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Assessing the importance of features for detection of hard exudates in retinal images

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Abstract: Diabetes disrupts the operation of the eye and leads to vision loss, affecting particularly the nerve layer and capillary vessels in this layer by changes in the blood vessels of the retina. Suddenly loss and blurred vision problems occur in the image, depending on the phase of the disease, called diabetic retinopathy. Hard exudates are one of the primary signs of diabetic retinopathy. Automatic recognition of hard exudates in retinal images can contribute to detection of the disease. We present an automatic screening system for the detection of hard exudates. This system consists of two main steps. Firstly, the features were extracted from patch images consisting of hard exudate and normal regions using the DAISY algorithm based on the histogram of oriented gradients. After, we utilized the recursive feature elimination (RFE) method, using logistic regression (LR) and support vector classifier (SVC) estimators on the raw dataset. Therefore, we obtained two datasets containing the most important features. The number of important features in each dataset created with LR and SVC was 126 and 259, respectively. Afterward, we observed different classifier algorithms' performances by using 5-fold cross validation on these important features' dataset and it was observed that the random forest (RF) classifier is the best classifier. Secondly, we obtained important features from the feature vector that corresponds with the region of interest in accordance with the keypoint information in a new retinal fundus image. Then we performed detection of hard exudate regions on the retinal fundus image by using the RF classifier.

Key words: Computer-aided analysis, computer vision, feature extraction, important features, image recognition

1. Introduction

The retina is a network layer containing light-sensitive cells. This network layer is the layer that performs eyesight. Diseases that occur in the retina threaten our eyesight directly. Diabetic retinopathy (DR) is damage of the network layer where there are vision cells, depending on diabetes mellitus, and can cause blindness. Timely diagnosis and treatment of DR can reduce the risk of severe vision loss significantly [1,2].

The diagnosis of DR is performed by feature information based on texture analysis of retinal images. Hard exudate (HE) is one of the lesions caused by DR, appearing at the early stages of the disease. In this paper, we present an approach to screening of HE from retinal fundus images by assessing the importance of features. Our methodology includes the following steps:

- Patch images (region of interest)

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- Feature extraction (raw dataset)
- Important features (obtained dataset)
- Training and testing datasets
- New retina analysis

The experimental validation was performed on a public image database, DIARETDB1 [3].

Contribution: Many studies that used keypoint detectors such as ORB, SURF, SIFT, and their descriptors were proposed in [4–6]. In this study, we obtained the important features vector by combining with ORB keypoint detector, DAISY descriptor algorithm, and RFE method.

The rest of this paper is organized as follows. In Section 2, related studies are examined. In Section 3, our proposed methodology is given. In Section 4, experimental results are given in a detailed way. Finally, in Section 5, discussions and future works are explained.

2. Literature review

There are numerous investigations on automatic retina analysis with emphasis on HE detection. HE candidate regions were extracted by combining histogram segmentation and morphological operations. Next, significant features were defined for each candidate region and classification was performed based on these features [7]. HEs were detected automatically by extracting a set of features from image regions and a selected subset providing the best discrimination between HEs and the retinal background, using logistic regression [8]. Various image processing techniques such as median filtering and image thresholding were used for detecting HEs [9]. A novel way for detection of HEs was introduced using the distance learning metric [10]. For detection of HEs, a technique based on morphological operations and H-maxima transform was proposed and then contrast enhancement on the L channel was applied in [11]. HEs were detected incorporating contextual information in retinal images. The context was described by means of high-level contextual-based features based on the spatial relation with surrounding anatomical landmarks and similar lesions [12]. HEs were segmented using mathematical morphology and achieving features. The extracted features were classified by using the soft margin support vector machine [13]. A novel method was proposed to identify HEs from digital retinal images using feature combination. It was based on stationary wavelet transform and gray level co-occurrence matrix. An optimized support vector machine with Gaussian radial basis function was used as a classifier [14]. In [15], following some key pre-processing steps, color retinal images were segmented using fuzzy C-means clustering. The segmented regions into exudates and non-xudates were classified with an artificial neural network classifier. In [16], after different properties of bright lesions and dark lesions were applied, two-step improved fuzzy C-means was applied in LUV color space for segmentation of candidate bright lesion areas. Finally, a hierarchical SVM classification structure was applied in order to classify bright nonlesion areas, exudates, and cotton wool spots. In [17], in order to perform the classification of retinal exudates, an algorithm was proposed based on Fisher's linear discriminant analysis and color information. In [18], for detection of HEs in fundus images, an expert decision-making system was designed using a fuzzy support vector machine classifier. In [19], after preprocessing, histogram thresholding was used for recognition of the background and lesions. In addition, the fuzzy C-means technique was applied to assign the pixels remaining unclassified in the last stage. In [20], with contrast adaptive histogram equalization as the preprocessing stage, contextual clustering algorithms were applied, and the key features were extracted and fed as inputs into an echo state neural network in order to discriminate between the normal and pathological image. In [21], after a feature combination based on stationary wavelet transform and gray level co-occurrence matrix were obtained, an optimized support vector machine with a gaussian radial basis function was employed as a classifier to identify HEs from digital retinal images.

