

# Different Methods for Detecting & Grading Diabetic Retinopathy using Fundus Images - A Review

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**Abstract:** Diabetes is a disease that occurs when body does not produce enough insulin in order to function properly. Diabetic Retinopathy is vascular disorder which is one of the world's leading causes of blindness. This condition can be prevented if, diagnosed and treated in early stage. Ophthalmologists recognize diabetic retinopathy based on features, such as blood vessel area, exudates, hemorrhages, microaneurysms and texture. The work extensively reviews, classifies and compares the algorithms and techniques previously proposed in order to support and provide current and future researchers with an elaborated summary of such algorithms.

**Keywords:** Diabetic Retinopathy, Microaneurysms, Blood Vessel area, Fundus images.

## I. INTRODUCTION

Diabetic Retinopathy is common cause of Diabetics. It can eventually lead to blindness. It is an ocular manifestation, a systemic disease, which affects up to 80 percent of all patients who have had diabetes for 20 years or more. Despite these intimidating statistics, research indicates that at least 90% of these new cases could be reduced if there were proper and vigilant treatment and monitoring of the eyes. The longer a person has diabetes, the higher his or her chances of developing diabetic retinopathy. Each year in the United States, diabetic retinopathy accounts for 12% of all new cases of blindness. It is also the leading cause of blindness for people aged 20 to 64 years.

Diabetic retinopathy involves changes to retinal blood vessels that can cause them to bleed or leak fluid, distorting vision. The earliest symptoms of Retinopathy are the Microaneurysms, which occur due to dilatations of the blood capillaries and they appear as dark red spots on the retina. Hemorrhages occur when the microaneurysms burst. Bright-yellow colored Lesions such as hard exudates occur as a result of fluid leaking into the retinal surface from the capillaries or from Microaneurysms. Diabetic Retinopathy is a progressive disease. The first stage of retinopathy is known as Non-Proliferative Retinopathy, during which the retinal lesions appear and increase as the disease progresses.

Initially, at least one microaneurysm is seen. With the progression of the disease, the blood vessels become blocked and are short of blood supply. In an attempt to create new paths for blood supply, abnormal and fragile new blood vessels are formed on the surface of retina in the stage of Proliferative Retinopathy that might leak blood into retina causing permanent blindness.

The various lesions associated with diabetic retinopathy are as shown in the figure below.

### A. FUNDUS Images

The eye images are taken with the help of ophthalmoscope.

The fundus images are taken by dilating the pupil with pharmaceutical eye drops. After that the patient is asked to stare at a fixation device in order to steady the eyes. While taking the pictures, the patient will see a series of bright flashes. The entire process takes about five to ten minutes. To ensure that DR treatment is received on time, the eye fundus images of diabetic patients must be examined at least once a year.

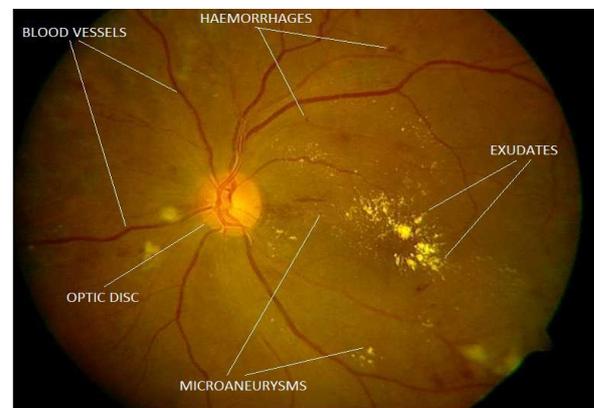


Fig.1 Different features in DR Image

## II. REVIEW OF METHODS

The methodologies used in the existing algorithms and techniques follow somewhat similar flow of process. Many techniques are based on mathematical morphology, neural networks, pattern recognition, region growing techniques; fuzzy C-means clustering, Gabor filter banks are available from the literature.

Several methods were applied to detect optic Disc. Such as Principal component analysis (PCA). Where the candidate regions for optic disc were derived by clustering of brighter pixels. PCA was applied to calculate the minimum distance between the image and its projection to find the optic disc center [5].

Optic Disc detection was also done using Hough Transform [6]. Microaneurysms and hemorrhages were detected using morphological operations with a structuring element and top-hat transformation [7].

