IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 7, July 2016

Automatic Detection of True Retinal Area and Diagnosing Retinal Disease using SLO Images

Geetanjali Arjun Argade[1], Prof. N. A. Dawande[2]

ME Student, Dept of E & TC (VLSI & ES) Engg, D.Y. Patil College of Engineering, Savitribai Phule Pune University, Pune, Maharashtra, India[1]

Associate Professor, Dept of E & TC Engg, D.Y. Patil College of Engineering, Savitribai Phule Pune University, Pune, Maharashtra, India[2]

Abstract: Artificial Neural Network (ANN) classifier can be wont to detection of retinal diseases. Scanning laser ophthalmoscopes (SLOs) will be used for early detection of retinal diseases. It is a technique of examination of the attention. The advantage of using SLO is its wide field of read, which will image an oversized a part of the tissue layer for higher identification of the retinal diseases. On the other facet, during the imaging method, artefacts such as eyelashes and eyelids also are imaged together with the retinal area. This brings a big challenge on the way to exclude these artefacts. In proposed novel approach to mechanically extract out true retinal space from An SLO image based mostly on image process and machine learning approaches. The Simple Linear Iterative Clustering (SLIC) is that the rule utilized in super-pixel calculation. To decrease the unpredictability of image getting ready errands and provide an advantageous primitive picture style. To reduce the complexness of image process tasks and supply a convenient primitive image pattern, also to classified pixels into completely different regions based mostly on the regional size and compactness, known as super-pixels. The framework then calculates image based options reflective textural data and classifies between retinal space and artefacts. The experimental evaluation results have shown sensible performance with a high accuracy.

Keywords: Feature selection, retinal artefacts extraction, retinal image analysis, scanning laser ophthalmoscope (SLO) Superpixel Classification.

I. INTRODUCTION

Digital funds photography is a common method in ophthalmology and provides important diagnostic data of retinal pathologies, such as diabetic retinopathy (DR), glaucoma, age-related macular degeneration, and vascular abnormalities. The research community has place forth a nice effort towards the automation of a computer screening system able to promptly discover DR in fundus pictures. An algorithmic program ready to automatically assess the quality of the fundus image is a vital pre-processing step for reliable diseases detection for a computer-based screening system.

The two dimensional retinal scans produces from imaging equipment [e.g., fundus camera, scanning laser ophthalmoscope (SLO)] could contain structures alternative than the retinal area; collectively considered artefacts. Exclusion of artefacts is important as a pre-processing step before automatic detection of features of retinal diseases. In a retinal scan, extraneous unwanted objects such as the eyelashes, eyelids, and dust on optical surfaces may be appear bright and focussed. Therefore, automatic segmentation of these diseases from a pictured retina isn't a trivial task. Early detection and treatment of retinal eye lesion is vital to avoid preventable vision loss. Retinal disease identification techniques are primarily based on manual annotation. Optometrists and ophthalmologists typically trust on image operations like modification of contrast and distinction to interpret these images and diagnose results supported their own experience and domain knowledge. These diagnostic techniques are time consuming. Automatic analysis of retinal pictures has the potential to reduce the time, which clinicians want to check out the images, which will expect additional patients to be screened and more consistent diagnoses is given during a time efficient manner.

SLIC may be an easy linear iterative clustering algorithm in which it is used for superpixel segmentation. Thefunction is that it takes the middle purpose of the image thereto of the adjacent purpose and from that the typical value istaken and produces the simplest result from it.Compared to that of the (GS04, NC05, TP09,Q309) SLIC provides the equal segmentation in order that there is nowastage of pixel quality. The step by step method is enclosed within the method therefore there's clarity of pixel quality. Incombination with the SLIC rule ANN (Artificial Neural Network)is used. It is primarily a dataset or machine thatperforms input and output operation.

