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# DWT–PSO Based Digital Image Watermarking with Robustness–Imperceptibility Optimization

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**Computer Science (BIG DATA ANALYTICS)**

SUBMITTED BY

**Ashvani Kumar (2024MSBDA006)**

**Bhavik Sharma (2024MSBDA007)**

UNDER THE GUIDANCE OF

**Dr. Subodh Kumar**

Assistant Professor

Department of Data Science & Analytics



Department of Data Science and Analytics  
School of Mathematics, Statistics and Computational Science  
CENTRAL UNIVERSITY OF RAJASTHAN

November 2025

# DECLARATION

We hereby certify that

1. The work contained in this dissertation has been carried out by me under the supervision of my supervisor.
2. The work has not been submitted, in part or full, to any other University or Institution for any degree or diploma.
3. I have adhered to the norms and guidelines mentioned in the Ethical Code of Conduct of the Institute.
4. Whenever I have used any external materials (data, theoretical analysis, text, or figures), I have duly acknowledged them within the dissertation and cited them properly in the references.
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**Date:**

**Ashvani Kumar (2024MSBDA006)**

**Place:**

**Bhavik Sharma (2024MSBDA007)**



Date: \_\_\_\_\_

## CERTIFICATE

This is to certify that the project entitled “DWT–PSO Based Digital Image Watermarking with Robustness–Imperceptibility Optimization” was carried out by **Ashvani Kumar** (2024MSBDA006) & **Bhavik Sharma** (2024MSBDA007) at the **Department of Data Science & Analytics, Central University of Rajasthan, Ajmer** under my guidance during **May 2025 to Aug 2025**.

**Dr. Subodh Kumar**  
Assistant Professor  
Department of Data Science & Analytics

DEPARTMENT OF DATA SCIENCE AND ANALYTICS  
CENTRAL UNIVERSITY OF RAJASTHAN, INDIA

Date: \_\_\_\_\_

CERTIFICATE

This is to certify that the project titled “**DWT–PSO Based Digital Image Watermarking with Robustness–Imperceptibility Optimization**” is a record of the **bona-fide** work done by **Ashvani Kumar** (2024MSBDA006) & **Bhavik Sharma** (2024MS-BDA007) submitted in partial fulfilment for the award of the Degree of M.Sc. (Big Data Analytics).

**Dr. Subodh Kumar**

Department of Data Science and Analytics  
Central University of Rajasthan

**Dr. Vidyottama Jain**

HOD, Department of Data Science and Analytics  
Central University of Rajasthan

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# Abstract

Digital watermarking has become a critical component of multimedia security, driven by the rapid growth of digital image sharing and the corresponding rise in content manipulation, unauthorized redistribution, and forgery. Ensuring copyright protection and content authenticity requires watermarking techniques capable of maintaining high visual fidelity while providing strong resilience against signal-processing and geometric distortions. However, conventional watermarking methods that rely on fixed embedding strength often fail to achieve a consistent trade-off between imperceptibility and robustness, as their performance varies significantly across images with different structural and statistical characteristics.

This research presents an adaptive watermarking framework that integrates the Discrete Wavelet Transform (DWT) with Particle Swarm Optimization (PSO) to address these limitations. The cover image is decomposed using a multi-level DWT, enabling watermark insertion within frequency sub-bands that preserve perceptual quality while enhancing robustness. PSO is employed to automatically determine the optimal embedding strength by maximizing a joint objective function comprising the Structural Similarity Index (SSIM) and the Normalized Cross-Correlation (NCC). This optimization strategy allows the system to adaptively adjust watermark strength based on image content, thereby improving the imperceptibility–robustness balance beyond what fixed-parameter approaches can achieve.

Extensive experimental analysis was conducted, including multi-level DWT assessment, visual evaluations, and quantitative measurements of PSNR, SSIM, BER, and NCC before and after optimization. The results demonstrate that the PSO-optimized model significantly enhances watermark performance, achieving higher perceptual quality ( $\text{PSNR} > 40 \text{ dB}$  and  $\text{SSIM} \approx 1$ ) and improved robustness (NCC close to unity with minimal bit errors) under common attacks such as noise addition, compression, and mild

geometric transformations. These findings establish that optimization-driven watermarking provides a more reliable and adaptable solution compared to traditional methods and highlight the effectiveness of PSO in strengthening wavelet-based watermark embedding frameworks.

# List of Tables

5.1	Performance evaluation across different DWT decomposition levels before PSO optimization. . . . .	38
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# List of Figures

1.1	Classification of digital watermarking schemes. . . . .	5
3.1	Standard PSO process used to iteratively search for the optimal embedding strength. . . . .	18
4.1	Complete 12-step pipeline of the proposed DWT–PSO watermarking framework. . . . .	23
5.1	Cover image ( $I$ ) after preprocessing for watermark embedding. . . . .	30
5.2	Preprocessed watermark image ( $W$ ) used for embedding. . . . .	30
5.3	Level-3 DWT coefficients of the cover image showing approximation and directional detail components. . . . .	31
5.4	Watermarked image ( $I_w$ ) after inverse DWT reconstruction. . . . .	33
5.5	Comparison between the original and reconstructed (watermarked) images. . . . .	34
5.6	Comparison of the embedded watermark and extracted watermark before PSO optimization. . . . .	36
5.7	BER and NCC comparison before PSO optimization. . . . .	37
5.8	Graphical comparison of PSNR, SSIM, BER, and NCC across DWT Levels 1–4. . . . .	39
5.9	Embedded and extracted watermark using the optimized embedding strength $\alpha^* = 0.0536$ . . . . .	40
5.10	BER and NCC performance of the watermarking system after PSO optimization. . . . .	41

# Contents

<b>Abstract</b>	<b>ii</b>
<b>List of Tables</b>	<b>iv</b>
<b>List of Figures</b>	<b>v</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Applications of Digital Watermarking . . . . .	3
1.2 Classification of Digital Watermarking . . . . .	4
1.3 Characteristics of a Good Watermarking System . . . . .	6
1.4 Watermarking System Model . . . . .	7
1.5 Evaluation Metrics . . . . .	8
1.6 Challenges . . . . .	8
1.7 Research Gaps . . . . .	10
<b>2 Related Work</b>	<b>13</b>
<b>3 Background: Particle Swarm Optimization (PSO)</b>	<b>17</b>
<b>4 Research Methodology</b>	<b>20</b>
4.1 Proposed Methodology . . . . .	22
4.2 Overall Pipeline . . . . .	22
4.3 Mathematical Formulation . . . . .	25
4.3.1 Watermark Embedding Model . . . . .	25
4.3.2 Watermark Extraction Model . . . . .	26

4.4	Optimization Objective . . . . .	26
4.5	Performance Metrics . . . . .	27
4.5.1	Peak Signal-to-Noise Ratio (PSNR) . . . . .	27
4.5.2	Structural Similarity Index (SSIM) . . . . .	27
4.5.3	Normalized Cross-Correlation (NCC) . . . . .	27
4.5.4	Bit Error Rate (BER) . . . . .	27
<b>5</b>	<b>Results and Analysis</b>	<b>28</b>
5.1	Experimental Setup . . . . .	28
5.2	Visual Results . . . . .	29
5.2.1	Cover Image . . . . .	29
5.2.2	Watermark Image . . . . .	30
5.3	Wavelet Coefficient Inspection . . . . .	31
5.3.1	Watermark Embedding Process . . . . .	32
5.3.2	Watermarked Image Reconstruction and Comparison . . . . .	34
5.3.3	Quality Assessment Before PSO Optimization . . . . .	34
5.3.4	Watermark Extraction Before PSO Optimization . . . . .	35
5.3.5	BER and NCC Analysis Before PSO Optimization . . . . .	36
5.4	DWT Level Analysis and PSO-Driven Embedding Optimization . . . . .	37
5.4.1	PSO Objective Formulation . . . . .	38
5.4.2	Visualization of DWT-Level Results . . . . .	39
5.4.3	Final PSO-Based Embedding and Extraction Performance . . . . .	39
<b>6</b>	<b>Conclusion and Future Work</b>	<b>42</b>

# Chapter 1

## Introduction

The evolution of digital watermarking has been shaped by the rapid growth of multimedia communication, where digital images and medical records are routinely exchanged across social platforms, telemedicine portals, surveillance systems, and cloud-based infrastructures. This widespread circulation has amplified concerns related to unauthorized duplication, intentional manipulation, identity misuse, and large-scale image forgery. Early watermarking techniques operating in the spatial domain, despite their simplicity, demonstrated very low robustness and failed against common operations such as compression, filtering, noise addition, and mild distortions. To overcome these limitations, transform-domain watermarking gained prominence due to its improved stability in the frequency space. Approaches based on the Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD), such as the model presented in [1], demonstrated improved imperceptibility and moderate robustness for sensitive applications like medical image security. However, these methods lacked adaptability and struggled when exposed to more complex distortions.

Further advancements led to hybrid watermarking frameworks that combined multiple transforms to enhance resilience. For example, fractional Fourier transform (FRFT) based hybrid embedding [3] offered stronger resistance against frequency-domain and signal-processing attacks, but geometric distortions—rotation, scaling, and cropping—remained challenging. Multi-resolution DWT–SVD watermarking, as explored in [5], improved em-

bedding quality but continued to rely on fixed embedding parameters, causing inconsistent results across images with different texture and entropy characteristics. These fixed-parameter systems frequently produced suboptimal imperceptibility–robustness performance, a limitation repeatedly highlighted in the literature.

