Detecting Venous Disorders via Near-Infrared Imaging

Observation of Varicose Vein Development

Huseyin A. Erdem
Department of Computer Engineering, The Graduate School of Natural and Applied Sciences
Dokuz Eylul University
İzmir, Turkey
e-mail: huseyinaerdem@gmail.com

Semih Utku
Department of Computer Engineering, Faculty of Engineering
Dokuz Eylul University
İzmir, Turkey
e-mail: semih@cs.deu.edu.tr

***Abstract*—In this study, a method by which progression stages of venous disorders can be detected using the near-infrared vein images is proposed. For this purpose, the superficial vein surveillance system, which was developed within the scope of the ongoing doctoral thesis, was re-trained to find the telangiectasia and varicose vein patterns in the images. The trainings were carried out using the You Only Look Once version 3 (YOLOv3) object detection algorithm. Confidence values of 0.90 and above were achieved in object detection experiments performed with artificial telangiectasia and varicose vein patterns. According to the test results, the developed system can detect Chronic Venous Disorder patterns with Accuracy Rate (1), Misclassification Rate (0), Precision (1), Prevalence (0.5) and F-Score (1) values. With this system, the patient and physician will be informed about the development of venous disorders at an early stage and a pre-diagnosis data will be created for the physician.**

Keywords - vein imaging; near-infrared light; telangiectasia; varicose; YOLOv3.

I. INTRODUCTION

Medical imaging devices are one of the primary auxiliary methods used in hospitals to diagnose different diseases. The devices used in this context work on the basis of visualizing the area to be viewed with light or sound waves. Imaging with light is carried out by utilizing different wavelengths in the electromagnetic spectrum. Medical imaging devices currently in use are classified according to the body tissue they can monitor and the effects of the light used to illuminate the area of interest on the body. While the X-Ray device, which emits harmful rays (ionizing radiation) to the body, is dominantly used in the imaging of bone tissue and abdominal diseases, Computed Tomography is used for imaging both bone tissue and internal organs [1]-[3]. In addition, Magnetic Resonance Imaging provides imaging of tissues with magnetic waves, whereas Ultrasound uses high-frequency sound waves for imaging [1][2].

Although technology advances at a dizzying pace, many lives are still lost due to late detection of diseases that can be easily cured if detected earlier. Despite the efforts to increase the awareness of early diagnosis for all kinds of diseases, modern people do not abandon the habit of going to the doctor after the disease occurs and often neglect routine controls. In these omissions, the concern of triggering other diseases by imaging devices working with harmful rays to the body during controls has a large share. However, currently developing technology techniques give a chance to produce harmless alternatives to detect some diseases early. Among them, varicose disease, which is one of the vascular diseases and caused by the enlargement of the veins close to the skin surface (i.e., superficial veins), can be counted.

Computed Tomography or Magnetic Resonance Imaging techniques can be used for vein imaging [2]. However, both the negative effects of these devices on human health and their high costs limit their use to hospital environments only. In addition, although the ultrasound device, which provides visualization of blood flow [1][2], is harmless to the body, it has a high cost and can generally be used and interpreted by radiologists in hospitals. Near-infrared light, which is a type of light that is harmless to the body, is used in hospitals within the scope of superficial vein imaging, especially during vascular access procedures.

The main advantage of near-infrared light in the scope of vein imaging is that photons of this type of light can be absorbed by hemoglobin molecules in the vein [4]-[6]. In this way, the veins in the tissue area illuminated with near-infrared light of a certain wavelength (in the studies carried out in [5]-[7], a wavelength of 850 nm was used, which usually gives optimum results) can be viewed with a camera having the same wavelength filter. In this way, the visualization of the superficial veins can be easily performed with only the light source and the camera (even an ordinary camera can be turned into a simple near-infrared camera by changing the filter on it). By applying digital image processing filters on the obtained near-infrared image, some improvements can be made on the image. In this way, the edges of the veins can be sharpened, only the relevant vein patterns can be revealed by eliminating the surrounding tissues or the noise in the image can be removed. Processed near-infrared vascular images can be used for many different purposes from disease pre-diagnosis to biometric recognition [8]-[11]. For these purposes, deep learning techniques (such as classification or object detection/recognition) are applied on images.

