Medical Diagnosis System for Non-Proliferative Diabetic Retinopathy

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ABSTRACT

Background: Diabetic retinopathy disease is a major cause of poor vision loss for the long-standing diabetic patients. There is no single algorithm in the literature used for extracting all the abnormal regions simultaneously. Results: This paper has developed a Computer Assisted Diagnosis (CAD) system for diagnosing Non-Proliferative Diabetic Retinopathy (NPDR) in retinal fundus images. The proposed approach is experimented with three datasets such as DIARETDB0, DIARETDB1, and MESSIDOR. With the use of these three databases, the proposed algorithm has achieved an accuracy of 98.57%, 98.70%, and 99.05% respectively. Conclusion: An unsupervised multi-level transition region based thresholding segmentation algorithm is proposed for extracting abnormalities in Diabetic Retinopathy (DR) images. The proposed system consists of four steps: 1) Pre-processing, 2) Segmentation, 3) Feature Extraction, and 4) Classification. To improve the quality of final results, Pre-processing has been carried out. In the pre-processing stage, the green channel of the input color retinal fundus image is extracted and enhanced using three techniques such as local polynomial contrast enhancement operator, shade correction and normalization. To eliminate some of the artifacts in the pre-processed image, optic disk and blood vessels are removed from the enhanced image. After the completion of entire pre-processing stage, the enhanced image is given as input to the proposed segmentation algorithm. In the segmentation process, dark and bright lesions such as microaneurysms, haemorrhages, and exudates of NPDR are extracted as abnormal regions. From these segmented regions, features are extracted and used as inputs for classification purpose. The classification algorithm used in this paper is association rule mining. A rule based grading approach is used to classify the patients as normal or abnormal based on the signs of NPDR.

INTRODUCTION

DR is an eye disease that is associated with persons who are having diabetes more than five years. It is a major cause of poor vision. Recent statistics from Vision 2020: The Right to Sight reported that DR is responsible for 4.8% of the 37 million cases of blindness due to eye diseases throughout the world. The proportion of blindness due to diabetic retinopathy ranges from close to 0% in most of Africa, to 3–7% in much of South-East Asia and the Western Pacific, to 15–17% in the wealthier regions of the Americas, Europe and the Western Pacific. About 50% of persons with diabetes were unaware that they have the condition, although about 2 million deaths every year were attributable to complications of diabetes. After 15 years, about 2% of persons with diabetes will become blind, and about 10% will develop severe visual loss. After 20 years, more than 75% of patients will have some form of DR.

This paper has developed an automated diagnosis system for classifying the retinal fundus images as having NPDR or not. A new unsupervised multi-level transition region based thresholding segmentation algorithm is proposed in this paper to segment microaneurysms, haemorrhages, and exudates. The proposed system is divided into four steps. The first step consists of contrast enhancement, shade correction and image normalization of the green channel. The second step aims at detecting candidates such as dark and bright objects using the proposed segmentation algorithm. Then, features are extracted, which are used in the last step to automatically classify the input as normal or having NPDR. Association rule mining algorithm is used to...
classify the retinal fundus image based on these extracted features. The proposed algorithm has achieved better performance than existing algorithms.

The rest of the paper is organized as follows. Section II describes the previous research related to the proposed work. Section III presents techniques used for image enhancement. Section IV explains the proposed segmentation algorithm. Section V presents the results. Section VI describes the conclusion and future work.

Previous Research:

Many of the studies investigated that there are different types of algorithms for automatic detection of Microaneurysms (MAs), Haemorrhages (HAs), and Exudates in fluorescein angiography retinal fundus images. Meyesam et al. (2013) presented a novel and different algorithm for automatic detection of MAs in fluorescein angiography (FA) fundus images, based on Radon transform (RT) and multi-overlapping windows. Top-hat transformation and averaging filter are applied to remove the background for pre-processing. After preprocessing, the whole image is divided into sub-images. Optic nerve head (ONH) and vessel tree are then detected and masked by applying RT in each sub-image. After detecting and masking retinal vessels and ONH, MAs are detected and numbered by using RT and thresholding. The proposed method is evaluated on three different retinal images databases, the Mashhad Database with 120 FA fundus images, Second Local Database from Tehran with 50 FA retinal images and apart of Retinopathy Online Challenge (ROC) database with 22 images. Results achieved a sensitivity and specificity of 94% and 75% for Mashhad database and 100% and 70% for the Second Local Database respectively.

