

Deep Safe: Securing Secret Images with Advanced Deep Learning Techniques

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Abstract: In an era of pervasive digital communication, ensuring the security and confidentiality of sensitive information, particularly in the form of images, is paramount. This research explores the development of an innovative approach, termed DeepSafe, for safeguarding secret images through the utilization of advanced deep learning techniques. The methodology involves the integration of state-of-the-art neural network architectures, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), to effectively encrypt and protect image data. DeepSafe employs a combination of encryption and steganography mechanisms, where sensitive information is embedded within images using imperceptible alterations, rendering it indiscernible to unauthorized parties. Furthermore, advanced encryption schemes and authentication protocols are implemented to enhance the robustness and resilience of the security framework. The effectiveness of DeepSafe is evaluated through comprehensive experimentation, encompassing various image datasets and security metrics. Results demonstrate the efficacy of the proposed approach in achieving high levels of security while preserving the visual fidelity and integrity of secret images. The implications of DeepSafe extend across diverse domains, including digital forensics, secure communication, and privacy-preserving applications, thereby addressing critical challenges in safeguarding sensitive information in the digital age.

Keywords: Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), DeepSafe, Security Framework, Error Correction Capacity, High Security and Privacy-Preserving, Quick Response Code, Visual Secret Sharing Scheme, etc.

1. INTRODUCTION

Ensuring the secrecy and protection of sensitive visual content has become crucial in a world where digital imagery is omnipresent and people rely more and more on social media sites for interaction and exchange of data. DeepSafe emerges as a pioneering endeavor aimed at fortifying the protection of secret images through the integration of advanced deep learning techniques. Recent applications of artificial intelligence and deep learning have demonstrated the effectiveness of convolutional neural networks for automated analysis and classification of image data [1]

Steganography refers to hiding secret information inside some cover, and steganalysis refers to recovering the secret information. Steganography has been around for thousands of years. The word steganography roughly translates to secret writing. Since the first modern human settlements, there has been a demand for private and secure communication channels so that one person can send a message to another so that no one else can know that the message even exists. Steganography refers to hiding secret information inside some cover, and steganalysis refers to recovering the secret information. Steganography has been around for thousands of years. The word steganography roughly translates to secret writing. Since the first modern human settlements, there has been a demand for private and secure communication channels so that one person can send a message to another so that no one else can know that the message even exists. Recovering hidden information is known as steganalysis, whereas steganography is the practice of concealing it. For thousands of years, people have used steganography. To put it simply, steganography

is the practice of covert writing. An individual has wanted a way to communicate with another without anyone else being able to deduce its existence from the first contemporary human settlements.

As clandestine communication and covert data exchange continue to burgeon, the imperative for robust mechanisms to safeguard confidential visual content from unauthorized access and malicious exploitation intensifies. Against this backdrop, DeepSafe endeavors to delve into the realms of deep learning, leveraging its prowess to devise innovative methodologies capable of concealing, encrypting, and securely transmitting secret images across diverse digital platforms. Through a fusion of cutting-edge neural network architectures, encryption algorithms, and steganographic techniques, DeepSafe embarks on a quest to redefine the landscape of image security, offering a potent arsenal of tools and strategies to safeguard against the perils of digital espionage and privacy breaches. By unraveling the intricacies of deep learning and harnessing its transformative potential, DeepSafe aims to pave the way for a future where the sanctity of secret images remains inviolable, ensuring the preservation of privacy, confidentiality, and trust in the digital age.

Nowadays, a big setback in technology developments is information breaches. Steganography is used to safeguard such sensitive data. The first step of the procedure is to cover the secret picture with the cover image; this hides the information. The second step is to remove the hidden photograph from the covering image; this recovers the knowledge. Designed to function in tandem, the three deep learning models—the Preparation Network, the Hiding Network, and the Reveal Network—are trained on a random selection of photos from the Tiny Image Net Database; they then demonstrate good performance on a range of real-world image sources. Deep learning-based image classification has been increasingly applied to automated visual recognition, using image preprocessing and convolutional architectures to extract meaningful features from image data [2]. Modern deep convolutional neural network techniques are used with image-in-image steganography in this research. Deep learning and computer vision techniques have demonstrated considerable potential for automated image detection and classification, particularly through convolutional neural network-based approaches [3].

