International Journal of Reconfigurable and Embedded Systems (IJRES)
Vol. 13, No. 2, July 2024, pp. 262~270
ISSN: 2089-4864, DOI: 10.11591/ijres.v13.i2.pp262-270

A novel compression methodology for medical images using deep learning for high-speed transmission

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Article Info

Article history:

Received Jan 9, 2023
Revised Sep 4, 2023
Accepted Sep 17, 2023

Keywords:

Compact form
Deep convolutional neural network
Deep learning
Medical image compression
Storage space-saving
Telemedicine

ABSTRACT

Medical imaging is a rapidly growing field having a high impact on the early detection, diagnosis and surgical planning of diseases. Several imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound (US) imaging generate a higher volume of data, necessitating additional storage and communication requirements. Hence, image compression is utilized in medical field to reduce redundancy and alleviate memory and bandwidth issues. This paper presents a novel deep learning-based compression method to reduce the size of medical images. This method employs a deep convolutional neural network for learning compact representations of medical images, then coded by a Huffman encoder. The compression process is reversed to reconstruct the original image. Several tests are conducted to compare the results with other well-known compression methods. The proposed model achieved a mean peak signal-to-noise ratio (PSNR) of 42.82 dB with storage space saving (SSS) of 96.15% for CT, 43.88 dB with SSS of 96.25% for MRI, 46.29 dB with SSS of 96.07% for US and 43.51 dB with SSS of 96.95% for X-ray images. The findings showed that the proposed compression technique could greatly compress the image size, saving storage space, facilitating better transmission and preserving critical diagnostic information.

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1. INTRODUCTION

Medical imaging techniques are becoming a crucial component of the diagnostic procedure in healthcare practices. The importance of medical imaging has increased significantly as a result of advancements in screening technologies. The improvements have led to great accuracy in medical imaging with better quality and improved image resolution [1]. Furthermore, a huge amount of data is generated by various imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT) and ultrasound (US). However, the development has caused an exponential rise in the amount of data that needs to be processed and stored in a local memory or transmitted over the network [2]. Therefore, image compression methods have become crucial in processing medical images.

A number of image compression methods have been designed so far to compress medical images and reduce the amount of bandwidth needed for transmission. Image compression methods are grouped into lossy and lossless compression. Lossless compression is preferable for medical image compression due to its characteristics of restoring the image to its original quality without loss of any data and quality. In general, traditional compression methods can be utilized to minimize medical image size, JPEG and their upgraded versions. It can be observed that these conventional methods do not appropriately handle diagnostic information and instead focus primarily on maintaining the quality of the image which may not be largely helpful. These characteristics must be taken into account while designing a compression system for medical images. Recently, deep learning networks have been used to compress images which achieved better compression rates. Furthermore, the use of deep learning models offers better flexibility in terms of the types of objects in the compressed images [3]–[6]. The compression method just has to be trained to new features because these networks do not rely on hand-crafted features. This paper builds a novel compression method to reduce the size of medical images while preserving diagnostic information and reducing the amount of bandwidth needed for transmission. The core contributions of this paper are given: i) two deep convolutional neural networks (DCNNs) are connected together in order to design an efficient compression method, ii) a novel compact-DCNN (C-DNN) is proposed to learn the compact representation of medical images containing diagnostic data, iii) a reconstruct-DCNN (R-DCNN) is designed to recover the compressed image with increased quality, iv) the performance of the developed system is analyzed utilizing different imaging techniques such as CT, MRI, US and X-ray, and v) extensive experiments are conducted and the outcomes are compared with traditional methods.

The article is outlined as section 2 discusses the review of previous works and provides a brief survey of earlier methods. Section 3 enumerates the introduced medical image compression system and describes the functioning of the method. Section 4 discusses the numerical outcomes and discussion with considerations on the obtained results. Section 5 summarizes the article.

2. REVIEW OF PAST APPROACHES

This section gives a brief overview of various existing techniques for compressing medical images. Ahilan *et al.* [7] designed a method for compressing the size of medical images. Particle swarm optimization (PSO) along with multilevel thresholding is used to select the optimal value to compress the image. This method archived better results in terms of peak signal-to-noise ratio (PSNR). However, the PSO needs more training to obtain good results.

As per Ammah and Owusu [8] discrete wavelet transform (DWT) and vector quantization were adapted to compress medical images. Input images were filtered using a median filter and then divided into many subbands using DWT. Then, the obtained coefficients were quantized and encoded. This approach failed to attain high PSNR due to floating point error.

