Research Journal of Applied Sciences, Engineering and Technology 8(13): 1563-1571, 2014
DOI:10.19026/rjaset.8.1134
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: June 11, 2014 Accepted: July 19, 2014 Published: October 05, 2014

Research Article

Segmentation and Classification of Optic Disc in Retinal Images

[1]S. Vasanthi and [2]R.S.D. Wahida Banu
[1]Department of ECE, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India
[2]Department of ECE, Government College of Engineering, Salem, Tamilnadu, India

Abstract: Image segmentation plays a vital role in image analysis for diagnosis of various retinopathy diseases. For the detection of glaucoma and diabetic retinopathy, manual examination of the optic disc is the standard clinical procedure. The proposed method makes use of the circular transform to automatically locate and extract the Optic Disc (OD) from the retinal fundus images. The circular transform operates with radial line operator which uses the multiple radial line segments on every pixel of the image. The maximum variation pixels along each radial line segments are taken to detect and segment OD. The input retinal images are preprocessed before applying circular transform. The optic disc diameter and the distance from optic disc to macula are found for a sample of 20 images. An Extreme Learning Machine classifier is used to train the neural network to classify the images as normal or abnormal. Its performance is compared with Support Vector Machine in terms of computation time and accuracy. It is found that computation time is less than 0.1 sec and accuracy is 97.14% for Extreme Learning Machine classifier.

Keywords: Circular transform, extreme learning machine, macula, optic disc, segmentation

INTRODUCTION

Diabetes can also be the cause of changes in the appearance of the retina. The changes from the normal appearance can be diagnostic of the diseases; tracking of the changes in sequential images can be used to assess treatment or the progress of the illness. Diabetic retinopathy is the result of micro vascular retinal changes. As new blood vessels form at the back of the eye as a part of Proliferative Diabetic Retinopathy (PDR), they can bleed (vitreous haemorrhage) and blur vision. The first time this happens, it may not be very severe. In most cases, it will leave just a few specks of blood, or spots, floating in a person's visual field, though the spots often go away after a few hours. Digital photography of the retinal image is used as a screening tool for patients suffering from sight threatening diseases such as Diabetic Retinopathy (DR) and Glaucoma. Hence an automatic screening system for retinal image diagnosis consisting of reliable and efficient detection of normal features like optic disc, blood vessels and fovea in the retinal images are required. And also OD location helps to build a retinal coordinate system that can be used to determine the position of other retinal abnormalities, such as exudates, drusen and hemorrhages. Typically the optic disc looks like an orange-pink donut with a pale centre. The orange-pink appearance represents healthy, well perfused neuro-retinal tissue.

In literature very few works have been reported about the location of optic disc and they haven't addressed about the boundary of optic disc. The optic disc is located by means of mathematical morphology filtering techniques and watershed transformation (Walter *et al*., 2002). Optic disc is localized (Lalonde *et al*., 2001) using a combination of two procedures including a Hausdorff based template matching technique on the edge map, guided by a pyramidal decomposition technique. OD localization methods can be classified into two main categories, appearance-based methods and model-based methods. Appearance-based methods identify the location of the OD as the location of the brightest round object within the retinal image. The optic disc represents the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together. The optic disc is also the entry point for the major blood vessels that supply the retina. The techniques that use this property of OD are such as intensity thresholding (Tamura *et al*., 1988) and (Liu *et al*., 1997), highest average variation (Goldbaum *et al*., 1996), matched spatial filter (Sinthanayothin *et al*., 1999) and principle component analysis (Li and Chutatape, 2004). For detection of optic disc, the optic disc center have been previously approximated as the centroid of the largest and brightest connected object in a binary retinal image obtained by thresholding the intensity channel. Another work (Reza *et al*., 2008) also used the watershed transformation for OD segmentation. A method is stated to detect the location

Corresponding Author: S. Vasanthi, Department of ECE, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India

of the OD by detecting the area in the image which has the highest variation in brightness (Sekhar *et al*., 2008). As the optic disc often appears as a bright disc covered in dark vessels, the variance in pixel brightness is the highest there.

