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Original Article

Enhancing DICOM Image Compression Using Sheep Flock Optimization Algorithm with Modified Haar Wavelet Approach

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Abstract - *Digital Imaging and Communication in Medicine (DICOM) is a medical imaging file standard employed for storing large amounts of data, such as imaging procedures, patient data, and the image itself. With the increasing use of medical imaging in medical diagnoses, it is imperative to have a secure and rapid technique for sharing a considerable number of medical images among medical staff, and compression has often been a choice. Different compression approaches are utilized, including lossless techniques such as Run-Length Encoding (RLE) and lossy methods such as JPEG and JPEG2000. Lossless compression preserves each image's information, which makes it fit for healthcare data where fidelity is vital, like in radiology. At the same time, lossy compression is used to sacrifice some image details to accomplish high compression ratios, frequently employed in situations where slight degradation in quality is acceptable, like in telemedicine applications or while transmitting larger datasets over a limited bandwidth network. DICOM compression standard ensures compatibility and interoperability over dissimilar medical imaging modalities and systems. This article introduces a new DICOM Image Compression Using a Sheep Flock Optimization Algorithm with Modified Haar Wavelet (SFOA-MHW) approach. The presented SFOA-MHW technique uses SFOA to resolve the wavelet discontinuities that take place while performing image compression via thresholding. The SFOA-MHW technique converts the input images into sub-band details and approximation by using MHW, which then employs the threshold. Finally, the SFOA is used to select the threshold values. The SFOA-MHW technique aids in DICOM image compression by preserving fine details with a high compression ratio. The performance evaluation of the SFOA-MHW model is verified utilizing DICOM image sample sets. The experimental values highlighted that the SFOA-MHW technique gains better performance over other techniques in terms of distinct measures.*

Keywords – *DICOM, Sheep Flock Optimization, Image Compression, Discrete Wavelet Transform, Threshold Value.*

1. Introduction

In the last few years, the medical field has seen a dramatic change due to the rise of digital technology, which has touched almost every area of patient care. The speedy development of non-invasive medical imaging devices is impressive; these devices are now a requirement for the purposes of diagnosis, treatment planning, and follow-up [1]. The explosive growth in data output has been made possible through the widespread use of imaging modalities such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasonography. As a consequence of the exponential growth of medical imaging data, the importance of storage, transmission, and interoperability standards that cover a wide range of healthcare platforms is growing [2]. The American College of Radiology and National Electrical Manufacturers Association (ACR-NEMA) originally created the DICOM standard to address these requests. DICOM creates a standardized medical picture representation, interchange, and archiving framework that assures compatibility across heterogeneous systems and imaging apparatus from different companies [3, 4]. DICOM files are crucial for secure transmission of data and clinical application in hospital networks, as they integrate pixel data and metadata, including patient information, collection parameters, and modality details [5]. However, the immense volume of DICOM images is a problem for telemedicine applications, network transmission, and storage systems in low-bandwidth environments [6]. To maximize storage and communication effectiveness, medical image compression is unavoidable. To avoid patient harm, medical image compression must preserve diagnostic integrity, a major difference from natural image compression. Lossy techniques can find high compression ratios at the cost of diagnostically critical features, while lossless techniques often only realize small data size reductions [7]. This means that the industry still has a big challenge to attain an equilibrium between good compression and picture quality. Due to this problem, various transform-based compression approaches have been studied. Traditional algorithms, such as the Discrete Cosine Transform (DCT), have been used due to their simplicity and effectiveness, even though they often create blocking artifacts if highly compressed [8]. Although the Discrete Wavelet Transform (DWT) supports simultaneous spatial and frequency domain localization and a multi-resolution representation of the image. Haar laid the groundwork for fidelity-sustaining and efficient image compression algorithms by his pioneering contributions to wavelets [9]. Discontinuities at thresholding can, however, lead to the loss of minute details that are often crucial for diagnostic applications in conventional DWT-based techniques.

To overcome these limitations, current studies have focused on the advancement of techniques for combining optimization algorithms with transform-based compression techniques. Maintaining image quality and making it possible to adjust threshold parameters have been enabled by employing evolutionary algorithms, which include Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimizers (GWO) [10-12]. In some cases, these techniques have limitations like premature convergence, high population requirement, or processing overhead. This paper aims to compress DICOM images in a more effective way by fusing the Modified Haar Wavelet (MHW) with the Sheep Flock Optimization Algorithm (SFOA). The MHW improves the Peak Signal-to-Noise Ratio (PSNR) and Compression Ratio (CR) by optimizing the basic Haar wavelet's ability to maintain clarity and fine structural details.

