



Department of Biomedical Engineering
National Taiwan University

Fundamentals of Biomedical Image Processing

Final Project Presentation

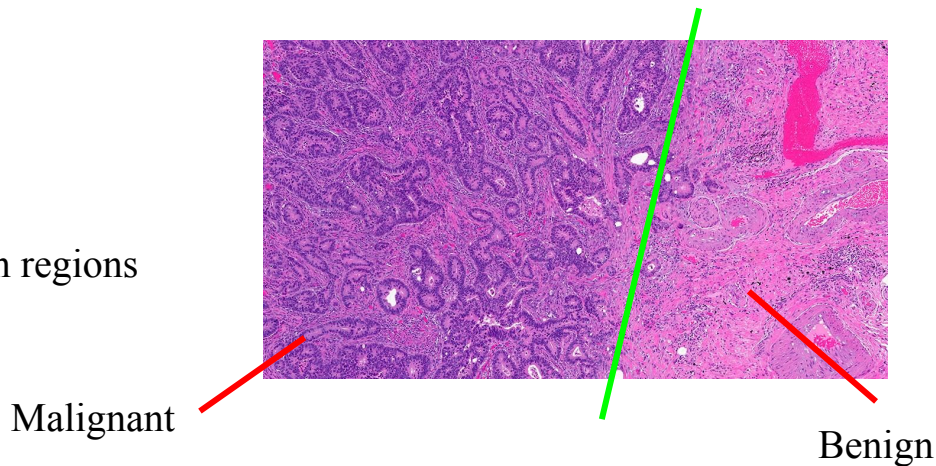
Unsupervised Segmentation of Pathology Images based on Haralick Textures

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Introduction

- **Traits of Biopsy Images:**

- ill defined margins
- Image changes dramatically between regions and intra-regional areas.



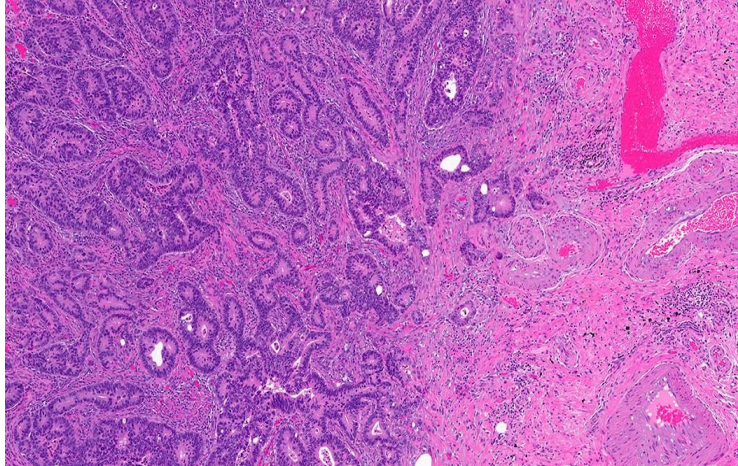
→ Biopsy Image Segmentation with image processing → ***lower time spent, higher Accuracy***

→ Extract features for AI model training → ***Increase model decision-making ability***

Introduction

- Traditional Methods
 - **Thresholding** (Local, Adaptive)
 - **Edge Detection** (Sobel Operator)
 - **Region-Based Methods** (Region Growing, Watershed Algorithm)
 - **Morphological Operations** (Erosion, Dilation ...etc.)
- ➔ Mostly are **First Order Statistics** image analysis

Introduction



Original Image

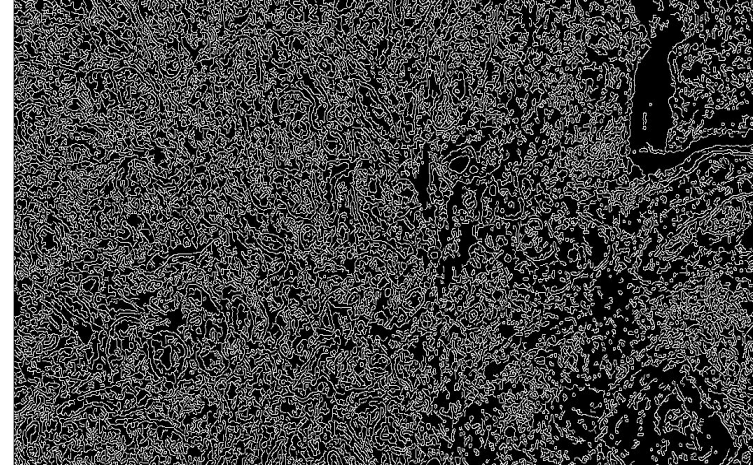


Image after applying Sobel Operator

- This inability makes first order statistics a blunt tool for quantifying changes in images, or any change in the spatial distribution of gray values.