Some other methods were based on the anatomical structure that all major retinal blood vessels radiate from the OD. The matching of the expected directional pattern of the retinal blood vessels is used as OD detection algorithm and the retinal blood vessels are segmented using a simple and standard 2-D Gaussian matched filter (Youssif *et al*., 2008). Location of the optic nerve based on fuzzy convergence (Hoover and Goldbaum, 2003) was proposed where the two methods were described and combined. The first method involves calculation of fuzzy and then applies the hypothesis generation. The second method equalizes the illumination of the image's green plane and then applies the hypothesis generation. The hypothesis generator returns either a location for the optic disc or no location at all. The matching of the expected directional pattern of the retinal blood vessels is used as OD detection algorithm and the retinal blood vessels are segmented using a simple and standard 2-D Gaussian matched filter.

An approach (Osareh *et al*., 2002) based on considering the largest area of pixels having highest gray level in the images for optic disc detection is also considered in which the optic disc was located by means of mathematical morphology filtering techniques and watershed transformation. This method was tested against a database of 30 retinal images out of that in 27 the exact contours were found. The parametric active contour model was used to detect the color morphology in Lab color space followed by the contour detection snakes based on an external image field called Gradient Vector Flow was reported (Mendels *et al*., 1999).

The proposed technique based on circular transform works for the all kind of retinal fundus images with the pathological lesions, image artifacts, exudates, hemorrhages etc. In the proposed work the circular transform detects and segments the OD simultaneously where other state of art methods uses different methods for OD detection and segmentation. Circular transform is not only used for OD detection, it can also be used to detect circular shaped objects such as blood vessels in the fundus images. For classification of OD, Support Vector Machine and Extreme Learning machine (Huang *et al*., 2012) is used. The ELM is used in blood vessel classification (Shanmugam and Wahida Banu, 2013) extracting lesion from dermoscopic images based on their size and shape (Vennila *et al*., 2012). The proposed classifier is ELM and it is the new classifier for the optic disc classification.

METHODOLOGY

Image acquisition: There were a set of 100 images collected from Aarthy Eye Hospital, Karur. Those fundus images were captured using the Carl Zeiss

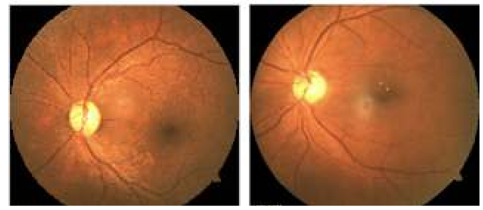


Fig. 1: (a) Input retinal image and (b) input reference image

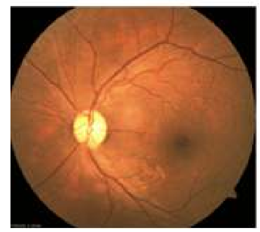
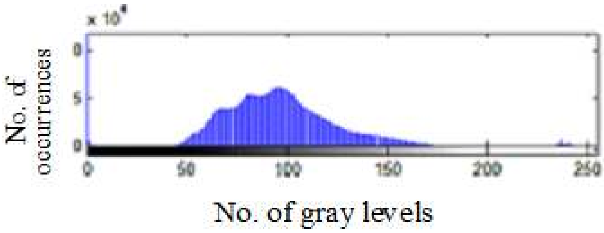


Fig. 2 Matched image

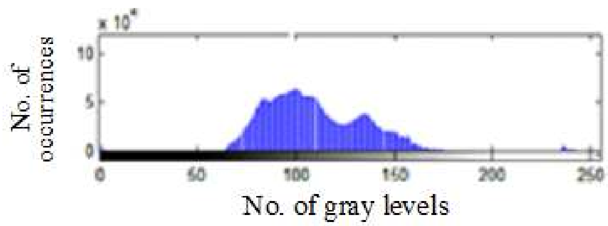
fundus digital camera with photographic angles of 20, 30 and 50°, respectively. The aim of this study is to detect and extract the exact boundary of optic disc using circular transform. The preprocessing steps are histogram equalization, converting the RGB (Red Green Blue) image into red and green components image, down sampling, median filtering, reducing the search space for optic disc detection. Circular transform uses the radial line operator. The radial lines operate on every pixel of the image and find the variation among the each line segment and the pixel with maximum variation on all line segments are taken into account for optic disc detection and segmentation.

Preprocessing: The first step in preprocessing is histogram equalization, to distribute the contrast equally in the image. This method usually increases the global contrast of the images, especially when the usable data of the image is represented by close contrast values. Due to 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 frequency intensity values. For the given retinal input image Fig. 1a is histogram equalized with the reference image Fig. 1b and the matched image in Fig. 2 is obtained with globally distributed contrast over the image.

