

Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography

Uchenna J. Nzenwata ^{1,✉}, Folasade Ayankoya ¹, Simon Awodele ¹

¹. Department of Computer Science, Babcock University, Ilishan-Remo, NGA

Received: August 28, 2025 | Review began: June 23, 2026 | Review ended: August 30, 2026 | Published: October 01, 2026

© Copyright 2026

This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract

Reversible image steganography is a steganography system that hides secret data in an image cover medium without arousing suspicion, and it is defined by the ability to reconstruct the cover medium with no visible distortion after the steganography system has been decoded by extracting the hidden data. The most common issue with image steganography systems is a lack of payload capacity, which is caused by the inappropriate selection of a cover medium. In this paper, a solution is proposed by employing Histogram of Pattern Set to prepare the image dataset for use in training the Support Vector Machine (SVM) and Deep Neural Network (DNN) algorithms. The precision values for SVM and DNN were revealed to be 83.39 and 98.11, respectively; the recall values for SVM and DNN were discovered to be 81.85 and 96.29, respectively; and the F-score values for SVM and DNN were discovered to be 82.61 and 97.19, respectively. Because the DNN selection model outperforms the SVM selection model, it was chosen as the cover image selection model for the implementation of reversible image steganography.

Categories: AI applications, Security and Privacy, Machine Learning (ML)

Keywords: support vector machine (svm), steganography, cover image, payload capacity, neural networks

Introduction

The ability to hide information in a cover image without raising any suspicion is known as image steganography. In research, the goal of steganography is explained to be an act of sending hidden data across public channels without arousing suspicion [1,2]. The most common method is to embed the secret data into the cover object by slightly changing the content of the cover. Because digital images are extensively used all over the world, they are frequently used as covers in steganography. To ensure security performance, contemporary steganography minimizes steganographic distortion caused by changes to a cover image [3]. Image steganography is more prevalent than other types of steganography because images, in general, are highly suitable media for steganography due to their enormous capacity and high redundancy [4-6].

Aside from image steganography, there are other forms of steganography based on the nature of the cover medium [7]. Image steganography uses the image as a cover medium; video steganography uses video or image frame sets as a cover medium; audio steganography uses audio file formats, where secret information is embedded within the audio bits; text steganography hides information within the position or the array indices of each character of the original text without any distortion in the meaning of the original text [8]. Also, steganography has been extended to include network steganography, where secret information is hidden using Internet Protocol (IP) address bits [9], and deoxyribonucleic acid or genome structures [10].

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

Image steganography has been identified in research [11-13] to have numerous use cases in security for covert data storage and private communication, protection of data integrity from alteration, access-control tools for digital content sharing, secure online voting, private banking, military purposes, and many more. Although steganography has gained much usage, there are limitations to the downside of steganography. Research [14] noted that steganography can be misused by terrorists for criminal activities as a tool in the hands of attackers to compromise privacy, especially in the film industry, where films are plagiarized, and can also be used for stealing personal information via social networks.

Image steganography was emphasized in research [15] to be faced with a triad challenge of payload capacity, security, and robustness, and this challenge limits the rate at which image steganography finds its application in confidential communication, data storage, and other similar applications. Research [16] stated that a proper cover image selection for image steganography always has favourable influences on boosting the security and payload capacity of image steganography. This implies that without a good measure in place for a proper cover selection, the strength of the steganography system is not guaranteed. The strategies for picking a suitable cover image were provided. Although these strategies included a lot of difficult mathematical calculations spanning from spatial domain techniques to frequency domain techniques. Other than the complexity associated with the spatial and frequency domain techniques, it was also discovered that these methods have the tendency to produce slight distortions in the steganographic contents, hence making it impossible to have a reversible image steganography. The study by Kadhim [17] suggested that classification methods could be used to make quality cover selections for image steganography. Also, the study used a dual-tree complex wavelet transform to ascertain a payload capacity. The focus was on selecting a region on the cover image with the highest number of redundancies. Finally, it suggested again that the histogram of pattern set can be used for a classification algorithm with selection criteria based on super-pixel and coefficient-plane-selection.

This recent work emphasizes cover selection as a significant problem that, if chosen incorrectly, might impede high-quality reversible image steganography. As a result, the Deep Neural Network (DNN) model is developed in this study, and it is supported based on the actual performance comparisons with Support Vector Machine (SVM).

Review of related studies

The quest to obtain good image steganography stems from the cover image selection process. This has been an actual fact in image steganography, where appropriate cover images are to be selected for sizeable secret messages. In an attempt to obtain a cover selection model, a fuzzy classification algorithm by Esfahani et al. [18] was used to identify cover images by calculating their Gray Level Co-occurrence Matrices. Some of the cover images were able to be selected based on their gray level but with poor security implementation. Also, the model could only achieve a reasonable selection level within gray-colored images. It was believed by Wang et al. [19] that steganographic distortion is attributed to the cover selection process, so they designed an algorithm to combine cover-selection and payload-allocation, so that the optimal stego-covers can be obtained without distortion. Their result shows that there was no steganographic distortion, but it is peculiar to a particular method. Hence, it cannot be used or adapted to any form of steganographic technique.

An efficient cover image selection framework was implemented by Abed et al. [20] based on spatial block analysis and Discrete Cosine Transform methods. The outcome of the study had a good visual quality, but with poor security, and could not be automatically selected as against the objective of the study. The study by Wendzel et al. [21] attributed the poor security in Abed et al. [20] to the level of knowledge the embedder had prior to cover selection, and they improved the security of the steganographic system using simple statistical measures. Duan et al. [22], Kuznetsov et al. [23], and Pandey [24] had collectively carried out image cover selection steganography methods based on image blocks similarity. Kadhim et al. [17] and Singh [25] proposed an adaptive cover selection steganography method which was adopted from the methodology used in Kadhim et al. [5], where the statistical features of image blocks and their neighborhood were used for the selection. Studies by Kadhim et al. [5], Kadhim et al. [17], and Singh [25] were differently examined with features based on wavelet and cosine transformations. The outcome of using the image blocks proved to have good security measures, but the complexity led to poor payload capacity. Wang and Zhang [26] used the Maximum Mean Discrepancy between two adjacent cover images to measure the discrepancies between them and the corresponding

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. *Cureus J Comput Sci* 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

secret images. The work improved the security of the system, but was limited in computational complexity and payload capacity. Subhedar [27] proposed a new framework for the optimal choice of cover image from an image database based on statistical texture analysis, and a nonlinear support vector machine was employed to classify a suitable cover from the image database. The outcome of the study shows that poor detection accuracy by the steganalyser confirms the efficacy of the proposed cover selection.

Deep learning approach was used by Qin et al. [28] to reduce the amount of distortion in the stego-image through a sparse adversarial perturbation by cover enhancement during the cover selection process. The outcome was able to improve the payload size and the security of the existing model, but it requires extensive experiments to show the strength of the system.

