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Automated Glaucoma Detection Techniques Using Fundus Image

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ABSTRACT: This paper presents automated glaucoma detection techniques based on neural network and Adaptive Neuro fuzzy Inference system (ANFIS) Classifier. Digital image processing techniques, such as preprocessing, morphological operations and thresholding, are widely used for the automatic detection of optic disc, blood vessels and computation of the features of fundus image. Glaucoma is a disease of the optic nerve caused by the increase in the intraocular pressure of the eye. Glaucoma mainly affects the optic disc by increasing the cup size. It can lead to the blindness if it is not detected and treated in proper time. The detection of glaucoma through Optical Coherence Tomography (OCT) and Heidelberg Retinal Tomography (HRT) is very expensive, this limitation is removed by this Glaucoma Diagnosis system with good performance. In addition to diagnosis of Glaucoma a Graphical user interface (GUI) is developed. This GUI is used for automatic diagnosing and displaying the diagnosis result in a more friendly user interface The results presented in this paper indicate that the features are clinically significant in the detection of glaucoma. Proposed system of this paper is able to classify the glaucoma automatically with a sensitivity and specificity of 98% and 95% respectively.

Keywords : Intra ocular pressure, Ocular Computing Tomography, Heidelberg Retinal Tomography, Cup to Disk Ratio, Support Vector System, Artificial Neural Network.

1 INTRODUCTION

This paper presents automated glaucoma detection techniques. Glaucoma is the second leading cause of blindness with an estimated 60 million glaucomatous cases globally in 2012 [1], and it is responsible for 5.2 million cases of blindness [2]. In India, the prevalence of glaucoma is 3-4% in adults aged 40 years and above, with more than 90% of the patients unaware of the condition [3] [4]. Clinically, glaucoma is a chronic eye condition in which the optic nerve is progressively damaged. Patients with early stages of glaucoma do not have symptoms of vision loss. As the disease progresses, patients will encounter loss of peripheral vision and a resultant “tunnel vision”. Late stage of glaucoma is associated with total blindness. As the optic nerve damage is irreversible, glaucoma cannot be cured. However, treatment can prevent progression of the disease. Therefore, early detection of glaucoma is crucial to prevent blindness from the disease. The digital color fundus image is a more cost effective imaging modality to assess optic nerve damage compared to HRT and OCT, and it has been widely used in recent years to diagnose various ocular diseases, including glaucoma. In this work, we will present a system to diagnose glaucoma from fundus images with MATLAB based Graphic User Interface (GUI) tool is developed for analysis of fundus image by the ophthalmologist for detection of Glaucoma.

2 STRUCTURE OF EYE AND EYE RELATED DISEASES

This section start with discussion on the anatomy of the eye and the functioning of the eye followed by eye related diseases Glaucoma is described in detail.

2.1 Anatomy of Eye

The anatomy of the human eye is presented in Fig 1.This illustrates a cross sectional view of the human eye with various ocular structures indicated. Basically, the human eye functions in a sequential manner. Firstly, the lights perceived will pass through the cornea and pupil to the lens (which is surrounded by the iris). Secondly, the lens will focus the lights onto the retina. Thirdly, the captured light is converted into signals. Finally the signals are transmitted to the brain, through the optic nerve, where the signals are perceived as images. With respect to the work described in this paper only a small number of the anatomical parts illustrated in Fig 1 are important, these are highlighted in the figure using red coloured labels. The retina is a thin layer located on the inside wall at the back of human eye, between the choroid and the vitreous body (the vitreous body is a clear gel posterior to the lens). The retina is composed of photoreceptors (rods and cones) and neural tissues that receives light, converts it into neural

