Non Machine Learning nailfold capillary detection and counting method

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Abstract

The objective of this poster is to present and elucidate the method I proposed and implemented for counting the number of capillaries in images. This method involves several steps, including the detection of the region of interest (ROI), image enhancement, and capillary detection. My aim is to demonstrate the effectiveness of this method and discuss its potential for improving accuracy and efficiency in the identification and counting of capillaries in medical images.

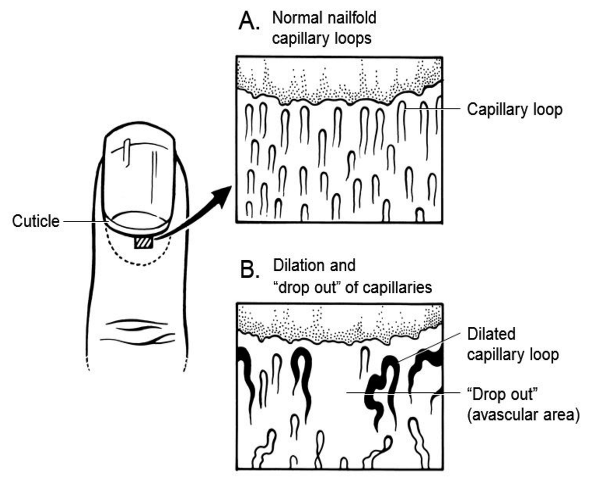

Figure 1. Nailfold capillaroscopy.

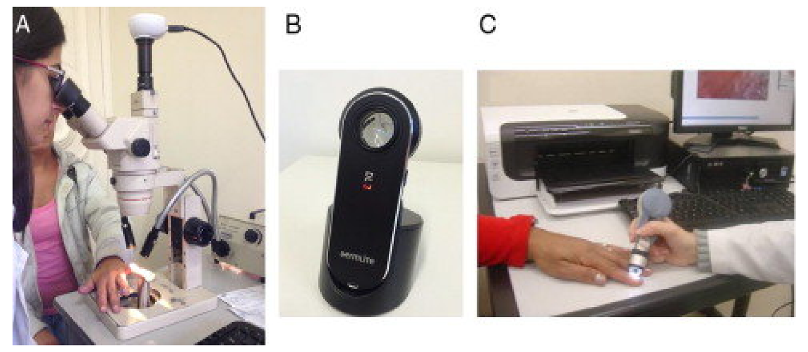

Figure 2. Illustration of the various ways in which capillary images are taken.

Introduction

Nailfold capillaroscopy is a non-invasive technique that allows for the visualization and analysis of capillaries in the nailfold region. It is a cost-effective method due to its simplicity and the fact that it does not require expensive equipment or procedures. Furthermore, it does not cause discomfort or harm to the patient, making it a preferred method for capillary examination.

The dataset I used is composed of 4 classes of individuals: images of the capillaries of 2 persons without disease (N1 and N2) and images of the capillaries of 2 persons with disease (S1 and S2). In total, I have 30 images with different illuminations, rotations, etc. This is why it is so challenging to detect and count each of the capillaries in this dataset.

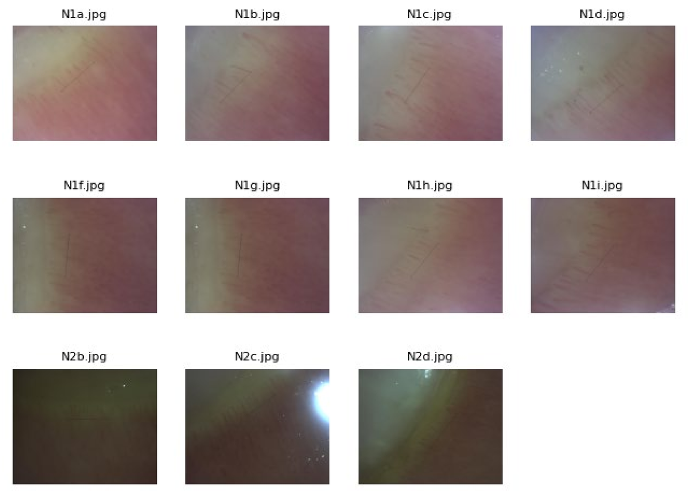

Figure 3. Images of nailfold capillaries of people without disease (with dashes).

