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Automated Glaucoma Diagnosis System Based on Fundus Images Features

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CDR (Cup to Disc Ratio)
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SVM (Support Vector Machine)

ABSTRACT

Glaucoma is a disease that can damage the eye's optic nerve and cause permanent vision loss or even total blindness if not detected in early stage and thus, it is important diagnose early to prevent blindness. Image processing techniques has been used to detect early glaucoma using the fundus images. In this paper, a computer aided glaucoma diagnosis system is proposed based on fundus image features. The optic disc and optic cup features are extracted from funds images and two parameters are calculated, namely: Cup to Disc Ratio (CDR) which indicates the enlargement of cup and the Inferior Superior to Nasal Temporal (ISNT) which determine the ratio of the thickness of the rim. Support Vector Machine (SVM) and k-Nearest Neighbor (KNN) classifiers are used to classify images into 'Normal' or 'Abnormal'. The quality of both classifiers is evaluated and compared in terms of three performance metrics, namely: sensitivity, specificity and accuracy and satisfactory results have been achieved where the system accuracy is 95%. Moreover; Patient data such as age, family history of the disease, eye pressure and the last eye examination record were taken in account. The proposed system can categorize images into five categories: 'no risk', 'low risk', 'moderate risk', 'high risk' and 'very high risk'.

نظام تشخيص الجلوكوما الآلي بناءً على ميزات صور قاع العين

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الكلمات المفتاحية:

CDR (Cup to Disc Ratio)
صور قاع العين
الجلوكوما
ISNT Ratio
KNN (k-Nearest Neighbor)
SVM (Support Vector Machine)

الملخص

الجلوكوما مرض يمكن أن يتلف العصب البصري للعين ويسبب فقدان البصر الدائم أو حتى العمى التام إذا لم يتم اكتشافه في مرحلة مبكرة، وبالتالي من المهم التشخيص المبكر للوقاية من العمى. يمكن الاستفادة من تقنيات معالجة الصور الرقمية للكشف عن الجلوكوما مبكرا باستخدام صور قاع العين. في هذه الورقة تم اقتراح نظام تشخيص الجلوكوما باستخدام الواجهة الرسومية لبرنامج الماتلاب. تم استخراج سمات القرص البصري والكأس البصري من صور قاع العين وحساب نسبة الكوب إلى القرص (CDR) التي تشير إلى تكبير الكأس والجزء السفلي من الأنف الصدغي (ISNT) الذي يحدد نسبة سمك الحافة وبناء على ذلك تصنف الصور "عادية" أو "غير طبيعية" باستخدام طرق التصنيف (SVM) و (KNN). تم تقييم جودة كلا المصنفين ومقارنتها من حيث ثلاثة مقاييس للأداء وهي: الحساسية والنوعية والدقة وقد تم تحقيق نتائج مرضية حيث تبلغ دقة النظام 95٪. بالإضافة الى ذلك؛ تم أخذ بيانات المريض مثل العمر والتاريخ العائلي للمرض وضغط العين وآخر سجل فحص للعين في الاعتبار. يمكن للنظام المقترح تصنيف الصور إلى خمس فئات: "لا توجد خطورة، أقل خطورة ، خطورة معتدلة، خطورة مرتفعة ، خطورة مرتفعة جدا.

Introduction

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Glaucoma is an eye condition that can cause permanent blindness at the point when the infection advances to a serious stage. It arises due inappropriate intraocular fluid pressure within the eye, which leads to damage the optic nerve. Consequently, an early diagnose is important to avoid blindness [1, 2].
Glaucoma can be detected using clinical methods available such as Optical Coherence Tomography (OCT), Heidelberg Retinal Tomography (HRT). However, these methods are very expensive and not readily available in hospitals [3]. Alternative method, which widely used by ophthalmologists to assist in diagnosis of glaucoma is by using fundus photography that can clearly show characteristic of glaucoma and is cost-effective. The assessment is based on calculation of the ratio between the area of optic disc and optic cup to detect glaucoma (CDR). However, manual assessment of the acquired fundus images may be disposed to inter-observer variation. Moreover, it requires skilled supervision. and time consuming, [4, 5] 6 . Therefore, there is a need for automated glaucoma diagnosis system based on the optic nerve features of fundus imaging. [6],
Recently, several notable efforts to develop the automatic glaucoma diagnosis system based on optic nerve features extracted from funds images, and a review of these methods is presented in [7, 8]. Most of existing methods focus mainly on calculation of the ratio between the area of optic disc and optic cup and employ different machine learning techniques for detecting glaucoma. However, there is still a challenge in designing a reliable and fast automated glaucoma diagnosis system in terms of analysis of the optic cup region, features extraction, and the selection of suitable machine learning techniques.
To detect glaucoma, Narasimhan and Vijayarekha [9] extracted the optical disc and the optical cup from the green component of fundus images, and measured the CDR ratio, and evaluated the images according to the CDR values obtained. They classified the fundus images by employed three machine learning techniques, namely: KNN, SVM, and Bayes classifiers.

