Instrumentation and Processing for Biomedical Applications

Identification of the level of redness of the eye using images of the bulbar conjunctiva.

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This report details the implementation of a method for image segmentation and quality assessment based on the provided code. The method employs a combination of K-means clustering, morphological denoising, contour detection, and region of interest (ROI) analysis to segment and assess the estimated occupancy of the blood vessels in relation to the total eye region analyzed.

Methodology

Image Segmentation

The process begins with image segmentation using K-means clustering. The kmeans_segmentation function takes a Lab image as input and applies K-means clustering to classify pixels into specified clusters. The number of clusters are 2. The resulting labels are then used to determine the center values for each cluster.

Contour Detection and ROI Extraction

Contours are detected on the segmented image, and only those surpassing a predefined area threshold are considered. These contours are approximated using convex hulls, and bounding rectangles are drawn around them using the coordinates_retacgle function. The ROI is cropped based on rectangular region.

Quality Assessment

To estimate the blood vessel occupancy in relation to the total eye region analyzed, the HSV color space is employed. The saturation channel is enhanced using CLAHE (Contrast Limited Adaptive Histogram Equalization), and a binary mask is generated based on saturation levels. The percentage of white pixels in the mask is then calculated, providing a quantitative measure of the blood vessel quality in relation to the total eye region analyzed (ROI).

Performance Evaluation

The performance is evaluated based on the accuracy, confusion matrices, and optimal thresholds obtained from the ROC curve analysis for the measured estimate (percentage of white pixels) compared to the label. The method demonstrates its capability to segment images and estimate blood vessel occupancy, providing valuable insights for automated blood vessel analysis.

Results

For the detection of the Region of Interest (ROI) (Figure 1), the first step involved applying K-means with a value of 2 in the Lab color space. Subsequently, contours were identified using cv2.convexHull. Once the convex area was identified, the coordinates of the convex area were used to find a rectangular area within the convex hull.

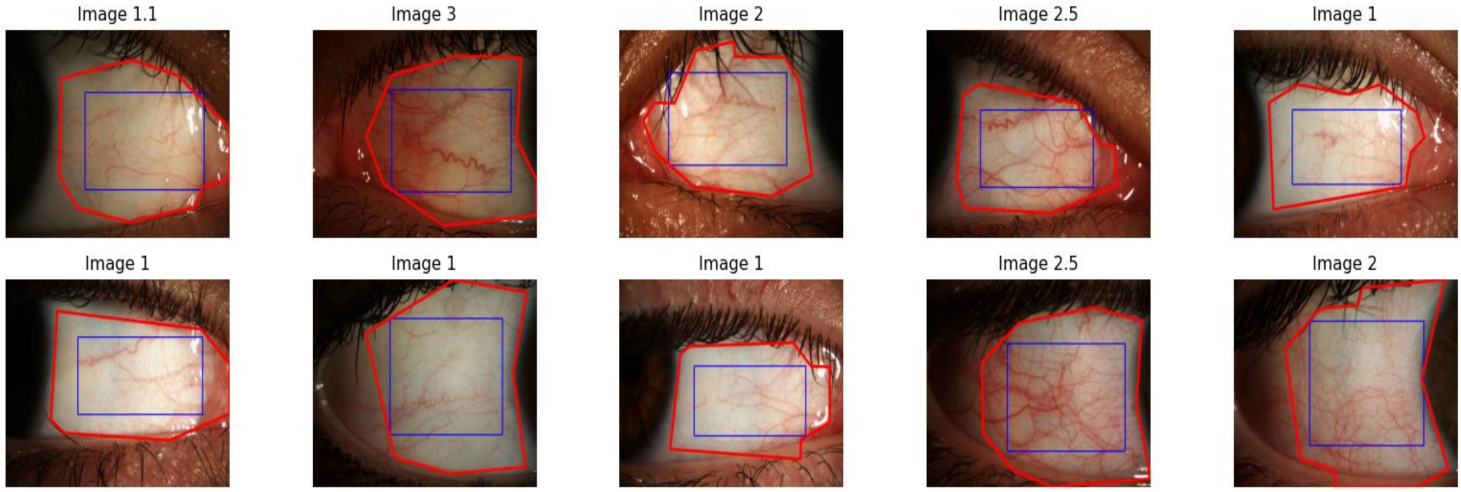

Figure 1- Identification of the Region of Interest (ROI).