The system, which was prepared within the scope of the ongoing doctoral study (near-infrared images of the right and left forearms were used) and which enables the superficial veins (in the near-infrared images) to be visualized as an e-health application in the home environment, was retrained in this study to monitor the vein enlargement. In this study, the vein enlargement patterns in the images are detected by the object detection algorithm. In addition, two artificial datasets (representing vein enlargements) to be used in training and testing of the YOLOv3 object detection algorithm [12] were created.

In Section 2, venous disorder stages are introduced and the re-trained YOLOv3 algorithm is explained so that the system can detect vein enlargement. How the datasets were created and the results obtained as a result of the trials are also stated in this section. In the last section, the study is discussed in general terms.

II. Vein Enlargement Detection: YOLOv3 Algorithm

Near-infrared imaging system is basically examined in two parts as hardware and software. While the hardware part is about the wavelength of the light source, Light Emitting Diode (LED) placements and camera features, the software part covers the extraction of vein patterns by making the veins in the obtained near-infrared images more prominent via digital image processing techniques. In this way, superficial veins can be visualized. The hardware part and digital image processing steps of this ongoing doctoral study were introduced in [10]. Also, the presentation of narrowing detections in processed images (using the YOLOv3 algorithm with a single class as stenosis_vein) to patients and physicians as a video-based indirect augmented reality environment was explained in [11]. In this study, the visualization of enlargements in superficial vein images is discussed.

When the valves of the superficial veins do not work properly, blood accumulations occur, and as a result, the veins expand and elongate, and form twisted folds, resulting in varicose veins [13][14]. Although varicose veins are most commonly observed in leg veins (which are under more pressure than other veins [13]), varicose veins can be encountered in every part of the body [15]. In general, however, the development of vascular disease in hand veins does not give results as dramatic as in leg veins. Chronic Venous Disorders (CVDs) affecting millions of people worldwide are caused by morphological and functional abnormalities of the venous system [16][17]. Risk factors, such as heredity (family history, height), lifestyle (long term standing/sitting, occupation, smoking), gain (age, pregnancy, obesity, deep vein thrombosis) or hormones (female gender, progesterone) can lead to venous disorders, such as vein enlargement [18][19]. CVD clinical stages are defined by the CEAP (Clinical, Etiological, Anatomical and Pathophysiological [16]) classification system: C0 (no visible signs of venous disease), C1 (visible veins, telangiectasia/spider veins), C2 (varicose veins), C3 (swelling/edema), C4 (changes to skin quality), C5 (healed ulceration), C6 (active ulceration) [17][20]. CVD is often overlooked in its early stages [16]. In case of early diagnosis, advanced symptoms, such as edema, skin changes or leg ulcers can be alleviated with the support of lifestyle changes [17][19]. The incidence of vascular disorders in adults in urban and rural Bonn area is 59% for telangiectasia vein and 14% for varicose vein, respectively [17].

As most superficial veins, varicose veins are also not easily visible to the naked eye, so near-infrared light is used to visualize these veins [21]. In this study, the hand vein dataset obtained with the superficial vein surveillance system developed within the scope of the ongoing doctoral study was used for the trials of the YOLOv3 algorithm, which was re-trained to detect CVD in the C1 (telangiectasia/spider veins) and C2 (varicose veins) stages. An example image from the dataset and its processed version are given in Fig. 1.

