Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

COMPUTER-BASED CLASSIFICATION OF EYE DISEASES

Rajendra Acharya U[1], Kannathal N[1], E. Y. K. Ng[2] , Lim Choo Min[1], Jasjit S. Suri[3]

[1] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore.

[2]School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore

[3]Fellow AIMBE, Idaho's Biomedical Research Institute, ID, USA and Biomedical Technologies Inc., CO, USA

Abstract - **Eye disorders among the elderly are a major health problem. With advancing age, the normal function of eye tissues decreases and there is an increased incidence of ocular pathology. The most common causes of age related eye disorder and visual impairment in the elderly are Cataracts, Iridocyclitis and Corneal Haze. Iridocyclitis is an inflammation of the iris (the colored part of the eye), while Corneal Haze is a complication of refractive surgery characterized by the cloudiness of the normally clear cornea. Computer-based intelligent system for classification of these eye diseases is very useful in diagnostics and disease management.**

This paper presents a comparison of three classification strategies to classify four kinds of eye data sets (three different kinds of eye diseases and a normal class). Our protocol uses three different kinds of classifiers: Artificial Neural Network, Fuzzy classifier and Neuro-Fuzzy classifier. Features are extracted from these raw images which are then fed to these classifiers. These classifiers are run on a database of 135 subjects using the cross-validation strategy. We demonstrate a sensitivity of more than 85% for these classifiers with the specificity of 100% and results are very promising.

Index Terms: **Eye, iridocyclitis, cataract, normal eye, corneal haze, image processing, features, classification, neural networks, fuzzy classifier, neuro-fuzzy classifier ANOVA test, sensitivity, specificity.**

I. INTRODUCTION

Most visual impairments are caused by disease and malnutrition. The World Health Organization (WHO) estimates that more than 42 million people in the world are currently blind [1]. According to WHO estimates in 2002, the most common causes of blindness around the world are: 1) cataracts (47.8%), 2) glaucoma (12.3%), 3) age-related macular degeneration (AMD) (8.7%), trachoma (3.6%), corneal opacity (5.1%), and diabetic retinopathy (4.8%), among other causes. Almost half of all blindness is caused by cataracts. There are currently approximately one million free cataract operations performed annually, but there are 1.5 million new cases of cataract blindness occurring in the world's indigent population per year. In other words, the world is slowly becoming blinder.

As the population ages, more people are affected by conditions that impair vision such as cataracts and glaucoma. These eye diseases develop slowly, and the patient normally may not be aware of the gradual loss of sight until very late in the disease when vision is seriously affected. The earlier the diseases are diagnosed and treated, the greater the chance of success in preventing visual loss, and the higher the possibility of cure. A brief description of the normal, cataract, iridocyclitis and corneal haze eye is given below.

The eye works like a camera. Light rays, reflected by the objects we look at, enter the eye through the cornea, which is like a window in the white of the eye and which provides most of the focusing power The cornea is the principal lens of the eye and it is on the cornea that refractive surgery will be practiced. Cataract is clouding of the eye's natural lens, which lies behind the iris and the pupil. Iridocyclitis (Iritis), is a condition an inflammation of the iris and ciliary body. The iris is the colored part of your eye that surrounds the pupil. The iris controls the amount of light entering the eye by enlarging or reducing the size of the pupil. Iritis occurs when the iris becomes inflamed. Symptoms of iritis may include eye pain, redness, blurred vision and light sensitivity. Corneal haze is the cloudiness of the normal (clear) cornea. Most types of haze disappear with time or after drug treatment. Severe corneal haze may lead to reduced visual acuity. It is a complication of refractive surgery characterized by the cloudiness of the normally clear cornea.

The vascular aetiology of glaucoma hypothesises that a compromised blood supply to the optic nerve head contributes to optic nerve head damage. Localized damage may occur when the ocular perfusion pressure falls outside the normal range of auto regulation. This may be the result of a systemic dysfunction (low systemic blood pressure, large nocturnal dips in blood pressure, or peripheral vasospastic disorders) [2] or a local abnormality in the ocular blood supply.

Iridocyclitis or uveitis seen with pauciarticular juvenile rheumatoid arthritis is usually chronic with long periods of active ocular inflammation, remissions and recurrences [3]. It can occur six months to four years before the onset of arthritis. This process can go undetected until sight is impaired. Iridocyclitis can recur, even when the joint disease is in remission. Undetected and untreated, it can eventually lead to loss of vision with band keratopathy, cataracts, synechiae and glaucoma. Periodic slit-lamp examinations are the best means of detection of chronic iridocyclitis.

