Grid Color Moment Features in Glaucoma Classification

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***Abstract*—Automated diagnosis of glaucoma disease is focused on the analysis of the retinal images to localize, perceive and evaluate the optic disc. Clinical decision support system (CDSS) is used for glaucoma classification in human eyes. This process depends mainly on the feature type that can be morphological or non-morphological. It is originated in the retinal image analysis technique that used color feature, texture features, extract structure, or contextual. This work proposes an empirical study on a narrative automated glaucoma diagnosis, classification system based on both Grid Color Moment method as a feature vector to extract the color features (non-morphological) and neural network classifier. Consequently, these features are fed to the back propagation neural network (BPNN) classifier for automated diagnosis. The proposed system was tested using an open RIM-ONE database with accurate gold standards of the optic nerve head. This work classifies both normal and abnormal defected retina with glaucoma images. The experimental results achieved an accuracy of 87.47%. Thus, the proposed system can detect the early glaucoma stage with good accuracy.**

***Keywords*—Glaucoma; Clinical decision support system; RIM-ONE image database; Classifier; Back Propagation Neural Network; color feature extraction; Grid Color Moment**

I. INTRODUCTION

Medical image processing is a promising domain that various researches try to develop as in [1-10]. Since, Glaucoma is one of the main reasons for blindness worldwide that affect around 80 million people by 2020. It is a disease that damages the optic nerve (ON) due to incessant increase in the intraocular pressure (IOP) in the eye, which can lead to vision loss and cause blindness. Thus, early diagnosis of glaucoma is necessary to prevent vision loss. Globally, glaucoma is a significant cause of vision loss that excessively affects women and Asians [11]. Additionally, glaucoma enlarges the cup size, which affects the optic disc (OD). Where the Optic disc is the observable portion of the optic nerve from which the nerve fibers exit the eye [12].

Hence, early diagnosis, detection and treatment of glaucoma are the only ways to prevent vision impairment and blindness. There are three well-established standard tests used by ophthalmologists to diagnose glaucoma: i) the IOP measurements [13, 14], ii) the assessments of the optic nerve (stereoscopic) [15], iii) Visual field tests.

Moreover, other measurements that calculate the changes in the retinal nerve fiber layer (RNFL) thickness or the ocular blood flow can be performed for glaucoma diagnosis. Jointly, these methods afford information on both structural and functional defects that require digital image analysis for recognizing the natural growth of the disease. This relies on qualitative assessments of the eye using computational techniques. Where, conventional ophthalmologist manufactures diagnoses are based on the doctor's experience and individual judgment. Therefore, automatic retina image analysis is considered a screening tool [16] for early detection of diseases. Thus, the main parameter that can be used with the screening programs is the OD [17] for diagnosis and to identify glaucoma.

Generally, automated CDSSs in ophthalmology are designed mainly for the identification of the disease pathology in human eyes. It is used to facilitate clinicians in diagnosis, support clinical decision-making and to reduce variability/ time. These systems are used for automated pattern recognition and image analysis that requires feature extraction.

Since, the feature is an attribute that can capture a definite visual image property, either locally for objects or globally for the whole image. Thus, texture feature classification is used for glaucoma diagnosis. An assortment of approaches can be derived from texture features such as: signal processing (Gabor and Wavelet transformation) [18, 19], co-occurrence matrices [20], Fourier power spectrum [21] and correlation features, neural networks [22], etc.

Meanwhile, color is invariance with regard to image translation, scaling, and rotation. Therefore, color is considered

a significant feature for image representation that is extensively used in image recovery and analysis.

Recent studies are concerned with the automatic feature extraction procedures in retinal images for automatic glaucoma detection. Typically, detection/ classification of the glaucoma by means of retinal image are controlled by the features selection and feature extraction approaches. The extracted features are then used as input to a classifier to determine the glaucoma class.

The feature type is divided into two categories, namely: I) morphological (requires segmentation process before measuring the geometric parameters), and II) non-morphological (doesn't require segmentation process and considers image-based features). Texture, shape, and color are features captured from the image without segmentation.

Through the CDSSs, features extracted are sorted into two types: structural features and texture features. Structural features commonly include the disk diameter, disk area, cup diameter, cup-to-disk ratio, rim area, and the topological features extracted from the image [23]. Approaches using non-morphological features such as color feature extraction for classification are promising at medical image classification tasks. That is based on Grid color moment, which represents the feature vector of the image.

