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Spectral Classifier with Predictive Rules For Diagnosis And Early Detection Of Diabetic Retinopathy On Digital Fundus Images

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ABSTRACT

Background: Diabetic retinopathy is a continuous eye disease resulting in blindness if not detected in an early stage and treated properly in time. Fundus images of humans play an important role in the detection and diagnosis of many eye diseases for ophthalmologists.In order to safeguard the vision of the patient on fundus images, early detection and diabetic retinopathy diagnosis is of significant importance.The automate detection of independent feature selected is a critical step for early detection of diabetic retinopathy. **Objective:** Aframework for diagnosis and early detection of diabetic retinopathy using Spectral Classifier with Predictive Rules (SC-PR) on digital fundus images is proposed. The framework extracts all possible features of optic cup in digital retinal fundus images. In order to extract the exact position of vessel segment in the fundus image, the system formulates a feature clustering for each region depending upon certain properties, i.e. area, convolution and feature ratio. Finally, we present a robust technique which combines the Spectral Classifier with Predictive Rules to the features extracted aiming at improving the accuracy of classification. **Results:** The proposed framework is evaluated using publicly available retinal image databases and achieved higher rate of sensitivity and specificity which is better than previously published methods.**Conclusion:**Analysis andexperimental results conducted with our technique for early diagnosis prediction of diabetic retinopathy concludes that the proposed technique is effective inimproving the sensitivity, specificity and classification accuracy compared to the state-of-the-art works.

KEYWORDS: Diabetic retinopathy, Fundus images, Bayes classifier, Sensitivity, Specificity

INTRODUCTION

Diabetic retinopathy (DR) occurs due to long term diabetes that eventually damages the eye's retina leading to blindness. Early detection of DR on digital fundus images helps the patient from minimizing the possibility of blindness. Much works has been carried out in this field by many researchers.

Automatic Detection of Optic disc and Macula (AD-OM) [1] presented a hybrid model for automated localization of optic disc and macula in digital fundus images based on edge detection. This resulted in the improvement of detection rate. Detecting Optic Disc Boundary (DODB) [2] in Digital FundusImages used morphological and edge detection techniques to improve the detection rate by applying voting type algorithm. In this sense OD plays an important role in detection of disease that acts as a key component in many algorithms. Prediction of diabetic retinopathy [3] on the other hand help estimate the disease severity through gene polymorphism.

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On the other hand employing blood vessel segmentation screening of diabetic retinopathy needs a segmentation technique. For this, retinal vessel segmentation technique has been used [4] to improve the accuracy with which the disease detection was made. In addition, early detection of diabetic retinopathy can also be made by efficient identification and classification of microaneurysms [5] [6]. Identification and classification of microaneurysms is used to improve the accuracy rate of detection with the aid of hybrid classifier combining the Gaussian Mixture Model and Support Vector Machine.

Blood vessel segmentation is also relevant for automated diagnosis of DR. One of them and may be the most noteworthy are vessel narrowing, complete occlusions or neovascularization [7]. The vessel narrowing is identified by formulating a detailed feature vector for all regions using Gaussian Mixture Model [8] classifier. On the other hand, detection of neovascularization was done in [9] using m-Mediods based classifier resulting in the improvement of classification accuracy of retinal images. Measures were also taken to prevent the progression of DR using multidisciplinary approach [10].

The remaining work is organized as follows: Section 2 contains brief review of some recently published work relevant to early detection of DR. A block diagram and overview of the proposed technique is presented in Section 3, discussing the complete framework and its different phases. The modeling of proposed Spectral Classifier with Predictive Rules on digital fundus images is described in Section 4 followed by the experimental results and comparisons with previous techniques in Section 5. The last Section 5 summarizes the paper.

Related works:

The identification of exudates is very crucial to detect diagnosis DR at an early stage. In the study of DR, most of the work was designed to measure microaneurysms. However, exudates detection is still an open issue. Thus several recent research works focus on diagnosing retinopathy based on image recuperation approach [11]. A semi-supervised based learning approach was designed in [12] for early detection of DR on fundus images. A method for screening of proliferative diabetic retinopathyusing blood vessel structure was presented in [13] to identify the vascular abnormalities with higher classification rate. In [14], optical disk localization and detection was performed on retinal images with the objective of improving the detection accuracy.

