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Codebook Generation using Hierarchical Radial Basis Function Neural Network with Wavelet Transform and Vector Quantization for Better Image Compression

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Abstract: Image compression is the technique of reducing the size of the image file without degrading the quality of the image. The compression in file size permits more images to be stored in theavailable amount of memory space. It also decreases the time needed for images to be uploaded over the Internet or downloaded from it. There are many techniques available in the lossyimage compression, in which wavelet transform based image compression is the best technique. Vector Quantization (VQ) is the most powerful toolfor image compression. One of the major steps in the Vector Quantization is the generation of the code book.In this proposed approach, a popular neural network technique called Hierarchical Radial Basis FunctionNeural Network(HRBFNN) approach is used to generate the code book. A combined approach of image compression based on vector quantization and wavelet transform is proposed using HRBFNN. This approach will be very helpful for medical imaging, criminal investigation where high precision reconstructed image is required. The experimental result shows that the proposed technique provides better PSNR value and also reduces the Mean Square Error value than the modified SOM and RBF.

Keywords: Image Compression, Neural Networks, Vector Quantization (VQ), Wavelet Transform, Radial Basis Function (RBF), Hierarchical Radial Basis Function Neural Network (HRBFNN)

I. INTRODUCTION

DIGITAL image broadcasting needs a huge amount of data and the time taken for the transmission over communication channels is very high. To overcome this difficulty, a many techniques to compress the amount of data for representing a digital image have been formulated to make its storage and transmission cost-effective. One of the most important complexities faced in image processing is the enormous amount of data used to store an image. Thus, there is a need to reduce the storage data volume. Image compression [8]approaches intends to eliminate the redundancy present in data in a way, which should not affect the image reconstruction. So, it is essential to find the statistical properties of the image to propose a suitable image compression technique. Image compression aids in decreasing the size in bytes of a digital image without degrading the quality of the image to an undesirable level [10]. There are two classifications in image compression: lossless and lossy compression. In recent years several lossy image compression techniques have been developed.

The recent development in the area of image compression is the Wavelet-based techniques. It recommends multi-resolution facility that does not exist in any of the other available methods. The wavelet transform [5] investigates an image signal in time and scale. Wavelet-based image compression provides better enhancements in picture quality even at higher compression ratios. It is an established transform [11] used for anumber of image compression standards in lossy compression methods.

The objective of Vector quantization is to encode the data from animage source, with some loss, with the intention that the best reproduction is attained. Vector quantization (VQ) technique provides more compression than scalar quantization. Vector quantization is one of the lossy compression techniques which can decrease the amount of data in the image.

The vital step in the vector quantization technique is that the Hierarchical Radial Basis FunctionNeural Network (HRBFNN) approach [17] is used for the generation of code book. It uses comparativelylesser number of nearby tuned units and it is basically adaptive in nature. RBFs are appropriate for image compression and classification [7, 15].

In this proposed approach, a combined approach of image compression, based on the wavelet transform [1] [2] and Vector quantization [3] is presented. This proposed method gives better results which are commonly applicable to any images. This proposed method of image compression is applicable to those areas of digital images where high precision reconstructed image is required like criminal investigations, medical imaging, etc.

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II. RELATED WORKS

Image compression is one of the major image processing techniques which plays significant role in signal processing and communication systems. Image compression mainly helps to reduce the storage space and also assist in reducing transmission bandwidth and therefore also the cost. Neural network techniques have established to be more consistent, robust and programmable and provide better performance when compared againsttraditionalapproaches. Ramanaiah and Raj [1] developed a new structural design for hardware implementation of neural network based image compression optimizing area, power and speed as particular to Application-Specific Integrated Circuit (ASIC) implementation and comparison with Field-Programmable Gate Array (FPGA).

