HARNESSING CONVOLUTIONAL NEURAL NETWORKS FOR ROBUST DIGITAL IMAGE WATERMARKING

A PROJECT REPORT

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ABSTRACT

In the era of digital communication and multimedia sharing, ensuring the integrity and ownership of digital content has become increasingly crucial. Digital watermarking techniques offer a solution by embedding imperceptible yet detectable signals within multimedia content, serving as a form of copyright protection and authentication. This research presents a novel approach to digital watermarking using convolutional neural networks (CNNs). The proposed technique involves the training of a CNN model to embed binary watermarks into images, followed by a demodulation and extraction process to recover the watermark from watermarked images. Evaluation metrics such as Bit Error Rate (BER), Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR) are employed to assess the fidelity of the watermarked images and the accuracy of watermark extraction. Comparative analysis with traditional watermarking techniques demonstrates the effectiveness of the CNN-based approach in terms of robustness and imperceptibility. The results showcase the potential of CNNs in enhancing the security and authenticity of digital content through watermarking, paving the way for advanced applications in digital rights management and content authentication.

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LIST OF ABBREVIATIONS

CNN	CONVOLUTIONAL NEURAL NETWORKS
DWT	DISCRETE WAVELET TRANSFORM
PSNR	PEAK SIGNAL-TO-NOISE RATIO
MSE	MEAN SQUARED ERROR
BER	BIT ERROR RATE

CHAPTER 1

CHAPTER 1

CONCEPTS OF WATERMARKING SYSTEM

1. INTRODUCTION

Most multimedia signals today are in digital formats which are easy to reproduce and modify without leaving any trace of manipulations. It istherefore very simple to tamper with any image and make it available to others. Authentication technologies fulfill an increasing need for trustworthydigital data in commerce, industry and defense. Watermarking has become a popular technique for copyright enforcement and image authentication.

Here, an effort has been made to present a novel method for image authentication with localization for the purpose of tamper detection.

This chapter presents an outline of the thesis in section 1.1. Section 1.2 defines elements of a general watermarking system starting with data embedding to data recovery. Protocol considerations and Applications of watermarking system are detailed in section 1.3 and section 1.4 respectively. General data authentication system through watermarking and requirements of data hiding based authentication are described in sections 1.5 and 1.6 respectively. Contribution of this thesis has been summarized in section 1.7.

1.1 OVERVIEW

The thesis is organized into six cohesive chapters, each contributing distinctly to the exploration and advancement of watermarking techniques for data security.

Chapter 1, "Introduction to Watermarking," initiates the journey by establishing a foundational understanding of watermarking. Here, the imperative

role of watermarking in safeguarding data integrity is underscored, accompanied by an elucidation of key terms and concepts essential for navigating the subsequent discourse.

In Chapter 2, "Literature Review," a panoramic survey of existing scholarship in the realm of watermarking is meticulously conducted. The chapter traverses through the diverse terrain of image authentication and allied disciplines, scrutinizing various fragile watermarking algorithms and addressing pertinent challenges therein.

Chapter 3, "Existing Watermarking Strategies," delves into an exhaustive examination of current methodologies employed in watermarking. By dissecting the intricacies of prevailing techniques and algorithms, this chapter elucidates the modalities of watermark embedding, featuring an in-depth exploration of hosting features and embedding rules, with particular emphasis on blind embedding schemes.

Building upon the insights gleaned from existing strategies, Chapter 4, "Proposed Watermarking Strategy," unveils a novel approach conceived within the research. Here, the theoretical underpinnings and practical intricacies of the proposed strategy are expounded upon, accompanied by an appraisal of its comparative advantages over established methodologies.

Chapter 5, "Results and Discussion," serves as the crucible wherein the efficacy of the proposed watermarking strategy is subjected to rigorous evaluation. Through empirical analysis and deliberation, the chapter elucidates the performance of the system under diverse conditions and adversarial scenarios, thus affording critical insights into its robustness and viability.

Lastly, Chapter 6, "Conclusion," serves as the denouement of the thesis,

encapsulating the culmination of findings and insights garnered throughout the research endeavor. Here, the implications of the research are delineated, alongside reflections on potential applications and avenues for future exploration, thus bringing closure to the narrative arc of the thesis.

1.2 PROBLEM DEFINITION

ELEMENTS OF A WATERMARKING SYSTEM

According to a widespread point of view, a watermarking system is much like a communication system consisting of three main elements: a transmitter, a communication channel, and a receiver [1]. To be more specific, the embedding of the to-be-hidden information within the host signal plays the role of data transmission; any processing applied to the host data after information concealment, along with the interaction between the concealed data and the host data itself, represents the transmission through a communication channel; the recovery of the hidden information from the host data acts the part of the receiver. By following the communication analogy, any watermarking system assumes the form given in Fig.1.1.

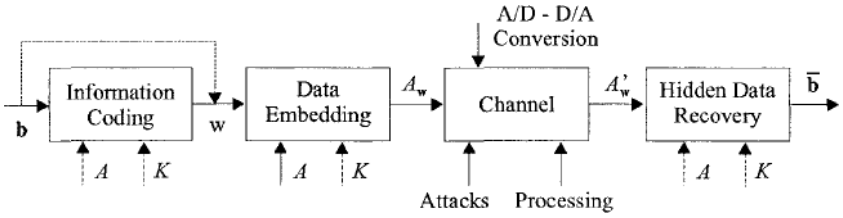


Fig.1.2.1: Data Hiding System

The information to be hidden within the host data represents the input of the system. Without losing generality, it is assumed that such information is given in

$$b = (b_1, b_2, b_3, b_4 \ldots . b_k) \qquad \ldots\ldots\ldots\ldots (1.1)$$

the form of a binary string.

With b_k taking values in {0, 1}. The string b is referred to as the watermark code. At the transmitter side, a data embedding module inserts the string b within a piece of data called host data or host signal. The host signal may be of any media type: an audio file, a still image, and a piece of video or a combination of the above. The embedding module may accept a secret key K as an additional input. Such a key, whose main goal is to introduce some secrecy within the embedding step, is usually used to parameterize the embedding process and make the recovery of the watermark impossible for unauthorized users which do not have access to K. The functionalities of the data embedding module can be further split into three main tasks: (i) information coding; (ii) watermark embedding; (iii) watermark concealment.

INFORMATION CODING

In many watermarking system, the information message **b** is not embedded directly within the host signal. On the contrary, before insertion, vector **b** is transformed into a watermark signal $\mathbf{w} = \{w_1,,w_2 \ldots w_n\}$ which is more suitable for embedding [2]. In a way that closely resembles a digital communication system, the watermark code **b** may be used to modulate a much longer spread-spectrum sequence, it may be transformed into a bipolar signal where zero's are mapped in +1 and one's in —1, or it may be mapped into the relative position of two or more pseudo-random signals in the case of position-encoded-watermarking [3]. Eventually, **b** may be left as it is, thus leading to a scheme in which the watermark code is directly inserted within *A*, the host image. In this case, the watermark signal **w** coincides with the watermark code **b**. Before transforming the watermark into the watermark signal, **b** may be channel-coded to increase robustness against

possible attacks. As a matter of fact, it turns out that channel coding greatly improves the performance of any watermarking system.

WATERMARK EMBEDDING

In watermark embedding, or watermark casting, an embedding function ε takes the host asset *A*, the watermark signal **w**, and, possibly, a key *K*, and generates the watermarked asset A_w:

$$\varepsilon(A, \mathbf{w}, K) = A_w \qquad \ldots\ldots\ldots\ldots (1.2)$$

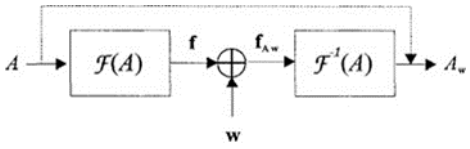


Fig.1.2.2: Watermark embedding via invertible feature extraction.

It is to be noted that the above equation still holds when the watermark code is embedded directly within *A*, since in this case **w** = **b**. The definition of ε usually goes through the selection of a set of asset features, called host features, which are modified according to the watermark signal. By letting the host features be denoted by

$f(A) = f_A = \{f_1, f_2 \ldots f_m\}$ watermark embedding amounts to the definition of an insertion operator ⊕ which transforms $f(A)$ into the set of watermarked features

$f(A_w)$

$$f(A_w) = f(\varepsilon(A, \mathbf{w}, K)) = f(A) \oplus \mathbf{w} \qquad \ldots\ldots\ldots\ldots (1.3)$$

In general m ≠ n, i.e. the cardinality of the host feature set need not be equal to the watermark signal length.

Though equations (1.2) and (1.3) basically describe the same process, namely

watermark casting within A, they tend to view the embedding problem from two different perspectives. According to equation (1.2), embedding is more naturally achieved by operating on the host asset, i.e. ε modifies A so that when the feature extraction function f is applied to A_w, the desired set of features $f_{Aw} = \{f_{w1}, f_{w2} \ldots f_{wm}\}$ is obtained.

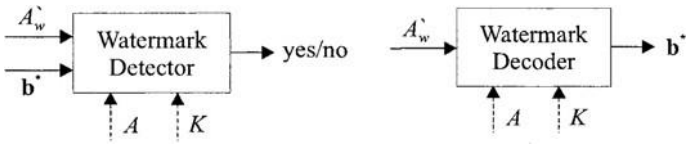
Equation (1.3) describes the watermarking process as a direct modification of f_A through the embedding operator ⊕. According to this formulation, the watermark embedding process assumes the form shown in Fig.1.2. First the host feature set is extracted from A, then the ⊕ operator is applied producing f_{Aw}, finally the extraction procedure is inverted to obtain A_w:

$$A_w = F^{-1}(f_{A_w}) \qquad \ldots\ldots\ldots\ldots (1.4)$$

RECOVERY OF THE HIDDEN INFORMATION

The receiver part of the watermarking system may assume two different forms. According to the scheme reported in Fig.1.3 (a), the watermark detector reads A'_w and a watermark code b*, and decides whether A'_w contains b* or not. The detector may require that the secret key K used to embed the watermark is known [5]. In addition, the detector may perform its task by comparing the watermarked asset A'_w with the original, non-marked, asset A, or it may not need to know A to take its decision. In the latter case, it is said that the detector is *blind*, whereas in the former case the detector is said to be *non-blind.*

Alternatively, the receiver may work as in Fig.1.3 (b). In this case the aim of the receiver is to extract b* from A'_w and the watermark code b* is not known in advance. As before, the extraction may require that the original asset A and the secret key K are known.



(a) Detectable watermarking (b) Readable watermarking

Fig.1.2.3: Watermark Recovery

The two different schemes given in Fig.1.3 lead to two different types of algorithms. One, where embedding a mark that can be *read* and other where inserting a code that can only be *detected.* In the former case, the bits contained in the watermark can be read without knowing them in advance (Fig.1.3 (b)). In the latter case, one can only verify if a given code is present in the document, i.e. the watermark can only be revealed if its content is known in advance (Fig.1.3 (a)). The extraction of a readable watermark is referred with the term watermark decoding, whereas the term watermark detection is used for the recovery of a detectable watermark.

In blind detectable watermarking, the detector is a three- argument function acceptingas input a digital asset *A*, a watermark code **b**, and a secret key *K*. As an output *D* decides whether *A* contains **b** or not, that is

$$D\ (A, \boldsymbol{b}, K)\ =\ yes/no \qquad \ldots\ldots\ldots\ldots (1.5)$$

In the non-blind case, the original asset A_{or} is a further argument of *D:*

$$D\ (A, A_{or}, \boldsymbol{b}, K) = \frac{yes}{no} \qquad \ldots\ldots\ldots\ldots (1.6)$$

In blind, readable watermarking, the decoder function takes as inputs a digital asset *A*

and a keyword *K*, and gives an output the string of bits b it reads from *A:*

$$D\ (A, K) = \boldsymbol{b} \qquad \ldots\ldots\ldots\ldots (1.7)$$

For, non-blind watermarking

$$D\ (A, A_{\gamma}, K) = \boldsymbol{b} \qquad \ldots\ldots\ldots\ldots (1.8)$$

It is to be noted that in readable watermarking, the decoding process always results ina decoded bit stream. Detectable watermarking is also known as 1-bit watermarking(or 0- bit watermarking), since, given a watermark, the output of the detector is just yes or no. As the 1-bit designation says, a drawback with detectable watermarking is that the embedded code can convey only one bit of information. Actually, this is notthe case, since if one could look for all, say *N*, possible watermarks, and then the detection of one of such watermarks would convey $log_2 N$ information bits. Unfortunately, such an approach is not computationally feasible, since the number of possible watermarks is usually tremendously high.

CAPACITY OF WATERMARKING TECHNIQUES

Although in general the watermarking capacity does not depend on the particular algorithm used, but it is rather related to the characteristics of the host signal, embedding distortion and attack strength. Capacity is a fundamental property of any watermarking algorithm, which very often determines whether a technique can be profitably used in a given context or not [6]. Possible requirements range from some hundreds of bits in security-oriented applications, where robustness is a major concern, through several thousands of bits in applications like captioning or labeling, where the possibility of embedding a large number of bits is a primary need.

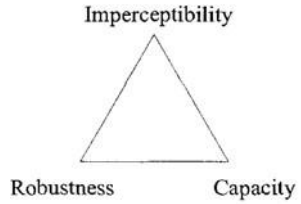


Fig.1.2.4: The watermarking trade-off.

Generally speaking, capacity requirements always struggle against two other important requirements, i.e. watermark imperceptibility and watermark robustness (Fig. 1.4). A higher capacity is always obtained at the expense of either robustness or imperceptibility (or both), it is thereby mandatory that a good trade-off is found depending on the application at hand.

ROBUSTNESS

Watermark robustness accounts for the capability of the hidden data to survive host signal manipulation, including both non-malicious manipulations, which do not explicitly aim at removing the watermark or at making it unreadable, and malicious manipulations, which precisely aim at damaging the hidden information.

Four qualitative robustness levels encompassing most of the applications can be considered as:

Secure watermarking: In this case, mainly dealing with copyright protection, ownership verification or other security-oriented applications, the watermark must survive both non-malicious and malicious manipulations [7]. In secure watermarking, the loss of the hidden data should be obtainable only at the expense of a significant degradation of the quality of the host signal.

Robust watermarking: In this case it is required that the watermark be resistant only against non-malicious manipulations. As to non-malicious manipulations,

they include a huge variety of digital and analog processing tools, including lossy compression, linear and non-linear filtering, cropping, editing, scaling, D/A and A/D conversion, analog duplication, noise addition, and many others that apply only to a particular type of media.

Semi-fragile watermarking: In some applications robustness is not a major requirement, mainly because the host signal is not intended to undergo any manipulations, but a very limited number of minor modifications such as moderate lossy compression, or quality enhancement [8]. This is the case, for example, of data labeling for improved archival retrieval, in which the hidden data is only needed to retrieve the host data from an archive, and thereby it can be discarded once the data has been correctly accessed. It is likely, though, that data is archived in compressed format, and that the watermark is embedded prior to compression. In this case, the watermark needs to be robust against lossy coding. In general, a watermark is said to be semi-fragile if it survives only a limited, well-specified, set of manipulations leaving the quality of the host document virtually intact [9].

Fragile watermarking: A watermark is said to be fragile, if the information hidden within the host data is lost or irremediably altered as soon as any modification is applied to the host signal. Such a loss of information may be global, i.e., no part of the watermark can be recovered or local i.e. only a partof the watermark is damaged. The main application of fragile watermarking is data authentication, where watermark loss or alteration is taken as evidence that data has been tampered with, whereas the recovery of the information contained within the data is used to demonstrate data origin [10].

CHAPTER 2

CHAPTER 2

LITERATURE SURVEY

A typical characteristic of digital products is that they are easy to manipulate, i.e. to store, duplicate, transmit, or modify. This is a critical issue, in return, as unauthorized use, copying, or modification of the multimedia products could be quite easy as well. Such kinds of operations are referred to as tampering and effective techniques are needed to make the multimedia contents tamper resistant and guarantee integrity and originality of the image. The most common means to defeat tampering is to embed a fragile watermark into the image to identify and localize any possible image alterations.

In this chapter a comprehensive review has been undertaken covering recent literature describing image authentication techniques. The basic watermarking principles, concept of integrity, classical examples of malicious manipulations and Generic image authentication system are described in section followed by detailed descriptions of the current algorithms of fragile authentication schemes in section 2.1.

