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AN ENHANCED APPROACH UTILIZING AN OPTIMIZED DISCRETE WAVELET TRANSFORM FOR IMAGE STEGANOGRAPHY IN MEDICAL IMAGING

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ABSTRACT

Image steganography constitutes a specific form of steganography wherein an image is employed as the concealing medium. Medical Image Steganography represents a distinctive subfield within the broader domain of Image Steganography. The safeguarding and confidentiality of sensitive patient data necessitate heightened scrutiny and scholarly investigation. Consequently, numerous techniques have been introduced over the past twenty years aimed at concealing patient information through the utilization of image steganography. In the present study, a new methodology is introduced for medical image steganography, leveraging Discrete Wavelet Transform (DWT) in conjunction with Particle Swarm Optimization (PSO). A Low-Density Parity Check was employed to encode the medical data prior to its concealment within the cover medical image. The experimental analysis was conducted on four distinct medical imaging modalities, namely X-ray, MRI, CT scan, and Ultrasound images, with the evaluation of performance based on metrics such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), and Structural Similarity Index Measure (SSIM). The findings of this investigation suggest that the PSO algorithm significantly enhances the efficacy of steganography, particularly when integrated with DWT techniques.

KEYWORDS

Image Steganography; Wavelet Transform; Particle Swarm Optimization, Medical Image, Image Coding.

1. INTRODUCTION

In contemporary society, advancements in digital communication play a pivotal role in our quotidian experiences. Innovations in internet technologies, coupled with the digitalization of information, have significantly augmented the utilization of data transfer on a remarkable scale (Kadhim et al., 2019). With the swift progression of multimedia technology, computer networks are increasingly vulnerable to malevolent intrusions (Gulia et al., 2016). The privacy and security of information have emerged as paramount concerns in our digital existence (A.Alasadi, 2017). The issue of privacy has escalated into a prominent apprehension for individuals. Particularly when disseminating information or any form of data across the extensively interconnected internet, it is imperative to ascertain that such data is thoroughly safeguarded. Various methodologies, including encryption, cryptography, and steganography, have been employed to realize this objective (Kadhim et al., 2019). The term steganography, signifying "hidden text," is etymologically derived from the Greek lexemes "steganos" and "graphie". Steganography refers to the practice of utilizing communication mediums to conceal confidential information. A communication medium may encompass text, images, audio, video, network protocols, or even DNA sequences. Recent advancements in technology and associated computational techniques have fostered the implementation of steganography applications, among which the exchange of medical images is particularly significant. In contemporary medical devices, the transmission of biomedical images has become an essential requirement for sustaining efficient and secure data communication over insecure channels (Subramanian et al., 2021). Currently, medical reports are transmitted over networks, and since these reports contain sensitive patient information that must remain concealed from unauthorized entities, a medical image steganography process is employed. In medical image steganography, confidential information is embedded within the medical image, thereby leaving no discernible evidence of any information during transmission, thus rendering it a secure, confidential, and time-efficient methodology. The most straightforward technique for concealing data within an image is referred to as least significant bit (LSB) insertion. In this methodology, a bit of concealed information is embedded within either the least significant bit of the Green or Blue matrix of a specified pixel, as determined by the secret key (Masud Karim et al., 2011).

