Ilkogretim Online - Elementary Education Online, 2021; Vol 20 (Issue 6): pp. 2669-2677
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2021.06.248

Hybrid Methodology For Retinal Vessel Segmentation Approach Based On Machine Learning

Manisha Deo M-Tech student, Patel College Of Science And Technology.

Animesh Dubey Associate Professor Patel College Of Science And Technology.

Abstract

Retinal vessel segmentation is an essential phase of diabetes detection. In detecting retinal vessels, image processing and machine learning play a vital role. Machine learning algorithms enhance the segmentation ratio of retinal images. This paper proposed machine learning-based retinal vessel segmentation methods. The proposed methods use wavelet transform methods to extract texture features and support vector machine applied for retinal vessel detection. The proposed algorithm improves the segmentation ratio of the retinal vessel. The lower content of the retinal image increases the range of the feature sample and maximizes the cover of the support vector. The proposed algorithm is simulated in MATLAB tools—the DRIVE dataset used to test the proposed algorithm.

Keywords: Segmentation, Retinal Image, SWT, SVM, CNN.

Introduction

Retinal vessel segmentation and delineation of morphological attributes of retinal blood vessels such as length, width, tortuosity, and branching pattern and angles are used in the diagnosis, screening, treatment, and evaluation of various cardiovascular and ophthalmologic diseases such as diabetes, hypertension, arteriosclerosis, and choroidal neovascularization. The retinal blood vessels contain a wealth of information about human health [1]. Retinal vessel segmentation can help ophthalmologists diagnose problems by revealing the features of vascular systems in fundus pictures. Retinal fundus images make it easier to investigate the retina's numerous structures. Fundus illnesses such as glaucoma, age-related macular degeneration, and diabetic retinopathy are all linked to morphological abnormalities in the retinal blood vessels [2]. As a conclusion, reliable segmented images of retinal blood vessels can aid professionals in the early detection and monitoring of the disorders mentioned above, preventing blindness. However, it is difficult to properly separate retinal blood vessels, manual labelling is time-consuming and labour-intensive, and there is a lot of subjectivity [3]. As an outcome, much study has gone towards automating the segmentation of retinal vessels. Automatic segmentation of retinal blood vessels has become an important technique for clinical medical illness screening and diagnosis. Furthermore, the technology can bring advanced medical technologies to individuals living in remote locations that are comparable to those found in developed places, thereby improving people's health and quality of life. In recent years, many retinal vascular segmentation approaches have been presented, which can be classified as supervised or unsupervised depending on whether prior information is necessary [4,5,6].A method for semi-supervised retinal vascular segmentation in multiple stages. Unsupervised classification is the initial stage, in which main vessel pixels are recovered from binary images obtained from a fundus green channel picture after pre-processing with a high pass filter and morphological filter. The major vessels are linked to the supervised classification conclusion in the final stage, which is supervised classification using the Gaussian mixture model (GMM) classifier. Gradient orientations, line characteristics, morphological filtering outputs, and Gabor wavelet responses are all combined to create a feature vector, which is then identified with an ensemble classifier. The pixels in [7] are represented using the Gabor wavelet transform characteristics achieved at various sizes. Retinal photography necessitates the use of a fundus camera, which is a complicated optical framework. It's a special low-force magnifying tool with a built-in camera that can both illuminate and image the retina at the same time. Its purpose is to depict the retina, optic plate, macula, and back post on the inside surface of the eye [11]. The fundus camera operates in three modes on a regular basis. The retina is evaluated in complete shading under the enlightenment of white light in color photography. The vessels and other structures in non-red photography are enhanced in the opposite direction, and the imaging light is filtered to remove the red hues. Fluorescent angiograms are obtained using the color following method. The angiography is acquired by capturing the fluorescence transmitted after lighting the retina with blue light at a frequency of 490 nanometers after infusing the blood with sodium fluorescein or indocyanine green [12].The retinal vasculature is made up of courses and veins that appear in the retinal picture as longer highlights with their tributaries readily apparent. Depending on the vessel width and the picture's goals, a wide range of vessel widths is accessible, ranging from one pixel to twenty pixels. In visual fundus images, the retina limit, the optic plate, and diseases such as cotton fleece patches, brilliant and dull lesions, and exudates can all be seen [13,14]. The vessel cross-sectional force profiles suggested a Gaussian form or a blend of Gaussians in the case where a focal vessel reflex is known. The direction and dim degree of a vessel do not abruptly shift; they are localized and change in power along their lengths [15]. The vessels may be required to be linked and form a parallel treelike arrangement in the retina. Veins, on the other hand, can vary greatly in shape, size, and neighboring dim degree, and some foundation highlights may have similar attributes to vessels. The profile model can be further complicated by vessel junction and stretching. Similarly, as with most clinical images, signal commotion, drift in picture power, and the lack of picture differentiation provide significant challenges in vain extraction [16]. The rest of paper describe as in section II related work in section III methods of blood vessel segmentation in section IV describe the experimental analysis and finally conclude in section V.

