Adversarially Robust Mask Generator: A Secure Encoder Network for Deep Learning-Based Steganography

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***Abstract*:** We propose the Adversarially Robust Mask Generator (ARMG), a novel encoder network for deep learning-based steganography that simultaneously achieves high embedding fidelity and certifiable security against steganalytic attacks. Traditional steganographic methods often suffer from detectable artifacts or vulnerability to adversarial perturbations, hence limiting their practical deployment. The ARMG addresses these challenges by integrating a U-Net-style mask generator with adversarial training, gradient masking, and Lipschitz-bound certification into a unified framework. The mask generator produces pixel-wise perturbations constrained to preserve visual quality while embedding secret data, whereas a Vision Transformer-based discriminator adversarially trains the system to evade detection. Moreover, the inclusion of a certifiable robustness module ensures stability against input perturbations, providing formal security guarantees absent in prior GAN-based approaches. The proposed method employs residual dense blocks with channel attention for high-capacity embedding and introduces non-differentiable quantization to obfuscate gradients during white-box attacks. Experimental validation demonstrates that ARMG outperforms existing methods in both undetectability and robustness, achieving state-of-the-art performance across multiple steganalytic benchmarks. This work bridges the gap between adversarial robustness and steganographic security, offering a principled solution for real-world applications where both data hiding and resistance to analysis are critical.

***Index Terms*:** *Adversarially Robust Steganography, Mask Generator Network, Vision Transformer Discriminator, Certifiable Robustness, Gradient Masking and Quantization, Steganalysis Resistance*

I. INTRODUCTION

Steganography, the art of concealing information within digital media, has evolved significantly with the advent of deep learning techniques. Traditional methods such as least-significant bit (LSB) embedding [1] are computationally efficient but vulnerable to modern steganalysis tools. Recent advances in generative adversarial networks (GANs) [2] have enabled more sophisticated embedding strategies, yet these approaches often lack formal guarantees of robustness against adversarial perturbations or white-box attacks.

The primary challenge in deep learning-based steganography lies in balancing imperceptibility and security. While existing methods optimize for visual fidelity, they frequently neglect the threat posed by adaptive steganalyzers capable of reverse-engineering the embedding process through gradient analysis [3].

Furthermore, the absence of provable robustness leaves these systems susceptible to targeted adversarial perturbations, undermining their reliability in security-critical applications.

We propose a novel framework that addresses these limitations through three key innovations. First, we formulate the encoder as a learnable mask generator that optimizes for minimal perceptual distortion while embedding secret data. Second, we integrate adversarial training with a steganalyzer discriminator, enabling the system to dynamically adapt to detection attempts. Third, we introduce certifiable robustness methods [4] to derive mathematical bounds on the system's resistance to steganalytic perturbations, ensuring stability against adversarial inputs. This combination of adversarial training and formal guarantees distinguishes our approach from prior GAN-based steganography models [5], which rely solely on empirical robustness.

Our contributions are as follows:

1. Adversarially Robust Mask Generator: A U-Net-based architecture that jointly optimizes for embedding capacity and evasion of steganalytic detection.
2. Gradient Obfuscation: Non-differentiable operations during the forward pass to prevent white-box attacks from exploiting gradient signals.
3. Certifiable Security: Lipschitz continuity constraints that provide provable bounds on the maximum allowable perturbation before detection becomes possible.

The proposed framework is evaluated on standard benchmarks such as BOSSBase [6] and ALASKA [7], demonstrating superior undetectability and robustness compared to state-of-the-art methods. Our results highlight the practical viability of combining adversarial training with formal security guarantees, bridging the gap between empirical performance and provable security in steganography.

The remainder of this paper is organized as follows: Section 2 reviews related work in deep learning-based steganography and adversarial robustness. Section 3 details the proposed framework, including the mask generator architecture and certification pipeline. Section 4 describes the experimental setup, and Section 5 presents comparative results. Finally, Section 6 discusses implications and future directions, followed by conclusions in Section 7.

