Nail Capillaries Segmentation and Counting

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Introduction

The analysis of nail capillaries provides valuable insights into systemic diseases related to heart and rheumatoid arthritis. Nailfold capillaroscopy is a non-invasive method used to examine microcirculation. The introduction highlights the need for efficient and accurate techniques for segmenting and counting capillaries, as manual methods are time-consuming and prone to errors. The proposed methodology in this project involves marker detection, region denoising, using the U2Net [1] model for segmentation, and post-processing for capillary counting. The use of deep learning, specifically the U-Net architecture, has shown promising results in medical image segmentation.

Methodology

1. **Image region acquisition:** Marker detection and alignment of the patch region through thresholding and contour detection, followed by the transformation of the cropped patch using a rotation matrix.
2. **Dataset preparation:**Preparation of training images through labeling and generating segmentation masks.
3. **Dataset prepossessing:** Dataset preparation for training the segmentation model by noise removal and image augmentation.
4. **Training segmentation model and Inference:** Denoise the cropped and aligned image region then train the U2Net model and prepare the inference pipeline to segment capillaries.
5. **Post Processing:** Post-process the segmented region using morphological operations to remove noisy pixels.
6. **Counting number of capillaries:** After removing noisy pixels, the number of capillaries is detected using contour detection, considering only those contours whose area is larger than the threshold.

