An Improved Image Compression Model Enabled by Adaptive Active Contour and Supervised Learning-Based ROI Classification

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ABSTRACT

This paper plans to develop a novel image compression model with four major phases: (1) segmentation, (2) feature extraction, (3) ROI classification, and (4) compression. The image is segmented into two regions by Adaptive ACM. The result of ACM is the production of two regions. This model enables a separate ROI classification phase. For performing this, the features corresponding to GLCM are extracted from the segmented parts. Further, they are subjected to classification via NN, in which new training algorithm is adopted. As a main novelty, JA and WOA are merged together to form J-WOA with the aim of tuning the ACM (weighting factor and maximum iteration) and training algorithm of NN, where the weights are optimized. This model is referred as J-WOA-NN. This classification model exactly classifies the ROI regions. During the compression process, the ROI regions are handled by JPEG-LS algorithm, and the non-ROI regions are handled by wavelet-based lossy compression algorithm. Finally, the decompression model is carried out by adopting the same reverse process.

KEYWORDS

Adaptive Active Contour Model, Image Compression, ROI Classification, Segmentation

1. INTRODUCTION

Over the decades, the demand for multimedia products attains faster growth in the field of communication. The digital images make the bandwidth insufficient as well as consume huge storage space of the memory devices (Miaou, *et al.*, 2009; Lin & Hao, 2005). Thus, there is a necessity to diminish the data redundancy in the image with the desire of saving the hardware space and the transmission bandwidth. In fact, compressing the images plays a very important role in storage as well as transmission purpose by performing the compression into the least number of bits with no loss in the essential information content encapsulated in the original image. In each image, there is redundant data, which represents the duplication of data (Chen, *et al.*, 2005; Shen & Rangayyan, 1997). The redundancy may be due to the frequent repetition of the pixels across the image. The redundancies in the image are distinguished into, psycho-visual redundancy spatial redundancy, and coding redundancy. The elimination of the correlation among the pixels in the natural image via transform coding or predictive coding is referred to as Inter-pixel Redundancy or spatial redundancy. The psycho-visual redundancy is done to reduce the quantity of data to make the visual information

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equally sensitive to all human eyes. The coding redundancy takes place with variable-length codes of the statistical model (Sanchez, *et al.*, 2008; Srikanth & Ramakrishnan, 2005).

In general, the main approaches in image compression are categorized as Lossless technique and Lossy technique on the basis of the reconstruction of the original image from the compressed image (Taquet & Labit, 2012). With the lossless compression, the reconstruction of the original image from the compressed image is a bit easier while compared to the lossy compression. In the lossy compression, there is a minute difference between the reconstructed image and original image and with the lossy compression, there is a higher compression rate (Velisavljevic, *et al.*, 2007; Creusere, 1997; Sanchez, *et al.*, 2010; de Queiroz, *et al.*, 2000). Run Length Encoding, Entropy Encoding, Huffman Encoding, Arithmetic Coding come under the lossless image compression technique. The lossy image compression includes Scalar Quantization and Vector Quantization (Kim & Cho, 2014; Lin, *et al.*, 2018). With the lossy image compression, the speed of encoding and decoding of images as well as the Signal to Noise Ratio and compression ratio are high.

The most popular image compression technique is DCT as it is efficient in blocking the artifact effect and making the sub-images visible. The JPEG baseline coding system is the common mode employed in DCT as it fits most of the compression applications. This JPEG technique has the lowest compression ratio, and RLE is sufficient only for the files with high repetitive data. The Fractal Encoding has an excellent mathematical-encoding frame, and in contrast, its encoding scheme is slow (Aliaga & Carlbom, 2005; Lee, *et al.*, 2015; Pang, *et al.*, 2019). The Arithmetic encoding makes uses of the fractional values, and these values have complex computations. With the Vector Quantization, there lacks coefficient quantization and hence this scheme is simple to use (Fu, *et al.*, 2018). But, the codebook generation in Vector Quantization is much slower and has low bit rates. The Huffman Encoding is more effective for text or program files other than images. Thus, with the desire of overcoming the issues in the existing image compression techniques, there is a necessity to have an appropriate image compression technique that will have a better compression and reconstruction rate.

The major contribution of this paper is portrayed below:

1. To develop an image compression model with the assistance of four main steps like (i) Segmentation (ii) Feature Extraction (iii) ROI classification, and (iv) Compression.
2. The input image is segmented into ROI and non-ROI regions using Adaptive ACM. The segmented image is subjected to feature extraction via GLCM.
3. The extracted features are subjected to optimized NN for deciding the ROI regions.
4. The proposed J-WOA is done for tuning ACM (weighting factor and maximum iteration), and training algorithm of NN in which the weights are optimized.
5. To handle the ROI regions of the image, the JPEG-LS algorithm is used and the non-ROI region is handled by the wavelet-based lossy compression algorithm. Finally, performance validation is done based on different performance metrics.

The overall organization of the paper is discussed as follows: The literature work on image compression along with the advantages and benefits of each model is reviewed in Section II. The proposed architecture of the image compression framework is portrayed in Section III. Section IV exhibits the ROI segmentation based on adaptive active contour segmentation and supervised learning. The compression process for ROI and Non-ROI are depicted in Section V. Section VI provides a compact explanation of the obtained results and Section VI depicts the summary.

2.LITERATURE REVIEW

2.1 Methodological Approaches

Karayiannis, *et al.*, (2008) proffered a novel image compression model on the basis of WSD and vector quantization model. The decomposition of the images into a smaller set of frequency sub-bands was accomplished using the wavelet filters. LBG algorithm was implied to vector quantization in order to quantize the resultant sub-bands.

Lahdir, *et al.*, (2019) projected SPIHT with the intention of compressing as well as encrypting the images and chaotic maps synchronization in non-linear orders. The images were compressed faster and effectively with the standard SPIHT coding. Moreover, the fractional-order chaotic maps override the shortcoming of the cryptosystem in generating the secret keys.

Francisco, *et al.*, (2012) formulated the post-processing deblocking technique as a new approach for encoding the compressed image. The total variation analysis and adaptive bilateral filtering were the benchmarks of the proposed model. MMP algorithm was utilized for the construction of filters for both lossy and lossless compression method.

Wu, *et al.*, (2009) proposed CADU with the desire of downsampling the image space in a uniform manner. The directional low-pass pre-filtering was employed to make the sampling adaptive. Moreover, a 2-D piecewise autoregressive model was used under the least-squares restoration process to upconvert the low-resolution image into an original image.

Wang, *et al.*, (2015) developed a new approach for the hyperspectral image compression system on the basis of LT-TD. Initially, the images were de-correlated with the help of lapped transform and the obtained transformed coefficients having varying frequency orders were organized into 3D wavelet sub-band structures. Further, the tucker decomposition was utilized with the desire of decomposing the 3D sub-bands into core tensor as well as three-factor matrices. The bit-plane coding algorithm was used to split the decomposed sub-bands into bit-streams.

Chiranjeevi & Jena, (2018) introduced a novel meta-heuristic optimization algorithm referred to as CS with the intention of optimizing the LBG codebook. The optimization of LBG was accomplished using the levy flight distribution function and the Mantegna's algorithm. The outcomes of the proposed model exhibited an enhancement in PSNR and fitness value while compared to the existing model.

Zhou, *et al.*, (2014) proposed a novel near-lossless algorithm with the desire of compressing the image in WCE. The Bayer Color Filter Array was utilized for performing the compression operation on the image directly. While combining the transform-based coding and predictive coding, there was an enhancement in the higher average image quality as well as in the bit-rate reduction.

