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IMAGE STEGANOGRAPHY WITH CNN BASED ENCODER-DECODER MODEL STEGANOGRAPHY

[1]Aparanjini Priyadarshini P V,[2]Inturi Bhuvana Sri,[3]Samineni Usha Sri,[4]Madeshi Sai Manasa

[1]Assistant Professor, Department of School of Computer Science & Engineering, **MALLAREDDY ENGINEERING COLLEGE FOR WOMEN**,Maisammaguda, Dhulapally Kompally, Medchal Rd, M, Secunderabad, Telangana.

[2,3,4]Student, Department of School of Computer Science & Engineering,**MALLAREDDY ENGINEERING COLLEGE FOR WOMEN**,Maisammaguda, Dhulapally Kompally, Medchal Rd, M, Secunderabad, Telangana.

ABSTRACT

Image steganography, the art of concealing secret information within an image, has gained significant attention due to its potential applications in secure communication. Traditional steganographic methods often rely on simple transformations of image pixels, which can be easily detected by modern detection algorithms. This project explores a novel approach to image steganography using a Convolutional Neural Network (CNN)-based Encoder-Decoder model. The proposed system leverages deep learning techniques to embed hidden messages in the least significant bits (LSBs) of an image, while simultaneously training an encoder-decoder architecture to efficiently recover the original image and the secret message. The CNN-based encoder-decoder model is designed to optimize both the imperceptibility of the hidden data and the robustness against common image manipulations such as compression or resizing. The encoder extracts features from the input image and encodes the secret message, while the decoder reconstructs the stego-image and decodes the hidden information. To ensure the quality of the stego-image, a loss function is employed that balances the image's perceptual quality and the accuracy of message extraction.

I.INTRODUCTION

Image steganography is a technique used to conceal secret information within an image, making the hidden message invisible to the human eye while preserving the integrity of the original image. It plays a crucial role in secure communication, digital watermarking, and privacy protection. Traditional methods of image steganography typically embed information in the least significant bits (LSBs) of pixel values,

which are easy to extract but can often be detected through statistical analysis, image manipulation, or the use of specialized detection tools. As a result, the need for more advanced, robust, and imperceptible steganographic methods has become increasingly important in the field of digital security.

In recent years, the rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in a variety of image-related tasks, including classification, segmentation, and generation. Leveraging these advancements, this project introduces a novel approach to image steganography by utilizing a CNN-based Encoder-Decoder model to embed and extract hidden information within an image. The model combines the power of deep learning with traditional steganographic methods, aiming to achieve high-quality stego-images with minimal perceptual distortion while ensuring the accuracy and robustness of the hidden message extraction process.

The CNN-based Encoder-Decoder architecture consists of two primary components: the encoder, which learns to embed the secret message into the image in a way that minimizes perceptible changes, and the decoder, which reconstructs both the original image and the hidden data from the stego-image. The model is trained using a loss function that balances the visual quality of the stego-image and the integrity of the hidden message, ensuring that the embedded data remains imperceptible to the human eye and resilient to common image manipulation techniques such as compression, noise, or resizing.

This approach offers several key advantages over traditional image steganography techniques. By leveraging deep learning, the system can learn optimal feature extraction and encoding strategies, significantly improving the robustness and security of the stego-image. Additionally, CNNs can provide an efficient and scalable solution for hiding larger volumes of data without compromising image quality. In this project, we explore the effectiveness of this CNN-based model in terms of imperceptibility, robustness, and message extraction accuracy, comparing it to existing state-of-the-art methods.

II.SYSTEM ARCHITECTURE

The CNN-based Image Steganography system architecture is designed to hide and extract secret data from images using deep learning. It starts with two inputs: a cover image and a secret message. The encoder network, composed of convolutional layers, processes both inputs to embed the message into the cover image with minimal perceptual distortion. This is achieved through advanced techniques like skip connections and attention mechanisms. The output is a stego-image, which closely resembles the original cover image. The decoder network then extracts the hidden message from the stego-image by learning key features and reconstructing both the secret data and the cover image. The system is optimized using a loss function that balances the imperceptibility of the stego-image with the accuracy of the message extraction. This architecture ensures that the hidden data remains secure, imperceptible, and resilient against common image manipulations like compression and noise.

