International Journal on Future Revolution in Computer Science & Communication Engineering ISSN: 2454-4248
Volume: 4 Issue: 3 421 – 428

Robust Retinal Vessel Segmentation using ELM and SVM Classifier

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Abstract—The diagnosis of retinal blood vessels is of much clinical importance, as they are generally examined to evaluate and monitor both the ophthalmological diseases and the non-retinal diseases. The vascular nature of retinal is very complex and the manual segmentation process is tedious. It requires more time and skill. In this paper, a novel supervised approach using Extreme Learning Machine (ELM) classifier and Support Vector Machine (SVM) classifier is proposed to segment the retinal blood vessel. This approach calculates 7-D feature vector comprises of green channel intensity, Median-Local Binary Pattern (M-LBP), Stroke Width Transform (SWT) response, Weber's Local Descriptor (WLD) measure, Frangi's vesselness measure, Laplacian Of Gaussian (LOG) filter response and morphological bottom-hat transform. This 7-D vector is given as input to the ELM classifier to classify each pixel as vessel or non-vessel. The primary vessel map from the ELM classifier is combined with the ridges detected from the enhanced bottom-hat transformed image. Then the high-level features computed from the combined image are used for final classification using SVM. The performance of this technique was evaluated on the publically available databases like DRIVE, STARE and CHASE-DB1. The result demonstrates that the proposed approach is very fast and achieves high accuracy about 96.1% , 94.4% and 94.5% for DRIVE, STARE and CHASE-DB1 respectively.

Keywords: *Retinal vessel segmentation, Stroke width transform, Frangi's vesselness, Bottom-Hat Transform, Local Binary Pattern, Weber's Local Descriptor, ELM classifier.*

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I. INTRODUCTION

The segmentation of retinal vessels plays a vital role in the diagnosis of many diseases including the non-ophthalmic diseases. Due to the similar nature of the vasculature of both the brain and the retina, retinal vasculature analysis can also be used to diagnose cardiovascular disease and stroke [1] Apart from medical imaging applications, the vasculatures in retinal images may be related to biometric applications. The retinal vasculature can be manually segmented using the existing image tools. But the manual segmentation task is very tedious, time-consuming job and also the accuracy of the result is highly dependent on the physician's proficiency. So, many automatic methods have been evolved for retinal vessel segmentation to reduce the dependency of the manual intervention and diminish error factors. In this paper, a novel method using the combination of ELM classifier and SVM classifier is proposed to segment the retinal vasculature. Considering that the green channel of the retinal image possesses a high contrast between the vessels and the background [2], the green channel is used as an input for the proposed segmentation method. The proposed method needs a pre-processing step to highlight the vessel information in the green channel image. The ELM classifier utilizes 7-D feature vector extracted from the pre-processed image to classify each pixel in the fundus image as a vessel or non-vessel. The learning speed of ELM classifier is faster when compared to the traditional feed-forward Neural Network (NN) algorithm [3]. The ridges are calculated from the enhanced bottom-hat transformed image and are combined with the ELM vessel map. The final segmented image is obtained by classifying the combined image using SVM classifier. The 4-D feature vector comprises of the high-level features such as solidity, extent, eccentricity and form-factor. The high-level features are extracted from the regions in the combined image and are used as input for the SVM classifier.

Organization of the paper is as follows: Section 2 discusses some of the related work on retinal vessel segmentation. The materials used in this work are described in section 3. The methodology and implementation of the proposed system are explained in section 4. The performance metrics and the robustness of the proposed algorithm along with the experimental setup are presented in section 5. At last, the conclusion and future directions are explicated in section 6.

II. RELATED WORKS

In recent years, many retinal vessel segmentation algorithms have been deployed which can be approximately categorized into five classes. They are machine-learning techniques, model-based, tracking-based, matched-filtering and multi-scale techniques. The machine learning techniques are further classified into supervised and unsupervised classification. Some of the latest articles which use machine learning techniques to extract the retinal vasculature are discussed below.

Shahab Aslani et al. [4] proposed a Random Forest (RF) classifier based retinal vasculature segmentation method. The method generates 17-D feature vector comprises of Gabor filter responses (13D), contrast-enhanced intensity(1D), Frangi's vesselness measure(1D), B-COSFIRE(Bar selective-Combination Of Shifted Filter REsponses) filter response(1D) and morphological top-hat transformed intensity(1D) and this hybrid feature vector is used to train the RF classifier. The author uses multi-scale Gabor wavelet transform to produce the 13 Gabor features. The Gabor filter responses for 18 different configurations are generated and which results in 54-dimensional feature vector comprises of real, imaginary and magnitude part. Out of this 54-D feature vector , a subset of 13 most discriminative Gabor features are selected by using feature selection algorithm as described in [5] and are used for further classification. Since the traditional B-COSFIRE filter gives a low response at the vessel endings, the author uses a new enhanced B-COSFIRE filter to circumvent this drawback and

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efficiently detect vessel endings. A vessel probability map is generated from the trained RF classifier and as a final step, a simple threshold value is applied over the probability map to classify a pixel as a vessel or non-vessel. To measure the robustness of the method, the author also performs the cross-training method using DRIVE and STARE datasets. The performance of the method on 10 pathological images in STARE is better than the other existing methods.

