# A Review on Detection of Diabetic Retinopathy

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*Abstract*—Diabetic retinopathy (DR) is a consequential complication arising from diabetes, impacting the retina and potentially leading to vision impairment or even blindness. This project centers on the development of an advanced diagnostic system for the early identification and assessment of diabetic retinopathy severity through the analysis of fundus images. The project's framework involves the application of deep learning methodologies, a subset of artificial intelligence, to analyze and interpret biomedical images. Specifically, Convolutional Neural Networks (CNNs) are utilized to discern intricate patterns and features within retinal images, enabling precise identification of retinopathic abnormalities. To ensure the model's robustness across diverse clinical scenarios, the project harnesses curated datasets comprising a varied range of fundus images for training. The primary objective is to create a software tool capable of automatically discerning different levels of diabetic retinopathy severity upon uploading fundus images.
The project's outcomes underscore the effectiveness of the developed system in providing swift and reliable assessments, enabling timely intervention and management of diabetic retinopathy. In conclusion, the incorporation of deep learning into biomedical imaging emerges as a promising avenue for improving the early detection of diabetic retinopathy. This research contributes to ongoing endeavors aimed at enhancing healthcare outcomes for individuals at risk of this sight-threatening complication.

***Keywords—Diabetic Retinopathy, Deep Learning, Biomedical Imaging, Convolutional Neural Networks, Fundus Images, Severity Assessment.***

## I. INTRODUCTION

Diabetes a chronic disorder which is caused due to increase in blood sugar (glucose) levels. This disorder develops when the body is unable to use the insulin that is produced, or is unable to create enough of the hormone that controls blood sugar. Diabetic Retinopathy is an eye disease caused by high blood sugar level due to diabetes. Over a time period it can damage the retina which is a light sensitive tissue that detects light & transmit visual information to the brain. It is the most often identified cause of blindness in people of working age.

Diabetic Retinopathy is a progressive disease; however, it is not addressed in the beginning because the disease indicates no signs of visual impairment. The best way to limit vision loss and prevent or reduce the advancement of diabetic retinopathy is by routine eye exams, early detection, and prompt treatment. Depending on the disease's severity and stage, management options may include intravitreal injections, surgery, or laser treatment (photocoagulation). Furthermore, maintaining blood pressure, cholesterol, and blood sugar levels is essential for the treatment of diabetic retinopathy. The most effective way to manage DR is detected at early stage using the available techniques. With the current DR screening treatments, retinal image analysis, which includes eye fundus examination, is a major tool for monitoring changes in the retinal region, enabling early diagnosis of DR in all diabetic patients, and guaranteeing that the effective course of treatment for DR is sustained over time.

The retina is a complicated structure, and as diabetic retinopathy advances through several phases, certain changes occur in different components of the retina :

1. Retinal Blood Vessels:

   Blood vessels in the retina weaken during the early stages of DR and may also leak fluid or blood into retina. This leakage is termed as diabetic macular edema.

   As the disease worsens, some blood vessels may clog, this leads to inadequate flow of blood to some parts of the retina.

2. Macula:

   It is the central part of the retina responsible for sharp central vision.

   When fluid accumulates in the macula due to macular edema, this leads to distorted or blur vision.

3. Neural Tissue:

   The neural tissue includes photoreceptors and layers of nerve cells.

Long term exposure to high blood sugar levels can harm nerve cells which may lead to impaired vision.

4. Optic Nerve:

The optic nerve transmits visual information from the retina to the brain.

In advance stages of DR, abnormal blood vessels may grow on the optic nerve. These vessels are prone to bleeding, leading to further complications such as vitreous haemorrhage or tractional retinal detachment.

The changes in these components takes place across different stages of diabetic retinopathy:

Non-proliferative Diabetic Retinopathy (NPDR):

- NPDR is characterized by mmicroaneurysms, hhaemorrhages, exudates in the retina. Although, these changes do not affect the vision initially, but they are indicators of damage to the blood vessels.
- Severe changes such as intraretinal microvascular abnormalities (IRMA) and venous beading occur as NPDR progresses.

Proliferative Diabetic Retinopathy (PDR):

- PDR is characterized by the growth of abnormal blood vessels on the surface of retina or optic nerve.
- The abnormal blood vessels are prone to bleeding, this leads to bleeding of gel like substance inside the eye.

Signs of Diabetic Retinopathy on the Retina Fig. 1. • Microaneurysms are bulges that occur when a capillary wall thickens up & move in an outward direction, later on these can leak plasma into retina. These are early signs of DR.

• Haemorrhages are larger version of microaneurysms if these appear in retinal nerve fibre layer and these have a flame-like shape while if these appear in the middle layers of the retina and have a red dot blot like appearance.

• Macular odema is extensive leakage from capillary or microaneurysms. The leaked fluid accumulates in the retinal layers.

