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Significant medical image compression techniques: a review

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ABSTRACT

Telemedicine applications allow the patient and doctor to communicate with each other through network services. Several medical image compression techniques have been suggested by researchers in the past years. This review paper offers a comparison of the algorithms and the performance by analysing three factors that influence the choice of compression algorithm, which are image quality, compression ratio, and compression speed. The results of previous research have shown that there is a need for effective algorithms for medical imaging without data loss, which is why the lossless compression process is used to compress medical records. Lossless compression, however, has minimal compression ratio efficiency. The way to get the optimum compression ratio is by segmentation of the image into region of interest (ROI) and non-ROI zones, where the power and time needed can be minimised due to the smaller scale. Recently, several researchers have been attempting to create hybrid compression algorithms by integrating different compression techniques to increase the efficiency of compression algorithms.

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1. INTRODUCTION

In earlier years, a large volume of medical image data was collected in hospitals and medical institutions through a variety of methods, including magnetic resonance imaging (MRI), x-ray imaging, ultrasound (US) imaging, computed tomography imaging (CT), positron emission tomography imaging (PET), and digital fluorography imaging (DF) [1]-[3]. The essential element of information and communication technology is the integrity of the transmitted medical images [4]. The objective of image compression is to reduce the amount of storage required and reduce the cost of image transmission while maintaining a good degree of quality and ensuring the rapid transmission of medical images. Compression is also done to remove information redundancy. There are three common types of image redundancy: 1) redundancy of coding; 2) redundancy of inter pixels; 3) psycho-visual redundancy based on information neglected by human vision [5]-[8].

The compression of medical images is essential so that the images can be transmitted quickly via a lower bandwidth and with high efficiency in remote areas [9]. The compression techniques can be divided into loss and lossless processes. The lossless technique allows complete retrieval of the original details from the compressed image, but only achieves a compression ratio of around 2 to 4%. An efficient compression strategy is needed to save a great number of image databases. The correlation between the data in the image makes it possible to reduce the content of the image data without much degradation of the image quality.

Lossless compression methodologies are used in most applications that have precise requirements, such as medical imaging. These techniques include run-length coding, Huffman coding, Lempel-Ziv-Welch (LZW) coding and area coding [10]. In most applications, lossy compression methods give greater compression ratios than lossless techniques and are used when image quality is not a problem. These methods include coding for transformation (such as discrete cosine transformation (DFT), discrete cosine transformation (DCT), discrete wavelet transformation (DWT), vector quantization (VQ) transform, and fractal coding) [11].

2. MEDICAL IMAGE COMPRESSION

In digital image processing, image compression is an interesting field concerned with reducing storage and transferring images faster [12]. Diagnostic feature extraction is better when colour medical images are taken compared to grayscale images, but colour medical images need greater storage capacity compared to greyscale images. There are several types of medical images, as shown in Figure 1.

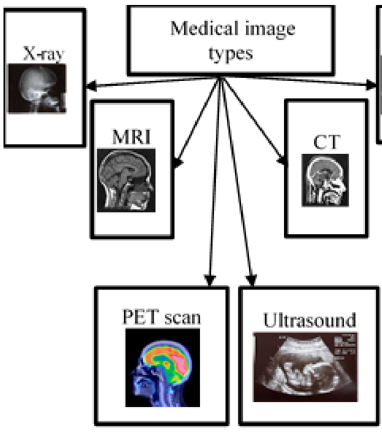


Figure 1. Medical image types

A medical image has important features that must be taken into account during the process of compression. First, it should have a high compression ratio that is lossless. Second, it should have better scalability for resolution and last, it must able to be decoded [13]. In the case of medical imaging, although lossy compression methods provide compression rates of 10-15%, they are not commonly used. Since images have large features, lossy compression at data of the lower bit rate can lead to a deterioration in the quality of the image is retrieved which may have an impact on diagnostics [14], [15].

Lossy compression should not be used for medical images for the following reasons: first, because the diagnosis will be inaccurate due to the lack of valuable knowledge; second, because operations such as image enhancement can underscore deterioration caused by lack of compression. Lossless compression reproduces an exact replica of the original image without any loss of quality. Effective lossless compression techniques for medical images are therefore required [1], [6]. There are many lossless image compression techniques, such as run-length coding, Huffman coding, LZW coding, lossless Joint Photographic Experts Group (JPEG format), and arithmetic coding [1], [7].

