Efficient Medical Image Compression Based on Wavelet Transform and Modified Gray Wolf Optimization

Shahla Sohail[1], S. Thenmozhi[2], Swetha Priyanka Jannu[3], R. Gayathiri[4,]
[1,2]Department of Electronics and Communication Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India.
[3]Department of Electronics and Communication Engineering, Vardhaman College of Engineering, Shamshabad, Telangan, India
[4]Department of Electronics and Instrumentation Engineering, Sri Sai Ram Engineering College, Chennai, TamilNadu, India.

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ABSTRACT

The use of medical images in diagnostic procedures is increasing, leadning to a significant rise in the memory and bandwidth requirements for preserving and transmitting these images. To address this issue, image compression techniques have garnered significant attention. These techniques are capable of reducing the data size necessary to represent an image, allowing for more efficient utilization of storage space and communication bandwidth by eliminating unnecessary information. Numerous research directions have focused on compressing medical images, but past approaches have been time-consuming and risked information loss. To trounce these limitations, this paper introduces an effiective method for reducing the size of medical images in telemedicine applications. The method utilizes Integer Wavelet Transform (IWT) and sophisticated algorithm. Primarily, input images undergo pre-processing with a circular median filter to eliminate noise and improve image quality. Subsequently, the pre-processed images are divided into multiple sub bands using IWT.Then, these sub bands are furhter divided into n X n non-overlapping matrices, and optimal coefficients are chosen by employing a modified grey wolf optimizer algorithm. Finally, the selected coefficients are encoded using Huffman coding for transmission. During decompression, the reverse process of image compression is applied. The introduced method is tested on various medical images, and the findings demonstrate its superior performance compared to previous methods, generating visually similar images with a smaller data size.

Corresponding Author:

Shahla Sohail,
Department of Electronics and Communication Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India.
Email: shahla-ece@dayanandasagar.edu

1. INTRODUCTION

Image compression plays a significant role in image storage and transmission. It deals with the process of shrinking the size of an image file while maintaining acceptable level of image quality. The reduction in image file size enables more images to be stored in the memory space and more effective internet transmission [1]. Over the past decades, numerous image compression methods have been developed using different strategies. These methods fall into one of two categories: lossy compression or lossless compression. Lossy compression causes information loss during decompression while lossless compression results in images that are identical to the original data when decompressed [2]. For medical images lossless compression is preferred.

Medical images like Computed Tomography (CT), Magnetic Resonance Imaginh (MRI), Positron Emission Tomography (PET), and Ultrasound (US) contain a vast quantity of pertinent information that assists doctors analyze the image properly and aids in patient care. The amount of storage space and bandwidth needed to preserve and transmit medical images is rising dramatically as their use in diagnostic procedure increases [3]. Further to this, speed and bandwidth are the two major drawbacks when transmitting medical images for telemedicine applications. This issue can be addressed by compressing medical images. Image compression has therefore gotten a lot of attention due to their capacity to minimize the amount of data needed to represent an image in medical field. Many researchers have attempted to develop an efficient method for compressing medical images while retaining important data. However, developing a lossless technique for compressing medical images is still a very difficult task.

As previously mentioned, lossless image compression is an efficient approach for compressing medical images. However, the presence of noise during image acquisition can negatively impact the image quality, leading to lower quality in the reconstructed image. Many researchers have employed Discrete Wavelet Transform (DWT) for medical images. Nevertheless, this DWT-based compression method truncates floating-point values to integers, resulting in some data loss. Therefore, there is a need to develop an efficient compression method to address this issue effectively. By considering all the challenges and issues related to the medical image compression, this paper presents an efficient method for medical image compression. The core contributions of this paper are listed below:

- An efficient compression method for compressing medical images is built by using Integer Wavelet Transform (IWT) and Modified Gray Wolf Optimizer (M-GWO).
- A Circular Median Filter (CMF) is proposed to suppress noise data while preserving important information
- A new M-GWO algorithm is proposed and employed to select salient coefficients from denoised coefficients in order to achieve efficient compression. This is the first attempt to pick the salient coefficients for compression using a metaheuristic algorithm.
- Scalability of the designed method is verified by using different imaging modalities.

The outline of the paper is systemized as follows: Section 2 provides a brief review of past approaches. Section 3 delineates the proposed image compression method. Section 4 discusses the experiential outcomes and compares the performance with well-known methods. Section 5 summarizes the paper.

2. REVIEW OF PAST METHODS

Medical images typically can be compressed in any of the following domains, spatial domain, frequency domain, and wavelet domain. Many researcher investigations have proved that the wavelet domain approaches provide high CR and PSNR when compared to other domain approaches.

Sreenivasulu et al. [2] proffered a compression method that combines DWT and metaheuristic algorithm. Medical images were segmented into Region of Interest (ROI) and Non-ROI regions. The ROI region was compressed using Discrete Cosine Transform (DCT) followed by Set Partitioning in Hierarchical Tree (SPIHT) whereas the non-ROI with DWT-MROA. However, this method uses different techniques for compressing ROI and non-ROI regions, resulting increased computational complexity. Boucetta and Melkemi et al. [3] suggested a hybrid approach by using DWT and Genetic Algorithm (GA) to reduce the size of the images. In this approach, input image was decomposed using DWT and then optimal thresholds were selected with GA. Vijayvargiya et al. [4] built a compression method by fusing IWT and Particle Swram Optimization (PSO) to achieve better Compression Ratio (CR). However, this method requires more time for searching best solution. Histogram based thresholding method to compress medical images was presented by Haridoss and Punniyakodi [5].

Table.1 A summary of recent investigations on medical image compression

Contributors	Images	Preprocessing	Method	Metrics
Sreenivasulu et al. [1]	MRI,CT,X-ray	-	DCT-SPIHT DWT-MROA	Peak Signal-to-noise Ratio (PSNR),Mean Structural Similarity Index(SSIM), time
Vijayvargiya [4]	MRI, CT	-	IWT-PSO	PSNR, CR
Haridoss and Punniyakodi [5]	MRI	-	Opposition based HSA	PSNR, SSIM, time
Ammah et al. [6]	MRI, CT	Median filter	DWT-VQ-HE	PSNR, SSIM, Mean Square Error (MSE), CR
Alkinani et al. [7]	MRI,CT,X-ray	-	DWT-PSO	PSNR,CR,MSE
Honsy et al. [8]	MRI,CT,X-ray	-	LMs-WOA	PSNR,CR,MSE,SSIM
Saravanan et al. [9]	MRI		Tetrolet transform - SPIHT	CR, PSNR,MSE, CT

Opposition based Harmony Search Algorithm (HAS) was proposed to select optimal thresholds for compression. Ammah et al. [6] recommended DWT and Vector Quantization (VQ) for medical image compression. Initially, medical images were preprocessed with median filter to discard noise. The preprocessed images were divided into multiple sub bands by using DWT. Detailed coefficients were encoded by vector encoder. Finally, the resultant outcomes and approximation coefficients followed by encoder. This approach encompasses a drawback of truncation error. Alkinani et al. [7] proffered a medical image compression scheme which is based on DWT and PSO. Modified haar wavelet transform was used to decompose an image into many sub images. For each sub image, PSO was applied to choose optimal threshold for compression. Honsy et al. [8] investigated the potential of Legendre Moments (LMs) and Whale Optimization Algorithm (WOA) for compressing medical images with acceptable image quality. Primarily, LMs were extracted from medical images and then WOA was used to select the LMs which have high information based on the fitness function. Tetrolet transform based compression method for representing medical images with less number of pixels was introduced by Saravanan et al. [9]. Input images were decomposed into approximation and detailed sub bands using tetrolet transform and then the sub bands were encoded by suing SPIHT. Results showed better performance than curvelet based methods. A summary of reviewed papers is given in Table.1.

