ANALYSIS AND DETECTION OF HAEMORRHAGES AND EXUDATES IN RETINAL IMAGES

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Abstract- Diabetic Retinopathy [DR] is an eye disorder caused by changes in the blood vessels of the retina. It is one of the major problems that lead to blindness in adults around the world today. Early detection of the disease is absolutely essential in preventing unnecessary blindness. So, we have proposed an automated system to detect diabetic retinopathy from retinal images. In this approach after pre-processing, texture features are extracted from retinal images to detect abnormal images. Then the abnormal images are processed to localize and identify the problem of exudates and haemorrhages.

Index Terms- Diabetic Retinopathy, Exudates, Fundus Images, Haemorrhages.

I.INTRODUCTION

In recent times, all over the world have been faced with an increase in age and society related diseases like diabetes. According to recent survey, 4% of the world population has been diagnosed of diabetes disease alone. It have been recognized and accepted as one of the major cause of blindness in the country when the diabetic disease is not properly treated and managed. Early detection and diagnosis have been identified as one of the way to achieve a reduction in the percentage of visual impairment. Diabetes is the major reason for visual loss. More emphasis on routine medical check with the use of special facilities for detection and monitoring of the diabetics diseases such as diabetic retinopathy which occur on the retinal part of the eye. By increasing the work pressure which loads on the personnel that may lead to increase the diabetes screening activities. A lot of approaches have been suggested and identified for reducing the stress caused by the constant checkup. Screening related activities which use of medical digital image signal processing for diagnosis of diabetes related diseases like DR by using images of the retina [1]. Diabetic Retinopathy is a major disease which may occur to a patient who having diabetic mellitus. Haemorrhages and exudates are the problem of Diabetic Retinopathy which occurs on the retina. Diabetes is nothing but a disorder of metabolism. The energy required for the body which is generated from glucose that produces a result of food digestion. Digested food enters the body stream with the aid of a hormone called “insulin” which is produced by the pancreas. It is an organ that lies near the stomach. During eating, the pancreas automatically produces the correct amount of insulin. It allows glucose absorption from the blood into the cells. In individuals with diabetes, pancreas either produces too little or no insulin or the cells do not react properly to the insulin that is produced. The build up of glucose in the blood, overflows into the urine and then passes out of the body. Therefore, the body loses its main source of fuel even though the blood contains large amounts of glucose [2]. DR is shown in Figure1and in Figure2.

Figure 1: Person Without Diabetic Retinopathy

Figure 2: Same Image Viewed by Affected Person

Diabetes may occur when the body does not have enough "insulin” [2]. This is mainly to regulate the body based on the food that had been taken. If the problem of diabetic mellitus occurs, then the body cannot balance in the usual way with sugar and other carbohydrates. Nearly one person in 25 in the world has diabetes mellitus. Some children have diabetes but developing diabetes is much more common later in life. Diabetes may cause more complications that result in different parts of the body. It may lead to produce an effect of the eyes. There are two types of diabetic mellitus are Type 1 and Type 2 diabetes. In type 1 diabetic is commonly occurring before the age of 30 and that produces the result does the body producing little or no insulin. These are primarily controlled by insulin an injection that is specified as “insulin dependent diabetes”. Type 2 diabetes occurs after the age of 40 that affects the body has produce some insulin but the amount is either not sufficient or the body is not able to make proper use of it. It is controlled by diet, exercise and tablets. Although some people in this category will use the insulin injections are called as non-insulin dependant diabetes. In general, the Diabetic Retinopathy falls under the three categories namely Background Diabetic Retinopathy (BDR), Proliferative Diabetic Retinopathy (PDR) and Severe Diabetic Retinopathy (SDR).

In BDR phase, the arteries in the retina become weakened and leak forming small dot as haemorrhages. This leaking vessel often leads to swelling in the retina and cause decreased vision.

In the PDR phase, circulation problems cause areas of the retina to become oxygen-deprived or ischemic. New fragile is generated on vessels that develop as the circulatory system. This attempts to maintain adequate oxygen levels with in the retina. Hence, this phenomenon is called neovascularisation. Blood can leak into the retina and vitreous region. This leads to spot or floaters of decreased vision.