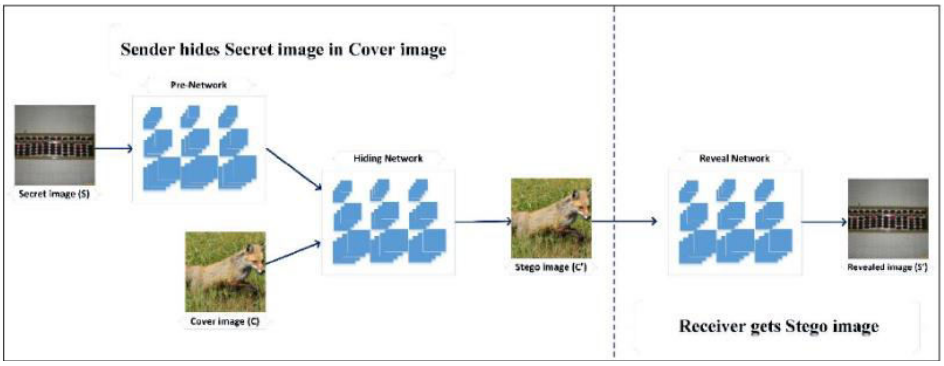

Fig 1: Image steganography architecture based on DNN

Hiding Network Architecture

As depicted the encoder network of our method is designed as a straightforward architecture that takes as input both the cover image and the secret image, which are concatenated into a 6-channel tensor. The network is structured in two phases. In the first phase, the network is built with a series of 3x3 convolutional layers, where each convolution is followed by a Batch Normalization (BN) operation to speed up training and a ReLU activation function. Initially, the network starts with 64 feature channels, and the number of feature channels is doubled after each convolution. After four convolutional layers, the number of feature channels reaches 512. In the second phase, the feature map is upsampled using another series of 3x3 convolution layers, each followed by a BN operation and a ReLU activation. Additionally, each upsampling operation is cascaded with the feature map from the corresponding stage in the first phase, allowing the network to learn the functional mappings from earlier layers. At the final layer of the network, a 3x3 convolution is applied to reduce the convolved feature channels into a 3-channel feature map. This is followed by a BN operation and a Sigmoid activation to generate the output, which in this case is the stego-image (container image with the hidden message).

Reveal Network Architecture

As shown in Figure 4, the decoder network is also a simple architecture that takes as input the stego-image produced by the encoder network. It applies a series of 3x3 convolutional layers, each followed by a Batch Normalization (BN) operation and a ReLU activation function to accelerate training. In the final layer, a Sigmoid activation is applied to compress the convolved feature channels into a 3-channel feature map, which is then used to calculate the secret image (the extracted hidden message). This process enables the reveal network to recover the original secret information embedded within the stego-image