The attacks on image authentication system are described in section concluded by the summary of different fragile watermarking methods in section. The conclusion and future research directions are presented in Section. This paves a path for the promising technology of authentication watermarking and its application for verifying the integrity of the data.

PRINCIPLE OF FRAGILE WATERMARKS

Most methods currently proposed for providing image authentication are based on a fragile watermark in opposition to robust watermark classically used for copyright protection. The basic idea underlying these techniques is to insert a specific watermark (generally independent of the image data [23]) so that any attempt to alter the content of an image will also alter the watermark itself. Therefore, the authentication process consists of locating watermark distortions in order to locate the regions of the image that have been tampered with as shown in Fig.2.1. The major drawback of these approaches is that it is difficult to distinguish between malicious and non- malicious attacks (e.g., most fragile methods consider a lossy compressed image as a tampered image, where as the semantic of the image is unchanged).

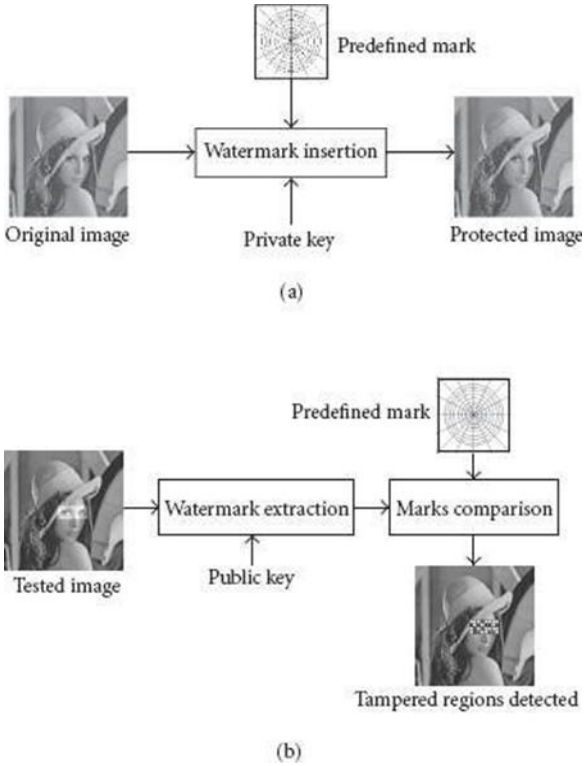


Fig.2.1: Generic fragile watermark scheme: a)Image security (b)Authenticity verification

Sattar et al. [48] proposed a fragile image watermarking scheme based on time-frequency analysis. Specifically, the watermark is chosen as an arbitrary non-stationary signal with a particular signature in the time-frequency plane. The proposed technique retains a high quality watermarked image since only a few pixels of the original image are used in the watermarking process. The advantages of this scheme are twofold. First, it can detect any small changes resulting from attacks such as scaling, translation, rotation, and compression. Secondly, the image quality is retained quite high because only a few pixels of the original image are affected in the watermarking process.

Patra et al. [49] suggested a hierarchical multiple image watermarking scheme for digital images. The main purpose of embedding two watermarks is that each watermark can be used for a specific purpose. The first watermark is intended for secure image authentication and the second one is to verify the ownership. The two watermarks are embedded into the least significant bits of the host image using a private secret key in such a way that these images remain perceptually invisible to human eyes. The multiple watermark images can be easily extracted at the receiver side blindly, without aid of the original host image. If the watermarked image is tampered in any way, the recipient can only extract the first watermark image and the region of tampering will appear on it, whereas the second extracted watermark image will reveal only a random noisy image. This indicates that the ownership verification can be carried out only with an un-tampered image. Further, if one attempts to extract the watermark(s) using a wrong secret key, then the watermark(s) will lead to meaningless random noise.

Taheri et al. [50] suggested a hierarchical fragile image watermarking scheme based on method introduced by **Byun** et al. [51]. The Byun's method was

modified to provide localization properties at the expense of higher computational complexity. To reduce the complexity of the method, the image is partitioned into blocks in a multilevel hierarchy, and then the SVD-based algorithm is employed at each level to insert authenticating data in sub-blocks. In the verification process, blocks at the lowest hierarchical level can detect modifications made to the watermarked image, while the higher level blocks locate these modifications. The advantage of this scheme is that it can indicate the location of the changes made to the image. It has been shown that a higher accuracy in tamper localization can be achieved by allowing for higher computational complexity.

Hongjie He et al. [52] suggested a fragile watermarking algorithm for secure image authentication. It uses a scrambling encryption scheme using chaotic key to extend the security and increase the capacity of the fragile watermarking algorithm. The scheme not only possesses excellent tamper localization properties, but also demonstrates a new useful feature, called tamper discrimination. That is, it can indicate whether the modification made to the image is on the contents or the embedded watermark or both. If only the watermark is modified, the verification algorithm will display isolated dots spread all over the image, not just the altered regions. Thus the authenticity of the image is assured, instead of being declared as a counterfeit.

Chuanmu Li et al. [64] proposed a fragile content-based image authentication scheme with location based on integer wavelet transform. In this scheme, the digest of each block is coded by a chaotic sequence to form its watermark, which is embeddedin another block which is selected by an ergodic matrix of a hyper-chaotic sequence. The encryption further strengthens the security. That all security parameters are user dependent makes the scheme not only robust against collage attack but also truly oblivious. The experiments demonstrate that the

proposed scheme can detect and localize any tampering of size 8x8 pixels. The MSE average was 2.18, the PSNR average was 48.8.

Information Leakage: Another classic attack tries to discover the secret key used to generate the watermark. This kind of attack, also called Brute Force Attack, is very well known by the security community. Once the key has been found, it is very easy for a "hacker" to falsify a watermark of an image that has been protected by this key. The only way to counter this attack is to use long keys to dissuade the attacker from trying to discover the key, because of the high cost of computing time.

Mark Transfer: This attack is designed for block-wise watermarking –based authentication. Attacks may use available watermarked signals to forge a valid mark for another, arbitrary media. One of the famous mark transfer attacks is the vector quantization attack proposed by **Holliman and Memon** [11]. Mark transfer attack can also be performed in the following ways: the mark is first removed, then the signal is modified and finally the mark is reinserted.

Radhakrishnan and Memon [66] proposed a **protocol attack** against the image authentication system **SARI** [67]. The image digest of the SARI system is not secure under certain circumstances. Specifically, if an attacker has the image digests for a multiple number of images where the same secret key has been used to generate the digest; it is possible to cause arbitrary images to be authenticated.

The Given Table Describes the author name and year and embedding domain.

TABLE I: LITERATURE SURVEY TABLE

Author	**year**	**Class**	**Mark**	**Embedding domain**	**Authentication information/method**
Lee and Won[45]	2000	Fragile	Image	LSB	Applied Reed-Solomon error correction codes to rows and columns of the scrambled version of the input image with LSB zeroed-out.
Wong[32]	2001	Fragile	logo	LSB	The cryptographic hash bits are either truncated or extended to the length that equals the number of pixels in a block and then XOR ed bit by bit with the corresponding watermark block and then inserted into the LSBs of pixels in the block
Sattar[48]	2003	Fragile	Non-stationary signal	LSB	Based on time-frequency analysis.
Jagdish C. Patra, Kah K. Ang and Ee- luang Ang[49]	2004	Fragile	b/w image	LSB	Embedding two b/w watermark images(for authentication & ownership verification) hierarchically into the host image using a secret key and the MD5 hash function

Phen-Lan Lin, Po-Whei Huang, An-Wei Peng[56]	2004	Fragile	Encrypted formof block signature	LSB	Watermark is embedded into the two low order bit planes of the block orderly from left -to - right and top - to- bottom.
Thai Duy Hien et al. [59]	2005	Fragile	logo	Wavelets	Watermark embedded into middle frequency sub-bands.

Author	**year**	**Class**	**Mark**	**Embedding domain**	**Authentication information/method**
Yiping[60]	2006	Fragile	Binary image	Wavelet	Secure watermarking for ROI of image authentication based onforeground extraction.
M. Hamad Hassanand S.A.M. Gilani[68]	2006	Fragile	T-channel	LSB	Watermark embedded is T channel randomly selected 2□2 blocks LSBs using 2D-Torus Auto-morphism.
Celik,G. Sharma and A.M. Tekalp[53]	2006	Fragile	Digital signatur e	LSB	Uses lossless G-LSB data embedding method.
Premaratne[61]	2007	Fragile	2D barcode	Wavelet	One barcode is inserted into the low frequency component of the image and a second barcode watermark is embedded intolowpass component ofanywaveletdecompos ition at a specific level

Jen –Sheng Tsai,Win-Bin Huang, Chao –Leih Chen,Yau-Hwang Kuo[69]	2007	Fragile(B LOCK BASE D)	Random noise	Feature points and characteristic regions	Hessian-Affine feature detector extracts characteristic regions of an image. copyright watermark is embedded into the characteristic regions. fragile block based watermark embedded into the remainder regions
Jun Sang and Mohammad S. Alam[62]	2007	Fragile/Semi Fragile	Binary Image	DFT	BPOF based watermarking method. It uses IR for detection.

Author	**year**	**Class**	**Mark**	**Embedding domain**	**Authentication information/method**
L. Parameswaran K. Anbumani[70]	2008	Fragile	Features of host image	DCT	Using Independent Component Analysis Features of host image embedded in Midfrequency DCT coefficients.
Chuanmu[64]	2008	Fragile	Digest of each block coded by chaotic sequence.	Wavelets	Encrypted watermark embedded in another block selected by an ergodic matrix of a hyper-chaotic sequence.
Chin-Chen Changetal.[63]	2008	Fragile	Image	DCT	Extracts the inherent image features and embeds them into the image as the watermark

CHAPTER 3

Chapter 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

HAAR WAVELET BASED

The watermarking model described implements a robust and efficient technique for embedding and extracting watermarks within digital images. Initially, the model loads and resizes both the original color image and the watermark image, ensuring compatibility in dimensions. Employing the Discrete Wavelet Transform (DWT) with the Haar wavelet, the model decomposes both images into four sub-bands, facilitating efficient data representation. During watermarking, the model modifies the low-frequency LL sub-band of the host image by adding a scaled version of the watermark's LL sub-band. This process seamlessly integrates the watermark into the host image while preserving its visual integrity. Subsequently, watermark extraction involves subtracting the LL sub-band of the original image from that of the watermarked image, followed by scaling to isolate the embedded watermark. Evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) ensure the fidelity of the extracted watermark. Furthermore, post-processing steps, including conversion to grayscale and median filtering, enhance the clarity and robustness of the extracted watermark. This watermarking model presents a comprehensive approach to digital watermarking, offering both embedding and extraction functionalities with considerations for accuracy and resilience against common image processing operations. Figure shows each step in the watermark embedding process outlined in the flowchart:

1. Load and Resize Images:

In this initial step, the original image intended for watermark embedding is loaded into memory. This image is then resized to a desired dimension to ensure compatibility with the watermark image. Additionally, the watermark image, which contains the desired information to be embedded, is also loaded and resized to match the dimensions of the original image. This ensures that the watermark can be seamlessly integrated into the host image without distortion.

2. Apply DWT (Discrete Wavelet Transform):

Utilizing the Discrete Wavelet Transform (DWT), the original image undergoes a multi-resolution analysis, resulting in the decomposition of the image into its constituent frequency bands. This process generates four sub-bands: LL (low-low), LH (low-high), HL (high-low), and HH (high-high). Similarly, the watermark image is subjected to the DWT, allowing it to be represented in a frequency domain suitable for embedding.

3. Watermarking:

The watermark embedding process begins by modifying the LL sub-band of the original image. This modification involves adding a scaled version of the LL sub-band of the watermark image to the LL sub-band of the original image. By doing so, the information encoded within the watermark is introduced into the host image while preserving its visual integrity. This step is crucial for ensuring that the watermark is robustly embedded and remains perceptually invisible within the host image.

4. Reconstruct Watermarked Image:

After embedding the watermark into the original image, the watermarked image is reconstructed using inverse Discrete Wavelet Transform (IDWT). This process combines the modified LL sub-band of the original image with the original LH,

HL, and HH sub-bands to produce the final watermarked image. The reconstructed image retains the visual characteristics of the original image while incorporating the embedded watermark, ready for further processing or distribution.

5. Display and Save Watermarked Image:

The watermarked image is displayed to visualize the result of the watermark embedding process. Additionally, the watermarked image is saved to a file for future reference or distribution. This step ensures that the embedded watermark is effectively integrated into the host image, ready for subsequent extraction or analysis.

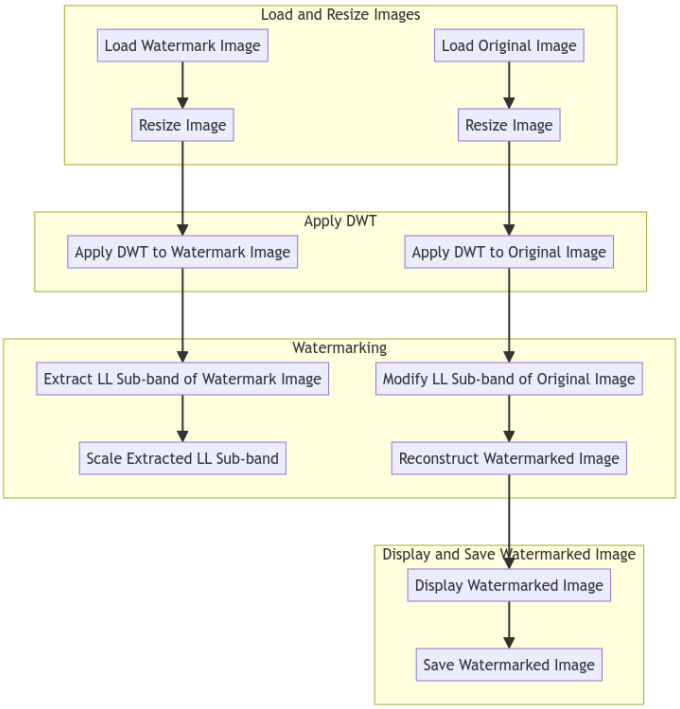


Figure 3.1.1 : Water mark embedding Process

Figure shows each step in the watermark extraction process outlined in the flowchart:

1. Load Watermarked Image:

The watermark extraction process begins by loading the watermarked image,

which contains the embedded watermark. This image is then resized if necessary to ensure consistency with the processing requirements.

2. Apply DWT (Discrete Wavelet Transform):

The loaded watermarked image undergoes the Discrete Wavelet Transform (DWT) to decompose it into its constituent frequency bands. This results in the extraction of the LL (low-low), LH (low-high), HL (high-low), and HH (high-high) sub-bands, which are essential for recovering the embedded watermark.

3. Extract Watermark:

The extraction of the watermark involves isolating the LL sub-band of the watermarked image, which contains the embedded watermark information. This sub-band is then processed by subtracting the LL sub-band of the original image, which serves to remove the original content and isolate the embedded watermark. Subsequently, the extracted LL sub-band is scaled to recover the original watermark information.

4. Evaluation Metrics:

To assess the fidelity of the extracted watermark, evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are calculated. These metrics provide quantitative measures of the similarity between the original watermark and the extracted watermark, aiding in evaluating the effectiveness of the extraction process.

5. Preprocessing:

In preparation for visualization and further analysis, the extracted watermark undergoes preprocessing steps. Firstly, it is converted to grayscale to simplify its representation. Additionally, median filtering is applied to the grayscale watermark to enhance its clarity and reduce noise, ensuring that the extracted

watermark is of high quality and suitable for further processing.

6. Display and Save Extracted Watermark:

Finally, the extracted watermark is displayed to visualize the result of the extraction process. Additionally, the extracted watermark is saved to a file for documentation or further analysis. This step ensures that the embedded watermark can be successfully recovered from the watermarked image, validating the effectiveness of the watermarking and extraction processes.

