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DETECTION OF HARD EXUDATES IN DIABETIC RETINOPATHY RETINAL IMAGES BY UTILIZING VISUAL DICTIONARY AND CLASSIFIER APPROACHES

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Abstract

Diabetic retinopathy is a disease that causes blindness resulting from damages that emerge in the retina depending on the diabetes mellitus. There are two stages of the disease including the non-proliferative and proliferative. Eyesight loss is blocked by means of early detection and diagnosis of non-proliferative DR findings. In this study, we designed a decision support system for automatic detection of hard exudates which are early stage DR lesions. This system consists of keypoint extraction, feature extraction, visual dictionary and classifying stages. We tested the performance of the system, which we carried out based on system learning and analysis of new retinal images, on the public DIARETDB1 retinal image dataset. Experimental results obtained with Artificial Neural Networks, Random Forest ve Decision Tree algorithms showed us that machine learning technique suggested by us is successful.
Keywords: Hard exudate, Keypoint extraction, Feature extraction, Visual dictionary, Classification

GÖRSEL SÖZLÜK VE SINIFLANDIRMA YAKLAŞIMLARINDAN FAYDALANARAK DİYABETİK RETİNOPATİLİ RETİNAL GÖRÜNTÜLERDE SERT EKSUDALARIN TESPİTİ

Özet

Diyabetik retinopati, şeker hastalığına bağlı olarak retinada ortaya çıkan hasarlanmaların sonucu körlüğe neden olan bir hastalıktır. Bu hastalığın erken evre (nonproliferatif) ve ileri evre (proliferative) olmak üzere iki aşaması vardır. Erken evre DR bulgularının erken tanı ve teşhisi sayesinde görme kaybının önüne geçilir. Bu çalışmamızda erken evre DR lezyonlarından olan sert eksuda bölgelerinin otomatik olarak tespiti için bir karar destek sistemi tasarladık. Bu sistem, anahtar nokta çıkarımı, özellik çıkarımı, görsel sözlük ve sınıflandırma aşamalarını içerir. Sistemin öğrenmesi ve yeni retinal görüntülerin analizi temeline dayanarak gerçekleştirdiğimiz bu sistemin performansını publik (herkese açık) DIARETDB1 retinal görüntü dataseti üzerinde test ettik. Yapay Sinir Ağları, Rastgele Orman ve Karar Ağacı algoritmaları ile elde ettiğimiz deneysel sonuçlar önerdiğimiz makina öğrenmesi tekniğinin başarılı olduğunu bize göstermiştir.
Anahtar Kelimeler: Sert eksuda, Anahtar nokta çıkarımı, Özellik çıkarımı, Görsel sözlük, Sınıflandırma

1 Introduction

Diseases such as hypertension, diabetes mellitus cause eyesight lost by giving cause for changes in the structure of the eye. Diabetic retinopathy (DR) is developing damage in blood vessels in retina because of diabetes mellitus. Early diagnosis and treatment of this disease can reduce the loss of eyesight significantly [1]–[2]. In our study, we presented a study detecting Hard Exudate (HE) lesions which arise out of in the early stages of the DR disease, by utilizing visual dictionary and classify approaches. The study consists of two main stages including learning of the system and analysis of the new retinal images. Learning of the system consists of region-of-interest (RoI), feature extraction, visual dictionary and classifying stages. We designed the decision support system with classifier algorithm exhibiting the best performance. The analysis of new retinal images consists of identification of keypoints, features extraction and detection of lesions stages. We performed experimental validation practices on a public image dataset, DIARETDB1 [3].

The rest of this paper is organized as follows. In Section 2, related studies are examined. In Section 3, the proposed methodology is introduced in detailed way. In Section 4, experimental results are given. In final section, conclusion is presented.

