Automatic Screening and Classification of Diabetic Retinopathy Fundus Images

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Abstract. Eye screening is essential for the early detection and treatment of the diabetic retinopathy. This paper presents an automatic screening system for diabetic retinopathy to be used in the field of retinal ophthalmology. The paper first explores the existing systems and applications related to diabetic retinopathy screening and detection methods that have been previously reported in the literature. The proposed ophthalmic decision support system consists of an automatic acquisition, screening and classification of diabetic retinopathy fundus images, which will assist in the detection and management of the diabetic retinopathy. The developed system contains four main parts, namely the image acquisition, the image preprocessing, the feature extraction, and the classification by using several machine learning techniques.

Keywords: Diabetic Retinopathy, Eye Screening, Eye Fundus Images, Image Processing, Classifiers.

1 Introduction

Screening is defined as testing on a population in order to identify individuals exhibiting attributes that could be early symptoms or indicators of predisposition associated with a particular condition. Screening is used to maximise the chances of any individual overcoming the threat or danger indicated by such attributes (Taylor and Batey, 2012).

The main purpose of diabetic retinopathy screening is to detect whether the individuals require follow up or referral for further treatment to prevent blindness (Taylor and Batey, 2012). Besides this main purpose, there are other purposes for diabetic retinopathy screening, which include: identifying the disease at an early stage; possibly detecting a requirement for blood pressure and blood sugar treatment; to educate the population on the diabetic retinopathy causes and on the ways to reduce the retinopathy risk; and, additionally, to potentially identify non-diabetic conditions through the screening process.

Diabetes Mellitus (DM) is a major public health concern, as it leads to an increasing number of acute and chronic complications, including sight-threatening conditions. Diabetic Retinopathy (DR) is one of the chronic complications of

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diabetes, and it is a microvascular complication of both insulin dependent (type 1) and non-insulin dependent (type 2) diabetes. DR is a complication of DM that damages blood vessels inside the retina at the back of the eye. Wild and co-workers (2004) revealed that the global prevalence of diabetes mellitus in 2000 was approximately 2.8% (171 million diabetics) and projected this to rise to 4.4% (366 million diabetics) in 2030. According to Taylor and Batey (2012), one major problem is that the diabetic eye disease does not interfere with sight until it reaches an advanced stage. Laser treatment can save sight, but only if it is used at an early stage and, hence, regular screening is essential. This shows the importance of regular screening, which can help detect the diabetic patients at an early stage of DR. Furthermore, earlier identification of any retinopathy can allow change in blood pressure or blood glucose management to slow the rate of the disease progression.

2 Existing Systems

There currently are several developed systems to detect and diagnose diabetic retinopathy (DR), and most of these existing systems are somewhat related to the proposed system and can be used as a benchmark. Diabetic retinopathy screening is a popular research area and a lot of researchers focus on and contribute towards the advancement of study in this area.

Some of them focused on finding and proposing an accurate technique or method for detecting certain features of DR fundus images, such as microaneurysms, hemorrhages and neovascularisation. An automated grading system with image processing methods that detect two DR features, which are the dot hemorrhages and microaneurysms, was developed by Larsen and colleagues (2002). Jelinek and others (2006) developed an effective tool for detecting microaneurysms, in order to identify the DR presence in rural optometric practices. A comparison of the automated system used with optometric and ophthalmologic assessment was performed by calculating the sensitivity and specificity of both methods.

Nonetheless, there are some researches that report the development of automated systems for detecting DR by classifying DR into general detection categories, such as normal (no apparent retinopathy) or abnormal (retinopathy presence). Also, there are other classification systems that provide more details about the retinopathy stages, which include normal, non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Priya and Aruna (2011) investigated and proposed a computer-based system for identifying normal, NPDR and PDR classes. The proposed system uses colour fundus images, where the features are extracted from the raw image with image processing techniques and fed to a Support Vector Machine (SVM) for classification. The system has been later enhanced by using two types of classifiers, a Probabilistic Neural Network (PNN) and a Support Vector Machine (Priya and Aruna, 2012). The classifiers are described in detail and their performances are compared. As a conclusion, it is shown that, from the results obtained, the SVM model is more effective compared to the PNN. Priya and Aruna (2013) proposed and compared three models, i.e., a Bayesian classifier while maintaining the PNN and the SVM in the developed system. Experimental results show that the SVM outperforms all other models and this proves, once again, that the SVM is a great choice to use in detecting and classifying DR categories. The detection of the DR disease and the classification with the help of Radial Basis Function Neural Network (RBFNN) method has been proposed in (Priya *et al*, 2013). However, the experimental results show that the accuracy of the proposed system is relatively low, (76.25%), and it is recommended that this method could be improved by finding more relevant features and by combining with other classification methods, in order to improve the accuracy rate. The Aravind Diabetic Retinopathy Screening (ADRES) 3.0, developed and presented by Permalsamy and colleagues (2007), is a software for reading and grading the DR. This simple tool is used to assist in the detection of the DR and it is offered as a supplementary checking method to an usual clinical examination by an ophthalmologist. Philip et al. (2007) presented a study on the efficiency of the manual versus automated "disease" or "no disease" grading systems against the reference standard.