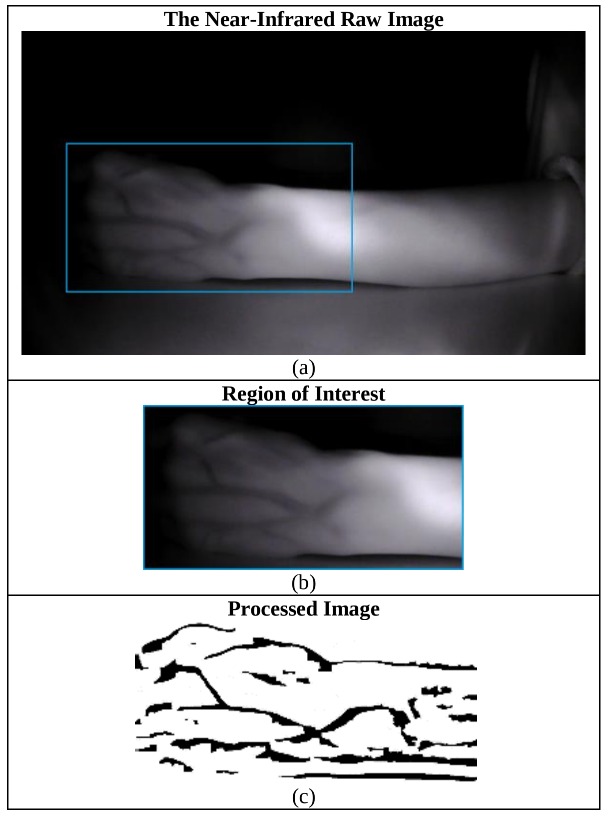

Figure 1. The near-infrared vein image. (a) The near-infrared raw image of hand dorsum. (b) Region of interest, containing only the veins to be examined. (c) Vein patterns obtained by digital image processing.

The YOLOv3 is a deep learning algorithm that performs object detection. With object detection algorithms, training can be performed for multiple objects (up to 80 classes [12] placed at certain locations on the image) that can represent different classes. In this study, the YOLOv3 algorithm was used for CVD detection in vein patterns obtained by image processing steps. The developed near-infrared imaging system was retrained in this study to detect CVD progression using two separate classes (spider_vein and varicose_vein).

There is currently no venous disorder dataset consisting of near-infrared images, available to the public. For this, a two-class training dataset was prepared (The dataset was created by the method of obtaining images from the video recordings described in the study [11]) by adding artificial

 ISBN: 978-1-68558-017-9

spider_vein and varicose_vein patterns on the near-infrared images. In this context, 5 spider_vein and 5 varicose_vein patterns were added onto 150 near-infrared images. Furthermore, 50 additional images were created from the existing images by data augmentation methods (10 degrees rotation, 30 degrees rotation, mirroring, noise addition and downscaling). In this way, an artificial training dataset containing 1000 spider_vein and 1000 varicose_vein patterns was obtained. The patterns in the images were labelled with the free (under General Public License version 3) makesense [22] web-based application.

A second dataset consisting of 300 images containing artificial vein enlargement patterns was prepared for the test process to be carried out after the trainings. The dataset was created by adding only a single spider_vein or varicose_vein pattern to each image in random rotations and locations (maintaining a certain figural format). In this way, 150 test images containing the spider_vein class and 150 test images containing the varicose_vein class were obtained. The confusion matrix of the object detection results of the YOLOv3 algorithm, obtained using the test dataset, is given in Table 1. As can be seen from the matrix, all of the searched objects (spider_vein and varicose_vein patterns) in the test images were detected correctly. The developed system can detect CVD patterns in C1 and C2 stages with Accuracy Rate (1), Misclassification Rate (0), Precision (1), Prevalence (0.5) and F-Score (1) values.

The YOLOv3 algorithm marks the locations of the objects detected onto the image with bounding boxes. In addition, the name of the class with the highest probability and the detection rate (confidence value is shown between 0.00 and 1.00 in the study) are printed on the box.

