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# Compressive Sensing Based Brain MRI Medical Image Compression and Encryption Using Three Different Basis Transformers

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**ABSTRACT:** Basis transformers and measurement matrices have an effective role in compressing and encrypting images. Therefore, choosing a suitable basis transformer for use in image sparsening with Compressive Sensing (CS) system is very important for image compression and encryption. There are different types of basis transformers such as discrete cosine transform (DCT), fast Fourier transform (FFT) and discrete wavelet transform (DWT). In this research, a CS algorithm is proposed with three different transformers for compression and encryption of brain MRI medical images. The three transformers DCT, FFT and DWT with daubechies1 (db1) filter are used for MRI image sparsity. CS with DWT is applied to three detail sub images that show the vertical, horizontal, and diagonal detail in the image. A random partial Fourier measurement matrix was used to generate the measurement matrix for image sparsity compression and encryption. The algorithm L1 norm was used to reconstruct the compressed and encrypted image. The main objective of this study is to compare the use of the three transformers with CS (CS with DCT, CS with FFT, and CS with DWT), thus choosing the appropriate transform with CS for compression and encryption of the brain MRI medical images. In this paper, eight different sensing matrices were also studied and the most suitable one with the sparse image was selected. The most appropriate choice was the random partial Fourier measurement matrix. The performance of the proposed system was evaluated using elapsed time, compression ratio (CR), compression factor (CF), space savings, power to signal ratio (PSNR), structural similarity index (SSIM), mean square error (MSE). Experimental results showed that the technique of CS with DWT outperformed the technique of CS with DCT and FFT. Compression technology of CS with DWT achieved the highest CR of 3.7786 with PSNR of 39.1039 dB, SSIM=0.9944, MSE=1.0984, the space savings=73.54 %, CF=0.2646 and elapsed time=24.312920 second.

**KEYWORDS**: Compressive Sensing, Sparsity, DCT, FFT, DWT, Sensing Matrix

## 1. INTRODUCTION

Considering the fast growth of multimedia transmissions over public networks, signal transformation and storage security is a serious concern. In order for signals to be transferred quickly and safely, they should be compressed and encrypted. Encryption transforms a signal into a difficult-to-understand format. Encryption is necessary since it keeps the data between the sender and the receiver as a secret. For fast transmission and effective data storage, compression is necessary [1]. Today, signal compression is a very popular approach because compression is used in every aspect of data processing and storage. Users may easily find information from a source by employing the sensing approach. Sensing is an extremely significant process; therefore, it requires certain requirements as well. The Nyquist theorem is the approach that is required for that processing. This theory is considered a fundamental standard for digital signal processing, and it may be used to reconstruct compressed signals accurately. According to the Nyquist theory, the sampling frequency must be twice the signal's highest frequency component. The Nyquist bandwidth could easily recover the compressed signal while maintaining a high level of precision and a minimum number of noise components. However, this conventional theory has considerable complexity and bounds. One of Nyquist's primary problems is that to recover a signal successfully, the signal must be sampled at a sampling rate higher than twice the signal's largest component. That's not often achievable because the information we need to utilize is too large. As a result, a novel method known as compressive sensing (CS) is being considered to solve this problem. Using only a minimum number of samples from the actual signal, this technique could recover the actual signal with less noise. This will not need to save as much data if this method is to be used [1].

Lately, CS technology that effectively collects and reconstructs signals has become a popular signal processing technique. This has attracted the interest of professionals working in the fields compression and encryption image at the same time [2]. For example, This is utilized to send medical images via the internet securely [3]. CS is as well extensively utilized in systems that require secure data deduplication [4].

CS is a method of getting the compressed signal from a considerably minimum number of samples than the Nyquist sampling model requires. The following three key principles underlying CS: The first is the transform domain's sparse presence of the original signal. The second is the incoherence of the sensor and transform matrix, while the third is a restricted isometry property (RIP). The number of measurements would determine if the reconstruction algorithm needed to restore the data that had been compressed correctly. Sparsity is a feature of the real signals in one domain or another. When the information obtained is not sparse for a specific domain the signal must be transformed into another domain [1].

The signal can be compressed if it is sparse, according to CS. The term "sparsity" refers to the presence of few non-zero values in a signal that contains the majority of a signal's information. A compression is caused by the measurement matrix. If the transmitter and receiver share the measurement matrix as a key, CS operates as a cryptosystem [1].

Several methods have been proposed to find sparse representation for the MRI image using transformers. A new method for compression MRI images based on CS is presented in [5], using three transforms: CDF 9/7 wavelet transform, DWT and DCT. For compressive sampling, three different measurement matrices were applied to the three transform coefficients of the MRI image. These measurement matrices are Gaussian matrix, random orthogonal matrix and Bernoulli matrix. To reconstruct the MRI image, orthogonal matching pursuit (OMP) and Basis Pursuit (BP) were applied. The experimental results showed that the proposed approach based on CDF 9/7 wavelet transform has a compression ratio higher than DCT and DWT in terms of image quality evaluation.

The CS with DWT and CS with DCT algorithms were used to compress a sample CT and MRI image in [6]. A Gaussian random matrix was used to compress the sparsified image. The compressed image had been reconstructed using the L1 norm. The experimental results showed that the compression technique based on CS and DWT outperformed the compression technique based on CS and DCT.

Image compression, privacy protection, and secure data collection are three important requirements in image-based medical monitoring systems. A new CS technology has been proposed to secretly sampling, compression, encryption and collect MRI images simultaneously in [3]. The sparsity of the MRI image was represented by DWT. A random Gaussian matrix was used to generate the measurement matrix. The OMP algorithm had been used to reconstruct the MRI image. The experimental results showed that this proposed system is characterized by a remarkable compression ratio, good accuracy and a high level of confidentiality.

