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Research Article

Detection of Microaneurysms in Fundus Images using ELM Classifier

G R Hemalakshmi*, N B Prakash

CSE Department, National Engineering College, K.R.Nagar, Kovilpatti, Tuticorin District, Tamilnadu
EEE Department, National Engineering College, K.R.Nagar, Kovilpatti, Tuticorin District, Tamilnadu

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ABSTRACT

The main objective of this paper is to detect the microaneurysms which is the sign and symptom for the retinal disease Diabetic Retinopathy (DR). In this work, the input image is preprocessed and then cross sectional scanning is applied for peak detection and property measurement. Feature set from the processed images is extracted and ELM classifier is used for MA detection. The experimental results show the proposed system provides better results compared to existing system.

Keywords: Fundus Image, Diabetic Retinopathy, Microaneurysms, Feature Extraction, ELM Classifier.

INTRODUCTION

Diabetic Retinopathy (DR) is an irreversible retinal issue in the diabetic patients. DR is primarily brought about because of the harm of retinal veins in diabetic patients. The veins start from the focal point of the optic plate and spreads over the whole district of the retina. Exudates injuries are framed in retinal picture because of the harm in retinal veins. Disregarding these injury side effects prompts the loss of vision, as these manifestations are not uncovered effectively and requires determination at a prior stage. Diabetes is a metabolic infection where the body is not able to manage the measure of sugar particularly glucose in the blood. Diabetes when not treated appropriately for a more extended time it clears route for a man influenced by Diabetic Retinopathy.

Diabetic retinopathy (DR) is a vascular confusion that influences the microvasculature of the retina. DR is an intricacy of diabetes and it is the most normal reason for visual deficiency over the world. The pervasiveness of Diabetic Retinopathy can be arranged into two types. Proliferative DR and Non-proliferative DR. At 40 years old and the patient has a family history of diabetic retinopathy then it is basic to have a total eye exam with an eye specialist regularly. On the off chance that any medical issues, for example, diabetes and a family history of glaucoma are at hazard for other eye sicknesses requires the expert of eye specialist all the more consistently. Early detection and treatment by ophthalmologist are the keys to preventing vision loss from DR.

Customary advanced picture investigation is hampered in the examination of pictures of the retina due to the intrinsic inconstancy of the fundi between people. In spite of the fact that this has been connected to the identification of particular elements, for example, microaneurysms, exudates, what's more, edema in diabetic retinopathy with some achievement, an application in diabetic screening has not been resolved.

Red lesions are the principal clinically detectable signs showing diabetic retinopathy. In this manner, their location is basic for a prescreening framework. The significant difficulties in red lesions recognition are: (1) division of little MA in the territories of low picture complexity and (2) the nearness of brilliant pathologies. Our essential concentration in this paper is to build up a computerized strategy which can distinguish pictures containing red lesions with a high affectability and a sensible specificity by extracting all the possible red lesions, while staying away from false reactions close splendid pathologies and other non-red lesion structures.

Existing methods

S.Y.Shen et al.[1] proposed to assess the prevalence and types of glaucoma in an Asian Malay population. They used some methods. Glaucoma was defined according to International Society for Geographical and Epidemiologic Ophthalmology criteria. The prevalence of glaucoma among Malay persons 40 years of age and older in Singapore is 3.4%, comparable to ethnic Chinese people in Singapore and other racial/ethnic groups in Asia. As in Chinese, Caucasians, and African people primary open-angle glaucoma was the main form of glaucoma in this population. More than 90% of glaucoma cases were undetected.

D.Michael et al.[2] proposed as primary eye care providers are optometrists must sort through various historical and clinical information to properly diagnose and manage glaucoma. Clinicians routinely used the cup-to-disc ratio as an indicator of the health of the optic nerve. A large cup-to-disc ratio indicates optic nerve damage. The optic disc and optic cup dimensions vary widely in the normal population. Simple clinical techniques are existing for measuring the size of the optic disc thereby allowing for a better understanding of the cup-to-disc ratio.

M. Niemeijer etal.[3] proposed the robust detection of red lesions in digital color fundus photographs is a critical step in the development of automated screening systems for

**Author for Correspondence: grhemalakshmi@gmail.com*

diabetic retinopathy. The first contribution is a new red lesion candidate detection system based on pixel classification. This technique is used to separate vasculature and red lesions from the background of the image. After the removal of connected vasculature the remaining objects are considered possible red lesions. In second an extensive number of new features are added to the proposed by Spencer-Frame. The detected objects are classified using a k-nearest neighbor classifier. An extensive evaluation was performed in the test set composed of images representative of those normally found in a screening set. To determining whether an image contains red lesions the system it achieves a sensitivity of 100% at a specificity of 87%.

