Detection of Diabetic Retinopathy and Maculopathy in Eye Fundus Images Using Fuzzy Image Processing

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Abstract. Diabetic retinopathy is a damage of the retina and it is one of the serious consequences of the diabetes. Early detection of diabetic retinopathy is extremely important in order to prevent premature visual loss and blindness. This paper presents a novel automatic detection of diabetic retinopathy and maculopathy in eye fundus images using fuzzy image processing. The detection of maculopathy is essential as it will eventually cause loss of vision if the affected macula is not timely treated. The developed system consists of image acquisition, image preprocessing with a combination of fuzzy techniques, feature extraction, and image classification by using several machine learning techniques. The fuzzy-based image processing decision support system will assist in the diabetic retinopathy screening and reduce the burden borne by the screening team.

Keywords: Diabetic retinopathy · Eye screening · Colour fundus images · Fuzzy image processing · Machine learning · Classifiers

1 Introduction

Diabetic Retinopathy (DR) is a complication of diabetes and it is the leading cause of blindness and visual disability. Regular eye examination is essential for an early detection of retinopathy in order to reduce visual loss and blindness caused by DR. The main purpose of diabetic retinopathy screening is to detect whether the individuals require follow-up referral for further treatment or not [1]. Therefore, an accurate and robust retinal screening system is required to assist the retinal screeners to classify the retinal images effectively and with high confidence.

An international clinical diabetic retinopathy and diabetic macula oedema disease severity scale was proposed by Wilkinson and others [2] to assist in the grading the fundus images into distinct categories based on retinal appearances. The scale is based on the Early Treatment Diabetic Retinopathy Study (ETDRS) on the classification of

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DR [3]. The DR lesions can be categorized into the so-called retinopathy stages, namely, mild DR, moderate DR, severe DR, proliferative DR and Advanced Diabetic Eye Disease (ADED).

Maculopathy is represented by yellow lesions near the macula and is a disease in the macula region of the retina. Macula is the centre of the retina and provides our central vision. The macula region is a very sensitive area where the centre of the macula, called fovea, a tiny area which is responsible for detailed vision as well as colour vision [1]. Therefore, the detection of maculopathy is very important because the loss of vision at the fovea alone causes legal blindness. Maculopathy is present when there are any exudates, haemorrhages or microaneurysms in the macula region. However, the visible signs of maculopathy are only indirect markers for the possible presence of macula oedema, which is the swelling of the retina [1]. The presence or absence of the maculopathy will determine the need for treatment or referral. The referral to the ophthalmologist is assigned if the maculopathy is present, while referral is not required and the screening is repeated in one year time, if the maculopathy is absent. Therefore, the combined detection of diabetic retinopathy and maculopathy is vital in order to effectively assist the management of the diabetic retinopathy screening.

In our earlier work, we have proposed a preliminary system for the diabetic retinopathy screening [4], which classified images into two main categories; normal (no apparent retinopathy) or abnormal (retinopathy presence) using non-fuzzy techniques. Then, we continued by presenting an automatic screening system to detect the earliest visible signs of retinopathy, i.e., microaneurysms, by using fuzzy image processing [5]. Four variants of microaneurysms detection systems, which utilize different techniques, with or without the implementation of fuzzy image processing, were presented and comparisons were made. For example, the second system variant, implementing the greyscale conversion, Fuzzy Histogram Equalisation and Circular Hough Transform was proven to produce better results compared to the first system variant which implemented the greyscale conversion, histogram equalisation and Circular Hough Transform techniques. The overall results show that the implementation of the fuzzy preprocessing techniques provides better contrast enhancement as well as other improvements for colour fundus images, and, hence, it greatly helps microaneurysms detection to be more efficient and reliable. However, we proposed individual system variants implementing different fuzzy processing techniques. In this paper, we are proposing a novel detection system for diabetic retinopathy and maculopathy by combining several consecutive fuzzy image preprocessing techniques in one system, based on the previous encouraging results on using fuzzy image processing obtained in [5]. In addition, the proposed system is following the current practice observed by the ophthalmologist in the classification and grading of diabetic retinopathy and maculopathy, which classifies into ten main classes, as explained under the proposed system section in [5] and outlined below in Section 6.