Introduction

- **Modified Haralick Texture Features (Löfstedt *et al.* [1])**
 - Utilize a Normalized GLCM
 - Asymptotically invariant to image quantization.
 - Retains most interpretations of original Haralick features
- ***GOAL* :** Use modified Haralick texture features for image segmentation.
 1. Separate benign and malignant areas in microscopy images.
 2. Leverage feature vectors to build models

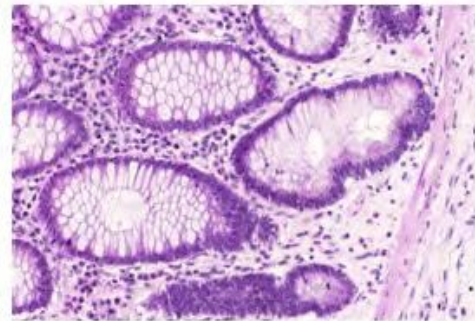
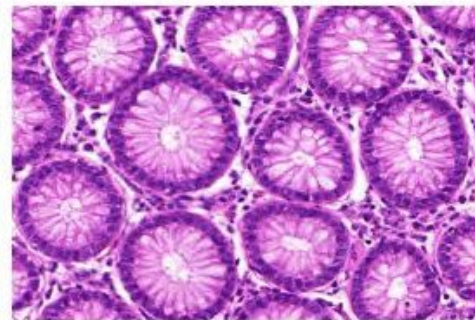
Materials and Methods

- **Dataset used in this project:**

warwick-qu-changed-dataset [7]

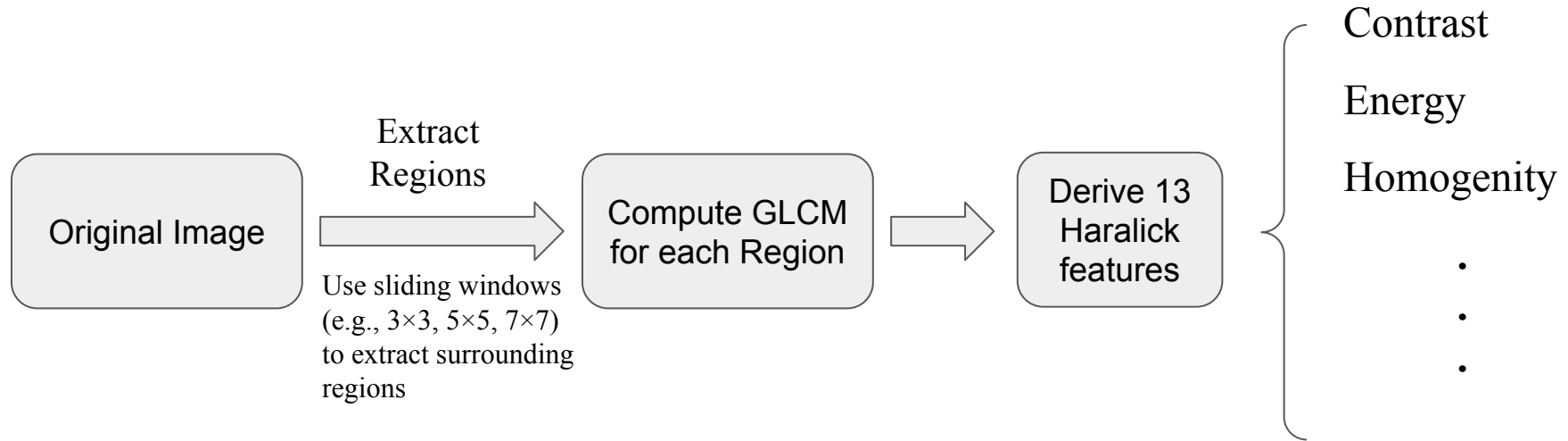
Data Card Code (1) Discussion (0) Suggestions (0)

- Benchmark dataset for biomedical image analysis.
- High-resolution histological images.
- Focus on segmentation, classification, and detection tasks.



