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Automatic Pathological Analysis of Diabetic Retinopathy Using Minimal Feature Vector Classifier

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Abstract: ***Rising technologies in health care aim at reducing unnecessary visits to medical specialists, minimizing overall cost of treatment and optimizing the number of patients seen by each doctor. In this paper explores a method that recommends referring a patient with diabetes for Diabetic Retinopathy(DR) assessment based on the image classification outcome, which is especially useful in remote and rural areas. Two stages of classifications are used to decide the need for referring the doctor. First stage is lesion detectors. The outcome of the lesion detectors gives the information about different kinds of lesions based upon Naïve Bayes classifier. Second stage is the referring stage, which is based on the lesion detectors decision scores and finding the high level feature vectors.***

Keywords: Diabetic Retinopathy, lesion detectors, Referral, Naïve Bayes classifier

1. Introduction

Diabetic retinopathy, a complication of diabetes that occurs as a result of vascular changes in the retina, It is a major cause of loss of vision. Automated image processing has the potential to assist in the early detection of diabetes, by detecting changes in blood vessel patterns in the retina. The use of computational methods that aid in the diagnosis of disease has contributed significantly to improve the quality of life of patients. In this context, several computational systems have been proposed for dealing with complications related to Diabetes Mellitus. According to the International Diabetes Federation, diabetes will nearly double to 552 million people by 2030 [8]. Diabetes related complications are also increasing in prevalence including diabetic retinopathy, which currently affects 2–4% of people with diabetes and is the main cause of blindness in the 20–74 age group in developed countries [11]. The development of a unified screening system that simultaneously identifies several different DR-related lesions has been described using a bag-of-visual-words (BoVW) model based upon visual dictionaries. This model needs a visual dictionary for each type of lesion, and hence, a specific classifier is required for each type of lesion. To decide on the level of DR progression (from mild to severe), or the need for referral, one must combine the separate classifiers into a unified model. In this paper, we propose a method that recommends referring a patient with diabetes for diabetic retinopathy assessment based on the image classification outcome, which is especially useful in remote and rural areas. The method captures retinal images from nonmydriatic or mydriatic cameras, evaluates the images in real time, and suggests whether or not the patient requires a review by an ophthalmic specialist within one year after the screening. The method consists of 1) detecting individual retinal anomalies and extracting the appropriate assessment scores, and 2) classifying the image as referable versus nonreferable by means of meta classification techniques built upon the output of several lesion detectors. Different from [1], [2], and [12], we explore alternatives for the BoVW lesion detectors because the performance of BoVW depends critically on the choices of coding and pooling the low-level local descriptors and aim at characterizing the properties and signs related to each kind of lesion of interest.

2. Existing System

Diabetic retinopathy, a complication of diabetes that occurs as a result of vascular changes in the retina. It is a major cause of loss of vision. Automated image processing has the potential to assist in the early detection of diabetes, by detecting changes in blood vessel patterns in the retina. Image processing techniques can reduce the work of ophthalmologists and the tools used automatically locate the exudates. In this paper the process and knowledge of Digital Image Processing (DIP) is used. Automated analysis techniques for retinal images have been an important area of research for developing screening programmers. By using MATLAB for programming to develop the DIP tool for diagnosis of eye infection. Two stages of classification are used to decide the need for referring the doctor. First stage is lesion detectors. The outcome of the lesion detectors gives the information about different kinds of lesions like Hard Exudates, Superficial Hemorrhages, Deep Hemorrhages, Red Lesions, Cotton Wool Spots, Drusen based upon SVM classifier. Second stage is the referring stage, which is based on the lesion detectors decision scores and finding the high level feature vectors. Which is used to deciding the patient should be referred to a doctor or not from the outcome of the SVM classifier. The existence of a DR-related lesion in a retinal image does not necessarily indicate a vision-threatening sign that requires a referral. The presence of microaneurysms, that characterize a moderate nonproliferative DR type, does not indicate an urgent consultation, but an indication of a follow-up between three months and 12 months depending on the number and location of the microaneurysms. Conversely, the presence of neovascularization indicates proliferative retinopathy and, if not under treatment, needs urgent referral for management by an ophthalmologist [13]. Other important retinal lesions are

