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SUPER-PIXEL BASED AUTOMATIC DIAGNOSIS OF RETINAL DISEASES USING ANN.

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ABSTRACT

In the computer-aided disease diagnosis the first important step is to distinguish the true retinal area from artefacts in SLO images and it is a more challenging task. Retinal diseases are fatal and if not detected and treated during the early stages itself then it results in the loss of eyesight. The purpose of retina is to receive the light from focused lens then convert it into neural signals, and send these signals to the brain, and the brain decide what the picture is. Hence the retina plays important role in visual recognition. If there is damage to the retina it causes permanent blindness. So we find out whether a retina is healthy or not for the detection of retinal diseases. Scanning Laser Ophthalmoscope (SLO) is used for capturing retinal images but in this imaging technique artifacts are also imaged with retinal area. It brings the big challenge that how to exclude these artifacts such as eyelids and eyelashes. In this paper we focuses on automatically extract out true retinal area from an SLO images and further we classify the retinal diseases based on machine learning approaches using ANN classifier.

Keywords: Feature selection, Retinal artifacts extraction, Retinal Disorders, Retinal image analysis, Scanning Laser Ophthalmoscope (SLO).

I. INTRODUCTION

In the early treatments of retinal eye diseases it is important to avoid the vision loss. Hence researchers focus is always on correctly segment artifacts from the retinal area. In the retinal area detection there are unessential objects involved like eyelids, eyelashes of an eye and dust on optical surface of camera. This is we called as EED are appear in focus. So, Automatic segmentation of these artifacts from a retinal area is an important as well critical task. If EED locating retina is not excluded properly by artifacts, then it will increase the danger of faulty acceptance and faulty recognition. Until now identification of retinal diseases is based on manual observations technique. In which patient's eye are captured using fundus camera or scanning laser ophthalmoscope (SLO). Optometrists and ophthalmologists use the image operations such as change of contrast and zooming to clarify these images and diagnose results based on their own experience and domain knowledge. Hence it is necessary to automatically extract out artifacts from true retinal area. Automated analysis of retinal images reduce the time of clinicians for looking at every image and diagnose it which can expect more patients

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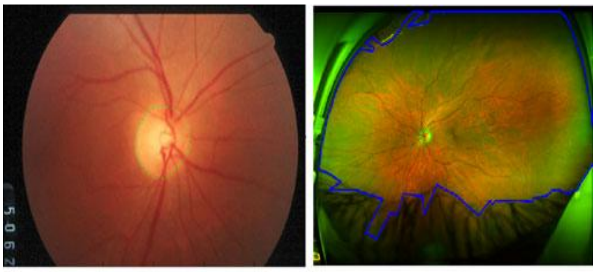
to be screened out and more accurate diagnoses can be given in less time. The purpose of this paper is to develop a method that can exclude artifacts from retinal images so as to improve automatic detection of disease features from the retinal scans. Hence this paper constructed a novel framework for the extraction of retinal area in SLO images which contains three main parts-

1) Determination of the features which can be distinguishes retinal area from artifacts;

2) Selection of features which are most suitable to the classification;

3) Construction of the classifier for classifying the different retinal diseases.

Different imaging features such as structural, textural, grey level information at various resolutions is used to differentiate the retinal area and the artefacts. Finally, we have constructed the classifier for selecting between the true retina and diseased retina.



(a) (b)

Fig.1 Example of (a) A fundus image and (b) An SLO image annotated with true retinal area.

II. RELATED WORKS

2.1 LITERATURE SURVEY:

There are several image based features which have been represent different retinal structures in fundus images such as color, illumination, intensity, skewness ,texture, histogram, sharpness etc.