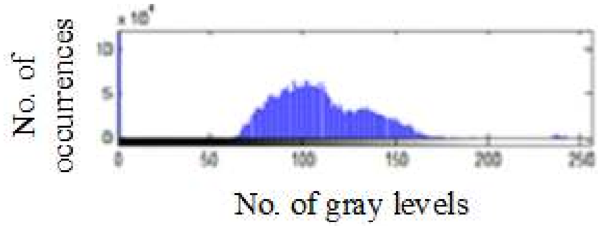
Figure 3 represents the image histogram where it plots the number of pixels for each tonal value. The horizontal axis represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone. As the blue color component of the retinal image contains only little information about the optic disc detection the blue color is eliminated from RGB image. The intensity of the image is obtained by combining the green and red color component of the image by the equation:



(a)

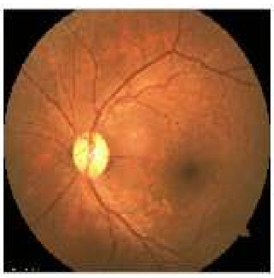


(b)

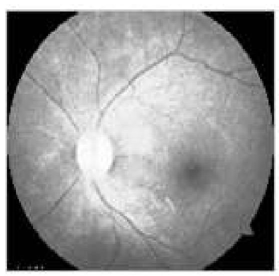


(c)

Fig. 3: Histogram analysis of the (a) input, (b) reference, (c) match image

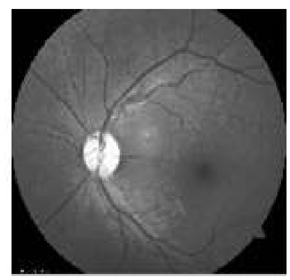


(a)



(b)

(c)



(d)

Fig. 4: (a) Input image, (b) red, (c) green, (d) blue color planes

Fig. 5: Intensity converted image

Fig. 6: Down sampled image

$$I = cI_r + (1-c)I_g \qquad (1)$$

where, I_r represent the red color component and I_g represents the green color component of the image and c represents the constant value which is maintaining the weights of I_r and I_g. The retinal vessels are more stronger in I_g, so to suppress the green color component the I_r is set with more weight. The constant c value is chosen as 0.75 for the proposed preprocessing steps.

The individual red, green and blue color component planes are shown in Fig. 4. The intensity converted image is shown in Fig. 5. Next step is the down sampling of the image to reduce its size and computational cost. Down sampling of an image reduces the number of samples that can represent the signal. In this study, the down sampling is done with the factor of 0.25. The down sampled image is shown in Fig. 6.

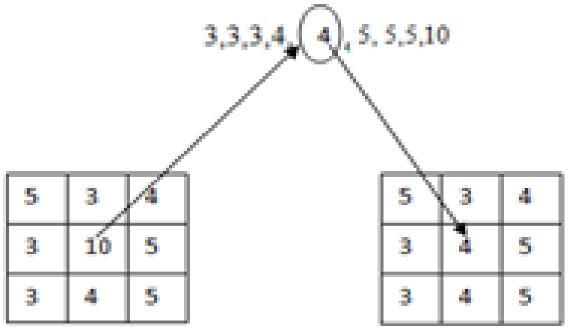


Fig. 7: Representation of median filter

Fig. 8: Binary template for Fig. 1

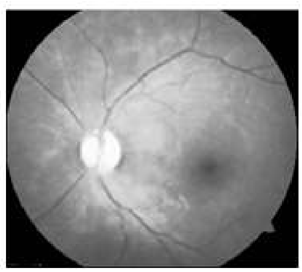


Fig. 9: Median filtered image

Fig. 10: Optic disc probability map

The median filter is used to eliminate the speckle noise and also the small image variations in the retinal blood vessels. The main idea of the median filter is to run through the pixel entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the window or template, which slides, over the entire signal or image. The pixel at the center will be replaced by the median of all pixel values inside the window. The operation of a median filter is explained in Fig. 7. For every input image the binary template as shown in Fig. 8 is created for its own in order to avoid complications. Thus the window is applied to every pixel of image. All the pixels of the window are arranged in ascending order the middle value of sequence is replaced to the window. Thus median operation of an image is performed. The obtained median filtered image is free from speckle noise and low frequency blood vessel variation as in Fig. 9.

