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BMR and BMW Metaphor-less Optimization for Robust Medical Image Watermarking in Telemedicine

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ABSTRACT: Medical images are frequently stored and exchanged through digital systems, making copyright protection and watermark recovery important requirements in telemedicine workflows. This study presents a blind, content-adaptive medical image watermarking framework in the 8×8 discrete cosine transform (DCT) domain. A 32×32 binary copyright logo is embedded repeatedly in the DCT blocks by exchanging two low-frequency AC coefficients. Instead of using one fixed embedding strength, six host-activity classes are formed from block variance and a separate strength is optimized for each class. The optimization is evaluated with five metaphor-less population methods: Rao-1, Rao-2, Rao-3, Best-Mean-Random (BMR), and Best-Worst-Random (BWR). The fitness function combines host-image PSNR with normalized correlation (NCC) obtained after Gaussian noise and JPEG quality-50 attacks. Experiments use a 512×512 grayscale medical cover image and a 32×32 binary watermark, with fourfold redundancy during blind extraction. The supplied implementation reports PSNR values of 38.65, 38.59, 38.59, 38.53 and 38.40 dB for Rao-1, Rao-2, Rao-3, BMR and BWR, respectively, while SSIM values range from 0.9478 to 0.9521. Across the tested attacks, NCC remains around 0.965 for most non-geometric operations, whereas the 2° rotation attack reduces NCC to 0.2703–0.3002. The results show the strength of the proposed blind DCT design against several common signal-processing operations, while also exposing the need for explicit geometric synchronization in future work.

1. INTRODUCTION

Medical images are now routinely handled as digital objects rather than as physical films. X-ray, CT and MRI images can be stored in archives, transferred between departments and reviewed remotely. This convenience also creates a practical need for mechanisms that can associate an image with an owner or source without changing the information required for visual inspection. Digital watermarking provides one such mechanism by placing a hidden signal inside the host image. Unlike encryption, the watermark can remain associated with the image after the image has been decrypted for normal viewing [1], [7], [21].

2. RELATED WORK

Early robust watermarking studies established the importance of transform coefficients and perceptual considerations [1]. Later work expanded this direction through DWT, SVD and hybrid transforms [2], [8], [9]. Reviews have documented a broad range of watermarking applications, attacks and design choices [7], [21], [27], [29]. Medical image watermarking adds an additional

concern: the embedded signal should not interfere with the interpretation of clinically useful structures. Studies have therefore explored robust transform-domain approaches specifically for medical information security [13], [14].

Optimization has also become part of watermarking design. PSO, Firefly, differential evolution and other population methods have been used to select scaling factors or transform-domain parameters [5], [6], [10]–[12], [16], [20], [26], [31], [32]. These methods can search a non-convex parameter space, but their implementations often contain algorithm-specific control parameters. The Rao algorithms were proposed as simpler metaphor-less alternatives [3]. BMR and BWR extend this line of work using best, mean, random and worst population information [4].

Based on the supplied implementation, the practical question addressed here is not whether one optimization family is universally better. The question is whether these five update rules can be compared fairly when they optimize exactly the same six-dimensional embedding-strength vector under the same image, watermark, redundancy and attack-coupled fitness calculation.

3. MATERIALS AND METHODOLOGY

3.1 Study Material

The experimental input consists of one grayscale medical cover image and one binary copyright logo. The implementation resizes the cover image to 512×512 pixels and the watermark to 32×32 pixels. The cover is therefore represented by 262,144 grayscale pixels, while the watermark contains 1,024 binary bits. The watermark is converted to a binary image using a threshold of 127.

