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Research Article

A NOVEL APPROACH FOR SEVERITY CLASSIFICATION OF RETINAL LESIONS USING ANN CLASSIFIER

Yamuna Rani V[1*], Sukumar P[2], Marimuthu CN[3]

[1]II-M.E.(Applied Electronics), Nandha Engineering College, Erode-52
[2]M.E., Assistant Professor, Nandha Engineering College, Erode-52
[3]Dean/ECE Department, Nandha Engineering College, Erode-52

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*Corresponding Author: **Yamuna Rani V**
Email: yamunarani.mercy@gmail.com

ABSTRACT

Diabetes mellitus is a heterogeneous group of disorders characterized by persistent hyperglycemia. Diabetes occurs when the pancreas does not secret enough insulin or the body is unable to process it properly. Over the time, diabetes affects the circulatory system, including that of the retina. Diabetic retinopathy is a medical condition where the retina is damaged because fluids leak from blood vessels into the retina. Opthalmolologists recognize DR based on features such as blood vessel area, hemorrhages, microaneurysms and exudates. In particular, the detection of microaneurysms, usually the first sign of diabetic retinopathy is of primary importance. The purpose of the project is to improve our automated microaneurysms detection method to help diagnose diabetic retinopathy. The proposed method realizes MA detection using canny edge mapping technique. A classifier is trained with expert based annotations to indicate the severity level of the disease.

Keywords: Diabetic Retinopathy(DR), Microaneurysyms(MA), Fundus Image, Retina.

INTRODUCTION

Diabetes mellitus is a heterogeneous group of disorders characterized by persistent hyperglycemia. The two most common forms of diabetes are type 1 diabetes previously known as insulin-dependent diabetes and type 2 diabetes previously known as non-insulin-dependent diabetes. Type I diabetes is caused by the autoimmune destruction of the beta cells of the pancreas. At present, lifelong insulin therapy is the only treatment for the disease. Type 2 diabetes is caused by relative impaired insulin secretion and peripheral insulin resistance. Typically, type 2 diabetes is managed with diet, exercise, oral hypoglycemic agents and sometimes exogenous insulin. However, it is associated with the same long-term complications as type 1 diabetes[1]. Both are caused by a combination of genetic and environmental risk factors. All forms of diabetes have very serious effects on health. In addition to the consequences of abnormal metabolism of glucose (e.g., hyperlipidemia, glycosylation of proteins, etc.), there are a number of long-term complications associated with the disease. These include cardiovascular, peripheral vascular, ocular, neurologic and renal abnormalities, which are responsible for morbidity, disability and premature death in young adults. Diabetic retinopathy, a micro-vascular complication of diabetes, is an important cause of vision loss in adults. All people with diabetes are at risk of developing retinopathy so thus at risk of vision loss or blindness. Screening for diabetic retinopathy to detect retinopathy and monitor progression has been shown to be effective in the prevention of vision loss. Screening involves an examination of the retina at the back of the eye and a test of visual acuity. This can be done by medical practitioners or optometrists who dilate the eye's pupil to examine the retina. Hence assessment of automatic detection of diabetic retinopathy is important, which reduces the cost of financing the manual trained graders by incorporating the computerized screening algorithm using the digitized retinal images.

Diabetic Retinopathy

Diabetic retinopathy is asymptomatic in its early stages and vision might not be affected until the disease becomes severe and much less amenable to treatment. There are two types: non-proliferative or proliferative. Non-proliferative diabetic retinopathy is the early stage of the disease and is less severe. Blood vessels in the eye start to leak fluid into the retina, which leads to blurred vision. Proliferative retinopathy is the more advanced form of the disease, and more severe. New blood vessels start to grow in the eye. These new vessels are fragile and can bleed (hemorrhage), which may cause vision