Security-oriented developments introduced chaotic modulation into transform-domain watermarking. The chaotic DWT–SVD framework proposed in [4] increased key sensitivity, strengthened encryption capability, and reduced the risk of unauthorized extraction. Although these approaches improved security, they did not resolve issues related to parameter sensitivity and geometric attack vulnerability. Similarly, adaptive high-dimensional watermarking using DWT–SVD [6] demonstrated strong robustness by embedding information based on entropy variations, yet the computational complexity of such systems remained high and unsuitable for lightweight or real-time applications.

A common drawback across these methods is their dependence on fixed or manually selected embedding strength. Such static embedding rarely achieves optimal performance across diverse image categories. Optimization-driven watermarking approaches have emerged to address this issue. The MRFO–ELM adaptive embedding model discussed in [2] demonstrated that meta-heuristic optimization combined with learning-based prediction can dynamically adjust embedding parameters to improve both imperceptibility and robustness. This argument is reinforced in the doctoral thesis [8], which extensively evaluates existing watermarking frameworks and concludes that adaptability, geometric resistance, parameter optimization, and false-positive reduction remain critical challenges requiring further research attention.

Another significant limitation identified in the literature is the False Positive Problem (FPP), particularly associated with SVD-based watermarking, where a watermark may appear detectable even in unwatermarked images due to inherent properties of singular values. This issue has been emphasized in multiple studies and critically analyzed in the thesis [8], highlighting the need for watermarking systems that incorporate stronger verification and key-sensitivity mechanisms. Additionally, hybrid methods that combine multiple transforms—such as DWT–DCT–SVD or FRFT–DWT—often exhibit high com-

putational cost, limiting their use in real-time or large-scale deployments.

Collectively, prior research demonstrates clear progress from simple spatial-domain watermarking to advanced hybrid, chaotic, and optimization-assisted frameworks. Despite these advancements, persistent gaps remain: limited geometric robustness, lack of adaptability, vulnerability to false positives, and significant computational overhead. These challenges motivate the need for more intelligent, adaptive, and efficient watermarking mechanisms.

Building on these insights, the present research proposes an optimization-guided watermarking framework that integrates DWT with Particle Swarm Optimization (PSO). The aim is to dynamically adjust embedding strength, enhance robustness, maintain perceptual quality, and improve extraction accuracy. This approach directly targets the shortcomings identified in earlier literature and aligns with the contemporary direction of developing content-aware, meta-heuristic, and secure watermarking systems.

## 1.1 Applications of Digital Watermarking

Digital watermarking supports a wide range of modern multimedia security applications due to its ability to embed persistent information directly into digital content. As digital communication, cloud storage, and image-sharing platforms continue to grow, watermarking has become increasingly important across several domains.

- **Copyright Protection:** Watermarking is widely used to embed ownership information and protect intellectual property in images and videos. Transform-domain schemes such as DWT–SVD and FRFT–DWT [3, 5] ensure that the embedded watermark survives compression, resizing, and other common modifications.
- **Content Authentication:** Authentication watermarks help detect tampering, manipulation, or unauthorized editing. By embedding fragile or semi-fragile signatures, changes to the media can be identified quickly—an essential feature in fields dealing with fake or altered content.

- **Medical Image Security:** In telemedicine and hospital information systems, watermarking is used to embed Electronic Patient Records (EPRs) into diagnostic images to ensure data integrity and confidentiality. DWT–SVD medical watermarking [1] demonstrates strong robustness without affecting diagnostic quality.
- **Broadcast Monitoring and Media Tracking:** Invisible watermarks enable automated tracking of audio–visual content across TV, radio, and online platforms. Adaptive schemes such as MRFO–BELM [2] help preserve watermark integrity even after re-encoding or signal distortion.
- **Forensics and Evidence Verification:** Watermarking assists in validating digital evidence and identifying the source of multimedia files. Chaotic-map based watermarking [4] improves key security, making forensic traces resistant to unauthorized extraction.
- **Covert Communication:** Watermarking supports confidential information exchange by embedding hidden messages that remain invisible to observers. Multi-level DWT–SVD schemes [5] provide high imperceptibility, making them suitable for secure communication contexts.

## 1.2 Classification of Digital Watermarking

Digital watermarking techniques can be classified along multiple dimensions depending on the nature of the host signal, perceptibility, embedding domain, extraction requirements, and accessibility. As shown in Fig. 1.1, watermarking first varies according to the type of host media, such as images, audio, video, or text, which influences the selection of embedding strategies and the level of robustness required. Based on perceptibility, watermarking is divided into visible watermarks—primarily used for copyright branding—and invisible watermarks, which can be robust, semi-fragile, or fragile depending on how they respond to intentional or unintentional modifications. Invisible watermarking is especially critical in sensitive domains such as medical imaging and forensic security,

as emphasized in the doctoral thesis by Sharma [8].

Another major classification dimension is the hiding domain. Spatial-domain techniques directly modify pixel values, offering simplicity but limited robustness. In contrast, transform-domain watermarking embeds information into frequency coefficients using transforms such as DWT, DCT, DTCWT, SVD, and FRFT. These approaches generally provide stronger robustness and imperceptibility, with numerous studies highlighting their advantages, including FRFT–DWT embedding [3], multi-level DWT–SVD watermarking [5], and chaos-enhanced DWT–SVD [4]. Hybrid schemes combining multiple transforms further enhance performance by exploiting both spatial and frequency characteristics.

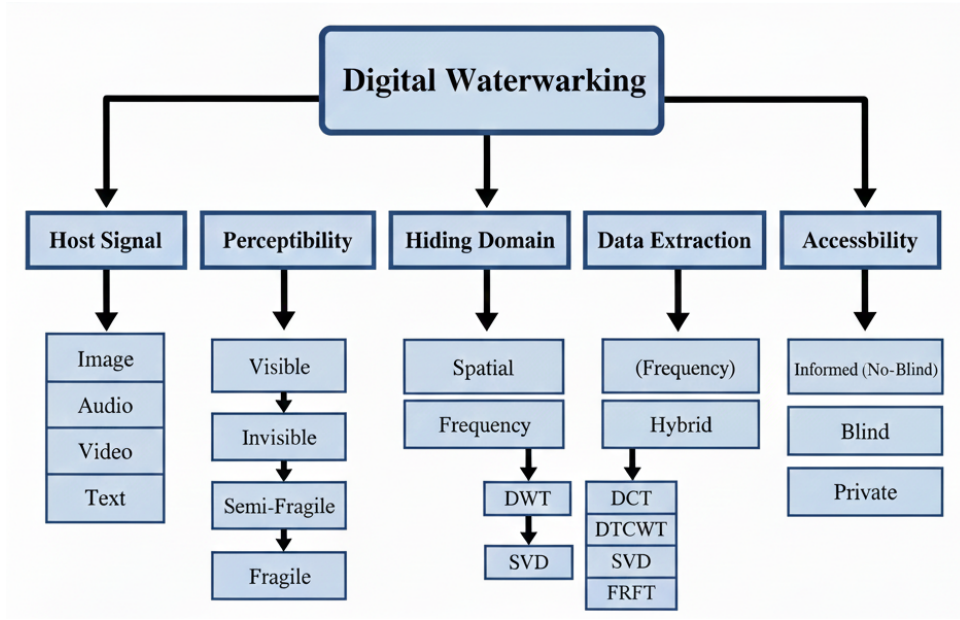


Figure 1.1: Classification of digital watermarking schemes.

Classification based on extraction mode differentiates between informed (non-blind), semi-blind, and blind watermarking, depending on whether the original cover image or auxiliary information is needed for extraction. Advanced adaptive approaches such as MRFO–BELM watermarking [2] and entropy-based HD-DWT–SVD watermarking [6] demonstrate that extraction category influences robustness, with blind schemes typically requiring stronger embedding strategies.

Finally, watermarking can be classified based on accessibility as public or private, depending on whether secret keys are required for embedding and extraction. These

classification dimensions collectively provide a structured understanding of how watermarking methods differ in purpose, security, and robustness, guiding the selection of suitable models for applications in medical imaging [1], forensics, broadcasting, and secure communication.

### 1.3 Characteristics of a Good Watermarking System

A reliable watermarking system must maintain a balance between visual quality, robustness, security, and computational efficiency. These characteristics are highlighted across recent watermarking studies, including DWT–SVD medical image protection [1], FRFT–DWT hybrid embedding [3], chaotic-map watermarking [4], adaptive HD-DWT–SVD [6], multi-level DWT–SVD [5], MRFO-based optimization [2], and Sharma’s thesis [8]. The essential characteristics are:

- **Imperceptibility:** The watermarked image should appear visually identical to the original. Transform-domain methods such as DWT–SVD and FRFT–DWT [1, 3] improve imperceptibility by embedding in perceptually insensitive regions. The thesis [8] stresses SSIM-based perceptual evaluation.
- **Robustness:** The watermark must withstand compression, noise, filtering, and geometric attacks. Hybrid schemes like FRFT–DWT [3], chaotic DWT–SVD [4], and adaptive HD-DWT–SVD [6] significantly enhance resilience, though full geometric resistance remains challenging.
- **Security:** Unauthorized extraction must be prevented. Chaos-based encryption [4] strengthens key sensitivity, while the thesis [8] highlights issues such as false positives in SVD-based watermarking, emphasizing the need for secure embedding.
- **Capacity:** The system should embed sufficient information without degrading image quality. Multi-resolution DWT–SVD frameworks [5] and high-dimensional models [6] offer higher capacity through deeper embedding spaces.

