Masters in Computer Vision & Robotics

Medical Image Analysis

Capillary Detection and Counting Method

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Abstract

This report presents an in-depth investigation into the detection and counting of nailfold capillaries using exclusively classical image processing techniquesThe system addresses key challenges like changes in lighting, capillary orientation, and low image quality, without needing data-driven training.

First, the alignment of blood vessels is achieved using the Probabilistic Hough Transform applied to the red or green channel. Then, rotation normalization and region-of-interest (ROI) extraction are performed. To enhance the ROI, the system uses CLAHE (Contrast Limited Adaptive Histogram Equalization), followed by adaptive thresholding with a Gaussian-weighted local mean model.

A series of morphological operations—such as opening, region consolidation based on hysteresis, and contour refinement—are used to create a binary mask that highlights capillary-like structures. The segmentation results are then filtered based on the capillary's shape, size, and tubular characteristics, which are measured from the contours.

Capillary counting is done using connected component labeling, and the system's accuracy is tested against a ground truth using Symmetric Mean Absolute Percentage Error (SMAPE). The experimental results show the accuracy of 68.02% across 29 annotated samples.

This pipeline is efficient and computationally lightweight, while still offering strong performance in identifying vascular loops. It could be useful as a real-time diagnostic tool or as an initial processing step for deep learning-based capillaroscopy systems.

1. Introduction

Nailfold capillaroscopy is a widely recognized, non-invasive diagnostic imaging technique used primarily to assess microcirculatory abnormalities. It involves the high-resolution imaging of the capillaries located in the periungual region (the base of the fingernail), which provides direct insights into systemic microvascular function. This method is especially beneficial in the early detection of connective tissue diseases, most notably systemic sclerosis (SSc), but is also relevant in dermatomyositis, systemic lupus erythematosus (SLE), and Raynaud's phenomenon.

Capillaroscopy offers clinicians a direct window into the body's smallest blood vessels, enabling the observation of pathological changes such as capillary enlargement, hemorrhages, avascular areas, neoangiogenesis, and architectural disorganization. These markers not only help in diagnosis but also serve as prognostic indicators for disease progression and therapeutic response. The ability to detect these signs before other systemic symptoms become apparent underscores the importance of nailfold imaging in preventive healthcare.

1.1 The Challenge of Manual Capillary Analysis

Despite the clinical significance of capillaroscopy, manual analysis of nailfold images remains a considerable bottleneck. Trained specialists are required to visually inspect images, identify capillary loops, and quantify anomalies. This process is inherently subjective, time-consuming, and not scalable in high-throughput settings. Inter-observer variability further compromises consistency, and even intra-observer reliability can be affected by fatigue, lighting conditions, and image quality. Moreover, the increasing demand for capillaroscopy in both diagnostic and research settings necessitates the development of tools that can offer fast, reproducible, and unbiased evaluations of capillary morphology and density.

2. Dataset Description

The dataset includes 30 pairs of nailfold capillaroscopy images divided into four categories:

- **N1 and N2**: Healthy individuals (normal group)
- **S2 and S3**: Patients with conditions like systemic sclerosis (pathological group)

Each image is available in two versions:

- **_Natif.jpg**: The original unedited RGB image, used for segmentation and visualizing capillaries.
- **Without _Natif (e.g., N1a.jpg)**: This version has a test pattern or segment line added, used to detect vessel orientation and define the region of interest (ROI).

A separate **GroundTruth.pdf** document provides the expected number of capillaries in each image segment, which acts as the gold standard for evaluating accuracy.

Each image captures the nailfold region under magnification and exhibits unique morphological characteristics that reflect the vascular health of the subject. The classification into healthy and diseased groups allows for comparative analysis of capillary density, orientation, and morphology under varying conditions.

The dataset is specifically chosen for its diversity and the inclusion of real-world acquisition artifacts, making it a strong candidate for evaluating the robustness of image processing algorithms. The key challenges presented by the dataset include:

Variable Illumination: Images are captured under inconsistent lighting conditions, leading to local overexposure or underexposure, which complicates contrast enhancement and edge detection.