Since, classification plays a significant role in the detection of some diseases in their early phases, such as diabetes that can be accomplished via comparison of the states of retinal blood vessels. Thus, our research is focused on a novel automated classification system for glaucoma. The extracted features can then be fed to the Back propagation neural network (BPNN) classifier to distinguish between normal and glaucomatous images accurately. To test the proposed system, the RIM-ONE database, a fundus image database is used for glaucoma disease.

The remaining part of this paper is organized as follows. Section II includes related work, followed by section III that represents the methodology via data acquisition and the proposed system. In section IV, the color feature extraction concept is presented, while the BPNN network classifier used for the glaucoma automated diagnosis is discussed in section V. The results obtained and the discussion is introduced in section VI. Finally, the paper is concluded and goes through the future work in section VII.

II. Related Work

Numerous studies focused on early detection of glaucoma, the objective/ quantitative measurements of the RNFL are calculated. Some of the prominent existing modalities for eye imaging are such as optical coherence tomography (OCT), Multifocal electroretinograph (mfERG), etc. have been used for the thickness and phase retardation; respectively. The application of OCT technology in clinical glaucoma practice has largely centered on imaging the peripapillary RNFL. This approach proved its sufficiency for assisting the clinician in both diagnosing glaucoma and detecting disease progression [24, 25].

Bock *et al*. [26] used non-morphological features that carried out via feature extraction methods such as Gabor Filter (textures), pixels intensity values, histogram model and Fourier Transform (FFT). The results achieved 86% accuracy with 2-stage classification and Support vector machine (SVM) classification methods. Archana in [27] initiated the Computer Based Diagnosis of glaucoma using digital fundus images. Where, images with different color variation inside the eye were compared using images taken by high definition laser camera. To identify whether the eye is suffering from glaucoma, a test is made using the image of a normal eye that is kept as a reference (zero) and then compared to the clinical observations of the person's image.

Matsopoulos *et al*. used 127 blood vessels fundus image database of the optic nerve head (ONH) a feature to detect glaucoma based on the blood vessel shape [28]. For classification the authors used multilayered Artificial Neural Network (ANN), which achieved 87.5% accuracy. A narrative glaucoma detection system via an arrangement of texture and higher order spectra features suggested by Rajendra *et al*. provided accuracy of more than 91% [29].

Yogesh and Sasikala illustrated texture analysis of the retinal layers in spectral domain OCT images to diagnosis the retinal disorders [30]. A method for automated segmentation of the SD-OCT images was presented with the texture analysis for the diagnosis of fluid filled regions associated with retinal disorders. Surfaces and features were extracted in each surface locally to distinguish texture properties across the macula. Classification was done based on 22 texture feature values. If the feature value deviates from the preset normal range, this indicates detected abnormalities. This work aimed to extract textural information from the SD-OCT scans that can be used for clinically important applications.

The authors in [31] developed a method for the RNFL texture classification based on Markov random fields. Two supervised classifiers named linear Ho-Kashyap rule and nonlinear Bayesian classifier based on Gaussian mixture model (GMM) were implemented. The experiments showed that the proposed textural features were reliable for RNFL texture descriptors using the fundus-OCT data pairs.

While, in [32] a glaucomatous image classification using texture features within images and efficient glaucoma classification based on Probabilistic Neural Network (PNN) of examining the efficiency of the features extracted was proposed. A wavelet-based texture feature set has been used for feature extraction.

Energy distribution over wavelet sub bands was applied to compute these texture features. Wavelet features were attained from the daubechies (db3), symlets (sym3), and biorthogonal (bio3.3, bio3.5, and bio3.7) wavelet filters. It uses to distinguish between normal and glaucomatous images through the proposed technique to extract energy signatures obtained using 2-D discrete wavelet transform and the energy obtained from the detailed coefficients. The observed accuracy, using features by DWT was around 95%, this demonstrates the effectiveness of these methods.

In order to early detection of glaucoma progression, the authors in [33] introduced a solution for the retinal nerve fiber layer loss estimation using fractal dimension (FD) and texture feature.

This enabled more comprehensive assessment of the retinal nerve fiber layer and was performing glaucoma detection using RNFL loss determining. Spearman correlation co-efficient was estimated for FD and texture feature for healthy, medium loss, and severe loss RNFL were 0.85, 56, and 35 respectively.

The proposed features can be used as a part of feature vector in glaucoma risk. The authors suggested that these features can be used in the glaucoma screening program together with other features such as RNFL thickness, etc. based on different methods.

In [34] a modified spatial fuzzy C-means for glaucoma detection has been applied using retinal images. The authors deployed both the K-Means clustering and C-Means clustering which provided accurate results.

