APPLICATION OF FUZZY FOR DIABETIC RETINOPATHY ANALYSIS

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Abstract: Retinopathy analysis is necessary by automated system because as world is moving fast in progress with technology, a human illness and defect in visibility of eyes is also growing rapidly. According to project survey for this paper almost 50-52% of world population has problems in their visibility. A method for segmentation of the diabetic retinopathy based of the image. The original image is to be converted to gray scale image. Then adaptive histogram equalization is applied. The fuzzy c-means clustering is applied to segment the blood vessels in the image. Gray Level Co-variance Method (GLCM) is used to extract 22 features. Finally, the images are classified by PNN (probabilistic neural network) classification. Algorithm is implemented in MATLAB and tested for various numbers of retinal images.

Index Terms **- Retinopathy, Fuzzy C means, Probabilistic neural network, segmentation.**

I. INTRODUCTION

Diabetes is one of group of metabolic diseases in which a person have high blood sugar, either the body does not produce enough insulin, or because cells do not respond to insulin that is produced. Diabetic retinopathy is one of the common complications of diabetes. It is a severe and widely spread eye disease. It damages the small blood vessels in retina resulting in loss of visual capacity. The risk of the eye disease increases with age and therefore, middle aged humans and older diabetics are prone to Diabetic Retinopathy. No proliferative diabetic retinopathy is an initial stage of diabetic retinopathy. In this stage tiny blood vessels within the retinas leaks blood or fluid. The leaking fluid from retina causes the retina to swell or to form deposits called exudates. Proliferative diabetic retinopathy is an attempt by the eye to grow or re-supply the retina with new blood vessels, due to wide spreading closure of the retinal blood supply.

II. EXISTING SYSTEM AND PROPOSED SYSTEM

2.1 Existing System

In existing system, the various diagnostic like mammogram analysis, MRI brain analysis, bone etc., using neural network approach result in use of back propagation network, extreme learning machine recurrently. Hybrid approach of Genetic algorithm and Particle swarm optimization is also commonly used for feature extraction and feature selection.

2.2 Proposed System

In Here we are providing new methods in Diabetic Retinopathy disease which causes vision loss rapidly. The input colour retinal images are of poor quality in visibility. So they were pre-processed using Gray scale conversion for input images. Then Adaptive Histogram Equalization will be applied. In Discrete Wavelet Transform, Matched filter and fuzzy C means segmentation, Will be find for gray scale images from the pre-processed images features were extracted for classification process. It will provide the segmented of blood vessels. Finally, the images will classify by PNN.

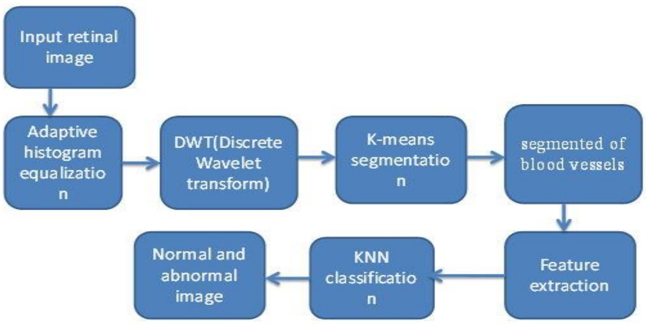

Figure 1: block diagram of proposed system

III. MODULES

This section comprises some of the literatures used for physiological signal measurement techniques developed by various researchers using non-invasive methods with their importance.

3.1 Pre-processing

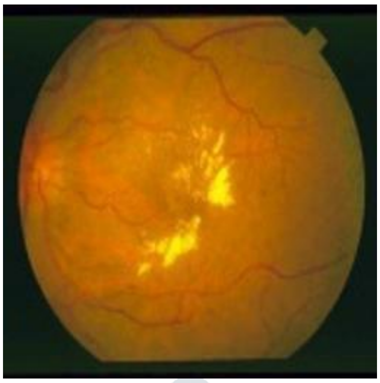

Figure 2: original input retinal image

In this module the input colour retinal images are of poor quality. So they were pre-processed using Grayscale conversion for input images.

