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Deep Artificial Neural Network based Blind Color Image Watermarking in YCbCr Color Domain using statistical features

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Abstract: A blind color image watermarking using deep artificial neural network (DANN) in YCbCr color model has been proposed aiming at achieving fair trade-off between imperceptibility and robustness. In the proposed watermarking a random generated watermark of length 512 bit is used for the training purpose and original watermark of length 512 bits is used for the testing. Principal component analysis (PCA) is applied to select the best 10 features out of 18 statistical features. Binary classification is used for watermark extraction. It shows the average imperceptibility of 33.34 dB and average SSIM of 0.9860 for four images Lena, Peppers, Mandril and Jet. It performs well in terms of balancing the imperceptibility and robustness, for the threshold value 32. The proposed scheme takes 7.56 seconds for watermark embedding and extraction. It also shows good robustness against common image attacks including the combination of image attacks except the gaussian noise with intensity 0.06 and cropping 20% attacks. The experiment result shows that the proposed watermarking technique performs well against other technique.

Keywords: Blind, Color Image, DANN, Robust, Watermarking, YCbCr

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1. Introduction

With continuously increasing digital data over the internet it has become need of the hour essential to secure the digital data in order to preserve its integrity. In today's era it is utmost important to safe the digital data from being accessed illegally. Going through the literature it is very obvious that cryptography is one of the ways to protect the digital content but it lacks in the sense that once the decryption is done it can be can be illegally copied any number of times. Steganography is another way to protect the digital content but it involves much overhead even for adding a tiny text in the original cover image [1]. Watermarking digital images is a technique for copyright

protection that allows for the permission of digital content [2]. In the process of watermarking a watermark image is added to the cover image using the 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 coefficient (NC) and bit error rate (BER) calculated between original and extracted watermark image and it should be between 0 and 1. In case of NC 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 value of BER shows the good robustness. Imperceptibility is another factor calculated using the peak signal to noise ratio (PSNR) and structured similarity index measurement (SSIM). High PSNR represent the excellent quality of the watermarked image. A watermarking method must be complex enough to permit the watermark image to be removed without significantly degrading the watermarked image's quality and capacity means the number of bits added to the cover image. Finding the right trade-off between robustness and imperceptibility is one of the common issues in the area of watermarking [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 an image watermarking is generally based on the spatial coefficients or transformation coefficients. Spatial domain based watermarking is easy to design but remain less effective for most of the image attacks as the manipulation is done on the pixels. In transformation domain based watermarking, a cover image is first converted to coefficients, followed by the addition of a watermark image using a set of rules, and finally the application of an inverse transformation to obtain the watermarked image. Various transformation domains has been previously applied for image watermarking like discrete-wavelet-transform (DWT) [4], redundant-discrete-wavelet transforms (RDWT) [5-6], Discrete-fourier-transform (DFT) [7], discrete-cosine-transform (DCT) [8-9], and integer/Lifting-wavelet-transform (IWT/LWT) [10-13, 15] for image watermarking. LWT has been utilized in the proposed image watermarking as it has various advantages over the conventional transformation methods and it is most significantly known for absorbing more image distortion.

Zear, A. et al. [12] offer a LWT-DCT-SVD-based non-blind dual watermarking for protecting color photos. In this study, a color cover picture with a resolution of 512x512 pixels is implanted with a text watermark of 64x64 pixels in size. The message digest hash algorithm is used to protect the watermark. Also, the findings are contrasted using the RGB, YIQ, and YCbCr color models with various scaling factors and text watermark sizes for various picture attacks. For the Y channel of the YIQ model, the highest PSNR obtained is 34.60 dB at scaling factor 0.01. A color image can be represented using a variety of models, including the RGB model, YIQ model, YUV model, and YCbCr model, each of which has advantages and disadvantages [12].

Mellimi, S. et al. [13] have identified a deep neural network-based blind image watermarking for grey-scale images. The LWT is used in the proposed watermarking system to transform images, and 100 images used for training and 600 images were used for testing purposes. The average PSNR discovered is 44.1148 dB. The neural network was built using 1 input layer, 4 hidden layers, and 1 output layer. In terms of ‘0’ and ‘1’ the output layer generates the output. To test the effects on robustness and imperceptibility, 17 different picture attacks have been used in the proposed work.