Therefore, the proposed study employed a non-morphological feature extraction via Grid Color Moment method, that to be the input to the BPNN classifier to distinguish between the normal and glaucoma cases.

III. Methodology and Proposed System

A. Data Acquisition

There are numerous public databases for retinal fundus images that are available for glaucoma research to automatically extract the features for glaucoma detection. An Open Retinal Image Database for Optic Nerve Evaluation (RIM-ONE) is a fundus image database that is related to glaucoma disease. I

It consists of 169 ONH images, where the images are divided into several classes as follows: normal 118 images, early glaucoma 12 images, moderate glaucoma 14 images, deep glaucoma 14 images and ocular hypertension (OHT) 11 images [35, 36]. In this study the RIM-ONE database is employed as it is considered precise gold standards of the ONH.

Fig. 1 demonstrates normal and abnormal glaucomatous images taken from the RIM-ONE database. Even if the images are clear, using the naked eye one can't distinguish between the normal (healthy) images and the abnormal (glaucoma) images, which necessities the automated system development. In recent years, the progress in digital imaging technologies generated a large growth in the number of digital images taken.

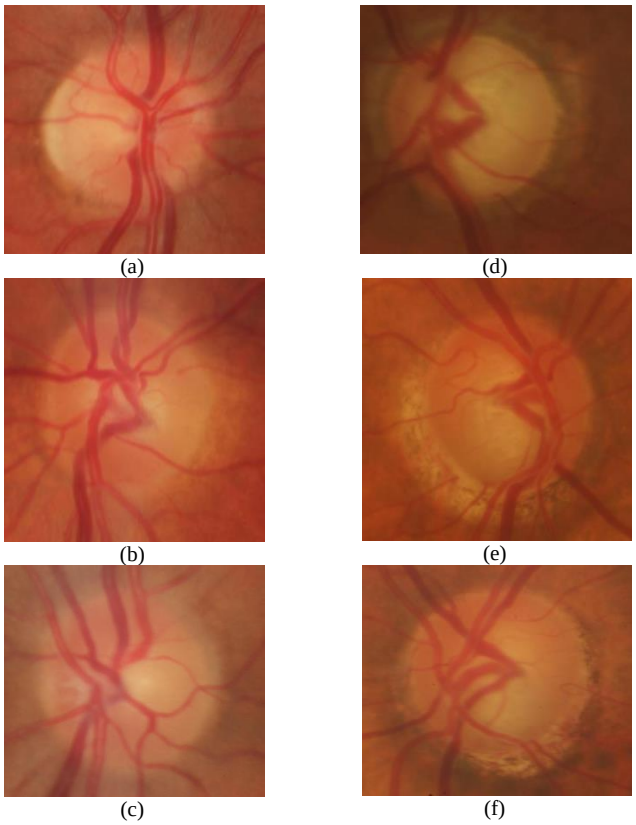

Fig. 1. Eye RIM-ONE database images: (a, b, c) Normal image, (d, e, f) Glaucoma image (abnormal)

B. Proposed System

The block diagram of the proposed system is illustrated in Fig. 2. It is divided into two subsystems, namely offline and real time systems. This work distinguishes between normal and glaucoma affected retina. Several features are required to be extracted using the Grid color moment that provides obvious results for distinct identification and classification. The classification method proposed is the use of a neural network classifier with the help of texture feature extraction of the localized area of the optic cup of images. The entire set of the RIM-ONE images (normal, abnormal) are attained in the first step in the offline mode. The Grid color moment features are then extracted from the RIM-ONE database images. Then, the extracted features are fed into the back-propagation neural network (BPNN) classifier. In the real time mode, the database images are used to extract the significant features and fed to the trained classifier for classification. It then performs the classification into normal and abnormal glaucoma classes based on the extracted significant colored texture features.

