

Statistical Texture Features Based Automatic Detection and Classification of Diabetic Retinopathy

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Abstract: Diabetes is a globally prevalent disease that can cause microvascular complication such as Diabetic Retinopathy (DR) in the human eye organs and it might prompt a significant reason for visual deficiency. The present study aimed to develop an automatic detection and classification system to diagnosing diabetic retinopathy from digital fundus images. An automated diabetic retinopathy detection and classification system from retinal images is proposed in our work to reduce the workload of ophthalmologists. This work comprises three main stages. Our proposed method first extracts the blood vessels from color fundus image. Secondly, the method detects whatever the input image as normal or diabetic retinopathy and then illustrates an automatic diabetic retinopathy classification technique through statistical texture features. It embeds Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) for second-order and higher-order statistical texture feature as a feature extraction technique into three renowned classifiers namely K-Nearest Neighbor (KNN), Random Forest (RF) and Support Vector Machine (SVM). The evaluation results containing a dataset of 644 retinal images indicate that the proposed method based on random forest classifier is found to be effective with a weighted sensitivity, precision, F1-score and accuracy of 95.53% 96.45%, 95.38% and 95.19% respectively for the detection and classification of diabetic retinopathy. These outcomes propose, that the method could decrease the cost of screening and diagnosis while achieving higher than suggested performance and that the system could be implemented in clinical assessments requiring better evaluating.

Index Terms: Diabetes, Diabetic Retinopathy, Run Length Matrix, Image Classification

1. Introduction

Diabetic retinopathy is one of the main causes of global blindness in the economically active population because it affects people between the ages of 20 and 74 [1,2]. It causes other problems like stroke, cardiovascular disease, diabetic nephropathy and diabetic neuropathy. The number of people with diabetic retinopathy is growing higher day by day. This number will estimate to grow from 126.6 million to 191.0 million by 2030 and the number with Vision-Threatening Diabetic Retinopathy (VTDR) will grow from 37.3 million to 56.3 million if no appropriate action is taken [3]. The rapid increase of diabetics especially in low-income countries, shortage of expert ophthalmologists and resources, high cost of treatment and time spent on labor-intensive screening are some of the limitations of manual DR detection. This helps in increasing the number of DR patients [4]. Regular eye examination remains the only way for early detection and treatment to prevent vision loss which can reduce the risk by 50% [5]. There are two types of clinical DR: Non-Proliferative Diabetic Retinopathy (NPDR) or Background Retinopathy and Proliferative Diabetic Retinopathy (PDR). Unfortunately, the DR is usually identified in advanced stages (PDR), with unfavorable forecast even with the right treatment [6]. Therefore, an accurate, automatic, fast and cost-effective technique is needed to detect DR. Although a high sensitivity is good for screening, a relatively low specificity will result in more false-positive cases in the real world [7]. Since 1982, the quantification of diabetic retinopathy and the detection of features such as exudates and blood vessels on fundus images were studied.