Recent studies published in 2024 and 2025 have further advanced the landscape of cover image selection and deep learning-based steganography, underscoring the need for more sophisticated selection approaches. Chahine and Kim [29] proposed an optimization-driven neural cover selection framework published at NeurIPS 2024, in which pretrained generative models, specifically Denoizing Diffusion Implicit Models (DDIM) and BigGAN are leveraged to select cover images by minimizing message recovery error within the latent space. Applied to the ImageNet, CelebA-HQ, and AFHQ-Dog datasets, their method reduced message embedding error rates by over 50% compared to randomly selected covers, achieving PSNR values in the range of 21.41-26.34 dB, while also demonstrating strong resistance to steganalysis with detection rates as low as 0.0% at 1-2 bpp. This work reinforces that intelligent cover selection, rather than random selection, is a critical determinant of steganographic security and payload efficiency.

In the area of reversible image steganography, Liu et al. [30] introduced RISRANet in 2025, a dual-branch invertible neural network incorporating shuffle attention mechanisms and dilated convolutions for multi-scale feature extraction. Evaluated on the Microsoft COCO and DIV2K datasets, RISRANet achieved a Peak Signal-to-Noise Ratio (PSNR) of 57.20 dB and Structural Similarity Index Measure (SSIM) of 0.9994 on DIV2K, and 51.20 dB PSNR and 0.9978 SSIM on COCO, with steganalysis resistance (StegExpose AUC) of 0.5010, closely approximating ideal imperceptibility. Similarly, Zhou et al. [31] proposed a steganographic framework combining latent space embedding with a smart decoder selection module in 2025, achieving a Secret Recovery Accuracy exceeding 98% and an SSIM of 0.99 across ImageNet and MetFACE datasets. These studies confirm that combining deep learning with intelligent selection mechanisms, whether for cover images or for decoders, significantly enhances both capacity and concealment quality in steganographic systems.

From the perspective of image classification within the steganography domain, Alrusaini [32] evaluated five deep learning architectures for steganalysis in 2025, reporting that EfficientNet achieved the highest baseline accuracy of 80.56%, with a precision of 83.13% and recall of 76.67% on the BOSSBase dataset. Li et al. [33] proposed an active learning-based steganalysis model integrating deep reinforcement learning and convolutional neural networks, achieving an F-measure of 93.152% on BossBase and 91.834% on BOWS-2 in 2025. Furthermore, Almhilbdi et al. [34] demonstrated in 2025 that a hybrid CNN-GRU model attained a multi-class steganography detection accuracy of 98% on a five-category LSB steganography dataset. These classification results in the steganography domain provide relevant benchmarks against which the proposed cover image selection model in the present study can be contextualized.

Materials And Methods

The materials used for this study are the Microsoft COCO dataset, Histogram of Pattern Set (HoPS), SVM and DNN. Precision, recall and F-score are the evaluation metrics used.

Image histogram pattern

Image histograms are an important tool for inspecting images. This technique permits the images to be analyzed so as to act as a graphical representation of the tonal distribution in a digital image. In this study, this technique was used to identify images of similar distribution pattern using the Euclidean distances given in Equations (1) and (2). This approach makes the image classification easy.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. *Cureus J Comput Sci* 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

$$d = ((p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_n - q_n)^2)^{1/2} \quad (1)$$

Where d is the Euclidean distance, p_1, p_2 and p_n are the measurable values for the first instance of data and q_1, q_2 and q_n are the measurable values for the second instance of data.

Since this study makes use of color images, therefore it seeks to measure the bit distance between each pixel's Red, Green and Blue (RGB) values. Equation (1) was therefore modified to accommodate the parameters of the colored images used. These parameters are the Red, Green and Blue (RGB) pixels. Hence, Equation (2) was yielded.

$$\text{Euclidean Distance} = ((R_1 - R_2)^2 + (B_1 - B_2)^2 + (G_1 - G_2)^2)^{1/2} \quad (2)$$

Where R_1 and R_2 are the red pixels of the two compared images; G_1 and G_2 are the green pixels of the two compared images; and B_1 and B_2 are the blue pixels of the two compared images.

In Table 7, once a pair of images are identified to have similar histogram patterns, such a pair is flagged as '1' otherwise, it is flagged as '0'. Table 7 presents the Euclidean distance values to twelve (12) decimal places. The occurring differences in the decimal place values are treated as noise. If the difference is greater than or equal to 0.4 then the outcome is taken as 0. Otherwise, the outcome becomes 1.

Image 1	Image 2	Euclidean distance/Hist pattern	Outcome
000000000009.jpg	000000000008.jpg	Img1: 27451.120414292745 Img2: 27451.120414292745	1
000000000022.jpg	000000000093.jpg	Img1: 49711.31076525744 Img2: 49711.31076525744	1
000000000097.jpg	000000000103.jpg	Img1: 41884.13040758994 Img2: 21567.00340757643	0
000000000118.jpg	000000000141.jpg	Img1: 21034.03109345762 Img2: 35629.35143950841	0

TABLE 1: Histogram pattern values of some randomly selected images for cover selection model

In Table 7, the outcome of a true flag '1' indicates that the pair is a good image steganography pair. On the other hand, the outcome of a false flag '0' indicates that the pair is not a good steganography pair.

Data preparation using HoPS

In order to ease the model training using the unlabeled image dataset, Histogram of Pattern Sets (HoPS) technique was adopted. HoPS was adopted for use in this study because it was found to be an important tool in the study [17], where it was used for image classification and object recognition. The outcome of this technique is a generated comma-separated value (csv) file, which served as a look-up file to the image repository and was used to train the algorithm that classifies suitable cover images and the corresponding secret image.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

The rationale for using the histogram pattern matching is to be able to generate useful colored images that are suitable and appropriate for image steganography, thereby eliminating gray-colored images that may affect the encoding model of a steganography system. Also, the HoPS presents the dataset with binary values (zeroes and ones). These values enable a classifier to make good classification judgements. The outcome of the HoPS is a csv file that serves as a look-up table to the main image file.

The csv file maps all images into a single file. The actualized data size is 250,000 with each image having 512×512 (262,144) pixels per image. The data was divided into 80% training set (200,000 data points; where the cover images and the secret images have 100,000 data points each) and 20% testing set (50,000 data points; where the cover and secret images have 25,000 data points each, and are balanced for both the DNN and SVM classifiers). The training set was used to train the DNN model and the SVM model. These two models are both classification models that were experimented with for classifying the pairs of images, and to ease the appropriate selection of the cover images that are suitable for a particular secret image.

Cover selection model

This study proposed the use of DNN, which was compared with the SVM cover selection model because of the nonlinearity of the dataset. The outcome of this comparison rationalizes the choice of the DNN proposed model.

