SYSTEM BASED ON THE NEURAL NETWORK FOR THE DIAGNOSIS OF DIABETIC RETINOPATHY

Dipika gadriye[1], Prof.Gopichand Khandale[2]
Department of Electronics Engineering
Wainganga College of Engineering & Management
Nagpur, India.

Abstract— **The legal cause of blindness for the workingage population in western countries is Diabetic Retinopathy - a complication of diabetes mellitus - is a severe and wide- spread eye disease. Digital color fundus images are becoming increasingly important for the diagnosis of Diabetic Retinopathy. In order to facilitate and improve diagnosis in different ways, this fact opens the possibility of applying image processing techniques .Microaneurysms is the earliest sign of DR, therefore an algorithm able to automatically detect the microaneurysms in fundus image captured. Since microaneurysms is a necessary preprocessing step for a correct diagnosis. Some methods that address this problem can be found in the literature but they have some drawbacks like accuracy or speed. The aim of this thesis is to develop and test a new method for detecting the microaneurysms in retina images. To do so preprocessing, gray level 2D feature based vessel extraction is done using neural network by using extra neurons which is evaluated on DRIVE database which is superior than rulebased methods. To identify microaneurysms in an image morphological opening and image enhancement is performed. The complete algorithm is developed by using a MATLAB implementation and the diagnosis in an image can be estimated with the better accuracy and in shorter time than previous techniques.**

Key words— **Diabetic retinopathy, feature extraction, fundus photograps, microaneurysms, Vessel Segmentation.**

I.INTRODUCTION

Diabetic Retinopathy (DR) is the most common diabetic eye disease and is the leading cause of blindness in a persons with diabetes within the age group 20 to 74 years in developed countries [1]. It is caused by the changes in the blood vessel of retina. It is provoked by diabetes-mellitus complications and, although diabetes affection does not necessarily involve vision impairment. About 2% of the patients affected by this disorder are blind,10% undergo vision degradation after 15 years of diabetes [2], [3] as a consequence of DR complications The estimated prevalence of diabetes for all age groups worldwide was 2.8% in 2000 and 4.4% in 2030, meaning that the total number of diabetes patients is forecasted to rise from 171 million in 2000 to 366 million in 2030 [4]. DR also becomes a great economic problem for Administrations since, only in U.S. cost of ophthalmic chronic complications caused by diabetes exceeded 1 billion dollars in 2007 [5]. Although the diabetic retinopathy is not curable and also DR patients perceive no symptoms until visual loss develops, usually in the later disease stages, when the treatment is less effective. But if the treatment is received in time patients can be prevented to become affected from this condition or atleast the progression of DR can be slowed down. Thus, mass screening of the patients suffering from the diabeties is highly desired, but manual grading is slow and resource demanding. Therefore more effort are being taken to design authentic computer - aided screening system based on color fundus images. The promising result reported by Antal et al.[6] indicate that the automatic DR screening systems are getting closer to be used in clinical practices. These types of automated systems have the potential to reduce the workload for screening ophthalmologists while maintaining a high sensitivity (i.e., above 90%) for the detection of patients with DR. Furthermore, itwould also result in economic benefits for public Health Systems, since cost-effective treatments associated to early illness detection lead to remarkable cost savings [7].

In this paper, a new methodology for blood vessel detection presented by Marin et al. [9] is optimized for the MA detection. It is based on pixel classification using a 2-D feature vector extracted from preprocessed retinal images and given as input to a neural network. Classification results (real values between 0 and 1) are thresholded to classify each pixel into two classes: vessel and nonvessel. Finally, a postprocessing fills pixel gaps in detected blood vessels and removes falsely-detected isolated vessel pixels.

Despite its simplicity, the high accuracy achieved by this method in blood vessel detection is comparable to that reported by the most accurate methods in literature. Moreover, it offers a better behavior against images of different conditions. This fact is especially relevant if we keep in mind that the main aim of implementing a vessel segmentation algorithm is its integration in systems for automated detection of eye diseases. This kind of systems should require no user interaction and, therefore, be field of retinal imaging, this involves a huge challenge, since large variability is observed in the image acquisition process and a natural variation is reported in the appearance of the retina. Applications are being developed in which a computer interprets an image to aid a physician in detecting possibly subtle abnormalities. A spell-checker indicates words or grammar it suspects to be incorrect. This may or may not be the case and the human operator, the writer in this case, either accepts or rejects the machine's suggestions. A similar process can be used for medical image analysis. The computer indicates places in the image that require extra attention from the physician because they could be abnormal. These technologies are called Computer Aided Diagnosis (CAD). Other emerging CAD applications are the automatic detection of polyps in the large intestine and automatic lung nodule detection. This thesis describes components of an automatic system which can aid in the detection of diabetic retinopathy.This is an eye disease and a common complication of diabetes that can cause blindness and vision loss if left undiagnosed at an early stage. As the number of people afflicted with diabetes increases worldwide, the need for automated detection methods of diabetic retinopathy will increase as well. To automatically detect

diabetic retinopathy, a computer should interpret and analyze digital images of the retina.

