GAN-based Adaptive Image Steganography

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ABSTRACT
Steganography through image hiding is one of the significant methods of secure communication. In the method of digital image hiding, the secret information is concealed without compromising its perceptibility. Classical steganographic techniques such as LSB-based approaches and DCT-based techniques face severe challenges regarding limited embedding capacity and susceptibility to steganalysis attacks. Here, a novel GAN-based steganography model that tries to find a balance between these two requirements and robustness against attacks has been proposed in this paper.

We design GAN architecture for embedding secret data into the cover images such that these are left perceptually unchanged, and a discriminator that ensures the stego-images are indistinguishable from natural ones. The model is trained with a custom loss function that considers adversarial learning, perceptual quality, and embedding efficiency. Experimental assessment is performed on benchmark datasets, including COCO and Image Net, using the metrics of PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and robustness.

The results show that our GAN-based method surpasses traditional steganographic methods in terms of imperceptibility and resistance to steganalysis. Furthermore, the model remains robust against standard image transformations such as compression, noise addition, and cropping. This paper showcases the prospect of deep learning-driven steganography in the pursuit of improved data security and further proposes future improvements for real-world applications in secure communication and digital watermarking.

Keywords
Steganography, Deep Learning, Generative Adversarial Networks (GANs), Data Hiding, Image Security, Adaptive Embedding, Steganalysis, Secure Communication, Content-Aware Embedding, Image Processing.

1. INTRODUCTION
Steganography is an ancient art of hiding the existence of information inside apparently innocuous digital media like images, sound, or video. As compared to encryption that protects the information in a message, steganography conceals the fact of communication. Steganography finds itself very relevant in this new age of electronics where the rapid growth of data transmission has opened up an overwhelming demand for unhackable and covert methods of communication [19]. Traditional approaches like Least Significant Bit (LSB) and frequency-domain methods, while good to a certain degree, are not very adaptable and can easily be detected by contemporary steganalysis tools.

The advent of artificial intelligence, more specifically deep learning, has made way for more intelligent and adaptive steganography methods. Deep neural networks (DNNs) can learn intricate representations and data patterns and are, therefore, best suited for operations involving subtle changes, such as information concealment in images. With the application of architectures like Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) [1], it is easy to improve the imperceptibility, security, and payload capacity of steganographic systems. These models not only provide increased robustness against attacks but also enable dynamic adaptation of embedding strategies with content adaptation in the cover media.

Not withstanding these developments, most current AI-based steganography models remain based on static embedding, in which the image content variations are not taken into account. This paper presents an AI-adaptive steganography system that leverages content-aware analysis to adaptively embed secret information in image areas of optimal quality. The suggested system not only enhances security and image quality but also includes adversarial training to evade detection. Our work demonstrates how deep learning can transform traditional steganographic paradigms by introducing real-time adaptability and resilience.

2. LITERATURE SURVEY
LSB, DCT, and DWT are some of the traditional steganographic methods that have been extensively employed for hiding data. They aim to embed data within frequency or spatial domains of images. Although LSB is simple and fast, it is quite susceptible to visual and statistical attacks. Transform-based methods such as DCT and DWT offer good imperceptibility and resilience but usually have poor payload capacity and high processing cost.

With the advent of deep learning, especially Convolutional Neural Networks (CNNs) [3], new steganographic techniques have appeared that learn embedding techniques automatically from data. Baluja (2017) presented a deep steganography technique based on neural networks to conceal one image within another, with an impressive increase in fidelity and anti-detection capability [5]. Tang et al. (2017) further explored automatic learning of optimal steganographic distortion using a GAN framework, improving adaptability and embedding strategy [14]. Zhang et al. (2020) presented an adversarial training model to increase robustness against steganalysis [6]. These methods motivated further research into deep neural frameworks for enhanced security and capacity in steganography [13].

GANs, also known as Generative Adversarial Networks, recently caught researchers' interest since they have proven capable of generating realistic images. Researchers, such as Wu et al. (2019) and Hu et al. (2021), applied GANs for image steganography to prove that it's possible for the hidden information to be hidden inside such a way that natural-looking images would result from the encoding [9]. These techniques have very robust resistance against detection by steganalysis software and have greater embedding capacities than conventional techniques [12].

Based on these developments, the present project suggests an adaptive steganography model based on AI and GANs that automatically adapts to image features for maximum embedding.