The cover selection is a classification problem that used the HoPS generated details as parameters. The cover image selection is part of the preparation phase in image steganography before the encoding phase. The goal of this phase is to assist in the selection of a cover image that will be most appropriate for hiding the secret message, as the selection of an appropriate cover image is essential in deciding the efficacy of a steganographic system. This study used the deep learning architecture known as the DNN for the purpose of cover image selection. A traditional machine learning classification algorithm, the SVM was used as the alternative model.

Figure 1 and Figure 2 show how these models can be used to achieve appropriate cover selection processes. The DNN model and the SVM were trained using the dataset in csv format. The csv file maps all the images in the image directory. The models were trained and tested to an acceptable accuracy where an appropriate cover can be selected for a particular secret image.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. *Cureus J Comput Sci* 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

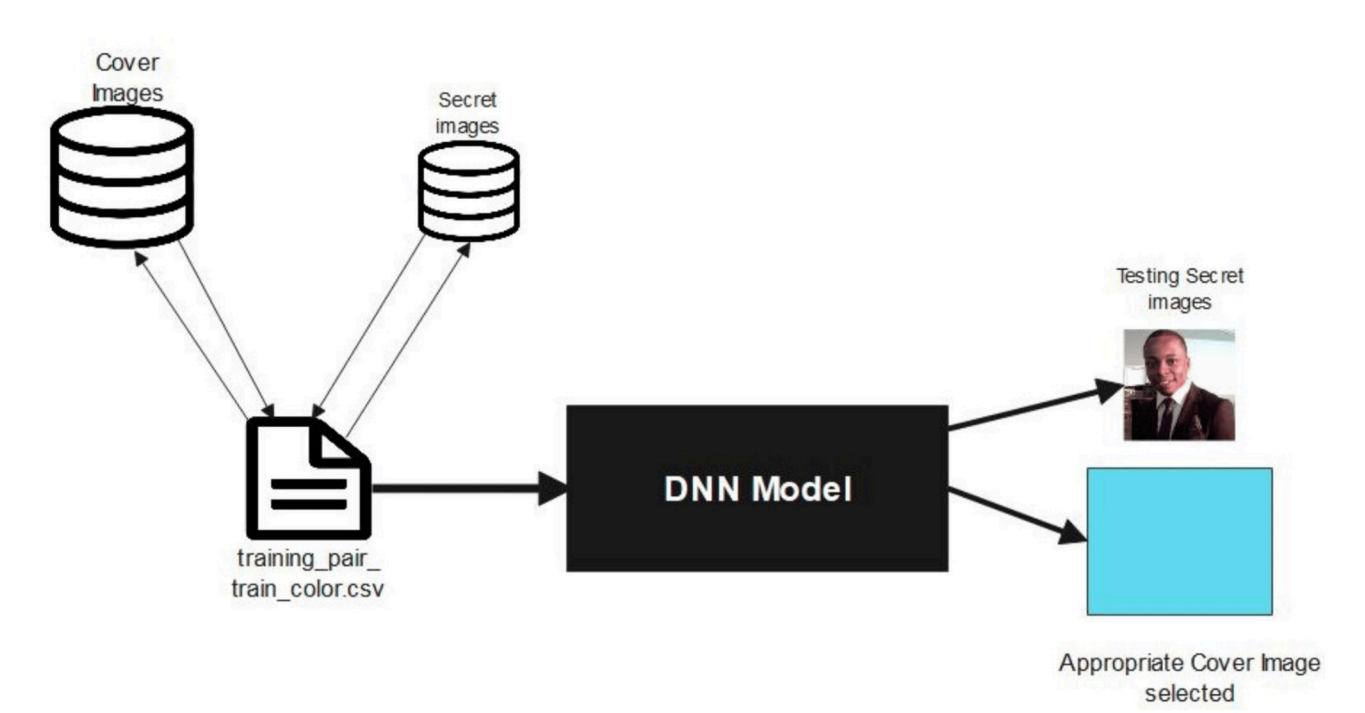


FIGURE 1: Deep Neural Network (DNN) selection model

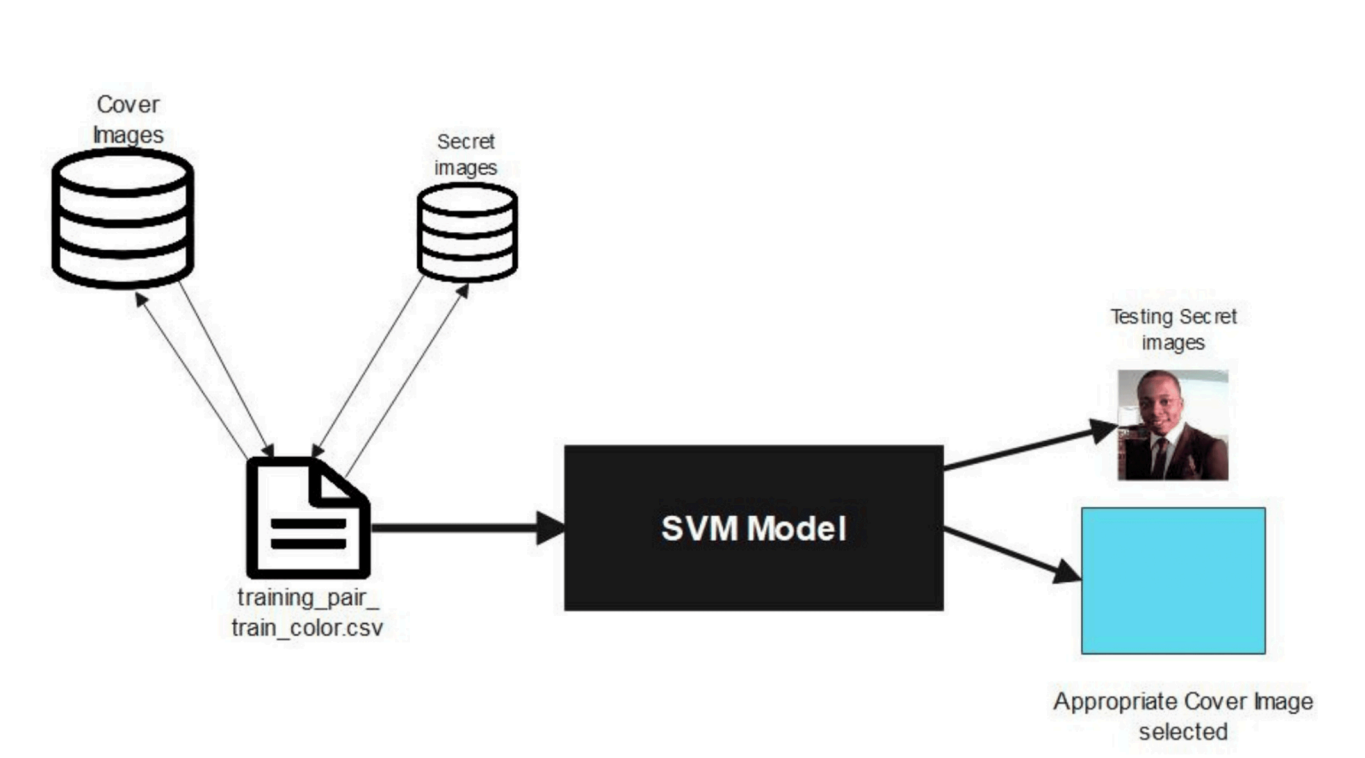


FIGURE 2: Support Vector Machine (SVM) selection model

Implementation and model development

In training the Neural Network (NN) selection model, the weights and the bias parameters of the model were adjusted simultaneously so as to ensure consistent output. Equation (3) was adopted for the forward propagation of the NN training model.

