Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

A Novel Hybrid framework of NAdamBound optimized Dilated Depthwise Separable CNN for deep learning based image steganalysis in digital forensics

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ARTICLE INFO

Received: 29 Dec 2024

Revised: 12 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

Introduction: Steganography is the method of hiding confidential information in different types of media, such audio, video, or photographs, while steganalysis is the process of finding and removing that information. Due to their capacity to automatically extract hierarchical features from input data, deep learning methods—in particular, those based on Convolutional Neural Networks (CNNs)—have recently surpassed conventional machine learning techniques in steganalysis tasks.

Objectives: CNN-based models frequently suffer from problems like overfitting, excessive power consumption, and expensive computational costs. These drawbacks make it difficult to use them in real-world situations, particularly when working with sizable or authentic datasets. In order to overcome these issues, this study attempts to create an accurate and effective CNN-based steganalysis model.

Methods: The suggested model DDS_SE-NB-Net incorporates dilated convolutions into a Depthwise Separable Convolutional Neural Network (DS-CNN) supplemented with Squeeze-and-Excitation (SE) blocks to capture multi-scale spatial data effectively while maintaining computational efficiency. To increase training stability, speed up convergence, and improve generalization, the model makes use of the NAdamBound optimizer, which combines the advantages of adaptive learning rate bounds with Nesterov momentum. In order to maintain high classification accuracy, the ideal dilation rate is also carefully chosen.

Results: The proposed DDS_SE-NB-Net achieved impressive accuracy rates of **94.0%**, **92.2%**, and **93.8%** in detecting steganographic content embedded using the WOW, S-UNIWARD, and HILL algorithms, respectively. These results demonstrate a significant improvement in performance compared to existing CNN-based architectures, particularly on real-world stego image datasets.

Conclusions: A user-friendly Python-based Graphical User Interface (GUI) is built using Tkinter. The GUI enables users to upload images, initiate classification, and instantly view the steganalysis results, thereby showcasing the model's real-world applicability in digital forensics. This integrated solution illustrates the practical potential of the proposed system in aiding law enforcement and forensic investigators in detecting covert communications.

Keywords: Steganalysis, Deep learning, Convolution Neural Network (CNN), Adam, NAdamBound, Digital Forensics

INTRODUCTION

Steganography, a technique with ancient roots, emphasizes its main goal of hiding information in other types of media. Steganography has advanced in many ways over the years. Steganalysis is the art of uncovering encoded messages in data packets using a variety of methods (Figure 1). As technology has advanced over the last 20 years,

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steganography has presented cybersecurity experts with a number of difficulties. Identifying potentially dangerous content hidden in digital visuals, audio, and videos is part of this challenge. Applications for steganalysis are numerous and include face modification detection, unauthorized access detection, cybersecurity, and forensic investigations. The collection, preservation, and examination of digital evidence are the main objectives of digital forensics. The experts tasked with addressing the difficulties posed by steganography are digital forensic investigators. Analysing electronic data and identifying the origins of a breach comprise a few of their duties. Various existing steganography and steganalysis methods are reviewed systematically in [1]. Steganalysts have previously used two main strategies. In the first, statistical features are extracted from clean and stego shots. Then, to distinguish between clean and stego photos, the statistical attributes are compared. The second strategy involves applying machine learning methods. The process includes obtaining features from images, training a classifier, and then presenting the model with unseen images for assessment. Deep learning based convolution neural network techniques are used in modern methodologies, which enable feature extraction and classification in a nearly automatic manner. Using depthwise separable convolutions, [2] addresses the overfitting issue and lowers the computational cost. Convolutions can use dilations [3] to expands the kernel without raising the parameters, which lowers computation and power consumption. The channels are adaptively weighed using squeeze and excitation blocks [4], which helps to minimize the number of parameters required. The current study uses a hybrid model named DDS_SE-NB-Net that incorporates all of these techniques and is inspired by our earlier work on the DDS_SE-Net architecture [5], which employed CNN with dilations and depthwise separable convolutions.

