# COMPARISON OF CLASSIFIERS FOR DETECTING THE CORNEAL ARCUS AS A SYMPTOM OF HYPERLIPIDEMIA

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**ABSTRACT**

*This paper presents the classification of the corneal arcus (CA), as an indicator of hyperlipidemia presence. We used two data-sets, comprising of the normal and abnormal eyes (CA). The first step is, to normalize the data-set, before extracting its features. These images extracted to get the statistical features using gray level co-occurrence matrix (GLCM). Next, used the statistical features as input to the classifier for training and testing the data features for classification. Our proposed system, using the Bayesian regularization (BR) classifier with a sensitivity of 94.1%, a specificity of 97.3%, and 96%, is accuracy. The results obtained shows that the proposed method able to classify the corneal arcus successfully. This classification allows the proposed method used to identify the presence of hypercholesterolemia in a way of a non-invasive test.*

Keywords: Specificity, sensitivity, accuracy, confusion matrix, Bayesian regularization.

## Introduction

Vision problems can lead to blindness if early action is not taken, it is also the problems that plague many human beings around the world. According to (Stevens et al. 2013) there were 32.4 million people were blind in 2010, while 191 million people suffer from the moderate-severe vision impairment (MSVI). This problem also reported in (World Health Organization 2010) of global data on visual impairments report 2010. There is also the problem of the eye, which does not obstruct the overall vision, but it is said to be associated with other systemic health problems, such as the cornea lipid deposits, known as the corneal arcus (CA).
The CA is frequently found in the older peoples. However, it can happen to young people who have high cholesterol in their blood. The CA is said can be used as an indicator, of the presence of lipid abnormalities in the blood vein. This is because the eye contains tiny blood veins that connect with the blood vessels in the human body. Although it could not give the exact content of cholesterol in the blood, such as the cholesterol amount using the blood test, but it is useful as an indicator of the presence of abnormal cholesterol. Based on these problems, we are experimenting with image processing to obtain the characteristics of a normal eye and eye problems.

The researchers (Fernández et al. 2007; Hickey et al. 1970; Ang et al. 2011; Cooke 1981; Bersohn et al. 1969; Chen et al. 2009; Halfon ST, Hames CG 1984; Pomerantz 1962; Navoyan 2003) have studied about CA, some of them agreed, the presence of CA are associated with the abnormal lipids in the human circulatory system.

According to (Fernández et al. 2007), corneal arcus associated to coronary heart disease, blood pressure, hypercholesterolemia (Macchiaiolo et al. 2014), xanthelasma, alcohol, cigarette smoking, diabetes (Bansal et al. 2015; Lesmana et al. 2011), and age.

Based on this, the presence of the CA that is detected during clinical eye examination can be used as an indicator that there is an increased lipid in the blood. Furthermore, the usage of CA is useful as a screening method that is non-invasive and painless.

The remainder of this paper is organized as follows sections; the relevant studies have been conducted regarding CA, methodology of this experiment, Result and discussion and the final section is the conclusion of this study.

**Related work**

The study of corneal arcus and hyperlipidemia has long been predicted and assessed, but the issue is still a matter of controversy. Most of the CA study conducted in the medical field, is to find the relationship with the lipid abnormalities, problem of blockage of blood vessels and heart disease. Among the studies that correlate with abnormal lipid (Roshan et al. 2011; Lee et al. 2013; Schaefer et al. 2016). We found that most of the medical research associated with this CA, conducted through the inspection eye manually and none of them, using automation technique for comparison. Thus, we find research studies regarding the CA, using automated methods to classify eye with symptoms CA for further study.

There are studies conducted stated, the presence of the CA sign, may provide an indication to the hyperlipidemia and cardio heart disease (CHD) (Crispin 2002; Coady et al. 2014). The ocular signs related to the symptoms associated to the systemic diseases are reported in many studies such as the kidney (Hussein et al. 2013), colon (Passarella & Fachrurrozi 2013), lung (tuberculosis) (Lai & Chiu 2010)(Coady et al. 2014), and diabetes (Bansal et al. 2015).

(Schaefer et al. 2016) has reported three cases CHD's patient, who have abnormal levels of cholesterol (HDL-C <40 mg / dL), was found to have the presence of sediment CA on the cornea of the eye. The situation of the CA in CHD's patients is also reported by (Roshan et al. 2011; Lee et al. 2013).

