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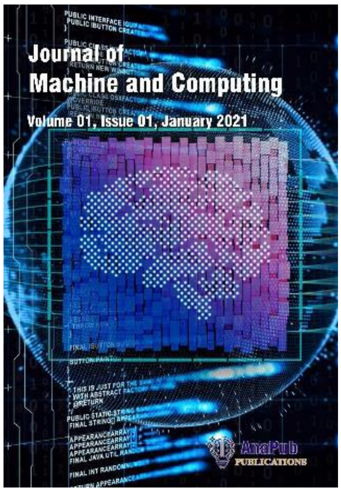

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Weight-Optimized Genetic Algorithm-Driven Machine Learning Models for Robust Digital Video Watermarking Methods

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Abstract

Video piracy is increasing due to the standard implementation of online streaming services and storage solutions, posing significant concerns about the security of multimedia content and Intellectual Property Rights (IPR). Digital Watermarking (DW) is a revolutionary technology that enables multimedia IPR by hiding and securing intellectual property from cyberattacks. DVW is now recognized as the primary point of study for data verification and IPR security measures. Watermarks are hidden tags used to detect IPR crimes and authenticate data reliability. The Least Significant Bit (LSB) to DVW is proposed to enhance data source verification, thereby increasing the possibility of reducing Mean Square Error (MSE). A Genetic Algorithm (GA) is employed to mitigate the adverse effects of LSB while enhancing the Peak Signal-to-Noise Ratio (PSNR), a crucial metric of watermarking quality. This research work employs statistical methods and experiments to analyze the difficulty of computation, accuracy, resource utilization, speed, and endurance as metrics for performance. With PSNRs exceeding 45.19 dB, the method demonstrates robustness against background noise, filtering, and video encoding. With empirical findings from experiments demonstrating a 75% Normalized Cross-Correlation (NCC), 97.89% training accuracy, and 96.78% validation accuracy, the proposed method outperforms hiding and security methods in terms of accuracy.

Keywords: Digital Video Watermarking, Genetic Algorithm, Intellectual Property Rights, Mean Square Error, Peak Signal-to-Noise Ratio, Accuracy.

1. Introduction

Digital Video Watermarking (DVW) secures network images by hiding data in cover images, requiring approval for accurate extraction. Watermarks can be hidden messages, random bits, or electronic signatures. DVW is an expansion of the Image Watermarking Technique (IMT) [1]. Watermarks, incorporating cryptography, noise transformation, and entropy, provide security by hiding from Machine Learning (ML) and human vision, while IWT ensures visibility even in corrupted images. DVW is a methodology employed in movies, which features a rapid number of frames to create the illusion of motion. A method that includes metadata about Intellectual Property Rights (IPR) precisely in the metadata of multimedia contents is identified as data integration. There is a difference between this method and cryptography in that encoding secures the data while it is being transmitted, and decoding must be performed to recover the data in its original form.

A watermark [2], however, is designed to be an integral part of the content, even when presented in its original form. Because of this, data can be accessed and refreshed without any delays being triggered. Hence, Digital Watermarking (DW) provides content creators and distributors, ranging from authors to service providers, with an effective means to preserve their IPR concerning multimedia data. These rights encompass the ownership of the work and the capacity to disseminate and alter it. A practical implementation of DW entails several key stages: generation, insertion, detection, and resilience against attacks.

Watermarking algorithms are invisible and robust—the values of these features conflict. Prominent scaling factors compromise cover image quality and algorithm robustness, whereas smaller values enhance invisibility [3]. The watermark may contain either verifiable and essential information or insignificant data that serves only as an identifier. Valid information can be readily verified; however, minor data typically requires encryption for further security. The embedding process, vital for watermarking, relies on achieving a delicate equilibrium between imperceptibility and robustness, which frequently conflict. Embedding data in the spatial domain is straightforward and has minimal impact on perceptual quality, particularly when utilizing the Least Significant Bits (LSB). However, it typically lacks the identical resilience as frequency domain approaches [4]. Using CNN, combined with historical data, automates the inverse problem, while a hidden watermark with edge positions and object labels enhances image processing. These methods encompass the utilization of the Arnold Transform (AT), Discrete Wavelet Transform (DWT), Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), and other methods. These methods include the watermark in specific frequency coefficients to maintain the integrity of the original image. Optimization methods, particularly Genetic Algorithms (GA), have enhanced embedding efficiency by identifying optimal positions for the watermark. This ensures that the watermark is undetectable and durable.