There exists a substantial body of research pertaining to steganography within the academic literature, specifically addressing both spatial domain and frequency domain methodologies. The complexities inherent in these methodologies primarily revolve around the volume of information that can be concealed, as well as the degree to which the technique ensures security (Karakus and Avci, 2020). In the work of, two algorithms within the spatial domain are introduced, namely Similarity-based LSB (SM-LSB) and Fuzzy Logic based LSB (FLLSB), wherein Magnetic Resonance (MR) images serve as cover images for the concealment of Electroencephalogram (EEG) data, and pertinent patient information along with physician's annotations are embedded within the headers of the MR images (Zheng and Qian, 2008). put forth an effective reversible method grounded in Wavelet Transform (WT). This approach predominantly hinges on utilizing B-spline WT to identify the QRS complex within the initial ECG signal. Following the detection of the R wave's original ECG signal, Haar lifting WT is applied to the original image. Subsequently, a comparative analysis is undertaken to select the non-QRS high-frequency coefficients, followed by the application of index subscript mapping (Marini and Walczak, 2015) The watermark is then embedded by shifting one bit of the identified coefficients to the left, after which the original signal is reconstructed through reverse Haar lifting WT. In, an alternative spatial domain algorithm is delineated. The embedding phase of this algorithm is distinct from that of SM-LSB, as it employs a genetic algorithm, termed Genetic Algorithm-Optimum Pixel Similarity (GA-OPS), for the selection of pixels to be modified in order to incorporate bits that encode the patients' confidential information. In, an IWT-based steganography technique is executed, wherein multiple images are amalgamated into a singular image utilizing left-flipping, while a dummy image is generated through the application of the Arnold Transform. In, a transform domain algorithm centered on Digital Imaging and Communications in Medicine (DICOM) medical images is proposed. This algorithm facilitates the embedding of a secret DICOM image within a cover DICOM image of equivalent dimensions, functioning through three distinct phases: preprocessing, embedding, and extraction. DICOM employs its own language, the Medical Management Information representation, which is based on a representation of the actual hospital setting (Abd-El-Atty, 2023). Introduces an innovative medical image steganography framework that leverages quantum walks, chaotic systems, and particle swarm optimization algorithms. A three-dimensional chaotic system, in conjunction with quantum walks, is employed to execute particle swarm optimization algorithms (Chowdhuri et al., 2023). Implement two divergent strategies, whereby Support Vector Machine (SVM) is initially utilized to differentiate the Region of Interest (ROI) from the Non-Region of Interest (NROI) within the medical image. Subsequently, IWT is utilized to embed confidential information within the NROI segment of the medical image (Cover Image). In, an end-to-end steganographic framework is presented, aimed at the efficient protection of medical images. This framework integrates adaptive medical-image steganography with a generative adversarial network dubbed “MedSteGAN”.

A coverless image steganography based on robust image wavelet hashing and Huffman encoding. Initially, the confidential data is encoded through lossless compression using Huffman Encoding, which reduces the payload and enhances the capacity for embedding. Second, segments of an 8-bit size are created from the compressed secret data. The efficient DWT hashing technique has been employed to generate a hash sequence for an image (Sultan, 2016).

It is imperative that both patients and healthcare practitioners are made aware of any modifications made to images, even if the intent is to securely integrate data. Images that have been modified must possess accompanying metadata or alternative identifiers that facilitate traceability, thereby allowing healthcare professionals to ascertain that masking techniques have been employed. It is essential to ascertain that the implemented procedures adhere to ethical and legal standards, including but not limited to HIPAA and GDPR, which mandate the preservation of both image integrity and data protection. It is crucial to meticulously document and publicly disclose any alterations to promote ethical transparency (Karakış et al., 2015). In the present study, a new algorithm is proposed for the implementation of medical image steganography, utilizing Particle Swarm Optimization (PSO) in conjunction with Discrete Wavelet Transform (DWT) (Jeevitha and Prabha, 2022). The integration of PSO and DWT in the context of image steganography has the potential to significantly improve both the resilience and volume of the concealed information (Zheng and Qian, 2008).

2. METHOD

In order to tackle the issue of employing image steganography algorithms for concealing patients' confidential medical reports within their medical imagery, this manuscript presents the integration of Discrete Wavelet Transform (DWT) with Particle Swarm Optimization (PSO) to enhance data confidentiality and safeguard patients' privacy, as depicted in Fig.1, which delineates the framework of the proposed methodology. The primary objective is to embed the secret bits into the least significant portions of the high-frequency coefficients within the wavelet domain (Chowdhuri et al., 2023).

2.1. Discrete Wavelet Transform

The Wavelet Transform constitutes a sophisticated mathematical methodology employed to convert an image into a collection of various frequency components, which may prove advantageous for concealing information within the image. The image undergoes a decomposition into several frequency sub-bands via the Wavelet Transform. Commonly utilized wavelets encompass Haar, Daubechies, and Symlets (Prabakaran et al., 2013). The fundamental procedures involved include: The wavelet fluctuation disaggregates the variances in a periodic series, thereby facilitating an analysis of changes. A wavelet transformation can manifest as either continuous or discrete. In the context of continuous wavelet transform, the translation and scale factors are represented as real numbers corresponding to continuous transformations (Subhedar and Mankar, 2016). Consequently, it becomes imperative to discretize the continuous wavelet transform, preserving information to the greatest extent feasible through reduced computational effort, and acquiring wavelet coefficients characterized by diminished redundancy, referred to as discrete wavelet transform. The Discrete Wavelet Transform (DWT) serves as a proficient method for the hierarchical disintegration of an image. In the DWT framework, the input image is primarily decomposed into four distinct labeled components: LL (Low), HL (Horizontal High), LH (Vertical High), and HH (High) (Khandelwal et al., 2022).