$$z = \sum (w_i \cdot x_i) + b \quad (3)$$

Where:

z : The output of the neuron before applying the activation function. This is the weighted sum of inputs plus a bias term.

w_i : The weight associated with the i -th input. Weights determine the importance of each input in contributing to the neuron's output.

x_i : The i -th input to the neuron. In this case, the inputs are likely derived from the image features (e.g., pixel values or features extracted from the HoPS).

b : The bias term, which shifts the activation function to allow better fitting of the model to the data.

Since the NN has the ability to learn the image features by itself, Equation (3) was modified to limit the number of features to three (3) features, the RGB (512,512, 3) pixel values. This modification yielded Equation (4)

$$z = w_r \cdot R + w_g \cdot G + w_b \cdot B + b \quad (4)$$

Where:

z : The output of the neuron before applying the activation function, similar to Equation (3). It represents the weighted sum of the RGB inputs plus the bias.

R : The Red pixel value of the input image. This is one of the three features used in the DNN model, representing the intensity of the red channel in the RGB color space.

G : The Green pixel value of the input image, representing the intensity of the green channel.

B : The Blue pixel value of the input image, representing the intensity of the blue channel.

w_r : The weight associated with the Red pixel value. This weight determines how much the red channel contributes to the neuron's output.

w_g : The weight associated with the Green pixel value, determining the contribution of the green channel.

w_b : The weight associated with the Blue pixel value, determining the contribution of the blue channel.

b : The bias term, which acts as a threshold or offset to ensure the model can classify beyond the expected output. The document specifies that the bias serves as a 'minimum threshold value' to prevent the model from classifying beyond the desired output range.

In this study, the cover-selection classifier was implemented as a feed-forward Multilayer Perceptron (MLP). Figure 3 presents a conceptual schematic of the model, illustrating the flow of information from the image-derived input features through two fully connected hidden layers to a single binary output node. The schematic uses the three RGB components (R, G, and B) to illustrate the input representation and shows the bias term incorporated into the neuron computations. The hidden layers represent the nonlinear transformation stages, while the output node produces a binary decision, where 1 represents a suitable cover-secret image pair and 0 represents an unsuitable pair. Figure 3 is therefore intended to illustrate the functional arrangement of the classifier, while the exact dimensions of the implemented network are presented in Figure 4.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