The paper is organized as follows. Section 2 presents the related work on the diabetic retinopathy and maculopathy detection, followed by Section 3, which details the proposed detection system. Section 4 describes the image preprocessing stage, while Section 5 explains the feature extraction part. Section 6 describes the classification, while Section 7 presents the results of the system and, finally, Section 8 details some conclusions of the work and a future plan.

2 Related Work on Diabetic Retinopathy and Maculopathy Detection

Grading of diabetic retinopathy is a challenging task for both automatic systems and medical doctors. Detection of normal and other two main classes of diabetic retinopathy, which are non-proliferative and proliferative diabetic retinopathy, was proposed by Mookiah et al. [6] and Priya et al. [7] by implementing certain preprocessing techniques. Meanwhile, the detection of maculopathy was proposed by Vimala and Kajamohideen [8], where some morphological operations were implemented. In addition, an automatic system which grades the maculopathy into severity levels was developed by Tariq et al. [9], Siddalingaswamy and Prabhu [10] also Punnolil [11]. An automatic diagnosis which highlighted the referable maculopathy in retinal images for diabetic retinopathy screening was proposed by Hunter et al. [12], while Chowriappa et al. [13] proposed an ensemble selection method for features and, later, performed the classification of the images into the corresponding classes of disease severity. However, fuzzy processing has not been implemented during the preprocessing stage within the maculopathy detection systems reported earlier in the literature.

Fuzzy image processing uses fuzzy techniques in the various stages of an image processing task. Fuzzy processing can help produce better representation of images and eventually improve the performance analysis. Fuzzy image processing has been used on medical and also non-medical images. The fuzzy histogram equalisation technique called the Brightness Preserving Dynamic Fuzzy Histogram Equalisation (BPDFHE) was proposed by Sheet et al. [14], and later was used in digital pathology images by Garud et al. [15]. Fuzzy filtering is another fuzzy image processing method that can be performed on images. Among the fuzzy filtering techniques, we can mention those proposed by Patil and Chaudhari [16], Toh et al. [17] and also Kwan [18]. In addition, fuzzy edge detection can be used as a preprocessing technique to enhance the image quality.

3 Proposed System

The proposed system implements a combination of fuzzy techniques in the image preprocessing part, which involves fuzzy filtering, followed by the fuzzy histogram equalization and finally the fuzzy edge detection. In order to test the system performance, the system is evaluated with the combination of normal and diabetic retinopathy fundus images from a novel data set, which was collected from the Eye Clinic, Department of Ophthalmology, Hospital Melaka, Malaysia. The dataset consists of 600 colour fundus images of size 3872 x 2592 pixels in JPEG format. The detailed explanation of the dataset is presented in [5].

The proposed screening system has been developed using Matlab R2014a. The system starts with the image acquisition process, where the system selects images for further processing (using the *imgetfile* followed by *imread* function). The selected images undergo preprocessing in order to improve the image contrast as well as perform other enhancements with the combination of fuzzy techniques. After that, the preprocessed images are used for feature extraction, where three features, namely, the area, the mean and the standard deviation of on pixels are extracted. Finally, in the classification phase, some machine learning classifiers are trained using these features to classify the images into the respective classes.

Figure 1 presents the block diagram of the proposed system for automatic screening and classification of the diabetic retinopathy using fuzzy image processing techniques. The individual stages are discussed in more detail in the following sections.