Setting a threshold for confirmation and verifying the presence of the watermark are both essential stages in the watermark detection process. Typically, the process involves using Normalized Cross-Correlation (NCC) to conduct these tests. This stage is significant as it establishes the foundation for future identification and assessment of the level of similarity with the original watermark and ownership certification [5]. The impact of this cannot be emphasised for instances where the watermark includes data of importance. Despite this, it sets the basis for the following recognition tries.

Watermarking video content, on the other hand, presents a distinct set of problems. Several distinct types of cyberattacks can be performed by adding watermarks to specific clips of video that are included within the spatial domain. There is a risk that these attacks will result in the watermark being modified or wiped out, making it hard for the person who received it to recognise it. A more complicated video watermarking is required to endure such modifications. This is why media content is vulnerable to change due to various factors. The introduction of watermarks has become increasingly challenging due to advancements in video manipulation and encoding methods, necessitating the adoption of different approaches [6].

For this explanation, the watermarks must not be changed in any process, not only by unexpected modifications but also by malicious attempts to eliminate or change them. In the modern digital media era, the accessibility of multimedia content is vital, and it is essential to watermark video content with an electronic signature that is easy to verify. As a result, we must develop enhanced DVW solutions that can withstand multiple attacks without compromising the video quality. In a context where IPRs are more vulnerable to copyright infringement, the development of such methods aims to enhance digital IPR governance and prevent unauthorized data distribution. This will enable the safeguarding of the authenticity of digital media and the associated ownership rights. A new differential evolution in wavelet domain color DVW algorithm utilizes color images as cover images, incorporating the Arnold transform on the watermark image before the embedding process, thereby improving performance based on singular value decomposition theory.

The main contributions of this paper are as follows:

a) An ML for DVW with data hiding has been deployed.

b) The DVW is adapted to handle multi-size original videos, generating better invisibility and robustness.

c) The invisibility and robustness of the proposed WOGA-LBS-DVW surpass those of existing works.

The overall structure of this article is as follows: Section 2 addresses related research on existing IMT, and Section 3 explains the WOGA-LBS-DVW proposed for use in DVW, using ML. In Section 4, the experiment's results are discussed, and in Section 5, this study concludes by presenting ideas for further research.

2. Related works

Opposition-based Particle Swarm Optimization (OPSO) was another idea by the researchers. In this model, every particle oscillates between the best value it has previously achieved and the best value achieved globally up to this stage [7].

The Cauchy's Mutation Method (CMM) is used for the particle that has been determined to be most effective globally [8]. The method entails including the global best value of the particle in each iteration. This results in the search space for the particle with the highest value being increased, which helps the particles move from their current location towards superior positions.

The researcher recommended an innovative method that featured the use of the contourlet transform and chaotic Particle Swarm Optimisation (CPSO). By employing the standard deviation and the neighborhood method, which utilizes low-frequency sub-bands, one can improve the image quality of low-resolution images. The result is that the image's overall quality has improved as a result of this process. To examine the optimum settings for an image that result in an enhanced image and better noise reduction, CPSO is performed [9].

One method the author suggested combines the DWT with PSO to segment the source image into four different sub-bands (LL, LH, HL, and HH); the DWT is used throughout the entire process. After that, it is linked to the frequency domain of the image that generates the output [10].

To introduce watermarks into the given frame, the authors conducted multiple investigations pertinent to watermark implementation using the DWT as the transform domain. At locations where watermark implementation is employed, high-frequency sub-bands have been selected for exploitation. While the study [11] indicates that the frequency domain has the advantage of achieving a higher level of security compared to the spatial domain, it is not successful in addressing a variety of circumstances involving attacks.

The researchers [12] introduced their concept of graph-based transform to the system of video compression, taking into account graph-based transform designs and edge-adaptive layouts for video encoding and decoding.

By integrating with Hybrid Grey Wolf Optimisation (GWO), the authors propose a large-scale optimisation that can be applied to address complex global optimisation problems. The authors propose a secure watermarking that uses hyperchaotic encryption on binary watermarks to enhance the security of the watermark [13]. The anticipated solution effectively attained high PSNR, NC, and SSIM ratios in the context of several attacks. The authors used graph-based transform, singular-value decomposition, and hyperchaotic encryption on specific video frames. Although the findings were acceptable, optimisation could still make them more efficacious [14].