A lot of work has been done in this field. A brief overview of the existing DR detection and classification method has been provided here using various digital image processing techniques. A new approach for routine DR detection by using Discrete Wavelet Transform (DWT) was proposed by Khademi et al. [8]. The method experimented on 38 normal and 48 abnormal images with 79% specificity, 85.4% sensitivity and 82.2% accuracy. Authors [9] presented an unsupervised approach to coarse segmentation for vessel detection with an average accuracy of 87%. They incorporated multiple concepts, i.e., mathematical morphology, curvature and spatial dependency to accurately define thin and elongated vessels from vessel pixels. However, the algorithm was unsuccessful in the determination of vessel diameter and was also found to be less satisfactory at segmenting vessel structures on low contrast images. Sarathi et al. [10] mentioned a real-time approach for Optic Disc (OD) segmentation where the boundary of the disks was extracted after the removal of blood vessels using regionally-adaptive threshold and ellipse fitting methods. The proposed technique achieved significant results when tested on standard databases like MESSIDOR and DRIVE with an average overlapping ratio of 89% and 87% respectively. The identification of diabetic retinopathy stage based on Convolution Neural Network (CNN) was developed in [11]. This method improved the performance of classification with 93.65% specificity and 83.68% accuracy. Matthew et al. [12] developed a model for automatic exudate detection in retinal images from diabetic patients. They presented a series of experiments on feature selection and exudates classification using KNN and SVM classifiers. Authors [13] reviews algorithm for extracting features based on blood vessel area, exudes, hemorrhages, microaneurysms and texture from digital fundus images for the automated detection of DR. Varun et al. [14] relied on the development and validation of a deep learning algorithm for automated detection of diabetic retinopathy and diabetic macular edema in retinal fundus photographs. Paper [15] used ensemble of machine learning classifying algorithms on features extracted from output of different retinal image to give decision about the presence of diabetic retinopathy and achieved 75.32% accuracy by applying Neural Network (NNET) classifier. A fully automated DR screening system based on Morphological Component Analysis (MCA) to differentiate between normal and pathological retinal structures was considered in Imani et al. [16]. A SVM classifier was employed to differentiate between normal and abnormal retinal images and achieved 92.01% sensitivity and 95.45% specificity on the Messidor dataset. Goh et al. [17] filtered the retinal healthy images from DR based on the result of exudates detection using the features of local sub-images as the input to multiple classifiers. The experimental results demonstrated that by applying ensemble classifiers they obtained an accuracy of 92% in detecting normal images and 91% in detecting abnormal images over 1000 retina images. A review of recent development on detection methods for the diagnosis of DR was presented in [18] that was developed by various computational intelligence and image processing techniques. A combination of fuzzy image processing techniques, the circular hough transform and several feature extraction methods were proposed by Rahim et al. [19] for automatic screening and classification of diabetic retinopathy and maculopathy. They reached the value of sensitivity, specificity and accuracy of 92.45%, 93.62% and 93% respectively by using radial basis function SVM classifier. Manjaramkar et al. [20] presented a simple, efficient and real-time method for the segmentation and detection of microaneurysm (MA) which are the clinical signs of DR. For this, they used a novel set of features based on statistics of geometrical properties of connected regions and attained the best performance on per-image evaluation on DIARETDB1 dataset with sensitivity of 88.09% at 92.65% specificity.

In our work, we have developed a Computer Aided Decision Support System (CADSS) for automated DR detection and classification based on statistical texture features. Our method is promising and effective over previous state-of-the-art approaches and thus reduces the number of false positives. To identify DR in the retinal images, this study utilizes GLCM and GLRLM as a feature extraction technique. The GLCM and GLRLM capacities describe the composition of an image by computing how regularly combines of the pixel with particular qualities and in a predefined spatial relationship happen in an image. The features are learned in different scales to provide scale-invariant features through GLCM and GLRLM then each image in the frame is classified as abnormal (PDR and NPDR) or normal (normal retinal image). This research represents a possible improvement in the detection and classification of diabetic retinopathy.

The remainder of the paper is as follows: a review of the necessary background required to effectively implement our algorithm is presented in section II. After that, application of the proposed system as well as experimental results is described in section III and section IV. Finally we draw a conclusion in section V.

2. Background

A. Acquisition of retinal image

A large number of publicly available DR datasets is a crucial factor for this purpose. However, the performance of any Computer-Aided Design (CAD) system depends on the training dataset [21], this proposed system utilizes more than 600 standard color fundus images from different sources. Most fundus photographs used in this study were DR (>78%) images and only 21% were normal retinal images. The sample dataset of two categories of DR along with normal retinal image is shown in Fig. 1.

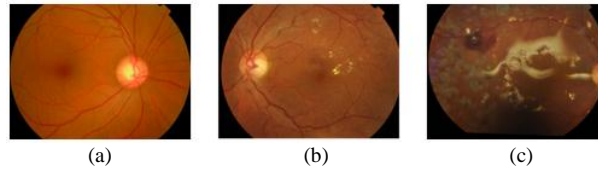


Fig. 1: Sample dataset: (a) normal retina, (b) non-proliferative DR and (c) proliferative DR

Important sources of the database include Indian Diabetic Retinopathy Image Dataset (<https://idrid.grand-challenge.org/Data/>) and Kaggle dataset (<https://www.kaggle.com/c/diabetic-retinopathy-detection>). Table 1 shows the distribution of dataset used in the proposed method.