A fuzzy-based image processing decision support system was presented in [15] to minimize the burden borne by the diabetic screening team. In [16] random forest was applied in order to classify the factors leading to DR. A nation-wide survey was conducted in [17] for screening DR based on various factors like, occupation, education and house hold income. In [18], the results of retinal image analysis for detection of DR were presented and categorized the severity of DR. On the other hand, fast localization [19] was performed based on retinal vessel orientation and OD brightness. A survey of early detection for DR screening was presented in [20].

This work describes a framework for diagnosis and early detection of DR on digital fundus images by extracting candidate regions through the features extracted. It obtains points from features extracted for each digital fundus images and measures the difference between the training and test sequence depending upon their categorization of disease level through varied factors like normal, mild, moderate or severe. The disease levels are categorized and classified using a spectral classifier algorithm which is a weighted combination of minimum difference and maximum difference. The main contribution of the work is that it improves the classification accuracies using predictive rule generation for diagnosis and early detection of diabetic retinopathy on digital fundus images. The proposed framework introduced the Spectral Classifier with Predictive Rules to enhance the rate of sensitivity and specificity before applying the classifier.

Methodology:

Diabetic retinopathy is predominantly split into two types namely, Diabetic Retinopathy (DR) screening and Diabetic Retinopathy monitoring. The independent system for screening of DR obtains a fundus image as an input and finds all the optimal features present in that image. On the other hand, DR monitoring observes the image changes between two images of the same eye taken at different time intervals.

In this work, we present a technique a method for DR screening using fundus images. Figure 1 shows a complete block diagram of the proposed technique. In a nutshell, the overall proposed technique is split into four stages, i.e. feature selection, feature extraction, Spectral Classifier for Diagnosis and Predictive Rule Generation for early detection. The feature selection phase develops a practical automated and assisted diabetic retinopathy diagnosis systemand selects all possible features on fundus images. Next, all possible features are extracted for each selected region using feature clustering distinct properties. With the features extracted, the classifier extensively categorizes the diseased portion into normal, mild, moderate or severe using spectral classifier. Finally, predictive rule generation is applied for early detection of diabetic retinopathy on fundus images.

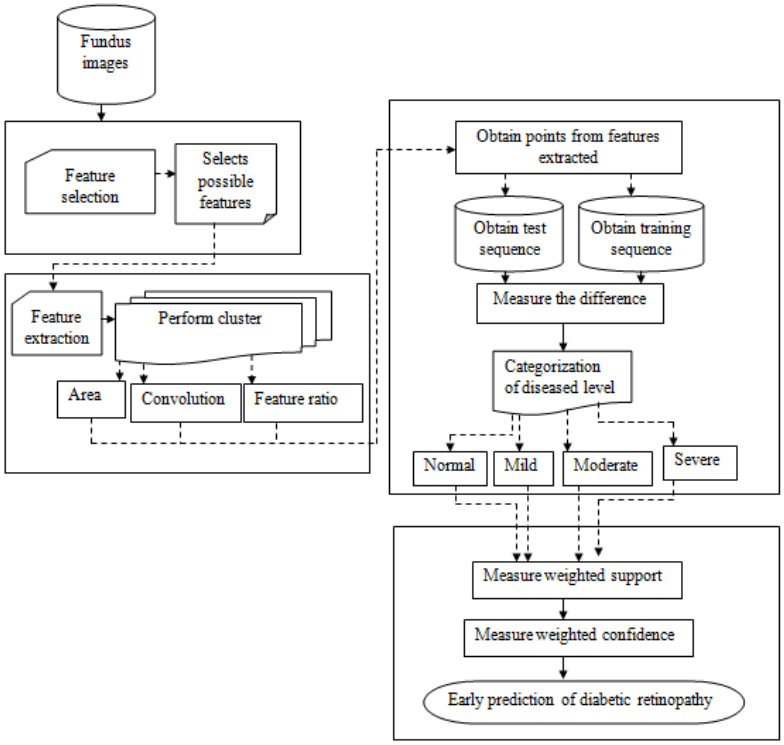
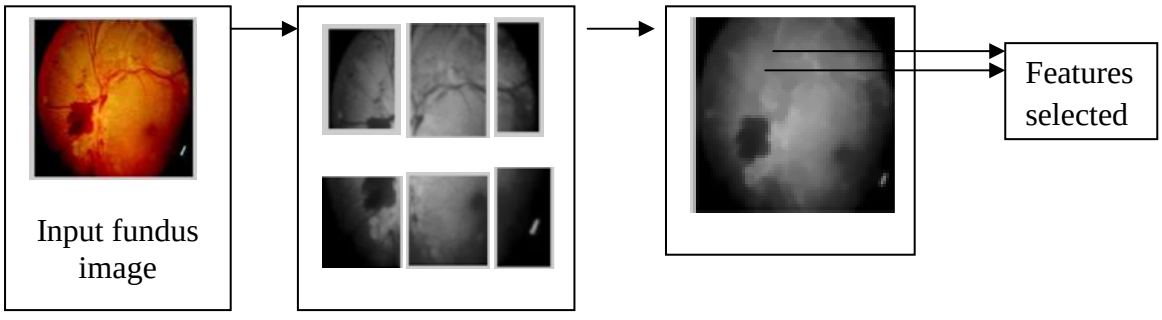