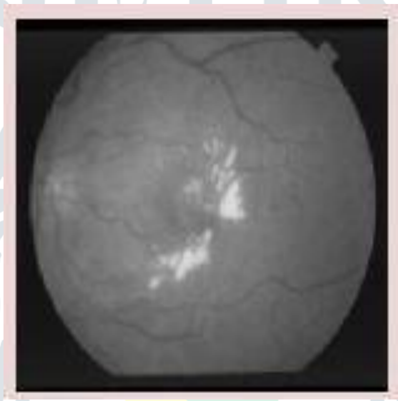

Figure 3: image after pre-processing

3.2 Adaptive Histogram Equalization

The original image will be converted to gray scale image. Then adaptive histogram equalization will be applied. Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from simple histogram equalization in respect that the adaptive method computes several histograms, each corresponding to a separate section of the image, and uses them to redistribute the lightness values of the image. Adaptive histogram equalization in it is a straightforward form presented above, both with and without contrast limiting, requires the computation of a different neighbor histograms and transformation function for each pixel in the image.

This thing makes the method very expensive computationally. Interpolation allows a significant improvement in efficiency without compromising the quality of the result. The image is partitioned into equally sized rectangular tiles as shown in the right part of the figure below. (64 squares in 8 columns and 8 rows is a common choice.) A histogram, Cumulative distributed function and transformation function is then computed for each of the squares.

The transformation functions are appropriate for the square center pixels- black squares in the left part of the figure. All other pixels are transformed with up to four transformation functions of the squares with center pixels closest to them, and are assigned interpolated values.

Pixels in the bulk of the image are bilinear interpolated, pixels close to the boundary are linearly interpolated, and pixels near corners are transformed with the transformation function of the corner square. The interpolation coefficients reflect the location of pixels between the closest square center pixels, so that the result is continuous as the pixel approaches near a square center.

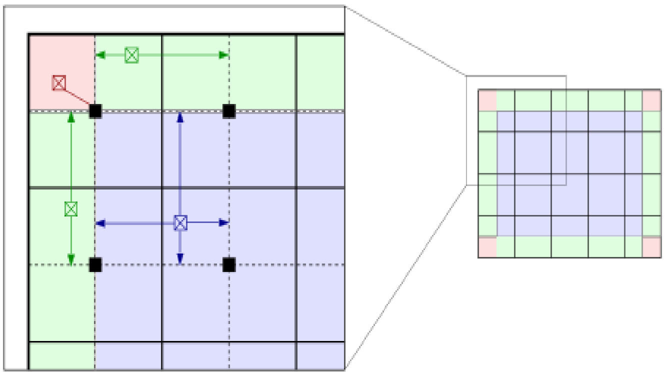

Figure 4: Pixel Approximation

This procedure reduces the number of transformation functions to be computed and only imposes the small additional cost of linear interpolation.

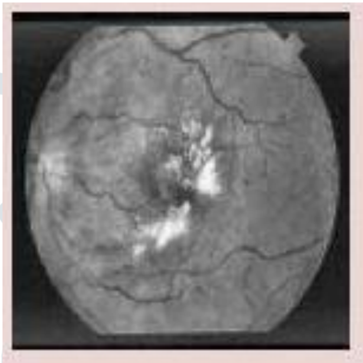

Figure 5: Histogram equalization Image

3.3 Discrete Wavelet Transform

Then discrete wavelet transform will be applied for adaptive histogram equalization image. A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretively sampled. As with other wavelet transforms, a key advantage it has is temporal resolution: it captures both frequency and location information. The discrete wavelet transform has a huge number of applications in engineering, mathematics and computer science. Most notably, it is used for signal coding, to represent a discrete signal in a more reducing form, often as a preconditioning for data compression. Practical applications can also be found in signal processing of accelerations for human gait analysis, in digital communications and many others. It is shown that discrete wavelet transform is successfully implemented as analog filter bank in biomedical signal processing for design of low power pacemaker and also in ultra-wideband wireless communications. The most commonly used set of discrete wavelet transforms. This formulation is based on the use of recurrence relations to generate progressive finer discrete samplings of an implicit main wavelet function; each resolution is twice that of the previous scale.

