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SEGMENTATION AND CLASSIFICATION OF DIABETIC RETINOPATHY IMAGES USING MULTIPLE FEATURES

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Abstract— Diabetic retinopathy is becoming as one of the common disease it also can lead to blindness. The longer a patient with diabetes more likely developing diabetic retinopathy. DR retinal blood vessel collapse is. Micro aneurysm is one of the earliest symptoms of Diabetic Retinopathy. Due to the swelling of capillaries and weak blood vessels isolated dark red spots are created which are called as micro aneurysms. Based on the number of micro aneurysms the severity of the DR disease. Earlier micro aneurysms detection can reduce the incidence of blindness. Micro aneurysms are reddish in colour with a diameter less than 125 µ m.

Detection of micro aneurysms in automated screening of diabetic retinopathy will be highly helpful in diagnosis and treatment. Generally MAs will appear as small red dots on retinal fundus images. In this paper we purpose a modified pre-processing method to remove background region and noisy pixels from retinal image, and to improve the efficiency of the detection median filter used along with Histogram. Feature extraction is done by GMM, KNN, and LMSE methods and Classification is done by RBF, Bays network. Based on the analysis carried out, the proposed system exhibits remarkable outputs.

Keywords—Retinal Image; Diabetic Retinopathy; Micro aneurysm; Classifiers; Segmentation

1. INTRODUCTION

Diabetes is a disease which occurs when the pancreas fail to secrete enough insulin or the body unable to process it properly. As diabetic progresses, the disease slowly affects the circulatory system including the retina of human eye and as a result of long term accumulated damage to blood vessels leads to declining the vision of patient which is termed as diabetic retinopathy. Diabetic Retinopathy is an eye disease that can lead to partial or even complete loss of visual capacity, if left undiagnosed at the initial stage. Retinal lesions associated with the disease are used to evaluate different stages and the severity of the disease [1].

1.1 RETINAL IMAGE OF HUMAN EYE

Retina as shown in Fig.1, a light-sensitive tissue lining on the inner surface of the eye again. Creating an image of the eye optics it serves the same function as the film in a camera, the retina, the visual world. A cascade of light striking the retina chemical at the end of the nerve stimulating and electric phenomena. This vision of the brain through the fibers was sent to various stations Nerve. Retinal synapses between the neurons in a layer structure consisting of several layers. Only neurons that are directly sensitive Light photoreceptor cells.

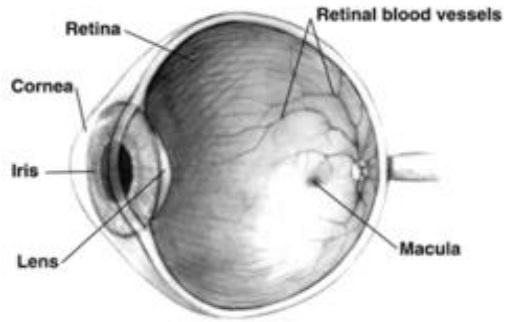

Fig. 1. Representation of human eye

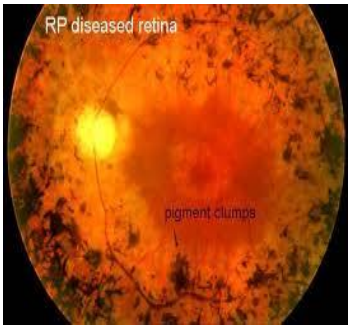

Fig. 2. Fundus Image

1.2 ABNORMALITIES ASSOCIATED WITH THE EYE

Abnormalities associated with the eye can be divided into two main classes; the first is disease of the eye such as cataract, conjunctivitis, blether it is and glaucoma. The second group is categorized as life style related disease such as hypertension, arteriosclerosis and diabetes. When the retina is been affected as a result of diabetes, this type of disease is called Diabetic Retinopathy (DR), if not properly treated it might eventually lead to loss of vision.

Ophthalmologists have come to agree that early detection and treatment is the best treatment for this disease. DR occurrence has been generally categories into three main stages based on the type and severity of the disease.

