

Analysis of Detection of Diabetic Retinopathy using LPB and Deep Learning Techniques

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Abstract - Diabetes mellitus (DM) arises when not the pancreas secretes enough insulin or the body has been unable to absorb it adequately. This contributes to an abnormal rise in the blood level of glucose. Many human body parts would be affected. One of those is also among those eyes. This high glucose level causes damage to blood vessels over time. It is estimated that 95 percent of individuals who are determined to have diabetes have category 2. Around eighty percent of falls into category 2 cases are overweight. Diabetic Retinopathy (DR) disease leads to visual loss. Regular screening and treatment are needed. Many approaches have applied for the detection and identification of the DR from the past decade using some mathematical and image processing algorithms, features extraction techniques, and artificial neural network classification. Few are failed during the pre-processing stage, feature extraction stage, vessel extraction, and the classification stage. In this paper, it is identified all stages of diabetic retinopathy during the early stage by developing the regions of a retina image to show the specific region of interest in terms of its severity level by collecting the large data from Kaggle, DIARETDB0, and DIARETDB1 dataset and then pre-trained the models and applied to LPB and deep learning classifiers and able to obtain the results and analysis those hypothesis results and achieve 65% predicted correctly.

Keywords — Diabetic Retinopathy, Hemorrhages, Exudates, Microaneurysms, NPDR.

I. INTRODUCTION

Nowadays the people are being worried about their work nature and are overstrained due to a lot of tension in their work. This has led to the cause for most of the diseases like diabetes, loss of sight, loss of memory, loss of patience, etc. Hence there is a scope for addressing the health issues to the working people of the age group of above 45 years and above. In this context, retinopathy is also one of the issues to be addressed. This research is about certain issues related to diabetic retinopathy.

Photos of the face fundus are shown in Figure1, like haemorrhage, maculopathy, blood vessels, microaneurysms, hard exudate, optic disc, macula, and soft exudates. [1] A common

diabetes complication, diabetic retinopathy, is (DR). It is so normal since it is the reason for visual inability in glob[2] operational populaces. Speed of diabetes is developing in created countries, yet additionally in immature nations. It is assessed that 75 percent of individuals with diabetic retinopathy live in industrialized countries.[3] In non-industrial nations, the circumstance is particularly terrible because there is a deficient finding. Individuals with diabetes, paying little heed to the clinical consideration circumstance in their nation of source, are multiple times bound to create visual deficiency comparative with individuals who don't experience this condition's ill effects [4]. DR is an idle condition that can be distinguished by the enduring just behind the eyelash adjustments have advanced to a point somewhere conduct is confounded and practically inconceivable. The event of diseases of eyelash changes as per the period at which Mellitus begins issue

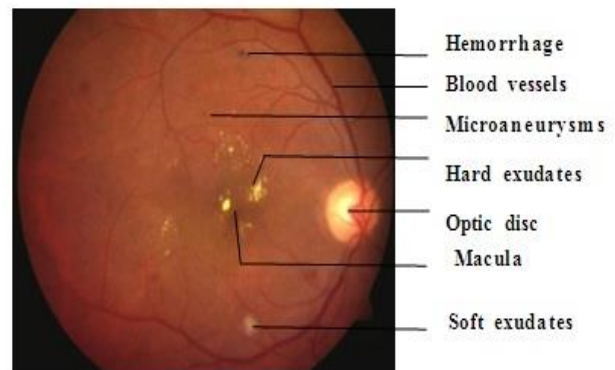


Figure 1: Eye fundus images with maculopathy.

So far, only in the first stages of the disease will the most appropriate medication for DR be given. Early detection by routine screening is, therefore, of utmost importance[5].

A. Stages Of Diabetic Retinopathy

Figure 2 shows the diagrams of Diabetic retinopathy stages classification. DR stages are mainly classified into NPDR (Non-proliferated Diabetic Retinopathy) & PDR (proliferative iabetic retinopathy). When the blood vessels in the retina of the eye get injured and leaks the fluid from it, then the NPDR occurs. Due to this, the retina will get wet, and it swells finally



