Volume 1, Issue 1 (16-25)

JOURNAL OF INNOVATION SCIENCE AND TECHNOLOGY

A NEURAL NETWORK-BASED INTELLIGENT SYSTEM FOR DIAGNOSIS OF SELECTED EYE DISEASES

Received: June 2019, Revised: October, 2019, Accepted: November,2019, Published online: October 2020

[1]Adeyanju, I.A., [2]Fagbola, T.M., [3]Bashir, S.A., and 1Fanijo, S.

[1]Department of Computer Engineering, Federal University, Oye-Ekiti, Nigeria
[2]Department of Computer Science, Federal University, Oye-Ekiti, Nigeria
[3]Department of Computer Science, Federal University of Technology, Minna, Nigeria

Corresponding author: ibrahim.adeyanju@fuoye.edu.ng

Abstract

The human eye is a vital organ of vision useful for most daily activities. However, there are many diseases, including cataracts, glaucoma, diabetic retinopathy, age-related macular degeneration, and retinoblastoma, which affect the human eye and can lead to blindness when not diagnosed early for treatment. The advent of digital health techniques has led to the provision of fast, cost-effective, accurate and automated diagnosis of common human diseases. This paper discusses the development of an intelligent system for the diagnosis of glaucoma and diabetic retinopathy eye diseases. The diagnosis is done using digital image processing techniques to analyse fundus eye images of suspected patients and Artificial Neural Network to classify the images as infected or not. The system prototype was implemented as a stand-alone application using MATLAB software and experiments conducted on three publicly available fundus image databases. An average accuracy of 95% was obtained with a neural network that classifies an input eye image as healthy, glaucoma or diabetic retinopathy infected. We intend to predict the stage of eye infection and investigate the use of non-fundus images for diagnosis in our future work.

Keywords: ANN, eye diseases, glaucoma, diabetic retinopathy, expert system, e-health

1.0 Introduction

The human eye is a vital organ of vision, which gives us the sense of sight and is of utmost importance in all day to day activities. However, many diseases affect the human eye and can lead to blindness. The major causes of blindness include cataract, glaucoma, diabetic retinopathy and other corneal and retinal infections (Oliveira, 2014). According to a report by the World Health Organization (2015), it is estimated that there are more than 285 million blind people worldwide. One of the five priorities of the World Health Organization is to tackle blindness, especially in children and the role of digital health in actualizing this priority cannot be overemphasized.

Medical professionals spend valuable time and energy to continually peruse and inspect a large number of fundus eye images during the diagnosis of eye diseases. However, such a per with a recommendation for future work.

method of eye disease detection and assessment is expensive and potentially subjective at the early stage based on the experience of the medical personnel. Therefore, it could be more cost-effective and beneficial if the initial task of analysing retinal (fundus) images is automated . Such a system would act as an early detection and warning system, where a person can get diagnosed to prevent extreme conditions or blindness. It can also assist an ophthalmologist to analyse numerous images within a short period and spend more time on those patients whose cases require further investigation .

There are several techniques in digital health that can be used for early detection of eye diseases by analysing fundus images. These techniques include the K-Nearest Neighbour algorithm (KNN) (Omidiora et al., 2013), Support Vector Machine (SVM) (Adeyanju et al., 2015), and Artificial Neural Networks (ANN) (Karegowda et al., 2010). KNN is robust especially while

dealing with noisy data and also effective if the training data is large; however, its major bottleneck is the task of determining the value of the parameter k (Alamelu et al., 2013). The merits of SVM includes the regularization parameter, which makes the user think about avoiding over-fitting as well as the kernel trick, which helps build in expert knowledge about a problem via engineering of the kernel. However, the major drawback in SVM is that the theory only really covers the determination of the parameters for a given value of the regularization, kernel parameters and choice of the kernel (Alamelu et al., 2013). Artificial Neural Network has the advantage of accuracy in problem-solving, adaptive nature of learning, fault tolerance and real-time operational mode quality over others (Karegowda et al., 2010). This paper presents an intelligent digital health system to diagnose glaucoma and diabetic retinopathy eye diseases using Artificial Neural Network.

Section 2 gives a brief theoretical background and critique of related literature while Section 3 explains the methodology employed in developing the system in terms of design and implementation. The experimental setup is presented in Section 4 together with a discussion of the results from the experimentation. Section 5 concludes the paper with a recommendation for future work.