3. PROPOSED METHODOLOGY

The fundamental focus of this work is to develop a compression method employing improved IWT and M-GWO to reduce the size of medical images for telemedicine application. The entire process flow for the introduced image compression technique is depicted in Figure .1. As in Figure.1, circular median filter is used for image preparation. Integer wavelet transform is then utilized for decomposition. M-GWO is employed to optimize sub band coefficients. The resultant values are subjected to Huffman encoding. At the time of decompression, an inverse process of compression is done to rebuild the image. Effectiveness of the introduced methodology is proved by using different medical images.

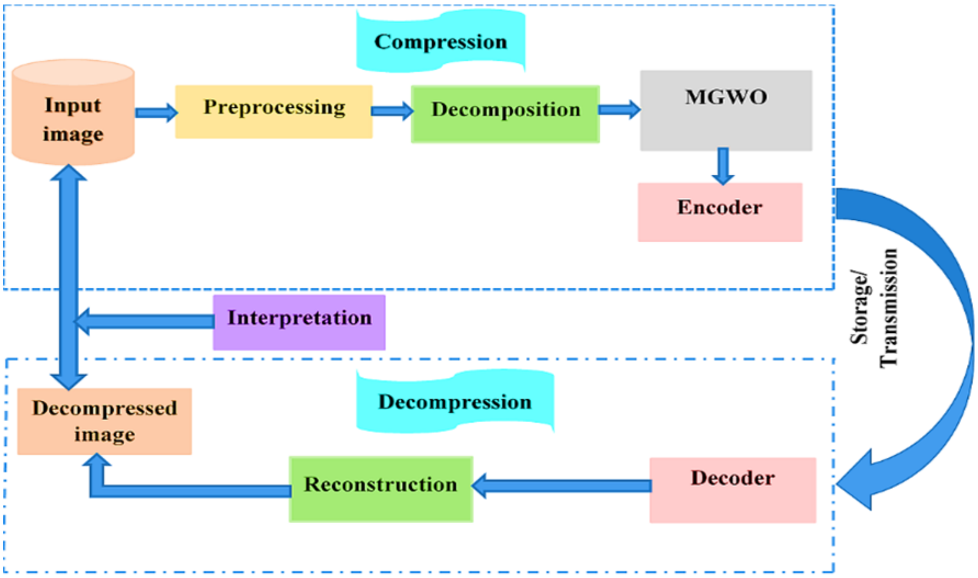


Figure .1 Overview of the suggested image compression technique

3.1. Image Preprocessing

Medial images are inherently corrupted with noise which severely affect the quality of these images and create difficulty for physicians in analysis and diagnosis. To obtain maximum benefit for medical images, preprocessing is an essential requirement. In this work, preprocessing is done in two ways: (i) noise removal and (ii) quality enhancement. A median filter is kind of non-linear filter that has the potential to smooth image by discarding unwanted data without losing the quality of the image. Many research studies have proved that the hybrid median filter preserves edges and boundaries better than other filter while denoising [6] [10] [11]. However, the drawback of hybrid median filter is that the window size increases, pixels are discarded resulting blocking artifact in the image. To avoid such an issue, circular median filter is proposed which uses circular window instead of square window. Salt and pepper noise is considered for MRI image while speckle noise is taken account for US image. Sample preprocessed images are shown in

Figure.2. Results proved that the circular median filter can efficiently preserves image details while denoising.

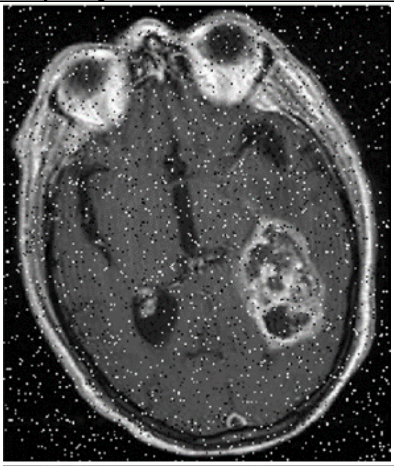
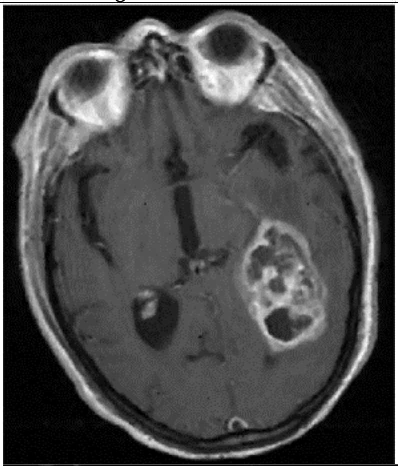
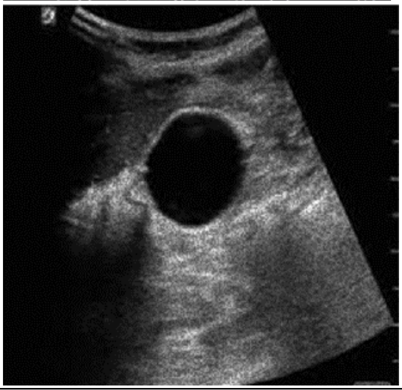
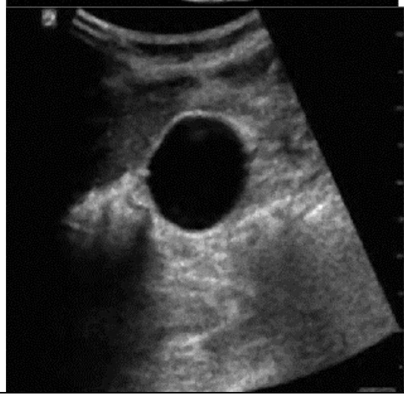
Image type	Noisy Image	Filtered image
MRI		
US		

Figure 2. Preprocessed images

3.2. Image decomposition

DWT is a mathematical tool that is used to compress images since it can offer better CR without losing more of the image's data. At level 1, DWT divides the image into one approximation sub band and three detailed sub bands. The most image information is found in the approximation sub band, and least information is found in the detailed sub bands. The image is reconstructed from these sub images with the help of inverse DWT. The image also can be divided more than one level, approximation sub band divided into four sub bands and so on [12]. However, the outcomes of DWT are floating points. The rounding error of the coefficients may lead to data loss. Additionally, dealing with floating points during compression necessitates intensive computations. In this investigation, IWT is used for decomposition. Utilizing IWT is advantageous over DWT because it is significantly faster, simpler to invert and retains greater spatial and spectral localization.