II.PROPOSED SYSTEM

The proposed system gives an automated method for blood vessel enhancement and segmentation. The input retinal image normally contains too many background pixels which are not required for further processing. A preprocessing is applied to remove the background and noise from the image. It takes colored retinal image as a input. Studies on retinal images have shownthat it is the green channel which gives the best contrast between the surface area and blood vessels. Furthermore in inverted green channel, blood vessels appear more lighter than background that is why we have used inverted green channel for blood vessel enhancement and segmentation. For detection of neovascularization, it is important to enhance the vascular pattern especially the thin and less visible vessels. The proposed algorithm uses two dimensional Gabor wavelet for vessel enhancement [10].
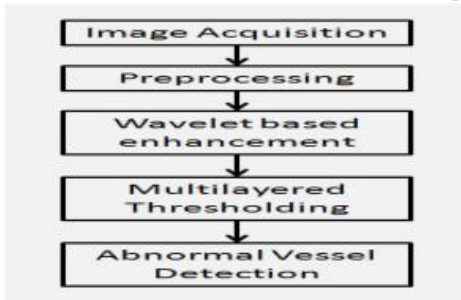

Fig.1. Flow diagram for proposed system

After vessel enhancement, multilayered thresholding and adaptive thresholding techniques are applied to create a binary mask for blood vessel segmentation. Then a sliding window is applied to find new abnormal blood vessel. Figure shows thecomplete flow diagram for proposed technique.

III.RETINAL IMAGES DATABASES

Fundus photography is the creation of a photograph of the interior surface of the eye, including the retina, optic disc, macula, and posterior pole. The fundus image of the retina is basically acquired with the digital fundus camera, which is a specialized camera that images the retina via the pupil of the eye. The fundus camera has the illumination system. Modern systems image at high-resolution and in color with Nikon or Canon digital SLR camera backends. The field of view (FOV) of the retina that is imaged can usually be adjusted from 25◦ to 60◦ (as determined from the pupil) in two or three small steps. The smaller FOV has better detail but this is at the expense of a reduced view of the retina. There are various publicly databases which are available online for the study or research purpose such as Messidor database, STARE, DRIVE, DIARETDB1 Database and private database from hospital. The databases available are for the study and research purpose. In this databases various images along with annotation file is provided in which pathological result for each image such as retinopathy grade and features which are present such as micro aneurysm, exudates, hemorrhages, neovascularization is mentioned.

IV.PREPROCESSING METHODS

The first step in preprocessing is to extract the green channel of the image. Since the input images are monochrome and obtained by extracting the green band from original RGB retinal images. The green channel provides the best vessel-background contrast of the RGB-representation, while the red channel is the brightest color channel and has low contrast, and the blue one offers poor dynamic range. Thus, blood containing elements in the retinal layer (such as vessels and microaneurysms) are best represented and reach higher contrast in the green channel [13].
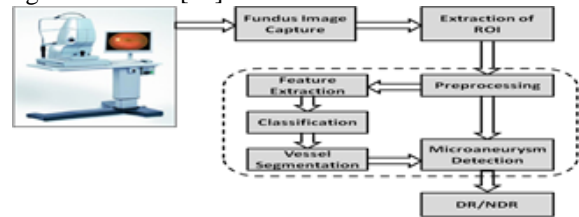

Fig.2.Framework of the proposed scheme

A. Fundus Mask Detection

The fundus can be easily separated from the background by converting the original fundus image from the RGB to HSI colour system where a separate channel is used to represent the intensity values of the image. The intensity channel image is thresholded by a low threshold value as the background pixels are typically significantly darker than the fundus pixels. A median filter of size 5×5 is used to remove any noise from the created fundus mask and the edge pixels are removed by morphological opening with a square structuring element of size 5×5.
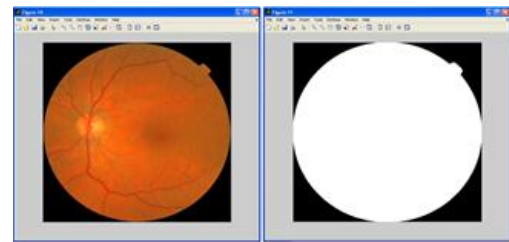

Fig.3.Automatic fundus mask generation. (a) Input image (b) Automatically generated fundus mask.