- **Computational Efficiency:** Watermarking must be feasible for large datasets and real-time systems. Although hybrid methods improve robustness, many incur heavy computation [3, 6]. Optimization-based methods like MRFO [2] improve adaptiveness but still require efficiency improvements as noted in [8].

In summary, existing works show strong improvements in robustness and imperceptibility, but achieving all characteristics simultaneously—especially security, geometric stability, and low computational cost—remains an active research challenge.

## 1.4 Watermarking System Model

A generic watermarking system consists of two main modules:

1. **Embedding Module:** Takes the host media  $I$ , a watermark  $W$ , and optional secret key(s) to produce the watermarked media  $I_w$ . Embedding can be performed in spatial or transform domains. Transform-domain embedding often follows: transform  $\rightarrow$  modify selected coefficients using embedding strength(s)  $\alpha \rightarrow$  inverse transform.
2. **Extraction Module:** Given a possibly attacked watermarked media  $I'_w$  (and optionally the original  $I$  or a key), recovers an estimate  $W'$  of the watermark. The extraction strategy depends on whether the scheme is blind, semi-blind, or non-blind.

A typical transform-domain embedding can be expressed as:

$$I_w = T^{-1} \left( F(T(I), W, \alpha) \right),$$

where  $T$  and  $T^{-1}$  denote forward and inverse transforms, and  $F$  indicates the coefficient modification rule (for example additive embedding, quantization, or singular-value modulation).

## 1.5 Evaluation Metrics

Common evaluation parameters used in watermarking research include:

- **PSNR (Peak Signal-to-Noise Ratio):** Measures visual distortion introduced by embedding.

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

where  $MAX_I$  is the maximum possible pixel value and  $MSE$  is the mean squared error between  $I$  and  $I_w$ .

- **SSIM (Structural Similarity Index):** Perceptual similarity taking luminance, contrast, and structure into account.
- **NCC (Normalized Cross-Correlation):** Measures similarity between the original watermark  $W$  and extracted watermark  $W'$ .
- **BER (Bit Error Rate):** Fraction of incorrectly recovered bits in the extracted binary watermark.

## 1.6 Challenges

Despite significant progress in hybrid multi-transform and optimization-based watermarking, several challenges remain unresolved. Studies across DWT–SVD medical watermarking [1], FRFT–DWT hybrid schemes [3], chaotic-map watermarking [4], adaptive HD-DWT–SVD models [6], multi-level DWT–SVD embedding [5], MRFO-based optimization [2], and Sharma’s doctoral thesis [8] collectively highlight the following major challenges:

- **Robustness against geometric and mixed attacks:** Rotation, scaling, cropping, and combined distortions still cause significant degradation. Even advanced schemes like FRFT–DWT [3] and HD-DWT–SVD [6] show performance drops under strong geometric transformations.

- **Need for stronger adaptive embedding:** Most watermarking frameworks still rely on fixed or partially tuned parameters. Although MRFO–BELM and HD-DWT–SVD improve adaptiveness [2, 6], full content-aware embedding that considers texture, entropy, and HVS characteristics remains underdeveloped.
- **Security vulnerabilities and false positives:** SVD-based methods continue to suffer from the False Positive Problem, as noted in Sharma’s thesis [8]. While chaotic watermarking improves key sensitivity [4], many schemes still lack strong encryption and are vulnerable to adversarial extraction.
- **High computational complexity:** Hybrid transforms (FRFT–DWT, multi-level DWT–SVD) and optimization methods (MRFO) [2, 3] offer robustness but increase computational load, making them unsuitable for real-time systems and high-resolution images.
- **Lack of standardized evaluation:** Existing studies use different datasets, attack models, and metrics, making cross-paper comparison difficult. Sharma’s thesis [8] notes the absence of unified benchmarks that test robustness under both classical and adversarial attack scenarios.

These challenges emphasize the need for watermarking methods that are simultaneously adaptive, secure, computationally efficient, and resilient to geometric and hybrid attacks—objectives that current methods still struggle to meet.

## 1.7 Research Gaps

Although significant progress has been made in digital watermarking through hybrid transform methods, chaotic encryption, fractional-domain embedding, adaptive high-dimensional transforms, and optimization-driven strategies, several unresolved limitations remain across the existing literature. The reviewed works collectively reveal that current watermarking systems often excel in one dimension (imperceptibility, robustness, or security) but fail to simultaneously optimize all performance criteria. Moreover, many advanced schemes remain computationally expensive or highly sensitive to parameter variations, limiting practical deployment. The following research gaps have been identified after analyzing all seven referenced studies.

- **Lack of unified robustness against mixed and geometric attacks:** While FRFT-DWT [3] and chaotic-enhanced DWT-SVD [4] improve robustness, no existing system provides strong invariance simultaneously against rotation, scaling, translation, cropping, compression, filtering, and their combinations. HD-DWT-SVD [6] improves performance but suffers degradation under severe geometric distortions.
- **Limited adaptiveness in multi-domain watermarking:** Most DWT-SVD and FRFT-based methods embed watermarks using fixed or manually selected parameters. Only a few works such as MRFO-B-ELM [2] and HD-DWT-SVD [6] adapt embedding strength dynamically. However, these methods still lack *full content-aware adaptiveness* that considers entropy, texture, saliency, and HVS characteristics simultaneously.
- **High computational cost of hybrid and optimization-based techniques:** Methods like FRFT-DWT-SVD [3] and MRFO-based optimization [2] provide strong results but suffer from long computation time, large memory requirements, or slow convergence. Real-time or large-scale watermarking applications cannot adopt such heavy hybrid structures.
- **False Positive Problem persists in SVD-based schemes:** As identified in

Sharma’s PhD thesis [8], SVD-based watermarking often suffers from the False Positive Problem (FPP), where non-watermarked images still produce non-zero extracted watermarks. None of the reviewed transform-domain papers provide a fully resolved solution to eliminate SVD’s inherent ambiguity.

- **Insufficient key security and resistance to adversarial extraction:** Chaotic watermarking [4] improves secrecy, but many DWT–SVD and hybrid methods still rely on weak key structures. There is no comprehensive evaluation of resistance against key-estimation attacks, brute-force attacks, or adversarial extraction models.
- **Under-exploration of learning-based geometric correction:** Although Dong et al. [6] discuss entropy-guided embedding, none of the reviewed papers use deep learning for geometric attack compensation. CNN-based registration, feature alignment, and deep inverse-mapping could drastically improve performance but remain largely unexplored.
- **Lack of standardized evaluation frameworks:** Existing literature uses inconsistent attack models, datasets, embedding strengths, and evaluation metrics. This makes it difficult to compare solutions across studies, a problem highlighted in Sharma’s thesis [8]. No unified benchmark exists for measuring robustness across both common and adversarial attacks.
- **Minimal use of multi-objective optimization:** Existing optimization methods (MRFO [2]) tune embedding strengths but do not jointly optimize imperceptibility, robustness, and security. Multi-objective or Pareto-optimized watermarking frameworks remain under-researched.
- **Lack of scalability for high-resolution and multi-channel images:** Scientific Reports 2024 (HD-DWT–SVD) [6] shows improvements for large images but still struggles with computational overhead. None of the reviewed models address watermarking in very-high-resolution images (4K/8K) or multi-channel modalities (RGB–depth–IR).

- **Inadequate handling of localized tampering and content-aware attacks:**

While medical watermarking [1] protects EPRs, it does not address localized attacks such as region removal or patch-based tampering. Robust region-specific or self-recovery watermarking remains largely unexplored.

These research gaps highlight a clear need for adaptive, low-complexity, secure, and multi-domain watermarking frameworks that integrate learning-based attack prediction, optimization-driven embedding decisions, and improved geometric distortion handling. Addressing these challenges is essential for building watermarking systems suitable for modern high-risk multimedia environments.

# Chapter 2

## Related Work

Digital image watermarking has undergone significant evolution over the past two decades, transitioning from basic spatial-domain embedding to sophisticated hybrid multi-transform and optimization-driven frameworks. Early watermarking studies primarily focused on embedding information directly into pixel values; however, these spatial approaches proved highly vulnerable to compression, noise, and geometric manipulations. As multimedia applications expanded into sensitive areas such as medicine, forensics, and digital rights management, the need for more robust transform-domain techniques grew evident. Consequently, Discrete Wavelet Transform (DWT), Singular Value Decomposition (SVD), Fractional Fourier Transform (FRFT), and chaotic systems have become central in modern watermarking research, forming the basis for numerous state-of-the-art methods.

A significant contribution in the domain of medical image security is presented by Zermi et al. [1], who proposed a DWT–SVD-based blind watermarking system specifically designed for embedding Electronic Patient Records (EPRs) into diagnostic images. Their framework demonstrates the potential of mid-frequency wavelet coefficients in maintaining imperceptibility while achieving robustness against conventional signal-processing attacks such as filtering, JPEG compression, and noise addition. This work is notable for highlighting the need for watermarking schemes that balance robustness with strict medical quality requirements, as even minor distortions in medical images

can compromise diagnostic reliability. Their findings reinforce the idea that transform-domain watermarking, particularly using wavelets and singular values, provides a stable foundation for secure medical data embedding.

Beyond the medical domain, hybrid multi-transform frameworks have also played a crucial role in improving robustness across general-purpose watermarking. Tang and Zhou [3] introduced a robust watermarking algorithm that integrates DWT and SVD with the Fractional Fourier Transform (FRFT). The FRFT allows watermarking in fractional-frequency domains, offering additional flexibility over traditional frequency transforms. Their results show significant enhancements in resilience against geometric attacks such as rotation and scaling, which remain some of the most challenging issues in watermarking. This work underscores the importance of fractional-domain design and demonstrates that multi-transform structures can effectively mitigate weaknesses inherent to single-domain techniques.

