

# Detection of Diabetic Retinopathy using Machine Learning

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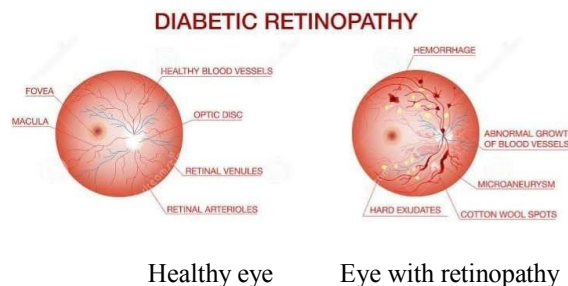
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**Abstract:** Diabetic retinopathy (DR) is a fast-spreading disease across the globe, which is caused by diabetes. The DR may lead the diabetic patients to complete vision loss. In this disease there is a progressive damage to the retina if the high blood glucose levels are not controlled. In this scenario, early identification of DR is more essential to recover the eyesight and provide help for timely treatment. DR has mainly two stages, Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). Non-proliferative diabetic retinopathy (NPDR) is the early stage of the disease in which symptoms will be mild or nonexistent. It is characterized by the presence of microaneurysms, retinal hemorrhages, and hard exudates. While Proliferative Diabetic Retinopathy (PDR) is the advanced stage, where neovascularization and retinal detachment can occur. The detection of DR can be manually performed by ophthalmologists and can also be done by an automated system. In the manual system, analysis and explanation of retinal fundus images need ophthalmologists, which is a time-consuming and very expensive task, but in the automated system, artificial intelligence is used to perform an imperative role in the area of ophthalmology and specifically in the early detection of diabetic retinopathy over the traditional detection approaches. This paper presents a detailed review of DR with machine learning algorithm and a retinal dataset.

**Keywords:** Diabetic retinopathy (DR)

## I. INTRODUCTION

Diabetes is a disease that occurs when your blood glucose, also called blood sugar, is too high. Blood glucose is your main source of energy and comes from the food you eat. Insulin, a hormone made by the pancreas, helps glucose from food get into your cells to be used for energy. Sometimes your body doesn't make enough—or any—insulin or doesn't use insulin well. Glucose then stays in your blood and doesn't reach your cells. Type 1: Type 1 diabetes is an autoimmune disease. The immune system attacks and destroys cells in the pancreas, where insulin is made. It's unclear what causes this attack. Type 2: Type 2 diabetes occurs when your body becomes resistant to insulin, and sugar builds up in your blood. It's the most common type—about 90% to 95% Trusted Source of people living with diabetes have type 2. Gestational: Gestational diabetes is high blood sugar during pregnancy. Insulin-blocking hormones produced by the placenta cause this type of diabetes. In past year localization of the optic disc (OD) from the retinal fundus images has been investigated extensively. The main task of these algorithm to find the location of the OD. For some application such as automatic glaucoma diagnosis found the fundal images, automatic segmentation of OD is needed. The objective of OD segmentation to find its boundary.



Glaucoma is a disease that gradually steal your vision often, glaucoma has no symptoms and suddenly result in vision loss. Glaucoma can lead to blindness the good news is early detection and treatment can lead to save in eye. The front part of the eye is filled with a clear fluid. The fluid flows out through the pupil. It is then absorbed into the bloodstream through the eye's drainage system. Proper drainage helps keep eye pressure at a normal level. The production, flow, and drainage of this fluid is an active, continuous process that is needed for the health of the eye. The inner pressure of the eye (intraocular pressure or IOP) depends on the amount of fluid in the eye. If your eye's drainage system is working properly, then fluid can drain freely out and prevent a buildup. Likewise, if your eye's fluid system is working properly, then the right amount of fluid can be produced. Your IOP can vary during the day, but normally stays within a manageable range. The Eye that contains Glaucoma with most types of glaucoma, the eye's drainage system becomes clogged so the intraocular fluid cannot drain. As the fluid builds up, it causes pressure to build inside the eye. High pressure damages the sensitive optic nerve and results in vision loss. Different method that are used to detect Glaucoma are as follow assessment of raised intraocular pressure (IOP), assessment of abnormal visual field and assessment of damaged optic nerve head. In, Intraocular pressure (IOP) is the fluid pressure of the eye. As pressure is a measure of force per area, IOP is a measurement involving the magnitude of the force exerted by the aqueous humor on the internal surface area of the anterior eye. The IOP can be theoretically determined by the Goldman equation, which is  $IOP = (F/C) + P$ , where F represents aqueous flow rate, C represents aqueous outflow, and P is the episcleral venous pressure. A change or fluctuation in any of these variables will inevitably alter the IOP.