Various compression algorithms were presented in [7], using different transformers such as DCT, DWT, DFT and hybridization based on the CS technique on some medical images such as brain MRI, brain CT, and chest X-ray. A Gaussian measurement matrix was applied to the sparsified images to compress the medical images. Then OMP had been applied to the sparsified and compressed images to reconstruct the medical images. Experimental results showed that the medical images compression generated by these algorithms is better than the traditional compression algorithms. When applying the CS technique to MRI images, it provides a significant reduction in scanning time. In this study [8], a technique was proposed to reconstruct an MRI image from under sample measurements. DWT was used to represent the sparsity of the MRI image. And the Gaussian measurement matrix is used for scattered image compression. The L1 norm algorithm has been used to reconstruct the MRI image. Experimental results showed that the proposed technique gives good quality in MRI image reconstruction. CS with multi-wavelet transform was used in [9], to reconstruct the MRI image from compressed sampling. A random Gaussian matrix was used to generate the measurement matrix. The L1 norm algorithm has been used to reconstruct the MRI image. The experimental results showed that the proposed system achieved a high compression ratio, but it required a longer processing time.

These studies indicate that in the future, CS approaches will be an interesting topic to study in order to overcome memory storage limitations. How to achieve high compression ratio and PSNR with simple techniques while producing high resolution is the main issue and problem in implementing CS especially on images. Paper [3] gives us good results and is simpler than the other papers' methods. The method suggested in paper [3] outperforms the other papers, so the CS scheme and the method used in this paper is suitable for compression of medical images.

This study proposes compression and encryption of MRI medical image using compressive sensing with various basis transformers. Three different transforms are used in this study which are: - Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) in order to choose the most suitable transform of the medical MRI images. This paper also studies eight various sensing matrices and selects the matrix that is most suitable to be used with the sparsified image.

## 2. COMPRESSIVE SENSING THEORY

According to the CS theory, the actual signal may be better reconstructed from the sampled data when sampling a sparse signal less than the Nyquist rate. It describes how a sparse signal can be expressed by a collection of smaller projections than the original signal. The sampling process may be stated as follows [10]:

$$y=\Phi . X \qquad (1)$$

Assume that $X$ is a sparse signal of size N x 1, Φ is the measurement matrix of size M x N (M<< N), y is a M x1 measurement vector. Figure (1) shows the structure for compressive sensing.

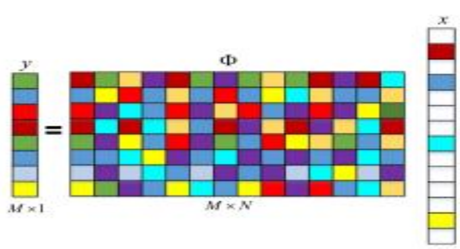



**Figure (1):** Structure for compressive sensing [3]

An important part of the compressive sensing system is the measurement matrix, the measurement matrix is responsible for compressing the data. Different matrices can be considered as measurement matrices like: Gaussian, Orthogonal, Bernoulli, Hadamard, Toeplitz, Circulant, etc. [11]. In most cases, the real signal is not sparse. When using CS theory to a real signal, it must first convert it to the frequency domain like as Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) in order to obtain the sparse form and then apply CS to this sparse signal. As a consequence, the sampling procedure for a real signals may be described as [10]:

$$y=\Phi.\Psi.S=\Phi.\ X \qquad (2)$$

Where $\boldsymbol{X}$ is the signal's sparse form S and Ψ is transform matrix. The signal's sparse $\boldsymbol{X}$ has K non-zero elements, it is called K-sparse. To reconstruct the original signal in its entirety, M = O (K $\log_2$ (N/K)) the parameters M, N, and K must all be joined and the measurement matrix Φ must be satisfied by the restricted isometry property (RIP). an assessment of $\boldsymbol{X}$, expressed as $\bar{x}$, may be determined while recovering an original signal via overcoming the following problem of optimization [10]:

$$min\|\bar{x}\|_0\ s.t\ y=\Phi.\ X \qquad (3)$$

Where $\|\bar{x}\|_0$ represents the $l_0$-norm, however, because the $l_0$ optimization issue is NP-hard, it is usually substituted with the $l_1$-norm. Many effective reconstruction approaches have recently been proposed, such the orthogonal matching pursuit (OMP) and smoothed $l_0$ norm (SL0) [10].

## 3. THE PROPOSED SYSTEM

In this section, the proposed system will be introduced which focuses on compression and encryption of the medical image using compressive sensing (CS) technique with different transformed matrices. The proposed system consists of two parts: transmitter and receiver. On the transmitter side, the following operations occur: sparse representation of MRI medical images, Hard thresholding, generation of measurement matrices, compression and encryption image. On the receiver side, the following operations occur: generation of the same measurement matrices used in the transmitter side, image reconstruction using l1 Norm minimization algorithm and inverse transform in order to reconstruct the original medical image. Finally, some parameters are used to evaluate the performance efficiency of the proposed system. All this is explained separately and in detail in this section.

### 3.1 Sparse Representation of MRI Medical Images

According to CS theory, the compressible image used should be sparse and then the original image can be recovered from a few numbers of samples. The original MRI medical image is represented by A with dimensions (N x N). A represents the image in the time domain. Then, this image is converted to the frequency domain and this is done by using basis matrix Ψ with dimensions (N x N) to obtain the sparsity for the image $\boldsymbol{X}$. The basis matrices DCT, FFT and DWT are used. CS and DWT with daubechies1 (db1) filter is applied to three detail sub images showing the vertical, horizontal, and diagonal detail in the image. The sparse image must have some of the large magnitude coefficients K and called (K-sparse) and some small magnitude coefficients which will be neglected. This K-sparse which will be used to reconstruct the original image because most of the important information is contained in the large magnitude coefficients.

### 3.2 Hard thresholding

**3.3** The Hard threshold is applied to the sparse image in order to neglect the small magnitude coefficients, and in this way, the elements whose value is less than the threshold value are deleted, and there will be some non-zero elements K-sparse after applying the hard thresholding.

When applying the hard thresholding to the DWT coefficients, Equations (4) and (5) mentioned in reference [12] are applied to three detailed vertical, horizontal and diagonal sub-images. When applying the hard thresholding to the FFT coefficients, Equations (4) and (5) are used.

$$\boldsymbol{\gamma = \sigma\sqrt{2\, ln(N)}} \tag{4}$$

$$\boldsymbol{\sigma = \frac{Median(|c|)}{0.6745}} \tag{5}$$

Where N is the length of the image, γ is the threshold value, σ is the standard deviation and c is the detailed coefficients of DWT and coefficients of FFT.