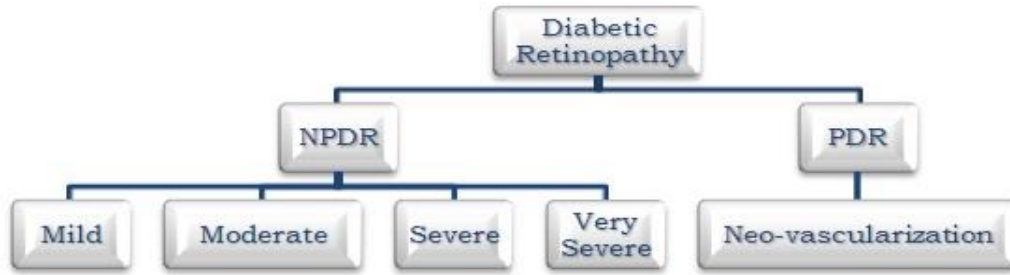
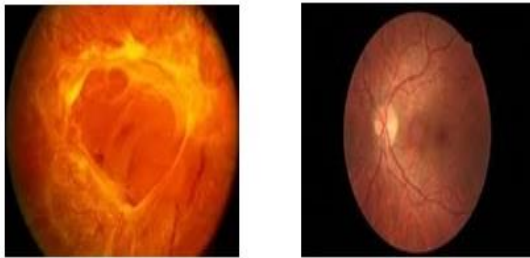


Figure 2: Diabetic Retinopathy stages.

This condition is a complex one that may lead to damage to the vision. DR is a type of progressive disease. The detection of this disease at its initial stage is essential to save the patient's vision. For this, continuous checking is required

- ii) Moderate Non proliferative diabetic retinopathy
- Severe Non -proliferative diabetic retinopathy



(a)PDR (b)NPDR

Figure 3: PDR and NPDR

Figure 3 (a) and (b) shows the types of DR such as PDR and NPDR.

B. Proliferative Diabetic Retinopathy

PDR is the latest diabetic eye disease stage, and the introduction of innovative cells in the retina is called neovascularization. When it bleeds more, it will affect the vision and cause blindness. The PDR is a very serious eye disease. The scar tissue leads to separate the retina, central, and peripheral vision, as shown in Figure3(a).

C. NPDR

In Figure 3, the NPDR is shown in (b). NPDR is considered the early Stage of DR. Blood vessels swell and often bulge or balloon at this point (aneurysm). The tiny blood vessels leak making the retina swell. Small tiny particles are formed in the retina is called exudates. The retina is affected by the NPDR, and it leads to loss of vision. The fluid concentrations that accumulate in the retina can clear it up independently, but fatty deposits that can impair vision often remain. Stages of NPDR

The various stages of NPDR include

- i) Mild Non- proliferative diabetic retinopathy

The mild NPDR is shown in Figure 4(a), and microaneurysms are produced in the retinal blood cells at this point and may spill fluid into the retina. The microaneurysms are small places of balloon like swelling. As the disease progresses, blood vessels that provide significant nutrition to the retina may swell and lose their capacity to transport blood. Figure 4(b) shows ModerateNPDR. Moderate NPDR without treatment can lead to loss of vision. Mild and mild NPDR is often graded as "early" Diabetic Retinopathy. At this point, blood circulation to the retina is impaired, leading to further damage to the blood vessels. Figure 4(c) SevereNPDR.

II. LITERATURE SURVEY

In [4], this paper presents, the authors presented a method to compute the vessel width using the largest circles that fit inside the vessels in a binarized retinal image.

In[5],the researchers suggest automatic separating normal – and- abnormal –retinal techniques.

In [6] Working on the Messidor dataset with machine learning techniques such as decision tree learning, Support Vector Machines, Naive Bayes, and Random Forests.

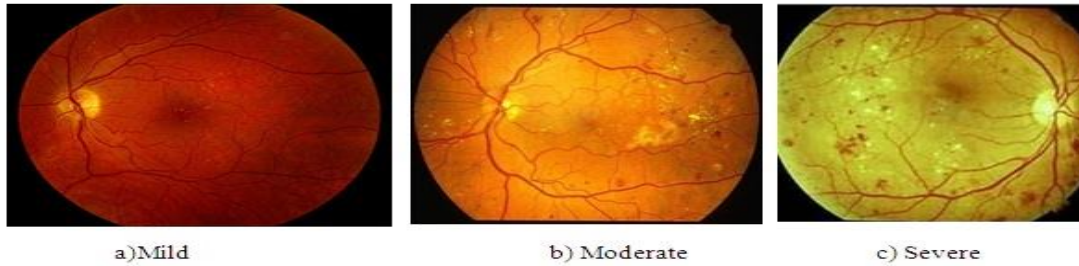


Figure 4: Types of NPDR

In [7] discussed the Neural Networks how to classify by utilizing patient lesions and their type as the Neural Network's inputs and the pixel intensity values.

