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# Medical Image Compression Using Hybrid Compression Techniques

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**Abstract:** Medical images are crucial in today's healthcare system for diagnosis, but managing the large volume of images generated by different imaging methods is a challenge for Hospital Management Systems (HMS). Image compression, the process of reducing redundancies in image data, helps to store and transmit images efficiently by reducing the file size. This not only saves storage space, but also makes it easier to send images over limited bandwidth channels. Image compression is therefore an important factor in managing medical images for storage and transmission. In this research many loss and lossless compression methods are tested. Then hybrid combinations of these method are used to design an accurate hybrid compression system suitable for medical image. The best compression result is acquired when the Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) are combined, their hybrid compression ratio is 9.348.

**Keywords**: *Medical image, lossless compression methods, lossy compression methods, hybrid compression methods.*

## 1. Introduction

Medical imaging encompasses a range of techniques used to produce images of different parts of the human body for medical diagnosis and treatment. These include X-ray, Fluoroscopy, MRI, CT scan, ultrasound, Endoscopy, Tactile imaging, medical photography, and functional nuclear medicine techniques like PET. Regular imaging is crucial in monitoring the progression of a medical condition, with MRI and CT scans allowing healthcare providers to evaluate the effectiveness of treatment and make necessary adjustments. This results in improved patient care, as the extensive information obtained from medical imaging provides a more comprehensive understanding of the patient's health [1].

Hospitals and medical facilities are quickly transitioning to digital methods for capturing, processing, storing, and transmitting medical images through telemedicine. Digital medical images are primarily obtained for diagnostic purposes and play a crucial role in documenting a patient's case history [4].

Medical images are now managed by IT systems called PACS, which handle the capturing, archiving, transmitting, and accessing of these images. These systems serve as modern replacements for traditional image storage methods and are used for both short-term and long-term storage of images obtained through different medical imaging techniques, such as CT scans, MRI, and X-rays. Computer image analysis plays a significant role in the diagnostic process, but the large size of medical images can lead to communication and storage challenges within the PACS system [5].

The large size of medical images can cause problems during their transmission. This issue is more pronounced in PACS systems where images are transmitted to various computers or devices for processing, viewing, analysis, and comparison to other medical images. The time required for transmission increases as the size of the medical image increases, and if the network is overwhelmed with too many requests, there is a risk of lost packages during transmission, which could result in errors in the interpretation of medical images [6].

In medical imaging, it is imperative to avoid using partially damaged images for diagnosis due to the critical nature of the data. Network issues can cause failed delivery attempts and retransmissions, leading to the need for appropriate digital image compression methods. Image compression helps to minimize the data size required for storage and representation while retaining crucial diagnostic information. With advancements in technology, digital image processing methods, previously only accessible in research labs, are now widely available for commercial use in various domains [9].

In various applications, including video conferencing, video telephony, multimedia systems, document processing and storage, high-resolution TV transmission systems, biomedicine, and others, image compression methods are essential. They are required to reduce the memory usage or capacity of telecommunication channels as they involve transmitting or storing a large

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amount of data for image representation. Medical image compression is unique in that errors or distortions in the compressed image must be kept to a minimum to ensure an accurate and reliable diagnosis, while still achieving high compression efficiency [7].

Image compression is a way to reduce the size of an image by removing redundant information. This is important for efficient storage and transmission of images, particularly digital medical images, which need to be accurately diagnosed. There are two types of image compression: lossless, which retains all image information but has a low compression rate, and lossy, which has a high compression rate but may result in loss of some data. In medical image compression, the region of interest (ROI) for diagnosis is compressed using lossless compression to ensure accurate diagnosis, while the non-ROI area is compressed using lossy compression for efficient transmission and storage [2],[3].

The contribution of this research is to represent the images with the smallest possible number of bits. This research discusses model of compression in region of interest and discusses lossy compression in other regions, establish advantages of multiple compression techniques. The work presented in this research is dedicated the most popular image compression methods available and concluding the best amongst them. The work is carried out by compression of both lossy and lossless techniques. The compression method used in this research includes (Lempel-Ziv Weich, Discrete Wavelet Transform, Huffman encoding, Fast Fourier Transform, Singular Value Decomposition, Joint Photographic Experts Group, Block Truncation coding, Wavelet Based compression, and Discrete Cosine Transform).

The paper is marshaled as follows. The related work is recorded in section 2. While, in section 3, the proposed compression system is described in details. The experimental results of the proposed method are given in section 4. In section 5, this paper concludes with some perspectives is recorded.

### 1-1 Type of image compression

Figure (1) illustrates a general diagram for image compression types.

