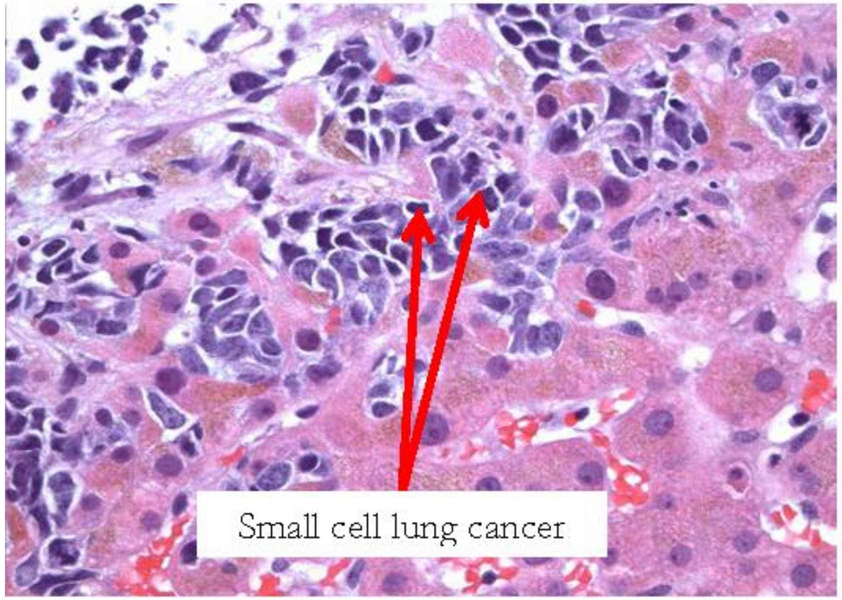
Nuclei Detection and Segmentation in Lung Histology Images

FINAL PROJECT FOR ECE 582 CREATED BY NOAH WAGNON

Project Background

- Advanced image processing techniques have opened the door for automated solutions to analyze microscopic images.
- Detecting and segmenting cell nuclei can aid in the ailment of many diagnoses, specifically those relating to cancer.
- Normal lung tissues, small cell cancerous lung tissue, and non-small-cell cancerous lung tissue show vast differences in the size, shape, and quantity of nuclei present per image.



Approach for Detection and Segmentation

Approach 1:

- Perform detection and segmentation simultaneously with low-level operations.
- **Detection**
  - Preprocess with top/bottom-hat filtering for contrast enhancement.
  - Perform morphological opening and binarization.
  - Perform Connected components analysis to compute (x,y) center coordinate for each nuclei.
  - Final result will be a “center map” which represents the center point of each nucleus detected.
- **Segmentation**
  - Begin with same preprocessing, opening, and binarization steps.
  - Perform edge detection and labelling via a Laplacian of Gaussian (LoG) filter.
  - Final result is edges overlaid on original image for segmentation.

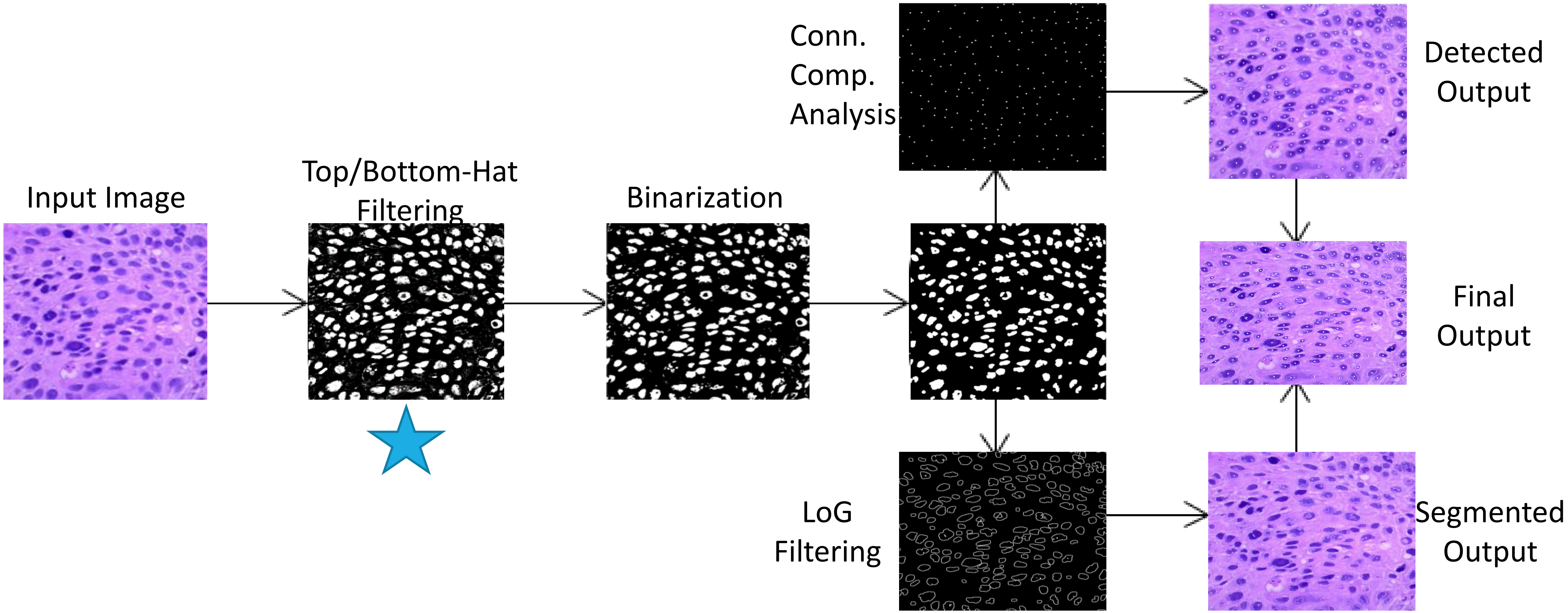
Approach 2:

- Utilize Mask-RCNN to perform both detection and segmentation simultaneously.
- Train the model on existing Kaggle dataset for nuclei detection.
- Test the model on LC25000 dataset.

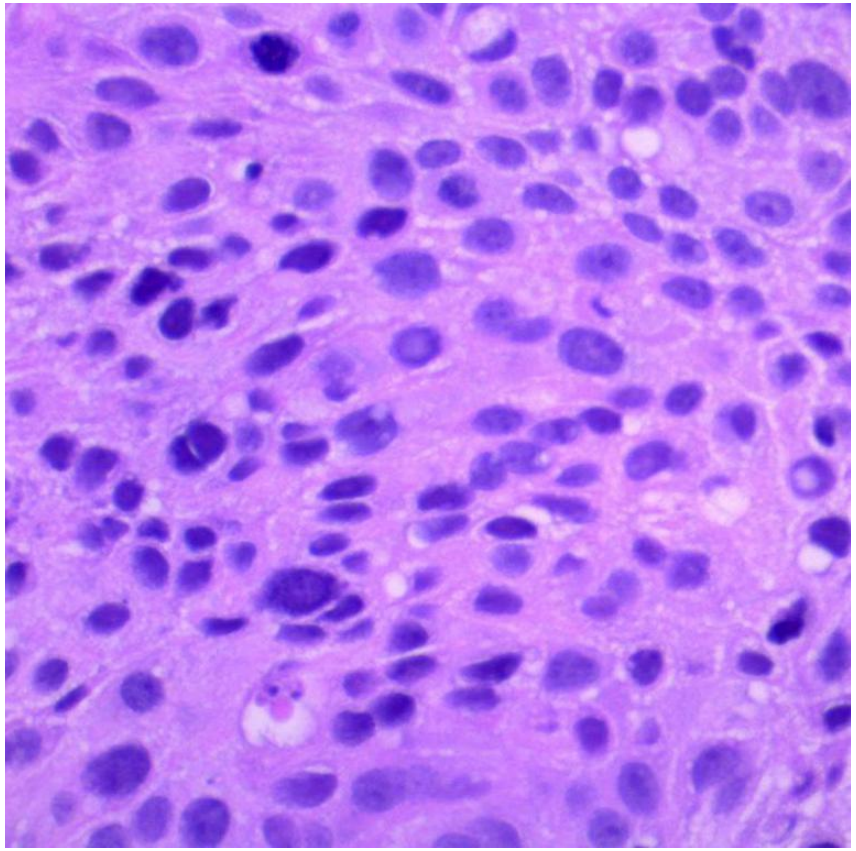
Project Goals

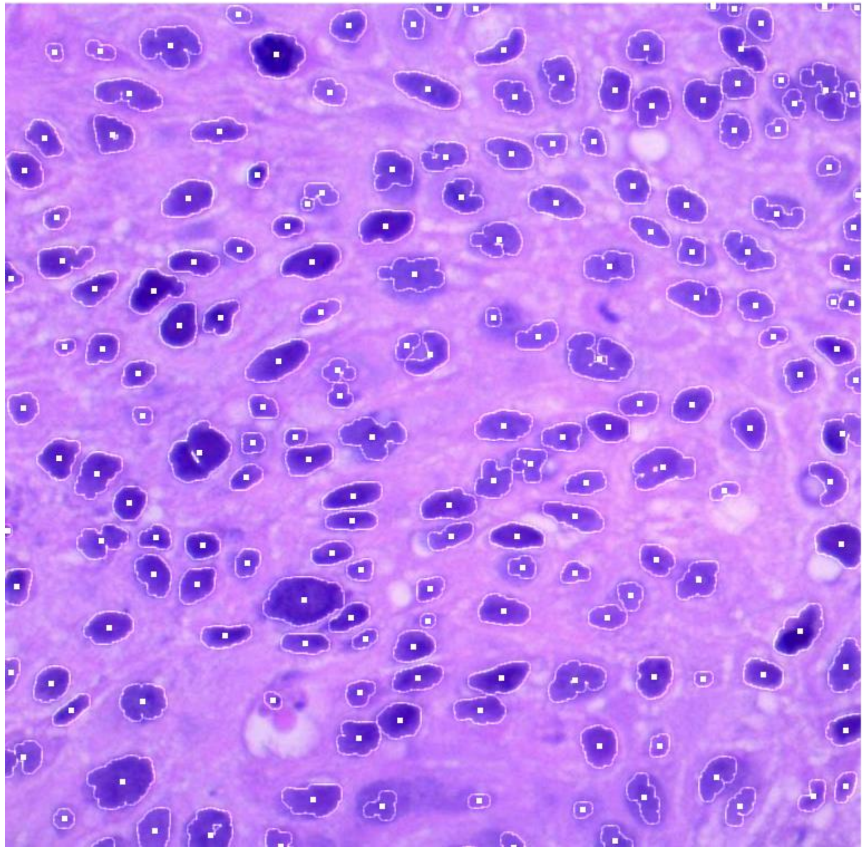
- Develop an efficient solution for both approaches.
- Evaluate the efficiency of each approach and compare results.
- Determine the pros and cons of using higher-level image processing techniques such as deep learning versus using lower-level image processing techniques such as morphological operations, filtering, etc.