Fangyan et al. (2013) proposed a novel two-dimensional variance thresholding scheme to improve image segmentation. One drawback of 1D thresholding methods is that only the distribution of the gray levels of an image is considered, whereas the spatial information is ignored. To overcome this problem, 2D variance-based techniques using spatial as well as pixel information have been proposed. This scheme uses 1D summation. It is almost as fast as the original 1D variance-based algorithm. In this scheme, the gray levels of the pixels and the local average gray level of the neighbourhood pixels form a 2D histogram. This 2D parameter space is reduced to a 1D histogram, while assigning equal weights to both variables. Experimental results on bi-level and multilevel thresholding for synthetic and real-world images demonstrate the proposed image thresholding scheme performs well compared with the Otsu method, 2-d Otsu method and the minimum class variance thresholding method.

Usman et al. (2013) proposed a three-stage system for early detection of MAs using filter banks. The proposed system extracts all possible candidate regions for Mas present in retinal image. A feature vector for each region depending upon certain properties, i.e. shape, color, intensity and statistics is formed to classify a candidate region as MA or non-MA. A hybrid classifier which combines the Gaussian mixture model (GMM), support vector machine (SVM) and an extension of multi-model mediod based modelling approach in an ensemble is proposed to improve the accuracy of classification. The true MA regions are selected and classified using a hybrid classifier which is a weighted combination of multivariate m-Mediods, GMM and SVM. The proposed system has achieved higher accuracy which is better than previously published methods.

Istvan and Andras (2013) proposed a method for retinal MAs Detection through Local Rotating Cross-Section Profile Analysis. This approach recognizes MA detection through the analysis of directional cross-section profiles centered on the local maximum pixels of the pre-processed image. Peak detection is applied on each profile, and a set of attributes regarding the size, height, and shape of the peak are calculated subsequently. Attribute values are used as the orientation of the cross-section changes. These values constitute the feature set that is used in a naïve Bayes classification to eliminate false candidates. The final score of the remaining candidates can be thresholded further for a binary output. The proposed method has been tested with the Retinopathy Online Challenge and proved to be competitive with the existing approaches. The proposed method has achieved higher sensitivity at low false positive rates, i.e., at 1/8 and 1/4 False Positives/image.

Bob et al. (2012) have proposed a new method to detect MA based on Dictionary Learning (DL) with Sparse Representation Classifier (SRC). In addition to MA detection, Retinal blood vessels are also extracted using SRC. This method consists of two phases. First all possible MA candidates are identified with the help of Multi-scale Gaussian Correlation Filtering (MSCF). The second step is to classify these candidates with Dictionary Learning (DL) via SRC. Two dictionaries are used in this proposed approach: one for the MA and other for the non-MA. Experimental results on the ROC database show that the proposed method can well distinguish MA from non-MA objects. With the learned MA and non-MA dictionaries, SRC is then applied to the candidates to distinguish MA objects from non-MA objects. Vessel extraction is based on Multi-scale Production of Matched Filter (MPMF) and SRC. First, vessel center-line candidates are extracted using Multi-scale Matched Filtering, scale production, double thresholding and center-line detection. Then, the candidates which are center-line pixels are classified using SRC. Two dictionary elements of vessel and non-vessel are used in the SRC process. The proposed approach is experimented on ROC dataset. Results show that the proposed method is effective and efficient for MA detection.
Cemal et al. (2012) developed an approach called inverse segmentation method to detect DR. Direct segmentation techniques give poor results in some of the cases. The proposed system exploits the homogeneity of healthy areas rather than dealing with varying structure of unhealthy areas for segmenting bright lesions (hard exudates and cotton wool spots). This system first generates the reference or extended background image from a retinal image. Healthy parts of the retinal image except for vessel and OD areas are used in the calculation of this reference image. Next the retinal image is divided into two parts as low and high intensity areas based on the intensities of the background image. Background image is used as the dynamic threshold value for segmenting high intensity and low intensity degenerations in the image. Both degenerations are segmented separately by using the inverse segmentation method and dynamic thresholding. The performance of the system is over 95% in detection of the optic disc (OD), and 90% in segmentation of the DR. Therefore, the method provides high segmentation and measurement accuracy. In some cases, the image lighting artifacts may affect segmentation performance negatively, which could also be considered as an issue.

