

# Coverless Information Hiding Using Machine Learning: A Review and Comparative Analysis

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## ABSTRACT

The exponential growth of digital communication demands innovative data security solutions that go beyond traditional encryption and steganography. Coverless Information Hiding (CIH) has emerged as a next-generation paradigm that avoids embedding secret information into cover media, thereby eliminating detectable distortions. This paper presents a comprehensive review of ML-driven CIH techniques, focusing on deep learning, generative adversarial networks (GANs), robust hashing, and hybrid feature extraction methods. By analyzing key approaches from recent works—including machine learning-based frameworks (2023), hashing-based high-capacity methods (2024), we provide a comparative evaluation of their capacity, robustness, and efficiency. The study highlights strengths, limitations, and future directions for scalable, intelligent CIH systems capable of resisting adversarial attacks while ensuring high payload capacity and real-time applicability.

**Keywords** : Coverless Information Hiding, Machine Learning, Steganography, GANs, Robust Hashing, Information Security.

## 1. INTRODUCTION

Digital communication has become the backbone of modern society, facilitating rapid exchange of information across personal, commercial, governmental, and military domains. However, this increasing reliance on digital platforms has raised serious concerns regarding data privacy and secure transmission. Traditional security mechanisms, such as encryption, protect the confidentiality and integrity of data by converting plaintext into ciphertext. While encryption ensures that only authorized parties with the correct key can access the information, it does not conceal the presence of secret communication itself. Encrypted data, when intercepted, appears suspicious and may attract attackers, making it vulnerable to cryptanalysis and surveillance.

To overcome this limitation, steganography has been widely adopted as a complementary technique. Steganography hides the existence of information by embedding secret messages within digital media such as images, audio, video, or text. The modified media, known as the *stego-object*, appears visually or acoustically identical to the original, preventing suspicion from casual observers [1]. Despite its utility, traditional steganographic techniques suffer from inherent weaknesses. Embedding operations, whether in the spatial or frequency domain, introduce subtle distortions and statistical anomalies in the carrier media. Advanced steganalysis tools—often

powered by machine learning classifiers—can detect these anomalies with high accuracy, compromising the secrecy of the hidden communication.

Coverless Information Hiding (CIH) eliminates this fundamental weakness by avoiding any modification of the cover object [1][2]. Instead of altering pixel values or frequency coefficients, CIH relies on two primary strategies: (i) mapping secret information to the intrinsic features of pre-existing media, such as color histograms, texture descriptors, or hash codes, and (ii) generating new media objects on demand through intelligent models that inherently encode the secret message. Since no embedding occurs, the resulting media is free from detectable distortions, providing resistance against even the most advanced steganalysis methods.

Shallow ML techniques such as clustering and hashing initially enabled efficient feature matching between messages and media databases. With the advent of deep learning, more powerful models—such as Convolutional Neural Networks (CNNs) for semantic feature extraction and Generative Adversarial Networks (GANs) for realistic content generation—have been employed. These models allow semantic-level understanding of images, enabling robust mapping between message components and media features while ensuring visual imperceptibility. Moreover, hybrid frameworks that combine robust hashing with generative modeling further increase payload capacity and resilience against attacks [1][2].

This paper presents a comprehensive review of ML-driven CIH frameworks, compares existing approaches, and evaluates their performance in terms of capacity, robustness, and computational efficiency. By analyzing both retrieval-based and generative-model-based strategies, the study identifies current limitations such as database dependency, computational overhead, and vulnerability to adversarial attacks. Furthermore, it highlights promising future research opportunities aimed at enhancing the scalability, intelligence, and security of CIH systems for real-world applications [1][2].

## 2. Literature Review

The development of Coverless Information Hiding (CIH) has evolved significantly in recent years, with machine learning techniques playing a pivotal role in improving robustness, capacity, and imperceptibility. This section reviews notable contributions across four major directions: ML-driven frameworks, surveys and classifications, robust hashing methods, and hybrid approaches.