SFOA uses a bio-inspired migratory mechanism to select threshold values adaptively, thus eliminating wavelet thresholding discontinuities, while attempting to balance search space exploration and exploitation. Through the use of SFOA, compression is both adaptive and diagnostically reliable, setting it apart from fixed or heuristic thresholding approaches. The proposed SFOA-MHW model seeks to fill a wide knowledge gap in medical image storage and transmission through transform-based compression supported by nature-inspired optimization. It is superior to existing methods founded on DCT, DWT, and SPIHT by having greater efficiency in compression without loss of diagnostic quality, which is its unique selling point. Practicalities are also considered in the approach. Some of these include the growing need for reliable medical data exchange, the excessive storage capacities of hospital information systems, and the limitations of bandwidth for telemedicine. Experimental results show that the suggested methods outperform the current state-of-the-art in compression ratio, PSNR, and structural similarity, as indicated by the DICOM image datasets employed to validate the contributions of the study.

2. Literature Review

The authors [10] Developed A Novel Wavelet Compression of DICOM images via a Hybrid Generalized Extreme Value Distribution-Based Continuous Wavelet-Based Contourlet Transform (HGE-CWBCT) and presented enhanced SPHIT coding approaches to perform sorting pass using Divot Quick Sort Algorithm (DQSA). The sorting can be made by a pair of pivot elements from LIS, and sorting is performed with a dual pivot element. Nagamani and Rayachoti [11] progress a novel DL-based technique utilizing OCT imageries. Next, the volumetric OCT imageries are categorized through a novel DL-based method. The OCT images of the human eye were utilized to determine a DL Network (DL-Net) method.

This study presents the Modified ResNet-50 model and Image Processing (IP) for many OCT image identification tasks. This study projects an effective analytic model for image segmentation dependent upon Bi-LSTM-based DRCNN. The altered SqueezeNet method analyses the volumetric separation of OCT imageries. In [12], the technique initially presented that the traditional techniques fail to estimate the probability of classification. Next, an intuitive and scalable structure for hesitation quantification in medical imagery segmentation is developed. Then, the use of k-fold cross-validation is proposed to overcome the necessity for seized calibration data.

Finally, the technique generates pseudo labels to acquire from unlabeled images and human-machine associations. In [13], the new aspect of the research is the partition of brain cancers utilizing a hierarchical DL model. The analysis and cancer identification are important for speedy and creative medicine, and medicinal IP utilizing Convolutional Neural Networks (CNNs) is providing outstanding results in this size. CNN employs an image portion to sequence the data and categorize them into cancer kinds. Hierarchical DL-Based Brain Tumor (HDL2BT) identification is projected with the aid of CNNs for the recognition and identification of brain cancers. Raza et al. [14] developed a new TL-based feature creation called VNL-Net, which is a collaborative of VGG16, Light Gradient Boosting Machine (LGBM) and Non-Negative Matrix Factorization (NMF) models. This exclusive VNL-Net feature extractor originally removes the spatial feature from the image's input data. Next, the collaborative feature set of

LGBM and NMF is removed from the spatial feature. Numerous innovative AI-based techniques are constructed on the newly produced feature set. Vikraman and Jabeena [15] project an effectual medicinal image compression dependent upon hybrid ML techniques. There are two main phases measured in this projected approach, called the segmentation phase. The ROI is known by the segmentation phase and assumed to be the subsequent phase. Segmentation was executed by a hybrid Grey Wolf Optimizer with Fuzzy C-Means (FCM), which was developed. Then, NN, i.e., enhanced CNN, constrains the ROI area of an input image dependent on the perceived parts. In the meantime, NROI is compacted by the RNN. Leng et al. [16] presented the valuation of organoid morphology utilizing DL.

Dependent upon the light-weight method YOLOX, a light-weight intestinal organoid recognition technique called Deep-Orga is presented. At initial, the Deep-Orga technique was equated with other traditional methods on the dataset of intestinal organoids. Next, ablation experiments were employed to authorize the enhancement of the method recognition performance by the enhanced unit. Lastly, Deep-Orga was equated with another technique. In [17], a highly improved DL technique is measured based on a CNN with a mass association study. Where an input database was originally occupied by pre-processing, while an Average Mass Elimination Algorithm (AMEA) was used. AMEA is to eliminate the noisy pixel from an image. The major features were made by utilizing the Median value. Next, the removed features are proficient by utilizing the CNN system dependent upon Mass Correlation Analysis (MCA), which aids in allocating the portion of weight.