In order to reduce the search space for the optic disc detection, the optic disc probability map was obtained. Here the brightest 20% pixels were extracted for OD detection and segmentation. The methodology is based on projection of image variation and image intensity along the horizontal and vertical direction and is given by the equation as follows:

$$HPM(x) = [HG(x,y) - VG(x,y)].I(x,y) \tag{2}$$

$$VPM(y) = [HG(x,y) + VG(x,y)].I(x,y) \tag{3}$$

where, HG (x, y) represents the image gradient along the horizontal direction, VG (x, y) represents the image gradient along the vertical direction, I (x, y) represents the intensity image. And finally the probability along the horizontal and vertical directions is combined to form the optic disc probability map:

$$OPM(x,y) = HPM(x).VPM(y) \tag{4}$$

In reference with Mahfouz's method, the brightest 20% pixels extracted for optic disc detection is shown in Fig. 10.

Circular transform: The Optic Disc in fundus image is a circular region. The circular transform uses the multiple oriented radial lines segments as in Fig. 11 applicable for all pixels of the image to find image variation along those radial lines. The maximum image variation pixels (PMs) along each radial line are taken; the number of radial line segments used is 180. As each of the radial line segments operate on pixels present on their own line segment and perform the variation difference on the pixels which are present adjacent. The maximum image variation of the pixels along each line segment is marked as PMs. This study uses 180 radial line segments and thereby 180 PMs are marked. The PMs with zero and negative variation are eliminated because they are not belonging to OD. In first filtering stage, the PMs with zero and negative variations are eliminated because they represent the macula and the retinal blood vessel. In second filtering stage, distance transform is used.

The remaining pixels are filtered based on distance transform. In radial line representation 'n' represents the number of radial lines and 'p' represents the length of each radial lines. The image variation along

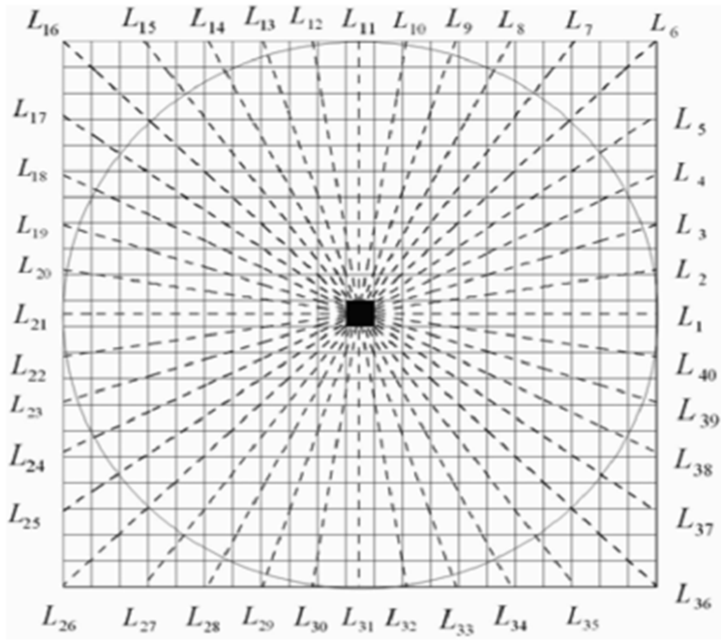


Fig. 11: Representation of radial line operator

each radial line is calculated by subtracting the each pixel with its neighboring pixel. The image variation is obtained using the formula:

$$U(x_{i,j}, y_{i,j}) = I(x_{i,j-1}, y_{i,j-1}) - I(x_{i,j+1}, y_{i,j+1}) \tag{5}$$

where, $i = 1,2,......., n$, $j = 1,2,........, p$.