Optic discs detection is another important component of the algorithms for computer based DR diagnosis. Marwan and Eswaran [9] detected and removed the optic disc by using median filter. The technique starts with focusing in the center of the image where the optic disc is most likely to be detected. Then median filter is applied to the image in order to fill up the thin blood vessels inside the optic disc. Then the contrast of the optic disc and the background was enhanced so that the thresholding can be performed easily in order to eliminate the optic disc from the image.

Acharya et al. [8] used morphological image processing to detect various lesions. First, an image with blood vessels was extracted by using ‘ball’ shaped structuring elements, in addition to morphological operations. Then, other image with the vessels as well as hemorrhages was extracted using the same technique but slightly increased the ball size. The final detection was obtained by subtracting the image with vessels alone from the image with vessels as well as hemorrhage.

Narasimhan et al. [12] proposed a detection method based on filtering operations. Morphological top-hat transformation was applied to the normalized green channel of the image. Then a geodesic reconstruction was used to recover the linear features. A thresholding technique was applied to enhance the image and region growing method was employed to extract features for the detection of microaneurysm and hemorrhage.

Shivaram et al. [16] and Fleming et al. [15] have also used morphological operators in their hemorrhage detection algorithms. Erosion, dilation, opening, closing and top-hat are some examples of operators utilized in these works.

### III. OVERVIEW OF DIABETIC RETINOPATHY

The process of Automatic Diabetic Retinopathy detection involves detection and segmentation of the abnormal features from the input images.

Some challenges are faced during accurate detection of these features, they are as follows:

- a. Similarity of retinal lesions to the landmark features like as blood vessels, optic disc and the macula (fovea).
- b. Variation in illumination and Changes in contrast across the image.

The input image is preprocessed in order to make it free from noise, which has occurred due to illumination; also the contrast of image is enhanced for further processing. The next step is to localize the retinal components such as Optic Disc, Fovea and blood vessels. In the next step, abnormal

Features are analyzed with different technique to perform severity classification of the disease as normal, mild, moderate, severe Non proliferative Retinopathy (NPDR) and Proliferative Retinopathy (PDR). [10]

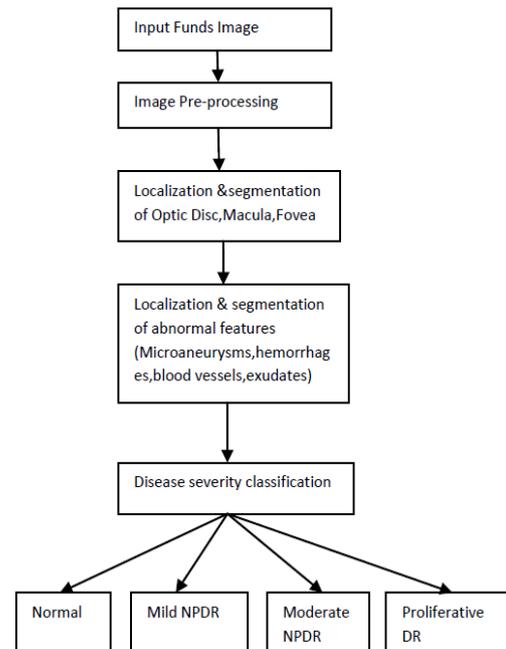


Fig.2 Block dia. of DR detection & classification

#### A. Pre-Processing

Image pre-processing is the initial step in automated retinal pathology diagnosis. It includes techniques such as contrast enhancement, gray/green component, image de-noising, etc. In the RGB images the green channel exhibits the best contrast between the vessels and background while the red and blue ones tends to be more noisy. Since the retinal blood vessels appear darker in gray image, the green channel is used to convert the intensity of the image. Filtering is used to remove the noise which gets added into the fundus image. Here median filtering is quite useful as it is very robust and has the capability to filter any outliers.

Adaptive Histogram equalization is a constant enhancement technique which provides an enhanced method for modifying the dynamic range and contrast of an image by altering the image. It is finding of cumulative distribution function for a given probability density function. The small area of pixels, considered to be noise, is removed after applying morphological operations. Post the transformation, the probability density function of the output will be uniform and the image will have high contrast. [17]

#### B. Localization & Segmentation of Optic Disc

Before detection of exudates, the localization & segmentation of optic disk is done. In [1] it is considered as large cluster of bright pixels, Circular Hough transform & PCA are used to detect the optic disc.