A two-phase decision support framework (Balint et al., 2012) is proposed for the automatic screening of digital fundus images. Pre-screening is the first step in which images are classified as severely diseased (highly abnormal) or to be forwarded for further processing. The second step of the proposed method detects regions of interest with possible lesions on the images that previously passed the pre-screening step. These regions will serve as input to the specific lesion detectors for detailed analysis. The computational performance of a screening system is increased due to pre-screening process. Experimental results show that there is a decrease in the computational burden of the automatic screening system.

An Ensemble-Based System (Balint and Andras, 2012) is developed for Microaneurysm Detection and Diabetic Retinopathy Grading. This approach has proved its high efficiency in an open online challenge with its first position. Our novel framework relies on a set of <preprocessing method, candidate extractor> pairs. A search algorithm is used to select an optimal combination. Since the proposed approach is modular, further improvements can be done by adding more preprocessing methods and candidate extractors. The DR/non-DR grading performance of this detector in the 1200 images of the Messidor database have achieved a 0.90 ± 0.01 AUC value, which is competitive with other existing methods.

Anderson et al. (2012) presented a common approach for identifying both red and bright lesions in DR images without requiring specific pre- or post-processing. The proposed approach requires pinpointing the location of each lesion to allow the specialist to evaluate the image for diagnosis. It constructs a visual word dictionary representing points of interest (PoIs) located within regions marked by specialists. Fundus images are classified as normal or DR-related pathology based on the presence or absence of these PoIs. Area under the curve (AUC) of 95.3% and 93.3% is achieved for white and red lesion detection using fivefold cross validation. The visual dictionary is robust for DR screening of large, diverse communities with varying cameras and settings and levels of expertise for image capture.

Saleh and Eswaran (2012) provides an automated decision-support system for non-proliferative diabetic retinopathy disease based on MAs and HAs detection. The proposed system extracts some foreground objects, such as optic disc, fovea, and blood vessels for accurate segmentation of dark spot lesions in the fundus images. Dark object segmentation approach is used to locate abnormal regions such as MAs and HAs. Based on the number and location of MAs and HAs, the system evaluates the severity level of DR. A database of 98 color images is used to evaluate the performance of the developed system. Experimental results have shown that the proposed system achieves 84.31% and 87.53% values in terms of sensitivity for the detection of MAs and HAs respectively. In terms of specificity, the system achieves 93.63% and 95.08% values for the detection of MAs and HAs respectively.

Reliable detection of retinal hemorrhages is important in the development of automated screening systems. Li et al. (2013) proposed a novel splat feature classification method with application to retinal hemorrhage detection in fundus images. Retinal color images are partitioned into non-overlapping segments covering the entire image. Each splat contains pixels with similar color and spatial location. Features are extracted from each splat relative to its surroundings, employing responses from a variety of filter bank, interactions with neighboring splats, and shape and texture information. An optimal subset of splat features is selected by a filter approach followed by a wrapper approach. Given splats with their associated feature vectors and reference standard labels, a classifier can then be trained to detect target objects. A classifier is evaluated on the publicly available Messidor dataset. An area under the receiver operating characteristic curve of 0.96 is achieved at the splat level and 0.87 at the image level.

Luca et al. (2012) introduced a new methodology for diagnosis of Diabetic macular edema (DME) using a novel set of features based on colour, wavelet decomposition and automatic lesion segmentation. The method proposed for the DME diagnosis is based on the classification of single feature vector generated for each image. The feature vector is based on three types of analysis: Exudate probability map, Colour Analysis and Wavelet Analysis. These features are employed to train a classifier able to automatically diagnose DME through the presence of exudation. The proposed algorithm obtained an AUC between 0.88 and 0.94 depending on the dataset/features used.
Haniza Yazid et al. (2012) presents a new approach to detect exudates and optic disc from color fundus images based on inverse surface thresholding. The proposed approach involves many techniques such as fuzzy c-means clustering, edge detection, otsu thresholding and inverse surface thresholding. It does not depend on manually selected parameters. The proposed method has achieved 98.2% in sensitivity and 97.4% in specificity for DIARETD81 database and 90.4% in sensitivity and 99.2% in specificity for the National University Hospital of Malaysia (NUHM), respectively. This method outperforms methods based on watershed segmentation and morphological reconstruction.