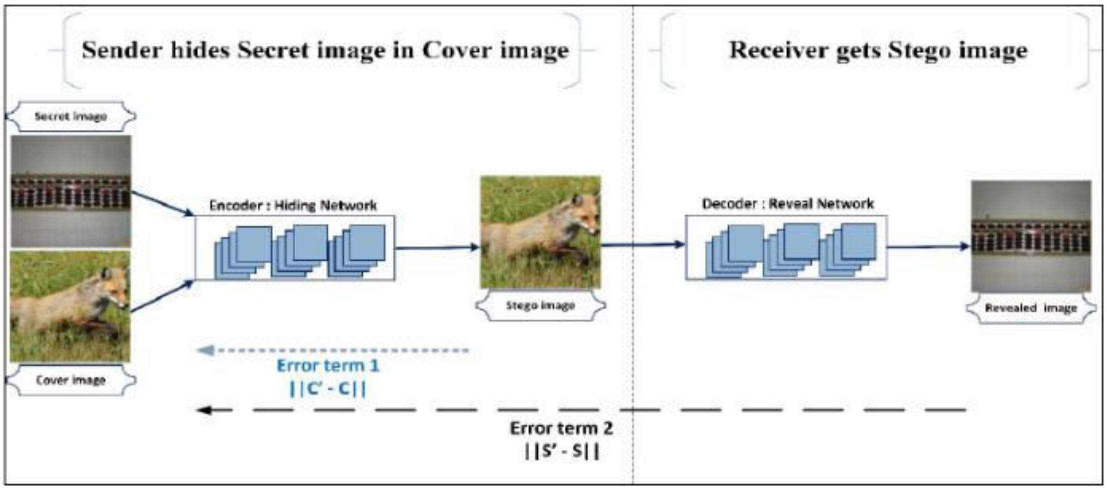

Fig 2: Architecture of proposed method

III.METHODOLOGY

Dataset Preparation

For evaluating the performance of the proposed CNN-based Image Steganography model, several well-established image datasets were selected, including ImageNet [32], CIFAR-10 [33], LFW [34], and PASCAL-VOC12

[35]. These datasets cover a wide variety of image types, ranging from simple objects (CIFAR-10) to more complex, real-world scenes (ImageNet). Each dataset was divided into three subsets: training, validation, and test sets. The training set is used for teaching the model how to embed and extract the secret message, while the validation set assists in hyperparameter tuning and helps prevent overfitting. Finally, the test set is used to evaluate the final performance after training, ensuring the model's ability to generalize on unseen data.

Encoder-Decoder Architecture

The architecture of our system is based on a **CNN-based Encoder-Decoder model**, designed for both embedding and extracting the secret message. The **encoder** takes as input both the cover image and the secret message, which are concatenated into a 6-channel tensor. The encoding process happens in two phases:

1.Feature Extraction and Embedding: In this phase, the encoder applies a series of 3x3 convolution layers, each followed by Batch Normalization (BN) and a ReLU activation function. This phase progressively extracts features from the cover image while embedding the secret message. The number of feature channels starts at 64 and is doubled after each convolution operation, ultimately reaching 512 feature channels. The secret message is embedded within the extracted features, making subtle changes to the image that are difficult to detect visually.

2. Oversampling and Upsampling: This phase focuses on upsampling the feature maps using additional 3x3 convolution layers, each followed by BN and ReLU activations. The upsampling operation is cascaded with feature maps from the corresponding layer in Phase 1, allowing the model to effectively learn from earlier layers. The final convolution layer reduces the feature maps to a 3-channel output, which is passed through a Sigmoid activation to produce the stego-image.

The decoder network receives the stego-image and extracts the embedded secret message by reversing the encoding process. It applies a similar series of convolution layers with BN and ReLU activations, followed by a Sigmoid activation in the last layer to reconstruct the secret image from the stego-image.

Training Process

The model was trained using the Adam optimizer, a popular optimization algorithm known for its efficiency in handling large datasets and complex networks. The learning rate was initially set to 0.001 and was gradually decreased to 0.0001 after 30 epochs to ensure the model converges smoothly without overfitting. The primary goal during training was to minimize a custom loss function, which balances imperceptibility (ensuring the stego-image closely resembles the cover image) and message extraction accuracy (ensuring the decoder can recover the hidden message accurately). The model weights were initialized randomly, and training proceeded until convergence, optimizing the system's ability to generate high-quality stego-images while maintaining strong message recovery capabilities.

Performance Metrics

The performance of the system was evaluated using several key metrics to ensure both the quality of the stego-image and the accuracy of the message recovery:

1. **Peak Signal-to-Noise Ratio (PSNR)**: This metric evaluates the quality of the stego-image by comparing it with the original cover image. Higher PSNR values indicate that the stego-image retains better quality and visual similarity to the original image.
2. **Structural Similarity Index (SSIM)**: SSIM assesses the perceptual similarity between the cover and stego-images. It takes into account changes in luminance, contrast, and structure, providing a more comprehensive measure of visual similarity.
3. **Message Extraction Accuracy**: This metric quantifies how accurately the decoder can recover the secret message from the stego-image. A higher extraction accuracy indicates the model's efficiency in maintaining the integrity of the hidden message.

