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A New Approach for Detection and Classification of Diabetic Retinopathy Using PNN and SVM Classifiers

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Abstract : *Diabetic Retinopathy (DR) is one of the leading retinal eye disease. In this disease, blood vessels of retina get damaged due to the leakage of blood and fluid in the surface of retina. The progression of disease will lead to the blindness or complete vision loss. Blood vessel extraction is very necessary for detection of diabetic retinopathy, as blood vessels get affected in DR. In this work, we have proposed a new method for blood vessel extraction. From the extracted vessels various features of blood vessels such as area, mean, standard deviation, energy, entropy, correlation, and homogeneity are calculated in order to distinguish different stages of DR. The different stages of disease are classified using two classifiers i.e. Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) classifiers. We demonstrate the same using a local database with good results. Also it is observed that PNN performs better than SVM.*

Keywords *- Diabetic Retinopathy (DR), Field of View (FOV), Fundoscopy, Graphical User Interface (GUI), Non-proliferative diabetic retinopathy (NPDR), Proliferative diabetic retinopathy (PDR).*

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I. Introduction

Human eye is an organ that reacts to light and sense the vision. Outer region of eye is coated with two layers cornea and sclera, while the interior portion of eye is coated with retinal layer [1]. Cornea is a transparent layer that covers the front part of the eye, while sclera is a white coating that covers the rest of the eye ball. Retina is an interior sensitive layer that contains sensitive receptors i.e. rods and cones that helps in vision making and an optic nerve responsible for transmitting information from brain to eye vice versa. To examine the internal retinal structure, various biomedical imaging techniques are being used by ophthalmologists.

World Health Organization (WHO) statistical data says that diabetes will be the 7th leading cause of death. The number of diabetes patients are increasing day by day due to obesity, bad diet, population growth, aging, urbanization, family history and physical inactivity. The total number of diabetes patients is predicted to increase from 171 million in 2000 to 366 million in 2030. Enlarging and leaking fluid from retinal blood vessels causes their impairment, which become leading cause of Diabetic retinopathy. Approximately 40% of diabetic patients suffer from diabetic retinopathy, out of which an estimated 5% face the sight threatening form of this disease, i.e. vision loss [2].

Fundoscopy is one of the techniques that enables the ophthalmologists to analyze the internal retinal structure and detect abnormalities, in case it exists. An image captured using fundoscopy, commonly known as fundus image that enables in visualizing internal eye structure which include optic nerve, optic disc region, macula, fovea and blood vessels in the internal retina [3].

The presence of diabetic retinopathy can be detected by examining the characteristics of the blood vessels. Therefore, blood vessel extraction plays a vital role in detecting diabetic retinopathy. This paper is organized as follows. A brief information diabetic retinopathy is given in section 2. In section 3 proposed algorithm for DR detection and classification schemes are described. In section 4 results obtained by proposed methodology are analyzed and according to that conclusion is made which is described in section 5.

II. Diabetic Retinopathy

Diabetic Retinopathy is one of the complicated vision disease. This is caused due to abnormalities in retina of diabetic patients. It occurs due to leakage of blood and protein from small diseased vessels into retina which serves as main cause of blindness among diabetic patients. Changes in blood vessel diameter, micro aneurysms, and exudates due to lipid and protein deposition, hemorrhages are the major symptoms of diabetic retinopathy [4]. Advance and effective image processing techniques can detect these symptoms from the retinal fundus images for automated diagnosis of the disease. This will help to protect from vision loss and blindness. Therefore, researches on automatic detection of diabetic retinopathy are very demanding and crucial now. Blood vessel segmentation plays an important role for detection of diabetic retinopathy. Several researchers have

developed many blood vessel segmentation algorithms, but finding the best segmentation algorithm is still a task.