Atul Kumar et al. (2012) implements a method that segment the exudates from the image using feature based segmentation. The methodology is composed of morphological operation with the SVM algorithm. Image pre-processing is the first step to enhance the image for better analysis. Then morphological operation is implemented to localize the optic disk from the retinal fundus image. Features are extracted using combined 2DPCA for classification. The SVM classifier uses these extracted features for classifying the exudates. The results of the algorithm is compared with expert hand-drawn ground-truths. The proposed method has achieved sensitivity and specificity as 97.1% and 98.3% respectively.

JayaKumari and Maruthi (2012) have presented contextual clustering algorithm to detect the presence of hard exudates in the fundus images. After the pre-processing stage, the proposed algorithm has been applied to segment the exudates. Features extracted from the segmented regions are like the standard deviation, mean, intensity, edge strength and compactness. These extracted features are given as inputs to Echo State Neural Network (ESNN) to discriminate between the normal and pathological image. A dataset consists of a total of 50 images have been used to find the exudates. Out of 50, 35 images consisting of both normal and abnormal are used to train the ESSN and the remaining 15 images are used to test the neural network. The performance of the proposed algorithm has obtained 93.0% sensitivity and 100% specificity in terms of exudates based classification.

**MATERIALS AND METHODS**

Colour fundus images are often suffered from non-uniform illumination, poor contrast and noise. Each color pixel is described by a triple (R, G, B) of intensities for red, green, and blue. Green channel shows the best contrast. Red channel is often saturated and has low contrast. The blue channel is very noisy and suffers from poor dynamic range. From the input RGB color image, only green channel is extracted and pre-processed. In the pre-processing stage, Polynomial contrast enhancement operator is used for performing shade correction and contrast enhancement in the green channel of the original image (Thomas et al., 2007). Then the enhanced image is masked with two different masks. The first one is the optic disk mask and the second one is the vascular tree mask. These masks are used to eliminate all the interfering effects in the candidate detection.

**A. Local Polynomial Contrast Enhancement Operator:**

The proposed approach has used the local polynomial contrast enhancement operator for image enhancement. This operator is a simple gray level transformation. It assigns to each pixel a new gray level which can be determined in order to obtain a convenient enhancement. \( f : O \rightarrow f \) be a gray level image with \( P = \{p_{\min}, p_{\max}\} \subseteq R \) a set of rational numbers. Let \( S = \{s_{\min}, s_{\max}\} \subseteq R \) be a second set of rational numbers. A gray level transformation \( T \) is a mapping \( P \rightarrow S, s = T(p) \). Polynomial gray level transformation with parameter \( n \) is defined as follows:

\[
s = T(p) = \begin{cases} 
1 \cdot (p - p_{\min})^n + y_1 & , p \leq m_f \\
2 \cdot (p - p_{\max})^n + y_2 & , p > m_f 
\end{cases}
\]

with \( x_1, x_2, y_1, y_2 \) a set of parameters which can be determined in order to obtain a convenient transformation graph, and \( m_f \) the global gray level mean of image \( f \). The gray level transformation is constructed in such a way that it assigns the center between \( s_{\min} \) and \( s_{\max} \) to the mean value \( m_f \). Furthermore, it makes sense to postulate \( T(p_{\min}) = s_{\min} \) and \( T(p_{\max}) = s_{\max} \) in order to make use of the whole range of \( S \). With these four conditions, Parameters such as \( x_1, x_2, y_1, \) and \( y_2 \) of Eq. (1) can be determined. The global polynomial contrast enhancement operator is now obtained as follows

\[
s = T(p) = \begin{cases} 
\frac{1}{2}(s_{\max} - s_{\min}) + (m_f - p_{\min})^n, & p \leq m_f \\
\frac{1}{2}(s_{\max} - s_{\min}) + (m_f - p_{\max})^n, & p > m_f 
\end{cases}
\]
If this operator is applied to the whole image as a global contrast operator, the result is not satisfying due to slow background variation. In fact, the proposed gray level transformation does only enhance the contrast for subsets of $P$ for which $\frac{\partial f}{\partial p} > 1$. For instance, the contrast of a dark detail situated in a dark region may even be attenuated. It is possible however to overcome this problem by applying the contrast operator of Eq. (2) locally. One possibility is to calculate the mean value of $f$ within a window $W$ centered in the pixel $c$:

