



RESEARCH ARTICLE – COMPUTER SCIENCE

A Comparative Study on Image Steganography based on Deep Learning

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Article Info.	Abstract
<i>Article history:</i> Received 1 June 2025 Accepted 2 October 2025 Publishing 30 September 2026	With the expansion and growth of technology in a sophisticated and noticeable way the protection of transmitted data has come to be one of the most important and prominent issues that have occupied specialists in the purview of data security. one of the most prominent fields used in information security is the technology of images steganography, as this technology enables us to hide data in images imperceptibly so that no one can notice it. Deep learning technology has gained more attention lately as it has become a potent tool in many applications, such as image steganography to secure and protect data transferred. this scientific paper aims to investigate and debate the different deep learning techniques that are available in the purview of image steganography. Image steganography deep learning techniques can be classified into three principal groups: CNN-based, GAN-based, and traditional methods.

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Keywords: Steganography, Image steganography, CNN, Deep Learning, Statistical analyses.

1. Introduction

In this era, data security is a crucial aspect of protecting information. In general, information security is divided into two principal categories: information encryption and information hiding. These two security systems are in charge of securing and protecting information, but each system has a different approach. Information encryption is a technology that makes communication secure. Even if there is a party trying to spy or falsify information or what is called a third party, as confidential data is converted using the key to an incomprehensible form. The second system is the information hiding system, which will not cause the content of the message to change, as is the case with information encryption, as information hiding is called steganography [1]. It is the science and art of hiding important and confidential information within the media in a way that appears innocent. It is considered a very important matter in sending and exchanging information in a secure manner [2]. As the scope of digital adoption today has increased and expanded on social media platforms and professional platforms, ensuring the security and confidentiality of information, as well as its need for protection, is important. significant and sensitive data has become one of the most important areas. As a result, there is an increasing demand for methods and techniques that work secretly and in a way that does not arouse suspicion [3]. steganography involves hiding secret information within a carrier file (e.g., images, audio files, videos, documents) that remains unchanged to the observer [4].

1.1 Types of steganography

Many types of data steganography help us in steganography of important data, which can be classified as follows,

1. Video Steganography: It is a method of hiding confidential information inside video files without significantly changing the perceptual quality of the video. The data is hidden inside the less important bits of the video frames. Hiding information in video is used in various and numerous applications, such as copyright protection, digital watermarks, and confidential communication [5].

2. Audio Steganography: It involves hiding secret information inside a digital audio file. This technology integrates the message inside the audio content itself in a way that the human ear cannot understand. The secret message is included inside the bits of lesser importance than the audio samples. To discover the secret messages in audio files, specialized algorithms must be used to analyze the audio samples and identify the slight changes [5].

3. Text Steganography: In this type, information is hidden inside the text and is done by changing the text format. This type of hiding is considered one of the difficult types compared to video, images, or image files because the text has fewer repetitions, and the text is hidden inside a book or document, and is considered one of the easy types to discover [6].

4. Network or Protocol Steganography: In this type, confidential information is hidden within the network, and based on the OSI model, it is classified into two methods: the first is network concealment within the protocol, and the second method is network concealment between the protocols [6].

5. Image Steganography: It is a technique used to conceal confidential information within images without any obvious change in the appearance of the image [7]. Image steganography is a type of steganography system where secret messages are placed in the specified image through some methods of concealment [8]. In the process of steganography of information in images, the steganography technique uses pixel density, i.e., the least significant bit is the most efficient in inserting secret messages [9]. Figure 1 shows the general structure of a steganographic system.

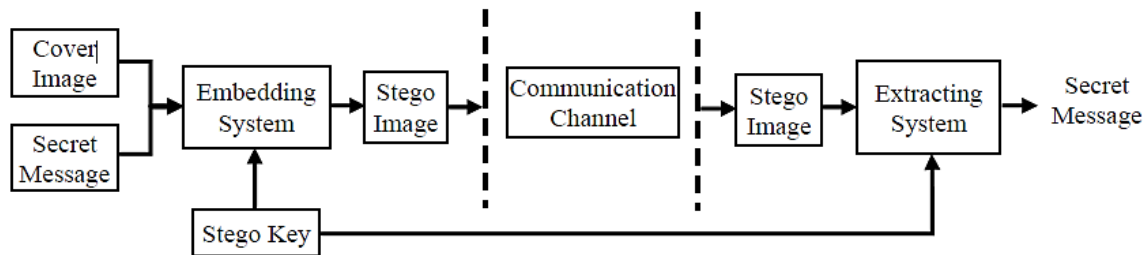


Fig.1. General structure of a steganographic system.

When hiding an image, the steganography technique must have several features for example, it must have a good load capacity, and the image to be hidden must be almost similar to the cover image, and the quality of the images must also be verified. The most important feature is that it is preferable for the steganography system to have a high degree of security as the method used in steganography must overcome attacks and analysis techniques.[10]Steganography technology contains two main parts: the first is the message, which is the secret data that is to be hidden, and the second part is the carrier that will carry the hidden message [11]. Steganographic methods can be classified into two groups: spatial domain and frequency domain [12] [13].