2. Related Work

Several computing techniques have been proposed for the detection of eye abnormalities and retinal diseases. Usher et al., (2003) described the development of an automated system to detect abnormalities such as microneurysm, haemorrhages, and exudates in colour retinal images. They used image processing to standardize colour and contrast enhancement, segmentation to reveal lesions followed by classification of lesions using neural network. Although a sensitivity of 100% and a mean number of 0.1 false positives per image were obtained, the resulting algorithm was tested using only ten eye images.

Enhancement techniques were performed on retinal fundus images to highlight the features for the detection of abnormal eyes (Noronha et al., 2006). The work determined the optic disk and its centre, the brightest part of each fundus image was located with Hough transform. A sensitivity of 92.8% and a positive predictive value of 92.4% in a small dataset of 30 retinal images were obtained during their experimental evaluation.

Nyul, (2009) devised a novel automated glaucoma classification technique, depending on image features from fundus photographs without the need for any manual assistance. Size differences, non-uniform illumination, and blood vessels were eliminated from the images followed by the extraction of high dimensional feature vectors. Compression was then carried out using principal component analysis and classification with support vector machine (SVM). The glaucoma risk index produced by the developed system with a 2-stage SVM classification scheme achieved an 86% success rate. This was comparable to the performance of medical experts in detecting glaucomatous eyes from such images.

A motion pattern-based image features were proposed for glaucoma detection from retinal images (Deepak et al., 2012). This was done by transforming the region of interest to a generalized moment pattern to ensure that the spatial extent of intensities corresponding to signal of interest within an image is accentuated; whereas other background intensities are remaining unchanged. Their method gave a success rate of 91% and able to distinguish between normal and glaucoma cases even when the decision on glaucoma was only at a suspect level.

The effect of image resolution on the automatic classification of diabetic retinopathy and storage memory was investigated (Abdullahi, et al., 2015). The fundus images were first pre-processed with resolutions of the original images reduced by 50%, 75%, 87.5%, and 93.75%. For each reduced resolution, four GLCM features were extracted and subsequently fed to a feed-forward backpropagation neural network. Evaluation results indicated no significant changes in accuracy and specificity values. However, the memory occupied by the images reduces significantly for every reduction in resolution. Also, there is a drop in the average classification performance for every reduction in resolution used.

An efficient diagnostic system for screening glaucoma disorder in the human eye using retinal images (Prakash & Selvathi, 2017). The optic disc (OD) and optic cup (OC) were segmented from retinal images and the

neuroretinal rim region was detected. Features such as effective local binary pattern (ELBP), gray level co-occurrence matrix (GLCM) and optic band features were then extracted from the neuroretinal rim region. These features were trained and classified using the Support Vector Machine (SVM) classifier. Experimental results gave 70.25% sensitivity, 99.71% specificity, and 99.30% accuracy. However, only 15 images were used in this work for both training and testing.

3. Methodology

The design of our eye disease diagnostic system consists of data acquisition, image pre-processing, feature extraction, neural network training, and classification modules. Two eye diseases were considered for diagnosis namely glaucoma and diabetic retinopathy.

3.1 Data Acquisition

Fundus retinal images of normal healthy eyes and infected eyes for glaucoma and diabetic retinopathy were acquired from five publicly available databases: Hossein Rabbani Eye Fundus Database (Hajeb et al., 2012), SPIE Eye Fundus Database (Mahmudi et al., 2014), ONH Standard Database (Abdullah, 2016), Jan Odstrcilik Eye Fundus Database (Budai, 2013) and ORIGA-light Eye Fundus Database .

Hossein Rabbani Eye Fundus Database: These fundus eye images (Hajeb et al., 2012) are provided by the Department of Bio-electrics & Biomedical Engineering, School of Advanced Technologies in Medicine, Isfahan University of Medical Sciences, Iran. The database consists of 35 diabetic fundus eye images, collected from 35 patients. The images were captured in digital form using a Canon CR5 non-mydriatic 3CCD camera at 45-degrees field of view. The images are of size 720 by 576 pixels, 8 bits per colour channel and have a field of view (FOV) of approximately 540 pixels in diameter. A sample of the images acquired is shown in Fig. 1.

