Novel approach for Blood Vessel Segmentation, Optic Disc Segmentation and Microaneurysm detection for automatic diabetic retinopathy detection

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Abstract: Today diabetes is the most common disease faced by world population. High glucose level is present in the diabetes patients. Excessive glucose level causes damage in retinal vasculature. This damage ultimately results in Diabetic Retinopathy. DR is major reason of blindness in middle age population. Lesions detection from retinal images can provide automatic DR detection tool. Any sophisticated image classifier can give higher accuracy in automatic DR classification if inputted with appropriate features for training and classification. These appropriate features can be extracted from original retinal image along with Blood Vessel Segmented, Optic Disc Segmented and Microaneurysm detected images. This paper presents idea of Blood Vessel Segmentation, Optic Disc Segmentation and Microaneurysm detection using adaptive thresholding, binarization and wavelet model respectively. If these segmented images along with original retinal image are used for feature extraction then it can produce great accuracy in automatic DR classification.

***Keywords*:** Diabetic retinopathy (DR), Adaptive Thresholding, Binarization, Wavelet Transform

1. Introduction:

Number of diabetes patients are increasing day by day. The heavy Glucose level in the blood of diabetes patients causes damages in the retinal vasculature. This includes hemorrhages (HMs), microaneurysms (MAs), and exudates (EXs). MAs are the primary sign of Non-proliferative diabetic retinopathy (NPDR), which is caused due to the thin vessel dilation. MAs are round in shape with small size and red in color. The HMs signs for DR are otherwise termed as blot or dot HMs [1].This retinal vasculature is termed as DR. DR progressively results in blindness and can be avoided with early detection. For such an early detection regular retinal screening is recommended for diabetes patients. Large number of diabetes patients imposes heavy load on ophthalmologists. And even there is scarcity of such expert ophthalmologists in many countries. Also Earliness of detection is varied by expert to expert too. Hence automatic detection of DR from retinal fundus images through regular eye screening of diabetes patients can help to control the spreading blindness due to DR. For such an automatic detection machine learning approach is highly recommended by considering its accuracy [2]. Automatic exudate detection becomes challenging due to poor contrast and uneven exposure in fundus images [3]. To tackle this complications four major types of techniques are used namely region growing based, pixel based classification, morphological based classification and thresholding based [3]

For early stage DR detection it is very important to detect Optic Disc automatically. Disc size, Cup area features and Neuro-retinal rim are important factors in DR detection. Even position of vessel origine (VO) and Optic Disc (OD) are proven to be major anatomical features in fundus images. There exists many image analysis processes which helps DR diagnosis using human retinal fundus images. However major role is played by image enhancement techniques which improves contrast and sharpness while reducing noises present. Some other classification and detection methods of image processing are also used to assist DR diagnosis from fundus images [4]. Conventional edge detection based methods such as Canny Filtering [5][6], Laplacian filtering [7][8] are susceptible to noise because noise present at false edges.

Various existing DR detection methods are surveyed in this section. Fraz, M.M., et al. [9] developed an ensemble classification for segmentation and localization of exudates from the retinal images. Here, the exudates were finely extracted using Gabor filter and morphological reconstruction at coarse and fine grain levels. However, the false positives were reduced using the contextual cues in the segmentation process. This method was highly robust and attained better accuracy. However, it was not effectively applicable for the large-sized dataset. Zhu, C., et al. [10] introduced an extreme learning machine (ELM) for segmenting the retinal vessel. Initially, the morphological features, discriminative features, and the divergence and hessian vector fields were extracted from pixels of fundus image. A matrix was generated for the pixel based on the manual labels and feature vector. This method was effectively suitable for disease screening, but the training model was very expensive. W. Zhou, C. et al. [11] developed an unsupervised classification model for detecting the microaneurysms using posterior cerebral artery (PCA). Based on the sparse PCA, suitable features were effectively selected. However, it failed to distinguish the microaneurysms from false positive based on the texture features. Moreover, it failed to detect the lesions, like hemorrhages, and hard exudates. Amin, J., et al. [12] introduced the structural predictors of bright lesions for classifying and detecting DR. Initially, the images were pre-processed using the Gabor filter, where the lesions were accurately detected. The mathematical morphology was used to effectively segment the candidate lesion. Here, the features sets were selected from the candidate lesion using the geometric and statistical features. However, this method failed to identify the indications, like hemorrhages, microaneurysms, and cotton wool spots.

