A Review Paper on Deep Learning-Based Image Steganography Techniques

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***Abstract*—The fast progress of communication and multimedia technologies means we need systems that can send data securely. Image steganography is a way to hide secret information in digital images without changing how they look. We use image steganography to conceal information within digital images while keeping the image quality good and making sure it is hard to notice.**

Traditional methods like Least Significant Bit (LSB) and Discrete Cosine Transform (DCT) have some problems. They cannot hide much information they are not strong and they can be easily detected [6].

Recent developments in Deep Learning, Neural Style Transfer and Generative Adversarial Networks have made image steganog-raphy systems work much better [2], [5], [7], [8].

This paper looks at all the ways that use Deep Learning for image steganography including Convolutional Neural Networks, Autoencoders, Generative Adversarial Networks, StyleGAN and Neural Style Transfer techniques.

The paper also talks about ways to keep data safe with encryption like AES and ECC and ways to detect information like steganalysis methods and it looks at datasets how to measure performance, challenges and what we can do in the future.

When we compare the traditional methods to the new Deep Learning methods we see that Deep Learning methods are better at keeping the image quality high and they can hide more information and they are harder to detect.

Deep Learning based image steganography approaches are superior to traditional image steganography methods and they have better PSNR, SSIM, payload capacity and resistance against steganalysis.

***Index Terms*—Image Steganography, Deep Learning, Neural Style Transfer, CNN, GAN, StyleGAN, AES, Image Security, Steganalysis.**

I. INTRODUCTION

The internet and multimedia have become really big in the few years. This means we need to find ways to send information safely. One way to do this is by using something called image steganography. It is a way to hide messages inside digital pictures without making any visible changes. Old methods like LSB, DCT and DWT are not very good because they cannot hide information they are not strong and people can easily find the hidden messages [6]. New techniques using Deep Learning like CNN, Autoencoders, GAN and Neural Style Transfer are much better [2], [5], [7], [8]. They make the hidden messages safer the pictures look better. We can hide more information. This paper is about what's new in using Deep Learning for image steganography especially the techniques that use Neural Style Transfer.

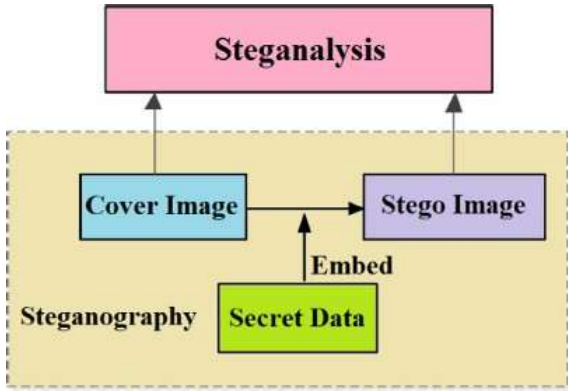

Fig. 1. Steganography and steganalysis process

II. Background of Image Steganography

Image steganography is a way of hiding information inside a picture. You take an image and put the secret information into it to make a new picture that has the secret information in it. The person who gets this picture can then get the secret information out of it using a special extraction method.

The main parts of image steganography are:

- Cover Image
- Secret Message/Image
- Embedding Algorithm
- Extraction Algorithm
- Stego Image

A. Traditional Steganography Techniques

Traditional image steganography methods include spatial domain methods and transform domain methods.

1) Least Significant Bit (LSB): LSB based steganography hides information by replacing the least significant bits of image pixels with secret data bits. This method is simple and computationally efficient. However LSB based steganography is highly vulnerable to attacks and image processing operations [6].

2) Discrete Cosine Transform (DCT): DCT based methods embed information into frequency domain coefficients. These methods provide better robustness against compression attacks.

3) Discrete Wavelet Transform (DWT): The Discrete Wavelet Transform decomposes images into different fre-quency bands and embeds data into selected coefficients. This improves imperceptibility and robustness.

III. Deep Learning in Image Steganography

Deep learning models automatically learn embedding and extraction patterns from datasets without relying on hand-crafted feature engineering.

A. Convolutional Neural Networks (CNN)

Convolutional Neural Networks are really good at handling pictures and finding details. The methods that use Convolu-tional Neural Networks for hiding secrets in pictures are better at putting the information in the picture without being noticed and keeping it safe from people who try to find it [3], [4].

Convolutional Neural Networks can automatically learn image features which makes them highly suitable for image steganography.

B. Autoencoder Based Methods

Autoencoders are made up of two parts: the encoder net-work and the decoder network. The encoder network embeds the secret information into the cover image while the decoder extracts it from the stego image.

Some autoencoders use convolutional layers. These deep convolutional autoencoders improve image reconstruction quality and

PSNR and SSIM values [5].

C. Generative Adversarial Networks (GAN)

Generative Adversarial Networks consist of a generator and discriminator network trained against each other. The generator creates realistic stego images while the discriminator attempts to distinguish between original and stego images.

Using GANs for image steganography makes it much harder to detect hidden information [7], [10]. GAN based methods improve image realism and resistance against steganalysis attacks.

D. Neural Style Transfer (NST)

Neural Style Transfer is a technique that transfers the artistic style of one image to another image while preserving content information. Neural Style Transfer can also be used for image steganography [8], [9]. Hidden information can be embedded into style patterns making it difficult to detect while maintaining visual quality.

