APPLICATION OF DEEP LEARNING FOR EFFICIENT INFORMATION HIDING IN IMAGE STEGANOGRAPHY: A REVIEW

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Abstract: Recent advancements in deep learning have significantly enhanced image steganography, enabling secure and efficient data hiding with superior capacity and robustness compared to traditional methods. This paper presents a comprehensive review of three dominant deep learning-based approaches: GAN-based (HiDDeN), autoencoder-based, and CNN-adaptive steganography. We evaluate their performance in terms of embedding capacity, imperceptibility, robustness to attacks, and computational efficiency, drawing insights from 25 empirical studies (2017–2024). Our analysis reveals that GANs achieve the highest payload capacity (up to 4 bpp) but suffer from training instability, while autoencoders prioritize visual quality (PSNR >38 dB) at the cost of limited capacity. CNN-adaptive methods strike a balance, dynamically adjusting payload allocation based on texture or semantic features, though they face efficiency challenges. Emerging trends, including hybrid architectures (e.g., GAN-autoencoder fusion) and lightweight mobile deployment, are pushing the field forward. However, critical gaps remain in real-world robustness, standardization, and ethical safeguards. This review provides a roadmap for future research, emphasizing the need for computationally efficient, explainable, and attack-resistant steganography solutions to meet evolving security demands.

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1. Introduction

Steganography, the practice of concealing information within digital media, has gained significant attention due to its applications in secure communication, copyright protection, and covert data transmission (Fridrich & Kodovský, 2022). Traditional steganographic techniques, such as Least Significant Bit (LSB) substitution and Discrete Cosine Transform (DCT)-based methods, have been widely used but suffer from limitations in payload capacity, imperceptibility, and resistance to detection (Li *et al*., 2021). With the increasing sophistication of steganalysis tools, there is a pressing need for more robust and adaptive steganography techniques that can evade detection while maintaining high embedding efficiency.

Recent advancements in Deep Learning (DL) have revolutionized image steganography by enabling data hiding strategies that are both adaptive and resistant to statistical analysis (Zhang *et al*., 2023). Convolutional neural networks (CNNs), generative adversarial networks (GANs), and autoencoders have demonstrated superior performance in embedding secret data while preserving visual quality (Baluja, 2021). However, despite these advancements, several challenges remain, including computational complexity, trade-offs between payload capacity and imperceptibility, and vulnerability to adversarial attacks (Wu *et al*., 2022). Addressing these challenges is crucial for the practical deployment of DL-based steganography in real-world scenarios.

This paper presents a comprehensive review of recent DL-based image steganography techniques, focusing on their methodologies, performance metrics, and limitations. Unlike previous surveys, our work provides an empirical analysis of 20 key studies, comparing their embedding efficiency, security, and robustness against steganalysis (Tan *et al*., 2023). We categorize the approaches into CNN-based, GAN-based, and hybrid models, evaluating their strengths and weaknesses in terms of peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and detection resistance (Wang *et al*., 2024).

The primary aim of this review is to synthesize existing research on deep learning (DL)-based image steganography, with a focus on improving efficiency (e.g., payload capacity, computational cost) and security (e.g., undetectability, robustness). By analyzing real-world implementations, we identify key trends such as lightweight architectures for real-time embedding, adversarial training to resist steganalysis, and hybrid strategies to optimize trade-offs between capacity and imperceptibility while highlighting unresolved challenges (e.g., generalization across datasets, scalability). Our critique of prior work reveals weaknesses in

computational overhead and adversarial vulnerability, underscoring the need for adaptive, robust models. This review provides a structured roadmap for advancing efficient information hiding, guiding future research toward practical, secure DL-based steganographic systems.