A new retinal vessel extraction technique based on the relation of neighbour pixels has been proposed by Yuji Hatanaka et al [5]. The author uses 105 mask patterns to calculate the shift-invariant High-Order Local Auto-Correlation (HLAC) features for each pixel. Along with this 105 feature values, maximum value, minimum value, mean and standard deviation of the pixel values in the Region Of Interest (ROI) are given as input to the first Artificial Neural Network layer (ANN). The ANN-1 is a three-layered feed-forward network with twelve neurons in the middle layer and only 10,000 randomly selected pixel samples from the 20 images are used for the training. To improve the performance, the author uses one more ANN (ANN2) to classify the pixel as a vessel or non-vessel pixel. The 5-D feature vector comprises of output from ANN1, Gabor filter response, Double-Ring filter response Black-Top-hat transform value and Green channel intensity. This 5-D feature vector is given as input to the five middle layered ANN2. The HLAC-based algorithm results in better performance while extracting blood vessels with low contrast.

Zhaohui Tang et al [7] proposed a retinal vessel segmentation method using a new feature named Influence Degree of Average Intensity (IDAI). The method includes three stages. The first stage is the candidate regions detection to rule out the false detection of optical interferences and lesions. In the next stage, a new feature IDAI is extracted based on the idea that the vessel pixel will decrease the average intensity of the local region whereas the non-vessel pixel will increase the average intensity of the local region. In the last stage, supervised classification using Support Vector Machine (SVM) classifier is performed to extract the vessel pixels. The author selects SVM as the appropriate classifier by evaluating the performance of different classifiers like SVM, AdaBoost, K-Nearest Neighbours (KNN) and Neural Network over STARE database. Here, the candidate vessel like region detection using Hessian values insures a pretty high true positive rate. The newly included IADI feature can easily differentiate the vessel pixel from their neighbourhood background pixels. So, the segmentation results are not only with a high sensitivity but also with a high specificity.

Eva Tuba et al [8] proposed an overlapping-block-based algorithm to extract the retinal vasculature by using SVM classifier. In this algorithm, the input image is divided into blocks and features which are extracted from each block are used to construct the input feature vector for the classifier. The 4-D input vector contains green channel intensity value of the centre pixel, the average green intensity value of the block, the standard deviation of the green intensity value of the block and the feature based on Discrete Cosine Transform (DCT) coefficients. For the SVM, Radial Basis Function (RBF) is used as kernel function and the parameters are tuned and set by using hierarchical grid search method. The method provides better accuracy when compared to the existing local entropy thresholding based approach [9] and region growing based approach [10].

A retinal vessel extraction method using deep convolution network has been proposed by Juan Mo et al [11] by leveraging multilevel hierarchical features. To overcome the problem of gradient vanishing in back propagation and improve the discriminative capability of features in lower layers of the deep network, an auxiliary deep supervision mechanism is incorporated in some of the intermediate layers. The author uses pre-trained filters in VGGNet to initialize the parameters of convolution layers [12]. The author proposed a network comprising a single stream deep network with the multiple branch outputs which have different receptive fields. The predicted vessel segmentation map can be obtained by fusing the multi-scale segmentation map output from each branch. The final segmentation result is obtained by applying the thresholding scheme over the probability map.

III. Materials

Similar to the existing retinal vessel segmentation algorithms, the proposed technique is evaluated on publically available databases, namely, DRIVE database, STARE database and the CHSE-DB1 database.

A. *DRIVE Database*

The retinal images of the DRIVE (Digital Retinal Images for Vessel Extraction) database were obtained from a diabetic retinopathy screening program in the Netherlands [12]. Out of the 400 diabetic subjects between the age of 25 and 90, 40 photographs have been randomly selected and JPEG compressed to create the DRIVE database. The 7 images in the database show the sign of mild diabetic retinopathy whereas the remaining images are normal. The photos were captured using Canon CR5 camera with 45-degrees Field-Of-View (FOV) and digitized using 8 bits per color plane at 768 by 584 pixels resolution. The dataset has been divided into two sets, namely, the training set and test set with 20 images in each set. Two manual segmentations of the retinal vasculature are available for the images in the test set, whereas, a single manual segmentation result is available for the images in the training set. The DRIVE database can be downloaded at http://www.isi.uu.nl/Research/Databases/DRIVE/.

