The Use of Convolutional Neural Network on Image steganalysis: A survey

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ABSTRACT- Steganalysis is the method of recognizing the existence of concealed messages over digital multimedia. These messages are concealed using steganography techniques in digital media. Steganalysis is a challenging task with the emergence of strong Steganography algorithms. Over the past few years, steganalysis has advanced significantly due to the development of deep learning methods. In this article, we present a comprehensive review of the most recent efforts on image steganalysis in spatial and transform domains. We focused on reviewing and analyzing the most recent works that utilize convolutional neural networks in image steganalysis. Also, the technical challenges of existing approaches are discussed, along with several exciting avenues for CNN-based steganalysis.

Keywords: steganography, steganalysis, convolutional neural networks .

المستخلص- تحليل إخفاء المعلومات هو طريقة للتعرف على وجود رسائل مخفية عبر الوسائط المتعددة الرقمية. يتم إخفاء هذه الرسائل باستخدام تقنيات إخفاء المعلومات في الوسائط الرقمية. يعد تحليل إخفاء المعلومات مهمة صعبة مع ظهور خوارزميات إخفاء قوية. على مدى السنوات القليلة الماضية ، تقدم تحليل الاخفاء بشكل كبير بسبب تطور أساليب التعلم العميق. في هذه المقالة ، نقدم مراجعة شاملة لأحدث الجهود على تحليل إخفاء الصور في المجالات المكانية والتحويلية. حيث تركز هذه الدراسة على مراجعة وتحليل أحدث الأعمال التي تستخدم الشبكات العصبية الالتفافية في تحليل إخفاء الصور.وأيضًا مناقشة التحديات التقنية التي تواجهها المنهجيات الحالية ومناقشة العديد من الجوانب المختلفة لتحليل إخفاء الصور باستخدام شبكات الالتفاف العصبية.

1. INTRODUCTION

Since the rise of network technologies and communication media, the most important factor of information technology and communication has been the security of information. Steganography is one of the ways to achieve secure message communication by hiding a confidential message within an unsuspicious one in a way that does not affect carrier or cover file quality and perceptual transparency [1]. Steganography is primarily used to conceal the existence of a message so that it cannot be detected by an unintended receiver [2], and it is crucial in national security and military matters. However, Steganography also can be used by people who do have not good directions. Steganography has also been used in malicious software, terrorist attacks, crimes, and other illegal activities in recent times. In such conditions, military and security departments in numerous countries are grappling with how to effectively supervise Steganography and prevent and block its malevolent or illegal deployment [3]. As a result, steganalysis has been intensively studied and improved in the field of information concealment. Steganalysis is the process of determining whether or not a stego picture includes hidden information after it has been published. Steganalysis is the opposite operation of Steganography. Due to the ease of multimedia communication via the internet, image steganography and steganalysis have gotten a lot of attention from security agencies and social media. Image steganography is the most usable type that is used as a cover because of quick and simple to send secret information. Image steganography is mainly classified into two types, spatial domain and transform domain. In spatial domain steganography, we directly change image pixel values Pixel values are altered to reach an acceptable goal but transform domain steganography relies on the transform domain coefficient. According to the classification of Steganography, steganalysis is also classified into spatial domain steganalysis and transform domain steganalysis from the same perspective.

Traditional image steganalysis procedures usually consist of two steps: extraction and classification of features. A set of handcrafted features is extracted from each image in the feature extraction step to capture the impact of embedding procedures, and the performance of steganalysis is largely dependent on the feature design. As a result, feature extraction is a critical stage in detecting steganography [4][5]. Early image steganalysis approaches used statistical characteristics with low dimensionality, usually only a few tens of dimensions. However, as image steganography evolves, the newly proposed steganography algorithm can keep more complicated statistical properties of images, causing steganalysis methods based on low-dimensional statistical features to fail more frequently. Steganography features have gradually evolved toward bigger dimensions and complexity to defeat more advanced steganography algorithms [6][7][8]. Currently, steganalysis approaches for detection often extract high-dimensional statistical characteristics. By combining the complementary information of different residual images, these approaches capture more complicated image statistics and effectively increase performance. However, feature creation like this is dependent on the researcher's experience, and it takes a lot of time and work. Furthermore, with the continued advancement of steganography, it will undoubtedly grow more difficult. Because deep learning can uncover the complex relationships hidden in the data by training the network structure model, it has been applied to image steganalysis to overcome these challenges. Deep learning can extract data features automatically, reducing the need for human experience and energy. It has been successfully employed in computer vision, semantic analysis, audio recognition, and natural language processing. As a result of this, some academics attempted to use deep learning to overcome the challenges associated with image steganalysis, resulting in a series of research findings. The usage of Convolutional Neural Networks-based deep learning architectures for image steganalysis is thoroughly studied and given in this comprehensive study.

The rest of the paper is organized as follows. A brief introduction to Convolutional Neural Networks is provided in Section 2. Section 3 presents the CNN Models used for steganalysis in the spatial domain and transform domain, respectively. Section 6 provide performance evaluation of the surveyed CNN models. In Section 5, challenges of the existing CNN-based image steganalysis are discussed. Finally, section 6 talks about the Conclusion of the study.