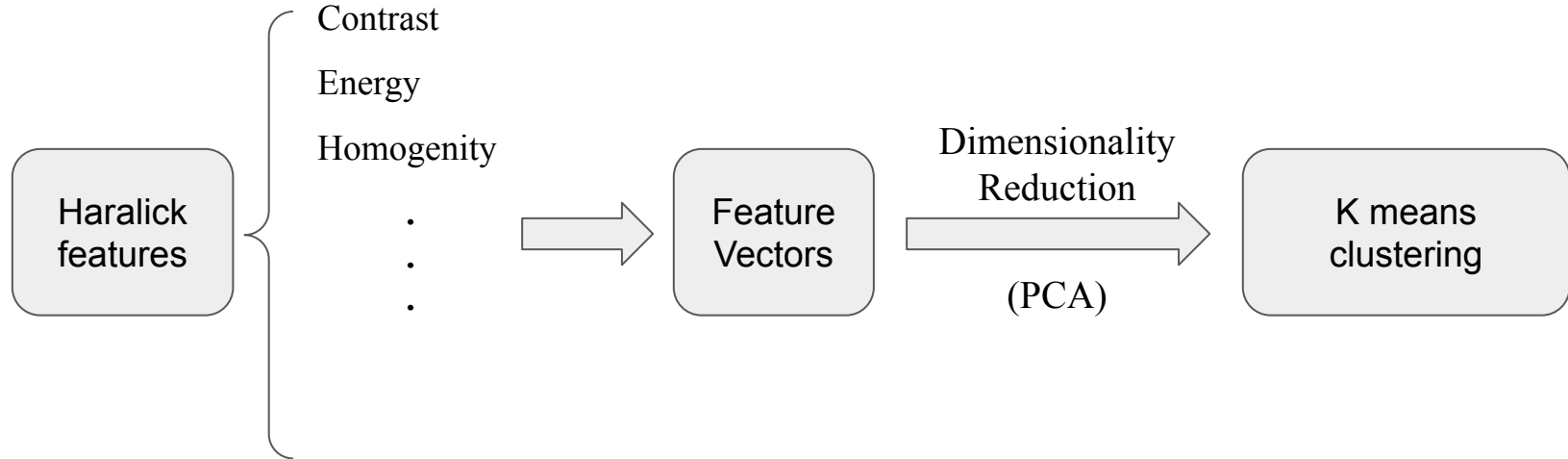
Materials and Methods

- **Texture Analysis**



Materials and Methods

- **Unsupervised Segmentation Model**



Materials and Methods

- Equilibrium k means

Algorithm 1: Equilibrium K-Means Algorithm

Input: A dataset $X = \{\mathbf{x}_n\}_{n=1}^N$, cluster number K ,
initial centroids $\{\mathbf{c}_k^{(0)}\}_{k=1}^K$, smoothing
parameter α

Output: Centroids $\{\mathbf{c}_1, \dots, \mathbf{c}_K\}$

$\tau = 0$;

repeat

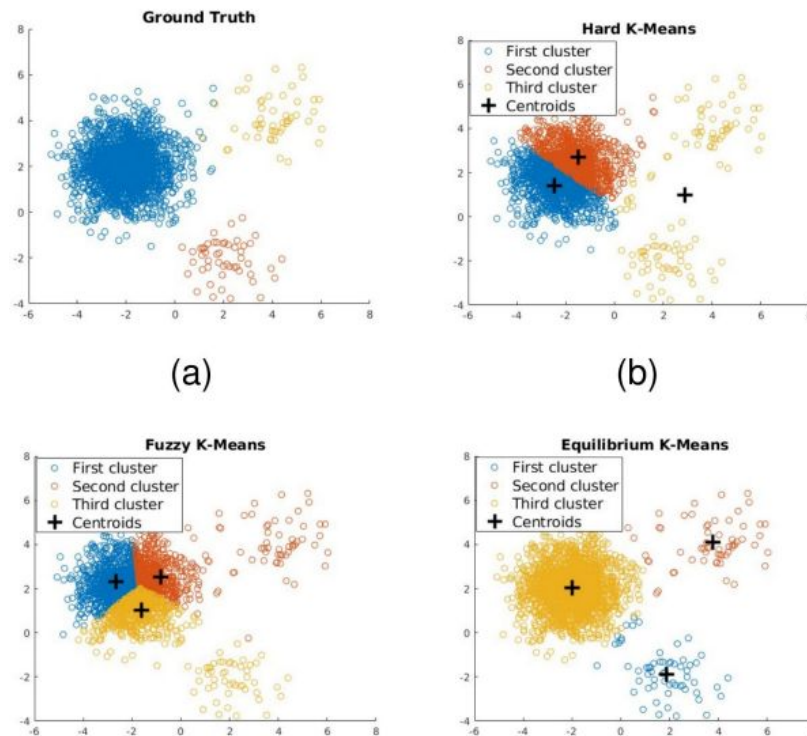
 Compute weight $w_{kn}^{(\tau)}$ by (38) for all k, n ;

