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A Novel Method for conducting Segmentation of Retinal Blood Vessels

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ABSTRACT

Diabetic Retinopathy (DR) is a complication of diabetes, caused by high blood sugar levels harming the back of the eye (retina).Diabetic retinopathy happens when these tiny blood vessels outflow blood and other fluids. This causes the retinal tissue to swell, causing in blurred vision. Precise segmentation of the blood vessels from a retinal image plays an important role in the careful inspection of the vessels. The research paper proposes a method to perform segmentation on the blood vessels of the retinal images. The proposed method have been elaborated in a flowchart and explained via a flowchart. The retinal images have been obtained from the Digital Retinal Images for Vessel Extraction (DRIVE) dataset. The Gaussian filter is used to enhance the retinal images. The Fuzzy C-Means (FCM) is used to segment the retinal images. The obtained output have been accompanied with the values of different performance evaluation parameters to justify the worth of conducted work. The research paper shows the implementation of the proposed method on the three retinal images from the DRIVE dataset.

KEYWORDS: blood vessels, Diabetic Retinopathy, DRIVE, retinal images, segmentation.

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I. INTRODUCTION

Individuals with diabetes can have an eye disease called diabetic retinopathy. This is when high blood sugar levels cause impairment to blood vessels in the retina. These blood vessels can swell and leak[1, 2, 3]. Image processing has a vital role in the accurate analysis of DR. Primarily, a low vision problem is encountered and at later stages, the formation of exudate wounds instigated due to the existence of lipids in the blood vessels may cause blindness if its appearance is around the macula [4, 5]. The adversative consequence takes place in the blood veins of the retina which can make capillaries and veins burst as the stream of blood passes near the retina [6, 7]. During the past few years, the research work carried out in the field of Diabetic Retinopathy (DR) has witnessed a huge boom. In the majority of cases, the DR is detected at later stages and by then the disease becomes incurable. However if such a deadly disease can be detected at early stages, the possibility of a patient recovering from DR increases many folds [8, 9]. If the detection process is fully automated, the intervention of manual efforts would be minimized which would further lead to reduced chances of errors [10, 11].

Section II of the research paper elaborates on the State-of-the-Art in context with DR. Section III elaborates on the research methodology adopted for the proposed technique via flowchart and detailed algorithm. Section IV expounds on the proposed technique implemented on retinal images from DRIVEdatasets displaying the obtained readings for the different participating performance evaluation parameters. Finally, Section V summarizes the work done in the research paper as a conclusion and elaborates on the future work that can be conducted in context with the conducted research work done in the research paper.

II. RELATED WORK

In 2019, Q. Li et al. [12]explained that diabetes is a severe disease that harms the human eye and it is termed DR (Diabetic Retinopathy). DR produces many unwanted blood vessels and may cause vision loss. The authors suggested the U-net-based automatic image segmentation and detection algorithm. The authors used convolution operation instead of max pooling. The suggested U-network contains 28 convolution layers. The execution of the anticipated algorithm attained a DSM (Dice Similarity Coefficient) of 0.80, PMC (Prevent Match Coefficient) is 85.7%, CR (Correspondence Ratio) is 71.26%, and ASSD (Average Symmetric Surface Distance) is 1.1568. The obtained values proved that the suggested method attained the best segmentation and detection outcomes. **In 2019, Y. Jiang et al**.**[13]** proposed a Fully Convolutional Neural Network based model for the segmentation of blood vessels followed by the original model of FCN. Thereafter the authors suggested the M3FCN (Multi-Scale, Multi-Path, and Multi-Output Fusion) method. The anticipated method is applied to three databases: CHASE, DRIVE, and STARE. The values for different performance evaluation parameters such as F1, accuracy, sensitivity, specificity, and AUC are calculated to check the worth of the conducted research work. The anticipated method obtained the F1 value of 83.21% for DRIVE, 85.31% for STARE, and 82.43% for CHASE. Similarly, the Accuracy of 97.06% is obtained for DRIVE, 97.77% for STARE, and 97.73% for CHASE. The values obtained for AUC are 98.80% for DRIVE, 99.23% for STARE, and 99.17% for CHASE. The anticipated model attained the best values in each case. **In 2019, D.A. Dharmawan et al. [14]**stated that the blood vessels in human eyes help to detect many eye problems. The segmentation of retinal images helps in detecting the infected portions of the eyes. As manual segmentation is a tedious and time-consuming task, the authors proposed an advanced algorithm for the segmentation of retinal images. The anticipated algorithm is a hybrid mixture of the enhancement method and CNN which is based on U- Net. The authors used DRIVE, STARE, and HRF data sets for the implementation of the proposed algorithm. Sensitivity, Specificity, G-mean, F1-score, and Matthew's correlation coefficient are evaluated to check the performance of the suggested algorithm. The calculated values of sensitivityare 83%, specificity is 97%, G-mean is 89% and MCC is 79% in the case of the DRIVE data set which proves the worth of the work done. **In 2020, J. Gao et al. [15]** proposed that image segmentation is a big challenge in the field of image processing. Many mathematical fundamentals have already been used in image processing and image segmentation. In the paper, the authors suggested a wavelet transformed-based method for the segmentation of the images. The suggested method of image segmentation is applied to the distinct images. The proposed WSM (Wavelet Segmentation Method) is compared with BSM (Bimodal Segmentation Method) and VTSM (Valley Threshold Segmentation Method) and it is found that the suggested method performed better than the other methods. Four types of images Lena images, Camera-man images, Ray images, and MRI images are used as data sets. Three evaluation parameters SNR, PSNR, and SSIM are used to check the authenticity of the work done. PSNR and SNR obtained in each case by WSM are better than the other methods. The values of PSNR obtained using WSM are 5.7071, 5.5865, 14.3991, and 7.4893 for Lena images, Camera images, Ray images, and MRI images respectively. **In 2021,Y. Zhou et al**.**[16]** stated that it is necessary to detect the disease at an early stage to avoid any type of harm to the eye like vision loss, hard and soft exudates, etc. The authors constructed a dataset comprising 2,842 images and named it FGADR. Thereafter, the authors elaborate on the DR segmentation, DR grading, and Transfer learning for the identification of the disease. The author made use of FCN-8S, Dl-V3+, U-Net, Multi-class U Net, Attention-Net, Gated U-Net, Dense U-Net, and U-Net++. The authenticity of the work done is calculated by the evaluation parameters like DICE (Dice Similarity Coefficient), AUC-ROC, AUR-PR, MAE (Mean Absolute Error), Cohen's Kappa, F-1 Score, and it is found that Dense U-Net attained the better results.

