* **Discussion: Evaluating the Impact of Assumptions on Bayesian Decision-Making in Medical Image Segmentation (Post by Day 4)**
  + Explain how the assumption of normally distributed likelihoods for pixel intensities impacts the effectiveness of minimum error thresholding in Bayesian decision-making for medical image segmentation.
  + Discuss how these changes would affect the computational complexity and practical implementation of the algorithm in real-world medical imaging applications.

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| **Algorithm** | **Advantages** | **Disadvantages** |
| **SODATA Algorithm** | * Does not require labels for classification of background or foreground pixels. * Easy to implement. * Time complexity is O(K); K being the size of the histogram [1]. | * Sensitive to outliers due to reliance on mean distributions. * The variance-based objective function generally performs better than the entropy-based one, except in cases with imbalanced class sizes [2]. * May be sensitive to local modes in the histogram [2]. * Performance depends on initial cluster center guesses, making it sensitive to initialization [2]. * Can be affected by noise, potentially causing inaccurate clustering [2]. |
| **Otsu Method** | * Does not require labels (unsupervised). * Produces binary images with a high degree of uniformity [2]. * Very efficient with pre-processed mean tables, and easy to implement using between-class variance:   A group of black and white math equations  Description automatically generated   * Time complexity is O(K); K being the size of the histogram [1]. | * Assumes a bimodal intensity distribution, making it less effective for complex images with multiple intensity peaks. * Sensitive to noise and low contrast, which may affect segmentation quality. |

Both algorithms have the following limitations:

* **Limited Adaptability to Complex Intensity Distributions**: For images with multiple tissue types or intensity peaks, these simple algorithms might not perform well.
* **Sensitivity to Noise**: These methods rely on histogram analysis; they are sensitive to noise and may fail to distinguish between relevant structures in noisy or low-contrast areas.
* **Single Threshold Limitation**: These methods yield a single threshold, which may not be suitable for segmenting multiple tissue types in complex medical images.

Image thresholding is important for tasks like image segmentation, which has benefited from tremendous advancements in Deep Learning for the last decades:

**Tumor Segmentation**

DL has transformed tumor segmentation in medical imaging, a crucial step in cancer diagnosis and treatment. In various imaging modalities, including MRI and CT scans, models such as CNNs, autoencoders, GANs, and RNNs have been successfully used to distinguish tumor tissue from healthy tissue.

**Lung Segmentation**

Lung image segmentation has also seen remarkable progress in deep learning, especially for diseases like lung cancer, pulmonary fibrosis, and emphysema. Beyond CNNs, attention-based models and U-Nets have proven effective for analyzing lung CT scans.

**Skin Image Segmentation**

In dermatology, deep learning has significantly enhanced skin image segmentation, improving the accuracy of diagnosing skin conditions.

Today, deep learning models set the state of the art in accuracy, DICE score, specificity, and other performance metrics in image recognition.

There are yet many challenges to address like:

* Segmentation in scenarios in which patients have complex medical conditions.
* Model generalizability across different patient populations
* Integration of multimodal imaging information.
* Personalized medicine, DL models need to evolve to provide patient-specific insights.
* Real-time segmentation
* Incorporation of AI into clinical workflows to augment rather than disrupt them

The next wave of Deep-Learning will bring even more innovative, explanatory, efficient, and trustworthy tools for medical image analysis.

**References**

* Burger, W., & Burge, M. J. (2013). Automatic thresholding. In *Principles of Digital Image Processing* (pp. 5-50). Springer
* Chaoxin Zheng, Da-Wen Sun, in [Computer Vision Technology for Food Quality Evaluation](https://www.sciencedirect.com/book/9780123736420/computer-vision-technology-for-food-quality-evaluation), 2008
* Md. Eshmam Rayed, S.M. Sajibul Islam, Sadia Islam Niha, Jamin Rahman Jim, Md Mohsin Kabir, M.F. Mridha, Deep learning for medical image segmentation: State-of-the-art advancements and challenges, Informatics in Medicine Unlocked, Volume 47, 2024, 101504, ISSN 2352-9148, https://doi.org/10.1016/j.imu.2024.101504.