3 Proposed System

In this paper, an automatic classification and screening of diabetic retinopathy (DR) using fundus images is presented. A combination of normal and DR affected fundus images from a public database, i.e., the Standard Diabetic Retinopathy Database Calibration Level 0 (DIARETDB0), have been used for the evaluation of the proposed system. The database consists of 130 colour fundus images, of which 20 are normal and 110 contain signs of diabetic retinopathy (hard exudates, soft exudates, microaneurysms, hemorrhages and neovascularisation). The original images, which are of size 1500 x 1152 in PNG format, were captured with a 50 degree field-of-view digital fundus cameras with unknown camera settings (Kauppi *et al*, 2006). The proposed screening system has been developed using open source software, OpenCV (Open Source Computer Vision) and Microsoft Visual C++ 2010. The OpenCV environment, developed by Willow Garage, is a programming library offered for real time computer vision (Itseez, 2014). OpenCV includes a collection of standardised image analysis and machine vision algorithms for use by developers. Most work in the area has used tools such as Matlab and SPSS for feature extraction and analysis, but by using OpenCV it is possible to build more efficient systems, with processing times suitable for use in real situations. Using OpenCV also simplifies the distribution of software due to permissive licensing, and it lowers the cost of development, use and maintenance because there are no purchase or licensing fees. Finally, OpenCV is portable, meaning that any machine that can run C can, most likely, also run OpenCV. OpenCV has been used on Windows, Linux, MacOS and Android, for example.

The proposed system starts with the image acquisition process, where the system will select images for further processing. The selected images will undergo preprocessing in order to improve the image contrast as well as perform other enhancements. After that, the preprocessed images will be used to extract a number of features, such as the area, the mean and the standard deviation of on pixels.

Four nonlinear classifiers, namely a binary decision tree, a k-nearest neighbour classifier, and two support vector machines, using radial basis function and polynomial function kernels, respectively, are then trained on the training data to find an optimal way to classify images into their respective classes. Finally, in the prediction phase, where the system might ultimately be used to help the clinician, the images are classified into two main groups: normal or DR.

The remainder of this paper is organised as follows. Section 4 describes the image preprocessing stage followed by Section 5, which explains the feature extraction part. Section 6 describes the nonlinear classification, while Section 7 presents the results of the system and, finally, Section 8 details the conclusions of the work and a future plan.

Figure 1 presents the block diagram of the proposed system for automating the screening and classification of the diabetic retinopathy. Individual stages will be discussed in more detail in the following sections.

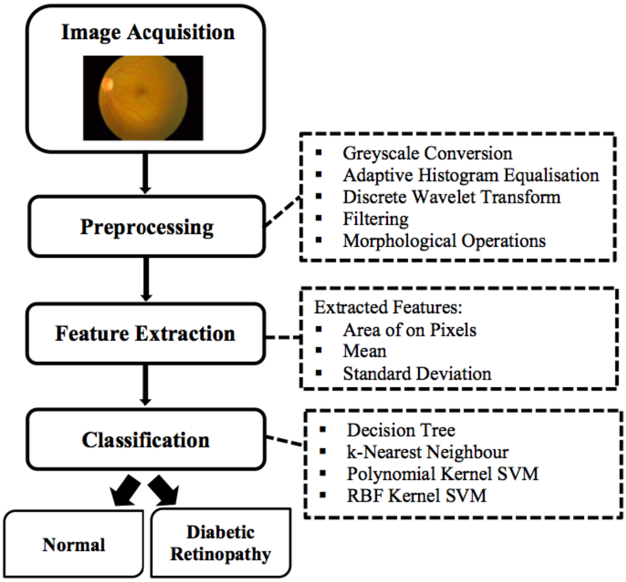

Fig. 1. Block diagram of the proposed automatic screening and classification of diabetic retinopathy

4 Image Preprocessing

Preprocessing is the process of image data improvement, where enhancing some image characteristics/features for the next processing part takes place. The image preprocessing techniques involved in the present work include Greyscale Conversion, Adaptive Histogram Equalisation, Discrete Wavelet Transform, Filtering and Morphological Operations.