III. RESEARCH METHODOLOGY

This section illustrates the proposedmethod intended to perform segmentation of the blood vessels of the retina. The segmentation is conducted on the pixels which are within the boundary of the retinal image. The pixels beyond the boundary of the retinal image have negligible clinical utility. FCM is used to segment the retinal images. FCM is a clustering technique that permits one piece of data to fitinto two or more clusters. Fuzzy logic is derived from fuzzy set theory and is a multi-valued logic. Haar feature extraction works on connecting rectangular regions at a specific location in a detection window and executes a summation of the intensities of the pixels in each region and calculates the difference between these sums.

Figure 1 depicts the flowchart illustrating the working of the proposed model followed by an algorithm.

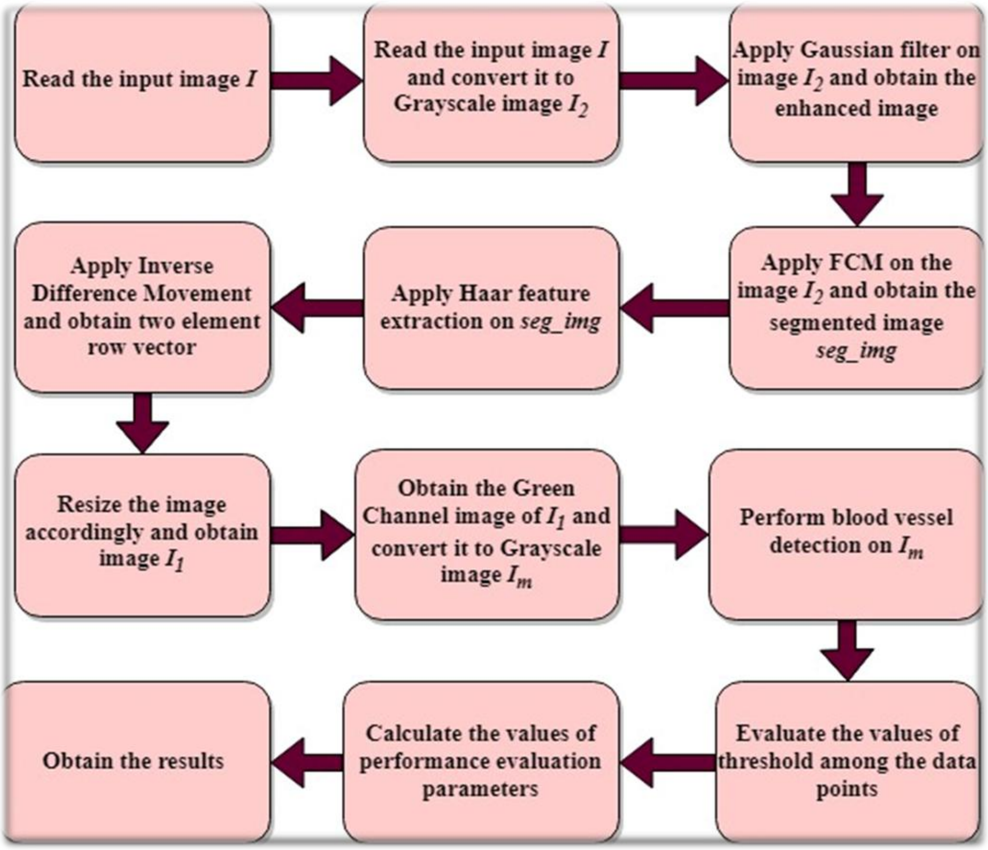

Figure1: Research methodology for the proposed model

Algorithm

- Input image I is converted to grayscale image I_2.
- Gaussian filter is used to enhance the image I_2.
- FCM is used to perform segmentation of *I2* to obtain segmented image *seg_img*.
- Apply Haar feature extraction on*seg_img*.
- Two-element row vector is obtained using Inverse Difference Movement.
- Resize the image accordingly and obtain image I_1.
- Obtain Green Channel Complement of image *I1* and obtain its grayscale image *Im*.
- Accomplish blood vessel detection on $I_m$and evaluate the values of the threshold among the data points.
- Perform calculations applying multiple formulas to obtain the values of performance evaluation parameters and get the results.

IV. IMPLEMENTATION & RESULTS

This section depicts different instances showing the implementation of the proposed model on the retinal images from the DRIVE dataset.

Instance 1 *– 21_training.tif*

Figure2a depicts the image *21_training.tif* from the DRIVE dataset given as input to the proposed model. Figure2b shows the grayscale conversion of the input image. The grayscale image is further converted using Green Channel Complement as shown in Figure2c. Thereafter, the blood vessels are detected as shown in Figure2d. Figure2e shows the Canny image and Figure2f shows the Dilated image of the detected blood vessels.

Figure2g shows the blood vessels after the removal of the boundaries of the retina. Finally, Figure2h shows the extracted blood vessels on the input image.

