

EFFECT OF FUNDUS IMAGE RESOLUTION ON THE PERFORMANCE OF ARTIFICIAL NEURAL NETWORK FOR DIABETIC RETINOPATHY CLASSIFICATION

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Abstract

Diabetic retinopathy (DR) is one of the major causes of blindness in the world which is caused by conditions associated with diabetes mellitus like hypertension and prolonged hyperglycemia. Early detection and mass screening are required to reduce the risk of vision loss. Feature extraction and classification techniques reduce the time spent on classification, reduce computational complexity and improve the accuracy of classification. In this paper, we investigated the performance of a feed forward back propagation artificial neural network (ANN) classifier for the classification of DR using five different fundus image resolutions by extracting second order gray level co-occurrence matrix (GLCM) based texture features.

The performance is evaluated in terms of sensitivity, specificity, accuracy and number of hidden neurones. Experiments are performed on a publicly available fundus image database (Messidor database). Experimental results show that the accuracy of the classifier for image resolutions of 64, 128 and 256 is 96.7% and for resolutions of 512 and 1024 is 93.3%. Also, results shows that the higher the resolution, the higher the number of hidden neurons used to train the classifier

Keywords: Diabetic retinopathy, Back propagation, Gray level co-occurrence matrix, Resolution.

1. Introduction

Fundus images (internal part of the eye) are often used for diagnosing various eye diseases including diabetic retinopathy (DR), glaucoma and cataract. The reason for the wide use of fundus images is because of their ease of use, reliability, non-invasiveness, better sensitivity and better abnormality detection [1]. The properties of the fundus image particularly its resolution plays an important role in differentiating an infected eye from a normal one.

The number of pixels in an image also known as the total number of pixels in the image representing the width and height of the image is known as 'image resolution' [11]. An image with 2048 pixels wide and 1536 pixels high (2048X1536) contains 3,145,728 pixels (or 3.1 Mega pixels) which is the image dimension. Units for measuring resolution are dots per inch (dpi) used for printers, sample per inch for scanners and pixel per inch (ppi) for monitors.

The higher the image resolution, the higher the quality of the image and therefore, higher memory space will be needed for storage [9]. Texture features extracted from a fundus image is proportional to the size of the

image, as the image size increases the statistical feature values increases, which affects the complexity and performance of classifiers. This work examines the effect of fundus image sizes (resolutions) on the performance of Artificial Neural Network (ANN) as a classifier with respect to diabetic retinopathy.

There are several works employing ANN in classifying fundus images of a particular resolution for DR diagnosis such as the one in [16] who developed a system for automatic detection of DR on digital fundus image using an image of 570×550 resolutions with 256 grey levels. The authors used ANN as a classifier to identify hard exudates which achieved a sensitivity of 88.5% and specificity of 99.7%. [13] on the other hand used an image of 1201×901 pixels with the same ANN, they achieved sensitivity and specificity of 95% and 98% respectively while [3], equally employed ANN with an image of 576×720 resolution achieving an improved accuracy of 2-3% and 5-8% lowering of the processing time when compared to the case when the entire image was used as a feature. There are several others but none of the works study the effects of different resolutions on the classifier they used, which is the basis for this research.

This paper is organized into six sections. Section one provides the general introduction, section two highlights the method used, in section three we present the results obtained after the practical, section four is the discussion on the results, conclusion is provided in section five and finally section six which is the reference section.

2.Methodology

Figure 1 is the block diagram used for classifying diabetic retinopathy (DR).

2.1 Data

A method to evaluate segmentation and indexing techniques in the field of retinal ophthalmology (MESSIDOR) database is used for the work. The database contains eye fundus colour numerical images of the posterior which were acquired by 3 ophthalmologic departments using a colour video 3CCD camera on a Topcon TRC NW6 non-mydratiac retinograph with a 45 degree field of view. The images were captured using 8 bits per colour plane at 1440×960 , 2240×1488 or 2304×1536 pixels. 800 images were acquired with pupil dilation (one drop of Tropicamide at 0.5%) and 400 without [10].