Turcza & Duplaga, (2017) constructed a new image compression–encryption hybrid algorithm for performing both the image compression as well as encryption together by means of storing or memorizing the key. For simultaneous compression and encryption of the image, the input image was split into four blocks. Further, with the help of random matrices, the pixels were exchanged between the two adjacent blocks.

Feifei Yang, *et al.*, (2019) developed a novel color image compression-encryption method. In this method, compression sensing (CS) method was exploited for compression image, and then utilizing Zigzag confusion, add modulus and BitCircShift diffuse encrypt the image.

Shuqin Zhu *et al.*, (2019) proposed a novel image compression–encryption hybrid method. Initially, a Gauss random matrix and a random scrambling matrix were generated by exploiting Chebyshev mapping and Logistic mapping, correspondingly. Subsequently, based on the principle which a scrambling Gauss matrix was still a Gauss matrix, a compression scheme for ciphertext images was modelled.

2.2 Motivation

Table 1 portrays the features and challenges of the existing image compression models. In WSD (Karayiannis, *et al.*, 2008), the requirements of computations are low and have a high compression

Table 1. Features and challenges of Conventional image Compression Models

Authors [Citation]	Adopted Methodology	Features	Challenges
Karayiannis <i>et al.</i> (2008)	WSD	<ul style="list-style-type: none"> • Low computational requirements • High compression ratios. 	<ul style="list-style-type: none"> • No quality gains • Maximum smoothing power is low
Lahdir <i>et al.</i> (2019)	SPIHT	<ul style="list-style-type: none"> • Large key space • High-level security • High obscure level 	<ul style="list-style-type: none"> • Not applicable for real-time secure image • Low PSNR
Francisco <i>et al.</i> (2012)	MMP	<ul style="list-style-type: none"> • Compressed still images and video sequences 	<ul style="list-style-type: none"> • Regions with high level details were not filtered • Low degree of adaptability
Wu <i>et al.</i> (2009)	CADU	<ul style="list-style-type: none"> • Reduces the workload • Energy consumption of the encoders is low 	<ul style="list-style-type: none"> • Consumes high bandwidth • Requires huge energy
Wang <i>et al.</i> (2015)	LT-TD	<ul style="list-style-type: none"> • Applicable for data mining, psychometrics, • numerical analysis and neuroscience applications 	<ul style="list-style-type: none"> • Low compression performance
Chiranjeevi <i>et al.</i> (2018)	CS	<ul style="list-style-type: none"> • Low convergence time • High PSNR 	<ul style="list-style-type: none"> • Bad reconstructed image quality
Zhou <i>et al.</i> (2014)	NLA	<ul style="list-style-type: none"> • Good image security • High compression performance 	<ul style="list-style-type: none"> • Produces NP-hard problem
Turcza <i>et al.</i> (2017)	CEHA	<ul style="list-style-type: none"> • High throughput • Very low clock frequency operation 	<ul style="list-style-type: none"> • High power consumption • Flash memory space increased

ratio. Apart from this, there are no quality gains in the compressed image, and the maximum smoothing power is low. There is large-key space in addition to a high level of security as well as high obscure in SPIHT, but it has low PSNR, and it is no applicable to real-time secure image (Lahdir, *et al.*, 2019). Then, MMP (Francisco, *et al.*, 2012) is efficient in compressing the still images and the video sequences. It has a drawback of non-filtering in the regions of high-level details, and the degree of adaptability is low. The workload is diminished and the power consumption of the encoders to have reduced with CADU (Wu, *et al.*, 2009) and the major drawback of the non-prefer ability of this model is due to its high bandwidth consumption and high energy consumption. The LT-TD (Wang, *et al.*, 2015) is applicable for data mining, psychometrics, numerical analysis, and neuroscience applications because of its high compression ratio. This model has low compression performance. Further, there is low convergence time and high PSNR in CS and had reconstructed image quality (Chiranjeevi & Jena, 2018). In NLA (Zhou, *et al.*, 2014), image security is high and has good compression performance. The major drawback of NLP is, it is much prone to NP-hard problem. CEHA (Turcza & Duplaga, 2017) has high throughput and low clock frequency operation. However, the power consumption is high and the space for flash memory is also high. From the table, it is clear that each method has its own advantages and challenges, and hence, there is a necessity to consider these drawbacks in upcoming research.

3.PROPOSED ARCHITECTURE OF IMAGE COMPRESSION

3.1 Architectural Representation

In the primary research work (Kumar, 2019) on image compression, the binary classification is utilized for segmenting the ROI (Generally, the idea of a ROI is exploited in numerous application

Figure 1. Diagrammatic representation of the proposed image compression model

areas. For instance, the boundaries of a tumor may be stated on an image or in a volume, for the reason of measuring its size in medical imaging), and non-ROI regions of the image, in which the segmented part was considered as ROI and the leftovers were considered as non-ROI. It is one type of unsupervised classification, which occur problem of misclassification, as it doesn't have any knowledge regarding the tumor region. Thus, with the intention of overriding these problems, the J-WOA image compression models is developed as per Fig. 1 on the basis of four major stages viz. (i) Segmentation (ii) Feature Extraction (iii) ROI classification (iv) Compression. Initially, the segmentation of the image is accomplished using ACM to partition the image into two regions; ROI and non-ROI. Let the input image be considered as S , $\hat{S}_{ROI}$ and $\hat{S}_{N-ROI}$. Then, the segmented binary regions are subjected to feature extraction using the GLCM. Once, the features are extracted, they are classified using NN. Moreover, JA and the WOA are merged together to form J-WOA for tuning ACM (weighting factor and maximum iteration) as well as the training algorithm of NN. Hence, the NN provides the labels that are associated with the separation of both ROI, and non-ROI regions exactly. Finally, the ROI regions of the image are compressed by the JPEG-LS algorithm, whereas the non-ROI region of the image is compressed by wavelet-based lossy compression algorithm. The outcome of this framework is an optimal compressed image. Hence, $\hat{S}_{C-(ROI)}$ and $\hat{S}_{C-(N-ROI)}$, which are fused together to obtain the final compressed image. At last, the same reverse process is performed in the decompression process that extracts the original image.

3.2 Objective Model

The proposed image compression model relies on two main objective functions.

