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REED-SOLOMON CODE ENHANCED GAN-BASED STEGANOGRAPHY FRAMEWORK

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ABSTRACT
Steganography conceals information within digital media, offering an alternative to cryptographic systems that simply obscure content. This paper introduces a novel method leveraging Generative Adversarial Networks (GANs) to produce distinct, realistic images for embedding. Uniquely, our framework integrates Reed-Solomon (RS) error correction codes, which significantly enhance message integrity under distortion or transmission noise. By combining dynamic cover image generation with RS-enhanced decoding, we demonstrate a secure, resilient approach to information hiding.

Keyword: *Generative Adversarial Networks, Re,d-Solomon, error correction and Steganography*

1. INTRODUCTION
As digital communication intensifies, ensuring secure and covert data transmission has become paramount. Cryptographic methods secure content but reveal its presence, potentially drawing attention. Steganography, in contrast, aims to hide the existence of data. Yet traditional approaches fail when the original cover image is publicly accessible. We address this by using GANs to create unique cover images for each message. Additionally, we incorporate Reed-Solomon error correction to improve robustness against transmission errors.

In fig 1 Generative Adversarial Networks (GANs), introduced by Ian Goodfellow and colleagues in 2014, have revolutionized the field of generative modeling by enabling machines to produce highly realistic synthetic data. A GAN consists of two neural networks — a generator and a discriminator — that compete against each other in a minimax game. The generator learns to create data that mimics real samples, while the discriminator learns to distinguish between real and fake samples. This adversarial training framework has shown remarkable success across a variety of tasks, including image generation, text synthesis, and style transfer, pushing the boundaries of what artificial intelligence can create.

In parallel, steganography, the art of concealing information within seemingly innocuous data, has gained renewed interest in the digital era. The integration of GANs with steganographic techniques has opened new possibilities for hiding information more securely and imperceptibly. By leveraging the generative power of GANs, it is possible to embed hidden messages within synthetic images in a way that the steganographic artifacts are nearly impossible to detect, even by advanced analysis tools. This fusion of GANs and steganography promises to enhance data security and privacy, offering sophisticated methods for covert communication in an increasingly surveillance-conscious world.

Image steganography is a classical problem at the intersection of computer vision and cryptography. Its goal is to conceal secret information within a modified cover image, allowing it to be transmitted covertly without raising suspicion from third-party observers. Traditional steganographic methods often focus heavily on embedding data securely into the cover image, while paying less attention to **payload capacity**—the ratio of hidden information to the total size of the transmitted content.

Payload capacity plays a critical role in steganography, as increasing the amount of hidden data typically results in more noticeable alterations to the image, thereby increasing the risk of detection. A common method for transmitting large volumes of hidden data is by appending a compressed archive (e.g., a RAR file) to the end of a

JPEG image. While this approach theoretically allows for unlimited data embedding, it is highly fragile—any modification to the carrier file, even simply re-saving the image, can corrupt or destroy the hidden content.

