Journal of Network and Innovative Computing
ISSN 2160-2174 Volume 4 (2016) pp. 046-054

Optic Disc Localization using Local Vessel Based Features and Support Vector Machine

Anum Abdul Salam[1] and Muhammad Usman Akram[2]

[1] National University of Sciences and Technology Islamabad, Pakistan
anum.abdulsalam@gmail.com

[2] National University of Sciences and Technology Islamabad, Pakistan
usmakram@gmail.com

***Abstract*: Optic disc is one of the fundamental regions located in the internal retina that helps ophthalmologists in analysis and early diagnosis of many retinal diseases such as optic atrophy, optic neuritis, papilledema, ischemic optic neuropathy, glaucoma and diabetic retinopathy. An accurate and early diagnosis requires an accurate optic disc examination. Presence of different retinal abnormalities and non-uniform illumination makes optic disc localization a challenging task. There is a need to detect and localize optic disc from fundus images with high accuracy to make the diagnosis using Computer Aided Systems developed for ophthalmic disease diagnosis more reliable. Proposed algorithm provides a novel optic disc localization and segmentation technique that detects multiple candidate optic disc regions from fundus image using enhancement and segmentation. The proposed system then extracts a hybrid feature set for each candidate region consisting of vessel based and intensity based features which are finally fed to SVM classifier. Final decision of Optic disc region is done after computing Manhattan distance from the mean of training data feature matrix. The evaluation of proposed system has been done on publicly available datasets and one local dataset and results shows the validity of proposed system.**

Keywords: Disc localization, Machine Learning, Glaucoma, Ophthalmic disease diagnosis, Fundus images, Computer Aided Diagnostics

I. Introduction

Human eye is an organ that responds to the light and helps in creating a vision. Human eye is composed of some layers. Outermost layer is Sclera. Front portion of the sclera that covers the eye ball is transparent membrane and is called cornea. Cornea enables the light from some external source to enter the eye. Iris controls the amount of light that enters the eye by contracting and relaxing the muscles depending upon the intensity of light. Internal layer of eye known as retina is composed to photoreceptor cells known as rods and cons. Light rays reflected from an object enters the eye and falls on retina, rods and cons converts them to neural signals which are transferred to the brain through optic nerve. Optic nerve enters the human eye at the region known as optic disc region. Optic disc region has no rods and cones and often called blind spot. A fluid called aqueous humor is produced by ciliary body in the eye. Internal eye pressure is maintained by keeping a balance of the amount of liquid produced and amount of liquid leaving the eye. The pressure is called intraocular pressure. Figure 1 shows the internal structure of eye.

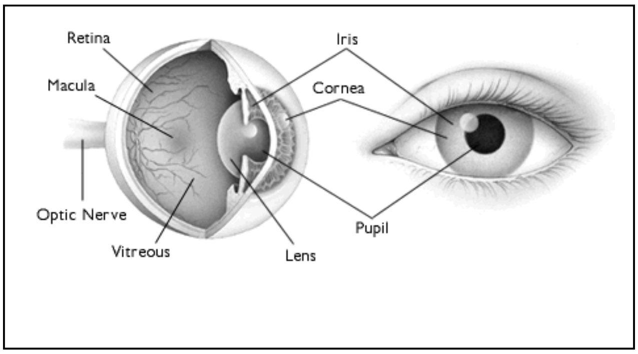


Figure 1. Internal Structure of Human Eye [1]

In today's era of technology research work is being done to design computer aided diagnostics that can aid the specialists in accurate and early analysis of any abnormalities. Computer aided diagnostics (CAD) are also being used in the field of ophthalmology to aid ophthalmologists. Many CAD algorithms based on machine learning and biomedical image processing process the images acquired from some biomedical imaging techniques to view and analyze the internal structure. Fundoscopy and optical Coherence Tomography (OCT) are two most widely used state of art imaging techniques that aids the ophthalmologists to acquire the internal state of eye and the layers of retina. Many algorithms are being proposed that analyze the images captured from Fundoscopy and OCT, helps in autonomous abnormality detection in the internal eye. This Research work is based on an algorithm for fundus images that helps in localization of optic disc from the fundus image. Figure 2 shows the fundus image of healthy eye. Circular black region is Fovea. Yellowish circular region is the optic disc region. Optic disc is centered by an intense yellowish region called optic cup.

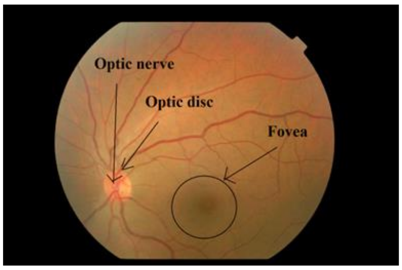


Figure 2. Fundus image of Healthy Eye

Accurate optic disc localization is quite challenging for the reason that fundus image may contain bright fringes, noisy spots, exudates and bright lesions which may be misclassified as optic disc by many CAD systems due to the resemblance in texture and color. This results in inaccurate disease detection.