 Update centroid $\mathbf{c}_k^{(\tau+1)}$ by (39) for all k ;

$\tau = \tau + 1$;

until convergence;

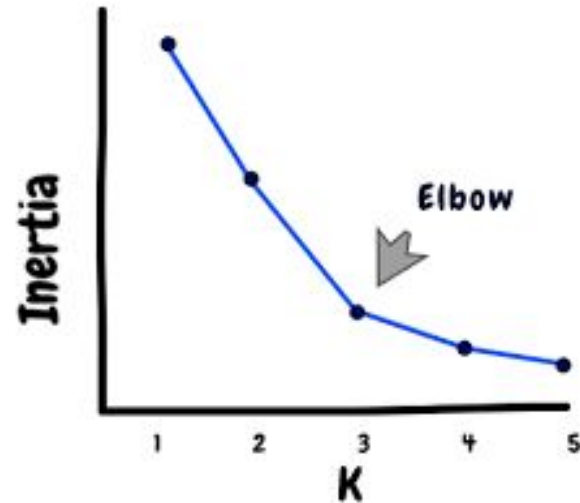
return $\{\mathbf{c}_k^{(\tau)}\}_{k=1}^K$



Materials and Methods

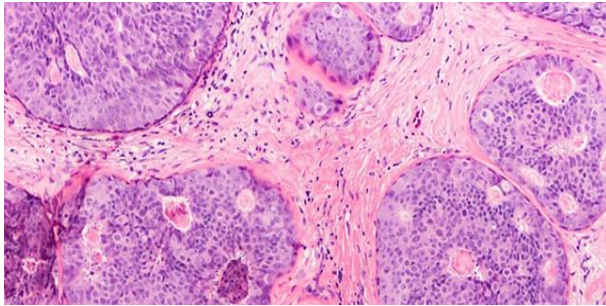
- **K-means Clustering with Automated Determination of Cluster Count**

$$\text{Inertia} = \sum_{i=1}^K \sum_{x \in C_i} \|x - \mu_i\|^2$$



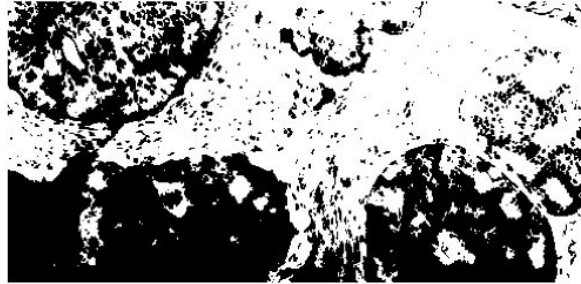
Results : Clustering Results Using Haralick Texture Features and RGB Pixel Values

Original image

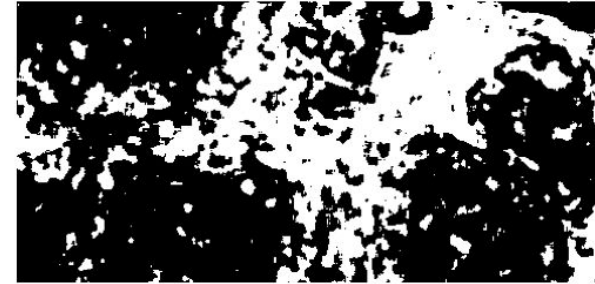


Black: malignant area
White: benign area

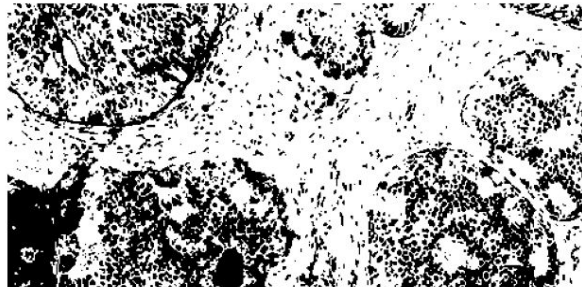
9*9 gray-level haralick features
combined with spatial and pixel features



