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DETECTION OF EXUDATES ON COLOR FUNDUS IMAGES USING TEXTURE BASED FEATURE EXTRACTION

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ABSTRACT
The World Health Organization (WHO) has predicted 300 million peoples will suffer from diabetes in 2025. Long-term diabetes can lead to diabetic retinopathy that can cause blindness in developing countries. One of the abnormalities of diabetic retinopathy is exudate. This paper proposes texture-based extraction of features from retinal images for distinguishing exudates from non-exudates. The green channel of the original retinal image is enhanced using contrast-limited adaptive histogram equalization (CLAHE). Meanwhile, in the red channel, median filtering and thresholding are conducted to detect and remove the optic disc. The enhanced green channel is multiplied by the segmented optic disc of red channel. The resulting image is then segmented based on clustering to obtain the region of interest for exudates. Feature extraction based on texture is conducted using a gray-level co-occurrence matrix (GLCM) and lacunarity. The results show that classification based on the "naïve" Bayes algorithm achieves accuracy, specificity and sensitivity of 92.13%, 96% and 87.18%, respectively.

Keywords: Fundus images; Exudates; Texture feature; GLCM; Lacunarity

1. INTRODUCTION

The World Health Organization (WHO) predicted that around 300 million people will suffer from diabetes in 2025 (Kanth et al., 2013). The long-term effects of diabetes can lead to change, leakage and damage to the retinal blood vessels, which increase the amount of glucose in the blood. This is known as diabetic retinopathy (DR) (Das et al., 2014; Paranjpe & Kakatkar, 2014; S. karthick & Priyadharsini, 2014). Diabetic retinopathy is the leading cause of blindness in developing countries (Sánchez et al., 2008). It causes permanent damage to the eyes; therefore, early detection and diagnosis are needed to reduce the incidence and severity of eye damage (Kanth et al., 2013).

Previous studies reported that 90% of blindness associated with diabetes can be prevented by screening (Ponnaiah & Baboo, 2013). Screening process needs longer time, is inefficient and requires trained personnel (Paranjpe & Kakatkar, 2014). Various medical image processing techniques have been techniques have been recommended to help ophthalmologists detect signs of DR (Kanth et al., 2013). DR is known to have specific indications, including microaneurysms (MAs), hard exudates, soft exudates or cotton wool spots (CWS), hemorrhages (HEM), neovascularization (NV) and macular edema (ME).

The main abnormal signs and the most primitive of the DR are exudates (Kande et al., 2009; Mookiah et al., 2013; S. karthick & Priyadharsini, 2014; SC et al., 2013).

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Exudates in the retina are turbidity generated from discharge of the plasma and white blood cells from damaged blood vessels. Early detection of exudates can prevent blindness (Somasundaram & Prabhu, 2013). Exudates are divided into two categories, i.e. hard and soft exudates, also known as cotton wool spots (CWS) (S. karthick & Priyadharsini, 2014).

Hard exudates appear yellowish with limited edges, sharply defined and shiny in imaging, appearing individually and collectively (S. karthick & Priyadharsini, 2014; Sánchez et al., 2008). Soft exudates appear whitish with indistinct edges, giving the impression of diffuse cotton shape. Soft exudates form due to blockage of nerve fibers that receive blood supply from the retinal arteries, so that the axons nerve fibers enlarges (S. karthick & Priyadharsini, 2014). Soft exudates are found in cases of hypertensive retinopathy and the serious condition of DR (SC et al., 2013). Figure 1 illustrates the differentiation between hard and soft exudates.

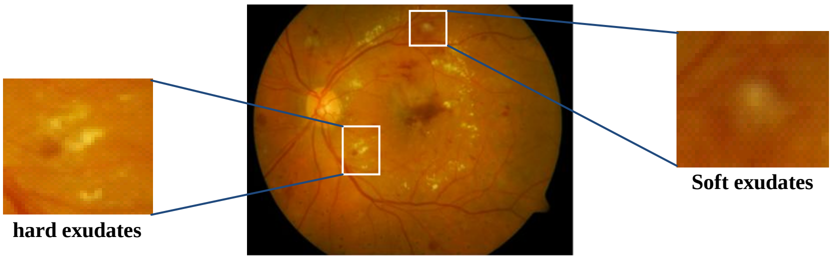


Figure 1 Visual differentiation between hard and soft retinal exudates (Kauppi et al., 2007)

Various studies have examined the detection of diabetic retinopathy. García et al. (2009) focused on the detection of hard exudates through lesions apparent on retinal fundus images. The candidate areas of exudates were obtained from a normalized image segmented by combining the global and adaptive thresholding methods.