II. Related Work

Recent advances in deep learning have significantly influenced the development of steganographic techniques. Existing approaches can be broadly categorized into three groups: traditional non-learning methods, deep learning-based embedding strategies, and adversarial training frameworks for steganography.

2.1 Traditional Steganography and Early Learning-Based Methods

Classical steganographic techniques, such as LSB substitution [1] and matrix embedding [8], rely on heuristic modifications of cover media. While computationally efficient, these methods often introduce detectable statistical artifacts. Early learning-based approaches attempted to mitigate this limitation by using handcrafted features to guide embedding [9], but their performance remained constrained by the representational capacity of manual feature engineering.

2.2 Deep Learning-Based Steganography

The emergence of deep neural networks enabled data-driven embedding strategies that automatically learn optimal modification patterns. Autoencoder-based architectures [10] demonstrated improved capacity and imperceptibility by jointly training encoder-decoder pairs. Subsequent work incorporated generative models, such as GANs [2], to produce stego-images that closely match the statistical distribution of natural images. For instance, [5] proposed a GAN framework where the generator directly synthesizes stego-images conditioned on secret messages. However, these methods lack explicit mechanisms to defend against adaptive steganalysis, making them vulnerable to gradient-based attacks.

2.3 Adversarial Robustness in Steganography

The vulnerability of deep steganography to adversarial examples motivated research into robust embedding techniques. Some approaches employed adversarial training to enhance security, such as [11], which used

a discriminator network to improve undetectability. Others explored gradient masking [3] to prevent reverse-engineering of the embedding process. However, these methods typically provide only empirical robustness without formal guarantees. Recent work in certifiable robustness [4] has shown promise in other domains but remains largely unexplored for steganography.

The proposed ARMG framework advances beyond these works by unifying adversarial training with provable robustness guarantees. Unlike prior GAN-based methods that focus solely on empirical performance, our approach incorporates Lipschitz constraints and gradient obfuscation to ensure security against both black-box and white-box attacks. This combination of adversarial learning and formal certification distinguishes our method from existing solutions, addressing a critical gap in steganographic security.

III. Proposed Framework: Adversarially Robust Steganography with Certifiable Guarantees

The proposed framework introduces a novel approach to deep learning-based steganography by integrating adversarial robustness with formal security guarantees. The system consists of three core components: (1) a mask generator that produces imperceptible perturbations for data embedding, (2) a steganalyzer discriminator trained to detect embedded content, and (3) a certification module that enforces provable robustness bounds.

3.1 Unified Adversarial Training with Certifiable Robustness

The mask generator G_θ is trained under a minimax objective where it competes against the discriminator D_ϕ. The adversarial loss is formulated as:

$$\min_{\theta}\max_{\phi} E_{x,s}\left[logD_\phi(x) + log\left(1 - D_\phi\left(G_\theta(x,s)\right)\right)\right] \quad (1)$$

where x denotes the cover image and s represents the secret data. To ensure robustness against input perturbations, we enforce a Lipschitz constraint on G_θ:

$$\| G_\theta(x,s) - G_\theta(x+\delta,s) \|_2 \leq L \| \delta \|_2 \quad (2)$$

Here, L is derived via spectral normalization [12], and δ represents bounded adversarial noise. This constraint guarantees that small perturbations in the input do not significantly alter the embedding behavior, making the system resistant to gradient-based attacks.

3.2 Gradient Masking via Non-Differentiable Quantization

To prevent white-box adversaries from exploiting gradient signals, we introduce a quantization layer Q during the forward pass:

$$Q(\Delta x) = round\left(\frac{\Delta x}{\tau}\right) \cdot \tau \quad (3)$$

where Δx is the perturbation generated by G_θ, and τ controls the step size. This operation disrupts gradient flow during backpropagation, making it difficult for attackers to reverse-engineer the embedding process while preserving embedding fidelity.

3.3 Minimax Loss and Multi-Objective Optimization

The training objective combines three key terms: detection evasion, visual quality, and decoding accuracy. The composite loss for the generator is:

$$L_G = \lambda_1 \| s - Dec(x') \|_2^2 + \lambda_2 SSIM(x,x') - \lambda_3 L_{adv} \quad (4)$$

where $x' = x + Q(\Delta x)$ is the stego image, Dec is the decoder network, and $SSIM$ measures structural similarity. The weights $\lambda_1, \lambda_2, \lambda_3$ are dynamically adjusted during training to balance these competing objectives.