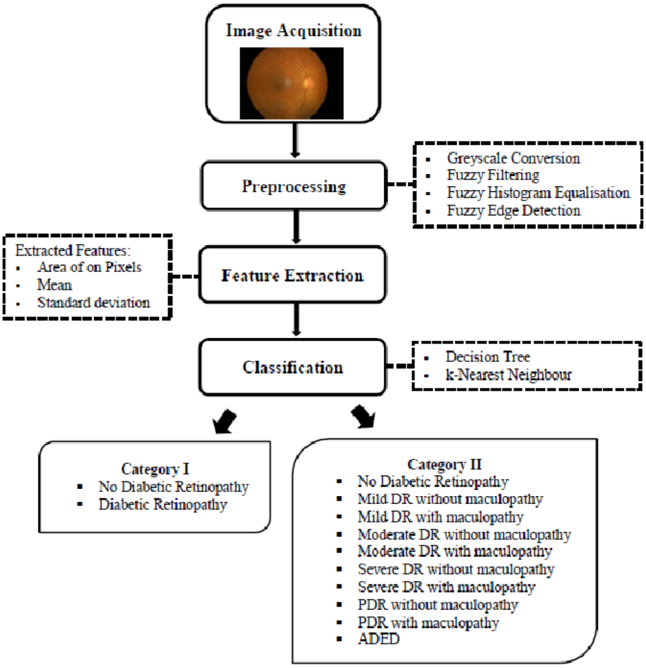


Fig. 1. Block diagram of the proposed automatic detection of diabetic retinopathy and maculopathy using fuzzy image processing

4 Image Preprocessing

Image preprocessing is the operation of improving the image data quality. Fuzzy approaches are implemented in this paper in the preprocessing stage. The image preprocessing techniques involved in the present work include greyscale conversion, Fuzzy Filtering, Fuzzy Histogram Equalisation and Fuzzy Edge Detection.

4.1 Greyscale Conversion

The greyscale conversion, which converts the original colour fundus images from the developed dataset into a greyscale image, is the first preprocessing technique used. The *rgb2gray* function is used to convert the colour image to the greyscale intensity image by eliminating the hue and saturation information while retaining the luminance.

4.2 Fuzzy Filtering

The second preprocessing technique is the implementation of the fuzzy approach in image filtering. Digital image filtering helps to improve the image quality or restore the digital image that is corrupted by noise. The original fundus images may be affected with some noise in its acquisition or transmission process. Thus, noise removal is required to enhance the image quality and it is an important step before any processing task. The proposed system implemented the median filter by employing fuzzy techniques. The Fuzzy Switching Median (FSM) filter by Toh et al. [17] was working well in removing salt-and-pepper noise while preserving image details and textures, by incorporating fuzzy reasoning in correcting the detected noisy pixels. However, this technique was not very well able to detect microaneurysms in fundus images, as presented by Rahim et al. [5]. The technique is used once again in this paper in order to investigate its performance in detecting diabetic retinopathy and maculopathy at the same time.

4.3 Fuzzy Histogram Equalisation

After filtering the image from noise, the histogram equalisation is performed. This is used to enhance the contrast of images by transforming the values in an intensity image to produce the output image that approximately matches a specified histogram. Since the colour fundus images are more challenging compared to another two modes of fundus photography examination which are angiography and red-free, therefore fuzzy approach is proposed to be used in the histogram equalisation technique in order to generate better contrast for the visualisation and detection. Rahim et al. [5] used the Brightness Preserving Dynamic Fuzzy Histogram Equalisation (BPDFHE) technique, which was proposed by Sheet et al. [14] for colour fundus images, while Garud et al. [15] used the same technique for pathology images. Due to the good performance of this technique for both types of medical images, it has been chosen as a preprocessing technique for the proposed diabetic retinopathy and maculopathy detection presented in this paper.

4.4 Fuzzy Edge Detection

An edge detection method sometimes produces small intensity differences between two neighbouring pixels which do not always represent an edge or which might represent a shading effect. Therefore, the use of membership functions would overcome such problems by defining the degree with which a pixel belongs to an edge or a uniform region. A Fuzzy Inference System (FIS) using a Mamdani-type system is proposed here for edge detection. The image gradient along the *x*-axis and *y*-axis of the image are the inputs for the FIS. For each input, a zero-mean Gaussian membership function is specified, where if the gradient value for a pixel is 0 (region), then it belongs to the zero membership function with a degree of 1. Another membership function is added which specifies the standard deviation for the zero membership function for the gradient inputs. For the output, which is the intensity of the edge-detected image, a triangular membership function is specified. Next, the two FIS rules are added to make a pixel white if it belongs to a uniform region where both inputs are zero, or otherwise the black pixel is presented if one of the inputs is not zero. In order to calculate the white pixels from the edge-detected image, the output image is converted or inversed to produce the black and white image. Figure 2 shows the membership functions of the inputs and outputs for the edge detection, while Figure 3 (a)-(f) shows the output after each of the preprocessing operations on the selected image, as explained previously.