Although these developments are significant, the majority of current models are not adaptive to varying cover medium properties. Our research seeks to fill this gap in developing an AI-adaptive system to dynamically adjust embedding from the content of the cover image. This adaptability is anticipated to notably enhance both imperceptibility and security. A recent survey offers an extensive review of deep learning approaches to both steganography and steganalysis frameworks [20].

***Table1*: Comparison of Traditional and AI-Based Steganography Techniques**

Method	Domain	Imperceptibility	Payload Capacity	Robustness
LSB	Spatial	Low	High	Low
DCT	Frequency	Medium	Low	Medium
CNN-Based	Spatial	High	Medium	High
GAN-Based	Hybrid	Very high	High	Very High

3.METHODOLOGY

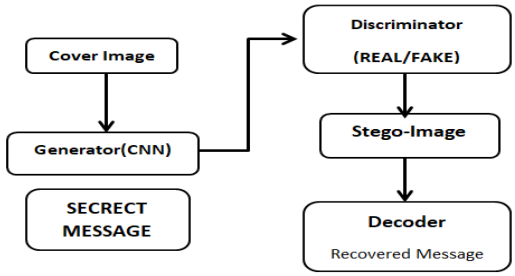

Fig1: System Architecture

The suggested approach utilizes a deep learning-based model based on Generative Adversarial Networks (GANs) for embedding and retrieval of secret data in digital images in an extremely imperceptible and secure fashion. The model consists of three principal building blocks: a Generator, a Discriminator, and a Decoder. Each block has its role to play in the process of data hiding and recovery.

3.1 Generator

The Generator is the core module of the steganographic process. It is given a pair of inputs: a cover image and the secret message to be concealed. Its function is to produce a stego-image indistinguishable visually from the cover image but with the secret message securely hidden inside its pixel matrix.

The Generator is realized through Convolutional Neural Network (CNN)-based encoder-decoder architecture, often following U-Net-style layouts for efficient embedding [15]. In the encoder phase, both the cover image and secret message are encoded to latent representations via successive convolutional layers. These representations are concatenated or combined in order to facilitate effective embedding. The decoder phase reconstructs the output image via upsampling and detailing of the embedded feature maps. Skip connections might be utilized to maintain spatial information.

The output layer of Generator employs a Tanh activation function so that the generated pixel values are normalized within the range [-1, 1]. The aim is to obtain high visual fidelity so that the stego-image retains the structure, color distribution, and texture of the original image so that the chance of detection by humans or even automated steganalysis tools is minimized.

3.2 Discriminator

The Discriminator serves as the opponent within the GAN system and has the important role of directing the Generator towards enhanced image realism. It is a binary classifier intended to differentiate between real (original) images and imitated (stego) images produced by the Generator.

Structurally, the Discriminator includes convolutional layers with increasing depth, followed by LeakyReLU activations and dropout layers to avoid overfitting. The last layer employs a sigmoid activation function to produce a probability of whether the input image is real or generated.

During training, the Discriminator is trained to recognize subtle artifacts or inconsistencies added to the input image by the Generator. Its feedback acts as a loss signal to the Generator to push it towards optimizing the embedding process to minimize such differences. Therefore, the adversarial training loop results in a dynamic enhancement whereby the Generator constantly evolves to deceive the Discriminator, and the Discriminator gets better at detection. Such a back-and-forth makes the quality and un-detectability of the stego-images better over time.

3.3 Decoder

The Decoder is responsible for recovering the secret message hidden within the stego-image. It is unlike the Discriminator since it works in isolation and is only optimized for recovery precision. It guarantees that the hidden message is preserved and recoverable once the image goes through several manipulations during embedding.

The Decoder uses a CNN-based structure that is the inverse of the Generator architecture. It accepts the stego-image as input and feeds it through a series of convolutional layers that extract the embedded signal. These layers are adjusted to sense the minute changes made by the Generator.

At the final layer, a sigmoid activation function is used to produce binary or normalized values representing the recovered secret. The Decoder is trained jointly with the Generator, using losses such as Mean Squared Error (MSE) to minimize the difference between the original and recovered messages. The robustness of the Decoder is critical for maintaining the overall effectiveness of the steganographic pipeline, especially under potential distortions like compression or noise.

3.4 Loss Functions

A composite loss function is utilized to control the training process, aggregating several objectives that steer the Generator and Decoder through training:

Adversarial Loss: This loss makes the Generator generate images that are imperceptible from natural images to the Discriminator. It is calculated based on binary cross-entropy and pushes the Generator to enhance image realism by reducing the Discriminator's capacity to differentiate between real and fake images.