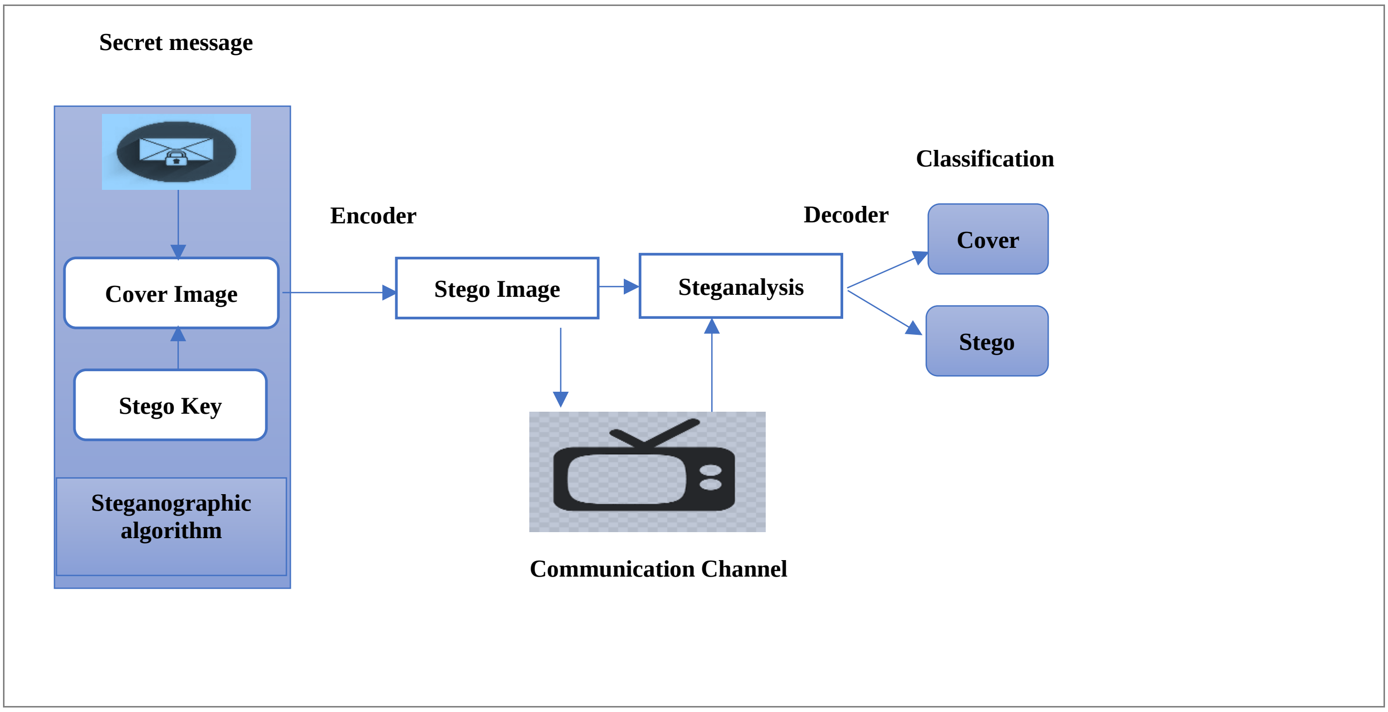

Figure 1. Flow Diagram of Steganography and Steganalysis

By making adjustments to the weights and biases in a neural network, optimizers play a significant part in lowering the rate of loss or errors produced by the network. The Adam [6] optimizer, which combines the benefits of momentum and adaptive learning rates, is frequently used in deep learning applications. Faster convergence is achieved by using Nesterov momentum [7] in Adam. Furthermore, a constant learning rate [8] is applied to all parameters to improve generalization. The current study makes use of the NAdamBound [9] optimizer to take advantage of these benefits.

The contribution of the proposed deep learning framework is:

1. Applying dilations in depthwise separable convolutions to reduce overfitting, cost of computation and consumption of power by using DDS_SE-Net
2. To reduce the usage of parameters, Squeeze and excitation blocks are involved.

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3. Adding Nesterov momentum and dynamic bounding to adaptive moment estimation to give quick convergence and good generalization by applying constant learning rate.
4. Creating python GUI application using Tkinter which assists users to submit their data and view the classification results.

RELATED WORKS

The collection, preservation, and examination of digital evidence are the main objectives of digital forensics. One group of experts in charge of figuring out how to overcome the difficulties posed by steganography are digital forensic investigators. Steganalysis plays a major role in digital forensics to identify any hidden data in images that are transferred in legal affairs. Deep learning based convolution neural network techniques are used in modern methodologies in image Steganalysis, which enable feature extraction and classification in a nearly automatic manner.

The idea of dilated convolution comes from wavelet decomposition. The dilated convolution operator, which performs wavelet decomposition, has been mentioned numerous times[10]. The conventional CNN's problem is that it consumes too much computing power. To tackle this problem, a dilated CNN model is built. The original hyper-spectral data and the morphological feature maps are combined in MDCNN, a more robust spectral-spatial feature extraction technique. CNN classifies hyper-spectral images using both dilated and normal convolution[11]. For steganalysis in the SNE network, a stego noise obtaining module was created especially [12]. A coupled dilated convolutional layer and a reversed bottleneck layer make up this module. By improving the network's receptive region, this particular architecture increases the globality and adaptability of stego noise extraction to the image's content.

In order to reduce the finding error rate and processing cost for steganalysis, CIRNet uses inverted residual blocks in conjunction with a self-attention mechanism. Lightweight depth-wise and point-wise convolutions, along with a self-attention module, are incorporated into the inverted residual blocks. The study's integration enhances the prominence of feature maps linked to the embedding regions while lowering the quantity of floating-point operations and network parameters [13]. Conventional convolutions were used to describe local features in [14] while 2-dimensional depthwise separable convolutions were used to improve the signal-to-noise ratio during the feature extraction stage of architecture. [15] presented a novel design for deeper convolutional neural networks which was influenced by Inception. This architecture uses depthwise separable convolutions in place of the Inception modules.