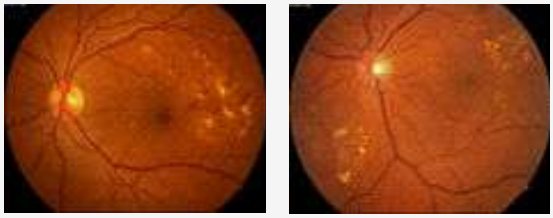


Fig 1: Sample diabetic fundus images from Hossein Rabbani eye fundus database

SPIE Eye Fundus Database: These fundus eye images are provided by SPIE (Mahmudi et al., 2014), a digital library for biomedical applications in molecular, structural, and functional imaging, San Diego, California, USA. The data set contains coloured fundus data of the left and right eyes of 50 healthy persons each with a resolution of 720 by 576. A sample of the images acquired is shown in Fig. 2.

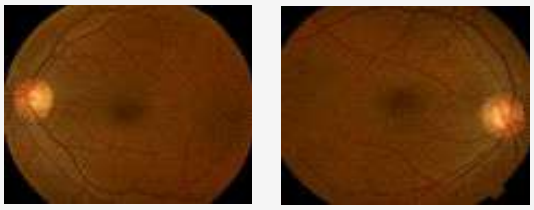
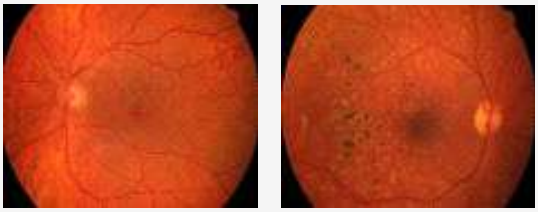


Fig 2: Sample healthy fundus images acquired from SPIE database

Jan Odstrcilik Eye Fundus Database: This public database, also known as the High-Resolution Fundus, HRF (Budai et al., 2013) is provided by the Pattern Recognition Lab (CS5), Department of Ophthalmology, Friedrich-Alexander University Erlangen-Nuremberg. It contains 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 30 images of glaucomatous patients. The images were captured using a Canon CR-1 fundus camera with a field of view of 45° and different acquisition settings. All images share approximately the same field of view, whereas small shifts were caused by eye movements between the acquisitions. The dataset was captured by Jan Odstrcilik. A sample of the images acquired is shown in Fig. 3.



(a) Diabetic (b) Glaucomatous

ORIGA-light Eye Fundus Database: The ORIGA-light eye fundus database , aims to share clinical ground truth retinal images with the public by providing open access for researchers to benchmark their algorithms. The database contains 650 retinal images annotated by trained professionals from the Singapore Eye Research Institute, which was acquired using a Canon CR-

Dgi fundus camera. The data set consists of 168 images from glaucomatous eyes and 482 images from randomly selected normal healthy eyes. A sample of the ORIGA-light fundus images acquired is shown in Fig. 4.

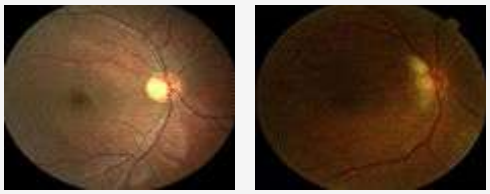


Fig. 4: Sample glaucomatous fundus images from ORIGA-light database

ONH Standard Database: This Fundus database is provided by the Department of Ophthalmology, Shifa International Hospital Islamabad, Pakistan (Abdullah et al., 2016). Named after Optic Nerve Head (ONH) Segmentation, the database consists of 100 fundus images of 760 x 570 resolutions. Images were captured from canon CR6 45MNf camera with 45° of FOV. Images were acquired from 50 patients for both left and right eyes, 28 out of which are diabetic. A sample of these images is shown in Fig 5.

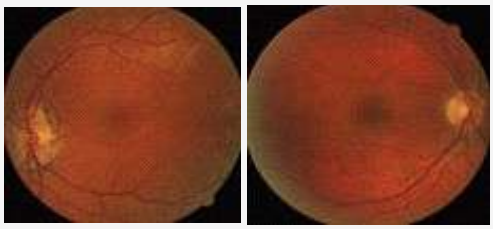


Fig. 5: Sample diabetic fundus images from ONH database

3.2 Image Pre-processing

Differences in luminosity, contrast, and brightness make it more complex to extract retinal features and make a distinction of the region of interests from other features in eye fundus images (Karegowda et al., 2010). Therefore, after an original fundus image is supplied into the diagnostic system, the first action required is to pre-process such an image. Pre-processing is used to improve contrast, reduce noise, eliminate irregular illumination and bring out more details from the input image. The image pre-processing techniques for our diagnostic system are grayscale conversion, histogram equalization, and thresholding.