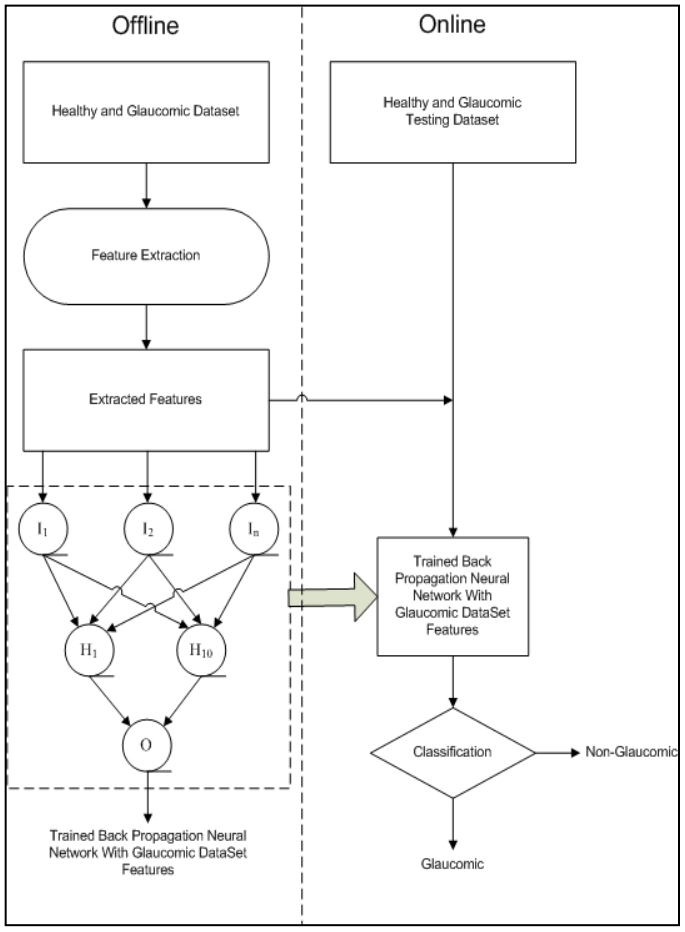

Fig. 2. The Automated Glaucoma Diagnosis Proposed System

IV. COLOR FEATURE CONCEPT

Typically, morphological feature extraction methods can produce features such as the disc diameter, cup diameter, and the neuroretinal rim. While, the features that can be formed with non-morphological feature extraction methods are such as parapapillary atrophy (PPA), RNFL and blood vessels. Septiarini and Harjoko recommended using non-morphological features for glaucoma detection as it yields higher accuracy than using morphological features [37]. Visual indexing procedures can be categorized into: pixel domain and compressed domain. The former is based on features as texture, color/histogram, shape, while the compressed domain indexing procedures can be generally classified into spatial domain and transform domain techniques.

Based on [37] this study is based on color features (non-morphological features) for glaucoma classification. Color feature is one of the broadly used features in low level feature. Compared with texture- and shape- feature, color feature provides superior stability and is further insensitive to the zoom of image and the rotation. There are several color descriptors such as color moment, Color Coherence Vector (CCV), and color histogram.

Color histogram is used to describe the color distribution in an image. However, since there is no local association between information on the color histograms, thus it cannot differentiate between objects [38]. To compensate this disadvantage, grid color moment can be used. Color moment represents the color distribution using standard deviation, mean and the third root of the skewness of each color channel [39].

The mean, variance, and standard deviation are described for an image of size $N \times M$ pixels as follows:

$$\bar{z} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} z_{ij}}{NM} \quad (1)$$

$$\gamma^2 = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(z_{ij} - \bar{z}\right)^2 \quad (2)$$

Where z_{ij} is the pixel intensity in H/S/V channels of the pixel in row i and column j. In addition, the skewness (H/S/V) is computed by:

$$\eta = \frac{\frac{1}{nm}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(z_{ij} - \bar{z}\right)^3}{\left(\frac{1}{nm}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(z_{ij} - \bar{z}\right)^2\right)^{3/2}} \quad (3)$$

Using the Grid Color Moment which is the feature vector for a given image, the algorithm used is [40]:

Algorithm: Grid color moment

Start
Input: colored RGB (Red-Green-Blue) image
Procedure:
Convert the image from RGB for HSV color space
Divide uniformly the image into 3x3 blocks
Compute the mean color (H/S/V) using equation (1) for each of these nine blocks
Compute its variance (H/S/V) using equation (2)
Compute its skewness (H/S/V) using equation (3)
Perform normalization for each of the 81 features by:

1- ***Compute*** the mean and standard deviation from the training dataset

$$\lambda = \frac{1}{G}\sum_{k=1}^{G} R_k \quad (4)$$

$$\sigma = \sqrt{\frac{1}{G}\sum_{k=1}^{G}\sum_{j=1}^{M}\left(R_k - \lambda\right)^2} \quad (5)$$

Where, G is the number of images in the training database, and R_k is the feature of the k^{th} training sample.