In the SDR phase, this disease generates the abnormal blood vessel growth and scar tissue. It may cause serious problems such as retinal detachment, glaucoma and gradual loss of vision.

Haemorrhages are one of the diabetic retinopathy diseases which affect the retinal part. It Occurs in the deeper layers of the retina and are often called 'blot' haemorrhages because of their round shape. Abnormal new blood vessels (neovascularisation) form at the back of the eye as a part of Proliferative Diabetic Retinopathy (PDR). It can burst and bleed (i.e., vitreous haemorrhage). Hence the new blood vessels are weak that causes blur vision. A retinal hemorrhage can be caused hypertension, retinal vein occlusion (a blockage of a retinal vein), or diabetes mellitus (which causes small fragile in blood vessels which are easily damaged).

Exudates are also a diabetic disease which affects the retina. There consist of a tiny swellings in the blood vessel walls. These blebs (micro aneurysms) appear as small red dots on the retina [3]. There are tiny yellow patches of hard exudates (fats from the blood) on the retina. Exudates are classified into two types Hard Exudates and Soft Exudates. Hard Exudates are appearing as bright yellow regions. Soft Exudates or cotton-wool spots which looks like gray - white fuzzy appearance. The haemorrhages and exudates are shown in Figure 3 and Figure 4.

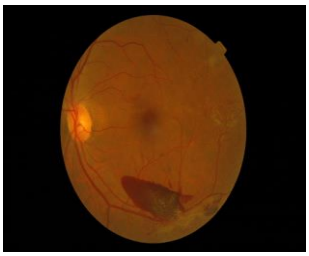


Figure 3: Haemorrhages

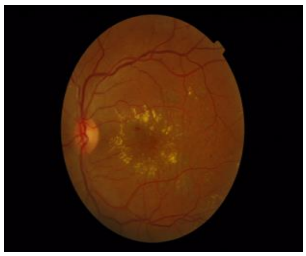


Figure 4: Exudates

In this paper, we analyze and detect the diseases of retina which is come under the category of diabetic retinopathy that are haemorrhages and exudates. In Section I describe the brief introduction about the diabetics and its diseases. Proposed System detail is shown in Section II, Modules of my automated system are presented in Section III, In Section IV specify the experimental results, Performance measures are shown in Section V and Section VI gives a brief conclusion of this paper.

II. PROPOSED SYSTEM

We have proposed an automated system for classifying the type of retinal diseases by using KNN classifier technique. The main goal of the proposed system is to automatically classify haemorrhages and exudates diseases. The input retinal images are taken from MESSIDOR database which is given as input to the pre-processing. After pre-processing, the features are extracted. K Nearest Neighbour classifier is used to classify the retinal images are normal or abnormal. Then the normal images are taken out and only concentrate on the abnormal images. Once again to extract the features from the abnormal images and then KNN classifier is used to classify these retinal images does contain haemorrhages or exudates problem. Block diagram of the proposed system is shown in Figure 5.

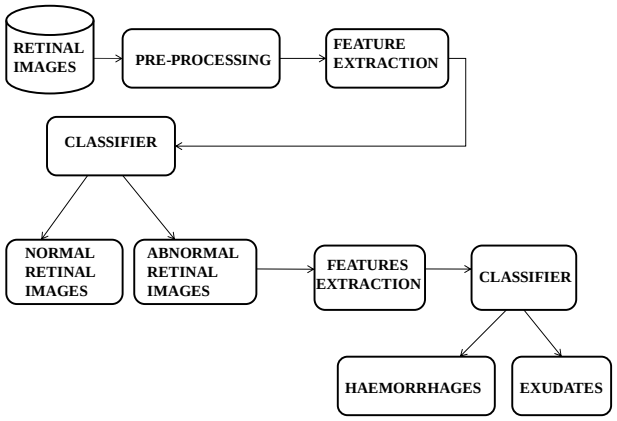


Figure 5: Block Diagram of the Proposed System

III. MODULES

Our proposed system consists of three modules which are A) Pre-processing the retinal image, B) Feature Extraction and C) Classify the output by KNN classifier technique.