A Arnold scrambling based color image watermarking using YCbCr color space has been proposed by Pandey, M.K. et al. [14] which is non-blind in nature. YCbCr space is used because of having high correlation property as compare to RGB color space. In this work Y channel has been selected for watermark embedding using different scaling factor. Stationary-wavelet-transform (SWT) and SVD is applied with Arnold key to scramble the watermark image. PSNR, SSIM and NC are used to evaluate the performance of the watermarking system. Experiment is performed for various scaling factors and PSNR of 41.26 dB is obtained for Lena for scaling factor 0.01 and it shows good robustness against most of the image attack.

A non-blind watermarking using YCbCr space has been proposed by Patvardhan, C. et al. [15] for color images. DWT along with SVD is used for the scheme. Four standard image including Lena and Mandril is used for the experiment. Here quick response (QR) code is used as a watermark and utilizing YCbCr color space enables to take the advantage of human vision system. This scheme shows the robustness against most of the image attacks. In both scheme [14, 15] SWT and DWT is used but in the proposed

scheme LWT is applied because of having several advantages as compared to SWT and DWT transformation and both the above watermarking scheme [14, 15] is of non-blind nature therefore it would be very interesting to apply it for the blind image watermarking.

Chang, T. J. et al. [16] proposed color image watermarking using DCT-2DLDA (two dimensions linear discriminate analysis) and Cover image is transformed into a YIQ 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. 2DLDA is used for watermark extraction.

Mahto, D. K. et al. [17] have provided a deep-learning-based multiple image watermarking technique. This idea is built on the spatial and transformations domain-based approach. The watermarked image is encrypted using an upgraded encryption algorithm, and a de-noising convolution neural network is used to further boost the suggested system's robustness. 14 typical color images are chosen for the experiment. The average PSNR and NC are, respectively, 57.7124 and 1, respectively.

Various watermarking technique in grey-scale domain and color domain shows that watermarking a color image requires some additional considerations as compare to watermarking grey-scale image. Looking at the past literature it is obvious that machine learning based image watermarking is grown 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 as a binary classification technique and various techniques for binary classification like SVM [10, 11], 2DLDA [16] and deep network [13, 17] is seen in the literature. 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 scheme to be non-blind or semi-blind. In this scheme, a blind technique for color watermarking is proposed to attaining high robustness and adequate imperceptibility using a deep artificial neural network approach and various seed keys are applied at various stages of watermarking for achieving security.

The contributions of the proposed work are as follows:

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

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

2. Proposed Blind Color Image Watermarking

In this study, a deep artificial neural network (DANN) based watermarking for a color image is proposed which is blind in nature. Here watermark extraction is done using binary classification. In the proposed scheme ten statistical features out of eighteen statistical features were considered for 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, 2x2 matrix using a quantization method. 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 512x18. Out of 18 statistical features, 1-16 features are taken from [10], and additional 2 features based on difference are introduced by us 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 neural network with 3 hidden layers is used and shown using figure 1.

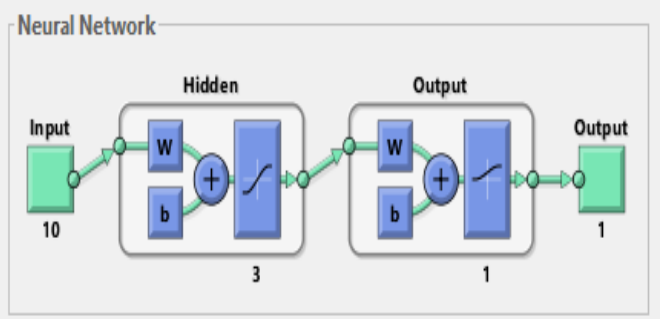

Figure 1: ANN Architecture

A single watermark made up of the signature and reference part is denoted by the symbols WAT and is represented using equation 1

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

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:

If wat_bit = 1,

$$x(mn)_i = x(mn)_i + TH,$$

if $\text{Diff}_i^{\max} < \max(\sigma, TH)$, Else $x(mn)_i = x(mn)_i$ (2)

if the wat_bit=0

$$x(mn)_i = x(mn)_i - \text{Diff}_i^{\max} \quad (3)$$

TH stands for threshold, while $\text{Diff}_i^{\max}$ 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:

$$\sigma = \frac{\sum_{i=1}^{Nws} \text{Diff}_i^{\max}}{Nws} \quad (4)$$

Here, N_{ws} denotes the total blocks present in LH3 sub-band where bits of watermark are attached.

