

(A High Impact Factor, Monthly, Peer Reviewed Journal) Website: <u>www.ijircce.com</u> Vol. 6, Issue 2, February 2018

A Study on Diabetic Retinopathy Using Exudate Segmentation

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ABSTRACT: Retinopathy is a condition profound in diabetic patients, which contributes to 5% of the total blindness globally. The high level of blood sugar damages the retinal blood vessels by altering the blood flow. In the early stages of Diabetic Retinopathy (DR) there are no symptoms and hence it is not possible to detect the disease without examination. Exudates are one of the main signs for the presence of DR, which occurs due to leakage of fats and proteins as yellow masses in various sizes. If the exudates are not diagnosed earlier, it may lead to complete blindness by the accumulation of exudates in the fundus oculi. Frequent screening procedure is necessary to detect early condition of DR. A major limitation faced by the clinicians is screening a large number of images, which is very expensive and also open to human error. In order to solve this problem a Computer Aided Diagnosis (CAD) is necessary to identify the stages of DR. The aim of this work is to develop CAD system to differentiate the abnormal images from the normal fundus images and also grade the abnormal images as mild moderate and severe.

KEYWORDS: Exudates; Computer Aided Diagnosis (CAD); differentiate the abnormal images from the normal fundus images; graded as mild, moderate and severe.

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the leading causes of visual impairment in the developed world. It is provoked by complications of diabetes mellitus. Although diabetes does not necessarily involve vision impairment, about 2% of the patients affected by this disorder are blind and 10% undergo vision degradation after 15 years of diabetes as a consequence of DR complications. DR patients perceive no symptoms until visual loss develops. So to ensure that the treatment is received on time, diabetic patients need annual eye fundus examination using digital retinal photography. The aim of the screening programs is to detect potentially sight threatening diseases, sufficiently early to allow timely and effective treatment.

Eye and Retina

The eye is located in the orbit, a cavity in the skull. It is connected to the brain via nerve fibres, which join in the optic nerve as shown in fig.1. The fundus of the eye is composed of three layers: sclera, choroid and retina. The retina is located in the inner surface of the eye. It is a transparent and thin layer (less than 0.5mm of thickness) but it is the most complex structure in the eye. It contains millions of photoreceptors that capture light rays and convert them into electrical impulses. These impulses travel along the optic nerve to the brain where they are converted into images.

There are two types of photoreceptors in the retina: rods and cones, named after their shape. Rod cells are very sensitive to changes in contrast even at low light levels, hence able to detect movement, but they are imprecise and insensitive to colour. They are generally located in the periphery of the retina and used for scotopic vision (night vision). Cones, on the other hand, are high precision cells capable of detecting colours. They are mainly concentrated in the macula, the area responsible for photopic vision (day vision). The very central portion of the macula is called the fovea, which is where the human eye is able to best distinguish visual details. All the photoreceptors are connected to the brain through a dense network of roughly 1.2 million of nerves [3].



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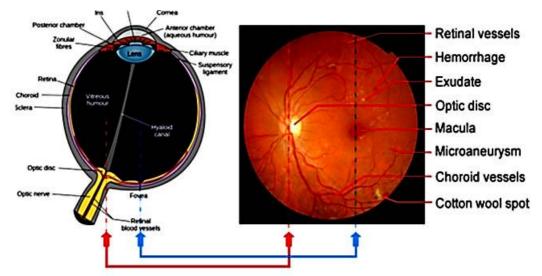


Fig.1. Anatomy of eye

All nerves leave the eye in a unique bundle in the optic nerve. In the retina there is a blind spot which is a result of the absence of retina photoreceptors where the optic nerve leaves the eye. Many retinal blood vessels supply the nutrients (oxygen and other components) to the inner and outer layer of the retina. The inner layer accounts for a smaller portion of the vessels (~ 35%), which are visible from the vitreous humour in common fundus images. The vessels in the outer layer are the source of ~ 65% of nutrients for the retina, and they are rarely visible in fundus images since they are situated in the choroid (situated at the back of the retina).

II. RELATED WORK

In the past, various exudate segmentation methods have been proposed. Alireza Osareh et al [8] proposed a computational intelligence based approach for detection of exudates in DR images. The pre-processing steps involved in this approach are color normalization and contrast enhancement. The preprocessed images are segmented using Fuzzy C Means clustering. A set of initial features that are extracted to classify the segmented regions into exudates and non-exudates are color, size, edge strength and texture. Genetic based algorithm is used to rank and identify a subset of features for better classification results. A multilayer neural network classifier is used for classification. The images were collected from Bristol Eye hospital for testing the algorithm. Doaa Youssef et al [9] proposed a fast and accurate method for early detection of exudates in fundus photographs. For noise reduction median filter is used and the contrast enhancement is done using top hat transform. The optic disc is extracted using Hough transform. Since this method is based on contour detection, snakes algorithm is used. The blood vessel is detected using morphological operations. The blood vessels and optic disc are eliminated from the edge detected image, to obtain an initial estimate of the exudates. Morphological reconstruction algorithm is used to get the final estimate of exudates. The images were collected from the NILES, Cairo University, Egypt and from STARE database. The technique proposed by R.F. Mansour et al [10] uses Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT) to create feature vector. SVM makes use of color information to perform the classification of retinal exudates. The performance of the algorithm is assessed using STARE and FI databases. Morium Aktar et al presented a morphology based method for the detection of DR through exudates from the color fundus images. The images are enhanced using histogram equalization. After contrast enhancement, the binary image is obtained by thresholding and the morphological operations are used to remove the blood vessels and optic disc. Watershed transform is applied to convert the image to RGB.



