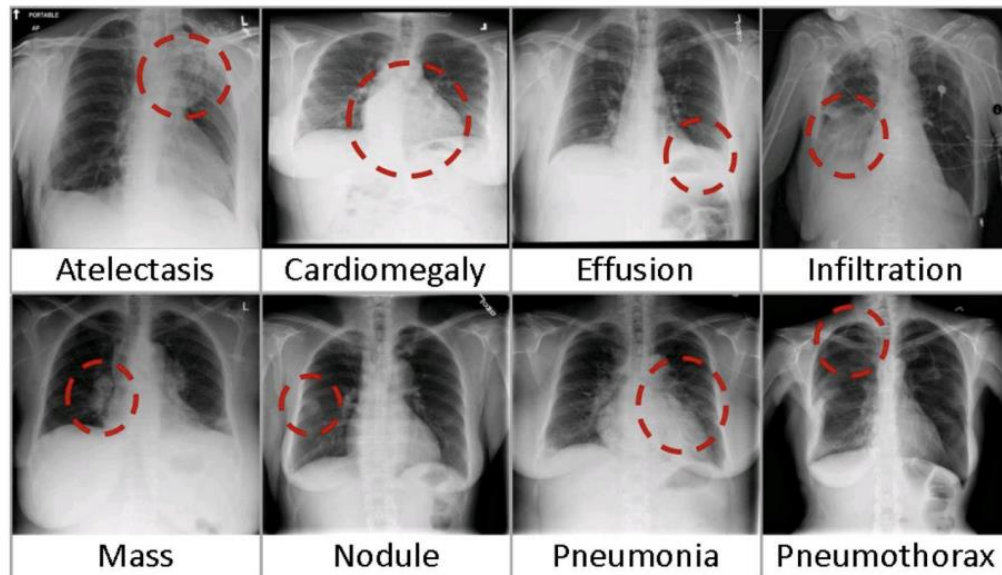


Medical Image Data Analysis (25t2)



Suchen Zheng
CBB 752 Spring 2025

Medical Image Data Analysis

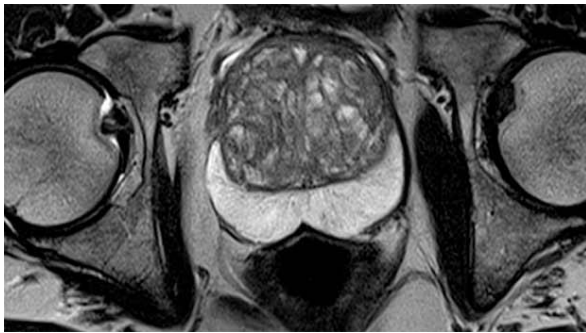
- Medical image analysis involves various tasks such as **image segmentation**, image registration, feature extraction, classification, and visualization.
- The primary objective of medical image processing is to extract meaningful information from medical images to aid in diagnosis, treatment planning, and therapeutic interventions

Motivation

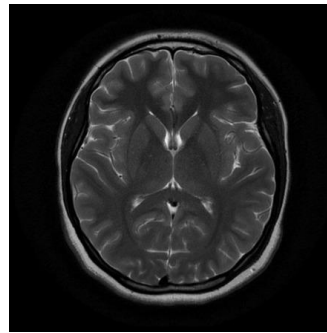
- Americans experience 12 million diagnostic errors a year (1 out of 20)
 - [Source: The Institute of Medicine; in the news: goo.gl/b7B1iq]
- Approximately 795,000 Americans experience permanent disability or death annually due to misdiagnosis of serious conditions
 - [Source: JHU; <https://bit.ly/4ih2TrQ>]
- Breast cancer misdiagnosis costs \$4B/year
 - [Source: CNBC <https://goo.gl/2THOG7>]

Medical Imaging

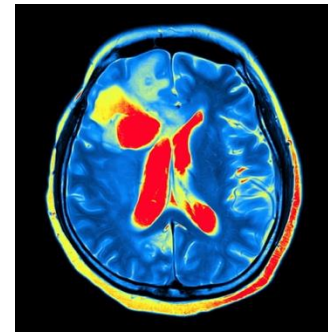
700 Billion images/year in the US alone



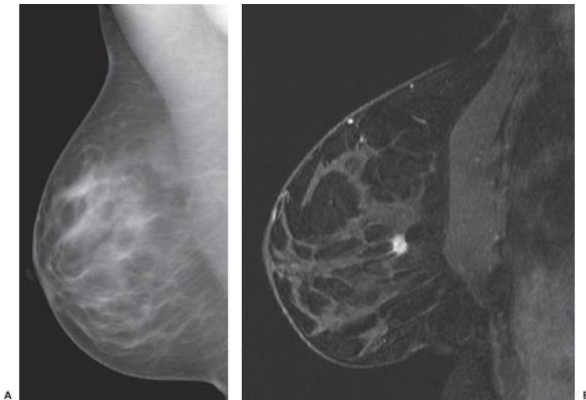
Prostate MR



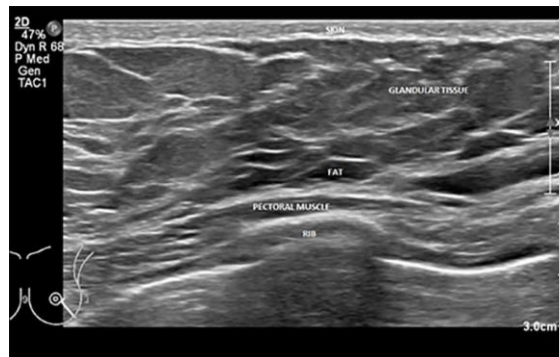
Brain MRI



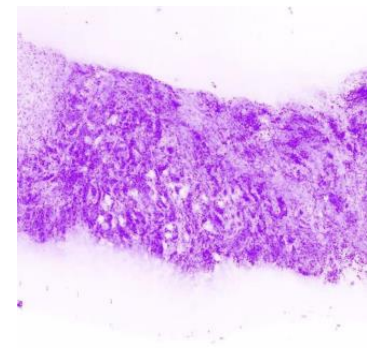
Parkinson PET



Breast cancer x-ray



Breast ultrasound (U/S)



Breast biopsy

Misdiagnosis



Is there a nodule?

Radiology is one of the specialties most liable to claims of medical **negligence**. Most often, a plaintiff's complaint against a radiologist will focus on a **failure to diagnose**.