3. Proposed Work

3.1. Proposed System

This paper proposes a new model called SFOA-MHW, or Sheep Flock Optimization Algorithm-Modified Haar Wavelet. The model is aimed at effectively compressing medical images based on DICOM data. The approach achieves optimal compression effectiveness while ensuring image quality by integrating the most important elements of wavelet-based image decomposition and evolutionary optimization. The Modified Haar Wavelet (MHW) structure, sub-band segmentation through thresholding, and adaptive threshold value determination through the Sheep Flock Optimization Algorithm (SFOA) are the three key elements of the process. The goal in each step is to maximize the Compression Ratio (CR) and Peak Signal-To-Noise Ratio (PSNR) with the simultaneous goal of minimizing picture data redundancy, preserving picture quality, and generating diagnostically relevant images. MHW is used on the input DICOM images at the first compression phase. The MHW alters the transformation process by applying it simultaneously to rows and columns, improving representation and reducing discontinuities, compared to the standard Haar wavelet transform, which uses sequential row-column decomposition. The image is segmented into small 2x2 matrices by the wavelet transform, which then produces new coefficients (A, B, C, D) using weighted averages of pixel values. The inverse transformation reconstructs the image with little distortion, whereas the forward transformation decreases the data's dimensionality. The reversibility of the transform is assured by its mathematical basis, which is a requirement for medical imaging owing to the need for maintaining vital diagnostic information. Through alterations in the decomposition process, the MHW can enhance structural detail and edge acuity retention, subsequently affecting visual fidelity and objective quality tests.

After decomposition, the image is subjected to thresholding and sub-band analysis. Three sub-bands-LH, HL, and HH-and one approximation sub-band (LL) are separated by the wavelet transform, which preserves horizontal, vertical, and diagonal features, respectively. The Leading Light (LL) sub-band preserves the most prominent features of the image, and the detail sub-band s pick up finer, higher-frequency information like contours and edges. The MHW is recursively applied to twelve sub-bands, three of which are LH, HL, and HH, in an effort to enhance compression efficiency. Recursive decomposition allows greater control in altering coefficients as well as better frequency localization.

Thresholding the sub-band detail coefficients comes next in an effort to reduce redundancy and storage needs. Insignificant coefficients within the range of the mean (μ) and standard deviation (σ) of sub-band coefficients are suppressed in the thresholding process. The data is reduced to a lower range of values due to the elimination of coefficients within the interval $\mu \pm \sigma$ and the retention of others. One of the ways to obtain such selective suppression is to preserve diagnostically important features while shrinking the search space. The approximation sub-band (LL) is spared thresholding because it has essential image data. To create a structured compression system, thresholding and recursive sub-band processing are combined. This approach reduces data irrelevance with preserved reconstruction quality.

The reconstruction quality and compression ratio are decided by the threshold values that are optimal, even though thresholding effectively eliminates data redundancy. The reason is that fixed thresholds often generate unsatisfactory results when used with diverse datasets. To address this optimization problem, SFOA is utilized, which dynamically calculates the optimal threshold values. The method is developed based on the real grazing activity of livestock, which is determined by a range of factors such as the commands of the shepherd, the experience of the animals, and their influence from the environment. Sheep and goats display this behavior. This similar behavior provides the basis for establishing a computer optimization method that effectively explores the solution space. The scheme relies upon assumed threshold values, and every sheep in the SFOA is a potential solution. The birds explore the search space collectively to find the best thresholds that maximize image quality while keeping high compression efficiency. The approach is controlled by two grazing radii, r_G sheep and r_GGoat, that changes from iteration to iteration and controls the balance between exploration and exploitation. Three factors affect sheep migrations: attraction toward the optimal solution for the flock, maintenance of individual optimal experience, and interaction with randomly chosen neighbors. When the control parameter T takes on higher values, the sheep show exploratory behaviors.

However, lower values favor the exploitation of potential areas. Goats make up about 10% to 20% of the population. By following the shepherd's guidance and going back to productive points, they bring diversity to the chase. By avoiding stagnation at the initial stage, this hybrid sheep-goat flock behavior ensures global convergence towards optimal solutions. Mathematically described motions of goats and sheep are marked by deterministic and random elements in the changes in their velocities. To promote exploratory diversity, randomization is introduced into the algorithm. The algorithm now modifies sheep placements by means of a weighted sum of global best, local best, and random sheep positions. Goats, as humans, check the global optimal alternative but also factor in the proportional impact of their most effective past experiences. This allows them to control their weight. The shepherd ensures that the flock is guided toward promising areas of the search space by keeping a record of the best solution found so far. The coordinates of the sheep and goats are updated iteratively until the maximum number of iterations is achieved in an attempt to find the best threshold. The best global solution is then found. The model for compression is able to adjust the thresholding method according to the statistical characteristics of the image data as a result of the integration of SFOA and MHW-based decomposition. To achieve high compression ratios and enhanced values for PSNR, this method makes dynamic adjustments in thresholds. The resilience of SFOA to a wide range of image types, varying from those with variably distributed to noisy textures, is complemented by its stochastic exploration. The model also addresses effectively the problems of conventional wavelet-based compression techniques, including degraded structural clarity and thresholding-induced discontinuities brought about by static thresholding. Figure 1 shows the overall process of the SFOA-MHW model. Figure 2 shows the flowchart of the system.