Bin Mansoor et al. (2008) proposed an enhancement method by increasing the image intensity with morphology fuzzy dilation and fuzzy erosion. However, that study could not distinguish between hard and soft exudates. Hani et al. (2012) enhanced low contrast of retinal fundus images based on independent component analysis (ICA) (Fadzil et al., 2009; Hani et al., 2012). That work focused on segmentation of retinal vasculature and FAZ areas using a hybrid method based on Retinex and ICA. Several researchers (Acharya et al., 2012; Amel et al., 2012; García et al., 2009; Rashid & Shagufta, 2013; S. karthick & Priyadharsini, 2014; SC et al., 2013) used CLAHE to improve the contrast of retinal fundus imagery and the uniformity of image brightness.

Acharya et al. (2012) presented a preprocessing method for retinal images that converted a red–green–blue (RGB) image into grayscale and enhanced the image contrast via adaptive histogram equalization. The next step was to extract features using a gray-level co-occurrence matrix (GLCM), which was subsequently input to a Support Vector Machine (SVM)-based classifier.

Several studies (Bin Mansoor et al., 2008; Eadgahi & Pourreza, 2012; Garcia et al., 2013) reported that hard and soft exudates are not clearly separated. Both hard and soft exudates have the same characteristics as that of the optic disc (color, luminance, contrast and texture). In grayscale images, exudates and the optic disc show similar average intensity (Chen et al., 2013). In color retinal fundus images, the presence of non-uniform illumination and varied contrast necessitates the enhancement process.

The focus of this work is to identify hard and soft exudates from enhanced retinal images, based on texture features. Segmentation is based on K-means clustering. GLCM and lacunarity are used to extract the texture features. The features are classified using a machine-learning algorithm. The rest of this paper is organized as follows: Section 2 describes the proposed method, followed by results and analysis in Section 3. Conclusions are presented in Section 4.

2. UNDERLYING THEORIES

The proposed methodology comprises four main processes: enhancement, segmentation, feature extraction and classification. Firstly, the channels of the original image are extracted. Poor-quality images are enhanced by applying contrast-limited adaptive histogram equalization (CLAHE) to the green channel. The red channel is used to detect and remove the optic disc area from the image by using median filtering and thresholding, which facilitates the subsequent step. The enhanced image is then segmented based on K-means clustering to acquire the exudate area. Extraction of texture features is achieved using GLCM. Additionally, lacunarity is also utilized to improve feature extraction. The extracted features are classified via a machine-learning algorithm. The classification steps are evaluated based on accuracy, sensitivity and specificity. The process is depicted in the flowchart in Figure 2.