In order to determine the value of the thresholding for the DCT coefficients, we must remember the Equation (6) mentioned in reference [13].

$$\boldsymbol{X_{DCT}(i,j) = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}\, C(i,j) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} P(x,y)\, cos\left[\frac{(2x+1)i\pi}{2M}\right] cos\left[\frac{(2y+1)j\pi}{2N}\right]} \tag{6}$$

Where i = 0,1, 2…….. M-1 and j = 0,1, 2…….. N-1, M and N the size of the image, P (x, y) is the input pixel value. We note from Equation (6) that the value of the DCT coefficients is scaled by $\sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}$ , so we suggested using γ in Equation (4) but after scaling it with $\sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}$ as shown in the following equation:

$$\boldsymbol{\gamma_{DCT} = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}\, \gamma} \tag{7}$$

Then, the Equation (8) of Hard thresholding is applied on the sparse image:

$$\boldsymbol{X = X(|X| > \gamma)} \tag{8}$$

### 3.4 Measurement Matrices Used

The measurement matrix plays an important role in compressing and reconstructing the image, and the selection of an effective measurement matrix is very important for CS. The dimensions of the measurement matrix Φ are (M x N) and the length of M must be much less than the length of the N because the measurement matrix is responsible for compressing the image. In this research, a set of different sensing matrices is studied and analyzed and the effect of each one on the system performance is evaluated. The most suitable one is the random partial Fourier measurement matrix and it is selected to be used with image sparsification.

### 3.5 Compress-Encrypt MRI Medical Image

According to CS theory, the image is compressed and encrypted using the sensing matrix. The sensing matrix is used to compress image when the measurement matrix Φ with dimensions (M x N) is multiplied by the image after taking the sparsity and performing the hard thresholding operation on it and this image should be with dimensions (N x N) to get the compressed image with dimensions (M x N) when (M << N).

The sensing matrix is used to encrypt the image when the sensing matrix is used as a key between the transmitter and receiver. The sensing matrix used at the receiver must be the same as the sensing matrix is used at the transmitter.

The medical image can only be recovered from the receiver after giving the same measurement matrix used at the transmitter and in this way the medical image is encrypted.

### 3.6 MRI Medical Image Reconstruction Using l1 Norm Minimization Algorithm

In compressive sensing $l_0$, $l_1$ and $l_2$ norm minimization methods are generally used for reconstruction. In this study $l_1$ norm minimization algorithm is used to reconstruct the MRI medical image in the receiving side by using a software package called L1-Magic [14]. $l_1$ norm minimization method gives the best solution if the image is sparse. And then the reverse conversion is determined by using IDCT, IDFT and IDWT.

### 3.7 The Performance Efficiency Evaluation of The Proposed System

The performance efficiency of the proposed system is evaluated using seven assessing parameters which are: Elapsed Time, Compression Ratio (CR), Compression Factor (CF), Space Savings, Power Signal to Noise Ratio (PSNR), Structural Similarity index (SSIM) and Mean Error.

#### 3.7.1 Elapsed Time

The time it takes to execute the program is determined using a ready function (tic, toc) in MATLAB.

#### 3.7.2 Compression Ratio (CR)

The compression ratio (CR) is a ratio between the size of the original image (uncompressed image) and the compressed image and it is defined as [15]:

$$CR=\frac{Size\ of\ the\ Original\ Image\ (Uncompressed\ Size)}{Size\ of\ the\ Compressed\ Image\ (Compressed\ size)}=\frac{N\ x\ N}{M\ X\ N}=\frac{N}{M} \quad (9)$$

Where N is the actual number of samples in the original image, M is the number of samples needed to reconstruct an image.

#### 3.7.3 Compression Factor (CF)

The compression factor (CF) is the inverse of the compression ratio and equals the ratio between the size of the compressed image and uncompressed image. CF values range from 0 to 1 and it is defined as [15]:

$$CF=\frac{1}{CR}=\frac{Compressed\ Size}{Uncompressed\ Size}=\frac{M\ x\ N}{N\ x\ N}=\frac{M}{N} \quad (10)$$

#### 3.7.4 Space Savings

Space saving is calculated to find the available space after compression. Space saving is equal to the subtraction between the uncompressed image size and the compressed image size divided by the uncompressed image volume as shown in equation (3.11) [16].

$$Space\ Savings=\frac{(Uncompressed\ Size-Compressed\ Size)}{Uncompressed\ Size}$$

$$=1-\frac{Compressed\ Size}{Uncompressed\ Size}=1-CF \quad (11)$$

#### 3.7.5 Peak Signal to Noise Ratio (PSNR)

The PSNR is a common metric for evaluating the quality of image recovery. The higher the PSNR number, the more the resulting image matches the original image. As shown in the following equations [3]:

$$PSNR=10log_{10}\left(\frac{Max^2}{MSE}\right) \quad (12)$$

The constant Max ($2^b$-1) represents the image's maximum potential pixel value, b is the number of bits. MSE is a mean square error and it will be explained in the next step .In image compression, acceptable values of PSNR are from 20 to 30 dB, and typical values of PSNR are from 30 to 50 dB.

### 3.7.6 Mean Square Error (MSE)

Mean Square Error (MSE) is analyzing the difference between the original image and the recovered image. MSE is used to assess the image quality. The main objective of MSE is to know the extent of distortion between the original and recovered image and the equation is given as [3]:

$$MSE=\frac{1}{M\times N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[C(x,y)-CW(x,y)]^2 \qquad (13)$$

Where C (x, y) is the original image, CW (x, y) is the recovered image and image's length and width are represented by M and N.

### 3.7.7 Mean Structural Similarity (MSSIM)

The image quality of compressed and recovered pictures is measured using Mean Structural Similarity (MSSIM). The MSSIM is a metric that compares the structural similarity between two images. The MSSIM between two images X and Y could be computed using the formulas below [10]:

$$MSSIM(x,y)=\frac{1}{M}\sum_{k=1}^{M} SSIM(x,y) \qquad (14)$$

$$SSIM(x,y)=\frac{(2\mu_x\mu_y+(k_1\times L)^2)(2\sigma_{xy}\mu_y+(k_2\times L)^2)}{(\mu_x^2+\mu_y^2+(k_1\times L)^2)(\sigma_x^2+\sigma_y^2+(k_2\times L)^2)} \qquad (15)$$

Where M is the number of image blocks, K1 and K2 are two variables; for an 8-bit grayscale picture, L = 255 is the grayscale level. x and y represent the original and reconstructed image, respectively. The average and variance values of block i are $\mu_i$ and $\sigma_i$ (i = x, y), respectively. The covariance of blocks x and y is $\sigma_{xy}$. According to the [17] recommendation, choose k1 = 0.01, k2 = 0.03, and M = 64. MSSIM values range from 0 to 1. The greater the MSSIM values, the farther identical the two pictures are [10].