loss and scarring of the retina. Having more severe diabetes for a longer period of time increases the chance of getting retinopathy. Retinopathy is also more likely to occur earlier and be more severe if the diabetes is poorly controlled. Almost everyone who has had diabetes for more than 30 years will show signs of diabetic retinopathy. Symptoms of diabetic retinopathy include Blindness, Blurred vision, Floaters and Shadows or missing areas of vision. The common sign of DR includes microaneurysms, hemorrhages, exudates, drusen and cotton wool spots. Diabetic retinopathy is the name given to changes in retina, the back part of the eye. It is made up of cells sensitive to light. A network of blood vessels feds retina and the changes in these cause difficulties with vision. The walls of blood vessels become fragile and start to break, leaking blood around them. The weakened area become ballooned out called microaneurysms. It has a maximally established clinical diameter usually less than that of the major optic veins.

Laser treatment is very effective for prevention of vision loss due to diabetic retinopathy, however, laser treatment cannot restore vision that has already been lost. Therefore it is essential to detect and treat diabetic retinopathy before any vision loss occurs[2]. A UK report considered a reduction in the diabetic retinal screening interval and included a review of the economic evidence on diabetic retinopathy screening[3,4]. The findings of this report support the current recommendation of annual screening and conclude that more patients could become blind with a 2-year rather than annual screening interval.

Related Work

Grading of diabetic retinopathy by the detection of microaneurysms dates back to early 1990's. spencer et al(1996) used morphological transformations to segment microaneurysms from fluorescein angiograms by opening i.e. erosion followed by dilation from the shade corrected image. He then used two dimensional Gaussian matched filter model of microaneurysms before thresholding in the resulted binary image containing MA's. Region growing was performed to finally segment them separately. The work resulted in 82%sensitivity and 86%specificity on four 10"x8" printed images containing MA's by producing 100 false positives per image. Cree et al (1997) extended spencers work by redesigning region growing and classification algorithm. The selection of region of interest was done to locate the disease. A classifier was trained on 68 fluoresce in images to detect features to locate the abnormalities. Further they trained 20 angiogram images containing 297 true MA's by achieving 82% sensitivity with 2 false positives per image. But they failed to work on low quality images. Hipwell et al(2000) improved MA's detection using digitalized 50 degree red free images. He followed same technique as spencer et al for preprocessing but classification algorithm was based on 102 images containing various degrees of retinopathy. Ege et al (2000) detected MA's and hemorrhages with 69% and 83% sensitivity on 30 images using mahalanobis classifier. Sinthanayothin et al (2002) adapted region growing technique after preprocessing the images and used neural network classifier to extract similar blood vessels. By performing operations on 30 images by a sensitivity and specificity of 77.55 and 88.7% was achieved[5-10].

Proposed Work

In this work, an automated approach for classification of the disease diabetic retinopathy using fundus images is presented. In order to diagnose the disease diabetic retinopathy, a number of features such as area, mean and standard deviation of the preprocessed images are extracted to characterize the image content. Artificial neural network training process is applied to analyze training data to find an optimal way to classify images into their respective classes namely PDR, NPDR or Normal. Experimental results show that the classification accuracy can provide a better result.

PREPROCESSING OF IMAGES

The image preprocessing techniques include Gray scale Conversion, Adaptive Histogram Equalisation, and canny edge detection for segmentation of blood vessels. The acquired image resolution is 1280 x 1024 in 24bit JPEG format.

Gray Scale Conversion

The color image of an eye is taken as input image and is converted to a grayscale image. The Original DR affected Eye Images are shown in Figure 1 (a)-(d) below . The results of eye images after applying gray scale conversion are shown in Figure 2 (a)-(d) below.

