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Advancement of Classical Wavelet Network over Artificial Neural Network in Image Compression

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ABSTRACT

Image compression is the technique which reduces the amount of data required to represent a digital image. Statistical properties of the image are used in design an appropriate compression technique. An image compression is used for compression, the good picture quality can be retrieved and also achieves better compression ratio. Also in the past few years Artificial Neural Network becomes popular in the field of image compression. The inputs to the network are the pre-processed data of original image, while the outputs are reconstructed image data, which are close to the inputs. By implementing the proposed scheme the influence of different compression ratios within the scheme is investigated. It has been demonstrated through several experiments to develop a better quality of image compression techniques using Multi-Layer Perceptron (MLP) with wavelet transform coefficients and report its application to image compression by using error metrics like Mean Square Error (MSE) and Peak-Signal-to-Noise Ratio (PSNR).

***Keywords*—** Wavelet Transformation, Artificial Neural Network, Multi-Layer Perceptron, Mean Square Error and Peak-Signal-to-Noise Ratio

I. INTRODUCTION

The fast development of computer applications came with high increase of the use of digital images, especially in the area of multimedia, games, satellite transmissions and medical imagery. Digital form of the information secures the transmission and provides its manipulation. Constant increase of digital information quantities needs more storage space and wider transmission lines. This implies more the research on effective compression techniques. The basic idea of image compression is the reduction of the middle number of bits by pixel (bpp) necessary for image representation. The aim of image compression is to reduce the quantity of bits necessary to describe them while keeping an acceptable visual aspect of the rebuilt images [1].

An effective image compression algorithm is proposed by introducing the artificial neural network [2] (ANN) on the place of quantization block of a general image compression algorithm. In this method, after the spatial information of the target image is transformed in to the equivalent frequency domain, the ANN stores each of the transformed coefficients in the networks synaptic weights. Furthermore at the decompression stage the ANN is fully capable of reproducing every single frequency component (coefficient values) with marginal error due to the fact that no information is reduced unlike in lossy method where some psycho visual redundancies are removed in the quantization.

1.1 Basic Concepts

An image (monochrome) is given as a two-dimensional function, *f(x,y)*, where x and y are spatial (plane) coordinates and the amplitude of function *f(x,y)* at any pair of coordinates *(x, y)* is known as the intensity level or gray level of the image at that point [1]. Digital images are discrete in both spatial coordinates and brightness. A digital image can be taken as a matrix whose rows and column indices identify a point in the image, and where the corresponding matrix element value identifies the gray level at that point. Whenever we have to manipulate images mathematically or otherwise, we treat images as matrices and perform number of operations on this image matrix. The individual elements of such a digital array are known as pixels. Digital image processing involves enormous use of hardware, software, complex and rigorous mathematical theory.

Therefore, image processing techniques require not only sophisticated equipment, but also a good theoretical grasp of the subject. When it comes to implementation of a particular 2 technique or an application (like the one we will be discussing in this project) one has to be well versed in software programming. The different elements of a digital image processing system are image acquisition, storage, processing, communication and display. Basic elements of a digital processing system are shown in figure 1.1.