Pinto and Brunese, "Spectrum of diagnostic errors in radiology", World J Radiol. 2010 Oct 28; 2(10): 377-383

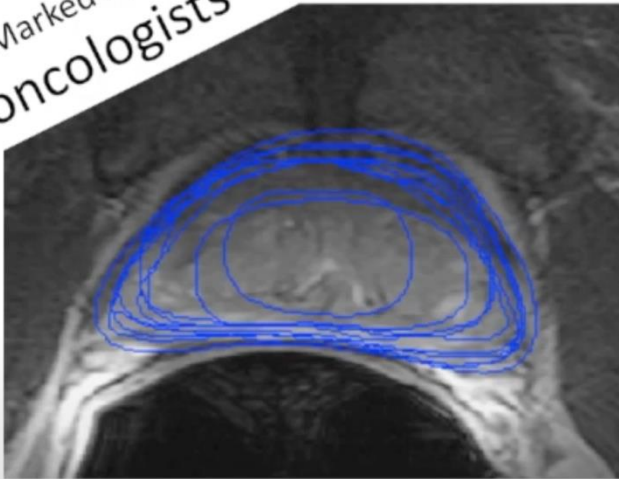
There types of error:

- 1) Scanning error
[radiologist fails to fixate in area of lesion]
- 2) Recognition error
[radiologist fails to detect the lesion]
- 3) Decision-making error
[almost 50% of error by incorrect interpretation of a malignant/benign as a benign/malignant lesion]

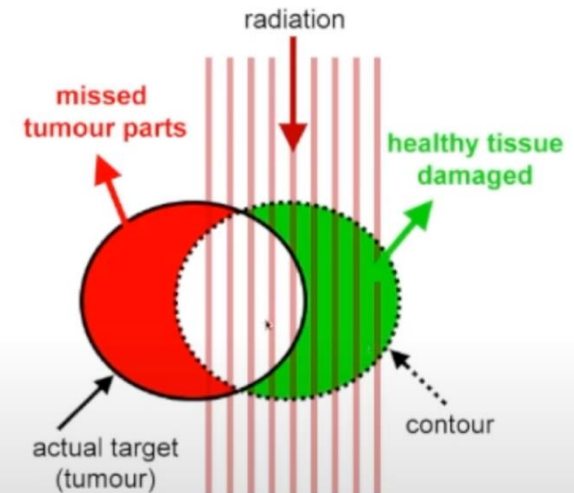
Example: 85% of cases sent for breast needle biopsy come back negative.

The Source of Problems:

Marked by
7 oncologists



Observer variability: Different doctors mark the same image differently



Wrong contouring prevents efficient treatment and may damage surrounding healthy tissue.

The Source of Problems:

Inter-Observer Variability (= error):

- Prostate 18%
- Bladder 32%
- Abdominal aorta 40%
- Breast lumpectomy cavity 45%
- Pulmonary nodules 54%

The Source of Problems:

- **What is going wrong in medical imaging?**

- Misdiagnosis
- Inaccurate/improper treatment planning

- **What is the reason for variability?**

- Imperfect information
- Complexity of diseases
- Subjective perception

- **What are the consequences?**

- Side-effects for the patient
- Prolonged treatment
- Reduced patient throughput
- Financial burden for patients/healthcare
- Legal ramifications

Precision Medicine

...predicting what treatment protocols are likely to succeed on a patient based on various patient attributes and the treatment context.

A machine learning approach to integrate big data for precision medicine in acute myeloid leukemia.

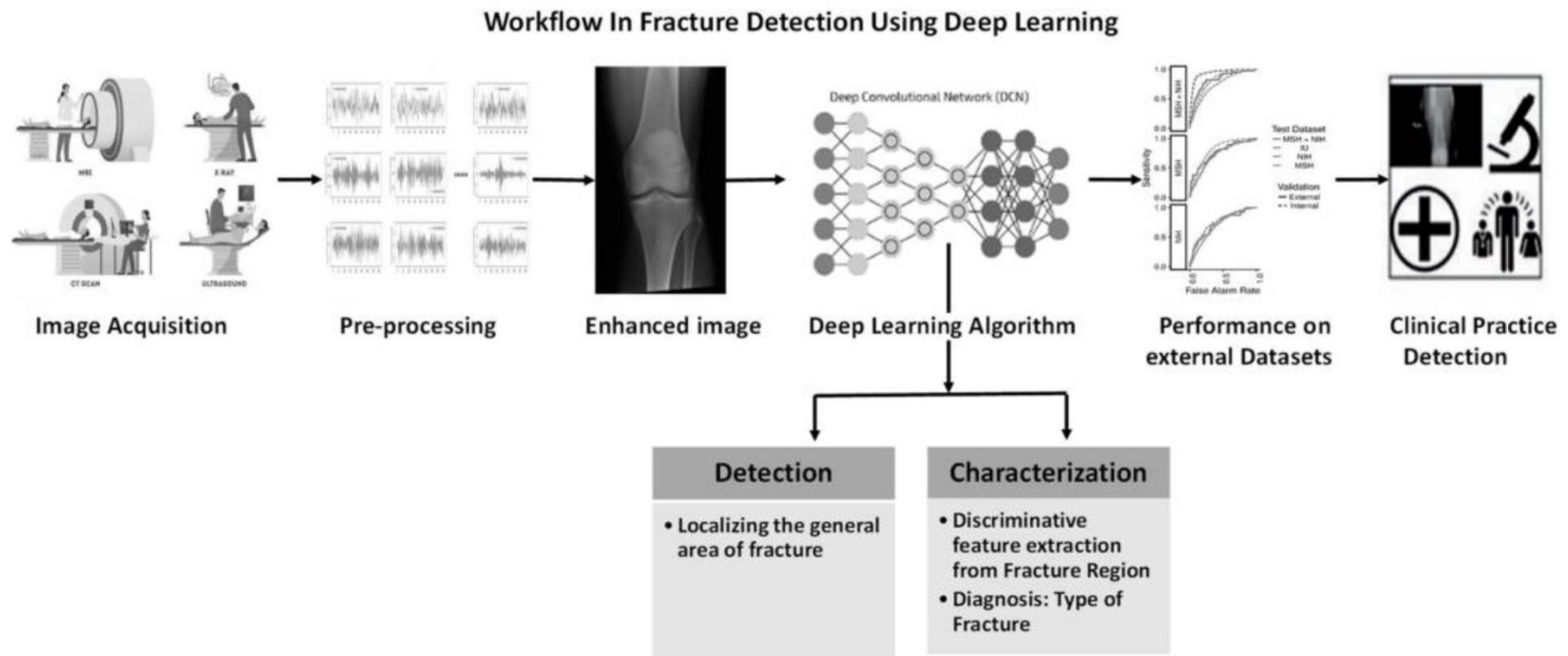
Lee SI, et al. Nat Commun. 2018 Jan 3; 9(1):42.