Fig.1: Block diagram of Diagnosis and early prediction of diabetic retinopathy

As shown in the figure 1, diagnosis and early prediction of diabetic retinopathy on digital fundus imagesis made in an efficient manner by applying spectral classifier and predictive rule generator. The spectral classifier measures the difference between the test and training sequence and makes efficient categorization of diseased level through points obtained from extracted features. Next, efficient prediction of diabetic retinopathy is made by measuring the weighted support and confidence for rules. This in turn improves the classification accuracy. The elaborate description is provided in the forthcoming sections.

Feature selection:

One of the important aspects of the feature selection is that the computer aided system should detect all potential regions in input fundus images for identification of lesion (i.e. categorization of classes). The proposed feature selection for efficient classification in input fundus images initially improves the rate of specificity and sensitivity by using sliding window approach. Next, using collection of sliding windows, varied level of features is obtained. Finally, the optimal feature selected based on non-overlapping functions with sliding windows reduces the feature selection time and increase the accuracy of classifier. Figure shows the results of feature selection by applying sliding windows.



(a) (b) (c)

Fig. 2: (a) original input fundus image (b) fundus images obtained based on sliding windows (c) feature selection

Finally, a rich set of features for each region depending on the sliding window approach is generated. As shown in the figure 2, the sliding window blocks divide fundus images into blocks, and use the rectangular shape division operation as shown in figure (b). Next, non-overlapping pixel that effectively ranks the diabetic retinopathy disease using DIARETDB1 - Standard Diabetic Retinopathy Database is presented in figure (c).

Feature extraction:

With the features selected upon given input fundus images, the feature extraction appears with distinguishable properties such as area, convolution and feature ratio. The features to be classified are smaller in size. For independent feature selection and to perform efficient categorization of classes, feature extraction is performed for each input fundus images with the resultant features being selected. The Spectral Classifier with Predictive Rules extracts the vessels and divides the features according to the area, convolution and feature ratio. Figure 3 shows the results of feature extraction by extracting the vessels according to area, convolution and feature ratio.

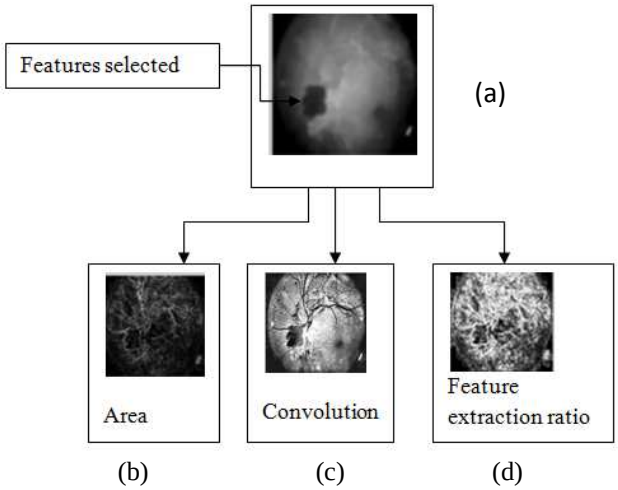


Fig. 3: (a) Features selected (b) vessel extraction based on the area (c) vessel extracted based on convolution (d) vessel extracted based on feature extraction ratio

Finally, a rich set of features are extracted for each set of features based on the area (b), convolution (c) and feature extraction ratio (d). With the extracted features, diagnosis of diabetic retinopathy on fundus images is designed in the forthcoming sections.

