Image Compression using Neural Networks and Haar Wavelet

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Abstract: - Wavelet-based image compression provides substantial improvements in picture quality at higher compression ratios. Haar wavelet transform based compression is one of the methods that can be applied for compressing images. An ideal image compression system must yield good quality compressed images with good compression ratio, while maintaining minimal time cost. With Wavelet transform based compression, the quality of compressed images is usually high, and the choice of an ideal compression ratio is difficult to make as it varies depending on the content of the image. Therefore, it is of great advantage to have a system that can determine an optimum compression ratio upon presenting it with an image. We propose that neural networks can be trained to establish the non-linear relationship between the image intensity and its compression ratios in search for an optimum ratio. This paper suggests that a neural network could be trained to recognize an optimum ratio for Haar wavelet compression of an image upon presenting the image to the network. Two neural networks receiving different input image sizes are developed in this work and a comparison between their performances in finding optimum Haar-based compression is presented.

Key-Words: - Optimum Image Compression, Haar Wavelet Transform, Neural Networks

1 Introduction

Compression methods are being rapidly developed to compress large data files such as images, where data compression in multimedia applications has lately become more vital [1]. With the increasing growth of technology and the entrance into the digital age, a vast amount of image data must be handled to be stored in a proper way using efficient methods usually succeed in compressing images, while retaining high image quality and marginal reduction in image size [2].

Wavelets are a mathematical tool for hierarchically decomposing functions. Image compression using Wavelet Transforms is a powerful method that is preferred by scientists to get the compressed images at higher compression ratios with higher PSNR values [3]. It is a popular transform used for some of the image compression standards in lossy compression methods. Unlike the discrete cosine transform, the wavelet transform is not Fourier-based and therefore wavelets do a better job of handling discontinuities in data.

Haar wavelet transform is a method that is used for image compression. Previous works using Haar image compression include an application which was applied to adaptive data hiding for the images dividing the original image into 8x8 sub-blocks and reconstructing the images after compression with good quality [4], and the use of Parametric Haar-like transform that is based on a fast orthogonal parametrically adaptive transform such that it may be computed with a fast algorithm in structure similar to classical haar transform [5]. Furthermore, Ye et al. [6] used wavelet transform to digitally compress fingerprints and reconstruct original images via components of the approximation, horizontal detail, vertical detail and diagonal detail from the input image transformation.

Artificial neural networks implementations in image processing applications has marginally increased in recent years. Image compression using wavelet transform and a neural network was suggested previously [7]. Moreover, different image compression techniques were combined with neural network classifier for various applications [8],[9]. A neural network model called direct classification was also suggested; this is a hybrid between a subset of the self-organising Kohonen model and the adaptive resonance theory model to compress the image data [10]. Periodic Vector Quantization algorithm based image compression was suggested previously based on competitive neural networks quantizer and neural networks predictor [11],[12].

More works using neural networks emerged lately. Northan and Dony suggested a work based on a multiresolution neural network (MRNN) filter bank and its potential as a transform for coding that was created for use within a state-of-the-art subband-coding framework [13]. Veisi and Jamzad suggested an image compression algorithm based on the complexity of the images after dividing each image into blocks and using the complexity of each block to be computed using complexity measure methods and one network is selected for each block according to its complexity value [14]. A direct solution method applied to image compression using neural networks [15]. Mi and Huang suggested using Principal Component Analysis based image compression and compared three algorithm performances on image compression depending on the SNR values [16]. Ashraf and Akbar suggested a neural network quantizer to be used in a way that an image is first compressed at a high compression ratio with loss and the error image is then compressed lossless resulting an image not only strictly lossless but also expected to yield a high compression ratio especially if the lossy compression technique is good [17]. However, none of these works have suggested using a neural network to determine optimum compression ratio.

The aim of the work presented within this paper is to develop an optimum image compression system using haar wavelet transform and a neural network. Recently the neural network based DCT compression system was applied to find the optimum compression ratios [18],[19]. These recent works used visual inspection and computational analysis based comparison criteria; as suggested in [20], to determine the optimum compression ratios for different training and testing images.

