Abstract: The correct diagnosis of proliferative diabetic retinopathy is essential; because it is a treatable disease and missing the diagnosis can lead to the patient becoming blind. This paper examined the ability of internists and ophthalmologists to diagnose proliferative retinopathy under optimal conditions. These papers - three physicians performed retinal examinations on ten diabetic patients and one normal patient with dilated pupils. Physician examiners This paperre members of a university medical center and included 10 internists, 2 diabetologists, 4 senior medical residents, 4 general ophthalmologists, and 3 ophthalmologists who This paperre subspecialists in retinal disease. Correct diagnosis was determined separately by the consensus of three ophthalmologists specializing in retinal disease, who reviThis paperd seven-view stereo fundus photographs and medical charts. Of a possible 483 individual eye examinations, 438 This paper re completed. The overall error rate was 61%. The error rate for missing the diagnosis of proliferative retinopathy varied from 0% for retinal specialists to 49% for internists, diabetologists, and medical residents. This paper concludes that potentially serious mistakes in diagnosis are currently made by the physicians who care for most diabetic patients. Experience and specialized knowledge lessen the error rate. Further education or greater use of referrals may be necessary to provide optimal patient care.

I. INTRODUCTION

Diabetes is the chronic state caused by an abnormal increase in the glucose level in the blood and which causes the damage to the blood vessels. The tiny blood vessels that nourish the retina are damaged by the increased glucose level.

Diabetic retinopathy (DR) occurs when diabetes damages the tiny blood vessels inside the retina, the light-sensitive tissue at the back of the eye. This tiny blood vessel will leak blood and fluid on the retina, forming features such as microaneurysms, haemorrhages, hard exudates, cotton wool spots, or venous loops. DR can be broadly classified as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Depending on the presence of features on the retina, the stages of DR can be identified.

II. LITERATURE SURVEY

Fleming et al. (2010) have shown the role of microaneurysm and hemorrhage in automatic grading of diabetic retinopathy. One of the most important steps in the automated detection of DR is the detection of microaneurysms. Microaneurysms are amongst the earliest observable signs of the presence of diabetic retinopathy.

Hipwell et al. (2000) adapted a technique originally developed for fluorescein angiograms, and applied it to microaneurysm detection in digitally acquired red-free retinal images.
Lee et al. (2001) used digitized colour retinal images and aimed to detect haemorrhages, microaneurysms, exudates and cotton wool spots.

Sinthanayothin et al. (2002) applied recursive region growing segmentation (RRGS) technique to segment vessels, microaneurysms and haemorrhages. The vessels were detected using a neural network. The remaining objects after vessels had been removed were labelled as microaneurysms and haemorrhages.

Niemeijer et al. (2005) proposed a method to detect candidate red lesions (microaneurysms and haemorrhages) using a pixel classification technique. Then the detected red lesion candidates were classified using a number of features and a k-nearest neighbour classifier.

Usher et al. (2004) used an RRGS, adaptive intensity thresholding and edge enhancement operator to extract the candidate red lesions.

Sanchez et al. (2004) combined color and sharp edge features to detect the exudates. The yellowish objects are detected first; the objects in the image with sharp edges are then detected using Kirsch’s mask and different rotations of it on the green component. The combination of results of yellowish objects with sharp edges is used to determine the exudates.

III. METHODOLOGY

A. Image Enhancement

Images taken at standard examinations are often noisy and poorly contrasted. Techniques improving contrast and sharpness and reducing noise are therefore required As an aid for human interpretation of the fundus images; As a first step toward automatic analysis of the fundus images.

B. Mass Screening

Computer-assisted mass screening for diagnosis of diabetic retinopathy is certainly the most important task to which image processing can contribute. Although the mechanisms for diabetic retinopathy are not fully understood, its progress can be inhibited by early diagnosis and treatment. However, as vision normally alters only in the later stages of the disease, many patients remain undiagnosed in the earlier stages of the disease, when treatment would be the most efficient. Hence, mass screening of all diabetic patients (even without vision impairment) would help to diagnose this disease early enough for an optimal treatment.

C. Monitoring of the Disease

In order to assess the evolution of the disease, physicians have to compare images taken at different medical examinations. This allows one to evaluate for each patient the efficiency of the ophthalmologic and diabetic treatments; evaluate the efficiency of new therapeutics in a population of patients; observe the development of single lesions (for example in order to study the turn-over effect of microaneurysms).

D. Applying Wiener Filter

The most important technique for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. From a signal processing standpoint, blurring due to linear motion in a photograph is the result of poor sampling. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be an amalgam of intensities from points along the line of the camera's motion.
E. Locating ROI (Rate of Interest)

There are two general reasons to draw a Region-of-Interest (ROI) on neuroimaging data to examine the morphological properties of an anatomic structure, and to extract data for a specific structure from a corresponding functional data set.

F. Using Hough Transform

The Hough transform is a technique which can be used to isolate features of a particular shape within an image. Because it requires that the desired features be specified in some parametric form, the classical hough transform is most commonly used for the detection of regular curves such as lines, circles, ellipses, etc. A generalized hough transform can be employed in applications where a simple analytic description of a feature(s) is not possible.

IV. PROBLEM STATEMENT

In this study, morphologic image-processing techniques were used to detect the blood vessels. The green channel of the fundus RGB image was used for obtaining the traces of blood vessels. First the image intensity levels were inverted. Adaptive histogram equalization was performed to improve the contrast of the image. A morphological ‘opening’ operation was conducted using the ‘ball’ structuring element to smooth the background and to highlight the blood vessels of the image. Each image was subtracted from the equalized image. This resulting image shows higher intensity values at the blood vessels compared with the background.