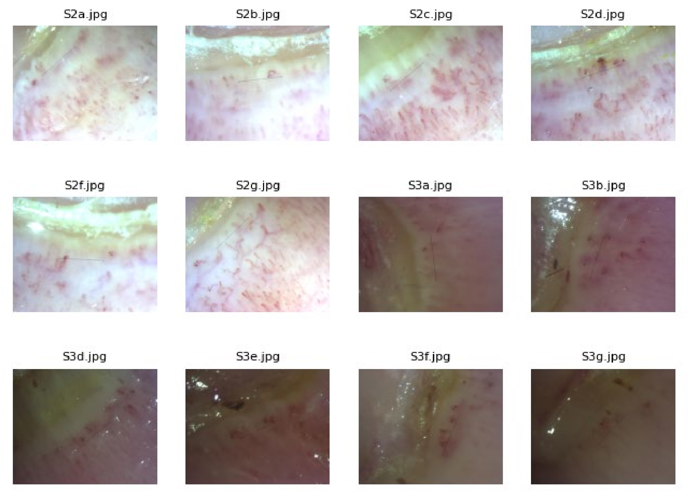

Figure 4. Images of nailfold capillaries of people with disease (with dashes).

Methodology

My method for counting capillaries in images involves preprocessing and processing stages. In the preprocessing stage, I begin with a full-color image and select only the green channel for further processing. I detect the region of interest (ROI) using a combination of Gaussian blur, Canny edge detection, and Hough line transformation. The longest line detected by the Hough transformation is used to rotate the image and extract the ROI.

In the processing stage, the ROI is enhanced to improve capillary visibility using histogram equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE). The parameters for these operations are adjusted based on the image's luminance.
Capillary detection involves morphological operations and thresholding techniques applied to the enhanced image. I identify and analyze contours in the image, classifying a contour as a capillary if it exhibits a tubular shape and is not horizontal. These conditions are determined by fitting an ellipse to the contour and examining the angle of the ellipse's major axis.

I also consider the proximity and orientation of contours. If two contours are close and lie along the same diagonal, they are considered part of the same capillary. This is determined by calculating the slope and distance between the centroids of the two contours. This ensures the algorithm does not overcount capillaries that are close to each other and aligned in the same direction.