Block diagram of IWT is evinced in Figure .3. The IWT composed of three steps, which are explained below:

Split: Input signal x(n) is split into odd, $X_o(n)$ and even, $X_e(n)$ samples

$$X_e(n) = x(2n) \tag{1}$$
$$X_o(n) = x(2n+1) \tag{2}$$

Predict: The even samples, $X_e(n)$ are multiplied by predictor value, P and resultant values are added to the odd samples, $X_o(n)$ to generate detailed coefficients, D(n). The detailed coefficients are defined as,

$$D(n) = X_o(n) - P[X_e(n)] \tag{3}$$

Update: The detailed coefficients, D(n) are multiplied by update factor, U and the results are added to $X_e(n)$. This produces the coarse coefficients, C.

$$C(n) = X_e(n) - U[D(n)] \tag{4}$$

For visual perception, decomposition of medical image using IWT is shown in Figure.4.

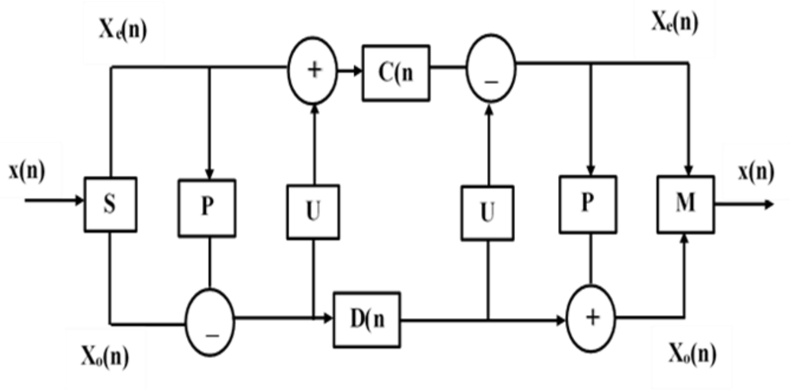


Figure 3. Integer wavelet transform process

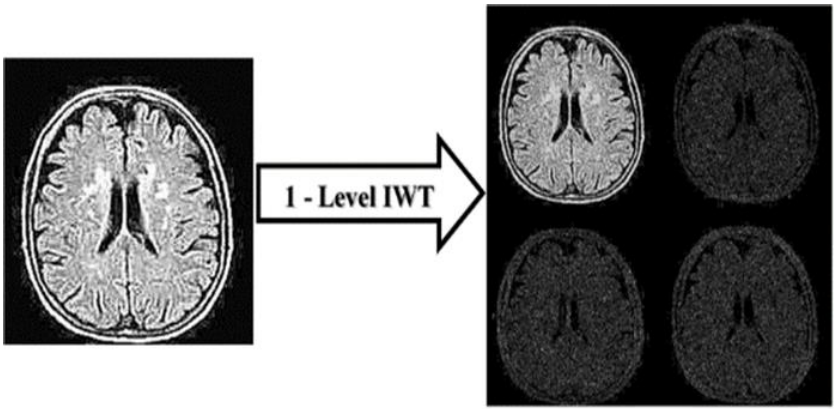


Figure.4 First level IWT decomposition of MRI image and its corresponding sub bands

3.3. Coefficients selection

A number of transform based medical image compression methods have been reported in the literature. Prior to encoding, most of the earlier methods have utilized quantization. Inverse quantization does not produce precise results, but it does increase CR by excluding some data from the medical images. As a result, transform based image compression cannot achieve perfect reconstruction. There will be some mismatch between the original and recovered images. Boucetta et al. [3] shown that the error can be reduced by using a GA to evolve wavelet coefficients. After that, many researchers used metaheuristic algorithms for optimization, but the majority of them were based on standard algorithms like PSO [4][7]. In this investigation, MGWO has been proposed and applied for coefficients optimization. GWO algorithm is a kind of swarm intelligence algorithm, introduced by Mirjalili et al. [13]. The hunting strategy and hierarchy of leadership of grey wolves were the inspiration behind GWO algorithm. The pseudo code of the proposed M-GWO algorithm is shown in figure5.

Research studies have shown that the GWO algorithm has superior exploration and exploitation properties to other algorithms like GA and PSO. In standard GWO, the convergence factor (a) in Equation (5) is linearly decreases from 2 to 0 over the period of iterations. But, the algorithm cannot linearly change during the convergence process, which results in the convergence factor failing to reflect the real optimization process. To rectify this problem, M-GWO is proposed by introducing a nonlinear convergence factor in Equation (7). As in Equation (7), the convergence factor decreases nonlinearly with the increase of iterations which enhances the optimization process. An algorithmic procedure of M-GWO is given in Table.2. The M-GWO is proposed to pick the best coefficient based on objective function in order to boost the recovered image's quality. Input image is divided into sub blocks of size N X N.

Input: wavelet coefficients
Objective function: PSNR
Output: selected coefficients
Set parameters
Number of grey wolves, X_i (i=1,2, 3, …. m)
Maximum iteration, Imax
Current iteration, t
Initialize the grey wolf population, X_i, I_{max}, a, A and C

$$\vec{A} = 2.\vec{a}.r1 - \vec{a} \quad (5)$$

$$\vec{C} = 2.r2 \quad (6)$$

$$\vec{a} = 2 - \left(e^{(t/I_{max})} - 1\right).\frac{2}{e-1} \quad (7)$$

r1, r2 are random numbers [0,1], e is the base of natural logarithm (e=2.718), t and Imax are current and maximum iterations respectively
for each X_i do
Evaluate the fitness value
end for
rank the wolf in descending order based on fitness value
W_α = First best agent , W_β = second best agent, and W_δ = third best agent

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{W}_\alpha - \vec{W}\right| \quad (8)$$

$$\vec{D}_\beta = \left|\vec{C}_2.\vec{W}_\beta - \vec{W}\right| \quad (9)$$

$$\vec{D}_\delta = \left|\vec{C}_3.\vec{W}_\delta - \vec{W}\right| \quad (10)$$

$$\vec{W}_1 = \vec{W}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right) \quad (11)$$

$$\vec{W}_2 = \vec{W}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right) \quad (12)$$

$$\vec{W}_3 = \vec{W}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \quad (13)$$

t=1
while t< Imax do
for i=1:m do
update position of current hunt agent, $\vec{W}(t+1) = \frac{\vec{W}_1+\vec{W}_2+\vec{W}_3}{3}$ (14)
end for
update $\vec{A}$, $\vec{C}$ and $\vec{a}$

for each X_i do
Calculate the fitness value
end for
update the position of W_α, W_β and W_δ
t=t+1
end while
Return the best agent found so far

Figure 5. Pseudocode of the proposed M-GWO

Based on the CR, Number of Coefficient (NOC) are defined as,

$$\mathrm{NOC} = \mathrm{round}\left(\left(1 - \frac{\mathrm{CR}}{100}\right)\right) \mathrm{X}\ \mathrm{N}^2 \quad (15)$$

Equation (15) is applied for each sub images to select optimal coefficients and then the selected coefficients are encoded using Huffman Encoding (HE) and then decompressed. The PSNR between the input and reconstructed image is calculated. This process is repeated to a predefined iteration. The selected coefficients which gives higher PSNR is taken as optimized coefficients. The optimization process is depicted in Figure.6.