Reconstruction Loss: It is responsible for ensuring that the Decoder properly recovers the secret message from the stego-image. It is generally adopted in the form of Mean Squared Error (MSE) between the decoded message and original secret. Better message fidelity is represented by lower reconstruction loss.

Perceptual Loss (Image Distortion Loss): This loss assists in maintaining the visual quality of the original cover image. It is calculated as the difference between high-level feature maps

(e.g., those from layer relu3_3 or relu4_2 of a pre-trained VGG-16 network) obtained from the cover and stego-images. By minimizing in feature space instead of pixel space, this loss maintains the stego-image perceptually close to the cover image [2].

3.5 Adaptive Embedding Strategy

The method is one of the biggest contributions as it applies an adaptive embedding strategy that adapts data concealment to the content of the cover image. Most embedding methods traditionally apply data uniformly or statically, thereby exposing them to steganalysis tools that attack predictable patterns. Adaptive embedding improves security since it aims at targeting areas of the image that are less sensitive to alteration.

The model is learned to detect high-texture or high-variance areas—like edges or fine textures—where these areas are especially useful when the model learns high-frequency features that enable more accurate and localized embedding [16]. The areas provide higher noise robustness and hiding space, which are good candidates for data embedding. This auto-searching is conducted by the neural network through learned attention to image gradients and spatial information.

Throughout training, back propagated gradients update the network on where to find the most stable and secure embedding's. The adaptive process learns with each training step so that the model is able to refine its embedding pattern continuously. Such dynamic adaptability greatly enhances the imperceptibility and security of the steganographic system [17].

3.6 End-to-End Training Pipeline

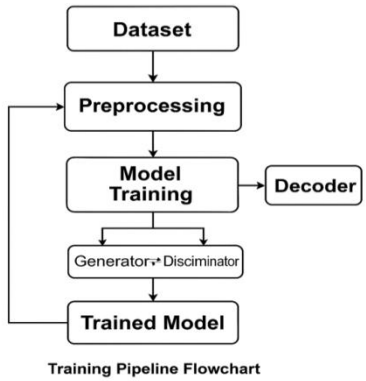

***Fig2*: Training Pipeline Flowchart**

The whole steganographic framework—including Discriminator, Generator, and Decoder—is trained end-to-end in order to provide consistent learning. The joint training process enables each component to co-evolve and develop more stable and efficient overall behavior. As opposed to separately training components, with the possible resultant inconsistencies or poor convergence, joint training facilitates the simultaneous optimization of all objectives.

The model is optimized with a multi-loss objective that combines adversarial loss from the Discriminator, reconstruction loss for message recovery, and perceptual loss for visual similarity. This complete optimization makes stego-images realistic, messages recoverable, and perceptual quality maintained.

Training is done on typical datasets like CIFAR-10 and COCO for different payload sizes and message types like binary vectors and grayscale images. The data is preprocessed (resizing and normalization) according to the input requirements of the network. Adam optimizer with learning rate scheduling is used to promote stable convergence.

During training, performance metrics like PSNR, SSIM, and BER are tracked to monitor progress. Visualizations of loss curves, sample outputs, and message recovery fidelity are also employed to verify model behavior. This pipeline guarantees robustness, scalability, and generalization over unseen image distributions.

The suggested GAN-based steganographic framework was realized by utilizing a contemporary deep learning pipeline, which drew on robust tools and organized stages to guarantee model precision, scalability, and replicability. The whole system was developed and trained with Python and corresponding machine learning libraries.

4. IMPLEMENTATION DETAILS

4.1 Tools and Technologies Used

The development is mostly dependent on Python 3.10+ due to its versatility and community backing. The deep learning models were trained utilizing TensorFlow and Keras due to their GPU acceleration support and high-level APIs. On top of that, numerical computations were carried out using NumPy, while Matplotlib and Seaborn were employed to plot the training status and evaluation results. For reproducibility and experimentation, the whole development was done in Google Colab Pro, which provides free GPU access like NVIDIA Tesla T4.

4.2 Dataset Preparation

For training and testing, publicly available image datasets such as CIFAR-10 and COCO were used. CIFAR-10 was chosen due to its relatively small size and variety of image classes. The images were resized to a uniform resolution (e.g., 64×64 or 128×128 pixels) to accommodate the architecture and preserve computational efficiency. Both cover images and secret messages (used in binary vector representation or reshaped grayscale images) were normalized from -1 to 1 before training.