Morphological operators followed by active contour models are also used for detection of optic disc. The detection of the macula and fovea is mainly determined by estimating the position in relation to other retinal features.

#### C. Blood Vessel

In[17] Kirsch’s non-linear edge detector is used to search

the maximum edge in a few determined directions. Taking a single mask and rotating it to 8 major compass orientations (East, West, North, South, South-East, South-West, North- West and North-East) helps find the edge direction based on the maximum magnitude produced.

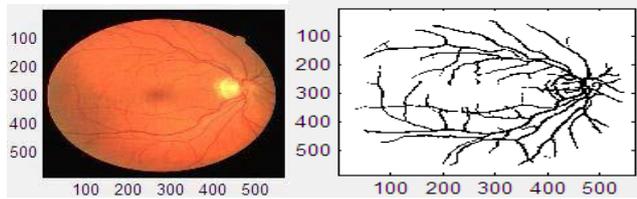


Fig. 3. Result of Blood Vessel Detection

#### D. Exudates

Exudates are basically formed due to lipid, protein accumulated over retina, which is bright in colour, Small yellow white patches with sharp margins and different shapes. Exudates are one of the early occurring lesions. Recursive Region growing algorithms, which assume pixel adjacency in terms of similarity in gray levels, were used to detect the boundary of a region [4]. Other methods using morphological reconstruction, neural networks, Fuzzy c-means clustering and computational intelligence techniques are also used.

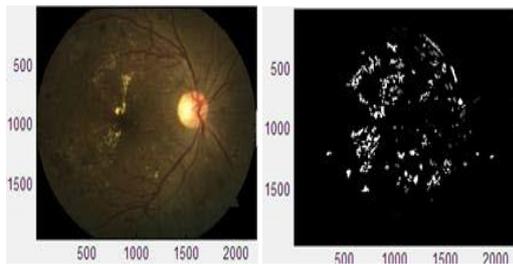


Fig.4. Result of exudates detection

#### E. Microaneurysms and hemorrhages detection

Initially Morphological operations using a structuring element, top-hat transformation were the methods used. The microaneurysms turnover was computed reliably from color fundus images [20]. They used a new method called MA- tracker to count microaneurysms. They showed that the microaneurysms remain stable over time, but only 29 % remain at the same place.

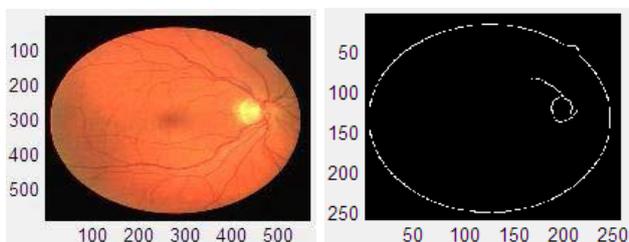


Fig. 5.Result of Microaneurysms Extraction

#### F. Severity Classification

- Normal Eye
- Mild DR: At least one microaneurysm with or without hemorrhages, exudates might be present.
- Moderate DR: Several microaneurysms with hemorrhages, exudates also present.

- Severe DR: microaneurysm with hemorrhages with vascular abnormalities
- Proliferative DR: signals, sent by the retina for nourishment, trigger the growth of new blood vessels. These blood vessels do not cause symptoms or vision loss. But, their walls are thin and fragile, this leads to a high risk that they leak blood . This leaked blood contaminates the vitreous gel and this causes severe vision loss .