A fusion method by combining burrows-wheeler transform (BWT) and move to front transform (MTF) was presented by Devadoss and Sankaragomathi [9]. The input image was divided into region of interest (ROI) and non-ROI with morphological operations. BWT-MTF and quasi fractal (QF) were adopted to compress ROI and non-ROI respectively since the block division was done in the ROI to reduce BWT time. Storage space saving (SSS) is reduced by increasing the block size.

Maheswari and Raghavan [10] designed a compression algorithm for medical images. In this work, tetrolet was applied to divide an image into multiple sub-images. The sub-images were divided into 4×4 pixels and then compressed. The performance of this method was validated on MRI and CT images. This work requires more time for reconstruction.

A hybrid method by integrating the quasi fractal and oscillation method (QFOM) was presented by Magar and Sridharan [11]. A bandpass filter was used to isolate the ROI region from its background. The ROI was compressed using QF whereas non-ROI was compressed with OM. A neural network-based compression method was proposed by Sabbavarapu *et al.* [12]. In this work, DWT and optimized recurrent neural network **(**RNN) were utilized for compressing ROI and non-ROI respectively. This method attained better compression ratio (CR) and PSNR.

Salih and Kadhim [13] presented a medical compression method based on set partitioning in hierarchical trees-binary array technique (SPIHT-BAT) algorithm. Reddy *et al.* [14] used discrete cosine transform (DCT), singular value decomposition (SVD) and SPIHT. Initially, DCT was applied over the input image and then SVD was followed by SPIHT. This method may lose some information. Rahman and Hamada [15] presented a detailed survey of image compression techniques.

3. PROPOSED IMAGE COMPRESSION METHOD

The proposed method consists of two DCNNs, C-DCNN, R-DCNN, huffman encoding (HE) [16] and decoding. During compression, the input image is represented compactly to preserve salient information of the medical image. Whereas during decompression, another R-DCNN is used to improve the recovered image quality. Figure 1 depicts the phases of the presented compression method.

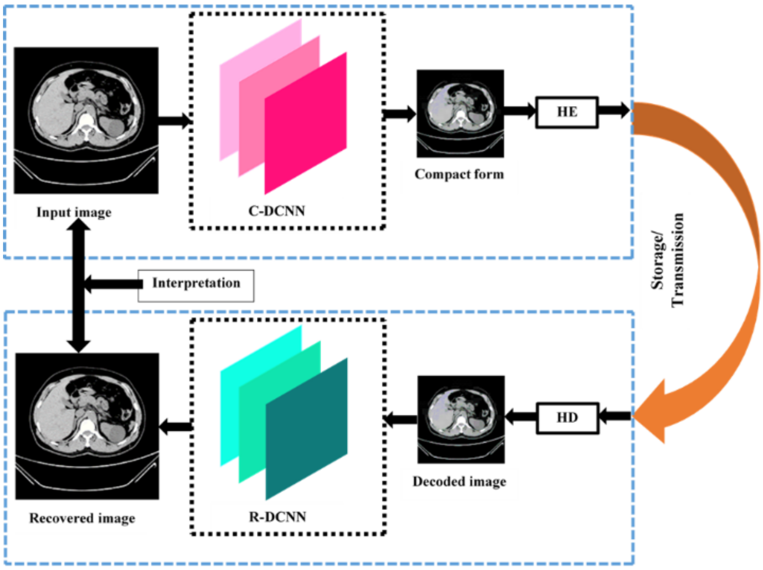

Figure 1. The structure of the designed compression technique

3.1. C-DCNN in compression

The C-DNN consists of three convolutional (Conv) layers [17], [18] as depicted in Figure 2. The integration of conv and rectified linear unit (ReLU) [19] is used at the first and second layers. The first Conv layer extracts the relevant information that eliminates the region that may overlap in the input image. The ReLU activation function and a total of 64 3×3 filters are employed to create 64 feature maps. The following layer performs two processes such as downsampling and enhancement employing convolution. The filters of size 3×3×64 and ReLU are utilized. The filters of 3×3×64 are used to create a compact representation in the last layer.