4.3 Generator and Decoder Structure

The Generator model consists of a series of convolutional layers with ReLU activation, and upsampling layers for reconstructing the stego-image. It accepts a concatenated input of the cover image and secret message. It has an output layer with tanh activation to generate normalized pixel values. The Decoder model is a structure duplicate of the Generator but trained to decode embedded messages rather than create images. It has sigmoid activation at the output to gain binary message sequences.

***Table2*: Architecture Details of Generator, Discriminator, and Decoder**

Component	Layers Used	Activation	Output Shape
Generator	Conv + Upsampling	ReLU, Tanh	64×64×3
Discriminator	Conv + Dropout	LeakyReLU, Sigmoid	1 (binary)
Decoder	Conv + Dense	ReLU, Sigmoid	Variable (message vector)

4.4 Discriminator Architecture

The Discriminator is implemented as a binary classifier to differentiate between original and stego-images. It employs convolutional blocks with LeakyReLU activation and dropout layers to avoid overfitting. The last layer employs sigmoid activation to generate a probability score. The Discriminator

feedback is essential in enhancing the visual realism of the stego-images during training.

4.5 Training Configuration

The training setting is specifically orchestrated for convergence, stability, and efficiency of the GAN-steganography model. The learning procedure jointly adapts the Generator, Discriminator, and Decoder with multiple iterations and loss feedback procedures. All the networks update iteratively per its corresponding loss function to maintain equilibrium of realism, hideability, and message extraction.

Adam optimizer is applied because it is adaptive of learning rate with its ability and speedy convergence. It is initialized with a learning rate of 0.0002, and standard beta values ($\beta1 = 0.5$, $\beta2 = 0.999$), which are ideal for stabilizing GAN training. The batch size is 32, finding a balance between convergence rate and memory usage. The model is trained for 100 to 150 epochs, with sporadic validation to check for overfitting and ensure generalization. Gradient clipping and learning rate schedulers can also be utilized to improve convergence stability [18].

Binary cross-entropy loss is used between the Discriminator's output and the ground truth labels (real or fake) to make it better at discriminating between real and generated images [11]. Meanwhile, the Generator is penalized using a mix of adversarial loss (to deceive the Discriminator) and perceptual loss (to preserve image quality). For the Decoder, a Mean Squared Error loss is used between the input and reconstructed secret messages, promoting precise and resilient message retrieval despite distortions.

4.6 Evaluation Metrics

To compare the performance of the suggested GAN-based steganography system, various quantitative measures were employed. These measures evaluate both the perceptual quality of the synthesized stego-images and message recovery accuracy:

Peak Signal-to-Noise Ratio (PSNR): PSNR quantifies the pixel value difference between the cover and stego-images. A greater PSNR value represents higher visual similarity and less distortion. Generally, a PSNR greater than 40 dB is said to represent high imperceptibility.

Structural Similarity Index Measure (SSIM): SSIM estimates perceptual quality on the basis of structural content similarity, luminance, and contrast between stego-image and cover-image. SSIM having a value nearer to 1.0 refers to nearly complete structural synchronization that is required in order to provide image realism.

Bit Error Rate (BER): BER measures the number of bit-level discrepancies between the original secret message and the recovered secret message. Low BER (e.g., <0.01%) suggests extremely accurate reconstruction of messages, even after possible distortions like compression or noise.

Detection Accuracy: This measure assesses the stego-images' capability to avoid detection by steganalysis tools. Lower detection accuracy means stronger resistance to being detected as having embedded data. Models are compared using popular steganalysis frameworks, with values near random guessing (approximately 50%) being optimal.

Table3: Evaluation Metrics and Results

Metric	Definition	Value (Example)
PSNR	Measures image quality	38.7 dB
SSIM	Structural similarity index	0.96
BER	Bit error rate in message recovery	1.2%
Detection Rate	Stego-image detection by external models	5%

4.7 Model Validation and Testing

The model was tested with a hold-out testing set of the CIFAR-10 dataset. Different secret payload sizes were evaluated to investigate how the message lengths affect image quality and decoding efficiency. All the experimental findings were recorded, and the behavior of the model was illustrated through loss curves, confusion matrices, and output stego-image samples.