B. *STARE Database*

The STARE (Structured Analysis of the Retina) database contains two different set of retinal images and out of which the second set has 20 retinal images with a reference indicating the retinal vasculature. The first set has 81 images with a reference indication the optic disk location. The images were captured by a TopCon TRV-50 fundus camera at 35-degrees FOV. The slides were digitized using 8 bits per color channel at 605×700 pixels resolution. The database is available online at http://cecas.clemson.edu/~ahoover/stare/.

C. *CHASE-DB1 Database*

The CHASE_DB1 is a retinal vessel reference database comprises 28 images acquired from 14 multi-ethnic school children in the program Child Heart And Health Study in England. The database is available online at https://staffnet.kingston.ac.uk/~ku15565/CHASE_DB1/assets/CHASE DB1.zip. The images were captured using a hand-held Nidek NM-200-D fundus camera at 30-degrees FOV with the resolution of 1280×960 pixels. The database also contains manual segmentations done by two independent observers.

IV. Methodology

A new supervised approach for blood vessel detection based on ELM and SVM classifier has been proposed in this paper. This work comprises of the following stages.1)pre-processing 2) Feature Extraction 3) Primary vessel map generation using ELM classifier 4) ridge detection 5) SVM classification to obtain a final segmented image. Since the green channel image provides a higher contrast between the vessel and the image background, it is used as the input image for the proposed approach. The block diagram of the proposed work is shown in Figure 1.

The 7-D feature vector is constructed from the features extracted from the green channel image. The feature vector is given as input to the trained ELM classifier and the output of the ELM classifier is considered as the primary vessel map. The image generated from the bottom-hat filter is enhanced and is used for the ridge detection. The detected ridges are combined with the primary vessel map generated from the ELM classifier and are further classified using SVM classifier to obtain the final segmented image. The high-level features extracted from the combined image are used for SVM classification. The following sections explain about the each stage in detail.