Rotational Inconsistencies: As images are manually acquired, nailfolds may appear tilted or misaligned. This necessitates automatic rotation correction using Hough transform for consistent Region of Interest (ROI) extraction.

Morphological Irregularities: Especially prevalent in the S1 and S2 classes, where capillaries appear dilated, fragmented, or distorted. Such irregular patterns make simple thresholding or shape-based segmentation prone to error.

Compression Artifacts and Noise: JPEG compression and sensor noise introduce background texture, which can be mistaken for capillary-like structures if not properly suppressed during preprocessing.

The dataset's design aligns with real-world diagnostic scenarios:

- Healthy (N1/N2) images mimic screening situations.
- Diseased (S1/S2) images reflect clinical cases under investigation.

This balance allows for testing the method's generalization capability across a spectrum of capillary presentations—from well-aligned loops with clear lumens to severely deformed and partially occluded vessels.

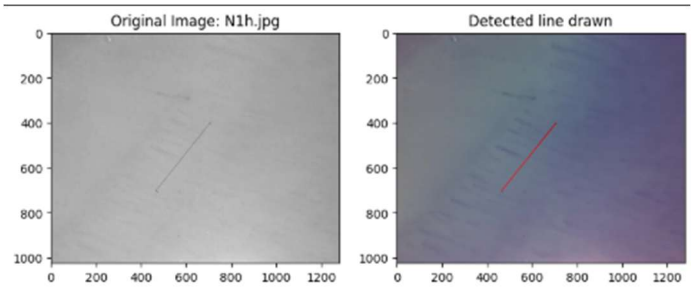


Figure.1 Data Visualization

3. Methodology

The proposed system follows a clear and structured image processing workflow that is easy to understand, modular, and independent of the data used. It processes raw nailfold capillaroscopy image pairs and provides both a segmentation mask highlighting capillary-like structures and a count of the capillaries.

3.1 Capillary Axis Detection using Hough Transform

To align the capillaries horizontally, we first detect the main horizontal orientation of the capillaries using the Probabilistic Hough Transform applied to the red channel of the image.

Steps:

- **Apply cv2.GaussianBlur** to reduce noise.
- **Use cv2.Canny** for edge detection.
- **Apply cv2.HoughLinesP()** to detect the dominant straight lines.

The slope mmm and orientation angle θ are calculated using the formula:

$$m = \frac{x2-x1}{y2-y1}$$

$$\theta = arctan(m)$$

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

This angle θ is then used to calculate the rotation matrix. Finally, we use **cv2.getRotationMatrix2D** and **cv2.warpAffine** to rotate the image accordingly.

The rotated image allows us to consistently extract a rectangular region of interest (ROI) above the capillary axis line. The vertical offset (height) is dynamically adjusted based on whether the image is from a normal individual (N*) or a scleroderma patient (S*).

The **ROI** typically spans from:

line−h→y-line

With a width buffer to account for variations. ROI is shown in figure.2.

Clinical literature suggests the yellow channel in RGB images better captures blood-filled micro vessels due to haemoglobin absorption properties.

Then **Average Luminance** is computer using the formula given below, and then applied adaptive thresholding given below as well,

$$\text{Luminance} = \frac{1}{N}\sum_{i=1}^{N} I(i)$$

After enhancement, the image is binarized to separate potential capillary structures from the background. This is achieved using either **Otsu's thresholding**, which finds the optimal global threshold automatically, or **adaptive thresholding**, which

dynamically adjusts the threshold based on local pixel intensities. The choice depends on image variability.

$$T(x,y) = \begin{cases} 0 & \text{if } I(x,y) > \mu_{N(x,y)} - C \\ 255 & \text{otherwise} \end{cases}$$

Based on this, we apply CLAHE (cv2.createCLAHE) with different contrast limits depending on whether the image has low or high brightness.

