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THE EFFECT OF IMAGE RESOLUTION ON THE PERFORMANCE OF AUTOMATIC CLASSIFICATION OF DIABETIC RETINOPATHY AND STORAGE MEMORY

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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. Early detection and mass screening are required to reduce the risk of vision loss. Feature extraction and classification techniques reduce the computational complexity and improve the accuracy of classification. Extracting statistical features using Gray Level Co-occurrence Matrix (GLCM) from a high resolution images and large database increases the memory demand of a DR screening system; hence, there is need for reduction of the image resolution for memory reduction. In this paper, we investigated the effect pixel resolution reduction has on the performance of diabetic retinopathy classification and memory reduction. A feedforward back propagation neural network classifier was trained and tested using ten GLCM features extracted from one hundred fundus images with image comprising (fifty normal and fifty proliferative DR) for five different image resolutions (2240*1488, 1120*744, 560*372, 280*186, 140*93). The result shows that a 50% reduction in resolution leads to a 75% reduction in memory and 0% reduction in performance, which means that GLCM features, can be extracted from fundus images with lower image resolutions in lossless format for fast feature extraction without the fear of reduction in classification performance.

KEYWORDS: Diabetic retinopathy, Gray level co-occurrence matrix, Resolution, Artificial Neural Network, Fundus Image

INTRODUCTION

Diabetic Retinopathy (DR) is a progressive and preventable disease that causes blindness if not detected early. It is one of the leading causes of blindness worldwide estimated to about 5% of total blindness (Foster and Resnikoff, 2005). Fundus images (internal part of the eye) are often used for diagnosing various eye diseases including 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 (Aibinu et al., 2007). The two major considerations taken when dealing with digital imaging are the resolution needed to view the object of interest and the space needed to store the image (Peterson and Wolffson, 2005). These two considerations are utilized with some compromise depending on the application to which the image is to be subjected to. According to (Peterson and Wolffson, 2005), to use a digital image for pathology detection and monitor progression, the resolution is needed to be sufficient enough to allow for detection of clinical features of interest while disregarding the image storage.

The number of pixels in an image representing the width and height of the image is known as ‘image resolution’ (Microbus, 2014). Fundus image resolution that can be adequately resolved by a human eye is 1000*1000 but adjusted to 1365*1000 for a rectangular shape of the camera sensors (British Diabetic Association, 1999). The higher the image resolution, the better the quality of the image and therefore, higher memory space will be needed for storage (Fitzgerald, 2009).

To reduce the memory required to save an image or reduce the image size by removing redundant information from the image is known as image compression. Information stored in an image can be retrieved entirely if the image is stored in a “lossless” format, such as Tagged Image File Format (TIFF), while in a “lossy” format such as the Joint Photographic Expert Group (JPEG), most of the information are lost and cannot be retrieved (Garcia et al, 2003). Processing high quality image with large file size reduces the speed of processing, thereby limiting the advantage of digital technology in terms of speed (Peterson and Wolffsohn, 2005). One of the successful techniques for extracting DR clinical features from fundus images for DR diagnoses is the second order gray level co-occurrence matrix (GLCM) technique. However, the image resolution (size) affects the time and value of the GLCM features, as the image size increases the texture feature values increases and the time it takes to extract the features increases which affects the complexity and performance of classifiers. Several works have been done in determining the effect of digital image resolution and compression on DR screening, however, its effect on GLCM has not been considered. Therefore, this work aimed at evaluating the effect of resolution reduction using a lossless TIFF format and GLCM feature extraction on the performance of an Artificial Neural network (ANN) for DR classification.

Peterson and Wolffsohn, (2005) studied the effect of digital image resolution and compression on anterior eye imaging; they determined the theoretical and clinical minimum image pixel resolution and maximum compression appropriate for anterior eye image storage. Fundus images taken at resolutions of 2048*1360 pixels, 1280*811 pixels and 767*569 pixels where saved in TIFF format were further compressed to other lower resolutions. The images were analyzed using objective image analysis grading and ranked for clarity by 20 Optometrists using a 15 inch monitor with resolution of 1280*1024. Their results suggested that the appropriate resolutions to store anterior eye images are between 1280*811 and 767*569 pixels and up to 1:70 JPEG compression. Newson et al., (2001) investigated the effect of digital image compression on DR grading accuracy. Forty nine fundus images were subjected to JPEG compression by 90%, 80%, 70% and 0%. Using two masked graders, 49 images for each resolution were graded for retinopathy and image quality. The result indicated significant loss in sensitivity of DR features with JPEG compressed images. In their work, Raman et al., (2004) investigated the effect of using a low resolution (640*480 pixels) images and a high resolution (1400*1200 pixels) images on the performance of DR screening system for Microaneurysms (MA) detection. The candidates MA were detected after contrast enhancement, illumination correction, thresholding segmentation and filtering. The results obtained shows that for lower resolution, the best sensitivity and specificity that could be obtained is 70%, the result also found that pixel resolution is important in obtaining higher sensitivity and specificity for automated segmentation.

