Detection of Lesions in Color Fundus Images for Diabetic Retinopathy Grading

Chitra Raju I, Lizy Abraham

***Abstract*—Advancement in technology has its impact in many areas especially in the field of medicine. Analysis of medical images have great significance in non-invasive treatment and clinical studies. In the context of computer aided diagnosis of diabetic retinopathy, a new algorithm for the detection of lesions is presented and discussed. The regions where these lesions are present determines the severity of diabetic retinopathy. Thus, the detection of these lesions plays a vital role in computer aided diagnosis. Detection of fovea is indispensable for this approach. Fovea is detected by means of morphological operations. The method has been tested on publicly available databases and the results are better than the conventional approaches.**

***Index Terms*—Diabetic Retinopathy (DR), exudates, fovea, hemorrhages**

I. INTRODUCTION

During the last few years, there is a significant progress in the diagnosis of human eye diseases, mainly due to rapid developments and innovations in technology. Taking into account the diversity and complexity of eye functions, a huge number of devices, methods and algorithms for diagnosis were developed. Retinal fundus images are used for diagnosis by trained clinicians to check for any abnormalities or any change in the retina. Specially trained clinicians can identify certain diseases by visual inspection of retinal images, but, this process is time consuming and resource intensive. In majority cases, the diagnosis is unsuccessful due to different factors as, for example, fatigue, diversity of shapes and texture, similarity, poor image quality and so on. In these situations, an automated disease detection system can highly reduce the effort of clinicians to limit the immediate attention to severe cases.

Diabetic retinopathy is a complication of diabetes which can lead to irreversible visual loss and blindness. It is one of the world leading cause of blindness and is accountable for 4.8% of 37 million cases of blindness worldwide [1]. About 382 million people live with diabetes (8.3% of the world's adult population in 2013) and by 2035 this will have increased by 55% to 592 million [2]. Diabetic retinopathy is a condition that arises as a result of damage to blood vessels in the retina at the back of the eye. Diabetic retinopathy usually affects both eyes and can lead to vision loss if not detected early and treated. Once vision has been lost, it usually cannot be restored. Specially trained clinicians or ophthalmologists diagnose diabetic retinopathy through visual inspection or using computer aided diagnosis systems with complex detection algorithms. Since the latter provides faster detection, automated detection of diabetic retinopathy became the area of interest among researchers. In fact, these systems can significantly save time and cost.

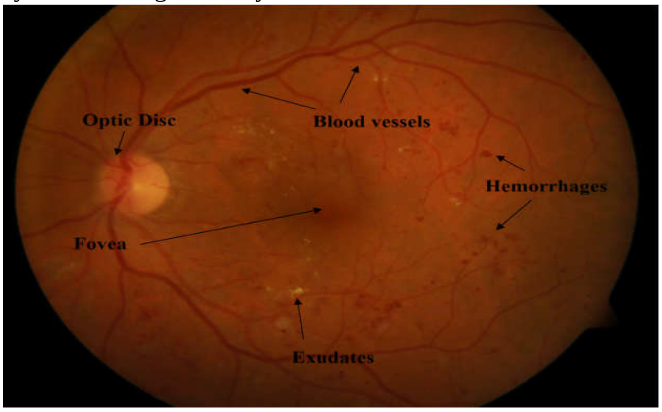

Fig.1 Fundus image

Diabetic retinopathy can be automatically detected by examining different lesions present in the retinal images. The successful detection of anatomical structures of retinal fundus images (optic disc, fovea and the blood vessels) is very significant for examining the presence of lesions. Different lesions that may be present in an affected retina are microaneurysms, hemorrhages and exudates. Fig.1 shows the color fundus image with the anatomical structures of retina and lesions labeled on it. Lesions are formed when blood vessels get damaged and blood or other fluids leak into the retina causing swelling of retinal tissue. Microaneurysms and hemorrhages, referred to as red lesions, are formed due to leakage of blood. Microaneurysms seen as red dots in the layers of retina, represents outpouching of the retinal capillaries. They are not necessarily permanent changes, but they may first appear and then disappear during some period of time. When microaneurysms bursts or rupture, some blood leaks out of the vessels and form hemorrhages. Hemorrhages can be seen as red, dot-blot or flame shaped regions. Exudates are bright lesions which are bright yellow lipid formations leaking from weakened blood vessels.