Squeeze-and-Excitation Networks were developed by stacking the SE blocks together. Using the RepVgg block in SFR-Net [16] increases inference performance while increasing memory utilization. The SE block may learn feature weights to generate feature maps which are valid or ineffective using moderate weights as well as efficient ones with massive weights, increasing the detection accuracy rate. In order to capture global as well as local dependencies in spatial domain image steganalysis, the convolutional vision transducer CVTStego-Net [17] combines the advantages of convolutions and attention processes. In the pre-processing step, a bifurcation consisting of 30 SRM filters is utilized to enhance steganographic noise. The noise extraction and examination stage use SE-Block with residual operations to improve sensitivity in steganographic noise and lessen the effect of redundant data. Both the local and global spatial relationships of the steganographic noise are connected during the classification step by combining SE-Block with a convolutional vision converter.

The NAdamBound optimizer[9] for steganalysis employs dynamic limits on learning rates to prevent oscillations in them and incorporates Nesterov momentum into Adam to help with accelerated convergence, thereby facilitating a seamless and progressive transition from adaptive techniques to SGD. This increases accuracy by enabling a potentially faster optimization process with a steadily declining loss. Dynamic bounds are added to the learning rates to confirm that they converge to a specific range.

METHODOLOGY

Convolution Neural Network in deep learning has given tremendous advancement in deep learning based Steganalysis. The combined framework used in this study includes dilation in depthwise separable convolutions which deals with issues like overfitting, computation cost and power consumption. Hybrid NAdamBound optimizer helps in quick convergence.

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1. Dilation and Depthwise Separable convolutions in CNN with SE Blocks

Dilation is a type of convolution operation that increases the responsive field of the network without increasing the number of parameters. Pixel skipping is used to cover a larger percentage of the input as shown in Figure 2. More complex feature maps could be created which in turn results in good efficiency.

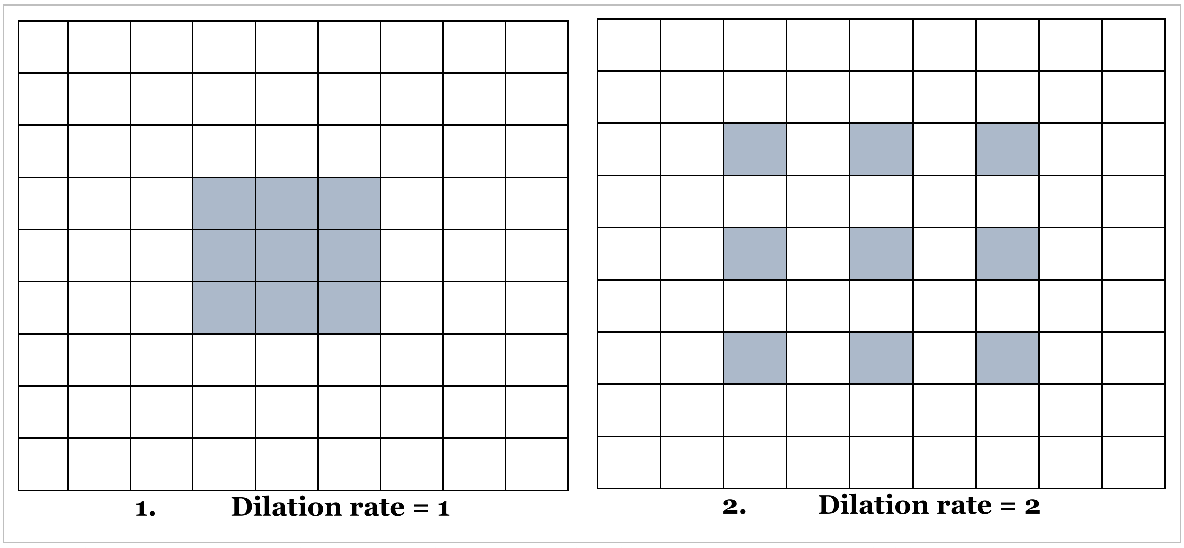

Figure 2. Feature detector in the input with dilation rate 1 in (a) and dilation rate 2 in (b)

Depthwise Separable Convolution divides a convolution operation into two components: pointwise convolution, which expands the dimension of the feature map by incorporating data from various channels, and depthwise convolution, which works on individual input channels. Comparing this method to normal convolution, fewer parameters and calculation are needed.

The Squeeze-and-Excitation Block is a structural block that allows a network to execute dynamic channel-wise feature adjustment, hence increasing its predictive power. Enhance beneficial features while suppressing fewer helpful ones.