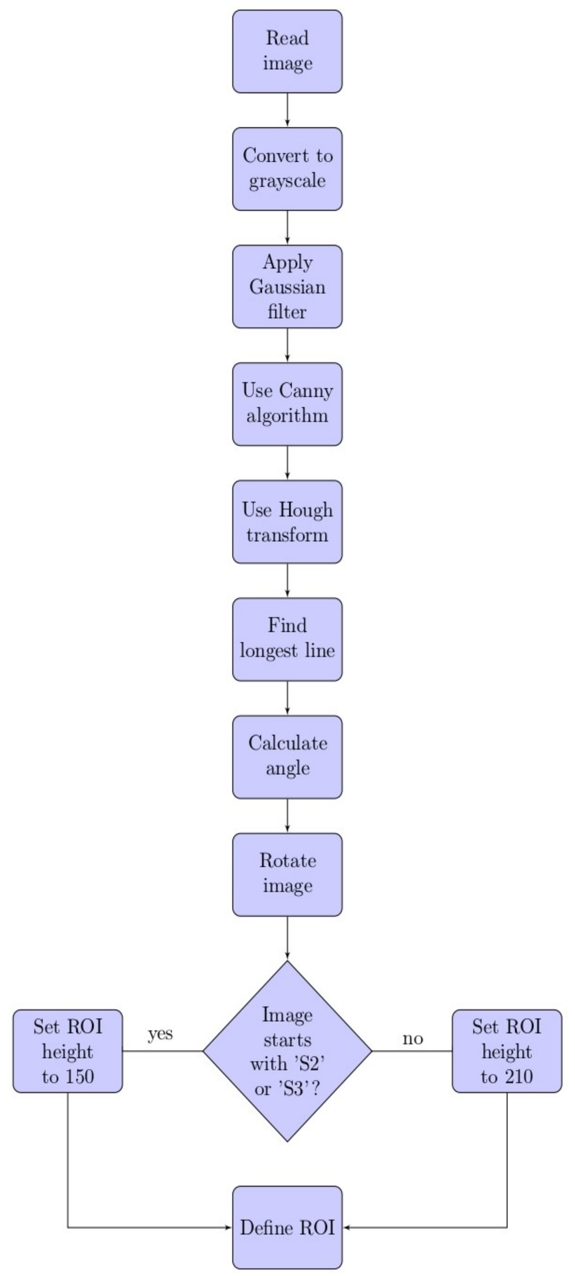

Figure 5. Flowchart for ROI definition.

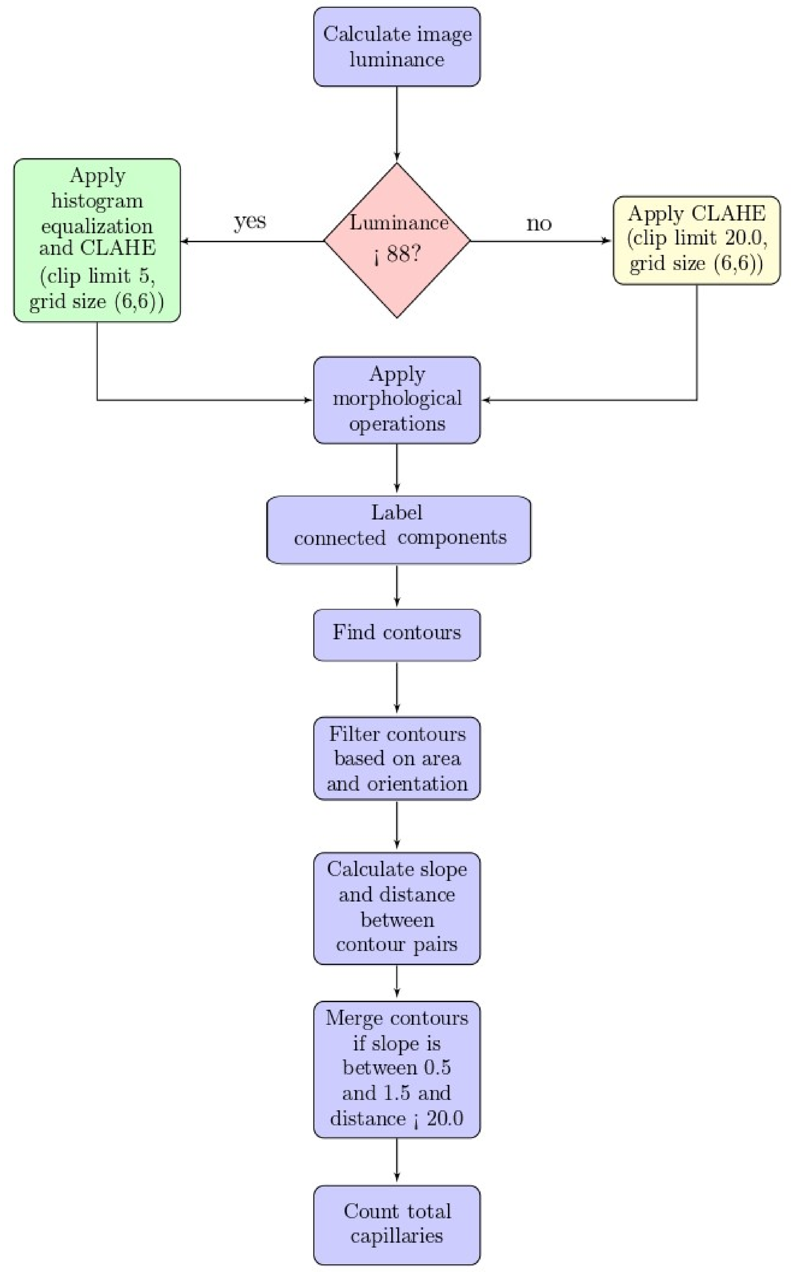

Figure 6. Flowchart for capillary detection and capillary counting.

