Improvement of Classical Wavelet Network over ANN in Image Compression

Gaurav Bajpai, Mr. Pratyush Tripathi

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).**

Index Terms— **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.

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II. LITERATURE REVIEW

Image compression technique involves removal of redundant data, the number of bits required to represent an image is minimized in compression process. Generally, all current images can be classified into either lossless or lossy compression. Lossless compression techniques achieve considerable compression ratio and at the same time the original data retained by the means of coding or inter pixel redundancy removal [3]. At present both these compression techniques lossy (JPEG,JPEG2000) and lossless (JPEG-LS,JPEG-lossless) are adopted in different communication and computer application [4].

Several existing image compression algorithms can actually be implemented by one neural network structural design empowered with different learning algorithm**s.** These are wavelet neural network, fractal neural network, predictive neural networks and cellular neural networks based on wavelet- transforms several neural networks designed for image processing and image representation [5] [6] [7]. When a signal S (t) is approximated by daughter of a mother wavelet h(t), for instance , a neural network structure can be recognize. It is novel neural network model with feed-forward pass and back-forward pass. In this type of network, the activation function is replaced by wavelet basis function. So wavelet networks have the qualities of both neural networks and wavelet transform. Fractal configured neural networks are based on iterated function system (IFS) codes, which represents another example along the direction of developing existing image compression technology in to neural networks [8] [9] .

III. 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.

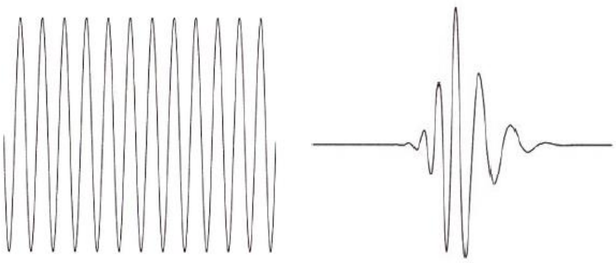

Figure.1: Demonstrations of (a) a Wave and (b) a Wavelet

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 splited. The wavelet packet tree for 3-level decomposition is shown in figure 3.

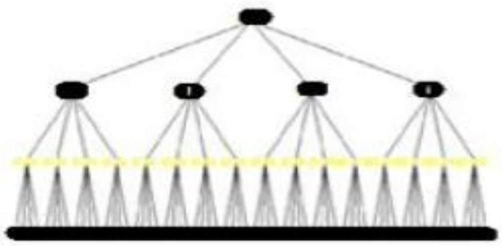

Figure.3: TCP/IP Model

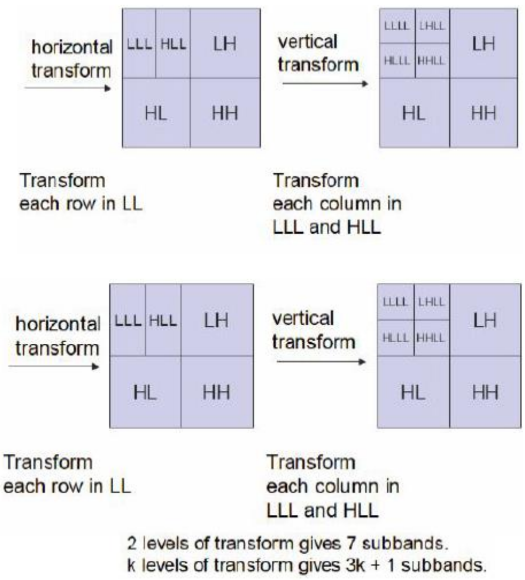

Figure.4: Transformation Process

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. There are number of applications of wavelet transform, also it can be used in different image processing application.

IV. 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.

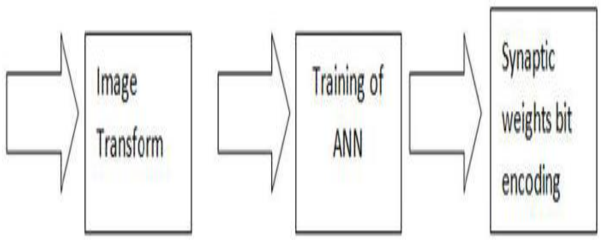

Figure.5: Generic Functional Blocks of Image Compression Algorithm

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 .

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.

V. 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. 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. 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).

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

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

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.

VI. 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. Our network is trained in order to reproduce in output the information given in input. We denote the input bloc by $X=(x_1,\ldots\ldots,x_m)$ and the output of the network by $Y=(y_1,\ldots\ldots, y_m)$. At the end of the training we aim at having Y=X for every block presented to the network.