II. RELATED WORK

The performance of a computer aided diagnosis system is generally influenced by the successful retinal anatomy detection. Retinal image analysis is a complicated task particularly because of the variability of the retinal anatomical pathological structure and the existence of particular features in different patients, which may lead to an erroneous interpretation. This has led to the development of many retinal image analysis methods.

Several approaches for diabetic retinopathy detection and classification are available from the literature. Some of these

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techniques are based on mathematical morphology, neural networks, pattern recognition, region growing methods, clustering methods and so on. Vallabha et al. [3] proposed a method where automatic detection and classification of abnormalities on the vascular network was done using Gabor filter bank outputs at several finer scales to obtain a scale and angle method of representation of energy variations, to classify the mild, moderate and severe stages of retinopathy. The proposed method classifies retinal images as either mild or severe cases based on the Gabor filter output. Sinthanayothin et al. [4] developed a method based on recursive region growing methods and moat operator to detect hemorrhages, microaneurysms and exudates.

The microaneurysms in retinal fluorescein angiograms was identified by first locating the fovea by sub-sampling image by factor of four in each dimension in the method proposed by Cree et al.[5]. The image was subjected to median filtering with a 5 x 5 mask to reduce high frequency components. The image was then correlated with a two dimensional circularly symmetric triangular function with modelled gross shading of the macula. A novel approach which combines brightness adjustment procedure with statistical classification method and local window base verification strategy was proposed by Wang et al. [6]. Their results indicate that they were able to achieve 100% accuracy in terms of identifying all the retinal images with exudates while maintaining a 70% accuracy in correctly classifying normal retinal images as normal. Hunter et al. [7] have studied neural network based exudates detection. They introduced a hierarchical feature selection algorithm based on sensitivity analysis to distinguish the most relevant features. The final architecture achieved 91% lesion based performance using a relatively small number of images. Osareh et al. [8] have presented results for fundus image based exudate classification. Their method evaluated different learning algorithms, such as neural network and support vector machine.

Ege et al. [9] have developed a tool which provides automatic analysis of digital fundus images. In this work, a Bayesian, a Mahalanobis and a k nearest neighbor classifier were used on 134 retinal images. The Mahalanobis classifier showed the best results: microaneurysms, hemorrhages, exudates and cotton wool spots were detected with a sensitivity of 69%, 83%, 99% and 80% respectively. Fully automated computer algorithms were able to detect hard exudates and hemorrhages and microaneurysms (HMA) using moat operator [10,11]. The sensitivity and specificity for exudates detection were 88.5% and 99.7% respectively and algorithm achieved a sensitivity of 77.5% and specificity of 88.7% for detection of HMA. Larsen et al. [12] have used image processing for the detection of both hemorrhages and microaneurysms Larsen et al. have used image processing for the detection of both hemorrhages and microaneurysms. Their algorithm demonstrated a specificity of 71.4% and a sensitivity of 96.7%. The robust detection of red lesions in digital color fundus photographs is a critical step in the development of automated screening systems for diabetic retinopathy [13]. Their method achieved a sensitivity of 100% at a specificity of 87% in detecting the red lesions. Bottom-up and top-down strategies were applied to cope with difficulties in lesions detection, such as inhomogeneous illumination [14]. After the application of appropriate strategy, they used local contrast enhancement, fuzzy C means and hierarchical support vector machine to classify bright non-lesion areas, exudates and cotton wool spots.