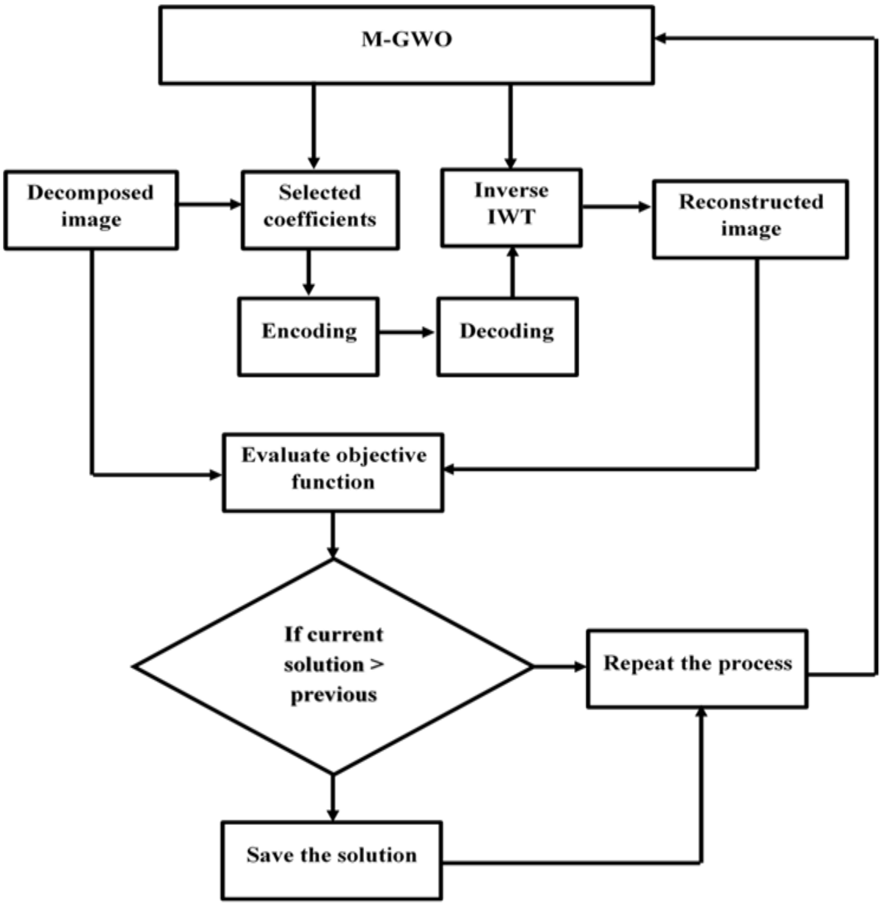


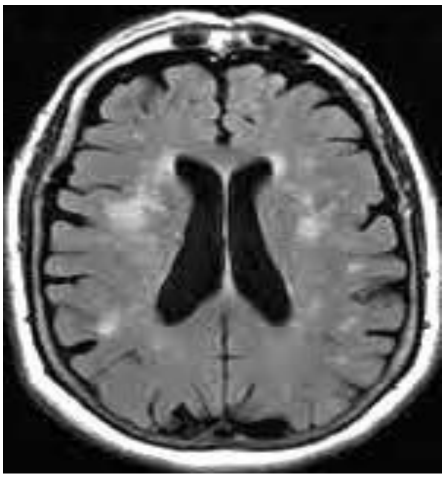
Figure 6. Workflow of coefficient optimization process

4. RESULTS AND DISCUSSION

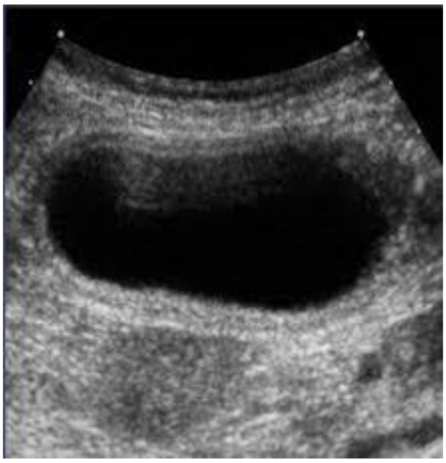
This section discusses the obtained results by applying the introduced compression method for reducing the size of medical images. The compression performance of the proposed method is assessed via series of experiments.

A set of medical images from different modalities such as MRT, CT, US and X-ray are gathered from the publicly available sources (Kaggle database) for validation. Figure.7 shows the medical images considered for experimentation.

(a) CT image



(b) MRI image



(c) US image

(d) X-ray image

Figure 7. Sample medical images considered for experimentation

4.1. Performance evaluation metrics

The degree of resemblance between the original and recovered images obtained using various CRs is an indicator that the introduced method is effective. The following metrics are used to evaluate the performance of the introduced compression method:

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

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

$$\mathrm{SSIM} = \frac{(2\mu_{\mathrm{O}}\mu_R + \mathrm{c}_1) + (2\sigma_{\mathrm{OR}} + \mathrm{c}_2)}{(\mu_{\mathrm{O}}^2\mu_{\mathrm{R}}^2 + \mathrm{c}_1)(\sigma_{\mathrm{O}}^2\sigma_R^2 + \mathrm{c}_2)} \quad (18)$$

$$\mathrm{MSSIM} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\mathrm{SSIM}_{\mathrm{i}} \quad (19)$$

$$\mathrm{CC} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} O(i,j)\times R(i,j)}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\big((O(i,j)\times O(i,j))\big)\times\sum_{i=1}^{M}\sum_{j=1}^{N}\big((R(i,j)\times R(i,j))\big)}} \quad (20)$$

Where, O and R represents the original and recovered images respectively.

