CMSC 630 Project Part 2 Report

Introduction

Part 2 of the image analysis project addresses edge detection, morphological operations, and image segmentation. This section of the project was also completed in C# without relying on any external libraries. The process is the same as before, involving reading in byte information into memory and then performing modifications on a byte array for performance. Single file in-application, single threaded batch, and multithreaded batch processing implementations have been made in this program. The multithreaded batch process is an excellent CPU stress test especially when computing Kirsch Compass Edge Operator, K-Means segmentation, and SLIC SuperPixel segmentation. Sample processed images are available on the GitHub release page for download.

Link to GitHub: https://github.com/talejl/CMSC-630-Image-Processing-Project

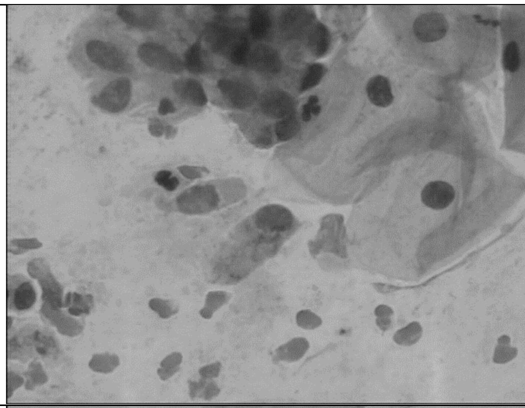
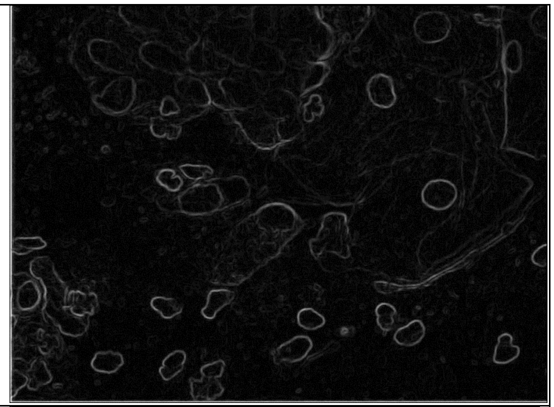
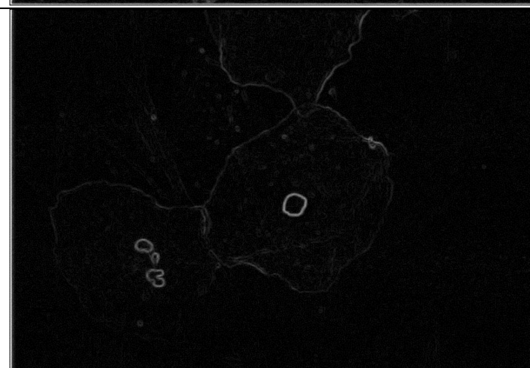
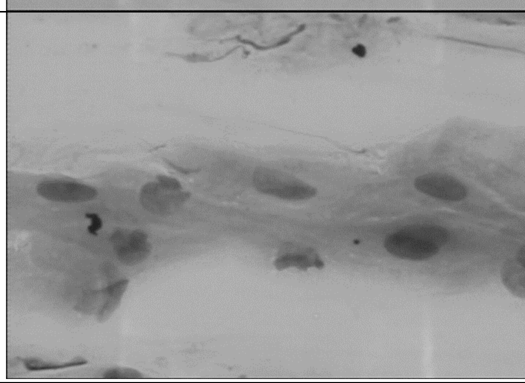
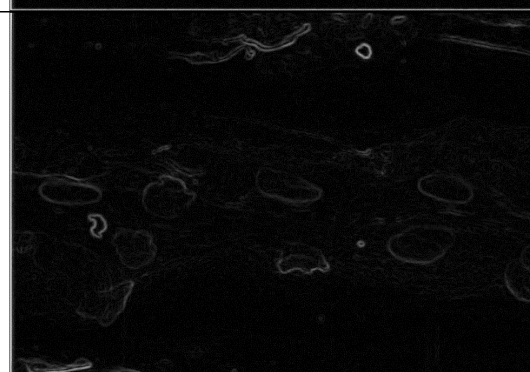
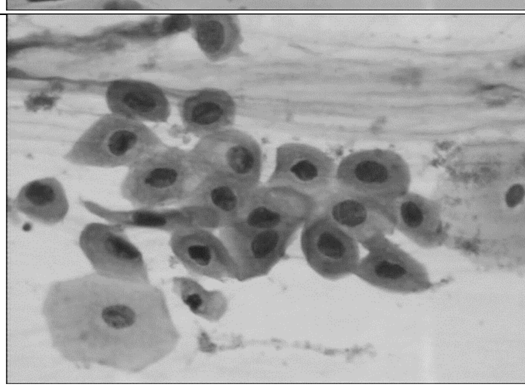
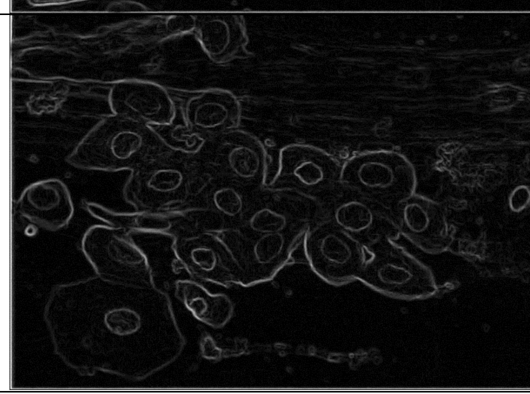
Link to Release binaries: https://github.com/talejl/CMSC-630-Image-Processing-Project/releases/tag/P2

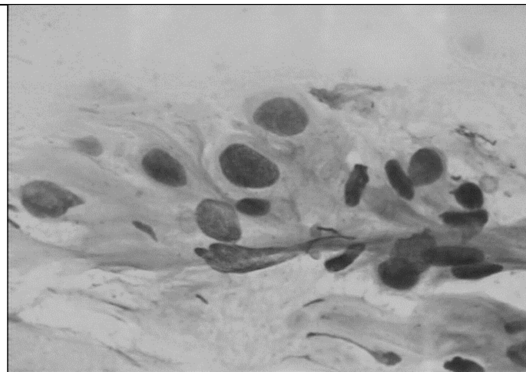
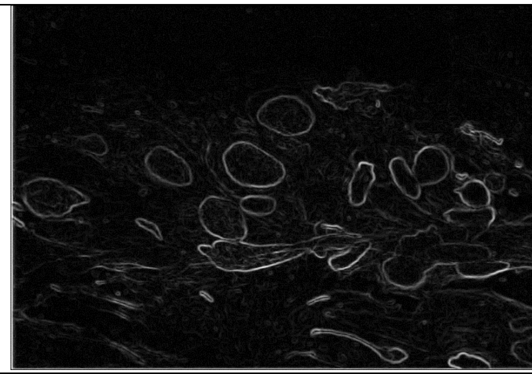
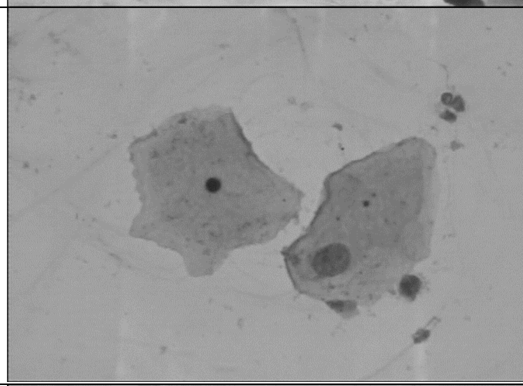
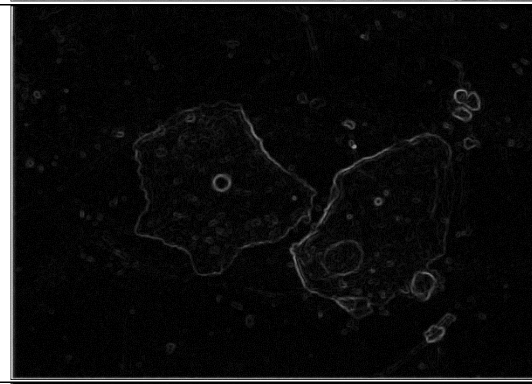
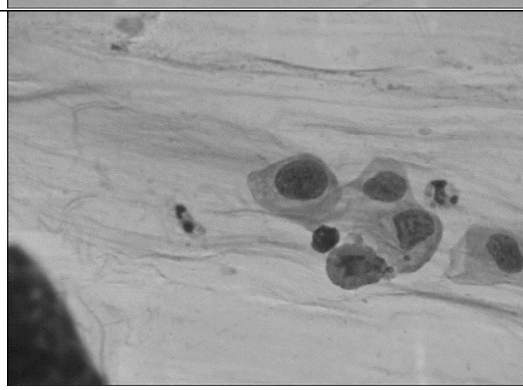
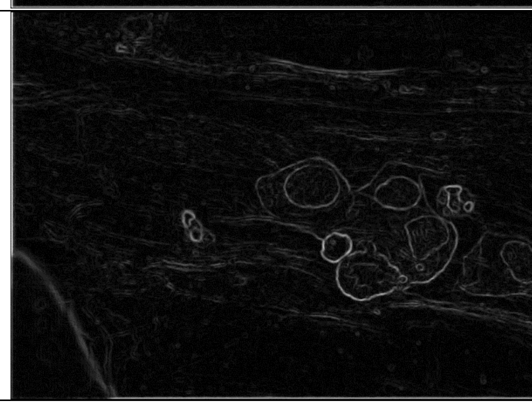
Edge Detection

Several edge detection filters were implemented for this project. Prewitt, Sobel, Improved Sobel operators are selectable options for the linear edge detection process. In addition, the Kirsch Compass edge detection operator was also added as a non-linear option to compare results with. The Prewitt operator provided the weakest edge detection, while the Sobel operator provided a somewhat improved result when compared to the Prewitt operator by displaying the edges and boundaries more prominently. The Improved Sobel operator yielded more edge detection, but also picked up more noise than Sobel and Prewitt operations, which led to the noise being included as edges. The Kirsch Compass operator yielded better results than the linear edge detectors, as it provided more defined edges, at the expense of more noise. However, it appears to be less noisy than the Improved Sobel filter. Therefore, it is important to consider the computational expense of the Kirsch Compass filter with relation to the results. In some cases, the Sobel filter may be more than adequate. All edge detection filters were implemented in a 3 x 3 kernel size. Please refer to the tables below for example results of the different edge detection operators.

<u>Prewitt Edge Detection Examples</u>

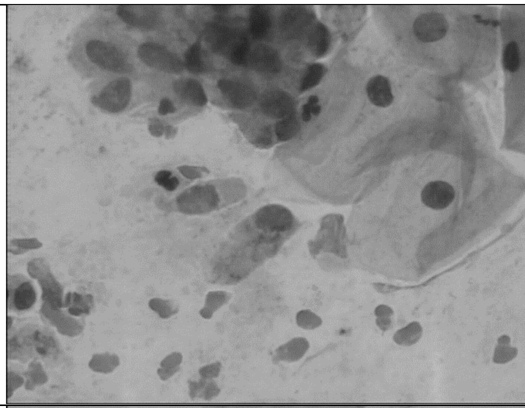
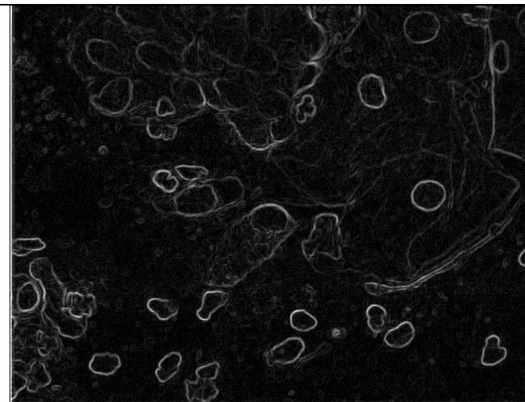
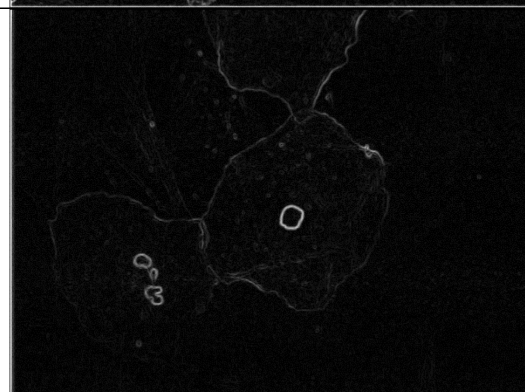
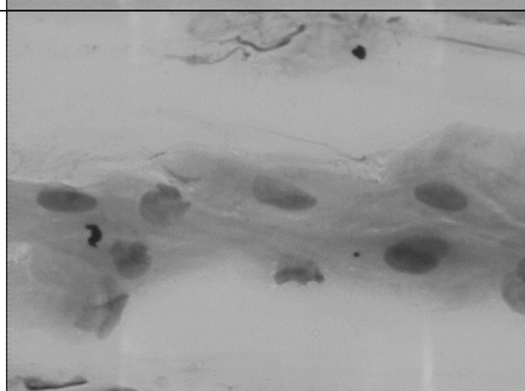
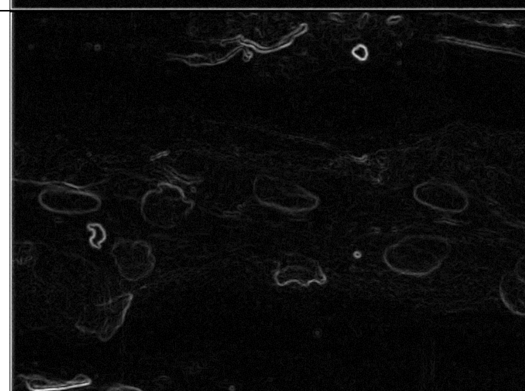
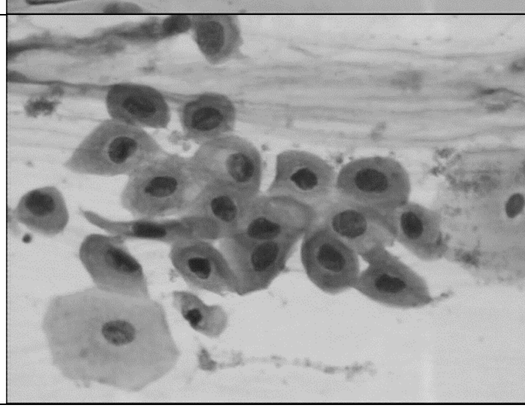
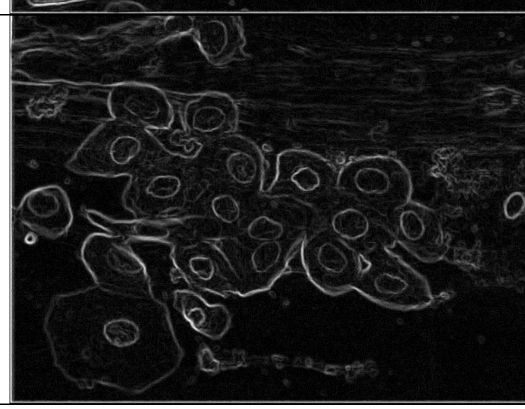
Cell Class	Original Grayscale	Prewitt Edge Detected

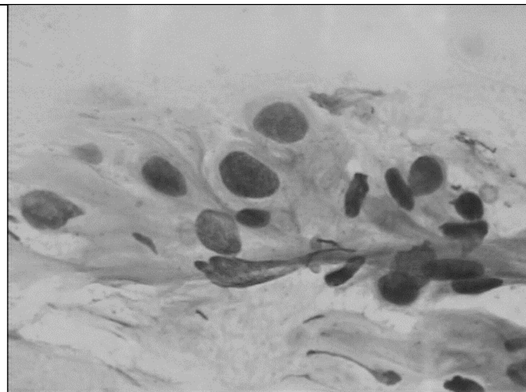
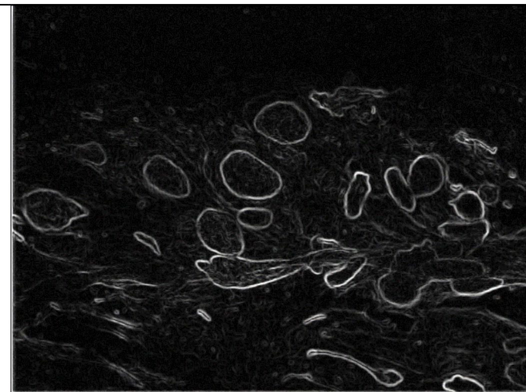
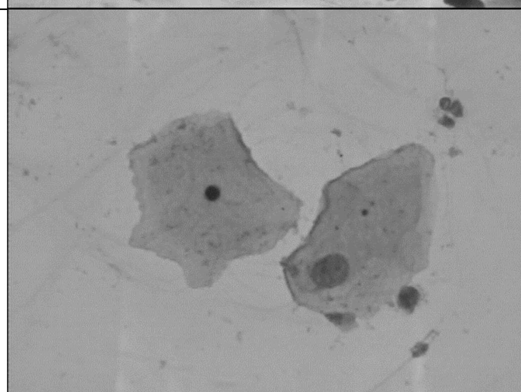
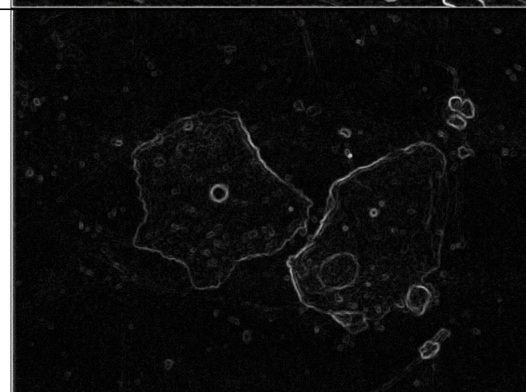
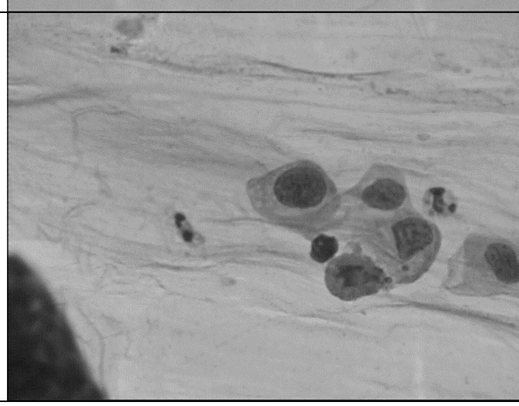
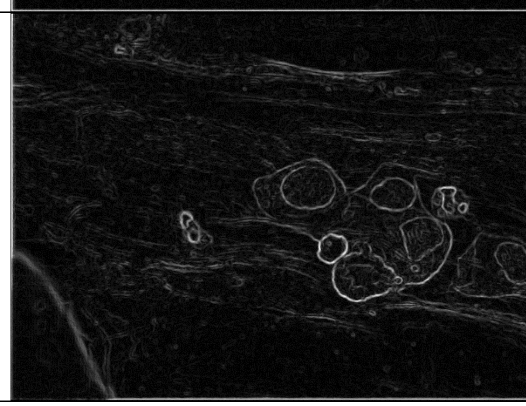
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

