Metadata of the chapter that will be visualized in SpringerLink

Book Title	Intelligent Human Centered Computing
Series Title	
Chapter Title	Deep Artificial Neural Network Based Blind Color Image Watermarking
Copyright Year	2023
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Abstract

Digital data is growing enormously as the year passes and therefore there is a need of mechanism to protect the digital contents. Image watermarking is one of the important tools for the human to provide copyright protection and authorship. For achieving the ideal balance between imperceptibility and robustness, a robust blind color image watermarking employing deep artificial neural networks (DANN), LWT and the YIQ color model has been presented. In the suggested watermarking method, an original 512-bit watermark is applied for testing and a randomly generated watermark of the same length is used for training. PCA is used to extract 10 statistical features with significant values out of 18 statistical features, and binary classification is used to extract watermarks here. For the four images Lena, Peppers, Mandril, and Jet, it displays an average imperceptibility of 52.48 dB. For the threshold value of 0.3, it does an excellent job of achieving good balance between robustness and imperceptibility. Except for the gaussian noise, rotation, and average filtering attacks, it also demonstrates good robustness against common image attacks. The results of the experiment demonstrate that the suggested watermarking method outperforms competing methods.

Keywords (separated by '-'): Color image - YIQ - Blind watermarking - Robust - DANN

Deep Artificial Neural Network Based Blind Color Image Watermarking

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Abstract. Digital data is growing enormously as the year passes and therefore there is a need of mechanism to protect the digital contents. Image watermarking is one of the important tools for the human to provide copyright protection and authorship. For achieving the ideal balance between imperceptibility and robustness, a robust blind color image watermarking employing deep artificial neural networks (DANN), LWT and the YIQ color model has been presented. In the suggested watermarking method, an original 512-bit watermark is applied for testing and a randomly generated watermark of the same length is used for training. PCA is used to extract 10 statistical features with significant values out of 18 statistical features, and binary classification is used to extract watermarks here. For the four images Lena, Peppers, Mandril, and Jet, it displays an average imperceptibility of 52.48 dB. For the threshold value of 0.3, it does an excellent job of achieving good balance between robustness and imperceptibility. Except for the gaussian noise, rotation, and average filtering attacks, it also demonstrates good robustness against common image attacks. The results of the experiment demonstrate that the suggested watermarking method outperforms competing methods.

Keywords: Color image · YIQ · Blind watermarking · Robust · DANN

1 Introduction

With continuously growing digital information it is very essential to secure the digital data in order to preserve the integrity of the digital content. In today's era it is utmost important to secure the digital content from being accessed illegally and produced in some other from without taking permission from the author. By digging the literature it is very clear that cryptography is one of the ways to protect the digital content but it can be illegally copied any number of times once the decryption is done. Another way to protect the digital content is to use steganography, but involves much overhead even for adding a tiny text in the original cover image [1]. Digital image watermarking is a technique used to achieve the copyright protection and authorization for the digital content [2]. In watermarking process a watermarking image is added to the cover image using the watermark embedding algorithm and watermark image is extracted using the watermark extraction algorithm. A watermark algorithm must satisfy requirements like robustness, imperceptibility, capacity, security and complexity. Robustness is measured using Normalized

S. Bhattacharyya et al. (Eds.): Human 2023, STHC, pp. 1–12, 2023.
https://doi.org/10.1007/978-981-99-3478-2_10

coefficient (NC) value calculated between original and extracted watermark image and it should be between 0 and 1. The value near to 1 indicates the more similarity among original and extracted watermark images. Bit error rate (BER) is just opposite to the NC and less NC value shows the good robustness. Imperceptibility is calculated using the peak signal to noise ratio (PSNR) and high PSNR represent the excellent quality of the watermarked image. A watermarking algorithm must be complex enough to remove the watermark image without seriously affecting watermarked image qualities and capacity means the number of bits added to the cover image. One of the common issues in image watermarking is to balance the imperceptibility and robustness in such a way that both PSNR and NC remain in a balance way [3]. An image watermarking algorithm can by blind, semi-blind or non-blind in nature, based on how the watermark image is extracted. Based on the robustness an image watermarking algorithm can be fragile, semi-fragile or robust [3].