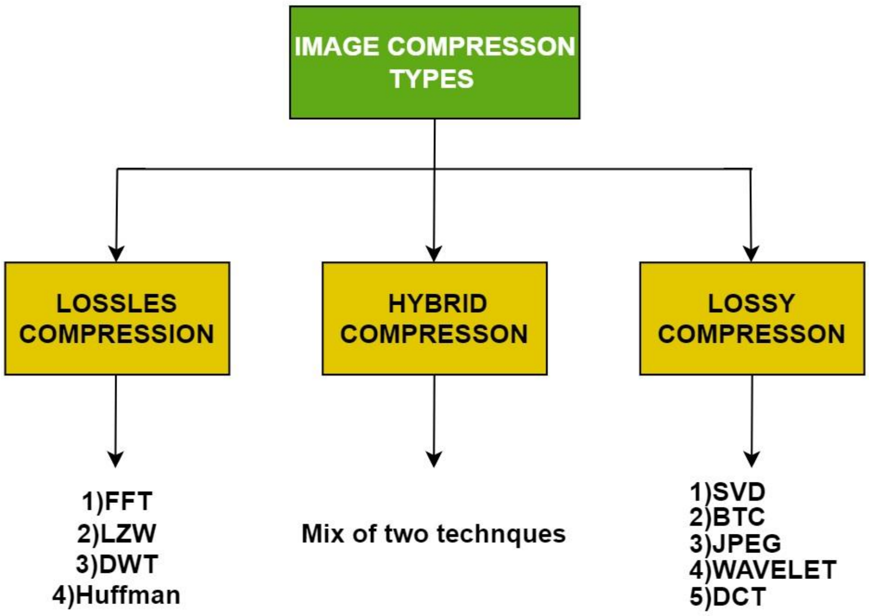


**Fig. 1** Image compression types

#### 1-1-1 Lossless Image Compression

- Lossless compression is a technique that ensures the decompressed data is an exact match to the original data. This approach guarantees that there is no discernible difference between the original and the compressed image. Lossless compression has potential applications in fields such as remote sensing, medical and space imaging, and multispectral picture documentation. However, due to the large amounts of data in these fields, lossy compression may be necessary for practical storage and transmission. An alternative approach to the lossy-lossless challenge in applications like medical imaging and remote sensing is to use a more adaptable compression method that provides a bit stream enabling dynamic image reconstruction. For instance, using wavelets, one can obtain a bit stream that provides various levels of rate and distortion. This approach has been proposed for use in tele-radiology, where a doctor may request higher-quality images of specific areas while receiving initial versions and less important parts at lower quality, thus reducing overall bandwidth requirements [9], [10]. The methods for lossless compression include:

- **Lempel-Ziv-Weich (LZW)**

LZW is a lossless compression technique that has been popularly used in Unix file formats and GIF image compression. This algorithm groups input symbols into strings, and then converts those strings into codes which are smaller in size, thus achieving compression. To create a dictionary, all elements of the image are appended, and then consecutive elements are checked for concatenation. If concatenation is present, a code is generated for the elements in the dictionary, and the code is mapped to the concatenated elements. The dictionary is updated by replacing elements and updating their indices. The encoded image contains codes generated based on the concatenation of the elements in the dictionary. During decoding, the generated codes are used to create a dictionary with an image vector based on concatenation, which reduces redundancy and avoids repeating similar elements with new values. LZW's effectiveness in lossless compression still makes it relevant today for a variety of applications [11][12].

- **Discrete Wavelet Transform (DWT)**

DWT is a lossless data compression method that employs the discrete sampling of wavelets to achieve compression. Wavelets are orthonormal series that can represent square-integrable functions in an image. The wavelets contain information in both time and data, allowing the wavelet transform to modify the time extension without affecting the function's shape. DWT provides the same information as the short-time Fourier transform, but with added wavelet properties. Compression with DWT can be applied at different levels of wavelet decomposition in the image. Haar wavelet decomposition and compression are commonly used because they have a short computation time and require no multiplication. The Haar wavelet also consists of many zero elements, which makes it easier to add new elements. When applying wavelet transformation to an image, coefficients are generated for each pixel, but no compression occurs during this stage. However, the coefficients generated tend to have a concentration of statistical information in a few of them, making them more amenable to compression. This compression technique is called transform coding. After the transformation, the coefficients are quantized and encoded to achieve compression. Among the different wavelets available, the Haar wavelet transform is the fastest and most efficient way to perform the compression. This wavelet captures both frequencies and the times at which they occur, allowing the wavelet to perform operations based on a discrete function [13][14].

- **Huffman encoding**

Huffman encoding is a lossless data compression method that was invented by David Huffman. It generates an optimal prefix code from a set of probabilities and has found widespread use in various compression applications. The codes generated by Huffman encoding are of variable length, using an integral number of bits. This approach reduces the average code length, resulting in a smaller overall size of compressed data than the original. The technique involves merging the lowest probabilities to create a binary tree. It is based on the probability of occurrence of values in a given data, with each character assigned a variable-length code determined by its frequency of occurrence. Characters that occur more frequently have shorter codes, while characters that occur less frequently have longer codes. This results in more efficient data compression, as shorter codes are used for the most frequent characters and longer codes for the less frequent ones [11][15][16].

- Fast Fourier Transform (FFT)

The FFT is a widely used algorithm in signal processing, image processing, and lossless data compression. However, for image compression, the DCT is the preferred transform since it can typically represent more information using fewer coefficients than other transforms. This is due to the DCT's implicit assumption of an even extension of the signal beyond the sampling domain, resulting in a smoother signal with fewer coefficients compared to the Discrete Fourier Transform, which can have discontinuities at the boundaries. In contrast, an image compression algorithm based on the FFT algorithm shows a more significant deterioration in image quality when reducing coefficients. This is because the FFT method's compression capability is limited to a maximum of 23% before causing severe distortion. On the other hand, Fourier techniques have been useful in image denoising, which takes advantage of the fact that image artifacts tend to have different frequencies than the rest of the image. By decomposing complicated objects into simpler components, Fourier techniques can remove redundant information and retain only the most important components of the image, allowing for effective compression and de-noising of images, audio, video, and other signals [16][17].

**1-1-2 Lossy compression**

- A lossy compression technique is a method of compressing data where the decompressed data may not be exactly the same as the original. This type of compression allows for a smaller file size, but at the expense of reduced quality or loss of information. The larger compression ratio is achieved by exploiting redundancies in the data, such as psychometric, encoding, or inter-pixel redundancies. This results in a trade-off between compression ratio and image quality. For instance, the use of one level of grey instead of two very similar levels can save space while still being indistinguishable to the human eye. The lossy compression methods are[15]:

- **Singular Value Decomposition (SVD)**

SVD is a compression method that achieves compression by using a smaller rank to approximate the original matrix that represents an image. It decomposes the original matrix, aiming to approximate a high-dimensional dataset with fewer dimensions. SVD works by reducing higher dimensional data into lower dimensional data, exposing the substructure of the original data, which orders the data from the most to the least variation. This helps identify the region of most variation, which can be used for reduction. SVD factorizes a given matrix with m rows and n columns into three matrices, providing a stable and reliable technique that yields a good compression ratio. The technique splits the image matrix into a set of linearly independent matrices, providing a practical solution to the image compression problem. The compressed output for different r values is displayed above, showing that the selection of the r value is critical in this SVD-based image compression technique [18].

