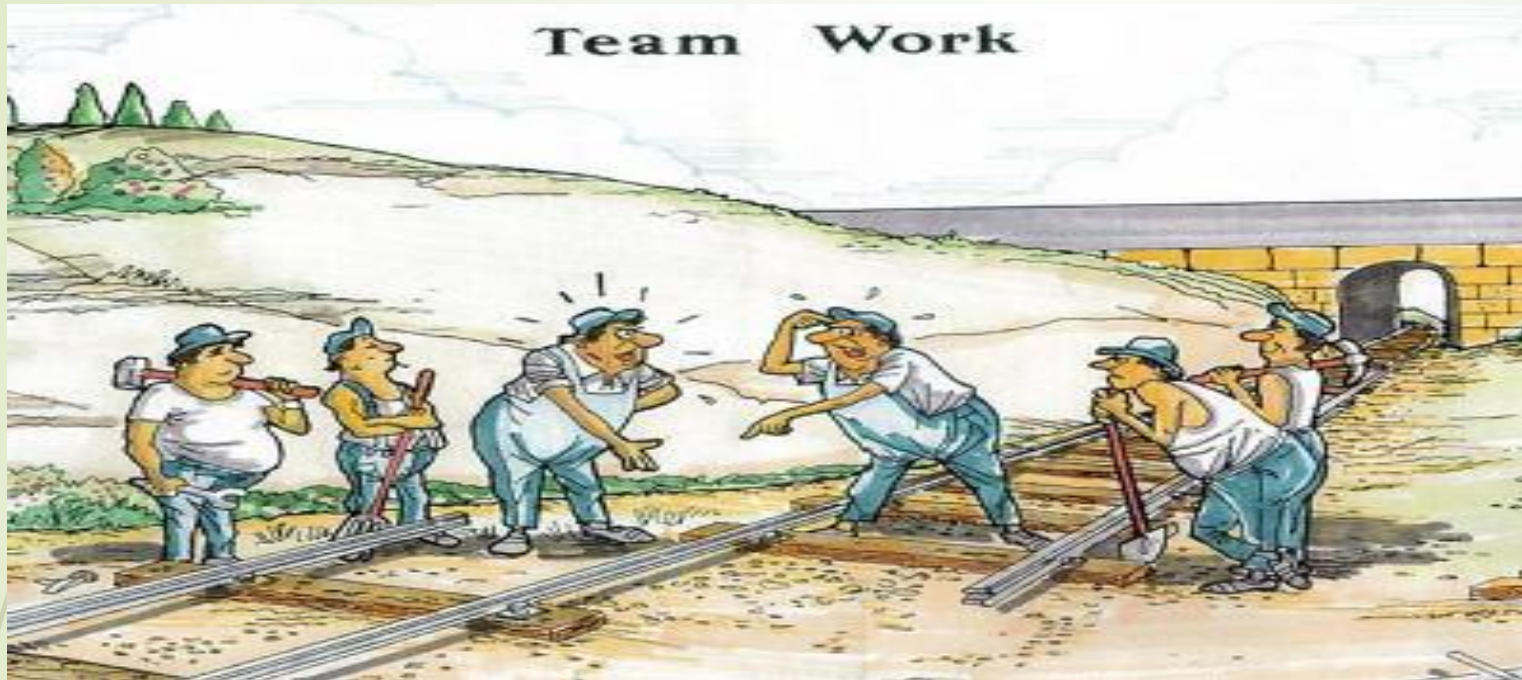
foundation models for various biomedical applications
–need biology/physics knowledge integration

4



Multi-modality & Multi-scale FM

Acknowledgements



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- ❖ Google Inc.
- ❖ Mevion Medical Systems

