# Classification of Glaucoma Images using Wavelet based Energy Features and PCA

N.Annu [1], Judith Justin [2]

**Abstract :** Glaucoma is the second leading cause of blindness worldwide. As glaucoma progresses, more optic nerve tissue is lost and the optic cup grows which leads to vision loss. This paper compiles a system that could be used by non-experts to filtrate cases of patients not affected by the disease. This project proposes glaucomatous image classification using texture features within images and it will be classified effectively based on Probabilistic neural network (PNN).Texture features within images are actively pursued for accurate and efficient glaucoma classification. Energy distribution over wavelet sub bands and Principal Component Analysis (PCA) were applied to find these important texture features. Features were obtained from daubechies (db3), biorthogonal (bio3.3, bio3.5, and bio3.7) and symlets (sym3) wavelet filters. It uses a technique to extract energy signatures obtained using 2-D Discrete Wavelet Transform and the energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images. A classification with a success of 90% and 95% has been obtained by PCA-PNN and DWT-PNN, respectively. This demonstrates the effectiveness of wavelet as feature extractor and PNN as classifier compared with other recent work.

**Index Terms :** Wavelet transform, Glaucoma, Image texture, PCA, Feature extraction, PNN.

## I.INTRODUCTION

Glaucoma is caused by increased intraocular pressure (IOP) due to the malfunction of the drainage structure of the eyes [1]. It is the second leading cause of peripheral blindness worldwide and results in the neurodegeneration of the optic nerve. As the revitalization of the degenerated optic nerve fibers is not viable medically, glaucoma often goes undetected in its patients until later stages. Unfortunately, glaucoma symptoms are painless and the brain compensates gradual vision impairment to a considerable extent. The prevalent model estimates that approximately 11.1million patients worldwide will suffer from glaucoma induced bilateral blindness in 2020 [2]-[3]. Most people are not aware of such blind areas until the optic nerve has been destroyed substantially already. If the entire nerve is destroyed blindness results.

Glaucoma diagnosis usually follows an investigation of the retina using the Heidelberg Retina Tomograph (HRT), which is a confocal laser scanning system developed by Heidelberg Engineering. It allows 3-dim images of the retina to be obtained and analyzed. This way the topography of the optical nerve head, called papilla, can be followed over time and any changes be quantitatively characterized [4]. The current investigation intends to improve on this side by proposing a systematic and automatic investigation of 2-dim level images. Pre-processing is the first step in automatic diagnosis of retinal images. The quality of image is usually not good. Here Z Score Normalization is used to improve the quality of retinal image.

The two central issues to automatic glaucoma recognition are: 1) feature extraction from the retinal images and 2) classification based on the chosen feature extracted. Features extracted from the images are categorized as either structural features or texture features. Commonly categorized structural features include disk area, disk diameter, rim area, cup area, cup diameter, cup-to-disk ratio, and topological features extracted from the image. In order to reduce the feature vector dimension and increase the discriminative power, the Principal Component Analysis (PCA) has been used. Principal component analysis is appealing since it effectively reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data. Limiting the feature vectors to the component selected by the PCA leads to an increase in accuracy rates.

At this point, it is important to make a distinction between wavelet feature selection and the general feature selection discussed in pattern recognition. Both selection methods aim at obtaining a compact representation of the image for classification. However, the two techniques are not exactly the same. First, for general feature selection methods, the explicit knowledge of the feature extraction process may not always be available. The input to the general feature selection process is usually a vector of values representing the different features without any *a* priori information about how these features were obtained [5]. On the other hand, the wavelet feature selection methods can take advantage of the tree structure of the wavelet decomposition for the selection process.