In Figure 2, the Region of Interest (ROI) is already visible after being cropped. In the same image, it is apparent that there are still some artifacts, such as parts of the eyelashes and the dark portion of the iris.

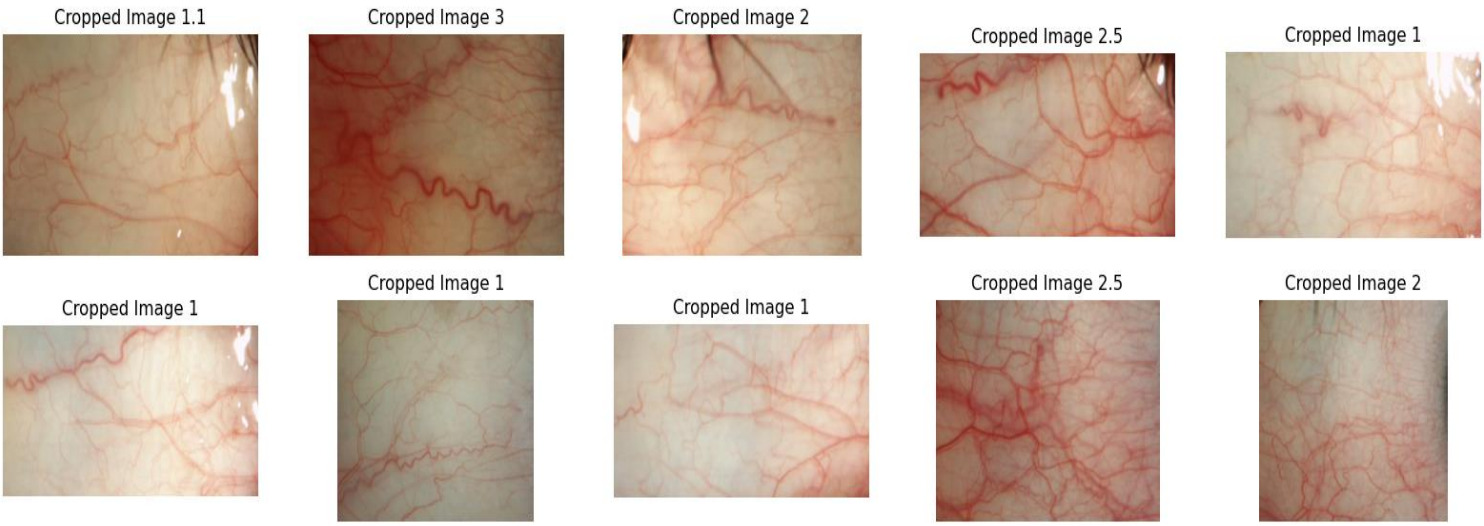

Figure 2- ROI cropped

In Figure 3, the percentage of the estimated occupancy of the blood vessels in relation to the ROI is displayed. The figure shows both the estimated percentage and the label for each image.

