3050571 Practical Clin Data Sci

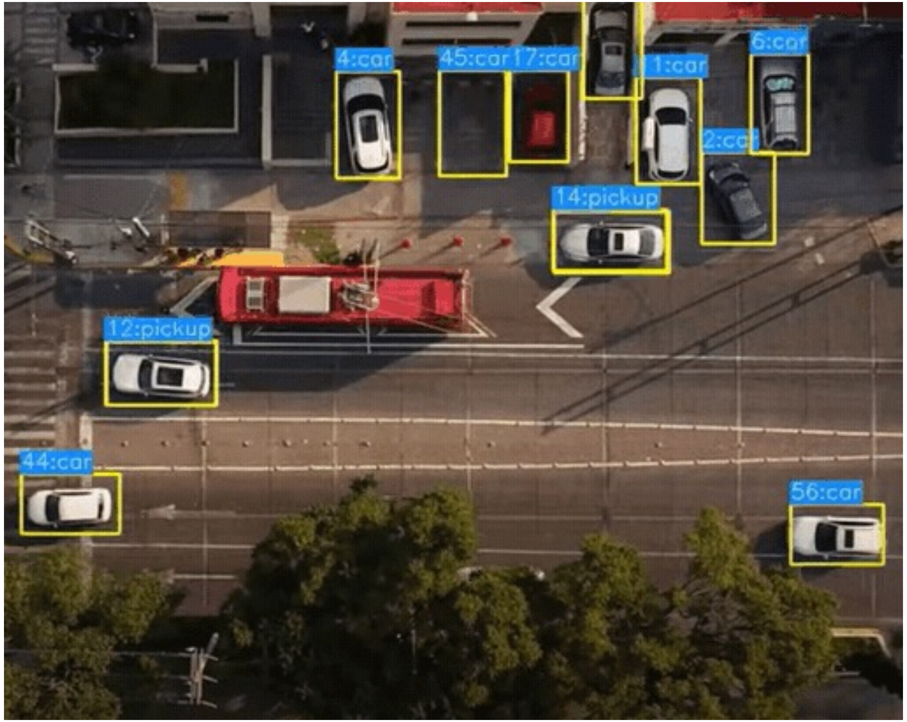
Session 13: Artificial intelligence

February 27, 2024

Sira Sriswasdi, PhD

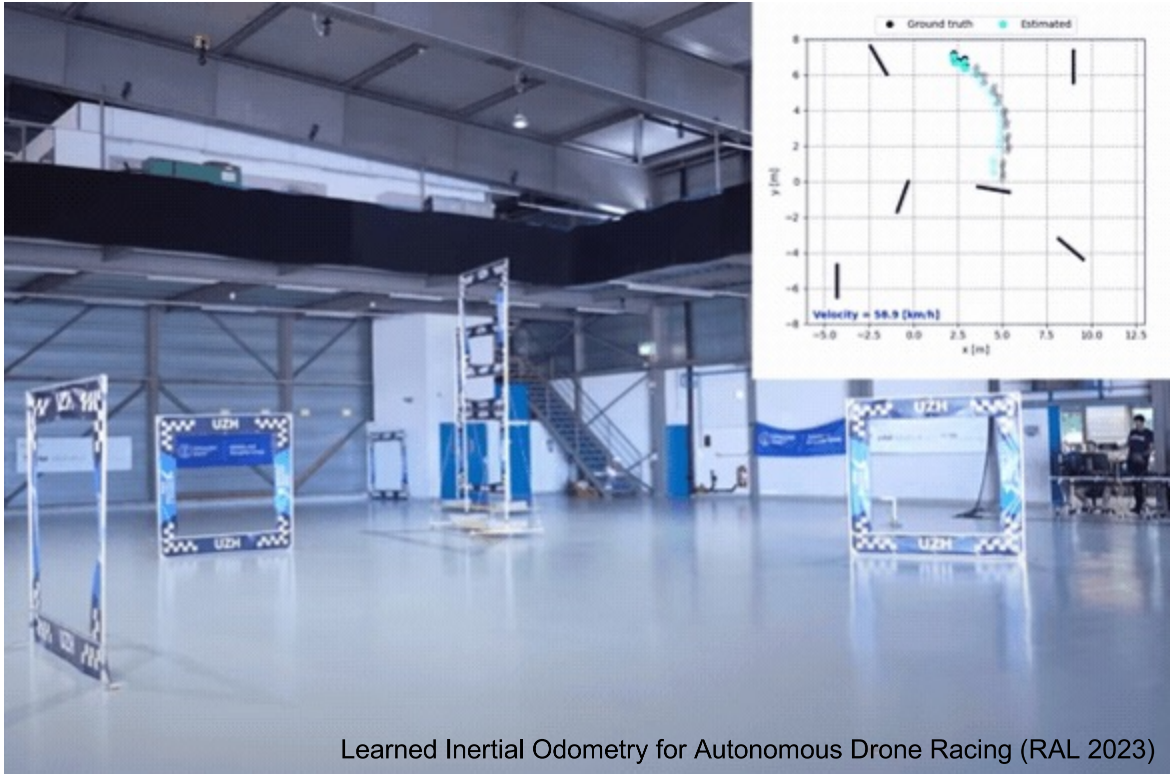
- Research Affairs
- Center of Excellence in Computational Molecular Biology (CMB)
- Center for Artificial Intelligence in Medicine (CU-AIM)

Real-time object recognition



Real Time Object Detection and Tracking with YOLO-NAS and DeepSORT on Custom Dataset

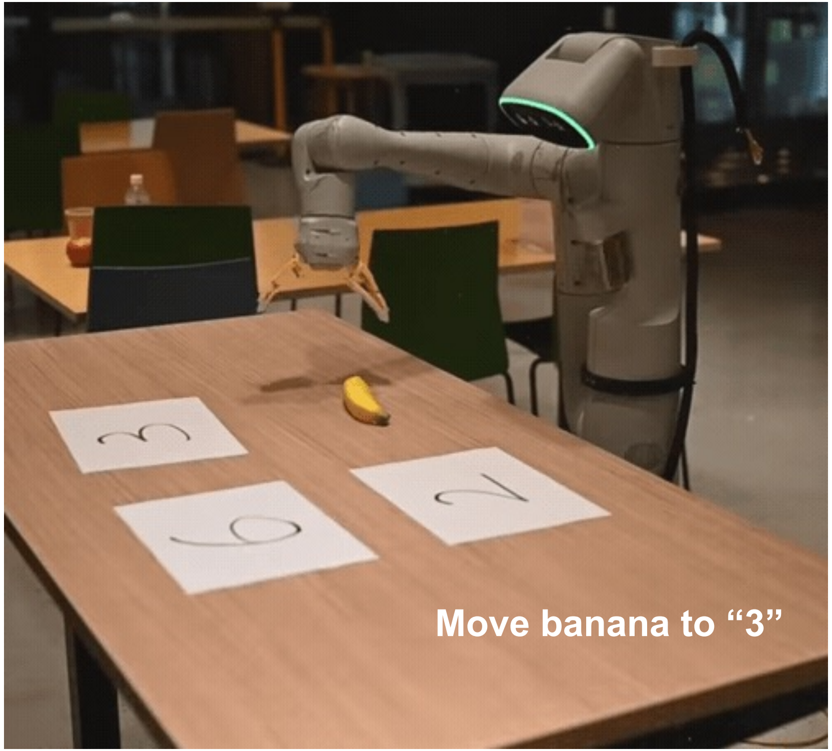
Interaction with real-world environment



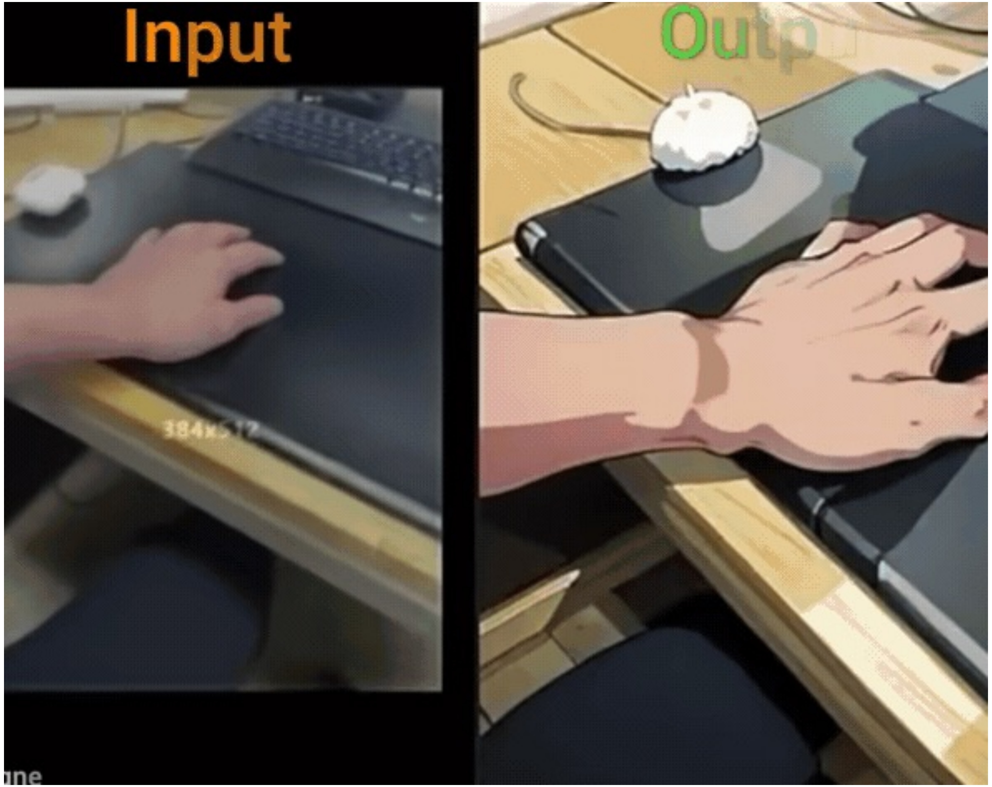
Learned Inertial Odometry for Autonomous Drone Racing (RAL 2023)

Google DeepMind's AlphaGo computer beats top player Lee Sedol for third time to sweep competition