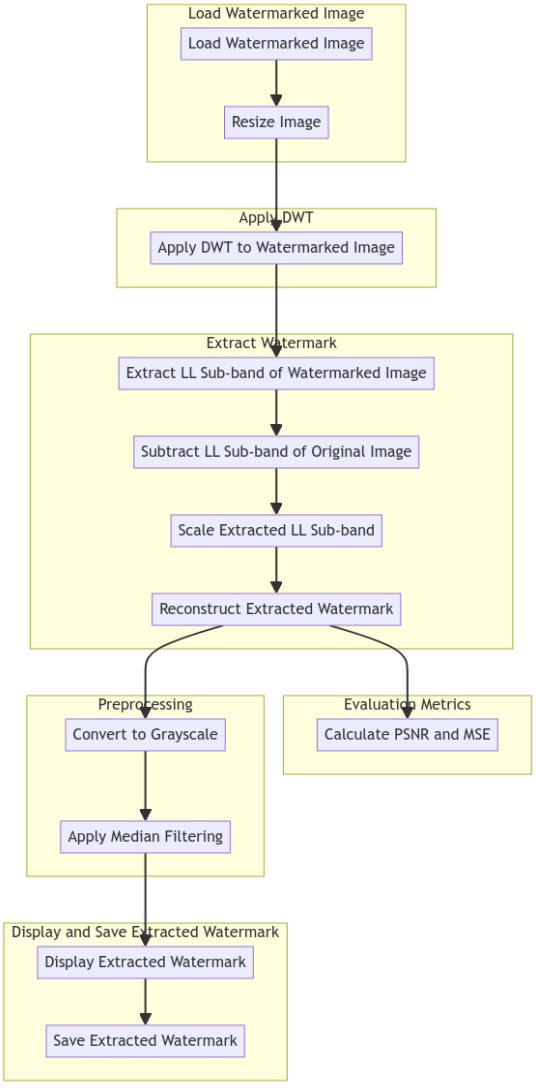


Figure 3.1.2: Watermark Extraction Process

3.2 PROPOSED SYSTEM

Proposed CNN Based Noise modulated watermarking

In the rapidly expanding digital landscape, the protection of intellectual property rights and the prevention of content piracy have become paramount concerns. Traditional watermarking techniques, while effective to a degree, often struggle to cope with the scale and diversity of digital media. To address these challenges, this paper proposes a novel approach leveraging Convolutional Neural Networks (CNNs) for automated noise modulation in image watermarking.

Watermark embedding is a fundamental process in digital watermarking, whereby a unique identifier or signal, known as the watermark, is invisibly embedded into the host multimedia content to assert ownership, authenticate the content, or convey additional information. This process is crucial for protecting intellectual property rights, combating content piracy, and ensuring the integrity and authenticity of digital assets.

The watermark embedding process involves several key steps to effectively conceal the watermark within the host multimedia content while minimizing perceptible distortion. First, the host content, such as images, videos, or audio files, is preprocessed to prepare it for watermark embedding. This preprocessing step may involve normalization, resizing, or other transformations to ensure consistency and compatibility with the watermark embedding algorithm.

Next, the watermark signal is modulated onto the host content using a specified embedding algorithm or technique. This process involves modifying certain features or characteristics of the host content to embed the watermark signal while minimizing perceptual impact. The embedding algorithm typically operates in the spatial or transform domain, altering pixel values, frequency coefficients, or

other relevant parameters to encode the watermark information.

Once the watermark signal is embedded into the host content, the watermarked content is generated and ready for distribution or further processing. It is essential to evaluate the quality and robustness of the watermarked content to ensure that the embedded watermark remains perceptually invisible and resistant to common attacks or manipulations.

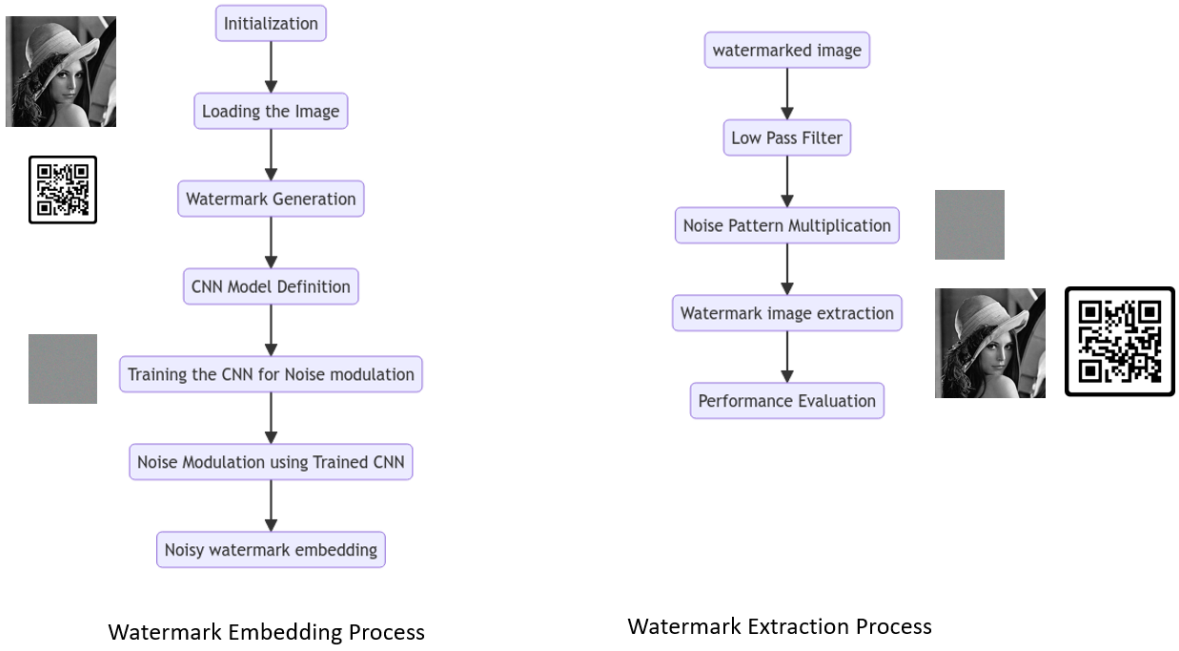


Figure 3.2.1: Proposed Process Flow of the Methodolody

The figure illustrates the proposed process flow of the methodology for CNN-based image watermarking. The process begins with data preparation, where input grayscale images are preprocessed and augmented to create a diverse training dataset. The CNN architecture design follows, involving the selection of network depth, layer configurations, and activation functions tailored for noise modulation in image watermarking. The training phase optimizes the CNN model parameters

using while testing evaluates the model's performance on separate test datasets.

Data Preparation

Data preparation is a crucial initial step in the proposed CNN-based image watermarking methodology. It involves several key processes to ensure the quality and suitability of the input data for training the neural network model.

Input Data Selection:

Grayscale images are selected as the input data for the CNN-based watermarking system. Grayscale images are preferred due to their simplicity and ease of processing, making them suitable for initial experimentation.

Preprocessing:

Input grayscale images undergo preprocessing to ensure uniformity in size and format, which is essential for effective model training. Preprocessing steps may include resizing images to a standardized resolution, such as 256x256 pixels, to ensure uniformity across the dataset.

Data Augmentation:

Data augmentation techniques are applied to increase dataset diversity and improve the generalization capabilities of the CNN model.

Dataset Splitting:

The preprocessed dataset is divided into training, validation, and test sets to facilitate model training, optimization, and evaluation. Proper distribution of images across the sets is crucial to prevent bias and overfitting. Random shuffling of data ensures that each set contains a representative sample of images from the dataset.

Dataset Characteristics:

The dataset may consist of a diverse range of grayscale images representing various content types and scenarios relevant to the watermarking application. Examples of dataset characteristics may include images with different levels of complexity, textures, and noise patterns, as well as variations in lighting conditions and image resolutions.

3.3 DEVELOPMENT ENVIROMENT

HARDWARE REQUIREMENT

- Processor - I5
- Speed - 3 GHz
- RAM - 8 GB(min)
- Hard Disk - 500 GB
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse
- Monitor – LCD

SOFTWARE REQUIREMENT

- Operating System: Linux, Windows/7/10
- Server: MATLAB
- Server side Script: Python