Some of the research studies related to CA, as presented by (Rajendra Acharya U et al. 2006; Acharya U et al. 2007), and (S.V. Mahesh Kumar 2016) discussed the classification. In (Rajendra Acharya U et al. 2006), they developed the automatic for detection of eye abnormalities using three different types of classifiers namely; the artificial neural network (ANN), Fuzzy, and Adaptive neuro-fuzzy inference system (ANFIS). They use about 135 eye samples in their study, in which the results of their proposed system showed an accuracy of 93% for both and ANFIS fuzzy classifier.

In other works, Acharya (Acharya U et al. 2007) used the radial basis function (RBF) neural network to classify the abnormal eye. For extract the features from the image, they used the fuzzy k-means. These features are used as the input to RBF network. Their work result obtains the overall accuracy is 95% for their proposed system. In another study (Rajendra Acharya U et al. 2006), they proposed the automation system for eye disease using different types of classifier namely, artificial neural networks (ANN), fuzzy classifier, and adaptive Neuro-fuzzy inference system (ANFIS). For this, they demonstrated a sensitivity of more than 85% and the specificity of 100% for these classifiers.

In previous work, the author proposed the OTSU threshold for classifies the eye image (Ramlee & Ranjit 2009), this technique has various drawbacks if the image intensity is used because it depends on the threshold value histogram.

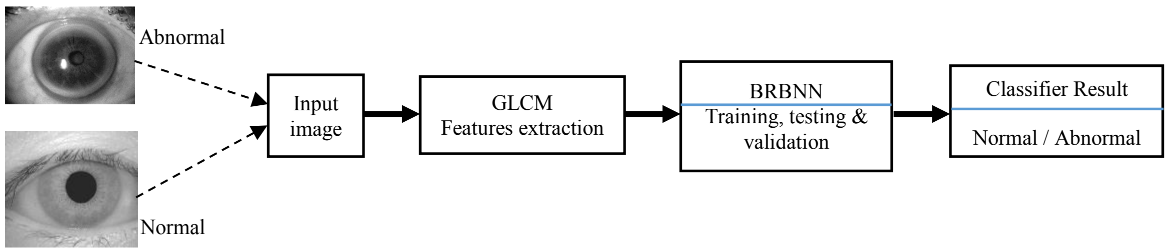
Thus, in this paper, we proposed the Bayesian regulation back-propagation neural network (BRBNN) with the features extract achieved from GLCM statistical attributes. Table 1, shows the method of classification of eye abnormalities with numbers of image or samples of images used in their work.

**Table 1: Methods used for classification the eye abnormalities**

| Authors | Types of diseases | Classifier | No. of images |
|---|---|---|---|
| (Rajendra Acharya U et al. 2006) | Eye abnormalities | ANN | 135 |
| (Rajendra Acharya U et al. 2006) | Eye abnormalities | Fuzzy | 135 |
| (Rajendra Acharya U et al. 2006) | Eye abnormalities | ANFIS | 135 |
| (Acharya U et al. 2007) | Eye abnormalities | RBF | 150 |
| (Ramlee & Ranjit 2009) | Arcus senilis | OTSU threshold | 30 |
| Proposed | Corneal arcus | BR | 125 |

**Data Acquisition**

**Figure 1: The framework of the proposed system**




The proposed system is shown in Figure 1, consists of four stages of work steps such as the input image, features extraction, classifier algorithm, and results of the classifier. In this study, we used a total of 125 eye images, which include 40.8% samples of the abnormal eye and 59.2% samples of the normal eye. The normal eyes are the samples which are free from any sign of the CA presence, and the abnormal data-set contain the samples with the signs of the CA presence, exists within the cornea area. The eye samples in both groups, divided in each folder individually, for further processing, such as training and test data. In the second block, the image extraction is done using the GLCM matrix in order to get the statistical features for represented the image categories. The features of this image, can then be summarized using statistical calculations. Next, the values of these statistics features are fed into the classifier, for the process of training, testing, and validation. This classifier will classify the images that have been trained according to each class, either normal or abnormal.

