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Optimized Rotation-Invariant Coordinate Convolutional Neural Network based Digital Image Watermarking Technique

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Abstract: The rapid growth of multimedia and network technology, accessing digital media has become increased easily. Watermarking techniques are essential for protecting digital images. Consequently, protecting intellectual property has heightened the need for effective image watermarking. Although various image watermarking approaches have been developed to address this need, they often face challenges related to robustness and transparency. In this manuscript, Optimized Rotation-Invariant Coordinate Convolutional Neural Network Based Digital Image Watermarking Technique (DIW-RICCNN-HBO) is proposed. Initially the images are collected from CIFAR10 and Pascal VOC2012 dataset. Then the collected images are preprocessing by Adaptive Variational Bayesian Filter (AVBF) to remove noise. Then the preprocessed images are embedding the cover image containing the secret data of the embedding network. After that Design an encoder network using Rotation-invariant coordinate convolutional neural network (RICCNN) to extract hidden features via both the cover images and the secret mark images. The Honey Badger Optimization (HBO) method is proposed to optimize the weight parameters of the RICCNN for improved results in digital image watermarking. The proposed DIW-RICCNN-HBO method is implemented on Python. The proposed method attains 35.66%, 32.73%, and 31.43% higher PSNR and 32.77%, and 28.93% higher SSIM comparing with existing techniques like Water chaotic fruit fly optimization-based deep convolutional neural network for image watermarking using wavelet transform (DIW-DCNN), A Robust Document Image Watermarking Scheme using Deep Neural Network (DIW-DNN) and ReDMark: Framework for residual diffusion watermarking based on deep networks (RDW-ReDMark) methods respectively.

Keywords: Adaptive Variational Bayesian Filter, CIFAR10 dataset, Honey Badger Optimization, Pascal VOC2012 dataset, Rotation-invariant coordinate convolutional neural network,

1. Introduction

During the big data era, digital images play a pivotal role across various domains, includes medicine, social media, forensics, cinematography, and learning. These photos frequently include delicate and private information about the content creator [1]. Unauthorized obtain to such sensitive images can result in significant issues, like privacy breaches, copyright infringement, and interference with medical diagnoses. Therefore, ensuring the security of digital images is of utmost importance [2]. Watermarking techniques are essential for safeguarding digital photos. Image watermarking incorporates copyright symbols into cover images in a way that is both imperceptible and robust. Traditional watermarking methods achieve this by either directly altering the pixel values or altering the transform coefficients of the cover image. In contrast to methods used in the spatial domain, transform domain methods offer superior robustness and flexibility [3]. Still, traditional watermarking schemes often struggle with resilience against attacks and have limited applications. Consequently, there is a need for an in-depth investigation into more effective and robust watermarking methods for digital images. Recently, deep learning-based watermarking has significantly advanced image content security, attracting a lot of attention for a variety of well-liked apps [4]. These are the primary advantages of watermarking with deep learning: identifying the optimal integrating positions throughout the cover media; finding the optimal level of embedding to balance imperceptibility and robustness; providing attack simulations for effective watermark extraction; also minimizing issues and noise in the extracted watermarks. Three main factors are used to determine how effective an image watermarking technique is: watermark capacity, robustness, and imperceptibility. Among these, robustness is generally the most crucial performance indicator. It is essential that the original media remains visibly undistorted after the hidden data has been embedded [5].

1.1 Problem statement and Motivation

This paper addresses the need for a robust and visually high-quality watermarking technique for digital images. Traditional methods often fail to resist attacks, compromising watermark security and integrity. Motivated by the need to protect digital content from unauthorized access and piracy, the research explores advanced deep learning technologies to improve resilience and visual quality beyond classical methods. These are motivated to do this research work.

The originality of the proposed DIW-RICCNN-HBO method is digital image watermarking. It introduces an AVBF based embedded network that preserves image quality and a denoising network to enhance robustness against distortions. Additionally, RICCNN employs unsupervised training, minimizing the need for manual adjustments and HBO algorithm is employed to fine-tune RICCNN parameters, delivering enhanced robustness and performance compared to existing methods.

1.2 Contribution

Major contribution of this research work is summarized below,

- In this manuscript, DIW-RICCNN-HBO is proposed.
- Utilizing AVBF for noise reduction ensures cleaner cover images, thereby improving the quality of embedded watermarks and overall performance.
- Rotational variance is addressed by introducing the RICCNN to extract latent characteristics from secret mark and cover images., ensuring watermark integrity remains preserved across various orientations.
- HBO optimizes RICCNN's weight parameters, leveraging its strengths in handling complex optimization landscapes and balancing exploration-exploitation dynamics. This enhances the watermarking technique's robustness and effectiveness significantly.

