

# Universal Deep Network Steganalysis of Color Based on Channel Representation

Mr. Nagesh R<sup>1</sup>, SP Vidya Sagar<sup>2</sup>, Sanjay M<sup>3</sup>, Suhas A<sup>4</sup>

Assistant Professor, Department of Information Science and Engineering<sup>1</sup>

Students, Department of Information Science and Engineering<sup>2,3,4</sup>

S J C Institute of Technology, Chickballapur, India

**Abstract:** *Up to now, utmost being steganalytic styles are designed for grayscale images, and they aren't suitable for color images that are extensively used in current social networks. To begin with, we divide the input image based on the different embedding spaces of its colors, resulting in three separate channels.. The proposed system includes preprocessing, convolutional, and bracket modules. To save the steganographic vestiges in each color channel, in preprocessing module, we originally separate the input image into three channels according to the corresponding embedding spaces(i.e RGB for spatial steganography and YCbCr for JPEG steganography), and also prize the image residuals with 62 fixed high- pass pollutants, eventually concatenated all abbreviated residuals for posterior analysis analysis rather than adding them together with normal complication like being CNN- grounded steganalyzers. To accelerate the network confluence and effectively reduce the number of parameters, in convolutional module, we precisely design three types of layers with different roadway connections and group complication structures to further learn high- position steganalytic features. In bracket module, we employ a global normal pooling and completely connected subcaste for bracket.*

**Keywords:** Machine learning, image processing, steganography, CNN

## I. INTRODUCTION

Image steganography aims to bed secret information into digital image without introducing obvious visual vestiges. On the contrary side, steganalysis aims to descry covert communication established via steganography. recently, utmost modern steganographic styles are image content adaptive, which significantly enhance the steganography security. thus, steganalysis is facing severe challenges. Image steganalysis ways can be divided into two orders, that is, traditional styles predicated on handcrafted features and CNN- predicated styles. For case, in spatial sphere, Aiming at color images, we design a universal deep steganalytic network predicated on channel representation in this paper. To enhance the steganographic noise signal in both spatial and JPEG disciplines, we combine 30 introductory direct adulterants from SRM and 32 Gabor adulterants for calculating image residuals. To well save steganographic vestiges in each color channel, we also concatenate all shortened residuals for posterior analysis rather of adding them together like being steganalytic networks. likewise, we precisely design three types of layers with different thruway connections and group complication structures to further learn high- position steganalytic features. extensive experimental results estimated on ALASKA II show that the proposed system can achieve state- of- the- art results compared with some modern CNN- predicated steganalyzers, while maintaining lower resource conditions and number of parameters. In addition we provided to verify the rationality of the network.

## II. LITERATURE SURVEY

[1] Title Yedroudj- Net An effective CNN for spatial steganalysis

Authors: Mehdi Yedroudj; Frédéric Comby; Marc Chaumont

Abstract: An ensemble classifier trained with rich features was used to detect the existence of a covert communication within an image, and this process was repeated approximately 10 times. In recent times, studies analogous as indicated that well- designed convolutional Neural Networks( CNN) can achieve analogous performance to the two- step

machine learning approaches. The focus of this paper is to introduce a Convolutional Neural Network (CNN) that demonstrates superior performance in terms of minimizing error probability when compared to existing models considered to be the best available. The proposition is in the continuity of what has been recently proposed and it's a clever conflation of important bricks used in various papers. Among the essential corridor of the CNN, one can cite the use of a pre-processing filterbank and a Truncation activation function, five convolutional layers with a Batch Normalization associated To enhance the effectiveness of our CNN, we incorporated a Scale Layer, and ensured that the fully connected section was of an appropriate size. Additionally, an augmented database was utilized to improve the training process. An experimental evaluation was conducted on our CNN, where it was pitted against the S-UNIWARD and WOW embedding algorithms. The results of this evaluation were then compared to those of three other models, one of which was an Ensemble Classifier along with a Rich Model and two other CNN steganalyzers.

**Methodology used:**

- Convolutional Neural Networks (CNN).

**Advantages**

- It's used for steganalysis performance improvement.

**Disadvantages**

- It is not used to prize hidden contents.