- Background Diabetic Retinopathy
- Proliferate Diabetic Retinopathy
- Severe Diabetic Retinopathy

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1.3 DIABETES RETINOPATHY RELATED PROBLEMS

BDR on the stage, the small arteries in the retina, forming dot-like hemorrhages, become weak and leak. These vessels leak or enema often lead to swelling in the retina and decreased vision PDR phase, circulation problems in the areas of the retina to become oxygen-deprived or cause ischemic. Attempts to maintain adequate oxygen levels within the retina of the circulatory system, as the new kit, to build ships. Lack of blood supply to the retina send signals to the body of PDR and the development of new blood vessels which trigger an advanced stage. By filling in the center of the blood vessels of the retina and the jelly-like substance (vitreous gel), can grow along the surface. However, they are fragile and abnormal; they cause symptoms or vision loss. It is only when their thin and weak walls leak blood, severe visual loss or even irreversible blindness would occur. In the SDR phase of the diseases there is a continued abnormal vessel growth and scar tissue, which may cause serious problems such as retinal detachment and glaucoma and gradual loss of vision.

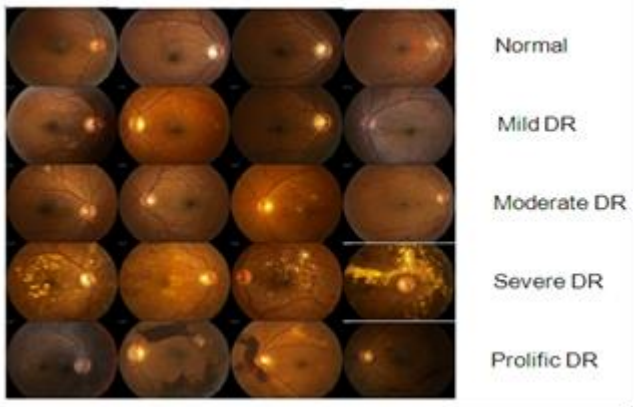

Fig. 3. Stages of DR

For many years, high blood glucose (sugar) level can weaken and damage the small blood vessels in the retina. This can cause various problems, including:

• Blow out the splendor of small blood vessels (Micro malt).
• Damaged blood vessels and small leaks fluid (exudates).
• Small (Flame), damaged blood vessels and bleeds

Blocked blood vessels may become just. Cut off the supply of blood and oxygen to the retina sections. Fluid leaks, and the ban will affect the blood vessels in the retina cells. In severe cases, damaged blood vessels vitreous humor (the jelly-like center) into the blood. It can affect vision by blocking light rays to the retina.

1.4 DIAGNOSING DIABETIC RETINOPATHY

This paper aims an automated method to detect the lesions belongs to diabetic retinopathy by applying digital image processing concepts in the field of medical diagnosis. Normally there are two kinds of lesions associated with diabetic retinopathy. They are red lesions and white lesions. By using an automated method to detect these lesions instead of stepwise screening process will gradually reduce the screening time.

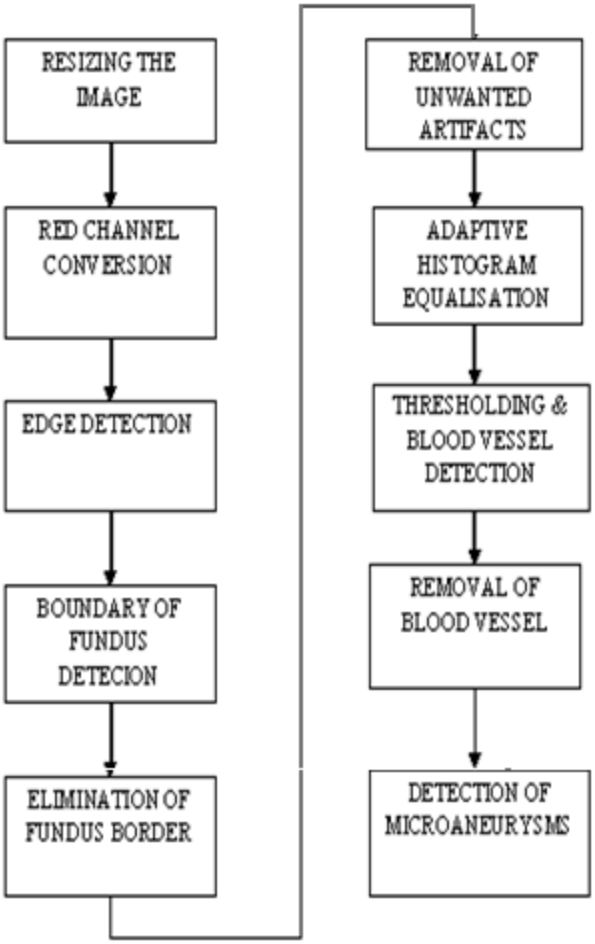

Fig. 4. Overriew of proposed model

This paper work is based on the detection of red lesion that is Micro aneurysms (MA) which is one of the lesions associated with Diabetic Retinopathy (DR) which is also the first sign of retinopathy and the diagnosis is done by applying the techniques of digital image processing on fundus images. Section 2 contains the clear explanation about the pre-processing of the image using the histogram equalization and median filter. Section 3 contains the explanation about segmentation and classification of the images done using GMM, LMSE and KNN methods. The Result of the algorithms are discusses in Section 4.