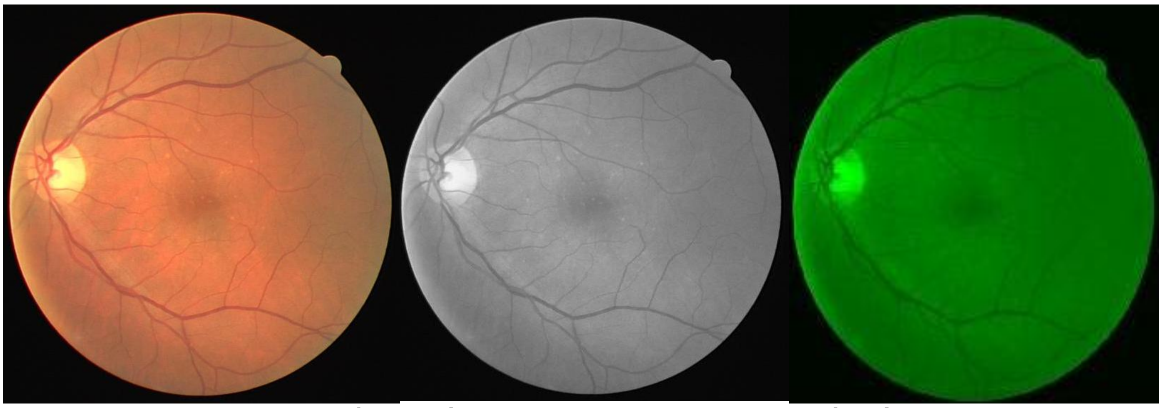

Figure2a: Input image Figure2b: Grayscale image Figure2c: Green Channel image

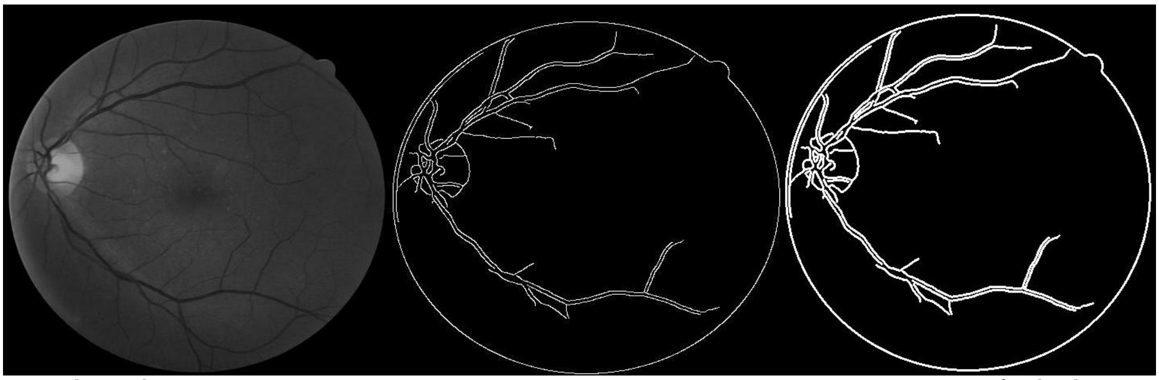

Figure2d: Vessel Detection Figure2e: Canny image Figure2f: Dilated image

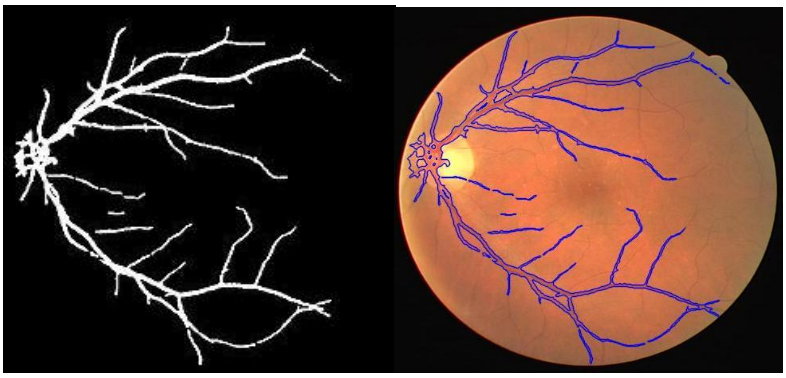

Figure2g: Approximate Figure. 2h: Extracted blood vessels

Table I shows the readings of different performance evaluation parameters obtained from the evaluation of retinal image *21_training.tif*.

Table I. Readings obtained after segmenting the retinal image *21_training.tif*

Parameters	**Readings**
Sensitivity	0.0520
Specificity	0.9823
Accuracy	0.9271
PPV	0.1567
NPV	0.9426
FNR	0.9480
FPR	0.0177
FDR	0.8433

FOR	0.0574
F1 Score	0.0781
MCC	0.0583