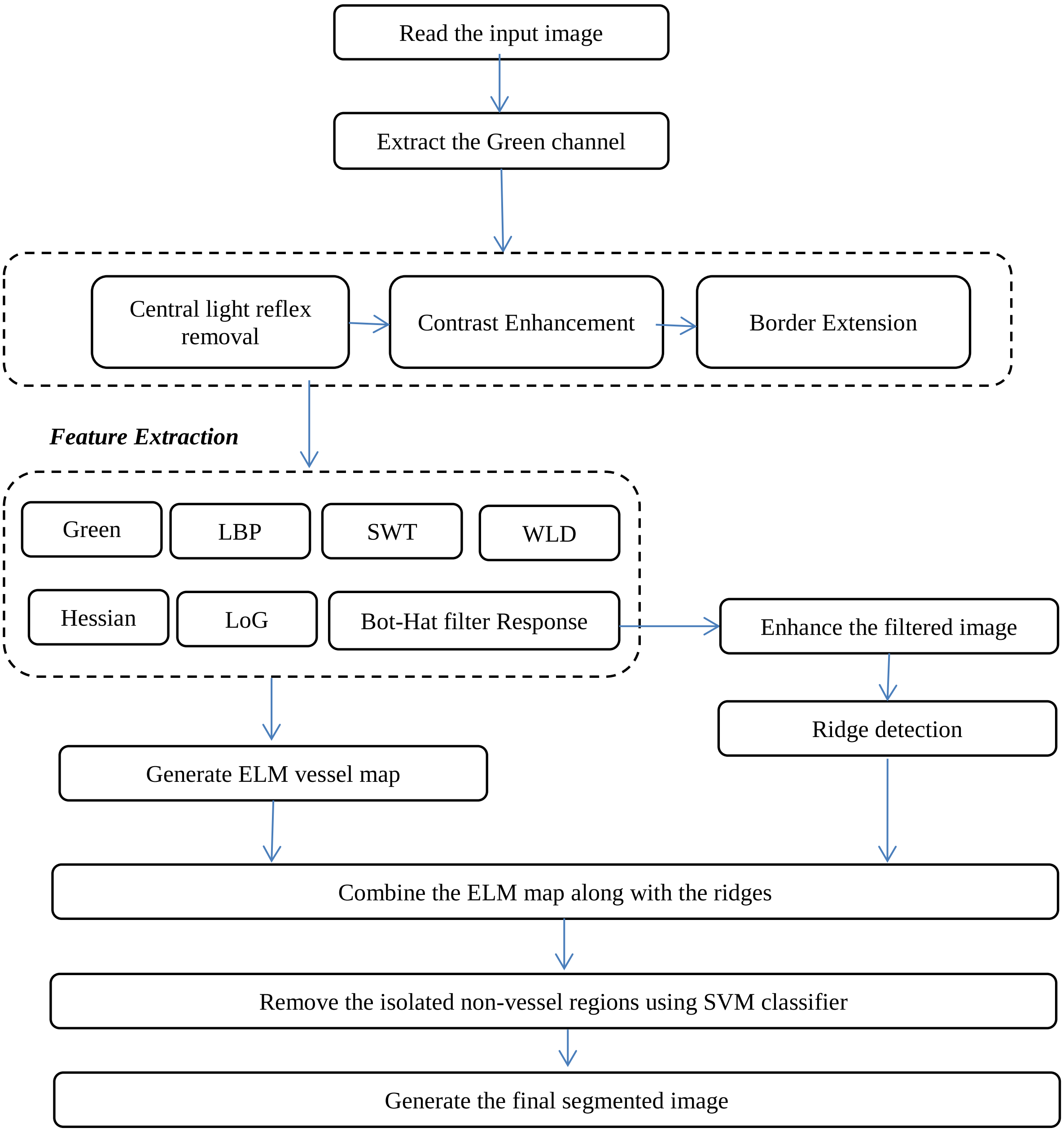

Figure 1. Block diagram of the proposed approach

A. *Pre-Processing*

Colour retinal images often contain artifacts like lightning variations, poor contrast and noise. A pre-processing method comprising the following steps is used to reduce the imperfections and generate the image more suitable for extracting the pixel features.

- *Central light reflex removal*

Since the green channel of the input image shows the highest contrast between the vessel pixels and the background, the green layer is isolated from the input color image and is used for further processing. Although the retinal vessels appear darker when compared to other retinal surfaces, a vessel with a light streak which runs down the central length (central light reflex) may be

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misunderstood as two vessels. To remove the light streak, a morphological opening using three- pixel diameter, disc defined in eight connectivity square grid as structuring element is performed. An example of a vessel with central light reflex and its removal is shown in Fig. 2. To avoid the over-amplification of noise and uniformly distributes the grey-level values, contrast limited adaptive histogram equalization (CLAHE) algorithm is applied over the central light reflex removal image.

(a)

(b)

Figure 2. Central light reflex removal (a) Fragment of an input image containing central light reflex. (b)After reflex removal.

- *Border Extension*

The border extension technique proposed by George Azzopardi et al., [14] is used to remove the artifacts produced near the border of the camera aperture. Initially, every black pixel which lies just on the exterior boundary of the FOV-mask is identified. For each black pixel, the mean value of the eight neighbours inside the ROI is calculated and the pixel values are replaced with this average value. So, this initial iteration increases the radius of ROI by one. This iteration is repeated for 50 times and the radius of ROI is incremented by 50.

B. *Feature Extraction*

The main aim of the feature extraction phase is to extract some quantifiable measurements from the input image which may be easily used in the classification stage to determine whether the pixels belong to the blood vessel or not. The 7-D feature vector comprises of green channel intensity, Median-Local Binary Pattern (M-LBP), Stroke Width Transform (SWT) response, Weber's Local Descriptor (WLD) measure, Frangi's vesselness measure, Laplacian Of Gaussian (LOG) filter response and morphological Bottom-hat transform and it is used for classification. All the feature values other than the green channel intensity are calculated from the preprocessed image.

- *Features*
  - *Green Channel Intensity*

The green channel image extracted from the colored input image provides better vessel-background contrast. So, the green channel intensity of the pixel is considered as one of the features and is included in the feature vector.

  - *Stroke Width Transform (SWT)*

SWT is a local descriptor that computes per pixel the width of the most likely stroke-like structure containing the pixel [15]. The size of the SWT image is same as the input image and each pixel contains the width of the stroke associated with the corresponding input pixel. First, the edge of the input image is computed using the canny edge detection method. Then, for each edge pixel p, a ray along its gradient direction is detected until it reaches another edge pixel q .The length of the ray k i.e. k = |p-q| is assigned as stroke width value to all the pixels which lie between p and q. If several rays intersect at a pixel, then the smaller value among the stroke width values will be assigned to that pixel. The SWT captures the line-like structures to some extent and hence considered for the classification.

- *Weber's Local Descriptors (WLD)*

WLD is a simple and robust local descriptor based on the Weber's law [16]. In this proposed work, the differential excitation component in the WLD is used as a feature. The differential excitation component D_x for a pixel x is calculated using 3x3 neighborhood pixels as follows:

$$D_x = arctan\left(\sum_{m\in N(x)}\frac{I(m)-I(x)}{I(x)}\right) \quad (1)$$

where I is the input image, N(x) is the set of neighborhood pixels.