The review of literature [3] shows that a image watermarking is generally based on the spatial coefficients or transformation coefficients, but spatial domain based image watermarking is easy to implement but remain less effective for most of the image attacks as the manipulation is done on the pixels of the cover image. In transformation domain-based image watermarking, a cover image is first transformed into some transformation, followed by the addition of the watermark image, and finally, the watermarked image is obtained by applying an inverse transformation. Various transformation domains has been previously applied for image watermarking like DWT [4], discrete cosine transform (DCT) [5, 6], Discrete fourier transform (DFT) [7], redundant discrete wavelet transforms (RDWT) [8, 9], and integer/Lifting wavelet transform (IWT/LWT) [10–13, 15] for image watermarking. LWT has various advantages over the conventional transformation methods and it is most significantly known for absorbing more image distortion due to having more energy compaction properties.

An LWT-DCT-SVD based non-blind dual watermarking is proposed by Zear, A. et al. [12] for securing color images. In this study, a text watermark with a size of 64 $\times$ 64 pixels is embedded into a color cover image with a size of 512 $\times$ 512 pixels employing the LH3 sub-band and secured using the message digest hash function. The obtained results are also compared using the RGB, YIQ and YCbCr color models using the different scaling factor, different size of text watermark for different image attacks. The greatest PSNR obtained is 34.60 dB at scaling factor 0.01 for the Y part of the YIQ model. A color image can be represented using various models like the RGB model, YIQ model, YUV, and YCbCr model, and each of the color models has its own merits and demerits [12]. Chang, T. J. et al. [14] have proposed a scheme for color image using DCT-2DLDA (two dimensions linear discriminate analysis) and Cover image is transformed into a YIQ model for watermark embedding, and extraction is done using the two dimension linear discriminate analysis (2D-LDA) machine learning model. The YIQ color model is used for embedding due to its benefit over the RGB color model and it is effectively robust to numerous image attacks. Similarly deep-learning based multiple images watermarking scheme has been given by Mahto, D. K. et al. [15]. The spatial and transforms domain-based approach is the foundation for this concept. Using improved encryption algorithm, the watermarked image is encrypted and the suggested system's robustness is increased even further by using a de-noising convolution neural network. For the experiment, 14 standard color images are selected. The average PSNR and average NC are both 57.7124 and 1, respectively.

Looking at different watermarking technique in grey-scale domain and color domain revels that watermarking a color image requires some additional considerations as compare to watermarking grey-scale image. Looking at the past literature it is very clear that machine learning based color image watermarking has been emerged as a possible solution for balancing PSNR and NC in a reasonable way and designing a robust color image watermarking system is more challenging task. Watermarking extraction is done like binary classification technique and various classification techniques like SVM [10, 11], SVD [4, 5, 12, 13, 20], 2DLDA [14] and deep network [13, 15]. Each of the above mentioned classification model have its own advantage and disadvantages like SVM faces problem while selecting the best kernel for classification, 2DLDA model is easy to train but it performance is highly dependent upon the number of image attacks and SVD requires a watermarking scheme to be non-blind or semi-blind in nature.

In this paper, a blind watermarking technique for color image watermarking is proposed to attaining high robustness and adequate imperceptibility using a deep Artificial neural network (DANN) approach and, for achieving security, various seed keys are applied at various stages of watermarking. The novelty of the proposed work is that two statistical features based on the coefficients difference is introduced, which is never experience in other related research papers.

The contributions of the proposed work are as follows:

- It does not need any watermark image or cover image as it is blind in nature.
- The use of LWT leads to the good quality of watermarked image and provide good robustness even in the presence of number of image attacks.
- The utilization of DANN provides good balance between PSNR and NC.
- The randomization used at the various levels using secret seed key increases the security of the system.
- Utilizing YIQ color model enhance the imperceptibility of the watermarked image.

The structure of the system is as follows: Introduction and related work is mentioned in Sect. 1, Embedding and extraction of watermark is mention in Sect. 2, Result is mentioned in Sect. 3, and Conclusion and future scope is mention in the Sect. 4 of the paper.

