Diabetic Retinopathy Detection

Submitted By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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NIRMA UNIVERSITY

AHMEDABAD-382481

May 2016

Diabetic Retinopathy Detection

Major Project

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Computer Science and Engineering

Submitted By

Juhi Shah

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Guided By

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Certificate

This is to certify that the major project entitled "**Diabetic Retinopathy Detection**" submitted by **Juhi Shah (Roll No: 14MCEI22)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Engineering of Nirma University, Ahmedabad, is the record of work carried out by him under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this major project part-I, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Statement of Originality

I, **Juhi Shah**, 14MCEI22 **Roll No.**, give undertaking that the Major Project entitled "**Diabetic Retinopathy Detection**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

_____

Signature of Student

Date:

Place:

Endorsed by

Dr. Priyank Thakkar

(Signature of Guide)

Acknowledgements

It gives me immense pleasure in expressing thanks and profound gratitude to **Dr. Priyank B Thakkar**, Associate Professor, Computer Science Department, Institute of Technology, Nirma University, Ahmedabad for his valuable guidance and continual encouragement throughout this work. The appreciation and continual support he has imparted has been a great motivation to me in reaching a higher goal. His guidance has triggered and nourished my intellectual maturity that I will benefit from, for a long time to come.

It gives me an immense pleasure to thank **Dr. Sanjay Garg**, Hon'ble Head of Computer Science and Engineering Department, Institute of Technology, Nirma University, Ahmedabad for his kind support and providing basic infrastructure and healthy research environment.

A special thank you is expressed wholeheartedly to **Dr. P. N. Tekwani**, Hon'ble Director, Institute of Technology, Nirma University, Ahmedabad for the unmentionable motivation he has extended throughout course of this work.

I would also thank the Institution, all faculty members of Computer Engineering Department, Nirma University, Ahmedabad for their special attention and suggestions towards the project work.

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Abstract

Diabetes is a disease which occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. This disease influences gradually the blood circulatory system including that of the retina. As diabetes advances, the vision of a patient may begin to fall apart and lead to Diabetic Retinopathy (DR). The focus of the thesis is to detect DR using deep learning techniques. To be specific, convolution neural network is used to detect presence or absence of Microaneurysms(MA).

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Chapter 1

Introduction

1.1 Problem Description

Diabetes is a disease which occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. This disease affects slowly the circulatory system including that of the retina. As diabetes progresses, the vision of a patient may start to deteriorate and lead to diabetic retinopathy.

1.2 Motivation

- Being leading cause of blindness in the working-age population, it is estimated to affect over 93 million people[3].
- According to WHO, 347 million people have diabetes worldwide[3].
- Detecting DR is a time-consuming and manual process which leads to delayed results[3].
- Advancement in vision impairment can be slowed if DR is detected in time[3].

1.3 Essential Medical Background

From the Doctor's point of view this disease is diagonsed by some symptoms classified into stages explained in this section.

1.3.1 Terminologies

- Microaneurysms: These are identified as tiny, dark red spots or miniscule haemorrhages, either appearing alone or in clusters, inherent to the light sensitive retina[4].
- Haemorrhages: These are also termed blot haemorrhages, with regard to their round shape. These are found in the deeper layers of the retina[4].
- Hard exudates: The hard exudates are found in diverse sizes from puny blots to booming tracts with clear peripheries and these are the vital symptoms of Diabetic Retinopathy[4].
- Soft exudates:The retinal pre capillary arterioles supplying blood to the nerve fiber. Layers are clogged and associatively the local nerve fiber axons get swollen; thereby creating a cotton wool spot[4].

