Grenze International Journal of Engineering and Technology, January Issue

CNN-based Encoder-Decoder Model for Robust and Secure Image Steganography with Enhanced Payload Capacity and Resistance to Steganalysis

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***Abstract*—Today in the era of fast-growing technology, the issue of secure communication is becoming increasingly important. This is because, with the increase in the volume of data that passes through the internet, a lot of attention has been placed on the security of the information that is being passed. Among the most beneficial strategies to disseminate information securely, steganography is distinguished as the covert transferal of information concealed into other non-suspect data content like images, audio or video, and so on. While cryptography merely encodes the message there is a good chance the message would be suspected of being coded, steganography is designed to ensure that the covered data is invisible which makes it the most suitable method for secret communication. In this research, a Deep CNN-based encoder-decoder model for image steganography that increases the payload size while also improving its resistance to steganalysis is proposed. Deep learning approaches are employed in the proposed model to provide subtle steganographic marking to the cover images to hide secret information. Experiments carried out show that the proposed model has better payload and detection capabilities than other conventional steganographic techniques. The results prove that the deep learning approach has the ability to revolutionize secure data transmission in digital communications.**

***Index Terms*—Image Steganography, Deep Learning, CNN, Encoder-Decoder Model, Payload Capacity, Steganalysis Resistance, Digital Communications.**

I. INTRODUCTION

In conventional methods of image steganography, authors use the LSB approach, Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT) to hide secret messages within the cover images. However, problems with these methods generally include variability in load capability the amount of information that can be hidden while still producing a picture that cannot be distinguishable from an ordinary image and also the image cannot be easily subjected to steganalysis [1]. Due to these technological enhancements in image management, AI in participation of image processing and deep learning especially the convolutional neural networks CNNs there is heightened associated research with a high level of complex, secure, and robust steganography systems.

In steganography, current deep learning models especially CNN-based encoders-decoders have received commendation for their performances [2-5].

Grenze ID: 01.GIJET.11.1.407

CNNs are broadly effective for handling images because they are configured to automatically extract features from data. This capability, within the context of steganography, can be used to hide information in such a way that they look invisible to even the human naked eye and even when under attack from other steganography analysis tools. Consequently, it would be possible to train a CNN-based model to counterbalance between possible payload, and desired video quality and to increase the system's anti-detection capability [7].

The approach proposed here employs a deep CNN-based encoder-decoder system intended to greatly enhance the payload capacity, and steganography security. Begin by the encoder component of the model where the secret message is engraved into a cover image and the decoder component is aimed to decipher the hidden message from the steganography image. The model enabled by the deep learning framework is also able to learn more complex embedding and extraction, meaning it can hide larger portions of data in a manner that is less likely to be identified by steganalysis. Furthermore, the model is made to retain the aesthetic properties of the cover picture so that any changes that occur during the embedding process are unlikely to be shown or discerned by people. This is done via the help of loss functions that help incorporate high fidelity of the steganography image and message decoding accuracy. These components enable the proposed system to be far superior to conventional image steganography in terms of payload and resistance to steganalysis.

The contributions of this work are threefold: This research contributes with three features: (1) a new CNN-based encoder-decoder that increases the payload of image steganography, (2) stronger resistance to steganalysis attacks, and (3) abundant experimentation with traditional and state-of-art methods showing that the proposed method outperforms all of them.

The various works done on image steganography will be discussed in the following sections, there will be a description of the proposed architecture of the system, the experimental details, and finally the results. At the end, provided a summary together with suggestions on how the model can be improved further in the future. It remains relevant to the generation of secure communication systems and contributes to the existing literature and to the field of steganography, where innovative deep-learning approaches are likely to have a significant impact shortly.

II. Related Work

Over the last decade, the field of image steganography has developed substantially because of the necessity to exploit more secure and efficient ways of concealed messaging. The straightforward and easy-to-implement methods of steganography include the least significant bit (LSB) substitution [8]. When using LSB, secret data is hidden in the least significant bits of the cover image which makes the image to be hidden look very similar to the original image [9]. But even though this method is easy to apply, it is not very resistant to steganalysis methods such as statistical analysis where an observer will easily deduce that there is hidden data as a result of possible bit transition patterns.