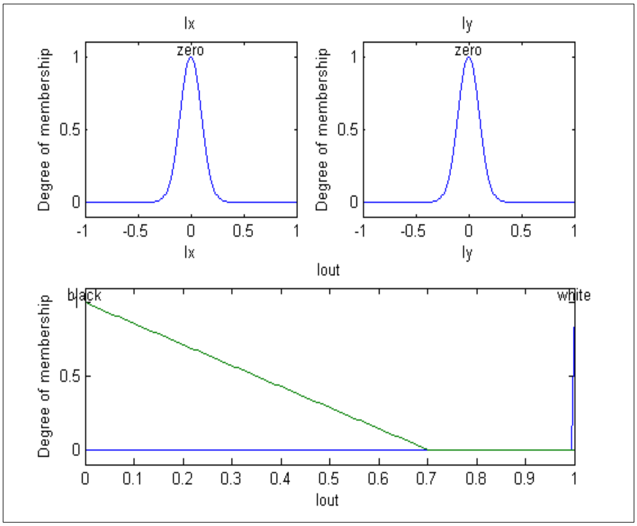


Fig. 2. Membership functions of the inputs and outputs

5 Feature Extraction

After performing the preprocessing techniques, feature extraction takes place to obtain the features from the preprocessed images. Three preliminary features are proposed, namely, the area of on pixels, the mean and the standard deviation are extracted for the detection purposes. The first feature is the number of white pixels on the black and white image, while the second and third features are the mean value and the standard deviation of on pixels, respectively. Other more sophisticated features could be extracted in addition to these three proposed features in order to improve the classification performance, and we will address this in our future work.

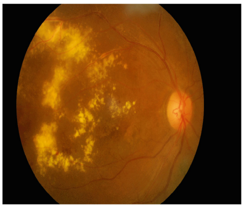
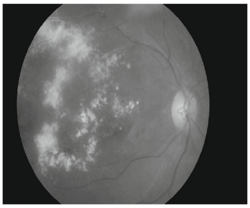
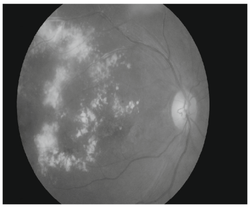
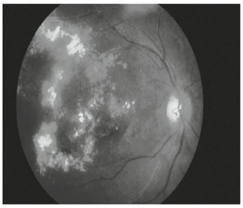
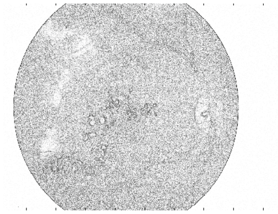
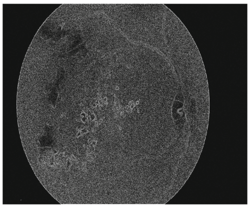
		
(a) Original image	(b) Greyscale conversion	(c) Fuzzy filtering
		
(d) Fuzzy Histogram Equalisation	(e) Fuzzy edge detection	(f) Edge-detected inversed image

Fig. 3. Preprocessing the output image

6 Classification

The extracted feature values were used in the classification stage, where the PRTools Matlab toolbox [19] for pattern recognition has been employed for this task. In order to generate a variety of results and performance analysis of the system, two types of classification were considered. First, the images have been classified into two classes, i.e., normal (276 images) and diabetic retinopathy (324 images). In addition, with the use of several machine learning classifiers, the images are then classified into ten classes which provide more details, i.e., No Diabetic Retinopathy (DR) with 276 images, and the other nine detailed classes of the DR cases, which are: Mild DR without maculopathy (72 images), Mild DR with maculopathy (27 images), Moderate DR without maculopathy (85 images), Moderate DR with maculopathy (83 images), Severe DR without maculopathy (23 images), Severe DR with maculopathy (11 images), Proliferative DR without maculopathy (6 images), Proliferative DR with maculopathy (10 images) and Advanced Diabetic Eye Disease (ADED, with only 7 images). Several machine learning classifiers, such as the binary decision tree classifier and the 1-nearest neighbour classifier have been selected to train and classify images into these categories.

