# Detection of Diabetic Retinopathy

**R. B. Kakkeri, Sayali Surve, Shahrukh Shaikh, Vinita Dhoble**

***Abstract— Diabetes is well known disease and may cause abnormalities in the retina (diabetic retinopathy), kidneys (diabetic nephropathy), nervous system (diabetic neuropathy) and is known to be a major risk for cardiovascular diseases. Diabetic retinopathy is a micro vascular complication caused by diabetes, which can lead to blindness. In early stages of diabetic retinopathy typically there are no visible signs but the number and severity of abnormalities increase during the time. Diabetic retinopathy typically starts with small changes in retinal capillaries. This phenomenon is called neovascularization, which is a serious eyesight threatening state and may cause sudden loss in visual acuity or even permanent blindness. For automated screening programs to work robustly efficient image processing and analysis algorithms have to be developed. This work examines recent literature on digital image processing in the field of early detection of diabetic retinopathy using fundus photographs. Diabetic retinopathy pathologies were further categorized into several groups. In this paper several different databases are presented and their characteristics discussed.***

***Keywords: diabetic nephropathy, diabetic neuropathy Diabetic, work, automated screening,***

## I. INTRODUCTION

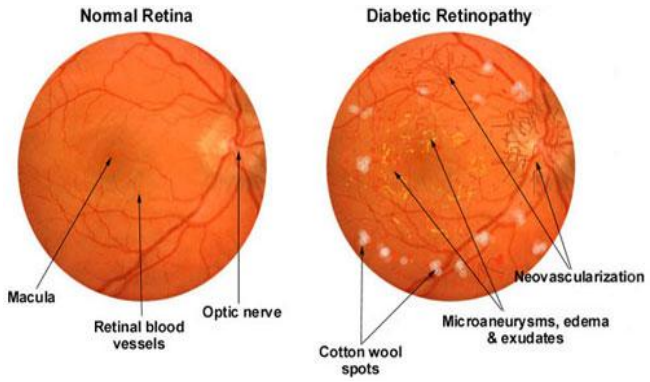


**Fig. 1: Retinal images of the eye**

### *1) Early diabetic retinopathy*

(Non-proliferative diabetic retinopathy) - the walls of the blood vessels weaken and micro aneurysms develop; these are tiny bulges in the walls of the blood vessels. Sometimes they leak blood and fluid - this does not generally affect vision. Eventually, however, the tiny blood vessels that nourish the macula may become damaged, leading to varying degrees of vision loss - the patient may find it hard to see things clearly at a distance and/or in fine detail, such as small print on paper.

### *2) Advanced diabetic retinopathy*

(Proliferative diabetic retinopathy) - in the more advanced stages of diabetic retinopathy the blood vessels that nourish the retina may become blocked. The body tries to make up for this by producing new blood vessels in the area. These new blood vessels may be unstable and can bleed into the clear, jelly-like substance (vitreous) that fills the center of the eye, causing blurred and patchy vision as leaking blood obscures the patient's sight. In time the bleeding can result in the formation of scar tissue which may pull the retina out of position (retinal detachment) - vision gets darker, more floaters appear, and the patient eventually loses his/her sight if the condition is left untreated.