Historical Perspective (1990s - 2020s)

- Early Approaches (1990s):
 - Traditional image processing techniques:
 - Image enhancement (gray-level mapping, filtering)
 - Segmentation and region extraction
 - Focused on improving image quality for manual interpretation
- Machine Learning Era (2010s):
 - Feature-based models for classification and segmentation
 - Big data workflows for processing large medical image datasets
 - More automation, but feature engineering was required
- Deep Learning Revolution (2020s):
 - CNNs, GANs, RNNs, and hybrid models dominate the field
 - Shift from manual feature extraction to end-to-end learning
 - Real-time processing, higher accuracy, clinical applications

Examples

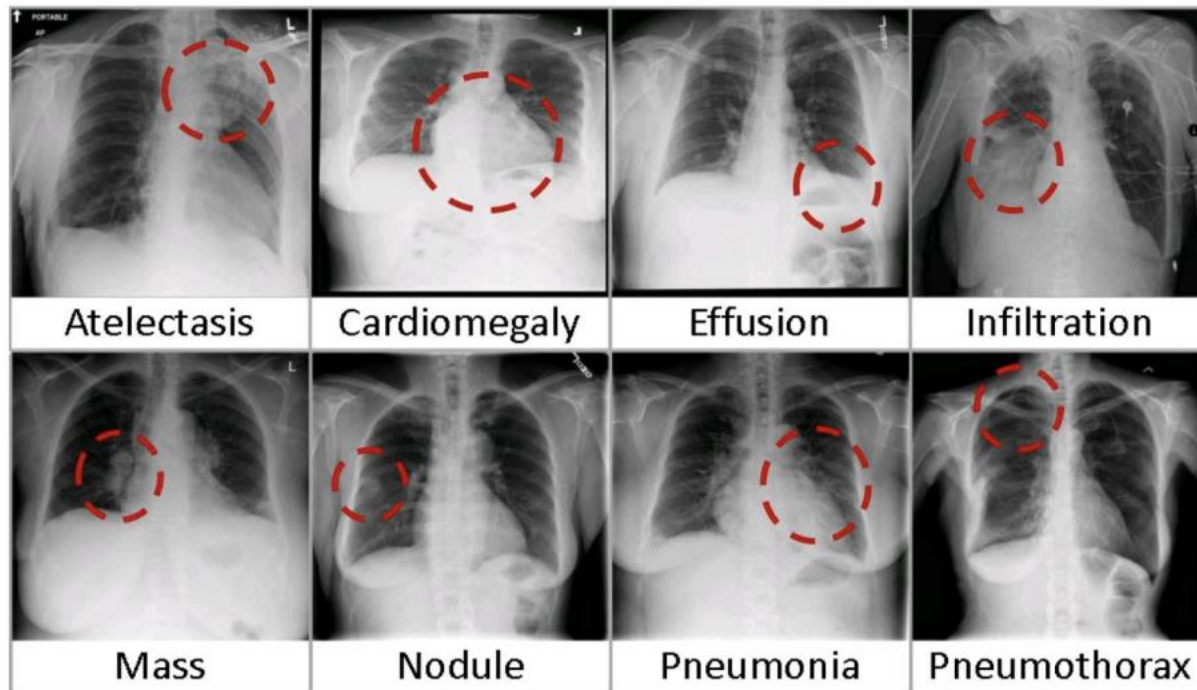
Bone Fracture Detection Using Deep Supervised Learning from Radiological Images



Examples

- Chest X-ray analysis for tuberculosis detection

B. Eight visual examples of common thorax diseases



Digital Image

- A digital image is a 2D array of values representing light intensity $\rightarrow f(x,y)$

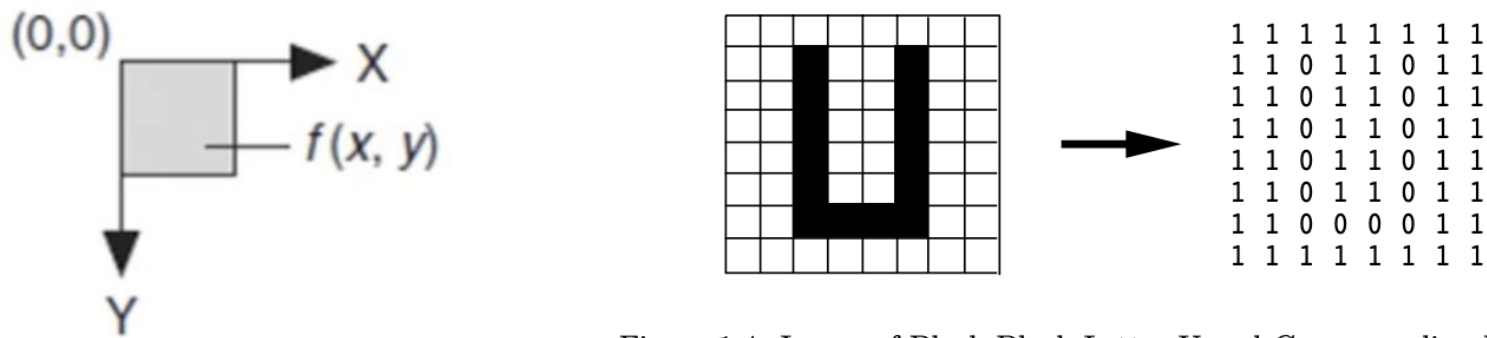


Figure 1.4: Image of Black Block Letter U and Corresponding Bitmap

Properties of Digital Images

- Image resolution/ Spatial resolution: $m \times n \rightarrow \text{Columns} \times \text{Rows}$
- dpi (Dots Per Inch)
- e.g. An 8" x 10" document that is scanned at 300 dpi has the pixel dimensions of 2,400 pixels (8" x 300 dpi) by 3,000 pixels (10" x 300 dpi).

- Image Definition: Number of shades $\rightarrow 2^n$, $n = \text{bit depth}$
(e.g. 8 bit image $\rightarrow 256$ shades, 16 bit image $\rightarrow 65,536$ shades)

Images $\rightarrow$ 8-bit, 10-bit, 12-bit, 14-bit, 16-bit, color encoded

- Number of Planes: Number of arrays of pixel.

Grayscale $\rightarrow$ 1 plane,

True-color Image $\rightarrow$ 3 planes (RGB)

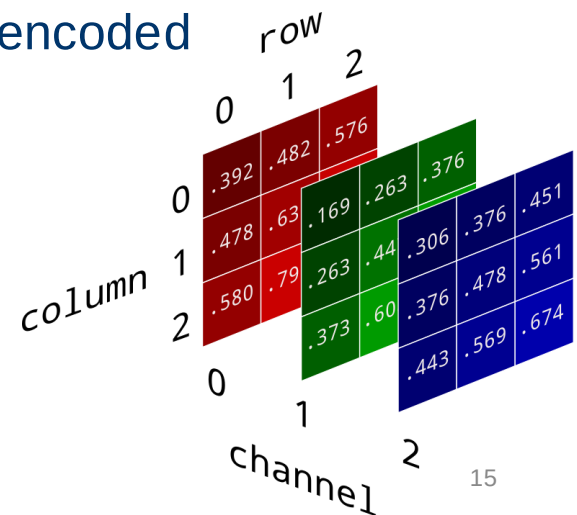
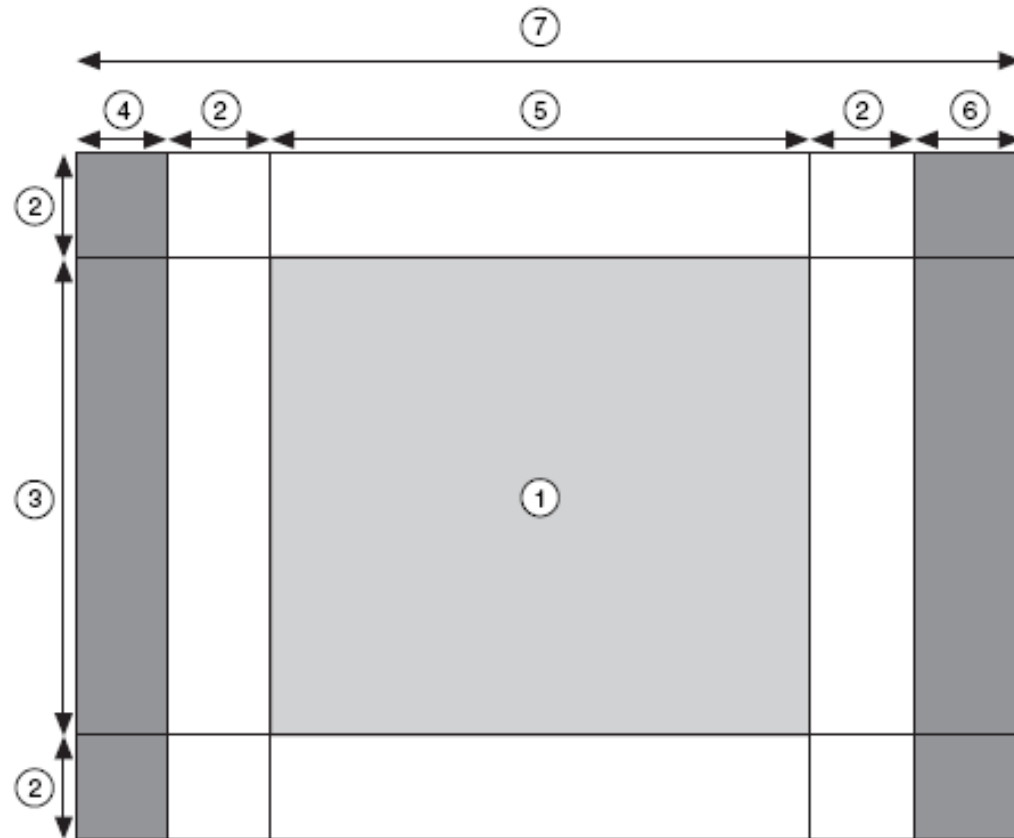


