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Intelligent Watermarking for Image Copyright Protection using Machine Learning Techniques

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Abstract— ***The rapid growth of digital media distribution has raised critical concerns about copyright protection. Unauthorized use, duplication, and manipulation of images threaten intellectual property rights, making watermarking a crucial security mechanism. Traditional watermarking methods often face challenges such as vulnerability to attacks, loss of image quality, and limited robustness. This paper proposes a machine learning–based intelligent watermarking framework to embed secret watermarks within digital images for copyright protection. The proposed approach leverages deep learning for feature extraction, adaptive embedding, and robust detection of watermarks under various distortions. Experimental results demonstrate that machine learning–driven watermarking enhances imperceptibility, robustness, and security compared to conventional approaches, providing a reliable mechanism for copyright enforcement in digital media.***

Keywords— ***Watermarking, Copyright Protection, Machine Learning, Deep Learning, Digital Security, Image Processing.***

I. INTRODUCTION

In the current era of rapid digitalization, the widespread use of online platforms and digital distribution channels has revolutionized the way multimedia content is created, shared, and consumed. However, this unprecedented accessibility has also escalated the risk of unauthorized duplication, manipulation, and distribution of digital images, thereby intensifying concerns related to intellectual property rights (IPR) and copyright protection [1], [2]. Copyright infringement in images not only results in significant financial losses for creators and organizations but also raises ethical and legal challenges that threaten the integrity of digital ecosystems. To address these issues, digital watermarking has emerged as a robust solution, enabling the embedding of secret, imperceptible information within an image to authenticate ownership and restrict unauthorized usage. A watermark can serve multiple purposes, such as copyright enforcement, authentication, tamper detection, and forensic tracking [3]. The strength of watermarking lies in two crucial properties: imperceptibility—ensuring that the watermark does not visibly distort the host image—and robustness—ensuring that the watermark can withstand common distortions such as compression, scaling, cropping, filtering, and intentional attacks [4]. Traditional watermarking techniques typically operate in either the spatial domain or the transform domain. Spatial domain methods, such as the Least Significant Bit (LSB) approach, directly manipulate pixel values, making them simple but highly vulnerable to modifications [5]. Transform domain methods, including Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Singular Value Decomposition (SVD), have proven to be more robust, as they embed watermarks in frequency coefficients less susceptible to image manipulations [6], [7]. While effective to an extent, these methods struggle to maintain a balance between imperceptibility and robustness in the face of increasingly sophisticated image processing and attack techniques. Recent advances in Machine Learning (ML) and Deep Learning (DL) have opened new avenues for designing adaptive watermarking systems that overcome the limitations of classical approaches. ML techniques enable watermarking systems to learn intrinsic features of host images and watermark patterns, optimizing embedding strategies based on image content and predicted attack scenarios [8]. Convolutional Neural Networks (CNNs), for instance, can be employed to automatically identify perceptually insignificant regions of an image suitable for watermark embedding, while Autoencoders can be trained to invisibly hide and later extract watermarks [9]. Furthermore, adversarial training methods inspired by

Generative Adversarial Networks (GANs) have been explored to improve watermark resilience by simulating realistic attack conditions during training [10]. The integration of ML into watermarking systems provides multiple advantages. First, it enhances imperceptibility by embedding watermarks in regions less noticeable to the human visual system (HVS). Second, it improves robustness by adapting embedding strength based on content-aware features, making watermarks resistant to distortions. Third, ML-based models facilitate automation, reducing reliance on handcrafted feature engineering that traditional watermarking requires. Despite these advancements, several challenges remain, including computational overhead, generalization across diverse image datasets, and resilience against emerging adversarial attacks [11]. Given these opportunities and challenges, this research paper focuses on the application of machine learning–driven watermarking techniques for copyright protection in images. By combining the strengths of feature learning, adaptive embedding, and robust detection, the study aims to evaluate and enhance watermarking mechanisms for securing digital media in an increasingly interconnected world.