Zangwill *et al.* [4] have studied the effect of pupil size and cataract on the reproducibility and image quality obtained with confocal scanning laser ophthalmoscopy. And it is determined that the pupillary dilation improved the image quality in many subjects by a small amount. The subjects with small undilated pupils and/or cataracts may benefit most from pupillary dilation. The age-related eye disease study system has successfully classified the different types of cataracts from photograph images [5].

This work deals with the comparison of classification of eye diseases (three different kinds of eye diseases and a normal class) using Artificial Neural Network, Fuzzy classifier and Neuro-Fuzzy classifier. The layout of the paper is as follows: Section II presents briefly the data acquisition and sample images. Preprocessing and feature extraction is presented in section III. Classification strategies used are presented in section IV. The results and performance is discussed in section V. Finally the paper concludes in section VI.

II. DATA ACQUISTION

For the purpose of the present work, about 135 subjects – patients suffering from glaucoma, cataract, corneal arcus as well as those in normal health – have been studied. These data were taken from the Kasturba Medical Hospital, Eye centre, Manipal, India. Images were stored in 24-bit TIFF format with image size of 128x128 pixels. Figure 1 shows the sample of normal, cataract, iridocyclitis and corneal haze images for different subjects.

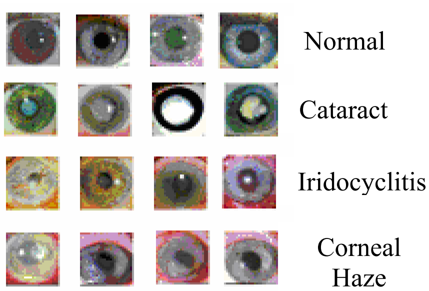


Figure 1 Sample normal, cataract, iridocyclitis, corneal haze optical images.

III. PREPROCESSING AND FEATURE EXTRACTION

In the process of doing the project, we made use of a few image processing algorithm such as image equalization, binarizing, and region of interest selection.

A. Histogram Equalization

Histogram equalization is the technique by which the dynamic range of the histogram of an image is increased [6]. Histogram equalization assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. It improves contrast and the goal of histogram equalization is to obtain a uniform histogram. This technique was used on the whole image.

B. Binarization

To binarize the image, a threshold should be carefully chosen. Too small threshold will produce an image that has edges linked together and choosing a too big threshold will produce edge segments that contain curves will not be closed. We obtained good results by setting the threshold at 25% of the gray intensities contained into the image (25% of the lower gray intensities are discarded).

C. Features used for the classification

i Big Ring Area (BRA)

The color at the outer surface of the cornea is not the same in all the four image classes. In the case of iridocyclitis and few cataract images, the outer surface of the cornea images have bright color as compared to the normal and corneal haze. Figure 2(a) shows the schematic diagram of the BRA detection in normal image. It consists of two circles: an inner circle C_i and an outer circle C_o. The region between the C_i and C_o is the BRA with C_i (r_i=55) and C_o (r_o=59) in this work are the concentric circles.

ii Small Ring Area (SRA)

The color at the inner surface of the cornea is not the same in all the four image classes. In the case of cataract and iridocyclitis images the inner surface of the cornea images are brighter as compared to the normal and corneal haze. Figure 2(b) shows the schematic diagram of the SRA detection in normal image. It consists of two circles: an inner circle C_i and an outer circle C_o. The region between the C_i and C_o is the SRA with C_i (5) and C_o (15) in this work are the concentric circles.

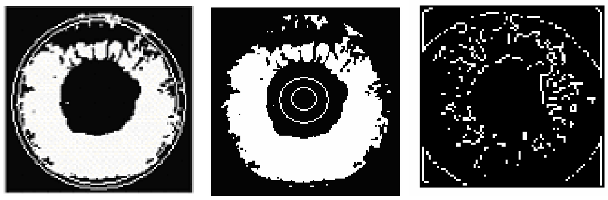
iii Homogeneity

Texture is repeating patterns of local variations in image intensity, which is too fine to be distinguished. Texture evokes the image of large number of structural primitive of (statistically) identical shape and size placed (statistically) uniformly.

Homogeneity measures the closeness of the distribution of elements in the gray level co-occurrence matrix (GLCM) to the GLCM diagonal values. Homogeneity between pairs of texture patches or similarity between textured images in general can be measured by a non--parametric statistical test applied to the empirical feature distribution functions of locally sampled Gabor coefficients.

iv BW Morph (BWM)

The normal, cataract and iridocyclitis images have too many sudden changes in the gray levels. Hence there will be many edges in their images as compared to the corneal haze. After binarizing the image becomes, black and white. This function BWMorph is used to find the area between the edges. BW Morph is a function in Matlab that does specific morphological operation on binary images. Results of the BWMorph for the normal eye is shown in figure 2(c).