➢ By conducting a comprehensive evaluation with a variety of metrics, the effectiveness and robustness of the DIW-RICCNN-HBO method in digital image watermarking are thoroughly assessed.

The remaining paper section-2 introduces the literature review, section-3 presents the proposed method, section-4 shows result and discussions and section-5 shows a conclusion.

2. Literature review

Among frequent investigative works on deep-learning based digital image watermarking; some of the recent researches were assessed here.

In 2023 Ingaleshwar et al, [6] have presented a DIW-DCNN. In this manuscript, Water Wave Chaotic Fruit Fly Optimization Algorithm (WCFOA) is offered by integrating the Water Wave Optimization (WWO) with the Chaotic Fruit Fly Optimization Algorithm (CFOA). The premature convergence is reduced and population diversity is increased by the propagation and refraction operators. This operator's breaking, propagation, and refraction demonstrate the efficiency of striking a balance among the search space's exploitation and exploration phases, as measured by fitness. It provides a high peak signal-to-noise ratio (PSNR) also the low normalized correlation (NC).

In 2023 Ge et al, [7] have presented DIW-DNN Multimedia Tools and Applications. This manuscript proposes a deep neural network-based end-to-end document image watermarking system. This approach includes the design of a watermark insertion encoder and an extraction decoder. To simulate real-world attacks, a noise layer is incorporated, which includes numerous types of distortions like cropout, dropout, gaussian blur, gaussian noise, resize, and JPEG compression. It provides a high Structural Similarity Index Measure (SSIM) also it provides low PSNR.

In 2023 Singh et al, [8] have presented the use of deep learning multimedia tools and applications for digital image watermarking. This manuscript, presents an innovative watermarking method for digital images utilizing a Convolutional Neural Networks (CNNs). Initially, an encoder network uncovers hidden characteristics in the cover and hidden photos, which, after concatenation, result in a marked image. To remove fluctuations in noise from the image that was received, a denoising AutoEncoder network is utilized on the receiving end. Subsequently, a CNN is utilized to extract the hidden watermark image. It provides high NC and low SSIM.

In 2023 Rai et al, [9] have presented an optimized deep fusion CNN-based digital color image watermarking method of the defense of copyright. This manuscript, presents a network for embedding and extraction created specifically to insert and remove the watermark. The embedding network incorporates an octave convolutional model, which captures numerous features and reduces spatial redundancy. Additionally, the Enhanced Chimp Optimization (ECO) method is introduced to regulate the ideal strength factor, thereby overcoming the compromise between imperceptibility and robustness. It provides high PSNR and low SSIM.

In 2023 Suresh et al, [10] have presented chronological bald eagle optimization depends deep learning for image watermarking. This manuscript uses LeNet to determine the ideal region for inserting the watermark into the cover image. The process of embedding includes the Haar Wavelet Transform (HWT) to enhance robustness. The CBEO algorithm is used to optimize LeNet's trainable parameters, which are utilized to choose the best area in the cover image. It provides high SSIM and low NC.

3. Proposed Methodology

This section, the DIW-RICCNN-HBO is proposed. The block diagram of the proposed DIW-RICCNN-HBO method is represented in Figure 1. Accordingly, a detailed description of all steps given as below,

In figure 1, the input images are collected from CIFAR10 and Pascal VOC2012 datasets is initially preprocessed with the AVBF to eliminate noise. Secret data is then embedded into cover images using a RICCNN, which improves visual quality. An encoder network based on the RICCNN extracts and combines latent characteristics of the secret mark and cover photos. The resulting marked image undergoes noise removal and reconstruction by a denoising AVBF. Finally, the HBO algorithm is employed to fine-tune the RICCNN's weight parameters for enhanced watermarking performance.

3.1 Image Acquisition

The input images are gathered via CIFAR10 dataset and the Pascal VOC2012 dataset [11, 12].

CIFAR10 dataset: In this dataset contains 60,000 color images, each sized 32x32 pixels also categorized into 10 classes, with 6,000 images per class. It is broadly utilized in a machine learning research; it serves primarily for image classification tasks. Images are labeled with categories offering a diverse set of objects. CIFAR10's compact image size and diverse categories make it a standard benchmark for developing and evaluating algorithms in image recognition and classification.