### 3.8 The Block Diagram of the Proposed System

The flowchart of the proposed system consists of two parts: the transmitter and the receiver. The compression process occurs on the transmitter side, and the reconstruction process occurs on the receiver side, as shown in Figure (2).

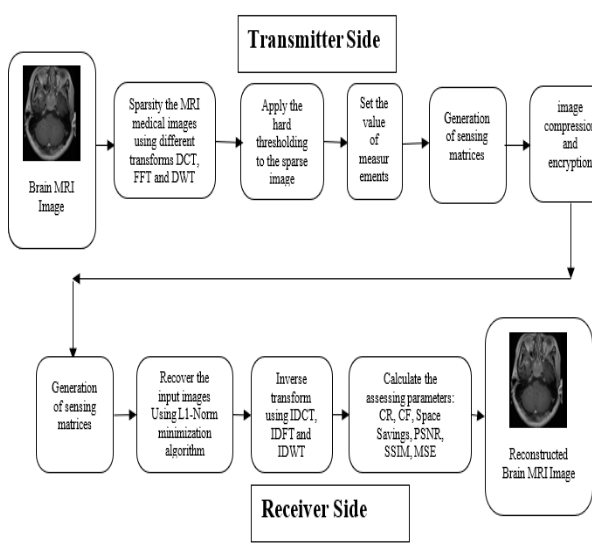



**Figure (2):** The proposed system block Diagram.

## 4. EXPERIMENTAL RESULTS

In this section, experimental results for medical image compression and encryption using CS technique are presented with three different transforms which are: DCT, FFT and DWT. also Eight measurement matrices were used to choose the appropriate measurement matrix to be used with the sparse image. This technique is applied to standard brain MRI images from [18] with size (512 x 512) using the MATLAB software. System performance is evaluated using Elapsed time, CR, CF, space savings, PSNR, SSIM and MSE.

### 4.1 Effect of Different Sensing Matrices on the CS scheme

In this study, eight sensing matrices were selected, which are: random Gaussian measurement matrix, random Bernoulli measurement matrix, partial Orthogonal random measurement matrix, random partial Fourier measurement matrix, random DCT measurement matrix, random partial Hadamard measurement matrix, Circulant measurement matrix and Toeplitz measurement matrix. To choose the appropriate sensing matrix with the sparsified image, CR 2.5 and 1.5 are selected. PSNR, SSIM, and MSE are used to evaluate system performance to select the appropriate sensing matrix. As shown in Table (1) and (2).

**Table 1:** Different sensing matrices and basis transformers at CR=2.5

| | DCT | | | FFT | | | DWT | | |
|---|---|---|---|---|---|---|---|---|---|
| **Sensing Matrix** | **PSNR** | **SSIM** | **MSE** | **PSNR** | **SSIM** | **MSE** | **PSNR** | **SSIM** | **MSE** |
| Random Gaussian Matrix | 33.7338 | 0.9782 | 2.8166 | 31.5448 | 0.8982 | 5.6609 | 39.6872 | 0.9961 | 1.0537 |
| Random Bernoulli Matrix | 33.7928 | 0.9788 | 2.7957 | 32.2000 | 0.8929 | 5.2178 | 39.6406 | 0.9961 | 1.0592 |
| Partial Orthogonal Random Matrix | 33.6048 | 0.9776 | 2.8977 | 31.6036 | 0.8986 | 5.5715 | 39.7403 | 0.9962 | 1.0431 |
| Partial Random Fourier Matrix | 35.8786 | 0.9816 | 2.0285 | 32.6154 | 0.8474 | 5.7108 | 39.9611 | 0.9955 | 1.0366 |
| Random DCT Matrix | 34.8413 | 0.9792 | 2.4779 | 31.9054 | 0.8743 | 5.6207 | 39.7170 | 0.9961 | 1.0450 |
| Random Partial Hadamard Matrix | 34.3092 | 0.9792 | 2.6182 | 31.9939 | 0.9088 | 5.0205 | 39.7122 | 0.9962 | 1.0524 |
| Circulant Matrix | 34.1975 | 0.9766 | 2.7422 | 32.1507 | 0.8903 | 5.4640 | 39.7257 | 0.9962 | 1.0463 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Toeplitz Matrix | 33.9931 | 0.9761 | 2.8276 | 31.7117 | 0.8716 | 6.1625 | 39.6123 | 0.9960 | 1.0629 |

**Table 2:** Different sensing matrices and basis transformers at CR=1.5

| **Sensing Matrix** | **DCT** | | | **FFT** | | | **DWT** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **PSNR** | **SSIM** | **MSE** | **PSNR** | **SSIM** | **MSE** | **PSNR** | **SSIM** | **MSE** |
| Random Gaussian Matrix | 38.3580 | 0.9945 | 1.4255 | 32.0639 | 0.9404 | 4.3945 | 46.0050 | 0.9992 | 0.5351 |
| Random Bernoulli Matrix | 38.2780 | 0.9945 | 1.4556 | 33.7088 | 0.9561 | 3.0708 | 46.2235 | 0.9992 | 0.5240 |
| Partial Orthogonal Random Matrix | 38.4163 | 0.9946 | 1.4213 | 32.5176 | 0.9585 | 3.7708 | 46.0250 | 0.9992 | 0.5335 |
| Partial Random Fourier Matrix | 39.8900 | 0.9944 | 1.0827 | 34.7929 | 0.9322 | 3.1436 | 46.7595 | 0.9991 | 0.5000 |
| Random DCT Matrix | 38.8353 | 0.9935 | 1.2382 | 33.6648 | 0.9625 | 3.2434 | 45.0708 | 0.9990 | 0.5818 |
| Random Partial Hadamard Matrix | 38.9974 | 0.9950 | 1.2892 | 33.0106 | 0.9489 | 3.5957 | 46.8020 | 0.9993 | 0.4896 |
| Circulant Matrix | 38.9883 | 0.9949 | 1.2619 | 33.2089 | 0.9434 | 3.8041 | 46.1116 | 0.9992 | 0.5249 |
| Toeplitz Matrix | 38.3444 | 0.9940 | 1.3621 | 33.3243 | 0.9432 | 3.5519 | 45.9058 | 0.9992 | 0.5363 |

As can be seen from Tables (1) and (2) and based on three parameters of PSNR, SSIM and MSE, the best measurement matrix is selected. It is very clear from the two tables that the random partial Fourier sensing matrix is the suitable sensing matrix when using the basis transformers DCT and FFT, but the measurement matrix has no significant effect when using the basis transformer DWT. As a result, the random partial Fourier measurement matrix is chosen as the appropriate sensing matrix with the sparsified image.