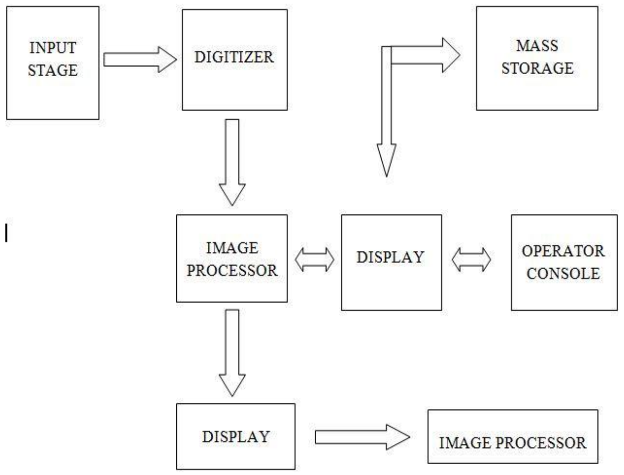

Figure 1: Elements of a Digital Image Processing System

It consists of a digitizer, image processor, digital computer, and display unit and storage device. We can also include an operator console, as shown in figure to monitor the ongoing data processing. A digital image processor consists of hardware modules performing image acquisition, storage, processing at low level (bit level), and display. A digitizer converts an image into mathematical (matrix) representation suitable for input into the digital computer. Normally used digitizers are photosensitive solid state arrays, videos cameras, living spot cameras, etc. image processors are usually interfaced with general-purpose computers, which work as a device for image acquisition, programming, and image display. Computer systems used for image processing range from powerful mainframes and workstations to microprocessors, depending on the type of application. Monochrome or colour television monitors, computer computers, LCDs and sometimes cathode ray tubes are used as display units in an image processing system. Due to the proliferation of digital data, rapid growth of internet, and multimedia, the need of the hour is to conserve the "storage space" for digital images; hence comes the need for image compression. Image compression is important not only in transmission of digital images over a channel, but also in applications like medical imaging, where storage of images can be a big problem.

Furthermore, processing of digital images generates large amount of data. This would be a concern not only for transmission but also in storage. We will now discuss concept of image compression.

1.2 Image Compression

Image compression is the technique which reduces the amount of data required to represent a digital image. The basis of the reduction process is the removal of redundant data. From a mathematical point of view, this amounts to transforming a 2-D pixel array into a statistically uncorrelated data set. The transformation is applied before, storage or transmission of the image. At some later time whenever required, the compressed image is decompressed and the original image or an approximation of it is reconstructed back. The initial focus of research efforts in this field was on the development of analog methods for reducing video transmission bandwidth, a process called bandwidth compression. A large amount of data is generated when a 2-D intensity function is sampled and quantized to create an image which is digital in nature.

We have two types of compression; these are lossless and lossy compression. In lossless compression, the reconstructed image is exactly same as the original image. The criterion of performance is not only the human eye perception but two physical quantities; namely the mean square error (MSE) and the peak signal to noise ratio (PSNR) [2].

They are calculated as follows:

$$\text{MSE} = \frac{1}{MXN}\sum_{j=0}^{M-1}\sum(F(i,j) - f(i,j))$$

Where F represents original image of size M × N and f is the reconstructed image of same size.

$$\text{PSNR} = 10\log_{10}\frac{1}{MMSE}$$

Where NMSE is the normalized mean square error and PSNR is measured in decibels. For lossless compression, the mean square error (MSE) is zero and the peak signal to noise ratio (PSNR) is infinity. However the numbers of applications in image processing do not require that the reconstructed image and the original image should be exactly same. This comes as an advantage for most applications, because that we can compress the original image to a value that would be suitable for our requirements. Hence lossy compression comes into the picture. The advantage of lossy compression is that we save a substantial amount of memory while storing and or transmitting images over a communication channel. The price we pay for compression comes as some distortion in the reconstructed image. In the type of lossy compression technique, the image quality definitely degraded due to loss of information. But lossy compression techniques for image compression generally offer much higher compression ratios as compare to the lossless techniques. Now we will discuss the parameter, which is most important for defining the effectiveness for image compression that is compression ratio.

II. WAVELET THEORY

A wavelet can be defined as a "small wave" that has its energy concentrated in time to give a tool for the study of transient, non-stationary, or time-varying phenomenon [10]. It has the oscillating wave-like properties but also capable to allow simultaneous analysis of time and frequency. Wavelet Transform has emerged as a powerful mathematical tool in many areas of science and engineering, more so in the field of audio and data compression. A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies; the Wavelet Transform gives good frequency resolution and poor time resolution also.