1. NAdamBound

Hybrid NAdamBound optimizer which induces Nesterov momentum into Adaptive moment estimation with bounded learning rate is used in the present framework. Adam smoothes out updates and modifies learning rates for quicker convergence by fusing the advantages of adaptive learning with momentum. Nesterov momentum calculates the gradient at the anticipated future position rather than the current position. Bounded learning rate helps in speeding up the convergence at the beginning and giving better generalization towards the end.

Pseudocode of NAdamBound

INPUT

Timestep 't' ; First and Second moment vectors 'm_o' and 'n_o'.

OUTPUT

Update *Model Parameter* θ_t

BEGIN

Obtain *Gradient 'g_t'* *(in relation to the stochastic objective)*
Compute *'m_t', 'n_t'* $\leftarrow$ *(First and Second moment estimates)*
Evaluate $'\widehat{m}_t'$ and $'\widehat{n}_t'$ *(Apply bias correction)*
Update *parameters* *Nesterov Momentum*

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Calculate η_lower_t and η_upper_t *(dynamic learning rate limits)*
Confine *learning rate* $'\eta_t'$.
Update *model parameters* $\theta_t \leftarrow \theta_t^{-1} - \eta_t \cdot \tilde{m}_t$ (1)
END

2. *Combined Framework DDS_SE-NB-Net*

Incorporating dilation in Depthwise Separable (DS) convolutions in CNN with Squeeze and Excitation (SE) and adjusting the model parameters with hybrid NAdamBound (NB) optimizer is done in the current framework as in Figure 3. for effective steganalysis in digital forensics.

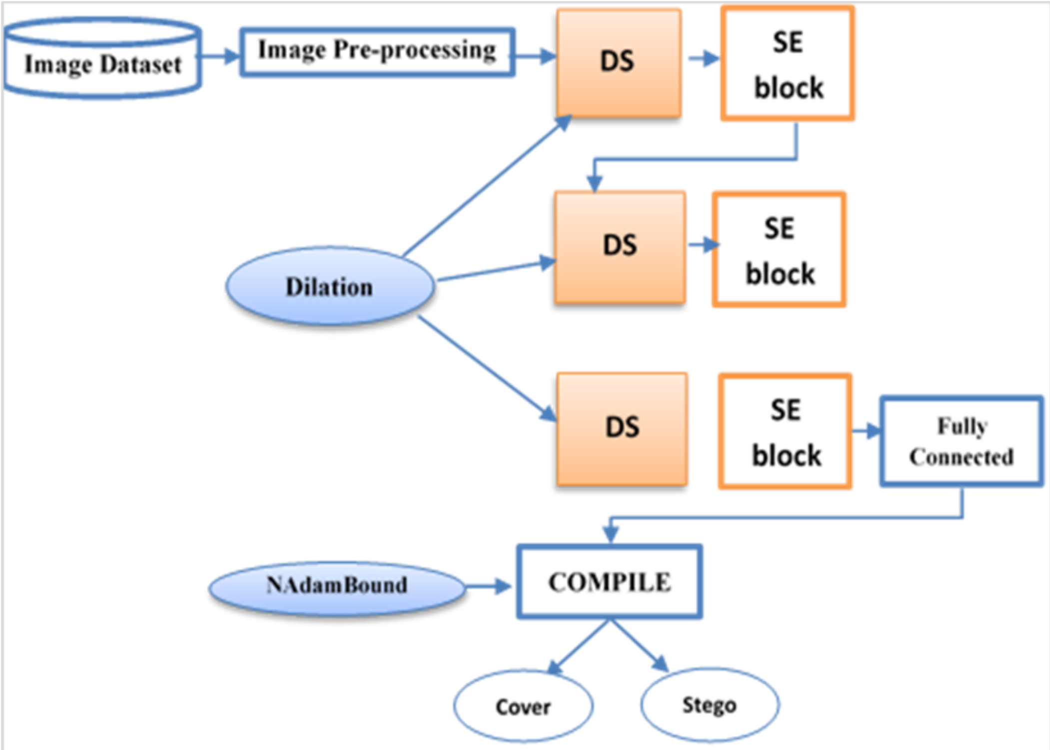

Figure 3. DDS_SE-NB-Net framework

EXPERIMENTS

1. *Resources*

For architectural development, Python 3.9.12 was used, and 64-bit Keras 2.10.0 was used for design. The operating system in use is Windows 10. 8 GB of RAM and an Intel(R) Core (TM) i5-3340M CPU running at 2.70GHz are included.

2. *Data Collection*

The experiments were conducted using data from BOSSBase[18], BOWS2[19], ALASKA[20] and Real-world datasets. 5000 images are collected as cover images. Images are primarily pre-processed to change them to the same dimension. Stego images are created using spatial steganographic algorithms WOW[21], S-UNIWARD[22] and HILL[23] with payload 0.4. Both cover and stego images are fed to the DDS_SE-NB-Net model through Tkinter application and the results are noted.

3. *Tkinter Application*

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A GUI application is created using Tkinter in Python to load data, conduct model training and calculate accuracy as in Figure 4. Basic steps involved are:

1. Bring the Tkinter module in.
2. Construct the container, or main window.
3. Include widgets in the primary window.
4. Give the widgets event triggers.