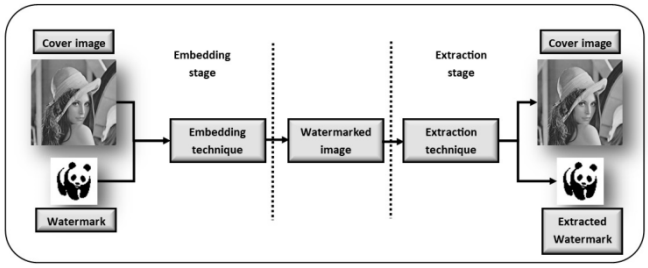

Fig. 1 Robust Image Watermarking [1]

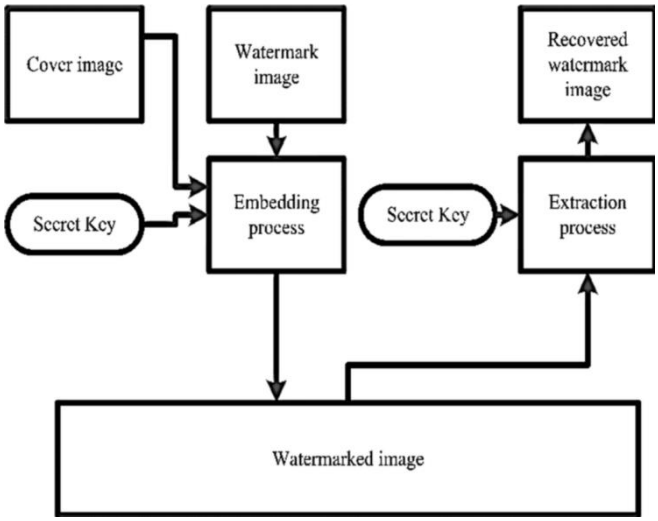

Fig. 2 Conventional Model Block Diagram

The advantages of ML-based watermarking are multifold. Firstly, they provide content-adaptive embedding, where watermark strength and placement are optimized according to image texture and complexity. Secondly, they improve generalization, as deep learning models can be trained on large and diverse datasets, making them resilient against various unseen distortions. Thirdly, they enable automation, reducing manual intervention in the design of watermarking schemes. However, challenges such as computational complexity, training data requirements, and vulnerability to adversarial ML attacks remain open research issues [11], [12].