Continuous Wavelet Transform

$$\Psi_x^{\psi}(\tau,s) = \int x(t)\cdot\psi^*_{\tau,s}(t)dt \qquad \psi_{\tau,s}(t)=\frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

Discrete Wavelet Transform

$$\Psi_x^{\psi}[n,a^j] = \sum_{m=0}^{N-1} x[m]\cdot\psi_j^*[m-n] \qquad \psi_j[n]=\frac{1}{\sqrt{a^j}}\psi\left(\frac{n}{a^j}\right)$$

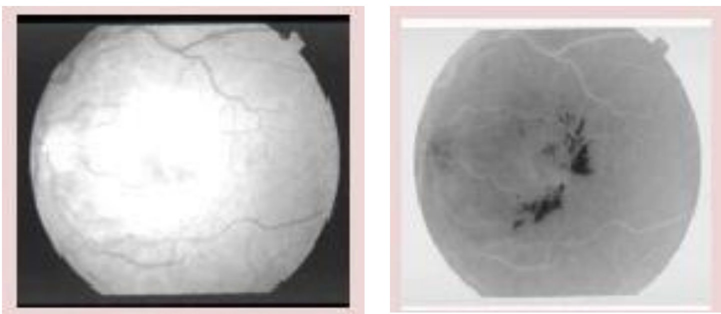

Figure 6: (a) Daubenches wavelet Image (b) Complement Image

3.4 Segmentation

In this module the fuzzy c means segmentation, will be find for gray scale images from the pre-processed images features were extracted for classification process. It will provide the segmented of blood vessels.

3.4.1 Mathematical Equation

1. *Initialize* $U=[u_{ij}]$ *matrix*, $U^{(0)}$
2. *At k-step: calculate the centers vectors* $C^{(k)}=[c_j]$ *with* $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

3. *Update* $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{\frac{2}{m-1}}}$$

4. *If* $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ *then STOP; otherwise return to step 2*

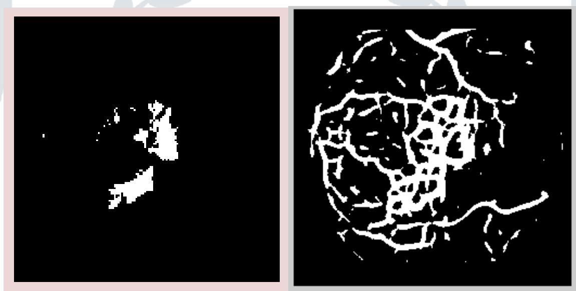

Figure 7: (a) FCM cluster Image (b) Threshold segmented Image

3.5 Feature Extraction

In current application we extract the features using Gray level co-occurrence matrix (GLCM) method. Below features cab be extracted, but we have considered only eight features.

- Autocorrelation
- Contrast
- Correlation
- Correlation
- Cluster Prominence
- Cluster Shade
- Dissimilarity
- Energy
- Entropy
- Homogeneity
- Homogeneity
- Maximum probability
- Sum of sqaures: Variance
- Sum average
- Sum variance
- Sum entropy
- Difference variance
- Difference entropy
- Information measure of correlation1
- Information measure of correlation2
- Inverse difference (INV)

– Inverse difference normalized (INN)
– Inverse difference moment normalized

3.6 Classification

Finally the segment image will be classified by PNN (probabilistic neural network) classification. It will provide the normal and abnormal images.
Using probabilistic neural network following features have been extracted and used for further classification and from training and testing data abnormality and sensitivity have been calculated.

3.6.1 Probabilistic Neural Network

PNN is a multilayered Feed forward network. There are four layers in it.

- Input layer
- Two hidden layers
- Output layer

There is one to one correspondence between pattern units and training examples. The activation function in PNN is developed from probability density function (PDF) based on training patterns.