Intraocular pressure is carefully regulated, and disturbances are often implicated in the development of pathologies such as glaucoma, uveitis, and retinal detachment. IOP exists as a fine-tuned equilibrium between the production and drainage of aqueous humor. The balance between IOP increases with increased systemic blood pressure. Sudden increases in IOP can cause mechanical stress and ischemic effects on the retinal nerve fiber layer, while sudden decreases in IOP can cause micro-bubbles to form from dissolved gases in microvasculature with resultant gas emboli and ischemic tissue damage. Chronic elevation of IOP has been infamously implicated in the pathogenesis of primary open-angle glaucoma (POAG) and other vision-damaging problems.

In approaching intraocular pressure, a basic understanding of the production and outflow of the aqueous humor is helpful. Aqueous humor is produced by the ciliary epithelium of the iris ciliary body pars within the posterior chamber of the anterior eye. Aqueous humor accumulates in the posterior chamber and flows through the pupil into the anterior chamber.

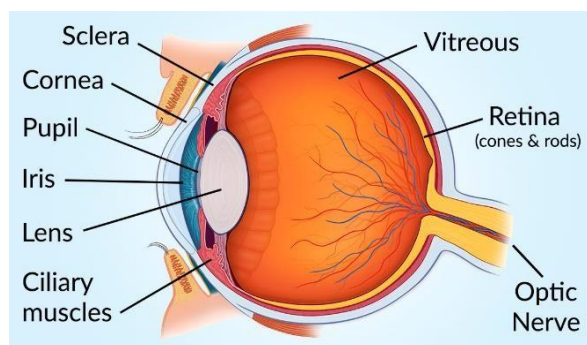


Diagram of eye

The visual field refers to the total area in which objects can be seen in the side (peripheral) vision as you focus your eyes on a central point. Confrontation visual field exam. This is a quick and basic check of the visual field. The health care provider sits directly in front of you. You will cover one eye, and stare straight ahead with the other. You will be asked to tell when you can see the examiner's hand.

Tangent screen or Goldman field exam. You will sit about 3 feet (90 centimeters) away from a flat, black fabric screen with a target in the center. You will be asked to stare at the center target and let the examiner know when you can see an object that moves into your side vision. The object is usually a pin or bead on the end of a black stick that is moved by the examiner. This exam creates a map of your central 30 degrees of vision. This exam is usually used to detect brain or nerve (neurologic) problems.

Goldman perimetry and Automated perimetry. For either test, you sit in front of a concave dome and stare at a target in the middle. You press a button when you see small flashes of light in your peripheral vision. With Goldman testing, the flashes are controlled and mapped out by the examiner. With automated testing, a computer controls the flashes and mapping. Your responses help determine if you have a defect in your visual field. Both tests are often used to track conditions that may worsen over time.