Pascal VOC2012 dataset: In this dataset the features images from diverse real-world scenes, each with segmentation masks and object bounding boxes annotated. The dataset encompasses 20 object categories, includes people, animals, vehicles, and indoor objects. Then, the collected images are served to Pre-processing.

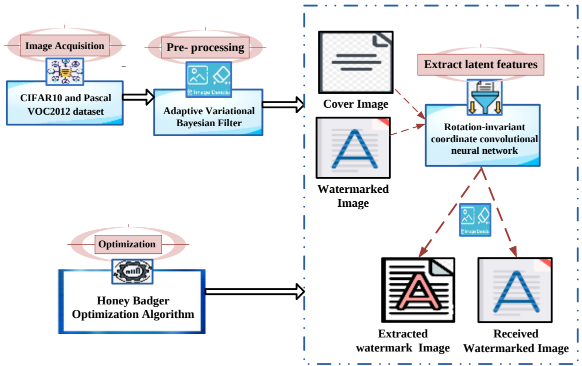

Figure 1: Block Diagram for proposed DIW-RICCNN-HBO method

3.2 Pre-processing using Adaptive Variational Bayesian Filter

In this step, image pre-processing using AVBF [13] is discussed. The proposed AVBF used to remove noises from the image. AVBF adapts to the statistical properties of an image, effectively distinguishing between noise and actual image content. Applying AVBF enhances image quality, making subsequent processing tasks more accurate. The AVBF effectively removes noise while preserving image details, thereby enhancing image quality and improving the accuracy of subsequent processing tasks. AVBF's adaptability makes it particularly effective across diverse image conditions. In a Gaussian domain, nonlinear filtering can then be reduced to the integration is calculated in equation (1).

$$\mathrm{int}(q) = \int_{G^s} q(a)m(a)ha \tag{1}$$

Where $\mathrm{int}(q)$ represent the integration of arbitrary nonlinear function, G^s denotes the whole state space, $m(a)$ is the Gaussian probability density function, ha is the cubature sampling points. Variational iterations optimize image estimates via cost function minimization, while cubature point sampling faithfully represents the posterior distribution. Employing AVBF, these methods effectively propagate images through nonlinear filtering, leading to improved noise reduction and preservation of fine details. Then information matrix of image is calculated in equation (2).

$$K_f^{(b+1)} = F_f^N (\tilde{D}_{f/f}^{(b+1)})^{-1} \tag{2}$$

Where $K_f^{(b+1)}$ represent the information matrix of image, F_f^N is the pseudo-measurement matrix in number of image, $\tilde{D}_{f/f}^{(b+1)}$ is the estimated information matrix of b^{th} iteration. AVBF adjusts filter parameters based on image statistics to remove noise. Using Bayesian inference, AVBF refines pixel values iteratively to distinguish noise from image features, improving image quality and clarity while preserving essential details. Then, output of AVBF is given in equation (3).

$$Z_{f/f}^{(b+1)} = {C_{f/f}^{(b+1)}}\Big/{K_s} \tag{3}$$

Where $Z_{f/f}^{(b+1)}$ denotes the output of AVBF, $C_{f/f}^{(b+1)}$ represent the removal of noises, K_s denotes the secret value of image. Finally, the noises are removed from the image by using AVBF method. Next, an embedding network uses the preprocessed images to incorporate the cover image's secret data into it.

3.3 Embedding network and Encoder Network using Rotation-Invariant Coordinate Convolutional Neural Network

The proposed watermarking image consists of two stages: (1) utilizing an embedding network to integrate the secret data into the front picture, also (2) taking out the marked image's hidden data. Additional information about the suggested plan is provided in the sections that follow.

Embedding network

The embedding network securely embeds secret data into the cover image by first normalizing the cover image and formatting the secret data. It then extracts features from the cover image using convolutional layers and integrates the secret data into the image's feature space through an embedding layer. The network reconstructs the marked image, ensuring high visual quality, and optimizes embedding accuracy and image quality during training with a loss function. The final output is a marked image that visually resembles the cover image but contains the embedded secret data is given to design an encoder network.