2 Proposed Blind Color Image Watermarking

This research proposes a blind color image watermarking using deep artificial neural network in which the watermark image is extracted by applying the binary classification technique. In the proposed work ten statistical features out of eighteen statistical features were considered for the training and testing purpose. A signature (original) watermark (SW) of length 512 bits and a reference watermark (randomly generated) (RW) of length 512 bits are combined with the help of a secret key and embedded into the color cover image coefficient of length 1024, 2×2 matrix using a quantization method. For adding randomly generated watermark bits, 1024, 2×2 matrixes is divided into 512 blocks each, one for adding reference watermark and second for the signature watermark. Here the RW bits are used for the training purpose and SW is use for the testing purpose. For training and testing using deep learning model, the statistical features such as Standard deviation (feature_1), Entropy (feature_2), Mean (feature_3), Variance (feature_4), Mode (feature_5), Median (feature_6), Moment (feature_7), Covariance (feature_8), Quartiles (feature_9), Kurtosis (feature_10), Skewness (feature_11), Poisson probability distribution function (feature_12), Coff_1 (feature_13), Coff_2 (feature_14), Coff_3 (feature_15), Coff_4 (feature_16), Coff_diff_1 (feature_17) and Coff_diff_2 (feature_18), are considered to form a feature set of size 512 × 18. Out of 18 statistical features, 1–16 features are taken from [10], and additional 2 features are introduced additionally to see the results under various image attacks. Principal component analysis (PCA) is applied to select the best 10 features for both training and testing. Here deep artificial neural network with 3 hidden layers is used and shown using Fig. 1.

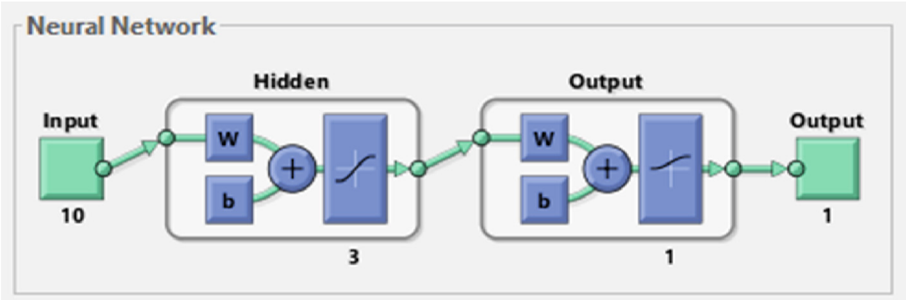

Fig. 1. DANN Architecture

A single watermark made up of the signature and reference sections is denoted by the symbols W and is represented using Eq. 1

$$W = R_{rs} + S_{rs} = w1 + w2+, \ldots\ldots\ldots, +w_{l_{rs}} + w_{l_{rs+1}}+, \ldots\ldots, +w_{l_{rs}+l_{ss}} \quad (1)$$

The training set is produced using the reference section, and the testing set is produced using the signature (original) watermark. The watermark bit (wat_bit) 1 and 0 could be set using the following mathematical formula:

$$\text{If wat\_bit} = 1, x(mn)_i = x(mn)_i - THR,$$

$$\text{if } \mathrm{Diff}_{\mathrm{i}}^{\max} < \max(\sigma, \mathrm{THR}),$$

$$\mathrm{E}lse\, x(mn)_i = x(mn)_i \quad (2)$$

$$\text{And, if the wat\_bit} = 0\, x(min)_i = x(mn)_i - \mathrm{Diff}_{\mathrm{i}}^{\max} \quad (3)$$

THR stands for threshold, while $\mathrm{Diff}_{\mathrm{i}}^{\max}$ displays the difference between the two biggest values in the corresponding i^{th} block. For all N_{ws} blocks the averaging coefficient difference value σ is shown as:

$$\sigma = \frac{\sum_{i=1}^{Nws} \mathrm{Diff}_{\mathrm{i}}^{\mathrm{max}}}{Nws} \tag{4}$$

Here, N_{ws} denotes the total blocks present in the LH3 sub-band where the watermark bits are attached. Figure 2 shows the watermark embedding steps.