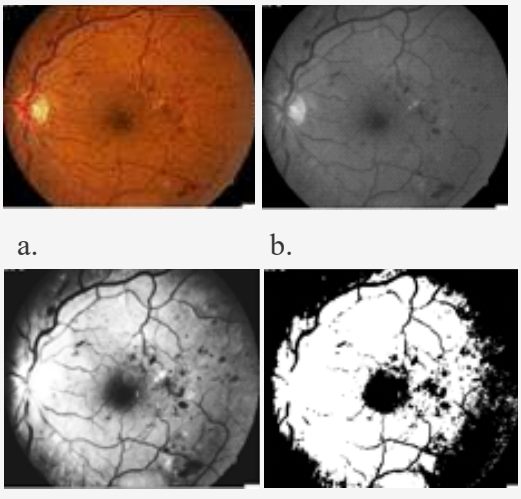
Grayscale Conversion: The coloured fundus images are converted into grayscale which is two dimensional, to make the image suitable for processing. The MATLAB im2gray() function was used in this work. Fig. 6(b) shows a sample fundus image from our dataset after grayscale conversion.

Histogram Equalization: To achieve uniform illumination, histogram equalization is used so that the dark area in the input image becomes brighter in the output image. The histeq() MATLAB function is used to achieve this. Fig. 6(c) shows a sample histogram equalized eye fundus image from our dataset.

Thresholding: Thresholding enables separation of the regions of interest away from the image background. This can be achieved using binarization on the basis that dissimilar intensities or colours occur in the foreground and background regions of an image. The local thresholding technique used is shown in equation (1)

$$\text{if } e(i,j) > T, bi,j = 255; \text{else } bi,j = 0 \qquad (1)$$

where e (i, j) is the histogram equalized fundus image, T the is average pixel intensity for the equalized image and bi, j is the binarized image. Fig. 6(d) shows a sample fundus image after thresholding.



a. b.

c. d.

Fig. 6: Different Stages of Eye image preprocessing

(a) Original fundus image, (b) Grayscale fundus image, (c) Equalized fundus image, (d) Thresholded fundus image

3.3 Feature Extraction with Gray Level Co-Occurrence Matrix (GLCM)

Feature extraction is the computation of characteristics of digital images in terms of their numerical value (Abdullahi et al., 2015). In our context, it involves the identification of the most

relevant characteristics from a fundus image for diagnosis of eye diseases. In this work, four textural features based on the gray level co-occurrence matrix (GLCM) are extracted from each image. Co-occurrence matrices are calculated for four directions: 0º, 45º, 90º and 135º degrees. The four features to be extracted using GLCM are contrast, correlation, energy, and homogeneity. Other features such as angular second moment, entropy, inverse difference moment, cluster shade, and cluster prominence were not considered as previous work from other researchers on diabetes retinopathy showed these four GLCM features as the best predictive feature for fundus images (Abdullahi et al., 2015)

Contrast: This feature returns a measure of the intensity contrast between a pixel and its neighbour over the whole image; the formula is shown in equation (2)

.

$$contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j) \right\}, |i-j| = n \qquad (2)$$

Where G is the number of gray levels in the image, P(i,j is a pixel point, and, i and j indicate the pixel row and column.

Correlation: This feature returns a measure of how correlated a pixel is to its neighbour over the whole image as shown in equation (3).

$$Correlation = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \qquad (3)$$

Where μi and μj are row and column wise means while σi and σj are row and column-wise standard deviations.

Energy: This is the property that returns the sum of squared elements for an input image, in the GLCM.

$$Energy = \sum_{i,j} p(i,j)^2 \qquad (4)$$

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

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \qquad (5)$$

3.4 Classification of Eye Images with Back Propagation Neural Network (BPNN)

The four GLCM features extracted from each of the acquired fundus images were fed into a Back Propagation Neural Network (BPNN) classifier. The neural network was used to classify a fundus eye image into normal (healthy) or abnormal (glaucoma and diabetic retinopathy).

The training of the back-propagation network involves the three stages: feedforward of the input training pattern with computation of neuron weights, and backpropagation of the associated error and weights adjustment. After the network has been trained, its application/testing involves only the feedforward phase. During feedforward, each input neuron receives an input signal and broadcasts it to the hidden neurons, which in turn compute the activation and passes it on by computing the activation to obtain the net output. The logarithmic sigmoid (logsig() in MATLAB) is used as activation function at the two hidden layers as well as the output layer. During training, the net output is compared with the target value. The difference between the expected output and net output is used in the computation of the error factors which are used to distribute the error back to the hidden layers and update weights updated accordingly. Fig. 7 shows the configuration of our neural network on MATLAB. The neural network has four inputs with two hidden layers each with three neurons in each layer as well as three neurons in the output unit.