9*9 gray-level haralick features only



9*9 RGB haralick features
combined with spatial and pixel features

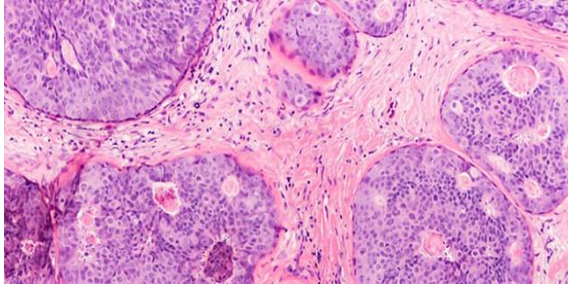


9*9 RGB haralick features only

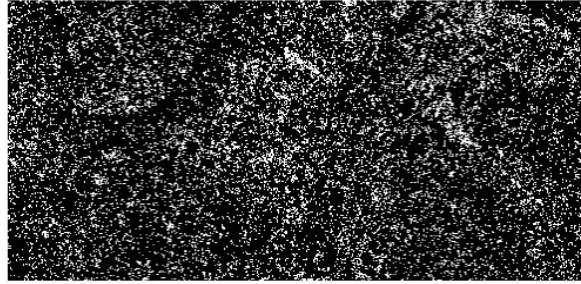


Results : Clustering Results Using Different Window Sizes for Extracting Haralick Texture Features