Shivaram et al. [15] used image arithmetic and mathematical morphology methods for detecting hemorrhages and suppressing blood vessels. The results are compared with ophthalmologists' hand-drawn ground truth images pixel by pixel. The results obtained for sensitivity, specificity and predictive value were 89.49%, 99.89% and 98.34% respectively. A morphological reconstruction method for segmentation of retinal lesions was proposed by Karnowski et al. [17]. The segmentation is performed at a variety of scales and ground truth data is used to separate nuisance blobs from true lesions. They created a "lesion population" feature vector from teach image to classify normal or abnormal classes.

Zhang et al. [18] proposed a spot lesion detection algorithm using multi-scale morphological processing. Blood vessels and over detection were removed by scale based lesion validation. The method was tested on 30 retinal images and it achieved the sensitivity and predictive value of 84.10% and 89.20 % respectively.

III. Proposed Method

Severity of diabetic retinopathy depends on the proximity of different lesions to the macula. Thus, fovea localization becomes an adequate step for disease grading and helps to provide a better description of other features in fundus images. In general, fovea detection forms a component of most systems that are designed for automatically analyzing retinal images. The challenge in fovea detection is that its size and/or position can vary with the chosen field of view (macula centric/ optic disc centric), magnification level, non-uniform illumination. The fovea can also suffer from partial or full occlusion due to pathological factors such as lesions, scars etc. The flowchart of the proposed method is shown in Fig.2.

A. Preprocessing

The aim is to enhance the features that can be used for feature extraction. It is important to separate the fundus from its background so that further processing is only performed for the fundus and not interfered by pixels belonging to the background. Thus, a mask is created by thresholding the intensity channel (V) of the HSV converted image of the input color image. Since the darker retinal structures (blood vessels, fovea and hemorrhages) are most prominent in the green layer of retinal images, the green channel component of the input color image is extracted, which is used as input for all subsequent processing.

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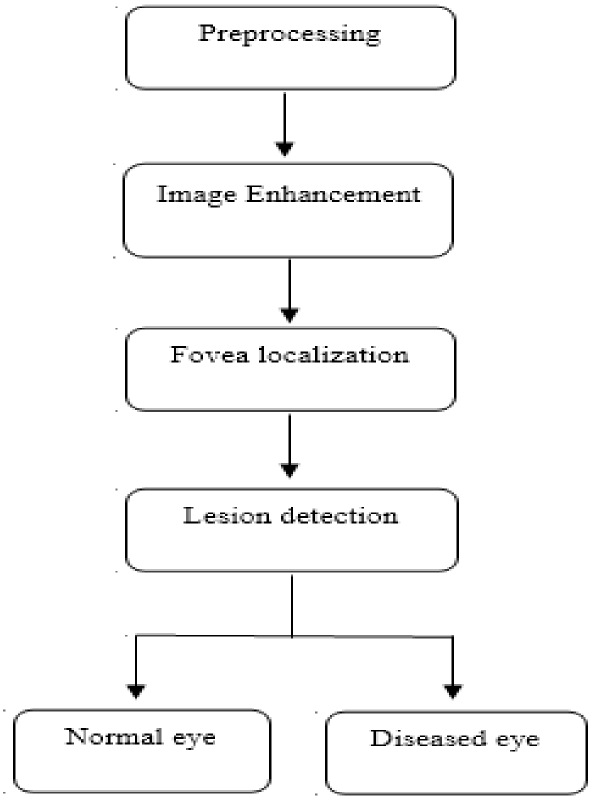


Fig. 2 Flowchart

Images taken at standard examinations are often noisy and poorly contrasted. Over and above that, illumination is not uniform. To improve contrast and sharpness, image enhancement methods are applied. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance the darker features.

