Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

Image Steganography With CNN-Based Encoder–Decoder Model

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Abstract

Image steganography is a critical domain in information security that focuses on concealing secret data within digital images to ensure secure and covert communication. Traditional steganographic techniques, such as Least Significant Bit (LSB) substitution and transform-domain methods, often suffer from limited payload capacity, low robustness, and vulnerability to detection. To overcome these limitations, this paper proposes a deep learning-based image steganography framework using a Convolutional Neural Network (CNN) integrated with an encoder–decoder architecture for efficient and secure data hiding. The proposed model consists of two main components: an encoder network and a decoder network. The model maximizes the quality of the recovered secret image.Experimental results demonstrate that the proposed approach significantly improves data hiding capacity and ensuring reliable reconstruction of hidden data. The model

provides a scalable and efficient solution for secure communication, making it suitable for applications such as digital watermarking, and covert information transfer.

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- Received Date: 11 Feb 2026
- Accepted Date: 02 Apr 2026
- Publication Date: 25 Apr 2026

Keywords

Image Steganography, Deep Learning, Convolutional Neural Network (CNN), Encoder–Decoder Architecture, Secure Data Hiding.

Introduction

Image steganography is an important and rapidly evolving area in the field of information security and computer vision. It focuses on developing techniques that enable machines to hide secret information within digital images in a way that is imperceptible to the human eye. Unlike traditional encryption methods, which only protect the content of data, steganography conceals the very existence of the communication, thereby providing an additional layer of security. This capability bridges the gap between data security and multimedia processing, enabling secure transmission of sensitive information across open networks.

With the increasing use of digital media and internet-based communication, the need for robust and secure data hiding techniques has grown significantly. Traditional steganographic approaches, such as Least Significant Bit (LSB) substitution and transform-domain methods, are simple to implement but suffer from several limitations, including low embedding capacity, poor robustness, and vulnerability to statistical and visual detection techniques. These drawbacks restrict their applicability in modern secure communication systems, where higher reliability and resistance to attacks are required. To address these challenges, deep learning has emerged as a powerful solution due to its ability to automatically learn complex patterns and representations from data. In particular, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image processing tasks such as feature extraction, classification, and reconstruction. By leveraging these capabilities, deep learning-based steganography methods can achieve improved imperceptibility, higher payload capacity, and enhanced robustness compared to conventional techniques.

In deep learning-based image steganography, the problem is formulated as a learning task where a model is trained to embed a secret image into a cover image and later recover it accurately. This is typically achieved using an encoder–decoder architecture. The encoder network processes both the cover image and the secret image to generate a stego image, which appears visually similar to the original cover image. The decoder network then extracts and reconstructs the hidden image from the stego image. This approach enables the system to learn optimal embedding strategies without relying on handcrafted rules.Such techniques have wide-ranging applications, including secure communication, digital watermarking, copyright protection, military data transmission, and privacy-preserving data sharing. In surveillance and forensic domains, steganography can be used to embed metadata or confidential information within images without raising suspicion. Additionally, it enhances the security of multimedia systems by preventing unauthorized access and detection of hidden data.The integration of deep learning into steganography not only improves the efficiency of data hiding but also enhances adaptability across different types of images and environments. These models can

Citation: Razia S, Khamer Taj Sk, Indupriya S, Ismail S Md, Dattatreya MN, Babji K. Image Steganography With CNN-Based Encoder–Decoder Model . GJEIIR. 2026;6(4):236.

generalize well to unseen data and maintain performance under various image transformations and distortions, making them suitable for real-world deployment.The primary objective of this research is to develop a CNN-based encoder–decoder model for image steganography that can securely embed and accurately reconstruct hidden images while preserving the visual quality of the cover image. The proposed approach focuses on improving embedding efficiency, robustness, and reconstruction accuracy through learned feature representations.

The remainder of the paper is organized as follows: Section II presents the literature survey of existing steganography techniques. Section III describes the proposed deep learning model and methodology. Section IV discusses the experimental results and analysis. Finally, Section V concludes the paper with future research directions.