A new image compression technique is presented by Abidi et al., [2]by using hybrid neural networks that combine two different learning networks, the Auto-Associative Multi-Layer Perceptron (AMLP) and the Self-Organizing Feature Map (SOFM). The neural networks concurrentlycarry out dimensionality reduction with the AMLP and classification with the SOFM to compress image data. Two hybrid neural networks forming parallel and serial architectures are investigated through hypothetical analysis and computer simulation. The parallel structure network considerably decreases the dimensionality of input pattern vectors by mapping them to several hidden layers of the AMLP chosen by winner-take-all units of the SOFM. The serial structure network classifies the input pattern vectors into different classes representing prototype vectors. Both the serial and parallel structures are mixtures of the AMLP and SOFM networks.

Cao Kai et al., in [3] proposed RBF [12, 14] neural network supported classification of remote sensing images based on TM/ETM+ in Nanjing. The categorization of remote sensing images is increasingly important along with the growth of society and economy. According to the defects general classification methods have, such as the accuracy, the efficiency etc, the design of `robust' classification system based on a Gaussian RBF [13] neural Network is used in this article to classify the TM/ETM+ image in Nanjing. The option of this neural network model is reasonable by some of its particular properties, i.e., local learning, quick training stage, capacity to identify when an input pattern has fallen into a region of the input space without training data, and ability to offer high classification accuracies on remote sensing images. For appraising the precision of the model in brief, over 1000 examples are chosen in this research, and the result shows that in the whole research area there is obvious improvement (86.6-89.7%) between MLC and this model. Besides, it is also better than the MLP NN model (87.9-89.7%). The result indicates that the model of RBF [16] NN is a good approach for the classification of remote sensing in this area based on TM/ETM+. Of course, there are also many aspects need to be revised and improved in the future research such as the accuracy and for other data source.

Kwang-Baek Kim et al., [4] puts forth a novel vector quantization approach for image compression using wavelet transform and enhanced SOM algorithm for medical image compression. The improved self-organizing technique is presented to enhance the defects of SOM algorithm, which, at first, reflects the error between the winner node and the input vector to the weight alteration by using the frequency of the winner node. Secondly, it adjusts the weight in proportion to the weight change at hand and the previous weight change as well. To reduce the blocking consequence and enhance the resolution, by using wavelet transform the vectors are constructed and applied the modified SOM algorithm to them.

III. METHODOLOGY

The proposed methodology deals with the combination of wavelet and vector quantization for image compression. The image compression technique proposed here is applicable to those areas of digital images where high precision reconstructed image is required like criminal investigations, medical imaging, etc., The image of certain quality is need to be transmitted by user in order to retrieve the original image without any loss in quality. This method is tested on gray scale images, but it can be easily extended to color images by processing the three color matrices separately.

Vector quantization is the most existing powerful tool for digital image compression. A vector quantizer (VQ) is defined as a mapping Q of K dimensional Euclidean space R^K in to a finite subset Y of R^K shown in the following equation: $Q: R^K \rightarrow Y$, where $Y = [\overline{y}_i;$ for $i = 1, 2, 3, \cdots, N]$, is the set of reproduction vectors and is called a vector quantizer codebook, and N is the number of vectors in Y. For generating codebook there exist different algorithms, like Linde, Buzo and Gray (LBG) algorithm, Self Organizing Feature Map (SOFM), Radial Basis Function Neural Network(RBFNN), etc. Hierarchical RBFNN[17] algorithm is used in the proposed method. The schematic diagram of vector quantizer is shown in Fig. 1.