A. Pre-processing

The input of the automated system is color fundus retinal image which is taken from MESSIDOR database. This stage corrects the problem of illumination variation during the pictures are taken [4] and [5]. The following pre-processing steps in my automated system consist of are:

i) Resizing the retinal gray images

The input retinal images are resized into small images. It is mainly to avoid overloading and time consumption.

ii) Color to gray scale conversion

To convert RGB colour fundus images into gray conversion.

iii) Median Filter

The median filter is a nonlinear filter, which can reduce impulsive distortions in an image and without too much distortion to the edges of such an image. It is an effective method that of suppressing isolated noise without blurring sharp edges.

Median filtering operation replaces a pixel by the median of all pixels in the neighborhood of small sliding window. The advantage of a median filter is that it is very robust and has the capability to filter only outliers. Noisy pixels are appeared with the background information. Hence we need to remove noisy pixels before contrast enhancement by using a median filter.

iii) Adaptive histogram technique

After gray-level conversion, adaptive histogram is used to enhance the "contrast" and to improve the quality of retinal image. One of the problems associated with fundus images is uneven illumination. Some areas of the fundus images are appear as brighter than the other. At the centre of the image are always well illuminated. Hence, it appears very bright while they far away from the poorly illuminated region and also appear as very dark. If the illumination decreases then the distance form the centre of the images are also increases. Many methods were tried to resolving this problem of un-even illumination, among which is the use of Adaptive Histogram Equalization Method (AHEM). AHEM gives better performance, higher processing speed and work well for all images are of different sizes, hence the reason for it being used as method of correcting un-even illumination. A variant of adaptive histogram equalization called Contrast Limited Adaptive Histogram Equalization (CLAHE). Images processed with CLAHE are of more natural appearance and facilitate the comparison of different areas of an image. To enhances the contrast of the grey scale images by transforming the values using contrast-limited adaptive histogram equalization (CLAHE). The main objective of this method is to define a point transformation within a local fairly large window. By assuming the assumption of intensity value within it is a stoical representation of local distribution of intensity value of the whole image. The local window is assumed to be unaffected by the gradual variation of intensity between the image centers and edges. The point transformation distribution is localized around the mean intensity of the window and it covers the entire intensity range of the image. Consider a running sub image W of N X N pixels centered on a pixel P (i,j) , the image is filtered to produced another sub image P of (N X N) pixels according to the equation below,

$$P_n = 255\left(\frac{[\emptyset_W(P)-\emptyset_W(min)]}{[\emptyset_W(max)-\emptyset_W(min)]}\right) \qquad (1)$$

where max and min are the maximum and minimum intensity in the whole image and P_n specifies the number of pixels.

B) Feature Extraction

In feature extraction, Texture analysis used to extract feature values from the input images. These features are used to attempts quantify intuitive qualities that are described in terms of rough, smooth and silky as a function of spatial variation are shown in pixel intensities [6]. Texture analysis can be helpful when objects in an image are more characterized by texture than by intensity. It consists of entropy, entropy filter, gray level co-occurrence matrix, range filter and standard deviation filter. The sample feature values are shown in table 1.

i) Entropy

Entropy is a statistical one which measures the randomness. It is used to characterize the texture of the input image. Syntax and formula for the entropy is shown below, the entropy formula is shown in equation 2.

$$H=-\sum_{k=0}^{M-1} P_k \log_2(P_k) \qquad (2)$$

Where M is the number of grey levels and p_k is the probability associated with grey level k.

ii) Entropy Filter

Entropy filter specifies the local entropy of the gray scale images. It performs entropy filtering function for all the input images. This filter is used to create a texture for an image. The entropy filter returns an array where each output pixel contains the entropy value of the 9-by-9 neighborhood around the corresponding pixel in the input image.

iii) Range Filter

Range Filter is found out the local range of the gray scale images. Mat lab function of range filter is used to generate ranges for the input images. It returns each output pixel that contains the range value which is greater value – smaller value find for every 3-by-3 neighborhood around the corresponding pixel in the input image.

iv) Standard Deviation Filter

Standard Deviation Filter calculates the local standard deviation for the input images. Standard Deviation Filter function is used from mat lab which returns each output pixel contains the standard deviation of the 3-by-3 neighborhood around the corresponding pixel in the input image.