In this study, I have created a completely unique framework for the extraction of retinal space in SLO pictures. Thethree main steps for constructing my implemented system include:

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 7, July 2016

1) Determination of features that may be won't to distinguish between the retinal space and therefore the artefacts;
2) Selection of features which are most relevant to the classification of the retinal area;
3) Construction of the machine learning approach which might classify out the Retinal space from SLO pictures.
For differentiating between the true retinal area and the artefacts, we've determined totally different image-based features that reflect textural information at multiple resolutions. Then, selected the featuresamong the big feature set, which are relevant to the classification. The feature selection method improves theclassifier performance in terms of process time.

II. LITERATURE SURVEY

The strategies for detection and segmentation of eyelids and eyelashes applied on pictures of the front of the eye that contains the pupil, eyelids, and eyelashes. On such a picture, the eyelashes are typically within the kind of lines or bunch of lines grouped along. Therefore, the primary step of detection them was the applying of edge detection techniques like Sobel, Prewitt, Canny, Hough transform [1], and wavelet transform [2]. The eyelashes on the iris were then removed by applying nonlinear filtering on the suspected eyelash areas [3]. Since eyelashes will be in either divisible kind or within the kind of multiple eyelashes classified together, Gaussian filter and Variance filter were applied so as to differentiate among each kinds of eyelashes [4]. The experiment showed that divisible types of eyelashes were most likely detecting by applying Gaussian filter, whereas Variance filters are a lot of preferred for multiple eyelash segmentation [5]. Initially, the eyelash candidates were localized using active shape modeling, and then, eight-directional filter bank was applying on the possible eyelash candidates. In [6] used focus score so as to vary the size of convolution kernels for eyelash detection. The size variation of the convolution kernels additionally differentiated between divisible eyelashes and multiple eyelashes. In [7] determined the features supported intensity and native normal variation so as to determine eyelashes. They were thresholded using Otsu's technique, which is an automatic threshold selection technique supported explicit assumptions regarding intensity distribution. All of those ways are applied on CASIA information [8], which is internet information of Iris pictures. In an image obtained from SLO, the eyelashes show as either dark or bright region compared to true retinal area depending upon however laser beam is concentrated because it passes the eyelashes. The eyelids show as reflectivity region with bigger reflectivity response compared to retinal space. Therefore, ought to determine features, which may differentiate among true retinal area and the artefacts in SLO retinal scans. Once visual observation in Fig. 1(b), the features reflective the textural and structural distinction could have been the recommended alternative. These features have been calculated for various regions in fundus pictures, mostly for quality of analysis. The characterization of retinal pictures were performed in terms of image features like intensity, skewness, textural analysis, histogram analysis, sharpness, etc. [9], [10]. In [11] determined four totally different classifiers using four kinds of options. They were analysed for the retinal area as well as colour, focus, contrast, and illumination. The outputs of those classifiers were concatenated for quality classification. For classification, the classifiers like partial least square (PLS) [12] and support vector machines (SVMs) [13] were used. PLS selects the foremost relevant features needed for classification. apart from calculating image features for whole image, grid analysis containing little patches of the image has additionally been planned for reducing computational complexity [9]. For determinative image quality, the features of region of interest of anatomical structures like optic nerve head (ONH) and fovea have additionally been analysed [14].
The features included structural similarity index, area, and visual descriptor etc. some of the higher than mentioned techniques recommend the use of grid analysis, which may be a time effective technique to generate features of particular region instead of every pixel. However grid analysis may not be a correct way to represent irregular regions within the image. Therefore, to make a decision the use of superpixels [15]–[18], that group pixels into totally different regions relying upon their regional size and compactness.
Implemented technique is based on analysing the SLO image-based features, that are calculated for a little region within the retinal image referred to as superpixels. The determination of feature vector for every superpixel is computationally efficient as compared to feature vector determination for every pixel. The superpixels from the images in the training set are assigned theclass/the category of either retinal area or artefacts depending upon the majority of pixels within the superpixel belonging to the particular class of image. The classification is performed when ranking and selection of features in terms of effectiveness in classification.