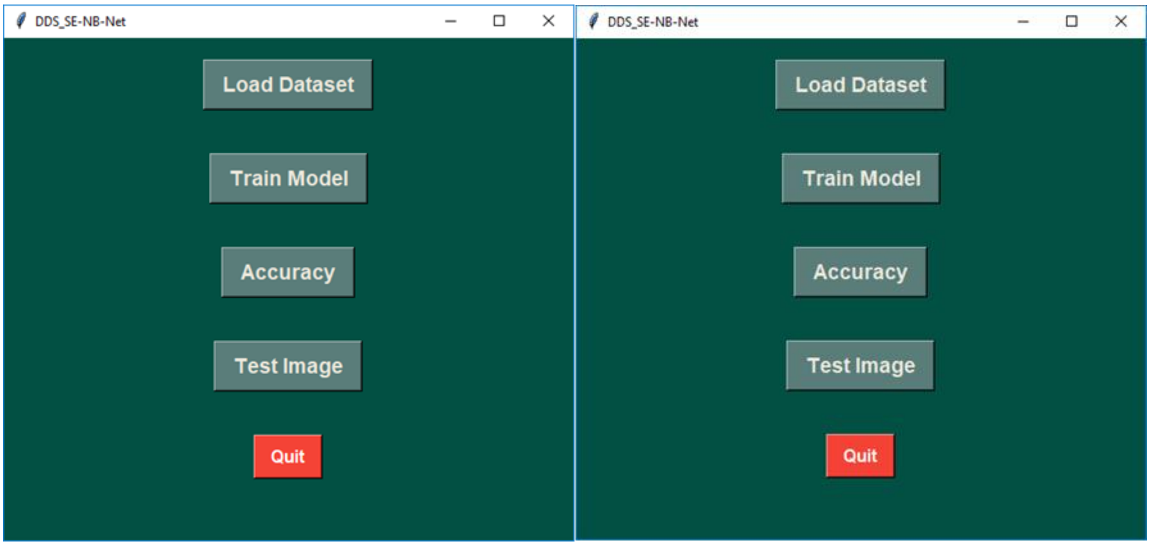
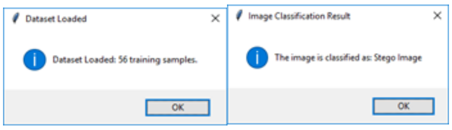


Figure 4. DDS_SE-NB_Net GUI samples of (a) loading images (b) testing image

1. *Classification metrics*

The study has selected the following evaluation metrics to assess the detector's performance. The most often used metric for assessment is Accuracy (ACC). But to evaluate the performance even while the data is uneven, we use F1-Score. From the Confusion matrix given in Table 1, the True Positives (TP) are images that are correctly predicted as Stego, The True Negatives (TN) are samples that are correctly predicted as Normal (Cover). The False Positives (FP): samples that are predicted as stego but actually normal (cover). The False Negatives (FN): samples that are predicted as normal (cover) but actually stego.

Table 1. Confusion Matrix



Actual	Predicted	
	Stego	Normal (Cover)
Stego	TP	FN
Normal (Cover)	FP	TN

Precision

The proportion of relevant instances among the recovered instances is known as precision, also known as positive predictive value given in Eq. (2).

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

Recall

The proportion of pertinent occurrences that were recovered is called as recall, often referred to as sensitivity as in Eq. (3).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1-score

The F1 score determines how frequently a model correctly predicted throughout the full dataset. It computes the harmonic mean of recall and precision resulting Eq. (4).

$$f1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Accuracy

The number of accurate forecasts divided by the entire number of predictions is used to compute it defined in Eq. (5).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Binary cross entropy loss

The predicted chances are compared to the true class result that can be either 0 or 1, using binary cross entropy. It is the negative mean of the log of adjusted predicted probabilities given by the Eq. (6). When N is the total number of samples and y is the true label representation for each sample in the dataset, then

$$Log\ loss = \frac{1}{N}\sum_{i=1}^{N} -(y_i * \log(p_i) + (1 - y_i) * \log(1 - p_i)) \tag{6}$$

Where pi is the probability of class 1(Stego) and (1-pi) is the probability of class 0 (Cover).

RESULTS AND DISCUSSION

The capacity of deep learning to automatically extract valuable features from the original data, thereby composing high-level features from low-level features has led to its rise in popularity in recent years. This study aims to detect stego images in digital forensic applications which is highly the need of the hour.

5000 images were chosen from BOSSBase, BOWS2, Alaska and Real-world dataset. Stego images and the cover images were fed to the DDS_SE-NB-Net model and the results are given in Table 2. DDS_SE-NB-Net gave increasing accuracy of 93.5% and 94% using BOSSBase and Alaska dataset respectively which are widely used for Digital Forensics researches against S-UNIWARD as it utilizes Universal Distortion function to insert payloads in digital media. Against BOWS2 and Real-world dataset, the accuracy was more against WOW which concentrates on complex regions of images to embed payloads, with 94.2% and 94% respectively. With four different datasets, the graph for Accuracy, Precision, Recall and F1-Score is given in Figure 5. Good Precision and Recall rate prove that the DDS_SE-NB-Net Model more accurately classifies Stego and Normal images.