Hybrid medical image compression is a methodology that brings a high compression rate with good quality to the region of interest (ROI). In other words, two different compression methods are used for the ROI and non-ROI. The overall objective is to preserve quality in diagnostically sensitive regions while encoding other regions so that the observer can evaluate the location of the critical regions in the original image. A lossy compression method is therefore sufficient for non-ROI sections to provide a full image to the user, whereas a lossless compression method is needed for ROI sections [9].

3. MEDICAL IMAGE COMPRESSION ALGORITHMS

The techniques used in medical image compression can be divided into seven different types of techniques: transformation, fractal, neural networks, Huffman, vector quantization, run-length encoding, and entropy coding techniques, as shown in Figure 2.

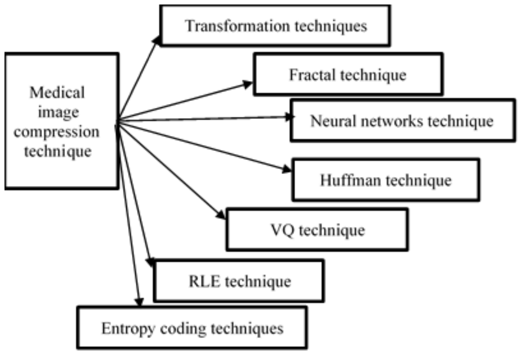


Figure 2. Most important techniques used in medical image compression

3.1. Transformation techniques

Shivaputra *et al.* [4] worked on a digital imaging and communications in medicine (DICOM) file and compressed it based on integer wavelet transform (IWT), then encoded it using an AES algorithm before transmitting it over a TCP/IP network. Venugopal *et al.* [15] proposed a method that focuses on analysing the medical colour image using a wavelet in high and low coefficients and then sends each transaction to the compression technique. It sends high transactions to the ripplet transformation before they are sent to Huffman to be compressed whereas low transactions are sent directly to Huffman to be compressed. Ukrit and Suresh [1] proposed a hybrid algorithm for compression of medical image sequences. The proposed method combines the super-spatial prediction technique with inter-frame coding and the innovative scheme of the Bose Chaudhuri Hocquenghem (BCH) codes to achieve a high compression ratio.

Anandan and Sabeenian [16] proposed a method that divides the medical image into three stages, depending on the fast discrete curvelet transform based on the wrapping technique. The resulting data at each stage were vector quantized to achieve the coefficients. Sharma *et al.* [9] proposed a method based on the division of the image into areas of importance (ROI) and areas of minor importance (non-ROI) and then combining two algorithms of transformation: set partitioning in hierarchical trees (SPIHT) algorithm for the ROI part and Daubechies (DB) wavelet transform algorithm for the non-ROI part, respectively, to generate the least amount of unnecessary data, which is then deleted, to build the original image. Mofreh *et al.* [17] presented a new image compression method consisting of a combination of linear predictive coding (LPC), DWT and Huffman coding. In this method, the image is first passed through the LPC transformation, then the wavelet transformation is applied to the LPC output, and finally Huffman coding codes the wavelet coefficients.

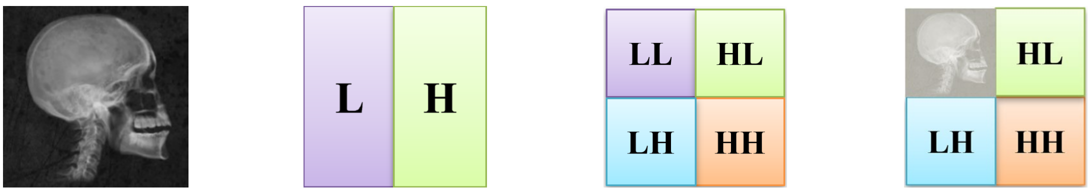
Vaishnav *et al.* [8] proposed the dual tree wavelet transform (DWT) and MRI compression arithmetic coding technique. CWT is a recent enhancement to the discrete wavelet transform (DWT), with significant additional properties. Abdelghany *et al.* [12] presented the hybrid compression method for mammogram image compression to exploit the properties of both the DWT and the DCT. First, the image is compressed by 3-level DWT, then transformed by one-dimensional DCT, and then encoded by arithmetic encoding. Parikh *et al.* [18] suggested the high efficiency video coding (HEVC) method for medical image compression. The compression method includes two processes: conversion of the image format and compression of the image.

