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INVESTIGATIONS ON DIABETIC MACULAR EDEMA USING MOTION PATTERN ESTIMATION TO PREVENT VISION LOSS

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ABSTRACT

Diabetic macular edema (DME) is a complication of diabetes. It can blur or distort patients' vision and make the blindness. It is categorized by the presence of lesions. Habitually the presence of lesions is detected by Ophthalmologists from the dilated retinal images captured by dropping chemical solution into an eye. This process peeves the patients. So, there is a need for an autonomous method to detect the presence of lesions using image processing algorithm from the non-dilated images to help the ophthalmologists to diagnose the disease without inconvenience and irritation to the patient and thus protects patients from vision loss. In this work, Meadian filter and Contrast Limited Adaptive Histogram Equalization used in image preprocessing. Motion pattern estimation with masking process used for segmentation. To extract the feature Grey Level Co-occurrence Matrix isused. Support vector machine used to classify the severity level for disease. The proposed algorithm has produced the sensitivity of 99.743%, specificity of 97.14% and accuracy of 97.711%.It is more helpful for ophthalmologist in the detection of DME. Since this method is automated, it detects faster and this level of accuracy in result helps the ophthalmologists to diagnose the disease very easily.

Keywords: diabetic macular edema, grey level co-occurrence matrix, lesions, motion pattern estimation, support vector machine.

1. INTRODUCTION

Diabetes is a serious disease to be diagnosed earlier. Diabetes affects the blood vessels and nerves of the various parts of the human body. The blood vessels in our eyes are severely damaged if the diabetes is not properly controlled for more than 5 years. When blood vessels are damaged, nerve signals can't grasp our eyes. In addition, diabetes can increase density from unsolidified, which can pad nerves and structure of the various parts in our eyes.

Macula is a minor, highly penetrating and focused central region of the retina. It grasps tightly crowded cones that offer sharp, pure and essential visualization to support a person to realize clearly in the direction of gaze. Macular edema arises due to deposition of fluids and protein on or under the macula of an eye and origins it to congeal and swell. The swelling may twist a person's vital visualization as the macula is adjacent to the center of the retina at the posterior of the eye, swelling in the macular region of the retina which is also known as macular edema. Diabetic macular edema (DME) is astate arising in entities with several years of diabetes mellitus, which roots a distinctive group of gashes in the macula and damage it. It is an innovative indication of diabetic macular edema and can lead to irrevocable vision loss. In order to detect the diabetic macular edema at an early stage, patients with diabetes should be evaluated with automatic detection technique. The use of digital nonmydriatic images has been preferred as the automated technique for examination and detection of diabetic macular edema. Ophthalmoscopy coupled with biomicroscopy and fundus photography is the accepted method for examining diabetic macular edema. But fundus photography is more sensitive in detecting macular edema than clinical examination. The use of the non mydriatic camera in the physician's clinic might be considered for follow-up of patients with diabetes in situations where dilated eye examination cannot be obtained.

Fathi and Nilchi [1] proposed a new vessel enhancement method to measure the diameter of blood vessel in retinal images and also used histogram based thresholding technique to get fine vessel network and circular operator to estimate their diameters. Agurto *et al*. [2] developed instantaneous amplitude and instantaneous frequency characteristics of a retinal image for lesion detection.

Akara Sopharak*etal* [3, 4] reported the result of an automated detection of HE from low contrast digital images of retinopathy patients with non-dilated pupils by Fuzzy C-Means clustering. Four features were applied as input for segmentation using the FCM clustering method. Perceived results were endorsed with expert ophthalmologists. Sensitivity, Specificity, Positive Predictive Value (PPV), Positive Likelihood Ratio (PLR) and accuracy were used to evaluate the overall enactment of the technique.

Atif Bin Mansoor *et al*. [5] used Fuzzy Morphology for detecting the Lesions. Color features on a Bayesian statistical classifier were used to classify each pixel into lesion or non-lesion classes. J. David Rekha Krishnan [6], proposed thresholding technique to identify the Lesions, optic disc and vascular network and neural network classifier was then used to evaluate the severity level of the disease. Youssef and Solouma [7] used edge detection algorithm and new feature-based algorithm to accurately detect the blood vessels, which improves the detection of exudates in fundus photographs. The algorithm used the blood vessel characteristics such as its width range, intensities and orientations for selective

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segmentation. The OD was detected using the Hough transform. The extracted blood vessel features and OD could be subtracted from the segmented image to obtain an initial estimate of exudates. The final estimation of exudates was done by morphological reconstruction based on the appearance of exudates.

