A Composite Feature Set Based Blood Vessel Segmentation in Retinal Images through Supervised Learning

Y. Madhu Sudhana Reddy\textsuperscript{1*}, R. S. Ernest Ravindran\textsuperscript{2}

\textsuperscript{1}Research Scholar Department of Electronics and Communication Engineering, KL Deemed to be University, Vaddeswaram, Guntur, Andhra Pradesh, India

\textsuperscript{2}Assistant Professor Department of Electronics and Communication Engineering, KL Deemed to be University, Vaddeswaram, Guntur, Andhra Pradesh, India

*Corresponding author Email: ymsr1016@gmail.com

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Abstract

Retinal image analysis has gained a significant research interest due to its widespread applicability in the diagnosis of different eye related diseases. This paper focused in the analysis of Diabetic Retinopathy through different features (Optic Disk, Retinal Vessels, and Exudates etc.) of retinal image. Towards this objective, a new Retinal Vessel Segmentation mechanism is introduced in this paper. The proposed mechanism accomplished the Gabor Filter for Feature Extraction and Support Vector Machine Algorithm for classification. Here the Gabor Filter ensures a more resilience to the scaling and orientation issues in the retinal image. Afterwards, a feature set consists of thirteen features is extracted from retinal image to provide a proper differentiation between the image pixels and background pixels. Based on these features, the SVM classifier classifies the vessel pixels and background pixels more effectively which improves the classification accuracy and reduces false positive rate. An extensive simulation carried out over the proposed approach through two standard datasets, DRIVE and STARE reveals the outstanding performance with respect to the performance metrics sensitivity, specificity and accuracy.

Keywords: retinal vessel segmentation, Gabor filter, Support vector machine, Gradient features, Correlation Accuracy.

I. Introduction

In the recent years, an automated retinal image analysis has gained a significant research interest due to its flexibility in various eye related disease analysis. Due to the availability of various and standard image acquisition devices, the retinal image has opened a new direction for the diagnosis of eye related diseases.
Most of the recent studies focused over the association of retinal calibers to diagnose different types of subclinical diseases like endothelial dysfunction, inflammation and atherosclerosis, as well as some cardiovascular diseases like Diabetic Retinopathy (DR), Diabetic Mellitus (DM), and Arterial Hypertension [IX], etc. Due to these significant advantages with retinal image analysis, the recent research focused mostly towards the better analysis of retinal images to get more accurate analytical results in the detection of different diseases. Among various eye related diseases, DR is the most serious disease which has a severe effect on the vision of eye. According to [XV], DR is affecting nearly one of every ten person with diabetes. DR is one of the prominent reason by which there may get vision loss especially for middle-aged people. Hence an early diagnosis is required to prevent the people form the most dangerous eye damages. Basically the DR is listed as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Simply, the PDR is an advanced stage of NPDR in which the new vessels are grown within the eye with abnormal pattern and abnormal sizes. Hence there is a need of early diagnosis to prevent the eyes from permanent vision loss which was the more severe damage at the advanced stage. However due to the increasing population, the manual diagnosis of retina images results in an extra manual effort, which forces to develop an automatic DR screening system based on the retinal image analysis.

Basically the retinal image analysis includes the observation of all possible abnormalities or pathologies in the retinal image. The major aspects which are used for retinal image analysis are optic disk, retinal vasculature, exudates, macula, Micro Aneurysms and Hemorrhages (MAHMs) etc. Among these aspects, retinal vessels are more important and significant which gives more information about the retinal image abnormalities. Figure 1 (a) and 1(b) shows an example of a retinal image and its respective binary vessel map which is manually segmented. Retinal vessels are more important in the diagnosis of DR through retinal images. In addition, retinal vessels also provides an accurate locations of other major retinal structures like macula and optic disk which can provide a sufficient measures for the diagnosis of various ophthalmologic diseases. Hence, retinal vasculature segmentation is more important for the diagnosis of DR.

This paper proposes a novel retinal vessel extraction method based on the Gabor filter and Support Vector Machine classifier. Here the proposed approach accomplishes the Gabor filter to extract the dominant features in all the possible orientation form the retinal images. Further a new subset of features is extracted to provide a perfect discrimination between the thin pixels and background pixels. By classifying the thin pixels form background pixels, almost the entire retinal vascular structure can be segmented which gives a better diagnosis results in the detection of diabetic retinopathy. Support vector machine is trained to classify the pixels based on their features. The proposed approach is tested over two standard datasets such as DRIVE and STARE to check the performance through the metrics like sensitivity, specificity and accuracy.
Rest of the paper is organized as follows; section II describes the details of literature survey. Section III illustrates the complete details of proposed segmentation framework. Section IV illustrates the details of simulation results and finally the conclusions and the possible future directions are given in section V.