[2] Title: Steganalysis of digital images using Deep residual network

Authors: Mehdi Boroumand; Mo Chen; Jessica Fridrich

Abstract: Steganography sensors erected as deep convolutional neural networks have forcefully established themselves as superior to the former discovery paradigm- classifiers grounded on rich media models. Being network infrastructures, still, still contain rudiments designed by hand, similar as constrained or fixed convolutional kernels and heuristic initialization of kernels, the thresholded direct unit that mimics truncation in rich models, quantization of point charts, and mindfulness of JPEG phase. In this work, we describe a deep residual armature designed to minimize the use of heuristics and externally enforced rudiments that are universal in the sense that it provides state- of- the- art discovery delicacy for both spatial- sphere and JPEG steganography expansive trials show the superior performance of this network with a significant enhancement, especially in the JPEG sphere. farther performance boost is observed by supplying the selection channel as a alternate channel.

**Methodology Used :**

- Deep residual armature

**Advantages**

- It's designed to minimize the use of heuristic design rudiments specific to steganalysis

**Disadvantages**

- It provides further noise

[3] Title: A customized convolutional neural network with low model complexity for JPEG steganalysis

Authors: Jiangqun Ni, Linhong Wan, JingwenYan

Abstract: Currently, convolutional neural network( CNN) is applied to different types of image bracket tasks and outperforms nearly all traditional styles. still, one may find it delicate to apply CNN to JPEG steganalysis because of the extremely low SNR(embedding dispatches to image contents) in the task. In this paper, a selection- channel- apprehensive CNN for JPEG steganalysis is proposed by incorporating sphere knowledge. Specifically, rather of arbitrary strategy, kernels of the first convolutional subcaste are initialized with hand- drafted pollutants to suppress the image content. also, abbreviated direct unit( TLU), a heuristically- designed activation function, is espoused in the first subcaste as the activation function to more acclimatize to the distribution of point charts. Eventually, we use a generalized residual literacy block to incorporate the knowledge of selection channel in the proposed CNN to further boost its performance. To evaluate the effectiveness of our proposed CNN and other competing JPEG steganalysis methods, we utilized J-UNIWARD, which is a highly advanced JPEG steganographic scheme. trial results show that

the proposed CNN steganalyzer outperforms other point-grounded styles and rivals the state-of-the-art CNN-grounded styles with important reduced model complexity, at different loads.

**Methodology Used:**

- Customized CNN-steganalyzer.

**Advantages**

- Kernel in pre-processing subcaste to prize the image residuals.

**Disadvantages**

- It consumes further training time.
- It isn't suitable for color images.

[4] Title A novel steganography for spatial color images predicated on pixel vector cost

Authors: Xinghong Qin; Bin Li; Shunquan Tan; Jishen Zeng

Abstract: Steganography aims to conceal secret data into common media, and steganalysis takes the inimical position by trying to reveal embedding traces. ultimate of the being steganographic schemes for spatial images are designed for gray-scale images. Their extensions to color images are constantly simply reused by treating each color channel as a single gray image and distributing weight slightly to different color channels. still, color images are generally used in quotidian life, and some effective steganalytic styles recently proposed for color images have bettered discovery performance with features designed by taking color correlations into consideration Our paper presents a fresh approach to steganography for spatial color images, which involves the use of color pixel vectors (CPVs) as coverlet units. CPVs are composed of color factors located at the same spatial position. The aim of our paper is to introduce a novel steganographic technique for spatial color images. Our method involves utilizing color pixel vectors (CPVs) as coverlet units, where each CPV consists of color factors from the same spatial position. By directly defining coverlet costs on CPVs, our approach allows for the explicit consideration of complex relationships among color channels, and enables adaptive assignment of coverlet weight to all three channels. To further enhance the performance, a shaped clustering modification directions strategy is incorporated. The experimental results show that the proposed scheme can effectively repel the steganalytic styles, especially with color-rich model features.

**Methodology used:**

- Color pixel vectors

**Advantages**

- It effectively repels the steganalytic styles.

**Disadvantages**

- It requires heavy work weight resources.