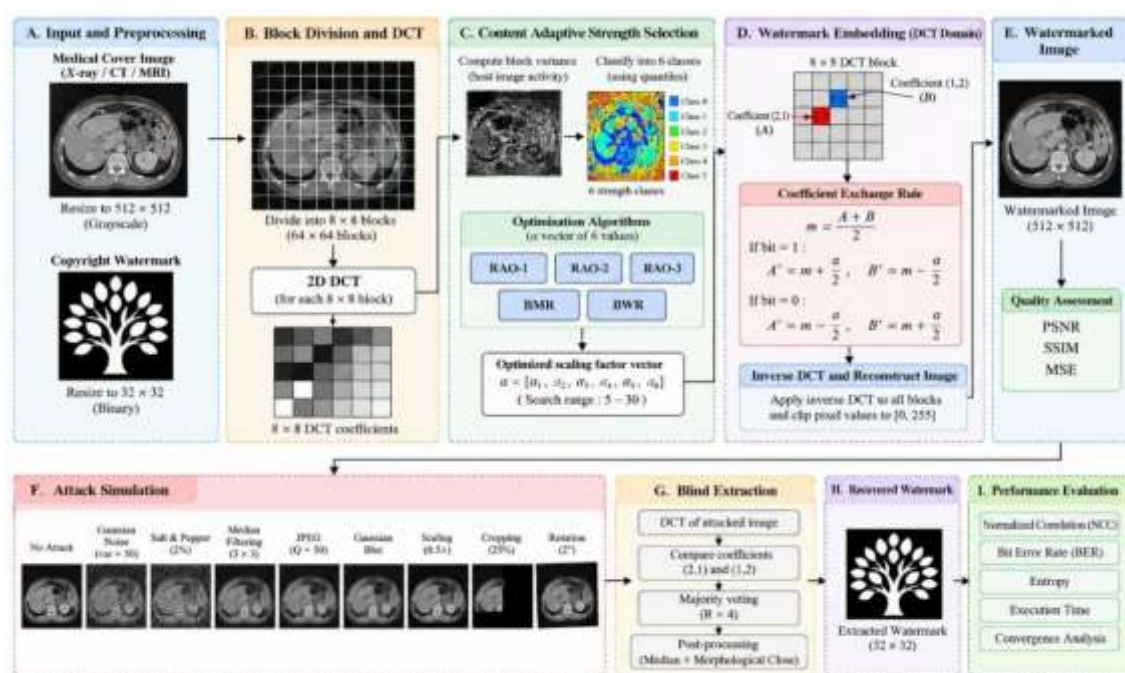


Figure 1. Methodology of the proposed content-adaptive DCT-based medical image watermarking framework using RAO-1, RAO-2, RAO-3, BMR, and BWR optimization algorithms.

3.2 DCT Block Representation

The cover is divided into non-overlapping 8×8 blocks. A two-dimensional orthonormal DCT is applied to every block. Let C_b denote an 8×8 cover block and D_b its DCT representation. The implementation uses the separable transform

$$D_b = \text{DCT}_2(C_b).$$

Two low-frequency AC coefficients are selected: $(u_1, v_1) = (2, 1)$ and $(u_2, v_2) = (1, 2)$. These coefficients are close to the low-frequency region and therefore provide a compromise between robustness and perceptual impact.

3.3 Content-Adaptive Strength Classes

For every 8×8 block, the spatial-domain variance is calculated. The variance values are divided into six classes using five quantile boundaries. Thus, the classification is relative to the activity distribution of the particular host image rather than based on fixed variance thresholds. Each class k receives an optimized strength α_k , giving the six-dimensional vector

$$\alpha = [\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5].$$

The search range for every strength is $[5, 30]$. Blocks with different activity levels therefore need not receive identical embedding strength.

3.4 Coefficient-Exchange Embedding

For a block assigned strength α_k , let A and B be the selected DCT coefficients and let $m = (A+B)/2$. For watermark bit $b=1$, the coefficients are set to $m + \alpha_k/2$ and $m - \alpha_k/2$; for $b=0$ their order is reversed. The difference between the two coefficients therefore carries the bit while their average remains unchanged. In compact form:

$$(D_1, D_2) = (m + \alpha_k/2, m - \alpha_k/2), b=1;$$

$$(D_1, D_2) = (m - \alpha_k/2, m + \alpha_k/2), b=0.$$

After inverse DCT, pixel values are clipped to the valid 8-bit range. The watermark is repeated across the available DCT blocks. For the 512×512 cover and 32×32 watermark, the implementation uses $R=4$ repetitions.

