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Grading Fundus Images for Diabetic Retinopathy

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ABSTRACT

Diabetic Retinopathy (DR) is an anomaly, found commonly among diabetic patients, which can lead to blindness if left untreated for a long period of time. Early detection of the complication, leads to better probability of cure. Lesions and cotton wool spots in retinal images, are the symptoms that help in the early detection of DR. Due to these lesions the image features will change throughout the retinal image, according to the level of the disease progression. Hence, in the proposed method, these changes in features are used to grade the retinopathy. There are three levels of disease progression and the classification method was able to classify all the three levels from the given retinal images. Also, Hough transform is used to detect the cotton wool spots since these spots have approximately the same intensity as that of the optic disc. The changes in features caused by the lesions and the cotton wool spots and exudates are the key to the detection. The feature extraction technique is Grey Level Co-occurrence Matrix (GLCM), which extracts about 44 features from the image data for further classification. Using an unsupervised classification method we have discovered the similar instances between data. The clusters are formed using K means classification technique. The retinal images, both normal and abnormal, were obtained from the Messidor database and the pixel size used was 2240 × 1488.

Keywords: Optic disc, exudates, edema, Euclidian distance.

1. INTRODUCTION

Diabetes mellitus is the most common disease that is occurring all over the world, especially in India. This disease affects brings in complications that affects the eye. This is known as diabetic retinopathy (DR) wherein the diameter of the retinal blood vessels changes or there occurs vessel swelling and fluid leakage. In other cases reported, abnormal blood vessels arise anew on the retinal surface. At first DR may cause very mild vision impairment or no problem at all. But if it is left untreated it may gradually lead to blindness[2]. The normal and diseased retina can be seen in Figure 1(a) and (b) respectively. By early detection techniques this vision complication proves better treatments. The severity of this disease increases gradually leading to blindness. There are three levels of severity; grade 1, 2 and 3. Early detection of DR is of peak importance since the disease is becoming a commonplace. Also the blood vessels of the eye gets damaged with regard to these exudates[3].

Even children are not an exclusion. Detection alone is not sufficient and so we go in for assessing the degree of progress of the disease. Optic disc detection is very essential for automatic DR screening. Since the pixels of OD and the bright lesions such as hard exudates, share the same intensity and color DR screening algorithms should not include OD information that cover the lesion features. Since geometric features are more common, intensity properties along with correlations help in distinguishing between the features of normal and abnormal fundus. These methods can be implemented in real time so that the medical personals or physicians can provide an immediate report to the patients and start the treatment as early as possible.

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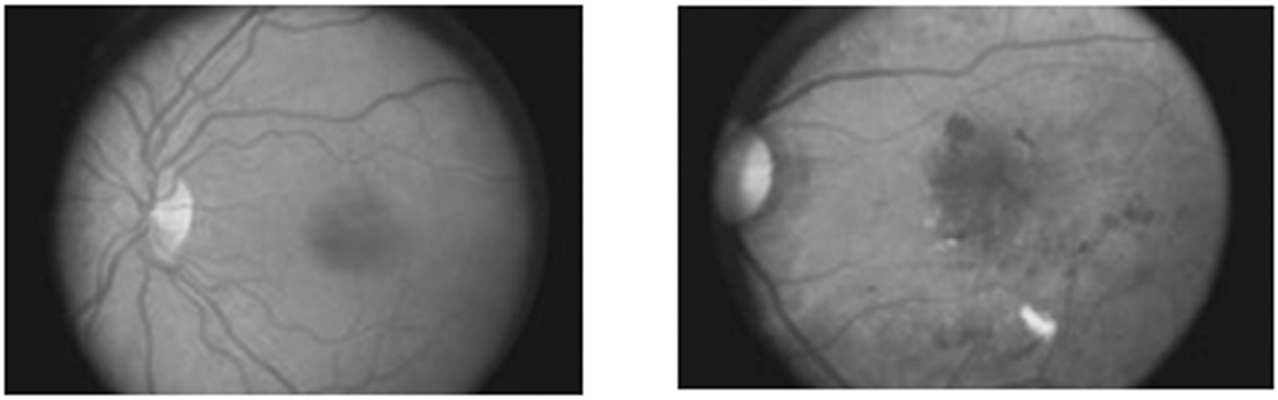


(a) (b)

Figure 1: Fundus images of normal and DR.