II. Related work

In this section describes recent work of retinal vessels image segmentation by incremental algorithms of machine learning and transform function. Some important contribution of authors describe here. In this [1] author propose a neural network design based on the Dense U-net and the Inception module is provided for retinal vascular segmentation. On the public DRIVE dataset, the Dice rate for the algorithm proposed in this study is 82.15 percent, and the AU-ROC and AU-PR are 0.98 and 0.91, respectively. Experiments show that the suggested technique is effective at segmenting retinal arteries automatically. In this [2] author presents a new U-form DL architecture based on lightweight convolution blocks for segmenting the retinal vascular tree, which retains high segmentation performance while reducing computational complexity. In this [3] author assembles a dozen pre-process pipelines from previously published retinal vascular segmentation studies and offers five broad patterns for these pipelines. The "HIERA" pipeline achieves the highest AUC score of 0.9793 on the DRIVE database and 0.9842 on the CHASEDB1 database. In this [4] author propose a multi-scale feature fusion retinal vascular segmentation model is based on U-Net, MSFFU-Net. Sen values of 0.78 and 0.79, SPE values of 0.97 and 0.9885, Acc values of 0.97 and 0.97, and AUC values of 0.98 and 0.97 were found in the DRIVE and STARE datasets, respectively. In this [5] author presents SVSN is a lightweight convolutional neural network for vessel segmentation. Encoder-decoder structures with spatial pyramid pooling modules are utilized to produce semantic segmentation. As a outcome, the detection accuracy on the DRIVE and STARE datasets is greatly improved, with scores of 0.96 and 0.97, respectively. In this [6] author propose a multifractal metric, is employed to segment the retinal vessels using a new retinal vasculature segmentation method based on multifractal vascular characterization to reduce noise and enhance vessels during segmentation. In this [7] author presents Segmenting retinal blood vessels with a new fractional filter and algorithm The recommended fractional filter is made up of a weighted fractional derivative and an exponential weight factor. On the STARE and DRIVE datasets, the suggested method has an average vessel segmentation accuracy of 95.73 percent and 94.76 percent, respectively, indicating that it is computationally economical. In this [8] author propose NFN+ is a new deep learning-based model for extracting multi-scale information and making full use of deep feature maps. their findings show that extended cascaded designs can improve performance, and the proposed NFN+ model obtained state-of-the-art retinal vascular segmentation accuracy on color fundus pictures, to their knowledge AUC: 98.30 percent, 98.75 percent and 98.94 percent, respectively. In this [9] author Compute offloading in F-RANs is designed to minimize the entire cost in terms of energy usage and offloading latency. Finally, simulation data are provided to demonstrate how their suggested joint optimization technique improves performance. In this [10] author propose HA net is a brand-new end-to-end deep learning architecture for retinal vascular segmentation. The proposed architecture surpasses existing state-of-the-art models in terms of segmentation accuracy, area under the receiver operating characteristic curve (AUC), and f1-score. In this [11] author propose a high-resolution representation network with multi-path scale MPS-Net for RVS with the goal of improving the performance of retinal blood vessel extraction. The encouraging segmentation outcomes show that their method has real-world promise and may be used to segment other medical images with future investigation. In this [12] author propose a provides automatic blood vessel segmentation in retinal pictures. When tested, they found that the proposed method had a sensitivity of 98.9%, a specificity of 83.74 percent, and an accuracy score of 98.8 percent for segmenting retinal pictures. In this [13] author using Convolutional neural networks to create automated segmentation models for the retinal vascular segmentation challenge. they achieve the greatest accuracy of 0.96/0.97, the lowest loss of 0.11/0.10, and the highest AUC of 0.98/0.99. The CNN models are also compared to other segmentation methods. The findings show that CNN-based techniques are highly effective. In this [14] author present using deep CNNs to achieve the goal of automatic blood vessel segmentation in retina images. The findings are compared to previously labelled data, and their model's performance is assessed using several metrics such as F1 score, accuracy, sensitivity, specificity, and precision. The values obtained for the various metrics stated above are 0.8321, 0.9716, 0.8214, 0.9860, and 0.8466, respectively.