Related Work

In recent years, image steganography has evolved significantly with the advancement of deep learning techniques. Early steganographic methods primarily focused on spatial domain approaches such as Least Significant Bit (LSB) substitution, which are simple and computationally efficient but highly vulnerable to detection and attacks. To overcome these limitations, researchers have explored transform-domain techniques; however, these methods often involve increased complexity and limited adaptability.

Baluja et al. [9] introduced a deep learning-based approach for image steganography using neural networks, where a model learns to hide a full secret image inside a cover image. The proposed method demonstrated that deep neural networks can effectively optimize the embedding process while maintaining visual similarity between the cover and stego images. This work laid the foundation for using encoder–decoder architectures in steganography.

Zhu et al. [10] proposed an end-to-end deep steganography network that jointly trains embedding and extraction processes. Their model utilizes convolutional layers to encode secret information into cover images and decode it efficiently. The study showed improved robustness and better hiding capacity compared to traditional techniques.

Hayes and Danezis [11] presented a generative adversarial network (GAN)-based steganography approach, where a generator creates stego images and a discriminator attempts to detect hidden data. This adversarial training improves the security of the steganographic system by making detection more difficult. However, GAN-based models may introduce training instability and higher computational requirements.

Wu et al. [12] explored the use of deep convolutional neural networks for adaptive steganography, where embedding locations are selected based on image content. This approach enhances imperceptibility by avoiding noticeable regions in images. The model learns complex spatial dependencies, improving resistance to steganalysis techniques.

Rehman et al. [13] proposed a CNN-based encoder–decoder architecture for image steganography, focusing on hiding images within images. The encoder embeds the secret image into the cover image, while the decoder reconstructs the hidden image. The model demonstrated improved reconstruction quality and robustness compared to traditional approaches.

Boroumand et al. [14] introduced a deep residual network for steganalysis, which focuses on detecting hidden information in images. Their work highlights the importance of designing robust steganography systems that can resist detection by advanced deep learning-based steganalysis methods.

Tancik et al. [15] presented a high-capacity steganography system using deep neural networks capable of hiding multiple images within a single cover image. This work emphasizes the scalability of deep learning approaches in increasing payload capacity without significantly degrading image quality.

Despite these advancements, existing methods still face challenges such as balancing embedding capacity, visual quality, and robustness against attacks. Some models suffer from overfitting, while others require large datasets and high computational resources.

In this context, the proposed work focuses on developing a CNN-based encoder–decoder model that efficiently embeds secret images into cover images while ensuring high imperceptibility and accurate reconstruction. The model aims to improve data hiding capacity and robustness while maintaining computational efficiency, addressing the limitations of existing techniques.

Proposed Methodology

A deep learning-based image steganography system is designed to securely embed secret information within digital images while maintaining high visual quality and robustness. By leveraging advanced computer vision techniques and deep neural networks, the system learns complex mappings between cover images and secret images, enabling efficient and imperceptible data hiding. The proposed approach utilizes a Convolutional Neural Network (CNN) combined with an encoder–decoder architecture, which allows automatic feature extraction, optimal embedding, and reliable reconstruction without manual intervention. This makes the system more adaptive and secure compared to traditional steganographic techniques.

The proposed framework consists of data collection, preprocessing, model design, training, and testing phases. A large dataset of images is used to ensure the model generalizes well across different textures, patterns, and image distributions. During preprocessing, both cover images and secret images undergo operations such as resizing, normalization, and augmentation to ensure uniformity and improved feature learning. Unlike conventional systems that rely on handcrafted rules, this model learns embedding strategies directly from data. The encoder network embeds the secret image into the cover image by learning optimal feature representations in a high-dimensional space, while the decoder network extracts and reconstructs the hidden image from the stego image. The training process focuses on minimizing reconstruction loss and embedding distortion simultaneously, ensuring both security and fidelity.

i) Image Preprocessing

Resizing: Both cover and secret images are resized to a fixed dimension (e.g., 224×224) to maintain uniformity across the dataset and ensure compatibility with convolutional neural networks. Fixed-size inputs allow efficient batch processing and consistent receptive field behavior across layers. Interpolation methods such as bilinear or bicubic interpolation are used during resizing to preserve important visual details and avoid distortion.