<u>Sobel Edge Detection Examples</u>

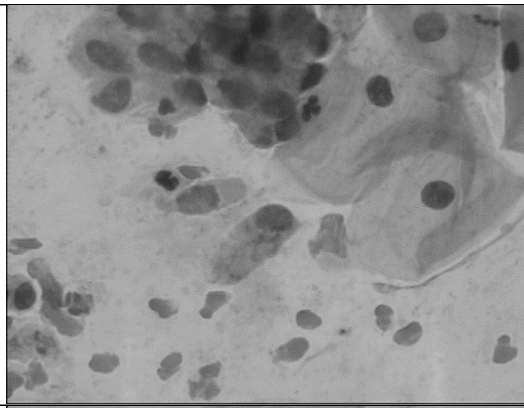
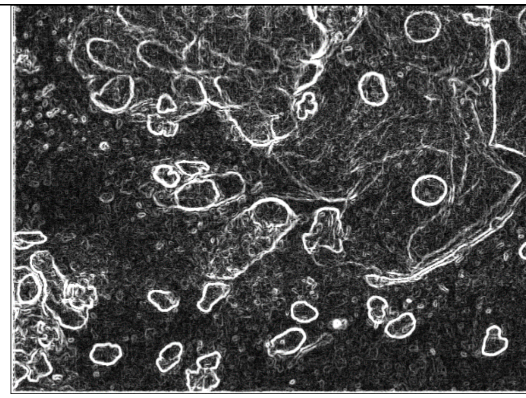
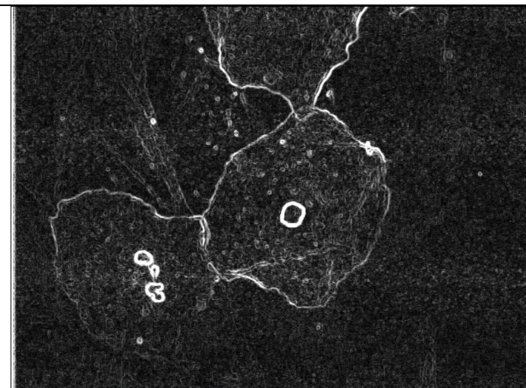
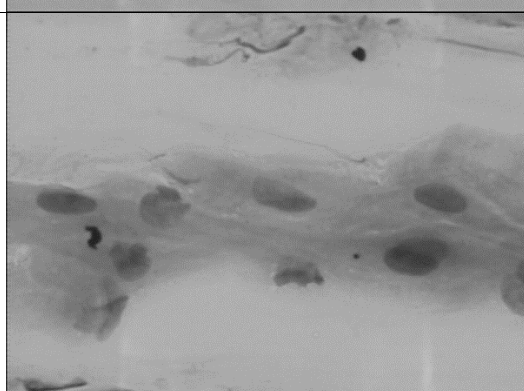
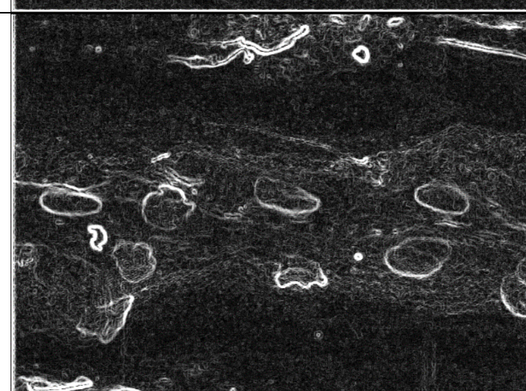
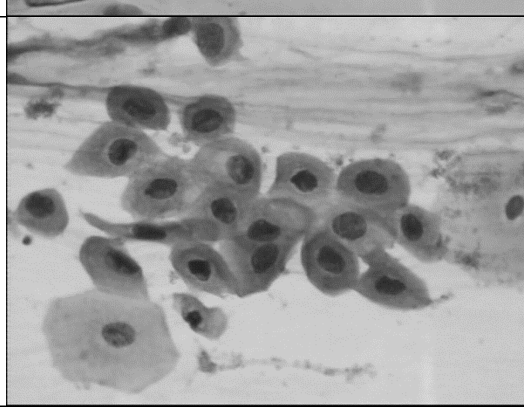
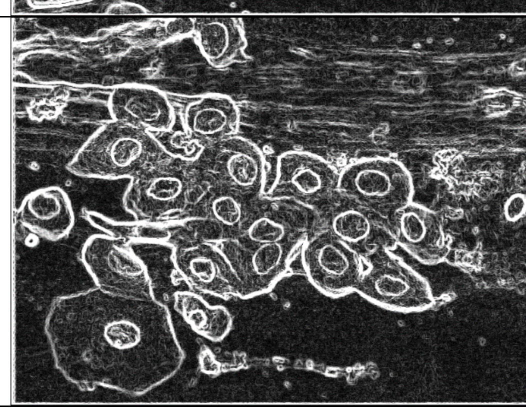
Cell Class	Original Grayscale	Sobel Edge Detected

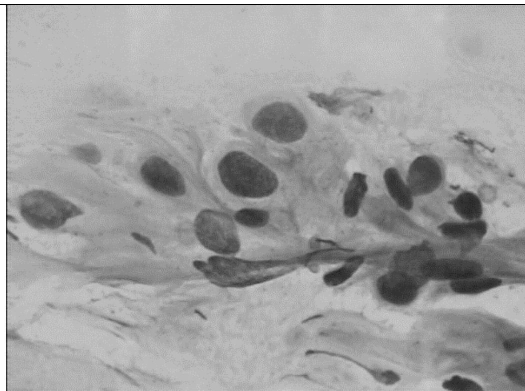
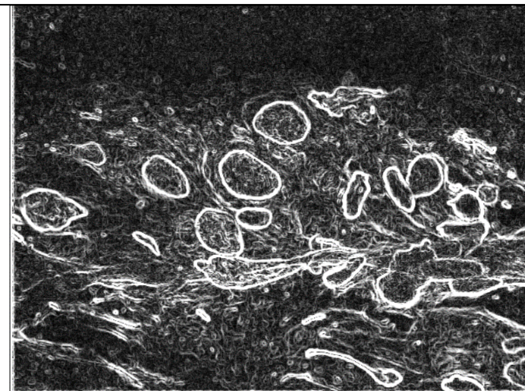
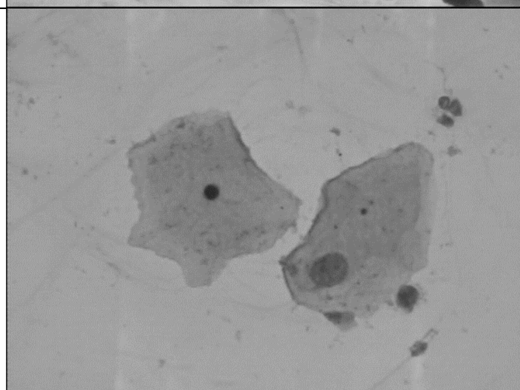
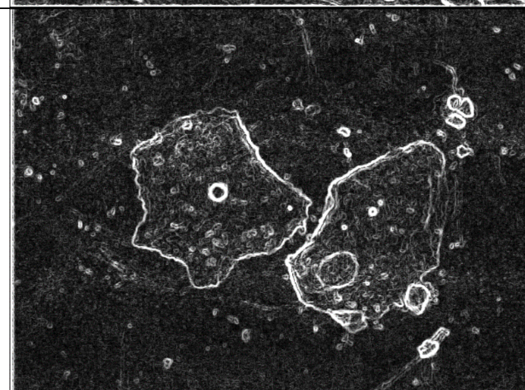
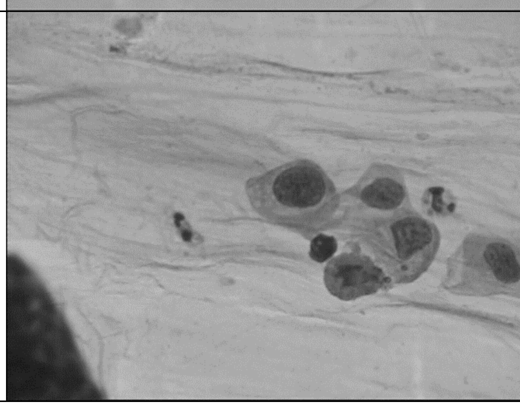
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

Improved Sobel Edge Detection Examples

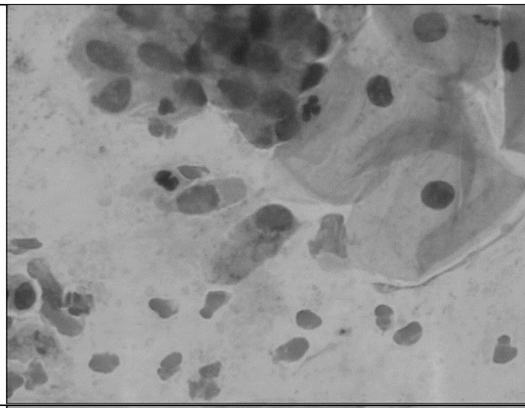
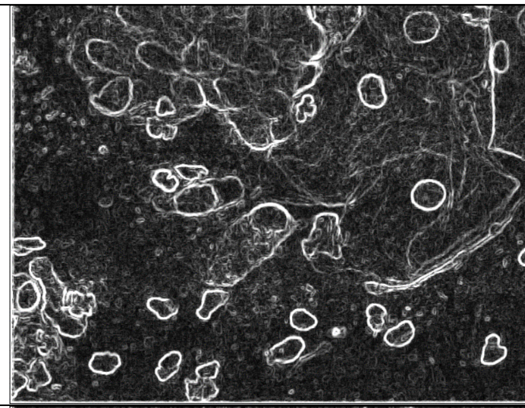
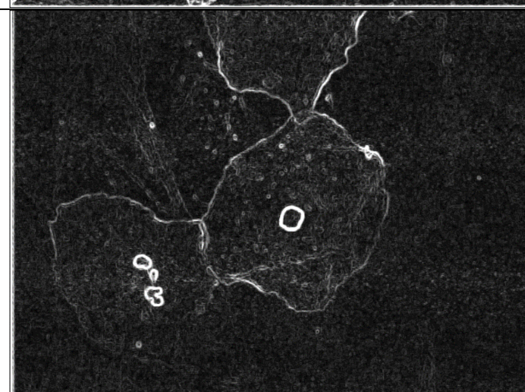
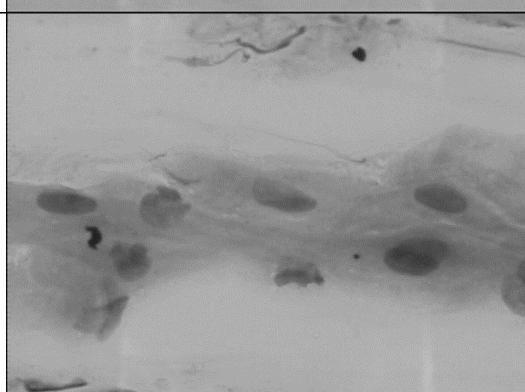
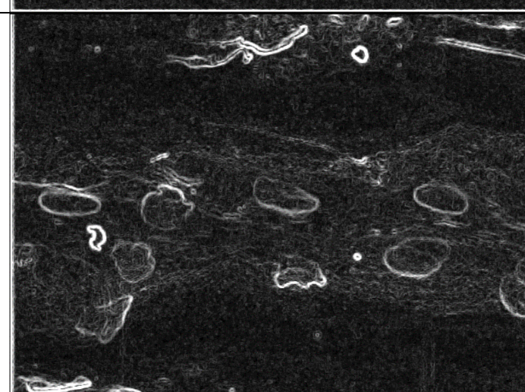
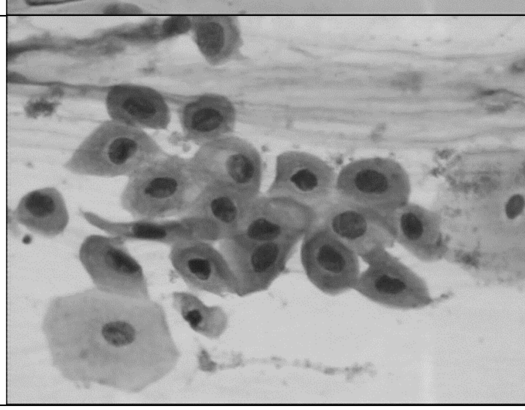
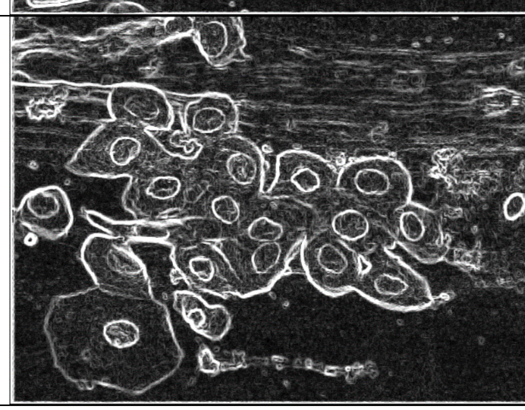
Cell Class	Original Grayscale	Improved Sobel Edge Detected

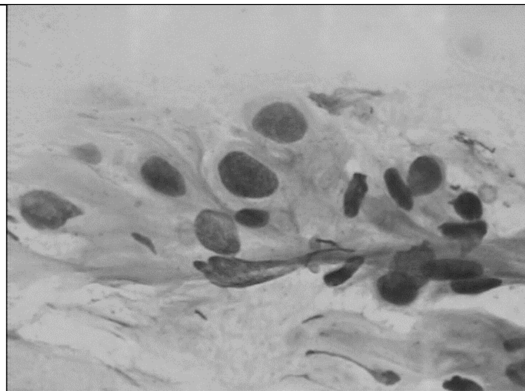
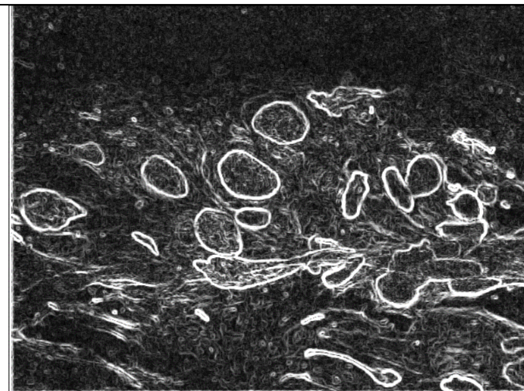
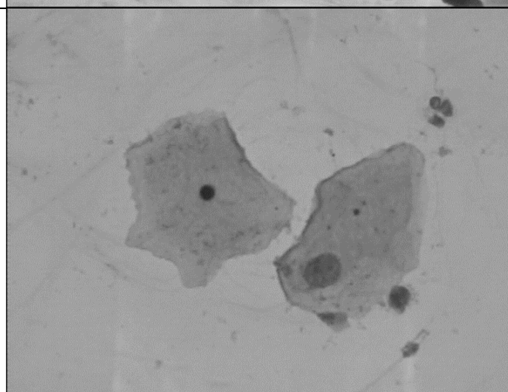
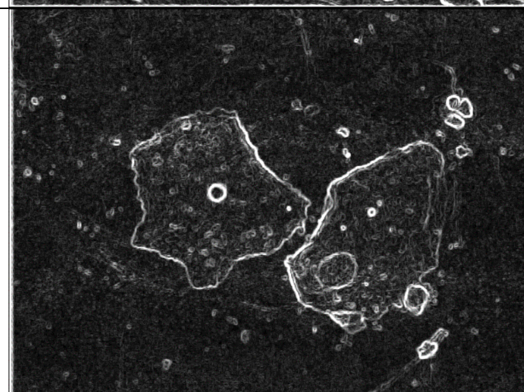
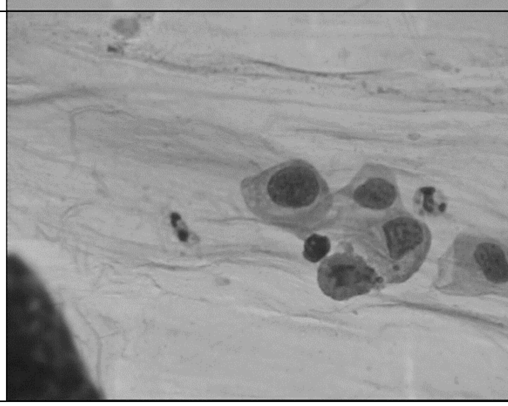
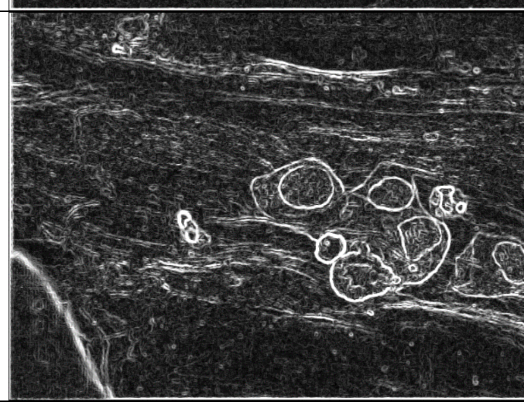
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

Kirsch Edge Detection Examples

Cell Class	Original Grayscale	Kirsch Edge Detected

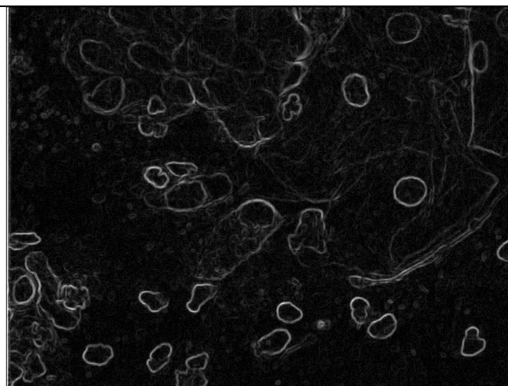
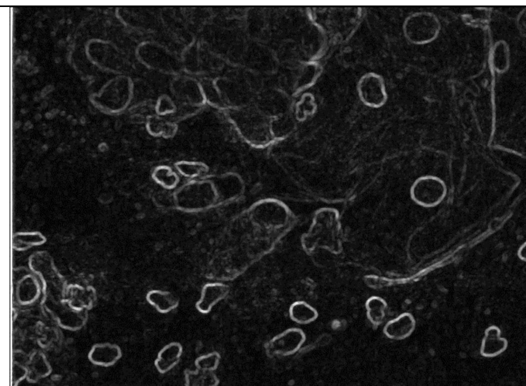
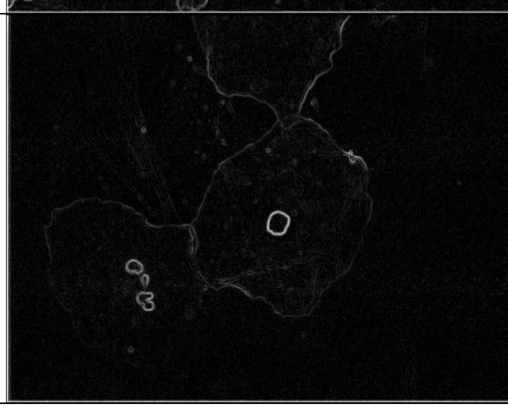
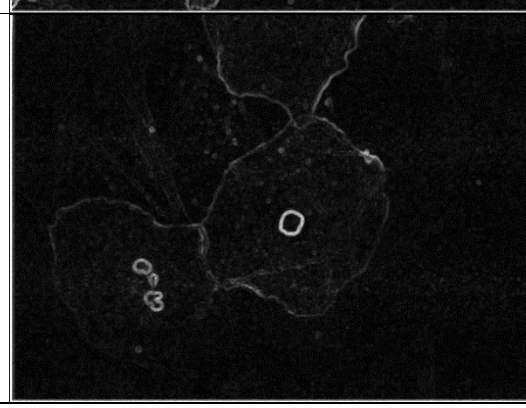
CYL		
INTER		
LET		
PARA		