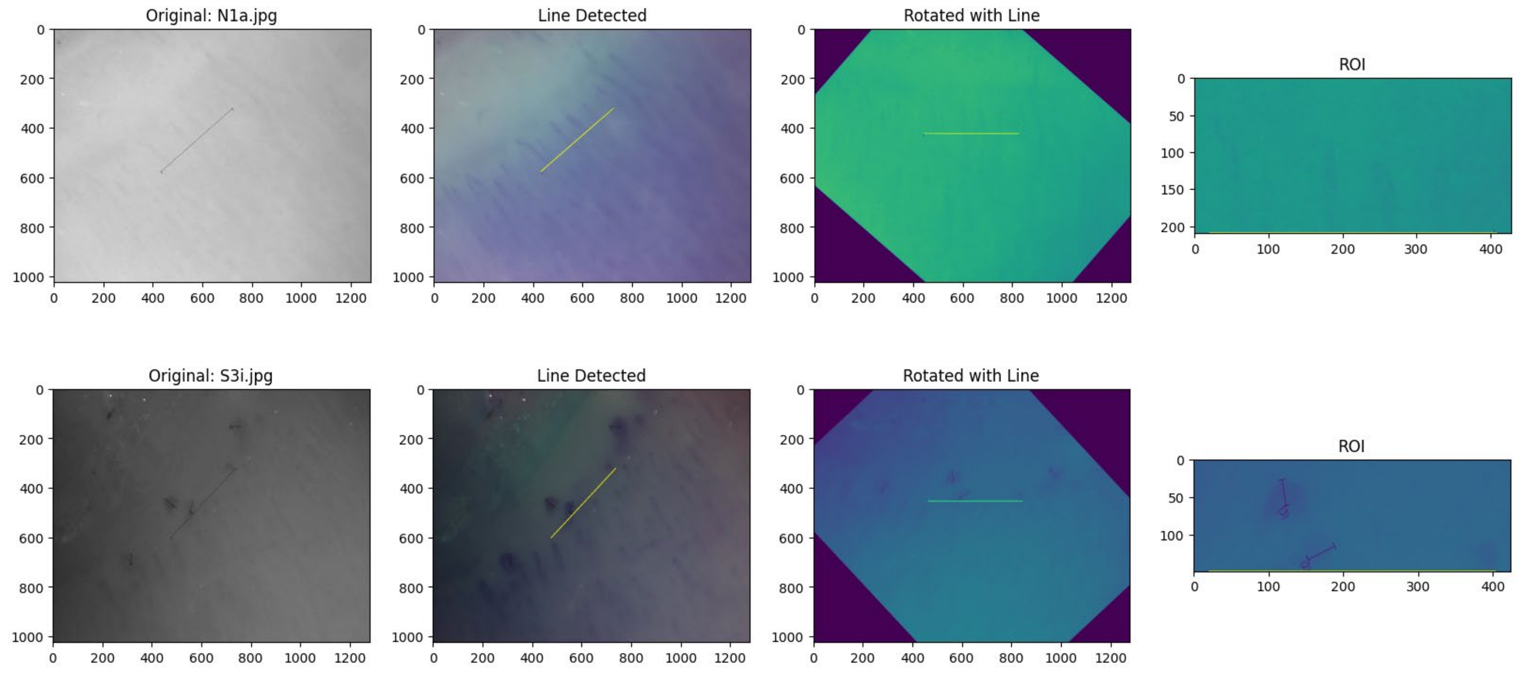

Figure 7. In the upper image you can see the definition of the ROI for the images without disease, so the height is greater than the lower image that has a lower height because this image is of diseased capillaries.