Spectral Classifier for Diagnosis (higher rate of sensitivity and specificity):

The classifier based on spectral model or Spectral Classifier (SC) is used for diagnosis of diabetic retinopathy. The SC based on the similarity and dissimilarity measure of attribute in different sequences (i.e. varied images) is obtained. For each interval of time, each set of features extracted as '$Res_{FE} = \{r_1, r_2, \dots, r_n\}$', where '$n$' is the number of sampled features. Let us consider the features extracted as given below.

$$R = [r_1, r_2, r_3, \dots, r_n] \quad (1)$$

Where '$a_1, a_2, a_3, \dots, a_n$' represents the features extracted with the resultant extracted features in 'A'. In order to obtain the number of points from the extracted features, the following function is evaluated and is as given below.

$$P = [p_1, p_2, p_3, \dots, p_n] = \frac{abs\ (R)}{MAX\ (ABS(R))} \quad (2)$$

Each element 'p_i' of 'P' represent the points for the corresponding element of 'P'. The element '$p_i = 1, 2, 3, \dots, n$' isthe selected points spectrum for further classification. Each spectrum is normalized with the maximum selected points.Let us consider a test sequence '$p_i = 1, 2, 3, .., n$' where the training sequence is '$P(s) = p_1(s), p_2(s), \dots, p_i(s), \dots p_n(s)$ '. The test sequence '$Test_{seq}$' and training sequence '$Train_{seq}$' is formulated as given below.

$$Test_{seq} = [p_1(0), p_2(0), \dots, p_m(0), \dots, p_n(0)] \quad (3)$$

$$Train_{seq} = \begin{bmatrix} P\ (1) \\ P\ (2) \\ \dots. \\ P(s) \\ \dots. \\ P\ (K) \end{bmatrix} = \begin{bmatrix} p_1\ (1)\, p_2(1)\, p_m(1)\, p_n\ (1) \\ p_1\ (2)\, p_2(2)\, p_m(2)\, p_n\ (2) \\ \dots \quad \dots. \quad \dots. \quad \dots. \\ p_1\ (s)\, p_2\ (s)\, p_m\ (s)\, p_n\ (s) \\ \dots \quad \dots \quad \dots \quad \dots \\ p_1\ (k) p_2\ (k) p_m\ (k) p_n\ (K) \end{bmatrix} \quad (4)$$

From (3) and (4), the mean of test sequence '$Test_{seq}$' and training sequence '$Train_{seq}$' is measured as given below.

$$\Delta diff_i(k) = [p_i(0) - p_i(k)] \tag{5}$$

$$\Delta Diff = \begin{bmatrix} \Delta d_1(1) & \Delta d_2(1) & \Delta d_m(1) & \Delta d_n(1) \\ \Delta d_1(2) & \Delta dp_2(2) & \Delta d_m(2) & \Delta d_n(2) \\ \dots & \dots. & \dots. & \dots. \\ \Delta d_1(s) & \Delta d_2(s) & \Delta d_m(s) & \Delta d_n(s) \\ \dots & \dots & \dots & \dots \\ \Delta d_1(K) & \Delta d_2(K) & \Delta d_m(K) & \Delta d_n(K) \end{bmatrix} \tag{6}$$

The categorization of diseased level (i.e. diabetic retinopathy) '$c(K)$' is calculated as given below

$$c(K) = \frac{\sqrt{(Diff(K)^2}}{\Delta Diff_{max} - \Delta Diff_{min}} \tag{7}$$
$$\Delta Diff_{max} = MAX[\Delta Diff(k)]$$
$$\Delta Diff_{min} = MIN[\Delta Diff(k)]$$

The dimension of the categorization of diseased level '$\alpha = c(1), c(2), c(3), \dots, c(K)$' is reduced from '$K$' to '$m$' dimension where '$m = 4$' in our study. The four major classes include '$Normal,\ Mild, Moderate, Severe$'. Figure 4 shows the Spectral Classifier algorithm for diagnosis of diabetic retinopathy on digital fundus images.