§ The initial objective is to induce the adaptiveness in ACM by hybrid optimization concept, by minimizing the compression ratio of the image. The objective function for optimizing the segmentation process is given in Eq. (1), and the calculation for the compression ratio is shown in Eq. (2), considering both ROI, and non-ROI compressed images.

$$(obj)_1 = \min(CR) \quad (1)$$

$$CR = \frac{Size[\hat{S}_{C-(ROI)} + \hat{S}_{C-(N-ROI)}]}{Size[S]} \quad (2)$$

§ The second objective is focused on ROI, and non-ROI image classification using NN. Here, the training of NN is done by proposed J-WOA, where the weights are optimized in such a way that the error between predicted and actual outcomes should be minimum as shown in Eq. (2), where $F(er)$ is given in Eq. (25).

$$(obj)_2 = \min(F(er)) \quad (2)$$

4.ROI SEGMENTATION BASED ON ADAPTVE ACTIVE CONTOUR WITH SUPERVISED LEARNING

4.1 Adaptive Active Contour Model

The primary step of image compression in this paper is image segmentation, which is accomplished via the active contour model on the basis of both background and foreground with correspondence to the least local regions. The input image is considered as S , and it resides in the δ . The initial process begins by setting the $\max^{(t)}$. The cc and it is said to be the zero level set belonging to the λ . The mathematical formula of the closed contour is represented in Eq. (4). The smoothed Heaviside function F (Lankton & Tannenbaum, 2008) manifests the interior of cc_{int} that is exhibited in Eq. (5). In addition, Eq. (6) represents the mathematical formula of exterior cc_{out} and the area under the curve is determined by using the Dirac delta's smoothed version and Eq. (7) represents this.

$$cc_{int} = \{a \mid \lambda(a) = 0\} \quad (4)$$

$$F\lambda(a) = \begin{cases} 1, & \lambda(a) < -\psi \\ 0, & \lambda(a) > \psi \\ \frac{1}{2} \left[1 + \frac{\lambda}{\psi} + \frac{1}{\pi} \sin \left(\frac{\pi \lambda(a)}{\psi} \right) \right], & \text{otherwise} \end{cases} \quad (5)$$

$$cc_{out} = (1 - F\lambda(a)) \quad (6)$$

$$\omega\lambda(a) = \begin{cases} 1, & \lambda(a) = \psi \\ 0, & |\lambda(a)| < \psi \\ \frac{1}{2\psi} \left[1 + \cos \left(\frac{\pi \lambda(a)}{\psi} \right) \right], & \text{otherwise} \end{cases} \quad (7)$$

Moreover, a and e , are used by the algorithm, which show the single point in δ . In Eq. (8) with correspondence to the radius parameters ρ , a characteristic function is introduced. The local regions are masked using the function $H(a, e)$. Further, in Eq. (9) an energy function is defined with the help of $H(a, e)$ on the basis of GFF , which is a generic internal energy measure that signifies the local adherence. In addition, for smoothing the curve, the regularization term is added. This regularization term will try to lower the parameters in order to improve smoothness. Adding a regularization term for the weights to the loss function is one way to reduce over fitting. The regularization term is also called weight decay. With the τ parameter having the default value 0.2, the penalization of the curve's arc length takes place. The final energy is manifested in Eq. (10) and the final evolution equation with respect to the initial variation of energy in terms of λ is depicted in Eq. (11).

$$H(a, e) = \begin{cases} 1, & ||a - e|| < \rho \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

$$FE(\lambda) = \int_{\delta_a} \omega\lambda(a) \int_{\delta_b} H(a, e) \bullet GFF(S(e), \lambda(e)) de da \quad (9)$$

$$FE(\lambda) = \int_{\delta_a} \omega\lambda(a) \int_{\delta_b} H(a, e) \bullet GFF(S(e), \lambda(e)) de da + \tau \int_{\Omega_x} \omega\lambda(a) || \nabla \lambda(a) || da \quad (10)$$

$$\frac{\partial \lambda}{\partial t} = \omega\lambda(a) \int_{\delta_a} H(a, e) \bullet \nabla_{\lambda(e)} GFF(S(e), \lambda(e)) de + \tau \omega\lambda(a) div \left(\frac{\nabla \lambda(a)}{|| \nabla \lambda(a) ||} \right) \quad (11)$$

The adaptive contour model splits the image into two regions viz. ROI and Non-ROI. The first major contribution of this work is the adaptiveness in the ACM model. Here, tuning of maximum iteration $\max^{(i)}$ is taken as a crucial part of the segmentation process. Thus, the proposed J-WOA helps in optimizing the $\max^{(i)}$ within the range of 100 to 500. In addition, for the smoothing function, the weighting factor τ should be optimized by the same J-WOA that should be within the range of 0.1 to 0.5. At the end of adaptive segmentation, the original image S is split into the ROI region $\hat{S}_{ROI}$ and the Non-ROI $\hat{S}_{N-ROI}$ region.

4.2 GLCM Feature Extraction

GLCM (Vallabhaneni & Rajes, 2018) is one of the most well-known statistical methods utilized for gathering texture extraction from the images. From the segmented $\hat{S}_{ROI}$ and $\hat{S}_{N-ROI}$, the GLCM features fp^{feat} are extracted. The features extracted from the image are contrast, correlation, energy and homogeneity, entropy, mean, variance, SD, dissimilarity, cluster proximity, maximum probability. The contrast is the ‘Sum of Square Variance’ and it is the difference between the color and the brightness of the image. The mathematical expression corresponding to contrast is specified in Eq. (12) in which the dimension of the W .

$$Contrast = \sum_{\hat{k}, \hat{l}=0}^{W-1} T_{\hat{k}, \hat{l}} (\hat{k} - \hat{l})^2 \quad (12)$$

In Eq.(14), when $\hat{k} - \hat{l} = 0$, there exists no contrast in the image. The linear dependency of grey levels of neighboring pixels is measured by the correlation. The correlation helps in estimating the deformation, displacement, strain and optical flow of the image. The mathematical formula for correlation is expressed in Eq. (13).

$$Correlation = \sum_{\hat{k}, \hat{l}=0}^{W-1} (\hat{k}, \hat{l}) T(\hat{k}, \hat{l}) - \sigma_{\hat{k}} \sigma_{\hat{l}} \quad (13)$$

The randomness that characterizes the texture of the input image is measured by Entropy. The mathematical expression corresponding to entropy is portrayed in Eq. (14).

$$Entropy = \sum_{\hat{k}, \hat{l}=0}^{W-1} \left(-T_{\hat{k}, \hat{l}} * \log T_{\hat{k}, \hat{l}} \right) \quad (14)$$

The energy is utilized to calculate the extent of pixel pair repetitions and the mathematical formula for energy is shown in Eq. (15). The tightness in the distribution of the elements to the diagonals is measured by the Homogeneity and Eq. (16) indicates the general Homogeneity in which the J . Eq. (17), Eq. (18) and Eq. (19) depict the general mathematical formula for mean, variance and standard deviation. In the ROI, the distance between pairs of pixels is represented as dissimilarity and the mathematical formula for dissimilarity is shown in Eq. (20). The mathematical formula for $(Pr o(Max))$ is shown in Eq. (21), which is the “measure of the maximum likelihood of producing the pixels of interest”. “The tendency of clustering the pixels in the region of interest” is referred to as $(Cluster (Pr ox))$, and the mathematical formula of cluster prominence character is mentioned in Eq. (22).

$$Energy = \sum_{\hat{k}, \hat{l}=0}^{W-1} \left(T_{\hat{k}, \hat{l}} \right)^2 \quad (15)$$

$$Homogeneity = \sum_{\hat{k}, \hat{l}=0}^{W-1} \frac{T_{\hat{k}, \hat{l}}}{1 + \left(\hat{k} - \hat{l} \right)^2} \quad (16)$$

$$Mean \ \mu_{\hat{k}} = \sum_{\hat{k}, \hat{l}=0}^{W-1} \hat{k} \left(T_{\hat{k}, \hat{l}} \right); \mu_{\hat{l}} = \sum_{\hat{k}, \hat{l}=0}^{W-1} \hat{l} \left(T_{\hat{k}, \hat{l}} \right) \quad (17)$$

$$Variance \ o_{\hat{k}} = \sum_{\hat{k}, \hat{l}=0}^{W-1} T_{\hat{k}, \hat{l}} \left(\hat{k} - \mu_{\hat{k}} \right); o_{\hat{l}} = \sum_{\hat{k}, \hat{l}=0}^{W-1} T_{\hat{k}, \hat{l}} \left(\hat{l} - \mu_{\hat{l}} \right) \quad (18)$$

$$SD \ \sigma_{\hat{k}} = \sqrt{o_{\hat{k}}^2} \ \sigma_{\hat{l}} = \sqrt{o_{\hat{l}}^2} \quad (19)$$

$$Dissimilarity = \sum_{\hat{k}, \hat{l}=0}^{W-1} T_{\hat{k}, \hat{l}} \left| \hat{k} - \hat{l} \right| \quad (20)$$

$$Pr o(Max) = \max T_{\hat{k}, \hat{l}} \text{ for all values of } \hat{k}, \hat{l} \quad (21)$$

$$Cluster \ (Pr \ ox) = \sum_{\hat{k}, \hat{l}=0}^{W-1} \left(\hat{k} + \hat{l} - \mu_{\hat{k}} \right)^4 T_{\hat{k}, \hat{l}} \quad (22)$$

All these entire GLCM features extracted from the segmented images fp^{feat} are fed to NN for classification.