3.5 Blind Extraction

Extraction does not require the original cover or the optimized α vector. The attacked watermarked image is transformed into 8×8 DCT blocks and the same two coefficients are compared. If $D_1 > D_2$ the recovered bit is one; otherwise it is zero. The four repeated copies are reshaped and majority voting is applied. A median filter followed by a 3×3 morphological closing operation is used only as a gentle post-processing step for the recovered binary logo.

3.6 Quality and Robustness Measures

Imperceptibility is measured using peak signal-to-noise ratio (PSNR) and structural similarity (SSIM). Watermark recovery is measured using normalized correlation (NCC). For two flattened watermark arrays W and W' , the implementation calculates

$$NCC(W, W') = \sum (W_i W'_i) / [\sqrt{\sum W_i^2} \cdot \sqrt{\sum W'^2_i}].$$

The fitness calculation normalizes PSNR by 45 dB and clips the normalized value to one. It then combines this value with the mean of two NCC values: one after Gaussian noise with variance 30 and one after JPEG compression at quality 50.

4. OPTIMIZATION FRAMEWORK

4.1 Common Search Configuration

All five algorithms operate on the same population representation. The population size is 14 and the maximum number of iterations is 18. Each candidate contains six strength values, so the optimization dimension is $K=6$. Candidate values are clipped to $[5, 30]$ after every update. The random generator is initialized with a fixed seed of 1 in the supplied implementation.

Table 1. Parameter settings of the proposed content-adaptive DCT-based watermarking framework and the common search configuration used for RAO-1, RAO-2, RAO-3, BMR, and BWR.

Parameter	Value	Purpose
Cover size	512×512	Standardized grayscale medical cover
Watermark size	32×32	1,024-bit binary copyright logo
Block size	8×8	DCT decomposition
Coefficient pair	$(2, 1), (1, 2)$	Low-frequency AC pair

Activity classes	6	Content-adaptive strength assignment
Search dimension	6	One α value per activity class
Bounds	5–30	Strength search interval
Population	14	Candidates per iteration
Iterations	18	Optimization budget
Redundancy R	4	Repeated watermark copies
Fitness weights	Algorithm-specific	PSNR/NCC trade-off

4.2 Rao-1, Rao-2 and Rao-3

Rao-1 uses the difference between the best and worst candidates to move each solution. For candidate X_i , the update implemented in the code is

$$X_i' = X_i + r_1(X_{\text{best}} - X_{\text{worst}}).$$

Rao-2 adds an interaction term based on a randomly selected population member X_j . If the current candidate has higher fitness, the interaction uses $X_i - X_j$; otherwise it uses $X_j - X_i$:

$$X_i' = X_i + r_1(X_{\text{best}} - X_{\text{worst}}) + r_2 \cdot I_{ij}.$$

Rao-3 uses the absolute values of the interacting candidates in its second term. The implementation is therefore

$$X_i' = X_i + r_1(X_{\text{best}} - X_{\text{worst}}) + r_2 \cdot J_{ij},$$

where J_{ij} is selected from $|X_i| - |X_j|$ or its reverse according to the fitness comparison. These formulations follow the Rao family described in [3].

4.3 BMR and BWR

BMR replaces the worst-based reference with the population mean and a random candidate. In the implementation, a random $T \in \{1, 2\}$ is selected at every candidate update:

$$X_i' = X_i + r_1(X_{\text{best}} - T \cdot X_{\text{mean}}) + r_2(X_{\text{best}} - X_{\text{rand}}).$$

BWR uses the best and worst candidates with a random reference:

$$X_i' = X_i + r_1(X_{\text{best}} - T \cdot X_{\text{rand}}) - r_2(X_{\text{worst}} - X_{\text{rand}}).$$

The manuscript retains the BWR name used in the supplied code. This avoids changing the terminology of the actual experiment. The underlying BMR/BWR formulations are based on the Rao and Pawar work listed as reference [4].