Eswaran. C *et al.* [8] used watershed segmentation method for identifying the Lesions, but it did not clearly distinguish Lesions and optic disc from blood vessels. An automatic detection of diabetic retinopathy through detecting Lesions through morphological process and the severity level of the disease were assessed by SVM classifier. The Lesions are identified by FCM and its severity level is assessed by means of CNN Classifier.

Phillips *et al.* [9] identified the HE by using Global and local thresholding. The contribution images were pre-processed to eliminate photographic non-uniformities and the contrast of the HE was enhanced. Other bright HE (such as cotton wool spots) could be identified mistakenly. Giancardo *et al.* [10] proposed Automatic retina HE segmentation without a manually labeled training set. In this work, HE were detected using two new methods but they didn't use a supervised learning step. Therefore, they did not involve using labelled HE training sets.

Giancardo.L *et al.* [11] proposed a Textureless macula swelling detection with multiple retinal fundus images. They used an Uncalibrated multiple view finds images to analyze the swelling of the macula. This origination enables the detection and quantitative depth of swollen areas by remote ophthalmologist. It is not available with a single image and dishonest to error with stereo fundus camera

Lazar and Hajdu [12] identified retinal microaneurysms with the help of directional cross-section profiles, where each profile is analysed for extracting features like size, height, and shape. Naive Bayes classification is also used to eliminate false candidates by evaluating statistical measures of those feature set. Wisaeng *et al.* [13] used FCM means clustering technique and morphological methods to detect the exudates.

Garcia *et al.* [14] mentioned in their paper that diabetic retinopathy is the main cause of visual impairment in developed countries. They examined and compared three different types of neural networks to detect Exudates in retinal images. Three types of neural networks are multi-layer perceptron, radial basis function networks and SVM machine classifiers.

Murugeswari [15] used GLCM for feature extraction and morphplogical for segmentation and KNN for classification.

In this work detecting the presence of lesions in different areas of the macula is now deliberated as a standard method to assess DME from color fundus images. In preprocessing stage green components are extracted from the RGB images then ROI is found by using rotational asymmetry metric and OD is removed using the mask. To label lesions, various features are extracted by using GLCM then the cruelty of DME is calculated by using Support vector machineshon in Figure-1.

2. METHODOLOGY

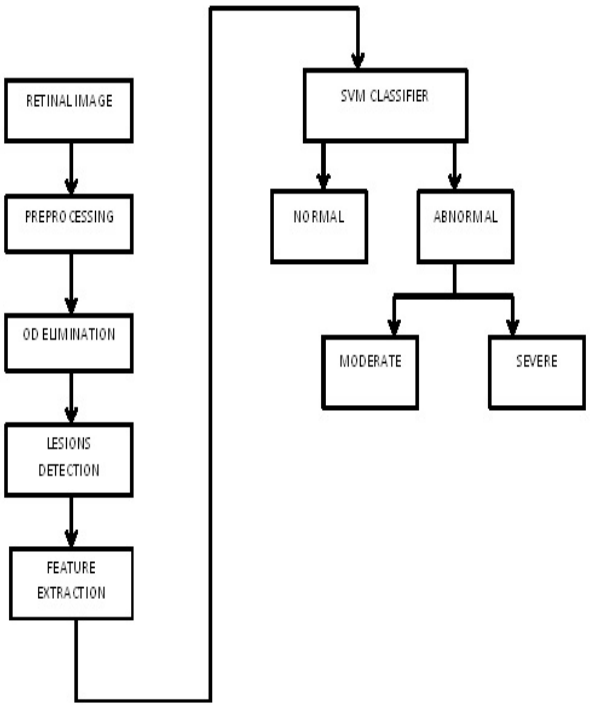

Figure-1. Proposed methodology.

A. Image acquisition

To estimate the enactment of this performance, the digital retinal images were developed using Topcon TRC-50 EX camera with a 50˚ field of view at RajansEye Care Hospital, Chennai.

B. Pre-processing

Pre-processing steps are needed to reduce these inadequacies and generate metaphors more suitable for extracting the pixel features by classification process. Since the green component contains more information, it is extracted from the input retinal images in RGB Color space. The pre-processing steps include extraction of green component from RGB Images, median filtering and Contrast Limited Adaptive Histogram Equalization (CLAHE).