B. Pre-processing

An input image is loaded in the computer to find the possible categories of retinal images using the proposed intelligent system. For better and faster calculation, all the input image is resized into uniform size (565 * 375) image.

Table 1. Our dataset: the distribution of retinal images used in our proposed system

Retinal image type	Short name	Number of images
Non-Proliferative Diabetic Retinopathy	NPDR	167
Proliferative Diabetic Retinopathy	PDR	341
Normal Image	-	136

C. Blood vessels extraction

In our proposed method, we have used kirsch's template for the extraction of blood vessels from the pre-processed retinal image. Kirsch's template technique uses a single mask of size 3×3 and rotates at 45° increments through each of the eight directions (south, east, north, west, northeast, southeast, southwest and northwest) to detect the edge as shown in Fig. 2. It can set and reset the thresholds values to find the most appropriate edges in the images [22]. The details procedure can be found in [23]. Fig. 3 demonstrates the vessel extraction procedure with Kirsch's template technique.

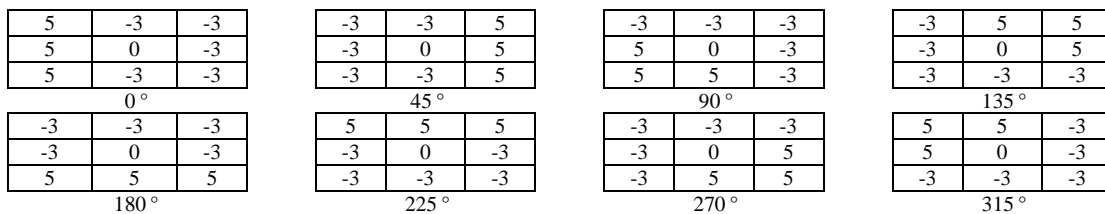


Fig. 2. Kirsch's convolution kernels

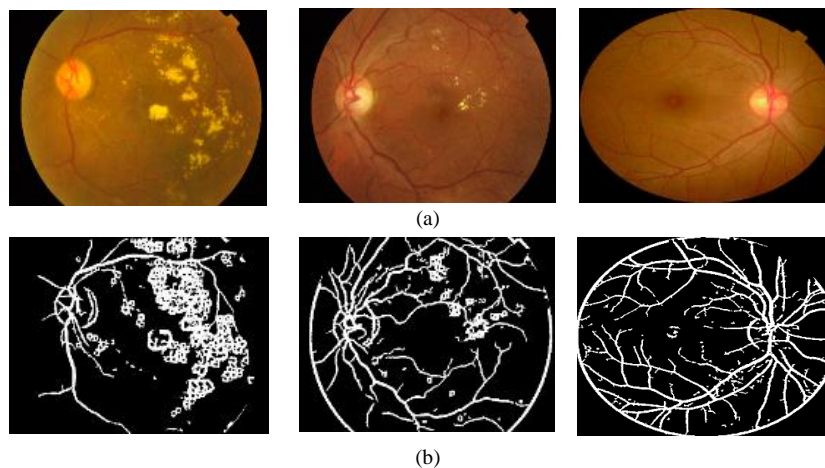


Fig.3. Resultant image after segmentation: (a) the first row shows the image of PDR, NPDR and normal retinal image respectively and (b) the last row indicates the blood vessel extraction results

D. Feature extraction

In feature extraction module, statistical texture features are applied on the segmented image. A feature vector is created by using a large number of training images.

The Gray Level Co-occurrence Matrix (GLCM) also known as Spatial Gray Level Dependence Matrix (SGLDM) is a way to gain second-order statistical texture feature. The GLCM method analyses the distribution of gray level pixel pairs. It provides better results where the textures are visually easily separable and are sensitive to the size of the texture samples being processed. Nine important GLCM features are selected as a second-order statistical texture feature.