II. Literature Review

Research techniques for accurate optic disc localization are being done to make the autonomous disease detection systems less error prone. This section summarizes some recent techniques from literature based on machine learning and image processing techniques. Ocular diseases such as optic atrophy, optic neuritis, papilledema, ischemic optic neuropathy, glaucoma and diabetic retinopathy [2] optic nerve and optic disc gets affected resulting in a structural change in the optic disc region and requires an accurate optic disc localization in order to be detected accurately.

G. Brenie Sekar et al. [3] proposed an algorithm for optic disc localization using histogram clusters. Candidate regions for optic disc are extracted using clustering approach on red plane and selecting the three brightest regions. Three Optic disc candidate regions are analyzed and candidate pixels for three regions are extracted using variance, difference and low pass filter methods n green plane. Sub images of the localized centers of the candidate regions are cropped and histogram of each region is plotted. Region with brightest pixels is categorized as optic disc region. Algorithm was tested on MESSIDOR dataset and found to be 99.5% accurate. In 2012 [4] an algorithm was proposed for optic disc localization based on Attanassov intuitionistic fuzzy histon segmentation (A-IFS) and found to be 93.4% accurate. Algorithm preprocesses the fundus image followed by adaptive histogram equalization to enhance the contrast in homogenous intensity areas to avoid the enhancement of noise. Vessel removal is done using Gabor 2D matching followed by morphological closing operation to reduce the interference effect of blood vessels in optic disc region. Optic disc segmentation is done based on column wise neighborhood operation followed by optic disc segmentation using A-IFS histon based segmentation.

An optic disc localization technique [5] based on some prior knowledge of features like disc size, cup size and cup to disc ratio was proposed in 2012. Optic disc localization was done using heuristics based approach followed by optimization using contour based iterative fitting. Accuracy analysis of algorithm was done on ONHSD and diaretdb0 datasets and found to be 94% and 93% accurate respectively. In 2013, a research [6] was conducted to localize the optic disc using image processing techniques. Image was preprocessed to enhance the contrast using adaptive histogram equalization followed by negative transformation of image. These steps will enhance all the bright regions in an image. Extended minima transformation was applied to get the candidate region for optic disc. Morphological opening and closing operations were performed to remove the noisy bright regions. Resultant image is subtracted from the green plane image to highlight the optic disc region. Algorithm was found to be 98.65% accurate as observed on MESSODOR dataset. Hussain F Jaafar et al. [7] proposed an algorithm for optic disc localization based on vasculature property of optic disc region. Image is processed and the area with highest vascular density is extracted. The extracted sub image is processed further using gradient operator to extract a rough approximation of disc area. Hough transform is applied to extract the circular boundary from the approximated information. STARE and DRIVE datasets were used to evaluate the accuracy of algorithm, 98.8% and 100% accuracy was achieved respectively.

Template cross correlation was used [8] to localize optic disc from fundus images. Green plane image was extracted and cross correlated with the template containing optic disc region. Pixel with highest correlation value was categorized as optic disc center. Morphological operations were applied to segment the optic disc. Gold standard dataset was used to evaluate the algorithm. 98.7% accuracy was achieved. In 2014 [9], an algorithm for optic disc localization used Fourier transform with the template to get an initial seed point. Green plane is extracted from RGB image followed by contrast enhancement. Image is processed using some morphological operations to remove the vessels. Region growing is done to segment the optic disc using the seed point extracted in the first step as initial point. Results were evaluated on DRIVE dataset with 100% accuracy. An optic disc localization technique was proposed in 2010 [10] to improve the optic disc localization in Automatic cup-to-disc Ratio measurement system for Glaucoma detection and AnaLysIs (ARGALI). In ARGALI region of interest is extracted by selecting a region containing 0.5% of the brightest pixels of the image. Sometimes, bright fringes may be misinterpreted as region of interest. To avoid the misconception bright fringes are removed from the boundaries of fundus image by taking the center and cropping the boundary of fundus image by estimating the circular region. After boundary removal, region of interest is extracted and segmentation techniques are applied to separate cup and disc region. Ellipse fitting is done for boundary smoothening.

An optic disc localization technique [11] was proposed that uses voting based approach. Three different techniques for center localization of optic disc were used. The three candidate regions were separately analyzed and reduced to a single candidate region by computing the average point. Resulting candidate region is used to extract Region of interest. Blood vessels were removed using morphological operations followed by Otsu's segmentation algorithm to segment the optic disc boundary. Hough transform is applied to extract circular optic disc boundary. MESSIDOR dataset is used for evaluation of algorithm and is found to be 99% accurate.