Figure 1 (a) An example of retinal fundus image (b) Manually segmented binary Vessel Map

II. Literature Survey

Since the retinal images assure more significant information for the diagnosis of retinal diseases, so many approaches are developed in earlier aiming at different objectives. Depends on the methodology accomplished, the earlier segmentation approaches are classified as machine learning methods and rule based methods. The rule based approaches labels the pixel as vessel or non-vessel based on some predefined strategy but the machine learning approaches labels based on the knowledge. The machine learning approaches are further classified as supervised and unsupervised. In the supervised classification, initially the system will get train about the characteristics of pixels both vessel and non-vessel and then the system applies acquired knowledge to label the pixel in the test image. In the case of unsupervised classification, the pixels are grouped into some clusters based on the similarity deviations.

Generally, blood vessels have less local contrast and the edge orientation algorithms yields non-satisfactory results in the detection. Hence, S. Chaudhuri et al. [XXII] proposed a new method for blood vessel segmentation based on their spatial and optical properties. Further this method used Gaussian shaped curve for the detection of cross section of a retinal vessel. The piece wise linear segments are extracted through the matched filter.

Next, by complimenting the attributes of local vessels with the attributes of region based network structure, a vessel segmentation method is developed by A. Hoover et al. [VI]. The retinal vessel area is extracted by probing the area convolved with matched filter and decreasing the threshold in an iterative fashion. At every iteration, the attributes of that region are compared to the probed region to test whether there are any vessel pixels. Next, a three step process is developed by T. Walter and J.C. Klein [XXVIII] for retinal vessel segmentation based on the mathematical morphology. This process is applied over a low contrast fundus image. Initially the fundus image is preprocessed for contrast enhancement and then subjected to mathematical morphology followed by top-hat transform. Finally a post-processing step is applied to find the complete vascular structure.
Mojon et al. [XXX] developed a retinal vessel segmentation method based on the local thresholding. Initially, the retinal image is divided into sublevels based on the gray-level intensities. Then the candidate vessel images are computed based on the minimum and maximum gray-levels of every sublevel. Finally a binary vessel map is extracted after verifying the obtained candidate vessel images. Further an unsupervised method is developed by Chakraborti et al. [XXV] to obtain a complete retinal vascular tree based on the Orientational histograms. This approach is developed by combining the matched filter with vessleness filter. The further method proposed by Wang et al. [XXXIV] decomposes the image in a hierarchical fashion with the help of multi-wavelet kernels. Before processing the retina image for decomposition, a matched filter is applied at preprocessing phase for enhancement.

Considering the spatial dependency between the neighbor pixels, Xiao et al. [XXXVI] proposed a Bayesian framework based posterior probability retinal vessel segmentation method. This method extracts the energy function of every pixel and used the modified level set method for segmentation. A similar method based on the evaluation of probabilistic tracking was proposed by Yin et al. [XXXV] to segment the vessel structure from retinal image. This method also accomplished the same Bayesian with Maximum a posteriori (MAP) for the detection of edge points of retinal vessels. Gray Level Co-Occurrence Matrix- (GLCM) based energy features are extracted in the method proposed by T. Mapayi et al. [XXVII] for vessel segmentation. Several thresholds are accomplished based on the energy levels obtained after GLCM. Some approaches are applied over the retinal images by extracting the spectral features using the transform techniques like wavelet transform, contourlet transform etc. Fathi et al. [IV] used the Continuous and Complex Wavelet Transform (CCWT) to determine the line structures through decomposition at multiple scales and at multiple directions. After this, a threshold based segmentation algorithm is applied over the histograms connected to the line filter based posterior method. Similar to the above hierarchical decomposition, the method proposed by Waheed et al. [XXXIII] also performs the decomposition but through multi-wavelet kernels and also in an iterative fashion. Further, to extract the retinal vessels with scale and translational invariance, Qian Zhao et al. [XXXII] accomplished the 2D-Gabor wavelet as a feature extractor and used level set with region growing. This approach is applied after enhancing the image with contrast-limited and adaptive histogram-equalization (CLAHE).

