Comparative Analysis of Automatic Exudate Detections with Traditional and Machine Learning Methods

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Abstract. To prevent and reduce the number of blindness in diabetic patients, periodic screening, automated early exudate detection, and early diagnosis are neccessary. Traditional automatic exudates detections requires many predefined parameters or features while machine learning methods learns and adjusts those parameter automatically but they need time to train. We implemente and investigate benefit of both approaches and a comparative analysis of traditional and machine learning of exudates detections, namely, mathematical morphology, fuzzy c-means clustering, naive Bayesian classifier, Support Vector Machine and Nearest Neighbour classifier is presented. Detected exudates are validated with expert ophthalmologists' hand-drawn ground-truths. The sensitivity, specificity, precision and accuracy of each method are also compared.

1 Introduction

In people with diabetes, diabetic retinopathy is the major cause of blindness. Early screening for diabetic retinopathy could improve the prognosis of proliferative retinopathy and risk factors lowers the blindness in diabetic patients [1-4]. Exudates are a visible and present an early stage of retinal abnormalities in diabetic retinopathy. From visual inspection, exudates appear in a yellowish or white colour with varying sizes, shape and locations. If the exudates extend into the macular area, vision loss can occur.

Many techniques have been employed to the exudate detection. B. Ege et al. [1] use thresholding to segment bright lesions and dark lesions, perform region growing, and then identify exudate regions with Bayesian, Mahalanobis and nearest neighbor classifiers. C. Sinthanayothin et al. [2] report the result of an automated detection of diabetic retinopathy using recursive region growing segmentation (RRGS). A. Osarah et al. [5, 6] use fuzzy c-means (FCM) clustering to segment color retinal image, then neural network and support vector machines (SVMs) are used to separate exudate and non-exudate areas. T. Walter et al. [7] use morphological reconstruction techniques to detect contour of exudates. C.I. Sanchez et al. [8] combine color and sharp edge features to detect exudate. D. Usher et al. [9] use a combination of RRGS and adaptive intensity thresholding to detect candidate exudate regions and the neural network is used to classify exudate and non-exudate. X. Zhang and O. Chutatape [10] use local contrast enhancement and FCM to segment candidate bright lesion areas. SVMs is also used to classify exudate and cotton wool spots.

Most techniques mentioned earlier worked on dilated pupils in which the exudates and other retinal features are clearly visible. Good quality images are required. The examination time and effect on the patient could be reduced if the system can succeed on non-dilated pupils. Automatic exudate detection on imagery acquired without pupil dilation is investigated to provide decision support and reduce ophthalmologists' workload.

In previous work, we have proposed and evaluated methods for automatic exudate detection using mathematical morphology techniques [11, 12], FCM [13], a combination of FCM and mathematical morphology [14], naive Bayesian classifier [15], SVMs classifier [16] and nearest neighbour classifier. In this paper, comparative analysis of these automatic exudate detection methods is presented.

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2 Method

All digital retinal images were taken without pupil dilation with a KOWA-7 non-mydriatic retinal camera with a 45° field of view and a size of 752 x 500 pixels. Exudate detection is our main purpose; however optic disc have to be removed first because it has some characteristics similar to exudates [17, 18]. We implemented two different techniques to increase reliability of the optic disk removal methods. First technique is based on morphological method which removes optic disc characterized by the largest high-contrast object among circular shape areas. The second technique transform original image to an entropy image and the optic disc is then detected by the largest connected component whose shape is approximately circular. In preprocessing steps, the original image was transformed to HSI space. A median filtering operation was then applied on I band to reduce noise before a Contrast-Limited Adaptive Histogram Equalization (CLAHE) was applied for contrast enhancement.

2.1 Exudate Detection

After optic disc is removed, we implement and analytically compare exudate detections using mathematical morphology, FCM, a combination of FCM and mathematical morphology, naive Bayesian classifier, SVMs and nearest neighbour classifier as presented in this section.

2.1.1 Mathematical Morphological

High contrast vessels are eliminated first by a closing operator before local variation operator is applied. The resulting image is thresholded to get rid of all regions with low local variation. To ensure that all the neighbouring pixels are also included in the candidate region, dilation operator is also applied. The result image is used as a mask, showing all possible candidate regions of exudates. The exudate detection areas are obtained by applying a threshold operator to the difference between the original image and the reconstructed image.

2.1.2 Fuzzy C-Means Clustering

Four features are experimentally selected as input for FCM clustering. They are the intensity value after pre-processing, the standard deviation of intensity, hue and number of edge pixels from an edge image. For the number of edge pixels, we apply a Sobel edge operator then eliminate the strong edges arising from blood vessels and the optic disc using decorrelation stretch [19] on the red band. To determine the suitable number of cluster for FCM clustering, quantitative experiments with a parameter of a number of clusters varying from two to eight clusters are tested.

2.1.3 Combination of Fuzzy C-Means Clustering and Morphological Method

Four features from previous experiment are selected as input for clustering in FCM. The result from FCM clustering is a rough estimation of the exudates. In order to get a better result, a fine segmentation using morphological reconstruction is applied.