Table 2. Evaluation Metrics of DDS_SE-NB-Net against WOW, S-UNIWARD and HILL with 0.4bpp using BOSSBase, BOWS2, ALASKA and Real-world Dataset.

Steganographic algorithm	Dataset	Accuracy %	Precision %	Recall %	F1 Score %	Loss %
WOW	BOSSBase	92.4	91.6	93.8	92.7	19.2

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S-UNIWARD		**93.5**	93.4	93.3	93.4	18.6
HILL		93.1	93.0	93.6	93.3	18.8
WOW	Alaska	92.1	92.9	91.6	92.3	19.0
S-UNIWARD		**94.0**	93.7	94.0	93.8	20.1
HILL		92.5	93.0	92.0	92.5	23.2
WOW	BOWS2	**94.2**	92.8	95.4	94.0	19.8
S-UNIWARD		92.7	92.8	92.6	92.7	19.2
HILL		93.1	93.1	92.7	92.9	20.5
WOW	Real-world	**94.0**	95.0	94.6	94.7	20.0
S-UNIWARD		92.2	91.7	92.0	91.8	19.6
HILL		93.8	93.5	94.6	94.0	18.0

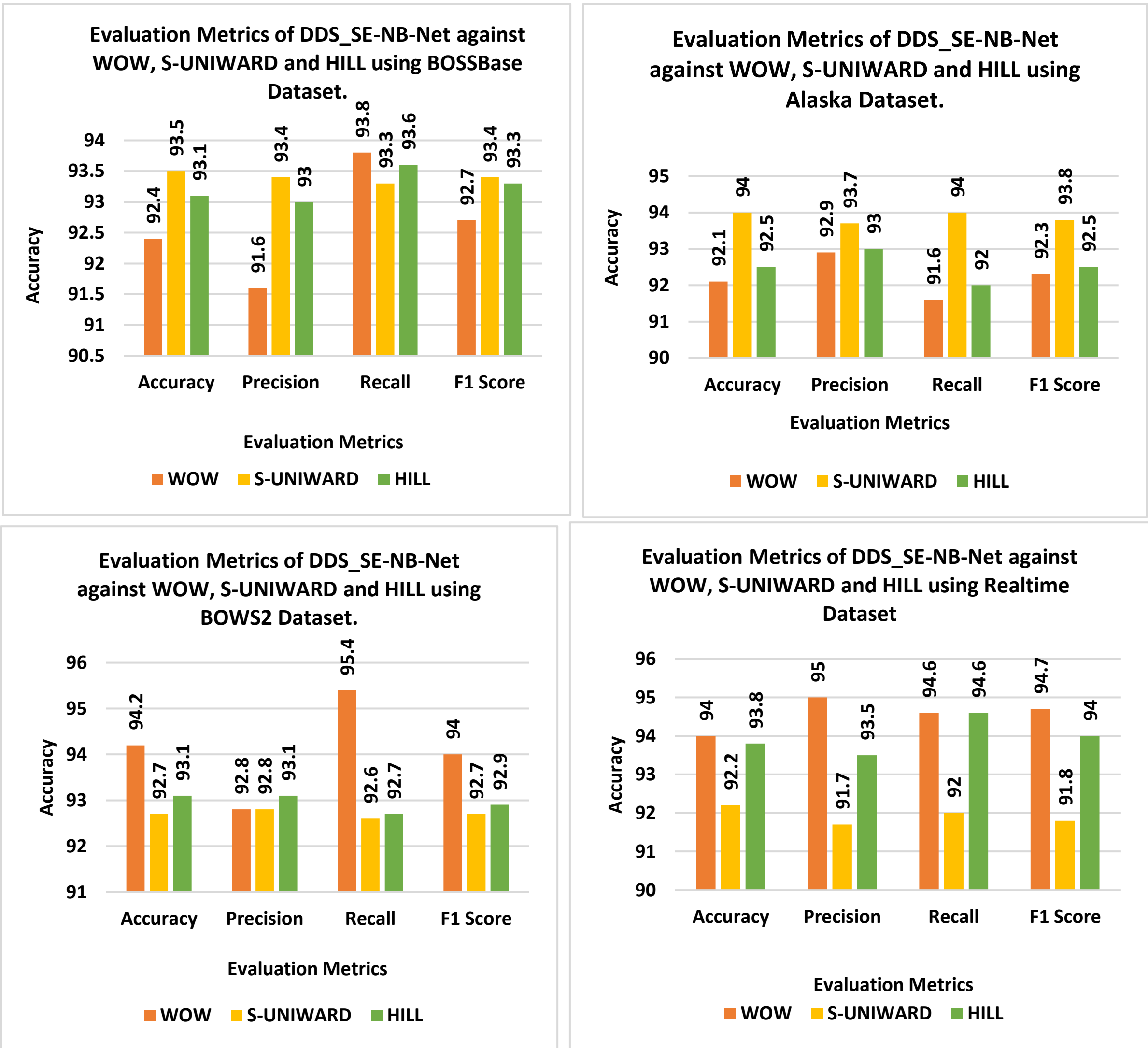

Figure 5. Evaluation metrics of DDS_SE-NB-Net with various datasets

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Table 3 gives the performance metrics of CNN with Depthwise Separable Convolutions, DDS_SE-Net without NAdamBound and with NAdamBound. With Depthwise Separable convolutions, Accuracy is good but lesser than the other models due to the fact that it tends to reduce parameters and computation which might end in underfit. This is solved in DDS_SE-Net by application of dilations. Moreover, Use of NAdamBound in DDS_SE-NB-Net gives best when comparing the three models (Figure 6).

