Blakley Parker

5/4/21

Project 4

Morphology in the context of image processing is a large set of morphological operations that involves analyzing pixel neighborhoods, usually in the form of shapes. These operations can allow for object classification, a core part of machine learning, and after determining how accurate the crafted model is, one can continue fine tuning it to achieve better results. Furthermore, as the dataset increases, the model will inevitably strengthen as there will be more training images to test from. For this project, the objective was to segment a volume of images and classify the resulting objects, then determine how accurate the training set was compared to the ground truth set.

To begin, the reference image (a grouping of cells) that was supplied seemed to have some type of noise or distortion which if left unchanged would create an inaccurate threshold with numerous misclassifications. To combat this, a self-specified filter is created layering a “disk” convolution with a radius of 3 pixels to the reference image, transforming it into a “blurrier” version of itself. This change allows the next thresholding step to be more accurate.

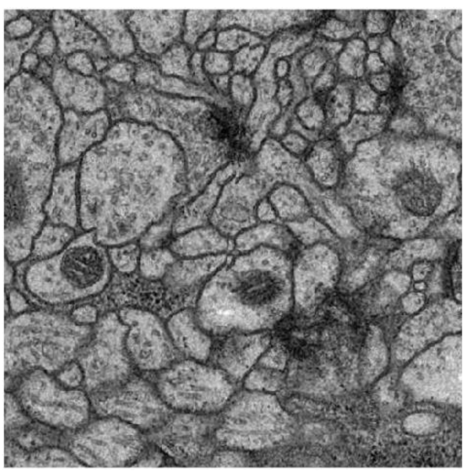

Figure 1: Reference image of a grouping of cells.

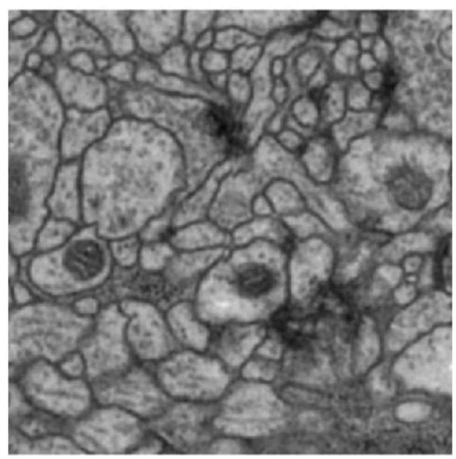

Figure 2: Reference image after 'disk' filter.

After filtering, a threshold can be applied allowing for a better differentiation of background and foreground and getting the image one step closer to the ground-truth. Misclassifications arise if a static threshold is applied, so to make a more accurate model a dynamic threshold is applied with Otsu’s method creating a unique threshold for each reference image in the training set. Then to fill in some of cell detail, aside from the nuclei, a basic *imdilate*() is performed on the newly segmented image with a “disk” structuring element of size 1. This creates an image with less holes and sharpens the image immensely.

The resulting image is as followed, but further morphological operations are required to get the image closer to the ground-truth.

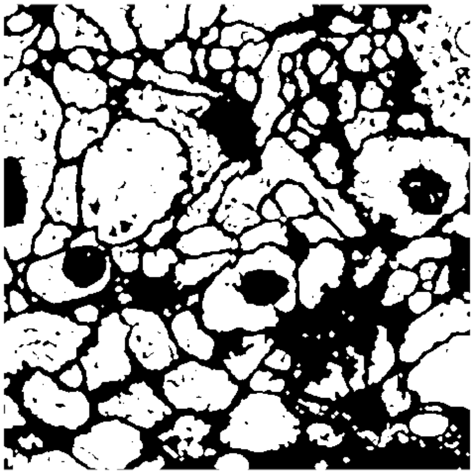

Figure 2: Segmented image using Otsu's method.

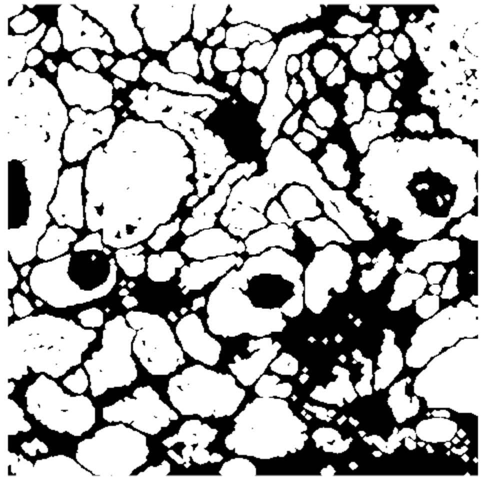

Figure 3: Segmented image after first dilation.

With the success of the first *imdilate(),* a second *imdilate*() with the same structuring element is performed further reducing the number of misclassified holes in the image and additionally sharpening the edges to create a smoother border of the regions of interest from the background. Finally, to clear any remaining holes, the *imfill*() function is called supplying the 'holes' parameter removing pixels surrounded by a contrasting background with pixel connectivity of 4 from the binary image.

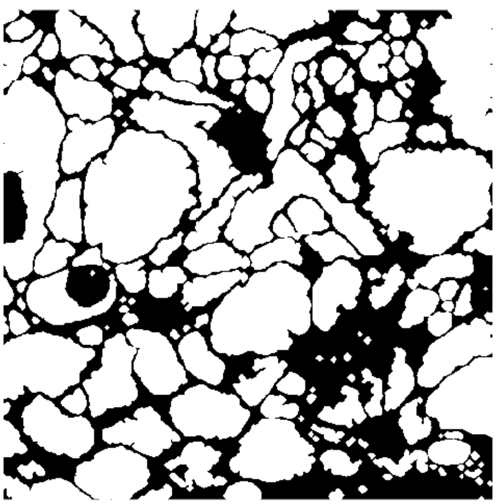

Figure 4: Final segmented image after second dilation and imfill().