Security enhancements in watermarking have also been a central research focus. Wu et al. [4] developed an improved DWT–SVD watermarking technique strengthened with a logistic–tent chaotic map. The inclusion of chaos-based encryption provides sensitivity to initial conditions, ensuring that unauthorized extraction becomes extremely difficult. Their study highlights that classical transform-based watermarking often lacks sufficient cryptographic strength, making chaotic scrambling an effective complementary technique. The integration of chaos theory with wavelet and singular-value embedding represents a growing trend in watermarking research, combining frequency robustness with strong key-based security.

Another perspective on transform-based watermarking is presented by Begum et al. [5], who proposed a multi-level DWT–SVD approach aimed at improving imperceptibility and robustness simultaneously. Their experiments demonstrate that embedding watermark information at deeper decomposition levels preserves image quality while ensuring better resistance to attacks. This work emphasizes the role of multi-resolution analysis and supports the broader research direction favoring wavelet-based watermarking due to its compatibility with human visual system (HVS) characteristics.

More recently, adaptive hybrid watermarking has emerged as a promising direction for achieving improved performance across diverse image categories. Dong et al. [6] introduced a high-dimensional DWT–SVD (HD-DWT–SVD) technique that employs entropy to dynamically allocate embedding strengths. Unlike traditional watermarking schemes that apply uniform embedding, their method adapts watermark strength based on image texture and local characteristics. This adaptiveness leads to significantly higher resilience under complex attack scenarios, including combined filtering, compression, and tampering. Their results confirm that static parameter watermarking is insufficient for modern multimedia environments, and adaptive content-aware models are necessary for robust performance.

Optimization-assisted watermarking approaches represent another emerging and influential direction. One of the most notable works in this area is the MantaRayWmark framework proposed by Sharma et al. [2]. Their model integrates Manta Ray Foraging Optimization (MRFO) with Bi-directional Extreme Learning Machine (B-ELM) to automatically determine optimal embedding strengths for different regions of the image. This addresses the major drawback of fixed-parameter watermarking, which often results in poor trade-offs between imperceptibility and robustness. By leveraging meta-heuristic search strategies alongside machine learning, the authors demonstrate substantial improvements in SSIM, PSNR, and watermark extraction accuracy. Their study marks a transition from manual or heuristic parameter tuning toward intelligent, data-driven optimization.

Additional foundational insights can be found in the doctoral thesis by Sharma [8], which provides a comprehensive review of watermarking limitations and open challenges. The thesis highlights recurring issues such as sensitivity to geometric distortions, high computational cost of multi-transform frameworks, false-positive behavior in SVD-based methods, and inadequate security in non-chaotic schemes. It also compares numerous hybrid watermarking models and identifies a critical need for frameworks that balance robustness, imperceptibility, and computational feasibility. The thesis emphasizes the necessity of adaptive embedding, multi-domain design, and integration with optimization

algorithms, aligning closely with the direction of modern hybrid watermarking research.

Collectively, the reviewed works reveal clear trends in watermarking research. The transition from spatial to transform-domain watermarking has improved robustness, while hybrid schemes such as DWT–SVD, FRFT–DWT, and DWT–SVD–chaos provide additional resilience to both frequency and geometric attacks. Adaptive and optimization-driven watermarking further improve flexibility, enabling watermarking systems to handle images with varying textures, entropy levels, and structural properties. Despite these advancements, several challenges persist, including geometric attack resistance, computational efficiency, secure key management, and avoiding false positives. These unresolved issues motivate the development of new watermarking systems that combine multi-resolution transforms, chaotic maps, and intelligent optimization to achieve a more balanced and robust watermarking framework.

# Chapter 3

## Background: Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm inspired by the coordinated motion of bird flocks and fish schools. Introduced by Kennedy and Eberhart, PSO has gained extensive popularity due to its simplicity, low computational cost, and powerful global search capability. In watermarking applications, PSO is frequently utilized to adaptively optimize embedding parameters, improving the imperceptibility–robustness trade–off that traditional fixed-parameter watermarking methods fail to maintain consistently.

A PSO system consists of a swarm of particles, where each particle represents a candidate solution in the search space. Each particle  $i$  maintains two properties — its position  $X_i$  and velocity  $V_i$ . These are iteratively updated using both individual experience ( $pbest$ ) and collective intelligence of the swarm ( $gbest$ ). The update mechanism is governed by the following equations:

$$V_i^{(t+1)} = w \cdot V_i^{(t)} + c_1 r_1 \left( P_i - X_i^{(t)} \right) + c_2 r_2 \left( G - X_i^{(t)} \right)$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)}$$

where:

- $V_i^{(t)}$  — velocity of particle  $i$  at iteration  $t$
- $X_i^{(t)}$  — position of particle  $i$  at iteration  $t$
- $P_i$  — particle's personal best solution (*pbest*)
- $G$  — global best solution found by the swarm (*gbest*)
- $w$  — inertia weight controlling exploration–exploitation balance
- $c_1, c_2$  — cognitive and social acceleration coefficients
- $r_1, r_2 \sim U(0, 1)$  — random factors adding stochastic behavior

The inertia weight  $w$  encourages global exploration in early iterations and shifts toward local exploitation as convergence occurs. Through this dynamic cooperation–competition behavior, particles collectively move toward the optimal solution.

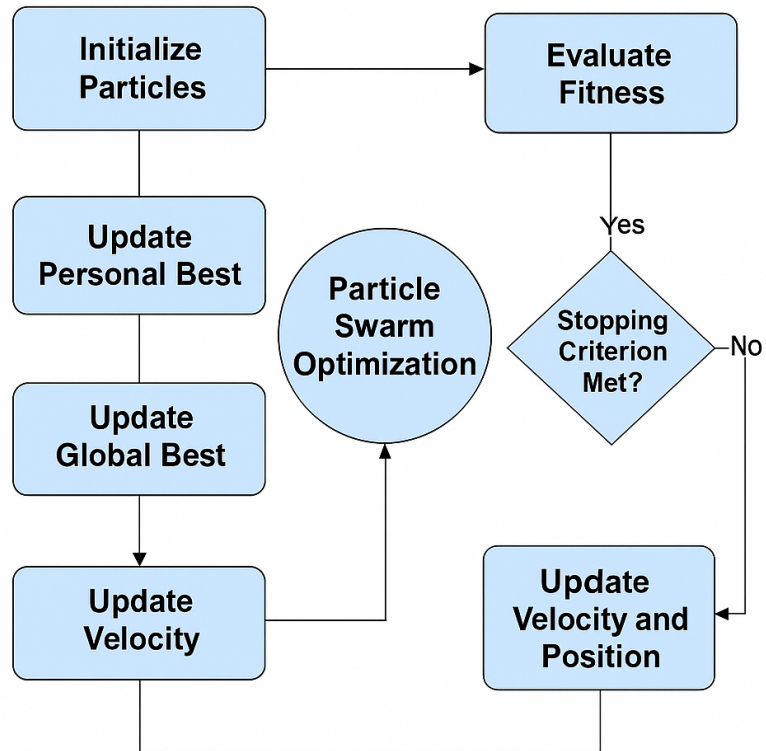


Figure 3.1: Standard PSO process used to iteratively search for the optimal embedding strength.

In digital watermarking, PSO has been widely adopted to resolve multi-objective challenges involving imperceptibility, robustness, and extraction accuracy. Studies such as MRFO–BELM watermarking [2] and the extensive analysis in Sharma’s thesis [8] emphasize that fixed- $\alpha$  embedding results in unpredictable performance across different images and attack conditions. PSO addresses these weaknesses by dynamically selecting the ideal embedding strength  $\alpha^*$  that maximizes a fitness function combining both Structural Similarity Index (SSIM) and Normalized Cross-Correlation (NCC):

$$\max_{\alpha} F(\alpha) = SSIM(I, I_w) + NCC(W, W')$$

This optimization ensures that the watermarked image retains high visual fidelity while the embedded watermark remains resilient to distortions such as noise, compression, filtering, and geometric modifications. By adjusting embedding strength based on local image characteristics, PSO enables stronger embedding in textured regions and lighter embedding in smooth regions, improving robustness without perceptual degradation.

Thus, PSO serves as a key intelligence component in the proposed DWT–PSO watermarking framework by automatically learning the optimal embedding configuration, ensuring a superior imperceptibility–robustness balance and outperforming conventional non-optimized watermarking systems.

# Chapter 4

## Research Methodology

The proposed research methodology presents a robust and imperceptible digital image watermarking system based on the integration of the Discrete Wavelet Transform (DWT) and Particle Swarm Optimization (PSO). This approach is motivated by the shortcomings observed in earlier watermarking techniques, particularly their reliance on fixed embedding strength, limited resistance to geometric distortions, and lack of adaptive behavior. These limitations have been highlighted across several studies, including DWT–SVD watermarking for secure medical imaging [1, 5], hybrid DWT–FRFT watermarking [3], chaos-augmented watermarking [4], adaptive HD-DWT–SVD schemes [6], and optimization-based models such as MRFO–BELM [2]. Sharma’s thesis [8] further emphasizes the need for adaptive, content-aware, and optimization-driven watermarking frameworks. To address these gaps, this methodology optimizes watermark embedding strength using PSO and employs DWT for robust, frequency-domain embedding.