Detection and Segmentation with Morphological Operations: Methodology



Flowchart Input and Output

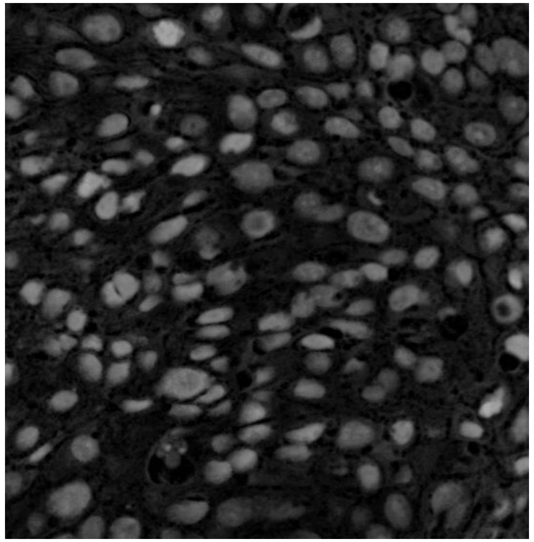




Top/Bottom-Hat Filtering to Enhance Contrast

1. $T_{hat}(f) = f - (f \circ b)$
2. $B_{hat}(f) = (f \text{ closed by } b) - f$
3. $I = f + (T_{hat}(f) - B_{hat}(f))$

1.



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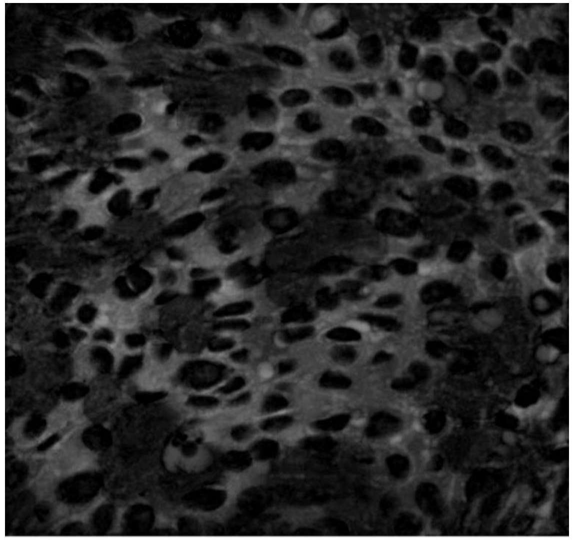

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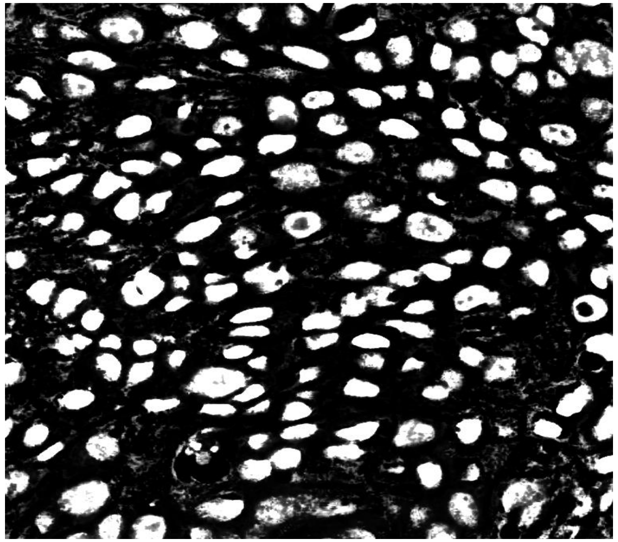
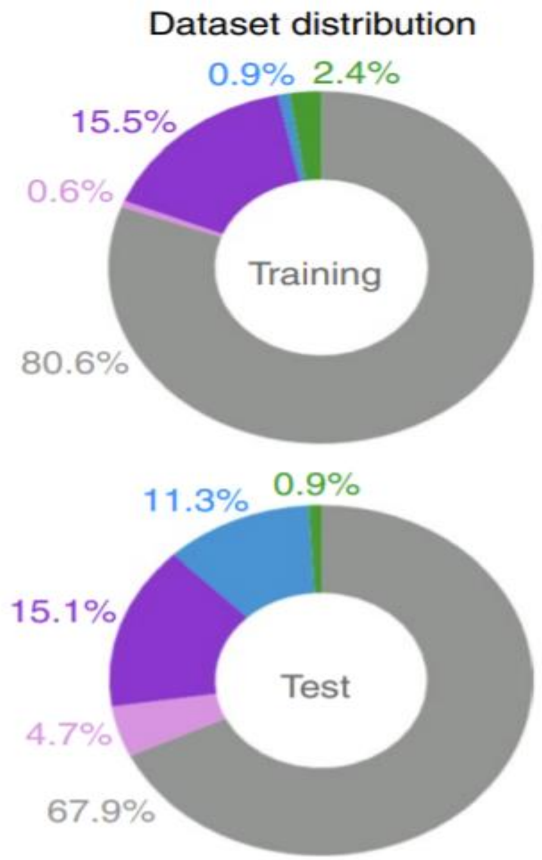


