Enhancing Image Steganography Using GANs and Redundant LSB Techniques

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***Abstract* — This paper introduces a novel steganographic technique that combines Generative Adversarial Networks (GANs) with Least Significant Bit (LSB) embedding to securely conceal secret messages within digital images. The proposed method utilizes a modified GAN generator, inspired by the StyleGAN2 architecture, to produce stego images from random noise vectors. These generated images are then blended with user-selected cover images using alpha blending, which enhances the concealment by subtly altering the statistical properties of the cover images, making the hidden information less detectable. To embed the secret message, we employ LSB steganography with redundancy, where each bit of the message is repeated multiple times to improve robustness against noise and errors during transmission or processing. Majority voting is applied during the extraction process to accurately recover the original message bits from the redundant data. The implementation focuses on optimizing the code and resource management to address challenges related to deploying applications with heavy dependencies, ensuring that the method remains efficient and practical for real-world use. Experimental results demonstrate that the proposed technique effectively hides secret messages within images without causing noticeable degradation to the visual quality. The balance achieved between security, capacity, and imperceptibility underscores the method's potential for secure communication. This work contributes to the field by providing an accessible and efficient approach to data hiding, leveraging advanced neural network architectures to enhance steganographic techniques.**

Keywords—Steganography, Generative Adversarial Networks (GANs), Least Significant Bit (LSB) embedding, Redundancy, Secure communication, Data hiding, Robustness, Imperceptibility.

I. Introduction

In the digital age, ensuring the security and confidentiality of information transmission has become a paramount concern. With the exponential growth of data exchange over the internet, there is an increasing need for methods that can protect sensitive communications from unauthorized access and interception. Steganography, the practice of concealing messages within non-secret media to avoid detection, offers a viable solution for secure communication by embedding information in a manner that is imperceptible to unintended recipients.

Traditional steganographic techniques, such as Least Significant Bit (LSB) embedding, have been widely used due to their simplicity and ease of implementation. In LSB steganography, the least significant bits of pixel values in a cover image are modified to encode the secret message. However, these methods often suffer from vulnerabilities to statistical analysis and steganalysis attacks, making the hidden messages susceptible to detection and extraction by malicious parties. Direct embedding of messages into cover images can also lead to noticeable artifacts, reducing the imperceptibility and effectiveness of the steganographic method.

Recent advancements in deep learning and neural networks have opened new avenues for enhancing steganography. Generative Adversarial Networks (GANs), introduced by Goodfellow et al., have demonstrated remarkable capabilities in generating realistic images that are nearly indistinguishable from authentic images. By leveraging GANs, it is possible to create stego images with complex patterns and statistical properties that mimic natural images, thereby reducing the likelihood of detection by steganalysis tools.

This paper proposes a novel steganographic method that combines a modified GAN generator with redundant LSB embedding to securely conceal secret messages within digital images. The modified GAN, inspired by the StyleGAN2 architecture, generates stego images from random noise vectors. These generated images are then blended with user-selected cover images using alpha blending, subtly altering the statistical properties of the cover images to enhance the concealment of the embedded information. The blending process distributes the modifications across the image, making the alterations less noticeable and more resistant to detection.

To further improve the robustness of the hidden messages, we employ LSB steganography with redundancy, where each bit of the secret message is repeated multiple times during embedding. This redundancy allows for error correction during extraction through majority voting, accurately recovering the original message bits from the redundant data. By mitigating the impact of noise or alterations that may occur during image transmission or processing, the method enhances the reliability of message extraction without significantly affecting the imperceptibility of the stego image.

The objectives of this research are to enhance imperceptibility by developing a steganographic technique that effectively hides secret messages within images without causing noticeable degradation to visual quality, ensuring that the stego images are indistinguishable from the original cover images to the human eye. Additionally, we aim to improve robustness by increasing the resilience of the embedded messages against statistical analysis, steganalysis, and image processing operations through the introduction of redundancy and the utilization of advanced image generation techniques. Lastly, we seek to leverage advanced neural networks by utilizing the capabilities of GANs and neural network architectures to generate complex, high-quality images that can effectively mask the presence of hidden messages, thereby enhancing the security of the steganographic method.