The proposed novel method suggests that a trained neural network can learn the non-linear relationship between the intensity (pixel values) of an image and its optimum compression ratio. Based on our hypothesis, a trained neural network could recognize the optimum haar compression ratio of an image upon its presentation to the neural network. The development and implementation of this image compression system uses 100 images of various objects, contrasts and intensities.

The paper is organized as follows: Section 2 describes the image database which is used for the implementation of our proposed system. Section 3

Fig. 1. An original image and its Haar compression at nine ratios

presents the two neural networks designs and their implementations. Section 4 introduces the evaluation method of the results and provides an analysis of the system implementation, in addition to a comparison of the performance of the two neural networks. Finally, Section 5 concludes the work that is presented within this paper and suggests further work.

2 Image Database

The development and implementation of the proposed optimum image compression system uses 100 images from our database that have different objects, brightness and contrast [21]. Haar compression has been applied to 70 images using 9 compression ratios (10%, 20%, 30%, … 90%) as shown in an example in Fig. 1.

The optimum Haar compression ratios for the 70 images were determined using the optimum compression criteria based on visual inspection of the compressed images as suggested in [20], thus providing 70 images with *known* optimum compression ratios and the remaining 30 images with *unknown* optimum compression ratios. The image database is then organized into three sets:

- Training Image Set: contains 40 images with *known* optimum compression ratios which are used for training the neural networks within image compression system. Examples of training image set are shown in Fig. 2.

- Testing Image Set 1: contains 30 images with *known* optimum compression ratios which are used to test and evaluate the efficiency of the trained neural networks. Examples of these testing images are shown in Fig. 3.

- Testing Image Set 2: contains 30 images with *unknown* optimum compression ratios which are used to further test the trained neural networks. Examples of these testing images are shown in Fig. 4.

The optimum ratios for Haar compression of the 40 images in the training image set database can be seen listed in Table 1, whereas examples of original images and their compressed version using their optimum compression ratios prior to training the neural networks are shown in Fig. 5.

Fig. 2. Training image Set examples

Fig. 3. Testing image Set 1 examples

Fig. 4. Testing image Set 2 examples

Table 1. Pre-determined Optimum Haar Compression Ratios (OHCR)

Image	OHCR	Image	OHCR
Image 1	80 %	Image 21	80 %
Image 2	70 %	Image 22	80 %
Image 3	90 %	Image 23	80 %
Image 4	80 %	Image 24	80 %
Image 5	90 %	Image 25	80 %
Image 6	80 %	Image 26	80 %
Image 7	80 %	Image 27	80 %
Image 8	90 %	Image 28	90 %
Image 9	90 %	Image 29	90 %
Image 10	80 %	Image 30	70 %
Image 11	80 %	Image 31	80 %
Image 12	80 %	Image 32	80 %
Image 13	90 %	Image 33	80 %
Image 14	70 %	Image 34	80 %
Image 15	90 %	Image 35	70 %
Image 16	80 %	Image 36	70 %
Image 17	80 %	Image 37	80 %
Image 18	90 %	Image 38	80 %
Image 19	80 %	Image 39	80 %
Image 20	90 %	Image 40	80 %


Image 36 Optimum Ratio (70%)


Image 40 Optimum Ratio (80%)


Image 29 Optimum Ratio (90%)

Fig. 5. Images with optimum Haar compression

3 Neural Network Implementation

The optimum image compression system uses a supervised neural network based on the back propagation learning algorithm, due to its implementation simplicity, and the availability of sufficient “input / target” database for training this supervised learner [22], [23]. This relationship can be seen in Fig. 6 which shows the different values of optimum compression ratios for the database images. The neural network relates the image intensity (pixel values) to the image optimum compression ratio having been trained using images with predetermined optimum compression ratios. The ratios vary according to the variations in pixel values within the images. Once trained, the neural network would select the optimum compression ratio of an image upon presenting the image to the neural network by using its intensity values.

Adobe Photoshop was used to resize the original images of size (256x256) pixels into (64x64) pixels and (32x32) pixels. The 64x64 images were used to train the first neural network (named ANN64), whereas the 32x32 images were used to train the second neural network (named ANN32). All images were presented to the neural networks using the one-pixel-per-node approach, thus resulting in 4096 pixel values per image for ANN64 and 1024 pixel values per image for ANN32.