2.1 Watermark embedding algorithm

In this section of the paper the embedding process is explained and the steps for watermark embedding are as follows:

1. Read color cover image and apply YCbCr model and select Cb component.
2. Read the watermark image of length 512 bits.
3. Applying seed key K1 to shuffle the obtained 3rd level obtained coefficients.
4. Group the obtained coefficient into blocks of size 2x2 and shuffle them using seed key K2.
5. Calculate average coefficient difference using equation 4.
6. Combine the signature and reference watermark having length N_w, shuffle them with secret key K3.
7. For each coefficients bits of N_w perform the following
   - 7.1 Determine the coefficient difference between two biggest coefficients and if watermark-bit is 1, modify largest block using eq. 2.
   - 7.2 If watermark bit equals to 0, modify largest coefficients using eq. 3.
8. Apply seed key Key1 and Key 2 for reshuffling blocks and coefficients and perform inverse transform and recombined obtained coefficients with the Y and Cr channel to get the watermarked image.

2.2 watermark extraction

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 30 to 45 and the threshold value used is 32. Figure 2 shows the embedding and extraction procedure.

The steps for embedding a watermark are as follows:

1. Read the watermarked color image and apply YCbCr model and select Cb 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, 2x2 blocks in blocks of size 512 each for training and testing.
5. Generate feature set $(\{fs_i(t)|t = 1, 2, \dots \dots 18\})$ of such blocks such blocks that contain the embedded reference watermark information.
6. PCA is employed for obtaining the reduced 10 feature set $(\{Fsr_i(t)|k = 1, 2, \dots \dots M\})$ where $M \leq N$
7. Train the deep neural network (having three hidden layer and epoch ranges from 30 to 45) 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. For extract the watermark bit w' test the model with testing set φ'
10. Re-shuffle using seed key K3 and re-shape the extracted watermark w' to size 32x16.