Priya and Ramya [19] presented a compression method for compressing medical images (DICOM), in which the image is segmented into two regions (ROI and non-ROI) using fuzzy C-means clustering. Using DWT, the ROI part containing the most important data is decomposed and compressed using SPIHT coding, which keeps the image quality similar to the original image. The N-ROI part containing the less important data is compressed using the context-adaptive variable-length coding (CAVLC) compression method.

Himani and Mishra [20] proposed a fast algorithm based on block processing with DCT for 3D medical image compression. First, DCT is used to stimulate image transformation. The DCT converts the image into multiple parts. Instead of processing entire images, block processing operations are performed on 8x8 image blocks.

Al-Khafaji and Sami [3] suggested a method that involves detecting medical image edges with sobel and then splitting it into two parts (ROI and non-ROI) where lossless polynomial coding is used for the ROI portion, while the scalar uniform quantizer is used for the non-ROI portion. Imane *et al.* [21] proposed a new method of compression of medical images that combines the model of geometric active contour and the transformation of quincunx wavelet. This method segments the part containing the disease, then the SPIHT algorithm is applied to the new image after extracting the ROI. Jasim [22] proposed a method that works by separating skin cancer images into two parts: ROI and non-ROI, and then using a hybrid technique of SPIHT and bat-inspired algorithms on the ROI. The DCT technique is applied to the non-ROI, and finally the two parts are combined and compressed with Huffman coding. Ahilan *et al.* [23] proposed using three methods (PSO, DPSO, and FODPSO) to estimate the threshold value where the proposed multilevel threshold is based on an improved multilevel optimisation technique for ROI extraction and image compression by an improved prediction lossless algorithm. Ramachandran *et al.* [24] proposed an image matrix method for effective image compression in the medical pitch using an effective hybrid technique (EHT). Rani *et al.* [25] presented two different compression methods for medical images (MRI, brain computed tomography (CT) images, and hand X-ray). The first technique involves singular value decomposition (SVD) using singular values, and the second technique uses wavelet transform based on the progressive structure of SPIHT to decrease the size of images for accurate diagnosis. Ammah and Owusu [26] proposed compressing images using a DWT-VQ method. In this hybrid process, speckle and salt and pepper noises in ultrasound are reduced, then images are filtered using DWT. The codebook is injected with a default codeword composed of zeroes, then the final codebook is used to encrypt the coefficients, and it is finally encrypted using the Huffman method. Sateesh and Harika [27] proposed a method for the use of DWT for different dataset image formats. Zanaty and Ibrahim [28] implemented a medical image compression method based on a combination of algorithms for region growth and wavelets. A region growing algorithm is used to divide the image into two parts, depending on the intensity values in the foreground (ROI) and background (non-ROI). Wavelet techniques are then applied to foreground regions, including major regions. In order to maintain the image's appearance, the ROI parts are compressed using lossless compression and the non-ROI parts using lossy compression using the SPIHT algorithm to reduce the file size.

Kulkarni *et al.* [13] presented an MRI compression method using IWT and a lossless compression technique considering the ROI and non-ROI. Salman and Rafea [29] proposed two methods. In the first method, the input image is split into blocks. The blocks are first converted into a string, then encrypted using arithmetic coding. To improve the compression ratio, the second method was used based on the YCbCr model. By using the discrete wavelet algorithm, images were decomposed into four sub-bands. Then, via DWT, the low-low sub-band was transmuted to low and high. Next, by using scalar quantization, these components were quantized and then scanned in a zigzag way. Ja'afar *et al.* [30] presented the development of compression algorithms using DWT and DCT. For the input image, three different medical modalities were used: CT, MRI and US images. Zanaty and Ibrahim [31] suggested an improved algorithm for highly efficient Haar wavelets (HEHW). It begins by dividing the original image into submatrices of 2*2, then the coefficients, obtained by working on submatrices instead of rows and columns in the original image, are transformed by the wavelets and the resulting coefficients for sub-matrices are re-computed. To complete the compression process, statistical thresholds on the data sub-bands are calculated. The Wavelet decomposition applied to the medical images shown in Figure 3.