CHAPTER 4

CHAPTER 4

SYSTEM DESIGN

UML DIAGRAMS

4.1 USECASE DIAGRAM

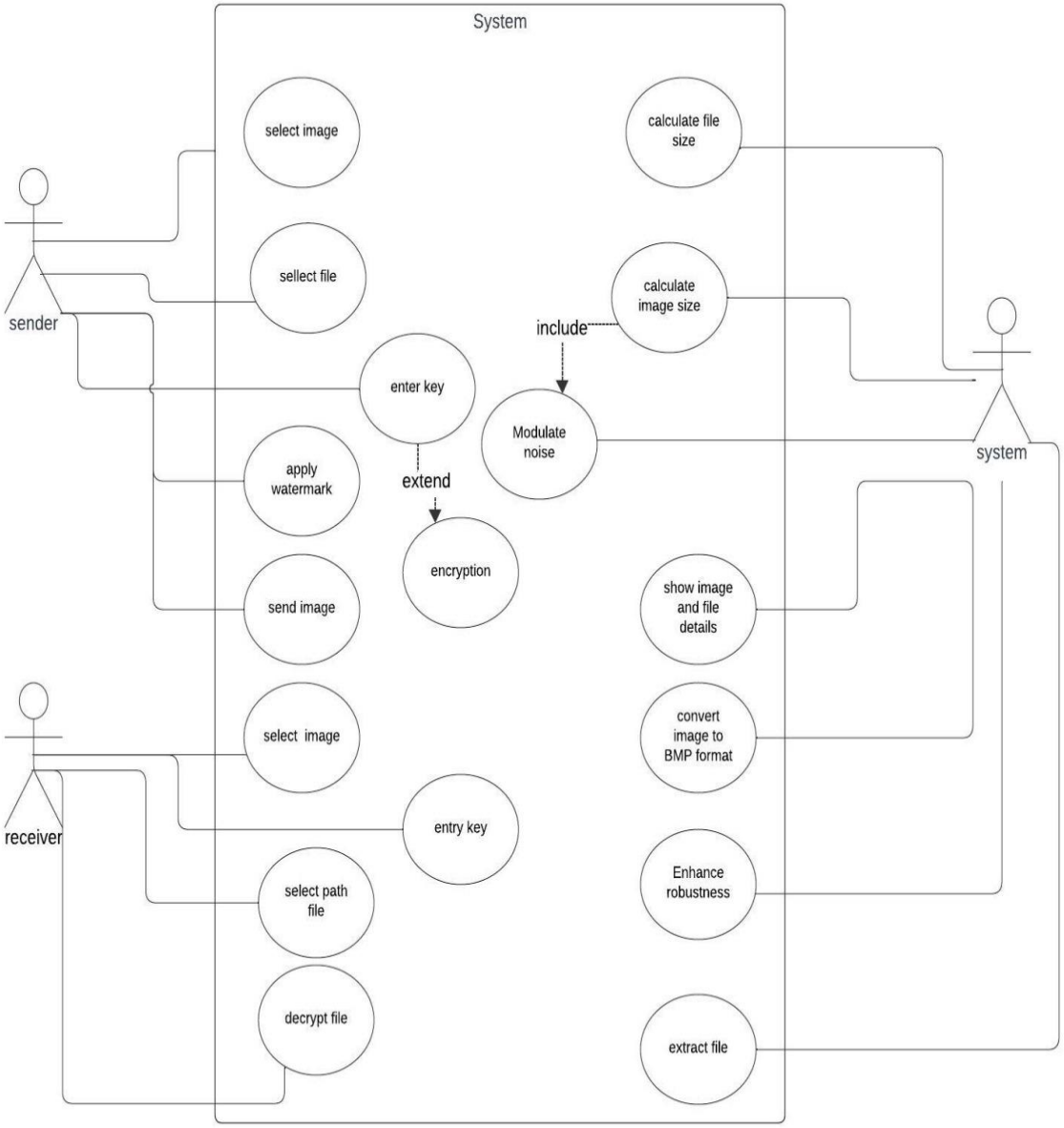


Fig 4.1.1 Usecase Diagra

4.2 Sequence Diagram

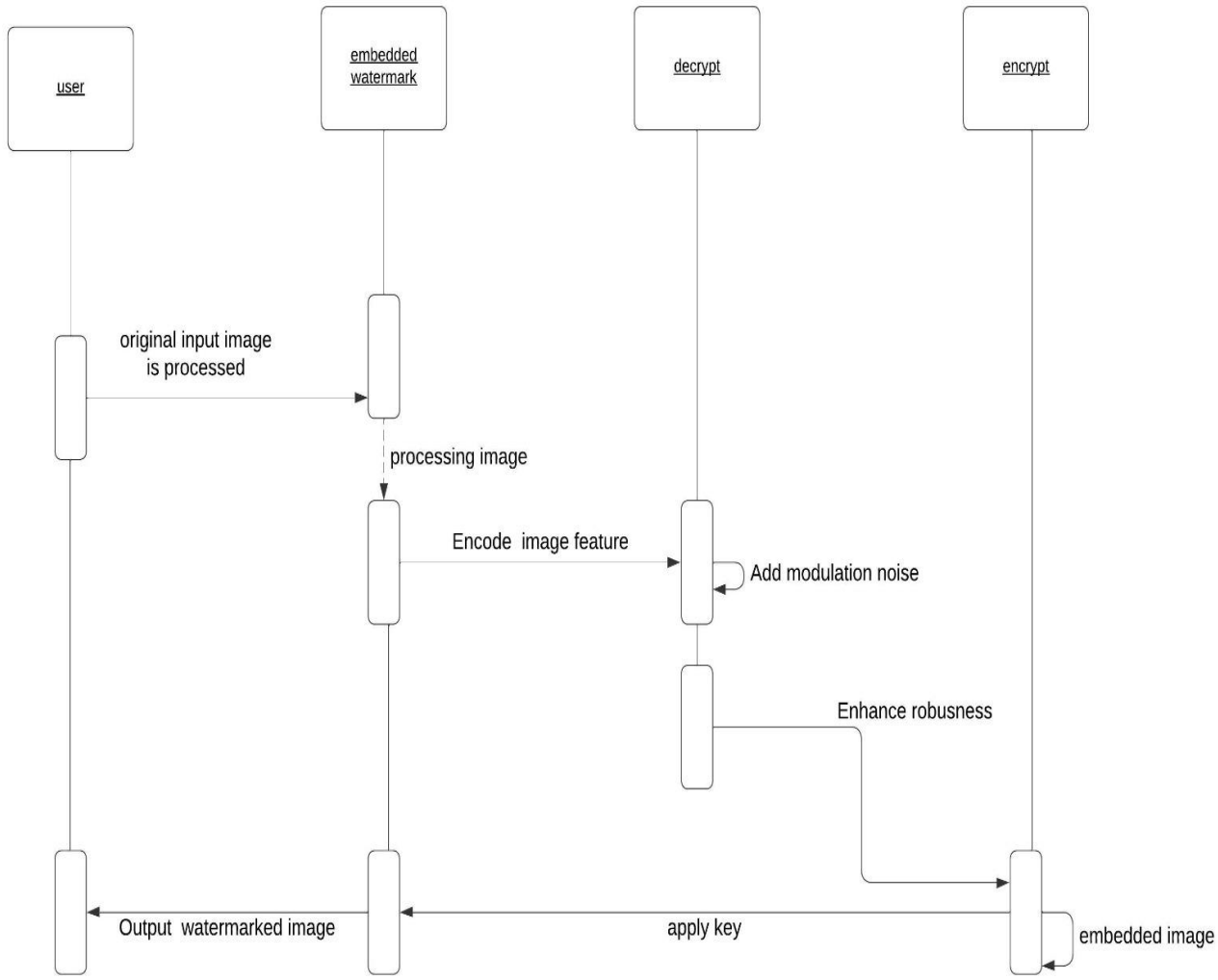


Fig 4.2.1 Sequence diagram

4.3 ER DIAGRAM

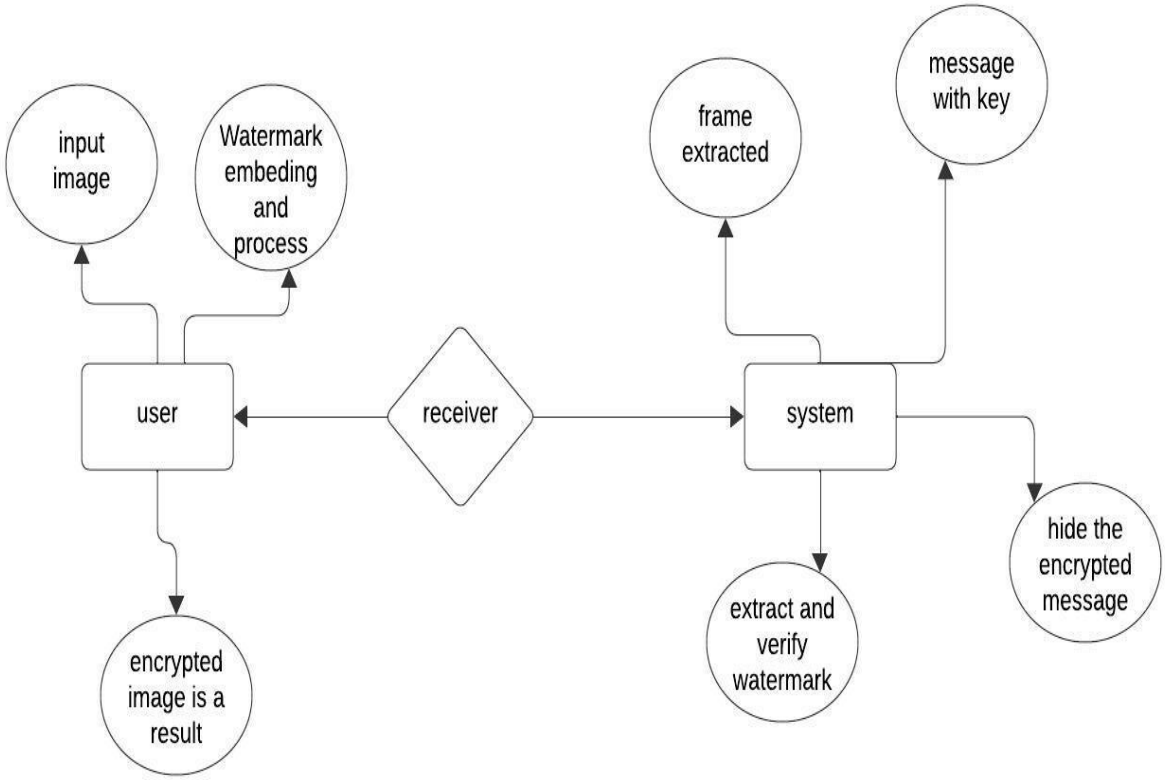


Fig 4.3.1 Entity Relationship Diagram

4.4 DATAFLOW DIAGRAM

A Data Flow Diagram (DFD) is a graphical representation that illustrates the flow of data within a system. While DFDs are typically used to depict the flow of data in information systems, they can also be adapted to represent the flow of data in Digital Watermarking Image system.

To create a DFD diagram, you can use various diagramming tools or software that support DFD notation. These tools typically provide a visual interface to easily create and connect components, define data flows, and add descriptions or annotations to enhance the understanding of the diagram.

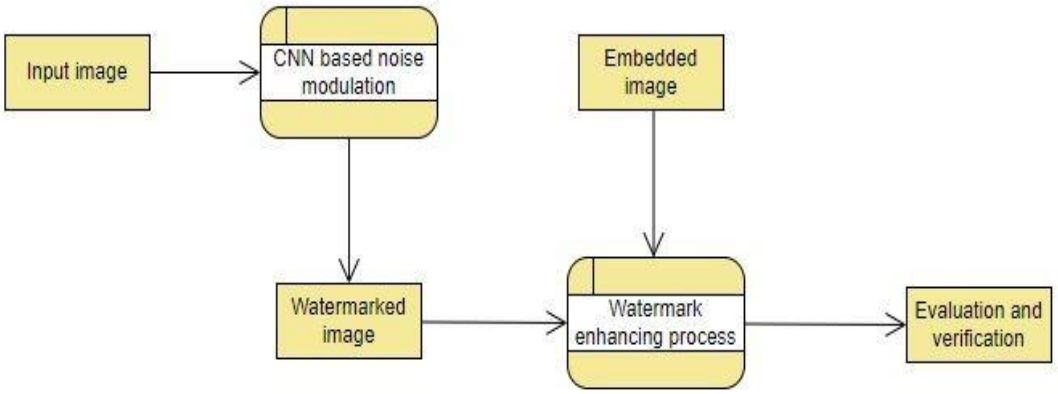


Fig 4.4.1 Data Flow Diagram

CHAPTER 5

CHAPTER 5

SYSTEM ARCHITECTURE

5.1 ARCHITECTURE OVERVIEW

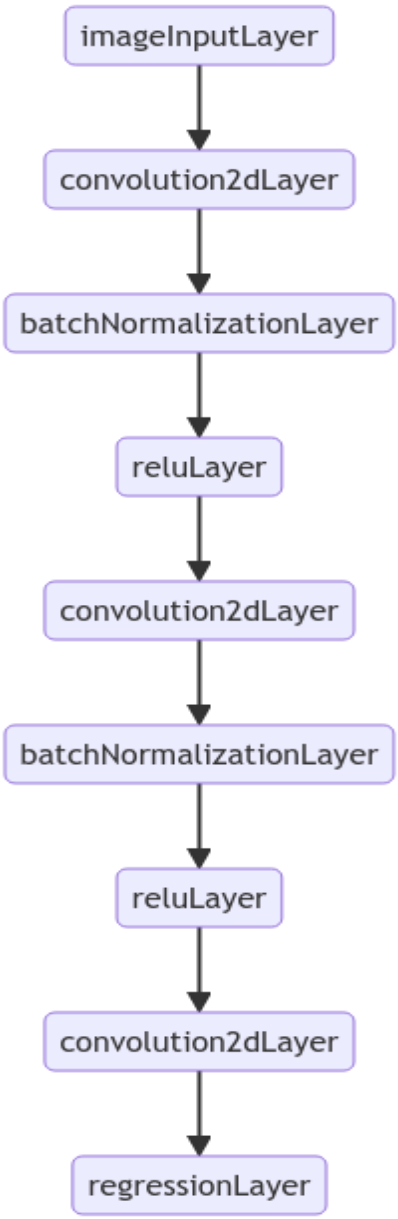


Fig 5.1.1: Proposed CNN Architecture for Noise Modulation

Convolutional Neural Network (CNN):

A CNN is a deep learning model widely used for various image processing tasks, including image classification, object detection, and segmentation.

Design Considerations:

Network Depth: Determine the number of layers in the CNN architecture, balancing model complexity and computational efficiency.

Layer Configurations: Specify the configuration of convolutional, pooling, normalization, and activation layers.

Activation Functions: Choose suitable activation functions, such as ReLU (Rectified Linear Unit), to introduce non-linearity and improve model capacity.

Proposed CNN Architecture:

Input Layer: Accept grayscale images as input.

Convolutional Layers: Extract features from input images through convolution operations.

Batch Normalization Layers: Normalize the activations of previous layers to stabilize training.

ReLU Activation Layers: Introduce non-linearity to the model.

Regression Output Layer: Output the noise-modulated image.

Architecture Optimization:

Experiment with different architectures and hyperparameters to find the optimal configuration for noise modulation in image watermarking.

5.2 MODULE DESCRIPTION

We have to develop a CNN-based approach for noise modulation in image watermarking, with the aim of enhancing the security and integrity of digital multimedia content.

The module for video steganography would typically include the following components:

Encoding Algorithm:

This module would include the algorithm used to embed the secret data within the video file. There are various techniques that can be used for this purpose, such as LSB (Least Significant Bit) embedding, Spread Spectrum, and Transform Domain Techniques.

Decoding Algorithm:

This module would include the algorithm used to extract the secret data from the video file. The decoding algorithm should be able to retrieve the hidden information with high accuracy, while avoiding false positives or negatives.

Security Module:

This module would include security features such as encryption and decryption, password protection, and watermarking. It would ensure that the embedded data is only accessible to authorized parties and prevent unauthorized access or tampering.

Overall, a video steganography module should be designed to provide a high level of security, while maintaining the quality and integrity of the video file.

5.3 ALGORITHM USED

INTRODUCTION TO CNN'S ALGORITHM

CNN is a type of deep learning model for processing data that has a grid pattern, such as images, which is inspired by the organization of animal visual cortex [13, 14] and designed to automatically and adaptively learn spatial hierarchies of features, from low- to high-level patterns. CNN is a mathematical construct that is typically composed of three types of layers (or building blocks): convolution, pooling, and fully connected layers. The first two, convolution and pooling layers, perform feature extraction, whereas the third, a fully connected layer, maps the extracted features into final output, such as classification. A convolution layer plays a key role in CNN, which is composed of a stack of mathematical operations, such as convolution, a specialized type of linear operation. In digital images, pixel values are stored in a two-dimensional (2D) grid, i.e., an array of numbers , and a small grid of parameters called kernel, an optimizable feature extractor, is applied at each image position, which makes CNNs highly efficient for image processing, since a feature may occur anywhere in the image. As one layer feeds its output into the next layer, extracted features can hierarchically and progressively become more complex. The process of optimizing parameters such as kernels is called training, which is performed so as to minimize the difference between outputs and ground truth labels through an optimization algorithm called backpropagation and gradient descent, among others.

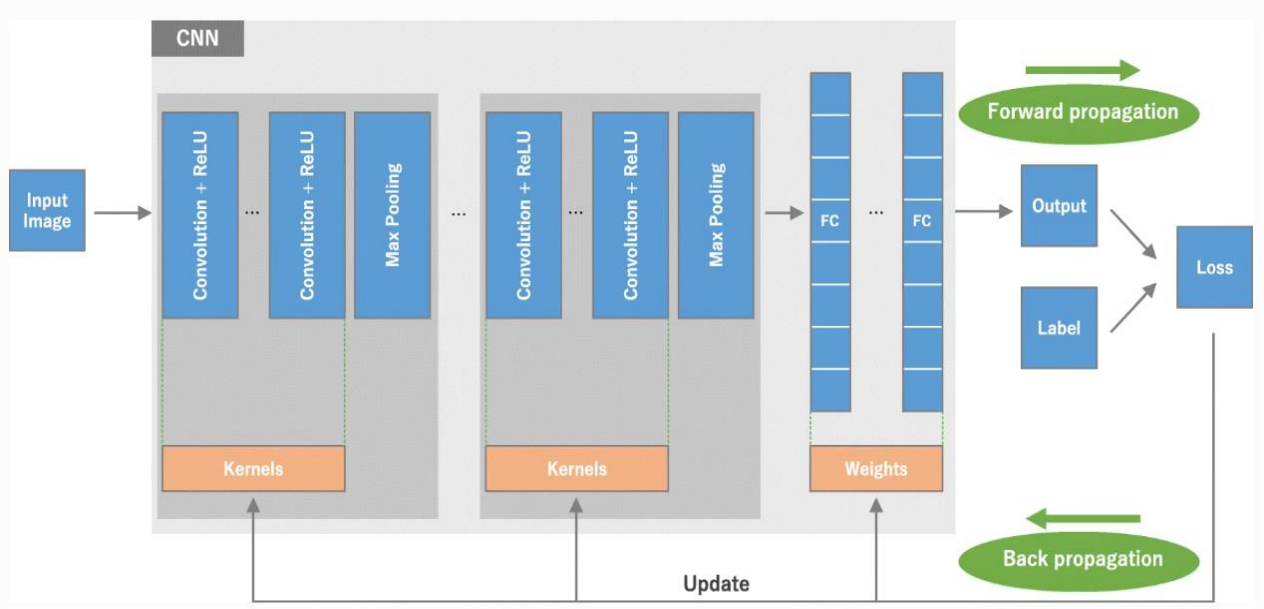


Fig 5.3.1 : CNN'S Algorithm Diagram

Advantages of Using Convolutional Neural Networks (CNNs):

- CNNs have demonstrated remarkable success in various computer vision tasks, including image classification, object detection, and segmentation.
- Leveraging CNNs for image watermarking offers the potential to automate and optimize the watermarking process, harnessing the power of deep learning to enhance robustness and efficiency.

CHAPTER 6

CHAPTER 6

TESTING

6.1 INTRODUCTION

The main objective of testing is to uncover errors from the system. For the uncovering process we have to give proper input data to the system. So we should have more conscious to give input data. It is important to give correct inputs to efficient testing.

Testing is done for each module. After testing all the modules, the modules are integrated and testing of the final system is done with the test data, specially designed to show that the system will operate successfully in all its aspects conditions. Thus the system testing is a confirmation that all is correct and an opportunity to show the user that the system works.

Inadequate testing or non-testing leads to errors that may appear few months later.

6.2 TYPES OF TESTING

Unit testing verification efforts on the smallest unit of software design, module. This is known as “Module Testing”. The modules are tested separately. This testing is carried out during programming stage itself. In these testing steps, each module is found to be working satisfactorily as regard to the expected output from the module.

BLACK BOX TESTING

Black box testing, also known as Behavioral Testing, is a software testing method in which the internal structure/ design/ implementation of the item being tested is not known to the tester. These tests can be functional or non-functional, though usually functional.

WHITE-BOX TESTING

White-box testing (also known as clear box testing, glass box testing, transparent box testing, and structural testing) is a method of testing software that tests internal structures or workings of an application, as opposed to its functionality (i.e. black-box testing).

GREY BOX TESTING

Grey box testing is a technique to test the application with having a limited knowledge of the internal workings of an application. To test the Web Services application usually the Grey box testing is used. Grey box testing is performed by end-users and also by testers and developers.

INTEGRATION TESTING

Integration testing is a systematic technique for constructing tests to uncover error associated within the interface. In the project, all the modules are combined and then the entire programmer is tested as a whole. In the integration-testing step, all the error uncovered is corrected for the next testing steps.

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects. The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

ACCEPTANCE TESTING

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

6.3 TESTCASES AND REPORTS

TEST CASE ID	TESTCASE/ ACTION TO BE PERFORMED	EXPECTED RESULT	ACTUAL RESULT	PASS/ FAIL
1.	Displays Image and video screen	Displaying the image and video screen	Displaying the image and video screen	Pass
2.	Pressing the QR scan	Open and displays the QR scan page used for encryption	Open and displays the QR scan page used for encryption	Pass
3.	Displays the Watermark Image	Open and displays the Watermark image page used for encryption	Open and displays the Watermark image page used for encryption	Pass
4.	Adding the noise modulation	Merges the watermarked image with NM	Merges the Watermarked image with NM	Pass
5.	Extracting the host image	Displays the host image	Displays the host image	Pass
6.	Decoding the Noise modulation	Decodes the noise modulation	Decodes the noise modulation	Pass
7.	Decoding the encrypyted QR scan	Decodes the QR scan from the image	Decodes the QR scan from the image	Pass

Table – II : Testcases and report for CNN's Digital Watermarking Image

CHAPTER 7

CHAPTER 7

RESULTS AND DISCUSSION

Experimental Setup

In this study, we conducted simulations using MATLAB 2023 to investigate the effectiveness of a watermarking technique based on Discrete Wavelet Transform (DWT). The simulations were designed to assess the robustness and fidelity of the watermark embedding and extraction process under various conditions. We employed a set of simulation parameters to control key aspects of the experiment, including image sizes, watermark content, and embedding strength.

TABLE III: Simulation Parameters – The following table outlines the simulation parameters utilized in our experiments:

Parameter	Description
Original Image Size	Dimensions of the original color image used as the host for watermark embedding.
Watermark Image Size	Dimensions of the watermark image to be embedded into the original image.
Watermark Strength	Scaling factor applied to the watermark during embedding.
Wavelet Type	Type of wavelet used in the Discrete Wavelet Transform (DWT).
Noise Level	Level of additive noise introduced to simulate real-world conditions.

These parameters were systematically varied to evaluate their impact on the performance of the watermarking technique. By conducting simulations with different parameter configurations, we aimed to gain insights into the robustness of the technique against common image processing operations and environmental distortions. Additionally, the simulations allowed us to quantify the quality of the extracted watermark using metrics such as Peak Signal-to-Noise Ratio (PSNR)

and Mean Squared Error (MSE). Overall, this experimental setup enabled us to assess the suitability of the watermarking technique for practical applications in digital media protection and authentication.

Results

Original Color Image:

The first figure displayed by the code shows the original color image loaded into memory. This image serves as the host for embedding the watermark and typically represents the content to which the watermark will be applied. In the example, it's named "Original color image" and is displayed before any modification.