2. PRE-PROCESSING MODELS

The output of the digital camera is a “raw” the brightness of a pixel of the image, or gray level, which is the digital image that contains an array of values for each value of the digital number. To improve the performance of image processing of image data are typically employed in the imaging chain. Compression image processing, feature detection, and classification [3-6] that involves are a very broad field. Common processing methods used to improve the image quality of the display; we will focus our discussion here. In particular, we like the map camas, average contrast enhancement methods of filtering, and then that the spatial filtering methods to sharpen edges to remove blur the picture looked. The images have an eight-bit dynamic range of

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measurement of land that can easily accept, generally the first step in the chain of image enhancement; Since the levels of gray, black and white image, the zero and 255, should be in the range 0-255, so, I mean, there are 28 = 256 possible gray levels. Color images that are combined to give the public the full spectrum of colors, red, green and blue images, there are three rows representing numbers. By separating the green airplane we need to focus on implementing a single-band images.Histogram Equalization

We try to balance the resulting map camas a gray level, which is trying to increase the contrast of the image by using conversion. It turns out that the gray level transform that we are seeking is simply a scaled version of the original image's cumulative histogram [7].

Consider a discrete greyscale image {x} and let in be the number of occurrences of gray level i. The probability of an occurrence of a pixel of level i in the image is

$$p_x(i) = p(x = i) = \frac{n_i}{n}, \quad 0 \leq i < L \tag{1}$$

L being the number of gray scale image (usually 256), n being the number of pixels in an image, and $p_x(i)$ being In fact, the pixel value of the normalized image map i [0,1].we also define the cumulative distribution function corresponding to Px as

$$cdf_x(i) = \sum_{j=0}^{i} p_x(j) \tag{2}$$

Furthermore, the accumulated image is normalized graph. We would like to create in the form of change y = T(x) to A flat map, a new image of {y}. This is an image such as a linear value to be set across the border, to take part, i.e.

$$cdf_y(i) = iK \tag{3}$$

A flat map, {y} a new image. Participate in a linear value, to be set up along the border, this is like a picture; it is defined as

$$y = T(k) = cdf_x(k) \tag{4}$$

Where K is range [0, L] in. T {x} is a normal map that we used, the range [0, 1] Note that the size of the drawings. In order to map the values back to their original range, the following should be used as a simple change:

$$y' = y \cdot (\max\{x\} - \min\{x\}) + \min\{x\} \tag{5}$$

Map camas case, the output probability densities, all in an equal portion of the input image should be the maximum number of active positions. Histogram equalization is realized selecting, for each pixel, a suitable neighbourhood on which the histogram equalization (or matching) is computed. More computational intensive, but neighbouring pixels shares most of the neighbourhood. Non overlapping regions may produce "blocky" effect.

2.1 MEDIAN FILTER

The median filter is a nonlinear digital filtering technique, often used to remove noise. These sound reduction (for example, an image node) to improve the processing of the results, is a common pre-processing step. Under certain conditions, removing noise, protecting the edges, because the average filter is the most widely used digital image processing. The main idea of the average filter entries neighbors instead of the average for each entry, the entry is the signal to drive through the entrance. Neighboring system, the entire signal, this slides on the post entry "window" to the world 2D images, the possibility of more complex window shapes. If you have an odd number of entries in the window, the average is simple to define: the number of entries in the window at all, then it is sorted, is the middle value. Also, a number of entries, there is one or more of the average. [8].

All smoothing techniques capable of removing soft patches or signal noise in smooth areas, but also adversely affect margins. At the same time, reducing the noise in a signal from time to time, it is important to protect the edges. For example, the edges of the images, the visual appearance is very important. Small (Gaussian) noise levels will be the referee, the average filter is a specific, fixed window size of removing noise while preserving margins than Gaussian blur, proved good [9].