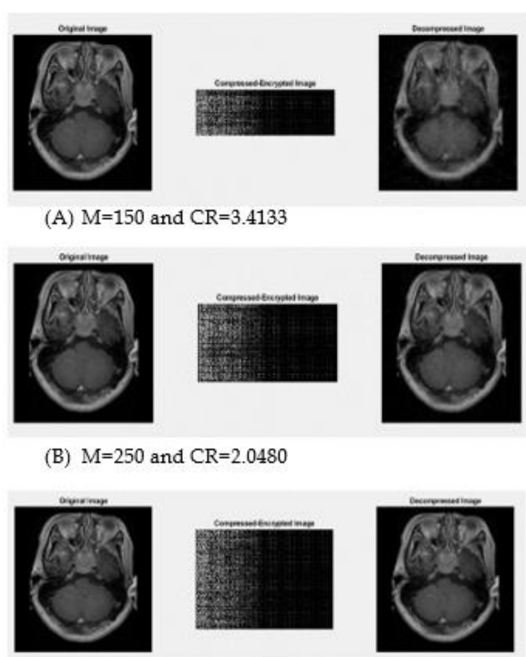
### 4.2 System Performance of CS with DCT

When CS with DCT is used to compress the brain MRI image. In the beginning, the effect of measurements (M) on the Elapsed Time (in second), CR, CF, Space Saving, PSNR (in dB), SSIM and MSE are obtained between the original and decompressed image. Evaluation parameters of CS with DCT is summarized in Table (3). The subjective performance of CS with DCT for brain MRI image is illustrated in Figure (3) under different no. of measurements.

**Table 3:** System Performance of CS with DCT

| **M** | **100** | **150** | **200** | **250** | **300** | **350** | **400** | **450** | **500** |
|---|---|---|---|---|---|---|---|---|---|
| Elapsed Time | 100.000982 | 178.402352 | 160.709695 | 164.750704 | 220.006610 | 302.734906 | 324.763421 | 444.199412 | 456.044085 |
| CR | 5.1200 | 3.4133 | 2.5600 | 2.0480 | 1.7067 | 1.4629 | 1.2800 | 1.1378 | 1.0240 |
| CF | 0.1953 | 0.2930 | 0.3906 | 0.4883 | 0.5859 | 0.6836 | 0.7813 | 0.8789 | 0.9766 |
| Space Savings | 0.8047 | 0.7070 | 0.6094 | 0.5117 | 0.4141 | 0.3164 | 0.2188 | 0.1211 | 0.0234 |
| PSNR | 32.3135 | 33.4211 | 35.8786 | 37.6354 | 39.8900 | 41.6529 | 45.1751 | 49.0936 | 58.3840 |
| SSIM | 0.9259 | 0.9580 | 0.9816 | 0.9893 | 0.9944 | 0.9965 | 0.9985 | 0.9994 | 0.9999 |
| MSE | 4.5408 | 3.3013 | 2.0285 | 1.5084 | 1.0827 | 0.8301 | 0.4965 | 0.2446 | 0.0424 |

As can be seen from the Table (3) and Figure (3) when applying CS with DCT, that the highest compression ratio can be achieved CR=2.0480 when M=250 with PSNR=37.6354, SSIM=0.9893, MSE=1.5084 and elapsed time=164.750704. This means that the space savings= 51.17 % is available and with CF=0.4883.




(A) M=150 and CR=3.4133

(B) M=250 and CR=2.0480

(C) M=350 and CR=1.4629

**Figure (3):** brain MRI Image under different number of measurements and different CR when using CS with DCT.

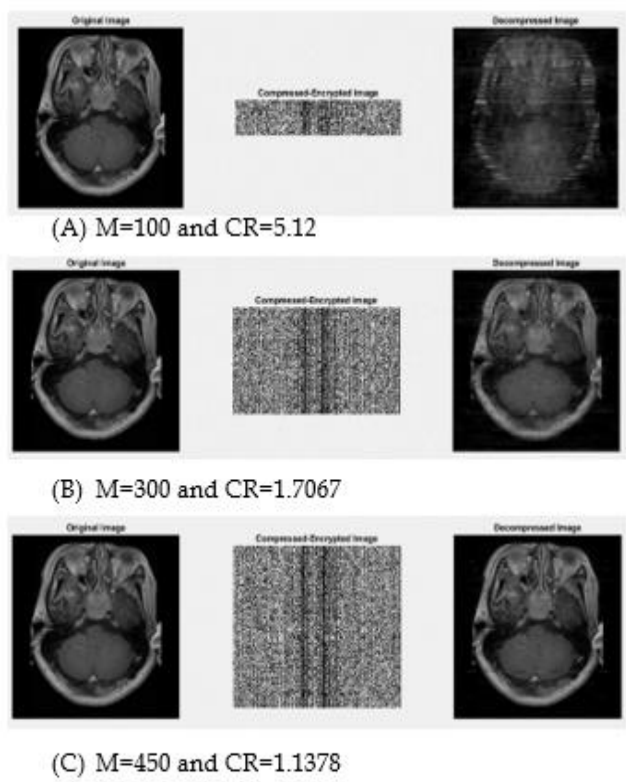



**Figure (4):** brain MRI Image under different number of measurements and different CR when using CS with FFT.

### 4.3 System Performance of CS with FFT

The effect of measurements (M) on the Elapsed Time (in second), CR, CF, Space Saving, PSNR (in dB), SSIM and MSE are obtained between the original and reconstructed brain MRI image when CS with FFT is used. Evaluation parameters of CS with FFT is summarized in Table (4). The subjective performance of CS with FFT for brain MRI image is illustrated in Figure (4) under different no. of measurements.