A. Super-pixel Classification Based Optic Disc and Optic Cup Segmentation for Glaucoma Screening, J. Cheng, J. Liu, Y. Xu, F. Yin, D. Wong, [2] presented super-pixel classification based methods for optic disc and cup segmentations for glaucoma screening. It has been demonstrated that CSS is beneficial for both disc and cup segmentation. One limitation of the proposed cup segmentation is that the trained classifier is slightly dominated by cups with medium sizes, so the proposed method underestimates the very large cups, while overestimating the very small cups when pallor is not obvious. Poposed segmentation methods have been estimated in a database of 650 images with optic disc and optic cup boundaries manually marked by trained professionals. Experimental results show an average overlapping error of 9.5% in optic disc and 24.1% in optic cup segmentation. The results also show an increase in overlapping error as the reliability score is reduced, which justifies the effectiveness of the self-assessment.

B. Retinal Fundus Image Analysis for Diagnosis of Glaucoma, M. Caroline Viola Stella Mary, Elijah Blessing Rajsingh, Ganesh R. Naik, [8] proposed the retinal images provide vital information about the true sensory part of the visual system. Retinal disorders like glaucoma, diabetic retinopathy, age related macular degeneration, retinopathy of prematurity that can lead to blindness as artifacts in the retinal image. An automated system can be used for offering standardized large-scale screening at a low cost which may reduce human errors, provide services to remote areas, as well as free from observer bias and fatigue.

Treatment of retinal diseases are available; the challenge lies in finding a cost effective approach with high sensitivity and specificity that can be used to huge population in a timely manner to identify those who are at risk in the early stages of the disease.

C. Automated image quality evaluation of retinal fundus photographs in diabetic retinopathy screening, H. Yu, C. Agurto, S. Barriga, S. C. Nemeth, P. Soliz, and G. Zamora [7] presents a system that can automatically determine whether the quality of a retinal image is adequate for computer-based diabetic retinopathy (DR) screening. The system integrates global histogram features, textural features, vessel density and local non-reference perceptual sharpness metric. A partial least square (PLS) classifier is trained to differentiate low quality images from normal quality images.

D. Splat feature classification with application to retinal hemorrhage detection in fundus images, Li Tang, Meindert Niemeijer, Joseph M. Reinhardt [3] presents a splat-based feature classification algorithm with application to large, irregular hemorrhage detection in fundus photographs. One of the limitations of the current study is that our reference standard was based on that of a single expert, reviewing only part of the dataset.With annotations from additional human experts, it would be possible to compare the variability of experts in interpreting the same set of images in terms of clinical relevance when given the same task description and to get a better
definition of the reference standard.

2.2 PROPOSED SYSTEM

Proposed system is based on analyzing the SLO image-based features, which are calculated for a small region in the retinal image called super-pixels. The feature vector determined for each super-pixel is computationally efficient as compared to feature vector determination for each pixel. The super-pixels from the images in the training set are assigned the class of either retinal area or artifacts based on the majority of pixels in the super-pixel belonging to the specific class. The classification is done after ranking and selection of features in terms of effectiveness in classification.

III. SYSTEM FRAMEWORK

The block diagram of the retinal area detector framework is shown in Fig.2. The framework contains three stages, namely training stage, testing and evaluation stage, and deployment stage. In the training stage it build the classification model based on training images and showing the boundary around the retinal area. In the testing and evaluation stages, Neural Network is used for training and testing of pre-processed images. Carefully select the database of color retinal images at different stages. In the deployment stage performs the automatic extraction of the retinal area from artifacts. Finally it diagnosis the retinal disorders from the input images by comparing it with the database images. System framework is briefly explained as follows:

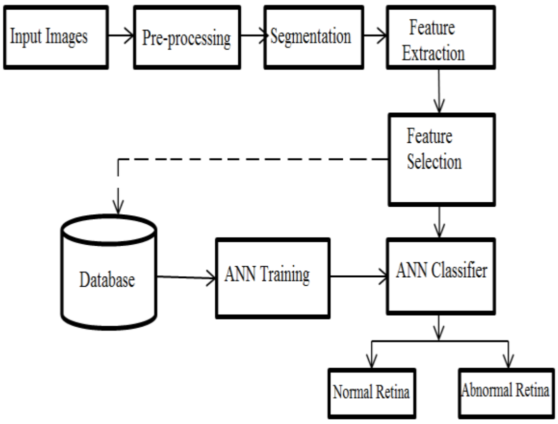


Fig. 2 Block diagram of retina detector framework

Image Data Integration: Data integration involves the combining or merging of data from multiple sources in an effort to extract better and more information It includes the integration of image data with their manual annotations around true retinal area.