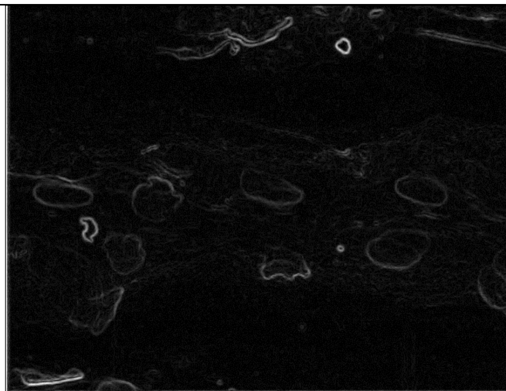
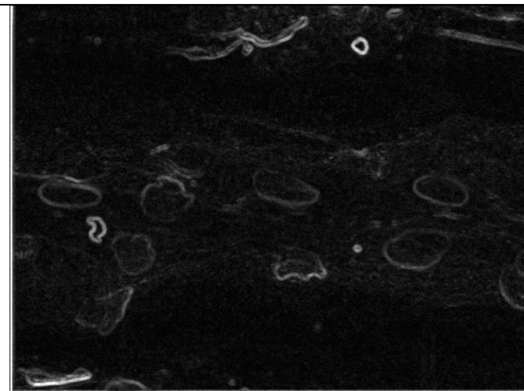
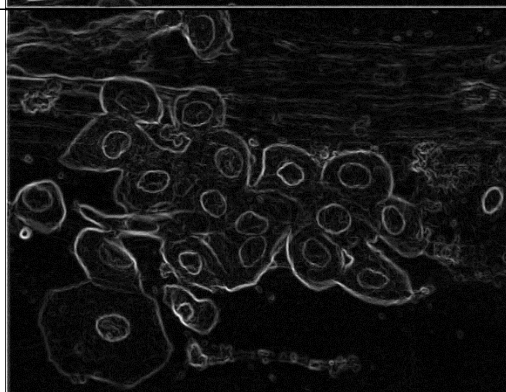
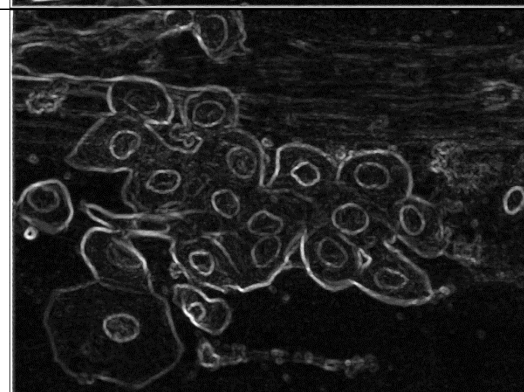
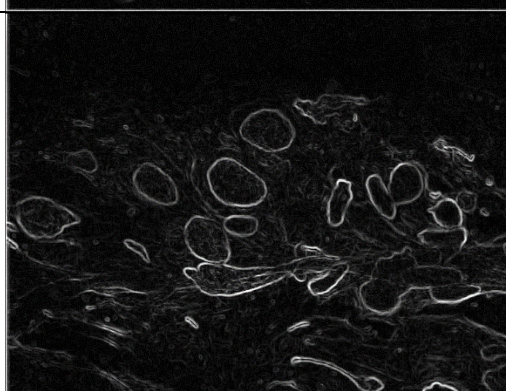
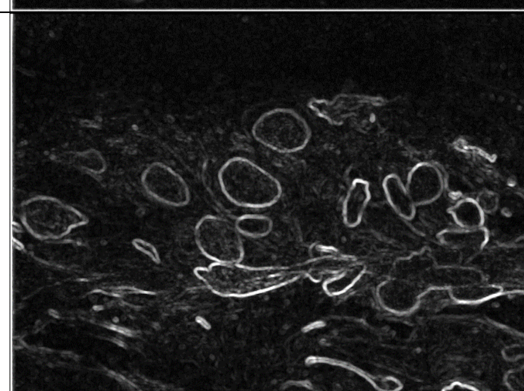
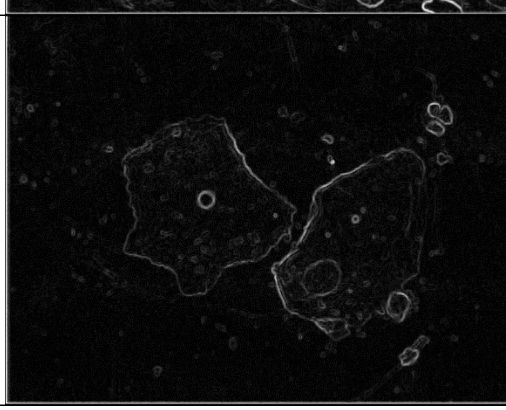
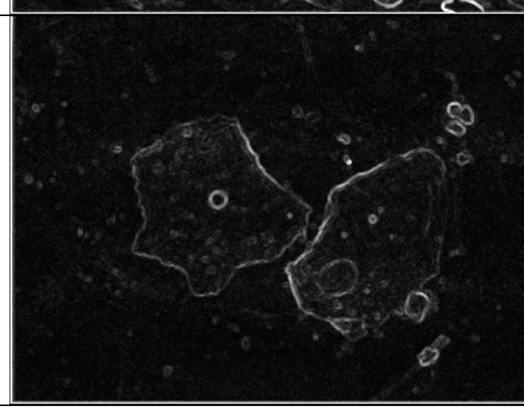
MOD		
SUPER		
SVAR		

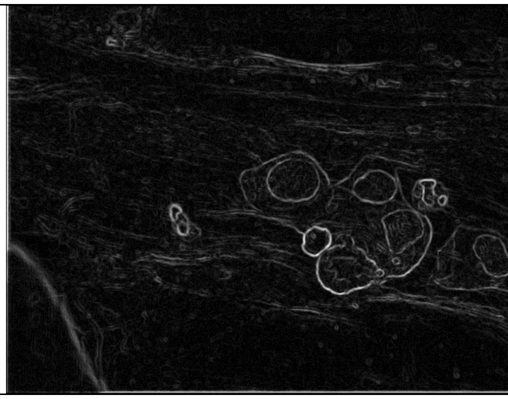
Morphological Operators

Dilation and Erosion are the two morphological operators implemented in this project. Dilation increases the foreground in comparison to the background, while erosion shrinks the foreground in comparison to the background. Dilation can fill gaps of missing information, while erosion removes links between objects in an image. Structuring elements are used to apply the morphological operations, with several types provided within this application. In this project, the user may select cross 3x3, box 3x3, cross 5x5, box 5x5, and circle 5x5 structuring element shapes. The size and shape of the structing element affects the strength of the morphological operations. The cross 3x3 structuring element provides smaller scale changes on the image, while the box 3x3 structuring element makes slightly more pronounced changes in the image. Moving to the 5x5 size shapes produces drastically stronger effects, in both erosion and dilation. For the purposes of this report, all morphological operations were performed on a Sobel edge detected image as the base since it is the easiest to see effects applied. Dilating by the cross shape in both 3x3 and 5x5 sizes provided more subtle increases in the boundaries, while the box shaped filters did a much rougher job. Eroding was much of the same story, with the box 5x5 filter nearly destroying many of the sample images. The 5x5 circle filter strength performs in between that of the 5x5 cross and 5x5 box filters; that is to say, it is more pronounced than the 5x5 cross, but not as blunt as the 5x5 box. Unfortunately due to the shape requirements of the circle structuring element, it is not possible to test it in a 3x3 size. It is important to note that denoising is important prior to edge detection and morphological operations, as they can be amplified by the dilation operation. Please refer to the tables below for sample images of dilation and erosion operations.

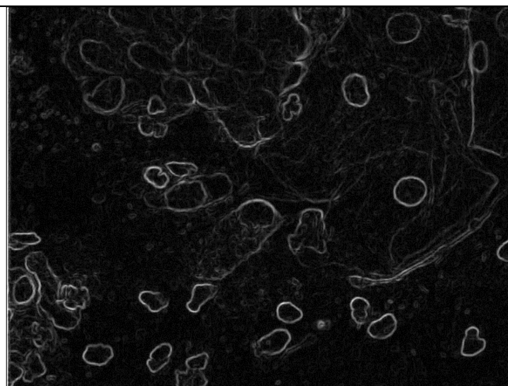
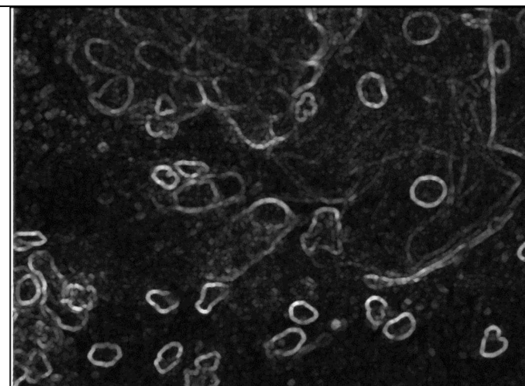
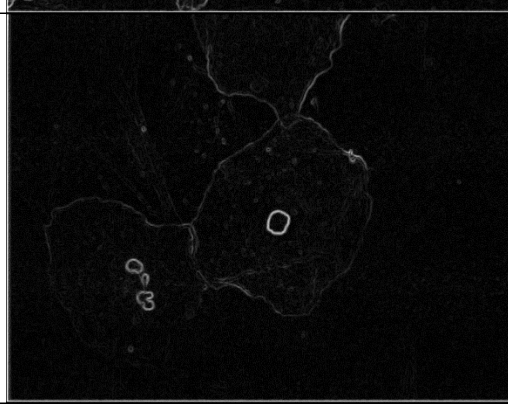
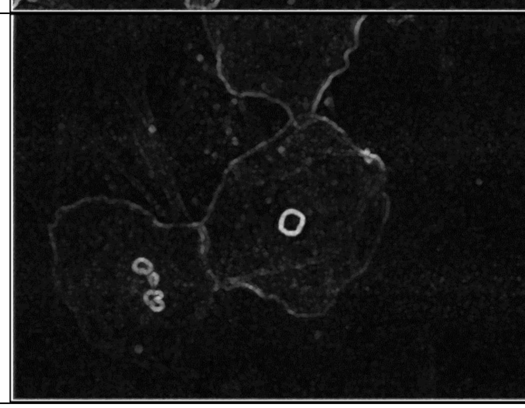
<u>Dilation by 3x3 Cross on Sobel Edge Detected Image</u>

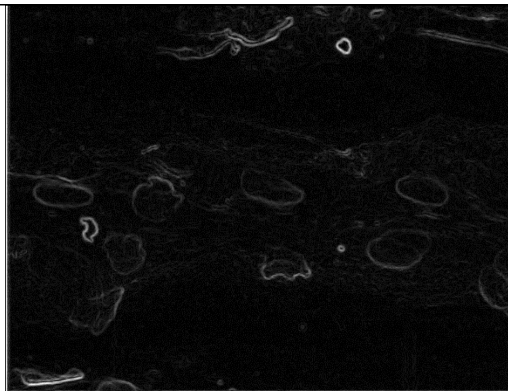
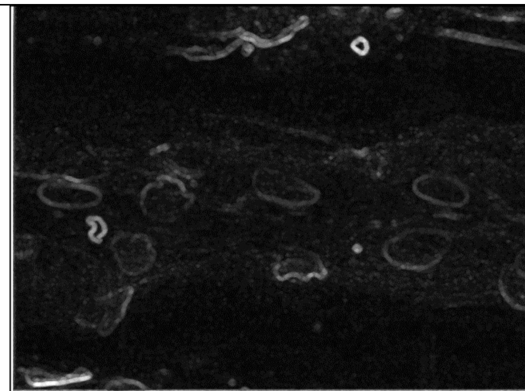
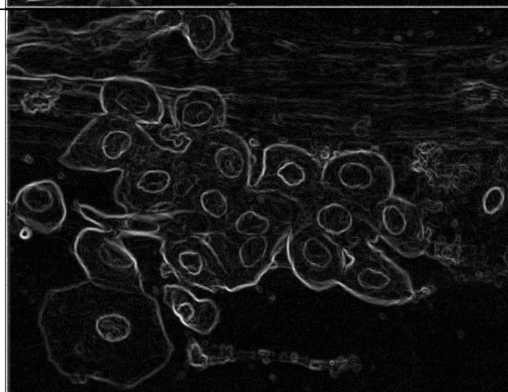
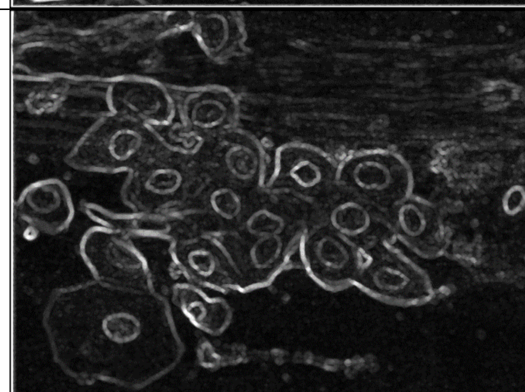
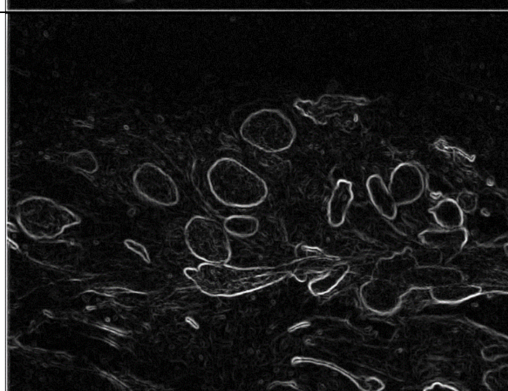
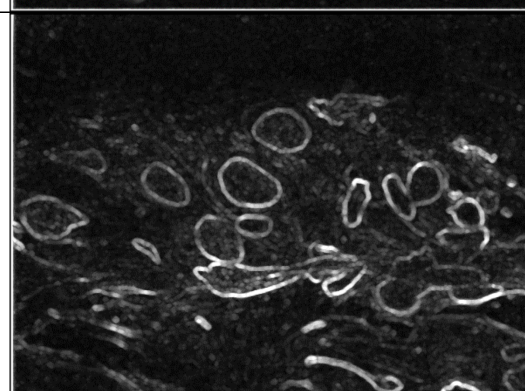
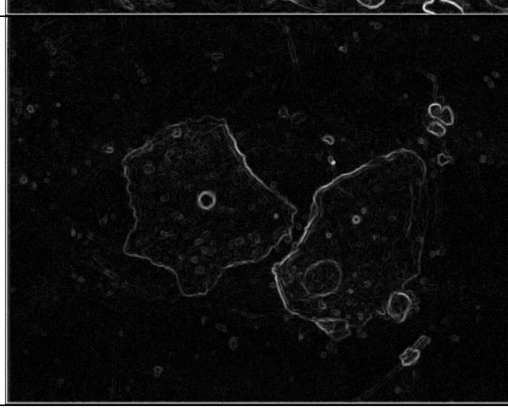
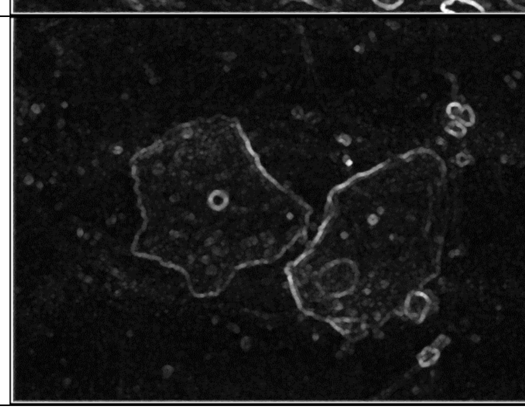
Cell Class	Sobel Image	Dilation by 3x3 Cross
CYL		
INTER		

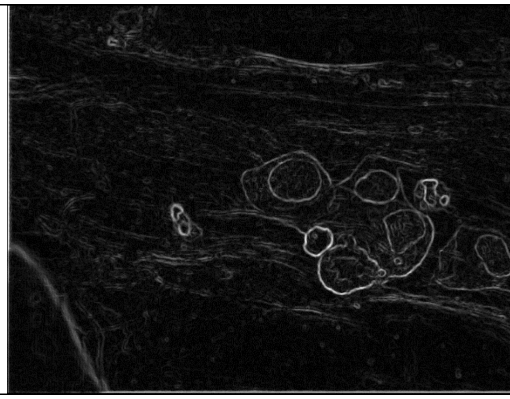
LET		
PARA		
MOD		
SUPER		

SVAR		

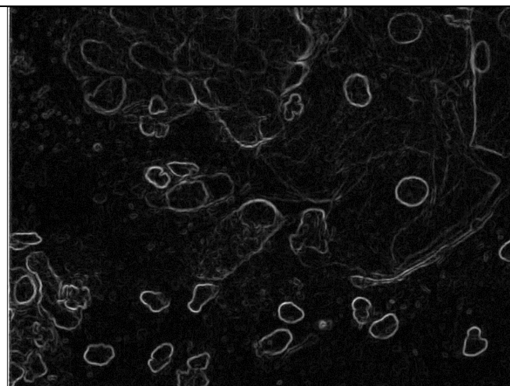
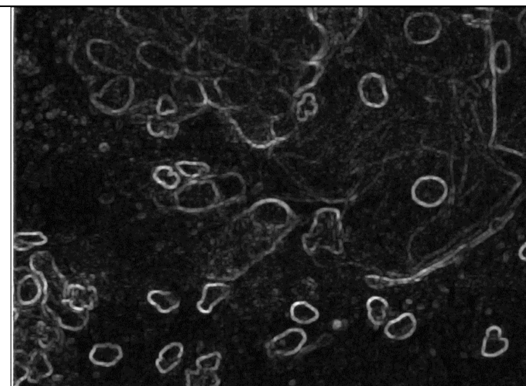
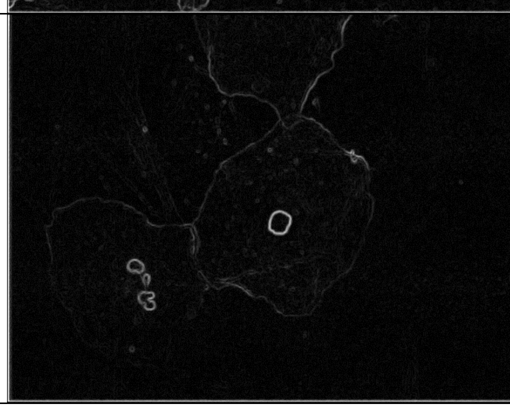
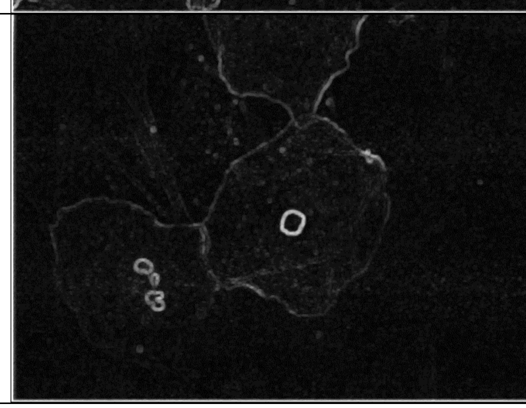
<u>Dilation by 5x5 Cross on Sobel Edge Detected Image</u>

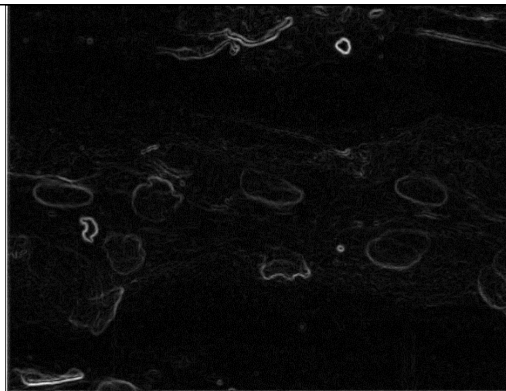
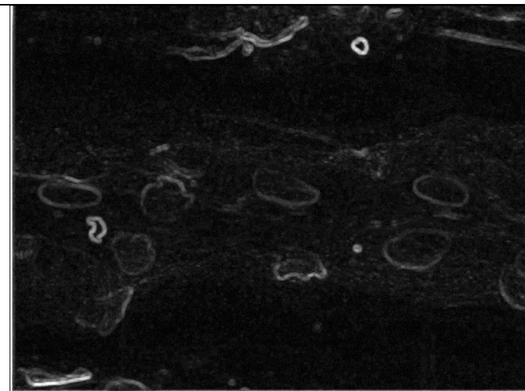
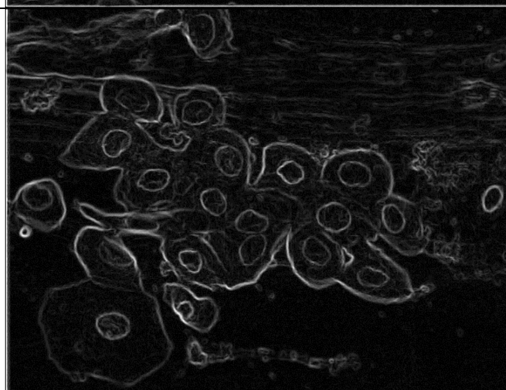
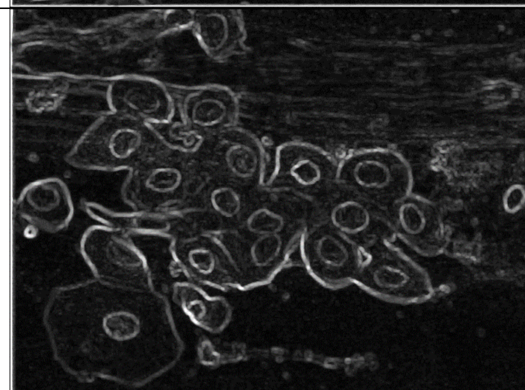
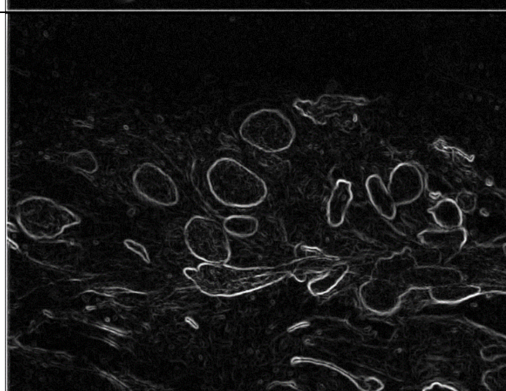
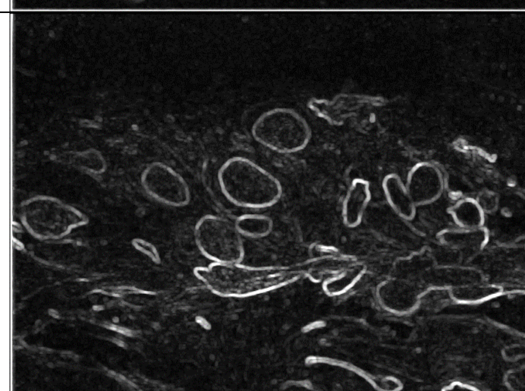
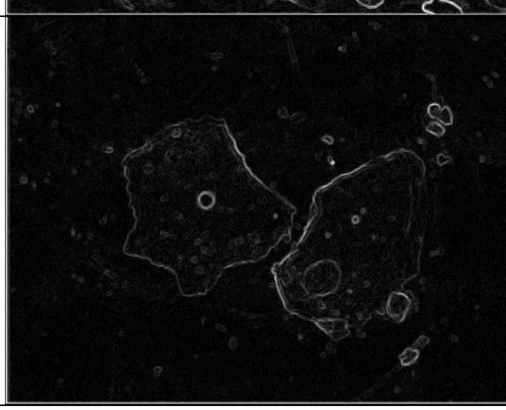
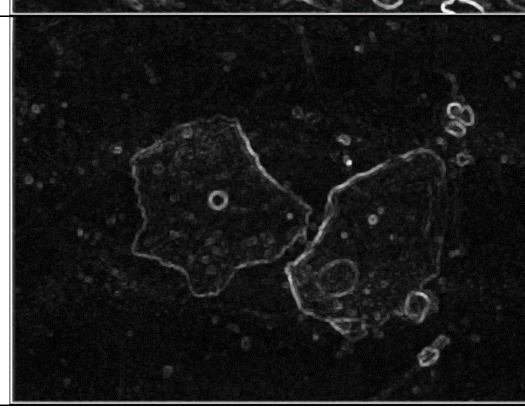
Cell Class	Sobel Image	Dilation by 5x5 Cross
CYL		
INTER		