2.1.4 Naive Bayesien Classifier

We used Weka data mining software [20] running on a standard PC for feature discretization and naive Bayesian classification. Fifteen features (including 4 features from previous experiment) are proposed to distinguish exudate pixel from non-exudate pixels. They are 1. the pixel’s intensity value after preprocessing, 2. the standard deviation of the preprocessed intensity value, 3. the pixel’s hue, 4. the number of edge pixel in a region around the pixel, 5. the average intensity of the pixel’s cluster, 6. the size (measured in pixels) of the pixel’s cluster, 7. the average intensity of the pixels in the neighborhood of the pixel’s cluster, 8. the ratio between the size of the pixel’s cluster and the size of the optic disc, 9. the distance between the pixel’s cluster and the optic disc and six Difference of Gaussian (DoG) filter responses with six different standard deviation values, namely DoG1, DoG2 and so on.

We first estimate the model from a training set using all features then evaluate the resulting classifier's performance on a separate test set. The average of the precision and sensitivity (PR) is used as criteria for features selection because it already used true positive, false positive and false negative in the calculation. Then we iteratively delete features until the average of the PR stops improving. On each step, for each feature, we delete that feature from the model, train a new classifier, and evaluate its performance on the test set. The PR of the best such classifier is compared to the PR of the classifier without deleted features. If PR improves, we permanently delete that feature then repeat the process. Finally, the best feature set and classifier are retained.

2.1.5 Support Vector Machines Classifier

We used libSVM's [21] implementation of the ν-SVM with the radial basis function kernel. The ν-SVM [22] with a radial basis function (RBF) kernel is used in which the parameter $\nu \in [0..1]$ controls how many support vectors are allowed to lie on the wrong side of the separating hyper-plane. We use the best feature set obtained from naive Bayesien as an initial feature set for the SVM. For a given feature set, to find optimal hyperparameters (ν, the tolerance for misclassified training examples, and γ, the width of the radial basis function) for the SVM, we performed a grid search, retaining the parameter values for which test set accuracy is maximized. We then add features to the SVM classifier one at a time and compare the PR of each classifier to that of the previous classifier. The sequence of the feature addition is the same with the naive Bayesien classifier's feature selection process. The feature-adding process is repeated until all features are added back. The best feature set is the set which provides the highest PR.

2.1.6 Nearest Neighbour Classifier

Nearest neighbor classifier with Euclidean and Mahalanobis distance metrics are used as our baseline for comparison. To be able to compare with naive Bayesian and SVM classifiers, we used the best feature sets obtained for naive Bayesian and the SVM.

3 Results

In this section, the experiment results of exudate detection using mathematical morphology techniques, FCM, a combination of FCM and mathematical morphology, naive Bayesian, SVMs and nearest neighbour classifier are presented. A population of 60 retinal images including 40 images with exudates and 20 images without exudates are tested on an AMD Athlon 1.25 GHz PC using MATLAB for mathematical morphology, FCM and FCM with morphology. For naive Bayesian and SVM, we only use 29 images for training and another 30 images for testing, including 10 images with exudates and 20 images without exudates. All exudate pixels and equal number of non-exudate pixels (randomly selected) are included in training set. Over all 29 training images, we obtained 115,867 examples of positive (exudate) pixels and an equal number of negative (non-exudate) pixels. Our 10 test images together contain 42,909 exudate pixels. Naive Bayesian is tested on Weka data mining software running on standard PC while SVMs and nearest neighbor are tested on a 20-node Gnu/Linux Xeon cluster. Finally, detected exudates are compared with the ophthalmologists' hand-drawn ground-truth images for verification. We fit the naive Bayesian model to the training set using all 15 features. We removed features from the classifier one by one and compared the resulting PR to PR obtained on the previous feature set. We continued this process until the PR stopped improving.

Finally, the best features for the naive Bayesian contained 6 features: 1. the pixel's intensity after preprocessing, 2. the standard deviation of the preprocessed intensities in a window around the pixel, 3. the pixel hue, 4. the number of edge pixels in a window around the pixel, 5. the ratio between the size of the pixel's intensity cluster and the optic disc, and 6. DoG4. For the SVM, the best performance is obtained using 10 features: 1. pixel's intensity after preprocessing, 2. standard deviation of the preprocessed intensities in a window around the pixel, 3. pixel hue, 4. number of edge pixels in a window around the pixel, 5. ratio between the size of the pixel's intensity cluster and the optic disc, 6. distance between the pixel's cluster and the optic disc, 7. DoG1, 8. DoG2, 9. DoG4, and 10. DoG6, with $\nu = 0.002$ and $\gamma = 0.98$. On best feature set obtained from the naive Bayesian classifier, the nearest neighbor classifiers have a PR of 61.54% and 61.81%, respectively. On the best feature set obtained from the SVM classifier, the nearest neighbor classifier achieved a PR of 65.15% and 64.99%, respectively. The results indicate that the naive Bayesian and SVM classifiers perform substantially better in PR than the nearest neighbor classifier. In addition, the nearest neighbour classifier using the best feature set obtained from the SVM classifier performs better than that using the best feature set for the naive Bayesian classifier. The testing performance is presented in Table 1. Example image of diabetic retinopathy retinal image and detected result superimposed on the original image are shown in Figure 1. Result images of exudate detection from all experiments are shown and compared in Figure 2.