In [8], this paper's authors work with Probabilistic Neural Networks (PNN) and machine learning techniques like Naive Bayes and SVM. They carried out with the Discrete Wavelet Transform, Adaptive Histogram Equalization, Fuzzy C-Means Segmentation, Matched Filter Response, and Morphological Processing on the Green channel images pre-processing stage. The test suits and train suits are split, and among 350 images, the authors used 250 of them for the test and only 100 for the training.

In [9] selected 15 handpicked features and operated on them. However, their dataset was extremely small, with only 39 images. Many attempts were made to detect the level of classification and the level of severity.

In [10] used SVM and KNN to classify images of Messidor and DB-reet into 3 classes. In this paper, the model could specify whether a fundus image is normal or not and if abnormal, then it is graded to level- 1 or level- 3.

In [11] discussed the AlexNet won the ImageNet image classification competition in 2012; Convolutional Neural Networks (CNN) approach can be used for any task that deals with images. Nowadays, the CNN algorithm is powerful enough to produce a high performance on the ImageNet challenge.

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III.METHODOLOGY

The block diagram of the diabetic retinopathy detection methodology is shown in figure 5.

A. Input Image Acquisition: Read an input image from the camera of the Fundus. Compared to conventional ophthalmoscopy, the fundus camera is more accurate, non-invasive, and simple to use. The eye fundus picture results in a higher degree of sensitivity, i.e., a higher rate of irregular eye detection[12]. Fundus. Initially fundus images are collected from various internet sources

Like Kaggle, drive, diaretdb0, diaretdb1, and local hospitals where fundus cameras are installed.

B. Image Preprocessing: Various techniques, such as contrast enhancement, grey part, image de-noising, etc., are used in image pre-processing. Initial RGB images are transformed and fed to the pre-processing stage in grey-scale. Green(G) Channel and Blue(B) Channel are isolated and processed in Red(R) Channel pre-processing [13]. In the event of any noise in the image, de-noising should be performed with appropriate filtering techniques and color spacing. CLAHE can be improved by (Contrast Limited Adaptive Histogram equalization) in the case of image contrast enhancement.

C. Optic Disc Extraction: The extraction of the optic disc was performed mainly based on the morphological operations of the principal component analysis(PCA) and stochastic watershed transformation used in the dilation and erosion and by using the sparse matrix. Whenever the minima of the image represent the points of interest, and the maxima are these boundaries of separation between objects, the watershed transformation algorithm is an efficient segmentation instrument[14]. Because of this fact, this method's input image is typically a gradient image. If the gradient image is treated as an input image, the watershed transformation generates a segmentation that can be interpreted as a collection of segmented regions' closed contours.

D. Blood Vessel Extraction: The Kirsch algorithm identifies the blood vessels. In this algorithm, to extract an object's contour, the Kirsch gradient operator is chosen[15]. Eight

philtres (i.e., eight masks[16] for the relevant eight key directions) are used to detect edges in the Kirsch edge detection applied to a given image.

E. Lesion Detection And Identification: All lesions like HA, MA, and Exudates will perform segmentation by edge detection and filtering techniques.

F. Feature Extraction: In this Stage, necessary features like LBP, mean, SD, Entropy, kurtosis, Skewness, Accuracy, specificity, and severity were extracted using morphological methods. Some local binary pattern is used separately in each channel to extract features[17,18]. Extract the texture characters for LBP depiction, then. To build the final characteristics, take the average of all channel features after that[19,20]. Last the properties are normal, range of error, Clutter, kurtosis and inequality.