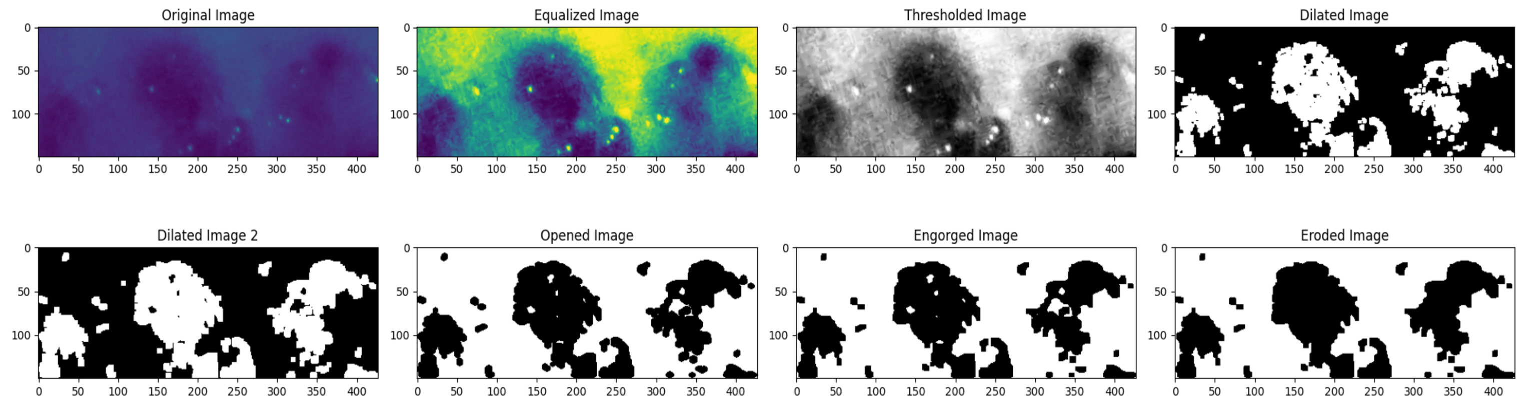

Figure 8. This is an example of image processing with a luminance greater than 88, where you can see the different morphological operations it must go through to finally find the contours of the capillaries.

Results

My capillary counting method showed minor variations in count depending on image luminance, differing by only one or two capillaries. Despite these variations, the method demonstrated excellent capillary segmentation, effectively identifying contours in the images. These results highlight the method's robustness and reliability in medical image analysis.

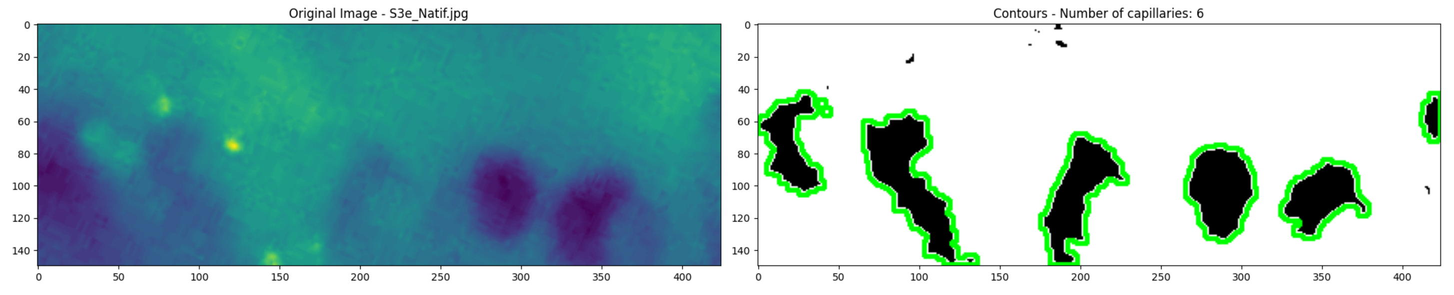

Figure 9. In the image you can see the detection of the capillaries in an image with diseased capillaries and it is possible to count 6, differing from the ground truth in only one, and achieving the correct segmentation of the same.

