Lecture Title and Date

25t2 - Medical Image Data Analysis (3/5/25)

Objectives of the Lecture

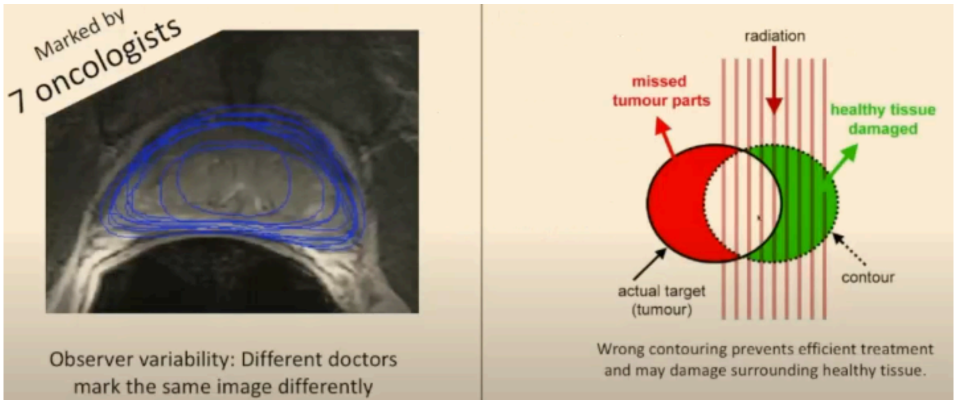
1. Understand the motivation and need for medical image data analysis
2. Understand the capabilities and limitations of medical image data analysis
3. Understand the fundamental concepts of image analysis and its applications in the medical space

Key Concepts and Definitions

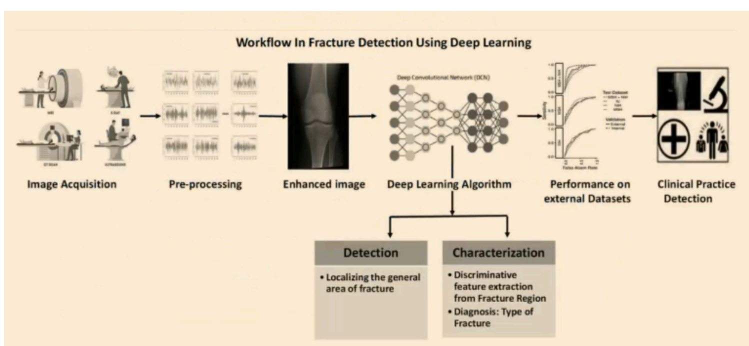
- Medical Imaging: Visual representation of parts of the human body (CT Scan, MRI, X-ray)
- Observer Variability: A Difference in medical professional interpretation of the same image
- Digital Image: 2D array of values representing light intensity
- Image/Spatial Resolution: m x n (Column x Rows)
- DPI: Dots Per Inch
- Image Definition: Number of shades (2^n)
- Number of Planes: Number of arrays of pixels
- Image Mask: Helps with image segmentation, classification, and feature extraction

Main Content/Topics

Although medical imaging is an integral part of the treatment process, misdiagnoses are frequent and costly. Misdiagnoses such as scanning error (radiologist fails to fixate on the area of lesion), recognition error (radiologist fails to detect the lesion), and decision making error (incorrect interpretation of malignant/benign lesion) are common sources of errors that is a major concern in the treatment process. Furthermore, there is inherent variability in traditional medical imaging results, stemming from a few factors, such as imperfect information (wrong contouring results in less representative images and can damage healthy tissues), complexity of diseases (Some diseases/areas are more error-prone), and subjective perceptions (Professionals have different opinions about the same piece of image/information). These uncertainties and the need for an accurate, efficient, and consistent diagnosis prompts the development of medical imaging data analysis techniques.

