International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 4 Issue 5, May 2015

Comparative Study of segmentation techniques in Diabetic Retinopathy Detection

Praveen S Palegar, Dr K.S. Prabhushetty

Abstract— **Diabetic retinopathy is the most common diabetic eye disease and a leading cause of blindness. However, if the symptoms are identified earlier and a proper treatment is provided through regular screenings, blindness can be avoided. In order to fasten the process of detection of diabetic retinopathy image processing techniques are used to detect the existence of exudates in the retinal images. In this paper, to diagnose diabetic retinopathy, three methods like Color Histogram Thresholding, Probabilistic Neural network (PNN) and Support vector machine (SVM) are described and their performances are compared.**

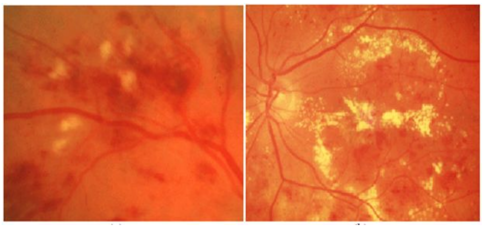
Index Terms—**Diabetic Retinopathy,Fundus Images,Exudates.**

I. INTRODUCTION

Patients identified with diabetes are likely to develop eye disorders namely cataracts and glaucoma and its effects on the retina may lead to vision loss. This study is called Diabetic Retinopathy (DR) which is produced by the damage to blood vessels of the retina . As diabetic patients population increases, screening for diabetic retinopathy has to be quicker which reduceses risk of blindness. Fundus images are employed for the purpose of detection and diagnosis of Diabetic retinopathy. Figure 1 depicts a typical retinal image labeled with various feature components of Diabetic Retinopathy. Diabetic retinopathy is caused by microvascular leakage in the retina. Because of the weakening of retinal capillary walls Serum lipoproteins leak from these microaneurysms and in the retina they get deposited as hard exudates. Hard exudates have a yellow waxy appearance with distinct margins and also vary in size. A white fluffy opaque lesion is formed and is known Soft exudates .

This paper focuses mainly on exudates for the reason that it provides information about early diabetic retinopathy. By employing color histogram, support vector machine and Probabilistic Neural Network methods we extract features in colour fundus image for the detection of hard and soft exudates, Which varifies existance of diabetic retinopathy. Along with this the performance of above methods are compared.

***Praveen S Plegar**,Dept of PG studies , VTU / Jnanasangama/ VTU belgaum, Belgaum, India, Phone/ Mobile No:08762101925*
***Dr K.S. Prabhushetty**, HOD, Dept of Electronics and Communication Engineering, VTU/ S.G Balekundri Institute of Technology, Belgaum, India, MobileNo9448304535.*



(a) (b)

Figure 1: An enlarge view of color fundus images showing exudates (a) Soft exudates (b) Hard exudates.

I. PROPOSED METHOD

The proposed integrated method for effective detection of exudates from color fundus retinal images is described in this section. . In this paper, to diagnose diabetic retinopathy, three methods like Color Histogram Thresholding, Probabilistic Neural network (PNN) and Support vector machine (SVM) are described and their performances are compared.

A. Color Histogram Thresholding

In imageprocessing and photography, a color histogram is a representation of the distribution of colors in an image. For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges, that span the image's color space, the set of all possible colors.

The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like RGBor HSV. For monochromatic images, the term intensity histogram may be used instead. For multi-spectral images, where each pixel is represented by an arbitrary number of measurements (for example, beyond the three measurements in RGB), the color histogram is *N*-dimensional, with N being the number of measurements taken. Each measurement has its own wavelength range of the light spectrum, some of which may be outside the visible spectrum.

B. Support Vector Machine

SVM is a robust technique for data classification and retrogression. SVM models search for a hyperplane that can linearly separate classes of objects (Fig.3). Support vector machine is used to discriminate the various categories. The support vector machine learning algorithm is applied to

ISSN: 2278 – 1323

produce the classification parameters according to calculated features.