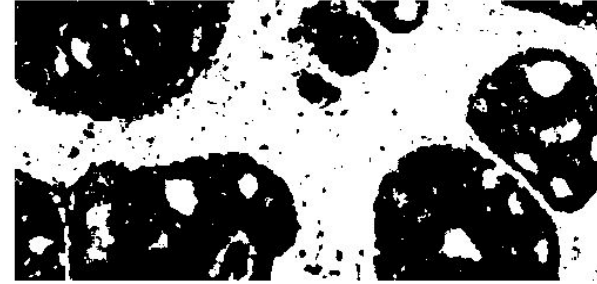
Original image



3×3 sliding window



5×5 sliding window



7×7 sliding window



9×9 sliding window

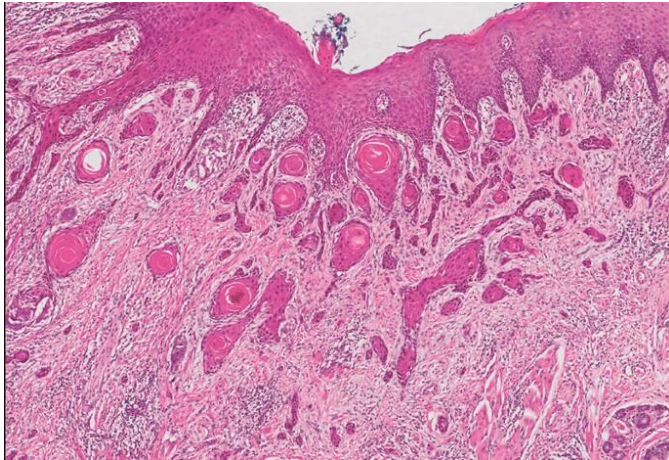


11×11 sliding window



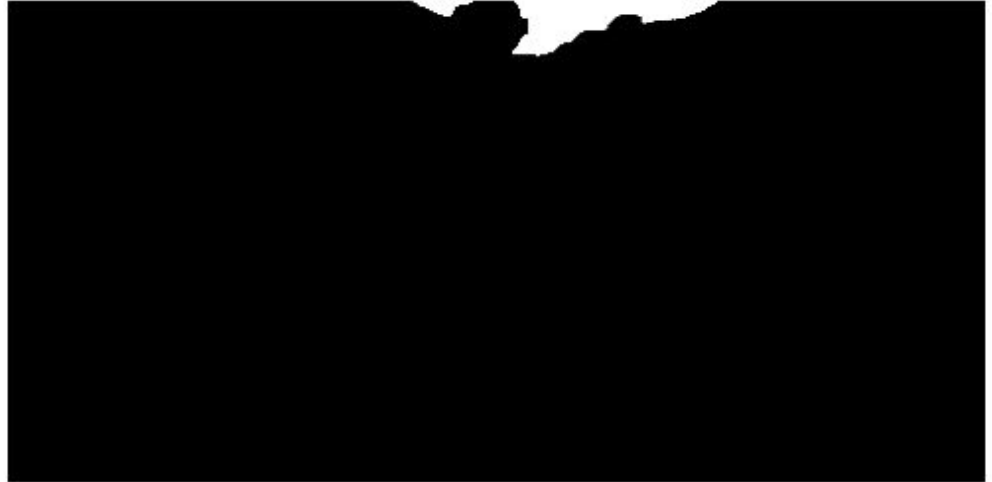
Results : K-means Clustering with Automated Determination of Cluster Count

Original image



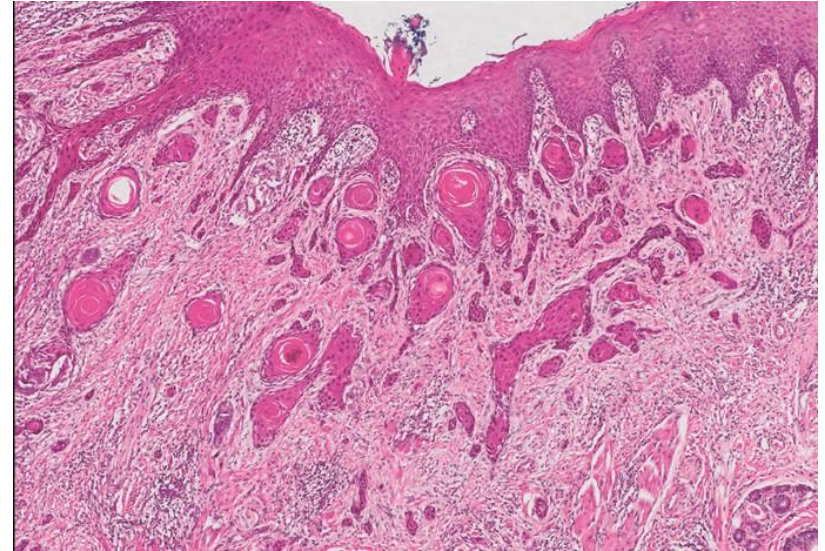
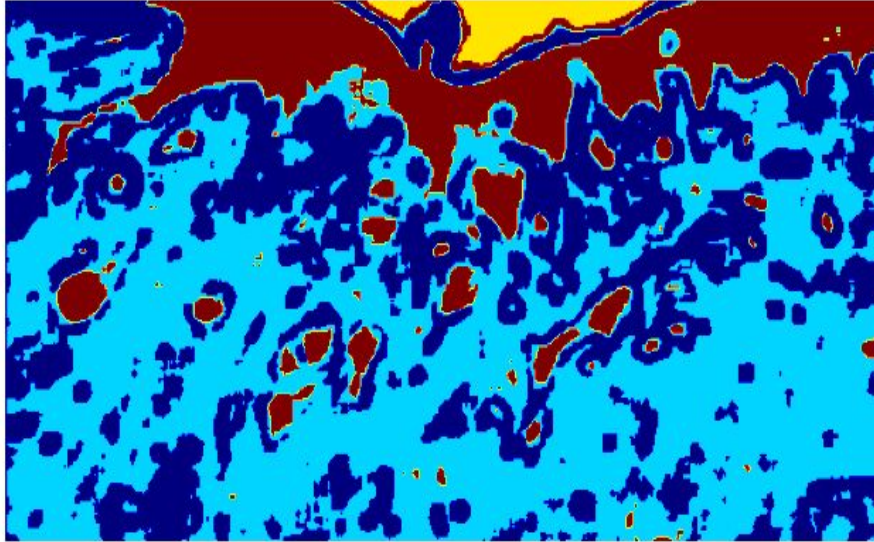
(Present with multiple components)