2. Overview of Convolution Neuron Networks CNNs is a type of deep learning model created in 1995 [9] by Yann LeCun and Yoshua Bengio for analyzing two-dimensional grid data (such as images). CNNs are primarily made up of two phases, which we'll refer to as modules: the convolution module and the classification module as illustrated in figure 1. Inside the convolution module, there are several macroscopic computation units that we will call blocks such as pooling operations, activation functions, and so on. A block is consisting of calculation units that take actual input values, do calculations, and return real values, which will be input to the next block.

2.1 Convolution model

There are several computation blocks in the convolution model as we mentioned in the last section. Each block contains several processes; including convolution (see Section 2.1.1), activation (see Section 2.1.2), and pooling (see Section 2.1.3). Let's now explain in more detail each step (convolution, activation, and pooling) within a block.

2.1.1Convolution operation

The input image is convolved with one or more kernels in the convolution block. Feature maps are the outputs of the convolution model. The number of kernels utilized corresponds to the number of feature maps. The equation for the convolution operation is given below:

$$O(i,j) = (I \times K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

Where

I– input image of m rows and n columns

K– Two-dimensional Kernel of I rows and j columns

O– Output image after convolution.

Convolution operation achieves sparse interactions/connectivity/weights by making the kernel smaller than the input. As a result, fewer parameters are saved, reducing the model's storage requirements and increasing statistical efficiency by computing the output in fewer operations [10]. Kernels are used to extract intricate characteristics of any image that are not visible to the naked eye.

2.1.2 Activation function

The convolution kernels make use of linear filtering operations. This linearity is broken in the next step by employing any one of the non-linear activations namely sigmoid, tanh, and Rectified Linear Unit (ReLU) to each of the feature maps. To aid the back-propagation algorithm i.e., used to train the CNN [9], the non-linear activations must be differentiable for computing the back-propagation error.

Below are the equations for several activation functions.

Sigmoid: $f\ (i) = \frac{1}{1+e^{-i}}$

Tan: $f\ (i) = \frac{e^{i} - e^{-i}}{e^{i} + e^{-i}}$

ReLU $f\ (i) = max(0, i)$

where i is the input to the activation function. In ReLU, any negative value in the input is converted to zero and only positive values are retained. This is done to improve convergence and prevent the problem of vanishing gradients.

2.1.3 Pooling Operation

The next operation is pooling, which is mostly used to reduce dimensionality. There are three types of pooling: minimum, maximum, and average pooling [5], which compute minimum, maximum, and average on a local neighborhood based on pool size. The feature maps have rotational invariance thanks to pooling procedures, particularly max pooling.

2.2 classification model

The classification model is the final block of the convolution module, which usually consists of one to three fully connected neural networks. The completely linked blocks frequently include a Softmax function that normalizes the network outputs between [0, 1], ensuring that the sum of the outputs equals one.

3. CNN MODELS-BASED IMAGE STEGANALYSIS

Convolutional neural networks made superior performance in different fields [11][12]. Researchers in the fields of image steganography and steganalysis have also shown that CNNs can be used in a variety of crucial areas of multimedia security. The use of CNNs in the creation of steganalysis has yielded incredible results. Without any prior feature selection, a CNN-based step analyzer allows us to automate feature extraction and classification processes in unique network architecture It has captivated the interest of many scholars and made significant progress, thanks to successful approaches based on CNN. Despite all progress made by CNNs, steganalysis is still facing some challenges. As a result, the CNN technique can be used to investigate these concerns.

3.1 CNN Models for spatial images steganalysis

In spatial Steganography, the message is hidden inside the image by manipulating distinct pixel values of the cover image, which affect the statistical feature of an image. This section examined various CNN-based approaches to spatial domain steganalysis and emphasized individual contributions.

The first structure of CNN-based spatial domain steganalysis had been proposed by Tan & Li[13] in 2014. They built CNN model with three convolution layers which are considered not deep enough and contain too large fully connected layers which made it slow. The network achieves better results than the SPAM [14], but not better than SRM [15]. Their network error rate is 48% and made use of random parameter initialization for detecting HUGO [16]. Qian et al. [17] proposed customized CNN architecture for steganalysis which is capable to capture complex dependencies among image pixels. The proposed CNN contains five convolution layers and also contains an image processing layer as a knowledge layer. The role of the image processing layer is to strengthen the weak stego noise. The proposed CNN achieved comparable results to Spatial Rich Model[15]. Similarly, piber et al.[18] developed a CNN model for steganalysis that achieved better detection accuracy when the embedding key is reused for different image Steganography. The author’s model consists of only two convolution layers and pre-processing layer that applies a high pass filter to input images before feeding the CNN. They also used the ReLU activation function in the convolution operation. Xu-NetV1 et al.[19] proposed well designed CNN model that achieved competitive results compared with SRM [15]. The proposed model takes absolute value using