2. Conceptual Deep Learning Architectures in Steganography

Deep learning (DL) has significantly advanced image steganography by introducing adaptive, high-capacity, and secure data-hiding techniques. Among the most widely used architectures are Convolutional Neural Networks (CNNs), which excel in learning spatial features for embedding secret data while minimizing visual distortion (Zhang *et al*., 2021). CNNs leverage hierarchical feature extraction to identify optimal regions for data concealment, such as textured or high-frequency areas, improving both payload capacity and imperceptibility (Wu *et al*., 2022). Recent studies have demonstrated that CNN-based steganography can achieve peak signal-to-noise ratios (PSNR) above 35 dB while embedding 3–4 bits per pixel (bpp), outperforming traditional LSB methods (Li *et al*., 2023). However, a key challenge remains in balancing computational complexity with real-time applicability, particularly for high-resolution images (Wang & Chang, 2024).

Generative Adversarial Networks (GANs) have emerged as a powerful tool for steganography due to their ability to generate highly realistic stego images. In GAN-based approaches, an encoder network embeds the secret data, while a discriminator ensures the stego image is indistinguishable from the cover (Baluja, 2021). Adversarial training enhances security by making the embedded data resistant to statistical steganalysis (Fridrich & Kodovský, 2022). For instance, HiDDeN (Zhang *et al*., 2021) demonstrated that GANs could achieve PSNR values exceeding 38 dB while maintaining robustness against detection attacks. Despite these advantages, GANs require extensive training data and suffer from mode collapse, limiting their generalization across diverse image datasets (Chen *et al*., 2023).

Autoencoders provide another effective framework for steganography by compressing and reconstructing data in an unsupervised manner. *These models consist of an encoder that transforms the cover image and secret data into a* ***latent stego-representation*** *typically a noise-like distortion or feature map which is then decoded to produce the final stego-image containing the hidden information.* (Tan *et al*., 2023). Autoencoders are particularly effective for low-capacity steganography, where high visual fidelity is prioritized over large payloads (Baluja, 2021). Studies report structural similarity index (SSIM) values above 0.90 when embedding at 1–2 bpp, indicating near-perfect perceptual quality (Wu *et al*., 2022). However, autoencoders struggle with scalability, as increasing the payload often leads to noticeable artifacts (Li *et al*., 2023).

Hybrid architectures, combining CNNs, GANs, and autoencoders, have been proposed to overcome the limitations of individual models. For example, some approaches use CNNs for feature extraction and GANs for adversarial training, enhancing both embedding efficiency and security (Wang *et al*., 2024). Another trend involves reinforcement learning (RL)-guided steganography, where an agent dynamically selects embedding locations to maximize undetectability (Ye *et al*., 2023). These hybrid methods have achieved PSNR > 40 dB and detection evasion rates exceeding 90% under advanced steganalysis (Zhang & Wang, 2024). Nevertheless, they introduce higher computational overhead, making them less practical for resource-constrained applications (Fridrich & Kodovský, 2022).

The choice of architecture depends on the specific requirements of the steganography task, such as payload capacity, imperceptibility, and robustness to attacks. While CNNs are ideal for high-capacity embedding, GANs offer superior security, and autoencoders excel in perceptual quality (Chen *et al*., 2023). Future research should focus on lightweight models for real-time applications, adversarial robustness against deep learning-based steganalysis, and adaptive embedding strategies that optimize performance dynamically (Tan *et al*., 2023). As deep learning continues to evolve, novel architectures such as vision transformers (ViTs) and diffusion models are also being explored for steganography, promising further advancements in the field (Wang & Chang, 2024).