Design an encoder network

In this step, Design an encoder network using RICCNN [14] model is proposed in order to extract latent features from the secret mark and cover images. Train the encoder network utilizing the training set to learn meaningful representations of the images. Concatenate the latent features extracted from the cover image and the secret mark image. Use the concatenated features to produce a marked image, where the secret mark is embedded imperceptibly into the cover image. Train the denoising AutoEncoder using the training set to remove noise variations via the received marked image also reconstruct clean images. Lastly, use the designated image to extract the secret data using RICCNN. To compute the sum of sampled values of a convolutional kernel using RICCNN, multiply each kernel weight by its corresponding pixel value in the input image patch, and then sum these products. This process integrates the weighted contributions of pixels within the kernel's receptive field, essential for extracting features in neural network convolutional layers. Then calculate the sum of sampled values of convolutional kernel is calculated in equation (4).

$$R = (q * \sin(\vartheta + \frac{j * 2\tau}{8q}) q * \cos(\vartheta + \frac{j * 2\tau}{8q})) \tag{4}$$

Where R denotes the sample value of convolutional kernel, q is the circle of radius, 2τ is the mathematical value calculated in image ϑ is the sigmoid calculation value, j is the sample point of image. Rotation-invariant coordinate convolution using RICCNN processes an image by applying a convolutional kernel that remains invariant to rotations. This technique samples kernel values in a rotation-invariant manner, ensuring consistent feature extraction regardless of the image's orientation. Consequently, this approach enhances the network's robustness to rotational variations in the input image. Then, the Rotation-invariant coordinate convolution acting on Y_0 is calculated in equation (5).

$$\varphi_{QJN-N}(Y_0 * E(Y)) = \sum_{R\varpi\tau_{y0}} z(r) * E(Y_0 + R) \tag{5}$$

Where φ_{QJN-N} represents the Rotation-invariant coordinate convolution acting in parameter value of image, Y_0 represents the value of Variety, $E(Y)$ denotes the feature value of marked image, $\sum_{R\varpi\tau_{y0}}$ is the classified marked image, $z(r)$ is the differentiation of image process.

Input the concatenated features into a trained decoder network to produce the final marked image, ensuring the secret mark is imperceptible in the cover image. Similarly, calculating the final marked image is given equations (6).

$$\varphi_{QJN-N}(Y_0 * E(Y)) = \sum_{R\varpi\tau_{y_0}} z(r) * E(Y_0 + r + (R-q)) \tag{6}$$

Where $(R-q)$ is the value calculation in the rotational invariance, r represent the corresponding to same feature of the image. The RICCNN model is utilized to extract latent features from the secret mark image as well as the cover image. Train the encoder network to learn meaningful representations of these images. Concatenate the extracted features to combine essential information from both images. Input the concatenated features into a trained decoder network to generate the final marked image, ensuring that secret mark is imperceptibly integrated in the cover image latent features is calculated in equation (7).

$$\varphi_{QJN-N}(Y_0 * E(Y)) = \sum_{R\varpi\tau_{y_0}} z(r) * E(Y_0 + r + \hbar r) \tag{7}$$

Where $\hbar r$ denotes the corrected latent feature from the image. Finally, extract the secret data from the marked image utilizing RICCNN. This work, the HBO is utilized to optimize the weight parameter of RICCNN. Here, the HBO is employed for change the weight and bias parameter of RICCNN.

3.4 Optimization using Honey Badger Optimization algorithm

This section, the weights parameter $R\, and\ q$ of RICCNN is optimized using the HBO [15]. By fine-tuning these weights, HBO enhances the RICCNN's performance in feature extraction and embedding. These results in improved watermarking image, ensuring the secret mark remains imperceptible in the cover image. The HBO optimization refines the network's ability to manage rotational variations and other feature extraction challenges. Consequently, the marked images retain high visual quality and robustness against distortions. Overall, HBO significantly boosts the reliability and efficiency of the digital image watermarking process. The HBO algorithm principle can be divided into seven major stages, which are includes in the following steps,

Step1: Initialization

Initial population of HBO is initially generated by randomness phase of population initialization creates collection of representative solutions that are randomly distributed throughout solution space. Initialize number of population size the weight balancing of generator and their locations is expressed in equation (8)

$$m_i = ha_i + r_1 \times (ub_i - tb_i) \tag{8}$$

Where, m_i represents the i^{th} honey badger location regarding candidate solution hb_i, ub_i denote supper and lower search domain bounds.

Step 2: Random generation

The input parameters are randomly generated. Considering their unique hyper-parameter circumstances, the weight $R, E(Y)$ parameter is generated arbitrarily using the HBO technique.