$K = 2$



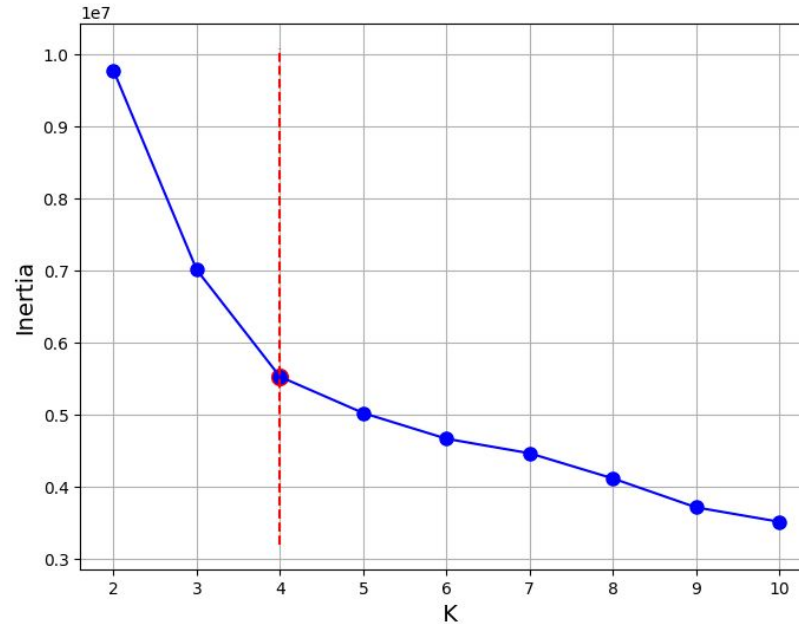
Results : K-means Clustering with Automated Determination of Cluster Count

K=4



Results : K-means Clustering with Automated Determination of Cluster Count

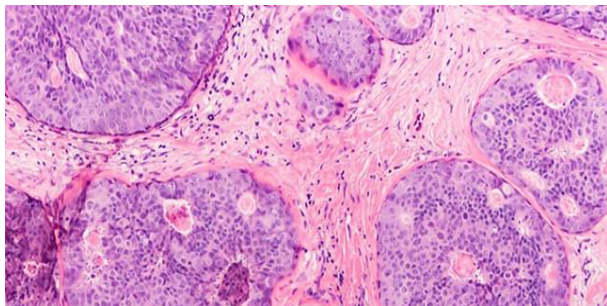
Inertia



Conclusions

- Using regional Haralick texture features with clustering methods is an effective approach for performing unsupervised segmentation of biopsy images
- A sliding window of 7×7 pixels or larger for extracting RGB image features yields better segmentation performance.

Original image



9*9 RGB haralick features only



References

- [1] Löfstedt, T., Brynolfsson, P., Asklund, T., Nyholm, T., & Garpebring, A. (2019). Gray-level invariant Haralick texture features. PLOS ONE, 14(2), e0212110. <https://doi.org/10.1371/journal.pone.0212110>
- [2] Naira Elazab, Wael Gab Allah, & Elmogy, M. (2024). Computer-aided diagnosis system for grading brain tumor using histopathology images based on color and texture features. BMC Medical Imaging, 24(1). <https://doi.org/10.1186/s12880-024-01355-9>
- [3] Öztürk, Ş., & Akdemir, B. (2018). Application of Feature Extraction and Classification Methods for Histopathological Image using GLCM, LBP, LBGLCM, GLRLM and SFTA. Procedia Computer Science, 132, 40–46. <https://doi.org/10.1016/j.procs.2018.05.057>
- [4] Belsare, A. D., Mushrif, M. M., Pangarkar, M. A., & Meshram, N. (2015, November 1). Classification of breast cancer histopathology images using texture feature analysis. IEEE Xplore. <https://doi.org/10.1109/TENCON.2015.7372809>
- [5] Eizan Miyamoto¹ and Thomas Merryman Jr.², Fast calculation of haralick texture features
- [6] Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural Features for Image Classification. IEEE Transactions on Systems, Man, and Cybernetics, SMC-3(6), 610–621. <https://doi.org/10.1109/tsmc.1973.4309314>
- [7] Sirinukunwattana, K., Snead, D. R. J., & Rajpoot, N. M. (2015). A Stochastic Polygons Model for Glandular Structures in Colon Histology Images. IEEE Transactions on Medical Imaging, 34(11), 2366–2378. <https://doi.org/10.1109/tmi.2015.2433900>
- [8] Yudong He, Imbalanced Data Clustering using Equilibrium K-Means <https://doi.org/10.48550/arXiv.2402.14490>



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Thanks!