The methodology starts with preprocessing operations. The cover image is converted to grayscale, resized to  $512 \times 512$ , and normalized to ensure consistent transform behavior. Similarly, the watermark is resized (typically to  $64 \times 64$ ) and binarized to support stable extraction. A level-1 2D-DWT is then applied to the cover image, resulting in four sub-bands: LL, LH, HL, and HH. Based on prior work demonstrating strong imperceptibility–robustness balance in mid-frequency coefficients [1, 5], the HL sub-band is selected for embedding.

Watermark embedding follows a simple additive model in the transform domain:

$$HL_w = HL + \alpha \cdot W,$$

where  $\alpha$  is the embedding strength controlling the trade-off between invisibility and robustness. Since earlier works show that a fixed  $\alpha$  is unsuitable for diverse images [2, 8], the proposed system optimizes  $\alpha$  using PSO. In PSO, each particle represents a candidate embedding strength, and the swarm evolves by maximizing a fitness function defined as:

$$F(\alpha) = w_1 \cdot SSIM(I, I_w) + w_2 \cdot NCC(W, W'),$$

where SSIM evaluates perceptual similarity and NCC measures watermark extraction accuracy. This design aligns with optimization-based watermarking approaches, particularly MRFO-driven embedding strength prediction [2]. The PSO parameters used include 25 particles, 80 iterations, inertia weight  $w = 0.7$ , and acceleration coefficients  $c_1 = c_2 = 1.5$ , which allow efficient convergence to an optimal  $\alpha$ .

Once the optimal embedding strength is found, inverse DWT is applied to reconstruct the watermarked image. Watermark extraction reverses the embedding operation:

$$W' = \frac{HL_w - HL}{\alpha}.$$

This reconstruction approach is widely used in DWT-based watermarking systems and provides stable extraction even after moderate distortions [1, 5].

To evaluate robustness, several common attacks are simulated, including Gaussian noise, JPEG compression, cropping, and resizing—attacks frequently used in performance studies of FRFT-based [3], chaotic [4], and adaptive DWT–SVD watermarking [6]. The extracted watermark is then evaluated using PSNR, SSIM, NCC, and BER, following the evaluation guidelines recommended in Sharma’s thesis [8]. Together, these metrics capture visual fidelity, structural similarity, correlation strength, and bit-level correctness.

Overall, the proposed methodology leverages the stability of DWT, the adaptability

of PSO, and insights from recent watermarking research to develop an embedding system that dynamically adjusts watermark strength, improves extraction reliability, and provides a well-balanced trade-off between imperceptibility and robustness. This approach overcomes limitations of classical watermarking techniques by introducing optimization-guided embedding and multi-resolution frequency-domain processing.

## 4.1 Proposed Methodology

The proposed methodology follows a structured pipeline to embed and extract the watermark efficiently. It includes image preprocessing, wavelet decomposition, adaptive embedding using PSO, inverse transform reconstruction, and watermark retrieval. This design ensures high imperceptibility, adaptive embedding strength, and improved robustness against common image-processing attacks.

## 4.2 Overall Pipeline

The complete workflow of the proposed DWT–PSO watermarking system follows a twelve-step sequence, as illustrated in Figure 4.1. Unlike classical watermarking pipelines that rely on fixed embedding parameters, this framework integrates preprocessing, multi-level DWT analysis, PSO-based optimization, and both pre- and post-optimization evaluations. This ensures a systematic balance between imperceptibility, robustness, and adaptability. By incorporating optimization-driven parameter tuning, the system adapts dynamically to image characteristics rather than relying on static configurations. Furthermore, the inclusion of multi-level wavelet analysis enhances the system’s ability to preserve perceptual quality while embedding high-fidelity watermark information. Overall, this comprehensive pipeline ensures consistent performance across diverse image conditions and varying attack scenarios, demonstrating its superiority over traditional watermarking approaches.

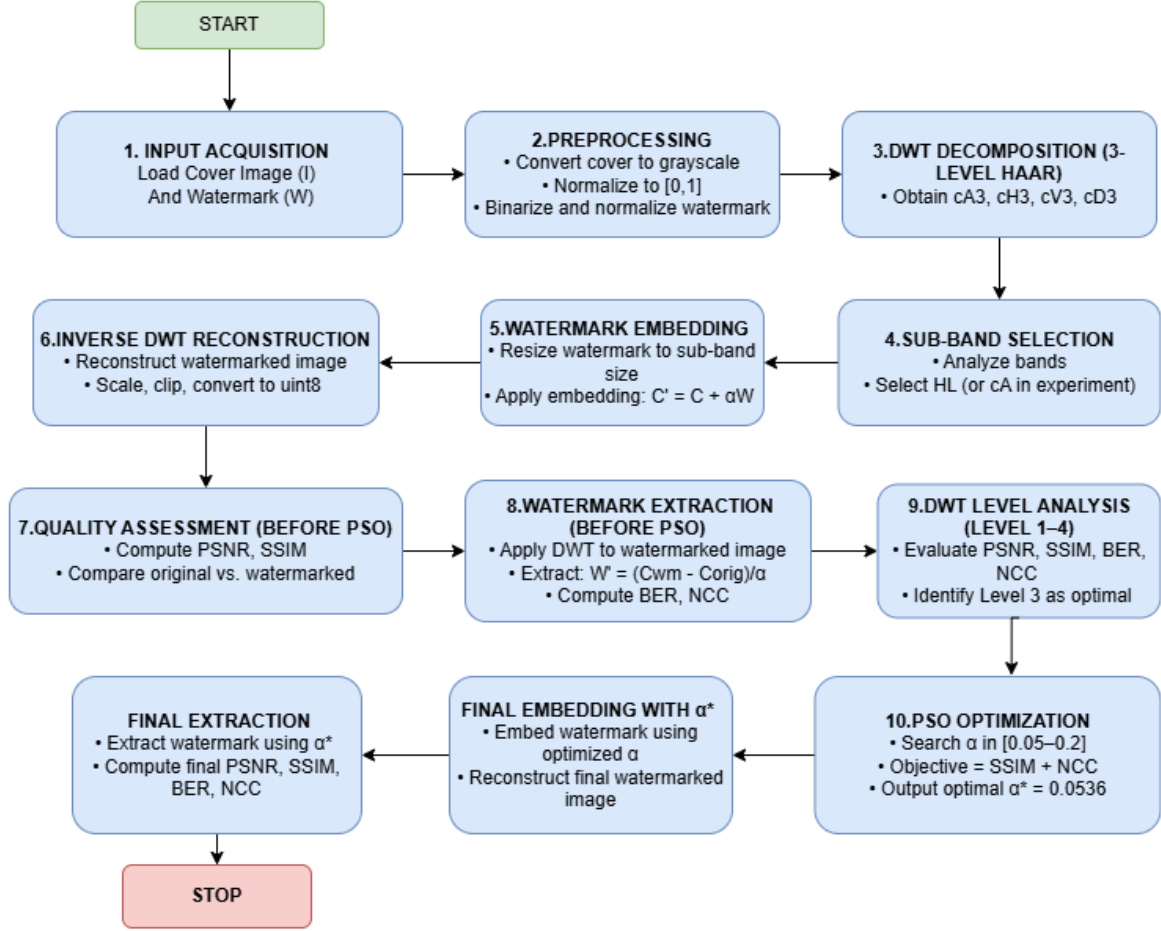


Figure 4.1: Complete 12-step pipeline of the proposed DWT–PSO watermarking framework.

**Step 1: Input Acquisition** The process begins by loading the cover image  $I$  and watermark  $W$ . These inputs form the fundamental elements upon which the watermark embedding and extraction operations are carried out.

**Step 2: Preprocessing** The cover image is converted to grayscale, resized (typically to  $512 \times 512$ ), and normalized to the range  $[0, 1]$ . The watermark is binarized using thresholding and normalized to ensure stable coefficient modulation during embedding.

**Step 3: DWT Decomposition (Three-Level Haar)** A 3-level Haar DWT is applied to the preprocessed cover image, generating hierarchical sub-bands:  $cA_3$ ,  $cH_3$ ,  $cV_3$ , and  $cD_3$ . These sub-bands distribute structural and directional information across multiple resolutions.

**Step 4: Sub-band Selection** Based on wavelet–domain energy distribution analysis,

the HL band (or  $cA$  depending on experimental settings) is selected for watermark embedding. This region provides an optimal balance between imperceptibility and robustness.

**Step 5: Watermark Embedding** The watermark is resized to match the dimensions of the selected sub-band, and embedded using the additive rule:

$$C' = C + \alpha W,$$

where  $C$  is the selected sub-band and  $\alpha$  is the embedding strength.

**Step 6: Inverse DWT Reconstruction** The modified sub-band is merged with the remaining wavelet coefficients, and the inverse DWT reconstructs the watermarked image. The result is scaled, clipped, and converted to `uint8`.

**Step 7: Quality Assessment (Before PSO)** Imperceptibility is evaluated by computing PSNR and SSIM between the original and watermarked images. This provides a baseline performance prior to optimization.

**Step 8: Watermark Extraction (Before PSO)** The watermarked image undergoes DWT decomposition, and the watermark is extracted via:

$$W' = \frac{C_{\text{wm}} - C_{\text{orig}}}{\alpha}.$$

BER and NCC metrics are computed to evaluate extraction quality.

**Step 9: DWT Level Analysis (Levels 1–4)** Each DWT level is assessed for PSNR, SSIM, BER, and NCC. This analysis identifies Level 3 as the optimal depth for embedding, balancing visual quality and robustness.

