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An Automated Cost-Effective Approach to Glaucoma Diagnosis in Human Using Artificial Neural Network

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ABSTRACT

Glaucoma is a term applied to eye condition that progressively brings about loss of vision by harming the optic nerve that sends visual pictures to the mind. This paper provides an automatic human eye diagnostic system utilized to detect glaucoma eye disease based on Artificial Neural Network, it covers acquisition of fundus images, pre-processing the fundus image, extracting useful features from the image, neural network training and classification of eye status. In this work, the back propagation neural network was used to develop the neuron model and the program developed using MATLAB. The developed system was deployed to act as a standalone application using MATLAB guide. The acquired fundus images were analyzed in MATLAB after they have been pre-processed and useful features such as contrast, correlation, homogeneity and energy have been extracted from the pre-processed fundus image. Here, 15% of acquired fundus images were utilized in the testing of the model and an average of 97% accuracy was achieved.

1. INTRODUCTION

The human eye is an important organ of vision, which enables the sense of sight, and it is very important in our day-to-day activities (Adeyanju I.A, 2020). However, the human eye is affected by a number of diseases such as cataract, glaucoma, corneal, retinal infections that could result to blindness if not diagnosed early (Oliveira, 2014). The state of medical diagnosis in developing countries, calls for digital health and artificial intelligence in medicine to back up medical practice. The diagnosis of glaucoma is dependent on the ophthalmologist ability to continually examine large number of fundus image for patients with glaucoma spending valuable time and energy. The current methods of detecting and assessing the Human eye disease are manual, expensive, and potentially inconsistent. Therefore, it would be more cost effective and beneficial if the methods of analyzing retinal (fundus) images are automated (Manoujitha, 2014).

According to the world health organization about 2.2 billion people across the globe have either distance or near vision impairment

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with 7.7million traceable to glaucoma (WHO, 2021). One of the major goals of the World Health Organization is to tackle blindness, especially in children (WHO, 2021), and the role of artificial intelligence in actualizing this priority cannot be overemphasized. Artificial neural networks are artificial intelligence model that has been used for medical diagnosis. They are machine learning tools which are patterned after biological neural system, they learn by training from past experience data (Kabari L.G, 2012). Various computing techniques have been proposed in diagnosing glaucoma eye disease. As in (S. Malik et al, 2019) developed a system for recording diagnostic data in a standard format to facilitate prediction of disease diagnosis based on symptoms using machine learning algorithms while (G.N Prasad et al, 2018) adopted a hybrid approach of fundus image classification for Diabetic Retinopathy. In (C.P Poojitha et al, 2016) implemented a glaucoma diagnosis system. In this study, wavelength filters were adopted for average and energy texture feature. A feed forward neural network was then used to classify glaucoma from a normal eye. The accuracy gotten from the method adopted in this research was 96.67% but it was still limited to the fact that the features extracted were fed into a feed forward neural network which does not have the ability to learn and Re-learn. Going forward (T. Ratanapakorn et al, 2019) carried out research on developing a digital image processing software for diabetic retinopathy from fundus photograph of patients affected by the diabetic retinopathy eye disease.

This paper presents a diagnostic system, to quickly detect glaucoma in patients. The purpose of this paper is to provide an early diagnostic means of detecting glaucoma in humans and help avoid worst case scenario of blindness. ANN is the major tool used in this study because of its advantages over other classifiers algorithms. The system architecture of ANN consists of three basic components which are: the knowledge base, the inference engine, and the user interface. This paper explored these ANN components to develop an expert system capable of diagnosing glaucoma eye diseases.

2. MATERIALS AND METHODS

In this research, a machine learning algorithm that employs back propagation neural network for training was considered. Artificial neural network was chosen because it has the advantage of solving problem accurately, it has an adaptive nature of learning, tolerates faults and has real time operational mode quality over another machine learning algorithm. Artificial neural network has been widely used in the diagnosis of several diseases and has been used in other public sectors to solve problems. This machine learning algorithm prides in its strong internal structure and design techniques which mimics the behavior of the human brain in a simplified computational form. The initial stage of development involves preliminary research to identify the initial requirements which are then implemented and tested.

The several system components used in describing the glaucoma diagnostic system is shown in the Figure 1.