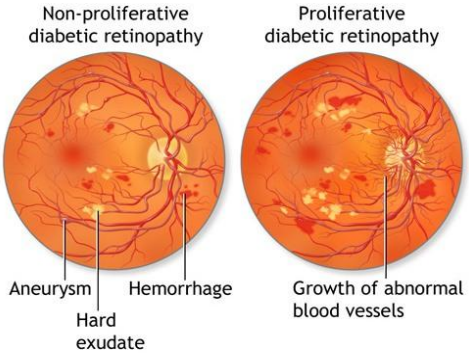

Fig. 1 Stages of Diabetic Retinopathy

Fig. 1 shows the different stages of diabetic retinopathy. There are mainly two stages of diabetic retinopathy i.e. non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). In NPDR stage, various features like micro-aneurysms, hemorrhages, soft exudates cotton wool spots are present. Depending upon number of these features the classification is performed. Accordingly, Non-proliferative stage can be categorized as Mild, Moderate, and Severe. In PDR stage, new abnormal blood vessels are formed at very high rate. This may result in severe vision loss [5].

III. Proposed Method

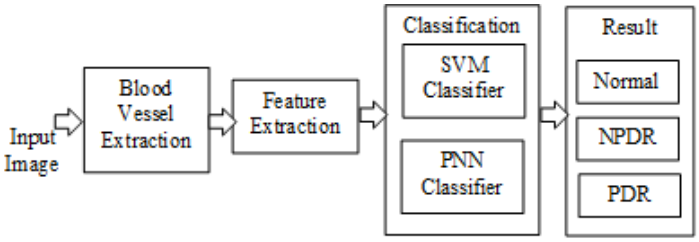

Fig. 2 Block diagram for proposed system

Fig. 2 shows the block diagram for the proposed system in which four basic function blocks are present. These blocks are explained in detail in further sections.

3.1 Database acquisition

A necessary tool for reliable evaluation and comparison of medical image processing algorithms is a database, which include a selected set of high quality medical images which are representatives of diabetic retinopathy and have been verified by experts. First, in order to conduct the experiment for detection of normal as well as abnormal retinal images, five publically available databases are used. They are: DRIVE (Digital Retinal Images for Vessel Extraction) [6], FIRE (Fundus Image Registration Dataset) [7], HRF (High Resolution Fundus database) [8], Color Fundus Image Dataset [9], DIARETDB1 (Diabetic retinopathy database and evaluation protocol) [10]. In this work, total 180 images are selected from all of these databases. Out of these images, 60 images are normal, 60 are from NPDR stage, and remaining 60 are from PDR stage. Out of each class 45 images are selected as training dataset and remaining 15 images from each are used as testing dataset. All of these images are resized at a resolution of 565×584 pixels in RGB color with 8 bits per color plane and some images are stored as TIF (Tagged Image Format), while other images are saved as JPEG (Joint Photographic Experts Group). All of these images are evaluated and validated by an ophthalmologist.

3.2 Blood Vessel Extraction Algorithm

The segmentation of blood vessels is very important in detection of diabetic retinopathy through image processing approach. In recent years many researchers, proposed various blood vessels segmentation approaches through morphological image processing techniques. Segmentation of blood vessels in retinal images provides early detection of disease. So, segmentation of blood vessels plays a vital role in detecting and curing the disease.

In the proposed method, illumination correction is performed to have a homogenous background by multiplying the constant correction factor followed by subtracting the median value. This is performed on original retinal image *I*. Then, pure green plane is extracted from the resultant image *I1*. This is because the green plane has maximum light absorbance capability than red and blue planes. Thus, it is used in analysis and detection of DR. The optic disk is removed by complimenting and morphological opening operation, so the resultant image is without optic disk. Then intensity value of an image is enhanced by scaling. From this scaled image, green plane is extracted for binarization process. This is done because binarization is performed only on 1-D image. The binarized image is finally filtered using median filtering to remove salt and pepper noise. The final image after median filtering gives extracted vessels from this algorithm.