Further reduction to the size of the images was attempted in order to reduce the number of input layer neurons and consequently the training time, however, meaningful neural network training could not be achieved thus, the use of whole images of sizes (32x32) and (64x64) pixels.

The hidden layers for both of the neural networks contain 50 neurons which assures meaningful training while keeping the time cost to a minimum. The output layers have nine neurons according to the number of possible compression ratios (10% - 90%). During the learning phase, initial random weights of values between 0.45 and -0.45 were used for both networks. The learning coefficient and the momentum rate were adjusted during various experiments in order to achieve the required minimum error value of 0.005; which was considered as sufficient for this application. Fig. 7a and Fig. 7b shows the topology of the ANN64 and ANN32 neural networks, respectively, within the image compression system.

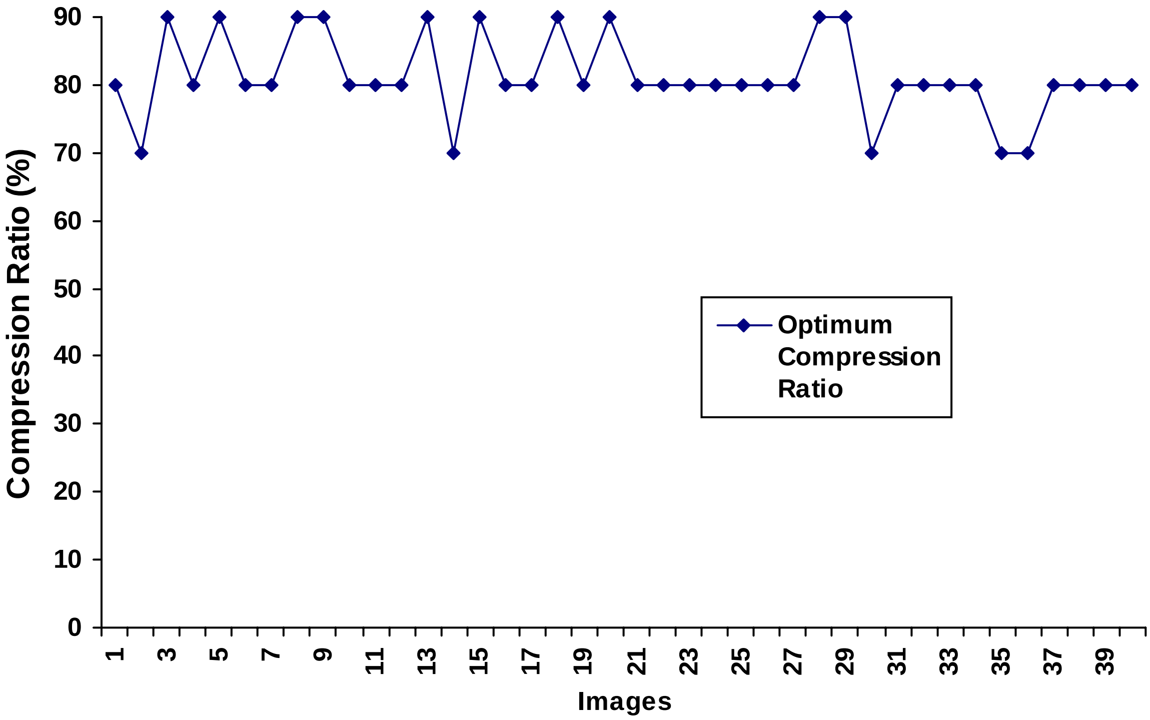

Fig. 6. Relationship between images and optimum compression ratios

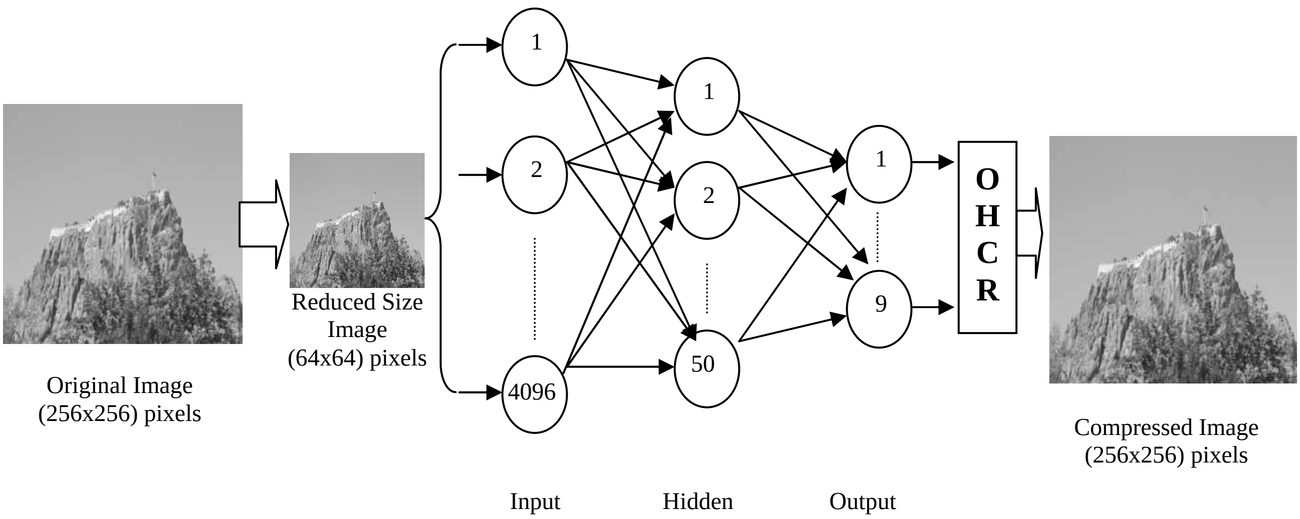

Fig. 7a. The optimum image compression system using ANN64. (OHCR: Optimum Haar Compression Ratio).

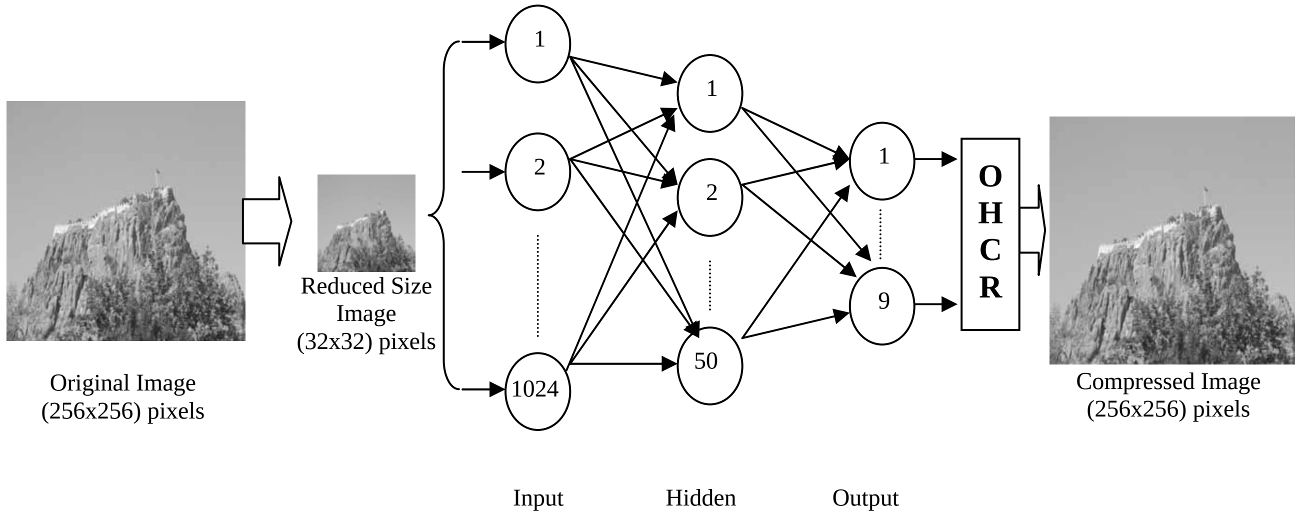

Fig. 7b. The optimum image compression system using ANN32. (OHCR: Optimum Haar Compression Ratio).