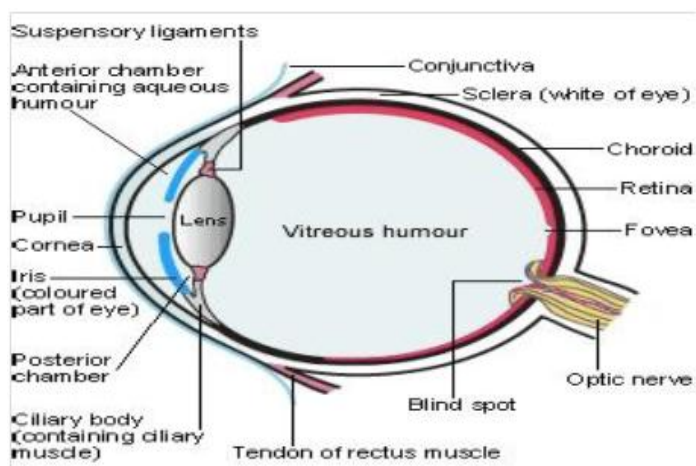

Figure 1 *Anatomy of Eye*

Signals, and sends the signals to the optic nerve. The proposed solutions presented in this paper are concerned with the screening for diseases related to the retina.The anatomical nature of the retina is therefore of particular interest. The optic disc is where the retinal blood vessels (central retinal artery and central retinal vein as shown in Fig 1) converge and

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communicate perceived signals to the brain through the optic nerve. Its horizontal and vertical diameters" are approximately1.7 mm and 1.9 mm respectively . The optic disc contains no photoreceptorand thus represents a psychological blind spot". The optic disc is clearly visiblewithin retinal images as shown in Figure 1.3 where the optic disc is the bright yellowcircle from which veins and arteries can be seen to emanate. The optic disc's locationwithin an image, together with the blood vessels, can be used to indicate whether theimage is of a left or right eye (the optic disc is located next to the subject's nose). Notethat the blood vessels are responsible for providing the nutrients required by the inner parts of the retina.

2.2 Background of Glaucoma

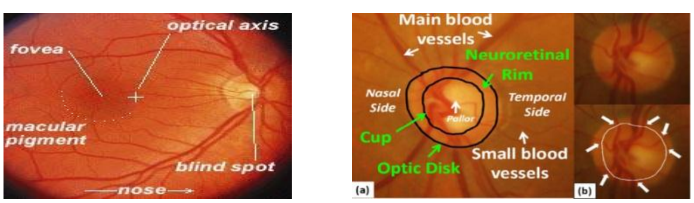
Glaucoma is a disease of progressive optic neuropathy with loss of retinal neurons and the nerve fibre layer, resulting in blindness if left untreated. Glaucoma describes a group of diseases that kill retinal ganglion cells. "High IOP is the strongest known risk factor for glaucoma but it is neither necessary nor sufficient to induce the neuropathy." Glaucoma is a group of diseases that can damage the eye's optic nerve and result in vision loss and blindness. There is a dose-response relationship between intraocular pressure and the risk of damage to the visual field. Glaucoma is a disease that damages the eye's optic nerve. The optic nerve is connected to the retina (a layer of light-sensitive tissue lining the back of the eye) and is made up of many nerve fibres, like an electric cable is made up of many wires. It is the optic nerve that sends signals from eye retina to the brain, where these signals are interpreted as the images you see.

Images of Eye Used in Glaucoma Assessment

There are two type of image of eye used for Glaucoma Assessment

A. Fundus image

B. Retinal image



(a) (b)

Figure 2 ***(a)*** *Fundus Image of eye* ***(b)*** *Retinal Image of eye*

3 Conventional Technique Used For Glaucoma

There are various type of technique for glaucoma assessment according to parameter changed some technique are as follows.

3.1 Optical coherence tomography (OCT)

Optical Coherence Tomography (OCT) is an optical imaging modality that uses near-infrared light to create high-resolution images of tissue microstructure. OCT is a sensitive non-invasive tool in detecting and quantifying the macular thickness. OCT is a new, noninvasive on contact, transpupillary imaging technology which can image retinal structures in vivo with a resolution of 10 to 17 microns. Cross-sectional images of the retina are produced using the optical backscattering of light in a fashion analogous to B- scan ultra-sonography. The anatomic layers within the retina can be differentiated and retinal thickness can be measured [9].