3.3 Feature extraction

To distinguish between three stages of diabetic retinopathy, various statistical features of segmented vessels are determined. These statistical features are used as input to the classification system to identify the exact stage of diabetic retinopathy disease. Following are various features extracted from segmented vessels [11]:

1) Mean

It is an estimate of an intensity of all pixels in the input image. It is calculated as:

$$\mu = \frac{1}{N} \sum_{i,j=0}^{N-1} x_{i,j} \quad \text{..... “Equation 1”}$$

where, x is an image,

N is the number of grey levels in image x,

i, j are number of elements in image x

2) Standard Deviation

It is the square root of the variance. It is defined as:

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i,j=0}^{N-1} (x_i - \mu)^2} \quad \text{..... “Equation 2”}$$

where, μ is mean of an image

N is the number of grey levels in image x,

i, j The number of elements in image x

3) Entropy

It is statistical measure of randomness that can be used to characterize the texture of an input image. Entropy is defined as:

$$E = - \text{sum} [p. * \log_2 (p)] \quad \text{..... “Equation 3”}$$

Where, p contains the histogram counts, which is calculated using histogram of an image. If the input image has more than 2 dimensions, entropy function treats it as a multi-dimensional grey scale image and not as RGB image.

4) Area of white pixels

It is statistical measure that specifies the actual number of pixels in the region. Area of an individual pixel is determined by looking at its 2-by-2 neighborhood.

Grey Level Co-occurrence Matrix: GLCM is generated by cumulative the total number of grey level pairs from the vessel extracted image. Each GLCM will be generated by defining a spatial distance ‘d’ and an orientation which can be 0^0, 45^0, 95^0, 135^0 at selected grey level ‘g’. GLCM produced will be of size N × N. From the co-occurrence matrix, various parameters can be extracted, out of which following three parameters are selected:

5) Correlation

It is measure of how correlated a pixel is to its neighbor over the whole image. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. It is calculated as:

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)\, p(i,j)}{\sigma_i\, \sigma_j} \quad \text{..... “Equation 4”}$$

6) Energy

Energy of an image is the sum of the squared elements in the grey level co-occurrence matrix. It has a value 1 for a constant image. The feature energy is also known as uniformity, and angular second moment. It is calculated as:

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \text{……. “Equation 5”}$$

7) Homogeneity

It is a value that measures the closeness of the distribution of an element in grey level co-occurrence matrix to the grey level co-occurrence diagonal. Homogeneity is 1 for diagonal GLCM. It is defined as:

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \text{ ……. “Equation 6”}$$

3.4 Classification

Classification is an essential feature to separate large datasets into classes for the purpose of Rule generation, Decision Making, Pattern recognition, Dimensionality Reduction, Data Mining etc. The Neural networks have emerged as an important tool for classification. The Neural Network techniques can be divided into supervised, unsupervised and reinforced techniques. [12] In this work, two classifiers are implemented and used for classification of diabetic retinopathy stages. They are SVM and PNN classifier. They both lies under supervised learning approach. In the recent years, SVM classifiers and PNN classifiers have demonstrated excellent performance in a variety of pattern recognition problems. They are briefly explained as follows:

3.4.1 Support Vector Machine (SVM)

The support-vector network is machine learning for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high-dimension feature space. In this feature space a linear decision surface is constructed. Special properties of the decision surface ensures high generalization ability of the learning machine. Given a set of training examples, each marked as belonging to one or the other of two categories. More formally, a support vector machine constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression, or other tasks. The input space is mapped into a high dimensional feature space. Then the hyperplane that maximizes the margin of separation between classes is constructed. The points that lie closest to the decision surface are called support vectors and directly affect its location. When the classes are non-separable, the optimal hyperplane is the one that minimizes the probability of classification error.