III. METHODOLOGY

To perform superpixel classification from scanning laser ophthalmoscope images by using simple linear iterative clustering methods. Also calculate the features of each image by using gray level co-occurrence method. After this process by using artificial neural network to classify the true retinal area and finding input image is normal (Healthy) or abnormal (Diabetic).
This block diagram is consisting of different modules they are feature extraction contains image pre-processing, superpixel generation, feature generation, feature selection, machine learning approach i.e. ANN classifier, create model, superpixel Classification, image post processing and automatic annotation. Features are then extracted from every image. Also this block diagram shows the three stages such as training stage, testing and evaluation stage, deployment stage. The training stage is

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 7, July 2016

involved with building of classification model supported training images and also the annotations reflective the boundary around retinal space. In the testing and evaluation stages, the automatic annotations are performed on the test set of pictures and also the learning machine approach performance is evaluated against the manual annotations for the determination of maximum accuracy. Finally, the deployment step produces the automatic extraction of retinal space. Textural information features are extracted for classification of retinal image and artefacts at multiple resolutions. In implemented system to use GLCM feature extractor for texture feature extraction. Then use ANN (artificial neural network) for classification.

The block diagram of implemented system is as shown in figure 1 below.

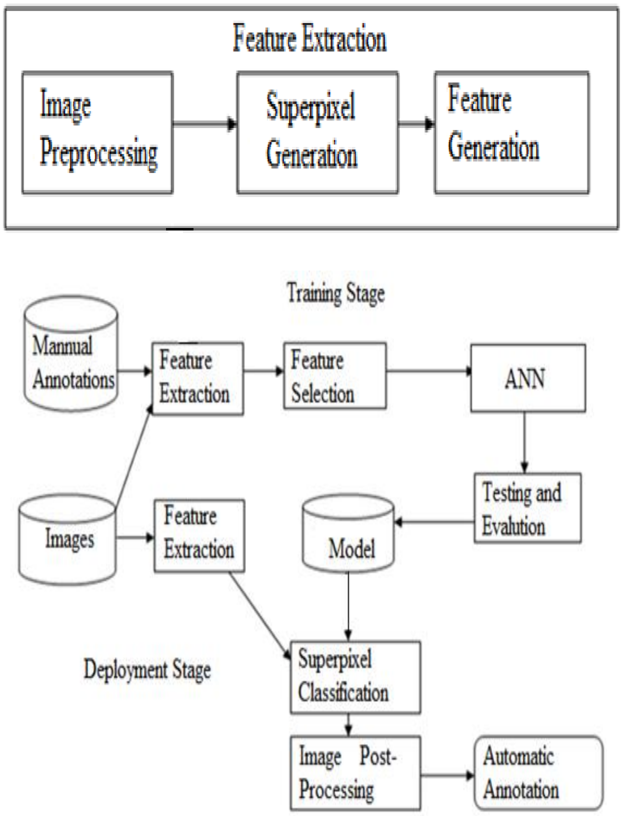

Fig.1 Block diagram of implemented system

1) Image Data Integration: It includes the integration of image information with their manual annotations around true retinal space.
2) Image Pre-processing: Images are then pre-processed in order to bring the intensity values of every image into a selected range.
3) Generation of Super-pixels: The training images after pre-processing are described by tiny regions known as super-pixels. The generation of the feature vector for each super-pixel makes the method computationally efficient as compared to feature vector generation for every pixel.