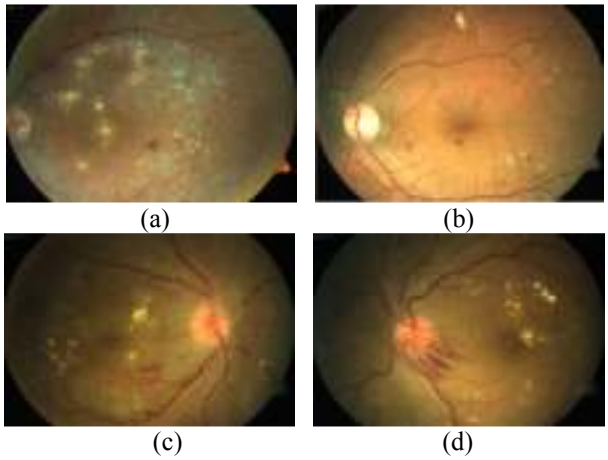

Figure 1: (a) -(d) are Original DR affected Eye Images

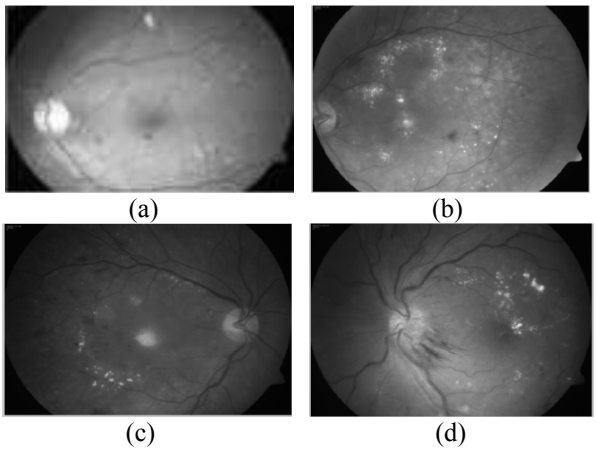

Figure 2: (a) – (d) are eye images after Gray Scale Conversion

A common strategy is to match the luminance of the grayscale image to the luminance of the color image. To convert any color to a grayscale representation of its luminance, first one must obtain the values of its red, green, and blue (RGB) primaries in linear intensity encoding, by gamma expansion. Then, 30% of the red value, 59% of the green value, and 11% of the blue value is added together . Colours in an image may be converted to a shade of gray by calculating the effective brightness or luminance of the colour and using this value to create a shade of gray that matches the desired brightness. The effective luminance of a pixel is calculated using the formula, Y= 0.3Red+0.59Green+0.11Blue. This luminance value can then be turned into a grayscale pixel . A grayscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information[11-14].

Adaptive Histogram Equalization

Adaptive histogram equalization is an image processing technique used to improve contrast in images. It is considered an image enhancement technique capable of improving an image's local contrast, bringing out more detail in the image. So it is applied to the gray scale converted eye image. The main objective of this method is to define a point transformation within a local fairly large window with the assumption that the intensity value within it is a stoical representation of local distribution of intensity value of the whole eye image. The local window is assumed to be unaffected by the gradual variation of intensity between the eye image centers and edges. The point transformation distribution is localized around the mean intensity of the window and it covers the entire intensity range of the image. Consider a running sub image W of N X N pixels centered on a pixel P(i,j) , the image is filtered to produce another sub image P of (N X N) pixels according to the equation below

$$P_w = 255\left(\frac{\left|\phi_w(P) - \phi_w(Min)\right|}{\left|\phi_w(Max) - \phi_w(Min)\right|}\right) \quad (1)$$

Where

$$\phi_w(P) = \left[1 + \exp\left(\frac{\mu_w - P}{\sigma_w}\right)\right]^{-1} \quad (2)$$

and Max and Min are the maximum and minimum intensity values in the , whole eye image while μw indicate the local window mean and σw indicate standard deviation which are defined as:

$$\mu_w = \frac{1}{N^2}\sum_{(i,j)\in W} P(i,j) \quad (3)$$

$$\sigma_w = \sqrt{\frac{1}{N^2}\sum_{(i,j)\in W}\left(P(i,j) - \mu_w\right)^2} \quad (4)$$

The following Figures 3 (a)-(d) shows the results of eye images after applying Adaptive Histogram Equalization.

As a result of this adaptive histogram equalisation, the dark area in the input eye image that was badly illuminated has become brighter in the output eye image while the side that was highly illuminated remains or reduces so that the whole illumination of the eye image is same.