Image Preprocessing: After data integration images are preprocessed to bring the intensity values of each image into a specific range. Image pre-processing is equivalent to the mathematical normalization of a data set.

Generation of Super-pixels: The training images after preprocessing are divided into small regions called super-pixels. The generation of the feature vector for each super-pixel makes the process computationally capable and it should be fast to compute, memory efficient, and simple to use.

Feature Generation: We generate image-based features which are used to differentiate between the retinal area and the artefacts. The image-based features like textural, gray scale, or regional information and they were calculated for each super-pixel of the image available in the training set. In testing stage, only those features are generated which are selected by feature selection process.

Feature Selection: Because of a large number of features, the feature array needs to be minimized before classifier construction. This involves features selection of the most important features used for classification.

Classifier Construction: In association with manual annotations, the selected features are then used to construct the binary classifier. The output of such a classifier is the super-pixel representing either the true retinal area or the artifacts.

Image Post-processing: Image post-processing is performed by morphological filtering to determine the retinal area boundary using super-pixels which are classified by the classification model.

IV. METHODOLOGY

4.1 Image acquisition:

The image acquisition is the first stage of any vision system, which is the process of capturing raw image data. The retinal image is captured using fundus camera from a specific distance. When an eye is properly stable then, the retinal image can be taken from this camera. In our case, Iris images were not captured using a camera. Instead, already available eye images were used. Images were taken from different individuals. Later, the images were converted to a gray scale image if it is a color image.

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4.2 Image Pre-processing:

The captured image may have some amount of noise factors. These factors may affect the speed and accuracy in retinal area detection process. Due to the presence of these noise factors, the performance of retinal recognition system gets affected. So, these noise factors must be removed in order to detect the retinal part. Preprocessing step helps to bring the intensity values to the particular range. It includes scaling, thresholding, histogram equalization etc.

4.3 Image segmentation:

Image segmentation is the process of partitioning a retinal image into multiple segments called super-pixels. The purpose of segmentation is to simplify and change the representation of an image which is more meaningful and easy to analyse. Image segmentation is typically used to locate objects and boundaries in images. Simply, image segmentation is the process of assigning a label to every pixel in an image such that pixels with same characteristics gives same label. The result of image segmentation is a set of segments or called super-pixels that collectively cover the entire image, or a set of contours extracted from the image. The pixels with similar characteristic, such as colour , intensity, or texture are in one region. Adjacent regions are significantly different with respect to the some characteristic.

4.4 Generation of Super-pixels:

The super-pixel algorithm groups pixels into different regions, which can be used to calculate image features to reduce the complexity of resulting image processing tasks. Super-pixels capture image redundancy and provide a convenient primitive image pattern. As far as fundus retinal images are concerned, the super-pixels have been generated for analyzing anatomical structures and retinal hemorrhage detection. For retinal hemorrhage detection, the super-pixels were generated using watershed approach but the number of super-pixels generated in our case need to be controlled. The watershed approach sometimes generates number of super-pixels of the artifacts more than desired. The super-pixel generation method used in our retina detector framework is simple linear iterative clustering which was shown to be efficient in terms of computational time, as well as in terms of region of compactness and adherence. The algorithm is initialized by defining number of super-pixels to be generated.

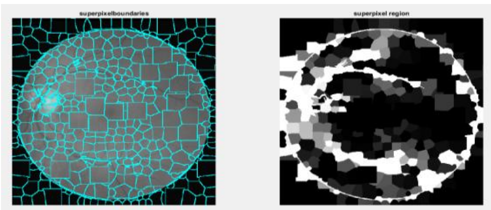


Fig.3 Super-pixel generation.

a) Super-pixel boundaries, b) Super-pixel region.