2 Related Works

There are numerous investigations on HEs detection. Firstly, HE candidate regions by combining histogram segmentation with morphological reconstruction were extracted. Next, significant features were obtained for each candidate region. Finally, HEs were detected by classifying these features with, Support Vector Machine [4]. In [5], authors detected hard exudates automatically by extracting a set of features from image and then selecting the subset best discriminating between hard exudates and the retinal background using the logistic regression method. The role of domain knowledge in improving the accuracy and robustness of detection of hard exudates in retinal images was demonstrated in [6]. In [7], authors proposed a method which uses various image processing techniques, such as median filtering, image thresholding etc. for detecting hard exudates. In [8], authors introduced a novel way for detection HEs, using the Distance Learning Metric. Also they introduced a new method to remove the optic disc in the post-processing stage based on variance calculation. A technique based on morphological image processing and fuzzy logic algorithms in order to detect hard exudates from DR retinal images was proposed in [9]. According this, at the initial stage, the exudates were identified, using mathematical morphology. Subsequently, hard exudate regions were obtained, using an adaptive fuzzy logic algorithm. In other study, primarily, optic disc and the blood vessels were detected and then eliminated from the image for analysis of hard exudates in retinal color image. Afterwards, hard exudates regions were found in [10] by mixture of morphological operation such as Top-hat, Bottom-hat and reconstruction operations. The detection of hard exudates in retinal images by means of high-level contextual-based features based on the spatial relation with surrounding anatomical landmarks and similar lesions was performed in [11]. In [12], authors presented an algorithm based on mixture models in order to separate hard exudates from background. In [13], authors segmented hard exudates using mathematical morphology and achieved features. Diseased regions were found by classifying these features. In [14], a novel method based on classifying of features obtained from stationary wavelet transform and gray level co-occurrence matrix was presented to identify hard exudates from digital retinal images. In [15], detection of hard exudates was performed based on Fisher's linear discriminant analysis. In [16], a new unsupervised approach based on the ant colony optimization algorithm, which performs better than the traditional Kirsch filter in detecting exudates, was presented. In [17], Multilayer Perceptron, Radial Basis Function and Support Vector Machine classifiers performances were investigated for detection of hard exudates in variable color, brightness and quality retinal images. In another study, contextual clustering algorithms the preprocessing stages of which are a state-of-art image processing techniques and then the contrast adaptive histogram equalization were used for segmenting the exudates. Afterwards, the key features were extracted and fed as inputs into Echo State Neural Network to discriminate between the normal and pathological image [18].

3 Methodology

3.1 Preprocessing Dataset

Light intensity changes in environment cause difficulties in extracting the information from image in RGB color space. For this reason, we practiced on image which is obtained with Contrast Limited Adaptive Histogram Equalization (CLAHE) method which proved itself to be effective in image analysis, for the stability of system. CLAHE is an adaptive contrast histogram equalization method where the contrast of an image is enhanced by applying contrast limited adaptive histogram equalization on small data regions rather than the entire image [19].

3.2 Keypoint and Feature Extraction

Keypoints obtained with the help of keypoint descriptors such SIFT, SURF and ORB which were surveyed in [20-22] respectively, provide us important points about image. There are a lot of works done in various areas on the image recognition and detection as in [23-27] studies based on this approach. In these studies, the RoIs around keypoints were analyzed with various pattern recognition and matching algorithms.

The keypoint identifiers (descriptors) representing the RoIs around keypoints are obtained. These descriptive information are able to sample data space in a good way. In this way, the success of the system which is designed by utilizing different methods and techniques system is higher. Because, the features representing a region that is processed in image processing are the most important element of computer-aided systems.

Daisy algorithm, which is surveyed in [28], based on the histogram of oriented gradients are used for extracting the features representing the image. This algorithm has been used in many studies such as image recognition in [29] and image matching in [30] through improved version of this algorithm.

3.3 Visual Dictionary (VD)

For digital images to be classified correctly by using their distinctive characteristics, VD is referred. VD is customization of bag-of-words method known as document analysis method. The distinguishing features of images which are obtained by the different filtering methods are used instead of word in a document. The analogy between words in VD and quadratic regions provides opportunities for classification of images.

VD allows the words in the same category obtained from images to be expressed in single word. For this, firstly the words to be evaluated must be taught to the system. After the visual words are designed, the each of the image is assigned to the closest visual word in the dictionary with clustering technique. This step is known as quantization. The distance between a training vector Xi and all the other training vectors Yj where i ≠ j is computed as in equation (1) [31]:

$$D = \sum_{j=1}^{k} \left(X_j - Y_{ij}\right)^2 \ where\ X \neq Y_i\ and\ 1 \leq i \leq N \tag{1}$$

The result is achieved by making calculations such as the distance between the query word and the visual words in the dictionary during questioning.

