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A DYNAMIC ROI BASED GLAUCOMA DETECTION AND REGION ESTIMATION TECHNIQUE

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Abstract*— Glaucoma is a visual issue caused because of expanded fluid pressure in the optic nerve. It harms the optic nerve and causes the loss of eye sight. The former methods checking strategies are filtering laser polarimetry, Heidelberg retinal tomography etc. These techniques are costly, require expert technician to operate and have problem in segmentation and boundary scaling. So there is a need to diagnose glaucoma with a minimal effort. Hence we propose a new strategy called the Region of Interest (ROI) based glaucoma detection and region estimation technique, in which first ROI is selected and then the Empirical Wavelet Transform (EWT) is applied. The EWT is utilized to break image into multiple positive and negative scenarios. The correntropy features are obtained from these EWT segments, these features are ranked based on the threshold value selection algorithm. Then these features are used for the classification of ordinary and glaucoma affected image by utilizing the LS-SVM classifier.

***Keywords*— Region of interest (ROI), Empiric wavelet Transfer (EWT), Least Square Support Vector Machine classifier (LS-SVM), correntropy**

I. INTRODUCTION

The major cause of the eyesight loss occurs because of the glaucoma. The eye is affected by glaucoma when the aqueous pressure in the ocular nerve increases. The percentage of glaucoma for people of all the ages is found to be 2.5% and for the people above 75 year ages is about 4.8%.The determination of glaucoma for most of the part is dependent on the Inter ocular pressure, medical history of patient and changes in the structure of the optic disc parameters like diameter, area and volume. Glaucoma affected will have IOP more the 21mmHg.

The former scanning methods are laser polarimetry, Heidelberg retinal tomography etc, which are unable to do proper segmentation, thresholding and boundary selection.

(a)

(b)

Fig 1: (a) Normal fundus image (b) Glaucoma affected fundus image

To overcome the disadvantages of existing methods we proposed a method that first finds the ROI in the eye image and applies EWT on the images. The EWT will break the images into various positive and negative scenarios. From these set of images the various characteristics are selected according to threshold testing. These selected characteristics are taken for the identification of ordinary eye and the glaucoma affected eye using the LS-SVM classifier .By using this method we got the efficiency of 99%.

II. RELATED WORK

M. R. Mookiah [1] provides an approach to automatically diagnose glaucoma via digital fundus image. In order to extract features for distinguishing between the glaucoma affected and normal eye image the author uses a discrete wavelet transform and higher order features. The support vector machine classification uses the selected features for making the decision. This method is able to recognize glaucoma with 95% correctness, 93% sensitivity, and 96.67% specificity.

Authors in[2] presented a method that detects the eye suffering from glaucoma. Here they utilize image processing techniques which are the digitalized techniques like thresholding, preprocessing and structural operations that automatically detect the various parameters like optic nerve, blood vessel, gap between the optic nerve head and optic nerve centre to optic nerve. Then neural network classifier is taken to classify the normal and abnormal eye images .The efficiency of this system for identifying glaucoma is 90%.

A novel method for automated diagnosis of the glaucoma affected and the normal eye is presented [3]. It takes both the texture and higher order spectra characteristics of digital fundus image for the purpose of analysis. These features provide the special values for standard and irregular images since they have the low p-value which helps in the discrimination process. They have used the random forest classifier best performs the classification of standard and glaucoma affected eye image with classification accuracy of 91%.

The authors S. V. Sree [4] presents a new method for the discrimination of normal and glaucoma affected eye via the wavelet based energy features. This gives the signatures of energy via the discrete wavelets transform. These features are then subjected to classification strategies like as support vector machine, random forest, naive bayes and sequential minimal optimization. They found around 93% of efficiency in distinguishing between normal and glaucoma image using tenfold cross validation.

III. IMPLEMENTATION

This section shows the implementation process followed.

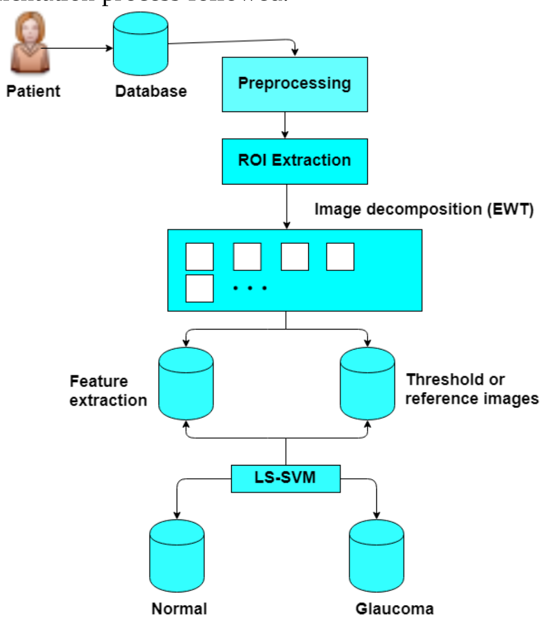


Fig 2: System Architecture

A. Dataset Collection

First the sample data is collected from the database, the pre-processing such as filtering is performed on the sample data image and the region of interest (ROI) is identified.

B. Empiric Wavelet Transfer

The EWT is applied on the selected ROI. The EWT is a technique which generate the various positive and negative scenarios of an image such that it forms the multiple set of images. From these set of images features can be extracted. Such that only exact part of the glaucoma can be detected. It does not contain anything beyond glaucoma.