3.2 Heidelberg retina tomography (HRT)

The Heidelberg Retina Tomography (HRT) is a confocal scanning laser ophthalmoscope that is capable of acquiring and analyzing three dimensional images of the optic nerve head and per papillary retina. It provides topographic measurements of the optic nerve head including the size, shape and contour of the optic disc, neuro-retinal rim, optic cup and measurements of the per papillary retina and nerve fibre layer. The typical application of the HRT is the assessment of the glaucomatous optic nerve head. The HRT also uses an imaging technique called 'scanning laser 'tomography', in which a laser light scans the retina sequentially, starting from above the retinal surface then through the retina at increasing depths [10].

3.3 Color fundus imaging (CFI)

The device produces a color fundus image of the retina. The image produced is an ultra wide field, high contrast optomap image that can aid in detecting and documenting retinal health. The optomap image allows viewing of up to 200 internal degrees of the fundus in one image. Along with a screening tool for early detection of diseases or abnormalities it can be used to facilitate the diagnosis and management of ocular pathology [11].

3.4 Medical Image Processing for Glaucoma detection

In this section some of the principles applied in this research work are included. These principles include: Color Space Conversion, Histogram Equalization, K-mean Clustering Algorithm, Classification, Image Morphological Operations and Skeletonization [12].

4 Proposed Method For Classification

In this section proposed classification technique is described which is based on Neural Network and Adaptive Fuzzy Inference system (ANFIS). So first of all neural network will explain in detail.

4.1 Delta Rule

The delta rule is a gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron. It is a special case of the more general back propagation algorithm. For a neuron j with activation function g(x) the delta rule for j's ith weight Wij is given by Equation 4.1

$$EA_j = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial i} = \sum_j EI_j W_{ij} \quad (4.1)$$

Where,

α small constant called learning rate

g(x) is the neuron's activation function

tj is the target Output

hj is the weighted sum of the neuron's inputs

yj is the actual output

xj is the ith input

It holds that Equation 4.2 and 4.3

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$$h_j = \sum x_i w_{ji} \quad (4.2)$$

$$y_j = g(h_j) \quad (4.3)$$

The delta rule is commonly stated in simplified form for a perceptron with a linear activation function in equation 4.4

$$\Delta w_{ji} = \alpha(t_j, y_j)x_i \quad (4.4)$$

The delta rule is derived by attempting to minimize the error in the output of the perceptron through gradient descent. The error for a perceptron with j outputs can be measured (Equation 4.5).

$$E = \sum_{\frac{1}{2}} \frac{1}{2} t_j y_j \quad (4.5)$$

In this case, we wish to move through weight space of the neuron (the space of all possible values of all of the neuron's weights) in proportion to the gradient of the error function with respect to each weight. In order to do that, we calculate the partial derivative of the error with respect to each weight. Because, we are only concerning ourselves with the jth neuron, we can substitute the error formula above while omitting the summation (Equation 4.6):

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial\left(\frac{1}{2}\left(t_j - y_j\right)^2\right)}{\partial w_{ji}} \frac{\partial y_i}{\partial w_{ji}} \quad (4.6)$$

4.2 Back propagation algorithm

Back propagation is a form of supervised learning for multilayer nets, also known as the generalized delta rule. Error data at the output layer is back propagated to earlier ones, allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications. The back propagation algorithm has been widely used as a learning algorithm in feed forward multilayer neural networks.

a. Learning with the back propagation algorithm

The back propagation algorithm is an involved mathematical tool; however, execution of the training equations is based on iterative processes, and thus is easily implement able on a computer. [8]

- Weight changes for hidden to output weights just like Widrow-Hoff learning rule.
- Weight changes for input to hidden weights just like Widrow-Hoff learning rule bu error signal is obtained by "back-propagating" error from the output units

During the training session of the network, a pair of patterns is presented (Xk, Tk), where Xk in the input pattern and Tk is the target or desired pattern. The Xk pattern causes output responses at teach neurons in each layer and, hence, an output Ok at the output layer. At the output layer, the difference between the actual and target outputs yields an error signal. This error signal depends on the values of the weights of the neurons I each layer. This error is minimized, and during this process new values for the weights are obtained. The speed and accuracy of the learning process-that is, the process of updating the weights-also depends on a factor, known as the learning rate.Before starting the back propagation learning process, we need the following:

- The set of training patterns, input, and target
- A value for the learning rate
- A criterion that terminates the algorithm
- A methodology for updating weights
- The nonlinearity function (usually the sigmoid)
- Initial weight values (typically small random values)

b. Implementation of back propagation algorithm

The back-propagation algorithm consists of the following steps:

- Each Input is then multiplied by a weight that would either inhibit the input or excite the input. The weighted sum of then inputs in then calculated

First, it computes the total weighted input Xj, using the formula:

$$X_j = \sum_i y_i W_{ij} \quad (4.7)$$

Where,

Y_i is the activity level of the j^{th} unit in the previous layer and W_{ij} is the weight of the connection between the i^{th} and the j^{th} unit. Then the weighed X_j is passed through a sigmoid function that would scale the output in between 0 and 1.

- Next, the unit calculates the activity y_j using some function of the total weighted input. Typically we use the sigmoid function:

$$y_j = 1/(1 + e^{(-x_j)}) \quad (4.8)$$

Once the output is calculated, it is compared with the required output and the total Error E is computed

- Once the activities of all output units have been determined, the network compute the error E, which is defined by the expression:

$$E = \frac{1}{2} \sum{}_j (y_j - d_j)^2 \quad (4.9)$$

Where yj is the activity level of the ith unit in the top layer and dj is the desired output of the ith unit.) Now the error is propagated backwards.

1. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \quad (4.10)$$

2. Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output

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of a unit changes as its total input is changed.

$$EI_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \times \frac{\partial y_j}{\partial x_j} = EA_j y_j (1 - y_j) \qquad (4.11)$$

3. Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$EW_j = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial W_{ij}} = EI_j = EI_j y_i \qquad (4.12)$$

4. Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multi-layer networks. When the activity of a unit in the previous layer changes, it affects the activities of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these separate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit

$$EA_j = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial i} = \sum_j EI_j W_{ij} \qquad (4.13)$$

By using steps 2 and 4, we can convert the EA's of one layer of units into EA's for the previous layer. This procedure can be repeated to get the EA's for as many previous layers as desired. Once we know the EA of a unit, we can use steps 2 and 3 to compute the EW's on its incoming connections.

4.3 Adaptive Neuro-Fuzzy Inference System as Classifier (ANFIS)

Adaptive Neuro-Fuzzy Inference Systems combines the learning capabilities of neural networks with the approximate reasoning of fuzzy inference algorithms. ANFIS uses a hybrid learning algorithm to identify the membership function parameters of Sugeno type fuzzy inference systems. The aim is to develop ANFIS-based learning models to classify normal and abnormal images from fundus image to detect glaucoma .An adaptive neural network is a network structure consisting of five layers and a number of nodes connected through directional links. The first layer executes a fuzzification process, second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the fuzzy membership functions, the fourth layer executes the consequent part of the fuzzy rules and finally the last layer computes the output of the fuzzy system by summing up the outputs of the fourth layer [24].Each node is characterized by a node function with a fixed or adjustable parameter. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. Based on this observation a hybrid learning rule is employed in this thesis which combines the gradient descent and the least-square method to find a feasible set of antecedent and consequent parameters. Adaptive Neuro Fuzzy Inference System (ANFIS) is the combination of ANN and the fuzzy logic ANFIS is a multilayer feed forward network which uses ANN learning algorithms and fuzzy reasoning to characterize an input space to an output .Takagi and Sugeno proposed the first systematically fuzzy modeling. The ANFIS approach uses Gaussian functions for fuzzy sets and linear functions for the rule outputs The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters) and the coefficients of the output linear functions.

a. ANFIS Architecture

In ANFIS, Takagi-Sugeno type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term or can be only a constant term. The final output is the weighted average of each rule's output. Basic ANFIS architecture that has two inputs x and y and one output z is shown in Figure 3.2 The rule base contains two Takagi-Sugeno if then rules as follows