Murthi et al. [4] presented and evaluated different segmentations and boundary detection methods aimed to detect neuro-retinal cup, and noted that the ellipse fitting algorithm performs a better estimate of the neuro-retinal optic cup boundary.
Anusorn et. al [2] developed a method to calculate the CDR automatically from fundus images. They determine and extract the optic disc and cup using an edge detection approach and a variation level-set approach separately. The segmentation of the optic cup is done by using a color component analysis method, and a threshold level-set method.
Instead of using a predefined mask image, Darsana and Nair [10] presented a method for segmenting fundus image features into ISNT quadrants using the array centroid method. The method involves centroid calculation, array initialization; mask image generation and, mask- feature image multiplication. The obtained segmented features can be used for the ocular parameter calculation such as Cup to Disc Ratio (CDR), Rim to Disc Ratio (RDR), Inferior, Superior Nasal, Temporal (ISNT) ratio etc.
In this paper, we aim to implement computer-aided diagnosis of glaucoma using MATLAB based GUI and evaluate the performance of the SVM and KNN classification technique for extraction features from two fundus image components, which are the red and green channels of funds images.
The paper is organized as follows. The section 2 presents proposed method. Section 3 shows the experimental results. Conclusion and future scope are presented in section 5.

METHODOLOGY

In this paper, we have employed a similar technique provided by Darsana S et.al [10] to distinguish glaucomatous images from normal. The block diagram shown in Figure 2 provides an overview of the proposed computer aided glaucoma diagnosis system. It comprises of the main components that are image level processing and data level processing.

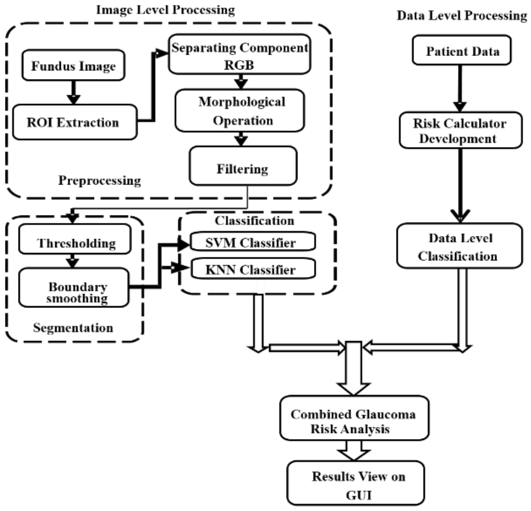

Figure 2. The system design block diagram

Image Level Processing

Image level processing composes of traditional machine learning techniques that follow a fixed procedure – (i) input image, (ii) pre-processing, (iii) segmentation, (iv) features extraction, (v). The preprocessing technique is applied to the fundus image. In the first step, the region-of-interest (ROI) is obtained from the fundus image as described in [8], then the red and green channels are selected for extraction each of optic disc and optic cup respectively [2]. The red and green channels are chosen due to the fact that the blue channel is characterized by low contrast and it does not contain much information. Moreover, the vessels are visible in the red and green channels. In order to enhance the quality of the fundus images before performing feature extraction, the equalization histogram is applied to the red and the green channels, followed by applying the morphological opening to remove vessels from the fundus images. Finally, Median filter is applied to smooth and reduce noise and artifact present in the fundus image. In the segmentation phase, an automatic threshold is applied to extract the features, and then, the morphological closing is performed to smooth and remove, unlike objects. In the classification phase, The KNN and SVM classifiers are used. k-nearest neighbor algorithm presented in [11] is adopted in proposed system. It is a simple machine that can be used to classify objects based on closest training examples in the feature space. The training process for k-nearest neighbor algorithm includes storing feature vectors and labels of the training images. In the classification process, the unlabeled query point is simply assigned to the label of its k nearest neighbors. Naturally, the object is classified based on the labels of its k nearest neighbors by majority vote, and the object is simply classified as the class of the object nearest to it if k=1. When there are only two classes, k must be an odd integer. In the proposed system, the Euclidean distance function for KNN is used and described as follows:

$$d(x,y) = \|x-y\| = \sqrt{(x-y).(x-y)} = \left(\sum_{i=1}^{m}((x_i-y_i)^2)^{1/2}\right) \quad (1)$$

where x and y are histograms in X = Rm. The visualizes of the KNN process classification is shown in Figure 3

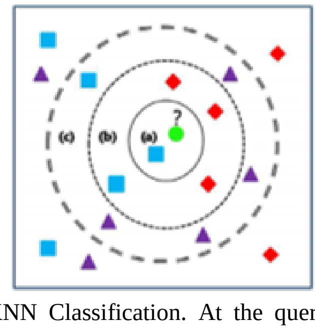

Figure 3. KNN Classification. At the query point of the circle depending on the k value of 1, 5, or 10, the query point can be a rectangle at (a), a diamond at (b), and a triangle at (c).

