International Journal of Engineering Research
Volume No.5, Issue No.7, pp : 555-559

ISSN:2319-6890)(online),2347-5013(print)
1 July 2016

Diabetic Classification by Blood Vessel Analysis of Fundus Images

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***Abstract**: Diabetes may cause damage to the blood vessels of the retina which may eventually leads to blindness. Automatic segmentation of the retinal vasculature is a primary step towards automatic assessment of the retinal blood vessel features. This paper presents an automated method for the enhancement and segmentation of blood vessels in fundus images. The proposed system consists of three stages-first is preprocessing of retinal image to separate the green channel and second stage is retinal image enhancement and third stage is blood vessel segmentation using morphological operations and the features are extracted using the ttest algorithm. The proposed approach requires less segmentation time and achieves consistent vessel segmentation accuracy on normal images as well as images with pathology when compared to existing supervised segmentation methods.*

Keywords: Fundus image, Gaussian mixture filter, morphological operation, cardiovascular.

I. Introduction

Diabetes affects the retina of the eye. It may cause blood vessels to leak blood and other fluid. So it is necessary to identify the blood vessels and segment it to identify any deviations from normal blood vessels. A three-stage blood vessel segmentation algorithm using fundus photographs is used. First, the number of pixels under classification is significantly reduced by eliminating the major vessels that are detected as the regions common to threshold versions of high-pass filtered image and morphologically reconstructed negative fundus image. The second major contribution is the identification of an optimal eight-feature set for classification of the fine blood vessel pixels using the information regarding the pixel neighborhood and first and second-order image gradients.

II. Related Work

M. Fraz et.al [10] proposed Retinal vessel segmentation algorithms which are the fundamental component of automatic retinal disease screening systems. This work examines the blood vessel segmentation methodologies in two dimensional retinal images acquired from a fundus camera and a survey of techniques is presented

M.Frax et. al [9] proposed a a new supervised method for segmentation of blood vessels in retinal photographs. This method uses an ensemble system of bagged and boosted decision trees and utilizes a feature vector based on the orientation analysis of gradient vector field, morphological transformation, line strength measures, and Gabor filter responses.

Roychowdhury et. Al [7] proposed a computer-aided screening system (DREAM) that analyzes fundus images with varying illumination and fields of view, and generates a severity grade for diabetic retinopathy (DR) using machine learning. Classifiers such as Gaussian Mixture Model (GMM), k-nearest neighbor (kNN), support vector machine (SVM), and AdaBoost are analyzed for classifying retinopathy lesions from non-lesions. GMM and kNN classifiers are found to be the best classifiers for bright and red lesion classification, respectively. A main contribution is the reduction in the number of features used for lesion classification by feature ranking using Adaboost where 30 top features are selected out of 78. A novel two-step hierarchical classification approach is proposed where the non-lesions or false positives are rejected in the first step. In the second step, the bright lesions are classified as hard exudates and cotton wool spots, and the red lesions are classified as hemorrhages and micro-aneurysms. This lesion classification problem deals with unbalanced data sets and SVM.

II. Methodology

2.1 MODULES:

- Preprocessing
- Extract major blood vessels.
- Extract remaining blood vessels.
- Diabetic Classification

2.1.1 Preprocessing

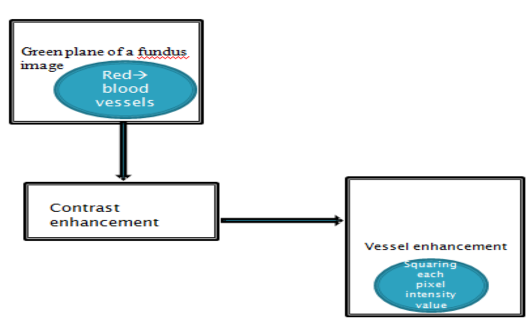

Fig. 1 Preprocessing

In this preprocessing red blood vessels are extracted fron the green plane of a fundus image.After applying contrast enhancement and vessel enhancement the red blood vessels be

ISSN:2319-6890)(online),2347-5013(print)
1 July 2016

more darker than the input image. So, it is easy to find out the blood vessels for segmentation.