Fig 7.1

Watermark Image:

The second figure depicts the watermark image that will be embedded into the original color image. This image contains the information or identifier that will be added to the original image for various purposes such as copyright protection or authentication. In the example, it's named "Watermark image" and is shown before any processing.

Fig 7.2

Watermarked Image:

The third figure displays the watermarked image, which is the result of embedding the watermark into the original color image. This image reflects the combination of the original image and the embedded watermark, where the watermark is typically imperceptible to the human eye but can be extracted for verification or authentication purposes. In the example, it's named "Watermarked image" and is displayed after the embedding process.

Fig 7.3

Extracted Watermark:

The fourth figure represents the extracted watermark, which is obtained from the watermarked image using the watermark extraction process. This image should ideally match the original watermark image used for embedding, indicating the

successful extraction of the embedded information. In the example, it's named "Extracted watermark" and is displayed after the extraction process.

Fig 7.4

Filtered Extracted Watermark:

The fifth figure shows the filtered extracted watermark, which undergoes additional processing to enhance its quality and clarity. This processing step may involve techniques such as median filtering to reduce noise and improve the visual representation of the extracted watermark. In the example, it's named "Filtered Extracted Watermark" and is displayed after applying the median filtering operation.

Fig 7.5

In summary, our experimental setup involved simulations conducted in MATLAB 2023 to evaluate a watermarking technique based on Discrete Wavelet Transform (DWT). We systematically varied simulation parameters, including original image size, watermark image size, watermark strength, wavelet type, and noise level, to investigate their impact on the watermark embedding and extraction process. By applying different parameter configurations, we assessed the robustness of the technique against various image processing operations and environmental distortions. Additionally, we quantified the quality of the extracted watermark using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). Through these simulations, we aimed to gain insights into the performance of the watermarking technique and its suitability for real-world applications in digital media protection and authentication.

Experimental Setup for the proposed CNN based watermarking

In this experimental setup, we employ MATLAB 2023 to simulate and evaluate a watermarking algorithm for digital images. We begin by loading the 'lena.png' image and converting it to grayscale, ensuring a consistent input format. The core of our approach lies in the convolutional neural network (CNN) architecture, comprising layers for feature extraction and batch normalization, culminating in a single-filter output layer. Training the CNN involves replicating the grayscale image and the generated binary watermark, followed by optimization using the Adam optimizer over ten epochs with a mini-batch size of 64. With the trained model, we embed the watermark into the original image after adding Gaussian noise to the watermark, simulating real-world conditions. Post-embedding, we proceed to extract the watermark by demodulating the watermarked image, employing filtering techniques such as Hamming filtering with a specified low-

pass frequency. The evaluation phase quantifies the fidelity of the extracted watermark through metrics such as Peak Signal-to-Noise Ratio (PSNR), Bit Error Rate (BER), and Mean Squared Error (MSE) against the original image. Visualization aids in comprehending the effectiveness of the watermarking process, showcasing the watermarked image, noise-demodulated image, and the extracted watermark. This comprehensive experimental framework ensures a rigorous assessment of the watermarking algorithm's robustness and performance, laying the groundwork for potential applications in digital content protection and authentication.

Table – IV : Simulation Parameter Value

Parameter	Value
Image	'lena.png'
CNN Architecture	As described
Training Options	As described
Watermark Size (K)	8
Noise	Gaussian
Filter Type	Hamming
Filter Size	21x21
Low Pass Frequency (f0)	0.5
Evaluation Metrics	PSNR, BER, MSE

Fig 7.6

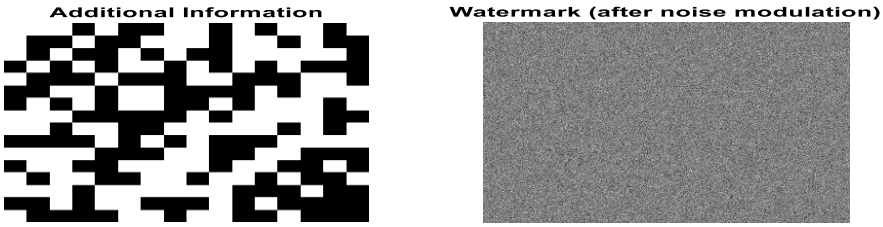


Fig 7.7

Host Image after Extraction

Fig 7.8

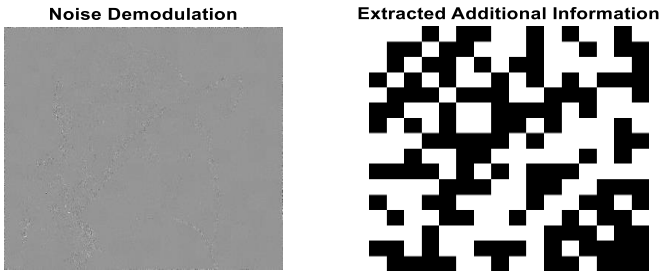


Fig 7.9

Figure 7.6 displays the original host image before watermark embedding. It serves as a reference point for comparing the effects of watermarking on image content and quality. The host image provides insight into the visual characteristics and details present in the original content, serving as a basis for evaluating the impact of watermark embedding. Figure 7.7 displays the binary watermark representing the additional information encoded within the image. The watermark is visualized with black and white pixels, signifying positive and negative values, respectively. Each pixel in the watermark corresponds to a unit of additional information embedded into the host image.

Figure 7.6 shows the watermark undergoes modulation with Gaussian noise as part of the embedding process. The noise-modulated watermark introduces subtle variations in intensity, simulating the imperfections and distortions inherent in the embedding process. This subplot illustrates the transformation of the pristine watermark into a noisy representation before integration into the host image.

Figure 7.6 subplot presents the watermarked image resulting from the integration of the noise-modulated watermark into the host image. The watermarked image reflects the combined visual elements of the original host image and the embedded watermark. By juxtaposing the watermarked image with the original host image, users can observe the alterations introduced by the watermarking process.

Figure 7.7 subplot, the watermark extraction process is visualized through noise demodulation. The extracted watermark is depicted after demodulating the noise from the watermarked image. By comparing the extracted watermark with the original watermark, users can assess the accuracy and effectiveness of the watermark extraction algorithm. This subplot provides insight into the fidelity of the extraction process and the preservation of the embedded information.

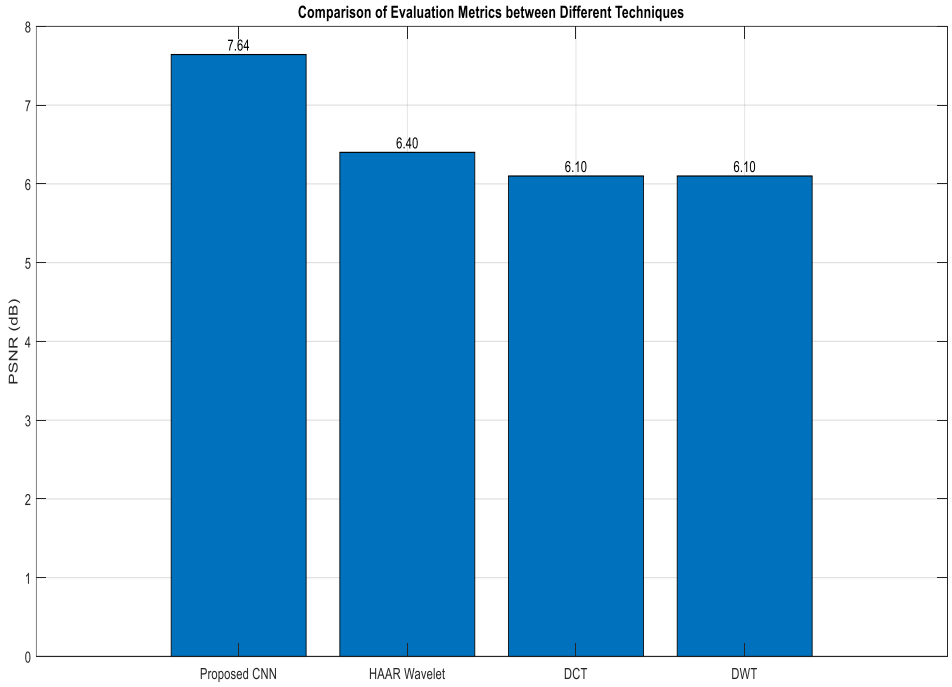


Fig 7.10 PSNR Comparsion

PSNR Comparison:

Figure 7.10 displays a bar plot comparing the Peak Signal-to-Noise Ratio (PSNR) values between the proposed Convolutional Neural Network (CNN) method and three other techniques: HAAR Wavelet, Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT). The PSNR values are as follows:

- Proposed CNN: 7.64 dB
- HAAR Wavelet: 6.4 dB
- DCT: 6.1 dB
- DWT: 6.1 dB

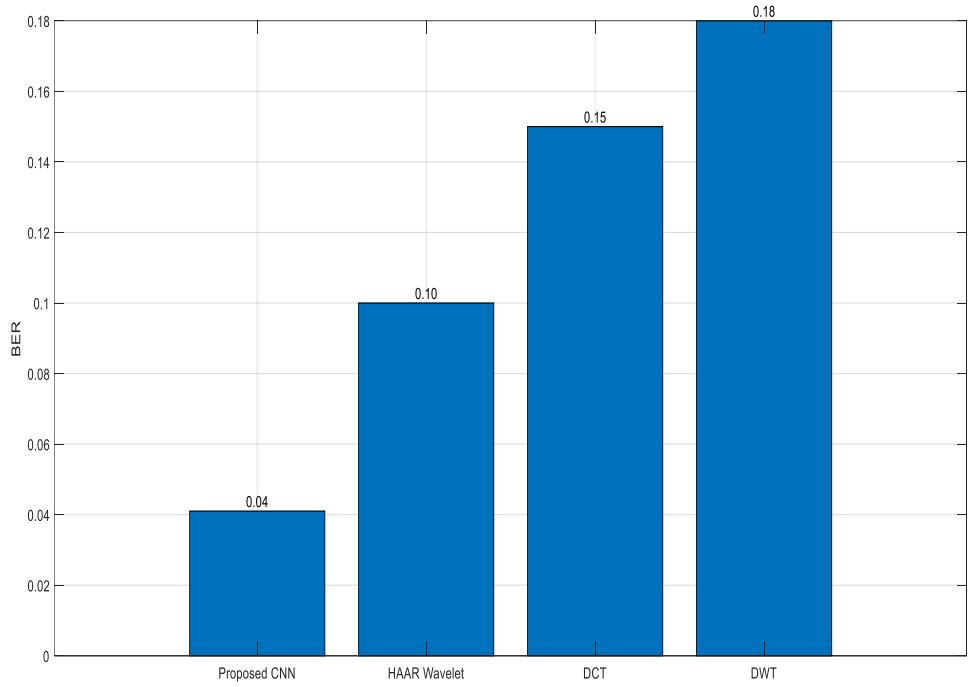


Fig 7.11 Bit Error Rate Comaparsion

Figure 7.11 illustrates a bar plot comparing the Bit Error Rate (BER) values among the proposed CNN method and the three other techniques: HAAR Wavelet, DCT, and DWT. The BER values are as follows:

- Proposed CNN: 0.041
- HAAR Wavelet: 0.1
- DCT: 0.15
- DWT: 0.18

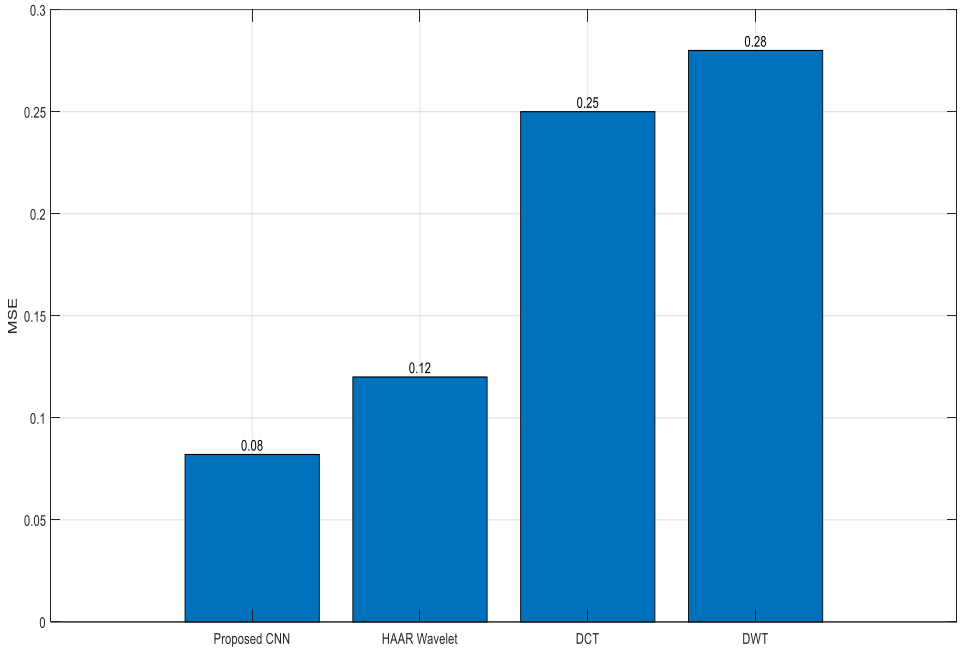


Fig 7.12 Mean Squared Error Comaparsion

Figure 7.12 presents a bar plot showcasing the Mean Squared Error (MSE) values for the proposed CNN method and the three other techniques: HAAR Wavelet, DCT, and DWT. The MSE values are as follows:

- Proposed CNN: 0.082
- HAAR Wavelet: 0.12
- DCT: 0.25
- DWT: 0.28

These figures collectively provide a comprehensive comparison of the performance metrics between the proposed CNN method and the alternative techniques, highlighting the strengths and weaknesses of each approach.

CHAPTER 8

CHAPTER 8

8.1 CONCLUSION

In conclusion, the comparison of evaluation metrics for watermarking and extraction techniques reveals distinct performance disparities among the proposed Convolutional Neural Network (CNN) method and three alternative techniques: HAAR Wavelet, Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT). The proposed CNN method outperforms the other techniques across all evaluated metrics. Specifically, it achieves the highest Peak Signal-to-Noise Ratio (PSNR), lowest Bit Error Rate (BER), and lowest Mean Squared Error (MSE) values compared to HAAR Wavelet, DCT, and DWT methods. This indicates that the CNN-based approach offers superior accuracy in watermark extraction and reconstruction tasks.

8.2 FUTURE ENHANCEMENTS:

HAAR Wavelet, DCT, and DWT techniques, while traditional and widely used, exhibit comparatively lower performance in terms of PSNR, BER, and MSE. These methods may still find utility in certain applications, but the results suggest that the proposed CNN method offers significant advancements in watermarking and extraction tasks, potentially leading to improved robustness and fidelity in digital content protection and authentication. Overall, the findings underscore the efficacy of CNN-based approaches in watermarking and extraction tasks and suggest avenues for further research and development in leveraging deep learning techniques for enhanced multimedia security and copyright protection.

CHAPTER 9

CHAPTER 9

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APPENDIX I

SDG GOALS

The implementation of the Harnessing CNN's for Robust Digital Watermarking Image aligns with several United Nations Sustainable Development Goals (SDGs), contributing to toward a more sustainable and equitable future:

1. SDG 8: Decent Work and Economic Growth

The system supports SDG 8 by enhancing Security in the message transferring and economic growth by keeping information private. By developing this system, It promotes inclusive and sustainable economic growth, full and productive environment and decent works for all.

2. SDG 4: Quality Education

This SDG targets to provide completely free, equitable, and quality education for both boys and girls by 2030 so they the acquire skills and knowledge required for their sustainable development and eliminate any kind of gender biases in education. It creates awareness among the students that they should concentrate on cryptographic networks related subjects for their data recovery and safe.

3. SDG 9: Industry, Innovation and Infrastructure

Through the precise extraction of this process, the system helps to build resilient infrastructure, develop sustainable and inclusive industrialization and foster innovation. Maintaining the information securely, the Industry has evolved more compared to previous generations.