The green channel of the retinal image shown in Figure-2 forms the input for all subsequent processing. To distribute the intensity uniformly throughout the image, noises are extracted and filtered out through a 3x3 median filter. An adaptive histogram equalization is applied to the filtered image to improve the clarity of the image.

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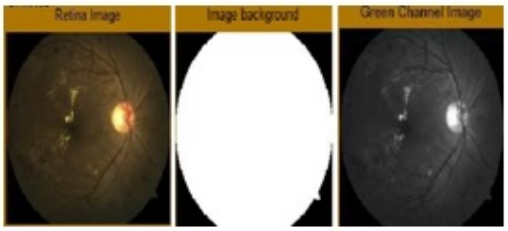

Figure-2. Extraction of green component.

C. Roi extraction

After completing the pre-processing steps, the image is applied to the segmentation process i.e. extracting the ROI. Before segmenting the image, the unwanted portion in the image should be eliminated. Here, optic disc (OD) and macula of an eye image have the intensity similar to the lesions. So it can be eliminated by extracting the ROI containing macula and OD.

D. OD elimination

OD detection is a main step while developing automated screening systems for diabetic macular edemaIn colored fundus images, the OD appears as a bright yellowish or white region. Since Lesions detection is the main purpose, it is necessary to remove the OD prior to the process because it appears with same intensity, contrast and color to other features in the retinal image. The OD is differentiated by the largest circular high contrast area. The OD is the brightest feature of the normal fundus, and it has approximately a slightly oval (elliptical) shape. In coloured fundus images, the OD appears as a bright yellowish or white region. Macula has high and similar intensity values of Optic disc. So it is necessary to eliminate the optic disc from the retinal image. This brighter optic disc should be masked and removed

Mask generation aims at labeling pixels belonging to the region of interest in the entire image. Masking process can be performed by smudging the original image and subtracting the smudged image from the original image. Then the mask is added to the original image. After this process, OD eliminated image can be obtained.

Thus the optical disc and fovea region are masked as shown in Figure-3(b) and 3(c).

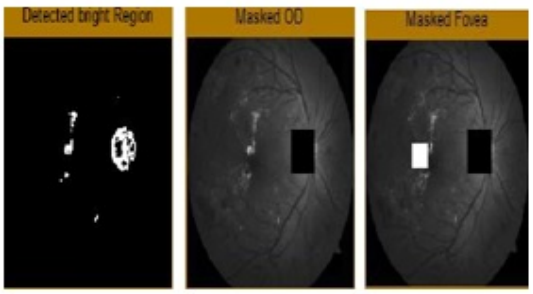

Figure-3. Masking the OD and fovea.

E. Edge detection

The process of classifying and placing sharp discontinuities in an image is called as the edge detection. The discontinuities are immediate changes in pixel concentration which distinguish boundaries of objects. Edge detection is a fundamental tool for image segmentation. It transforms original images into edge images obtained from the changes of grey tones in the image. Edge detection algorithm is applied on the preprocessed image to make it suitable for detecting the optic disc, blood vessels and various lesions. Canny edge detector is employed for the contour detection. This algorithm finds the edges where the grayscale intensity of the image changes and this variation can be found by determining gradients of the image. It enhances the blurred edges by preserving all local maxima in the gradient image. It can detect the boundaries optimally. The edge detected image is shown in Figure-4. Then, the mask image was created in which region of interest in the image is optic disc. The region outside the optic disc is appeared to be dark. The masked image is subtracted from the edge detected image in order to eliminate the optic disc.

Figure-4. Result of Canny edge detector.

F. Image segmentation

The effect of motion in an visual system motivated to create a motion pattern . A set of spatially samples are characterized by the intensities in an image . When camera is logging the human eyes, this method becomes uniform.

This operation is simulated in a single image by inducing motion. Accumulation of signal at sensor locations in human eyes and camera gives smearing effect. Motion in a given image is induced in order to simulate this effect and to generate a sequence of images. These are united by relating a function to coalesce the intensities at each location to give rise to a motion pattern.

Let the given ROI be represented as I (r). A motion pattern I_{MP} for I is consequent as follows:

$$I_{MP}(r) = f[(G_N(r)] \quad (1)$$

Where are signifies the location of pixel, G_N is a transformation of the prompted motion which is assumed to be rigid.