- **Joint Photographic Experts Group (JPEG)**

JPEG is a popular lossy image compression standard that is widely used to store and transfer images across devices and limited bandwidth environments. It achieves high compression ratios while maintaining almost lossless quality, making it well-suited for photos and realistic scenes with uniform changes in tone and color. However, it may not be suitable for images with many edges and sharp changes, as this can result in image artifacts. Lossless formats like PNG, TIFF, or GIF are better suited for these types of images. JPEG is not recommended for medical and scientific applications where image accuracy is crucial and slight errors can result in the loss of important data. Frequent editing and saving of JPEG images can also result in further loss of quality, which can be minimized by editing and saving images in a lossless format and only converting them to JPEG format before the final transfer. JPEG image files typically have extensions like JPG, JPEG, or JPE. Transform coding, DCT, and wavelet transform are used to obtain the correct image, with transform coding being a critical part of modern image and video processing applications that relies on the principle that quality in the image is displayed and linked with adjacent quality [19].

- **Block Truncation Coding (BTC)**

BTC is a lossy technique designed to compress grayscale images. The method works by dividing the image into blocks and reducing the number of grey levels within each block through quantization while keeping the same mean and standard deviation. BTC has also been modified for video compression. The technique was first introduced by Professors Mitchell and Delp at Purdue University. Another version of BTC is AMBTC, which preserves the first absolute moment instead of the standard deviation and mean.

By compressing sub-blocks of 4x4 pixels with 8-bit integer values used during transmission or storage, BTC can achieve compression of approximately 25%. Larger blocks can achieve greater compression, but the quality of the resulting image decreases as the block size increases due to the nature of the algorithm [5][6].

- **Wavelets based compression**

Wavelet-based compression is a lossy technique that involves decomposing a signal into wavelet coefficients, which are used to measure the signal features and scale the energy components in the signal. The wavelet transform is based on representing an arbitrary function as a linear combination of a set of wavelets obtained from a single mother wavelet by dilations and translations. The wavelet transform is used to change the data from the time-space domain to the time-frequency domain, which results in better compression. Wavelets are a class of functions that can localize a signal in both space and scaling domains, and a family of wavelets can be constructed from a mother wavelet. The use of wavelets for compression allows for multi-resolution analysis, which means analyzing the signal at different scales or resolutions. The advantage of wavelets over other compression methods is that they can adapt to both high-frequency and low-frequency components of a signal. Unlike other transform-based methods, wavelet-based compression is less affected by local mistakes, which means small changes in the wavelet representation correspond to small changes in the original signal[8].

- **Discrete Cosine Transform (DCT)**

The Discrete Cosine Transform (DCT) is a type of lossy compression technique used to compress images by using a sequence of data points obtained by summing cosine functions oscillating at different frequencies. It is based on the Fourier Transform with real numbers, where Fourier series coefficients of a periodic sequence are used. While DCT is generally lossy, it can also be used as a lossless technique to compress images by using the coefficients generated after performing the transform. Compression is achieved by multiplying the image matrix with the DCT matrix and its transpose, using a masking square matrix to reduce the number of coefficients and, hence, the size of the image. The larger the masking, the higher the compression, but the more significant the loss in quality. The masking matrix is predefined and can be changed as required. To compress images using DCT, an 8x8 pixel block case is created to find the DCT coefficients. The entries of the pixel block case are either 0 or 1, which are used for masking the image matrix. [12], [16]

**1-1-3 Hybrid compression**

A new image compression technique is needed to improve the compression rate. It involves the use of two compression methods to achieve efficient image compression. The quality of the compression is evaluated based on the difference between the original image and the reconstructed image, which is referred to as distortion. A smaller difference between the input and reconstructed image indicates a high-fidelity reconstruction and vice versa.

## 2. Related work

In the last decade, various studies have been conducted to investigate the compression of medical images and address related concerns. The methodology chosen by researchers depends on the specific application and problem they aim to address.

Prasantha et al. [20] introduced a new image compression technique utilizing a modified version of Singular Value Decomposition (SVD). The proposed solution utilizes a lossy compression method, as it provides the best compression ratio. To minimize computation complexity, the authors preprocessed the SVD to create a modified SVD.

Magar et al. [21] utilized oscillation theory to develop a novel approach for biomedical image compression. By repeatedly extracting the principal component from medical images, they achieved higher compression ratios compared to other works in the field. This approach allows the end-user to choose any principal variable that suits their needs and applications. With each iteration, the number of theory components increases, leading to an increased compression ratio.

Kundlik et al. [22] proposed a novel approach for biomedical image compression that combines oscillation theory with Discrete Cosine Transform (DCT). This method is similar to the previous one, but with the added benefit of DCT. The DCT transforms the image signal into elementary frequency components, which are commonly used in medical image compression and allow for holding a significant amount of information in fewer pixels. By combining oscillation theory with DCT, the proposed approach provides a high compression ratio with high-quality compressed images.

Li et al. [23] introduced a novel approach for medical image compression that involves both lossy and lossless encoding of 16-bit depth images. The optimization of JPEG_XT algorithm, known as OPT. JPEG_XT, is used to compress the medical images by amplifying the DCT coefficients. This helps to preserve the tiny integer information in the digital components of the medical images, improving compression efficiency. The method begins by dividing a 16-bit depth image into two 8-bit depth sub-images and using 2D-DCT to separate the largest DCT coefficients (DC) from the rest (AC). Instead of using the conventional baseline JPEG process, the method employs Zig-Zag scanning. The DC and AC coefficients are amplified for N terms and by a certain NDP's to retain all the data from the AC coefficients, with the final rounded DC and AC coefficients being stored in the compressed data.