Table 3. Comparison of Evaluation Metrics of Depthwise Separable CNN, DDS_SE-Net without NAdamBound (NB) and with NAdamBound (DDS_SE-NB-Net) against WOW, S-UNIWARD and HILL with 0.4bpp using Real-world dataset

CNN Model	Steganographic algorithm	Accuracy %	Precision %	Recall %	F1 Score %	Loss %
Depthwise Separable CNN	WOW	90.4	90.1	91.09	90.5	23.1
	S_UNIWARD	88.3	87.65	88.20	87.93	35.2
	HILL	89.1	88.17	90.8	89.5	31.3
DDS_SE-Net	WOW	92.9	91.5	94.0	92.7	21.0
	S_UNIWARD	89.2	91.4	86.9	89.0	31.9
	HILL	89.8	91.5	87.9	89.6	30.3
DDS_SE-NB-Net	WOW	**94.0**	95.0	94.6	94.7	**20.0**
	S_UNIWARD	**92.2**	91.7	92.0	91.8	**19.6**
	HILL	**93.8**	93.5	94.6	94	**18.0**

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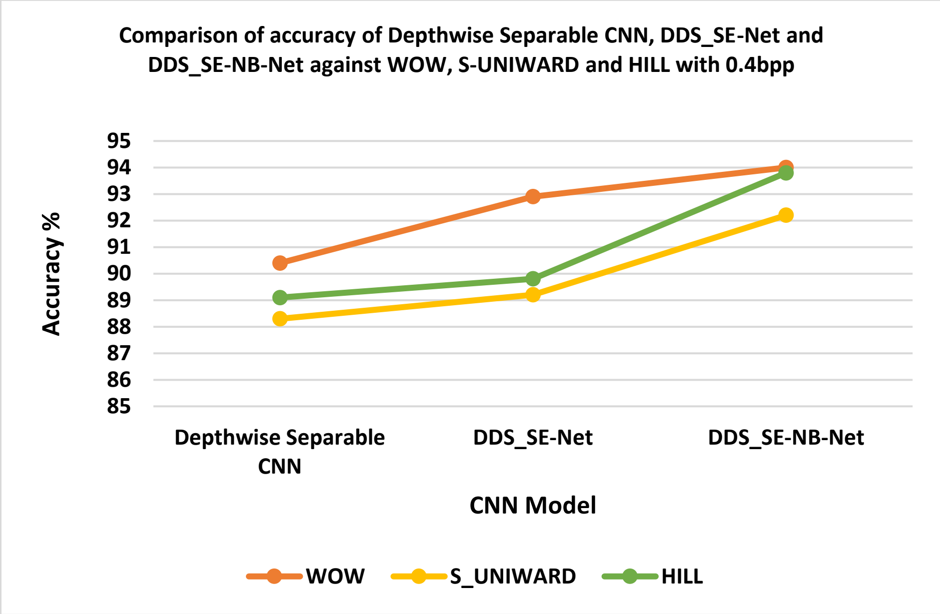

Figure 6. Comparison of accuracy of Depthwise Separable CNN, DDS_SE-Net and DDS_SE-NB-Net against WOW, S-UNIWARD and HILL with 0.4bpp

Accuracy with NB is 2.04% more than without NB against WOW, 3.31% against S-UNIWARD and 4.3% against HILL algorithms. This proves that NB helps to give bounds to the learning rate and results in good convergence which in turn helps to reduce loss and increase accuracy. Table 4 gives the comparison of accuracy of various Steganalysis models using CNN like Yedroudj-Net[24], GBRAS-Net[25], CVTStego-Net[17] with DDS_SE-NB-Net (Figure 7) which shows that it out performs the other models against BOSSBase dataset. Here the comparison is done using BOSSBase as it was originally used by the chosen architectures for comparison in their study.