- *Local Binary Pattern (LBP)*

The LBP is a rotation and gradient invariant measure used for classification in many diverse applications. Instead of the classical LBP, the LBP_{med} is used in this work to segment the blood vessel. LBP_{med} is less sensitive to noise when compared to the classical measure[17].The central pixel value is replaced with the median of itself and the neighbors. LBP_{med} for a central pixel (Pc) is calculated as follows :

$$LBP_{med}(P_c)=\sum_{h=0}^{8} s(g_h-\tilde{g})\,2^h \quad (2)$$

Where $\tilde{g}$ represents the median of the neighbours and the central pixel, g_h is the value of the neighbor pixel and the comparison function s(z) is given as follows:

$$s(z)=\begin{cases}1 & if\ \ z\geq 0\\ 0 & otherwise\end{cases} \quad (3)$$

The LBP_{med} operator assigns a label to every pixel of an image by thresholding the 3*3 neighborhood of each pixel with the median value and the result is considered as a binary number.

- *Hessian vesselness measure*

The Hessian-based vessel enhancement filters use the eigen values from the Hessian matrix to determine the geometrical structures which are tubular in nature [18]. The eigen vectors and the eigen values of Hessian matrix are closely related to the vascular direction and intensity. The vesselness function $v_0(\sigma)$ can be defined as follows [19]:

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$$v_0(\sigma) = \begin{cases} 0, & if\ \lambda_2 > 0 \\ exp\left(-\frac{R_B^{\,2}}{2\beta^2}\right) \times \left(1 - exp\left(-\frac{S^2}{2\gamma^2}\right)\right), & otherwise \end{cases} \quad (4)$$

In this work, the threshold factors β and ϒ are chosen as 0.5 and 20 respectively. The parameters R_B and S in the vesselness equation are calculated using eigen values λ_1, λ_2 of Hessian matrix as follows

$$R_B = \frac{|\lambda_1|}{|\lambda_2|}$$

$$S = \sqrt{\lambda_1^{\,2} + \lambda_2^{\,2}} \quad (5)$$

The filter is applied at multiple scales varying from 1 to 10, and the maximum response is selected to be a final estimate of vesselness and included in the feature vector.

- *Bottom-Hat Transform*

Bottom hat transformation very well enhances the retinal blood vessels and so included in the feature vector and considered for classification. The bottom hat transform ( ) is applid over the preprocessed image and is calculated as follows:

$$T_b(g) = g \otimes b - g \quad (6)$$

where g is the preprocessed image, b is the structuring element, ⊗ is a morphological closing operation. The morphological operation is performed using a three-pixel diameter disc as structuring element.

- *Laplacian Of Gaussian(LoG)*

The Laplacian of an image is often used for edge detection since it highlights the rapid intensity change and it gives a better result if it is applied over the smoothed image. Mostly, the Laplacian is applied to an image which has been previously smoothed with the Gaussian filter in order to reduce its sensitivity to noise. The output image is obtained by convolving the filtered image with an input image and it can be expressed as follows:

$$O(x,y) = L(x,y) * I(x,y) \quad (7)$$

$$L(x,y) = \left(\frac{x^2 + y^2 - \sigma^2}{\sigma^4}\right) exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (8)$$

where $O(x,y)$, $L(x,y)$, σ(scaling factor) and $I(x,y)$ are the output image, Log filter image, standard deviation, and the input image respectively. The preprocessed image is convolved with LoG filters that vary in the value of their scale parameter σ i.e. from 0.2 to 0.8 and retain the maximum response at every pixel as a feature value.

C. *Extreme Learning Machine classifier*

Extreme learning machine is a simple machine learning algorithm for Single Hidden Layer Feed Forward Neural Networks (SFLNs) [20] which randomly select the input weights and analytically determines the output weights. Though it was initially proposed for SLFNs, it was then enhanced to the generalized SLFNs.In ELM, the hidden node parameters are completely independent from the training data. There is no need to spend much time in tuning and training learning machines except the predefined network architecture. The learning speed of the ELM is much faster when compared with the other conventional methods. In the existing gradient-based techniques, the issues like over-fitting and local-minima are needed to be resolved by using weight decay or early stopping techniques. But, in the ELM, the input-hidden weights are randomly assigned and the hidden-out weights are calculated by least square regression or ridge regression. ELM contains an input layer, hidden layer and an output layer. The structure of the ELM with 'N' input nodes and 'P' hidden nodes is shown in Figure 3. The ELM algorithm works as follows:

Given an input of training set of 'N' samples, activation function g(x) and the number of hidden neurons 'P'.

- Assign a random value to the input weight vectors a_i and hidden node impact factor b_j where i = 1...N and j = 1..P.
- Calculate the hidden layer output matrix

$$H = \begin{bmatrix} g(a_1, b_1, x_1) & \dots & g(a_p, b_p, x_1) \\ \vdots & \dots & \vdots \\ g(a_1, b_1, x_N) & \dots & g(a_p, b_p, x_N) \end{bmatrix}_{NXP}$$

- Calculate the output weight β using $\beta = H^+T$ where H^+ is the Moore-Penrose generalised inverse of H and T is the output of the training sample.