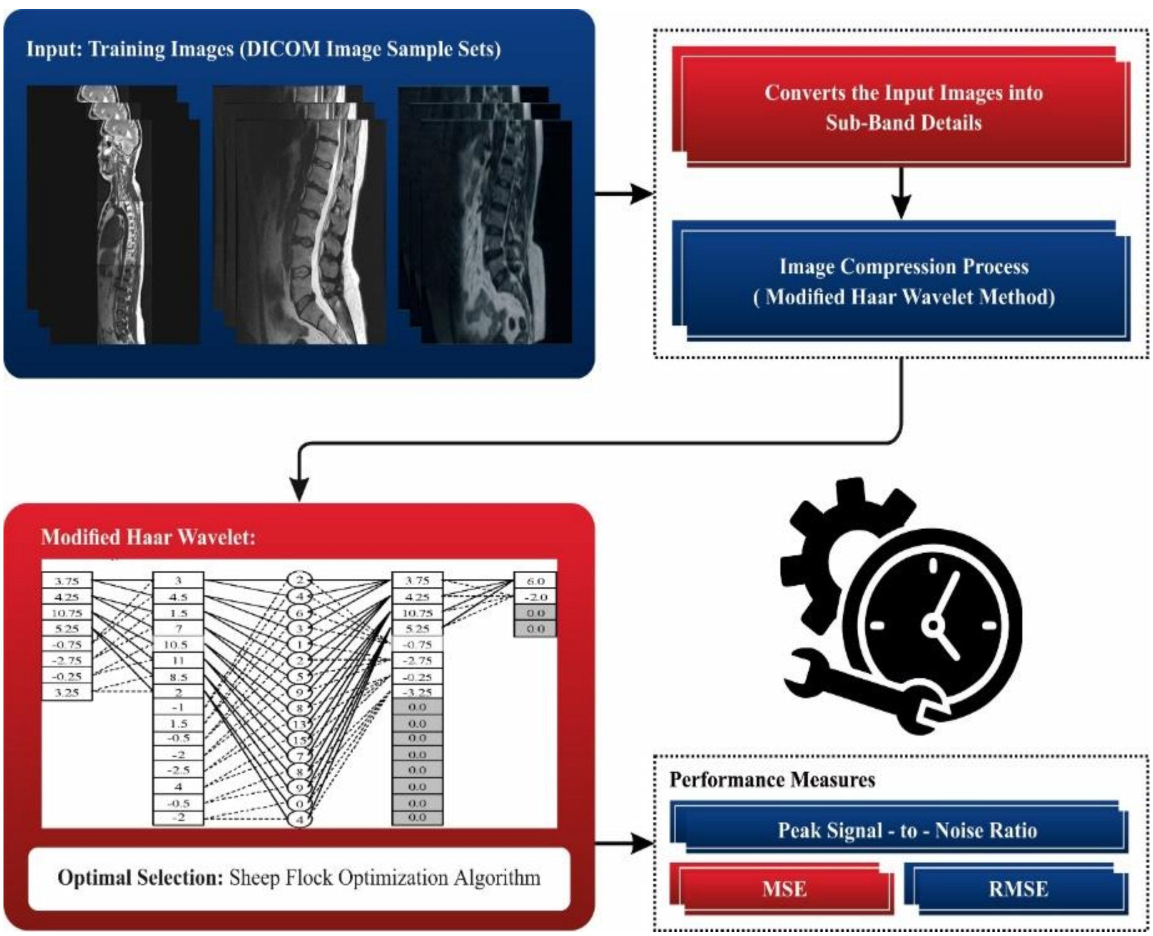

Fig. 1 Overall process of the SFOA-MHW model

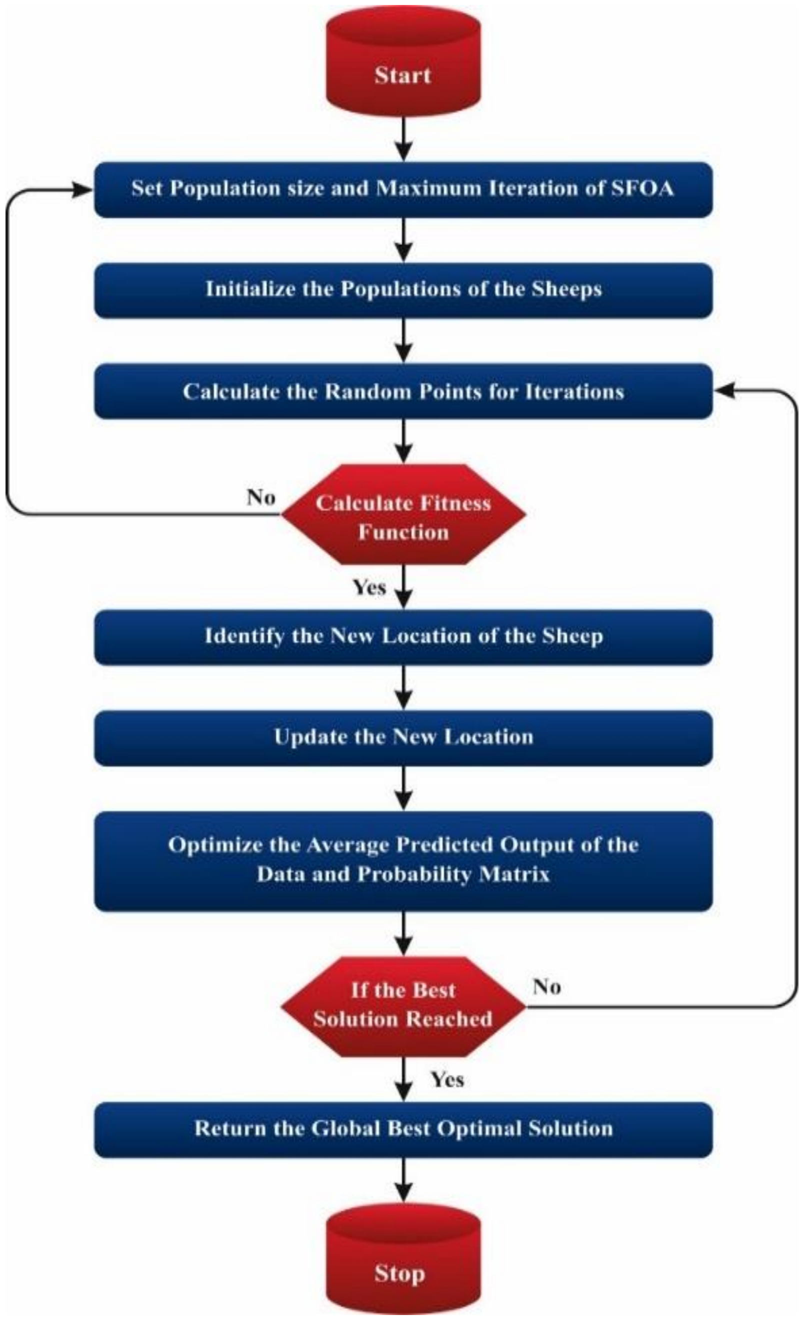

Fig. 2 Flowchart of SFOA

3.2. Pseudocode

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Input: DICOM image I of size W × H
Output: Compressed image Ic
1. Apply the Modified Haar Wavelet (MHW) transform on I
2. Decompose image into sub-band s: LL, LH, HL, HH
3. Apply recursive MHW on the detail sub-bands to generate 12 sub-bands
4. For each detail sub-band :
     Compute μ and σ
     Apply threshold function T(x)
5. Initialize SFOA parameters: N (population), MaxIteration, UB, LB
6. For each iteration until MaxIteration:
```

For each sheep and goat:
Calculate grazing radius rG
Update movement using Equations (15-27)
Update positions X
Evaluate fitness using PSNR and CR metrics
Update X_GBest and X_Lbest
7. Select optimal threshold values from SFOA
8. Apply inverse MHW using optimized thresholds
9. Generate compressed image Ic

3.3. Glossary

- Digital Imaging and Communications in Medicine (DICOM): Standard for storing and transmitting medical images.
- Modified Haar Wavelet (MHW): An improved Haar transform designed to enhance PSNR and CR by reducing artifacts.
- Sub-band Decomposition: Splitting transformed coefficients into approximation and detail components.
- Peak Signal-to-Noise Ratio (PSNR): Quality metric indicating image fidelity after compression.
- Compression Ratio (CR): Ratio representing the efficiency of compression.
- Sheep Flock Optimization Algorithm (SFOA): A metaheuristic optimization method inspired by the grazing behavior of sheep and goats.
- Shepherd: An entity in SFOA that records the global best solution discovered by the flock.
- Thresholding: The Process of setting insignificant coefficients to zero to reduce redundancy.