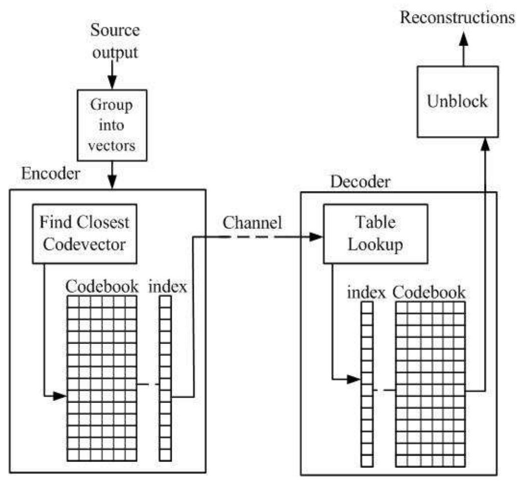

Fig. 1- Schematic Explanation of Vector Quantization

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Radial Basis Function has been embedded into a two-layer feed forward neural network. Such a network comprises of a set of inputs and a set of outputs. A hidden unit is the processing unit which exists between the input node and output node. Each of them implements with a radial basis function. The network inputs correspond tothe data samples at certain past time-laps, whereas the network has only one output denoting a signal value. In the generation of code book, the inputs correspond to feature entries, while each output corresponds to a class. The hidden units correspond to subclasses. Fig.2 shows the detailed process of RBF [13] Neural Network.

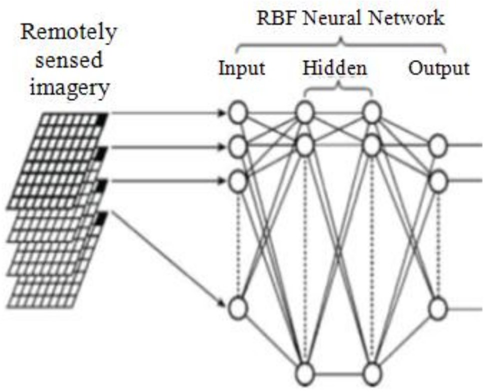

Fig.2- Schematic Explanation of the RBF

A. Hierarchical RBFNN Model

The function set F and terminal instruction set $T$are exploited for generating a Hierarchical RBF model are describedas $S = F \cup T = \{+_2, +_3, \dots, +_N\} \cup \{x_1, \dots, x_n\}$,where $+_i(i = 2,3, \dots, N)$represent non-leaf nodes' instructions and taking i arguments. $x_1, x_2, \dots, x_n$represents leaf nodes' instructions and taking no other arguments.The output of a non-leaf node is computed as a RBF neural network model (seeFig.2). Based on this, the instruction $+_i$ is also called a basis functionoperator with i inputs.

The basis function operator is can be given as

$$y = \sum_{i=1}^{m} \omega_i \psi_i(x; \theta) \tag{1}$$

$$\psi_i(x; \theta) = \prod_{j=1}^{n} \exp\left(-\frac{\|x_j - b_j\|^2}{a_j^2}\right) \tag{2}$$

and the number of basis functions exploited in hidden layer is similar with the numberof inputs, that is, $m = n$.

In the codebook generation processusing HRBFNN, when a non-terminal instruction, i.e.,$+_i(i = 2, 3, 4, \dots, N)$ is chosen, i real values are arbitrarilyproduced and usedfor representing the connection strength between the node $+_i$ and its children.Additionally, $2 \times n^2$modifiable parameters a_i and b_i are arbitrarilyproducedasGaussian radial basis function parameters. The output of the node $+_i$ can becalculated by using (1). The entire output of HRBFNN can be computed from left to right by depth-first method, recursively.

A 3-level 2-D DWT is firstly applied to the test image in the proposed method (i.e. the image to be compressed) and then VQ is used to different subbands for compression. Ten subbands are created after the application of 3-level 2-D DWT using SOFM, and thus all these codebooks are used for this all subbands individually. 3-level 2-D DWT is applied to images because the low frequency subband, which contains the maximum energy content of the original image, becomes of smaller size so that in case of vector quantization this subband is treated with a codebook size of 7-bits only. These vector indices are processed using Huffman coding [6] for improving the compression ratio of the transmitted data. The entire compression process of this work is segmented into three steps, a) Codebook generation, b) Encoding of the original image and c) Decoding of the image. The proposed method totally uses twenty codebooks, ten codebooks for original image reconstruction and other ten are used to reconstruct the error images.

