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GLCM based FNN for Automated Drusen Detection in Fundus Images

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Abstract

Drusen made up of protein and calcium salts in the macula region characterizes the Age-Related Macular Degeneration (ARMD), a common eye condition and a leading cause of irreversible vision loss among the people over the age of 65. It is crucial to detect and treat ARMD at the earliest stage to avoid preventable vision loss. In this paper, a novel method for detecting drusen present in the retinal image using Artificial Neural Network (ANN) based classifier is proposed. The aim of the proposed scheme is to automatically detect drusen and to grade them without human supervision using Artificial Neural Network. Due to undesirable disturbances during the acquisition process these images suffer with noise, low contrast and non-uniform which hinders further analysis. Hence, initially the fundus image was pre-processed for illumination correction, contrast normalization and denoising. Further, the textural features in the retina are extracted using the Gray level co-occurrence matrix (GLCM) to distinguish the scope of the disease spread in the retina. Finally the textural statistics such as autocorrelation, sum average and sum variance obtained from the GLCM matrix are fed into to Multilayer Feed Forward network for further classification. The performance was analyzed by comparing the result with labelled ground truth image graded by the experts. The Receiver operating curve (ROC) of the decision system provides all vital information about the quantity and quality of the drusens with 98.9% accuracy.

Keywords: Morphological Operators; Feature Descriptors; Texture Segmentation; Artificial Neural Network;

INTRODUCTION

ARMD is an irreversible eye-condition responsible for 8.7% of all blindness worldwide in 2007 [1], and due to the result of population ageing, it is expected to double by 2020. This painless disease progressively degrades macula a specific part of the eye that is responsible for fine and detailed central vision, over the age of 65 around the world. The accumulation of extra cellulose materials beneath the retina characterize drusen, the early stage of ARMD and their qualitative analysis is important in the follow of treatment. The severity of ARMD can be prohibited if it is detected in the early stage and it will benefit the effectiveness of the treatment [2, 3]. The evaluation of drusen in fundus image is difficult to reproduce manually. Hence the importance and necessity during long time treatment requires more accuracy in automatically classifying drusen in fundus images without human intervention.

In the literature, we found many classification techniques for determining the drusen from the given fundus images such as Saurabh Garg et al.[4] developed method for drusen identification using texture descriptors. But the algorithm fails to detect small and faint drusens. F. Moitinho et al have developed an approach for quantification of drusen using Levenberg-Marquardt methodology to model each drusen region, but the algorithm is not reliable when OD is not clearly visible in the retinal image [5]. G G Gardner et al used backpropagation neural network to detect blood vessels and exudates in the retinal image but the detection rate of blood vessel were 91.7% [6]. Maurizio Baroni et al used ANN classifiers for detection and evaluation of the lesions present in the retinal image, where the Specificity is better, but, the sensitivity during the detection is worse [7].

In this paper, we propose a GLCM based Feed Forward Neural Network to improve the detection and to classification of drusen.

METHODS

The proposed algorithm to segment and grade drusen from the fundus image is depicted in Figure 1.

In RGB image the channel which consists of high contrast is passed as an input to reduce the computational complexity. The selected channel was pre-processed to normalize the contrast and illumination of the image. The macula region is segmented using morphological operators and the features present in the segmented region are extracted from the GLCM. The Feed Forward ANN is trained by these feature extracted from the GLCM of the macula region.

