Adaptive Image Enhancement Techniques For Improved Microaneurysm Detection In Fundus Images

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***Abstract*—**Diabetic retinopathy is a severe and widely spread eye disease. It is the commonest cause of legal blindness in the working-age population of developed countries. That is the reason for the intensified effort that has been undertaken in thelast years in developing tools to assist in the diagnosis of diabetic retinopathy. In this framework of computer assisted diagnosis of diabetic retinopathy, a new algorithm for detection of microaneurysm is presented. The presence of microaneurysm within the macular region is a main hallmark of diabetic macular edema and allows its detection with a high sensitivity. Hence, detection of microaneurysm is an important diagnostic task, in which computer assistance may play a major role.Microaneurysm is found using their high grey level variation, and their contours are determined by means of an Ensemble process. These microaneurysm are identified, compared with the input image and is reported so that the diagnosis of this disease will be convenient.

IndexTerms–Diabeticretinopathy(DR), Microaneurysm(MR), Ensemble process.

I. INTRODUCTION

1.1. Diabetic Retinoapthy

Diabetic retinopathy is a disorder of the retina that eventually develops to some degree in nearly all patients with long-standing diabetes mellitus. While defects in neurosensory function have been demonstrated in patients with diabetes mellitus prior to the onset of vascular lesions, the earliest visible clinical manifestations of retinopathy include microaneurysms and hemorrhages. Vascular alterations can progress to retinal capillary non perfusion, resulting in a clinical picture characterized by increased numbers of hemorrhages, venous abnormalitie, and intraretinalmicrovascular abnormalities (IRMA). A later stage includes closure of arterioles and venules and proliferation of new vessels on the disc, retina, iris, and filtration angle.Increased vasopermeability results in retinal thickening (edema) during the course of diabetic retinopathy. Visual loss results mainly from macular edema, macular capillary nonperfusion, vitreous hemorrhage, and distortion or traction detachment of the retina.

1.2. MICROANEURSYMS

The earliest clinically recognizable hallmark of diabetic retinopathy is the microaneurysm (Figure.1.1). These are small round dark red dots on the retinal surface (not arising from visible vessels) that are by definition less than the diameter of the major optic veins as they cross the optic disc.

They increase in number as the degree of retinal involvement progresses. Increasing numbers of microaneurysms are associated with capillary occlusion (visible on fluorescein angiography) leading to retinal ischemia (lack of oxygen) and progression ofretinopathy.

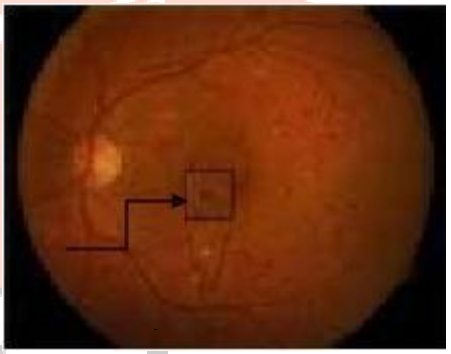


Fig. 1. Microaneurysm

1.3. STAGES OF DIABETIC RETINOPATHY

A. Mild Nonproliferative Retinopathy:

At this earliest stage, microaneurysms occur. They are small areas of balloon-like swelling in the retina's tiny blood vessels. Clinical signs of mild non- proliferative diabetic retinopathy (NPDR) include,

- Intraretinal hemorrhage(Microaneurysm)
- Lipid exudates(Hard Exudates)
- Cotton wool spots (Soft Exudates)
- Venous beading
- Intra retinal microvascular abnormalities

Moderate Nonproliferative Retinopathy: As the disease progresses, some blood vessels that nourish the retina are blocked.

II. SEVERE NONPROLIFERATIVE RETINOPATHY:

Many more blood vessels are blocked, depriving several areas of the retina with their blood supply.

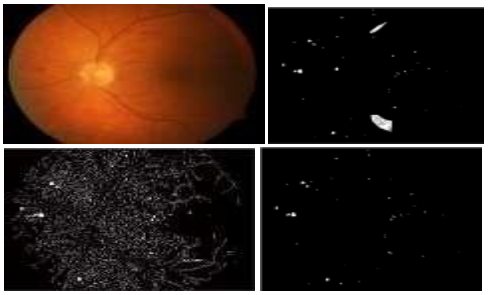
II. IMPLEMENTATION

2.1. System Design

The color fundas image when processed cannot be taken directly and processed, so it is converted to RGB (Red, Green, Blue) channels to find the brighter and darker lesions.After the image is converted the channels are analysed individually. Then green channel is initially taken to analysisthe image clearly. After analysis the green channels negativeis taken and is applied with limited adaptive histogram (enhances the contrast of the grey scale) so that the darker lesion particles and the nerve particles are identified.