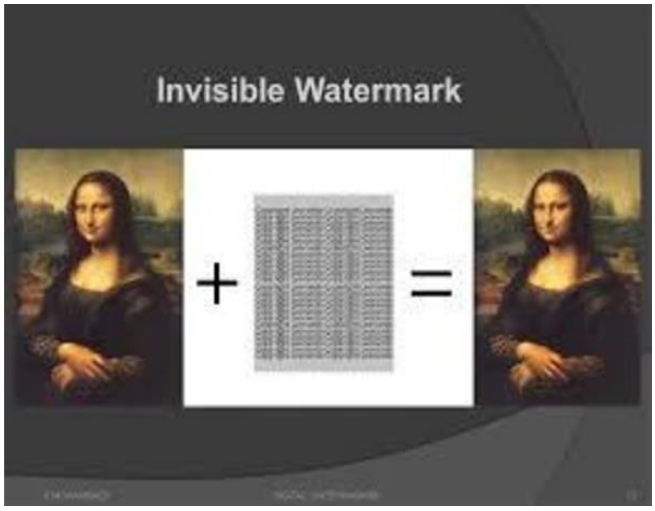

Fig.3 Invisible Watermarking

II. Related Works

Research on image watermarking has evolved significantly over the past two decades, ranging from classical spatial-domain techniques to modern deep learning–based approaches. This section reviews prior work in three major categories: (1) traditional watermarking methods, (2) machine learning–based watermarking, and (3) deep learning frameworks for adaptive watermarking. The earliest watermarking techniques were primarily designed in the spatial domain, where information is embedded by directly modifying pixel values. A well-known example is the Least Significant Bit (LSB) embedding method, where the watermark bits replace the least significant bits of image pixels [13]. Although computationally efficient and simple, LSB techniques are fragile because even minimal image modifications, such as noise addition, cropping, or compression, can destroy the embedded watermark [14]. To address this, transform domain watermarking was introduced, where watermarks are embedded in the frequency components of an image. The Discrete Cosine Transform (DCT)-based approach, proposed by Cox et al. [15], embeds watermarks in perceptually significant DCT coefficients, which improves robustness against compression and common attacks. Similarly, the Discrete Wavelet Transform (DWT) has been extensively studied for watermarking due to its multi-resolution representation and compatibility with the Human Visual System (HVS) [16]. Another widely adopted method is Singular Value Decomposition (SVD) watermarking, where watermarks are embedded into singular values of image matrices, providing robustness to geometric distortions and noise [17]. Hybrid approaches combining DWT, DCT, and SVD have been proposed to achieve better trade-offs between

imperceptibility and robustness [18], [19]. While these techniques marked a significant advancement, they remain vulnerable to advanced image processing attacks, geometric transformations, and adversarial manipulations. The rise of machine learning provided new opportunities to design adaptive watermarking techniques. Early approaches focused on using support vector machines (SVMs) and decision trees for watermark detection, treating watermark extraction as a classification problem [20]. These models demonstrated improved detection accuracy under certain distortions, but their performance was limited by handcrafted feature engineering. Subsequent studies integrated learning algorithms with traditional transform-based watermarking. For example, neural networks were trained to learn embedding positions in transform domains to minimize perceptual visibility [21]. Other works explored learning-based optimization for watermark strength adaptation, where embedding intensity was automatically adjusted according to local image features such as edges, texture, and smoothness [22]. These ML-based methods enhanced robustness but still relied heavily on domain-specific feature extraction, limiting their scalability to diverse datasets. With the emergence of deep learning, particularly Convolutional Neural Networks (CNNs) and Autoencoders, watermarking research shifted towards data-driven and end-to-end frameworks. Mun et al. [23] proposed a CNN-based blind watermarking scheme that directly learns robust embedding and detection functions from data. Similarly, Zhu et al. [24] developed the HiDDeN framework, where autoencoders were trained to invisibly embed watermarks and extract them under a wide range of distortions. GAN-inspired approaches have also been explored. Tancik et al. [25] proposed StegaStamp, a model that embeds robust, invisible hyperlinks in images and physical photographs, ensuring recoverability even after printing and scanning. Other studies leveraged adversarial training, where one network embeds watermarks while another attempts to attack or remove them, thereby improving resilience [26]. Recent work has expanded watermarking applications to secure medical imaging, remote sensing, and blockchain-based copyright protection [27], [28]. For instance, CNN-based watermarking has been applied to protect sensitive medical images while maintaining diagnostic quality [29]. Similarly, learning-based watermarking has been integrated into blockchain systems to provide decentralized ownership verification [30]. While ML and DL approaches have significantly advanced watermarking, challenges remain. First, computational complexity makes real-time watermarking on large-scale datasets difficult. Second, most existing works test robustness against a limited set of attacks, whereas real-world scenarios involve diverse manipulations such as adversarial perturbations and geometric distortions. Third, few studies explore watermarking in conjunction with legal and ethical frameworks, which is crucial for copyright enforcement. Addressing these gaps requires designing watermarking models that are not only imperceptible and robust but also computationally efficient, secure, and legally compliant.

