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Classification of Diabetic Retinopathy Using Image Processing and Soft Computing Techniques

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Abstract: Diabetic retinopathy is a neovascular disorder caused by diabetes and for severe cases; it may also lead to blindness. Hence early detection is very useful to prevent this catastrophe. We have proposed an automated method to detect Diabetic retinopathy and categorize it as diabetic retinopathy proliferative (DRP) or diabetic retinopathy non-proliferative (DRNP). The proposed automated method is implemented in three stages, viz., image processing, feature extraction & dimension reduction and classification. In the first stage we have applied Canny edge detection and histogram equalization methods to improve the feature enhancement of the given input image. In the second stage we have employed principal component analysis (PCA) for feature extraction and dimensionality reduction. In third stage, support vector machines (SVM) and neural networks (NN) of soft computing techniques have been employed for classifying the given fundus image into DRP or DRNP. We tested our method with various fundus images and the preliminary results show that SVM is better than NN for this purpose.

Keywords: Diabetic retinopathy, fundus images, principal component analysis (PCA), support vector machines (SVMs), Neural Networks (NNs).

INTRODUCTION

The population of diabetic patients has been increasing against the total world population. Uncontrolled and prolonged diabetes can damage the vital organs of the body such as eyes and kidneys. The damage caused to the tiny blood vessels in the retina of the human eye, is known as **Diabetic Retinopathy (DR)**. According to the WHO[1], among the worldwide population, 346 million people are now suffered by diabetes and it is expected to rising towards 438 million by the year 2030. From the several guidelines many were planning and implementing services to manage DR. The detection of DR based on fundus images that are collected from various ophthalmologists. The manual process to identify the DR is somewhat complicated and it will take much time and effort. For that reason several works are going on and some automated methods are implemented by the professionals to easily identify the DR disease.

In 2000, Ege B.M. et al [1] is proposed an automated method to classify the diabetic retinopathy using digital images in their study they used several classifiers in those they got best results with Mahalanobis classifier. In 2001, Osareh A. et al. [2] is proposed a method to detect exudates regions by using fuzzy c-means clustering and classify the regions into exudates and non-exudates using artificial neural networks. Their result produced as 92% sensitivity and 82% specificity. In 2007, Niemeijer M. et al [3] proposed an automated method to detect exudates and cotton-wool spots in color images. In their method they used receiver operating characteristic curve (ROC) as matric and classify the images by using k nearest neighbors. They produced result as they got sensitivity/specificity like 0.95/0.86, 0.70/0.93 and 0.77/0.88 for the detection of exudates, cotton-wool spots and drusen. In 2010, Silberman N. et al [4] proposed an automated method to detect exudates and optic disc from retinal images by using support vector machines. They produced results as accuracy 98.4% for optic disk detection and 87% for exudates detection. In 2011, Gowda A. et al [5] is proposed a method to detect exudates by using back propagation neural network. They stated results as sensitivity is 96.97%, specificity is 100% and classification accuracy is 98.45%. In 2011, Kavitha S. and Duraiswamy K. [6] are focused on automated method to detect exudates on color fundus images either soft or hard exudates by using image processing techniques. In 2012, pilar perez et al [7] proposed an automated method to classify fundus images into diabetic retinopathy proliferative and non proliferative by using image processing and classification methods svm,nn and knn. They produced result as knn is gave best result.

We have proposed an automated method to classify the diabetic retinopathy images into two categories viz., diabetic retinopathy proliferative (DRP) and diabetic retinopathy non proliferative (DRNP). The automated method has three stages. In the first stage, image preprocessing techniques such as canny edge detection and histogram equalization methods have been applied for better feature extraction. In the second stage, Principal Component Analysis (PCA) has been employed to extract principal components as features. In the third stage, we have chosen Support Vector Machines (SVM) and Neural Networks two classify the given image into DRNP or

[1] www.who.org

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DRP. Our experimental result shows that Support Vector Machine is better than neural network. The remaining paper is organized as follows. Section 2 gives a brief about diabetic retinopathy. Section 3 describes the methodology that has been applied in this work. Section 4 shows the comparison study of SVM and NN for classifying the given input image as DRP or DRNP. Section 5 gives the future scope of the present work

DIABETIC RETINOPATHY

Diabetic retinopathy, the most common diabetic eye disease, occurs when blood vessels in the retina change. Sometimes these vessels swell and leak fluid or even close off completely. In other cases, abnormal new blood vessels grow on the surface of the retina. There are mainly two types of diabetic retinopathy disease; they are diabetic retinopathy non proliferative (DRNP) also called as Background diabetic retinopathy and diabetic retinopathy proliferative (DRP). These two diseases are explained below in details.

Diabetic Retinopathy Non-Proliferative (DRNP)

DRNP is the earliest stage of diabetic retinopathy. With this condition, damaged blood vessels in the retina begin to leak extra fluid and small amounts of blood into the eye. Sometimes, deposits of cholesterol or other fats from the blood may leak into the retina. DRNP can cause changes in the eye, because Micro aneurysms, hemorrhages, Hard exudates, Macular edema and Macular ischemia.