4.3 Neural Network-based ROI Extraction

The features extracted using GLCM are fed as input to the classifier NN with the desire of classifying the ROI and Non-ROI regions preciously (Yang & Ma, 2019). NN model consists of three layers like an input layer, a hidden layer, and an output layer. The network model of NN is clearly explained in Eq. (23) and Eq. (24). The hidden neurons in NN are manifested as z , where $z = 1, 2, \dots, N_z$. The input neuron is represented as p where $p = 1, 2, \dots, N_p$ and the output neuron is represented as o where $o = 1, 2, \dots, N_o$. The bias weight of the hidden neurons z is depicted as wg_{bz}^N . The bias weight of output neurons is indicated as wg_{bo}^r . In addition, wg_{pz}^N represents the weight from p^{th} input neuron to z^{th} hidden neuron and wg_{zo}^r is the weight from z^{th} hidden to o^{th} output neuron. Further, Eq. (24) exhibits the predicted output of the network, R_{pre} . Eq. (25) represents the error function $F(er)$ between actual outputs R_{act} and predicted the output. The total features $fp^{feat} = fp^{feat(1)}, fp^{feat(2)} \dots fp^{feat(n^*)}$ refer to the extracted features got from segmented images and $\hat{n}$ indicates the count of features. The activation function in Eq. (23) and Eq. (24).

$$Hi = AF \left(wg_{bz}^N + \sum_{p=1}^{N_p} wg_{pz}^N fp^{feat} \right) \quad (23)$$

$$R_{pre} = AF \left(wg_{bo}^r + \sum_{z=1}^{N_z} wg_{zo}^r Hi \right) \quad (24)$$

$$F(er) = \arg \min_{\{wg_{bz}^N, wg_{pz}^N, wg_{bo}^r, wg_{zo}^r\}} \sum_{o=1}^{N_o} |R_{act} - R_{pre}| \quad (25)$$

After classifying both ROI and non-ROI regions separately, the ROI images are compressed by JPEG-LA and the non-ROI regions are compressed by the wavelet-based lossy image compression algorithm.

4.4 Solution Encoding

In order to make the compression process more precise in ACM, the weighting factor τ and the maximum iteration $\max^{(i)}$ are selected optimally by the proposed J-WOA. The minimum and maximum bounding limit $\max^{(i)}$ is 100 to 500 and the minimum and maximum bounding limit of τ is 0.1 to 0.5. Fig. 2 represents the solution for adaptive ACM. For classifying the ROI, and non-ROI regions, the GLCM features $fp^{feat(n)}$ are subjected to NN classification, where the weights as shown

in Fig. 3, which is collectively represented as M_1 need to be optimized in order to diminish the error between predicted and actual outcomes. In Fig. 3, $\hat{n}$ is the count of weights that is utilized in NN architecture.

Figure 2. Solution encoding for adaptive active contour model

Figure 3. Solution encoding for optimal trained NN

4.5 Existing Whale Optimization Algorithm

WOA (Mirjalili & Lewis, 2016) was developed by Mirjalili and Lewis, the Australian researchers in the year 2016. They had developed WOA on the inspiration gained from the hunting mechanism of the humpback whales.

- (i) *Encircling Prey*: The humpback whales have an excellent capability of encircling their prey only after localizing the prey. The mathematical formula for the encircling of prey mechanism is shown in Eq. (26) and Eq. (27), in which the current iteration is portrayed as g and both D and

U depicts the coefficient vector. In terms of position as well as magnitude, the best solution is obtained so far is represented as M^* . The distance between the whale and the prey is represented as A .

$$A = |UM^*(g) - M(g)| \quad (26)$$

$$M(g+1) = M^*(g) - D \cdot A \quad (27)$$

In Eq. (26), and Eq. (27) the vectors D and U are analyzed as per Eq. (28) and Eq. (29), respectively. In both the exploration and exploitation phase, the value of q keeps linearly decreasing from 2 to 0 over the iterations.

$$D = 2q.h - q \quad (28)$$

$$U = 2.h \quad (29)$$

(ii) *Bubble-Net Attacking Method (Exploitation Phase)*: It includes the process of shrinking encircling as well as the spiral updating position process.

(a) *Shrinking encircling mechanism*: This is achieved by means of decreasing q value as it is called the control parameter and the value of q lessens linearly from 2 to 0 in the interval $[-1, 1]$. Moreover, it is easier to evaluate the value of the new position of the unique hump-back in between the current position, and the best position, when a random value q lies within the range $[-1, 1]$.

(b) *Spiral updating position*: Eq. (30) and Eq. (31) depicts the mathematical model of the spiral updating position of the whales. The dimension of the logarithmic spiral is depicted by a constant d and a random number m lies within the limit $[-1, 1]$.

$$M(g+1) = A' e^{dm} \cdot \text{Cos}(2\pi m) + M^*(g) \quad (30)$$

$$A = |M^*(g) - M(g)| \quad (31)$$

The final updating formula of WOA is portrayed in Eq. (32) in which the random number between $[0, 1]$ is symbolized as φ .

$$M(g+1) = \begin{cases} M^*(g) - D A & \text{for } \varphi < 0.5 \\ A' e^{dm} \cdot \text{Cos}(2\pi m) + M^*(g) & \text{for } \varphi \geq 0.5 \end{cases} \quad (32)$$

(iii) *Search for Prey (Exploration Phase)*: In the exploration phase, on the basis of the randomly chosen individual whale, the leftovers update their position. This updating is represented by the mathematical formula as shown in Eq. (33) and Eq. (34), in which the position of a randomly selected whale from current whale population is represented as $M_{(rand)}$

$$A = \left| U \cdot M_{(rand)} - M \right| \quad (33)$$

$$M(g+1) = M_{(rand)} - D \cdot A \quad (34)$$

4.6 Jaya Algorithm

JA (Rao, 2016) was introduced by VenkatRao in the year 2015 for generating a solution to the constrained as well as unconstrained optimization problems. the iteration is denoted as g . For each of the iterations, there are j number of design variables where, $s = 1, 2, 3, \dots, h$ and h is the count of candidate solutions. The population size is represented as $y = 1, 2, \dots, h$. During g^{th} iteration, the value of s^{th} variable for the specific y^{th} candidate is represented in Eq. (35). Here, $M_{s,best,g}$ and $M_{s,worst,g}$ are the best and the worst value of s^{th} variable, respectively. Then, in the range $[0,1]$, there are two random values for s^{th} variable at g^{th} iteration is depicted as $t_{1,s,g}$ and $t_{2,s,g}$. In addition, the updated value of $M_{s,y,g}$ is portrayed as $M_{s,y,g}^*$.

