Learning based Coding for Medical Image Compression

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***Abstract*—The area of Image processing has emerged with different coding approaches, and applications which are ranging from fundamental image compression model to high quality applications. The advancement of image processing, has given the advantage of automation in various image coding applications, among which medical image processing is one of the prime area. Medical diagnosis has always remained a time taking and sensitive approach for accurate medical treatment. Towards improving these issues, automation systems have been developed. In the process of automation, the images are processed and passed to a remote processing unit for processing and decision making. It is observed that, images are coded for compression to minimize the processing and computational overhead. However, the issue of compressing data over accuracy always remains a challenge. Thus, for an optimization in image compression, there is a need for compression through the reduction of non-relevant coefficients in medical images. The proposed image compression model helped in developing a coding technique to attain accurate compression by retaining image precision with lower computational overhead in clinical image coding. Towards making the image compression more efficient, this research work introduces an approach of image compression based on learning coding. This research achieves superior results in terms of Compression rate, Encoding time, Decoding time, Total processing time and Peak signal-to-noise ratio (PSNR).**

Keywords—Image compression; medical image processing; neural network; learning based coding; peak signal-to-noise ratio

I. Introduction

Image processing and its related applications has ascended in different levels of coding approach which are stretching from rudimentary image compression model to astronomical data processing and clinical image processing, considered as high end applications. For example in telemedicine, sending and receiving images by overcoming the bandwidth limitation is a major problem faced by the hospitals nowadays. In this situation, an engineer’s main aim is to develop new methods using which the transmission of multiple images with lower bitrate can be made easy. It should also need to achieve a good image quality at receiver side in image processing applications like progressive image encoding, multimedia transmitting, image browsing etc. Since, the images are of huge features, coding without the loss of information into lower bit rates may intern results to the degradation in the quality of image under retrieval. Along with this, encoding in the noise environment becomes too much complex and results in the heavier degradation in the quality of image. Several approaches were proposed in the past for encoding and compression of images, but none of them found to be efficient under specific environments.

All the earlier proposed approaches give efficient results if the systems have high bandwidth and are failed to perform under systems with low bandwidth which becomes one of the limitation. This problem can be overcome if the encoding technique is in a way such that the compressed bit rate will be compatible with low bit rate. To achieve this objective the image coding approaches has to compress the image effectively to the required data rate. Various image processing oriented services [1] requires higher accuracy with high processing data rate. In clinical image processing every image need to be processed for compression before it was streamed to remote place via a channel for further processing. There exists many image compression techniques but computational overhead and the lower retrieval accuracy are two major problems in such type of applications. The proposed work is undertaken to overcome these problems especially in clinical image processing and fill research gap for future researchers.

This research work objective was to develop an effective image coding system with less computational overhead and also achieves increased retrieval accuracy in medical image compression. Towards making the image compression more efficient, this work introduces a modified technique for image compression using neural networks.

II. Literature Review

Image compression is an evolving area in multi-disciplinary applications. This arena is growing exponentially, due to its numerous applications in digital imaging and encoding. Various applications need high effective image compression. In variety of applications, medical image processing is a rapidly evolving area. In case of medical image processing, medical samples are moved from one location to another location through a channel. In such transmissions, the practitioner needs exact information to perceive a perfect diagnosis results.

In earlier, various compression approaches are developed to perform medical image compression. The earlier developed most popular image compression techniques are Embedded Block Coding with Optimized Truncation (EBCOT) [2], Set Partitioning in Hierarchical Trees (SPIHT) [3], Joint Photographic Experts Group 2000 (JPEG-2000) [4], JPEG [5] and lifting scheme based compression techniques [6]. All the earlier compression techniques are classified as lossless and lossy. In lossy compression [7] the probability of accurate information retrieval at receiver side is very less which results in lower PSNR. Basically the faster encoding applications require this type of compression. Lossless compression is preferred in the scenarios where the information loss is not tolerable. Lossless compression method [8] is a scheme that permits the accurate data reconstruction from the compressed data at the receiver side. In [9] a lossless compression scheme is proposed based on the wavelet transform and an adaptive prediction. This compression scheme aimed to achieve maximum compression ratio. A lifting based lossless compression scheme is also proposed in [10] to attain a reduced information loss in the reconstructed image.