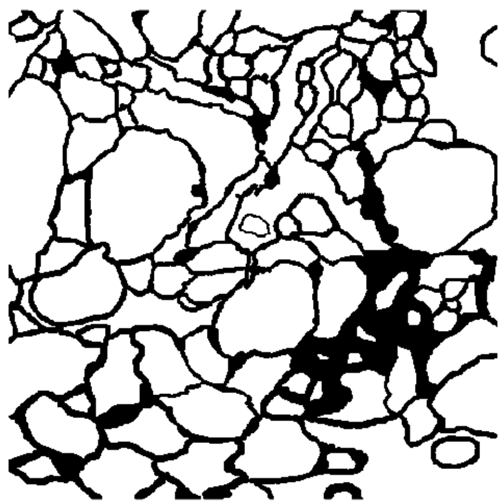

Figure 5: Ground-truth image

To determine the accuracy of the segmented images compared to the ground-truth, a set of calculations are performed to determine the accuracy percentage and the F1 score. To calculate, the total number of true positives, true negatives, false positives, and false negatives are gathered and aggregated inside an accuracy formula which essentially provides the total number of correctly classified pixels over the total number of pixels in the image. Afterwards, the F1 is calculated utilizing the true positives and false positives allowing for a more robust measurement of accuracy. The calculations are as followed.

$$ACC = \frac{TP + TN}{(TP + TN + FP + FN}$$

$$F1 = \frac{2TP}{2TP + FP + FN}$$

The results were satisfactory with a relatively high accuracy and F1 score, but further morphological operation might increase these scores slightly. Storing each of resulting accuracies and F1 scores into individual arrays, two graphs are created for better analysis of the efficacy of the model.

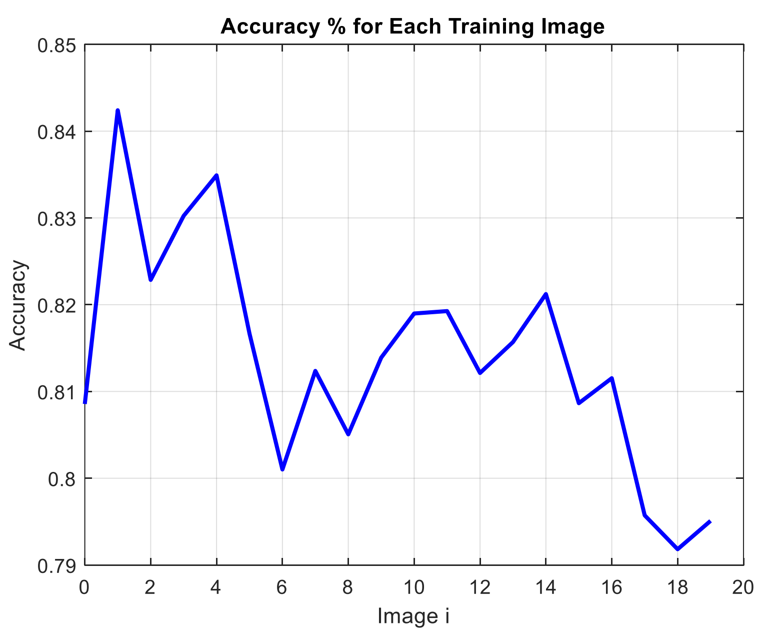

Figure 9: Accuracy percentage comparing each segmented image to its corresponding ground-truth

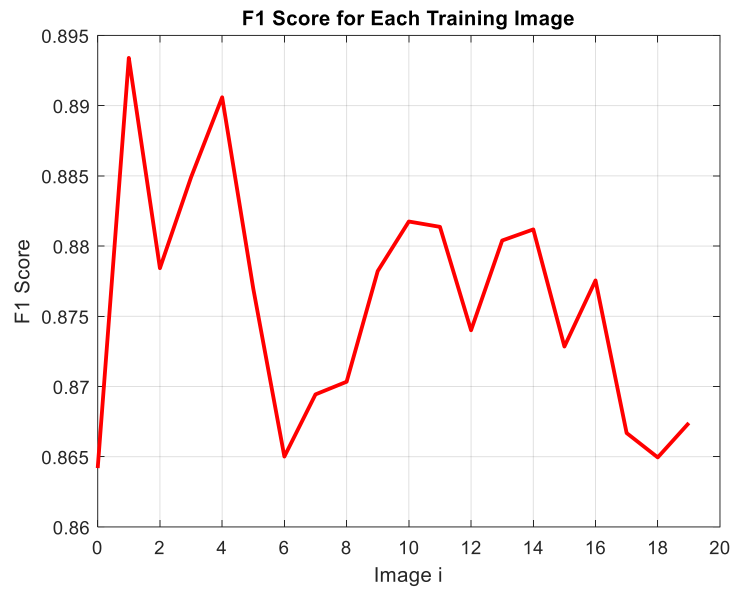

Figure 10: F1 Score comparing each segmented image to its corresponding ground-truth

In conclusion, the model provided a significant increase in accuracy employing techniques ranging from filtering to image dilation and erosion. The highest accuracy score was calculated to be around 84.2% , the lowest around 79.5%, and the F1 score had a maximum of .8925 and a minimum of .865. With the current training volume there could be numerous ways of correctly segmenting the image, but with dynamic thresholding and unique structuring elements this model yielded the highest accuracy and F1 score.