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Feature Selection For Disease Monitoring By Means Of Support Vector Machine

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Abstract:

Eye disease is a major cause of preventableblindness in the world. It is a complication of diabetes whichcan also affect various parts of the body. When the smallblood vessels have a high level of glucose in the retina, thevision will be blurred and can cause blindness eventually.This is known as diabetic retinopathy. Regular screening isessential in order detect the early stages of diabeticretinopathy for timely treatment to prevent or delay furtherdeterioration.This project describe a method for automaticallydetecting new vessels on the optic disc using retinalphotography.Abnormal vessels are segmented using watershed segmentation. Features are extracted from the image. The main aim of this project is to develop a computer-based approach to detect the different diabetic retinopathy stages using fundus images.

Key words: *Segmentation,Features Extraction,disease monitoring.*

1. Introduction

Diabetes is fast becoming an epidemic around the world andespecially in the Indian society. This is leading to Diabetesrelated disorders like Diabetic Retinopathy (DR). When thesmall blood vessels have a high level of glucose in the retina,the vision will be blurred and can cause blindness eventually.The main mechanism by which vision is lost due to diabeticretinopathy is proliferative retinopathy.Proliferativeretinopathy is the more serious condition as it involves thedevelopment of new vessels which are prone to bleedandultimately retinal detachment occurs.These complications if not dealt with on time can lead to lot of disability on the part of the patient and huge cost and work load on the specialists and the government. Hence there is a need to develop an automated

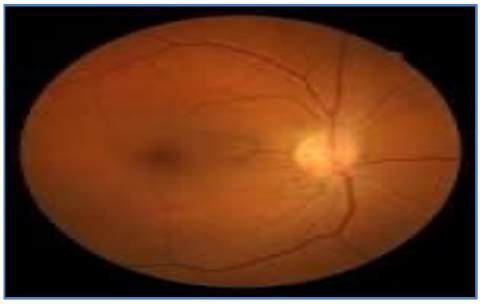

Figure 1: Retinopathic image

diagnostic system to expedite the work of the practitioner and reduce morbidity of the patients.Color fundus images are used by ophthalmologists to study eye diseases like diabetic retinopathy.Figure.1 shows a typical retinal image labeled with various feature components of Diabetic Retinopathy. Microaneurysms are small saccularpouches caused by local distension of capillary walls andappear as small red dots. This may also lead to big blood clots called hemorrhages.Hard exudates are yellow lipid circular region from where the blood vessels emanate is called the optic disk. The foveadefines the center of the retina, and is the region of highest visual acuity. These deposits which appear as bright yellow lesions. The bright spatial distribution of exudates and microaneurysms and hemorrhages, especially in relation to the fovea can be used to determine the severity of diabeticretinopathy.

2. Related Work

Detection of microaneurysm by using the diameter closing and an automatic threshold scheme[2]. Some investigations have been made for detecting haemorrhages and exudates.This uses the high grey level variation for detecting exudates.Some methods that uses neural network-based shape recognition to detect venous bleeding[7]. In this paper proposed method by combining the prior works of Optic Disc Segmentation and detection of new vessels to detect disease Proliferative Diabetic Retinopathy. Since the optic disc is the entry point of most of the blood vessels, focused on the

attention towards the optic disc. A number of studies regarding the detection of microaneurysm is the sign of diabetic retinopathy[5][8]. The work was based on the algorithm that enhances the features and classifies it as based on the intensity and size of thefeatures[8]. Analying the performance of different matching algorithmswith respect to the detection of blood vessels in the retinalimages for both gray level and color images[9]. Blood vesselsdetection using 2D Gaussian matched filtering gives the complete and continuous vessel map of the blood vessels[15].Many of the features such as blood vessel, exudates and optic disk are accurately measured using morphological operations[6].It also classifies the segmented regions into disjoint classes, exudates and non-exudates and comparing theperformance of various classifiers[4][6] by using Backpropagationneural network (BPNN), the Bayesian neuralnetwork (BNN).

3.Methodology

3.1.Pre Processing

Patient movement, poor focus, bad positioning, reflections, inadequate illumination can cause a significant proportion of images to be of such poor quality as to interfere with analysis.Blood vessels are extracted in this paper for the identification of diabetic retinopathy.

The contrast of the fundus image tends to be bright in the centre and diminish at the side, hence preprocessing is essential to minimize this effect. Preprocessing of such images can ensure adequate level of success in the automated abnormality detection.

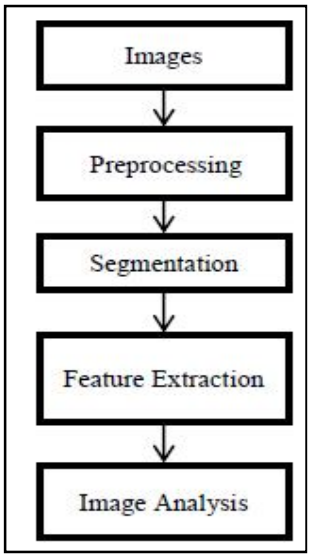

Figure 2:Flow diagram

3.1.1.The Green Plane Extraction

The green color plane is used in the analysis since it shows the best contrast between the blood vessels and retina. Next, the color space of the image is adjusted to gray image, extracting only the intensity component of the original image.