cotton wool spots, especially if there are more than five [14]. A nurse-managed primary care clinic is an essential step toward ensuring a satisfactory cost reduction as well as the opportunity of screening, assessment, and treatment reaching remote communities. Nurse-led screening programs are designed to verify the presence of any DR-related lesion, as well as to identify the lesion and whether referral is required. Screening programs for DR have been developed in many countries such as the Netherlands [3], U.K. [4], and Australia [5]. Two well-known examples are the EyeCheck project [3] and the Challenge2009 [15]. In [16], the authors reported that both programs have statistically similar results (Areas under the receiver operating characteristic (ROC) curve (AUCs) of 82.0% for Challenge2009 [15] and 84.0% for EyeCheck [3]). Both programs focus on the detection of specific lesions and require pre- and post processing.

3. Proposed System

The proposed method is also based on the three level feature extraction. The development of a unified screening system that simultaneously identifies several different DR-related lesions has been described using a bag-of-visual-words (BoVW) model based upon visual dictionaries. This model needs a visual dictionary for each type of lesion, and hence, a specific classifier is required for each type of lesion. To decide on the level of DR progression (from mild to severe), or the need for referral, one must combine the separate classifiers into a unified model. In this paper, we propose a method that recommends referring a patient with diabetes for diabetic retinopathy assessment based on the image classification outcome, which is especially useful in remote and rural areas. The method captures retinal images from nonmydriatic or mydriatic cameras, evaluates the images in real time, and suggests whether or not the patient requires a review by an ophthalmic specialist within one year after the screening.

3.1 Detection of Individual DR-Related Lesions

Detecting individual retinal anomalies and extracting the appropriate assessment scores. Finding a large number of feature vectors in the images [usually around points of interest (POIs)] and assigning these vectors to "visual words" using a dictionary of visual appearances. Six lesion detectors are considered hard exudates, red lesions, superficial hemorrhages, deep hemorrhages, cotton-wool spots, and drusen. Speeded-Up Robust Features (SURF) is employed to detect the PoIs in the images and extract the local feature vectors based on local patches around the PoIs. The PoIs are detected based on approximations of the Hessian matrix in a scale-space, and the feature vectors are based upon the Haar-wavelet responses around the PoIs. An identical protocol is applied to create the visual dictionary associated with the individual detectors. Using a training set of images, two sets of SURF feature vectors are extracted, one coming from regions annotated by medical specialists as containing lesions (positive) and one coming from healthy image regions (negative). A k-means clustering algorithm then finds k/2 clusters from the vectors obtained using SURF and associated with images containing lesions and k/2 clusters associated with those images not containing lesions. The centroids of the clusters of the two sets are used as the visual words in a visual dictionary of size M = k/2 + k/2 with a total dictionary size of 500 words. We have set the dictionary size to 500 words (250 visual words for each class of interest) although more automated schemes could be employed to find the best size for each lesion detector. Where the visual dictionary is obtained from an indiscriminate sample of local features. We create a visual dictionary for each lesion/nonlesion case containing specific visual words for each class. The visual dictionaries are used to transform the low-level local feature vectors extracted by SURF onto mid-level BoVW feature vectors. This transformation requires first a coding step in which the low-level feature vectors are given a representation based on the dictionary. Then, for each image, all encoded vectors are aggregated in a pooling step (using operators such as sum, average, and max). An outline of the mathematical description of the coding and pooling step follows. Once the visual dictionary is created, the visual dictionary can be represented as C = {ci}, i ∈ {1, . . . , M}, where ci ∈ Rd is a visual word in d-dimensional space. Then, for a given image, we start with the set of local descriptors X = {xj }, j ∈ {1, . . . , N}, where xj ∈ Rd is a local feature and N is the number POIs. Let z be the final BoVW vector representation.