Spatial domain techniques work by embedding hidden data (payload) based on the relationships between pixel values in the image, whereas frequency domain methods manipulate high and low-frequency components, modifying specific coefficients in a way that preserves the image's visual appearance [14]. Adaptive steganography, known as "statistics-aware embedding", allows for the identification of the specific pixel that requires alteration in the image, or estimating the bit count to be incorporated into the image pixel, or the identification of the modification technique. Based on these characteristics, it can be described as a human visual system powered by artificial intelligence and machine learning, which recognizes, grasp, and processes visual signals. In the HVS it is difficult to identify and recognize the concealment information contained in the pixels of the cover image. Also, the human visual system technology identifies the edge areas or complex areas to hide secret messages to maintain the unawareness and maintain imperceptibility of secret messages[15].several aspects must be taken into account when working on or developing steganography systems [16]:

- 1. Robustness:** its robustness against different image processing and compression techniques.
- 2. Security:** The security of hidden information is of great importance, so the image steganography technology must be designed in a way that makes it resistant to attacks such as brute force attacks and statistical analysis.
- 3. Efficiency:** The technology must be able to hide information in images in a fast and effective manner.
- 4. Concealment:** The information in the image must be hidden in a way that cannot be easily detected.
- 5. Retrieval:** It is important that the hidden information is fully recovered by the authorized party using the decryption key or algorithm [16].
- 6. Capacity:** It is the quantity of data that can be hidden within the cover image, often referred to as the payload.

2. Statistical analyses

Steganography is an old and effective method in the technique of hiding data, where information may be hidden without distorting the cover image, and the secret data resembles the point that human perception cannot detect it, and the effectiveness of the algorithm can be measured through different statistical analyses, as statistical analyses are divided into several types, the most prominent of which are mentioned in Table 1:

Table 1. The most important and prominent standards used in measuring the quality of steganography images.

Metrics Name	Definition	Equations	Equation Symbols Explanation												
1- Payload Capacity [17]	It is also called the embedding capacity and refers to the number of secret bits that are hidden within the pixels of the cover image. The algorithm must also have a high capacity while ensuring that the embedded image's quality is satisfactory and free of visual distortions.	$ER = \frac{Z}{M*N} \text{ bpp (1)}$	Z: “Number of secret bits.” M: Width of the image. N: Height of the image.												
2- Confusion matrix [18]	The main objective of steganalysis is to detect if secret information is embedded within a suspected medium. This indicates that its primary focus is determining whether a test medium falls into the cover or stego category.	<table><tr><td></td><td>Yes</td><td>No</td></tr><tr><td>Yse</td><td>TP</td><td>FN</td></tr><tr><td>No</td><td>FP</td><td>TN</td></tr><tr><td>Total</td><td>P'</td><td>F'</td></tr></table>		Yes	No	Yse	TP	FN	No	FP	TN	Total	P'	F'	True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP).
	Yes	No													
Yse	TP	FN													
No	FP	TN													
Total	P'	F'													
3- Accuracy [19]	The method used to verify that an image is a Stego image, i.e. it determines whether this image is a Stego or not. Accuracy is the total number of predictions that were correct compared to the classifications made by the model.	$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (2)$	Calculates how well the classification system performs on balanced datasets, highlighting correct predictions.												
4- Mean Absolute Error (MAE) [20]	It calculates the mean absolute error (MAE), which is the average of the absolute differences between corresponding pixels in the retouched and original images.	$MAE = \left(\frac{1}{N}\right) * \sum i = 1 \text{ to } N \mid I(i) - S(i) \quad (3)$	Here, N represents the total pixel count in the images, while S(i) and I(i) denote the pixel intensities at location i in the stego (modified) image and the original image, respectively.												
5- Root means square error (RMSE) [21]	The RMSE is usually applied as a measure of quality where it can be computed utilizing the square root of the MSE.	$RMSE = \sqrt{MSE} \quad (4)$	RMSE derives directly from MSE to give a comparable measure of quality in the same units as pixel intensity.												
6- Signal to Noise Ratio (SNR) [18]	This value gives the quality of the signal that has been reconstructed and the stego image is better the higher the value.	$SNR = 10 \log_{10}\left(\frac{\sigma_x^2}{\sigma_\epsilon^2}\right) \quad (5)$	Where σ_x and σ_ϵ They are two symbols used to represent the mean squared value of the input image and the difference in mean												