Text to action: Google RT-2



Art and deepfake

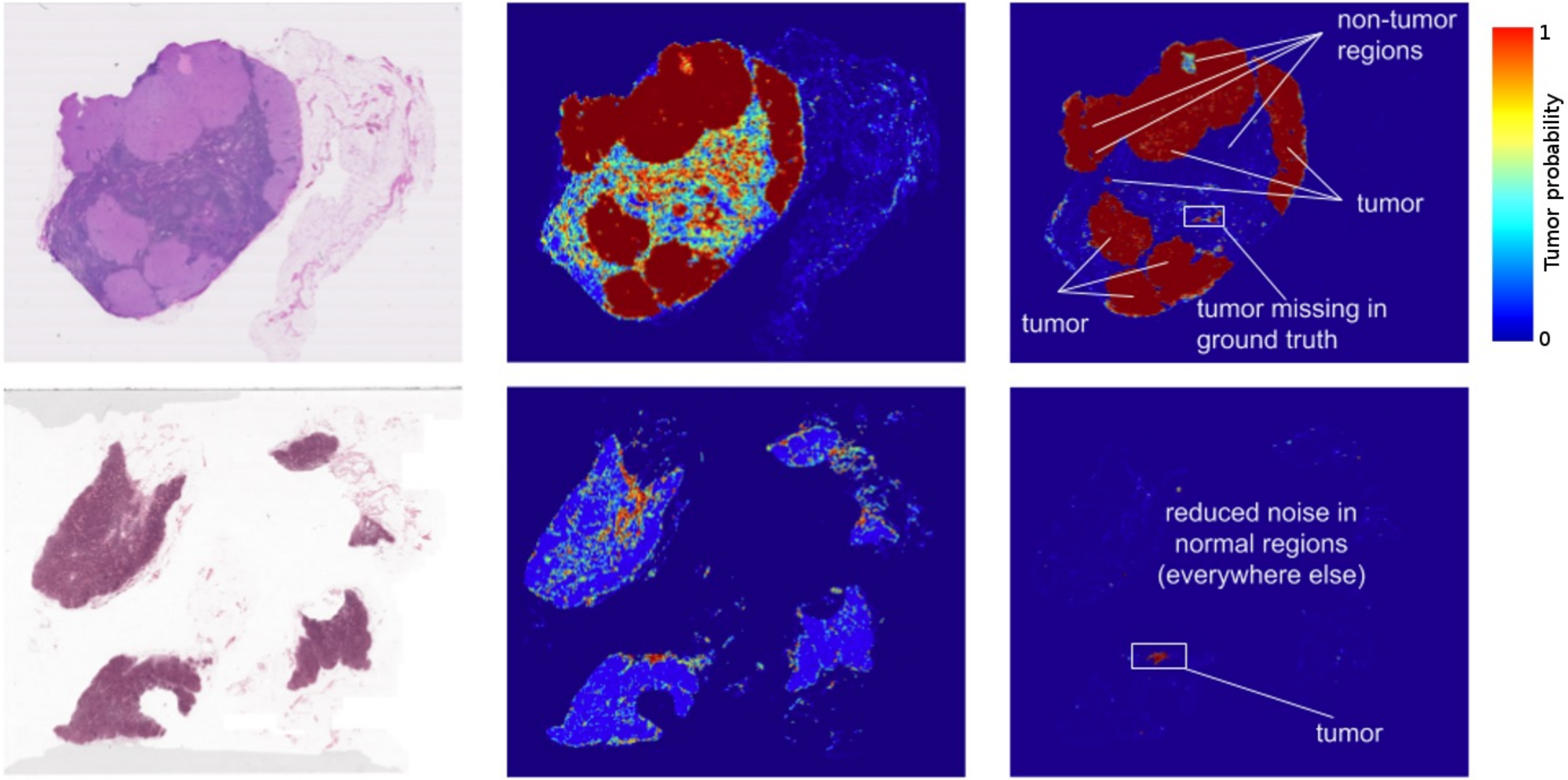


Talking head anime: https://github.com/pkhungurn

Stable Diffusion: 8

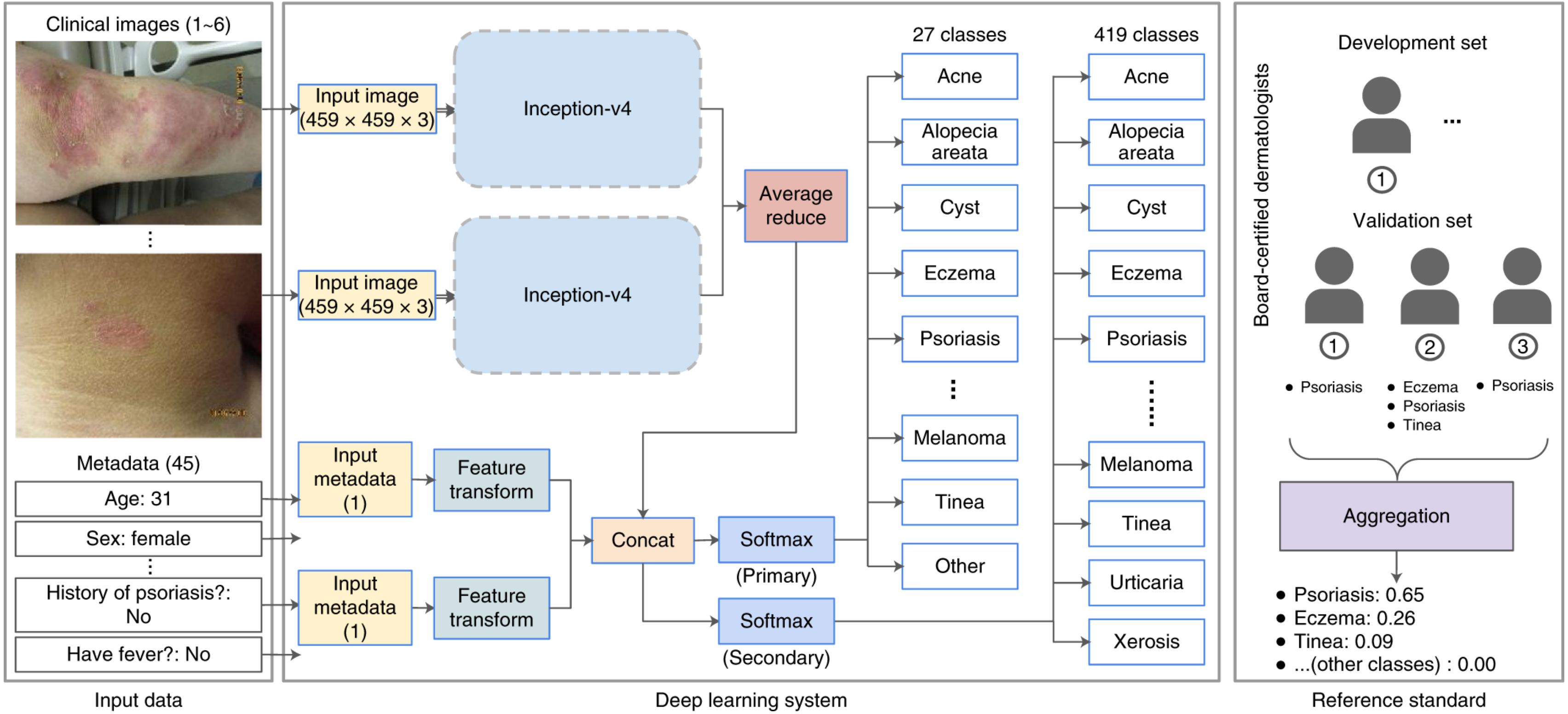
AI in medicine and healthcare

Tumor segmentation



Skin lesion assessment

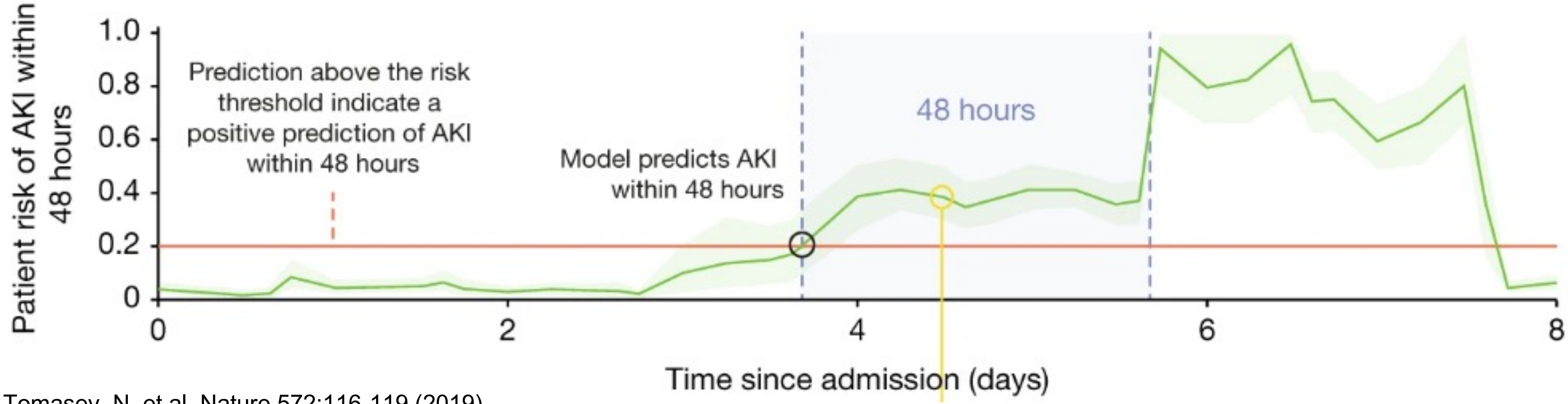
Liu, Y. et al. Nature Medicine 26:900-908 (2020)



Early warning for acutekidney injury

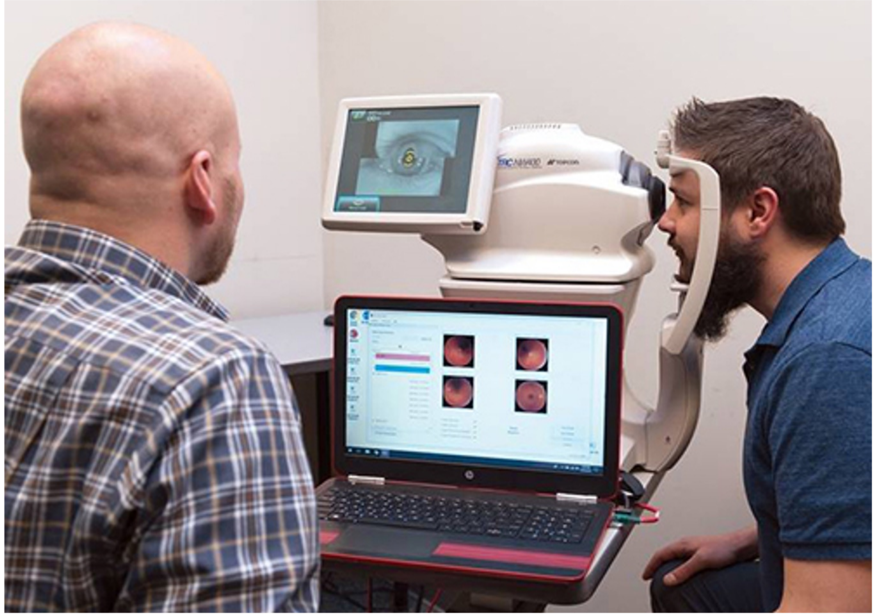
- **Inputs**
  - Medical record
  - Blood tests
- **Outputs**
  - Risk of AKI in the next 48h

Using AI to give doctors a 48-hour head start on life-threatening illness



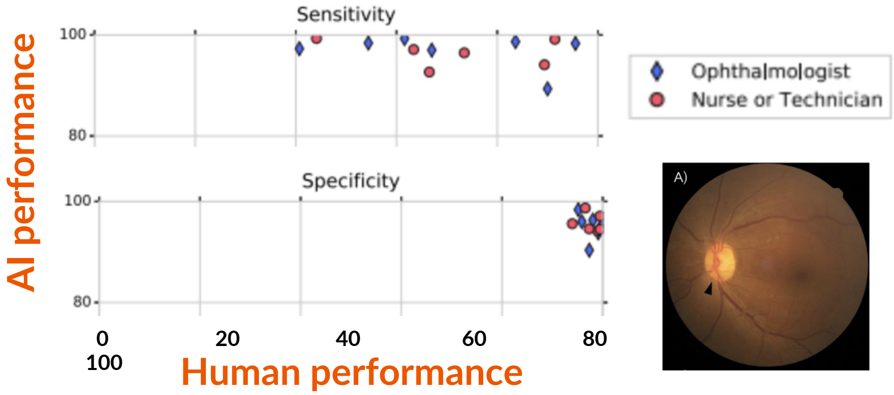
Tomasev, N. et al. Nature 572:116-119 (2019)

National diabetic retinopathy screening



ARTICLE OPEN

Deep learning versus human graders for classifying diabetic retinopathy severity in a nationwide screening program

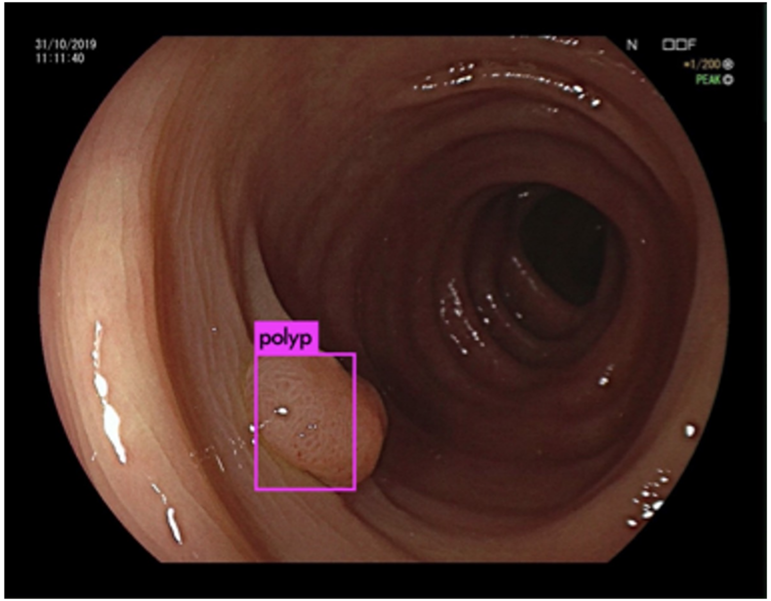


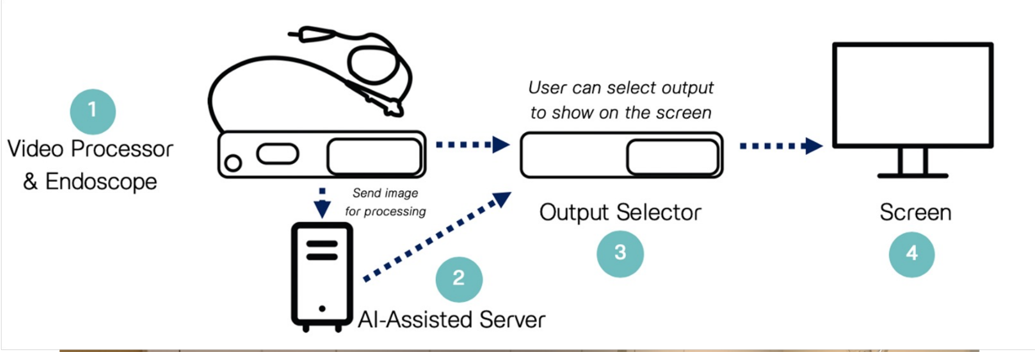
- 25k fundus images from 7,517 patients in Thailand