2- ***Perform*** the "whitening" transform for all the data (including both the training data and the testing data), and get the normalized feature value:

$$R_k^{'} = \frac{R_k - \lambda}{\sigma} \quad (6)$$

Output: normalized color feature vector
End

Where, each block 9 features, and thus the entire image will have 9x9=81 features. It is noted that the normalization step is done for the 81 features to achieve good numerical behavior before performing the classification that will be discussed in the next section.

V. NEURAL NETWORK CLASSIFIER

Color feature analysis is imperative in numerous applications of computer image analysis for classification/ segmentation of medical images based on local spatial variations of intensity or color. The objective of the color classification is to allocate an indefinite sample image to one of a set of recognized color classes. A significant application area in classifications based color are industrial and biomedical surface examination, such as discovering the defects and disease, satellite or aerial imagery classification, etc.

The classification of color features is useful to an ophthalmologist's clinical analysis and engages separating the selected feature space according to the glaucoma class. Image classification is the facility to split normal and abnormal (glaucoma affected) regions by applying feature based image extraction methods. Classification is classically achieved using an assessment function.

In the proposed system, the Neural Network based back-propagation (BPNN) classifier is used for the automated diagnosis of glaucoma. The BPNN is briefly clarified below:

A. Neural Network

A significant tool for the classification is the Neural networks (NN). Recent neural classification has ascertained that NN is a capable alternative to diverse conventional classification methods. The neural network improvement appeared in [41], as it's used for medical application. Neural networks have various features as follows:

- Are data driven, self-adaptive techniques that can adjust themselves to the data, without any clear specification of with the underlying model.
- Can approximate any function with arbitrary accuracy.
- Are nonlinear models that are able to modeling complex real world applications.
- Provide the basis in set up the classification rules and achieve statistical analysis.
- Are successfully applied to an extensive variety of real world classification such as speech recognition, medical diagnosis, etc.
- Play a vital role in classifications using its supervised and unsupervised techniques.

The NN architecture is made up from input, output and one or more hidden layers. Input layer represents the raw information that is fed into the network. Each neuron in a particular layer is connected with all neurons in the next layer. The connection between the i^{th} and j^{th} neuron is characterized by the weight coefficient W_{ij} and the i^{th} neuron by the threshold coefficient ϑ_i. The weight coefficient replicates the degree of significance of the given connection in the neural network. The output value (activity) of the i^{th} neuron x_i is determined as follows [42]:

$$x_i = q(\psi_i) \tag{7}$$

$$\psi_i = \vartheta_i + \sum_{j \in \Gamma_i^{-1}} W_{ij} x_j \tag{8}$$

Here, ψ_i is the i^{th} neuron potential and the function $q(\psi_i)$ is the transfer function.

The supervised adaptation process varies the threshold coefficients and weight coefficients to minimize the sum of the squared differences between the computed and required output values. This is achieved by minimization of the objective function p:

$$P = \sum_o \frac{1}{2}(x_o - \hat{x}_o)^2 \tag{9}$$

x_o and $\hat{x}_o$ are the computed and required activity vectors of the output neurons; respectively.

B. Back-propagation Neural Network (BPNN)

One of the trendiest NN algorithms is back propagation algorithm. Rojas in [43] declared that the BP algorithm could be broken down to four main steps. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the compulsory corrections. The algorithm can be decomposed in the following four steps: i) Feed-forward computation ii) Back propagation to the output layer iii) Back-propagation to the hidden layer iv) Weight updates. The algorithm stops when the value of the error function has become adequately small.

The steepest-descent minimization method is used in the back-propagation algorithm. For adjustment of the weight and threshold coefficients it holds that:

$$W_{ij}^{(k+1)} = W_{ij}^{(k)} - \lambda \left(\frac{\partial P}{\partial W_{ij}} \right)^{(k)} \tag{10}$$

$$\vartheta_{ij}^{(k+1)} = \vartheta_{ij}^{(k)} - \lambda \left(\frac{\partial P}{\partial \vartheta_{ij}} \right)^{(k)} \tag{11}$$

λ is the learning rate. The calculation of the derivatives $\left(\frac{\partial P}{\partial \vartheta_{ij}} \right)$ and $\lambda \left(\frac{\partial P}{\partial W_{ij}} \right)$ is the key parameter of the algorithm.

For cluster based classification of medical images, neural networks are constructive. This method can be used in computer-aided diagnostic decision making.

C. Performance measures

To perform the classification using the extracted features, the entire dataset is divided into parts. The experimental dataset contains both normal and glaucoma images. The process begins with the training of 80% of the data and 10% for testing. Then, the validation was done using the remaining 10% part. The accuracy, PPV (positive predictive value), sensitivity and specificity are computed for each iteration. The average of all ten folds gives the actual accuracy, PPV, sensitivity and specificity.