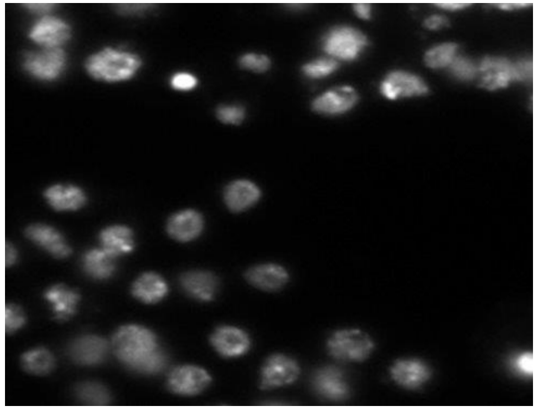
Deep Learning Approach: Methodology

- **Network Used: Mask-RCNN**
  - Performs detection and segmentation.
  - Relatively easy to train and configure.
- **Dataset Used: 2018 Kaggle Data Science Bowl**
  - One of only datasets found with ground truth labelling.
  - 5 stain types (we are only interested in H&E)
- **Training Procedure**
  - 40 Epochs (20 for heads only and 20 for all layers).
  - Use flips, rotations, and gaussian blur for augmentation.
  - Train time: 52 minutes on single RTX6000 GPU
  - $L = L_{class} + L_{bbox} + L_{mask}$