Saran et al. [24] proposed a hybrid technique for medical image compression that involves two steps. First, the saliency-based Fuzzy C-Means clustering algorithm is used to extract the Region of Interest (ROI) from a medical image, and then the SPIHT algorithm is used to compress the ROI with high bit rates in the ROI and low bit rates in non-ROI regions. The authors are also concerned with reducing computational complexity. The experiments were carried out using the widely used BRATS dataset [25]. This approach resulted in accurate ROI shape image detection with a high compression ratio and good visual quality compression.

In spite of the many research that conducted in medical image compression area, the hybrid compression methods do not examine dramatically. This task is the main contribution of this research.

## 3. The Proposed System

This research was implemented in four steps: -steps1, lossy image compression and decompression, step2, lossless image and decompression, step3, hybrid lossy and lossless compression, step4, evacuation of compression techniques. Figure 2 shows the overview of the proposed system steps. The lossy and lossless methods are tested to select the best method to build the hypered compression system for medical image which is the main goal of this paper.

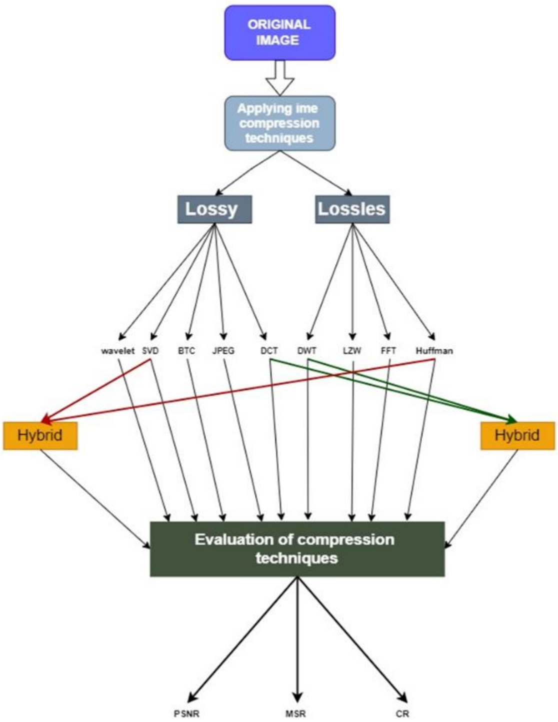


**Fig. 2** The proposed compression system

### 3.1 Lempel-Ziv-Weich (LZW)

To use LZW for compressing an image, the following steps are typically followed:

1. Create a table with a fixed number of entries, often 4096.
2. Assign codes 0 to 255 to represent single bytes in the table.
3. Use codes 256 to 4095 to represent repeated sequences in the data to be compressed.
4. Identify repeated sequences in the image data and add them to the code table.
5. Perform the compression by replacing the repeated sequences with their corresponding codes.
6. Decoding is done by translating the code table back to the original data it represents.

### 3.2 DWT

To compress an image using DWT, the following steps must be taken in MATLAB:

1. Open the image file.
2. Apply the wavelet transform to generate four coefficient matrices: cA (approximation), Ch (horizontal details), CV (vertical details), and CD (diagonal details) for level 1.
3. Store the coefficients in vectors.
4. Perform level 2 decomposition using the level 1 approximations, and store the resulting coefficients in the same vector as the level 1 decomposition coefficients.
5. Use the "ddencmp" and "wpdencmp" commands in the wavelet toolbox to compress the decomposed data.
6. Compress both the level 1 and level 2 decomposed data in the vector to prevent any degradation of the image.

### 3.3 Huffman encoding

To compress an image using Huffman coding, the following steps should be taken in MATLAB:

1. Open the image file in MATLAB.
2. Invoke a function to identify the symbols in the image that are not repeated.
3. Invoke another function to calculate the probability of occurrence of each symbol.
4. Sort the probabilities in decreasing order, and merge the probabilities with the lowest values until only two probabilities remain.
5. Assign codes to each symbol according to the rule that the symbol with the highest probability gets assigned a shorter code.
6. Perform Huffman encoding, which involves mapping the code words to the corresponding symbols to generate the compressed data.

### 3.4 FFT

To compress an image using FFT, the following steps are necessary:

1. Subdivide the medical image into 8x8 blocks and store them in RAM for FFT computation.
2. Preprocess the image to suppress unwanted distortions or enhance image features. This may involve down-sampling to reduce the sampling rate, which reduces computation and memory requirements.
3. Compute the FFT coefficients of the image to represent it in the frequency domain, with frequencies ranging from low to high.
4. Quantize the FFT coefficients to make the algorithm lossy. A quantization matrix is designed to set the values close to zero to zero, and reduce the other values.
5. Use Huffman coding to eliminate coding redundancy, which is associated with the representation of information. This is a simple and popular compression method that removes redundancy in coding.

**3.5 SVD**

To compress an image using SVD, the following steps should be followed:

1. Convert the image from RGB to YCBCR color space.
2. Extract the three components: Y, CB, and CR.
3. Apply SVD to each component to generate three vectors.
4. Use the reconstruction algorithm to obtain the intermediate image from the components.
5. Obtain the frequency components for U and V components.
6. Use the threshold values of U and V matrices to obtain the resultant image.
7. Concatenate the Y, CB, and CR components to form the final image.
8. Calculate the compression ratio.

**3. 6 JPEG**

To compress an image using JPEG, the following steps should be followed:

1. Split the image into 8*8 blocks, where each block is considered as 1 pixel.
2. Convert the RGB color space to YCbCr color space to remove color information that is less sensitive to the human eye.
3. Apply the Discrete Cosine Transform (DCT) to each block. This represents the image as a sum of sinusoids of varying magnitudes and frequencies.
4. Quantize the data using the quantization table.
5. Perform zigzag scanning to exploit redundancy and serialize the data.
6. Apply Differential Pulse Code Modulation (DPCM) on DC elements, which define the strength of colors.
7. Encode the image using either Run Length Encoding (RLE) or Huffman Encoding to convert it into binary form (0,1) for compression.