Ideas of wavelet packet is the same as wavelet, the only difference is that wavelet packet offers a more complex and flexible analysis because in wavelet packet analysis the details as well as the approximation are spitted. The wavelet packet tree for 3-level decomposition is shown in figure 3.

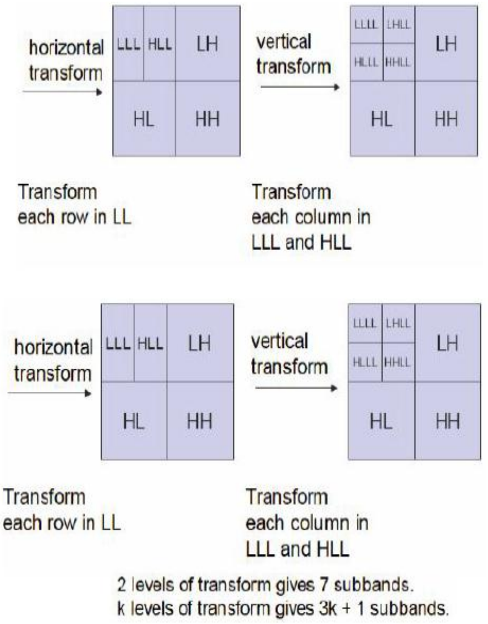

Figure.2: Transformation Process

Wavelet transformation provides fast computation and also overcomes previously used transformation techniques such as STFT, DTFT etc. Scaling of frequency and time dilation is provided by wavelet transformation so this can used for the analysis of both stationary and non-stationary signals efficiently.

III. ANN FOR IMAGE COMPRESSION

ANN'S are basically a collection of massively interconnected nodes or commonly known as processing elements or nodes emulating the biological neuronal activities.

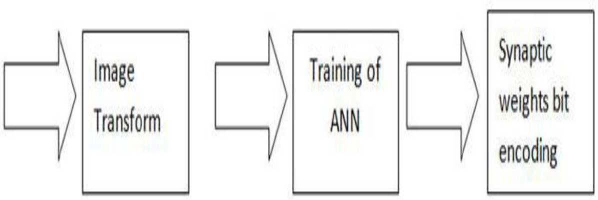

Figure.3: Generic Functional Blocks of Image Compression Algorithm

First we divided into blocks of m by l pixels before performing a suitable image transform to the pixels on the block. Through this step, complexity of the computation and the required memory space to store the calculation temporary can be reduced thus resulting in faster transformation time. Each of the coefficients in the transformed blocks with the corresponding horizontal position, x and vertical position , y will then be propagated through the ANN block by block sequentially .The inputs to the ANN will be the spatial x and y coordinates while the output for the network will be relevant transform coefficients [3] .

At the decompression stage, the values of the coefficients in each block can be recomputed by setting the input of the neural network to the specific spatial coordinates under consideration. Subsequently, the network will produce the equivalent transform coefficient which will then be inverse transformed to get back original pixel value. The effectiveness of the compression algorithm is gauge using two parameters which are the MSE for accessing the quality of the decompress image and the image compression ratio.

IV. IMAGE COMPRESSION USING MLP

To compress the image we have used MLP (Multilayer Perceptron), it was conventional method for image compression with neural networks. In this method, first we developed an MLP network. In this network there are three layers named input layer, hidden layer and output layer [5]. The input is given to the input layer, this is the frequency value of image that means the pixel vale of original image is applied to input neurons.

