Automatic Prediction of Diabetic Retinopathy and Glaucoma through Retinal Image Analysis and Data Mining Techniques

R. Geetha Ramani
Associate Professor
Department of Information Science and Technology,
Anna University, Chennai, India
rgeetha@yahoo.com

Lakshmi Balasubramanian
Ph. D research Scholar
College of Engineering, Guindy.
Anna University, Chennai, India
latchu234@gmail.com

Shomona Gracia Jacob
Ph. D Research Scholar
Anna University, Chennai, India.
graciarun@gmail.com

***Abstract*—Application of computational techniques in the field of medicine has been an area of intense research in recent years. Diabetic Retinopathy and Glaucoma are two retinal diseases that are a major cause of blindness. Regular Screening for early disease detection has been a highly labor - and resource- intensive task. Hence automatic detection of these diseases through computational techniques would be a great remedy. In this paper, a novel computational approach for automatic disease detection is proposed that utilizes retinal image analysis and data mining techniques to accurately categorize the retinal images as Normal, Diabetic Retinopathy and Glaucoma affected. Three feature relevance and sixteen classification Algorithms were analyzed and used to identify the contributing features that gave better prediction results. Our results prove that C4.5 and random tree classification techniques generate the maximum multi-class categorization training accuracy of 100% in classifying 45 images from the Gold Standard Database. Moreover the Fisher's Ratio algorithm reveals the most minimal and optimal set of predictive features on the retinal image training data.**

Keywords—Diabetic Retinopathy; Glaucoma; Feature Selection.

I. INTRODUCTION

Research in the field of medicine suggests that abnormal pressure and glucose levels are a major cause of several critical ailments. Such aberration can lead to other complications in various organs of the body. In this paper we place focus on Diabetic Retinopathy and Glaucoma, the former being a disorder in the retina of the eye caused mainly due to Diabetes [1] leading to imperfect/loss of vision and the latter being associated with elevated pressure in the eye causing damage to the optic nerve [2].Diabetic Retinopathy and Glaucoma are asymptomatic in the preliminary stages and findings reveal that treatment may be useful only when detected early. Regular screening of the people who have high risk of the disease may help detect the disease at an early stage. Detecting retinal abnormalities in a large number of images generated by screening programs is a time-, resource and labor – intensive task. Automatic detection of the disease from the retinal images is thus an important area of ongoing research.

In this paper we place emphasis on automatic diagnosis of eye abnormalities (Diabetic retinopathy and Glaucoma) wherein the image is primarily preprocessed and statistical, GLCM based and histogram based measurements are calculated. The measured data are given to a classifier. The classifier categorizes the fundus image to the disease category to which it belongs. This research aims at automatic detection of diabetic retinopathy and glaucoma through image processing and feature extraction of the entire fundus image and classification using data mining techniques.

The manuscript is organized as follows. Section 2 focuses on the literature survey in the related field. Section 3 highlights the proposed methodology while Section 4 presents the experimental results. Section 5 concludes the paper.

II. LITERATURE WORK

Diabetic retinopathy and Glaucoma are the two most threatening retinal diseases which lead to deteriorated vision or vision loss in patients. Diabetic Retinopathy is detected by a number of abnormal structures viz, microneurysms, hemorrhages, exudates, cotton wool spots etc. Glaucoma detectors include the cup to disc ratio (CDR), ratio of the distance between optic disc center and optic nerve head to diameter of the optic disc, and the ratio of blood vessels area in inferior-superior side to area of blood vessel in the nasal-temporal side (ISNT ratio). Different attempts in the past have been made to automatically detect the presence of diabetic retinopathy and Glaucoma, some of which are summarized here.

Fuzzy C-Means based clustering and Artificial Neural Networks (ANN) was used to classify exudates yielding a sensitivity and specificity of 95 and 88.9% [3]. Changira et.al, [4] designed a system in which Principle Component Analysis (PCA) and multi layer perception neural networks were used demonstrating a sensitivity and specificity of 80.21 and 70.26% respectively. Sagar [5] adopted dynamic thresholding and edge detection to identify the exudates providing a sensitivity and prediction of 99 and 93%. In 2008, Clara used Fisher's linear discriminant analysis, providing a sensitivity of 88% in identification of hard exudates [6]. ANN with inputs viz. areas of hard exudates, area and perimeter of blood vessels and the contrast showed a classification accuracy of 93% [7]. SVM with inputs from Higher Order Spectra classified with a sensitivity and specificity of 82 and 88% respectively [8]. Fuzzy C-Means clustering to intensity, standard deviation, hue and number of edge pixels detected exudates with an accuracy of 99.11% [9]. In 2010, Vijaya et.al, proposed a system that detected exudates using feature extraction, template matching and MDD classifiers [10] classify 38 from 39 images. Back Propagation Neural network with inputs *viz.*hue, intensity, mean intensity, standard deviation intensity and distance