G_N (I), is stated as follows:

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$$G_N(I) = \{ R_{\Theta n}(I) \} \quad (2)$$

Where R is a spin matrix. The spin angle $\Theta_n = n\,\Theta_0$ with n=0, 1,… N; Θ_0 denotes the rotation step. When n=0, we have no rotation and hence $R_0(I) = I$. Thus G_N is a set of rotated kinds of the given and the total number of rotated metaphors $N=2\pi/\Theta$.

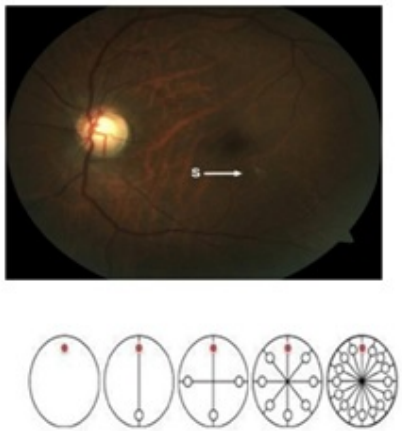

Figure-5. Graphical depiction of motion pattern.

A disk with one lesions shows in first pattern (presented as a red dot). The residuals are obtained by applying motion with decreasing rotation steps: π, $\pi/2$, $\pi/4$, $\pi/8$. The union of the patterns of each case are obtained after a complete cycle of rotation (0 to 2 π) is shown in Figure-5.

Severity of the condition is directly related to the radial space of lesions in the circular ROI so that rotational motion is induced to make the desired I_{MP}. The motion pattern generation is shown graphically in Figure-6. Consider a disk with a single circle near the periphery.

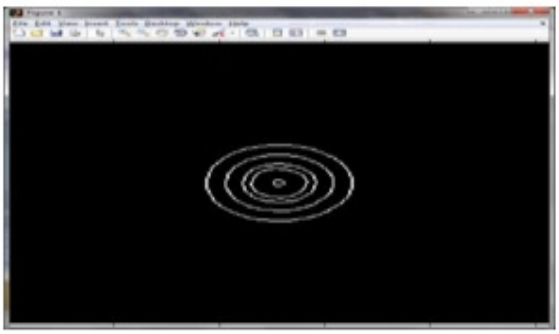

Figure-6. Generation of motion patterns.

The coalescing function Mean tries to realize the averaging effect perceived in motion blur .Maximum tries to abuse the fact that Lesion usually appear brighter than any other structures in the background at the same radial distance.

G. Feature extraction by Glcm

Features are observable patterns in the image which gives information about the image. The accuracy of the classification depends on the feature extraction stage. Texture features are able to isolate normal and abnormal lesions with masses and micro calcification. The input features required for the SVM classifier were extracted using Gray Level Co-occurrence Matrix (GLCM). GLCM is used for mining the features of the given input image. It comprises information about the locations of pixels having similar gray level values. This matrix is a two-dimensional array P in which both the rows and the columns characterize a set of probable image standards.

It contains information about the positions of pixels having similar gray level values. It can make use of distance vector. The gray-level co-occurrence matrix is represented as G[i,j] which is used to calculate all pair of pixels separated by distance vector having gray levels ati and j. Based on the analyzed matrix and the texture information, the parameters like correlation, contrast, cluster prominence, cluster shade, energy, entropy, homogeneity and maximum Probability were obtained. The parameters can be obtained through the expressions listed below and values are given in Table-1.

$$1.\,contrast = \sum_{i,j=0}^{N-1} p_{ij}\,(i-j)^2 \quad (3)$$

$$2.\,correlation = \sum_{i,j=0}^{N-1} p_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (4)$$

$$3.\,cluster\ prominence = sgn(B)|B|^{\frac{1}{4}} \quad (5)$$

$$4.\,cluster\ shade = sgn(A)|A|^{\frac{1}{3}} \quad (6)$$

$$5.\,energy = \sum_{i,j=0}^{N-1} (p_{ij})^2 \quad (7)$$

$$6.\,entropy \sum_{i,j=0}^{N-1} \ln(p_{ij})p_{ij} \quad (8)$$

$$7.\,homogeneity = \sum_{i,j=0}^{N-1} \frac{p_{ij}}{1+(i-j)^2} \quad (9)$$

$$8.\,maximum\ probability = \max(p_{ij}) \quad (10)$$

Where, $P_{i,j}$ is probability of element i,j of the normalized symmetrical GLCM, N is a number of gray levels in the image,μ is the GLCM mean (being an estimate of the

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intensity of all pixels in the relationships that contributed to the GLCM), estimated by using following equation.

$$\mu = \sum_{i,j=0}^{N-1} i p_{ij} \quad (11)$$

let σ^2 = the variance of the intensities of all reference pixels in the relationships that contributed to the GLCM, estimated as,

$$\sigma^2 = \sum_{i,j=0}^{N-1} p_{ij} (i - \mu)^2 \quad (12)$$

In this method three distances are also calculated as follows.