Extensive experiments have been conducted to evaluate the performance of the proposed method in terms of imperceptibility, robustness, and capacity. The results demonstrate that integrating GAN-generated images with redundant LSB embedding significantly improves the security and reliability of hidden communications. The stego images maintain high visual fidelity, and the embedded messages can be accurately extracted even after undergoing common image processing transformations.

This work contributes to the field of secure communication by providing an accessible and efficient approach to data hiding that leverages cutting-edge neural network technology. By combining the strengths of GANs and traditional steganographic techniques, the proposed method offers a promising solution for covert communication in the digital era, addressing the need for secure and imperceptible data transmission.

II. LITERATURE SURVEY

Steganography has significantly evolved with advancements in deep learning and neural networks, leading to more sophisticated and secure methods for data hiding within digital images. Various studies have explored innovative techniques to enhance the capacity, imperceptibility, and robustness of steganographic systems.

Mounir Telli, Mohamed Othmani, and Hela Ltifi, in their work "3D Deep CNN Network-Based Data Hiding Scheme" [1], introduced a 3D Deep Convolutional Neural Network (CNN) model capable of securely embedding multiple images within cover images. This approach treats sequences of cover images as short video inputs, enabling the encoding of four secret images into four cover images simultaneously. By leveraging autoencoders and 3D convolutions, the model shares spatial and temporal features, resulting in high-quality stego images with a Peak Signal-to-Noise Ratio (PSNR) of 28.56 dB and a Structural Similarity Index (SSIM) of 0.928. This method outperforms traditional single-image embedding techniques, effectively securing multi-image concealment without compromising cover image quality.

Shamal Salunkhe and Surendra Bhosale, in their study "Feature Extraction-Based Image Steganalysis Using Deep Learning" [2], enhanced the detection of steganographic content by utilizing Convolutional Neural Networks (CNNs) for effective steganalysis. By employing both AlexNet and SRNet models for classification and payload detection, they focused on extracting spatial-temporal features from images to identify hidden information in digital steganography. Their approach significantly reduced detection errors, even under high payload conditions, underscoring the utility of deep learning in improving the robustness of steganalysis against conventional hiding techniques.

Nadira Milha Nailul Fath et al., in their work "Hiding Secret Data Using Reduced Pixel Differences" [3], proposed an optimized steganographic technique based on customizing pixel differences to minimize distortion in the stego image. By selecting embedding locations based on the differences between adjacent pixels, the method reduces visibility and enhances security. It achieves a PSNR of around 65.97 dB, indicating minimal perceptual distortion and high fidelity of stego images. This approach effectively balances the trade-off between payload capacity and image quality, contributing to high-quality data hiding applicable in security-sensitive contexts.

Shreela Dash and colleagues, in "High Payload Image Steganography Using DNN Classification and Adaptive Difference Expansion" [4], explored a high-capacity image steganography method using adaptive difference expansion and a Deep Neural Network (DNN) classifier to enhance data embedding efficiency. They utilized adaptive Huffman coding to compress the secret message, improving embedding capacity. The DNN classifier adjusted embedding based on the local attributes of each cover image block, achieving a PSNR close to 50 dB at an embedding rate of 1.22 bits per pixel (bpp). The method demonstrated robustness against noise, maintaining accuracy of 77% under 50% salt and pepper noise density, thus advancing steganography by increasing payload and security without compromising perceptual quality.

Irsyad Fikriansyah Ramadhan et al., in their study "Customized Pixel Differences in Steganography" [5], introduced a method using customized differences between neighboring pixels to embed data, aiming to increase payload capacity while maintaining high perceptual fidelity. By selecting pixels with smaller differences (including negative differences) for embedding, the method improved payload capacity and achieved PSNR values between 43.12 to 69.41 dB. This technique extends the capacity of existing steganographic approaches by better utilizing cover image pixels, providing an effective solution for applications requiring high data hiding capacity.