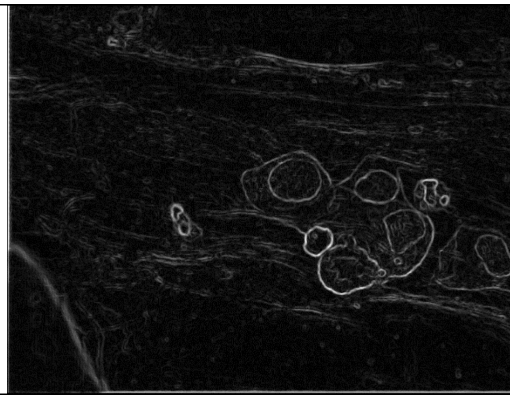
LET		
PARA		
MOD		
SUPER		

SVAR		

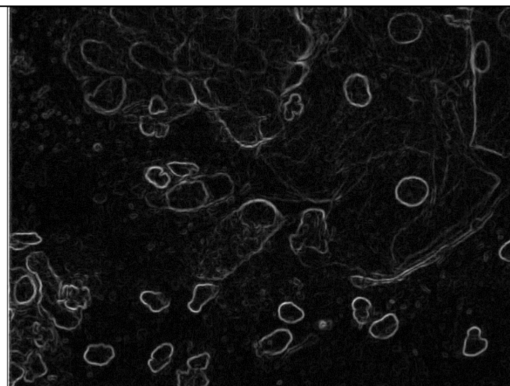
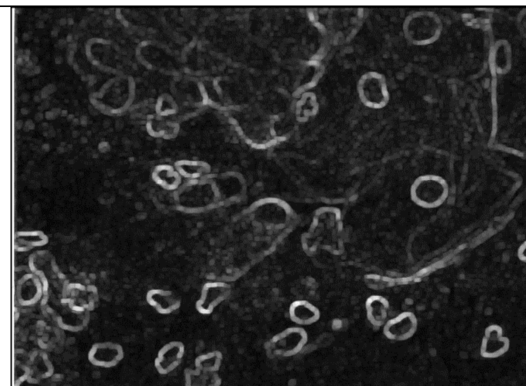
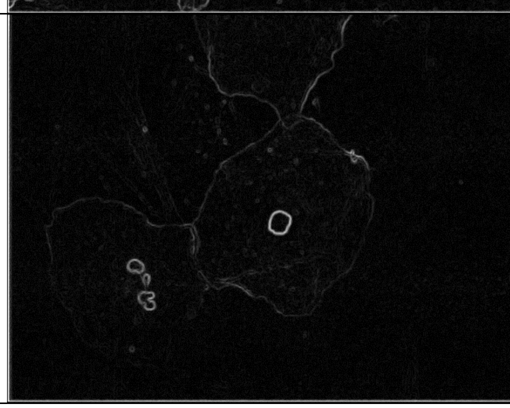
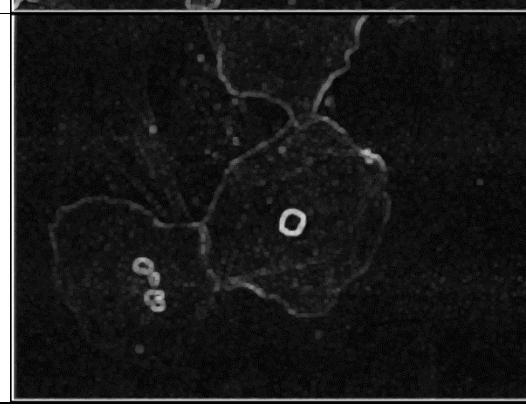
Dilation by 3x3 Box on Sobel Edge Detected Image

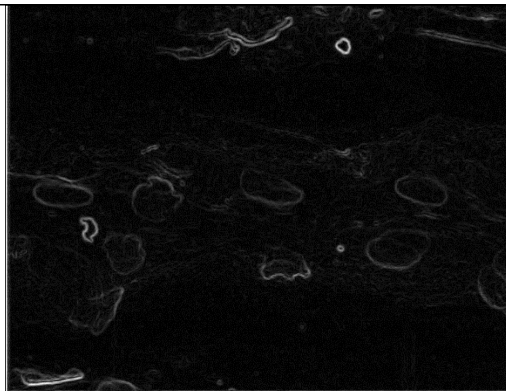
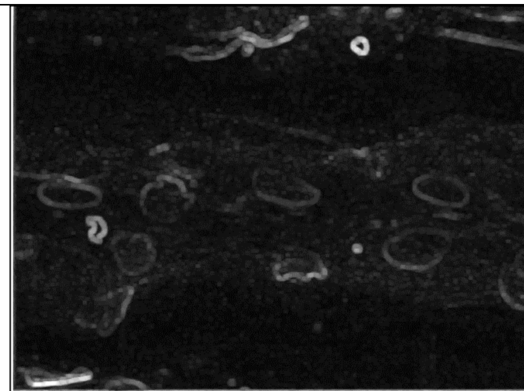
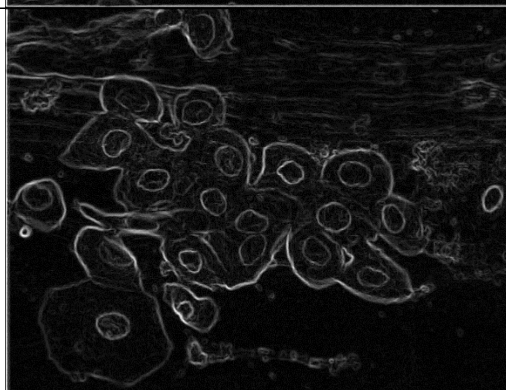
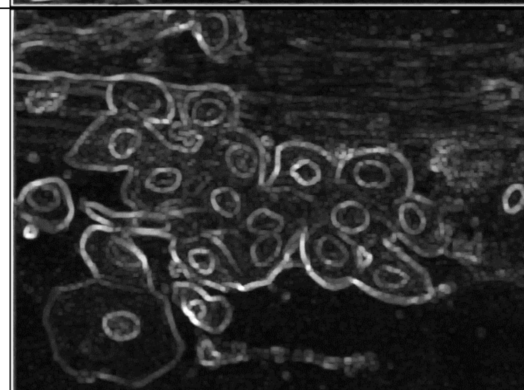
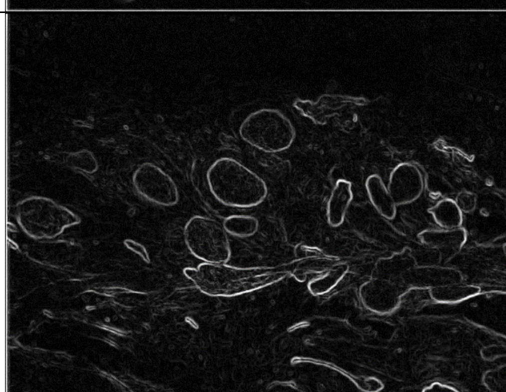
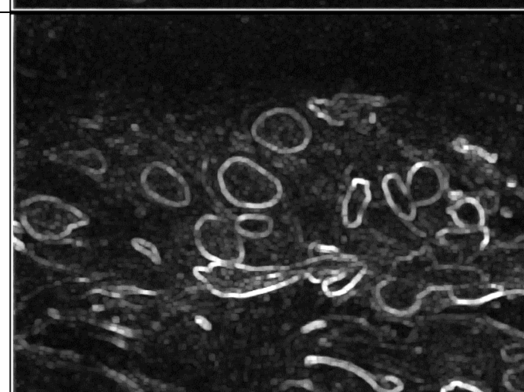
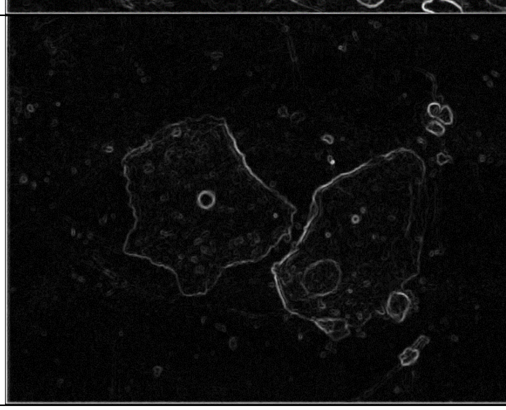
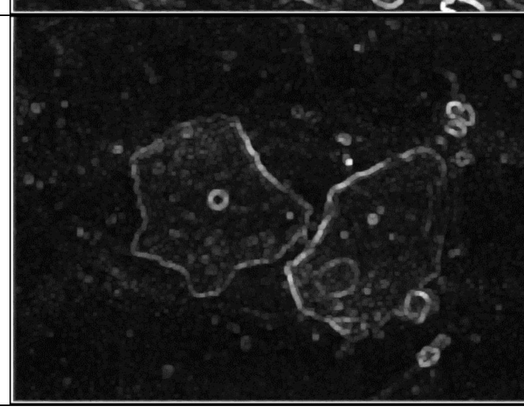
Cell Class	Sobel Image	Dilation by 3x3 Box
CYL		
INTER		

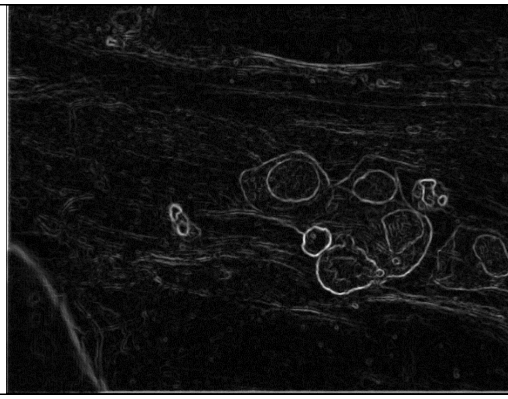
LET		
PARA		
MOD		
SUPER		

SVAR		

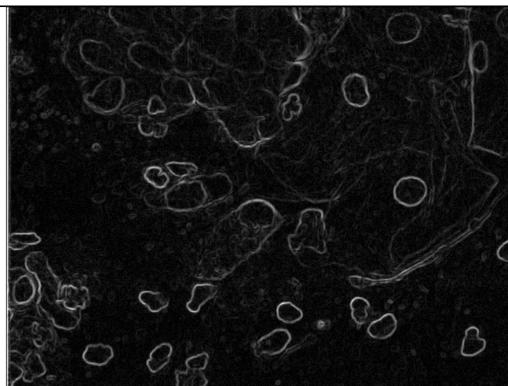
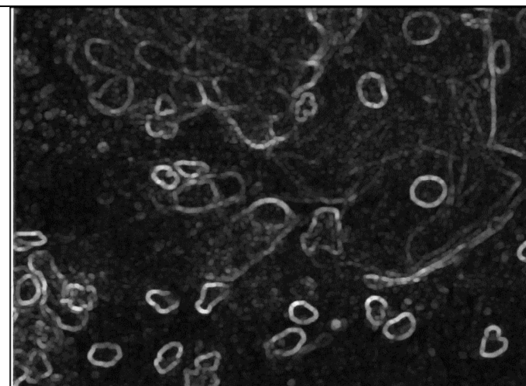
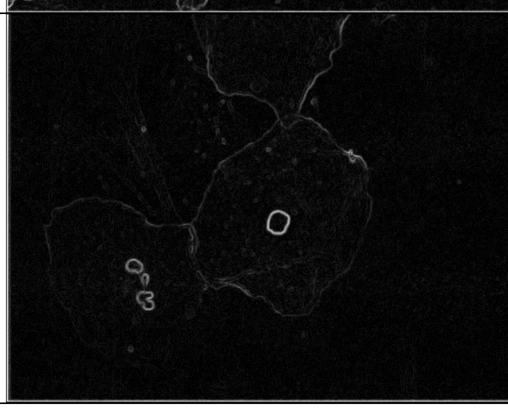
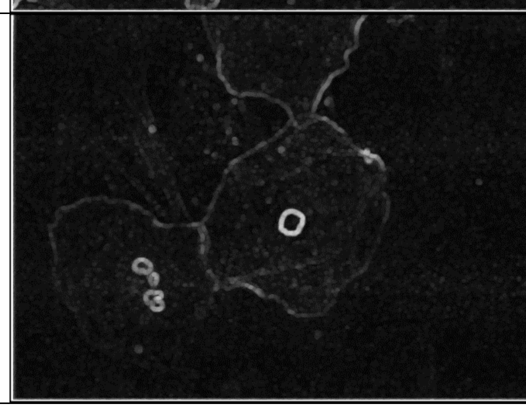
<u>Dilation by 5x5 Box on Sobel Edge Detected Image</u>

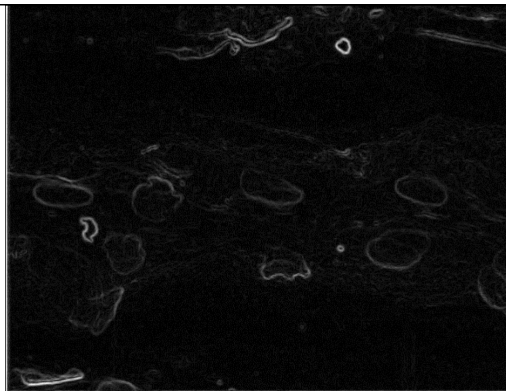
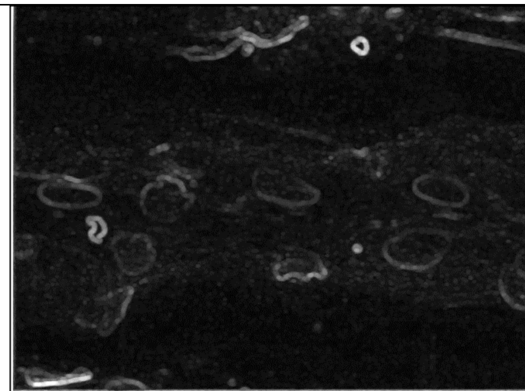
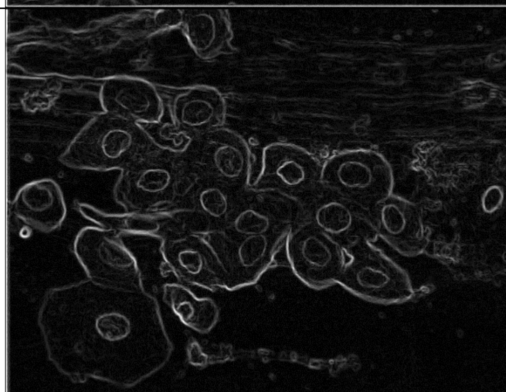
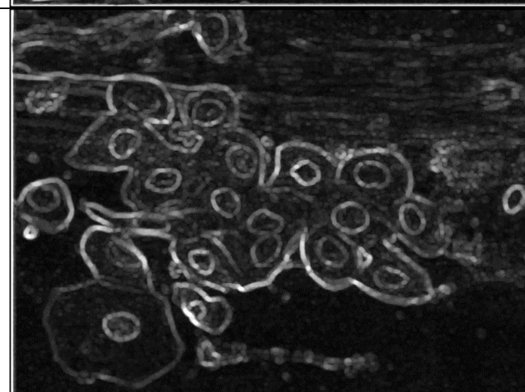
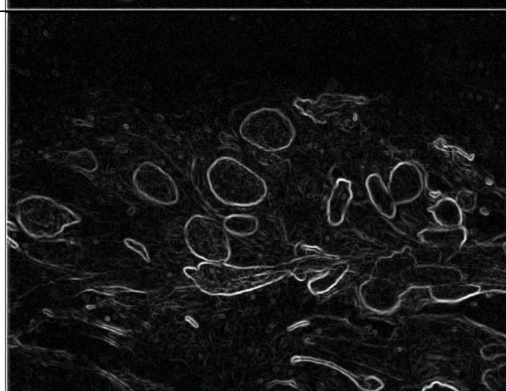
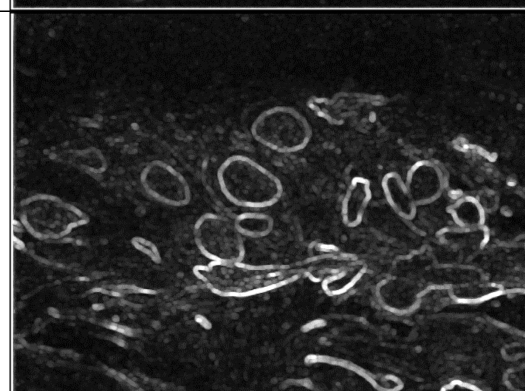
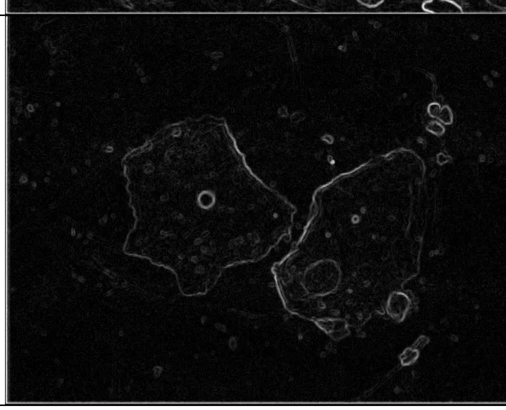
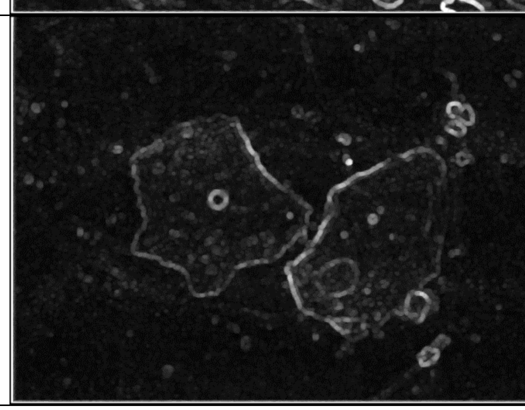
Cell Class	Sobel Image	Dilation by 5x5 Box
CYL		
INTER		

