Diabetic Retinopathy Stages Identification Using Retinal Images

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Abstract—Diabetic retinopathy is the leading cause of blindness. The identification of diabetic retinopathy stages is needed for timely treatment. In this work, the presence of clinical sign of symptoms are investigated, namely, vessels, exudates, microaneurysm and haemorrhages. Four stages of diabetic retinopathy are identified: normal, mild non-proliferative diabetic retinopathy, moderate non-proliferative diabetic retinopathy and severe non-proliferative diabetic retinopathy. An association rule and C4.5 classifier are used to predict the unknown class. The results are validated with the expert ophthalmologist’s reviews. The performance of the system shows the average accuracy up to 87%, a sensitivity of 85% and a specificity of 89%.

Index Terms—C4.5 Classifier, Diabetic Retinopathy, Retinal Images.

I. INTRODUCTION

Diabetic retinopathy is a diabetic eye disease which occurs to the retina due to diabetes. It causes severe vision loss and blindness. The distorting vision could happen due to bleed or lead fluid at retinal blood vessels. The patients with diabetes often unnoticed until vision loss occurs. Early detection can protect against vision loss. Signs of diabetic retinopathy include abnormal vessels, exudates (lipid leaking from blood vessel appear as yellow lesions), microaneurysms (swelling of capillaries appear as small dark red lesions) and haemorrhage (appear similar to microaneurysms in the deeper layers of retina) [1], [2]. Diabetic retinopathy doesn’t tend to cause any symptoms in the early stages. Therefore, stage progressive identification is important. It could be used to improve efficiently medical investigate and timely treatment.

In literature review, data mining techniques are widely used in medical image classification [4]-[7]. S. Kharya used data mining approaches for breast cancer diagnosis and prognosis [4]. Brain tumor classification using association rule mining with decision tree is presented [7]. The normal, benign and malignant stages are classified. The haemorrhage detection using data mining is proposed by D. Deepa and S. Sumathi [3]. The number and shape of haemorrhage are used to classify images into normal NPDR and PDR. N.D. Panse et al. [9] proposed glaucoma and diabetic retinopathy diagnosis using image mining. SVM classifier is used to detect the categories of retinal disease. The bispectral invariant features of higher-order spectra techniques and SVM classifier are used to classify the diabetic retinopathy stages by A.U. Rajendra et al. [10]. The experiment indicated that data mining techniques could be used to improve the performance of classification.

Depending on the presence of abnormal vessels, exudates, microaneurysms and haemorrhage on the retina, the stage of DR can be identified in four stages as shown in Table I and Fig. 1. In previous work, we have proposed of features extraction [11]-[13] with a significant accuracy. This paper will focus on diabetic stage identification using the presence of those features.

| TABLE I |
|-----------------|------------------|
| Stages | Diabetic Retinopathy Stages |
| No DR. | No presence of EX, MA and H |
| Mild non-proliferative | At least one MA with or without HA. Presence of EX, cotton wool spots or venous loops. |
| Moderate non-proliferative | Presence of numerous EX, MA and H. Presence of cotton wool spots and limited amount of venous beading |
| Severe non-proliferative | Numerous MA and H in four quadrants of the retina, venous beading in at least two or more quadrants, intra retinal, microvascular abnormalities in at least one quadrant. |

[EX= Exudate, MA=Microaneurysm, H=Haemorrhage]

II. PROPOSED METHOD

A. Image Acquisition

The retinal images are taken from the Thammasart hospital without pupil dilation. Image size is 752x500 pixels. It consists of 100 images, corresponding to four categories: normal, Mild non-proliferative, Moderate non-proliferative and Severe non-proliferative. There are 20 normal images and 80 abnormal images which are divided in four categories equally.

B. Image Enhancement

To improve the quality of the images, noises and slow background variation are removed. A shade correction algorithm and contrast limited adaptive histogram equalization (CLAHE) are applied.
C. Feature Extraction

Four clinically significant retinal features are extracted from the retinal image. They are vessels, exudates, microaneurysms and haemorrhage. Fig.2 shows the presence of the features. Vessels and exudates are extracted using a set of mathematical morphology operations. Optic disc is also detected and removed to avoid misclassification. Microaneurysms are extracted using SVM. The pixel intensity, pixel hue, standard deviation of shade corrected image, difference of Gaussian, area of the candidate MA, eccentricity of the candidate MA, circularity of the candidate MA, mean intensity of the candidate MA on shade corrected image, ratio of the major axis length and minor length of the candidate MA are used. The haemorrhage are extracted by subtract the vessels image from vessels with haemorrhage image. Each features’s attributes are examined. They are area, mean intensity, numbers of presence and location.