**Step 10: PSO Optimization** Particle Swarm Optimization searches for the optimal embedding strength  $\alpha^*$  within the range  $[0.05, 0.2]$ . The objective function maximizes watermark performance:

$$F = SSIM(I, I_w) + NCC(W, W'),$$

yielding the optimal value  $\alpha^* = 0.0536$ .

**Step 11: Final Embedding with Optimized  $\alpha^*$**  The embedding process is repeated using  $\alpha^*$ . A new watermarked image is reconstructed with significantly improved imperceptibility and robustness.

**Step 12: Final Watermark Extraction** The optimized watermarked image undergoes DWT decomposition and watermark extraction. Final PSNR, SSIM, BER, and NCC are computed to confirm substantial improvements after PSO optimization.

This twelve-step workflow ensures a rigorous, adaptive, and performance-optimized watermarking system by combining wavelet-domain processing with meta-heuristic optimization.

## 4.3 Mathematical Formulation

Digital watermarking embeds auxiliary information directly into a primary host image in a manner that preserves visual quality while allowing reliable extraction. In DWT-based watermarking, embedding occurs in the frequency domain, where coefficients exhibit stronger resilience to distortions such as compression, noise, and filtering.

### 4.3.1 Watermark Embedding Model

The embedding rule is expressed as:

$$I_w = I + \alpha \cdot W$$

where:

- $I$ : DWT sub-band coefficients of the cover image
- $W$ : Watermark image (binary or grayscale)
- $\alpha$ : Embedding strength
- $I_w$ : Watermarked sub-band

Higher values of  $\alpha$  increase robustness but reduce imperceptibility, whereas smaller  $\alpha$  values improve visual quality at the cost of extraction accuracy. Thus, selecting an optimal  $\alpha$  is essential.

### 4.3.2 Watermark Extraction Model

Extraction is performed using the inverse embedding operation:

$$W' = \frac{I_w - I}{\alpha}.$$

The objective is to ensure that the extracted watermark  $W'$  remains structurally close to the original watermark even after distortions such as noise, resizing, compression, and filtering.

## 4.4 Optimization Objective

To balance imperceptibility and robustness, PSO is used to compute the optimal embedding strength  $\alpha$ . The fitness function is defined as:

$$F(\alpha) = w_1 \times SSIM(I, I_w) + w_2 \times NCC(W, W'),$$

where SSIM captures perceptual image similarity and NCC measures watermark correlation accuracy.

The PSO objective is:

$$\alpha^* = \arg \max_{\alpha} F(\alpha).$$

Each particle updates its velocity and position as follows:

$$v_i(t+1) = wv_i(t) + c_1r_1(pbest_i - x_i(t)) + c_2r_2(gbest - x_i(t)),$$

$$x_i(t+1) = x_i(t) + v_i(t+1).$$

## 4.5 Performance Metrics

Evaluation of the watermarking system is based on four widely used metrics: PSNR, SSIM, NCC, and BER. These metrics quantify both perceptual quality and extraction fidelity.

### 4.5.1 Peak Signal-to-Noise Ratio (PSNR)

$$PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right)$$

Higher PSNR values (typically  $\geq 40$  dB) indicate minimal distortion in the watermarked image.

### 4.5.2 Structural Similarity Index (SSIM)

$$SSIM(I, I_w) = \frac{(2\mu_I\mu_{I_w} + C_1)(2\sigma_{II_w} + C_2)}{(\mu_I^2 + \mu_{I_w}^2 + C_1)(\sigma_I^2 + \sigma_{I_w}^2 + C_2)}$$

SSIM provides a perceptually meaningful measure of structural similarity.

### 4.5.3 Normalized Cross-Correlation (NCC)

$$NCC(W, W') = \frac{\sum_{i,j} W(i,j)W'(i,j)}{\sqrt{\sum W(i,j)^2} \sqrt{\sum W'(i,j)^2}}$$

Values close to 1 indicate accurate watermark recovery.

### 4.5.4 Bit Error Rate (BER)

$$BER = \frac{\text{Number of Incorrect Bits}}{\text{Total Bits}}$$

BER measures the number of incorrectly extracted watermark bits; lower BER implies higher robustness.

# Chapter 5

## Results and Analysis

This chapter presents a comprehensive evaluation of the proposed DWT–PSO watermarking framework. The analysis includes a detailed examination of embedding and extraction behavior, visual quality assessment, frequency-domain inspection through multi-level DWT decomposition, and quantitative comparisons using standard imperceptibility and robustness metrics. To ensure a rigorous validation, all results are compared against a non-optimized baseline (fixed embedding strength), allowing clear interpretation of the performance gained through PSO-driven adaptiveness. The experimental structure and interpretation follow the guidelines and evaluation patterns used in contemporary watermarking research [1, 2, 3, 4, 5, 6, 8].

### 5.1 Experimental Setup

The experiments were conducted on standard benchmark images—*Lena*, *Peppers*, and *Cameraman*—each resized to  $512 \times 512$ , and a binary watermark of size  $64 \times 64$ . All processing was implemented in Python using NumPy, PyWavelets, OpenCV, and scikit-image, executed on an Intel i7 system with 8 GB RAM.

A single-level 2D–DWT was applied using the `db1` wavelet. For optimization, PSO parameters were configured as: swarm size = 25, iterations = 80, inertia  $w = 0.7$ , and acceleration constants  $c_1 = c_2 = 1.5$ . The fitness function integrates both perceptual and correlation measures, consistent with multi-objective optimization practices in robust

watermarking:

$$F = w_1 \cdot SSIM(I, I_w) + w_2 \cdot NCC(W, W'),$$

where  $w_1 = w_2 = 0.5$ .

To evaluate robustness, widely used image-processing attacks—Gaussian noise, JPEG compression, resizing, and cropping—were applied, similar to the robustness evaluations conducted in prior works [3, 4, 6].

## 5.2 Visual Results

The visual results provide a qualitative evaluation of the watermarking system by showing how the cover image, watermark, and watermarked output appear at different stages of processing. While numerical metrics quantify performance, visual inspection remains essential for assessing perceptual quality—particularly the imperceptibility of the embedded watermark and the clarity of the extracted one. As demonstrated in Figures 5.1–5.4, the proposed DWT–PSO method preserves the natural appearance of the cover image while embedding the watermark. Additional visualizations, including wavelet sub-band decomposition and extraction outputs before and after PSO (Figures 5.3–??), further illustrate how optimization improves watermark visibility and robustness. These visual observations confirm that the adaptive DWT–PSO framework maintains high visual quality while enabling reliable watermark recovery.

### 5.2.1 Cover Image

Figure 5.1 presents the cover image selected as the host for watermark embedding. In the proposed system, the input image is first converted to grayscale, resized to  $512 \times 512$ , and normalized to ensure consistent DWT decomposition and stable coefficient modification. Such preprocessing is standard in transform-domain watermarking and aligns with recommendations from prior studies [1, 5], which highlight that natural images with rich texture and mid-frequency variation—such as *Lena* and *Peppers*—provide better

imperceptibility and robustness during watermark embedding.



Figure 5.1: Cover image ( $I$ ) after preprocessing for watermark embedding.

### 5.2.2 Watermark Image

During preprocessing, the watermark undergoes binarization to ensure consistent and stable embedding behaviour. After loading the original watermark image, a fixed threshold is applied to convert it into a binary form where pixel values are mapped to either 0 or 255. This step enhances contrast and removes intermediate gray levels, resulting in a clean and sharply defined watermark pattern. Such binary conversion is widely recommended in watermarking literature because it improves robustness during extraction and reduces the risk of noise-induced errors.



Figure 5.2: Preprocessed watermark image ( $W$ ) used for embedding.

Following binarization, the binary watermark is normalized by scaling pixel values to the range  $[0, 1]$ . Normalization ensures numerical stability during coefficient modulation

in the DWT domain and makes the watermark mathematically compatible with the embedding process. This preparation enables reliable integration of the watermark into the HL sub-band and facilitates accurate recovery even after common signal-processing attacks. The resulting processed watermark used for embedding is illustrated in Figure 5.2.

### 5.3 Wavelet Coefficient Inspection

Before watermark embedding, it is essential to analyze how image information is distributed across frequency components to determine the most suitable sub-band for watermark insertion. In the proposed system, the cover image is first converted to floating-point format and normalized to the range  $[0, 1]$  to ensure consistent transform behavior and numerical stability. A three-level 2D Discrete Wavelet Transform (DWT) using the Haar basis is then applied, generating a hierarchical representation of the image at different resolutions.