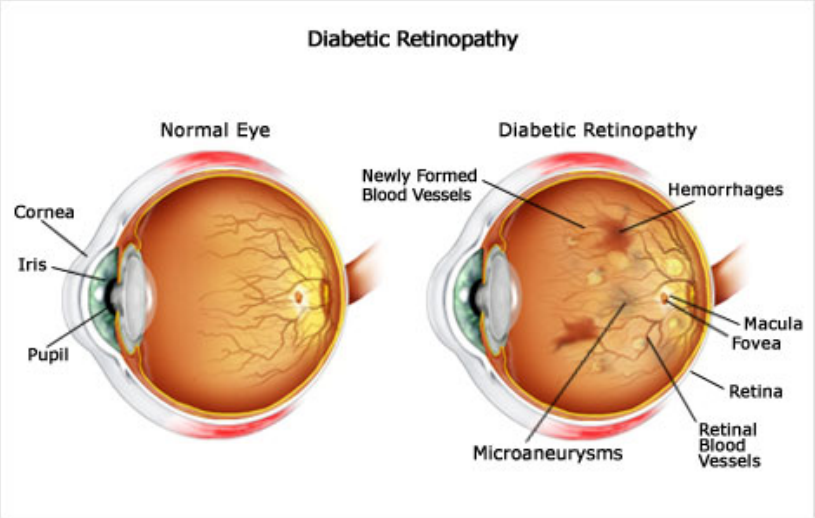

Figure 1.1: The difference between normal and DR eye[1]

1.3.2 Stages of Diabetic Retinopathy

- Mild NPDR: at least one microaneurysm with or without the presence of retinal haemorrhages, hard exudates, cotton wool spots or venous loops. Approximately 40 of people with diabetes have at least mild signs of diabetic retinopathy[5].

- Moderate NPDR: numerous microaneurysms and retinal haemorrhages are present. A limited amount and cotton wool spots of venous beading can also be seen 16% of the patients with moderate NPDR will develop PDR within 1 year[5].

- Severe NPDR: is characterized by any one of the following characteristics:numerous haemorrhages and microaneurysms in 4 quadrants of the retina venous beading in 2 or more quadrants Intraretinal microvascular abnormalities in at least 1 quadrant . Severe NPDR carries a 50% chance of progression to PDR within 1 year[5].

- PDR: is the advanced stage; 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 and even blindness. About 3% of people, with this condition, may experience severe visual loss[5].

1.4 Computer Vision

From the Computer's point of view this disease can be diagonsed by[6]:

- Pre-processing: Illumination correction, contrast enhancement, removal of Optic Disc

- Feature Extraction: Statistical features for blood vessels, haemorrhages, exudates,etc

- Classification: Training model uses features extracted via pre-orocessing

- Deep Learning: No pre-processing or feature extraction is required in Deep Learning

1.5 Problem Statement

Non-MA

MA

To identify signs of Diabetic Retinopathy in eye images. The system should be capable of assigning a score based on presence or absence of MA[3].

- Non-MA

- MA

1.6 Scope

Deep Learning is less explored and little or no pre-processing is needed than other techniques. Highest acccuracy reported on DRIVE database is AUC= 0.98[7]. It is used to detect presence or absence of MA. But negligible work is done to classify different stages of DR Deep Learning should be explored to achieve high accuracy in classifying different stages of Diabetic Retinopathy.

1.7 Details of various chapter

This chapter explained about the symptoms and diagnosis of DR from the Doctor's point of view as well as by Computer Vision. Chapter 2 deals with methods surveyed. Chapter 3 explains the fundamental base paper and the approach followed. Implementation will be expalined and compared to the base paper in chapter 4. Lastly this work will be concluded in chapter 5.

Chapter 2

Literature Survey

2.1 Methodology

There are various methods by which DR can be detected.It is either classified into stages or it can be classified as presence or absence of any feature(symptoms).

Acharya et al. have classified DR into 5 stages:Normal retina, Mild NPDR, Moderate NPDR, Severe NPDR and PDR using SVM,achieved 85.9% accuracy in 2009[5]. But in 2013 , Acharya et al. classified DR into:Normal, NPDR, PDR using Probabilistic Neural Network and achieved 96.15% accuracy[6].

M. Haloi classified DR in terms of presence or absence of microaneurysms:MA and Non-MA, using Deep Neural Network achieved AUC = 0.98(ROC)[8]. Melinscak et al. classified DR in terms of presence or absence of Retinal Vessel:Vessel, Non-Vessel using deep max-pooling convolution neural network achieved 94.66% accuracy and AUC=0.9749[7]

Jaafar et al. classified hard exudates as HE and non-HE. It was pre-processed using median, Gaussian filters and CLAHE. Rule based classifier was applied after adaptive thresholding and achieved Sensitivity-98.4% and Specificity-90.5%[9]

Casanova et al. used Random Forest(RF) and Logistic Regression to classify DR into 4 stages:No DR, mild-DR, moderate DR, severe DR and achieved accuracy higher than 75%[10]

Osareh et al. classified DR in terms of exudates and non-exudates using multilayer neural network, preprocessed using color normalization and contrast enhancement, fuzzy c-means (FCM) clustering, Genetic algorithms and acheived higher specificity with 94.6% accuracy with a lower sensitivity equal to 96.0%[11]