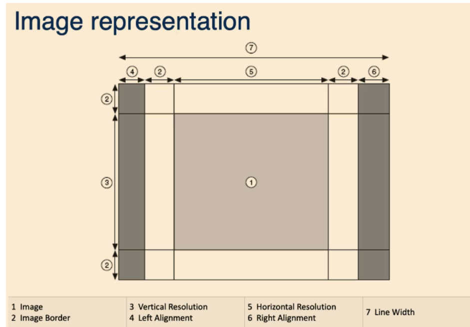


The improvement of medical image data analysis has been an ongoing effort, where people tend to focus on different factors, depending on the current advances of technology at that point in time. In the 1990s, early and traditional image processing focused on the improvement of image quality, using techniques such as gray-level mapping, filtering, and segmentation and region extraction. Moving on to the 2010s, the rise of machine learning has prompted the integration of these technologies into medical image processing, leading research efforts to focus on image feature optimization, since higher quality features may lead to better models. As a result, feature engineering is a crucial step in the process. This development also enabled the analysis of much larger datasets efficiently. Forwarding to the 2020s, improvements in deep-learning technologies steered the focus into end-to-end learning to help improve the neural networks that dominate the research in the field, leading to higher accuracy and enabling real-time analysis. For example, convolutional neural networks (CNN) have been used to help detect different types of diseases from chest X-rays, and deep learning algorithms have been used to characterize different types of fractures from X-ray images.

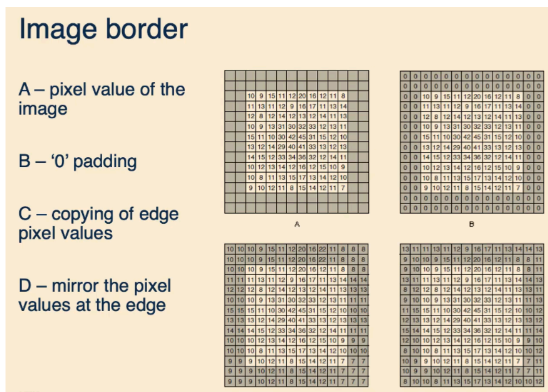


To better understand the idea behind the improvements of image analysis, we revisit the fundamental concepts of image data analysis. Digital images are comprised of blocks in a bitmap represented by x,y coordinates with a value representing the light intensity (0 for black to 1 for white). The image resolution is determined by the dots per inch (DPI) of an image's dimensions (ex. 8”x10” image with 300 DPI has a resolution of 2400 x 3000 pixels). Meanwhile, the image definition is determined by the number of shades (2^n). To produce a grayscale image, 1 plane (number of pixel arrays) is used, while an RGB image compiles 3 different planes to synthesize colors.

Images can be represented by the following guidelines:

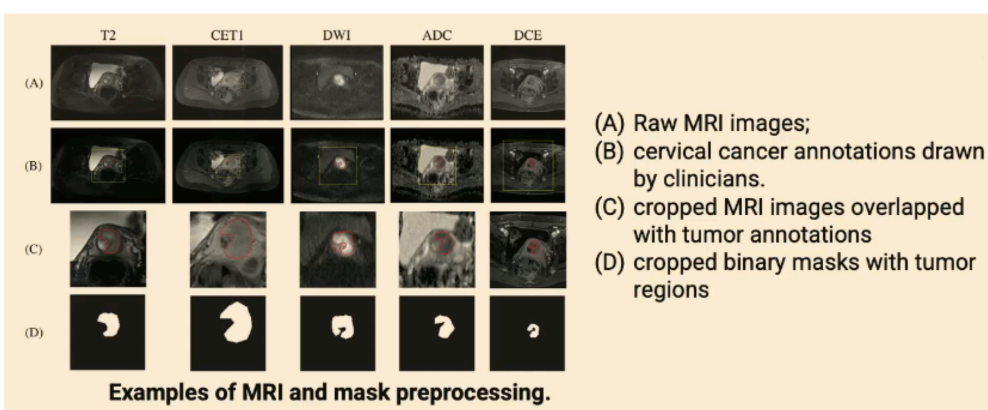


Although the actual image is located in the middle, the surrounding elements also contribute to the image quality and may impact the overall accuracy of algorithms. For instance,



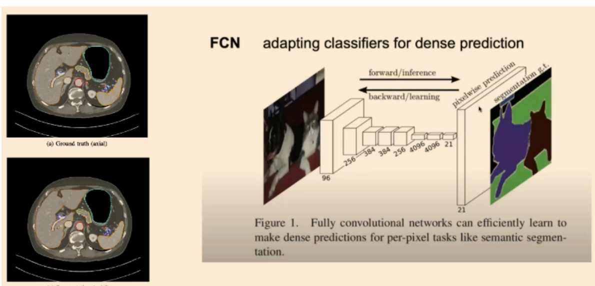
Different image border techniques are used to "protect" the image to ensure efficient storage and is used in different cases. In applications like MRI or CT scan, copying or mirroring the pixel values might be better to preserve the edge information.