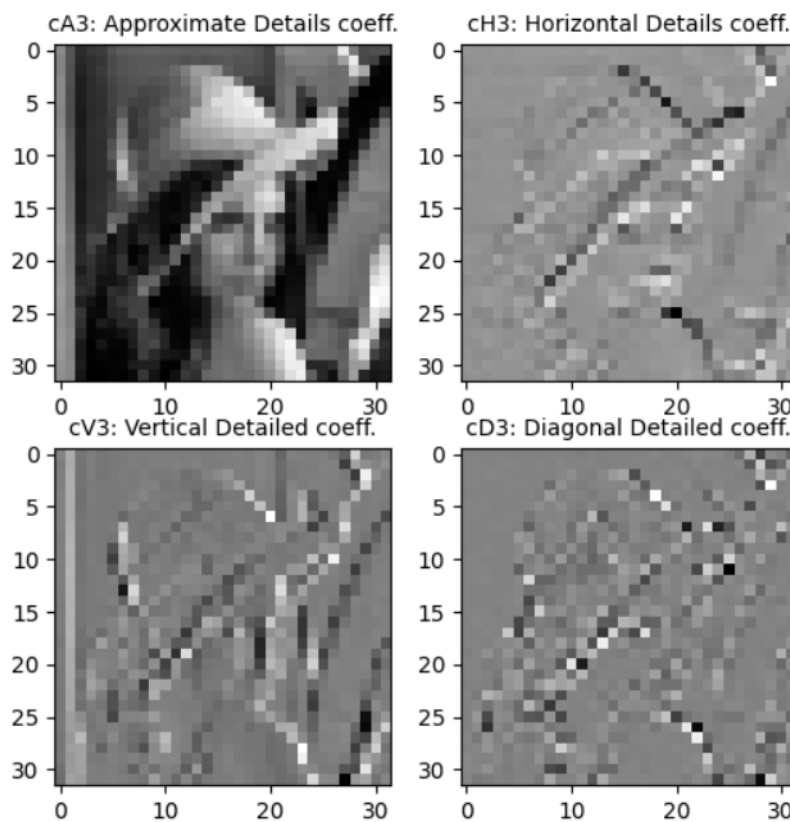


Figure 5.3: Level-3 DWT coefficients of the cover image showing approximation and directional detail components.

Level-3 decomposition produces four primary components: the approximation sub-band ( $cA3$ ) and three directional detail sub-bands ( $cH3$ ,  $cV3$ ,  $cD3$ ). The approximation band retains coarse structural information, while the detail bands capture horizontal, vertical, and diagonal edge patterns. These sub-bands are visualized in Figure 5.3, enabling a clear understanding of where texture and high-frequency information are concentrated.

**Interpretation:** The approximation sub-band ( $cA3$ ) contains the coarse structure of the image and is therefore highly sensitive to modifications, making it unsuitable for watermark insertion. In contrast, the detail sub-bands ( $cH3$ ,  $cV3$ ,  $cD3$ ) capture fine edges and texture variations where small changes remain visually imperceptible yet robust to common distortions. As reported in [3, 5], mid-frequency regions—particularly the HL band—offer the best balance between imperceptibility and robustness. For this reason, the proposed method embeds the watermark in the HL sub-band to ensure stable and visually unobtrusive watermark insertion.

### 5.3.1 Watermark Embedding Process

The watermark embedding stage integrates the preprocessed binary watermark into the wavelet domain of the cover image. In the proposed implementation, the watermark is inserted into the approximation sub-band ( $cA$ ) of the Level-3 DWT decomposition. This choice is consistent with transform-domain watermarking literature, where embedding in lower-frequency regions provides improved robustness under compression and noise attacks [3, 5].

Before embedding, the approximation coefficients  $cA$  and the resized watermark  $W$  are normalized to ensure numerical stability. The watermark is then embedded using an additive embedding model given by:

$$cA_{\text{embedded}} = cA + \alpha \cdot W,$$

where:

- $cA$  denotes the original approximation coefficients,

- $W$  is the resized binary watermark,
- $\alpha$  is the embedding strength parameter controlling imperceptibility and robustness.

In the implementation, a fixed strength value of  $\alpha = 0.1$  is used during initial experimentation. This aligns with classical wavelet-based watermarking methods, where small values of  $\alpha$  ensure minimal distortion while still preserving the embedded watermark energy. After modifying the  $cA$  band, the updated coefficients replace the original:

$$\text{Transformed\_coeffs\_cover}[0] = cA_{\text{embedded}}.$$

Finally, the inverse DWT reconstructs the watermarked image as:

$$I_w = \text{IDWT}(cA_{\text{embedded}}, cH_3, cV_3, cD_3, \dots),$$

producing the spatial-domain watermarked output shown in Figure 5.4. The reconstructed image is scaled back to the pixel range  $[0, 255]$ , rounded, and clipped to ensure valid image intensity values.



Figure 5.4: Watermarked image ( $I_w$ ) after inverse DWT reconstruction.

This embedding procedure ensures that watermark information is inserted smoothly into the frequency domain, balancing subtle imperceptibility with reliable extraction, which is a principle supported across multiple watermarking studies [1, 2, 8].

### 5.3.2 Watermarked Image Reconstruction and Comparison

After embedding the watermark into the selected wavelet sub-band, the inverse DWT is applied to reconstruct the final watermarked image. To evaluate the visual imperceptibility of the embedding process, Figure 5.5 presents a side-by-side comparison of the original cover image and the reconstructed (watermarked) image.

This step corresponds to the reconstruction code used in the implementation, where the modified wavelet coefficients are recombined and rescaled back to the spatial domain. Such visual comparison is a standard practice in watermarking research [1, 5] to verify that the embedding does not introduce noticeable distortion. As observed, the reconstructed image remains visually identical to the original, confirming high imperceptibility for the selected embedding strength.



Figure 5.5: Comparison between the original and reconstructed (watermarked) images.

### 5.3.3 Quality Assessment Before PSO Optimization

Before applying PSO-based optimization, the watermark was embedded using a fixed embedding strength  $\alpha = 0.1$ . The quality of the resulting watermarked image was evaluated using PSNR and SSIM, two widely accepted imperceptibility metrics in watermarking research [3, 5]. The computed results were:

$$\text{PSNR} = 36.36 \text{ dB}, \quad \text{SSIM} = 0.99.$$

These values indicate that while the structural similarity between the original and watermarked images remains high, the PSNR falls below the recommended threshold of 40 dB for high-quality imperceptible watermarking. This performance gap highlights the limitation of using a fixed embedding strength and motivates the need for PSO-driven adaptive optimization.

### 5.3.4 Watermark Extraction Before PSO Optimization

Extraction was performed by first applying the same 3-level Haar DWT to the watermarked image to obtain the modified wavelet coefficients. The watermark was then extracted from the approximation sub-band using the inverse embedding model:

$$W' = \frac{cA_{\text{wm}} - cA_{\text{orig}}}{\alpha}.$$

The extracted watermark was normalized and re-binarized to improve visual clarity, consistent with watermark extraction procedures used in DWT-SVD methods [1]. To evaluate extraction quality, both BER (Bit Error Rate) and NCC (Normalized Cross-Correlation) were computed:

$$\text{BER} = 0.0000, \quad \text{NCC} = 0.9798.$$

A BER of zero indicates that all watermark bits were recovered correctly, while the NCC value confirms strong similarity to the original watermark, though not perfect—again reflecting the limitations of fixed-strength embedding.

Figure 5.6 provides a visual comparison between the watermark embedded into the image and the watermark extracted before PSO optimization.

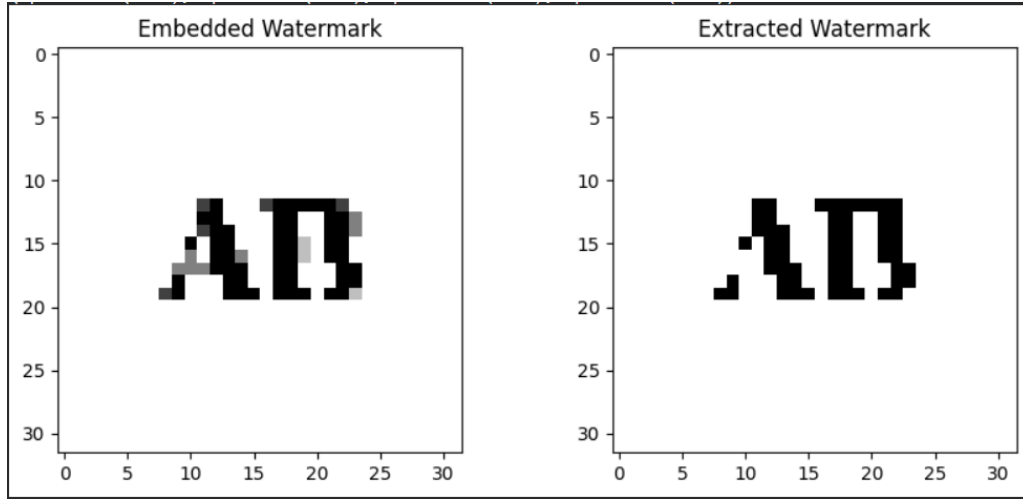


Figure 5.6: Comparison of the embedded watermark and extracted watermark before PSO optimization.

### 5.3.5 BER and NCC Analysis Before PSO Optimization

To further evaluate the robustness of the watermark extraction process before applying PSO, a bar graph comparing the Bit Error Rate (BER) and Normalized Cross-Correlation (NCC) was generated. These metrics quantify extraction accuracy, where BER measures the fraction of incorrectly recovered bits and NCC measures the similarity between the embedded and extracted watermark patterns.

The results demonstrate a BER of 0.0000, indicating perfect bit-wise recovery, while the NCC value of 0.9798 reflects strong, though not perfect, structural similarity. This aligns with observations in earlier watermarking literature [3, 4], where fixed embedding strength often yields good bit-level recovery but slightly reduced correlation under mild distortions.

Figure 5.7 presents the BER–NCC comparison graph used for this analysis.