However these lossless and lossy image compression techniques become invalid in the case of medical images. In order to achieve a faster encoding and an increased accuracy, the image compression is carried out with the help of Artificial Intelligence (AI) techniques. “Artificial Neural Network (ANN)” [11, 12] is one of the most popular among various AI techniques through which there will be a superior performance in medical image compression when dealing with incomplete or noisy data. Though the ANN based approaches are accurate, the computational overhead is very high. A NN based medical image compression technique was proposed by Lanzarini et.al, [13] in which the compression and decompression ratio is fixed at 8:1 and the loss percentage is 2. This approach created back propagation network for the calculations of correspondent patterns of input and outputs.

Similarly, “Feed Forward Network (FFN)” based back propagation algorithm was proposed in [14]. This approach performs image compression by evaluating the activation values and coupling weights of hidden layer neurons. This method is observed as a better approach compared to the JPEG through the obtained PSNR values.

Recently, many more approaches were proposed by combining the Neural Networks (NN) with various techniques [15-17] to achieve an increased compression ratio. But, none of these approaches has obtained the required optimal compression ratio. In [18], a new image compression is developed by combining the bipolar coding with NN. Here the main purpose of bipolar coding is to achieve maximum similarity between the pixel values of the original and reconstructed image. The decimal values of image are converted into the equivalent binary code words through bipolar coding. This approach achieved an efficient compression ratio along with quality of image. A similar approach is developed in [19] for Genetic Algorithm (GA) with NN. The main focus of this method is on GA through which the small data is classified and mapped.

To achieve a faster encoding, a multilayer perceptron (MLP) algorithm based NN approach is developed by Gaidhane et al., in [20]. In this approach, the information which is below the threshold level is replaced by zero or removed to achieve the faster encoding performance. Thus the quality of image reconstructed at received side is observed to be poor. A similar approach was developed in [21, 23], named as “Vector Quantization” by which the generation of code vectors is takes place using the “self-organizing feature map” concept. Then the block set attached with the code vectors are designed by cubic surface to achieve an efficient perceptual fidelity of the decompressed images. A similar method is proposed by Allaf [22] based on NN for medical image compression. From the obtained results of convergence speed, PSNR and compression ratio, the proposed approach is observed to be optimal approach.

The Region(s) of interest (ROI) [24] methodology is used to achieve high compression ratios. In order to meet the requirements of less storage and minimum encoding time for medical imaging applications [25] and video related applications by preserving the diagnostic features in regions(s) of interest; the concept of heterogeneous (multiple) quality constraints are mostly used and give attractive results.

In the area of clinical image processing, the information loss is not accepted strictly due to the compact coding, because the lossy compression may removes some of the important information required for diagnosis, and also adds an extra artifacts which may give wrong diagnosis results [26]. Thus, for medical image processing applications generally lossless compression is preferred, because it results to more accurate diagnosis. The standard image compression techniques such as Discrete Wavelet Transform (DWT) based compression [2] are even not able to reconstruct the entire image because of the rounding process involved to round of the floating point values into integers.

ANN is a system modeled very loosely on the brain of human. The filed continues with so many names such as neuro computing, connectionism, machine learning system, parallel processing system, natural intelligent processing system and ANN. It is appropriate for special hardware or software in an attempt to simulate the multiple layers of neurons that is the normal processing elements. Connectivity to a variety of modules which represent the strengths of each neuron is linked to some of its neighbors. Neural networks with their extraordinary capability to derive meaning from complex or unclear data, identify patterns realized either humans or other computer techniques used to detect trends that are too complex. A trained NN can be treated as an “expert” who can give correct information based on the information given it for analysis. Many image compression algorithms [27-36] were proposed in the past but given the new circumstances, to provide estimates of the experts, the interest and the questions "what" can be used to answer and hence this research work is undertaken.

A. Advantages to Neural Network Coding

Adaptive learning: An ANN has ability to learn how to perform the tasks given based on the information provided for raining or starting experience.

Self-Organization: An ability to organize the information representation, received while learning process.

Real Time Operation: An ANN has a capability of parallel processing and the specialized hardware devices are manufactured and designed by taking the advantage of capability of ANN.