ABS for elements in the feature generated from the first convolution layer. This model improved statistical modeling for the subsequent layers by using batch normalization and Tan H activation. Hence provide better detection according to the state of the art at that time. Saloman et al.[20] proposed good performance CNN for steganalysis when the embedding key is reused. The proposed network consists of only two convolutional blocks in the network & increases the number of activation maps in each convolutional layer, as well as removing the pooling layer, which is detrimental to later steganalysis operations due to noise smoothing. Ye et al.[21] proposed CNN model for steganalysis that achieved superior performance across all tested steganographic algorithms (WOW[22], UNIWARD[23], and HILL[24]) for a wide variety of payloads. This model consists of ten layers and applies selection-channel-information and data augmentation techniques to boost the CNN. Yedroudj et al.[25] developed a successful CNN model for spatial steganalysis that consists of preprocessing layer and five convolution layers and one classification layer. This model uses the SRM kernels to precede the input image. The proposed model achieves exultant performance compared with state-of-the-art like Xu[19] & Ye[21]. Another successful CNN model was ReSt-Net proposed by Li et al.[26] this study presented Diverse Activation Modules and Parallel Subnets-Based CNN for Spatial Image Steganalysis. This model was derived from Xu–CNN [19] and uses three simultaneous HPF subnets to accept additional preprocessed inputs. The proposed CNN also employs the (DAMs) diversified activation modules to activate the convolved data in a variety of ways before combining their outputs for the subsequent layers. Liu et al.[27] developed an efficient and effective CNN framework that consists of five blocks and ends with a fully connected layer and a two-way softmax layer. The first block computes the residuals of the inputs by using HPF and truncated linear units (TLU)[28] to process the output of the convolutional layer. Also, this framework used 4 sub-networks (convolutional operation, batch normalization (BN), average pooling, and activation layers) in all remaining blocks to achieve better results. Lu et al[27]. presented CNN steganalysis framework based on Yedroudj-Net [25] and Dense-Net [29] which is considered an improvement for these networks. The authors introduce the notation of adding TLU in the pre-processing module to boost the detection rate and make performance improvements in other areas such as accelerating the training phase. Another well-performance CNN model was proposed by Jin et al.[30] called IAS-CNN. It contains a preprocessing layer to strengthen the stago signals, five convolutional layers for feature extraction, two fully connected layers for classification, two dropout layers for feature refining, and a two-way softmax function. IAS-CNN improved its performance by using a selection strategy. Wu et al. [31] propose a successful CNN steganalizer method by incorporating well designed pre-processing layer into CNN architecture. The feature subset selection method is used to design the pre-processing layer. According to the convolution operation's mechanism and pixel correlations, this solution eliminated several high-pass and derivative filters. The model's training efficiency is improved when this strategy is used. As a result, this method provides an optimal balance of computational complexity and detection accuracy. Liu et al.[32] proposed effective CNN model for image steganalysis consists of one image processing layer, seven convolutional layers, one fully connected layer, and a soft-max layer. The main contribution of the authors' study is the use of diverse filter modules (DFMs) & squeeze-&-excitation modules (SEMs), which can better capture the weak stego signals. Another intelligent approach proposed by You et al.[33] by investigating the possibility of building a steganalysis model that can deal with images of varying sizes without retraining its parameters. The proposed model employs Siamese architecture[34] to compute similarities between extracted features and then produce the final class. The model consists of three phases preprocessing features extraction and classification, these phases contain a lot of operations like HPF, convolution, pooling, BN, and ReLU function. Most of the deep learning frameworks based on the spatial domain were covered in this section. in the same year T.-S. Reinel et al[35] proposed a novel CNN architecture named GBRAS-Net that used skip connections, depth-wise and separable convolutional layers, and filter banks to enhance steganographic noise during the feature extraction step. This study employs 30 HPF in the pre-processing layer and global avg-pooling followed by softmax for classification.

We found that good network design can further increase the accuracy of deep learning frameworks. Steganalysis researchers achieved better results by using the CNN technique. But there are still a lot of issues that have not been addressed very well. **Table 1** lists shortcuts of methodologies and results of the most common CNN models applied to images steganalysis

Table 1: Summary of CNN architectures most used for image steganalysis

References	**Methods**	**Dataset**	**Steg-analysis type**	**Results** Steganographic algorithm bits per pixe(bpp)/error rate
Tan & Li[13]	CNN model with three convolutions, tow max pooling & tow fully connected layers &softmax fully connected	BOSSbase1.01	Spatial domain	HUGO 0.4/0.31
Qian et al.[17]	and introducing the High Pass Filter layer and Gaussian Activation function. Uses five convolutional, three average pooling & three fully connected layers.	BOSSbase1.01	Spatial domain	HUGO WOW S-UNIWARD 0.3/0.33 0.3/0.34 0.3/0.35 0.4/0.28 0.4/0.29 0.4/0.30 0.5/0.25 0.50./35 0.5/0.26
Xu-NetV1et al.[19]	Create noise residuals to improve the CNNs' detection capabilities. the used High Pass Filter layer same as Qian net. used 5x5 average pooling and 5 groups of Convolution layers.	BOSSbase1.01	Spatial domain	HILL S-UNIWARD 0.1/0.41 0.1/0.42 0.4/0.20 0.4/0.19
Ye et al. [21]	applies selection-channel-information and data augmentation techniques to boost CNN. Uses ten conv&avg-pooling	BOSSbase1.01 & LIRMMbase 1.01	Spatial domain	HUGO WOW S-UNIWARD 0.05/0.43 0.05/38 0.050./43 0.1/0.38 0.1/0.32 0.1/0.39 0.2/0.32 0.2/0.24 0.2/0.32 0.3/0.28 0.3/0.20 0.3/0.25 0.4/0.22 0.4/0.17 0.4/0.19 0.5/0.19 0.5/0.14 0.5/0.16
Yedroudj et al.[25]	similar to Xu-Net1, five sets of Conv layers were used. used layers of BN and ABS. The preprocessing layer uses the same 30-filter bank as Ye-Net.	BOSSbase1.01	Spatial domain	WOW S-UNIWARD 0.2/0.27 0.2/0.36 0.4/0.14 0.4/0.22