2. METHODOLOGY

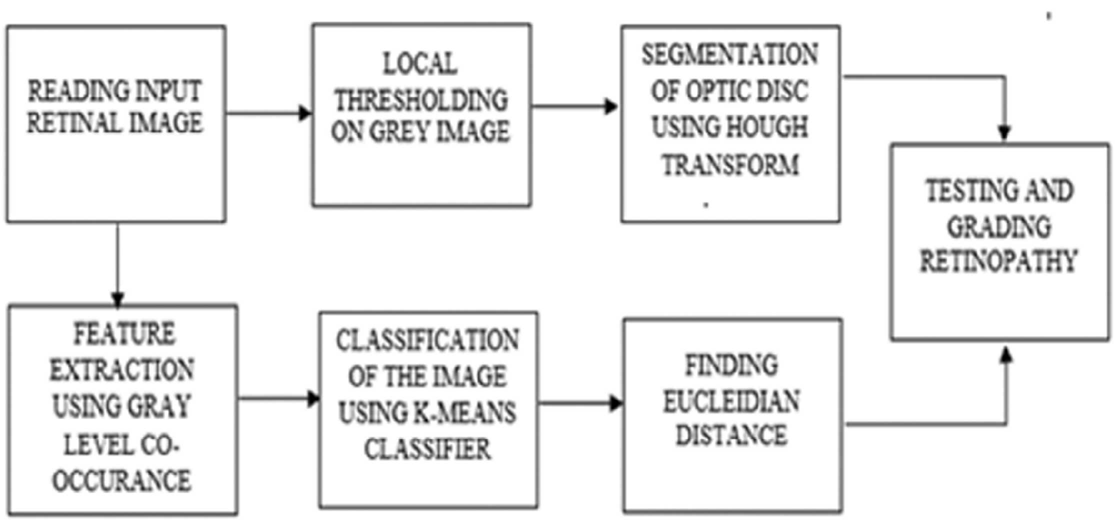


Figure 2: Block diagram of the grading

2.1. Image Description

Three ophthalmologic departments were involved in creating the image database by using Topcon TRC NW6 non-mydriatic retinograph with an angle of 45 degrees FOV. The image size used was 1488 × 2240.

2.2. Local Thresholding

From figure 2 the overall process of the methods used can be understood. The grey scale images are obtained by coverting RGB fundus images and the histogram of the same is retrived. Autothresholding[1] is done from the obtained histograms. The pixels which have high intensity will have the highest peak in the histogram. Since our aim is to choose the highest intensity area, the highest peak detected is used for thresholding. Local thresholding will enhance the edges of the image which is an important criterion for the next process-OD (Optic Disc) segmentation.

2.3. OD Segmentation

Hough transform[8] is used for segmentation. The main idea of using this segmentation technique is that, OD contains pixels with high intensity values and appears as the brightest part of the image. This intensity parameter is exploited to segment the OD.

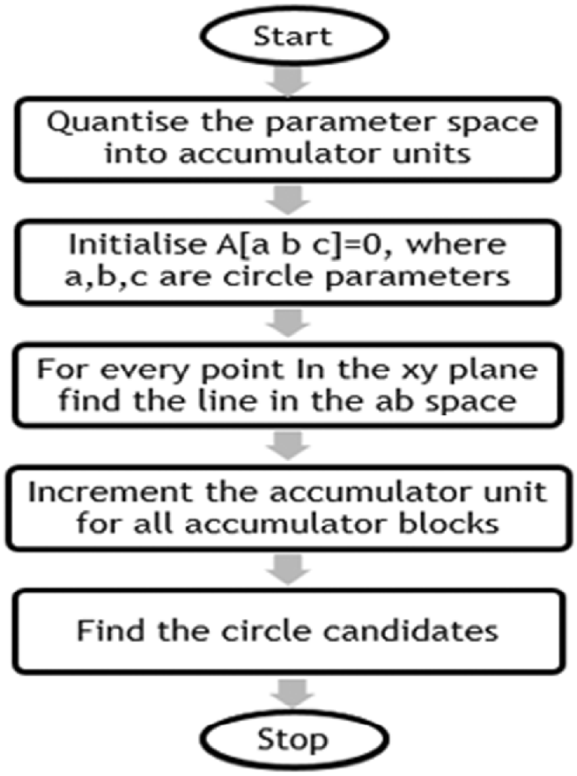


Figure 3: Stages of OD segmentation

Apart from OD, the exudates[10] and the cotton wool spots also share the same intensity as that of the OD. Therefore we can also find these lesions which are the symptoms used in the detection of diabetic retinopathy.

2.4. Feature Extraction

Every image has features which describes the image [7]. Also the features change for the least change in the image. This phenomenon is extensively used to differentiate the normal from abnormal images. The normal images will have certain feature values which will not be retained in the abnormal ones. The reason behind this is that the captures that show abnormality, contains lesions which will deviate the feature values from those of the normal. Therefore feature extraction has a major role to play in differentiating the normal from diseased images.

The extracted features are stored in a database[9]. These are training sets. There are 44 values that are extracted from 23 features. These features are-Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity, Energy, Homogeneity, Entropy, Maximum probability, Sum of sqaures: Sum average, Sum variance, Sum entropy, Variance, Difference entropy, Difference variance, Information measure of correlation1, Information measure of correlation2, Inverse difference normalized (INN), Inverse difference moment normalized, Inverse difference (INV).