Fault Tolerance via Redundant Information Coding: ANN has the capability to retain even under the destruction partially or majorly.

This research developed a new learning based coding for proper coefficient selection such that the system accuracy precision will not be reduced. It is observed that in image compression, there are pixels in the image region which are less significant in representation, and the elimination of such coefficient will not affect much to the visual quality. This learning based coding will select such coefficient so as to minimize the number of coding coefficient achieving higher compression rate.

III. Research Methodology

In this work, a new Artificial Intelligence based image compression approach is developed as shown in Fig. 1 using the neural network concept.

A. *Proposed Image Compression Model*

Pre-processing Unit: The pre-processing unit read the medical image sample and acquires the intensities of grey pixels for further processing. These intensities are the output of this unit. The obtained grey intensities of pixels are processed as array for further decomposition unit.

Spectral Decomposition unit: This decomposition unit takes the array of gray intensities as inputs and extracts their multi-resolution features as outputs. These outputs are obtained through a spectral decomposition in a pyramidal fashion. This decomposition is carried out through a recursive process of low pass and high pass filters. The entire process of decomposition is termed as DWT.

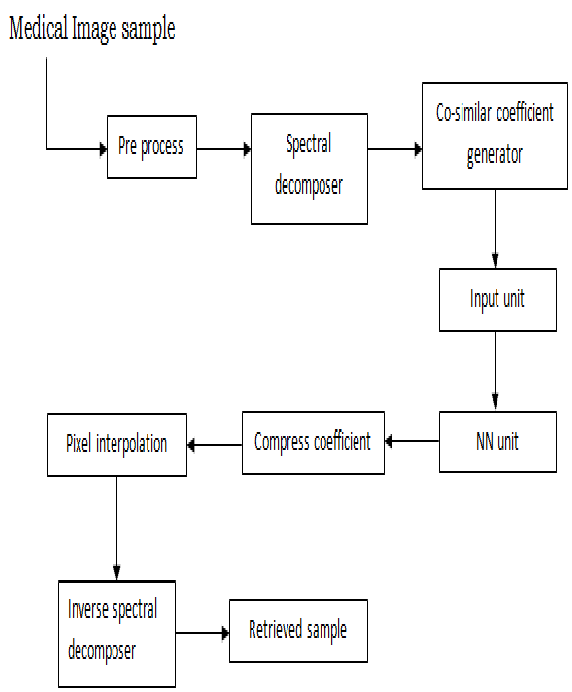


Fig. 1. Step by Step Representation of Proposed Image Compression Model.

Co-similar Coefficient Generator Unit: After obtaining the spectral coefficients from the decomposition unit, they are processed to extract co-similar coefficients. The spectral coefficients which exhibit similar properties are paired. These coefficients are termed as redundant coefficients. This is considered as a first level compression in which there is reduction of redundant information from the image. Further a NN is modeled for the obtained co-similar coefficients.

Input Unit: This unit considers the selected co-similar coefficients as inputs, normalizes them and then passed to neural network. The coefficients are extracted through column wise and then normalize to highest pixel value.

NN Unit: A matlab command ‘newff’ of matlab tool is used to realize this feedforward neural network (FF-NN) unit. This NN unit creates a FF-NN by extracting the min-max value for a given input coefficients through the least average learning algorithm. A sigmoid kernel functions for the creation of this network unit. This unit is created with a network coverage having an error of 0.1 and 50 epochs. The coefficient values are trained through this network and create a FF-NN.

Compress Coefficient unit: Further this compress coefficient unit is created to store the coded coefficients obtained after the feed forward neural network. This buffer is formulated through an array logic in which the coded coefficients are stored for further usage.

Pixel Interpolation unit: This unit is created to reconstruct the compressed image into its original size through interpolation logic. After obtaining interpolated coefficients, they are rearranged according to their order acquired from the encoder side.

Inverse Spectral Decomposition unit: The interpolated coefficients obtained from the above units are processed back to achieve its multi-resolution information through a successive low pass and high pass filters. The obtained recursive result is given as input for next level to reconstruct further resolution information. This entire process of inverse spectral decomposition is termed as inverse Discrete Wavelet transform (IDWT). The final output of this unit is a decompressed image file.