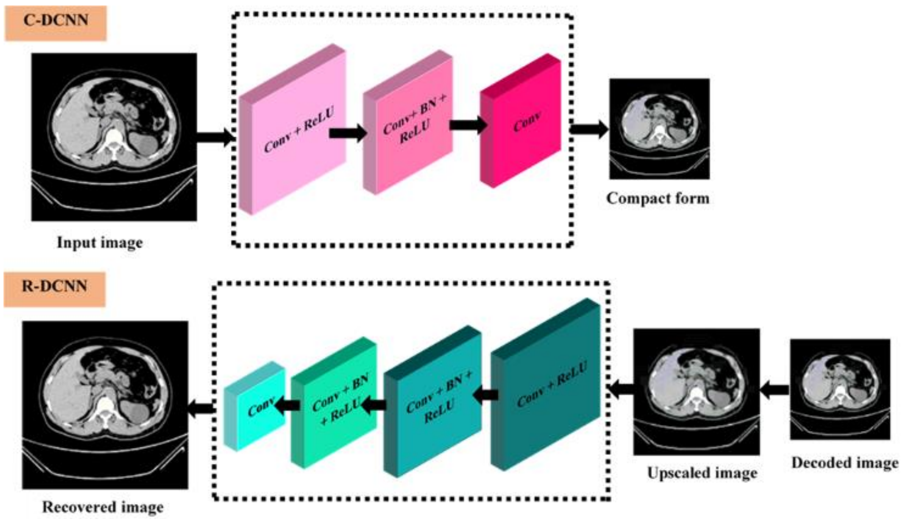

Figure 2. Process of C-DCNN and R-DCNN

3.2. R-CNN in decompression

The R-CNN has many layers including Conv+ReLU, Conv+ReLU+batch normalization (BN) [20] and Conv. Feature maps are created in the first layer using 64 filters of size 3×3, then ReLU. In the subsequent layers, 64 filters with a 3×3 size are used and BN is added with Conv and ReLU. The filters of size 3×3×64 are used in the last layer to reconstruct the image. The BN is used to improve results. The bicubic interpolation method will upscale the compressed image to the size of the input image.

3.3. Learning algorithm and loss function

The developed compression method intends to reduce medical image size and reconstruct the image with better quality. The optimization goal can be expressed as,

$$(\hat{\theta}_x, \hat{\theta}_y) = argmin_{\theta_x, \theta_y} \left\| R\left(\theta_{y,} HE\left(C(\theta_x, X)\right)\right) - X \right\|^2 \tag{1}$$

where X is the input image, HE is the Huffman encoder, C is the compression, R is the reconstruction, C(.) is C-DCNN and R(.) is R-DCNN. In (1) shows that the image X is given on the phases of compression, including C-DNN, HE and R-DCNN for decoding and the result of the reconstructed image $\hat{X}$. In (1) utilizes a rounding function that is non-differentiable when executing the backpropagation algorithm. To fix the issue, an iterative optimization training algorithm is proposed. Initially, by fixing θ_y , it is obtained as,

$$\hat{\theta}_x = argmin_{\theta_x} \left\| R\left(\theta_{y,} HE\left(C(\theta_x, X)\right)\right) - X \right\|^2 \tag{2}$$

by setting θ_x, it is obtained as,

$$\hat{\theta}_y = argmin_{\theta_y} \left\| R\left(\theta_{y,} HE\left(C(\theta_x, X)\right)\right) - X \right\|^2 \tag{3}$$

let $\hat{X}_r$ is the compact form and it can be defined as,

$$\hat{X}_r = HE\left(C\left(\hat{\theta}_x, X\right)\right) \tag{4}$$

to update θ_y, (3) and (4) are combined and are written as,

$$\hat{\theta}_y = argmin_{\theta_y} \left\| R\left(\theta_y, \hat{X}_r\right) - X \right\|^2 \tag{5}$$

$$\hat{X}'_r = argmin_{\widehat{X_r}} \left\| R\left(\hat{\theta}_y, \hat{X}_r\right) - X \right\|^2 \tag{6}$$

it is assumed that $D\left(\hat{\theta}_r, .\right)$ is monotonic concerning $\hat{X}'_r$ and is denoted as, $\left\|\tau - \hat{X}'_r\right\|^2 \geq \left\|\varphi - \hat{X}'_r\right\|^2$, if and only if,

$$\left\| R\left(\hat{\theta}_y, \tau\right) - X \right\|^2 \geq \left\| R\left(\hat{\theta}_y, \varphi\right) - X \right\|^2 \tag{7}$$

let $\tilde{\theta}_x$- solution of $\left\|HE(C((\theta, X) - \hat{X}_r\right\|^2$, for any probable θ^*_x, it fulfills,