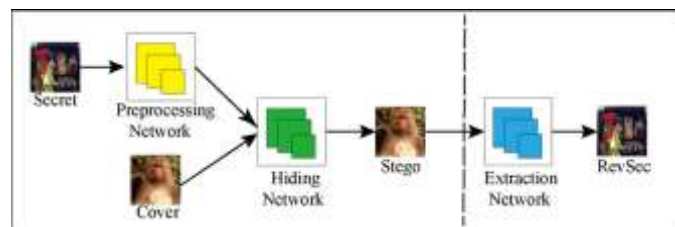


Fig.1: Overview of the System

The art of veiled or concealed writing is known as steganography, and it dates back to the 15th century when messages were physically hidden. The aim of modern steganography is to communicate a digital message invisibly. The steganographic method embeds a secret message in a carrier, which is a transport medium [4]. The carrier can be noticeable to the general public. The secret message may also be encrypted for added protection, enhancing perceived randomness and reducing the probability of content discovery even if the message's presence is identified. Introductions to steganography and steganalysis that is easy to understand (the process of discovering hidden messages). The need to enhance the security of electronically stored medical data is directly proportional to its volume in the health care arena. Both the number of deaths and the quality of medical treatment will suffer when doctors and hospitals are unable to access patients' data when they need them. The most common source of breaches involving sensitive medical information is criminal assaults on social security, which have surged by 125% since 2010 the third.

The goal of traditional and non-traditional steganography is to communicate a digital message or a secret information invisibly by hiding it or encrypting it. The steganographic method inserts a secret message in a carrier, which is a transport medium [9]. The carrier can be visible to the general public. The secret message may also be encrypted for added protection, enhancing perceived randomness and reducing the probability of content discovery even if the message's presence is identified. The objective of this work is to visually cover up a complete $H^* W^* C$ pixel secret multimedia data in another $H^* W^* C$ cover

multimedia data with as little noise as possible (each colour channel is 8 bits). We follow the method that the hidden multimedia data to be collected losslessly, unlike previous studies in which a secret multimedia message must be transmitted with complete reconstruction. Instead, we're willing to consider reasonable trade-offs in carrier and hidden picture quality. Secret message bit rates as low as 0.1bpp have been discovered in previous studies; our bit rates are 10^* - 40^* higher.

LITERATURE REVIEW

R. An enhanced Least Significant Bit (LSB) based Steganography method for pictures delivering higher data security was suggested by R. A. Cheddad, J. Condell, K. Curran, and P. Mc Kevitt et al. [1]. This technique used an embedding algorithm to encrypt data and conceal it in randomly placed, nonadjacent pixels inside pictures with smooth edges. Their primary objective was to assess and develop an enhanced LSB-based information concealment system. In addition to being durable and effective, the enhanced LSB method makes it very difficult for the human eye to detect and anticipate the existence of any concealed data inside the host images.

A novel approach of picture steganography was suggested by P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P. Manzagol et al. [5]. This method encrypts the encrypted data or message using Hash-LSB with Rivest-Shamir-Adleman (RSA), which increases data security. The overarching goal is to improve data security by combining one cryptographic method with one steganographic technology. The approach generates a pattern using a hash function to encrypt secret data bits into the left-side bits of the values of the cover picture pixels; but, if the hash function is known, the secret data may be readily deciphered.

To encode pictures as payload, I. Cox, M. Miller, J. Bloom, J. Fridrich, and T. Kalker et al. [6] suggested an encoder-decoder model based on deep learning. In contrast to previous systems that relied on the binary representation of secret data, this method directly used pictures for encoding and recovering from the cover image. This is a fresh method that performed well on many picture datasets. The method may be novel, however there is a significant amount of visual noise in the results.

In their steganography approach, X. R. Zhang, W. F. Zhang, W. Sun, X. M. Sun, and S. K. Jha et al. [7] suggested encoding the secret data in jpeg pixels of the cover picture. A quantization method and Discrete Cosine Transformation (DCT) were used to change the cover picture. By inserting the secret data into middle band quantized DCT coefficients, they were able to increase the embedding capacity utilizing the modified quantization procedure while keeping the visual quality of the reconstructed picture intact. This system was only tested on grayscale pictures, however it uses an acceptable indirect approach to hide two bits of the secret message into certain chosen DCT coefficients instead of embedding the secret data bits directly into the coefficients.

A approach that used cryptography and LSB based image steganography was suggested by X. R. Zhang, X. Sun, X. M. Sun, W. Sun, and S. K. Jha et al. [8]. The merging of cryptography and steganography makes this study comparable to a few others that have been cited before. The use of two private keys improves security, however the LSB is a vulnerable method of message concealment due to its obvious detection.