The pixel ($x_{i,j}$, $y_{i,\ j}$) has its neighboring position pixels as ($x_{i,j-1}$, $y_{i,\ j-1}$) and ($x_{i,j+1}$, $y_{i,j+1}$). These image variations will be positive because the OD will be brighter than surrounding regions. The position of the PMs for a pixel at (x_0, y_0) along the n evenly oriented line segments are indexed by a vector as:

$$M(x_0, y_0) = [m_1,.........m_i,......., m_n] \tag{6}$$

where, m_i indicates the position of the PM along the i^{th} radial line segment. The maximum image variation along the radial line segments can be denoted as:

$$U(x_0, y_0) = [u(x_1, m_1, y_1, m_1),........, \\ u(x_i, m_i, y_i, m_i),........, u(x_n, m_n, y_n, m_n)] \tag{7}$$

For a pixel at (x_0, y_0), the distance of the PMs are determined using the vector as:

$$S(x_0, y_0) = [s_1(x_0, y_0),...s_i(x_0, y_0),.......s_n(x_0, y_0)] \tag{8}$$

And d_i (x_0, y_0) is the distance of (x_0, y_0) to PM of the i^{th} radial line segment at (x_i, m_i, y_i, m_i) can be obtained using the formula:

$$d_i(x_0, y_0) = [(x_i, m_i - x_0)^2, (y_i, m_i - y_0)^2]^{\frac{1}{2}} \tag{9}$$

Some pixels may lie outside the OD boundary due to retinal vessels or presence of abnormalities, so they have to be eliminated based on OD constraints. The PMs with the zero and negative variations are to be eliminated. After that distance threshold is made to minimize the number of pixel. The final OD map is obtained by:

$$OD(x, y) = \\ \left(\sum U''(x, y)\right) \Big/ \left(\sum \left(S''(x, y)\right) - \left(S_\mu''(x, y)\right)^2\right)^{\frac{1}{2}} \tag{10}$$

where, U'' (x, y) is maximum variation and S'' (x, y) is maximum distance of PMs. With these PMs, the pixel at the global peak is the OD center and the remaining is used with fitting method for OD boundary extraction. The final optic disc map is obtained by combining:

$$ODM = OPM.OD \tag{11}$$

The OD map obtained is mapped into retinal image for extracting the optic disc boundary. The down sampled retinal input image with PMs for OD boundary is shown in Fig. 12. The PMs on the down sampled median filtered image are then marked on the original input retinal image. The obtained PMs are connected together to extract the optic disc boundary. The segmented optic disc boundary is shown in Fig. 13.

Feature extraction: The optic disc diameter and distance of macula were found as features. The average

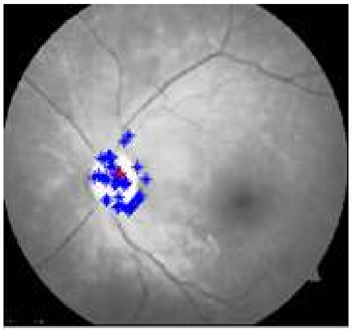


Fig. 12: Marked PMs on the median filtered image

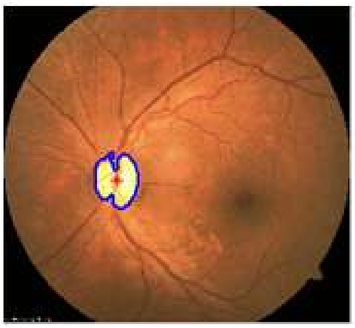


Fig. 13: Segmented optic disc using the PMs

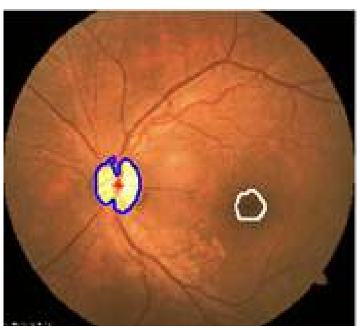


Fig. 14: Segmentation of optic disc and macula

optic Disc Diameter (DD) obtained was 70 to 100 pixels. For segmentation of macula first the search area was defined. In standard retinal image the macula will be represent at two times the optic disc diameter, so the width of search area is 2DD. In obtained search area the part with lowest intensity is taken as macula, macula present the darkest portion of image. The segmented macula is shown in Fig. 14.

Classification of optic disc: The optic disc in retinal images are classified as normal and abnormal using Support Vector Machine and Extreme Learning Machine classifiers.

Support vector machine: A Support Vector Machine (SVM) is a supervised type of learning that classifies the set of input data by analysing their features. SVM has two main learning features:

- In SVM, the training data are first mapped into a higher dimensional feature space through a nonlinear feature mapping function.
- The standard optimization method is then used to find the solution of maximizing the separating margin of two different classes in this feature space while minimizing the training errors.