Contrast enhancement

Contrast is an important factor in any subjective evaluation of image quality. Contrast is created by the difference in luminance reflected from two adjacent surfaces. In other words, contrast is the difference in visual properties that makes an object distinguishable from other objects and the background. In visual perception, contrast is determined by th difference in the colour and brightness of the object with other objects.

2.1.2 Extract major blood vessels:

First process

To extract the dark blood vessels two strategies are implemented in this step. The image is first processed in order to extract the features, which describe its contents. To extract the dark blood vessel regions from I_e, two different preprocessing strategies are implemented. First, a smoothened low-pass filtered version of I_e is subtracted from I_e to obtain a high-pass filtered image. This high-pass filtered image is thresholded to extract pixels less than 0 and the absolute pixel strengths of the thresholded image are contrast adjusted to extract the vessel regions. This is referred to as the preprocessed image H.

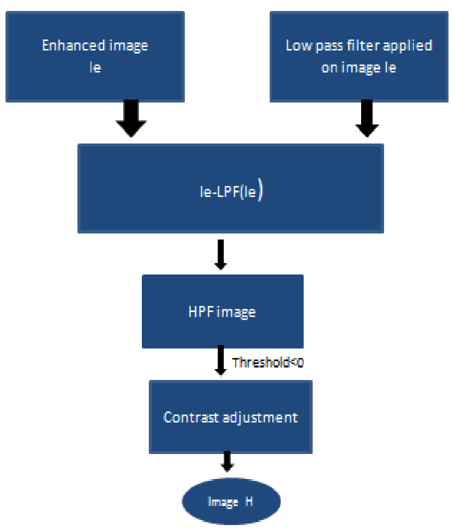

Fig. 3 Extraction of green blood vessels

Second process

For the second preprocessed image, the red regions corresponding to the dark pixels are extracted from the negative of image I_e, thus resulting in image R. These two preprocessed images H and T can be thresholded to obtain baseline unsupervised models. The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers to provide better input for other automated image processing techniques. Tophat reconstructed filter is used to remove the dark background from the image. From that in each pixel location the higher intensity value is selected. After Tophat reconstructing image the Red blood vessels are extracted.

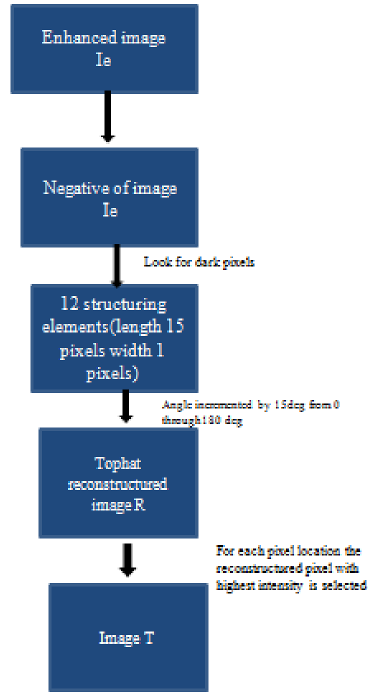

Fig. 4 Extraction of red blood vessels

After the extraction of red blood vessels then combine the output of green plane and red plane ,from that major blood vessels are extracted

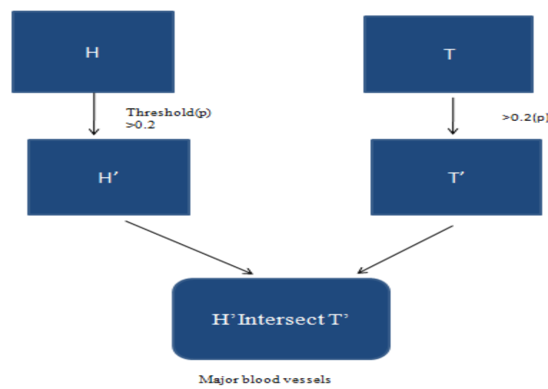

Fig. 5 Extraction of major blood vessels

Tophat Reconstruction

Tophat Reconstruction is a filter it removes the dark background from the image. Top-hat filtering computes the morphological opening of the image and then subtracts the result from the original image