3.1.2.Resampling

Resampling refers to change the pixel dimensions of an image primarily for viewing. Nearest neighbor determines the grey level from the closest pixel to the input coordinates, and assigns that value to the output coordinates.

This method is considered as the most efficient in terms of computation time. Because it does not alter the grey level value a nearest neighbor interpolation in the grey level need to be retained if the image is to be resampled.

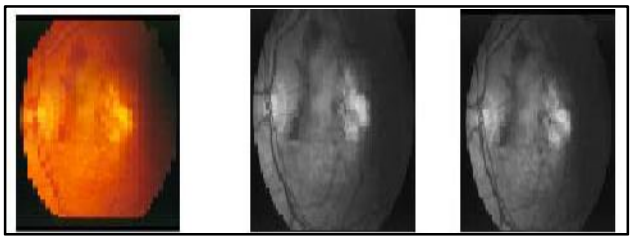

Figure 3:(a) Input image (b) The Green channel image (c)Resampled image

3.2.Segmentation

The consequence is that watershed transformations produce usually over-segmented image. Segmentation using the watershed transform works better if we can identify or "mark"foreground objects and background locations. The watershed transform can be classified as a region-based segmentation approach.

3.2.1.Marker Controlled Watershed Segmentation

Marker-controlled watershed segmentation follows some basic procedure to compute a segmentation function. By computing foreground markers background markers. Modification of the segmentation function so that it only has minima at the foreground and background marker locations. Hence it is the watershed transform of the modified segmentation function. Segmentation using the watershed transform works better if you can identify, or "mark," foreground objects and background locations. Usually external markers, or pixels belong to the background and internal markers specify the target location.

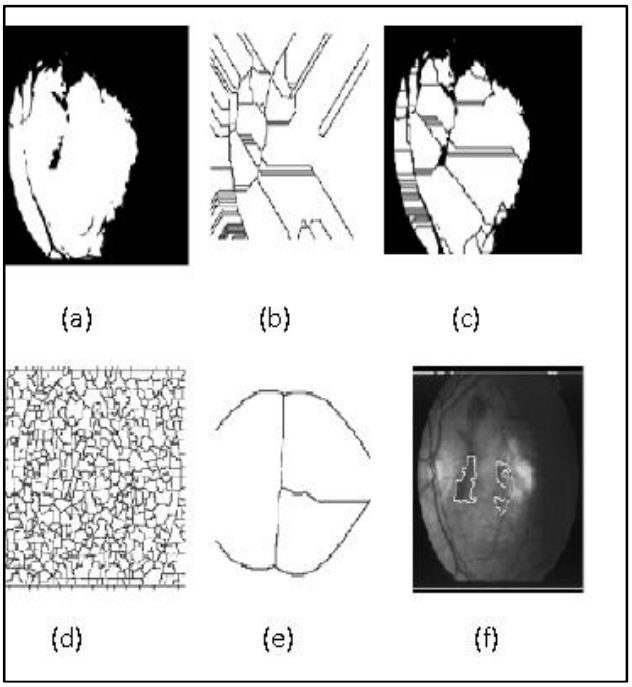

Figure 4: watershed segmentation on an image of data set (a) Binary image, (b) Distance transformed image,(c) Superimposed image, (d) Watershed transformed image,(e) Marker controlled image, (d) Marker controlled watershed transformed image.

3.3.Feature Extraction

The aim of the feature extraction stage is characterized by means of feature vector, a pixel representation in terms of some quantifiable measurements which may be easily used in the classification stage.One of the most important aspects of diabetic retinopathy identification process is the feature extraction from the image data. The purpose of feature extraction is to reduce data by measuring certain properties, which distinguish input patterns.

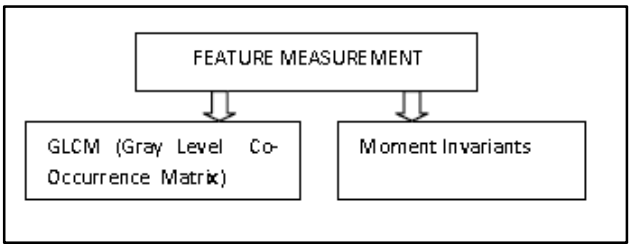

Figure 2

An object is characterized by measurements, whose values are very similar for objects in the same class.