**3.7 BTC**

BTC involves breaking down an image into smaller, non-overlapping blocks of equal size and processing each block independently. This process is reversible and linear and results in transform coefficients that are quantized and coded. The transformation process aims to remove correlations between the pixels of each sub-image. For an input image of size M * N, it is divided into sub-images of size n * n, resulting in MN = n^2 sub-image transforms arrays. After quantization, coefficients with the least amount of information are eliminated. The decoder then uses an inverse sequence of steps to decompress the image.

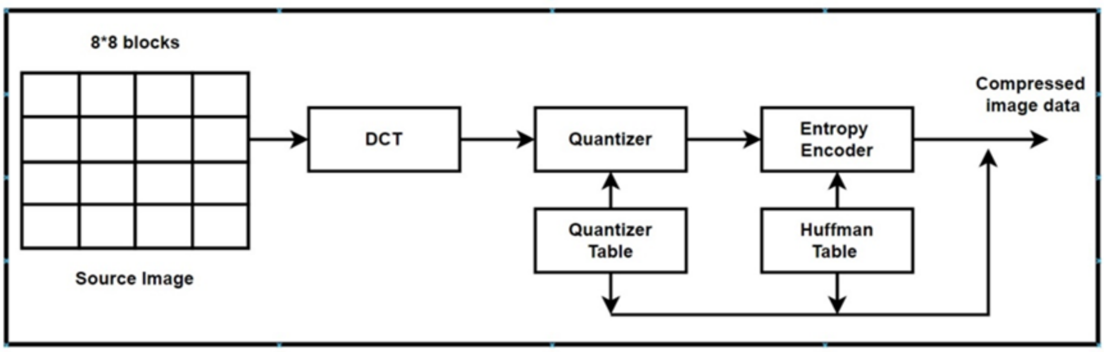


**Fig. 3** illustrates this process.

**3.8 Wavelet based compression**

To perform wavelet-based image compression, the following steps should be taken:

1. Digitization: The first step involves characterizing the digitized image by its intensity levels, ranging from 0 (black) to 255 (white), and its resolution in

pixels per square inch. The image is then decomposed into a sequence of wavelet coefficients.

2. Thresholding: In some cases, many wavelet coefficients are close to or equal to zero. Thresholding is used to modify the wavelet coefficients and create a new sequence W'.
3. Quantization: The subsequent stage in the process is quantization, where the continuous floating-point values in W' are transformed into a series of integers q, typically by rounding to the nearest integer.
4. Entropy encoding: To achieve compression, the next step after quantization is entropy encoding. Despite using wavelets and thresholding to process the signal, there is no actual compression until this step. The most common method to compress the data is Huffman entropy coding. This technique converts the integer sequence q into a shorter sequence e, which contains fewer bits and is more efficient to store and transmit.

### 3. 9 DCT

The DCT algorithm is a compression technique used to compress images. It involves dividing the original image into blocks of 8 x 8 pixels and then using a pixel block case that contains entries of 0 or 1 to mask the image matrix. The DCT matrix, which is available in the MATLAB image processing toolbox, is then multiplied with the image matrix and its transpose to generate DCT coefficients. The resulting matrix is then multiplied with the pixel block case to obtain a compressed image matrix. The upper left corner of the DCT matrix contains the higher energy coefficients, which contribute more to the compressed image. A flowchart of these steps can be seen in Figure 4.

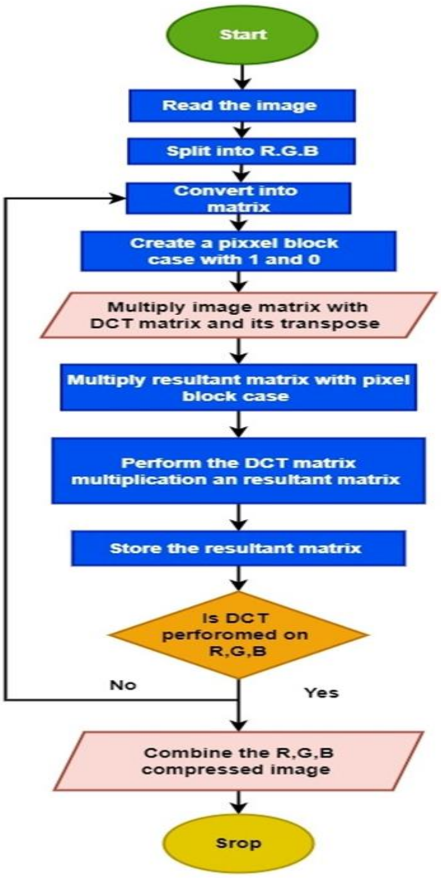


**Fig. 4** Flowchart of DCT

### 3.10 Hybrid compression

The compression of the image involves the use of two compression techniques, which are lossy and lossless. When combined, these techniques produce a compressed image with a high-quality compression ratio while preserving the overall quality of the reconstructed image. The lossy compression method is responsible for producing a higher compression ratio, while the lossless compression technique ensures that the quality of the compressed image is maintained. The hybrid compression system for medical images is depicted in Figure (5).

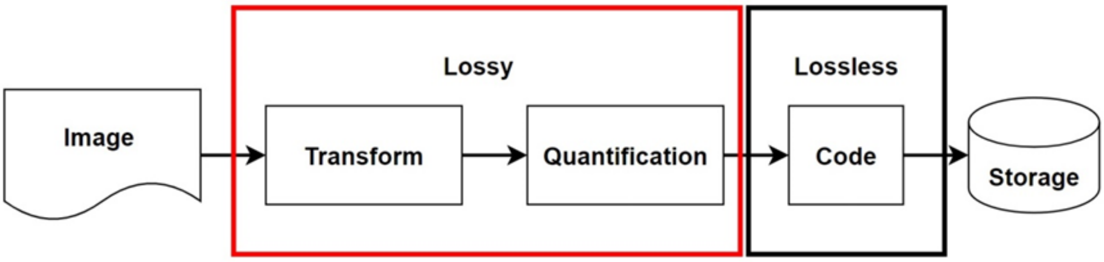


**Fig. 5** Block diagram of BTC

## 4. Experimental Results Evaluation and Discussion

In this section the experiential results for lossy, lossless and hybrid compression methods are illustrated. Fig (6) records the LZW algorithm implementation result. The binary images are used, the implementation of algorithm depend on using dictionary and mapping of code generated to the elements in dictionary. DWT results in lossless image after compression. wavelet is quantized and compressed to give binary images as shown in in fig (7). Huffman encoding also produces lossless image after compression. Huffman uses probability function to encode and compress as shown in fig (8)