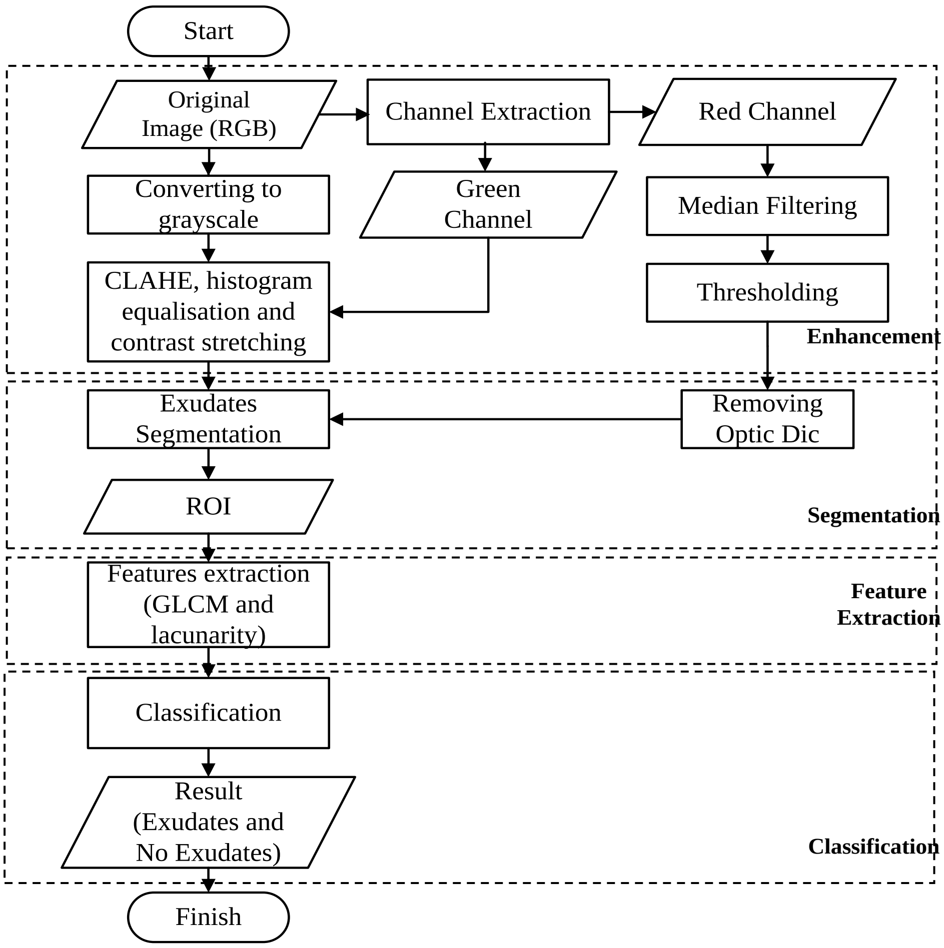


Figure 2 Flowchart depicting the approach

2.1. Contrast Enhancement

Retinal fundus images of poor quality influence the segmentation process and therefore require enhancement. In some cases, it is expected to enhance the image contrast by histogram equalization. However, this method is effective only for images with low noise density. Usually, the enhancement process converts an RGB image to grayscale with the aim of simplifying the enhancement process.

In the proposed method, the green channel of the image is subject to contrast-limited adaptive histogram equalization (CLAHE) resulting in easier detection of exudates (Yazid et al., 2012). In this method, the local areas of the histograms are calculated and the intensity values are then equalized within those areas that have the effect of increasing the contrast. Some enhancement techniques are used for comparison with the proposed enhancement method. Mean square error (MSE) and peak signal-to-noise ratio (PSNR) are used to evaluate the contrast of the enhanced image.

2.2. Segmentation

The Eliminating the optic disc from the image can facilitate detection of exudates. To obtain the region of interest (ROI) of exudates in the retinal fundus images, the enhanced image is segmented using K-means clustering to differentiate exudate and non-exudate areas. The K-means clustering partitions n data into k clusters based on the nearest distance between data points and the cluster center (Gogula et al., 2014).

2.3. Feature Extraction

The GLCM matrix can be established by the second order of the histogram. The co-occurrence matrix has a size of $L \times L$ (L is the number of gray levels) with elements of P (X_1, X_2) which describe the joint probability distribution. The GLCM features consist of angular second moment (ASM), contrast, inverse different moment (IDM), entropy and correlation. These features are mathematically formulated in Equations 1–5 (Haralick et al., 1973).

$$ASM = \sum_{i=1}^{L}\sum_{j=1}^{L}(GLCM(i,j))^2 \tag{1}$$

$$Contrast = \sum_{n=1}^{L} n^2\{\sum_{|i-j|-n} GLCM(i,j)\} \tag{2}$$

$$IDM = \sum_{i=1}^{L}\sum_{j-1}^{L}\frac{(GLCM(i,j))^2}{1+(i-j)^2} \tag{3}$$

$$Entropy = -\sum_{i=1}^{L}\sum_{j-1}^{L} GLCM(i,j)\log GLCM(i,j) \tag{4}$$

$$Correlation = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}(ij)(GLCM(i,j)) - \mu_i^{'}\mu_j^{'}}{\sigma_i^{'}\sigma_j^{'}} \tag{5}$$