The SVM classifier is trained with the features extracted to classify the optic disc in retinal images. On the basis of prediction SVM classifies which input data set belongs to which class. In this study the classes defined were the segmented part is optic disc or not. For binary classification SVM, a maximum margin is generated to find an Optimal Separating Hyper plane (OSH) between two categories of data. To construct an OSH, SVM maps data into a higher dimensional feature space. SVM performs nonlinear mapping of data to high dimension feature space by using a kernel function. Kernels commonly used with SVMs include: the polynomial kernel, the Gaussian kernel, the Gaussian radial basis function, Laplace Radial Basis Function (RBF) kernel. The proposed study have used RBF kernel as:

$$K\left(x_i, x_j\right) = e^{-\gamma \, \| x_i - x_j \|^2}, \; \gamma \geq 0 \tag{12}$$

Then, SVM constructs a linear OSH between two categories of data in the higher feature space. Support Vectors (SVs) are the data vectors which are nearest to the OSH in the higher feature space and contain all information required for classification. The decision making function is:

$$f\left(x\right) = sign\left(\left(w.x\right) + b\right) \tag{13}$$

where,
w : The weight of the hidden nodes
b : The bias of the hidden nodes

Extreme learning machine: Extreme Learning Machine is the feed forward network, which consists of three layers. This is similar to SVM the only difference is, in ELM the input weights and hidden biases are randomly generated instead of tuned. Thereby the nonlinear system is converted to a linear system:

$$H\beta = T \tag{14}$$

where,
β : Weight vector between hidden layer neurons and the output layer neuron

T : Target vector for training dataset
H : Hidden layer output matrix:

$$H = \{h_{ij}\} \text{ where } i = 1,2,......., N \text{ and } j = 1,2,......., K \quad (15)$$

$$h = g(w.x + b) \quad (16)$$

where, g (x) is the activation function used. In ELM the hidden elements are independent from the training data and target functions, so the training time for classification is less compared with SVM. ELM works for the "generalized" Single-hidden-Layer Feed forward Networks (SLFNs), but the hidden layer (or called feature mapping) in ELM need not be tuned. In summary, the implementation of ELM algorithm can be given as follows:

- Initialize all weights connecting the input and the hidden node w_i and bias b_i as small random numbers.
- Calculate the output of the hidden layer H.
- Determine the weights connecting the hidden and output node.

RESULTS AND DISCUSSION

This section presents the PM markings and segmentation results of the optic disc. In the proposed work for the radial line operator, the number of radial line segments used is 180. As each of the radial line segments operate on pixels present on their own line segment and perform the variation difference on the pixels which are present adjacent. The maximum image variation of the pixels along each line segment is marked as PMs. This study uses 180 radial line segments and thereby 180 PMs are marked. Some of the PMs are eliminated by two filtering stages. In first filtering stage, the PMs with zero and negative variations are eliminated because they represent the macula and the retinal blood vessel. In second filtering stage, distance transform is used. The resulting PMs