System Achitecture

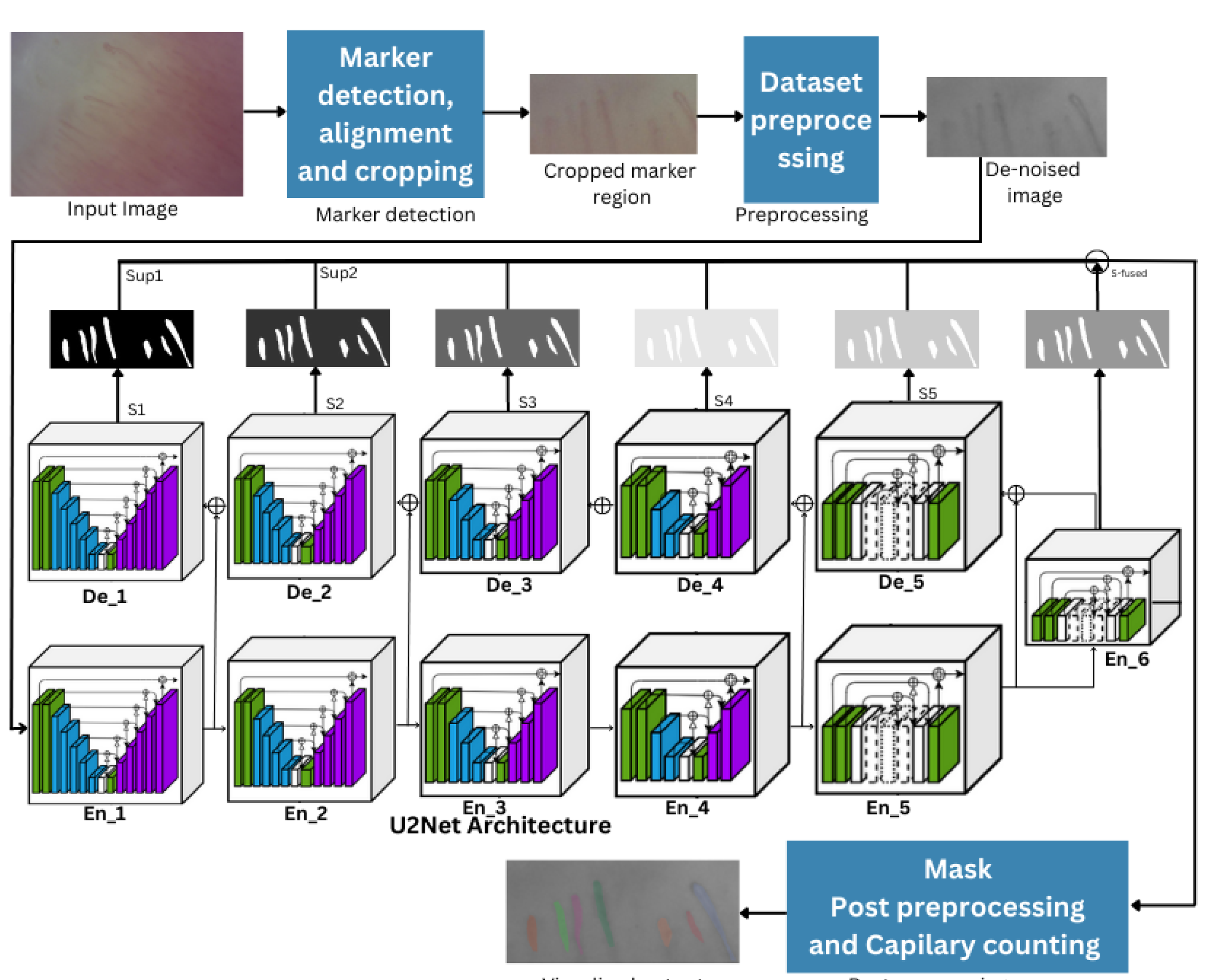

Figure 1. System architecture of the Nail Capillaries Segmentation and Counting

Data proprocessing

1. **Marker Detection and region Cropping**. We begin by detecting markers in a reference image and using them to crop the desired region. To ensure accurate alignment, we rotate the line defined by the markers.
2. **Image Denoising Techniques:**. To improve the quality of the cropped image, we apply image denoising techniques. Gaussian blur and median filtering are utilized to reduce noise and enhance the clarity of the capillary structures..

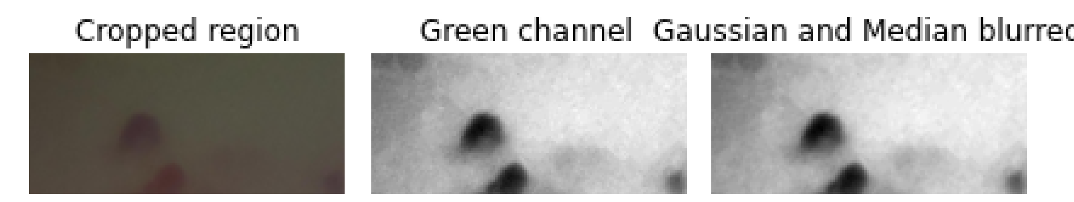

Figure 2. Result after post-processing

Training segmentation model

1. **Dataset preparation:** Training image and ground truth(mask label) was prepared manually by using [2] labelme tool.
2. **Data augmentation:**. Salt and pepper noise, additive Gaussian noise, and sharpening is used to agument training samples.

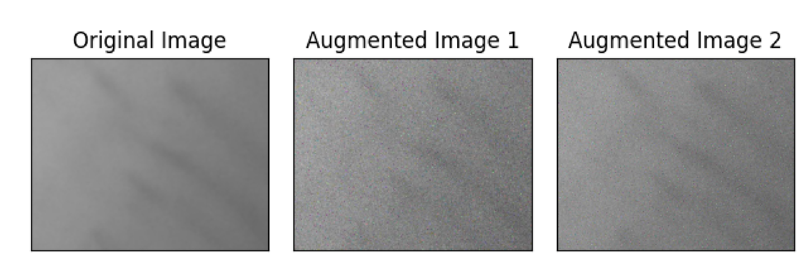

Figure 3. Data augmentation

3. **Training:** COCO pretrained model was fine tuned upto 10000 iterations with training and target loss of 0.31 & 0.015 on Google Colab T4 with batch size 4. Random flip and crop techniques were applied as data augmentation methods to enhance the training process.