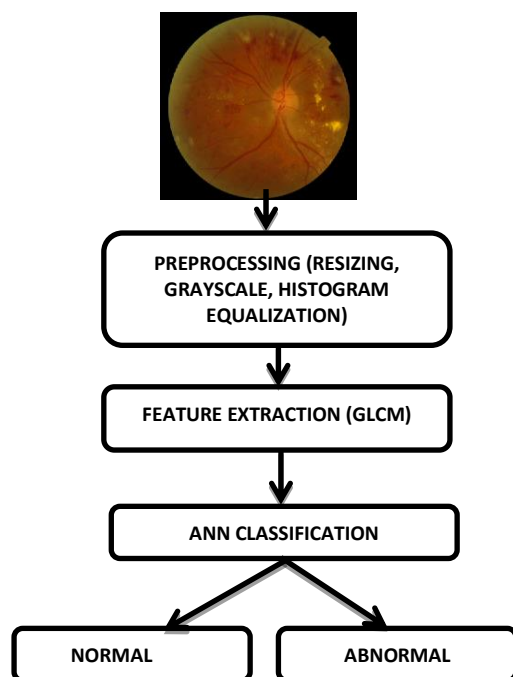


Figure 1: Block diagram to classify DR

2.2 Preprocessing

Medical images are usually not of good quality when acquired especially fundus images. The common problems that can be associated with them are uneven illumination, uneven contrast and noise [1].

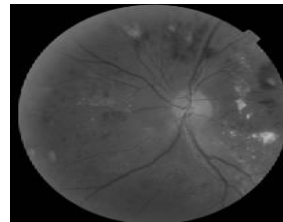
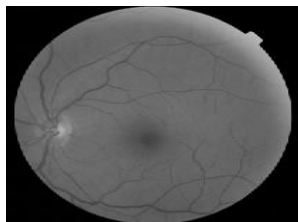
The fundus images were converted to gray scale, resized to five different dimensions which investigation will be carried on. The dimensions are 64*49, 128*98, 256*196, 512*393 and 1024*788 selected to maintain an aspect ratio (height/width) of 1.3. Then median filtering is performed to reduce noise enhancement that is likely to occur due to histogram equalization, contrast limited adaptive histogram equalization is then applied on the filtered images to improve their contrast and bring out more details from the images. Figure 2 shows the effect of preprocessing on the original image.

2.3 Feature Extraction

Feature extraction is a method of capturing visual content of images for image information retrieval and indexing. It is the operation that quantifies image quality through various parameters and functions applied to the original image [12].

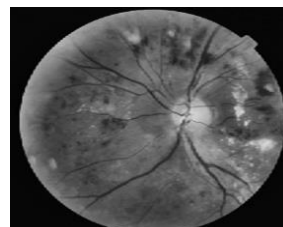


(a): normal coloured fundus image (b): DR coloured fundus image



(c): normal gray scale image

(d): DR gray scale image



(e): histogram equalized image

(f): histogram equalized DR image

Figure 2: Pre-processing effects on fundus images.

[8] defines feature extraction as the computation of the characteristics of a digital image in terms of its numerical value that will make the description of the texture properties possible. Image features can be spectral, geometric or pattern. Texture feature extraction is either first order or second order.

2.3.1 Glcm Feature Extraction

Textures are examined in second order feature extraction by comparing the partial relationship of pixels [18]. Gray Level Co-occurrence Matrix (GLCM)

assesses image properties associated to Second-Order statistics. [18] Shows that the number of gray level 'G' of an image is represented by the row and column of GLCM and the element used by the matrix is given as:

$$P(i, j | \Delta x, \Delta y) \text{ and } P(i, j | d, \theta) \quad 1$$

Where $p(i, j)$ represent the frequency of the matrix element separated by the distance $\Delta x, \Delta y$ and i, j at a distance d and angle θ represent the second order probability values for changes between gray levels. Figure 3 shows an example of GLCM.

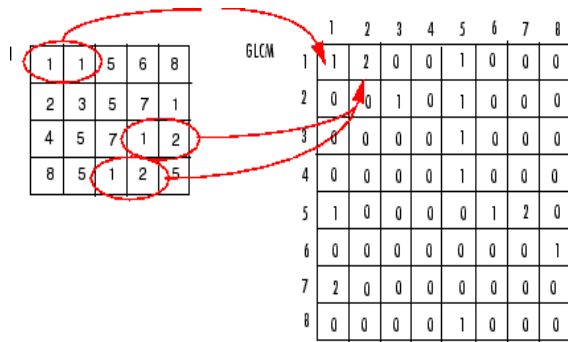


Figure 3: gray level co-occurrence matrix [14].