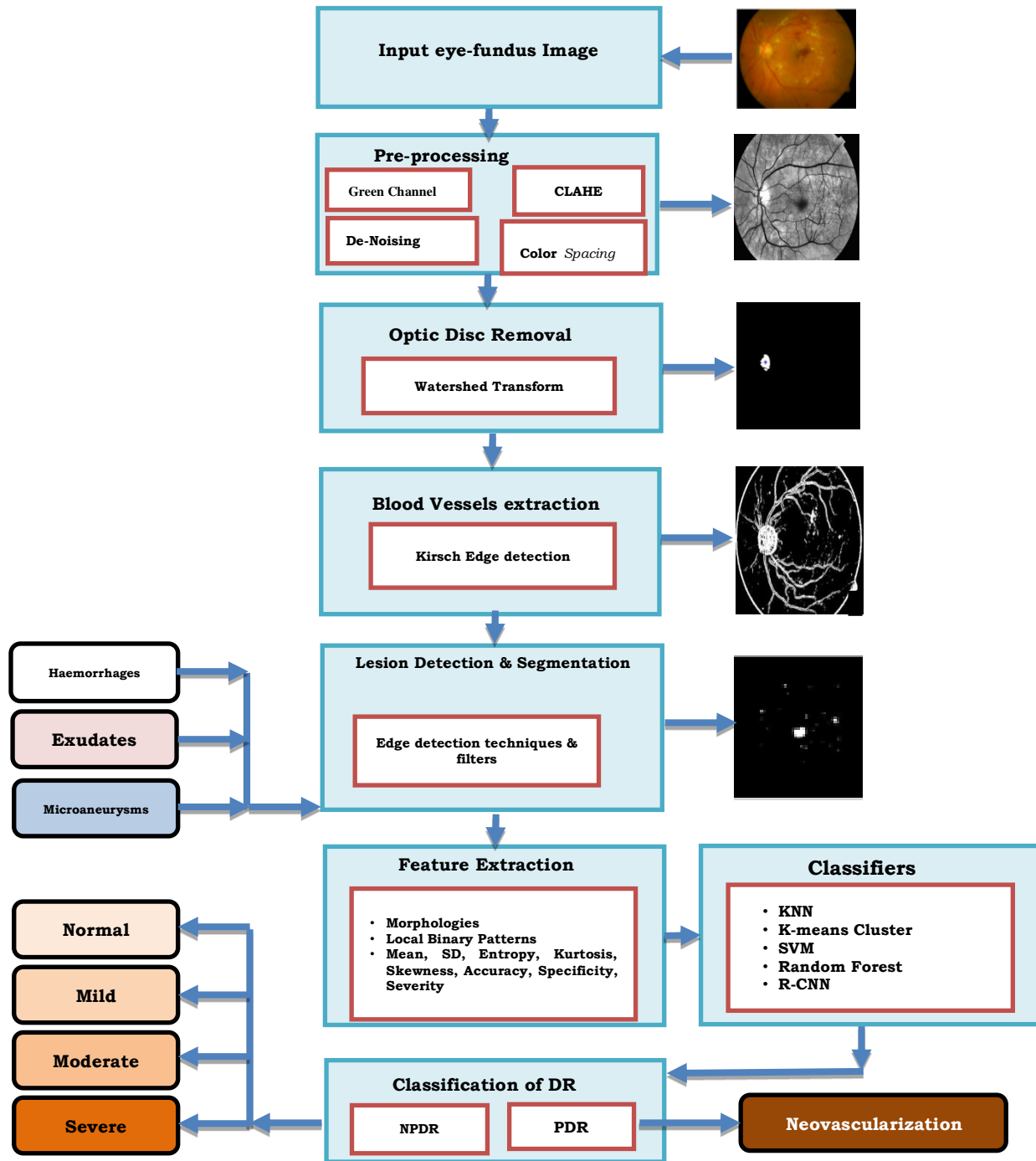


Figure 5: Block diagram of Diabetic retinopathy detection Methodology

The LBP equation is given as follow:

$$LBPP_{p,R} = \sum_{p=0}^{p-1} s(g_p - g_c) \cdot 2^p, f(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases} \dots\dots\dots (1)$$

$$VAR_{p,R} = \frac{1}{p} \sum_{p=0}^{p-1} (g_p - \mu)^2, \mu = \sum_{p=0}^{p-1} g_p \dots\dots\dots (2)$$

$$\text{Mean } (\mu_i) = \frac{\sum_{x=1}^M \sum_{y=1}^N I(x,y)}{M \times N} \dots\dots\dots (3)$$

$$\text{Variance } \sigma_i^2 = \frac{\sum_{x=1}^M \sum_{y=1}^N I(x,y)^2}{M \times N} \dots\dots\dots (4)$$

$$\text{Skewness} = \frac{\sum_{x=1}^M \sum_{y=1}^N I(x,y)^3}{M} \dots\dots\dots (5)$$

$$\text{Kurtosis}(K) = \frac{\sum_{x=1}^M \sum_{y=1}^N I(x,y) - \mu^4}{M \times N} \dots\dots\dots (6)$$