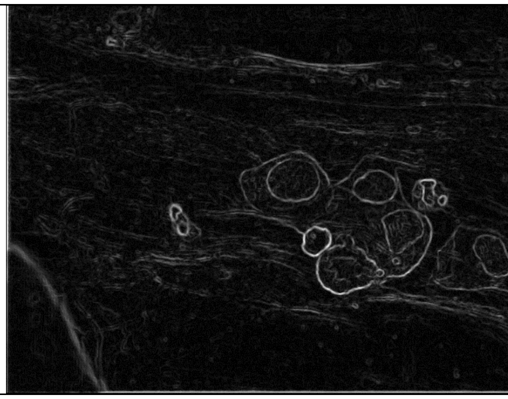
LET		
PARA		
MOD		
SUPER		

SVAR		

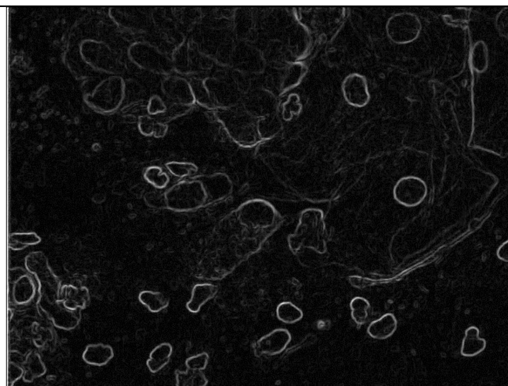
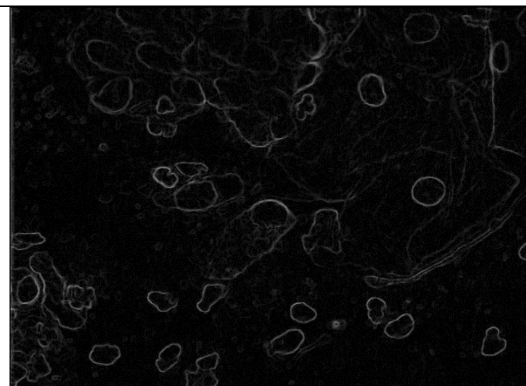
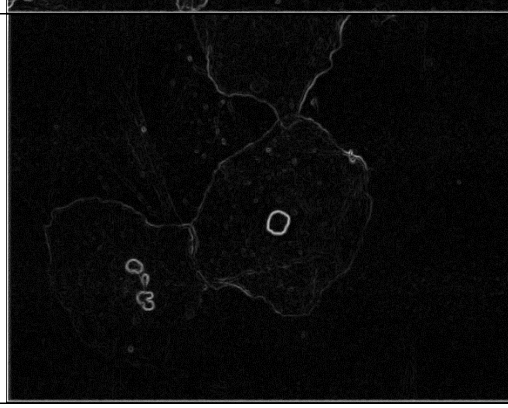
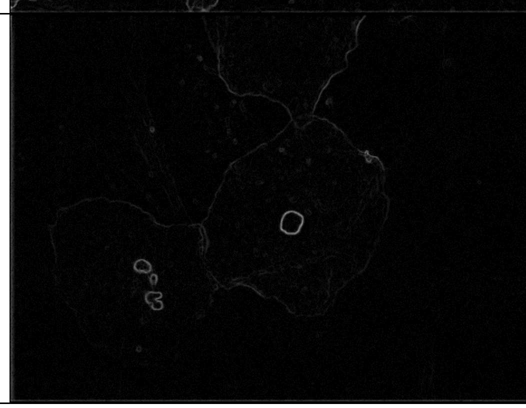
Dilation by 5x5 Circle on Sobel Edge Detected Image

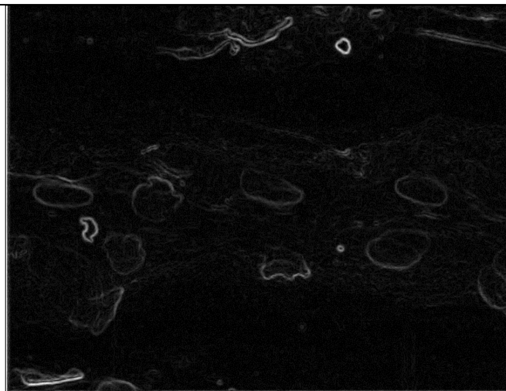
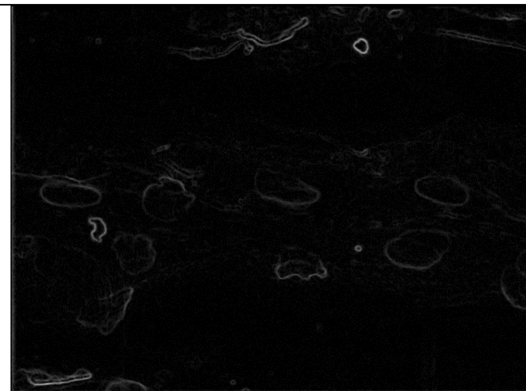
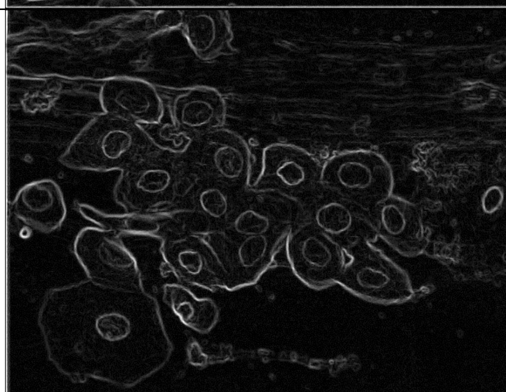
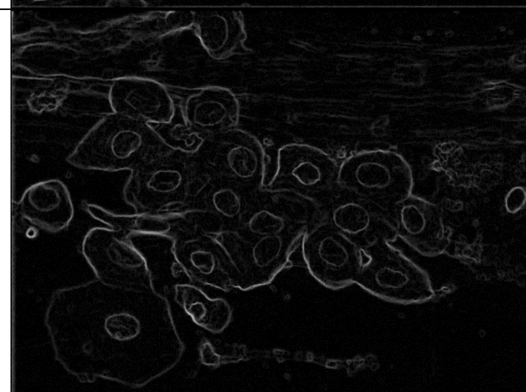
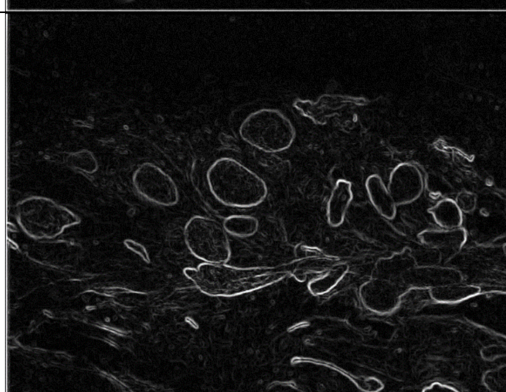
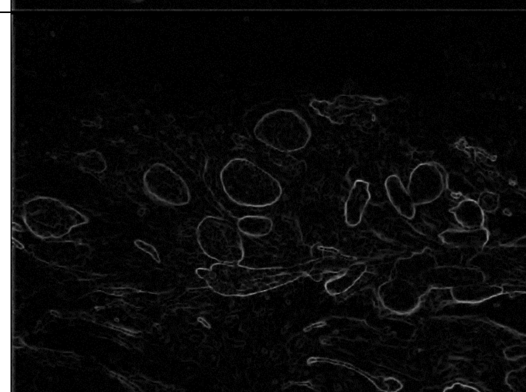
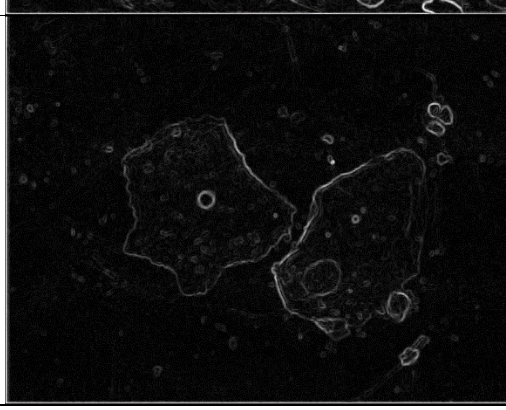
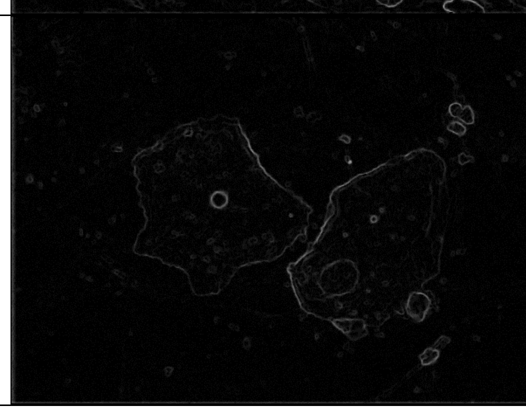
Cell Class	Sobel Image	Dilation by 5x5 Circle
CYL		
INTER		

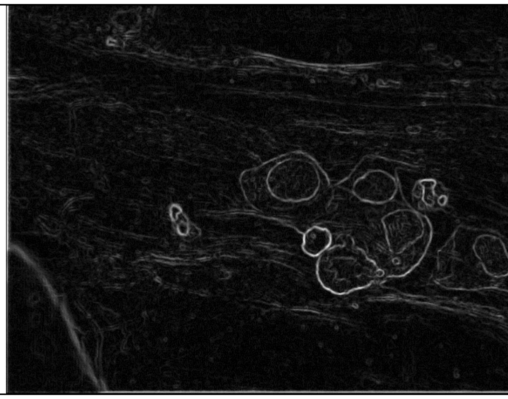
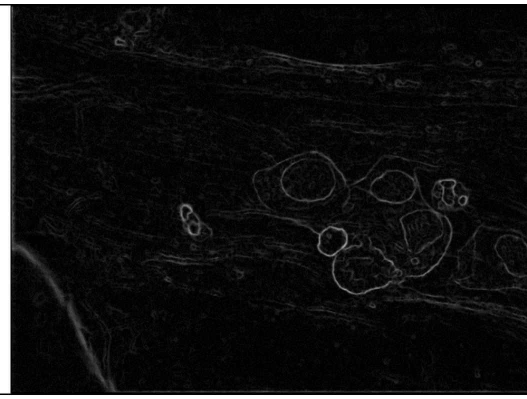
LET		
PARA		
MOD		
SUPER		

SVAR		

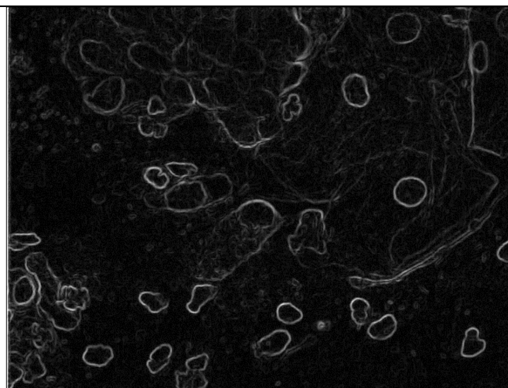
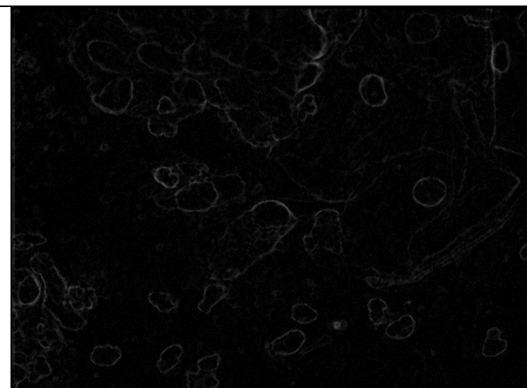
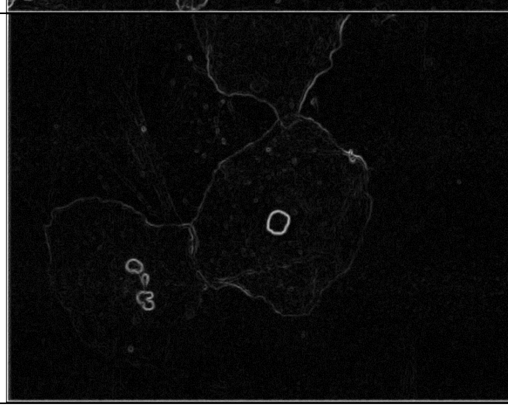
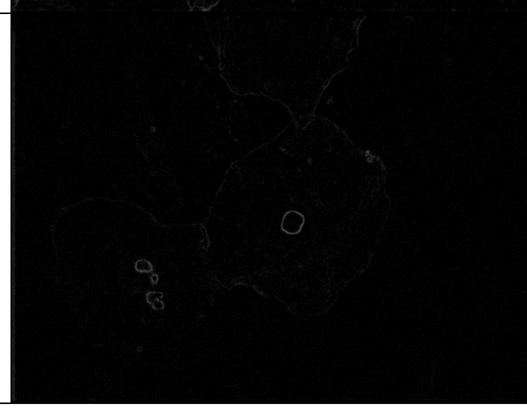
Erosion by 3x3 Cross on Sobel Edge Detected Image

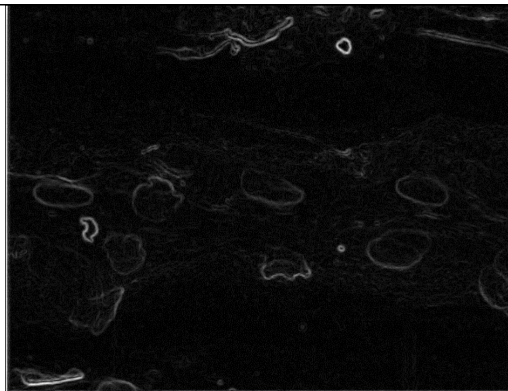
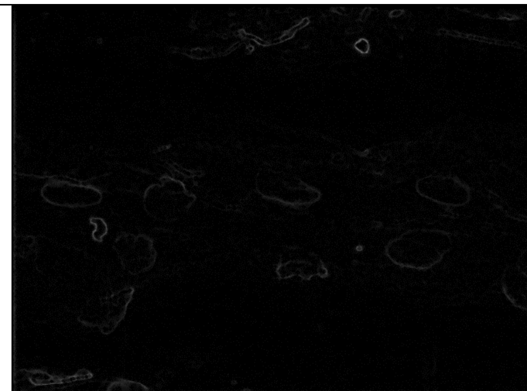
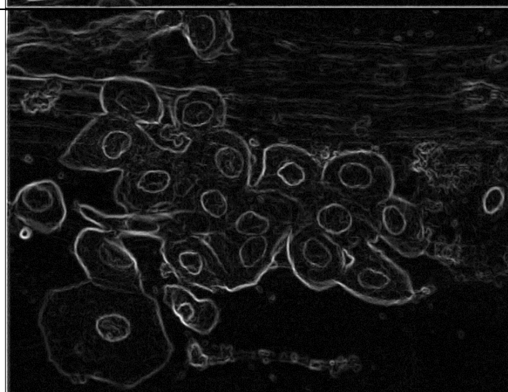
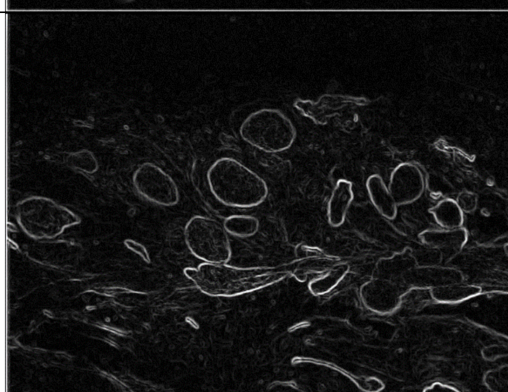
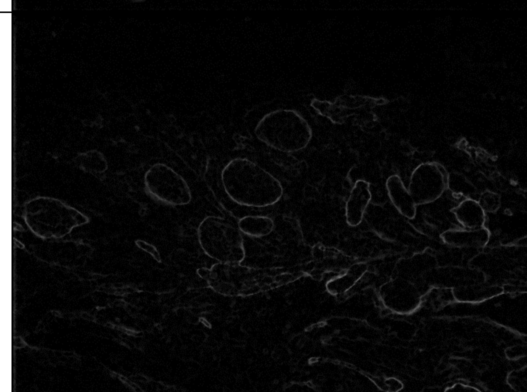
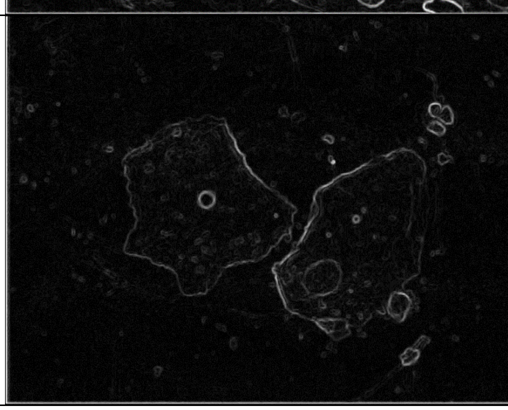
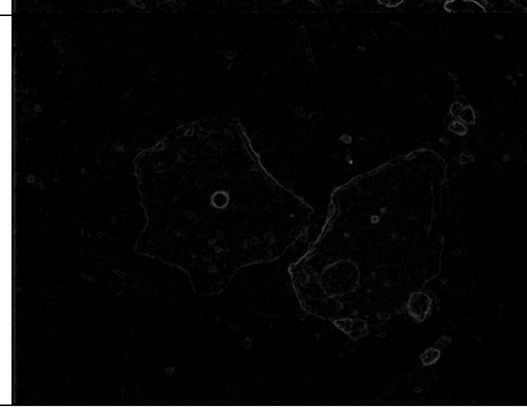
Cell Class	Sobel Image	Erosion By 3x3 Cross
CYL		
INTER		

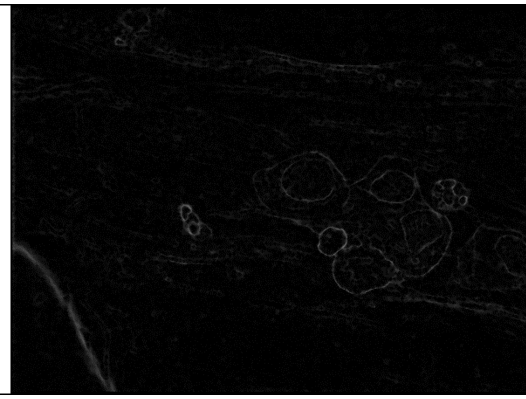
LET		
PARA		
MOD		
SUPER		

SVAR		

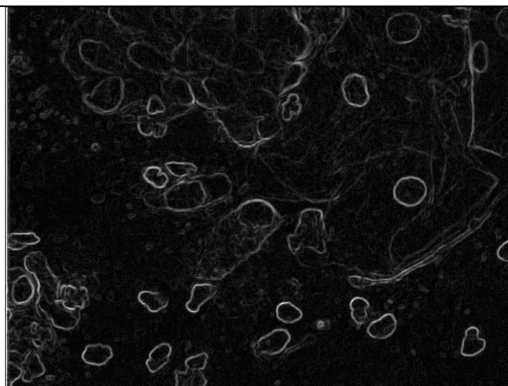
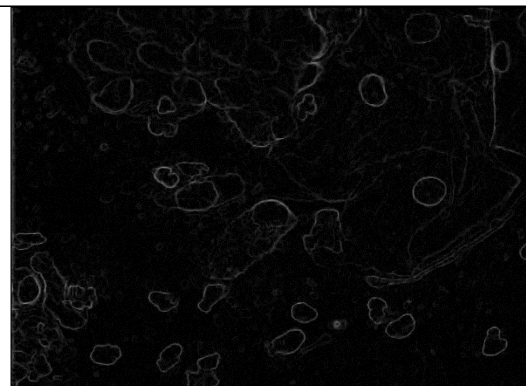
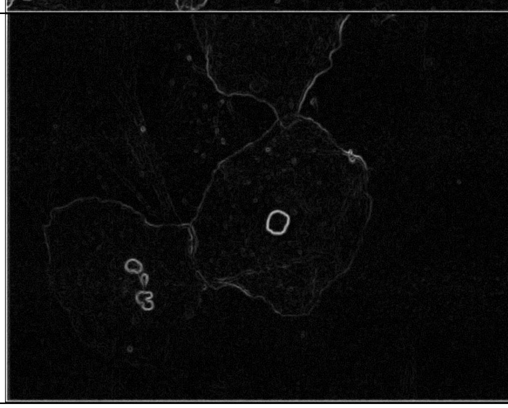
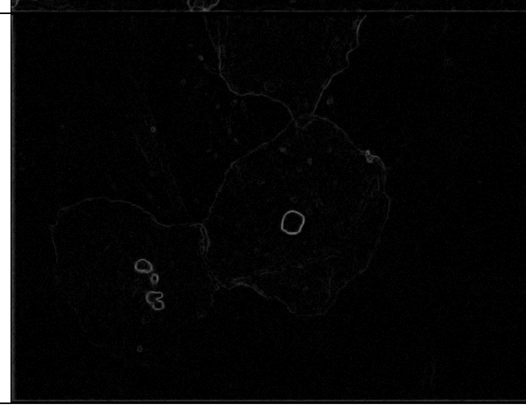
Erosion by 5x5 Cross on Sobel Edge Detected Image