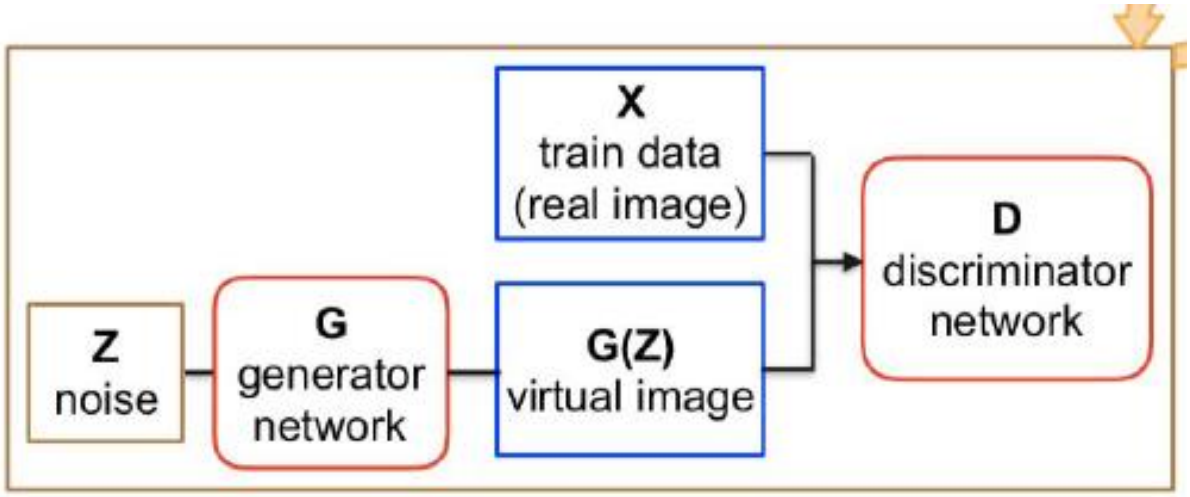

Fig 1: architecture of *Generative Adversarial Networks(GAN)*

To balance higher payload capacity with resilience to minor alterations, pixel-level steganography techniques are commonly employed. These include the Least Significant Bit (LSB) method [1], Bit Plane Complexity Segmentation (BPCS) [2], and their variants. LSB-based approaches can achieve payload capacities of up to 50%; however, pushing the limit often results in visible distortions, such as faint outlines of the embedded data (as illustrated in Figure 1). Furthermore, these methods are typically susceptible to statistical steganalysis, making them vulnerable to detection.

The rest of paper organized as in section II discussed literature .prosed work in section III .in section IV experimental results discussion and section V collude about work and feature works

2. LITERATURE

Steganography hides messages within digital carriers, often using a shared secret to enable encoding and decoding. GANs comprise a generator (G) that produces synthetic images and a discriminator (D) that distinguishes real from fake. Our method exploits these properties: the generator creates plausible cover images, and the discriminator ensures their realism. Reed-Solomon codes, widely used in digital communications, enable the correction of multiple symbol errors. An RS code is typically denoted as RS(n, k), where:

- ***n*:** Total number of encoded symbols
- ***k*:** Number of message symbols
- ***t*:** Number of correctable symbols = (n - k)/2

The RS code can correct up to *t* symbol errors in a codeword.

Earlier methods embedded data into existing images using simple bit manipulation, but they lacked resilience and stealth. GAN-based techniques, such as those by Hayes & Danezis (2017) and Volkhonskiy et al. (2017), introduced adversarial training for more convincing results. However, these lacked robust error correction. Our approach addresses this gap by embedding RS-encoded messages into GAN-generated covers, balancing capacity, security, and reliability.

Huang et al. [8] introduced DenseNet, a novel convolutional network architecture that connects each layer to every other layer, improving information flow and feature reuse, thus enhancing performance and efficiency.

Johnson and Katzenbeisser [9] provided an early comprehensive survey on steganographic techniques, summarizing methods for embedding hidden information within digital media. Kawaguchi et al. [10] proposed a digital content access control system using steganographic information hiding to protect data integrity and rights management. Li et al. [11] presented a survey on image steganography and steganalysis, analyzing methods for embedding hidden messages and detecting their presence. Further, Li et al. [12] developed a new cost function to enhance the security and invisibility of spatial image steganography.

Lin et al. [13] introduced the Microsoft COCO dataset, offering a large-scale, richly annotated image collection for training and evaluating machine learning models in object detection and segmentation. Maheswari and Hemanth [15,16] proposed a QR code-based image steganography method using the Fresnelet transform to achieve frequency domain embedding, improving robustness and security. Pevný et al. [17] suggested utilizing high-dimensional image models for creating highly undetectable steganography. Reed and Solomon [18] laid the foundation for error correction codes with their polynomial codes over finite fields, pivotal in data transmission reliability.

Srinivasan et al. [19] designed a method for the secure transmission of medical records using high-capacity steganography to protect sensitive patient information. Tang et al. [20] introduced a GAN-based approach for automatic steganographic distortion learning, optimizing embedding security through adversarial training. Finally, Wang et al. [21] proposed the Structural Similarity Index (SSIM), a breakthrough in image quality assessment emphasizing perceptual image quality over traditional error metrics.