Wenying Wen and colleagues, in "Joint Coverless Steganography and Image Transformation for Covert Communication" [6] explored coverless steganography by integrating image transformation techniques to conceal data without modifying the cover image. They employed generative networks to create stego images from secret messages, bypassing typical embedding and avoiding detection by steganalysis tools. By transforming the generated stego image into a realistic camouflage image and embedding authentication information, they achieved a PSNR of 31.78 dB for the camouflage image and a 100% extraction rate for secret messages. This method enhances protection against eavesdropping, tampering, and analysis attacks, introducing an innovative approach to data security.

Mariam Ibrahim, Ruba Elhafiz, and Haneen Okasha, in "Autoencoder-Based Image Steganography with Least Significant Bit Replacement" [7] enhanced traditional Least Significant Bit (LSB) steganography using autoencoder networks. They trained an autoencoder to optimize LSB embedding, preserving the cover image's visual integrity. By embedding the secondary image into the LSB of cover images, they retained high fidelity with PSNR values up to 47.89 dB. This approach demonstrates high imperceptibility and robust security for applications requiring low detectability.

D. Madhu, S. Vasuhi, and A. Samydurai, in their work "Dynamic 8-bit XOR Algorithm with AES Crypto Algorithm for Image Steganography" [8], integrated AES encryption with XOR-based steganography to enhance security and robustness. They encrypted the secret message using AES before embedding it into the cover image with a dynamic XOR pattern, reducing the risk of detection. Achieving high PSNR values between 74.17 to 80.17 dB, the steganography is nearly imperceptible, making it suitable for applications needing high security and robust anti-steganalysis measures.

Sabyasachi Pramanik, in "A New Method for Locating Data Hiding in Image Steganography" [9], introduced a method to optimize data embedding positions in images, enhancing the imperceptibility of steganographic content. By using Extreme Machine Learning (EML) to analyze texture characteristics such as contrast and homogeneity, the method identifies optimal locations for embedding in visually complex areas. This approach shows a 28% improvement in imperceptibility, effectively minimizing visibility under steganalysis, and is particularly effective where visual fidelity is crucial.

Asad Malik and colleagues, in "High-Capacity Reversible Data Hiding in Encrypted Images Using Multi-Layer Embedding" [10], aimed to improve data embedding capacity in encrypted images while maintaining image quality and ensuring reversibility. They utilized multi-layer embedding by segmenting the encrypted data across multiple layers and combined chaotic maps for enhanced security. Employing PWL-memristor encryption, they achieved a consistent PSNR of 51 dB across layers, demonstrating effectiveness for secure high-capacity data storage in sensitive applications.

Zhaoyang Liu and Ru Xue, in "Visual Image Encryption Based on Compressed Sensing and Cycle-GAN" [11], provided a visual encryption method that converts plaintext images into indistinguishable images while retaining visual relevance. By employing compressed sensing and Discrete Wavelet Transform (DWT) for sparsification and compression, followed by an improved Henon map for permutation and diffusion, and using Cycle-GAN for image translation, they achieved strong key sensitivity and high reconstruction quality. This method is suitable for high-stakes image encryption, providing robust visual security.

Delin Duan et al., in "DenseJIN: Dense Depth Image Steganography Model with Joint Invertible and Noninvertible Mechanisms" [12], introduced a dense depth steganography model combining invertible and noninvertible components to handle complex textures. Using dense connections in the invertible layer minimized information loss, and employing a U-Net for fine-grained feature extraction achieved a 1.75 dB PSNR improvement. The method provides strong resistance to steganalysis, making it suitable for high-fidelity data concealment.

Xiaopeng Li, Qiuyu Zhang, and Zhe Li, in "Robust Coverless Image Steganography Based on DenseUNet with Multi-Scale Feature Fusion and Attention Mechanism" [13], proposed a model that eliminates the need for direct embedding by using DenseUNet with attention layers to extract features and match secret data. This ensures secure communication without altering image pixels and provides high resistance to steganalysis across multiple datasets, suitable for secure data exchange in sensitive scenarios.