Figure3 shows the graphical representation of the obtained readings in Table I of different performance evaluation parameters for image *21_training.tif*.

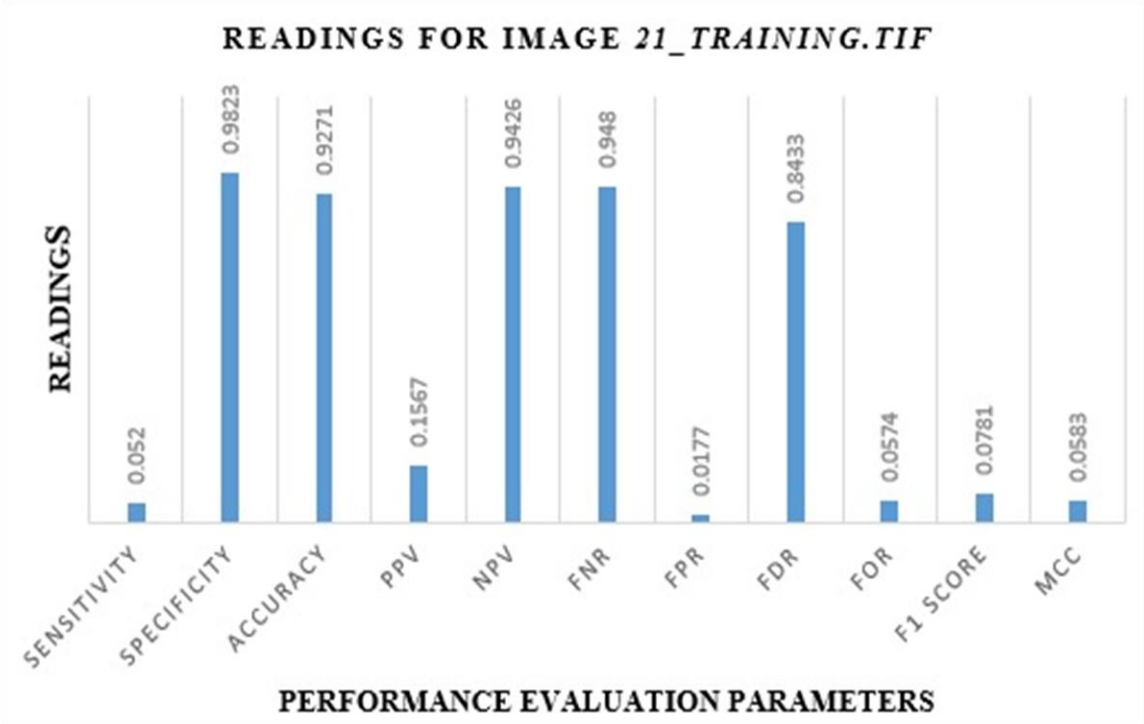

Figure3: Graphical representation for readings obtained in Table I

***Instance 2** – 22_training.tif*

Figure4a depicts the image *22_training.tif* from the DRIVE dataset given as input to the proposed model. Figure4b shows the grayscale conversion of the input image. The grayscale image is further converted using Green Channel Complement as shown in Figure4c. Thereafter, the blood vessels are detected as shown in Figure4d. Figure4e shows the Canny image and Figure4f shows the Dilated image of the detected blood vessels. Figure4g shows the blood vessels after the removal of the boundaries of the retina. Finally, Figure4h shows the extracted blood vessels on the input image.