Table 1: Features Extracted

s.no	Entropy	Entropy filter	Range filter	Standard deviation filter
1	4.6221	2.6765	13.4905	4.9812
2	5.1892	2.7745	16.5111	6.0997
3	5.1502	2.7475	16.8775	6.2220
4	4.4395	2.4714	13.6801	5.0616
5	4.6133	2.6296	17.6331	6.5250

C) KNN Classifier

KNN stands for "K-Nearest Neighbour algorithm". It is one of the simplest but widely using machine learning algorithms. An object is classified by the "distance" from its neighbours, with the object being assigned to the class which is most common among its k distance-nearest neighbours [7]. If k = 1,

the algorithm simply becomes nearest neighbour algorithm and the object is classified to the class of its nearest neighbour.We are also given a single number "k". This number decides how many neighbors (where neighbor are defined based on the distance metric) influence the classification. This is usually an odd number if the number of classes is 2. Distance is a key word in this algorithm, each object in the space is represented by position vectors in a multidimensional feature space. It is usual to use the Euclidean distance to calculate distance between two vector positions in the multidimensional space. Each of the training data consists of a set of vectors and class label associated with each vector. In the simplest case, it will be either + or – (for positive or negative classes). But KNN, can work equally well with arbitrary number of classes [8]. The advantages of KNN classifier are analytically tractable, simple implementation, nearly optimal in the large sample limit (N→∞), lends itself very easily to parallel implementations and uses local information, which can yield highly adaptive behaviour and the disadvantages of KNN classifier are large storage requirements and computationally intensive recall. The KNN classifier example is shown in Figure 6.

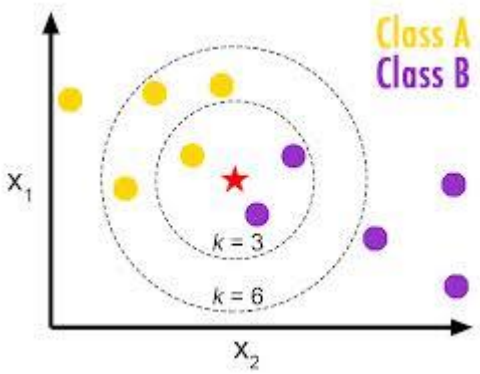
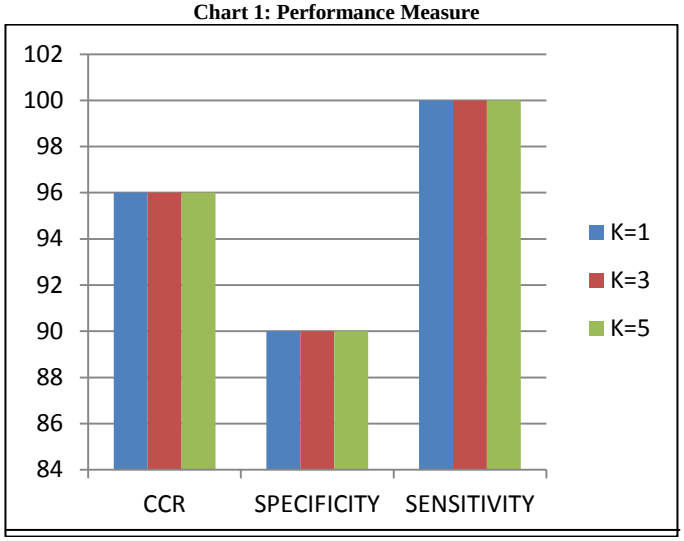


Figure 6: KNN Classifier Example

The test samples are taken as (red star) that should be classified either to the first class of yellow circle or to the second class of purple circle. If *k = 3* (solid line circle) which is assigned to the second class because there are 2 purple circles and only 1yellow circle inside the inner circle. If *k = 5* (dashed line circle) it is assigned to the first class (3 yellow circle vs. 2 purple circle inside the outer circle).