Two sample result images of the YOLOv3 algorithm test process (venous disorder detection with confidence value of 0.99 for spider_vein and 0.90 for varicose_vein classes) are shown in Fig. 2.

Although all classes in the test images were predicted correctly, the YOLOv3 algorithm had a lower confidence value for some patterns. Among 150 images containing spider_vein patterns, 130 had a confidence value in the range of 0.95-1.00, 13 in the range of 0.90-0.94, 6 in the range of 0.80-0.89, and 1 of them was determined as 0.32. When the pattern with the confidence value of 0.32 is examined, it is determined that it is not much different from the patterns in the training dataset (mostly large-sized patterns were used) or other test patterns, but it is smaller in size, as can be seen in Fig. 3. It was evaluated that this situation may result in a low confidence value.

TABLE I. THE CONFUSION MATRIX OF YOLOV3 ALGORITHM RESULTS OBTAINED WITH SPIDER_VEIN AND VARICOSE_VEIN CLASSES

n=300		Predicted Class	
		Positive (spider_vein)	***Negative (varicose_vein)***
Actual Class	***Positive (spider_vein)***	True Positive=150	False Negative=0
	Negative (varicose_vein)	False Positive=0	True Negative=150

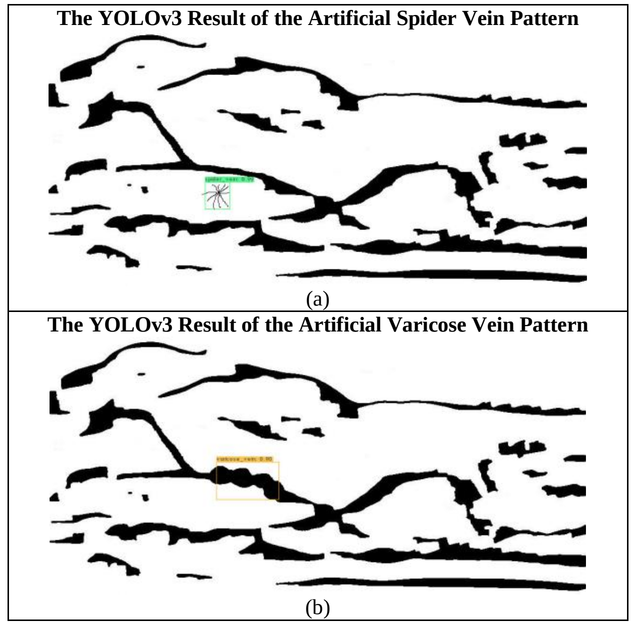

Figure 2. The YOLOv3 algorithm test process result images. (a) 0.99 confidence valued result for spider_vein class. (b) 0.90 confidence valued result for varicose_vein class.

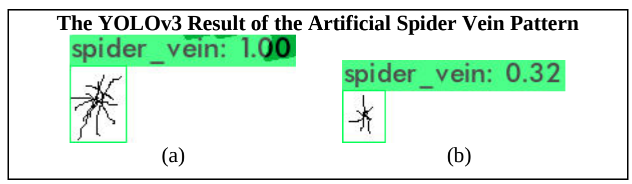

Figure 3. Artificial spider_vein patterns shown in accordance with their actual dimensions. (a) Pattern with the confidence value of 1.00. (b) Pattern with the confidence value of 0.32.

Among the 150 images containing varicose_vein pattern, 126 had a confidence value in the range of 0.95-1.00, 6 had a range of 0.90-0.94, 11 had a range of 0.80-0.89, and 7 had a range of 0.79-0.30. When the 7 patterns with the lowest confidence values are examined, it is determined that these patterns are slightly different (U-shaped, twisted) from the patterns in the training dataset or other test patterns (mostly linear line patterns were used) which can be seen in Fig. 4. It was evaluated that this condition may lead to a low confidence value.