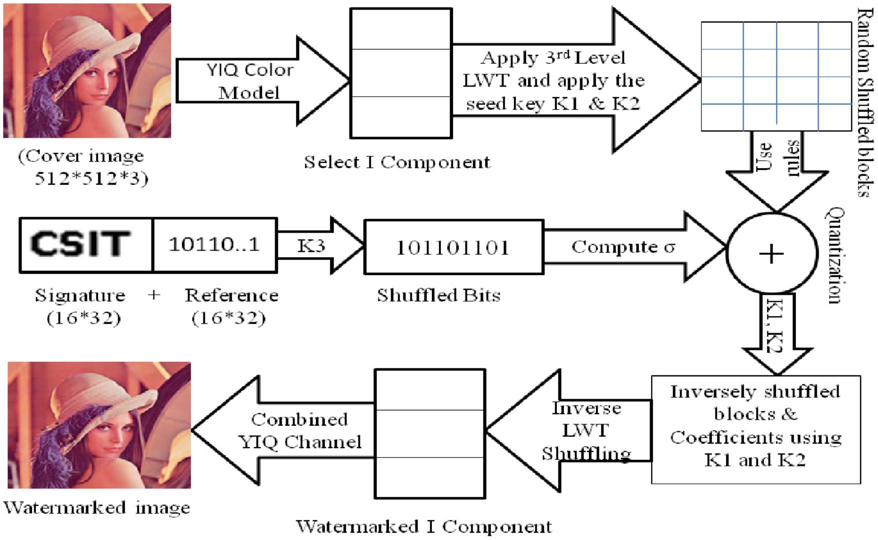

Fig. 2. Watermark embedding steps

2.1 Watermark Embedding Algorithm

For watermark embedding, I component of YIQ color model of color cover image is considered and LWT transformed is applied using mother wavelet 'Haar' to obtain LH3 sub-band. Here I component is selected because it mostly contains the color information.

The steps for embedding a watermark are as follows:

1. Read color cover image and apply YIQ color model and select I component.
2. Apply LWT transform to select LH3 sub-bands.
3. Read the watermark image of length 512 bits.
4. Applying seed key K1 to shuffle the obtained 3rd level obtained coefficients.
5. Group the obtained coefficient into blocks of size 2 × 2 and shuffle using seed key K2.
6. Calculate average coefficient difference using Eq. 4.
7. Combine the signature and reference watermark having length N_w, shuffle with secret key K3.

8. For each coefficients bits of N_w perform the following
   8.1 Determine the coefficient difference between two biggest coefficients and if watermark bit is 1, modify largest block using Eq. 2.
   8.2 If watermark bit equals to 0, modify largest coefficients using Eq. 3.
9. Apply seed key Key1 and Key 2 for reshuffling blocks and coefficients and perform inverse transform and recombined the Y and Q channel to get the watermarked image.

2.2 Watermark Extraction Algorithm

Here watermark extraction is done as a binary classification having two class labels “0” and “1”. An artificial neural network with 3 hidden layers is used where the epoch ranges from 20 to 30 and the threshold value used is 0.3. Figure 3 shows the watermark extraction steps.

