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IMAGE STEGANOGRAPHY WITH CNN BASED ENCODER-DECODER MODEL STEGANOGRAPHY

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ABSTRACT

The practice of picture steganography, which involves hiding information inside an image, has recently attracted a lot of interest because of the secure communication problems it may solve. Simple pixel changes, used by many older steganographic techniques, are now readily identified by state-of-the-art detection algorithms. Using an Encoder-Decoder model based on Convolutional Neural Networks (CNNs), this study investigates a new method of picture steganography. In order to retrieve both the original picture and the hidden message effectively, the suggested system uses deep learning methods to insert messages into an image's least significant bits (LSBs) and trains an encoder-decoder architecture concurrently. To maximise the concealed data's imperceptibility and resilience against typical picture alterations like compression and resizing, the CNN-based encoder-decoder model is meticulously built. While one part of the system reconstructs the stego-image and deciphers the concealed information, the other part gathers characteristics from the input picture and encodes the secret message. The stego-picture is guaranteed to be of high quality by using a loss function that strikes a compromise between the perceptual quality of the image and the accuracy of the message extraction.

I.INTRODUCTION

picture steganography is a method of secretly inserting data into a picture without altering the original in any way, such that it remains unreadable to the naked eye. image. When it comes to digital watermarking, privacy protection, and private communication, it is essential. Statistical analysis, picture editing, or specialised detection techniques may frequently unearth information hidden in the least significant bits (LSBs) of pixel values, which is a common target for traditional image steganography methods. Therefore, in the realm of digital security, there is a growing demand for steganographic technologies that are more sophisticated, resilient, and undetectable.

Classification, segmentation, and creation are just a few of the image-related tasks that have shown promise because to the fast development of deep learning, especially Convolutional Neural Networks (CNNs). Making use of these developments, this study presents a new method for picture steganography that embeds and extracts hidden information inside images using a CNN-based Encoder-Decoder model. In order to create high-quality stego-images with little perceptual distortion and to ensure the accuracy and durability of the hidden message extraction process, the model blends the power of deep learning with classic steganographic approaches.

In a convolutional neural network (CNN)-based encoder-decoder architecture, the encoder is responsible for learning to conceal the secret message inside the picture while the decoder is responsible for restoring the original image together with the concealed data from the stego-image. If the embedded data can withstand typical image manipulation techniques like compression, noise, or resizing, and yet remain undetectable to the human eye, then the model has successfully been trained using a loss function that strikes a balance between the stego-image's visual quality and the integrity of the hidden message.

When compared to more conventional methods of picture steganography, this approach has a number of significant benefits. The system can discover the best tactics for feature extraction and encoding with the help of deep learning, which greatly improves the stego-image's resilience and security. Also, convolutional neural networks (CNNs) can hide more data with less degradation in picture quality in an effective and scalable way. In this study, we compare our CNN-based model to current state-

of-the-art approaches and investigate its efficacy in terms of imperceptibility, robustness, and message extraction accuracy.

II.SYSTEM ARCHITECTURE

Image steganography is a system architecture that uses convolutional neural networks (CNNs) to conceal and retrieve hidden data from pictures using deep learning. Two things are needed to begin: a cover picture and a hidden message. With the use of convolutional layers, the encoder network incorporates the message into the cover picture while minimising perceptual distortion. It handles both inputs. Skip connections and attention processes are two examples of the sophisticated methods used to do this. The resulting stego-picture is quite similar to the source cover image. After then, the decoder network learns important traits and reconstructs the cover picture and secret data in order to decipher the stego-image and reveal the message. A loss function that finds a happy medium between the stego-image's imperceptibility and the accuracy of the message extraction is used to optimise the system. The concealed data is protected, undetectable, and resistant to typical picture alterations like noise and compression thanks to this design.

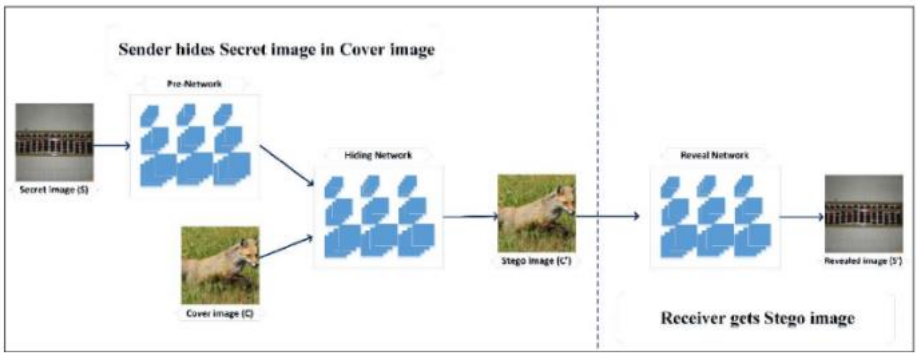

Fig 1: Image steganography architecture based on DNN

Hiding Network Architecture

The encoder network of our technique is shown as an architecture that is simple and accepts as input a 6-channel tensor that contains both the cover picture and the secret image. Two distinct stages make up the network's architecture. Starting with a stack of 3x3 convolutional layers, the network is constructed using a ReLU activation function and Batch