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \{ \sum_{i=1}^G \sum_{j=1}^G P(i, j) \}, |i - j| = n \quad (1)$$

$$\text{Correlation} = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i*j\} * P(i, j) - \{\mu_x * \mu_y\}}{\sigma_x * \sigma_y} \quad (2)$$

$$\text{Energy} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2 \quad (3)$$

$$\text{Entropy} = - \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) * \log(p(i, j)) \quad (4)$$

$$\text{Inverse Different Moment} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i, j) \quad (5)$$

$$\text{Variance} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu)^2 P(i, j) \quad (6)$$

$$\text{Sum Average} = \sum_{i=0}^{2G-2} iP_{x+y}(i) \quad (7)$$

$$\text{Sum Entropy} = - \sum_{i=0}^{2G-2} P_{x+y}(i) \log(P_{x+y}(i)) \quad (8)$$

$$\text{Difference Entropy} = - \sum_{i=0}^{G-1} P_{x+y}(i) \log(P_{x+y}(i)) \quad (9)$$

Where, G is the number of gray levels used; μ is the mean value of P; μ_x , μ_y , σ_x and σ_y are the means and standard deviations of P_x and P_y ; $P_x(i)$ is the i th entry in the marginal matrix obtained by summing rows of co-occurrence matrix, $P(i, j)$.

The Gray Level Run Length Matrix (GLRLM) has been considered for the description of higher-order statistical texture feature implemented within the segmented image. The GLRLM method quantifies gray level runs of consecutive pixels with the same gray level value, which are defined as the length in number of pixels. The run length features are the least efficient texture features. We consider seven run length matrix features.

$$\text{Short Run Emphasis} = \frac{1}{n_r} \sum_{i=1}^M \sum_{j=1}^N \frac{Q(i, j)}{j^2} \quad (10)$$

$$\text{Long Run Emphasis} = \frac{1}{n_r} \sum_{i=1}^M \sum_{j=1}^N Q(i, j) * j^2 \quad (11)$$

$$\text{Long Gray Level Emphasis} = \frac{1}{n_r} \sum_{i=1}^M \sum_{j=1}^N \frac{Q(i, j)}{i^2} \quad (12)$$

$$\text{High Gray Level Emphasis} = \frac{1}{n_r} \sum_{i=1}^M \sum_{j=1}^N Q(i, j) * i^2 \quad (13)$$

$$\text{Gray Level Non-uniformity} = \frac{1}{n_r} \sum_{i=1}^M (\sum_{j=1}^N Q(i, j))^2 \quad (14)$$

$$\text{Run Length Non-uniformity} = \frac{1}{n_r} \sum_{j=1}^N (\sum_{i=1}^M Q(i, j))^2 \quad (15)$$

$$\text{Run Percentage} = \frac{n_p}{n_r} \quad (16)$$

Where $P(i, j)$ is the run-length matrix, n_r is the total number of runs and n_p is the number of pixels.

E. Classification

This module handles the classification of feature vector into three classes (Normal, NPDR and PDR). The whole feature vector is divided into two modes: training and testing modes by using K-fold cross-validation [24]. In training mode, GLCM and GLRLM features are extracted from segmented images. The input feature vector consists of 16 different features which are combined together for training with three different classifiers namely KNN [25], SVM [26] and RF [27]. Our proposed system first detects whether the unknown sample contains DR or not. If it contains DR then the unknown sample is classified as NPDR or PDR and it goes to the post-processing module. If it does not contain DR then the unknown sample is classified as normal.

F. Post-processing

The outcome of the classification module is used to produce new image on which possible types of diabetic retinopathy are appropriately labeled. An illustration of this technique shown in Fig. 4.