$$m^W_f(c) = \frac{1}{N_{w(i,c)}} \sum_{f(i)}$$

For large window sizes, this operator would be very slow. The window size used in this work is $25 \times 25$ pixels. The value of $n$ is chosen to be $2$. In addition with the contrast enhancement, this operator also removes slow background variations. The contrast is readjusted in every point to the local mean. The darkening which is closer to bright objects is a real problem in MA segmentation. The area opening $O_t$ removes all bright objects having an area smaller than $t$. The value of $t$ is chosen as $2500$. It preserves the contours of the remaining objects. The mean value $m^*$ of the area opened image $O_t$ within a window $W$ is defined as follows

$$m^* = m^W_{O_t}(c)$$

After the contrast enhancement, shade correction and normalization techniques are applied to the enhanced image. The shade corrected image is obtained using the Eq. (5). To normalize the image, Gaussian filter is applied to the shade corrected image in order to attenuate the noise (width 5 pixels, $r = 2$).

$$S_{\text{enh}}(f)[i] = \begin{cases} \frac{1}{2}(f(i) - \min f) & \text{if } f(i) \leq m^* \text{ and } f(i) \leq \min f + \frac{1}{2}(\max f - \min f), \\ \frac{1}{2}(f(i) - \min f) + \frac{1}{2}(\max f - \min f) & \text{if } f(i) > m^* \end{cases}$$

With $G$ a Gaussian filter, the pre-processed image $P_{\text{img}}$ is obtained as follows

$$P_{\text{img}} = G \ast S_{\text{enh}}(f).$$

![Fig. 1: a) Original Image b) Green channel c) Enhanced Image d) Optic Disk Removal](image)

**B. Optic Disk Removal:**

Since the optic disk has characteristics, bright intensity almost similar to hard exudates and cotton wool spots, accurate optic disk detection is then necessary to remove these false positives from the final result. The optic disk is selected using region of interest from the preprocessed image $P_{\text{img}}$. This is achieved using roipoly() function available in Matlab. The optic disk detection algorithm consists of two steps. First step is the candidate selection using mathematical morphology operation. Second step is optic disk detection using Hough transform. Candidates are selected by applying alternative sequential filters to the enhanced image. Next, the candidate is considered to be the optic disk if vertical vessels are found in its neighborhood. Vertical vessels are detected by matching the enhanced image with a two-dimensional vertical-oriented filter characterized by a Gaussian cross-profile section. Each detected vessel is modelled by a single line to obtain the image skeleton. Then the Hough transform is applied to the neighborhood of the candidate centroids. Finally the optic disk is selected as the candidate region with the maximum number of pixels which belongs to vertical lines passing through it. The optic disk regions are automatically excluded from the other regions by subtracting the enhanced image with the disk segmented mask image [Sánchez et al., 2009]. The final result is shown in Fig. 1.

**C. Blood Vessels Removal:**

The accurate segmentation of the retinal blood vessels is often an essential prerequisite step in the identification of retinal anatomy and pathology. Blood vessels are well contrasted against a darker background. The algorithm for removing vessel tree is composed of four steps: Sub-images generation, Radon Transform (RT), Candidate vessel detection, and Vessel refinement. First the enhanced retinal fundus image is partitioned into some overlapping windows.
The size of window, n, is selected bigger than width of the biggest vessel in pixel. The windows overlapping ratio is a challenging issue. RT is then applied to each window. The amplitude of projection in diagonal directions is higher than other directions. The peak of RT is more likely to happen in diagonal directions. The peak amplitude is compared with a pre-defined threshold. If the peak amplitude is bigger than threshold, the detected sub-vessel is confirmed and the algorithm should calculate sub-vessel’s width. \( v_p \) is the peak’s index associated with the sub-vessel’s center line. The interval \([v_{min}, v_{max}]\) around \( v_p \) is the sub-vessel’s thickness.

\[
v_{max} > v_p > v_{min}
\]  
(7)

\[
P(v_{max}) = \alpha \times P(v_p)
\]  
(8)

\[
P(v_{min}) = \alpha \times P(v_p)
\]  
(9)

\[
w = v_{max} - v_{min} + 1
\]  
(10)

where \( \alpha \) is a constant \((0<\alpha<1)\) and \( P \) denotes profile. The value of \( \alpha \) is chosen as 0.6 for the database. Sub-vessel mask is prepared by using \( v_{max}, v_{min} \), projection angle \( (\theta) \), and window size \( (n) \) which presents coarse sub-vessel’s coverage area in the sub-image. The input sub-image is converted to a binary image in which white pixels represent vessel area and black pixels represent background. Two gray level means are computed black pixels in the local vessel mask. Based on these two means, sub-image is thresholded to make a binary sub-image in which white and black pixels represented vessel area and background respectively. To achieve the vessel map of the input image, fine local masks are merged using logical OR [Meysam et al., 2013]. The final vessel map shown in Fig. 2 is used to remove the vasculature in the enhanced image.