			squared error between the background image and the cover image.
7- Weighted Peak Signal-To-Noise Ratio (WPSNR) [22]	It is the signal-to-noise ratio (WPSNR), which is an Alternative measurement quality. This measure uses an additional parameter called (NVF).The WPSNR is approximately equal to the PSNR in areas that are flat because the NVF in smooth areas approach one. In edge areas, the WPSNR is higher than the PSNR because the NVF in complex areas approaches zero.	$WPSNR = 20 \log_{10} \left(\frac{255}{\sqrt{MSE \times NVF}} \right) \quad (6)$ $NVF = NORM \left(\frac{1}{1 + \delta_{block}^2} \right) \quad (7)$	where δ Indicates the variance in luminance for the 8×8 block of the image.
8- Structural similarity index measure (SSIM) [21][23]	It is a measure used to check the degree of similarity between two images. In other words, it represents a method of comparing two images.	$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (8)$	μ_x and μ_y They are the average values of image x and image y . σ_x^2 and σ_y^2 is the variance of x and y . σ_{xy}^2 It expresses the covariance x and y . c_1 and c_2 they are express the stability coefficients.
9- The IQM using R measurement [24]	The R measure is used to evaluate the similarity between a stego image and a carrier image.	$R = \frac{\sum_{i=1}^N \sum_{j=1}^N (p_{ij} - p^2)x(q_{ij} - q^2)}{\sqrt{(\sum_{i=1}^N \sum_{j=1}^N (p_{ij} - p^2)^2)x(\sum_{i=1}^N \sum_{j=1}^N (q_{ij} - q^2)^2)}} \quad (9)$	The p^- and q^- They are the medium pixel values of the stego image and the carrier image, respectively.
10- Normalized cross correlation (NCC) [25][26]	The NCC indicates the closeness of two digital images.	$NCC = \frac{\sum_{x=1}^M \sum_{y=1}^N (S(x, y) * C(x, y))}{\sum_{x=1}^M \sum_{y=1}^N S(x, y)^2}$	$S(x, y)$: stego image pixel at (x, y) $C(x, y)$: cover image pixel at (x, y) M : horizontal resolution (number of columns) N : vertical resolution (number of rows).
11- Average difference (AD) [27]	It measures the average difference between the reference signal and the test image.	$AD = \frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N C(x, y) - S(x, y) \quad (11)$	M : The number of rows (vertical dimension) of the image. N : The number of columns (horizontal dimension).
12- The Image Fidelity (IF) [25]	is another metric for image quality measurement.	$IF = 1 - \frac{\sum_{x=1}^M \sum_{y=1}^N C(x, y) - S(x, y)}{\sum_{x=1}^M \sum_{y=1}^N C^2(x, y)} \quad (12)$	M : The number of rows (vertical dimension) of the image. N : The number of column

			(horizontal dimension) of image. C(x,y):The pixel value at coordinates (x,y)in the original image. S(x,y):The pixel value at coordinates(x,y) in the ste image.
13- Relative entropy [17]	During the process of embedding secret information, relative Entropy is used to evaluate The statistical changes that occur in the cover image.	$R(PC PS) = \sum PC \log_2 \left(\frac{PC}{PS} \right)$ (13)	where PC and PS they indicate the probability distributions of pixels values in the stego image and the cover image.

3. Image steganography based on CNN

It is a type of artificial neural network in deep learning that has been specially designed to deal with image and video data, where it takes the input roots and classifies them after feature extraction from the input images[28]. And it is a powerful subcategory of machine learning that allows multiple processing layers of models to learn and identify data using a technique that mimics the perception of the human brain by using interconnected cells known as neurons[29]. Deep neural networks have become very popular due to their increasing daily use, as they have begun to enter into speech and image recognition applications, as well as in medical fields and many other industrial fields [30]. Deep learning in recent years has seen rapid and effective growth as it has been widely used to effectively address a lot of traditional tasks.

Deep learning has also outperformed machine learning techniques in many fields, for example, it has been used in cybersecurity, natural language processing applications, robot control, and medical information processing, Machine intelligence is useful in some cases or situations that are beyond the ability of experts to solve, which means that deep learning can solve some of these problems, such as the lack of human capabilities, or cases where there is a new update to the problem over time (forecasting stocks or weather) or cases where the size of the problem is large[31] The application of deep learning techniques in hiding information with images has increased in recent years. Different neural network techniques can be used in hiding information with images because their process, model or properties are consistent with hiding information with images. Convolutional neural networks (CNN) and generative adversarial networks (GAN) are used in image information steganography techniques. Due to the development of modern devices and the increase in data sets, the use of convolutional neural networks has become widespread. Convolutional neural networks also have several advantages, including learning high-level features. This has made them applicable to image information steganography. They can also reduce distortions present in steganographic images[32].

Modern CNN approaches used for information steganography rely primarily on encoder-decoder structures, where the encoder receives paired inputs (the cover image and the secret image) to generate the hidden image, and then the decoder processes them to recover the original secret image. Although committed to this basic model, researchers have explored some structural differences. These differences appear in the ways of linking the inputs of the cover image and the secret image, as well as in the configurations of the convolution layers and in the designs of the pooling layers. They also found differences in the choice of the activation function and the formulation of the loss function. It is worth noting that all applications require that the dimensions of the secret image be identical to the cover image for each pixel to be fully embedded [33] .

CNNs are effective at recognizing complex image shapes because they can extract features and learn automatically from images without the need for human intervention or prior knowledge via successive convolutional layers, pooled, and fully connected layers [34]

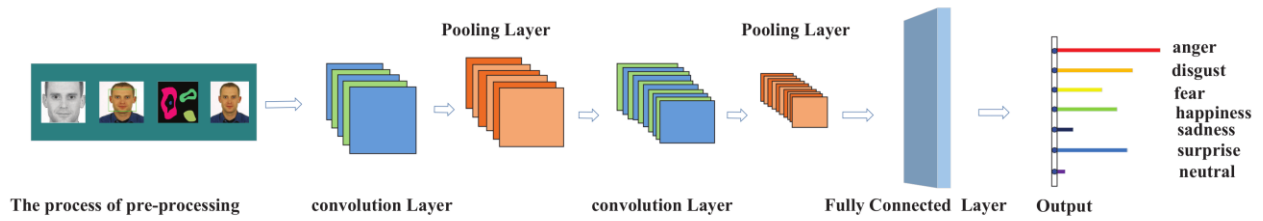


Fig. 2. CNN architecture.