U Rajendra et al. classified DR in 4 Stages:normal retina, moderate NPDR severe NPDR, PDR using Backpropagation (BPA) algorithm and achieved Sensitivity-91.7%, Specificity -100%, Positive predictive accuracy-84%[12]

Lončarić et al. classified retinal vessels using deep max-pooling convolution neural network and 2D filtering and achieved Average Accuracy-94.66% AUC-0.9749 on DRIVE database.[7]

Sinthanayothin et al. detected DR in terms of symptoms Exudates, HMA using Segmentation algorithm combined with Moat Operator, ANN and achieved Sensitivity-88.5% and Specificity -99.7% for Exudate detection and Sensitivity-77.5% and Specificity -88.7% for HMA[13]

Akram et al. classified DR in terms of presence or absence of microaneurysms using Hybrid classifier combining Gaussian mixture model (GMM), support vector machine (SVM) and an extension of multimodel mediod based modeling and achieved Accuracy-99.68%, 99.53% and 99.49% respectively on A, B, C set.[14]

Acharya et al. in 2009 classified DR into 5 Stages:Normal retina, Mild NPDR, Moderate NPDR, Severe NPDR, PDR using morphological image processing and support vector machine (SVM) and achieved Sensitivity-82%, Specificity-86%, Accuracy-85.9%[5]

Techniques surveyed are shown in Literature Survey table: 2.1 [5][6] [8][7][10, 14, 15, 9, 11, 16, 17, 18, 19, 20, 4, 21, 12, 22, 23, 24, 13, 7]

	Year	feature extraction methods	Classification Method	Dataset Size	Class Label	Performance
Melinscak et al.	2015	2D filtering	deep max-pooling convolution neural network	40	Retinal Vessel: Vessel Non-Vessel	Average Accuracy-94.66% AUC-0.9749
M. Haloi	2015	do not require	Deep Neural Network	50, 1200, 89	Microaneurysms: MA, non-MA	AUC- 0.98 (ROC)
Casanova et al.	2014		Random Forest (RF) and logistic regression classifiers	3443	4 Stages:No DR, Mild DR, Moderate DR, Severe DR	Accuracy>75%
Acharya et al.	2013	2D Gabor filter, IFS Histon morphology, MCN, LBP, LTE	Probabilistic neural network (optimized with GA and PSO)	156	Stages: Normal, NPDR, PDR	Sensitivity-96.27%, Specificity-96.08%, Accuracy-96.15%
Akram et al.	2013	morphological operations, contrast normalization and filter banks.	Hybrid classifier of GMM, SVM and an extension of multimodel mediod based modeling	219	Microaneurysms: MA, non-MA	Accuracy-99.68%, 99.53% and 99.49% respectively on A, B, C set

Akram et al.	2012	Gabor Filters, image averaging and Hough Transformation	Gaussian Mixture Model (GMM)		Exudates:Exudate region, Non-exudate region	Sensitivity-96.36%, Specificity-98.25%, PPV-97.45%, Accuracy-97.59%
Jaafar et al.	2011	Median Filter, Gaussian filter, CLAHE	adaptive thresholding,Top down image segmentation,rule-based classifier	236	Hard Exudates:HE, Non-HE	Sensitivity-98.4% Specificity-90.5%
Acharya et al.	2009	Adaptive histogram equalization, Canny edge detector, Median and Wiener filtering	support vector machine (SVM)	331	5 Stages:Normal retina, Mild NPDR, Moderate NPDR, Severe NPDR PDR	Sensitivity-82% Specificity-86 % Accuracy-85.9%

Table 2.1: Literature Survey

Chapter 3

Microaneurysms detection

3.1 Base Paper

3.1.1 Improved Microaneurysm Detection using Deep Neural Networks

Mrinal Haloi has classified DR into presence or absence of Microaneurysms: MA, non-MA using Deep Neural Network,achieved 0.98 AUC in 2015[8].

