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An Approach on Diabetic Macular Edema for Diabetic Retinopathy

J. Esther Anitha[1], *W. Sharon Inbarani*[2], Isabella[3],

PG Scholar, Department of CSE, A.S.L Pauls College of Engineering, Coimbatore. India

PG Scholar, Department of CSE, A.S.L Pauls College of Engineering, Coimbatore. India

Assistant Professor, Department of CSE, A.S.L Pauls College of Engineering, Coimbatore. India

Abstract

Diabetic Macular Edema (DME) is an advanced symptom of diabetic retinopathy and can lead to irreversible vision loss. In this paper, a two-stage methodology for the detection and classification of DME severity from color fundus images is proposed. DME detection is carried out via a supervised learning approach using the normal fundus images. A feature extraction technique is introduced to capture the global characteristics of the fundus images and discriminate the normal from DME images. Disease severity is assessed using a Spatial Gray Tone Feature extraction (SPTF). The performance of the proposed methodology and features are evaluated against several publicly available datasets. The detection performance has a sensitivity of 100% with specificity between 74% and 90%. The severity classification accuracy is 87% for the moderate case and 100% for severe cases. These results establish the effectiveness of the proposed solution.

Keywords – DME, HE, Retinopathy, Exudates.

1. Introduction

Diabetic macular edema (DME) caused due to diabetes is a high risk complication which can cause irreversible loss of vision. Early detection of even a minor sign of DME is essential as it may also appear without any external symptoms. Once detected during retinal examination, it demands immediate treatment ranging from glycemic and blood pressure control, to laser surgery. DME is generally detected directly or indirectly. Direct ways are using stereoscopy (for manual examination) or optical computed tomography images. Indirect method is by detecting the presence of hard exudates (HE) in the retina. HE is formed due to secretion of plasma from capillaries resulting from the complications of retinal vasculature and could lead to retinal swelling.

Detecting the presence of hard exudates (HE) in different areas of retina is now considered a standard method to assess DME from color fundus images The severity of the risk of edema is evaluated based on the proximity of HE to the macula, which is defined to be a circular region centered at fovea and with one optic disc (OD) diameter. The risk for DME increases when the HE locations approach the macula, with the risk being the highest when they are within the macula. This is an important factor in DME assessment for further referral of the patients to an expert.

Diabetes can also cause other retinal complications all of which are collectively termed as diabetic retinopathy (DR). Given the potential for vision loss and blindness due to DR [2], screening programs have been launched in many countries and color fundus image forms the basis for manual assessment in screening. Such manual assessment however is not scalable in large-scale screening scenario, particularly in developing countries either due to the scarcity of skilled manpower or unavailability of high end imaging equipment at the point of care. Solutions such as tele-screening using permanent and mobile units to enable screening of retinal disorders in remote areas have been proposed.

In such a scenario, an automatic disease detection system can significantly reduce the load of experts by limiting the referrals to those cases that require immediate attention. The reduction in time and effort will be significant where a majority of patients screened for diseases turn out to be normal. The ratio of normal patients to the ones showing disease symptoms can be as high as 9 to 1 in DR screening.

2. Literature Review

a) Automatic Retina Exudates Segmentation

Diabetic macular edema (DME) is a common vision threatening complication of diabetic retinopathy which can be assessed by detecting exudates (a type of bright lesion) in fundus images [3]. In this work, two new methods for the detection of exudates are presented which do not use a supervised learning step; therefore, they do not require ground-truthed lesion training sets which are time consuming to create, difficult to obtain and prone to human error.

Advantage:

Image normalization procedure gives a substantial computational advantage. The median filter with morphological reconstruction approach maintains a good contrast of the foreground structures by limiting the effects of the noise.

Disadvantage:

This makes a direct comparison almost impossible, as emphasized by many of the authors themselves. Our implementation of two algorithms did not perform as well as in the respective datasets employed.

b) Automated Detection of Diabetic Retinopathy

Diabetic retinopathy, an eye disorder caused by diabetes, is the primary cause of blindness in America and over 99% of cases in India. India and China currently account for over 90 million diabetic patients and are on the verge of an explosion of diabetic populations. This may result in an unprecedented number of persons becoming blind unless diabetic retinopathy can be detected early. Aravind Eye Hospitals is the largest eye care facility in the world, handling over 2 million patients per year. The hospital is on a massive drive throughout southern India to detect diabetic retinopathy at an early stage. To that end, a group of 10 − 15 physicians are responsible for manually diagnosing over 2 million retinal images per year to detect diabetic retinopathy.