In this [15] author propose A method for analysing retinal blood vessels using traditional methods is proposed. Pixel-based feature extraction is used in this suggested system. The system's accuracy was determined to be 96.18 percent for DRIVE and 94.56 percent for STARE, respectively. The proposed method gets satisfactory outcomes in tests, according to the outcomes. In this [16] author propose a novel scale and context sensitive network was developed. The experimental outcomes show that the suggested SCS-Net is effective in attaining better segmentation performance than existing state-of-the-art techniques, particularly in demanding scenarios with large scale changes

III. Proposed methods

The proposed algorithm is combination of discrete wavelet transform (DWT) and support vector machine. The DWT function extract the lower content of retinal images. The extracted features pass through the support vector machine and process of segmentation performed. The processing of algorithm describes here.

1. Input: a DWT features(f1,f2,....,fn), SVM
2. Output: $retinalareadetected$
3. Compute $D_{(P_t,k)}$and $k-d(p_t)$
4. for all $DP \in SVM_{(f_t,k)}$do
5. estimate local features$-Lp(f_t, DP)$
6. end for
7. for all $DP \in W_{\text{update}}$ and $FP \in M_{(DG,K)}$do
8. Update $k - disimarilty(DP)$ and $cluester - ds(,DP)$
9. if $DP_{(FP,k)}$then
10. $W_{\text{update}} \leftarrow W_{\text{update}} \cup \{DP\}$
11. end if
12. end for

13. for all $DP \in W_{\text{update}}$ do
14. Update $FD(DP)$ and $FD(\{GSO_{o,k}\})$
15. end for
16. return $FD(forgeddetection)$
17. if value of difference is near about zero.
18. The process of retinal detection detection
19. Measure value of parameters