(a) (b) (c) (d)

Figure 3. Wavelet decomposition used in the medical images: (a) input medical image, (b) first level decomposition, (c) second level decomposition, and (d) low frequency sub band medical image

3.2. Fractal techniques

Kaur and Wasson [32] proposed an algorithm including two compression techniques. The medical image is divided into two regions: ROI and non-ROI. Using a context tree, the ROI part is compressed without loss. This approach relies on splitting the image into a group of blocks and then splitting each block into four small blocks, after which each block is compared to the parent block in search of the most similar blocks to be compressed; this continues for the remainder of the blocks. Liu *et al.* [33] proposed a compression algorithm for MRI images based on a fractal technique. The method proposed is to convert 3D images into a sequence of 2D images. Then, according to the inherent spatiotemporal resemblance of 3D objects, range and domain blocks are classified. Rahman *et al.* [34] suggested a peer adjacent to the sum of absolute difference (SAD) mapping to improve the speed of the Full-search fractal image (FIC) while still maintaining the quality of the resulting image.

3.3. Neural networks (NN) techniques

Chaabouni *et al.* [35] proposed a method in which the ROI is separately encoded using incremental self organizing map (ISOM) and the background (BG) region is encoded independently with a low resolution of the ISOM. Eventually, the two regions are merged at low bit rates in order to achieve a reasonable visual quality of the processed medical image. Ravikiran and Jayanth [10] focused on developing a feed-forward neural network for medical image compression using the hybrid genetic and particle swarm optimization (HGAPSO) technique to optimise weights. HGAPSO is used in this technique to overcome the back-propagation algorithm (BPA) disadvantage. Rani *et al.* [36] suggested the feed forward back propagation artificial neural network (FFBPANN) model using the Huffman coding technique and Levenberg–Marquardt (LM) training function for brain MRI image compression with high image quality.

3.4. Huffman technique

Suma and Sridhar [37] proposed the Huffman compression system based on the Urdhava Tiryakbhyam approach, which performs vertical and crossover multiplication and removes the excess data without distorting the image. This system leads to higher power consumption required for compressing grey and colour medical images by minimising the frequency of the clock. In [17], [22] and [26] used the Huffman technique in addition to transformation techniques. Liu *et al.* [33] used the Huffman technique in addition to fractal techniques. Yao *et al.* [38] proposed a lossless compression method based on the differential probability of the image for medical images in CT and MRI images in DICOM format. This differential method reduces the number of Huffman coding values used, thereby shortening the compression code length to obtain the optimal compression. The example of the Huffman tree is shown in Figure 4

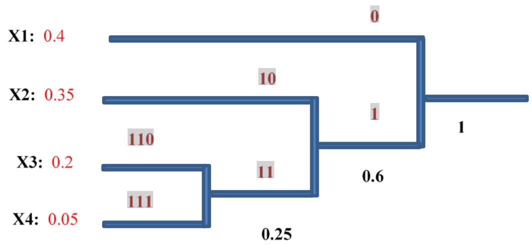


Figure 4. Example of Huffman tree

3.5. Vector quantization (VQ) technique

Rani and Chitra [7] proposed a method that focuses on compressing medical images with different codebook sizes using a vector quantization method for the ROI and non-ROI. There are three stages to the proposed method. The first stage segments the image into three parts: Image1, Image2 with 8x8 size, and ROI with a block size of 2x2. The second stage is to apply vector quantization with different block sizes to these three components. Finally, by choosing the blocks with high variance for applying VQ, initial seeds are generated in the third stage to improve the quality of the codebook. Two studies, [16] and [26] used the VQ technique in addition to transformation techniques.

3.6. Run length encoding (RLE) technique

Kazeminia *et al.* [6] proposed a novel method to eliminate non-ROI data from bone x-ray images. This method separates the image into two parts, the ROI and the non-ROI, then finds the ROI area specified and extracts the binary representation mask to separate the two parts. Finally, the binary mask is compressed using the RLE method. Suma and Sridhar [37] used the RLE technique in addition to the Huffman technique. Kulkarni *et al.* [13] used the RLE technique in addition to transformation techniques.

