# Automatic Detection And Classification Of Diabetic Retinopathy Stages In Retinal Image

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# Abstract

This paper summarizes the different imaging techniques and methodologies used to perform classification of the different stages of a disease called diabetic retinopathy. In particular it focuses on deep learning techniques to perform such detection on the fundus images of the patient's eye. Diabetic retinopathy is a progressive disease that causes the patient to lose eyesight if not diagnosed and treated at an early stage. Ophthalmologists usually diagnose the patient of this disease by screening the retinal fundus images to look for lesions. But the inaccuracy of such diagnosis together with the delay between diagnosis and treatment motivated researchers to automate this process of diagnosis. Using neural networks to train the system on a set of training images, it is possible to make systems that are more accurate and faster the human experts.

# Contents

# Chapter 1

# Introduction

## 1.1 General Overview

Visual perception is an integral part of human life. The eye is an organ that helps humans in this perception by allowing them to interact with the world. It involves sophisticated parts in the retinal region of the eye that reacts to the lighting condition to which it is exposed to. Such parts include the light sensitive rods and cones that send nervous impulses once light falls on it. These nervous impulses triggers the brain and causes it to detect the object that the person sees.

Although this method of sensing is very crucial to the humans, it can be easily impaired by various diseases, causing them to become blind in extreme cases. One such disease is Diabetic Retinopathy (DR) that is very common in diabetic patients and is one of the major reasons for such patients to lose their vision. It is also the fastest growing cause of blindness in the world. But it is possible to eliminate the risk of this disease if it is detected early and treated for accordingly.

The symptoms of this disease include growth of small legions or hemorrhages at its initial stages. Ophthalmologists can detect such symptoms of the disease by screening the fundus images of the eye. These are images of the retina taken through the pupil. Any hemorrhages or legions detected in the image ensures that the patient is positive of the disease. But detection of such lesions are difficult and often time consuming since they are very small and complex structures. Hence researchers are looking for ways to automate the detection procedure so that the ophthalmologists can concentrate on treating the disease rather than detecting.

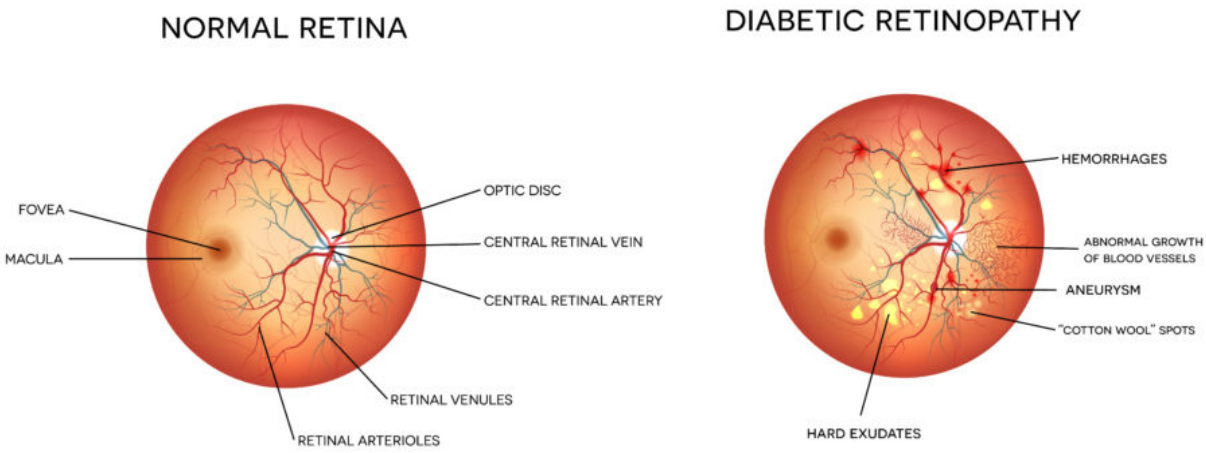



Figure 1.1: Normal versus diseased retina.

## 1.2 Motivation

The increasing number of diabetic patients and the influx in blindness among these patients caused by DR motivated us to work in this field. Also, the toll it takes on the ophthalmologists to detect the complex symptoms, motivated us to automate the system of detection so that they can concentrate more on treatment rather than detection. The delay between the detection and treatment procedure also drove us to work on this field because machines can detect the disease faster than humans.

