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Exudates Detection in Digital Fundus Images Using GLCM Features With SVM Classifier

Parashuram Bannigidad
Department of Computer Science
Rani Channamma University
Belagavi, Karnataka, India
E-mail: parashurambannigidad@gmail.com

Asmita Deshpande
Department of Computer Science
Rani Channamma University
Belagavi, Karnataka, India
E-mail: asd_bca@yahoo.com

Abstract: Diabetes affects a number of human organs, the most common organ being the human eye. Diabetic Retinopathy, Glaucoma, Macular Edema are some of the common ophthalmic disorders found in diabetic patients. If Diabetic Retinopathy is not treated in earlier stages then it can lead to vision loss or blindness. The proposed algorithm consolidates morphological operations for blood vessel removal, segmentation and optic disk removal followed by Exudates detection. The proposed technique extracts GLCM features and uses SVM classifier to distinguish between diseased and healthy retinal images. GLCM features enhance the detection of affected regions in a retinal image as it depicts how often different combinations of gray levels co-occur in an image or image section. The SVM classification algorithm builds a model that assigns the images as belonging to healthy or diseased category. The proposed algorithm demonstrates promising outcomes with higher PPV, sensitivity and accuracy values. It is observed from the experimentation that the average values of PPV are 100 % for all the databases considered in the experiment. The sensitivity of proposed method yielded 96.4% for DIARETDB0 database, 95.5% for DIARETDB1 database, 82.9% for e-Ophtha EX Database and 91.8% for Messidor database. The proposed algorithm also exhibits 96.4%, 95.5%, 82.9% and 91.8% accuracy values for DIARETDB0, DIARETDB1, e-Ophtha EX and Messidor databases respectively.

Keywords: Diabetic retinopathy, Fundus images, Blood Vessels, Morphological operations, GLCM Features, Exudates

I. INTRODUCTION

The Diabetes is a lifestyle disorder that affects 422 million people globally. It deteriorates the functioning of a number of human organs particularly the human eye. Diabetic patients develop ophthalmic complications such as Diabetic Retinopathy, Glaucoma and Macular Edema. Such diseases can be diagnosed by ophthalmologists by examining the affected portion of retina. A Heidelberg Retina Tomograph or a non-mydriatic fundus camera can also be employed to diagnose these disorders. The fundus camera aids in documenting the interior portion of the eye giving a view of fovea, optic disc, macula and retina. Microaneurysms are the earliest signs of diabetic retinopathy that appear as small red dots caused by swellings of the capillaries. As the disease progresses exudates appear on the retina as a result of breakdown of the vessels, leaking serum proteins or lipids. Exudates are the yellow lesions of irregular shape and size, spread all over the fundus image nearer to blood vessels. A fundus image with exudates is shown in Figure 1.

Most of the researchers have explored image processing techniques to detect exudates in a fundus image. Chen et. al. [1] have prominently used histogram based segmentation and morphological operations for detection of exudates and obtained 90% PPV and 94% specificity.

Figure 1. Fundus image with exudates

Garcia et. al. [2] worked on a lesion based criteria to select a subset of features and achieved 95% specificity and 85.7% PPV. Kemal Akyol et. al. [3] have used an approach where the features were extracted from patch images consisting of hard exudates and normal regions using the DAISY algorithm based on the histogram of oriented gradients. Support vector classifier has yielded 93.27% specificity and 88.46% PPV. In [4] Mohamed Omar et. al. identified exudates using texture features and Local Binary Pattern (LBP) variants along with ANN classifier to 98.68% sensitivity and 96.73% accuracy. M. Usman Akram et. al. [5] have used filter banks to extract candidates and a Bayesian classifier to detect exudates. They have obtained sensitivity 93.7% and PPV 97.54%. N.B. Prakash and D. Selvathi [6] have proposed a histogram based technique and mathematical morphological operations to detect hard and soft exudates. They have achieved 94.6% specificity and 96.7% sensitivity. N. Mukherjee and H.S.Dutta [7] have worked on a data set of 130 images and obtained 94.98% sensitivity. Pan and Bing Kun [8] have suggested preprocessing the green channel and histogram based thresholding. They have also used Fuzzy C- means technique to obtain 87.5% PPV and