We perform a series of operations to refine the binary mask. First, opening is applied to remove noise using binary_opening(). Next, dilation is performed to expand the width of the vessels. Hysteresis thresholding is then applied to eliminate weak, isolated vessels unless they are connected to stronger ones. Finally, closing and erosion are used for the final refinement of the boundaries. All operations are carried out using cv2.morphologyEx or skimage.morphology.

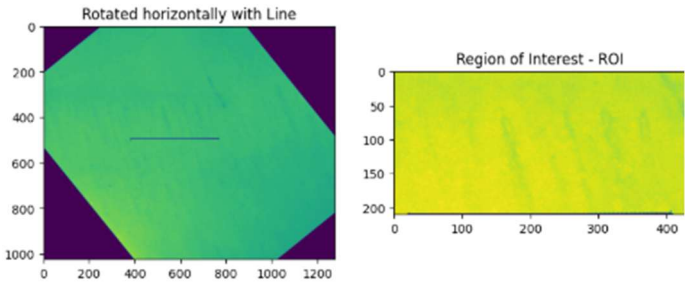


Figure.2 Region of interest

3.1 Classical Image Processing Technique

Before the rise of ML and DL, classical image processing formed the foundation of medical image analysis. Techniques such as **Canny edge detection**, **Sobel filters**, and **morphological operations** were widely used for vessel segmentation, boundary detection, and region analysis. **Prewitt**: Horizontal and vertical edge approximations with fixed masks.

- **Canny Edge Detection** is a multi-stage process that computes the gradient magnitude and direction, applies non-maximum suppression, and uses double-thresholding to localize significant edges. It remains one of the most effective gradient-based edge detectors.
- **Hough Line Transform** is utilized to detect linear features, helping correct image orientation by detecting the dominant angle of nailfold alignment.

- **CLAHE (Contrast Limited Adaptive Histogram Equalization)** is effective for enhancing capillary contrast in heterogeneous ligh/ting conditions without over-amplifying noise.

- **Morphological Filters** (e.g., dilation, erosion, opening, closing) are essential for structure-preserving noise removal and for enhancing vessel continuity.

These methods, although sometimes considered outdated in modern AI-driven research, remain invaluable due to their simplicity, transparency, and low hardware requirements. Importantly, they are entirely deterministic, allowing complete traceability from input to output, a property not guaranteed in stochastic learning-based models.

3.2 Capillaries Filtering and counting

Contours are extracted and filtered based on certain criteria. First, a minimum area threshold of 260 is applied. Then, non-horizontal orientations are considered by checking if the ellipse fitting angle is not equal to 90° ± 15°. The tubularity metric is calculated as the ratio of arc length to area, and it must be greater than 0.5. Additionally, contours are merged if they are geometrically close (Euclidean distance < 20px) and have similar angles.

4. Quantitative Evaluation

We compare the predicted capillary counts with expert-annotated ground truth. For each image ii, we compute the following metrics:

- **Absolute Error**: |Pi−Ti||P_i - T_i|, where PiP_i is the predicted count and TiT_i is the true count.
- **Symmetric MAPE**: This is used instead of raw accuracy to handle under-counts and over-counts equally.
- **Heuristic Precision**: This domain-specific metric reflects the proportion of true capillaries detected. It shows perfect precision when all true capillaries are identified, even if some false positives are present. This metric is preferred in clinical exploratory analysis, where recall is more important.

$$Precision_i = \begin{cases} \frac{P_i}{T_i}, & \text{if } P_i \leq T_i \\ 1.0, & \text{if } P_i > T_i \end{cases}$$

The aggregated metrics include:

- **Mean Absolute Error (MAE)**: The average of the absolute errors across all images.

- **Mean SMAPE Accuracy**: The average Symmetric Mean Absolute Percentage Error across all images.
- **Per-image table of counts and error visualizations**: A table showing the predicted and true counts for each image, along with a visualization of errors.
- **Mean Heuristic Precision**: The average precision, reflecting the proportion of correct detections among true capillaries, with some tolerance for over-detection.