4.4 Greedy Selection

After new candidates are generated and clipped to the search interval, the fitness of each new candidate is evaluated. A candidate replaces its current solution only when its new fitness is higher. The best fitness observed in the population is retained at every iteration for the optimization curve.

5. FITNESS FUNCTION AND ATTACK MODEL

5.1 Attack-Coupled Fitness

The purpose of the fitness function is to prevent the optimizer from selecting a strength solely because it produces a visually high-quality watermarked image. Each candidate is first embedded into the cover. The resulting PSNR is normalized using 45 dB. Two attacked copies are then produced: Gaussian noise with variance 30 and JPEG compression with quality factor 50. NCC is calculated from the extracted watermark after each attack.

For algorithm a , the fitness can be written as

$$F_a = w_P \cdot \min(\text{PSNR}/45, 1) + w_N \cdot [\text{NCC}_G + \text{NCC}_J]/2.$$

The weights are (0.6,0.4) for Rao-1, (0.5,0.5) for Rao-2, (0.5,0.5) for Rao-3, (0.6,0.4) for BMR and (0.4,0.6) for BWR. These values are part of the supplied experimental implementation and are not tuned after observing the final attack table.

5.2 Robustness Attack Battery

After optimization, the final watermarked image from each algorithm is evaluated under nine conditions: no attack, Gaussian noise with variance 50, salt-and-pepper noise at 2%, 3×3 median filtering, JPEG quality 50, 3×3 Gaussian blur, scaling to half size and back to 512×512, a 25% corner crop represented by zeroing the upper-left quarter, and a 2° rotation. NCC is calculated after blind extraction and the same recovery enhancement operation.

Table 2. Attack battery and implementation settings used for the robustness evaluation of the watermarked images.

Attack	Implementation setting	Metric reported
No attack	Original watermarked image	NCC
Gaussian noise	Variance 50	NCC
Salt & pepper	Density 2%	NCC
Median filter	3×3	NCC
JPEG	Quality 50	NCC
Gaussian blur	3×3	NCC
Scaling	0.5× then restored	NCC
Cropping	Upper-left 25% zeroed	NCC
Rotation	2°	NCC

5.3 Implementation Environment

The supplied notebook is written in Python and uses NumPy, OpenCV, pandas, Matplotlib, SciPy and scikit-image. The workflow is designed for Google Colab, where the cover image and copyright logo are uploaded interactively. The implementation includes a fallback random-array mode if no image is uploaded. The reported results in this paper are the medical-image run supplied with the question, not the fallback random-array test.

6. EXPERIMENTAL DESIGN

The experiment follows a common pipeline. First, the cover and watermark are standardized. Second, the same DCT embedding and blind extraction routines are used for every optimizer. Third, only the six-dimensional strength vector and its optimizer update rule are changed. Finally, the optimized result is subjected to the complete attack battery. This design reduces the risk that differences in the embedding implementation are mistaken for differences between optimization algorithms.

7. RESULTS

7.1 Imperceptibility Results

Table 2 presents the PSNR and SSIM values returned by the supplied implementation. Rao-1 produces the highest PSNR and SSIM among the five tested methods in this run. The PSNR range is narrow: the highest value is 38.65 dB and the lowest is 38.40 dB. SSIM varies from 0.9478 to 0.9521. The close values indicate that all five optimizers reach solutions in a similar visual-quality region for the tested cover.

Table 3. Imperceptibility (PSNR and SSIM) and no-attack NCC of the watermarked images obtained with RAO-1, RAO-2, RAO-3, BMR, and BWR.