VI. Results and Discussion

In this study, Grid color moment feature based glaucoma classification using back propagation network has been proposed.

A. Classification Results

In the current study, features were computed. Individually, if these features are considered using the proposed model, then the corresponding classification obtained accuracies were shown in Table 1. Table 1 reported the effective classification accuracy (87%) with the Grid color moment feature.

In this work, high risk of the proposed system signifies the glaucoma and low risk of the proposed system signifies non-glaucoma (normal) cases. While, defining the standard performance metrics, four parameters were adapted for performance analysis named the True Negative (TN), True Positive (TP), False Negative (FN) and False Positive (FP).

TN involves the total number of non-Glaucomic cases in the proposed system that is classified as Glaucomic cases. TP is the total number of Glaucomic cases in proposed system that is classified as Glaucomic cases.

FN indicates the total number of non-Glaucomic cases in the proposed system that is classified as Glaucomic cases. FP is the total number of Glaucomic cases in proposed systems that are classified as non-Glaucomic cases.

These metrics are shown in the confusion matrix illustrated in Fig. 3.

From Figure 3, it is clear that in case of Grid color moment analysis, the TP and TN values are 38.5% and 7% and FP and FN are 49% and 5.5%; respectively. Supplementary metric measures are computed using the previous four parameters as follows.

1) Sensitivity: is identified as the probability that a classifier will mark a Glaucomic label for Glaucomatous dataset, and is computed as:

$$\text{Sensitivity}=\frac{TP}{(TP+FN)} \tag{12}$$

2) Specificity: is a measure of the probability that the classifier will result in a non-Glaucomic label when used on low risk Glaucomic patients and is calculated as:

$$\text{Specificity}=\frac{TN}{(TN+FP)} \tag{13}$$

Fig. 3. Confusion Matrix

3) Positive predictive value (PPV): is described as the probability of patient's label as Glaucomic correctly diagnosed, is denoted as:

$$\text{PPV}=\frac{TP}{(TP+FP)} \tag{14}$$

4) Negative predictive value (NPV): is the probability of patient's label as Glaucomic incorrectly diagnosed and is calculated as:

$$\text{NPV}=\frac{TN}{(TN+FN)} \tag{15}$$

5) Accuracy: is the ratio of the number of correctly classified Glaucomic patients to the Glaucomic patients, and is calculated as:

$$\text{Accuracy}=\frac{TP+TN}{(TP+TN+FP+FN)} \tag{16}$$

Since, a high specificity and high sensitivity indicate an ideal test scenario. A positive outcome in this case means the condition is likely and a negative outcome in this case means the condition is unlikely. The proposed Grid color moment approach achieved 87.50% Sensitivity, 87.45% Specificity, PPV of 84.54% value, NPV of 89.92%, and 87.47% accuracy.

In fig. 4, the regression curves are shown for the different features used. It demonstrates the network outputs with respect to targets for training, validation, and test sets. The dashed line indicates the perfect result – outputs = targets. The solid line specifies the best fit linear waning line between the outputs and targets. The linear regression (R) value identifies the connection between the outputs and the targets. If R = 1, this characterizes an exact linear relationship between the outputs and targets. If R is near to zero, then there exists no linear relationship between outputs and targets. In this study, R=0.78, which denotes some linear relationship between outputs and targets, where (output=0.65*Target+0.18).