Diabetic Retinopathy Proliferative (DRP)

DRP mainly occurs when many of the blood vessels in the retina close, preventing enough blood flow. In an attempt to supply blood to the area where the original vessels closed, the retina responds by growing new blood vessels. This is called neovascularization. However, these new blood vessels are abnormal and do not supply the retina with proper blood flow. The new vessels are also often accompanied by scar tissue that may cause the retina to wrinkle or detach. DRP may cause more severe vision loss than DRNP because it can affect both central and peripheral vision. DRP affects vision in the following ways: Vitreous hemorrhage, Traction retinal detachment and Neovascular glaucoma.

PROPOSED AUTOMATED METHOD

We have proposed an automated method to classify the fundus images into two types either Diabetic retinopathy proliferative or Diabetic retinopathy non proliferative. The automated method has three stages; they are 1.image preprocessing, 2.feature extraction and 3.classification, which is also shown in the **fig 1.**

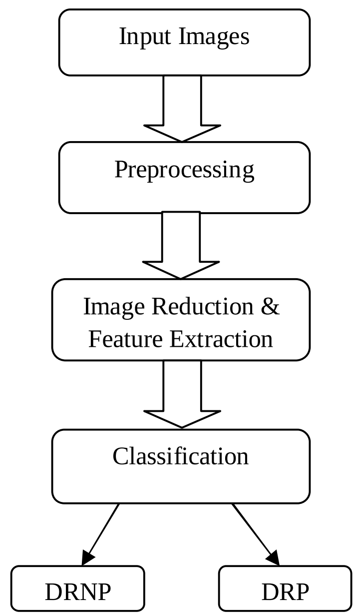

Fig 1: The overview of an automated method

Image Preprocessing

The purpose of this stage is to eliminate the noisy and improve the quality to images for identifying various features in next steps easily. At this stage we used canny edge detector [8] and histogram equalization [8] that should be shown in **fig 2.**

Canny Edge Detection:

Canny's development is based on a one dimensional continuous domain model of a step edge of amplitude h_E plus additive white Gaussian noise with standard deviation σ_n. It is assumed that edge detection is performed by convolving a one-dimensional continuous domain noisy edge signal *f(x)* with an antisymmetric impulse response function *h(x)*, which is of zero amplitude outside the range *[-W,W]*. An edge is marked at the local maximum of the convolved gradient f(x) * h(x).

Histogram Equalization:

Histogram equalization is a method for improving the image contrast and certain areas in the image are represented in brighter way. This will use cumulative distribution function and then use inverse distribution function for normalized image

Feature Extraction

In order to classify the given fundus image as DRP or DRNP, first we have to extract features.

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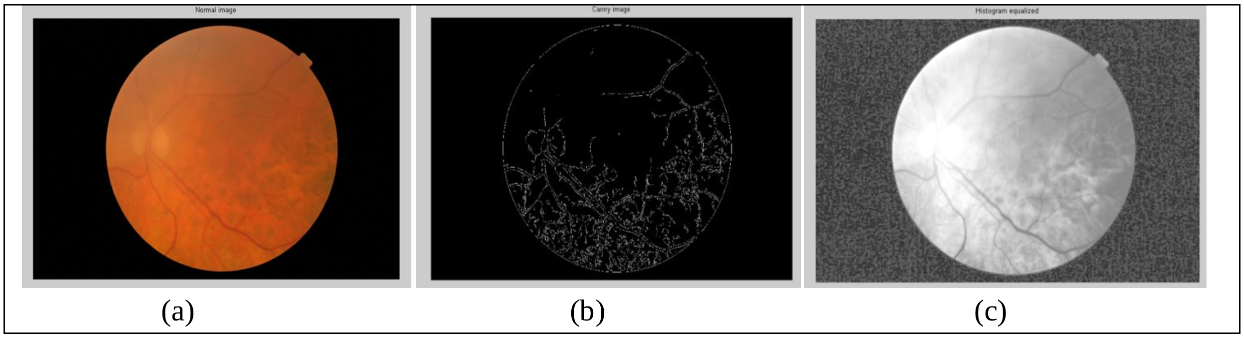

Fig 2: image preprocessing stage a) normal image, b) canny image, c) histogram equalized image

For feature extraction we have used PCA of M. Turk and A.Pentland[9]. This algorithm creates an eigen fundus images based on the concept of eigen faces [9]. In classification stage, we have to give important details (which are unique) of each image, train it as efficiently as possible, and compare one encoded image with a data set using a model encoder based on similarly. Therefore, we have used principal component analysis in order to find the significant features (principal components) of the distribution of the image data set.