Normalization: Pixel intensities are scaled to a predefined range such as [0,1] or [-1,1] to stabilize gradient flow during training. Normalization reduces internal covariate shift and helps the optimizer converge faster. In some cases, channel-wise mean subtraction and standard deviation scaling are also applied to standardize the dataset distribution.

Data augmentation: To improve generalization and robustness, multiple augmentation techniques are applied. These include geometric transformations (rotation, flipping, scaling, cropping), photometric adjustments (brightness, contrast, saturation), and noise injection. Augmentation simulates real-world variations and helps the model learn invariant features, thereby reducing overfitting and improving performance on unseen data.

ii) Input Preparation

processed through parallel feature extraction paths before fusion. Care is taken to maintain synchronization between cover–secret pairs during training. Batch processing is employed to utilize GPU acceleration efficiently and to stabilize gradient updates.

iii) Encoder Network

The encoder network is designed to embed the secret image into the cover image while preserving perceptual quality. It consists of stacked convolutional layers with nonlinear activation functions (e.g., ReLU or Leaky ReLU) to capture complex feature representations. Initially, separate feature maps are extracted from the cover and secret images. These feature maps are then fused using operations such as concatenation, addition, or attention-based mechanisms. The fused representation is passed through deeper convolutional layers to distribute the secret information across the spatial domain of the cover image. In some implementations, skip connections are used to retain low-level details and improve gradient flow. The final output of the encoder is the stego image, which visually resembles the original cover image but contains embedded information in a distributed and imperceptible manner.

iv) Decoder Network

The decoder network is responsible for extracting and reconstructing the hidden secret image from the stego image. It takes the stego image as input and processes it through multiple convolutional layers to detect subtle embedded patterns. The architecture is typically symmetric to the encoder, enabling effective inversion of the embedding process. Feature maps are progressively refined to reconstruct the secret image with minimal

v) Model Training

The model is trained in an end-to-end fashion using paired datasets of cover and secret images. The objective function combines multiple loss components, such as embedding loss (difference between cover and stego image) and reconstruction loss (difference between original and recovered secret image). This dual-objective optimization ensures a balance between imperceptibility and accurate recovery. Backpropagation is used to compute gradients, and optimizers like Adam are employed for efficient parameter updates. Learning rate scheduling may be applied to improve convergence. Regularization techniques such as dropout, batch normalization, and early stopping are incorporated to prevent overfitting and enhance generalization. Training is performed over multiple epochs until the model achieves stable performance.

vi) Testing Phase

During testing, the trained encoder is used to generate stego images from unseen cover–secret image pairs. These stego images are then passed through the decoder to recover the hidden images. The evaluation focuses on reconstruction accuracy and visual similarity, ensuring that the embedded information is retrieved correctly while the stego image remains visually indistinguishable from the cover image. The system is also tested under different conditions such as noise addition, compression, or minor distortions to evaluate robustness. The results demonstrate that the proposed model can securely embed and reliably extract hidden.

Proposed Deep Learning Architecture

The proposed model is a deep learning-based image steganography architecture that uses a Convolutional Neural Network (CNN) integrated with an encoder–decoder framework to securely hide and retrieve images. Unlike sequence-based models, this architecture is fully image-driven and focuses on embedding a secret image into a cover image and reconstructing it accurately from the stego image.

The model consists of two parallel input layers: one for the cover image and another for the secret image. These inputs are first processed through convolutional layers to extract low-level and high-level features such as edges, textures, and structural information. Feature extraction is essential to capture meaningful representations required for effective embedding. The extracted features from both inputs are then reshaped and combined using concatenation. This fusion step allows the network to learn the relationship between the cover and secret images. The combined feature map is passed through multiple convolutional layers that perform the embedding process. These layers distribute the secret image information across the spatial domain of the cover image, generating a stego image that is visually similar to the original cover image.