The empirical wavelet function $E_n(V)$ can be described as

$$E_n(V) = \begin{cases} 1, & if\,(1+\lambda)\omega_n \le |V| \le (1-\lambda)\omega_{n+1} \\ \cos[\frac{\pi}{2} P(\lambda, \omega_{n+1})], & if\,(1-\lambda)\omega_{n+1} \le |V| \le (1+\lambda)\omega_{n+1} \\ \mathrm{Sin}\left[\frac{\pi}{2} P(\lambda, \omega_n)\right], & \mathrm{if}(1-\lambda)\omega_n \le |V| \le (1+\lambda)\omega_n \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Where ω_n denotes segment limit ranges from 0 to π and $0 < \lambda < 1$.Where $P(\lambda, \omega_n)$ and $P(\lambda, \omega_{n+1})$ is represented as

$$P(\lambda, \omega_n) = P\left(\frac{1}{2\lambda\omega_n}(|V| - (1-\lambda)\omega_n)\right) \quad (4)$$

$$P(\lambda, \omega_{n+1}) = P\left(\frac{1}{2\lambda\omega_{n+1}}(|V|(1-\lambda)\omega_{n+1})\right) \quad (5)$$

C. Fetching Features

Features extraction from decomposed EWT images is done by using correntropy. The correntropy is the measure of the comparison between the different samples of the decomposed EWT images. It is used to measure the changes in the structure of nerve fibers and optic disc parameters like area, diameter, and volume.

Consider for the lag B the correntropy CP(B) is represented by

$$CP(B) = \left(\frac{1}{N-B+1}\right)^2 \times \sum_{i1.i2=B}^{N} \tau(p[i1, i2] - p[i1-B, i2-B]) \quad (6)$$

Where $p[i1, i2]$ denotes the 2-D signal, N denotes the number of columns and rows and Gaussian kernel function $\tau(p[i1, i2] - p[i1-B, i2-B])$ is represented as

$$\tau(p[i1, i2] - p[i1-B, i2-B]) = \frac{1}{\sqrt{2\pi}\,\epsilon} \times exp\left[-\frac{(p[i1, i2] - p[i1-B, i2-B])^2}{2\,\epsilon^2}\right] \quad (7)$$

Where ϵ is the Gaussian parameter width controller.

D. Selecting Feature

The process of selection of features plays a significant role in the performance evaluation. Extremely discriminative features are chosen using the student's t-test calculation. The t-test considers the normal distribution of features sets of different classes. These features are then fed to the least square support vector machine classifier for the classification of normal and glaucoma affected eye.

IV.RESULT

The section demonstrates the result of the experiment that is carried out and shows the comparison between the existing methods and the proposed method used for the automated glaucoma diagnosis.

Table 1 represents the comparison between the 3 techniques that automatically diagnose glaucoma using the SVM classifier in existing system.

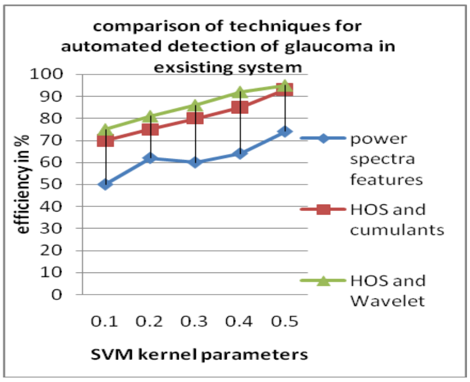
Table 1: comparison between 3 techniques in existing system

	Method used	Classifier	Efficiency
1	Power spectra features	SVM	74%
2	HOS and cumulants	SVM	93%
3	HOS and Wavelet	SVM	95%

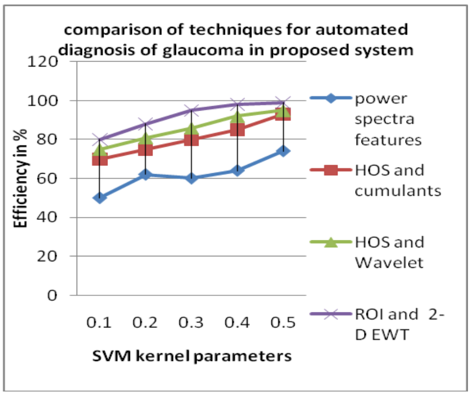
Table 2 represents the comparison between the 4 techniques used for the automated glaucoma diagnosis using SVM classifier in proposed system.

Table 2: comparison between techniques in proposed system

	Method used	Classifier	Efficiency
1	Power spectra features	SVM	74%
2	HOS and cumulants	SVM	93%
3	HOS and Wavelet	SVM	95%
4	ROI and 2-D EWT	SVM	99%



(a) Existing system



(b) Proposed System

Fig 3 (a): comparison graph of existing system (b) comparison graph of proposed system

Fig 3(a) Represents the graph of comparison of techniques for automatic diagnosis of glaucoma in existing system, (b) comparison of techniques for the automated diagnosis of glaucoma in proposed system using SVM classifier.

From the above graph it is clear that the proposed method provide the better efficiency in the detection of glaucoma than the existing method.

V. CONCLUSION

This paper presents a ROI based technique for the automated diagnosis of glaucoma and for the region estimation. It first finds the region of interest and then applies the EWT on the selected region to generate the multiple decomposed images with different frequency levels. The correntropy features are extracted from these decomposed images and are used for the classification using LS-SVM classifier. The classification efficiency in classifying the normal and glaucoma affected image is found to be 99%.

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