The optic nerve is a bundle of more than 1 million nerve fibers that carry visual messages. You have one connecting the back of each eye (your retina) to your brain. Damage to an optic nerve can cause vision loss. The type of vision loss and how severe it is depending on where the damage occurs. It may affect one or both eyes. Disorders of the optic nerve and retina are common causes of afferent visual loss in clinical neurology. The diagnosis of optic neuropathy should be considered when the following clinical features are present: (1) visual loss in association with a swollen, pale, or anomalous optic disc or (2) visual loss (affecting visual acuity, color vision, or visual field) combined with an afferent pupillary defect (APD) (see Chapter 17), despite a normal disc appearance. The specific cause for optic neuropathy in a given patient often can be established without the need for neuroimaging on the basis of clinical history (i.e., character/progression of vision loss), whether one or both eyes is involved, the pattern of visual field loss, and the optic disc appearance. Acquired optic neuropathies can be classified according to whether the optic disc appears normal, swollen, or pale. Table 15-1 groups possible causes by appearance of the optic disc. Chapter 14 describes the various patterns of visual field loss and clinical history typically elicited in patients with specific optic nerve disorders. This chapter presents the differential diagnosis for optic neuropathies based on the optic disc appearance and discusses retinal disorders of particular interest in neurology.

## II. BLOCK DIAGRAM OF PROPOSED SYSTEM



## III. METHODOLOGY

In this, we first take a fundus image as input for detection of DR. On this input image we perform certain pre-processing operations to further do the adaptive histogram equalization. The output of that process is further sliced using SLIC for super pixel generation. After completion of SLIC process we apply K-means clustering, optic Disk Segmentation, Gabor filter for feature extraction. Further we perform certain Morphological Operation on the fundus image and then the Optic cup segmentation is done. Here after performing all the mentioned operations, we calculate the area of Optic Disc and the area of optic cup which then is used for CDR measurement. The output of this computation is then compared with the threshold value for us to detect the Glaucoma.

### 3.1 Optic Disc Segmentation

- Adaptive Histogram Equalization
- Super pixel Generation Using SLIC
- Feature Extraction using Gabor Filter
- Morphological Operations

### **Adaptive Histogram Equalization**

Adaptive Histogram Equalization enhances the contrast of the grayscale image  $I$  by transforming the values using contrast-limited adaptive histogram equalization (CLAHE). CLAHE operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image. Steps to get adaptive histogram equalization for color image:

- Separate out all the three-color component i.e., Red, Green, and Blue
- Apply adaptive histogram equalization on each color component individually.
- Combine all three-histogram equalized image.

### **SUPER PIXEL GENERATION USING SLIC**

#### **Simple Linear Iterative Clustering (SLIC)**

It is used to aggregate nearby pixels into super pixels in retinal fundus images.

#### **Preprocessing steps for SLIC**

Select area of interest

Resize the given image to dimensions  $250 * 250$  pixels.

Convert the RGB to Lab color space.

#### **SLIC Algorithm**

By default, the only parameter of the algorithm is  $k$ , the desired number of approximately equally-sized super pixels. Clustering procedure begins with an initialization step where  $k$  initial cluster centers  $C_k$  are sampled on a regular grid spaced  $S$  pixel apart. To produce roughly equally sized super pixels, the grid interval is

$$S = (N/k)^{1/2}$$
 from the image with pixels.

The centers are moved to seed locations corresponding to the **lowest gradient position in a  $3 * 3$  neighborhood**.

This is done to avoid: centering a super pixel on an edge, and to reduce the chance of seeding a super pixel with a noisy pixel.

Since the expected spatial extent of a super pixel is a region of approximate size  $S * S$ , the search for similar pixels is done in a region  $2S * 2S$  around the super pixel center.

### **GABOR FILTER**

Gabor filter is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination.

A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image.

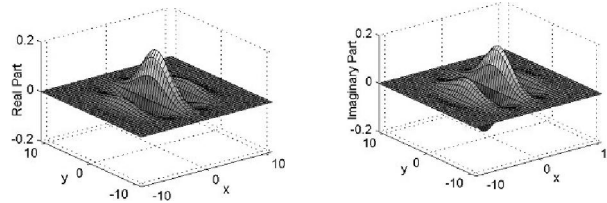
Feature extraction using Gabor filters is a commonly used technique in image processing and computer vision applications. Gabor filters are a type of linear filter that can be used to capture texture information from an image.