### 2.1 Machine Learning-Driven CIH

Jadeja et al. (2023, *Journal of Computational Analysis and Applications*) presented one of the first comprehensive studies on the integration of machine learning into CIH. Their framework leverages **Convolutional Neural Networks (CNNs)** [1] for high-level feature extraction and **Generative Adversarial Networks (GANs)** for image generation. Unlike conventional embedding-based methods, this approach ensures *zero embedding distortion* by either mapping secret data to existing image features or generating entirely new synthetic images aligned with the message content.

The strength of this method lies in its **imperceptibility** and **resistance to steganalysis** [1], since the generated stego images are visually indistinguishable from natural images. Moreover, the semantic-level understanding achieved through CNNs enables more flexible and robust mapping strategies. However, the framework also presents significant **challenges**:

- **Computational cost** – Training and deploying deep learning models such as GANs is resource-intensive.
- **Adversarial ML attacks** – GANs and CNNs are vulnerable to adversarial perturbations, which could potentially reveal or distort the hidden communication.
- **Database dependence** – Although reduced compared to hashing methods, generative approaches still require curated datasets for effective training.

This work highlights the potential of deep learning in revolutionizing CIH but also underlines the need for efficient, lightweight, and attack-resilient models.

## 2.2 Survey of Coverless Techniques

Another significant contribution comes from Jadeja et al. (2023, *Sirjana Journal*), who provided a broad **survey of CIH techniques**. The study classified CIH methods into two primary categories:

1. **Mapping-based CIH** – establishing relationships between image features (e.g., texture, color histograms, hash sequences) and secret information [2].
2. **Structured CIH** – directly generating stego images from key data using predefined rules or generative models.

The survey highlighted the evolution of CIH techniques from early **hashing-based methods** (e.g., SIFT, perceptual hashing) to **deep-learning-based feature extraction** approaches, including **DenseNet** for robust semantic feature mapping and **Mask-RCNN**[2] for segmentation-based steganography.

While the article offered a **clear taxonomy** and comprehensive overview of emerging methods, its primary limitation was the absence of **comparative performance evaluation**. Metrics such as payload capacity, computational complexity, and robustness against attacks were discussed qualitatively but not experimentally validated. Nevertheless, this survey serves as a useful foundation for categorizing CIH approaches and identifying research gaps.

## 2.3 Robust Hashing for High-Capacity CIH

The African Journal of Biomedical Research (2024) emphasized **robust hashing techniques** as a cornerstone of high-capacity CIH [1]. Unlike purely generative approaches, hashing-based CIH encodes secret information into *hash sequences* derived from image features, thereby avoiding carrier modification.

Notable methods discussed include:

- **CIHMSB (Coverless Information Hiding using Most Significant Bit)** [1]– maps secret data to the MSB values of image fragments, offering improved imperceptibility and robustness.
- **CIHLHF (Coverless Information Hiding using Lowest and Highest Fragment values)** – an extension of CIHMSB that doubles embedding capacity by using both low- and high-intensity fragments.
- **DenseNet + DWT hybrid models** – combining deep feature extraction with Discrete Wavelet Transform to generate robust hash sequences resistant to geometric distortions and noise.

The review demonstrated that robust hashing-based methods significantly **improve hiding capacity** while maintaining resilience against **JPEG compression, additive noise, and filtering attacks** [2]. However, these methods remain heavily dependent on **large-scale image databases** to ensure sufficient hash diversity. Scalability and storage requirements thus pose practical barriers to deployment.

The integration of Machine Learning (ML) into Coverless Information Hiding (CIH) has significantly advanced the field by enabling automated feature extraction, semantic mapping, and media generation. Compared to traditional embedding-based steganography, ML-driven CIH achieves higher imperceptibility and robustness against steganalysis. This section compares major CIH-ML approaches across four representative works.