The tendency of the obtained solution to get closer to the best solution is indicated as $t_{1,s,g} \left(M_{s,best,g} - \left| M_{s,y,g} \right| \right)$, and the ability of the solution to suppress out the worst solution is indicated as $-t_{2,s,g} \left(M_{s,worst,g} - \left| M_{s,y,g} \right| \right)$. Further, $M_{s,y,g}^*$ gets accepted only if it generates a better functional value.

$$M_{s,y,g}^* = M_{s,y,g} + t_{1,s,g} \left(M_{s,best,g} - \left| M_{s,y,g} \right| \right) - t_{2,s,g} \left(M_{s,worst,g} - \left| M_{s,y,g} \right| \right) \quad (35)$$

4.7 Proposed Hybrid J-WOA Optimization Algorithm

The conventional WOA algorithm (Mirjalili & Lewis, 2016) requires a huge number of steps to reach the optimal solution. Moreover, JA algorithm (Rao, 2016) loses their solution diversity after a few iterations and gets trapped at the local optima. Hence, the proposed model plans to introduce a new hybrid optimization model that hybridizes JA into WOA. In the proposed model, when the absolute random value $|D|$ of WOA is less than 1, the current position of the search agent is updated by Eq. (27) of WOA and when the absolute random value $|D|$ is greater than equal to 1, the updating of the current search agent is done using the update formula of JA algorithm, which is based on Eq. (35). The pseudo-code of the proposed J-WOA model is exhibited in Algorithm 1. Fig. 4 illustrates the flow chart of the proposed model.

Figure 4. Flow chat of the proposed model

5. COMPRESSION PROCESS FOR REGION OF INTEREST (ROI) AND NON-ROI

5.1 ROI Compression by JPEG-LS

The segmented ROI image $\hat{S}_{ROI}$ is fed as input to J-PEG for compression. JPEG-LS algorithm (Zuo, *et al.*, 2015) is utilized to handle the ROI regions. The context modeling, adaptive prediction, and Golomb-Rice coding are the three major processing steps of the JPEG-LS algorithm. In the raster scan mode, the image is processed by the JPEG-LS predictor/modeler. The raster scan mode process the image in two major operating modes viz., “regular” and “run” mode. Typically, for the smooth region, the run mode is coded in the form of pixels, whereas, the regular mode codes the leftover pixels. Further, with the intention of coding the pixel ae , the pixel needs to be predicted with the help of MED. As per Eq. (36), MED is efficient in predicting the gray values v, w and x of 3 neighboring pixels. MED predictor is preferred due to its simplicity and its enhancement in performance over the conventional predictors.

$$a\tilde{e} = \begin{cases} \min(v, w), & x \geq \max(v, w) \\ \max(v, w), & x < \min(v, w) \\ v + w - x, & \text{otherwise} \end{cases} \quad (36)$$

Algorithm 1: Proposed J-WOA

Population of whales $M_i (\hat{i} = 1, 2, \dots, \hat{n})$ is initialized
For each of the search agent, calculate the fitness
M^* is the best search agent
While $(g < \text{maximum iteration})$
For each of the search agent
If1 $(\varphi < 0.5)$
If2 $(D < 1)$
Update the current location of the search agent by Eq.(27)
Else If 2 $(D \geq 1)$
Update the current location of search agent by Eq.(35)
End if 2
Else if 1 $(\varphi \geq 0.5)$
Update the location of the current search agent by Eq.(30)
End if 1
End for
Find whether any of the search agent has gone beyond the search space and amend it
Evaluate the fitness value for each search agent
If there is a better solution, update M^*
$g = g + 1$
End while
Return M^*

In addition, d_{it} represents the prediction endurance and it is determined by subtracting the acquired prediction value from the encoded present value. The mathematical formula for predicting d is shown in Eq. (37). Further, on the basis of four different pixels $\{v, w, x, y\}$, the evaluation of the pixel content takes place. In addition, the difference between the pixels PD_1, PD_2 and PD_3 in Eq. (38), Eq. (39) and Eq. (40), respectively are quantized. The local gradient is indicated by the quantized differences, and hence the activity level surrounding the pixel exhibiting the statistical behavior of errors can be captured.

$$d = ae - a\tilde{e} \quad (37)$$

$$PD_1 = y - w \quad (38)$$

$$PD_2 = w - x \quad (39)$$

$$PD_3 = x - v \quad (40)$$

The total amount of the different context of this algorithm is 365. For each context, the prediction error distribution is evaluated in terms of prediction errors. Further, on the basis of the context-based probabilistic model, the value corresponding to d be an integer and it is encoded. This encoding is accomplished via the Golomb-Rice code. Further, d lies in the range of $[-2^{w-1}, -2^{w-1} - 1]$ and here the pixel bit precision is depicted as w . Before, undergoing the coding process, the non-zero average value of d having geometric distribution (2-sided) is assessed and eliminated by JPEG-LS's bias correction. Further, the positive prediction error, as well as the negative prediction error, is interleaved in order to map the 2-sided geometric distribution into a 1-sided geometric distribution format. The Golomb-Rice code is utilized with the aim of coding the 1-side geometric distribution in an efficient way. Thus the compressed ROI image is referred to as $\hat{S}_{C-(ROI)}$.

5.2 Non-ROI Compression by Wavelet

The non-ROI regions i.e. the blurred region of the image is handled using the Wavelet-based lossy compression (Bruylants, *et al.*, 2015). The segmented non- ROI image $\hat{S}_{N-ROI}$ is fed as input to wavelet for compression. The determination of each and every individual image takes place in the form of a 2D-array of coefficient, and each of the coefficients tells about the brightness level corresponding to each peculiar point. In general, the natural images and the sharp edges among the smooth deviations indicate the smooth color deviation of the image enclosing fine details. In technical terms, the low-frequency variation represents the smooth variation in color, and the high-frequency variation depicts the sharp variations. Here, the image base comprises of the low-frequency components, and the refining of the image is accomplished by the high-frequency components and this, in turn, provides a detailed view of the image. This is the reason behind the high demand for smooth deviations rather than the details. In addition, image decomposition performs the image details and smooth variation with the aid of DWT. In DWT, the range of frequency is split into equal accurate halves by the selected low and high pass filters. The low pass filter is provided for each of the rows during the initialization process. The compressed Non-ROI image is portrayed as $\hat{S}_{C-(N-ROI)}$.

Thus, the compressed images are obtained from the outcomes of both the JPEG-LS algorithm and wavelet-based lossy compression. Further, to reconstruct the original image with no loss in image quality, the decompression using the same reverse is performed.