The Gabor filter is a function that combines a sinusoidal wave with a Gaussian function. The sinusoidal wave captures the spatial frequency of the texture, while the Gaussian function controls the size and orientation of the filter. By varying the parameters of the filter, different texture features can be extracted from the image.

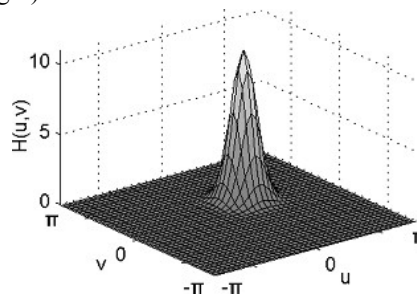
The output of the Gabor filter is a set of complex values that represent the response of the filter at different locations in the image. These complex values can be further processed to obtain a feature vector that captures the texture information in the image. This feature vector can then be used for a variety of tasks, such as classification and recognition.



One advantage of using Gabor filters for feature extraction is that they are robust to small variations in texture and illumination, making them useful for real-world applications. However, the use of Gabor filters requires careful selection of the filter parameters, which can be challenging and time-consuming.



The real part(left) and imaginary part(right) of a Gabor filter.



The frequency response of a Gabor filter.

### MORPHOLOGICAL OPERATION

Morphology is a broad set of image processing operations that process images based on shapes. In a morphological operation, each pixel in the image is adjusted based on the value of other pixels in its neighborhood. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image.

Morphology is a comprehensive set of image processing operations that process images based on shapes [1]. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors.

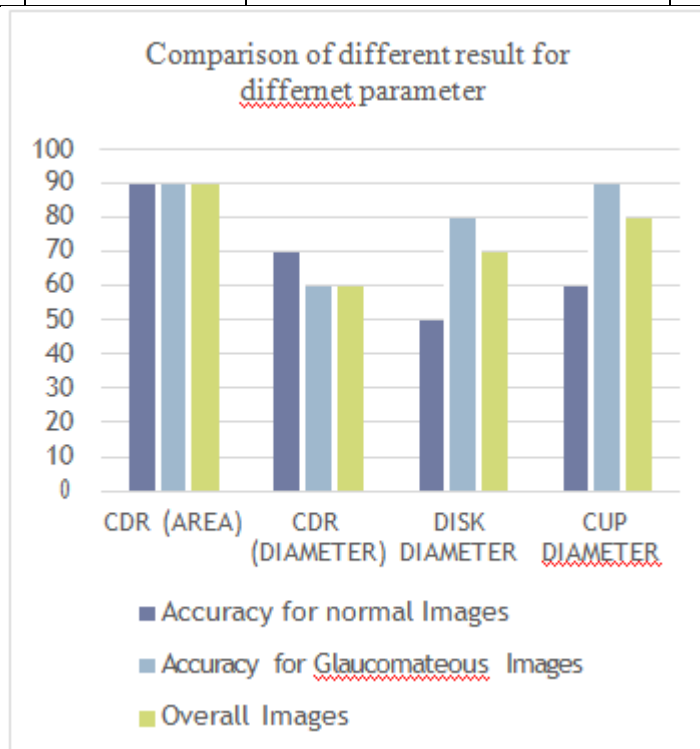
There is a slight overlap between Morphology and Image Segmentation. Morphology consists of methods that can be used to pre-process the input data of Image Segmentation or to post-process the output of the Image Segmentation stage. In other words, once the segmentation is complete, morphological operations can be used to remove imperfections in the segmented image and deliver information on the shape and structure of the image

Image properties are important in image processing steps. Among common formats like jpeg, png, tiff, bmp, svg, gif, webp and etc. which are available for image compressing, high quality jpeg and png are frequently used in the retina fundus databases. The jpeg lossy compression algorithm is suitable for images with smooth variation of tone and color as the pixels are the true color (24-bit) rated as 8 bit/color which means between 0 and 255 in each (red, green, blue) to give 16,777,216 color variation. The fundus images from camera could have artifacts like eye reflecting, motion blur, tilting and rotating that in these cases, preprocessing is needed.