Ahmed E. Mahfouz et al. [12] proposed a more robust and efficient optic disc localization algorithm. Instead of processing the fundus image, 1-D projection vectors are used based on the vessel orientation and intensity based properties of optic disc region. These two 1-D projection vectors are used to localize the position of optic disc as the peaks in the vectors indicates the location of optic disc. STARE, DIARETDB0, DIARETDB1 and DRIVE were used to evaluate the proposed algorithm. Accuracies of 92%, 98%, 97% and 100% were achieved respectively.

In 2012 [18], a robust disc localization algorithm was proposed. The proposed technique used level set approach and directional filters. Candidate regions are extracted using template matching. Noise and small bright lesions are removed by applying morphological operations. Different templates are created to encounter the images with different resolutions. Optic disc region is separated from the rest of the regions using vessel density based properties. Vessel removal is done using morphological operations to remove the interference in optic disc region. Optic disc was segmented using hybrid level set approach. Boundary of segmented optic disc was smoothened using ellipse fitting. An optic disc localization algorithm proposed in 2011[19] used model based optic nerve head segmentation. Image was preprocessed to remove the blood vessels effect from the optic disc region. RGB plane was converted to a 2D image space by selecting an appropriate plane from Red, Green or Blue depending upon the saturation of image. Mean of each plane is compared with the threshold value to select one of the Red, Green or Blue plane. Canny edge detector is applied on the selected plane to extract the edge map. Edge map is used to approximate the circle in the fundus image using Hough transform. Center of circle with varying radius was used to approximate the circle's boundary. Edges of extracted disc were smoothened using ellipse fitting. 325 fundus images were used for algorithm testing and 10% error was observed. An optic disc localization technique was proposed in 2015 [20] that comprised of two stages. Vessel segmentation followed by optic disc localization. Vessel segmentation was done using morphological operations by selecting a structuring element to extract vessels from the retinal fundus image. Optic disc localization was done by selecting the brightest region from the image using histogram matching approach. Dan Popescu et al. provided an algorithm [21] for optic disc localization using gliding window approach that extracts the textural features in a local window region with window size set such that it can fit the optic disc region. STARE database was used to evaluate the algorithm. AN optic disc localization algorithm [22] was proposed that used gliding box technique to divide the image into sub images. Sub images were analyzed based on textural and vessel segmentation properties to extract the location of optic disc.

Literature techniques are comprised of the techniques based on either vessel based properties or intensity based properties to discriminate between disc and non-disc regions. This may sometimes leads to a misconception. As many times fundus image may contains noisy spots and bright lesions which are interpreted as optic disc. Proposed algorithm will combine vessel and intensity based features and correlate the results to decide between disc or non-disc region. This hybrid feature based approach has increased the efficiency and accuracy of algorithm and is less error prone.

III. Methodology

Localization of optic disc is one of the ongoing research topics as it helps in more accurate diagnosis of many ocular diseases [13]. Optic disc region is a palor region accompanied by large amount of blood vessels where optic nerve enters the human eye. Proposed methodology takes an input fundus image captured using Fundoscopy. Image is preprocessed to enhance the optic disc from the image followed by candidate regions extraction. For each candidate region a set of local features like vessel density, intensity, mean, variance and mean are computed. Support Vector Machine (SVMs) are used to classify a region as optic disc region from the candidate regions based on the features extracted. As discussed earlier optic disc region has highest vessel density and more intense in color. This section explains the implementation details of the proposed system. Fig. 3 shows an overview of proposed methodology.

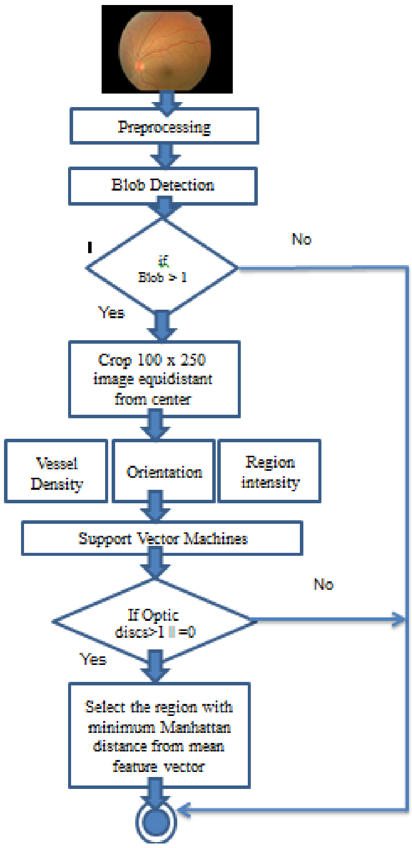


Figure 3. Flow Chart of Proposed Methodology

A. Preprocessing

Preprocessing includes background segmentation. Green plane is extracted and segmentation is done using mean as threshold value. Median filter is applied to remove noise followed by opening and closing operations to extract the background from the noisy segmented image. Connected component labeling is done to extract the largest connected region which is the fundus background region.