[5] Title Color image steganography grounded on inter-channel correlations and differences for non-additive cost function

Authors: Yaofei Wang; Weiming Zhang; Weixiang Li; Xinzhi Yu

Abstract: Despite the fact that color images are widely used for communication, previous research in steganography has largely focused on grayscale images. This is problematic, as color images possess three interrelated color channels, and the interplay between these channels can significantly impact the security of steganography. The objective of this paper is to introduce a steganographic method for spatial color images, which utilizes the correlations and distinctions that exist between the color channels. We find that the G channel has a stronger correlation with R and B than the one between R and B, and therefore, coinciding the revision directions of the R and B channels with those from the G channel will have better resistance to discovery. In addition, the cargo capacity and the distribution of complex regions between channels are different. Our paper proposes a novel approach for determining non-additive costs in the context of color image steganography, which we refer to as the GINA strategy. The GINA strategy can make the revision directions of the R and B channels harmonious with those of the G channel and can adaptively distribute the embedding capacity between the three channels. Specifically, this strategy won't violate the Complexity previous rule. The results

of the experiments demonstrate that the GINA strategy that was proposed can greatly enhance the performance of color image steganalysis when compared to previous approaches.

**Methodology Used:**

- G- channel- related Inter-channel Non-Additive (GINA) Strategy.

**Advantages**

- Significantly improve the performance in terms of defying color image steganalysis.

**Disadvantages**

- Time taken for training the network is too long.
- Heavy resources demanded

**III. METHODOLOGY**

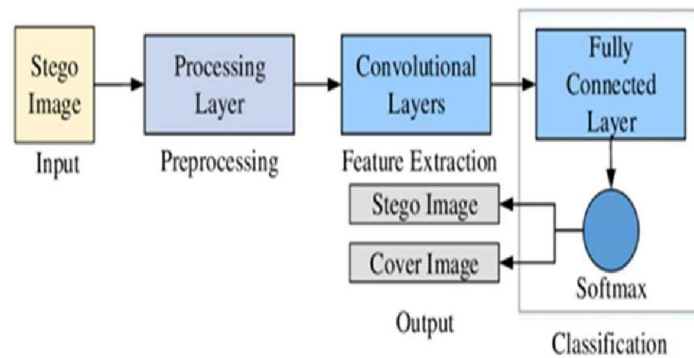


FIG 1: System architecture

The proposed framework is illustrated in Fig. 1, showing that the feature representations obtained from a pre-trained CNN for detecting stegos.

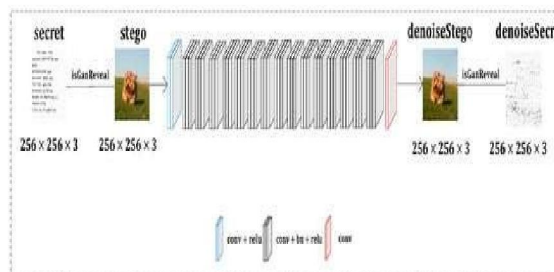


FIG 2: The feed forwarding denoising convolutional neural network

Figure 2 depicts a deep convolutional steganography removal network with multiple layers. The first layer uses 64 filters of size  $3 \times 3 \times 3$  and is followed by a ReLU activation function. Subsequent layers, from the second to the last (D-1), use 64 filters of size  $3 \times 3 \times 64$  and include batch normalization layers between the Conv and ReLU layers to speed up training and improve steganography removal performance. These layers gradually remove the secret image from the stego image.

$$loss = \frac{\sum_{i=1}^I \sum_{j=1}^J |C_{i,j} - R_{i,j}|}{I \odot J}$$

FIG 3: Loss Function

The last layer uses three filters of size  $3 \times 3 \times 64$  to reconstruct the image and generate the output of the steganography removal model. The loss function used in DnCNN compares the original image to the image after removing the steganographic message and aims to minimize the difference between the two. This helps retain as much of the original image's quality as possible after removing the secret message, as well as enhance the stego and purified images.

**IV. DESIGN**

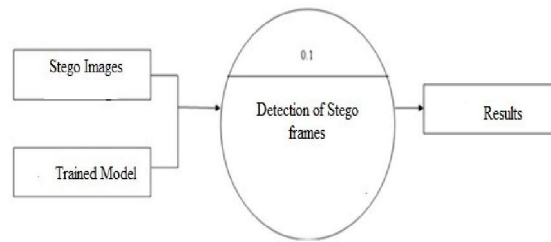


FIG 4: DFD level 0

LEVEL 0: Describes the overall process of the project. We are passing stego image and its Trained Model as an input system that will efficiently analyze the frames and detect which frame stego bits are represented.