Several features can be extracted from GLCM which are used to train classifiers whose performance depends on the extracted features. Some second order features that can be extracted from GLCM as given by [18] are;

1. Angular second moment (ASM) or Homogeneity

The ASM is known as uniformity or energy. It measures the homogeneity of an image. When pixels are very similar, the ASM value will be large. It is given as:

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2 \quad 2$$

2. Entropy

Entropy shows the amount of information of the image that is needed for image compression. It measures the loss of information or the amount of energy permanently lost during reaction given as: $Entropy = -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i, j) * \log(p(i, j))$ 3

3. Contrast

It is a measure of intensity contrast between a pixel and its neighbor over the whole image. It is zero for constant image.

$$contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) \right\}, |i - j| \quad 4$$

4. Inverse difference moment

Inverse Difference Moment (IDM) is the local homogeneity which is high when local gray level is uniform and inverse GLCM is high.

$$IDM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1 + (i - j)^2} \quad 5$$

Other second order features that can be extracted from GLCM also known as Haralick features include variance, inverse difference moment, difference entropy, correlation, cluster shade etc.

GLCM feature extraction has been applied successfully for most diagnostic systems and performs better than principal component analysis (PCA) feature extraction technique [15]. Extracting second order features at higher gray levels makes the performance of classification better but at higher computation time [6].

Sixteen features were extracted from the fundus image after preprocessing from thirty (30) samples, 15 normal and 15 abnormal. The features include contrast, energy, homogeneity, entropy, variance, inverse difference moment, difference entropy, autocorrelation, correlation, difference variance, correlation paper, maximum probability, cluster prominence, information measure on correlation 1, information measure on correlation 2, and cluster shade. The algorithm for the GLCM features extraction as follows:

1. Start
2. Set GLCM gray levels and pixel-pair distance
3. Compute GLCM
4. Compute size of GLCM
5. Calculate GLCM sum
6. Calculate GLCM mean
7. Compute GLCM features
8. Stop

2.4 Classification

Classification in pattern recognition is a procedure for sorting pixels and assigning them to specific group or categories using classifiers. Pixels are characterized by features such as texture, gray value, colour and so on [5].

Artificial neural networks (ANN) are computation tools which constitute by highly interconnection of artificial neurones that mimic the behavior of the brain [2], used for modelling complex real-world problems. They are used to perform computations like pattern recognition, pattern matching, classification and forecasting. Mathematically, the function of k^{th} neuron in a neural network is given by [17] as:

$$U_k = \sum_{j=0}^m W_{kj} X_j \quad 6$$

with $X_0 = 1, b_k = W_{k0}$ and $y_k = f(b_k)$

ANN learns by changing its synaptic weight [4], Figure 4 shows interconnection of neurons respectively.

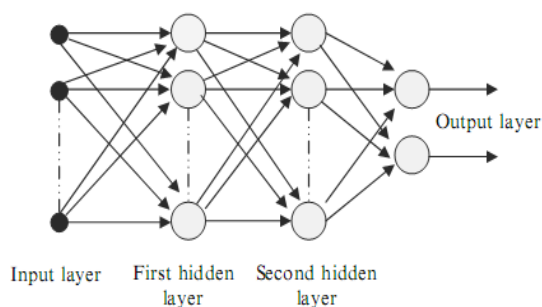


Figure 4: A simple 3-layer ANN [8]

A two layered feed forward back propagation neural network classifier with radial basis function was used for classification of the fundus image into normal or abnormal (proliferative diabetic retinopathy). Classification was performed for five different image resolutions and sixteen texture features. 30 images (15 normal and fifteen abnormal) was used for training, testing and validation in the ratio 70:20:10 respectively. For each resolution, the classifier was trained and the performance recorded.

3. Results

Performance of the classifier was measured in terms of sensitivity, specificity and accuracy. Accuracy measures the correctly classified normal and abnormal cases, sensitivity measures correctly classified normal cases while specificity measures correctly classified abnormal cases. MATLAB version R12a was used for the implementation of this work.