978-1-4673-2322-2/12/$31.00

between optic disc and intensity of optic disc eliminated image showed an accuracy of 98.45% [11]. Recurrent Echo State Neural Network and Fuzzy C-Means clustering on standard deviation, intensity, edge strength and compactness of the disease related features demonstrated sensitivity and specificity of 93 and 100% [12]. Microneurysms and hemorrhages, extracted using vessel enhancement [13] on DiaRetDB data provided a sensitivity of 57.4%, 35.37% and 62.68% for ophthalmologists 1, 2 and 3 respectively. Coarse segmentation using morphology techniques and fine segmentation using Bayes Naïve classification to detect the microneurysms [14] revealed 18 per pixel features yielding an accuracy of 99.99%. ANN with Singular Value Decomposition and PCA detected hemorrhages and exudates with an accuracy of 95 to 98% [15]. A fuzzy inference system identified exudates from a threshold, optic disc removed image [16] with accuracy of 93.84%.

Various attempts have also been made in the past to automatically diagnose the presence of Glaucoma. Neural networks with inputs: CDR and ISNT ratio, calculated from the extracted optic disc and blood vessels [17], performed with a sensitivity and specificity of 100% and 80% respectively. The texture and Higher Order Spectra features [18] after z-score normalization and feature selection, and when combined with a random-forest classifier, correctly identified the glaucoma images with an accuracy of more than 91%. K means clustering which was used in extraction of optic disc and hence in CDR calculation gave 90% match with clinical CDR [19]. Ho et.al, [20] proposed a system that involved vessel detection, vessel in painting, CDR calculation [21] and neuro-retinal rim for ISNT rule. K-Nearest Neighbor, SVM and Bayes Classifier with CDR and ISNT ratio [22] yielded a classification accuracy of 95%. CDR and ISNT Ratio using Neural Networks and SVM [23] gave a sensitivity of 99%.

Thus the existing work first primarily focused on extracting the disease related structures and calculating relevant measurements that served as input to the classifiers that ultimately detect the presence or absence of the disease. In this paper, automated diagnosis of diabetic retinopathy and glaucoma through data mining techniques is presented in the following section.

III. PROPOSED METHODOLOGY

Automatic detection of the two most alarming retinal diseases viz, Diabetic Retinopathy and Glaucoma is necessary to aid ophthalmologists in detecting the disease early at less cost. The proposed system attempts to classify the given image as normal, Diabetic Retinopathy or Glaucoma affected image. The proposed framework is presented in Figure 1.The computational approach is designed to comprise of two phases: the training phase and the test phase. The former involves fundus image pre-processing, measurement calculations, feature relevance analysis followed by generation of classification rules that constitutes the Knowledge Base. The test phase includes presenting an unlabeled test data to the system that determines the class of the unlabeled image based on the classification rules obtained in the training phase.

A. Retinal Images – Training data

The data consists of 45 images taken from the publicly available Gold Standard Database [24]. The database contains 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients. This data is generated by a group of experts working in the field of retinal image analysis and clinicians from the cooperated ophthalmology clinics.