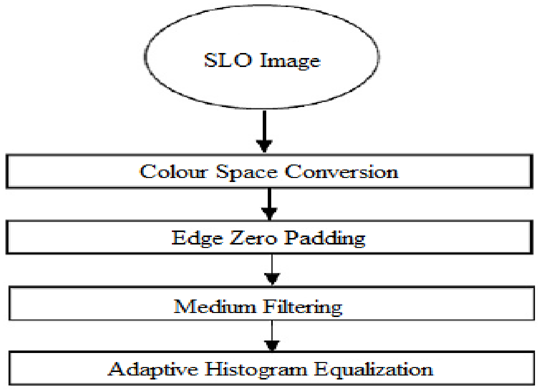

Fig.2 Image pre-processing steps

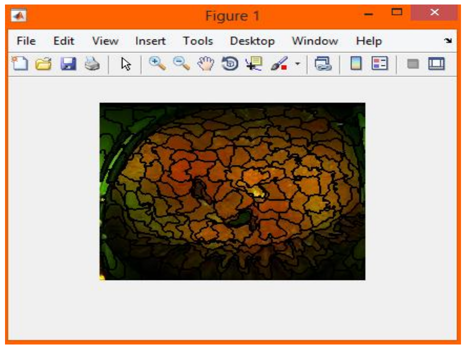

Fig.3 super pixel Classification for input image

4) Feature Generation: Generate image-based features that are used to distinguish between the retinal area and also the artefacts. The image-based features replicate textural information and they were calculated for every super-pixel of the image present within the training set. In testing stage, only those features can be generated that are selected by feature selection method. Gray level co-occurrence method is used for finding the texture feature. GLCM finding different feature like Autocorrelation, Cluster Shade,Cluster Prominence, Contrast, Correlation, Difference Entropy,Dissimilarity, Energy, Entropy, Homogeneity,Information Measures 1, Sum average, Sum Entropy, Sum of Squares: Variance, Sum of Variance, Maximum Probability. In this features Area Under the Curve is above 0.9 of feature value is selected.
5) Feature Selection: Due to a more number of features, the feature array needs to be reduced before classifier construction. This involves features choice of the most vital features for classification. For feature selection sequential forward selection approach is selected.
6) Classifier Construction: In conjugation with manual annotations, the selected features are then accustomed construct the binary classifier. The result of such a classifier is the super-pixel representing either the true retinal area or the artefacts. This processis done by using ANN classifier. Itgives more accurate accuracy as compare to other classifier such as SVM and kNN.
7) Image Post processing: Image post processing is performed by morphological filtering thus as to confirm the retinal space boundary using super-pixels classified by the classification model.