IV. Experimental Results

This section gives the comprehensive details about the evaluation and performance of the developed compression approach. Medical images of size 512 × 512 pixels have been taken for experimental purpose. Simulation results are obtained using Matlab software along with Neural Network toolbox to encode Medical images of size 512 × 512 at a rate of 0.25 bit per pixel. The experimental results are shown below. Fig. 2 presents a visual comparison for Encoding of given medial test image and the retrieved image under normal conditions.

The evaluation and performance of developed NN coding is measured through parameters such Compression Rate (CR), Encoding Time (ET), Decoding Time (DT), Total Time (TT) for processing and Peak Signal to Noise Ratio (PSNR) and compared with the existing JPEG coding.

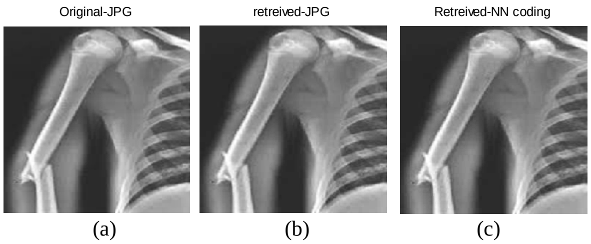


Fig. 2. (a) Original Image, (b) Retrieved Image after JPEG Coding (c) Retrieved Image after NN Coding.

The intermediate results obtained during the evaluation of NN coding on the test medical sample is shown in the below Fig. 3, Fig. 4, Fig. 5 and Fig. 6.

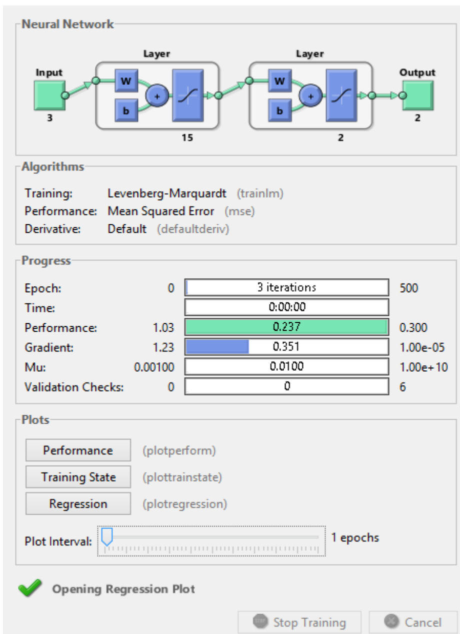


Fig. 3. Neural Network Training Tool (NN-Tool).

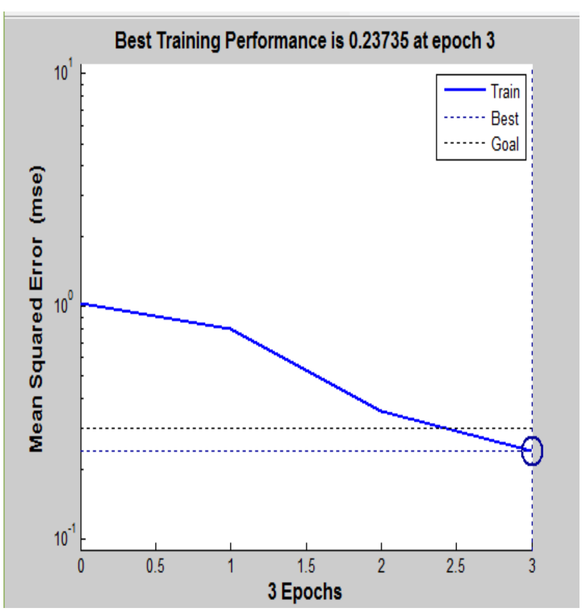


Fig. 4. Best Training Performance Curve.