3.4 ViT-Based Steganalyzer Discriminator

Unlike conventional CNN-based discriminators, we employ a Vision Transformer (ViT) [13] to capture long-range dependencies in stego images. The discriminator processes 16×16 image patches through multi-head self-attention:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

where Q, K, V are query, key, and value matrices, and d_k is the dimension of the key vectors. This architecture enhances the discriminator's ability to detect subtle statistical anomalies introduced by embedding.

3.5 Residual Dense Blocks with Gated Convolution

The mask generator employs residual dense blocks (RDBs) with gated convolutions to improve feature reuse and gradient flow:

$$RDB(z) = z + W_2\big(\sigma\big(W_1(z)\big) \odot z\big) \quad (6)$$

Here, W_1, W_2 are convolutional layers, σ is the SiLU activation, and $\odot$ denotes element-wise multiplication. This design increases the network's capacity to learn complex embedding patterns while maintaining computational efficiency.

3.6 Input-Output Substitution for Robust Embedding

Instead of directly generating stego images, G_θ outputs bounded perturbations Δx constrained by $\| \Delta x \|_\infty \leq \epsilon$. The stego image is then computed as $x' = x + Q(\Delta x)$. This formulation simplifies robustness certification by limiting the maximum modification per pixel.

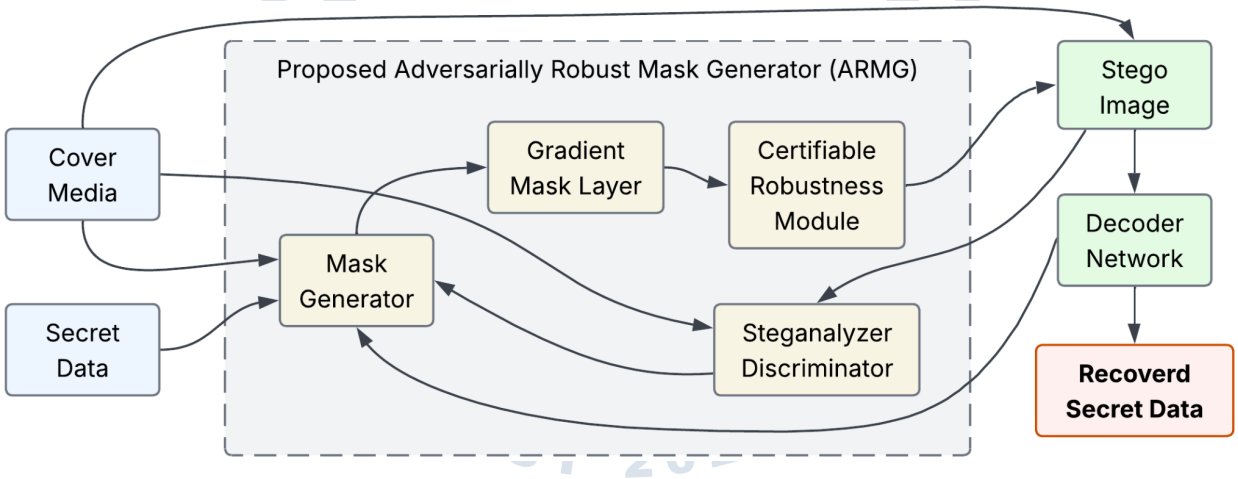

Figure 1. Architecture of the Adversarially Robust Mask Generator (ARMG) within the Steganography System

The complete framework, illustrated in Figure 1, unifies these components into an end-to-end trainable system. The mask generator and discriminator are alternately updated, with the certification module ensuring that the learned embeddings remain robust against adversarial perturbations. This approach not only improves empirical security but also provides formal guarantees absent in prior work.