After that the mask is obtained by extracting the pixels having the values greater than 0 over the range of $0 – 255$ and then FOV is obtained by multiplying the mask image with greatest pixel value i.e. 255. Figure 4.2 shows the example of the fundus mask.Color fundus images often show important lighting variations, poor contrast and noise. In order to reduce these imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, a preprocessing comprising the following steps is applied: 1) vessel central light reflex removal, 2) background homogenization, and 3) vessel enhancement.

B. Vessel Central Light Reflex Removal

Since retinal blood vessels have lower reflectance when compared to other retinal surfaces, they appear darker than the background. Although the typical vessel cross-sectional gray-level profile can be approximated by a Gaussian shaped curve (inner vessel pixels are darker than the outermost ones), some blood vessels include a light streak (known as a light reflex) which runs down the central length of the blood vessel.

To remove this brighter strip, the green plane of the image is filtered by applying a morphological opening using a three-pixel diameter disc, defined in a square grid by using eight-connexity, as structuring element. Disc diameter was fixed to the possible minimum value to reduce the risk of merging close vessels. Iγ denotes the resultant image for future references.

C. Background Homogenization

A Fundus images often contain background intensity variation due to nonuniform illumination.

Consequently, background pixels may have different intensity for the same image and, although their gray-levels are usually higher than those of vessel pixels (in relation to green channel images), the intensity values of some background pixels is comparable to that of brighter vessel pixels. Since the feature vector used to represent a pixel in the classification stage is formed by gray-scale values, this effect may worsen the performance of the vessel segmentation methodology. With the purpose of removing these background lightening variations, a shade-corrected image is accomplished from a background estimate. This image is the result of a filtering operation with a large arithmetic mean kernel, as described. Firstly, a 3×3 mean filter is applied to smooth occasional salt-and-pepper noise. Further noise smoothing is performed by convolving the resultant image with a Gaussian kernel of dimensions $m \times m = 9 \times 9$, mean $\mu = 0$ and variance $\sigma = 1.82$, $G_{m\mu,\sigma2} = G_{90,1.82}$. Secondly, a background image IB, is produced by applying a 69×69 mean filter . When this filter is applied to the pixels in the FOV near the border, the results are strongly biased by the external dark region. To overcome this problem, out-of-the FOV gray-levels are replaced by average gray-levels in the remaining pixels in the square. Then, the difference D between Iγ and IB is calculated for every pixel

$$D(x,y)=I\gamma(x,y)-IB(x,y) \qquad (1)$$

To this respect, literature reports shade-correction methods based on the subtraction of the background image from the original image [12] or the division of the latter by the former [13]. Both procedures rendered similar results upon testing. Moreover, none of them showed to contribute any appreciable advantage relative to the other. The subtractive approach in (1) was used in the present work.

Finally, a shade-corrected image ISC is obtained by transforming linearly RD values into integers covering the whole range of possible gray-levels ($[0-255]$, referred to 8-bit images).The proposed shade-correction algorithm is observed to reduce background intensity variations and enhance contrast in relation to the original green channel image.

Besides the background intensity variations in images, intensities can reveal significant variations between images due to different illumination conditions in the acquisition process. In order to reduce this influence, a homogenized image IH [Fig. 3(a)] is produced as follows: the histogram of ISC is displaced toward the middle of the gray-scale by modifying pixel intensities according to the following gray-level global transformation function:

gout = 0 ; for g < 0
=255 ; for g > 255 (2)
= g ; otherwise
Where,
g=gin+128−gin-max (3)
gin= gray level variable of shade corrected image (ISC)
out = gray level variable of homogeneous image (IH)
gin-max= gray level containing highest no. of pixel in ISC.

By means of this operation, pixels with gray-level gin-max , which are observed to correspond to the background of the retina, are set to 128 for 8-bit images.

Thus, background pixels in images with different illumination conditions will standardize their intensity around this value.