6. RESULTS AND DISCUSSIONS

6.1 Experimental Setup

The proposed J-WOA-NN image compression technique is carried out in MATLAB, and the results obtained for analysis. In this research work, the image compression data is acquired from the BRATS database (<https://www.smir.ch/BRATS/Start2015#7s8d6f87>) (Access date on 01-03-2019). The total iteration of the algorithmic model is fixed as 25 and the population size is fixed as 10. To the next of the implementation, the proposed J-WOA-NN image compression model is compared with the existing image compression models like LM-NN (Ngia & Sjoberg, 2000), FF-NN (Lv, *et al.*, 2019), GWO-NN (Kohli & Arora, 2018), WOA-NN (Mirjalili & Lewis, 2016) and JA-NN (Rao, 2016) in terms of like MEP, SMAPE, MASE, MAE, RMSE, one-Norm, two- Norm and infinity –Norm. The initial parameter setting of WOA are population size=100 with number of iterations=1000, dimension = 30, and boundary range from 1 to 30. The Jaya algorithm is a novel optimization algorithm which

Figure 5. Experimental results of proposed image compression and decompression

Table 2. Statistical Analysis on proposed compression model over the existing compression models focusing on MEP, SMAPE, MASE, MAE, RMSE, One-Norm, Two-Norm and Infinity -Norm

MEP						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	1.8346	1.8346	1.8346	1.8346	1.8346	1.8346
Worst	88.395	88.316	88.316	88.316	88.395	88.395
Mean	26.743	20.857	18.358	21.529	25.298	26.743
Median	6.7857	5.8485	6.0111	6.0111	6.2703	6.7857
Standard Deviation	28.46	25.767	23.68	26.107	27.977	28.46
SMAPE						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	12.281	12.281	12.281	12.281	12.281	12.281
Worst	133.13	129.84	129.84	129.84	133.13	129.84
Mean	55.047	47.51	44.686	48.332	53.033	43.312
Median	34.126	31.31	32.597	32.597	33.227	31.842
Standard Deviation	38.767	35.187	32.474	35.637	38.142	31.516
MASE						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	1.02	1.02	1.02	1.02	1.02	1.02
Worst	29.505	29.505	29.505	29.505	29.505	29.505
Mean	8.3026	8.3076	8.4664	8.4478	8.054	8.0045
Median	6.2068	6.2019	5.9646	6.3025	5.8482	5.4226
Standard Deviation	6.5812	6.7189	7.006	6.6982	6.65	7.0393
MAE						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	0.01896	0.01896	0.01896	0.01896	0.01896	0.01896
Worst	95.453	95.453	95.453	95.453	95.453	95.453
Mean	23.375	21.882	18.253	21.565	22.391	17.727
Median	5.7484	5.3707	4.3314	5.3165	5.5035	4.2668
Standard Deviation	25.524	24.993	23.222	24.73	25.058	23.018
RMSE						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	0.51231	0.51231	0.51231	0.51231	0.51231	0.51231
Worst	133.56	133.56	133.56	133.56	133.56	133.56
Mean	48.186	46.033	40.692	45.631	46.802	39.77
Median	28.196	24.626	21.488	25.04	25.104	19.784
Standard Deviation	41.628	40.852	38.37	40.522	40.944	37.982

continued on next page

Table 2. Continued

MEP						
One-Norm						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	700.75	700.75	700.75	700.75	700.75	700.75
Worst	3.35×e ⁰⁵	3.35 E+06	3.35 ×e ⁰⁵	3.35 E+06	3.35 ×e ⁰⁵	3.35 ×e ⁰⁵
Mean	9.65 ×e ⁰⁵	9.10 ×e ⁰⁵	7.71 ×e ⁰⁵	8.96 ×e ⁰⁵	9.30 ×e ⁰⁵	7.52 ×e ⁰⁵
Median	2.20 ×e ⁰⁵	2.10 ×e ⁰⁵	1.86 ×e ⁰⁵	2.12 ×e ⁰⁵	2.14 ×e ⁰⁵	1.84 ×e ⁰⁵
Standard Deviation	1.06 ×e ⁰⁵	1.05 ×e ⁰⁵	9.95 ×e ⁰⁵	1.04 ×e ⁰⁵	1.05 ×e ⁰⁵	9.92 ×e ⁰⁵
Two-Norm						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	98.491	98.491	98.491	98.491	98.491	98.491
Worst	25719	25719	25719	25719	25719	25719
Mean	9727.4	9312.8	8262.5	9227.1	9463.9	8087
Median	5241.8	4635.3	4052.5	4682	4667	3740.2
Standard Deviation	8539	8423.8	8002.2	8355.8	8437.8	7948.8
Infinity -Norm						
Metrics	LM-NN (Ngia & Sjoberg, 2000)	FF-NN(Lv, <i>et al.</i> , 2019)	GWO-NN(Kohli & Arora, 2018)	WAO-NN(Mirjalili & Lewis, 2016)	JA-NN(Rao, 2016)	J-WOA-NN
Best	32.86	32.86	32.86	32.86	32.86	32.86
Worst	539.24	539.24	539.24	539.24	539.24	539.24
Mean	259.99	262.84	266.71	262.99	261.64	266.25
Median	287.16	287.72	287.54	287.39	287.29	287.92
Standard Deviation	124.23	126.29	130.5	127.22	125.5	129.95

is parameter less and therefore parameters tuning is not needed. Fig.5 shows the image results for the proposed compression, and decompression model.

6.2 Performance Analysis

Table 2 portrays the performance evaluation of the proposed image compression model in terms of MEP, SMAPE, MASE, MAE, RMSE, L1-Norm, L2- Norm and L-infinity –Norm. The analysis is done for J-WOA-based ACM with J-WOA-NN-based ROI, and non-ROI region classification followed by two compression techniques. For obtaining the performance of ROI, and non-ROI region classification, the training algorithm of NN using proposed J-WOA is compared over the existing conventional optimization algorithms. Table II shows the Statistical Analysis on proposed compression model over the existing compression models with respect to the MEP, SMAPE, MASE, MAE, RMSE, One-Norm, Two-Norm and Infinity –Norm.

6.3 Analysis on Compression Ratio

Fig. 6 manifest the statistical analysis of compression ratio for J-WOA-based proposed compression over the conventional models like LM-NN, FF-NN, GWO-NN, WOA-NN and JA-NN in terms of different scenarios like best case, worst case, mean, median and standard deviation. Here the evaluation is done for various optimized NN combined with J-WOA-based ACM followed by two compression schemes (ROI by JPEG-LS algorithm, non-ROI by wavelet-based lossy compression algorithm).

6.4 Overall Performance Analysis

Table 6 exhibits the overall performance analysis of the proposed J-WOA-ACM+J-WOA-NN model over the existing JCF-LA-ACM model in terms of mean.

7.CONCLUSION

This paper had accomplished a novel image compression framework by following the steps like (i) Segmentation (ii) Feature Extraction (iii) ROI classification (iv) Compression. Initially, adaptive ACM has employed to segment the image into two regions viz., ROI and non-ROI. Further, GLCM features were extracted from the segmented images, which was further subjected to optimal trained NN for classifying the ROI, and non-ROI regions. As the main contribution, the weighting factor and maximum iteration in ACM, and the training algorithm of NN was tuned properly by the hybrid JA-WOA algorithm. Moreover, in the compression phase, ROI regions were compressed by the JPEG-LS algorithm and the non-ROI region were compressed by a wavelet-based lossy compression algorithm. The decompression process was accomplished by reversing the same procedure. In the end, a comparative analysis was made between J-WOA-NN over the conventional models like M-NN, FF-NN, GWO-NN, WOA-NN and JA-NN in terms MEP, SMAPE, MASE, MAE, RMSE, One-Norm, Two-Norm, and Infinity-Norm. From the experimental results, the overall MAE of the proposed J-WOA-NN model was 24% and 18.8% better than LM-NN and FF-NN, 2.7%, 17.6% and 20.6% superior to the traditional models like GWO-NN, WOA-NN, and JA-NN, respectively. Hence, the enhanced image compression model was successfully substantiated by validated analysis. The future extension of the work is aimed at developing image compression techniques with advanced segmentation models based on the hybrid optimization model.