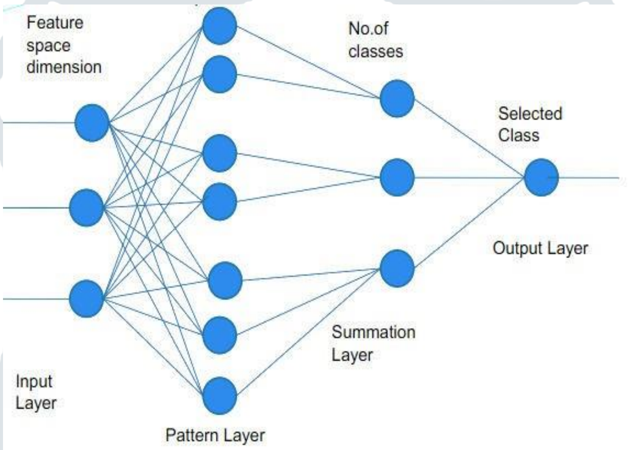

Figure 8: probabilistic neural network diagram

PNN having advantages of Fast training process, Orders of magnitude faster than back propagation, An inherently parallel structure, Guaranteed to converge to an optimal classifier as the size of the representative, training set increases, No local minima issues and Training samples can be added or removed without extensive retraining.

3.6.2 Mathematical Equation

Pattern layer having a probability of,

$$p_r(S_i|x) = \frac{p(x|S_i)\, p_r(S_i)}{p(x)} \qquad (3.1)$$

pr (Si) i = 1,2,3,…,k a priory probability of class
p(x) assumed to e constant

Probability density function is given as,

$$P(x|S_i) = \frac{1}{(2\pi)^{m/2}\sigma_i^{m}|S_i|} \sum_{j=1}^{n_i} \exp\left[\frac{-(x-x_j^{(i)})^T(x-x_j^{(i)})}{2^*\sigma_i^2}\right] \qquad (3.2)$$

Where,

xj(i) is the jth exempler pattern or training pattern from class Si,

| Si | = ni It denotes the cardinality of the set of patterns in class Si

σi is the smoothing parameter

At the summation layer,

$$\frac{\| x - x_j^{(i)} \|^2}{2\sigma_i^2} = \frac{1}{\sigma_i^2}\left[x^T x_j^{(i)} - \frac{1}{2}(\|x\|^2 + \|x_j^{(i)}\|^2) \right] \tag{3.3}$$

Norm of the real-valued vector x is ||x|| = √xTx

Estimate is given as,

$$P(x|S_i) = \frac{1}{(2\pi)^{m/2}\,\sigma_i^m\,|S_i|} \sum_{j=1}^{ni} \left[\exp \frac{-(x - x_j^{(i)})T(x - x_j^{(i)})}{2\sigma_i^2} \right] \tag{3.4}$$

IV. CONCLUSION

As an achievement of this work has been mostly divided into two categories, feature extraction and classification. All the techniques used for the classification were good in performance, but PNN is more efficient than other from the obtained results. Thus, proposed work has given a successful Diabetic Retinopathy, Diagnosing method that helps to diagnose the disease in early stage, which mutually reduces the manual work and switches to automatic method.

REFERENCES

[1] Inan Guler and Elif Derya U beyli, ‖ Multiclass Support Vector Machinesfor EEG- Signals Classification‖,IEEE Transactions On Information Technology In Biomedicine, vol. 11, no. 2, March, 2011.

[2] Lili Xu, Shuqian Luo,‖ Support Vector Macidne Based Method For Identifying Hard Exudates In Retinal Images‖, IEEE, 2010.

[3] Priya.R , Aruna.P, ‖ Automated Classification System For Early Detection Of Diabetic Retinopathy In Fundus Images‖, International Journal Of Applied Engineering Research,2010.

[4] Fundus Camera:http://en.wikipedia.org/wiki/Fundus_camera Vapnik. V, ―Statistical learning theory ley‖, New York, 2009.

[5] D. F. Specht, ―Probabilistic neural networks,‖ Neural Networks, vol. 3,no. 1, PP. 109–118, 2009.

[6] C. Sinthanayothin, V. Kongbunkiat, S. Phoojaruenchanachai, A. Singalavanija,‖Automated screening system for diabetic retinopathy, in: 3rd International Symposium on Image and Signal Processing and Analysis, vol. 44, no. 2, 2008, pp. 767–771

[7] Neural network fundamentals with Graps, Algorithms and Application By : N.K.Bose and P.Liang