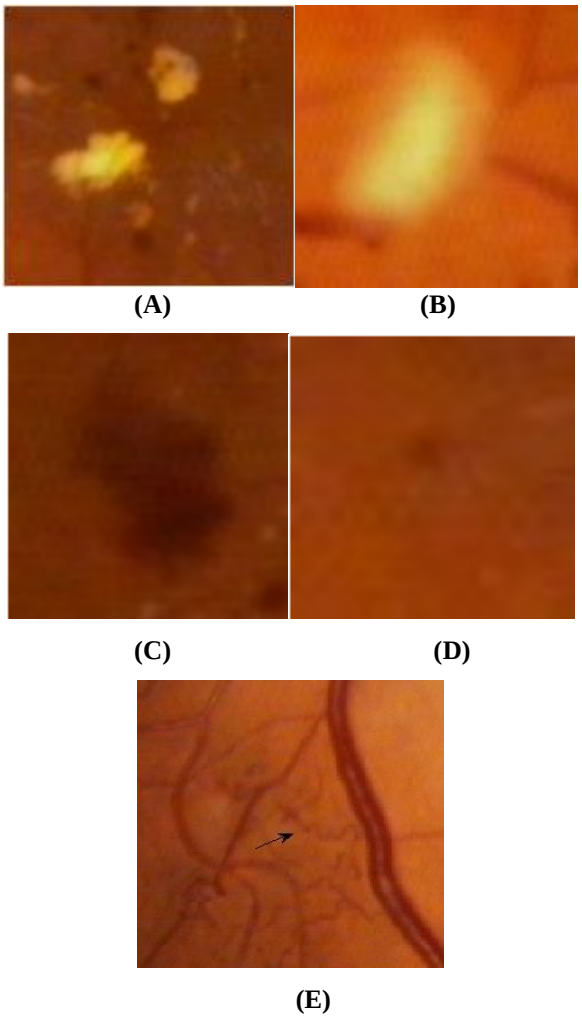


**Fig. 2: (a) Hard exudates. (b) Soft exudates.(c) Haemorrhages (d) Micro aneurysms. (e) Neovascularization**

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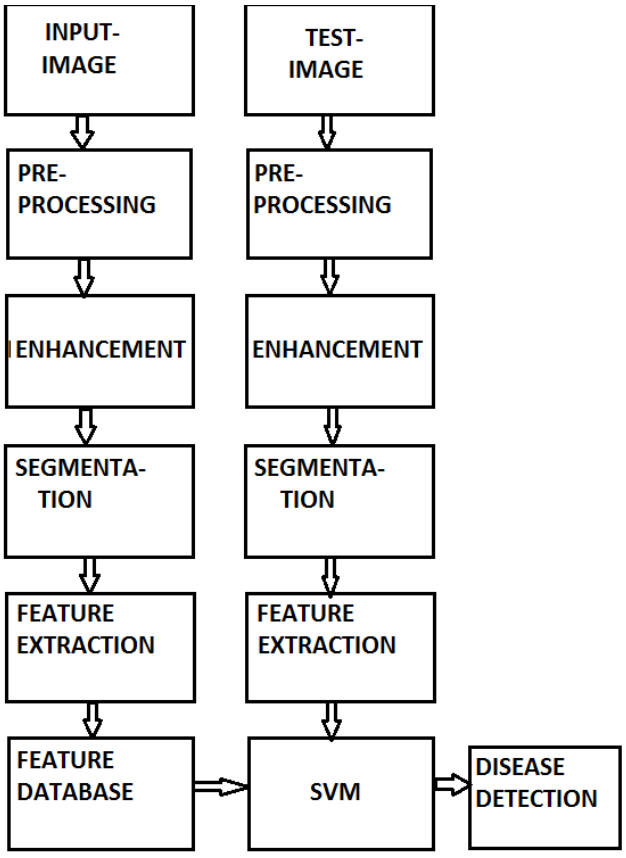
After diagnosis of diabetic retinopathy, regular monitoring is needed due to progressive nature of the disease. Sadly, broad screening cannot be performed due to the fact that fundus image examination requires medical experts. For the screening, automated image processing methods must be developed and to develop automated image processing methods high quality databases for algorithm evaluation are required.

## II. SCHEMATIC APPROACH

The below block diagram shows the blocks that are included in cataract detection which include following blocks

1. Input image
2. Preprocessing of the input image
3. Enhancement of the input image
4. Segmentation of the input image
5. Feature extraction of the input image
6. Test image
7. Preprocessing of the test image
8. Segmentation of the test image
9. Feature extraction of the test image
10. Feature database
11. SVM (Support Vector Machine)
12. Disease detection




## III. ALGORITHM

We propose an algorithm for the detection of Haemorrhages from Diabetic Retinopathy images. The algorithm proceeds through three main steps

1. Color image enhancement
2. Image subtraction to extract blood vessels and hemorrhages and
3. Use of set of optimally adjusted morphological operators to suppress blood vessels and to highlight only haemorrhages. These automatically detected haemorrhages are validated by comparing with expert ophthalmologists' hand-drawn ground-truths. Quantitative performance of our algorithm is evaluated by calculating sensitivity and specificity and predictive value (PV).