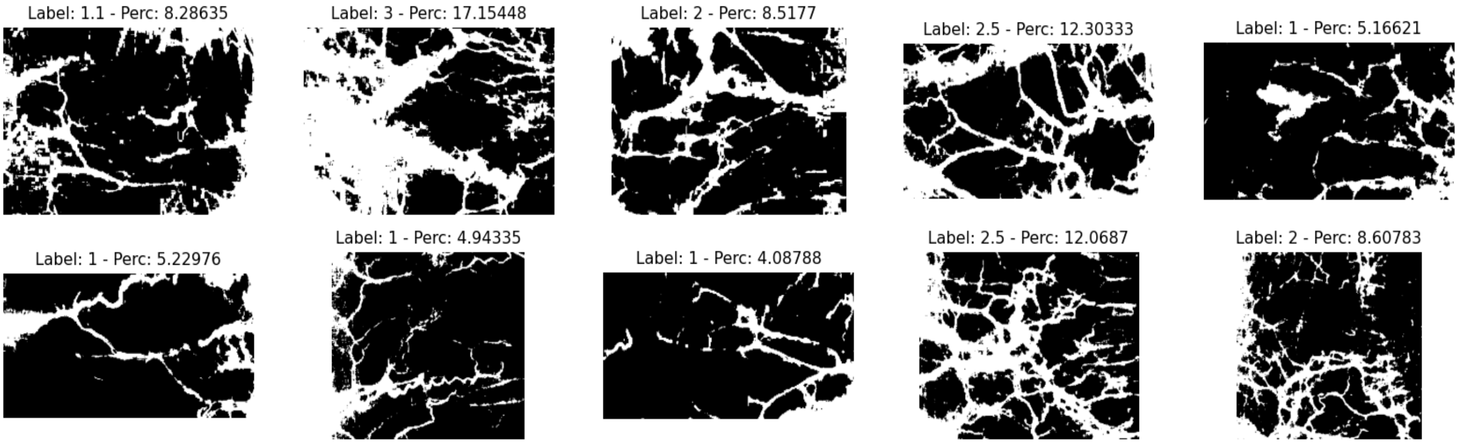

Figure 3- The percentage of the estimated occupancy of the blood vessels in relation to the ROI.

For the classification of the label, we use the following encoding:

```
def assess_level(x):
    if 0 <= x < 1:
        return "Normal"
    elif 1 <= x < 1.5:
        return "Low_level"
    elif 1.5 <= x < 2.5:
        return "Medium_level"
    elif 2.5 <= x <= 3:
        return "High_level"
    else:
        return "Out_of_range"
```

As we can see, there is a certain ordinality in the categories. Therefore, we use the ROC curve to find the optimal threshold between 'Low_level' and 'Medium_level', as well as between 'High_level' and 'Medium_level'.

<u>'Low level' and 'Medium level':</u>

New Label: ['Low_level' 'Medium_level' 'Low_level' 'Low_level' 'Low_level' 'Low_level' 'Medium_level']
Category Label: [0, 1, 0, 0, 0, 0, 1]

New prediction: [8.29 8.52 5.17 5.23 4.94 4.09 8.61]

Specificity: 1.0
Sensitivity: 1.0

Confusion Matrix:
[[5 0]

[0 2]]

Accuracy: 1.0
Threshold: 8.5177

The model effectively discriminates between 'Low_level' and 'Medium_level' categories with perfect accuracy. The confusion matrix and ROC analysis suggest that the chosen threshold (8.5177) optimally separates the two classes, resulting in no false positives or false negatives. The model exhibits high specificity and sensitivity, indicating robust performance.

<u>'High level' and 'Medium level':</u>

New Label: ['High_level' 'Medium_level' 'High_level' 'High_level' 'Medium_level']
Category Label: [1, 0, 1, 1, 0]

New prediction: [17.15 8.52 12.3 12.07 8.61]

Specificity: 1.0
Sensitivity: 1.0

Confusion Matrix:
[[2 0]
 [0 3]]

Accuracy: 1.0
Threshold: 12.0687

Similar to the previous case, the model effectively distinguishes between 'High_level' and 'Medium_level' categories with perfect accuracy. The confusion matrix and ROC analysis indicate that the chosen threshold (12.0687) optimally separates the two classes, resulting in no misclassifications. High specificity and sensitivity further emphasize the reliability of the model in this classification task.

Conclusion

The developed pipeline performs exceptionally well in discriminating between different levels, achieving perfect accuracy in both scenarios. The selected thresholds effectively balance specificity and sensitivity, thereby contributing to the model's robustness and reliability in categorizing 'Low_level,' 'Medium_level,' and 'High_level' instances.

Files Overview:

- **Lab 1.ipynb**
- **Results.pdf**