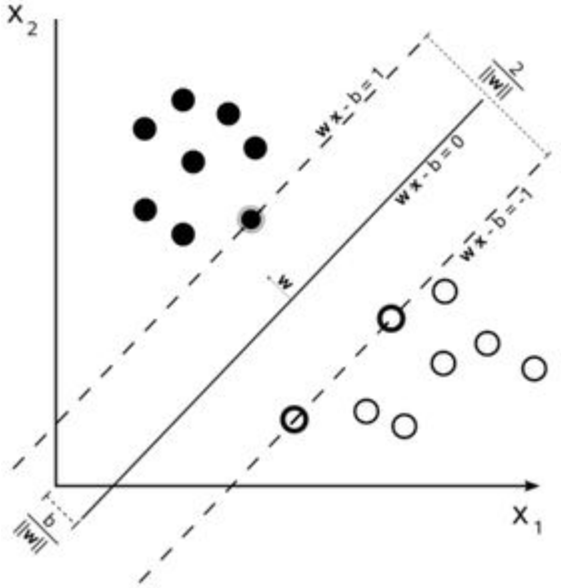


Figure.3: Architecture of SVM

The image content can be distinguished into the various categories in terms of the designed support vector classifier.. SVM can be applied to non-linear classification using non-linear kernel functions to map the input data onto a higher dimensional feature space in which the input data can be separated with a linear classifier (Fig. 3 b). Kernel function K(x,y) represents the inner product $\langle \emptyset(x), \emptyset(y) \rangle$ in feature space. In this work, we have used polynomial kernel which is given by,

$$K(x, x') = (x.x' + 1)^d \qquad (1)$$

Where x and x` are the training vectors, d is the kernel parameter. The size of the input training vector is 250 * 6. The output can be one of the three categories namely normal, NPDR and PDR.

A. Probabilistic Neural Network

The PNN was first proposed in [24].The architecture of a typical PNN is as shown in Fig. 4. The PNN architecture is composed of many interconnected processing units or neurons organized in successive layers. The input layer unit does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern x from the input layer, the neuron xij of the pattern layer computes its output.

$$\emptyset_{ij}(x) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d} exp\left[-\frac{(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}\right] \qquad (2)$$

where d denotes the dimension of the pattern vector x, σ is the smoothing parameter, and xij is the neuron vector .Suppose, Wdn is the input to the pattern layer for W_{dn} varies from 1, 2, ... 250, corresponding to 250 tested images and 'n' varies from 1, 2, ..., 6 corresponding to the feature vector. The pattern layer can be processed and the output layer has a node for each pattern classification. The sum for each hidden node is sent to the output layer and the highest values wins.

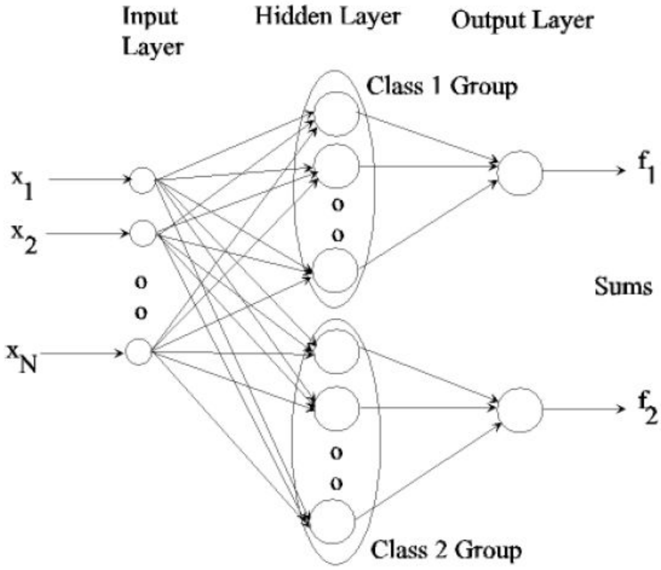


Figure.4: Architecture of Probabilistic neural Network

II. MATH

The Proposed method was implemented in Matlab and Microsoft Visual Basic 6.0. Figure 5 – Figure 8 are the snapshots for Color Histogram, PNN and SVM Output Results.