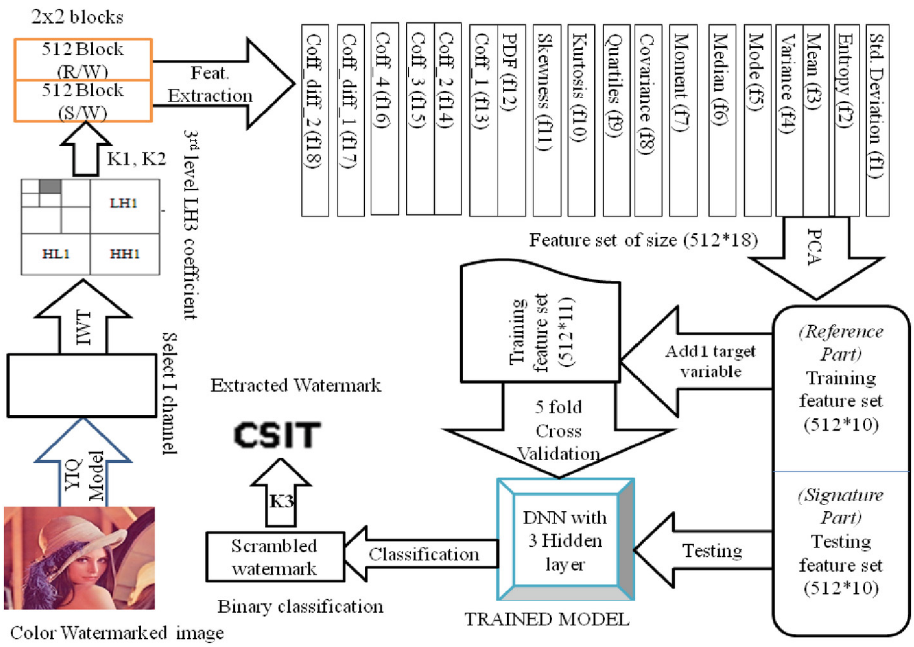

Fig. 3. Watermark extraction steps

The steps for embedding a watermark are as follows:

1. Read the watermarked color image and apply YIQ color model and select I component.
2. Using the IWT transform, obtain the third stage LH3 sub-band
3. LH3 sub-bands coefficients and blocks are re-shuffled utilizing key K1and K2 respectively.
4. Divide the 1024, 2 × 2 blocks in blocks of size 512 each for training and testing.

5. Generate feature set $\left(\{fs_i(t)|t = 1, 2, \ldots\ldots 18\}\right)$ of such blocks such blocks that contain the embedded reference watermark information.
6. PCA is employed for obtaining the reduced 10 feature set $(\{Fsr_i(t)|k = 1, 2, \ldots\ldots M\})$ where $M \leq N$
7. Train the deep neural network (having three hidden layer and epoch ranges from 20 to 30) using training set and five-fold cross validation to obtain trained network.
8. Using the blocks with the embedded signature watermark bits, create the testing pattern φ' set like training set $\varphi' = \{(f_i'(1), f_i'(2), ., '(9), f_i'(10))\}$
9. In order to extracts the watermark w' test the model with testing set φ'
10. Re-shuffle using seed key K3 and re-shape the extracted watermark w' to size 32 × 16.

3 Result and Discussion

A deep artificial neural network (DANN) based robust image watermarking has been proposed and result is shown in this section of the paper. Four color cover image such as Lena, Peppers, Mandril and Jet, each of dimension 512 * 512, and a pixel is represented using 24 bits and one binary watermark image of size 16 * 32 is used for the experiment purpose. Color images have been taken from [16]. The experiment is performed on MATLAB (2016a), and Intel i7 processor is used for the experiment and performance matrixes used are PSNR, NC and BER. Figure 4 shows the standard original cover image used for the experiment purpose.

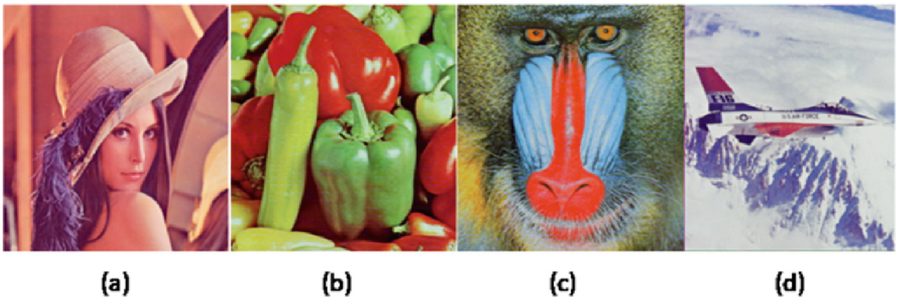

Fig. 4. Color test image: (a) Lena, (b) Peppers, (c) Mandril, (d) Jet

Mean square error (MSE) between the original image (CImg) and watermarked image (WImg) is obtained using

$$\mathrm{MSE} = \frac{1}{\mathrm{M} * \mathrm{N}} \sum_{\mathrm{ij}=0}^{\mathrm{MN}} \mathrm{CImg(i, j)} - \mathrm{WImg(i, j)} \tag{5}$$

where M and N shows the dimension of the images and CImg(i, j) and WImg(i, j) represents the grey value at position (i, j). The PSNR can be represented as

$$\mathrm{PSNR} = 10\log_{10}\frac{255^2}{\mathrm{MSE}}. \tag{6}$$

NC value and BER value can be calculated as follows:

$$\mathrm{NC} = \frac{\sum_{\mathrm{i}} \mathrm{WC}_{\mathrm{ij}} \sum_{\mathrm{j}} \mathrm{WC}'_{\mathrm{ij}}}{\text{height} * \text{width}} \tag{7}$$