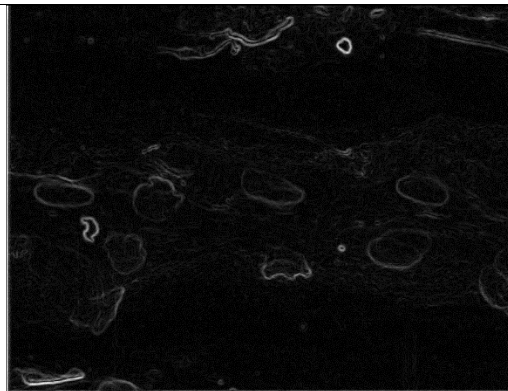
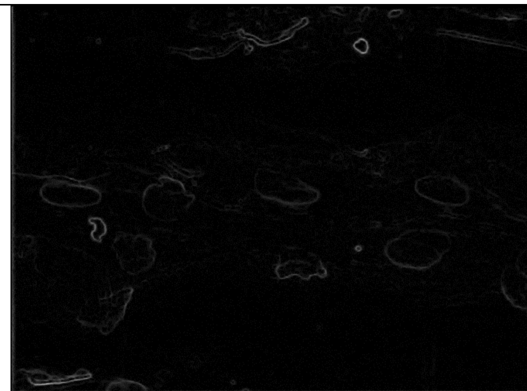
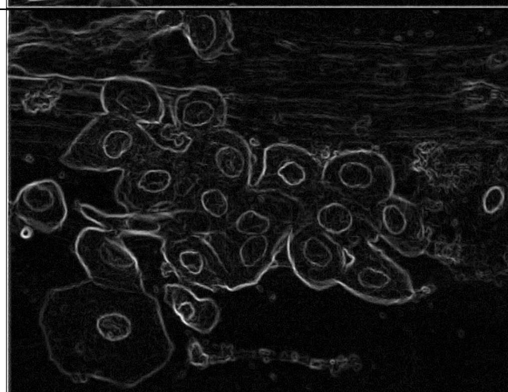
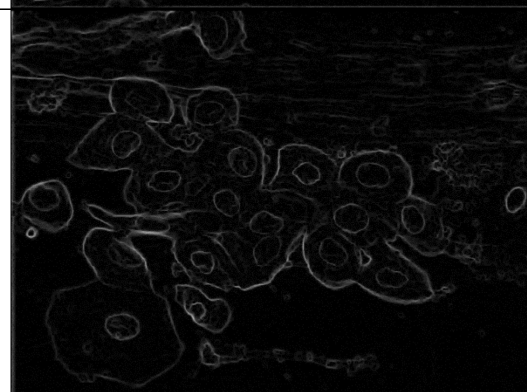
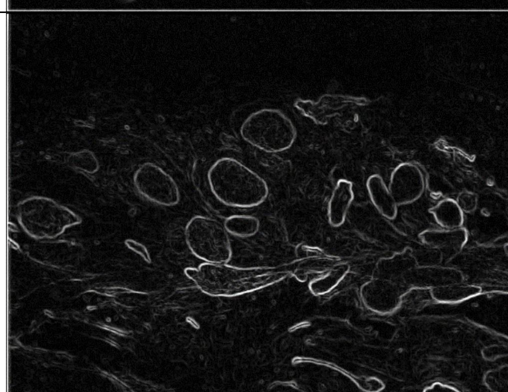
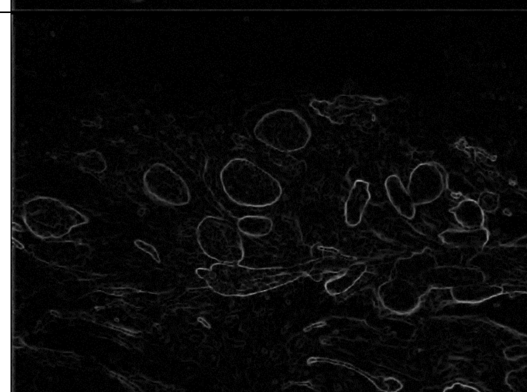
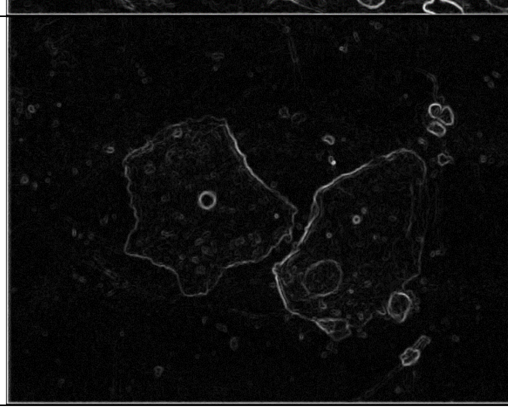
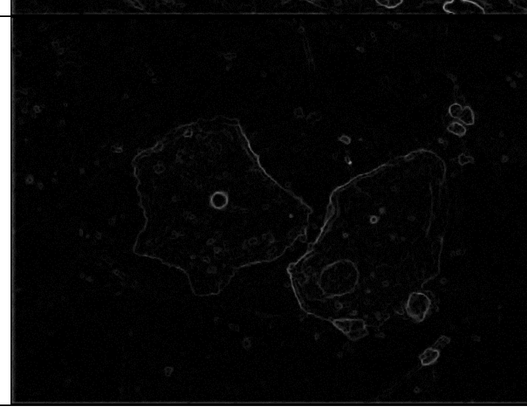
Cell Class	Sobel Image	Erosion By 5x5 Cross
CYL		
INTER		

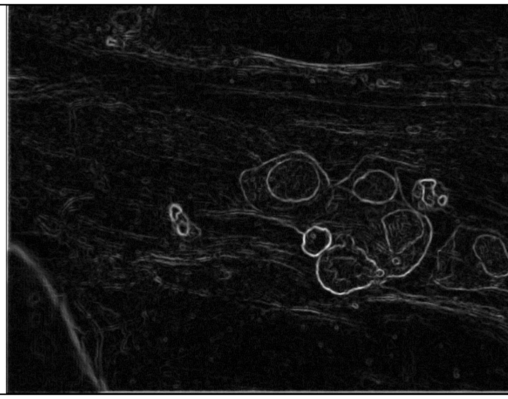
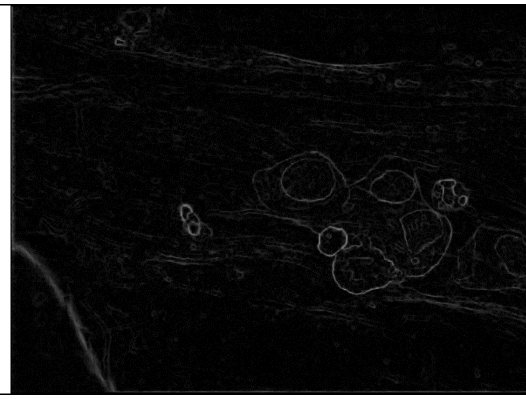
LET		
PARA		
MOD		
SUPER		

SVAR		

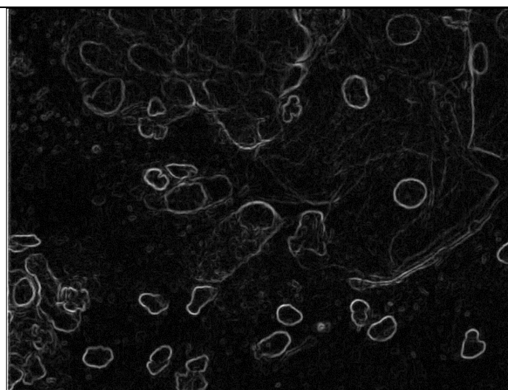
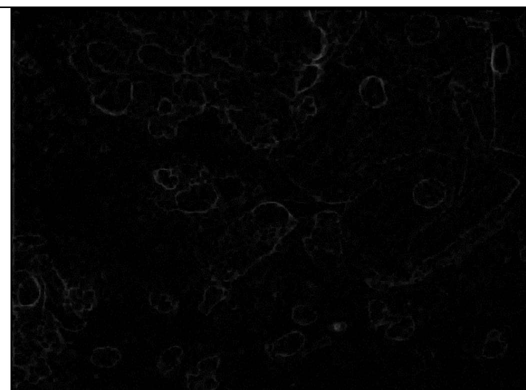
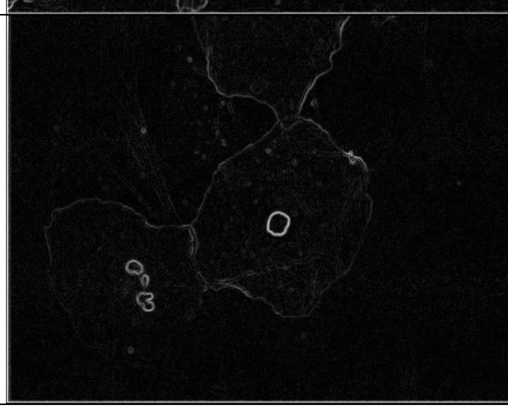
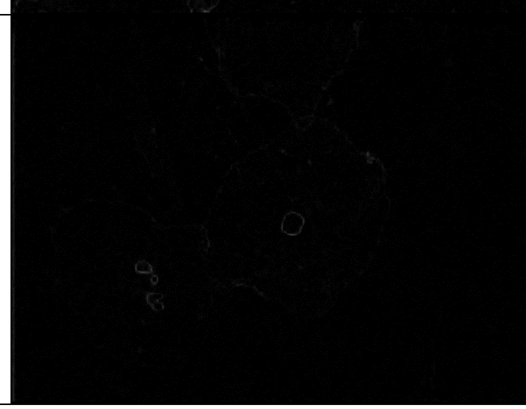
<u>Erosion by 3x3 Box on Sobel Edge Detected Image</u>

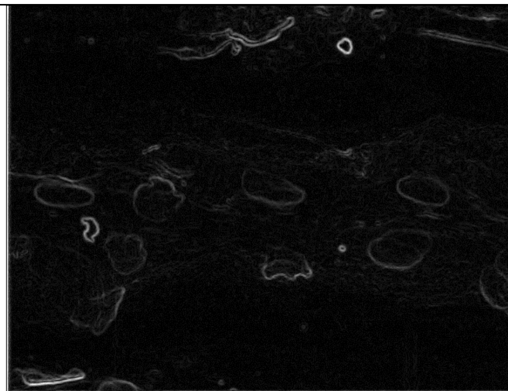
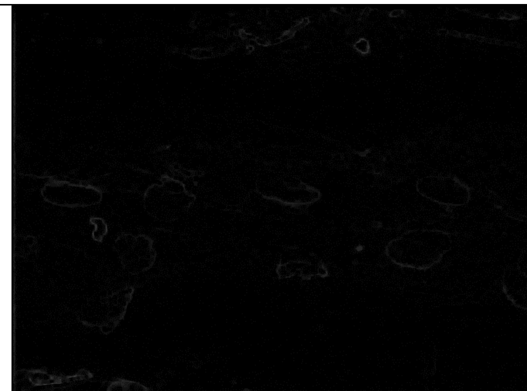
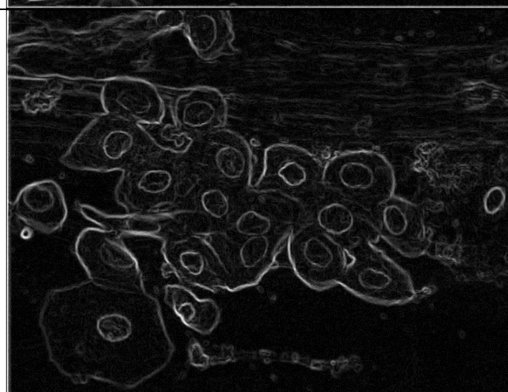
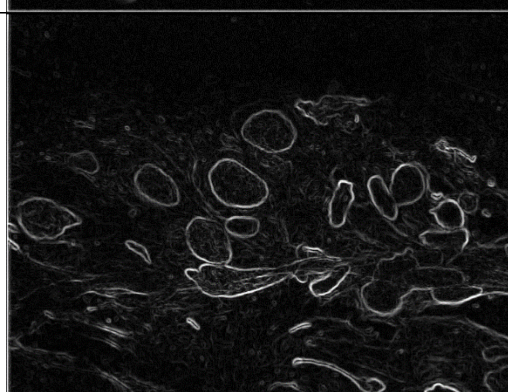
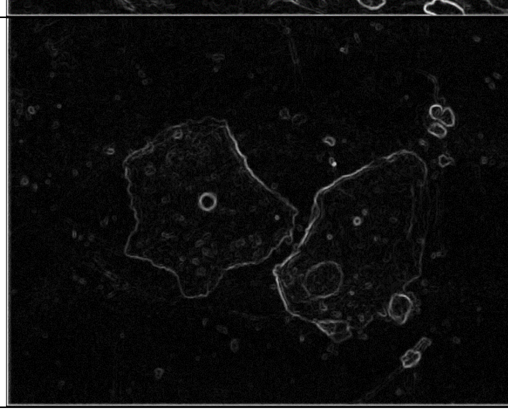
Cell Class	Sobel Image	Erosion By 3x3 Cross
CYL		
INTER		

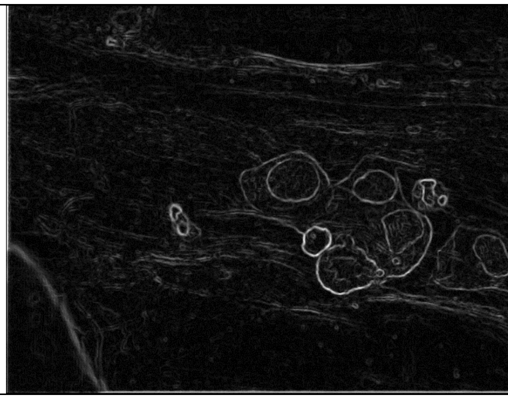
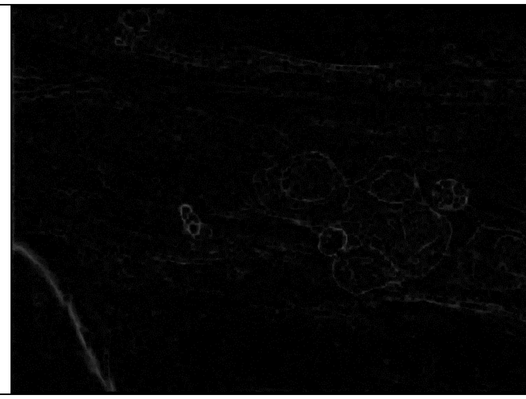
LET		
PARA		
MOD		
SUPER		

SVAR		

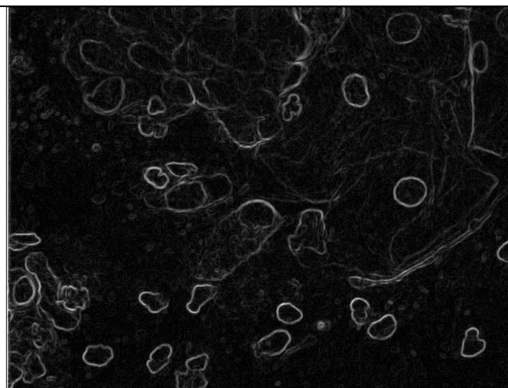
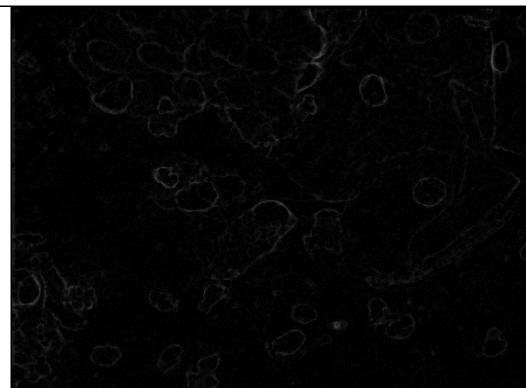
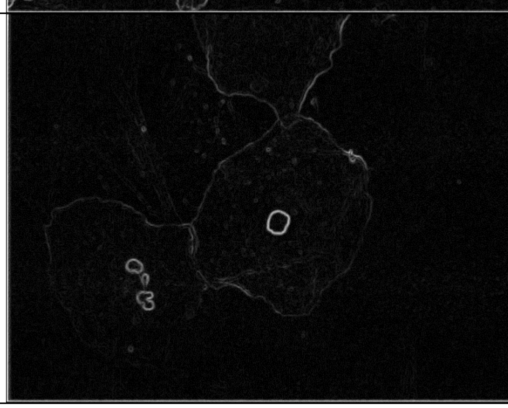
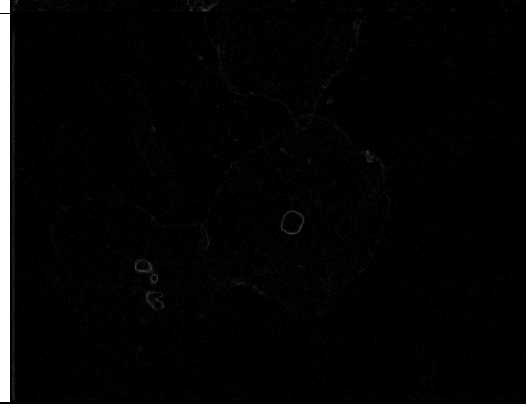
Erosion by 3x3 Box on Sobel Edge Detected Image

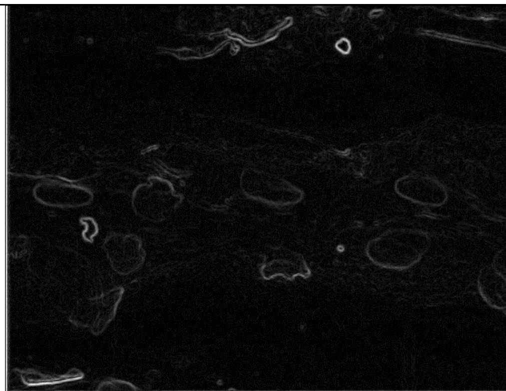
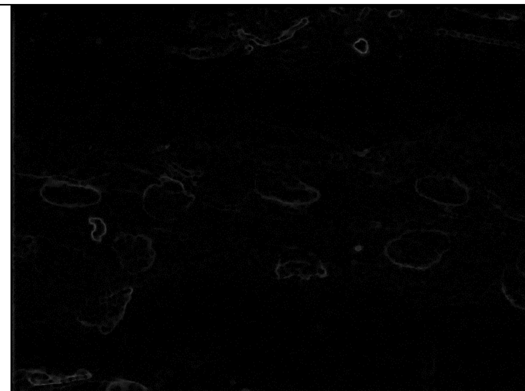
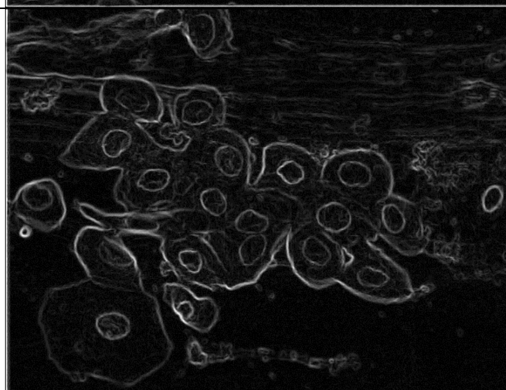
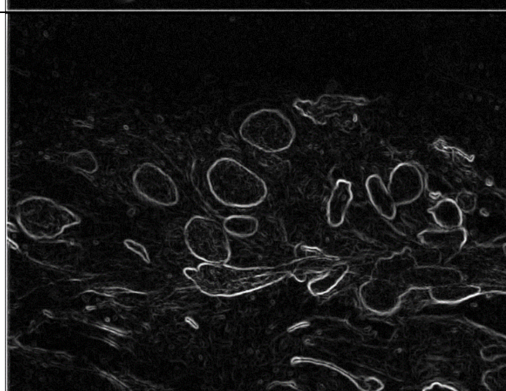
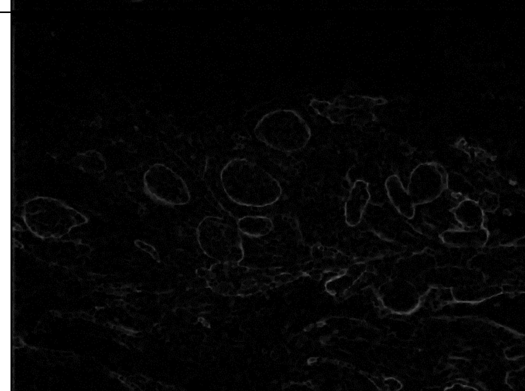
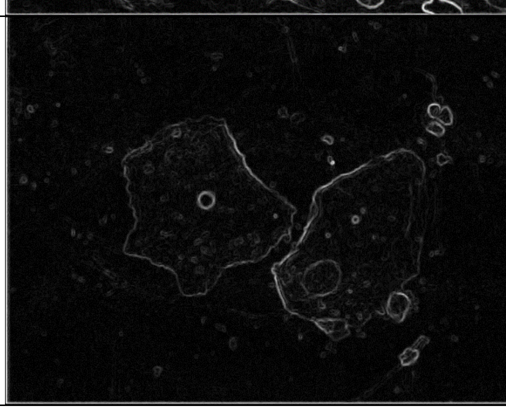
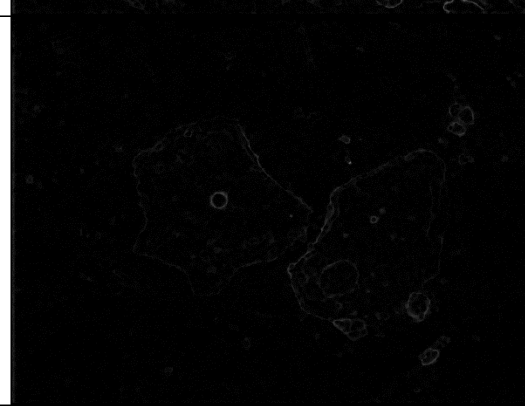
Cell Class	Sobel Image	Erosion By 5x5 Box
CYL		
INTER		