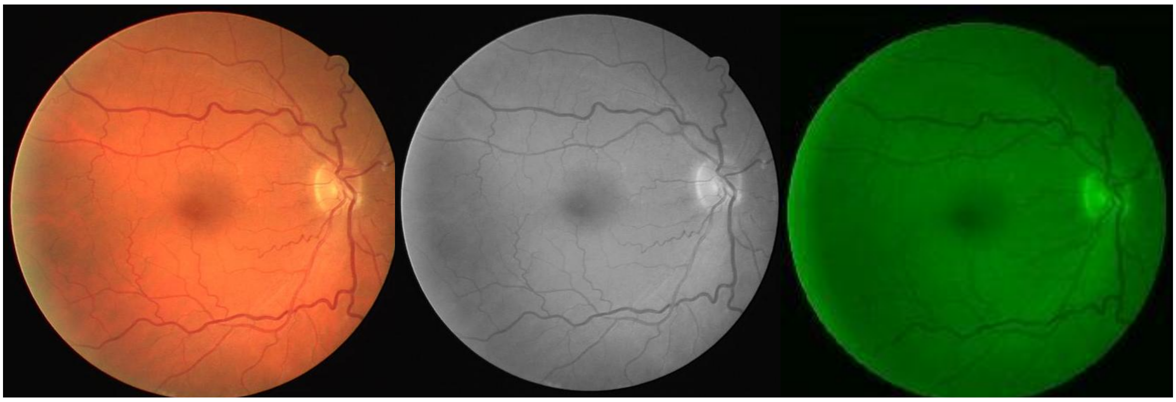

Figure4a: Input image Figure4b: Grayscale image Figure4c: Green Channel image

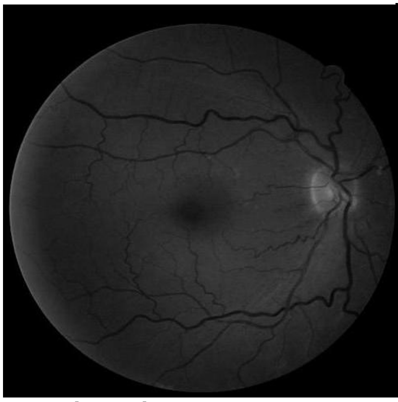
Figure4d: Vessel Detection

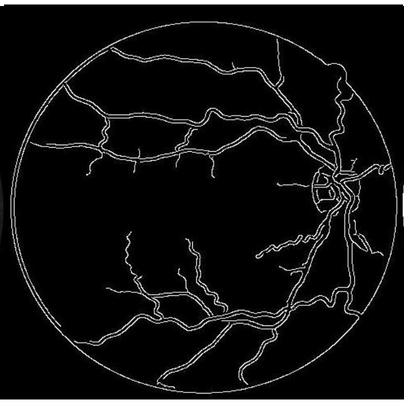
Figure4e: Canny image

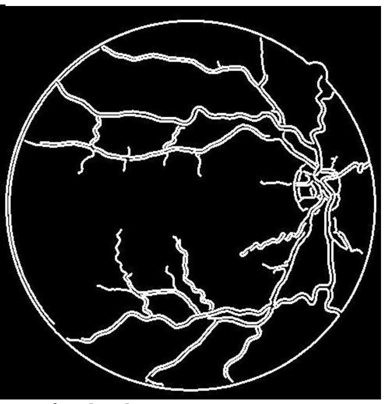
Figure4f: Dilated image

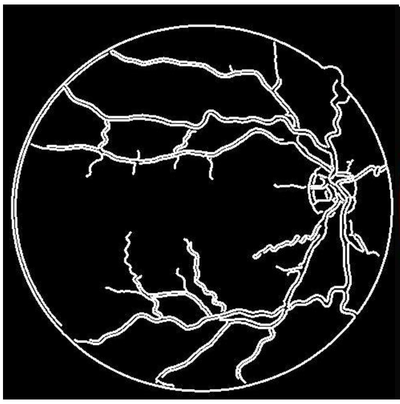
Figure4g: Approximate

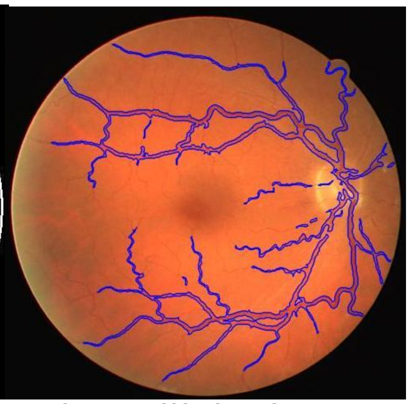
Figure4h: Extracted blood vessels

Table II shows the readings of different performance evaluation parameters obtained from the evaluation of retinal image *22_training.tif*.

Table II. Readings obtained after segmenting the retinal image *22_training.tif*

Parameters	**Readings**
Sensitivity	0.0551
Specificity	0.9690
Accuracy	0.9147
PPV	0.1009
NPV	0.9420
FNR	0.9449
FPR	0.0310
FDR	0.8991
FOR	0.0580
F1 Score	0.0713
MCC	0.0322

Figure5 shows the graphical representation of the obtained readings in Table II of different performance evaluation parameters for image *22_training.tif*.