3. Proposed Methodology of Weight Optimized Genetic Algorithm Based Least Significant Bit Substitution Method for DVW (WOGA-LBS-DVW)

DVW is an expansion of DVT. In the context of DVW, a rapid succession of frames is displayed to create the perception of motion, similar to the method employed in movies. It is a method that integrates IPR data directly into the data of multimedia files. This method differs from encryption in that encryption protects the material during transmission and requires decryption to access the original data [15]. On the other hand, a watermark is designed to be a permanent part of the content, even in its original form. This enables the material to be accessed and updated without any hindrance. Hence, DVW provides content creators and distributors, ranging from authors to service providers, with a potent means to preserve their IPR concerning multimedia data. These rights encompass the ownership of the work and the capacity to disseminate and alter it.

A practical implementation of watermarking involves several key stages, including generation, insertion, detection, and resilience against attacks [16]. The watermark may contain either verifiable and vital information or insignificant data that serves only as an identifier. Valid information can be readily verified; unimportant data typically requires encryption for further security [17]. The embedding process for DVW involves balancing imperceptibility and robustness, which can frequently conflict. Spatial embedding, primarily using the LSB, is straightforward but has low perceptual quality.

However, it lacks the resilience of frequency domain methods, like AT, DFT, DCT, and DWT, which are used to embed watermarks into specific frequency coefficients, thereby ensuring the integrity of the original image. Optimization, particularly Genetic Algorithms (GA), has enhanced embedding efficiency by identifying optimal positions for the watermark. This ensures that the watermark is undetectable and durable. Setting a threshold for confirmation and verifying the presence of the watermark are both essential stages in the watermark detection process. Typically, the process involves using Normalized Cross-Correlation (NCC) to perform these procedures. This stage is significant as it establishes the foundation for future identification and assessment of the level of similarity with the original watermark and ownership certification. This is especially important when the watermark contains valuable data.

Additionally, it establishes the foundation for subsequent identification. However, DVW content presents its distinct challenges. Applying watermarks to individual video frames within the spatial domain is vulnerable to different attacks. These attacks might lead to the alteration or destruction of the watermark, making it undetectable to the recipient [18].

Given the susceptibility of the medium, it is necessary to employ a more complicated method of DVW that is sufficiently resilient to withstand such alterations. Through the use of spatial domain watermarking methods and a focus on the frequency domain, the study presents an enhanced approach to video watermarking. Due to its faint visibility to the human eye, the blue color plane is the subject of careful processing for every video frame. An Evolutionary Algorithm (EA) is used to strategically embed a binary watermark into the blue plane, aiming for a high Peak signal-to-noise ratio (PSNR) and a small mean square error. Watermarks are meticulously recovered using an extraction approach focusing on the least significant portion of the blue plane for robustness, even in the case of frame loss. The work also explores the watermarking of 24-bit color films, using PSNR analysis for efficacy assessment and DFT for frequency domain modulation to provide a complete digital security layer [19].

- **Frame Partitioning:** The initial step involves partitioning the digital video into individual frames, establishing the foundation for subsequent watermark embedding processes.
- **Color Plane Segmentation:** Segmentation within each frame occurs in fundamental color planes (RGB). The emphasis on the blue plane is due to its reduced visibility to the human eye, making it an ideal candidate for covert watermark embedding.

- **LSB Substitution:** The LSB of the blue plane is intended to be the endpoint of the watermark encoding procedure. This method allows for less graphical impact while simultaneously generating distance for an array of data in the video.
- **GA for Optimization:** Designing a WOGA helps refine the method of embedding. To ensure the integrity and transparency of the integrated watermark, this method maximizes the setting variables to reduce MSE. An Equation (1) that can be applied to symbolise the optimisation method is as follows:

$$Optimization: \theta^{*} = argmin(1/N \sum_{i=1}^{N} (Y_i - \widehat{Y_i})^2) \quad (1)$$

- **Peak Signal-to-Noise Ratio (PSNR) Evaluation:** The PSNR is a statistical measure used to assess the performance of the watermarking procedure. It is determined for each colour plane following the watermark has been set. To ensure the authenticity of the graphic representation, the plane with the finest PSNR, which implies the lowest MSE, has been chosen for implementation. In Equation (2), the PSNR Equation is provided by:

$$PSNR = 10 \log_{10}(\frac{MAX^2}{MSE}) \quad (2)$$

- **Frame Reconstruction:** To rebuild the watermarked structure, the colour planes are restored. This ensures that the implanted watermark will remain invisible and secure for every frame of the video.
- **Repetition Across Frames:** It is necessary to perform every stage of watermarking on every frame to ensure that the watermarking is reliable and uniform across the entire video format.
- **Frequency Domain Modulation using DFT:** Applying DFT, pixels shift from the spatial domain to the frequency domain to allow improved watermarking in 24-bit colour videos. The DFT is expressed as Equation (3), which introduces a phase that adds to the method's complexity.

$$F(u, v) = f(x, y). e^{-j2\pi(ux+vy)} dxdy \quad (3)$$

- **Pseudorandom (PN) Sequence Modulation:** To achieve a higher degree of security and originality throughout the watermarking procedure, the watermark is applied by the practice of a PN signal after the frequency domain change.
- **Final Watermarked Video Output:** Upon applying the proposed methodology to each frame sequentially, the output is a fully watermarked digital video. Integrating WOGA,

LSB substitution, and frequency domain modulation contributes to an effective and secure DVW.