Li et al. [26]	Used three parallel conv subnet The SRM linear, SRM nonlinear, and Gabor filters were employed.	BOSSbase1.01	Spatial domain	HILL S-UNIWARD 0.1/0.37 0.1/0.34 0.2/0.29 0.2/0.28 0.3/0.23 0.3/0.21 0.4/0.18 0.4/0.14 0.5/0.13 0.5/0.12
XU et al.[36]	20-layer deeper network, Res-Net architecture, and 44 DCT pre-processing	ImageNet	Transform domain	J-UNIWARD 0.1/0.41 0.2/0.29 0.3/0.20 0.4/0.14
Chen et al.[37]	ported the JPEG phase-awareness idea to Xu-Net used two directional Gabor filters and the Katalyst Kernel.	BOWS2	Transform domain	UED-JC S-UNIWARD 0.1/0.17 0.1/0.35 0.2/0.08 0.2/0.21 0.3/0.03 0.3/0.12 0.4/0.02 0.4/0.06 0.5/0.01 0.5/0.03
Yang-Net et al. [38]	Used a very deep CNN model with 32 convolution layers. Used batch normalization and 16 HPF Performed better than Xu-Net	BOSSbase1.01	Transform domain	J-UNIWARD 0.1/0.37 0.2/0.25 0.3/0.16 0.4/0.1

3.2 CNN Models for transform domain image steganalysis

The transform domain steganographic algorithms modify coefficient values such as DCT, DWT, and DFT after transformation. There is a lot of transform-domain steganalysis-based CNN frameworks available, although some of them are unreliable or time intensive. Significant progress has been made in transform domain steganalysis by designing appropriate CNN models or incorporating phase-aware concepts into CNN architectures.

The significance of using a large number of layers in CNN is proposed by XU et al.[36]. The proposed CNN model contains 20 convolutional layers and the preprocessing layer that transform the JPEG image to the spatial domain and then passes the features map to the next convolution layer. Also proposed CNN uses batch normalization and ReLU functions between convolution layers. Chen et al.[37] proposed CNN model for JPEG steganalysis that introduces the concept of phase-split inspired by the JPEG compression algorithm. The proposed model is based on Xu-Net [36] but differs by dividing the feature maps into 64 parallel parts to port the jpeg phase aware in their network. P-Net and V-Net are two methods for bringing phase awareness into network architecture that they introduced in their network. On J-UNIWARD and UED, the experimental findings show that the suggested CNN structure outperforms SCA-GFR. Yang-Net et al. [38], proposed a very deep CNN model which contains 32 convolution layers. The proposed model introduces the concept of feature reuse by concatenating all features from previous layers to improve the flow of information and gradient. The proposed method also used 16 HPF to strengthen the stego signals. The method can reduce the detection error rate, according to the results of experiments. Huang et al. [39] proposed a successful CNN model for transform domain image steganalysis. The proposed study incorporates a domain knowledge layer that applies a selection-channel-aware in the first stage of the model and then uses the TLU activationfunction to guarantee better distribution of feature maps. To improve the proposed CNN's performance, the approach also employs a generalized residual learning block to include selection channel knowledge. Experimental results show improved performance against traditional machine learning methods and comparable performance against the state-of-the-art method, also showing the low complexity of the proposed model. Another milestone for transform domain image steganalysis made a significant contribution proposed by Su et al. [39]. The method is called RXGNet and is based on ResNeXt [40] with Gauss partial derivative (GPD) filters [41] as a preprocessing layer to capture the weak signals generated by the Steganographic operations. Also, the proposed method employs a residual learning module behind the pre-processing layer with six groups to convert the residual images into image features for classification. Excremental results against J-UNIWARD [32] Steganographic method, show that the proposed CNN has a better performance compared with the state-of-the-art CNN-based method Xu-Net and SCA-GFR[42]. Xiao-Qing Deng et al [28] proposed a successful steganalysis-based CNN method which consists of pre-processing layer and four groups of operations, the first group consists of convolutional layers and each of the remains consists of two convolutional layers flowed by pooling layers. This architecture used 62 HPF and a truncation function (TLU) in the pre-processing layer. Also used global covariance pooling[28] in group 4 while average pooling in the other groups.

4. PERFORMANCE EVALUATION OF THE SURVEYED CNN MODELS

Figures 2, 3, and 4 provide comparative results of errors rate for the surveyed CNN models developed for detecting HOGO, S-UNIWARD, and WOW stenographic algorithms respectively.