Entry immediately preceding and following each of the three using a window, demonstrate, mix an average filter is used to signal the simple 1D:

x = [2 80 6 3]

So, on average, the filter output signal y:
y[1] = Median[2 2 80] = 2
y[2] = Median[2 80 6] = Median[2 6 80] = 6
y[3] = Median[80 6 3] = Median[3 6 80] = 6
y[4] = Median[6 3 3] = Median[3 3 6] = 3

I.e. y = [2 6 6 3].

3. SEGMENTATION AND CLASSIFICATION

Segmentation means to divide up the image into a patchwork of regions, each of which is homogeneous, that is, the same in some sense such as Intensity, texture, colour [10-11].Classification means to assign to each point in the image tissue class, where the classes are agreed in advance. The classifiers used in this paper are GMM, KNN and LMS.

3.1 GAUSSIAN MIXTURE MODEL

Gaussian mixture model (GMM) is a weighted sum of Gaussian component density as a parameter, which is the probability density function. In general, such a speaker in the voice recognition system GMMS-intestinal related continuous measurements of the spectral features or features such as a biometric system, the probability distribution of the sample was used as a parameter. GMM model parameters from well-trained iterative expectation-maximization (EM) algorithm or the maximum posterior (MAP) and the estimation estimated using the training data [12].
Gaussian component density is given by the equation where M is a Gaussian mixture model is a weighted sum,

$$p(x|\lambda) = \sum_{i=0}^{M} w_i \, g(x|\mu i, \Sigma i) \tag{6}$$

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where x is a D-dimensional continuous-valued data vector (i.e. measurement or features), wi, i = 1, . . . ,M, are the mixture weights, and g(x|μi, Σi), i = 1, . . . ,M, are the component Gaussian densities. Each component density is a D-variate Gaussian function of the form,

$$g(x|\mu i, \Sigma i) = 1 \div (2\pi)^{D/2} |\Sigma_i|^{1/2} EXP\{-1/2(x-\mu_i)' \Sigma_i^{-1}(x-\mu_i)\} \quad (7)$$

With mean vector μi and covariance matrix Σi. The mixture weights satisfy the constraint that

$$\sum_{i=1}^{M} w_i = 1 \quad (8)$$

The complete Gaussian mixture model is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities. These parameters are collectively represented by the notation,

$$\lambda = \{w_i, \mu_i, \Sigma_i\} \; i = 1, \ldots, M \quad (9)$$

There are several variants on the GMM. The covariance matrices, Σ_i, can be full rank or constrained to be diagonal. Additionally, parameters can be shared, or tied, among the Gaussian components, such as having a common covariance matrix for all components, The choice of model configuration (number of components, full or diagonal covariance matrices, and parameter tying) is often determined by the amount of data available for estimating the GMM parameters and how the GMM is used in a particular biometric application [13-14]. It is also important to note that because the component Gaussian is acting together to model the overall feature densities, full covariance matrices are not necessary even if the features are not statistically independent. The linear combination of diagonal covariance basis Gaussians is capable of modelling the correlations between feature vector elements. The effect of using a set of M full covariance matrix Gaussians can be equally obtained by using a larger set of diagonal covariance Gaussians.

3.2 K NEAREST NEIGHBOUR CLASSIFIER

Among the various methods of supervised statistical pattern recognition, nearest neighbor rule is drawn from examples of practice prior assumptions about distributions, without having achieved consistently high. Positive and negative, in both cases it involves the training set. The new model, which calculates the distance to the nearest train case by ads; Identify the point that determines the classification model. K-NN classifier K nearest points in time, taking the majority of the population extends this idea by assigning identification. It is common to choose to break relations small and odd K (generally 1, 3 or 5). K values of the training data set to help reduce the impact of noise points, k is done by selecting the frequent cross-validation.

3.3 LEAST-MEAN-SQUARE ALGORITHM

Least mean square (LMS) gradient vector calculation simplification, which is made possible by modifying the objective function of a search algorithm. It is related to the LMS algorithm, as well as others, are widely used in various applications for its computational simplicity adaptive filter. The stability of the convergence characteristics of the LMS algorithm [15] that is guaranteed to be studied in order to establish a limit on the convergence factor. LMS convergence speed is shown to be dependent on the input signal correlation matrix of the Eigen value spread. In this chapter, the characteristics of the LMS algorithm and monitoring the performance of standard and non-standard situations are discussed, including Miss Adjustment. A large number of analysis results are verified by simulation examples.