2.1 Data Collection

The data collected for the development of glaucoma eye disease diagnostic system was in two formats. The fundus images of infected eyes (glaucoma) as shown in Figure 2 and the fundus images of non-infected eyes (healthy) as shown in Figure 3. In this work, the fundus images used were in jpg form and they were acquired from SPIE database, and origa light data base for glaucoma and healthy fundus images

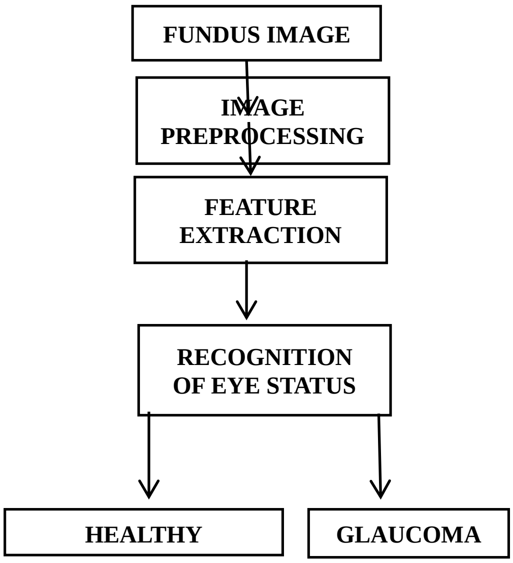


Figure 1: Block diagram of the glaucoma eye disease diagnostic system

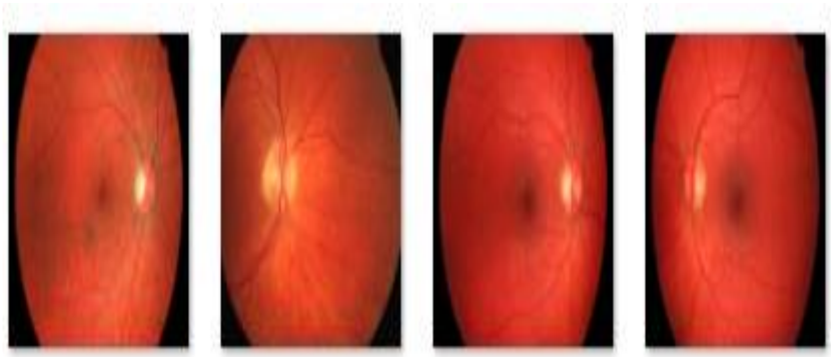


Figure 2: Set of glaucoma fundus images (Zhang Zhuo, 2010)

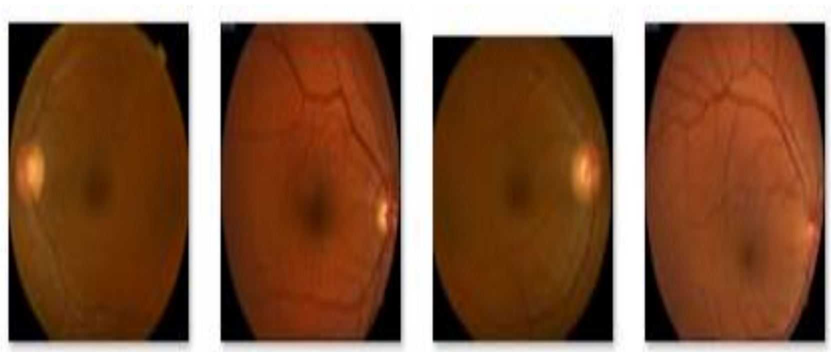


Figure 3: Set of healthy fundus image (T. Mahmudi, 2014)

2.2 Image Preprocessing

Image preprocessing are usually carried out to optimize contrast, reduce unwanted noise of the images, eliminate irregular illumination and bring out more details from the input image of RGB mode. Preprocessing is done because the various fundus images used in this paper differs in brightness, contrast and luminosity. Therefore, without preprocessing it will be difficult to obtain retinal features and differentiate between the region of interest and other features in the images (A.G Karegowda, 2011). However, in this work, the preprocessing of the original fundus images passed through three different stages: grayscale conversion, histogram equalization and thresholding in that order as shown in Table 1.