4.1 Greyscale Conversion

The first preprocessing technique used is converting the colour fundus image into a greyscale image, as greyscale is usually the ideal format for image processing. A greyscale image is an image where each pixel holds a single value, only the pixel intensity information. It is also known as “black and white” image. The intensity is calculated by using a common formula combination of 30% of red, 59% of green and 11% of blue.

4.2 Adaptive Histogram Equalisation

Adaptive Histogram Equalisation (AHE) is a computer image processing technique for improving the image’s contrast. The difference between the adaptive histogram equalisation and the ordinary histogram equalisation is that the adaptive histogram equalisation computes several histograms, for different sections of the image, and subsequently distributes the lightness values. This technique is used to improve the local contrast and bringing out more details of the image. However, the adaptive histogram equalisation has limitations, as it produces over-amplification of noise in the homogeneous regions of an image. Therefore, the Contrast Limited Adaptive Histogram Equalisation (CLAHE) is used in the proposed system in order to prevent the overamplification of noise. CLAHE functions by clipping the histogram at the predefined value before computing the cumulative distribution function.

4.3 Discrete Wavelet Transform

Discrete wavelet transform is the discrete variant of the wavelet transform. The discrete wavelet transform is an $O(N)$ algorithm and it is also often referred to as the fast wavelet transform. The Haar wavelet is implemented in the proposed system development as it is a simple wavelet transform and it is being used in many methods of discrete image transforms and processing. Discrete wavelet transforms can be used to reduce the image size without losing much of the resolution. Since the fundus images are of high resolution and of quite large size, the Haar wavelet is recommended to be used.

4.4 Filtering

Image filtering is used to improve the image quality or restore the digital image which has been corrupted by some noise. A comparison of the performance between three different edge operators, i.e., Sobel, Prewitt and Kirsch has been proposed for the detection and segmentation of blood vessels in the colour retinal images (Karasulu, 2012). The experimental results show that the edge-based segmentation using Kirsch compass templates is superior by far to other methods. Based on this result, the Kirsch operator has been chosen for filtering in the proposed system development. The Kirsch edge detection uses eight filters, which means eight masks for the related eight main directions are applied to a given image to detect edges. These eight filters are a rotation of a basic 3x3 compass convolution filter. The Kirsch filter is applied on the wavelet transform image to create the eight filtered output image.

4.5 Morphological Operations

Morphological operations are used for certain purposes including the image preprocessing, enhancing object structure, segmenting objects from the background and also for quantitative description of objects (Sonka *et al*, 2008). In the proposed system development, morphology operators involving dilation and erosion are implemented to extract the blood vessels. A closing operation is defined as dilation followed by erosion operator. Joshi and Karule (2012) implemented the closing operation for retinal blood vessel segmentation, where the disk shaped structuring element for morphological operation is used. The dilation operates in greyscale images to enlarge brighter regions and it closes the small dark regions, while the erosion operator shrinks the dilated objects back to the original size and shape. As a result, the vessels being thin dark segments laid out on a brighter background are closed by the closing operation. Figure 2 (a)-(f) shows the output after each of the preprocessing operations on an image selected, as explained previously.