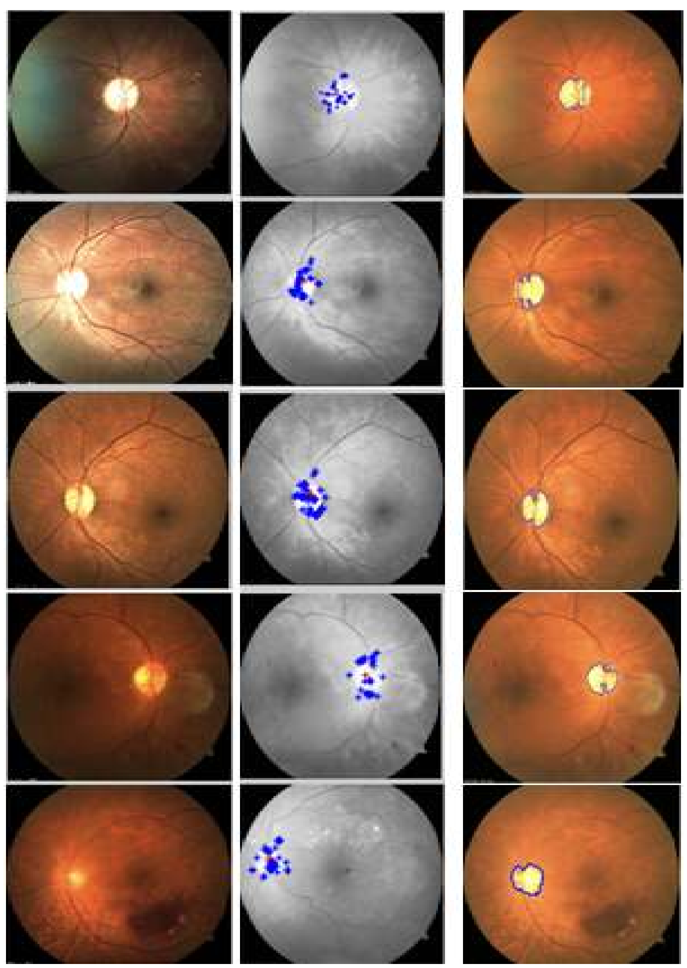


Fig. 15: First coloumn represents the input retinal images, middle coloumn represents obtained PMs on the retinal image and third coloumn represents the segmented OD

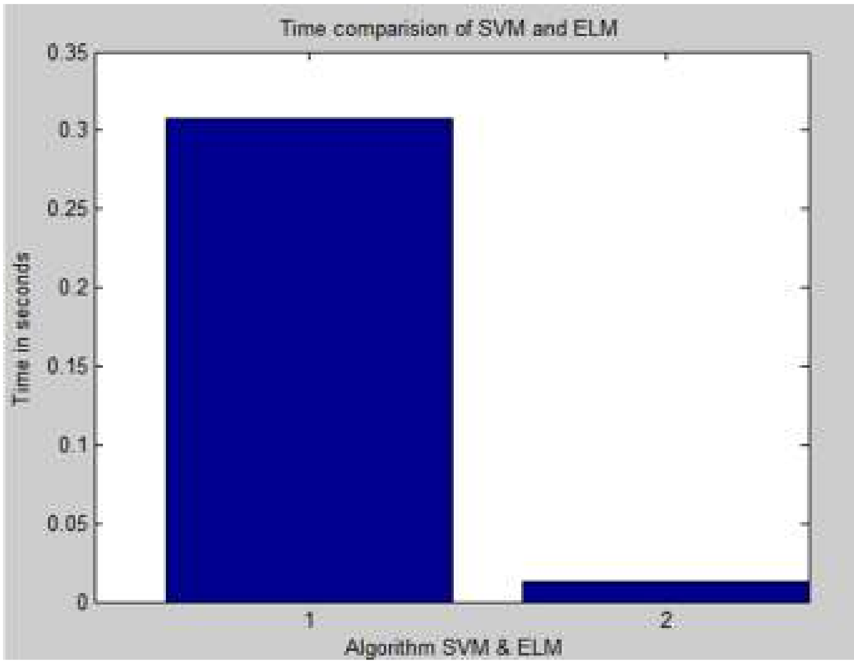


Fig. 16: Training time comparison of SVM and ELM

Table 1: OD diameter and distance of macula from OD

Sample images	OD diameter (in pixels)	Macula distance from OD (in pixels)
1	62	242
2	57	No macula
3	62	245
4	69	224
5	63	245
6	61	222
7	29	247
8	70	199
9	72	No macula
10	68	253
11	18	270
12	32	192
13	69	199
14	67	230
15	71	224
16	69	221
17	63	262
18	64	251
19	62	249
20	61	248

Table 2: Performance measurements

Classifier	Sensitivity	Specificity	Accuracy
SVM	82.35	100	87.33
ELM	94.11	100	97.14

are used to extract the boundary of OD as shown in Fig. 15.

Table 1 represents the equidiameter of the segmented OD and the position of optic disc center in the original image. The equidiameter is calculated by the formula:

$$ED = \sqrt{\frac{4 * A}{\pi}} \tag{17}$$

where,
A : Number of pixels in segmented OD

The performance of the classifiers used is measured in terms of parameters like specificity, sensitivity and accuracy. The sensitivity relates to the test's ability to identify positive results. Specificity relates to the test's ability to identify negative results. The formulas for determining parametric values are as follows:

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

$$Sensitivity = TP/(TP + FN) \tag{19}$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{20}$$

where,

True Positive (TP) = correctly identified by proposed algorithm
False Positive (FP) = incorrectly identified by proposed algorithm
True Negative (TN) = correctly rejected by proposed algorithm
False Negative (FN) = incorrectly rejected by proposed algorithm

In the proposed study, the performance results obtained for the retinal images are shown in Table 2.