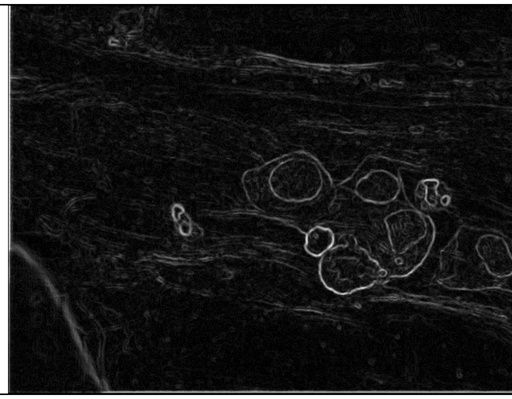
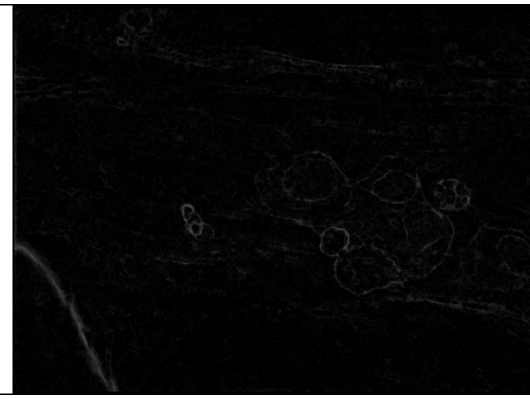
LET		
PARA		
MOD		
SUPER		

SVAR		

Erosion by 5x5 Circle on Sobel Edge Detected Image

Cell Class	Sobel Image	Erosion By 5x5 Circle
CYL		
INTER		

LET		
PARA		
MOD		
SUPER		

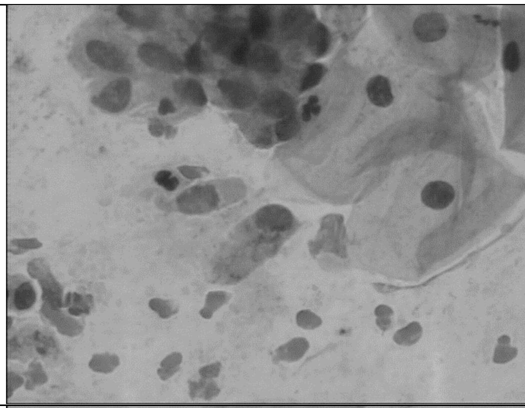
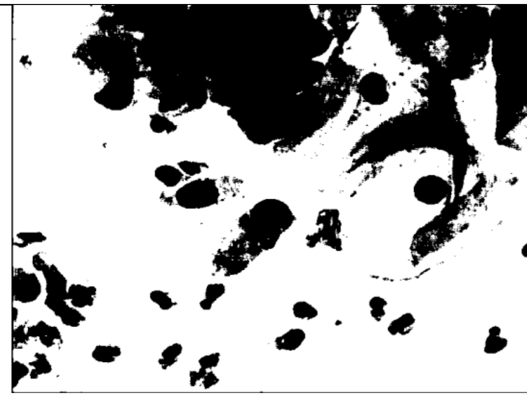
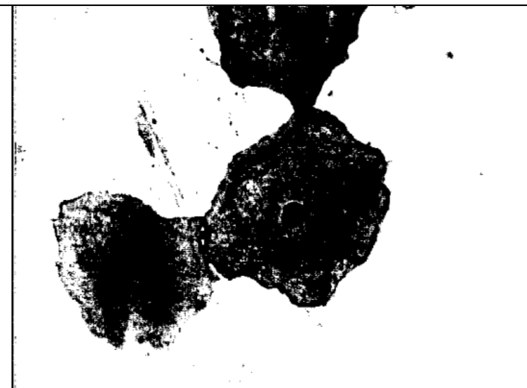
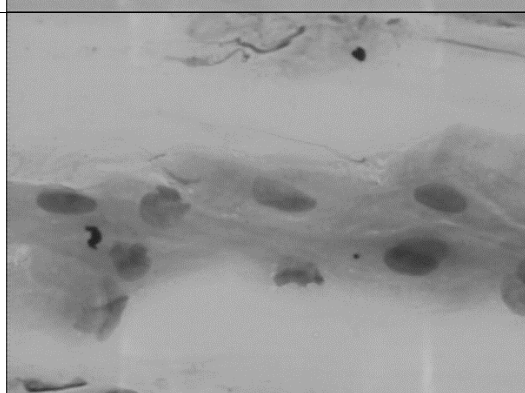
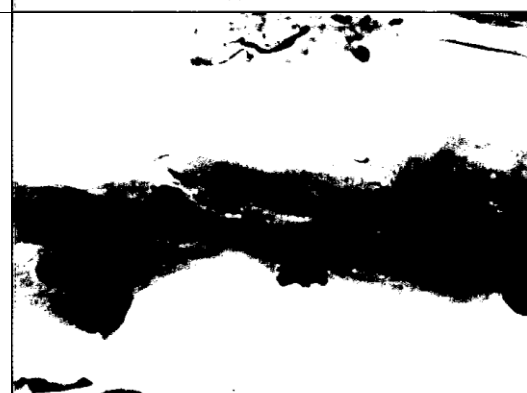
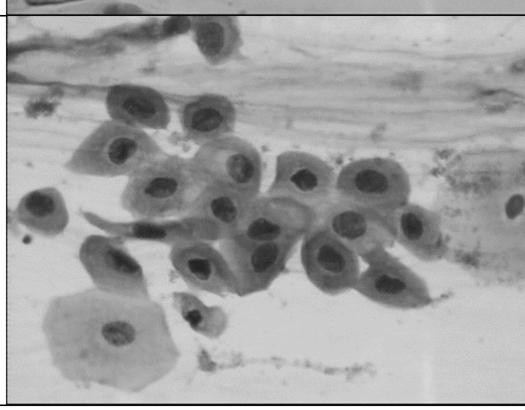
SVAR		

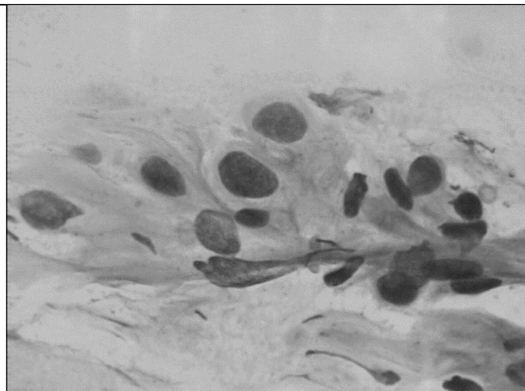
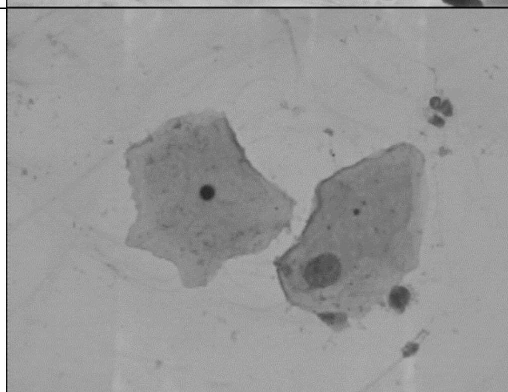
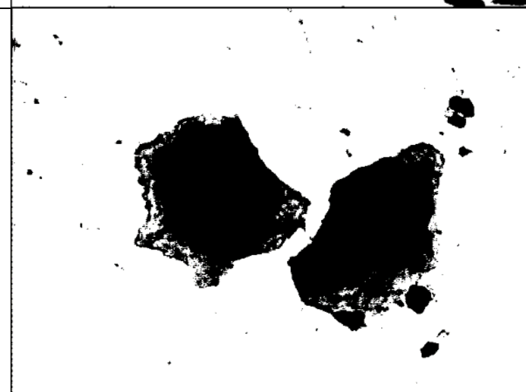
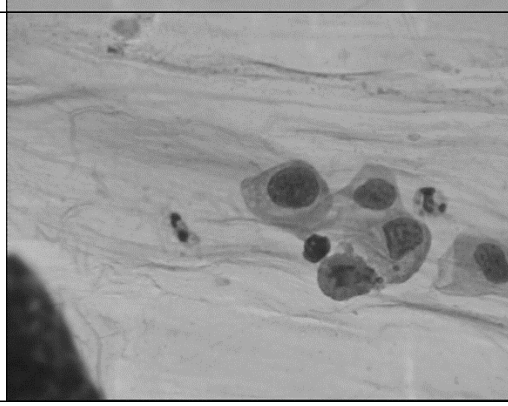
Segmentation

Several segmentation methods have been included in this application. The selected methods include global histogram thresholding, Otsu histogram thresholding, K-means clustering segmentation, and SuperPixel. Global histogram thresholding is a simple binary segmentation of an image. The initial threshold in this case, is defined by the average intensity of the image. Means are then calculated for the set of values above the threshold, and the set of values below the threshold. The two means are then averaged together, to create the new threshold. Values below the threshold are mapped to 0, while values above are mapped to 255, yielding a very rough binary segmentation. Otsu segmentation works similarly to global thresholding but relies on Otsu's method for finding the optimal threshold by maximizing inter-class variance. It yields a slightly more detailed binary segmented image. However, in one of the test images in the INTER class of cells, the Otsu segmented image resulted in less information compared to the global thresholding method. K-means functions differently than the simple thresholding segmentation algorithms. The user may specify an integer K in the application, which then prompts the algorithm to create K number of centers in the grayscale color space. These 5 intensities are selected at random. All intensities are then reassigned to the nearest center, which is determined by Euclidian distance. K-means will continue assigning points to centers until convergence is achieved. It is a relatively fast process and can lead to richer segmentation in comparison to Global and Otsu thresholding by highlighting more features in the image. The SuperPixel method is based on K-means but differs in that it compares centroids locally instead of globally. SuperPixel also reduces the complexity of the information in an image, while retaining essential structures. Both K-means and SuperPixel are unsupervised, and only require one parameter to be supplied by the user (K). Please refer to the tables below for sample images for the different segmentation methods.

<u>Global Histogram Thresholding Segmentation Examples</u>

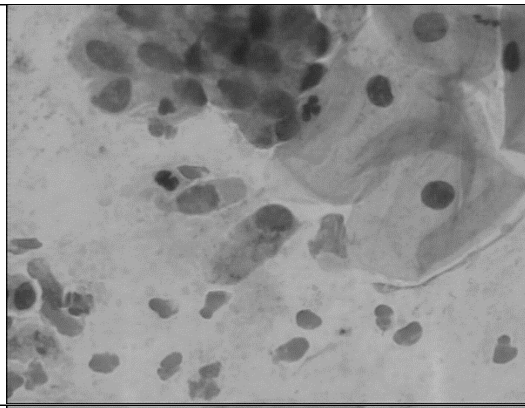
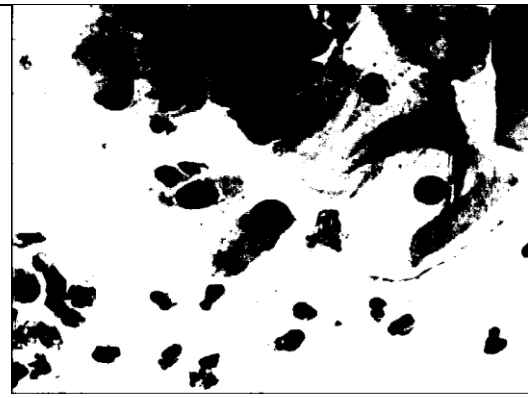
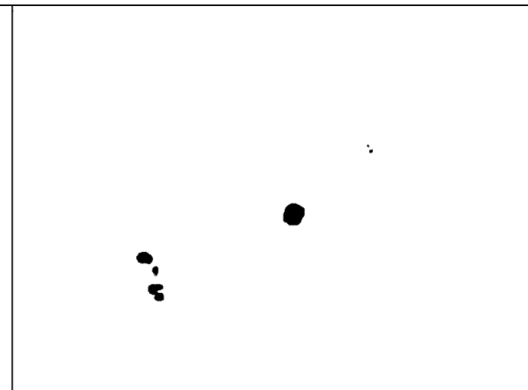
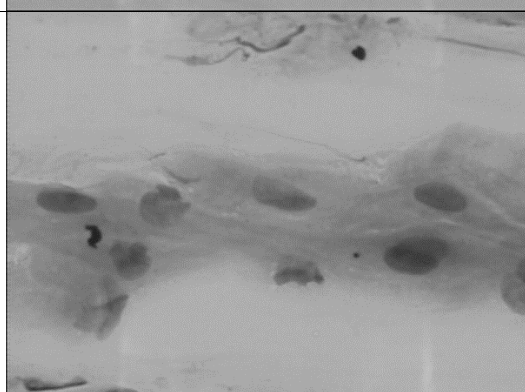
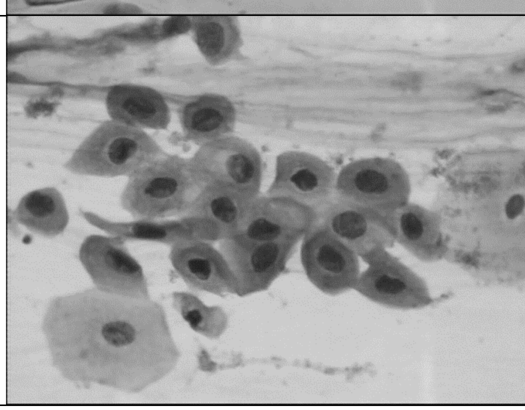
Cell Class	Original Grayscale	Global Threshold Segmented

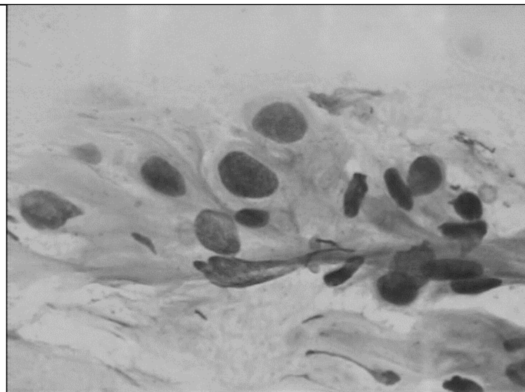
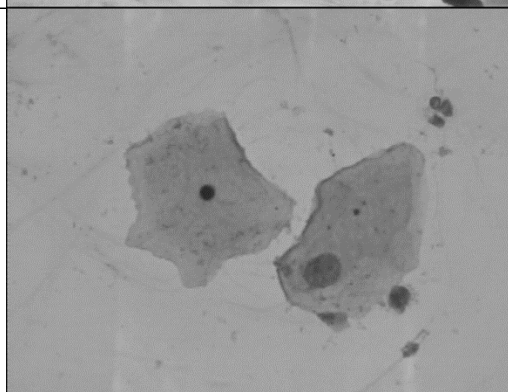
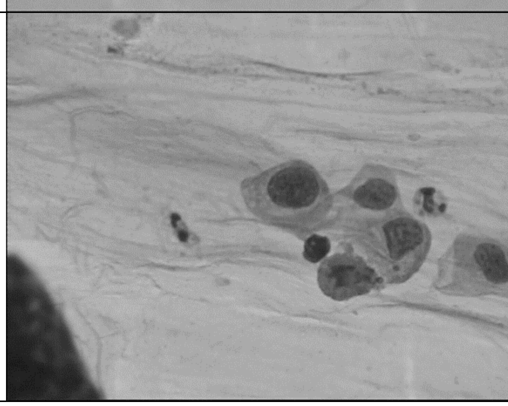
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

Otsu Histogram Thresholding Segmentation Examples

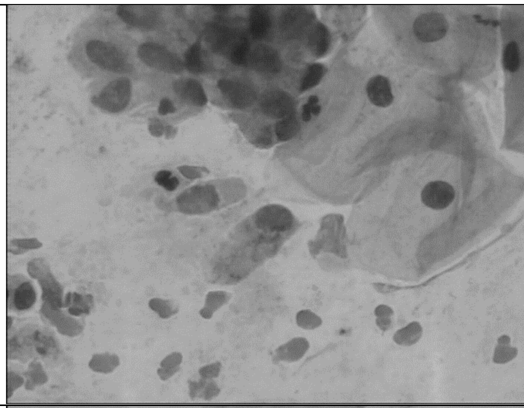
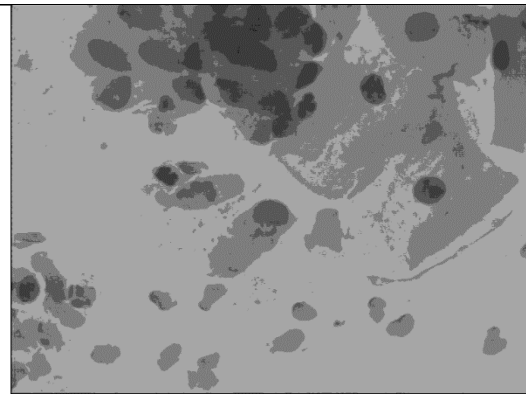
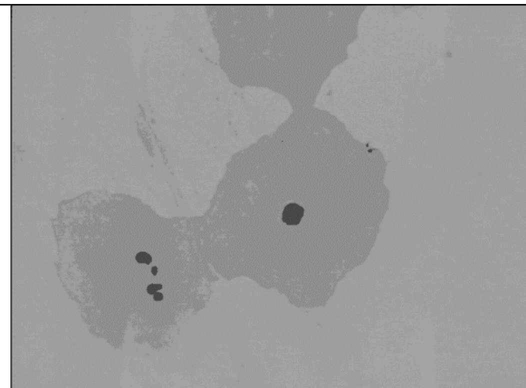
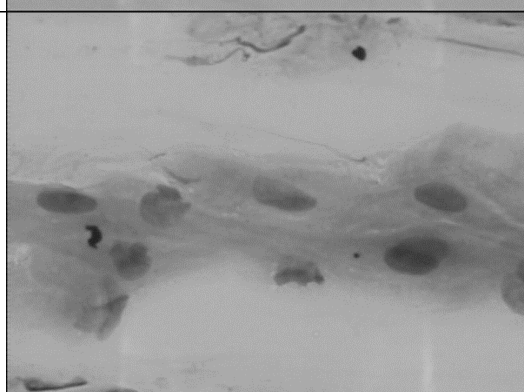
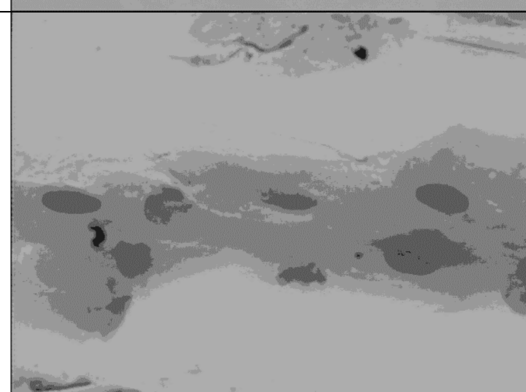
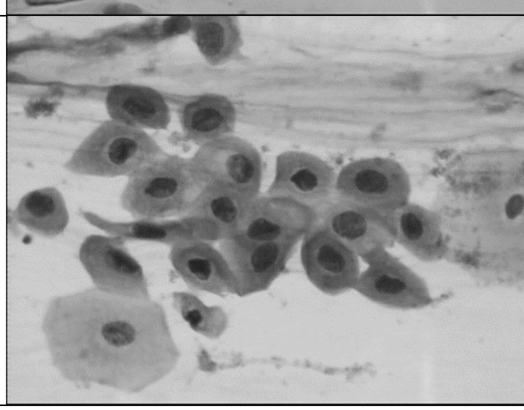
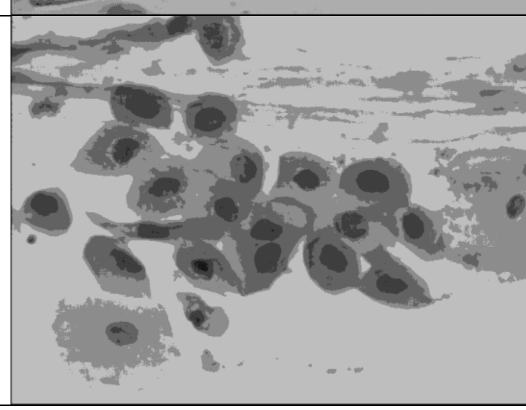
Cell Class	Original Grayscale	Otsu Threshold Segmented