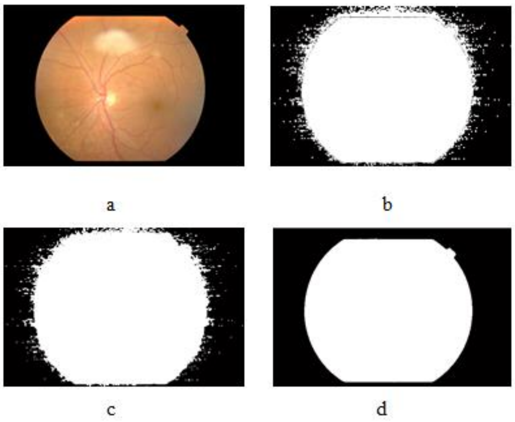


Figure 4. (a) Fundus Image; **(b)** Thresholded image; **(c)** Median filtering; **(d)** Segmented Background

B. Optic Disc Segmentation

Fundus image is analyzed to extract the bright regions (candidate regions) from fundus image. RGB image is converted to 2D image by either converting it to gray scale image or selecting Red plane from the RGB image. Decision is based on the mean value of image. If the image is more saturated in Red plane gray scale image is used instead of Red plane. To enhance the bright regions from fundus image Laplacian of Gaussian (LoG) is applied, for the reason to detect all the blobs from fundus image [14]. Eq. 1 and Eq. 2 represents LoG. LoG has intense effects at the boundary or edges which may affect the optic disc localization if optic disc is localized on the boundary. To avoid the blurring on boundary the image is padded with the mask to extend the image boundary. Back ground segmented mask is eroded and multiplied with the resized fundus image to obtain an enlarged fundus image. This enlarged fundus image is added with the original fundus image to get a padded boundary.

$$h_g(n_1,n_2) = e^{\frac{-(n_1^2+n_2^2)}{2\sigma^2}} \tag{1}$$

$$h\,(n_1,n_2) = \frac{-(n_1^2+n_2^2-2\sigma^2)h_g(n_1,n_2)}{2\pi\sigma^6\sum_{n_1}\sum_{n_2}h_g} \tag{2}$$

In above equations σ represents standard deviation whereas n1 and n2 shows the row and column respectively. To increase the robustness of code LoG is applied in frequency domain as it makes the computations fast. Image obtained contains bright regions (blobs). Some opening and closing operations are applied on the image to remove noise and unwanted bright lesions. Segmentation is done by selecting 40% of the bright pixels from the resultant image Gkm. Eq. 3 represents the thresholding step with T as resultant image.

$$T = 0.6 \times Gkm \tag{3}$$

Resultant image may contain more than one bright region. Each of the bright regions is considered as candidate region for optic disc. If the resultant image contains one bright region it is directly classified as optic disc region, however in case of more candidate regions image is passed to machine learning module for optic disc classification among extracted candidate region.

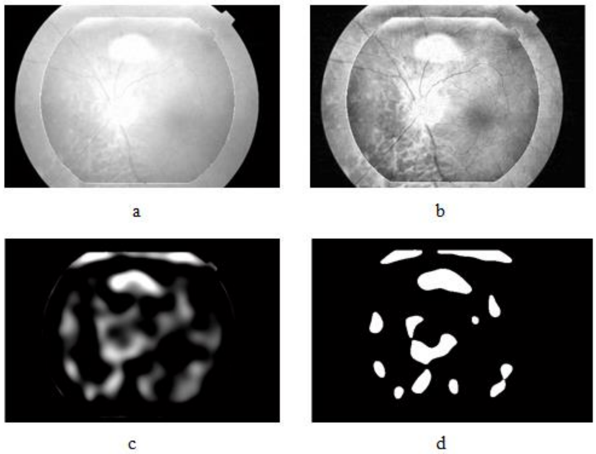


Figure 5. (a) Padded image; **(b)** Contrast Enhanced image; **(c)** LoG Blob detection; **(d)** Segmented image

C. Vessels Segmentation

Local vessel density based feature is among one of the features used to discriminate between disc and non-disc regions. To compute vessel density, vessel segmentation is done using 2D Gabor wavelet filters [15]. 2D Gabor wavelets are used because they have the selection capability in every orientation and thus results in vessel segmentation at a high resolution. Green plane contains more details of vessels thus green plane is extracted from RGB fundus image. Gabor wavelets are applied in 18 orientations and 9 scales. Highest Gabor wavelet response is selected from the 18x9 results to proceed further. Image is thresholded using multi-thresholding technique [16] to enhance the minor details of blood vessels.