Leontidis, G., [13] developed a machine learning-based framework for feature analysis and retinal imaging for the retinal disease. It includes various stages, like registration, segmentation, feature extraction, and classification. The statistical inferences were made using the linear mixed model. This method failed to perform vein or artery classification. L. Ngo and J. H. Han, [14] developed a multi-level deep neural network for segmenting the blood vessel in fundus image. It used the max-resizing model for increasing the generalization of training process. It attained better detection rate, but lowered the classification accuracy. Abbas, Q., et al. [15] developed an automatic recognition system to find the level of severity in DR. Here, the deep visual features were effectively extracted from the fundus image using gradient location and scale invariant histogram models. It used the deep learning method to learn the visual features. It effectively predicts the type of diabetes, but used single image for recognition process. W. Zhou, et al. [16] developed a superpixel multifeature classification model for detecting the exudates automatically. Initially, the entire image was segmented into superpixels termed as candidates. However, each candidate was characterized using the contextual, and the intensity features. The multi variable classification model effectively separated the true exudates from spurious candidates.

This paper focus on formation of basis for effective feature vector for any of the effective DR detection classifier.

2. Segmentation and detection process in Diabetic Retinopathy fundus image

Once the input image is selected from the database then, it is required to perform the segmentation strategy. The segmentation and the detection process makes the image fit for further processing. Here, the blood vessel segmentation, optic disc segmentation, and MA detection processes are performed using the adaptive thresholding, binarization, and the wavelet model. The optic disc, blood vessel, and the MA are effectively detected and segmented from the diabetic retinopathy fundus image.

2.1 **Blood vessel segmentation**

The input image T_u is selected and the blood vessel exists in the fundus image is segmented using the adaptive thresholding model [17]. The adaptive thresholding approach performs the edge detection operation by convolving the fundus image with the matrices termed as detectors or operators. Here, the convolution offers a slope or measure of gradient within the dimension of detectors. It selects the prewitt operators for effectively segmenting the blood vessels. At each pixel in the image, the operators are convolved into the image T_u for capturing the direction of image, as diagonal, vertical, anti-diagonal, and horizontal orientations. However, the absolute values in the convolutions are compared with the above directions and the greatest value among the absolute one is used to indicate the edge information of pixel. Moreover, the gradient values collected from the fundus image are termed as edge image τ . It is assumed that the edge values or gradients of pixels situated at the boundary of objects are greater than the edge values present at the interior and background of objects. The pixel values are divided into strong edge and weak edge groups. The pixels belonging to the weak edge are assigned as '0', while the remaining pixels are considered as the pixels in the boundary of objects. The major advantage of using the adaptive thresholding approach is to effectively separate the pixels situated at the boundary region of image from other location, which helps to distinguish the weak pixel edges from strong edges in the edge image τ . The output obtained from the blood vessel segmentation process is denoted as T_b .

2.2 **Optic disc segmentation**

The input image T_u is selected to perform the optic disc segmentation using the binarization model. The main task of binarization is to segment the location of optic disc so that the area containing the defects will overlap in the original image. It highlights the position of edge pixels, and effectively adjusts the thresholding surface. Here, the thresholding surfaces are moved by adding or subtracting a constant with the intensity values, as the edge pixel have different intensity value. The key strategy of the binarization model is to reduce the absolute value between the pixels at the edge location. Once the thresholding surface is found then, the segmentation process is carried out by extracting the objects from image. The result obtained after segmenting the optic disc is represented as T_o .

2.3 Microaneurysm (MA) detection

The input image T_u is applied into the wavelet model [18] to detect the MA. The wavelet model generates a set of values through wavelet coefficients. The major characteristic features of wavelet model are specified as follows:

- It can be effectively used to reconstruct the non-stationary, non-periodic, and finite signals.
- It provides both the space and frequency information, which helps to find the exact location of image, where the frequency appears.

The wavelet model decomposes the image using the dilated and the scaling function and effectively detects the MA with respect to the pixel values. The output generated after detecting the MA is represented as, T_a. Finally, the result of blood vessel segmentation, optic disc segmentation, and MA detection processes are denoted as, $\{T_b, T_o, T_a\}$, respectively.

