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Detection of Diabetic Retinopathy Diseases for Color Fundus Images

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Abstract::- Here we address the detection of Hemorrhages and microaneurysms in color fundus images. In pre-Processing we separate red, green, blue color channel from the retinal images. The green channel will pass to the further process. The green color plane was used in the analysis since it shows the best contrast between the vessels and the background retina. Then we extract the GLCM(Gray Level Co-Occurance Matrix) feature. In the GLCMs, several statistics information are derived using the different formulas. These statistics provide information about the texture of an image. Such as Energy, Entropy, Dissimilarity, Contrast, Inverse difference , correlation Homogeneity, Auto correlation, Cluster Shade Cluster Prominence, Maximum probability, Sum of Squares will be calculated for texture image. After feature Extraction, we provide this feature to classifier. Finally it will predict about the retinal whether it is hemorrhages or microaneurysms . After predicting the about the retinal image we will localize the affected place. For segmenting the localized place we will use adaptive thresholding segmentation. .

Keywords: *GLCM, Fundus, Hemorrhages, Microaneurysms*

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I. Introduction:

Images and pictures

As we mentioned in the preface, human beings are predominantly visual creatures: we rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough feeling for a scene with a quick glance. Humans have evolved very precise visual skills: we can identify a face in an instant; we can differentiate colors; we can process a large amount of visual information very quickly. However, the world is in constant motion: stare at something for long enough and it will change in some way. Even a large solid structure, like a building or a mountain, will change its appearance depending on the time of day (day or night); amount of sunlight (clear or cloudy), or various shadows falling upon it. We are concerned with single images: snapshots, if you like, of a visual scene. Although image processing can deal with changing scenes, we shall not discuss it in any detail in this text. For our purposes, an image is a single picture which represents something. It may be a picture of a person, of people or animals, or of an outdoor scene, or a microphotograph of an electronic component, or the result of medical imaging. Even if the picture is not immediately recognizable, it will not be just a random blur.

II. Aspects of image processing:

It is convenient to subdivide different image processing algorithms into broad subclasses. There are different algorithms for different tasks and problems, and often we would like to distinguish the nature of the task at hand.

- Image enhancement: This refers to processing an image so that the result is more suitable for a particular application.
- Image restoration: This may be considered as reversing the damage done to an image by a known cause.
- Image segmentation: This involves subdividing an image into constituent parts, or isolating certain aspects of an image:

These classes are not disjoint; a given algorithm may be used for both image enhancement or for image restoration. However, we should be able to decide what it is that we are trying to do with our image: simply make it look better (enhancement), or removing damage (restoration).

An image processing task

We will look in some detail at a particular real-world task, and see how the above classes may be used to describe the various stages in performing this task. The job is to obtain, by an automatic process, the postcodes from envelopes. Here is how this may be accomplished:

- Acquiring the image: First we need to produce a digital image from a paper envelope. This can be done using either a CCD camera, or a scanner.
- Preprocessing: This is the step taken before the _major_ image processing task. The problem here is to perform some basic tasks in order to render the resulting image more suitable for the job to follow. In this case it may involve enhancing the contrast, removing noise, or

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identifying regions likely to contain the postcode.

- Segmentation: Here is where we actually get the postcode; in other words we extract from the image that part of it which contains just the postcode.
- Representation and description: These terms refer to extracting the particular features which allow us to differentiate between objects. Here we will be looking for curves, holes and corners which allow us to distinguish the different digits which constitute a postcode.
- Recognition and interpretation: This means assigning labels to objects based on their descriptors (from the previous step), and assigning meanings to those labels. So we identify particular digits, and we interpret a string of four digits at the end of the address as the postcode.