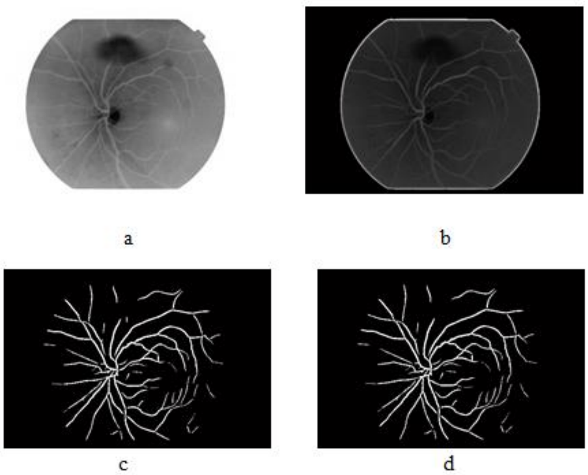
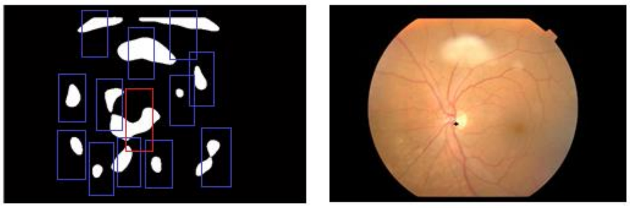


Figure 6. (a) Extracted green plane; (b) Gabor Wavelet application; (c) Extracted Vessels; (d) Multi-thresholding of vessels

D. Features Extraction and Optic disc Localization

To localize the optic disc a sub region 100 x 250 equidistant from center of the candidate region is extracted and some local vessel based features i.e. vessel density, vessel orientation variance and some local intensity based features minimum, maximum, mean, standard deviation are extracted. Feature vector 1 x 6 is passed to SVM to classify the region as a disc or non-disc region. If more than one region is classified as optic disc region least distance classifier is used to classify the region with the least Manhattan distance from the average of feature vectors in training dataset is classified as optic disc region.



a b

Figure 7. (a) Candidate Regions; **(b)** Localized optic disc

IV. Results and Conclusion

Proposed algorithm is implemented on MATLAB R2014a. Algorithm is evaluated using local and public databases. Machine learning module used two fold training and testing. Data randomization is done to compute the average accuracy of the proposed system. Training phase includes supervised learning of optic disc and non-optic disc regions. Local databases used for evaluation of algorithm are collected from Armed Forces Institute of Ophthalmology (AFIO). Public available databases used include MIESSIDOR, STARE, DRIVE, DIARETDB0 and DIARETDB1. Table 1 shows the quantity of images, resolution of images and format of images that databases are composed of.

Digital Retinal Images for vessel extraction (DRIVE) database is composed of 40 images which are captured using Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV) [19]. Each image's resolution is 8 bits per plane with 768 x 564 pixels. For images having diameter of 1080 pixels Circular FOV is used. Structured Analysis of Retina (STARE) database is contains 400 retinal images which are acquired using TopCon TRV-50 retinal camera having 700 x 605 resolution and 35 degree FOV of 35 [23]. DIAbetic Retinopathy DataBase (DIARETDB) has 89 fundus images [24] which are highly affected by different retinal abnormalities. Images were captured with 50 degrees FOV and resolution of 1500 x 1152. Methods of Evaluation of Systems of Segmentation and Indexation Dédiées to Opthalmologie Rétinienne (MESSIDOR) database [25] is another public available dataset used to analyze accuracy of the algorithm. The database consists of 1200 fundus images using a 3CCD camera on a Topcon TRC NW6 with FOV of 45 degree. The images have resolution of 1440 x 960, 2240 x 1488, and 230 x 1536.

Dataset	**Image Quantity**	**Resolution**	**Format**
MIESSIDOR	1200	2240 x 1488	TIFF
Digital Retinal Images for vessel extraction (DRIVE)	40	768 x 564	TIFF
Structured Analysis of the Retina (STARE)	81	700 x 605	PNG
Standard Diabetic Retinopathy Database 1 (DiaRetDB1)	89	1500 x 1152	PNG
Local Database 1	462	1504 x 1000	JPG
Local Database 2	100	1504 x 1000	JPG

Table 1. Datasets used in evaluation of proposed algorithm

Table 2 shows the results of the proposed algorithm on different publicly available and locally collected datasets. It shows the highest accuracy is achieved for DIARETDB1 which is 100%. All the optic disc regions are truly classified as optic disc with no false positives and false negatives. For Local datasets 98% and 96.75% accuracy is achieved with miss ratio of 2 and 15 from 100 and 462 images respectively. One optic disc is misclassified in DRIVE dataset and 97.5% accuracy is achieved. Algorithm localized optic discs in MESSIDOR with 99.6% accuracy. Analyzing the algorithm for STARE results in 97.5% accuracy.