After histogram it is followed by erosion and dilation. In erosion the edges in the image are detected so that on a whole where it is taken individually and in dilation the portion in those detected one is dilated. This result will be a blurred one which will be approximately near to the original one, then compared with the first result and is converted from grey scale to binary which form a exact black and white image and is applied with a threshold of 0.1 variation to the pixel. The salt and pepper noise is removed and is compared with the initial result to get the edge detected image.

Unless, like the previous one, the result is eroded and dilated with different parameter (Disk). This results with an edge detected image where the edges are detected and its holes are filled which is then reduced from the edge detected image so that the filled holes will be visible and this will be the result of the pre-processing method.Here the initial process erosion and dilation is done with a threshold of 0.08 to get more detailed edges. After removing the salt and pepper noise from the result it is filled and doubly filled to find the edges of the result. It is then reduced from the initial result so that the unwanted edges are removed. Its holes are now filled to get the result of the candidate extraction.



(a) Input Image (b) Pre-Processing Method (c) Candidate Extraction (d) Ensembled Framework

Fig. 2. Experimental Procedure

(b)

The image requires different similarity criteria for each. Consequently, when comparing images, image regions corresponding to different objects should be compared using different combinations of image features. Therefore, the proposed method expresses the similarity of a pair of images in terms of similarities of the corresponding image regions, and allows different regions to be compared using different similarity criteria Human perception of image similarity is based on the similarity of objects appearing in the image. In order to distinguish different image objects, different similarity criteria are necessary for each object.

So the result of pre-processing and candidate extractions was analyzed and the common pixels of both are compared to get the detected microaneurysm. Thus the results of pre-processing method and candidate extraction are ensemble to get the microaneurysm. This willbe the expected output which reveals the microaneurysm.

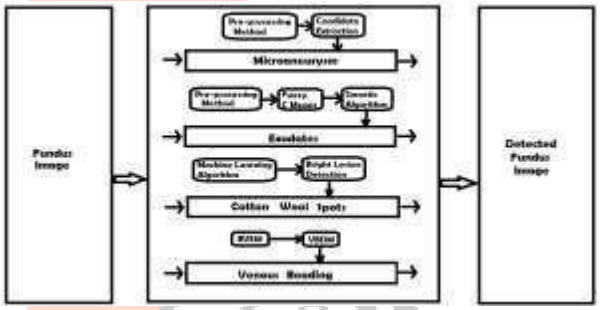


Fig. 3. Overall System Design

III. SYSTEM MODULES

3.1. Microaneurysm

An ensemble-based framework to improve microaneurysm detection was formed. Unlike the well-known approach of considering the output of multiple classifiers, a combination of internal components of microaneurysm detectors, namely preprocessing methods and candidate extractors.

3.1.1. Preprocessing methods

We present the selected preprocessing methods, which consider to be applied before executing MA candidate extraction. The selection of the preprocessing method and candidate extractor components for this framework is a challenging task. Since preprocessing methods need to be highly interchangeable, we must select algorithms that can be

used before any candidate extractor and do not change the characteristics of the original images.

3.1.2. Candidate Extraction

Candidate extraction is a process that aims to spot any objects in the image showing MA-like characteristics. Individual MA[1] detectors consider different principles to extract MA candidates. In this section, we describe our ensemble creation approach. First we apply the preprocessing method to the inputimage and then we apply the candidate extractor to this result. That is, such a pair will extract a set of candidates from the original image.

3.2. EXUDATES

DR is usually asymptomatic until the disease is at a late stage, making early detection and treatment essential. Thus, there is an increasing attention for setting up medical systems that can screen a large number of people to diagnose the DR early enough for an optimal treatment. These systems should detect early signs of retinopathy and provide objective diagnosis based on criteria defined by ophthalmologists. To build such automated systems, different components are needed for recognizing retinal anatomical features, i.e., optic disc, fovea, blood vessels, and certain pathologies, such as exudates, hemorrhages, and microaneurysms.

3.2.1. Pre-Processing Method

We put our data through two preprocessing steps[2] before commencing the detection of exudates. The first step is to normalize the color of the retinal images across the dataset. The second step, the contrast between the exudates and the retina background was enhanced to facilitate later segmentation. We applied local contrast enhancement to distribute the values of pixels around the local mean.

3.2.1. Fuzzy c-Mean

Fuzzy approaches provide a mechanism to represent and manipulate uncertainty and ambiguity, and allow pixels to belong to multiple classes with varying degrees of membership. The first task in color image processing is to choose an appropriate representation using a color space definition. In a suitable color space, color pixels of interest can be clustered into well defined, less overlapping groups, which are easily bounded by segmentation algorithms in the color space.

3.2.2. Genetic Algorithm

Once our color retinal images are segmented, each image is represented by its corresponding segmented regions. These regions, however, need to be identified in terms of exudates and nonexudates[2]. This is attempted, in a bottom-up approach, by extracting a set of features for eachregion and classifying the regions based on the generated feature vectors.