It can be noticed from these figures when the payload capacity is high (from 3pbb to 5pbb) the error values will be small for the CNN architectures. It is because more hidden information leads to high steganography noise and the steganalysis models will have more information to learn about the stego noise.

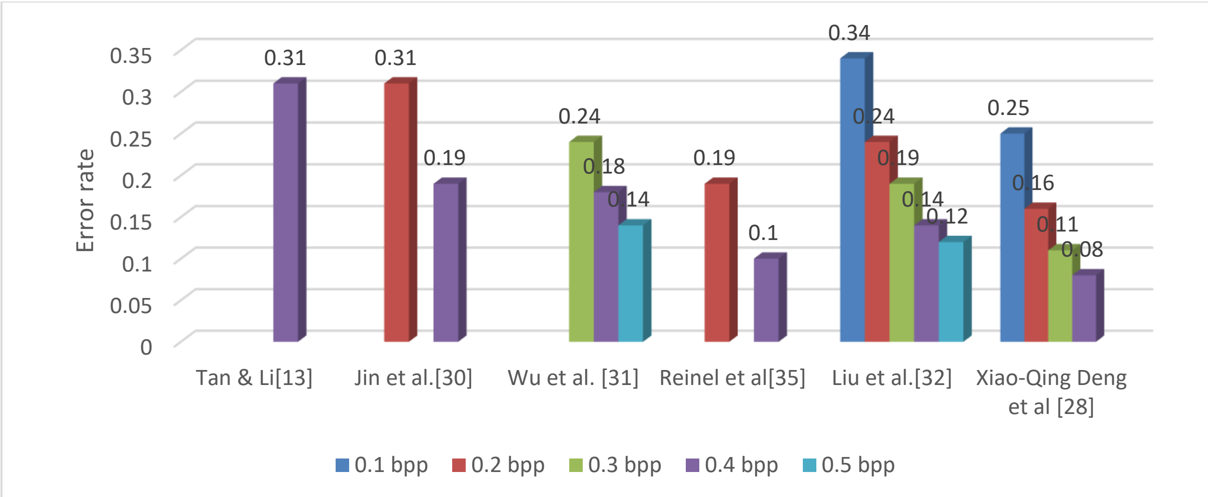

Figure 2. Comparison of Error rate for different models for the HUGO steganographic algorithm

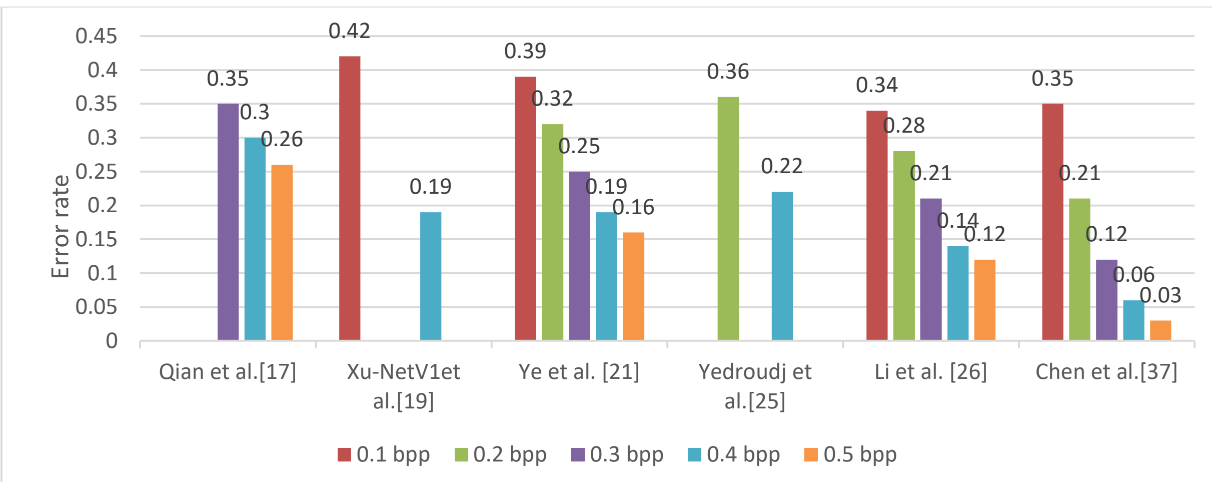

Figure 3. Comparison of Error rate for different models for the S-UNIWARD steganographic algorithm.