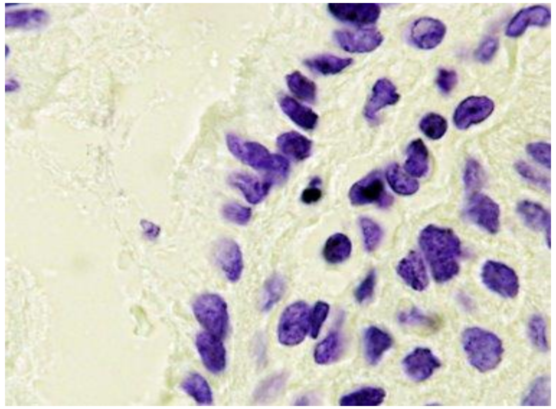


Examples of Different Stain Types in Dataset

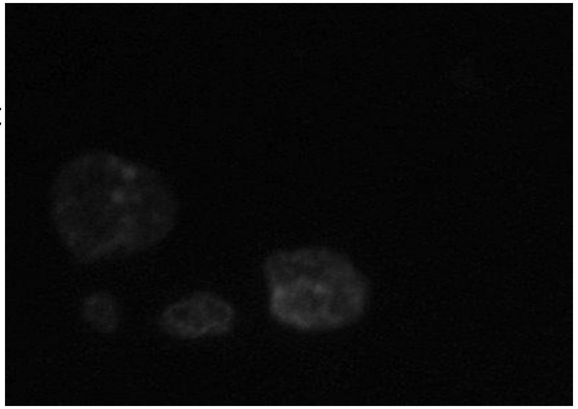
Small Fluorescent



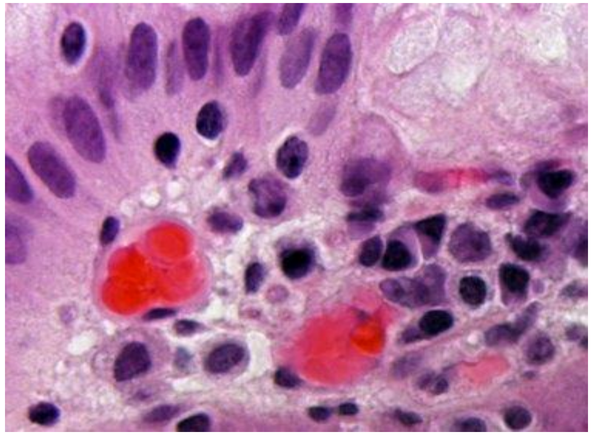
Purple Tissue

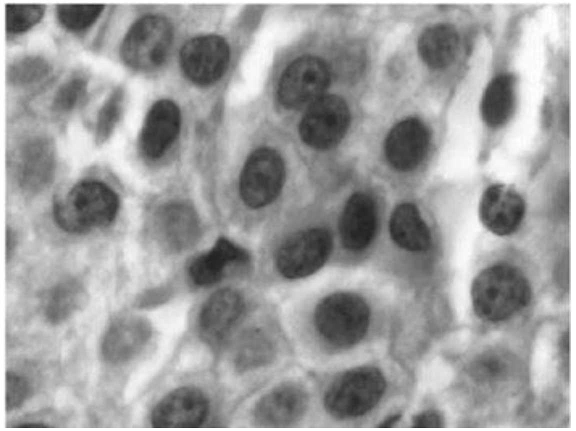


Large Fluorescent



Pink and Purple Tissue