3. Experimental results:

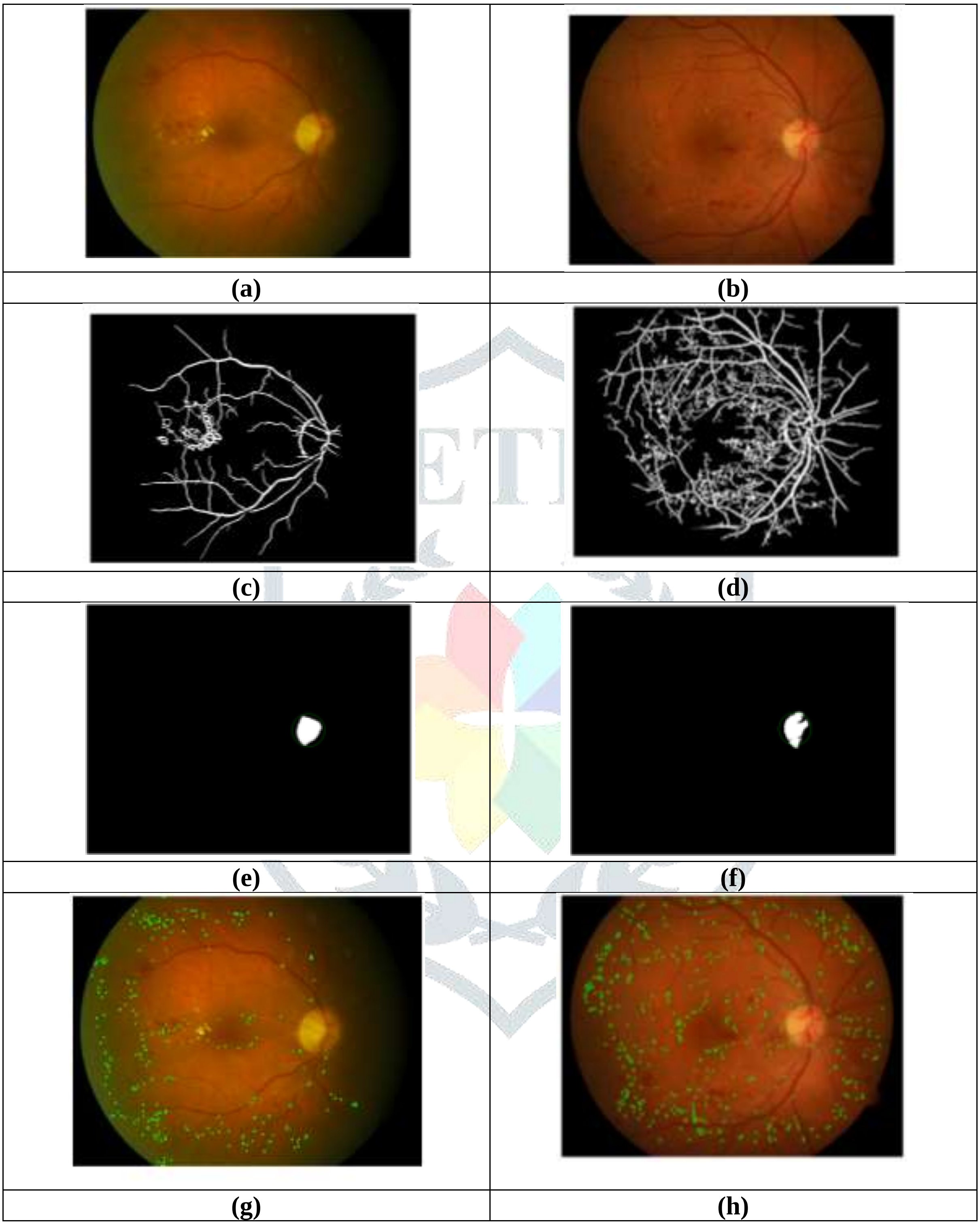

Figure 1. Experimental results, a) input fundus image-1, b) input fundus image-2, c) blood vessel segmentation using fundus image-1, d) blood vessel segmentation of fundus image-2, e) optic disc segmentation of fundus image-1, f) optic disc segmentation of fundus image-2, g) MA detection of fundus image-1, h) MA detection of fundus image-2

4. Conclusion:

This paper presents novel approach for formation of basis for effective feature vector which can be effectively used by any of the DR detection classifier. From input retinal fundus image the blood vessels are segmented using adaptive thresholding, the optic disc segmentation is carried out using binarization process, and the microaneurysms are detected using the wavelet model. From these results efficient features can be extracted which will form an efficient feature vector for diabetic retinopathy detection classifier.

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