Rule 1. If x is A1 and y is B1, then $f_1 = p_1 x + q_1 y + r_1$

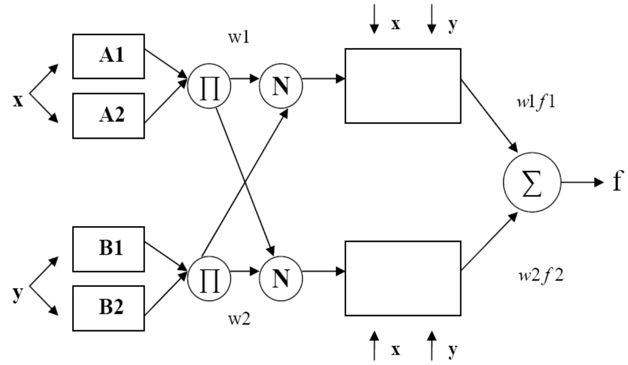

Figure 3 *ANFIS Architecture*

Rule 2. If x is A2 and y is B2 , then $f_2 = p_2 x + q_2 y + r_2$

b. ANFIS learning algorithm

From the proposed ANFIS architecture above (Figure 4.6.6), the output f can be defined as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

Figure 4 *Takagi-Sugeno Fuzzy Inference System*

$$f = \overline{w_1}(p_1 x + q_1 y + r_1) + \overline{w_2}(p_2 x + q_2 y + r_2) \qquad (4.14)$$

$$f = (\overline{w_1} x) p_1 + (\overline{w_1} y) q_1 + (\overline{w_1}) r_1 + (\overline{w_2} x) p_2 + (\overline{w_2} y) q_2 + (\overline{w_2}) r_2$$

Where p1, q1, r1, p2 , q2 and r2 are the linear consequent parameters. The methods for updating the parameters are listed as below:

1. Gradient decent only: All parameters are updated by gradient decent back propagation

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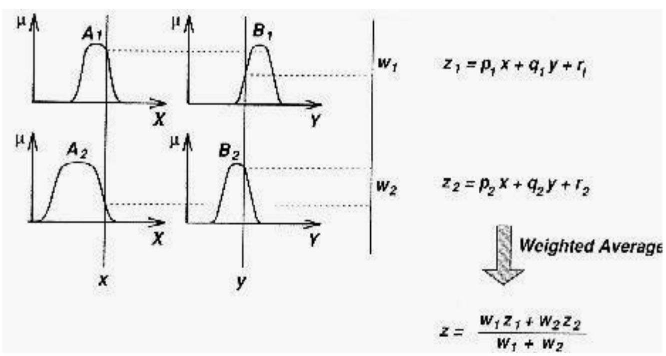
2. Gradient decent and One pass of Least Square Estimates (LSE): The LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient descent takes over to update all parameters.
3. Gradient and LSE: This is the hybrid learning rule.

Since the hybrid learning approach converges much faster by reducing search space dimensions than the original back propagation method, it is more desirable. In the forward pass of the hybrid learning, node outputs go forward until layer 4 and the consequent parameters are identified with the least square method. In the backward pass, the error rates propagate backward and the premise parameters are updated by gradient descent Parameters used for clustering are shown in Table-I

TABLE-I *Parameter used for clustering*

Range of influence	0.5
Squash Factor	1.25
Accept Ratio	0.5
Reject Ratio	0.15



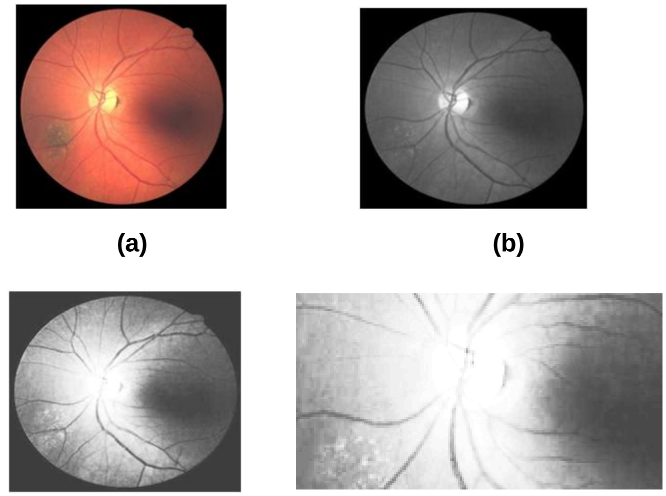
5 RESULT AND SIMULATION

In this chapter experimental results are presented in support of the claims made about the proposed methods in the earlier chapters. The simulations were performed using MATLAB R2010a.For the simulation the images are used from Origa image database

5.1 Image pre-processing Result

In the pre-processing of input image various type of pre-processing is applied which is described in earlier chapter.Results of pre-processed image are as follows.