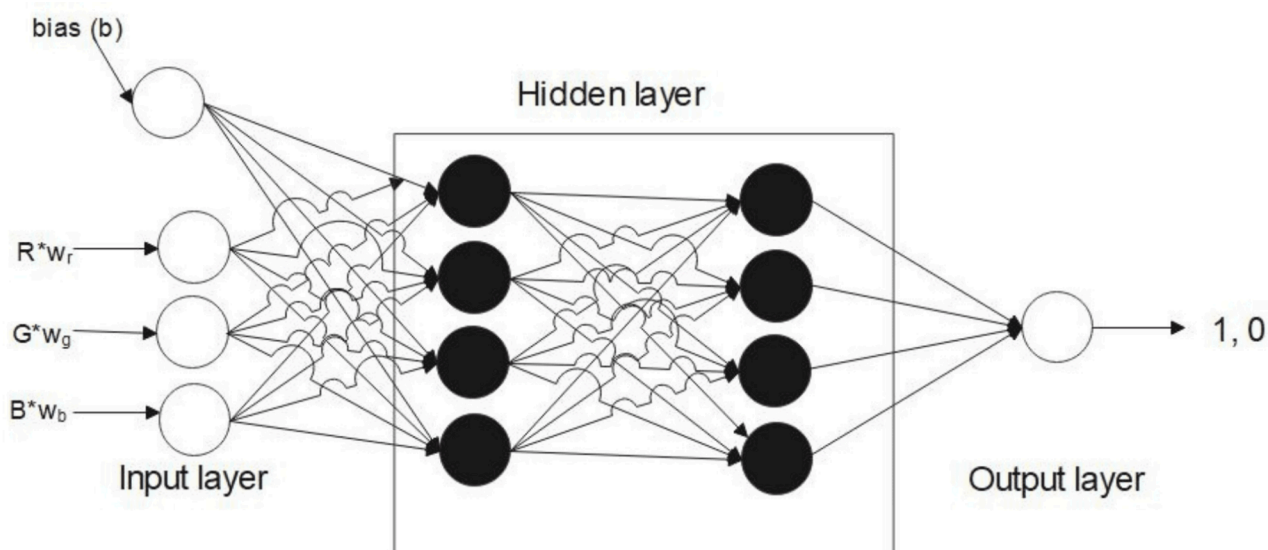


FIGURE 3: Conceptual architecture of the MLP-based cover selection model

MLP, Multilayer Perceptron

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

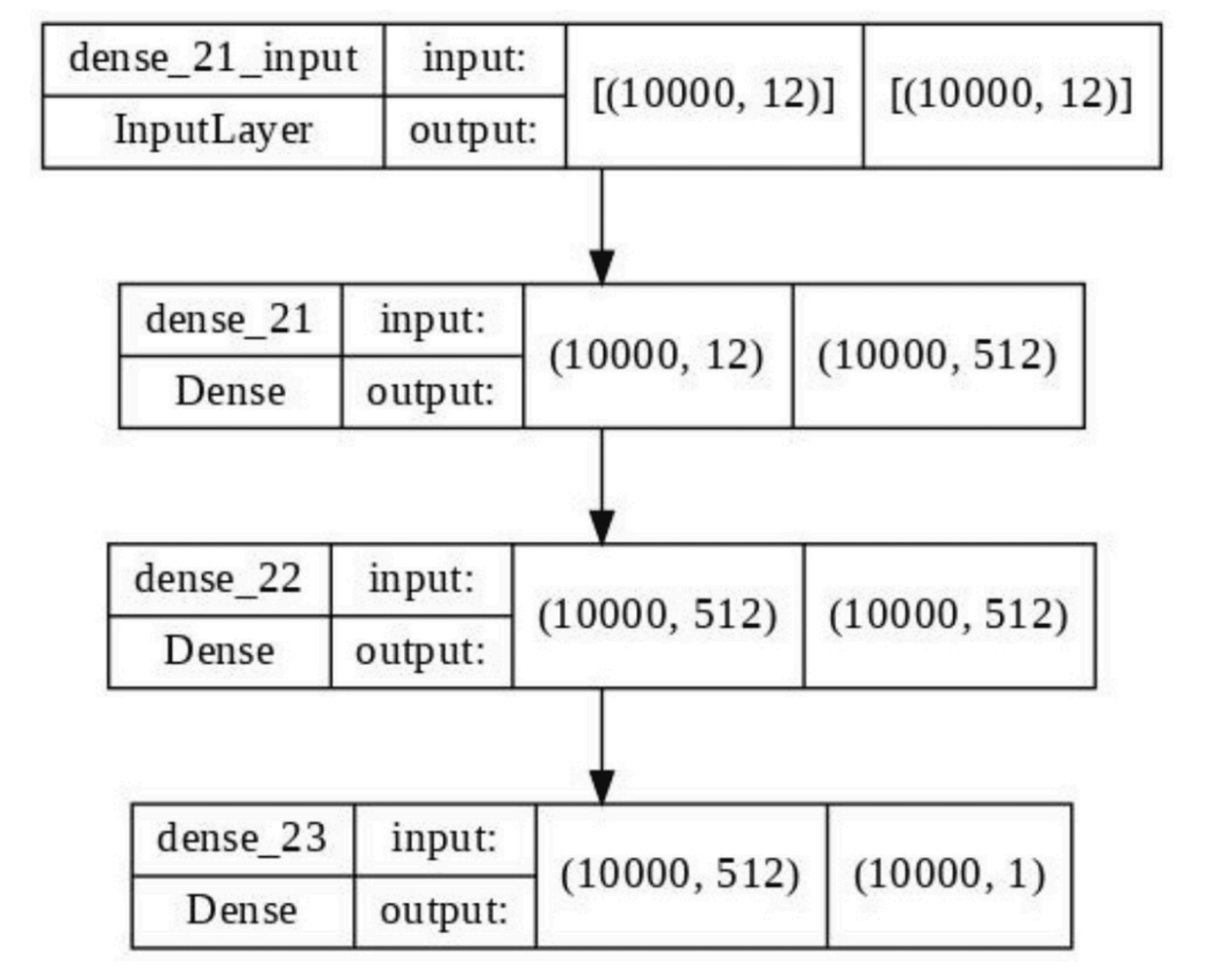


FIGURE 4: Compiled architecture of the MLP-based cover selection model

MLP, Multilayer Perceptron

During model training, the original images, which had a resolution of 512×512 pixels with three RGB channels, were first resized to 64×64 pixels as a preprocessing step to reduce the computational cost associated with processing the high-resolution images. The pixel values were subsequently normalized by dividing each pixel value by 255, thereby scaling the RGB values from the range (0, 255) to (0, 1). These preprocessing operations were performed independently of the training batch size. A batch size of 64 was then used during model training, meaning that 64 training samples were processed before each gradient-based parameter update. The remaining model hyperparameters were configured as presented in Table 2.

How to cite this article:

S. No.	Hyperparameters	Values
1.	batch_size	64
2.	no_of_layers	4
3.	square of image size	Linear (6 * square of image size, 512)
4.	activation function	ReLU: Rectified Linear Unit function; Sigmoid()
5.	learning_rate	0.001: constant
6.	epoch	10
7.	loss_function	Binary cross entropy
8.	model optimizer	Adam: Adaptive model optimizer

TABLE 2: DNN hyperparameters and set values

DNN, Deep Neural Network

Considering the large dataset used for training the model, a batch size of 64 was selected to provide a practical mini-batch size for gradient-based training while balancing computational efficiency and the stability of gradient estimates. The number of layers was set to 4 (1 input layer, 2 hidden layers, and 1 output layer) to have a layer size that would help with the backpropagation of the error after the first batch training. ReLU was used as the activation function for the hidden layers, and sigmoid was used as the activation function for the output layer because it is a binary classification problem. The model solves a classification problem that requires linear data, but the dataset used is a nonlinear data set. Hence, ReLU ensures a linear transformation result; if the function gets a negative input, it simply returns the value 0, but if it receives a positive input, it returns that value as a linear function. The learning rate was set to a minimal value of 0.001, which minimizes the loss in the model and improves how fast the DNN model learns. The epoch defines the number of times a training cycle takes to complete. It was set to 10, which is relatively small. This was done to reduce the time taken for the model training to be completed. The loss function used is the binary cross-entropy because the selection model is a binary classification model; it also aids in reducing the model loss. To optimize the model, we used the Adam optimizer because it is adaptive to any NN algorithm alongside the number of batches used and the static learning rate we adopted.

On the other hand, Equations (5) and (6) were used during the training phase of the SVM selection model. The SVM model takes into its parameter (gamma) the aggregate sum of the pixel bits of the image pair, and selects the cover image whose aggregate pixel bits are similar to those of the secret image pixel bits.

$$\text{aggregate}_{\text{pixel}} = \text{num}_{\text{features}} \times X_{\text{var}}() \quad (5)$$

$$\gamma = \frac{1}{\text{aggregate}_{\text{pixel}}} \quad (6)$$

Where the $\text{num}_{\text{features}}$ is the RGB pixels

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

X = value of each pixel bit

$X_{var}()$ is the predefined function in python programming language used for finding the variance of X.

The SVM selection model uses gamma as its single parameter to define how far the influence of a single training example reaches, and then uses this value to compare a pair of images. If the similarity is high, then an appropriate cover is selected, which represents 1; otherwise 0.

In achieving a minimum error because of the nonlinearity of the dataset, we used the Radial Basis Function Kernel (RBF-K) as the default kernel for the SVM selection model.

DNN algorithm

Train the cover selection model (bDNN) with image sets to obtain image pairs (C_i, S_i)

Input : $C_{source}, S_{source}, t, c$

Output : C_i, S_i

$\Rightarrow n = \sum(C_{source})$

$\Rightarrow m = \sum(S_{source})$

$\Rightarrow t = 1$

for $i = 1$ *to* n

//loop through all cover images from 1 to n

for $i = 1$ *to* m

//loop through all secret images from 1 to n

set $c = arbitrarybiasvalue$

train $bDNN(C_{source}, S_{source})$

if ($C_i == S_i$)

end for

end for

$\rightarrow save(C_i, S_i)$

Results

Experimental setup

The experiments were conducted using the Microsoft COCO dataset, which consists of color images with a resolution of 512×512 pixels, each having three channels (Red, Green, and Blue). The dataset was preprocessed using the HoPS technique to generate a csv file, which served as a lookup table for the image repository. This csv file mapped image pairs and assigned binary labels (1 for suitable steganography pairs and 0 for unsuitable pairs) based on Euclidean distance calculations of their histogram patterns. The dataset comprised 250,000 image pairs, split into 80% training (200,000 pairs, with 100,000 cover images and 100,000 secret images) and 20% testing (50,000 pairs, with 25,000 cover images and 25,000 secret images).