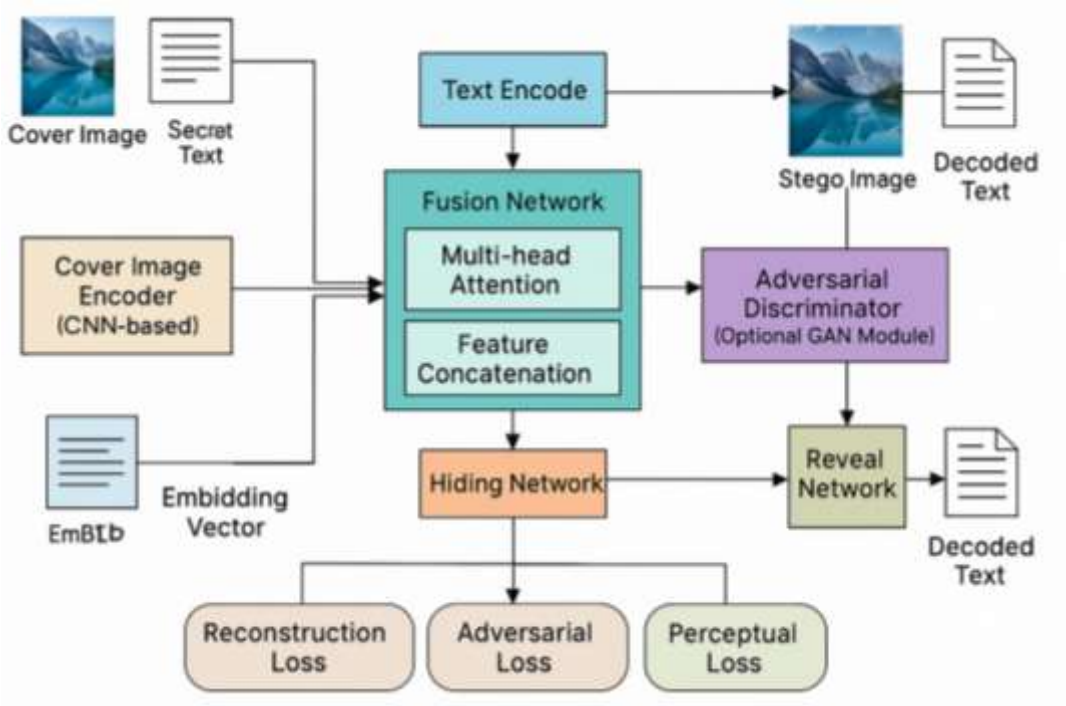

Figure 1: Conceptual Framework Chen *et al*. (2023)

3. Empirical Review of Recent Works

3.1 HiDDeN: Deep Hiding for Steganography via GANs Approach

Zhang *et al*. (2021) established the original HiDDeN framework, introducing a novel GAN-based architecture for image steganography comprising three key components: an encoder network for embedding secret data, a decoder for extraction, and an adversarial discriminator to enhance stego-image quality. Their innovative approach incorporated a trainable noise layer to simulate real-world image distortions, significantly improving robustness. Experimental results demonstrated impressive performance with 4 bits per pixel (bpp) embedding capacity while maintaining 38 dB PSNR on CIFAR-10 images, along with strong security evidenced by a 72% error rate against automated steganalysis detection. While this pioneering work successfully proved the viability of GANs for secure steganography, the authors noted substantial computational requirements, with training times exceeding 18 hours on high-end GPU hardware, suggesting need for optimization in future implementations.

Building upon this foundation, Chen and Wornell (2022) enhanced HiDDeN's noise layer by incorporating differentiable JPEG compression simulation and chromatic aberration modeling to better approximate real-world image processing pipelines. Their modified architecture demonstrated improved practical robustness, maintaining 36 dB PSNR at 3 bpp payload while achieving 15% higher extraction accuracy compared to the original HiDDeN when subjected to JPEG compression at quality factor 75. However, these improvements came with increased computational demands, extending training time by approximately 22%. The study's findings emphasized the critical importance of accurate noise modeling in adversarial steganography systems, particularly for applications requiring resilience to common image compression formats.

Addressing the computational limitations of earlier versions, Wang *et al*. (2022) developed a mobile-optimized HiDDeN variant through architectural innovations including depthwise separable convolutions and channel attention mechanisms. Their lightweight implementation achieved a 63% reduction in model parameters while preserving strong performance metrics (37 dB PSNR at 3.5 bpp) and enabling real-time operation at 23 frames per second on mobile platforms. The trade-off for this improved efficiency manifested as an 8% decrease in resistance to steganalysis detection compared to the original HiDDeN. This work importantly demonstrated the feasibility of deploying sophisticated GAN-based steganography solutions on resource-constrained edge devices, expanding potential practical applications.