• Hard Exudates are caused by retinal edema and it develop at the junction of normal and swollen retina. They are made up of lipoproteins and lipid filled macrophages and they are waxy yellow colour in appearance with the distinct margins.

*A. Survey on Cameras used for fundus images* Field retinal images that capture 30° -50° of the posterior retina, this includes the macula and optic disc. These are the images that are commonly used in ophthalmology clinics for DR status. It is observed that certain screening programs makes use of a single-field CFP during initial screenings. Despite this use of two or three field CFP images gains higher sensitivity and specificity in detection of DR. The user of multiple fields helps in covering a wider area. This in turn helps in detecting subtle changes associated with DR.

Some of the cameras used for capturing CFP are as below:

**Mydriatic desktop fundus cameras** and **NM (NonMydriatic) desktop fundus cameras** are both valuable instruments in the field of ophthalmology, with each providing unique benefits adapted to specific clinical demands.

Before imaging using mydriatic desktop fundus cameras, the patient's pupils must be dilated. This process, known as mydriasis, broadens the field of view, allowing for a thorough investigation of the retina's delicate components. These cameras are especially popular in clinical settings because they give high-resolution pictures that are critical for accurately diagnosing and monitoring disorders like as diabetic retinopathy, macular degeneration, and glaucoma. In contrast, NM desktop fundus cameras provide a noninvasive option, avoiding the requirement for pupil dilation. This not only improves patient comfort, but also makes the imaging procedure easier for practitioners. Although NM cameras have a somewhat shorter field of vision than mydriatic cameras, they are useful for rapid screenings in primary care settings, allowing for early diagnosis of retinal disorders.

The choice between different camera types is determined by a variety of criteria, including the unique clinical situation, patient preferences, and resource availability. While mydriatic cameras thrive in comprehensive examination and surveillance in clinical settings, NM cameras are more convenient and efficient for general screening programs and primary care visits.

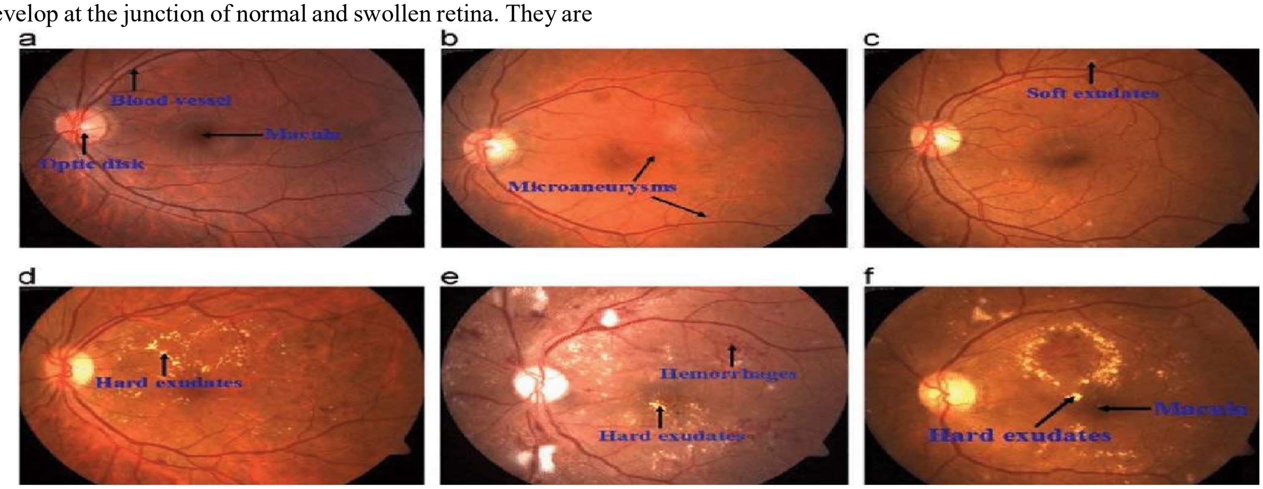


Fig. 1 Signs of Diabetic Retinopathy.