Algorithm	PSNR (dB)	SSIM	No-attack NCC
Rao-1	38.65	0.9521	0.9656
Rao-2	38.59	0.9490	0.9656
Rao-3	38.59	0.9490	0.9656
BMR	38.53	0.9478	0.9656
BWR	38.40	0.9480	0.9656

An important observation is that the no-attack NCC is identical at four decimal places for all five algorithms. This is consistent with the use of the same watermark, coefficient pair, redundancy factor and majority-voting extractor. The optimization primarily changes the embedding strengths, which affects host-image distortion and attack behaviour rather than the underlying watermark layout.

7.2 Attack-wise NCC

Table 4. Attack-wise NCC of the extracted watermark for RAO-1, RAO-2, RAO-3, BMR, and BWR under the tested attack conditions.

Algorithm	No attack	Gauss	S&P	Median	JPEG	Blur	Scale	Crop	Rot. 2°
Rao-1	0.9656	0.9654	0.9640	0.9656	0.9656	0.9656	0.9656	0.9656	0.2703
Rao-2	0.9656	0.9656	0.9678	0.9656	0.9656	0.9656	0.9656	0.9656	0.3002
Rao-3	0.9656	0.9656	0.9665	0.9656	0.9656	0.9656	0.9656	0.9656	0.3002
BMR	0.9656	0.9669	0.9654	0.9669	0.9656	0.9656	0.9669	0.9656	0.2951
BWR	0.9656	0.9654	0.9648	0.9656	0.9656	0.9656	0.9656	0.9656	0.2965

Except for rotation, the extracted watermark remains close to an NCC of 0.965 or above in the supplied run. The highest observed NCC is 0.9678 for Rao-2 under the 2% salt-and-pepper attack, while BMR reaches 0.9669 for Gaussian noise, median filtering and scaling. The rotation results are substantially lower, with NCC between 0.2703 and 0.3002. This difference is important because the current extractor compares fixed DCT blocks and has no geometric registration step.

7.3 Robustness Profile

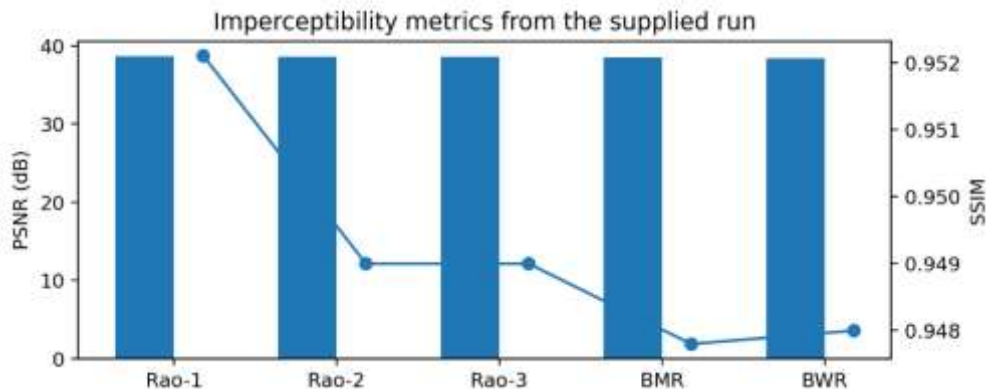


Figure 2. Comparison of imperceptibility performance of RAO-1, RAO-2, RAO-3, BMR, and BWR based on PSNR and SSIM.