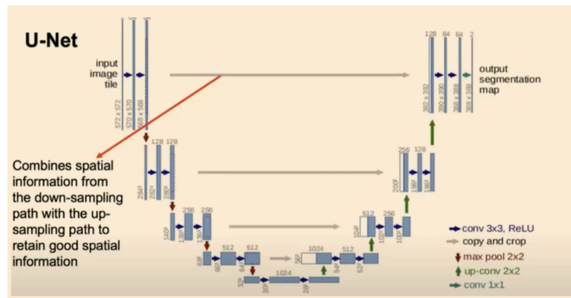
Meanwhile, image masks are typically grayscale/binary images used to isolate specific regions of interest for processing, playing an important role in segmentation, classification, and feature extraction.



Examples of MRI and mask preprocessing.

Benefitting from image mask, image segmentation labels each pixel in the image with a category label that ignores planes/ instances. The segmentation is evaluated by Diced Index ($\frac{2|X\cap Y|}{|X|+|Y|}$), or Jaccard Index ($Jaccard(A, B) \ = \ \frac{|A\cup B|}{|A\cap B|}$). Traditionally, the Threshold Method is used for image segmentation, which simply sets a threshold of light intensity for each pixel to label them. Another traditional method is edge detection, where softwares are used to enhance and highlight the edges in the images, generating the final segmentation. As the technology improves, the incorporation of deep learning allowed researchers to use CNN to produce latent representations and segmentation results. Another popular deep learning method is U-Net, which encodes the image, producing a lower-resolution representation and then decodes the image by upsampling to produce a segmentation map, helping highlight the important features of the given image.





Circling back to the classification of chest X-rays using deep learning, given a chest X-ray image, a pre-trained deep-learning model (DenseNet-121) extracts deep features from the image and returns a K most similar set of images, where a majority vote would determine the most probable disease. This method was also optimized by performing tests on cropped images to focus the deep features extraction on the partial image and concatenating the results as well, improving accuracy.

Lastly, Large Language Models (LLMs) are implemented to analyze tweets to help process pathology-related tweets. The process involves collecting and filtering relevant pathological tweets with images, selecting the most liked and relevant reply, and finally using that info to fine-tune LLMs, helping further medical image diagnosis.

Discussion/Comments

<u>Data bias:</u> Medical imaging datasets often suffer from class imbalance across demographic groups.
<u>Human-machine collaborations:</u> What is the role of humans and machines in future diagnosis?

List all suggested reading here and please answer:

1. Huang, Z., Bianchi, F., Yuksekgonul, M. et al. "A visual–language foundation model for pathology image analysis using medical Twitter." Nature Medicine 29, 2307–2316 (2023). https://doi.org/10.1038/s41591-023-02504-3

Overview: The paper introduces visual-language foundation models, which increase the integration of different modalities in medical AI.

2. "Recent Trends in Image Processing and Pattern Recognition" P84-94, 5th International Conference, RTIP2R 2022
3. "An optimal big data workflow for biomedical image analysis" Informatics in Medicine Unlocked, Volume 11, 2018, Pages 68-74

   Overview: This paper provides an overview of practical frameworks with big data solutions in the biomedical imaging context.

Other suggested readings: Lu, M.Y., Chen, B., Williamson, D.F.K. et al. A multimodal generative AI copilot for human pathology. Nature 634, 466–473 (2024). https://doi.org/10.1038/s41586-024-07618-3

References ISL/ESL (if any)

ISL: Chapter 10.3 Convolutional Neural Networks discusses deep learning on images
ESL: Chapter 11: Neural Networks discusses deep learning

Other Suggested references for many of the key concepts

1. Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical image computing and computer-assisted intervention, MICCAI 2015