Image Steganography Using CNN

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IMAGE STEGANOGRAPHY USING CNN

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***Abstract*- The main factors that led me to choose steganography from the list of potential project ideas were my lack of acquaintance with it and my interest in it. It also guarantees data security, which is another defence. [1] Even if a hacker (or intruder) succeeds in infiltrating and acquiring access to our system, they won't be able to access our information; that is, even if the intruder has access to our image files. [2] The attraction is greatly enhanced by this feature. The goal of the project is to teach text steganography through the use of visuals. Image steganography is utilised for images, and the necessary information is decrypted to obtain the message image. Because there are many different ways to employ image steganography, research is done on it, and one of the techniques is used to demonstrate it. [3] The practice of steganography involves hiding information, such as text, images, or audio files, within another picture or video file. Simply said, the main objective of steganography is to hide the needed information within any image, audio, or video that is not immediately obvious to be hidden. The foundation of image-based steganography is a simple idea. Digital information (pixels) that defines the contents of an image, typically the colours of all the pixels, makes up an image. [4] Given that we are aware that each pixel in an image contains three values (red, green, blue).Intruders won't be able to see the image we are trying to hide because it will be completely absorbed by the cover image. [5]**

***Keywords*- Image Steganography; Steganography; Steganography using CNN; Deep learning**

1. INTRODUCTION

1.1 Theoretical Background

Steganography is the art and science of hiding information within other information in such a way that the hidden message cannot be detected. Image steganography is a method of hiding secret data within images. In recent years, Convolutional Neural Networks (CNNs) have been extensively used in computer vision tasks and have shown remarkable performance in image classification, object detection, and segmentation. [6] The use of CNNs in image steganography has also been explored, and it has been shown that CNNs can be used to improve the robustness and security of steganographic systems.

The main objective of image steganography using CNN is to develop a system that can hide secret data within an image in a way that is imperceptible to the human eye. The system should also be able to extract the hidden data from the image without any loss of information. [7] The CNN-based steganography system involves three major steps: embedding, detection, and extraction.

The use of CNNs in image steganography has several advantages over traditional steganography techniques. CNNs are more robust to noise and can handle large amounts of data. They also provide a higher level of security as they are more difficult to detect and can be used to create stego images that are indistinguishable from the cover images. However, the use of CNNs in steganography also has some limitations, such as the need for large amounts of training data and the possibility of attacks that can exploit vulnerabilities in the CNN-based steganography system. [8]

1.2 Motivation

This concept was inspired by the need for more effective and secure covert communication techniques. The importance of privacy and security has increased significantly as a result of the development of digital technology. One method that has gained popularity recently is image steganography since it enables covert communication without raising suspicion. The amount of data that may be concealed and the assault resistance of current steganography algorithms are both constrained. On the other hand, CNNs have demonstrated tremendous promise for image processing and analysis. We intend to create a covert communication strategy that is more effective and secure by investigating the use of CNNs for steganography. [9]

1.3 Aim of the Proposed Work

The purpose of this project is to investigate how convolutional neural networks (CNNs) might be used for image steganography, the art of concealing sensitive information in images. We seek to examine the efficacy and robustness of this strategy for covert communication by training a CNN to learn how to embed and extract hidden messages. [10] This project intends to provide a greater understanding of the capabilities of CNNs for this purpose and to contribute to the expanding field of steganography research. The ultimate objective is to create a steganography algorithm based on CNN that can successfully conceal information in photos while preserving visual quality and integrity.

1.4 Objective(s) of the Proposed Work

➔ Our image normalisation process scales any dataset, regardless of its size, to a 255 x 255 dimension. This approach ensures that image size does not impact the accuracy of our model's results, which is not the case for other models that fail to provide appropriate results when using images of varying sizes.

➔ We declared the beta variable to weight the losses of the secret and cover images, and we set its value to the most feasible option.

➔ Our function generates an encoder Keras model composed of the Preparation and Hiding Networks. Once hosted, anyone can use this model for encoding.

➔ Similarly, our function generates a decoder Keras model composed of the Reveal Network.

➔ To improve training accuracy, we added Gaussian noise with 0.01 standard deviation and a differential enhancement magnitude of 1.0.