2.2.1 Gray scale conversion

The conversion of the original fundus images from RGB mode to grayscale is one of the simplest preprocessing techniques required for enhancement of the original fundus image. A gray scale image brings the value of each pixels into a single sample representing only an amount of light which carries only intensity information.

$$Gray\ scale = \frac{R}{3} + \frac{G}{3} + \frac{B}{3} \qquad (1)$$

Where;
R= Red color
G= Green color
B= Blue Color

2.2.2 Histogram Equalization

Due to the fact that the illumination of the fundus image is uneven in such a way that some part of the image is brighter than other parts of the image (A.G Karegowda, 2011), histogram equalization preprocessing technique is introduced as it makes the dark part of the input image brighter when passed through the histogram equalization process.

$$h_{(rk)} = n_k \qquad (2)$$

Where;
$rk\ is\ the\ Kth\ gray\ level$
$n_k\ is\ the\ number\ of\ pixels\ in\ the\ image\ with\ that\ gray\ level$
$n\ is\ the\ total\ number\ of\ pixels\ in\ the\ image$
$k = 0, 1, 2, \dots, L-1$

$$Normalized\ histogram\ is\ P_{(rk)} = {}^{nk}/_{n} \qquad (3)$$

2.2.3 Thresholding

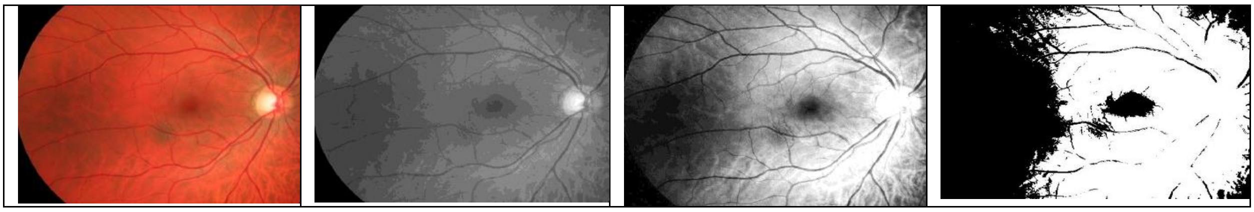
Thresholding is a way of finding the histogram of gray level intensity (A.S Natheem, 2018). In digital image processing, thresholding is the main technique used for image segmentation i.e. partitioning an image into foreground and background. Thresholding, most times makes it easy and convenient to facilitate better binarization on the basis of different intensities in the foreground and background region of an image. This process is expressed mathematically as in equation (4);

$$Threshold = \frac{\max\left(I_{ms}(x,y)\right) + \min\left(I_{ms}(x,y)\right)}{2} \qquad (4)$$

$$I_{bin}(i,j) = \begin{cases} 1\ if\ I_{ms}(i,j) \geq threshold \\ 0\ if\ I_{ms}(i,j) < threshold \end{cases} \qquad (5)$$

Table 1: Preprocessed fundus image results

Original Fundus Image	After Grayscale	After Histogram equalization	After Threshold



2.3 Gray Level Co-Occurrence Matrix

Feature extraction is an important process in machine learning used for capturing important information from the fundus image datasets. According to (Abdullahi, 2015) feature extraction is the computational characteristics of digital images represented in terms of their numerical values which involves identifying the most important and useful properties from a fundus image that will be used in diagnostic process of glaucoma eye disease. The feature extraction process makes it possible for the diagnostic system to differentiate between each fundus image and also makes it easy for identification between a healthy eye and a glaucoma infected eye as the parameters differs for all fundus images. In this paper, four features namely, contrast, correlation, energy and homogeneity were extracted from each fundus image based on gray level co-occurrence matrix, the gray level co-occurrence matrix is a technique that evaluates the texture of image by taking into consideration the spatial relationship of pixels with matrices distances usually in degrees of various form at 0°, 45°, 90° and 135°.

2.3.1 Contrast

In this property, the measure of the intensity contrast between two neighboring pixels over the whole image is returned. Contrast is 0 for a constant image.

$$Contrsat = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} |i - j|^2 (i,j) P_\theta^d(i,j) \qquad (6)$$

2.3.2 Correlation

This property returns a measure of how correlated a pixel is to its neighbor over the whole image with value ranging from -1 to 1, where -1 is perfect negatively correlated, 0 is uncorrelated and 1 is perfect positively correlated.

$$Correlation = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} \frac{ijP_\theta^d - \mu x\mu y}{\sigma x\sigma y} \qquad (7)$$

2.3.3 Energy

This property returns the sum of squared elements for an input image. Energy is 1 for a constant image in the gray level co-occurrence matrix

$$Energy = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} [\,P_\theta^d(i,j)]^2 \quad (8)$$

2.3.4 Homogeneity

This property returns a value that measures the closeness in the distribution of GLCM elements to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM

$$Homogeneity = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} \frac{1}{1+(1-j)^2} P_\theta^d(i,j) \qquad (9)$$

2.4 Eye Status Classification

After the neural network have been created, four features namely contrast, correlation, homogeneity and energy are extracted from the fundus images using the gray level co-occurrence matrix technique immediately after pre-processing the images. The extracted features are then passed into the back propagation neural network for classifying the fundus image into glaucomatous or healthy eye in a supervised learning system.