- **Normalized Cross Correlation (NCC):** The NCC measures the similarity between the original and extracted watermarks, with a value ranging from 0 to 1. Different Initial Populations with 64-variable random matrices start the GA. Creating population: 100 chromosomes with 64 variables each. The Highest Fitness Value is selected by roulette: rank scales and single-point cross-over. The mutation Rate is 0.04, and the cross-over fraction is 0.8. 400 Generations and 5 Elites are used in Equation (4).

$$\mathrm{NCC} = \frac{\sum_{i=0;j=0}^{m-1;n-1} DW(i,j)W_{Ext}(i,j)}{\sum_{i=0;j=0}^{m-1;n-1} DW(i,j)W(i,j)^2} \tag{4}$$

3.1. Genetic Algorithm (GA)

GA is to optimize genetic traits through heredity, mutation, selection, and crossover processes. It generates a random population of *'n'* variables, assesses it in *'M'* iterations, and selects parents from the fittest [20]. The algorithm stops when the population reaches a satisfactory fitness level or generates the maximum number of generations.

In the GA, the most critical factors that are used here:

- **Selection:** It implements Darwin's principle of survival of the fittest, removing weaker populations while maintaining the strongest. Low-fitness individuals are eliminated, leaving N-N as promising candidates for reproduction and for future generations to inherit.
- **Cross Over:** By selecting a crossover point between their first and last genomic factors and exchanging each other's tails, two Ngood parents can produce new offspring.
- **Mutation:** The offspring are born with fresh features entirely distinct from their parents. This results in the integration of genetic diversity into the population.

3.2. Arnold Transform (AT)

For secure image transmission, image encryption breaks pixel order. Arnold, Fibonacci, Hilbert curve, Affine, Magic square scrambling, Grey code transformation, and Latin square orthogonal transform are frequently used transform methods [21]. AT's relatively simple computation, setup, and cyclical features, known as the cat face transform, make it useful in watermark image encryption (Equation 5).

$$\begin{bmatrix} a' \\ b' \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} MOD(n), where, (a,b) \in \{0,1,\ldots n-1\} \tag{5}$$

The original image's pixels are represented by (a, b), while the transformed image's pixels are represented by (a', b'), with the processed square image's height or width being *'n'*.

3.3. Discrete Wavelet Transform (DWT)

Wavelet transform improves on the Fourier transform's constant resolution to propose multi-resolution and regional signal processing. It performs frequency analysis and digital signal processing. The method is commonly employed in Discrete Digital Algorithms (DDA), particularly DWT. DWT splits an image into four sub-bands, LL, HL, LH, and HH, and simulates the sub-bands. Low-frequency subbands are separated into four. This method has been employed across numerous domains.

3.4. Discrete Fourier Transform (DFT)

A signal's Fourier transform can be described as a sequence of equal-frequency bits in the DFT. The Fourier series illustrating cyclic sequences is the DFT of finite-length sequences, so they are interrelated. Frequently recurring functions are the sum of sines and cosines with distinct frequencies or their average multiplied by a weighting function. The frequency domain is the 2D DFT of the image.

The DFT handles 1 discrete-time signal and 1 discrete number of frequencies. The information is contained in a time-limited signal (0, 1, ..., $L-1$) with $N \geq L$ frequencies, and it's beneficial to examine the effects of removing frequencies except N for periodic signals, Equation (6).

$$DW_k = \frac{2\pi}{N} k; x = 0,1,..N-1 \tag{6}$$

- **Discrete-Time Fourier Transform (DTFT) Review:** The study reviews the DTFT and its inverse for a standard unpredictable signal *x (DW)*, as shown in Equation (7).

$$x(DW) = \sum_{n=-\infty}^{\infty} x(n)e^{-wn} \tag{7}$$

- **Discrete-time Fourier Series (DTFS) Review:** Recall that for an N-periodic signal $x(N)$, Equation (8).

$$x(N) = \sum_{k=0}^{N-1} c_k e^{\frac{2\pi}{N} kn} \tag{8}$$

The frequency domain is determined by *F(u)* values, which are the frequencies of each of the *M* terms of *F(u)*. Periodic functions are formed by multiplying sines and cosines of different frequencies, while non-periodic functions are expressed as sines and cosines multiplied by a weighting function [22].