4.2. Experimental treatment

The introduced method has been implemented in MATLAB and tested by using different medical images including CT, MRI, US, and X-ray. To demonstrate the superb performance, CR varies from 50% to 85%. The compression potential of IWT-GWO and IWT-M-GWO was evaluated and results are reported in Table.2 and in Table 3. According to observations, almost all of the CRs reveal a considerable improvement in compression when using the introduced IWT-M-GWO method over the IWT-GWO algorithm. For instance, the mean PSNR, MSSIM, and CC for CT image with a CR of 50% were attained using IWT-GWO and IWT-M-GWO were (65.05dB and 83.29dB), (0.817 and 0.965), and (0.991 and 0.998) respectively. For MRI image with a CR of 70%, the mean values for the IWT-GWO method's PSNR, MSSIM, and CC were 68.27 dB, 0.789, and 0.968 respectively. The presented method achieved mean PSNR of 79.43dB, mean MSSIM of 0.923, and mean CC of 0.991. For X-ray images with a CR of 75%, IWT-GWO and IWT-M-GWO reached mean PSNR value of (66.02dB and 80.99dB), MSSIM of (0.708 and 0.931), and CC of (0.974 and 0.996). The findings explicitly prove that the introduced compression method produced superior outcomes to standard GWO algorithm. Further to this, MSSIM determines the image quality; if the value is close to 1, the compressed image is more similar to original image. By comparing the MSSIM values form Table 3 and 4, it can be shown that for all image taken into consideration, the IWT-GWO method has a higher MSSIM value than the IWT-GWO.

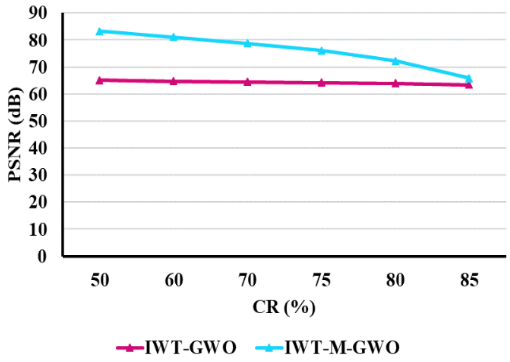
Figure.8 (a), Figure 8. (b), Figure. 8(c), and Figure.8(d) displays the mean PSNR values at different CRs for CT, MRI, X-ray, and US images respectively. With respect to mean PSNR, the standard GWO algorithm achieved highest PSNR value of 78.09dB at CR is 50 for US image and low PSNR of 59.7dB at CR is 85% for X-ray image. It is noted that the proposed method attained mean PSNR values above 70dB for CR ranging from 50 to 80 for almost all the images, proving its supremacy. Figure.9 (a), Figure.9 (b), Figure.9 (c), and Figure.9 (d) shows the mean MSSIM at different CRs for CT, MRI, X-ray, and CT images. The proposed method provided excellent performance by reaching MSSIM value above 0.85 for almost all of the images. Figure.10 (a), Figure.10 (b), Figure.10 (c), and Figure.10 (d) shows the mean CC at different CRs for CT, MRI, X-ray, and CT images. It is observed from the Figure.10 that the proposed method provided better performance than the standard GWO in light of CC.

Table 2. Performance of the proposed compression method

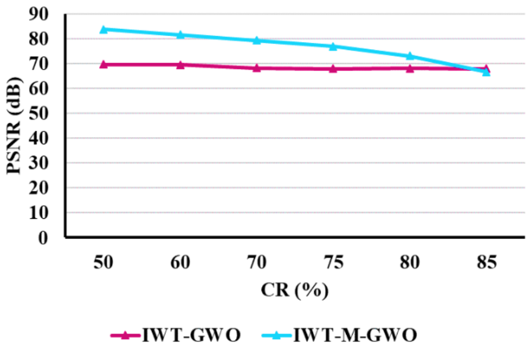
Type of image	metrics	Coefficients are optimized by GWO						Coefficients are optimized by M-GWO					
	CR (%)	50	60	70	75	80	85	50	60	70	75	80	85
CT 1	PSNR (dB)	65.39	65.12	64.82	64.76	64.59	64.49	83.37	81.13	79.06	76.34	72.31	65.62
	SSIM	0.791	0.788	0.786	0.785	0.784	0.782	0.960	0.937	0.942	0.910	0.863	0.809
	CC	0.991	0.991	0.991	0.99	0.989	0.985	0.999	0.998	0.998	0.997	0.996	0.992
CT 2	PSNR (dB)	66.03	66	65.88	65.63	65.47	64.32	84.80	82.60	80.16	77.56	73.72	67.44
	SSIM	0.8222	0.821	0.817	0.816	0.815	0.813	0.968	0.962	0.890	0.946	0.928	0.898
	CC	0.993	0.992	0.991	0.99	0.899	0.897	0.999	0.999	0.999	0.998	0.998	0.995
CT 3	PSNR (dB)	63.74	63.08	62.85	62.3	61.77	61.66	81.70	79.43	77.05	74.53	70.91	64.73
	SSIM	0.839	0.836	0.834	0.828	0.826	0.82	0.969	0.963	0.898	0.947	0.932	0.897
	CC	0.991	0.99	0.99	0.99	0.989	0.989	0.999	0.999	0.998	0.998	0.997	0.993
MRI 1	PSNR (dB)	64.67	64.54	64.33	64.67	64.79	64.79	85.43	83.16	80.74	78.01	73.97	66.88
	SSIM	0.853	0.852	0.768	0.771	0.77	0.769	0.977	0.969	0.939	0.950	0.926	0.882
	CC	0.986	0.955	0.951	0.986	0.949	0.95	0.999	0.998	0.998	0.997	0.996	0.992
MRI 2	PSNR (dB)	72.64	72.5	70.09	70.08	70.05	69.94	82.94	80.78	78.69	76.18	72.46	66.05
	SSIM	0.872	0.717	0.716	0.715	0.716	0.722	0.949	0.939	0.926	0.909	0.880	0.797
	CC	0.991	0.975	0.971	0.971	0.971	0.969	0.997	0.997	0.996	0.995	0.993	0.986
MRI 3	PSNR (dB)	71.91	71.59	70.4	69.33	69.32	69	83.16	81.10	78.86	76.57	72.90	0.910
	SSIM	0.877	0.817	0.876	0.877	0.875	0.873	0.975	0.971	0.906	0.957	0.942	
	CC	0.988	0.985	0.984	0.981	0.98	0.98	0.999	0.999	0.998	0.998	0.997	0.994