2.5. Image Classification

Classification leads to the grading of retinopathy. As known earlier, an unsupervised training is compared to that of a classroom without a teacher. Therefore the classifier will not have any kind of feedbacks[5] and the classifier will not be sure if the outcome it produces is correct or not. But this classifier itself is sufficient to grade the retinopathy, since in training phase we train all the 3 grades of retinopathy alongside normal images. The classifier was found to perform better when the number of the training images were more, that is, the probability of mis-classifying was at its least. The images, after feature extraction are classified into 5 clusters by an unsupervised classification method called K means clustering. This will give a distance measure, which determines the similarity calculation of 2 elements, and how it influences the shape of the clusters. This distance measured is commonly known as the Euclidean Distance[4].

The Euclidean distance also called 2-norm distance is given by:

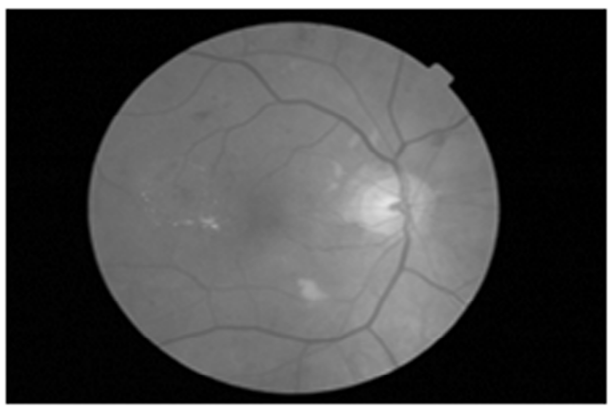
$$d(x,y)=\sum_{i=1}^{p}|x_i - y_i|$$

Since we have four different types of training images, the unknown image or the test image will place itself under any one of these 4 types-whichever gives a closest match.

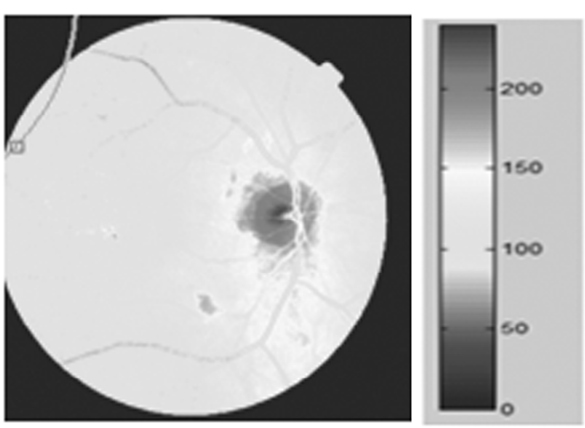
3. RESULTS AND DISCUSSION

The images of normal eye and the inflicted eye, obtained from Messidor datsbase were subjected to various images processing techniques and the results were obtained with 70% quality. From the Figures 4(a) and 4(b) the images of normal and damaged fundus respectively can be seen.

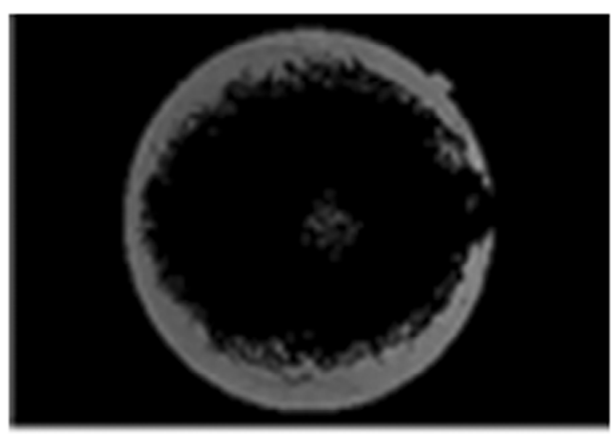
The figure 4b shows the intensity scale where one can clearly infer that the pixel intensity of the edema is approximately 150 thereby showing the maximum damage, exudates, and severity of retinopathy. Also in the grading process the K value taken was 5 i.e., 5 clusters were used to classify the image features.



(a)



(b)



(c)

Figure 3: (a) DR grade 3 fundus images from database,
(b) Fundus image after the processing with Hough transform with intensity scale,
(c) The fifth cluster elements showing maximum difference to grade the image.

The fifth cluster was most helpful in grading the image and hence marked with grade 3 severity.

4. CONCLUSION

The objective of retinopathy grading was achieved successfully by using the various methods discussed. Also it was found that when the number of training sets were increased the results were more accurate, because the method of classification used, is an unsupervised method. Since many features were considered and the changes in the overall image were taken into account, the proposed method was found to be quite reliable. Yet there were a few problems of spurious classifications, which could be attributed to the lower number of training sets that were considered initially. The performance of the algorithm proposed was 70% accurate.

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