3.5. Algorithm 1 for WOGA-LBS-DVW

Algorithm 1 WOGA-LBS-DVW

Input: Test Digital Video Footage

Output: DVW

Step 1: Input actual Digital Video Footage HI

Step 2: Apply a random transformation to reposition the Original Image (OI) to generate a Reordered Image (RI)

Step 3: Decode OI is divided as: {LL, HL, LH, HH} using WOGA

Step 4: Choose all the high bands of LL, HL, LH, HH, and then apply WOGA to all to attain {SH1, SH2, SH3}

Step 5: Apply a single level of WOGA, split into DVW images as sub bands: {LL1, HL1, LH1, HH1}

Step 6: $DVW_n = DVW_i + DVW_j$, where i = 0, 1, 2 to change {SH1, SH2, SH3}

Step 7: Generate {LL, LH01, HL01, HH01} using the updated WOGA confusion matrix

Step 8: Assign inverse WOGA to all high bands of {LL01, LH01, HL01, HH01}

Step 9: Assign the inverse WOGA

Step 10: Applying the inverse random DVW, shift to the actual image location to generate a DVW image

3.6. Algorithm 2 for Video Frame Selection

Algorithm 2 Video Frame Selection

Input: N ← Total Video Frames; M = Mean (M); S = Std Deviation (T); $M_b \leftarrow M + \alpha S$; $F_k \leftarrow$ Frame difference

Output: Selected (T)

Begin

For j←1 to T

{

Input (T) and Store in variables

Estimate the tolerance between video frames and store it in F_k

If ($F_k > M_b$) **Then**

{

Select and Class

Apply a random key between video frames from multiple classes

Store Video Frames in the database server

}

End If

}

End

4. Results and Discussion

All experiments, including model training, inference, and evaluation, were executed using a hybrid software-hardware configuration optimized for ML tasks. The training phase was conducted on a workstation equipped with an NVIDIA RTX A6000 GPU (48 GB VRAM), an AMD Ryzen Threadripper 3970X 32-core CPU, and 256 GB DDR4 RAM, operating under Ubuntu 22.04 LTS. All deep temporal models were implemented in Python 3.10 using the PyTorch 2.0 framework with CUDA 11.8 backend for GPU acceleration. Data preprocessing and signal transformation pipelines were executed using NumPy, SciPy, and scikit-learn libraries, with visualization performed via Matplotlib and Seaborn. Edge deployment testing was performed on a Jetson Xavier NX module (16 GB RAM) running NVIDIA JetPack SDK 5.0, with TensorRT 8.5 used for real-time inference acceleration. Cloud-based analytics and data storage were supported using a private PostgreSQL instance and Grafana dashboard for real-time monitoring. This integrated configuration ensured that training and deployment pipelines remained consistent across development and embedded execution environments, enabling reliable transferability of experimental findings.

The host image and logo were the 512 × 512 Grayscale Lena image and a 64 × 64 grayscale GRIET emblem [23]. The proposed watermarking was measured against many attacks, including sharpening, averaging, rotation, scaling, Gaussian noise, motion blur, disk blur, JPEG compression, vertical flipping, horizontal flipping, and cropping. The PSNR and NCC are applied to measure the performance of the DVW [24].

An 8 × 8 matrix, which is effectively a grid and may be supposed of as being analogous to a tableau or a mosaic. Each cell in this matrix is like a square in an image; it stores a numerical value that falls anywhere within a broad spectrum ranging from 0 to 16,777,215 inclusive. Imagine that each number is a unique colour on an artist's palette and that they are all coming together to build a more incredible image [25]. The enormous numerical range corresponds to the depth and richness of colours possible in a 24-bit RGB colour space, a colour system in which each colour is formed by combining red, green, and blue components.

In this high-definition space, every colour is defined by a combination of these three main colours, and each primary colour is permitted a range of 256 shades, ranging from its purest form (255) to the lack of colour (0). This allows for a total of 16.7 million possible colour combinations. When these values are changed to their 24-bit binary equivalents, we can see three distinct levels or "planes"—one for each of the primary colours: RGB. It's similar to taking apart a woven tapestry to uncover the individual RGB strands that make up the rich tapestry's colours when intertwined. These colour planes, in their binary forms, expose the underlying digital DNA of the test image. The 0 and 1 are interwoven to bring the colours to life, and the binary structure of the colour planes reveals this digital DNA.