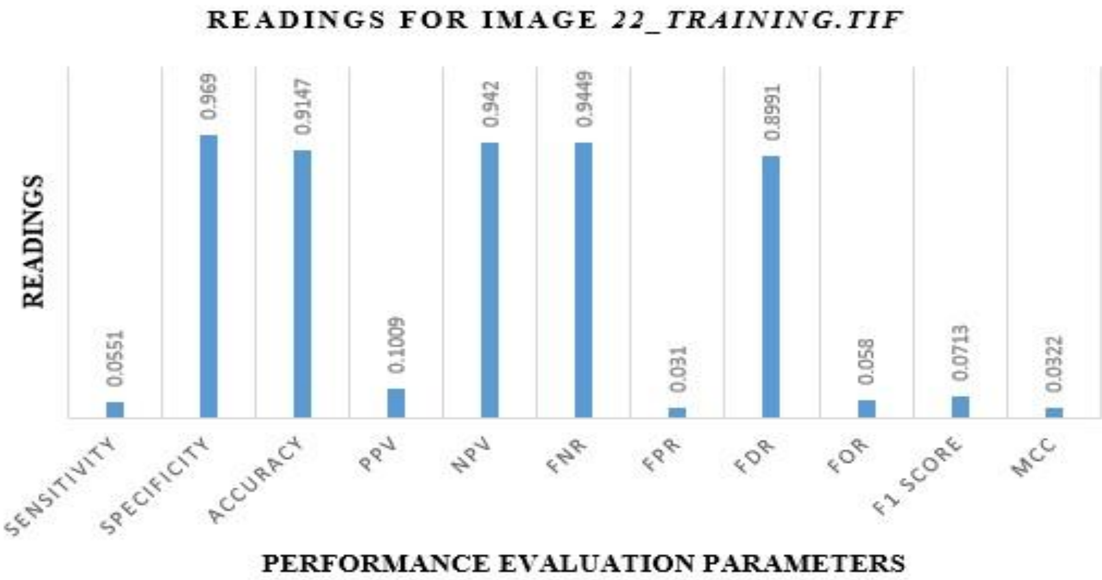

Figure5: Graphical representation for readings obtained in Table II

Instance 3 *– 23_training.tif*

Figure6a depicts the image *23_training.tif* from the DRIVE dataset given as input to the proposed model. Figure6b shows the grayscale conversion of the input image. The grayscale image is further converted using Green Channel Complement as shown in Figure6c. Thereafter, the blood vessels are detected as shown in Figure6d. Figure6e shows the Canny image and Figure6f shows the Dilated image of the detected blood vessels. Figure6g shows the blood vessels after the removal of the boundaries of the retina. Finally, Figure6h shows the extracted blood vessels on the input image.