## 1.3 Purpose of this report

This report initially elaborates on what the different stages of Diabetic Retinopathy are and what are the symptoms of such stages. It also includes the motivation that has driven us to work on this problem of automation. It then summarizes all the related works that have been done on detection of Diabetic Retinopathy using imaging techniques including works that have been done both with and without deep learning techniques. Lastly we conclude the report with our proposed methods and future works that can still be done in this field of research.

# Chapter 2

# Diabetic Retinopathy

## 2.1 Stages of Diabetic Retinopathy

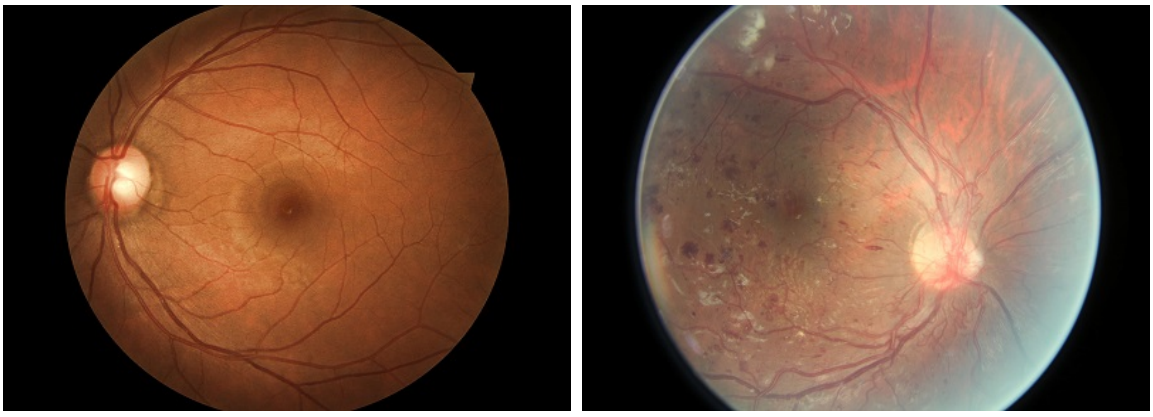
Diabetic Retinopathy (DR) occurs when tiny blood vessels in the retina are damaged due to diabetes. These blood vessels leak blood or fluid forming lesions or hemorrhages that blur the vision of the patient. Each eye of a patient can be at different stages of the disease. But for the sake of simplicity, we broadly categorize the the disease into two categories:

- Non-proliferate diabetes retinopathy (NPDR)
- Proliferate diabetes retinopathy (PDR)

Non-proliferate PDR is the initial stage of DR where the biological abnormalities starts growing. Depending on the extent of the growth, the stages can be further categorized into mild and severe NPDR. If the disease still goes untreated, the final stage of the disease, Proliferate DR is achieved.

Once PDR is reached, new blood vessels start growing at a very fast rate. The tendency of the blood vessels to change and leak at the same time causes blindness or complete loss of vision. Hence the level of severity of the disease can be classified into 5 distinctive stages ranging from stage 0 to stage 4. Stage 0 is the safe state whereas stage 4 is the most severe stage that usually leads to blindness. The stages are:

- Stage 0: no DR
- Stage 1: mild DR
- Stage 2: moderate nonproliferative DR
- Stage 3: severe nonproliferative DR
- Stage 4: proliferative DR or Macular edema(ME)



(a) Stage 0 (b) Stage 4

Figure 2.1: Safe state versus severe state.

## 2.2 Image Dataset Available

In order to find a reliable model of neural network, we need a set of consistent high quality images that can be used to train and compare the performance of the networks. Some available datasets are DIARET DB0 [1], DIARET DB1 [2], MESSIDOR [3], and Kaggle [4]. Here we have listed the publicly available fundus image datasets that are available:

- Messidor-2 [3]: Dataset of 1748 labelled color fundus images of 874 subjects with diabetes. Images of both the eyes of the subject are present in the dataset.
- Kaggle Dataset [4]: Dataset of 35126 labeled color fundus images of diabetic subjects. The dataset contains images of both the eyes of the patients. But the number of images in different classes are unbalanced and the images are of different aspect ratio. So, they need to be pre-processed before training.