3. Methodology

3.1. Keypoint detector and local descriptors

Keypoints are salient image patches that contain rich local features of an image. Salient patch images, based on keypoint information extraction, have been frequently used in the retrieval and classification of imagery data [22]. Images can be automatically detected using various keypoint detectors, which are surveyed in [23] and used in many areas [24–27]. We used the oriented FAST and rotated BRIEF (ORB) keypoint detector algorithm and DAISY local descriptor algorithm. The ORB and DAISY algorithms were introduced as fast and efficient in [28] and in [29], respectively.

3.2. Feature selection and important features

The feature selection problem in machine learning is a well-known area. There have been numerous studies on the variables and feature selection so far. A method commonly used to reduce feature space dimensionality is projecting on the first few principal directions of the data. New features, linear combinations of the original features, are obtained with such a method. Original input features can be eliminated, which is one of the shortcomings of projection methods [30].

The feature vector, obtained by descriptor algorithms, does not always indicate information exactly and these negative situations occur:

- Noisy
- Overfitting
- Slowing down training/testing data

It is aimed to overcome these drawbacks by obtaining important features from the feature vector. It should be noted in particular that machine memorizing is a basic problem encountered in the field of classification in particular and machine learning process in general. The reduction of the feature vector is required to overcome this situation. Feature-ranking techniques are particularly attractive in performing feature selection. The useless features are eliminated by these methods yet they do not yield precise feature sets because of the abundance of the features. For this ranking criterion, a variety of correlation coefficients are used as in Eq. (1) [30].

$$w_i{=}\left(\mu_i\left(+\right)-\mu_i\left(-\right)\right)/\left(\sigma_i\left(+\right)+\sigma_i\left(-\right)\right)w_i=(\mu_i\left(+\right)-\mu_i\left(-\right))/(\sigma_i\left(+\right)+\sigma_i\left(-\right)), \tag{1}$$

where μ_i and σ_i are the mean and standard deviation of the feature expression values of feature i for all the patients with class (+) or class (–), i = 1 ... n. Large negative w_i values indicate strong correlation with class (–) whereas large positive w_i values indicate strong correlation with class (+). In computing each coefficient, information about a single feature is used and mutual information between features is of no importance and therefore is neglected. A way of using feature ranking is to design a class predictor based on weighted voting of the features proportionally. The weighted voting scheme yields a particular linear discriminant classi?er as in Eq. (2) [30]:

$$D(x) = w.(x - \mu), \tag{2}$$

where w is defined in Eq. (1) and μ is defined in Eq. (3).

$$\mu = (\mu(+) + \mu(-)) / 2\mu = (\mu(+) + \mu(-))/2, \tag{3}$$

where μ is the mean vector over all training patterns. We denote by X (+) and X (–) the training sets of class (+) and (–). A primary method is the ranking features with the magnitude of the weights of a linear discriminant classifier. A cost function computed on training examples only replaces this ideal objective for the aim of training. Such a cost function is chosen as a result of convenience and efficiency. Thus, removing a given feature or, equivalently, by bringing its weight to zero leads to the change in cost function. The effect of removing one feature at a time on the objective function is predicted by the criteria. When it comes to removing several features at a time, the good features become very suboptimal and they are necessary in order to obtain a small feature subset [30].

In this study, we investigated an RFE method that eliminates some of the original input features and retains a subset of important features that yields the best classification performance and is an iterative procedure as follows [30]:

- Training of the classifier.
- Computing the ranking criterion for all features.
- Removing the feature with the smallest ranking criterion.

We used LR and SVC estimators in the process of obtaining the important attributes with the RFE method. Mathematical models that can describe the relationship between outcome variable and other variables are established by using LR and SVC estimators. Therefore, new feature sets are obtained that are have the least variable in the most compatible way based on these models.

3.3. Classification techniques

Classification is a decision-making process used in many disciplines and consists of two steps. In the first step, identifying information about the object to be classified is obtained. In the second step, the decision making process is applied within the framework of the classification rules. The best performance is achieved with the best sampling of data space in classification. In image classification, an image is classified according to its visual content. For example, whether it contains pathological information is an issue to be considered. Image classification is a well-studied topic in the field of image processing and computer vision. Being used commonly, classification algorithms that are used in this study are as follows.

3.3.1. Support vector machine (SVM)

SVM is the highest margin classifier based on statistical learning theory. An optimal hyper plane is located in space of attributes for classes at the highest margin to form SVM classifiers [31].

3.3.2. Artificial neural network (ANN)

ANN is an information processing technology that has been improved and inspired from the information processing techniques in the human brain. ANN is made up of cells that are connected to each other hierarchically and communicate with each other with the help of weighted connections. ANN may be made up of several layers. However, it should consist of at least two layers, namely the input layer and the output layer. Each layer consists of a certain number of nerve cells. There are hidden layers or interlayers except for the input and output layers [31].