G. Classification: Finally, certain classifiers like KNN, K-means, SVM, Radom [21,22] forest and faster R-CNN algorithms extracted the conclusive highlights and classified Normal and Diabetic retinopathy stages like all NPDR and PDR disease identification[23,24]. Further in Normal, NPDR and PDR level zero, one, two, three an four. Which are of mild, moderate, severe, neovascularisation respectively is identified and it is validated by an ophthalmologist[25].

IV. RESULTS AND DISCUSSION

Retinal disease detection procedure using LBP is depicted in the, Figure 6 and it also shows the process performed. The primary step is to Acquiring the excitation image from the database. The acquired image is undergo for pre-processing by extraction of the RGB. Next stage the feature extractions can be done using an RGB image.

Final Average features of RGB Channels of Test Images Table are as shown in the above table 1.

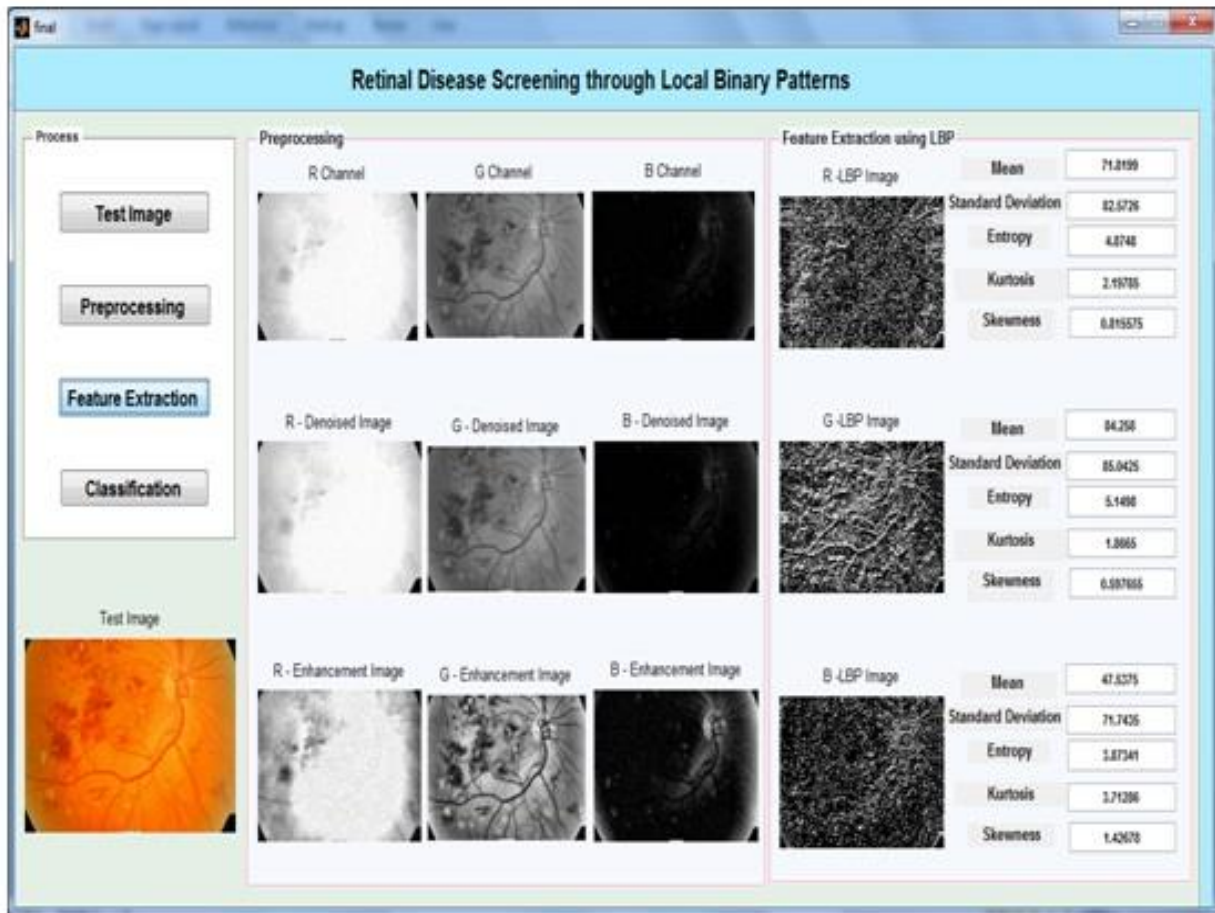


Figure 6: Classification and detection of DR using LBP