Step 3: Fitness function

The initialized assessments are used to create random solutions. It is calculated with the parameter optimization value for optimizing the weight parameter HBO of the RICCNN as given in equation (9).

$$FitnessFunction = optimizing\ [R\, and\, q] \tag{9}$$

Step4: Defining Intensity for Optimizing R

The amount of prey present and the space among it and the honey badger affect how difficult the hunting is; L_i denotes prey's smell strength; if the smell is strong, the motion is swift and vice versa provided by Inverse Square Law as expressed in equations (10).

$$L_i = t_2 \times R \frac{M}{4\Pi k_i^2} \tag{10}$$

Where, M denotes source, concentration strength. k_i Represents distance among prey i^{th} badger, t_2 denotes random number.

Step5: Update density factor for Optimizing q

Time-varying unpredictability is managed by the density factor, which makes the transfer via exploration to exploitation smooth. Revise the factor of reduction using each iteration to gradually reduce unpredictability. Thus it is expressed in equation (11).

$$\alpha = C \times Expq\left(\frac{-n}{n_{Max}}\right) \tag{11}$$

Here, $r_{\max}$ represents maximum amount of iterations, C denotes constant ≥ 1.

Step 6: Updating the agent positions

In HBO, agent positions are updated based on their performance and interactions to enhance the search for optimal solutions. This iterative adjustment process improves the agents' ability to find better weight parameters for the neural network. The goal is to refine the optimization and achieve better results in tasks such as digital image watermarking.

Step 6.1: Digging phase

In the digging phase of HBO, agents explore the solution space more thoroughly to uncover potentially superior options. This phase focuses on deeper probing to improve the quality of the solutions discovered and it is expressed in equation (12).

$$a_{new} = a_{prey} + E \times \chi \times X \times a_{prey} \times E \times \gamma \times s_3 \times g_a \left|\cos(2\theta s_4) \times (1 - \cos(2\theta s_5)\right|$$

Where a_{new} represent best position found in image, a_{prey} is the position of the prey, E is the quality of the image, χ is the equivalent factor, X is the inverse matrix of parameter, γ is the agents explore solution, s_3, s_4, s_5 is the random numbers in image, g_a is the parameter of image distance information.

Step 6.1: Honey phase

In the honey phase of HBO, agents focus on refining and improving the most promising solutions discovered earlier. This phase intensifies the search around these high-potential areas to enhance solution quality is given by the Equation (13).

$$a_{new} = a_{prey} + E \times \gamma \times s_7 \times g_a$$

Where s_7 is the random numbers in image.

Step 7: Termination

The weight parameter value of $R\,and\,q$ from RICCNN is optimized by utilizing HBO; and it will repeat step 3 until it obtains its halting criteria $m = m+1$.Then DIW-RICCNN-HBO defectively assesses the analyzes for improved results in digital image watermarking by higher PSNR.

4. Result and Discussion

This section displays several simulation results to establish the effectiveness of the suggested plan. To assess the performance of recovering and embedding, the marked image's also the recovered mark image's quality was assessed using three metrics: PSNR, SSIM, and NC. More information is provided about the outcomes and analysis of the proposed scheme in the sections that follow. The experimental analysis of proposed DIW-RICCNN-HBO simulations is compared to the existing method such DIW-DCNN [11], DIW-DNN [12] and RDW-ReDMark [13]

4.1 Performance Metrics

The efficiency of the suggested technique is verified by analyzing the performance metrics listed below.

4.1.1 Peak signal-to-noise ratio

The PSNR quantifies the ratio of the higher possible signal value to the noise power that compromises the representation's accuracy. The PSNR is calculated in equation (14).

$$PSNR = 10.\log_{10}\left(\frac{Q^2}{MAE}\right) \tag{14}$$

Where $PSNR$ denotes the PSNR, Q represents the maximum possible pixel value of image, MAE represents the Mean Squared Error among original image and the reconstructed image.

4.1.2 Structural Similarity Index Measure

SSIM evaluates the supposed quality of digital images by considering structural information, luminance, and contrast. The SSIM is calculated in equation (15).

$$SSIM(i,j)=\frac{(2\mu_i\mu_j+D_1)(2\vartheta_{i\,j}+D_2)}{(\mu_i^2+\mu_j^2+D_1)(\vartheta_i^2+\vartheta_j^2+D_2)} \tag{15}$$

Where $SSIM(i,j)$ represent the SSIM of image i also j, $\mu_i\mu_j$ signifies the average values of the images i also j, $\vartheta_{i\,j}$ is the covariance of image i also j, $\vartheta_i^2,\vartheta_j^2$ is the variances of the images i and j, D_1, D_2 denotes the constants in order to maintain the division's weak denominator.