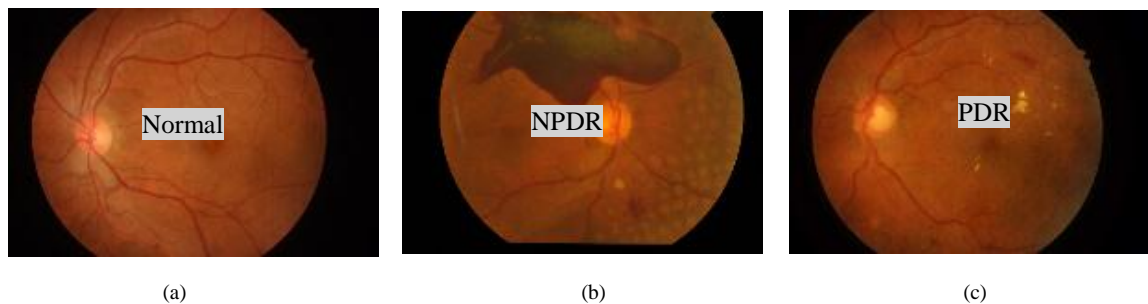


Fig. 4. System's output after post-processing: (a) normal retinal image, (b) NPDR image, and (c) PDR image

3. Methodology

Fig. 5 shows the methodology of our proposed system. The proposed methodology is summarized as follows.

A. Proposed Algorithm

1. Capture the digital fundus image as input image.
2. Pre-process all input image into a uniform size.
3. Apply Kirsch's template technique to extract blood vessels from the preprocessed image.
4. Execute second-order and higher-order statistical texture feature algorithm on the segmented image found from step 3.
5. Generate a Feature Vector (FV) for each training image.
6. Implement three classifiers (SVM, KNN, and RF) to test the train image for classification and evaluate the performance of the results.

4. Experiment simulation and Result Analysis

To assess efficiency of the proposed system, we evaluated four performance metrics for each class: sensitivity, precision, F1-score and accuracy. Sensitivity also known as recall is the ratio of correctly predicted positives cases to the all observations in actual class. The precision metric indicates the correct positive outcomes out of all the positive outcomes. The accuracy of a classifier is simply the ratio of correctly predicted class to total class. F1-score is estimated by applying the weighted average over precision and recall. In case we have an uneven class proportion, F1-score is generally more valuable than precision because it takes both false positives and false negatives into account. Our main purpose is to construct a model that classifies diabetic retinopathy as accurately as possible. We used DR database with 644 images for the evaluation, where the entire dataset is distributed within the training and test dataset. The performance of detecting and classifying DR using three different classifiers are shown in Table 2, Table 3, Table 4, and Table 5 respectively. Finally, the sensitivity, precision, F1-score, and accuracy scores across the three different classes of each classifier is shown in Table 6. From Table 6 to Table 7, "Sn" is for sensitivity, "Pre" for precision, and "Acc" for accuracy.