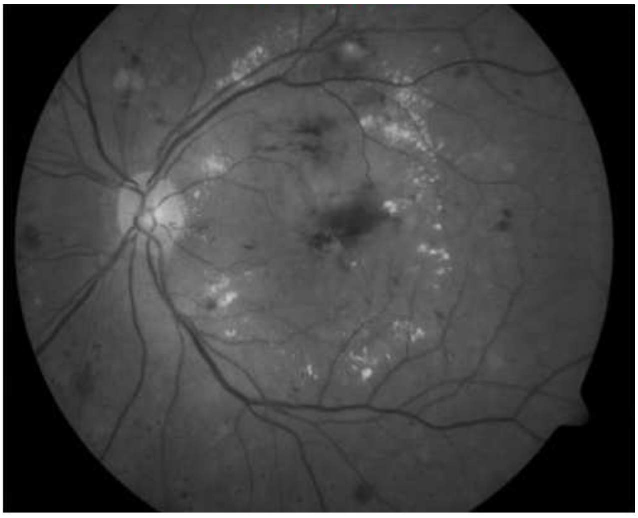
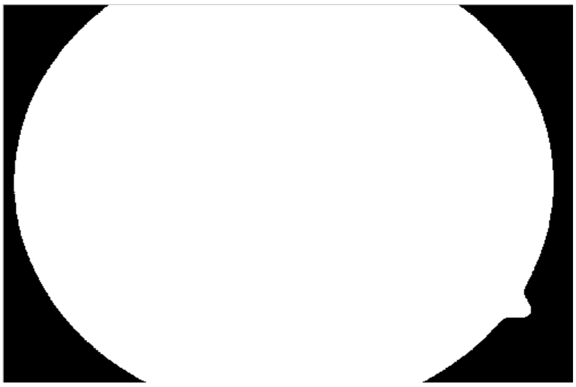
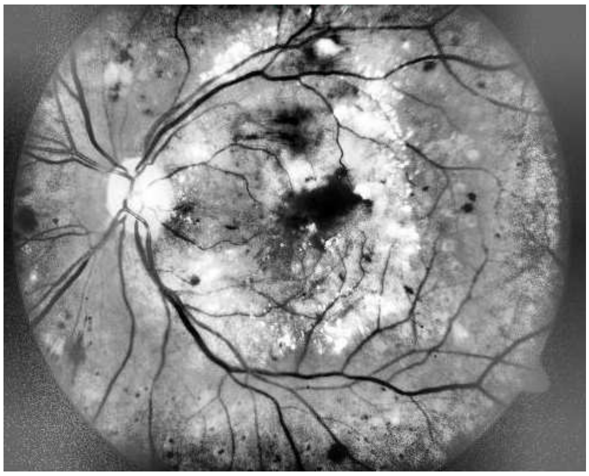


Fig. 3 Green channel of the color fundus image

Histogram equalization is the common technique for contrast enhancement. It is applied to obtain the background information from the retinal images. The retinal fundus images have different bright (optic disc, exudates) and dark regions (macula, blood vessels and hemorrhages). Therefore, the global contrast enhancement techniques do not produce efficient results.



(a)



(b)

Fig.4 (a) Mask (b) After CLAHE

CLAHE is a region based enhancement technique, which resists the effect of other dark and bright regions. In CLAHE, the image is divided into N x N tiles and histogram equalization is applied locally to each tiles. The clip limit of CLAHE ensures that the local contrast is limited and does not increase to the maximum. The center and edges of the retinal images are not affected with gradual variation in the intensity range within the local window. However, result of histogram equalization increases the background in homogeneity, a region based Wiener filtering (3 x 3) is applied to smoothen the background.

B. Fovea Localization

Fovea is the center of macula region. Macula is a dark structure located roughly at the center of retina. For localizing fovea, the inverted image of the output from preprocessing stage is used. The image is then thresholded to obtain the bright features. Next, Alternate Sequential Filtering (ASF) is applied.