Datasets	**Images**	**OD Localized**	**OD missed**	**Accuracy**
Local	100	98	2	98%
DRIVE	40	39	1	97.5%
STARE	81	79	2	97.5%
DiaRetDB1	89	89	0	100%
MESSIDOR	1200	1196	4	99.6%
Local	462	447	15	96.75%

Table 2. Quantitative Analysis of Algorithm using different data sets

Table 3, 4, 5 and 6 shows the accuracy analysis of algorithm on different datasets explained above and comparison of accuracy with other techniques explained in the literature [2, 6, 7, 9, 11, 12, 17]. It can be seen from the tables below that for MESSIDOR accuracy of proposed system is approximately equivalent to already proposed techniques. For DIARETDB1 accuracy has been improved from 97.8% to 100%. STARE dataset is the noisiest dataset with large number of bright lesions and fringes. Introducing machine learning and hybrid features with classification using SVM have improved the optic disc localization accuracy in STARE dataset as compared to literature. It can be observed from the tables that the overall average accuracy has been increased.

Author	**Technique**	**Database**	**Accuracy**
H.Yu et al. [17]	Directional match filtering and level set approach	*MESSIDOR*	99%
Zubair et al. [6]	CLAHE, Morphological and intensity feature	*MESSIDOR*	98.65%
Sekar et al. [2]	Clustering and histogram techniques	*MESSIDOR*	100%
Aquino et al. [11]	Morphological, edge detection and feature extraction	*MESSIDOR*	99%
Proposed Method	Local Vessel Based Features and Support Vector Machine	*MESSIDOR*	99.6%

Table 3. Comparison of Results on MESSIDOR Dataset with Literature Techniques

Author	**Technique**	**Database**	**Accuracy**
Mahfouz et al. [12]	Image features projection	*DRIVE*	100%
Saleh et al. [9]	FFT based template matching	*DRIVE*	100%
Proposed Method	Local Vessel Based Features and Support Vector Machine	*DRIVE*	97.5%

Table 4. Comparison of Results on DRIVE Dataset with Literature Techniques

Author	**Technique**	**Database**	**Accuracy**
Mahfouz et al. [12]	Image features projection	*STARE*	92.6%
Hussain F Jaafar et al. [7]	Optic disc localization based on Vusculature properties	*STARE*	98%
Proposed Method	Local Vessel Based Features and Support Vector Machine	*STARE*	97.5%

Table 5. Comparison of Results on STARE Dataset with Literature Techniques

Author	**Technique**	**Database**	**Accuracy**
Mahfouz et al. [17]	Image features projection	*DIARETDB1*	97.8%
Proposed Method	Local Vessel Based Features and Support Vector Machine	*DIARETDB1*	100%

Table 6. Comparison of Results on DIARETDB1 Dataset with Literature Techniques

Fig. 8 shows output from different steps i.e. first column shows the results from vessel segmentation on different images from different datasets. Second column shows the results of image padding on different images as explained in section III, Optic disc segmentation. Third column shows the results of Blob detection described in Features Extraction and Optic disc Localization under Methodology. Last column depicts the results from optic disc localization module after separating the candidate regions and applying SVM as explained in Methodology. Selected images have bright lesions, noise and exudates. However, the proposed algorithm has localized the optic disc with great accuracy.