To improve feature learning and stability, the architecture may include dense connections and normalization layers. These help in efficient gradient flow, reducing training difficulties in deeper networks, and improving overall performance.

The decoder network takes the stego image as input and applies a sequence of convolutional operations to extract the embedded information. It learns to identify hidden patterns introduced during encoding and reconstructs the secret image. The decoder is designed to mirror the encoder structure, ensuring effective recovery of the hidden content.Additional layers such as dropout are used to prevent overfitting by randomly deactivating neurons during training. This improves the generalization capability of the model. The final output layer reconstructs the secret image with dimensions similar to the original input.

The entire architecture is trained end-to-end, optimizing both embedding and extraction processes simultaneously. The model ensures that the stego image maintains high visual similarity with the cover image while enabling accurate reconstruction of the secret image. This CNN-based encoder–decoder architecture provides an efficient, robust, and secure solution for image steganography

SOFTWARE REQUIREMENTS

- Operating System: Windows 10 / 11
- Coding Language: Python 3.11
- Framework: Django
- Front-End: HTML, CSS, JavaScript
- Development Tool: PyCharm
- Database: MySQL or SQLite
- Libraries: TensorFlow / Keras, NumPy, OpenCV

HARDWARE REQUIREMENTS

- System: Pentium Dual Core or higher
- Hard Disk: 120 GB

- Monitor: 15" LED Monitor
- Input Devices: Keyboard and Mouse
- RAM: 4 GB minimum (recommended)

Feasibility Study

The feasibility study evaluates whether the proposed system can be implemented effectively within available resources. The following aspects are considered.

Technical Feasibility

The system uses widely available technologies such as Python, Django, and deep learning libraries. These technologies are reliable and capable of implementing the proposed steganography model. Therefore, the system is technically feasible.

Economic Feasibility

The project is economically feasible because most of the software tools and libraries used are open-source and freely available. This significantly reduces the overall development cost.

Social Feasibility

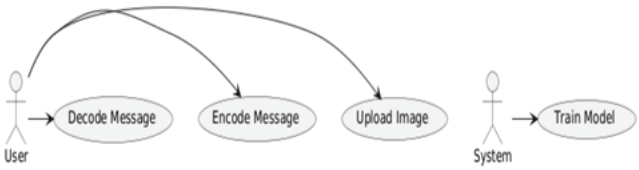
The system provides a secure method for protecting sensitive information, which increases its acceptance among users. The user interface is simple and easy to use, ensuring that users can easily operate the system without technical difficulties.

DESIGN

Software design sits at the technical kernel of the software engineering process and is applied regardless of the development paradigm and area of application. Design is the first step in the development phase for any engineered product or system.

USE CASE DIAGRAM:

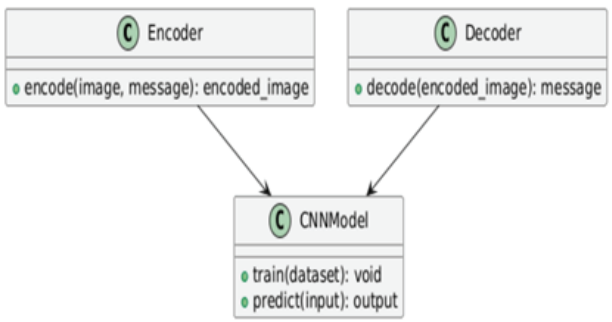
The diagram represents the use case of the system where the user interacts by selecting encoding or decoding operations. The user uploads an image and provides a secret message for encoding, while decoding retrieves hidden data.



Use Case Diagram

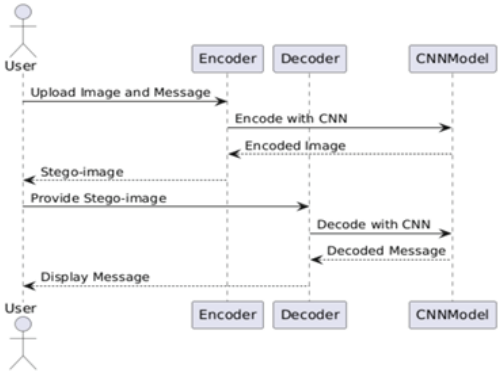
CLASS DIAGRAM:

The class diagram showing the structure of the system with three main classes: Encoder, Decoder, and CNNModel. The Encoder class embeds the secret message into the image, while the Decoder extracts it from the stego-image.