84.8% sensitivity. Qing Liu et. al. [9] have explored location to segmentation strategy and random forest classifier to get 76% sensitivity and 75% PPV. Ravitej Rekhi et. al. [10] worked on adaptive thresholding with SVM classifier to achieve 90% accuracy. Swati Gupta and Karandikar A. M. [11] proposed an approach to detect exudates based on morphological operations. They have extracted GLCM and Splat features and obtained 87% sensitivity and 88% accuracy. Somkuwar et. al. [12] devised a mechanism for detecting hard exudates by using 6 dimensional intensity based features. The exudates and non exudates (background) classification is performed using Euclidean Distance classifier. They have obtained an average accuracy of 96.08% and 95% for e-ophtha and Messidor databases respectively. Xeiwei Zhang et. al. [13] have suggested a segmentation method based on mathematical morphology, extracted contextual features and used random forest classifier to detect exudates with AUC 0.95. Parashuram Banngidad and Asmita Deshpande [17] explored segmentation based on thresholding along with texture features and k-NN classifier to extract exudates in fundus images. B.V Shilpa and T. N Nagabhushan [18] have explored an ensemble based approach for exudates detection. Gram – staining approach for bacterial cell images using color and geometric features has been carried out by Hiremath and Parashuram Bannigidad [22].

II. MATERIALS AND METHODS

For the purpose of implementation, the digital fundus images are obtained from publicly available databases, namely DIARETDB0[15], DIARETDB1[20], e-Ophtha EX [19] and Messidor[21]. DIARETDB0[15] is a publicly available database consisting of digital fundus images captured with a 50 degree field-of-view digital fundus camera and can be used by the research community to test their algorithms. The database consists f 130 fundus images, among these 110 images show symptoms of Diabetic Retinopathy whereas 20 images are normal. DIARETDB1 [20] data set is referred to as "calibration level 1 fundus images". The fundus images from this database are captured with 50 degree field-of view. It consists of totally 89 fundus images. Among them 5 are normal and the remaining 84 contain signs of Diabetic Retinopathy. e-Ophtha EX [19] is a freely available database of color fundus images specially established for research in Diabetic Retinopathy. It contains 47 images with exudates and 35 images with no lesions. Image sizes are in the range 1440 × 960 pixels to 2544 × 1696 pixels. The Messidor[21] is a rich fundus database of 1200 images that has been created to encourage automated diagnoses of diabetic retinopathy. These images are represented with 8 bits per color plane at 1440x960, 2240x1488 or 2304x1536 pixels captured using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field-of-view.

III. PROPOSED METHOD

Our proposed method is a multi-stage approach to detect and identify exudates present in a fundus image. The multistage process initially performs preprocessing, blood vessel removal, segmentation, optic disk removal, and exudates detection followed by feature extraction and classification. The proposed method is depicted in the flow diagram shown in the below Figure 2.