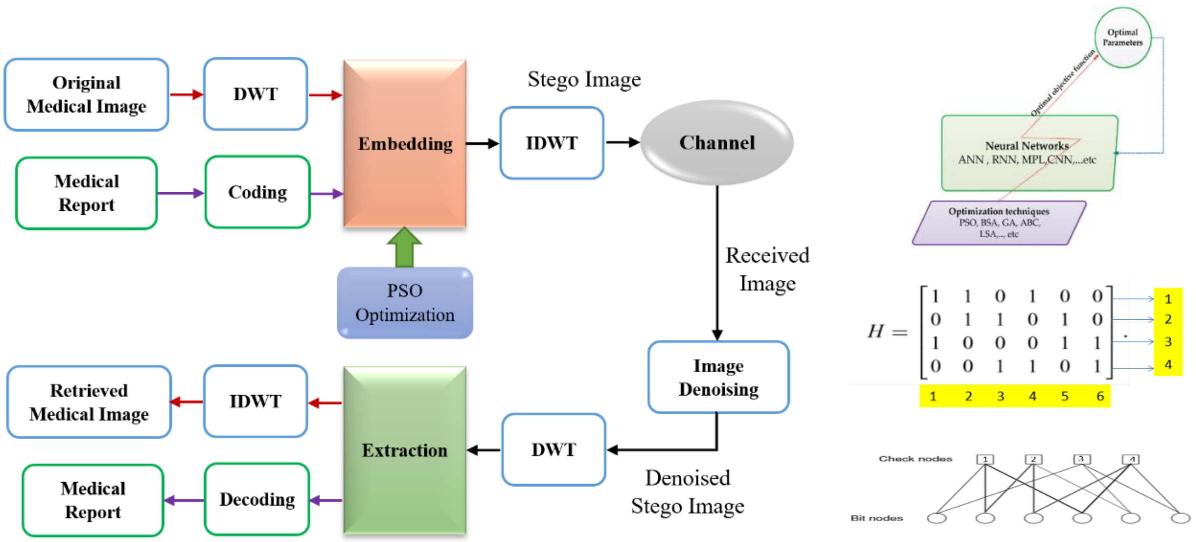


Fig. 1: Block Diagram of the Proposed System for Medical Image Steganography

2.2. Particle Swarm Optimization (PSO)

Evolutionary algorithms serve an indispensable role in the formulation of contemporary image steganography methodologies, aimed at maximizing payload capacity while simultaneously preserving the aesthetic integrity of the stego image. Particle Swarm Optimization represents an optimization paradigm derived from the collective behaviors observed in avian and aquatic species (Abd-El-Atty, 2023). This technique can be employed to refine the parameters involved in the embedding process, including the selection of sub-bands, the volume of information to be embedded, and the distribution of said information throughout the image. PSO is an optimization strategy that was developed to ascertain predictive controls through the minimization of the constrained multivariate standard.

Within the framework of PSO, each particle signifies a distinct solution. To execute the PSO algorithm, each particle i is characterized by an initial state, pbest (li), gbest (gi), and the two principal components: velocity (vi) and position (xi). The velocity and position for each particle can be recalibrated utilizing.

$$v_{ij}(t+1) = \mu v_{ij}(t) + c1 \times r1_j(t)\left(l_{ij}(t) - x_{ij}(t)\right) + c2 \times r2_j(t)\left(g_{ij}(t) - x_{ij}(t)\right)$$

$$x_{ij}(t+1) = v_{ij}(t+1) + x_{ij}(t)$$

Where j represents the dimension of the particle i, l denotes the inertia coefficient, c1, and c2 are the collective and subjective parameters and r1 and r2 are random numbers in the interval (0, 1).