III. Literature Survey

The role of hemorrhage and exudates detection in automated grading of diabetic retinopathy

Automated grading has the potential to improve the efficiency of diabetic retinopathy screening services. While disease/no disease grading can be performed using only micro aneurysm detection and image-quality assessment, automated recognition of other types of lesions may be advantageous. This study investigated whether inclusion of automated recognition of exudates and hemorrhages improves the detection of observable/referable diabetic retinopathy. Automated

Automated detection of micro aneurysms in digital red-free photographs: a diabetic retinopathy screening tool

To develop a technique to detect micro aneurysms automatically in 50 degrees digital red-free Fundus photographs and evaluates its performance as a tool for screening diabetic patients for retinopathy. Candidate micro aneurysms are extracted, after the image has been modified to remove variations in background intensity, by algorithms that enhance small round features. Each micro aneurysm candidate is then classified according to its intensity and size by the application of a set of rules derived from a training set of 102 images. An automated technique was developed to detect retinopathy in digital red-free Fundus images that can form part of a diabetic retinopathy screening programme. It is believed that it can perform a useful role in this context identifying images worthy of closer inspection or eliminating 50% or more of the screening population who have no retinopathy.

Automatic detection of red lesions in digital color Fundus photographs

The robust detection of red lesions in digital color Fundus photographs is a critical step in the development of automated screening systems for diabetic retinopathy. In this paper, a novel red lesion detection method is presented based on a hybrid approach, combining prior works by Spencer et al. (1996) and Frame et al. (1998) with two important new contributions. The first contribution is a new red lesion candidate detection system based on pixel classification. Using this technique, vasculature and red lesions are separated from the background of the image. After removal of the connected vasculature the remaining objects are considered possible red lesions. Second, an extensive number of new features are added to those proposed by Spencer-Frame. The detected candidate objects are classified using all features and a k-nearest neighbor classifier. An extensive evaluation was performed on a test set composed of images representative of those normally found in a screening set. When determining whether an image contains red lesions the system achieves a sensitivity of 100% at a specificity of 87%. The method is compared with several different automatic systems and is shown to outperform them all. Performance is close to that of a human expert examining the images for the presence of red lesions.

Automatic detection of micro aneurysms in color Fundus images

This paper addresses the automatic detection of micro aneurysms in color Fundus images, which plays a key role in computer assisted diagnosis of diabetic retinopathy, a serious and frequent eye disease. The algorithm can be divided into four steps. The first step consists in image enhancement, shade correction and image normalization of the green channel. The second step aims at detecting candidates, i.e. all patterns possibly corresponding to MA, which is achieved by diameter closing and an automatic threshold scheme. Then, features are extracted, which are used in the last step to automatically classify candidates into real MA and other objects; the classification relies on kernel density estimation with variable bandwidth. A database of 21 annotated images has been used to train the algorithm. The algorithm was compared to manually obtained grading of 94 images; sensitivity was 88.5% at an average number of 2.13 false positives per image.

Fast detection of the optic disc and fovea in color Fundus photographs.

A fully automated, fast method to detect the fovea and the optic disc in digital color photographs of the retina is presented. The method makes few assumptions about the location of both structures in the image. We define the problem of localizing structures in a retinal image as a

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regression problem. A KNN repressor is utilized to predict the distance in pixels in the image to the object of interest at any given location in the image based on a set of features measured at that location. The method combines cues measured directly in the image with cues derived from a segmentation of the retinal vasculature. A distance prediction is made for a limited number of image locations and the point with the lowest predicted distance to the optic disc is selected as the optic disc center. Based on this location the search area for the fovea is defined. The location with the lowest predicted distance to the fovea within the fovea search area is selected as the fovea location. The method is trained with 500 images for which the optic disc and fovea locations are known. An extensive evaluation was done on 500 images from a diabetic retinopathy screening program and 100 specially selected images containing gross abnormalities. The method found the optic disc in 99.4% and the fovea in 96.8% of regular screening images and for the images with abnormalities these numbers were 93.0% and 89.0% respectively.