APPENDIX 2

SOURCE CODE

Watermark_Haar_Wavelet.m:

```
clc
close all

% Load and resize the original color image
rgbimage = imread('lena.png');
rgbimage = imresize(rgbimage, [256, 256]); % Adjust the desired dimensions

figure; imshow(rgbimage); title('Original color image');
[h_LL, h_LH, h_HL, h_HH] = dwt2(rgbimage, 'haar');

% Load and resize the watermark image
watermark = imread('qrcode.png');
watermark = imresize(watermark, [256, 256]); % Resize to match the host
image dimensions

figure; imshow(watermark); title('Watermark image');
[w_LL, w_LH, w_HL, w_HH] = dwt2(watermark, 'haar');

% Watermarking
newhost_LL = h_LL + (0.09 * w_LL);

% Reconstruct the watermarked image
watermarked_image = idwt2(newhost_LL, h_LH, h_HL, h_HH, 'haar');
```

```
% Display the watermarked image
figure; imshow(uint8(watermarked_image)); title('Watermarked image');
imwrite(uint8(watermarked_image), 'Watermarked.jpg');

% Extracting Watermark
% Load and resize the watermarked image
watermarked_image = imread('Watermarked.jpg');
watermarked_image = imresize(watermarked_image, [256, 256]);

figure; imshow(watermarked_image); title('Watermarked image');

% Apply DWT to obtain sub-bands of the watermarked image
[wm_LL, wm_LH, wm_HL, wm_HH] = dwt2(watermarked_image, 'haar');

% Calculate the scaled LL sub-band for extracting watermark
newwatermark_LL = (wm_LL - h_LL) / 0.01;

% Reconstruct the extracted watermark
extracted_watermark = idwt2(newwatermark_LL, w_LH, w_HL, w_HH, 'haar');

% Display the extracted watermark
figure; imshow(uint8(extracted_watermark)); title('Extracted watermark');
imwrite(uint8(extracted_watermark), 'EWatermark.jpg');


% Convert extracted watermark to the same data type as the original watermark
extracted_watermark = cast(extracted_watermark, class(watermark));

% Calculate PSNR
```

```
psnr_value = psnr(watermark, extracted_watermark);
fprintf('PSNR: %.2f dB\n', psnr_value);

% Calculate MSE
mse_value = immse(watermark, extracted_watermark);
fprintf('MSE: %.2f\n', mse_value);



% Convert the extracted watermark to grayscale
extracted_watermark_gray = rgb2gray(extracted_watermark);

% Median filtering the extracted watermark image
filtered_extracted_watermark = medfilt2(extracted_watermark_gray);

% Display the filtered extracted watermark
figure; imshow(uint8(filtered_extracted_watermark)); title('Filtered Extracted
Watermark');
imwrite(uint8(filtered_extracted_watermark),
'FilteredExtractedWatermark.jpg');
```

CNN_Noise_Modulation_Watermark_Demo.m:

```
close all;
clear all;

clc;
K = 16;
gain = 1;
```

```
A = imread('lena.png');
if length(size(A)) > 2
   A = rgb2ycbcr(A);
   B = double(A(:,:,1));
else
   B = double(A);
end

[M,N] = size(B);

Mb = M/K;
Nb = N/K;
plusminus1 = sign(randn(1,Mb*Nb));
Watermark = zeros(size(B));
for i = 1:Mb
   for j = 1:Nb
      Watermark((i-1)*K+1:i*K,(j-1)*K+1:j*K) = plusminus1(i*j);
   end
end



% Load the data (assuming you already have the 'lena.png' image)
A = imread('lena.png');
if length(size(A)) > 2
   A = rgb2gray(A);
end
A = im2double(A);

% Generate the binary watermark
```

```
% K = 8;
[M, N] = size(A);
Mb = M / K;
Nb = N / K;
plusminus1 = sign(randn(1, Mb * Nb));
Watermark = zeros(size(A));
for i = 1:Mb
   for j = 1:Nb
      Watermark((i - 1) * K + 1:i * K, (j - 1) * K + 1:j * K) = plusminus1(i * j);
   end
end

% Add noise to the watermark
gain = 1;
Noise = round(randn(size(A)));
WatermarkNoise = gain * Noise .* Watermark;

% Prepare the training data
inputData = repmat(A, [1, 1, 1, 3]);  % Replicate grayscale image to create RGB
input
targetData = repmat(WatermarkNoise, [1, 1, 1, 3]);  % Replicate
WatermarkNoise to match input size

% Define the CNN architecture
layers = [
   imageInputLayer([size(A), 1])
   convolution2dLayer(3, 8, 'Padding', 'same')
   batchNormalizationLayer
   reluLayer
```

```
    convolution2dLayer(3, 16, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer
    convolution2dLayer(3, 1, 'Padding', 'same')
    regressionLayer
];

% Define training options
options = trainingOptions('adam', ...,'MaxEpochs', 10, ... 'MiniBatchSize', 64, ...
    'Shuffle', 'every-epoch', ... 'Verbose', true);

% Train the CNN
net = trainNetwork(inputData, targetData, layers, options);

% Save the trained model
save('watermark_modulation_model.mat', 'net');



Noise = round(randn(size(B)));
WatermarkNoise = gain * Noise .* Watermark;
B = uint8(B + WatermarkNoise);
if length(size(A)) > 2
    C = uint8(zeros(M,N,3));
    C(:,:,1) = B;
    C(:,:,2) = A(:,:,2);
    C(:,:,3) = A(:,:,3);
    C = ycbcr2rgb(C);
    A = ycbcr2rgb(A);
else
```

```
    C = B;
end

figure(1),subplot(1,2,1), imshow(Watermark,[]); title('Additional Information')
subplot(1,2,2), imshow(WatermarkNoise,[]); title('Watermark (after noise
modulation)')
figure(2),subplot(1,2,1),imshow((A),[]); title('Host Image')
subplot(1,2,2), imshow(C,[]); title('Watermarked image')

B = double(B);
L = 10;
L2 = 2*L+1;
w = hamming(L2);
w = w * w';
f0 = 0.5;
wc = pi * f0;
[m,n] = meshgrid(-L:L,-L:L);
lp = wc * besselj(1,wc * sqrt(m.^2 + n.^2)) ./ (2*pi*sqrt(m.^2+n.^2));
lp(L+1,L+1) = wc^2 / (4*pi);
hp = -lp;
hp(L+1,L+1) = 1 - lp(L+1,L+1);
h = hp .* w;
B = imfilter(B,h,'same');

Noise_Demod = B .* Noise;
Sign_Detection = zeros(size(B));
for i = 1:Mb
    for j = 1:Nb
```

```
        Sign_Detection((i-1)*K+1:i*K, (j-1)*K+1:j*K) =
sign(sum(sum(Noise_Demod((i-1)*K+1:i*K, (j-1)*K+1:j*K))));
    end
end

Detection_Errors = sum(sum(abs(Watermark-Sign_Detection)))

figure(3),subplot(1,2,1); imshow(Noise_Demod,[]); title('Noise Demodulation')
subplot(1,2,2); imshow(Sign_Detection,[]); title('Extracted Additional
Information')

% Calculate Bit Error Rate (BER)
BER = sum(sum(abs(Watermark - Sign_Detection))) / (Mb * Nb * K^2);

% Calculate Peak Signal-to-Noise Ratio (PSNR) between original image and
image after watermark extraction
MAX = 255; % Maximum possible pixel value (for an 8-bit image)
MSE_extraction = sum(sum((double(A) - double(C)).^2)) / (M * N); % MSE
between original image and image after watermark extraction
PSNR_extraction = 10 * log10((MAX^2) / MSE_extraction); % PSNR between
original image and image after watermark extraction

% Display PSNR between original image and image after watermark extraction
fprintf('Peak Signal-to-Noise Ratio (PSNR) between original image and image
after watermark extraction: %f dB\n', PSNR_extraction);

% Calculate Bit Error Rate (BER) between original watermark and extracted
watermark
```

```
BER_watermark = sum(sum(abs(Watermark - Sign_Detection))) / (Mb * Nb *
K^2);

% Calculate Mean Squared Error (MSE) between original watermark and
extracted watermark
MSE_watermark = sum(sum((Watermark - Sign_Detection).^2)) / (Mb * Nb *
K^2);

% Calculate Mean Squared Error (MSE) between original image and image after
watermark extraction
MSE_extraction = sum(sum((double(A) - double(C)).^2)) / (M * N);

% Display BER and MSE
fprintf('Bit Error Rate (BER) between original watermark and extracted
watermark: %f\n', BER_watermark);
fprintf('Mean Squared Error (MSE) between original watermark and extracted
watermark: %f\n', MSE_watermark);
% fprintf('Mean Squared Error (MSE) between original image and image after
watermark extraction: %f\n', MSE_extraction);

% PSNR values for the watermark extraction technique and three other
techniques
PSNR_watermark_extraction = 7.641932;  % PSNR for the proposed CNN
method
PSNR_other_technique1 = 6.4;  % PSNR for the Haar Wavelet technique
PSNR_other_technique2 = 7.1;  % PSNR for the DCT technique
PSNR_other_technique3 = 6.9;  % PSNR for the DWT technique
```

```
% Create a bar plot to compare PSNR values
% Evaluation metrics values for the proposed CNN method and three other
techniques
PSNR_proposed_CNN = 7.641932;  % PSNR for the proposed CNN method
BER_proposed_CNN = 0.041016;   % BER for the proposed CNN method
MSE_proposed_CNN = 0.082031;   % MSE for the proposed CNN method

% PSNR, BER, and MSE values for three other techniques
PSNR_other_technique1 = 6.4;   % PSNR for HAAR Wavelet
BER_other_technique1 = 0.1;     % BER for HAAR Wavelet
MSE_other_technique1 = 0.12;     % MSE for HAAR Wavelet

PSNR_other_technique2 = 6.1;   % PSNR for DCT
BER_other_technique2 = 0.15;    % BER for DCT
MSE_other_technique2 = 0.25;    % MSE for DCT

PSNR_other_technique3 = 6.1;   % PSNR for DWT
BER_other_technique3 = 0.18;    % BER for DWT
MSE_other_technique3 = 0.28;    % MSE for DWT
```