The effect each resolution (64*49, 128*98, 256*196, 512*393 and 1024*788) on the classification of DR into normal and abnormal is given in Table 1. Receiver operating characteristic plots showing the performance of the classifier is shown in Figure 5 indicating the true positive and false positive rates. Figure 6 is a graph showing the percentage of each resolution with respect to classifier performance.

Table 1: Performance of image resolutions

Image Resolution	Accuracy (%)	Sensitivity (%)	Specificity (%)
1024*788	93.3	93.3	93.3
512*393	93.3	86.7	100
256*196	96.7	100	93.3
128*98	96.7	100	93.3
64*49	96.7	93.3	100

4. Discussion

Fundus images used for diagnosing DR was analysed for different image sizes. Texture features extracted from image resolutions of 64*49, 128*98 and 256*196 classifies normal and abnormal images with an accuracy of 96.7%, while features extracted for resolutions 512*393 and 1024*788 classifies normal and abnormal cases with an accuracy of 93.3%. Also the number of hidden neurones used is 10 for 64*49 pixels, 15 for 128*98, 15 for 256, 25 for 512*393 and 25 for 1024*788 pixels. The research will allow researchers to use lower image sizes other than the ones in the databases as it will reduce computation cost and improves classifier performance.

5. Conclusion

This work presented a study of the effect fundus image resolutions on ANN classifier performance for diabetic retinopathy classification. The fundus images were preprocessed, 16 GLCM features were extracted for 5 different fundus image resolutions. The results shows that as the image size reduces the performance of ANN classifier increases and the number of hidden neurons used also decreases. Also the time spent on extracting the features is also reduced. For future work, it is recommended that

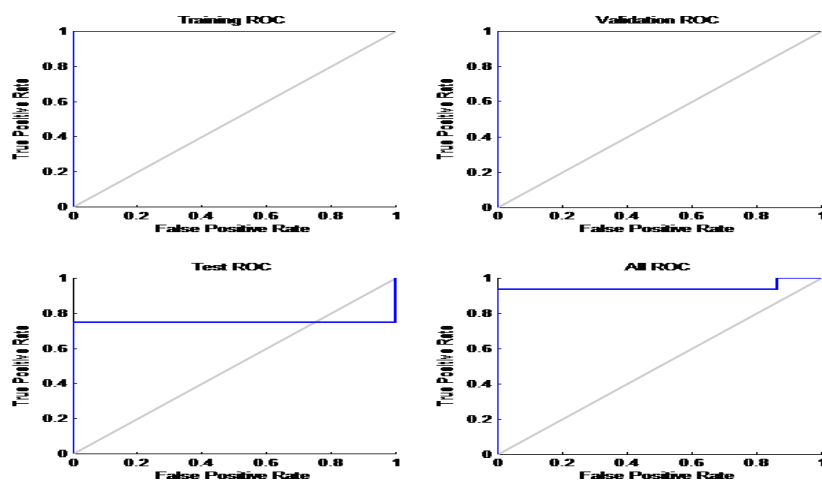


Figure 5: ROC plot for 256*196 pixels.

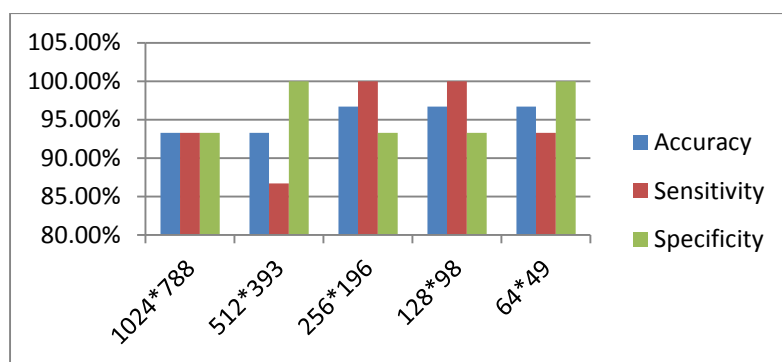


Figure 6: performance of different resolutions

more training data should be used for training and testing, different classifiers with different training function s should also be evaluated.

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