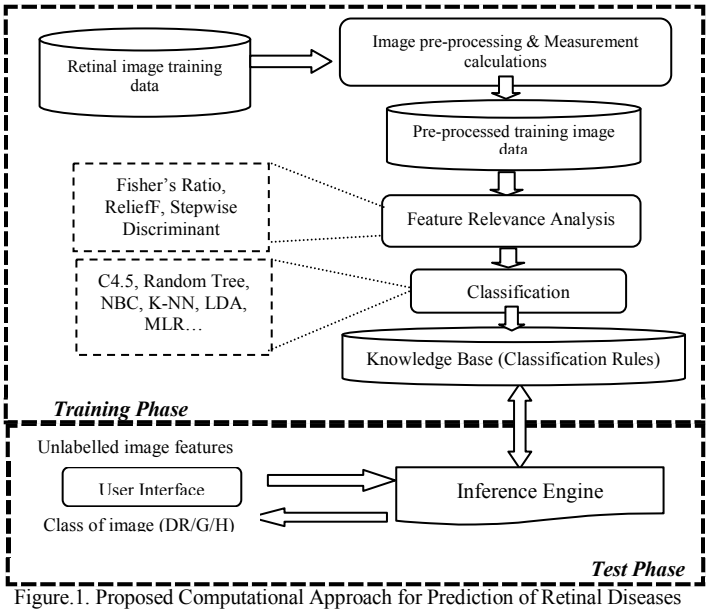

Figure.1. Proposed Computational Approach for Prediction of Retinal Diseases

B. Pre-processing of the Fundus Image.

The fundus image was pre-processed before feature relevance analysis. Average filtering was applied to remove the noise present in the image. The green channel (G) of the resultant image was separated. Histogram equalization (H) was applied to the Green channel (G) of the image. Measurements were extracted from the H and G images. 32 measurements were made on each image. These included statistical measurements, Grey-Level Co-occurrence Matrix (GLCM) based measurements and histogram based measurements. The measurements are used as attributes of the training data set. All the 32 measurements are continuous data. The class field is the 33rd attribute (output) which holds the value *g* (Glaucoma), *h* (Healthy) or *dr* (Diabetic Retinopathy). Table I presents the attributes and its abbreviations.

TABLE I FUNDUS IMAGE MEASUREMENTS

Attribute Name	Abbreviation	Formula
Statistical Based Measurements		
Mean [25]	Mean	$\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N} H(i,j)$
Standard deviation [25]	Std	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(H(i)-mean)^2}$
Variance [25]	Var	$(Standard\ Deviation)^2$
Entropy [25]	Ent	$-\sum_{i=1}^{n} H(i) * log_2 H(i)$
Maximum H intensity [25]	Hmax	$Max(H(i,j))$
Minimum H intensity [25]	Hmin	$Min(H(i,j))$
Maximum G intensity	gmax	$Max(G(i,j))$
Minimum G intensity	Gmin	$Min(G(i,j))$
Histogram Based Measurements		
Mean	h-mean	$\sum prob * GreyVector$
Variance	h-var	$\sum prob * (Greyvector-mean)^2$
Skewness	h-skew	$\frac{\sum prob * (Greyvector-mean)^3}{variance^{3/2}}$
Kurtosis	h-kurt	$\frac{\sum prob * (Greyvector-mean)^4}{variance^2}$

GLCM Based Measurements		
Contrast [26]	g-ctrst	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*(i-j)^2$
Correlation [26]	g-cr	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*\frac{(i-mean(x))(j-mean(y))}{std.dev.(x)*std.dev.(y)}$
Energy[26]	g-egy	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)^2$
Homogeneity [26]	g-homo	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{GLCM(i,j)}{1+\lvert i-j\rvert}$
Auto-correlation [27]	g-ac	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*(i-j)$
Cluster performance [27]	g-cp	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*(i*j-mean(x)-mean(y))^4$
Cluster shade [27]	g-cs	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*(i*j-mean(x)-mean(y))^3$
Dissimilarity [27]	g-diss	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*\lvert i-j\rvert$
Inverse difference Moment [27]	g-idm	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{GLCM(i,j)}{1+(i-j)^2}$
Maximum probability [27]	g-maxprob	$Max(GLCM(i,j))$
Sum squares [26]	g-sosv	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} GLCM(i,j)*(i-mean)^2$
Sum average [26]	g-savg	$\sum_{i=2}^{2*N_g} i*GLCM_{(x+y)}(i)$
Sum entropy [26]	g-sent	$-\sum_{i=2}^{2*N_g} GLCM_{(x+y)}(i)*\log\left(GLCM_{(x+y)}(i)\right)$
Sum variance [26]	g-sov	$\sum_{i=2}^{2*N_g} GLCM_{(x+y)}(i)*(1-sum\ of\ entropy)^2$
Difference variance [26]	g-dvar	$Variance(GLCM_{(x-y)}(i))$
Difference entropy [26]	g-dent	$-\sum_{i=0}^{N_g-1} GLCM_{(x-y)}(i)*\log\left(GLCM_{(x-y)}(i)\right)$
Information measure of correlation 1 [26]	Inf1	$\frac{HXY-HXY1}{\max(HX,HY)}$
Information measure of correlation 2 [26]	Inf2	$\left(1-e^{\{-2*(HXY2-HXY)\}}\right)^{0.5}$
Normalised inverse difference [28]	Idnorm	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{GLCM(i,j)}{1+\lvert i-j\rvert/N_g}$
Normalized inverse difference moment [28]	Idmnorm	$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{GLCM(i,j)}{1+((i-j)/N_g)^2}$

C. Feature Relevance Analysis

The ultimate objective of feature selection is to identify and choose a subset of the input variables by analyzing and eliminating features with little or no predictive information [29]. The Fisher Filtering algorithm was considered the most appropriate to use on the retinal image dataset since the number of features considered significant were the most minimum in this techniques. The algorithm is described below.