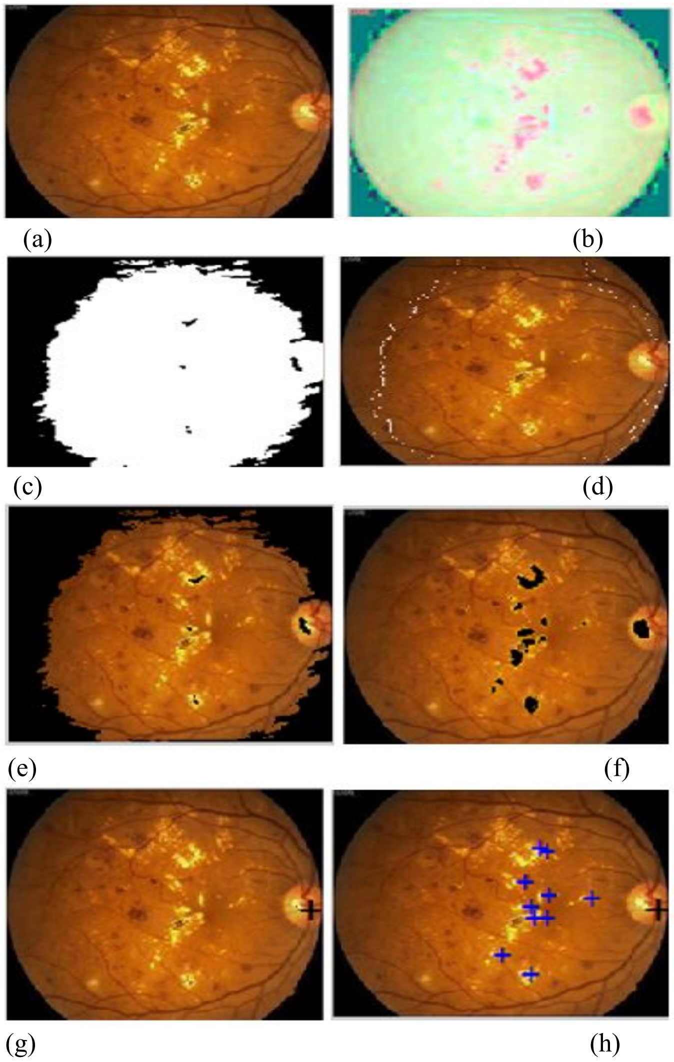


Figure 5: Color Histogram Output Results (a) Input Color

Fundus Retinal Image (b) CIELab Color Space Conversion (c) Fundus Mask (d) Area Used by the Algorithm (e) Segmented Image (f) Image showing the region marked with similar intensity (g) Optic Disc Localization (h) Classification of Soft and Hard Exudates.

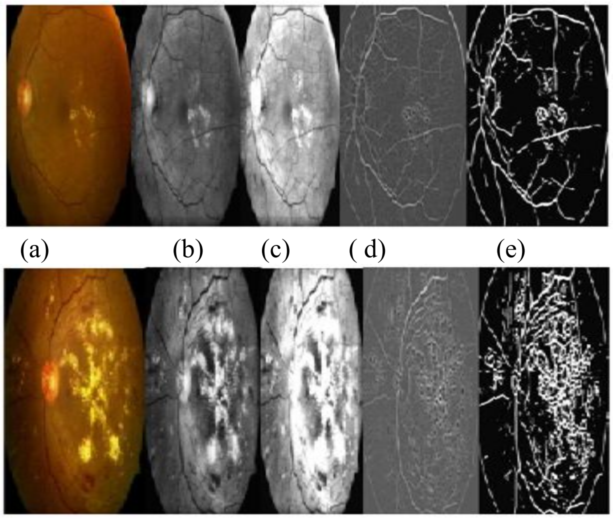


Figure. 6: PNN and SVM Output Results (a) NPDR affected Eye Image (f) PDR affected Eye Image (b),(g) Histogram Equalization (c),(h) Discrete Wavelet Transform (d),(i) Matched Filter Response (e),(j) Fuzzy C-means segmentation.

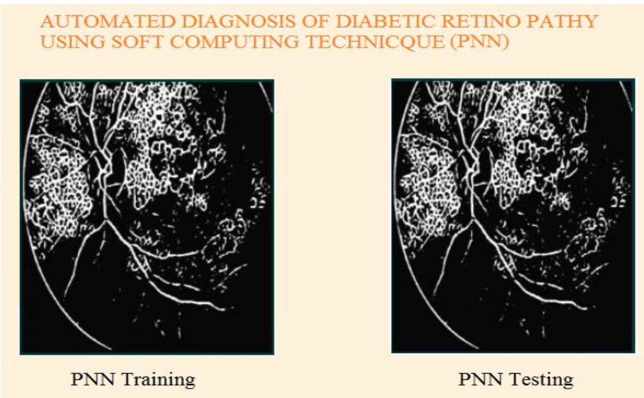


Figure. 7: Snapshots for PNN Classification.