$$\left\| HE\left(C(\theta^*_x, X)\right) - \hat{X}'_r \right\|^2 \geq \left\| HE\left(C\left(\tilde{\theta}_x, X\right)\right) - \hat{X}'_r \right\|^2 \tag{8}$$

$$\left\| R\left(\hat{\theta}_y, HE\left(C(\theta^*_x, X)\right)\right) - X \right\|^2 \geq \left\| R\left(\hat{\theta}_y, HE\left(C(\theta^*_x, X)\right)\right) - X \right\|^2 \tag{9}$$

$$\tilde{\theta}_x = argmin_{\theta_x} \tilde{\theta}_x = argmin_{\theta_x} \left\| R\left(\hat{\theta}_{y,} HE\left(C(\theta_x, X)\right)\right) - X \right\|^2 \tag{10}$$

$$\hat{\theta}_x = \tilde{\theta}_y$$

$$\hat{\theta}_x = argmin_{\theta_x} \left\| HE\left(C(\theta_x, X)\right) - \hat{X}'_r \right\|^2 \tag{11}$$

HE is a coding function, (11) becomes,

$$\hat{\theta}_x \approx argmin_{\theta_x} \left\| C(\theta_x, X) - \hat{X}'_r \right\|^2 \tag{12}$$

combining (7) and (12),

$$\hat{\theta}_x = argmin_{\theta_x} \left\| R\left(\hat{\theta}_{y,} C(\theta_x, X)\right) - X \right\|^2 \quad (13)$$

in (13) is employed to train the model.

Let X and $\theta_j$be the collection of input images and trained variables, mean square error (MSE) is used as the loss function to train C-DCNN and it is represented as:

$$Loss_x(\theta_x) = \frac{1}{2M}\sum_{p=1}^{M} \left\| R\left(\hat{\theta}_y, C(\theta_x, X_p)\right) - X_p \right\|^2 \quad (14)$$

similarly, with a collection of compact form $\hat{X}_r$ from C-DCNN and input images X, MSE is used as the loss function to train R-DCNN.

$$Loss_y(\theta_y) = \frac{1}{2M}\sum_{p=1}^{M} \left\| res\left(HE\left(\theta_x, \hat{X}_{r_p}, \theta_y\right)\right) - \left(HE\left(\hat{X}_{r_p}\right) - X_p\right) \right\|^2 \quad (15)$$

4. NUMERICAL RESULTS AND DISCUSSION

4.1. Details of the dataset

In this research work, a robust method is proposed for compressing medical images without losing image quality. The proposed method has been implemented and verified in MATLAB-2019a, executed in Intel core i5-processor @ 3.60 GHZ, 16 GB RAM. The proposed method is validated on various medical images of Medpix [21] and Kaggle [22] databases. A total of 600 images are randomly chosen for training, as given in Table 1. The remaining images are employed to validate the presented method. Figure 3 shows the original images.

Table 1. Data source information

Sl. No.	Image type	Number of images
1.	CT	200
2.	MRI	200
3.	US	200
4.	X-ray	200

Figure 3. Sample medical images

4.2. Performance metrics

The effectiveness of the presented compression technique is assessed based on PSNR [23], CR, mean structural similarity index (SSIM) [24] and SSS [25]. In summary, higher PSNR and SSIM indicate that the recovered images, R are identical to the original images, O. The definition of these metrics as (16)-(21).

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[O(i,j) - R(i,j)]^2 \quad (16)$$

$$PSNR = 10 * log_{10}\left({255^2}/{MSE}\right) dB \quad (17)$$

$$SSI = \frac{(2\mu_O\mu_R + c_1) + (2\sigma_{OR} + c_2)}{(\mu_O^2\mu_R^2 + c_1)(\sigma_O^2\sigma_R^2 + c_2)} \tag{18}$$

$$SSIM = \frac{1}{N}\sum_{i=1}^{N} SSI_i \tag{19}$$

$$CR = \frac{Size\ of\ original\ image}{Size\ of\ compressed\ bitstream} \tag{20}$$

$$SSS = 1 - \frac{Size\ of\ compressed\ image}{Size\ of\ original\ image}\ X\ 100 \tag{21}$$

4.3. Experimental study

4.3.1. Performance evaluation of CT images

The prime target of this method is to obtain medical images with high CR, SSIM, and PSNR. Table 2 summarizes the efficiency of the presented compression technique over CT images. There are five different CT images taken to compute metrics which are furnished in Table 2. The presented method yielded mean PSNR, CR, SSIM and SSS values of CT images as 42.82 dB, 26.14, 0.95 and 96.15% respectively. Figure 4 displays the input and reconstructed CT images.