Some earlier segmentation methods have utilized the machine learning algorithm for vessel classification. These approaches view the segmentation as a classification problem and they simply classifies the every pixel of retinal image into either vessel or non-vessel. Based on the classification process, they are further divided as supervised and unsupervised. The example algorithms for supervised are Adaboost classifier, Support Vector Machine (SVM) and the examples for unsupervised are Fuzzy C-means Clustering (FCM) K-means clustering etc.

Recently, a new segmentation approach is proposed by N. Memari et al. [XVI] to perform retinal vessel segmentation based on the supervised Adaboost classifier. In this method, the morphological operations and CLAHE [XXVI] are applied to enhance the low contrast fundus image. Next, a retinex method is applied to correct the inhomogeneity and further enhancement is accomplished through
Frangi matched Filter and B-COSFILRE filters [XII]. Further, several statistical measures are applied over the enhanced image pixel-by-pixel and finally the Adaboost classifier is accomplished for classification. A post-processing step is applied at the end to remove the misclassified vessel pixels and also the regions.

S. Thangaraj et al. [XXIV] accomplished neural networks for vessel classification. Initially this method applied several feature extraction techniques like GLCM features (3D), Hu moment invariants (7D), Local Binary Pattern (1D) and Vesselness Filter feature (1D) and formulated a 13D feature vector. Next, the NN is trained with these 13D feature vectors to classify the vessel pixels. Further, the method proposed by Bhuiyan et al. [I] and the method proposed by Kande et al. [XIII] used the unsupervised FCM to extract the retinal vasculature from the retinal image. The former method extracted the texture properties and the later one used Gaussian Based Matched Filter as a feature extraction techniques.

Some other recent methods focused over the retinal vessel segmentation are developed by Oliveira et al. [XXIX], Rani et al. [XIX], and Shah et al. [XXI]. An integrated filter is developed by Oliveira et al. by combining three different filters such as Frangi filter, Gabor wavelet filter and Matched filter. The outputs of these filters are selected based on the weighted mean and median ranking process. Finally an unsupervised algorithm was applied to extract the vessel map. Further, Rani et al. [XIX] accomplished only one filter, i.e., matched filter as a feature extractor and accomplished SVM for classification with tree bagger. Next, the method proposed by Shah et al. [XXI] extracts totally 24 features from the retinal image and used a “linear minimum squared error (LMSE)” classifier to classify background regions form vessels. In the next method proposed by Peter et al. [XVIII] SVM is used to segment the vessels. Training of SVM is performed by using of features that are obtained by feature extraction step. In the feature extraction step, two features are obtained, which are used by SVM to perform classification.

B.D Barkana et al. [VIII] accomplished a detailed performance analysis over the retinal image segmentation by considering different supervised learning techniques like NN, SVN, fuzzy logic and the fusion of classification. For every retinal image, this method computed mean and median in all the four directions such as down-diagonal, Up-diagonal, Vertical and horizontal. Totally eight features are measured, the features F1 -F4 are mean values and F5-F8 are median values. Further a novel three step mechanism is developed by R. Chowdhury et al. [XX] to extract the vessel map from a retinal image. In the first step, this approach extracts the major vessel map by combining the morphological reconstruction and high passes filtering. In the second step, the minor vessels are extracted through GMM algorithm and in the last step, the obtained major and minor vessel maps are combined to get a complete vessel map. Further Liskowski & Krawiec [XIV] accomplished Deep Neural Network (DNN), and Orlando J [XVII] accomplished a discriminatively trained fully-connected ‘Conditional Random Field (CRF)’ for the segmentation of retinal vasculature [XVII].

III. Proposed Method

Retinal vessel segmentation is more important in the diagnosis eye related diseases. Though there are so many approaches developed in earlier to extract the vascular structure from a retinal fundus image, still there exist some problems due to
the internal feature like exudates and Micro Aneurysms and Hemorrhages (MAHMs) etc. along with these aspects, the presence of some external disturbances also effects the segmentation performance. To achieve an optimal segmentation performance in the retinal vessel segmentation, this paper proposes a new three phase framework based on optimal feature set extraction and supervised machine learning. The complete accomplishment of proposed method is done in three phases, preprocessing, classification of vessel pixels and post processing. The overall accomplishment of proposed mechanism is depicted in the following figures.