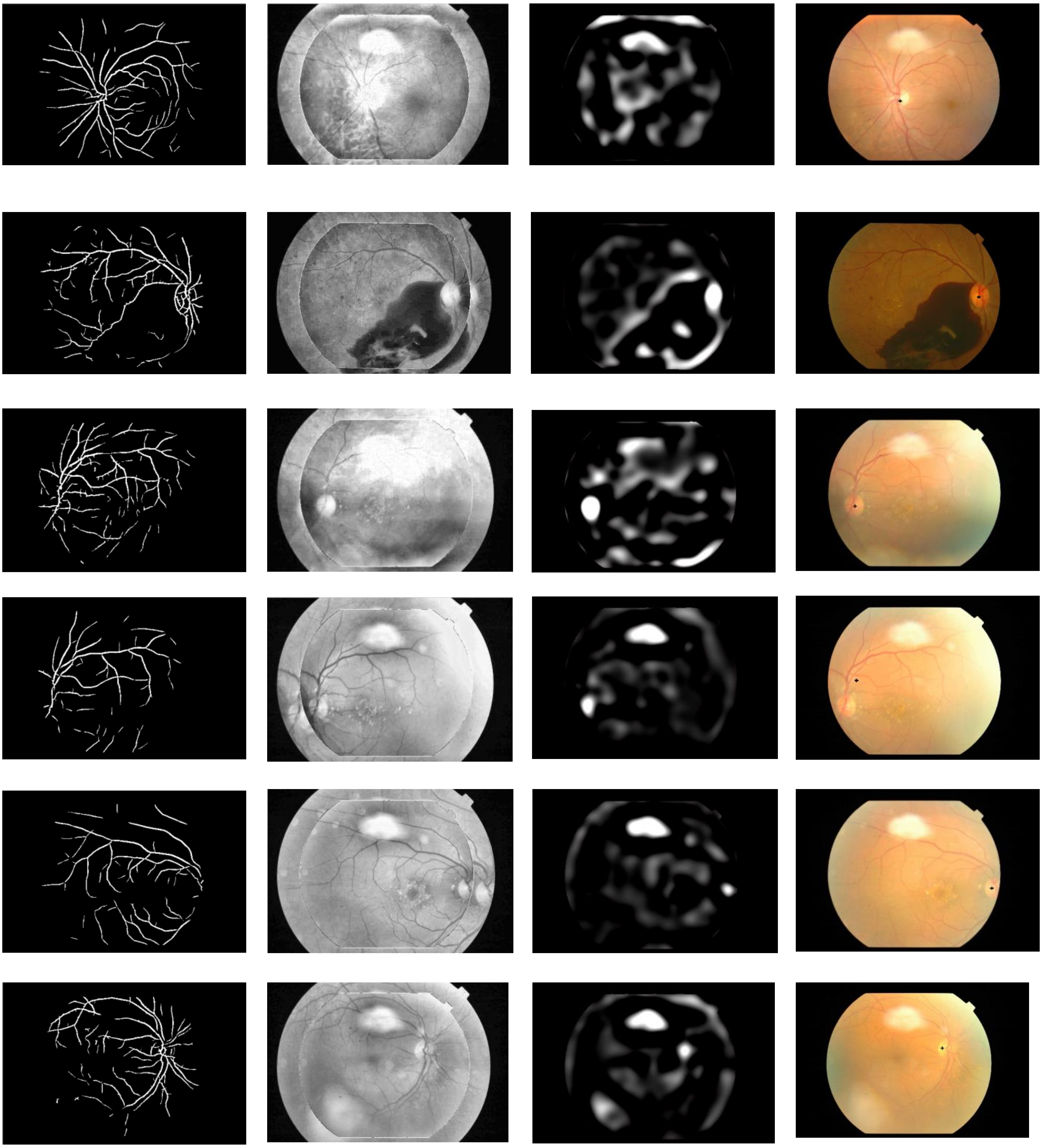


Figure 8. Results of the proposed system from different modules

References

[1] "The Human Eye" available on-line at http://www.internal.schools.net.au/edu/lesson_ideas/optics/optics_wksht2_p1.html

[2] Sekar, G. Brenie, and P. Nagarajan. "Localisation of optic disc in fundus images by using clustering and histogram techniques." In Computing, Electronics and Electrical Technologies (ICCEET), 2012 International Conference on, pp. 584-589. IEEE, 2012.

[3] Sekar GB, Nagarajan P. Localisation of optic disc in fundus images by using clustering and histogram techniques. In Computing, Electronics and Electrical Technologies (ICCEET), 2012 International Conference on 2012 Mar 21 (pp. 584-589). IEEE.

[4] Acharya UR, Chua CK, Min LC, Ng EY, Mushrif MM, Laude A. Application of intuitionistic fuzzy histon segmentation for the automated detection of optic disc in digital fundus images. InBiomedical and Health Informatics (BHI), 2012 IEEE-EMBS International Conference on 2012 Jan 5 (pp. 444-447). IEEE.

[5] Qureshi TA, Amin H, Hussain M, Qureshi RJ, Al-Diri B. Automatic localization of the optic disc in retinal fundus images using multiple features. In Bioinformatics & Bioengineering (BIBE), 2012 IEEE 12th International Conference on 2012 Nov 11 (pp. 488-493). IEEE.

[6] Zubair M, Yamin A, Khan SA. Automated detection of Optic Disc for the analysis of retina using color fundus image. In Imaging Systems and Techniques (IST), 2013 IEEE International Conference on 2013 Oct 22 (pp. 239-242). IEEE.

[7] Jaafar HF, Nandi AK, Al-Nuaimy W. Automated localisation of the optic disc and fovea to assist diabetic retinopathy screenings. InSignal Processing Conference (EUSIPCO), 2013 Proceedings of the 21st European 2013 Sep 9 (pp. 1-5). IEEE.

[8] GeethaRamani R, Dhanapackiam C. Automatic localization and segmentation of Optic Disc in retinal fundus images through image processing techniques. In Recent Trends in Information Technology (ICRTIT), 2014 International Conference on 2014 Apr 10 (pp. 1-5). IEEE.

[9] Saleh MD, Salih ND, Eswaran C, Abdullah J. Automated segmentation of optic disc in fundus images. In Signal Processing & its Applications (CSPA), 2014 IEEE 10th International Colloquium on 2014 Mar 7 (pp. 145-150). IEEE.