3.4 Classification

Classification phase, which consists of the training and the testing processes, and being necessary and important step for machine learning, is a common technique used for determining to which class the data analyzed belong. There are many approaches including robust features and classification algorithms. The goal of image classification is to predict the class of the input image.

3.4.1 Artificial neural networks (ANN)

ANN is computer systems that were developed with the aim to automatically perform the abilities such as to be able to create new knowledge and to be able to explore through learning as features of human brain without any help. For a nonlinear mapping from a set of inputs to a set of outputs, ANNs are generally designed. In attempting for biological system performance to be performed, ANNs are developed with the help of a dense interconnection of simple processing elements analogous to biological neurons [32].

3.4.2 Decision Tree (DT)

A hierarchical partitioning of the data relating the different partitions at the leaf level to the different classes is designed by DT. The use of a split criterion designs the hierarchical partitioning at each level. The split criterion might either use a condition (or predicate) on a single attribute, or a condition on multiple attributes. The classified data by using decision tree technique is a two-step process including learning and classification. In the learning stage, a training data already known is analyzed by the classification algorithm in order to create the model. The learned model is shown as classification rules or decision tree. As for in the classification step, the test data is used to determine the accuracy of the classification rules or the decision tree. If the accuracy is an acceptable rate, the rules are used for the classification of new data [33].

3.4.3 Random Forest (RF)

A random forest classifier, introduced by Breiman [34], including a lot of trees and with each tree grown using some form of randomization, is one of machine learning techniques and it is a very efficient and well known for classification and regression problems. [33]. The RF allocates each node to branches, using the best one selected randomly from each node variables. Each dataset is generated from the original dataset in a displacable way. Then trees are developed, using a random selection feature [35].

3.5 Performance Measures

When evaluating a diagnostic test, conditions encountered are as follows:

- TP is the number of real positive found as positive.
- TN is the number of real negative found as negative.
- FP is the number of real negative found as positive.
- FN is the number of real positive found as negative.

The evaluation of "The disease is either present or absent" is performed for all items in the dataset. As a result of these assessments, performance of the system is tested with the Sensitivity, Specificity and Accuracy values. In Equation 2, the sensitivity defines the proportion of TP in a total group of subjects with the disease. In equation 3 the specificity is defined as a proportion of TN in total group of subjects without the disease. In equation 4, the accuracy is the proportion of true results in data analysis [36-37].

$$\text{Sensitivity (SN)} = \frac{TP}{TP + FN} \qquad (2)$$

$$\text{Specificity (SP)} = \frac{TN}{TN + FP} \qquad (3)$$

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + FP + TN + FN} \qquad (4)$$