3.3.3. Random forest (RF)

The RF algorithm, an ensemble learning method, is a very popular and effective machine learning technique introduced by Breiman [32] and the RF classifier was designed with great numbers of decision trees. Each dataset is generated from the original dataset. Afterward, the trees are developed using a random selection feature [31].

3.4. Performance measures

The question "whether this region is sick or not" is an important question that should be answered in the medical field. That region is analyzed by various methods and techniques to learn the answer to this question. Namely, it is divided into two classes as having disease or not.

The classification accuracy of the diagnosis is assessed using the sensitivity (SN) and positive predictive value (PPV) measures in the analysis of such data. In Eq. (4), the SN of a diagnostic test quantifies its ability to identify correctly abnormal findings with the disease condition. It is the proportion of true positives that are correctly identified. The PPV in Eq. (5) is the probability that the disease is present given a positive test result [33–35]. The accuracy (Acc) in Eq. (6) is the proportion of true results in data analysis [35].

$$SN = \frac{TP}{TP + FN} \tag{4}$$

$$PPV = \frac{TP}{TP + FP} \tag{5}$$

$$Acc = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{6}$$

In these equations, TP is the number of exudate regions found as exudate and TN is the number of normal regions found as normal. FP is the number of normal regions found as exudate and FN is the number of exudate regions found as normal in our study.

3.5. K-fold cross-validation

Cross-validation is ideal model for detecting and preventing overfitting. The accuracy and validity of a statistical model are assessed by this method. The available dataset is split into k-parts of approximately equal sizes, and each part is used in turn for testing of a classifier established on the pooled remaining k-1 parts. The model is trained with the selected k-1 part and then used to predict the values in the part k of the data. A valid model should present good predictive accuracy [36].

4. Experimental results

4.1. Database

We worked on the publicly available DIARETDB1 color fundus image database, all of the same size (1500 × 1152). The marking of pathologies was performed by four ophthalmologists on this database. The red circled area indicates the exudate region in Figure 1.

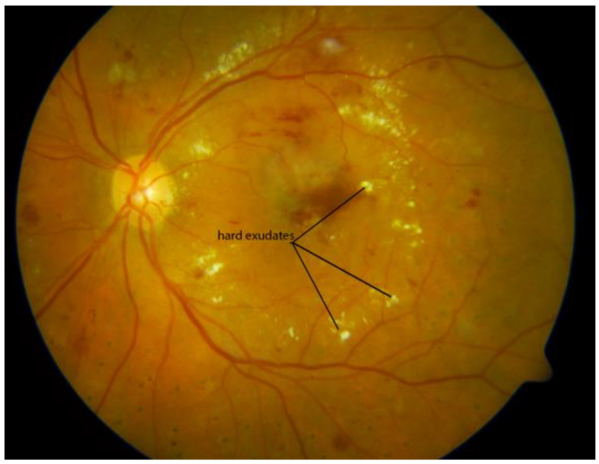

Figure 1. Original retinal fundus image from DIARETDB1 database [3].

Changes in light intensity of the environment cause difficulties in extracting the information from an image in RGB color space. The normalizing process eliminates any effects of intensity changes on the image that may occur. Contrast limited adaptive histogram equalization (CLAHE), being effective in image analysis, is an adaptive contrast equalization process. CLAHE is contrasted and enhanced by applying contrast limited histogram equalization (CLHE) on small data regions rather than the entire image. The histogram is cut at some threshold and afterward equalization is applied in CLHE [37].

Within the settings of this study, we performed light intensity equalization, normalizing, and then CLAHE on each retinal fundus image. In this way, we prepared retinal fundus images for the analysis.

4.2. Modeling process and experimental results

Firstly, we performed system modeling and then we carried out model testing within the framework of external validation rules with the application developed. As can be seen in Figure 2 basically, our methodology consists of learning and testing stages.

In the learning stage, we obtained the feature vectors dataset using the DAISY local descriptor algorithm. It will be used by the RFE method later. We showed in Figure 3 126 and 259 important features based on the RFE method using LR and SVC estimators for the features, respectively. It is necessary to specify the number of important features in other importance of feature methods (e.g., n = 5) and this situation causes restrictions. As for the RFE method, important features information is obtained dynamically.

For training the classifier, we fed it with the important features vector achieved using the training image examples called pathological and nonpathological. To assess the performance of these various classification schemes on our dataset better, we employed 5-fold cross-validation.