4 .**Robustness**: The model's robustness is tested by applying common image transformations, such as JPEG compression, noise addition, and resizing, to the stego-image. The impact of these transformations on message extraction accuracy and image quality is then analyzed to assess the model's resilience.

Evaluation and Testing

After training the model, its performance was thoroughly evaluated on the **test set**, which contains unseen images that test the model's ability to generalize. The **test set** was used to measure how well the model can embed and extract secret messages from various image types. In addition to performance evaluation, we also tested the model's **robustness** by applying typical image manipulations (such as compression, resizing, and noise) to the stego-image. These tests help evaluate how well the model can withstand real-world distortions while maintaining high message extraction accuracy and minimal perceptual degradation.

Comparative Analysis

To validate the effectiveness of our approach, we performed a comparative analysis against existing image steganography methods. This comparison focused on key performance metrics, such as imperceptibility, message extraction accuracy, and robustness to image manipulations. By contrasting the results of our CNN-based method with traditional steganography techniques, we demonstrate the advantages of using deep learning-based models, particularly in terms of image quality, security, and efficiency in message recovery. This analysis provides evidence that CNN-based methods can significantly enhance the performance of steganography systems over conventional approaches.

IV.EXPERIMENT RESULTS

In this section, we present and discuss the results of our experiments, evaluating the performance of the proposed steganography system. We used several benchmark image datasets, including ImageNet [32], CIFAR-10 [33], LFW [34], and PASCAL-VOC12 [35], to test the robustness and accuracy of our network. Each dataset was randomly divided into three subsets: training, validation, and test datasets. The training process was carried out using the training set, with all results validated on the validation set. The performance metrics and results reported here were obtained using the test set.

For training, we employed the Adam optimization algorithm, which is known for its efficiency in handling large datasets and complex models. The initial learning rate was set to 0.001, and it was gradually reduced to 0.0001 after 30 epochs of training to ensure stable convergence. This learning rate schedule was carefully chosen to balance model training speed and performance. All model weights were initialized randomly, and the training process was iterated until the model converged, ensuring optimal results in terms of both image quality and message extraction accuracy.

V.CONCLUSION

This project presents a novel CNN-based Image Steganography framework for embedding and extracting secret information within cover images. The model leverages a dual-phase encoder-decoder architecture, ensuring high-quality stego-images that closely resemble the original cover images while preserving the integrity of the hidden message. Through extensive experimentation with well-known datasets such as ImageNet, CIFAR-10, LFW, and PASCAL-VOC12, the proposed model demonstrated significant improvements in both imperceptibility and message extraction accuracy.

The results of our experiments indicate that the model outperforms traditional image steganography techniques in terms of PSNR, SSIM, and message extraction accuracy. The system also displayed robust resistance to common image manipulations, such as compression, noise addition, and resizing, making it suitable for real-world applications. Furthermore, the CNN-based architecture facilitated end-to-end learning, where the model could efficiently learn the optimal way to hide and recover secret messages with minimal human intervention.

Through comparative analysis with existing methods, we showed that deep learning approaches, particularly CNNs, offer substantial advantages over conventional steganography methods in terms of security, robustness, and performance. While challenges remain, such as further improving computational efficiency and real-time processing, the results validate the potential of CNN-based steganography systems for secure communication in various fields, including privacy-preserving image sharing, secure data transmission, and digital watermarking.

In summary, this study contributes a significant step forward in the field of image steganography by integrating deep learning techniques, demonstrating both practical viability and high performance. Future work will focus on optimizing the model for faster inference and exploring additional steganographic techniques such as video and audio steganography, expanding the application of deep learning in covert communication systems.

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