As can be seen from the Table (4) and Figure (4) when applying CS with FFT, that a maximum compression ratio can be achieved CR=1.7067 when M=300 with PSNR=34.7929, SSIM=0.9322, MSE=3.1436 and elapsed time=495.929101. This means that the space savings= 41.41 % is available and with CF=0.5859.

**Table 4:** System Performance of CS with FFT

| **M** | **100** | **150** | **200** | **250** | **300** | **350** | **400** | **450** | **500** |
|---|---|---|---|---|---|---|---|---|---|
| Elapsed Time | 240.706660 | 255.185074 | 321.102488 | 404.158054 | 495.929101 | 496.360198 | 596.071122 | 597.876906 | 660.138798 |
| CR | 5.1200 | 3.4133 | 2.5600 | 2.0480 | 1.7067 | 1.4629 | 1.2800 | 1.1378 | 1.0240 |
| CF | 0.1953 | 0.2930 | 0.3906 | 0.4883 | 0.5859 | 0.6836 | 0.7813 | 0.8789 | 0.9766 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Space Savings | 0.8047 | 0.7070 | 0.6094 | 0.5117 | 0.4141 | 0.3164 | 0.2188 | 0.1211 | 0.0234 |
| PSNR | 31.1860 | 32.3266 | 32.6154 | 34.2833 | 34.7929 | 35.6783 | 37.7505 | 40.8566 | 45.7262 |
| SSIM | 0.7546 | 0.8101 | 0.8474 | 0.9157 | 0.9322 | 0.9689 | 0.9805 | 0.9952 | 0.9986 |
| MSE | 8.7864 | 6.6779 | 5.7108 | 3.4900 | 3.1436 | 2.2204 | 1.4965 | 0.8014 | 0.4864 |

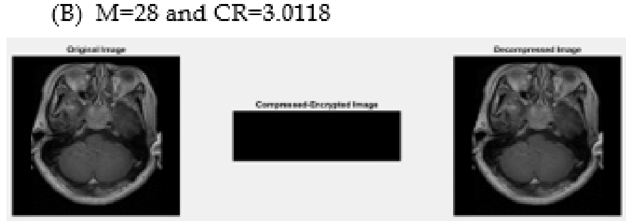
### 4.4 System Performance of CS with DWT

The effect of measurements (M) on the Elapsed Time (in second), CR, CF, Space Saving, PSNR (in dB), SSIM and MSE are obtained between the original and reconstructed brain MRI image when CS with DWT is used. Evaluation parameters of CS with DWT are summarized in Table (5). The subjective performance of CS with DWT for brain MRI image is illustrated in Figure (5) under different no. of measurements.

As can be seen from the Table (5) and Figure (5) when applying CS with DWT, that the highest compression ratio can be achieved CR=3.7786 when M=5 with PSNR=39.1039, SSIM=0.9944, MSE= 1.0984 and elapsed time=24.312920. This means that the space savings= 73.54 % is available and with CF=0.2646.


(A) M=5 and CR=3.7786


(B) M=28 and CR=3.0118




(C) M=80 and CR=2.0645

**Figure (5):** MRI Image under different number of measurements and different CR when using CS with DWT.

**Table 5:** Performance of CS with DWT

| **M** | **5** | **10** | **20** | **28** | **40** | **80** | **160** | **200** | **250** |
|---|---|---|---|---|---|---|---|---|---|
| Elapsed Time | 24.312920 | 26.958714 | 29.216051 | 29.081831 | 31.129023 | 52.121761 | 70.970216 | 84.913458 | 85.334932 |
| CR | 3.7786 | 3.5804 | 3.2405 | 3.0118 | 2.7234 | 2.0645 | 1.3913 | 1.1963 | 1.0179 |
| CF | 0.2646 | 0.2793 | 0.3086 | 0.3320 | 0.3672 | 0.4844 | 0.7188 | 0.8359 | 0.9824 |
| Space Savings | 0.7354 | 0.7207 | 0.6914 | 0.6680 | 0.6328 | 0.5156 | 0.2813 | 0.1641 | 0.0176 |
| PSNR | 39.1039 | 39.0507 | 39.1759 | 39.4133 | 39.6934 | 41.0572 | 46.0837 | 51.7153 | 53.1456 |
| SSIM | 0.9944 | 0.9946 | 0.9943 | 0.9948 | 0.9952 | 0.9968 | 0.9990 | 0.9998 | 0.9998 |
| MSE | 1.0984 | 1.1072 | 1.1044 | 1.0874 | 1.0659 | 0.9313 | 0.5359 | 0.2655 | 0.2082 |

### 4.5 Comparison Between Transformers

To select the appropriate transformer with CS for brain MRI medical images, a comparison was made between the three transducers (DCT, FFT and DWT) in Table (6) under different compression ratios.

**Table 6**: Comparison between transformers used under different CR

| **CR** | **Transformer type** | **Elapsed time (in seconds)** | **PSNR (in dB)** | **SSIM** | **MSE** |
|---|---|---|---|---|---|
| **3.4** | DCT | 178.402352 | 33.4211 | 0.9580 | 3.3013 |
| | FFT | 255.185074 | 32.3266 | 0.8101 | 6.6779 |
| | DWT | 29.216051 | 39.1759 | 0.9943 | 1.1044 |
| **2** | DCT | 164.750704 | 37.6354 | 0.9893 | 1.5084 |
| | FFT | 404.158054 | 34.2833 | 0.9157 | 3.4900 |
| | DWT | 52.121761 | 41.0572 | 0.9968 | 0.9313 |
| **1.2** | DCT | 324.763421 | 45.1751 | 0.9985 | 0.4965 |
| | FFT | 596.071122 | 37.7505 | 0.9805 | 1.4965 |
| | DWT | 84.913458 | 51.7153 | 0.9998 | 0.2655 |

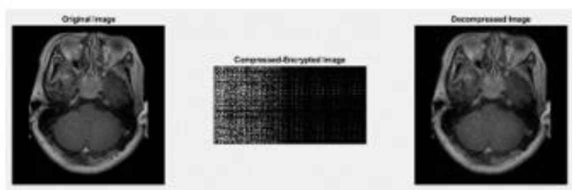
The tabulated results in Table (6) show that CS with DWT performs the best performance with a high compression ratio and with a high PSNR, less MSE and less time to execute with a high SSIM compared to CS with DCT and CS with FFT. but When a comparison is made between CS with DCT and CS with FFT, it shows that CS with DCT is better than CS with FFT when applied to the medical image of brain MRI. The subjective performance of CS with DCT, FFT and DWT for brain MRI images is illustrated in Figure (6) and Figure (7) when CR=3.4 and CR=2.