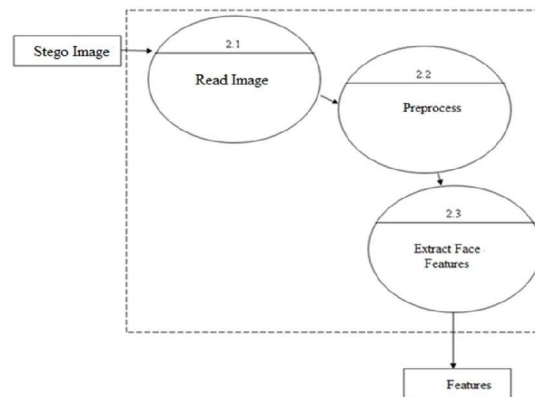


FIG 5: DFD level 1

LEVEL 1: The initial phase of the project involves utilizing a steganography image system to scan followed by a preprocessing step to extract various features such as color, edges, and curves.

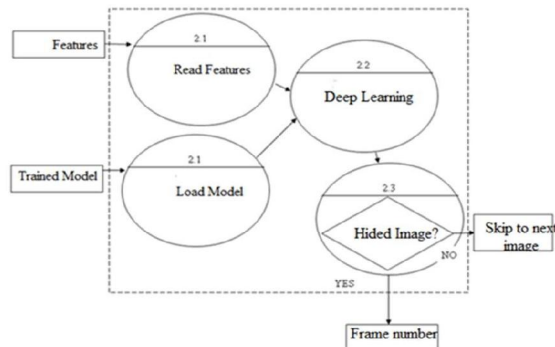


FIG 6: DFD level 2

LEVEL 2: It describes the final step process of the project. We are passing extracted features data from level 1 and trained model as input. The system will read features Load the model and detect any hidden image if it is detected system will give the frame number of the given image sequences.

The first step in the system is data collection, where a large dataset of cover and stego images is collected and stored in a database. This dataset serves as the basis for training and testing the steganalysis system. In the preprocessing module, the collected images are processed to extract various features such as color, edges, and curves. The preprocessing module is crucial in enhancing the quality of the images, making it easier for the subsequent modules to extract useful features from them. The feature extraction module extracts features from each channel using a deep neural network. These extracted features are then stored in a separate database. In the training module, the deep neural network model is trained on the extracted features to distinguish between cover and stego images. When the steganalysis method is used on a video, it processes the frames sequentially, starting from the first frame. Each frame is analyzed, and if it is determined to be a stego frame, its frame number is recorded. The steganalysis method uses a deep neural network to

distinguish between cover and stego frames. The network is trained on a large dataset of cover and stego images to recognize patterns that are unique to stego images. If the steganalysis method detects a wrong frame, it goes back to the training module to fine-tune the network and improve its performance. This iterative process continues until the steganalysis method is able to detect the correct frames with a high degree of accuracy. Once the steganalysis method has detected the stego frames, it extracts the hidden information from these frames using a decoding algorithm. This hidden information can be in the form of text, images, or other types of data.

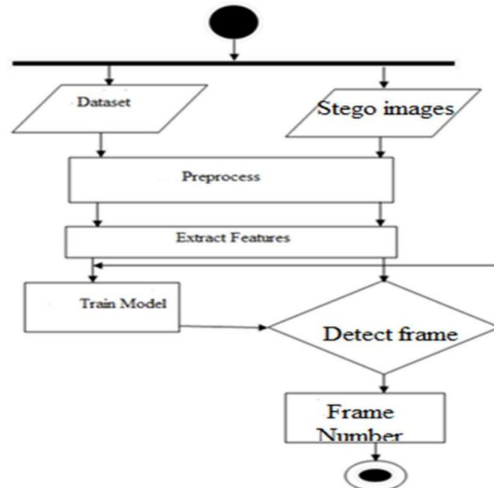


FIG 7:ACTIVITY DIAGRAM

## V. CONCLUSION

Universal Deep Network Steganalysis of Color Based on Channel Representation is a novel method for detecting steganography in images. The system uses a deep neural network to extract features from color and texture channels of images, and then trains the network to distinguish between cover and stego images. The proposed method outperforms other state-of-the-art steganalysis techniques and provides accurate results. The use of channel representation and deep neural networks provides a robust approach to detecting hidden information in images. However, the system has limitations such as the need for a large dataset and the complexity of the training process. Nevertheless, the Universal Deep Network Steganalysis of Color Based on Channel Representation is a promising method for detecting steganography and has the potential for future development in the field of digital forensics.

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