Then the image was binarized by the thresholding method. Median filtering was conducted on this binarized image to remove the noise. A border was created around the image for extracting blood vessels. Then the remaining noise within the image was eliminated. The intensity values of image with only borders were subtracted from the inverted intensity values of this image to eliminate the edges.

Then the pixel values of the images are inverted to obtain the final image with only blood vessels. Figure 1 shows the result of the blood vessel detection for normal, mild DR, moderate DR, severe DR, and PDR.

![Fig. 1 Results of the detection of blood vessels for normal, mild DR, moderate DR, severe DR, and PDR stages](image)

V. IMPLEMENTATION

a. Preprocessing

Contrast showed a tendency to diminish towards the edge of the images. Intensity varied between images, and there were considerable color variations due to differing ethnic origin. Locally adaptive contrast enhancement was therefore applied to the intensity band to enhance contrast and normalize intensity. To simplify subsequent processing color was standardized towards that of a preselected ‘typical’ normal fundus image.
b. Noise Removal

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be introduced into an image, depending on how the image is created.

c. RGB to GRAY conversion

Image formation using sensor and other image acquisition equipment denote the brightness or intensity I of the light of an image as two dimensional continuous function F(x, y) where (x, y) denotes the spatial coordinates when only the brightness of light is considered. Sometimes three-dimensional spatial coordinate are used. Image involving only intensity are called gray scale images.

Gray levels represent the interval number of quantization in gray scale image processing. At present, the most commonly used storage method is 8-bit storage. There are 256 gray levels in an 8 bit gray scale image, and the intensity of each pixel can have from 0 to 255, with 0 being black and 255 being white. Another commonly used storage method is 1-bit storage. There are two gray levels, with 0 being black and 1 being white a binary image, which, is frequently used in medical images, is being referred to as binary image. As binary images are easy to operate, other storage format images are often converted into binary images when they are used for enhancement or edge detection.

d. ROI (Region of Interest)

Diagnostically critical region is given as about 5 pixels inside and outside of the colon wall in typical scan images. It would like to add practical value to our system by automatically segmenting this critical region. This segmentation algorithm relies on
a 3-D extension of mathematical morphology, a branch of science that is built upon set theory with many application areas in image processing. It includes generation of mappings for each pixel according to the pixel's local neighborhood. Many researchers have used this technique to segment eye images. Segmenting the colon from the eye data set consists of three steps:
- The air is separated away from the tissue by intensity thresholding.
- The colon wall that surrounds the air is extracted by a 3D extension of Sobel’s derivative operation.
- A morphological 3-D grassfire operation determines the colon-wall region within the 5-pixel margin mentioned above. This algorithm finds points that are at equal distance from a layer of points. The outputs of the three stages of segmentation are depicted in figure 8.3. Each pixel in the segmented ROI is coded in a lossless manner, while the rest is lossily compressed. Figure 4(a) includes only a little portion of the complete image in Figure 5(b), and this brings a considerable amount of compression efficiency.

e. Support Vector Machine

In recent years, SVM classifiers have demonstrated excellent performance in a variety of pattern recognition problems. SVMs were initially designed for the two-class problems but subsequently extended to multi-class problems. A brief description of the two-class approach is given below.

The SVM searches for a hyper plane as a decision surface which separates positive and negative examples from each other with the maximum margin. This involves orienting the separating hyper plane to be perpendicular to the shortest line separating the convex hulls of the training data for each class, and locating it midway along this line.

Let the separating hyper plane be defined by $x, w+b=0$, where $w$ is its normal. For linearly separable data labelled $\{x_i, y_i\}$, $y_i=\{-1, 1\}$, $i=1, 2, ..., N$ the optimum boundary chosen with maximum margin criterion can be found by minimizing the objective function

For automated detection of microaneurysms, two measures are mostly used: sensitivity and specificity. Confusion matrix is used for measuring the sensitivity and specificity. Confusion matrix is used for measuring the sensitivity and specificity. Sensitivity is the probability of a positive test given that the patient has disease.
Specificity is the probability of a negative test given that the patient has no disease.

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sensitivity = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}}
\]

Specificity is the probability of a negative test given that the patient has no disease.

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specificity = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}}
\]

Sensitivity is essentially how good a test is at finding something if it is there, means the proportion of actual positives which are correctly identified. Specificity is a measure against false positives, how accurate a test is, means the proportion of negatives which are correctly identified.

VI. CONCLUSION AND FURTHER WORK

Automatic detection of micro aneurysm presents many of the challenges. The size and color of micro aneurysm is very similar to the blood vessels. Its size is variable and often very small so it can be easily confused with noise present in the image. In human retina, there is a pigmentation variation, texture, size and location of human features from person to person. The more false positives occur when the blood vessels are overlapping or adjacent with micro aneurysms. So there is a need of an effective automated micro aneurysm detection method so that diabetic retinopathy can be treated at an early stage and the blindness due to diabetic retinopathy can be prevented. The SVM algorithm could detect Micro aneurysms on very poor quality images. Although further development of this algorithm is still required, the results are satisfying. The outcome is quite successful with sensitivity and specificity of 81.61% and 99.99%, respectively. The system also provided ophthalmologists with the number of Micro aneurysms for grading the Diabetic retinopathy stage. In order to apply to a clinical application, the proposed method will be combined with an exudates detection system.

In conclusion, with further development the automated detection of DR could become a highly effective way of reducing the burden on screening services by filtering out normal images, allowing the screener to classify only those images with a high chance of abnormality. This has major implications for the reduction of cost and improvement of efficiency of a diabetic screening program employing digital retinal images.

References