Morphological Operations on Binary Images

Morphological operations are affecting the form, structure or shape of an object when applied on binary images (black & white images). They are used in pre or post processing (filtering, thinning, and pruning) or for getting a representation or description of the shape of objects/regions (boundaries, skeletons convex hulls).The two principal morphological operations are dilation and erosion. Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized for an application by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded[15-17].

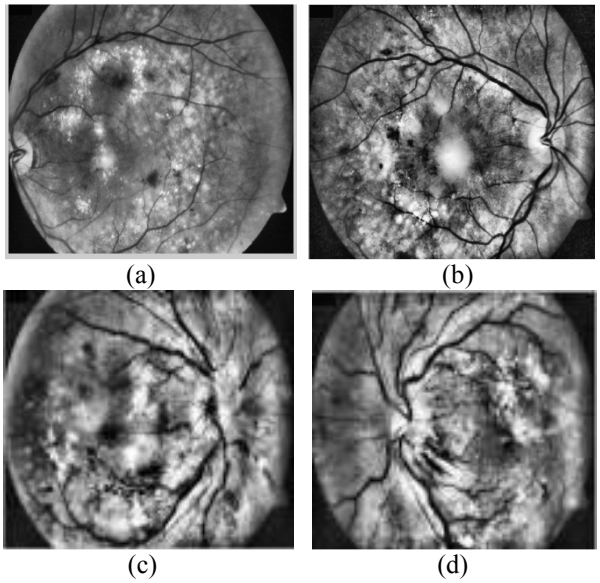

Figure 3: (a) – (d) are eye images after Adaptive Histogram Equalization

The dilation process is performed by laying the structuring element **B** on the image **A** and sliding it across the image in a manner similar to convolution. The notation for dilation is A ⊕b. It is best described in a sequence of steps: i)If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel. ii)If the origin of the structuring element coincides with a 'black' in the image, make black all pixels from the image covered by the structuring element.

The erosion process is similar to dilation, but we turn pixels to 'white', not 'black'. The notation is AΘB. As before, the structuring element is slide across the image and then following steps are followed: i) If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel. ii) If the origin of the structuring element coincides with a 'black' pixel in the image, and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image (corresponding to the position on which the center of the structuring element falls) from 'black' to a 'white'. The following Figure 4 shows the results of eye images after applying morphological operations over the binary images.

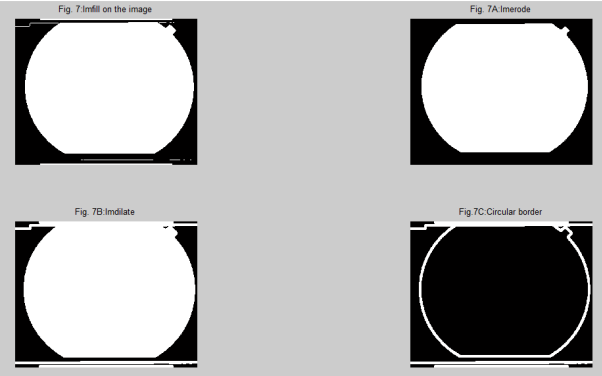

Figure 4: Images after morphological operation

These two basic operations, dilation and erosion, can be combined into more complex sequences. The most useful of these for morphological filtering are called opening and closing. Opening consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element. In this case the structuring element is often called a probe, because it is probing the image looking for small objects to filter out of the image.

The illustration of the opening process is $A \circ B = (A \ominus B) \oplus B$ .Closing consists of a dilation followed by erosion and can be used to fill in holes and small gaps. It can be illustrated by $A \bullet B = (A \oplus B) \ominus B$.

EDGE DETECTION

Segmentation

Segmentation refers to the procedure that partitions the image into regions of interest according to pixel intensity values, based on either discontinuities (abrupt changes in intensity values such as edges) or similarities (such as grouping pixels based on predefined criteria).The block diagram indicating the proposed system is given in the Figure 5 which indicates the detection of retinal lesions.