B. Codebook Generation

In the codebook generation step (i.e. the training stage) four different standard images (namely Lena, Couple, Frog, and Baboon) are used to generate ten original codebooks and also ten error codebooks are generated in this step. 3-level 2-D DWT is applied to each of these original training images in all ten codebook generation step. These generate ten wavelet sub bands for each of the original images. Similar sub bands of each image are then combined to form a single frame and this frame is then considered as a new image. Therefore there are ten separate images available at this stage. Using these ten separate images, ten separate codebooks are generated using HRBFNN. Then in the error codebook creation step, using these generated ten codebooks ten sub band images are vector quantized and then these sub bands are reconstructed images are vector quantized and then these sub bands are reconstructed. The obtained ten reconstructed images are compared with the real ten images in the wavelet domain. The error of this comparison was taken to create the error codebooks. In this case Radial Basis Function neural network is used.

C. Encoding

In this step, 3-level 2-D DWT is applied to the test image (i.e. the image to be compressed). The detailed schematic diagram of the encoder is shown in Fig.3.Then each of these existing ten subbands is vector quantized using the original codebooks, so that separate codebook is used for different sub bands. The codebook indices of this VQ process are transmitted to the decoder after Huffman coding. At the encoder end image is reconstructed using the transmitted image indices and peak signal to noise ratio (PSNR) of this transmitted image is calculated to test the image quality. If the calculated PSNR is higher or equal to the desired PSNR then the process ends, otherwise the iterative error correction method is executed.

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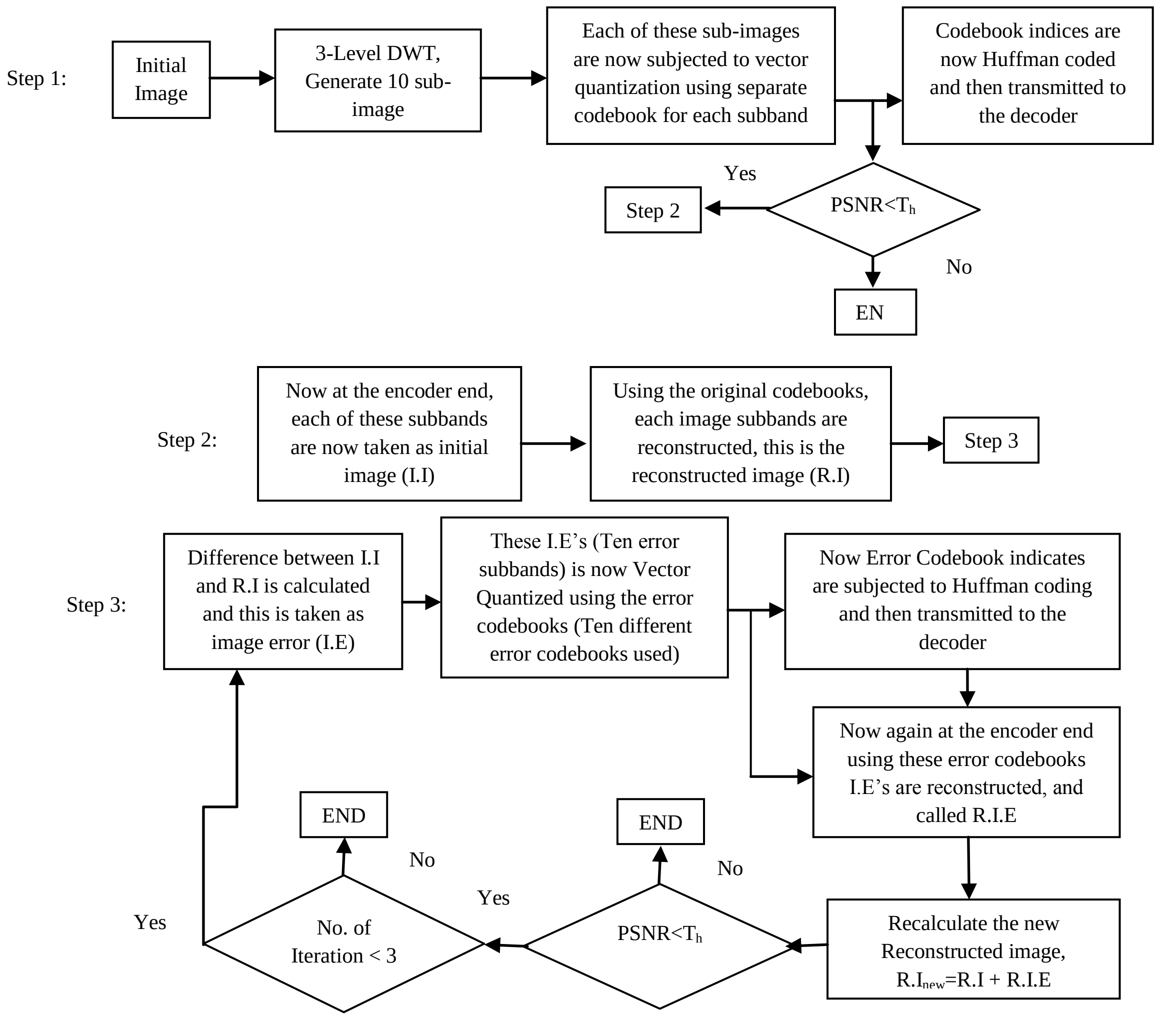