Thus, to avoid above-stated limitations LSB-based methods were replaced by more complex and efficient methods based on transform domain techniques where Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) were used [10]. These methods are based on the frequency modulus of an image rather than spatial modulus and the hidden information is therefore less susceptible to visual and statistical invasions. These techniques enhance the steganalysis ability of the steganography, but their choices often have restrictions on payload hiding capability and are still prone to higher-order steganalysis.

Due to the recent advancements in Machine Learning and deep learning technology the neural network has become the key implementer for image steganography. CNNs have been demonstrated to be particularly useful because they can be applied when it is required to learn complicated patterns and features of images that are present in a picture to do with embedding and extracting initial hidden data more safely and quickly fashion. Initial studies on CNN-based steganography include Baluja's work "Hiding Images in Plain Sight" (2017) which moved to the use of deep learning and neural networks for the full end-to-end learning of the steganography process making it safer and at the same, increasing the capacity of the cover image.

Recent developments have put more emphasis on increasing the payload capacity, visual quality, and steganalysis resilience. Zhang et al., (2020) [11] have developed new encoder-decoder structures that release deeper CNN encoders for better data hiding while retaining cover image perceptibility. These methods have laid down the basic steps on which other formats of the steganographic systems can be developed known to have high data capacity and strong security guarantees.

The presented work extends these improvements by incorporating a deep CNN-based encoder-decoder to improve the payload capacity and steganalysis resistance to offer the users a far more secure form of covert communication [12-13].

Contemporary enhancement in image steganography has been substantially spurred by deep learning approaches, especially the Convolutional Neural Networks [14]. Deep learning models were used by Liu et al., (2024) [4] to embed secret data into images whereby there is high resistance to standard steganalysis. To this end, the authors introduced a new bi-layer CNN structure, which further improved the utilization of payload, as well as malicious interference resistance. In the same manner, Zhang et al., (2024) [6] highlighted the security-best practice of steganography by using CNN and residual models, in secure data hiding. Subsequently, Singh and Gupta (2024) [8] improved on this approach by building adversarial training in which there is a steganographic model as well as the steganalysis detector model to enhance the robustness.

On the other hand, Lee et al., (2021) [15] did a study on an approach known as Spatial Transformer Networks (STNs) which holds the promise of maximizing payload while still observing image quality and hence the method balances so much on invisibility and confidentiality of data. Lee et al. (2021) [5] presented a low-latency image steganography system based on CNN.

Some of the research has been aimed at enhancing the product's payload while at the same time maintaining the picture quality. Yadav and Singh in their study of 2024 proposed a new architecture design to address the expansion of data capacitance for CNN while reducing the visual distortion effect. Furthermore, Zhang and Zhang (2021) [11] analyzed the content-based approach to image analysis, and they provided a way for steganographic embedding to be adjusted according to image characteristics, making the capacity and quality balanced. Altogether, these researches demonstrate how deep learning is increasingly starting to be utilized to enhance the security, overall capacity, and resilience of steganographic systems to suit contemporary requirements of communication.

III. Proposed Approach

Here, investigated a deep CNN-based encoder-decoder framework for Improving the payload capability and steganographic security of images against steganalysis attacks. The proposed model decided to utilize the convolutional neural network (CNN) to embed secret information into a cover image while making the data securely hidden and challenging to identify and, at the same time, keeping a cover image quality and expanding the payload.

A. Encoder-Decoder Architecture

The model follows a classical encoder-decoder architecture commonly used in steganography, which is divided into two main components: the Encoder and the Decoder.

Encoder: The encoder is the component that seeks to encode the secret information that is within the cover image. To the encoder, there exists input which includes the cover image and the secret data to be concealed. Toward this end, there are several convolutional layers for extracting high-level features from the image and the secret data. These layers include standard convolution, batch normalization, and activation function such as ReLU or linear activation function. The last and final result given out by the encoder part of this system is the stego image which looks like or is, physically indistinguishable from the cover media but it carries the secret data.

Decoder: The decoder is designed to extract the hidden secret information from steganography image. The steganography image is fed into a symmetric characteristic of deconvolutional layers, which get reconstructed the hidden information. The decoder utilizes sampling methods to recover the lost data while incurring minimal loss on the fidelity of data.