Input: Image '$Image_i = Image_1, Image_2, \dots, Image_n$', Test sequence '$Test_{seq}$', Training sequence '$Train_{seq}$'
Output: Improved rate of sensitivity and specificity
Step 1: Begin Step 2: For each digital fundus image '$Image_i$' Step 3: For each Test sequence '$Test_{seq}$' Step 4: Select the features based on sliding window Step 5: Extract from the selected features based on area, convolution and feature ratio and stored in 'R' Step 6: For each extracted features 'R' Step 7: Obtain the number of points from the extracted features using (2) Step 8: Evaluate mean using (5) Step 9: Measure categorization of diseased level using (7) and store it in 'α' Step 10: If '$\alpha = c(1), c(2), c(3), \dots, c(K)$' Step 11: Specify the class is belongs to '$Normal,\ Mild, Moderate, Severe$' Step 12: End if Step 13: End for Step 14: End for Step 15: End for Step 16: End

Fig.4: Spectral Classifier algorithm

As shown in the figure 4, the Spectral Classifier algorithm efficiently categorizes the disease level to normal, mild, moderate or severe using the spectral classifier. The spectral classifier classifies the disease level according to the extracted features and obtaining their mean based on the test and training sequence. According to the resultant value, the diseased level stored in '$\propto$' specifies the class it belongs to. This in turn improves the rate of sensitivity and specificity for early diagnosis of diabetic retinopathy on digital fundus images.

Predictive Rule Generation for early detection:

Once the diagnosis of diabetic retinopathy on digital fundus images for early prediction is made, predictive rule is investigated for early detection of disease. In this section, the Predictive Rule Generation for early detection for early detection of disease is discussed. With the candidate set is generated based on spectral classifier, the attribute set that does not satisfies the given minimum support '$\min_sup$' and minimum confidence '$\min_conf$' values are removed and not considered for further analysis. Based on the record weight for each attribute set along with the categorization of class, the weighted support 'w_sup' and weighted confidence 'w_conf' is measured. Based on these two factors, the predictive rules are generated for early detection of diabetic retinopathy on digital fundus images.

For example, in diabetic retinopathy HbA1c, Blood Pressure plays the major role. Hence the attribute value associated with this test value holds maximum weightage in our work (though many attribute values have their influence in measuring diabetic retinopathy, our work considered these two factors). Weight of two different attributes (that are considered in our work) for predicting the probability of diabetic retinopathy is given in Table 1 serves as the minimum support and minimum confidence.

Table 1: Weight of symptoms for diabetic retinopathy (the values provided in the table slightlyvaries according to the methods used)

S. no	HbA1c – level	Risk factor	Weight
1	4% - 5.6%	Normal range	0.1
2	5.7% - 6.4%	Increased risk of diabetes	0.2
3	>6.5%	Indicates diabetes	0.3
S. no	Blood Pressure	Risk factor	
1	115 over 75 mmHg	Normal range	0.4
2	120 over 80 mmHg	Ideal blood pressure	0.5
3	140 over 90 mmHg	Increased risk	0.6

Let us consider a rule (HbA1c = 6.2%) -> (Blood Pressure = 140/90) then weighted support 'w_sup' for rule 'R' is measured as given below:

$$w_\sup(R) = \frac{sumofrecordweighthavingHbA1c=6.2\%\ andBP=140/90}{sumofweightofalltransactions} \tag{8}$$

Once the weighted support value is evaluated, the weighted confidence 'w_conf' is measured, after removing the attribute set that does not satisfies the 'min_conf' threshold values (as provided in table 1). It is the ratio of weighted support '$A \cup B$' and the weighted support 'A'. Therefore, weighted confidence 'w_conf'is measured as given below.

$$w_{conf}(R) = \frac{w_\sup(A \cup B)}{w_\sup(A)} \tag{9}$$

The weighted confidence of the rule 'R' where (HbA1c = 6.2%) -> (Blood Pressure = 140/90) is measured as given below.

$$w_{conf}(R) = \frac{sumofrecordweighthavingHbA1c=6.2\%\ andBP=140/90}{sumofrecordweighthavingHbA1c=6.2\%} \tag{10}$$

In a similar manner, calculating the weighted support 'w_sup' and weighted confidence 'w_conf' for all attributes (as provided in table 1), finally the rules are generated. The predictive rules generated 'PR' are of the form '$(A_i, B_j), (A_m, B_n), \dots, (A_n, B_n) \rightarrow R$' where '$R \in \alpha$', where left hand side refers to attributes and right hand side is the class generated based on the predictive rules. Figure 5 shows the predictive rule mining algorithm for early detection of diabetic retinopathy on digital fundus images.