Manhattan distance

$$d = \sum_{i=1}^{n} |x_i - y_i| \quad (13)$$

Euclidean distance

$$d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \quad (14)$$

Minkowski distance

Minkowski distance of order p between two points is defined as:

$$\left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p} \quad (15)$$

The above extracted features are applied to the SVM classifier in order to find the severity of the disease.

Table-1. Statistical analysis of features extracted.

Features of images	Normal	Abnormal (Moderate)	Abnormal (Severe)
Contrast	0 - 0.1	0.1 - 0.15	0.15 - 0.2
Correlation	0.9 – 0.94	0.95-0.97	0.971-0.99
Cluster prominence	< 100	101 – 200	>200
Cluster shade	≤ 0 (in negative value or zero)	0.1 – 5	5.1 – 10
Energy	0.2 – 0.3	0.301 – 0.35	0.351 – 0.399
Entropy			
Homogeneity	0 – 10	10.01 – 15	> 15.01
Maximum probability	0 – 0.1	0.101 – 0.15	0.151 – 0.2

A. DETECTION OF HARSHNESS OF MACULAR EDEMA

After the detection of exudates, the normal and abnormal images are separated using SVM Machine (SVM) classifier. SVM minimizes the empirical risk and prevents the over fitting problem which achieves good performance. After segmenting exudates regions in colour retinal images, the segmented image is applied to SVM machine classifier. This classifier is used to evaluate training data to find a best way to classify images into different cases such as moderate or severe.

The SVM classifier consists of three layers namely input, hidden and output layer. Figure-7 shows the architecture of the SVM classifier.

To classify the disease, the relevant features of each and every normal and abnormal images should be extracted. Then the extracted features of all normal and abnormal images are combined to form a matrix and it is saved as a matrix file. This matrix file is given as input to the classifier. After that, the training mode is also saved as a matrix file, because it is needed for classifier testing mode.

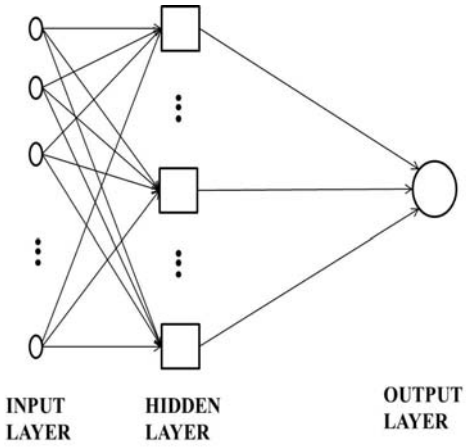

Figure-7. Architecture of SVM.

Then for testing an image, the relevant features of the test image are extracted and combined to form a matrix file. This matrix file is given to the SVM classifier before that the matrix file of training mode is loaded in order to recognize the severity of the disease. By using the kernel function described in equation (16).

$$K_f(x,y) = \sum_{f=1}^{K} \beta_f e^{\left(-\gamma_f \chi_f^2 (x_f, y_f)\right)} \quad (16)$$

Where

$$\chi^2(x,y) = \sum \frac{(x_i - y_i)^2}{x_i + y_i}$$

and f is a kernel parameter. SVM classifies the normal and abnormal images based on this kernel function.

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Further, the abnormal images are classified as moderately affected or severely affected shown in Figure-8(a),(b),(c).

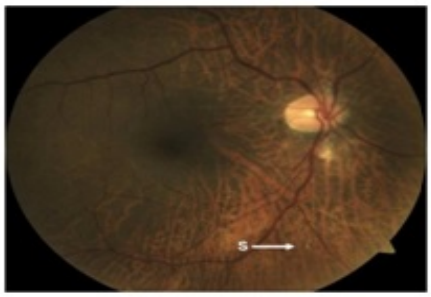

Figure-8. (a) Lesion nearer to macula.