Fig.3- Detailed Schematic Diagram of the Encoder

In this iterative error correction method, error between the original image and the reconstructed image (I.E), is evaluated in the wavelet domain. Vector quantization using the accessible error codebooks is then applied to these subband errors between the original and reconstructed image (R.I.). Error codebook indices are also transmitted to the decoder after Huffman coding. The transmitted error image is reconstructed from the transmitted error codebook indices (at the encoder or transmission end). Then the reconstructed image errors (R.I.E) are added (algebraically) to the previously reconstructed image, and thus R.I. is modified. This iterative error correction process is continued till the PSNR of the modified reconstructed image is better than or equal to the preferred PSNR value is reached.

D. Decoding

In the decoding stage the decoder first receives the Huffman coded bit-stream of the VQ indices equivalent to the original wavelet coefficients from the channel. The codebook indices of the different wavelet sub bands are recreated.

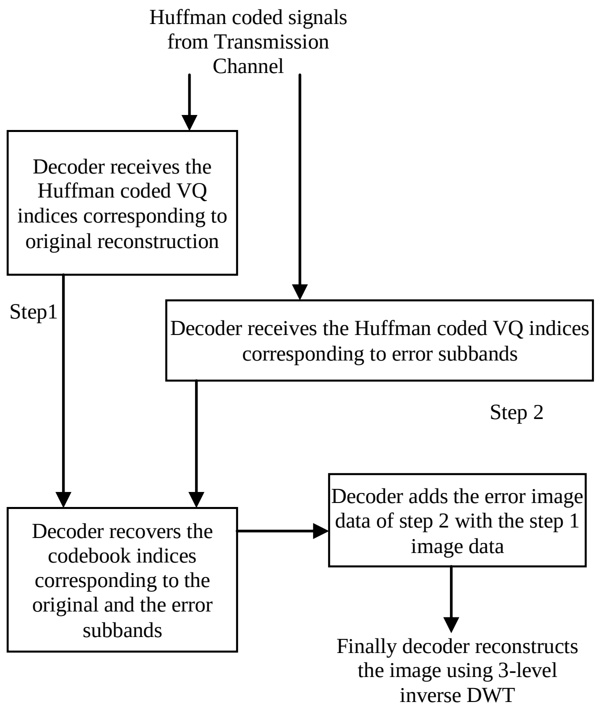

Fig.4- Detailed Schematic Diagram of the Decoder

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At the initial stage the receiver receives the reconstructed image and consecutively in the next steps the receiver receives image errors. The receiver subsequently adds the received errors of each sub band. In the final step the image is reconstructed using 3-level inverse 2-D DWT.