IV. Proposed Methodology

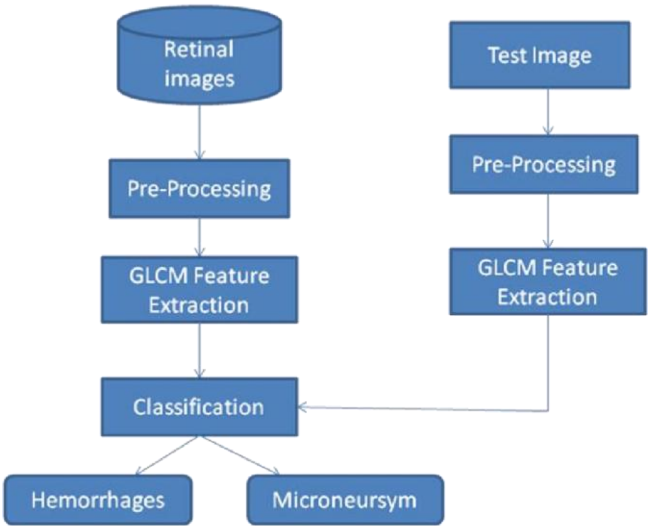

Fig: System Architecture Pre-Processing:

The green color plane was used in the analysis since it shows the best contrast between the vessels and the background retina. The grey levels were normalized by stretching the image contrast to cover the full pixel dynamic range, excluding the surrounding dark border pixels and any image labels.

Colour Component Separation:

Each image is subjected to colour component separation. Here we separate each image to have three components such as R, G, B. This is an additive colour system based on trichromatic theory. Often found in systems that use a CRT to display images. RGB is easy to implement but non–linear with visual perception. It is device dependent and specification of colors is semi–intuitive. RGB is very common, being used in virtually every computer system as well as television, video etc.

V. Analysis of Result

Performance parameter for evaluation:

Suppose a computer program for recognizing dogs in photographs identifies 8 dogs in a picture containing 12 dogs and some cats. Of the 8 identified as dogs, 5 actually are dogs (true positives), while the rest are cats (false positives). The program's precision is 5/8 while its recall is 5/12. When a search engine returns 30 pages only 20 of which were relevant while failing to return 40 additional relevant pages, its precision is 20/30 = 2/3 while its recall is 20/60 = 1/3. So, in this case, precision is "how useful the search results are", and recall is "how complete the results are".

In statistics, if the null hypothesis is that all items are irrelevant (where the hypothesis is accepted or rejected based on the number selected compared with the sample size), absence of type I and type II errors corresponds respectively to maximum precision (no false positive) and maximum recall (no false negative). The above pattern recognition example contained 8 − 5 = 3 type I errors and 12 − 5 = 7 type II errors. Precision can be seen as a measure of exactness or quality, whereas recall is a measure of completeness or quantity.

Table 1. Performance Evaluation

Test Result	Present	Absent
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

T$PSensitivity$ (Precision)= TP / $TP+F$P

$Specificity$(Recall)= TP / $TP+FP$+TN+FN

Table 2 shows the sensitivity and specificity of various grades of images from the dataset images and the results are also compared with the expert opinion. Out of 32 sever images all 32 is detected as sever, out of 18 moderate images all 18 are detected as moderate, out of 24 mild images, 3 images were detected as healthy and out of 26 healthy images 3 images are detected as mild. Figure 8 shows the graph of Sensitivity and Specificity of Grade 0, Grade1, Grade 2 and Grade 3 images from the dataset.

VI. Conclusion

The automatic detection of the hemorrhages presents various challenges. The hemorrhages are hard to distinguish from background variations because it typically low contrast.

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Automatic detection of hemorrhage can be confused by other dark areas in the image such as the blood vessels, fovea, and microaneurysms. Hemorrhages have a variable size and often they are so small that can be easily confused with the images noise or microaneurysyms and no standard database that classify hemorrhage by shape. The most false detection is the case when the blood vessels are adjacent or overlapping with hemorrhages. So the effective detection of hemorrhages methodology is needed.

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