**a. Feature extraction**

The eye image features will be extracted using matrix GLCM. Some parameters from this matrix can be obtained such as; contrast, homogeneity, energy, correlation, and entropy. These parameters are used as inputs to the neural network (NN) to enable it to learn, test and validate the input data. In this experiment, we used Bayesian regulation back-propagation neural network (BRBNN), for classification of the samples. All these statistic attributes are calculated from the GLCM matrix. The parameters were as follows:

i. *Contrast;* the local variation will be calculated from the GLCM matrix.
ii. *Correlation;* measures the amount of joint probability occurrence of the specified pixel pairs in these images.
iii. *Homogeneity;* measures the nearness of the distribution of components in the GLCM to the GLCM diagonal.
iv. *Energy;* provides a number of squared elements contain in the GLCM matrix, also known as the angular second moment or uniformity.
v. *Entropy;* used to calculate the statistical attributes for determined the image texture.

Bellows are the statistical features calculated from the GLCM characteristic matrix. Five statistical features, use in this experiment, functioning as the input of the classifier, which is using BRBNN model for this classification, as following;

$$\text{Contrast} = \sum_{i,j} |i-j|^2 \, p(i,j) \qquad (1)$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu i)p(i,j)}{\sigma_i \sigma_j} \qquad (2)$$

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \qquad (3)$$

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \qquad (4)$$

$$\text{Entropy} = -\sum_{k=0}^{M-1} p_k \log_2(p_k) \qquad (5)$$

**b. Bayesian regulation backpropagation neural network (BRPNN) classifier**

In this paper, we use the BRBNN (Figure 2) to perform the classification of the eye images. In this network, we use a combination of 5:10:2 for an input, hidden, and output neurons, respectively. The input to the neural network is derived from the image extraction features using GLCM matrix. In BRBNN the network only does train and test for the data input. The structure of two layers BRBNN design with all nodes is shown in Figure 2.

In BR framework, the network weights are defined as the random variables. These weights of network and training set are assumed as the Gaussian distribution. The factors α and β, as in (6) are obtained from Bayes' theorem. In (7), the variables A and B, are defined from Bayes' theorem contains posterior and prior probability variables (Li & Shi 2012). Yue (Yue et al. 2011) described, the regularized training objective function, denote as F(ω) as write in (6).

$$F(\omega) = \alpha E_\omega + \beta E_D \qquad (6)$$

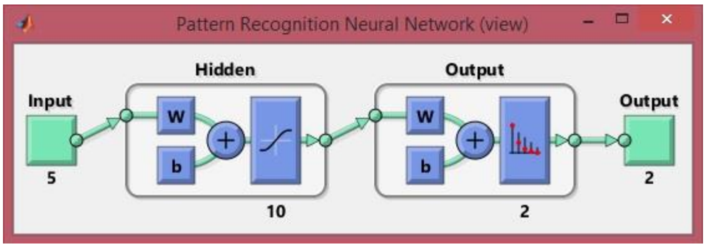
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (7)$$

Referring to (7), the P(A|B) is the conditional of A and B of posterior probability and conversely for P(B|A). Meanwhile, the P(A) and P(B) is the prior of the probability of event A and event B, accordingly. In (8), the equation is used to minimize the $F(\omega)$ from (6), in order to optimize the weight space. The variables $\alpha$ and $\beta$ in (8) are the factors need to be optimized.

$$P(\alpha, \beta|D, M) = \frac{P(D|\alpha, B, M)P(\alpha, \beta|M)}{P(D|M)} \quad (8)$$

Referring to (8), where; D is the distribution of weight, while the M is the architecture of NN. Thus, $P(D|M)$ is the factor of normalization. The P(α,β│M) is the regularization parameters and P(D│α,B,M) is the function likelihood of D with respect to α,B,M.

**Figure 2:** The two layers architecture of the BRBNN




**c. Evaluation**

To evaluation the output performance of this model we use the confusion matrix (Table 2) and the statistical calculation from the confusion matrix attributes. From these attributes some statistical parameters for showing the algorithm performance can be calculated such as the specificity, sensitivity, and accuracy.