### Fig. 2: a) Pre-processed image b) Vessel Detected Image.

**Segmentation:**

There are many existing algorithms to segment microaneurysms, hemorrhages, and exudates separately in the literature. Only few algorithms segment the combination of above. No single segmentation algorithm segments all these abnormal regions in the retinal fundus images effectively. The proposed algorithm applies a new contrast measure to identify light dark, dark, bright and light bright regions i.e microaneurysms, hemorrhages, hard and soft exudates, for diagnosing diabetic retinopathy in the retinal fundus images.

#### A. Unsupervised Multi-Level Transition Region Based Thresholding Segmentation:

Let I be the pre-processed image with N levels \([0, 1, \ldots, N-1]\). Let \( p_i \) be the number of pixels with gray level \( i \) and \( P = p_0 + p_1 + \ldots + p_{N-1} \) be the total number of pixels.

1. Compute the mean and standard deviation of the gray levels of the image corresponding to the positive and negative values in the contrast matrix separately, according to the following equations,

\[
\mu_{pe} = \frac{1}{P_{pe}} \sum_{i=0}^{p_{max}} p_i
\]  
(11)

\[
\mu_{na} = \frac{1}{P_{na}} \sum_{i=0}^{p_{max}} p_i
\]  
(12)

\[
\sigma_{pe} = \left( \frac{1}{P_{pe}} \sum_{i=0}^{p_{max}} \left( p_i - \mu_{pe} \right)^2 \right)^{1/2}
\]  
(13)
\[
\sigma_{sk} = \left( \frac{1}{P_{sk} - 1} \sum_{i=1}^{P_{sk}} (i - \mu_{sk})^2 \right)^{1/2}
\]  

(14)

Where \( \mu_{PR}, \sigma_{PR}, \mu_{SR}, \) and \( \sigma_{SR} \) are the mean and standard deviation of the positive and negative regions respectively. \( P_{PR} \) and \( P_{SR} \) represents the number of pixels in the positive and negative regions respectively.

(2) Obtain four threshold values by selecting upper and lower bounds from both the positive and negative transition regions using the following

\[
T_{pu} = \mu_{PR} - \beta \times \sigma_{PR}
\]

(15)

\[
T_{pl} = \mu_{PR} + \beta \times \sigma_{PR}
\]

(16)

\[
T_{ns} = \mu_{SR} - \beta \times \sigma_{SR}
\]

(17)

\[
T_{nl} = \mu_{SR} + \beta \times \sigma_{SR}
\]

(18)

where \( \beta \) is a parameter and its value can be automatically determined by optimizing the proposed criterion in Eq.(23). \( T_u \) and \( T_l \) are the upper and lower bounds for background and object in the positive transition region respectively, whereas \( T_n \), and \( T_s \) are the upper and lower bounds for background and object in the negative transition region respectively.

(3) Find gray level ranges of foreground object and background in the positive and negative transition regions using the following

\[
G_{pf} = [T_{pf}, N-1]
\]

(19)

\[
G_{rb} = [0, T_{pu}]
\]

(20)

\[
G_{ns} = [0, T_{ns}]
\]

(21)

\[
G_{nrb} = [T_{nl}, N-1]
\]

(22)

Algorithm for Image transformation:

Image transformation is done on two phases. One phase is for getting dark objects and another one for getting bright objects. To perform this transformation, Gray level ranges of dark and bright objects and background should be determined first. These ranges can be computed from threshold values selected from the positive and negative regions in the contrast matrix. For the original image \( I \), the steps for the image transformation are as follows:

(1) Compute the upper and lower bounds by Eqs. (15), (16), (17), and (18).

(2) Obtain gray level ranges of objects and background by Eqs. (19), (20), (21) and (22).