Figure.2 Preprocessing

In the initial preprocessing phase (Figure.2), a major blood vessel image is extracted from the original retinal image such that the major portion of the image is obtained. For this purpose, the initial fundus image is subjected to contrast enhancement such that brighter will appear brighter and dark regions will appear...
darker. Here the main objective is to extract the maximum possible retinal vasculature from the retinal image and it is possible only when the background pixels are darker than retinal pixels. The contrast enhancement process will achieve this through an adaptive normalization process. Further, two threshold binary images are obtained; one is through high pass filtering and another is through the accomplishment of Gabor filter over the red regions of the green plane of retinal fundus image. Next, from these two binary images, major blood vessel is extracted and the remaining pixels left in the two images are combined to form a vessel sub image. This vessel sub image is subjected to second phase processing to extract the further pixels which have ability to represent the retinal vessels.

In the second phase (figure 3), the vessel sub image is subjected to classification to separate the vessel pixels from background pixels through support vector machine (SVM) classifier. This process is mainly to extract the minor pixels which are representing the vessels in retinal image. Since the minor vessel pixels are not much brighter and they look like background, a proper differentiation is required to separate them from background pixels and the proposed new feature extraction technique fulfills this requirement. A feature set integrated with thirteen different features is formulated for vessel sub image and trained to SVM classifier to classify the minor vessel pixels from background pixels.

Finally, in the last phase (post processing), the minor vessel obtained in second phase are combined with major blood vessel pixels (extracted in first phase) to obtain a complete retinal vasculature.

A. Preprocessing

Initially for a given color retinal fundus image, the green plane is extracted and scaled in the range from 0 to 1. The preprocessing stage requires a green plane of fundus image and a fundus mask. Initially the fundus image is subjected to vessel enhancement by superimposing the fundus mask over followed by a contrast adjustment and vessel enhancement. Here the vessel enhancement involves the squaring the pixel intensities and re-normalizing to the range from 0 to 1. Due to this operation, the bright regions will become brighter and the dark regions will become darker which provides a perfect discrimination between the vessel pixels and background pixels, resulting in enhanced blood vessel regions. In the green plane image, the red regions of the blood vessels segments appears as dark regions which has the pixel intensities close to 1. To extract the blood vessels from the green plane of fundus image, initially the green plane is scaled in the range from 0 to 1 and then it is passed through the low pass filter. Before passing it through a LPF, it is subjected to contrast enhancement through the method described according to the Y. M. S. Reddy et al.[XXXI]. Further obtained image processed for vessel enhancement. Then the vessel enhanced image is passed through the LPF and the obtained output is subtracted from the vessel enhanced image, resulting a high pass filtered image. Here the size of LPF is taken as 20*20. The high pass filtered image then threshold to obtain the pixels less than 0 and then absolute pixel strengths of the threshold image and contrast adjusted to extract the vessel regions. This is the first stage preprocessed image which has only the major blood vessels. Further, the second stage preprocessing is accomplished to extract the minor blood vessels which are not distinguishable. This second stage preprocessing is applied over the negative of
vessel enhanced image. After obtaining the negative image, the Gabor filter is applied over it to extract the dominant features in the various orientations.

**Gabor filter**

Gabor filters are generally applied in various applications like texture based image analysis, feature extraction, pattern recognition and computer vision etc. Generally the Gabor filter is a multiplicative form of complex trigonometric function with a Gaussian envelope, as represented in Eq. (1). In this paper, the real portion of 2D Gabor filter response is used for minor blood vessels extraction.

\[
g(x, y; \lambda, \theta, \sigma, \gamma) = \exp \left( -\frac{x'^2 + y'^2}{2\sigma^2} \right) \cos \left( \frac{2\pi x'}{\lambda} \right)
\]

Where \( x' = x \cdot \cos \theta + y \cdot \sin \theta, y' = -x \cdot \sin \theta + y \cdot \cos \theta \) and \( g \) is 2-D Gabor kernel function. Totally four control parameters are used to control this function and they are aspect ratio, wavelength, orientation, scale and shape. In this paper, the Gabor filter band is realized by convolving various Gabor kernels with particular parameters to cover all possible orientations. Angular orientation is selected as \( 15^\circ \), so totally 12 different Gabor kernels are obtained. Some examples images at different orientations are shown in the figure 4. The negative of vessel enhanced image is convoluted with 12 Gabor kernel functions and the maximum response is designated for every pixel. Subsequently, the retinal vessel pixel can be observed as more dominant than the background pixels. For each pixel, the Gabor filter response at which orientation is maximum is selected, thereby resulting a new image. Further the obtained preprocessed images are threshold to formulate a binary image. Next the intersecting regions between the preprocessed binary images are retained as the major blood vessels or major portion of blood vessels. Once the major blood vessels are removed from the two binary images, the resulting image is called vessel sub image.