The SVM classifier is suitable for both linearly separable and linearly non-separable data [11]. It uses variant planes in space to split data points by planes. The SVM model is a representation of the examples as points in space, mapped so that the examples of the classes are divided by a dividing plane that maximizes the margin between different classes. This is because if the separating plane has the largest distance to the nearest training data points of any class, it will lower the generalization error of the overall classifier. The test points or query points are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Figure 4 shows the linear kernel function used in the proposed system, and can be represented as,

$$K(x_i, x_i) = x_i^T x_j \qquad (2)$$

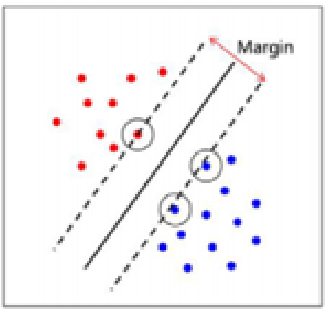

Figure 4. SVM Classification. In multidimensional space, support vector machines find the hyperplane that maximizes the margin between two different classes. Here the support vectors are the dots circled.

Data Level Processing

To increase the accuracy of the proposed diagnosis system and detect the disease early, patient data such as age, a family history of glaucoma, eye pressure and the last eye examination record are taken into account as propose in [10] .

RESULTS

The proposed glaucoma diagnosis system was evaluated using 57 fundus color images captured by fundus camera in Diabetic Clinic datasets in Sebha city. These images of size 2976×2976 pixels, and were stored in JPEG format. 17 images were used in the training and 40 images were used for testing, and the number of normal images is 32 and the number of glaucomatous images is 8. Moreover, patient data such as age, a family history of glaucoma, eye pressure and the last eye examination record are provided as input to the system. The images were categorized using both the KNN and SVM classifiers. The quality of both classifiers is evaluated with three performance metrics, namely: sensitivity, specificity and accuracy which were calculated according to the following equations[12]:

$$\text{Sensitivity} = \frac{T_p}{T_p+F_n}$$

$$\text{Specificity} = \frac{T_n}{T_n+F_p}$$

$$\text{Accuracy} = \frac{T_n+T_p}{T_p+F_p+T_n+F_n}$$

Where: Tp is the number of glaucoma images classified as glaucomatous, Fp is the number of normal images classified as glaucomatous, Tn is the number of normal images classified as normal images and Fn is the number of glaucomatous images classified as normal. Table 1 shows the results of the performance metrics for SVM and KNN classifiers.

Table 1 Performance metrics of the classification system

Performance / Classifier	Specificity (%)	Sensitivity (%)	Accuracy (%)
SVM	93.75	100	95
KNN	93.75	100	95

The results of the classifiers were compared to the method presented in [9]. It has been chosen to evaluate the proposed system due to its similarity to proposed technique in terms of using SVM and KNN classifiers. The number of normal images in method [9] was 22 where 7 of them were used in the training and 15 on the testing. The number of used abnormal images in training were 9 while 21 images were used in the testing. In the proposed system, the number of normal images in the training was 10 while 32 used in the testing. The number of abnormal images used in the training was 7 while 8 were used for testing. The performance of classifiers is shows in Figure 5.

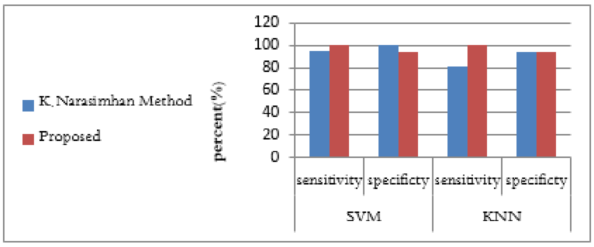

Figure 5. Comparison between the proposed system and the method reported in [9] using SVM and KNN classifiers

In method [9], the green channel is considered for the extracting the optic disc and optic cup. The ROI was selected manually. While in the proposed system, two channels were employed. The Red channel for extracting the optic disc and the Green channel for extracting the optic cup, and an adaptive threshold was implemented to automatically select each image as each image is not fixed in size. The proposed system was implemented using MATLAB program, and figure 6 shows the user interactive interface of the proposed system.

Figure 6. Graphical User Interfaces of the proposed system.

Conclusion

A glaucoma detection system was implemented which based on processing of fundus images and patient data. The success of the proposed method depends on optimal extraction of the optic disc and optic cup region, where the best extraction for the optic cup region can be obtained whenever the optic disc and optic cup contrast is greater. Therefore, the red component of funds image was used to extract the optic disc and the green component was used to determine the optic cup. The performance of SVM and KNN classifiers were compared in terms of three metrics, namely; the sensitivity 100%, specificity 93.75% and accuracy 95%. It was found that there is no difference between the performance of the two classifiers. The proposed system is simply characterized by designing where simple processing techniques have been used and which have yielded effective results.

This work can be further extended by integrating more factors in image- based analysis which reflects the glaucoma symptoms. These factors include notching, disc hemorrhage, inter eye symmetry, peripapillary atrophy etc. **Furthermore, image datasets can be extended for evaluating the performance of the proposed system**

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