(A) CS with DCT at CR=3.4

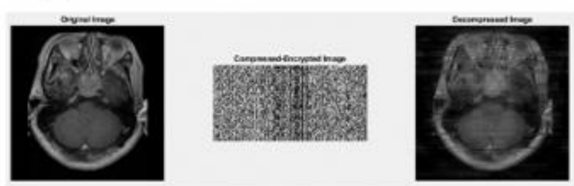

(B) CS with FFT at CR=3.4


(C) CS with DWT at CR=3.4

**Figure (6):** The subjective performance of CS with DCT, FFT and DWT for brain MRI image at CR=3.4




(A) CS with DCT at CR=2

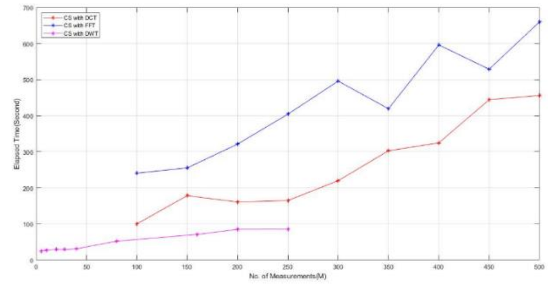



(B) CS with FFT at CR=2


(C) CS with DWT at CR=2

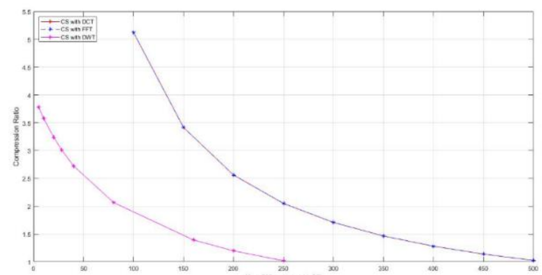
**Figure (7):** The subjective performance of CS with DCT, FFT and DWT for brain MRI image at CR=2

Based on the results obtained in Table (3), (4) and (5) the effect of the number of measurements versus Elapsed Time for three transformers are illustrated in Figure (8a).



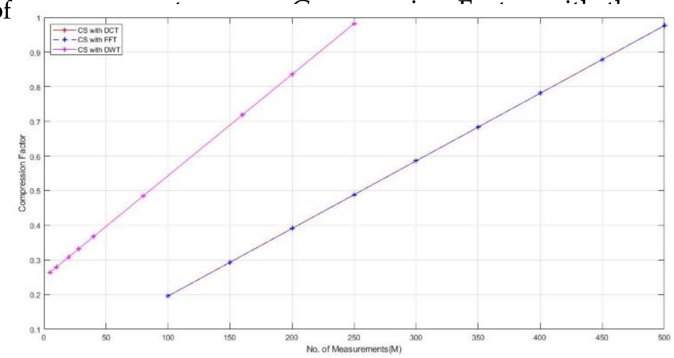

**(a)**

The effect of the number of measurements versus Compression Ratio with three transformers are illustrated in Figure (8b).

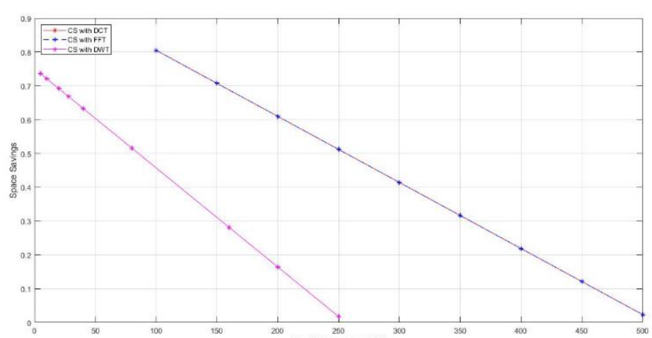



**(b)**

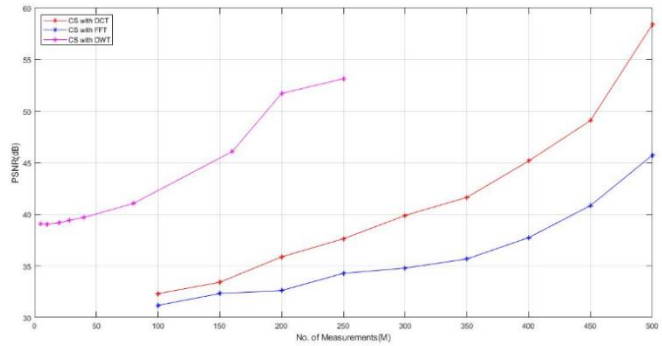
The effect of the number of transformers are illustrated in Figure (8c).



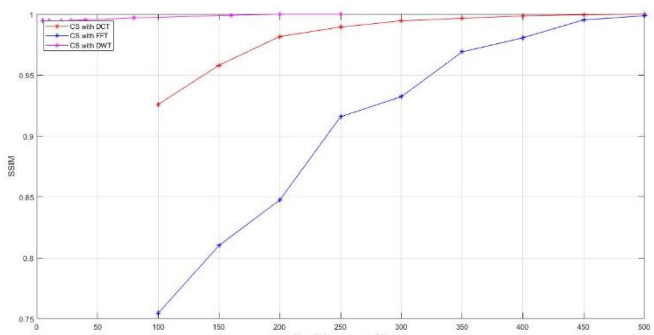

**(c) The effect of the number of measurements versus Space Savings for three transformers are illustrated in Figure (8d).**