3.1 Building blocks of CNN architecture

1-Convolution: It is considered the basic component or basic unit of the CNN structure, as it extracts features and is considered the place where filters, or what is called the kernel, are applied to the original input image [35][36][37]. The convolution layer consists of linear and nonlinear operations, i.e., it contains the convolution operation and the activation function. The convolution process extracts a high-level feature map on the input data by applying filters of different sizes[38]. Each filter maintains the depth of the input, i.e. it has the same depth as the feature map or input image, but its spatial dimensions are much smaller, i.e. it has a smaller height and width. The 3*3 filter is the most commonly used shape [39], [40]. The main purpose of the convolution layer is to detect edges, visual elements, and lines [41].

2- Pooling layer: In convolutional neural networks, pooling layers down- sampling feature maps by reducing their spatial dimensions. This is achieved by either taking the maximum or the average value within the filter window. The down-sampling process simplifies the network's computations while preserving important feature information [42][43].

3- Activation Functions: Neural networks use activation functions to map inputs to outputs. Activation functions act as nonlinear transformers in neural networks, transforming weighted inputs into outputs that propagate to subsequent layers. The choice of functions is determined based on the requirements of the task. For example, the SoftMax function is used for multi-class classification, the Sigmoid function for binary classification, and ReLU (Rectified Linear Unit) is the prevailing default choice for hidden layers. Each function offers specific nonlinear properties specifically designed for different learning objectives [31][28].

4-Fully Connected Layer: Fully connected layers represent the third basic type of layers in convolutional neural networks, where each input neuron is connected to all output neurons, and each output neuron produces a linear combination of all the inputs of the previous layer and passes through nonlinear functions [44].

4. Related works

1- The study in [45] introduces a secure and robust image data steganography technique that combines (LSB), (DCT), and (CNN)-based Autoencoder with (CAEDLF). The methodology involved LSB-based steganography where the least significant bits of image pixels are used to hide the secret data without causing noticeable distortion, Discrete Cosine Transform (DCT) is applied to the secret image to reduce the correlation between neighboring pixels, which makes the stealth more robust, and CAEDLF is a deep learning framework that integrates CNN and Autoencoder to effectively reveal hidden information in images. The experimental results show that the proposed hybrid approach achieves high PSNR (up to 49.5193 dB), SSIM (up to 0.9876), and BPP (up to 0.39 bps), demonstrating excellent image quality and data hiding ability, respectively. The CAEDLF model is able to effectively extract hidden secret images from modified steganographic

images with high accuracy. Ultimately, the combination of LSB, DCT, and CNN-CAEDLF autoencoder provides a robust, secure, and imperceptible image steganography technique while improving the steganalysis process to identify and extract covert data embedded within digital imagery.

2- The authors of [46] An innovative approach to image steganography by using CNNs with improved generalization capabilities is proposed to hide two secret images inside a single image. In this paper, the researchers focused on overcoming the traditional limitations, including low adaptability to different image types, weak detection, and low payload capacity, by leveraging FCDenseNet for feature fusion and extraction. The CNN is designed to learn complex spatial features, allowing the secret data to be seamlessly embedded into the cover image while maintaining its quality.

This method used an extensive training dataset and an improved loss function to balance the security and accuracy of data embedding. Experimental results showed that the proposed approach achieved an average (PSNR) of 35.85 dB, ensuring that the embedded data cannot be perceived. The model showed strong resistance to Steganalysis tools, achieving an AUC $\approx$ of 0.5, which is a near-random guess against StegExpose. This demonstrates the power and effectiveness of the proposed approach. The study concludes that SteganoCNN significantly improves image steganography by providing an efficient, secure, and suitable solution for modern applications in secure communications and data protection.

3- J. Liu et al [47] The researchers presented a novel approach to improve image steganography using a self-supervised convolutional neural network (SS-Net). The paper focused on effectively addressing the suppression of hidden messages in stego images without relying on cover-stego pairs by leveraging self-supervised learning. The proposed method allowed the model to automatically learn relevant features from the image data, significantly reducing the reliance on labeled training data. The SS-Net model was designed with two main groups: the first group is a technical unit that reduces spatial correlation between pixels and removes secret messages while maintaining image quality, and the second group is an enhancement unit that enhances texture details while reducing visual artifacts. Experimental results showed that the method used in this paper maintained a high image quality SSIM $\approx$ of 0.99 and achieved a high message suppression rate BER $\approx$ 0.5. The study concluded that using self-learning with CNNs opens up new possibilities for steganography sanitization. This provides a scalable and efficient solution that does not require extensive data, making it highly applicable in data-constrained operational environments.

4- In [48] This paper presents a method for secure image hiding by combining the discrete wavelet transform, image obfuscation techniques (namely, pixel swapping and quantum image encryption), and convolutional neural networks. This paper aims to enhance the security of embedding by encrypting secret images. It first uses pixel swapping and quantum image encryption, then applies the discrete wavelet transform to securely embed the hidden information into the cover image. The smoothing process is used to improve the quality of the embedding image, and the CNN model is used to improve the quality of the extracted secret image. The proposed method in this work not only increases the embedding capacity but also aims to increase the security of the embedding process and maintain the fidelity of the stego image. The results showed that the used method reduced the detection rate of steganalysis tools due to the use of image encryption before the embedding process, which significantly enhances the security. Also, the PSNR values ranged from 43.2671 dB to 48.9779 dB. It also improved the SSIM values, which indicates strong resistance to conventional and advanced detection methods as well. This paper concludes that the combination of convolutional neural networks with DWT and image encryption techniques provides effective and secure stealth and is suitable for applications where high embedding capacity and undetectability are essential and important.