Table 2. Effectiveness of the compression method on CT images

Image no.	PSNR (dB)	CR	SSIM	SSS (%)
1	41.72	23.91	0.930	95.82
2	43.16	26.95	0.960	96.29
3	43.34	23.38	0.909	95.72
4	43.18	28.88	0.986	96.54
5	42.69	27.57	0.971	96.37
Mean	42.82	26.14	0.95	96.15

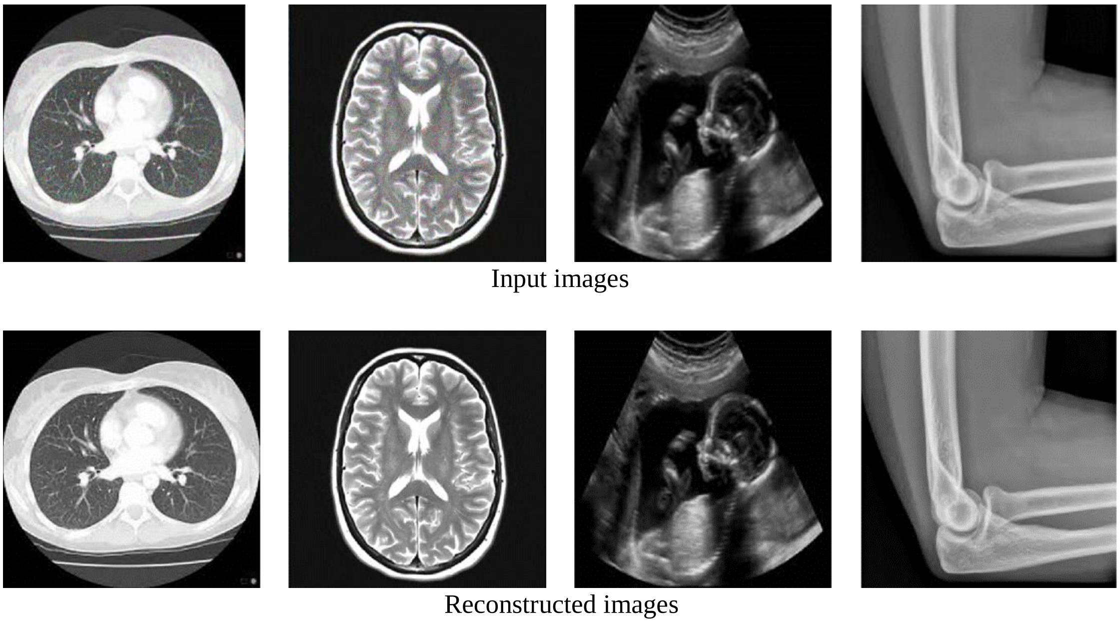

Figure 4. Samples of the input and recovered images employing the proposed technique

4.3.2. Performance evaluation of MRI images

In this sub-section, the performance of the proposed compression method is analyzed using MRI images. There are five MRI images considered to estimate the PSNR, CR, SSIM and SSS. Table 3 lists the effectiveness of the suggested strategy when applied to MRI images. The suggested technique achieved mean values of 43.88 dB, 26.81, 0.96 and 96.25% for PSNR, CR, SSIM and SSS, respectively. Figure 4 displays the input and reconstructed MRI images.

Table 3. Effectiveness of the compression method on MRI images

Image no.	PSNR (dB)	CR	SSIM	SSS (%)
1	43.88	29.15	0.998	96.57
2	43.40	27.18	0.964	96.32
3	43.11	28.63	0.972	96.51
4	44.78	25.73	0.956	96.11
5	44.24	23.35	0.907	95.72
Mean	43.88	26.81	0.96	96.25

4.3.3. Performance evaluation of ultrasound images

The introduced compression technique is targeted to enhance the CR, PSNR, SSIM and SSS of the medical image without losing significant information. Table 4 displays how well the proposed method performs compression over US images. To evaluate the effectiveness of the suggested strategy, five US images are used. A mean PSNR of 46.29 dB, CR of 25.76, SSIM of 0.98 and SSS of 96.07% were all attained using the suggested approach. Figure 4 displays the original and recovered US images.