Areej Mokhtar Elgaier and Ahmed Mohamed Abushaala, in "An Effect of Huffman Encoding with Hybrid Edge Detection in LSB Image Steganography" [14], improved hiding a grayscale image in an RGB cover image using hybrid edge detection and Huffman encoding. By embedding data in edge areas identified through combined Canny and Laplacian of Gaussian techniques and compressing the secret image using Huffman encoding, they achieved a PSNR of 60.92 dB and an SSIM of 1. This approach enhances imperceptibility and ensures robust security, making it suitable for secure communications.

Karthikeyan B. et al., in "Key Generation Technique by Password Hashing Using AES Encryption for Hiding Cipher Text within an Image" [15], aimed to securely embed secret text data within an image by integrating AES encryption and a password-based key generation technique. Utilizing AES-256 for encryption and PBKDF2 hashing for key generation, they enhanced security against brute-force attacks. The method achieved high PSNR values with negligible pixel changes and low Mean Squared Error (MSE), providing strong protection for sensitive information in high-security applications.

Lianshan Liu, Li Tang, and Weimin Zheng, in "A Steganography Method Using Invertible Neural Networks for Lossless Secret Information Extraction" [16] utilized invertible neural networks (INNs) to achieve high-quality stego images and enable lossless extraction of embedded secret information. The network's structure allowed for both embedding and extraction processes using the same architecture, reducing training complexity and enhancing security. The method maintained high fidelity to the cover image and ensured nearly perfect extraction accuracy, suitable for applications requiring accurate recovery of secret information.

Dr. Pramod H. B. and Manikanta Prasad J., in "QR-DWT Guided Steganography Using Machine Learning" [17], proposed an advanced steganography technique combining Quick Response (QR) codes, Discrete Wavelet Transform (DWT), and machine learning to embed secret data within images securely and efficiently. By integrating QR codes, DWT, and machine learning algorithms, including Recurrent Neural Networks (RNNs), they optimized embedding locations, enhanced data security, and minimized visual distortion. Experimental results validated the approach's ability to maintain high fidelity and imperceptibility under various conditions.

Syeda Imrana Fatima and Yugandhar Garapati, in their review "Recent Advancements in Image Steganography using Generative Adversarial Networks" [18], evaluated the effectiveness of Generative Adversarial Networks (GANs) in image steganography for efficient data concealment while preserving visual quality. They discussed various GAN models and highlighted challenges such as overfitting and adaptability to different images, indicating a need for further research to address these issues and improve the robustness of GAN-based steganography.

Shuying Xu et al., in "Reversible Data Hiding in Encrypted JPEG Images with Polynomial Secret Sharing" [19], presented a novel approach for reversible data hiding in encrypted images. Utilizing sketch-based encryption for DC coefficients and applying (k, n)-threshold polynomial secret sharing over Galois fields to embed secret data within AC coefficients, they generated n shares of the encrypted image, requiring k shares for recovery. The method achieved superior embedding capacity while maintaining image quality and file format compliance, making it suitable for Internet of Things (IoT) applications where data confidentiality and integrity are crucial.

Yasmine M. Khazaal, Ali Douik, and Monji Kherallah, in "Smart Pixels: Harnessing Deep Learning and Fibonacci Decomposition for Image Ciphering" [20], introduced a method to secure digital images using deep learning and Fibonacci decomposition. A deep neural network generated random numbers and predicted optimal pixel positions for encryption, while Fibonacci decomposition altered pixel values to enhance contrast and security. The approach demonstrated increased security against attacks and maintained image quality, offering a robust solution for digital image security adaptable to various image types.