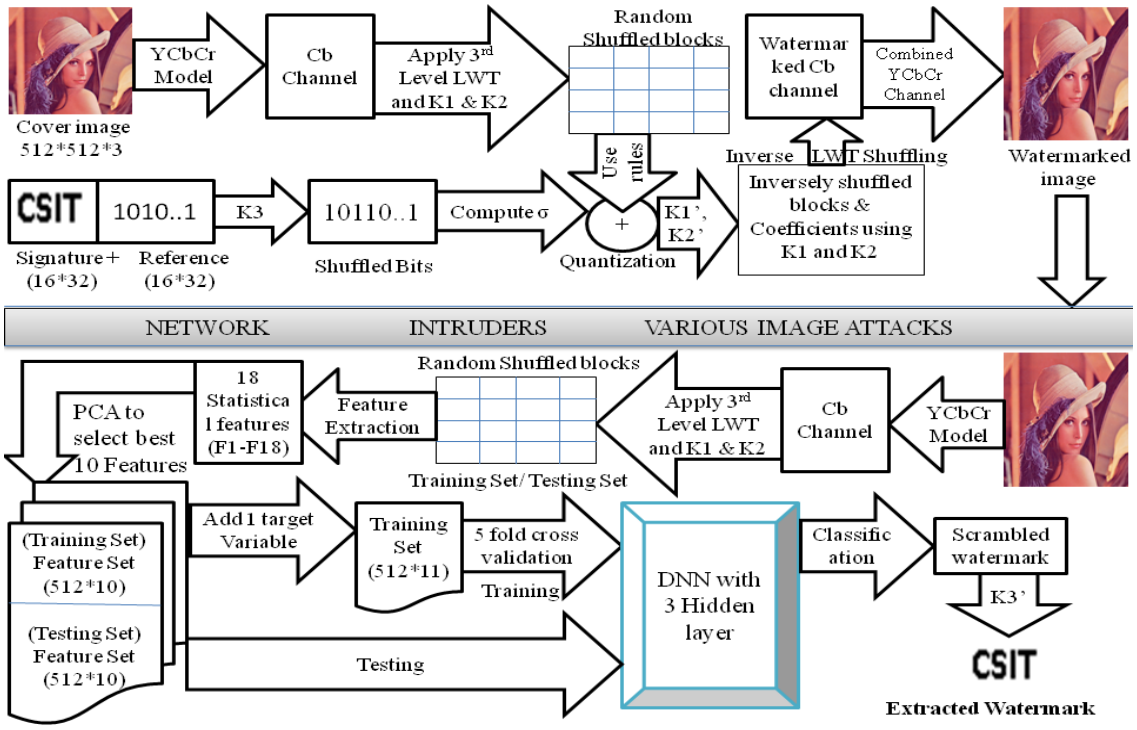

Figure 2: Watermark embedding and extraction procedure

3. Results and Discussion

A DANN based robust color image watermarking has been proposed and result is shown in this section of the paper. Standard color images have been used for the research available at http://www.imageprocessingplace.com/root_files_V3/image_databases.htm

Four standard color cover image such as Lena, Peppers, Mandril and Jet, each of size 512*512*3, and a pixel is represented using 24 bits and one binary watermark of size 16*32 is used for the experiment purpose. The experiment is performed on MATLAB (2016a), and Intel i5 processor is used for the experiment and performance matrixes used are PSNR, NC and BER. Figure 3 shows the standard original cover image used for the experiment purpose.

Figure 3: Color images: (a) Lena, (b) Peppers, (c) Mandril, (d) Jet

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

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

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

$$\text{PSNR} = 10\log_{10}\frac{255^2}{\text{MSE}} \quad (6)$$

Structured similarity index measurement (SSIM) is used to measure the imperceptibility and it shows the similarity of watermark image with cover image on the basis of the structure and it is obtained using

$$\text{SSIM}(C, W) = \frac{(2\mu_x\mu_y + c1)(2\sigma_{xy} + c2)}{(\mu^2x + \mu^2y + c1)(\sigma^2x + \sigma^2y + c2)} \quad (7)$$

Where μ_x and μ_y shows the mean and σ^2x and σ^2y shows the variance σ_{xy} shows the covariance and cover image is denoted by C and watermarked image is denoted by W.

.NC value and BER value can be calculated as follows:

$$\text{NC} = \frac{\Sigma_i \text{WC}_{ij} \Sigma_j \text{WC}'_{ij}}{\text{height} * \text{width}} \quad (8)$$

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.

$$\text{BER} = \frac{\text{WDB}}{\text{height} * \text{width}} \quad (9)$$

Where WDB equal to the wrongly detected bit, and height and width is the dimension. Watermarked color image and corresponding extracted watermark image is shown using figure 4.

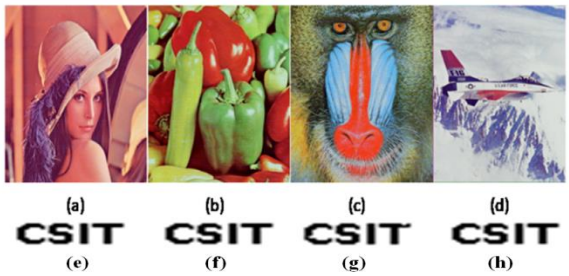

Figure 4: (a)-(d) watermarked images, (e)-(h) extracted watermark images

3.1 Selection of embedding threshold value

From the past literature it is obvious that balancing PSNR and NC is very important in image watermarking and both of these value highly depends on the threshold value therefore in order to determine best threshold values in the range 28 to 36 a test is performed on Lena image where six image attacks are performed to see the performance and is shown using table 1.

Table 1: SSIM, PSNR, NC for different threshold value on Lena standard image

Image attacks	**TH= 28**	**TH= 30**	**TH= 32**	**TH= 34**	**TH= 36**
SSIM	0.985	0.985	0.984	0.983	0.983
PSNR (in dB)	**33.38 dB**	**32.84 dB**	**32.28 dB**	**31.86 dB**	**31.42 dB**
CR(10)	0.95	0.93	0.97	0.92	0.98
SCL (0.5)	1.0	1.0	1.0	1.0	1.0
RT(0.1)	0.99	0.99	0.99	0.96	0.97
SLP(0.01)	1.0	1.0	1.0	1.0	1.0
SPLN (0.01)	0.99	1.0	1.0	1.0	1.0
AVGF (3x3)	0.98	0.98	1.0	0.97	0.96
AVG NC	0.82	0.98	**0.99**	0.97	0.98

From table 1 it is seen that the proposed image watermarking is performing well for threshold value TH=32 as the average NC of 0.99, with PSNR of 32.28 dB, SSIM of 0.984 is obtained for standard image Lena. Lena image is considered as it is one of the most frequently used image for the experiment

3.2 Robustness analysis

For the experiment purpose fourteen different attacks like Salt and Pepper noise (SLP), Speckle noise (SPLN), Gaussian noise (GN), Scaling (SCL), Rotation (RT), Cropping attacks (CR), Median filter (MF), Average filter (AVG) attacks and combinational image attacks have been considered.