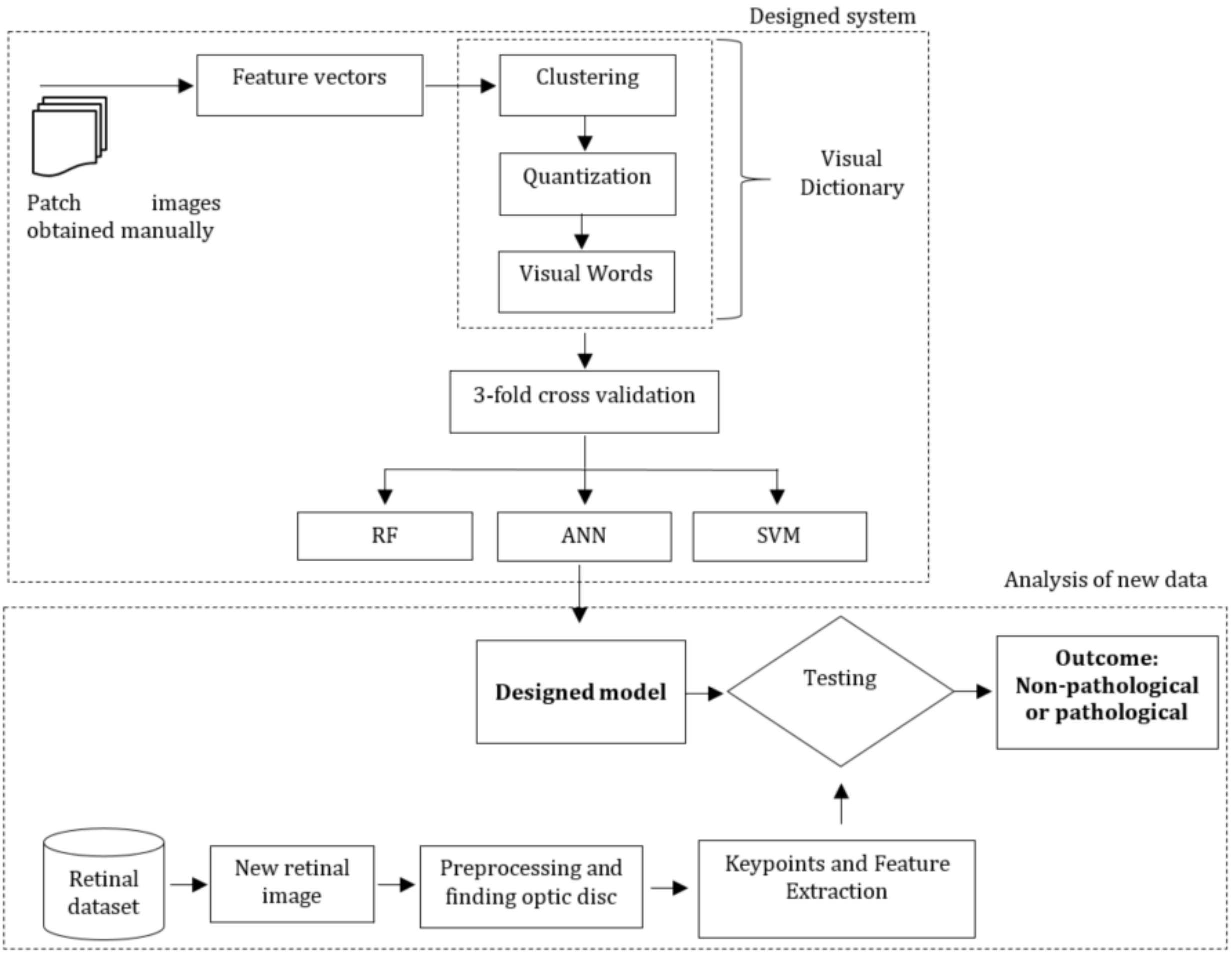

Figure 1. Work flow of our methodology.

4 Modeling Process and Experimental Results

We tested our approach on the publicly available DIARETDB1 color fundus image dataset, all of same size (1500×1152). In the first phase of the study, we converted all RGB (Red, Green and Blue) fundus images in the dataset into gray scale image with CLAHE method.

The brightness values of hard exudate and optic disc regions are same approximately. Therefore the optic disc region should not be included in the analysis of lesions. For this, we identified which one of the regions around keypoints is optic disc with texture analysis. And then we enrolled the coordinate information of this region to the system. So we did not process the keypoints around this coordinate information in detection of lesions. We carried out this procedure in the analysis of new retinal images as well.

Fig. 1 shows the work flow of our methodology we designed as the learning afterwards the analysis of new data. The learning process is as follows: We obtained manually 91 positive and 79 negative samples randomly in size and coordinates from a few retinal image. Then we achieved Daisy features from these regions which will be used for training and testing. We designed a set of visual words with these features. In the next step, we performed the assignment of each of image to the closest visual word of the dictionary with K-Means clustering algorithm (quantization). There are different approaches for obtaining VD, but we preferred this clustering technique widely used. After quantization process, for training the classifier we fed it with visual words calculated, using the training image examples. We tested performance of classification algorithms using 3-fold cross-validation method and presented experimental results in Table 1. In the table, we demonstrated the success of each classifier algorithm in the confusion matrix in its own section for each classifier. Besides, we presented the Sensitivity, Specificity and Accuracy values which are obtained in order to evaluate the classifiers performances, in Table 2. And in Fig. 2, we demonstrated the correct classification percentages of each of the classifiers.

Table 1. Classification results.