True colors could be saved in an array of color channels which could be processed to get desired features from color gradients. In order to subtract local mean color from image, image was processed through equation 1.8 and saturated. With splitting the color channels, the green channel could be used for CLAHE processing or the image could be converted to a gray-scale/binary image. Local contrast improving enhances the edge definitions with limited amplification by redistributing the exceeded part from clip limit in several histogram equalization. Morphological transformations like opening and closing are applied on images with a structuring element or kernel of elliptical array as a sequential filtering. The resulted image includes blood vessels and hard exudates with a further CLAHE reprocessing. Image matrix could be converted to a sharpened binary image by replacing the pixels values which are greater than a limiting constant with 255.

**IV. RESULT**

Various Parameter	Normal Images (10) Accuracy (%)	Glaucomatous image (17) Accuracy (%)	Overall Result Accuracy (%)
Area of optic cup to disc ratio (CDR)	9(90%)	15(88%)	93%
Cup to disc diameter ratio (CDR)	7(70%)	10(58%)	66%
Glaucoma detection based on disc diameter	<b>5(50%)</b>	<b>14(82%)</b>	<b>70%</b>
Glaucoma detection based on cup diameter	<b>6(60%)</b>	<b>15(88%)</b>	<b>83%</b>



**V. CONCLUSION**

This paper is implemented by using machine learning for detection of diabetic retinopathy. the testing accuracy is 92.4% and successfully predicted into different stages. The proposed method achieves high classification accuracy when differentiating glaucomatous subjects from healthy ones.

**REFERENCES**

- [1]. J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. Ginneken, "Ridge-based vessel segmentation in color images of the retina," IEEE Trans. Med. Imag., vol. 23, no. 4, pp. 501–509, Apr. 2004.
- [2]. A. Hoover and M. Goldbaum, "Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels," IEEE Trans. Med. Imag., vol. 22, no. 8, pp. 951–958, Aug. 2003.
- [3]. M. Foracchia, E. Grisan, and A. Ruggeri, "Detection of optic disc in retinal images by means of a geometrical model of vessel structure," IEEE Trans. Med. Imag., vol. 23, no. 10, pp. 1189–1195, Oct. 2004.
- [4]. Z. Zhang, B. H. Lee, J. Liu, D. W. K. Wong, N. M. Tan, J. H. Lim, F. S. Yin, W. M. Huang, and H. Li, "Optic disc region of interest localization in fundus image for glaucoma detection in argali," in Proc. Int. Conf. Ind. Electron. Appl., 2010, pp. 1686–1689.

- [5]. X. Zhu and R. M. Rangayyan, "Detection of the optic disc in images of the retina using the hough transform," in Int. Conf. IEEE Eng. Med. Biol. Soc., 2008, pp. 3546–3549.
- [6]. J. B. Jonas, W. M. Budde, and S. Panda-Jonas, "Ophthalmoscopic evaluation of the optic nerve head," *Surv. Ophthalmol.*, pp. 293–320, 1999.
- [7]. J. Cheng, J. Liu, Y. Xu, D. W. K. Wong, B. H. Lee, C. Cheung, T. Aung, and T. Y. Wong, "Superpixel classification for initialization in model based optic disc segmentation," in Int. Conf. IEEE Eng. Med. Biol. Soc., 2012, pp. 1450–1453.
- [8]. J. A. Giacony, S. K. Law, A. L. Coleman, and J. Caprioli, *Pearls of Glaucoma Management*. New York: Springer, 2010.
- [9]. C. Muramatsu, T. Nakagawa, A. Sawada, Y. Hatanaka, T. Hara, T. Yamamoto, and H. Fujita, "Automated segmentation of optic disc region on retinal fundus photographs: Comparison of contour modeling and pixel classification methods," *Comput. Methods Programs Biomed.*, vol. 101, pp. 23–32, 2011.
- [10]. X. Ren and J. Malik, "Learning a classification model for segmentation," in Int. Conf. Comput. Vis., 2003, vol. 1, pp. 10–17.