5- The authors of [49] A comprehensive method for image steganography was proposed, the method used combined and convolutional neural networks. where the study focused on using

DTCWT to transform images in a way that allows more secure data embedding by preserving important image features. SVD was used to decompose the image into its singular values, which are then processed to embed the hidden data. CNN is used to improve the quality of the extracted secret image by learning spatial and frequency domain features. The combination of these techniques ensures high robustness, non-perceptibility, and robustness against steganalysis. Experimental results showed that the proposed method achieved empirical validation, confirming the proposed technique's attainment of a signal-to-noise ratio of 45.93 dB and an embedding capacity of 0.9998 bits per pixel for some test images. The study concluded that the combination of DTCWT, SVD, and CNN provides a highly effective and secure solution with excellent performance in both detection and embedding resistance.

6- J. Bin Wu et al [50] presented a modification-free approach to image hiding using CNN for image classification and data embedding. The research focused on creating a method that does not change the structure of the original image, i.e., generating new hidden images by associating small icons based on the behavioral habits of social media users without the need to modify the original image, which ensures that traditional methods cannot detect hidden data. The main function of convolutional neural networks in this research was to classify small icons and create maps between icons and small sequences, and by arranging icons into puzzle-like images that simulate social media content, the method avoids third-party suspicion. Experimental results showed that this approach achieved minimal visual distortion. In addition, it has high robustness against attacks (0% BER under Gaussian noise) and a high hiding capacity of 170 bits per pixel using 36 icons, each icon containing 5 bits. The study concludes that the modification-free CNN-based stealth algorithm provides an effective solution for secure image communication and reduces the probability of detection while maintaining high image quality.

7- The proposed system [51] provides a comprehensive evaluation of various deep learning-based image steganography techniques with a particular focus on CNN. This paper compares multiple models to evaluate their performance in terms of embedding capacity, image quality, and resistance to detection by steganalysis tools. A diverse set of image datasets, including 6616 images with dimensions of 256*256 pixels, was used to evaluate CNN models. The models used indicated that deep learning techniques significantly outperform traditional methods in terms of efficiency and security. The study demonstrated that CNN-based methods can achieve high embedding capacities while preserving the structural similarity of images. The three models used (U-Net, V-Net, U-Net++) were able to steganography a 256*256-pixel color image within the same dimensions cover image, achieving a constant relative embedding capacity rate of 1 byte/pixel, which is twice as fast as previous techniques that relied on grayscale images. The resulting test images also showed that the difference between the original images and the extracted images was very small, indicating the good performance of the models in data hiding. The study concluded by emphasizing that deep learning techniques, especially CNNs, provide improved performance, adaptability, and higher security by avoiding modification of the original image.

8- The reference [52] A new information steganography technique specifically designed for infrared images is presented. The method combines convolutional neural networks and smooth wavelet transform (SWT) to securely embed the secret information while preserving the integrity of the infrared images. To decompose the infrared image into multiple frequency components, the smooth wavelet transform was used, which allowed for accurate embedding of the embedding data into low-frequency regions that are less likely to be detected. The infrared image was first divided into point and cross-section clusters and preprocessed using SRCNN to improve the spatial resolution, and then decomposed into low-frequency (LL) and high-frequency (HL, LH, HH) sub-bands via SWT. The SE attention mechanism is integrated into the CNN-based predictor (CNNP) to prioritize critical features during embedding. The experiments used two infrared datasets: 113 wind turbine images (90 for training, 23 for testing) and 100 substation equipment images (80 for training, 20 for testing). The CNN was used in this research to improve the embedding process by

learning the best feature patterns from the infrared images and adapting them to different attack scenarios. The results showed the highest PSNR of 62.93 dB at 5000-bit (substation dataset), and an average PSNR improvement of 1000 dB. 0.17 dB compared to advanced methods (such as LPVO and IPPVO), low prediction error (MSE = 36.91, 38% lower than CNNP), and maximum embedding capacity of 30,000 bits per image with PSNR >55 dB. The study concluded that the combination of neural networks and smooth waveform transform provides a good solution for securely hiding infrared images, especially in the fields of remote sensing and military surveillance, to protect the copyright of infrared images.

9- **The authors in** [53] explore the integration of convolutional neural networks with steganography techniques to improve the efficiency and security of image steganography. In this paper, the researchers propose a novel hybrid approach where Steganography Assistant CNN (SA-CNN) is used to dynamically adjust the parameters of the S-UNIWARD algorithm based on the features of the cover image, which makes the embedded data less detectable by steganalysis tools. SA-CNN does not directly deal with detection or embedding, but rather works on optimizing the parameters of the steganography algorithm, which leads to an increase in the error rate of steganalysis tools such as Yedroudj-Net. Using CNN, the model is able to learn complex features and patterns from the cover image, which allows for efficient embedding and less susceptibility to secret information detection. They validated their method by using a diverse dataset, and the experimental results on BOSS Base (10,000 images) and ImageNet (10,000 images) datasets showed that SA-CNN improved the stealth analyzer error rate from 28.2% to 37.2% on similar datasets and from 46.0% to 49.1% on dissimilar datasets. The embedding rate was fixed at 0.4 bits per pixel (bpp). While the discrete version of SA-CNN performed less than expected (error rate dropped to 18.1%), the continuous version demonstrated robustness against detection. The study concluded that steganography with the help of convolutional neural networks represents a major advance and development in the field of image stealth because it provides a robust solution for secure data transmission and communication.