4.1.3 Normalized correlation

NC assesses the similarity among the original image also the watermarked or reconstructed image, quantifying how closely 2 images align NC is calculated in equation (16).

$$NC=\frac{\sum_{x=1}^{T}\sum_{x=1}^{W}X(x,y)\bullet H(x,y)}{\sqrt{\sum_{x=1}^{T}\sum_{x=1}^{W}X(x,y)^2\bullet\sum_{x=1}^{T}\sum_{x=1}^{W}X(x,y)^2}} \tag{16}$$

Where NC represent the Normalized correlation, $X(x,y)$ denotes the pixel values of original image, $H(x,y)$ denotes the pixel values of watermarked image.

4.2 Performance analysis

Figure 2-4 and table 1 depicts stimulation results of DIW-RICCNN-HBO proposed method. Then, the proposed DIW-RICCNN-HBO method is likened to existing methods like DIW-DCNN, DIW-DNN, and RDW-ReDMark respectively

4.2.1 Performance Analysis using CIFAR-10 dataset

The proposed methodology DIW-RICCNN-HBO demonstrates significant improvements in image quality metrics across the CIFAR-10 datasets. Table 1 highlight that DIW-RICCNN-HBO achieves higher PSNR, SSIM, and MC while being faster than existing approaches. Overall, DIW-RICCNN-HBO proves to be more efficient and effective in enhancing image quality.

Table 1: Performance Analysis using CIFAR-10 dataset

Methods	Peak signal-to-noise ratio (db)	Structural similarity index measure (%)	Normalized correlation (bits/j)
DIW-DCNN	23.9	0.69	0.64
DIW-DNN	19	0.6	0.8
RDW-ReDMark	12	0.65	0.87
DIW-RICCNN-HBO (proposed)	27.8	0.7	0.95

4.2.1 Performance Analysis using Pascal VOC2012 datasets

Performance analysis of the Pascal VOC2012 datasets shows that DIW-RICCNN-HBO significantly enhances image quality, achieves higher PSNR, SSIM, also MC values linked to existing methods. The results demonstrate the methodology's robustness and efficiency in various image enhancement tasks. Overall, it proves to be an effective approach for enhancing image quality on the Pascal VOC2012 datasets**.**

Figure 2 depicts PSNR. The PSNR utilized within the RICCNN framework helps evaluate and refine the quality of extracted latent features by comparing the similarity among the original and processed images. This method enables RICCNN to optimize feature extraction, reducing noise and distortion. By leveraging PSNR, RICCNN enhances its capability to preserve image details and improve overall image quality, thus proving more effective for accurate image analysis and reconstruction tasks. In this context, the proposed DIW-RICCNN-HBO method achieves 35.66%, 32.73%, and 31.43% higher PSNR for a number of images 500; 26.76%, 28.67%, and 32.75% higher PSNR for several images 1500; 32.45%, 25.56%, and 26.89% higher PSNR for several images 2500 are compared with the existing methods like DIW-DCNN, DIW-DNN, and RDW-ReDMark methods respectively.