An optimal hyperplane is here defined as the linear decision function with maximal margin between the vectors of the two classes. In Fig.3, it is observed that to construct such optimal hyperplanes one only has to take into acconnt a small amount of the training data, the so called support vectors, which determine this margin. It was shown that if the training vectors are separated without errors by an optimal hyperptane the expectation value of the probability of committing an error on a test example is bounded by the ratio between the expectation value of the number of support vectors and the number of training vectors.

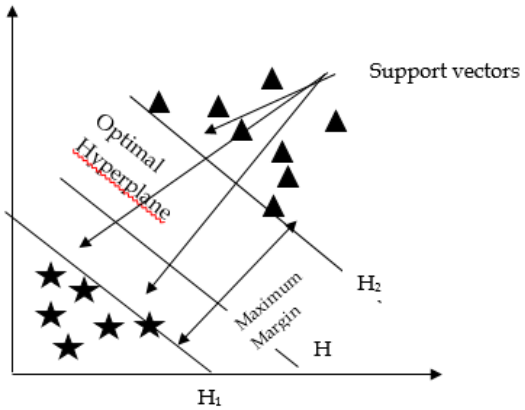

Fig. 3. Optimal Hyperplane, maximizing margin and support vectors

3.4.2 Probabilistic Neural Network (PNN)

A Probabilistic Neural Network (PNN) is widely used in classification and pattern recognition problems. In the PNN algorithm, the Parent Probability Distribution Function (PDF) of each class is approximated by a Parzen window and a non-parametric function. It is a feed forward neural network, which was obtained from the Bayesian network and a statistical algorithm called Kernel Fisher discriminant analysis. PNN is predominantly a classifier which maps any input pattern to a number of classifications. By this method, the probability of mis-classification is minimized.

The architecture of Probabilistic neural network for this system is shown in Fig.4. There are three layers in architecture first layer is input layer, second is radial basis layer, and third is competitive layer. When an input is presented, the RBS layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input. The competitive layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, *compete* transfer function on the output of the second layer picks the maximum of these probabilities, and produces a one for that class and a zero for the other classes.

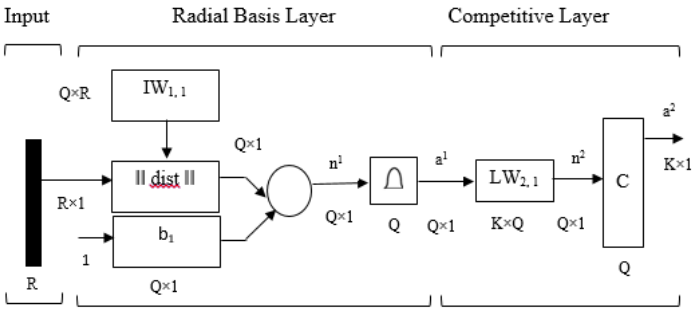

Fig. 4. Architecture of PNN Classifier

It is assumed that there are Q input vector/target vector pairs. Each target vector has K elements. One of these element is one and the rest is zero. Thus, each input vector is associated with one of K classes. The first layer input weights, $IW^{1,1}$ are set to the transpose of the matrix formed from the Q training pairs, P'. When an input is presented the ||dist|| box produces a vector whose elements indicate how close the input is to the vectors of the training set. These elements are multiplied, element by element, by the bias and sent the radbas transfer function. An input vector close to a training vector will be represented by a number close to one in the output vector a^1. If an input is close to several training vectors of a single class, it will be represented by several elements of a^1 that are close to one.

The second layer weights, $LW^{1,2}$, are set to the matrix T of target vectors. Each vector has a one only in the row associated with that particular class of input, and zeros elsewhere. The multiplication Ta^1 sums the elements of a^1 due to each of the K input classes. Finally, the second layer transfer function, compete, produces a one corresponding to the largest element of n^2, and zeros elsewhere. Thus, the network has classified the input vector into a specific one of K classes because that class had the maximum probability of being correct. A PNN is guaranteed to converge to a Bayesian classifier providing it is given enough training data. These networks generalize well [13].