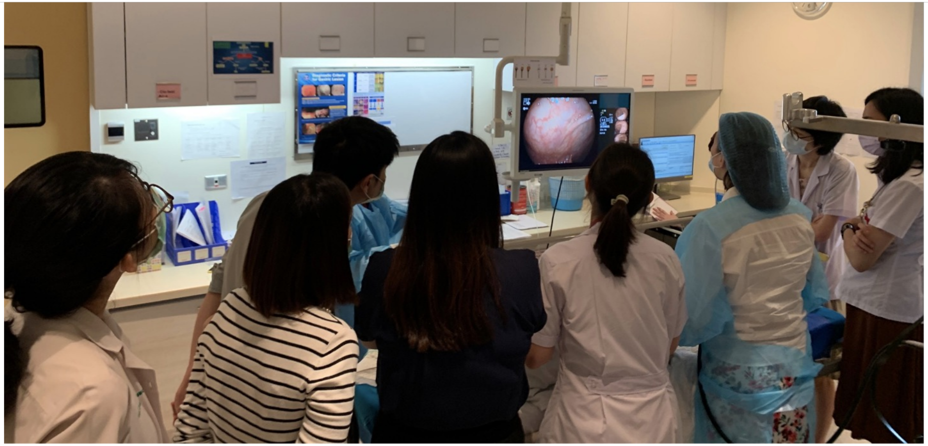
DeepGI

AI-assisted endoscopy

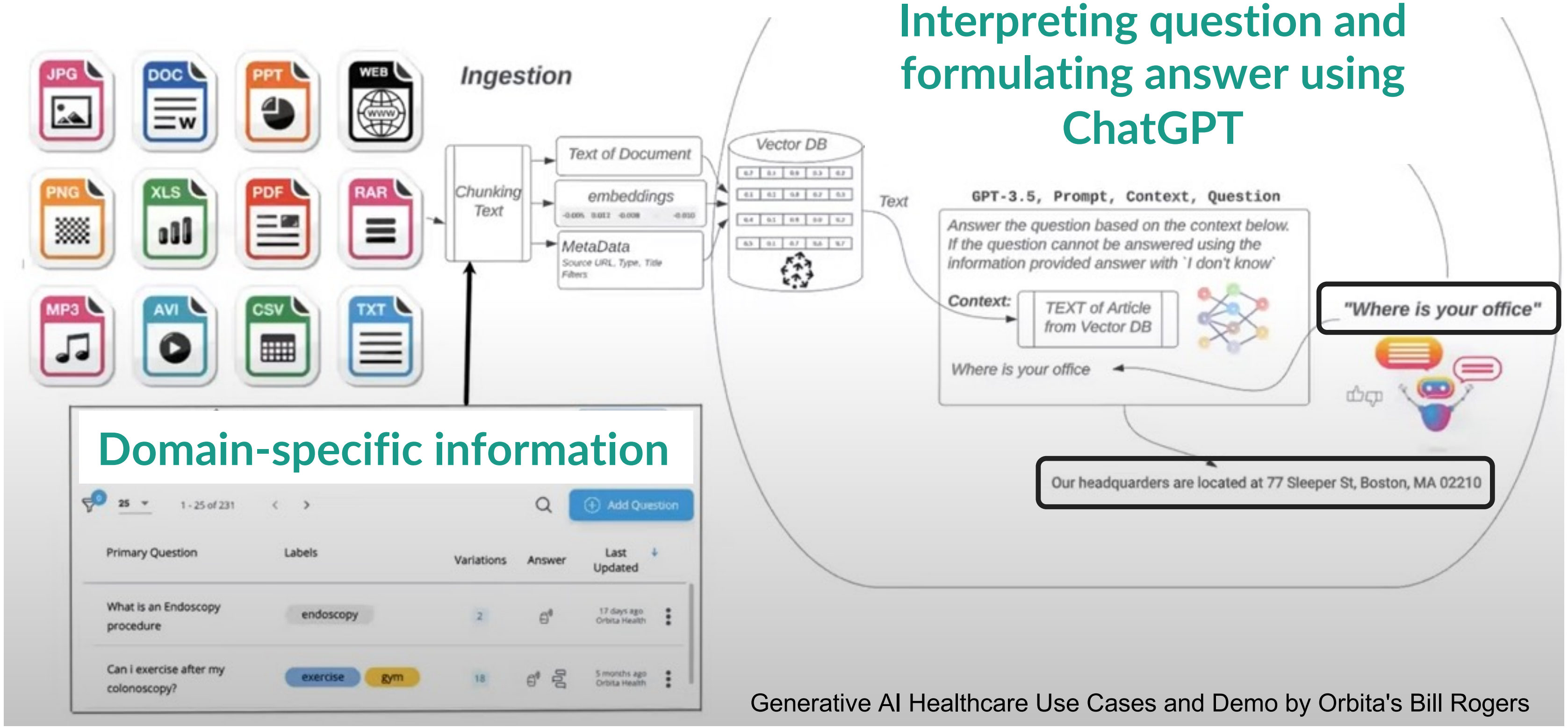
Real-time polyp detection





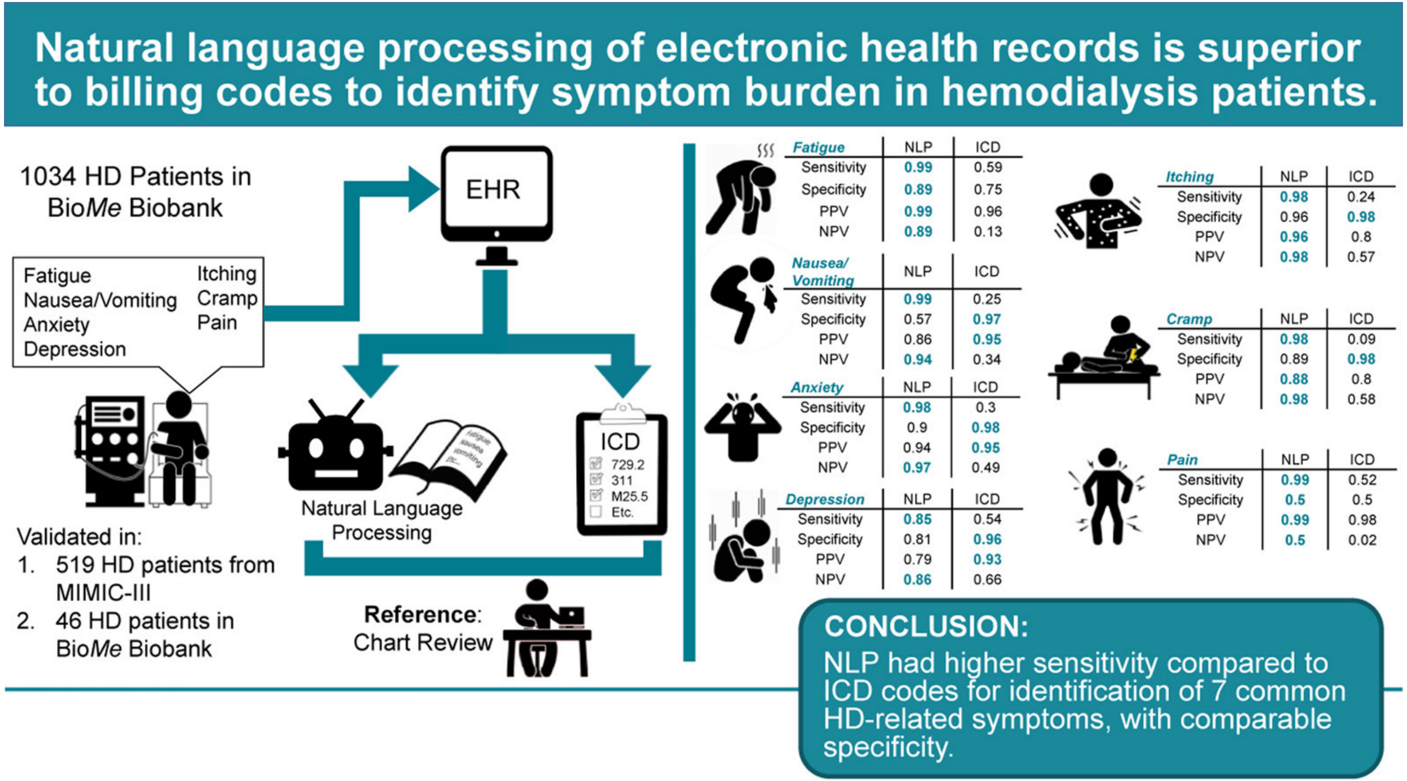


Question answering service via ChatGPT

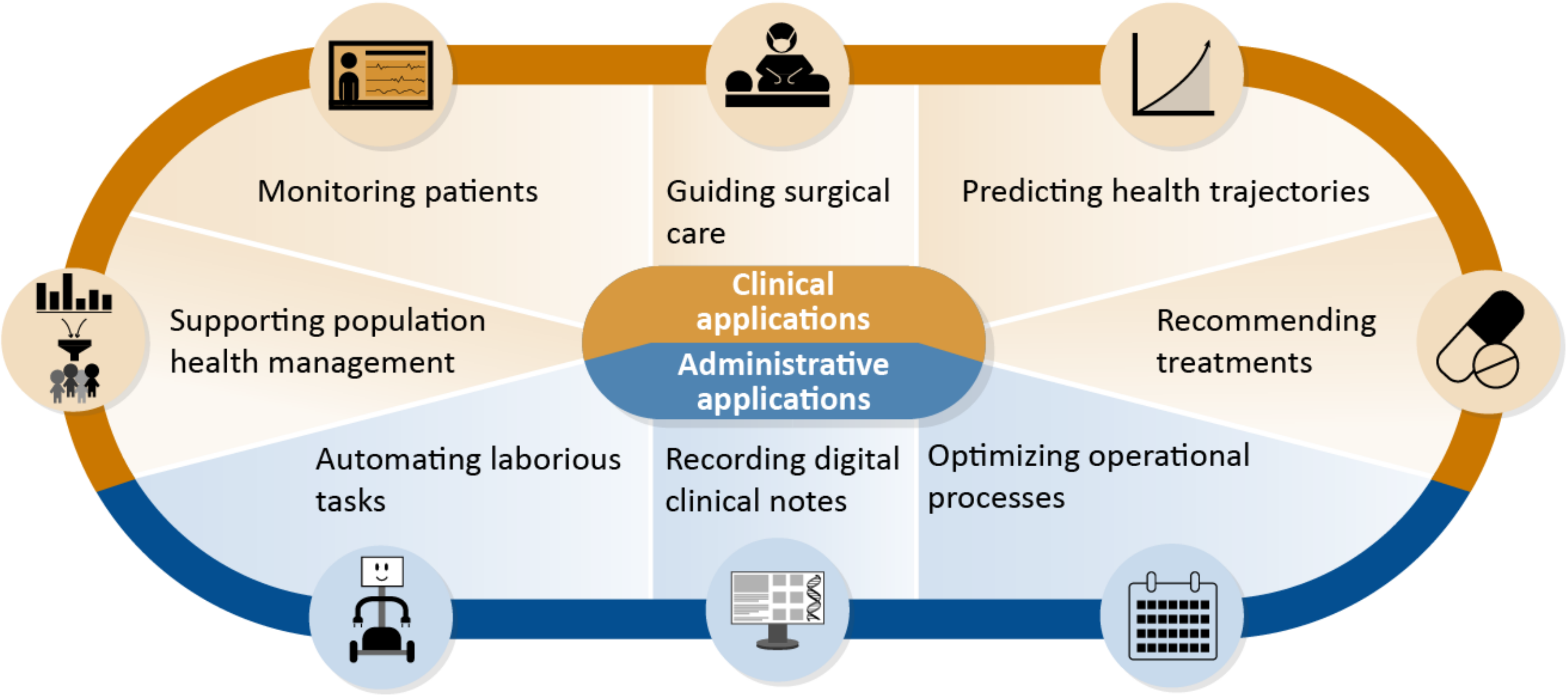


Information extraction from electronic health record

Chan, L. et al. Kidney International 97:383-392 (2020)