Here, $\mu_i^{'}$, $\mu_j^{'}$, $\sigma_i^{'}$ and $\sigma_j^{'}$ describe the means and deviation of $GLCM(i)$ and $GLCM(j)$. Lacunarity is a fractal measurement that can be used to obtain textural features (Kadir & Susanto, 2012), and is defined in Equations 6–8.

$$L_s = \frac{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn}^{\ 2}}{\left(\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} P_{kl}\right)^2} - 1 \quad (6)$$

$$L_a = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|\frac{P_{mn}}{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} P_{kl}} - 1\right| \quad (7)$$

$$L_p = \left(\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(\frac{P_{mn}}{\frac{1}{MN}\sum_{k=1}^{M}\sum_{l=1}^{N} P_{kl}} - 1\right)^p\right)^{1/p} \quad (8)$$

MxN describes the size of the image, *M* is the pixel row of the image and *N* is the pixel column. P_{mn} shows the pixel intensity at *(m x n)*. L_s, L_a and L_p are the squared representation, absolute representation and mean representation of lacunarity, respectively. Arbitrarily chosen order values for *p* are 2, 4, 6, 8 and 10 (Canada et al., 2011; Kadir & Susanto, 2012).

2.4. Classification

In this step, the "naïve" Bayes method is used to classify the extracted features. Classification is run using the Weka machine-learning algorithm (Hall et al., 2009). K-cross validation provides accurate performance estimation (Refaeilzadeh et al., 2009) and is therefore chosen to evaluate the training and testing of the dataset features. The classification step is evaluated for accuracy, sensitivity and specificity.

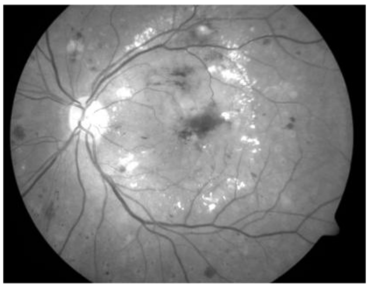
3. RESULTS AND DISCUSSION

In this works, dataset retinal fundus images are taken from DIARETDB1 (Kauppi et al., 2007), consisting of 89 images in PNG format. The results show that the proposed method successfully enhances retinal fundus images, as shown in Figure 3. CLAHE, histogram equalization and contrast stretching are used for comparison with the proposed method. Table 1 shows average MSE and PSNR values for the various methods.

Table 1 MSE and PSNR values of each method

Method	MSE	PSNR
Green channel + Contrast stretching	14.22	36.63
Green channel + Histogram equalization	15.74	36.16
Green channel + CLAHE	**10.55**	**37.94**

Table 1 shows that the CLAHE technique provides good-quality enhancement of the green-channel image. The red channel contains useful information for detection of the optic disc. Median filtering is applied to the red channel of the image in order to differentiate the candidate area of the optic disc. Thresholding is then applied to remove the optic disc region from the retinal fundus images, as shown in Figure 4.


Green channel: Contrast stretching


Green channel: Histogram equalization

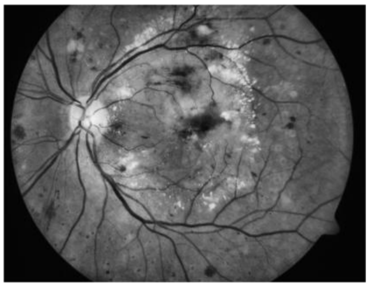
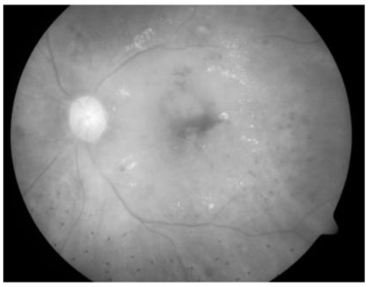
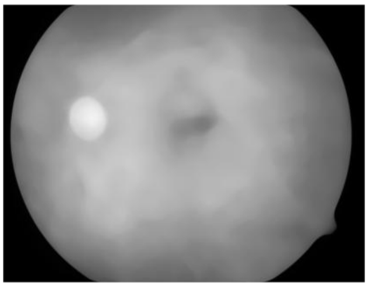
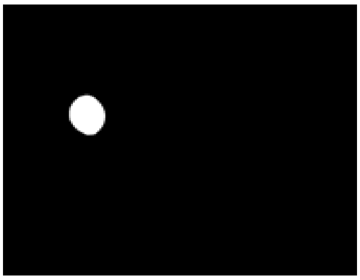