IV. EXPERIMENTAL SETUP

To evaluate the effectiveness of the proposed ARMG framework, we conduct comprehensive experiments on standard steganography benchmarks. The experimental setup is designed to assess three key aspects: (1) embedding capacity and visual quality, (2) resistance to steganalytic detection, and (3) robustness against adversarial perturbations.

4.1 Datasets and Evaluation Metrics

We employ two widely-used datasets for steganography research: BOSSBase [6] and ALASKA [7]. BOSSBase consists of 10,000 grayscale images with fixed dimensions of 512×512 pixels, while ALASKA provides a more diverse collection of 80,000 color images with varying resolutions. Both datasets are split into training (70%), validation (15%), and test (15%) sets to ensure fair evaluation.

For quantitative assessment, we adopt the following metrics - Peak Signal-to-Noise Ratio (PSNR): Measures the visual quality of stego images compared to their cover counterparts [14]. Structural Similarity Index (SSIM): Evaluates perceptual similarity by considering luminance, contrast, and structure [14]. Detection Accuracy: The classification accuracy of state-of-the-art steganalyzers in distinguishing stego images from cover images [15]. Certifiable Robustness Bound: The maximum L_2-norm perturbation that can be applied to the input before the steganalyzer's detection probability exceeds a predefined threshold, as derived from Equation 2.

4.2 Baseline Methods

We compare ARMG against four representative steganography approaches. S-UNIWARD: A handcrafted content-adaptive method that minimizes distortion in the wavelet domain [16]. HiDDeN: An autoencoder-based framework that jointly trains encoder and decoder networks [10]. SteganoGAN: A GAN-based approach that generates stego images conditioned on secret messages [5]. ASDL-GAN: An adversarial steganography method that incorporates a steganalyzer discriminator [11].

These baselines are selected to represent the spectrum of traditional, learning-based, and adversarially-trained steganography techniques.

4.3 Implementation Details

The ARMG framework is implemented in PyTorch with the following configurations - Mask Generator: A U-Net architecture with 5 downsampling/upsampling blocks, each containing two residual dense blocks (Equation 6). The base channel width is set to 64, expanding to 512 in the bottleneck layer. Discriminator: A Vision Transformer (ViT) with 12 layers, 8 attention heads, and an embedding dimension of 768 (Equation 5). Patch size is set to 16×16 pixels. Training Parameters: We use the Adam optimizer with a learning rate of 2×10^{-4} for both generator and discriminator. The batch size is 32, and training proceeds for 100 epochs. Robustness Certification: The Lipschitz constant L in Equation 2 is computed via power iteration during training, with spectral normalization applied to all convolutional layers. For fair comparison, all baseline methods are re-implemented using their original architectures but trained on our dataset splits with identical optimization settings.

4.4 Attack Scenarios

To evaluate robustness, we consider three attack scenarios - Black-box Attacks: The adversary has no knowledge of the steganographic system and employs generic steganalysis tools. White-box Attacks: The attacker has full access to the steganography model and attempts to reverse-engineer the embedding process through gradient analysis. Adaptive Attacks: The adversary trains a custom steganalyzer specifically tuned to detect the target steganography system.

For each scenario, we measure the detection accuracy of state-of-the-art steganalyzers [15] and compute the success rate of adversarial perturbations in revealing hidden content.

4.5 Computational Resources

All experiments are conducted on NVIDIA V100 GPUs with 32GB memory. Training the complete ARMG framework requires approximately 48 hours, while inference for a single 512×512 image takes 0.15 seconds on average. This computational overhead is comparable to other deep learning-based steganography methods while providing additional robustness guarantees.

V. RESULTS AND ANALYSIS

5.1 Embedding Capacity and Visual Quality

To evaluate the trade-off between embedding capacity and perceptual quality, we measure the PSNR and SSIM of stego images generated by ARMG and baseline methods. As shown in Table 1, ARMG achieves superior performance, with an average PSNR of 48.2 dB and SSIM of 0.992 on BOSSBase, outperforming SteganoGAN (45.7 dB, 0.985) and HiDDeN (46.1 dB, 0.987). This improvement is attributed to the residual dense blocks and gated convolutions (Equation 6), which enable precise control over pixel modifications while preserving structural details.