7 Results and Discussion

Figure 4 shows the user interface snapshot of the proposed developed system. The performance of the proposed system, including the misclassification error, accuracy of the individual classifiers and also the specificity and sensitivity of the two classifiers for both categories are presented in Table 1 based on the confusion matrix generated. Since the dataset is hugely imbalanced for some classes, i.e., mild DR with maculopathy, severe DR without and with maculopathy, proliferative with and without maculopathy, Advanced Diabetic Eye Disease (ADED), the minority class was oversampled by running the system with images from these classes for several times in order to get various feature extracted values and balance the dataset. The developed dataset is split randomly into 90% for training and the remaining 10% for testing. The process is repeated ten times in a cross-validation procedure in order to generate unbiased results. The average results on the ten runs for each of the two classifiers are reported. The experimental results show that the two classifiers, and especially the k-nearest neighbour, are able to identify well for both main categories. The two classifiers identified much better the diabetic retinopathy cases, in the two classes' case, as there were more examples of such images in the database compared to ten classes' case for some of the ten classes. The maculopathy can be seen clearly from the inversed edge-detected image and the area of on pixels will have a higher value for those images with maculopathy.

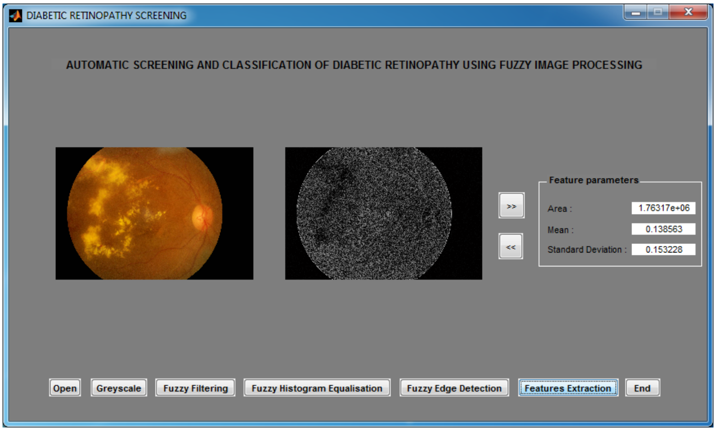


Fig. 4. Snapshot of the proposed system user interface

Table 1. Average results when using the classifiers

	Category I : 2 classes		Category II : 10 classes	
	Binary decision tree	k-nearest neighbour	Binary decision tree	k-nearest neighbour
Misclassification error	0.2539	0.2139	0.4395	0.2975
Accuracy	0.7461	0.7861	0.5605	0.7025
Specificity	0.4536	0.5572	0.4500	0.6500
Sensitivity	0.8403	0.8598	0.5956	0.7297

8 Conclusions and Future Work

An automatic system for the detection of diabetic retinopathy and maculopathy in colour fundus images using fuzzy image processing techniques has been developed in this paper. The system can be enhanced by implementing different other combinations of preprocessing techniques including those based on fuzzy approaches. The proposed developed system could be a benchmark for the development of other retinopathy signs' detection systems, such as for microaneurysms, exudates, hemorrhages and neovascularisation. As a conclusion, employing fuzzy image processing can help produce a more reliable screening system. In addition, it helps achieve the overall aim of the screening, which is to detect earlier the sight threatening diseases and to ensure a timely treatment in order to prevent vision loss. There are manifold future possibilities on other machine learning research on this, e.g. by including the human-in-the-loop [20] concept. For any such approach, one would first need a relevant and robust digital content representation from the image data. However, traditional pixel-based image analysis techniques do not effectively extract and represent the content. Consequently, a promising approach would be to extract graphs from images [21], which would enable a lot of other experiments, e.g. with evolutionary algorithms [22].

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