2.3. Coding

A low-density parity-check (LDPC) code is characterized by a parity-check matrix exhibiting low density, specifically, the parity-check matrix H contains a minimal quantity of 1s. It has been demonstrated that certain classes of these codes can asymptotically attain the Shannon bound, with the density approaching zero as the block length tends toward infinity. Additionally, the theorem posits that such codes can be generated with a probability converging to one if the parity-check matrix H is constructed in a random manner (Gallager, 1962). Nevertheless, the development of practical decoders is substantially facilitated if a specific structure is imposed upon the parity-check matrix. Let C represent a linear code of length n over the finite field F with a generator matrix G, where q denotes the power of a prime p. In the case where p = 2, the code is referred to as binary. The dimension of C is denoted as k, thus indicating that the number of elements within C is equivalent to qk. A parity-check matrix, H, corresponding to an [n, k] code C is defined as a [n − k] × n matrix whose rows consist of linearly independent parity checks. The minimum distance of a code, denoted as d, refers to the smallest distance between any two distinct code words. For a received code word x of a code C with parity-check matrix H, the syndrome, denoted as s, is calculated by the equation s = H · x. As shown in the figure above: parity-check matrix and Tanner graph (Johnson, 2006).

3. THE PROPOSED METHOD FOR COMBINING PSO AND DISCRETE WAVELET TRANSFORM IN MEDICAL IMAGE STEGANOGRAPHY

The confidential medical data is integrated within the coefficients of one or more sub-bands of the medical imaging modality. By selecting the appropriate sub-bands (typically, lower frequency bands are preferred for enhanced imperceptibility), the alterations can be rendered less conspicuous. The principal phases encompassed within this algorithm are delineated as follows:

a) Preprocessing: Transform the confidential data into an appropriate format (e.g., binary representation).

b) Wavelet Transform: Implement the Wavelet Transform to the primary image to decompose it into various frequency sub-bands (Pan et al., 2022).

c) PSO Optimization: Employ Particle Swarm Optimization (PSO) to ascertain optimal parameters for embedding, such as: Selection of wavelet sub-bands for information incorporation. Scaling factors pertinent to data embedding. Distribution strategy for embedding across the sub-bands (Mohsin et al., 2019).

d) Embedding Information: Integrate the confidential data into the optimized wavelet sub-bands in accordance with the parameters identified through PSO.

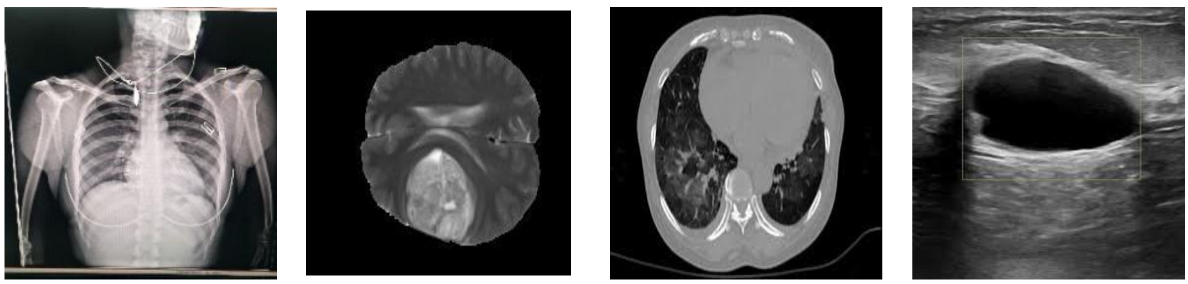
e) Different quality factors of the hidden image were taken into consideration in the hiding stage, and then the hidden medical image was sent via wireless gene affected by four types of noise: Gaussian, salt and pepper, poisson , speckle (Nagaraju and ParthaSarathy, 2015).

f) Inverse Wavelet Transform: Execute the Inverse Wavelet Transform to derive the stego-image that conceals the information (Chun-Lin, 2010).

g) Postprocessing: Conduct supplementary processing to augment the resilience and visual fidelity of the stego-image (Adeshina et al., 2025).