The above cited literatures did not considerthe effect on statistical feature extraction and classifiers whose application have the capability to significantly improve DR classification performances (Sakthivel and Rengarajan, 2014). The employment of GLCM for extracting fundus image features of a particular resolution for DR diagnosis had been presented in several literatures, Selvathi, Prakash and Balagopal, (2012) employed feature extraction using GLCM and support vector machine (SVM) classifier for DR diagnosis, segmentation techniques were employed to detect lesions and GLCM used to extract the texture features. The images used were obtained from 3 databases with different resolutions, DRIVE database with resolution 565*584 pixels in TIFF format, MESSIDOR database with three resolutions 1440 x 960, 2240 x 1488 or 2304 x1536 pixels and DIARETDB1whose resolution was not stated. The system Accuracy was 93%.

Priya and Aruna (2012) evaluates the performance of two classification modelsto classify fundus image with resolution 1280*1024 in JPEG format as normal, non-proliferative DR, and proliferative DR, The accuracy of SVM and PNN are 97.6% and 89.6% respectively. None of the works reviewed studied the effects of varying resolutions on GLCM features extraction, memory implication and classification performances; which is the aim of this research.

METHOD

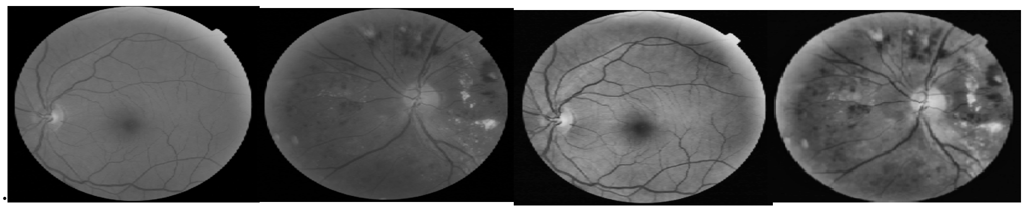
The fundus images were first pre-processed; the reference image pixel resolution (size) was then reduced by 50%, 75%, 87.5% and 93.75%. For each resolution, four GLCM features were extracted and were subsequently fed to a feed forward back propagation ANN.

Dataset

One hundred fundus images used for this work were captured using 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field of view (FOV). The images resolution (size) is 2240*1488 pixels at 8bit saved in TIFF format whose DR grades had been manually screened by expert ophthalmologist acquired by Service d'Ophtalmologie - Hôpital Lariboisière Paris. The images were randomly selected from Base 11, 12, 13 and 14 of the MESSIDOR public retina database which can be found in http://messidor.crihan.fr.

Pre-processing

The fundus images were pre-processed to improve their contrast, reduce noise and bring out more details from the image. The images were first converted to gray scale, Median filtering was then applied to remove noise before applying adaptive histogram equalization for contrast enhancement. The images were later resized to four other lower resolutions by dividing the reference resolution 2240*1488 by 2, 4, 8 and 16, to obtain resolutions 1120*744, 560*372, 280*186, 140*93 respectively. Figure 1 shows the effect of preprocessing on the original image. Figures 1 a and b are normal and proliferative DR gray images, while Figures c and d are the median filtered histogram equalized images of images a and b respectively



(a) (b) (c) (d)

Figure 1: Preprocessing Effect on Fundus Image

Feature Extraction

Feature extraction is a method of capturing visual content of images for information retrieval and indexing. It is the operation that quantifies image quality through various parameters and functions applied to the original image (Mohanaiah et al., 2013). GLCM Feature Extraction Textures are examined in second order feature extraction by comparing the partial relationship of pixels (Zulpe and Pawar, 2012). Gray Level Co-occurrence Matrix (GLCM) assesses image properties associated to Second-Order statistics. Zulpe and Pawar, (2012) 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:

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

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.