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 7, July 2016

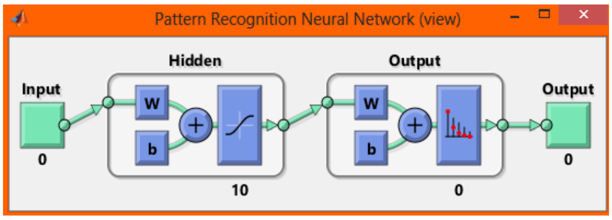

Fig.4 Artificial Neural Network

Flowchart of the implemented system as below,

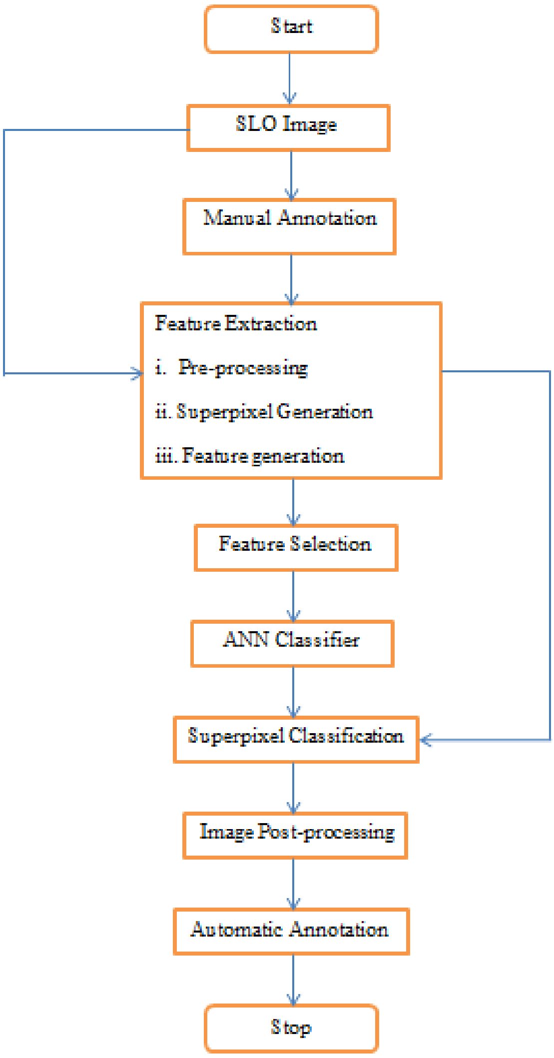

Fig.5 Flowchart for proposed system

As shown in flowchart initially take SLO images from database, and then find out free hand sketch by using manual annotation in Matlab software. Feature extraction includes three steps like image pre-processing, superpixel generation and feature generation. After this select feature by using sequential forward selection approach. Design ANN classifier and create model. After construction of classifier to classify superpixel. In post processing and automatic annotation gives output as true retinal area and input image is healthy or diabetic. It is more beneficial with clinician to find out which type of disease.

IV. RESULT AND DISCUSSION

Super-pixel classification results and final output after post-processing of different examples of healthy and diseased retinal images. ANN classifier is able to achieve the average accuracy nearer to that of other two classifiers, while saving significant computational time when processing maximum number of images for automatic annotations.

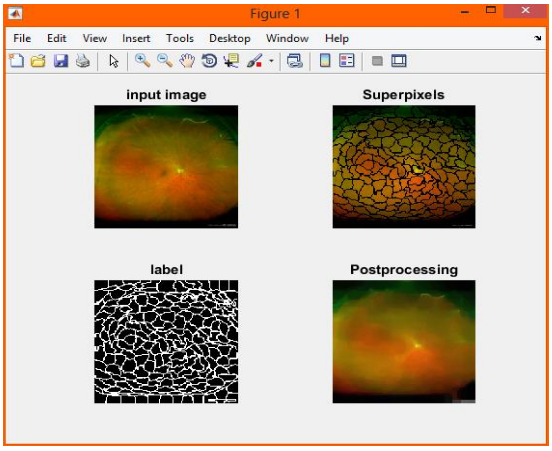

Fig.6 Input image, Super pixel of input image and Post processing of image

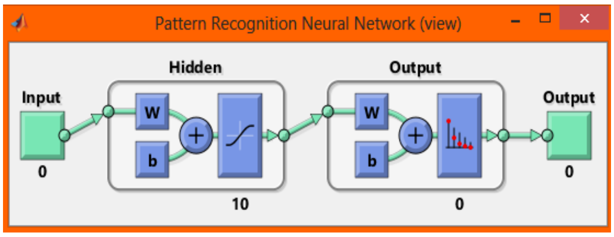

Fig.7 Pattern recognition of ANN

Consider example of healthy scanning laser ophthalmoscope images with different outputs like input image, segmentation or divide image into number of pixel called as super-pixel, also give the labelling of the super-pixel image, neural network pattern recognition, training for ANN classifier, true retinal area, graph for ROC, then classify input image is healthy or diabetic.