Figure 16 represents the time taken by ELM and SVM to perform the classification.

CONCLUSION

Thus the OD center and OD boundary was obtained simultaneously using the single method circular transform. This technique can be applied to the image having lesions and with imaging artifacts such as illusions, hazing etc and can accurately detect OD with radial line function. The radial line operator is used to locate the OD more accurately than the methods using the anatomical structures such as blood vessels and optic nerves. Thus the optic disc is classified using SVM and ELM with accuracy of 87.33 and 97.14% respectively and the training time taken for ELM is much less than SVM.

REFERENCES

Goldbaum, M., S. Moezzi, A. Taylor, S. Chatterjee, J. Boyd, E. Hunter and R. Jain, 1996. Automated diagnosis and image understanding with object extraction, object classification, and inferencing in retinal images. Proceeding of IEEE International Conference on Image Processing, 3: 695-698.

Hoover, A. and M. Goldbaum, 2003. Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels. IEEE T. Med. Imaging, 22(8): 951-958.

Huang, G.B., H. Zhou, X. Ding and R. Zhang, 2012. Extreme learning machine for regression and multiclass classification. IEEE T. Syst. Man Cy. B, 42(2): 513-529.

Lalonde, M., M. Beaulieu and L. Gagnon, 2001. Fast and robust optic disc detection using Pyramidal decomposition and Hausdorff-based template matching. IEEE T. Med. Imaging, 20(11): 1193-1200.

Li, H. and O. Chutatape, 2004. Automated feature extraction in color retinal images by a model based approach. IEEE T. Biomed. Eng., 51(2): 246-254.

Liu, Z., O. Chutatape and S. M. Krishnan, 1997. Automatic image analysis of fundus photograph. Proceeding of IEEE Conference on Engineering in Medicine and Biology Society, pp: 524-525.

Mendels, F., C. Heneghan and J.P. Thiran, 1999. Identification of the optic disk boundary in retinal images using active contours. Proceeding of Irish Machine Vision and Image Processing Conference, pp: 103-115.

Osareh, A., M. Mirmehdi, B. Thomas and R. Markham, 2002. Colour morphology and snakes for optic disc localization. Proceeding of the 6th Medical Image Understanding and Analysis Conference, pp: 21-24.

Reza, A.W., C. Eswaran and S. Hati, 2008. Automatic tracing of optic disc and exudates from color fundus images using fixed and variable thresholds. J. Med. Syst., 33: 73-80.

Sekhar, S., W. Al-Nuaimy and A.K. Nandi, 2008. Automated localisation of retinal optic disk using Hough transform. Proceeding of International Symposium on Biomedical Imaging. Nano Macro, pp: 1577-1580.

Shanmugam, V. and R.S.D. Wahida Banu, 2013. Retinal blood vessel segmentation using an extreme learning machine approach. Proceeding of IEEE Point-of-Care Healthcare Technologies (PHT, 2013), pp: 318-321.

Sinthanayothin, C., J.F. Boyce, H.L. Cook and T.H. Williamson, 1999. Automated localisation of the optic disk, fovea, and retinal blood vessels from digital colour fundus images. Brit. J. Ophthalmol., 83: 902-910.

Tamura, S., Y. Okamoto and K. Yanashima, 1988. Zero-crossing interval correction in tracing eye-fundus blood vessels. Pattern Recogn., 21(3): 227-233.

Vennila, G.S., L.P. Suresh and K.L. Shunmuganathan, 2012. Dermoscopic image segmentation and classification using machine learning algorithms. Proceeding of International Conference on Computing, Electronics and Electrical Technologies (ICCEET, 2012), pp: 1122-1127.

Walter, T., J.C. Klein, P. Massin and A. Erginary, 2002. A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in color fundus images of the human retina. IEEE T. Med. Imaging, 21(10): 1236-1243.

Youssif, A.A.H.A.R., A.Z. Ghalwash and A.A.S.A.R. Ghoneim, 2008. Optic disc detection from normalized digital fundus images by means of a vessels' direction matched filter. IEEE T. Med. Imaging, 27(1): 11-18.