4.5 Feature Generation

After the generation of super-pixels, the next step is to determine their features. Our purpose is to differentiate between the retinal area and artefacts. Hence we can use textural, regional based, and grayscale gradient features. Textural and gradient based features are calculated from red and green channels on different Gaussian blurring scales, also known as smoothing scales. In SLO images, no feature was calculated for the blue channel because blue channel is set to zero. The regional features are determined for the image irrespective of the color channel. Out of these features texture features gives good results hence we use textural feature generation method in this paper.

Textural Features: Texture can be analyzed using Haralick features by gray level co-occurrence matrix (GLCM) analysis. Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines the fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. The Gray Level Co-occurrence Matrix (GLCM) is second order statistical texture features extracting method. GLCM determines how often a pixel of a gray scale value *i* occurs adjacent to a pixel of the value *j*. Four angles for observing the pixel adjacency are used, i.e., $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$, These directions are shown in Fig. 3(a). GLCM also needs an offset value **D**, which defines pixel adjacency by certain distance.

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, one with intensity 'i' and the other with intensity 'j' are separated by a pixel distance (Δx, Δy) respectively, occur within a given neighborhood. The GLCM's are very sensitive to the size of the texture samples on which they are predicted. Thus the number of gray levels is often reduced. The mean value in each direction was taken for each Haralick feature and they were calculated from both red and green channels.

1	$Energy = \sum\sum P^2(i,j)$
2	$Entropy = \sum\sum (i,j)\ \log[P(i,j)]$
3	$Variance = \sum_i \sum_j (i-\mu)^2 g_{ij}$
4	$Homogeneity = \sum_i \sum_j \frac{1}{1+(i-j)^2} g_{ij}$
5	$Correlation = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y}$
6	$Mean = \sum\sum i\ P(i)$
7	$SumAverage = \sum_{i=2}^{2Ng} i g_{x+y}(i)$
8	$SumEntropy = -\sum_{i=2}^{2Ng} g_{x+y}(i) \log\{g_{x+y}(i)\}$
9	$SumVariance = \sum_{i=2}^{2Ng} (i - SumAverage)^2 g_{x+y}(i)$
10	$Difference Variance = \mathrm{var}\,ianceof\ (g_{x-y}(i))$
11	$Difference Entropy = -\sum_{i=0}^{2Ng-1} g_{x-y}(i) \log\{g_{x-y}(i)\}$

Table.1 GLCM features.

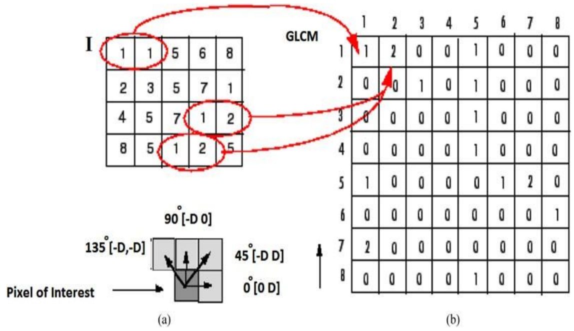


Fig.4 a) GLCM directions. b) Process of creating GLCM using the image I.

4.6 Feature extraction:

After applying preprocessing techniques like histogram equalization we obtain a better contrast image. The image-based features are distinguished from the true retinal area and the artifacts. The image-based features reflect gray scale, textural, and regional information and pattern analysis. In our case, we are using Kirch's Kernel for feature extraction. Kirsch templates are of size 3x3 used for the extraction of blood vessels from retinal image. Generally the output of edge detection through Kirsch template is to produce an image containing gray level pixels of value 0 or 255. The zero value of pixel indicates a black pixel and the value 255 indicates a white pixel. Edge detection of an image is checked by determining the brightness level of the target pixel and its neighboring pixels. If there is no large difference in the brightness levels, then there is no possibility of edge in that image. This edge detection procedure is most commonly used and fundamental approach among all the edge detection algorithms such as, Prewitt, Sobel etc. The Kirsch's edge detection algorithm uses a single mask of size 3x3 and rotates it in 45 degree increments through all 8 compass directions. Hence it gives better results than other operators like Prewitt, Sobel etc. which moves only in horizontal and vertical directions.

