Diabetic Retinopathy Detection from Retinal Images

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Abstract – Diabetes occurs when the pancreas fails to secrete enough insulin, and slowly affects the retina of the human eye. As it progresses, the vision of a patient starts deteriorating(depleting), leading to diabetic retinopathy. In this regard, retinal images acquired through fundal camera aid in analysing the consequences, nature, and status of the effect of diabetes on the eye. The main aim of this study is to detect blood vessels, identify haemorrhages and to classify different stages of diabetic retinopathy into normal, moderate and severe non-proliferative diabetic retinopathy. The basis of the classification of different stages of diabetic retinopathy is to detect and quantify the blood vessels and haemorrhages that is present in the retinal image. Retinal vascular is differentiated utilising the contrast between the blood vessels and surrounding background. Haemorrhage candidates were detected using density analysis and bounding box techniques. Classification of the different stages of eye disease was done using Random Forest technique based on the area and perimeter of the blood vessels and haemorrhages. Accuracy of final and classified output revealed that normal cases were classified with 90% accuracy while moderate and severe cases were 87.5% accurate.

Keywords: diabetic retinopathy, blood vessels, retinal blood vessels, MATLAB R2013a, MATLAB R2013a, Operating system: Windows 7 and above.

1. INTRODUCTION

Diabetic retinopathy causes blindness. Diabetic retinopathy is one of the eye diseases which is caused due to retinal blood vessel extraction. Diabetic retinopathy affects blood vessels in the light-sensitive tissue that is called the retina that lines to the back of the eye. It is the most common cause of vision loss among people with diabetes and the leading cause of vision impairment and blindness among working-age adults. Here we proposed a system where we extracted retinal blood vessels for detecting eye diseases. Manually extracting the retinal blood vessels is a tedious task and there are many automated methods are available which makes work easier. Here we proposed an algorithm to extract blood vessels from retinal images. We used filtering strategies to get rid of noise and environmental interference from image. Local entropy thresholding and various successive filter methodology has been adopted during this system. We had implemented this system in MATLAB. User will input retina image into system. System will apply filtering techniques. Image pre-processing steps are applied to get accurate result. System will remove all unwanted objects from image. System will apply this algorithm to extract retinal blood vessels. Finally, system will detect diabetic retinopathy.

2. BACKGROUNG STUDY

Earlier, Otsu, (1979) presented a nonparametric and unsupervised method of automatic threshold selection for picture segmentation. This utilises only the zeroth- and the first-order cumulative moments of the grey-level histogram. Chaudhuri et al., (1989) addressed the problem of detecting blood vessels which have usually poor local contrast and emphasises that existing edge detection algorithm yield unsatisfactory results. They planned associate degree operator for feature extraction supported optical and spatial properties of the article to be recognized. Patton et al., (2006) outlined the segmentation of retinal landmarks upon which retinal digital image analysis is based. Hatanaka et al., (2007) described an improved method for detecting haemorrhages in fundus images. The overall detection scheme consisted of six stages - image digitisation, image normalization, extraction of optic nerve head, detection of haemorrhages candidates, elimination of false positives (FP) in blood vessels, and elimination of FPs by feature analysis. However, the method for elimination of the blood vessels for the successful detection of haemorrhage candidates was not dealt here. Yun et al., (2008) proposed automatic classification of different stages of diabetic retinopathy - mild non-proliferative retinopathy, moderate no proliferative retinopathy, severe non-proliferative retinopathy and proliferative retinopathy using neural network from six features that are extracted from the retinal images. In this work, we propose a new method of blood vessel extraction which is an improvement over the previously developed matched filter, a new method of haemorrhages detection and classify the retinal cases using an advanced nonparametric method with higher classification accuracy. The objectives of this work are: (i) detection of blood vessels, (ii) detection of haemorrhages, and (iii) classification of the detections into traditional, moderate non-proliferative diabetic retinopathy (NPDR) and severe NPDR.