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Zhang proposed a robust exudate segmentation method from color retinal images for mass screening of DR. This method comprises of pre-processing, exudate candidate detection, classification and individual risk evaluation. Pre-processing is done to remove bright structures including reflections, and bright regions along the borders of field of view. The candidates are extracted using a novel two scale exudate candidate's segmentation method. Large exudate candidates are obtained from the preprocessed image using a mean filter followed by a reconstruction. Small exudate candidates are directly computed from the green channel of the original image by means of morphological top-hat transform. The features are extracted from the candidates and random forest method is used to perform classification. Chowdary et al, proposed an exudate segmentation technique in which Fuzzy C – Means clustering and morphological operations are performed to extract hard exudates. Jayakumari et al implemented contextual clustering technique for segmenting hard exudates from a Contrast Limited Adaptive Histogram Equalized (CLAHE) image and performed classification using Echo State Neural Network (ESNN).

III. IMAGING TECHNIQUES

An eye fundus image is taken by a "fundus camera", which is a specialized microscope with an attached camera. A typical fundus camera views 30 to 50 degrees of retinal area, with a magnification of 2:5 [4]. The observation light goes through a series of lenses, and enters the eye through the cornea onto the retina. The reflected light from the retina goes back to the microscope and the camera captures the image immediately. An example of fundus camera is shown in Fig. 2. Blood vessels come into the retina through the optic disc. This point is also known as the blind spot, because it doesn't contain photoreceptor cells. In eye fundus images, the optic disc appears as a white ellipse. In the direction from optic disc to the temple is the fovea. This is the more light sensitive area in the eye. The macula contains no vessels, and appears generally as a dark region. Optic disc and macula are two reference points in fundus images. Their position reveals basic information, for example, the left or right eye. Given the limited angle of fundus cameras, only a part of the retina is captured in each image. The diagnosis protocol of diabetic retinopathy states that the diagnosis should include at least two fundus images of 45° per eye, one macula centred, and another optic disc centred.



Fig.2. Colour digital fundus camera

Apart from colour digital fundus cameras, Abramoff et al. [5] add the following imaging modalities to a broader category of fundus imaging:

- **Stereo fundus photography:** at the same time two or more view angles of the fundus are acquired by this instrument. This allows the perception of the depth by the ophthalmologist.
- **Hyperspectral imaging:** it is a fundus camera that does not employ the visible light only, but can select specific wavelength bands. This allows particular applications such as oximetry, the quantification of oxygen levels in the bloodstream.
- **Fluorescein Angiography (FA):** is a fundus image of the photons emitted by a contrast agent injected in the patient's blood stream. Fluorescein or indocyanine green fluorophore are the agents typically used.



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• Scanning Laser Ophthalmoscope (SLO): An instrument that uses low powered lasers to image the retina or choroid. It uses a very narrow moving beam of light which can bypass most ocular media opacities (i.e. corneal scars, cataracts, vitreous haemorrhage) to reach the surface of the retina and record its surface detail. With SLO, the optics of the eye serves as the objective lens. Confocal SLO is SLO equipped with a confocal aperture. Adaptive optics SLO optically corrects the laser reflections by modelling the aberrations in its wave front.

The other imaging technique that is becoming increasingly important is Optical Coherence Tomography (OCT). OCT is a non-destructive imaging technique that uses interferometry techniques to measure the time of flight of the light backscattering through the retina. By rapidly scanning the eye, it can acquire an in vivo representation of the anatomic layers within the retina. Because of that it can be used to diagnose diseases such as DME, AMD and Glaucoma with generally a greater precision than with a simple fundus image [6]. However, DR cannot be directly diagnosed because the vessels and many other key features of the retina are invisible in this modality (even if it is possible to algorithmically infer the location of the vasculature by employing the visible shadows as shown by Niemeijer et al. [7]. Other drawbacks of this modality are: the steeper learning curve to use the instrument than a colour fundus camera, the greater acquisition time required to acquire a Field Of View (FOV) comparable to a fundus camera and the substantially higher cost.