➔ Our model can handle both grayscale and RGBA color values. Therefore, the color of the image does not affect the results, and we have defined corresponding functions for both in the code.

➔ We compared our model using three different activation functions, RELU, SELU, and TANH, and included an Adam optimizer layer.

➔ We evaluated our model using various comparison matrices and found that our accuracy was better than the majority of the models identified in the literature review.

2. LITERATURE REVIEW

Steganography techniques that are based on tradition methods: -

Traditionally, the Least Significant Bits (LSB) replacement technique has been used for image steganography. Images often have greater pixel quality, but not all of the pixels are used. [14] The LSB technique is predicated on the idea that small changes in pixel values won't have a significant impact. The encrypted data is converted to binary form. Scanning the cover picture yields the least important bits in the noisy region. The binary bits from the hidden image are then used to replace the LSBs of the cover image. The alternative method must be utilised with care since overloading the cover image may cause visible changes that make the existence of the hidden information obvious.

GAN – BASED methods used in Steganography: -

Deep convolutional neural networks (CNN) are a subclass of general adversarial networks (GAN). A GAN will utilise game theory to train a generative model using an adversarial learning approach in order to complete picture generating tasks. In GAN architecture, two networks, known as the generating networks and the discriminator networks, compete with one another to produce an ideal picture. The data are placed into the generator model, and what comes out is a picture that is quite similar to the one that was provided as input. [11] The produced pictures are assigned a status of either false or true based on how they are evaluated by the discriminator networks. The two networks are trained in such a manner that the generator model tries to replicate the input data as closely as possible while producing as little noise as feasible. This is done in order to maximise accuracy. [12]

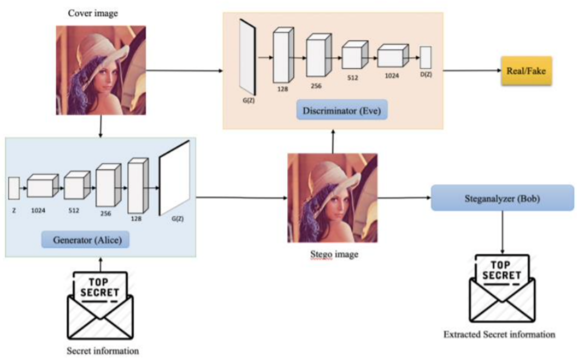
Existing techniques for image steganography that make use of a GAN architecture can be broken down into the following five categories: a three-network-based GAN model; cycle-GAN-based architectures; sender receiver GAN architectures; coverless models; and models in which the cover image is generated randomly rather than being given as input. [13]

The generator and the discriminator make up the core of a GAN model. These are the model's two primary components. A new network known as the steganalyzer is introduced in some of the approaches for picture steganography. The following is an explanation of the fundamental roles of these three components:

• A model, denoted by the letter G, for the generation of stego pictures using the cover image and the random message as input.

• A discriminator model denoted by the letter D, which can decide if the picture that is produced by the generator is genuine or not.

• A steganalyzer, denoted by the letter S, to assess whether or not the picture being analysed includes confidential or secret data.



Steganography techniques that are based on CNN:-

Steganography that makes use of CNN models has had a significant amount of impact on the encoder-decoder design. The cover picture and the secret image are both inputs that are used to create the stego image. [15] The decoder receives the stego image and then outputs the embedded secret image. The cover picture and the secret image are both inputs that are used to produce the stego image. Although the fundamental idea has not changed, several methodologies have been developed that experiment with alternative organisational patterns. [16] Concatenating the input cover picture with the hidden image is handled differently by various methods, and there is room for flexibility in both the convolutional layer and the pooling layer. The number of filters that are used, the number of strides that are taken, the filter size that is utilised, the activation function that is utilised, and the loss function that is utilised varies from one strategy to the next. One thing to keep in mind is that the cover picture and the secret image need to be the same size. This is necessary in order to ensure that each pixel of the secret image is appropriately represented in the cover image.[17]

The convolution operation is a form of linear operation that represents the degree to which two functions overlap one another when those functions are superimposed on top of one another. Convolutional networks are a type of basic neural network that employs convolution rather than the more common matrix multiplication. These networks include at least one layer. Encoding and decoding data using an architecture based on a CNN offers a number of benefits, some of which are listed below:

CNN is able to automatically extract a variety of visual characteristics. [18]

The image is "down sampled" by CNN by utilising the information from neighboring pixels, first through the process of convolution and then, finally, by the application of a prediction layer.