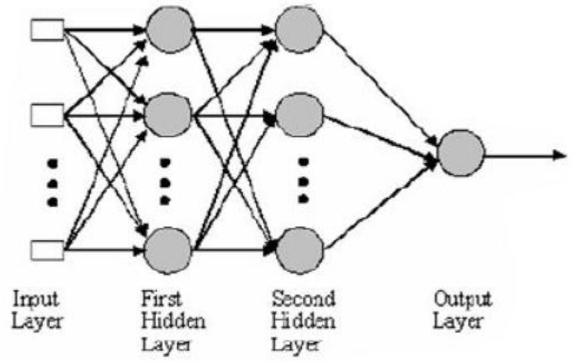

Figure 4: MLP Model

The number of neurons at the input is same as the number of pixels in the image. The number of neurons at the middle layer (hidden layer) is lesser than number of neurons at the input layer, to achieve compression. By adding more number of hidden layers we can increase our compression rate. Number of neurons at the output layer is similar to the number of neurons at the input layer to approximate original image.

As the preparation of image compression, there are some steps have been followed .These steps are as follows:-

STEP1. First, image segmentation is necessary that means segment the image into a set of m blocks l by l pixels and reshaping each one into column vectors.

STEP2. In this step we arrange all column vectors in a matrix. The m blocks of sub –images are applied as inputs for the neural networks.

STEP3. Then a three layer neural network is used, an input layer with M neurons with l by l pixels an output layer with

N neurons (here N=M) and a hidden layer with K number of neurons, K is always smaller than M ;(K<M) and it is based on activation functions.

STEP4. Our neural network is trained in order to reproduce the information given by input layer in output layer. We denote the input by $X=(x_1,x_2,\ldots\ldots.,x_M)$ and the output of the network by $Y=(y_1,y_2,\ldots\ldots.y_N)$.At the end of training process our target is to have X=Y for every input. In short the steps for training process:-

- Choose suitable training algorithm
- Define training parameters and iterations
- Define number of hidden neurons and initial condition

STEP5. Simulation of network by using input data, result matrices and an initial error value.

STEP6. Reconstruction of the original image

STEP7. Terminate the calculation of error is smaller than threshold.

There are number of different kinds of neural networks. Here we will mention the multi-layer perceptron's and the method which involves wavelet transformation with multilayer perceptron's for the process of image compression.

In practice, there exist two acceptable assessments for the quality of reconstructed images which are PSNR (Peak Signal to Noise Ratio) and NMSE (Normalized Mean-Square Error).

$$\text{PSNR} = 10 \log \frac{255^2}{\frac{1}{nN}\sum_{i=1}^{n}\sum_{j=1}^{N}(\overline{P_{ij}}-P_{ij})^2} \quad (1)$$

$$\text{NMSE} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{N}(\overline{P_{ij}}-P_{ij})^2}{\sum_{i=1}^{n}\sum_{j=1}^{N}P_{ij}^{\;2}} \quad (2)$$

Where P(i,j) is the intensity value of pixels in the original images and P'(i,j) is the intensity value of the pixels in the reconstructed image.

V. PROPOSED ALGORITHM

In order to compress the image, first, it's required to segment it in a set of m blocks l by l pixels. These blocks are used as inputs for our designed neural network. A three layer feed-forward neural network is used: an input layer with m neurons with l×l bloc pixels, an output layer with m neurons and a hidden layer with a number of neurons smaller than m[4]. Our network is trained in order to reproduce in output the information given in input. We denote the input bloc by $X=(x_1,\ldots..,x_m)$ and the output of the network by $Y=(y_1,\ldots...,y_m)$. At the end of the training we aim at having Y=X for every block presented to the network.