For a Disease Eye mean value exceeds 50, and SD exceeds 75, Entropy greater than 4, Kurtosis is less than 3, skewness is less than one. For a Normal Eye Mean value is less than 50, and SD is less than 75, Entropy less than or equal to 4, Kurtosis is greater than 3 and Skewness is greater than 1. Figure. 8 shows the statistical analysis of the diabetic retinopathy stages detected among 8408 fundus images 6150 images are normal (level-0), 588 images are

mild (level-1), 1283 images are moderate (level-2), 221 are severe (level-3), and 166 images are identified as neovascularization. Since the deep learning concept is adopted, huge data set is considered. Among 8408 fundus images, 5461 are predicted as true, and 2947 are predicted as false. All false positive and true negative is also mentioned as a hypothesis result.

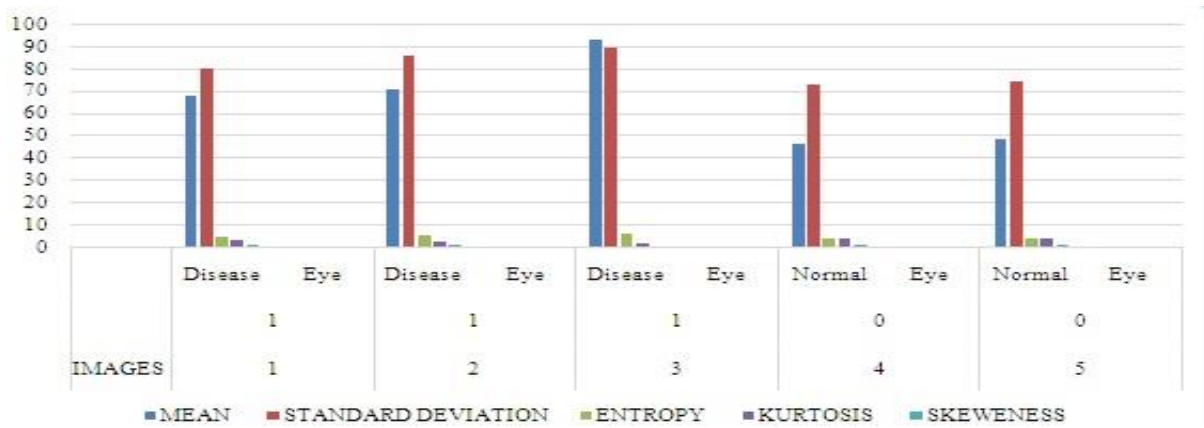


Table 1: Average features of RGB Channels of Test Images

TEST IMAGES	CLASS	OUTPUT	MEAN	STANDARD DEVIATION	ENTROPY	KURTOSIS	SKEWENESS
1	1	Disease Eye	67.8718	79.7862	4.63267	2.5924	0.94667
2	1	Disease Eye	70.307	85.7867	4.76419	2.27223	0.877669
3	1	Disease Eye	92.7413	89.275	5.49873	1.69132	0.48017
4	0	Normal Eye	45.7051	72.8796	3.76383	3.89013	1.50173
5	0	Normal Eye	47.9789	73.9333	3.87598	3.68938	1.43468

Table 2: Diabetic retinopathy raw image classification accuracy.