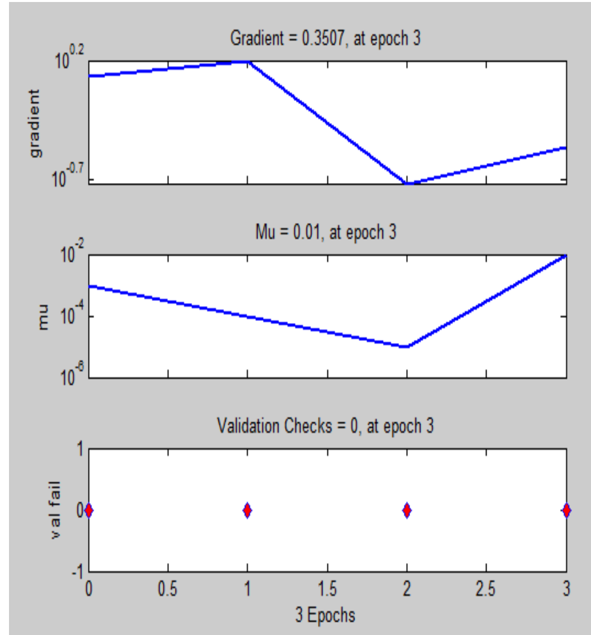


Fig. 5. Training State Curve.

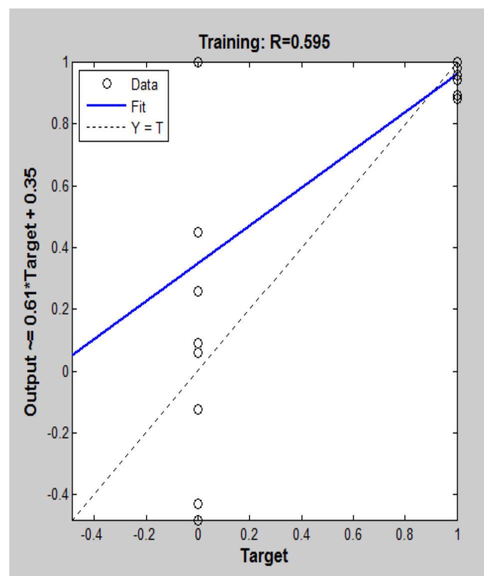


Fig. 6. Regression Curve.

The experimental results for the above test image sample in comparison with the earlier JPEG coding are shown in Table I.

In a similar, manner more samples are given for testing and the obtained results are shown below in Table II.

TABLE I. EVALUATION METRICS

Metric	**JPEG-coding**	**NN-coding**
Compression Rate (Bpp)	1.25	2.8234
Encoding Time Taken (sec)	5.125	6.8438
decoding Time Taken (sec)	9.0625	2.5469
Total processing Time Taken (sec)	14.1875	9.3906
PSNR (dB)	40.2530	50.2530

TABLE II. EVALUATION METRICS

Metric	Sample-1		Sample-2		Sample-3	
	JPEG	***NN***	***JPEG***	***NN***	***JPEG***	***NN***
Compression Rate	2.015	3.493	1.203	2.762	1.671	3.250
Encoding Time	5.218	6.812	4.640	7.437	5.250	6.968
Decoding Time	9.406	2.078	7.218	2.046	9.765	2.765
Total Processing Time	14.625	8.890	11.859	9.4844	15.015	9.734
PSNR (dB)	39.886	49.886	42.590	52.590	39.555	49.555

The quality of the sample images is assessed using peak signal to noise ratio (PSNR), mean square error (MSE) and spatial similarity index measure (SSIM). PSNR is usually expressed in terms of the logarithmic decibel scale.

$$PSNR(dB) = 10log_{10}\left(\frac{I_{peak}^2}{MSE}\right) \quad (1)$$

Where Ipeakis the peak values of the input video. MSE is a squared error loss. MSE measures the average squared error between true and estimated values. The mathematical formulation of MSE is given by,

$$MSE = \frac{1}{MXN}\sum(f-\hat{f})^2 \quad (2)$$

Where f - ground truth video

fˆ- interpolated video after extraction

The SSIM is given as,

$$SSIM = \frac{\sum_i \sum_i f(i,j) \otimes f_W(i,j)}{\sum_i \sum_i (f(i,j))^2} \quad (3)$$

For improved imperceptible data quality the similarity factor is closer to 1. The obtained values are presented in the following figures.