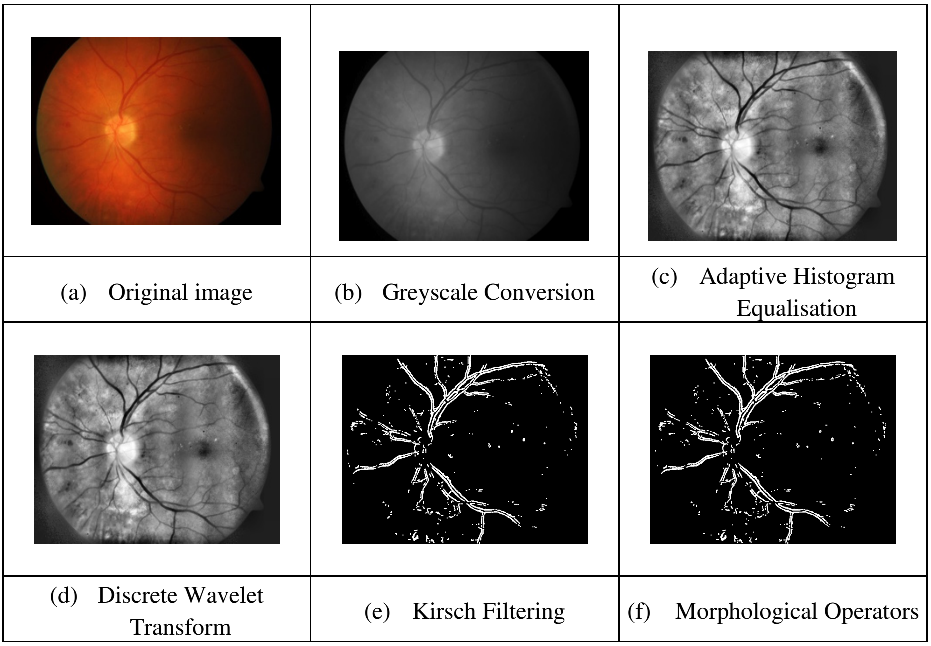

Fig. 2. Preprocessing the output image

5 Feature Extraction

After performing the preprocessing techniques, feature extraction takes place in order to obtain the features from the given images. Features such as the area of on pixels, mean and standard deviation are extracted for diabetic retinopathy (DR) detection purposes. These values for both normal and DR images are used to create a model for training. Table 1 presents the details of the feature extracted including the generated code.

Table 1. Feature extraction in the proposed system

Feature	Description	Snippet Code

Area of on pixels	Number of white pixels on the black and white image, where white pixels on are all pixels above a threshold of 100.	`maxS = cvGet2D(gray, y, x);`
		`val = maxS.val[0];`
		`if(val > 100) {`
		`count++;`
		`sum += val; }`

Mean	Mean value of on pixels	`mean = sum / count;`

Standard deviation	Standard deviation of on pixels	`maxS = cvGet2D(gray, y, x);`
		`val = maxS.val[0];`
		`if(val > 100) {`
		`count++;`
		`val = (mean-val);`
		`sum += val*val; }`
		`sdv = sqrt(sum) / count;`

6 Classification

The feature extracted values from the developed system have been passed to Matlab for the classification stage in order to benefit from various classifiers available in Matlab. The PRTools, a Matlab toolbox for pattern recognition has been downloaded and used in Matlab (Duin *et al*, 2007). Nonlinear classifiers can provide better classification results compared to linear classifiers. Therefore, four nonlinear classifiers, namely the binary decision tree classifier, the k-nearest neighbour classifier, the RBF kernel based support vector classifier and the polynomial kernel based support vector classifier have been selected to train and classify images into two classes, i.e., normal and diabetic retinopathy, respectively, based on the three extracted features as explained previously in Section 5. Decision tree is a classifier in the form of a tree structure and classifies instances or examples by starting at the root of the tree and moving through it until a leaf node is reached. In the k-nearest neighbour classifier, the object is classified by a majority vote of its neighbours, with the object being assigned to the most common class among its *k* nearest neighbours. The 1-nearest neighbour rule (1-NN) is used in the particular implementation of the system presented in the paper. A support vector machine (SVM) performs the classification by constructing an *N*-dimensional hyperplane that optimally separates the data into two categories. The support vector machine classifier can use various kernel functions, such as linear, polynomial or radial basis function (RBF). The kernel function transforms the data into a higher dimensional space in order to be able to perform the separation in the nonlinear region. Two different types of kernel functions provided in Matlab for SVM classification were used, i.e., the second order polynomial kernel SVM, *svc (ATrain, 'p', 2)*, and the radial basis function kernel SVM, *rbsvc (ATrain)*. The results show that RBF kernel outperformed the results obtained with the second order polynomial kernel.