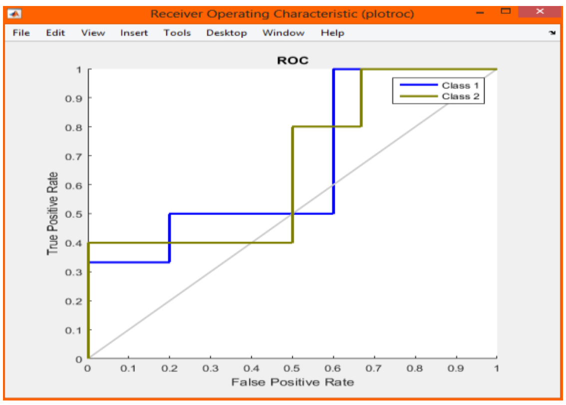

Fig.8 ROC graph of input image

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 7, July 2016

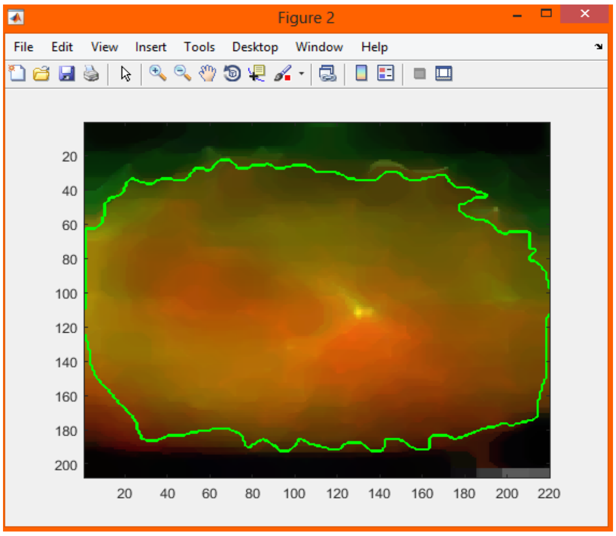

Fig.9 True retinal area for input image

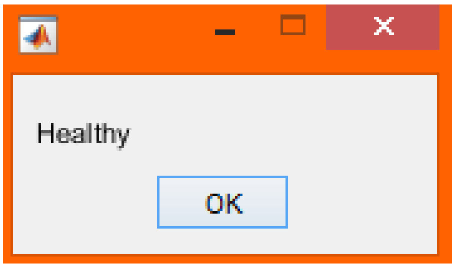

Fig.10 Healthy image

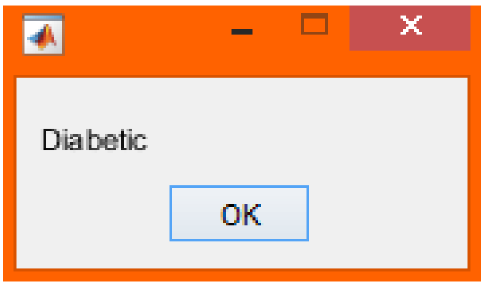

Fig.11 Diabetic Image

Fig.12 Overall output of system for abnormal image with Graphical User Interface

V. CONCLUSION AND FUTURE SCOPE

Differentiate between true retinal space from artefacts in SLO images is a difficult task, which is also the primary necessary step towards computer-aided disease diagnosis. In this work, proposed image primarily based feature set for automatic detection of retinal area in SLO images. Superpixels used to represent different irregular regions in a compact approach and reduce the computing price. A classifier has been built primarily based on chosen features to extract out true retinal area. The experimental evaluation result shows that image primarily based options proposed methodology achieves a high accuracy in segmentation of retinal area from SLO image. Since most artefacts detection methods have been applied previously to the fundus images, proposed method serves as a primary step towards the process of ultra- wide field SLO images. Moreover, a complete retinal scan is feasible if the retina is imaged from different angles using an ultra-wide field SLO and then montaging the resulting image. Montaging can be potential only if the artefacts are removed before.Future work is to reduce the computational time and using best algorithm. Also increase accuracy for the system to find out the better machine learning approach. Future scope is it can be applied to categorize the disease of diabetic retinopathy. In future work, conduct more images tests with this project algorithm. Also, enhance iris recognition accuracy by interpolating the detected eyelash area and not excluding them. Robust algorithm is important for future development. Future work will explore the integration of other factors to improve diagnostic outcomes towards a more reliable and efficient glaucoma screening system. In the future, the application of various combinations of GLCM features on the CLCM principle and also classification for specific applications will be researched. In the future, the reflection of unwanted signal can be removed before detecting eyelid boundaries using the live-wire technique which likely to be affected by such noise. This would increase the segmentation accuracy. Future prospects are alerting and preventive actions, such as a large scale screening of high-risk individuals, are required. Future work is to improve the current image capturing process and support the development of new applied imaging technologies, such as spectral imaging of the eye fundus.

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, Eds., Digital Image Processing, 3rd ed. Englewood Cliffs, NJ, USA: Prentice-Hall, 2006.