Green channel: CLAHE

Figure 3 Results of the enhancement method


Red channel

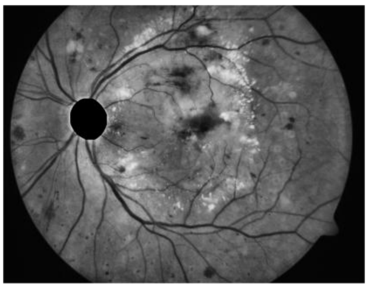

Median filtering


Thresholding


Removed optic disc

Figure 4 Removal of optic disc from image

Having enhanced the retinal fundus images and removed the optic disc, it is easy to separate the object from its background. By applying segmentation based on K-means clustering, exudate areas can be detected. The segmented image in Figure 5 depicts both hard and soft exudates.


Original image

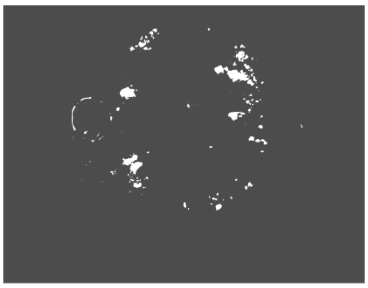
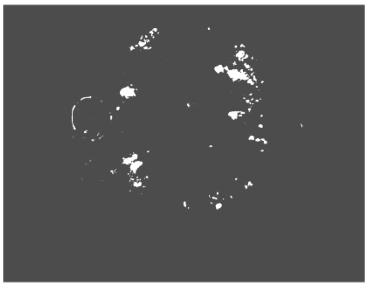

Segmented image

Figure 5 Segmented hard and soft exudates

The segmented image is then validated against the ground truth image to establish the accuracy of the process, as shown in Figure 6.


(a)

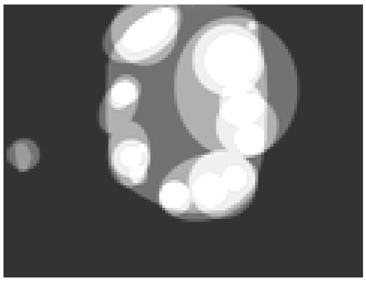

(b)

Figure 6 Examples of (a) segmented exudates and (b) ground truth

First step of the GLCM-based method defined the framework matrix with resolution of 1500×1152 pixels. The framework matrix is processed with a transpose matrix to obtain a symmetrical matrix; the symmetrical matrix is then normalized. The relationship between pairs of pixels are calculated for four angles of Θ, i.e. 0°, 45°, 90°, 135° and default distance d=1. Finally, a total of 12 features are calculated, comprising 5 features of GLCM (ASM, contrast, IDM, entropy and correlation) and 7 features of lacunarity (i.e. 1s, 1a, 12, 14, 16, 18 and 110).

The extracted features are used as inputs to the classification process. The "naïve" Bayes method is used as a machine-learning package to train and test these extracted features on the dataset. The results achieve accuracy, sensitivity and specificity of 92.13%, 87.18% and 96%, respectively for detection of exudates. Two sets of textural features are defined, which can be used to separate hard, soft and non-exudates in the retinal fundus images. Table 2 shows a comparison of the classification results for the two sets of features that are tested.

Table 2 Comparison of classification result of textural features

Evaluated	GLCM	Lacunarity	GLCM+Lacunarity
Accuracy	75.28%	91.01%	**92.13%**
Sensitivity	48.72%	84.62%	**87.18%**
Specificity	96%	96%	**96%**

4. CONCLUSION

The proposed method successfully enhances retinal fundus images and is facilitates segmentation of exudates based on K-means clustering. Median filtering and thresholding of the red channel successfully segment the optic disc. Extracted textural features are classified using the "naïve" Bayes classifier. The accuracy, specificity and sensitivity of classification are 92.13%, 96% and 87.18%, respectively. These findings are useful to assist ophthalmologists in detecting and recognizing hard and soft exudates from retinal fundus images for diagnosis of diabetic retinopathy. The results are expected to contribute to material considerations in decision making.

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