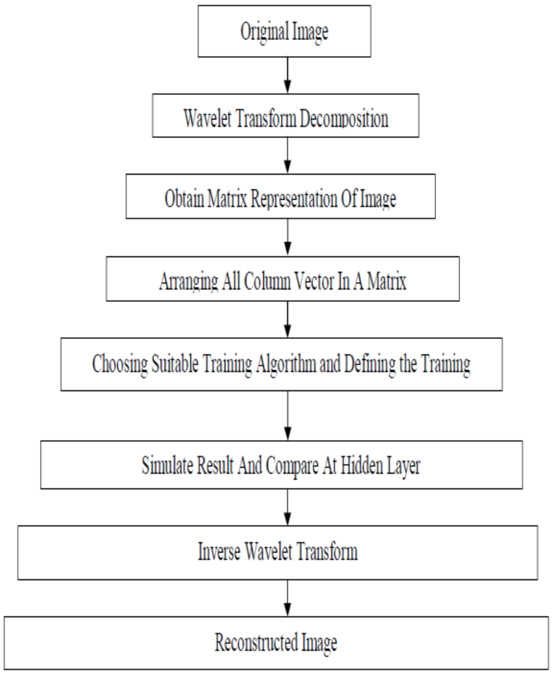

Figure 5: Flow chart for Image Compression by MLP with WT

VI. RESULTS

We have taken three images under consideration for this method. Table 1, shows the compression of LENA image by MLP with wavelet coefficients. Table 2 represents the compression of Gandhi ji image and Lena image by this method.

Table 1 shows the training conditions involved in the training of our neural network; we have taken 512×512 image dimension which is gray image. All common training parameters are shown in this table.

Table 1: Training Conditions

Image dimension	512×512
Block size	8×8
Training algorithm	Gradient descent
Level of WT	2-level WT decomposition
Type of wavelet used	Haar wavelet
Input and Output size(M=N)	64
Maximum iteration	1000
Learning rate	$5.6629e^{-4}$

Table 2 shows the results for image compression by MLP with wavelet coefficients .We have taken results for different compression rates .Now from this table it can be observed that there is very small variation in PSNR and MSE as we increasing compression ratio.

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Table 2: Compression by MLP with wavelet coefficients (Lena image)

Compression ratio (%)	PSNR (in dB)	MSE	No. of hidden neuron
25	21.0143	153.4669	16
50	21.0119	154.8085	32
75	20.9375	160.9141	48
87.5	20.0478	181.9356	56

Table 3, another image of lena have taken for image compression process by MLP with wavelet coefficients. Image dimension and training conditions are similar to previous one**.**

Table 3: Compression of Cameraman Image

Compression ratio (%)	PSNR (in dB)	MSE	No. of hidden neuron
25	19.3312	120.2882	16
50	19.2483	110.0423	32
75	19.1624	107.7509	48
87.5	19.3894	106.2011	56

IMAGE COMPRESSION BY MLP (CLASSICAL APPROACH)

ANN is directly used in this process. First an MLP neural network has developed with three layers; input layer, hidden layer and output layer. This network uses the back propagation training algorithm to correct the connection weights by minimizing the propagation error. Here the amplitude values that mean pixel values are directly applied to the input layer of neural networks. The compression is achieved at hidden layer and at output layer the original image is reconstructed again.

Training conditions are same as in case of image compression by MLP with wavelet coefficients.

Table 4 Image of Lena has been taken for image compression process by MLP neural network without wavelet decomposition.

Table 4: Image Compression by MLP Neural Network (Lena image)

Compression ratio (%)	PSNR (in dB)	MSE	No. of hidden neuron
25	-20.3457	127.4040	16
50	-21.3776	127.7430	32
75	-26.0051	128.0162	48
87.5	-27.0960	129.0178	56

Table 5 is used for the image compression all training parameters and image dimensions are similar for lena image.

Table 5: Compression of Lena Image

Compression ratio (%)	PSNR (in dB)	MSE	No. of hidden neuron
25	-11.276	145.8129	16
50	-13.4085	145.9110	32
75	-13.4293	146.3231	48
87.5	-12.7205	146.2588	56

GRAPHICAL REPRESENTATION

Graphs shown below represents the PSNR values for three test images already have been taken for our experimental results. Figure 6 shows comparative PSNR values for Lena image. From analysis of this figure we get conclusion that MLP with wavelet coefficients gives better PSNR as compare to classical MLP (ANN).