IV. METHODOLOGY

In order to monitor the affected level of DR condition a grading classification algorithm is necessary. A set of standard graded fundus images are collected from ophthalmologist which are graded according to the level of retinopathy condition. It spans into four classes no DR condition or normal, mild DR, moderate DR and severe DR. The ability to detect abnormalities in fundus images due to DR leads to the formulation of a system which can generate diagnosis without human interventions. The automatic screening system is trained to classify the fundus images similar to the classified image as that of ophthalmologist. In a real time environment there are many aspects which affects the grading of the image and results in error output. For this reason a pre-processing step is performed for correct diagnosis. The pre-processing step comprises of green channel extraction, image enhancement by adjusting the contrast value, vessel central light reflex removal, background homogenization and vessel enhancement for vessel segmentation. The second step is to apply entropy filter followed by removal of the optic disc and blood vessels in order to segment exudate. The texture features of Grey Level Co-occurrence Matrix (GLCM) are extracted from the segmented image. The classifiers like Support Vector Machine (SVM), multilayer network Scaled Conjugate Gradient - Back Propagation Network (SCG-BPN) and Generalized Regression Network (GRN), Probabilistic Neural Network (PNN), Radial Basis Network (RBF) are tested. It is found that SVM classifier is more accurate and exhibit high performance. The classifier classifies the fundus images as normal, mild, moderate and severe. The images and the severity of DR are transferred to the physician by mail which can be viewed in his mobile phone. The algorithm is tested at a remote location of 25Km away from the Aravind Eve Hospital, Coimbatore and the results are viewed by the vitro surgeon through his mobile phone. The fig.3 shows the methodology in a flow diagram.

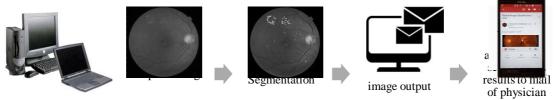


Fig.3. Flow diagram of Methodology

V. PROPOSED ALGORITHM

In the proposed method, preprocessing step enhances the quality of the image. Further to improve the contrast between exudate and non-exudate regions, shade correction is performed. The second stage involves segmentation of exudates from the green channel image after removal of blood vessels and optic disc. The GLCM features are extracted



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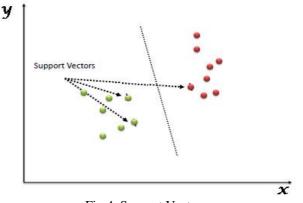
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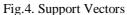
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from the segmented region. Using the extracted feature five classifiers SVM, SCG-BPN, GRN, PNN, and RBF are trained and tested for obtaining the best classifier.

Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well as shown in fig.4.





Support Vectors are simply the co-ordinates of individual observation. Support Vector Machine is a frontier which best segregates the two classes (hyper-plane/line). SVMs are efficient learning approaches for training classifiers based on several functions like polynomial functions, radial basis functions, neural networks etc. SVM is a linear classifier that maps the points into the space with separate categories such that they have wider space with a clear gap in between. A hyper-plane is chosen to classify the data. The separating hyper-plane must satisfy the constraints.

$$y_i[(w, x_i) + b] \ge 1 - \xi_i, \xi_i \ge 0$$

Where w = the weight vector b = the bias ξ_i =The slack variable

The SVM requires the parameters such as the kernel function and the regularization parameter C. In this work Radial Basis Function (RBF) kernel function is used.

Back Propagation Neural Network

BPN is the predominantly used supervised artificial neural network. The structure consists of three-layers and selection of the architecture is crucial before beginning a process. An input vector is required and the corresponding desired output is necessary. The input is propagated forward through the network to compute the output vector. The output vector is compared with the desired output and errors are determined. The process is repeated until the errors are minimized. The weight values are updated based on the difference value. During the training phase, the weights of the network performance are iteratively adjusted to minimize the network performance function.

$$E=\sum (T-Y)^2$$

Where T is the target vector, Y is the output vector. The SCG-BPN is designed to reduce the time consumption and to reduce the complexity of the algorithm.



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Generalized Regression Network

It is a radial basis function that is often used for functional approximation. The use of this network is especially due to its ability to the underlying function of the data with only few training data available [21]. The probability density function used in GRN is the normal distribution. Each training sample Xj, is used as the mean of a normal distribution.

$$Y(X) = \frac{\sum_{i=1}^{n} Y_i \exp(\frac{-D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} \exp(\frac{-D_i^2}{2\sigma^2})}$$

The distance D_i between the training sample and the point prediction is used as a measure of each training sample.

Probabilistic Neural Network

PNN is often used in classification problems. When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, at transfer function on the output produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes. For PNN networks there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category. The pattern neurons add the values for the class they represent.

Radial Basis Function

In the field of mathematical modelling, a radial basis function network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many uses, including function approximation, time series prediction, classification, and system control. The classifiers accuracy shows that SVM holds the better classification result. Hence the SVM classifier is used in the algorithm for classification.

VI. CONCLUSION AND FUTURE WORK

Early detection of DR can be effective in preventing blindness. The proposed approach is designed for the detection of exudates to diagnose DR. The entropy based segmentation method segments the exudates precisely and clearly. The SVM classifier gives better accuracy and performance compared to SCG-BPN, GRN, PNN, and RBF. This automated system can filter out the exudate images and thereby reduces the burden on ophthalmologist in classifying the exudate images manually. It further classifies the given input image as normal, mild DR, moderate DR and severe DR. This provides the patients to get treated according to their severity level. The results are also sent to the physician's e-mail which can be viewed by him in his desktop or mobile phone. This work mainly reduces the time consumption needed for the diagnosis of mass screening processes.

ACKNOWLEDGEMENTS

Our sincere thanks to the experts supported this work and their valuable comments.

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