Image illumination correction results



(a) **(b)** **(c)** **(d)**

Fig 5 *(**a**) original image (**b**)Green channel of original image (**c**) illumination corrected image (**d**) ROI cropped Image*

Feature extraction result and performance analysis

In this section extracted feature are calculated which is result of used method. First result of cup detection analysis

Optic cup detection

1. To assess the area overlap between the computed region and ground truth of the optic cup pixel wise precision and recall values are computed

$$\mathrm{Precision} = \frac{TP}{TP + FP} \qquad (5.1)$$

$$\mathrm{Recall} = \frac{TP}{TP + FN} \qquad (5.2)$$

Where TP is the number of True positives, FP is the number of false positive and FN is the number of false negative pixels.

2. Another method of evaluating the performance is using F Score given by $F = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{(\mathrm{Precision} + \mathrm{Recall})}$ **(5.3)**

Value of F score lies between 0 – 1 and score will be high for an accurate method. Average F score for thresholding and component analysis are compared and listed in Table II.

TABLE II: *F score for cup segmentation*

Images	**Threshold**	**Component analysis**	**Proposed**
1	.67	.72	.82
2	.69	.76	.89
3	.66	.74	.86
4	.63	.70	.81
5	.54	.69	.79

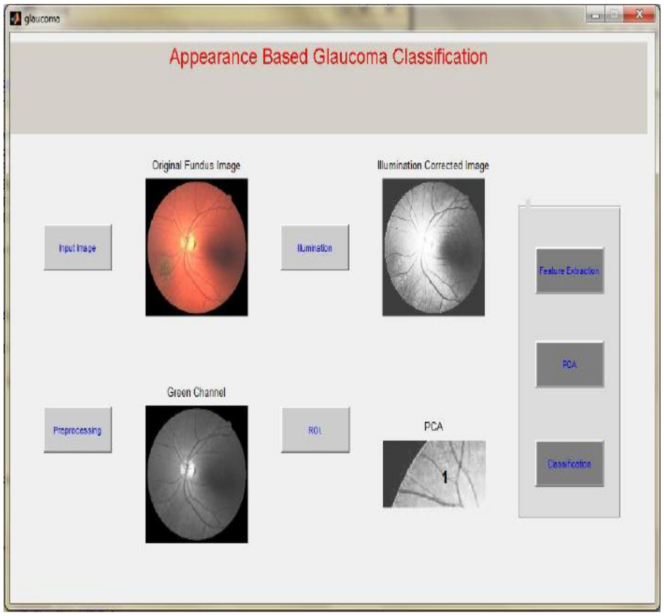


Figure 6 *GUI of Proposed Glaucoma diagnosis system*

TABLE III: *Performance Analysis of Features*

Features	Sensitivity (%)	Specificity (%)	Accuracy (%)
Cup to disk ratio	93.5	95.3	94.2
Pixel intensity value	96.1	94.3	97.2
fft coefficient	92.5	93.6	95.5
B-spline coefficient	93.8	96.5	99.2

5.2 Classification Results and analysis

Classifiers namely ANFIS, SVM and Back Propagation Neural network are used to classify between normal and abnormal cases of glaucoma. Parameters that are used for generating Fuzzy Inference System (FIS) are shown in Table-IV. ANFIS integrates the learning capabilities of neural networks with approximate reasoning of fuzzy inference algorithms [11].