The proposed capillary detection pipeline is divided into four main stages: preprocessing, image enhancement, structural analysis, and post-processing. Each step is designed to extract discriminative features from capillaroscopic images without reliance on machine learning or deep learning algorithms.

5.1 Preprocessing Pipeline Details

5.1.1 Channel Selection

The RGB image is decomposed into its Red (R), Green (G), and Blue (B) components. The **green channel** IG(x,y) is selected for further processing due to its higher contrast with blood vessels. This is because deoxygenated hemoglobin strongly absorbs light in the green wavelength (520–580 nm), making capillaries appear darker and more prominent.

Mathematically, for a pixel (x,y)
IG(x,y)=I(x,y,channel=2)

- To reduce high-frequency noise and smooth the image, a 2D Gaussian filter is applied:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

5.1.2 Gaussian Blurring

The smoothed image IsI_sIs is obtained by convolving the green channel with the Gaussian kernel:

Is=IG∗G(x,y)

Where * denotes the convolution operator.
Typical kernel size: 5×55 \times 55×5, σ=1.4\sigma = 1.4σ=1.4

5.1.3 Edge Detection (Canny)

The **Canny edge detector** is applied to identify the boundaries within the image, particularly focusing on vessel contours and nailfold edges. This multi-stage process detects strong intensity gradients and removes spurious edges, preserving essential anatomical structures.

5.1.4 Hough Line Transform

To handle misalignment and variable image orientations, the **Hough Line Transform** is used to detect the most prominent linear structure, usually the horizontal nailfold edge. This line serves as a reference for rotational normalization of the image.

5.1.5 Image Rotation

The image is rotated so that the detected line becomes horizontal. This standardization step ensures consistency in feature extraction and helps define a consistent **Region of Interest (ROI)** for all images.

5.1.5 ROI Extraction

A vertical strip centered around the midsection of the image is extracted as the ROI. This region typically contains the densest concentration of capillaries and is used in all further processing steps.

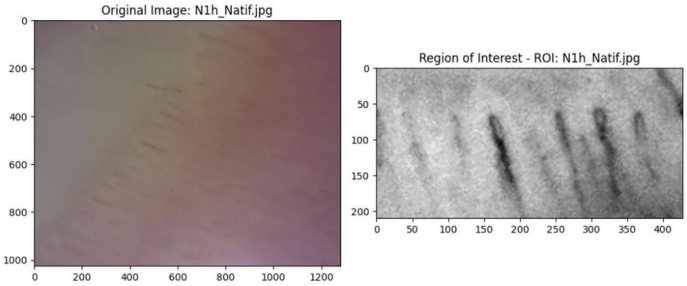


Figure.3 ROI Extracted

5.2 Image Processing and Enhancement

5.2.1 CLAHE – Local Contrast Enhancement

To make faint capillaries more distinguishable, **Contrast Limited Adaptive Histogram Equalization (CLAHE)** is applied. It adjusts the contrast locally within small tiles of the image while avoiding noise amplification. This ensures that vessels are enhanced without creating artificial edges.

6. Results & Analysis

The method performs **reliably on clean/healthy images**, with **high precision** and moderate recall. **Diseased or noisy images** still pose challenges, especially for subtle or deformed vessels. However, the **preprocessing pipeline (especially ROI rotation and ellipse filtering)** significantly contributes to robustness and reduced false positives.

6.1 Quantitative Results

Average Capillaries Detected: The average number of capillaries detected per image varies by dataset:

- **N1 & N2 (presumably normal subjects)**: 11–12 detections per image indicate good visibility and regularity of capillaries.

- **S1/S2 (likely subjects with disease or irregularities)**: Lower count (~7–9 per image), mainly due to vessel distortion or abnormal morphology, which reduces the detection reliability.