To facilitate efficient training, images were rescaled from 512×512 to 64×64 pixels and normalized by dividing pixel values by 255. The experiments were performed on a computing environment equipped with a 3.2 GHz Intel Core i7 processor, 16 GB of RAM, and an NVIDIA GTX 1080 GPU. The software environment utilized Python 3.8 with TensorFlow 2.4 for the DNN implementation and scikit-learn 0.24 for the SVM implementation.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

The DNN model was configured with four layers: one input layer (3 nodes for RGB values plus a bias), two hidden layers (4 nodes each with ReLU activation), and one output layer (1 node with sigmoid activation). Hyperparameters were set as follows: batch size of 64, learning rate of 0.001, 10 epochs, binary cross-entropy loss function, and the Adam optimizer. The SVM model used the RBF kernel with a gamma parameter to measure the similarity between image pairs based on their aggregate pixel bits. Both models were trained to classify image pairs as suitable or unsuitable for steganography, with performance evaluated using precision, recall, and F-score metrics.

Evaluation result

Precision, recall and F-score were the metrics used to evaluate the DNN and SVM models. Precision is the proportion of the actual appropriate cover images among those labeled as appropriate by the models. To put it in a general way, the number of genuine positives divided by the total number of false positives + true positives. This is represented as shown in Equation (7).

precision = tp / (tp + fp) (7)

Where *tp* is the true positive herein, actual appropriate cover images the model truly classified and, *fp* is the false positive herein, the number of cover images the model wrongly selected as appropriate.

Recall, also known as sensitivity, is the proportion of actual appropriate cover images among the total number of appropriate cover images. In other words, the number of genuine positives divided by the number of false negatives. This is represented as shown in Equation (8).

recall = tp / (tp + fn) (8)

Where *fn* is the false negative herein, the number of cover images the model failed to select as appropriate cover images.

Therefore, Table 3 shows the precision and recall values for the DNN selection model and the SVM selection model.

Model	Precision value	Recall value
DNN Selection Model	98.11	96.29
SVM Selection Model	83.39	81.85

TABLE 3: Approximate precision and recall values for the DNN and SVM selection models
DNN, Deep Neural Network; SVM, Support Vector Machine

Discussion

Experimental analysis

In order to justify the selection of the DNN model, the f-core metric had to be computed using the precision and recall values of each model.

The F-score is the harmonic mean of the precision and recall values, given in Equation (9)

$$F\text{-score} = 2 \left(\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \right) \quad (9)$$

The F-score metric was computed using the precision and recall values in Table 3, this gives the exact performances of these model from the geometric mean point of view.

The experimental results, as presented in Table 3, demonstrate that the DNN selection model significantly outperforms the SVM selection model across all evaluated metrics: precision, recall and F-score. The DNN model achieved a precision of 98.11, a recall of 96.29, and an F-score of 97.19, compared to the SVM model's precision of 83.39, recall of 81.85 and F-score of 82.61. These results indicate that the DNN model is more effective at identifying suitable cover images for reversible image steganography, with higher accuracy in both correctly classifying appropriate cover images (precision) and capturing the majority of relevant cover images (recall).

The superior performance of the DNN model can likely be attributed to its ability to capture complex, nonlinear patterns in the image dataset, which was preprocessed using the HoPS technique. The DNN's architecture, consisting of four layers (one input layer with three RGB nodes, two hidden layers with four nodes each using ReLU activation, and one output layer with sigmoid activation), allows it to learn hierarchical feature representations directly from the RGB pixel values. This capability is particularly advantageous for the nonlinear dataset used in this study, as it enables the model to discern subtle differences in histogram patterns that indicate suitable steganography pairs.

In contrast, the SVM model, which relies on the RBF kernel and a single gamma parameter to measure similarity between image pairs, appears less capable of handling the complexity of the dataset. The SVM's performance, while respectable, suggests that its linear or near-linear decision boundaries are less effective for this classification task compared to the DNN's ability to model nonlinear relationships. The lower F-score of the SVM (82.61) compared to the DNN (97.19) further underscores the DNN's advantage in balancing precision and recall, making it a more robust choice for cover selection.

To further contextualize the performance of the proposed DNN cover image selection model, Table 4 presents a comparative analysis against recently published solutions in the deep learning steganography and cover selection literature (2024-2025). It is acknowledged that direct metric-for-metric comparison is constrained by differences in task definition and evaluation protocol across studies, some papers optimize for image quality (PSNR/SSIM), others for classification accuracy or error rate. Nonetheless, the comparison provides meaningful context for the proposed model's classification performance.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

Study	Year	Method	Task	Dataset	Key Metric	Value
Chahine and Kim [29]	2024	DDIM-based Neural Cover Selection	Cover Selection (optimization)	ImageNet, CelebA-HQ, AFHQ-Dog	Message Error Rate	0.019%–1.85%
Liu et al. [30]	2025	RISRANet (Attention + Invertible NN)	Reversible Steganography	COCO, DIV2K	PSNR / SSIM	57.20 dB / 0.9994
Zhou et al. [31]	2025	Latent Embedding + Smart Decoder Selection	Steganography with Decoder Selection	ImageNet, MetFACE	Secret Recovery Accuracy	>98%
Alrusaini [32]	2025	EfficientNet (DL Steganalysis)	Image Classification (Steganalysis)	BOSSBase	Precision / Recall	83.13% / 76.67%
Li et al. [33]	2025	Active Learning + CNN + DRL	Steganalysis Classification	BossBase, BOWS-2	F-measure	93.152%
Almhlbdi et al. [34]	2025	CNN-GRU Hybrid	Multi-class LSB Detection	LSB Steganography Dataset	Accuracy	98.00%
Proposed DNN Model	2025	DNN + HoPS Feature Extraction	Cover Image Selection (Classification)	MS COCO (250,000 pairs)	Precision / Recall / F-score	98.11% / 96.29% / 97.19%

TABLE 4: Comparative analysis of proposed DNN model against recent published solutions

DNN, Deep Neural Network; DDIM, Denoising Diffusion Implicit Model; NN, Neural Network; CNN, Convolutional Neural Network; HoPS, Histogram of Pattern Set; PSNR, Peak Signal-to-Noise Ratio; SSIM, Structural Similarity Index Measure