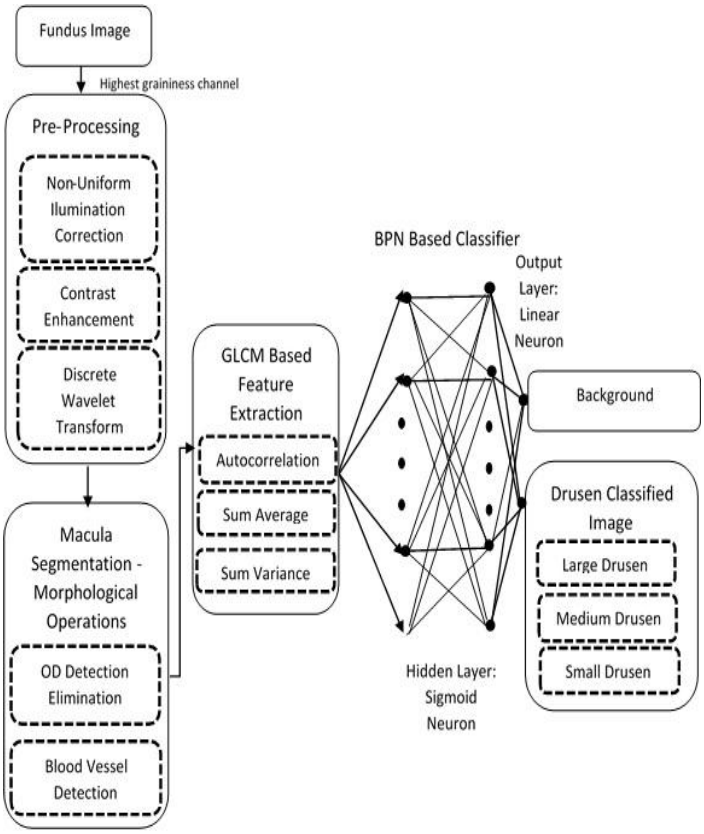

Figure 1: Block Diagram of Drusen Segmentation Algorithm

1. Pre-processing

Due to the imaging device, the retinal image obtained may have low contrast and poor illumination and some noise may be added during acquisition. Hence the image was processed with contrast limited adaptive histogram equalization and homomorphic filtering to enhance the contrast and to compensate non uniform illumination by compressing the brightness range. The noise present in the retinal image was removed by applying Discrete wavelet transform, a denoising procedure by shrinking the wavelet coefficients in the wavelet domain.

2. Macula Segmentation

Macula is located roughly in the center of the retina, temporal to the optic nerve. It is more serious when drusen is located in the macula region, a small and highly sensitive part responsible for most of the useful photopic vision and color perception. Macula region is segmented based on optic disc center and the direction of the inferior and superior vascular arcades from the pre-processed image. The macula region can be segmented from the retinal image using the algorithm that we have developed for retina localization, OD and blood vessel segmentation which are described elsewhere[8].The morphological operators were used to detect OD and the temporal superior and inferior vascular arcades.

3. Features Extraction

The textural features present in the macula region are extracted from GLCM. GLCM is a joint probability of occurrence of two gray level values at a given offset both in the terms of distance and orientation [9]. Various features can be extracted from P (GLCM), μ the mean value of P, σ is the standard deviation of P. To calculate the different textural features contained in the co-occurrence matrices Haralick et al (1973) proposed various statistical measures. The use of all heterogeneous information will degrade the diagnostic accuracy and increase their computational complexity. Therefore a reliable set of feature vectors should be considered to reduce the amount of irrelevant information. In order to classify drusen from the background three reliable texture features have been used to train the classifier. The selected features were classified as follows:

Autocorrelation

It is used to compute the gray tone linear dependencies of the drusen in the retinal image.

$$AUTOC = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times p(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \quad (1)$$

The value ranges between -1 to 1. -1 infers maximally uncorrelated and 1 implies maximally correlated.

Sum Average

It is used to measure the average skewness for each image by calculating the section-based skewness of the image.

$$\delta O_k = o_k(E)(1 - o_k(E))(t_k(E) - o_k(E))$$

$$P_{x+y}(i) = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} p(i,j) \quad (2)$$

Where $P_{x+y}(i)$ is the i^{th} entry obtained by summing the rows and columns of *p(i, j)*

$$Aver = \sum_{i=0}^{2G-2} iP_{x+y}(i) \quad (3)$$

Sum Variance

It is a measure of heterogeneity and its variance increases when the gray level values differ from their mean.

$$\Delta_{ij} = \eta \delta_{Hj} x_i$$

$$SVAR = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-\mu)^2 p(i,j) \quad (4)$$

For robust classification these features were extracted to train the classifier.

Classification Using ANN Extraction

Neural networks are widely used in pattern classification. A neural network is a set of input and output where a weight is associated with each connection. For training we use a feed-forward backpropagation neural network, which is adopted with sigmoid neurons in the hidden layer and linear neuron in the output layer, as depicted in the figure. The multilayer perceptron can be divided into feedforward and backpropagation [10]. In feed forward the input is fed into the left input layer and the information propagates forward towards layer by layer to generate an output. An error signal is computed by comparing the network's output with the expected output. Then the backpropagation works by changing the weights, principally a gradient descent method for efficient classification of the inputs. The error is propagated back to the hidden unit and terminates when the network reaches the global minimal error.