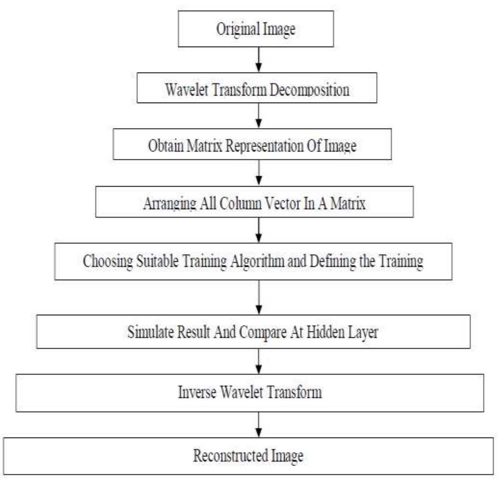

Figure.6: Flow chart for Image Compression by MLP with W T

VII. 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 Malaviya 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.

Table 2: Compression by MLP with wavelet coefficients (Malaviya ji 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 3 Image of Malaviya ji has been taken for image compression process by MLP neural network without wavelet decomposition.

Table 3: Image Compression by MLP Neural Network (Malaviya ji 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 4 is used for the image compression all training parameters and image dimensions are similar for lena image.

Table 4: 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 7 shows comparative PSNR values for Malaviya ji image. From analysis of this figure we get conclusion that MLP with wavelet coefficients gives better PSNR as compare to classical MLP (ANN).

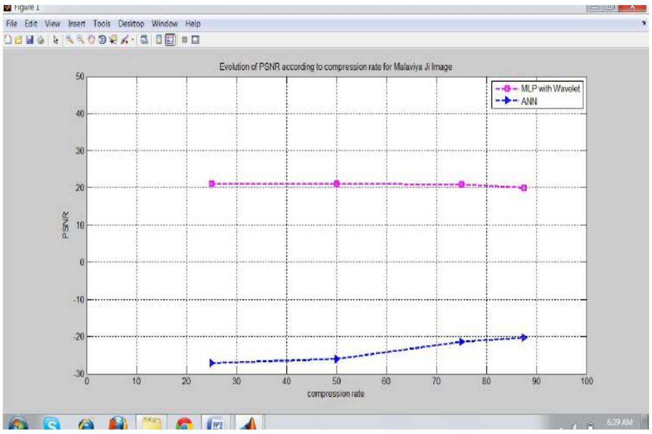

Figure 7: PSNR v/s Compression rate for Malaviya Ji image

Figure 8 shows the PSNR values for Lena image by two approaches and figure 6.3 shows the performances by MLP classical approach and MLP with wavelet coefficients.

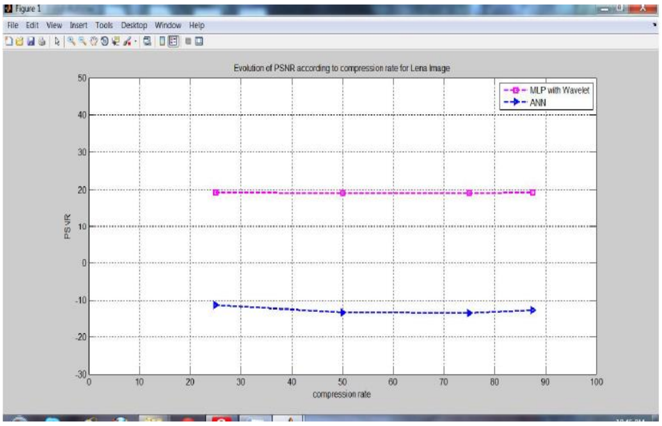

Figure 8: PSNR v/s Compression rate for Lena image

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.

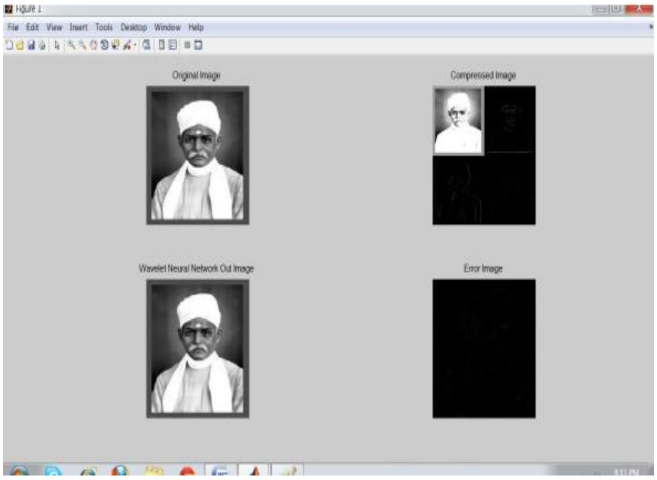

Figure 9: Image compressions by MLP with wavelet coefficients (25% compression)