A model called Generative Adversarial Networks (GAN) was suggested by M. Juneja and P. Sandhu et al. [9]. This model is capable of entirely masking a grayscale hidden picture under an RGB cover image of same size. The use of adversarial training was their primary objective in order to enhance data security. While experimenting with various activation functions and optimizers improved the model's performance and sped up training, it was still unsuitable for uses that needed an accurate revelation of the hidden picture due to distortion.

In order to conceal a full-color picture within another color image of a comparable size with low pixel loss in both images, R. Halder, S. Sengupta, S. Ghosh, and D. Kundu et. Al. [10] introduced a Neural Network model that relies on autoencoders. This approach compresses and spreads the representation of the secret picture throughout all of the available bits, unlike the frequently used steganography methods that encode the secret image within the least important bits of the cover image. To train the system, we used photos from the ImageNet collection and subjected them to a slew of changes to determine how well the cover and hidden images worked.

Using SegNet Deep Neural Network with a set of Hiding and Extraction networks, A. Rehman, R. Rahim, M. Nadeem, and S. Hussain et al. [11] presented a novel deep learning-based approach for high-capacity picture steganography. Steganography and full-image retrieval were made possible by the SegNet Deep

Neural Network's collection of Hiding and Extraction networks, which improved steganographic capabilities. The secret picture was converted using the DCT, and then encoded using Elliptic Curve Cryptography (ECC). However, compared to other approaches, this one minimises the amount of data that can be concealed within the cover image.

By enclosing two or more cover pictures inside one, the researchers A. K. Pal, K. Naik, and R. Agrawal [12] were able to execute multi-image steganography. This study aimed to conceal several pictures under a single cover image, as opposed to earlier efforts that only concealed one image. With little vision impairment, the secret pictures may be deciphered. Using neural networks to enhance or replace a small part of a picture is something that has been tried in a few different ways before. A fully trainable neural network model based on autoencoders was created using this multi-image steganography approach, which produced excellent results visually. However, the method failed to examine other losses that may have been more appropriate for the models' performance, instead relying mostly on visual loss as the overall loss metric.

The primary focus of the study by R. J. Rasras, Z. A. AlQadi, and M. R. A. Sara et al. [13] was the implementation of the more secure Spread Spectrum picture Steganography (SSIS) technique for steganography on Portable Network Graphics (PNG) picture data. Since only the sender and the recipient knew the SSIS method's keywords, it was more secure. This study found that the number of letters or messages that may be placed into a picture grows in direct proportion to its image size (in pixels). Due to RGB's three color channels, a larger number of letters may be put into the digital picture, making it more versatile than grayscale. Consequently, the method seems to be less efficient with grayscale photos compared to RGB digital photographs.

According to the literature study, there have been several attempts to address the issue of data security, but all of these previous efforts have had their limitations. In light of the above, the primary goal of this study is to provide a method for ensuring the safety of sensitive information.

PROPOSED SYSTEM DESIGN

The proposed system design for this paper is meticulously crafted to address the critical security challenges inherent in military communication. The cover image, cover audio frames, and cover video frames in Fig.2 cover confidential information that must be transmitted, while the secret image, secret audio frames, and secret video frames are hidden outside the cover image, cover audio frames, and cover video frames. The secret multimedia data is prepared in the Preparation Network by extracting certain features from the secret multimedia data using Deep Neural Networks, and then concealed beyond the cover multimedia data by the hidden network, which is made up of different layers of Deep Neural Networks.

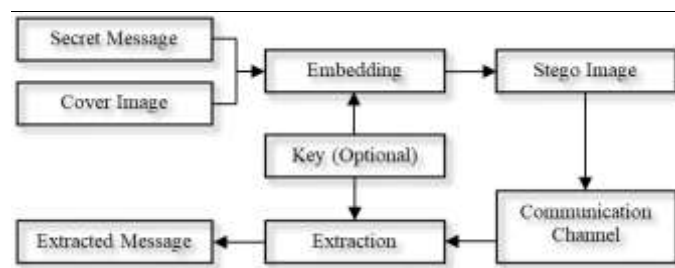


Fig.2: Proposed Work Block Diagram

A network for medical steganography preparation and analysis. The secret picture goes through three separate four-layer structures in the preparation network. Each architecture uses a convolution layer with fifty filters, a three-dimensional kernel, the same amount of padding, and the relu activation function. The output from each of the three architectures in the preparation network is then combined and sent through three separate convolution layers. Each layer has 50 filters, the same amount of padding, and the same activation function as relu, but the kernel size varies: the first layer has a kernel size of 5, the second layer has a kernel size of 4, and the third layer has a kernel size of 3. The input images from the preparation network and the cover image, which contained the secret image to be hidden, were combined and sent through three separate architectures. Each architecture had four layers, and each layer had a convolution