A. Mizutani et al.[4] proposed Micro aneurysm in the retina is one of the signs of simple diabetic retinopathy. A computerized method for the detection of microaneurysms on retinal fundus images. The computerized scheme was developed by using twenty five cases. After image preprocessing the candidate regions microaneurysms were detected using a double-ring filter. If any potential false positives located in the regions then the blood vessels were removed by automatic extraction of blood vessels. The candidate lesions were classified into microaneurysms or false positives using the rule-based method and an artificial neural network.

A.D.Fleming et al.[5] proposed that Image segmentation is the partition of an image into a set of non overlapping regions whose union is the entire image. In Image decomposition the image is decomposed into meaningful parts which are uniform with respect to certain characteristics. In this paper presents a methodology for evaluating medical image segmentation algorithms wherein the only information available is boundaries outlined by multiple expert observers. The results of the segmentation algorithm are evaluated against the multiple observers' outlines. To illustrate the use of this methodology by evaluating image segmentation algorithms on two different applications in ultrasound imaging. In first application to find the epicardial and endocardial boundaries from cardiac ultrasound images, and in the second l is to find the fetal skull and abdomen boundaries from prenatal ultrasound images.

A.E.Mahfouz et al.[6] proposed that Optic Disc (OD) localization. In this paper, present a fast technique that requires less than a second to localize the OD. The technique is based on two projections of certain image features that encode the x- and y- coordinates of the OD. The resulting 1-D projections are searched to determine the location of the OD. It avoids searching the 2-D image space and enhances the speed of the OD localization process. Image features are retinal vessels orientation and the OD brightness used in the proposed method. Four publicly-available databases are including STARE and DRIVE used to evaluate the technique.

MA Detection

The proposed method for the detection of microaneurysms is shown in figure.1as block diagram representation.

Image Preprocessing

Image pre-processing method is the initial step for the proposed system. We selected MA detection, so we removed noise from the image. We require ROI as the input image. Preprocessing method is applied for brightness, correction, gamma correction, and contrast enhancement. The contrast between the MA and retinal area is highest in the green-channel of the color image, so we obtained the green-channel component of the color image for the MA detection. To remove the high frequency component from the image we use the Gaussian mask. It smoothes the image by the same amount in all directions. Gaussian smoothing is very effective for removing Gaussian noise as shown in figure.2

Local Maximum Region [LMR] Extraction

The preprocessed image has local intensity maximum structures. Each MA regions contains one regional maximum. Each pixel has constant value and it is connected to LMR of the grayscale image. This LMR preprocessed images are considered as the MA candidate region. Every image has pixels. Each pixel processed using simple first search algorithm. First select one pixel and compared to their eight neighbors. If all neighbors have a lower intensity, then the pixel is in a LMR. The neighbors have a higher intensity then the pixel not be a maximum. Suppose the neighboring pixels have same intensity, the pixels are stored in a queue and repeat the above procedure until the queue is empty and connected to a LMR component. Result of this process the local intensity variation is high in a raw retinal image and the maximum region extracted image is shown in figure.3

Cross sectional scanning

Consider a single maximum pixel in MA candidate regions and examine surrounding pixels. Apply discrete line segments in different ways which provides the intensity values. Consider these as the central pixels and are recorded as the candidate pixel. Using this method find the set of cross sectional intensity profiles. In this intensity profiles are used to identify and evaluate the properties of central peak pixels. The figure.4 shown below gives the cross sectional scanning view.

Peak Detection and Property Measurement on the Cross-Section Profiles:

In the previous step we find the cross sectional profiles. These profiles are used for the next process of peak detection. If a peak is identified in the middle of the profile then the properties of the peak and the final feature set are measured. The final feature set contains a set of arithmetic measures. Figure.5 shows the peak detection image obtained and table.1 shows the peak detection and property measured values.

Feature Set Classification

We find several statistical measurements of the peak properties after the steps cross sectional and peak detection for the candidate. Related values of peak properties define five sets. There are RHEIGHTS, RSLOPES, TWIDTHS, THEIGHTS and PHEIGHT. This feature set tabulated in table.2 able to differentiate MAs from the object.