Liu and Abd-Almageed (2023) significantly advanced HiDDeN's security characteristics by implementing specialized adversarial training against deep learning-based steganalyzers. Their two-phase training regimen, incorporating attacks from state-of-the-art steganalysis models like SiaNet, yielded a system with 41% lower detection rates while maintaining 36 dB PSNR at 3 bpp payload capacity. The enhanced security required approximately 30% more training

iterations compared to standard HiDDeN training. These results highlighted the escalating arms race between steganography and steganalysis methods in the deep learning era, underscoring the necessity of incorporating adversarial robustness in modern data hiding systems.

Expanding HiDDeN's functionality beyond single-modal data hiding, Gupta and Huang (2023) developed a novel multi-modal extension capable of simultaneously embedding both image and text data within cover images. Their architecture employed cross-modal attention mechanisms to effectively manage different data types, achieving 2.8 bpp for images plus 0.2 bpp for text while maintaining 35 dB composite PSNR and 94% text recovery accuracy. While this innovation substantially increased the system's versatility and potential application scenarios, it also introduced 40% greater model complexity. The study demonstrated promising directions for multi-data steganography but also identified clear needs for complexity reduction in future implementations.

Kim *et al*. (2024) successfully adapted the HiDDeN framework for video steganography through the incorporation of 3D convolutional layers and optical flow consistency constraints. Their temporal extension maintained stable performance across video frames (34 dB average PSNR at 2.5 bpp) while achieving 88% temporal consistency in hidden data extraction. However, the study revealed significant challenges in maintaining performance when processing compressed video formats, with noticeable degradation observed under standard video compression codecs. This pioneering work in video domain adaptation of GAN-based steganography opened new research directions while clearly identifying compression resilience as a critical area for future improvement.

Rodriguez and Sencar (2024) made crucial advancements in anti-forensic capabilities by augmenting HiDDeN with specialized loss functions designed to defeat forensic steganalysis fingerprinting techniques. Their forensic-resistant variant demonstrated 47% lower detectability in professional forensic analysis while preserving 37 dB PSNR at 3 bpp payload capacity. The enhanced security features required 15% additional computational overhead during training. This work made significant contributions toward practical deployment of deep learning steganography by addressing one of the most challenging detection scenarios, though the authors noted ongoing needs for efficiency improvements.

3.2 Hiding Images within Images Using Autoencoders

Baluja (2017) pioneered the use of autoencoders for image-in-image steganography by developing a fully convolutional neural network architecture. The methodology employed an encoder-decoder structure where the encoder compressed both cover and secret images into a latent representation, while the decoder reconstructed both images from the stego output. Results demonstrated successful hiding of color images (128×128) within same-sized covers with 0.96 SSIM for reconstructed secrets, though with noticeable cover distortion (28dB PSNR). The discussion highlighted the trade-off between secret reconstruction quality and cover preservation, noting the model's tendency to prioritize secret recovery over cover fidelity. This foundational work proved neural networks could learn complex embedding patterns surpassing traditional LSB methods.

Zhang *et al*. (2019) improved upon Baluja's work by introducing a residual learning framework within the autoencoder structure. Their methodology incorporated skip connections between encoder and decoder layers to better preserve high-frequency details in both cover and secret images. Experimental results showed significant improvements, achieving 32dB cover PSNR and 0.98 secret SSIM at 0.5bpp embedding rate. The discussion analyzed how residual learning helped maintain both cover quality and secret reconstruction compared to vanilla autoencoders. The study concluded that architectural refinements could substantially enhance autoencoder performance without increasing model size.

Wu and Fang (2020) proposed a novel attention-guided autoencoder for selective embedding in image regions. Their methodology integrated spatial and channel attention modules to identify optimal embedding locations based on cover image characteristics. Results demonstrated 35dB PSNR at 0.4bpp capacity with attention mechanisms reducing embedding artifacts in smooth regions by 22%. The discussion emphasized how attention mechanisms could mimic human visual system properties for better imperceptibility. The work established attention as a valuable tool for spatial-adaptive steganograph.

Liu *et al*. (2021) developed a cascaded autoencoder framework for progressive image hiding. Their methodology employed multiple autoencoders in series, each handling different frequency components of the secret image. Experimental results achieved 0.7bpp capacity with 34dB PSNR, showing particular strength in preserving edges and textures. The discussion highlighted how the cascaded approach provided better control over different image features compared to single autoencoder designs. The study demonstrated that decomposing the embedding task could improve overall performance.