7 Results and Discussion

Figure 3 shows the user interface snapshot of the proposed developed system. The performance (misclassification error) of the four classifiers is presented in Table 2. Since the dataset is hugely unbalanced, the minority class was oversampled by duplication in order to balance the dataset. The DIARETDB0 data 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 four classifiers are reported. For more clarity, in Table 2, we also presented the confusion matrix for the first out of the ten experiments, in order to show the relative performance of the four classifiers. The classification performance of the diagnosis system is assessed using the accuracy of the individual classifiers and also the specificity and sensitivity. The experimental results show that the four classifiers, and especially the k- nearest neighbor, are able to identify well both classes, i.e., the normal and the diabetic retinopathy cases. All the four classifiers identified much better the diabetic retinopathy cases, as there were more examples of such images in the database.

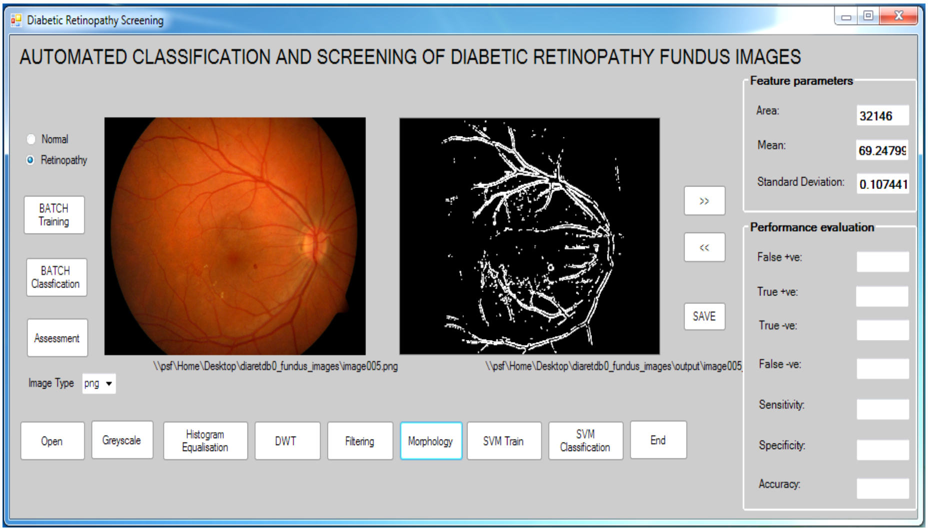

Fig. 3. Snapshot of the proposed system user interface

Table 2. Average results when using the four classifiers

	Binary decision tree	**k-nearest neighbour**	**RBF kernel SVM**	**Polynomial kernel SVM**
Misclassification error	0.2091	0.01364	0.0909	0.3182
Accuracy	0.7909	0.9864	0.9091	0.6818
Specificity	1	1	1	0.5545
Sensitivity	0.5818	0.9727	0.8182	0.8091
Confusion matrix for the first experiment Labels (1 : Normal, 2: DR)	True | Estimated Labels Labels | 1 2 | Totals -------|----------|--------- 1 | 11 0 | 11 2 | 5 6 | 11 -------|----------|--------- Totals | 16 6 | 22	True | Estimated Labels Labels | 1 2 | Totals -------|----------|--------- 1 | 11 0 | 11 2 | 0 11 | 11 -------|----------|--------- Totals | 11 11 | 22	True | Estimated Labels Labels | 1 2 | Totals -------|----------|--------- 1 | 11 0 | 11 2 | 2 9 | 11 -------|---------|--------- Totals | 13 9 | 22	True | Estimated Labels Labels | 1 2 | Totals -------|----------|--------- 1 | 6 5 | 11 2 | 2 9 | 11 -------|---------|--------- Totals | 8 14 | 22

8 Conclusions and Future Work

An automatic system for screening and classification of the diabetic retinopathy (DR) using fundus images has been developed. The system will be enhanced on the classification part by building an ensemble of classifiers. Unbalanced learning techniques will also be considered to be used for training the individual classifiers in the ensemble. In addition, more sophisticated features will be used in our future work to properly discriminate the various diabetic retinopathy signs (i.e., different features extraction for microaneurysms, hemorrhages, exudates, etc.). The system will also be extended to get more details on the DR classification, namely to classify into no apparent retinopathy, mild non-proliferative, moderate non-proliferative, severe non-proliferative and proliferative DR cases. In addition to the classification diagnosis, the system will provide the recommended follow-up schedule for each stage, as underlined by the American Academy of Ophthalmology and, hence, this will become a complete system to be used in a diabetic retinopathy screening practice.

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