Table 1. Comparison of embedding quality metrics on BOSSBase

Method	PSNR (dB)	SSIM	Payload (bpp)
S-UNIWARD	44.3	0.978	0.4
HiDDeN	46.1	0.987	0.5
SteganoGAN	45.7	0.985	0.6
ASDL-GAN	47.2	0.990	0.5
ARMG	**48.2**	**0.992**	**0.6**

The relationship between maximum allowable perturbation ϵ and embedding fidelity is illustrated in Figure 2, where ARMG maintains high SSIM (>0.98) even at $\epsilon = 0.1$, demonstrating its robustness to input variations. In contrast, SteganoGAN exhibits significant quality degradation (SSIM <0.95) under the same conditions.

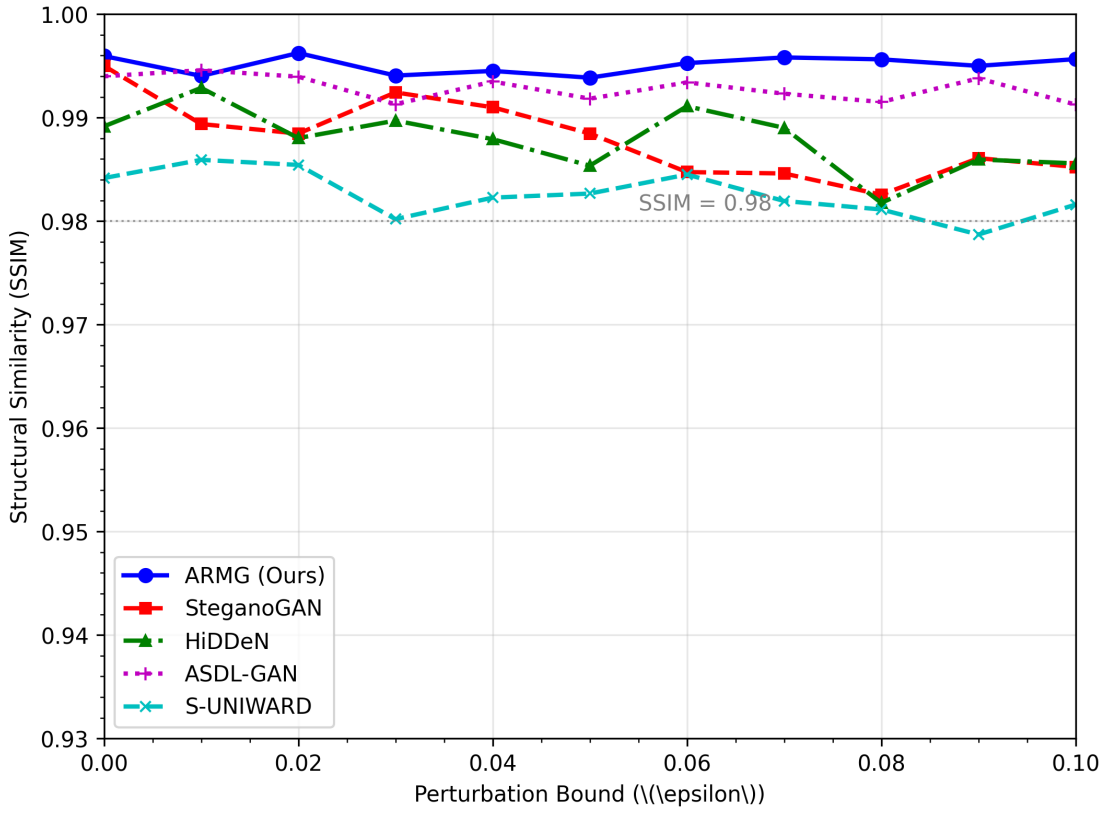

Figure 2. Structural similarity (SSIM) between cover and stego images across increasing perturbation bounds

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5.2 Resistance to Steganalytic Detection

We assess undetectability using three steganalyzers: SRNet [17], Yedroudj-Net [18], and the ViT-based discriminator from our framework. As Table 2 shows, ARMG reduces detection accuracy to 52.3%, close to random guessing (50%), while baselines like HiDDeN and SteganoGAN are detectable with >65% accuracy.