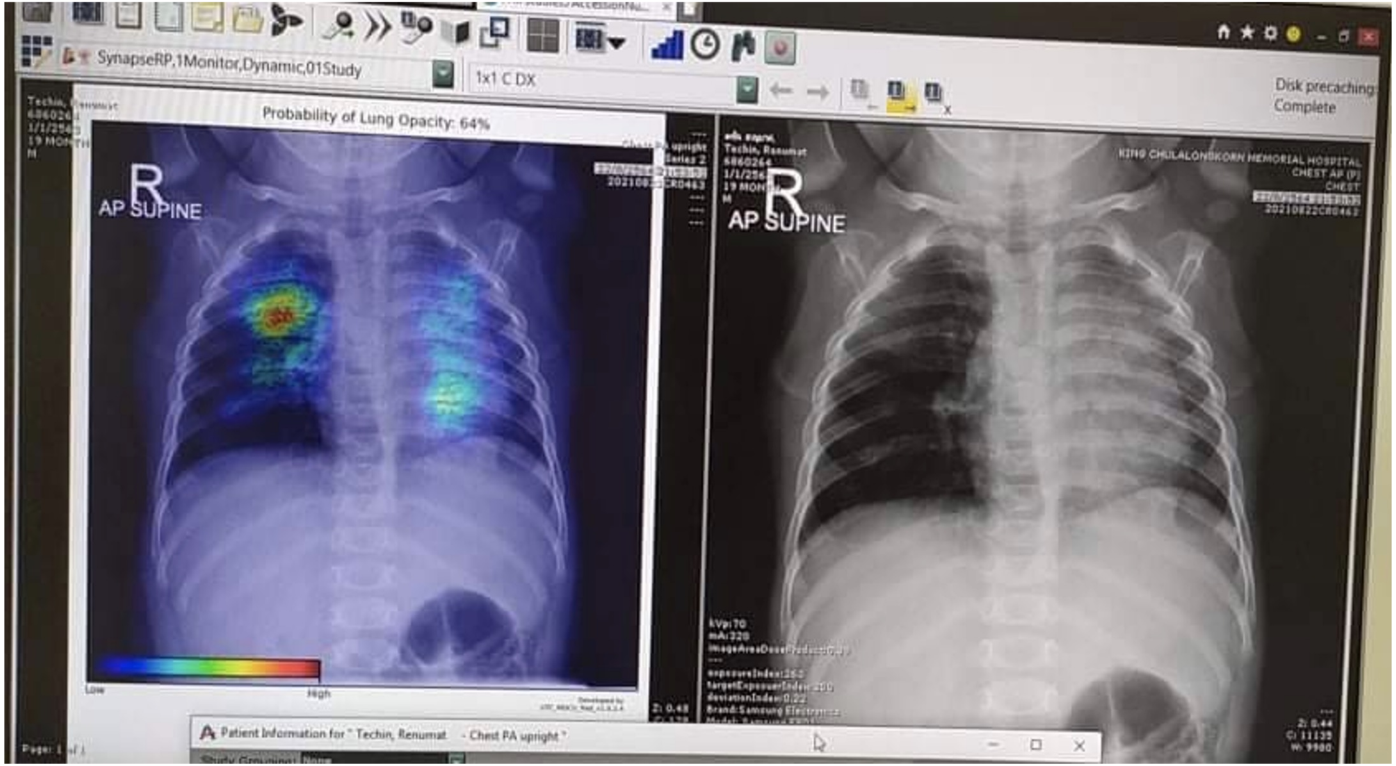
Use cases for AI in healthcare



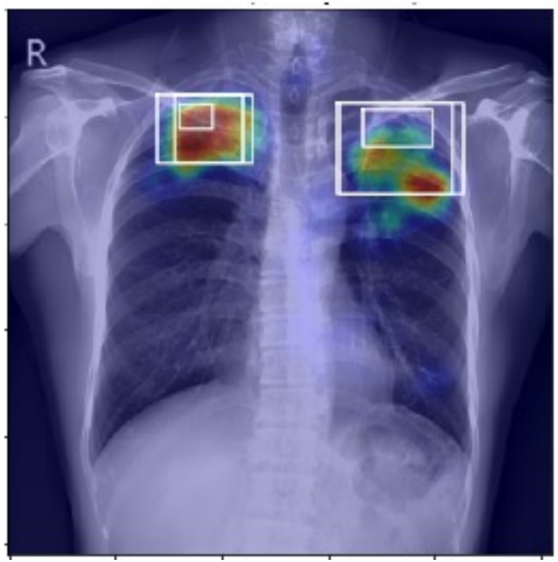
Source: GAO. | GAO-21-7SP

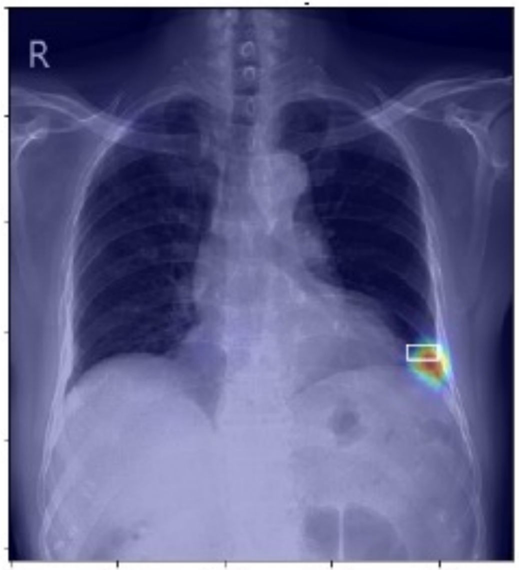
Medical AI at MDCU

Our local CXR AI



Accurate lesion localization





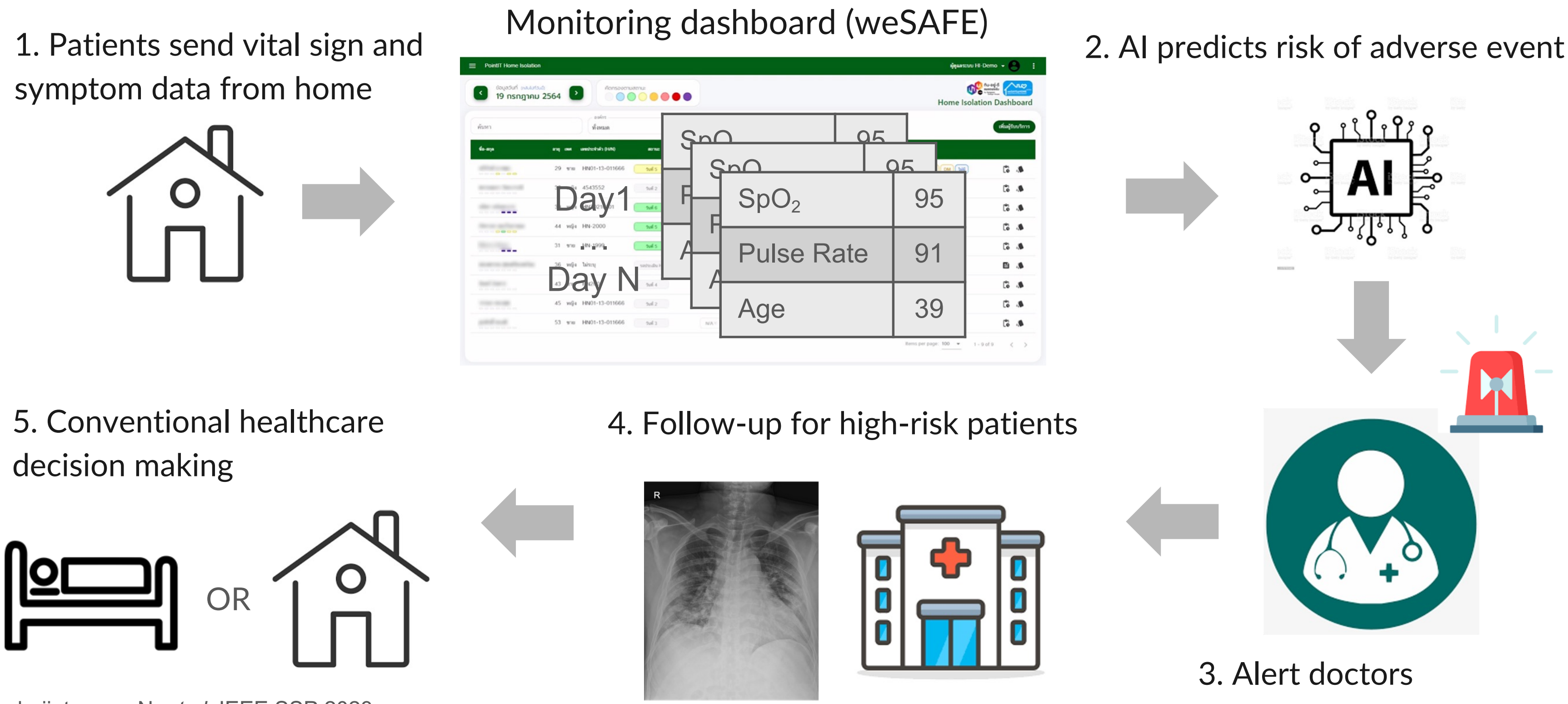
- Trustworthy AI must be able to provide evidence supporting prediction

Automatic radiologist report generation

X-ray	Ground truth	LSP
	frontal and lateral views of the chest were obtained. there are streaky linear opacities at the lung bases which are likely due to atelectasis with chronic changes. no definite focal consolidation is seen. there is no pleural effusion or pneumothorax. no pneumothorax is seen. the aorta is calcified and tortuous. the cardiac silhouette is top normal to mildly enlarged. dual-lead left-sided pacemaker is seen with leads in the expected positions of the right atrium and right ventricle. chronic-appearing rib deformities on the right is again seen.	frontal and lateral views of the chest were obtained. there is a small left pleural effusion with overlying atelectasis. there is no focal consolidation, pleural effusion or pneumothorax. there is no pleural effusion or pneumothorax. the aorta is calcified and tortuous. the heart is mildly enlarged. a left-sided pacemaker is seen with leads in the expected position of the right atrium and right ventricle. the patient is status post median sternotomy and cabg. the lungs are otherwise clear.

Preechakul *et al.* NeurIPS 2021

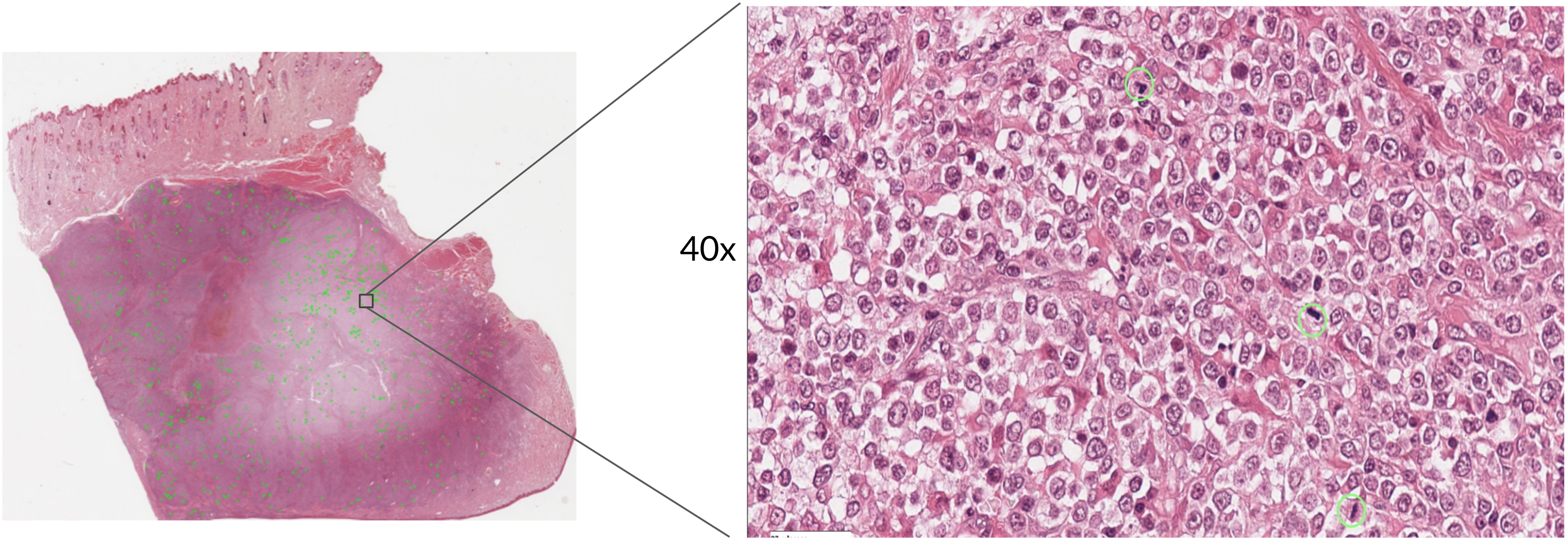
AI-assisted COVID-19 monitoring



Ruengchaijatuporn, N. *et al*. IEEE SSP 2023

Digital pathology

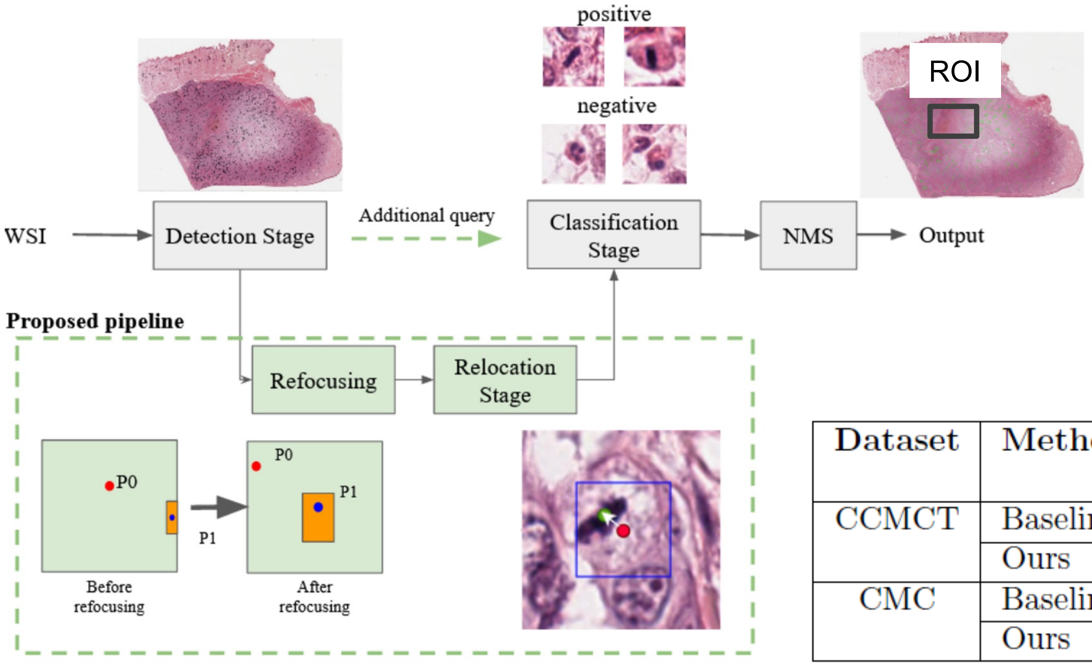
Pain point: locating ROIs with highest object counts



Whole-slide image (150,000 x 150,000 pixels)

