# EMPIRICAL WAVELET TRANSFORM AND GLCM FEATURES BASED GLAUCOMA CLASSIFICATION FROM FUNDUS IMAGE

**D.Maharaja**
*M.E. (ECE) Applied Electronics*
*Sathyabhama University,Chennai.*
*akmaharaja.d@gmail.com*

**Dr.S.Maflin Shaby**
*Assistant Professor,*
*Department of ECE ,*
*Sathyabhama University,Chennai.*
*maflin.s@gmail.com*

**Abstract:** Glaucoma is an ocular disorder caused due to increased fluid pressure in the optic nerve. It damages the optic nerve subsequently causes loss of vision. There is a need to diagnose glaucoma accurately with low cost. In this paper, a new methodology for an automated diagnosis of glaucoma using digital fundus images based on Empirical Wavelet Transform (EWT) is proposed. The EWT is used to decompose the image and Gray Level Concurrence Matrix (GLCM) features are obtained from decomposed EWT components. Then, these features are used for the classification of normal and glaucoma images using Neural Network (NN) classifier. The evaluation of the system is carried on using 46 generated images from that 20 images are used for training purpose and 26 images are used for testing purpose. In this the classification rate of the proposed system is satisfied. Overall accuracy of the proposed system is 96%.

**Key words:** Fundus Images, Empirical Wavelet Transform, Gray Level Cooccurence Matrix, Neural Network.

## 1. Introduction

The detection of glaucoma based on ISNT rule using Support vector machine (SVM) from digital fundus image is presented in [1]. The glaucoma screening system is suitable for both normal eyesight and myopia. For myopia eye, only one clinical indicator is not sufficient. So, there are two steps are followed as indicators: image processing and machine learning. Cup to disc ratio (CDR) and rim width based on ISNT rule is done in image processing step and this information will be used as features in glaucoma classification step. SVM classifier is done in machine learning step for classification function.

Optic disc segmentation using morphological operations and hybrid level-set methodology for glaucoma diagnosis is described in [2]. The methodology makes use of optic disc and cup segmentation. Optic disc is segmented using morphological operations and hybrid level-set methodology. Optic cup is segmented by first detecting blood vessels using

SVM classifier and then the bending points on the circum linear vessels. Parameters such as vertical CDR, cup to disc area ratio (CDAR) are calculated and used for glaucoma detection.

The assessment of glaucoma using optic disc and optic cup segmentation from monocular colour retinal images is presented in [3]. In multidimensional feature space, the information of local image is integrated around each point of interest for optic disc segmentation. For cup segmentation, the region of support concept is used to detect vessel bends. Then, the right scale is selected automatically for examination. Bends in a vessel are robustly detected using a region of support concept, which automatically selects the right scale for analysis. A multi-stage strategy is employed to derive a reliable subset of vessel bends called r-bends followed by a local spline fitting to derive the desired cup boundary.

The detection of optic disc and optic cup from colour retinal images for glaucoma detection is approached in [4]. An automatic system is developed for glaucoma detection by extracting various features like vertical CDR, Horizontal to Vertical CDR (H-V CDR), CDAR and Rim to Disc Area Ratio from digital fundus images through segmentation of Optic disc, cup and neuro retinal rim. Optic disc segmentation is done using Geodesic active contour model and CMY color space is used for detection of cup using color information of the region of pallor in M channel. Then they are fed to the classification stage with supervised classifiers such as k-Nearest Neighbor (k-NN), SVM and Naive Bayes (NB).

The haralick texture features based glaucoma detection from digital fundus image is presented in [5]. The method for glaucoma detection using a haralick texture Features from digital fundus images. K Nearest Neighbors (KNN) classifiers are used to perform supervised classification. This method demonstrate that the haralick texture features has Database and classification parts, in Database the image is loaded and Gray Level Co-occurrence Matrix (GLCM) and thirteen haralick features are combined to extract the image features, correctly identifies the glaucoma images with an accuracy.

To detect glaucoma using moment and wavelet features to prevent vision loss is approached in [6]. There are three wavelet and fifteen moment features are used for image decomposition. Three wavelet features such as Daubechies, symlets and Biorthogonal. Fifteen moment features are computed using combination of HH (Diagonal) and HL (Vertical). The z-score normalization is applied on features before classification. Extracted features are applied to classifier such as SVM, K-Nearest Neighbor and Error Back-Propagation Training Algorithm (EBPTA) for classification.