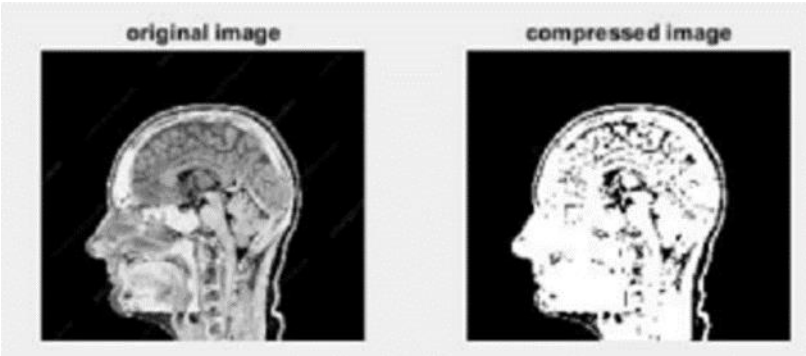


**Fig. 6** LZW

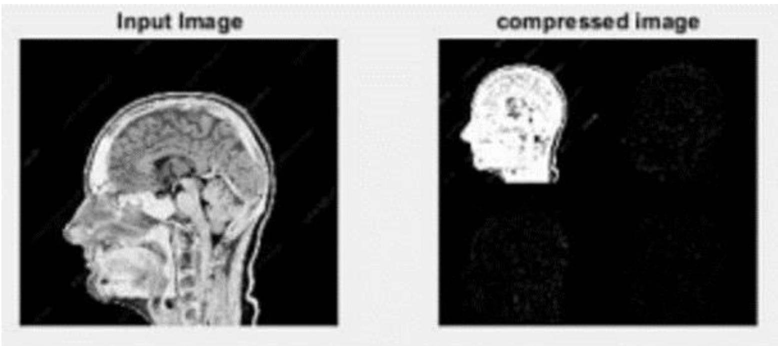


**Fig. 7** DWT

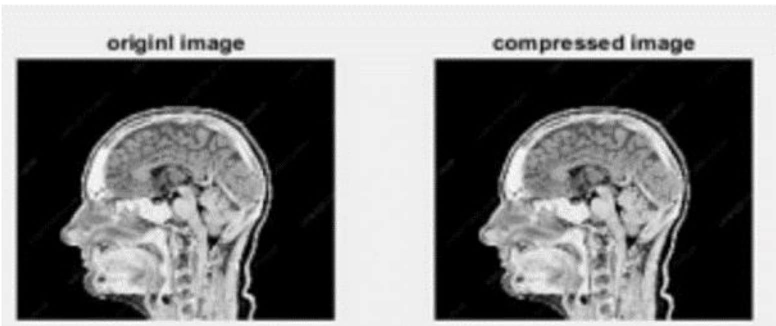


**Fig. 8** Huffman

SVD techniques provide stable and practical solution to image compression. The result shown clearly display the compressed output for different singular value. Thus, selection of singular value plays a crucial role in this

SVD based image compression technique as shown in fig(9).

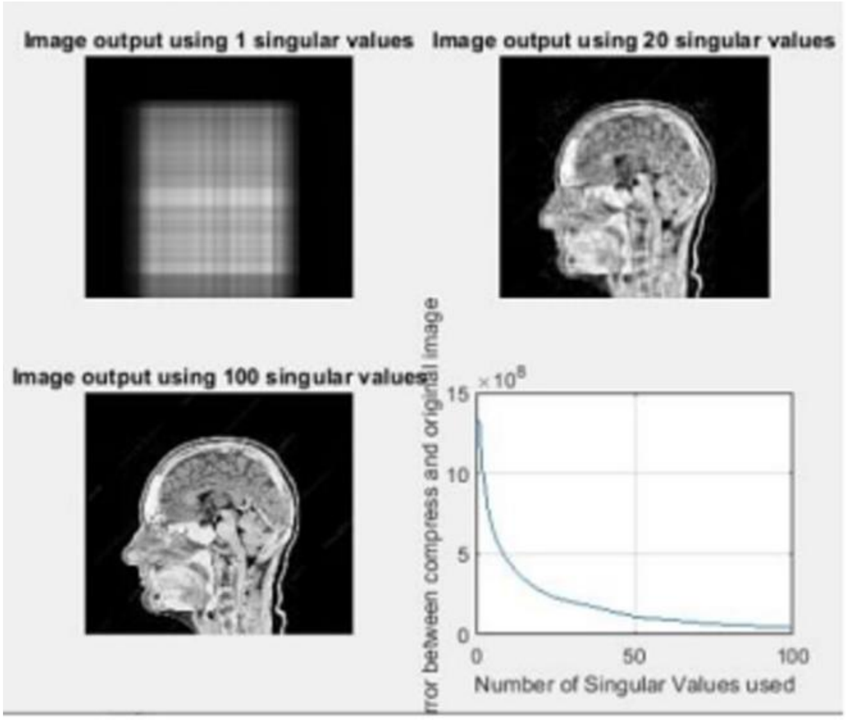


**Fig. 9** SVD

JPEG Produce lossy image compression, this method can easily store more number of images and reduces its size as illustrates in figure (10).