Input: Image '$Image_i = Image_1, Image_2, \dots, Image_3$', Minimum support '$min_sup$', minimum confidence '$min_conf$', Rules '$R$'
Output: improved classification accuracy
Step 1: Begin Step 2: For each image '$Image_i$' Step 3: Assign minimum support 'min_sup' based on table 1 Step 4: Assign minimum confidence 'min_conf' based on table 1 Step 5: Measure 'w_sup' for rule 'R' using (8) Step 6: Measure 'w_conf'for rule 'R' using (9) Step 7: End for Step 8: End

Fig.5: Predictive rule mining algorithm

As shown in the figure, the predictive rule mining algorithm, efficiently predicts the rule generated for early detection of diabetic retinopathy on digital fundus images. This is performed only if the rule 'R' passes the minimum support threshold 'min_sup' (where$(A_i, B_j), (A_m, B_n), \dots, (A_n, B_n) \rightarrow R >$ min $_sup$) and if the rule 'R' passes the minimum confidence threshold 'min_conf' (where $(A_i, B_j), (A_m, B_n), \dots, (A_n, B_n) \rightarrow R >$ min $_conf$). This in turn improves the classification accuracy.

Experimental settings:

Spectral Classifier with Predictive Rules (SC-PR) on digital fundus images is developed in MATLAB platform. SC-PR technique uses the DIARETDB1 - Standard Diabetic Retinopathy Database which is a public database used for benchmarking diabetic retinopathy detection.The idea of the SC-PR technique is to define a database with a testimage used as benchmark images for diagnosing and early detection of diabetic retinopathy on digital fundus images.

The Standard Diabetic Retinopathy Databaseconsists of 130 color fundus images of which 20 are normal and 110 contain signs of the diabetic retinopathy (hard exudates, soft exudates, micronaneuyrysms, hemorrhages and neovascularization). Images were captured with a 50 degree field-of-view digital fundus camera with unknown camera settings. The data correspond to practical situations, and can be used to evaluate the general performance of diagnosis methods. This data set is referred to as "calibration level 0 fundus images"

By using DIARETDB1database and the defined testing method results are comparedto the existing method. SC-PR technique is compared with the existing Automatic Detection of Optic disc and Macula (AD-OM) [1] and Detecting Optic Disc Boundary (DODB) [2] in Digital FundusImages. The experiment is conducted on factors such as sensitivity, specificity rate and classification accuracy.

Sensitivity is measure of the percentage of wrong detection of diabetic retinopathy as abnormal, multiplied by 100 to turn it into a percentage.

$$Sensitivity = \frac{(TP)}{(TP+FN)} * 100 \tag{11}$$

From (11), sensitivity is measured in terms of percentage (%). Higher the rate of sensitivity more efficient the method is said to be. Specificity gives the measure of correct detection of diabetic retinopathy as correct, multiplied by 100 to turn it into a percentage.

$$Specificity = \frac{(TN)}{(TN+FP)} * 100 \tag{12}$$

From (12), specificity is measured in terms of percentage (%). Higher rate of specificity confirms to the efficiency of the technique. Classification accuracy is the measure of correct predictions (i.e. diabetic retinopathy) made divided by the total number of predictions made, multiplied by 100 to turn it into a percentage.

$$C_{accuracy} = \frac{Correctpredictions}{Totalnumberofpredictions} * 100 \tag{13}$$

From (13), the classification accuracy is measured in terms of percentage (%).

Discussion:

The result analysis ofSpectral Classifier with Predictive Rules (SC-PR) on digital fundus imagesfor diagnosis and early detection of diabetic retinopathy is compared with existing Automatic Detection of Optic disc and Macula (AD-OM) [1] and Detecting Optic Disc Boundary (DODB) [2].

Impact of sensitivity:

The Table 2 represents the sensitivity obtained using MATLAB simulator and comparison is made with two other methods, namely AD-OM [1] and DODB [2].

Table 2: Tabulation for sensitivity

No. of images	Sensitivity (%)		
	SC-PR	AD-OM	DODB
10	81.25	72.13	64.89
20	83.14	75.09	68.29
30	86.93	76.85	68.35
40	89.21	80.16	72.21
50	82.16	73.11	65.31
60	84.32	75.27	68.47
70	87.13	78.08	70.28

Figure 6 illustrates the sensitivity for early diagnosis and prediction of diabetic retinopathy on fundus images versus number of images provided as input. As shown in the figure, the average sensitivity is proportional to the number of input images. With the increase in the simulation time, the SC-PR technique improves the rate of sensitivity compared to AD-OM [1] and DODB [2]. At the same time, the average rate of sensitivity is not linear and varies due to the noise in images resulting in the variation in the rate of sensitivity.