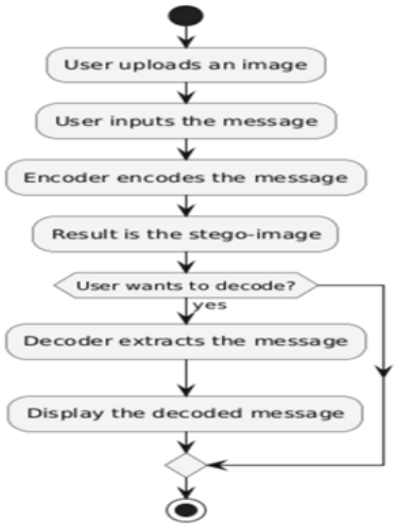
SEQUENCE DIAGRAM:

The sequence diagram illustrates the step-by-step interaction between the user, encoder, decoder, and CNN model. The user uploads an image and message, which the encoder processes using the CNN to produce a stego-image.



ACTIVITY DIAGRAM:

The activity diagram shows the workflow of the system starting from image upload and message input by the user. The encoder embeds the message into the image to generate a stego-image. A decision step checks if decoding is required, after which the decoder extracts the message. The process ends with displaying the decoded message to the user.

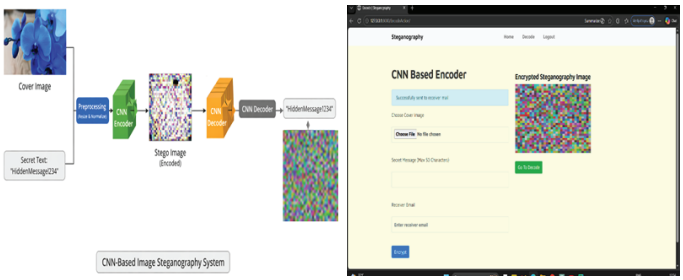


Implementation And Results

This section presents a comprehensive account of the outcomes derived from the experiments carried out using the proposed image steganography methodology. The dataset utilized in this research was collected from publicly available sources such as Kaggle and consists of a large number of natural images. In this work, each sample is formed by pairing a cover image with a corresponding secret image. The cover image acts as the carrier, while the secret image contains the information to be hidden. Unlike image captioning datasets, this dataset does not include textual descriptions but focuses entirely on image-to-image data embedding. Fig. 3 shows some sample cover images, secret images, generated stego images, and reconstructed outputs.

Image preprocessing plays a crucial role in the proposed system. Both cover and secret images are resized to uniform dimensions and normalized before being fed into the model.

Data augmentation techniques are also applied to improve dataset diversity and enhance the robustness of the model. These preprocessing steps ensure that the model can effectively learn meaningful representations and perform well on unseen data. Proper preprocessing loss. Techniques such as upsampling, transpose convolutions, or residual connections may be used to improve reconstruction quality. The decoder is trained to be sensitive to hidden signals while being robust to noise and minor distortions in the stego image.



CNN-based image steganography system

Feature extraction in the proposed system is carried out using deep Convolutional Neural Networks (CNNs), which are highly effective in capturing hierarchical spatial information from images. The encoder network processes both the cover image and the secret image through multiple convolutional layers, where low-level features such as edges and textures are extracted in the initial layers, and higher-level semantic patterns are captured in deeper layers. These feature maps from both inputs are then combined using fusion techniques such as concatenation or element-wise operations to form a unified latent representation. This representation encodes the essential information required to embed the secret image within the cover image. The encoder further refines this combined representation through successive convolutional transformations to generate the stego image. The resulting stego image is visually indistinguishable from the original cover image while securely containing the hidden data. On the decoding side, the decoder network analyzes the stego image and learns to identify subtle embedded patterns introduced during encoding. Through a sequence of convolutional and reconstruction layers, it progressively recovers the hidden secret image with minimal information loss. This process highlights the strength of deep learning models in automatically learning complex, non-linear data hiding and extraction mechanisms without the need for manual feature engineering.