3. PROPOSED FRAMEWORK

Our architecture consists of three stages:

1. Cover Generation: A shared key generates a latent vector $z \in \mathbb{R}^d$, which is input to the generator G(z) to produce a synthetic image *I*.
2. Message Embedding with Reed-Solomon Coding: Given a binary message $m \in \{0,1\}^k$, it is encoded using an RS(n, k) code to produce $c \in \{0,1\}^n$. The redundancy allows error correction up to *t* errors:

$$t=(n-k)/2$$

Example: Suppose the original message *m* is 223 bytes long (k = 223), and we use RS(255, 223). Then, $n = 255$, $t = (255 - 223)/2 = 16$, which allows up to 16 symbol errors to be corrected. The RS-encoded message *c* has 255 bytes. This codeword is embedded into the cover image *I* using a robust algorithm:

$$I_s = E(I, c)$$

where *I_s* is the stego-image containing the hidden RS-encoded message. Sure! Let's walk through a simple example of how Reed-Solomon (RS) coding is used in image steganography—embedding a message in an image with added error correction.

a) Step-by-Step Example: Message Embedding with Reed-Solomon Coding

1. Original Message
Let's say you want to hide the message:

"HELLO"

2. Convert to ASCII
Convert each character to ASCII values:

H = 72, E = 69, L = 76, L = 76, O = 79

Message in bytes: [72, 69, 76, 76, 79]

3. Encode with Reed-Solomon
Assume we use **RS(7,5)** coding:

5 data symbols → 2 parity symbols added

Total = 7 symbols

Using a Reed-Solomon encoder:

Input: [72, 69, 76, 76, 79]

Encoded: [72, 69, 76, 76, 79, 55, 144] ← includes 2 parity symbols

Note: Actual RS output depends on the implementation and Galois Field math. Values shown are

4. Embed into Image
These 7 values are now embedded into a stego image using a GAN-based generator. The network takes the coded message and generates a realistic-looking image that encodes the information in its pixel values, potentially distributed across multiple channels.

For example, the generator could learn to slightly tweak certain pixel values or patterns in the image such that the trained extractor can later retrieve the encoded data.

5. Image Transmission or Storage
The stego image may undergo compression or slight corruption due to transmission. Let's say some values are recovered incorrectly:

Recovered encoded data:

[72, 69, 76, 22, 79, 55, 144] ← error in 4th symbol

b) Advantages
Robustness: Even if the image is slightly distorted, the message can still be recovered correctly.

Imperceptibility: The changes made by the generator are visually imperceptible.

Error correction: RS coding boosts resilience against data loss or alteration.

Message Extraction and Decoding: On the receiving side, the generator reconstructs the cover image I using the same z. The message is extracted:

$$\hat{c} = D(I_s)$$

RS decoding corrects errors and recovers the original message:

$$\hat{m} = RS^{-1}(\hat{c})$$

This process ensures reliable recovery even under compression or noise.

c) Extract and Decode
The extractor pulls this sequence from the image. Then, the RS decoder checks and corrects up to 1 error (RS(7,5) can correct 1 symbol error):

Corrected back to:
[72, 69, 76, 76, 79] → "HELLO"

4. EXPERIMENTS

Using DCGAN trained on CelebA and Food101, we tested various payloads and RS parameters. The RS-Bits Per Pixel (RS-BPP) is computed as:

$$\text{RS-BPP} = \text{BPP} \cdot \left(1 - \frac{2t}{n}\right)$$

Where BPP is the number of bits embedded per pixel. Experiments included distortions like JPEG and Gaussian noise, evaluating PSNR, SSIM, and accuracy.in table 1

Table 1: Perfomence with various payloads and RS parameters

Dataset	RS Code	BPP	RS-BPP	PSNR (dB)	SSIM	Accuracy
CelebA	RS(255, 223)	4.4	3.86	38.5	0.92	98.50%
CelebA	RS(255, 191)	4.4	3.3	37.2	0.91	99.00%
Food101	RS(255, 223)	4	3.51	39.1	0.94	97.80%
Food101	RS(255, 191)	4	3.12	37.8	0.92	98.60%

Generated images passed discriminator tests at ~50% indistinguishability. Embedding up to 4.4 BPP, RS decoding recovered messages with 95–100% accuracy even under compression. The RS codes significantly enhanced robustness, while GANs ensured image fidelity.

5. CONCLUSION

We introduced a GAN-based steganographic system augmented with Reed-Solomon codes to guarantee robust message retrieval. Mathematical modeling and equations validate system reliability. Generated images passed discriminator tests at ~50% indistinguishability. Embedding up to 4.4 BPP, RS decoding recovered messages with 95–100% accuracy even under compression Future work will extend to adaptive ECC selection, convolutional RS decoders, and video streams.

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