1) Fisher's Ratio

Fisher Filtering is a supervised feature selection algorithm [29]. This component ranks the input attributes according to their importance and relevance. A cutting rule facilitates the selection of subset of these attributes. This technique reported two features namely gmax and Ent to be significant. The predictor features selected by the feature relevance algorithms are detailed in the section on Experimental Results.

D. Classification

Classification [29] is the process of finding a set of models that describe and distinguish data classes. This is done to achieve the goal of being able to use the model to predict the class whose label is unknown. The algorithms that reported best accuracy are briefed about in the following sub-sections.

1) C4.5 (Decision Tree) Algorithm

C4.5 is an algorithm used to generate a decision tree developed by Ross Quinlan [29]. C4.5 relies on greedy search, selecting the candidate test that maximizes a heuristic splitting criterion. C4.5 operates on two criteria viz, information gain and gain ratio.

A sample rule generated by the Quinlan's C4.5 classification algorithm is given in Figure.2.

ent < 5.3578
*gmax < 148.5000 then class = **dr***
*gmax >= 148.5000 then class = **g***
ent>= 5.3578
gmax < 198.0000
*gmax < 157.5000 then class = **dr***

Figure 2. Sample rule of C4.5 Algorithm on Retinal Image data

2) Random Tree Algorithm

The Random tree [29] algorithm can be applied to both classification and regression problems. Random trees are a collection or assembly of tree predictors that is called **forest** [13]. The random trees classifier takes the input feature vector, classifies it with every tree in the forest, and outputs the class label that received the majority of votes.

A sample rule generated by the Random tree classification algorithm is given in Figure.3.

ent < 5.3578
*gmax >= 148.5000 then class = **g***
ent >= 5.3578
g-cr < 0.9927
ent < 5.4966
gmax < 174.5000
*ent < 5.4413 then class = **dr***

Figure 3. Sample rule of Random Tree Algorithm on Retinal Image data

E. Test Phase

In order to evaluate the classifier, a test retinal image dataset was given to the system knowledge base built on obtained classification rules and the class of the images (h/g/dr) was accurately predicted by the generated rules.

IV. EXPERIMENTAL RESULTS

The performance metrics used for the evaluation of the classifier are detailed below.

A. Performance Measures

The performance measures used for evaluation of the classifier is classification accuracy [29]. Classification accuracy is the percentage of tuples that are correctly classified by the classifier.

B. Feature Relevance Analysis

The Fisher's Ratio (FR), Stepwise Discriminant Analysis (SD) and ReliefF(RF) feature relevance algorithms were investigated in this work. Fisher's ratio selected two features as significant, while ReliefF denoted four. The detailed results are given in Table II.

TABLE II PERFORMANCE OF FEATURE RELEVANCE ALGORITHMS

S.No	Feature Relevance Algorithm	No. of features filtered	Feature Description
1.	Fisher's Ratio	2	gmax, ent
2.	Stepwise Discriminant	3	Gmax, ent,g-cr
3.	ReliefF	4	Gmax, ent, g-cs,g-cp

The graphical representation of the performance of classification techniques is graphically presented in Figure 4.

C. Classifier Performance

The performance of the classification algorithm is compared in Table III. The results affirm the maximum accuracy generated by c4.5 and random tree algorithm on the retinal image dataset.