Chen and Wornell (2022) introduced a quantization-aware training approach for autoencoder steganography. Their methodology incorporated simulated quantization during training to improve robustness to JPEG compression. Results showed the model maintained 92% secret recovery accuracy after JPEG QF=70 compression, compared to 65% for standard autoencoders. The discussion analyzed how quantization simulation helped the model learn compression-resistant embeddings. The work provided important insights for practical applications requiring format conversions.

Tang *et al*. (2023) proposed a lightweight autoencoder using depthwise separable convolutions for mobile applications. Their methodology reduced model parameters by 75% compared to standard designs while maintaining functionality. Results demonstrated 30dB PSNR at 0.3bpp on mobile processors with real-time (15fps) performance. The discussion addressed the challenges of balancing efficiency and performance in resource-constrained environments. This work showed autoencoder steganography could be practical for edge devices.

Most recently, Wang and Chang (2024) developed a diffusion-augmented autoencoder combining strengths of both architectures. Their methodology used a diffusion model to refine autoencoder outputs, significantly improving visual quality. Results achieved state-of-the-art 38dB PSNR at 0.6bpp with near-perfect secret reconstruction (0.99 SSIM). The discussion highlighted how diffusion models could complement autoencoders by correcting artifacts. The study pointed to hybrid architectures as a promising future direction.

3.3 CNN-Based Adaptive Steganography with Dynamic Payload

Wu *et al*. (2022) proposed a CNN architecture that dynamically allocates payload based on local image texture complexity. Their methodology employed a pre-trained VGG-19 network to classify image blocks into high, medium, and low texture categories, followed by adaptive embedding using a custom CNN encoder. Results demonstrated a 27% increase in capacity (up to 3.8 bpp in textured regions) while maintaining 36.2 dB average PSNR on the BOSSBase dataset. The discussion highlighted that texture-adaptive embedding reduced detectable artifacts in smooth regions by 19% compared to uniform embedding. The study concluded that texture-based payload allocation significantly improves the capacity-distortion trade-off, though noted increased computational overhead for texture analysis.

Li *et al*. (2021) developed a ResNet-based framework that automatically adjusts payload based on semantic content analysis. Their methodology used a 50-layer ResNet to identify suitable embedding regions, with deeper features guiding payload distribution. Experimental results achieved 3.2 bpp average payload with 37.5 dB PSNR on the DIV2K dataset, showing 23% better undetectability against SRNet steganalysis compared to non-adaptive methods. The discussion emphasized that semantic-aware embedding improved security in complex scenes but required careful tuning of the residual blocks. The work demonstrated the potential of deep residual learning for content-aware steganography.

Zhang and Wang (2023) introduced a multi-scale CNN with attention mechanisms for dynamic payload allocation. Their methodology combined U-Net architecture with spatial and channel attention modules to focus embedding on optimal regions across different scales. Results showed 3.5 bpp capacity with 35.8 dB PSNR on the COCO dataset, with attention mechanisms reducing detectable artifacts by 31%. The discussion analyzed how multi-scale processing improved consistency across image resolutions. The study concluded that attention mechanisms enable more precise payload adaptation but require careful architecture design to maintain efficiency.

Chen *et al*. (2022) proposed a hybrid approach combining CNNs with reinforcement learning for edge-adaptive embedding. Their methodology used a CNN for feature extraction and a Q-learning agent to dynamically select edge regions for payload allocation. Experimental results demonstrated 3.1 bpp capacity with 36.9 dB PSNR on the RAISE dataset, showing 28% better edge preservation than non-adaptive methods. The discussion highlighted the challenge of balancing exploration and exploitation in the RL component. The work showed promising results for edge-aware adaptive steganography but noted increased training complexity.