3.7 Entropy coding (EC) techniques

Jagadeesh and Nagabhooshanam [39] proposed a new model for image compression based on bands, coefficients, and bit pattern matching. This model based on the spectral correlation logic and entropy coding is achieved by incorporating the decomposition of multi wavelets and the model of image compression using band selection and modelling of coefficient selection. Reddy *et al.* [40] proposed a method of lossless medical image compression using delimiter-based compression for medical images. In the encoding process, the image matrix is converted into a binary row vector and entropy encoding is applied whereas in the decoding process, this encoding process is applied in reverse order.

4. DISCUSSION

It is noted that most researchers used lossless compression algorithms because accurate medical image data is very important for obtaining the correct diagnosis. Since transfers operations do not lead to loss of values, they have been used extensively in most research where they are used in the pre-processing stage as well as in the processing stage and to obtain pressure without loss. The results of previous research undertaken with regard to compressing medical images can be divided into seven sections depending on the methods used in the compression process, as follows:

Studies [7]-[9], [12], [13], [15]-[17], [19]-[22], [24]-[31], and [35] used transformations (DWT, CT, IWT, and curvelet transform). These algorithms are characterised by their speed and their ability to segment the image data to the lowest level to reach the surplus and remove it without affecting the image after its retrieval. The transformations are used with lossless or hybrid compression methods, which contain lossless and lossy compression, and are not used with lossy compression methods alone in any algorithm due to the risk of losing important data in the image. Moreover, it is noted that the algorithms of these studies were not limited to one type of pressure method, but rather many methods were used, including Huffman, arithmetic coding and SPIHT.

Studies [32]-[34] used the fractal method. Their algorithms are characterised by good results, as the research results show high compression ratios, good quality of the reconstructed image, and a fast and straightforward decoding process. However, one of the disadvantages of this method is that the encryption and compression process takes a long time because the search process is comprehensive and requires complex calculations.

Studies [17], [22], [26], [33], [37] and [38] used the Huffman method whose algorithms are characterised by dynamism of computing and searching for duplicates. It is used as the last step in the compression process after a series of processors to be used efficiently. As for its disadvantages, its speed is relatively slow because searching for duplicates of values and combining them consumes a lot of time.

Studies [10], [35] and [36] used neural network algorithms, which are characterised by speed of delivery and accuracy of results. At the same time, there are many disadvantages associated with their use, such as the network's need for training to reach the best results, as well as the fact that the number of mock models for each type of medical image must be increased to obtain good accuracy in compression and the adoption of good initial values to exceed the additional time in the calculation and length of implementation.

Two studies, [39] and [40], used entropy coding algorithms, which compress the quantitative values in a lossless manner, which gives better compression in general. Time is one of the most significant problems facing these algorithms due to their use of the laws of probability for the occurrence of each element in the image. Studies [6], [13] and [37] used RLE algorithms, which are distinguished by great effectiveness in processing text and images compared to audio data. This method is considered a lossless type and is good when the image is grey. In colour images, however, the image must be converted into a one-dimensional vector. It is often used with other techniques and best results are achieved when working with quantization technology.

Studies [7], [16] and [26], whose algorithms used VQ techniques, are suitable for compressing lost data and can also be used to correct missing data and estimate density. It is considered a simple method that does not need much time and the amount of error is small, but it is of the lossy compression type. It is used in medical images on a background of the medical image (non-ROI) that does not contain important data, so losing it does not affect the accuracy of the results. It is generally much used in hybrid algorithms that use lossy and lossless compression techniques

It is noted in Table 1 (see Appendix) that most of the medical images used in the research are the MRI type concerning brain diseases due to the large number of imaging bases for them and the ease of dealing with them. In addition, the frequent use of these databases makes it easy to make comparisons regarding the results of the research algorithms for compressing images of the same type. Table 1 shows the types of medical images used as databases and the types of compression techniques used on them, in addition to showing the effect of the algorithms used in these techniques on the measurement values.

Table 1 shows the measures used in compression studies that we dealt with in the proposed methods section. From Table 1, it is noted that most medical image compression studies used the first three measures (mean square error (MSE), peak signal to noise ratio (PSNR), and compression ratio (CR)) to prove the effectiveness of their algorithms. The interest in these measures is due to the achievement of the algorithm in providing a high compression ratio without data loss and the lowest error ratio whereas other measures appear to be ineffective in determining the quality of the recovered image in terms of the efficiency and accuracy of the algorithm to reconstruct the original image, hence the frequent use of these metrics to enable researchers to develop efficient algorithms.