CNN is more reliable and performs better than its competitors. Utilizing a deep neural network, or CNN in this case, allows one to obtain a reasonable notion of the patterns that are present in real photographs. The network will be able to identify which regions are superfluous, making it possible for extra pixels to be buried in particular regions. The quantity of concealed data may be increased by reducing the amount of space taken up by superfluous regions. The network will conceal data that is unavailable to anybody who does not have the weights since both the structure and the weights can be randomized. [19]

We will be making use of the Tiny ImageNet, which is comprised of one hundred thousand photos, each of which is assigned to one of two hundred classes (with 500 images assigned to each class), and which has been shrunk to contain just 64 × 64 coloured images. In each of the three classes, there are a total of 500 training photos, 50 validation images, and 50 test images. [20]

3. THE PROPOSED APPROACH

3.1 Introduction and Related Concepts

In this study, we utilised a CNN-based solution to hide an image within another image. This effectively conceals the secret image from anyone who views the cover image. The neural networks we used in our research identify the optimal locations in the cover image for hiding the information, making them a more effective approach than LSB modification. To extract the hidden image from the container image, we also trained a decoder network. This process does not significantly alter the container image, and any changes made to it are not visible. [21] Therefore, it can be assumed that an unauthorised party does not have access to the original image. The secret image is concealed effectively in all three colour channels of the container image.

Review on various schemes

The process of hiding information in a cover image—which could be text, an image, or a video—is known as image steganography. The secret information is hidden so that only those with special vision may see it. Deep learning technology has attracted a lot of interest recently for its potency in a number of applications, including image steganography. The main objective of this study is to examine and explain the many deep learning methods available in the field of photo steganography that we found in the mentioned studies. The three different deep learning methods used for image steganography are traditional methods, Convolutional Neural Network-based methods, and General Adversarial Network-based methods.In addition to the technique, this work contains a thorough explanation of the datasets used, experimental setups investigated, and widely used assessment metrics. [22] A table summarising all of the information is also provided for easy reference.