Image representation



1 Image
2 Image Border

3 Vertical Resolution
4 Left Alignment

5 Horizontal Resolution
6 Right Alignment

7 Line Width

Image border

A – pixel value of the image

B – '0' padding

C – copying of edge pixel values

D – mirror the pixel values at the edge

		10	9	15	11	12	20	16	12	11	8			
		11	13	11	12	9	16	17	11	13	14			
		12	8	12	14	12	13	12	14	11	13			
		10	9	13	31	30	32	33	12	13	11			
		15	11	10	30	42	45	31	15	12	10			
		13	12	14	29	40	41	33	13	12	13			
		14	15	12	33	34	36	32	12	14	11			
		10	12	13	14	12	16	12	15	10	9			
		10	8	11	13	15	17	13	14	12	10			
		9	10	12	11	8	15	14	12	11	7			

A

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	10	9	15	11	12	20	16	12	11	8	0	0	0
0	0	11	13	11	12	9	16	17	11	13	14	0	0	0
0	0	12	8	12	14	12	13	12	14	11	13	0	0	0
0	0	10	9	13	31	30	32	33	12	13	11	0	0	0
0	0	15	11	10	30	42	45	31	15	12	10	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

B

10	10	10	9	15	11	12	20	16	22	11	8	8	8	8
10	10	10	9	15	11	12	20	16	22	11	8	8	8	8
10	10	10	9	15	11	12	20	16	12	11	8	8	8	8
11	11	11	13	11	12	9	16	17	11	13	14	14	14	14
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15	15	15	11	10	30	42	45	31	15	12	10	10	10	10
13	13	13	12	14	29	40	41	33	13	12	13	13	13	13
14	14	14	15	12	33	34	36	32	12	14	11	11	11	11
10	10	10	12	13	14	12	16	12	15	10	9	9	9	9
10	10	10	8	11	13	15	17	13	14	12	10	10	10	10
9	9	9	10	12	11	8	15	14	12	11	7	7	7	7
9	9	9	10	12	11	8	15	14	12	11	7	7	7	7
9	9	9	10	12	11	8	15	14	12	11	7	7	7	7

C

13	11	11	13	11	12	9	16	17	11	13	14	14	13	13
9	10	10	9	15	11	12	20	16	12	11	8	8	8	11
9	10	10	9	15	11	12	20	16	12	11	8	8	8	11
13	11	11	13	11	12	9	16	17	11	13	14	14	13	13
8	12	12	8	12	14	12	13	12	14	11	13	13	11	11
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11	15	15	11	10	30	42	45	31	15	12	10	10	10	12
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10	9	9	10	12	11	8	15	14	12	11	7	7	11	11
10	9	9	10	12	11	8	15	14	12	11	7	7	11	11
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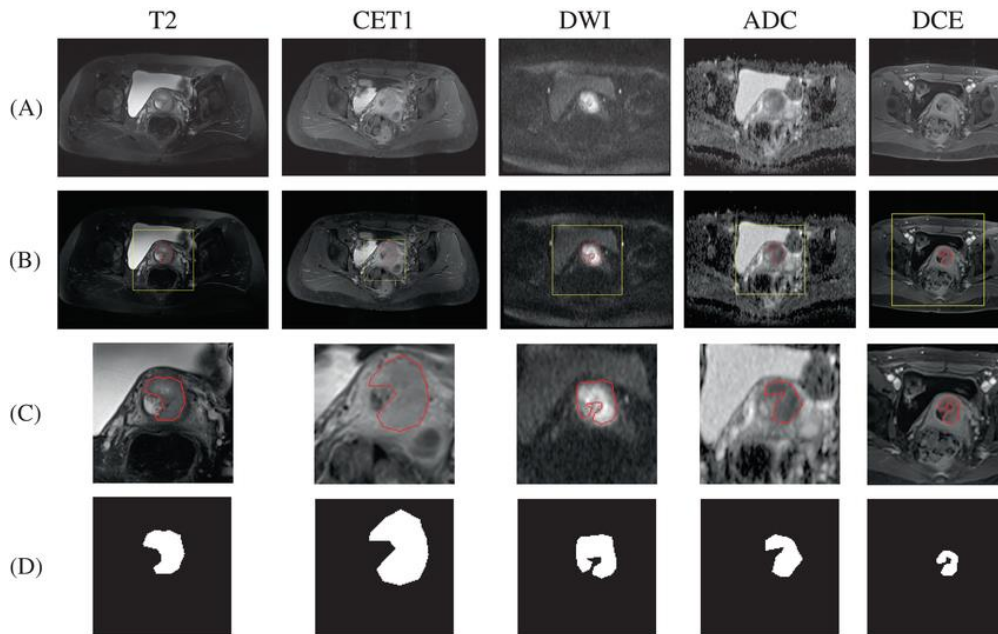
D

Image Mask

- An image mask isolates parts of an image for processing.
- An image mask is used to highlight specific regions of interest (ROI)
- An image mask is typically a grayscale or binary image where:
 - White (1) or a specific intensity level represents the region of interest (e.g., a tumor, blood vessel, or organ).
 - Black (0) or another intensity level represents the background or non-relevant areas.

Image Mask

- Within a biomedical image. In medical imaging, masks play a crucial role in **segmentation, classification, and feature extraction**, helping in tasks such as tumor detection, organ segmentation, and lesion analysis.