[2] M. J. Aligholizadeh, S. Javadi, R. S. Nadooshan, and K. Kangarloo, "Eyelid and eyelash segmentation based on wavelet transform for iris recognition," in Proc. 4th Int. Congr. Image Signal Process., 2011, pp. 1231–1235.

[3] D. Zhang, D. Monro, and S. Rakshit, "Eyelash removal method for human iris recognition," in Proc. IEEE Int. Conf. Image Process., 2006, pp. 285–288.

[4] A. V. Mire and B. L. Dhote, "Iris recognition system with accurate eyelash segmentation and improved FAR, FRR using textural and

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 7, July 2016

topological features," Int. J. Comput. Appl., vol. 7, pp. 0975–8887, 2010.

[5] Y.-H. Li, M. Savvides, and T. Chen, "Investigating useful and distinguishing features around the eyelash region," in Proc. 37th IEEE Workshop Appl. Imag. Pattern Recog., 2008, pp. 1–6.

[6] B. J. Kang and K. R. Park, "A robust eyelash detection based on iris focus assessment," Pattern Recog. Lett., vol. 28, pp. 1630–1639, 2007.

[7] T. H. Min and R. H. Park, "Eyelid and eyelash detection method in the normalized iris image using the parabolic Hough model and Otsu's thresholding method," Pattern Recog. Lett., vol. 30, pp. 1138–1143, 2009.

[8] Iris database. (2005). [Online]. Available: http://www.cbsr.ia.ac.cn/IrisDatabase.htm

[9] H. Davis, S. Russell, E. Barriga, M. Abramoff, and P. Soliz, "Vision-based, real-time retinal image quality assessment," in Proc. 22nd IEEE Int. Symp. Comput.-Based Med. Syst., 2009, pp. 1–6.

[10] H. Yu, C. Agurto, S. Barriga, S. C. Nemeth, P. Soliz, and G. Zamora, "Automated image quality evaluation of retinal fundus photographs in diabetic retinopathy screening," in Proc. IEEE Southwest Symp. Image Anal. Interpretation, 2012, pp. 125–128.

[11] J. A. M. P. Dias, C. M. Oliveira, and L. A. d. S. Cruz, "Retinal image quality assessment using generic image quality indicators," Inf. Fusion, vol. 13, pp. 1–18, 2012.

[12] M. Barker and W. Rayens, "Partial least squares for discrimination," J. Chemom., vol. 17, pp. 166–173, 2003.

[13] J. Paulus, J.Meier, R. Bock, J. Hornegger, and G.Michelson, "Automated quality assessment of retinal fundus photos," Int. J. Comput.Assisted Radiol.Surg., vol. 5, pp. 557–564, 2010.

[14] R. Pires, H. Jelinek, J.Wainer, and A. Rocha, "Retinal image quality analysis for automatic diabetic retinopathy detection," in Proc. 25th SIBGRAPI Conf. Graph., Patterns Images, 2012, pp. 229–236.

[15] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk, "Slic superpixels compared to state-of-the-art superpixel methods," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 11, pp. 2274–2282, Nov. 2012.

[16] A. Moore, S. Prince, J.Warrell, U. Mohammed, and G. Jones, "Superpixel lattices," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2008, pp. 1–8.

[17] O. Veksler, Y. Boykov, and P. Mehrani, "Superpixels and supervoxels in an energy optimization framework," in Proc. 11th Eur. Conf. Comput. Vis., 2010, pp. 211–224.

[18] L. Vincent and P. Soille, "Watersheds in digital spaces: An efficient algorithm based on immersion simulations," IEEE Trans. Pattern Anal. Mach. Learning, vol. 13, no. 6, pp. 583–598, Jun. 1991.

[19] Muhammad Salman Haleem, Liangxiu Han, Jano van Hemert, Baihua Li, and Alan Fleming, Retinal Area Detector From Scanning Laser Ophthalmoscope (SLO) Images for Diagnosing Retinal Diseases, IEEE Journal Of Biomedical And Health Informatics, Vol. 19, No. 4, July 2015

[20] Optos. (2014). [Online]. Available: www.optos.com