The images in the dataset are represented as i_1, $i_2 \ldots i_N$ and for every image we need to create an Eigen vector Γi, and then find average image vector as shown in equation 1.

$$\overline{X} = \frac{1}{N}\sum_{i=1}^{N} \Gamma i \qquad (1)$$

Then subtract the fundus vector from the mean vector as given in equation 2.

$$\Phi i = \Gamma i - \overline{X} \qquad (2)$$

From this we calculate the Eigen values and Eigen vectors using covariance matrix and projected all the principal components in a lower dimensional subspace. These projected values are employed as features for classification purpose. In the next section we describe the techniques that have been employed for classification purpose.

Soft Computing Techniques

These techniques are used to classify the images either DRP or DRNP based on the input principal components.

Neural Networks

The neural networks are useful for learning tasks. The network is seems look like a human brain. It will contain the neurons and nodes that are interconnected. This network is useful for calculating the solutions easily for difficult problems. The network is structured as 3 layers. Those are input, hidden and output layers. In this method we are using feed forward network. Remaining details are in [10].

Support Vector Machines

The support vector machines (SVM) are part of the computational learning theory for structural risk minimization principal. The SVM is mainly useful for classify the dataset based on training dataset either linear separable or non linear separable cases. Mostly linear separable case is used by many classifications. In this case an optimal hyper plane is used for classification. In this maximum two output states are available so the test data either positive side or negative side placed based on training dataset. The non linear case mainly uses to represent datasets into high dimensional feature space using several kernels like polynomial, radial basis functions, Fourier series and splines according to the requirements. For further information about SVM please see [11].

EXPERIMENTAL WORKS

For our experimental purpose we have chosen Messidor database images of resolution 1440*990 with pupil dilated and without pupil dilated and also we have tested 150*130 images of resolutions of STARE database fundus images. The total no. of images is 300. In those 130 images are DRNP of 1440*990 and 110 are DRP images with same resolution. Similarly from STARE, 30 are DRP and 30 are DRNP images collected.

For the image preprocessing stage we have used techniques canny edge detection and histogram equalization methods for all images that are implemented

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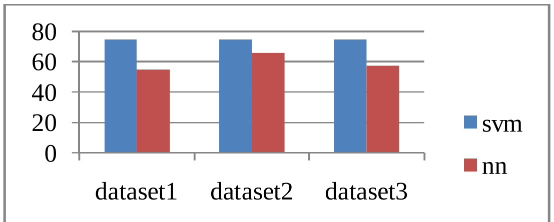
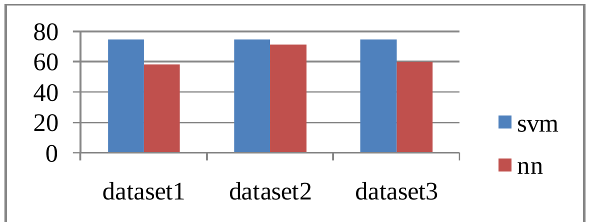
in mat lab software. The sample resulted images are shown in **fig 2**.

Table1: F-measure average for datasets

	150*130 fundus images (Dataset1)		1440*990 fundus images before pupil dilated (Datset2)		1440*990 fundus images after pupil dilated (Dataset3)	
	based on Canny	based on Histogram	based on Canny	based on Histogram	based on Canny	based on Histogram
SVM	65.0	70.0	68.0	74.0	62.0	66.0
NN	55.0	58.3	65.7	71.4	57.5	60.0



3a) canny based performance



3b) histogram based performance

Fig 3: Performances comparison between three datasets shown in fig 3a) and 3b).

In the feature extraction stage, we have extracted the features of the principal components from all images by using PCA of Turk and Pentland method [9]. In the classification stage we have used the soft computing techniques such as SVM and NN. From these classifiers we are calculating the performances of sensitivity, specificity and f-measure and shown in equations 3, 4 and 5 respectively.

Sensitivity or precision= TP/ (TP+FP) (3)

Specificity or recall= TP/ (TP+FN) (4)

F-measure= 2(precision*recall) / (precision+recall)* (5)

Where TP (True Positive) corresponds to the number of correct predictions for correct example, TN (True Negative) corresponds to the number of negative examples correctly predicted, FP (False Positive) corresponds to the number of negative examples wrongly predicted as positive and FN (False Negative) corresponds to the number of positive examples predicted as negative. The experimental results are shown in table1. The comparison between SVM and NN performances based on three datasets using canny and histogram methods is shown in figures 3(a) and 3(b).

CONCLUSIONS

We have presented an automated method to classify the fundus images. In this method we have used Canny edge detector, histogram equalization methods for image preprocessing, PCA is used for feature extraction and dimensionality reduction and finally SVM and NN have been employed for classifying the fundus image into either DRP or DRNP. From the preliminary results we have clearly verified that the histogram based images gave best results compared to canny. Our experimental results show that the SVM classifier is more suitable than NN for this work. For future work, we can use larger dataset; classify the given images into more categories and performance comparison between PCA and similar ones.

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