4 Results and Discussion

The first neural network (ANN64) learnt and converged after 1635 iterations and within 1582.56 seconds, and the second neural network (ANN32) learnt and converged after 2003 iterations and within 530.09 seconds, whereas the running time for both generalized neural networks after training and using one forward pass was 0.0150 seconds for ANN32 and 0.0160 seconds for ANN64.

These results were obtained using a 2.0 GHz PC with 2 GB of RAM, Windows XP OS and Matlab 2008a software. Table 2 lists the final parameters of the successfully trained ANN32 and ANN64 neural networks. Fig. 8a and Fig. 8b show the error versus iteration graphs of the ANN32 and ANN64 respectively during the neural network training.

The evaluation of the training and testing results was performed using two measurements: the recognition rate and the accuracy rate. The recognition rate is defined as follows:

$$RR_{OHC} = \left(\frac{I_{OHC}}{I_T} \right) * 100 , \qquad (1)$$

where RR_{OHC} is the recognition rate for the neural network within the optimum Haar compression system, I_{OHC} is the number of optimally compressed images, and I_T is the total number of images in the database set.

The accuracy rate RA_{OHC} for the neural network output results is defined as follows:

$$RA_{OHC} = \left(1 - \frac{\left(\left| S_p - S_i \right| \right) * 10}{S_T} \right) * 100 , \qquad (2)$$

where S_P represents the pre-determined (expected) optimum compression ratio in percentage, S_i represents the optimum compression ratio as determined by the trained neural network in percentage and S_T represents the total number of compression ratios.

The Optimum Compression Deviation (OCD) is another term that is used in our evaluation. *OCD* is the difference between the pre-determined or expected optimum compression ratio S_P and the optimum compression ratio S_i as determined by the trained neural network, and is defined as follows:

$$OCD = \left(\left| S_p - S_i \right| \right) * 10 . \qquad (3)$$

The OCD is used to indicate the accuracy of the system, and depending on its value the recognition rates vary.

Table 2. Neural Networks Final Parameters

Final Parameters	ANN64	ANN32
Input Neurons	4096	1024
Hidden Neurons	50	50
Output Neurons	9	9
Learning Coefficient	0.006	0.006
Momentum Rate	0.4	0.4
Minimum Error	0.005	0.005
Iterations	1635	2003
Training Time (seconds)	1582.56	530.09
Run Time (seconds)	0.0160	0.0150

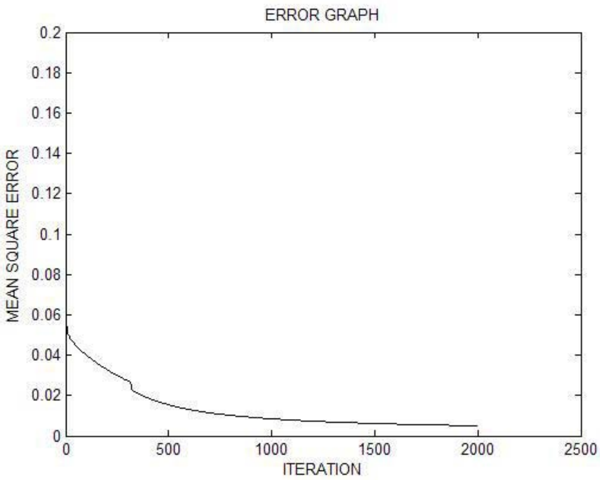

Fig. 8a. Learning curve of ANN32

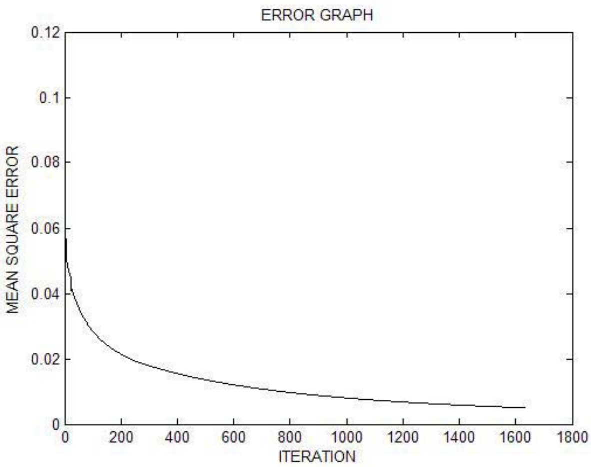

Fig. 8b. Learning curve of ANN64

Table 3 shows the three considered values of OCD and their corresponding accuracy rates and recognition rates. The evaluation of the system implementation results uses (*OCD* = *1*) as it provides a minimum accuracy rate of 89% which is considered sufficient for this application.