2.5 System Algorithm and Data Flow

The developed glaucoma diagnosis system using artificial neural network works according to the data flow in Figure 4:

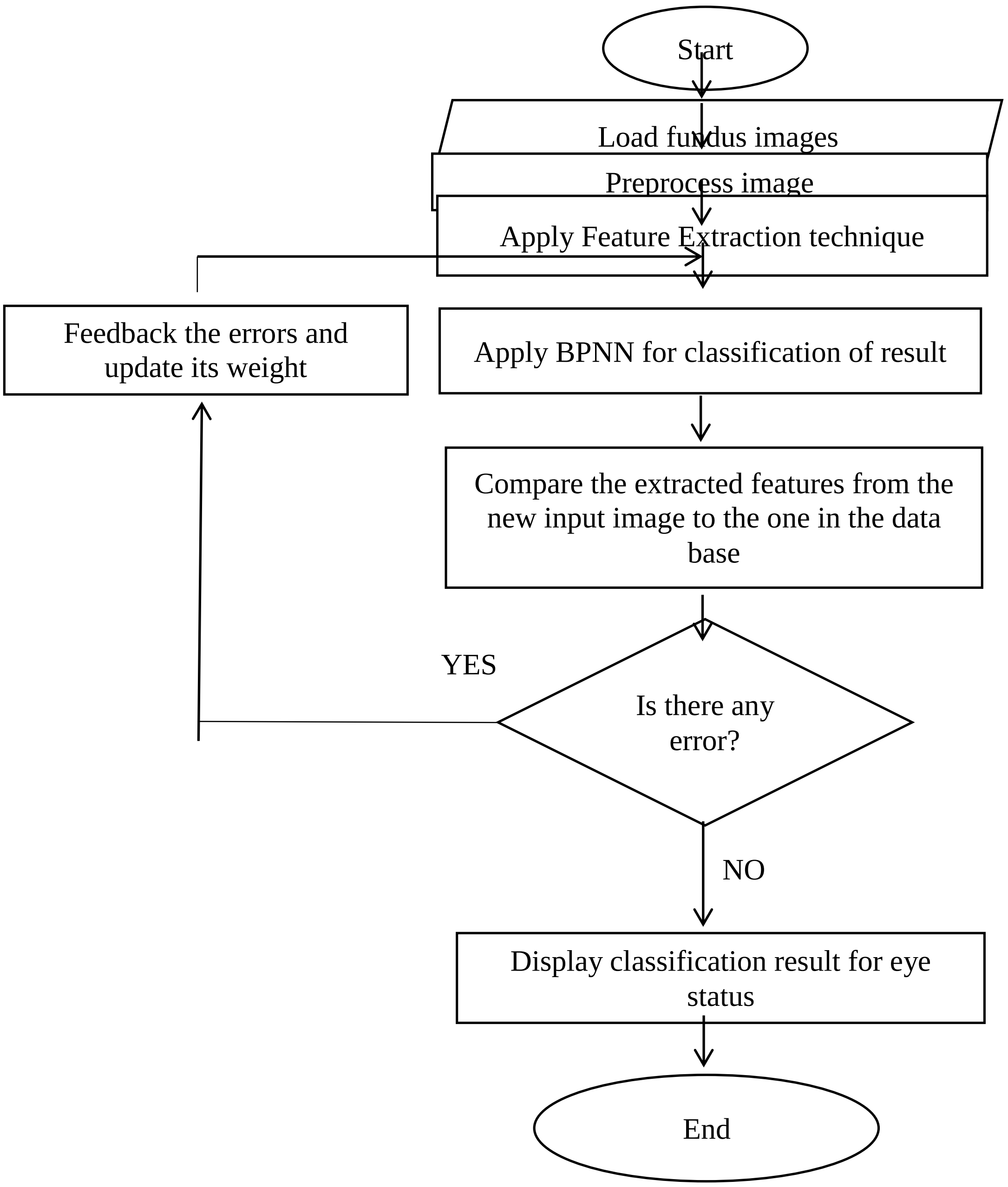


Figure 4: Process flow of the glaucoma diagnostic system

3. RESULTS AND DISCUSSION

The network was trained with a data split of 70% utilized for training, 15% utilized for testing, then the rest 15% utilized for validation of the data sets, so as to prevent overfitting of the neural network. The four different features extracted from the fundus images were fed into the back propagation neural network as the input, with an output layer of 2 neurons while the hidden layer was set by trial and error. It was found that the network performed best utilizing two hidden layers each with three hidden neurons. The training data sets had 1050 images consisting of 525 images from glaucoma and healthy fundus images, which was randomly selected from a total of 1500 images. The test set had 224 images with 112 images from each class; these images were different from the images used in the training sets. Finally, diagnosing glaucoma eye disease was evaluated utilizing the remaining 112 images from the data collected; these evaluations was done utilizing the standard evaluation metrics of accuracy. Figures 5 and 6 illustrate the result while testing the developed glaucoma diagnostic system as it has been able to effectively minimize the stress of diagnosing multiple fundus images with an average accuracy of 97% achieved.