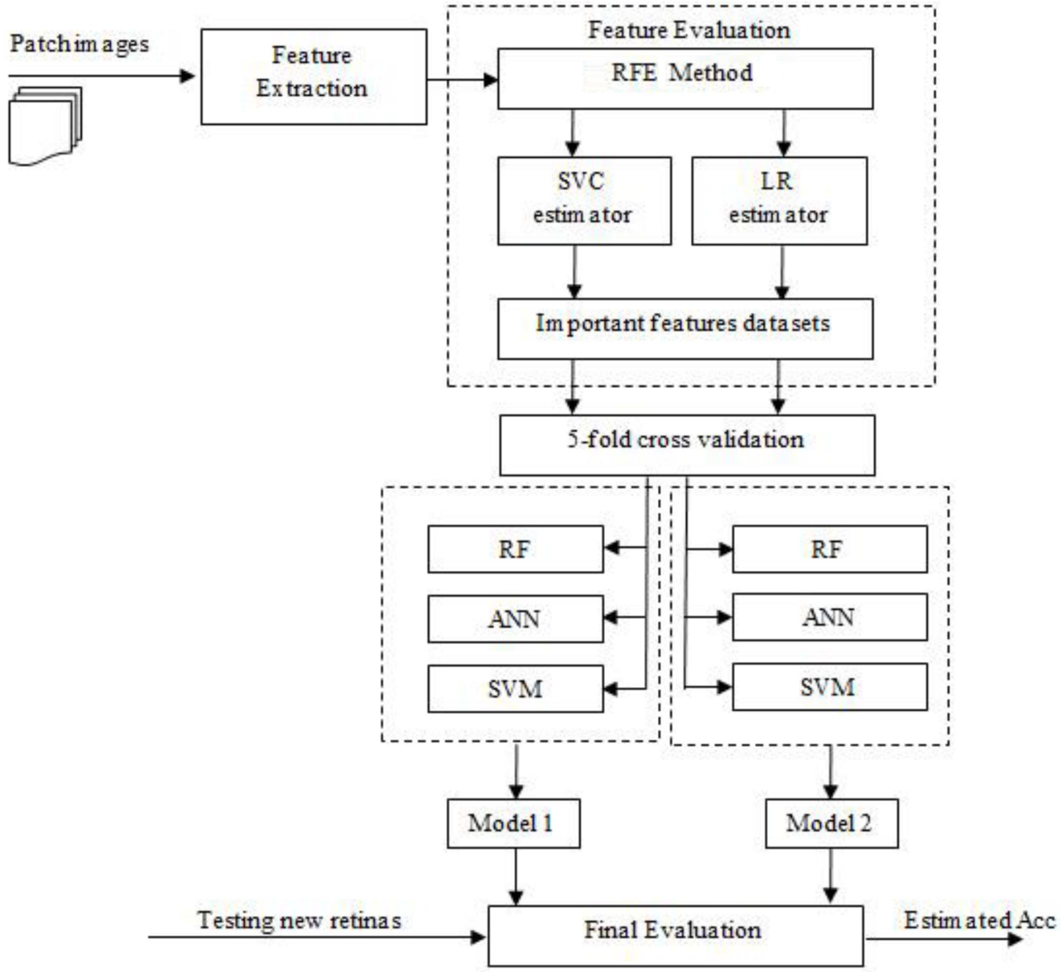

Figure 2. Work flow of our methodology.

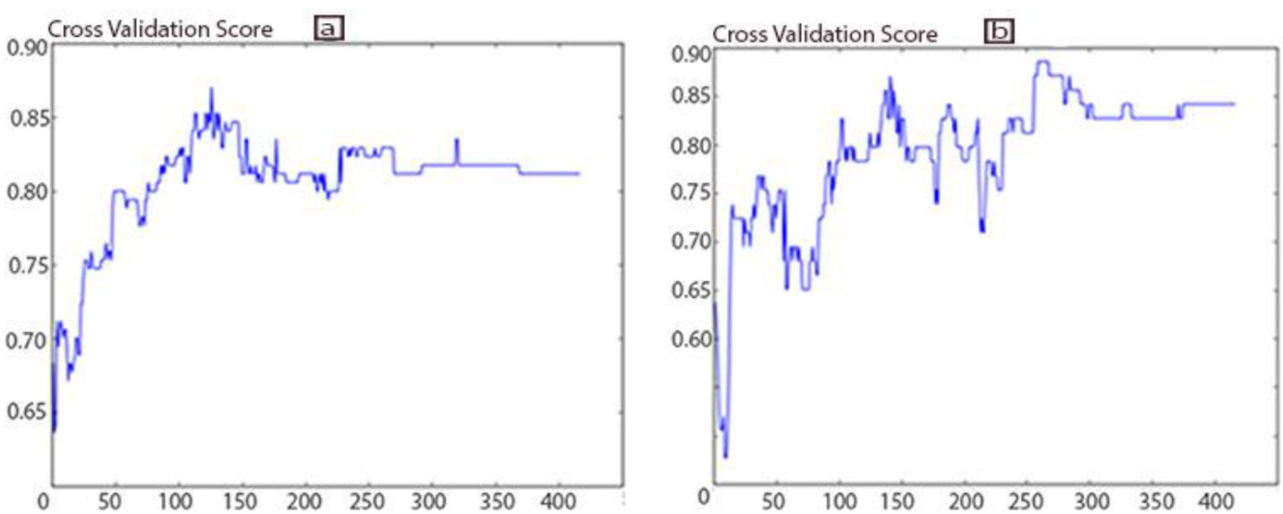

Figure 3. Obtaining important features: a) Number of features selected with LR: 126. b) Number of features selected with SVC: 259.