Table 3. Performance of the proposed compression method continuation

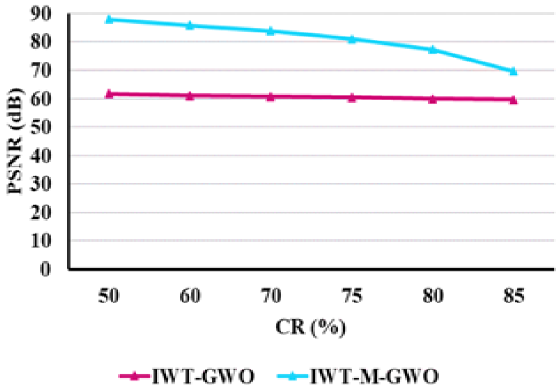
Type of image	metrics	Coefficients are optimized by GWO						Coefficients are optimized by M-GWO					
	CR (%)	50	60	70	75	80	85	50	60	70	75	80	85
X ray1	PSNR (dB)	54.37	53.87	53.41	53.23	52.55	52.38	86.25	83.87	81.91	79.59	76.22	70.53
	SSIM	0.646	0.643	0.634	0.632	0.627	0.623	0.975	0.960	0.965	0.943	0.912	0.885
	CC	0.955	0.953	0.951	0.95	0.946	0.945	0.998	0.998	0.998	0.997	0.996	0.992
X ray 2	PSNR (dB)	77.25	76.16	75.95	75.52	75.03	74.87	85.46	83.87	82.00	79.58	75.49	68.90
	SSIM	0.62	0.613	0.615	0.616	0.615	0.611	0.938	0.927	0.914	0.894	0.856	0.787
	CC	0.995	0.994	0.993	0.992	0.991	0.99	0.998	0.997	0.997	0.996	0.994	0.988
X ray 3	PSNR (dB)	53.56	53.21	52.99	52.51	52.05	51.85	92.02	89.73	87.60	83.82	80.10	69.39
	SSIM	0.786	0.784	0.781	0.768	0.759	0.756	0.977	0.971	0.964	0.955	0.936	0.877
	CC	0.938	0.936	0.932	0.931	0.928	0.926	0.999	0.999	0.999	0.998	0.997	0.992
US 1	PSNR (dB)	76.3	76.18	75.55	74.72	74.15	73.98	86.48	84.25	82.22	79.32	75.07	68.01
	SSIM	0.697	0.696	0.695	0.691	0.688	0.687	0.976	0.940	0.964	0.919	0.867	0.840
	CC	0.993	0.993	0.992	0.99	0.899	0.896	0.998	0.998	0.997	0.996	0.994	0.988
US 2	PSNR (dB)	82.37	81.44	81.1	80.93	80.44	80.2	89.8	87.5	85.3	82.1	78.3	71.7
	SSIM	0.755	0.751	0.751	0.75	0.749	0.748	0.969	0.957	0.950	0.927	0.888	0.835
	CC	0.995	0.994	0.994	0.993	0.992	0.991	0.998	0.998	0.997	0.996	0.994	0.988
US 3	PSNR (dB)	75.62	75.53	75.09	74.66	74.44	73.91	86.58	84.57	82.47	79.62	75.31	68.73
	SSIM	0.688	0.685	0.684	0.682	0.681	0.679	0.968	0.961	0.953	0.939	0.913	0.858
	CC	0.993	0.993	0.991	0.99	0.898	0.897	0.998	0.998	0.997	0.996	0.995	0.989



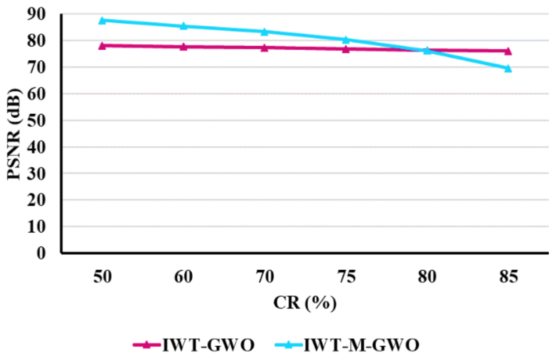
(a) CT image



(b) MRI image

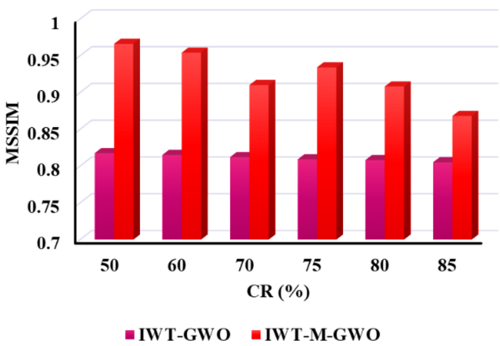


(c) X-ray image

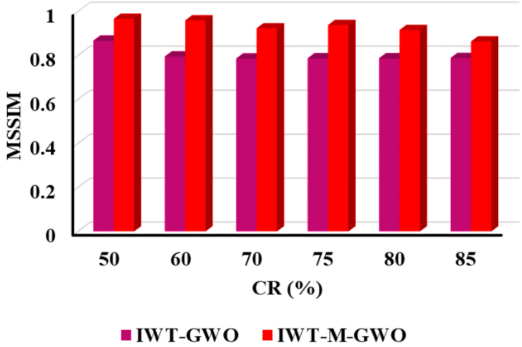


(d) US image

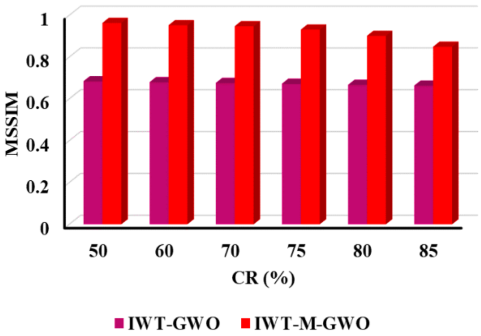
Figure 8. Performance comparison in terms of PSNR