Table 2 shows a summary of related work covered in this paper.

Table 2. Summary of related work covered in this paper.

<i>Ref</i>	<i>Research objectives and hypotheses</i>	<i>The method used</i>	<i>Results and findings</i>	<i>Achievements and significance</i>	<i>Limitations and future work</i>
[45]	The main objective of this study, conducted by the researchers, is to present an effective approach for image steganography by using a combination of LSB, DCT, and a convolutional automatic decoding model with CAEDLF-based encoding and decoding. The researchers' aim of this study was to improve the	The researchers used least significant bit techniques to hide the secret data inside the least significant bits in the cover image. They then applied DCT to the secret image to reduce the correlation between neighboring pixels. They then used DCT coefficients to replace the LSB of the cover image. They then used a CAEDLF model that combined CNN and an autoencoder to reveal the hidden information in the hidden image.	The proposed technique using LSB and DCT with CAEDLF showed good results in terms of SSIM, image quality PSNR, and hidden data amount BPP, where the modified image maintained high SSIM and bpp values, indicating the effectiveness of the method.	The proposed method showed high performance in terms of security, imperceptibility, and image quality, making it a seminal advancement in image steganography and image analysis.	There are no specific limitations to the study in this research, but the researchers suggested that improvements could be made by exploring more advanced auto-coding models and using larger, higher-quality data.

	robustness and strength of the steganography technique and also to improve the analysis process.				
[46]	A new model of SteganoCNN is proposed, which can efficiently embed and extract two secret images into a single carrier image. The researchers hypothesize that the model can achieve high-capacity image steganography while guaranteeing the integrity and security of the hidden image.	The researchers used three hidden network structures inside the CNN: regular SteganoCNN, U-Net, and FCDenseNet, where the vector image connected to the two secret images is the input to the encoder and the steganographic image is the output. The decoder consists of two extraction networks to reconstruct the two secret images with the steganographic image.	The empirical findings demonstrate the proposed model demonstrates superior performance metrics, achieving higher PSNR and SSIM values compared to existing methods, and payload capacity, as the payload capacity = 47.92 bpp. Also, the stego image showed good resistance against analysis detection.	The Stego CNN model achieved a high payload capacity = 47.92 bpp, and this study maintained the integrity of the visual image and showed good resistance to analysis detection.	The authors state that in the future, they plan to further improve the model by reducing the number of parameters and achieving faster masking and retrieval operations and also aim to implement the solution on mobile devices.
[47]	This work advances the field by proposing an effective sterilization method for image steganography using a self-supervised convolutional neural network (SS-Net). The researchers aimed to reduce storage and computational costs, reduce dependence on hidden and cloaked image pairs, and improve training efficiency.	The researchers proposed an SS-Net network that included a purification unit and an enhancement unit. They used the purification unit to take samples by mixing pixels and centrally masked convolutions, and other blocks of expanded convolutions used to remove secret messages while maintaining image quality. The enhancement unit was used to improve image details and boundaries.	The empirical findings demonstrate that SS-Net effectively removes secret messages embedded by steganographic algorithms, including DMAS, GMAS, and LSB, and maintain high image quality. The method achieves a high bit error rate for the extracted secret messages.	The proposed SS-Net method can fully detect secret messages in stego images without prior knowledge of the specific steganography algorithm. This makes the method very effective for real-world applications in social networks.	The researchers indicated that the method used is limited to dealing with known steganography algorithms and that more research is needed to expand its capabilities to adapt to new steganography techniques. They indicated that future work could focus on improving the efficiency and robustness of the model to handle a wider range of steganography scenarios.

[48]	The main objectives of this research are 1- Developing a technique for information steganography that can effectively steganography the secret images inside the cover image 2- Improving the quality of the steganographic image using the smoothing process 3- Improving the quality of the extracted secret image using CNN.	The methodology involves three steps: 1- Select the best suitable cover image by comparing the cover image with the secret image. 2- Encrypt the secret image using pixel swapping and quantum image encryption. 3- Apply DWT to the original image and the encrypted secret image and then mix the resulting frequency components. 4- Apply DWT in reverse to generate the steganographic image. 5- Improve the quality of the steganographic image using smoothing. 6- Extract the secret image from the stealth image and enhance its quality using a CNN model.	The results showed that the proposed technique provided high quality stealth images with PSNR values ranging from 41 dB to 43 dB before the smoothing process and up to 44 dB after the smoothing process. Also, the NCC values were high.	The proposed technique showed significant improvement in the Visual quality of the extracted secret image and the hidden image, and also the combination of the proposed techniques makes the proposed method more secure and effective for practical applications.	The proposed study could not explore the robustness of Resilience of the method to adversarial threats such as stealth analysis or image processing. Subsequent investigations could systematically assess the method's efficacy under different attack scenarios and discovering ways to further improve its robustness and security.
[49]	The main objective of the study is to create a highly secure image steganography algorithm that can effectively steganograph images within the cover image while maintaining the quality of the steganographic image. Also, the researchers aim to use CNN to optimize the quality of the secret image.	The proposed methodology included the following steps: 1- Apply DTCWT to the cover image to be able to obtain two sets of wavelet coefficients. 2- Using the modified image encryption algorithm, the secret image is encrypted. 3- Apply SVD to the real part of the coefficients and to the encrypted secret image. 4- To generate the stego image, DTCWT is applied in reverse. 5- Using the reverse process, the secret image is extracted from the stego image.	The proposed method achieved SSIM values greater than 0.99 in all cases, with PSNR values ranging from 45.51 to 30.08 dB for the captured image and 45.93 dB for the extracted secret image.	The proposed method demonstrates its effectiveness in steganography of secret images within a cover image and at the same time tries to maintain the quality of the stego image. The use of CNN-based post-processing improves the quality of the extracted stego image, making the system reliable and robust.	The proposed method demonstrates its effectiveness on steganography of secret images within a cover image and at the same time, tries to maintain the quality of the stego image. The use of CNN-based post-processing improves the quality of the extracted stego image, making the system reliable and robust.