The ELM gives a result with a minimum training error and the best generalization performance. The minimum norm least-square solution of $H\beta = T$ is also unique.

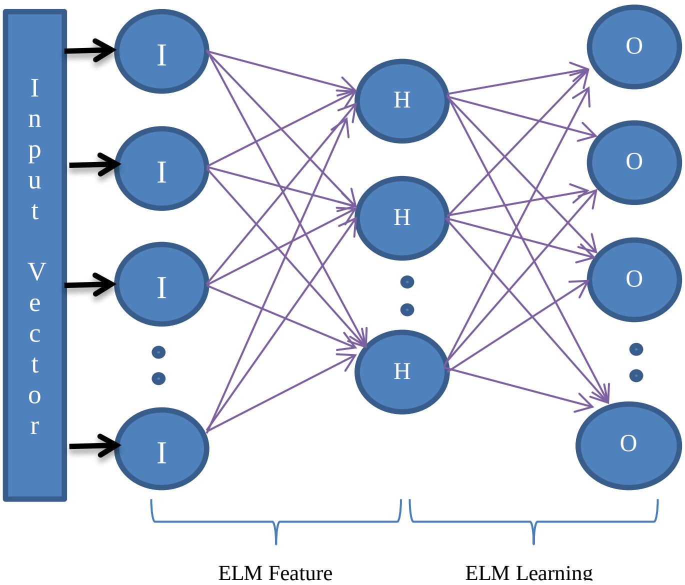


Figure 3. Structure Of the ELM

D. *Classification using ELM*

The ELM classifier is trained with different configurations and the model which gives better accuracy is used for classification. Some commonly used activation functions in ELM model are sigmoidal, fourier, hard-limit, wavelet, Gaussian function etc. In the proposed work the ELM model with 930 hidden neurons and the sigmoidal activation function is used for classification. In the training phase, it is found that the model with 930 hidden neurons using sigmoidal activation function performs well and produces results with a high accuracy. The performance comparison between ELM models with different activation function is shown in Figure 4.

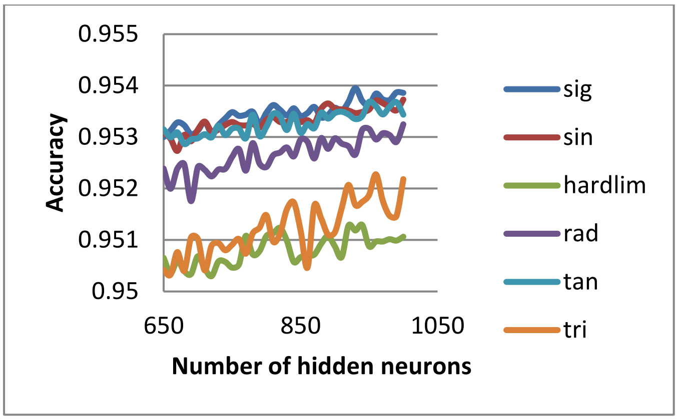


Figure 4. Performance comparison – ELM model with different configuration sig-sigmoidal, sin-sinusoidal ,hardlim-hard-limit, rad – radial basis, tan – hyperbolic tangent, tri-triangular

The classification time for ELM with a different configuration is given in Figure. 5.It is found that the processing time for ELM model with triangular activation function is low when compared to the other functions. So, an analysis has been made to check whether the ELM model with more number of neurons using triangular function produces a better result with less processing time. But, there is no significant improvement in performance even by increasing the number of neurons up to 1500.So, the model with sigmoidal function is finalized for classification. The classification result obtained from the ELM classifier is considered as the primary vessel map.