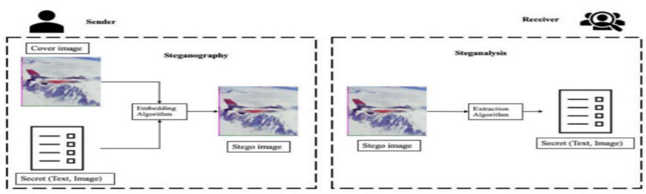


Fig 1.1 : General principle of steganography

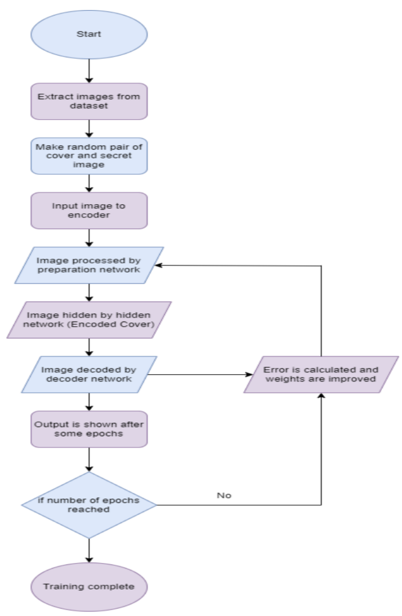


Fig 1.2 : Flow diagram

3.2 Framework, Architecture or Module for the Proposed System

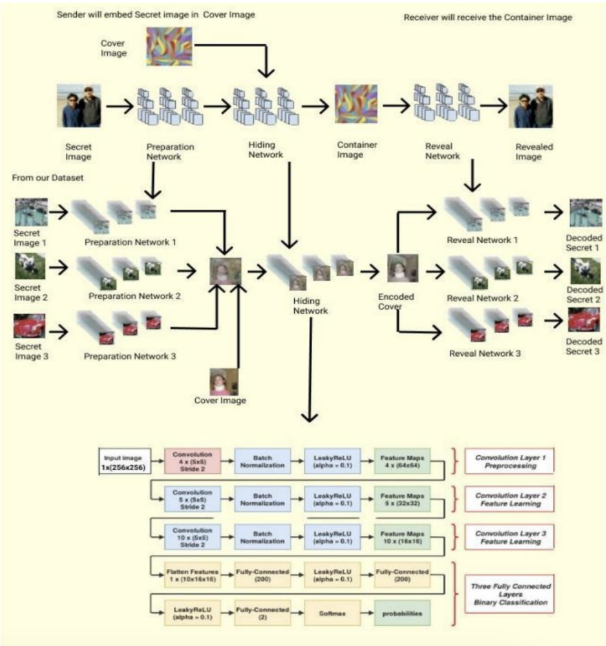


Fig 1.3 : Architecture diagram

In order to execute picture steganography, an image must be concealed under a cover image. The cover image must contain hidden images that can be recovered with little loss. The encoded cover image must look the same as the original cover image.

We send carrier images and the generated data over the Hiding network after transferring secret images over the prep network. The concept of having a decoder for each secret image is then put into practise in order to extract the secret image from the container image.[26]

We extend the idea of embedding a secret picture with noise in the original cover image and inserting the secret photographs on the original cover's LSBs image to increase the security of our image retrieval technique.

The encoder/decoder framework used in our method is briefly described below:

ENCODER: A preparation network called an encoder corresponds to a secret image input. The cover image and the prep network's outputs are merged before being sent through the hiding network.

DECODER: The reveal networks that make up the decoder network have each been trained to decode a different message.

The typical structure is as follows:

Prep Networks: Every prep network consists of two layers that are piled on top of one another. Three separate Conv2D layers make up each layer. [27] These three Conv2D layers have 50, 10, and 5 channels apiece, with 3, 4, and 5 kernels for each layer, accordingly. The stride length is fixed at one along both axes. Each Conv2D layer is given the proper padding in order to maintain the output image's dimensions. A Relu activation is used after each Conv2d layer. [23]

Concealing Network: A three-layer aggregation makes up the concealing network. These layers are composed of three separate Conv2D layers for each one. The Conv2D layers in the hidden network and the Conv2D levels in the prep network share a similar fundamental structure.[24]

Reveal Network: The reveal network includes three tiers of Conv2D layers that are identical in shape, and its basic structure is similar to that of the hidden network. [25]

3.3 Proposed System Model

The network was put to the test using three distinct activation functions and a range of learning rates.

These activation mechanisms were employed:
1. RELU :Rectified Linear Unit (RELU), the standard for the majority of CNN networks
2. Tanh
3. SELU :To avoid the vanishing gradient issue brought on by the RELU activation function, the Scaled Exponential Linear Unit (SELU) has been adopted.

Advantages:
1. CNNs discover the best method for concealing the hidden image inside the container image, which is unpredictable for humans. As a result, it increases steganography's security by making the procedure unpredictable. [26]
2. The modifications are tougher to see because the container picture has not been significantly changed. [27]
3. Only the decoder network that has been specially taught to do it can detect the changes. [28]
4. The procedure is adaptable, allowing for the picture to be modified before being sent to the network in order to increase security.

Disadvantages:
1. The original image can be partially recovered and the alterations can be detected by a network that has been particularly trained to do so.
The benefits of this approach far exceed the drawbacks, therefore we picked it. [29]

4. RESULTS AND DISCUSSION

Each node in the large dataset known as ImageNet, which is composed of images from the WordNet hierarchy, includes hundreds of photographs. ImageNet was developed by the Internet Archive to catalog the world's images. There are no copyrights associated with the image that is hosted on ImageNet; all that it offers are links or thumbnails that go to the actual image. A dataset is constructed from photos of varying sizes. The number of pictures, the categories to which they are assigned, the backdrop, and the size of the images may all be modified according to the specifications.