As shown in Table 4, the proposed DNN-based cover image selection model achieves competitive results when positioned against the most recently published solutions in the steganography domain. Chahine and Kim [29] addressed cover selection as a latent space optimization problem using generative diffusion models, achieving very low message error rates; however, their framework requires access to large pretrained generative models and does not report classification metrics directly comparable to those in the present study. Liu et al. [30] and Zhou et al. [31] focused on steganographic image quality and decoder selection respectively, demonstrating excellent PSNR/SSIM values and recovery accuracy exceeding 98%, which confirms the broader trend towards neural approaches for selection and embedding quality. Among classification-based methods in the steganography domain, Alrusaini [32] reported a precision of 83.13% and recall of 76.67% using EfficientNet for steganalysis, while Li et al. [33] achieved an F-measure of 93.152% using active learning with CNNs. The proposed DNN model surpasses these classification benchmarks, achieving precision of 98.11%, recall of 96.29%, and F-score of 97.19% on the Microsoft COCO dataset with 250,000 image pairs, the

How to cite this article:

largest dataset used among the compared studies. Almhilbdi et al. [34] achieved 98% accuracy with a CNN-GRU hybrid for multi-class LSB detection, which is comparable to the proposed model but was achieved on a different classification task. These comparisons demonstrate that the proposed HoPS-driven DNN cover selection model delivers classification performance that is not only superior to the baseline SVM model but also competitive with the most current deep learning approaches in the steganography literature, while addressing the specific and underexplored problem of cover image suitability classification for reversible steganography.

The decision to limit the DNN training to 10 epochs was made to reduce computational time, yet the model still outperformed the SVM. This suggests that even with a constrained training regime, the DNN's architecture is well-suited for the task. However, the relatively low F-scores for both models (particularly the SVM) indicate potential for improvement with a larger dataset or increased number of epochs, which could enhance the models' ability to generalize and further reduce classification errors.

The experimental setup also revealed that preprocessing steps, such as rescaling images to 64×64 pixels and normalizing pixel values, were critical in managing computational complexity while maintaining model performance. The use of the Microsoft COCO dataset, with its diverse set of color images, provided a robust foundation for training and testing, ensuring that the models were evaluated on a realistic and varied dataset. These findings support the adoption of the DNN model for cover image selection, as its superior performance metrics suggest it can enhance the payload capacity and security of reversible image steganography systems.

Conclusions

This study addressed the critical challenge of cover image selection in reversible image steganography by proposing a DNN model and comparing its performance against an SVM baseline. Using HoPS for feature extraction, both models were trained on a dataset of 250,000 image pairs to classify suitable cover-secret image combinations. The evaluation results demonstrated that the DNN selection model significantly outperformed the SVM model across all metrics, achieving precision, recall, and F-score values of 98.11%, 96.29% and 97.19%, respectively, compared to 83.39%, 81.85% and 82.61% for SVM. Consequently, the DNN was adopted as the preferred cover selection model for this study.

The primary contribution of this work lies in establishing that deep learning architectures can effectively automate cover image selection for steganographic systems, yielding superior classification accuracy over traditional machine learning approaches. When benchmarked against recently published solutions from 2024 to 2025, including neural cover selection approaches using diffusion models, attention-based reversible steganography networks, and deep learning classification models in the steganalysis domain, the proposed DNN model demonstrates competitive or superior classification performance, confirming that the HoPS-based DNN approach remains a relevant and effective solution for cover image selection in reversible image steganography. The proposed DNN-based selection framework provides a robust foundation for enhancing both payload capacity and security in reversible image steganography, as it ensures optimal pairing of cover and secret images prior to the encoding phase. Future work will focus on scaling the dataset and optimising epoch parameters to further improve model performance, as well as integrating this selection module with encoder and decoder components to realize a complete reversible image steganography system.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Uchenna J. Nzenwata, Simon Awodele

Acquisition, analysis, or interpretation of data: Uchenna J. Nzenwata, Folasade Ayankoya, Simon Awodele

Drafting of the manuscript: Uchenna J. Nzenwata

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. *Cureus J Comput Sci* 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

Critical review of the manuscript for important intellectual content: Uchenna J. Nzenwata, Folasade Ayankoya, Simon Awodele

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with [the ICMJE uniform disclosure form](#), all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work.
- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

References

1. Li Q, Wang X, Ma B, Wang X, Wang C, Xia Z, Shi Y: [Image steganography based on style transfer and quaternion exponent moments](#). *Applied Soft Computing*. 2021, 110:107618. [10.1016/j.asoc.2021.107618](#)
2. Yang Z, Hu Y, Huang Y, Zhang Y: [Behavioral security in covert communication systems](#). *Digital Forensics and Watermarking*. IWDW 2019. *Lecture Notes in Computer Science*. Wang H, Zhao X, Shi Y, Kim H, Piva A (ed): Springer, Cham; 2020. 12022:377-392. [10.1007/978-3-030-43575-2_31](#)
3. Liao X, Qin Z, Ding L: [Data embedding in digital images using critical functions](#). *Signal Processing: Image Communication*. 2017, 58:146-156. [10.1016/j.image.2017.07.006](#)
4. Hussain M, Wahab AWA, Idris YIB, Ho ATS, Jung KH: [Image steganography in spatial domain: A survey](#). *Signal Processing: Image Communication*. 2018, 65:46-66. [10.1016/j.image.2018.03.012](#)
5. Kadhim IJ, Premaratne P, Vial PJ, Halloran B: [Comprehensive survey of image steganography: Techniques, Evaluations, and trends in future research](#). *Neurocomputing*. 2019, 335:299-326. [10.1016/j.neucom.2018.06.075](#)
6. Subramanian N, Elharrouss O, Al-Maadeed S, Bouridane A: [Image steganography: a review of the recent advances](#). *IEEE Access*. 2021, 9:23409-23423. [10.1109/access.2021.3053998](#)
7. Rahman S, Uddin J, Zakarya M, Hussain H, Khan AA, Ahmed A: [A comprehensive study of digital image steganographic techniques](#). *IEEE Access*. 2023, 11:6770-6791. [10.1109/access.2023.3237393](#)
8. Pund-Dange S: [Steganography: a survey](#). *Cyber Security. Advances in Intelligent Systems and Computing*. Bokhari M, Agrawal N, Saini D (ed): Springer, Singapore; 2018. 729:327-333. [10.1007/978-981-10-8536-9_32](#)
9. Bedi P, Dua A: [Network steganography using the overflow field of timestamp option in an IPv4 packet](#). *Procedia Computer Science*. 2020, 171:1810-1818. [10.1016/j.procs.2020.04.194](#)
10. Al-Harbi OA, Alahmadi WE, Aljahdali AO: [Security analysis of DNA based steganography techniques](#). *SN Applied Sciences*. 2020, 2:172. [10.1007/s42452-020-2011-3](#)
11. Bieniasz J, Szczypiorski K: [SocialStegDisc: application of steganography in social networks to create a file system](#). 3rd International Conference on Frontiers of Signal Processing (ICFSP). IEEE, Paris, France; 2017. 76-80. [10.1109/ICFSP.2017.8097145](#)
12. Ajala JA, Singh S, Mukherjee S, Chakraborty S: [Application of steganography technique in cloud computing](#). *International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*. IEEE, Dubai, United Arab Emirates; 2019. 532-537.