Texture features using Wavelet Transforms (WTs) [12] in image processing are often employed to overcome the generalization of features. We propose to use three well-known wavelet filters, the daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) filters [2].We calculate the averages of the detailed horizontal and vertical coefficients and wavelet energy signature from the detailed vertical coefficients. We subject the extracted features to Probabilistic Neural Network (PNN) classification. A PNN is a multilayered feed forward network with four layers namely input layer, pattern layer, summation layer and output layer[6]. This approach includes classification with huge scale of data and consuming times and energy if done

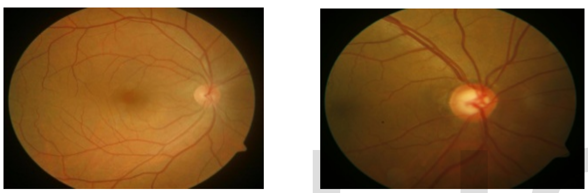
*(1) PG Scholar, Dept. of Medical Electronics, Avinashilingam University, Coimbatore. Email: annunatarajan1@gmail.com*
*(2) Faculty, Dept of Biomedical Instrumentation Engg, Avinashilingam University, Coimbatore. Email: judithvjn@yahoo.co.in*

manually. We aim to bring a comparison between wavelet based energy features/PNN and Principal components/PNN.

The rest of this paper is organized as follows. Section I presents about the data base. Section II describes our proposed feature extraction method. The classification of glaucoma and normal fundus image using Probabilistic Neural Network (PNN) is shown in section IV. Its experimental results and comparisons are given in Section V. Finally, we conclude briefly in Section VI.

## II.MATERIAL USED

The digital retinal images were collected from the ophthalmology department of a hospital, which manually curated the images based on the quality and usability of samples. The images were grouped into a set of normal retina images and a set of images clinically diagnosed with glaucoma. All the images were taken and stored in JPEG format.



(a) (b)

Fig.1. Typical fundus images (a) normal (b) glaucoma. In glaucoma, the optic nerve damages by the elevation in the intraocular pressure inside the eye, causing irreversible damage to the optic nerve and to the retina.

## III.IMAGE PREPROCESSING

Differences in luminosity, contrast and brightness inside retinal images make it complex to extort retinal features and make a distinction of exudates from other bright features in images. Hence image pre-processing is required in equalization of the irregular illumination associated with retinal images. Each image is subject to $z$-score normalization [2], [1]. Z-score normalization converts to common scale with an average of zero and standard deviation of one.

$$y_{new} = \frac{y_{old} - mean}{std} \quad (1)$$

Average of zero shows that it avoids introducing aggregation distortion. Here, $y_{old}$ is the original value, $y_{new}$ is the new value and the mean and $std$ are the mean and standard deviation of the original data range, respectively.

## IV.FEATURE EXTRACTION

### A . I LEVEL 2D DWT – BASED FEATURES

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved [3]. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training. Feature extraction is a general term which depicts to extract only valuable information from given raw data. The main objective of feature extraction is to represent raw image in its reduced form and also to reduce the original dataset by measuring certain properties to make decision process easier during classification. A feature is nothing but the significant representative of an image which can be used for classification, since it has a property which distinguishes one class from other. The extracted features provide characteristics of input pixel to the classifier [8].The spatial features can be extracted by statistical and co-occurrence methods.

It is a well-known fact that Fourier Transforms (FT) can be useful for extracting frequency contents of a stationary signal. However, it cannot provide time-evolving effects of frequencies in non-stationary signals. STFT suffers from the limitation that it employs a fixed width of window function, chosen a priori, and hence it creates a problem for simultaneous analysis of high frequency and low frequency non-stationary signals.

Table.
Results of Texture Features for Normal and Glaucoma Classes

| Feature | Normal | Glaucoma | P-Value |
|---|---|---|---|
| Energy | 8.0830E-004 ± 4.1659E-005 | 3.9611E-004 ± 3.7244E-004 | ≤ 0.0001 |