We present the results of the classification algorithms in Tables 1 and 2. According to these results, the best performance was achieved with the RF classifier. For example, as seen in Table 1 (a) and Table 2 (a), the successful classification ratio of the RF classifier is 88.25%, including 100% of pathological situation and 76.5% of nonpathological situation. Thus, we chose the RF for the best overall classification accuracy in the modeling of the system necessary for the analysis of a new retina.

Table 1. Classification evaluation results based on LR estimator: a) Dataset 1. b) Dataset 2. c) Dataset 3. d) Dataset 4. e) Dataset 5.

		Classifiers					
		SVM (%)		ANN (%)		RF (%)	
a)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	100.0	0.0	71.4	28.6	100	0.0
	Non-HE	58.8	41.2	47.1	52.9	23.5	76.5
b)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	87.5	12.5	93.8	6.2	93.8	6.2
	Non-HE	53.3	46.7	80.0	20.0	6.7	93.3
c)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	84.6	15.4	61.5	38.5	84.6	15.4
	Non-HE	77.8	22.2	50.0	50.0	0.0	100
d)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	75.0	25.0	81.2	18.8	75.0	25.0
	Non-HE	60.0	40.0	13.3	86.7	0.0	100
e)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	100.0	0.0	77.8	22.2	88.9	11.1
	Non-HE	38.5	61.5	15.4	84.6	7.7	92.3

Table 2. Classification evaluation results based on SVC estimator: a) Dataset 1. b) Dataset 2. c) Dataset 3. d) Dataset 4. e) Dataset 5.

		Classifiers					
		SVM (%)		ANN (%)		RF (%)	
a)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	100.0	0.0	71.4	28.6	100	0.0
	Non-HE	58.8	41.2	29.4	70.6	23.5	76.5
b)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	87.5	12.5	87.5	12.5	93.8	6.2
	Non-HE	53.3	46.7	33.3	66.7	6.7	93.3
c)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	84.6	15.4	61.5	38.5	100	0
	Non-HE	77.8	22.2	33.3	66.7	0	100
d)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	75.0	25.0	93.8	6.2	75.0	25
	Non-HE	60.0	40.0	33.3	66.7	0.0	100
e)		HE	Non-HE	HE	Non-HE	HE	Non-HE
	HE	100.0	0.0	100.0	0.0	88.9	11.1
	Non-HE	38.5	61.5	38.5	61.5	7.7	92.3

Table 3 shows the SN, PPV, and Acc values for the classification algorithms and each estimator. On the other hand, we demonstrated correct classification ratios of classifier algorithms in Figure 4.

Table 3. Classification evaluation results based on LR and SVC estimators.

Datasets (Based on LR estimator)	Classifiers								
	SVM (%)			ANN (%)			RF (%)		
	SN	PPV	Acc	SN	PPV	Acc	SN	PPV	Acc
Dataset 1	62.97	100	70.6	60.25	71.4	62.15	80.97	100	88.25
Dataset 2	62.14	87.5	67.1	53.97	93.8	56.9	93.33	93.8	93.55
Dataset 3	52.09	84.6	53.4	55.16	61.5	55.75	100	84.6	92.30
Dataset 4	55.56	75	57.5	85.93	81.2	83.95	100	75	87.50
Dataset 5	72.2	100	80.75	83.48	77.8	81.2	92.03	88.9	90.60
Datasets (Based on SVC estimator)	Classifiers								
	SVM (%)			ANN (%)			RF (%)		
	SN	PPV	Acc	SN	PPV	Acc	SN	PPV	Acc
Dataset 1	62.97	100	77.6	70.83	71.4	55.38	80.97	100	88.25
Dataset 2	62.14	87.5	67.1	72.43	87.5	77.1	93.33	93.8	93.55
Dataset 3	52.09	84.6	53.4	64.87	61.5	64.1	100	100	100
Dataset 4	55.56	75	57.5	73.8	93.8	80.25	100	75	87.5
Dataset 5	72.2	100	80.75	72.2	100	80.75	92.03	88.9	90.6