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. *Cureus J Comput Sci* 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>

[10.1109/ICCICE47802.2019.9004347](https://doi.org/10.1109/ICCICE47802.2019.9004347)

13. Serpa-Andrade L, Garcia-Velez R, Pinos-Velez E, Flores-Urgilez C: [Analysis of the application of steganography applied in the field of cybersecurity](#). Advances in Artificial Intelligence, Software and Systems Engineering. AHFE 2021. Lecture Notes in Networks and Systems. Ahram TZ, Karwowski W, Kalra J (ed): Springer, Cham; 2021. 366-371. [10.1007/978-3-030-80624-8_45](https://doi.org/10.1007/978-3-030-80624-8_45)
14. Parkavi R, Anitha S, Gayathri R: [Digital steganography security](#). Critical Concepts, Standards, and Techniques in Cyber Forensics. IGI Global Scientific Publishing, Hershey, PA; 2020. 144-173. [10.4018/978-1-7998-1558-7.ch009](https://doi.org/10.4018/978-1-7998-1558-7.ch009)
15. Sharma A, Batta A, Sharma VK: [A review on image steganography and its applications](#). IEEE, 2021. 1466-1473. [10.1109/I-SMAC52330.2021.9640877](https://doi.org/10.1109/I-SMAC52330.2021.9640877)
16. Menon N, Vaithyanathan: [A survey on image steganography](#). 2017 International Conference on Technological Advancements in Power and Energy (TAP Energy). IEEE, Kollam, India; 2017. 1-5.
17. Kadhim IJ, Premaratne P, Vial PJ: [High capacity adaptive image steganography with cover region selection using dual-tree complex wavelet transform](#). Cognitive Systems Research. 2020, 60:20-32. [10.1016/j.cogsys.2019.11.002](https://doi.org/10.1016/j.cogsys.2019.11.002)
18. Esfahani R, Norozi Z, Jandaghi G: [Cover selection for more secure steganography](#). International Journal of Security and Its Applications. 2018, 12:21-36. [10.14257/ijisia.2018.12.1.02](https://doi.org/10.14257/ijisia.2018.12.1.02)
19. Wang Z, Zhang X, Yin Z: [Joint cover-selection and payload-allocation by steganographic distortion optimization](#). IEEE Signal Processing Letters. 2018, 25:1530-1534. [10.1109/lsp.2018.2865888](https://doi.org/10.1109/lsp.2018.2865888)
20. Abed S, Al-Roomi SA, Al-Shayegi M: [Efficient cover image selection based on spatial block analysis and DCT embedding](#). EURASIP Journal on Image and Video Processing. 2019, 2019:87. [10.1186/s13640-019-0486-8](https://doi.org/10.1186/s13640-019-0486-8)
21. Wendzel S, Caviglione L, Mazurczyk W, et al.: [A revised taxonomy of steganography embedding patterns](#). The 16th International Conference on Availability, Reliability and Security (ARES'21), August 17--20, 2021, Vienna, Austria. 2021, 1-12.
22. Duan X, Nao L, Mengxiao G, Yue D, Xie Z, Ma Y: [High-capacity image steganography based on improved FC-DenseNet](#). IEEE Access. 2020, 8:170174-170182. [10.1109/access.2020.3024193](https://doi.org/10.1109/access.2020.3024193)
23. Kuznetsov O, Frontoni E, Chernov K: [Beyond traditional steganography: enhancing security and performance with spread spectrum image steganography](#). Applied Intelligence. 2024, 54:5253-5277. [10.1007/s10489-024-05415-z](https://doi.org/10.1007/s10489-024-05415-z)
24. Pandey HM: [Secure medical data transmission using a fusion of bit mask oriented genetic algorithm, encryption and steganography](#). Future Generation Computer Systems. 2020, 111:213-225. [10.1016/j.future.2020.04.034](https://doi.org/10.1016/j.future.2020.04.034)
25. Singh S: [Adaptive PVD and LSB based high capacity data hiding scheme](#). Multimedia Tools and Applications. 2020, 79:18815-18837. [10.1007/s11042-020-08745-5](https://doi.org/10.1007/s11042-020-08745-5)
26. Wang Z, Zhang X: [Secure cover selection for steganography](#). IEEE Access. 2019, 7:57857-57867. [10.1109/access.2019.2914226](https://doi.org/10.1109/access.2019.2914226)
27. Subhedar MS: [Cover selection technique for secure transform domain image steganography](#). Iran Journal of Computer Science. 2021, 4:241-252. [10.1007/s42044-020-00077-9](https://doi.org/10.1007/s42044-020-00077-9)
28. Qin C, Zhang W, Dong X, Zha H, Yu N: [Adversarial steganography based on sparse cover enhancement](#). Journal of Visual Communication and Image Representation. 2021, 80:103325. [10.1016/j.jvcir.2021.103325](https://doi.org/10.1016/j.jvcir.2021.103325)
29. Chahine K, Kim H: [Neural cover selection for image steganography](#). 38th Conference on Neural Information Processing Systems (NeurIPS 2024). 2024, 1-22.
30. Liu L, Tong S, Xue Q: [Reversible image steganography based on residual structure and attention mechanism](#). Scientific Reports. 2025, 15:19355. [10.1038/s41598-025-04441-2](https://doi.org/10.1038/s41598-025-04441-2)
31. Zhou Y, Wang N, Hong X, Peng Y, Shao S: [Deep learning-based image steganography with latent space embedding and smart decoder selection](#). Entropy. 2025, 27:1223. [10.3390/e27121223](https://doi.org/10.3390/e27121223)
32. Alrusaini OA: [Deep learning for steganalysis: evaluating model robustness against image transformations](#). Frontiers in Artificial Intelligence. 2025, 8:1532895. [10.3389/frai.2025.1532895](https://doi.org/10.3389/frai.2025.1532895)
33. Li B, Li N, Yang J, et al.: [Image steganalysis using active learning and hyperparameter optimization](#). Scientific Reports. 2025, 15:7340. [10.1038/s41598-025-92082-w](https://doi.org/10.1038/s41598-025-92082-w)
34. Almhilbdi AM, Altowairqi ND, Alshutayri AO, Qarout RK: [Deep learning-based multi-class detection of LSB steganography in digital images](#). IEEE Access. 2025, 13:191543-191553. [10.1109/access.2025.3628784](https://doi.org/10.1109/access.2025.3628784)

How to cite this article:

Nzenwata U J, Ayankoya F, Awodele S (October 01, 2026) Performance Evaluation of Support Vector Machine and Deep Neural Network for Cover Image Selection Model in Reversible Image Steganography. Cureus J Comput Sci 3 : es44389-025-00084-6. DOI <https://doi.org/10.7759/s44389-025-00084-6>