D. Vessel Enhancement

The final preprocessing step consists on generating a new vessel-enhanced image (IVE), which proves more suitable for further extraction of gray level based features. Vessel enhancement is performed by estimating the complementary image of the homogenized image IH , IHC, and subsequently applying the morphological Top-Hat transformation

IVE=IHCγ(IHC) (4)

Where γ is a morphological opening operation using a disc of eight pixels in radius. Thus, while bright retinal structures are removed (i.e., optic disc, possible presence of exudates or reflection artifacts), the darker structures remaining after the opening operation become enhanced (i.e., blood vessels, fovea, possible presence of microaneurysms or hemorrhages). Samples of vessel enhancement operation results are for two fundus images with variable illumination conditions.

Fig .4.(a) Homogenized Image IH (b) Vessel Enhanced Image IVE

V.DETECTION OF NEOVASCULARIZATION

The study of the blood vessel is very important for the detection of the neovascularization. Neovascularization is the appearance of new blood vessels in the fundus area and inside the optical disk which is the sign of proliferative diabetic retinopathy (PDR). So the segmentation of blood vessel becomes important step to detect neovascularization. have proposed the system which gives an automated method for the blood vessel enhancement and segmentation. A preprocessing algorithm given in [11] is applied to remove the background and noise from the image. It takes colored retinal image as a input. This algorithm uses 2D Gabor wavelet for vessel enhancement [15]. For vessel enhancement normally matched filters (MFs) are used but the drawback is that MFs not only enhance blood vessels edges they also enhance bright lesions. So 2D Gabor wavelet is best option due to its directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies. By performing subsequent iteration of decreasing threshold the segmented image is skeletonized to eliminate falls edges . In order to find abnormal vessels, a window of size 15 x 15 is slided over segmented blood vessels. For each position energy and density of blood vessels are computed and if they are more than the normal behavior of blood vessels then that segment contains abnormal blood vessel which is a sign of PDR.

VI.FEATURE EXTRATION

To recognize or classify an object in an image, one must first extract some features out of the image, and then use these features inside a pattern classifier to obtain the final class.

Feature extraction (or detection) aims to locate significant feature regions on images depending on their intrinsic characteristics and applications. These regions can be defined in global or local neighborhood and distinguished by shapes, textures, sizes, intensities, statistical properties, and so on. Local feature extraction methods are divided into intensity based and structure based. Intensity-based methods analyze local intensity patterns to find regions that satisfy desired uniqueness or stability criteria. Structure-based methods detect image structures such as edges, lines, corners, circles, ellipses, and so on. Feature extraction tends to identify the characteristic features that can form a good representation of the object, so as to discriminate across the object category with tolerance of variations.Gray level based Feature are the features based on the differences between the gray-level in the candidate pixel and a statistical value representative of its surroundings. Since blood vessels are always darker than their surroundings, features based on describing gray-level variation in the surroundings of candidate pixels seem a good choice. A set of gray-level-based descriptors taking this information into account were derived from considering only a small pixel region homogenized images IH centered on the described pixel (x,y). swx,y stands for the set of coordinates in a w × w sized square window centered on point (x,y) . Then, these descriptors can be expressed as

F1(x,y)=IVE(x,y)　　　　　　(5)
F2(x,y)=meanIVEx,y　　　　　(6)
S3×3x,y

VII.CLASSIFICATION

In the feature extraction stage, each pixel from a fundus imageis characterized by a vector in a 2-D feature space such as:

F(x,y) = (f1(x,y), f2(x,y))　　　　(7)

After that classification procedure assigns class C1 as Vessel and C2 as Nonvessel to every candidate pixel. Since training dataset available for testing algorithm was not linearly separable because of the presence of vasculature structures. Some of nonlinear classifier can be found in the existing literature on Bayesian classifier, Neural network, Support Vector Machine , and kNN method . In the proposed method feed forward back propagation neural network is selected. There are two stages of neural network, one is design stage and other is application stage. In design stage configuration and training of neural network is performed. In application stage trained neural network is used to classify every pixel as Vessel or Nonvessel to obtain binary vessel image.

A. Neural Network Design:

A multilayer feedforward network, consisting of an input layer, three hidden layers and an output layer, is adopted in this paper. The input layer is composed by a number of neuron
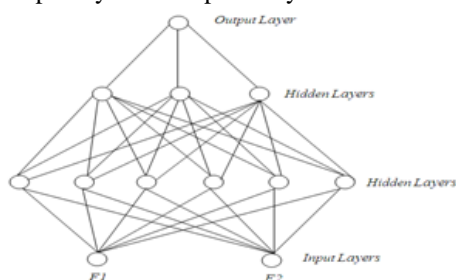