The numbers supplied are a condensed representation of this colourful tapestry in numerical form; they are now waiting to be translated into a binary language that computers can comprehend. This process of embedding and decoding is analogous to a hidden conversation between the creator and the machine. It's a secret message sent in the language of numbers and binary, and it becomes wholly logical only after it is retranslated back into the colourful language of visual perception. It is an act of subtle modification, a whispered secret carved into the artwork itself when a watermark is embedded into the least significant portion of the blue colour plane.

A watermark is a binary pattern symbolising a signature or a hidden image. A watermark may be embedded into the blue colour plane. It is as if the artist has left an almost undetectable trace, a marker that may identify the work as legitimate while not detracting from the overall beauty of the artwork. This study is a testament to the unfolding of an evolutionary story within the world of digital expertise as a GA works to refine the watermarking. The algorithm selects the best watermark that fits the image, ensuring that the concealed signature does not compromise the image's quality in the same way that normal selection favors characteristics that improve an organism's chances of survival without risking its capacity to continue existing. The layout that has been visualised is an investigation of visual data, encryption, and the balancing act that must be managed between accessibility and secrecy. The idea has been integrated into its colours as well as the watermark that is set within it.

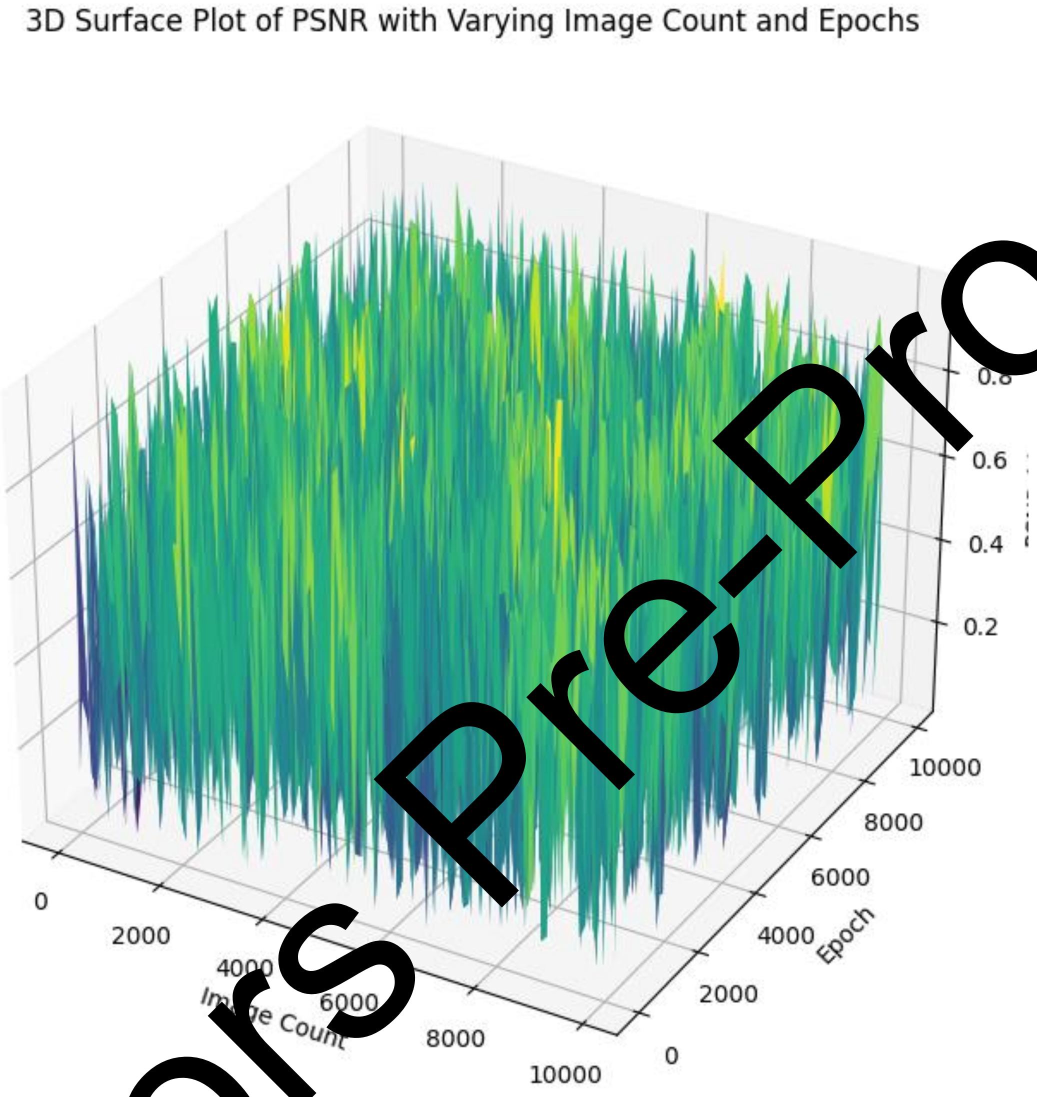

Figure 1. Comparison of PSNR.