4. EXPERIMENTAL SETUP

The proposed algorithm integrates Discrete Wavelet Transform (DWT) alongside Particle Swarm Optimization (PSO), and image denoising through the application of a median filter. This algorithm has been executed in two distinct phases: embedding and extraction. The medical imaging utilized within the framework of this algorithm was sourced from various datasets encompassing a range of modalities, including X-ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Ultrasound images as illustrated in Fig. 2.



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

Fig. 2: Sample Medical Image Modalities, a) X-ray, b) MRI, C) CT scan, and (d) Ultrasound

In the present algorithm, the efficacy of medical image steganography is quantitatively assessed through three analytical parameters, specifically the Mean Square Error (MSE), the Peak Signal-to-Noise Ratio (PSNR), and the Structural Similarity Index Measure (SSIM). These three metrics play a crucial role in evaluating the quality of the image. The assessment of the quality of the Stego image is contingent upon these parameters:

MSE is defined as the Mean Square Error, which serves as an indicator of image quality. An image of high quality will exhibit a minimal MSE value. The calculation of MSE can be performed utilizing the formula:

$$MSE = \frac{1}{m * n} \sum_{p=1}^{m} \sum_{q=1}^{n} \| I(p,q) - J(p,q) \|^2$$

where m and n are the total number of rows and columns, I(p,q) is the pixel of the cover image in the pth row and qth column, J(p,q) is the pixel of the stego image in the pth row and qth column.

PSNR is the measure of the quality of the image. The PSNR of the image is represented in terms of the MSE between the stego image and the cover image. The formula for PSNR is:

$$PSNR = 10log_{10}\left(\frac{255}{MSE}\right)$$

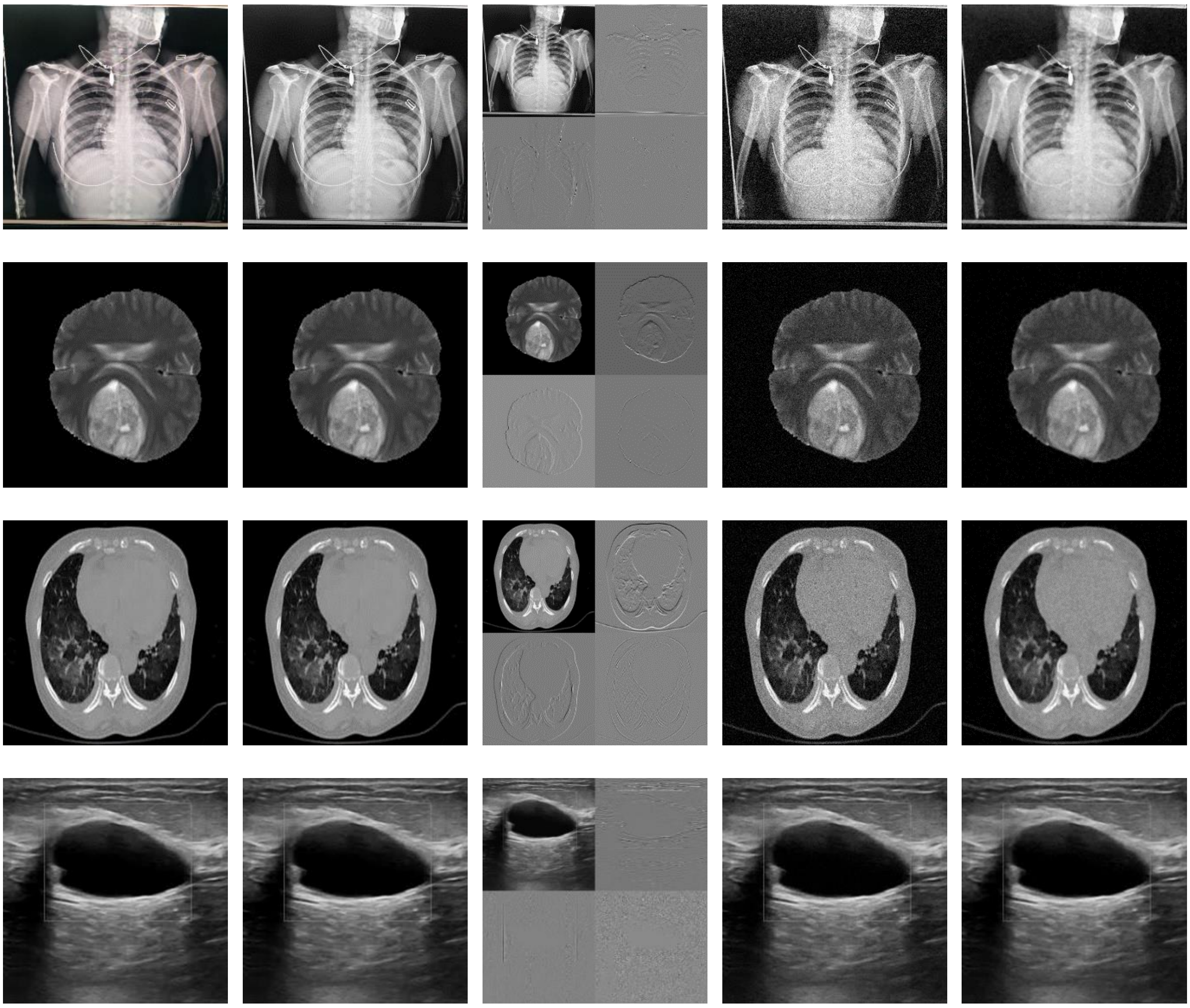
The SSIM is designed to consider three factors: luminance, contrast, and structure. It better simulates the working way of the Human Visual System (HVS). The SSIM is defined by:

$$SSIM(I,J) = \frac{(2 * \mu_I * \mu_J + d_1) * (2 * \sigma_{IJ} + d_2)}{(\mu_I{}^2 + \mu_J{}^2 + d_1) * (\sigma_I{}^2 + \sigma_J{}^2 + d_2)}$$

where and are the local means of both images I and J, respectively, and are the standard deviations of both images I and J, respectively. is the cross-covariance. and are two variables to stabilize the division with a weak denominator (Nipanikar et al., 2018).

5. RESULTS AND DISCUSSION

In this section, the outcomes of the proposed Image Steganography methodology are delineated and subjected to both qualitative and quantitative analysis. Four distinct modalities of imaging were evaluated and subjected to experimentation for the purpose of medical image steganography. The initial step involves the application of the input medical image (designated as the cover image) onto the Discrete Wavelet Transform (DWT) employing various wavelet filters (Haar, Db2, Sym4, Coif1, and bior2.2) for a singular level of decomposition. The Low-Density Parity Check (LDPC) coding technique is incorporated within this algorithm to encode the medical data. In order to conceal this medical information within the cover medical image, the combination of DWT and Particle Swarm Optimization (PSO) is executed as a form of image steganography. When transmitting the stego image through a communication medium characterized by noise, the resilience of the steganographic technique is rigorously evaluated. Types of Noise: Gaussian Noise: Emulates real-world auditory disturbances such as sensor imperfections or transmission inaccuracies. Salt-and-Pepper Noise: Introduces arbitrary black and white pixels, thereby simulating abrupt interference. Speckle Noise: Frequently encountered in radar and medical imaging modalities. Poisson Noise: Represents the statistical behavior of photon noise. At the receiving end, the median filter is employed to enhance the efficacy of the received image by diminishing the noise levels present in the image and improving its aesthetic quality. Fig. 3 illustrates the principal procedure that is executed during the embedding phase utilizing various techniques across four modalities of medical imaging, specifically; row 1 showcases X-ray images, row 2 displays MRI images, row 3 presents CT images, and row 4 features Ultrasound image outcomes. In Fig.3, the Haar wavelet filter is applied, Gaussian noise with a variance of 0.005 is introduced, and a median filter with a window size of 5 is utilized.



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

Fig. 3: Embedding Process, (a) Original Image, (b) Stego Image, (c) DWT Image, (d) Transmitted Image, and (e) Received Image.