(a) (b) (c)
Figure 2(a) result of BRA feature, (b) result of SRA feature (c) result of BWMorph on normal eye image.

V. CLASSIFICATION STRATEGIES

In this work, the feedforward architecture neural network classifier, Sugeno fuzzy model based fuzzy classifier and adaptive neuro-fuzzy inference system (ANFIS) system is used in neuro-fuzzy classifier.

i. Artificial Neural Network (ANN)

The structure of the feedforward neural network classifier used for this work. The neural network has one hidden layer and twelve neurons in this layer. The output layer has four neurons, giving rise to an output domain of sixteen possible classes. However, the network is trained to identify only four classes given by decoded binary outputs [001, 010, 100].

ii Fuzzy Classifier

In a fuzzy classification system, pattern space is divided into multiple subspaces, and for each subspace, the relationships between the target patterns and their classes are described by if-then type fuzzy rules. The useful capability of this system is that a nonlinear classification boundary can be easily implemented. Unknown patterns are classified by fuzzy inference, and patterns that belong to an unknown class which was not considered at learning can be easily rejected. Ishibuchi et al [7; 8] proposed methods to acquire a fuzzy classification system automatically by a simple learning procedure and a genetic algorithm. With these methods, however, a pattern space is divided lattice-like. Therefore, many fuzzy rules corresponding to fine subspaces are required to implement a complicated classification boundary. A fuzzy classifier [9] using subtractive clustering and Sugeno fuzzy inference system is used in this work.

iii. Adaptive Neuro Fuzzy Classifier

The neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method [10]. This allows the fuzzy systems to learn from the data they are modeling. The network structure of the ANFIS is similar to neural network. The inputs are fuzzified through input membership functions. The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters.

IV. RESULTS AND DISCUSSION

In this study, we have extracted four features namely, big ring area (BRA), small ring area (SRA), homogeniety (H) and negative of the BWMorph from the raw eye images. Big Ring Area is the number of pixels within the outer ring of the cornea. SRA is the number of pixels within the inner ring of the cornea. Homogeniety measures between pairs of texture patches. Inversion of the BWMorph is used to get the edges of cornea. And in this function, the area between the edges is used as a feature. These features are used to classify the four eye classes (three different kinds of eye diseases and a normal class) using three classifiers: i) Neural network classifier ii) Fuzzy classifier iii) Neuro-Fuzzy classifier. The neural classifier gives 100% classification efficiency for normal images and classifies 81% of iridocyclitis images. The Fuzzy and Neuro-Fuzzy classifiers, is superior than the neural network classifier. They both yield correct classification of normal, cataract and iridocyclitis images for more than 90% of the cases. Table I shows the ranges of the three parameters used to feed as input to the ANN. For the purpose of training and testing the classifier, a data base of 135 patient samples is divided into two sets – a training set of 76 arbitrarily chosen samples and a test set of 54 samples (Table II). The training consisted of 5,000 iterations. During the training phase, each output of the ANN is an analog value in the range 0 →1.0, whereas the 'desired' output is either 0 or 1.0. During the recall phase, the output signal is approximated to binary levels by comparing it with threshold value of 0.5. The mean square error of the ANN was set to 0.001. The fuzzy and neuro-fuzzy classifiers, is superior than the neural network classifier. They both yield correct classification of normal, cataract and iridocyclitis images for more than 90% of the cases (table II). Table III shows the result of sensitivity, specificity, positive predictive values for the four classes (three different kinds of eye diseases and a normal class) eye images using neural network classifier.

Table I: Range of input parameters to ANN classification model.

Parameter	Normal	Cataract	Irido cyclitis	Corneal Haze	p-test
Big Ring (BR)	826.08± 164.41	706.8± 212.51	937± 126.56	569.1± 225.70	P<0.0001
Small Ring (SR)	26.9± 60.08	593.3± 65.60	172.1± 181.38	381± 278.32	P<0.0001
Homo geneity	0.0568 ± 0.0027	0.0670± 0.0045	0.058± 0.0049	0.063± 0.0072	P<0.0001
BWM	1.23E+3± 203.39	1E+03± 170.59	1E+03± 183.18	8.64E+2± 335.94	P<0.0001

Table II: Training and testing data set.