3.3.1.Moment Invariants

Features based on moment invariants for describing small image regions formedby the gray-scale values of a window centered on the represented pixels.Moment invariants have been frequentlyused as features forimage processing shape recognition. Moments can provide characteristics of an object that uniquely represent its shape.Hu that first set out the mathematical foundationfor two-dimensional moment invariants.The invariant featurescan be achieved using central moments, which are defined asfollows:

$\mu pq=\iint (x-\bar{x})(y-\bar{y})f(x,y)dx\,dy$ (1)

p,q = 0,1….

$\bar{x}$=m10/m00 (2)

$\bar{y}$=m01⁄m00 (3)

The pixel point $(\bar{x},\bar{y})$ are the centroid of the image. Thenormalized central moments are defined as follows:

Hpq=μpq/μγ00(4)

γ=[(p+q)/2]+1 (5)

μ*pq*computed using the centroid of the image is equivalentto the mpq whose center has been shifted to centroid of theimage. Therefore, the central moments are invariant to imagetranslations. In terms of the central moments, the sevenmoments are given as,

- M1 = (η20 + η02),
- M2 = (η20 −η02)2 + 4η2
- M3 = (η30 −3η12)2 + (3η21 −η03)2,
- M4 = (η30 + η12)2 + (η21 + η03)2,
- M5 = (η30 −3η12)(η30 + η12)[(η30 + η12)2– 3(η21 + η03)2] + (3η21 −η03)(η21 + η03)[3(η30 + η12)2 −(η21 + η03)2],
- M6 =(η20−η02)[(η30+η12)2−(η21+η03)2]+4η11(η30 +η12)(η21+ η03),
- *M7 = (3η21 − η03)(η30 + η12)[(η30 + η12)2− 3(η21 + η03)2] –(η30 + 3η12)(η21 + η03)[3(η30 +η12)2 − (η21 + η03)2]* .(6)

3.3.2.Gray Level Co-occurrence Matrix

Features based on the differences between the gray-level in the particular pixel and a statistical value representative of its surroundings.In 1973, Haralick introduced the co-occurrence matrix and histexture features which are the most popular second-order statistical features. Texture features can be extracted in several methods, namely:statistical,structural,model-based,and transform information. Each method has different techniques.Best algorithm to extract texture features is the use of Gray Level Co-occurrence Matrices (GLCMs).Texture is a significant feature of an image that has been widely used in medical image analysis, image classification, automatic visual inspection, content-based image retrieval, and remote sensing. The GLCM defines the probablitiy of joining two pixels i andj with distance d. Haralick proposed two steps for texture feature extraction:

Moment Invariant Features	Image1	Image2	Image3	Image4
M1	6.189765	6.228532	6.029539	6.468739
M2	18.73726	19.95227	18.34357	23.12302
M3	25.20876	26.33469	25.35447	26.97498
M4	23.05345	22.50894	22.22065	25.98606
M5	47.73730	47.09200	47.79942	54.92515
M6	35.91640	33.16931	32.13368	37.88696
M7	47.68054	48.28983	47.26928	

Table 1: Moment Invariant feature values for Various images.

GLCM Features and their corresponding formulae

Entropy=Σln(Pij)pij

Energy=Σ(Pij)^2

Homogeneity=ΣPij÷((1+(i-j)^2))

Correlation=ΣPij (i-μ)(j-μ)/Σiσj

Cluster Shade =ΣPij(i-j)^2

Cluster Prominence =Σ((i-μi)+(j-μj))^4 c(i,j)

Dissimilarity =ΣPij(i-j)

Variance = ΣΣ(i-μ)^2 p(i,j)

Max probability = Max(Pij)

Autocorrelation = ΣΣPij/(1+|i-j|)

P(i,j) - probability corresponding to the ith row and jth

column.

μi, μj – mean

σi, σj- standard deviation.

Features	**Image1**	**Image2**	**Image3**	**Image4**
Maximum Probability	0.3645	0.4494	0.4255	0.3653
Contrast	0.0930	0.0825	0.1877	0.0921
Correlation	0.9437	0.9293	0.9517	0.9615
Cluster Prominence	29.973	21.643	28.673	26.712
Cluster shade	0.9978	2.2594	3.7651	2.6731
Dissimilarity	0.0779	0.0819	0.0576	0.0674
Energy	0.2779	0.332	0.6743	0.8435
Entrophy	1.5309	1.4106	0.9258	1.4571
Homogenetiy1	0.9633	0.4591	0.9242	0.7633
Homogenetiy2	0.9626	0.4944	0.9424	0.6543
Auto Correlation	5.756	4.5094	6.4356	4.9867

Table 2: GLCM Feature values for various images

4. Conclusion

Marker controlled watershed segmentation segments the abnormal blood vessels. Then feature extraction involves extracting feature values from various fundus images. The work can be extended by selecting the valid features and to classify them based on abnormalities which will demonstrate an automated system which is able to distinguish normal and abnormal vasculature on the optic disc. It could form part of a system to reduce manual grading and a workload or a tool to prioritize patient grading queues.

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