Tenmost used second order texture features namely; Contrast, Homogeneity, Variance, Entropy, Energy, Correlation, Dissimilarity, Difference Entropy, Auto-Correlation and Inverse Difference Moment, were extracted from the 100 pre-processed fundus images using GLCM at image resolution of 2240*1488. The process was repeated for the four other lower resolutions. The GLCM parameters chosen for second order feature extraction are as follows: GLCM gray level (GL) was set to 8, the orientation used was the average value or mean of four orientations (0^o, 45^o, 90^o and 135^o) at a pixel pair distance of 1.

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 (Chijindu et al., 2012). Artificial neural networks (ANN) are computation tools which are made up of highly interconnected artificial neurones that mimic the behavior of the brain (Alvisi et al., 2006). They are used for modelling complex real-world problems and to perform computations like pattern recognition, pattern matching, classification and forecasting. ANN learns by changing its synaptic weight [4]; mathematically, the function of kth neuron in a neural network is given by (Tahseen et al., 2011).

A two layered feed forward back propagation neural network classifier with scaled conjugate gradient training function (trainscg) was used for classification of the fundus image into normal or abnormal (proliferative diabetic retinopathy). The network input layer has 5 input neurones, 10 to 25 neurones in the hidden layer, and 1 output neurone in the output layer. Classification was performed for five different image resolutions and ten GLCM texture features. For each resolution, 70 images (35 normal and 35 abnormal) were used for training while 30 images (15 normal and 15 abnormal) were used for testing the classifier.

Performance Evaluation

The performance of the classification was calculated using equations 2, 3 and 4 as reported in Priya and Aruna, (2012)

$$Sensitivity = \frac{TP}{TP + FN} \qquad 2$$

$$Specificity = \frac{TN}{TN + FP} \qquad 3$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad 4$$

Where;

TP (True positive): correctly classified positive cases.

TN (True negative): correctly classified negative cases.

FP (False positive): incorrectly classified negative cases.

FN (False negative): incorrectly classified positive cases.

RESULTS AND DISCUSSIONS

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 R2012a neural network toolbox was used for the implementation of this work. The effect of each resolution on the classification performance of DR is shown in Table 1.

Table 1: Performance of Image Resolutions

Resolution (Pixels)	Memory (KB)	Accuracy (%)	Sensitivity (%)	Specificity (%)
2240*1488	9779.20	95.70%	100%	93.30%
1120*744	2447.36	95.70%	100%	93.80%
560*372	610	91.30%	100%	83.30%
280*186	152	91.30%	92%	90.90%
140*93	38.2	73.90%	77%	70%

There was no significant change in sensitivity off the first three resolutions which are 100%, the first two accuracy and specificity values were also constant which are 95.7% and 93.30%. The memory occupied by the images reduces significantly as shown in Figure 2.

