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Automatic Detection of Diabetic Retinopathy Level Using SVM Technique

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ABSTRACT: The human eye is an organ which gives a sense of sight. Diabetic retinopathy is a most common diabetic eye disease which is a leading cause of blindness in India. Diabetic Retinopathy is a disease in which the retinal blood vessels swell and it may even leak. This damages the retina of the eye and may lead to vision loss if the level of diabetes is very high. Early diagnosis of Diabetic Retinopathy can prevent vision loss in patients. The method proposed in this paper for detection of Diabetic Retinopathy(DR) disease level emphasizes on determination of three important types of Diabetic Retinopathy; Macula Edema, Hemorrhages and Exudates. These types can be extracted using fundus images of patients and processing these fundus images through an appropriate image processing technique. Based on the presence of these types and their amount in the fundus image will determine the level of diabetic Retinopathy in patients.

KEYWORDS: Diabetic Retinopathy, Macula Edema, Haemorrhages, Exudates, SVM classifier

1 INTRODUCTION

The human eye is an organ that reacts with light and has several purposes. As a conscious sense organ, the mammalian eye allows vision. Rod and cone cells in the retina allow conscious light perception and vision including color differentiation and the perception of depth [22]. Therefore any damage to the retinal blood vessels affects the vision.

Diabetes occurs when the pancreas fails to secrete enough insulin. This leads to the increase in blood glucose level [22]. The blood vessels of the retina might get damaged due to increase in blood glucose level, which may even lead to vision loss. Diabetic Retinopathy (DR) is a medical condition where the retina is damaged because fluid leaks from blood vessels into the retina [20],[1]. Thus early detection of DR disease is important to overcome vision loss.

In this paper, section I includes the importance of early detection of DR disease and flow of the adopted method in the project. Section II emphasizes on the pre-processing steps on the fundus images. Section III explains the Segmentation of the pre-processed images implemented for segmenting images for presence of Macula Edema, Hemorrhages and Exudates. Section IV includes the various features extracted on the segmented images which will act as input to the SVM classifier. Section V explains the SVM classifier and its implementation in classifying the images for presence of Macula Edema, Hemorrhages or Exudates.

The detection of DR disease can be done by processing the fundus images of patients using an appropriate image processing technique providing accurate results.

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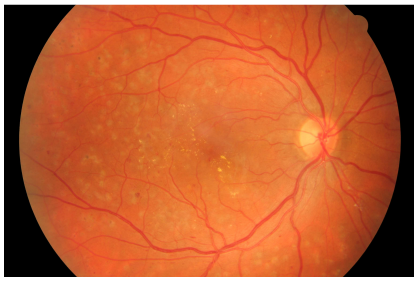


Figure 1. Normal Fundus Image

The method proposed in this project emphasizes on the detection of Diabetic Retinopathy disease level in order to prevent vision loss in humans. Exudates, Macula Edema and Hemorrhages indicate levels of Diabetic Retinopathy that is taken into consideration for the detection of level of this disease [9]. The proposed method is as shown in figure (2).

The method involves pre-processing of the colour fundus images. The colour fundus image of a normal patient (not affected by Diabetic Retinopathy) is as shown in figure (1). The detection is done by taking an input fundus image (RBG) and converting it into a Grey Scale Image. The output grey scale image is then filtered using Median Filtering for noise removal. Histogram Equalization is performed on the filtered image in order to improve the contrast of an image. After pre-processing of fundus image, the segmentation of image is performed using Histogram Thresholding. The segmented image is then fed for Feature Extraction which extracts different features of an image. The extracted features are then applied as input to SVM classifier which classifies the image based on presence Macula Edema, Hemorrhages or Exudates. The entire processing of fundus images for detection of DR disease is carried out in MATLAB.