Normalisation (BN) operations placed between each convolution to expedite training. There are 64 feature channels in the network to begin with, and after each convolution, that number is doubled. Upon completion of four convolutional layers, two

There are 512 feature channels. Subsequently, a ReLU activation and BN operation follow each 3x3 convolution layer in the feature map upsampling phase. To further aid the network in learning the functional mappings from previous layers, the feature maps from each step in the first phase are cascaded with each upsampling operation. The convolved feature channels are reduced to a 3-channel feature map at the last network layer by using a 3x3 convolution. The final product, a stego-image (a container image containing the concealed message), is generated by a Sigmoid activation and a BN operation.

Unveil the Framework of the Network

Figure 4 shows that the decoder network, like the encoder network, has a basic design that accepts the stego-image as input. It uses a ReLU activation function and a sequence of 3x3 convolutional layers to speed up training, with each layer followed by a Batch Normalisation (BN) operation. In the last layer, the convolved feature channels are compressed into a 3-channel feature map using a Sigmoid activation. This map is then used to compute the secret picture, which is the retrieved hidden message. Through this procedure, the reveal network is able to get the initial secret data encoded inside the stego-image.

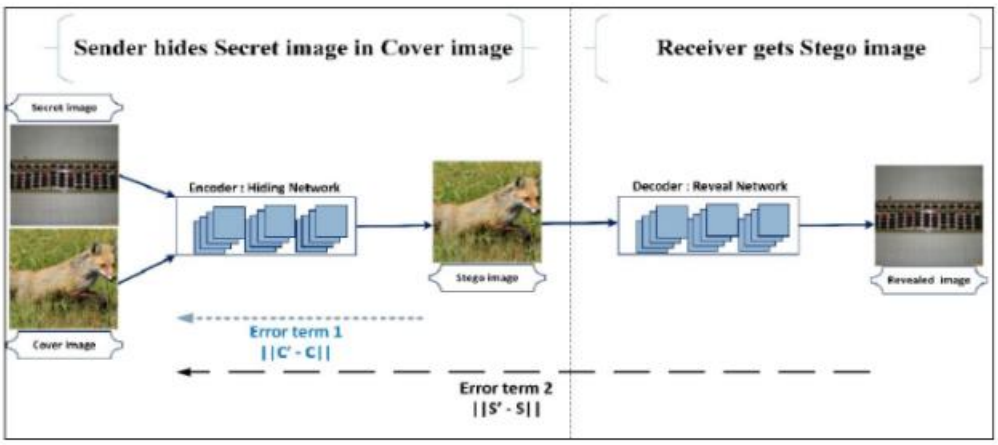

Fig 2: Architecture of proposed method

III.METHODOLOGY

Dataset Preparation

The suggested CNN-based picture Steganography model was tested on a number of popular picture datasets, such as ImageNet [32], CIFAR-10 [33], LFW [34], and PASCAL-VOC12.

The number 35. From basic items (CIFAR-10) to sophisticated real-world sceneries (ImageNet), these datasets cover it all. The three parts of each dataset were training, validation, and test. While the training set instructs the model on hidden message embedding and extraction, the validation set aids in hyperparameter adjustment and overfitting prevention. Last but not least, the test set is used to assess the model's performance after training, guaranteeing its capacity to extrapolate to new data sets.

Encoder-Decoder Architecture

Designed to both embed and extract the secret message, our system's architecture is built on a CNN-based Encoder-Decoder model. The encoder receives a 6-channel tensor containing the cover picture and the secret message joined together. There are two steps to the encoding process:

The first step is feature extraction and embedding, which involves the encoder using a sequence of 3x3 convolution layers, Batch Normalisation (BN), and a ReLU activation function. This step involves inserting the hidden message into the cover picture while gradually extracting its elements. Each convolution process doubles the number of feature channels, which begins at 64 and eventually reaches 512. The retrieved characteristics include the hidden message, which modifies the picture subtly and is so hard to see with the naked eye.

2. Upsampling and Oversampling: In this step, we employ extra 3x3 convolution layers to upsample the feature maps, and then we activate BN and ReLU on each of those layers. Phase 1 feature maps are cascaded into the upsampling procedure so that the model may successfully learn from preceding layers. The stego-image is created by passing the 3-channel output of the last convolution layer through a Sigmoid activation, which decreases the feature mappings.

Once the decoder network has the stego-image, it reverses the encoding process to get the hidden message. It uses a Sigmoid activation in the last layer of a comparable sequence of convolution layers with BN and ReLU activations to rebuild the hidden picture from the stego-image.