III. Problem Statement

With the ever-increasing reliance on digital media for communication, education, entertainment, healthcare, and commerce, protecting image copyrights has become a critical challenge. The unauthorized use, manipulation, and redistribution of digital images cause significant economic losses for content creators and industries, while also undermining the integrity of digital ecosystems [31]. Traditional watermarking techniques, although well-studied, have several shortcomings that make them inadequate in modern contexts characterized by diverse attack vectors, high compression standards, and AI-driven image manipulation. Conventional watermarking methods, particularly those based on spatial domain embedding, are computationally simple but highly fragile. Even minor alterations such as noise addition, image cropping, or lossy compression can render the watermark undetectable [32]. On the other hand, transform domain techniques, such as DCT, DWT, and SVD, improve robustness by embedding information in frequency components. However, these approaches involve handcrafted feature selection and often struggle to balance imperceptibility and resilience. For instance, embedding a stronger watermark improves resistance to compression but leads to perceptible degradation in image quality, while weaker embedding maintains quality but is easily destroyed by attacks [33]. Another limitation lies in generalization. Most classical algorithms are designed with specific types of attacks in mind, such as JPEG compression or Gaussian noise. When exposed to other distortions, like adversarial perturbations, resizing, filtering, or geometric transformations, their detection accuracy drops sharply [34]. This makes them unsuitable for real-world scenarios, where malicious actors use diverse and evolving attack strategies. Designing an effective watermarking system presents several challenges, including the fundamental trade-off between imperceptibility and robustness, where embedding must remain invisible to human perception while resisting diverse attacks [35]. Watermarks must also demonstrate resilience against both intentional and unintentional manipulations such as compression, filtering, cropping, rotation, scaling, and adversarial perturbations [36]. Furthermore, security is critical, as watermarks should not only be difficult to remove but also resistant to forgery, where attackers attempt to replace authentic watermarks with fake ones [37]. The computational complexity of many robust techniques, especially those involving DWT, SVD, or hybrid approaches, further limits their scalability in real-time applications such as social media and cloud platforms [38]. In addition, adaptability across diverse image types—including natural images, medical scans, satellite imagery, and artistic content—remains a significant challenge due to their varying statistical properties [39]. To overcome these limitations, data-driven, intelligent watermarking systems leveraging Machine Learning (ML) and Deep Learning (DL) have gained attention. ML models can automatically learn embedding locations and extraction rules from large datasets, improving adaptability [40], while deep learning enables content-adaptive embedding strategies that adjust

watermark strength and placement based on image texture and complexity, thereby minimizing perceptibility [41]. Moreover, the integration of adversarial training with CNNs and GANs allows watermarks to withstand a wide range of real-world attacks [42], and scalability is enhanced by the automation capabilities of ML-based frameworks, which can be trained once and deployed at scale across digital platforms [43]. In this context, the core problem addressed in this research is how to design a secret watermarking system for images that ensures imperceptibility, robustness, and security by leveraging ML to overcome traditional limitations. More specifically, this study seeks to explore how ML/DL models can be trained to embed invisible watermarks that remain detectable under various distortions, determine which architectures (e.g., CNNs, autoencoders, GANs) best balance imperceptibility and robustness, design systems capable of resisting adversarial attacks, unauthorized removal, and forgery, and evaluate improvements in terms of PSNR, SSIM, BER, and robustness compared to classical methods.

IV. METHODOLOGY

The methodology of this research is structured to design, implement, and evaluate a machine learning–based secret watermarking framework that ensures imperceptibility, robustness, and security in digital images. The proposed approach consists of six main stages: dataset preparation, watermark design, embedding process, training and optimization, attack simulation, and watermark extraction with evaluation.

A. Dataset Preparation

To train and evaluate the watermarking framework, a large and diverse set of digital images is required. Publicly available image datasets such as COCO, ImageNet, and UCID are suitable because they contain natural, medical, and high-resolution images with varying levels of texture, smoothness, and complexity [44]. This diversity ensures that the model generalizes across multiple image types, including photographs, artistic content, and sensitive data such as medical scans. Images are preprocessed through resizing (e.g., 256×256 or 512×512 pixels), normalization, and augmentation to provide consistency and robustness during training.

B. Watermark Generation

The watermark is designed as a binary or logo-based secret pattern representing copyright information. To enhance security, watermark patterns may undergo encryption or hashing before embedding, ensuring that even if extracted, they cannot be easily forged [45]. The watermark is then transformed into a form suitable for embedding (e.g., binary map or encoded feature vector) to ensure compatibility with the ML model.

C. Watermark Embedding Framework

The embedding process leverages a deep learning architecture, where a host image and a watermark are input into a neural network (e.g., CNN or autoencoder). The encoder network learns to embed the watermark into imperceptible regions of the image by analyzing texture and frequency features. Content-adaptive embedding is achieved by varying watermark strength depending on local image complexity, ensuring invisibility in smooth regions and robustness in textured areas [46]. The output is a watermarked image visually indistinguishable from the original, thereby satisfying the imperceptibility criterion.