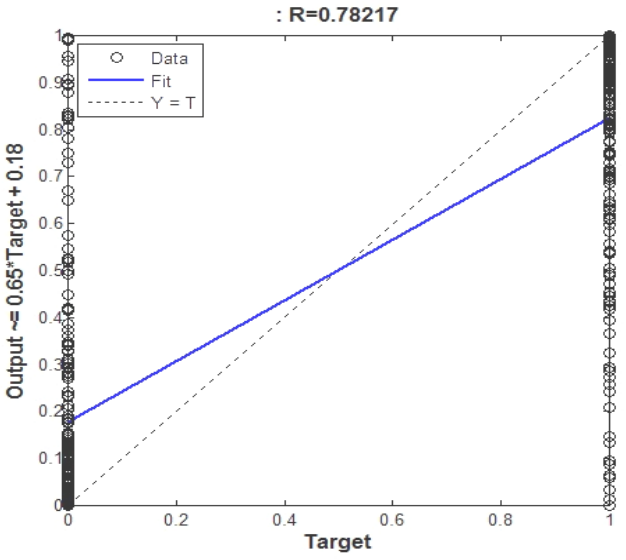

Fig. 4. Regression curve

The Receiver Operating Characteristic (ROC) curve shown in Fig. 5 facilitates the classifiers' performance measurement. This graph has a plot that indicates the false positive rate on the X axis and the true positive rate on the Y axis. The point (0,1) indicates the perfect classifier. It performs accurate classification for all the positive cases and negative cases correctly. The (0,1) point denotes that the false positive rate is 0 (none) and the true positive rate is 1 (all). The (0,0) point denotes a classifier that predicts all the cases to be negative, whereas the point (1,1) corresponds to a classifier that predicts each and every case to be positive. Point (1,0) is the classifier which represents that it is incorrect for all the classifications. From Fig. 5, it is clear that the Grid color moment RCO curve has decreased error slowly, which yields to improved RCO.

Figure 6 designates the Performance validation, as it includes all information concerning the training of the neural network. The trace of a matrix (tr) structure assists in tracking different variables during the training, such as the gradient magnitude, the value of the performance function, etc. The property (tr) best epoch finds the number of iterations for which the validation performance has a minimum value.

In this study, best validation performance is 0.158 at the 11th using the Grid color moment approach. The neural network model which performs a function approximation task will be using a continuous error metric such as mean squared error (MSE). All the errors will be summed up over the validation set of inputs and outputs, and then normalized by the size of the validation set.

Fig. 7 illustrates the error histogram with the 20th bin. It is used to attain additional verification of network performance. In figure 7, the blue bars represent training data. The histogram can provide an indication of outliers, which are data points where the fit is extensively worse than the majority of data. The error is calculated as the (Target-network output). The large center peak specifies very small errors that refer to output that is very close to the targeted value.