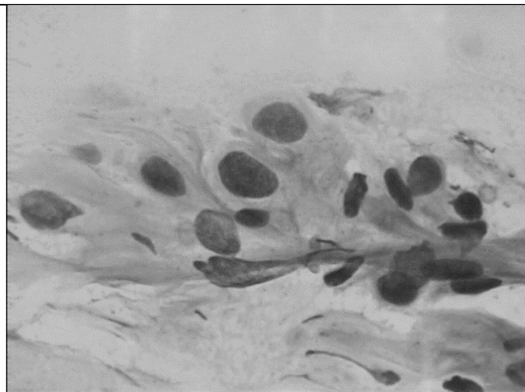
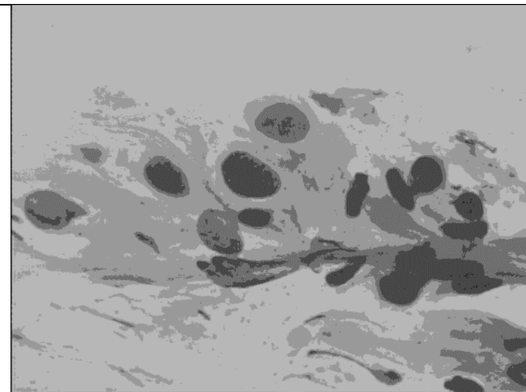
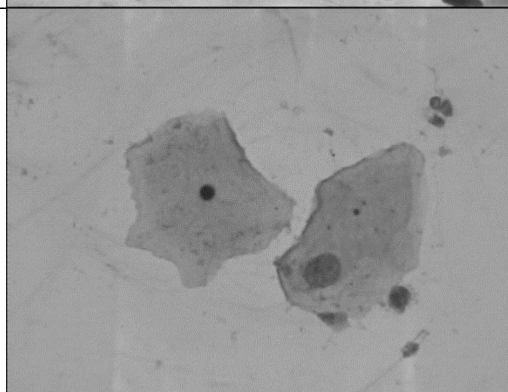
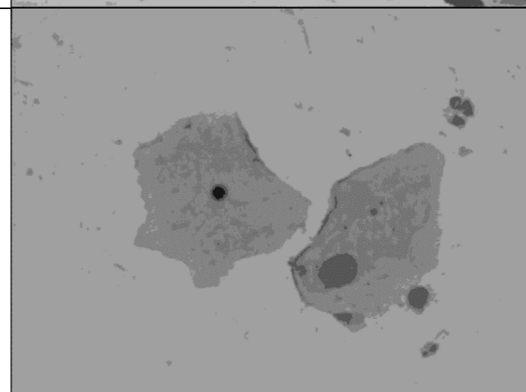
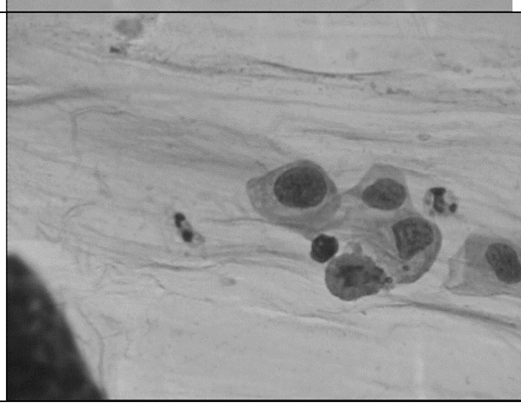
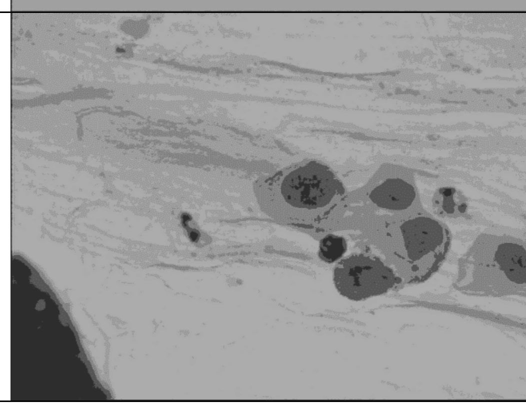
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

<u>K-Means Segmentation Examples (K=5)</u>

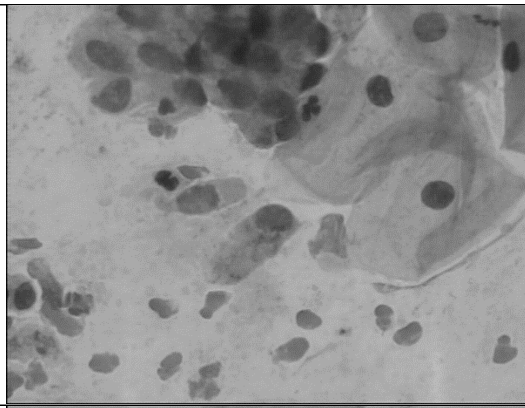
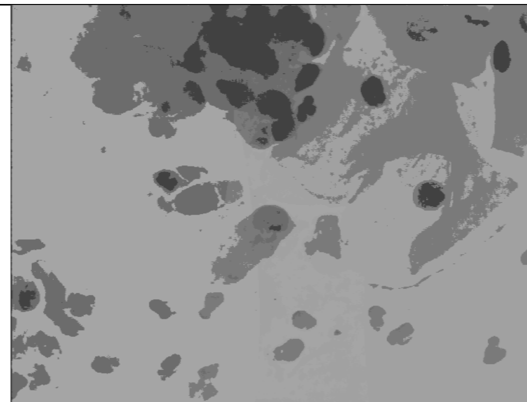
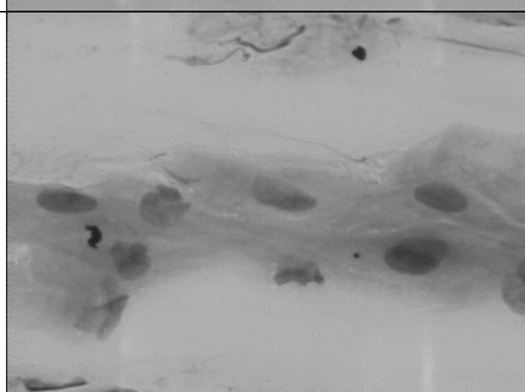
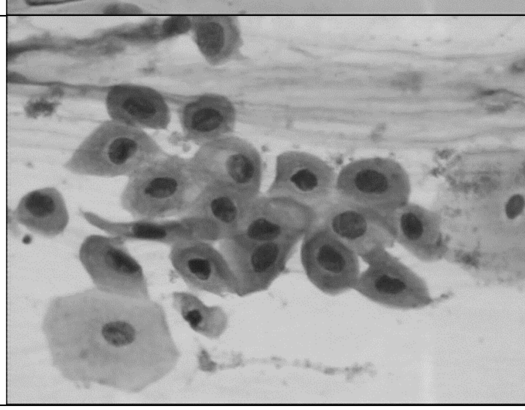
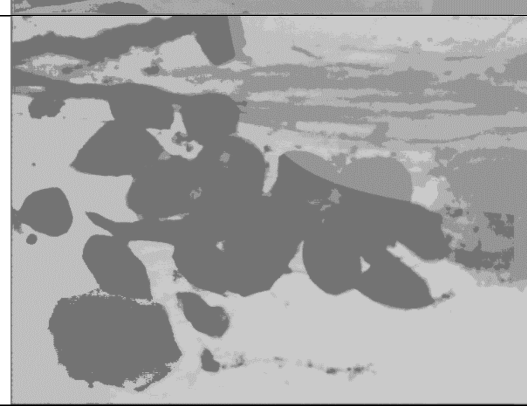
Cell Class	Original Grayscale	K-Means Segmented (K=5)

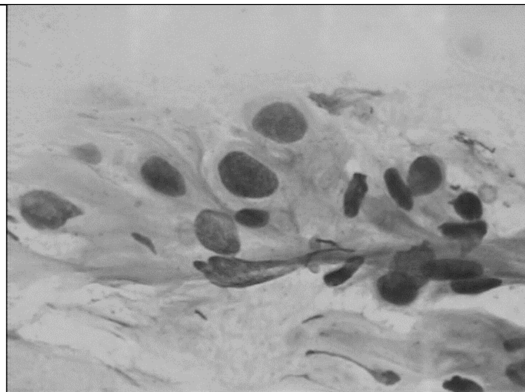
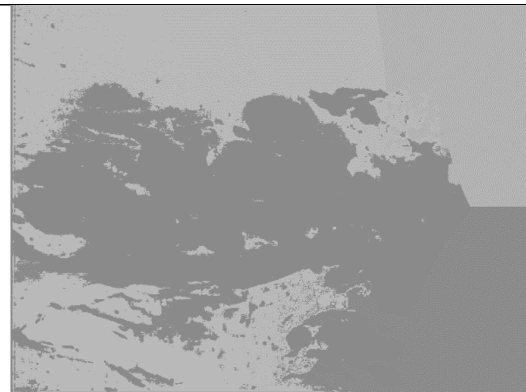
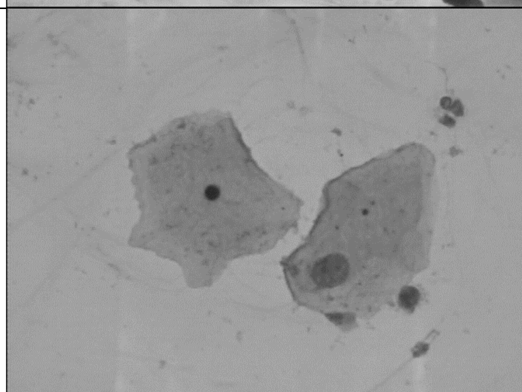
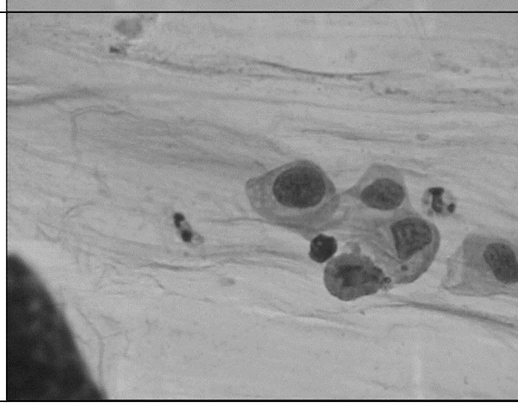
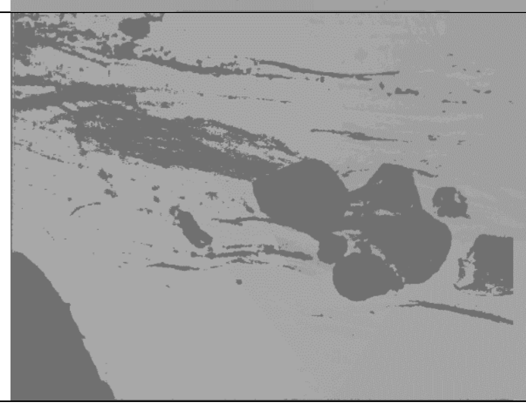
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

<u>SuperPixel Segmentation Examples (5 SuperPixels)</u>

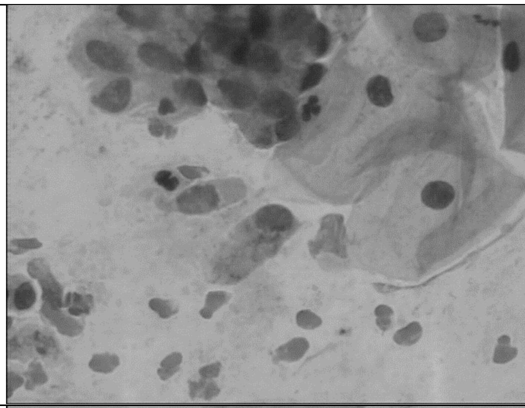
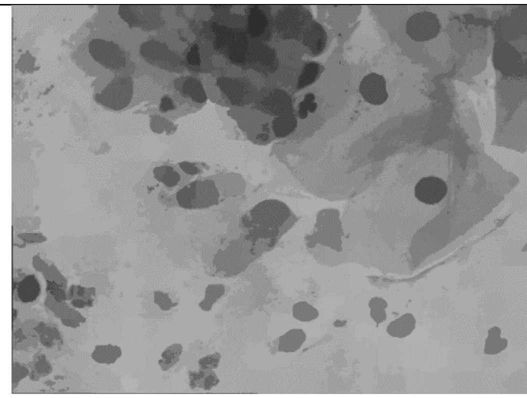
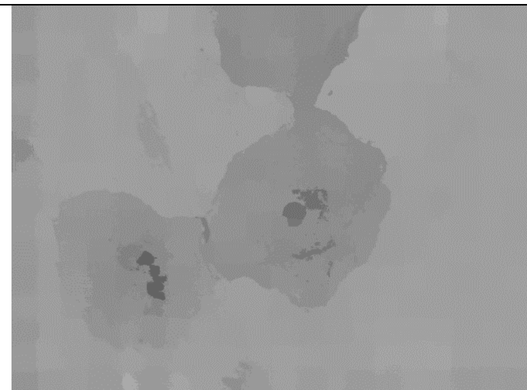
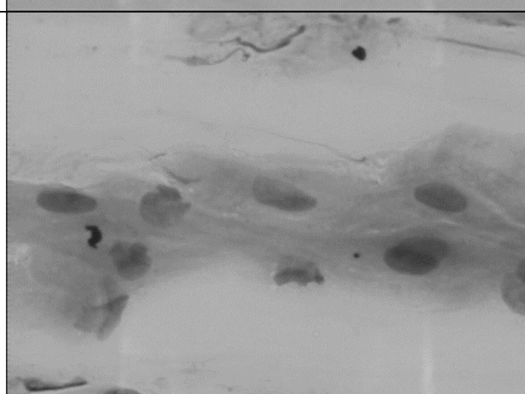
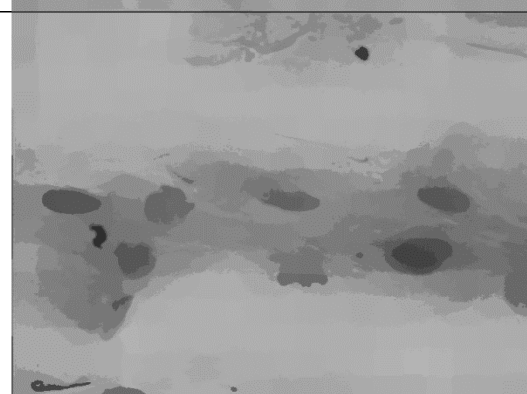
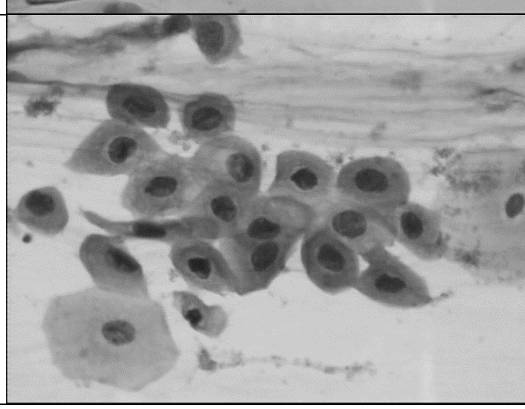
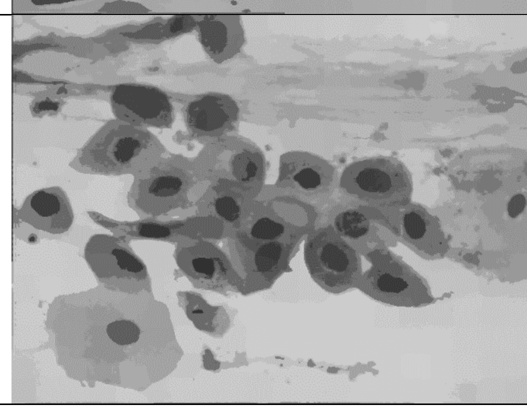
Cell Class	Original Grayscale	SuperPixel Segmented (5 SuperPixels)

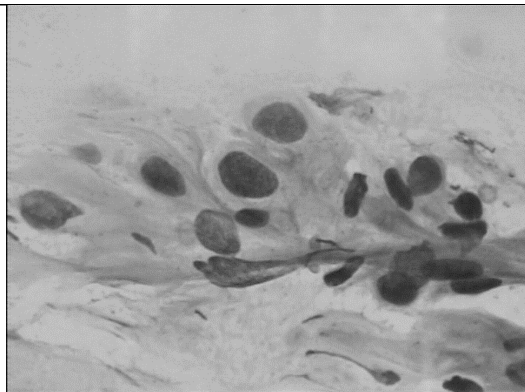
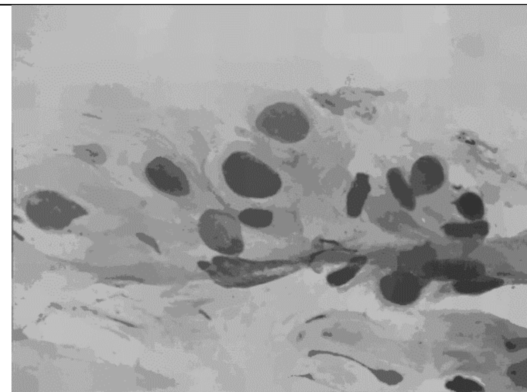
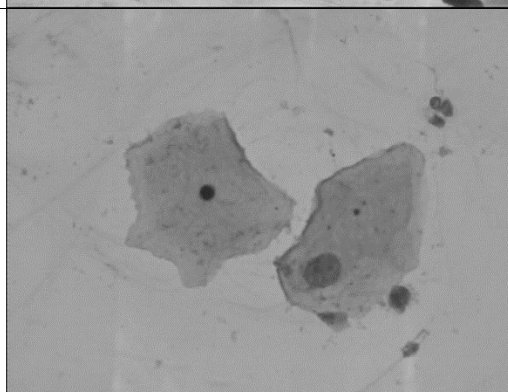
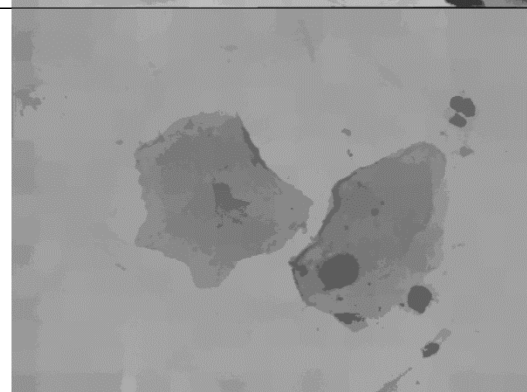
CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR		

SuperPixel Segmentation Example (300 SuperPixels)

Cell Class	Original Grayscale	SuperPixel Segmentation (300 SuperPixels)

CYL		
INTER		
LET		
PARA		

MOD		
SUPER		
SVAR