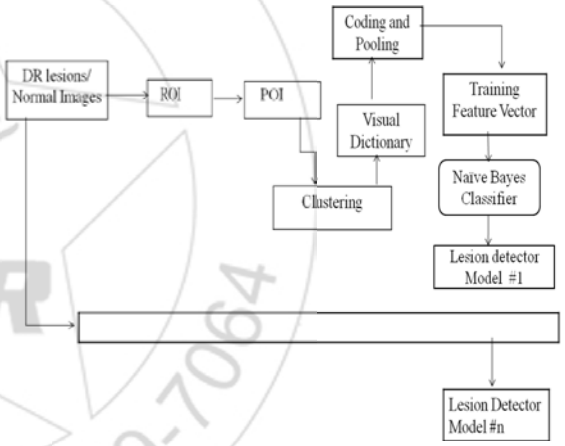

Figure 1: Block diagram of individual lesion detection

The coding step transforms the low-level descriptors onto a representation based upon the code words. The coding step can be modeled by a function f: Rd → RM , f(xj) = αj that take the individual local descriptors xj and maps them onto individual codes αj . The classical BoVW model employs the "hard assignment" of a low-level descriptor to the closest codeword:

$$\alpha_{m,j} = 1 \text{ if } m = \arg\min_{k} \|c_k - x_j\|_2^2 \text{ else} \quad (1)$$

Where, $\alpha m,j$ is the mth component of the encoded descriptor. As a local descriptor can be roughly equidistant to several visual words, the method described in this paper proposes the use of a soft-assignment coding (degrees of association between the low-level descriptors and the elements of the codebook are allowed while avoiding the boundary effects of hard assignment). To achieve this, a codeword uncertainty algorithm is employed:

$$\alpha_{m,j} = \frac{G_\sigma(\|\mathbf{c}_m - \mathbf{x}_j\|_2)}{\sum_{\mathbf{c}\in\mathcal{C}} K_\sigma(\|\mathbf{c} - \mathbf{x}_j\|_2)} \quad (2)$$

Where, Gσ is the Gaussian kernel with σ = 45. We use the max-pooling approach that is applied here for creating the lesion detectors, taking the maximum activation of each codeword:

$$g(\{\alpha_j\}) = \mathbf{z} : \forall m,\ z_m = \max_{j\in\{1,\ldots,N\}} \alpha_{m,j} \quad (3)$$

The common HARD–SUM (hard-assignment coding/sum pooling) and the more recent SOFT–MAX (soft-assignment coding/max pooling) approaches are applied here for creating the lesion detectors. The final classification step for the individual lesion detectors is based upon a two-class Naïve Bayes classifier, which employs the mid-level BoVW feature vectors for training and classification.

The Naive Bayes Classifier technique is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high.

3.2 High-level feature Extraction and Referral Classifier

Classifying the image as referable versus nonreferable by means of meta classification techniques built upon the output of several lesion detectors. The information provided by each individual lesion detector is insufficient for deciding on whether a referral is necessary based on the lesion detector output because the lesions can be minor, just a few, they may not indicate there will be future deterioration of visual function, and their location might also be important (a few lesions present in the fovea may need referral whereas lesions in the periphery may not). Our aim is to combine the results of the individual detectors in a meta classification step that indicates whether or not a patient should be referred to an ophthalmologist for further review. This step can be interpreted as the creation of a high-level feature vector from the decision scores of all the lesion detectors. The meta classification is made possible by an annotated dataset (not used in the training of any lesion detector), with images from patients tagged as referable versus nonreferable by two independent experts. The goal is to have a high sensitivity (very few false negatives), while also keeping high specificity (few false positives): the former is important to ensure that no patient in need stays without care, the latter is important to avoid swamping the health care professionals with unneeded referrals.

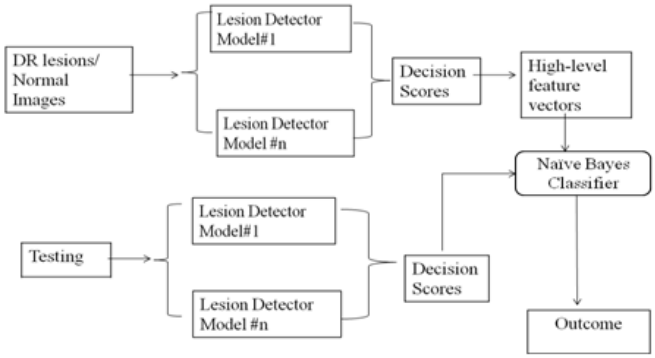

Figure 2: Block diagram of Referral approach

For each training image, we have *n* decision scores, one for each lesion detector. Then extracting the high-level feature vectors from the scores of the Naïve Bayes classifier and deciding whether the patients need referral or non referral.