IV. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed approach of image compression using HRBFNNbased vector quantization,4 standard imagesare considered. The work is implemented using MATLAB. The evaluation of the proposed approach in image compression was performed based on the followingfactors,

The PSNR is most familiarly used as a measure of quality of reconstruction of lossy image compression,

$$PSNR = 10\ \log_{10}\left[\frac{255^2}{MSE}\right](db)$$

The MSE (Mean Square Error) is the cumulative squared error among the compressed and the original image,

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

where *M* and *N* are the number of rows and columns in the input images, respectively.

Formula for calculating bpp (bits per pixel) is given in the following formula,

$$bpp = \frac{Encoded\ number\ of\ bits}{Number\ of\ pixels}$$

The experimental results that evaluate the performance of the proposed approach by comparing it with the modified self-organizing map and RBF are tabulated. Table 1 shows the experimental results applied for 4 standard images.

TABLE I: PSNR AND MSEVALUE COMPARISON

Standard Images	PSNR (dB)			MSE		
	Modified SOM	RBF	HRBFNN	Modified SOM	RBF	HRBFNN
Lena	36.25	42.36	45.67	7.921	5.256	3.264
Camera man	32.25	39.56	42.46	6.512	5.014	4.859
Boat	33.45	40.54	41.97	8.256	6.729	5.428
Baboon	34.25	41.27	44.32	7.653	5.105	3.215

TABLE II: BPP RESULTED FOR STANDARD IMAGES

Standard Images	Modified SOM	RBF	HRBFNN
Lena	4.69	4.95	5.36
Camera man	4.21	4.52	5.24
Boat	4.45	4.82	5.18
Baboon	4.51	4.76	5.04

TABLE III: COMPARISON OF COMPRESSION RATIO

Standard Images	Modified SOM	RBF	HRBFNN
Lena	35	41	56
Camera man	28	35	48
Boat	29	37	44
Baboon	31	38	40

The comparison of HRBFNNwith RBF and Modified SOFM based on PSNR Value and MSE value is shown in Fig 5. From the Fig. 5(a) it is very clear that the proposed approach based on HRBFNNhas higher PSNR value than the Modified SOM and RBF technique. From the Fig. 5(b), it is observed that the proposed approach has very low MSE value when compared to the Modified SOFM and RBF technique. Fig. 5(c) shows the resulted bits per pixel (bpp) for the proposed and conventional approach. It can be seen that the proposed approach resulted in better bpp value ie., higher than the conventional technique. Also, the proposed approach results in better compression ratio than the conventional technique. It is represented in fig. 5(d).