3.5 Implementation

The eye-disease diagnostic system was implemented as a software application. A graphical user interface (GUI), as shown in Fig. 8, was designed for the system with MATLAB and integrated to act as standalone application software. It has facilities for loading fundus images, pre-processing, feature extraction and ANN classification. It can test one image or all test images in a folder. It also has a panel for ANN training parameters i.e. hidden layers and neurons.

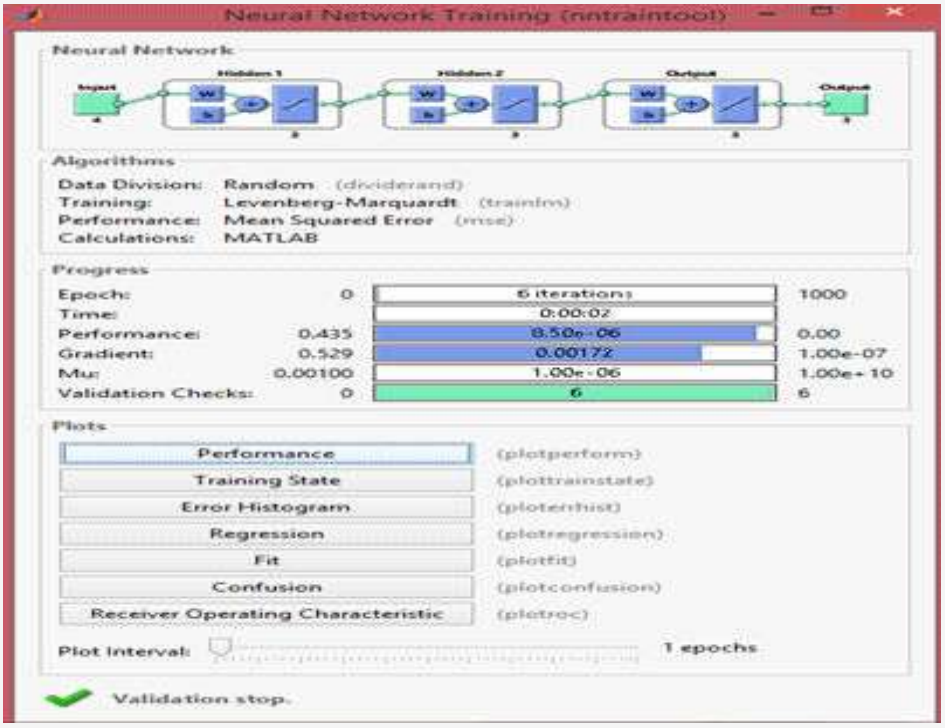


Fig. 7: Neural Network Configuration

4. EXPERIMENTAL EVALUATION

The fundus database used during experimentation had 135 fundus eye images; 45 images each for healthy, diabetic retinopathy and glaucoma classes. These fundus images were acquired and selected from five (5) publicly available fundus databases online: Hossein Rabbani Eye Fundus Database (15 diabetic), SPIE Eye Fundus Database (45 healthy), ONH database (22 diabetic), Jan Odstrcilik Eye Fundus Database (8 diabetic and 30 glaucomatous), and ORIGA-light Eye Fundus Database (15 Glaucomatic). The selection was done across the different databases to ensure that any trained neural network is well generalized and able to predict whether any eye image is infected with diabetic retinopathy, glaucoma or health. Also, an equal number of images were selected across all three classes to reduce the possibility of any class being overfitted during the training of the neural network. All images were pre-processed to remove unwanted noise, solve the problem of uneven illumination, prevent their salient features, remove any form of background interference and preserve the most needed region of interest in the image for the sake of feature extraction.

4.1 Determination of Neural Network Parameters

An empirical evaluation was done on the backpropagation neural network (BPNN) classifier, based to determine the optimal parameters (number of hidden layers and threshold value) for the configuration of the neural network (NN). The entire 135 images were used in the training set and also in the test set for these empirical experiments to determine the best NN parameters to use.