- μ and σ: Mean and standard deviation of coefficients used for adaptive threshold selection.

4. Result and Discussion

In this section, the DICOM image compression outcomes of the SFOA-MHW system are investigated in detail. Table 1 and Figure 3 show the comparative MSE results of the SFOA-MHW model with recent techniques [10]. The results demonstrated that the SFOA-MHW method has proficient enhanced performance with the least MSE values. With image1, the SFOA-MHW method has reduced MSE of 0.259, whereas the WT and CWBCT techniques have increased MSE of 0.810 and 0.425, respectively. Also, with image2, the SFOA-MHW method has reduced MSE of 0.346 while the WT and CWBCT techniques have attained enhanced MSE of 0.830 and 0.436, respectively. Additionally, with image3, the SFOA-MHW system has gained a decreased MSE of 0.294 while the WT and CWBCT approaches have increased MSE of 0.740 and 0.415, respectively. Meanwhile, with image4, the SFOA-MHW model has decreased MSE of 0.234 while the WT and CWBCT systems have achieved increased MSE of 0.770 and 0.423, respectively. Furthermore, with image5, the SFOA-MHW model has gained a decreased MSE of 0.378; however, the WT and CWBCT methods have achieved an enlarged MSE of 0.790 and 0.438, respectively.

Table 1. MSE analysis of the SFOA-MHW technique with existing models under different images

Images	Wavelet Transformation	CWBCT	SFOA-MHW
1	0.810	0.425	0.259
2	0.830	0.436	0.346
3	0.740	0.415	0.294
4	0.770	0.423	0.234
5	0.790	0.438	0.378

The PSNR results of the SFOA-MHW technique are compared with other techniques in Table 2 and Figure 4. The experimental values inferred that the SFOA-MHW technique resulted in better performance with enlarged PSNR values. With image1, the SFOA-MHW technique has attained improved