7.4 Comparison of the Optimizers

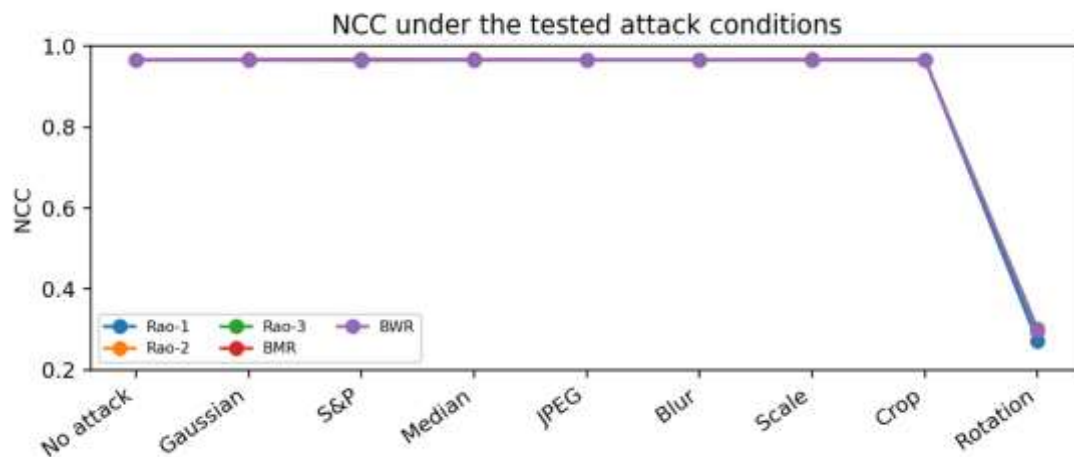


Figure 3. NCC-based robustness comparison of RAO-1, RAO-2, RAO-3, BMR, and BWR under the tested attack conditions.

The results should be read as an implementation-level comparison rather than a universal ranking of optimization algorithms. Rao-1 has the highest PSNR (38.65 dB) and SSIM (0.9521) in this particular run. Rao-2 has the highest NCC recorded in the attack table (0.9678 under salt-and-pepper noise). BMR records 0.9669 under three tested conditions. BWR has the lowest PSNR in the run, at 38.40 dB, but its attack NCC values remain close to the other methods for non-geometric operations.

The small PSNR differences are also useful from a practical perspective. A difference of 0.25 dB separates the highest and lowest values, while SSIM differs by 0.0043 between the highest and lowest values. Therefore, the choice of optimizer cannot be justified from visual quality alone. The attack-specific behaviour and the intended deployment conditions need to be considered together.

8. DISCUSSION

The content-adaptive part of the framework is a useful feature of the implementation. A single α value is often too simple for a medical image because homogeneous and highly textured blocks do not respond in the same way to coefficient modification. Here, block variance provides a simple activity measure and quantile-based classes ensure that all six classes are populated according to the host's own variance distribution.

The coefficient-exchange rule also has a clear extraction advantage. Because the bit is represented by the ordering of two coefficients rather than by an absolute coefficient value, the decoder does not need the original cover image or the optimized

strength vector. This is the main reason the method can be described as blind. Repeating the 1,024-bit watermark four times and using majority voting adds another layer of protection against isolated bit errors.

8.1 Why Rotation Remains Difficult

The rotation result deserves separate attention. The attack rotates the entire 512×512 image by 2° using an affine transform and fills the exposed area with intensity 128. The extractor then immediately divides the image into the original fixed 8×8 grid. Even a small rotation shifts block boundaries, so the DCT coefficients no longer correspond to the same embedded coefficient pair. Consequently, the redundancy mechanism cannot fully compensate for the geometric misalignment.

This result should not be described as a failure of the complete watermarking concept. It is a limitation of the current registration-free extractor. A future version could estimate rotation and translation before extraction, or use a synchronization pattern that survives geometric transformations. Such additions, however, were not part of the supplied code and are therefore not claimed as achieved results in this paper.

8.2 Interpretation of the High NCC Values

The near-constant NCC values across several attacks should also be interpreted carefully. The watermark is small, binary and repeated four times, and extraction uses majority voting. These design choices make the recovered logo relatively stable when the attacks do not significantly change the ordering of the selected DCT coefficient pair. The result is therefore an interaction between the optimizer and the embedding/extraction design, not evidence that an optimizer alone creates robustness.