The LMS algorithm is by far the most widely used algorithm in adaptive filtering for several reasons [16-17]. The main features that attracted the use of the LMS algorithm are low computational complexity, proof of convergence in stationary environment, unbiased convergence in the mean to the Wiener solution, and stable behaviour when implemented with finite-precision arithmetic. The convergence analysis of the LMS presented here utilizes the independence assumption.

$$y(n) = \sum_{i=0}^{N-1} w_i(n).x(n-i) \quad (10)$$

$$e(n) = d(n) - y(n) \quad (11)$$

We assume that the signals involved are real-valued. The LMS algorithm changes (adapts) the filter tap weights so that *e(n)* is minimized in the mean-square sense. When the processes *x(n)* &*d(n)* are jointly stationary, this algorithm converges to a set of tap-weights which, on average, are equal to the Wiener-Hop solution.

Filtering: $y(n) = W^T(n).x(n)$ (12)

Error Estimation: $e(n) = d(n) - y(n)$ (13)

4. RESULTS AND CONCLUSION

The proposed method for the detection of MAs is implemented in MATLAB simulation software and its outcomes are shown as follows. Database collected contains 40 retinal images in the test set where 10 abnormal and 30 normal are analyzed by an ophthalmologist were used for testing the algorithms of our proposed model. The test set was not used during the development but only for testing the algorithms and for computing sensitivity and specificity values. The pre-processing stage outcomes are as follows Fig.5. shows the original resized 720*576 image output. Fig.6. shows the red plane image outcome and Fig.7. shows the Green plane image outcome and Fig.8. shows the Blue plane image outcome.

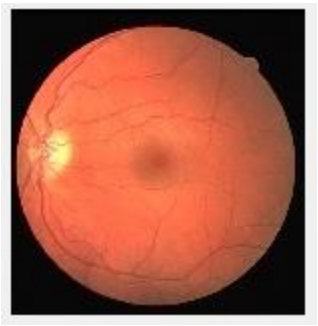

Fig. 5. Original resized720*576 image

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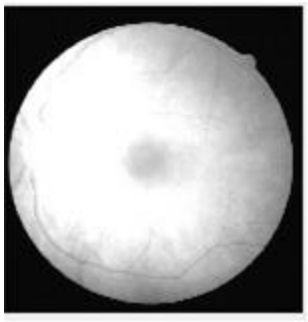

Fig. 6. Red plane image

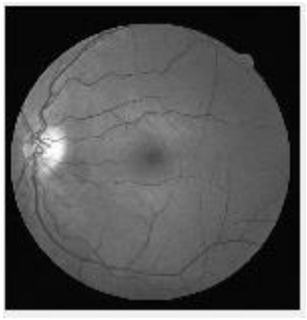

Fig. 7. Green plane image

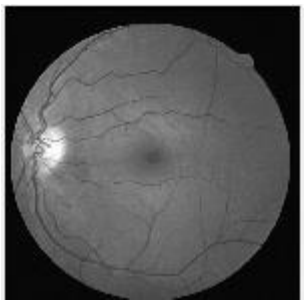

Fig. 8. Blue plane image

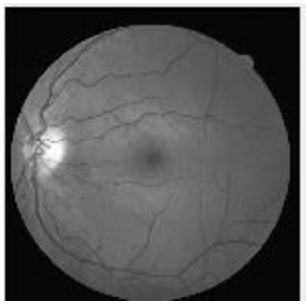

Fig. 9. Median filter image

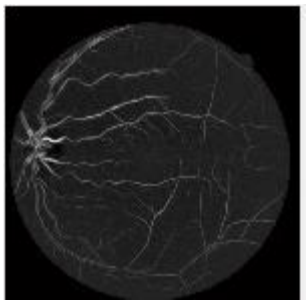

Fig. 10. Segmented images

Fig. 11. Image with micro aneurysms

Blood vessel detection technique is performed by doing adaptive histogram equalisation technique as shown in Fig.10. Followed by micro aneurysms detection is achieved by applying least mean square error, KNN, and GMM classifiers. As shown in Fig.11.

The aim of this proposal is to develop a new featured algorithm to detect MA that is one of the lesions associated with DR which is considered as the earliest sign. Work carried in this paper consists of some pre-processing steps feature extraction and classification. From the literature analysis a comparative study of various works are carried out in detecting the lesions are analyzed. The best methods generating a very good performance are chosen in this work in order to build a better automated algorithm. This analysis is done based on better sensitivity and specificity to ensure high accuracy of the disease. Database collected from the Research Institute had drawback in luminance which failed to undergo image processing techniques. So the standard database which was publicly available is used.

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