The trained neural networks recognized correctly the optimum compression ratios for all 40 training images as would be expected, thus yielding 100% recognition of the training set. Testing the ANN64 trained neural network using the 30 images from Test Set 1 that were not presented to the network before yielded 96.67% recognition rate, where 29 out of the 30 images with known optimum compression ratios were assigned the correct ratio. However, testing the ANN32 trained neural network using the same 30 images yielded 93.3% recognition rate, where 28 out of the 30 images with known compression ratios were assigned the correct ratio.

The trained neural networks were also tested using the remaining 30 images with unknown optimum compression ratios from the testing set. The results of this application are shown in Table 4, whereas Fig. 11 shows examples of the optimally compressed images as determined by the trained neural network.

5 Conclusion

A novel method to image compression using neural networks is proposed in this paper. The method uses Haar compression with nine compression ratios and a supervised neural network that learns to associate the grey image intensity (pixel values) with a single optimum compression ratio. The implementation of the proposed method uses haar image compression where the quality of the compressed images degrades at higher compression ratios due to the nature of the lossy wavelet compression. The aim of an optimum ratio is to combine high compression ratio with good quality compressed image.

The proposed system was developed and implemented using 100 images of various objects, contrasts and intensities, and two neural networks; namely ANN32 and ANN64.

The ANN64 neural network within the image compression system learnt to associate the 40 training images with their predetermined optimum compression ratios within 1582.56 seconds, whereas the ANN32 neural network learnt to associate the 40 training images with their predetermined optimum compression ratios within 530.09 seconds. Once trained, The ANN64 neural network could recognize the optimum compression ratio of an image within 0.016 seconds however ANN32 neural network could recognize the optimum compression ratio of an image within 0.015 seconds upon presenting the image to the network.

Table 3. Optimum Compression Deviation and Corresponding Rates

OCD	Accuracy Rate (RA_{OHC})	ANN64 Recognition Rate (RR_{OHC})	ANN32 Recognition Rate (RR_{OHC})
0	100 %	16/30 (53.3%)	12/30 (40%)
1	89 %	29/30 (96.67%)	28/30 (93.3%)
2	78 %	30/30 (100%)	30/30(100%)

Table 4. Optimum Haar Compression Ratios (%) as determined by the neural networks

Image	OHCR ANN32	OHCR ANN64
Image71	80 %	80 %
Image72	90 %	90 %
Image73	80 %	80 %
Image74	80 %	80 %
Image75	90 %	90 %
Image76	80 %	80 %
Image77	80 %	70 %
Image78	90 %	80 %
Image79	80 %	90 %
Image80	90 %	90 %
Image81	80 %	80 %
Image82	90 %	90 %
Image83	80 %	90 %
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Image86	70 %	80 %
Image87	80 %	70 %
Image88	90 %	90 %
Image89	70 %	80 %
Image90	80 %	90 %
Image91	80 %	80 %
Image92	80 %	80 %
Image93	80 %	90 %
Image94	70 %	70 %
Image95	90 %	80 %
Image96	90 %	80 %
Image97	80 %	80 %
Image98	70 %	70 %
Image99	90 %	90 %
Image100	80 %	90 %

In this work, a minimum accuracy level of 89% was considered as acceptable. Using this accuracy level, the first neural network (ANN64) yielded 96.67% correct recognition rate of optimum compression ratios, whereas, the second neural network (ANN32) yielded 93.3% correct recognition rate. The successful implementation of our proposed method using both neural networks was shown throughout the high recognition rates and the minimal time costs when running the trained neural networks- 0.016 second for ANN64 and 0.015 second for ANN32. However, the first neural network (ANN64) is considered as superior to the second neural network in providing an optimum Haar-based image compression ratio, due to its higher recognition ratio.