While the task is extremely laborious, a large fraction of cases turn out to be normal indicating that much of this time is spent diagnosing completely normal cases [1]. This paper describes our early experiences working with Aravind Eye Hospitals to develop an automated system to detect diabetic retinopathy from retinal images. The automated diabetic retinopathy problem is a hard computer vision problem whose goal is to detect features of retinopathy, such as haemorrhage's and exudates, in retinal color fundus images. We describe our initial efforts towards building such a system using a range of computer vision techniques and discuss the potential impact on early detection of diabetic retinopathy.

Advantage:

This approach classifies each new image in less performed an evaluation of our optic disc detection mechanism.

Disadvantage:

The equal error rate is 87%.

c) Detection of exudates using clustering algorithm

Diabetic Retinopathy is a kind of disorder which occurs due to high blood sugar level. This disorder affects retina in many ways. A blood vessel in the retina gets altered. Exudates are secreted, hemorrhages occur, swellings appear in the retina. Diabetic Retinopathy is the major cause of blindness. Automatic Recognition of DR lesions like Exudates, in digital fundus images can contribute to the diagnosis and screening of the disease.

In this approach, an automatic and efficient method to detect the exudates is proposed [4]. The real time retinal images are obtained from a nearby hospital. The retina images are pre-processed via. Contrast limited adaptive histogram equalization. The preprocessed color retinal images are segmented using K-means Clustering technique. The segmented images establish a dataset of regions. To classify these segmented regions into Exudates and Non- Exudates, a set of features based on color and texture are extracted. Classification is done using support Vector Machine. This method appears promising as it can detect the very small areas of exudates.

Advantage:

1. Reduce the Computational time.
2. Flexibility to represent complex functions

Disadvantage:

Complexity by minimizing an upper bound on the generalization error.

d) Detection of exudates using split and merge algorithm

Retinal image analysis is commonly used for the diagnosis and monitoring of diseases. In fundus photographs, bright lesions representing hard and soft exudates are the earliest signs of diabetic retinopathy. In this paper, an automated method for the detection of these exudates in retinal images is presented. Candidates are detected using a combination of coarse and fine segmentation. The coarse segmentation is based on a local variation operation to outline the boundaries of all candidates which have clear borders [5]. The fine segmentation is based on an adaptive thresholding and a new split-and-merge technique to segment all bright candidates locally. Due to its distinctive performance measures, the proposed method may be successfully applied to images of variable quality. Retinal image with the main features and

exudates. They employed morphological techniques for fine-tuning after the segmentation step and reported results of 87.28% sensitivity, 99.2% specificity. However, this method is designed to detect exudates in retinal images automatically. It uses a split-and-merge algorithm based on image features. This method includes four main stages; first the green component of the color image is preprocessed to normalize and smooth the image and then eliminate the optic disk. The second stage is coarse exudate detection using a local variation operator followed by classification making use of non-exudate features. The third stage is fine exudate detection using an adaptive thresholding technique with dynamic image partitioning. Optimal partitioning is based on a split-and-merge algorithm. The final stage is a combination of the two segmentation results using a morphological operation to obtain the final detection of exudates.

Advantage:

Improvement in the specificity and accuracy measures.

Disadvantage:

Very competitive results in exudates detection.

3. Diabetic Macular Edema

Diabetic macular edema is a common complication of diabetic retinopathy due to the presence of exudates in proximity with the fovea [6]. A feature extraction technique is introduced to capture the global characteristics of the fundus images and discriminate the normal from DME images. Disease severity is assessed using feature extraction and SVM Classifier.

a) Color Component Separation and Extraction of ROI Region

Given a color fundus image, HSV color space conversion is applied upon it. The value color component is used for further processing. Region of interest (ROI) is first extracted by applying fundus mask upon it. The severity of DME is determined based on the location of HE clusters relative to the macula, the images acquired for DME detection usually focuses around the macular region. We find the best fit closed region within the fundus mask with macula at the center, for a given image. The region within this mask is the desired ROI denoted as I.

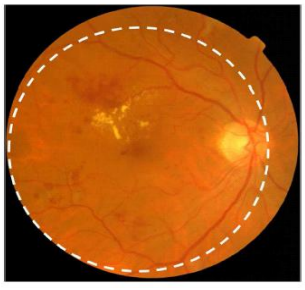


Fig 1 Sample fundus image and the circular region of Hue Saturation Value (Travis):

These are the RGB-HSV conversions given by Travis. To convert from RGB to HSV (assuming normalised RGB values) first find the maximum and minimum values from the RGB triplet.