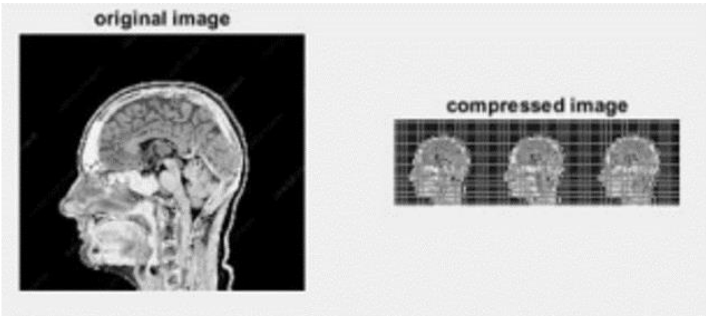


**Fig. 10** JPEG

BTC mainly used for grayscale images and come under the category of lossy image compression. The BTC output data set includes a binary bit plane ,as shown in fig(11)

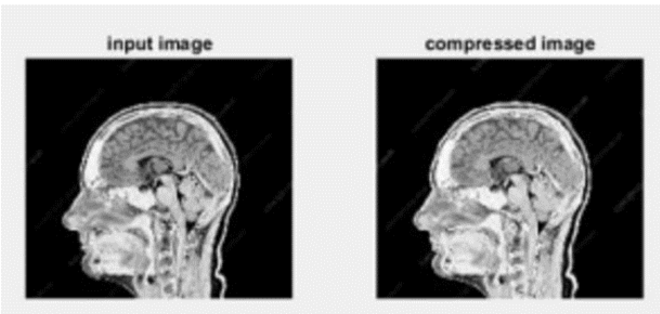


**Fig. 11** BTC

Wavelet image compression achieve better performance than other coding, since there is no need to block the input image and its basis functions have variable length, wavelet based coding schemes can avoid blocking artifacts as shown in fig(12).

While, DCT produces a lossy image as the masking matrix is adjusted in order to produce a image with lossy in the quality as shown in fig(13).

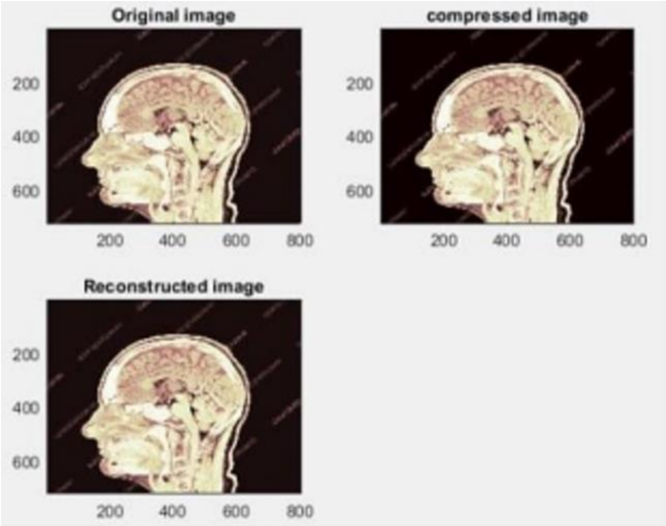


**Fig. 12** Wavelet

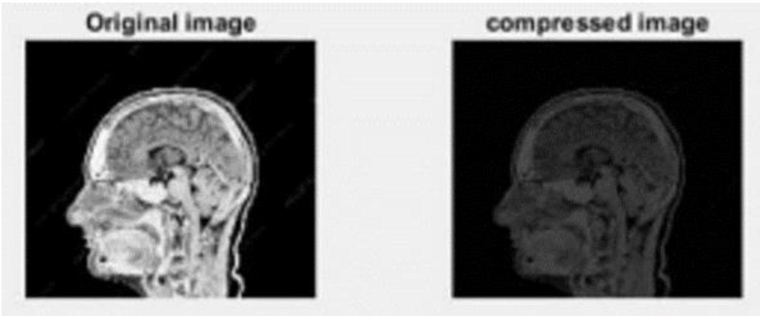


**Fig. 13** DCT

In this research, hybrid compression technique contains of (SVD and Huffman techniques) and (DCT and DWT techniques) are implemented. The algorithm of these techniques was explained in previous sections. In first hybrid techniques combines between lossy technique (DCT)and lossless technique (DWT) to obtain a high-quality compression ratio as shown in fig (14).

The second hybrid techniques combine between lossy technique (SVD)and lossless Huffman technique as shown in fig (15).