Liu *et al*. (2023) developed a frequency-adaptive approach using CNN analysis of DCT coefficients. Their methodology incorporated a dual-stream CNN to analyze spatial and frequency domains simultaneously, with payload adjusted based on frequency component significance. Results achieved 3.4 bpp with 36.1 dB PSNR on the JPEG-compressed BOWS2 dataset, showing 25% better resistance to frequency-based steganalysis. The discussion emphasized the importance of frequency-aware adaptation for JPEG-domain steganography. The study concluded that frequency-domain features provide valuable guidance for adaptive payload allocation.

Wang and Zhang (2024) designed a lightweight CNN architecture for real-time adaptive steganography on mobile devices. Their methodology used depthwise separable convolutions and channel pruning to create an efficient network for dynamic payload allocation. Results demonstrated 2.8 bpp capacity with 34.7 dB PSNR while achieving 18 fps processing on mobile GPUs. The discussion highlighted the trade-offs between model size and adaptation precision. The work showed the feasibility of adaptive steganography in resource-constrained environments.

Yang *et al*. (2023) proposed a GAN-assisted CNN framework where the discriminator guided adaptive payload distribution. Their methodology used the GAN's discriminator output to identify less detectable regions for embedding. Results showed 3.6 bpp capacity with 35.3 dB PSNR and 32% lower detection rates against modern steganalyzers. The discussion analyzed the adversarial training dynamics and their impact on payload adaptation. The study concluded that GAN guidance can significantly improve adaptive steganography security but requires careful training stabilization.

4. Comparative Analysis and Trends

This section synthesizes key trends across three dominant approaches in modern steganography: GAN-based (HiDDeN), autoencoder-based, and CNN-adaptive methods, drawing from the empirical reviews of 22 studies (2017–2024). We compare their performance, robustness, and practical applicability using quantitative metrics and qualitative insights.

Table 1: comparison of approaches in terms of Capacity, PSNR, steganalysis resistance and computational cost

Approach	Avg. Capacity (bpp)	Avg. PSNR (dB)	Steganalysis Resistance	Comp. Cost (GPU hrs)
GAN-based (HiDDeN)	3.5–4.0	36–38	High (68–72% error rate)	18–24
Autoencoder-based	0.3–2.8	34–38	Moderate (50–65% error rate)	6–12
CNN-adaptive (Dynamic)	2.8–3.8	35–37	Very High (75–80% error rate)	12–18

The performance matrix reveals critical trade-offs between embedding capacity, imperceptibility, and computational demands across the three approaches. GAN-based methods (HiDDeN) achieve the highest average capacity (3.5–4.0 bpp) due to their adversarial training framework, which optimizes both embedding and security simultaneously. However, this comes at the cost of moderate perceptual quality (36–38 dB PSNR) and significant computational overhead. In contrast, autoencoder-based methods prioritize visual fidelity (34–38 dB PSNR) but are limited to lower capacities (0.3–2.8 bpp), making them suitable only for applications where imperceptibility is paramount. CNN-adaptive methods strike a balance, offering competitive capacity (2.8–3.8 bpp) and PSNR (35–37 dB) by dynamically adjusting payloads based on texture or semantic features. This adaptability allows them to outperform non-adaptive methods in steganalysis resistance while maintaining reasonable computational costs.

Notably, the choice of method depends heavily on application requirements. For high-capacity covert communication, GANs are ideal despite their complexity. Autoencoders excel in scenarios like medical imaging or copyright protection, where minimal distortion is critical. CNN-adaptive approaches, with their dynamic payload allocation, are increasingly favored for real-world applications requiring a balance of capacity, quality, and detectability. The performance matrix underscores that no single approach dominates all metrics, highlighting the need for context-specific solutions and hybrid architectures to bridge these gaps.

4.2. Computational Efficiency

Table 2: Inference speed of the Approaches

Method	FPS (1080Ti)	Model Size (MB)
HiDDeN	15	450
Autoencoder (Lightweight)	45	25
CNN-adaptive (Mobile)	60	18

Computational demands vary dramatically across approaches. GANs, while powerful, require 18–24 hours of training on high-end GPUs (e.g., NVIDIA V100) due to the instability of adversarial training and the need for equilibrium between generator and discriminator. Autoencoders, by contrast, converge faster (6–12 hours) but are bottlenecked by their limited capacity. CNN-adaptive methods fall in between (12–18 hours), according to Wang and Zhang, (2024) though lightweight variants like MobileStega reduce this to <6 hours via depthwise separable convolutions. These differences are critical for deployment: GANs are impractical for edge devices, while autoencoders and optimized CNNs enable real-time applications.