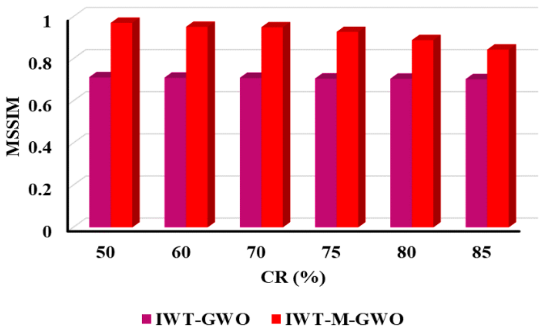
(a) CT image



(b) MRI image

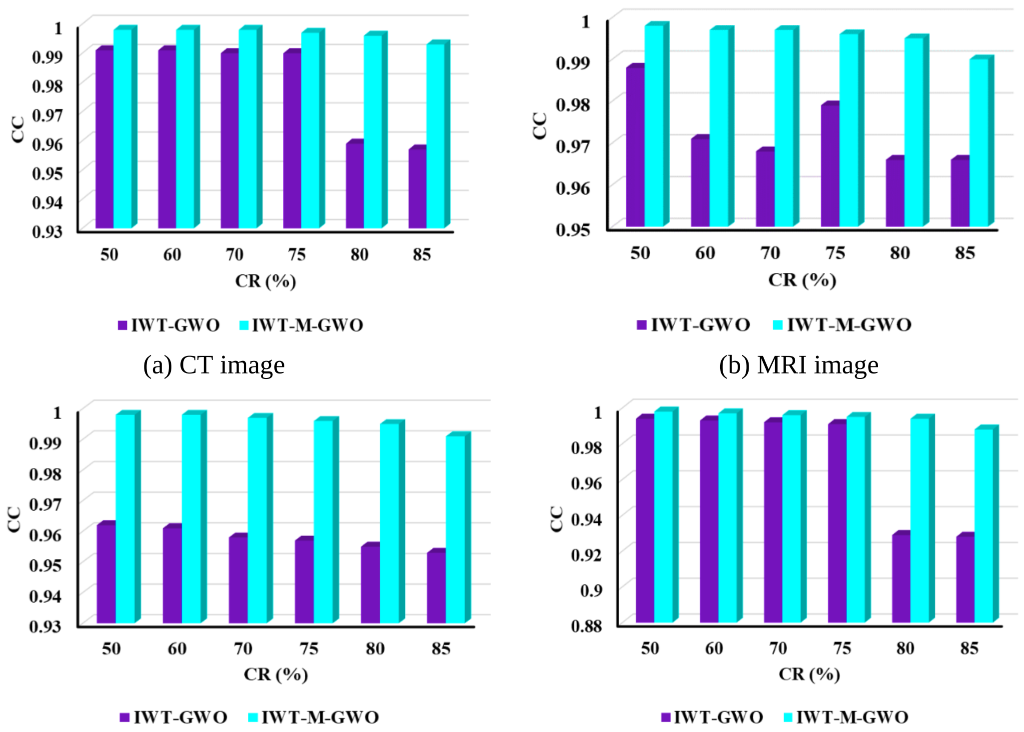


(c) X-ray image



(d) US image

Figure. 9 Performance comparison in terms of MSSIM



(a) CT image (b) MRI image

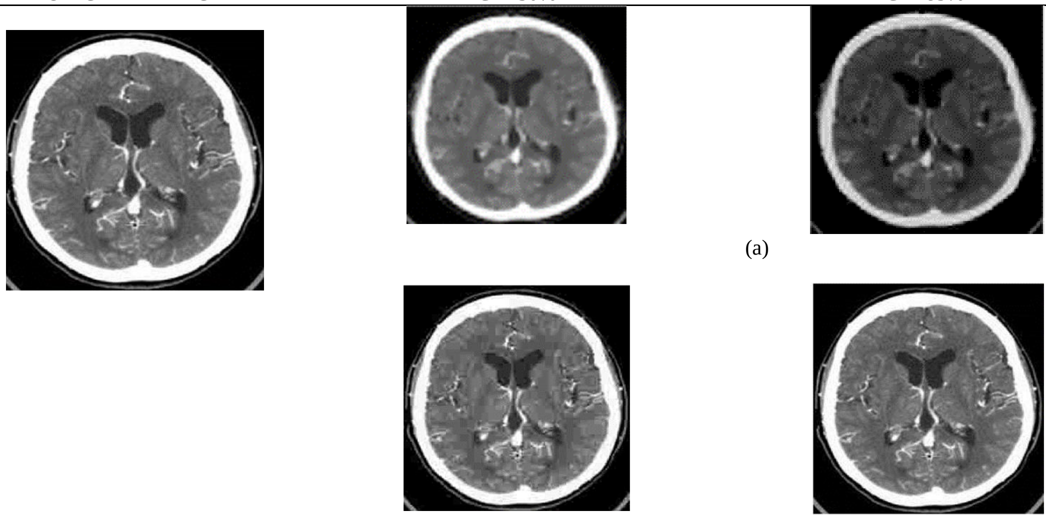
(c) X-ray image (d) US image

Figure 10. Performance comparison in terms of CC

It is observed from the above Figure.8, Figure.9, and Figure.10 that the proposed method outperformed the standard GWO for CR ranging from 50 to 85 for all images. From the empirical findings, it is proved that the presented method can significantly reduce the size of medical image with out losing diagnostic information.

Since the visual inspection plays a vital role in image quality assessment, a comparison is done between IWT-GWO and IWT-M-GWO compression method at varies CRs. Figure.11 showed the original and decompressed CT images. From the Figure.11, the visual quality of the proposed method is better that the IWT-GWO method. It is also noted that the difference between original and IWT-M-GWO based decompressed images gets more noticeable at higher CRs. Similarly, experiments were conducted with MRI, US and X-ray images where consistent outcomes were obtained and demonstrated in Figure.12, Figure.13 and Figure.14 respectively.

ORIGINAL IMAGE	CR=50%	CR=85%



(a)

(b)