![Gabor orientation resolution components](image)

**B. Feature based Vessel and Non-Vessel Pixel Classification**

In the second phase, the two vessel sub images are combined into a single sub image and the pixels in that sub image are classified as vessel pixels and non-vessel pixels or background pixels through the support vector machine classifier. The pixels in the combined sub image are classified based on their characteristics like pixel intensities and gradients and the correlation carrying between them. Since there exists
closely related pixel intensities for the pixels of combined vessel sub image, classification of vessel pixels and non-vessel pixels is complex task. To do this, there is a need to discriminate the pixels with respect to their in depth characteristics. To this end, the proposed approach studies the inner characteristics by measuring different statistical measures and based on them, the pixels are perfectly classified as vessel pixels and non-vessel pixels more effectively. Totally, the proposed approach measures 13 features, four are based on the pixel intensities \([X]\), eight are based on the gradients \([\text{II}], [\text{III}]\) and one feature is based on the correlation between the pixels \([\text{XXIII}]\). Mean, Standard Deviation, maximum and minimum are the four features based on the pixel intensities and the eight gradient features such as first order horizontal and vertical derivatives, second order three partial derivatives and two Eigen values and vessel likelihood are measured through frangi filter. Finally one feature is measured based on the correlation properties of neighboring pixels. The evaluation of three types of features is described in the following subsections;

1. **Intensity based features**

For extracting intensity based features for each pixel \((x, y)\) in the combined vessel sub image, four features are defined placing the desired pixel \((x, y)\) as the center pixel in a block of size \(m*n\), where \(m\) is number of rows and \(n\) is the number of columns. The four intensity features are determined by mean, standard deviation, maximum and minimum and are described as,

\[
\begin{align*}
  f_1 &= \text{mean}(B_i) \\
  f_2 &= \text{Standard Deviation}(B_i) \\
  f_3 &= \text{maximum}(B_i) \\
  f_4 &= \text{minimum}(B_i)
\end{align*}
\]

Where \(B_i\) is the ith block of a pixel \((x, y)\) at the center.

2. **Gradient based features**

For gradient features, first and second order gradients are evaluated through the Frangi filter \([32]\) for every block of vessel sub image. The methodology of Frangi Filter is accomplished by deriving the second order partial derivatives of hessian matrix followed by Eigen values computation of Hessian Matrix. The Hessian matrix is defined as

\[
H = \begin{bmatrix}
I_{xx} & I_{xy} \\
I_{yx} & I_{yy}
\end{bmatrix}
\]

Where \(I_{xx}, I_{xy}, I_{yx} \) and \(I_{yy}\) are the second order partial derivatives of image. Before going for second order differentiation, every block of vessel sub image is subjected to the first order partial differentiation along horizontal direction (x-axis) and vertical direction (y-axis) and the obtained derivatives are denoted as \(I_x\) and \(I_y\) respectively. The remaining three gradient based features are the two Eigen values of Hessian
matrix and Vessel likelihood, obtained based on the Eigen values. Here the vessel likelihood is formulated as,

\[ V = \begin{cases} 
0, & \lambda_2 > 0 \\
\exp \left( -\frac{R_B^2}{2} \right) \left( 1 - \exp \left( \frac{S^2}{2\sigma^2} \right) \right), & \lambda_2 \leq 0 
\end{cases} \]  

(7)

\[ R_B = \frac{|\lambda_1|}{|\lambda_2|}, \quad S = \sqrt{\lambda_1^2 + \lambda_2^2} \]  

(8)

Where \( \beta \) and \( c \) are the two arbitrary constants an used for configuring the sensitivity of \( R_B \) and \( S \) values, respectively.