- (A) Raw MRI images;
- (B) cervical cancer annotations drawn by clinicians.
- (C) cropped MRI images overlapped with tumor annotations
- (D) cropped binary masks with tumor regions

Examples of MRI and mask preprocessing.

Image segmentation

- Definition: Label each pixel in the image with a category label
- Do not differentiate planes/instances, only care about pixels

The process of medical image segmentation can be divided into the following stages:

1. Obtain medical imaging data set
2. Preprocess the images
3. Use appropriate medical image segmentation method
4. Performance evaluation

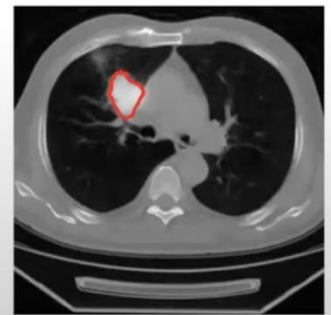
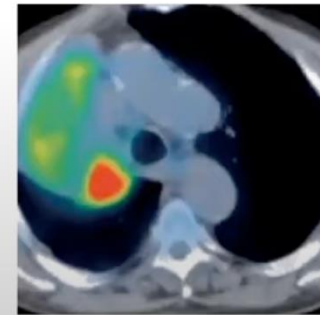
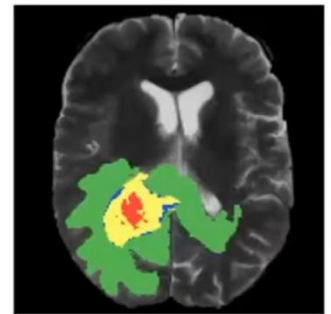
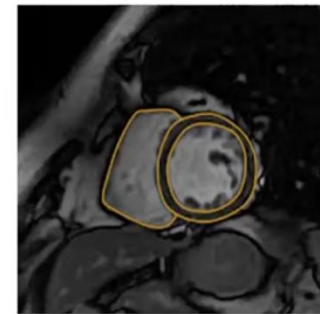
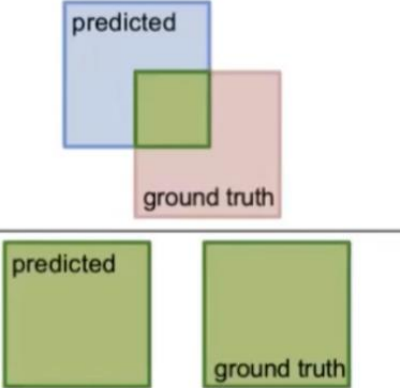


Image segmentation

- Evaluation metrics

$$\text{Diced index} = \frac{2|X \cap Y|}{|X| + |Y|}$$

$$\text{Dice Coefficient} = \frac{2 \times \text{area of overlapped (green)}}{\text{total area (green)}} =$$


$$\text{Jaccard Index} \quad Jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

Image segmentation

- Traditional Method

1. Threshold method

- Simple calculation, high efficiency
- Only consider the characteristics of the pixel point grayscale value itself, generally do not consider space characteristics
- more sensitive to noise, and the robustness is not high.

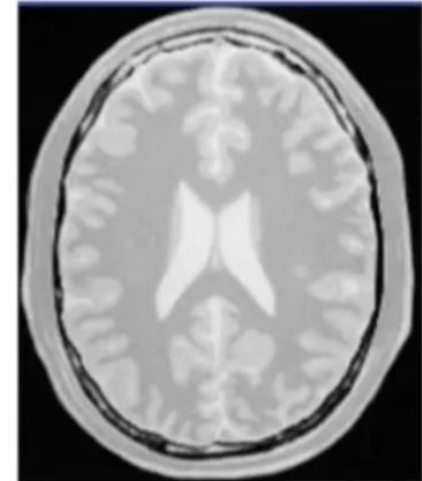
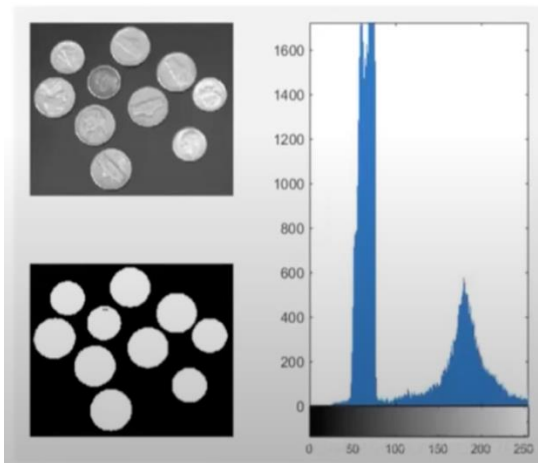


Figure 3. Original image.



Image segmentation

- Traditional Method

2. Edge detection-based Method



Fig.1. Original lungs CT image with salt-and- pepper noise.

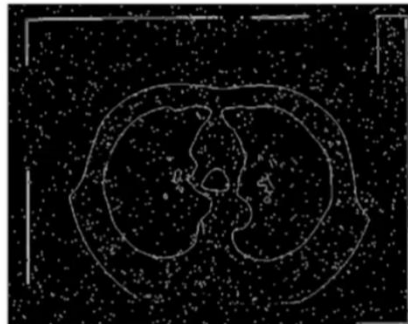


Fig.3. Lungs CT image processed by Sobel detector.

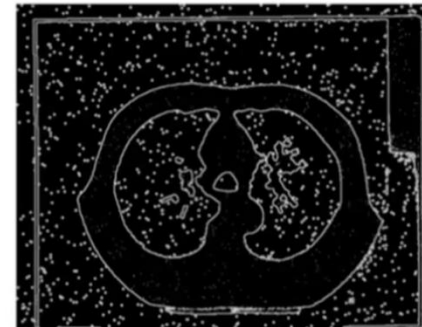


Fig.5. Lungs CT image processed by dilation residue edge detector.

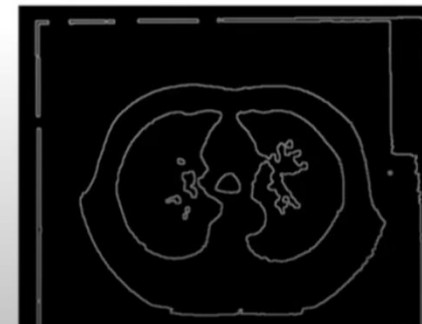
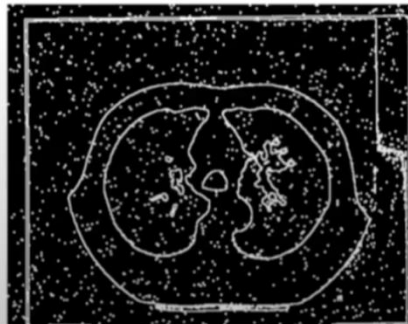
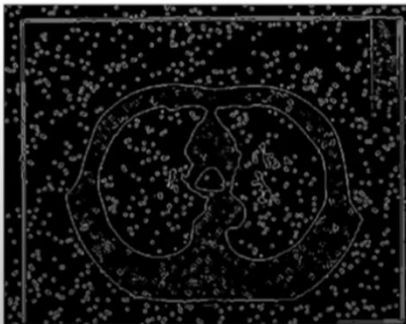
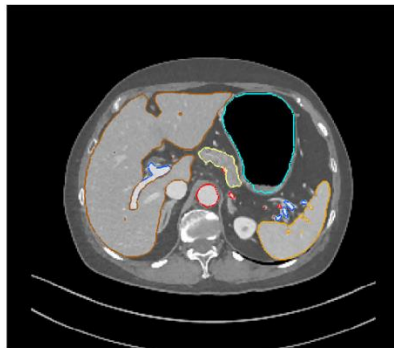