Saturation, S, is then:

$$S = \frac{max - \min}{\max}$$

d Value V, is:

$$V = \max$$

The Hue, H, is then calculated as follows. First calculate R'G'B':

$$R' = (max - R)/(max - min)$$
$$G' = (max - G)/(max - min)$$
$$B' = (max - B)/(max - min)$$

If saturation, S, is 0 (zero) then hue is undefined (i.e. the colour has no hue therefore it is monochrome) otherwise:

Hue, H, is then converted to degrees by multiplying by 60 giving HSV with S and V between 0 and 1 and H between 0 and 360. To convert back from HSV to RGB first take Hue, H, in the range 0 to 360 and divide by 60:

$$Hex = \frac{H}{60}$$

Then the values of primary colour, secondary colour, a, b and c are calculated. The primary colour is the integer component of Hex (e.g. in C floor (Hex);

secondary colour = Hex - primary colour

The region of ROI is automatically detected the OD shares a brightness characteristic similar to HE.

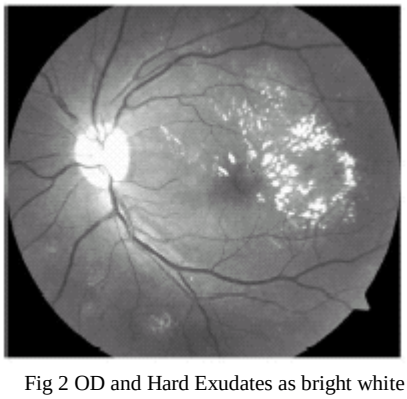


Fig 2 OD and Hard Exudates as bright white lesions

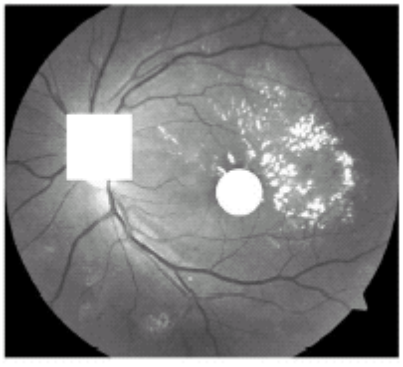


Fig .3 automatically detected and masked the OD

It is also automatically detected and masked. The result of macula and optic disc detection can be seen.

b) Exudate Detection by score computation

Detection is performed by assigning a score for each exudate candidate. The exudate candidates are selected by running an 8-neighbour connected component analysis. Capture the external edges of the lesion candidate. This edge detector is based on the kernel k evaluated at 8 different directions. The kernel outputs are combined together by selecting the maximum value found on each pixel output.

The average edge outputs under each lesion cluster are calculated and assigned to the lesion. The thresholds used to evaluate the final output.

Kirsch's edges try to capture the external edges of the lesion candidate. This edge detector is based on the kernel k evaluated at 8 different directions. The kernel outputs are combined together by selecting the maximum value found on each pixel output.

The average edge outputs of I_{kirsch} under each lesion cluster are calculated and assigned to the lesion in its entirety.

The analysis starts from the labeled image in the dataset and each lesion is compared to the automatic segmentation one by one.

c) Spatial Gray Tone feature Extraction

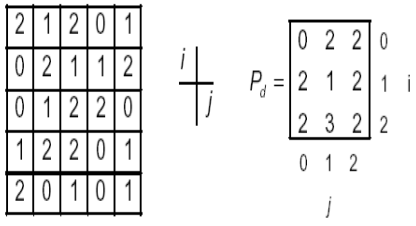
A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values. A co-occurrence matrix is a two-dimensional array, P, in which both the rows and the columns represent a set of possible image values.

A GLCM Pd[i,j] is defined by first specifying a displacement vector d=(dx,dy) and counting all pairs of pixels separated by d having gray levels i and j. From the co-occurrence matrix obtained, we have to extract the 12 different statistical features.

We have utilized both information gain and gain ratio based methods to rank features.

Feature selection process can also reduce noise and in this way enhance the classification accuracy, since tenfold cross validations are performed along with selection process.

For example, if d=(1,1)



The principal method examined is the use of spatial gray tone dependence. This method reduces the gray levels within a moving window into a two-dimensional spatial gray tone dependence matrix which can be interpreted as a probability matrix of gray tone pairs.