Mitotic figures

Lesson: AI does not have to do everything



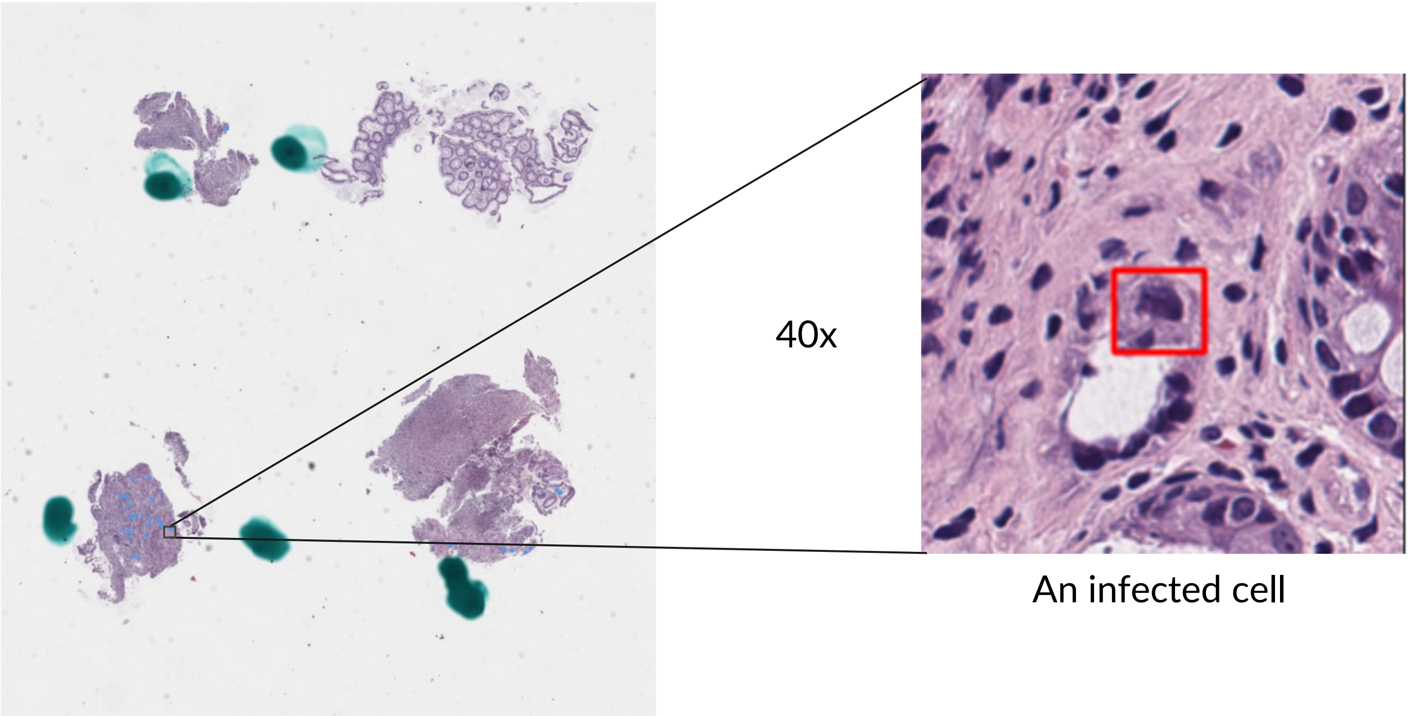
- **Minimize ROI search**

- <2 mitotic count error when **a pathologist is involved**

Dataset	Method	Fully-Automated		Human-In-The-Loop	
		MAPE	MAE	MAPE	MAE
CCMCT	Baseline	18.8	10.5	11.2	4.4
	Ours	**10.5**	**8.3**	**6.8**	**1.9**
CMC	Baseline	7.8	3.1	8.1	2.4
	Ours	**5.6**	**1.9**	**5.6**	**1.6**

Piansaddhayanon, C. *et al.* Artificial Intelligence in Medicine 135:102462 (2023)

Pain point: detecting rare infected cells



Whole-slide image (150,000 x 150,000 pixels)

An infected cell

Low sensitivity and confidence of visual inspection

Sample	Ground truth	# of infected assessments	# of uninfected assessments	# of unsure assessments
1	Infected	1	2	6
2	Infected	2	3	4
3	Infected	1	6	2
4	Infected	4	3	2
5	Infected	1	8	
6	Uninfected	1	6	2
7	Uninfected		2	7
8	Uninfected		9	1
9	Uninfected		6	3
10	Uninfected	1	6	2
11	Uninfected	2	6	1
12	Uninfected		7	3

Lesson: AI does not have to be perfect to be useful

Development

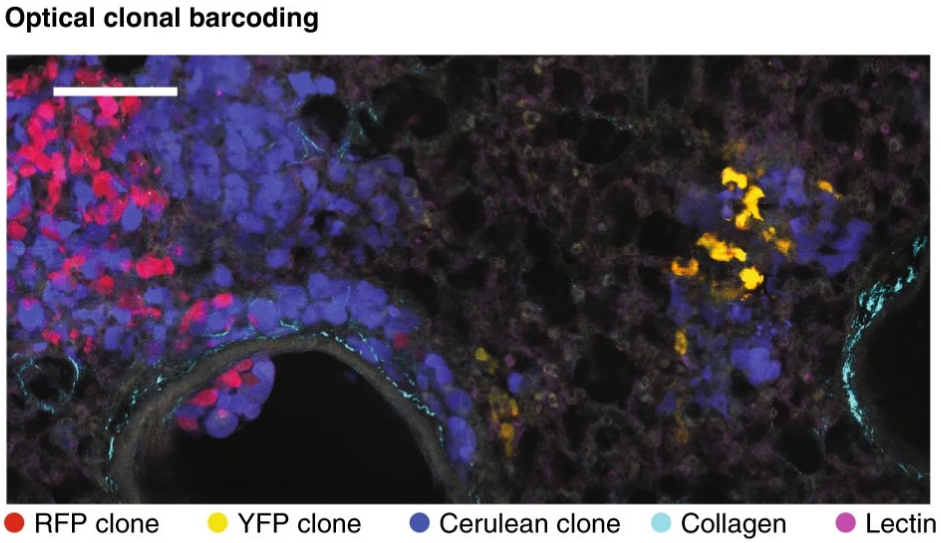
- 1,239 annotated infected cells from 68 whole-slide images
- 34.2% F1 score

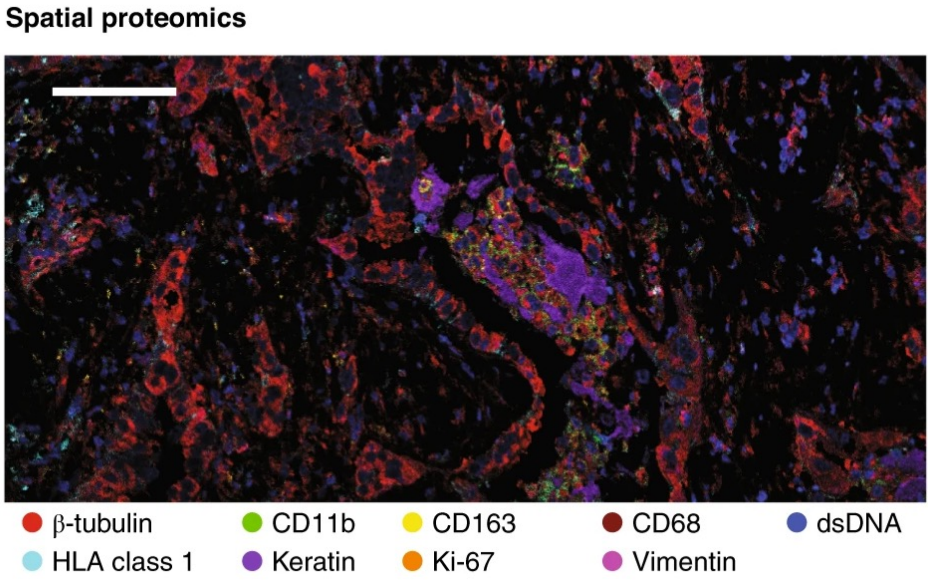
Evaluation

- AI proposes the **top 10 likely cells per slide**
- Pathologists classify whole-slide based on only proposed cells
    - Preliminary result = **100% sensitivity**

H&E 2.0

Spatial omics and multiplexed imaging



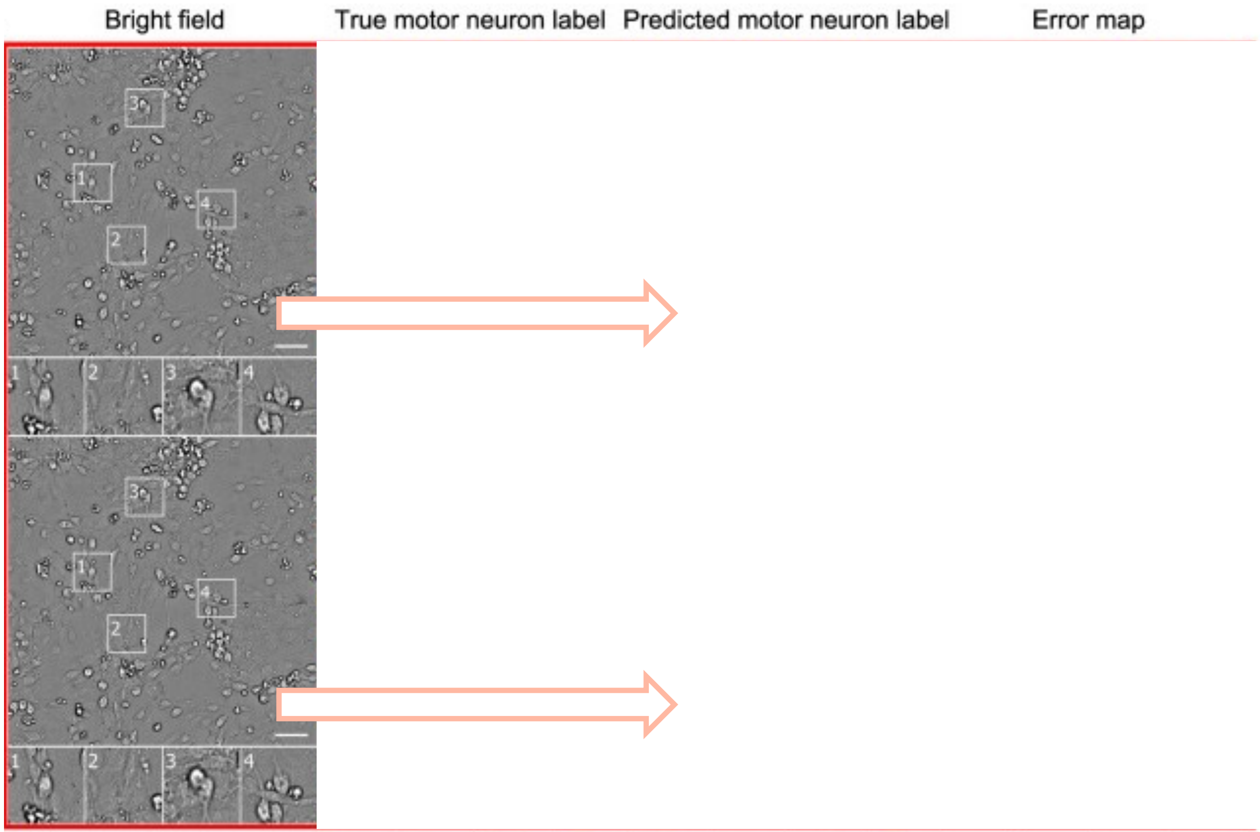


Lewis, S.M. *et al*. Nature Methods 18:997-1012 (2021)

- Enable single-cell interpretation of tissue images

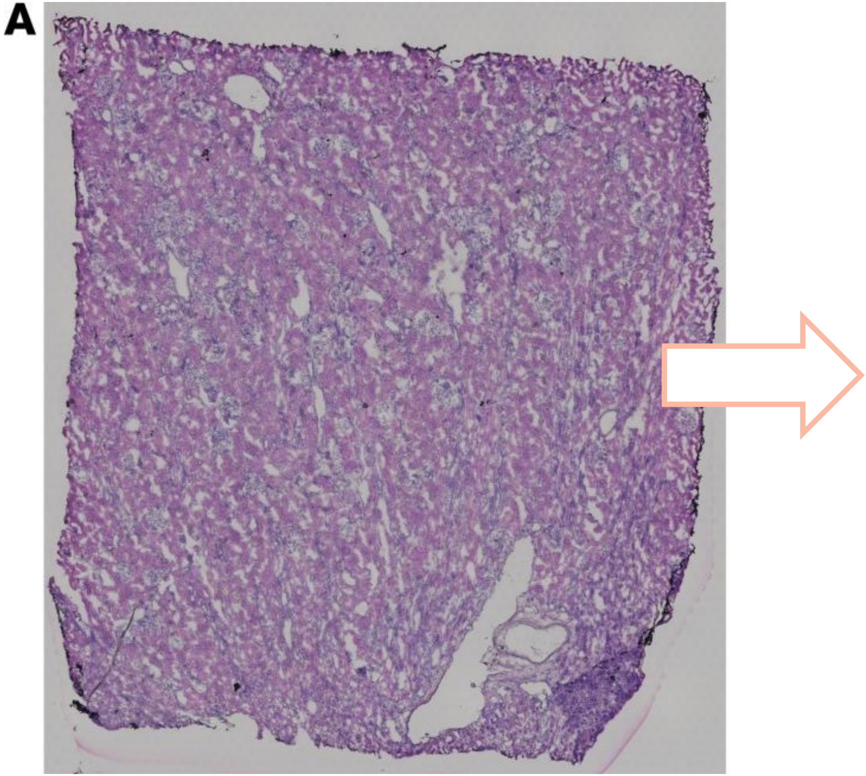
In silico labeling with AI

Christiansen, E.M. et al. Cell 173:792-803 (2018)