Image segmentation

- Deep learning based method - FCN



(a) Ground truth (axial)



(c) Segmentation (axial)

FCN adapting classifiers for dense prediction

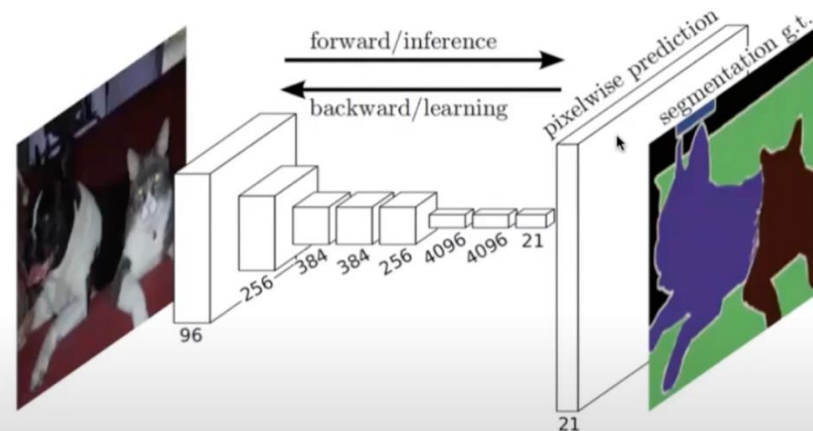


Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

Image segmentation

- Deep learning based method – U-Net

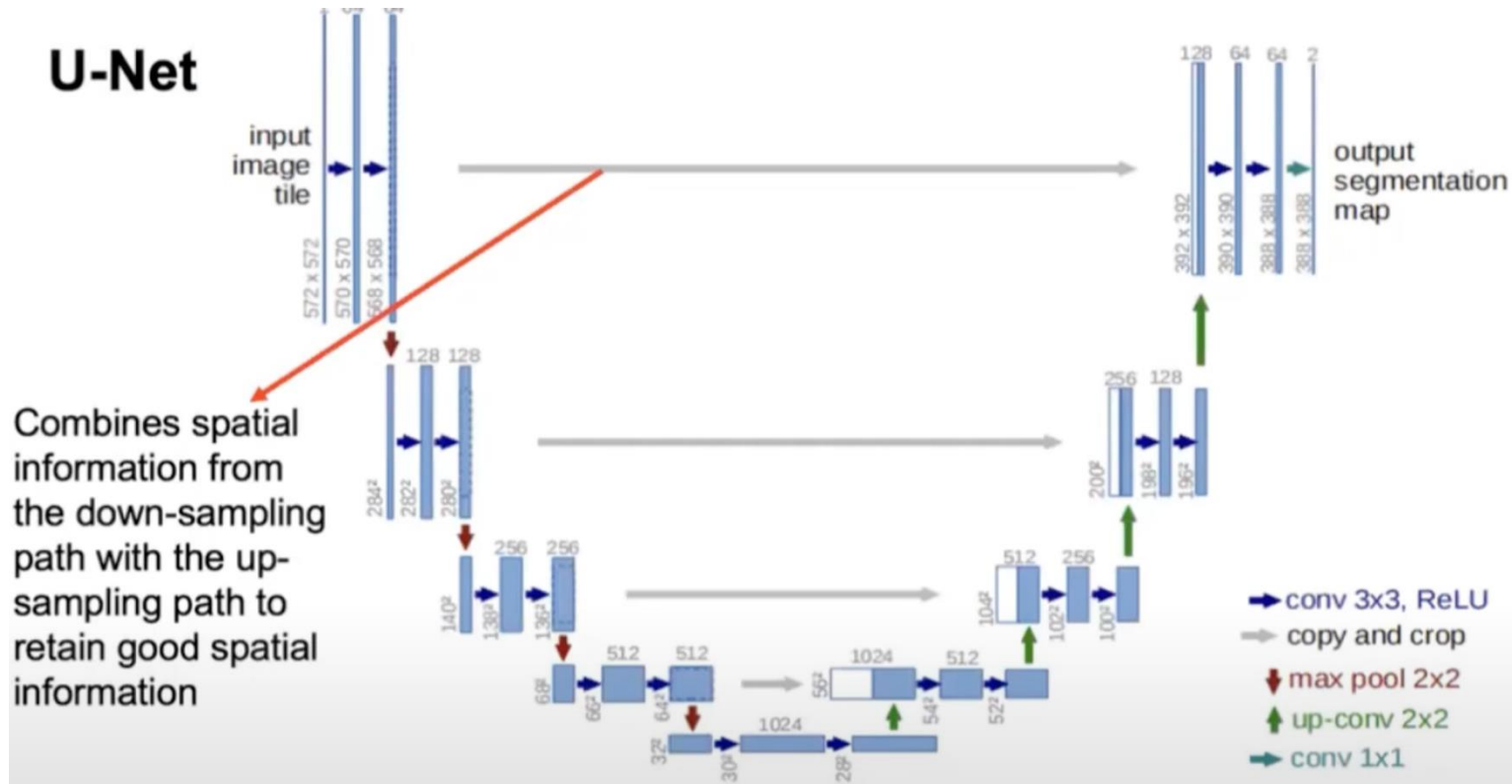


Image segmentation

- Deep learning based method – U-Net

U-Net

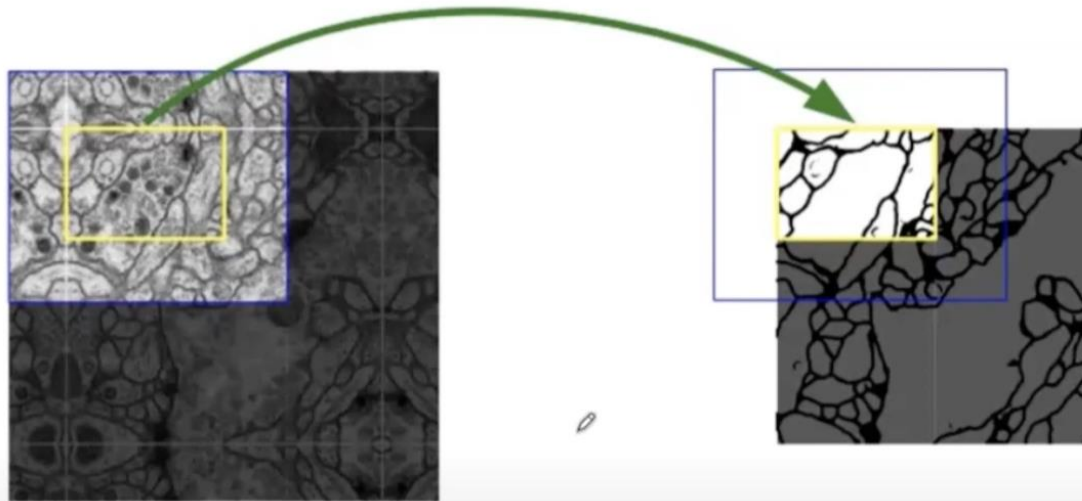
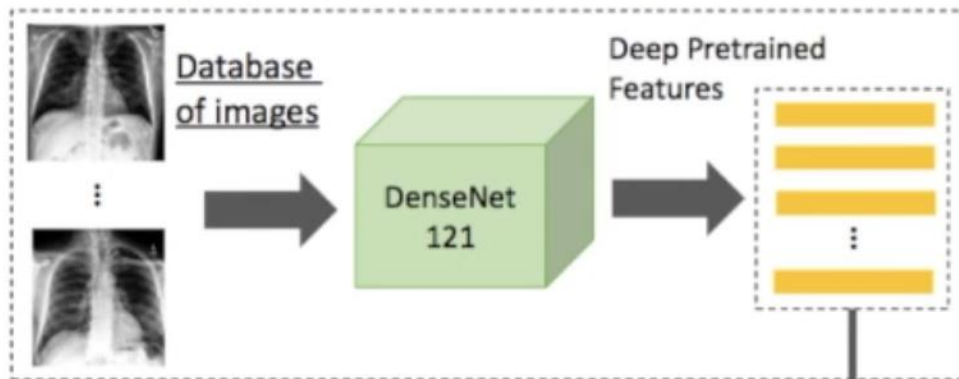