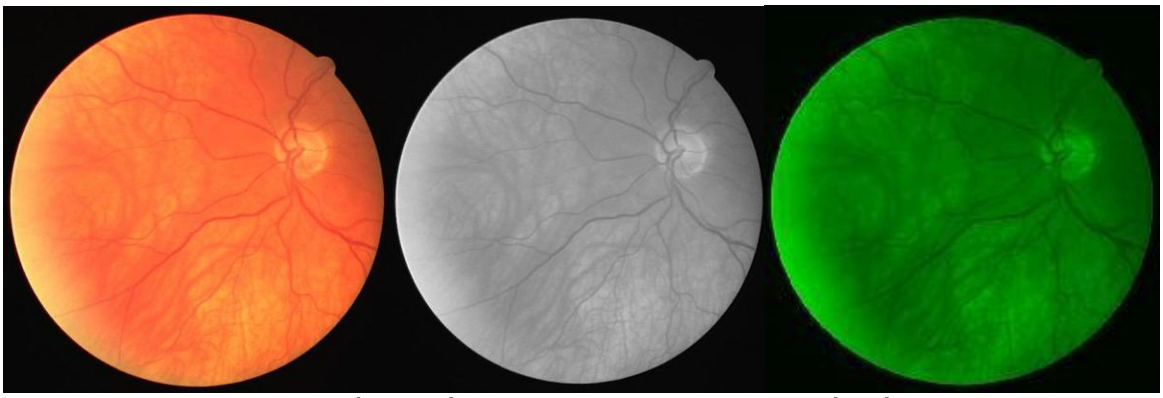

Figure6a: Input image Figure6b: Grayscale image Figure6c: Green Channel image

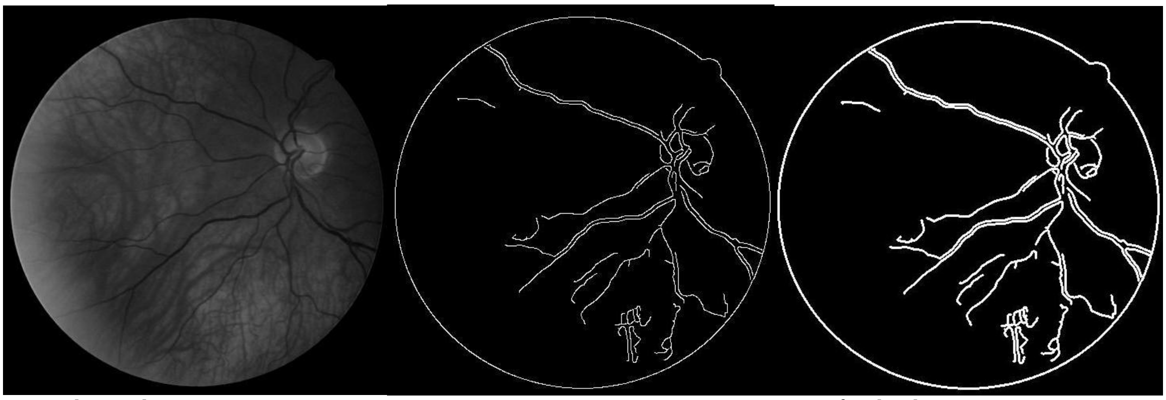

Figure6d: Vessel Detection Figure6e: Canny image Figure6f: Dilated image

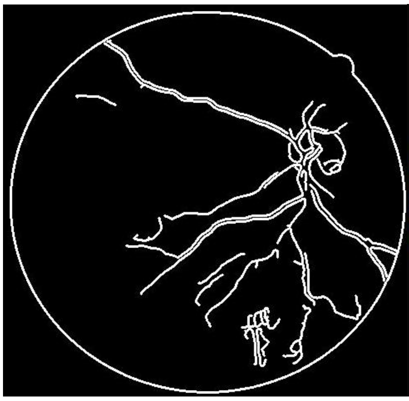

Figure6g: Approximate

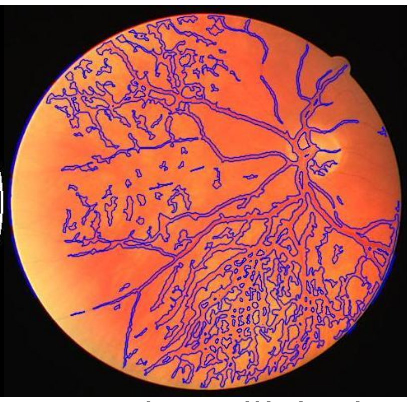

Figure6h: Extracted blood vessels

Table III shows the readings of different performance evaluation parameters obtained from the evaluation of retinal image *23_training.tif*.

Table III. Readings obtained after segmenting the retinal image *23_training.tif*

Parameters	Readings
Sensitivity	0.1796
Specificity	0.7491
Accuracy	0.7153
PPV	0.0432
NPV	0.9353
FNR	0.8204
FPR	0.2509
FDR	0.9568
FOR	0.0647
F1 Score	0.0697
MCC	0.0391

Figure7 shows the graphical representation of the obtained readings in Table III of different performance evaluation parameters for image *23_training.tif*.

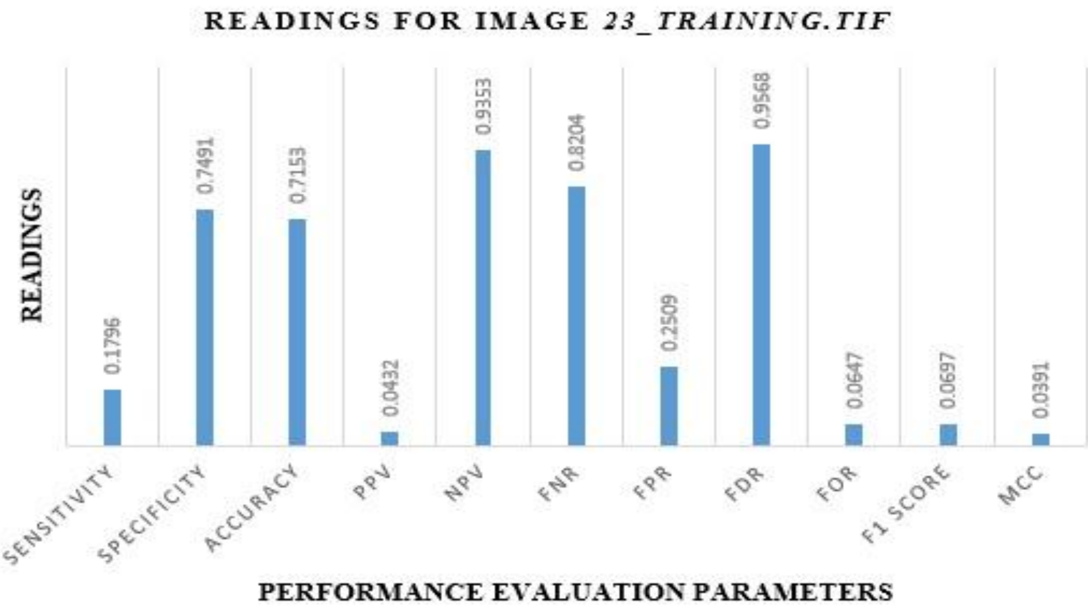

Figure7: Graphical representation for readings obtained in Table III

The results for different retinal images from the DRIVE dataset have been depicted in Table IV below.