The sigmoid function calculates the weighted sum *S*, from the units connected to it. Given a network *E,* a real valued input *S* the weighted sum can be calculated for the hidden layer and the output layer as

$$\sigma(s) = \frac{1}{1+e^{-s}} \tag{5}$$

In weight training calculations the error term for the output nodes δO_k and the hidden nodes δH_k can be calculated as

$$\delta O_k = o_k(E)(1-o_k(E))(t_k(E)-o_k(E)) \tag{6}$$

$$\delta H_k = h_k(E)(1-h_k(E)) \tag{7}$$

Where O_k is the actual activation value of the output node *k* and t_k is the expected target output for node *k* and $o_k(k)(1-o_k(E))$ term is the derivative of the sigmoid function. The weight associated between the input and the hidden units can be adjusted by adding a value Δ_{ij}, the change in weight

$$\Delta_{ij} = \eta \delta_{Hj} x_i \tag{8}$$

Where η is the learning rate which indicate the relative change in weights. The weights between hidden layer and the output layer can be adjusted by adding a value Δ_{ij}

$$\Delta_{ij} = \eta \delta_{Oj} h_i(E) \tag{9}$$

The classification is divided into training and testing phase. The classifier is trained with the features extracted from the GLCM matrix of the retinal image where the diagnosis is known. After the training phase the network classifier is stored for testing the retinal image. Then the input image is stimulated with the trained networks to classify the background from the affected region of the retinal image.

RESULTS AND DISCUSSION

Fundus images can serve as a screening tool to identify drusen and for monitoring the progression of the disease. The fundus images used in the proposed work were collected from Aravind eye hospital, Madurai. The proposed method was implemented in MATLAB. The RGB channel with highest contrast value of the image enabled us to select the appropriate channel for further processing. The selected channel was pre-processed with homomorphic filtering and CLAHE that take advantage of the neglected picture values to correct the illumination and to improve the contrast which provides better definition and more information for further classification. The DWT was employed using daubechies function to decompose the image into different levels of resolution, where the gaussian noise was removed and the significant

features were extracted from the fundus image.

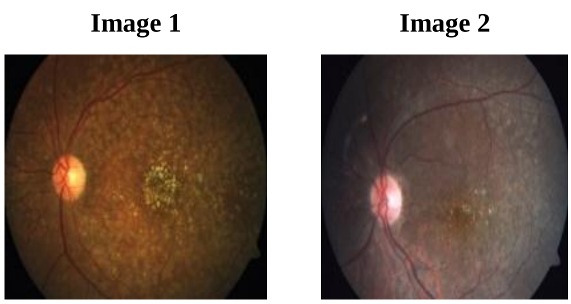

Figure 2: Input retinal image used for drusen detection.

The OD and the blood vessels were detected using mathematical morphology, which sharpens the regions and fills the gap in the binarized image. It assists in extracting the image components that are useful in description and representation of the region properties such as shapes and area. These image components lead to segment the macula region from the retinal image which is responsible for most of the Centre vision.

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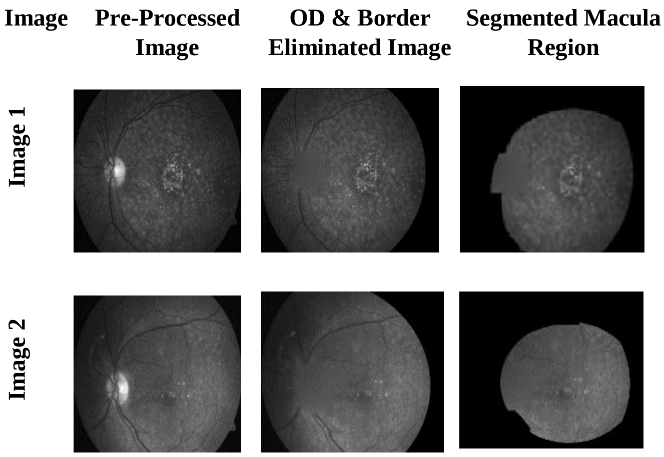