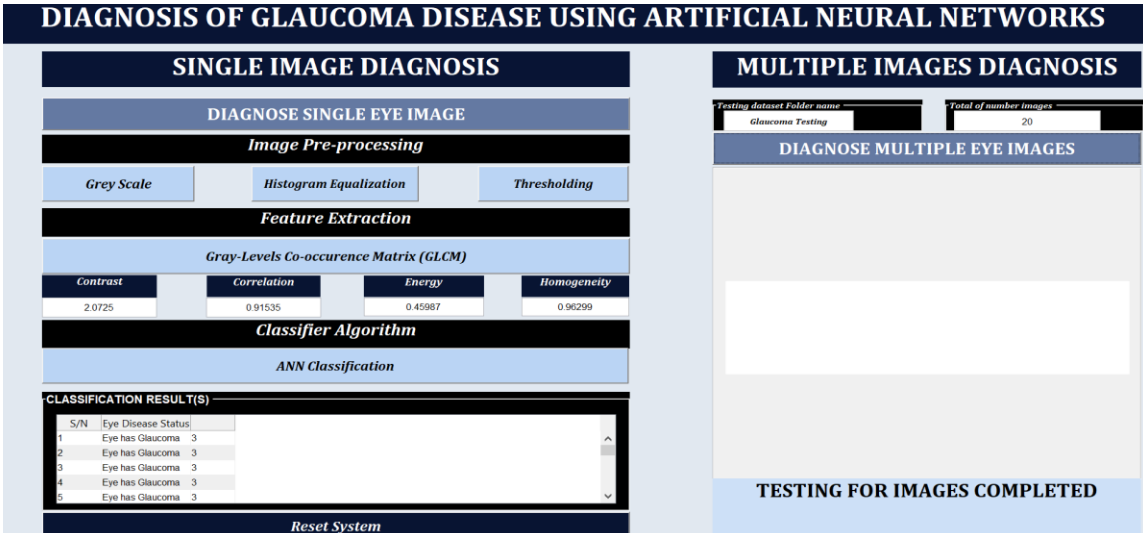


Figure 5: Result from diagnosing multiple glaucoma eye fundus image

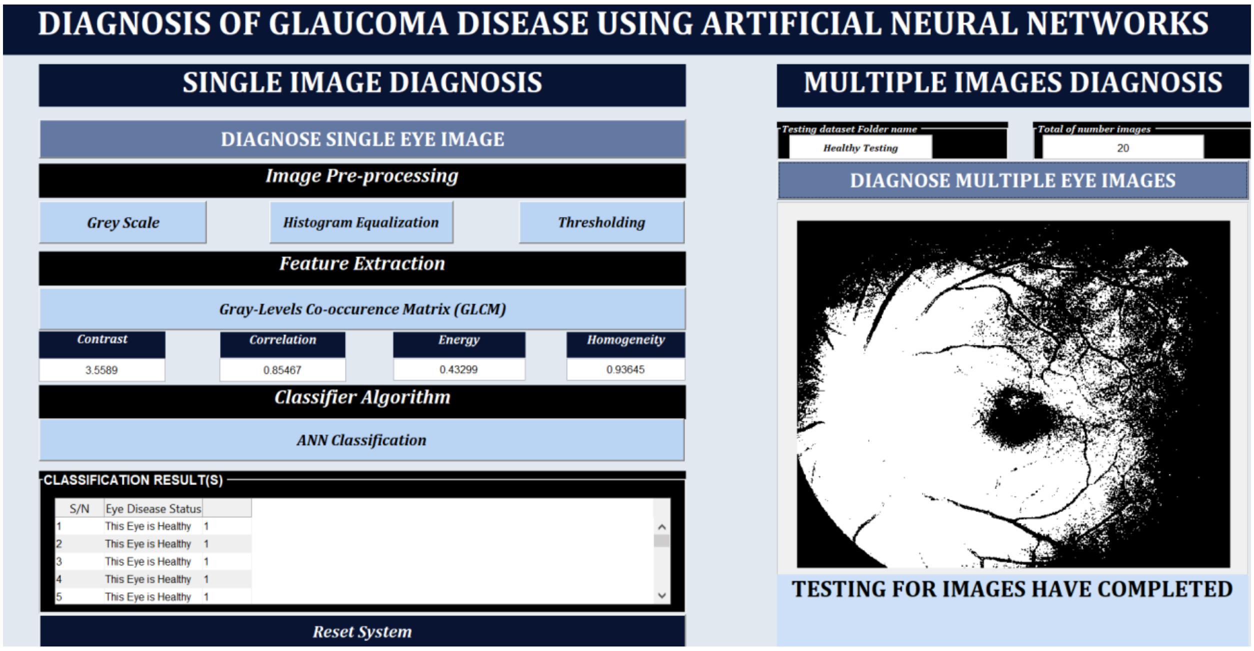


Figure 6: Result from diagnosing multiple healthy eye fundus image

3.1 Validation

The validation of the created glaucoma diagnosis system was assessed in view of the exactness of the arrangement, sensitivity i.e. (true positive rate), and specificity (True negative rate) to prevent overfitting of data. Confusion matrix is used to measure the accuracy. It contains True positive (TP), True Negative (TN), False positive (FP) and False negative (FN). Based on the way the machine learning algorithm works, the acquired data sets were split into three; train, test and validation where 70% of the data were used for training, and 15% for testing then the rest 15% were used for validation. The validation data was used in validating the glaucoma diagnosis system after training and testing. Validation was necessary to know how well the glaucoma diagnosis system would perform in situation where the data has not been seen before. However, the true positive (TP) contains the number of data that are correctly seen to be positive while the false positive (FP) contains the number of data which are seen to be negative but predicted as positive and the true negative (TN) is the number of data that are identified as negative and were predicted negative. Finally, the false negative (FN) is the number of data that are positive but predicted as negative. Thus, Sensitivity, specificity and accuracy are calculated using the formula below.