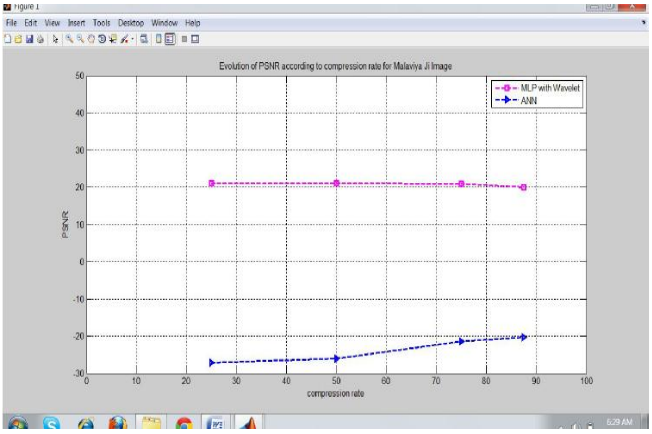

Figure 6: PSNR v/s Compression rate for cameraman image

Figure 7 shows the PSNR values for Lena image by two approaches and figure shows the performances by MLP classical approach and MLP with wavelet coefficients.

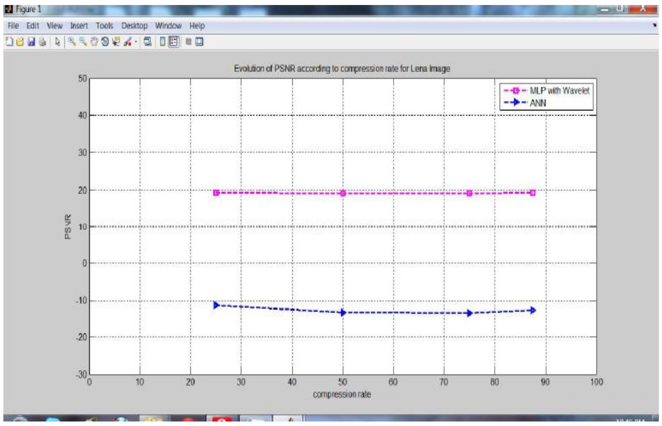

Figure 7: PSNR v/s Compression rate for Lena image

IMAGE COMPRESSION FOR MALAVIYA JI IMAGE

Now figures shown below represent the image compression process first original image have been shown then compressed and reconstructed (decompressed) images are shown along with error image. The error image shows the error between original and reconstructed image.

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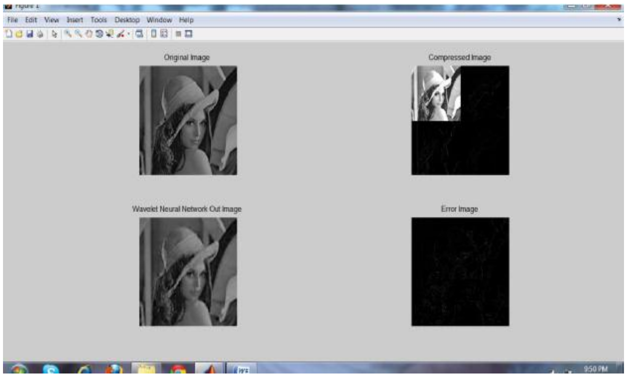

Figure 8: Image compressions by MLP with wavelet coefficients (25% compression)

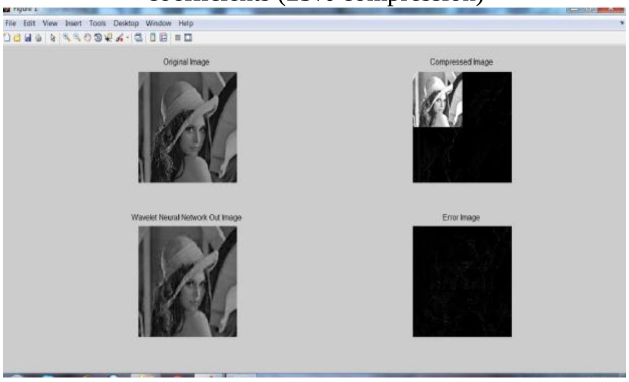

Figure 9: Image compression by MLP (25% compression)