Hence, wavelet transform arose as an effective tool for those situations where one needs multiresolution analysis, providing short windows at high frequencies and long windows at low frequencies[7].Here each image is represented as a $p \times q$ gray-scale matrix $I[i,j]$. The resultant 2-DDWTcoefficients are the same irrespective of whether the matrix is traversed top-to-bottom or bottom-to-top. Hence, it is sufficient that we consider four decomposition directions corresponding to 0◦ (horizontal, *Dh*), 45◦ (diagonal, *Dd*), 90◦ (vertical, *Dv*), and 135◦ (diagonal, *Dd*) orientations. The decomposition structure for one level is illustrated in Fig.2. In this figure, $I$ is the image, $g[n]$ and $h[n]$ are the low-pass and high-pass filters, respectively, and $A$ is the approximation coefficient. Where, 2ds1 indicates that rows are down sampled by two and columns by one. 1ds2 indicates that rows are down sampled by one and columns by two. The "×" operator indicates convolution operation. Since the number of elements in these matrices is high, and since we only need a single number as a representative feature, [2]we employed averaging methods to determine such single valued features. These are obtained by the following equations,

$$Average\ Dh1 = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dh1(x,y)| \quad (2)$$

$$Average\ Dv1 = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x,y)| \quad (3)$$

$$Energy = \frac{1}{p^2 \times q^2} \sum_{x=\{p\}} \sum_{y=\{q\}} \big(Dv1(x,y)\big)^2 \qquad (4)$$

Energy signatures provide a good indication of the total energy contained at specific spatial frequency levels and orientations [9].The energy-based approach assumes that different texture patterns have different energy distribution in the space-frequency domain. The energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy. Hence these energy features are highly discriminatory. This approach is very appealing due to its low computational complexity involving mainly the calculation of first and second order moments of transform coefficients.

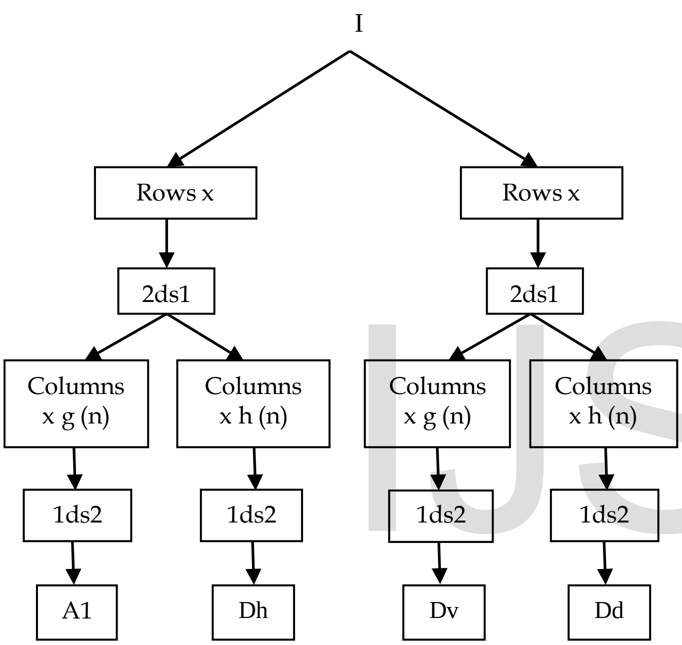



Fig.2. 2-Dimention Discrete Wavelet Transform decomposition.

## B.PCA– BASED FEATURES

Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and Principal Component Analysis (PCA) are some of the techniques used for feature extraction, among them PCA is a powerful method in image formation [21]. Data patterns, similarities and differences between them are identified efficiently. The other main advantage of PCA is dimension reduction by avoiding redundant information, (Daugman, 1993) without much loss. It captures big principal variability in the data and ignores small variability and reduces the dimensionality of a data set by finding a new set of variables, smaller than the original set of variables. Better understanding of Principal Component Analysis is through statistics and some of the mathematical techniques used are Eigen values and Eigen vectors [23].Principal Component Analysis (PCA) is a mathematical procedure that uses linear transformations to map data from high dimensional space to low dimensional space. The low dimensional space can be determined by Eigen vectors of the covariance matrix.

## V . CLASSIFIER USED

The Probabilistic Neural Network (PNN) was developed by Donald Specht. Classification refers to the analysis of the properties of an image. Depending upon the analysis, the dataset is further referred into different classes. Input features are categorized as 0 and 1.The classification process is divided into two phases: training phase and testing phase [15]. In the training phase, known data is given and in testing phase an unknown data is given. Classification is done by using classifier after training phase [14]. This network provides a general solution to pattern classification problems. The features extracted from wavelet and PCA were used for the classification of normal and glaucoma images.