Training Process

To train the model, we used the Adam optimiser, a well-liked optimisation method that excels at dealing with complicated networks and massive datasets. To avoid overfitting and guarantee a smooth model convergence, the learning rate was first set to 0.001 and then reduced to 0.0001 after 30 epochs. While training, we mainly focused on minimising a custom loss function that strikes a compromise between imperceptibility (making sure the stego-image looks a lot like the cover picture) and message extraction accuracy (making sure the decoder can correctly retrieve the hidden message). To optimise the system's capacity to produce high-quality stego-images while preserving robust message recovery capabilities, the model weights were first set at random and training continued until convergence.

Performance Metrics

Several important measures were used to assess the system's performance, guaranteeing both the stego-image quality and the message recovery accuracy:

One measure is the Peak Signal-to-Noise Ratio (PSNR), which compares the stego-image to the original cover picture to determine its quality. A higher PSNR number means that the stego-image is more faithful to the source picture in terms of quality and appearance.

Second, the Structural Similarity Index (SSIM) evaluates how visually similar the cover and stego-images are. It incorporates variations in structure, contrast, and brightness to provide a more thorough evaluation of visual similarity.

Message Extraction Accuracy: This statistic measures the decoder's ability to correctly retrieve the secret message from the stego-image. An improvement in the model's ability to preserve the secret message is reflected in its extraction accuracy.

4. Reliability: The stego-image is subjected to standard picture changes including JPEG compression, noise addition, and scaling in order to assess the model's reliability. In order to evaluate the model's robustness, we examine how these changes affect the precision of message extraction and the quality of the images.

Evaluation and Testing

The test set, which includes unseen photos to assess the model's generalisability, was used to conduct a comprehensive evaluation of the model's performance after training. Using the test

set, we evaluated the model's ability to embed and extract hidden messages from different kinds of images. Along with evaluating the model's performance, we also examined its durability by subjecting the stego-image to common picture alterations including compression, resizing, and noise. The model's robustness to real-world distortions, with respect to both message extraction accuracy and perceptual deterioration, may be assessed using these tests.

Comparative Analysis

We compared our method to other known picture steganography techniques to ensure it was successful. Important performance criteria including imperceptibility, message extraction accuracy, and resilience to visual modifications were the primary focus of this comparison. By comparing our CNN-based approach to more conventional steganography methods, we show that deep learning-based models are superior, especially when it comes to picture quality, security, and message recovery speed. This research shows that compared to traditional methods, CNN-based techniques may greatly improve steganography system performance.

IV.EXPERIMENT RESULTS

Our studies, which tested the efficacy of the suggested steganography method, are detailed and discussed here. In order to ensure that our network was accurate and resilient, we tested it on many benchmark picture datasets, such as ImageNet [32], CIFAR-10 [33], LFW [34], and PASCAL-VOC12 [35]. The datasets were split into three equal parts: training, validation, and test. All findings were double-checked on the validation set once the training procedure was completed on the training set. The test set was used to acquire the performance measurements and findings mentioned here.

We trained using the Adam optimisation method because of its reputation for effectively managing complicated models and massive datasets. After 30 training epochs, the learning rate was progressively lowered to 0.0001 from an initial value of 0.001 to guarantee steady convergence. To achieve a happy medium between training speed and performance, this learning rate plan was painstakingly selected. For the best possible picture quality and message extraction accuracy, we used a random initialisation for all model weights and iterated the training process until the model converged.

V.CONCLUSION

In order to conceal and retrieve sensitive data from cover photos, this research introduces a new framework for image steganography that uses convolutional neural networks (CNNs). To guarantee high-quality stego-pictures that faithfully mimic the original cover graphics while safeguarding the secret message, the model employs a dual-phase encoder-decoder design. After rigorous testing on popular datasets including ImageNet, CIFAR-10, LFW, and PASCAL-VOC12, the suggested model showed considerable improvements in imperceptibility and accuracy of message extraction.

Our experimental findings show that the model achieves better outcomes than conventional picture steganography methods with respect to PSNR, SSIM, and the accuracy of message extraction. The system's strong resilience to typical picture alterations like compression, noise addition, and scaling further solidified its suitability for practical use. As an added bonus, the CNN-based design allowed for end-to-end learning, which meant the model could figure out how to conceal and retrieve secret messages best with no human input at all. Deep learning techniques, and convolutional neural networks (CNNs in particular), provide significant improvements over traditional steganography methods in terms of performance, resilience, and security, as shown by our comparisons with current methods. Although there are still some obstacles to overcome, like increasing computational efficiency and implementing real-time processing, the findings confirm that CNN-based steganography systems have great promise for secure communication in many domains, such as digital watermarking, secure data transmission, privacy-preserving picture sharing, and more.

Through the integration of deep learning algorithms, this work showcases both practical feasibility and excellent performance, therefore making a substantial contribution to the area of picture steganography. Improving the model for quicker inference and investigating other steganographic methods, such audio and video steganography, will be the primary goals of future research into deep learning's potential in clandestine communication systems.

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