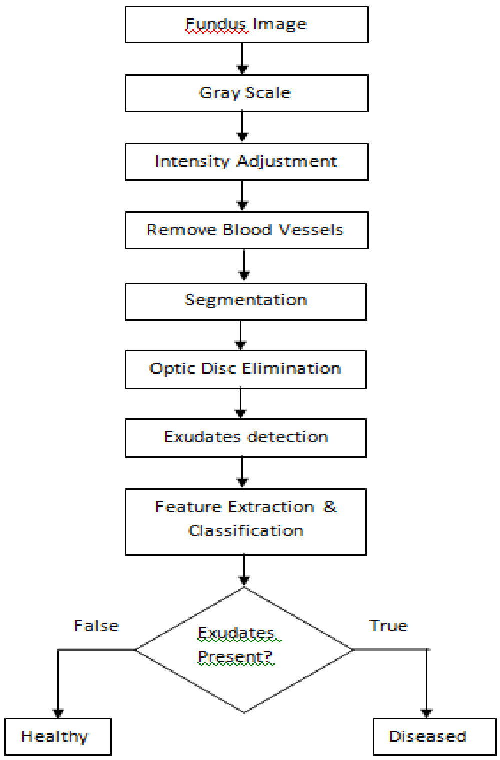
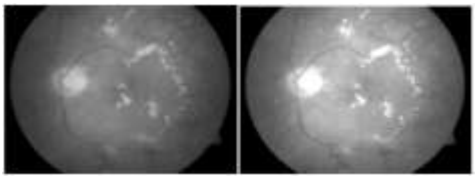


Figure 2. Flow diagram of the proposed method

A. Preprocessing

An important aim of preprocessing in a digital fundus image is to highlight smaller details in the fundus like blood vessels lesions and exudates. Most fundus images suffer from illumination differences. They exhibit more contrast towards the centre and less contrast moving outwards from centre [17]. During the preprocessing stage, the input image is resized to 576 X 720 standard size and converted into grayscale. The contrast of the grayscale image is enhanced by transforming the values. The image intensity level is mapped to higher intensities so as to increase the contrast between foreground and background. Figure 3(a) shows the grayscale image and Figure 3(b) shows the contrast adjusted image.



(a) **(b)**

Figure 3. (a) Grayscale Image **(b)** Contrast adjusted image

Canny edge detection is further applied to the contrast adjusted image to highlight the edges. This is followed by detection and masking of outer circular border of the fundus image. Now thresholding is applied and the image is binarized.

B. *Blood Vessel Removal*

In order to highlight the affected portion of retina comprising of exudates it is necessary to detect the entire vasculature of blood vessels and eliminate it. The vessel path is detected and closed using morphological operations. A disc shaped structuring element is chosen and morphological opening and closing operations are applied as follows:

$$A(x,y)=(I\oplus S)(x,y)=\max\{I(x-x',y-y')+S(x',y')\} \quad (1)$$

$$B(x,y)=(I\ominus S)(x,y)=\min\{I(x+x',y+y')-S(x',y')\} \quad (2)$$

$$I_n = A(x,y) - B(x,y) \quad (3)$$

where, I(x,y) is the image obtained after external border masking during preprocessing and S(x’,y’) is the structuring element. These alternating opening and closing operations increase the size of exudates and remove other components like blood vessels. Next, a ball shaped structuring element is defined and once again morphological closing operation is applied to eliminate blood vessels completely. The image obtained after removal of blood vessels is shown in Figure 4.

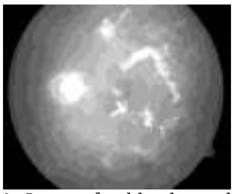


Figure 4. Image after blood vessel removal

C. *Segmentation and Optic Disc Removal*

Fundus images are characterized by variations in intensity as well as variations in foreground and background texture. Hence, segmentation based on local thresholding is proposed. Column wise neighborhood operation is performed on In. The image is then converted to binary and a fixed threshold is applied to filter the lesions.

$$I(x,y) = 1 \quad \text{if } p(x,y) > T \quad (4)$$

$$I(x,y) = 0 \quad \text{if } p(x,y) < T \quad (5)$$

where, T = 0.45. In the grayscale image In, pixels with intensity p(x, y) that lie between 0.45 - 1 is converted as white and pixels with intensity p(x, y) that lie between 0.45 - 0 is converted to black. Exudates and Optic disc are the brighter regions of the retina and hence represented as white pixels in the binarized image.

Optic disc is the brightest spot on the retina. It is a normal circular anatomical structure present near the left or right border of the retina. Identification of the Optic disc poses an important challenge in processing of fundus images because the exact location of the optic disc is not fixed. The optic disc not only needs to be identified but eliminated too since it may wrongly be identified as exudates region.