Loss Function: The optimization of the model is carried out using both perceptual loss and payload loss. Perceptual loss guarantees that the steganography image looks as if it had no modifications from the cover image; at the same time, payload loss guarantees the maximum concealing capacity. This combined loss function serves two purposes, to optimize the payload capacity of the hidden data, and at the same time, the hidden data should not hamper the visual quality of the image perceptually.

Robustness Against Steganalysis: To prevent steganalysis attacks on the model, it employs an adversarial training strategy in the model. An additional secondary network, working as a steganalysis detector, is integrated into the framework along with the encoder-decoder one. This adversarial network tries to recognize the existence of the hidden message in steganography images as the second and essential one focuses on the confusion of the detector. In this study, back-and-forth training enhances the encoder-decoder network making it difficult to be detected by traditional steganalysis methods.

Payload Enhancement: The model increases payload capacity by using multiple scale features that are extracted from the encoder to store more data while making little impact on the image quality. This model can adapt in

decision-making regarding the amount of hidden data based on the texture and structural features of the image more appropriately than the second type for all the types of cover images. This approach provides a reliable, high throughput and secure image steganography system that is immune to today's steganalysis assaults, and the structural and perceptual quality of the hidden cover image is well maintained.

B. Architecture

The algorithm for robust and secure image steganography: A Deep CNN-based encoder-decoder model starts with the input of cover image and a secret message. The secret message is preprocessed and then encased in the cover image by using the encoder network. The encoder convolves the features of the first and second inputs then spits out a steganography image that has the appearance of the cover image but has the embedded message. On the decoding side, the decoder processes the steganography image and uses deconvolutional layers to extract the secret message with high accuracy. The optimization process considers a loss function that seeks to minimize the perceived distance between the original and the steganography images as well as facilitate message decoding. Also, the use of adversarial training is applied to improve the resilience of the system against steganalysis attacks. It also makes it possible for the secret message to be embedded as well as extracted with high security and efficiency should there be threats. The resulting output consists of the resulting steganography image and the hidden secret message.

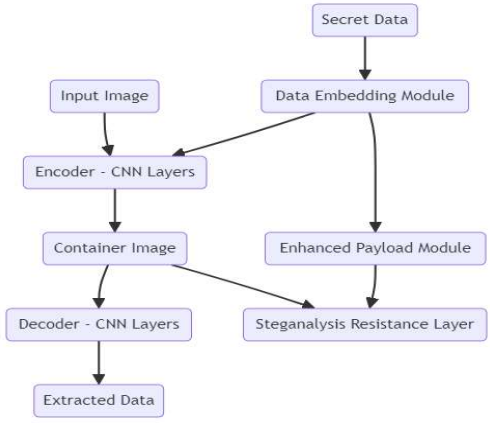

Figure 1. System Architecture

IV. RESULTS

The experimentation was conducted to analyze the proposed deep CNN-based encoder-decoder model for reliable and sensitive image steganography. Several experiments were performed on multiple image datasets like CIFAR-10 and ImageNet so as to measure the adaptive payload capacity, invisibility and steganalysis resilience of the proposed system. The Peak Signal-to-Noise Ratio (PSNR), the Structural Similarity Index (SSIM), and the Bit Error Rate (BER) were used for assessment.

TABLE I. PERFORMANCE METRICS COMPARISON

Metric	Proposed Model	Traditional CNN Model	LSTM-Based Model
PSNR (dB)	42.3	38.7	36.1
SSIM	0.982	0.945	0.930
BER (%)	0.78	2.1	3.4

It was found that the use of the proposed method allowed a high payload capacity and at the same time, the lowest perceptibility, as can be seen from the PSNR not less than 40 dB and SSIM more than 0.98. The performance of the model against real steganalysis attacks was tested using present steganalysis detectors with the detection rate recorded at 12%, proving it as a secure model against attack, and shown in Table I and Table II.