Detection of glaucoma using Higher Order Spectra features (HOS) and Texture features is discussed in [7]. The method for glaucoma detection using a combination of texture and HOS features from digital fundus images. SVM, sequential minimal optimization, naïve bayesian, and random-forest classifiers are used to perform supervised classification. It demonstrates that the texture and HOS features after z-score normalization and feature selection, and when combined with a random-forest classifier, performs better and correctly identifies the glaucoma images with accuracy.

An analysis of Optic cup feature in color fundus image using Stochastic Watershed transformation for glaucoma diagnosis is explained in [8]. An automatic glaucoma diagnosis algorithm based on retinal fundus image is presented. This algorithm uses anatomical characteristics such as the position of the vessels and the cup within the optic nerve. Using several color spaces and the stochastic watershed transformation, different characteristics of the optic nerve were analyzed in order to distinguish between a normal and a glaucomatous fundus.

A review for glaucoma detection using cross validation algorithm [9] including algorithms such as Association, Classification, Clustering, Fuzzy decision tree etc was done. This introduces the probability of having glaucoma by using classification prediction technique. Random sample data was collected for patients of different age. The probability of having glaucoma by using classification data mining technique and prediction model on the basis of decision tree and cross-validation.

The features of wavelet energy based glaucoma detection using ANN is discussed in [10]. The early detection of glaucoma is important in order to enable appropriate monitoring, treatment and to minimize the risk of irreversible visual field loss. Although advances in ocular imaging offer the potential for earlier diagnosis, the best method is to involve a combination of information from structural and functional tests. Here structural and energy features are considered and then analyzed to classify as glaucomatous image. Energy distribution over wavelet sub bands were applied to find these important texture energy features. Finally extracted energy features are applied to multilayer perceptron and back propagation NN for effective classification by considering normal subjects extracted energy features.

Automatic detection of glaucoma based on Principle Component Analysis (PCA) using Bayes classifier in retinal fundus image is explained in [11]. Optic disc center is located using the combination of thresholding and distance transformation. Eigenvector spaces of normal set and glaucoma set are obtained respectively using PCA. A test image is projected onto these two spaces and the distance between projection and each template is calculated. Finally, decision is made according to bayes classifier.

A review for detection of glaucoma based on structural features from digital fundus images is described in [12]. The functional and structural features and their significance with respect to digital fundus and optical coherence tomography images for glaucoma detection are described. It concludes that structural features are more precise for early glaucoma detection as compared to functional features.

## 2. Methodology

The proposed system for the classification of glaucoma images is built based EWT and NN for classification. The theoretical background of all the approaches is introduced in this following section.

### 2.1. EWT (Empirical Wavelet Transform)

The Empirical Wavelet Transform (EWT) aims to decompose a signal or an image on wavelet tight frames which are built adaptively. In 1D, the procedure consists in detecting the supports of some "modes" in the Fourier spectrum and then using these supports to build Little wood-Paley type wavelets. In 2D, based on the same principle, we propose empirical versions of the tensor wavelet transform, a 2D little wood-Paley transform, the Ridge let transform and the Curve let transform. The advantage of this empirical approach is to keep together some information that otherwise would be split in the case of dyadic filters. The provided Mat lab toolbox performs all these transforms.