Fig. 2. Overlap-tile strategy for seamless segmentation of arbitrary large images (here segmentation of neuronal structures in EM stacks). Prediction of the segmentation in the yellow area, requires image data within the blue area as input. Missing input data is extrapolated by mirroring

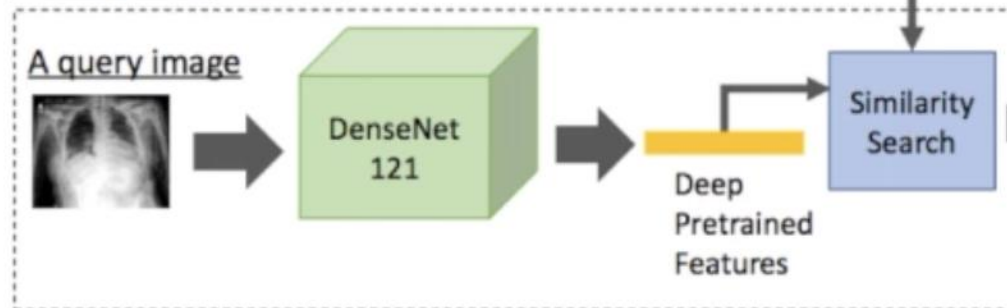
Image Classification

Use deep features for identification of Chest Issues

Phase 1: Tagging Images with Deep Pretrained Features



Phase 2: Image Search



Phase 3: Classification

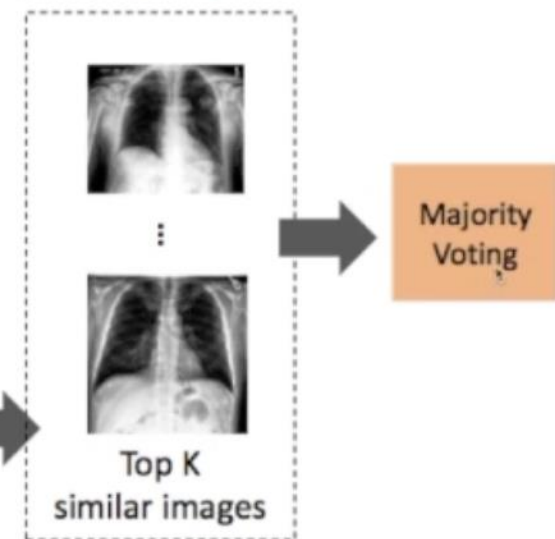
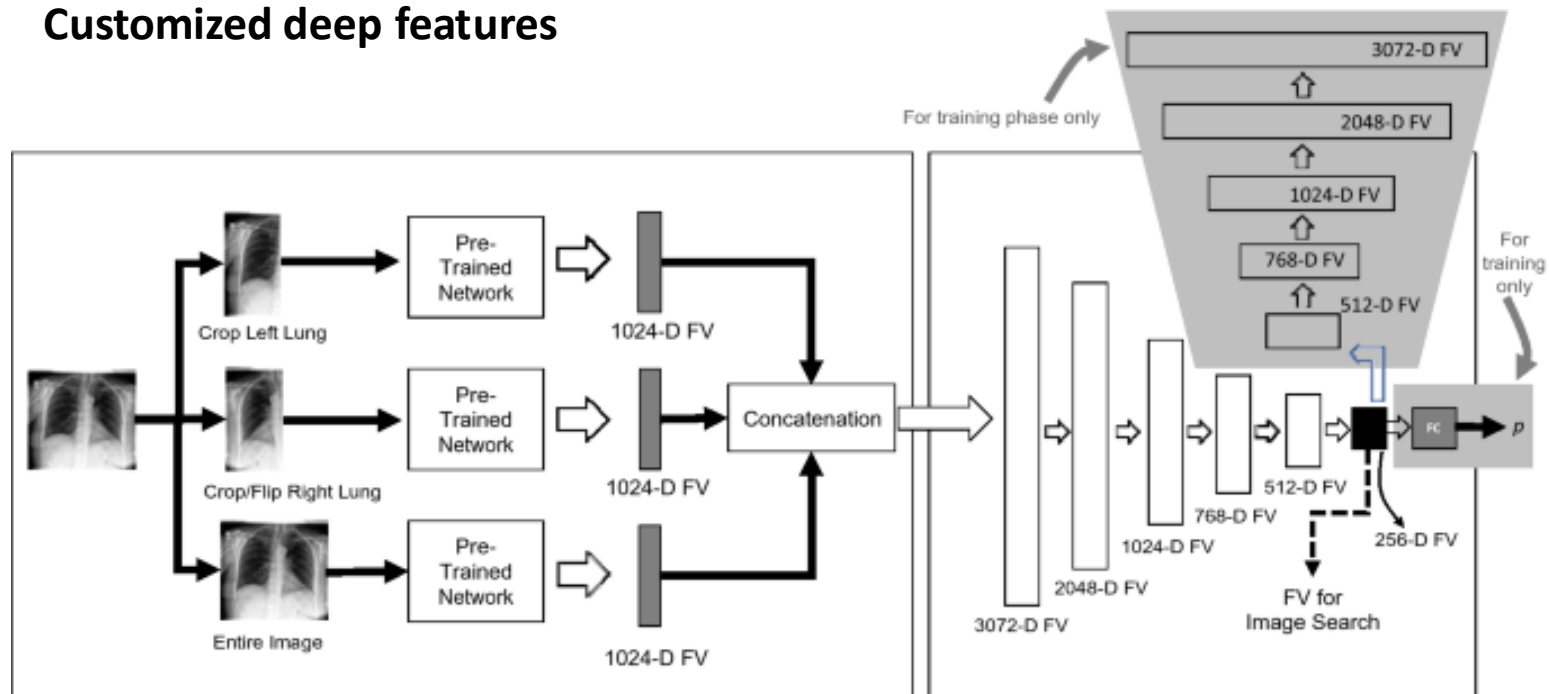