Within the evaluation of DVW networks, the results of different methods are measured using the PSNR statistic. Other methods, including those considered state-of-the-art and those considered standard, are being investigated in the frequency, spatial, and hybrid domains. To perform an in-depth assessment, standard video datasets are used, which encompass a broad spectrum of types, resolutions, and varying degrees of data complexity.

From the method of correlating the watermarked videos with the original videos, the PSNR for each DVW is computed. This includes helpful data on the efficiency and robustness of the methods used. The research aims to expand knowledge of how effectively different methods perform in real-world situations by presenting the advantages and disadvantages of each method.

The data that follows illustrates the recommended approach used to decrease the MSE of that specific image. As shown in Figure 1, the PSNR statistic is used to analyze numerous DVWs in a detailed manner, assessing the results. A broad range of methods, comprising innovative and conventional methods, have been integrated into the assessment. These approaches cover the frequency, spatial, and hybrid domains. To conduct an in-depth study, standard video datasets are utilized that encompass a diverse range of formats, resolutions, and data complexities.

To collect valuable data on the performance and adaptation of these methods, the PSNR and NCC for each DVW must be determined by comparing watermarked videos with the raw footage. Applying a logical method, the research examines the positive and negative features of several methods, thereby gaining a deeper understanding of their effectiveness.

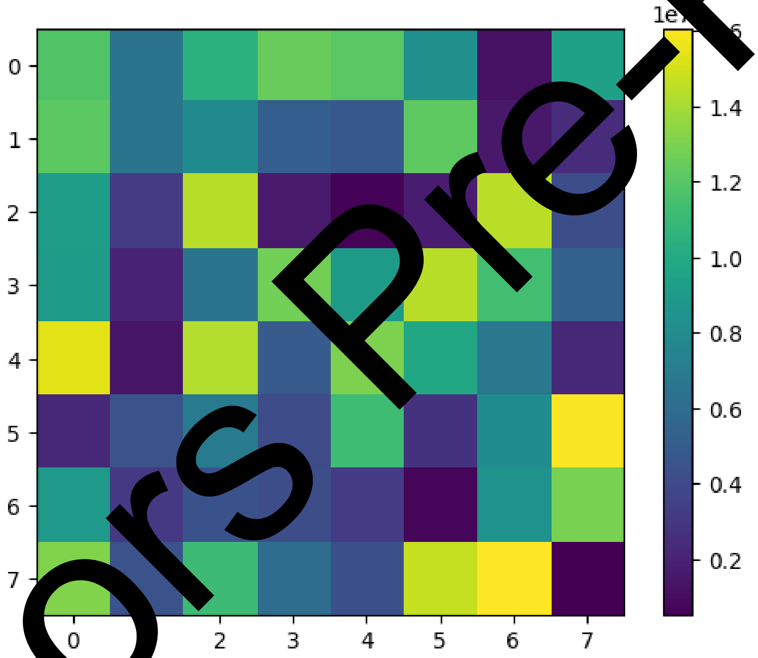

Figure 2. The pixel dimension of the matrix (8 × 8)

Figure 2 demonstrates the pixel dimensions of a matrix with an 8 × 8 configuration, presenting a visual representation of the data's basic structure.

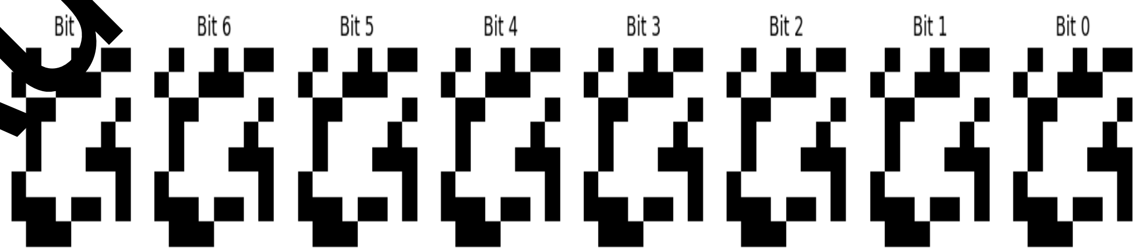

Figure 3. RGB bit plane.