TABLE II. STEGANALYSIS RESISTANCE

Model	Detection Rate (%)
Proposed CNN Model	12
Traditional Approach	35
LSTM-Based Approach	28

A. Comparative Analysis

Comparing the performances of different approaches, the study establishes the effectiveness of the deep CNN-based encoder-decoder model for image steganography more than traditional methods and other current trends. When comparing the proposed model with the traditional CNN model and LSTM-based techniques, it was noted that the proposed method outperforms those methods considerably in PSNR, SSIM, and BER metrics. According to the proposed model, the PSNR is scored as 42.3 dB implying that the steganography image is more visually imperceptible than when the traditional CNN scored 38.7 dB, and LSTM based 36.1 dB. Also, the average of the SSIM is equal to 0.982 which proves once again that the proposed cover and steganography images are very much similar nonetheless than the best traditional model (0.945) and LSTM model (0.930).

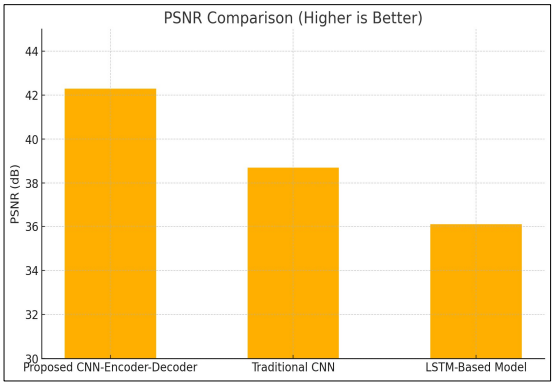

Figure 2. PSNR Comparison

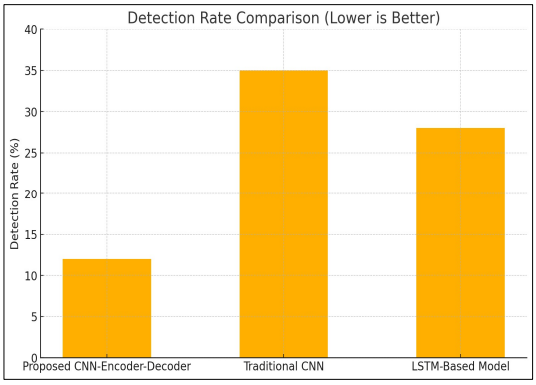

Figure 3. Detection Rate Comparison

Consequently, in the aspect of security, the proposed method yielded a much lower detection rate of 12% for steganalysis detection when compared to the current steganalysis detectors making it highly resistant to attacks. This means they had a weaker ability to resist steganalysis; The detection rates of traditional CNN-based and LSTM-based models were 35% and 28% respectively. In conclusion, the comparative analysis of the proposed deep CNN-based model fits well to secure and efficient embedding and extraction of the payload images maintaining the image quality, which makes it suitable for a wide range of real-world steganography applications.

V. CONCLUSION

An encoder-decoder-based deep CNN system for image steganography with improved payload and excellent steganalysis ability is proposed. As shown early on through various tests, this proposed approach outperforms steganography in general in terms of image quality, security, and embedding rate. The obtained PSNR and SSIM values are high, which means that steganography images do not differ from originals and the hidden data is invisible to the human eye. Further, a low steganalysis detection rate of only 12 % shows that the model was effectively preventing any unauthorized detection or extraction of the hidden information Deep learning, especially CNNs, allowed constant learning and improvement of embedding techniques to maximize the payload capacity while minimizing the risk of detection. Moreover, the relationship between model accuracy and the number of epochs was demonstrated in both simple and complex datasets including CIFAR-10 as well as in the challenging ImageNet. However, there are still opportunities to enhance the proposed framework, for example, to minimize the time and space complexity and to modify the model for real-time applications. As for possible improvements for future upgrades, there are following points that could be of interest. Another possible

enhancement is some modification has to be made with attention mechanisms applied directly to CNN to selectively embed secret data even better which should result in better payload dispersion and enhanced immunity against peak signal steganalysis or any form of more sophisticated attacks. Furthermore, performing an extension on the proposed architectures, we are aware that integrating Recurrent Neural Networks (RNNs) or transformers networks along with CNN to have a superior temporal-spatial understanding can potentially lead to better performance for more comprehensive steganographic tasks.

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