(a) (b) (c)

Figure 1. Exudates detection. (a) Original images. (b) Detected result. (c) Result of (b) superimposed on image (a).

4 Conclusions and Discussion

In this paper we propose the comparison results of automatic exudates detection using traditional and machine learning approaches. Mathematical morphology, FCM, combination of FCM and morphology method, naive Bayesian classifier, SVMs classifier and nearest neighbour classifier are investigated.

The weakness of traditional exudates detection is that they require many predetermined features while the machine learning approaches takes time to learn and search for best feature set. Mathematical morphology is a simple method and computationally low cost but it does not achieve good sensitivity. FCM clustering could detect most of exudates region, however, false positive are also high at the same time. Using FCM clustering followed by mathematical morphology reconstruction, gives higher accuracy with a lower false positive value. Even though, Naive Bayesian and SVM which are supervised classifiers do not require predefined features, they are computationally expensive during training process. SVM classifier is also sensitive to parameter modification but it gains higher precision value. Performances of all exudate classifiers discussed in this paper depend on optic disc and vessel detection. In future work, we plan to explore using the system as a practical aid to help ophthalmologists for diabetic retinopathy screening.

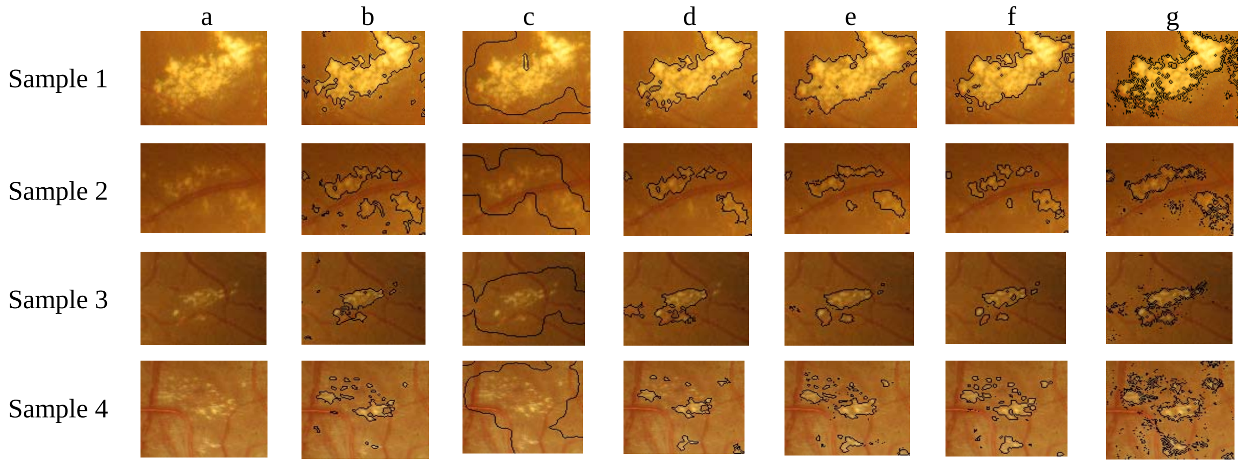

Figure 2. Result of exudate detection. (a) Original images. (b) Morphological classification results. (c) FCM classification results. (d) FCM with Morphological classification results. (e) Naive Bayesien classification results. (f) SVM classification results. (g) Nearest Neighbor (Euclidean distance) classification results on best feature set obtained from naive Bayesien.

Classifier	Sensitivity (%)	Specificity (%)	Precision (%)	PR (%)	Accuracy (%)
Mathematical morphology	80.00	99.46	51.78	65.89	99.29
Fuzzy c-means (8 clusters)	97.29	85.43	51.62	5.94	85.62
Fuzzy c-means (8 clusters) + Morphology	87.28	99.24	42.77	65.02	99.11
Naive Bayesian	93.38	98.14	47.51	70.45	98.05
Support vector machines	92.28	98.52	53.05	72.67	98.41
Nearest neighbor on best feature set for naive Bayesian (Euclidean)	90.48	96.62	32.60	61.54	96.51
Nearest neighbor on best feature set for naive Bayesian (Mahalanobis)	90.44	96.71	33.18	61.81	96.60
Nearest neighbor on best feature set for SVM (Euclidean)	91.44	97.40	38.86	65.15	97.29
Nearest neighbor on best feature set for SVM (Mahalanobis)	91.11	97.41	38.87	64.99	97.30

Table 1. Testing performance.

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