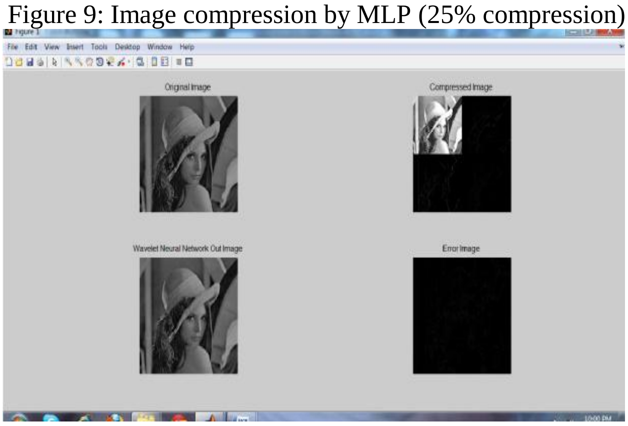

Figure 10: Image compressions by MLP with wavelet coefficients (50 % compression)

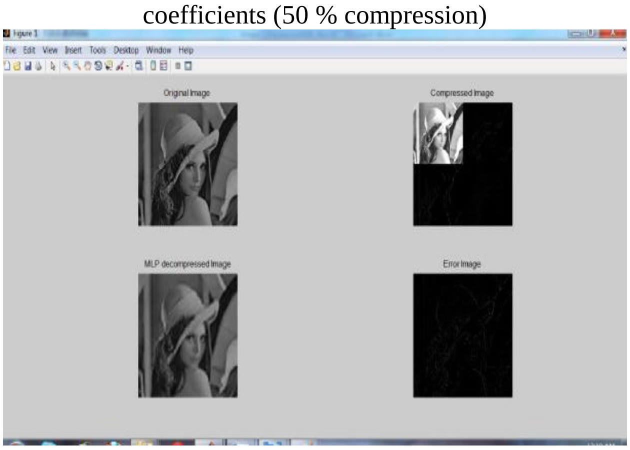

Figure 11: Image compression by MLP (50 % compression)

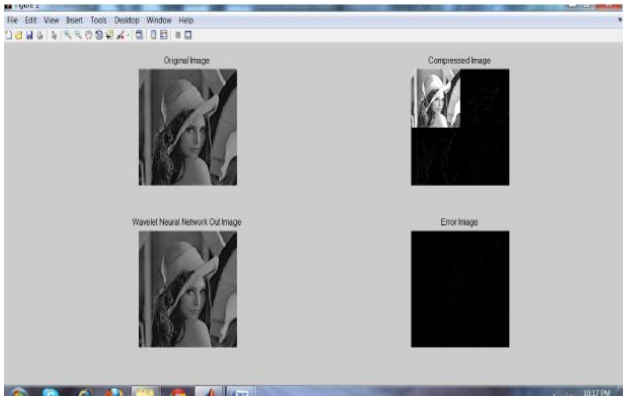

Figure 12: Image compressions by MLP with wavelet coefficients (75% compression)

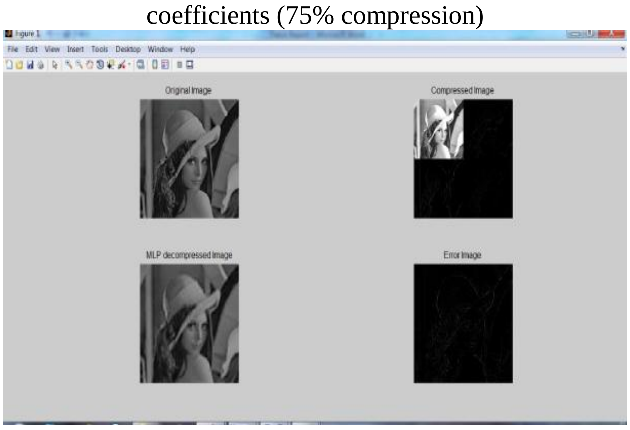

Figure 13: Image compression by MLP (75% compression)