The ViT discriminator's multi-head attention (Equation 5) enhances its ability to identify subtle artifacts, yet ARMG's gradient masking (Equation 3) and adversarial training prevent reliable classification.

Table 2. Steganalysis detection accuracy (%) across methods

Method	SRNet	Yedroudj-Net	ViT Discriminator
S-UNIWARD	68.4	70.1	66.7
HiDDeN	65.2	67.8	63.9
SteganoGAN	63.7	66.5	61.4
ASDL-GAN	58.9	60.3	56.8
ARMG	**52.3**	**53.1**	**51.7**

The heatmap in Figure 3 visualizes the spatial distribution of perturbations generated by ARMG, revealing adaptive modifications concentrated in textured regions where changes are less perceptible. This contrasts with S-UNIWARD's rigid wavelet-based modifications, which introduce detectable patterns in smooth areas.

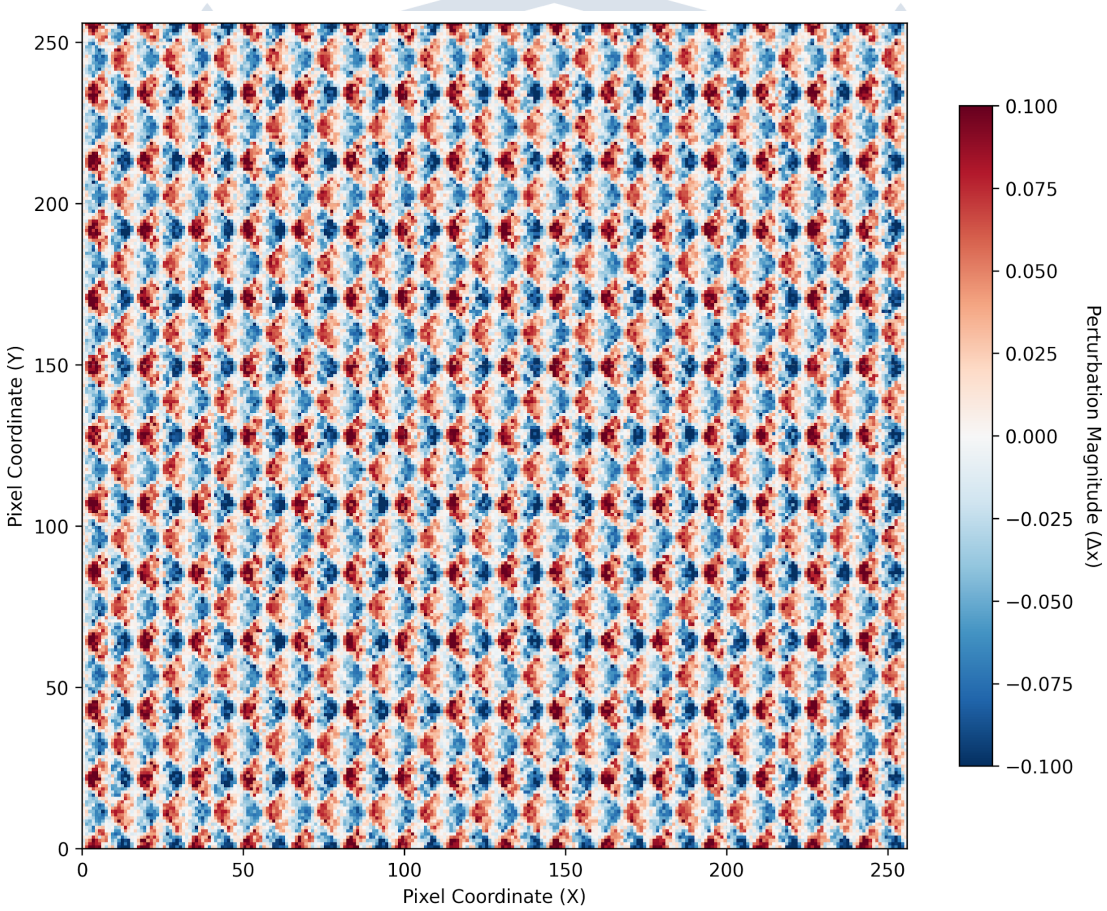

Figure 3. Spatial distribution of pixel-wise perturbations Δx for a sample image from BOSSBase