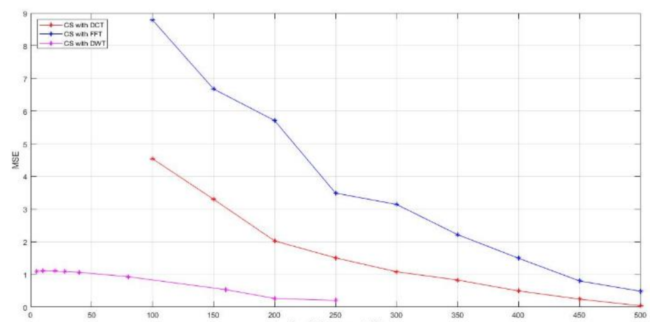
**(d) The effect of the number of measurements versus PSNR for three transformers are illustrated in Figure (8e).**




**(e)** The effect of number of measurements versus SSIM for three transformers are illustrated in Figure (8f).




**(f) The effect of the number of measurements versus MSE for three transformers are illustrated in Figure (8g).**




**(g)**

**Figure (8):** Plots for seven criteria of brain MRI image quality versus no. of measurements of the proposed system CS with DCT, FFT and DWT

The experimental results from the Figure (8) show that the proposed system CS with DWT is superior to the other sparse basis transforms (DCT and FFT). When using CS with DWT we get less the execution time less, higher CR, less CF, more Space Savings, higher PSNR, higher SSIM and less MSE. This is what is required for a successful medical image compression technique.

### 4.6 Comparison Among Previous Works and The Proposed System

The performance of the proposed system for CS with DCT, FFT and DWT is compared with the performance of systems in previous works at different CR. Table (7) illustrates the results of previous works, while the results of the proposed system for DCT, FFT and DWT at different CR are clarified to be able to compare with previous works based on PSNR, SSIM and MSE.

According to Table (7), it was found that in [6] the CS system was used with DWT and DCT, and in [7] the CS system was used with DWT, DCT and FFT, and in [8] the CS system was used with DCT. When comparing the results of [6], [7] and [8] with the results of the proposed system at the same CR used, it was found that the proposed system gives good results with high quality. Because we got high compression ratio, high PSNR, high SSIM and less MSE.

Moreover, in [3] and [9] the CS system with DWT was used. When comparing the results between [3] and [9] with the proposed system, it was found that the PSNR of [3] and [9] is greater than the PSNR of the proposed system. But the SSIM of the proposed system is better than the SSIM of [3] and [9]. As a result, the proposed system performs well and can be applied to medical images successfully.

**Table 7:** Comparison among previous works and the proposed system at different compression ratio.

| **Methods** | **Transform** | **CR** | **PSNR (dB)** | **SSIM** | **MSE** |
|---|---|---|---|---|---|
| **[6]** | DWT | 3.01 | 31.6732 | NA | NA |
| | DCT | 1.5789 | 13.1774 | NA | NA |
| **[3]** | DWT | 5 | 55 | NA | NA |
| **[7]** | DWT | 1.05 | 34.82 | 0.9060 | 21.41 |
| | DCT | | 28.29 | 0.6403 | 96.46 |
| | FFT | | 29.64 | 0.6953 | 70.65 |
| **[9]** | DWT | 3.01 | 47.76 | 0.712 | NA |
| **[8]** | DCT | 1.42 | 25.5 | NA | NA |
| **Proposed System** | DWT | 3.01 | 39.4133 | 0.9948 | 1.0874 |
| | | 4 | 39.5493 | 0.9956 | 0.9806 |
| | | 1.05 | 53.1104 | 0.9998 | 0.2098 |
| | DCT | 1.5789 | 41.0616 | 0.9958 | 0.9244 |
| | | 1.42 | 42.2063 | 0.9972 | 0.7636 |
| | | 1.05 | 54.1397 | 0.9998 | 0.1011 |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | **FFT** | **1.05** | **44.1367** | **0.9978** | **0.5434** |

## 5 CONCLUSIONS

In this study, a CS technique is proposed for compression and encryption brain MRI images with three transforms. MRI images of the brain were used for testing. First, DCT, FFT and DWT transforms were used to represent image sparsity. After that the Hard threshold was used to trim the sparse coefficients. For image compression and encryption, a random Fourier matrix was used. Then the L1 Norm algorithm was used to reconstruct the image. The aim of this paper is to compare the effect of DCT, FFT, and DWT on CS technology and to select the appropriate transform for compression and encryption of medical MRI images of the brain. Seven parameters were used to evaluate the performance of the system, which are the elapsed time, CR, CF, space savings PSNR, SSIM and MSE.

It can be concluded from the experimental results that:

- The random partial Fourier measurement matrix is selected from among eight different measurement matrices as an appropriate sensing matrix with the sparse images.
- The time taken to implement the program is directly proportional to the number of measurements. The transformer that takes the least the least execution time is when applying CS technology with DWT, and the least execution time is 24.312920 seconds.
- The compression ratio is inversely proportional to the number of measurements, and the largest value for the compression ratio was obtained when applying CS with DWT. The highest value of the compression ratio was achieved, which is 3.7786.
- The compression factor is directly proportional to the number of measurements, and the largest value for the compression factor was obtained when applying CS with DWT. The highest value of the compression factor was achieved, which is 0.2646.
- The space savings are inversely proportional to the number of measurements. The largest available space is obtained when applying CS with DWT and the largest space savings obtained is equal to 73.54 %.
- PSNR is directly proportional to the number of measurements, and a suitable PSNR value was obtained at the highest obtained compression ratio value, which is when CS is applied with DWT and is equal to 39.1039 dB.
- SSIM is directly proportional to the number of measurements. High values of SSIM were obtained when applying CS with DWT, and the highest value of SSIM obtained is 0.9944.
- MSE is inversely proportional to the number of measurements. Few values of MSE were obtained when applying CS with DWT, and the lowest value of MSE obtained is equal to 1.0984.
- It can be seen that the proposed system increases the image quality when the number of measurements increases.
- As it can be seen from the results, CS with DWT outperforms CS with DCT and CS with FFT when applied to the medical image of MRI. When making a comparison between CS with DCT and CS with FFT, it shows that CS with DCT is better than CS with FFT.
- When comparing the proposed system with the previous works, it was found that the proposed system performs well and is very acceptable.

- The final conclusion arrived at in this study is that the CS algorithm with DWT can be used to compress and encrypt medical images successfully.

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