Performance Measure of Classifiers

The system is trained and tested for a dataset shown in Table-III. Classification accuracy is the ratio of the total number of correctly classified images to total number of misclassified images [11]. Table IV shows the Classification Accuracy of the classifiers that shows that the proposed method has the highest classification rate with SVM as classifier. The classification accuracy achieved by ANFIS, SVM and Back Propagation is also shown in this table.In this work 50 images are used for training and 100 images for testing. 150 images, 50 from each of the class for training and 100 images (50 normal, and 50 abnormal) for testing were used for classification.

TABLE IV: *Dataset for Fundus Image Classification*

Category	No. of training Images	No. of testing Images	No. of Images/Class
Normal	50	100	150
Abnormal	50	100	150
Total	100	200	300

Classification accuracy

Classification accuracy is the ratio of the total number of correctly classified images to the, total number of misclassified images. Table-V shows the performance measure of the classifiers and classifier accuracy.A screened fundus is considered as a true positive (TP) if the fundus is really abnormal and if the screening procedure also classified it as abnormal. Similarly, a true negative (TN) means that the fundus is really normal and the procedure also classified it as normal. A false positive (FP) means that the fundus is really normal, but the procedure classified it as abnormal. A false negative (FN) means that the procedure classified the screened fundus as normal, but it really is abnormal. Sensitivity is the percentage of abnormal funduses classified as abnormal by the procedure.

TABLE V: *Classification Accuracy of Classifiers*

Category	No. of Test Images	SVM			Back Propogation			ANFIS		
		CCI	MI	CA	CCI	MI	CA	CCI	MI	CA
Normal	100	93	7	93	95	5	95	97	3	97
Abnormal	100	94	6	94	96	4	96	98	2	98

CCI = Correctly Classified Images, MI = Misclassified Images, CA = Classification Accuracy (in %)

$$\text{Sensitivity} = \frac{TP}{TP + FN} \qquad (5.4)$$

Specificity is the percentage of normal funduses classified as normal by the procedure.

$$\text{Specificity} = \frac{TN}{TN + FP} \qquad (5.5)$$

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TABLE VI: *Performance Measure of the Classifier*

CLASSIFIER	SPECIFICITY (%)	SENSITIVITY (%)	ACCURACY (%)
SVM	93	94	96.5
BACK PROPAGATION	95	96	97.4
ANFIS	97	98	98.9

TABLE VII: *Classification Rate of Classifiers*

Classifier	Normal (%)	Abnormal (%)
SVM	94.3	93.5
ANN	95.6	94.5
ANFIS	97.5	96.6

The higher the sensitivity and specificity values, the better the procedure. Performance of each classifier is measured in terms of sensitivity, specificity, and accuracy. Sensitivity is a measure that determines the probability of results that are true positive such that the person has glaucoma. Specificity is a measure that determines the true negatives that the person is not affected by glaucoma. Accuracy is a measure that determines the results that are accurately classified. The same dataset is used for neural network based Back propagation classifier. MATLAB (version 2010 a) is used for implementation of the work. Comparative analysis performed between the classifiers based on correctly classified images, is shown in Table-VI and Table-VII From above result analysis it can be shown that the performance of ANN and ANFIS classifier improved with respect to SVM classifier in terms of sensitivity, specificity and accuracy and we can conclude that proposed classifiers gives better Performance in comparison of SVM classifier. Classification rate is also improved by the proposed classifier.

6 CONCLUSION

In this paper an appearance based Glaucoma diagnosis system is developed for detection of glaucoma abnormal eyes through fundus images using image processing techniques and neural network algorithm. k means clustering provides a promising step for the accurate detection of optic cup boundary.Proposed classification technique which is based on ANFIS and neural network achieves good classification accuracy with a smaller convergence time compared to support vector machine classifier. Performance of the proposed approach is comparable to human medical experts in detecting glaucoma. Proposed system combines feature extraction techniques with segmentation techniques for the diagnosis of the image as normal and abnormal. The method of the considering features like B-spline coefficient, FFT coefficient, cup to disk ratio can be used as an additional feature for distinguishing between normal and glaucoma or glaucoma suspects. The proposed system can be integrated with the existing ophthalmologic tests and clinical assessments in addition to other risk factors according to a determined clinical procedure and can be used in local health camps for effective screening.

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