PNN is adopted for it has many advantages. Its training speed is many times faster than a BP network. Additionally, it is robust to noise examples. However, we choose a basic Matlab PNN for its simple structure and training manner. The most important advantage of PNN is that training is easy and instantaneous. Weights are not “trained” but assigned. Existing weights will never be alternated but only new vectors are inserted into weight matrices when training. So it can be used in real-time [11].

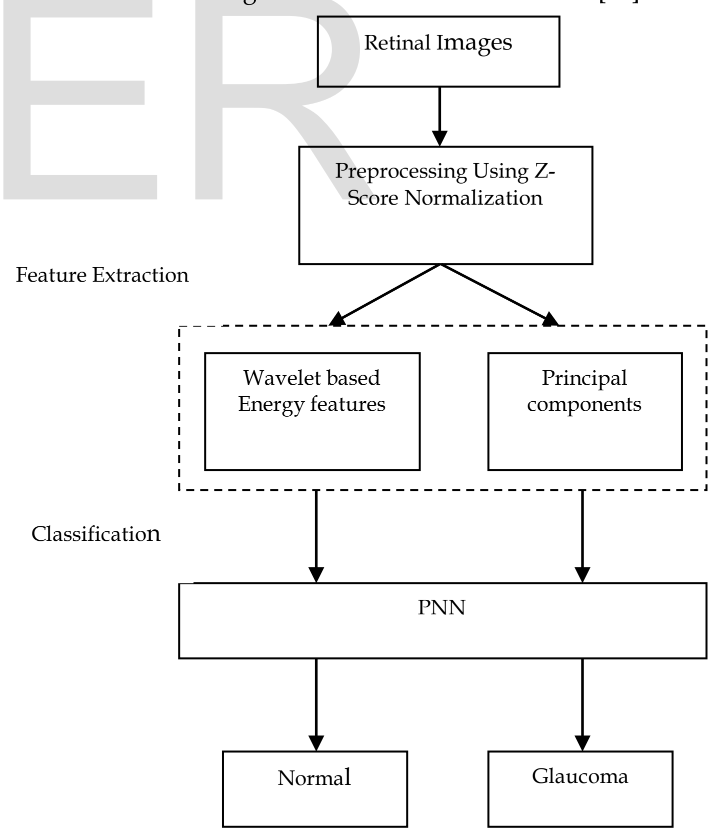



Fig.3. Block diagram of Classification of Glaucoma and Normal Retinal Images.

Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast. The network classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input layer, Radial Basis function Layer and the Competitive Layer. Equation (5) determines the Probabilistic Neural Network process.

$$output = f^{\sum Woli} + BIAS \quad (5)$$

Where, $Wo$ is weight, $li$ is input, BIAS is called activation function. The training set of PNN must be done through representative of the actual population of effective classification and it is characterized by the following, more demanding than most NN's, sparse set sufficient and erroneous samples and outliers tolerable. Adding and removing training samples simply involves adding or removing "neurons" in the pattern layer. The training of PNN is fast as orders of magnitude faster than backpropagation. Fig.3 represents the basic operations of the process for classification of normal retinal eye images and glaucomatous retinal eye images.

## VI.IMAGE QUALITY EVALUATION METRICS

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert which is complicated and does not give the exact quality. There are various metrics used for objective evaluation of an image. Sensitivity is the probability of abnormal class being classified as abnormal.

$$sensitivity = \left(\frac{TP}{TP+FN}\right) \times 100\% \quad (6)$$

Specificity is defined as the probability of normal class being identified as normal.

$$specificity = \left(\frac{TN}{TN+FP}\right) \times 100\% \quad (7)$$

The Positive Predictive Accuracy (PPV) shows the accuracy of detecting the normal and abnormal cases.

$$PPV = \left(\frac{TP}{TP+FP}\right) \times 100\% \quad (8)$$

The accuracy shows quality or ability of the performance.

$$accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (9)$$

Where, True Negative (TN) is the number of normal images classified as normal images, False Negative (FN) is the number of glaucomatous images classified as normal, True Positive (TP) is the number of glaucoma images classified as glaucoma and False Positive (FP) is the number of normal images classified as glaucomatous

## VII.EXPERIMENTAL RESULTS AND DISCUSSION

The following section provides a detailed description of the results obtained from our pre-processing, feature ranking and classification.