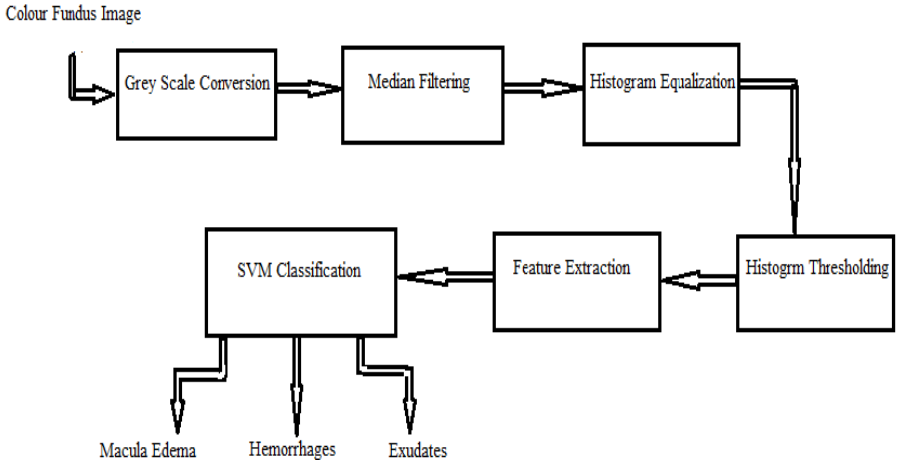
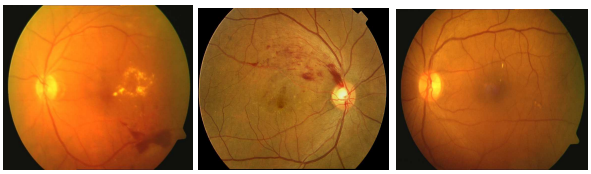


Figure 2. Detection of level of DR Disease

The fundus images of patients with features like Hemorrhages, Macula edema and Exudates is as shown in figure (3).



(a) **(b)** **(c)**

Figure 3. Features indicating DR level (a) Exudates (b) Hemorrhages (c) Macula Edema

2 PRE-PROCESSING OF COLOUR FUNDUS IMAGES

The pre-processing of colour fundus images is required to perform before the image is subjected to the actual detection mode. The pre-processing techniques include, converting the fundus image into a Grey scale image, performing Median

Filtering on the grey scaled image for removal of noise, subjecting the filtered image to Histogram Equalization in order to increase the contrast of the image.

2.1 CONVERTING COLOUR FUNDUS IMAGE INTO GREY SCALE IMAGE

Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured.

2.2 MEDIAN FILTERING

Median filter is the nonlinear filter more used to remove the impulsive noise from an image. Furthermore, it is a more robust method than the traditional linear filtering, because it preserves the sharp edges.

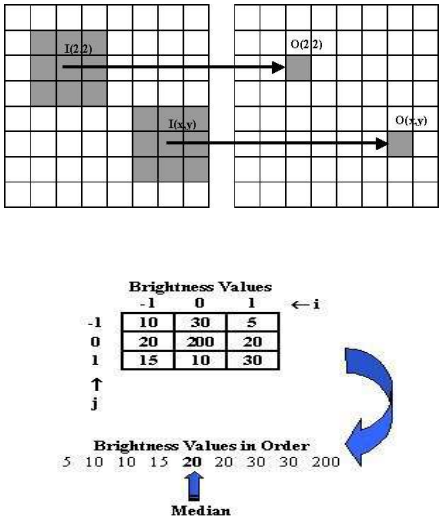


Figure 4. Median Filtering technique

Median filter is a spatial filtering operation, so it uses a 2-D mask that is applied to each pixel in the input image. To apply the mask means to center it in a pixel, evaluating the covered pixel brightness and determining which brightness value is the median value.

The median value is determined by placing the brightness in ascending order and selecting the center value. The obtained median value will be the value for that pixel in the output image. Figure shows an example of the median filter application, as in this case, habitually a 3x3 median filter is used.