performance with an increased PSNR of 54.00dB, while the WT and CWBCT models have displayed decreased PSNR values of 49.05dB and 51.85dB, correspondingly. Additionally, with image2, the SFOA-MHW system has enhanced performance with an enlarged PSNR of 52.74dB, whereas the WT and CWBCT techniques have shown reduced PSNR values of 48.94dB and 51.74dB, respectively. In line with image 3, the SFOA-MHW method has developed performance with an enlarged PSNR of 53.45dB, whereas the WT and CWBCT approaches have exhibited decreased PSNR values of 49.44dB and 51.95dB, correspondingly. Concurrently, with image4, the SFOA-MHW procedure has reached enhanced performance with an enlarged PSNR of 54.44dB, while the WT and CWBCT models have established decreased PSNR values of 49.27dB and 51.87dB, respectively. Simultaneously, with image5, the SFOA-MHW methodology has enhanced performance with an enlarged PSNR of 52.36dB, whereas the WT and CWBCT methodologies have exhibited decreased PSNR values of 49.15dB and 51.72dB, respectively.

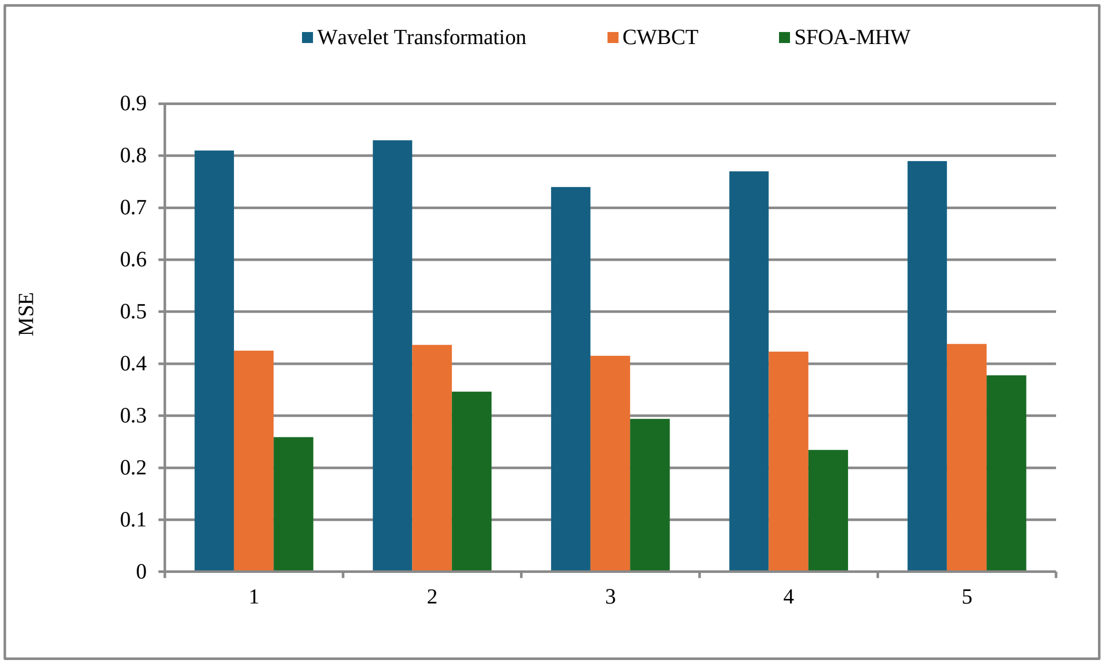

Fig. 3 MSE analysis ofthe SFOA-MHW technique under various images

Table 2. PSNR analysis of the SFOA-MHW model with existing models under different images

Images	Wavelet Transformation	CWBCT	SFOA-MHW
1	49.05	51.85	54.00
2	48.94	51.74	52.74
3	49.44	51.95	53.45
4	49.27	51.87	54.44
5	49.15	51.72	52.36

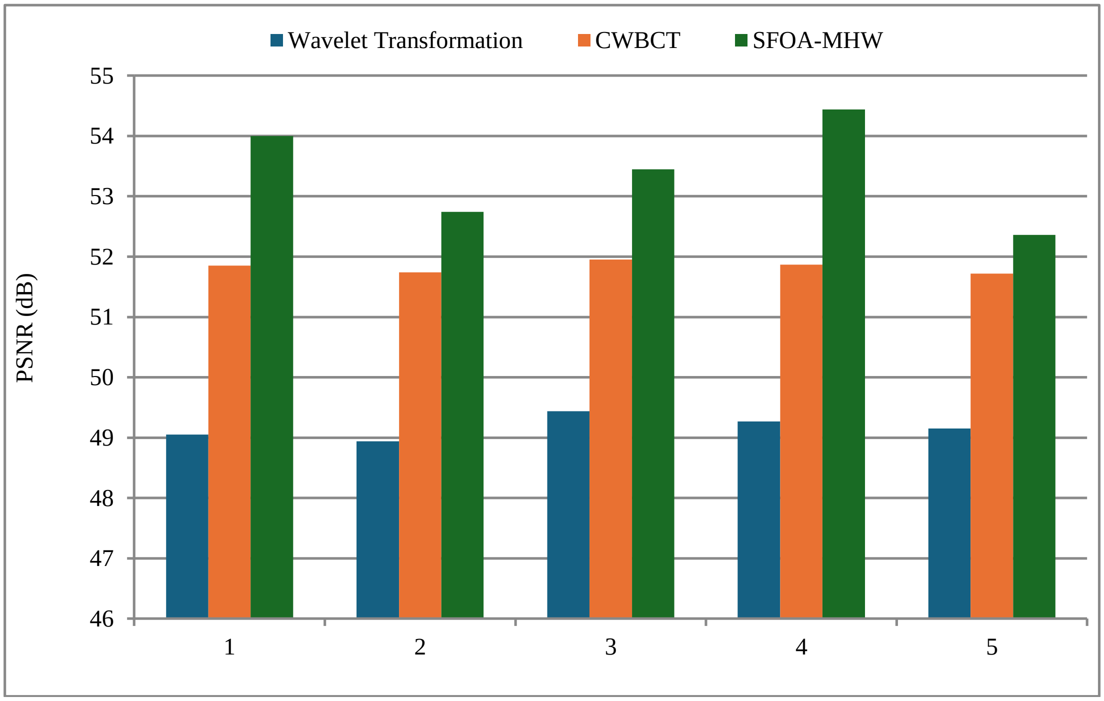

Fig. 4 PSNR analysis of the SFOA-MHW technique under various images

Table 3 and Figure 5 give the comparative RMSE outcomes of the SFOA-MHW technique with current methods. The results verified that the SFOA-MHW method has proficient improved performance with the least RMSE values. With image1, the SFOA-MHW approach has obtained a reduced RMSE of 0.509 while the WT and CWBCT models