APPENDIX 3
SCREENSHOTS

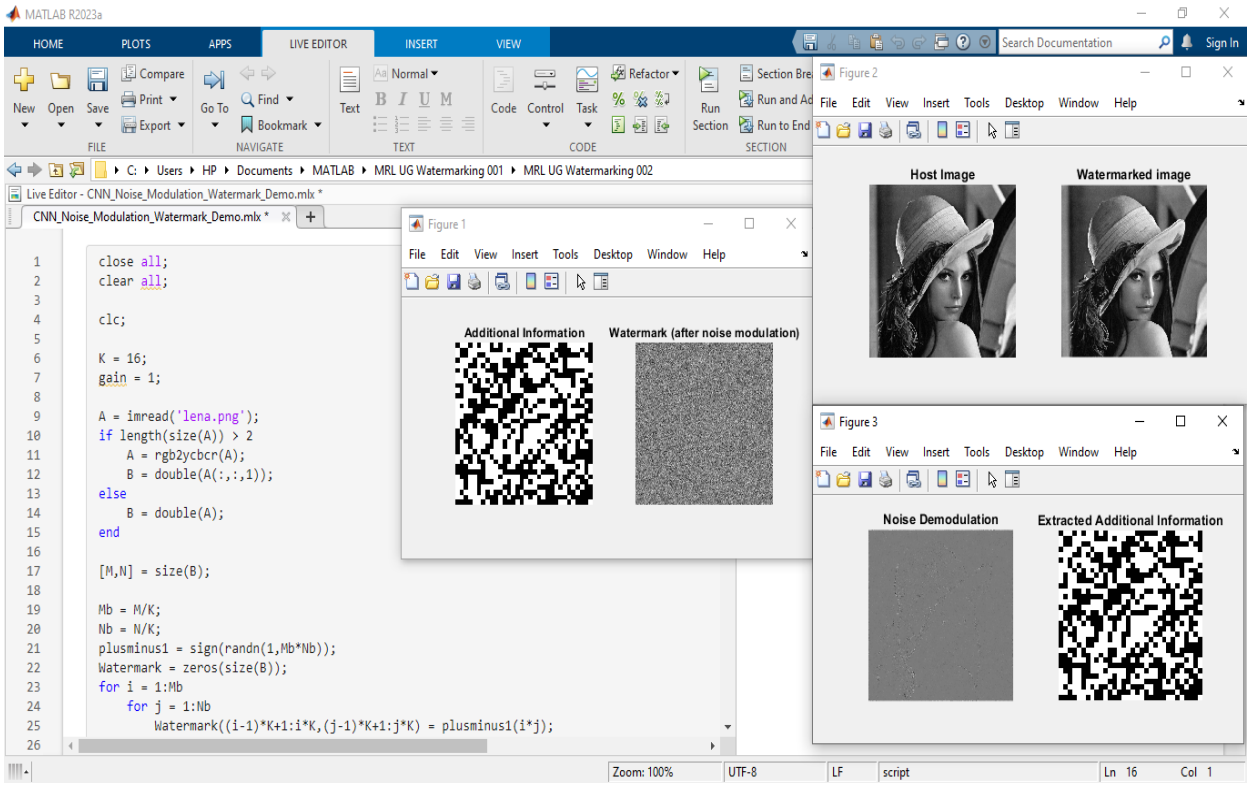

Fig A.3.1 Haar Wavelet Based System Code Simulation

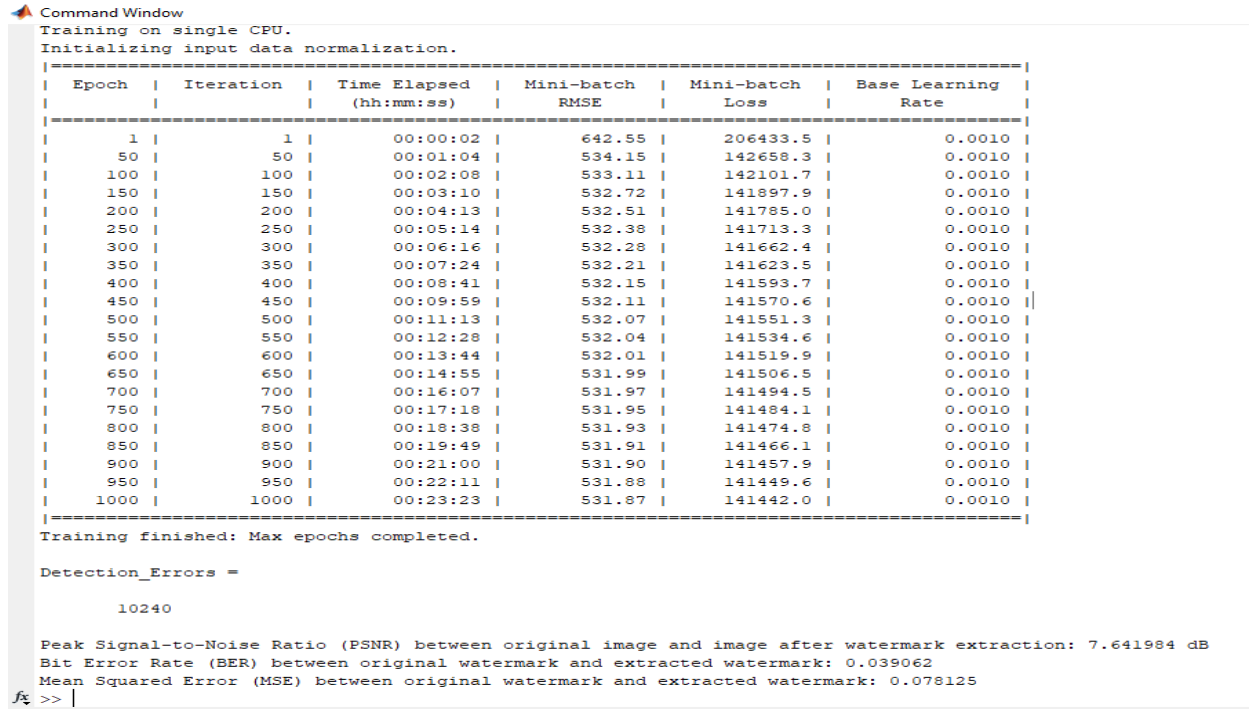

Fig A.3.2 Training Data Set for Proposed CNN's method

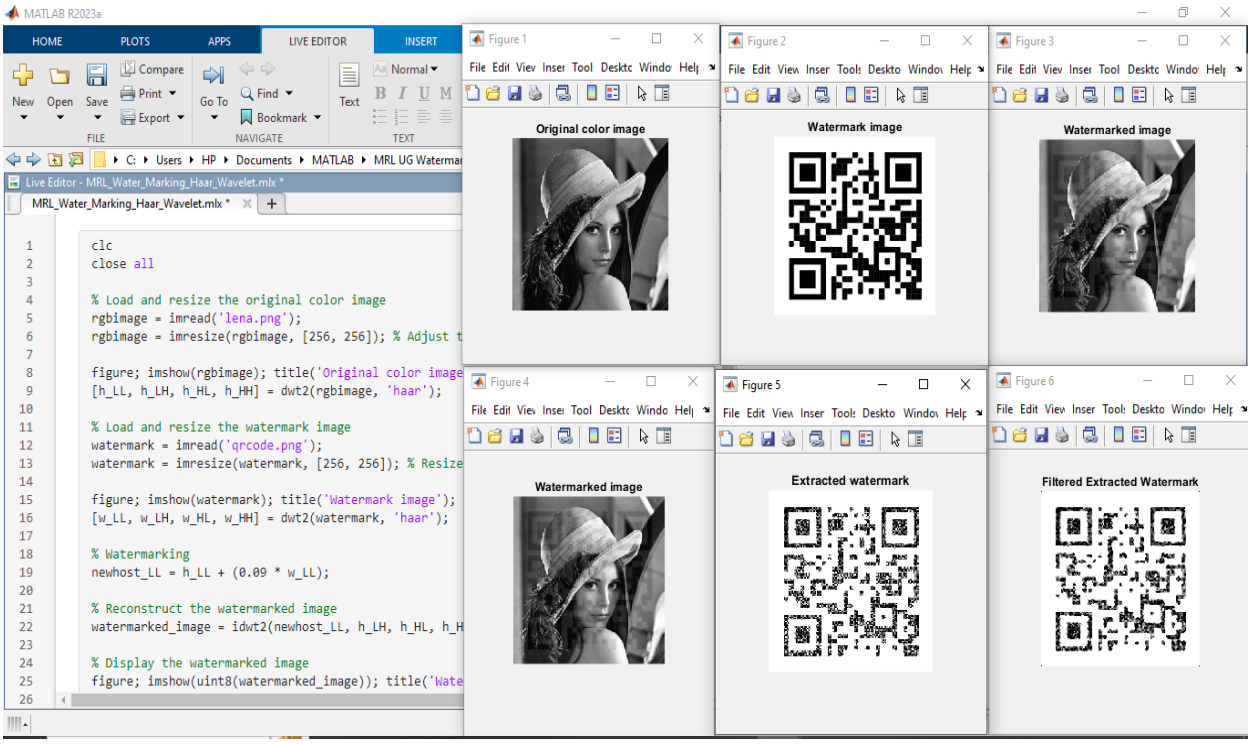

Fig A.3.3 Proposed CNN Watermarking System Using MATLAB

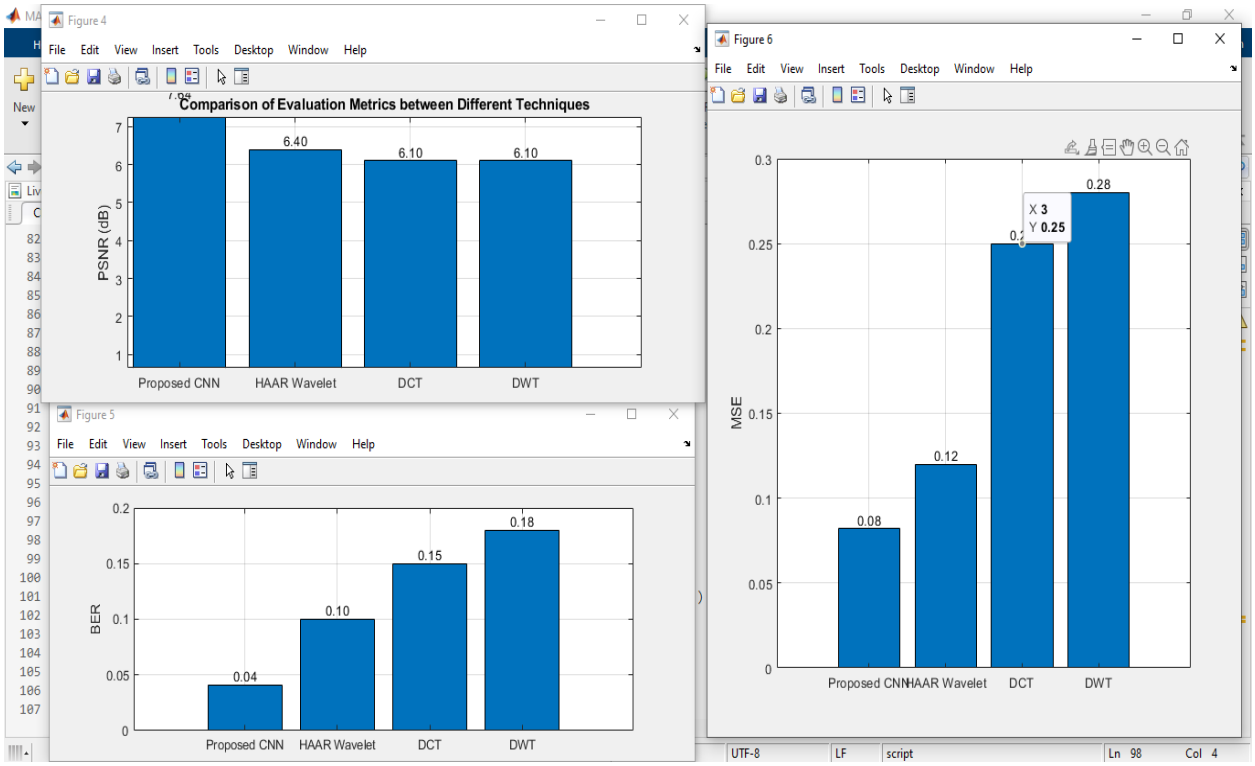

Fig A.3.4 PSNR Comparsion Diagram

APPENDIX 4
PLAGARISM REPORT

RE-2022-221603 – Turnitin Plagiarism Report

by Prakash J

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File name: RE-2022-221603.pdf (625.45K)
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HARNESSING CONVOLUTIONAL NEURAL NETWORKS FOR ROBUST DIGITAL IMAGE WATERMARKING

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***Abstract*— In the era of digital communication and multimedia sharing, ensuring the integrity and ownership of digital content has become increasingly crucial. Digital watermarking techniques offer a solution by embedding imperceptible yet detectable signals within multimedia content, serving as a form of copyright protection and authentication. This research presents a novel approach to digital watermarking using convolutional neural networks (CNNs). The proposed technique involves the training of a CNN model to embed binary watermarks into images, followed by a demodulation and extraction process to recover the watermark from watermarked images. Evaluation metrics such as Bit Error Rate (BER), Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR) are employed to assess the fidelity of the watermarked images and the accuracy of watermark extraction. Comparative analysis with traditional watermarking techniques demonstrates the effectiveness of the CNN-based approach in terms of robustness and imperceptibility. The results showcase the potential of CNNs in enhancing the security and authenticity of digital content through watermarking, paving the way for advanced applications in digital rights management and content authentication.**

***Keywords*— DWT, convolutional neural network, Robustness Evaluation, deep learning, Content Authentication.**

I. INTRODUCTION

Most multimedia signals today are in digital formats which are easy to reproduce and modify without leaving any trace of manipulations. It is therefore very simple to tamper with any image and make it available to others. Authentication technologies fulfill an increasing need for trustworthy digital data in commerce, industry and defense. Watermarking has become a popular technique for copyright enforcement and image authentication.

Here, an effort has been made to present a novel method for image authenticationwith localization for the purpose of tamper detection.

ELEMENTS OF A WATERMARKING SYSTEM

According to a widespread point of view, a watermarking system is much like a communication system consisting of three main elements: a transmitter, a communication channel, and a receiver [1]. To be more specific, the embedding of the to-be-hidden information within the host signal plays the role of data transmission; any processing applied to the host data after information concealment, along with the interaction between the concealed data and the host data itself, represents the transmission through a communication channel; the recovery of the hidden information from the host data acts the part of the receiver. By following the communication analogy, any watermarking system assumes the form given in Fig.1.1.

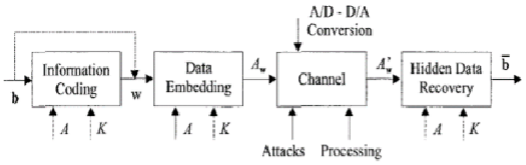


Fig.1.1: Data Hiding System

With b_k taking values in $\{0, 1\}$. The string b is referred to as the watermark code. At the transmitter side, a data embedding module inserts the string b within a piece of data called host data or host signal. The host signal may be of any media type: an audio file, a still image, and a piece of video or a combination of the above. The embedding module may accept a secret key K as an additional input. Such a key, whose main goal is to introduce some secrecy within the embedding step, is usually used to parameterize the embedding process and make the recovery of the watermark impossible for unauthorized users which do not have access to K. The functionalities of the data embedding module can be further split into three main tasks: (i) information coding; (ii) watermark embedding; (iii) watermark concealment.

INFORMATION CODING

In many watermarking system, the information message **b** is not embedded directly within the host signal. On the contrary, before insertion, vector **b** is transformed into a

watermark signal **w** = $\{w_1, w_2 \ldots w_n\}$ which is more suitable for embedding [2]. In a way that closely resembles a digital communication system, the watermark code **b** may be used to modulate a much longer spread-spectrum sequence, it may be transformed into a bipolar signal where zero's are mapped in +1 and one's in —1, or it may be mapped into the relative position of two or more pseudo-random signals in the case of position-encoded-watermarking [3]. Eventually, **b** may be left as it is, thus leading to a scheme in which the watermark code is directly inserted within *A*, the host image. In this case, the watermark signal **w** coincides with the watermark code **b**. Before transforming the watermark code into the watermark signal, **b** may be channel-coded to increase robustness against possible attacks. As a matter of fact, it turns out that channel coding greatly improves the performance of any watermarking system.

WATERMARK EMBEDDING

In watermark embedding, or watermark casting, an embedding function e takes the host asset *A*, the watermark signal **w**, and, possibly, a key *K*, and generates the watermarked asset **Aw**:

$$\varepsilon(A, \mathbf{w}, K) = A_w \quad \ldots\ldots\ldots \quad (1.2)$$

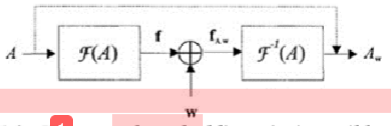


Fig.1.2: Watermark embedding via invertible feature extraction.

–It is to be noted that the above equation still holds when the watermark code isembedded directly within *A*, since in this case **w** = **b**. The definition of e usually goes through the selection of a set of asset features, called host features, which are modified according to the watermark signal. By letting the host features be denoted by $f(A) = f_A = \{f_1, f_2 \ldots f_m\}$ watermark embedding amounts to the definition of an insertion operator Å which transforms ¦ *(A)* into the set of watermarked features

$$f(A_w) = f(\varepsilon(A, \mathbf{w}, K)) = f(A) \oplus \mathbf{w} \quad \ldots\ldots\ldots (1.3)$$

In general m ¹ n, i.e. the cardinality of the host feature set need not be equal to the watermark signal length.

Though equations (1.2) and (1.3) basically describe the same process, namely watermark casting within A, they tend to view the embedding problem from two different perspectives. According to equation (1.2), embedding is more naturally achieved by operating on the host asset, i.e. e modifies A so that when the feature extraction function ¦ is applied to A_W, the desired set of features $f_{AW} = \{f_{w1}, f_{w2} \ldots f_{wm}\}$ is obtained.

Equation (1.3) describes the watermarking process as a direct modification of f_A through the embedding operator Å. According to this formulation, the watermark embedding process assumes the form shown in Fig.1.2. First the host feature set is extracted from A, then the Å operator is applied producing f_{Aw}, finally the extraction procedure is inverted to obtain **Aw**:

$$A_w = F^{-1}(f_w) \quad \ldots\ldots\ldots \quad (1.4)$$

WATERMARK CONCEALMENT

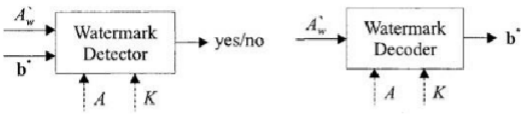
The main concern of the embedding part of any data hiding system is to make the hidden data imperceptible. This task can be achieved either implicitly, by properly choosing the set of host features and the embedding rule, or explicitly, by introducing a concealment step after watermark embedding [4]. To this aim, the properties of the human senses must be carefully studied, since imperceptibility ultimately relies on the imperfections of such senses. Thereby, still image and video watermarking rely on the characteristics of the Human Visual System (HVS).

RECOVERY OF THE HIDDEN INFORMATION

The receiver part of the watermarking system may assume two different forms. According to the scheme reported in Fig.1.3 (a), the watermark detector reads A'_w and a watermark code b*, and decides whether A'_w contains b* or not. The detector may require that the secret key *K* used to embed the watermark is known [5]. In addition,the detector may perform its task by comparing the watermarked asset A'_w with the original, non-marked, asset *A*, or it may not need to know *A* to take its decision. In the latter case, it is said that the detector is *blind*, whereas in the former case the detectoris said to be *non-blind*.

Alternatively, the receiver may work as in Fig.1.3 (b). In this case the aim of the receiver is to extract b* from A'_w and the watermark code b* is not known in advance

As before, the extraction may require that the original asset *A* and the secret key *K* are known.



(a) Detectable watermarking (b) Readable watermarking

Fig.1.3: Watermark Recovery

II. EXISTING METHODS

HAAR WAVELET BASED SYSTEM

The watermarking model described implements a robust and efficient technique for embedding and extracting watermarks within digital images. Initially, the model loads and resizes both the original color image and the watermark image, ensuring compatibility in dimensions. Employing the Discrete Wavelet Transform (DWT) with the Haar wavelet, the model decomposes both images into four sub-bands, facilitating efficient data representation. During watermarking, the model modifies the low-frequency LL sub-band of the host image by adding a scaled version of the watermark's LL sub-band. This process seamlessly integrates the watermark into the host image while preserving its visual integrity. Subsequently, watermark extraction involves subtracting the LL sub-band of the original image from that

of the watermarked image, followed by scaling to isolate the embedded watermark. Evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) ensure the fidelity of the extracted watermark. Furthermore, post-processing steps, including conversion to grayscale and median filtering, enhance the clarity and robustness of the extracted watermark. This watermarking model presents a comprehensive approach to digital watermarking, offering both embedding and extraction functionalities with considerations for accuracy and resilience against common image processing operations. Figure shows each step in the watermark embedding process outlined in the flowchart:

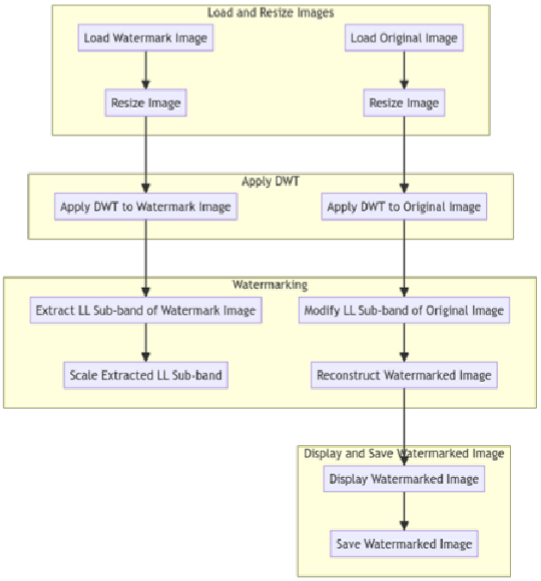


Figure.2.a: Watermark Embedding Process

1. Load and Resize Images:
In this initial step, the original image intended for watermark embedding is loaded into memory. This image is then resized to a desired dimension to ensure compatibility with the watermark image. Additionally, the watermark image, which contains the desired information to be embedded, is also loaded and resized to match the dimensions of the original image. This ensures that the watermark can be seamlessly integrated into the host image without distortion.