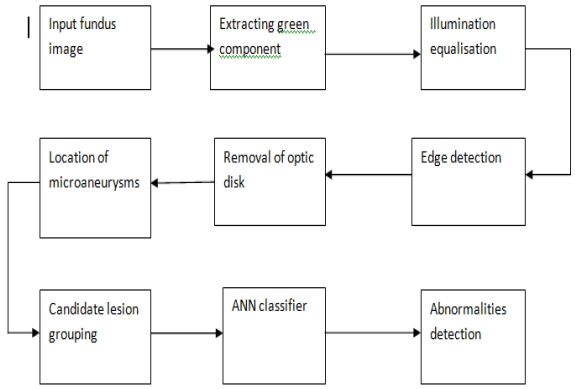

Figure 5: Workflow of the proposed method

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. An optimal edge detector means, good detection – the algorithm should mark as many real edges in the image as possible. Good localization – edges marked should be as close as possible to the edge in the real image. Minimal response – a given edge in the image should only be marked once, and where possible, image noise should not create false edges. To satisfy these requirements Canny used the calculus of variations – a technique which finds the function which optimizes a given functional. The optimal function in Canny's detector is described by the sum of four exponential terms, but it can be approximated by the first derivative of a Gaussian. An edge in an image may point in a variety of directions, so the Canny algorithm uses four filters to detect horizontal, vertical and diagonal edges in the blurred image. Figure 6 indicates the detected blood vessel boundaries without circular border.

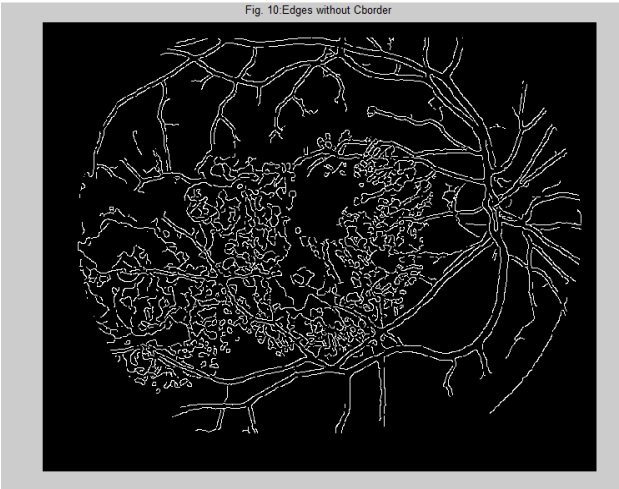

Figure 6: Detection of edges of blood vessel without circular border

Feature Analysis

After performing the above mentioned preprocessing steps, the new eye image is obtained.

Feature extraction is used to obtain the features from the given images.

i) Area of on pixels: It is the area of the white pixels with value 1 on the black and white image.

ii) Mean: The mean is the arithmetic average of a set of values, or distribution. Here in the eye image, it is obtained by adding all of the pixel values together, then dividing by the number of original values.

iii) Standard Deviation: The Standard deviation for an image is found by squaring each pixel values of all the individual samples, and then calculating average for the number of samples, N. The standard deviation measures the spread of the data about the mean value. The standard deviation is approximately equal to the average deviation from the mean . The features are trained with the help of ANN classifier and the classification of the disease was done to predict the nature of the disease accurately.

ANN MODELLING

An artificial neural network is composed of many artificial neurons that are linked together according to a specific network architecture. The objective of the neural network is to transform the inputs into meaningful outputs.

Each neuron in ANN receives a number of inputs. An activation function is applied to these inputs which results in

activation level of neuron (output value of the neuron). An Artificial Neural Network is specified by:
Neuron Model: the information processing unit of the NN. An Architecture: a set of neurons and links connecting neurons. Each link has a weight. Learning Algorithm: used for training the NN by modifying the weights in order to model a particular learning task correctly on the training examples.
Artificial neural networks are inspired by the learning processes that take place in biological systems. The synapse strength modification rules for artificial neural networks can be derived by applying mathematical optimisation methods. Neural networks can be considered as nonlinear function approximating tools (i.e., linear combinations of nonlinear basis functions), where the parameters of the networks should be found by applying optimisation methods.