Fig.4.Structure of the Multilayer Perceptron Neural Network

equal to the dimension of the feature vector (two neurons). Regarding the hidden layers, several topologies with different numbers of neurons were tested. A number of two hidden layers, each containing 6 and 3 neurons, provided optimal NN configuration. The output layer contains a single neuron and is attached, as the remainder units, to a nonlinear logistic sigmoid activation function, so its output ranges between 0 and 1. This choice was grounded on the fact of interpreting NN output as posterior probabilities.The training set, ST , is composed of a set of N candidates for which the feature vector [F- (7)], and the classification result (C1 or C2 : vessel or nonvessel) are known

ST={F(n), Ck(n) n=1,2…,N; K∈{1,2}}　　　(8)

The samples forming were collected from manually labeled non vessel and vessel pixels in the DRIVE training images. Specifically, around 48,000 pixel samples, fairly divided into vessel and non-vessel pixels, were used. Unlike other author [8], who selected their training set by random pixel-sample extraction from available manual segmentations of DRIVE and

STARE images, we produced our own training set by hand.1 As discussed in literature, gold-standard images may contain errors due to the considerable difficulty involved by the creation of these handmade images.

B. Neural Network Application

At this stage, the trained NN is applied to an "unseen" fundus image to generate a binary image in which   blood vessels are identified from retinal background: pixels' mathematical descriptions are individually passed through the NN. In our case, the NN input units receive the set of features.

Since a logistic sigmoidal activation unction wfas selected for the single neuron of the output layer, the NN decision determines a classification value between 0 and 1. Thus, a

Fig.5.Output of Vessel Segmentation Method

vessel probability map indicating the probability for the pixel to be part of a vessel is produced. Illustratively, the resultant probability map corresponding to a DRIVE database fundus image [Fig.5] is shown as an image in Fig.5. The bright pixels in this image indicate higher probability of being vessel pixel. In order to obtain a vessel binary segmentation, a thresholding scheme on the probability map is used to decide whether a particular pixel is part of a vessel or not. Therefore, the classification procedure assigns one of the classes C1 (vessel) or C2 (nonvessel) to each candidate pixel, depending on if its associated probability is greater than a threshold Th . Thus, a classification output image ICO , is obtained by associating classes C1 and C2 to the gray level values 255 and 0, respectively. Mathematically

ICO = { 255 (= C1) , if p(C1| F(x,y)) ⩾ Th　　(9)
0 (= C2) ,
otherwise

where p(C1| F(x,y)) denotes the probability of a pixel (x,y) described by feature vector F(x,y) to belong to class C1. The optimum value of Th is selected as 80.

VIII.MICROANEURYSMS DETECTION

For microaneurysms detection we consider the output of vessel segmentation process i.e. IVE and after that the intensity of the image is adjusted such that intensity values in grayscale image IVE to new values in intensity adjusted image, IAI such that 1% of data is saturated at low and high intensities of IVE. This increases the contrast of the output image IAI. In addition to this it will also enhance microaneurysms structure which were difficult to identify in the vessel enhance image, IVE as shown in fig 6.

Fig.6. Final Vessel Image
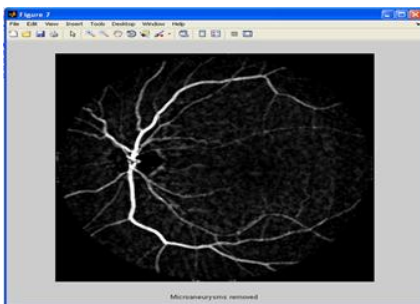

Fig.7. Intensity Adjusted Image

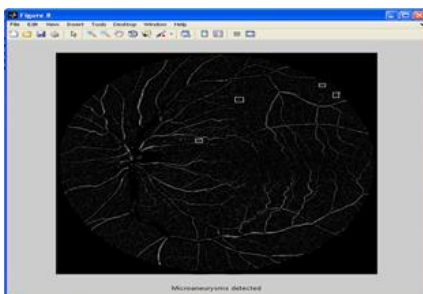**Fig.8. Morphologically opened to remove Microaneurysms**

Fig.9..Difference image IMD

IX.CONCLUSION

The proposed algorithm is able to detect the microaneurysms from the fundus image without the need of doing fundus flourescene angiography and it is simple, flexible and robust. Vessel segmentation has been done using two pixel feature,

still an appreciable accuracy is attained. The advantage of the proposed method is less computation time, so that an ophthalmologist can concentrate on more severe patients rather than testing every patient. With such a screening system a person with little training can able to do testing of patient so it is not necessary to have expert ophthalmologist. Since this system is able to detect microaneurysms at earliest stage there will be remarkable cost saving in treatment.

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