Table 1 presents a thorough evaluation of the efficacy of steganography employing wavelet transform across various noise conditions. In the context of Poisson Noise, the stego images demonstrate no discernible distortion, attaining optimal metrics (PSNR = ∞, MSE = 0, SSIM =

1). This observation implies that wavelet-transform-based steganography possesses an inherent resilience to Poisson noise, which is typically a consequence of the quantum characteristics of imaging systems. Conversely, Gaussian Noise introduces a moderate level of distortion across all modalities. The PSNR values fall within the range of 20 to 21, whereas SSIM reflects a comparatively low metric for structural similarity, particularly evident in MRI and X-ray imaging. This finding indicates that although wavelet-based methodologies can mitigate the effects of Gaussian noise to a degree, the structural fidelity of the images is nonetheless partially compromised. Salt & Pepper Noise engenders considerable degradation, particularly pronounced in MRI and X-ray modalities (PSNR ~16–17 and SSIM ~0.3). This specific type of noise is characterized by its high-frequency components, which can significantly disrupt the embedding and retrieval processes integral to steganography. Speckle Noise results in a lower level of distortion than Salt & Pepper noise but exceeds that observed with Gaussian noise, with PSNR values ranging from 25 to 32 and SSIM often exceeding 0.6. The comparatively elevated SSIM values suggest that wavelet-based techniques can proficiently maintain structural integrity under speckle noise, particularly in Ultrasound and MRI modalities. MRI reveals the highest vulnerability to Salt & Pepper noise yet retains substantial structural integrity when subjected to Speckle noise (SSIM = 0.9). CT displays a moderate degree of resistance to both Gaussian and Salt & Pepper noise while exhibiting commendable performance under Speckle noise. Ultrasound demonstrates resilient performance in the presence of Speckle noise (SSIM = 0.84), aligning with its prevalent application in low-SNR environments. X-ray images, akin to MRI, are significantly affected by Salt & Pepper noise yet exhibit moderate resistance to Speckle noise.

The multi-resolution analysis afforded by the wavelet transform adeptly addresses the high-frequency components within images, rendering it particularly effective in counteracting Speckle and Gaussian noise. Nevertheless, its susceptibility to Salt & Pepper noise may necessitate the incorporation of supplementary preprocessing techniques, such as denoising or filtering, to bolster its overall robustness.

Conversely, the histogram of the stego image reflects the pixel distribution subsequent to the embedding of data into the original image, which may result in shifts or alterations within the histogram. Such modifications can be nuanced, as effective steganography endeavors to minimize perceptible changes in order to evade detection. The existence of observable shifts or the emergence of new peaks within the histogram of the stego image may signify that the embedding process has substantially altered pixel values. An examination of Figs 4, 5, 6, and 7 reveals that there are no distinct discrepancies between the histogram of the cover image and that of the stego image across all image modalities, thereby indicating a more proficient concealment of the information.

Table 1: Evaluation Metrics for Steganography Using Wavelet Transform under Different Noise Types

Image Modality	Noise Type	PSNR	MSE	SSIM
MRI	gaussian	21.49271	461.1149	0.176628
	salt & pepper	16.61537	1417.568	0.297294
	speckle	32.74285	34.57763	0.901436
	poisson	Inf	0	1
CT	gaussian	21.13939	500.1974	0.299687
	salt & pepper	17.31615	1206.327	0.372791
	speckle	28.3394	95.31037	0.782583
	poisson	Inf	0	1
Ultrasound	gaussian	20.55046	572.8408	0.329957
	salt & pepper	17.82274	1073.511	0.396277
	speckle	29.54622	72.18682	0.843874
	poisson	Inf	0	1
X-ray	gaussian	20.54766	573.2112	0.222179
	salt & pepper	17.68726	1107.527	0.303745
	speckle	25.73103	173.7712	0.605284
	poisson	Inf	0	1

Table 2 presents a quantitative analysis comparing five distinct wavelet filters (Haar, Db2, Sym4, Coif1, and bior2.2) at a singular level of decomposition. This comparative assessment is conducted across four medical imaging modalities (X-ray, MRI, CT scan, and Ultrasound) and its efficacy is evaluated through metrics such as PSNR, MSE, and SSIM. It is evident that the bior2.2 wavelet filter achieves the highest PSNR values in both X-ray and MRI medical images, whereas the Db2 filter demonstrates superior performance in the context of CT imaging.

For the four medical images analyzed, the efficacy of the proposed algorithm (DWT-PSO) is systematically compared with two distinct methodologies: PSO devoid of DWT and the conventional LSB techniques. Within the framework of the proposed methodology, the process of image steganography is executed in a two-phase approach, wherein LDPC is employed for text encoding, while DWT-based PSO facilitates the concealment of the encoded medical information within the medical image. The proposed algorithm demonstrates superior performance with respect to both PSNR and SSIM, as evidenced in Fig. 8. Given the critical and sensitive nature of medical images, it is imperative that the method guarantees that the incorporated data does not undermine the diagnostic integrity of the images.