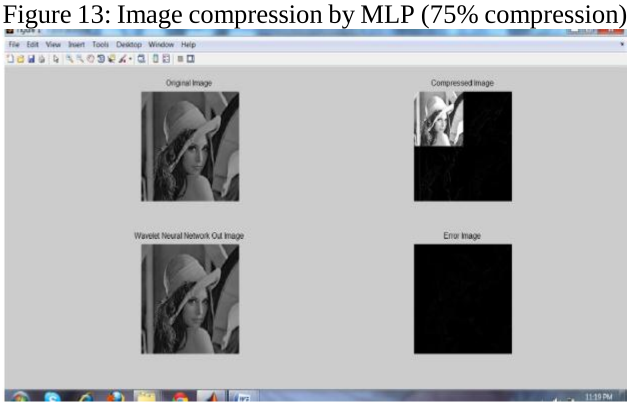

Figure14: Image by MLP with wavelet coefficients (87.5% compression)

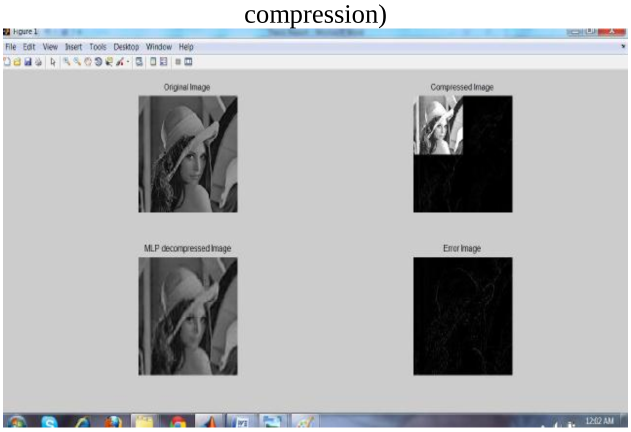

Figure 15: Image by MLP (87.5% compression)

From these results it is concluded that MLP with wavelet coefficients provides better compression as compare to MLP classical approach for Lena image.

VII. CONCLUSION

At first the fundamental theory of artificial neural network (ANN) and wavelet theory with wavelet transformation have reviewed. Then this thesis expresses the training algorithm for multi-layer perceptron (MLP) and multi-layer perceptron with wavelet coefficients. At last this thesis gives number of experimental results. The results include two different kinds of neural networks act on different images under different compression rates. From these different results we get conclusion that, MLP with wavelet coefficients achieve better effect on image compression as compare to MLP (multi-layer perceptron).We have taken three images for our experimental results. These three images have same dimensions and similar learning conditions. The compression results vary for the different images because number of bits that are required to represent an image differs for different images, but all images shows better compression performance when wavelets are used with MLP as compare to classical MLP approach. Our algorithm gives good results for the compression rate up to 87.5% but beyond this limit it gives undesirable results. This algorithm has flexibility in the sense that we can improve compression ratio as per our requirement by increasing the number of hidden neurons. The reconstruction quality can be improved by increasing the iterations. Another positive feedback have been obtained that the PSNR value is good and have very less variation as we are increasing our compression rates from 25% to 87.5%.We can compress any image which is gray in nature, but before apply to this algorithm the normalization of pixels needed. According to our results we can find that the PSNRs are high enough, even we are increasing compression rate. So, if we need higher compression ratio with good reconstruction quality (more than 75% compression ratio) the use of wavelet decomposition with MLP (i.e MLP with wavelet coefficients) provide better result. It comprises the advantages of both ANN and Wavelet for the compression of digital images.

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