Table 2: PSNR, SSIM and NC for different image attacks

Attacks	Lena	Peppers	Mandril	Jet
PSNR (in case of no attack)	**32.28 dB**	**32.64 dB**	**32.26 dB**	**32.19 dB**
SSIM	**0.9844**	**0.9848**	**0.9848**	**0.9897**
No attack	**1.0**	**1.0**	**0.9961**	**1.0**

SLP(0.01)	1.0	0.9649	0.9766	1.0
SLP(0.02)	0.9922	0.9883	0.9844	1.0
SLP(0.06)	0.9804	0.9453	0.9649	0.9688
SPLN(0.01)	1.0	0.9922	1.0	0.9883
SPLN(0.02)	1.0	0.9961	0.9922	0.9922
SPLN(0.06)	0.9883	0.9570	0.9812	0.8828
GN(0.01)	0.9922	0.9688	0.9922	1.0
GN(0.02)	0.9766	0.9106	0.9805	0.9961
GN(0.06)	0.7930	0.7656	0.8164	1.0
SCL(0.5)	1.0	0.9961	0.9805	0.9688
SCL(0.9)	1.0	0.9648	1.0	1.0
SCL(1.5)	1.0	0.9961	1.0	1.0
SCL(2.0)	0.9998	0.9876	0.9922	0.9976
RT(0.01)	0.9961	0.9809	0.9922	0.9960
RT(0.1)	0.9961	0.9766	0.9609	0.9844
CR(10%)	0.9727	0.9453	0.9414	0.8795
CR(20%)	0.8867	0.8710	0.8867	0.8633
AVG(3x3)	1.0	0.9375	0.9766	0.9688
AVG(5x5)	1.0	0.9023	0.9962	0.8164
MF(2x2)	1.0	0.9922	1.0	1.0
MF(3x3)	1.0	0.9961	1.0	0.9922
MF(5x5)	0.9883	0.9375	0.9063	0.9961
Wiener(2x2)	1.0	1.0	1.0	1.0
Wiener(3x3)	1.0	0.9883	0.9922	0.9922
Wiener(5x5)	1.0	0.9414	0.9805	0.9492
HE	0.9844	0.9766	0.9844	0.9962
JPEG(70)	0.9961	0.9688	0.9883	0.9883
JPEG(80)	0.9766	0.9453	1.0	0.9922
JPEG(90)	1.0	0.9844	1.0	0.9922
GN(0.01)+ SPLN(0.01)	0.9844	0.9766	0.9531	0.9609
GN(0.02)+ SPLN(0.02)	0.9570	0.8672	0.9180	0.8594
RT(0.1)+ SCL(0.5)	0.9922	0.9609	0.9766	0.9961

Here table 2 shows the imperceptibility and NC value of extracted watermark under various image attacks.

3.3 Comparison with other schemes

Table 3: NC comparison with [14, 15, 18-22] for common image attacks

Literature	SLP (0.01)	SPLN (0.01)	GN (0.01)	SCL (2.0)
Patvardhan, C. et al. (2017) [15]	0.981	--	0.992	--
Abdelhakim et al. (2018) [18]	0.837	0.856	0.578	0.988
Pandey, M.K. et al. (2018) [14]	0.980	0.98	0.91	--
Abdul-Rahman, A. K. et al. (2019) [19]	0.946	0.872	0.854	0.977
Kang, X. et al. (2020) [20]	0.851	0.858	0.804	1.0
Sharma, S. et al. (2021) [21]	0.941	0.915	0.938	0.995
Jaiswal, S. and Pandey, M. K. (2022) [22]	0.94	0.96	--	--
Proposed	**1.0**	**1.0**	**0.99**	**0.998**