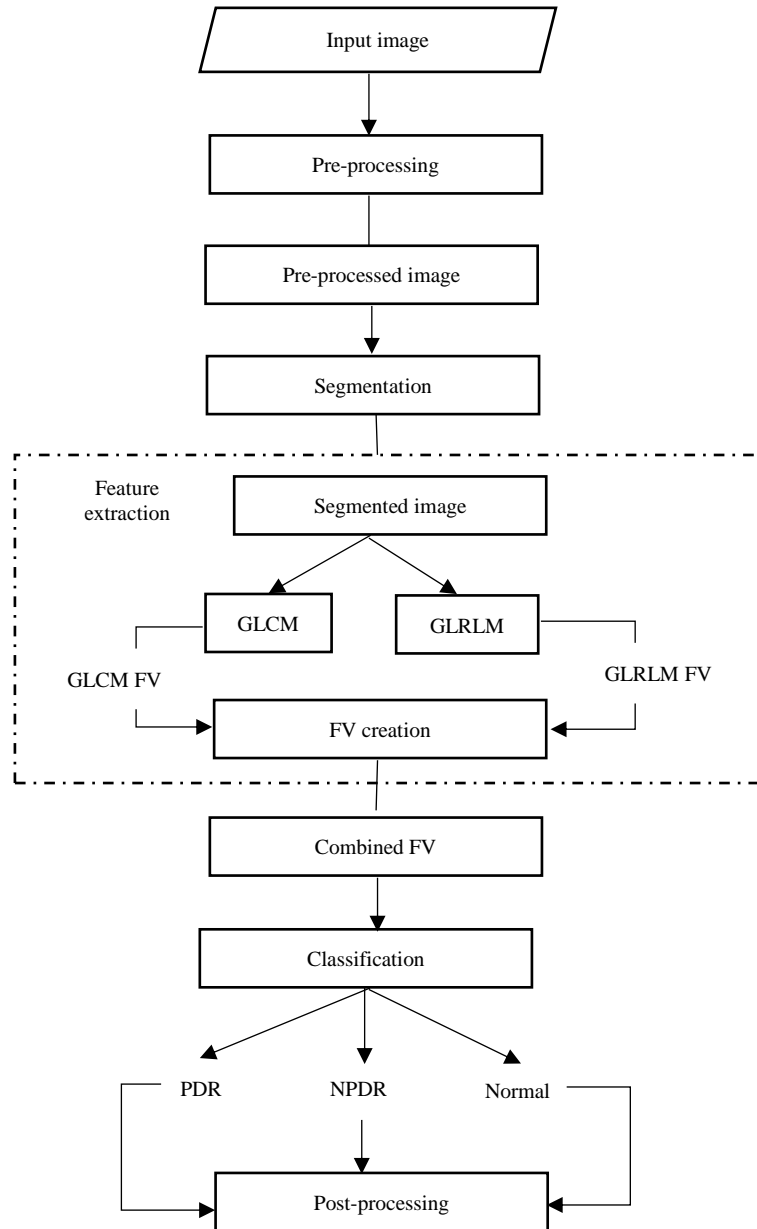


Fig. 5. Detailed diagram of the proposed methodology

Table 2. Confusion matrix of our proposed system using SVM classifier

	PDR	NPDR	Normal
PDR	326	11	4
NPDR	19	136	12
Normal	4	3	129

Table 3. Confusion matrix of our proposed system using KNN (K=3) classifier

	PDR	NPDR	Normal
PDR	302	23	16
NPDR	21	127	19
Normal	18	14	104

Table 4. Confusion matrix of our proposed system using KNN (K=5) classifier

	PDR	NPDR	Normal
PDR	308	17	16
NPDR	21	136	10
Normal	18	19	99

Table 5. Confusion matrix of our proposed system using RF classifier

	PDR	NPDR	Normal
PDR	333	5	3
NPDR	6	149	12
Normal	2	3	131

From the confusion matrix of Table 2, Table 3, Table 4 and Table 5 we see that the random forest classifier made a correct prediction of 333 PDR, 149 NPDR and 131 Normal images out of 341 PDR, 167 PDR and 136 Normal images which is higher than the other two classifiers. For performance evaluation parameters of each transform individually, where we can see that using random forest classifier, the highest sensitivity is in PDR images which comes out to be 98% and the worst sensitivity is 90% which is in normal images. Similarly both the precision and F1-score we get the highest rate of 98% in PDR images. Our method attains the highest accuracy of 97.52% for the detection of PDR images. Table 7 contains the result of weighted measurement of each classifier.

Table 6. Sensitivity, precision, F1-score and accuracy of each classifier

Image Type	SVM				KNN (K=3)				KNN (K=5)				RF			
	Sn	Pre	F1	Acc	Sn	Pre	F1	Acc	Sn	Pre	F1	Acc	Sn	Pre	F1	Acc
PDR	93	96	94	94.1	89	89	89	87.89	89	90	90	88.82	98	98	98	97.52
NPDR	91	81	86	93.01	77	76	77	88.04	79	81	80	89.6	95	89	92	95.92
Normal	89	95	92	96.43	75	76	76	89.6	79	73	76	90.22	90	96	93	96.89

Table 7. Weighted measure of each classifier

Name of the classifier	Weighted Measure			
	Sn	Pre	F1-score	Acc
SVM	91.63	91.89	91.35	94.30
KNN (K=3)	82.93	82.88	83.14	88.29
KNN (K=5)	83.66	84.07	84.45	89.31
RF	95.53	96.45	95.38	95.19

Based on Table 7, the result obtained that the weighted accuracy value of the proposed method reached 95.19% using RF classifier. Sensitivity, precision and F1-score of the proposed method respectively 95.53%, 96.45% and 95.38%. A graphical representation of the performance metrics of each classifier is shown in Fig. 6.