The training process for KNN consists only of storing the feature vectors and class labels of the training samples. One major problem to using this technique is the class with the more frequent training samples would dominate the prediction of the new vector, since them more likely to come up as the neighbour of the new vector due to their large number. Choosing an appropriate K is essential to make the classification more successful. For performance comparison by using KNN nearest neighbour class variation, we have calculated CCR, Specificity and Sensitivity. Chart 1 specifies the overall performance measures of three classes of KNN are K=1, K=3 and K=5. The accuracy of all classes is showing same result.

Chart 1: Performance Measure



IV. EXPERIMENTAL RESULT & ANALYSIS

The grey colour fundus images were used in this experiment to detect the retinal images having Diabetic Retinopathy problem or not. We have taken 100 retinal images (70 normal images and 30 abnormal images) from MESSIDOR database for evaluating the proposed approach. We have trained KNN classifier by using 50 normal and 25 abnormal images. These images are classified by KNN classifier as normal or abnormal. After classify, to separate abnormal images for further process and then once again to extract the features for abnormal images. After feature extraction, KNN classifier is applied to classify the abnormal retinal images as haemorrhages or exudates. The experimental results are shown in Figure 7, Figure 8, Figure 9 and Figure 10.

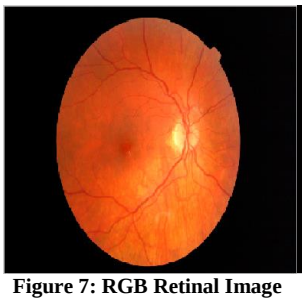


Figure 7: RGB Retinal Image

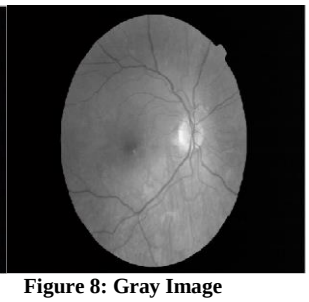


Figure 8: Gray Image

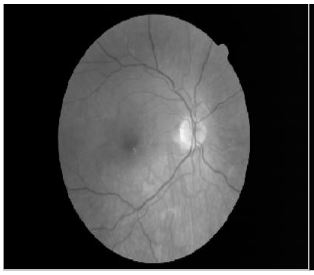


Figure 9: Median Filter

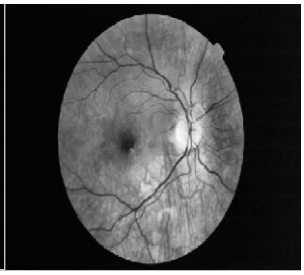


Figure 10: Adaptive Histogram Technique

i) Correct Classification Rate (CCR)

CCR is the most obvious accuracy measure to evaluate performance of a classification system.It can be calculated by using equation 3.

$$CCR = \frac{\text{CORRECTLY CLASSIFIED TEST}}{\text{TOTAL NUMBER OF TEST DATA}} \quad (3)$$

ii) Specificity

Specificity measures the proportion of negatives which are correctly identified as such (e.g. the percentage of normal healthy people who are correctly identified as not having the condition, sometimes called the *true negative rate*). Specificity formula is shown in equation 4.

Formula: Specificity = TN/ (TN+FP) (4)

TN – True negative and
FP – False Positive

iii) Sensitivity

Sensitivity also called the *true positive rate* or the *recall rate* in some fields. It measures the proportion of actual positives which are correctly identified as such (e.g. the percentage of DR people who are correctly identified as having the condition). Sensitivity is shown in equation 5.

Formula: Sensitivity = TP/ (TP+FN) (5)

TP – True Positive and
FN –False Negative

V. CONCLUSION

We have proposed an automated system to identify patients having diabetic retinopathy using fundus images from MESSIDOR database. After pre-processing we have extracted texture features and used KNN to classify normal and abnormal fundus images. Then from the abnormal images we have extracted standard deviation of the texture features and apply classifier to classify and detect diabetic retinopathy diseases such as haemorrhages (red patches) or exudates (yellowish dots) which falls between Back ground Diabetic Retinopathy (BDR) and Proliferative Diabetic Retinopathy (PDR) stages of the disease. In performance comparison, we have achieved specificity as 90%, sensitivity as 100% and CCR as 96%.

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