- Dataset:-

  ROC-50

  Messidor-1200

  Diaretdb1v2-89[8]

- Algorithm:-Deep Neural Network[8]

- Classified into :-MA, non-MA[8]

- Performance:-

  Messidor(R0 vs R1):-Accuracy 95.4%

  Messidor(No-DR vs DR):-Accuracy 96%

  ROC:-AUC=0.98[8]

3.1.2 Architecture of Base Paper

Layer	Type	Maps and Neurons
0	input	3 x 129 x 129
1	Conv	64 x 63 x 63
2	MP	64 x 31 x 31
3	Conv	64 x 27 x 27
4	MP	64 x 13 x 13
5	Conv	64 x 9 x 9
6	MP	64 x 4 x 4
7	FC	290
8	FC	2

Table 3.1: Deep Neural Network Architecture[8]

3.2 Architecture Followed

3.2.1 Alexnet

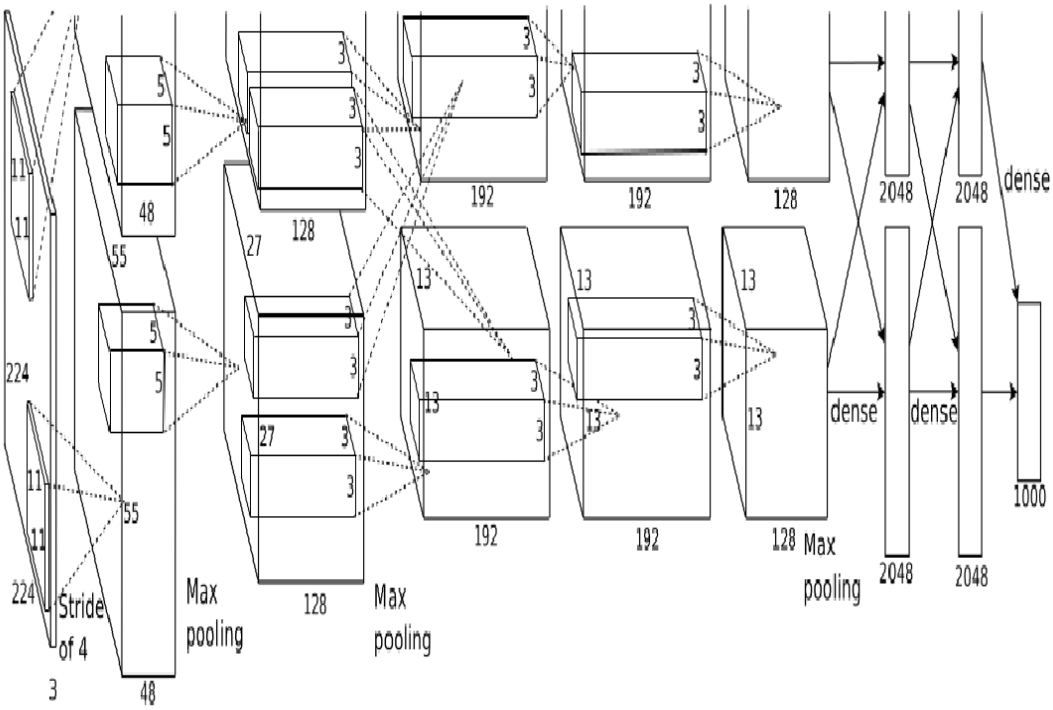

Figure 3.1: Architecture of AlexNet[2]

- 30 epochs of AlexNet model
- 5 convolutional layers and 3 fully connected layers[2]

- Down-samples the images to a fixed resolution of 256 x 256[2]
- The first convolutional layer filters the 224 x 224 x 3 input image with 96 kernels of size 11 x 11 x 3 with a stride of 4 pixels[2]
- The second convolutional layer takes as input the (response-normalized and pooled) output of the first convolutional layer and filters it with 256 kernels of size 5 x 5 x 48.[2]
- The third convolutional layer has 384 kernels of size 3 x 3 x 256 connected to the (normalized, pooled) outputs of the second convolutional layer[2]
- The fourth convolutional layer has 384 kernels of size 3 x 3 x 192 [2]
- the fifth convolutional layer has 256 kernels of size 3 x 3 x 192.[2]
- The fully-connected layers have 4096 neurons each[2]

3.2.2 Models Experimented

Model	**No. of Conv layers**	**No. of FC Layers**	**kernels**
Model 1	5	3	4
Model 2	3	2	5
Model 2	3	2	3
Model 2	6	3	3
Model 2	7	3	6

Table 3.2: Various Models Experimented

3.2.3 Datasets

There are six publicaly available datasets:

	Number of images	**Type**	**Size**	**Class Labels**
DIARETDB0	130	PNG	1-2MB	redsmalldots, hemorrhages, hardexudates, softexudates
DIARETDB1	89	PNG	1-2MB	
DRIVE	40	TIF	1-2MB	
MESSIDOR	1200	TIF	around 9MB	retinopathy grade
STARE	400	PPM	1.21MB	Diagnosis, Diagnosis codes
ROC	50	JPG	425kB	Microaneurysms

Table 3.3: publicaly available datasets

Among these datasets MESSIDOR is preferable because it has more number of images which makes it sufficient for training whereas ROC has only 50 images.

ha

Chapter 4

Implementations and Results

4.1 Tools

The following tools were used during this work:-

- Operating System: Ubuntu 14.04 LTS
- RAM: 12 GB
- CPU: Intel®Core™ i7-4790
- GPU : Tesla K40c
- Framework: OpenCV 3.0 , Caffe

4.2 Results

4.2.1 Base Paper's Result

Classification:-

The classification accuracy for presence or absence of MA / DR in Base Paper are given in table 4.1

Dataset	**Class**	**Accuracy**
Messidor	R0 vs R1	95.4%
Messidor	No-DR vs DR	96%
ROC	MA vs non-MA	0.98 AUC

Table 4.1: Accuracy of different classes[8]

4.2.2 Result

We have experimented different CNN models by making variations in the parameters like number of convolution and fully-connected layers and size of kernels.

Alexnet

Fold	**Accuracy**
Fold 1	78.37%
Fold 2	78.37%
Fold 3	77.67%
Fold 4	77.87%
Fold 5	77.87%
Average	78.03%

Table 4.2: Accuracy achieved by Alexnet on Messidor (R0 vs R1)

Fold	**Accuracy**
Fold 1	57.23%
Fold 2	58.10%
Fold 3	56.45%
Fold 4	57.03%
Fold 5	56.97%
Average	57.15%

Table 4.3: Accuracy achieved by Alexnet on Messidor (No-DR vs DR)

Model 1

Fold	**Accuracy**
Fold 1	50.33%
Fold 2	52.14%
Fold 3	50.65%
Fold 4	52.78%
Fold 5	52.25%
Average	51.62%

Table 4.4: Accuracy achieved by Model 1 on Messidor (R0 vs R1)

Model 2

Fold	**Accuracy**
Fold 1	45.67%
Fold 2	46.11%
Fold 3	45.73%
Fold 4	46.92%
Fold 5	46.19%
Average	46.12%

Table 4.5: Accuracy achieved by Model 2 on Messidor (R0 vs R1)

Model 3

Fold	**Accuracy**
Fold 1	54.56%
Fold 2	55.42%
Fold 3	54.63%
Fold 4	57.43%
Fold 5	56.21%
Average	55.65%

Table 4.6: Accuracy achieved by Model 3 on Messidor (R0 vs R1)

Fold	**Accuracy**
Fold 1	44.32%
Fold 2	45.68%
Fold 3	44.92%
Fold 4	46.37%
Fold 5	44.62%
Average	45.18%

Table 4.7: Accuracy achieved by Model 3 on Messidor (DR vs no-DR)

Model 4

Fold	Accuracy
Fold 1	52.21%
Fold 2	53.67%
Fold 3	51.98%
Fold 4	52.34%
Fold 5	51.26%
Average	52.29%

Table 4.8: Accuracy achieved by Model 4 on Messidor (R0 vs R1)

Model 5

Fold	Accuracy
Fold 1	20.42%
Fold 2	21.31%
Fold 3	19.12%
Fold 4	20.01%
Fold 5	18.31%
Average	19.83%

Table 4.9: Accuracy achieved by Model 5 on Messidor (R0 vs R1)

Amongst all models Alexnet gives more accuracy on Messidor DR vs no-DR but its confusion matrix is very poor. It predicts the class which has more number of images.

		Predicted Class	
		No-DR	mild-DR
Actual Class	No-DR	87	0
	mild-DR	24	0

Figure 4.1: Confusion matrix of AlexNet on Messidor(R0 vs R1)

Chapter 5

Conclusion

The task of detecting presence or absence of Microaneurysms (MA) from fundus images is focused in the thesis. A well known deep learning neural network - ALEXNET and its variants are employed for detection. It is evident from the results that none of the architectures is suitable for the given task. This presents a real opportunity for the researchers to investigate and figure out suitable architecture for the task.

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