5. CONCLUSION

The medical image is a digital resource for the hospital information system. The physician has to exchange the images in a reliable, safe and quick transition in order to diagnose and analyse the disease. The most difficult problem with exchanging medical files is data storage and enhancing network performance. This issue inspired the researchers to propose a variety of compression algorithms.

This paper discusses several of the compression methods used to compress medical photographs during the last two decades. These technologies are capable of maintaining precision, protection, and reducing storage capacity. After reviewing the paper, it was concluded that the efficiency of the compression method depends on the compression ratio when retaining essential details. Thirty-eight manuscripts are analysed in this paper and grouped into seven categories: transformation, fractal, neural networks, Huffman, VQ, RLE, and entropy coding techniques.

By shedding light on previous research related to medical image compression, some aspects are deduced by this paper, namely that: 1) it is desirable to use compression methods that do not result in loss of data; 2) the most used approaches of compression algorithms are transformation techniques; 3) the only way to achieve high compression ratios without missing essential details is by using hybrid techniques which techniques are the best; 4) the best and most widely used metrics for measuring performance are MSE, PSNR, CR and SSIM.

APPENDIX

Table 1. Comparison of compression techniques used by previous studies

Ref.	Medical Image types	Compression Lossless	Compression Lossy	Steerages	Performance Metrics	Performance algorithm
[4]	Image types were not mentioned	Yes	No	IWT and prediction method	MSE, PSNR, CR	The distortion level increases the CR while the PSNR parametric values decrease.
[15]	CT MRI	Yes	No	Ripplet transform and Huffman coding	MSE, PSNR, CR, Structure similarity index (SSIM), Bits per pixel (BPP)	Achieve high CR.
[32]	Image types were not mentioned	Yes	Yes	Fractal and context tree algorithm	MSE, PSNR, CR	Provide outcomes that are more precise and quicker than previous methods, i.e. IWT and RBC scalable.
[6]	X-ray	Yes	No	RLE	Average bit rate (BPR)	Capable of effective reduction of the statistical and spatial redundancies. It achieved the bit rate of 1.633
[1]	MRI and CE	Yes	No	Super-spatial structure prediction, motion estimation and motion compensation	MSE	Algorithm achieves 30% more reduction than other state-of-the-art lossless image compression methods.
[37]	MRI	Yes	No	Urdhava Tiryakbhyam sutra, quantization, RLE and enhanced Huffman coding	MSE, PSNR, CR, Compression size (CS)	Proposed system offers approximately 57% of the reduction in size without any significant loss of data.
[16]	MRI, CT and Ultrasound	Yes	No	Discrete curvelet wrapping, VQ and arithmetic encoding	MSE, PSNR	Attains high PSNR and compression rate.
[9]	Brain Image, Human Skull	Yes	Yes	SPIHT, DB wavelet transform	MSE, PSNR, SSIM	Provides high PSNR and SSIM.
[7]	MRI, Iris image, Mammogram and PET	No	Yes	VQ and K-Means clustering	MSE, PSNR, CR	Good quality images in less computation time when compared with K-means with random seeds.
[17]	Image types were not mentioned	Yes	No	LPC, DWT and Huffman coding	MSE, PSNR, CR, Signal to noise ratio (SNR), Root Mean square error (RMSE)	Faster and higher CR
[35]	Ultrasound image	Yes	Yes	DWT and ISOM	MSE, PSNR	Very appropriate for low bit-rate compression, ROI coding, high PSNR, and low MSE.

Table 1. Comparison of compression techniques used by previous studies (continue)