8.3 Reproducibility and Scope

The supplied code provides a compact reproducibility specification: image dimensions, transform block size, coefficient locations, number of classes, search bounds, population, iterations, fitness attacks, optimizer equations and final attack battery are all explicit. This is an advantage compared with experiments where the optimization settings are only described qualitatively.

At the same time, the current experiment is limited to the supplied run. The manuscript does not claim performance across a large medical-image database because the code/output supplied for this revision contains one reported cover-image run. Likewise, no statistical significance test, runtime comparison, convergence-time table, BER table or multi-image average is introduced here because those measurements are not present in the supplied output.

9. LIMITATIONS

Several limitations should be considered when interpreting the results. First, the reported experiment is based on a single 512×512 grayscale medical cover image and one 32×32 binary copyright logo. Second, the watermark capacity is intentionally small because the design prioritizes repeated blind recovery. Third, the geometric attack result shows that fixed-grid extraction is not rotation invariant. Fourth, the optimization budget is modest at 14 candidates and 18 iterations. Finally, the supplied experiment does not include clinical-region protection, region-of-interest constraints, encryption of the watermark, or a large statistical evaluation across independent medical-image samples.

10. PRACTICAL IMPLICATIONS

For a telemedicine-oriented implementation, the current design can be viewed as a lightweight copyright or source-identification layer. It can be added without storing the original cover image at the extraction side, which is useful when the receiving system has only the watermarked image. The method is also based on commonly available Python libraries and standard DCT operations, making the approach straightforward to reproduce in a research environment.

However, a watermark should not be treated as a replacement for access control, encryption, audit logging or clinical data governance. The watermark is one component of a wider protection architecture. In particular, the current results do not establish suitability for irreversible clinical decisions or for detecting malicious tampering beyond the tested image-processing attacks.

11. CONCLUSION

This paper presented an implementation-based comparison of Rao-1, Rao-2, Rao-3, BMR and BWR for blind medical image watermarking in the 8×8 DCT domain. The common embedding pipeline uses two low-frequency AC coefficients, six content-

adaptive strength classes, a 32×32 binary copyright watermark, fourfold redundancy and majority-voting extraction. The optimizer is responsible only for finding the six embedding strengths; the embedding, extraction and fitness routines remain common across the compared methods.

In the supplied experimental run, Rao-1 produced 38.65 dB PSNR and 0.9521 SSIM, followed closely by Rao-2 and Rao-3 at 38.59 dB and 0.9490 SSIM. BMR produced 38.53 dB and 0.9478 SSIM, while BWR produced 38.40 dB and 0.9480 SSIM. The no-attack NCC was 0.9656 for all five methods. Under Gaussian noise, salt-and-pepper noise, median filtering, JPEG compression, blur, scaling and the tested corner-crop operation, NCC remained close to 0.965 or higher. In contrast, 2° rotation reduced NCC to approximately 0.27–0.30 for all five methods.

The results support two practical observations. First, content-adaptive coefficient exchange combined with redundancy can provide stable blind recovery under several common signal-processing operations. Second, geometric synchronization is the major missing piece in the present implementation. Future work should therefore focus on multi-image evaluation, statistically repeated trials, explicit geometric registration, region-aware embedding and stronger authentication mechanisms. These extensions can be added without changing the basic idea of using a common watermarking pipeline to compare simple metaphor-less optimization strategies.

12. DATA AVAILABILITY

The medical cover image used in this paper was obtained from a publicly available **Kaggle dataset**. The experiments were implemented in **Python using Google Colab** and the reported results were taken directly from the supplied execution output.

13. AUTHOR CONTRIBUTIONS

Tanushree Mohapatra: Conceptualization, implementation, investigation and manuscript preparation.

Madhumita Panda, Partha Pratim Sarangi: methodology, technical review and supervision.

14. CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

15. ETHICS STATEMENT

The study uses digital image processing and does not introduce an intervention involving human participants. No additional ethical approval was reported for the computational experiment described here.

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