For classification we used ELM and Genetic algorithm. The generalization performance of ELM algorithm for bench mark dataset image classification. Appropriate

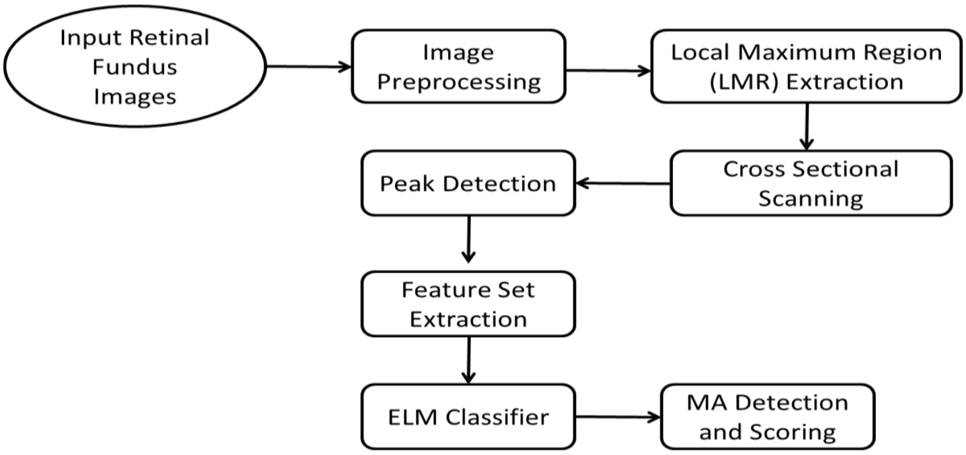


Figure 1: Block diagram of proposed methodology.

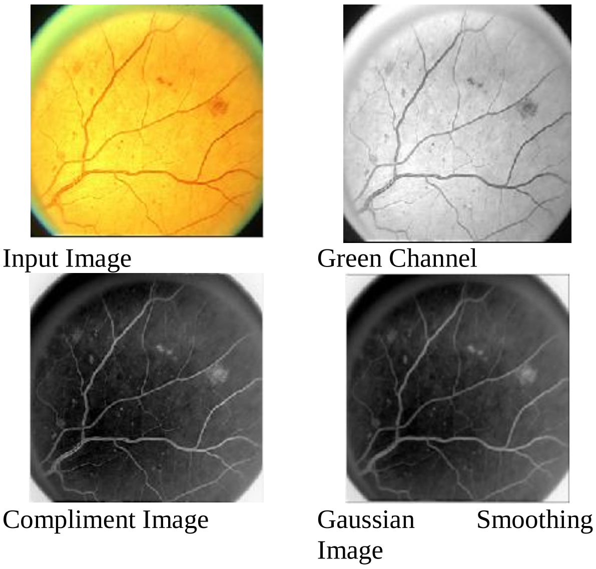


Figure 2: Image preprocessing and smoothening.

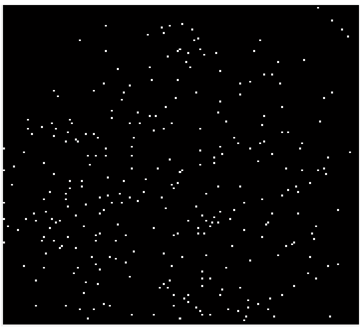


Figure 3: Maximization Region Extraction

selection of the input weights, hidden bias and number of hidden neurons for minimal image data pose a significant effect on the classification performance due to fewer training samples. ELM proved enhanced performance in comparison to other classifiers for larger training samples. Custom selection of parameters randomly with suitable feature extraction technique, feature sub selection model obtains better classification accuracy for smaller training samples .To solve the feature sub-selection, genetic algorithm is designed, where the genetic operators select

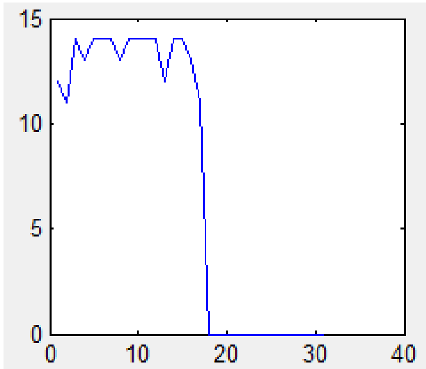


Figure 4: Cross Sectional Scanning.

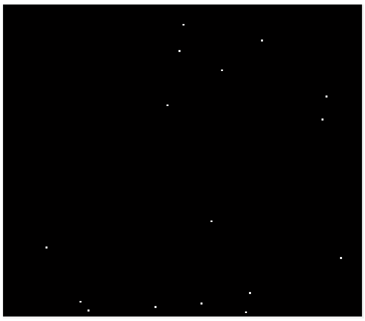


Figure 5: Peak Detection.

the most relevant set of features for good classification accuracy. Therefore, training an SLFN is equivalent to finding a least squares solution β of the linear system Hβ = T, equation(1).

$$\left\| \mathbf{H}(\mathbf{w}_1,\ldots,\mathbf{w}_{\tilde{N}},b_1,\ldots,b_{\tilde{N}})\hat{\beta}-\mathbf{T} \right\| = \min_{\beta} \left\| \mathbf{H}(\mathbf{w}_1,\ldots,\mathbf{w}_{\tilde{N}},b_1,\ldots,b_{\tilde{N}})\beta-\mathbf{T} \right\|. \quad \ldots\ldots(1)$$

A gradient based learning algorithm shown in figure.6 can be used to minimize the ***Hβ* = *T*** by adjusting the parameters *wi*, *bi* and *βi*, when the H hidden layer matrix is unknown iteratively.