2.3 HISTOGRAM EQUALIZATION

Indicate the given name and family name clearly. Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

To accomplish the equalization effect, the remapping should be the cumulative distribution function (cdf). For the histogram H(i) , its cumulative distribution is $H'(i)$:

$$H(i) = \sum_{0<j<i} H(j) \qquad (1)$$

To use this as a remapping function, we have to normalize H'(i) such that the maximum value is 255 (or the maximum value for the intensity of the image). Finally we use a simple remapping procedure to obtain the intensity values of the equalized image:

$$equalized(x, y) = H'(src(x, y)) \quad (2)$$

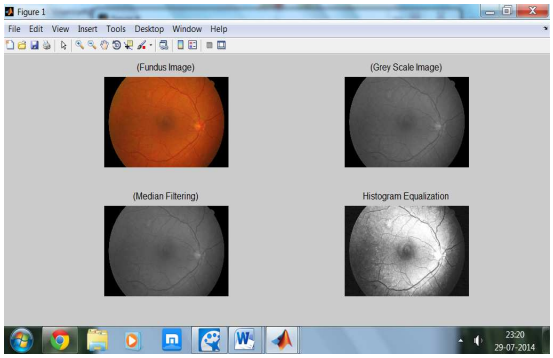


Figure 5. Pre-processing of Fundus Image

The quality of the pre-processed image can be determined by calculating two important factors of pre-processed images, i.e., MSE and PSNR.

The Mean Squared Error (MSE) represents the average of the squares of the "errors" between our actual image and our noisy image. The error is the amount by which the values of the original image differ from the degraded image. Peak Signal-to-Noise Ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. The PSNR is usually expressed in terms of the logarithmic decibel scale.

The higher the PSNR, the better degraded image has been reconstructed to match the original image.

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad (3)$$

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\| f(i, j) - g(i, j) \|^2 \quad (4)$$

Where,

f- represents the matrix data of our original image
g- represents the matrix data of our degraded image
m- represents the numbers of rows of pixels of the images and 'i' represents the index of that row
n- represents the number of columns of pixels of the image and 'j' represents the index of that column
MAX_f - is the maximum signal value that exists in our original "known to be good" image.

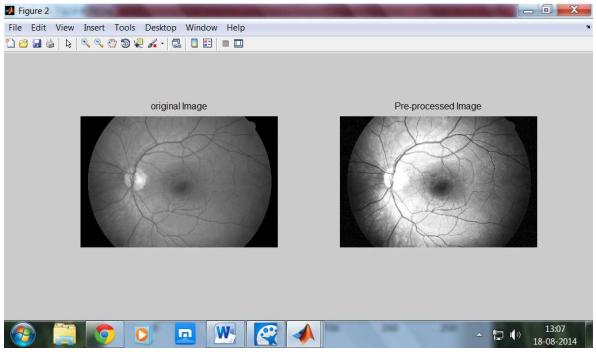


Figure 6a. Original Image and Pre-processed Image

For one of the pre-processed fundus image as shown in figure(6a), the PSNR and MSE value calculated is as shown in figure(6b).

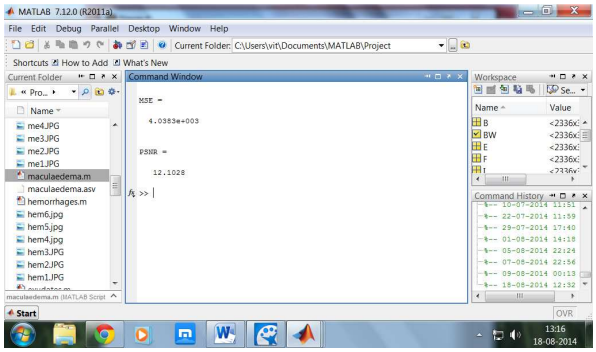


Figure 6b. MSE and PSNR calculation

3 HISTOGRAM THRESHOLDING FOR SEGMENTATION OF FUNDUS IMAGES

Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. In this project, Histogram Thresholding technique is used in order to segment images containing Macula Edema, Hemorrhages and Exudates.