**Table 2: The confusion matrix distribution elements**

| | Reference | |
|---|---|---|
| Predicted | Class I | Class II |
| Class I | TP | FP |
| Class II | FN | TN |

*TP= true positive, TN=true negative, FP=false positive, FN=false negative*

$$\text{Sensitivity} = \text{TPR} = \frac{TP}{P} = \frac{TP}{TP + FN} \quad (9)$$

$$\text{Specificity} = \text{SPC} = \frac{TN}{N} = \frac{TN}{TP + FN} \quad (10)$$

$$\text{Accuracy} = \text{ACC} = \frac{TP + TN}{P + N} \quad (11)$$

**The Experimental Results Analysis**

In this section, we present the classifier performance generated in this experiment. Table 3 below shows, the comparison between the accuracy achieved by some previous algorithms with our proposed method.

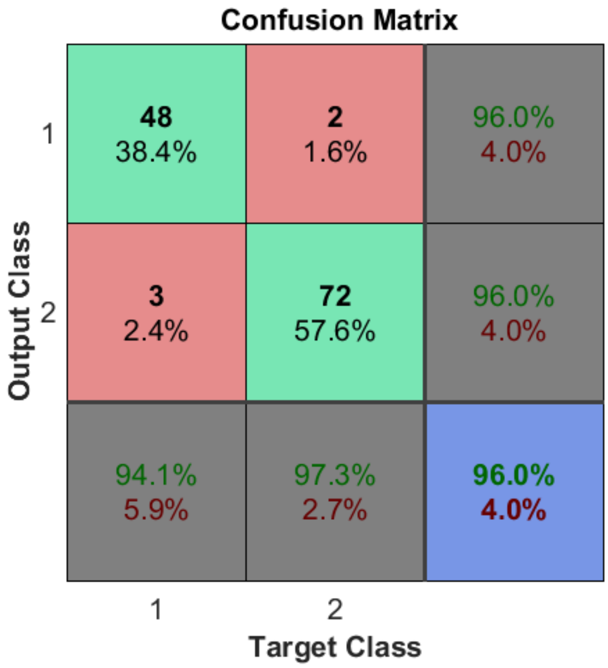
**Table 3: accuracy of the classifiers used for classifying the corneal arcus**

| Authors | Classifier / other | Accuracy (%) |
|---|---|---|
| (Rajendra Acharya U et al. 2006) | ANFIS | 91 |
| (Rajendra Acharya U et al. 2006) | ANN | 93 |
| (Rajendra Acharya U et al. 2006) | FUZZY | 93 |
| (Acharya U et al. 2007) | RBF | 95 |
| (Ramlee & Ranjit 2009) | OTSU | - |

| | | |
|---|---|---|
| **Proposed classifier** | BR | 96 |

As shown in the table, our proposed algorithm give the best accuracy compared to another algorithm. The nearest accuracy is as proposed by (Acharya U et al. 2007) using RBF classifier with an accuracy of 95%.

**Figure 3:** The confusion matrix for all input types.




The next evaluation is using confusion matrix as shown in Figure 3. Where, this matrix classification is used to get the classification performance either positive or negative result. This $2 \times 2$ matrix comprises of $C(m, n)$, where m is the row and n is the columns. For example, in Figure 3, the $C(1,1)$ for training confusion matrix is represented by the value of 48 samples of the images. This equal to 38.4% of the image detected as correct class of diseases eye (TP). Meanwhile, the element shows in matrix element C(2,2), represent as the numbers of the normal eye (TN).

Other statistical values gain from this training confusion matrix are accuracy (96%), sensitivity (94.1%) and specificity (97.3%). Based on the results obtained, it indicates that this classifier can recognize the normal and abnormal with good performance.

**Conclusion**

The classification framework of the CA is presented in this work. Our proposed output of the classifier using BR is compared to previous work to determine the best performance of the classification. The statistical features are extracted from the GLCM matrix and used as the input to the classifier. The BR classifier will use this data for training and test the algorithm, for classification the CA. The architecture of this network used five inputs, ten neurons of hidden branches and two neurons of output. We choose the BR classifier because, this proposed system improved the result, compare to another method, with an accuracy of 96%. Where the best previous work by another researcher is 95%. In the future, we plan to test this classification framework, using different type classifier in order to improve the result.
However, the limitation of this study relates abnormal image data set, in which case it should be improved, so that the level of the captured image can be enhanced.

**Acknowledgement**

The authors would like to thank the Universiti Putra Malaysia (UPM), University of Technical Malaysia Melaka (UTeM) and the Ministry of Higher Education, which provides guidance, support, and sponsorship for this study.

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