Figure 3 illustrates RGB bit planes, illustrating how each bit of the color channels RGB contributes to the overall composition of an image.

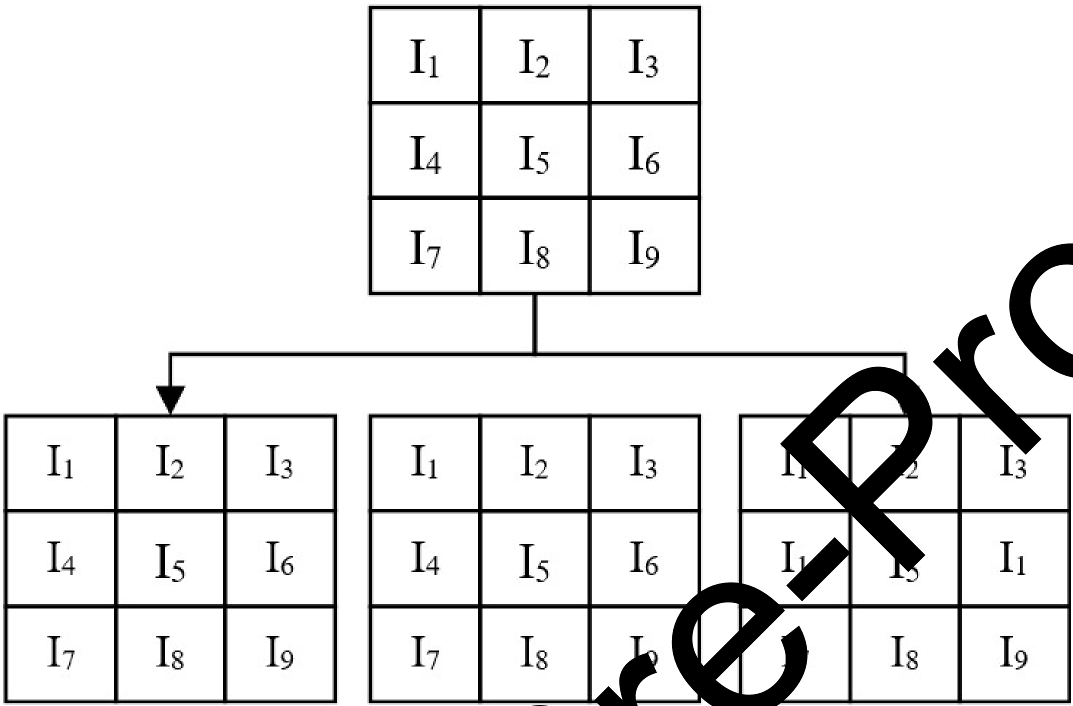

Figure 4. GA was used to optimize the MSE.

Figure 4 proves the EA used to minimize the mean square error of images. This GA is pivotal in refining the watermarking process, contributing to enhanced performance and robustness in practical applications. The visual representations accompanying the text elucidate the complexities and optimizations involved in the comparative analysis and the EA utilized in the study.

5. Conclusion and Future Work

The watermarking procedure becomes increasingly complicated as multimedia editing and encoding methods become more cutting-edge. Not only will this prevent unexpected evolution, but it will also prevent premeditated attempts to eliminate or manipulate the watermarks on them. Applying a reliable digital signature to watermark footage is of the utmost importance in this digital age, considering the ease with which multimedia content can be duplicated and shared. This highlights the vital requirement to develop more robust watermarking methods that can withstand numerous types of attacks without compromising the quality of the footage. Enhancements in digital rights management and security against illegal transmission are the primary objectives of these methods, which are being implemented in a context where IPR is more vulnerable to piracy. Securing the authenticity and IPR of multimedia will be rendered feasible by technology. The Weight Optimized Genetic Algorithm has provided a robust and untraceable method to the DVW-based Least Significant Bit Substitution Method for Digital Video Watermarking (WOGA-LBS-DVW). It outperforms invisibility and robustness, with 75% Normalized Cross-Correlation, 97.89% training accuracy, and 96.78% validation accuracy.

Complete security analyses, content-based adaptive embedding methods, real-time application optimisation, performance-enhancing Deep Learning integration, and increased support for multiple types of videos are all potential future improvements.

Additional research into probable applications, such as user authentication for online media, could enhance the method’s value and adaptability in evolving computing environments.

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