[50]	The study in this paper aims to validate the efficacy of the proposed algorithm in terms of bit error rate, robustness, capacity, and rationality of the content of the stitched images.	In this study, the researchers used a CNN to train and classify a set of small icons. These icons were then stitched together based on people's behavioral habits on social media platforms to create a hidden image that represents the secret message. To enhance the robustness of the algorithm, the researchers introduced overlapping samples into the training set.	Empirical evaluations verify that the algorithm exhibits strong resistance to attacks. defense ability and can improve stealth capability compared with traditional stego algorithms without modification.	This algorithm can steganographically detect secret messages with high capacity in steganographic images without the need to modify the original vector. This makes it safe against traditional steganographic analysis and also improves the steganographic capability compared to traditional algorithms.	This study adopted only 32 small libraries, and it is possible in the future to build a larger icon library to expand the algorithm even more.
[51]	The study aimed to determine the architecture that achieves the best performance in terms of image quality, image reconstruction, and embedding capacity.	In this study, the researchers implemented three information steganography techniques based on deep learning by using (U-Net, V-Net, and U-Net++) as encoding data. They also designed a unique and powerful decoding architecture that can extract the secret image from the embedding image. The researchers trained and tested models on a set of secret and implicit image data.	The experimental results show that the U-Net-based encoder outperforms the (V-Net and U-Net++) encoders in terms of various performance metrics, such as (MSE), (PSNR), (SSIM), Entropy, and (BRISQUE) score. The U-Net encoder produces pristine stego images and accurately reconstructed secrets, preserving fidelity.	The study demonstrates the potential of U-Net-based image steganography for real-world applications, such as healthcare, scientific data management, and defense, where secure data transmission and storage are crucial.	The researchers acknowledge the need to explore the integration of encryption techniques with the proposed steganography methods to further enhance the overall security. Additionally, investigating the robustness of the techniques against advanced steganalysis attacks could be an area for future research.
[52]	The main objectives of this research are to improve the accuracy of infrared image pixel prediction by combining SWT and CNN, and also to develop an inverse infrared image steganography algorithm with high non-perceptibility and watermarking	The input infrared image is divided into two groups: the first group is the Dot group, and the second group is the cross group. Then, they used the super-resolution convolutional neural network (SRCNN) to process the cross-group. Then, they applied SWT to decompose the low- and high-frequency sub bands of the image. Then, they used the CNNP-based prediction model with	The empirical findings demonstrate that the proposed SSCNNP (SRCNN followed by CNNP) model exhibits enhanced predictive precision at the pixel level relative to competing approaches. The PSNR values of the watermarked images are also higher, indicating better imperceptibility.	The researchers demonstrated that their proposed SSCNNP model outperformed other algorithms in terms of the ability to watermark infrared images and imperceptibility.	The authors emphasized the need for the experimental images to be close to the real-time images and to provide sufficient diversity to ensure the effectiveness and feasibility of the algorithm. they also suggested exploring optimized CNN architectures coupled with frequency-domain wavelet analysis to simultaneously

	capability.	attention to improve the prediction accuracy. Then, they performed inverse embedding based on the prediction error using a histogram transform.			enhance computational efficiency and model performance.
[53]	The researchers aimed to use the steganography-assisted CNN (SA-CNN) to modify the parameters of the S-UNIWARD algorithm, making it more effective and adaptive to cover images. This is expected to increase the algorithm's resistance to discovery by steganalyzers.	The researchers used the BOSSBase 1.01 image dataset to train and evaluate their models and used the S-UNIWARD algorithm as the steganography method and the Yedroudj-Net model as the steganalyzer. The SA-CNN was trained to predict the optimal multiples of the S-UNIWARD parameters to maximize the error rate of the Yedroudj-Net model.	The researchers found that using the SA-CNN to adjust the S-UNIWARD parameters increased the error rate of the Yedroudj-Net steganalyzer by 8.1 percentage points when tested on a similar dataset, and by 3.1 percentage points when tested on a dissimilar dataset. They also found that modifying the wet cost parameters and epsilon in addition to the sigma parameter, had a significant impact on the effectiveness of the approach.	The researchers were able to increase the error rate of a state-of-the-art steganalyzer by up to 14.4 percentage points, indicating a significant improvement in the effectiveness of the steganographic algorithm.	The researchers were unable to achieve comparable results with a discrete output space for the SA-CNN, likely due to the limited options available in the discrete space. Future work could explore alternative approaches to incorporating machine learning into steganographic algorithms, as well as testing the method against additional steganalysis techniques.