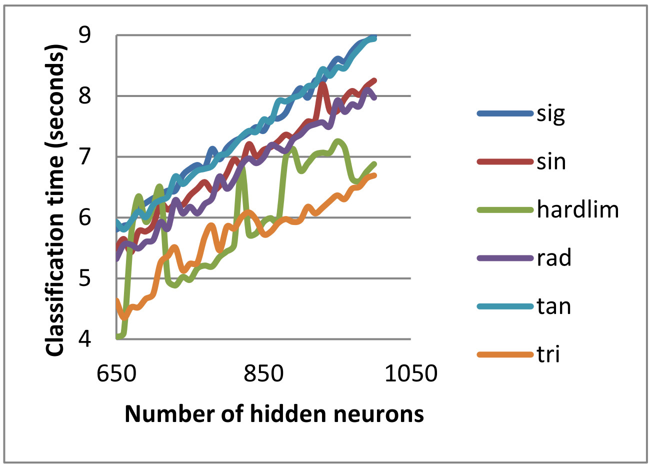
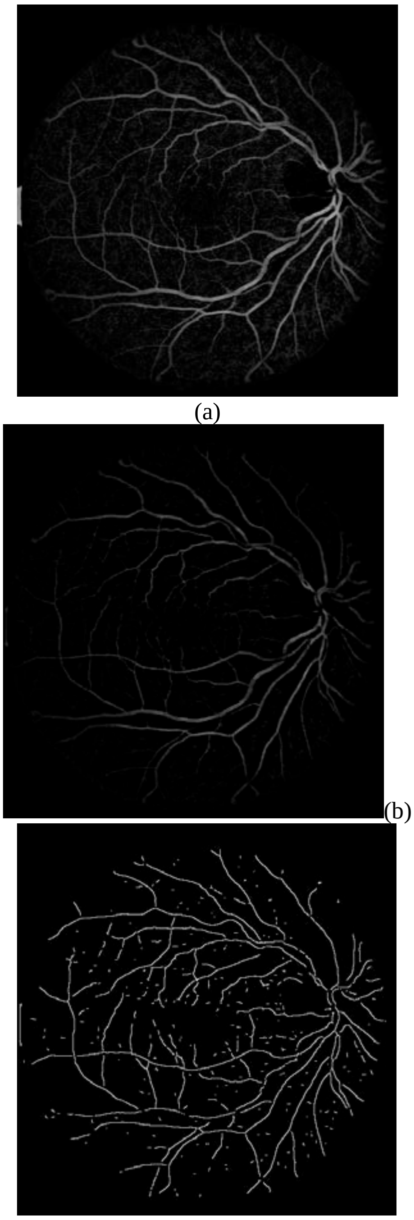


Figure.5. Processing time for ELM model with different configuration. (sig-sigmoidal, sin-sinusoidal ,hardlim-hard-limit, rad – radial basis, tan – hyperbolic tangent, tri-triangular)

E. Ridge Detection and SVM Classifier



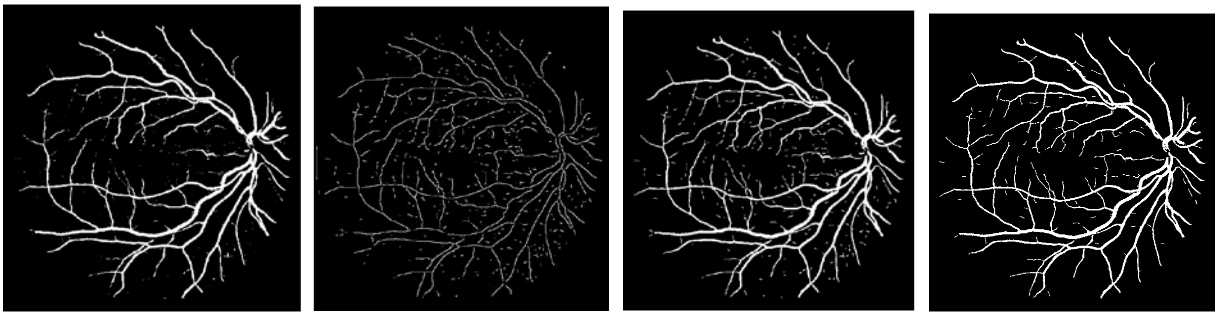
(c)

Figure 6. Ridge Detection (a)Bottom-Hat filtered image. (b)Enhanced Bottom-Hat image (c)Ridge image

Though the ELM classifier results with better performance, it fails to detect the thin vessels. So, in order to cover the thin vessels, the ridges detected from the enhanced bottom-hat filtered image are combined with the primary vessel map. The background lightening variation in the bottom-hat filtered image is removed by subtracting the background image from itself. The background image is generated by applying mean filter over the bottom-hat filtered image. In this proposed work, the mean filter of size 45 * 45 is used to generate the background image. The ridge image for a sample image is shown in Figure 6.

The primary vessel map generated by the ELM classifier and the ridge detected image is combined and is further classified with the SVM classifier to produce the final segmented image.

The high-level features namely, solidity, eccentricity, form factor and extent are extracted from the regions in the combined image and given as input to the SVM classifier. The SVM classifier with radial basis function (RBF) kernel with sigma value as 1.0 is used in this proposed work for final classification. The form-factor and eccentricity measure shows how nearly the region is circular. The measure extent tells how the shape is close to the rectangle. The solidity measure tells how the shape is concave and convex. The output generated by the SVM classifier is the final segmented image and the performance measure is calculated for that image. The final segmented image for a sample image is given in Figure 7.