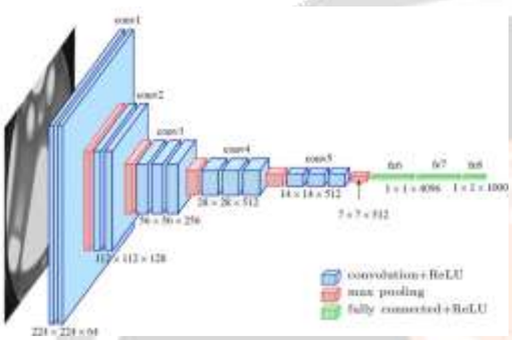

Fig. 2. Neural Style Transfer

E. StyleGAN Based Methods

StyleGAN is an advanced GAN architecture capable of generating highly realistic images with fine-grained control over image style and content. StyleGAN improves image fidelity and reduces visual artifacts in stego images.

IV. Review of Recent Research Works

Nithiyanantham et al. proposed a system for hiding secret images using Neural Style Transfer and StyleGAN techniques [1]. AES encryption was also used to improve security and protect hidden information.

Duan et al. proposed a high-capacity image steganography method using Elliptic Curve Cryptography and deep neural networks [2]. Their method achieved high PSNR and improved security.

Bai et al. developed a CNN based steganography framework using Smooth Wavelet Transform and attention mechanisms for infrared images [3].

Subramanian et al. proposed an end-to-end deep convo-lutional autoencoder based image steganography model with improved reconstruction quality and robustness [5].

Selvaraj et al. presented deep learning based steganalysis methods capable of detecting hidden information efficiently [4].

Li et al. developed GAN based image steganography and style transformation techniques that improved imperceptibility and image quality [10].

V. Comparative Analysis

TABLE I
Comparative Analysis of Deep Learning Based Image Steganography Methods

Method		Technique Used	PSNR	SSIM	Advantages
NST + StyleGAN		NST + GAN + AES	45.20	0.987	High security and imperceptibility
SegNet-DNN		DNN + ECC	43.13	0.9602	High payload capacity
Deep Convolutional AE		Autoencoder	34.55	–	Better reconstruction quality
SteganoGAN		GAN	44.33	0.93	Improved image realism
DL-Steg		SAE + LSTM + ECC	45.59	0.9877	High robustness and security

VI. Performance Metrics

Several performance metrics are used to evaluate image steganography systems.

A. Peak Signal-to-Noise Ratio (PSNR)

PSNR measures the quality of the stego image compared to the original image.

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE}$$

Higher PSNR values indicate better image quality and lower distortion.

B. Mean Squared Error (MSE)

MSE measures the average error between cover and stego images.

often suffer from training instability making optimization difficult [7].

Another significant challenge is maintaining a proper bal-ance between payload capacity and imperceptibility because increasing hidden data capacity can reduce image quality and increase detectability.

Furthermore implementing real-time secure steganography systems remains difficult due to latency processing overhead and hardware limitations.

VIII. Future Research Directions

Future research in image steganography should focus on creating lightweight deep learning models that require less computational power while maintaining high security and embedding performance. Attention based neural networks and transformer based steganography models can improve feature extraction payload capacity and imperceptibility by capturing long-range dependencies more effectively.

Another important direction is combining encryption and steganography to provide multiple layers of security for confidential communication. Quantum image steganography is also a promising research area that may enhance security using principles of quantum computing.

Future systems should also focus on robust adversarial de-fense mechanisms and real-time secure communication frame-works capable of secure and reliable hidden data transmission. Improving robustness adaptability and efficiency will play an important role in developing next-generation steganography

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - K(i,j))^2$$

Lower MSE values indicate lower image distortion.

C. Structural Similarity Index (SSIM)

SSIM measures the structural similarity between the cover image and stego image. Higher SSIM values indicate better visual similarity and imperceptibility.

D. Learned Perceptual Image Patch Similarity (LPIPS)

LPIPS evaluates perceptual similarity between images using deep learning based feature extraction. Lower LPIPS values indicate better image quality and lower perceptual distortion.

VII. Challenges in Deep Learning Based Steganography

Despite recent advancements in deep learning based image steganography several challenges still remain unresolved. One major issue is the high computational complexity of deep learning models which increases training time and resource consumption. Most models also require large training datasets to achieve better accuracy and generalization.

Deep learning based image steganography also has to deal with advanced steganalysis attacks that threaten the security and robustness of hidden data [4]. GAN based approaches systems.

IX. Conclusion

This review paper presented various deep learning based image steganography and steganalysis techniques. Traditional image steganography methods suffer from low payload capac-ity weak robustness and vulnerability to attacks. However deep learning models such as CNNs GANs Neural Style Transfer and StyleGAN significantly improve image quality payload capacity and security [5], [7], [8], [10].

Comparative analysis shows that deep learning based meth-ods provide higher PSNR SSIM and better resistance against steganalysis attacks. Hybrid techniques combining encryption GANs and Neural Style Transfer further improve security and imperceptibility.

Although deep learning based image steganography pro-vides better performance several challenges still remain includ-ing computational complexity and real-time implementation issues. Future research should focus on lightweight secure and robust steganography systems suitable for real-world applica-tions.

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