The notions of training loss and validation loss play a crucial role in evaluating and monitoring the performance of the proposed model. Training loss quantifies how well the model fits the training dataset by measuring the difference between predicted outputs and actual targets during training iterations. Validation loss, on the other hand, evaluates the model's ability to generalize by testing it on unseen data that is not used during training. Fig. 4 illustrates the trend of both training and validation loss over multiple epochs. A steady and consistent decrease in both curves indicates that the model is learning meaningful representations and converging effectively. However, if the training loss continues to decrease while the validation loss stagnates or increases, it indicates overfitting, where the model memorizes the training data but fails to generalize. To address this, techniques such as regularization, dropout, and early stopping can be applied. In the proposed system, a balanced reduction in both losses is observed, demonstrating stable training behavior and strong generalization capability across different image inputs.

The visual quality of the stego image is a critical factor in determining the effectiveness of any steganographic system. The experimental results show that the stego images generated by the proposed model maintain high perceptual similarity to the original cover images, ensuring that the presence of hidden information is not visually detectable. This imperceptibility is achieved by distributing the embedded information across complex feature spaces learned by the CNN, rather than modifying pixel values directly as in traditional methods. At the same time, the decoder network achieves high reconstruction accuracy, The system presents representative outputs at various stages, including the cover image, secret image, generated stego image, and the reconstructed image. These outputs provide a clear visualization of how effectively the model performs both the embedding and extraction processes. The stego image remains visually indistinguishable from the original cover image, indicating high imperceptibility, while the reconstructed image closely resembles the original secret image, demonstrating accurate information recovery. This validates the capability of the model to maintain a balance between hiding capacity and visual fidelity.

In comparison with traditional steganographic techniques such as Least Significant Bit (LSB) substitution, the proposed deep learning-based approach offers significant improvements in security, robustness, and adaptability. Conventional methods rely on fixed and predictable embedding rules, making them highly vulnerable to statistical analysis and steganalysis attacks. These approaches often fail when subjected to common image processing operations such as compression, noise addition, or filtering. In contrast, the proposed Convolutional Neural Network (CNN)-based encoder–decoder architecture learns adaptive and data-driven embedding strategies. This enables the system to distribute hidden information across complex feature representations rather than fixed pixel locations, thereby enhancing resistance to detection and improving robustness against various distortions.

Furthermore, the end-to-end training mechanism ensures that both embedding and extraction networks are jointly optimized. This joint optimization minimizes information loss during transmission and maximizes reconstruction accuracy. The encoder learns to embed information in a manner that is both imperceptible and recoverable, while the decoder is trained simultaneously to accurately reconstruct the hidden content from the stego image. This synergy between the two components significantly improves overall system efficiency and reliability.

Overall, the proposed model achieves efficient, robust, and secure image steganography by effectively balancing imperceptibility and reconstruction accuracy. Quantitative evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) further confirm the high visual quality of the stego images and the fidelity of the reconstructed images. High PSNR values indicate minimal distortion between the cover and stego images, while strong SSIM scores reflect preserved structural information.

The system demonstrates strong applicability in real-world scenarios, including secure communication, digital watermarking, copyright protection, and confidential data transmission. Its ability to conceal large amounts of information without noticeable degradation makes it suitable for modern data security requirements

Conclusion

In conclusion, this research has demonstrated the effectiveness of deep learning techniques in the domain of image steganography using a CNN-based encoder–decoder architecture. By utilizing convolutional neural networks for feature extraction and designing an efficient encoder–the Decoder framework, the proposed model successfully embeds a secret image within a cover image while preserving visual quality and enabling accurate reconstruction. The developed system establishes a secure and reliable approach for such cases.

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