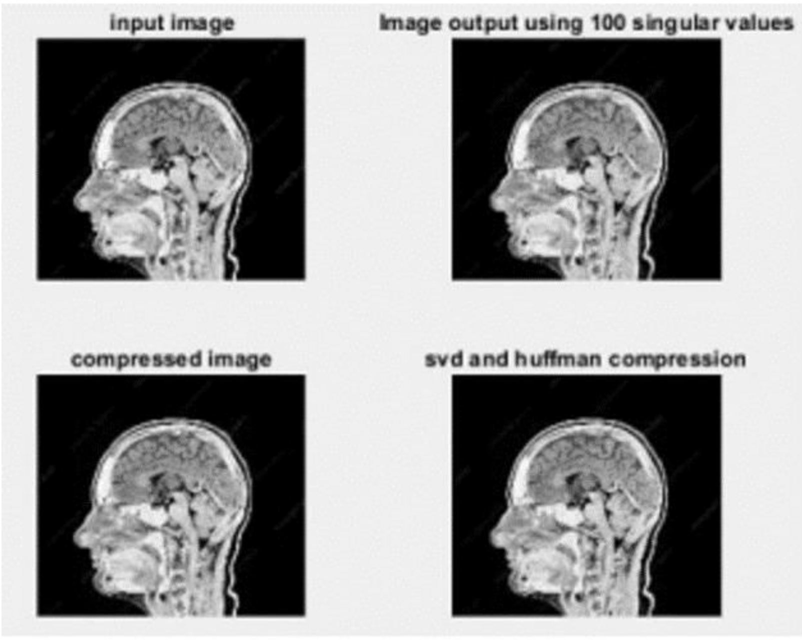


**Fig. 14** SVD + Huffman

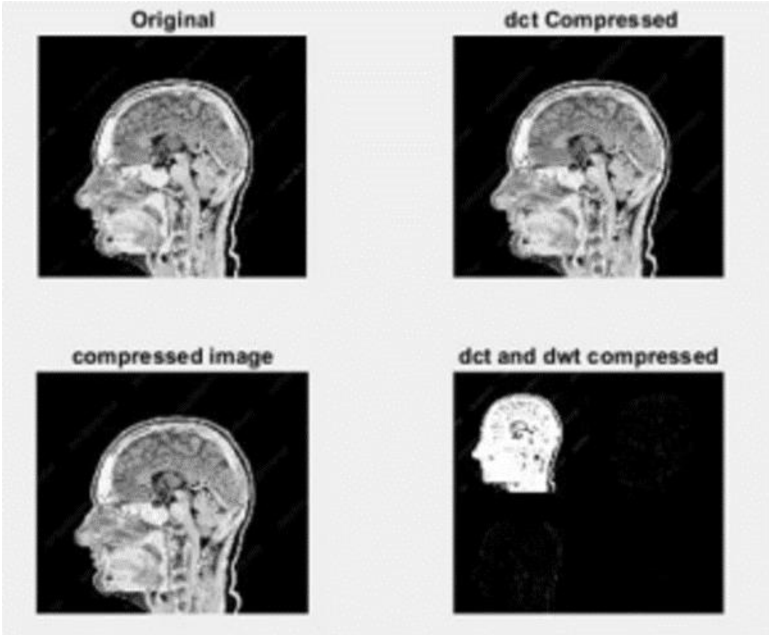


**Fig. 15** DCT+DWT

To evaluate the compression performance for the designed hybrid compression system and the lossless and lossy compression techniques different standard evaluation methods are used. The first method is Compression Ratio (CR). CR is a measure of the percentage difference between the original size of a file and its size after being compressed. The compression ratio is affected by various factors, such as the initial state of the file and the compression algorithm employed. A higher compression ratio requires more resources to either compress or decompress the data. In lossy compression, a higher compression ratio results in a smaller image size but lower image quality, whereas in lossless compression, a higher compression ratio produces a compressed image of higher quality. Equation 1 defines the compression ratio.

$$compression\ ratio = \frac{uncompressed\ size}{Compressed\ size}$$

The second method is PSNR. It is a metric that calculates the maximum error between two images, typically used to assess the quality of a compressed image in comparison to its original. A compressed image with a higher PSNR score is considered to have better quality than a lower one.

When an image's pixels are represented using 8 bits per sample, the maximum possible pixel value is 255, which is also referred to as "Max".

$$PSNR = 10\log_{10}\left(\frac{MAX2}{MSE}\right)$$

The third method is Mean Squared Error (MSE). It is a metric used to determine the total squared error between the original and compressed image. It is calculated using the following formula, where M and N are the dimensions of the digital image. During image compression, it is desirable to minimize the MSE, especially in hybrid compression techniques.

$$MSE = \frac{1}{MN}\sum_{J=1}^{M}\sum_{K=1}^{N}(X_{J,K} - X_{J,K}^{2})^2$$

The evaluation results for the lossless and lossy compression method results of compression techniques for medical image are recorded in table ().

| Compression Techniques | COMPRESSION RATIO | PSNR | MSE |
|---|---|---|---|
| 1- FFT | **23.42** | **8.152** | $\mathbf{9.95e^{+3}}$ |
| 2-LZW | **29.40** | **7.2679** | $\mathbf{1.219e^{03}}$ |
| 3-DWT | **3.701** | **27.955** | **104.94** |

| | | | |
|---|---|---|---|
| 4-Huffman | **2.65** | **7.2566** | **1.23$e^{+03}$** |
| 5-DCT | **9.58** | **10.25** | **6.13$e^{+3}$** |
| 6-Wavelet | **51.14.707** | **47.3096** | **1.2081** |
| 7-SVD<br>At 1singular value<br>At 20 singular value<br>At 100 singular value | **7.4199**<br>**3.515**<br>**2.898** | **14.48**<br>**21.48**<br>**29.847** | **2.34$e^{+3}$**<br>**462.21**<br>**67.35** |
| 8-JPEG | **2.33** | **73.437** | **0.0030** |
| 9-BTC | **3.385** | **21.07** | **507.57** |

**Table 1** Result of compression techniques

Compression need technique with a high Compression Ratio (CR), a high PSNR and low MSE to get the best compression for the image, and thus we keep the data from loss and the image quality is better as we note in the table of evaluation. In hybrid technique combine both lossy and lossless technique to provide compression without much loss of the image. The best hybrid compression is DCT and DWT because it gives high compression ratio. The results explain in table (2).

| **Hybrid Technique** | COMPRESSION RATIO | PSNR | MSE |
|---|---|---|---|
| **DCT and DWT** | 9.348 | 28.003 | 103.9 |
| **SVD and Huffman** | 2.651 | 74.88 | 0.0021 |

**Table 2** Result of hybrid technique Conclusion

The primary objective of this paper was to develop an effective compression method for medical images. The initial approach involved lossy compression algorithms such as SVD, JPEG, BTC, Wavelet, and DCT, which resulted in the loss of crucial diagnostic information in critical areas. On the other hand, lossless compression algorithms, including LZW, DWT, Huffman, and FFT, did not provide a significant compression ratio or memory space. As a result, researchers turned to region-based compression as a potential solution to achieve higher compression rates while maintaining essential diagnostic data. The study found that a hybrid compression approach combining SVD and Huffman techniques or DCT and DWT techniques provided better results than other techniques in terms of MSE, CR, and PSNR enhancements without losing important information. Compressed medical images occupy less memory, thereby saving storage space and facilitating faster transmission between centers with lower bandwidth. Additionally, compressed medical images can contribute to more efficient database management in Picture Archiving and Communication Systems (PACS).

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