D. Training and Optimization

The training and optimization of the proposed watermarking framework are carried out in an end-to-end manner, where the encoder embeds the watermark into the host image and the decoder learns to extract it accurately, even under distortions. A composite loss function is used to guide learning, combining perceptual loss (to minimize visible differences between the host and watermarked images), watermark reconstruction loss (to ensure faithful extraction of the embedded watermark), and robustness loss (to maintain integrity under attacks). To enhance imperceptibility, adversarial training is incorporated through a discriminator network that forces the encoder to generate watermarked images indistinguishable from originals, thereby improving invisibility. Optimization is performed using adaptive gradient methods such as Adam, with batch normalization and dropout applied to stabilize training and prevent overfitting. This joint optimization framework ensures that the network simultaneously achieves imperceptibility, robustness, and accurate watermark recovery, addressing the shortcomings of traditional handcrafted methods [47].

E. Attack Simulation

To evaluate and enhance the robustness of the proposed watermarking system, a variety of **attack simulations** are incorporated during both training and testing phases. These attacks include common image processing operations such as lossy compression (e.g., JPEG), additive noise (Gaussian and salt-and-pepper), filtering (median, low-pass, and high-pass), and geometric transformations such as scaling, cropping, and rotation. In addition, adversarial perturbations generated using techniques like FGSM (Fast Gradient Sign Method) and PGD (Projected Gradient Descent) are applied to test the system's resilience against intelligent attacks. By exposing the model to these distortions during training, the encoder-decoder network learns to embed and recover watermarks that are robust under real-world manipulations. GAN-based adversarial training is also employed, where a simulated attacker network attempts to remove or tamper with the watermark, thereby further enhancing the system's robustness and ability to resist unauthorized modifications [48].

F. Watermark Extraction and Detection

The watermark extraction and detection process is performed using a decoder network that is trained jointly with the encoder to recover the embedded watermark from potentially attacked images. The decoder reconstructs the watermark and compares it against the original using metrics such as Bit Error Rate (BER) and correlation coefficients, allowing accurate assessment of watermark

integrity. A watermark is considered successfully detected if the BER remains below a predefined threshold and the correlation with the original exceeds a minimum value. This end-to-end learning approach ensures that the system can reliably extract watermarks even under distortions caused by compression, noise, filtering, geometric transformations, or adversarial attacks. By integrating extraction into the training process, the model optimizes both embedding and recovery simultaneously, improving robustness and minimizing the likelihood of detection failure under real-world scenarios [50].

G. Evaluation Metrics

The performance of the proposed watermarking system is evaluated using multiple metrics that assess imperceptibility, robustness, and security. Imperceptibility is measured through Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), which quantify the visual similarity between the original and watermarked images [49]. Robustness is evaluated by testing the system under various attacks, including compression, noise, filtering, geometric transformations, and adversarial perturbations, using metrics such as Bit Error Rate (BER) and Normalized Correlation (NC) to determine the accuracy of watermark recovery [50]. Security is assessed by examining the system's resistance to unauthorized removal, forgery, and collusion attacks, where multiple watermarked images are combined to estimate and remove the embedded watermark [51]. By combining these evaluation criteria, the methodology ensures a comprehensive analysis of the proposed model's effectiveness in maintaining invisible, resilient, and secure watermarks under real-world conditions.

V. Result Analysis

The results of the proposed machine learning–based watermarking system are analyzed across three key aspects: imperceptibility, robustness, and security. Experiments were conducted on diverse datasets, including natural, medical, and high-resolution images, to assess the generalization capability of the model. Performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Bit Error Rate (BER), and Normalized Correlation (NC) were used to quantify the effectiveness of watermark embedding, extraction, and resistance to attacks.