Histograms are constructed by splitting the range of the data into equal-sized bins (called classes). Then for each bin, the number of points from the data set that fall into each bin is counted. The vertical axis of histogram shows Frequency (i.e., pixel counts for each bin) and Horizontal axis shows Intensity of pixels.

In Histogram Thresholding, based on the histogram obtained for a particular pre-processed image, a threshold point is selected. This threshold value will segment the image in order to obtain the required contour (region of interest). Suppose that the gray-level histogram corresponds to an image f(x,y) composed of dark objects on the light background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold 'T' that separates these modes. Then any point (x,y) for which f(x,y) < T is called an object point, otherwise, the point is called a background point.

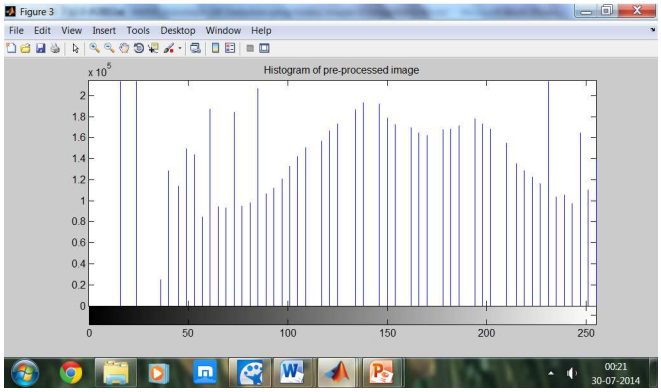


Figure 7. Histogram of one Pre-processed Fundus Image

In this paper, the Histogram Thresholding technique will segment the images to determine the region of interest, i.e., Macula Edema, Hemorrhages and Exudates.

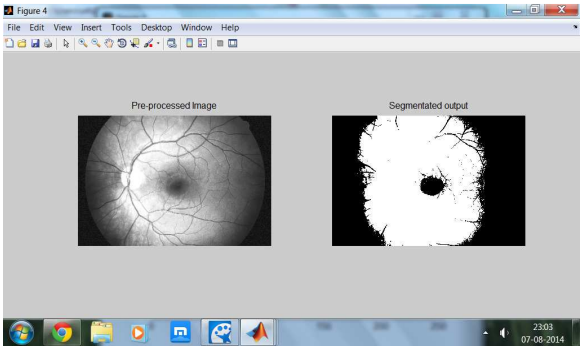


Figure 8a: Segmented output showing presence of Macula Edema

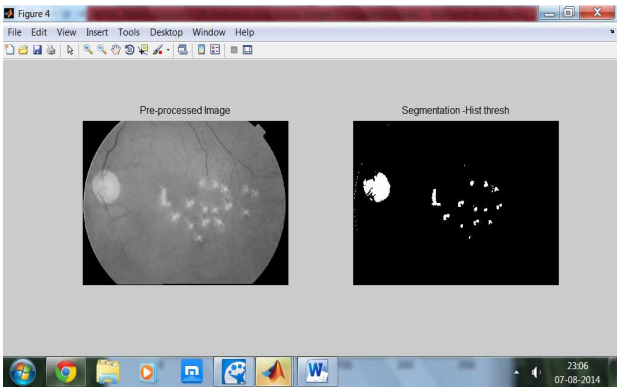


Figure 8b: Segmented output showing presence of Exudates

4 FEATURE EXTRACTION

The feature extraction is a process wherein various features of the segmented image are extracted. These features then act as the input to the classifier which can further classify the images for the presence of diabetic level.

In order to capture the spatial dependence of grey-level values, a two-dimensional dependence matrix known as a grey-level co-occurrence matrix (GLCM) is extensively used. The grey-level co-occurrence matrix P [i, j] is defined by first specifying a displacement vector d = (dx, dy) and counting all pairs of pixels separated by 'd' having grey levels 'i' and 'j'. For example, consider the simple 5 x 5 image having grey levels 0, 1, and 2 as shown in Figure 9(a). Since there are only three grey levels, P

[i, j] is a 3 x 3 matrix. Let the position operator is specified as (1, 1), which has the interpretation: one pixel to the right and one pixel below.