[10] Zhang Z, Lee BH, Liu J, Wong DW, Tan NM, Lim JH, Yin F, Huang W, Li H, Wong TY. Optic disc region of interest localization in fundus image for Glaucoma detection in ARGALI. InIndustrial Electronics and Applications (ICIEA), 2010 the 5th IEEE Conference on 2010 Jun 15 (pp. 1686-1689). IEEE.

[11] Aquino A, Gegúndez-Arias ME, Marín D. Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques. Medical Imaging, IEEE Transactions on. 2010 Nov;29(11):1860-9.

[12] Mahfouz AE, Fahmy AS. Fast localization of the optic disc using projection of image features. Image Processing, IEEE Transactions on. 2010 Dec;19(12):3285-9.

[13] Kaur, Jaspreet, and Dr HP Sinha. "Automated localisation of optic disc and macula from fundus images." International journal of advanced research in computer science and software engineering 2, no. 4 (2012): 242-249.

[14] Kong, Hui, Hatice Cinar Akakin, and Sanjay E. Sarma. "A generalized laplacian of gaussian filter for blob detection and its applications." Cybernetics, IEEE Transactions on 43, no. 6 (2013): 1719-1733.

[15] Usman, Anam, Sarmad Abbas Khitran, M. Usman Akram, and Yasser Nadeem. "A Robust Algorithm for Optic Disc Segmentation from Colored Fundus Images." In Image Analysis and Recognition, pp. 303-310. Springer International Publishing, 2014.

[16] Akram, M. Usman, and Shoab A. Khan. "Multilayered thresholding-based blood vessel segmentation for screening of diabetic retinopathy." Engineering with computers 29, no. 2 (2013): 165-173.

[17] Yu, H., Barriga, E. S., Agurto, C., Echegaray, S., Pattichis, M. S., Bauman, W., & Soliz, P. (2012). Fast localization and segmentation of optic disk in retinal images using directional matched filtering and level sets. *Information Technology in Biomedicine, IEEE Transactions on*, *16*(4), 644-657.

[18] Yu, Honggang, et al. "Fast localization and segmentation of optic disk in retinal images using directional matched filtering and level sets." Information Technology in Biomedicine, IEEE Transactions on 16.4 (2012): 644-657.

[19] Lalonde, Marc, Langis Gagnon, and Marie-Carole Boucher. "Non-recursive paired tracking for vessel extraction from retinal images." In Vision Interface, pp. 61-68. 2000.

[20] Aggarwal MK, Khare V. Automatic localization and contour detection of Optic disc. InSignal Processing and Communication (ICSC), 2015 International Conference on 2015 Mar 16 (pp. 406-409). IEEE.

[21] Popescu, Dan, Loretta Ichim, and Traian Caramihale. "Computer—Aided localization of the optic disc based on textural features." In Advanced Topics in Electrical Engineering (ATEE), 2015 9th International Symposium on, pp. 307-312. IEEE, 2015.

[22] Ichim, L., Popescu, D., & Cirneanu, S. (2015, November). Combining blood vessel segmentation and texture analysis to improve optic disc detection. In E-Health and Bioengineering Conference (EHB), 2015 (pp. 1-4). IEEE.

[23] Hoover, Adam, and Michael Goldbaum. "Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels." Medical Imaging, IEEE Transactions on 22.8 (2003): 951-958.

[24] Kauppi, T., Kalesnykiene, V., Kamarainen, J.-K., Lensu, L., Sorri, I., Raninen A., Voutilainen R., Uusitalo, H., Kälviäinen, H., Pietilä, J., DIARETDB1 diabetic retinopathy database and evaluation protocol, Technical report

[25] Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology (http://messidor.crihan.fr/index-en.php)

Author Biographies

Anum Abdul Salam is Lab Engineer in College of Electrical & Mechanical Engineering, National University of Sciences & Technology, Pakistan. She Holds a Master's degree in Computer Engineering with specialization in Signal and image processing from University of Engineering & Technology, Taxila Pakistan. Her research areas are image processing, medical image analysis and Machine learning.

Muhammad Usman Akram is Assistant Professor in college of Electrical & Mechanical Engineering, National University of Sciences & Technology, Pakistan. He Holds a PhD degree in Computer Engineering with specialization in medical image analysis from National University of Sciences and Technology, Islamabad Pakistan and is among the youngest PhDs in Pakistan. His research areas are image/signal processing, biometrics, medical image analysis and pattern recognition. He is a recipient of different national and international awards such as P@SHA 2014, APICTA 2014, P@SHA 2013, APICTA 2013, P@SHA 2012, APICTA 2012. His research areas are image/signal processing, biometrics, medical image analysis and pattern recognition.