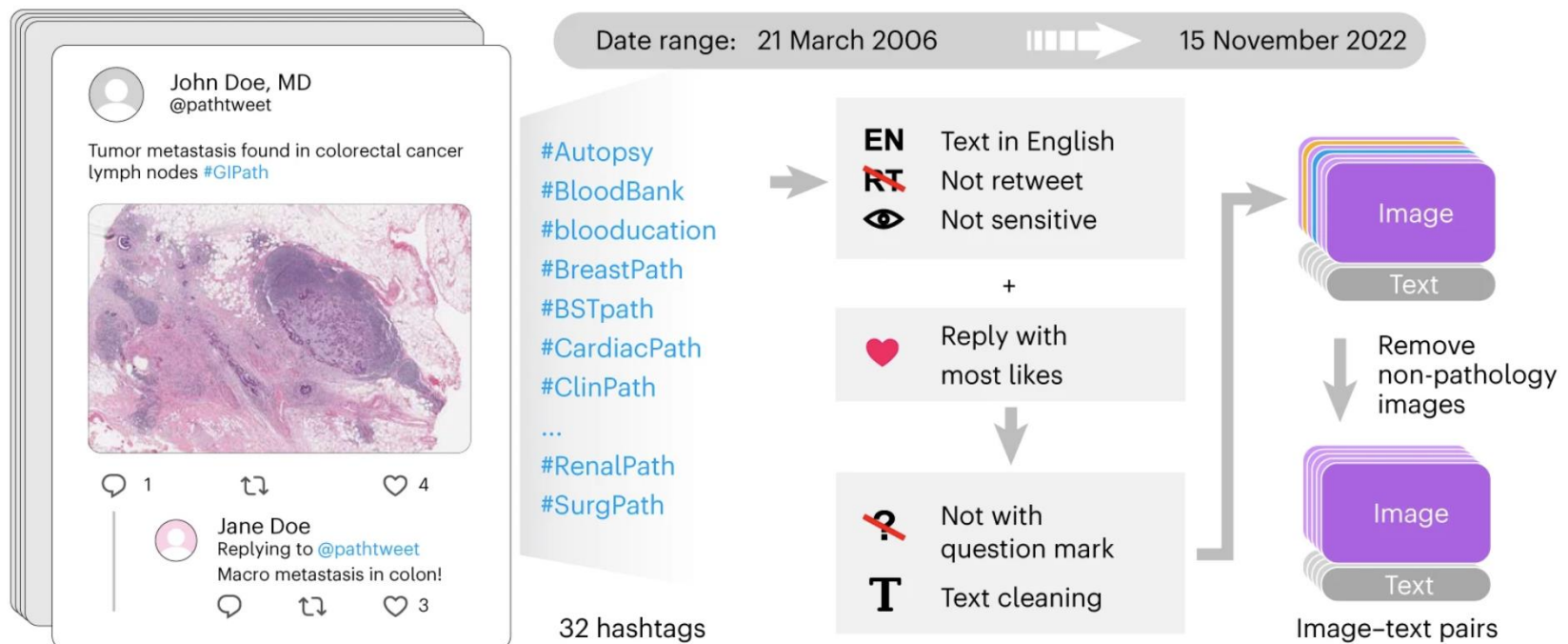
Image Classification

Customized deep features



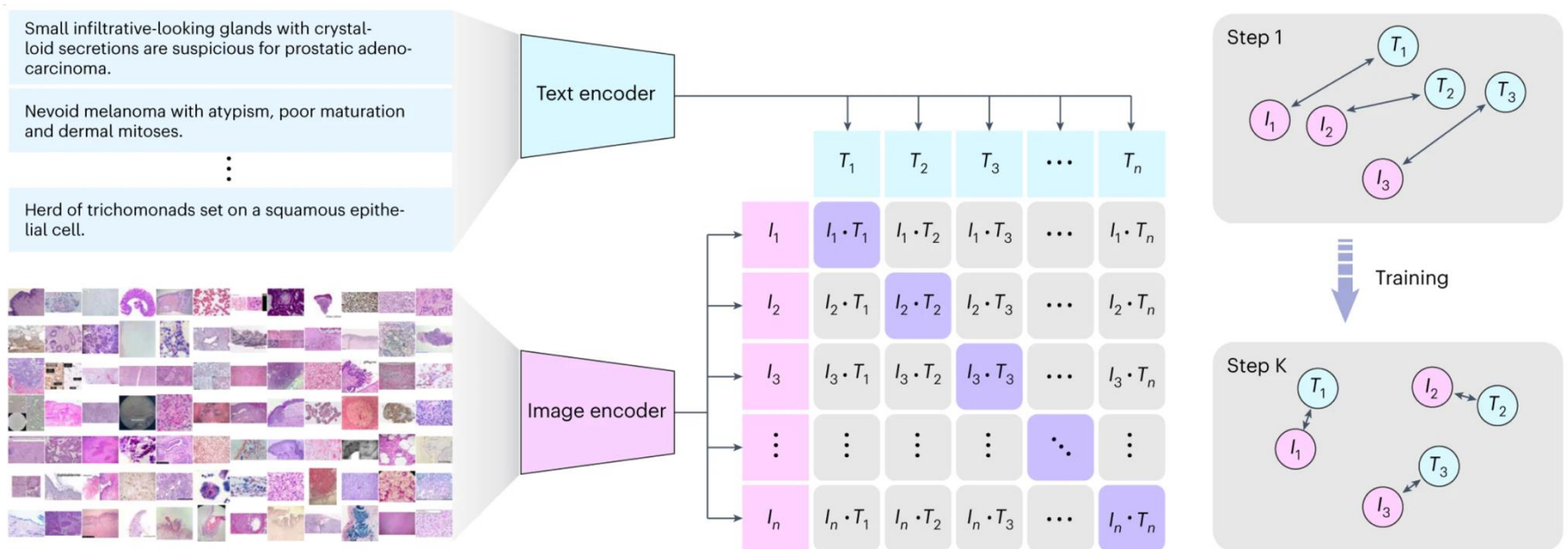
LLM - Text & Images

Pathology text-image data pair from Twitter (X)



LLM - Text & Images

Contrastive learning for multi-modality data



Suggested readings

- Huang, Z., Bianchi, F., Yuksekgonul, M. *et al.* A visual–language foundation model for pathology image analysis using medical Twitter. *Nat Med* **29**, 2307–2316 (2023).
<https://doi.org/10.1038/s41591-023-02504-3>
- Recent Trends in Image Processing and Pattern Recognition P84-94
5th International Conference, RTIP2R 2022, Kingsville, TX, USA, December 1-2, 2022, Revised Selected Papers
- An optimal big data workflow for biomedical image analysis
Informatics in Medicine Unlocked, Volume 11, 2018, Pages 68-74

Thanks!