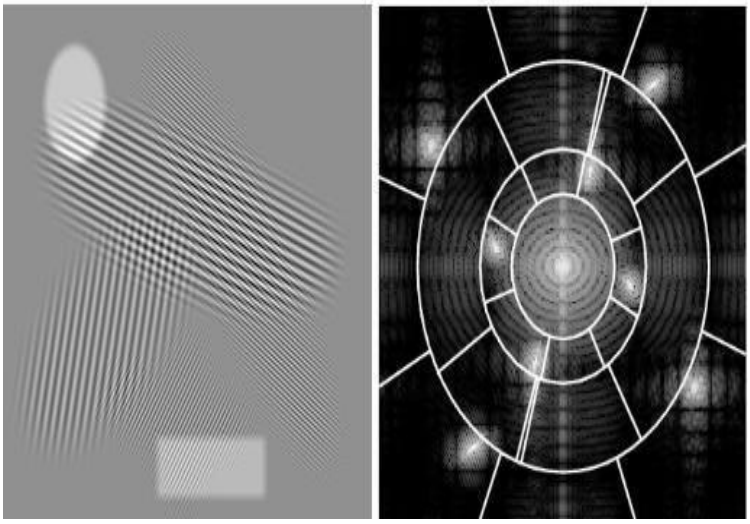


Fig.1 (a) Input Image (b) Detected Fourier Supports

## 2.2 GLCM (Gray Level Concurrence Matrix)

A co-occurrence matrix or co-occurrence distribution is a matrix that is defined over an image to be the distribution of co-occurring pixel values (grayscale values, or colors). A statistical method of examining texture that considers the spatial relationship of pixels is the GLCM, also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. (The texture filter functions, described in Texture Analysis cannot provide information about shape, i.e., the spatial relationships of pixels in an image.) After you create the GLCMs, you can derive several statistics from them using the graycoprops function. These statistics provide information about the texture of an image. The following table lists the statistics.

## 2.3 NN (Neural Network Classifier)

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse.

## 3. Proposed System

There are two different phases are represented in the proposed system for the classification of glaucoma in fundus images that's training phase and classification phase are explained in detail in the following sections.

## 4. Training Phase

Using the EWT scheme, the given images are first decomposed. Then the decomposed images are considered for feature extraction stage. GLCM technique is used to extract the features from the decomposed image. From the database the NN classifier is trained which is generated in the training phase.

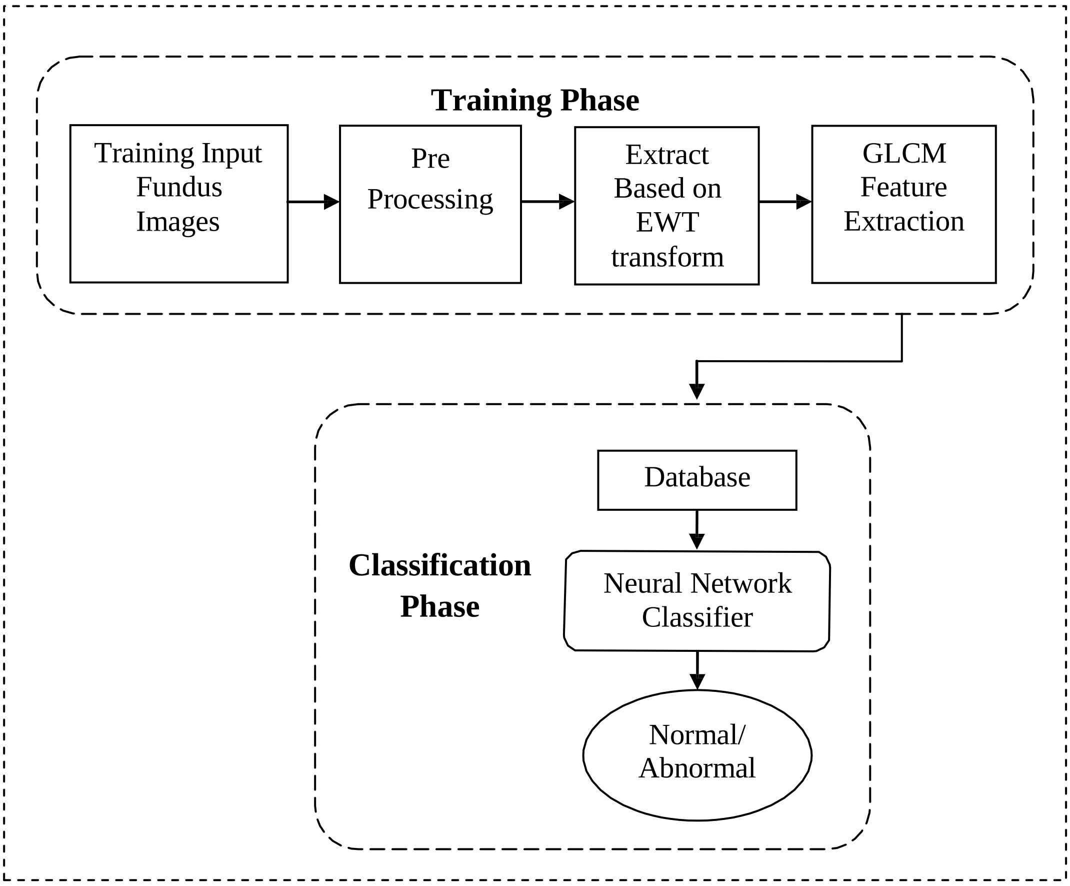
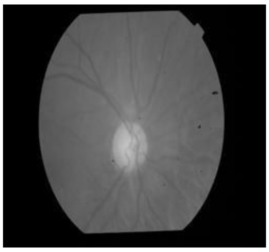