Table 3. Performance Analysis Of Proposed Compression Model Over The Existing Compression Models Focusing On MEP, SMAPE, MASE, MAE, RMSE, One-Norm, Two-Norm And Infinity -Norm

MEP				
Methods	Worst	Mean	Median	Standard deviation
LM-NN (Ngia & Sjoberg, 2000)	0.7%	35%	11%	19%
FF-NN (Lv, <i>et al.</i> , 2019)	0.7%	21%	3.4%	10.5%
GWO-NN (Kohli & Arora, 2018)	0.7%	6.3%	-	2.5%
WOA-NN (Mirjalili & Lewis, 2016)	0.7%	24%	-	11.8%
JA-NN (Rao, 2016)	0.7%	31.7%	3.3%	17.5%
SMAPE				
LM-NN (Ngia & Sjoberg, 2000)	2.5%	22%	6.7%	18.6%
FF-NN (Lv, <i>et al.</i> , 2019)	-	8.8%	1.5%	10.2%
GWO-NN (Kohli & Arora, 2018)	-	3%	2.1%	2.8%
WOA-NN (Mirjalili & Lewis, 2016)	-	10.3%	2.1%	11.5%
JA-NN (Rao, 2016)	2.5%	18.3%	4.2%	17.3%
MASE				
LM-NN (Ngia & Sjoberg, 2000)	-	3.6%	12.9%	7.2%
FF-NN (Lv, <i>et al.</i> , 2019)	-	3.7%	13%	4.2%
GWO-NN (Kohli & Arora, 2018)	-	4.8%	8.4%	0.4%
WOA-NN (Mirjalili & Lewis, 2016)	-	5.2%	14.2%	5.7%
JA-NN (Rao, 2016)	-	0.6%	6.8%	5%
MAE				
LM-NN (Ngia & Sjoberg, 2000)	-	24%	26.4%	10.8%
FF-NN (Lv, <i>et al.</i> , 2019)	-	18.8%	20.7%	8.2%
GWO-NN (Kohli & Arora, 2018)	-	2.7%	2.3%	0.8%
WOA-NN (Mirjalili & Lewis, 2016)	-	17.6%	20%	7.3%
JA-NN (Rao, 2016)	-	20.6%	23.6%	7 8.7%
RMSE				
LM-NN (Ngia & Sjoberg, 2000)	-	21%	29%	9.7%
FF-NN (Lv, <i>et al.</i> , 2019)	-	13.6%	20%	7.7%
GWO-NN (Kohli & Arora, 2018)	-	0.75%	7.9%	1.4%
WOA-NN (Mirjalili & Lewis, 2016)	-	12.9%	21.2%	6.4%
JA-NN (Rao, 2016)	-	15%	21.5%	7.3%
one-norm				

continued on next page

Table 3. Continued

MEP				
LM-NN (Ngia & Sjoberg, 2000)	-	22.1%	16.3%	89.3%
FF-NN (Lv, <i>et al.</i> , 2019)	-	17.3%	12.5%	89.4%
GWO-NN (Kohli & Arora, 2018)	-	2.4%	0.9%	0.3%
WOA-NN (Mirjalili & Lewis, 2016)	-	16.1%	13.5%	89.5%
JA-NN (Rao, 2016)	-	19.1%	14.1%	89.4%
L2-norm				
LM-NN (Ngia & Sjoberg, 2000)	-	16.8%	28.6%	6.9%
FF-NN (Lv, <i>et al.</i> , 2019)	-	13.1%	19.3%	5.6%
GWO-NN (Kohli & Arora, 2018)	-	2.1%	7.7%	0.6%
WOA-NN (Mirjalili & Lewis, 2016)	-	12.3%	20.1%	4.8%
JA-NN (Rao, 2016)	-	14.5%	19.8%	5.7%
Infinity-Norm				
LM-NN (Ngia & Sjoberg, 2000)	-	2.3%	0.2%	4.4%
FF-NN (Lv, <i>et al.</i> , 2019)	-	1.2%	0.06%	2.8%
GWO-NN (Kohli & Arora, 2018)	-	0.17%	0.13%	0.4%
WOA-NN (Mirjalili & Lewis, 2016)	-	1.2%	0.18%	2.1%
JA-NN (Rao, 2016)	-	1.7%	0.21%	3.4%

Figure 6. Analysis on the compressed ratio of the proposed image compression over the existing image compression model for (a) ROI compression by JPEG-LS algorithm (b) Non-ROI compression by Wavelet based-lossy compression

Table 4. Performance Analysis of Proposed Compression Model over the Existing Compression Models Focusing On ROI Compression by JPEG-LS Algorithm and Non-ROI Compression by Wavelet-Based Lossy Compression

ROI compression by JPEG-LS algorithm				
Methods	Worst	Mean	Median	Standard Deviation
LM-NN (Ngia & Sjoberg, 2000)	-	3.5%	3.8%	4.7%
FF-NN (Lv, <i>et al.</i> , 2019)	-	3.8%	3.7%	4.5%
GWO-NN (Kohli & Arora, 2018)	12%	-	25%	3.5%
WOA-NN (Mirjalili & Lewis, 2016)	10.2%	6.8%	3.6%	4.6%
JA-NN (Rao, 2016)	-	-	26.7%	3.2%
Non-ROI compression by Wavelet-based lossy compression				
LM-NN (Ngia & Sjoberg, 2000)	-	0.8%	0.82%	-
FF-NN (Lv, <i>et al.</i> , 2019)	-	0.79%	0.8%	-
GWO-NN (Kohli & Arora, 2018)	-	0.83%	0.84%	-
WOA-NN (Mirjalili & Lewis, 2016)	-	0.81%	0.8%	-
JA-NN (Rao, 2016)	-	0.78%	0.82%	-

Table 5. Performance Analysis of the Proposed J-WOA-ACM+J-WOA-NN Model over the Existing JCF-LA-ACM Model

Measures	JCF-LA-ACM(Kumar, 2019)	J-WOA-ACM+J-WOA-NN
MEP	40.917	26.743
MASE	7.3833	8.0045
RMSE	61.03	39.77
Two-norm	12041	8087
SMAPE	88.51	43.312
MAE	28.463	17.727
One-norm	1.1048×e ⁰⁶	7.5165×e ⁰⁶
Infinity-norm	84.688	266.25
Compression ratio	0.0855	0.08065

Table 6. Performance Analysis of proposed compression model over the existing compression Models

Measures	JCF-LA-ACM(Kumar, 2019)
MEP	34.6%
RMSE	34.83%
Two-norm	32.8%
SMAPE	51.06%
MAE	37.7%
Compression ratio	5.67%