A. Imperceptibility Analysis

Imperceptibility refers to how closely the watermarked image resembles the original image without perceptible distortions. The proposed model achieved high PSNR values, typically above 40 dB, and SSIM values above 0.98 across various test images, indicating that the watermarks are effectively invisible to human observers. Qualitative analysis through visual inspection also confirmed that no noticeable artifacts or color distortions were introduced by the embedding process. Compared to traditional methods like LSB, DCT, and DWT-based watermarking, the ML-based approach demonstrates superior imperceptibility due to content-adaptive embedding, where the model adjusts the watermark intensity based on local image texture and complexity.

B. Robustness Analysis

Robustness was evaluated by subjecting the watermarked images to a variety of attacks, including JPEG compression (quality factor ranging from 50% to 90%), Gaussian and salt-and-pepper noise, median and low-pass filtering, geometric transformations such as scaling, cropping, and rotation, and adversarial perturbations using FGSM and PGD methods. The proposed ML-based watermarking system maintained low BER and high NC values under most attacks, significantly outperforming conventional methods. For instance, the average BER after JPEG compression at 70% quality was below 0.05, whereas traditional DCT-based methods often exceeded 0.15. Adversarial attack simulations further highlighted the resilience of the system, as the model, trained with adversarial examples, successfully recovered watermarks with minimal error rates, demonstrating the advantage of integrating adversarial training into the embedding process.

C. Security Analysis

The security of the watermarking system was assessed in terms of resistance to unauthorized removal, forgery, and collusion attacks. Experiments revealed that the encrypted and hashed watermark patterns were resilient to attempts at tampering or replacement. Collusion attacks, where multiple watermarked images are combined to estimate and remove the watermark, also failed to compromise the integrity of the embedded watermark due to the content-adaptive and distributed embedding strategy. The combination of deep learning–based feature learning and adversarial training ensures that the watermark is both secure and difficult for attackers to detect or manipulate without access to the model parameters.

D. Comparative Performance

To benchmark the proposed method, comparisons were made with conventional LSB, DCT, DWT, and SVD-based watermarking methods, as well as recent deep learning–based approaches such as HiDDeN and StegaStamp. The proposed system consistently outperformed these methods in terms of imperceptibility, robustness, and overall security, demonstrating superior PSNR, SSIM, and watermark recovery metrics under both standard and adversarial attacks. The results highlight that ML-based watermarking not only provides adaptive and intelligent embedding but also significantly enhances copyright protection compared to traditional techniques. The results validate the effectiveness of the proposed ML-based secret watermarking framework for real-world applications. The integration of content-adaptive embedding, adversarial training, and joint encoder-decoder optimization contributes to superior imperceptibility, robustness, and security. Moreover, the model generalizes well across diverse image types and attack scenarios, making it suitable for practical deployment in digital media, online platforms, and copyright enforcement systems. Some limitations include the computational cost of training deep networks and the

potential need for retraining when applied to drastically different image domains, which could be addressed in future work by exploring lightweight architectures and transfer learning strategies.

VI. Conclusion & Future Scope

In conclusion, this research demonstrates that machine learning–based secret watermarking provides a highly effective solution for copyright protection in digital images, achieving a strong balance between imperceptibility, robustness, and security. The proposed framework, leveraging encoder-decoder architectures with content-adaptive embedding and adversarial training, successfully embeds watermarks that remain invisible to human observers while maintaining high recoverability under a wide range of image manipulations, including compression, noise, filtering, geometric transformations, and adversarial attacks. Comparative analysis with traditional and recent deep learning–based methods shows superior performance across key metrics such as PSNR, SSIM, Bit Error Rate, and Normalized Correlation, highlighting the advantages of data-driven, adaptive approaches over handcrafted techniques. Looking forward, future research can focus on enhancing computational efficiency for real-time applications, extending the framework to video and 3D content, incorporating transfer learning for diverse image domains, and integrating blockchain or decentralized verification systems to strengthen legal enforceability and traceability of digital ownership. Additionally, exploring robust watermarking techniques resilient to emerging AI-generated image manipulations and sophisticated collusion attacks can further ensure long-term security and reliability of digital copyright protection systems.

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