### A . Z-SCORE NORMALIZATION

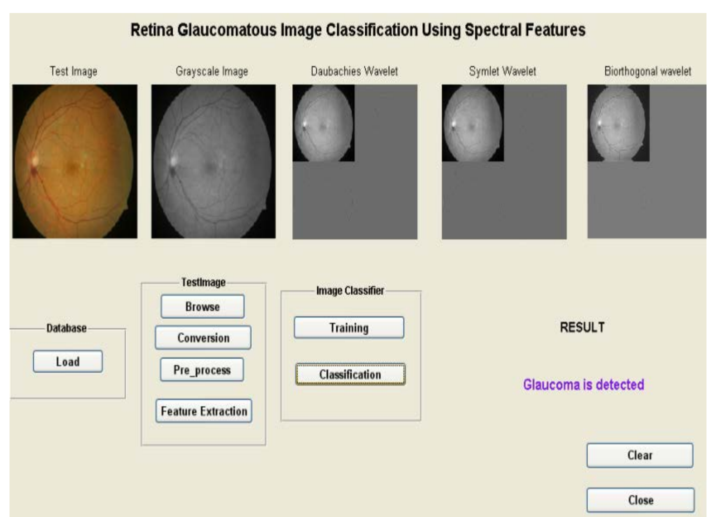
Fig. 4 shows the resulting retinal images obtained after pre-processing. Fig.4. (a) shows the image before z-score normalization and (b) shows the image after z-score normalization.

(a) (b)

Fig.4. (a) and (b). Shows 'before' and 'after' process of Z-Score Normalization

### B . FEATURE EXTRACTION USING WAVELETS

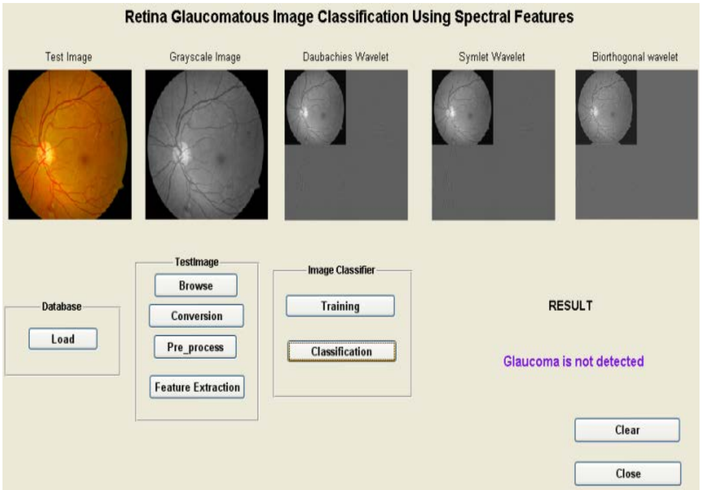
The energy-based approach assumes that different texture patterns have different energy distribution in the space-frequency domain. This approach is very appealing due to its low computational complexity involving mainly the calculation of first and second order moments of transform coefficients [12]. Figure 5 provides a snapshot of the results obtained from Feature extraction described in the methodology section.




(a)

The different texture patterns have different energy distribution in the space-frequency domain. Figure 5 shows the energy feature extraction using Discrete Wavelet

Transform. Here one level Wavelet decomposition is done, and the wavelet filters used here were, the daubechies (db3), the symlets (sym3), and the biorthogonal (bio3.3, bio3.5, and bio3.7) filters. The extracted features were used for




(b)

Fig. 5 (a) and (b) shows the energy feature extraction using 2D-DWT and Classification of glaucoma images

Classification [2]. Secondly, we use Principal Component Analysis for feature extraction. The features extracted were used as an input for the classification using PNN.