Algorithm:

- Count all pairs of pixels in which the first pixel has a value *i*, and its matching pair displaced from the first pixel by d has a value of *j*.
- This count is entered in the i^{th} row and j^{th} column of the matrix $P_d[i,j]$
- $P_d[i,j]$ is not symmetric, since the number of pairs of pixels having gray levels [i,j] does not necessarily equal the number of pixel pairs having gray levels [j,i].

The derivation of the spatial gray tone dependence matrix is a function of:

1. The number of gray tones in an image;
2. The angle along which the frequency of spatial gray tone dependence is calculated;
3. The size of the moving window; and
4. The distance between gray tone pairs.

The derivation of the spatial gray tone dependence matrix is a function of the following parameters:

1. The number of gray levels within an image. The computation of the texture feature is related to the square of the number of gray levels.

2. The angle along which the frequency of occurrence is derived. For example, there are four independent angles for a distance of one, and eight for a distance of two resulting in four and eight independent features for each image.

3. The size of the moving window. Small window sizes will not adequately sample the spatial gray tone dependence probabilities of land cover classes. Conversely larger window sizes will degrade the resolution of remotely sensed imagery.

4. The distance between pixels in tabulating the co-occurrence matrix. The co-occurrence matrix for a single distance contains most of the significant texture information.

4. Implementation Results

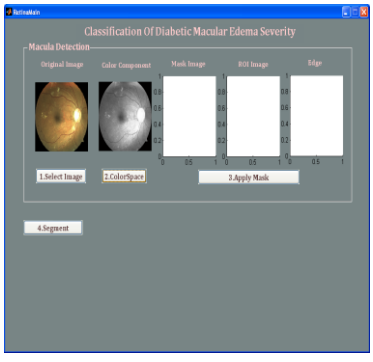


Fig .4 Color Conversion

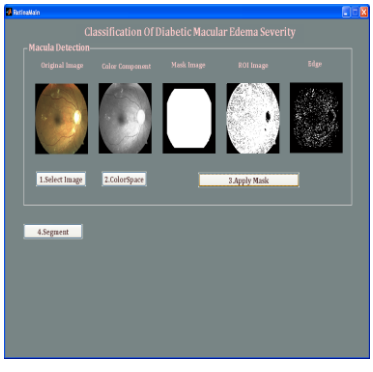


Fig .4 Region of Interest

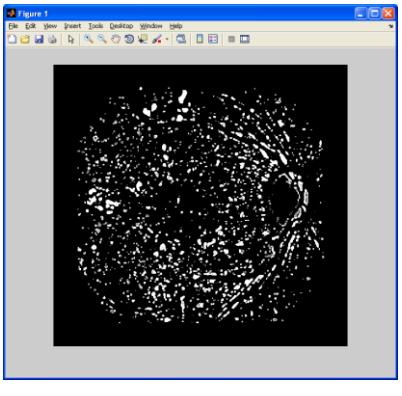


Fig .5 Edged Images

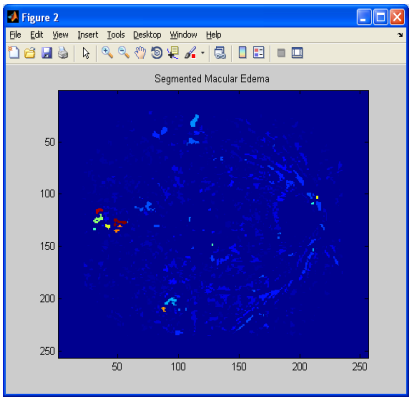


Fig .6 Segmented Mascular Edema

5. Conclusion

The Diabetic macular edema (DME) is an advanced symptom of diabetic retinopathy. DME detection is carried out via a supervised learning approach using the normal fundus images. Detected the abnormal DME images using spatial gray tone feature extraction. A feature extraction technique is introduced to capture the global characteristics of the fundus images and discriminate the normal from DME images. Disease severity is assessed using feature extraction and SVM Classifier.

In the first level, a supervised technique based on learning the image characteristics of only normal patients is used for detecting the abnormal cases pertaining to HE. This approach has the inherent advantage of reducing the effort of building a computer aided design system by removing the need for annotated (at the lesion level) abnormal images. Such annotations are required for both supervised and unsupervised classification schemes in order to find suitable system parameters for detection. The approach facilitates separating the normal patients from those showing disease symptoms, as practiced in DR screening.

In the second level, the severity of the abnormality is assessed by extracting the features and by using the Support Vector Machine Classifier.

The proposed methodology enhances the existing DR screening infrastructure by helping automate the detection and assessment of DME.

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