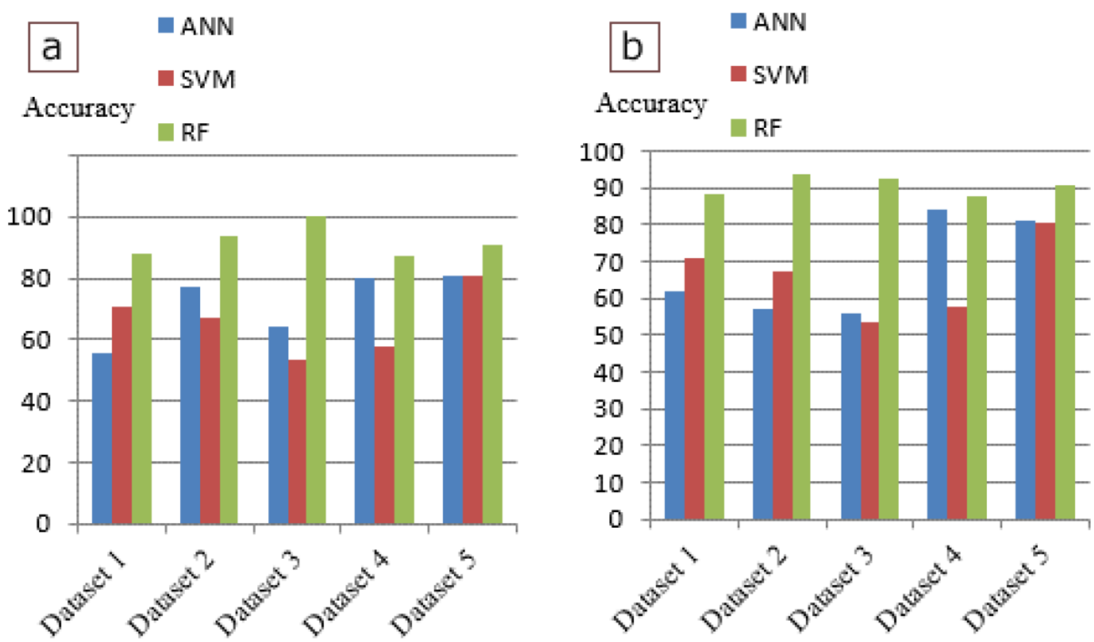

Figure 4. Correct classification ratios of algorithms: a) Datasets (based on LR estimator), b) Datasets (based on SVC estimator).

In addition, as seen in Figure 5, we presented total running times with raw features set and important features set in a system with the same hardware characteristics. The significance of modeling with the important features is understood better when considering the classification performance.

We evaluated the methodology on testing 20 new retinas and demonstrated the robustness and reliability of the approach, assessing the importance of features. The workflow to classify a new retinal image is as follows:

- Determining the optic disc area on the retinal fundus image and saving this information into the system manually.

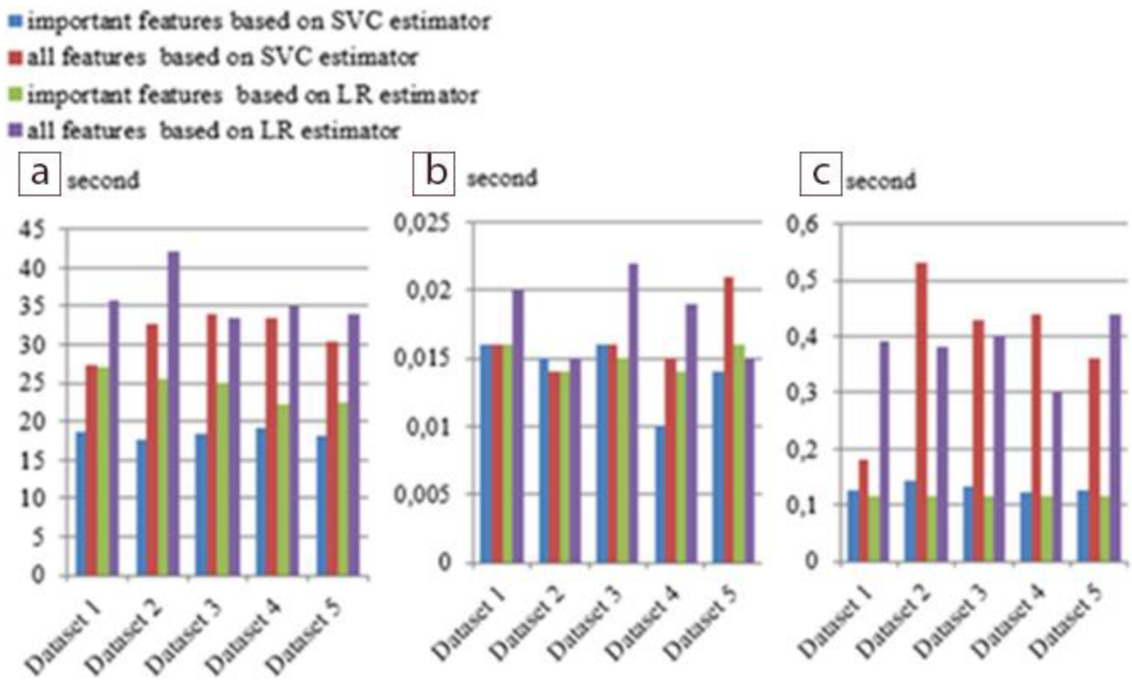

Figure 5. Total running times of algorithms: a) ANN classifier, b) SVM classifier, c) RF classifier.

- Computing the points of interest (PoIs) of the image using the ORB algorithm.
- Describing regions of interest (RoIs) corresponding to PoIs.
- Obtaining feature vectors corresponding to RoIs.
- Obtaining important features by using the RFE method from feature vectors, and then sending the found values to the RF classifier, which will classify an image into pathological or nonpathological regions.