Future work will include the implementation of this method using biorthogonal wavelet transform compression and comparing the performance with Haar-based image compression.

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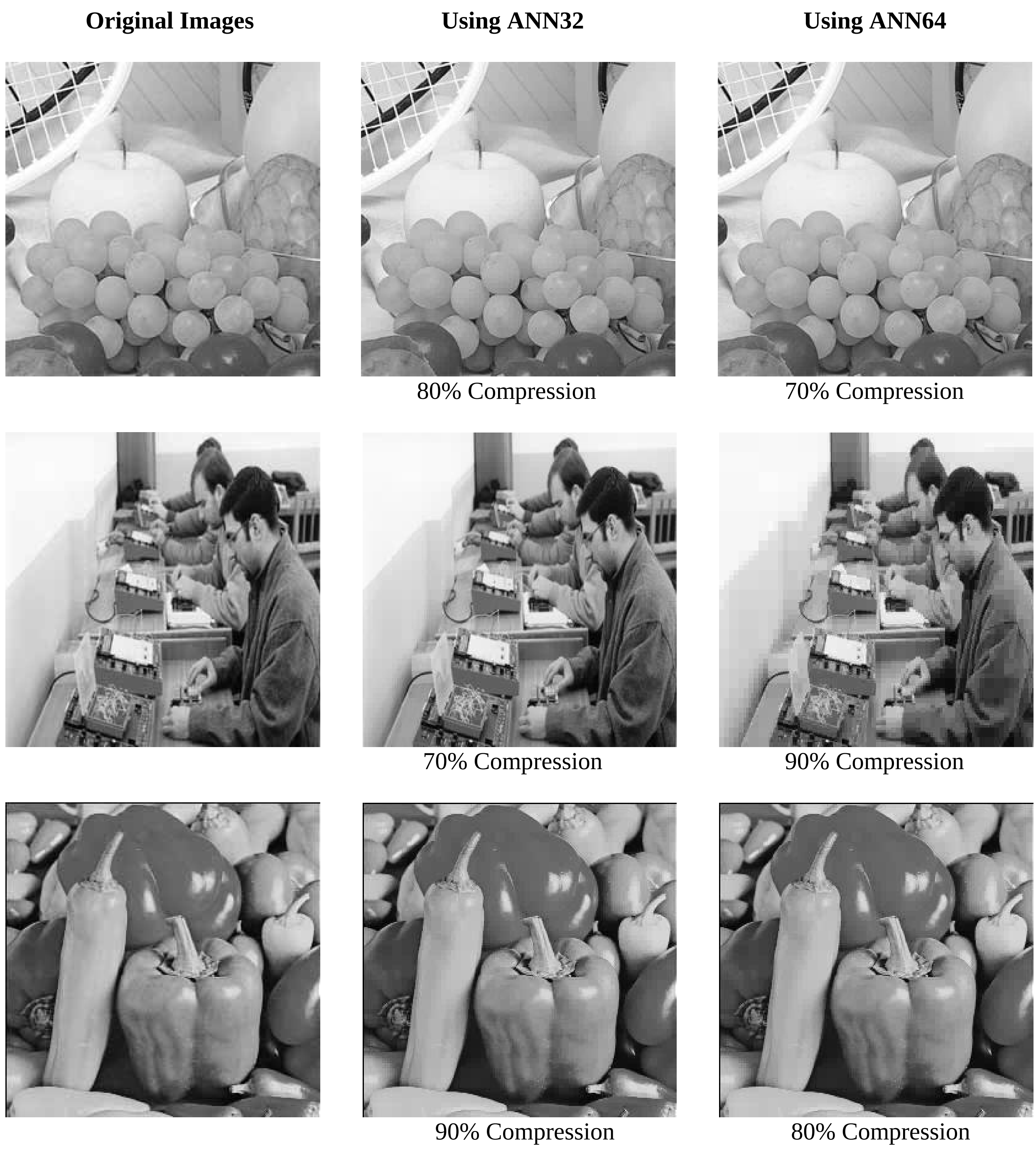

Fig. 11. Optimum Haar Compression using ANN32 and ANN64 trained neural networks

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