To locate the optic disc, the largest connected component in the segmented image is computed [18]. This largest connected component is the disc. The largest value of the columns of image and its coordinates is retrieved. The mask is computed with mesh grid vectors x and y as well as the medians of row and column coordinate vectors based on the equation of a circle as follows:

$$\boldsymbol{Im} = \sqrt{(\boldsymbol{x}-\boldsymbol{mc})\mathbf{2}-(\boldsymbol{y}-\boldsymbol{mr})\mathbf{2}} \quad (6)$$

The mask is subtracted from the segmented image Ixy to eliminate optic disc.

$$\mathbf{Ind} = \mathbf{I}(\mathbf{x},\mathbf{y}) - \mathbf{Im} \quad (7)$$

Next the outer circular border is eliminated from Ind to obtain image Inc. Now, morphological closing operation is used to get accurate shape of exudates.

$$\mathrm{Iex} = \mathrm{f}(\mathrm{Inc}) \quad (8)$$

Further, contrast enhancement is applied using CLAHE in order to distinguish between exudates and non exudates region. ϕ(Iex) complements the image and converts white pixels to black and vice versa. This is followed by inverting, ψ(Iex) to highlight all dark feature pixels. A simple ‘AND’ operation on these two images extracts all the white pixels within the connected region of the exudates.

$$\mathrm{Ie} = \mathrm{AND}(\varphi(\mathrm{Iex}), \psi(\mathrm{Iex})) \quad (9)$$

The segmented image after the optic disc elimination is then shown in Figure 5.

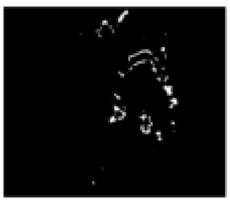


Figure 5. Image after segmentation and optic disc removal

IV. FEATURE EXTRACTION AND CLASSIFICATION

This algorithm explores GLCM [4] for classification as they play an important role in medical image analysis. The Gray Level Co-occurrence Matrix (GLCM) and associated texture feature calculations are image analysis techniques. GLCM features enhance the detection of affected regions in a retinal image as it depicts how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity or image texture at the pixel of interest. These features are particularly useful in applications that involve automatic extraction of features that distinguish a normal tissue from an abnormal tissue. The various features that are considered in this algorithm are:

- Energy – It is the sum of squared elements in the GLCM.

$$\text{Energy} = \sum_{i,j=0}^{N-1}(Pij)\,2 \quad (10)$$

- Contrast – The contrast feature is a measure of local variations in a GLCM matrix.

$$\text{Contrast} = \sum_{i,j=0}^{N-1}(i-j)2 \quad (11)$$

- Homogeneity – It is a measure of homogeneity of an image. A homogeneous scene will contain only a few gray levels, giving a GLCM with only a few but relatively high values of P(i, j).

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1}\frac{Pij}{1+(i-j)2} \quad (12)$$

- Correlation – Given a pair of pixels, this feature measures the probability of occurrence for the joint pixel pairs.

$$\text{Correlation} = \sum_{i,j=0}^{N-1} Pij\,\frac{(i-\mu)(j-\mu)}{\sigma 2} \quad (13)$$

where, P_{ij} is the element in the GLCM matrix, N is the number of gray levels in the image and μ is the GLCM mean.

The proposed method employs SVM classifier to distinguish the images as diseased or healthy. In machine learning, Support Vector Machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. The SVM classification algorithm builds a model that assigns the images as belonging to healthy or diseased category.