We demonstrated the successful classification ratios, performed with each model, in Figure 6 for 20 diseased retinas in the dataset. Figure 6a shows successful classification ratios of the model obtained with the LR estimator and Figure 6b shows successful classification ratio of the model obtained with SVC estimator for new retinas. The success of both models is approximately the same. Some of the obtained results from various retinal fundus images are shown in Figure 7.

In addition, markings of pathologies were re-checked and confirmed by an ophthalmologist, an experienced retinal disorders specialist.

4.3. Comparison of results obtained using different methods

The performance of the method is compared with existing methods as shown in Table 4. From the table, we can easily conclude that proposed method displayed a rather good level of success.

5. Results and discussion

Automatic detection of the HEs that occur in the early stages of DR is very important in terms of preventing this disease and for eye health.

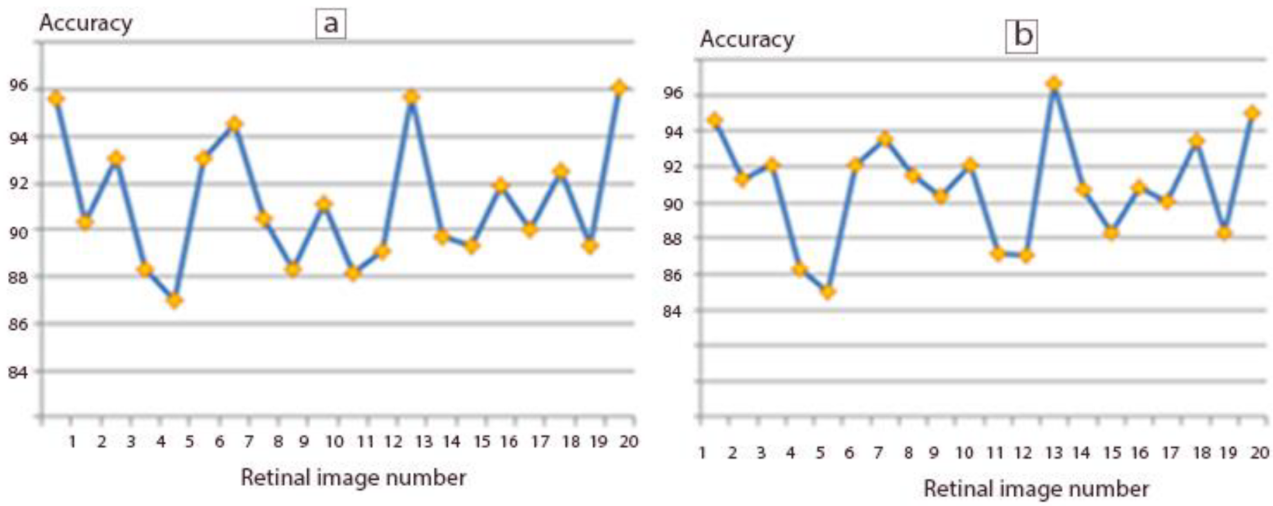

Figure 6. Successful classification ratios for retinas: a) Model 1 (RF classifier and RFE method based on LR estimator), b) Model 2 (RF classifier and RFE method based on SVC estimator).