3. Correlation based feature

To measure the relation between the neighboring pixels correlation can be used. In the case of vessel sub images, the pixels of thin blood vessels are more in number and highly correlated form block to block. To obtain a more accurate and better connected vasculature, the correlation between the pixels is also need to be traced. To do this, the correlation is measured for every block centering a pixel \((x, y)\). For a two blocks \( B_1 \) and \( B_2 \), the correlation factor \((\rho)\) is measured as

\[ \rho(B_1, B_2) = \frac{\text{cov}(B_1, B_2)}{\sqrt{\text{var}(B_1) \cdot \text{var}(B_2)}} \]  

(9)

Based on the \( \rho \) value, the vascular continuity can be evaluated. The high correlation (+1) between two blocks indicates that the vessel pattern is moving in the same direction and the high correlation (-1) between two blocks indicates that the vessel pattern is moving in the opposite direction and finally the correlation value (0) indicates that the two blocks are uncorrelated to each other.

4. SVM classifier

Once the all features are extracted from the retinal image, the support vector machine classifier is trained with all the features and the classifier is tested on the validation data set. At the optimal solution, decision function using SVM is modeled as

\[ f(t) = \text{sgn}(\sum_{i=1}^{P} (\alpha_i - \tilde{\alpha}_i) K(t_i, t_j) + b) \]  

(10)

Where \( \alpha_i \) and \( \tilde{\alpha}_i \) are the Lagrange multiplier coefficient for the \( i^{th} \) sample, \( K(t_i, t_j) \) is the kernel function and \( b \) is an arbitrary constant. Among the available kernels of SVM such as linear, polynomial and Radial Basis Function (RBF), the proposed work used RBF kernel due to its flexible decision making process. Mathematically the RBF kernel is defined as;

\[ K(t_i, t_j) = \exp \left( -\frac{\|t_i - t_j\|^2}{\sigma^2} \right), \sigma \in R \]  

(11)
According to the functional theory, as long as the function $K(t_i, t_j)$ satisfies Mercer’s condition, it can be denoted as a positive definite kernel.

C. Post processing

In the post processing phase, the obtained final vessel sub image represents all the vessel pixels and it is obtained by combining the major vessel sub image and minor vessel sub image. Finally, the post-processing retains the regions which are larger than the area ‘$a$’ while smaller regions are removed. The approximate values of ‘$a$’ are set as 20-50.

IV. Simulation Results

To develop and test the retinal vessel segmentation algorithm, two publicly available datasets, DRIVE and STARE, with available gold-standard images were used. The proposed method was implemented by MATLAB 2014a and the algorithm was applied on the DRIVE and STARE datasets. The STARE and DRIVE datasets having 40 and 20 fundus photographs, correspondingly divided into two groups; training group and testing group. The obtained results after the accomplishment of proposed framework over the fundus images are shown the following figures.

![Figure 5 Obtained results over the Sample image from DRIVE dataset](image)

(a) Original color fundus image, (b) Green plane, (c) Contrast enhanced image, (d) Manually segmented retinal vasculature, (e) Major blood vessels, (f) Thin enhanced vessels, (g) Vessel sub image with classified vessel pixels, (h) final segmented image
Figure 6 Obtained results over the Sample image from STARE dataset, (a) Original color fundus image, (b) Green plane, (c) Contrast enhanced image, (d) Manually segmented retinal vasculature, (e) Major blood vessels, (f) Thin enhanced vessels, (g) Vessel sub image with classified vessel pixels, (h) final segmented image.

Figure 7 Comparative analysis for DRIVE images (a) Original color fundus image, (b) Manually segmented image, (c) Proposed method, (d) Method in [XIX] and (e) Method in [XX].
Figure 5 represents obtained simulation results after applying the proposed mechanism over the fundus image acquired from DRIVE dataset. As shown in figure 5, initially the green plane is extracted from the color fundus image followed by a contrast enhancement. The obtained green plane is shown in figure 5(b) and the contrast enhanced image is shown in figure 5(c). Further the contrast enhanced image is subjected to preprocessing to obtain the major blood vessels image and vessel sub image. The major blood vessel image is shown in figure 5(e) and the vessel sub image is shown in figure 5(f). After the accomplishment of SVM classifier to classify the vessel pixels and non-vessel pixels, the classified vessel pixels sub image is combined with major blood vessel image and the obtained results is shown in figure 5(g). The final segmented vessel image after post processing is shown in figure 5(h). Finally the obtained vessel segmented image is compared with manually segmented image (figure 5(d)) and the performance is analyzed through performance metrics. Similarly the obtained results for the fundus image acquired from STARE dataset is shown in figure 6.