Inference speeds further highlight these disparities. GAN-based HiDDeN processes 15 FPS on a 1080Ti GPU, while autoencoders and CNN-adaptive methods achieve 45–60 FPS in lightweight implementations. Model sizes reflect similar trends: HiDDeN's 450 MB footprint dwarfs autoencoders (25 MB) and mobile-friendly CNNs (18 MB). This efficiency gap is driving research into pruning, quantization, and knowledge distillation to make GANs viable for resource-constrained environments. For now, CNN-adaptive methods offer the best compromise, balancing performance with deployability.

4.3 Robustness to Attacks

GAN-based steganography demonstrates strong resistance to conventional steganalysis, with adversarial training enabling error rates of 68–72%

against tools like SRNet. However, their robustness falters under JPEG compression (quality factor <70), where extraction accuracy drops by 40% unless specialized noise layers are incorporated. Autoencoder-based methods, while less secure against steganalysis (50–65% error rate), show better resilience to mild noise and compression when augmented with quantization-aware training. For example, Chen *et al*. (2022) achieved 90% recovery accuracy post-JPEG compression by simulating quantization during training. This makes autoencoders viable for environments where images undergo standard processing but less suitable for high-security applications.

CNN-adaptive methods exhibit the most consistent robustness, leveraging dynamic payload allocation to evade detection (75–80% error rate) while maintaining functionality post-attack. According to Zhang and Wang, (2023) Techniques like attention-guided embedding reduce artifacts in sensitive regions, making steganalysis 31% less effective. However, geometric distortions (e.g., rotation, cropping) remain challenging for all approaches, with autoencoders particularly vulnerable (30% recovery degradation). Recent advancements in anti-forensic training are addressing these gaps, but robustness under arbitrary transformations remains an open problem (Rodriguez & Sencar, 2024) .

4.4 Emerging Trends

Hybrid architectures are gaining traction, combining the strengths of GANs, autoencoders, and CNNs. For example, GAN-autoencoder hybrids (Wang *et al*., 2024) use diffusion models to refine outputs, achieving 38 dB PSNR at 0.6 bpp while reducing artifacts by 40%. Similarly, ViT-CNN fusion (Zhao *et al*., 2023) leverages transformers for global context and CNNs for local adaptation, improving semantic-aware embedding. These hybrids aim to overcome individual limitations, such as GANs' instability or autoencoders' low capacity, though they often increase computational costs.

Another key trend is the push toward edge deployment. Lightweight autoencoders (Tang *et al*., 2023) and CNN-adaptive models (Wang & Zhang, 2024) now support real-time steganography on mobile devices, with some achieving >60 FPS. Concurrently, anti-forensic techniques are being integrated to combat advanced steganalysis, using forensic-aware loss functions to erase detectable fingerprints (Rodriguez & Sencar, 2024). Future work may focus on energy-efficient training and cross-modal steganography (e.g., hiding text in images) to expand applicability.

5. Weaknesses of Each Approach

5.1 GAN-based (HiDDeN) Approaches

While GAN-based methods like HiDDeN achieve high embedding capacity and strong resistance to steganalysis, they suffer from significant drawbacks. Training instability remains a critical issue, with mode collapse and convergence difficulties leading to inconsistent performance across datasets (Zhang *et al*., 2021). Additionally, their computational demands are prohibitive for real-time or edge-device applications, often requiring 18+ hours of GPU training and large model sizes (~450MB). Robustness to post-processing attacks (e.g., JPEG compression) is also limited unless augmented with specialized noise layers, which further increases complexity (Chen & Wornell, 2022). Most studies fail to address these scalability challenges, focusing instead on idealized datasets rather than real-world conditions.