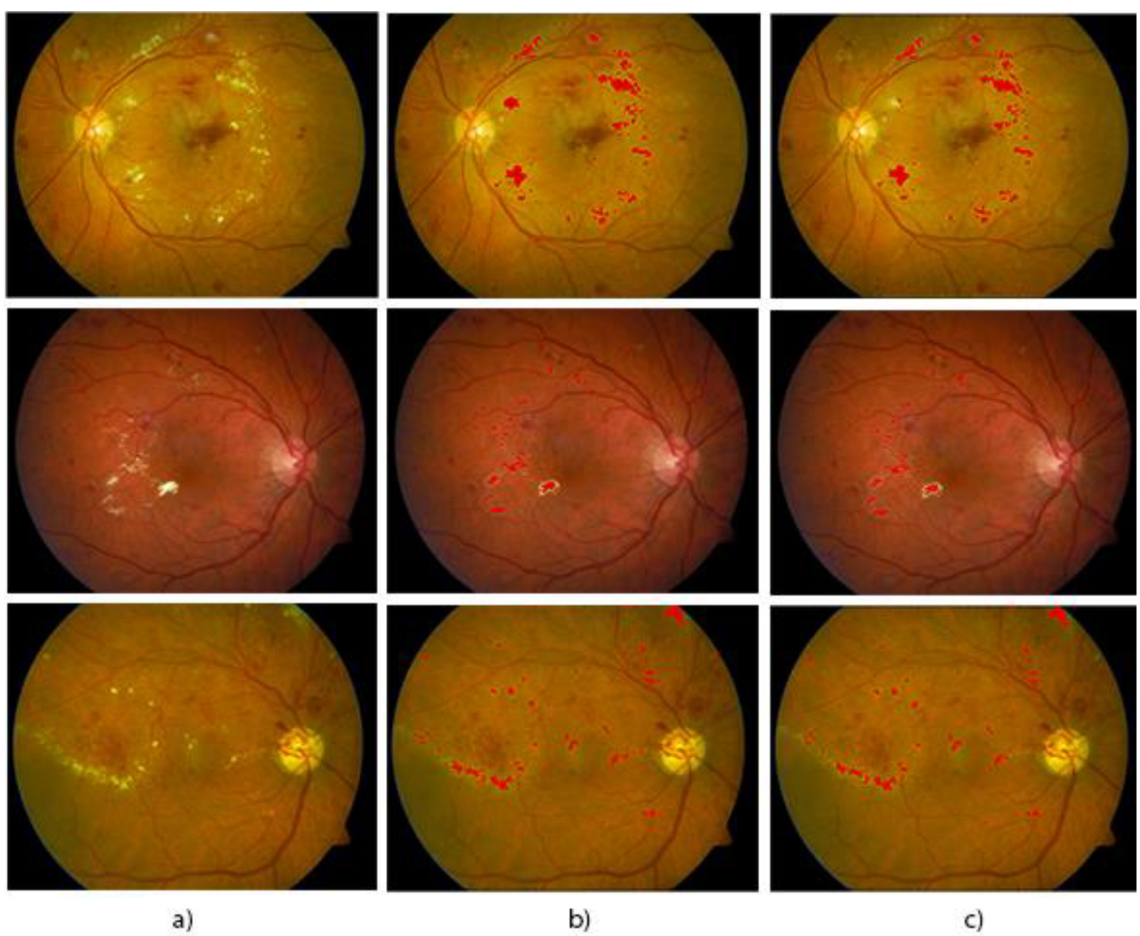

Figure 7. Some of the results: a) original images, b) the hard exudates obtained with Model 1, c) the hard exudates obtained with Model 2.

Table 4. The comparison of the methods of hard exudate detection performed on retinal fundus image datasets.

Authors	Technique	Dataset	SE (%)	PPV (%)
Chen et al. [7]	Histogram segmentation, morphological operations, significant features and classification	DIARETDB1	94.7	90.0
Garcia et al. [8]	Features and selected the subset features and classification methods (lesion-based criterion)	DIARETDB0	95.9	85.7
Kayal and Banerjee [9]	Various image processing techniques	DIARETDB0DIA RETDB1	97.25	-
Welfer et al. [11]	Morphological operations and H-maxima transform	DIARETDB1	70.48	-
Osareh et al. [15]	Preprocessing, fuzzy C-means clustering and an artificial neural network classifier method.	142 color retinal images	93.0	89.3
Zhang and Chutatepe [16]	Local contrast enhancement, fuzzy C-means, and hierarchical SVM classification.	30 retinal images from Singapore National Eye Center	88.0	84.0
Sanches et al. [17]	Fisher's linear discriminant analysis and classification	58 retinal images	88.0	-
Jaya et al. [18]	Circular Hough transform, features and fuzzy support vector machine classifier	200 retinal images	94.1	-
Pan and Bing-Kun [19]	Preprocessing, histogram thresholding and the fuzzy C-means technique	DIARETDB0	84.8	87.5
JayaKumari and Maruthi [20]	Contrast adaptive histogram equalization, contextual clustering algorithm, key features, and echo state neural network algorithms	50 retinal images	93.0	-
Xu and Luo [21]	A feature combination based on stationary wavelet transform and gray level co-occurrence matrix and an optimized support vector machine classifier method	14 retinal images from Beijing Tongren Hospital	88.0	-
Proposed method (model 1 and model 2)	Keypoint detection, important features vector via RFE method, and classifier methods	DIARETDB1	93.27 93.27	88.46 91.54

An image is expressed as a features set in machine learning and this information is used to distinguish images in different categories from each other. Some disadvantages such as noise, overfitting, and slowing down training/testing data may arise from this information in terms of machine learning. RFE is one of the algorithms developed in order to overcome these disadvantages. In this study, we obtained a features set belonging to different patch images that are non-HE and HE diagnosed in the commonly accepted and used DIARETDB1 dataset. Then we pointed out the importance of features using the RFE method on this features set. Afterwards, we introduced achievements of the different classifiers within the framework of k-fold cross-validation rules for the detection of HEs by using the important features set obtained in the previous step. As a result of experimental studies, we can say that we achieved better performance by utilizing the RF classifier and important features. In this respect, we designed a decision support system that is fast and efficiently detects lesions called HEs in the retinal fundus image. Afterwards, we presented the effectiveness of the study on new retinal images by using this system.

Working with more data will improve the stability of the system. However, it is clear that it causes increases in the calculation and process time as the size of the dataset grows. In order to overcome these problems, it is seen that working with important features decreases the calculation and process time significantly.

This study also illustrates new aspects of the applicability of important features in knowledge discovery and data mining. As a future work, we are going to propose a practice with important features algorithms on new feature vectors and distinctive attributes by using local descriptor algorithms. We can increase the efficiency of classification based on the idea of using new descriptors. Another future work proposal is going to be the identification of the other retinal pathologies such as hemorrhage and microaneurysm.

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