have reached amplified RMSE of 0.900 and 0.652, correspondingly. Likewise, with image2, the SFOA-MHW approach has decreased RMSE of 0.588 while the WT and CWBCT approaches have achieved improved RMSE of 0.911 and 0.660, respectively. Also, with image3, the SFOA-MHW model has reduced RMSE of 0.542 while the WT and CWBCT systems have reached increased RMSE of 0.860 and 0.644, respectively. While with image4, the SFOA-MHW technique has acquired a declined RMSE of 0.484, the WT and CWBCT models have achieved increased RMSE of 0.877 and 0.650, respectively. Besides, with image5, the SFOA-MHW approach has gained a decreased RMSE of 0.615, whereas the WT and CWBCT techniques have improved RMSE of 0.889 and 0.662, respectively.

Table 3. RMSE analysis of the SFOA-MHW method with existing models under dissimilar images

Images	Wavelet Transformation	CWBCT	SFOA-MHW
1	0.900	0.652	0.509
2	0.911	0.660	0.588
3	0.860	0.644	0.542
4	0.877	0.650	0.484
5	0.889	0.662	0.615

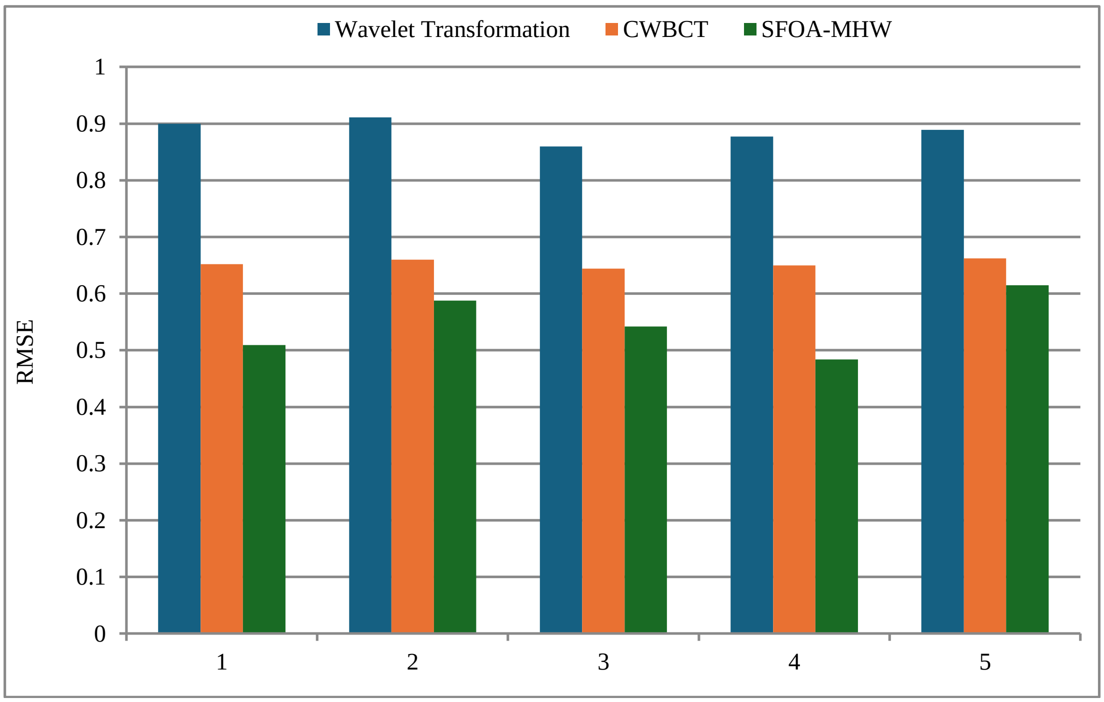

Fig. 5 RMSE analysis of the SFOA-MHW technique under various images

The SFOA-MHW model can face the challenge, as confirmed by actual medical image compression tasks. The Modified Haar Wavelet (MHW) improves frequency localization and removes discontinuities, providing a better PSNR and compression ratio compared to traditional Haar wavelet-based schemes. The integration of the Sheep Flock Optimization Algorithm (SFOA) is a notable breakthrough in adaptive threshold selection.

The algorithm allows the system to change thresholds dynamically according to the sub-band coefficients' distribution. This makes diagnostically important items remain in compressed data without increasing redundancy. The results also show that the new approach is more scalable and robust compared to the conventional static threshold techniques.