Classes	No. of data set used for training	No. of data set used for testing	Percentage (%) of correct classification		
			ANN	FUZZY	ANFIS
Normal	30	20	100.00	100.00	100.00
Cataract	22	15	86.67	93.33	93.33
Glaucoma	15	11	81.82	90.91	90.91
Corneal Ulcer	9	8	87.50	87.50	87.50
		Average	89.00	92.94	92.94

Table III: Results of sensitivity, specificity, positive predictive value, for complete eye classes using neural network, fuzzy and ANFIS.

Classifier	TN	TP	FP	FN	Sensitivity	Specificity	Positive Predictive Accuracy
ANN	20	29	0	5	85.29	100	100
FUZZY	20	31	0	4	88.57	100	100
ANFIS	20	31	0	4	88.57	100	100

The fuzzy and neuro-fuzzy classifiers, is superior than the neural network classifier. They both yield correct classification of normal, cataract and iridocyclitis images for more than 90% of the cases. Their sensitivity is 88%, higher than the neural network classifier. Sensitivity is the ability to correctly detect disease and the specificity: is the ability to avoid calling normal things as disease. The specificity and positive predictive accuracy is 100% for all the classes indicating that, the results are clinically significant.

The accuracy of the system can further be increased by increasing the size (training data more than 200) and quality of the training set. The classification results can be enhanced by extracting the proper features from the optical images. The environmental conditions like the reflection of the light influences the quality of the optical images and hence the percentage of classification efficiency.

In this paper, we have discussed the performances of neural, fuzzy and adaptive neuro-fuzzy classifiers as diagnostic tool to aid the physician in the detection of these eye abnormalities. However, these tools generally do not yield results with 100% accuracy. The accuracy of the tools depend on several factors, such as the size and quality of the training set, the rigor of the training imparted, and also parameters chosen to represent the input. It is evident, from the results that the adative neuro-fuzzy classifier is effective to the tune of more than 85% accuracy.

VI. CONCLUSION

Eye diseases like iridocyclitis, cataract as well as corneal haze are becoming more prevalent throughout the world and are attributed to factors such as diet and lifestyle. These diseases are the largest cause of blindness and often cannot be remedied because the patients are diagnosed too late with the diseases.

In this paper, we have discussed the performances of neural, fuzzy and adaptive neuro-fuzzy classifiers as diagnostic tool to aid the physician in the detection of the eye abnormalities. However, these tools generally do not yield results with 100% accuracy. The accuracy of the tools depend on several factors, such as the size and quality of the training set, the rigor of the training imparted, and also parameters chosen to represent the input. It is evident, from the results that our classifiers make the correct classification the unknown images with an accuracy of more than 85%.

Acknowledgement: The authors wish to thank Dr. Jagadish Nayak, Manipal Academy of Higher Education, Manipal, India for providing the eye data for this work.

REFERENCES

1. http://www.owsp.org/problem.htm
2. Hayreh SS, Zimmerman MB, Podhajsky P, *et al.*, "Nocturnal arterial hypotension and its role in optic nerve head and ocular ischemic disorders", Am J Ophthalmol. 117, 1994, 603–624.
3. Sampath, P, Murray, HP, "long-term outcome among patients with juvenile rheumatoid arthritis", Frontiers in Bioscience, 3, 1998, 13-22.
4. Zangwill L, Irak I, Berry CC, Garden V, de Souza Lima M, Weinreb RN., "Effect of cataract and pupil size on image quality with confocal scanning laser ophthalmoscopy", Arch Ophthalmol.115(8), 1997,983-990.
5. Age-Related Eye Disease Study Research Group, "The age-related eye disease study (AREDS) system for classifying cataracts from photographs: AREDS report no. 4", Am J Ophthalmol., 131(2), 2001, 167-75.
6. Gonzalez R.C., P. Wintz., "Digital Image Processing", 2nd edn. Addison-Wesley. Reading, MA, 1987.
7. Nozaki, Ishibuchi nd Tanaka "Selecting fuzzy if-then rules with forgetting in fuzzy classification systems", Journal of Japan Society for Fuzzy Theory and Systems, 6(3), 1994,585-602.
8. Ishibuchi, Murata and Tanaka "Construction of fuzzy classification systems using genetic algorithms", Journal of Japan Society for Fuzzy Theory and Systems, 7(5), 1995, 1022-1040.
9. George Klir , Bo Yuan, "Fuzzy Sets and Fuzzy Logic: Theory and Applications", Prentice Hall India, 1995.
10. Jang, J.S.R., "ANFIS: Adaptive Network based Fuzzy inference Systems," IEEE Transactions on Systems, Man, and Cybernetics, 23(3), 1993, 665-685.