

DIABETIC RETINOPATHY ANALYSIS



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TOPIC OVERVIEW

Diabetic Retinopathy

Diabetic Retinopathy is an eye disease which is a complication of diabetes. It occurs when high blood sugar levels damages the blood vessels of the light-sensitive tissue in the retina of the eye.

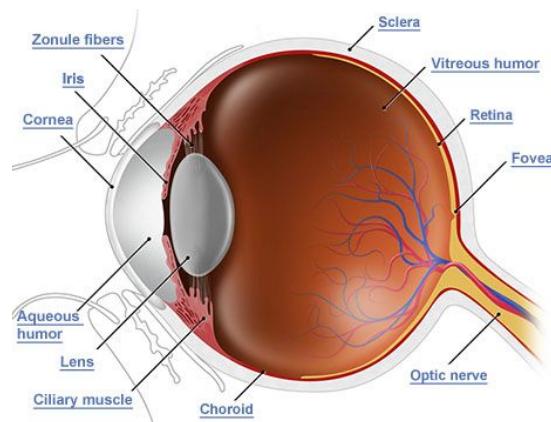


Figure 1: Components of the eye

As a result of diabetic retinopathy, vision is blurred, dark patches are observed and colours get harder to perceive. Based on the severity, the disease could also cause blindness. The age group mainly affected is population in their 40s, 50s or beyond. Patients who have had diabetes for over 10 years have an 80% chance to get affected by diabetic retinopathy.

Recently, studies have indicated the growing prevalence of diabetic retinopathy in India. Diabetic retinopathy in India is reported to have an average prevalence of nearly 20% all over the country. Research works have quoted it as the “An Emerging Eye Disease in India” and “The Emerging Epidemic”. Nearly 65 million people in India are diagnosed with diabetes and 1 out of every 10 such people is

affected by diabetic retinopathy. The zone-wise prevalence of the disease is shown in Figure 2.

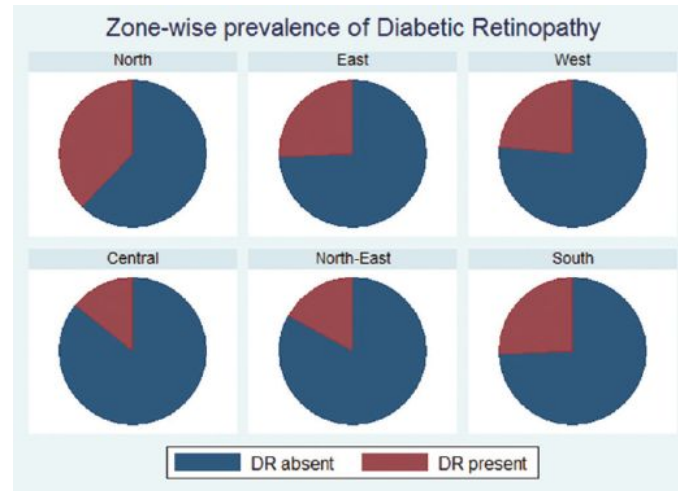


Figure 2: Prevalence of Diabetic Retinopathy in India

The eye is studied through FUNDUS images that are photograph of the back of the eye. The images captures the retina, the neurosensory tissue which converts the optical images we see through our eyes, into the electrical impulses that our brain can process. These image can be processed, segmented and analyzed for detecting abnormalities, lesions and other distortions. Studying fundus image can not only assist diabetic retinopathy, but can also help measure hypertension and improve clinical eye treatment.



Figure 3: Sample FUNDUS image

The major types of lesions that could potentially cause diabetic retinopathy are:

- Bright Lesions
- Red Lesions

Bright lesions include:

- Cotton Wool Spots
- Hard Exudates

Red lesions include:

- Micro-aneurysms
- Hemorrhages

DIABETIC RETINOPATHY

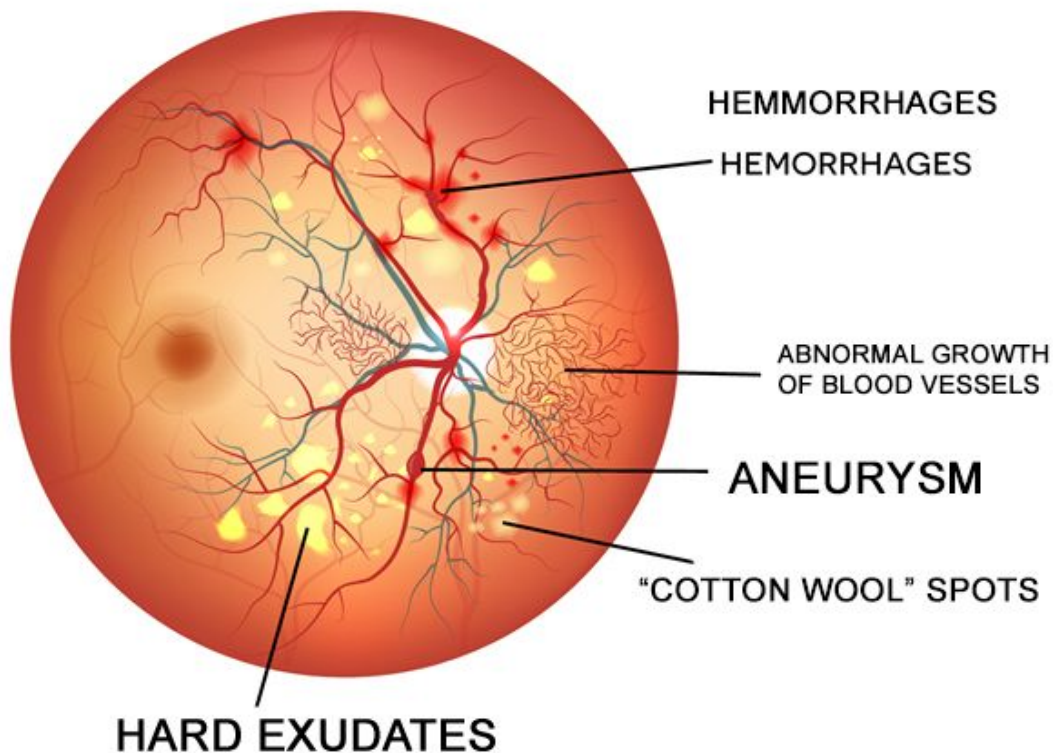


Figure 4: Illustration highlighting lesions in the FUNDUS image

A severity grade is assigned to every retinal image implying the level of diabetic retinopathy:

- GRADE 0 - No Diabetic Retinopathy
- GRADE 1 - Mild Diabetic Retinopathy
- GRADE 2 - Moderate Diabetic Retinopathy
- GRADE 3 - Severe Diabetic Retinopathy

This grade is obtained by counting the number of Micro-aneurysms (MA) and the number of hemorrhages (HA) as follows:

Grade	Description
0	$(MA = 0) \text{ and } (HA = 0)$
1	$(0 < MA \leq 5) \text{ and } (HA = 0)$
2	$(5 < MA \leq 15) \text{ or } (0 < HA < 5)$
3	$(MA \geq 15) \text{ or } (HA \geq 5)$

Figure 5: Severity Grade Calculation Metric

METHODOLOGY ADOPTED

Approach used in the paper:

DREAM: Diabetic Retinopathy Analysis Using Machine Learning

The paper followed a 3 stage methodology, where stage 1 was image segmentation, stage 2 was a 2-step hierarchical lesion classification and stage 3 was the diabetic retinopathy severity grade deduction. The paper adopts this technique on a lesion annotated train set containing 89 FUNDUS images and a test set containing non annotated 1200 images. Before the stage 1, the images had to be preprocessed. For this, the green plane was extracted from the image and histogram equalization and pixel scaling was performed on the images. Gaussian and median filter was applied to further remove noise and enhance the images.

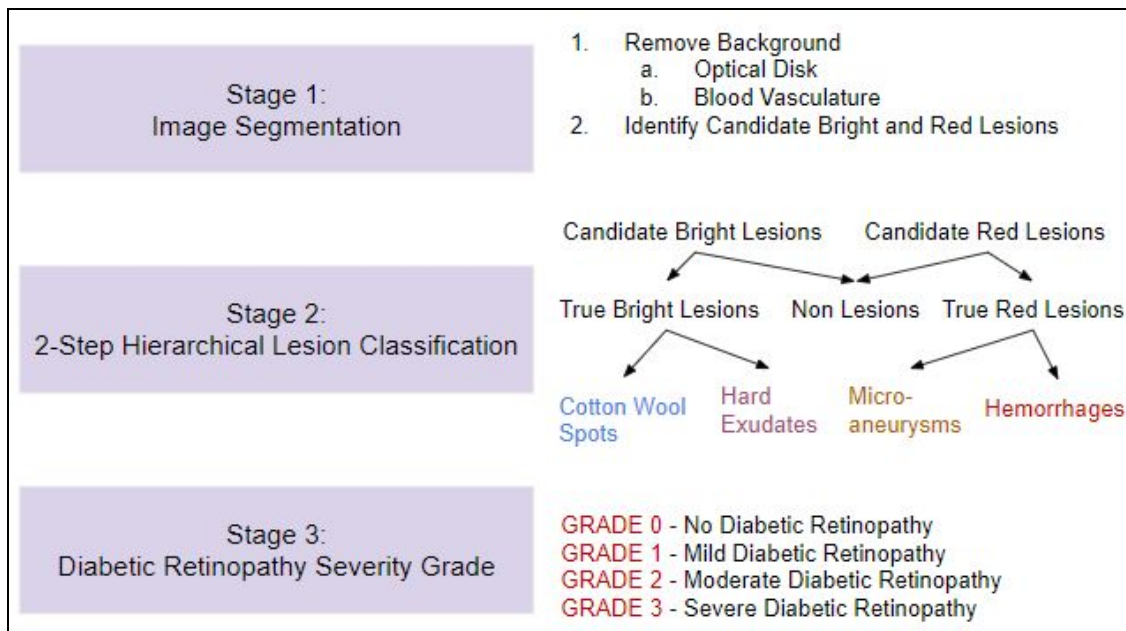


Figure 6: Methodology adopted in the paper

In stage 1, the image was segmented and optical disk was detected using the Minimum Intensity, Maximum Solidity Algorithm. Next, the blood vasculature was detected and finally, candidate red and bright lesions are detected.