Moreover, the hybrid exploration-exploitation strategy of SFOA allows it to produce consistent outcomes in a broad variety of image forms, such as those with complex structures and noise patterns. In medical environments where diagnoses need to be accurate, images in DICOM format are useful, and SFOA-MHW achieves an acceptable balance between compression effectiveness and image integrity, increasing redundancy.

5. Conclusion

The Sheep Flock Optimization Algorithm (SFOA) and Modified Haar Wavelet (MHW) were utilized in this research to establish the possibility of adaptive image compression. The aforementioned distortions and discontinuities that are exhibited at thresholding are corrected by the proposed approach, thus eliminating the drawbacks of traditional wavelet-based compression. To improve the accuracy of reconstruction, the MHW reconfigures the decomposition step by preserving fine details from the image, thus lowering data dimensionality. Adaptive thresholding is achieved using SFOA to achieve maximum compression efficiency without loss of diagnostic quality. This considerably strengthens the framework.

The SFOA-MHW model's higher efficiency and robustness are testified to by its superior PSNR values and comparable compression ratios to classical methods, as shown by experimental results. The methodology can be applied to compress images in medical environments, thus making storage more efficient and transmitting without loss of important clinical data, as these results show. Potential future adaptations include incorporating SFOA with other evolutionary algorithms or expanding the model to multimodal medical data to maximize its relevance and usefulness further.

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