V. EXPERIMENTAL RESULTS AND DISCUSSION

For the purpose of experimentation digital fundus images were obtained from publicly available database DIARETDB0 [15], DIARETDB1[20], e-Ophtha EX[19] and Messidor[21] which are treated as standardized database and many researchers have worked on it. In all, 114 images from DIARETDB0 database, 89 from DIARETDB1, 82 from e-Ophtha EX and 74 from Messidor database are tested in this experiment. The proposed algorithm is implemented using MATLAB R2015b and Intel Core i3 processor. The Figure 6(a), shows sample original fundus image from DIARETDB0 database and Figure 6(b) depicts the segmented image after application of the proposed algorithm. The Figure 6(c), shows sample original fundus image from DIARETDB1 database and Figure 6(d) depicts the segmented image after application of the proposed algorithm. The Figure 6(e), shows sample original fundus image from e-Ophtha EX database and Figure 6(f) depicts the segmented image after application of the proposed algorithm. The Figure 6(g), shows sample original fundus image from Messidor database and Figure 6(h) depicts the segmented image after application of the proposed algorithm.

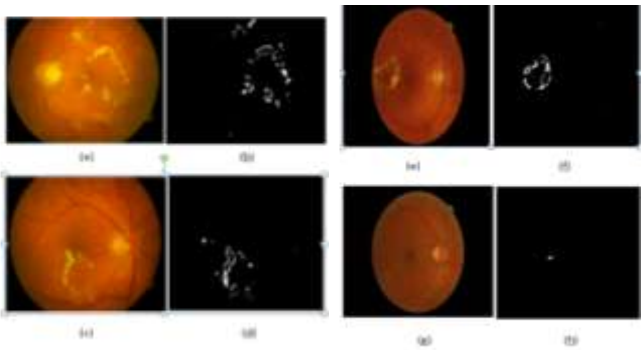


Figure: 6. (a) Sample original fundus image from DIARETDB0 database (b) Segmented image (c) Sample original fundus image from DIARETDB1 database (d) Segmented image (e) Sample original fundus image from e-Ophtha EX database (f) Segmented image (g) Sample original fundus image from Messidor database (h) Segmented image

The classification of images from DIARETDB0, DIARETDB1, e-Ophtha EX, and Messidor databases based on the clinical test parameters using proposed algorithm with Support Vector Machine classifier is shown in the Table 1.

Table 1. Clinical test parameters for DIARETDB0, DIARETDB1, e-Ophtha EX and Messidor databases

Database	***Digital Fundus Images***						
	Diseased	*Healthy*	*Total*	*TP*	*FP*	*FN*	*TN*
DIARETDB0	110	04	114	110	00	04	00
DIARETDB1	85	04	89	85	00	04	00
e-Ophtha EX	68	14	82	68	00	14	00
Messidor	68	06	74	68	00	06	00

The proposed algorithm is evaluated based on the following performance evaluation measures [16]:

- Sensitivity (Se): It measures the proportion of TruePositives(TP) correctly identified from a given set of images.

$$\text{Se} = \text{TP}/(\text{TP}+\text{FN}) \quad (14)$$

• Accuracy (Ac): It measures the proportion of sum of True Positives (TP) and True Negatives (TN) to the total population.

$$Ac = TN + TP/(TP + FP + TN + FN) \quad (15)$$

• Positive Predictive Value (PPV): It indicates the percentage of population that actually shows the symptoms of the disease. It measures the proportion of True Positives (TP) to the sum of True Positives (TP) and False Positives (FP).

$$PPV = TP/(TP + FP) \quad (16)$$

The comparative results of clinical test statistics based on the test parameters on DIARETDB0, DIARETDB1, e-Ophtha EX and Messidor databases are given in the Table 2.