TABLE III COMPARISON OF CLASSIFICATION ALGORITHMS

Classifier	Description	Accuracy (%)			
		Without feature selection	With feature selection		
			FR	RF	SD
C4.5	Decision Tree	100	100	100	100
RT	Random Tree	100	100	100	100
C-RT	Classification Tree	68.89	68.89	68.89	68.89
CS-CRT	Cost-sensitive Classification	68.89	68.89	68.89	68.89
CS-MC4	Classification with least misclassification cost	75.56	71.11	75.56	75.56
C-SVC	SVM for classification	84.44	71.11	77.78	75.56
ID3	Iterative Dichomotiser	33.33	33.33	33.33	33.33
KNN	K-Nearest Neighbor	33.33	77.78	77.78	82.22
LDA	Linear Discriminant Analysis	82.22	68.89	73.33	77.78
MP	Multilayer Perceptron	80	66.67	55.56	75.56
MLR	Multinomial Logistic Regression	22.22	66.67	75.56	77.78
NBC	Naïve Bayes Continuous	66.67	66.67	75.56	73.33
PLS-DA	Partial Least Squares – Discriminant Analysis	75.56	68.89	71.11	71.11
PLS-LDA	Partial Least Squares – Linear Discriminant Analysis	82.22	68.89	75.56	77.78
P-NN	Prototype- Nearest Neighbor	33.33	68.89	77.78	71.11
RBF	Radial Basis Function	66.67	68.89	75.56	71.11

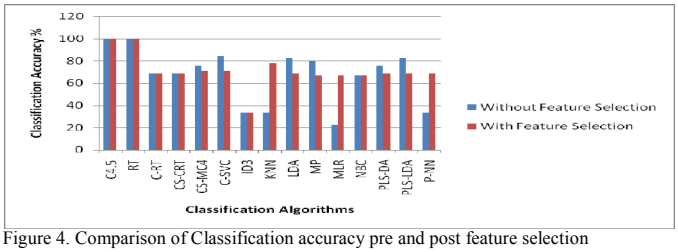

Figure 4. Comparison of Classification accuracy pre and post feature selection

V. CONCLUSION

Data mining techniques have been generously applied in the field of medical diagnosis and prognosis in the past. This work specifically places focus on the feature relevance and classification techniques to accurately categorize the disease associated with the retina based on the features extracted from retinal images through image processing techniques. Moreover a detailed comparison of feature relevance and classification algorithms has been performed to justify the statement of reporting C4.5 and Random tree algorithm to be the most accurate classifiers of the retinal image dataset. We believe implementation of the proposed system will certainly serve as an aid in assisting ophthalmologists in detecting retinal defects and disease in a timely and precise manner.

REFERENCES

[1] "Eye Diseases and Conditions A-z " Available at: http://www.geteyesmart.org/eyesmart/diseases/index.cfm

[2] "Glaucoma symptoms, Treatment options, surgery, causes and medications" Available at http://www.medicinenet.com/glaucoma/article.htm

[3] A Osareh et.al,, "Automated identification of diabetic retinal exudates in digital colour images", *British Journal of Opthalmol*, vol. 87, pp. 1220-1223, 2003.

[4] Chanjira Sinthanayothin, et.al,. "Automated Screening System for Diabetic Retinopathy". *Proc. Of the 3rd International Symposium on Image and Signal Processing and Analysis*, 2003, vol. 15, pp. 915-920.

]5] Anantha Vidya Sagar, S.Balasubramaniam and V.Chandrasekaran, "A Novel Integrated Approach using Dynamic Thresholding and Edge Detection (IDTED) for Automatic Detection of Exudates in Digital Fundus Retinal Images", *Proc. of the International Conference on Computing: Theory and Applications*, 2007, pp. 705-710.

[6] Clara I. Sanchez et.al, "A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis", *Medical Engineering and Physics,* vol. 30, pp. 350-357, 2008.

[7] Jagadish Nayak et.al, "Automated Identification of Diabetic Retinopathy Stages Using Digital Fundus Images', *Journal of Medical Systems*, vol. 32, pp. 107-115, 2008.

[8] Rajendra Acharya U et.al, "Application of Higher Order Spectra for the Identification of Diabetes Retinopathy Stages", *Journal of Medical Systems*, vol. 32, pp. 481-488, 2008.

[9] Akara Sopharak, Bunyarit Uyyanonvara and Sarah Barman, "Automatic exudate detection from non-dilated diabetic retinopathy retinal images using fuzzy C-means clustering", *Sensors*, vol.9, no. 3, pp. 2148-2161, 2009.

[10] V. Vijaya Kumari and N. SuriyaNarayanan, "Diabetic Retinopathy-Early Detection Using Image Processing Techniques", *International Journal of Computer Science and Engineering*, vol. 2, no. 2, pp. 357-361, 2010.

[11] Asha Gowda Karegowda et.al, "Exudates detection in retinal images using back propagation neural network", *International Journal of Computer Applications*, vol. 25, no. 3, pp. 25-31, 2011.