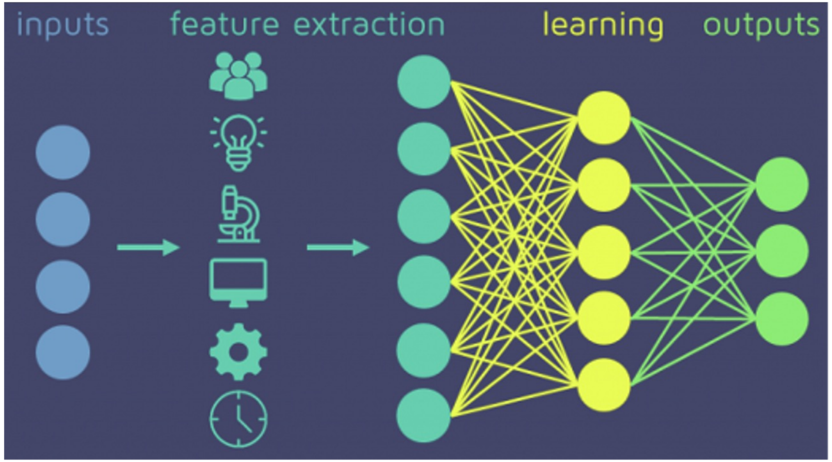
H&E with AI annotations

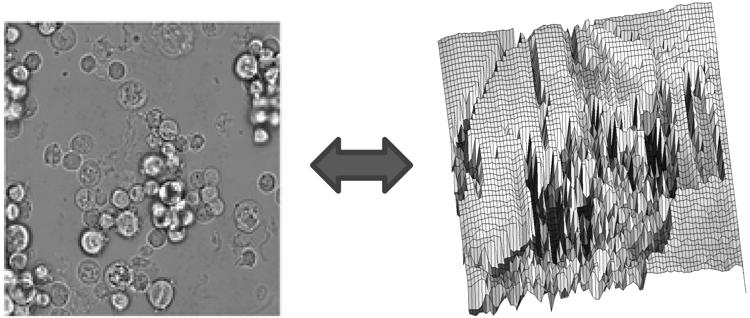
Ferrerira, R.M. et al. JCI Insight 6:e147703 (2021)

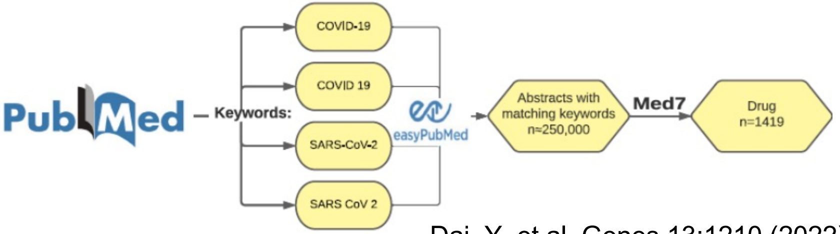


How did the magic happen?

Limitation of classical (non-deep) learning



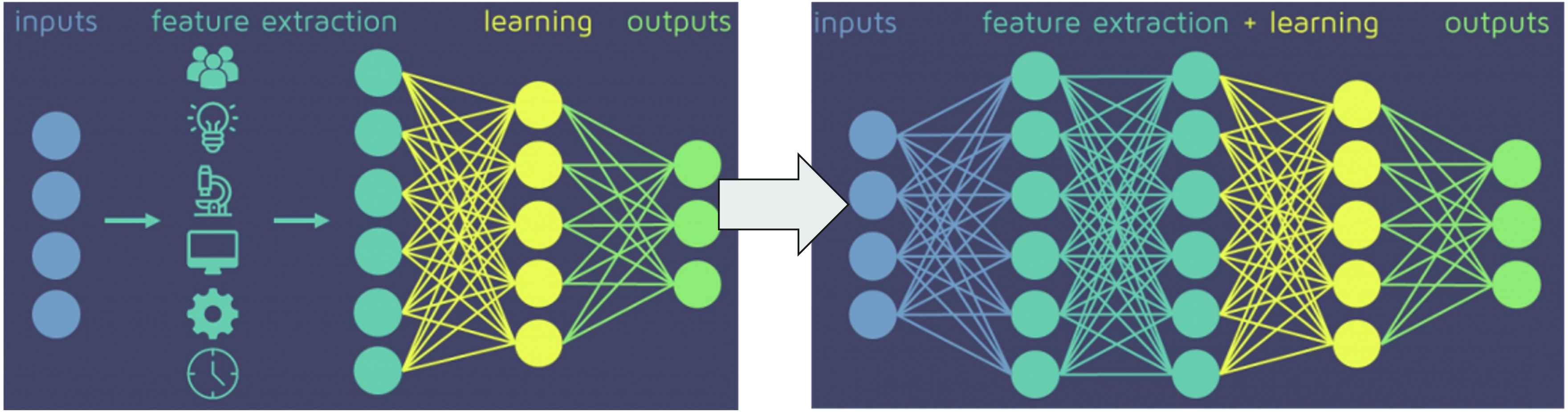




Dai, Y. et al. Genes 13:1210 (2022)

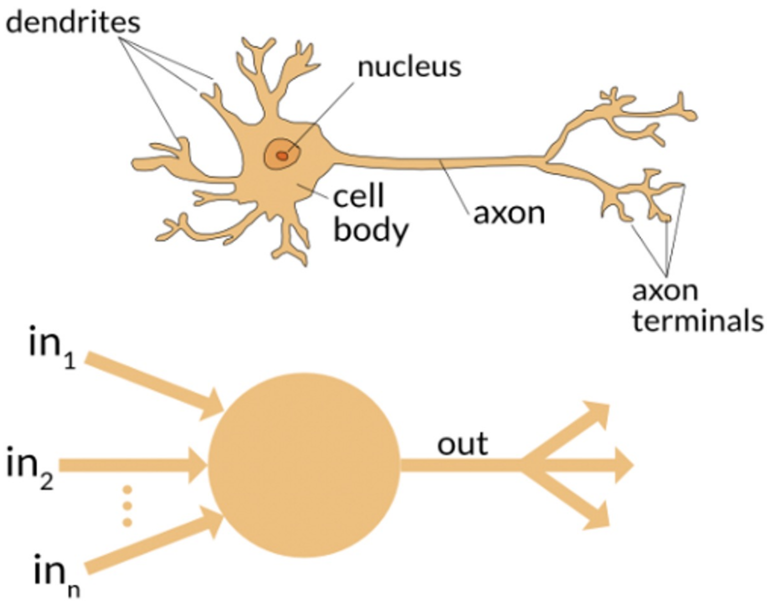
- Classical machine learning requires the input to be formatted and pre-processed by human

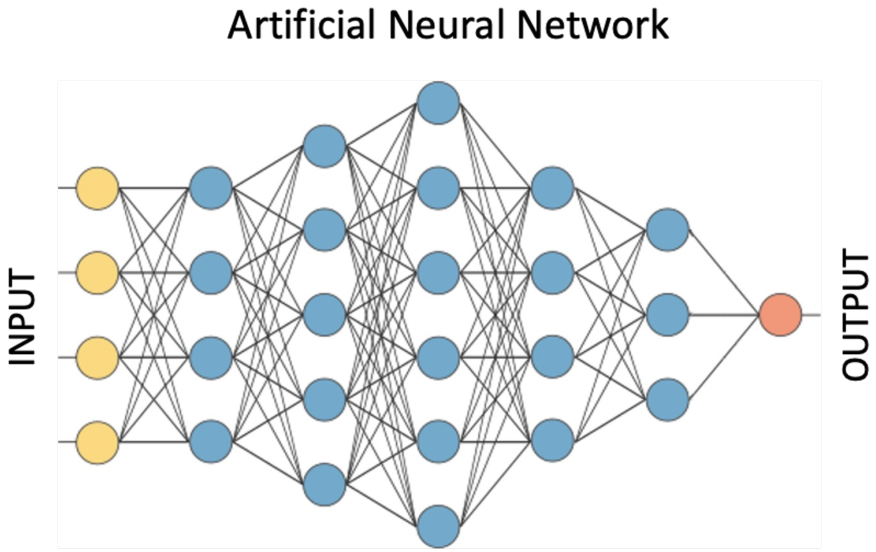
End-to-end learning



- Deep learning, via artificial neural network models, can learn to extract useful information from raw input directly
- The catch is a lot of data and supervision is needed

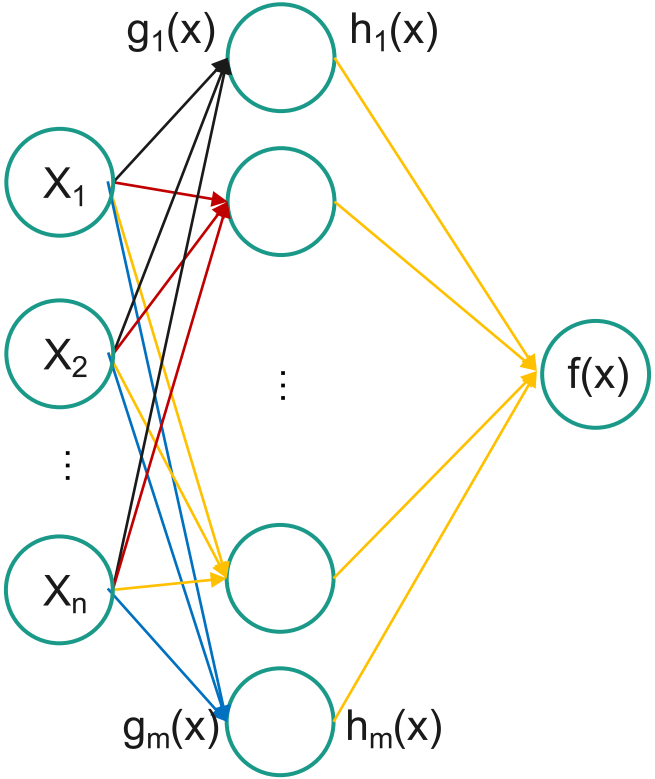
Artificial neural network





- Network of simple computation nodes: $out = f(w_1 in_1 + w_2 in_2 + \ldots + w_n in_n)$

Calculations inside neural nentwork



Linear neuron input

- $g_1(x) = w_{1,1}x_1 + \cdots + w_{1,n}x_n$
- $g_m(x) = w_{m,1}x_1 + \cdots + w_{m,n}x_n$

Sigmoid activation

- $h_1(x) = \frac{1}{1+e^{-g_1(x)}}$
- $h_m(x) = \frac{1}{1+e^{-g_m(x)}}$

Linear aggregated output

- $f(x) = u_1 h_1(x) + \cdots + u_m h_m(x)$

Universal approximation theorem (Cybenko, 1989)

Universal Approximation Theorem: Fix a continuous function $\sigma : \mathbb{R} \to \mathbb{R}$ (activation function) and positive integers d, D. The function σ is not a polynomial if and only if, for every continuous function $f : \mathbb{R}^d \to \mathbb{R}^D$ (target function), every compact subset K of $\mathbb{R}^d$, and every $\epsilon > 0$ there exists a continuous function $f_\epsilon : \mathbb{R}^d \to \mathbb{R}^D$ (the layer output) with representation

$$f_\epsilon = \boxed{W_2 \circ \sigma \circ W_1}$$

where W_2, W_1 are composable affine maps and $\circ$ denotes component-wise composition, such that the approximation bound

$$\boxed{\sup_{x \in K} \|f(x) - f_\epsilon(x)\| < \varepsilon}$$

holds for any ϵ arbitrarily small (distance from f to f_ϵ can be infinitely small).