Table 2. Comparative results of clinical test statistics based on the test parameters on DIARETDB0, DIARETDB1, e-Ophtha EX, Messidor databases

Database	Authors	PPV	Sensitivity	Accuracy
DIARETDB0	Mohammed Omar et. al.[4]		98.68%	
	Garcia et. al. [2]	85.7%	95.9%	
	Lin P., Bing-Kun Z [8]	87.5%	84.8%	
	M. Usman Akram et. al. [5]	97.5%	93.7%	
	Proposed Method1 Bannigidad andDeshpande [17]	100%	98.2%	96.4%
	Proposed Method2	100%	96.4%	96.4%
DIARETDB1	Shilpa and Nagbhushan [18]	89.13%	100%	
	Kemal AKYOL et.al.[3]	88.46%	93.27%	
	Chen et.al. [1]	90%	94%	
	Proposed Method1 Bannigidad and Deshpande [17]	100%	95.5%	95.5%
	Proposed Method2	100%	95.5%	95.5%
e-Ophtha EX	Xewei Zhang et. al. [13]	0.95(AUC)		
	Qing Liu et.al. [9]		76%	75%
	Somkuwar et. al. [12]			96.08%
	Proposed Method1 Bannigidad and Asmita Deshpande [17]	98.5%	83.7%	82.9%
	Proposed Method2	100%	82.9%	82.9%
Messidor	N.B Prakash et. al. [6]		96.1%	
	Ravitej Rekhi et.al. [10]		76%	90%
	Swati Gupta and Karandikar A.M. [11]		87%	88%
	Proposed Method1 Bannigidad and Deshpande [17]	98.5%	95.71%	94.5%
	Proposed method2	100%	91.8%	91.8%

From the above Table 2, it can be clearly observed that **the** average PPV is 100% for the fundus images from DIARETDB0, DIARETDB1, e-Ophtha EX and Messidor databases considered in this experiment. The sensitivity of the proposed algorithm is 98.2% for DIARETDB0, 95.5% for DIARETDB1, 82.9% for e-Ophtha EX and 91.8% for Messidor databases. The proposed algorithm also exhibits 96.4%, 95.5%, 82.9% and 91.8% accuracy values for DIARETDB0, DIARETDB1, e-Ophtha EX and Messidor databases, respectively. Thus, the proposed algorithm is robust in detecting exudates and examining the presence of Diabetic Retinopathy in digital fundus images.

VI. CONCLUSION

This paper presents a multistage approach for exudates detection in fundus images. The proposed algorithm consolidates morphological operations for blood vessel removal, segmentation, optic disk removal and exudates detection. The proposed technique extracts GLCM features and uses SVM classifier to segregate diseased and healthy images. GLCM features enhance the detection of affected regions in a retinal image as it depicts how often different combinations of gray levels co-occur in an image or image section. The SVM classification algorithm builds a model that assigns the images as belonging to healthy or diseased category. The proposed multistage approach demonstrates promising outcomes with higher PPV, sensitivity and accuracy values. It is observed from experimentation that the average values of PPV are 100 % for all the databases considered in the experiment. The sensitivity of proposed method yielded 96.4% for DIARETDB0 database, 95.5% for DIARETDB1 database, 82.9% for e-Ophtha EX database and 91.8% for Messidor database. The proposed algorithm also exhibits 96.4%, 95.5%, 82.9% and 91.8% accuracy values for DIARETDB0, DIARETDB1, e-Ophtha EX and Messidor databases, respectively. The promising values of performance evaluation measures indicate the robustness of the proposed algorithm.

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AUTHOR'S BIOGRAPHIES

Dr. Parashuram Bannigidad is an Assistant Professor in the Department of Computer Science, Rani Channamma University, Belagavi, KA, INDIA. He is specialized in image processing and Pattern recognition, Biomedical, Document image analysis and nanotechnology. He has published more than 40 research papers in international journals and conference proceedings and completed four research projects funded by Govt. of Karnataka, UGC, New Delhi, RCU Belagavi. He also obtained Young Scientist Award by VGST Govt. of Karnataka

Asmita S. Deshpande received her B.Sc in Computer Science from Karnatak University, Dharwad and MCA from IGNOU, New Delhi in 1998 and 2009, respectively and presently working as a Lecturer in Gogte College of Commerce, BCA Department. She is also pursuing her Ph.D. from Rani Channamma University, Belagavi, Karnataka, India. She is specialized image and pattern recognition and medical image processing.