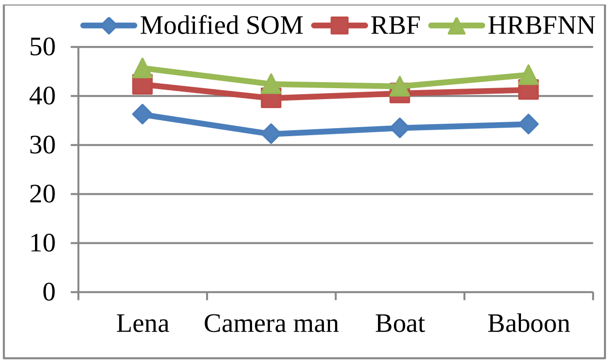

Fig. 5 (a): Comparison of PSNR Value

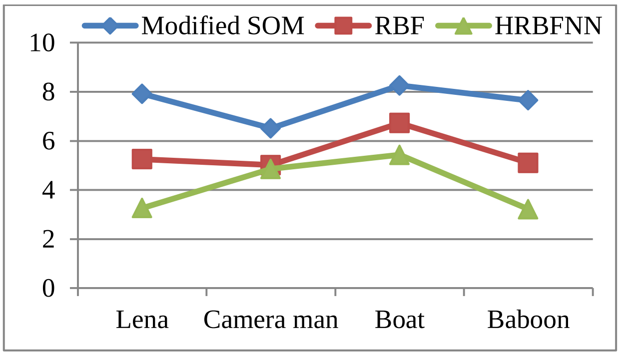

Fig. 5 (b): Comparison of MSE Value

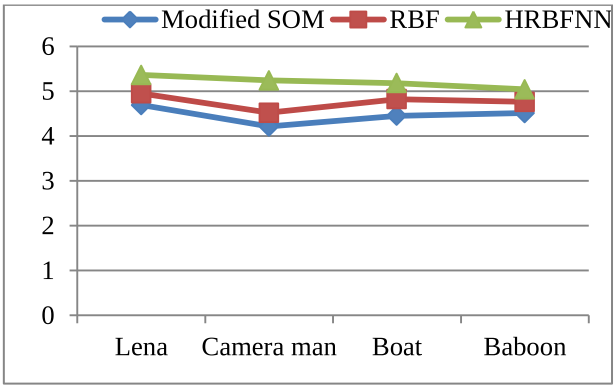

Fig. 5 (c): Comparison of BPP Value

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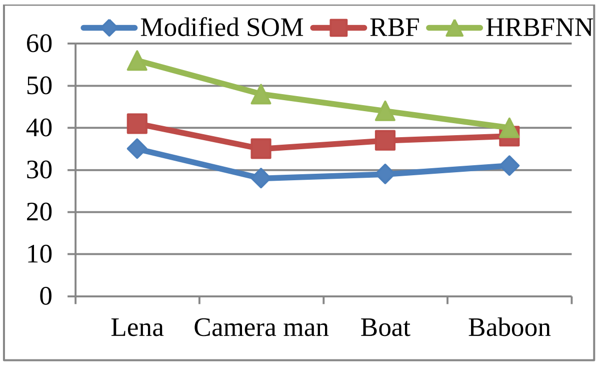


Fig. 5 (d): Comparison of Compression Ratio

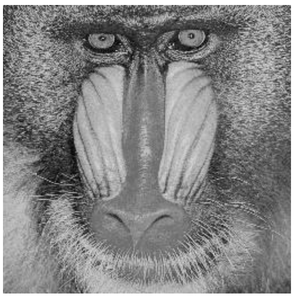
The output of the proposed approach is shown in the Fig. 6. The resultant image shows that the output of the proposed approach yields high quality compressed image with betterPSNR value and very low MSE. Thus, it is confirmed that the proposed approach gives good quality compressed images compared to the existing techniques.

(a) Lena Image

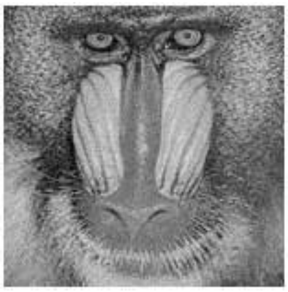
(b) Resultant Image by Proposed Approach

(c) Cameraman Image

(d) Resultant Image by Proposed Approach



(e) Baboon Image



(f) Resultant Image by Proposed approach

Fig. 6: Compressed Imagesusing Proposed Approach

V. CONCLUSION

Radial Basis Function is a popular neural network method and has been widely for many techniques like image classification and compression. In this approach, a technique for image compression as well as decompression is proposed using wavelet transform and vector quantization. This proposed approach introduced the use of HRBFNNfor Vector Quantization (VQ) codebook generation. Many limitations in the existingapproach are solvedusing the HRBFNNmethod. The quality of the compressed image has increased because of the proposed HRBFNNbased image compression using vector quantization and wavelet transform. To evaluate the performance of HRBFNNbased vector quantization for image compression some standard image set are considered. The experimental results confirmed that the compression ratio of the proposed approach is high when comparing with other conventional image compression techniques. The future work may concentrate on the reduction of the number of iterations effectively.

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