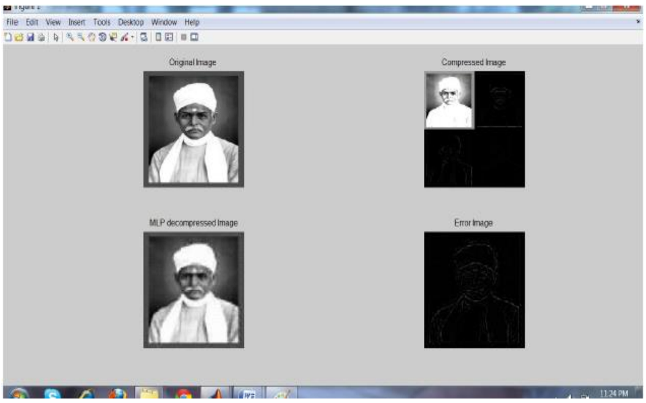

Figure 10: Image compression by MLP (25% compression)

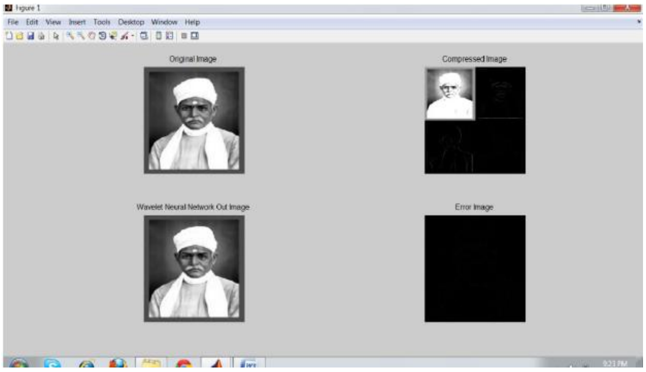

Figure 11: Image compressions by MLP with wavelet coefficients (50 % compression)

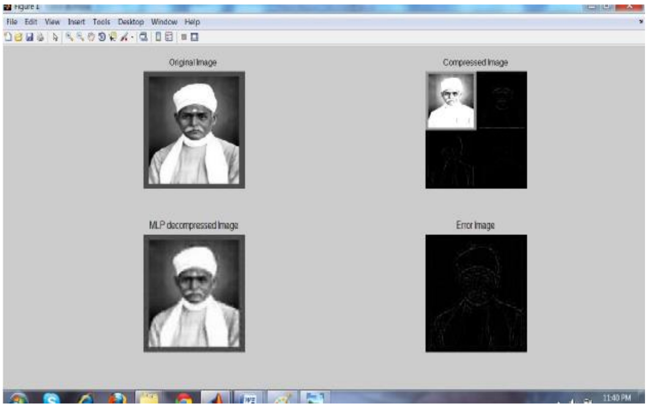

Figure 12: Image compression by MLP (50 % compression)

From figure 12 and 11 indicates that MLP with wavelet coefficients provides better compression performance for 50 % compression rate also.

Figure 13: Image compressions by MLP with wavelet coefficients (75% compression)

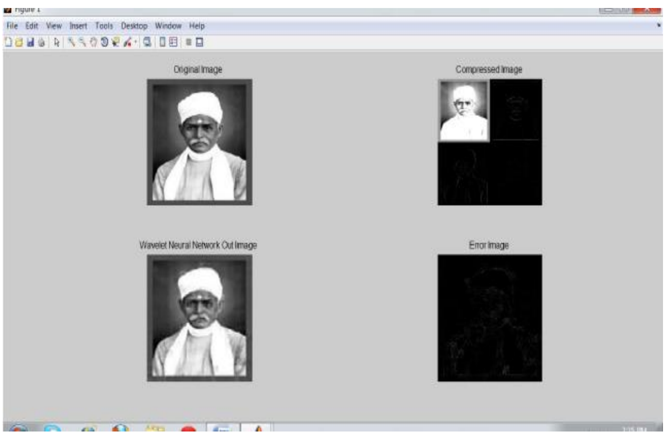

Figure 14: Image compression by MLP (75% compression)

Figure15: Image by MLP with wavelet coefficients (87.5% compression)

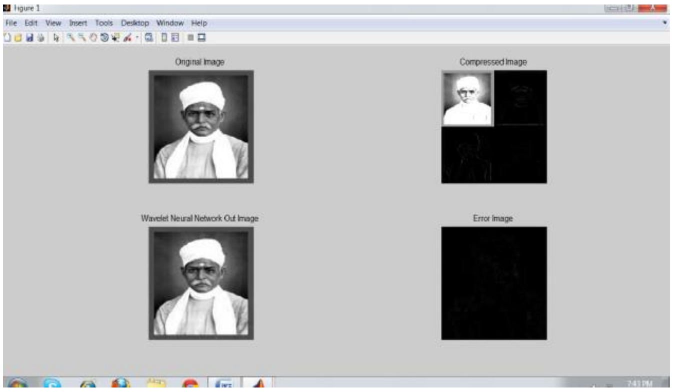

Figure 16: Image by MLP (87.5% compression)

Figures shown above previously indicates that the difference between these two techniques. From these results it is concluded that MLP with wavelet coefficients provides better compression as compare to MLP classical approach for Malaviya ji image.

VIII. 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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