### 3. Comparative Table: CIH using ML

Method	Year	Technique/Model Used	Secret Data Type	Strengths	Limitations
Hash-based Image Retrieval	2014–2016	Image Hashing + Lookup Table	Text	Simple, fast retrieval, avoids modification of cover image	Low capacity, limited security
LBP-based CIH	2016	Local Binary Pattern (LBP) Hashing	Text	High robustness against steganalysis, no cover modification	Low embedding capacity
GAN-based CIH	2017–2018	Generative Adversarial Networks (WGAN, DCGAN)	Image/Text	High imperceptibility, generates realistic images	Training complexity, requires large dataset

Method	Year	Technique/Model Used	Secret Data Type	Strengths	Limitations
CNN-based CIH	2018–2019	Convolutional Neural Networks	Image	High security, flexible mapping	Computationally expensive
Image Retrieval + Deep Hashing	2019	Deep Hash Learning	Text	High retrieval accuracy, scalable	Vulnerable to hash collisions
Transformer-based CIH	2020+	Vision Transformers (ViT), Text-Image Mapping	Text/Image	High accuracy, supports multimodal hiding	Needs high computational power
Multi-Modal CIH	2021+	Cross-modal Hashing + Deep Learning	Text, Image, Audio	Large capacity, supports diverse data	Complex system, higher storage needs
Diffusion Model-based CIH	2023+	Denosing Diffusion Probabilistic Models	Image	Ultra-realistic generation, high resistance to detection	Computationally very expensive

## 4. Challenges and Open Issues

Despite significant progress, Coverless Information Hiding (CIH) using Machine Learning faces several challenges that limit its widespread adoption. These challenges are primarily related to scalability, computational efficiency, security vulnerabilities, and trade-offs between performance factors.

### 4.1 Database Dependency

Mapping-based CIH methods rely on large-scale image libraries to map secret data onto image features such as hash codes, color histograms, or texture descriptors. While these libraries ensure greater mapping diversity and embedding capacity, they introduce several issues:

- **Storage overhead:** Maintaining massive image datasets requires substantial memory and storage resources.
- **Retrieval bottleneck:** As dataset size grows, efficient indexing and fast retrieval of matching images become difficult, impacting real-time performance.
- **Scalability concerns:** In real-world deployments, continuously updating and managing such databases to meet diverse communication requirements is challenging. Addressing this dependency is crucial for the practical deployment of mapping-based CIH systems.

## 4.2 Computational Cost

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have enhanced CIH by providing semantic feature extraction and realistic image synthesis. However, these models are computationally intensive:

- **High training requirements:** GANs require vast datasets and prolonged training to generate high-quality stego-images.
- **Inference overhead:** Deploying these models for real-time communication requires powerful hardware, limiting usability on resource-constrained devices (e.g., mobile IoT nodes).
- **Energy consumption:** The computational load translates into high energy consumption, which is impractical for lightweight or embedded applications. Thus, the development of **lightweight, resource-efficient CIH models** is an open research area.

## 4.3 Adversarial Machine Learning Attacks

While CIH eliminates embedding distortion, ML-driven systems are vulnerable to **adversarial perturbations**. Small, imperceptible changes to an image can mislead CNNs or GANs into incorrect mappings or faulty image generation. This introduces two major risks:

- **Security breach:** Attackers could manipulate the system to misinterpret or reveal hidden data.
- **Robustness loss:** Adversarial attacks undermine the reliability of ML-based CIH in hostile environments. To address this, **adversarially robust training methods** and **defensive mechanisms** must be integrated into CIH frameworks.

## 4.4 Capacity vs. Efficiency Trade-Off

A persistent challenge in CIH research is balancing **payload capacity** with **system efficiency**:

- **High-capacity systems** often involve overlapping blocks, complex hashing, or hybrid ML architectures, which increase computational overhead.
- **Real-time systems** prioritize efficiency but usually sacrifice payload capacity.
- **Practical deployments** require finding a middle ground, where acceptable capacity is maintained without overwhelming computational resources. Future work must focus on optimizing **capacity-to-efficiency ratios**, possibly through hybrid frameworks that intelligently combine hashing with generative modeling.

## 5. Future Research Directions

The rapid advancement of Coverless Information Hiding (CIH) using Machine Learning has opened new avenues for secure communication. However, to achieve practical, scalable, and attack-resistant CIH systems, future research must address current challenges while exploring innovative directions. Several promising research frontiers are highlighted below.