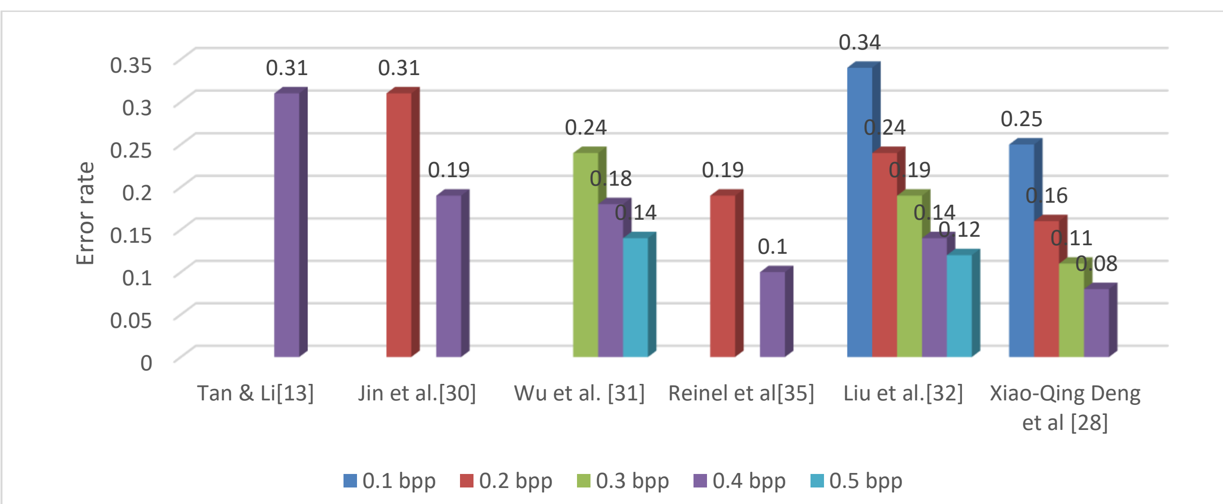

Figure 4. Comparison of Error rate for different models for the WOW steganographic algorithm.

5. CHALLENGES

Recent years have seen a lot of interest in steganalysis, but several issues have not been addressed yet. Here we will present some interesting challenges.

First, the CNN models discussed in this study are created to work with certain datasets. Currently, no CNN model can find hidden messages in unobserved data.

Second, low payload capacity in steganography operations is the most challenging issue for steganalyst. The statistical characteristics of the weak steganographic signal are quite difficult to distinguish. Therefore, improving the detection effectiveness of the steganalysis algorithm depends significantly on the selection of training samples and learning strategies.

When the steganalysis detector is trained on one dataset and tested on another dataset, cover source mismatch issues occur, leading to the overfitting problem[43].

To master small sample size training in-depth and get strong detection results, a lot of training sets are required. However, training with a high sample size takes a lot of time and effort, and obtaining a big number of samples can occasionally be challenging. There is an urgent need to develop efficient deep learning-based steganalysis frameworks with few training data.

6. CONCLUSION

In this study, we examined the research that has been done on digital image steganalysis based-CNNs. Despite CNNs achieving better performances compared to the classical machine learning approach in the steganalysis discipline. The detection of steganographic images using CNN models is still in its infancy, hence the CNN models must be resistant to steganographic methods.

This work evaluated scholars' approaches to discussing challenges with image steganography-based CNNs. We also covered significant concerns and issues related to image steganalysis to show how these challenges might be turned into fruitful future research directions. When the CNN technique is applied to image steganalysis, it is concluded that significant improvement will be made if all existing frameworks' limitations are considered.

7. REFERENCES

[1] D. Bandyopadhyay, K. Dasgupta, M. J. K, and P. Dutta, "A Novel Secure Image Steganography Method Based on Chaos Theory in Spatial Domain," *Int. J. Secur. Priv. Trust Manag.*, vol. 3, no. 1, pp. 11–22, 2014, doi: 10.5121/ijsptm.2014.3102.

[2] M. A. Saleh, "Image Steganography Techniques - A Review Paper," *Ijarcce*, vol. 7, no. 9, pp. 52–58, 2018, doi: 10.17148/ijarcce.2018.7910.

[3] Y. Qian, J. Dong, W. Wang, and T. Tan, "Feature learning for steganalysis using convolutional neural networks," *Multimed. Tools Appl.*, vol. 77, no. 15, pp. 19633–19657, 2018, doi: 10.1007/s11042-017-5326-1.

[4] W. Wang and X. Yuan, "图像隐写分析研究新进展 董," *IEEE/CAA J. Autom. Sin.*, vol. 4, no. 3, pp. 410–436, 2017.

[5] Y. H. Tang, L. H. Jiang, H. Q. He, and W. Y. Dong, "A review on deep learning based image steganalysis," *Proc. 2018 IEEE 3rd Adv. Inf. Technol. Electron. Autom. Control Conf. IAEAC 2018*, no. Iaeac, pp. 1764–1770, 2018, doi: 10.1109/IAEAC.2018.8577655.

[6] P. Wang, Z. Wei, and L. Xiao, "Fast projections of spatial rich model feature for digital image steganalysis," *Soft Comput.*, vol. 21, no. 12, pp. 3335–3343, 2017, doi: 10.1007/s00500-015-2011-z.

[7] J. Yu, F. Li, H. Cheng, and X. Zhang, "Spatial Steganalysis Using Contrast of Residuals," *IEEE Signal Process. Lett.*, vol. 23, no. 7, pp. 989–992, 2016, doi: 10.1109/LSP.2016.2575100.

[8] W. Cao, Q. Guan, X. Zhao, K. Wang, and J. Han, "Constructing local information feature for spatial image steganalysis," *Multimed. Tools Appl.*, vol. 76, no. 11, pp. 13221–13237, 2017, doi: 10.1007/s11042-016-3751-1.