Tiny ImageNet contains a subset of the full ImageNet dataset, which can be found here. The dataset includes 6464 colored photos selected from a total of 100,000 photographs and organized into 200 categories, with each category containing 500 images. Within each class, there are a total of 500 training photos, as well as 50 validation images and 50 test shots.

A wide number of techniques are utilized in order to evaluate the quality of image steganography. Each of these approaches assesses a distinct facet of the overall steganographic result. [30] Some of the more common methods are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and Structured Similarity Index Measure (SSIM).

We were able to achieve an MSE value of 0.006259255611669444, PSNR value of 76.21412244818211 dB, and SSIM value of 0.9651267817491244.

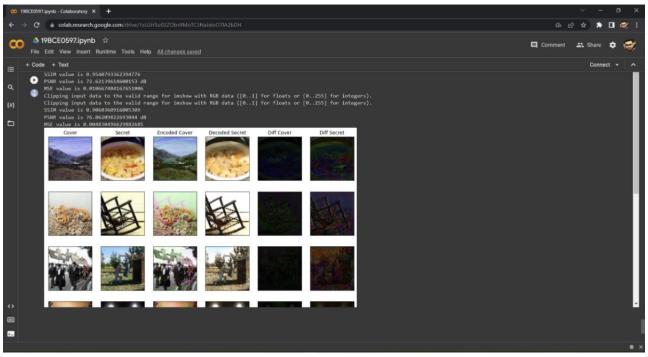


Fig 1.4 : Showing MSE value , PSNR value , SSIM value

Pixel wise average errors for Secret Image were 27.152718 on a scale of 256.
Pixel wise average errors for Cover Image were 20.411884 on a scale of 256.

Along with the above distribution of errors in cover and secret images has been shown below.

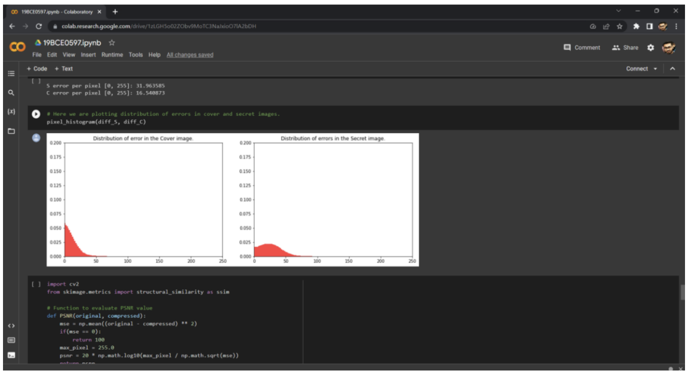


Fig 1.5 : Distribution of errors in cover and secret images

The loss through epochs has been shown below:-

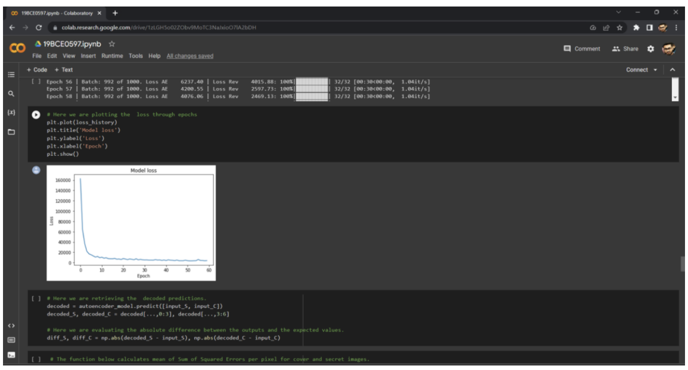


Fig 1.6: Loss through epochs

The cover picture, hidden image, container image, and disclosed image are all shown in the image below, respectively. With various activation functions, RELU activation function produced the best results while SELU activation function produced the worst results. The results from utilising various activation functions are listed below.