[12] C.Jayakumari and R.Maruthi, "Longitudinal time-series of color retinal Fundus Image for Diabetic Retinopathy", *International Journal of Computer Applications*, vol. 33, no. 10, pp. 43-46, 2011.

[13] R. Vidyasari, I. Sovani, T.L.R. Mengko and H. Zakaria, "Vessel Enhancement Algorithm in Digital Retinal Fundus Microaneurysms Filter for Nonproliferative Diabetic Retinopathy Classification", *Proc. Of International Conference on Instrumentation, Communication, Information Technology and Biomedical Engineering*, 2011, pp. 278-281.

[14] Akara Sopharak, Bunyarit Uyyanonvara and Sarah Barman, "Fine Microaneurysm Detection from Non-dilated Diabetic Retinopathy Retinal Images Using a Hybrid Approach", *Proc. of the World Congress on Engineering*, 2012, vol. 2.

[15] Archana Deka and Kandarpa Kumar Sarma, "SVD and PCA Features for ANN based Detection of Diabetes Using Retinopathy", *Proceedings of the CUBE International Information Technology Conference*, 2012, pp. 38-41.

[16] M. Ponni Bala and S. Vijayachitra, "Computerised Retinal Image Analysis to Detect and Quantify Exudates Associated with Diabetic Retinopathy", *International Journal of Computer Applications*, vol. 34, no. 2, pp. 7-12, 2012.

[17] Jagadish Nayak, Rajendra Acharya U. P. Subbanna Bhat, Nakul Shetty and Teik-Cheng Lim, "Automated Diagnosis of Glaucoma Using Digital Fundus Images", *Journal of Medical Systems,* vol.33, no. 5, 337-346, 2009

[18] U. Rajendra Acharya, Sumeet Dua, Xian Du, Vinitha Sree S, and Chua Kuang Chua, "Automated Diagnosis of Glaucoma Using Texture and Higher Order Spectra Features", *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 3, 2011.

[19] T. R. Ganesh Babu and S. Shenbagadevi, "Automatic Detection of Glaucoma Using Fundus Image", *European Journal of Scientific Research*, vol. 59, no.1, pp. 22-32, 2011

[20] Chih-Yin Ho et.al, "An Atomatic Fundus Image Analysis System for Clinical Diagnosis of Glaucoma", *International Conference on Complex, Intelligent and Software Intensive Systems, 2011, pp. 359-364.*

[21] Naoto Inoue, et.al, "Development of a simple diagnostic method for the glaucoma using ocular Fundus pictures", Proc. of the 2005 IEEE Engineering in Medicine and Biology, 2005, vol. 4, pp.3355-3358.

[22] K.Narasimhan and K.Vijayarekha, "An Efficient Automated System For Glaucoma Detection Using Fundus Image*", Journal of Theoretical and Applied Information Technology*, vol. 33, no. 1, pp. 104-110, 2011.

[23] Wisam Shehadeh, Mohammad Rousan and Ahmed Ghorab, "Automated Diagnosis of Glaucoma using Artificial Intelligent Techniques", *Journal of Communications and Computer Engineering,* vol. 2, no. 1, pp. 35-40, 2012.

[24] "Gold Standard Database for Evaluation of Fundus Image Segmentation Algorithms" Available at http://www5.informatik.uni-rlangen.de/research/data/fundus-images/

[25] Jestin V.K., J.Anitha, and D.Jude Hemanth, "Genetic Algorithm for Retinal Image Analysis", *InternationalJournal of Computer Application; Special Issue on Novel Aspects of Digital Image Processing,* pp. 48-52, 2011.

[26] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features of Image Classification", *IEEE Transactions on Systems, Man and Cybernetics*, vol. 3, no. 6, 1973.

[27] L. Soh and C. Tsatsoulis, "Texture Analysis of SAR Sea Ice Imagery Using Gray Level Co-Occurrence Matrices", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 2, pp. 780 -795, 1999.

[28] D A. Clausi, "An analysis of co-occurrence texture statistics as a function of grey level quantization", *Canadian Journal of Remote Sensing*, vol. 28, no. 1, pp. 45-62, 2002.

[29] Jacob S.G, R.G, Ramani, "Discovery of Knowledge Patterns in Clinical Data through Data mining Algorithms: Multi-Class categorization of Breast Tissue Data", International Journal of Computer Applications, Vol.32, No. 7, pp.48-53, 2011.