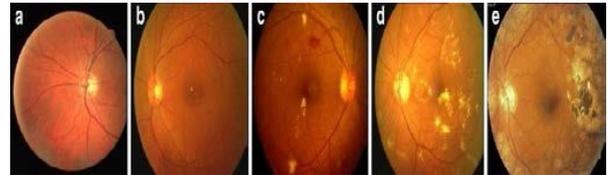


Fig.6.Different Fundus images a)Normal eye  
b) Mild NPDR c)Moderate NPDR d) Severe NPDR  
e) Proliferative DR

Colour features were used on Bayesian statistical classifier classifies each pixel into lesion or non-lesion classes. They have achieved 100% accuracy in identifying all the retinal images with exudates, and 70% accuracy in classifying normal retinal images as normal. DR and normal retina was classified automatically using image processing and multilayer perceptron neural network. The system yielded a sensitivity of 80.21% and a specificity of 70.66%. Automated diagnosis of NPDR, based on three lesions: hemorrhages and microaneurysms, hard exudates, and cotton wool spots, was studied. The method was able to identify the NPDR stage correctly with an accuracy of 81.7 %. Exudates, hemorrhages, and microaneurysms were used for screening of DR subjects. The sensitivity and specificity of their software was 74.8% and 82.7 %, respectively in differentiating DR and normal subjects correctly.

Early detection of DR (presence of microaneurysms) was proposed based on decision support system by Kahai et al. [18]. Bayes optimality criteria were used to detect microaneurysms. Their method was able to identify the early stage of DR with a sensitivity of 100% and specificity of 67%. Normal, mild, moderate, severe and prolific DR stages were automatically classified using both area and perimeter of the RGB components of the blood vessels together with a feed forward neural network. System average classification efficiency was 84% and sensitivity, specificity were 90% and 100% respectively.

Nayak et al. have used exudates and blood vessel area along with texture parameters coupled with neural network to classify fundus images into normal, NPDR and PDR [19]. They obtained a detection accuracy of 93%, sensitivity and specificity of 90% and 100% respectively. A system, designed by Estabridis et al., has detected features such as fovea, blood vessel network, optic disk, bright and dark lesions, which are associated with DR successfully [14]. It has achieved a classification accuracy of 90%.

As seen from literature, the classification efficiency

improves if, all features such as Microaneurysms, exudates, blood vessels, textures, hemorrhages are used for classification.

#### G. Performance Measure

The performance evaluation is in terms of Sensitivity, specificity, Positive predictive value, Negative predictive value.

Sensitivity  $TP/(TP+ FN)$

Specificity  $TN/(TN+ FP)$

PPV=  $TP/(TP+ FP)$

NPV= $TN/(TN +FN)$

Accuracy  $(TN+TP)/( TN+TP+FN +FP)$

Sensitivity and specificity metrics are the ratio of well-classified vessel and nonvessel pixels, respectively. Positive predictive value is the ratio of pixels classified as vessel pixels that are correctly classified. Negative predictive value is the ratio of pixels classified as background pixels that are correctly classified. Finally, accuracy is a global measure providing the ratio of total Well-classified pixels.[13]

#### IV. IMAGE DATABASE USED FOR EXPERIMENTATION AND RESEARCH

Most of the methods were evaluated on DRIVE and STARE database images with available gold-standard images. Since the images' dark background outside the FOV is easily detected. Sensitivity, specificity, positive predictive value, negative predictive value and accuracy values were computed for each image considering FOV pixels only. Since FOV masks are not provided for STARE images, they were generated with an approximate diameter of 650 550. Other important datasets are MESSIDOR, REVIEW and HELMED.

#### V. CONCLUSION

Diabetic Retinopathy is basically caused by leaking fluid from the blood vessels of retina. The stage and severity is decided, based on the blood vessels, exudes, hemorrhages, microaneurysms and texture. In this review paper, we have discussed different methods for features extraction and automatic DR stage detection. An ophthalmologist uses an ophthalmoscope to visualize the blood vessels to detect the DR stages. Recently digital imaging became available as a tool for DR screening. It provides high quality permanent records of the retinal appearance, which can be used for monitoring of progression or response to treatment and which can be reviewed by an ophthalmologist, digital images have the potential to be processed by automatic analysis systems. An accurate detection & diagnosis helps the patient to save his sight.