Figure 3: Retinal Border and Macula Segmented Image

The statistical features such as sum average, sum variance and autocorrelation were extracted from GLCM of the macula region of each image. These extracted texture features are considered as input for training the neural net classifier. These features are applied to multilayer feed forward network for classification which consists of neurons, the processing element with continuous differentiable activation function. The classifier is designed with 3 input neurons, 3 hidden neurons and 2 output neurons. The network will work better when the size of hidden layer is assigned between the input layer and the output layer size, hence it is assigned with 3 hidden neurons. The combination of Sigmoidal and the linear activation functions was found more convenient for the drusen classification problem. The sigmoidal neuron in the activation function produces the output over the 0 to +1 range. As the output of the hidden neuron is close to the limits, the derivation of these functions decreases. Similarly the linear neurons in the output layer produces a binary value in response to the sign of the input, +1 for positive input and 0 if it is not. In addition, it was observed that the linear function in the output layer had a positive effect on the performance of the drusen classification network. The weights associated with the network are sequentially updated to classify drusen from the background correctly and to minimize the error. If the error rate is large it is propagated back to the hidden unit. The training stops when the network classifier reaches higher accuracy with minimum training and testing errors. The three textural features of each pixel are calculated for the input vector of size 1958*2588. This training outperformed by classifying the retinal image in 12 epochs with an average training time of 236 seconds. The performance and the outcome of the network are listed in Table. I

Table I: Performance measure of BPN training algorithm.

Number of Epochs	12
Training Time	236 Seconds
Training Performance	0.0594
Validation Performance	0.0886
Testing Performance	0.0510
Gradient	0.00264
Learning Rate	0.01

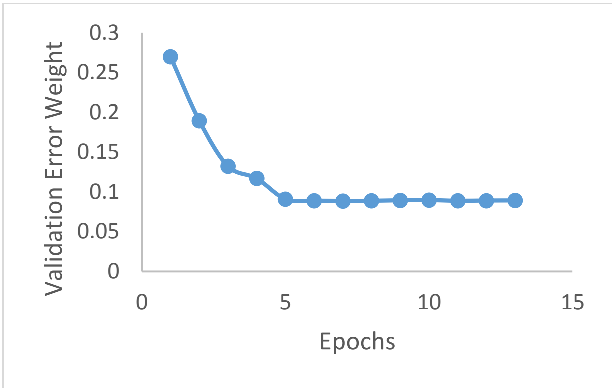

Figure 4: Mean Square Error by Epoch.

After each epoch the learning rate will change the preceding error weight to some extent. Figure .4.shows the error weigh adjustment in each epoch during training the network.

If the learning rate is too large then the learning of the network will be fast but, because of its large variableness the network may not learn properly which results in improper drusen classification. Hence the learning rate is set to a small value, 0.01 which resulted in efficient classification. The error is measured with Mean squared error (MSE) which gives the mean of the squared error between the desired output and the actual output of the network. The network was trained until the validation error failed to decrease for six iterations. Figure.5. shows the performance of the network during training.

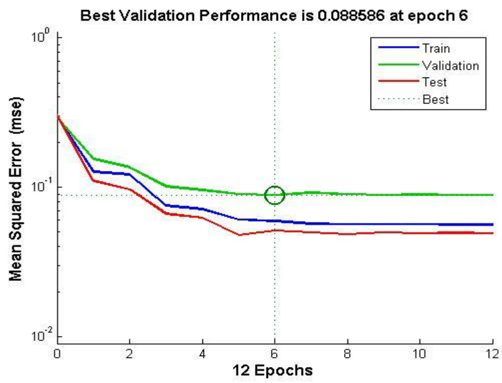

Figure 5: Classifier training performance.

The plot depicts that the actual output is in well agreement with the desired output. Overfitting of data cannot occur because the test curve is below the validation curve, then it also indicates that there is no problem while training the samples. The output of the network was specified as 0 for background region and 1 for the drusen region. Then the segmented drusen regions are labelled based on the connected component properties. A sliding window technique is used to determine if a given pixel is a drusen or not. It results in a labelled image, where the pixels corresponding to a drusen region share a common label while the background region is labelled zero. Then by combining the total number of pixels with same label gives the area of the single drusen and by combining and calculating the total number of area pixels yields the overall drusen affected area.