Figure 11. Reconstructed CT images (a) IWT-GWO (b) IWT-M-GWO

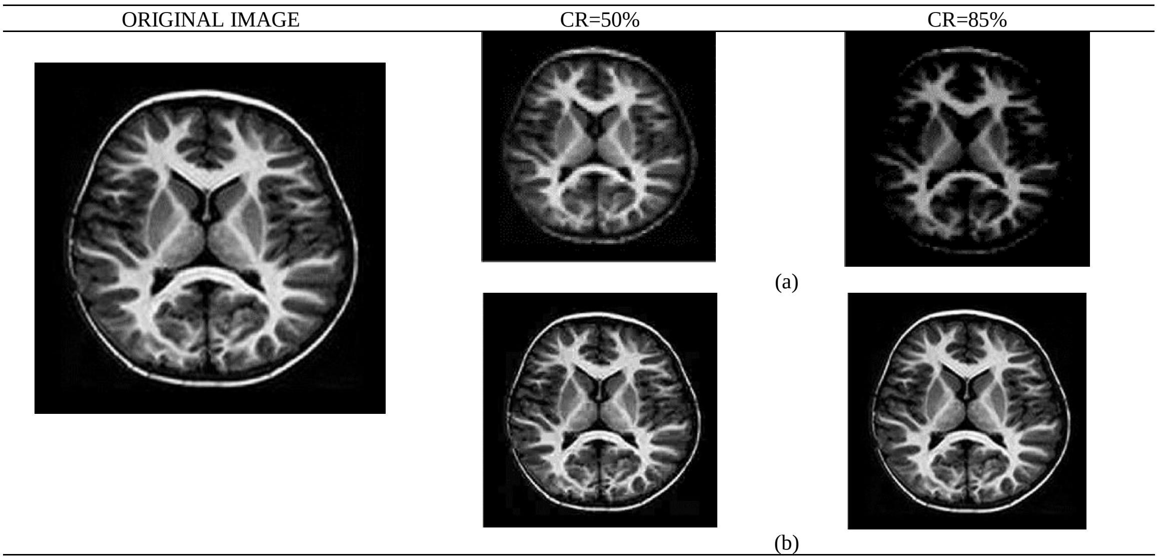


Figure 12. Reconstructed MRI images (a) IWT-GWO (b) IWT-M-GWO

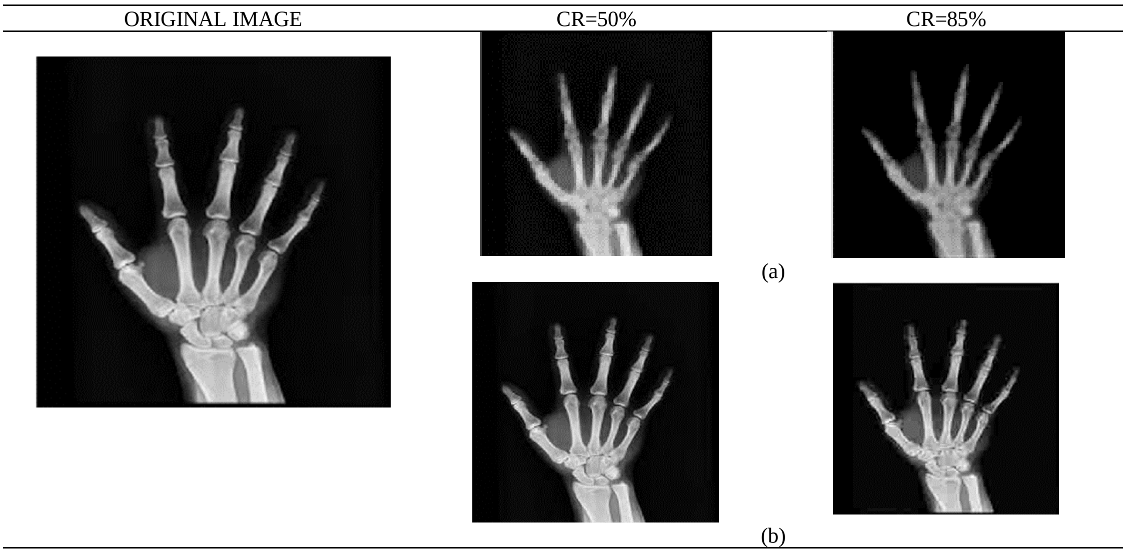


Figure 13. Reconstructed X-ray images (a) IWT-GWO (b) IWT-M-GWO

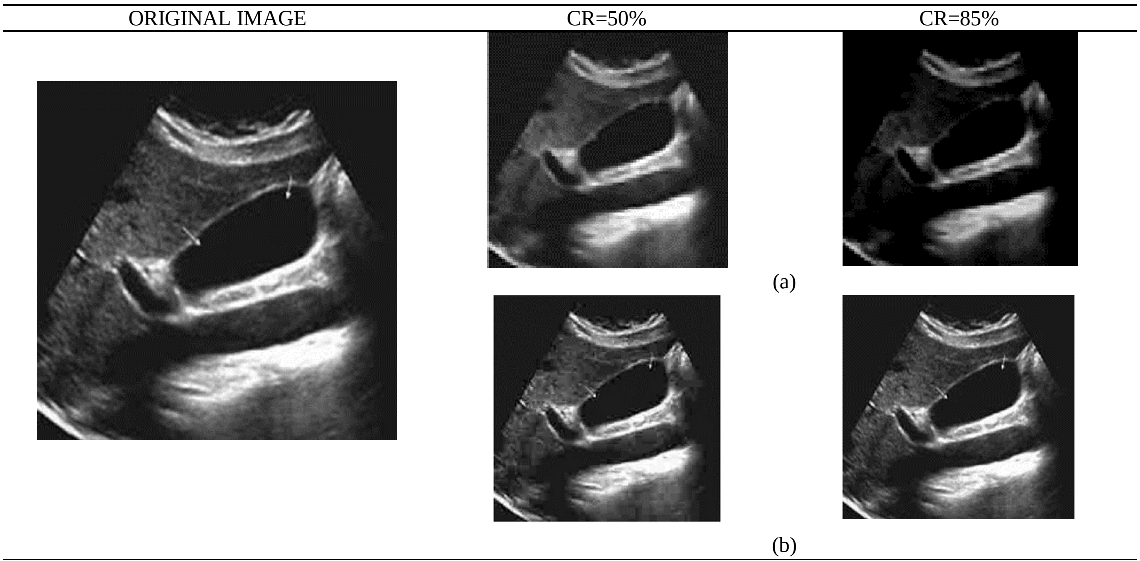


Figure 14. Reconstructed US images (a) IWT-GWO (b) IWT-M-GWO

In order to further prove the efficacy, the presented method is compared to two earlier approachs, namely Haar-PSO [7] and LMs-WOA [8], in terms of PSNR. These earlier methods were built and tested using the same set of images obtained from the Kaggle database. The comparison outcomes are tabulated in Table. 4. Alkinami et al. [8] presented a compression method using Haar-PSO.In this approach, Haar is used for decomposition and PSO is used for selecting sub band threshold values for compression. This approach achived highest PSNR of 48.69dB for CT and 55.76dB for MRI, 57.65dB for x-ray, and 53.69dB for US images. Honsy et al. [8] introduced a compression scheme which is based on LMs and WOA. This method yields highest PSNR values of 68.24dB,70 dB, 80.1dB, and 76.45dB for CT, MRI, X-ray, and US images. The presented method attained highest PSNR of 83.29dB for CT, 83.84dB for MRI, 87.91dB for X-ray, and 87.62dB for US image, showing the superiority of the method. This is because of the usage of the MGWO algorithm for selecting salient coefficients.

Table 4. Comparison with past approaches

Researchers	**Method**	**PSNR (dB)**			
		CT	**MRI**	**X-RAY**	**US**
Alkinami et al. [7]	Haar-PSO	48.69	55.76	57.65	53.69
Honsy et al. [8]	LMs-WOA	68.24	70	80.1	76.45
Proposed	IWT-MGWO	83.29	83.84	87.91	87.62

5. CONCLUSION

A reliable and effective compression technique is essential for compressing medical images while retaining their diagnostic information. This paper has presented an optimized method for compressing medical images by using IWT and MGOA. The unique feature of the compression method introduced in this study is its utilization of MGOA for sub band coefficient selection. The effectiveness of the introduced method is verified by using various imaging modalities, such as MRI, CT, X-ray, and US. The experimental results clearly demonstrated that the introduced method exhibited exceptional performance when compared to other well-known approaches, as evidenced by its superiot PSNR. Further research will explore the potential impact of incorporating machine learning models into the compression process.

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BIOGRAPHIES OF AUTHORS

Shahla Sohail is Assistant Professor at Dayananda Sagar College of Engineering, Bangalore, Karnataka, India. She received B.E from A.T.B.U Bauchi, Nigeria, M.Tech degree from B.I.H.E.R , Chennai and pursuing PhD under Visweswaraiah Technological University, Belgaum, Karnataka. Her area of interest includes signal processing, Image processing, ANN

Dr.S.Thenmozhi, Currently working as an Associate Professor in Department of Electronics and Communication Engineering, Dayananda Sagar College of Engineering, Bangalore, Karnataka, India. She received her B.E degree from Bharathidasan University, Trichy, M.E and Doctoral degree from Anna University, Chennai. Her research areas are image/signal processing, Information security, and IoT She is a life time member in ISTE, Fellow in IETE. She can be contacted at email: thenmozhi-ece@dayanandasagar.edu.

Swetha Priyanka Jannu is working as Assistant Professor in the Department of ECE at Vardhaman College of Engineering, Hyderabad, Telengana, India. She received her B.Eand M.E degree from and pursuing PhD under Visweswaraiah Technological University, Belgaum, Karnataka. Her area of interest includes Image processing, IoT, wireless sensor networks.

R.Gaythiri is working as Assistant Professor in the Department of EIE at Sri Sairam Engineering College, Chennai, Tamilnadu, India. She received her B.E and M.E degree from Annamalai University and pursuing PhD under Anna University,Chennai. Her research areas are Image processing,Instrumentation