Table 4. Effectiveness of the compression method on US images

Image no.	PSNR (dB)	CR	SSIM	SSS (%)
1	46.45	28.40	0.982	96.48
2	45.12	21.40	0.965	95.33
3	47.25	25.98	0.992	96.15
4	46.52	24.24	0.988	95.88
5	46.11	28.78	0.959	96.53
Mean	46.29	25.76	0.98	96.07

4.3.4. Performance evaluation of X-ray images

The efficacy of the introduced technique is examined using the X-ray image in this sub-section. Five X-ray images are employed. The outcomes of this method are applied to the X-ray images and summarized in Table 5. The presented method achieved the mean PSNR, CR, SSIM, and SSS values as 43.51 dB, 29.97, 0.98 and 96.95% respectively. Figure 4 displays the input and reconstructed X-ray images.

Table 5. Effectiveness of the compression method on X-ray images

Image no.	PSNR (dB)	CR	SSIM	SSS (%)
1	44.39	34.68	0.987	97.12
2	44.92	27.94	0.973	96.42
3	43.30	27.39	0.969	96.35
4	41.05	30.04	0.983	96.67
5	43.90	29.79	0.979	98.21
Mean	43.51	29.97	0.98	96.95

4.4. Discussions on the results

To demonstrate the proposed compression method's superiority, its efficiency is compared with other well-known techniques in light of PSNR, CR and SSS. The previous methods considered for comparison are PSO-based thresholding BWT-MTF [9] tetrolet [10] QFOM [11] optimized RNN [12] and SPIHT-BAT [13] because all the previous models process the MRI images. Ahilan *et al.* [7] used multilevel thresholding of PSO to extract ROI. The computed ROI and non-ROI regions are compressed using the blending method. As per Devadoss and Sankaragomathi [9] morphological operations are used to distinguish the ROI from non-ROI areas. The ROI is reduced with quadtree and non-ROI is compressed with the fusion BWT-MTF. After compression, the data is encoded with HE. Maheswari and Raghavan [10] used the tetrolet method to compress medical images. Magar and Sridharan [11] compressed the ROI region using quasi-fractal and non-ROI with OM. In the study by Sabbavarapu *et al.* [12] the ROI region is compressed using DWT and the non-ROI region is compressed using optimized RNN. In this method, a hybrid gravitational search algorithm-PSO (GSA-PSO) is adopted to optimize the RNN's parameters.

A comparison of the proposed strategy with earlier methods is shown in Table 6. A pictorial representation of CR and PSNR with previous methods is shown in Table 6. It is quite clear from the comparative study that the introduced technique achieves high CR while keeping decent PSNR in contrast to the prior methods used for comparison.

The PSO method has low CR and PSNR because it uses thresholding and blending methods to compress an image. The PSNR and CR of the developed method are higher than PSO, QFOM, RNN and BWT-MTF. It demonstrates that the proposed method recovers images with good quality, also the results proved that the efficiency of the proposed method is enhanced in light of PSNR, CR and SSS. The proposed method produces better CR, PSNR and SS than the earlier methods, because of the usage of the deep learning network in medical image compression.

Table 6. Comparative outcomes of the proposed method with previous approaches

Contributors	Method	PSNR (dB)	CR	SSS (%)
Ahilan *et al.* [7]	PSO	22.7	2.13	-
Devadoss and Sankaragomathi [9]	BWT-MTF	34.6	4.63	78.42
Maheswari and Raghavan [10]	TETROLET	19.65	4.12	-
Magar and Sridharan [11]	QFOM	33.5	24.61	-
Sabbavarapu *et al.* [12]	RNN	35.2	23.34	95.71
Salih and Kadhim [13]	SPIHT-BAT	36.71	21.41	95.07
Proposed	DCNN-MRI	43.88	26.81	96.25
	DCNN-CT	42.82	26.14	96.15
	DCNN-US	46.29	25.76	96.07
	DCNN-X-ray	43.51	29.97	96.95

5. CONCLUSION AND FUTURE WORKS

This paper presents image compression using the CNN for medical images. To achieve a better tradeoff between compression rate and image quality, two CNNs are connected to design an efficient compression method. The proposed method employed deep learning for learning the compact demonstration of the input image and then coded by HE. Finally, the encoded image is recovered with higher quality. The outcomes showed the power of the proposed technique, achieving mean PSNR of 42.82 dB, 43.88 dB, 46.29 dB and 43.51 dB for CT, MRI, US and X-ray images. In the future, this method shall be implemented in real-time applications and be used for other emerging applications. Likewise, the performance of this method can be improved by optimizing the hyperparameters of the CNN model.

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