2.1.3 Extract remaining blood vessels:

The pixels in sub images are combined to form a vessel sub image C and the pixels in C are classified using a GMM classifier that classifies each pixel as vessel (class 1) or non vessel (class 0). Thus, for all pixels in C, a GMM classifier is trained once using the images from the Train set of images and tested on the DRIVE. To select the most discriminating features from the pixel-based features we performed feature ranking and leave-one-out double cross validation on the 20 images from the dataset using GMM classifiers.

ISSN:2319-6890)(online),2347-5013(print)
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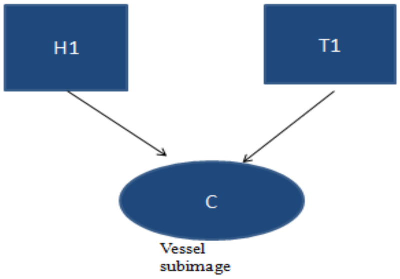

Fig.6 Vessel Subimage

Gaussian Mixture Model classifier

A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters.

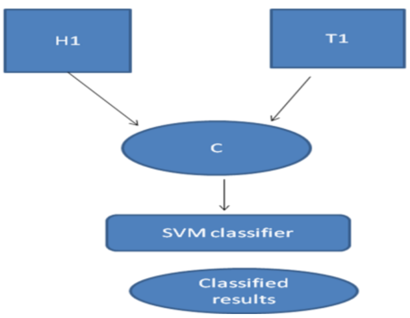

Fig. 7 Usage of SVM classifier

2.1.4 Diabetic classification:

The pixels in subimages H1 and T1 are combined to form a vessel subimage C. In the post processing stage, all the pixels in the sub image that are classified as vessels by the SVM classifier are combined with the major vessels to obtain the segmented vasculature. Support Vector Machine performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables.

III. Experimental Results

Fig. 8 Input image

The above figure shows the input image.It is used to find out the blood vessel segmentation.

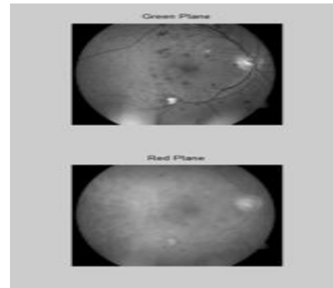

Fig. 9 Green plane and red plane image

The above figure shows the green plane and red plane image.These images are extracted from the fundus input image.

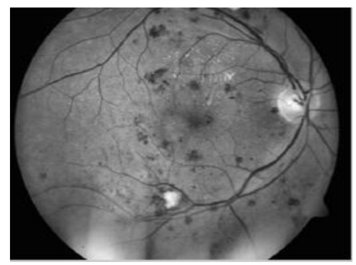

Fig. 10 Contrast enhancement

The above figure shows the contrast enhancement. After applying Low pass filter and High pass filter the blood vessels are darker, when compared with the input image.So.it is very easy to find out the blood vessels for segmentation

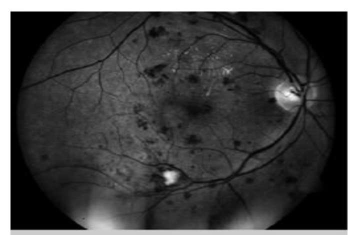

Fig. 11 Vessel enhanced image green

In the vessel enhancement image ,squaring each pixel intensity value be shows the Green region blood vessels more darker than contrast enhancement.