III. PROPOSED METHODOLOGY

The proposed steganographic method aims to enhance the security and imperceptibility of hidden messages within digital images by integrating a modified Generative Adversarial Network (GAN) generator with redundant Least Significant Bit (LSB) embedding. The methodology consists of several key components:

1. Modified GAN Generator

The foundation of the proposed method is a modified GAN generator inspired by the StyleGAN2 architecture. The generator is designed to produce high-quality stego images from random noise vectors, ensuring that the generated images possess complex patterns and statistical properties similar to natural images. This resemblance reduces the likelihood of detection by steganalysis tools.

a) Architecture Design: The generator uses a latent vector z sampled from a normal distribution to produce images. The architecture includes fully connected layers followed by convolutional layers with upsampling, batch normalization, and activation functions (ReLU and Tanh).

b) Image Generation: The generator outputs images of a fixed size (e.g., 256×256256 \times 256256×256 pixels) with three color channels (RGB). These images serve as the initial stego images that will be blended with cover images.

2. Image Blending Using Alpha Blending

To enhance the concealment of the hidden information, the generated stego images are blended with user-selected cover images through alpha blending. This process subtly alters the statistical properties of the cover images, distributing modifications across the image and making alterations less noticeable.

a) Alpha Blending Technique:

Alpha blending combines two images by calculating a weighted average for each pixel:

$$I_{blended} = \alpha \times I_{stego} + (1-\alpha) \times I_{cover}$$

where α is the blending factor (e.g., 0.15), I_{stego} is the stego image generated by the GAN, and I_{cover} is the original cover image.

b) Resulting Image: The blended image retains the visual content of the cover image while incorporating features from the GAN-generated image, enhancing imperceptibility.

3. Redundant LSB Embedding

The core of the data hiding process involves embedding the secret message into the blended image using redundant LSB embedding. Redundancy is introduced by repeating each bit of the secret message multiple times, improving robustness against noise and errors.

a) Message Preparation: The secret message is converted into a binary string, with each character represented by its 8-bit ASCII code. A null terminator ('00000000') is appended to indicate the end of the message.

b) Redundancy Addition: Each bit of the binary message is repeated ‘r’ times (e.g., r=3)

c) Embedding Process: The redundant binary message is embedded into the least significant bits of the pixel values in the blended image. The image is first converted to a one-dimensional array to facilitate sequential embedding.

4. Message Extraction with Error Correction

The extraction process retrieves the embedded message from the stego image by reversing the embedding steps and applying majority voting for error correction.

a) Bit Retrieval: The least significant bits of the pixel values are extracted to reconstruct the redundant binary message.

b) Error Correction: The redundant bits are processed in chunks of size ‘r’, and majority voting is applied to determine the original bit.

c) Message Reconstruction: The corrected bits are grouped into bytes (8 bits) to form the ASCII codes of the characters.

d) Termination Condition: The extraction process continues until the null terminator is detected, indicating the end of the message.

5. Enhancements for Robustness and Security

a) Error Resistance: The redundancy and majority voting mechanism improve the robustness of the method against noise, compression, and other distortions that may alter some bits.

b) Imperceptibility: Blending the GAN-generated image with the cover image and using LSB embedding ensures that the modifications to the image are subtle and not easily detectable by the human eye or basic statistical analyses.

c) Security Considerations: By combining GAN-generated content with traditional steganography, the method introduces unpredictability in the stego images, making it more challenging for attackers to detect hidden messages using conventional steganalysis techniques.