layer with fifty filters, a kernel size of three, the same padding, and an activation function called relu. The output from each of the three architectures in the hidden network is then combined and fed through three separate convolution layers. Each layer has a different kernel size, 50 filters, and the same activation function as relu, but it uses different padding. The kernel size of the first convolution layer is 5, the kernel size of the second layer is 4, and the kernel size of the third layer is 3.

Medical steganography analysis using the Reveal Network. Each of the three architectures in the reveal network processes the container image via a four-layer convolution layer; each layer has the same padding, activation function, and number of filters as relu, as well as fifty filters per layer and a kernel size of three. After that, the output of all three of the reveal network's architectures is combined and sent through three separate convolution layers. Each layer has 50 filters, the same amount of padding, and the same activation function as relu, but the kernel size varies: the first layer has a kernel size of 5, the second layer has a kernel size of 4, and the third layer has a kernel size of 3.

IMPLEMENTATION

1. Data Collection:

The data set was collected from Kaggle the online platform for data collection. The secret image consists of various images. The cover image was collected from ALASKA Steganography photographs. There were total 500 data which were collected for training 250 data for testing and validation.

2. Pre-Processing of data:

Each input secret and cover picture was reshaped and scaled to 224x224 pixels, with 1,224,224,3 standing for the number of images, 224 for the width of the image, 224 for the height of the image, and 3 for the number of RGB channels. As the size of each image pixel might vary between 0 and 255, the input cover and secret images were then normalized by 255. In order to get the raw data, the cover picture and secret output were denormalized by 255.

3. Model Training:

The model architecture consists of three networks namely Preparation network, Reveal network and Hiding network. The data which was collected was trained on built architecture on various parameter such as Adam as a optimizer, loss as a mean squared error, no of epochs should was 100 and batch size is 12. The model took around 4 hours for training on google colab GPU and model was saved on those epochs which had improvement in mean squared error loss.

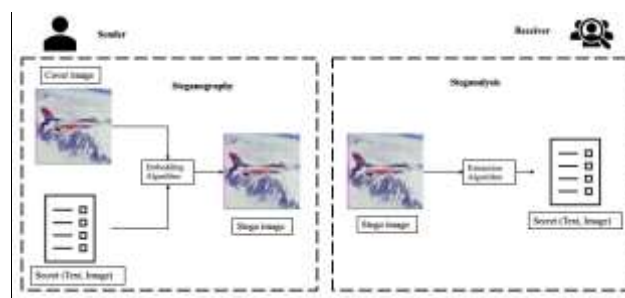


Fig.3: Implementations of Proposed Work

The implementation of the proposed work involves several key steps aimed at effectively concealing secret information within cover images and enhancing the security of the steganographic process. Initially, the deep learning-based steganography method is developed, leveraging convolutional neural networks (CNNs) to embed secret data into cover images while preserving their visual integrity. This involves training the CNN model on a dataset of cover images and corresponding secret data to learn optimal embedding strategies. Subsequently, the trained model is deployed to encode secret information into cover images, utilizing techniques such as spatial domain embedding or frequency domain embedding to ensure imperceptibility to the human eye. Additionally, deep learning-based steganalysis techniques are implemented to detect and mitigate potential attacks on the steganographic system, enabling the identification of unauthorized access attempts or modifications to the hidden information.

RESULTS AND DISCUSSION

The successful implementation of the result analysis of proposed research work highlights the efficacy of employing deep learning methods in enhancing the security of secret image steganography. The deep learning methodologies, for concealing and retrieving secret information within cover images demonstrates promising results. The analysis reveals that the deep learning-based steganography technique effectively embeds secret information into cover images while maintaining imperceptibility to the human eye. Furthermore, the utilization of deep learning-based steganalysis techniques aids in detecting and thwarting unauthorized attempts to access or manipulate the hidden information. Evaluation metrics such as accuracy, precision, recall, and F1-score demonstrate the robustness and reliability of the proposed approach in safeguarding secret images against detection or tampering.