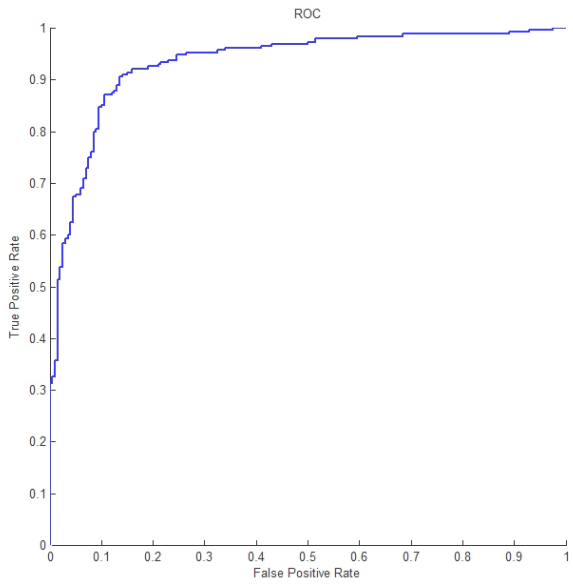

Fig. 5. The ROC curve

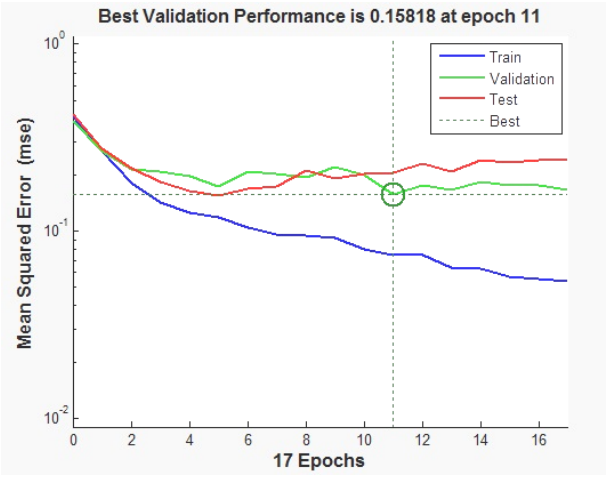

Fig. 6. Performance validation

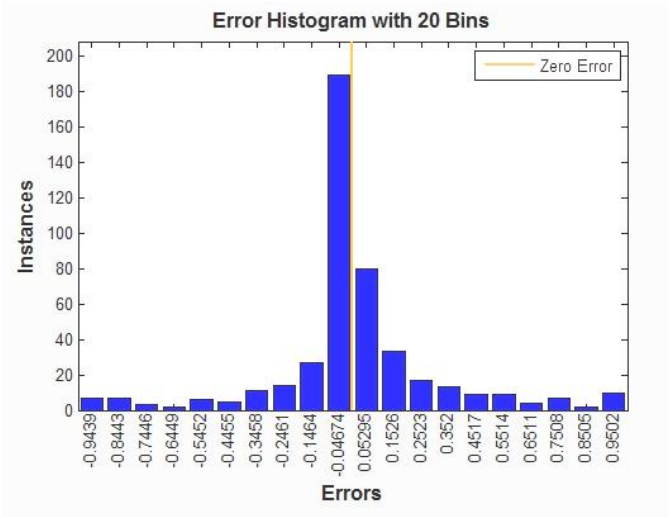

Fig. 7. Error histogram

Commonly, numerous studies have been conducted on the classification of normal and glaucoma classes. Further, most of the work carried out in the literature classifies the RIM-ONE database images into normal and glaucomatous classes. Classification of normal and glaucoma images using Grid color moment feature vector provided 87.47% accuracy.

The main contribution of this current study has been achieved as:

1) Developed an algorithm that automatically analyzes the retina images and classifies normal images and diseased glaucoma images with indicating the defected portions.

2) Neural Network is used to automatically classify the images as normal or abnormal eye images. The proposed system automatically extracts features and uses them with the BPNN classifier to predict the class (normal, glaucoma).

3) The proposed system is able to automatically identify the abnormal subjects as abnormal with an NPV of 89.92%, as the Specificity of the system is 87.45% and accuracy.

4) From all the previous experimental results, the proposed method is able to diagnose the early stage of glaucoma with an accuracy of 87.47%.

5) Using the color features based Grid color moment approach to detect the early stage of glaucoma is the novelty of this paper.

VII. Conclusion and Future Work

Glaucoma is a disease which arises by the deterioration of the optic nerves (optic disc). It is an optic neuropathy that causes the loss of retinal ganglion cells and damage to the retinal nerve fiber layer (RNFL). The CDSS is based on the retinal image analysis techniques to extract structural, textural or contextual features from the images. Therefore, it is able to effectively differentiate between normal and glaucoma diseased samples. Retinal image analysis is based on computational techniques to make a qualitative inspection of the eye more objectively.

Therefore, enormous studies have been working in the domain of the automated diagnosis of glaucoma disease. These studies have been focused on the analysis of retinal database images to localize, detect and evaluate the optic disc. An open RIM-ONE database images with accurate gold standards of the optic nerve head is implemented in the current study. Classification of the glaucoma affected eye has been performed via training the BPN.

Widespread research has been carried out for efficient eye disorder and glaucoma treatment and a number of research reports have been submitted with different accuracy levels for different diagnostic methods. In this paper, a CDSS system based on color features and a multiple NN classification scheme is presented. The major goal of this method is to reduce the changeability that is arising between different clinical diagnoses of the structural characteristics of the human eye. As well as preventing the vision loss with the early identification and diagnosis of glaucoma.

In the proposed system, the back propagation neural network classifier is used to classify normal and abnormal glaucoma retinal images. The Grid color moment that indicates the feature vector extracted from the whole image for the region of interest (ROI) proves its efficiency as it provides 87.47% accuracy that shows the effectiveness of the proposed system.

As a suggested future work:

1) Design a complete, integrated, automated system to classify all different types of glaucoma namely: Primary Open-Angle Glaucoma, Normal Tension Glaucoma, Angle-Closure Glaucoma, Acute Glaucoma, Pigmentary Glaucoma, Exfoliation Syndrome and Trauma-Related Glaucoma.

2) Develop a system that combines the three test parameters for diagnosis. For example, features extracted from cup to disk ratio and RFNL can be used for classification and can be used to develop a glaucoma risk index (GRI) which can classify the different stages of glaucoma with just a single number.

3) Make ranking for the features discrimination index.

4) Add pre-processing step, for de-noising.

5) Combine both color and texture feature extraction: contribute to determine the visual appearance of images in a different way.

6) Use another modified NN instead of the BP, and compare with the current. Also, use different classifiers and compare the results.

7) Make test on various fundus databases to prove the proposed system robustness. Also, to increase the accuracy of the system further using huge databases with diverse images, another nonlinear feature and better classifiers.

8) Measure the complexity and the convergence time for each feature.

9) In order to obtain high performance, clinically significant features essential to be extracted from diverse huge database. This will necessitate a huge storage space for the CAD system.

10)Use a combination of different features for automatic glaucoma detection/ classification.

11)Perform classification of glaucoma that is not only distinguished as normal or glaucoma, but the several stages of glaucoma (early, mild and advance).

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