I. TABLE 1. COMPARISON OF CAMERAS USED FOR CAPTURING FUNDUS IMAGES.

| Model | Type | Dimensions (mm) | Weight (kg) | Power Supply | Field of View | Resolution (MP) | Pupil Size (mm) |
|---|---|---|---|---|---|---|---|
| Topcon TRC-NW400 | Non mydriatic fundus camera | 383 x 660 x 700 | 18 | AC 100–240 V | 45° | 20 | 4 |
| Canon CR-2 AF | Non mydriatic fundus camera | 305 x 473 x 500 | 15 | AC 100–240 V | 45° | 20.2 | 4 |
| Nidek AFC 330 | Non mydriatic fundus camera | 316 x 518 x 579 | 29 | 300 W | 45° | 16.2 | 4 |
| Retina Vue 100 | Handheld non-mydriatic fundus camera | 150 x 230 x 250 | 1.2 | 100-240V | 45° | 8 | 3.3 |
| Eidon AF | Confocal scanning laser ophthalmoscope | 360 x 480 x 480 | 15 | 100-240V | Up to 110° | 18 | 2.5 – 7 |
| Remidio on Fundus Phone | Smartphone-based fundus camera | 150 x 100 x 60 | 0.5 | Battery | 40° | 5 | 3 |
| Optomed Aurora | Handheld fundus camera | 170 x 160 x 230 | 1.2 | USB | 40° | 12 | 3.5 |
| Zeiss Cirrus 600 | Non mydriatic fundus camera | 408 x 480 x 680 | 33 | AC 100–240 V | 45° | 12 | 4 |
| Center Vue DRS | Non mydriatic fundus camera | 580 x 550 x 330 | 19 | Power cord | 45° | 20 | 3.8 |
| Optos Daytona | Ultra widefield imaging | 570 x 1760 x 800 | 45 | 100-240 VAC, | Up to 200° | 50 | 2.5 |

In the end, mydriatic and NM desktop fundus cameras are invaluable instruments in the global toolbox of ophthalmologists, making a substantial contribution to the diagnosis, treatment, and monitoring of retinal disorders. Comparison of some cameras used for capturing Fundus images is shown in Table 1.

### *B. Datasets*

Various datasets are available publicly for detection of DR. The images provided in the datasets are used for training, testing and validating the performance of different systems against each other. Retinal images are available in two forms Viz. optical coherence tomography (OCT) and fundus color images. OCT images are captured using low-coherence light, these provide information about retinal structure and thickness. Whereas fundus images are captured using reflected ight these are 2-dimensional images. Following are the referred datasets:

- Messidor [11]: It is a publicly available dataset that contains 1200 color fundus images which are acquired at 45° these are annotated to 4 DR stages.
- Messidor-2 [11]: It is a publicly available dataset that contains 1748 color fundus images which are acquired at 45°
- Drive [12]: A public dataset that contains 40 images of size 565 x 584 pixels acquired at 45°.

- Kaggle [13]: It contains images collected using different cameras. The images are classified into 5 DR stages.
- STARE [14]: A dataset used for blood vessel segmentation, contains 20 images acquired at 35°.
- India Diabetic Retinopathy Image dataset (IDRiD) [15]: Contains 516 images acquired at 50° divided into 5 DR stages.

Table 2. Gives information of various datasets.

Survey on Diabetic Retinopathy Detection

An emphasise on metabolic pathways that shows how oxidative stress is a direct pathway for hyperglycemia to develop into DR is given in [1]. The author has Also given a brief about test conducted on animals to test malfunction of insulin resulting into DR as insulin play an important role in absorption of different macromolecules. It discusses risk factors, and therapeutic techniques, emphasizing the need of early identification in preventing visual loss. Prospects for the future encompass developments in microvascular issues and novel therapies aimed at addressing biochemical alterations and neurodegeneration. With the rising prevalence of diabetic retinopathy worldwide, it is imperative to develop better diagnostic and preventative techniques.

Grauslund, J. [2] focuses onto bringing DR detection in Handheld Devices and discusses the use of various deep learning algorithms for DR screen, it highlights the possible improvements in diagnostic performance. The challenges in integrating these technologies with clinical facilities are also addressed.

Jiwani, N., Gupta, K. and Afreen, N. [3] used CNN based on binary grading using IDRiD dataset for DR classification. This CNN model resulted into a training accuracy of 73% and test accuracy of 68%. The goal was to increase the efficiency of DR detection.

The application of various deep learning techniques are addressed in [4] for classification of DR. It highlights the importance of early detection and the challenges in manual diagnosis. CNNs, Adaboost and self-supervised methods are compared

The authors of [5] have reviewed various datasets available, device used for their acquisition, resolution & their particular uses. They use these datasets for various algorithms observe the result & then combine multiple datasets to model specific algorithm in order to get the best possible accuracy.

An overview of use of deep learning algorithms for both detection and classification of DR is provided [6]. Also, various studies and datasets used for the same are discussed. It also covers performance parameters, image processing techniques etc. used.

[7] is a comparison of various Methodology such as Adaboost, Ensemble, Improved Matched Filtering, CNN and RF, Variants of CNN. Yang, Zhengwei and Tan, etc

[8] takes into consideration previously used classification which include Grading of individual lesions, Hammersmith grading system, Modified airlie house classifications – the ETDRS severity scale, WESDR, ICDR. Next it focuses on Limitations of current DR classification systems & in conclusion it suggests new developments that will influence DR classification system.

[9] The authors analytically compared 28 hybrid architecture for automated binary classification of DR with 7 Deep learning architectures. Özçelik, Y.B. and Altan, A.

[10] presents a model that employs four-step procedure that includes 2D-SWT, fractal analysis, feature extraction utilizing statistical functions and entropy, a chaotic-based wrapper technique, and an RNN & LSTM architecture.

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