Table IV. Readings of performance evaluation parameters of retinal images from the DRIVE dataset

Parameters	26_training	27_training	28_training	29_training	30_training	31_training	32_training
Sensitivity	0.0762	0.0591	0.0654	0.0655	0.0717	0.0574	0.0626
Specificity	0.9505	0.9564	0.9803	0.9357	0.9410	0.9431	0.9880
Accuracy	0.8986	0.9031	0.9260	0.8840	0.8894	0.8905	0.9331
PPV	0.0886	0.0788	0.1732	.0604	0.0713	0.0599	0.2481
NPV	0.9422	0.9415	0.9432	0.9407	0.9414	0.9406	0.9435
FNR	0.9238	0.9409	0.9346	0.9345	0.9283	0.9426	0.9374
FPR	0.0495	0.0436	0.0197	0.0643	0.0590	0.0569	0.0120
FDR	0.9114	0.9212	0.8268	0.9396	0.9287	0.9401	0.7519
FOR	0.0578	0.0585	0.0568	0.0593	0.0586	0.0594	0.0565
F1 Score	0.0819	0.0675	0.0950	0.0628	0.0715	0.0586	0.0999
MCC	0.0286	0.0177	0.0729	0.0011	0.0127	0.0005	0.0985

Figure 8 shows the graphical representation of readings of different performance evaluation parameters for multiple retinal images acquired from the DRIVE dataset.

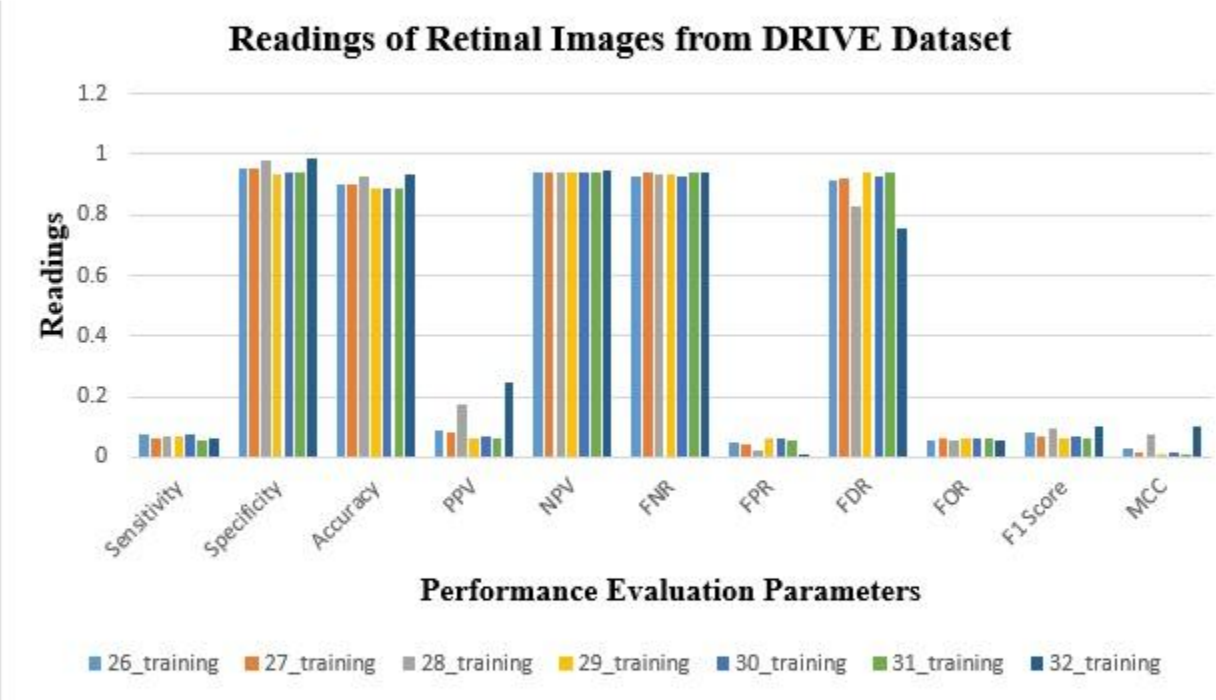

Figure 8: Graphical representation of performance evaluation parameters for retinal images from the DRIVE dataset

IV. CONCLUSION AND FUTURE SCOPE

The conducted research work is an effort to accommodate the need for fast and reliable segmentation of retinal images. The automatic analysis of retinal images has turned out to be constructive assistance in routine eye care. The performed research work proposed a technique for conducting the segmentation of retinal images obtained from the DRIVEdataset. Section III provides a detailed flowchart and algorithm depicting the methodology adopted for performing the segmentation of the retinal images. Section IV shows the different phases of implementation of three instances of retinal images from the DRIVE dataset. The readings of multiple performance evaluation parameters in different Tables in the research paper show the effectiveness of the proposed method.

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