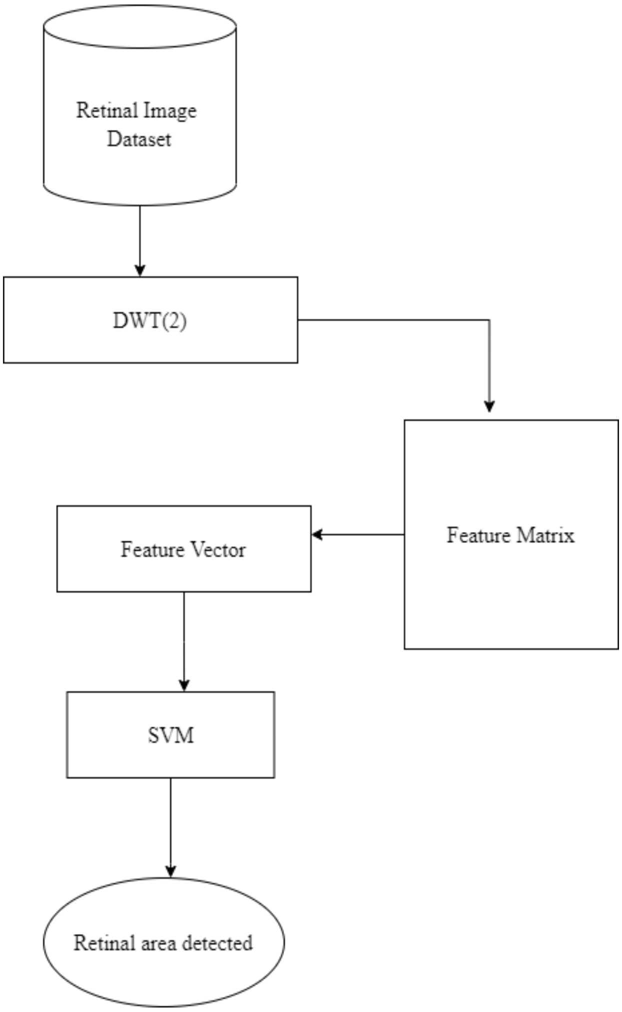

Figure 1 proposed model of retinal vessels image segmentation.

IV. Experimental analysis

To validate the proposed algorithm of retinal vessels detection uses MATLAB tools. The system configuration of simulation machine is windows 10 operating system, I7 process and 16GB RAM. The 200 set of image uses for testing obtained form DRIVE dataset of diabetic retinopathy. The following standard parameters estimated for the comparative study of proposed algorithm [16].

sensitivity = $\frac{TP}{TP+FP}$

specific= $\frac{TP}{TP+FN}$

Accuracy = $\frac{TP+TN}{TP+TN+FN+FP}$

Table 1: Shows performance comparison of Specificity, Sensitivity and Accuracy rate using GF, CNN and PROPOSED method with various input images and different threshold values.

Input	Method	Threshold Value	Specificity (SP)	Sensitivity (SE)	Accuracy (AU)
Image 1	GF	10	89.56	63.31	94.23
	CNN	10	91.96	65.76	95.96
	PROPOSED	10	94.03	67.46	96.06
Image 2	GF	10	91.25	65.78	92.51
	CNN	10	93.65	66.36	92.96
	PROPOSED	10	95.54	67.46	93.06
Image 3	GF	10	91.45	64.87	92.54
	CNN	10	92.87	66.36	94.52
	PROPOSED	10	93.67	67.46	96.87
Image 4	GF	10	94.96	66.94	93.56
	CNN	10	96.21	67.36	94.21
	PROPOSED	10	97.78	68.46	95.35
Image 5	GF	10	93.47	68.31	96.23
	CNN	10	94.24	69.76	97.24
	PROPOSED	10	96.35	70.46	98.32

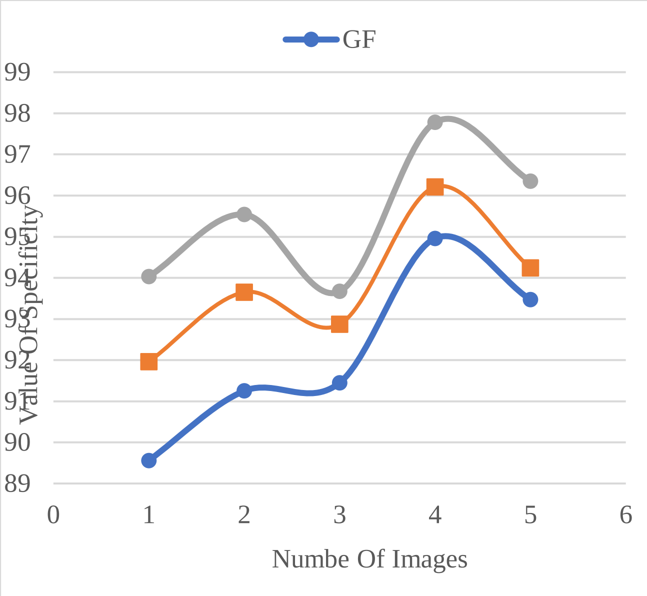

Figure 2: Shows that the Comparative evaluation of Specificity GF, CNN and PROPOSED Method using various images with threshold value of 10.