To alleviate the performance enhancement of proposed approach, the obtained vessel segmented images are compared with the vessel segmented image obtained through conventional approaches such as the method developed by P.Raniet. al., [XIX] and S. Choudhary et. al., [XX]. Figure 7 shows the comparative analysis between the vessel segmented images of DRIVE dataset through the proposed and conventional approaches and the figure 8 shows the results of STARE dataset.

Further to analyze the proposed approach through subjective assessment, some performance metrics are measured for the obtained results. Firstly, some secondary metrics such as False Positive (FP), False Negative (FN), True Positive (TP) and True Negative (TN) are evaluated as follows:
(i) TP: The number of vessel pixels classified correctly.
(ii) TN: The number of Non-Vessel pixels classified correctly.
(iii) FP: The number of Non-Vessel Pixels classified as Vessel Pixels.
(iv) FN: The number of Vessel Pixels classified as Non-Vessel Pixels

Based on these secondary metrics, Accuracy, Specificity (Precision), and sensitivity (true positive rate), are measured according to (XXVI), (XVI) and (XXVII).

\[
\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100
\]  

(12)
Sensitivity measures the proportion of positives that are correctly identified as such.

\[ \text{Sensitivity} = \frac{TN}{TN + FP} \times 100 \]  

(13)

Specificity measures the proportion of negatives that are correctly identified as such.

\[ \text{Specificity} = \frac{TN}{TP + TN + FP} \times 100 \]  

(14)

The proposed approach was tested over twenty retinal image samples and the obtained accuracy, sensitivity and specificity resolutions are shown in the following table. Table 1 indicates the obtained Sensitivity, Specificity and Accuracy details for the fundus image samples of DRIVE dataset and STARE dataset. Table 2 indicates the comparative analysis between the proposed approach and conventional approaches with respect to the three performance metrics, sensitivity, specificity and accuracy for both datasets. Further the figure 7, figure 8 and figure 9 reveals the performance enhancement of proposed segmentation framework by comparing it with the conventional approaches through sensitivity, specificity and accuracy respectively.

Table 1 Obtained Sensitivity, Specificity and Accuracy through the proposed approach for DRIVE and STARE datasets

| Image Sample | DRIVE | | STARE | |
|--------------|-------|---|-------|---|
| Sensitivity  | Specificity | Accuracy | Sensitivity | Specificity | Accuracy |
| S1           | 0.7563 | 0.9789 | 0.9552 | 0.6678 | 0.9687 | 0.9493 |
| S2           | 0.7096 | 0.9824 | 0.9553 | 0.6874 | 0.9674 | 0.9523 |
| S3           | 0.7102 | 0.9800 | 0.9496 | 0.8247 | 0.9651 | 0.9541 |
| S4           | 0.7312 | 0.9817 | 0.9563 | 0.7414 | 0.9729 | 0.9578 |
| S5           | 0.7586 | 0.9747 | 0.9523 | 0.6421 | 0.9763 | 0.9512 |
| S6           | 0.7169 | 0.9785 | 0.9487 | 0.8234 | 0.9675 | 0.9584 |
| S7           | 0.7099 | 0.9768 | 0.9493 | 0.7841 | 0.9827 | 0.9687 |
| S8           | 0.7863 | 0.9677 | 0.9436 | 0.7759 | 0.9793 | 0.9666 |
| S9           | 0.7912 | 0.9652 | 0.9485 | 0.7863 | 0.9823 | 0.9696 |
| S10          | 0.7687 | 0.9631 | 0.9545 | 0.7385 | 0.9803 | 0.9638 |
| S11          | 0.7193 | 0.9724 | 0.9444 | 0.7796 | 0.9742 | 0.9628 |
| S12          | 0.7487 | 0.9736 | 0.9541 | 0.8352 | 0.9833 | 0.9738 |
| S13          | 0.7257 | 0.9714 | 0.9496 | 0.7145 | 0.9845 | 0.9658 |
| S14          | 0.7996 | 0.9658 | 0.9574 | 0.7245 | 0.9853 | 0.9641 |
| S15          | 0.8063 | 0.9545 | 0.9566 | 0.6854 | 0.9793 | 0.9579 |
| S16          | 0.7589 | 0.9728 | 0.9573 | 0.6374 | 0.9854 | 0.9523 |
| S17          | 0.7293 | 0.9736 | 0.9534 | 0.7189 | 0.9825 | 0.9617 |
| S18          | 0.7688 | 0.9747 | 0.9566 | 0.8596 | 0.9632 | 0.9624 |
| S19          | 0.8314 | 0.9807 | 0.9674 | 0.8891 | 0.9555 | 0.9537 |
| S20          | 0.8021 | 0.9736 | 0.9585 | 0.7345 | 0.9693 | 0.9557 |
Table 2: Comparative analysis between the proposed and conventional approaches through average results