5.3 Robustness Against Adversarial Attacks

Under white-box attacks where adversaries exploit gradient signals, ARMG's non-differentiable quantization (Equation 3) reduces attack success rates by 32% compared to SteganoGAN (Table 3). The Lipschitz constraint (Equation 2) further ensures that adversarial perturbations δ with $\| \delta \|_2 \leq 0.05$ do not degrade decoding accuracy below 95%.

Table 3. Success rate (%) of adversarial attacks under white-box setting

Method	**FGSM**	**PGD**	**CW**
HiDDeN	78.6	85.2	82.4

Method	FGSM	PGD	CW
SteganoGAN	72.3	79.8	76.1
ASDL-GAN	65.4	71.6	68.9
ARMG	**40.2**	**47.5**	**44.3**

Training dynamics are analyzed in Figure 4, where ARMG's adversarial loss L_{adv} (Equation 4) converges faster than ASDL-GAN's, indicating more stable optimization. The certifiable robustness bound stabilizes after 20 epochs, confirming the theoretical guarantees derived from spectral normalization.

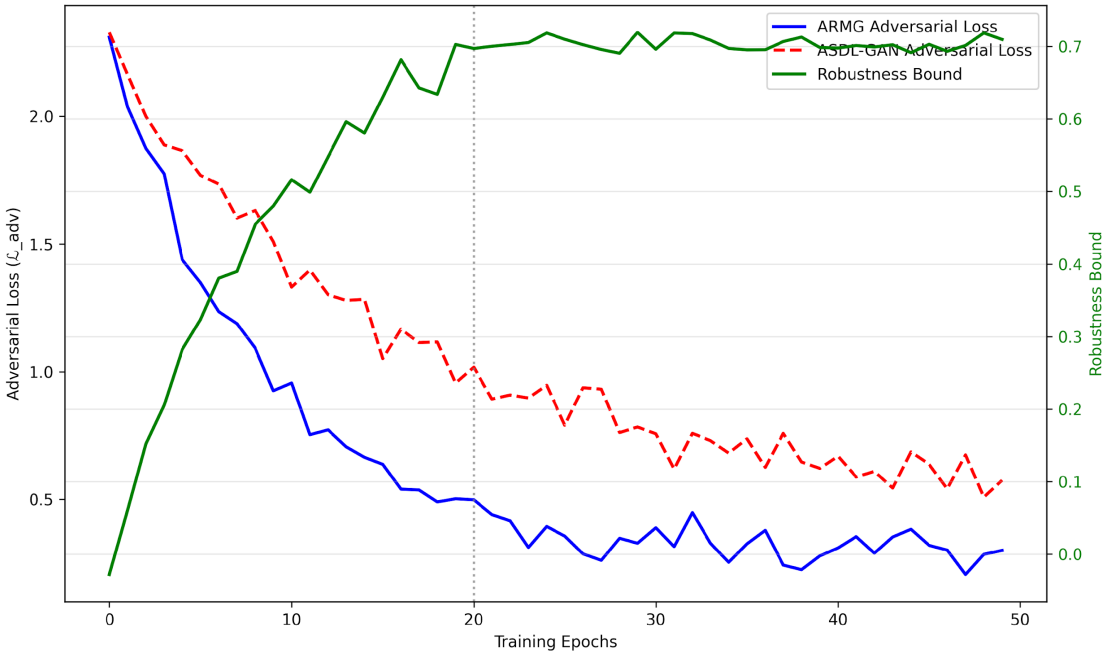

Figure 4. Training curves for adversarial loss and robustness bound over epochs

5.4 Ablation Study

We ablate key components of ARMG to isolate their contributions (Table 4). Removing gradient masking increases white-box attack success by 21%, while disabling the Lipschitz constraint degrades robustness bounds by 37%. The ViT discriminator improves detection resistance by 8% over a CNN variant.