4.1.1 Determination of Optimal Number of Hidden Layers and Neurons

The NN was trained using four different configurations of hidden layers with a slightly varying number of neurons as shown in Table 1 while the output threshold value was kept constant at 0.9 which is the default for Neural Networks in MATLAB. This means that an output value of less than 0.9 will be treated as 0. The implication for our three-class problem is that 0-0.89 will be predicted as 0 (healthy), 0.9-1.89 will be predicted as 1(Diabetic Retinopathy) and any value above 1.9 will be predicted as 2 (Glaucoma). The results, as shown in Table 1, clearly indicates that the neural network was best when trained using two hidden layers each with three hidden neurons (3-3) with an accuracy of 87.8% compared to 50.4%, 51.1% and 50.4% for the configurations

with three hidden layers each with three hidden neurons (3-3-3), three hidden layers each with five hidden neurons (5-5-5) and two hidden layers each with five hidden neurons (5-5).
Table 1: Accuracy results from Empirical evaluation of different hidden layer configurations

No of hidden layers & neurons	Classifier accuracy (%)
3-3-3	50.4
3-3	***87.8***
5-5-5	51.1
5-5	50.4

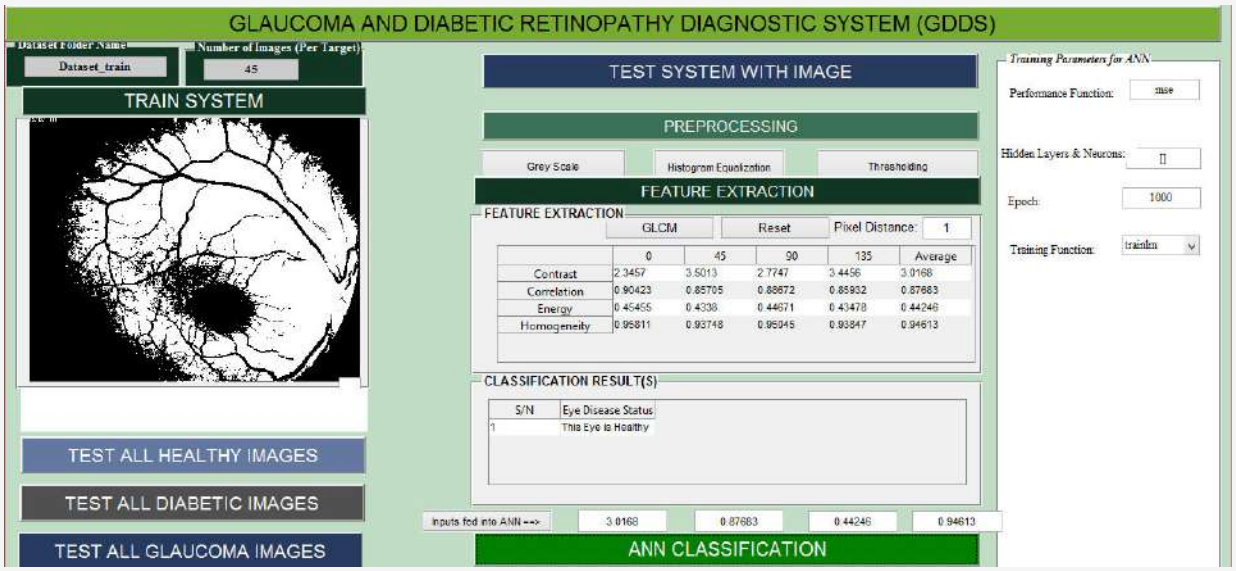


Fig 8: GUI screenshot for Eye diseases diagnostic system

4.1.2 Determination of Optimal Output Threshold
We also carried out empirical experiments to determine the best output threshold values that will give the best performance accuracy for the neural network. Table 2 shows the performance accuracy results using varying threshold values of 0.9, 0.8, 0.7, 0.6, 0.5, 0.4 and 0.3. The neural network used the optimal two hidden layers each with three neurons (3-3) as determined from previous experiments. The best accuracy result was obtained for a threshold value of 0.6. This accuracy outperformed other threshold values experimented with as shown in Table 2.

Threshold Value	Classifier accur (%)
0.9	87.8
0.8	51.9
0.7	51.9
0.6	***93.3***
0.5	86.7
0.4	86.7
0.3	50.4

4.2 Classification of Eye Diseases with Back Propagation Neural Network

Based on the results from empirical evaluation as discussed in Section 4.1, a backpropagation neural network was implemented with two hidden layers each with three neurons (3-3) and an output threshold value of 0.6. The training data dataset had 135 eye images consisting of 45 images from each class of healthy, diabetic retinopathy and glaucoma-infected, randomly selected as discussed in Section 4. The test set had 60 images with 20 images from each class; these images were exclusive from the ones used in the training set. All the 20 tested eye fundus images known to be in the healthy class were from the SPIE database. For diabetic retinopathy testing, 4, 12 and 4 images were selected from the Hossein Rabbani database, ONH database, and Jan Odstrcilik database respectively. Lastly, glaucoma diagnosis was evaluated using 5 images from the Jan Odstrcilik database and 15 images from the ORIGA-light database.