Figure.2 Block diagram of the proposed system

Previously generated images are given as input. First decompose the image using EWT technique. Then pass the decomposed images which obtained by technique to the feature extraction stage. Here features are extracted using GLCM and repeat this procedure for all images. Finally the features for database are obtained.



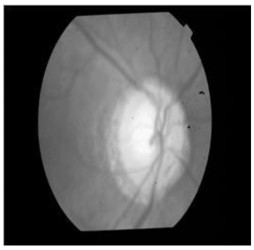


Fig.3 (a) Normal Eye (b) Abnormal Eye

## 5. Classification Phase

Unknown images are classified in the phase of classification. After the extraction of the unknown images, the feature vector is processed with the features in the database by using the NN classifier. Unknown images and the database are the input image. Then test the images with the NN classifier. Finally find the images whether it is normal or abnormal image.

## 6. Experimental Results

In this section, the experimental results of the proposed system are discussed and verified. A set of 46 images with normal and abnormal are generated. These images are decomposed using EWT technique. Using GLCM feature 13 features are obtained from the decomposed image. Then the features are classified using NN classifier.

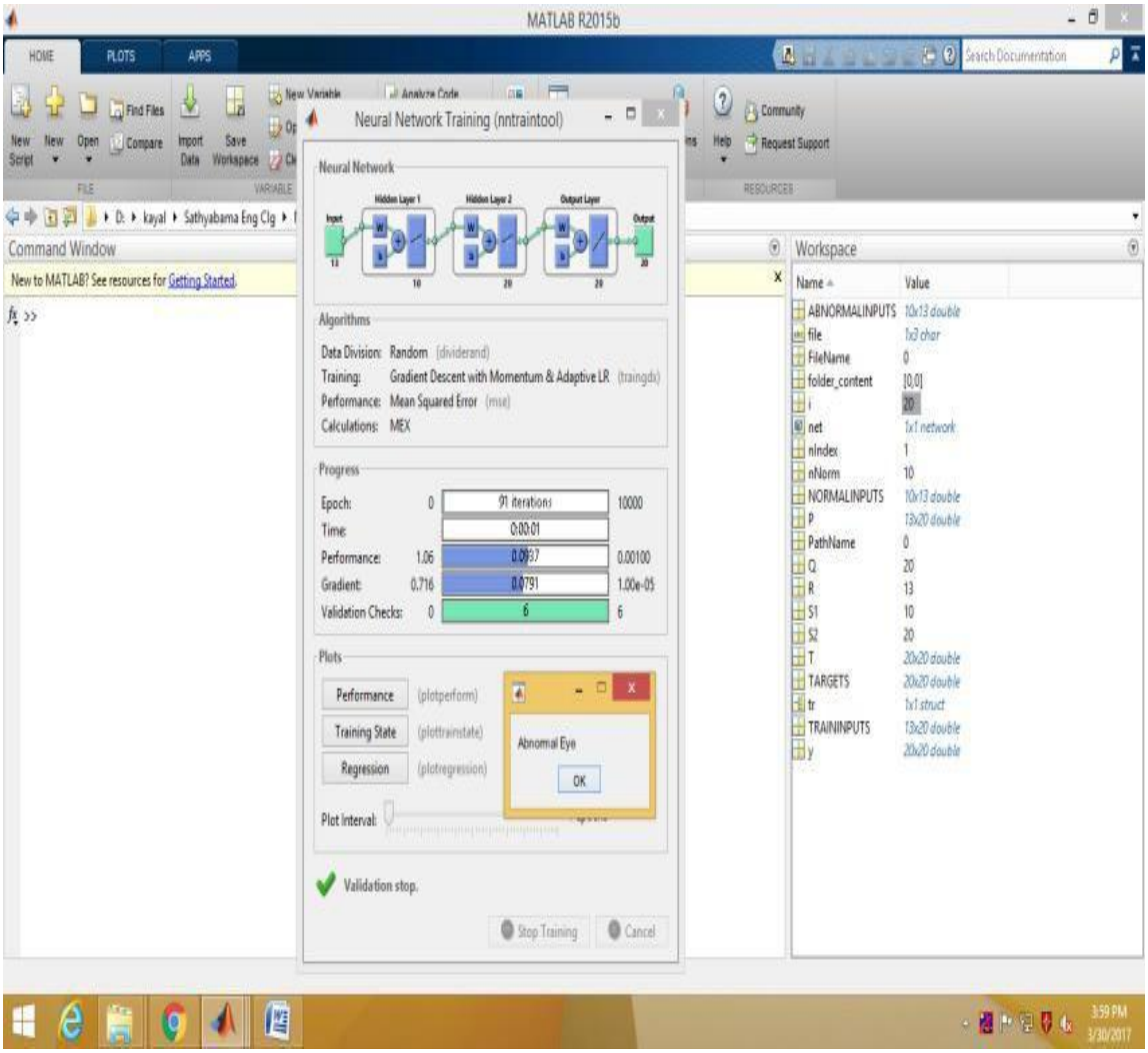



Fig.4 Ouput with Neural Network Training

Fig.4 shows the output snapshot of the proposed system using EWT method. Classification rate for this proposed system of Normal is 100% and Abnormal is 92%.

## 7. Conclusion

An approach for glaucoma classification based on GLCM features and NN classifier is presented in this paper. EWT technique is presented in this system for decomposition. GLCM features are used for feature extraction in the proposed system. The proposed methodology need to test for huge database and also can be extended to diagnose glaucoma at an early stage. From the experimental results, it is cleared that the classification accuracy of glaucoma is very reliable. Overall accuracy of the proposed system is 96%.

## References

[1] Ruengkitpinyo, et al, (2015). An Automatic Glaucoma Screening Algorithm using Cup to-disc ratio and ISNT rule with Support Vector Machine. IEEE 41st Annual Conference of the Industrial Electronics Society. 517-521.