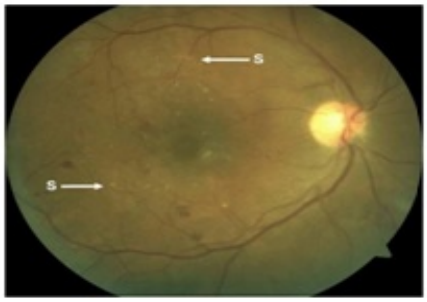

Figure-8. (b,c) Lesion position with reference to macula. Annotation (S) indicates location of lesion.

H. PERFORMANCE MEASUREMENT

Two performance measurement parameters, sensitivity and specificity are measured using the formulae given in equation (17) and (18).

$$\text{Sensitivity} = TP / (TP + FN) \quad (17)$$

$$\text{Specificity} = TN / (TN + FP) \quad (18)$$

- True positive = correctly identified
- False positive = incorrectly identified
- True negative = correctly rejected
- False negative = incorrectly rejected

Sensitivity refers to the ability of the classifier to identify positive results and specificity relates to the ability of the classifier to identify negative results. In this work, 450 images were used for justification of the projected method. Out of 450 images, 294 are normal and 156 are abnormal metaphors. Then these features are used by the SVM for classifying the images into normal and abnormal images. Among the abnormal images, SVM classifier can classify whether it is moderately or severely affected.

3. RESULTS AND CONCLUSIONS

In this paper the severity of macular edema is classified and detected from color retinal images. Initially retinal images were collected from the datasets. From that retinal images green channel images extracted. Then optical disc and fovea are masked. By using motion pattern estimation we found the distance between the fovea and lesions. Feature extraction is done by GLCM. SVM classifier is used to compare the trained features with the extracted features of the given input image. Depending upon the presence of Lesions the severity of DME can be determined.

Our method provides the best result compared to the previous method. It is more efficient than the PCA DD classifier which was used in the existing method shown in fig 8. In future we find the level of severity of Macula by detecting both hard Lesions and soft Lesions. It is more helpful to the ophthalmologist in the detection of DME. This detection of these lesions will be useful for the ophthalmologists to diagnose the disease diabetic macular edema with high clarity and to apply proper treatment for the patients. Since this method is automated, it detects symptoms faster and works effectively even on a poor computing system.The proposed algorithm has produced the sensitivity of 99.743%, specificity of 97.14% and accuracy of 97.711% shown in table.2.Since this method is automated, it detects faster and this level of accuracy in result helps the ophthalmologists to diagnose the disease very easily.

Table-2. Accuracy, sensitivity and specificity for different Fundus images.

Images	Accuracy	Sensitivity	Specificity
1	97.5	100	96.831
2	97.7258	99.774	97.9032
3	97.667	99.833	95.8432
4	97.7369	99.9631	97.2921
5	97.6952	99.804	96.831
6	97.6475	99.8525	95.1619
7	97.7378	99.7622	97.321
8	97.063	99.7397	98.111
9	97.7213	99.7787	97.747
10	97.7389	99.7611	98.36
11	97.8048	99.6952	98.69
12	97.7726	99.7274	99.541
13	97.7743	99.7274	99.296
14	97.7384	99.7616	98.344
15	97.704	99.796	97.139
16	97.706	99.794	97.209
17	97.6369	99.8604	94.139
18	97.7044	99.7956	97.182
19	97.8021	99.6979	99.3021
20	97.6576	99.8424	95.51
Average value	**97.711**	**99.743**	**97.14**

4. ACKNOWLEDGEMENTS

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REFERENCES

[1] Abdolhossein Fathi and Ahmed Reza Naghsh Nilchi. 2013. "Automatic wavelet based retinal blood vessels segmentation and vessel diameter estimation," Biomed Signal Process, Vol. 8, No. 1, pp. 71-80.

[2] Agurto Murray, Barriga, Murillo, Pattichis, Davis, S. Russell, M. Abramoff and P. Soliz. 2010. Multiscale am-fm methods for diabetic retinopathy lesion detection. IEEE T Med Imaging, February. 29:2, pp. 502 –512.

[3] Akara Sopharak, Bunyarit Uyyanonvara and Sarah Barman. 2009. Automatic Exudate Detection from Non-dilated Diabetic Retinopathyretinal images using Fuzzy C-Means Clustering. Journal of Sensors, Vol. 9, No. 3, pp 2148- 2161, March.