Fig. 7 shows the variation of MSE over noise density. The obtained MSE is higher with the increase in noise density. Higher noise variance causes obtained MSE to be high. The developed coding system shows a decrease in MSE due to proper coefficient selection in comparison to JPEG coding. MSE values for noise density remains the same which is of about 0.2 and 10-50% of decrease in MSE is obtained in case of proposed developed approach.

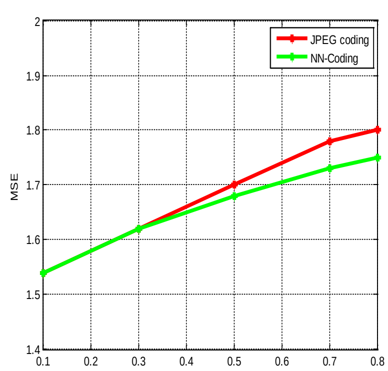


Fig. 7. Experimental Values with Noise Variation for MSE.

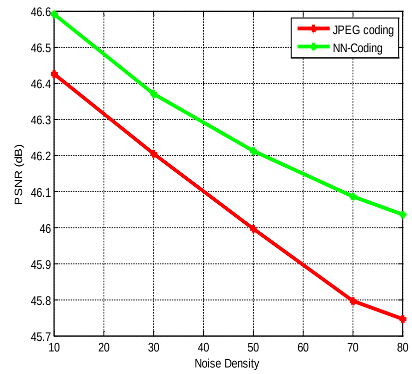


Fig. 8. PSNR Over Variation in Noise Density for Test Images.

Experimental results show that retrieved data quality is degraded due to raise in noise density. This impacts the content and overall quality of the image. PSNR in Fig. 8 shows the quality degradation results. About 2dB of improvement is achieved using the proposed developed approach in comparison with the conventional JPEG coding. SSIM values over varying noise density is computed and presented in Fig. 9 for the given test sample. SSIM for retrieved image using proposed approach is 0.6 in comparison to 0.48 attained using conventional approaches. The experimental metric values for a test image sample are presented in Table III.

A comparable analysis is carried out for variation in learning iteration made. The system is simulated for different offered data rate as a measuring parameter is carried out for various image samples. Fig. 10, Fig. 11 and Fig. 12 shows the experimental observations which are superior due to higher content similarity.

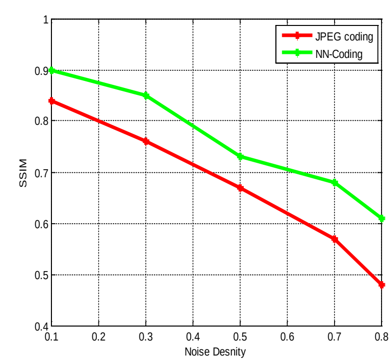


Fig. 9. Experimental Values of SSIM Over Noise Density Variation in Images.

TABLE III. EXPERIMENTAL VALUES FROM THE DEVELOPED SYSTEM OVER JPEG SYSTEM FOR AN IMAGE TEST SAMPLE UNDER DIFFERENT NOISE VALUES

Noise Variance	JPEG Coding System			Proposed Coding System		
	MSE	***PSNR***	***SSIM***	***MSE***	***PSNR***	***SSIM***
0.1	1.56	47.42	0.74	1.56	47.52	0.79
0.3	1.67	45.3	0.71	1.67	45.48	0.72
0.6	1.76	46.9	0.52	1.72	47.13	0.56
0.8	1.83	43.35	0.38	1.79	44.25	0.47

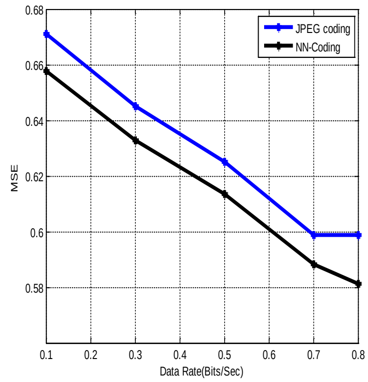


Fig. 10. MSE Observed for Variant Learning Iteration.