5.2 Autoencoder-based Approaches

Autoencoders excel in perceptual quality but are fundamentally constrained by low embedding capacity (typically <3 bpp), making them unsuitable for high-payload applications (Baluja, 2017). Their fragility to geometric transformations (e.g., rotations reduce recovery by 30%) and limited robustness to steganalysis tools are recurring weaknesses (Wang & Chang, 2024). Many studies (e.g., Tang *et al*., 2023) overlook the trade-off between lightweight design and performance, with "efficient" models often sacrificing too much capacity or security. Furthermore, autoencoders lack dynamic adaptation, embedding payloads uniformly rather than optimizing for regional texture or semantics, which limits their practicality compared to CNN-adaptive methods.

5.3 CNN-Adaptive Approaches

CNN-adaptive methods balance capacity and imperceptibility but introduce their own challenges. The reliance on texture or semantic analysis for dynamic payload allocation increases computational overhead, with many studies (e.g., Wu *et al*., 2022) reporting only marginal gains over non-adaptive CNNs in real-world tests. While attention mechanisms improve undetectability (Zhang & Wang, 2023), they often require manual tuning of hyperparameters, reducing generalizability. Lightweight variants (Wang & Zhang, 2024) address efficiency but at the cost of payload flexibility, struggling with high-resolution images (>1024px). A key weakness across studies is the lack of standardized evaluation under diverse attacks (e.g., adversarial steganalysis or combined JPEG+noise), with most reporting metrics only on controlled datasets.

5.4 Cross-Cutting Limitations

All three approaches share critical gaps: (1) inadequate testing against modern steganalysis tools (e.g., Ye-Net or Zhu-Net), with many studies still using outdated detectors; (2) poor generalization across image domains (e.g., medical vs. natural images); and (3)

ethical concerns, as few papers discuss safeguards against misuse. For GANs and CNN-adaptive methods, the "black-box" nature of feature adaptation also raises reproducibility issues. Future work must address these weaknesses through rigorous benchmarking, explainable AI techniques, and standardized threat models.

6. Methodology

Generally, methodology entails pathways to be procedurally/systematically followed in a bid to gather data, digging deep and carrying explorative review on the works of notable authors in the problem domain with the view of proceeding into developing models which have the capacity to fill the gaps under review.

For this review, the investigation was launched into a good number of recent journals articles, lecture notes, newsletters. Furthermore, standard TIFF, SIPI images were obtained in readiness for the full implementation after review.

7. Conclusion

Deep learning has revolutionized image steganography, offering unprecedented improvements in embedding capacity, imperceptibility, and security compared to traditional methods. This review systematically analyzed three dominant approaches—GAN-based (HiDDeN), autoencoder-based, and CNN-adaptive steganography—revealing their respective strengths, limitations, and evolving trends.

GAN-based methods excel in high-capacity embedding and adversarial security but suffer from computational complexity and instability during training. Autoencoder-based approaches prioritize visual fidelity with excellent reconstruction quality but are constrained by limited payload capacity and vulnerability to geometric distortions. CNN-adaptive techniques strike a balance, leveraging dynamic payload allocation to optimize both capacity and robustness, though they face challenges in computational efficiency and scalability for high-resolution images. Emerging trends, such as hybrid architectures (e.g., GAN-autoencoder and ViT-CNN fusion) and lightweight mobile deployment, are pushing the boundaries of what is possible, while anti-forensic techniques are enhancing resistance to advanced steganalysis.

Despite these advancements, critical challenges remain, including robustness to real-world image processing (e.g., compression, noise), generalization across diverse datasets, and ethical considerations regarding misuse. Future research should focus on (1) improving computational efficiency for real-time applications, (2) developing standardized benchmarks for evaluating robustness, and (3) incorporating explainable AI to enhance reproducibility and trust. By addressing these gaps, deep learning-based steganography can evolve into a more reliable and adaptable tool for secure data hiding, with applications ranging from privacy-preserving communication to digital watermarking.

Ultimately, the choice of method depends on specific use-case requirements whether prioritizing capacity (GANs), imperceptibility (autoencoders), or adaptability (CNNs). As the field progresses, interdisciplinary collaboration between cybersecurity, computer vision, and machine learning will be key to unlocking the full potential of deep steganography while mitigating its risks.

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