1. RELU

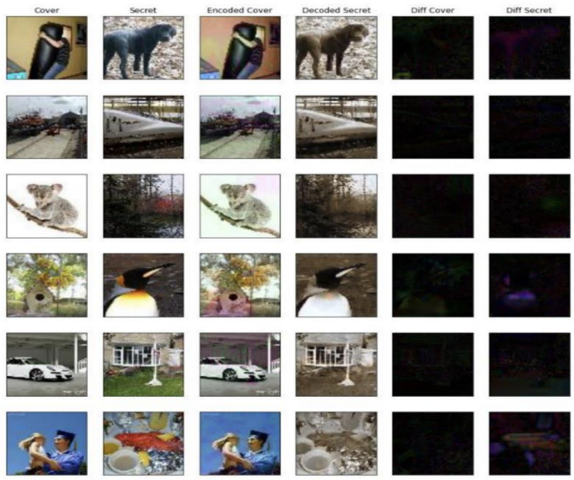


Fig 1.7 : RELU

SSIM value is 0.8939719109993859
PSNR value is 72.71192127985658 dB
MSE value is 0.010447430573533138;

SSIM value is 0.9244448899031624
PSNR value is 76.21412244818211 dB
MSE value is 0.004664331104070731;

SSIM value is 0.92911087801986
PSNR value is 74.67211487481308 dB
MSE value is 0.006652580734333079;

SSIM value is 0.9651267817491244
PSNR value is 73.82109884139598 dB
MSE value is 0.008092668651015305;

SSIM value is 0.9280019574836267
PSNR value is 74.93678898322835 dB
MSE value is 0.006259255611669444;

SSIM value is 0.897791248823328
PSNR value is 74.78361509242083 dB
MSE value is 0.006483956730341666

2. TANH

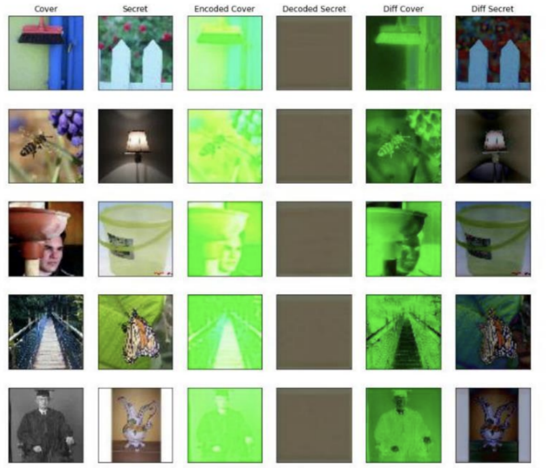


Fig 1.8 : TANH

SSIM value is 0.7249706379747698
PSNR value is 57.778771985527754 dB
MSE value is 0.32533022816724777;

SSIM value is 0.6853665491588302
PSNR value is 57.97070994579716 dB
MSE value is 0.3112652170478809;

SSIM value is 0.6125868370464277
PSNR value is 55.291631894645086 dB
MSE value is 0.5768175525002196;

SSIM value is 0.5114901347567362
PSNR value is 55.76227153024707 dB
MSE value is 0.5175764130335532;

SSIM value is 0.718185592713867
PSNR value is 56.32913410752248 dB
MSE value is 0.45424294067568477

3. SELU

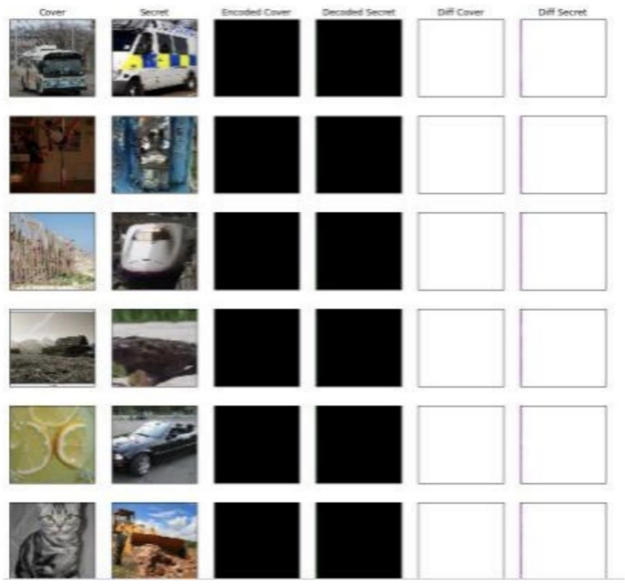


Fig 1.9 : SELU

SSIM value is -0.0749665991475593
PSNR value is 41.390807342395384 dB
MSE value is 14.161878601022435;