REFERENCES

- Aliaga, D. G., & Carlbom, I. (2005). A spatial image hierarchy for compression in image-based-rendering. *IEEE Image Processing 2005*.
- Bruylants, T., Munteanu, A., & Schelkens, P. (2015). Wavelet based volumetric medical image compression. *Signal Processing Image Communication*, 31, 112–133.
- Chen, Z., Feng, D. D., Cai, W., & Fulton, R. (2005). Performance evaluation of functional medical imaging compression via optimal sampling schedule designs and cluster analysis. *IEEE Transactions on Biomedical Engineering*, 52(5), 943–945.
- Chiranjeevi, K., & Jena, U. R. (2018). Image compression based on vector quantization using cuckoo search optimization technique. *Ain Shams Engineering Journal*, 9(4), 1417–1431.
- Creusere, C. D. (1997). A new method of robust image compression based on the embedded zerotree wavelet algorithm. *IEEE Transactions on Image Processing*, 6(10), 1436–1442.
- de Queiroz, R. L., Fan, Z., & Tran, T. D. (2000). Optimizing block-thresholding segmentation for multilayer compression of compound images. *IEEE Transactions on Image Processing*, 9(9), 1461–1471.
- Francisco, N. C., Rodrigues, N. M. M., da Silva, E. A. B., & de Faria, S. M. M. (2012). A generic post-deblocking filter for block based image compression algorithms. *Signal Processing Image Communication*, 27(9), 985–997.
- Fu, C., Yi, Y., & Luo, F. (2018). Hyperspectral image compression based on simultaneous sparse representation and general-pixels. *Pattern Recognition*, 116, 65–71.
- Karayannis, N. B., Pai, P., & Zervos, H. (2008). Image compression based on fuzzy algorithms for learning vector quantization and wavelet image decomposition. *IEEE Transactions on Image Processing*, 7(8), 1223–1230.
- Kim, S., & Cho, N. I. (2014). Hierarchical Prediction and Context Adaptive Coding for Lossless Color Image Compression. *IEEE Transactions on Image Processing*, 23(1), 445–449.
- Kohli, M., & Arora, S. (2018). Chaotic grey wolf optimization algorithm for constrained optimization problems. *Journal of Computational Design and Engineering*, 5(4), 458–472.
- Kumar, S. (2019). Region of Interest-based Adaptive Segmentation for Image Compression: Jaya-Lion Mathematical Approach. *International Journal of Computers and Applications*, ●●●, 1–12.
- Lahdir, M., Hamiche, H., Kassim, S., Tahanout, M., & Addouche, S. (2019). A novel robust compression-encryption of images based on SPIHT coding and fractional-order discrete-time chaotic system. *Optics & Laser Technology*, 109, 534–546.
- Lankton, S., & Tannenbaum, A. (2008). Localizing Region-Based Active Contours. *IEEE Transactions on Image Processing*, 17(11).
- Lee, C., Youn, S., Jeong, T., Lee, E., & Serra-Sagristà, J. (2015). Hybrid Compression of Hyperspectral Images Based on PCA With Pre-Encoding Discriminant Information. *IEEE Geoscience and Remote Sensing Letters*, 12(7), 1491–1495.
- Lin, T., & Hao, P. (2005). Compound image compression for real-time computer screen image transmission. *IEEE Transactions on Image Processing*, 14(8), 993–1005.
- Lin, Y., Amit, A., Marcellin, M., & Bilgin, A. (2018). Task-Based JPEG 2000 Image Compression: An Information-Theoretic Approach. *2018 Data Compression Conference*, 423–423.
- Lv, L., Zhao, J., Wang, J., & Fan, T. (2019). Multi-objective firefly algorithm based on compensation factor and elite learning. *Future Generation Computer Systems*, 91, 37–47.
- Miaou, S., Ke, F., & Chen, S. (2009). A Lossless Compression Method for Medical Image Sequences Using JPEG-LS and Interframe Coding. *IEEE Transactions on Information Technology in Biomedicine*, 13(5), 818–821.
- Mirjalili, S., & Lewis, A. (2016). The Whale Optimization Algorithm. *Advances in Engineering Software*, 95, 51–67.

- Ngia, L. S. H., & Sjoberg, J. (2000). Efficient training of neural nets for nonlinear adaptive filtering using a recursive Levenberg-Marquardt algorithm. *IEEE Transactions on Signal Processing*, 48(7), 1915–1927.
- Pang, C., Zhou, R., Hu, B., Hu, W. W., & El-Rafei, A. (2019). Signal and image compression using quantum discrete cosine transform. *Information Sciences*, 473, 121–141.
- Rao, R. V. (2016). Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. *International Journal of Industrial Engineering Computations*, 7, 19–34.
- Sanchez, V., Abugharbieh, R., & Nasiopoulos, P. (2010). 3-D Scalable Medical Image Compression With Optimized Volume of Interest Coding. *IEEE Transactions on Medical Imaging*, 29(10), 1808–1820.
- Sanchez, V., Nasiopoulos, P., & Abugharbieh, R. (2008). Efficient Lossless Compression of 4-D Medical Images Based on the Advanced Video Coding Scheme. *IEEE Transactions on Information Technology in Biomedicine*, 12(4), 442–446.
- Shen, L., & Rangayyan, R. M. (1997). A segmentation-based lossless image coding method for high-resolution medical image compression. *IEEE Transactions on Medical Imaging*, 16(3), 301–307.
- Srikanth, R., & Ramakrishnan, A. G. (2005). Contextual encoding in uniform and adaptive mesh-based lossless compression of MR images. *IEEE Transactions on Medical Imaging*, 24(9), 1199–1206.
- Taquet, J., & Labit, C. (2012). Hierarchical Oriented Predictions for Resolution Scalable Lossless and Near-Lossless Compression of CT and MRI Biomedical Images. *IEEE Transactions on Image Processing*, 21(5), 2641–2652.
- Turcza, P., & Duplaga, M. (2017). Near-lossless energy-efficient image compression algorithm for wireless capsule endoscopy. *Biomedical Signal Processing and Control*, 38, 1–8.
- Vallabhaneni, R. B., & Rajes, V. (2018). Brain tumour detection using mean shift clustering and GLCM features with edge adaptive total variation denoising technique. *Alexandria Engineering Journal*, 57(4), 2387–2392.
- Velisavljevic, V., Beferull-Lozano, B., & Vetterli, M. (2007). Space-Frequency Quantization for Image Compression With Directionlets. *IEEE Transactions on Image Processing*, 16(7), 1761–1773.
- Wang, L., Bai, J., Wu, J., & Jeon, G. (2015). Hyperspectral image compression based on lapped transform and Tucker decomposition. *Signal Processing Image Communication*, 36, 63–69.
- Wu, X., Zhang, X., & Wang, X. (2009). Low Bit-Rate Image Compression via Adaptive Down-Sampling and Constrained Least Squares Upconversion. *IEEE Transactions on Image Processing*, 18(3), 552–561.
- Yang, F., Mou, J., Sun, K., Cao, Y., & Jin, J. (2019). Color Image Compression-Encryption Algorithm Based on Fractional-Order Memristor Chaotic Circuit. *IEEE Access: Practical Innovations, Open Solutions*, 7, 58751–58763.
- Yang, J., & Ma, J. (2019). Feed-forward neural network training using sparse representation. *Expert Systems with Applications*, 116, 255–264.
- Zhou, N., Zhang, A., Zheng, F., & Gong, L. (2014). Novel image compression–encryption hybrid algorithm based on key-controlled measurement matrix in compressive sensing. *Optics & Laser Technology*, 62, 152–160.
- Zhu, S., Zhu, C., & Wang, W. (2018). A Novel Image Compression-Encryption Scheme Based on Chaos and Compression Sensing. *IEEE Access: Practical Innovations, Open Solutions*, 6, 67095–67107.
- Zuo, Z., Lan, X., Deng, L., Yao, S., & Wang, X. (2015). An improved medical image compression technique with lossless region of interest. *Optik (Stuttgart)*, 126(21), 2825–2831.

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