Inference and post-processing

Denoised image is passed to trained U2Net model to generate semantic map of capillaries. Input size of the model is 320×320

Figure 4. Semantic map generated by segmentation model

Morphological operation is performed on a semantic map generated by a segmentation model. The erosion function is utilized with a 5x5 matrix called a kernel, which serves as a structuring element for morphological operations. Only contours having area > 100 are considered after finding contours.

Figure 5. Result after post-processing

Results and Discussion

Table compares the ground truth values with the predicted values. Out of the 35 samples of capillary images, the predictions were accurate for 29 images. These results demonstrate a significant improvement in accuracy compared to conventional image processing techniques used for segmenting objects in a noisy background.

Normal Images	G.T	Predicted	Clinical Images	G.T	Predicted
N1a	6	5	S2a	1	1
N1b	7	7	S2b	2	2
N1c	9	9	S2c	2	2
N1d	8	8	S2d	5	5
N1e	8	8	S2e	4	3
N1f	9	8	S2f	1	1
N1g	9	8	S2g	4	4
N1h	7	7	S3a	5	5
N1i	7	7	S3b	5	4
N1j	8	8	S3c	2	2
N2a	11		S3d	5	4
N2b	10	10	S3e	5	5
N2c	9	9	S3f	4	4
N2d		6	S3g	5	5
			S3h	4	4
			S3i	2	2
			S3j	5	5

Table 1. Comparison between ground-truth and predicted of normal and clinical images

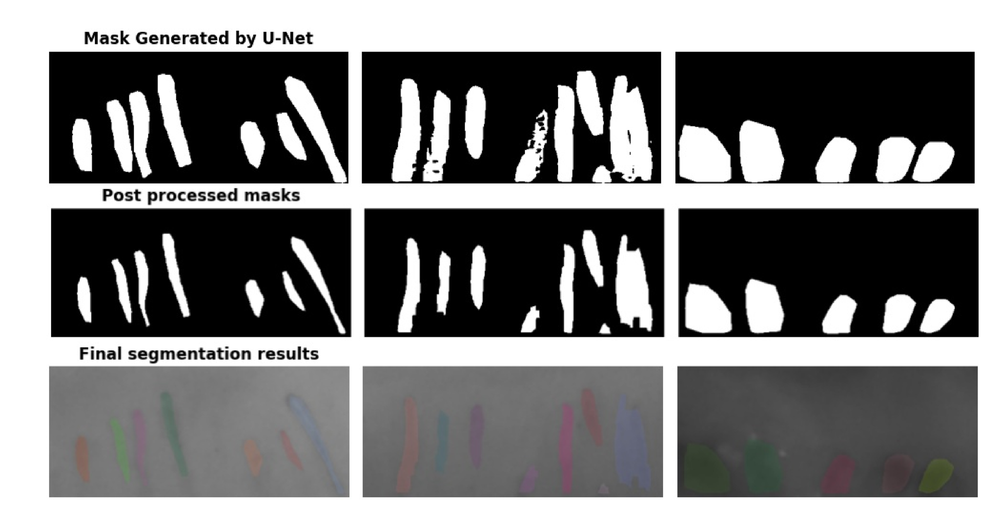

Figure 6. Segemantation and Count results

Conclusion

In this project, a comprehensive approach has been presented for the segmentation and counting of nail capillaries. Through data preprocessing, data augmentation techniques, a robust deep learning architecture, and post-processing, the proposed algorithm can classify nail capillaries with an 86 % classification accuracy. This result indicates the algorithm's potential for aiding medical diagnostics in nail capillary analysis.

References

[1] Xuebin Qin, Zichen Zhang, Chenyang Huang, Masood Dehghan, Osmar Zaiane, and Martin Jagersand. U2-net: Going deeper with nested u-structure for salient object detection. volume 106, page 107404, 2020.

[2] Bryan C Russell, Antonio Torralba, Kevin P Murphy, and William T Freeman. Labelme: a database and web-based tool for image annotation. *International journal of computer vision*, 77(1):157–173, 2008.