Ref.	Medical Image types	Compression Lossless	Compression Lossy	Steerages	Performance Metrics	Performance algorithm
[8]	MRI	Yes	No	DWT complex and arithmetic coding	MSE, PSNR, CR, SSIM	The average PSNR value obtained is 65.30 with a low MSE of 27.24 and a structure similarity index of 0.915 for the test images.
[12]	Brain, Breast, Body side view, Knee, Liver, Shoulder, Hip, Ort	Yes	No	DWT, DCT and arithmetic encoding	MSE, PSNR, CR, Entropy (E)	Technique meets halfway between high CR and acceptable PSNR.
[39]	Image types were not mentioned	Yes	No	Spectral correlation logic and entropy redundancy coding	MSE, PSNR, CR	Higher PSNR with lower computation time.
[18]	MRI, CT and CR Chest	No	Yes	HEVC-intra and inter coding modes	PSNR, SSIM	55% reduction in computational complexity with negligible increase in file size.
[19]	MRI	Yes	No	Fuzzy C-means clustering, CAVLC method, DWT and SPIHT	CR, SSIM	Better compression is achieved in this technique than compressing the entire image without trading the image quality.
[20]	Image types were not mentioned	Yes	No	DCT	MSE, PSNR, CR	The proposed algorithm significantly reduced the compression size, maximized the PSNR at 6%, and improved CR and MSE.
[40]	X-ray, CT , MRI, Ultrasound	Yes	No	Delimiter and entropy coding	CR, BPP	High CR, less time for encoding and better BPP values.
[21]	MRI, Ultrasound	Yes	No	Quincunx wavelet and geometric active contour and SPIHT	MSE, PSNR, CR, Mean structure similarity index (MSSIM)	Very satisfactory in terms of CR and compressed image quality.
[3]	Image types were not mentioned	Yes	Yes	Polynomial coding	CR	High CR.
[22]	Skin Cancer images	Yes	Yes	SPIHT, bat-inspired algorithms, DCT and Huffman coding	MSE, PSNR, CR	High CR with low computational complexity. The proposed system passes all the randomness tests provided by NIST.
[33]	MRI	Yes	No	Range block, domain block, fractal compression method and Huffman coding	MSE, PSNR, CR	PSNR is high.
[23]	CT	Yes	No	PSO, DPSO and FODPSO	MSE, PSNR, CR, Structural content (SC), Least mean square error (LMSE), Classification and blending prediction (CBP)	Higher value of PSNR.
[10]	Image types were not mentioned	Yes	No	Feed forward neural network	MSE, PSNR, CR	A CR of 75% is reached. The findings obtained showed that the PSNR could be increased by 1.98% with adequate training.
[24]	X-ray	Yes	No	CT and WT	MSE, PSNR, CR	Achieved around 70% of improvement in compressing and reconstructing the image.
[25]	MRI, CT and X-ray	Yes	No	SVD, 2D DWT and SPIHT	MSE, PSNR, CR	SPIHT technique with more encoding loops (13) is better in phrases of PSNR, MSE and CR than SVD technique.
[26]	CT, MRI, and Ultrasound	Yes	No	DWT, VQ and Huffman coding	PSNR, SSIM, BPP, Root Mean Square Error (RMSE)	High PSNR.
[27]	CT, MRI, X-ray	Yes	No	DWT	MSE, PSNR, CR	Achieved a CR of maximum 20.
[28]	Ct, MRI, and X-ray	Yes	Yes	Combining region growing, SPIHT and WT	MSE, PSNR, CR	Increase CR values three times more than the existing wavelet methods.

Table 1. Comparison of compression techniques used by previous studies (continue)

Ref.	Medical Image types	Compression Lossless	Lossy	Steerages	Performance Metrics	Performance algorithm
[36]	MRI	Yes	No	Feed forward back propagation artificial neural network, Huffman coding and HGAPSO technique	MSE, PSNR, CR, SSIM	LM training method of Quasi Newton algorithm reveals better medical image compression and reconstructs the original image at the receiver without decreasing the quality with high PSNR.
[13]	MRI	Yes	Yes	IWT, SPIHT and RLE	MSE, PSNR, CR	Less algorithmic complexity and takes less time for encoding and decoding process.
[29]	MRI, X-ray, CT scan	Yes	No	DWT and arithmetic coding	MSE, PSNR, CR	Compression gain of 10–12% and less time consuming when applying this form of coding to each block rather than to the whole image.
[38]	2-D CT and MRI	Yes	No	Difference matrix and Huffman coding	CR	In 3D medical images, the proposed method has the highest CR among the control methods.
[34]	Radiography	Yes	No	FIC and SAD techniques	MSE, PSNR, CR	PSNR value above 40 dB on average and able to compress as high as 90.85.
[30]	CT, MRI and Ultrasound	Yes	No	DWT and curvelet transform	MSE, PSNR, CR	Achieves a high PSNR and compression rate.
[31]	X-Ray, CT and MRI	Yes	No	Haar wavelets	MSE, PSNR, CR	Higher CR and PSNR have been obtained with lower MSE.

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