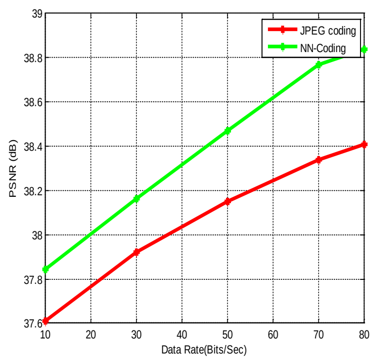


Fig. 11. PSNR Observed for Variant Learning Iteration.

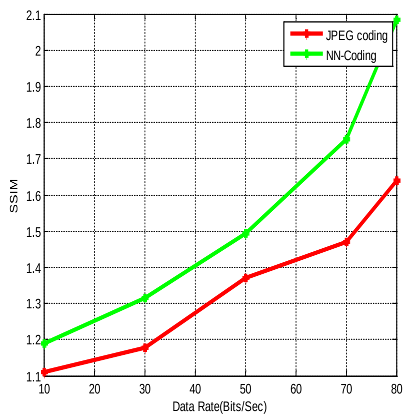


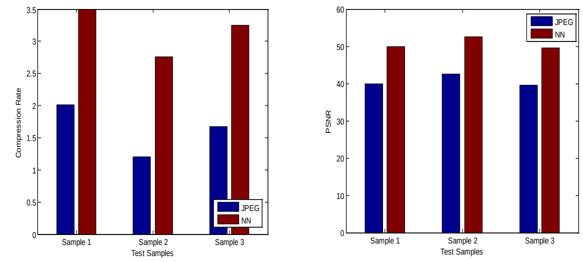
Fig. 12. SSIM Observed for Variant Learning Iteration.

The observed experimental values are presented in Table IV.

TABLE IV. EXPERIMENTAL VALUES FROM THE DEVELOPED SYSTEM OVER JPEG SYSTEM FOR AN IMAGE SAMPLE UNDER DIFFERENT LEARNING ITERATION

Learning Iteration	**JPEG Coding System**			**Proposed Coding System**		
	MSE	***PSNR***	***SSIM***	***MSE***	***PSNR***	***SSIM***
10	0.69	38.71	1.21	0.685	38.94	1.28
30	0.653	36.55	1.15	0.641	37.27	1.42
60	0.527	37.11	1.31	0.49	37.89	1.57
80	0.71	38.0	1.702	0.672	38.41	2.203

Fig. 13 shows the comparative analysis of various test samples for compression rate, PSNR followed by Fig. 14 which presents the encoding time and decoding time.



(a) (b)

Fig. 13. Comparative Analysis (a) Compression Rate, (b) PSNR.

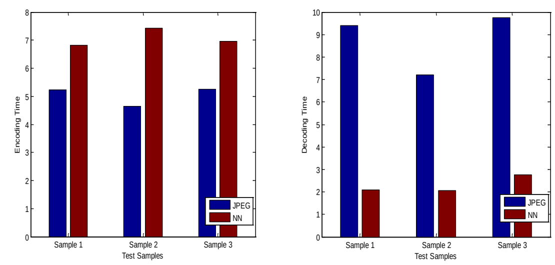


Fig. 14. Comparative Analysis (a) Encoding Rate, (b) Decoding Time.

Fig. 15 shows the total time comparative analysis of various test samples.

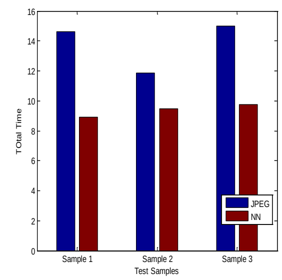


Fig. 15. Total Time Comparative Analysis.

V. CONCLUSION

This work presents an image compression approach for medical image compression using neural network approach. The coding is developed for the image pixel selection, where the learning approach of neural network is used for the selection of significant coefficients. The neighbor pixel value count is used for pixel selection, where the redundant coefficients are used for the coding of compressed data using weight optimization. One of the main limitations faced by the researcher is due to the hardware dependence of neural networks in conducting the experiment. The obtained result for the developed approach is compared with the conventional compression model of JPEG coding, and the observed quality metrics of PSNR and SSIM illustrates an improvement for the compressed data. However in the suggested coding the learning error convergence is observed to be more. This work can be further extended to achieve the objective of optimal rule formation; a new coding of image compression using fuzzy logic is suggested as a future work to this work.

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