For each image in the database fundus mask was detected, that helps the detection of vessel pixels within the region of interest. One of the colored input retinal image is shown in fig.5(a), all retinal images converted into grey scaled images as shown in fig5(b). After that all grey scaled images processed by kirsch's templates and it extracts blood vessels through edge detection technique as shown in fig. 5(c).

Fig. 5 (a) Input Color retinal image.

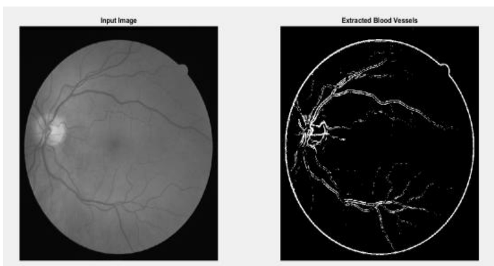


Fig.5 (a) Gray retinal image, (b) Extracted blood vessels from retinal image.

4.7 Feature Selection:

Feature selection techniques are used for following purposes : determination of the features which are most relevant to the classification ,simplification of models to make them easier to interpret by user, reducing execution and training times, to avoid the curse of dimensionality ,enhanced generalization by reducing over-fitting. Feature extraction creates new features from functions of the original features, whereas feature selection returns a subset of the features. A feature selection algorithm is the combination of a search technique for proposing new feature subsets, along with an evaluation measure which results the different feature subsets. The simplest algorithm is to test each possible subset of features to find the one which minimizes the error rate. The evaluation metric is used to choose the algorithm, and distinguish it between the three types of feature selection algorithms i.e. wrappers method, filter method and embedded methods.

4.8 Classifier Construction:

The classifier is constructed to determine the different classes in input image. In this it is a two class problem: true retinal area and artifacts. We have used PCA & ANN classifier and check the results for it.

Principal Component Analysis: Principal Component Analysis (PCA) is an unsupervised dimensionality reduction method. Depending on the field of application, PCA is also called as discrete Karhunen–Loève transform (KLT), the Hotelling transform, proper orthogonal decomposition (POD), singular value decomposition (SVD) and empirical orthogonal function (EOF). PCA explore to reduce the dimension of the data by finding a few orthogonal linear combinations of the original variables with the largest variance. As per the number of the original variables there are as many principal components. The first several PCs explain most of the variance, so that neglect the rest can be with minimal loss of information, for many datasets. In PCA transformation first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. To reduce the dimensionality of the huge data along with retaining as much information as possible in the original dataset, PCA is used.

Drawbacks:

(1) Poor discriminatory power
(2) High computational load
(3) The covariance matrix is difficult to be evaluated in an accurate manner
(4) The simplest invariance is not captured by the PCA unless the training data explicitly provides this information.

Artificial Neural Network:

The ANN is the classification algorithm which is inspired by the human brain. It is composed of many interconnected units called as neurons. ANN takes training samples as input and determines the model that best fits to the training samples. There are three basic layers of ANN, i.e. input layer, hidden layer and output layer. The advantage of using ANN is its high computational efficiency in terms of testing time. Although the training time of ANN is longer as compared to the other classifiers but the training time is once in a lifetime process and once the model is deployed, it can process any image. Hence ANN is able to save the significant computational time when processing millions of images for automatic annotations. The principle advantage of ANN is to generalize, adapting to signal distortion and noise without the loss of robustness. The squared error between an input and the output is generally minimized by the network of the class to which the input pattern belongs. This property of ANN enables us to classify an unknown input pattern. The unknown pattern is fed to all the networks and is classified to the class with minimum squared error.

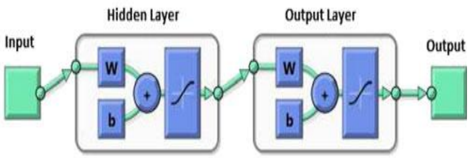


Fig.6 AANs diagram.

4.9 Image Post-processing:

After classification of the test image, the super-pixels are refined using morphological operation so as to remove misclassified isolated super-pixels. The morphological closing operation was performed so as to remove small gaps among super-pixels. The size of disk structuring element can be a smaller value. For better results, we can perform area opening operation so as to remove one or two misclassified isolated super-pixels.