			DT		ANN		RF	
			Expected		Expected		Expected	
			Non-Exudate	Exudate	Non-Exudate	Exudate	Non-Exudate	Exudate
Dataset 1 (Fold 1)	Observed	Non-Exudate	27	4	28	3	28	3
		Exudate	4	22	8	18	1	25
Dataset 1 (Fold 2)	Observed	Non-Exudate	19	1	18	2	20	0
		Exudate	11	26	6	31	8	29
Dataset 1 (Fold 3)	Observed	Non-Exudate	22	6	17	11	22	6
		Exudate	6	22	6	22	1	27

Table 2. Performance evaluation results for classification algorithms.

	Performance	DT	ANN	RF
Dataset 1 (Fold 1)	SN	84.61	69.23	96.15
	SP	87.09	90.32	90.32
	Acc	85.96	80.70	**92.98**
Dataset 2 (Fold 2)	SN	70.27	83.78	78.37
	SP	95.0	90.0	100
	Acc	78.94	85.96	**85.96**
Dataset 3 (Fold 3)	SN	78.57	78.57	96.42
	SP	78.57	60.71	78.57
	Acc	78.57	69.64	**87.50**

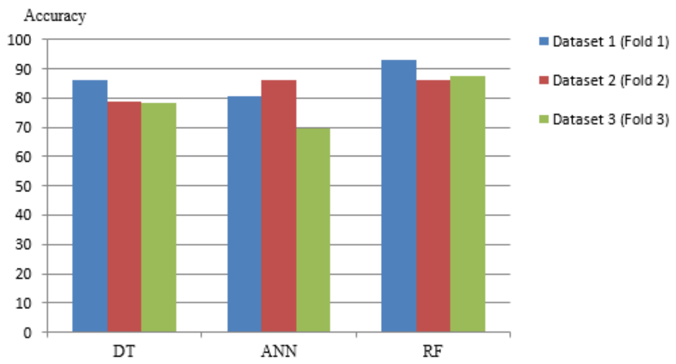

Figure 3. Performances of classifier algorithms.

As can be seen by careful examination the Fig. 2 and the data in Table 1 and Table 2, we chose the RF classifier because it offers the better performance in comparison with others. Thus, we designed the decision support system required for the analysis of new retinal images. The workflow which is necessary for the analysis of new retinal images is as follows:

- Detection of the keypoints by using ORB keypoint algorithm.
- Obtaining of features representing RoI around keypoint, using Daisy algorithm.
- Sending of the features to the model which is designed with VD and RF classifier, in order to decide pathological or non-pathological.

We analyzed the success of the system on 4 diseased retinal image randomly selected and we presented the evaluation results of each retina in Table 3. For example, actually whereas there are 65 pathological and 30 non-pathological regions on the image in number 1, correctly classified 58 pathological and 23 non-pathological regions are observed and accordingly successful classification rate is 85.26%. When examined all evaluation results, it is seen that we can say the decision support system we designed is successful.

Table 3. Analysis results of the new retinal fundus images

		Retinal image no: 01		Retinal image no: 02		Retinal image no: 03		Retinal image no: 04	
		Expected		Expected		Expected		Expected	
		Non-Exudate	Exudate	Non-Exudate	Exudate	Non-Exudate	Exudate	Non-Exudate	Exudate
Observed	Non- Exudate	23	7	22	4	27	12	21	2
	Exudate	7	58	9	46	11	55	20	64
		Acc	85.26	Acc	83.95	Acc	78.09	Acc	79.44

5 Conclusion

DR disease is a major eye disease that affects human life negatively. In the beginning stages of this disease, eyesight problems do not occur but irreversible eyesight loss occurs as disease increases. For this reason, early diagnosis and treatment is the most important way to stop this disease. We designed a system which performs the detection of hard exudate lesions which emerge in the initial stages of DR disease. We showed the effectiveness of the system designed by us on new retinal fundus images by utilizing the VD and the RF compliance which we achieved better performance.

As a future work we plan to work with the new features using various local descriptor algorithms. In addition, we aim to achieve more stable results by enlarging the dataset and running of the designed system real-time in the best way. The identification of the other retinal pathologies such as hemorrhage, microaneurysm is another future work we intend to perform.

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