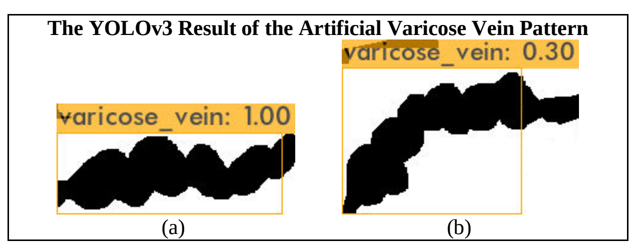

Figure 4. Artificial varicose_vein patterns are shown in accordance with their actual dimensions. (a) Pattern with the confidence value of 1.00. (b) Pattern with the confidence value of 0.30.

Since small-sized spider_vein patterns represent the early stages of CVD and varicose_vein patterns can also twist and fold (may not follow a linear line) over time, such patterns are important in the detection system. Therefore, in order to overcome the low confidence values of spider_vein and varicose_vein classes, smaller-sized patterns and new patterns in different rotations (U-shaped) will be added to the training dataset as part of the future work.

III. CONCLUSION

In this study, it was investigated how the superficial vein surveillance system, which was prepared within the scope of the ongoing doctoral study, could be expanded to detect vein enlargement. The study is based on superficial vein imaging by using near-infrared light which is harmless to the body. The YOLOv3 algorithm was used to detect Chronic Venous Disorder patterns in the near-infrared images obtained. According to the test results obtained with artificial patterns including spider_vein and varicose_vein classes, confidence values of 0.90 and above were achieved in object detection. The developed system could perform object detection of the related classes with Accuracy Rate (1), Misclassification Rate (0), Precision (1), Prevalence (0.5) and F-Score (1) values. In this way, a system in which the development of Chronic Venous Disorder can be followed within the scope of pre-diagnosis has been created. It is vital to inform the doctor about the possibility of the detected telangiectasia vein turning into a varicose vein. In this way, it will be possible to start the treatment without delay. Within the scope of future studies, the system will be tested with real patient data. Also, the vein enlargement detection feature will also be integrated into the superficial vein surveillance system that offers video-based indirect augmented reality, therefore informing the patient and physician.

ACKNOWLEDGMENT

The authors would like to thank Işıl Erdem (Civil Engineer, MSc) for making the final edits of this paper.

REFERENCES

[1] M. Y. M. Chen, T. L. Pope, and D. J. Ott, Basic Radiology, 2nd ed., McGraw Hill: Lange Clinical Medicine, 2011.

[2] Inside View: A Blog For Our Patients, From UVA Radiology and Medical Imaging. *Different Imaging Tests, Explained.* 17.Sep.2017. [Online]. Available from: https://blog.radiology.virginia.edu/different-imaging-tests-explained/ [retrieved: July, 2022]

[3] Bravo Imaging. *Medical Imaging Modality Options and Their Uses.* 20.Jul.2008. [Online]. Available from: https://www.bravoimaging.com/medical-imaging-equipment-miami/medical-imaging-modality-options-and-their-uses/ [retrieved: July, 2022]

[4] V. P. Zharov, S. Ferguson, J. F. Eidt, P. C. Howard, L. M. Fink, and M. Waner, "Infrared Imaging of Subcutaneous Veins", Lasers in Surgery and Medicine: The Official Journal of the American Society for Laser Medicine and Surgery, 34(1), pp. 56-61, 2004, doi.org: 10.1002/lsm.10248.

[5] R. Fuksis, M. Greitans, O. Nikisins, and M. Pudzs, "Infrared Imaging System for Analysis of Blood Vessel Structure", Electronics and Electrical Engineering, System Engineering, Computer Technology, 97(1), pp. 45-48, 2010.

[6] N. Bouzida, A. H. Bendada, and X. P. Maldague, "Near-Infrared Image Formation and Processing for the Extraction of Hand Veins", Journal of Modern Optics, 57(18), pp. 1731-1737, 2010, doi.org: 10.1080/09500341003725763.