On feature sub-selection for in terms of spectral and intensity characteristics using Genetic Algorithm and last

Table 1: Peak Detection and Property Measurement Values.

20	5	1	6	0.142857	0.75	255
15	2	1	18	0.5	1.63636	255
15	2	14	1	1.55556	0.25	255
15	8	20	2	6.66667	0.5	255
28	4	167	1	11.9286	0.1	255
21	11	2	14	0.666667	2	255
25	13	21	2	4.2	0.285714	255

Table 2: Generated Feature set values

20	5	7	0.892957	255
15	2	19	2.13636	255
15	2	15	1.80556	255
15	8	22	7.16667	255
28	4	168	12.0286	255
21	11	12	1.33333	255
25	13	23	4.48571	255

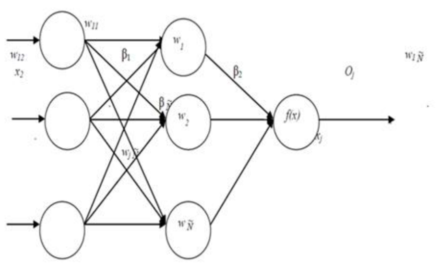


Figure 6: Gradient Based Learning Algorithm flow diagram.

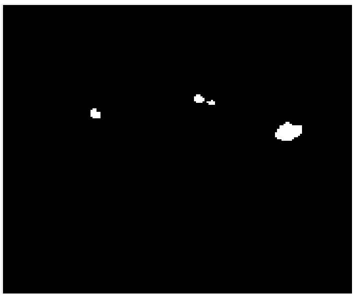
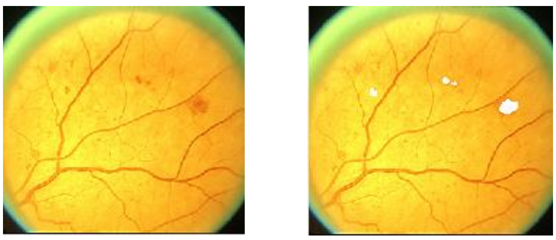


Figure 7: Image showing MA after ELM Classification.



Original Image Candidate Image

Figure 8: Original image and MA mapped candidate image.

on ELM used to build a robust classifier model for images. The ELM classified image is shown in figure. 7The genetic algorithm then creates a population of solutions and applies genetic operators such as mutation and crossover to evolve the solutions in order to find the best one(s). This presentation outlines some of the basics of genetic

Table 3: Performance Measures comparison.

Images	KNN accuracy	NB accuracy	ELM accuracy
Image 1	82.13	89.56	99.04
Image 2	83.56	89.23	99.12
Image 3	82.06	88.15	99.09
Image 4	83.23	88.59	99.23
Image 5	83.59	90.12	98.26

algorithms. The three most important aspects of using genetic algorithms are: (1) definition of the objective function, (2) definition and implementation of the genetic representation, and (3) definition and implementation of the genetic operators. Once these three have been defined, the generic genetic algorithm should work fairly well. Beyond that you can try many different variations to improve performance, find multiple optima (species - if they exist), or parallelize the algorithms.

MA Score Calculation

All MA candidates have score values and it's classified as true MAs. The score value contains shape, symmetry, sharpness and contrast of the candidate. The score value of MA candidate is calculated using the equation (2) is tabulated in table.3

$$\text{score} = \frac{\min_{\text{PHEIGHTS}} \cdot \mu_{\text{RSLOPES}}}{1 + \sigma_{\text{PWIDTHS}} + \sigma_{\text{TWIDTHS}} + \sigma_{\text{RSLOPES}} + \sigma_{\text{RHEIGHTS}} + \sigma_{\text{PHEIGHTS}}}$$

.. (2)

where the $\min_{\text{PHEIGHTS-}}$ is the value of PHEIGHT etc... If the score value is maximal then the variables in the denominator like zero

The final obtained image with microaneurysms detection is mapped with the original image shown in figure. 8

Experimental Results

In our experiment results of proposed system compared to existing system. The below table show that result. The proposed system gives good performance for accuracy. Table.4 shows the comparison of different methods used in MA detection. The methods used are KNN, NB, ELM. Compared to these methods the ELM method provides good results.

CONCLUSION

In our paper the MA detection has been detected using ELM classifier. Finally MA score has been calculated for classification of fundus images into normal and abnormal which can be utilized for the future scope of our work. Compared to other existing classifier systems our proposed method provides better performance in accuracy rate.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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