(a) (b) (c) (d)

Figure 7 Final classification (a)ELM primary vessel map (b)Ridge image (c) Combined image (d)Final segmented image

V. EXPERIMENT AND RESULT

The proposed approach is implemented in Matlab 2015 on a PC with 360 GHz Intel Core i7 processor system and 20 GB RAM. The *ridgedetection* plugin in *ImageJ 1.5* software tool is used to detect the ridges in the enhanced bottom-hat filtered image. The performance of the proposed method is qualified by comparing the results with the manually segmented results available for DRIVE, STARE and CHASE-DB1. The performance is evaluated on the basis of sensitivity, accuracy, specificity and Area Under the Curve (AUC).The average value of performance metrics is given in Table 1. The performance result for each image in DRIVE and STARE databases are shown in Table 3 and Table 4 respectively.

TABLE I. PERFORMANCE MEASURES FOR DRIVE, STARE AND CHASE-DB1

Measure	DRIVE	STARE	CHASE-DB1
Accuracy	0.9615	0.9444	0.9450
Sensitivity	0.7120	0.6392	0.6060
Specificity	0.9857	0.9827	0.9706
AUC	0.8488	0.811	0.7883

Though the final segmented image includes most of the major and thin vessels, the sensitivity of the resultant image is low due to the presence of false positives. The future work will be carried out including a postprocessing stage to remove the false positives and hence improve the performance in terms of sensitivity. The proposed algorithm is very fast and the average processing time for the databases is given in Table 2.

VI. CONCLUSION AND FUTURE WORK

In this proposed work, the retinal vasculature is extracted by using the combination of ELM, ridge detector and the SVM classifier. The ELM classifier uses pixel-wise 7-D feature vector to generate the primary vessel map.

TABLE II. PROCESSING TIME FOR DRIVE, STARE AND CHASE-DB1

Processing Time (seconds)	DRIVE	STARE	CHASE-DB1
Classification Time	16.22566	20.71069	38.8058059
Feature Extraction Time	24.84628	32.28129	67.0208153

Whereas, the SVM classifier uses high-level features to remove the non-vessel regions from the combined image. The pixel-wise features are generated from the well pre-processed image to overcome the problem of homogeneity variations in the input image. The proposed algorithm demonstrates the performance advantage in terms of accuracy. But, some non-vessel structures located near the blood vessels and are connected to the vessel network and hence they are detected as vessel segments. So, especially the pathological images results in low sensitivity. This problem has not been resolved in the proposed work and will be considered as future work by including post-processing step by employing some morphological operations.

TABLE III. PERFORMANCE RESULT ON DRIVE DATABASE

Image No.	Accuracy	Sensitivity	Specificity	AUC
1	0.9654	0.7840	0.9832	0.8836
2	0.9600	0.7212	0.9873	0.8543
3	0.9533	0.6828	0.9833	0.8330
4	0.9621	0.6540	0.9933	0.8237
5	0.9580	0.6518	0.9896	0.8207
6	0.9571	0.6471	0.9905	0.8188
7	0.9562	0.6598	0.9860	0.8229
8	0.9536	0.6687	0.9805	0.8246
9	0.9622	0.6708	0.9879	0.8293
10	0.9622	0.6848	0.9871	0.8360
11	0.9572	0.6924	0.9833	0.8378
12	0.9634	0.7119	0.9871	0.8495
13	0.9550	0.6645	0.9865	0.8255
14	0.9607	0.7607	0.9783	0.8695
15	0.9643	0.7513	0.9808	0.8660
16	0.9638	0.7458	0.9854	0.8656
17	0.9628	0.7025	0.9868	0.8447
18	0.9678	0.7648	0.9853	0.8751
19	0.9750	0.8371	0.9875	0.9123
20	0.9698	0.7840	0.9846	0.8843
Average	**0.9615**	**0.7120**	**0.9857**	**0.8489**

TABLE IV. PERFORMANCE RESULT ON STARE DATABASE

Image No.	Accuracy	Sensitivity	Specificity	AUC
1	0.9346	0.6918	0.9593	0.8256
2	0.9544	0.6900	0.9699	0.8300
3	0.9384	0.7134	0.9521	0.8328
4	0.9440	0.5499	0.9747	0.7623
5	0.9366	0.6586	0.9693	0.8140
6	0.9406	0.6429	0.9790	0.8110
7	0.9467	0.6837	0.9860	0.8349
8	0.9379	0.6144	0.9895	0.8019
9	0.9471	0.6771	0.9848	0.8309
10	0.9178	0.5624	0.9819	0.7721
11	0.9510	0.6642	0.9880	0.8261
12	0.9609	0.7060	0.9943	0.8501
13	0.9335	0.5833	0.9910	0.7872
14	0.9406	0.6217	0.9894	0.8055
15	0.9492	0.6273	0.9953	0.8113
16	0.9214	0.5324	0.9913	0.7619
17	0.9446	0.6323	0.9917	0.8120
18	0.9749	0.6703	0.9949	0.8326
19	0.9669	0.6563	0.9877	0.8220
20	0.9473	0.6061	0.9851	0.7956
Average	**0.9444**	**0.6392**	**0.9828**	**0.8110**

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