[4] Akara Sopharak, Mathew N. Dailey, Bunyarit Uyyanonvara, Sarah Barman, Tom Williamson and Yin Aye Moe. 2011. Machine Learning approach to automatic Lesions detection in retinal images from diabetic patients. Journal of Modern optics, Vol. 57, No. 2, pp. 124-135, November.

[5] Atif Bin Mansoor, Zohaib Khan, Adil Khan and Shoab Ahmad Khan. "Enhancement of Lesions for the Diagnosis of Diabetic Retinopathy using Fuzzy Morphology," IEEE Conference on INMIC, pp.128 – 135.

[6] David Rekha Krishnan, Sukesh Kumar A. 2008. Neural Network based Retinal image analysis. IEEE Conference on Image and Signal Processing, DOI .1109/CISP.2008.666, pp.49-53, September.

[7] Doaa Youssef and Nahed H. Solouma. 2012. Accurate detection of blood vessels improves the detection of exudates in color fundus images," Comput Meth Prog Bio, 108:3, pp.1052-1061.

[8] Eswaran. C, Ahmed Wasif Reza and Subhas Hati. 2008. Extraction of the Contours of Optic Disc and Lesions Based on Marker Controlled Watershed Segmentation. International Conference on Computer Science and Information Technology, Singapore, Vol.1, pp. 719 – 723, September.

[9] Fleming. AD, Philips. S, Goatman. KA, Williams. GJ, Olson. JA and sharp. PF. 2007. Automated detection of Lesions for Diabetic Retinopathy Screening", Journal of Phys. Med. Bio., vol. 52, no. 24, pp. 7385-7396.

[10] Giancardo. L, Meriaudeau F., Karnowski T. P., Li Y., Tobin K.W., Jr. and Chaum E. 2011. Automatic retina Lesions segmentation without a manually labelled training set," In: Proceeding of 2011 IEEE Int. Symp. Biomed.Image: From Nano to Macro, March, pp. 1396–1400.

[11] Giancardo L., Meriaudeau F., Karnowski T., Tobin K., Grisan E., Favaro P., Ruggeri A. and Chaum E. 2011. Textureless macula swelling detection with multiple retinal fundus images. IEEE Trans. Biomed. Eng., Vol. 58, No. 3, pp. 795–799, March.

[12] Istvan Lazar and Andras Hajdu. 2013. Retinal Microaneurysm Detection through Local Rotating Cross-Section Profile Analysis. IEEE T Med Imaging, February 32:2, pp.400-407.

[13] Kittipol Wisaeng, Nualsawat Hiransakolwong and Ekkarat Pothiruk. 2012. Automatic detection of Exudates in Diabetic Retinopathy images," J Comp Sci. 8:8. pp.1304-1313.

[14] Maria Garcia, Clara I. Sancheza, Maria I. Lopezb, Daniel Abasoloa and Roberto Horneroa. 2009. Neural network based detection of hard exudates in retinal images," Comput Meth Prog Bio, 9:3, pp. 9–19.

[15] Murugeswari, Sukanesh. 2014. Detection of diabetic maculopathy using KNN algorithm. Applied Mechanics and Materials. Vol. 573 pp 791-796Online available since 2014/Jun/18.

[16] Ahmed wasif Reza and C. Eswaran Subhas Hati. 2009. Automatic Tracing of OD and Exudates from colour fundus images using fixed and variables Thresholds. J Med Syst, February, Vol. 33 No. 1, pp. 73 – 80.

[17] Istvan Lazar and Andras Hajdu. 2013. Retinal Microaneurysm Detection Through Local Rotating Cross-Section Profile Analysis. IEEE Transactions on Medical Imaging, Vol. 32, No. 2, February.

[18] Sai Deepak K. and Sivaswamy J. 2012. Automatic Assessment of Macular Edema from Colour Retinal Images. Medical Imaging, IEEE Transactions, Vol. 31, No. 3, pp. 766-776, March.

[19] Niemeijer B.V., Ginnekan S. R., Russell M. and M. D. Abramoff. 2007. Automated detection and differentiation of drusen, Lesions and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis. Journal on

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Investigate Ophthalmol. and Visual Science, Vol. 48, No. 2 pp. 2260-2267.

[20] Wang Huan, Hsu Wynne and Lee Mong Li. 2009. Effective Detection of Retinal Exudates in Fundus Images. IEEE Conference on Biomedical Engineering and Informatics, Tianjin, pp. 1-5, October.