[2] Asha Merin Jose & Arun A. Balakrishnan, (2015). A Novel Method for Glaucoma Detection Using Optic Disc and Cup Segmentation in Digital Retinal Fundus Images. International Conference on Circuit, Power and Computing Technologies. 1-5.

[3] Gopal Datt Joshi, et al, (2011). Optic Disk and Cup Segmentation From Monocular Color Retinal Images for Glaucoma Assessment. IEEE Transactions on Medical Imaging. 30(6):1192-1205.

[4] Megha Lotankar, et al, (2015). Detection of Optic Disc and Cup from Color Retinal Images for Automated Diagnosis of Glaucoma. IEEE UP Section Conference on Electrical Computer and Electronics.1-6.

[5] Simonthomas, et al, (2014). Automated Diagnosis of Glaucoma using Haralick Texture Features. IEEE conference on Information Communication and Embedded Systems.1-6.

[6] Gaurav O. Gajbhiye & Ashok N. Kamthane, (2015). Automatic Classification of Glaucomatous Images using Wavelet and Moment Feature. IEEE conference on INDICON. 1-5.

[7] Rajendra Acharya, et al, (2011). Automated Diagnosis of Glaucoma Using Texture and Higher Order Spectra Features. IEEE Transactions on information technology in biomedicine. 15(3):449-455.

[8] Andres Diaz, et al, (2016). Glaucoma Diagnosis by Means of Optic Cup Feature Analysis in Color Fundus Images. IEEE Conference on Signal Processing. 2055-2059.

[9] Kavita Choudhary & Sonia Wadhwa, (2014). Glaucoma Detection using Cross Validation Algorithm. IEEE 4th International Conference on Advanced Computing & Communication Technologies. 478-482.

[10] Gayathri, R., et al, (2014). Automated Glaucoma Detection System based on Wavelet Energy features and ANN. IEEE International Conference on Advances in Computing, Communications and Informatics. 2808-2812.

[11] Li Xiong, et al, (2014). Automatic Detection of Glaucoma in Retinal Images. 9th IEEE Conference on Industrial Electronics and Applications. 1016-1019.

[12] Anum Abdul Salam, et al, (2015). A Review Analysis on Early Glaucoma Detection Using Structural Features. IEEE International Conference on Imaging Systems and Techniques (IST). 1-6.