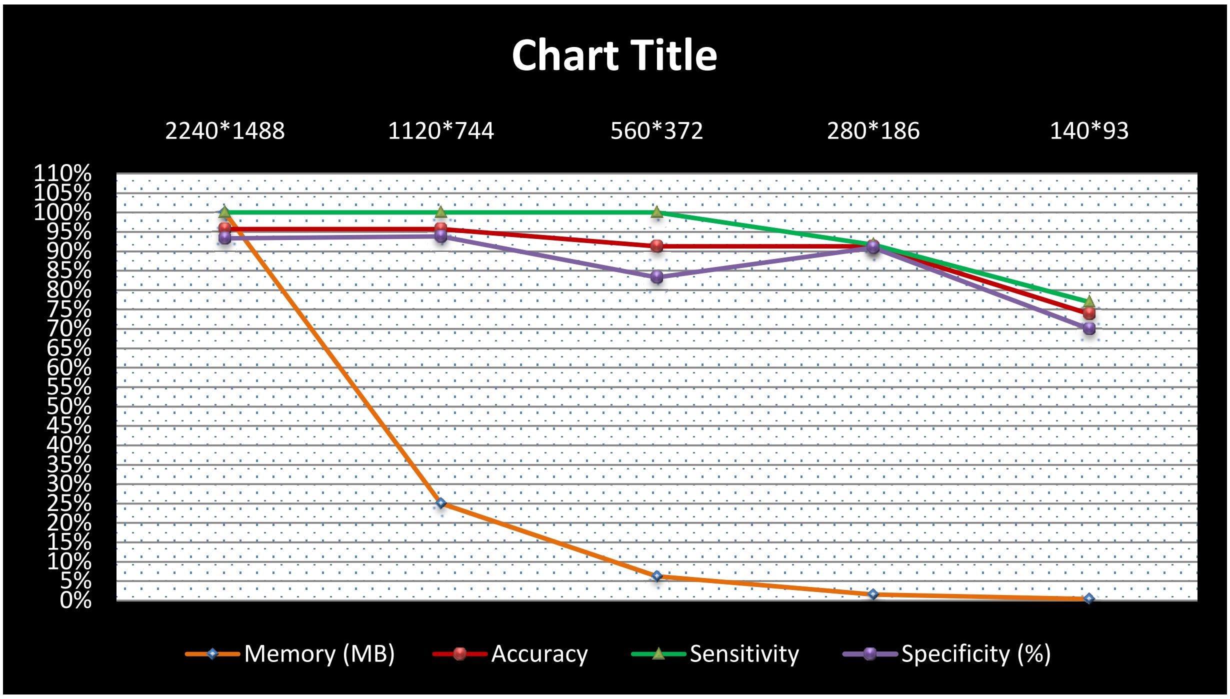


Figure 2: Performance of Different Resolutions

Figure 3 shows the percentage reduction in resolution, memory, accuracy, sensitivity and specificity. For a 50% reduction in resolution, the classification performance is the same with the highest resolution except for the specificity, which shows better result. For a 75% and 83.3% reduction in resolution, the performance drops to an average of 91% while the average was 73% for 93% reduction in resolution.

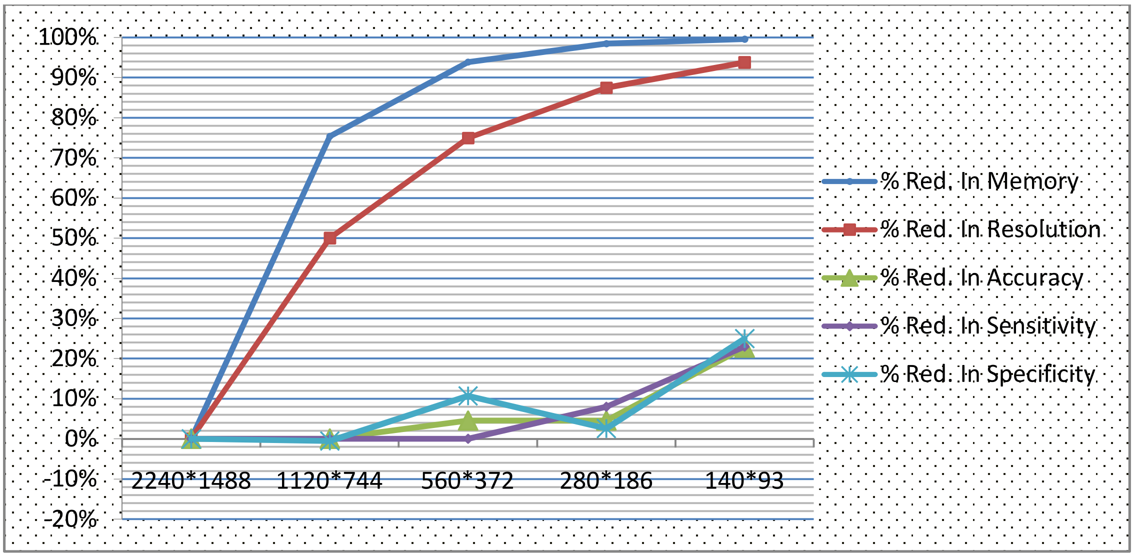


Figure 3: Percentage Reduction in Resolution, Memory, Accuracy, Sensitivity and Specificity

CONCLUSIONS

A 50% reduction in resolution resulted in a 75 reduction in disk space required to save the image, without a decrease in the performance of classification. The research outcome will assist researchers in this field to make good choices on the image resolution that will lead to faster, better feature extraction and improved DR classification performance. For future work, more training data could be used for training and testing, different classifiers with different training functions could also be tested.

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