The performance of our eye disease diagnostics system was evaluated using the standard evaluation metric of accuracy. Table 3 shows the accuracy results across each diagnosed eye disease class along with the healthy class. The bar chart in Figure 10 also gives accurate results as a graph. The average accuracy obtained based on our evaluation is 95% where 57 of the 60 images tested were correctly classified. The healthy class had 100% accuracy with all the 20 tested images correctly classified while the diabetic retinopathy and glaucoma classes had 90% (18/20) and 95% (19/20) respectively.

Table 3: Results for each class of diagnosed eye disease

Class	Test Set	Correct response	Accuracy (%)
Healthy	20	20	100
Diabetic Retinopath	20	18	90
Glaucoma	20	19	95
Aggregate (Totabr Average)	**60** (Total)	**57**(Total)	**95** (Average

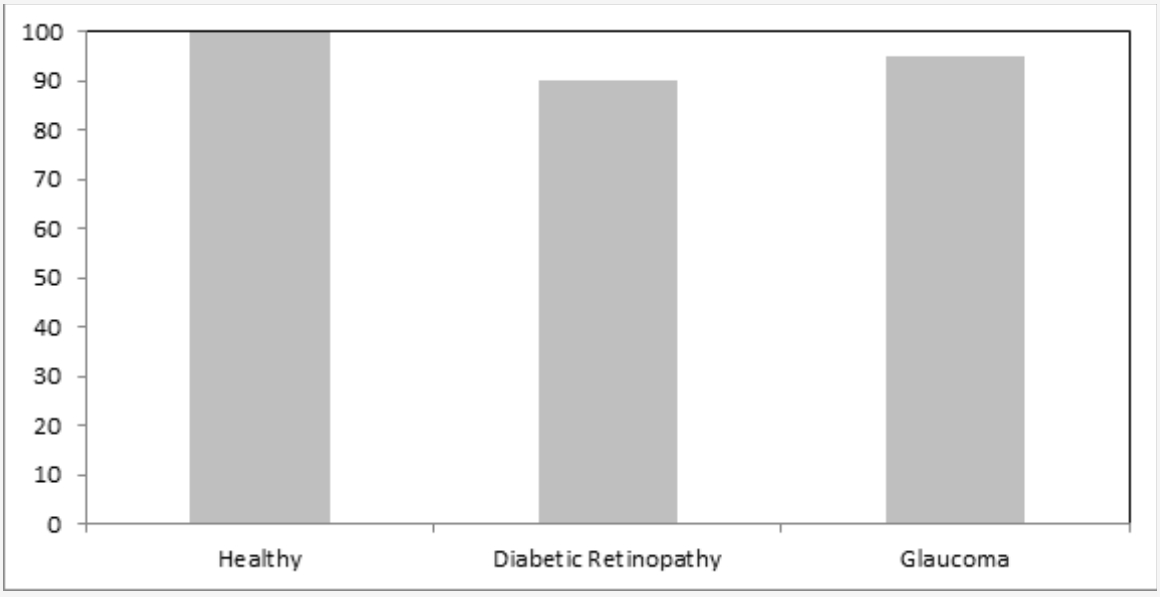


Figure 9: Accuracy results across the diagnosed eye diseases

Further investigation on the two misclassified test images for the diabetic retinopathy class indicated that they were both from the Jan Odstrcilik database. This database had just 8 images in the training set and 4 images in the test set. Hence, we reckon that the small number of images from the Jan Odstrcilik database used in the training of the neural network might have adversely affected the performance of the system on the test images from this database. A similar trend was noted for the single misclassified glaucoma test image which came from the ORIGA-light database. The selected glaucoma training set had 30 images from the Jan Odstrcilik database and 15 images from the ORIGA-light database. Hence, the misclassified test image was from the database with a smaller number of training instances. This trend is intuitive and correlates well with the fact in machine learning and data mining that the more the training data, the better the classifier.