3.3. COTTON WOOL SPOTS

Diabetic retinopathy is the most common cause of blindness in the working population of the United States.1 Early diagnosis and timely treatment have been shown to prevent visual loss and blindness in patients with diabetes. To describe and evaluate a machine learning– based, automated system to detect exudates and cottonwool spots in digital color fundus photographs and differentiate themfrom drusen, for early diagnosis of diabetic retinopathy.

3.3.1. Machine Learning Algorithm

To perform detection and differentiation of bright lesions, if any, in a previously unseen image, the following steps were performed.

Each pixel was classified, resulting in a so-called lesion probability map that indicates the probability that a pixel is part of a bright lesion.Pixels with high probability were grouped into probable lesion pixel clusters.Based on cluster characteristics each probable lesion pixel cluster wasassigned a probability indicating the likelihood that the pixelcluster was a true bright lesion.Each bright lesion cluster likely to be a bright lesion was classified as exudate, cotton-wool spot or drusen.

3.2.2. Bright Lesion detection

By setting the threshold at 60% (pixels with a probability higher than 60% are considered part of a bright lesion and retained) by grouping connected pixels above this threshold, a set of bright lesion pixel clusters is obtained[5].

3.4. VENOUS BEADING

Retinal (fundus) images provide information about the blood supply system of the retina. The information about blood vessels (veins) can be used to assess the severity of retinal diseases such as diabetic retinopathy, hypertension, and various vascular disorders. The detection of venous beading in retinal images provides an early sign of diabetic retinopathy and plays an important role as a preprocessing step in diagnosing ocular diseases.

We present a computer-aided diagnostic system to automatically detect venous beading of blood vessels. It comprises of two modules, referred to as the blood vessel extraction module (BVEM) and the venus beading detection module (VBDM).

3.4.1. BVEM(Blood Vessels Extraction Method)

Extracting blood vessels is a crucial step for diagnosis of venous beading detection. This section presents the first

system module of an automatic diagnostic detection of venous beading, the BVEM[3]. The BVEM can be implemented in four sequential stages: extraction of blood vessels, segmentation of the extracted blood vessels, edge smoothing of extracted blood vessels and noise suppression, and detection and elimination of branching points.

3.4.2. VBDM(Venous Beading Detection Module)

The BVEM only produces an image showing blood vessels with all bifurcations removed. It does not provide any means to detect venous beads; hence, this section develops a VBDM. The major component of the VBDM is the shape cognitron (SC), which was originally devised to recognize shape patterns of micro calcifications in mammograms.

It was particularly designed to classify clustered microcalcifications into malignant and benign, using a set of shape features it generates. It is known that malignant clustered micro calcifications generally have irregular shapes as opposed to round- shaped or egg-shaped benign clustered microcalcifications. SC captures the shape curvatures of clustered microcalcifications and provides a crucial indication of malignancy. Using a set of orientation patterns as templates, the SC is able to generate a hexadecimal number for each pixel that represents a shape curvature at this pixel finding the bead.

IV EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

We have tested this algorithm on normal and abnormal fundus images using Matlab version 7.5. Fig3.1show the results of the algorithm for normal and abnormal fundus images. The performance of our algorithm is evaluated quantitatively by comparing theresulting extractions with ophthalmologists' hand- drawn ground-truth images pixel by pixel. In order to facilitate theexpert to produce ground-truth images, at first draft of ground truth image was created by us. We have marked theoptic nerve head using a photo manipulation program withone color. Then the first draft images were shown to expert with the original images. The phthalmologist then made some changes by adding some missing pixels and/or removing some misunderstood pixels of optic nerve head region.

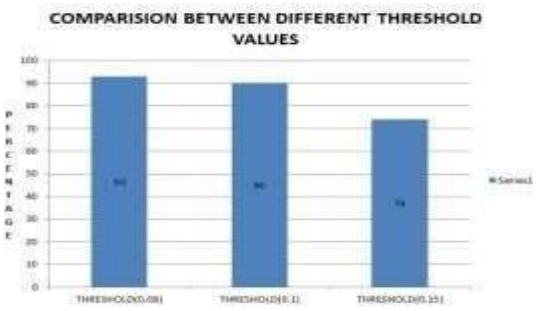


Fig. 4. Threshold Analysis

V CONCLUSION

This audit assessed the performance of an automated system based on microaneurysm/dot haemorrhage detection and image quality assessment operating on a large, unselected population of people with diabetic retinopathy affected results.

In this framework, an ensemble creation approach *E* is a set of (Preprocessing method, Candidate extractor)or PP, CE pairs. The meaning of a pair is that first we apply the preprocessing method to the input image and then we apply the candidate extractor to this result. That is, such a pair will extract a set of candidates from the original image.

Ensemble creation is a process where all ensembles *E* from an ensemble pool *E* is evaluated and the best performing one *E* regarding an evaluation function on a training set is selected. Since our approach is modular, we can expect further improvements by adding more preprocessing methods and candidate extractors. The grading performance of this detector is done in the 1200 images of the Messidor database and has achieved a 0.90± 0.01 AUC values, which is competitive with the previously reported results on other databases.

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