## IV. WORKING

### *A. Input Images*

For the input images we use fundus photography. Fundus imaging has an important role in diabetic retinopathy detection and monitoring because eye fundus is sensitive to vascular diseases and we can consider fundus imaging as a candidate for non-invasive screening. The success of this type of screening approach depends on accurate fundus image capture, and especially on accurate and robust image processing and analysis algorithms for detection of abnormalities. Many algorithms have been proposed for fundus image analysis using different methods and approaches.

### *B. Pre-processing*

The main objective of image pre-processing methods is to attenuate image variation by normalizing the original retinal image against a reference model. Variations typically arise within the same image (intra-image variability) as well as between images (inter-image variability) and to enable efficient image analysis it is necessary to compensate for this variability. Intra-image variations arise due to differences in light diffusion, the presence of abnormalities, variation in fundus reflectivity and fundus thickness. Inter-image variability is caused by factors including differences in cameras, illumination, acquisition angle and retinal pigmentation.

The illumination component of a digital retinal photograph is characterized by gradual non-uniform spatial variations. A number of general-purpose techniques have been investigated for attenuating this variation. Early approaches investigated space-variant filtering schemes supporting locally adaptive contrast enhancements. High pass filtering and mathematical modelling of the non-uniformity followed by subtraction of this component from the observed image have also been investigated for the correction of non-uniform illumination. Several authors proposed image formation models for describing the observed retinal image, typically in terms of a foreground image, background image and an acquisition transformation function. The foreground image contains the vasculature, optic disk and any visible lesions. The background image contains all illumination variation due to the transformation function of the original image. Shade-correction is a method in which the background image is first approximated by smoothing the original image with a mean or median filter whose size is larger than the largest retinal feature. The original image may then be divided by the filtered image or the filtered image subtracted from the original image.

In authors apply alternation sequential filters to calculate the background approximation in order to avoid artifacts at borders of bright regions. A method was proposed for correcting the non-uniform illumination using a nonlinear point transformation to correct image intensity. Authors used a parameterized model to normalize the output image. Colour model describes colours in a formal way according to a certain specification. Usually colour models represent a colour in the form of tuples (generally of three). For example, according to RGB (Red, Green, Blue), white colour is represented by the tuple (0, 0, 0) and the black colour is represented by (255,255,255). The purpose of a colour model is to facilitate the specification of colours in a certain way and common standard. Colour models lend themselves to (in principle) reproducible representations of colour, particularly in digital representations, such as digital printing or digital electronic display.

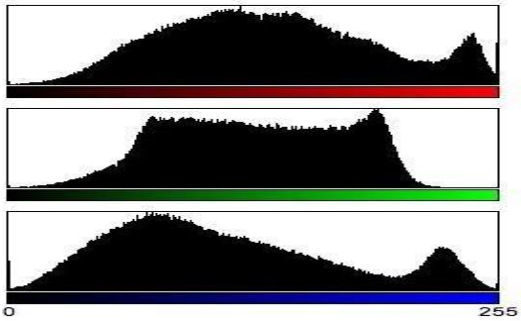



**Fig. 3 : Color histogram diagram of three channels (R, G and B).**

### *C. Enhancement of the input image*

In enhancement the most important part is the histogram. The color histogram is a method for describing the color content of an image, it counts the number of occurrences of each color in an image. The color histogram of an image is rotation, translation, and scale-invariant [3]; therefore, it is very suitable for color-based CBIR: content-based image retrieval using solely global color features of images. However the main drawback of their use is that they do not take account of space information concerning the color. This can lead to unexpected errors.