WC_{ij} and WC'_{ij} are valued at (i, j) of cover and watermarked image, and it is set as 1 if it is a watermark bit 1; otherwise, it is set as -1; height and width are watermark image dimensions, respectively.

$$\mathrm{BER} = \frac{\mathrm{WDB}}{\text{height} * \text{width}} \tag{8}$$

where WDB denotes the wrongly detected bit, and height and width is the dimension. Watermarked color image and corresponding extracted watermark image is shown using Fig. 5.

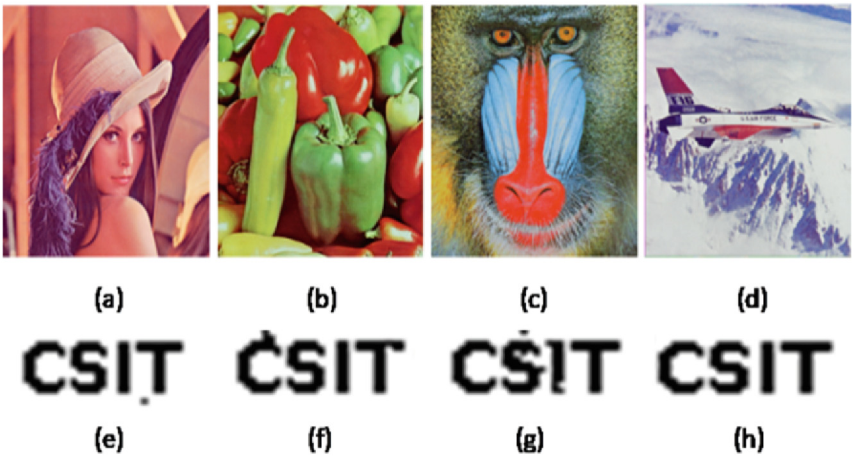

Fig. 5. (a)–(d) watermarked images with PSNR = 53.77 dB, 52.94 dB, 52.81 dB and 50.39 dB (e)–(h) extracted watermark image

For the experiment purpose ten types of different attacks like Salt and Pepper noise (SLP), Speckle noise (SPLN), Gaussian noise (GN), Scaling (SCL), Rotation (RT), and Average filter (AVG) attacks have been considered. Here Table 1 shows the imperceptibility and NC value of extracted watermark under various image attacks.

Table 1. PSNR of watermarked image and NC values of extracted watermark

Attacks	Lena	Peppers	Mandril	Jet
PSNR (in case of no attack)	53.77 dB	52.94 dB	52.81 dB	50.39 dB
No attack	0.9960	0.9882	0.9789	1.0
SLP(0.01)	0.9476	0.9414	0.9141	0.8633
SLP(0.02)	0.8007	0.8477	0.8594	0.8985
SPLN(0.01)	0.9648	0.9609	0.8985	0.8281
SPLN(0.02)	0.9140	0.7969	0.7852	0.6016
GN(0.01)	0.7461	0.6758	0.4258	0.8242
SCL(0.9)	0.9766	0.8985	0.5195	0.8906
SCL(1.5)	0.9805	0.9532	0.7070	0.8710
SCL(2.0)	0.9982	0.9609	0.9023	0.9922
RT(0.1)	0.0937	0.4296	0.2032	0.3045
AVG(3x3)	0.6602	0.1836	0.2344	0.7226

Table 2. NC comparison with [17–21] for common image attacks

Literature	SLP (0.01)	SPLN (0.01)	GN (0.01)	SCL (2.0)
Abdelhakim et al. (2018) [17]	0.837	0.856	0.578	0.988
Abdul-Rahman, A. K. et al. (2019)[18]	0.946	0.872	0.854	0.977
Kang, X. et al. (2020) [19]	0.851	0.858	0.804	1.0
Sharma, S. et al. (2021) [20]	0.941	0.915	0.938	0.995
Jaiswal, S. and Pandey, M. K. (2022) [21]	0.94	0.96	–	–
Proposed	0.947	0.964	0.746	0.998