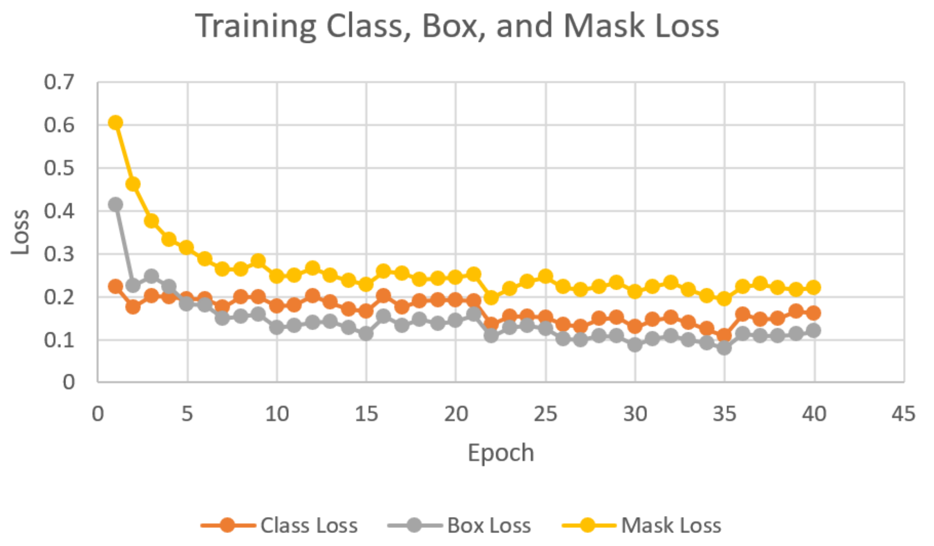


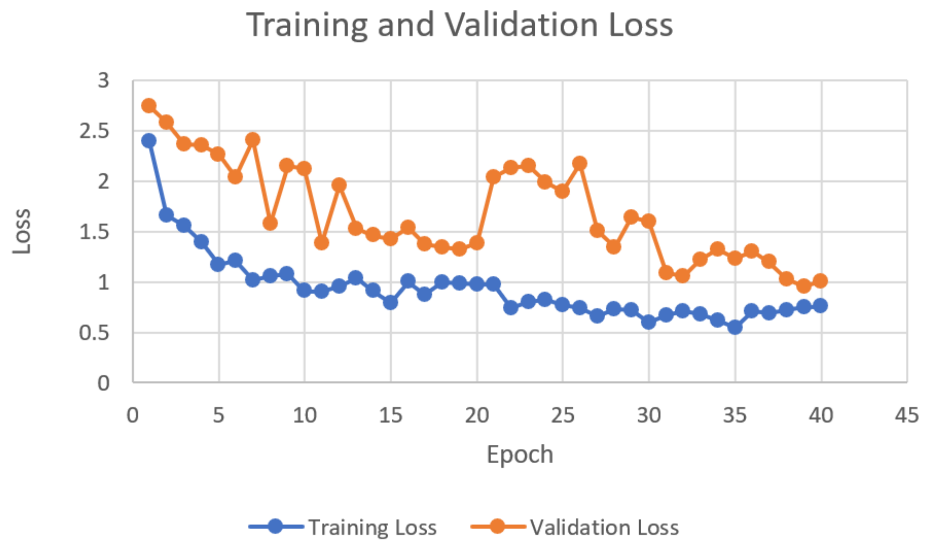


Grayscale Tissue

Training Results

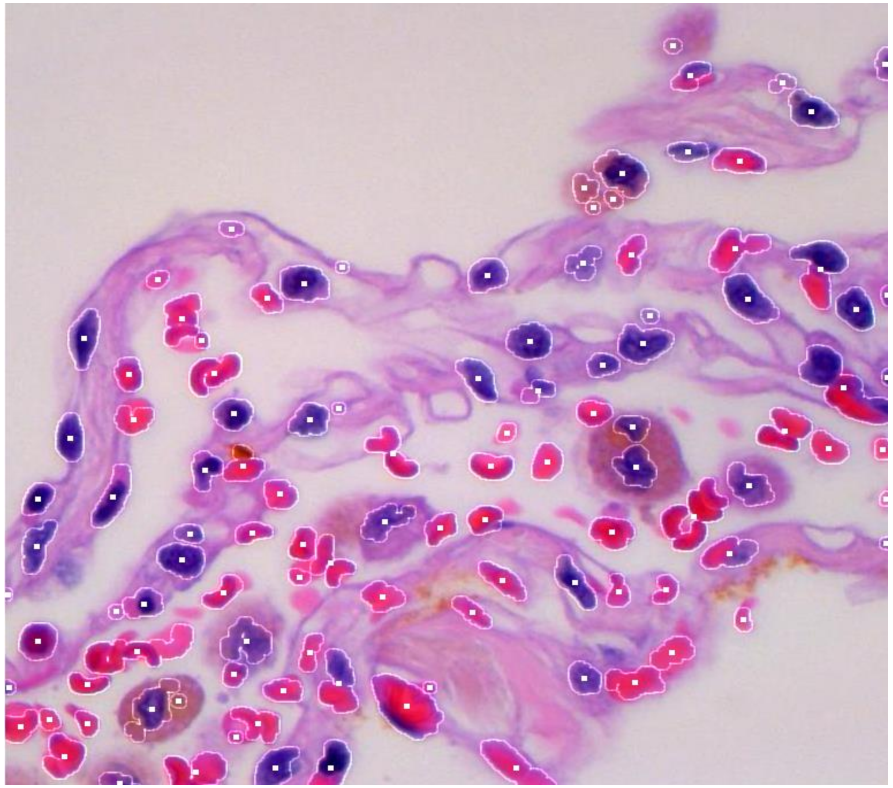
- Minimum Class Loss: 0.1091
- Minimum Bbox Loss: 0.0793
- Minimum Mask Loss: 0.1936
- Minimum Train Loss: 0.5411
- Minimum Val Loss: 0.9500