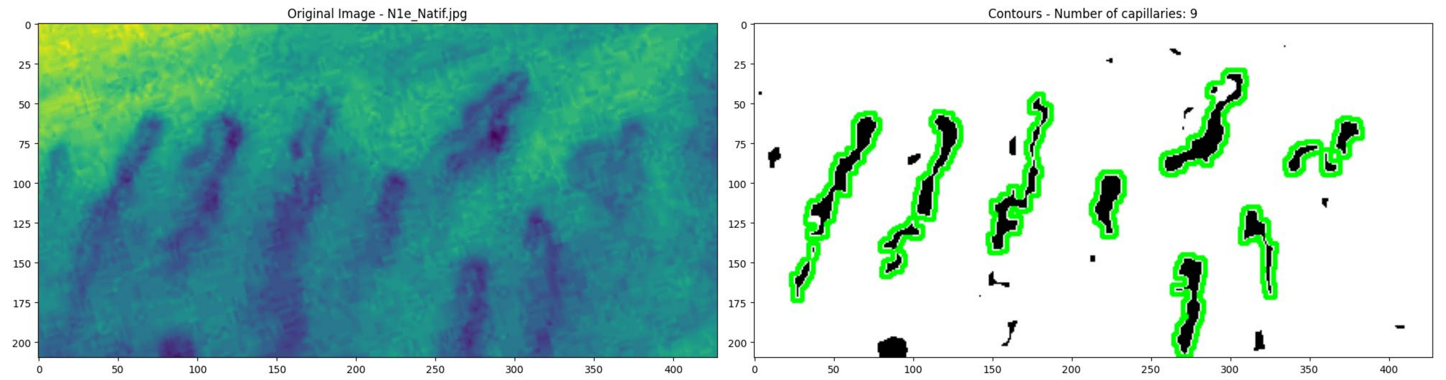

Figure 10. In the image you can see the detection of the capillaries in an image with capillaries without disease and is able to count 8 differing from the ground truth in only one also, and achieving the correct segmentation of the same.

Conclusions

My method for counting capillaries in images has shown to be effective and reliable, with only minor variations in the count depending on the image's luminance. Despite these variations, the method demonstrated excellent capillary segmentation, effectively identifying contours in the images. However, there are some limitations to consider. The method's performance may be affected by the quality of the images, including their illumination and rotation.
For future work, I plan to increase the size and diversity of the dataset, investigate other techniques like deep learning architectures or machine learning, and evaluate the method in real-world clinical settings. This will help to further improve the method's robustness and applicability in medical image analysis.

Image	Number of Capillaries
N1a_Natif.jpg	6 capillaries
N1b_Natif.jpg	6 capillaries
N1c_Natif.jpg	9 capillaries
N1d_Natif.jpg	9 capillaries
N1e_Natif.jpg	9 capillaries
N1f_Natif.jpg	3 capillaries
N1g_Natif.jpg	3 capillaries
N1h_Natif.jpg	7 capillaries
N1i_Natif.jpg	5 capillaries
N1j_Natif.jpg	10 capillaries
N2b_Natif.jpg	10 capillaries
N2c_Natif.jpg	10 capillaries
N2d_Natif.jpg	7 capillaries
S2a_Natif.jpg	9 capillaries
S2b_Natif.jpg	4 capillaries
S2c_Natif.jpg	8 capillaries
S2d_Natif.jpg	6 capillaries
S2e_Natif.jpg	6 capillaries
S2f_Natif.jpg	7 capillaries
S2g_Natif.jpg	6 capillaries
S3a_Natif.jpg	1 capillaries
S3b_Natif.jpg	5 capillaries
S3c_Natif.jpg	8 capillaries
S3d_Natif.jpg	8 capillaries
S3e_Natif.jpg	6 capillaries
S3f_Natif.jpg	3 capillaries
S3g_Natif.jpg	6 capillaries
S3h_Natif.jpg	4 capillaries
S3i_Natif.jpg	5 capillaries
S3j_Natif.jpg	3 capillaries

Figure 11. Result of each of the images with their respective capillary count.

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References

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2.Tutuncu, K., & Buber, M. (Date). Segmentation of Capillaroscopic Images. Selcuk University, Konya/Turkey.
3.Cutolo, M., Trombetta, A. C., Melsens, K., Pizzorni, C., Sulli, A., Ruaro, B., Paolino, S., Deschepper, E., & Vanessa. (Date). Automated Assessment of Absolute Nailfold Capillary Number on Videocapillaroscopic Images: Proof of Principle and Validation in Systemic Sclerosis.