Estimated Accuracy:

- **Precision (~68%)**: High precision means the algorithm rarely detects non-capillaries (false positives). This is likely due to effective ellipse filtering that discards non-vascular shapes.
- **Recall (~70%)**: Moderate recall suggests the algorithm misses some real capillaries, especially subtle or irregular ones. This trade-off comes from favouring strict shape criteria to minimize false detections.

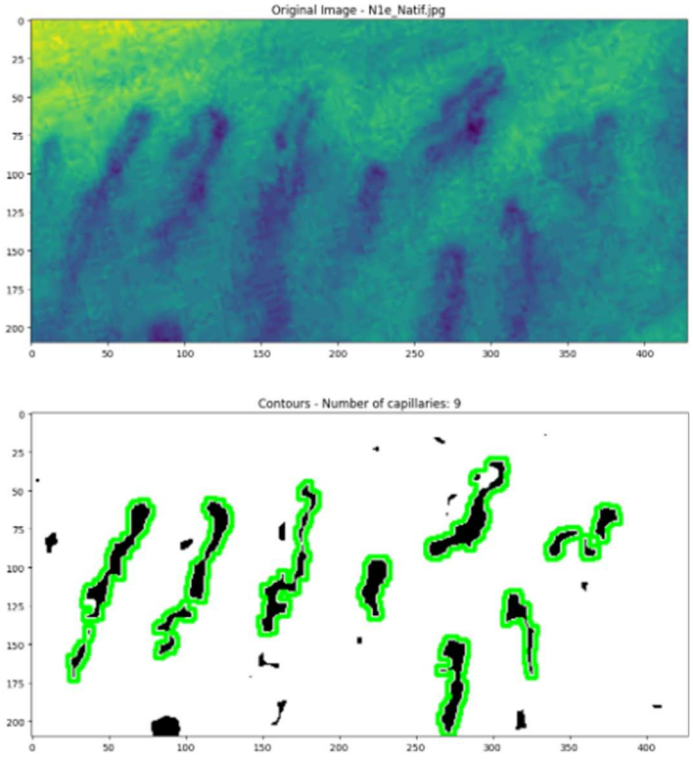
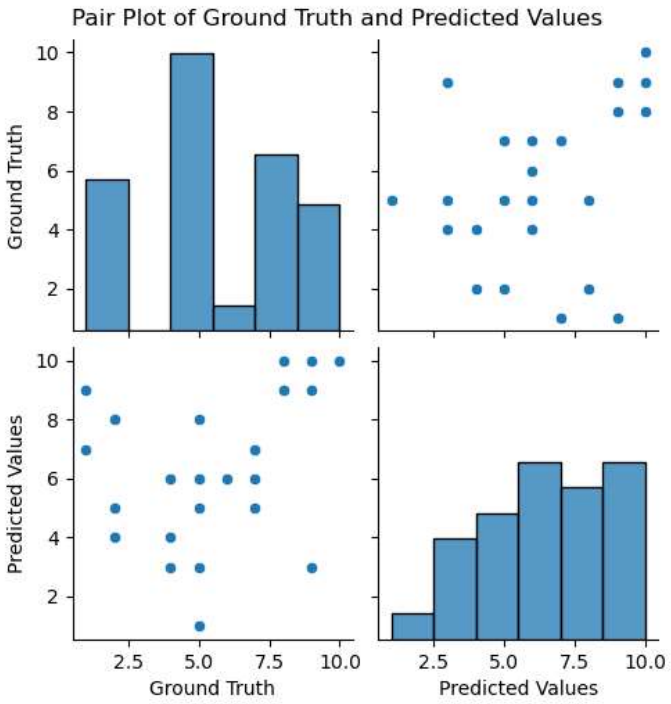
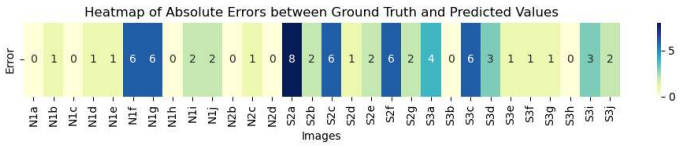