SSIM value is -0.09671444293532629
PSNR value is 42.51343772482506 dB
MSE value is 10.935983550429427;

SSIM value is -0.21655353029185795
PSNR value is 40.57839780171014 dB
MSE value is 17.07504446106052;

SSIM value is -0.22549568482169927
PSNR value is 40.96982659191187 dB
MSE value is 15.603390647455749;

SSIM value is -0.3066082760567415
PSNR value is 40.92396672988879 dB
MSE value is 15.7690285743913;

SSIM value is -0.1350593767657198
PSNR value is 41.3890867141432 dB
MSE value is 14.16749116299357

4.1 Comparative Study

In this section the results of the proposed methodology are compared with the existing.

Table 1.1 proposed methodology are compared with the existing

Parameter	**[Paper 1]**	**[Paper 2]**	**[Paper 3]**	**Proposed Algorithm**
Dataset	Lena and Baboon	ImageNet	RGB image	Tiny Image Net
Method Used	GAN	GAN	LSB	CNN
Architecture	Traditional Method	U NET	Traditional Method	Encoding and decoding
MSE	0.13	-	-	0.006
PSNR	56.95	40.66	62.53	76.214

SSIM	-	0.964	-	0.965

Paper 1: A. Arya and S. Soni, "Performance evaluation of secrete image steganography techniques using least significant bit (LSB) method," Int. J. Comput. Sci. Trends Technol., vol. 6, no. 2, pp. 160–165, 2018.

Paper 2: X. Duan, K. Jia, B. Li, D. Guo, E. Zhang, and C. Qin, "Reversible image steganography scheme based on a U-Net structure," IEEE Access, vol. 7, pp. 9314–9323, 2019.

Paper 3: K. A. Al-Afandy, O. S. Faragallah, A. Elmhalawy, E.-S.-M. El-Rabaie, and G. M. ElBanby, "High security data hiding using image cropping and LSB least significant bit steganography," in Proc. 4th IEEE Int. Colloq. Inf. Sci. Technol. (CiSt), Oct. 2016, pp. 400– 404.

PSNR Value

Table 1.2 : PSNR value

Method	Dataset	PSNR Value
High security data hiding using image cropping and LSB least significant bit steganography	RGB Image	62.53
Performance evaluation of secrete image steganography techniques using least significant bit (LSB) method	Lena and Baboon	56.95
Reversible image steganography scheme based on a U-Net structure	ImageNet	40.66
Generative steganography with Kerckhoffs' principle based on generative adversarial networks	USC-SIPI	64.7
LSB based image steganography using dynamic key cryptography	Lena	32.09
Our implemented method	Tiny ImageNet	76.214

SSIM Value

Table 1.3 SSIM Value

Method	Dataset	SSIM Value
Provably secure generative steganography based on autoregressive model	ImageNet	0.64
Reversible image steganography scheme based on a U-Net structure	ImageNet	0.964
Our implemented method	Tiny ImageNet	0.965

MSE Value

Table 1.4 MSE Value

Method	Dataset	MSE Value
Performance evaluation of secrete image steganography techniques using least significant bit (LSB) method	Lena and Baboon	0.13
Coverless steganography for digital images based on a generative mode	DTD and COCO2017	0.354
Our implemented method	Tiny ImageNet	0.006

5. CONCLUSIONS

-The network was constructed, and now it is functioning in an efficient manner. Despite the fact that it is capable of effective encoding and decoding, it is not an entirely flawless system. This is due to the fact that every breakthrough in technical capability has limitations.

-As was indicated under the limitations of this research, there is a significant amount of space for advancement in this field. For example, networks may one day be trained specifically to recognize when one picture has been disguised within another image.

-This project could be improved by designing a better architecture, or by changing the architecture of the network, and improving performance even further. This would make the secret image more difficult to decode by programs other than the decoder, and it would also make it more difficult to detect the presence of any secret image within the encoded image.

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