2. Apply DWT (Discrete Wavelet Transform):
Utilizing the Discrete Wavelet Transform (DWT), the original image undergoes a multi-resolution analysis, resulting in the decomposition of the image into its constituent frequency bands. This process generates four sub-bands: LL (low-low), LH (low-high), HL (high-low), and HH (high-high). Similarly, the watermark image is subjected to the DWT, allowing it to be represented in a frequency domain suitable for embedding.

3. Watermarking:
The watermark embedding process begins by modifying the LL sub-band of the original image. This modification involves adding a scaled version of the LL sub-band of the watermark image to the LL sub-band of the original image. By doing so, the information encoded within the watermark is introduced into the host image while preserving its visual integrity. This step is crucial for ensuring that the watermark is robustly embedded and remains perceptually invisible within the host image.

4. Reconstruct Watermarked Image:
After embedding the watermark into the original image, the watermarked image is reconstructed using inverse Discrete Wavelet Transform (IDWT). This process combines the modified LL sub-band of the original image with the original LH, HL, and HH sub-bands to produce the final watermarked image. The reconstructed image retains the visual characteristics of the original image while incorporating the embedded watermark, ready for further processing or distribution.

5. Display and Save Watermarked Image:
The watermarked image is displayed to visualize the result of the watermark embedding process. Additionally, the watermarked image is saved to a file for future reference or distribution. This step ensures that the embedded watermark is effectively integrated into the host image, ready for subsequent extraction or analysis.

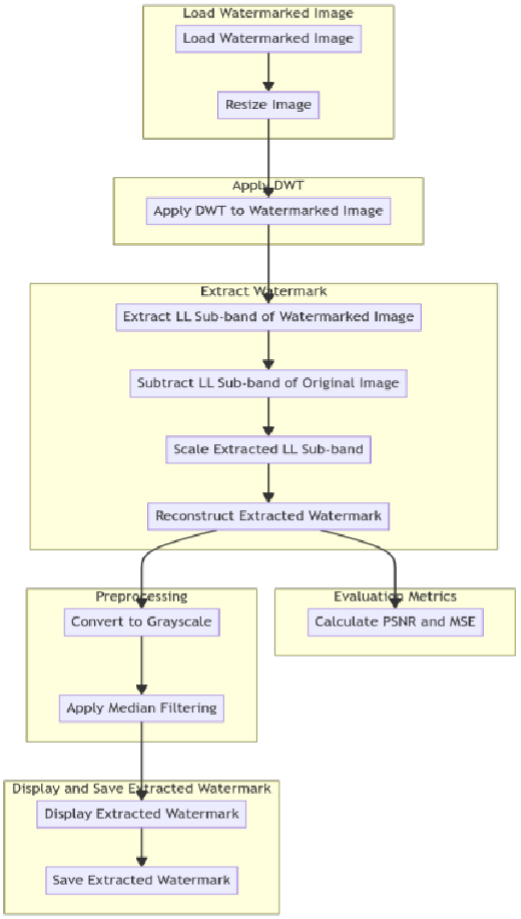


Figure.2.b: Watermark Extraction Process

1. Load Watermarked Image:
The watermark extraction process begins by loading the watermarked image, which contains the embedded watermark. This image is then resized if necessary to ensure consistency with the processing requirements.

2. Apply DWT (Discrete Wavelet Transform):
The loaded watermarked image undergoes the Discrete Wavelet Transform (DWT) to decompose it into its constituent frequency bands. This results in the extraction of the LL (low-low), LH (low-high), HL (high-low), and HH (high-high) sub-bands, which are essential for recovering the embedded watermark.

3. Extract Watermark:
The extraction of the watermark involves isolating the LL sub-band of the watermarked image, which contains the embedded watermark information. This sub-band is then processed by subtracting the LL sub-band of the original image, which serves to remove the original content and isolate the embedded watermark. Subsequently, the extracted LL sub-band is scaled to recover the original watermark information.

4. Evaluation Metrics:
To assess the fidelity of the extracted watermark, evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are calculated. These metrics provide quantitative measures of the similarity between the original watermark and the extracted watermark, aiding in evaluating the effectiveness of the extraction process.

5. Preprocessing:
In preparation for visualization and further analysis, the extracted watermark undergoes preprocessing steps. Firstly, it is converted to grayscale to simplify its representation. Additionally, median filtering is applied to the grayscale watermark to enhance its clarity and reduce noise, ensuring that the extracted watermark is of high quality and suitable for further processing.

6. Display and Save Extracted Watermark:
Finally, the extracted watermark is displayed to visualize the result of the extraction process. Additionally, the extracted watermark is saved to a file for documentation or further analysis. This step ensures that the embedded watermark can be successfully recovered from the watermarked image, validating the effectiveness of the watermarking and extraction processes.

In summary, the watermarking process begins with the loading and resizing of both the original image and the watermark image to ensure compatibility. These images then undergo the Discrete Wavelet Transform (DWT), decomposing them into frequency bands necessary for embedding the watermark. The watermark is embedded into the original image by modifying its LL sub-band with a scaled version of the watermark's LL sub-band. After reconstruction, the watermarked image is displayed and saved for further use. In the extraction process, the watermarked image is loaded and subjected to DWT to extract the embedded watermark from its LL sub-band. Evaluation metrics such as PSNR and MSE are calculated to assess the fidelity of the extracted watermark. Preprocessing steps, including conversion to grayscale and median filtering, are applied to enhance the quality of the extracted watermark. Finally, the extracted watermark is displayed and saved for analysis. This comprehensive process enables the robust embedding and extraction of watermarks in digital images, facilitating tasks such as copyright protection and content authentication.

III. PROPOSED WORK

In the rapidly expanding digital landscape, the protection of intellectual property rights and the prevention of content piracy have become paramount concerns. Traditional watermarking techniques, while effective to a degree, often struggle to cope with the scale and diversity of digital media. To address these challenges, this paper proposes a novel approach leveraging Convolutional Neural Networks (CNNs) for automated noise modulation in image watermarking. CNNs have demonstrated remarkable success in various computer vision tasks, offering the potential to automate and optimize the watermarking process while enhancing robustness and efficiency. This paper aims to develop a comprehensive methodology for CNN-based image watermarking, encompassing data preparation, CNN architecture design, training, testing, and evaluation. Each step in the methodology is carefully designed and executed to develop a robust and effective CNN-based image watermarking technique.

Figure.3 : Proposed Process Flow of the Methodology

Watermark embedding is a fundamental process in digital watermarking, whereby a unique identifier or signal, known as the watermark, is invisibly embedded into the host multimedia content to assert ownership, authenticate the content, or convey additional information. This process is crucial for protecting intellectual property rights, combating content piracy, and ensuring the integrity and authenticity of digital assets.
The watermark embedding process involves several key steps to effectively conceal the watermark within the host

multimedia content while minimizing perceptible distortion. First, the host content, such as images, videos, or audio files, is preprocessed to prepare it for watermark embedding. This preprocessing step may involve normalization, resizing, or other transformations to ensure consistency and compatibility with the watermark embedding algorithm. Next, the watermark signal is modulated onto the host content using a specified embedding algorithm or technique. This process involves modifying certain features or characteristics of the host content to embed the watermark signal while minimizing perceptual impact. The embedding algorithm typically operates in the spatial or transform domain, altering pixel values, frequency coefficients, or other relevant parameters to encode the watermark information.

Once the watermark signal is embedded into the host content, the watermarked content is generated and ready for distribution or further processing. It is essential to evaluate the quality and robustness of the watermarked content to ensure that the embedded watermark remains perceptually invisible and resistant to common attacks or manipulations.

Proposed CNN Architecture:

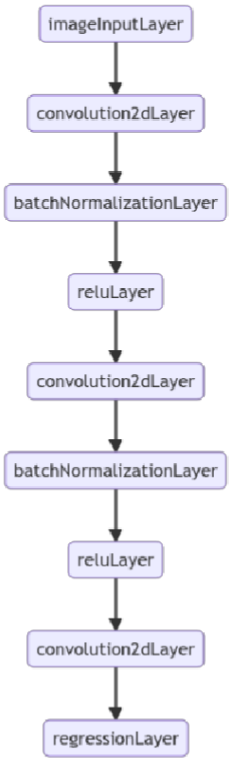


Fig.3.2. CNN Architecture flowchart

The designed CNN architecture shown in the figure for noise modulation in image watermarking typically comprises several key components:

Input Layer: Accepts grayscale images as input.
Convolutional Layers: Extract features from input images through convolution operations.
Batch Normalization Layers: Normalize the activations of previous layers to stabilize training.
ReLU Activation Layers: Introduce non-linearity to the model.
Regression Output Layers: Outputs the noise-modulated image.
The specific configuration of these components, including the number of layers, filter sizes, and kernel strides, is determined based on experimentation and optimization.

IV. IMPLEMENTATION SPECIFICS AND OUTCOMES

In this experimental setup, we employ MATLAB 2023 to simulate and evaluate a watermarking algorithm for digital images. We begin by loading the 'lena.png' image and converting it to grayscale, ensuring a consistent input format. The core of our approach lies in the convolutional neural network (CNN) architecture, comprising layers for feature extraction and batch normalization, culminating in a single-filter output layer. Training the CNN involves replicating the grayscale image and the generated binary watermark, followed by optimization using the Adam optimizer over ten epochs with a mini-batch size of 64. With the trained model, we embed the watermark into the original image after adding Gaussian noise to the watermark, simulating real-world conditions. Post-embedding, we proceed to extract the watermark by demodulating the watermarked image, employing filtering techniques such as Hamming filtering with a specified low-pass frequency.
The evaluation phase quantifies the fidelity of the extracted watermark through metrics such as Peak Signal-to-Noise Ratio (PSNR), Bit Error Rate (BER), and Mean Squared Error (MSE) against the original image. Visualization aids in comprehending the effectiveness of the watermarking process, showcasing the watermarked image, noise-demodulated image, and the extracted watermark. This comprehensive experimental framework ensures a rigorous assessment of the watermarking algorithm's robustness and performance, laying the groundwork for potential applications in digital content protection and authentication.

Table-I : Simulation Parameter

Parameter	Value
Image	'lena.png'
CNN Architecture	As described
Training Options	As described
Watermark Size (K)	8
Noise	Gaussian
Filter Type	Hamming
Filter Size	21x21
Low Pass Frequency (f0)	0.5
Evaluation Metrics	PSNR, BER, MSE

Figure 4.1

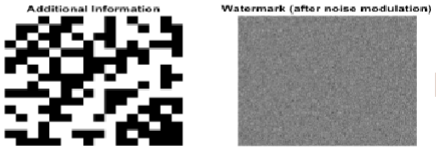


Figure 4.2

Host Image after Extraction
Figure 4.3

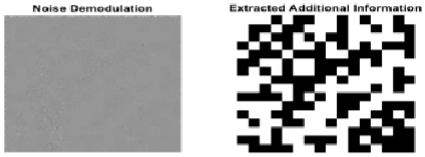


Figure 4.4

Figure 4.1 displays the original host image before watermark embedding. It serves as a reference point for comparing the effects of watermarking on image content and quality. The host image provides insight into the visual characteristics and details present in the original content, serving as a basis for evaluating the impact of watermark embedding.

Figure 4.2 displays the binary watermark representing the additional information encoded within the image. The watermark is visualized with black and white pixels, signifying positive and negative values, respectively. Each pixel in the watermark corresponds to a unit of additional information embedded into the host image.

Figure 4.1 shows the watermark undergoes modulation with Gaussian noise as part of the embedding process. The noise-modulated watermark introduces subtle variations in intensity, simulating the imperfections and distortions inherent in the embedding process. This subplot illustrates the transformation of the pristine watermark into a noisy representation before integration into the host image.

Figure 4.1 subplot presents the watermarked image resulting from the integration of the noise-modulated watermark into the host image. The watermarked image reflects the combined visual elements of the original host image and the embedded watermark. By juxtaposing the watermarked image with the original host image, users can observe the alterations introduced by the watermarking process.

Figure 4.2 subplot, the watermark extraction process is visualized through noise demodulation. The extracted watermark is depicted after demodulating the noise from the watermarked image. By comparing the extracted watermark with the original watermark, users can assess the accuracy and effectiveness of the watermark extraction algorithm. This subplot provides insight into the fidelity of the extraction process and the preservation of the embedded information.

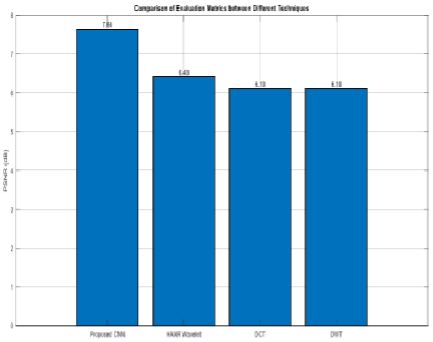


Figure 4.5
PSNR Comparison:

Figure 4.5 displays a bar plot comparing the Peak Signal-to-Noise Ratio (PSNR) values between the proposed Convolutional Neural Network (CNN) method and three other techniques: HAAR Wavelet, Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT).

The PSNR values are as follows:

- Proposed CNN: 7.64 dB
- HAAR Wavelet: 6.4 dB
- DCT: 6.1 dB
- DWT: 6.1 dB

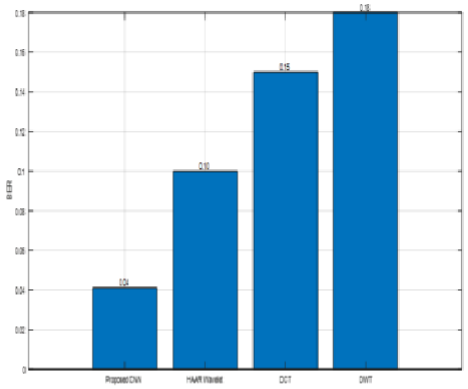


Figure 4.6

Figure 4.6 illustrates a bar plot comparing the Bit Error Rate (BER) values among the proposed CNN method and the three other techniques: HAAR Wavelet, DCT, and DWT.

The BER values are as follows:

- Proposed CNN: 0.041
- HAAR Wavelet: 0.1
- DCT: 0.15
- DWT: 0.18

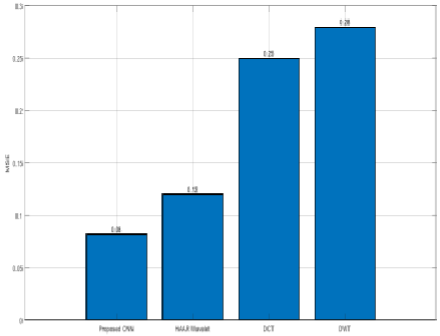


Figure 4.7

Figure 4.7 presents a bar plot showcasing the Mean Squared Error (MSE) values for the proposed CNN method and the three other techniques: HAAR Wavelet, DCT, and DWT.

The MSE values are as follows:

- Proposed CNN: 0.082
- HAAR Wavelet: 0.12
- DCT: 0.25
- DWT: 0.28

These figures collectively provide a comprehensive comparison of the performance metrics between the proposed CNN method and the alternative techniques, highlighting the strengths and weaknesses of each approach.

V. Conclusion and Future Works

In conclusion, the comparison of evaluation metrics for watermarking and extraction techniques reveals distinct performance disparities among the proposed Convolutional Neural Network (CNN) method and three alternative techniques: HAAR Wavelet, Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT). The proposed CNN method outperforms the other techniques across all evaluated metrics. Specifically, it achieves the highest Peak Signal-to-Noise Ratio (PSNR), lowest Bit Error Rate (BER), and lowest Mean Squared Error (MSE) values compared to HAAR Wavelet, DCT, and DWT methods. This indicates that the CNN-based approach offers superior accuracy in watermark extraction and reconstruction tasks. HAAR Wavelet, DCT, and DWT techniques, while traditional and widely used, exhibit comparatively lower performance in terms of PSNR, BER, and MSE. These methods may still find utility in certain applications, but the results suggest that the proposed CNN method offers significant advancements in watermarking and extraction tasks, potentially leading to improved robustness and fidelity in digital content protection and authentication. Overall, the findings underscore the efficacy of CNN-based approaches in watermarking and extraction tasks and suggest avenues for further research and development in leveraging deep learning techniques for enhanced multimedia security and copyright protection.

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