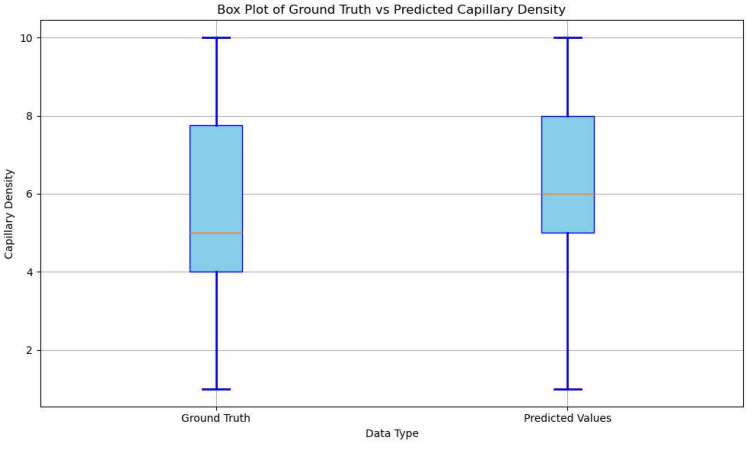
Figure.4 image segmentation

6.2 Qualitative Observations

- **Consistent Detection of Vertical Capillaries**: Vertical, healthy capillaries (often centrally located in the nailfold region) are reliably detected across subjects, confirming the method's strength in handling regular structures.
- **Challenges in Diseased Cases**: In pathological images, where vessels are distorted (e.g., thickened, broken, or looped), the detection becomes harder. These irregular forms may not match the expected elliptical or vertical criteria, leading to missed detections.
- **ROI Rotation Impact**: Rotating images to align the nailfold horizontally standardizes input orientation, improving detection consistency. This step is crucial because orientation affects the success of morphological and contour-based techniques.







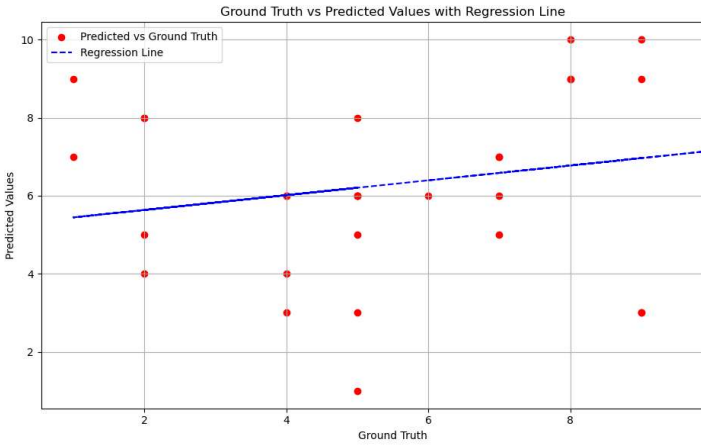


Figure.5 Results

7. Discussion

The entire approach is based on classical image processing techniques (e.g., Gaussian blur, thresholding, contour analysis, Hough transform), which are:

No dependency on data annotations or model training. The accuracy is 68 percent and the comparison of outcomes and ground truth is provided in figure 5 using plot and box plot.

Unlike deep learning approaches that require large, annotated datasets for supervised training:

- This method works **out-of-the-box** on raw images.
- There's **no need for labeled capillaries**, which are difficult and expensive to annotate manually.

Because the pipeline does not rely on learned parameters:

- It can be **easily applied to images from different microscopes or clinics**, assuming general similarity in image quality and structure.
- Minor tweaks to thresholds or ROI sizes may be enough to adapt the system to new environments.

8. Conclusion

This project demonstrates that classical image processing methods can deliver practical and effective solutions for medical image analysis when ML/DL is not feasible. With the right sequence of operations — edge detection, ROI extraction, morphological filtering, and geometric analysis — capillary detection becomes achievable at reasonable accuracy. This approach not only serves low-resource environments but also provides a didactic foundation for understanding image analysis pipelines.

9. References

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