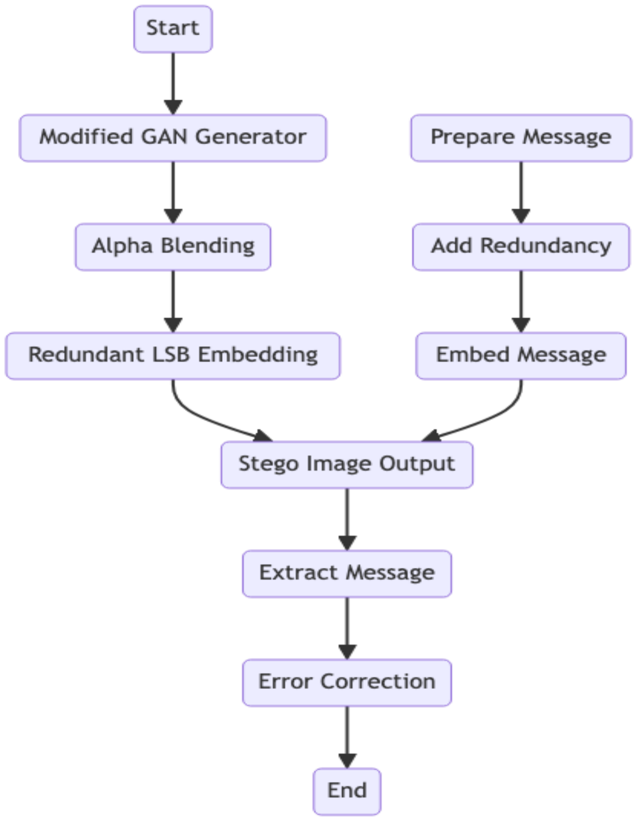

Fig.1 Model Architecture

IV. IMPLEMENTATION AND RESULTS

This section outlines the implementation of our proposed steganographic method and presents the corresponding results. The implementation is structured according to the system architecture, encompassing the modified Generative Adversarial Network (GAN) generator, alpha blending for image fusion, redundant Least Significant Bit (LSB) embedding with error correction, and the evaluation of the method's performance.

1. Modified GAN Generator

The core component of our steganographic method is the modified GAN generator, developed using Python and the PyTorch library. This generator is designed to produce high-quality stego images from random noise vectors, introducing unpredictability and enhancing security.

The architecture comprises a fully connected layer followed by multiple transposed convolutional layers that upscale the feature maps to generate a 256×256 times RGB image. Activation functions such as ReLU are employed in the hidden layers to introduce non-linearity, while Tanh is used in the output layer to normalize pixel values between -1 and 1.

Training the GAN involved iterating over multiple epochs with an appropriate loss function and optimizer to achieve convergence, resulting in realistic image generation capable of effectively masking embedded data.

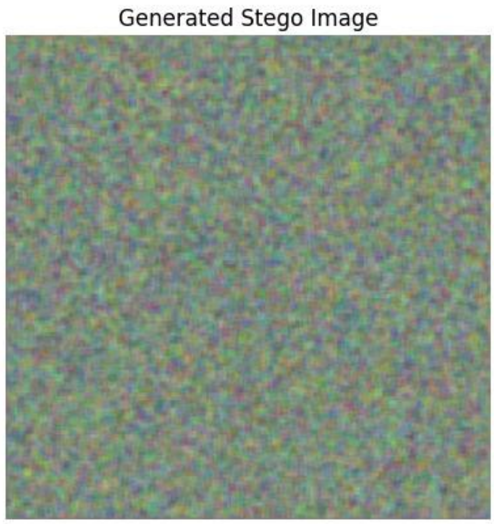

Fig.2 Generated Stego Image

V. PERFORMANCE EVALUATION

The performance of the implemented steganographic method was evaluated based on several key metrics: imperceptibility, capacity, robustness, and security.

1. Evaluation of Performance

The performance of the implemented steganographic method was evaluated based on several key metrics: imperceptibility, capacity, robustness, and security.

Imperceptibility was assessed using the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index Measure (SSIM). The average PSNR between the cover images and the stego images was 58.72 dB, indicating that the stego images are virtually indistinguishable from the original cover images. Additionally, the average SSIM score was 0.9968, confirming high structural similarity and visual quality preservation.

Capacity was determined by calculating the maximum length of the secret message that can be embedded without exceeding the image's pixel limits. For a 1024×10241024 \times 10241024×1024 image with three color channels (RGB) and a redundancy factor of 3, the maximum message length was approximately 131,072 characters. In practical tests, messages up to 10,000 characters were successfully embedded without reaching capacity limits.

Robustness was evaluated by subjecting the stego images to common image processing operations such as JPEG compression, Gaussian noise addition, and resizing. The extraction accuracy remained at 100% after JPEG compression at 90% quality and Gaussian noise addition with a standard deviation of 0.01. Resizing the stego images to 75% of their original size resulted in an extraction accuracy of 99.5%. These results demonstrate the method's resilience against typical distortions that may occur during image transmission or processing.