# Chapter 3

# Review of Technical Literature

Most non-deep learning approaches consist of several steps. Preprocessing steps such as contrast enhancement are usually carried out initially to lessen image variation by normalizing the original retinal image. Afterwards, irrelevant anatomical components such as the optic disk and vessels are removed. Finally, only the remaining pathological features of DR are retained for subsequent classification.

Non-deep learning methods from 2015 or earlier can be grouped into two types: exudate (EX) segmentation and red lesion (RL) segmentation.

## 3.1 EXUDATE SEGMENTAION

EXs are lipoprotein intraretinal deposits due to vascular leakage. They appear in retinal images as yellowish lesions with well-defined edges. Their shape, size, brightness, and location vary among different patients. When clusters of EXs are located in the macular region, they are indicative of macular edema (ME), which is the main cause of visual loss in DR patients. For this reason, many researchers introduced the idea of a coordinate system based on the location of the fovea to determine DR grading. Different techniques have been proposed for EXs detection. They can be divided into four categories:

### 3.1.1 REGION GROWING METHOD

**o Automated detection of diabetic retinopathy on digital fundus images (2008).**

- Authors: Sinthanayothin et al
- Purpose: develop an automated screening system to analyse digital colour retinal images for important features of non-proliferative diabetic retinopathy (NPDR).
- Method: High performance pre-processing of the colour images was performed. Previously described automated image analysis systems were used to detect major landmarks of the retinal image (optic disc, blood vessels and fovea). Recursive region growing segmentation algorithms combined with the use of a new technique, termed a Moat Operator, were used to automatically detect features of NPDR. These features included haemorrhages and microaneurysms (HMA), which were treated as one group, and hard exudates as another group.
- Features:
  - Hard exudates : identified as adjacent pixels with similar colour or grey level.
  - HMA : sharpened using Moat Operator then identified by thresholding.
- Classifier: Multilayer perceptron neural network to identify blood vessels
- Data: 112 digital fundus images of patients attending a DR screening service
- Results: sensitivity and specificity for exudate detection were 88.5% and 99.7%

### 3.1.2 THRESHOLDING METHOD

**o Detection of exudates in retinal images using a pure splitting technique (2010).**

- Authors: Jaafar et al
- Method: an adaptive thresholding based on a novel algorithm for pure splitting of the image is proposed. A coarse segmentation based on the calculation

of a local variation for all image pixels is used to outline the boundaries of all candidates which have clear borders. A morphological operation is used to refine the adaptive thresholding results based on the coarse segmentation results

- Features:
  - Exudates : local variation for each pixel of exudate region with clear margins
  - Non-exudates : discriminated using major axis length, minor axis length, area, solidity
- Data: 50 abnormal images from DIARETDB0 database
- Results: 91.2% sensitivity, 99.3% specificity

**o Automated detection of diabetic retinopathy on digital fundus images (2009).**

- Authors: Osareh et al
- Objective: Automated identification of exudate pathologies in retinopathy images based on computational intelligence techniques
- Method: The color retinal images are segmented using fuzzy c-means clustering following some preprocessing steps, i.e., color normalization and contrast enhancement. The entire segmented images establish a dataset of regions. To classify these segmented regions into exudates and nonexudates, a set of initial features such as color, size, edge strength, and texture are extracted. A geneticbased algorithm is used to rank the features and identify the subset that gives the best classification results. The selected feature vectors are then classified using a multilayer neural network classifier.
- Features:
  - Exudate discrimination : compactness of region, region size, region edge strength, mean Luv values inside and outside the region and Gabor filter response features.
- Classifier: three-layer perceptron NN with 65 node input
- Data: large image dataset consisting of 300 manually labeled retinal images
- Results: 96.0% sensitivity, 94.6% specificity

### 3.1.3 MATHEMATICAL MORPHOLOGY METHODS

### 3.1.4 CLASSIFICATION METHODS

**o Automated detection of diabetic retinopathy on digital fundus images (2009).**

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**o Neural network based detection of hard exudates in retinal images (2009).**

- Authors: Garcia et al 2009
- Method: an algorithm which includes a neural network (NN) classifier. Three NN classifiers were investigated: multilayer perceptron (MLP), radial basis function (RBF) and support vector machine (SVM)