D. Data Mining

Two data mining techniques, namely association rule mining and C4.5 classifier are used. The association rule mining is applied to predict the disease severity.

Association rule based classifier

Association rule mining [14, 15] is a method to find associations between items in a transactional database. It used to produce a combination of attributes. It could predict not only class labels but also predict other attribute. The frequent of patterns are analyzed using the criteria support and confidence. Support is an indication of how frequently the items appear in the database. Confidence is the number of times that it predicts correctly and expressed as proportion of all instances to which it applies called accuracy. An association rule has the form LHS $\Rightarrow$ RHS, where LHS (Left Hand Side) and RHS (Right Hand Side) are disjoint sets of items. A rule has a left-hand set of items and a right-hand set of items. A rule "LHS $\Rightarrow$ RHS" with a support $s$ and 'confidence' $c$ means that the underlying frequent set (LHS + RHS) occurred together in at least $s$ transactions, and for all the transactions LHS occurred in, RHS also occurred in at least the fraction $c$ (a number from 0 to 1).

$$\text{LHS} \Rightarrow \text{RHS}$$

$$\text{Confidence (LHS} \Rightarrow \text{RHS}) = \frac{\text{support}(\text{LHS, RHS})}{\text{support(\text{LHS})}}$$

C4.5 classifier

C4.5 classifier [16] is an algorithm to generate a decision tree. The decision tree generated by the C4.5 algorithm can be used as a classifier. At each node of the tree, C4.5 chooses one attribute of the data that most effectively splits data set of samples $S$ into subsets that can be one class or the other. It is the normalized information gain (difference in entropy) that results from choosing an attribute for splitting the data. The attribute factor with the highest normalized information gain is
E. Performance Evaluation

The image-based evaluation is performed. The accuracy, sensitivity and specificity are used to evaluate classifier performance. Accuracy measures the degree of veracity of a diagnostic test on a condition. The sensitivity measures the true condition that is correctly detected over total number of subjects with given condition. The specificity measures how condition is correctly detected over total number of subjects without given condition. The equation of each values are given below

\[
\text{Accuracy}(\%) = \frac{\text{Total number of correct prediction}}{\text{Total number of instances prediction in test data}} \times 100
\]

\[
\text{Sensitivity}(\%) = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \times 100
\]

\[
\text{Specificity}(\%) = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Positive (FP)}} \times 100
\]

where TP is the number of classes correctly classified as positive, TN is the number of classes correctly classified as negative, FP is the number of test instances that is falsely classified as positive and FN is the number of test instances that is falsely classified as negative.

III. RESULT AND DISCUSSION

The experiment is conducted in non-dilated retinal images. The totally 100 images of size 752x500 consists of 20 normal images, 35 mild non-proliferative diabetic retinopathy images, 25 moderate non-proliferative diabetic retinopathy images and 20 severe non-proliferative diabetic retinopathy images. A randomly images are used as training data and the remaining are used as test data. To evaluate the performance, sensitivity, specificity and average accuracy are used. The results are compared with the expert ophthalmologist’s reviews. As the numbers of normal and abnormal retinal images are few, a ten-fold cross-validation is performed. The association rules are applied. The support is 10% and the confidence is 0% in the training. The blood vessel, exudates, microaneurysm and haemorrhage are observed in order to identify the stage of DR.

The results indicate that the classifier has 87% correct prediction of unknown class. The No DR, moderate DR, mild DR and severe DR are correctly predict at 86%, 85%, 90% and 87% respectively. The results show that our proposed diabetic retinopathy grading system based on non-dilated retinal images can be used to pre-screening diabetic patients. Uncertainties medical data classification reduction is needed to improve classification accuracy. Eventually, normal images are classified as abnormal images due to incorrect or wrong detect of exudates and unclear blood vessels but no abnormal images are classified as normal images. None of patients with the symptoms are classified as normal. The suspect patients are need for further treatment by the experts. The system is able to help the ophthalmologists in screening process.

IV. CONCLUSION

In the present work, the DR stages are classified using image processing and data-mining techniques. The system can identify four stages with an average accuracy at 87%, a sensitivity of 85% and a specificity of 89%. In future work, the performance can be increased with more images data and better feature detection.

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