#### C . PRINCIPAL COMPONENT ANALYSIS

Retinal images are not distributed uniformly in the brightness space because strong spatial relation in multiple scales is met. Therefore, without significant loss of information, equivalent description in a reduced subspace can be achieved. The main idea of the PCA is to estimate the vectors set that best describe the distribution of retinal images in a low-dimensional space.

Some of the basic steps involved in extracting principal components are, mean valve S of the given data set" S" is found and by subtracting the mean value from "S" a new matrix is obtained "A" . Covariance is obtained from the matrix$C = AA^T$. Eigen values are obtained from the covariance matrixes .□Finally Eigen vectors are calculated for covariance matrix C. Any vector S or S □□$ can be written as linear Combination of Eigen vectors. To form lower dimension data set Only Largest Eigen values are kept.

$$\hat{s} - \bar{s} = \sum_{i=0}^{1} b_1 u_1 \qquad (10)$$

The signature of each image is found by multiplying the transpose of zero mean vectors with feature vectors.

#### D . CLASSIFICATION USING PNN

Probabilistic Neural Network (PNN) is a kind of supervised neural network that is widely used for pattern recognition [14]. The PNN is applicable to the same class of problems for which the back propagation neural network BPNN is typically used. Experimental results indicate that PNN has a number of major advantages over other traditional neural networks. Figure 5 shows classification result using PNN, the retinal images are classified as either 'glaucoma is detected' or 'glaucoma is not detected'. First, the Wavelet Transform technique is employed to extract the energy distribution features of the distorted signal at one level decomposition. Then, the PNN classifies these extracted features to identify the normal and abnormal retinal images according to the energy features. Experiments have been carried out to verify the ability of the PNN in achieving good classification rate. In this approach, we have considered 20 retinal images. Out of the 20 images, 10 are normal retinal images and the remaining are glaucomatous images and 15 images are used for training. Results are presented in Table II.

Table II
Classification Accuracies (%) of Classifier after Normalization and Feature Extraction

| Feature extractor and Classifier | Sensitivity | Specificity | Positive Predictive Accuracy | Accuracy |
|---|---|---|---|---|
| DWT-PNN | 100% | 90% | 90.9% | 95% |
| PCA-PNN | 100% | 80% | 83.3% | 90% |

Table II summarizes the classification, accuracy Sensitivity, Specificity obtained by the feature extraction and classifier used. The accuracy obtained by Wavelet as feature extractor is high compared to the PCA feature extractor. The main reason for the low classification rate of Principal Component Analysis is that, in classification we would like to find a set of projection vectors that can provide the highest discrimination between different classes. Thus, choosing the largest principal components as the bases for dimensionality reduction may not be optimal. Secondly, PCA is an unsupervised and statistical type algorithm to extract features in input data since it does not use the class information of input data. The accuracy obtained by using PCA-PNN is 90%.Thus the highest Sensitivity, Specificity, Positive Prediction Accuracy and Accuracy using wavelet transform and Probabilistic Neural Network were 100%, 90%, 90% and 95% respectively.

## VIII.CONCLUTION

In this paper, a wavelet-based texture feature set and PCA have been used. The texture feature set is made up of the energy of sub images. Wavelet transform are very efficient tools for feature extraction and they are very successfully used in biomedical image processing. Classification technique is developed to automatically detect whether glaucoma is present or not. The accuracy of results obtained using wavelet energy features/PNN is high (95%) as in table II and the accuracy of results of Principal Components/PNN is lower (90%). The feature extraction using PCA is unsupervised and statistical type as it does not use the class information of the input data. For this reason the extracted features may not be fitted for classification. Due to these reasons Principal Components are not always useful for classification. This could be the reason for the observed lower value (90%) of accuracy.

Features by DWT give maximum classification accuracy of and it is rapid, easy to operate, non-invasive and inexpensive compared to PCA feature extractor. We have carried out the classification by Probabilistic Neural Network for the purpose of examining the efficiency of the feature extracted. If more powerful classifiers used, classification accuracy may further be improved. The approach will be left as a future work.

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