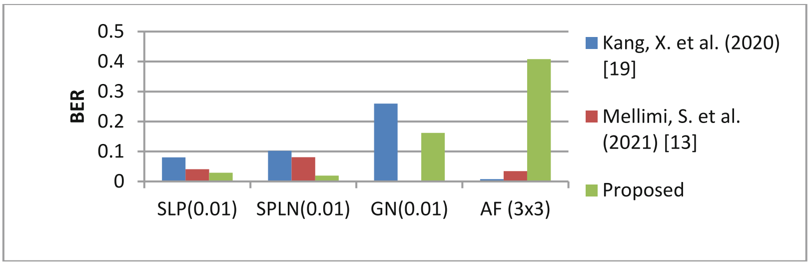

Fig. 6. BER comparison with [13, 19] for common image attacks on Peppers

Table 2 shows the NC comparison with [17–21] for common image attacks for Lena standard image. Figure 6 and Fig. 7 shows the BER comparison with Kang, X.

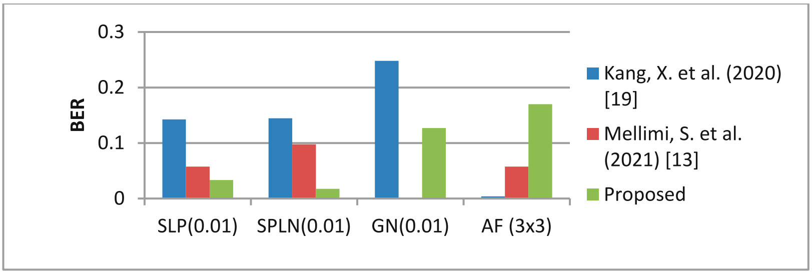

Fig. 7. BER comparison with [13, 19] for common image attacks on Lena

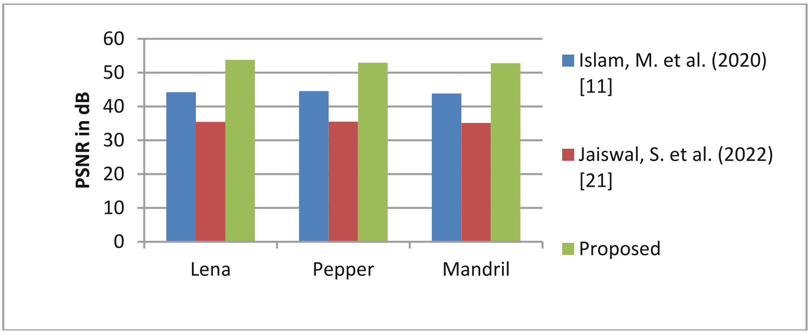

Fig. 8. PSNR comparison with [11, 21] in terms of dB

et al. [19] and Mellimi, S. et al. [13] for Peppers and Lena standard image respectively. The proposed watermarking method performs good against SLP(0.01), SPLN(0.01) and SCL(2.0) attacks, but for GN(0.01) attack it is not performing well, it could be because the GN(0.01) attacks affects the pixels relationship badly. Figure 8 shows the PSNR comparison with [11, 21] in terms of dB for Lena, Pepper and Mandril color image.

3.1 Embedding Payload

The payload of watermarking system tells about the payload per pixels and here a watermark of length 512 is embedded into color cover image of size 512 × 512 therefore the embedding payload is calculated as.

Embedding payload = (16 * 32)/(512 * 512 * 3) = 0.00065 bits per pixel.

4 Conclusion

Protecting the digital content is very much important for human and proposed color image watermarking technique is designed for protecting the digital contents. Here a DANN with 3 hidden layers is designed for the blind watermark extraction of color image using YIQ color model with the objective of balancing imperceptibility and robustness. The utilization of YIQ model enhances the imperceptibility of the proposed system and involvement of secret seed key increases the security of the proposed system. With the exception of the Gaussian noise, rotation, and average filter attacks, it demonstrates satisfying robustness for most image attacks with approximate 53 dB imperceptibility for Lena, Peppers, and Mandril images. The gaussian noise, rotation and average filter attacks might affect the relationships of the watermarked image badly therefore the watermark extraction is not so good. In future this technique can be used for the video watermarking.

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Chapter 10

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