In stage 2, the candidate red lesions are categorized into true red lesions and non lesions, similarly, the candidate bright lesions are categorized into true bright lesions and non lesions. The true bright lesions are further classified into Cotton Wool Spots and Hard Exudates and the true red lesions are classified into Microaneurysms and Hemorrhages. This is achieved by specifying a set of features and selecting the best 30 using Adaboost. In stage 3, the severity grade is calculated using Figure 5.

METHODOLOGY ADOPTED

Our Approach

Our initial task was to reproduce the above paper. For this, we acquired the two datasets they had used in their work - DIARETDB1, which contain 89 FUNDUS images with masks and lesion annotations and MESSIDOR, which contains 1200 FUNDUS images with severity grade information.

We preprocessed the data in the same manner. The green plane was extracted from the images and contrast enhancement was performed. Next, the optical disk was detected and masked out, followed by blood vasculature removal.

After preprocessing and Stage 1, we applied KNN on the data after calculating mean distance as a feature.

As part of extension of our project, we tried to apply a Deep Convolutional Neural Network on the MESSIDOR dataset using a ResNeXt 50 architecture which consist of a inception modules in the Resnet model.

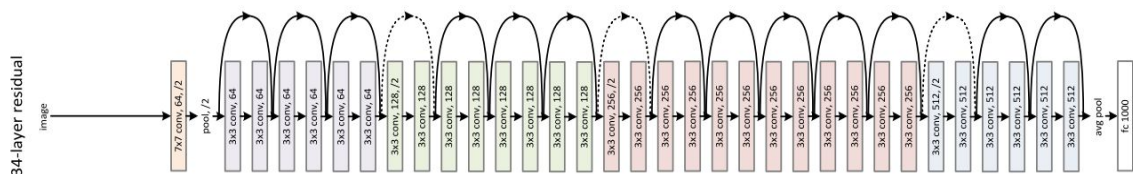


Figure 7: Resnet Architecture

A convolutional neural network applies a series of transformations on the image and extracts relevant features in every layer. CNNs maintain local connectivity and parameter sharing as a result of

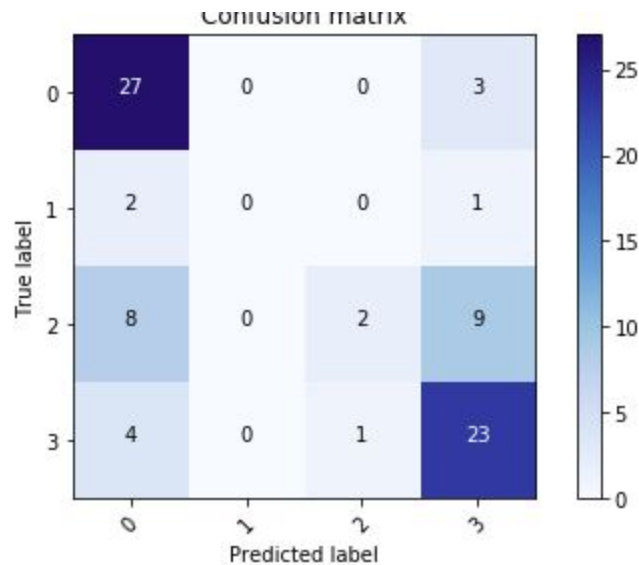
which, the number of learnable weights are significantly reduced. Hence CNNs are considered efficient for the purpose of applying learning techniques on images.

Due to the lack of data it was not feasible to train a CNN from scratch hence we resorted to using a pretrained model which was fine tuned using the methods like Cyclic Learning Rates, Differential Learning Rates along with Cosine Annealing.

For providing the final decision on the test set, we calculate the values over various transformations of the image and the mean is given as the decision. This helps in reducing the dependency on the spatial variability.

RESULTS OBTAINED

Following are the results we have obtained using the CNN approach:



	precision	recall	f1-score	support
class 0	0.66	0.90	0.76	30
class 1	0.00	0.00	0.00	3
class 2	0.67	0.11	0.18	19
class 3	0.64	0.82	0.72	28
avg / total	0.63	0.65	0.58	80

Accuracy: 0.65 = 65%

Matthew's correlation coefficient (MCC): 0.4841748389444794

For comparison we had implemented another CNN model with 3 layers and 128,128,64 nodes in each layer respectively. We got an accuracy of 36% after various tweaks to get the best result.

Thus,our model performs significantly better than the baseline CNN model, but is a little behind the DREAM paper in terms of specificity and sensitivity.Hence we can conclude that without explicit feature learning, the CNN is a good alternative for the diabetic retinopathy.