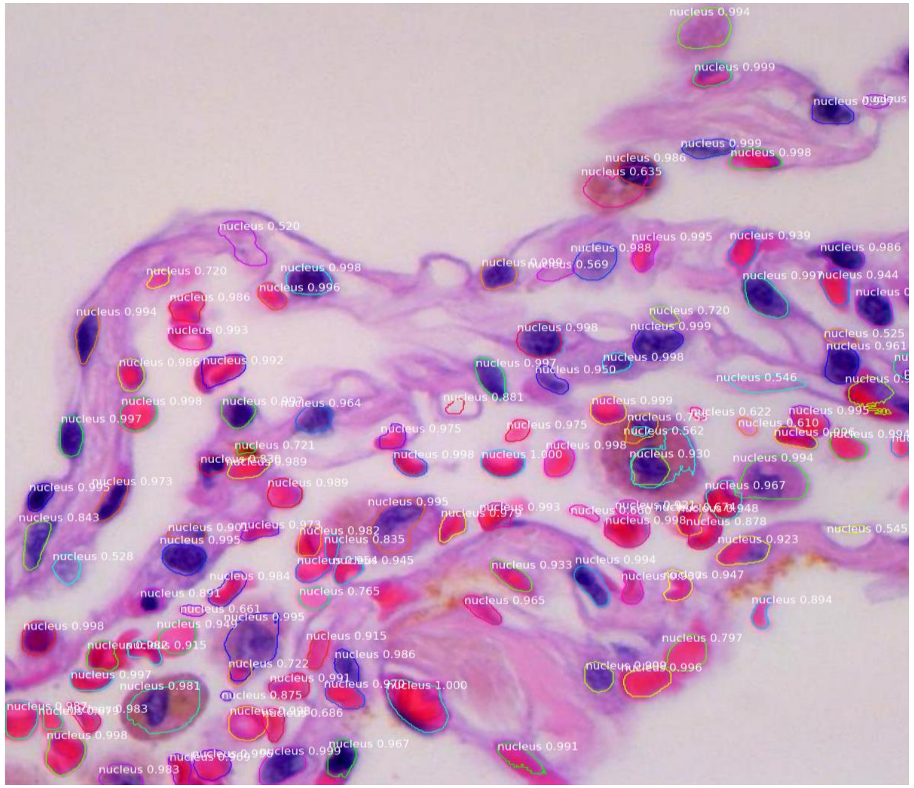


Testing on a Normal Lung Cell Image

MORPHOLOGICAL PROCESSING OUTPUT

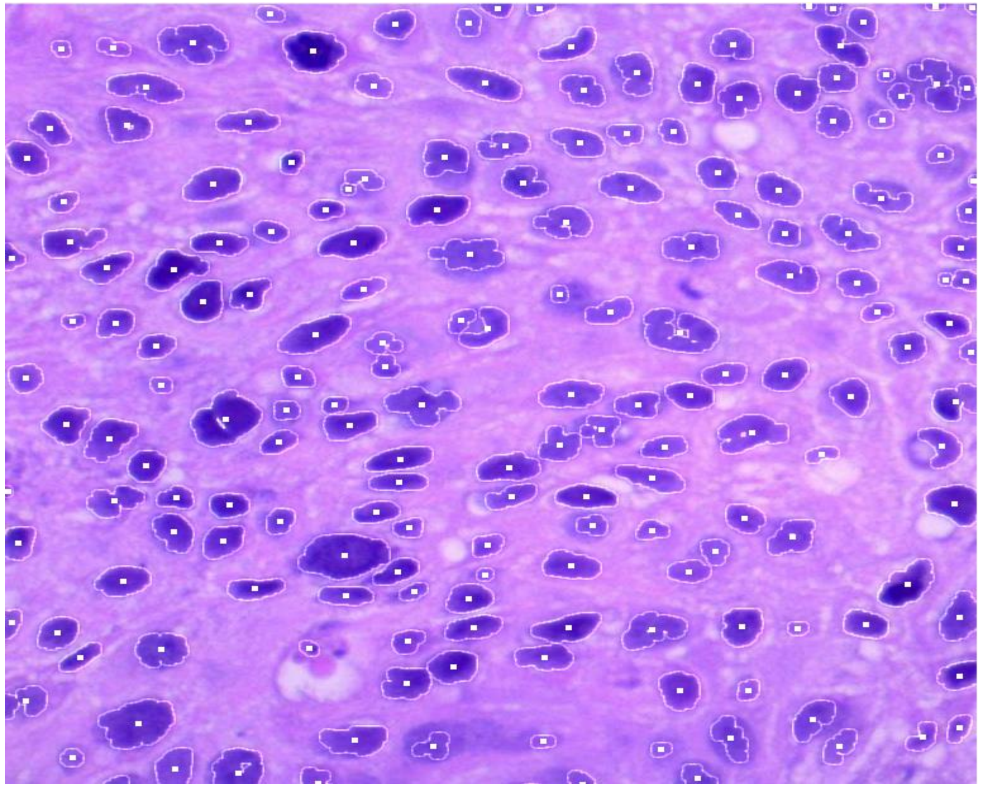


DEEP LEARNING OUTPUT

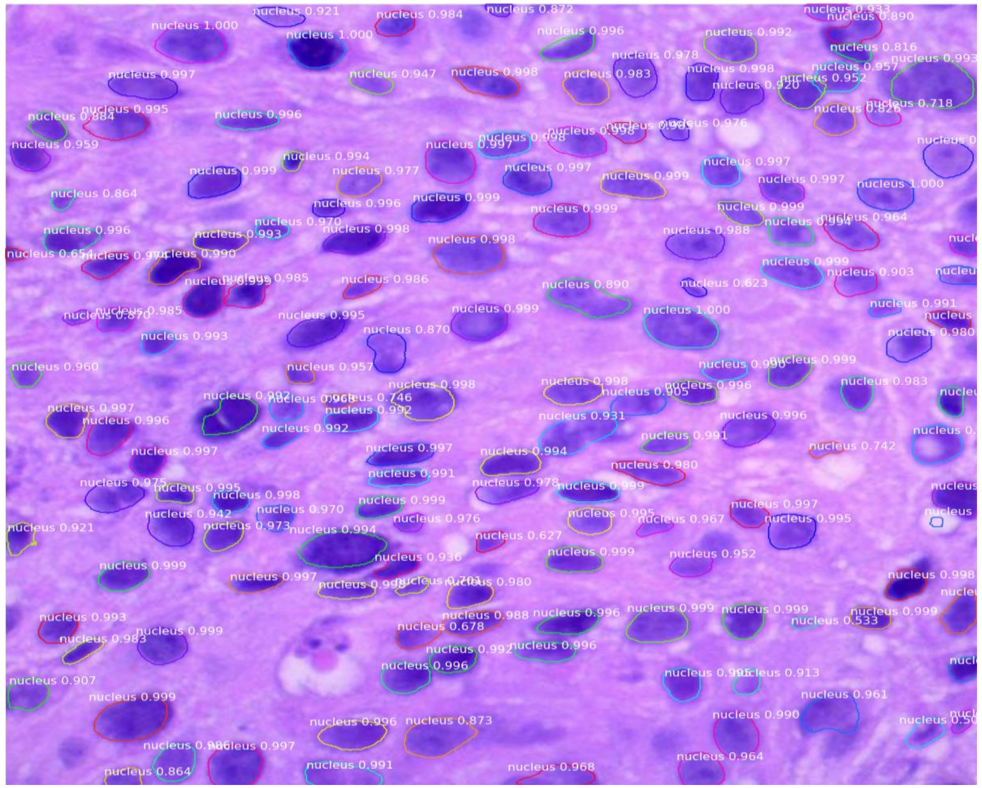


Testing on a Squamous Cell Lung Cancer Image

MORPHOLOGICAL PROCESSING OUTPUT

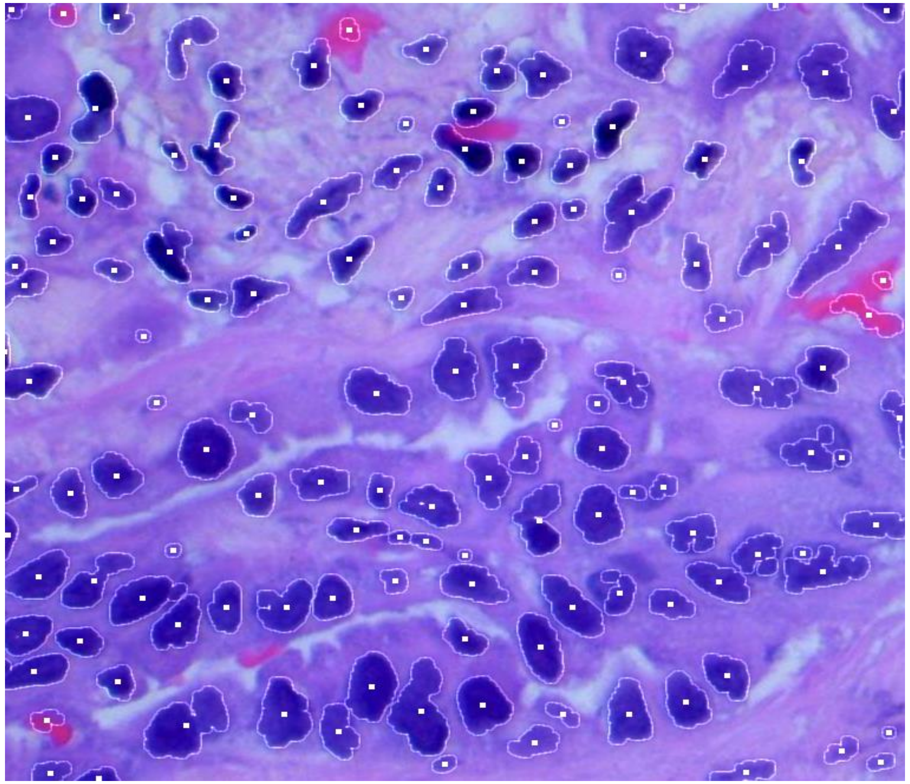


DEEP LEARNING OUTPUT

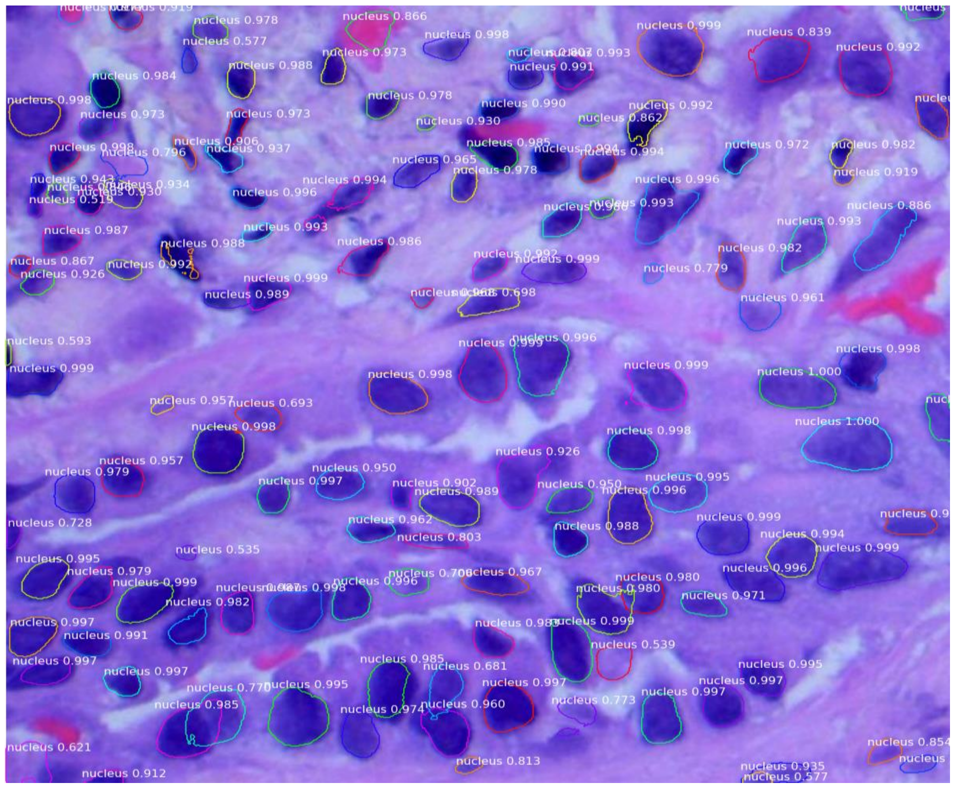


Testing on an Adenocarcinoma Image

MORPHOLOGICAL PROCESSING OUTPUT



DEEP LEARNING OUTPUT



Evaluation Using Squamous Cell Example

MORPHOLOGICAL DETECTION CONFUSION MATRIX

175 true positives	11 false negatives
7 false positives	N/A (No true negative info)

- Accuracy = 90.67%
- Precision = 96.15%
- Recall = 94.09%
- F1 Score = 0.9511

DEEP LEARNING DETECTION CONFUSION MATRIX

160 true positives	25 false negatives
1 false positive	N/A (No true negative info)

- Accuracy = 86.02%
- Precision = 99.38%
- Recall = 86.49%
- F1 Score = 0.9249

Discussion and Comparison of Two Methods

MORPHOLOGICAL PROCESSING

+ Higher accuracy

+ Higher recall

- Lower precision

+ Not affected by shortage of ground truth data

+ Good performance on SCC and normal lung tissue

- Lower performance on Adenocarcinoma tissue

- No bounding box or true masks

+ Generates center (x,y) coordinate

- Segmentation is slightly less accurate

DEEP LEARNING APPROACH

+ Higher precision

- Lower accuracy and recall

- Training is affected by shortage of ground truth data

+ Good performance on Adenocarcinoma and SCC tissue

- Lower performance on normal lung tissue

+ Generates masks and bounding boxes

++ Potential to become much more robust

Questions