3. CLASSIFICATION

This involves three different stages – (1) training stage: identifying representative training areas and developing a numerical description of the attributes of each class type through training set, (2) classification stage: data set is classified into the class it most closely resembles, and (3) output stage: the process consists of a matrix of interpreted category types. In this work, an advanced a non-parametric Tree-type classifier – Random Forests (RF) (Breiman, 2001) is used for classification. RF are ensemble methods using tree-type classifiers {hx k (,), 1, Θ = k} where they are i.e. random vectors and x is the input pattern. They are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. It uses bagging to make an ensemble of classification tree. RF is distinguished from other bagging approaches in that at each splitting node within the underlying classification trees, a random subset of the predictor variables is used as potential variables to define split. In training, it creates much Classification and Regression Tree trained on a bootstrapped sample of the original training data, and searches only across randomly selected subset of the input variables to determine a split for each node. RF utilises Gini index of node impurity to determine splits within the predictor variables. For classification, every tree casts a unit vote for the most popular class at input x. The output of the classifier is decided by a majority vote of the trees that result in the greatest classification accuracy. It is superior to several tree based algorithms, because it lacks sensitivity to noise and does not over fit. The trees in RF don't seem to be pruned; therefore, the computational complexity is reduced. As a result, RF can handle high dimensional data, using a large number of trees in the ensemble. This combined with the actual fact that random selection of variables for a split seeks to minimise the correlation between the trees within the ensemble, results in error rates that have been compared to those of Ad boost, at the same time being much lighter in implementation. Breiman and Cutler (2005) suggests RF "unexcelled in accuracy among current algorithms". RF has conjointly outperformed CART and similar boosting and bagging-based algorithm. In the current work, RF has been implemented using a Linux based random forest package, available in R interface.

4. Features

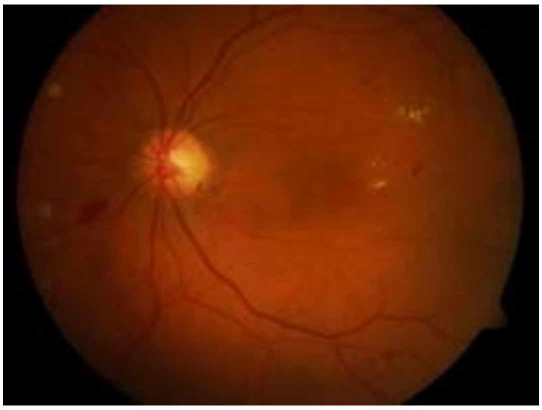
- User will input retinal blood vessel image.
- Algorithm is applied to extract blood vessels from image.
- Filtering method are used to remove noise from image
- Local entropy thresholding and alternative sequential filter methodology is implemented to extract.
- Image pre-processing steps are applied to get accurate result.
- System will remove all unwanted objects from image.
- System will apply the algorithm to extract retinal blood vessels.
- Finally, system will detect diabetic retinopathy.

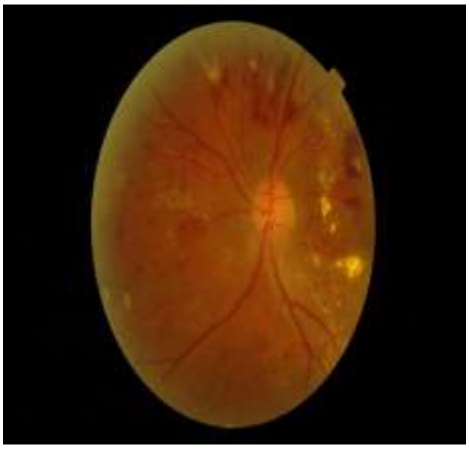
5. RESULT

A. Blood Vessel Extraction In a RGB retinal image, contrast is greater when the green channel alone is utilised in fundal image feature extraction. Adaptive histogram equalization was used to enhance the contrast of the features of interest against the background. A 3 x 3 median filter was used to remove the noise. Blood vessels were detected after applying the designed matched filter. The matched filtered image was converted to binary equivalent with a global threshold value of 0.1490 determined through observation, where presence of discontinuous lines was observed. Perception based binarization was carried out by generating a matrix, to store the matched filter number, and then the pixel grey level in that particular direction, multiplied by a factor, was checked for a threshold level.

B. Haemorrhage Detection Two smoothened images of different window sizes were obtained using smoothening filter and differenced to extract blood vessels and detect haemorrhage candidates. The image was thresholder using a global thresholding value. The false positive blood vessels were eliminated using bounding box technique. The ratio of major axis length and the minor axis length of each segment were calculated and those with higher values (>1.57) were eliminated. The haemorrhages were detected and their density was calculated by finding the number of white pixels in the image

C. Classification of different stages of Diabetic Retinopathy Six features – area and perimeter in each of the R, G, B components of the blood vessels and haemorrhages were extracted. Area is the number of white pixels (blood vessel and haemorrhage candidates) present within the vessels and perimeter was determined by the number of pixels present on the periphery of the vessels. These extracted features were used as inputs to the RF classifier for categorizing the three stages of retinal pictures. The range of the area and perimeter values of blood vessels and haemorrhages for each stage of the diabetic retinopathy with the different RGB layers.





6. DISCUSSION AND CONCLUSION

The analysis revealed that TP=14, FP=0, TN=9, FN=2, sensitivity=0.875, specificity=1, positive predicted value (PPV)=1, and negative predicted value (NPV)=0.8181. The unknown test cases were classified correctly by 88.46%. This shows that the proposed method of classification based on area and perimeter of blood vessels and haemorrhages produce motivating results.

7. REFERENCES

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