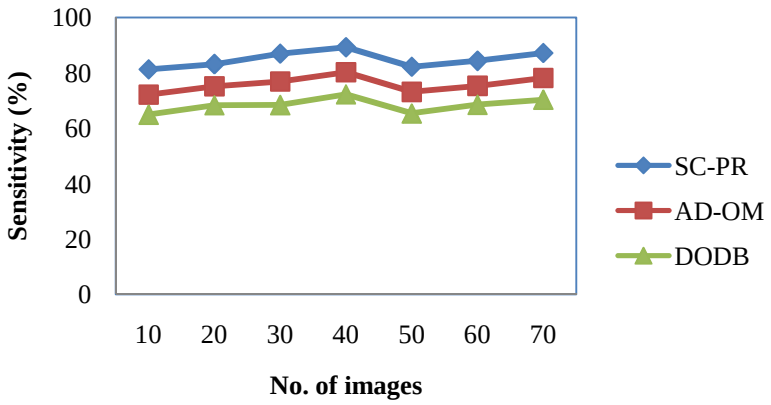


Fig. 6: Measure of sensitivity

Fromresults, we observed that as the number of imagesincreases though average rate of sensitivity increases, comparatively the performance of SC-PR technique isbetter than that of AD-PM by 10.68% and DODB by 19.58%. Here the SC-PR technique improves the sensitivity rate as we are classifying the disease level by performing Spectral Classifier (SC) that obtains the similarity and dissimilarity measure of attribute in different sequences on varied digital fundus images. As a result, it increase the rate of sensitivity for early diagnosis and detection of diabetic retinopathy and efficiently presents the results to the patients at an early stage.

Impact of specificity:

The specificity involved while diagnosis and early detection of diabetic retinopathy is presented in table 3 with respect to 70 different images. With respect to the increasing number of images, though not linear, specificity is also increased compared to [1] [2].

Table 3: Tabulation for specificity

No. of images	Specificity (%)		
	SC-PR	AD-OM	DODB
10	84.14	75.32	63.14
20	88.21	79.31	67.15
30	90.35	81.45	69.35
40	92.14	83.24	71.09
50	86.13	77.23	65.08
60	88.24	79.34	67.18
70	90.13	81.23	69.08

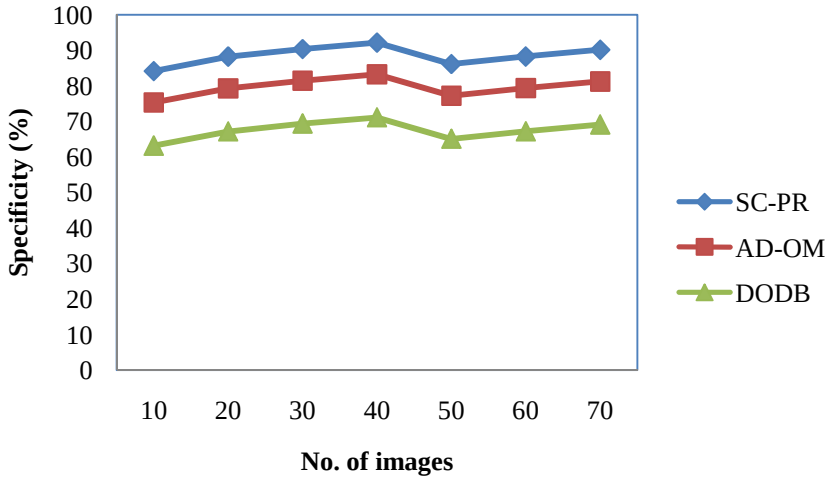


Fig. 7: Measure of specificity

Figure 7 shows the quantitative results to compare the specificity performance of the three methods. To investigate the impact of specificity, we ran a simulation varying the number of digital fundus images from 10 –

70 where 20 normal images and 50 images that contains signs of diabetic retinopathy is used. Figure shows that the specificity with varying number of images increases by applying all the methods. However, by applying SC-PR technique, the specificity achieved is comparatively high. This is because of the evaluation of mean value that in turn efficiently categorizes the diseased level based on the points for the corresponding elements, leading to minimum number of classification, improving the rate of specificity. Therefore the specificity is improved in SC-PR by 10.05% compared to AD-OM and 23.79% compared to DODB.