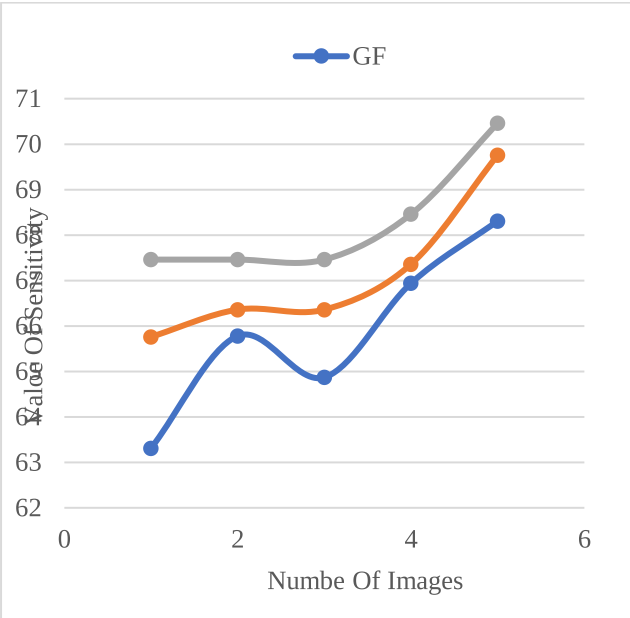

Figure 3: Shows that the Comparative evaluation of Sensitivity by GF, CNN and PROPOSED Method using various images with threshold value of 10.

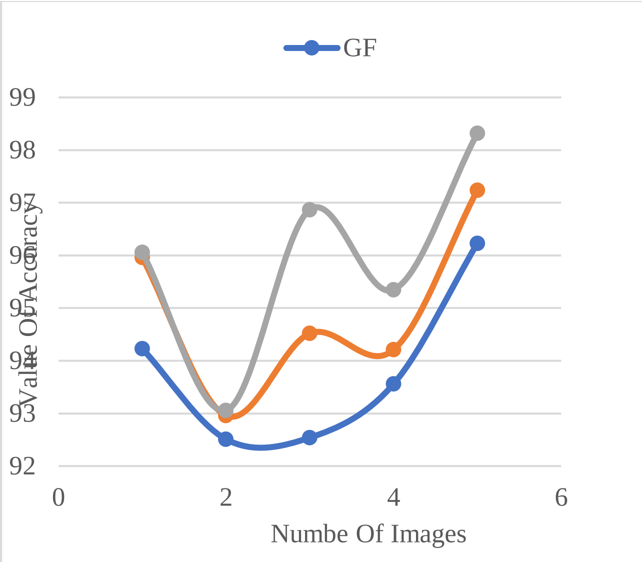

Figure 4: Shows that the Comparative evaluation of Accuracy by GF, CNN and PROPOSED Method using various images with threshold value of 10.

V. Conclusion & Future Work

This paper proposed a hybrid methods of retinal vessels segmentation. The proposed method of retinal vessels segmentation apply DWT transform method and SVM classification algorithm. The proposed algorithm is very efficient in terms of accuracy and sensitivity value. In the case of proposed algorithm sensitivity rate is decrease. The DWT transforms function basically used for the extraction of feature of retinal vessel image. We compare the proposed method with different algorithm such as GF and CNN. It also used Our experimental result shows that the proposed method gives the best segmentation results whatever the shape and the position of the initial contour and the resulting contours are thin and present no discontinuities.

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