5. Performance Comparison of image steganography-based on CNN

Table 3 Comparison between the most prominent metrics used in the experimental results, robustness against attacks, the role of CNN in image steganography.

Table 3. Comparison between the most prominent metrics used in the experimental results.

Ref	Payload Capacity (bpp)	PSNR (dB)	SSIM	Robustness Against Attacks	CNN Role	Notes
[45]	0.48 bpp	49.5193	0.9876	It resists Statistical Steganalysis attacks, detection attacks, and prevents unauthorized information extraction.	CNN is used to hide images securely, and also the convolutional layers in CNN are used to extract important features from the input image, and later these features are used to detect the presence of hidden information.	Suitable for high-security, high-quality applications.

[46]	47.92 bpp (Because two images are hidden in one carrier image, this doubles the amount of hidden data compared to traditional research) .	35.852	0.981	Resists steganalysis attacks by keeping the hidden image indistinguishable from the cover image.	CNN architecture facilitates both embedding and extraction of secret data within cover images, while the SteganoCNN variant employs CNN to simultaneously encode dual secret images with optimized reconstruction fidelity.	High payload capacity and adaptability to diverse image types.
[47]	Not mentioned	49.00888	0.99415	Resisting Steganography attacks by Preventing Covert Communications	CNN was used to remove hidden messages in steganography images and also maintain image quality, while SS-Net was used to purify images and improve details.	Excels in sterilizing steganographic images with minimal distortion.
[48]	It was not mentioned because the research focused on the quality of the hidden image and improving security.	48.9779 (after smoothing)	0.9996	Resists Steganalysis attacks, and DWT embedding obscures prevents discovery of hidden data.	CNN improves the quality of the extracted secret image by enhancing the features.	The research uses encryption and discrete waveform transformation for image steganography and also uses CNN to improve image quality.
[49]	It is not indicated because the capacity of the embedding depends on the size of the embedded secret image.	45.5152	0.9998	It resists steganalysis, resists noise, and also prevents unauthorized extraction.	The system enhances the fidelity of reconstructed secret images through noise suppression and visual quality optimization.	Outstanding in robustness and extraction accuracy.
[50]	170 bits/image (Resulting from the use of a mosaic of classified icons without modifying the original image)	Not mentioned	Not mentioned	Robust against Salt & Pepper noise (up to 0.6 intensity), filtering (mean/median) and Steganalysis resistance	It classifies small icons (AlexNet) to assign binary data to icons and also enhances robustness by training on icons that have been subjected to noise and compression attacks.	High security and concealment efficiency, suitable for covert communications.
[51]	1 bpp	38.00	98.75	Resists deep learning-based steganalysis by reducing detectable artifacts in stego-images	Serve as adaptive encoders (U-Net, V-Net, U-Net++) to embed secret data into cover images while optimizing stealth and payload.	Demonstrates stable performance across multiple datasets with the potential to serve multi-purpose utility such as defense and

						healthcare.
[52]	30,000 bits/image	62.93	Not mentioned	The paper explicitly resists detection by steganalyzers (e.g., Yedroudj-Net) by reducing prediction errors and improving PSNR	Improves pixel prediction accuracy in infrared images. It processes half of the image using SRCNN and predicts the other half, which reduces prediction error and enhances steganography performance.	Tailored for thermal imaging applications with specialized datasets.
[53]	Not mentioned	Not mentioned	Not mentioned	resists steganalysis attacks, particularly those using deep learning-based detectors like Yedroudj-Net	Dynamically adjusts steganography parameters to make hidden data harder to detect, increasing Steg analyzer error rate from 28.2% to 37.2%.	Balances between modern CNNs and traditional steganography for practical use cases.

6. Conclusion

This study comprehensively and talked about the field of information steganography in images using deep learning, it emphasizing its effective role in protecting sensitive data and transferring important data confidentially. The research focused on data steganography methods that use convolutional neural networks due to their significant role in improving and developing the capacity, robustness, and quality of steganography techniques. The main performance measures were also addressed, and their importance in the field of information steganography was clarified to evaluate the accuracy of the extracted images and their conformity with the original image.

This paper also showed how CNN can be combined with traditional techniques in steganography by addressing nine recent research works and analyzing them, delineating the advantages and constraints of each research method. The strengths of modern steganography techniques lie in several areas, including security, as the encryption-based methods mentioned in this research have succeeded in improving analysis resistance by up to 9%. As for the embedding capacity, some methods were able to achieve up to 170 bits and 30,000 bits per image. As for the hybrid methods, they achieved PSNR values of up to 49.51 dB and SSIM values of 0.9876, indicating that they maintain visual clarity.

Finally, this study confirmed that image steganography is broader than just data hiding, but rather works as a prominent tool for protecting privacy and information security. By providing an analysis of the current methods, this research provides a strong foundation for progress in this field. With the continuous development of AI, it is expected that CNNs will play a more active role in the field of image steganography.

7. References

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