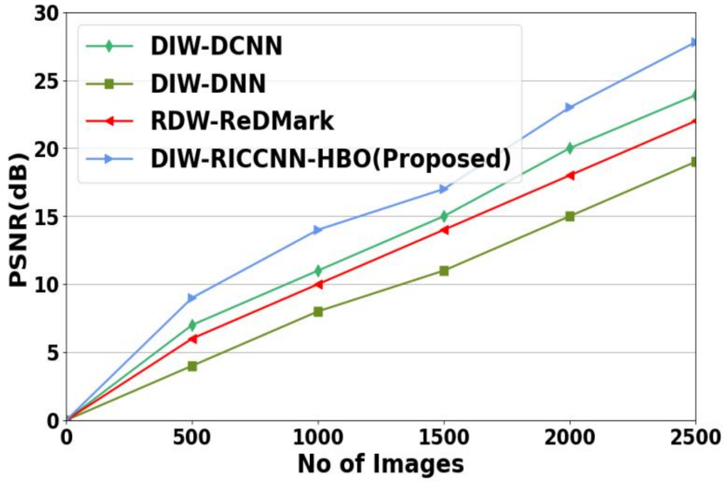

Figure: 2 Performances analysis of peak signal-to-noise ratio

Figure 3 depicts SSIM. The SSIM is utilized within the RICCNN to assess and refine the quality of extracted latent features. This integration supports RICCNN in preserving robust feature representations and enhancing image quality. By incorporating SSIM, improves its effectiveness in precise image analysis and reconstruction tasks. In this context, the proposed DIW-RICCNN-HBO method achieves 32.77%, and 28.93% higher SSIM for several images 500; 27.73%, 22.67%, and 32.54% higher SSIM for a number of images 1500; 38.69%, 34.45%, and 25.87% higher SSIM for several images 2500 compared with the existing methods like DIW-DCNN, DIW-DNN, and RDW-ReDMark methods respectively.

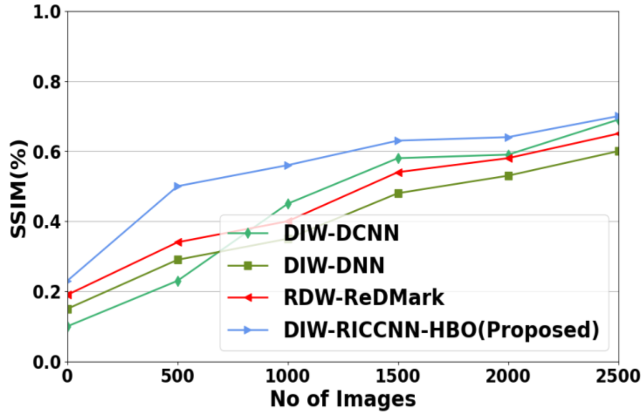

Figure: 3 Performances analysis of structural similarity index measure

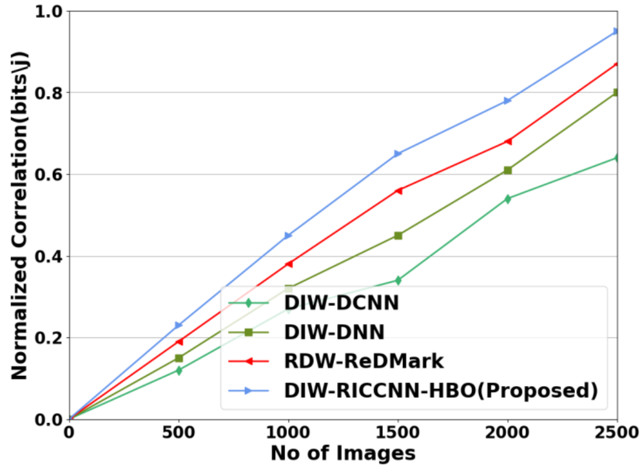

Figure: 4 Performances analysis of normalized correlation

Figure 4 depicts Normalized Correlation (NC). The NC is employed within the RICCNN framework enhances the assessment and refinement of extracted latent features by calculating the similarities among the original and processed images. By emphasizing NC, RICCNN improves its effectiveness in precise image analysis and reconstruction, ensuring that the reconstructed images closely match the originals with minimal distortion. The proposed DIW-RICCNN-HBO method achieves an improvement of 24.54%, 23.65%, and 23.62% higher NC for a number of images 500; 31.53%, 24.76%, and 24.61% higher NC for several images 1500; 23.87%, 21.83% and 23.27% higher NC for several images 2500 are compared with the existing method like DIW-DCNN, DIW-DNN, and RDW-ReDMark methods respectively.

5. Conclusion

The proposed DIW-RICCNN-HBO has successfully implemented. This work presents a RICCNN based, reliable watermarking method for digital photos. The proposed method leverages learning capabilities of a RICCNN to reduce human intervention by using unsupervised training to automatically learn also simplify the watermarking methods. The method is imperceptible also effectively defends the mark image against assaults thanks to the use of embedding and extraction networks. The technique significantly enhances performance, improving 4.54%, 23.65%, and 23.62% higher NC compared to existing method such as DIW-DCNN, DIW-DNN, and RDW-ReDMark. Future improvements will focus on increasing embedding capacity for practical applications. Additionally, dual watermarking, which offers more authentication and meets practical demands, will be explored in a future publication. Future work will also examine the performance of the algorithm with enhanced capacity and color images.

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