4. Result and Analysis

The proposed Naïve Bayes classifier is implemented. Naïve Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes'theorem with strong independence assumptions between the features. The comparison curve between the existing and proposed method is given below, the green curve indicates the existing method and red curve indicates the proposed method.

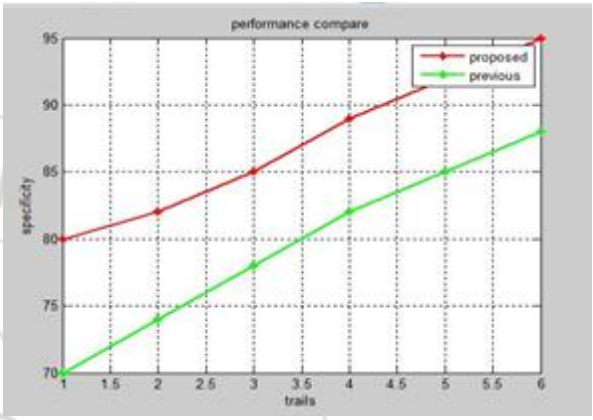

Figure 3: Comparison of Specificity

Figure 3 shows the Specificity vs. trails graph. Specificity is also called the true negative rate (TN). It measures the proportion of negatives that are correctly identified. Mathematically, Specificity (SPC) is found by using the formula,

$$SPC = \frac{TN}{(TN+FN)} \quad (4)$$

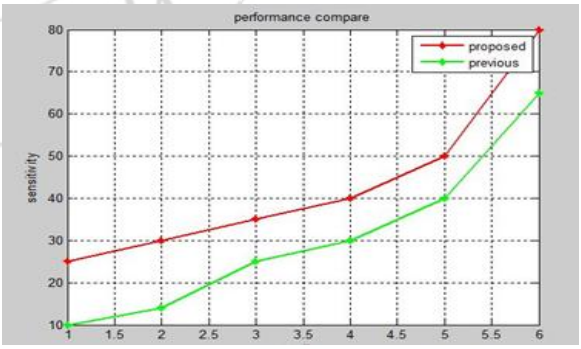

Figure 4: Comparison of Sensitivity

Figure 4 shows the Sensitivity vs. trails graph. Sensitivity is also called the true positive rate (TP). It measures the proportion of positives that are correctly identified.

Thus sensitivity quantifies the avoiding of false negatives (FN) , as specificity does for false positives (FP). Mathematically, Sensitivity (TPR) is found by using the formula,

$$TPR = \frac{TP}{(TP+FN)} \quad (5)$$

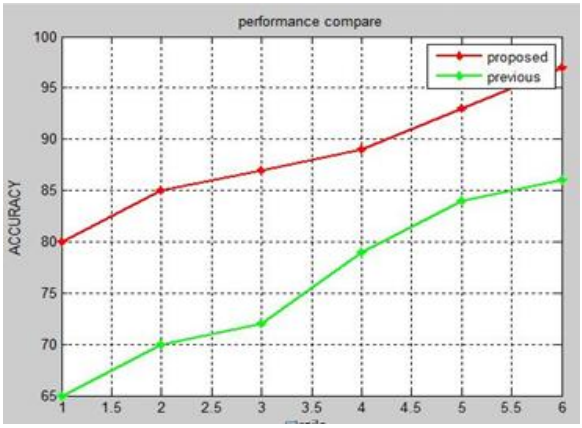

Figure 5: Comparison of Accuracy

Figure 5 shows the Accuracy vs. trails graph. Accuracy is the proximity of measurement results to the true value. Mathematically, Accuracy (ACC) is found by using the formula,

$$ACC = \frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (6)$$

5. Conclusion and Future Work

Thus automatic identifying Diabetic Retinopathy from individual lesions is proposed. This method builds lesion detector and decides whether a patient needs referral to ophthalmic specialist within one year or not. It also extracted three level feature vectors based on the decision scores. The Naïve Bayes Classifier is used to training the feature vector and gives the strong assumptions between the features.

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