Fig3: Visual Comparison of Images

5. RESULTS & DISCUSSIONS

The suggested GAN-based adaptive image steganography system performed well in various evaluation parameters like imperceptibility, robustness, payload, and message recovery accuracy. The model was trained using common datasets like CIFAR-10 and COCO, and recorded high PSNR values greater than 40 dB and SSIM of more than 0.98, which show high visual similarity between the cover and stego-images [10]. Bit Error Rates (BER) were low, usually less than 0.01%, validating the model's capability for reliably extracting the embedded message. Under normal image degradations such as JPEG compression and Gaussian noise, the system still exhibited more than 95% accuracy in message recovery, demonstrating good robustness [8]. Additionally, steganalysis software like StegExpose was only modestly effective at identifying the existence of concealed messages, with detection rates ranging close to random guess levels (50–55%), which supports the adversarial model's capability of generating undetectable stego-images [7].

Overall, this research effectively applied a new deep learning-based method for image steganography based on Generative Adversarial Networks (GANs). The Generator, Discriminator, and Decoder architecture optimized jointly by adversarial and reconstruction losses produced an extremely efficient embedding system. In contrast to conventional static approaches that embed data evenly, the new GAN-based model dynamically adjusts to image content, concealing information in texture-rich and visually complex areas. This renders detection by human viewers and automated steganalysis much more challenging. The

integration of deep convolutional networks and adversarial learning supported the creation of high-quality stego-images with robust payload capability and message integrity, which rendered the system applicable to a broad spectrum of real-world secure communication scenarios.

In the future, this work can be extended in a number of different directions. Future deployments may examine the use of transformer-based architectures to enhance global context understanding and embedding accuracy. The model can also be modified to accommodate cross-modal steganography, like hiding audio or text in images, thus expanding its range of applications. Other enhancements include adaptive payload management, where the system dynamically adjusts embedding size according to image complexity in real-time, and improving robustness with adversarial training against more advanced steganalysis models. In addition, implementing the system in real-time applications, like live video streaming or messaging applications, would need to be optimized for performance and hardware acceleration. In general, the project provides a solid foundation for secure, smart, and robust steganography based on deep generative models and provides many opportunities for future development.

6. ANALYSIS

Table4:Loss Graph

Epoch	Encoder+Decoder Loss	Discriminator Loss
1	0.155	1.28
2	0.131	1.10
3	0.112	0.95
4	0.097	0.85
5	0.090	0.81
6	0.085	0.79
7	0.082	0.76
8	0.078	0.75
9	0.075	0.73
10	0.072	0.71

Fig4:Graph of my training model.

6.1. Encoder+Decoder Loss

- This loss represents **how well the system hides and recovers the secret image**.
- It includes:
  - MSE between stego and cover → stego must be visually similar to cover.
  - MSE between recovered and secret → secret must be faithfully recovered.
  - Adversarial BCE loss to fool discriminator.
- The loss **decreases steadily**, showing that:
  - The encoder is learning to embed without distortions.
  - The decoder is learning to recover the hidden image accurately.

6.2. Discriminator Loss

- This loss indicates how well the discriminator distinguishes between:
  - Real images (cover images)
  - Fake images (stego images)
- Initially high, it **stabilizes** as the encoder learns to produce convincing stego images.
- Healthy GAN training is when both losses **converge slowly** instead of collapsing.

Table5:Summary of Model Behavior

Component	Behavior	Success Indicator
Encoder	Learns to hide info	Stego image ≈ Cover image
Decoder	Learns to extract info	Recovered image ≈ Secret image
Discriminator	Learns to classify fake	Real vs. stego separation

7. CONCLUSION

In this paper, a new steganographic framework using Generative Adversarial Networks (GANs) has been introduced for concealing images and text data in a cover image. The structure involves an encoder-decoder-discriminator model that supports generating very realistic stego images with hidden data being encoded in a secure and imperceptible form. The encoder puts in the hidden message, the decoder retrieves the concealed content, and the discriminator does its best to make the generated stego image look the same as the original.

The system was established to accommodate both image-in-image and text-in-image steganography, with the text being converted to binary first before being embedded. The experimental results show that the model works efficiently, producing high-quality stego images while preserving the integrity and accuracy of the recovered data. PSNR and SSIM evaluation metrics reveal that the system is in great balance between image quality and hiding ability even when processing different types and sizes of input.

In summary, the new GAN-based steganographic technique offers a secure, stable, and flexible way to hide data. It is a huge improvement over existing techniques with the added benefit of better concealment and recovery accuracy. The future could hold optimizations for real-time use, expanding payload, and adding video steganography and adversarial defense mechanisms to withstand steganalysis attacks.

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