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#### REFERENCES

- [1]. Chaudhuri, S., Chatterjee, S., Katz, N., Nelson, M., and Goldbaum, M., Detection of blood vessels in retinal images using two-dimensional matched filters. IEEE Trans. Med. Imag.8 (3):263–269, 1989.
- [2]. Grisan, I. E., Pesce, A., Giani, A., Foracchia, M., and Ruggeri, A., A new tracking system for the robust extraction of retinal vessel structure, 26th Annual International Conference of the IEEE EMBS San Francisco, USA, pp.1620-1623, 2004.
- [3]. Vallabha, D., Dorairaj, R., Namuduri, K., and Thompson, H., Automated detection and classification of vascular abnormalities in diabetic retinopathy, Proceedings of 13th IEEE Signals, Systems and Computers 2:1625-1629, 2004.
- [4]. Sinthanayothin, C., Boyce, J., Williamson, T., Cook, H., Mensah, E., LaI, S., Usher, D., 2002. Automated detection of diabetic retinopathy on digital fundus images. Diabet. Med. 19,105- 112
- [5]. Li, H., Chutatape, O., 2004. Automated feature extraction in color retinal images by a model based approach. IEEE Trans. Biomed. Eng. 5 1,246-254
- [6]. Noronha, K., Nayak, J., and Bhat, S. Enhancement of retinal fundus image to highlight the features for detection of abnormal eyes. In Proceedings of the IEEE Region10 Conference (TENCON2006)(2006)
- [7]. Lay, B., Baudoin, C., Klein, J.-C., 1983. Automatic detection of micro aneurysms in retinopathy fluoro-angiogram. Proc. SPIE 432,165.
- [8]. Acharya, U. R., Chua, K. C., Ng, E. Y. K., Wei, W., and Chee, C. Application of higher order spectra for the identification of diabetes retinopathy stages. J. Med. Systems, 2008, 32(6), 48 1-488
- [9]. Marwan DS, Eswaran C, "An automated decision-support system for non-proliferative diabetic retinopathy disease based on MAs and Has detection," Comput. Methods Programs Biomed., electronically published, April 2012.
- [10] Madhura Jagannath Paranjpe, M N Kakatkar" Review of methods of Diabetic Retinopathy Detection & severity Classification" International J of Research in Engineering and Technology eISSN: 2319-1163 pISSN: 2321- 7308
- [11] Raju Maher, Sangrarsing Kayte, Dr. Mukta Dhopeshwarkar"Review of Automated Detection for Diabetes Retinopathy Using Fundus Images"
- [12] Narasimhan K, Neha VC, Vijayarekha K, "An efficient automated system for detection of diabetic retinopathy from fundus images using support vector machine and bayesian classifiers," In: 2012 Int. Conf. Computing, Electron. Elect. Technologies, pp. 964-969, March 2012.
- [13] P. Kumar and L. Godlin Atlas, An Efficient Method for Retinal Hemorrhages Detection in Fundus Images Using Anfis and Cross Section Profile Analysis.
- [14] Estabridis K, de Figueiredo RJP, Automatic detection and diagnosis of diabetic retinopathy. IEEE Int. Conf. Image Processing, ICIP 2007.
- [15] Fleming, D. A., Philip, S., Goatman, A. K., Williams, J. G., Olson, A. J., and Sharp, F. P., Automated detection of exudates for diabetic retinopathy screening. Phys. Med. Biol. 52(24):7385–7396, 2007.
- [16]Shivaram JM, Patil R, Aravind HS, "Automated etection and quantification of hemorrhages in diabetic retinopathy images using image arithmetic and mathematical morphology methods," Int. J. Recent Trends Eng., vol. 2(6), pp. 174-176, November 2009.
- [17] Meera Valvekar ,Geeta Salunke "Detection of Diabetic Retinopathy with Feature Extraction using Image Processing" Int J of Emerging Technology and Advanced Engineering Journal, Volume 5, Issue 1, January 2015.
- [18] Kahai, P., Namuduri, K. R., and Thompson, H., A decision support framework for automated screening of diabetic retinopathy. Int. J. Biomed. Imag. 2006:1–8, 2006.
- [19] Nayak, J., Bhat, P. S., Acharya, U. R., Lim, C. M., and Kagathi, M., Automated identification of different stages of diabetic retinopathy using digital fundus images. J. Med. Syst., USA, 32 (2):107–115, 2008.
- [20]Bernardes, R., Nunes, S., Pereira, I., Torrent, T., Rosa, A., Coelho, D., and Cunha-Vaz, J., Computer-assisted microaneurysm turnover in the early stages of diabetic retinopathy. Ophthalmologica 223(5):284–291, 2009.
- [21] Gonzalez, R. C., and Woods, R. E., Digital image processing, 2 nd edition. Prentice Hall.