Table 8. Performance comparison among different methods

Authors	Methodology	Dataset	Accuracy
Khademi et al. [8]	Shift-invariant discrete wavelet transform	86	82.2%
Neto et al. [9]	Unsupervised coarse-to-fine algorithm	60	87%
Sarathi et al. [10]	Ellipse fitting	63	92%
Garcia et al. [11]	CNN	35,126	83.68%
Rahim et al. [19]	Fuzzy image processing techniques	990	93%
Manjaramkar et al. [20]	Statistical geometric features	89	88.09%
Proposed Method	Statistical texture features	644	95.19%

Table 8 shows the comparison of our proposed method with existing approaches. We compare the methods focused on the detection and classification of two main types of DR.

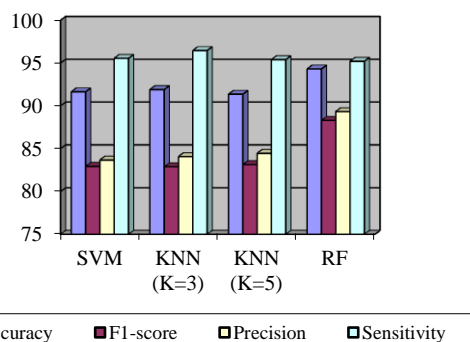


Fig. 6. Graphical performance of the model for different evaluation criteria

5. Discussion

Retinal color photography is an efficient screening method for diagnosing diabetic retinopathy because of it's faster with easier acquisition, storage and transmission of retinal images. Most of the middle and lower-income countries require a cost-effective retinal imaging framework for regular diabetic retinopathy screening [28]. Therefore, an automatic system for the detection and classification of diabetic retinopathy using statistical texture features has been created. The system proposes a combination of retinal blood vessels segmentation, followed by the feature extraction and, finally, the classification with some machine learning algorithms. We incorporate both second-order and higher-order statistical texture feature as a feature extraction tool. As texture features can be extracted using several methods such as structural, statistical, model-based and transform information, we consider statistical methods. According to non-deterministic properties, statistical methods describe the texture indirectly. We have used 10-fold cross-validation for splitting the whole dataset to protect against overfitting. To extract statistical texture descriptors from vessel images, the GLCM and GLRLM features have been used that can demonstrate sound performance in image classification of different categories. An ideal screening test can be measured by its sensitivity i.e., high probability of detecting disease. The experimental results demonstrate that the three classifiers are able to identify well both categories and particularly random forest classifier performed better in most of the cases than the other two classifiers. The sensitivity of retinal images using RF classifier was high (98%) for PDR and for NPDR was also high (95%). Based on the offered results, it can be seen that the sensitivity for normal cases is slightly low (90%). The explanation may be the functionality of kirsch's template technique which was used for the detection of blood vessels. Some of the blood vessels were not detected by this technique.

6. Conclusion and Future works

A large number of diabetic patients and the incidence of DR among them have promoted a great development in automatic DR diagnosing systems. In this study, we developed a computer-aided DR detection and classification system form color fundus images in order to reduce the workload of ophthalmologists to detect DR at the early stages which may go undetected and evolve into blindness. Weighted value of sensitivity, precision, F1-score and accuracy of the suggested method respectively 95.53% 96.45%, 95.38%, and 95.19% which shows that the proposed method can detect and classify DR well. In the future, these methods should be tested on integrating a larger dataset with high-resolution images. Finally, we will add more classes of non-proliferative diabetic retinopathy viz. low, medium, severe condition. It will enable the patients to know their condition with better accuracy.

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