V. EXPERIMENTAL EVALUATION

The main purpose of determining the feature set is to determine retinal boundary which include large part of retinal area and keep the artifacts out of boundary. Therefore we construct ANN classifier which takes training samples as an input and determine the model which best fits the training samples using linear regression. The images for training and testing have been obtained from Optos and are acquired using their ultra-wide field of SLO. The device captures the retinal image, through a small pupil of 2 mm. These retinal images has two channels: red and green. The green channel with wavelength:532 nm provides information about the sensory retina to retinal pigment epithelium, whereas the red channel of wavelengh:633 nm shows deeper structures of the retina toward the choroid. Each image has a dimension of 3900 × 3072 and each pixel is represented by 8-bit on both red and green channels. The dataset is composed of true retina and diseased retinal images. The system has been trained with 100 images and tested against 60 images. For training purpose retinal area was applied after super-pixel generation. We compare the performance of different classifiers across different feature sets. As far as classification accuracy is concerned, the outputs of different classifiers are slightly different. The advantage of using ANN is its high computational efficiency in terms of testing time Although the training time of ANN is longer compared to its other classifiers, the training time is once in a lifetime process and once the model is deployed, it can process any image. ANN gives higher accuracy than that of other classifiers, also it saves significant computational time when processing number of images for automatic annotations.

VI. RESULTS & DISCUSSION

Digital retinal imaging playing an important role in the diagnosis and treatment of eye diseases and the extraction of clinically useful information has become vital task. In this paper the dataset of 100 retinal images is used to evaluate the method. Images that suffered from non-uniform illumination and poor contrast were subjected to preprocessing, before subjected to segmentation. In preprocessing stage we convert color retinal image into grey-scale retinal image as shown in fig. 7a).After pre-processing step, there is segmentation of blood vessels from color retinal images shown in fig.7b) and generation of super-pixel shown in fig.7c). In feature selection we use texture based features because it gives good results for that purpose we use GLCM in this paper. Finally for classification between true retina and retina with disorders we construct ANN classifier because it gives high accuracy and less computational time as compared to other classifiers. Figure 7d) gives the final result of the system in that retinal detachment disease is detected for given retinal image.

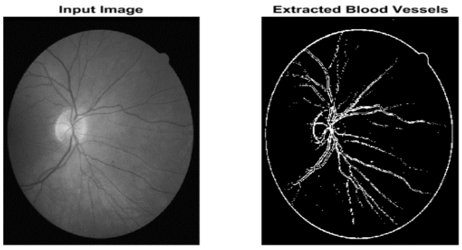
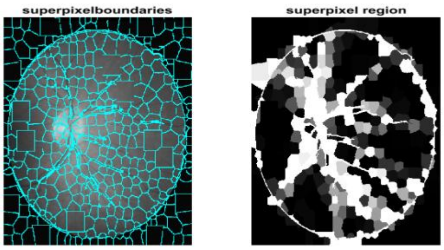


Fig.7 (a) Gray retinal image, (b) Extracted blood vessels from retinal image.



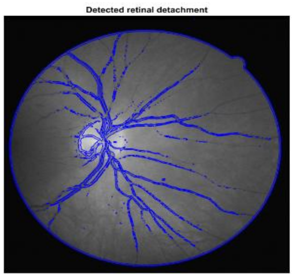


Fig.7 c) Super-pixel generation.   Fig.7 d) Diseased retina detected retinal detachment.

VII. CONCLUSION

This paper focuses on survey of techniques for distinguishing true retinal area from artifacts in the SLO or fundus images. It is a challenging task, which is also the first important step towards computer-aided disease diagnosis. Paper present super-pixels to represent different irregular regions in a compact way and reduce the computing cost. ANN classifier has been built based on selected features to extract out true retinal area. Ann is compatible while saving the computational time than other classifiers. After distinguishing true retinal area from artifacts ,classifier classify the various disorders in retina like Age Related Macular Degeneration (ARMD), diabetic retinopathy, retinal detachment etc.

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