[7] Y. Ayoub et al., "Diagnostic Superficial Vein Scanner", International Conference on Computer and Applications (ICCA 2018), IEEE, Aug. 2018, pp. 321-325, doi.org: 10.1109/COMAPP.2018.8460229.

[8] C. L. Lin and K. C. Fan, "Biometric Verification Using Thermal Images of Palm-Dorsa Vein Patterns", IEEE Transactions on Circuits and Systems for Video Technology, 14(2), pp. 199-213, 2004, doi.org: 10.1109/TCSVT.2003.821975.

[9] R. Garcia-Martin and R. Sanchez-Reillo, "Vein Biometric Recognition on a Smartphone", IEEE Access, 8, pp. 104801-104813, 2020, doi.org: 10.1109/ACCESS.2020.3000044.

[10] H. A. Erdem, I. Erdem, and S. Utku, "Near-Infrared Mobile Imaging Systems for e-Health: Lighting the Veins", The Twelfth International Conference on eHealth, Telemedicine, and Social Medicine (eTELEMED 2020), IARIA, Valencia, Spain, November 21-25, 2020, pp. 80-84.

[11] H. A. Erdem and S. Utku, "Augmented Reality Aided Pre-Diagnosis Environment for Telemedicine: Superficial Vein Surveillance System", European Journal of Science and Technology, 2022.

[12] J. Redmon and A. Farhadi. "Yolov3: An Incremental Improvement", arXiv preprint arXiv:1804.02767, 2018.

[13] N. Özbayrak, "Varis Çoraplarının Performans Özelliklerinin İncelenmesi (An Investigation About Performance Properties of Compression Stockings)", Master's Thesis, Uludag University, Bursa, Turkey, 2009. Thesis in Turkish with an abstract in English.

[14] A. E. Gabbey and J. Marcin (reviewed by), Healthline. *Varicose Veins.* 8.Mar.2019. [Online]. Available from: https://www.healthline.com/health/varicose-veins [retrieved: July, 2022]

[15] Health. Johns Hopkins Medicine. *Varicose Veins.* [Online]. Available from: https://www.hopkinsmedicine.org/health/conditions-and-diseases/varicose-veins [retrieved: July, 2022]

[16] T. Feodor, S. Baila, I. A. Mitea, D. E. Branisteanu, and O. Vittos, "Epidemiology and Clinical Characteristics of Chronic Venous Disease in Romania", Experimental and Therapeutic Medicine, 17, pp. 1097-1105, 2019, doi.org: 10.3892/etm.2018.7059.

[17] H. Partsch, "Varicose Veins and Chronic Venous Insufficiency", Vasa: European Journal of Vascular Medicine, 38(4), pp. 293-301, 2009, doi.org: 10.1024/0301–1526.38.4.293.

[18] G. Piazza, "Varicose Veins", Circulation, 130(7), pp. 582-587, 2014, doi.org: 10.1161/CIRCULATIONAHA.113.008331

[19] N. Labropoulos, "How Does Chronic Venous Disease Progress from the First Symptoms to the Advanced Stages? A Review". Advances in Therapy, 36(1), pp. 13-19, 2019, doi.org:10.1007/s12325-019-0885-3.

[20] S. Behring and A. Gonzalez (reviewed by), Healthline. *What Are the Stages of Chronic Venous Insufficiency?.* 10.Jun.2021. [Online]. Available from: https://www.healthline.com/health/chronic-venous-insufficiency-stages [retrieved: July, 2022]

[21] N. Kahraman et al., "Detection of Residual Varicose Veins with Near Infrared Light in the Early Period After Varicose Surgery and Near Infrared Light Assisted Sclerotherapy", Vascular, 2021, doi.org: 10.1177/17085381211051489.

[22] P. Skalski, Makesense, Alpha. *Free To Use Online Tool For Labelling Photos.* [Online] Available from: https://www.makesense.ai/ [retrieved: July, 2022]