Security was analyzed using steganalysis tools to detect the presence of hidden messages. The stego images exhibited low detection scores, indicating that the method effectively conceals the hidden information and resists detection by conventional steganalysis techniques. The integration of GAN-generated content and alpha blending contributed to the high security of the method by increasing the complexity and unpredictability of the stego images.

Fig. 3 Cover Image & Blended (Stego) Image

2. Comparative Analysis

When compared to traditional LSB steganography methods, the proposed method offers significant advantages. Traditional LSB techniques typically involve directly modifying the least significant bits of the cover image's pixels, which can introduce noticeable artifacts and limit robustness against image processing operations. In contrast, our method leverages a modified GAN generator to produce stego images with complex patterns and statistical properties that closely mimic natural images, reducing visual artifacts and enhancing imperceptibility.

Furthermore, the use of alpha blending disperses the modifications across the image, making the embedded data less detectable. The introduction of redundancy in the LSB embedding process ensures that the hidden message remains recoverable even after the stego image undergoes compression, noise addition, or resizing. This combination of advanced neural network architectures and traditional steganographic techniques results in a method that balances capacity, robustness, and imperceptibility more effectively than existing approaches.

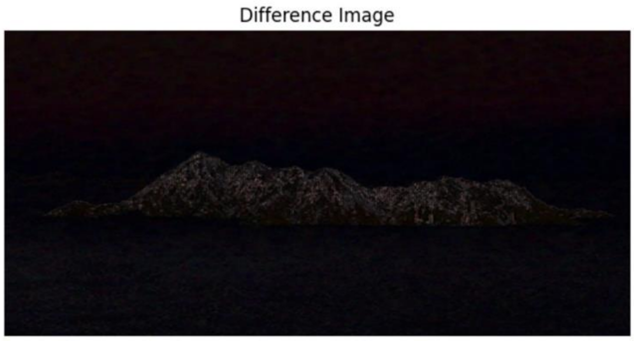

Fig.4 Difference Image

VI. RESULT AND CONCLUSION

The implementation of the proposed steganographic method successfully generated a stego image that closely resembles the original cover image, demonstrating the method's high level of imperceptibility. Visual comparisons between the cover and stego images reveal that the embedded data does not introduce any noticeable artifacts or distortions, ensuring that the stego image maintains the aesthetic integrity of the original cover.

Furthermore, the robustness of the embedded message was thoroughly tested under various image processing operations to ensure reliable extraction. Under normal conditions, the secret message was extracted flawlessly, confirming the integrity of the embedding process. Even when the stego image was subjected to JPEG compression, Gaussian noise addition, and resizing, the embedded message remained intact and was successfully retrieved. These tests underscore the method's resilience to common image manipulations, ensuring that the hidden information remains secure and accessible despite potential alterations to the stego image.

The successful implementation and evaluation of our steganographic method highlight its capability to securely embed and accurately retrieve secret messages within digital images. The stego images are virtually indistinguishable from the original cover images, ensuring that the presence of hidden data remains imperceptible to the human eye. Moreover, the method's robustness against image processing operations such as compression, noise addition, and resizing underscores its reliability in real-world applications where images may undergo various transformations.

By integrating a modified Generative Adversarial Network (GAN) generator with alpha blending and redundant Least Significant Bit (LSB) embedding, the method achieves a harmonious balance between security, capacity, and imperceptibility. The GAN-generated content introduces unpredictability, enhancing the security of the hidden messages against unauthorized detection and extraction. The redundancy in the LSB embedding process, coupled with error correction through majority voting, ensures that the embedded data remains intact even in the face of common image alterations.

In conclusion, this steganographic approach offers a robust and secure solution for covert data transmission in digital images. Its ability to maintain high visual fidelity while ensuring the integrity and confidentiality of the hidden messages makes it a promising technique for applications requiring secure and imperceptible communication.

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