- Features:
  - Exudates : mean RGB values inside and outside the region and their standard deviations, region size, compactness and edge strength
- Data: 117 images with variable colour, brightness, and quality. 50 of them (from DR patients) were used to train the NN classifiers and 67 (40 from DR patients and 27 from healthy retinas) to test
- Results: Using a lesion-based criterion, a mean sensitivity (SEl) of 88.14% and a mean positive predictive value (PPVl) of 80.72% for MLP. With RBF, SEl = 88.49% and PPVl = 77.41%, while SEl = 87.61% and PPVl = 83.51% using SVM

**o Automated detection of exudates for diabetic retinopathy screening (2007).**

- Authors: Fleming et al
- Method: Candidate exudates were detected using a multi-scale morphological process. Based on local properties, the likelihoods of a candidate being a member of classes exudate, drusen or background were determined. This leads to a likelihood of the image containing exudates which can be thresholded to create a binary decision
- Features:
  - Exudate candidate : normalized luminosity and its standard deviation, normalized boundary gradient, candidate area, distance from nearest MA detected, and standardized colour features
- Classifier: SVM having radial basis function kernel
- Data: 13,219 images of which 300 contained exudates
- Results: sensitivity 95.0% and specificity 84.6%

**o Automated Detection and Differentiation of Drusen, Exudates, and Cotton-Wool Spots in Digital Color Fundus Photographs for Diabetic Retinopathy Diagnosis (2007).**

- Authors: Niemeijer et al

- Purpose: To describe and evaluate a machine learningbased, automated system to detect exudates and cotton-wool spots in digital color fundus photographs and differentiate them from drusen, for early diagnosis of diabetic retinopathy
- Method: Each pixel was classified, resulting in a so-called lesion probability map that indicates the probability that a pixel is part of a bright lesion. Pixels with high probability were grouped into probable lesion pixel clusters. Based on cluster characteristics each probable lesion pixel cluster was assigned a probability indicating the likelihood that the pixel cluster was a true bright lesion. Each bright lesion cluster likely to be a bright lesion was classified as exudate, cotton-wool spot or drusen.
- Features:
  - True bright lesion detection : area, perimeter, compactness, length, width, mean gradient, mean of green channel pixels, mean CIE-LUV intensities, local pixel contrast, distance to closest red lesion.
- Classifiers: k-NN and a linear discriminant analysis classifier
- Data: Three hundred retinal images from one eye of 300 patients with diabetes were selected from a diabetic retinopathy telediagnosis database (nonmydriatic camera, two-field photography): 100 with previously diagnosed bright lesions and 200 without
- Results: The system achieved an area under the receiver operating characteristic (ROC) curve of 0.95 and sensitivity/specificity pairs of 0.95/0.88 for the detection of bright lesions of any type.

## 3.2 RED LESION SEGMENTATION

MAs are small saccular bulges in the walls of retinal capillary vessels. In color fundus images, MAs appear like round red dots with a diameter ranging from 10 to 100 m. MAs are difficult to distinguish from dot-HEMs, which are a little bigger. MAs are normally the first retinal lesions that appear in DR and their number has a direct relationship to DR severity. Several approaches have been proposed for MAs segmentation through color image analysis. The techniques for RL detection can be also divided into four categories:

# Chapter 4

# Conclusion

As discussed in this report, many work related to this field have already been done using deep learning and feature based learning. But still, there is a scope to further enhance the techniques to improve efficiency and the complexity of the algorithms.

## 4.1 Proposal

- Use the combination of layers in a neural network that gives a higher amount of accuracy for the dataset being used in the minimum amount of time and complexity.
- Use different preprocessing steps that increase the accuracy of the model such as:
  - Enhancement on images might enhance dirt on the lens making images of level 0 appear as level 4. So we need to compensate for this problem.
  - Images could be of different resolution. Enlarging all images to one common resolution might result in details to be lost. So we need to find optimum resolution for which the best accuracy is achieved.
  - Separation of training and validation datasets should be done before the augmentation as it results in overfitting otherwise.
  - There can be an unbalanced number of images in different classes. So we need to ensure consistency in the preprocessing step without overfitting.

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