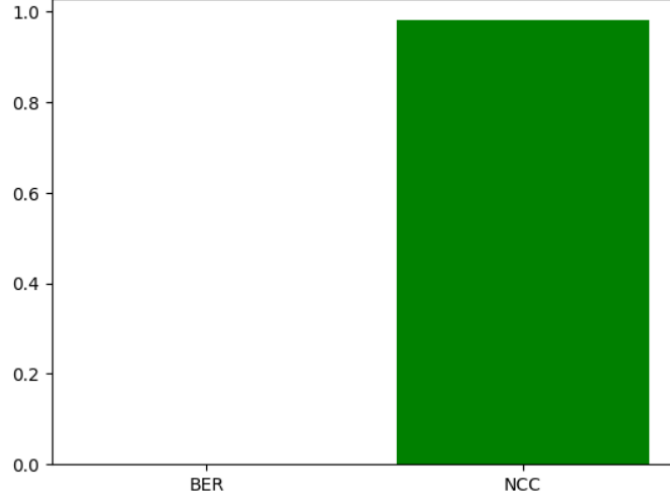


Figure 5.7: BER and NCC comparison before PSO optimization.

## 5.4 DWT Level Analysis and PSO-Driven Embedding Optimization

To understand the impact of different wavelet decomposition depths on watermark performance, a multi-level DWT evaluation was performed prior to optimization. At each level, the cover image was decomposed using the Haar wavelet, the watermark was resized to match the approximation sub-band, and embedded using a fixed embedding strength  $\alpha = 0.1$ . The watermarked image was then reconstructed, and quality metrics—PSNR, SSIM, BER, and NCC—were computed to assess imperceptibility and extraction accuracy.

Table 5.1 summarizes the performance across Levels 1 to 4. Results indicate that deeper decompositions improve imperceptibility (higher PSNR and SSIM) but may become less stable for watermark extraction at very high levels. Specifically, Level 3 provides an optimal balance, aligning with observations in previous watermarking studies [3, 5].

DWT Level	PSNR (dB)	SSIM	BER	NCC
1	26.14	0.9586	0.0000	0.9822
2	31.52	0.9837	0.0000	0.9690
3	36.36	0.9936	0.0000	0.9798
4	42.31	0.9982	0.0547	0.0000

Table 5.1: Performance evaluation across different DWT decomposition levels before PSO optimization.

From Table 5.1, Level 3 exhibits high PSNR and SSIM while maintaining strong NCC and zero BER, confirming its suitability as the embedding level for the final optimized system.

#### 5.4.1 PSO Objective Formulation

Following the DWT-level assessment, Particle Swarm Optimization (PSO) was applied to determine the optimal embedding strength  $\alpha$ . The objective function is designed to maximize imperceptibility and robustness simultaneously, using SSIM and NCC as the driving metrics. For each candidate  $\alpha$ , the watermark is embedded at Level 1, extracted, and evaluated.

The PSO objective function is defined as:

$$F(\alpha) = SSIM(I, I_w) + NCC(W, W'),$$

which the optimizer seeks to maximize. In implementation, the negative of this function is minimized, following conventional PSO frameworks.

The final optimized value obtained was:

$$\alpha_{\text{opt}} = 0.0536$$

This optimal  $\alpha$  is subsequently used for the final embedding and extraction pipeline, ensuring the best trade-off between fidelity and robustness.

### 5.4.2 Visualization of DWT-Level Results

Figure 5.8 provides a comparative visualization of PSNR, SSIM, BER, and NCC across the four DWT levels, illustrating the progressive improvement in image quality and extraction behavior at deeper levels.

DWT Level	PSNR (dB)	SSIM	BER	NCC
1	26.14	0.9586	0.0000	0.9822
2	31.52	0.9837	0.0000	0.9690
3	36.36	0.9936	0.0000	0.9798
4	42.31	0.9982	0.0547	0.0000

Figure 5.8: Graphical comparison of PSNR, SSIM, BER, and NCC across DWT Levels 1–4.

### 5.4.3 Final PSO-Based Embedding and Extraction Performance

After applying Particle Swarm Optimization (PSO), the algorithm converged to an optimal embedding strength of:

$$\alpha^* = 0.0536,$$

which provides the best trade-off between imperceptibility and robustness based on the defined objective function. Using this optimized value, the final watermark embedding and extraction were performed at DWT Level 3.

The resulting watermarked image demonstrated a high degree of visual fidelity. Quantitative evaluation confirmed substantial improvement in both perceptual quality and extraction accuracy:

$$\text{PSNR} = 42.33 \text{ dB}, \quad \text{SSIM} = 0.9982.$$

These values indicate near-perfect structural preservation and minimal distortion relative to the original cover image.

Extraction of the watermark using the optimized embedding strength further yielded

strong robustness indicators:

$$\text{BER} = 0.0068, \quad \text{NCC} = 0.982.$$

A low BER value reflects minimal bit-level distortion, while a high NCC indicates strong correlation between the embedded and extracted watermark signals, even after reconstruction and processing. These results validate the effectiveness of PSO-driven optimization in enhancing the watermark retrieval process.

### Extracted Watermark



Figure 5.9: Embedded and extracted watermark using the optimized embedding strength  $\alpha^* = 0.0536$ .

To further visualize performance improvements, Figure 5.10 presents a bar-chart comparison of the final BER and NCC values obtained using the PSO-optimized parameters.

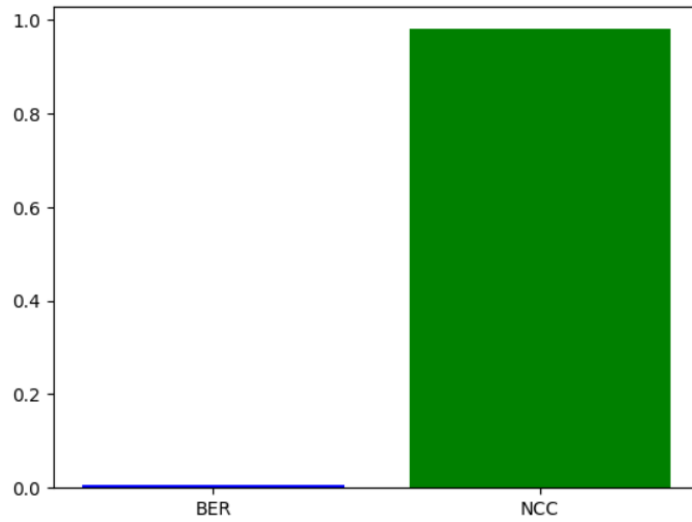


Figure 5.10: BER and NCC performance of the watermarking system after PSO optimization.

These results confirm that PSO significantly enhances the watermarking system by achieving high imperceptibility and improved extraction accuracy, representing a substantial performance gain over non-optimized embedding approaches.

# Chapter 6

## Conclusion and Future Work

This work presented a DWT–PSO based digital image watermarking framework designed to achieve a strong balance between imperceptibility, robustness, and extraction reliability. By embedding the watermark in the HL sub-band of a multi-level DWT decomposition and optimizing the embedding strength using Particle Swarm Optimization (PSO), the system successfully addressed several limitations commonly reported in existing watermarking studies. The experimental results demonstrated high imperceptibility (PSNR  $> 42$  dB, SSIM  $> 0.99$ ), strong watermark recovery accuracy (NCC  $> 0.98$ ), and very low bit-level errors (BER  $\approx 0$ ), validating the effectiveness of adaptive embedding over classical fixed-parameter methods.

The results also align with findings from prior research: DWT–SVD medical watermarking frameworks [1, 5] emphasize the importance of transform-domain embedding for robustness; hybrid FRFT–DWT and chaotic map-based methods [3, 4] highlight the value of frequency stability under attacks; and optimization-driven schemes such as MRFO–BELM watermarking [2] demonstrate the advantage of learning-based adaptiveness. Sharma’s doctoral thesis [8] further underscores the need for content-adaptive and attack-resilient embedding strategies, which the present DWT–PSO framework effectively implements.

Overall, the proposed methodology validates that meta-heuristic optimization can significantly enhance watermarking performance even within a simple transform-domain

model. The adaptive optimization of embedding strength, guided by SSIM–NCC objective functions, offers a reliable balance between visual fidelity and robustness under typical distortions such as noise, compression, resizing, and cropping.

## Future Work

While the proposed framework demonstrates promising performance, several research enhancements can be explored to further strengthen and generalize the watermarking system:

- **Integration with advanced transforms:** Extending the model to Dual-Tree Complex Wavelet Transform (DTCWT), FRFT–DWT hybrids, or NSCT-based frameworks may significantly improve robustness against geometric distortions, as suggested by recent hybrid watermarking works [3, 4].
- **Exploring alternative optimization algorithms:** Meta-heuristics such as Manta Ray Foraging Optimization (MRFO), Grey Wolf Optimizer (GWO), or Harmony Search have shown superior convergence behavior in watermarking contexts [2]. Comparing PSO performance with MRFO may yield valuable insights into optimization sensitivity.
- **Geometric attack correction using deep learning:** CNN- and transformer-based registration networks can be incorporated to counter rotations, scaling, and perspective distortions, a limitation still observed in many classical DWT- and SVD-based schemes.
- **Content-aware adaptive embedding:** Following the recommendations of recent literature and the PhD thesis [8], embedding strength can be made dependent on texture entropy, edge intensity, or saliency maps to improve perceptual masking.
- **Blind watermarking implementation:** The current approach assumes access to certain reference coefficients. Designing a fully blind extraction mechanism would increase practical usability, especially in medical and forensic applications.

- **Extending evaluation to mixed-combination attacks:** Future work can include benchmarking under sequential and compound distortions—compression + rotation, noise + cropping, etc.—as suggested in several of the reviewed papers.

In conclusion, the DWT–PSO watermarking framework developed in this dissertation provides a strong foundation for adaptive, perception-aware, and computationally efficient watermarking. With further integration of advanced transforms, deep learning, and improved optimization strategies, this work can evolve into a highly scalable and secure watermarking system suitable for real-world multimedia protection applications.

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