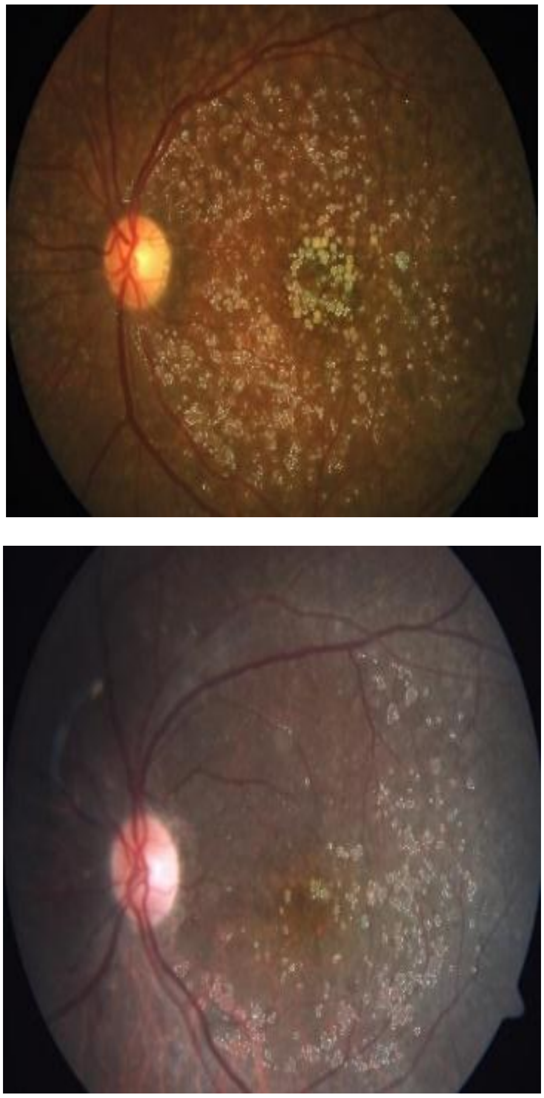

Figure 6: Drusen Detected in Fundus Images.

Sensitivity and specificity are used as a measure to evaluate the accuracy of our proposed system. The FAR and FRR obtained in the proposed study are listed in Table II.

Table II: Performance Evaluation

Drusen Type	FRR%	FAR%
Large Drusen (> 125 µm)	0.4	0
Medium Drusen (63-125 µm)	2.4	1.6
Small Drusen (< 63 µm)	0.4	4.4

250 samples were considered for individual drusen types to compute FAR and FRR. Table II shows the results obtained in classification of drusen under each grade. It was observed from the table that 249 samples were exactly identified as large drusen resulting in 99.6% accuracy. In case of medium drusen, the proposed system correctly classified 244 samples and misclassified 4 sample regions. Similarly 249 samples have been correctly classified to be small drusen and 11 samples are misclassified to be small drusen. There is an increase in the FAR of small and medium drusen because those regions which are not identified as drusen in the ground truth image can become drusen in the near future. The proposed system was able to identify 742 drusens out of 750 drusens yielded 98.9% accuracy.

The receiver operating characteristic (ROC) curve of automated drusen detection was used to distinguish the relationship between sensitivity and specificity. The performance of the proposed system will be better when the ROC curve approaches closer to the top left corner.

The ROC curve reflects that the proposed system agrees with the ground truth detection. Figure.7. shows the ROC curve of automated drusen detection algorithm.

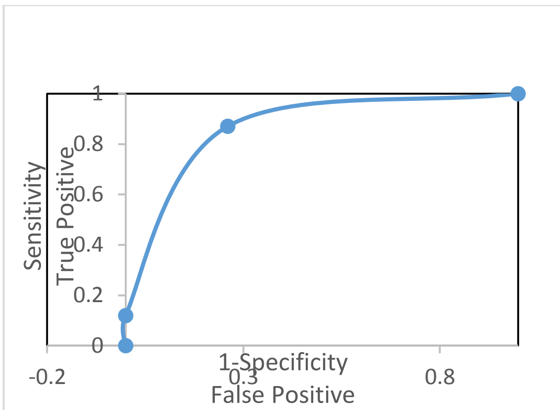

Figure 7: ROC curve of BPN based drusen detection algorithm.

The area under the curve (A_z) measures the overall classification performance of the algorithm and it indicates how reliably the detection can be performed. The performance computed from the area under the ROC curve was A_z=0.8676.

Hence AUC of the ROC curve reflects that the proposed system agrees with the ground truth detection.

CONCLUSION

The proposed system for automatic drusen detection based on ANN will qualitatively detect and grade drusen from the fundus image. It will assist in decision making in clinical diagnosis and will aid doctors to take appropriate treatment steps. The algorithm involves pre-processing which is responsible for non-uniform illumination correction and contrast enhancement. The image was subjected to wavelet transform to reduce the noise a common problem arises during image acquisition. The pre-processed image was subjected to morphological top-hat transform to segment the macula region from the retinal image. In order to improve the accuracy of drusen detection the GLCM textural features were extracted from the macula region to train the multi-layer feed forward neural network, which resulted in better classification of drusen from the background. The performance of the proposed system was assessed using ROC curve, which shows 98.9% of accuracy in quantifying the relevant drusen.

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