- Neural network with one hidden layer can mimic any mathematical function

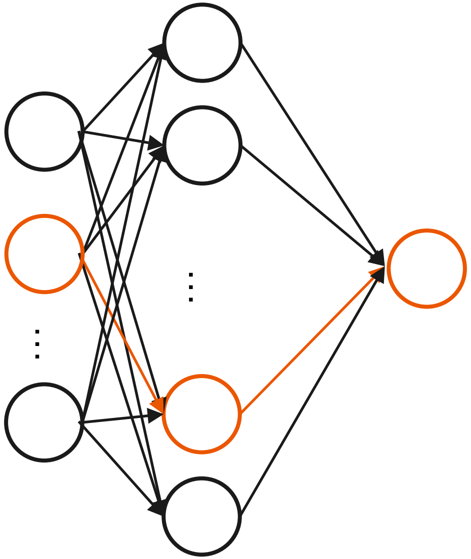
Gradient of a neural network

Neuron input: $g_i(x) = w_{i,1}x_1 + \cdots + w_{i,n}x_n$

Sigmoid activation: $h_i(x) = \frac{1}{1+e^{-g_i(x)}}$

Linear output: $f(x) = u_1 h_1(x) + \cdots + u_m h_m(x)$

MSE loss: $L(f(x), y) = \frac{1}{2}\|f(x) - y\|^2$

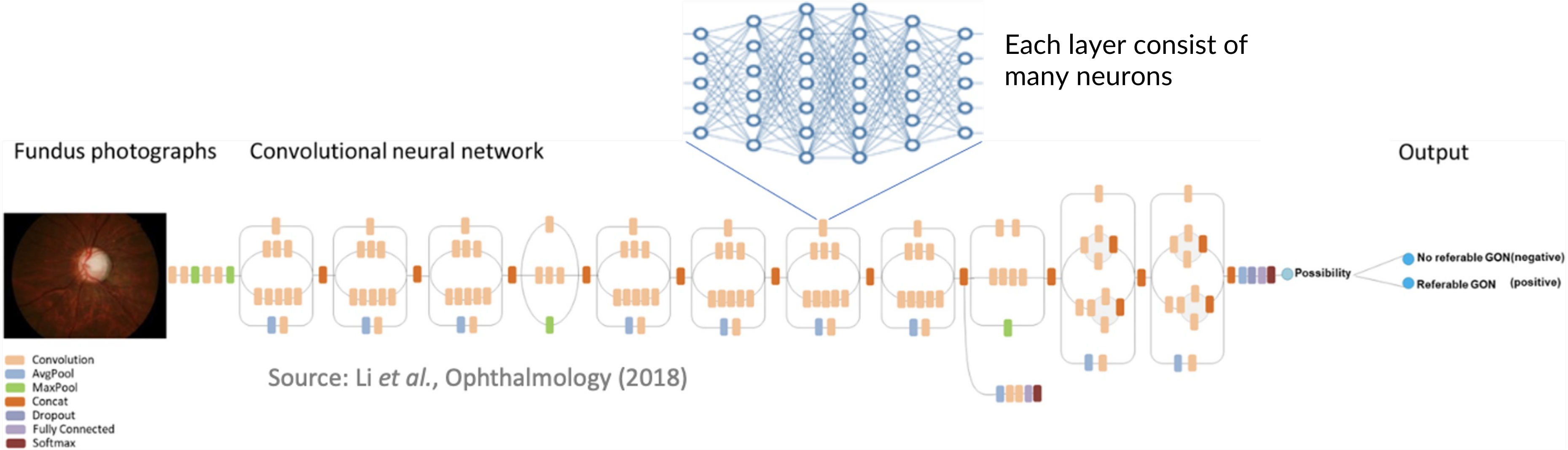


Gradient: $\frac{\delta L}{\delta w_{i,j}} = ?$ ($w_{i,j}$ is the weight for *j*-th feature entering *i*-th neuron)

$$\frac{\delta L}{\delta w_{i,j}} = \frac{\delta L}{\delta f}\frac{\delta f}{\delta h_i}\frac{\delta h_i}{\delta g_i}\frac{\delta g_i}{\delta w_{i,j}} = (f(x) - y) \cdot u_i \cdot g_i(\mathrm{x})(1 - g_i(\mathrm{x}))\, x_j$$

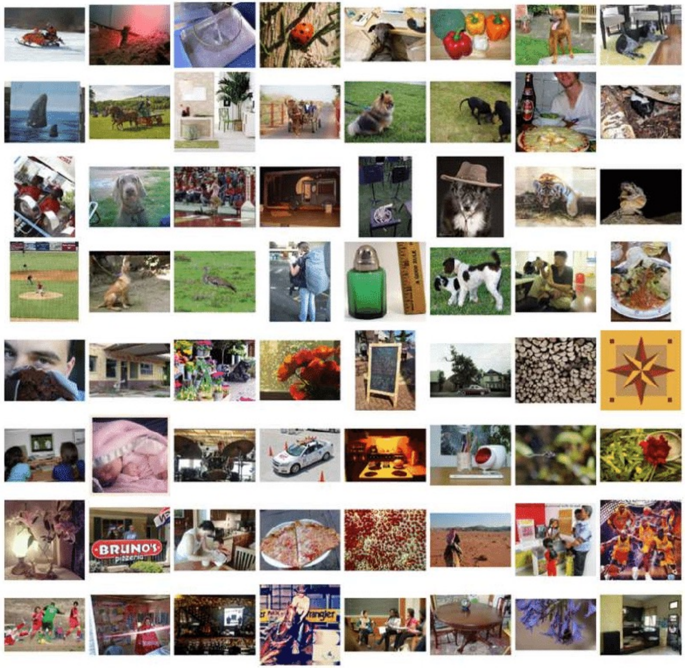
Toward deep(er) learning

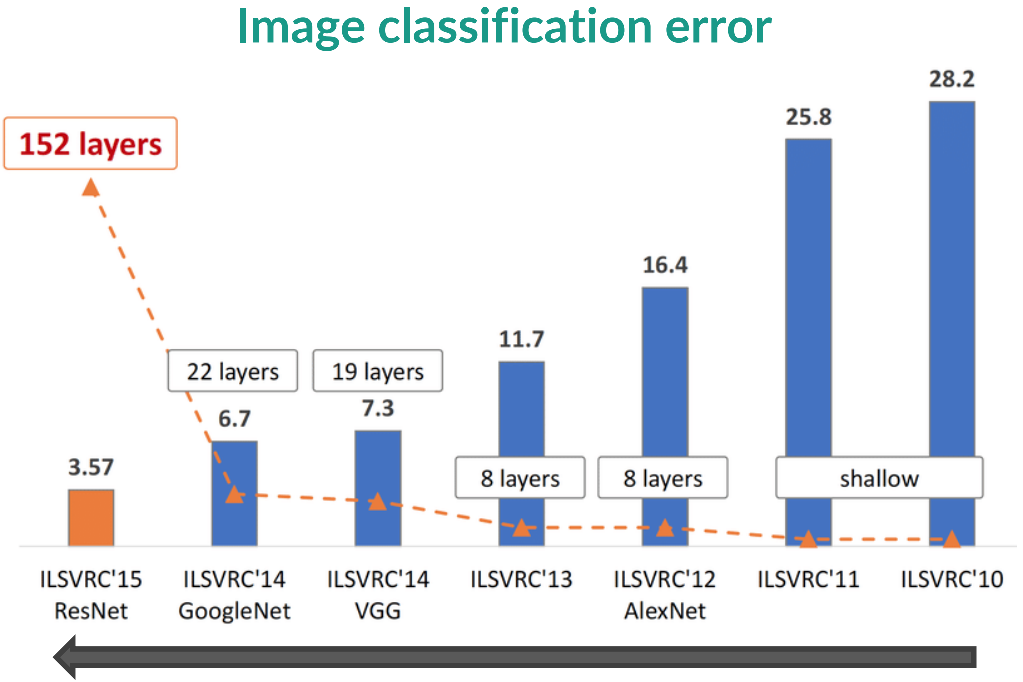
Deep artificial neural network



- Up to billions of parameters
- Deep learning is the technique for developing deep artificial neural network and theory on how such feat is possible

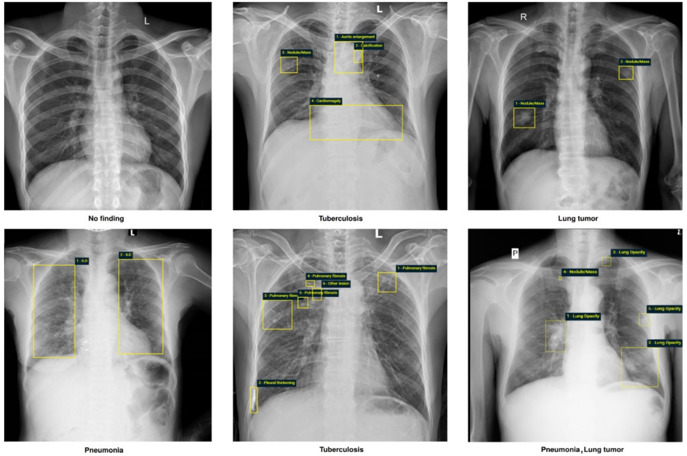
ImageNet: The rise of deep artificial neural network





Medical imaging databases

18,000 annotated CXR images



Repository for all imaging data of cancer cases

THE CANCER IMAGING ARCHIVE

Dataset	Source Institution	Disease Labeling	# Images	# Reports	# Patients
Open-I	Indiana Network for Patient Care	Expert	8,121	3,996	3,996
Chest-Xray8	National Institutes of Health	Automatic (DNorm + MetaMap)	108,948	0	32,717
CheXpert	Stanford Hospital	Automatic (CheXpert labeler)	224,316	0	65,240
PadChest	Hospital Universitario de San Juan	Expert + Automatic (Neural network)	160,868	206,222	67,625
MIMIC-CXR	Beth Israel Deacones Medical Center	Automatic (CheXpert labeler)	473,057	206,563	63,478

>1,000,000 CXR images with report

Graphical processing unit (GPU)

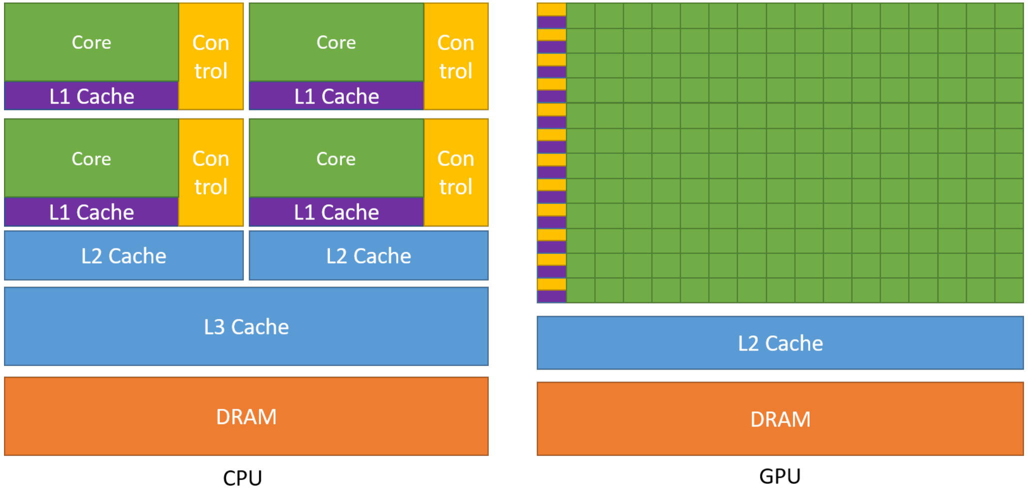


Image from analyticsvidhya.com

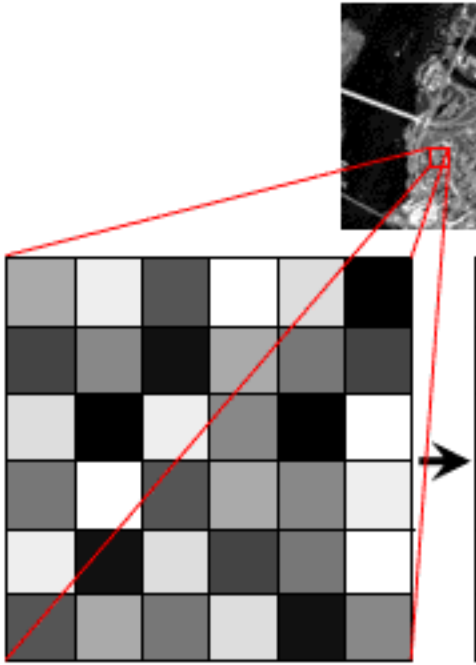
- Calculation of gradient for an ANN requires millions of simple operations that can be performed in parallel → Similar to the calculation of graphics

Representation learning

Naïve representations

	1	2	3	4	5	6	7	8	9
man	1	0	0	0	0	0	0	0	0
woman	0	1	0	0	0	0	0	0	0
boy	0	0	1	0	0	0	0	0	0
girl	0	0	0	1	0	0	0	0	0
prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

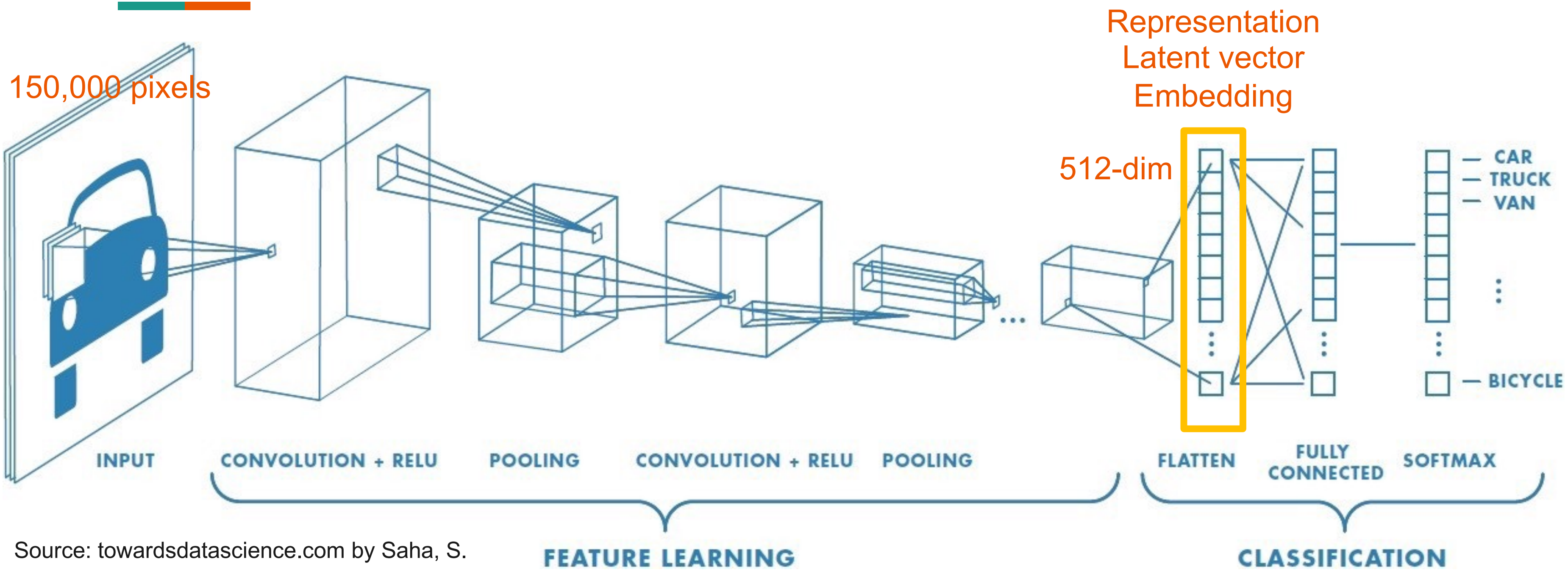
Image from hackermoon.com



170	238	85	255	221	0
68	136	17	170	119	68
221	0	238	136	0	255
119	255	85	170	136	238
238	17	221	68	119	255
85	170	119	221	17	136