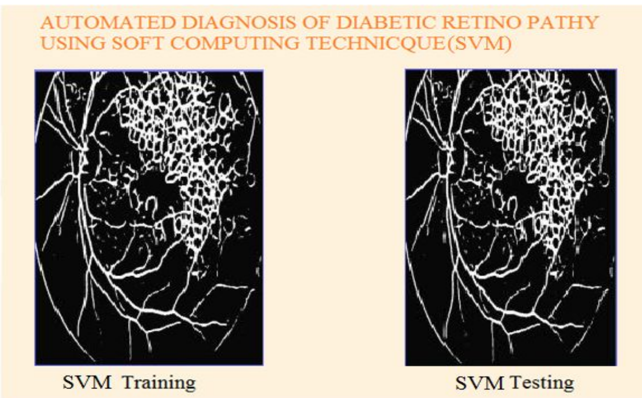


Figure. 8: Snapshots for SVM Classification.

III. PERFORMANCE MEASUREMENT

The results of the classification Procedures are shown in Table 1. Table 2 shows the result of Sensitivity, Specificity and Percentage of accuracy for the three classes of eye images using the Color Histogram Thresholding, PNN and SVM methods. Figure.9 gives the comparison of Accuracy, Sensitivity and Specificity for the three methods. Thus Color Histogram Thresholding method overwhelms SVM and PNN method.

Sensitivity=TP/(TP+FN) (3)

Specificity=TN/(TN+FP) (4)

Accuracy= (TP+TN)/(TP+FP+TN+FN) (5)

TABLE 1: RESULTS OF COLOR HISTOGRAM THRESHOLDING, PNN AND SVM CLASSIFICATION

Models	True Positive	True Negative	False Positive	False Negative
PNN	181	45	7	21
SVM	197	49	2	4
Color Histogram Thresholding	199	48	1	2

TABLE 2: RESULTS OF SENSITIVITY, SPECIFICITY, % OF ACCURACY

Models	Sensitivity	Spesificity	Accuracy
PNN	91	87	89.6
SVM	97	95	97.6
Color Histogram Thresholding	99	98	98.9

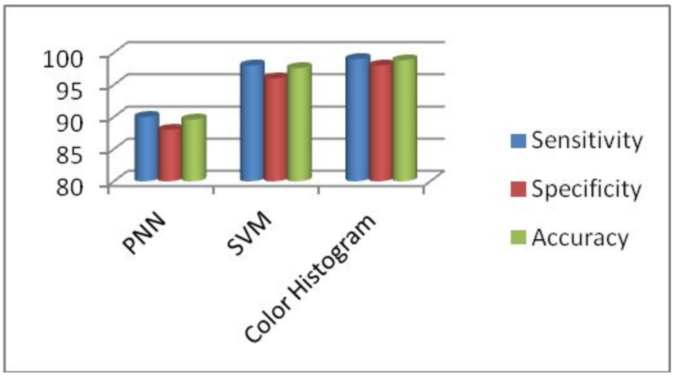


Figure 9: Graph for Comparison of Sensitivity, Specificity and Accuracy of PNN and SVM, and Color histogram Thresholding.

ISSN: 2278 – 1323

IV. Conclusion

In the diagnosis of diabetic retinopathy, image processing of color fundus images has a significant role to play. In this paper colour histogram, SVM and PNN methods used to diagonose the color fundus retinal images for exudates detection. All the three techniques used for the classification were good in performance, but Color Histogram Thresholding is more efficient than PNN and SVM from the obtained results. Thus this work has given a successful Diabetic Retinopathy Diagnosing method which helps to diagnose the disease in early stage which mutually reduces the manual work.

Acknowledgment

Authors are grateful to Mrs. Latha B M, Assistant professor, G M Institute of Technology, Davangere, Karnataka, India, for all the technical guidance, encouragement and analysis of the data throughout this process.

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Praveen S Palegar: M.tech in VLSI and EmbeddedSystem,DeptofPGstudeis,JnanaSangamaCampu,VTUbelgaum.

Dr K.S. Prabhushetty: HOD, Dept of Electronics and Communication Engineering, S.G Balekundri Institute of Technology, Belgaum, India.