Impact of classification accuracy:

The comparison of classification accuracy is presented in table 4 with respect to the total number of predictions in the range of 15 – 105. With increase in the number of predictions, the classification accuracy rate also gets increased.

Table 4: Tabulation for classification accuracy

Total number of predictions	Classification accuracy (%)		
	SC-PR	AD-OM	DODB
15	75.83	55.19	42.16
30	79.19	62.09	48.24
45	83.24	66.14	53.29
60	85.16	68.06	55.21
75	80.21	63.11	51.26
90	84.13	67.03	53.18
105	88.92	71.82	58.97

To conduct experiments and analyze classification accuracy, a scenario with 105 predictions with an average of 90 images with 10 normal and 90 images containing signs of diabetic retinopathy is considered. The results observed were the correct predictions made out of 15 predictions were observed to be 11 using SC-PR, 8 using AD-OM and 6 using DODB respectively. Table 5 shows the tabulation for classification accuracy and the resulting graph is plotted in figure 8.Its performance increases with the increase in the number of total predictions made. In figure 8 we can see that the Predictive Rule Generation deployed in SC-PR technique performs better in terms of classification accuracy compared to the other conventional methods [1] [2].

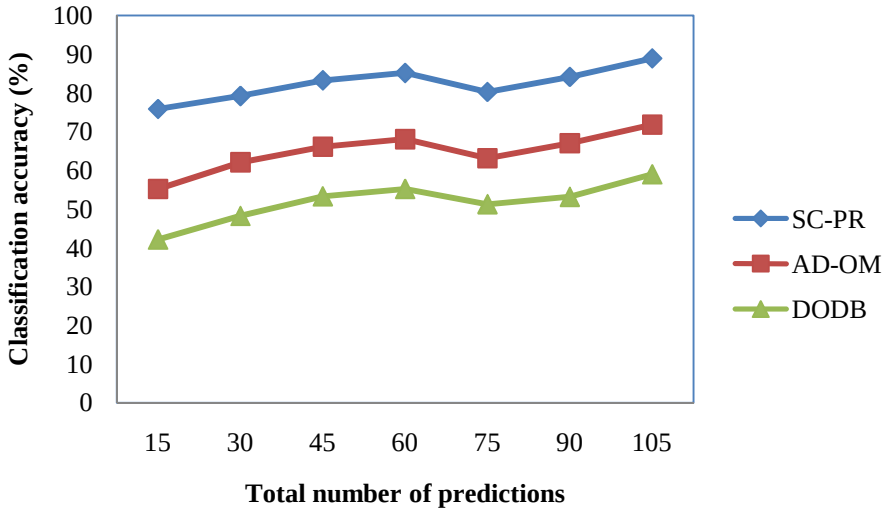


Fig. 8: Measure of classification accuracy

The results utilizing SC-PR technique shows that using predictive rule mining algorithm has resulted in better classification accuracy compared to [1] [2]. While AD-OM and DODB improved accuracy but cost of sensitivity whereas, applying the predictive rule mining algorithm, not only the sensitivity rate is improved but at the rate of improved classification accuracy. On the other hand, by applying minimum support '*min _sup*' and minimum confidence '*min _conf*',weighted support '*w_sup*' and weighted confidence '*w_conf*', are measured based on the record weight for each attribute set along with the categorization of class, improving the classification accuracy. In figure 8, the SC-PR framework achieves an increase of about 21.47% and 37.31% in classification accuracy.

Conclusion:

In this work, we have proposed SC-PR on digital fundus images for early diagnosis and prediction of diabetic retinopathy, aSpectral Classifier with Predictive Rules. The SC-PR technique first selects the features with the help of a simple sliding window. This analysisreveals that an optimal features are extracted therefore reduces the average extraction time for early diagnosis of diabetic retinopathy on each fundus images. The technique also examines the weighted support and weighted confidence value, and demonstrates that the point obtained from the extracted features, early diagnosis of diabetic retinopathy is made and therefore improving the rate of sensitivity and specificity. Finally, predictive rule generation assigns the rules to be predicted based on the minimum support and minimum confidence to enhance the classification accuracy and therefore the predictive rate.We demonstrate through analysis andexperiments that our technique for early diagnosis prediction of diabetic retinopathy technique is effective improving the sensitivity, specificity and classification accuracy compared to the state-of-the-art works.

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