ASF is based on successive application of morphological openings and closings. The size of structuring element is increased by 2 in each iteration. ASF operation is performed with 3 iterations, using a disk-shaped structuring element of radius 5 pixels. The resulting image is then masked and morphological opening is applied again to isolate the candidate fovea region. The centroid of the region is found and fovea is localized.

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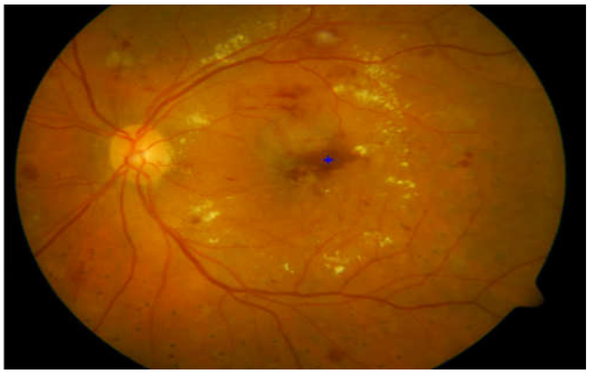
(a)



(b)

Fig.5 (a) Alternate Sequential Filter (ASF) (b) Fovea detected

C. Exudate Detection

The inverted enhanced image is thresholded to extract the bright features (optic disc and exudates). For the grading process, elimination of optic disc is adequate. To locate optic disc, find the location of pixel with maximum intensity. Since optic disc extraction is done as part of another work, the optic disc radius is obtained manually. With the optic disc location and radius, a mask for optic disc is created and optic disc is eliminated from the extracted bright features. The remaining bright features are exudates and their distribution is checked for grading.

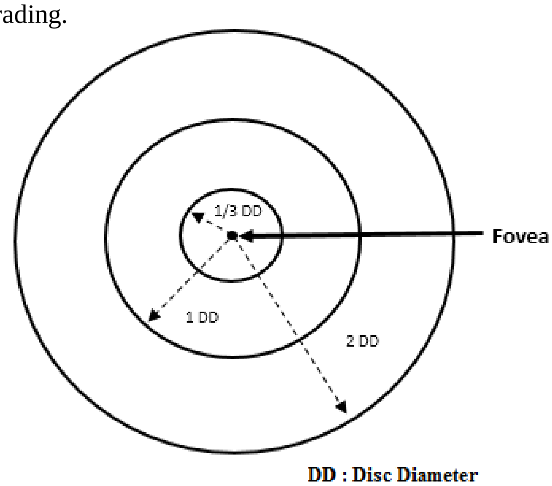
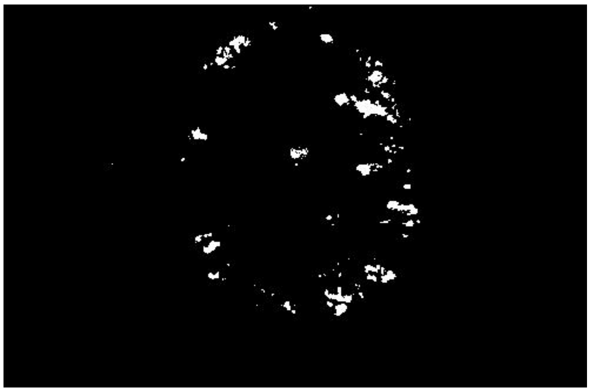


Fig. 6 Region classification

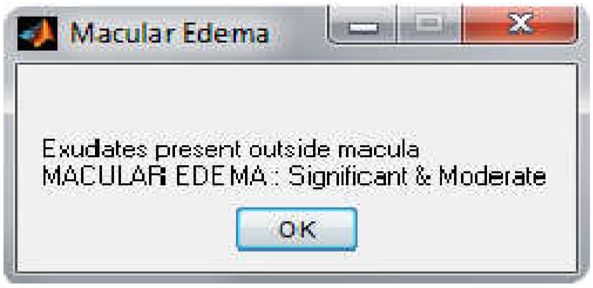
The proximity of these exudates to the macula plays a vital role in determining a condition called as Macular Edema (ME). The regions are classified into circular regions whose radius is calculated using optic disc diameter. Region classification is shown in Fig.5. Macular edema detection is done based on the region classification according to Table I.