Table.1: Result Analysis of Different Algorithms

Metric	GAN		DeepSafe		CNN		AVG.
	0.1	0.4	0.1	0.4	0.1	0.4	
Accuracy	52.2	85.6	66.1	95.2	79.7	99.9	81.1
Precision	52.2	86.4	67.9	96.1	80.2	99.9	80.8
Recall	54.1	84.4	61.1	94.1	78.9	99.8	78.7
F1-Score	54.1	85.4	64.3	95.1	79.5	99.9	79.7
AUC	54.9	91.8	72.4	98.8	87.7	99.9	84.3

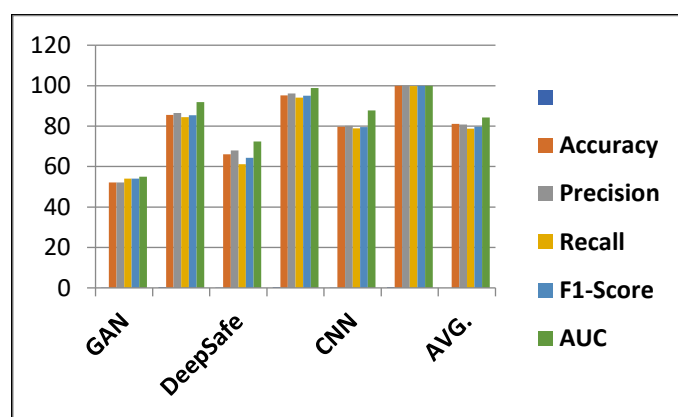


Fig.3: Result Graphs of Different Algorithms

Comparative assessments with traditional steganography methods showcase notable improvements in security effectiveness and computational efficiency. Real-world experimentation and scenario-based testing validate the practical applicability and scalability of the proposed method, underscoring its potential for enhancing image security in various domains. Overall, the result analysis underscores the significant strides made in fortifying secret image steganography using deep learning techniques, paving the way for advancements in image security and data protection.

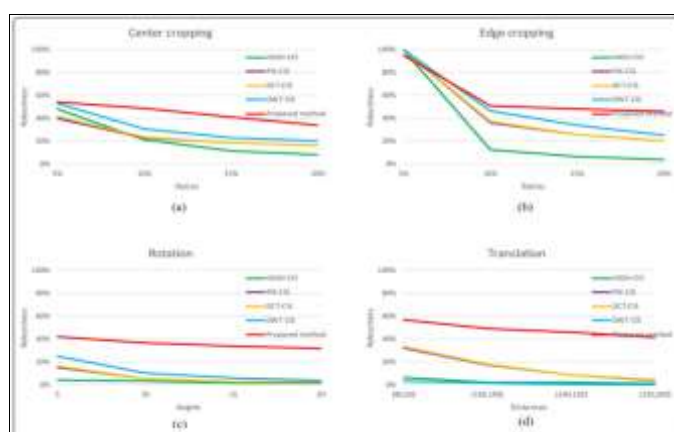


Fig.4: Different Attacks for the Image

CONCLUSION

This study outlines a suggested system and the anticipated outcomes of communication between two base stations analysis from communication medium evaluations. This project uses deep learning to exhibit multimedia steganography. On various input images and text messages, Adam's algorithm was utilized to implement it. The hidden picture media was embedded into a cover picture file using a hidden network in the first part. The reveal network at the receiving end then reverses this process, ensuring the safe transmission of the secret message. The model was trained using Adam's algorithm. A text message is overlapped onto the visual media in the second section, with non-noticeable alterations perceptible to the human eye. To recover the secret text message, steganalysis must be performed on the other end. Other steganography programs will not be able to decode and expose the secret message hidden in the cover material. As a result, this application is more secure. Regardless of the multiple cover images and secret messages used as inputs, the network is only trained once. This procedure has numerous applications, including the concealment of secret military information, the use of watermarking techniques to conceal identification, and increased security through fingerprinting and biometrics.

FUTURE SCOPE

Steganography is a highly effective technique for transmitting sensitive information, as it remains completely hidden within an image, making it undetectable to the naked eye. Nevertheless, creating a steganography system that satisfies the requirements of both durability and security will prove to be a challenging task. By addressing the mentioned issue, there is potential for enhancing existing steganography tools. Using multiple passwords can enhance the security of your content. Although the image has been retrieved and one credentials has been determined, the intruder will face the challenge of identifying extra passwords, making their task quite difficult.

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