[9] L. Yann and B. Yoshua, "Convolutional Networks for Images, Speech, and Time-Series," *Handb. brain theory neural networks*, pp. 255–258, 1995, [Online]. Available: https://www.researchgate.net/profile/Yann_Lecun/publication/2453996_Convolutional_Networks_for_Images_Speech_and_Time-Series/links/0deec519dfa2325502000000.pdf%0Ahttps://www.researchgate.net/profile/Yann_Lecun/publication/2453996_Convolutional_Networks_fo

[10] A. Selvaraj, A. Ezhilarasan, S. L. J. Wellington, and A. R. Sam, "Digital image steganalysis: A survey on paradigm shift from machine learning to deep learning based techniques," *IET Image Process.*, vol. 15, no. 2, pp. 504–522, 2021, doi: 10.1049/ipr2.12043.

[11] I. Hussain, Q. He, and Z. Chen, "Automatic Fruit Recognition Based on DCNN for Commercial Source Trace System," *Int. J. Comput. Sci. Appl.*, vol. 8, no. 2/3, pp. 01–14, 2018, doi: 10.5121/ijcsa.2018.8301.

[12] M. H. Pinson, L. K. Choi, and A. C. Bovik, "Temporal video quality model accounting for variable frame delay distortions," *IEEE Trans. Broadcast.*, vol. 60, no. 4, pp. 637–649, 2014, doi: 10.1109/TBC.2014.2365260.

[13] S. Tan and B. Li, "Stacked convolutional auto-encoders for steganalysis of digital images," *2014 Asia-Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. APSIPA 2014*, no. 1, 2014, doi: 10.1109/APSIPA.2014.7041565.

[14] V. Holub and J. Fridrich, "Random projections of residuals for digital image steganalysis," *IEEE Trans. Inf. Forensics Secur.*, vol. 8, no. 12, pp. 1996–2006, 2013, doi: 10.1109/TIFS.2013.2286682.

[15] J. Fridrich and J. Kodovsky, "Rich models for steganalysis of digital images," *IEEE Trans. Inf. Forensics Secur.*, vol. 7, no. 3, pp. 868–882, 2012, doi: 10.1109/TIFS.2012.2190402.

[16] T. Pevný, T. Filler, and P. Bas, "Using high-dimensional image models to perform highly undetectable steganography," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 6387 LNCS, pp. 161–177, 2010, doi: 10.1007/978-3-642-16435-4_13.

[17] Y. Qian, J. Dong, W. Wang, and T. Tan, "Deep learning for steganalysis via convolutional neural networks," *Media Watermarking, Secur. Forensics 2015*, vol. 9409, p. 94090J, 2015, doi: 10.1117/12.2083479.

[18] L. Pibre, J. Pasquet, D. Ienco, and M. Chaumont, "Deep learning is a good steganalysis tool when embedding key is reused for different images, even if there is a cover sourcemismatch," *IS T Int. Symp. Electron. Imaging Sci. Technol.*, pp. 14–18, 2016, doi: 10.2352/ISSN.2470-1173.2016.8.MWSF-078.

[19] G. Xu, H. Z. Wu, and Y. Q. Shi, "Structural design of convolutional neural networks for steganalysis," *IEEE Signal Process. Lett.*, vol. 23, no. 5, pp. 708–712, 2016, doi: 10.1109/LSP.2016.2548421.

[20] M. Salomon, R. Couturier, C. Guyeux, J. F. Couchot, and J. M. Bahi, "Steganalysis via a convolutional neural network using large convolution filters for embedding process with same stego key: A deep learning approach for telemedicine," *Eur. Res. Telemed.*, vol. 6, no. 2, pp. 79–92, 2017, doi: 10.1016/j.eurtel.2017.06.001.

[21] J. Ye, J. Ni, and Y. Yi, "Deep Learning Hierarchical Representations for Image Steganalysis," *IEEE Trans. Inf. Forensics Secur.*, vol. 12, no. 11, pp. 2545–2557, 2017, doi: 10.1109/TIFS.2017.2710946.

[22] S. Binghamton, "DESIGNING STEGANOGRAPHIC DISTORTION USING DIRECTIONAL FILTERS Vojtˇ ech Holub and Jessica Fridrich," *Ieeexplore.Ieee.Org*, pp. 234–239, 2012, [Online]. Available: http://ieeexplore.ieee.org/abstract/document/6412655/

[23] V. Holub and J. Fridrich, "Digital image steganography using universal distortion," *IH MMSec 2013 - Proc. 2013 ACM Inf. Hiding Multimed. Secur. Work.*, pp. 59–68, 2013, doi: 10.1145/2482513.2482514.

[24] T. Filler and J. Fridrich, "Gibbs construction in steganography," *IEEE Trans. Inf. Forensics Secur.*, vol. 5, no. 4, pp. 705–720, 2010, doi: 10.1109/TIFS.2010.2077629.

[25] M. Yedroudj, F. Comby, and M. Chaumont, "Yedroudj-Net: An Efficient CNN for Spatial Steganalysis," *ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc.*, vol. 2018-April, no. 1, pp. 2092–2096, 2018, doi: 10.1109/ICASSP.2018.8461438.

[26] B. Li, W. Wei, A. Ferreira, and S. Tan, "ReST-Net: Diverse Activation Modules and Parallel Subnets-Based CNN for Spatial Image Steganalysis," *IEEE Signal Process. Lett.*, vol. 25, no. 5, pp. 650–654, 2018, doi: 10.1109/LSP.2018.2816569.