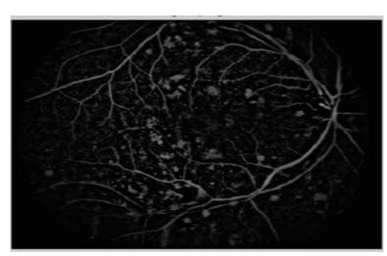

Fig. 12 Visible Green blood vessels

In the high frequency image,the Green region blood vessels only be visible.

Fig. 13 Green segmented image

After the vessel enhancement from the input image the Green plane region only be extracted.

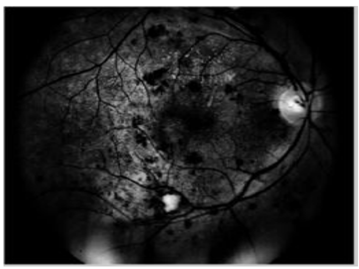

Fig. 14 Vessel enhanced image red

In the vessel enhancement image ,squaring each pixel intensity value be shows the Red region blood vessels more darker than contrast enhancement.

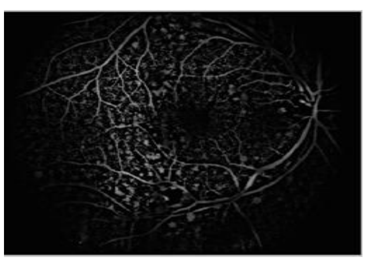

Fig. 15 High frequency image red

In the high frequency image,the red region blood vessel only be visible.

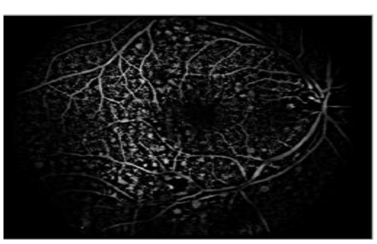

Fig. 16 Reconstructed image red

The above figure shows the Reconstructed image of red plane image.

Fig. 17 Red segmented image

After the vessel enhancement from the input image the Red plane region only be extracted.

Fig. 18 H+T image

The above figure shows the combination of the output of Green segmented image (H) and the output of Red segmented image(T).

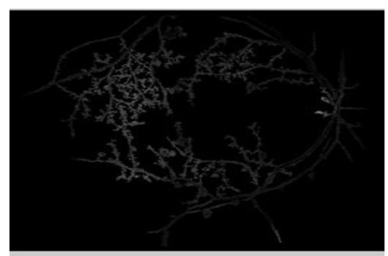

Fig. 19 Fused sub image

The above figure shows the fused sub image.After applying Gaussian Mixture Model classifier(GMM) ,the input image is fused and the blood vessels only be clearly visible.

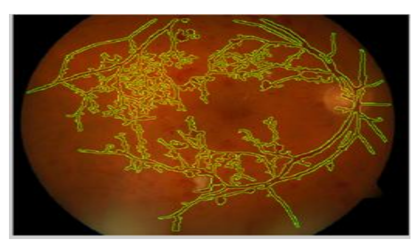

Fig. 20 Final vessel segmented image

The above figure shows the final vessel segmented image of the input.

International Journal of Engineering Research ISSN:2319-6890)(online),2347-5013(print)
Volume No.5, Issue No.7, pp : 555-559 1 July 2016

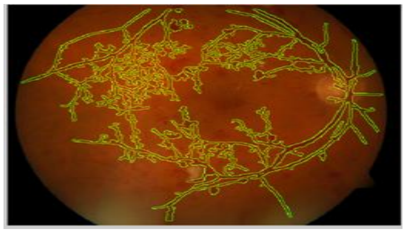

Fig. 21 Vessel region

The above figure shows the segmented blood vessel region.

IV. CONCLUSION

A novel three-stage blood vessel segmentation algorithm is used in fundus photographs. The major vessels are removed from the thresholded preprocessed images to generate a vessel sub image. A GMM classifier with two Gaussians is then used to identify the fine vessel pixels in this vessel sub image. A set of features is then identified, that discriminate non vessel pixels from fine vessel pixels in the vessel sub image. These features are ranked based on the mRMR criterion.

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