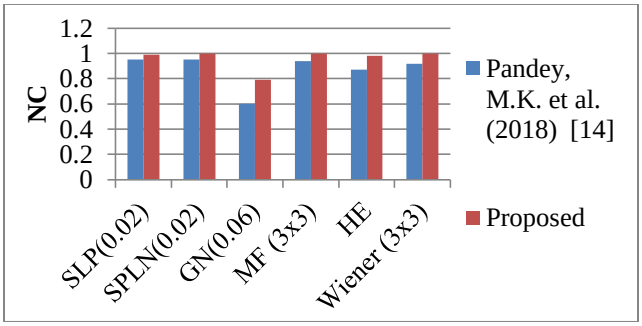

Figure 5: NC comparison with Pandey, M.K. et al. (2018)

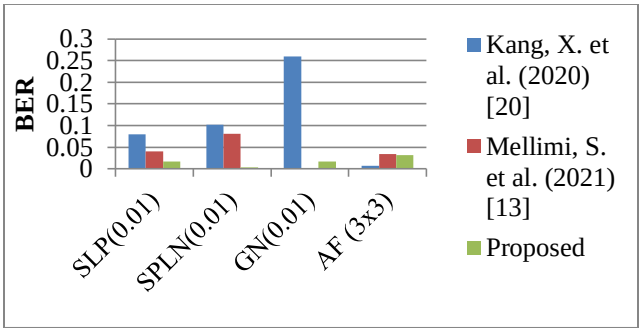

Figure 6: BER comparison with [19, 13] for common image attacks on Peppers

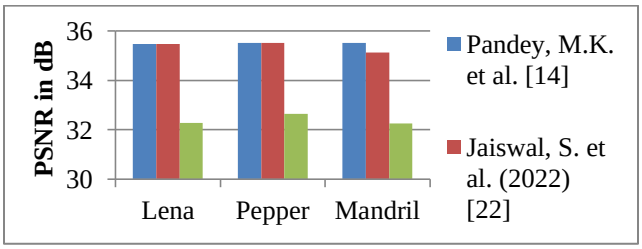

Figure 7: PSNR comparison with [11, 21] in terms of dB

Table 3 shows the NC comparison with [14, 15, 18-22] for common image attacks for Lena standard image. Figure 5 and figure 6 shows the NC and BER comparison with Pandey, M. K. et al. [14] and Kang, X. et al. [20], Mellimi, S. et al. [13] respectively. The proposed watermarking method performs good against SLP(0.01), SPLN(0.01) and SCL(2.0) attacks, but for GN(0.06) and CR(20%) attacks it is not performing well, it could be

because the GN(0.06) and CR(20%) attacks affects the pixels relationship badly. Figure 7 shows the PSNR comparison with [14, 22] in terms of dB for Lena, Pepper and Mandril color image.

3.4 Embedding capacity

In the proposed scheme a watermark of 16*32 is embedded into color image of size 512*512*3, so the embedding capacity is determined as

Embedding capacity = (16x32)/(512x512x3) = 0.00065 bit per pixel.

3.5 Embedding time

The proposed image watermarking is implemented on MATLAB 2016a using Intel i5 processor and time taken for embedding and extraction is 7.56 seconds.

Table 4: Comparison with other schemes

Schemes	[18]	[23]	Proposed
Total time taken (in sec)	23.41 Sec.	16.36 Sec.	7.56 Sec.

Table 4 shows the comparison in terms of time taken for embedding and extraction process with other schemes in terms of seconds. The proposed scheme takes less time as compare to Abdelhakim, A. M., & Abdelhakim, M. [18] and Sharma, S. et al. [23], because proposed watermarking scheme usages the LWT based decomposition which leads to the fast decomposition of the image.

4. Conclusion and Future Scope

In the modern world, securing digital content is crucial, and the suggested color image watermarking approach is made to do just that. A deep neural network with three hidden layers is used in this instance to extract the watermark from a color image using the YCbCr color model. With the exception of the Gaussian noise with intensity 0.06 and cropping for 20% attacks, it demonstrates adequate robustness for the majority of image attacks, with around 33 dB imperceptibility for Lena, Peppers, Mandril, and Jet images. The watermark extraction is not so good since gaussian noise with an intensity of 0.06 and 20% cropping attacks may negatively affect the relationships of the watermarked image. This method may be used in the future to watermark videos.

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