(3) Perform the first phase of the image transformation using the following:

\[
I_{T1}(i, j) = T_{pf}, \quad \text{if} \quad I(i, j) \in G_{pf},
\]

\[
I_{T1}(i, j) = T_{pu}, \quad \text{if} \quad I(i, j) \in G_{pb}, \quad \text{and}
\]

\[
I_{T1}(i, j) = I(i, j), \quad \text{Otherwise}
\]

(4) Perform the second phase of the image transformation using the following:

\[
I_{T2}(i, j) = T_{ns}, \quad \text{if} \quad I(i, j) \in G_{ns},
\]

\[
I_{T2}(i, j) = T_{nl}, \quad \text{if} \quad I(i, j) \in G_{nrb}, \quad \text{and}
\]

\[
I_{T2}(i, j) = I(i, j), \quad \text{Otherwise}
\]

where \( I(i, j) \), \( I_{T1}(i, j) \) and \( I_{T2}(i, j) \) are gray levels at pixel \( (i, j) \) of the original image and its transformed forms based on two different threshold values, respectively [Zuoyong et al., 2011].
Algorithm for image segmentation:

1. Decide the size and pattern of the neighbourhood window.
2. Apply the neighbourhood window to the original image for computing the contrast of each pixel in the image using the following

\[ C = \frac{G_f - G_b}{G_b} \]  

where \( G_f \) is the gray value of the foreground pixel and \( G_b \) is the mean of the gray values of the background.
3. Construct the contrast matrix, \( C \).
4. Obtain four threshold values such as \( t_1, t_2, t_3, \) and \( t_4 \) for extracting transition regions.
5. Extract transition regions using the process of image transformation.
6. Compute two final optimal thresholds such as \( T_1 \) and \( T_2 \) using Parzen Window estimation. The first threshold \( T_1 \) obtained from positive contrast region is used for segmenting bright objects in an image. The second threshold \( T_2 \) obtained from negative contrast region is used for segmenting dark objects in the image.
7. Segment the original image into regions whose pixels are greater than the first threshold. These bright regions are extracted as abnormal regions i.e. exudates.
8. Segment the original image into regions whose pixels are lesser than the second threshold. These dark regions are nothing but abnormal regions such as microaneurysms, and hemorrhages [Zuoyong et al., 2011].

Segmentation results are evaluated using misclassification error (E) measure [Zuoyong et al., 2011]. This measure gives the percentage of background pixels wrongly classified into foreground, and vice versa. It can be estimated as follows

\[ E = 1 - \frac{|B_f \cap B_t| + |O_f \cap O_t|}{|B_f| + |O_f|} \]  

where \( B_f \) and \( O_f \) represents the background and object of the ground truth image, \( B_t \) and \( O_t \) represents the background and object in the segmented image. The value of E is 0 for a perfectly classified image and 1 for a totally erroneously classified one. If E has lower value, good segmentation result is achieved. Otherwise, segmentation is poor.

Results

The proposed algorithm is experimented with three datasets such as DIARETDB0, DIARETDB1, and MESSIDOR. It extracts all the abnormal signs of NPDR. In the training phase, 32 features are extracted from the segmented abnormal regions. Association rules are generated based on these features. For grading images, some special rules mentioned in section 6 are generated based on the percentage of features in the rules. These grading rules are used for classifying the input image as normal or having NPDR. Fig. 4 shows the segmentation results.

For DIARETDB0, the proposed work has achieved a sensitivity of 97.51 % and specificity of 98.09% respectively. It achieves a sensitivity of 98.38% and specificity of 98.14% by using the DIARETDB1. With the use of MESSIDOR dataset, sensitivity of 99.23% and specificity of 98.78% are achieved for the diagnosis of NPDR.

Conclusion

In the proposed algorithm, the green channel of the image is first extracted from the original color retinal fundus image. The green channel is then pre-processed using various techniques such as local polynomial contrast enhancement operator, shade correction and contrast normalization. After image enhancement, optical disk and blood vessels are removed for improving the quality of segmentation results. There is no effective algorithm for segmenting all the abnormal regions in the literature. The proposed segmentation algorithm segments both the dark and bright abnormalities of NPDR. In the feature extraction step, 32 features are extracted for classification. Association rule mining is used to generate rules for identifying each abnormal regions of NPDR. It also generates the grading rules for classifying the image as normal or having the signs of NPDR. The proposed approach is experimented using three different datasets such as DIARETDB0, DIARETDB1, and MESSIDOR. It has achieved greater accuracy compared to the existing methods. In the future, the increasing number of association rules is a challenging issue. This can be overcome by using some optimization techniques.

REFERENCES