Diabetic retinopathy symptoms	Level	count	test data	positive results	classification accuracy
Micro aneurysms	1	< 5	1524	1260	82.67%
	2	> 5 &< 15	1482	1104	74.49%
	3	> 15	1520	1200	78.74%
Hemorrhages	1	< 5	1524	1260	82.67%
	2	> 5 &< 15	1482	1104	74.49%
	3	> 15	1520	1200	78.74%
Neovascularization	3	>1	1520	1200	78.74%
Exudates	3	> 1	54	45	83.33%

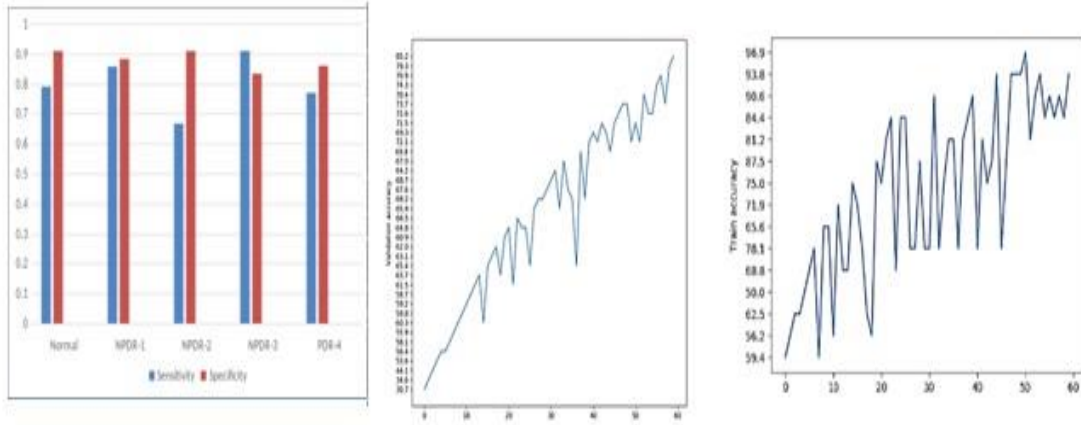


Figure.7. Plot of sensitivity and severity

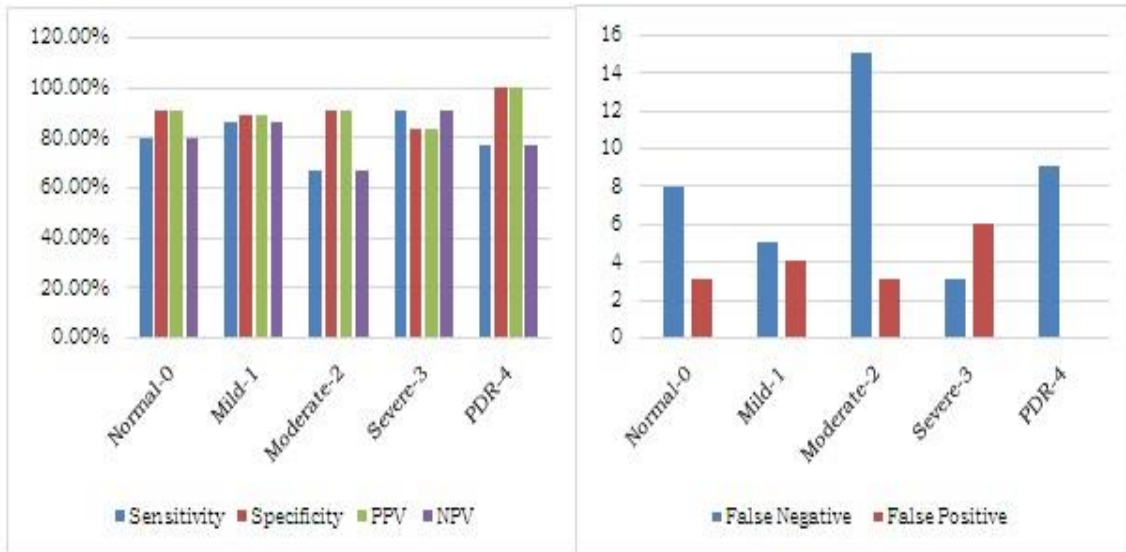
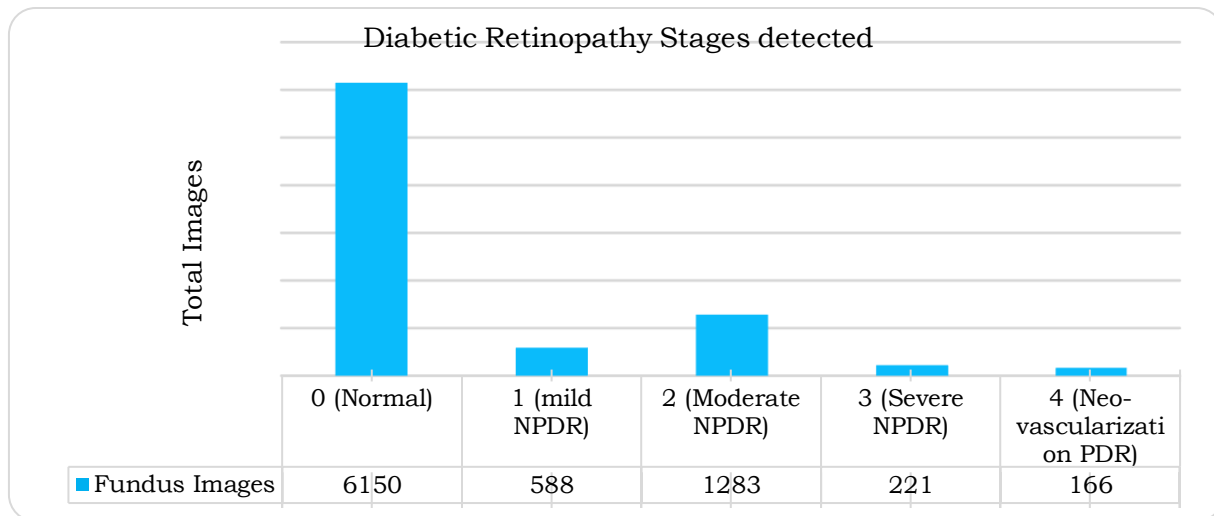
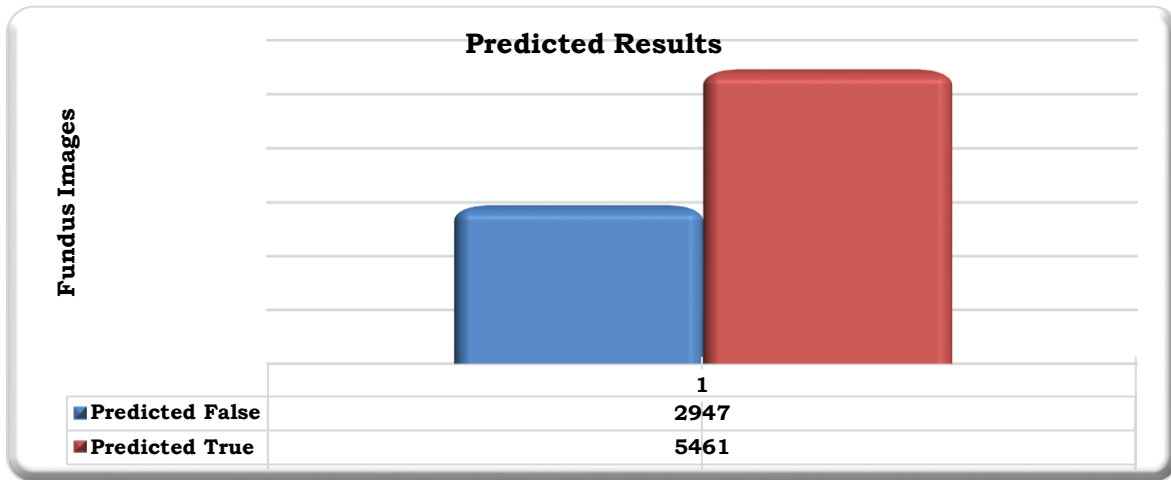


Figure 8: Statistical results of diabetic retinopathy

	Normal-0	Mild-1	Moderate-2	Severe-3	PDR-4
Sensitivity	78.95%	85.71%	66.67%	90.91%	76.92%
Specificity	90.91%	88.24%	90.91%	83.33%	100.00%
PPV	90.91%	88.24%	90.91%	83.33%	100.00%
NPV	78.95%	85.71%	66.67%	90.91%	76.92%
	Normal-0	Mild-1	Moderate-2	Severe-3	PDR-4
False Negative	8	5	15	3	9
False Positive	3	4	3	6	0



CONCLUSION

This work has been made towards characterization and analysis of diabetic retinopathy with the differential geometrical method as an image processing application and computational algorithms. With this method, the dr classifications like exudates and microaneurysms were computed, and the results were satisfactory. Further, the algorithm with the windowing technique has shown better results. The results have been validated with ophthalmologists' opinions and remarks. In addition, some studies recorded here have enhanced the early detection of diabetic retinopathy.

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