2	1	2	0	1
0	2	1	1	2
0	1	2	2	0
1	2	2	0	1
2	0	1	0	1

Figure 9a: A 5 x 5 image with three gray levels 0, 1, and 2.

In a 5 x 5 image there are 16 pairs of pixels which satisfy this spatial separation. We now count all pairs of pixels in which the first pixel has a value of 'i' and its matching pair displaced from the first pixel by 'd' has a value of 'j', and we enter this count in the i^{th} row and j^{th} column of the matrix P[i, j]. For example, there are three pairs of pixels having values [2, 1] which are separated by the specified distance, and hence the entry P[2, 1] has a value of 3. The complete matrix P[i,j] is shown in Figure 9(b). Note that P[i, j] is not symmetric since the number of pairs of pixels having grey levels [i,j] does not necessarily equal the number of pixel pairs having grey levels [j, i]. The elements of P [i,j] are normalized by dividing each entry by the total number of pixel pairs. In our example, each entry is divided by 16. This normalized P[i, j] is then treated as a probability mass function since the entries now add up to 1.

P (i , j)

1/16 *

0	2	2
2	1	2
2	3	2

Figure 9b: The grey-level co-occurrence matrix for d = (1,1)

The following features of the segmented fundus image are extracted and applied as an input to the classifier.

4.1 ENERGY

Energy corresponds to the mean squared value of the image typically measured with respect to the global mean value. Energy of an image returns the sum of squared elements in the GLCM.

$$Energy = \sum_{i,j} [p(i, j)]^2 \quad (5)$$

4.2 CONTRAST

The contrast function enhances the contrast of an image. It creates a new grey colour map that has an approximately equal intensity distribution. All three elements in each row are identical. Contrast of an image returns a measure of the intensity contrast between a pixel and its neighbour over the whole image.

$$Contrast = \sum_{i,j} |i - j|^2 * p(i, j) \quad (6)$$

4.3 CORRELATION

The operation called correlation is closely related to convolution. In correlation, the value of an output pixel is also computed as a weighted sum of neighbouring pixels. The difference is that the matrix of weights, in this case called the correlation kernel, is not rotated during the computation. The correlation operation therefore returns a measure of how correlated a pixel is to its neighbour over the whole image.

$$Correlation = \sum_{i,j} \frac{[(i - \mu i) * (j - \mu j) * p(i, j)]}{[\sigma_{i*} \sigma_j]} \quad (7)$$

4.4 HOMOGENEITY

Homogeneity reflects the uniformity of several pixels in an image and expresses how similar all of them are. Homogeneity of image returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{i,j} \frac{[p(i,j)]}{[1+|i-j|]} \quad (8)$$

4.5 ENTROPY

Entropy is a feature which measures the randomness of grey-level distribution.

$$Entropy = -\sum_{i,j} p(i,j) * \log 2(p(i,j)) \quad (9)$$

Note that the entropy is highest when all entries in P[i, j] are equal; such a matrix corresponds to an image in which there are no preferred grey-level pairs for the specified distance vector d.

These features are calculated for various segmented fundus images, i.e. normal fundus images and abnormal (DR) fundus images.

These features are applied as input to (Support Vector Machine) SVM classifier.

5 SVM CLASSIFIER

This unnumbered section is used to identify people who have aided the authors in accomplishing the work presented and to acknowledge sources of funding. The machine learning is a very vital step in image processing. A Support Vector Machine (SVM) performs classification by constructing an N-dimensional hyper-plane that optimally separates the data into two categories. SVM models are closely related to neural networks. In the parlance of SVM literature, a predictor variable is called an attribute, and a transformed attribute that is used to define the hyper-plane is called a feature. The task of choosing the most suitable representation is known as feature selection.