[27] Y. Y. Lu, Z. L. O. Yang, L. Zheng, and Y. Zhang, "Importance of Truncation Activation in Pre-Processing for Spatial and Jpeg Image Steganalysis," *Proc. - Int. Conf. Image Process. ICIP*, vol. 2019-Septe, pp. 689–693, 2019, doi: 10.1109/ICIP.2019.8803800.

[28] X. Q. Deng, B. L. Chen, W. Q. Luo, and D. Luo, "Universal Image Steganalysis Based on Convolutional Neural Network with Global Covariance Pooling," *J. Comput. Sci. Technol.*, vol. 37, no. 5, pp. 1134–1145, 2022, doi: 10.1007/s11390-021-0572-0.

[29] E. Mocsari and S. S. Stone, "Colostral IgA, IgG, and IgM-IgA fractions as fluorescent antibody for the detection of the coronavirus of transmissible gastroenteritis.," *Am. J. Vet. Res.*, vol. 39, no. 9, pp. 1442–1446, 1978.

[30] Z. Jin, Y. Yang, Y. Chen, and Y. Chen, "IAS-CNN: Image adaptive steganalysis via convolutional neural network combined with selection channel," *Int. J. Distrib. Sens. Networks*, vol. 16, no. 3, 2020, doi: 10.1177/1550147720911002.

[31] L. Wu, X. Han, C. Wen, and B. Li, "A Steganalysis framework based on CNN using the filter subset selection method," *Multimed. Tools Appl.*, vol. 79, no. 27–28, pp. 19875–19892, 2020, doi: 10.1007/s11042-020-08831-8.

[32] F. Liu, X. Zhou, X. Yan, Y. Lu, and S. Wang, "Image steganalysis via diverse filters and squeeze-and-excitation convolutional neural network," *Mathematics*, vol. 9, no. 2, pp. 1–13, 2021, doi: 10.3390/math9020189.

[33] W. You, H. Zhang, and X. Zhao, "A Siamese CNN for Image Steganalysis," *IEEE Trans. Inf. Forensics Secur.*, vol. 16, pp. 291–306, 2021, doi: 10.1109/TIFS.2020.3013204.

[34] H. Jansen, M. P. Gallee, and F. H. Schroder, "Analysis of sonographic pattern in prostatic cancer: Comparison of longitudinal and transversal transrectal ultrasound with subsequent radical prostatectomy specimens," *Eur. Urol.*, vol. 18, no. 3, pp. 174–178, 1990, doi: 10.1159/000463903.

[35] T. S. Reinel *et al.*, "GBRAS-Net: A Convolutional Neural Network Architecture for Spatial Image Steganalysis," *IEEE Access*, vol. 9, pp. 14340–14350, 2021, doi: 10.1109/ACCESS.2021.3052494.

[36] G. Xu, "Deep convolutional neural network to detect J-UNIWARD," *IH MMSec 2017 - Proc. 2017 ACM Work. Inf. Hiding Multimed. Secur.*, pp. 67–73, 2017, doi: 10.1145/3082031.3083236.

[37] M. Chen, V. Sedighi, M. Boroumand, and J. Fridrich, "JPEG-phase-aware convolutional neural network for steganalysis of JPEG images," *IH MMSec 2017 - Proc. 2017 ACM Work. Inf. Hiding Multimed. Secur.*, pp. 75–84, 2017, doi: 10.1145/3082031.3083248.

[38] J. Yang, Y.-Q. Shi, E. K. Wong, and X. Kang, "JPEG Steganalysis Based on DenseNet," pp. 1–7, 2017, [Online]. Available: http://arxiv.org/abs/1711.09335

[39] A. Su, X. He, and X. Zhao, "JPEG steganalysis based on ResNeXt with Gauss partial derivative filters," *Multimed. Tools Appl.*, vol. 80, no. 3, pp. 3349–3366, 2021, doi: 10.1007/s11042-020-09350-2.

[40] S. Xie, R. Girshick, and P. Doll, "Aggregated Residual Transformations for Deep Neural Networks http://arxiv.org/abs/1611.05431v2," *Conf. Comput. Vis. Pattern Recognit.*, pp. 1492–1500, 2017.

[41] Y. Zhang, F. Liu, C. Yang, X. Luo, X. Song, and J. Lu, "Steganalysis of content-adaptive JPEG steganography based on Gauss partial derivative filter bank," *J. Electron. Imaging*, vol. 26, no. 1, p. 013011, 2017, doi: 10.1117/1.jei.26.1.013011.

[42] T. Denemark, M. Boroumand, and J. Fridrich, "Steganalysis Features for Content-Adaptive JPEG Steganography," *IEEE Trans. Inf. Forensics Secur.*, vol. 11, no. 8, pp. 1736–1746, 2016, doi: 10.1109/TIFS.2016.2555281.

[43] I. Hussain, J. Zeng, Xinhong, and S. Tan, "A survey on deep convolutional neural networks for image steganography and steganalysis," *KSII Trans. Internet Inf. Syst.*, vol. 14, no. 3, pp. 1228–1248, 2020, doi: 10.3837/tiis.2020.03.017.