5. Conclusion

This paper discussed the development of an intelligent diagnostics system for glaucoma and diabetic retinopathy using a neural network with very good evaluation accuracy of 95%. This diagnostic system can be of significant benefit for mass diagnosis in rural areas, especially where the patient-to-ophthalmologist ratio is very high. We intend to extend this work by implementing it as an embedded system with the capability to capture fundus or ocular images directly to allow better flexibility. We also want to develop similar diagnostic tools for other retinal diseases.

References

Abdullah, M., Moazam, M. F., & Barman, S. A. (2016). Localization and segmentation of optic disc in retinal images using circular Hough transform and grow-cut algorithm. National Institutes of Health. doi:10.7717/peerj.2003

Abdullahi, I. M., Arulogun, O. T., Adeyanju, I. A., & Nuhu, B. K. (2015). The Effect of Image Resolution on The Performance Of Automatic Classification Of Diabetic Retinopathy And Storage Memory. IMPACT: International Journal of Research in Engineering & Technology, 3(3), 29-36.

Adeyanju, I. A., Omidiora, E. O., & Oyedokun, O. F. (2015). Performance Evaluation of Different Support Vector Machine Kernels for Face Emotion Recognition. SAI Intelligent Systems Conference (pp. 804-806). London: SAI Intelligent Systems.

Alamelu, J. M., Satej, W., & Kumar, V. S. (2013). An Improved k Nearest Neighbor Classifier Using Interestingness Measures for Medical Image Mining. International Journal of Medical Health Biomedical Bioengineering and Pharmaceutical Engineering, Vol 7, Issue 7, 36-40.

Budai, A., Bock, R., Hornegger, J., & Michelson, G. (2013). Robust Vessel Segmentation in Fundus Images. International Journal of Biomedical Imaging.

Deepak, K. S., Jain, M., Joshi, G. D., & Sivaswamy, J. (2012). Motion pattern-based image features for glaucoma detection from retinal images. In Proceedings of the Eighth Indian Conference on Computer Vision, Graphics and Image Processing. Mumbai, India: ACM.

Hajeb, S., Rabbani, H., & Akhlaghi, M. (2012). Diabetic Retinopathy Grading by Digital Curvelet Transform. Computational and Mathematical Methods in Medicine, 1607-1614.
Karegowda, A. G., Bharathi, P., Jayaram, M., & Manjunath, A. (2010). Automatic Detection of Exudates in Diabetic Retinopathy using Traditional & Machine Learning Techniques: An Overview". In International Conference on Computing (pp. 27-38). New Delhi.

Mahmudi, T., Kafieh, R., & Rabbani, H. (2014). Comparison of macular OCTs in right and left eyes of normal people. In Biomedical Applications in Molecular, Structural, and Functional Imaging. San Diego, California, United States: SPIE. doi:10.1117/12.2044046

Manoujitha, K., & Goonetileke, O. (2014). e-Opthalmologist Intelligent Eye Disease Diagnosis System. Fifth International Conference on Intelligent Systems, Modelling and Simulation. Langkawi: Conference Publishing Services CPS.

Noronha, K., Jagadish, N., & Bhat, S. (2006). Enhancement of retinal fundus Image to highlight the features for detection of abnormal eyes. Hong Kong: IEEE.

Nyul, G. L. (2009). Retinal image analysis for automated glaucoma risk evaluation. In Proceedings of Sixth International Symposium on Multispectral Image Processing and Pattern Recognition. Yichang, China: SPIE.

Oliveira, A. (2014). Design of a Mobile Application for Eye Signs Screening. Porto: Instituto Superior de Engenharia do Porto.

Omidiora, E., Adeyanju, I., & Fenwa, O. (2013). Comparison of Machine Learning Clasifiers and Recognition of Online and Offline Handwritten Digits. Computer Engineering and Intelligent Systems, 4(13), 39-47.

Prakash, N., & Selvathi, D. (2017). Segmentation of retinal blood vessels in colour fundus images using ANFIS classifier. International Journal of Biomedical Engineering , 24(4), 338-355.

Usher, D., Dumskyj, M., Himaga, M., Williamson, T., Nussey, S., & Boyce, J. (2003). Automated detection of diabetic retinopathy in digital retinal images: a tool for diabetic retinopathy screening. Diabetes UK. Diabetic Medicine, 21, 84-90.

World Health Organization. (2015). Chronic diseases Report. Retrieved June 27, 2017, from Chronic diseases Report: www.who.int/chp/chronic_disease_report

Zhang, Z. (2010). "ORIGA-light : An Online Retinal Fundus Image Database for Glaucoma Analysis and Research. Annual International Conference of the IEEE, 32.