$$\text{Sensitivity (True positive rate)} = \frac{TP}{TP+FN} \quad (10)$$

$$\text{Specify (True negative rate)} = \frac{TN}{TN+FP} \quad (11)$$

$$\text{FPR} = 1\text{- Specificity} = \frac{FP}{TN+FP} \quad (12)$$

$$\text{Overall accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

Where; TP= True positive, TN= True negative, FP= False positive, FN= False negative

Metric	Healthy Class	Glaucoma class	Overall
True positive	112	109	221

False positive	0	3	3
True Negative	112	109	221
False negative	0	3	3
Sensitivity	100%	97%	98.5%
Specificity	100%	97%	98.5%
Accuracy	100%	97%	98.5%

Table 2: Performance evaluation results

4. Conclusion

This paper has presented a glaucoma diagnosis system using artificial neural network. The system was designed to detect if a human eye is glaucomatous or healthy using a back propagation neural network classifier algorithm in performing the training function. The system introduced speed to the diagnosis process of glaucoma eye disease by making it possible to analyze numerous fundus images within a short period of time. This system has been able to effectively minimize the stress of diagnosing multiple fundus images with an average accuracy of 97% achieved. Adoption of this system is believed will improve access to quick medical glaucoma treatment especially in developing environment where experts are few and often overwhelmed by workload of patience. Future works direction is suggested to be towards developing eye diagnostic system for other disease.

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