### 5.1 Lightweight Machine Learning Models

While CNNs and GANs have improved semantic mapping and image generation in CIH, their **computational complexity** limits real-time deployment. Future efforts should focus on:

- **Model compression and pruning:** Reducing the number of parameters in CNNs and GANs to enable faster inference.
- **Knowledge distillation:** Training compact “student models” using large, powerful “teacher models” to achieve near-equal performance with lower computational cost.
- **Hardware-aware optimization:** Designing CIH models tailored for deployment on **edge devices, IoT nodes, and mobile platforms**, where resources are limited. Lightweight ML models will enable practical CIH applications in everyday secure communications.

### 5.2 Hybrid Frameworks

A promising direction is combining the strengths of **robust hashing** and **generative modeling** into hybrid CIH systems. Potential developments include:

- **Feature-based hashing + GAN synthesis:** Using robust feature extraction (e.g., SIFT, LBP, DenseNet) to create hash codes while employing GANs to synthesize natural-looking stego-images.
- **Adaptive hybrid methods:** Dynamically switching between retrieval-based hashing and generative models depending on system requirements (e.g., high capacity vs. high efficiency).
- **Multi-level hybrid CIH:** Integrating hashing at lower levels and generative models at semantic levels to achieve better trade-offs in capacity, robustness, and efficiency. Such frameworks could **mitigate database dependency** while enhancing both scalability and resilience.

### 5.3 Quantum-Secure CIH

The rise of quantum computing threatens conventional cryptography and may indirectly affect CIH frameworks. While CIH itself avoids traditional embedding, **post-quantum security integration** will be critical for long-term resilience. Future directions include:

- **Quantum-resistant encryption + CIH:** Combining CIH with lattice-based or hash-based cryptographic schemes to ensure end-to-end security.
- **Quantum machine learning (QML) for CIH:** Leveraging quantum algorithms to enhance feature extraction and pattern matching for faster and more secure CIH.
- **Quantum coverless steganography:** Exploring the potential of encoding information in **quantum states of media (qubits, quantum images)**, thus achieving theoretically unbreakable secrecy.

### 5.4 Cross-Modal CIH

Most existing CIH research focuses on **images**, but extending CIH to **other media types** can significantly increase payload capacity and application diversity. Future studies can explore:

- **Audio CIH:** Mapping secret data into audio features such as spectrograms, MFCCs, or pitch variations.
- **Video CIH:** Utilizing temporal redundancy and deep video generation models to encode larger payloads across frames.
- **Multimodal CIH:** Embedding across **multiple modalities simultaneously (image + audio + text)** to distribute payloads, making detection even more difficult. Cross-modal CIH would enhance not only **capacity** but also the **robustness and flexibility** of secure communication systems.

### 5.5 Toward Real-World CIH Applications

For CIH to transition from research to practical adoption, additional considerations must be addressed:

- **Standardized benchmarks and datasets** for fair performance evaluation.
- **Integration with blockchain** for secure CIH-based data authentication.
- **Privacy-preserving federated learning** to train CIH models without exposing sensitive datasets.

## 6. CONCLUSION

Coverless Information Hiding (CIH) using Machine Learning has emerged as a transformative approach to secure communication, overcoming the weaknesses of traditional embedding-based steganography. By avoiding direct modifications of cover media, CIH minimizes detectable artifacts and achieves higher imperceptibility. Its evolution demonstrates a steady advancement—progressing from hashing-based retrieval methods, to deep learning frameworks using CNNs and GANs, and finally to hybrid approaches such as LBP-WGAN, which combine robust feature extraction with generative synthesis. These advancements have significantly improved hiding capacity, robustness, and resistance to steganalysis, establishing CIH as a leading candidate for next-generation secure communication. Nevertheless, critical challenges remain, including database dependency in retrieval-based methods, high computational costs of generative models, vulnerability to adversarial ML attacks, and the persistent capacity–efficiency trade-off that hinders real-time applicability. Future research must therefore focus on lightweight ML models for edge devices, scalable hybrid frameworks that merge hashing with generative models, quantum-secure CIH mechanisms, and cross-modal expansion into audio, video, and multimodal payloads. In conclusion, while CIH has already shown superiority over conventional steganography, its full potential lies in the integration of efficient machine learning, hybrid design, and emerging technologies. With these advancements, CIH can mature into a practical, scalable, and quantum-resilient solution for safeguarding sensitive information in the digital era.

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