Table 4. Comparison of Accuracy percentage of DDS_SE-NB-Net with Yedroudj-Net, GBRAS-Net and CVTStego-Net against WOW, S-UNIWARD and HILL with 0.4bpp against BOSSBase Dataset

CNN Model	Steganographic algorithm	Accuracy %
Yedroudj-Net	WOW	85.1
	S_UNIWARD	77.4
	HILL	75.2
GBRAS-Net	WOW	89.8
	S_UNIWARD	87.1
	HILL	81.9
CVTStego-Net	WOW	**93.8**
	S_UNIWARD	90.5
	HILL	85.8
DDS_SE-NB-Net	WOW	92.4
	S_UNIWARD	**93.5**
	HILL	**93.1**

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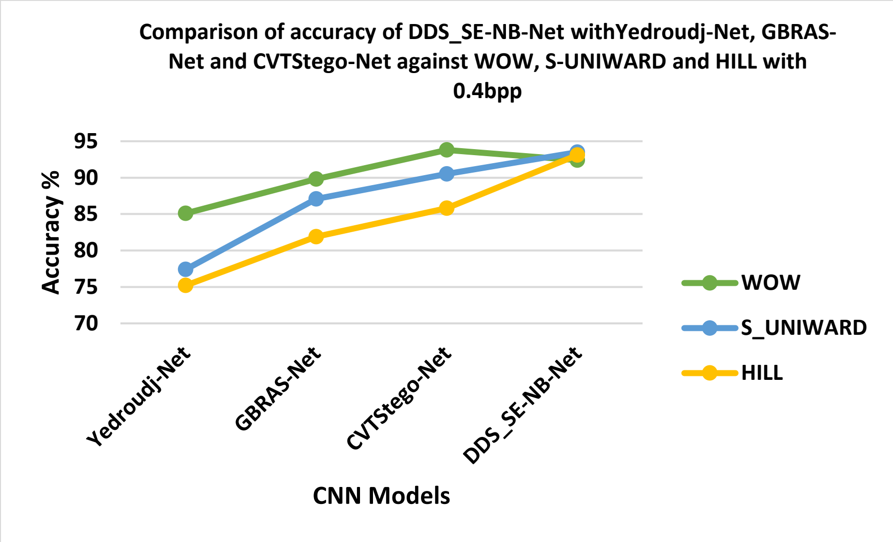

Figure 7. Comparison of accuracy of DDS_SE-NB-Net with Yedroudj-Net, GBRAS-Net and CVTStego-Net against WOW, S-UNIWARD and HILL with 0.4bpp

From Table 5 it could be clearly noted that compared to Traditional CNN, DDS_SE-NB-Net has 31.5% less trainable parameters. Compared to the regular CNN model, the DDS_SE-NB-Net model is just two-thirds in size which proves its refinement in solving **Space Complexity**. The evaluation time of DDS_SE-NB-Net is around 27.5% lower than that of the model that uses Conventional CNN due to the fast convergence of NAdamBound. It shows the model solves **Time complexity**. DDS_SE-NB-Net is computationally more efficient due to its 1.188 billion FLOPs, which require less operations to generate a prediction. It finishes inference faster and consumes less power. Dilated convolution increases the efficient receptive field by spatially widening the kernel. Although accuracy is improved, the computational cost may go up a little. By dividing a typical convolution into two stages, depth-wise separable convolutions lower the number of parameters required and lower computing costs. By combining these two approaches, the network can employ fewer parameters, collect more data, and increase accuracy and efficiency.

Table 5. The performance improvement of DDS_SE-NB-Net (in contrast with Traditional CNN)

CNN	Traditional CNN	DDS_SE-NB-Net
Time required	220.46 seconds	172.90 seconds
Number of Trainable Parameters	1,989,346	1,512,979
Model size	23209.66 kilo bytes	15677.45 kilo bytes
FLOPs	1.876 billion	1. billion

CONCLUSION AND FUTURE WORK

In this study, a combined framework of deep learning model DDS_SE-NB-Net is proposed to extract high-level features and classify stego images and normal images in digital forensics with hybrid NAdamBound optimizer. The problem is most critical for capturing stego images and protecting the digital world from fraudulent. The proposed architecture outperforms conventional ensemble models such as Yedroudj-Net, GBRAS-Net, CVTStego-Net and DDS_SE-Net in terms of generalization with the use of Dilation, Depthwise separable convolution with SE blocks and NAdamBound. The experiment is carried out using digital forensics datasets BOSSBase, BOWS2 and ALASKA which are available online and also with real-world dataset collected from google which is very important as steganography can occur in random in any type of image which is a threat in present day cyber security. The proposed strategy gives an accuracy of 94%, 92.2% and 93.8% against steganographic algorithms WOW, S-UNIWARD and HILL respectively using real world dataset. Moreover, it proves consumption of less memory, a smaller number of parameters and minimized computational complexity when compared to traditional CNN based deep learning models in steganalysis.

Future work could involve using a more specific datasets to determine the reliability of the suggested model. More improved feature extraction methods would be developed for increasing accuracy in a better range

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