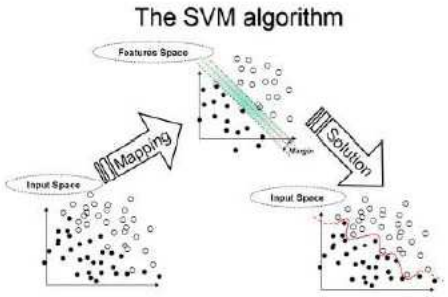


Figure 9: SVM Technique

A set of features that describes one case (i.e., a row of predictor values) is called a vector. So the goal of SVM modeling is to find the optimal hyper-plane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other size of the plane. The vectors near the hyper-plane are the support vectors.

In this paper, SVM classifier is trained with the features of known images, i.e., images whose Diabetic Retinopathy level is already known. This process is known as Learning of SVM classifier. The test fundus image is then applied as an input to SVM classifier which provides at the output the level of Diabetic Retinopathy.

6 RESULTS AND DISCUSSION

The Diabetic Retinopathy (DR) level in humans can be detected by scanning the human fundus image for the presence of Macula Edema, Hemorrhages and Exudates. Macula Edema indicates Mild level of DR, Hemorrhages indicates Moderate

Level of DR and Exudates indicate Severe level of DR in humans. The SVM classifier is trained with 100 fundus images which show different levels of DR. The input test image fed to the classifier appropriately classifies the level of DR based on the training of SVM Classifier.

The segmented output as shown in figure (8a) shows presence of Macula Edema. The features are extracted of this segmented image and then the features are subjected to SVM classifier. The output of the classifier is as follows:

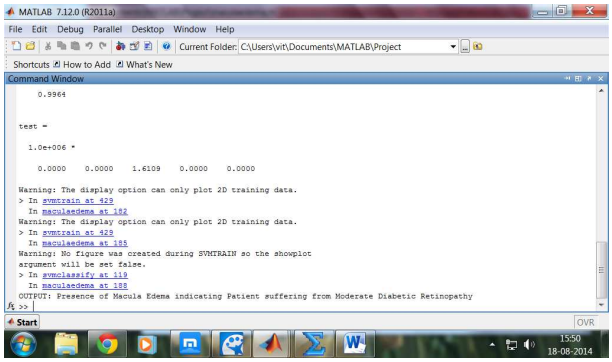


Figure 10a: SVM output indicating Moderate Level of Diabetic Retinopathy

The figure (10a) shows the output of classifier indicating presence of Moderate Level of Diabetic Retinopathy as required. Similarly the segmented output shown in figure (8b) undergoes feature extraction process followed by feeding the features to the SVM classifier. The SVM output is as follows:

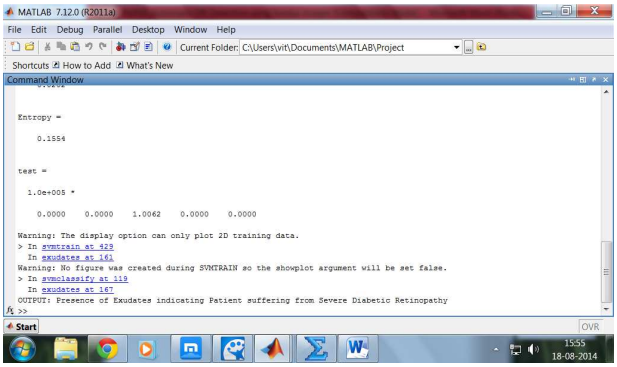


Figure 10b: SVM output indicating Severe Level of Diabetic Retinopathy

Thus figure 10(b) rightly shows SVM classifier output as Severe Level of Diabetic Retinopathy

7 CONCLUSION

The method adopted in this paper for early detection of DR disease in humans is reliable and shows accurate results.

The method implemented can be used for screening of patients eyeballs for detecting level of DR in a cost effective manner.

This technique helps in determining levels of DR in its early stage and thus preventing vision loss.

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