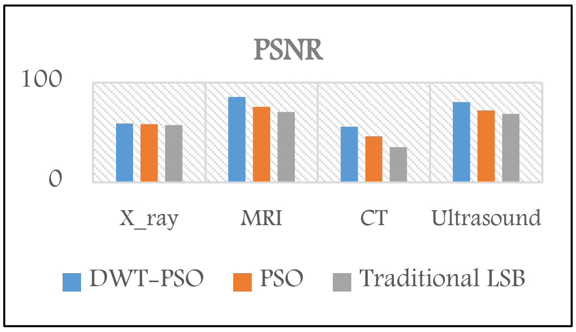
Table 2 Additional Metrics

Image Modality	Wavelet Filter	PSNR	MSE	SSIM	Entropy	AUC
X-ray	Haar	53.1691	0.313461	0.999611	6.8	0.95
	db2	69.2893	0.0076599	0.99999	7.4	0.98
	sym2	67.9321	0.0104681	0.99997	7.3	0.97
	coif1	70.4841	0.0058174	0.99999	7.5	0.99
	bior2.2	73.6064	0.00283432	0.99999	7.8	0.995
MRI	haar	59.75001	0.06892	0.99989	7.0	0.96
	db2	63.37692	0.02992	0.99998	7.2	0.97
	sym2	63.00822	0.03254	0.99998	7.2	0.97
	coif1	63.43221	0.02954	0.99998	7.3	0.975
	bior2.2	64.51451	0.02307	0.99997	7.4	0.98
CT	haar	49.942	0.659367	0.999446	6.5	0.91
	db2	57.4822	0.116123	0.999886	6.8	0.94
	sym2	48.021	1.02593	0.999349	6.4	0.9
	coif1	53.7841	0.272071	0.999799	6.7	0.93
	bior2.2	51.5944	0.45051	0.999727	6.6	0.92
Ultrasound	haar	59.05001	0.08092	0.99963	6.9	0.96
	db2	80.4411	0.0011	1.000	8.0	1.0
	sym2	80.4414	0.00061	1.000	8.1	1.0
	coif1	56.2104	0.1561	0.9999	6.7	0.95
	bior2.2	57.6714	0.1119	0.9999	6.8	0.96

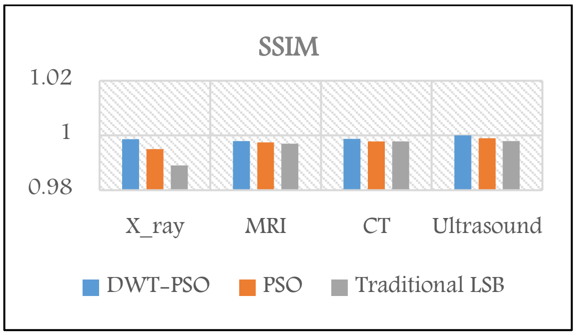
Bit Error Rate (BER): 0.0000

Number of Hidden Words: 124

Maximum Embedding Capacity (bits): 262144



(a)



(b)

Fig. 8: Comparison between DWT-PSO, PSO and LSB methods in terms of a) PSNR, b) SSIM.

6. CONCLUSION

In the present study, a comprehensive framework has been established for the domain of medical image steganography. The remarkable performance metrics and minimal computational complexity associated with the algorithm utilized in image steganography substantiate the efficacy of the proposed methodology. The suggested approach advocates for the integration of Discrete Wavelet Transform (DWT) and Particle Swarm Optimization (PSO) techniques in the context of image steganography. The medical data is encoded utilizing Low-Density Parity-Check (LDPC) codes and subsequently concealed within the host medical image. A thorough evaluation was conducted across four distinct imaging modalities, namely

X-ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, and Ultrasound images to assess the effectiveness of DWT in the realm of image steganography. The comparative analysis reveals that the combination of DWT with PSO demonstrates superior performance metrics, particularly in terms of Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index Measure (SSIM). With its commendable performance, the proposed methodology provides substantial support to healthcare professionals in the concealment of critical information within medical applications.

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