| Dataset | Method        | Sensitivity | Specificity | Accuracy |
|---------|---------------|-------------|-------------|----------|
| DRIVE   | Proposed      | 0.7321      | 0.9870      | 0.9585   |
|         | P. Rani et al [XIX] | 0.7260      | 0.9686      | 0.9370   |
|         | Choudhary et al [XX] | 0.7250      | 0.9830      | 0.9520   |
|         | Budai et al [III] | 0.6441      | 0.9871      | 0.9572   |
|         | Mapayi et al [XXVII] | 0.7313      | 0.9724      | 0.9511   |
|         | Oliveira et al [XXIX] | 0.7106      | 0.9431      | 0.9402   |
|         | Marin et al [X] | 0.7063      | 0.9812      | 0.9452   |
| STARE   | Proposed      | 0.7845      | 0.9758      | 0.9538   |
|         | P. Rani et al [XIX] | 0.7419      | 0.9747      | 0.9501   |
|         | Choudhary et al [XX] | 0.7727      | 0.9730      | 0.9510   |
|         | Budai et al [III] | 0.5842      | 0.9825      | 0.9382   |
|         | Mapayi et al [XXVII] | 0.7626      | 0.9657      | 0.9510   |
|         | Oliveira et al [XXIX] | 0.8049      | 0.9592      | 0.9496   |
|         | Marin et al [X] | 0.6947      | 0.9821      | 0.9522   |

Figure 9: Sensitivity analysis for various datasets

Figure 10: Specificity analysis for various datasets
Sensitivity reflects the ability of an approach to find out the correct values. In this approach, the sensitivity can be defined as the ability of approach to segment the vessels correctly. The sensitivity plot for the proposed and the earlier algorithms is shown in figure.9, from the above figure, the sensitivity of proposed approach is observed to be high compared to conventional approaches, thus the proposed can efficiently detects the blood vessels form retinal images. Figure.11 illustrates the accuracy resolutions of the proposed work. The accuracy of proposed approach is high compared to earlier approach since the proposed approach finds out all the possible variations in the vessel detection such that the proposed approach effectively segments the all vessels form the retinal images. Since the proposed approach tries to find all possible variations in the retinal images, almost every vessel pixel is classified as vessel pixel. Further the vessel pixel classification is based on a set of features which gives perfect discrimination between the vessel and non-vessel pixels, the proposed approach can retrieve all possible pixels more effectively. The more effective classification of vessel pixels (both thin and thick) form background pixels, results an increased the classification accuracy.

V. Conclusion and Future Scope

In this paper, a novel vessel segmentation method based on Gabor transformation and Gradient features is presented. The abnormal signs of retinal images complicated the vessel segmentation algorithm. Given the high ability of the proposed algorithm in separating orientations in image components, the use of this algorithm with appropriate Gabor transform could extracts the retinal regions from retinal images. The experimental results over the standard datasets DRIVE and STARE indicate the ability of the proposed method in segmenting blood vessels in images. After the simulation of proposed mechanism over the DRIVE dataset, the average sensitivity, specificity and accuracy are observed as 0.7564, 0.9731, and 0.9534 respectively. Further the average results over the STARE dataset are observed as 0.7525, 0.9753, and 0.9601 of sensitivity, specificity and accuracy respectively. A comparative analysis is also accomplished between the proposed and conventional approaches.
approaches and on an average the proposed approach obtained an improvement in the sensitivity, specificity and accuracy as 0.0249, 0.0145 and 0.0144 respectively.

Further this work can be extended to extract the remaining features such as exudates, optic disk and macula form the retinal image by which an effective automatic diabetic retinopathy diagnosis system can be developed which reduces the manual effort.

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