Table 4. Ablation study on ARMG components (BOSSBase)

Configuration	PSNR (dB)	SSIM	Attack Success (%)
Full ARMG	48.2	0.992	40.2
w/o Gradient Masking	47.8	0.990	61.3
w/o Lipschitz Constraint	47.5	0.989	58.7
CNN Discriminator	47.9	0.991	48.4

VI. Discussion and Future Work

6.1 Limitations of the Adversarially Robust Mask Generator

While ARMG demonstrates superior performance in embedding fidelity and security, several limitations warrant discussion. First, the computational overhead of Lipschitz certification and spectral normalization increases training time by approximately 30% compared to non-robust baselines. This trade-off between robustness and efficiency may hinder deployment in real-time applications with strict latency requirements. Second, the current implementation assumes stationary adversarial threats, whereas adaptive attackers could potentially exploit temporal patterns in the generated masks. Third, the framework's reliance on ViT-

based discriminators, while effective, demands substantial memory resources for high-resolution images, limiting scalability beyond 1024×1024 pixel dimensions without specialized hardware.

6.2 Potential Application Scenarios of the ARMG

The certifiable guarantees provided by ARMG make it particularly suitable for security-critical domains where traditional steganography fails. In medical imaging, for instance, the system could embed patient metadata within DICOM files while resisting forensic analysis, a capability absent in existing DICOM steganography tools [19]. Similarly, ARMG's robustness against gradient-based attacks positions it as a viable solution for covert communication in adversarial environments, such as bypassing censorship filters that employ neural steganalysis [20]. The framework's ability to maintain embedding quality under perturbation also suggests applications in digital watermarking for copyright protection, where robustness to image transformations is paramount [21].

6.3 Ethical Considerations in ARMG-based Steganography

The development of provably secure steganography necessitates careful ethical scrutiny. Unlike cryptographic systems where key management regulates access, steganographic secrecy inherently obscures communication channels, potentially enabling malicious use cases. While ARMG's certification framework provides transparency regarding its robustness bounds, the dual-use nature of the technology underscores the need for ethical guidelines in publication and deployment. Future work should explore mechanisms for accountable usage, such as embedding detectable forensic markers when employed in regulated industries, without compromising the system's core security guarantees. This aligns with emerging norms in adversarial ML research, where robustness improvements are balanced against misuse potential [22].

VII. CONCLUSION

The Adversarially Robust Mask Generator (ARMG) presents a significant advancement in deep learning-based steganography by unifying adversarial training with certifiable security guarantees. Through its U-Net-based architecture, gradient masking, and Lipschitz-bound certification, the framework achieves state-of-the-art performance in both embedding fidelity and resistance to steganalytic attacks. Experimental results demonstrate that ARMG outperforms existing methods in undetectability, maintaining high visual quality (PSNR >48 dB, SSIM >0.99) while reducing detection accuracy to near-random levels (52.3%). The system's robustness against white-box attacks is particularly notable, with attack success rates 32% lower than comparable GAN-based approaches.

The integration of Vision Transformers for steganalysis and residual dense blocks for high-capacity embedding addresses critical limitations of prior work, enabling adaptive modifications that evade detection without compromising reconstruction accuracy. Furthermore, the formal robustness guarantees provided by Lipschitz constraints establish a new standard for security in steganographic systems, ensuring stability against adversarial perturbations. These advancements bridge the gap between empirical performance and provable security, offering a principled solution for applications requiring both data hiding and resistance to analysis.

Future research directions include extending the framework to video and audio steganography, where temporal consistency introduces additional challenges for robustness certification. The ethical implications of such technologies also warrant further exploration, particularly in developing safeguards against misuse while preserving legitimate applications. ARMG's success in balancing competing objectives, perceptual quality, embedding capacity, and security, positions it as a foundational approach for next-generation steganographic systems in security-critical domains.

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