### *D. Segmentation*

The segmentation of the retinal vasculature is very important because retinal vasculature contains many useful information about the patients' health. Accurate segmentation of the retinal blood vessels is often an essential prerequisite step in the identification of the retinal anatomy and pathology. Segmentation of blood vessels is important for image registration or spatial alignment of images.

The retinal vasculature is composed of arteries and veins. The central retinal artery bifurcates at or on the optic disk into divisions that supply the four quadrants of the inner retinal layers. The vessels have a lower reflectance compared to other retinal surfaces and because of that they appear darker relative to the background. Occasionally a light streak running the length of the vessel is reflected from the transparent convex wall of the arteriole. There are many different algorithms for segmentation of blood vessels. Matched filtering for the detection of the vasculature convolves a 2D kernel with the retinal image. Authors proposed a two-dimensional linear kernel with a Gaussian profile for segmentation of the vasculature. The profile of the filter is designed to match that of a blood vessel, which typically has a Gaussian or a Gaussian derivative profile. The kernels are typically rotated in 30–45 degree increments to fit into vessels of different orientations. The highest response filter is selected for each pixel and is typically thresholded to provide a vessel image. Further post processing is then applied to identify vessel segments. Matched filtering performs well when used in conjunction with additional processing techniques but there are some problems. Convolution kernels may be quite large and need to be applied in several orientations which can be very computationally expensive. Kernel responds optimally to vessels that have the same standard deviation of the underlying Gaussian function specified by the kernel. Retinal background and low contrast of smaller vessels increase the number of false responses around bright objects. Several authors have proposed refinements and extensions which address many of these problems.

### *E. Feature Extraction*

In the feature extraction mainly the filters are used. The filters which we are going to use the are Wiener filter and gabor filter.

### *F. FILTERS*

#### *4.1 Wiener Filter*

The inverse filtering is a restoration technique for deconvolution, i.e., when the image is blurred by a known lowpass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering. However, inverse filtering is very sensitive to additive noise. The approach of reducing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously.

#### *4.2 Gabor Filter*

A Gabor filter is obtained by modulating a sinusoid with a Gaussian. For the case of one dimensional (1D) signals, a 1D sinusoid is modulated with a Gaussian. This filter will therefore respond to some frequency, but only in a localized part of the signal. Let $g(x,y,\theta,\varphi)$ be the function defining a Gabor filter centered at the origin with $\theta$ as the spatial frequency and $\varphi$ as the orientation. We can view Gabor filters as:

$$G(x,y,\theta,\varphi) = \exp(-x2 + y2\ \sigma 2)\exp(2\pi\theta i(x\cos\varphi + y\sin\varphi))) \quad (1)$$

It has been shown that $\sigma$, the standard deviation of the Gaussian kernel depends upon the spatial frequency to measured, i.e. $\theta$. In our case, $\sigma = 0.65\theta$.

## V. RESULT ANALYSIS

The GUI will consist of a page which will ask user for his fundus picture of retina. This image will then be processed by our software and tell the user the exact amount of infection present in his eye due to diabetic retinopathy. It will also highlight the percentage of infection.

## VI. CONCLUSION

A fast and reliable detection method for detecting Hemorrhages has been presented in this work. This method is developed to detect hemorrhages from DR images. The microaneurysm and blood vessel detection could also be added in order to facilitate ophthalmologists' decision on severity of the disease and to give laser treatment. Future work will address an issue of improving sensitivity by improving the results of other tasks such as detection of faint and small hemorrhages. Early detection of diabetic retinopathy is very important because it enables timely treatment that can ease the burden of the disease on the patients and their families by maintaining a sufficient quality of vision and preventing severe vision loss and blindness. Positive economical benefits can be achieved with early detection of diabetic retinopathy because patients can be more productive and can live without special medical care. Image processing and analysis algorithms are important because they enable development of automated systems for early detection of diabetic retinopathy. In this paper we gave a short overview of major image processing components required to build an automated system for early detection of diabetic retinopathy.

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