IV. Results & Analysis

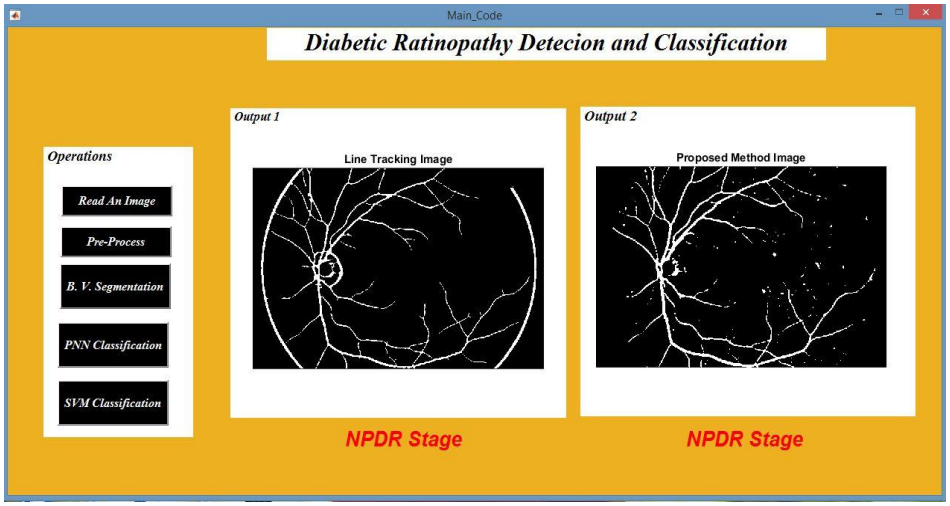

Fig. 5. GUI for proposed system

Fig. 5 shows the GUI for detection and classification of diabetic retinopathy. Efficiency of classifier is calculated by applying testing dataset to both classifiers. Table 1 shows classification result for both classifiers.

Table 1. Classification Results

Classes	No. of Training Images	No. of Testing Images	Correctly Classified by SVM	Correctly Classified by PNN
Normal	45	15	10	14
NPDR	45	15	10	15
PDR	45	15	6	15

From Table 1, it seen that SVM classifier is able to distinguish between normal and diseased stage, but for some images it is not able to distinguish between NPDR and PDR stage of Diabetic Retinopathy. While, PNN classifier shows the best results of classification for all testing images.

4.1. Performance Evaluation of Classifiers

Performance of classification for both classifiers can be examined by evaluating the performance of sensitivity, specificity, accuracy and precision. For this true positive (TP), true negative (TN), false positive (FP) and false negative (FN) parameters are calculated. From these parameters, additional parameters like sensitivity, specificity and accuracy are calculated and performance is verified. They are calculated using following formulas: [14]

Sensitivity: Measurement of true positive ratio

$$Sensitivity = \frac{TP}{TP+TN} \quad \text{“Equation 7”}$$

Specificity: Measurement of true negative ratio

$$Specificity = \frac{TN}{TN+FP} \quad \text{“Equation 8”}$$

Accuracy: Measurement of correct classification

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad \text{“Equation 9”}$$

Table 2 shows values for sensitivity, specificity, accuracy for three classes of eye images for both classifiers.

Table 2. Comparison between SVM and PNN classifier

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM	77.77	93.33	70
PNN	100	100	100

V. Conclusion

This Graphical User Interface (GUI) of proposed system aids the user to accomplish blood vessels segmentation in the diabetic retinopathy images. The Probabilistic Neural Network (PNN) and Support Vector Machine (SVM) classifiers successfully classify the different stages of diabetic retinopathy using proposed blood vessel extraction algorithm. PNN classifier gives 100% accuracy, while SVM classification gives 77.77% accuracy. The development of this automated detection and classification of diabetic retinopathy disease effectively work, thereby reducing the burden on ophthalmologists. In addition it helps to improve efficiency of diabetic screening program and reduction of cost is achieved.

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