Image from naushardsblog.wordpress.com

Encoder-Decoder view of neural network



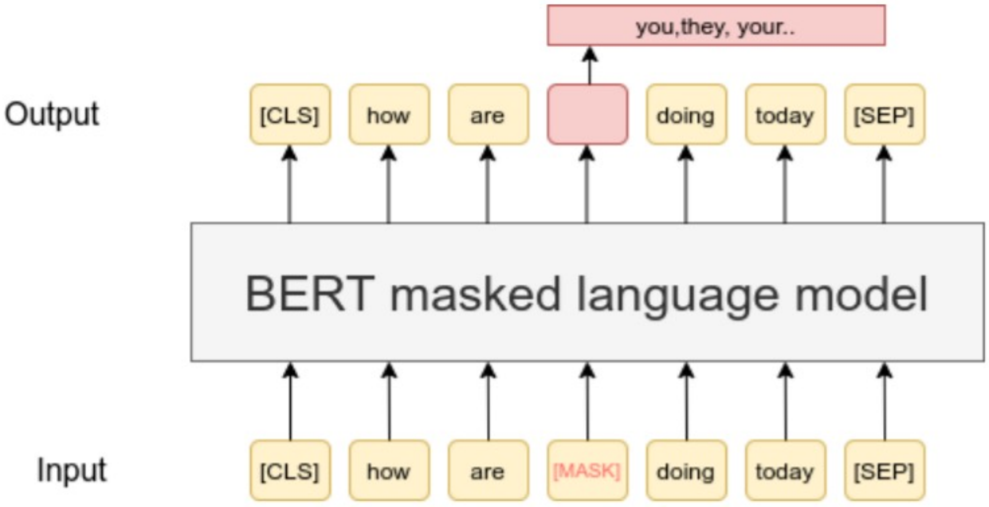
Source: towardsdatascience.com by Saha, S.

- Encode raw data into useful features → decode features for prediction

Word representation learning

- Transforming words to vectors (embeddings) that capture some meanings or characteristics

- The model obtains good embeddings by learning to predict the missing words



https://www.sbert.net/examples/unsupervised_learning/MLM/README.html

Meaningful word embedding

man →

woman →

king →

queen →

Word

Word embedding

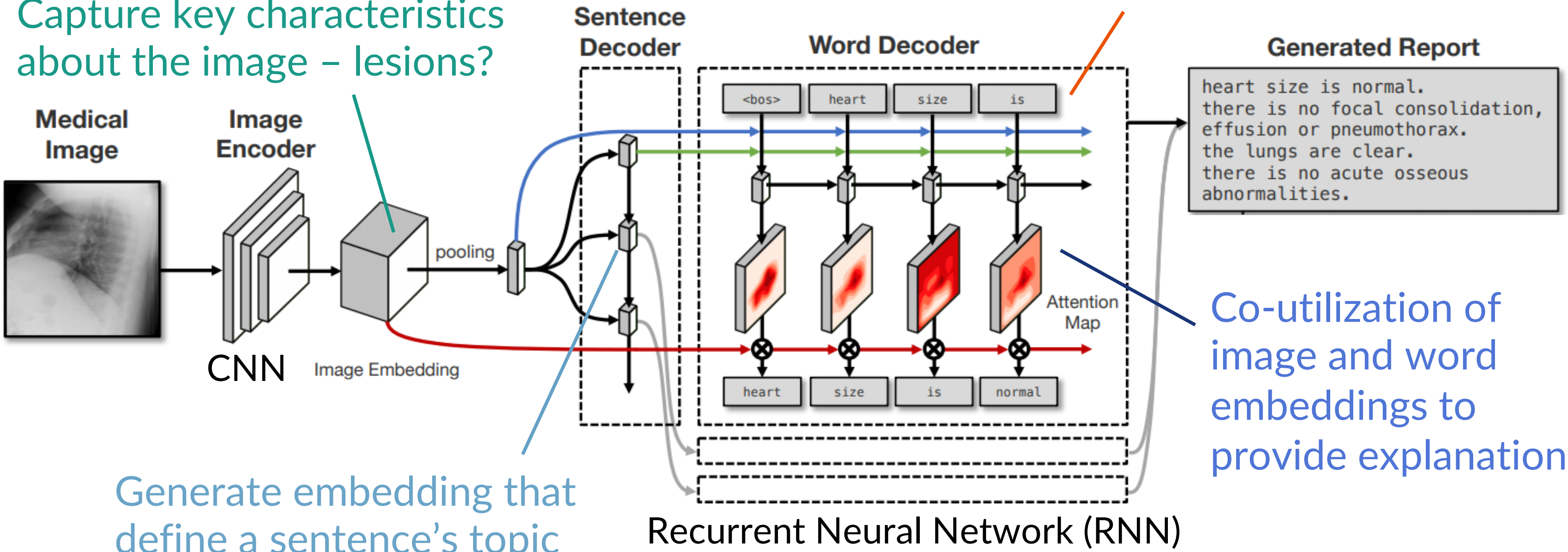
Dimensionality reduction

Visualization of word embeddings in 2D

Combining image and word embeddings

Sequentially generate words that follow the learned language and defined topic

Capture key characteristics about the image – lesions?

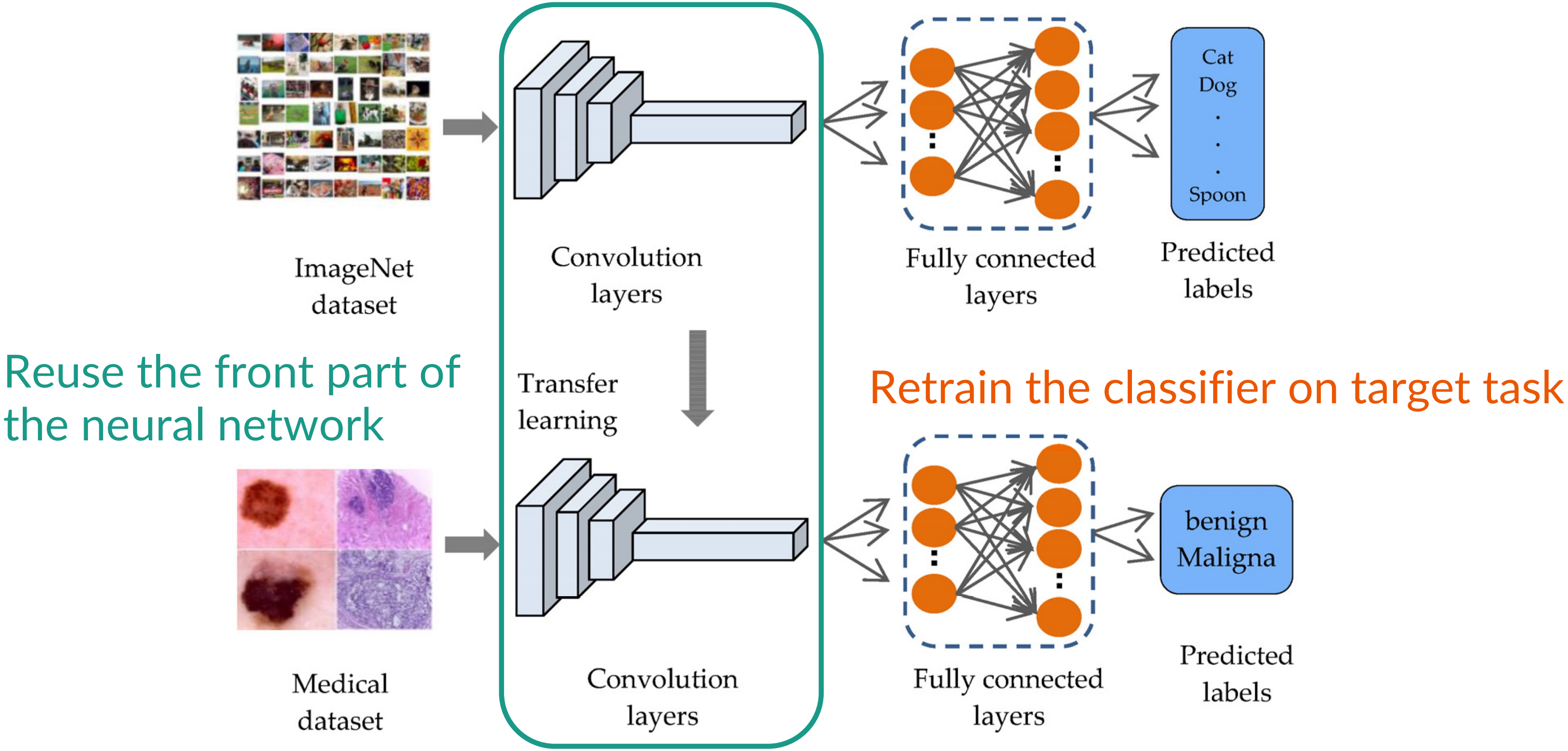


Co-utilization of image and word embeddings to provide explanation

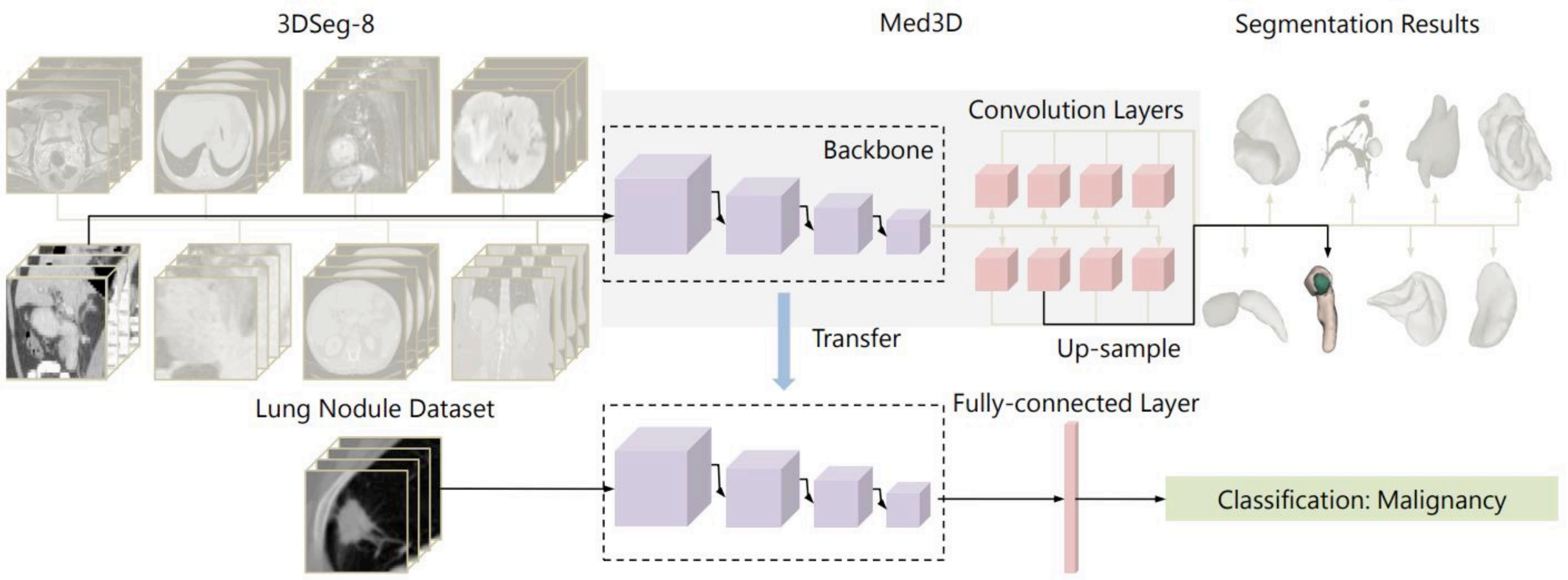
Generate embedding that define a sentence's topic

Liu et al. Clinically Accurate Chest X-Ray Report Generation (2019)

Transfer learning reduces data requirement



Shared encoder for multiple domains



Chen et al. arxiv.org/pdf/1904.00625 (2019)

Any questions?

See you on February 29th