Table I

Region	Severity
No exudates	Normal eye
Within 1/3 DD	Severe
Within 1 DD	Moderate
Within 2 DD	Mild but clinically significant ME
Beyond 2 DD	Clinically insignificant ME



(a)



(b)

Fig. 7 (a) Exudates detected (b) Macular edema result

D. Hemorrhage Detection

The enhanced image from the pre-processing stage is used as input for hemorrhage detection. Onto this image, top hat transformation is applied. The output image so obtained is then thresholded to extract the dark features which include the macula region, hemorrhages and the blood vessels. From this, we have to eliminate non-hemorrhage candidate i.e, macula region and the blood vessels. Macula region is eliminated by creating a mask with fovea position which we found earlier.

To eliminate blood vessels, the shape property of hemorrhages is used. The candidate objects are labelled and roundness is checked.

$$Roundness = \frac{length\ of\ longest\ side}{length\ of\ smallest\ side} \qquad (1)$$

Since hemorrhages are relatively circular in shape, their roundness factor is almost unity whereas for blood vessels, it exceeds unity. The detected hemorrhage objects are counted in all four quadrants and if they exceed 20 in number, severity

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is high. If hemorrhages are present but count is less than 20, then, the severity is moderate.

IV. Experimental Results

The efficiency and performance evaluation of the proposed method can be analyzed by comparing the results with manually graded images by specially trained ophthalmologists. Based on these observations, several parameters such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) can be calculated. For an abnormal image, the result is true positive if the output is abnormal and false negative if the output is normal. Similarly for a normal image, the result is true negative, if the output is normal and false positive if the output is abnormal. These parameters are further used in the calculation of accuracy, sensitivity and specificity. Sensitivity is the measure of abnormal images classified as abnormal. Specificity is the measure of normal images classified as normal. Accuracy gives the measure of total number of well classified normal and abnormal images. Higher the sensitivity and specificity, better the diagnosis. Sensitivity and specificity are also referred to as True Positive Rate (TPR) and True Negative Rate (TNR), respectively.

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (2)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (3)$$

$$Accuracy = \frac{(TP + TN)}{(TP + FN + TN + FP)} \quad (4)$$

These measures are chosen based on related work, wherein most of the publications use these measures. It is also important to have a balance between the values of sensitivity and specificity. If sensitivity is high and specificity is low, it implies that the method detected most of the lesions and other non-lesion candidates were also erroneously detected as lesions. If sensitivity is low and specificity is high, then it means that the method detected non-lesion candidates correctly but failed to detect all lesion candidates.

The performance of the method was tested on publicly available database DIARETDB1 [16]. The database consists of 89 color images, each of size 1500 x 1152 in png format. Out of these 5 images are healthy and 84 images are unhealthy. Table II shows the measures obtained for each lesion detection with the proposed method.

Table II

Lesion	Sensitivity (%)	Specificity (%)
Exudate	85.53	80
Hemorrhage	86.42	75

V. Conclusion

This paper presented a new method for lesion detection in color fundus images. The early signs of diabetic retinopathy can be noticed by the presence of these lesions in fundus images. Among these lesions, exudates and hemorrhages plays a vital role in diabetic retinopathy diagnosis. Detection of these lesions solely depends upon the successful detection of anatomic features of retina. Fovea detection thus became the core process for lesion detection. A new method for fovea localization based on alternating sequential filtering and morphological methods have been discussed and implemented. Efficient algorithms for exudate and hemorrhage detection have been presented. The results are encouraging and further evaluation will be undertaken in order to be able to integrate the presented algorithm in a tool for diabetic retinopathy diagnosis.

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