EXPERIMENTAL RESULTS

The proposed method was implemented entirely in MATLAB. The average computational time of an image was approximately 2s, without parallelization, using a PC with an IntelCore2 Quad Q8200 Processor and 2 GB RAM.
The detection of blood vessels inside the region of interest is done and Figure 7 demonstrates the minute vessels using edge mapping technique. Further more the Figure 8 demonstrates the segmentation of blood vessels in order to identify the MA s present inside them such that the accuracy of the lesion detection is improved.

Figure 7: Detection of blood vessels inside the circular border

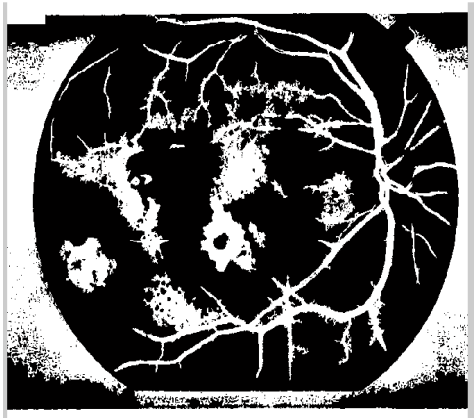

Figure 8: Segmentation of blood vessels

Detection of Microaneurysms

The aim of blob detection is to find small regions that are either dimmer or brighter than their background in gray-level images. The basic principle of the blob detection method presented here is that a group of pixels in the original image are considered as a dark blob if all pixels in the group are darker than any of neighboring pixels surrounding the pixel group. Figure 9 demonstrates the detection of smaller lesions.
Respectively, if all the pixels in the group are brighter than any pixel outside the group, the group is considered as a bright blob. Since maximum and minimum pixel values are searched in the method, even a single noise pixel (for example a bright noise pixel inside a dark blob) can make the method fail. Therefore the original image is filtered with a small median filter prior to blob detection.

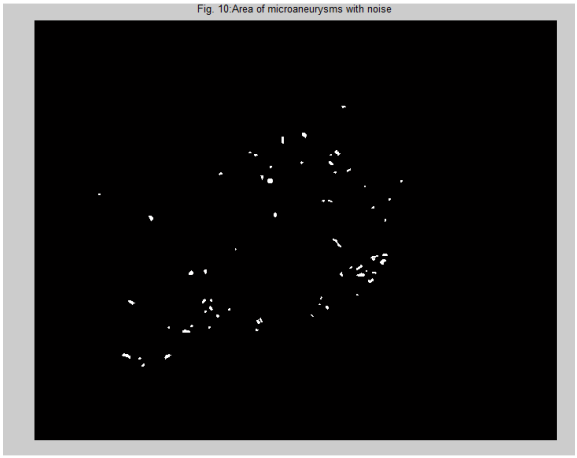

Figure 9: Detection of microaneurysms

The level of the disease can be well predicted with the help of the ANN classifier. Various features were extracted and the classifier is trained with 60 images and the corresponding results were obtained. Figure 10 indicates the disease level. The validated results were given in the form of confusion matrix obtained as result of ANN modeling.

Figure 10: Command window indicating the disease category

The performance measures can be best depicted with the help of receiver operating characteristics. Figure11 gives the performance results of the proposed work. The ROC is also

known as a relative operating characteristic curve, because it is a comparison of two operating characteristics (TPR and FPR) as the criterion changes. The true positive refers to the sensitivity while the true negative refers to specificity.

Figure11: Performance measures of the proposed system

CONCLUSION

To summarize, canny edge detection is applied with application of microaneurysms detection in fundus photographs. The technique is able to model shapes of various lesions efficiently regardless of their variability in appearance, texture or size. ANN classifier was trained incorporating several features to categorize the disease efficiently. The technique can be extended to detect other retinal lesions caused due to diabetic retinopathy. The lesion detector could be integrated into comprehensive screening systems assisting ophthalmologists in the detection of diabetic retinopathy.

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